An Investigation into Factors Which Explain the Scores and Voting Patterns of the Eurovision Song Contest.

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I certify that this dissertation which I now submit for examination for the award of MSc in Computing (Data Analytics), is entirely my own work and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the test of my work.

This dissertation was prepared according to the regulations for postgraduate study of the Dublin Institute of Technology and has not been submitted in whole or part for an award in any other Institute or University.

The work reported on in this dissertation conforms to the principles and requirements of the Institute's guidelines for ethics in research.

Signed: Oisín Leonard

Date: **25 January 2018**

ABSTRACT

The Eurovision Song Contest (ESC) is an annual international television song competition. Participating countries send a group or individual artist to perform an original song at the competition. The winner is decided by all participating countries using a voting system that incorporates both a public televote and an expert jury vote. Countries are excluded from voting for their entry and the country with the highest score wins. A high scoring performance and the voting patterns of the ESC can be explained by a complex set of factors. These factors can be divided into three groups; performance factors, competition factors and external factors. Performance factors relate to the performance itself, such as the song and the music. Competition factors relate to the way the competition is run and organised, such as the type of voting method used and the order of appearance for the performers. External factors encompass the social, cultural and political factors that influence voting at the Eurovision. The research presented here focuses on among other factors, whether voting blocs, music factors derived from Echo Nest services and migration patterns can explain the points and voting patterns of the 2016 ESC. The data was stratified into three datasets based on the voting systems; combined vote, televote and jury vote. A multiple linear regression model was fitted to each dataset and the significance of the predictor variables in explaining the response variable Points were evaluated using T-tests. The results showed that both the voting blocs and migration patterns were significant in explaining the scores and voting patterns of the competition. With regards to the music factors, the most successful songs appeared to be more acoustic and less dance orientated.

Key words: *2016 Eurovision Song Contest, Factors, Multiple Linear Regression, T-tests*

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1. INTRODUCTION

1.1 Background

Since the first Eurovision Song Contest (ESC) in 1956, the competition has expanded and developed into one of the most watched non-sporting events of the twenty first century. Currently up to 42, mostly European, countries participate in the competition each year. The competition consists of a set of semi-finals and a final. In the final of the competition, participating countries vote for their favourite performing countries and the country with the highest score wins. This research will focus on the 2016 instalment of the competition which was hosted in Stockholm Sweden and ran from the 10th May untill the 14th May. Forty-two countries participated across two the semi-finals and the final. Eighteen countries participated in each of the two semi-finals, with the top 10 ranking performances progressing to the final. The five sponsoring nations Italy, France, Germany, United Kingdom and Spain, and the host nation Sweden were not required to perform in the semi-finals. According to the official ESC website, the viewership of the competition has continued to increase from year to year. Notably, the 2016 competition was viewed by more than 204 million people, an increase of 5 million in comparison to the 2015 contest. Furthermore it was the first competition to broadcast the final in the United States of America.[1] The research in this dissertation aims to investigate the factors that influence the voting patterns in the ESC with the objective of building a model that can contribute towards predicting the winning song.

A special note should be made on the 2016 ESC voting system, which featured substantial change in comparison to previous competitions. The final results are a combined and equally weighted total between the public televote and expert jury vote. Each participating country has two sets of votes to distribute among the other performing countries, one set coming from the televote and the other set coming from the jury vote. The votes vary on a magnitude ranging from 1 to 8, and then 10 and 12. The televote comes from the audience at home, who vote for performances via telecommunication

[1] Eurovision. (2016). Stockholm 2016. Retrieved from https://eurovision.tv/event/stockholm-2016

services provided by the contest. The jury vote comes from a panel of specially selected music and performance experts, who assign votes based on their expertise.[2,3] From an analytical standpoint, appropriate inferences can be made on the televote as a popular vote and the jury vote as a specialist vote. Further detail on the data involved is provided in Chapter 3 Design and Methodology. Tables on the results of the competition can be found in Appendix A.

1.2 Research Project / Problem

In order to score highly at the ESC a performance needs to stand out and appeal to a large proportion of the audience. As such, there are a lot of factors to consider when trying understand why some performances are more successful others. These factors can be divided into three broad groups; performance factors, competition factors and external factors. Performance factors relate to the type of song, music and dance being used in the performance. It is also important to recognise that there are other factors outside the control of the performer such as competition factors and external factors that influence the final scoring at the ESC. Competition factors relate to the way the competition is run and organised, such as the type of voting method used and the order of appearance for the performers. External factors encompass the social, cultural and political factors that influence voting at the Eurovision.

This research focuses on how effectively three specific subgroups of factors can explain the scores and voting patterns of the 2016 ESC. The three subgroups are Echo Nest music factors, migration factors and voting blocs. The Echo Nest music factors are music related factors derived using Echo Nest services available on Spotify. These services provide measurements of music features such as key, tempo or energy. Voting blocs are communities of countries who systematically exchange votes regardless of the performance quality. The presence of voting blocs in the ESC has been consistently identified in past research. The effects of migration patterns have also been identified and observed in the ESC. It is often insinuated that a significantly large proportion of

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[2] Jordan, P. (2016). Biggest change to Eurovision Song Contest voting since 1975. Retrieved from https://eurovision.tv/story/biggest-change-to-eurovision-song-contest-voting-since-1975

[3] Jordan, P. (2016). Turning back time. Retrieved from https://eurovision.tv/story/turning-back-time-2016-in-review

nationals living abroad can swing the televote of the residing country towards their home country.

1.3 Research Objectives

1. Define the performance, competition and external factors to be investigated in the research.

2. Collect data on the defined performance, competition and external factors from the 2016 ESC.

3. Perform an exploratory data analysis on the collected data; derive descriptive statistics and construct visualisations.

4. Process the collected data in accordance with the exploratory data analysis; handle incomplete observations, standardise the data, dummy encode the categorical factors and perform a data reduction.

5. Iteratively fit multiple linear regression models to three stratified datasets based on the voting system; combined vote, televote and jury vote.

6. Evaluate the required model assumptions and fit of the fitted models using visualisations and statistical tests.

7. Construct T-tests using the estimated coefficients of the final models to test the significance of the predictor variables in explaining the response variable points.

8. Investigate the effects of the predictor variables on the response variable points in the final model by noting the signs of the estimated coefficients and the differences in R-squared with the inclusion or exclusion of predictor variables.

1.4 Research Methodologies

The research presented here is secondary research as it predominantly involves the summarising, gathering and synthesising of existing research. The factors investigated were collected from freely available online resources, the vast majority of which were previously researched and identified in academic journals and proceedings.

The objective of this research is quantitative, in that numeric data is utilised to make inferences about the scores and voting patterns of the 2016 ESC. A multiple linear regression model was fitted to the collected data and the significance of each predictor variable in explaining the response variable points was tested using T-tests. Inferences on the practicality of these factors in explaining the scores and voting patterns were then drawn from the results.

There are two forms to the research; constructive and empirical. The research is constructive as a solution to existing problem of explaining the scores and the voting patterns of the 2016 ESC is developed. The research is also empirical as the feasibility of the solution is tested and supported with empirical evidence.

Inductive reasoning is the core form of reasoning utilised in this research, as the 2016 competition is used as a specific instance to make a general conclusion for all related ESC.

1.5 Scope and Limitations

The scope of this research is to investigate whether voting blocs, migration factors and Echo Nest music factors can explain the scores and voting patterns of the 2016 ESC. The research aims to investigate whether the historic voting blocs still have an impact today, and if so, what is that effect on the points and scores. The research also aims to identify whether migration trends in Europe have an impact on the points and voting patterns of the 2016 ESC. Specifically, the research investigates whether a significantly large proportion of citizens from one country living in another country, will influence the vote of the residing country towards the home country. The music is very integral to the entertainment aspect of the competition, furthermore it is very tough to quantify musical concepts. This research aims to determine whether musical factors derived using Echo Nest services can explain the scores.

Overall, the research aims to uncover what drives success in the competition and how the audience votes. This in turn will shed light on the influence of the performers, the competition and the audience on the results of the event. This is particularly relevant to the performers themselves, as a winning performance benefits the artist with short term exposure and air time.

There are a number of limitations to this research. Firstly, due to both the size and the voting structure of the 2016 ESC, the results can only be generalised to ESC with similar sizes and voting structures; such as the 2015 and 2017 competition. However, the older competitions that were either smaller in size or utilised a different structure may not be on comparable scales. Furthermore, the investigated factors themselves may have developed over time, making these results incomparable with older competitions. For example the migrations trends and tendencies seen in the 2016 competition may not be comparable to the migration trends and tendencies seen in older competitions.

1.6 Document Outline

1.6.1 Literature Review and Related Work

The literature review is divided into three sections. The first section reviews previous research on the performance, competition and external factors of the competition. The second section explores the research into the voting blocs using social network analysis. The final section reviews other relevant papers to the research, specifically the use of Echo Nest music services in pop hit classification and the effect the order of appearance had on the Queen Elizabeth Music competition. The key points and methodologies from each of the papers will be provided, as well as a short critique on their relevance to this research. The chapter will end by identifying the gaps in the literature review that this research attempts to answer.

1.6.2 Design and Methodology

The design and methodology chapter is outlined using the CRISP-DM lifecycle. There are six sections to this chapter, which correspond to the six stages of the CRISP-DM lifecycle. The chapter begins by exploring the research problem. Next all necessary methods related to understanding the data are explored. This is followed by a section on the data processing techniques utilised in the research. The fourth section is on the data modelling stage, where all the methods associated with modelling the data are described. The fifth section outlines how the model assumptions and fit are evaluated. The final section describes how the results of the model will be used to answer the research problem. The key findings will be extracted from the final models using variety of methods; most notably T-tests to test whether the predictor variables can explain the response variable points.

1.6.3 Implementation and Results

The implementation and results chapter documents the results of the design and methodology chapter. There are six sections to the chapter; data collection, exploratory analysis, data processing, data modelling, model evaluation and results. The data collection section summarises the sources and results of the data collection. The exploratory analysis section explores the visualisations and descriptive statistics derived from the collected data. The data processing section outlines how the collected data was processed in accordance with the exploratory analysis. This includes the handling of missing observations, dummy encoding the categorical variables, standardising the numeric variables to be on a common scale and magnitude, and finally performing a data reduction to facilitate the data modelling stage. The data modelling stage itself outlines the results of iteratively fitting models to three stratified datasets based on the voting system; combined vote, televote and jury vote. The model evaluation section outlines results of the model's fit and whether model's assumptions are valid. The final chapter outlines the keys findings from the fitted model. These in turn will be used to answer the research problem.

1.6.4 Analysis, Evaluation and Discussion

The analysis, evaluation and discussion chapter utilises the results from the previous chapter and answers the research problem. There are four sections to this chapter that discuss whether the voting blocs, migration patterns or Echo Nest music factors can explain the scores and voting patterns of the 2016 ESC. Furthermore this chapter discusses how the results agree or disagree with previous research on the ESC, and gives possible reasons for the results.

1.6.5 Conclusion

The concluding chapter gives an overall summary of the research. The chapter gives an overview of the research problem, the methodologies used and results of the analysis. The chapter also discusses the impact and contribution of this research to the existing body of research on the ESC. Furthermore the chapter makes some suggestions for any future research on this topic.

2. VOTING IN THE ESC: A LITERATURE REVIEW

2.1 Introduction

This chapter outlines research relevant to voting in the ESC. The chapter starts by discussing factors related to the music, the performance and competition which can be considered to influence voting in the ESC. It then moves on to consider the geographic, cultural influences and the historic voting blocs of the competition and how these influence voting. Finally the use of Echo Nest services in pop hit classification and how this can be used to model music performance is discussed. The identified gaps that dissertation attempts to answer will also be outlined through this chapter.

2.2 ESC Performance and Competition Factors

There has been considerable research into how competition and performance influence the final scores and voting patterns of the ESC. A lot of the factors identified in previous research relate to this dissertation project and shall be incorporated in some shape or form in the model. The research into the performance factors has investigated how factors such as the gender of lead singers, compositional musical elements and use of musical instruments influence the final scores and rankings of the competition. The research into the competition factors has investigated how the order of appearance and the presence of semi-finals influence the scores.

2.2.1 Mere-Exposure Effect

Verrier (2012) investigated whether the mere-exposure effect influenced the voting patterns of the ESC. Verrier defines the mere-exposure effect as the increased tendency of someone to appreciate something more after repeated exposure to it. His research utilised the ESC as a two-round event; where contestants who performed in the semi-final would be more familiar to the audience in the final. The semi-finals can be viewed as a proxy variable for familiarity, as the audience is more likely to view the semi-final in which their own country is performing. Data was collected over a four year period from the 2008 competition to the 2011 competition. The data consisted of the points given in the ESC finals, indicating whether the countries exchanging votes had performed in a semi-final. Verrier modelled the voting patterns of the audience using a two-way mixed ANOVA model to analyse how each of the participating countries distributed their points. The results showed evidence that the mere-exposure effect was influencing the scores of the ESC final. Performances that had previously participated in a semi-final were more likely to receive more points than performances that had not previously participated in a semi-final. This evidence indicates that the mere-exposure effect, as well as other previously identified factors such as cultural and geographical closeness, influences the points and voting patterns of the ESC.

As the mere-exposure effect has been identified to have an effect on the points and voting patterns of the ESC, it shall be incorporated into this research as a round identifier. It should be noted that Verrier does not empirically investigate the influence of migration patterns, voting blocs and Echo Nest music factors in his research.

2.2.2 Voting Method

Haan, Dijkstra and Dijkstra (2005) compared the differing results of the jury vote with the televote in the ESC. Throughout history, there have been a long discussion on whether experts can judge the true quality of cultural output. Similarly, there have been discussions into whether the opinion of the general public has any merit. Their research attempts to draw conclusions on this discussion by analysing the difference in judgement between the experts and the general public in the ESC. Two specific datasets were developed for the research, one for the ESC finals and one for national finals of participating countries. The datasets were modelled using a multiple linear regression model, with results showing that the experts were unambiguously better judges of quality than the general public, as their results were less biased by irrelevant and exogenous factors that do not influence the quality of the performance output. However, the results also showed that the order of appearance does influence both the experts and the general public. Participants who performed earlier or later on in the competition did substantially better on average, even though the order of appearance was determined randomly prior to the start of the competition.

These findings are relevant to this dissertation as the data being used will be stratified base on the voting method; combined vote, televote and jury vote. The televote and jury vote show different characteristics, and are sensitive to certain factors. I would forecast that the televote data will be more susceptible to exogenous factors, such as migration pattern and cultural factors. Furthermore, they note the effect of the order of appearance on the scores in the competition and utilise a multiple linear regression to model the data. It should also be noted that they not empirically investigate the effect of migration patterns, Echo Nest music factors and historic blocs on the results.

2.2.3 Order of Appearance

Flores and Ginsburgh (1996) researched how the order of appearance for participants in the Queen Elisabeth Musical Competition affected the final scores. The world renowned Queen Elisabeth Musical Competition specialises in classical violin and piano. It is considered among the classical music community as being one of the most prestigious and demanding competitions. It attracts approximately forty violinists and eighty-five pianists, from many countries around the world. Winning the competition has a significant impact on the future career of the performer. Flores and Ginsburgh's paper aimed at investigate whether the final ranking is fair, or whether the rankings depend on confounding factors related to the organisation of the competition. They specifically examined whether the order of appearance of a performer influenced their final ranking. The results showed that the final ranking was not independent of the day in which the performer participated. In fact, there was a significant statistically effect found, especially for piano performers. Those who appeared earlier on in the competition had a lower chance of being ranked higher in the competition. In contrast those who performed later on in the competition had a higher chance of being ranked higher up in the competition. They infer that this result was due to the way the competition was organised, and suggested some changes to be implemented in order to avoid this unfair bias.

Ginsburgh and van Ours (2002) analysed how the order of appearance affected the judge's opinion and results in the Queen Elizabeth musical competition. Pianists who previously achieved high scores and won the Queen Elizabeth musical competition had been subsequently rewarded with success in their careers. Pianists who scored highly in the competition were more likely to be offered record deals. Data was collected on eleven consecutive competitions, with the aim of determining whether the rankings of performers were dependent on the order of their appearance. Results showed that the order and time of appearance were good predictors of the final rankings. As the order and time of appearance are randomly determined prior to the competition, they cannot affect later success and are unique variables for explaining the final rankings of the competition. However success in the competition was consistently found to have a positive impact on the performer's future career, regardless of their true quality. Furthermore, the opinion of critics was determined to be more influenced by the rankings than by the true quality of the performer. The research concluded that the judges' rankings were affected by the order and timing of appearance and thus sheds doubt on their ability to cast fully objective judgements.

The research of Flores, Ginsburgh and van Our research directly influenced this research by suggesting the inclusion of the order of appearance as an additional predictor factor in explaining the points score of the ESC. Furthermore this research will attempt to analyse the effect the order of appearance has on the points, in addition to other predictor variables such as migration patterns, Echo Nest Musical factors and voting blocs.

2.3 Geographical and Cultural Factors

There has also been considerable research into the effect of geographical and cultural factors on the voting patterns of the ESC. These factors would be outside the control of the performers and the competition.

Ginsburgh and Noury (2005) have investigated the effects of cultural voting in the ESC. Their research aimed to identify the determinants of success in the ESC, starting with the 1956 competition. Their dataset allowed them to test for the presence of vote trading between countries. Although the distribution of votes may appear to be resulting from logrolling, results indicate that they may actually be driven by linguistic and cultural associations between the participating countries. They utilised a multiple linear regression model to analyse the significance of the linguistic and cultural factors in explaining the scores of the ESC. The linguistic and cultural factors modelled include the lexical distance between language countries, power distance, individualism, masculinity and uncertainty avoidance. They determined the effect of vote trading between countries, if it existed, was small. In fact, once the cultural and linguistic factors were incorporated into the model, the effects of vote trading disappeared altogether. Furthermore, they suggested that patterns of migration may also be a determinant of success, whereby migrants living in a participating country were more likely to vote for their home country. Furthermore they suggested that the migrants were more likely to participate in voting for the competition than the country's nationals, thus biasing the vote in favour of their home country.

Munoz-Zavala and Hernandez-Aguira (2009), Ocha-Zezzatti, Hernandez-Aguira, Jons and Padilla (2008) and Ochoa-Zezzatti, Munoz-Zavala and Hernandez-Aguira (2008) proposed three separate hybrid systems that determined the ranking of particular participants in the ESC. Each paper aimed to create a hybrid prediction model, which combined data mining techniques and partial swarm optimisation to predict the ranking of either a new, debutant or returning country in the ESC. They collected data on the voting patterns and distribution of points from both the jury vote and televote for every ESC. Similar to previous research, in order to account for as much variation as possible, they proposed models that incorporated factors that represent both voting behaviour and cultural characteristics. Furthermore, historical voting information was incorporated into the models as well as factors that described the characteristics of the music, lyrics and performance. In particular, these performance factors included the language of the song, the type of lyrics used and the genre of music being performed. They aimed to utilise this detailed dataset to determine the qualities of a successful performance in the ESC, and apply it to new, debutant or returning countries. Furthermore, like other papers, the setup of the model, allowed them in turn to directly test the presence of vote trading in the ESC. Similar to Ginsburgh and Noury's (2005) research, their results showed that distribution of votes is most likely driven by linguistic and cultural association between the participating countries, rather than vote trading between countries.

Spierdijk and Vellekoop (2006) have investigated the effect of geographical, cultural and religious factors on the voting patterns of the ESC. Their research aimed to test whether the voting between countries was politically charged by examining geographical factors.

They collected data on votes cast between the 1975 competition and the 2003 competition. They defined a variety of variables to distinguish political voting from biases based on cultural, linguistic, ethnic, and religious factors. Furthermore, they explored the voting patterns for each country separately. The results confirmed that the geographical factors did affect and influence the voting patterns. Even after accounting for cultural, linguistic and other factors many countries had biases towards the songs of neighbouring countries, which suggested that geographical preferences may have reflected political voting. Several countries preferred the songs of participants who shared a similar religious background, while other countries showed the contrary. By collecting data on Turkish diaspora, they showed that countries with a substantial Turkish population favoured the Turkish songs. These results showed that religious and patriotic voting has significantly increased since the introduction of the televote. Although their analysis uncovers significant geographical patterns that suggested political voting, they did not establish any empirical evidence for the claims of political voting purely amongst geographical groups of countries, such as the Nordic and Baltic countries.

Spierdijk and Vellekoop (2009) researched the effect of utilising peer based voting systems in the ESC. Their research aimed to assess whether common characteristics of jury vote or televote affected the outcomes of the overall voting system, and to what extent these common features resulted in voting bias. They utilised the ESC as the basis for their research, as there is a vast amount of historical voting data available online. For each individual country, they analysed the magnitude of bias resulting from the common factors. As a result, they tested for the effect of regional voting blocs between groups of countries. The results gave strong evidence for the presence of voting bias in the ESC. The identified bias was a product of factors related to geography, culture, language, religion and ethnicity. The research concluded that voting countries had a preference for songs in a related language, being performed by a neighbouring country who had similar culture and religious customs. However, this was not the case for all participants, in fact the voting bias for some participant countries consisted of unexplainable noise. Although their research confirmed voting bias as a product of geographical patterns that in turn suggested political voting, there was sparse evidence to support the publicly debated accusations of regional voting blocs by certain countries.

Budzinski and Pannicke (2016) researched how globalization has influenced the spread and success of pop music amongst participating countries in the ESC. They outlined how globalization developed from the digitalization of cultural outputs and the international availability of the internet. Globalization processes homogenized and increased the demand for goods, such as music and films, across countries worldwide. This implies that the same music hits and artists should be popular across multiple countries and cultures. Budzinski and Pannicke tested this using the voting patterns and scores of ESC. They collected data spanning across 41 years of the competition, from 1975 to 2016. This period saw the rise of globalisation both world-wide and within the ESC. The voting patterns in the ESC should have become concentrated towards the leading artists and less structured by regional differences in musical taste. To test concentration trends in the distribution of points, they constructed a variety of different indicators. They calculated the concentration ratio which represented the total number of points of the top three, five and ten performances in the competition. They then calculate the Herfindahl-Hirschman-Index which measured the market concentration. Finally they derived the Gini-Coefficient for each competition. They modelled these indicators using time-series analysis and tested the trend lines for statistical significance. The results showed no evidence to support their hypothesis that voting patterns had become concentrated towards the leading artists. Furthermore, some of the derived indicators suggested a weak de-concentration trend in the voting patterns of the ESC.

Blangiardo and Baio (2014) investigated the ESC for signs of biased voting by modelling the voting patterns using Bayesian hierarchical models. The differences between the televote and jury vote has resulted in suggestions of tactical voting, whereby tactical voting induces bias in the final results. Blangiardo and Baio investigated the voting patterns for signs of positive or negative bias, based on geographical proximity, migration and cultural characteristics. They modelled the problem using Bayesian hierarchical models, which are effective in dealing with complex data and relationships. They collected data on the final round of votes from the 1998 competition to the 2012 competition, as the televote was introduced from the 1998 competition onwards. The data included the language in which each song was sung, the gender of the performer, the type of performance, migration stocks and the geographical neighbouring structures. Most notably, the migration stocks originated from the World Bank and were intended to account for a diaspora effects. As such, biased voting occurs due to large stocks of people who originated from the performer’s country, currently residing in the voter’s country. The neighbouring structure, was a binary variable that indicated whether the countries shared a border. This neighbour indicator also acted as an indicator for similar geographical characteristics. The results from the model concluded that no real negative bias appeared in the televote. Furthermore, there appeared to be no substantial negative bias occurring across all pairs of participating countries. However a positive bias ranging from moderate to substantial did exist. This positive bias could be explained by strong similarities in culture, more so than geographical proximity and migrations.

The research on geographical and cultural factors is relevant to this dissertation in a number of ways. Firstly, although a number of papers don’t formally test for the effects of migration patterns, they suggest it as a possible determinant of success. Spierdijk and Vellekoop (2006) did specifically test for the effects of the Turkish diaspora, and Blangardo and Baio (2014) attempted to model the effect of migration patterns using population stocks. A core part of this research is to expand upon this gap and test whether migration patterns across participating countries do indeed have an impact on the voting patterns of the 2016 ESC. Secondly, this research will utilise a similar methodology, modelling the data using a multiple linear regression model. Furthermore, it should be noted they do not test the effect of voting blocs and Echo Nest music factors on the voting patterns. Finally, they also concluded that the televote system has increased the amount of bias in the voting patterns of the ESC. This research will similarly analyse purely the televote data, to see which factors best explain the bias and variance in the televote.

2.4 Voting Blocs of the ESC

There has been extensive research into the use of social networks to model the ESC voting patterns of participating countries. Research indicates that voting blocs or communities exist within the competition. It is thought that these voting blocs are driven by underlying social, geographical, political and cultural factors. For example, neighbouring countries within a geographical region, such as the Balkans or Scandinavia tend be biased to vote for one another based on common similarities. This research directly relates to the current research as some of the methods discussed below will be used to extract voting communities from the 2016 ESC, and use them to model the scores of the competition.

Yair (1995) produced one of the first ESC papers, in which he modelled the voting structures of the competition. He collected data on the voting patterns from the 1972 competition to the 1992 competition. Yair believed that the various political and cultural relationships within Europe could be inferred from the voting patterns of the ESC. A voting matrix for the competition was constructed by averaging over the total point's award from country to country. The voting matrix revealed a generic structure that acted as a proxy for the international relationships of Europe. Yair also analysed the fairness of the competition using social network analysis and cluster analysis. He analysed the relationships among participating countries in the network and concluded the existence of voting blocs in the data. He suggested that the strength of relationships within the voting blocs was determined by different sentiments and interests among the countries. Yair viewed the Western bloc as a coalition of countries based on similar historical and political factors. He determined that the strength of relationships in the Northern bloc were the product of similar cultural and linguistically factors. Similarly, the Mediterranean Bloc achieved its cohesion from similar cultural factors. The results concluded that the Western bloc dominated the entire structure of the voting network, whereby winning the majority of points and contests. This bias counteracts the apparent fairness of the competition with the result that peripheral nations, such as Monaco and Malta do not have an equal chance of winning the contest compared to the western countries such as England, France and Germany.

Yair and Maman (1996) investigated the voting patterns of dominant countries in the ESC. Yair's earlier paper focused on identifying voting blocs in the ESC, this study focused on identifying the voting patterns between the identified voting blocs. The competition promotes an unbiased voting procedure by allowing equal voting opportunities for the participating countries. Yair and Maman feel the competition had drifted away from its ideal principles to a competition which is systematically driven by biased voting blocs. They utilised social network analysis and block density analysis to identify the patterns of dominance between voting countries, whilst maintaining that all other countries had no independent relationships among them. Patterns of dominance were found to be present in the Western bloc due to its unique structural position. The results showed that the peripheral countries in the voting network tended not to exchange votes with one another. Furthermore, it was the relationship between peripheral countries and other countries or that made them the most important countries in the competition. In fact the Western bloc benefited significantly from both internal voting, where its members exchange points amongst themselves, and peripheral voting. The Northern and Mediterranean blocs on the other hand, appeared to avoid each other, which resulted in any surplus votes from the blocs being allocated to the Western bloc.

Orgaz, Cajias and Camacho (2014) compared the effect of the televote system with the jury vote system in the ESC. The televote system encourages the audience at home to call up and vote for their favourite performance. Due to this high level of involvement from the general public, inferences on both social and political tendencies can be extracted from the ESC voting patterns. Data was collected over two independent five year periods, the jury system from the 1992 to 1996 competitions, and the televote system from the 2004 to 2008 competitions. The independent two time periods allowed them to compare and contrast changes in the voting patterns between the two systems. They utilised social network analysis to investigate the impact of the televote and jury vote on the scores. Results concluded the presence of voting blocs in the voting network of the ESC. The voting blocs were derived from the two datasets using cluster percolation and edge betweenness. Once the voting blocs were identified, they were observed across the two time periods to determine how they evolved and distributed their votes. They suggested that the countries within the voting blocs share historical, social and cultural similarities. They also identified evidence of diaspora influencing the voting patterns, whereby groups of Turkish migrants in north-east Europe were observed to consistently vote for Turkey.

Fenn, Suleman, Efstathiou and Johnson (2008) investigated the relationships between the voting countries in the ESC. They simulated historic voting data from the ESC and constructed a series of dynamic social networks, in an attempt to determine how compatible the participating countries were in general. The ESC voting patterns can be viewed as an international forum, where participating countries voice their opinions on one another free from any economic or political pressure. They collected data on the voting patterns of the participating countries who appeared most often from 1993 to 2003 competitions. They used cluster analysis to confirm that there were indeed unofficial voting blocs of countries in the ESC. Further evidence supporting unofficial voting blocs was provided by a reciprocal analysis. Furthermore, using the identified voting blocs as a guide, they investigated the historical voting data and simulated random data for each country individually. The results showed that the observed probabilities connecting countries within a voting bloc in the historic voting data were significantly greater than the corresponding probabilities in random voting data. However, the observed probabilities for countries who were not a part of a voting bloc in the real voting data were observed to be the same as those in the probabilities in the corresponding random voting networks. The analysis identified the countries who appeared to be the most connected in the ESC. They identified the UK as very compatible with the rest of Europe, and France as not very compatible with the rest of Europe.

Clerides and Stengos (2012) researched the ESC voting network for signs of biased voting. The competition provides a forum where participating countries can voice their opinions of one another, free from political pressure. Clerides and Stengos collected data on the voting patterns from the 1981 competition to 2005 competition. Results showed evidence for the existence of voting blocs of countries who systematically exchange votes regardless of performance quality. This biased exchange of votes is seen as large fluctuations in the voting patterns. Once confounding factors such as taste were accounted for, these large fluctuations reflect the interaction of various affinity factors and deeper sociological ideas among participating nations. These cultural, geographical, economic and political affinity factors explain how countries exchange points, for example the country’s language, geographical proximity and total trade. They tested for the effect of competition factors, such as the order of appearance, the gender of the performer and the host nation, as well as previous votes. Results showed that affinity factors such as geographical proximity, order of appearance and past votes given explain a substantial number of points. Interestingly the results found no evidence of strategic voting overall. However some evidence was found to support reciprocal voting during the period prior to the introduction of the televote system.

Dekker (2007) modelled the 2005 ESC as a friendship network. The paper focused how alleged political influence implicates the voting patterns of the competition. Dekker constructed a friendship network with weighted edges by adjusting the voting patterns to account for the song quality. Friendship networks have a more general use and application, as they do not require large volumes of data, and can be used for studying social structures such as the ESC which are in a dynamic state of change. The friendship network gave a simplified summary of European relations and politics. Dekker used a statistical analysis to show that friendship among countries was mostly driven by geographical factors. The friendship network was divided up into a five-bloc structure consisting of the Western bloc, Eastern bloc, Nordic bloc, Balkan bloc, and Eastern Mediterranean bloc. This identified structure was a development upon the structures identified in previous studies. In contrast, the Western bloc was now the least central and least cohesive, while the Central Europe bloc had grown in importance and stature. The past dominance of the Western bloc could be seen from its connections to other blocs, excluding the Balkans. Dekker concluded from the high centrality score for Turkey, that large immigrant groups swayed national votes towards their home country. Furthermore countries such as Switzerland and Austria appeared to act as bridges between the voting blocs. Similarly the Eastern Mediterranean bloc appeared to act as a bridge for the Balkan countries and other voting blocs.

Garcia and Tanase (2013) investigated the influence of cultural dynamics in the voting patterns of the ESC. Inferences on the effect of culture in the competition can be made as the competition utilised crowd-based voting systems in the shape of the televote and jury vote. They modelled the cultural relationship among countries using a newly derived metric called the Friend-or-Foe coefficient, which measured the voting biases among participants of the competition whilst accounting for variation on the perception of culture. A random biased ESC was simulated in order to cross-validate how effective the metric quantified cultural similarities were. The metric was applied to 37 years of data, spanning from the 1975 competition to the 2012 competition. Results concluded that the metric could identify negative affinities and also provide an estimate for positive affinities. Patterns of asymmetric voting and clustering were found to be present in the ESC. Furthermore, they measured how political decisions of participating EU countries influenced the way their populations interacted with other participating EU countries and cultures. A measure of vote polarization detected a sudden increase of asymmetric voting and clustering during 2010 and 2011 competitions. These years in particular were very turbulent due to debt and austerity measures implemented by the EU. Overall, this suggests that political climates influence how countries and societies interact with one another.

Gatherer (2006) compared simulated ESC results with actual ESC results to reveal the presence of voting blocs in the competition. Gather outlined how the ESC gives the participating countries an opportunity to voice their opinions of other participating countries and critique them on their political behaviour. Gather statistically detected changes in the voting patterns by comparing simulated ESC with actual competitions. Specifically, he recreated each competition from 1975 to 2005 using exact parameters, with the only exception being the 2004 and 2005 competitions, where only a minor approximation could be made. This approach to modelling the ESC did not require a full mathematical solution. Results showed that the competitions after the mid-90s saw the growth and development of large geographical voting blocs. The voting blocs originally developed from small voting partnerships, which initially appeared in the early 1990s and have since accelerated in growth ever since the turn of the millennium. The results concluded that the Balkan Bloc vote was sufficiently large to influence the result of the competition to a Balkan Bloc member in 2003 and 2005. While in the 1999 and 2002 competition, the Scandinavian voting bloc swayed the result of the competition into their favour. Furthermore, Gather suggests that the voting blocs developed as voters realised that it increased their own country's chance of winning the contest.

The research on the voting blocs of the ESC is relevant to this dissertation in a number of ways. This research intends to model the voting blocs with other factors such as migration patterns and Echo Nest music factors in an attempt to explain the voting patterns of the 2016 ESC. In particular, although Yair's first paper is one of the older ESC research papers, a lot of meaningful insights can be drawn from it. This research will implement a very similar methodology to derive the voting blocs for the 2016 competition. A voting matrix consisting of average points will be constructed and two clustering techniques will be utilised to extract the voting blocs from the data. Similar to the research on the voting blocs of the ESC, edge betweenness clustering will be used to derive the voting blocs. However, in contrast, this research also intends to utilise short random walks clustering to derive the voting blocs.

2.5 Musical Factors

A number of papers have documented the use of Echo Nest services to derive music factors from recordings for classifying their popularity and hit status. These music factors include key, mode, acousticness, tempo, loudness and danceability. With regards to this dissertation, these features will be utilised to explain the voting patterns and final scores of the 2016 ESC.

Borg and Hokkanen (2011) have investigated what makes a hit pop song. The construction of hit song prediction algorithms is both academically interesting and industry motivated. Several companies have maintained that they have the resources to make such predictions. However publicly available research concluded that these methods are inefficient and produce inaccurate predictions. Borg and Hokkanen trained Support Vector Machines on a variety of music and song features as well as YouTube view counts. They utilised the Echo Nest API to derive music related features such as tempo, loudness and danceability on the songs they collected. The results were not successful and they concluded that the musical features alone were insufficient at accurately classifying the songs popularity. They then redefined the research problem to constructing an automated genre classification algorithm. Similarly, the algorithm would take the previously extracted music features from the songs as input. The results for classifying genre were much more successful than the results for predicting popularity. They produced two automated classifiers that performed five times better than random chance for ten genres. The algorithms were a two step-process whereby K-Means clustering was utilised prior to fitting Support Vector Machines or Random Forest classifiers.

Fan and Casey (2011) attempted to predict Chinese and UK hit songs. The top 40 chart is used as a popular resource for discovering new music and as a guide for purchasing new music. Previous research on classifying hit songs focused on Western pop music. Fan and Casey's research expanded on hit song classification by incorporating pop songs from other areas of the world. Pop songs from other regions of the world exhibit different characteristics. They collected 40 weeks of data from both the Chinese and the UK pop music charts, with the goal of predicting future hit songs. They derived 10 music related features on each song using Echo Nest services. Specifically the features they used were danceability, duration, energy, key, liveness, loudness, mode, speechiness, tempo and time signature. The data was modelled using a time-weighted linear regression model and support vector machines. The results showed that danceability, energy, liveness, mode, speechiness and time signature were significant in predicting hit songs from the UK. In contrast, danceability, energy, liveness and speechiness were found to be significant in predicting hit songs from China. Furthermore the results indicated that hit songs from China could be predicted more accurately than hit songs from the UK. The research concluded that the audio feature characteristics of Chinese hit songs differ significantly from those of UK hit songs. .

Herremans, Martens and Sorensen (2014) investigated hit dance song prediction. Each year record labels invest huge amounts of money and resources into developing new musical talent. Determining the underlying structures which classify a song's potential as a hit is a major benefit both commercially and academically for the music industry. In their research, they attempted to develop an algorithm that could classify whether a dance song would be a hit or not. They collected data on dance hit songs from 1985 to 2013. The data included both basic musical features and advanced features which captured the temporal concepts of the dance songs. They derived these musical factors for each dance song using Echo Nest services. Echo Nest services are utilised by industry leaders such as Spotify, MTV, and EMI. They developed a variety of different classification models to classify dances. They outlined that the best model should have performed well when classifying whether a song is a top ten dance hit or a bottom ten hit. Results showed that the popularity of dance songs could be classified using the musical factors derived using Echo Nest services. The positive result was most likely due to the presence of more advanced temporal features. Alternatively the positive result may be the product of utilising only modern songs, which fails to capture the change of dance songs over time. Furthermore the research focused on one specific genre of music, which removes any possible error of miss-classifying other genres.

The research on the use of Echo Nest music factors in pop hit classification has directly influenced this dissertation in a number of ways. Most importantly in the inclusion of musical factors derived from Echo Nest services in predicting the scores and voting patterns of the 2016 ESC. Furthermore this research builds upon this by incorporating other predictors such as migration patterns and voting blocs to explain the scores and voting patterns of the competition. Although they were not very effective on classifying pop hits according to Borg and Hokkanen, they may be useful in explaining the total variation in predicting ESC scores and may give some indication in what drives the underlying voting patterns in the ESC.

2.5 Conclusions

The goal of the literature review was to identify possible factors to be incorporated into the research. These factors will be utilised in explaining the scores and voting patterns of the 2016 ESC. The section on performance, competition and external factors has focused on previously identified factors related to the ESC. In contrast the section on modelling the ESC with social networks has focused on how voting blocs can be derived and analysed from the voting patterns of the ESC. Finally the section on other related papers has specifically investigated two types of factors; the order of appearance and musical factors derived from Echo Nest services.

The literature review has also identified gaps in previous research which has incorporated a variety of different techniques when trying to understand the points and voting patterns of the ESC. However, there has not been any research on the 2016 ESC, and among other factors, there has been no research on the specific combination of voting blocs, Echo Nest music factors and migration patterns. For example, the papers which model competition, performance and external factors fail to capture the effect of the voting blocs identified in the social network analysis papers and the musical features derived using Echo Nest from the hit song classification papers. This research attempt to fill that gap by incorporating among other variables, voting blocs, migration patterns and Echo Nest music factors, to test whether they can explain the scores and voting patterns of the 2016 ESC.

3. DESIGN AND METHODOLOGY

3.1 Introduction

This chapter outlines the design and methodology of this dissertation using the CRISP-DM lifecycle (Figure 3.1). There are six sections to this chapter, which correspond to the six stages of the CRISP-DM lifecycle; research question understanding, data understanding, data preparation, data modelling, model evaluation and drawing conlcusions. The interpretation of all analytical, statistical and social network analysis techniques utilised in this research were guided by De Veaux, Velleman and Bock (2005), Tabachnick and Fidell (2001) and Wasserman and Faust (1994). They are recognised as seminal educational texts in the area of statistics and social network analysis. This includes all the methodologies described in the data understanding, data preparation, data modelling and model evaluation sections.

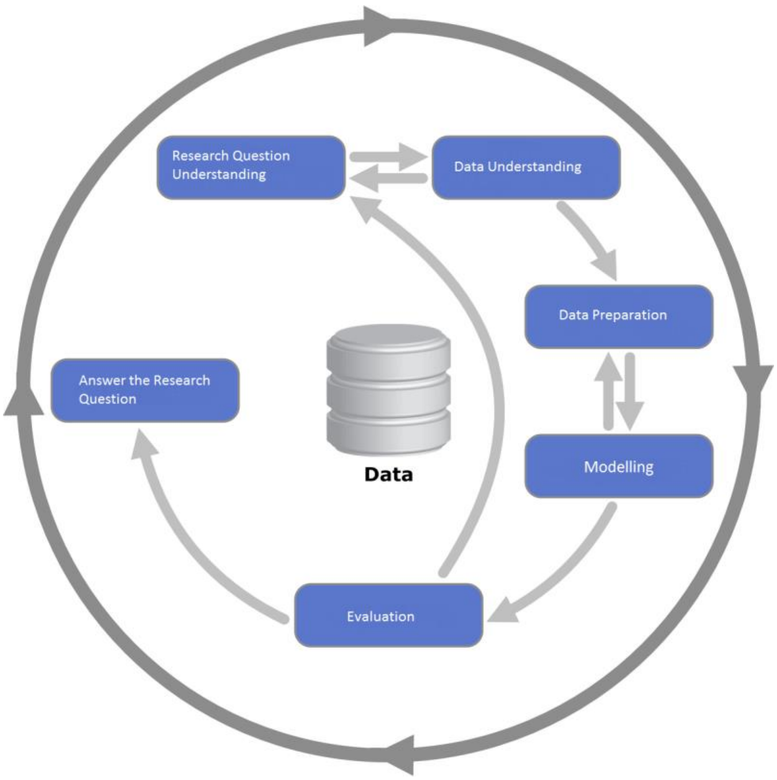

Figure 3.1 – CRISP-DM Lifecycle

3.2 Research Question Understanding

The objective of this research is to see if the points of the 2016 ESC can be explained using three sets of factors; performance factors, competition factors and external factors. In particular, this research focuses on whether voting blocs, migration patterns and Echo Nest music factors can explain the scores of the 2016 ESC. This research problem can be converted into a statistical problem by modelling the data using multiple linear regression. The model would represent the relationship between the performance factors, competition factors and external factors with points as a linear relationship, consisting of predictor variables and the response variable. The statistical problem is concerned with whether the predictor variables are significant in explaining the response variable points.

3.3 Data Understanding

3.3.1 Data Description

As previously mentioned, there are three broad categories for the factors being investigated; competition factors, external factors and performance factors. The competition factors (Table 3.1 on page 26) are factors directly linked to the competition itself that may have an influence on the final scores of the contest such as the order of appearance, the round of the competition and the host nation of the competition.
The performance factors (Table 3.2 on page 26) are factors that directly related to the performances in the contest such as the gender of the singer, the type of performance and musical factors. The latter include, in particular, Echo Nest music factors such as the tempo, time signature and acousticness of the music performed.
The external factors (Table 3.3 on page 27) are factors that are outside the control of the performers and the competition. These include voting blocs, migration trends, economic effects and cultural aspects such as language. In particular, the voting blocs and migration patterns are a fundamental part of this dissertation.

Competition Variables			
ID	**Name**	**Type**	**Description**
1	Host Nation	Binary	The host nation of the competition.
2	OOD	Integer	The order of appearance for the TC (To Country)
3	Round	Nominal	The round of the competition.
4	Voting Method	Nominal	The voting method.

Table 3.1 – Competition Factors

Performance Variables			
ID	**Name**	**Type**	**Description**
1	FC SONG LANG	Nominal	The language sung in for FC (From Country)
2	TC SONG LANG	Nominal	The language sung in for TC
3	Com LANG FAM	Binary	The performances share a common language family
4	Com SONG LAN	Binary	The performances share a common song language
5	TC Perf Type	Nominal	The performance type of TC
6	TC Singer Gender	Nominal	The gender of the TC performers
7	Danceability	Range[0,1]	A measure of how danceable the music is
8	Energy	Range[0,1]	A measure of how energetic the music is
9	Key	Nominal	The estimated overall key of the music
10	Loudness	Real	The overall loudness of the music in dB
11	Mode	Binary	The modality (Major / Minor) of the music
12	Speechiness	Real	Detects the presence of spoken word in music
13	Acousticness	Range[0,1]	A measure of how acoustic the music is
14	Instrumentalist	Range[0,1]	A measure of how instrumental the music is
15	Liveliness	Range[0,1]	A measure of how live the music is
16	Valence	Range[0,1]	A measure how positive or negative the music is
17	tempo	Real	The estimated overall tempo of the music in BPM
18	Duration	Real	The duration of the music in milliseconds
19	Time signature	Integer	An estimated overall time signature of the music

Table 3.2 – Performance Factors

External Variables			
ID	**Name**	**Type**	**Description**
1	TC Num Neigh	Integer	The number neighbours TC has
2	FC GDP mil	Real	The GDP of FC
3	TC GDP mil	Real	The GDP of TC
4	GDP PROP	Real	A proportion based on the GDP of FC and TC
5	FC CAP LAT	Degrees	The latitude degrees for the capital city of FC
6	FC CAP LON	Degrees	The longitude degrees for the capital city of FC
7	TC CAP LAT	Degrees	The latitude degrees for capital city of TC
8	TC CAP LON	Degrees	The longitude degrees for capital city of TC
9	CAP DIST km	Real	The distance between the FC and TC capital cities
10	VBlocs1 FC	Nominal	Edge betweenness voting blocs for FC
11	VBlocs2 FC	Nominal	Short random walks voting blocs for FC
12	VBlocs1 TC	Nominal	Edge betweenness voting blocs for TC
13	VBlocs2 TC	Nominal	Short random walks voting blocs for TC
14	Com VBloc	Binary	The countries share a voting bloc
15	FC LANG FAM	Nominal	The language family of the FC
16	TC LANG FAM	Nominal	The language Family of the TC
17	Neighbours	Binary	The countries are neighbours
18	FC NonCOB	Integer	The number of people born in FC residing in TC
19	FC NonCitizens	Integer	The number of citizens of FC residing in TC
20	FC COB	Integer	The number of people born in FC residing in FC
21	FC Citizens	Integer	The number of citizens of FC residing in FC
22	FC Population	Integer	The population of FC
23	METRIC COB	Real	An immigration measure based of COB
24	METRIC Citizens	Real	An immigration measure of Citizens
25	METRIC COBCit	Real	An immigration measure of COB and Citizens
26	Average Points	Real	The average points awarded

Table 3.3 – External Factors

There are four remaining factors (Table 3.4 on page 28) that represent the voting network of the 2016 ESC. The primary key id is the product of To_country, From_country, Round and Voting_Method sorted alphabetically. The points factor will become the dependant variable in the regression model. It is important to note that To_country and FC_country will not be modelled as predictor variables. Most notably, the To_country factor acts as a proxy for the scores of the competition, whereby the successful countries such as the Ukraine and Australia received the highest number of points.

Voting Factors			
ID	**Name**	**Type**	**Description**
1	id	Integer	A primary key for the dataset
2	From country	Nominal	The country sending the points
3	To country	Nominal	The country receiving the points
4	Points	Integer	The points being awarded

Table 3.4 – Voting Factors

3.3.2 Tools

The analysis was conducted using R studio and several additional R packages, including ggplot2, dplyr, igraph, car, MASS and nortest. The ggplot2 package was used for constructing the visualisations in the exploratory analysis section. The dplyr package was used for some data manipulation. The igraph package was used for constructing the voting blocs and visualising the voting networks. The car package was used for evaluating the model assumption and fit. The MASS package was used for extracting the studentised residuals from the fitted models. Finally, the nortest package was used for conducting the normality tests in the model evaluation section. Note that the dataset and R script for this research are available on GitHub.[4]

3.3.3 Data Collection Methodologies

A variety of data collection methods were implemented during this research. For the most part, the majority of the data was collected directly from freely available online websites. However, there were several factors such as the voting blocs, migration patterns and the music features that required additional derivation.

[4] Leonard, O. (2017). MSc-ESC. Retrieved from https://github.com/oislen/MSc-ESC

The Echo Nest music factors were generated using the Spotify Web API Console. As previously mentioned in the section 2.5, Echo Nest provides services to generate musical features from specified audio tracks. Spotify acquired Echo Nest in 2014 and has since integrated Echo Nest services into their Web API Console. The Web API Console can generate all the features outlined in the literature review, the data description and more on tracks stored in Spotify's digital library. In order to access and generate the musical features for a specified audio track, the user needs to request a free authorisation token and afterwards submit the Spotify track ID.[5]

Previous research has found voting blocs to be consistently present in the ESC. As a result, voting blocs have been incorporated into this research on the 2016 competition. The voting blocs were generated in a similar fashion to Yair's (1995) method. This method was outlined in his 1995 paper and was simplistic in nature, but for the purpose of this research it was deemed appropriate. First a voting matrix was created by averaging over all the points exchanged between the 2016 participating countries from the 1975 competition to the 2015 competition. Note that the votes included both the televote and jury vote systems. Following this, a weight directed graph was constructed from the voting matrix, where the direction represents the direction of the vote and the weights represent the average points. Once the graph was generated, two different hierarchical clustering algorithms were used to generate the voting blocs. These clustering algorithms were edge betweenness clustering and short random walks clustering. The average votes between countries were used as the criterion for constructing the clusters. Two countries were classified as part of the same voting bloc if one country received a higher than average number of points from the other country. The short random walks clustering built upon this concept by modelling the weighted edges as a Markov chain and calculated the long run probabilities using a transition matrix.

Past research has indicated that the distance between countries is a geographical factor that influences the ESC, as such it was incorporated into this research. The distance was measured in kilometres and was derived using the great circle distance between the

[5] Spotify Developer. (2017). Spotify Developer – Get Audio Features for a Track. Retrieved from https://developer.spotify.com/web-api/get-audio-features/

longitude and latitude coordinates between the capital cities. The formula for the great circle distance between two points is;

$$\cos^{-1}(\sin(\alpha1) * \sin(\alpha2) + cos(\alpha1) * \cos(\alpha2) * \cos(\beta2 - \beta1)) * \gamma$$

where $\alpha1$ and $\beta1$ are the latitude and longitude coordinates for the From_country capital city, $\alpha2$ and $\beta1$ are the latitude and longitude coordinates for the To_country capital city and γ is the radius of the earth in kilometres.[6]

Previous research on the ESC has identified migration patterns as a possible factor that influences the voting patterns of the ESC. Most papers on the ESC have only investigated the effect of Turkish migrants abroad. The only exception being Blangiardo and Baio research which utilised stock counts from the World Bank to measure the effects of migration. Three separate measures of migration have been used in this research. All three migration measures have the same underlying principle; that if there is a sufficiently large population of people from the To_country residing in the From_country, then the From_country is more likely to vote for the To_country, and they have been expressed with the following formula:

Migration measure 1 based on citizenship (METRIC_Citizens);

$$\frac{\alpha1}{\beta - \gamma1}$$

where $\alpha1$ is the number of To_country citizens residing in the From_country, β is the population of the From_Country and $\gamma1$ is the number of From_country citizens residing in the From_country.

Migration measure 2 based on country of birth (METRIC_COB);

$$\frac{\alpha2}{\beta - \gamma2}$$

[6] Veness, C. (2007). Calculate distance, bearing and more between Latitude / Longitude points. Retrieved from https://www.movable-type.co.uk/scripts/latlong.html

where $\alpha2$ is the number of people born in the To_country who are residing in the From_country, β is the population of the From_Country and $\gamma2$ is the number of people born in the From_country who are residing in the From_country.

Migration measure 3 based on both citizenship and country of birth (METRIC_COBCit);

$$\frac{\alpha1 + \alpha2}{2 * \beta - \gamma1 - \gamma2}$$

this is a measure of migration patterns that utilise both the citizenship and the country of birth.

3.3.4 Exploratory Analysis

An exploratory analysis was conducted on the collected data. The underlying distributions and tendencies of the factors were examined using descriptive statistics and visualisations. The exploratory analysis was important for two reasons. Firstly, the exploratory analysis helped to uncover what was going on in the data. Secondly, the exploratory analysis helped in exposing any data processing tasks needed prior to the data modelling stage.

Each of the categorical factors were visualised using bar charts, and their associations with both the points and one another were measured using chi-squared tests of association. The chi-squared test of association requires both factors to be nominal, therefore, the points factor was converted into a nominal factor with ten levels. Furthermore, a variety of descriptive statistics such as mode, mode percentage and missing values were calculated.

Each of the numeric factors were visualised using histograms, and their association with both the points and one another were measured using correlation plots and tests. The correlation tests require both factors to be numeric, therefore, the points factor was treated as an integer. Furthermore, a variety of descriptive statistics such as mean, variance and range were calculated.

The migration patterns for the televote and jury vote were visualised using social networks. The goal was to see if the voting networks differed, and if so, how these differences do impacted the voting patterns of the 2016 ESC.

3.4 Data Preparation

In order to facilitate the data modelling stage, the data was processed in accordance with the exploratory analysis. Firstly, any missing observations were processed. Secondly, the nominal factors were dummy encoded. Thirdly, the numeric factors needed to be standardised to a common scale and magnitude. Finally a data reduction was implemented to reduce the dimensions of the data.

3.4.1 Handling Missing Observations

There were a few options available for handling the missing observations. The missing values could be either removed or imputed. Removing any incomplete observations was considered to be the most straight forward and easiest method, however it would result in a loss data. This could have been particularly detrimental to the research if only a small subset of the data was left after the removal of the incomplete observations. Alternatively, the missing values could be imputed. If numeric values were missing in the data, those missing values could be imputed using the mean or a linear regression model. If categories were missing in the data, those categories could be imputed using the mode or a multinomial regression model.

3.4.2 Dummy Encoding of Categorical Factors

As the data was modelled using a multiple linear regression model, the nominal factors were dummy encoded into binary factors. This is because linear regression can only handle numeric inputs. The dummy encoding transformed each level of a nominal factor into a separate binary factor, where one represents the presence of that category and zero represents the absence of that category.

3.4.3 Standardise the Numeric Factors

As the scale and magnitude of the numeric factors might vary, they were standardised to a common scale and magnitude. This way, two numeric factors could be compared, for example the GDP factor was measured in thousands while the order of appearance was an integer ranging from 1 to 26. The numeric factors were standardised to have mean 0 and standard deviation 1. However, the order of appearance factor was standardised in relation to each of the three rounds, thus maintaining the integrity of the factor.

3.4.4 Data Reduction

Finally, a data reduction was implemented to reduce the dimensions of the dataset. As some of the nominal factors were likely to have lots of levels, the dimensions of the data were likely to drastically increase due to the dummy encoding stage. Any unary factors or binary factors which have only one integer value present, either 0 or 1, were removed from the dataset. Secondly, any binary factors that formed a linear combination within the data were also be removed. Thirdly any binary factors that have high associations with other binary factors were removed. These associations were measured using chi-squared tests of associations. Furthermore, removing highly associated factors reduced the chance of multi-collinearity, as some binary factors were likely be derived from common nominal factors.

Similarly, any numeric factors which had a correlation coefficient higher than 0.9 were removed. Again, this only reduced the number of dimensions but also reduced the chance of multi-collinearity, as some numeric factors such as the migration patterns, represented the same concept.

Note, a data reduction utilising Principle Components Analysis and Multiple Correspondence Analysis was considered. However, it was later rejected due to difficulties in relation to the interpretation of newly defined dimensions and the research problem.

3.5 Data Modelling

The processed data was modelled using a multiple linear regression model. There were many other possible regression models such as ordinal regression and multi-nominal regression. However, multiple linear regression was chosen due to its versatility and interpretability. The data itself was stratified into three groups based on the voting system; combined vote, televote and jury vote. For each of the three groups, a multiple linear regression model was iteratively built.

3.5.1 Multiple Linear Regression Model

Multiple linear regression models model the data as a linear relationship between the response variable and a set of predictor variables;

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n$$

where the response variable y is points, the multiple predictor variables x_1 to x_n are a combination of the performance factors, competition factors and external factors, and the coefficients β_0 to β_n are the slopes of the predictor variable.

3.5.2 Modelling Approach

A stratified analysis approach was utilised to analyse the data, whereby the data was stratified based on the voting method, as the voting method represented the division between the general public's opinion and the judgments of music experts. This resulted in three separate datasets to be modelled and analysed; combined vote data, the televote data and the jury vote data. Previous research suggested that both the televote and jury vote suffered from biased voting, however it was the opinion of the general public that was found to be more susceptible to biased voting.

3.5.3 Model Building

Each model was built iteratively using the three groups of factor: performance factors, competition factors and external factors. Once the most significant and useful factors from each groups had been identified, they were modelled collectively. In order to facilitate the model building stage, both stepwise fitting using AIC criterion and manually fitting were implemented. Stepwise fitting with AIC criterion allowed the multiple linear regression model to automatically select predictor variables based on a specified criterion. The AIC criterion determined the model of best fit for the data whilst accounting for the complexity of the model.

3.5.4 Transformation of Response Variable

If necessary, a transformation of the dependant variable was applied to normalise further the model's residuals. A Box-cox transformation was initially applied to the response variable, which attempted to normalise the residuals of the resulting model;

$$y^{(\theta)} = \begin{cases} \dfrac{y^{(\theta)} - 1}{\theta} & if\ \theta\ \neq 0 \\ \ln(y) & if\ \theta\ = 0 \end{cases}$$

Alternatively, an appropriate transformations was decided upon, based on trial and error in relation to the results of the model evaluation section.

3.6 Model Evaluation

The assumptions and fit of each fitted model was evaluated using a variety of visualisations and statistical tests on the studentised residuals of the models. Studentised residuals are a type of standardised residual derived by dividing each residual by the estimated standard deviation of the residuals. This standardised the residuals to be on a common scale and magnitude.

3.6.1 Assumptions of Multiple Linear Regression

Multiple linear regression requires the residuals of the model to be independently identically normally distributed with a mean of 0 and constant variance. If these assumptions are not fully satisfied, then any inferences or conclusions drawn from the model may be invalid.

The initial independence assumption was valid as the scores of the dependant variable points were independent of one another.

The normality assumption was assessed using an Anderson-Darling normality test and a variety of residual plots such as residual histograms, residual vs fit plots and residual

QQ-plots. The null hypothesis of the Anderson-Darling normality test is that the data follows a normal distribution. The residual histogram should follow a normal bell shaped distribution. The residual vs fit plots should show a symmetric cloud of points with extra density along the horizontal 0 line. The residual QQ-plot should fall along the normality line and fit comfortably between the error brackets. In the case that the model didn't satisfy the normality assumption of multiple linear regression, the model was instead used as an approximation. (Box, 1976)
The constant variance assumption was accessed using residual vs fits plots, spread-level plots and non-constant variance tests. The null hypothesis of the non-constant variance test is that the data does have a constant variance.

3.6.2 Accessing the Model Fit

It was important to access whether the model fitted the data well and could sufficiently explain the underlying patterns and structures of the data. If the model did not comfortable fit the data, then any inferences or conclusion derived from the model might be invalid. The fit of the model was evaluated using the R-squared statistic, variance inflation factors (VIF), Cooks distance, residual vs fits plots and an F-test of overall significance.
The R-squared statistic measures the amount of variability captured by the model. The higher the R-squared statistic is, the more variation the model captures in the data.
The plots residual vs. fits plot shows if there is any underlying pattern in the data that the model is failing to capture, such as non-constant variance or skew.
The VIF access the model for signs of multi-collinearity among the predictor variables. Multi-collinearity occurs when the model includes two or more variables that are highly correlated and represent the same concept. This affects the fit of model as the variables will be inefficient at explaining the variance in the data, due to the presence of the other highly correlated variables.
Finally the F-test of overall significance tests whether the fit of the final model is better than the intercept only model.
The fitted data was examined for outliers and influential observations using Crooks distance.

3.7 Drawing Conclusions

The research question was answered using three methods; T-test, sign effects and explained variance.

3.7.1 T-test

The research question is interested in testing the significance of the predictor variables in explaining the response variable points. The significance of the predictor variables in explaining points was evaluated using T-tests constructed from the estimated coefficients of the predictor variables. The null hypothesis for the T-test is that the coefficient of the predictor variable is zero. In other words, the predictor variable does not explain the response variable. The tests statistic for β_i, the coefficient of the i^{th} predictor variable is;

$$t_{\beta_i} = \frac{\widehat{\beta_i}}{SE_{\widehat{\beta}_i}}$$

where $\widehat{\beta_i}$ is the estimated coefficent of i^{th} predictor variable and $SE_{\widehat{\beta}_i}$ is the standard error of $\widehat{\beta_i}$.

3.7.2 Sign Effect

The sign effect of a predictor variable was evaluated by examining the sign of the corresponding estimated coefficient. This gave an indication of whether the predictor variable had a positive or negative effect on the response variable points, given that the predictor variable was significant in explaining the response variable.

3.7.3 Explained Variance

The additional increase of explained variance by a predictor variable was evaluated by examining the differencing in R-squared values for the models with and without that predictor variable. This gave an indication whether the addition of the predictor variable helped explain a sufficient amount of the variation.

3.8 Summary

This chapter outlined the research design and methodology using the CRISP-DM lifecycle. The chapter is divided into six sections which correspond to the six stages of the CRISP-DM lifecycle.

The research problem is interested in determining whether voting blocs, migration patterns and Echo Nest musical factors can explain the voting patterns of the 2016 ESC. The research problem was converted into a statistical problem by modelling the relationship between the points and the voting blocs, migration patterns and Echo Nest music factors using multiple linear regression.

The data was split up into three groups of factors; performance factors, competition factors and external factors. The Echo Nest music factors were derived from the Spotify Web API. The voting blocs were derived using two clustering techniques; edge betweenness clustering and short random walks clustering. An exploratory analysis explored the underlying patterns and structures in the data using a variety of descriptive statistics and visualisations.

The data preparation stage was informed by the exploratory analysis, and any data preparation techniques were implemented to facilitate the data modelling stage. The most notable data preparation tasks included handling any missing observations, dummy encoding any nominal factors, normalising any numeric factors and performing a data reduction to facilitate the data modelling stage.

The data modelling stage consisted of fitting multiple linear regression models to the processed data. The data was stratified into three sets based on the voting method; combined vote, televote and jury vote. The regression models were then iteratively constructed using stepwise fitting and manual fitting. The predictor variables were fitted to the models in groups of factors; performance factors, competition factors and external factors. Once the most useful factors from each group had been identified they were then fitted collectively.

The assumptions and fit of the models were evaluated using a variety of statistical tests and visualisations. Multiple linear regression requires the residuals of the model be independently identically distributed with a mean of 0 and constant variance. These assumptions were evaluated using statistical tests including Anderson-Darling tests and non-constant variance tests, and residual plots such as residual scatterplots and QQ-plots. The fit of the models was examined using VIF and crooks distance.

The research problem was answered by testing the significance of the predictor variables using T-tests, examining the sign effects of the estimated coefficients and examining the additional variance explained by the predictor variables.

4. IMPLEMENTATION AND RESULTS

4.1 Introduction

This chapter outlines the results of the research methodologies described in the previous chapter. In total, there are six sections to this chapter; data collection, exploratory analysis, data processing, data modelling, model evaluation and results. The data collection section outlines the sources and results of the data collection. The exploratory analysis explores the structures and patterns of the collected data using descriptive statistics and visualisations. The data processing section documents the techniques used to prepare the data for modelling. The data modelling stage details the results of iteratively fitting models to the processed data. The model evaluation section evaluates the assumptions and fit of each model. The results section outlines the results of the T-tests, sign effects and amount of variation explained by the models.

4.2 Data Collection

The majority of the data was collected from freely available online resources and websites, and stored in a Microsoft excel spreadsheet. Once the data was collected, the .xlsx file was converted to a .csv file for the analysis. Note, a number of data cleansing and data wrangling techniques were implemented in excel prior to the analysis. This was to help facilitate the construction of the final dataset for the research. These include the renaming and derivation of columns.

4.2.1 The Voting Data

The core voting data used for this research was downloaded from the data world website[7]. The data contains all the votes from the 1975 competition to the 2016 competition. The file consists of seven columns; Year, (semi-) final, edition, jury or televoting, from country, to country and points. The points column lists all the points distributed from country to country over the forty-one years. The points column mostly consisted of 0

[7] Okhuijsen, S. (2016). All the scores from the Eurovision Song Contest editions 1975 till 2016. Retrieved from https://data.world/datagraver/eurovision-song-contest-scores

points scores, which indicated the countries who did not vote for each other. These 0 points scores were removed from the dataset, as this research is interested in the countries who did vote for each other. This significantly reduced the size of the dataset. The jury or televoting column was renamed to voting method. The (semi-) final column was renamed to round. The edition column was removed from the dataset as it was a product of the (semi-) final and year columns. All the years except 2016 were removed and saved to a separated file called historic voting data. The historic voting data file was used for constructing the voting blocs.

4.2.1 Performance Features

Data on the performance type, song language and singer genders of the 2016 competition was collected from two specialist ESC websites; eurovision.tv[8] and eschome.net.[9]

4.2.1.1 Echo Nest Music Factors

The Echo Nest music data was collect using the Spotify Web API Console.[10] Unfortunately, the Spotify digital library did not stock the music of the actual 2016 ESC. However, the majority of the songs performed in the competition were available under the performing artist's page. Although this is not ideal, the studio record versions should still give some indication as to the influence of the music on the voting patterns of the competition. Furthermore, a number of songs were not available on Spotify, specifically the songs by Albania, Bulgaria, Georgia, Greece, Montenegro and Serbia.

4.2.2 Competition Features

Data on the round and voting method for the 2016 ESC was download from data world[11]. The remaining competition factors, order of appearance and host nation were collected from the eurovision.tv and eschome.net websites.

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[8] Eurovision song Contest. (2017). Stockholm 2016. Retrieved from https://eurovision.tv/event/stockholm-2016
[9] Flecht, M. (2017). ESC Database. Retrieved from http://eschome.net/
[10] Spotify AB. (2017). Spotifyl Web API Console – Get Audio Features for a Track. Retrieved from https://developer.spotify.com/web-api/console/get-audio-features-track/
[11] Okhuijsen, S. (2016). All the scores from the Eurovision Song Contest editions 1975 till 2016. Retrieved from https://data.world/datagraver/eurovision-song-contest-scores

4.2.3 External Features

The economic data was collected from the World Bank.[12] The Land Borders and neighbours data was collected from the world fact book.[13] Data on the longitude and latitude coordinates of participating countries were collected from Maxmind's free world cities database.[14] The great circle distance between the capital cities was calculated using this data. The language families for each participating country was classified using the lexical distance map of European languages (Figure 4.3 on page 45)[15].

4.2.3.1 Voting Blocs

Data on the average points and voting blocs was collected using the historic voting data file, which was derived from the dataset downloaded from data world. Figure 4.1 on page 43 shows the resulting dendrogram of the edge betweenness clustering algorithm. Figure 4.2 on page 43 shows the resulting dendrogram of the short random walks clustering algorithm. Table 4.1 on page 44 gives a summary of the identified historic voting blocs in the 2016 ESC.

[12] The World Bank Group. (2017). GDP (current US$). Retrieved from https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?end=2016&start=1960
[13] Central Intelligence Agency. (2017). The World Fact Book. Retrieved from https://www.cia.gov/library/publications/the-world-factbook/rankorder/2078rank.html
[14] Maxmind. (2017). Free World Cities Database. Retrieved from https://www.maxmind.com/en/free-world-cities-database
[15] Jacobs, F. (2017). A Map of Lexical Distances Between Europe's Languages. Retrieved from http://bigthink.com/strange-maps/a-map-of-lexical-distances-between-europes-languages

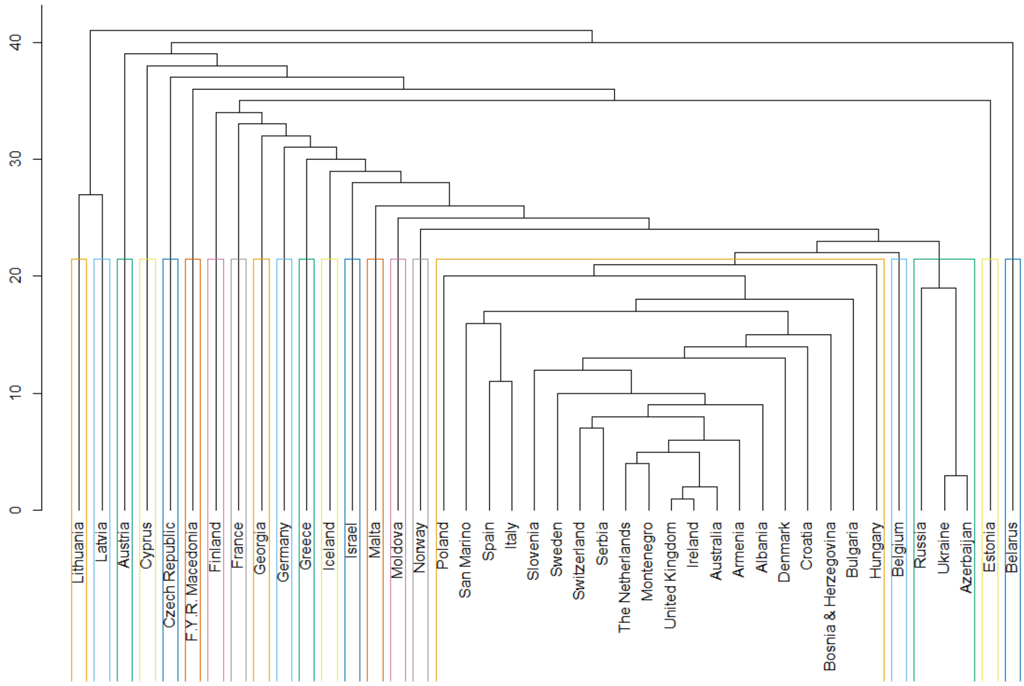

Figure 4.1 – Edge Betweenness Voting Blocs

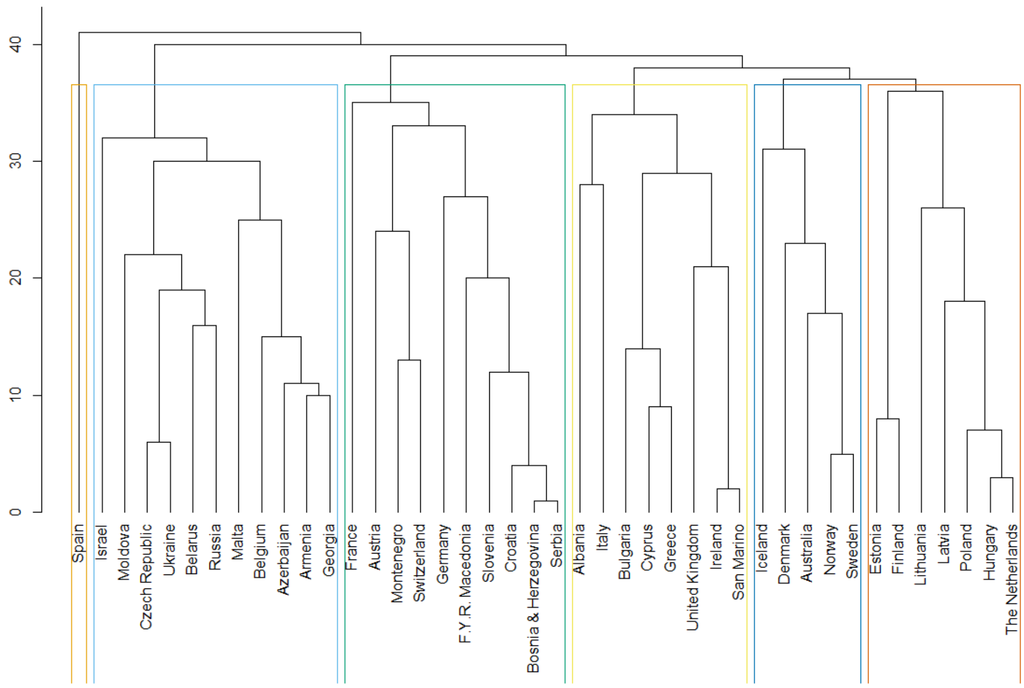

Figure 4.2 – Short Random Walks Voting Blocs

2016 ESC Voting Blocs					
Country	**VBlocs1 EB**	**VBlocs2 SRW**	**Country**	**VBlocs1 EB**	**VBlocs2 SRW**
Albania	1	3	Iceland	15	1
Armenia	1	1	Ireland	1	5
Australia	1	4	Israel	16	1
Austria	2	6	Italy	1	3
Azerbaijan	3	1	Latvia	17	5
Belarus	4	1	Lithuania	18	6
Belgium	5	1	Malta	19	1
Bosnia & Herzegovina	1	2	Moldova	20	1
Bulgaria	1	3	Montenegro	1	2
Croatia	1	2	Norway	21	1
Cyprus	6	3	Poland	1	5
Czech Republic	7	1	Russia	3	1
Denmark	1	4	San Marino	1	5
Estonia	8	5	Serbia	1	2
F.Y.R. Macedonia	9	2	Slovenia	1	2
Finland	10	5	Spain	1	3
France	11	1	Sweden	1	4
Georgia	12	1	Switzerland	1	5
Germany	13	2	The Netherlands	1	5
Greece	14	3	Ukraine	3	1
Hungary	1	5	United Kingdom	1	4

Table 4.1 – 2016 ESC Voting Blocs

4.2.3.2 Migration Patterns

Data on the migration patterns of the participating European countries was collected from the Eurostat website.[16] In particular, the two databases queried for the data were 'migr_pop1ctz' and 'migr_pop3ctb'. These databases stored the population of the European countries by age group, sex, citizenship and country of birth as of the 1 January 2016. Specifically, data on the population, citizenship and country of birth of the participating countries was extracted from these databases. Furthermore the measures on migration patterns; METRIC_COB, METRIC_Citizen and METRIC_COBCit were

[16] Eurostat. (2017). Database. Retrieved from http://ec.europa.eu/eurostat/data/database

derived using this data. Note, there were two countries not included in these databases; Israel and Australia. Furthermore, a lot of the migration data from 2016 was not available for many of the EU countries, for example Albania and Germany.

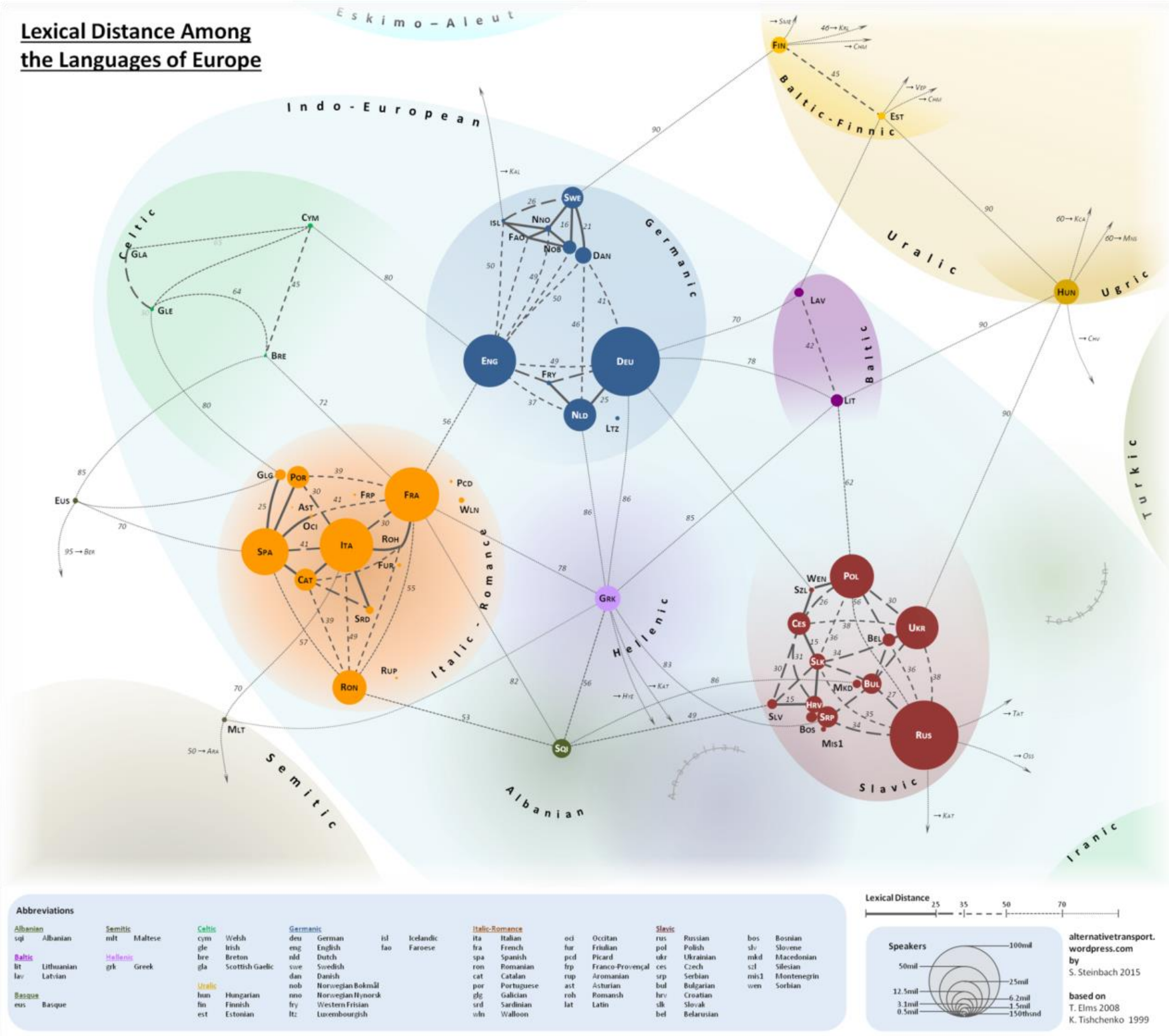

Figure 4.3 – Lexical Distance between European Languages

4.3 Exploratory Analysis

Once the data collection was completed, an exploratory analysis was conducted. The exploratory analysis consisted of a variety of visualisations and descriptive statistics. The exploratory analysis helped develop an understanding of the underlying structures and patterns in the data. Furthermore, the exploratory analysis informed the data processing stage, prior to the data modelling stage.

4.3.1 Visualisations

Starting with the response variable points, Figure 4.4 displays a bar chart of points with a uniform distribution. This is in keeping with the rules of the contest, as each country is given two sets of 10 votes to allocate to the performing countries. Furthermore, this indicates that points may require a transformation to satisfy the normality assumptions of multiple linear regression.

Figure 4.5 on page 47 displays the distribution of the voting blocs for the 2016 ESC. The voting blocs constructed using short random walks clustering appear to be more evenly distributed. Furthermore, the large number of levels suggests that a lot of sparse binary variables will be created following the dummy encoding.

Figure 4.6 on page 47 shows the distributions of the migration measures. The distribution of the migration measures are heavily right skewed. Furthermore Figure 4.7 on page 48 shows a scatterplot of the migration measures against points. The scatterplot appears to show a weak positive linear relationship between the migration patterns and points. This suggests that the migration patterns can explain the points to a slight degree.

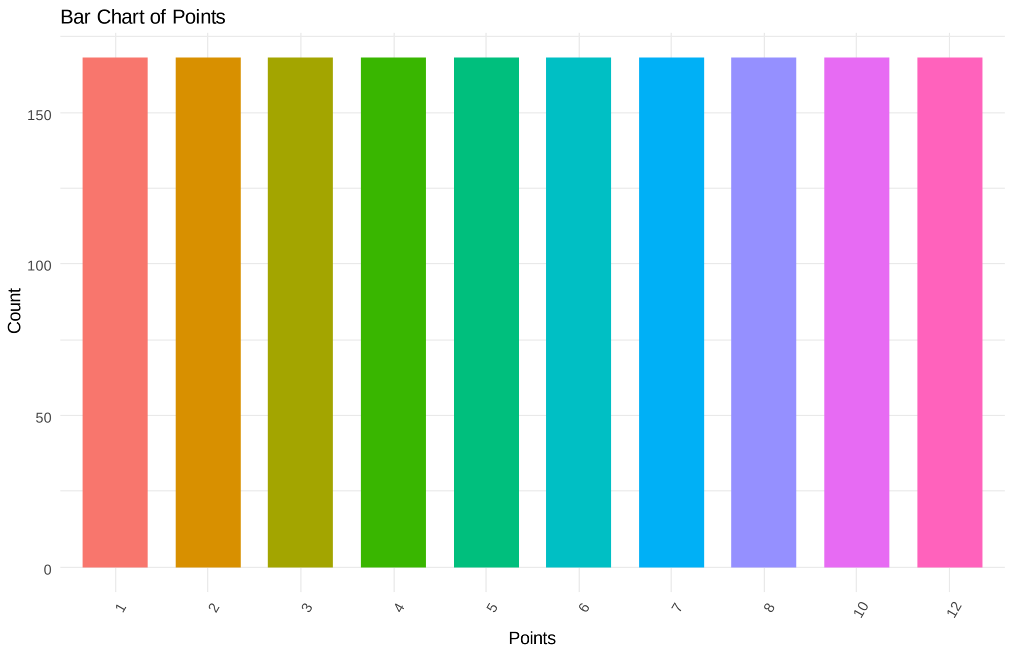

Figure 4.4 – Distribution of Points

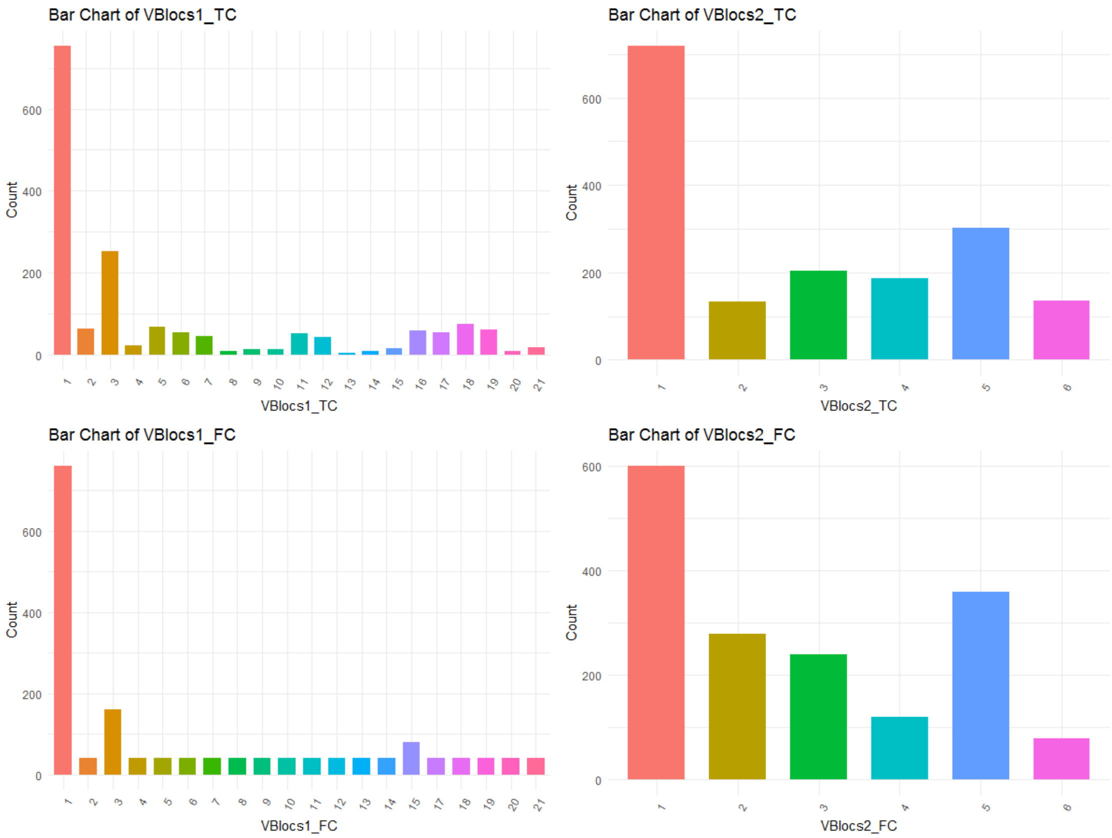

Figure 4.5 – Distribution of Voting Blocs

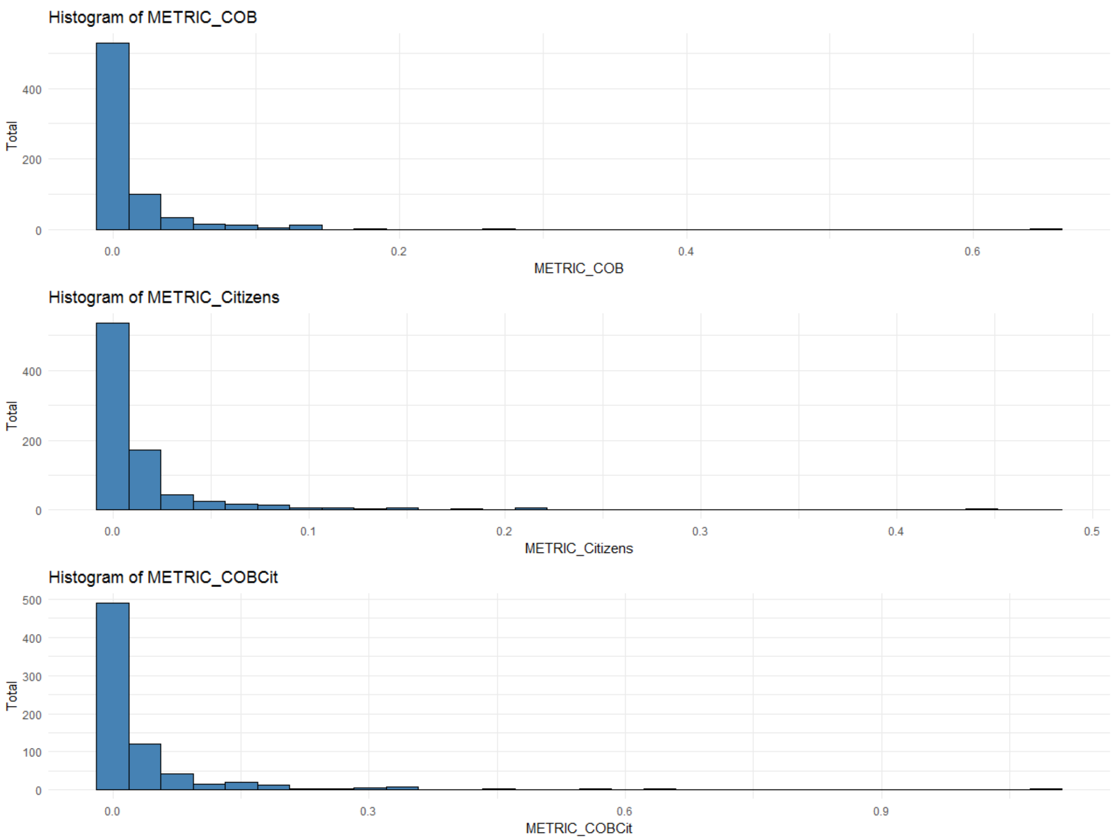

Figure 4.6 – Distribution of Migration Patterns

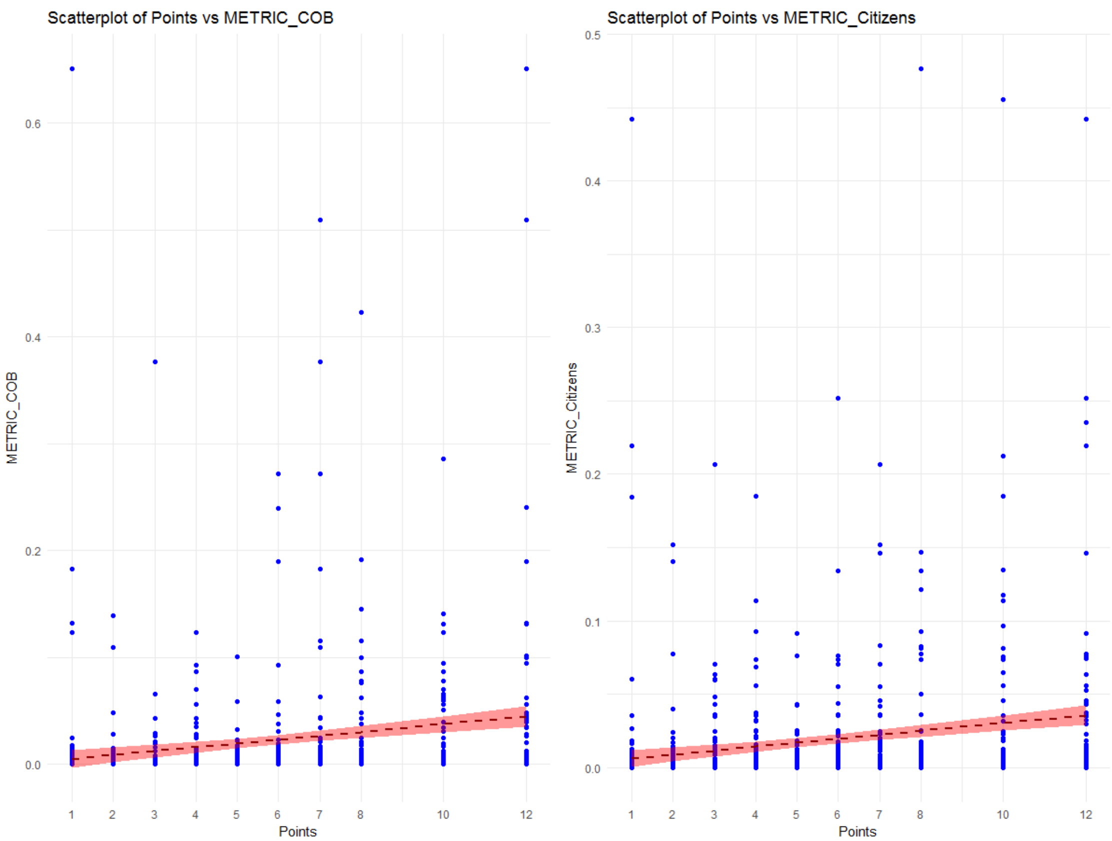

Figure 4.7 – Scatterplot of Migration Measures vs Points

Figures 4.8 and 4.9 on page 49 display the voting networks of countries with high levels of migration in the televote and jury vote respectively. The networks are constructed using METRIC_COBCit greater than 0.15. The weighted directed edges represent the direction of the awarded points. Two countries are connected if they have a high migration level and exchange a vote. There are a few notable differences between the televote and jury networks. The televote network contains three relatively complex sub networks, while the jury network contains one relatively complex sub network. Furthermore the televote network appears to distribute points with higher magnitudes. There are six 12 points and eleven 10 points distributed in the televote network, while the jury vote network only distributes one 10 points. Overall, this gives a further indication that the migration patterns do influence the points of the 2016 ESC, especially in the televote.

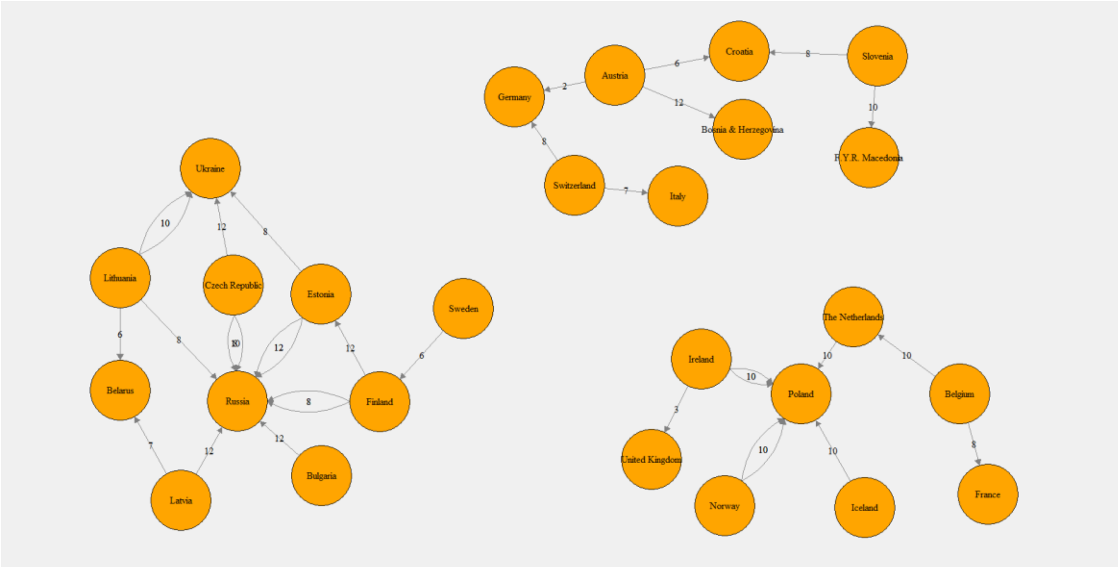

Figure 4.8 – Voting Network of High Migration in Televote

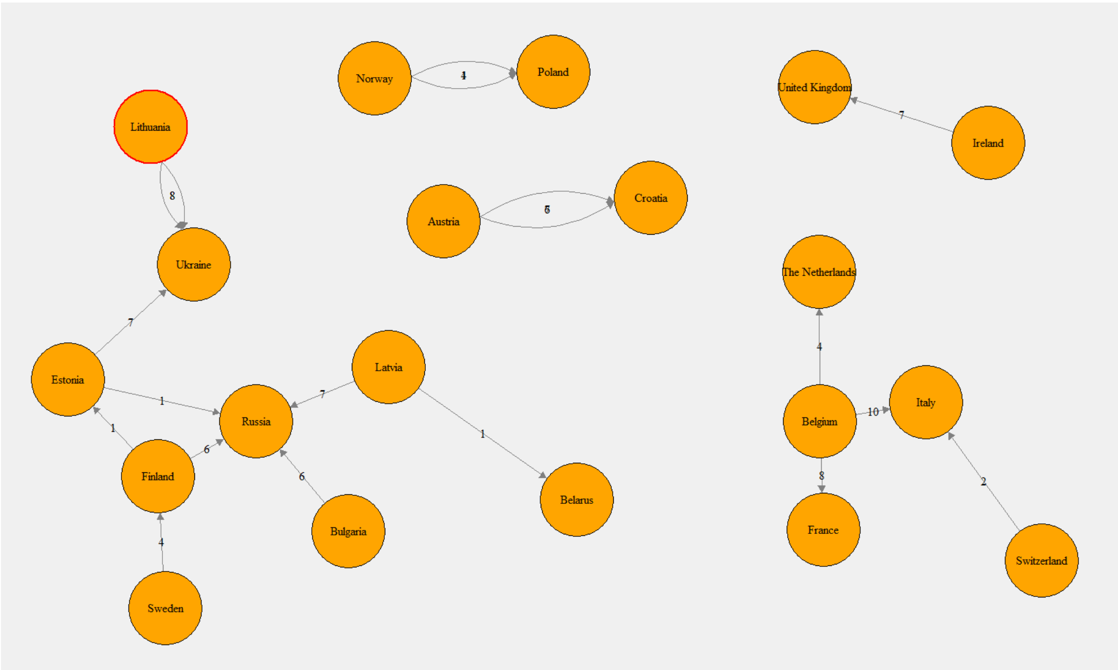

Figure 4.9 – Voting Network of high Migration in Jury vote

See Appendix B for additional visualisations derived from the exploratory analysis.

4.3.2 Descriptive Statistics

4.3.2.1 Categorical Variables

Categorical Descriptive Statistics						
Name	**levels**	**1st mode**	**1st mode %**	**2nd mode**	**2nd mode %**	**NA %**
From country	42	Albania	2.38	Armenia	2.38	0
To country	42	Australia	6.85	Ukraine	6.07	0
Round	3	f	50	sf1	25	0
Voting Method	2	J	50	T	50	0
Host Nation	2	n	97.26	y	2.74	0
VBlocs1 FC	20	1	45.24	3	9.52	0
VBlocs2 FC	6	1	35.71	5	21.43	0
VBlocs1 TC	21	1	44.88	3	15.06	0
VBlocs2 TC	6	1	42.74	5	17.98	0
Com VBlocs1	2	n	78.21	y	21.79	0
Com VBlocs2	2	n	76.19	y	23.81	0
FC LANG FAM	13	Germanic	28.57	Slavic	28.51	0
TC LANG FAM	12	Slavic	32.68	Germanic	26.07	0
Com LANG FAM	2	n	78.93	y	21.07	0
Neighbours	2	n	89.11	y	10.89	0
TC Perf Type	4	Solo	90.83	Group	7.38	0
TC Singer Gender	4	Female	53.04	Male	45.48	0
FC SONG LANG	5	English	80.95	Mixed	11.9	0
TC SONG LANG	5	English	78.04	Mixed	16.55	0
Com SONG LAN	2	y	63.69	n	36.31	0
key	12	5	12.5	NA's	11.55	11.55
mode	2	0	49.76	1	38.69	11.55
Time signature	2	4	84.76	NA's	11.55	11.55

Table 4.2 – Categorical Descriptive Statistics

Table 4.2 displays the descriptive statistics for the categorical factors. A lot of the factors that represent commonalities between factors, such as ComVBlocs, are disproportional, whereby the absent level is observed much more than the present level. This suggests a lot of sparse binary factors will be derived as a result of dummy encoding. This also applies to the host nation binary factor, where Sweden only accounts for 2.74% of the data. Thus, there may not be enough data to conclude that the host nation has an effect or not. Furthermore, there appears to be approximately 12% of the Echo Nest music data missing from the dataset.

Y ~ X Chi-Square Test of Associations					
Predictor	**P-Value**	**Significant**	**Predictor**	**P-Value**	**Significant**
From country	1	n	TC LANG FAM	0.01 *	y
To country	0 ***	y	Com LANG FAM	0 ***	y
Round	1	n	Neighbours	0 ***	y
Voting Method	1	n	TC Num Neigh	0 ***	y
Host Nation	0.70468	n	TC Perf Type	0.38826	n
OOA	0 ***	y	TC Singer Gender	0.023 *	y
VBlocs1 FC	1	n	FC SONG LANG	1	n
VBlocs2 FC	1	n	TC SONG LANG	0.10815	n
VBlocs1 TC	0 ***	y	Com SONG LAN	0.92661	n
VBlocs2 TC	0.002 **	y	Key	0 ***	y
Com VBlocs1	0.44128	n	Mode	0.21293	n
Com VBlocs2	0.003 **	y	Time signature	0.033 *	y
FC LANGFAM	1	n			

Table 4.3 – Y ~ X Chi-Square Tests of Associations

Table 4.3 displays the Chi-square tests of association between the categorical factors and points. There are a number of notable factors which have an association with points; OOA, VBlocs1_TC, VBlocs2_TC, ComVBlocs2, TC_LANGFAM, ComLANGFAM, Neighbours, TC_NumNeigh, TC_SingerGender, Key and time_signature. This indicates that these categorical factors may be useful in explaining the voting patterns of the 2016 ESC.

4.3.2.2 Numeric Variables

Table 4.4 on page 52 displays the descriptive statistics for the numeric factors. There are a number of observations to note from the descriptive statistics. Firstly, a lot of the numeric factors such as OOA and FC_COB are not on comparable scales or magnitudes. OOA has a much lower mean, variance and range compared to FC_COB. It will be necessary to standardise these numeric factors to be on a common scale and magnitude. Secondly, there is a significantly large percentage of data missing from the migration patterns. The highest being METRIC_COBCit, which is missing over 56% or approximately 940 observations.

Numeric Descriptive Statistics						
Name	**mean**	**variance**	**min**	**max**	**range**	**NA %**
Points	5.8	11.17	1	12	11	0
OOA	11.76	41.44	1	26	25	0
Average Points	5.18	6.71	0	12	12	0
TC NumNeigh	3.4	5.93	0	9	9	0
FC NonCOB	24641.89	4925002695	1	844024	844023	55
FC NonCitzens	24012.5	5690815617	0	928257	928257	46.131
FC COB	10189782.74	1.8304E+14	290507	54758099	54467592	54.762
FC Citizens	16452411.52	4.4687E+14	306044	73523726	73217682	45.238
FC Population	15021478.42	4.431E+14	33005	82800000	82766995	4.762
METRIC COB	0.02	0	0	0.65	0.65	56.31
METRIC Citizens	0.02	0	0	0.48	0.48	49.464
METRIC COBCit	0.04	0.01	0	1.09	1.09	56.369
FC GDP mil	474131.91	6.1928E+11	1500	3466757	3465257	0
TC GDP mil	445230.48	3.8784E+11	1500	3466757	3465257	0
GDP PROP	11.07	1218.21	0	513.9	514	0
FC CAP LAT	46.09	217.99	-35.47	64.13	99.6	0
FC CAP LON	29.46	2026.91	-21.82	253	274.82	0
TC CAP LAT	41.94	491.08	-35.47	64.13	99.6	0
TC CAP LON	41.46	3293.15	-21.82	253	274.82	0
CAP DIST km	3404.96	18368089.7	82.15	17570.78	17488.63	0
danceability	0.57	0.02	0.17	0.81	0.64	11.548
energy	0.72	0.02	0.41	0.92	0.5	11.548
loudness	-5.09	2.99	-12.4	-0.48	11.92	11.548
speechiness	0.05	0	0.03	0.16	0.13	11.548
acousticness	0.24	0.06	0	0.84	0.84	11.548
instrumentalness	0	0	0	0.03	0.03	11.548
liveness	0.14	0.01	0.02	0.43	0.41	11.548
valence	0.38	0.03	-0.55	0.76	1.31	11.548
tempo	123.1	550.4	71.92	205.01	133.09	11.548
Duration ms	184161.46	103274107	166173	232947	66774	11.548

Table 4.4 – Numeric Descriptive Statistics

Y ~ X Correlation Tests							
Predictor	**Cor**	**P-Val**	**Sign**	**Predictor**	**Cor**	**P-Val**	**Sign**
Average Points	0.28	0 ***	y	TC CAP LAT	-0.11	0 ***	y
OOA	0.1	0 ***	y	TC CAP LON	0.1	0 ***	y
TC NumNeigh	0.12	0 ***	y	CAP DIST km	0.07	0 ***	y
FC NonCOB	0.15	0 ***	y	Danc.	0.16	0 ***	y
FC NonCitzens	0.12	0 ***	y	energy	0.05	0.06	n
FC COB	0	1	n	Key	0.05	0.06	n
FC Citizens	0	1	n	Loudin.	0.05	0.04 *	y
FC Population	0	1	n	Mode	0.02	0.55	n
METRIC COB	0.19	0 ***	y	Speech.	0.18	0 ***	y
METRIC Citizens	0.19	0 ***	y	Acoustic.	0.14	0 ***	y
METRIC COBCit	0.2	0 ***	y	Instr.	0.08	0 ***	y
FC GDP mil	0	1	n	liveness	-0.11	0 ***	y
TC GDP mil	0.07	0 ***	y	valence	0.06	0.03 *	y
GDP PROP	-0.02	0.33	n	Tempo	0.01	0.72	n
FC CAP LAT	0	1	n	Duration ms	0.01	0.74	n
FC CAP LON	0	1	n				

Table 4.5 – Y ~ X Correlation Tests

Table 4.5 displays the correlation tests between the numeric factors and points. The majority of numeric factors do have some sort of a linear relationship with points. However the vast majority of these linear relationships are weak, with the correlation coefficients being less than 0.2. The numeric factors with the highest correlation coefficients are Average Points, METRIC_COB, METRIC_Citizens, METRIC_COBCit, speechiness, danceability, FC_NonCOB and acousticness. This is a good indication that these numeric factors will be useful in explaining the scores of the 2016 ESC.

4.4 Data Processing

As outlined in the design and methodologies chapter, the data processing stage consists of four sections; handling missing observations, dummy encoding the categorical factors, standardising the numeric factors and performing a data reduction.

4.4.1 Handling Missing Data

As previously identified in the exploratory analysis, a large percentage of the data is missing, predominantly from the migration patterns. Unfortunately it is unrealistic to impute these missing values as the percentage of missing data is too large. To do so, could incorporate a large amount of bias into both the migration patterns and the dataset. Furthermore, in order to impute these variables, additional data that is strongly correlated with the migration patterns would need to be collected. Currently the only correlated variables with the migration patterns are the economic factors. A similar argument can be made for the missing observations in the Echo Nest music factors.

Thus, all incomplete observations were removed from the dataset. This resulted in 1022 observations being removed and a complete dataset of 658 observations. This was not ideal, as approximately 60% of the data was removed. However, for the sake of this research, 658 observations should be sufficient for testing whether migration patterns, Echo Nest music factors and voting blocs explain the scores of the 2016 ESC.

4.4.2 Dummy Encoding the Nominal Factors

In order to model nominal factors in multiple regression, the nominal factors were dummy encoded into binary factors, where 1 represents the presence of the category and 0 represents the absence of the category. The dummy encoding of the nominal factors resulted in the creation of a large number of new binary factors. The original 3 nominal competition factors transformed into 7 binary dummy competition factors. The original 10 nominal external factors transformed into 86 binary external factors. The original 8 categorical performance factors transformed into 36 binary performance factors.

4.4.3 Standardising the Numeric Variables

As previously identified in the exploratory analysis, many of the numeric factors were not on comparable scales or magnitudes. This can cause numerical issues when fitting the regression models to the data. A numeric factor that has a greater scale and magnitude can over shadow other numeric factors that have a smaller scale and magnitude. Thus all numeric factors were standardised to have mean 0 and standard deviation 1.

4.4.3 Data Reduction

As result of the dummy encoding, the number of dimensions of the dataset substantially increased. In total, 111 factors were added to the dataset, this corresponds to a 200% increase in the number of dimensions. To help facilitate the data modelling stage and to avoid the curse of dimensionality, a data reduction was performed on the dataset. It would require a lot of time and resources to model and evaluate all 162 variables in the data modelling stage. The data reduction stage consists of five sections; irrelevant factors, unary factors, linear combinations and highly associated or correlated factors.

4.4.3.1 Irrelevant Factors

A couple of factors, such as the longitude and latitude coordinates, were used in deriving a specific factor like the distance between European capital cities. These factors themselves are irrelevant when trying to explain the scores and voting patterns of the 2016 competition. Thus the longitude and latitude coordinates were removed from the dataset.

4.4.3.1 Unary Factors

A unary factor is a factor with only one specific observation. Due to the handling of missing observations and the dummy encoding of nominal factors, there were 25 binary factors with only 0 observations. In total, 22 of these factors came from the external factors and 3 factors came from the performance factors. All 25 of these unary factors were removed from the dataset as they failed to add any additional information to the data. See Table 4.6 on page 56 for a summary of all unary factors.

4.4.3.2 Linear Combinations

Additionally, due to dummy encoding of the nominal factors, a number of the binary factors form linear combinations. For example, semi-final 2 is the combination of final and semi-final 1. It is appropriate to remove one factor from each of the linear combinations, as these additional binary factors fail to add any extra information to the data. See Table 4.7 on page 56 for a summary of all linear combinations in the data.

Unary Factors				
VBlocs1 FC 3	VBlocs1 FC 12	VBlocs1 TC 12	FC LANG FAM Hellenic	TC LANG FAM Albanian
VBlocs1 FC 4	VBlocs1 FC 13	VBlocs1 TC 14	FC LANG FAM Kartvelian	TC LANG FAM Kartvelian
VBlocs1 FC 6	VBlocs1 FC 14	VBlocs1 TC 20	FC LANG FAM Semetic	TC Singer Gender Mixed
VBlocs1 FC 9	VBlocs1 FC 19	FC LANG FAM Albanian	FC LANG FAM Semitic	FC SONG LANG Bosnian
VBlocs1 FC 11	VBlocs1 FC 20	FC LANG FAM Armenian	FC LANG FAM Turkic	FC SONG LANG Macedonian

Table 4.6 – Unary Factors.

Linear Combinations		
Mode 0	Mode 1	
Time signature 3	Time signature 4	
Host Nation n	Host Nation y	
Com VBlocs1 n	Com VBlocs1 y	
Com VBlocs2 n	Com VBlocs2 y	
Voting Method T	Voting Method J	
TC Perf Type Duet	TC Perf Type Solo	TC Perf Type Group
Com VBlocs1 n	Com VBlocs1 y	
Com VBlocs2 n	Com VBlocs2 y	
Neighbours n	Neighbours y	
Round sf2	Round sf1	Round f

Table 4.7 – Linear Combinations

4.4.3.3 Highly Associated or Correlated Factors

The majority of data reduction was based on Chi-square tests of associations and correlation tests. There are many binary factors in the dataset that represent the same concept, such as the language of a song, voting blocs or the key of a song. Furthermore, many of these factors are sparse due to dummy encoding the nominal factors. Thus, many of these factors were highly associated and returned a significant Chi-square test result. It is unnecessary to keep such factors in the dataset, as they add to the dimensions, increase the chance of multi-collinearity and fail to add any substantial information to the data. Tables 4.8, 4.9, 4.10 and 4.11 on pages 57, 58 and 59 display the Chi-square test results for voting blocs, language families, song languages and keys. All the factors stored in the X columns of the tables were removed from the data, as they were found to be associated with the factors stored in the Y columns.

Table 4.12 on page 59 displays the correlation tests for the highly correlational numeric factors. The migration patterns and economic factors appear to be all highly correlated. In particular the migration measures METRIC_COB, METRIC_Citizens and METRIC_COBCit are all highly correlated, suggesting that multi-collinearity could be an issue. As such, METRIC_COB and METRIC_COBCit were be removed from the dataset.

Highly Associated Voting Blocs					
X	**Y**	**P-Val**	**X**	**Y**	**P-Val**
VBlocs1 FC 2	VBlocs1 FC 1	0 ***	VBlocs1 TC 10	VBlocs1 TC 1	0.02 *
VBlocs1 FC 5	VBlocs1 FC 1	0 ***	VBlocs1 TC 11	VBlocs1 TC 1	0 ***
VBlocs1 FC 7	VBlocs1 FC 1	0 ***	VBlocs1 TC 11	VBlocs1 TC 3	0.043 *
VBlocs1 FC 8	VBlocs1 FC 1	0 ***	VBlocs1 TC 15	VBlocs1 TC 1	0.03 *
VBlocs1 FC 10	VBlocs1 FC 1	0 ***	VBlocs1 TC 16	VBlocs1 TC 1	0 ***
VBlocs1 FC 15	VBlocs1 FC 1	0 ***	VBlocs1 TC 16	VBlocs1 TC 3	0.043 *
VBlocs1 FC 17	VBlocs1 FC 1	0 ***	VBlocs1 TC 17	VBlocs1 TC 1	0 ***
VBlocs1 FC 21	VBlocs1 FC 1	0 ***	VBlocs1 TC 18	VBlocs1 TC 1	0 ***
VBlocs2 FC 2	VBlocs2 FC 1	0.005 **	VBlocs1 TC 18	VBlocs1 TC 3	0.015 *
VBlocs2 FC 2	VBlocs2 FC 5	0 ***	VBlocs1 TC 19	VBlocs1 TC 1	0 ***
VBlocs1 TC 2	VBlocs1 TC 1	0 ***	VBlocs1 TC 21	VBlocs1 TC 1	0.045 *
VBlocs1 TC 2	VBlocs1 TC 3	0.021 *	VBlocs2 TC 2	VBlocs2 TC 1	0 ***
VBlocs1 TC 4	VBlocs1 TC 1	0.013 *	VBlocs2 TC 2	VBlocs2 TC 2	0 ***
VBlocs1 TC 5	VBlocs1 TC 1	0 ***	VBlocs2 TC 2	VBlocs2 TC 4	0.03 *
VBlocs1 TC 5	VBlocs1 TC 3	0.019 *	VBlocs2 TC 2	VBlocs2 TC 5	0.003 **
VBlocs1 TC 6	VBlocs1 TC 1	0 ***	VBlocs2 TC 3	VBlocs2 TC 1	0 ***
VBlocs1 TC 7	VBlocs1 TC 1	0.001 ***	VBlocs2 TC 3	VBlocs2 TC 4	0.027 *
VBlocs1 TC 8	VBlocs1 TC 8	0 ***	VBlocs2 TC 3	VBlocs2 TC 5	0.002 **

Table 4.8 – Highly Associated Voting Blocs

Highly Associated Language Families		
X	**Y**	**P-Value**
FC LANG FAM Baltic	FC LANG FAM Germanic	0 ***
FC LANG FAM Baltic	FC LANG FAM Slavic	0 ***
FC LANG FAM Baltic	FC LANG FAM Uralic	0 ***
FC LANG FAM Italic Romance	FC LANG FAM Germanic	0 ***
FC LANG FAM Italic Romance	FC LANG FAM Slavic	0.026 *
FC LANG FAM Italic Romance	FC LANG FAM Uralic	0.015 *
TC LANG FAM Armenian	TC LANG FAM Germanic	0 ***
TC LANG FAM Armenian	TC LANG FAM Slavic	0.002 **
TC LANG FAM Baltic	TC LANG FAM Germanic	0 ***
TC LANG FAM Baltic	TC LANG FAM Italic Romance	0.049 *
TC LANG FAM Baltic	TC LANG FAM Slavic	0 ***
TC LANG FAM Hellenic	TC LANG FAM Germanic	0.002 **
TC LANG FAM Hellenic	TC LANG FAM Slavic	0.01 *
TC LANG FAM Italic Romance	TC LANG FAM Baltic	0.049 *
TC LANG FAM Italic Romance	TC LANG FAM Germanic	0 ***
TC LANG FAM Italic Romance	TC LANG FAM Slavic	0 ***
TC LANG FAM Semetic	TC LANG FAM Germanic	0 ***
TC LANG FAM Semetic	TC LANG FAM Slavic	0.003 **
TC LANG FAM Semitic	TC LANG FAM Germanic	0 ***
TC LANG FAM Semitic	TC LANG FAM Slavic	0.005 **
TC LANG FAM Turkic	TC LANG FAM Germanic	0 ***
TC LANG FAM Turkic	TC LANG FAM Slavic	0.016 *
TC LANG FAM Uralic	TC LANG FAM Germanic	0 ***
TC LANG FAM Uralic	TC LANG FAM Slavic	0.002 **

Table 4.9 – Highly Associated Language Families

Highly Associated Song Languages		
X	**Y**	**P-Value**
FC SONG LANG French	FC SONG LANG English	0 ***
FC SONG LANG Mixed	FC SONG LANG English	0 ***
TC SONG LANG Bosnian	TC SONG LANG Bosnian	0 ***
TC SONG LANG Bosnian	TC SONG LANG English	0 ***
TC SONG LANG French	TC SONG LANG English	0 ***
TC SONG LANG Macedonian	TC SONG LANG English	0 ***

Table 4.10 – Highly Associated Song Languages

Highly Associated Keys					
X	**Y**	**P-Value**	**X**	**Y**	**P-Value**
Key 0	Key 1	0.024 *	Key 2	Key 2	0 ***
Key 0	Key 3	0.005 **	Key 9	Key 3	0.044 *
Key 0	Key 4	0.002 **	Key 9	Key 4	0.022 *
Key 0	Key 5	0.002 **	Key 9	Key 5	0.022 *
Key 0	Key 7	0.001 ***	Key 9	Key 7	0.018 *
Key 0	Key 10	0.035 *	Key 9	Key 11	0.044 *
Key 0	Key 11	0.005 **	Key 10	Key 0	0.035 *
Key 1	Key 0	0.024 *	Key 10	Key 3	0.019 *
Key 1	Key 3	0.013 *	Key 10	Key 4	0.008 *
Key 1	Key 4	0.005 **	Key 10	Key 5	0.008 *
Key 1	Key 5	0.005 **	Key 10	Key 7	0.006 *
Key 1	Key 7	0.004 **	Key 10	Key 11	0.019 *
Key 1	Key 11	0.013 *			

Table 4.11 – Highly Associated Keys

X ~ X Correlation Tests			
X	**Y**	**Correlation**	**P-Value**
FC NonCOB	FC NonCitzens	0.91531	0 ***
FC COB	FC Citizens	0.99978	0 ***
FC COB	FC Population	0.99914	0 ***
FC COB	FC GDP mil	0.92752	0 ***
FC Citizens	FC Population	0.99904	0 ***
FC Citizens	FC GDP mil	0.93506	0 ***
FC Population	FC GDP mil	0.91609	0 ***
METRIC COB	METRIC Citizens	0.83307	0 ***
METRIC COB	METRIC COBCit	0.96724	0 ***
METRIC Citizens	METRIC COBCit	0.94621	0 ***

Table 4.12 – X ~ X Correlation Tests

4.5 Data Modelling

The first stage of the model fitting involved fitting the factors individually based on the three factor groups; competition factors, performance factors and external factors. Stepwise fitting using AIC was used for variable selection. All the fitted variables found to be significant in explaining points progressed to the next stage, where all the significant variables from each bloc were fitted together. Stepwise fitting using AIC was again utilised for variable selection. This process was applied to the three stratified datasets based on the voting method; combined vote, televote and jury vote.

In an attempt to normalise the residuals of the final three fitted models, the response variable points for each model was transformed. A Box-Cox power transformation was performed on the response variable Points for the combined vote model and televote model. This sufficiently normalised the residuals of the televote model, but unfortunately not the combined vote model. Due to this violation of the normality assumption, the combined vote model shall be used as an approximation. A Box-Cox transformation on the response variable points of the jury vote model resulted in normalisation of the residuals, but also non-constant variance. Through trial and error a power transformation of ¾ was found to be the most suitable for the jury vote model, as it resulted in near normality and constant variance. Thus the jury vote model shall be used as an approximation. Table 4.13 on page 60 and Table 4.14 on page 61 show the fitting stages of the combined vote model. Table 4.15 on page 62 and Table 4.16 on page 63 show the fitting stages of the televote model. Tables 4.17 and 4.18 on page 64 show the fitting stages of the jury vote model.

4.5.1 Combined Vote Model

Stage 1 Fitted Combined Vote Model		
Competition Factors		
Average Points	OOA	
Performance Factors		
Speechiness	TC_PerfType Solo	FC SONGLANG English
Acousticness	COMSONGLANG n	liveness
Key 3	Time signature 4	Key 2
Key 5		
External Factors		
METRIC Citizens	VBlocs1 TC 3	Com LANGFAM y
CAP DIST km	VBlocs1 TC 13	Com VBlocs1 TC 1
FC NonCitizens	VBlocs1 TC 1	

Table 4.13 – Stage 1 Fitted Combined Vote Model

Stage 2 Fitted Combined Vote Model		
Variable	**Estimate**	**P-Value (T-Test)**
Intercept	2.20107	0 ***
Average Points	0.20808	0.001 **
VBlocs1 TC 3	0.58153	0.003 **
CAP DIST km	0.12954	0.044 *
FC NonCitizens	0.17855	0.012 *
Com LANGFAM y	0.37800	0.007 **
Liveness	-0.29223	0 ***
Key 3	0.51047	0.028 *
METRIC Citizens	0.09698	0.154
TC PerfType Solo	0.94943	0 ***
Key 2	-0.92510	0.04 *
VBlocs1 TC 13	-1.99317	0.071
Key 6	-1.38873	0.002 **
Time signature 4	-0.8815	0.015 *
ComVBlocs1 y	-0.40286	0.022 *
VBlocs1 TC 1	0.50874	0.003 **
Key 5	-0.48380	0.012 *
OOA	0.47418	0.047 *
Speechiness	0.10033	0.133

Table 4.14 – Stage 2 Fitted Combined Vote Model

$$
\begin{aligned}
&Points^{(0.5454)} \\
&\quad = 2.20107 + 0.20808\ Average_{Points} + 0.58153\ VBlocs1_{TC_3} \\
&\quad + 0.12954\ CAP_{DIST_{km}} + 0.178555\ FC_{NonCitizens} \\
&\quad + \ 0.378\ ComLANGFAM_y - 0.29223\ Liveness \\
&\quad + \ 0.51047\ Key_3 + 0.09698\ METRIC_{Citizens} \\
&\quad + 0.94943\ TC_{PerfType_{Solo}} - 0.92510\ Key_2 \\
&\quad - 1.99317\ VBlocs1_{TC_{13}} - 1.38873\ Key_6 \\
&\quad - 0.8815\ Time_{signature_4} - 0.40286\ ComVBlocs_{TC_{13}} \\
&\quad + 0.50874\ VBlocs1_{TC_1} - 0.48380\ Key_5 + 0.47418\ OOA \\
&\quad + 0.1003\ speechiness
\end{aligned}
$$

4.4.2 Televote Model

Stage 1 Fitted Televote Model		
Competition Factors		
Average Points	OOA	
Performance Factors		
Key 11	Mode 1	Acousticness
Key 7	TC SONGLANG Mixed	Instrumentalness
Danceability		
External Factors		
METRIC Citizens	VBlocs1 TC 3	Com LANGFAM y
VBlocs1 TC 13	VBlocs2 TC 1	

Table 4.15 – Stage 1 Fitted Televote Model

Stage 2 Fitted Televote Model		
Variable	**Estimate**	**P-Value (T-Test)**
Intercept	2.26304	0 ***
METRIC Citizens	0.34461	0 ***
Average Points	0.39603	0 ***
VBlocs1 TC 3	1.07370	0.003 **
VBlocs2 TC 1	-0.77013	0.002 **
Mode 1	0.70492	0 ***
Key 11	0.99686	0.002 **
OOA	0.65497	0.067
Acousticness	0.32378	0.017 *
Danceability	-0.30145	0.018 *
Key 7	-0.69771	0.073
VBlocs1 TC 13	-1.87918	0.1
Com LANGFAM y	0.30175	0.143

Table 4.16 – Stage 2 Fitted Televote Model

$$\begin{aligned} Points^{(0.6262)} = {} & 2.26304 + 0.34461\ METRIC_{Citizens} + 0.39603\ Average_{Points} \\ & + 1.07370\ VBlocs1_{TC_3} - 0.77013\ VBlocs2_{TC_1} + 0.70492\ Mode_1 \\ & + 0.99686\ Key_{11} + 0.65497\ OOA + 0.32378\ Acousticness \\ & - 0.30145\ Danceability - 0.69771\ Key_7 - 1.87918\ VBlocs1_{TC_{13}} \\ & + 0.30175 \end{aligned}$$

4.5.3 Jury Model

Stage 1 Fitted Jury Vote Model		
Competition Factors		
Average Points		
Performance Factors		
Key 4	Liveness	Key 3
TC PerfType Solo	TC SONGLANG English	TC SONGLANG Mixed
External Factors		
VBlocs2 TC 4	VBlocs1 TC 3	Com LANGFAM y
Com VBlocs1 y	TC NumNeigh	

Table 4.17 – Stage 1 Fitted Jury Vote Model

Stage 2 Fitted – Jury Model		
Variable	**Estimate**	**P-Value (T-Test)**
Intercept	2.3002	0.007 **
VBlocs2 TC 4	3.5875	0 ***
Key 3	2.0224	0 ***
TC PerfType Solo	3.0015	0.001 ***
Liveness	-0.5143	0.001 **
Com VBlocs1 y	-0.9192	0.04 *
Com LANGFAM y	0.7984	0.049 *

Table 4.18 – Stage 2 Fitted Jury Vote Model

$$Points^{\frac{3}{4}} = 2.3002 + 3.5875\, VBlocs2_{TC_4} + 2.0224\, Key_3 + 3.0015\, TC_{PerfType_{Solo}} - 0.5143\, Liveness - 0.9192\, ComVBlocs1_y + 0.7984\, ComLANGFAM_y$$

4.6 Model Evaluation

The model evaluation section consists of assessing the assumptions required by multiple linear regression and the overall fit for each of the three fitted models. The assumptions required by multiple linear regression were assessed using normality tests, QQ-plots, residual plots and non-constant variance tests. The overall fit of the models was assessed using variance inflation factors, crooks distance, outlier tests, residual plots and R-squared coefficients.

4.6.1 Combined Vote Model

4.6.1.1 Combined Vote Model Assumptions

The residual versus fits (Figure 4.10 on page 69) plot shows signs of non-constant variance and non-normality. The variance appears to have a diamond shape and the spread of the residuals around the fitted line does not appear to be normal.
The distribution of the studentised residuals seem to approximately fall along the normality line in the QQ-plot (Figure 4.11 on page 69). However, there is notable curvature in the upper tail of the plot, which suggests the studentised residuals are distributed with a long left tail. The distribution of the studentised residuals do appear to be slightly left skewed in the histogram (Figure 4.12 on page 70). This is particularly noticeable when the ideal normality distribution is superimposed on top of the histogram. An Anderson-Darling normality test was conducted (Table 4.20 on page 70) to test if the studentised residuals were normally distributed. The Anderson-Darling test tests the null hypothesis that the studentised residuals are normally distributed. As the p-value was significant the null hypothesis was rejected in favour of the alternative hypothesis. Thus the studentised residuals are not normally distributed.
The spread-level plot (Figure 4.13 on page 71) for the combined vote model shows signs of non-constant variance. A non-constant variance test (Table 4.21 on page 71) was conducted to assess whether the studentised residuals of the model had a constant variance. The non-constant variance test tests the null hypothesis that the studentised residuals have a constant variance. As the p-value for the test was not significant, the null hypothesis was not rejected in favour of the alternative hypothesis. Thus the studentised residuals do have a constant variance.

4.6.1.2 Combined Vote Model Fit

The Cooks distance Plot (Figure 4.14 on page 72) shows no influential observations greater than 1. There are no signs of multi-collinearity affecting the data, as all the VIF (Table 4.22 on page 72) are below 10. According to the adjusted R-squared value (Table 4.19 on page 68), the overall model explains 18.67% of the variation in the data. Although this isn't a high degree of variation explained by the model, it is sufficient for making inferences on whether the predictor variables explain the points and voting patterns. Furthermore, the F-test of overall significance (Table 4.19 on page 68) concludes that the fit of the overall model is significantly greater than just the intercept model.

4.6.2 Televote Model

4.6.2.1 Televote Model Assumptions

The residual versus fits plot (Figure 4.15 on page 73) shows some signs of non-constant variance and non-normality. The variance appears to have a diamond shape and the spread of the residuals around the fitted line does not appear to be normal.

The distribution of the studentised residuals seems to fall approximately along the normality line in the QQ-plot (Figure 4.16 on page 74). However, there is notable curvature throughout the plot, particularly in the upper tail. This suggests the studentised residuals are distributed with a long left tail. The distribution of the studentised residuals does appear to be slightly left skewed in the histogram (Figure 4.17 on page 74). This is particularly noticeable when the ideal normal distribution is superimposed on top of the histogram. An Anderson-Darling normality test was conducted to test whether the studentised residuals were normally distributed (Table 4.24 on page 75). The Anderson-Darling test tests the null hypothesis that the studentised residuals are normally distributed. As the p-value was not significant the null hypothesis was not rejected in favour of the alternative hypothesis. Thus the studentised residuals are normally distributed.

The spread-level plot (Figure 4.18 on page 75) for the televote model shows signs of non-constant variance. A non-constant variance test (Table 4.25 on page 75) was conducted to assess whether the studentised residuals of the model had a constant variance. The non-constant variance test tests the null hypothesis that the studentised residuals do have a constant variance. As the p-value for the test was not significant, the null hypothesis was not rejected in favour of the alternative hypothesis. Thus the studentised residuals do have a constant variance.

4.6.2.2 Televote Model Fit

The Cooks distance Plot (Figure 4.19 on page 76) shows no influential observations greater than 1. There are no signs of multi-collinearity affecting the data, as all the VIF (Table 4.26 on page 76) are below 10. According to the adjusted R-squared value (Table 4.23 on page 73), the televote model explains 29.46% of the variation in the data. This is notably larger than the combined vote model, and it is sufficient for making inferences on whether the predictor variables explain the points of the televote model. Furthermore, the F-test of overall significance (Table 4.22) concludes that the fit of the televote model is significantly greater than just the intercept model.

4.6.3 Jury Model

4.6.3.1 Jury Model Assumptions

The residual versus fits plot (Figure 4.20 on page 77) shows signs of non-constant variance and non-normality. The variance appears to have a diamond shape and the spread of the residuals around the fitted line does not appear to be normal.

The distribution of the studentised residuals seems to approximately fall along the normality line in the QQ-plot (Figure 4.21 on page 77). However, there is notable curvature throughout the plot, particularly in the lower tail. This suggests that the studentised residuals are distributed with a long right tail. The distribution of the studentised residuals do appear to be slightly right skewed in the histogram (Figure 4.22 on page 78). This is particularly noticeable when the ideal normality distribution is superimposed on top of the histogram. An Anderson-Darling normality test (Table 4.28 on page 78) was conducted to test if the studentised residuals were normally distributed. The Anderson-Darling test tests the null hypothesis that the residuals are normally distributed. As the p-value was not significant the null hypothesis was not rejected in favour of the alternative hypothesis. Thus the studentised residuals are not normally distributed.

The spread-level plot (Figure 4.23 on page 73) for the overall model shows signs of non-constant variance. A non-constant variance test (Table 4.29 on page 79) was conducted to assess whether the studentised residuals of the model had a constant variance. The non-constant variance test tests the null hypothesis that the studentised residuals have a constant variance. As the p-value for the test was significant, the null hypothesis was not rejected in favour of the alternative hypothesis. Thus the studentised residuals do have a constant variance.

4.6.3.2 Jury Model Fit

The Cooks distance Plot (Figure 4.24 on page 80) shows no influential observations greater than 1. There are no signs of multi-collinearity affecting the data, as all the VIF (Table 4.30 on page 80) are below 10. According to the adjusted R-squared value (Table 4.27 on page 76), the jury vote model explains 19.42% of the variation in the data. Although this is not a high degree of variation, it is sufficient for making inferences on whether the predictor variables explain the voting patterns of the competition. Furthermore, the F-test of overall significance (Table 4.27 on page 76) concludes that the fit of the jury vote model is significantly greater than just the intercept model.

Adjusted R-Squared and F-Test for Combined Vote Model			
Adj. R-squared	Degrees of freedom	F-statistic	P-value:
0.1867	639	9.379	0 ***

Table 4.19 – Adjusted R-Squared and F-Test for Combined Vote Model

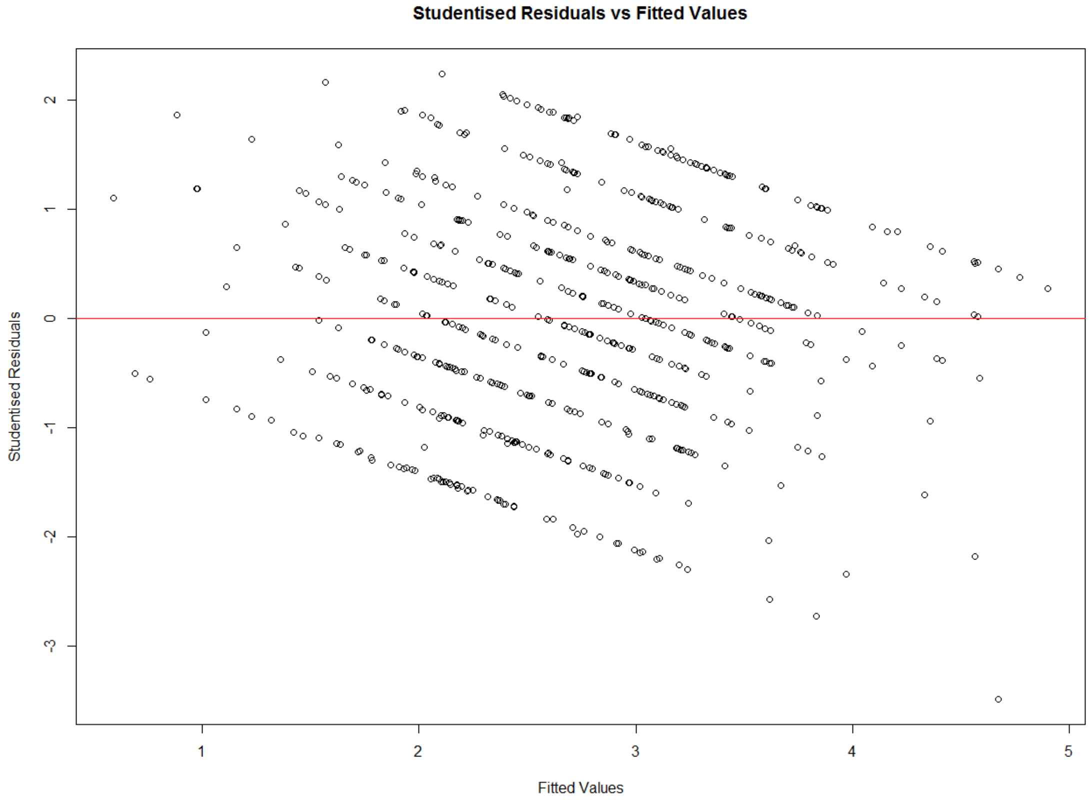

Figure 4.10 – Residual vs Fitted Values Plot for Combined Vote Model

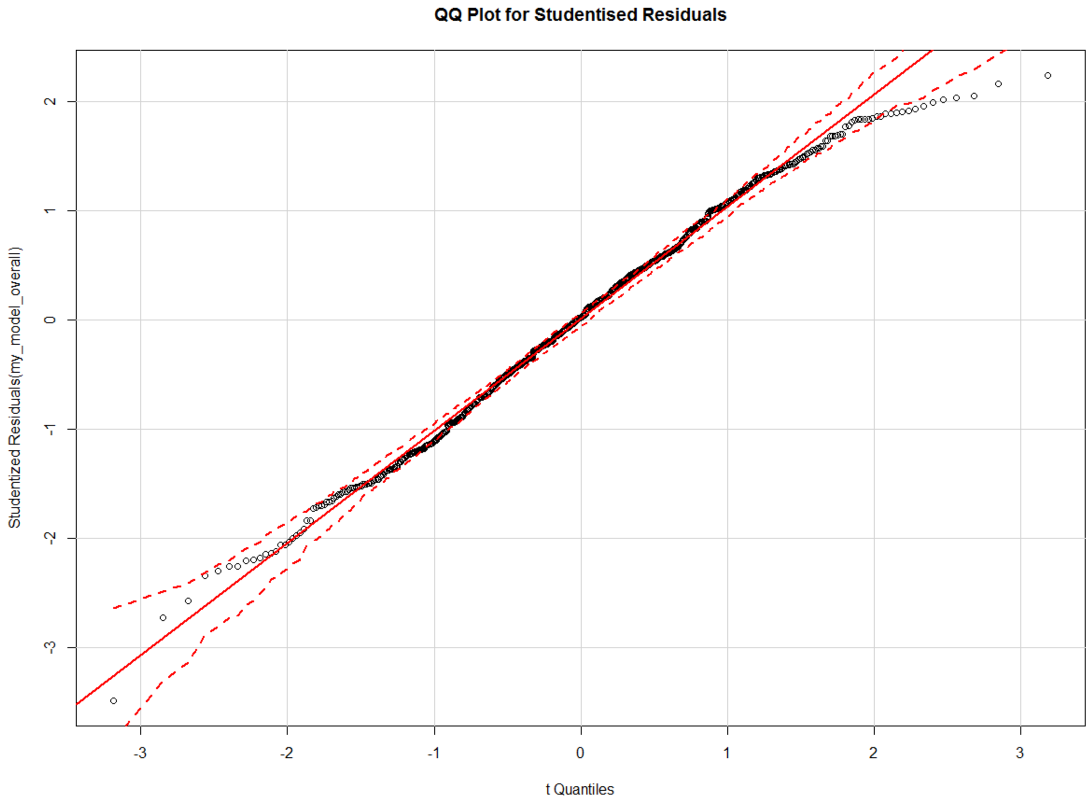

Figure 4.11 – QQ-Plot of Combined Vote Model Studentised Residuals

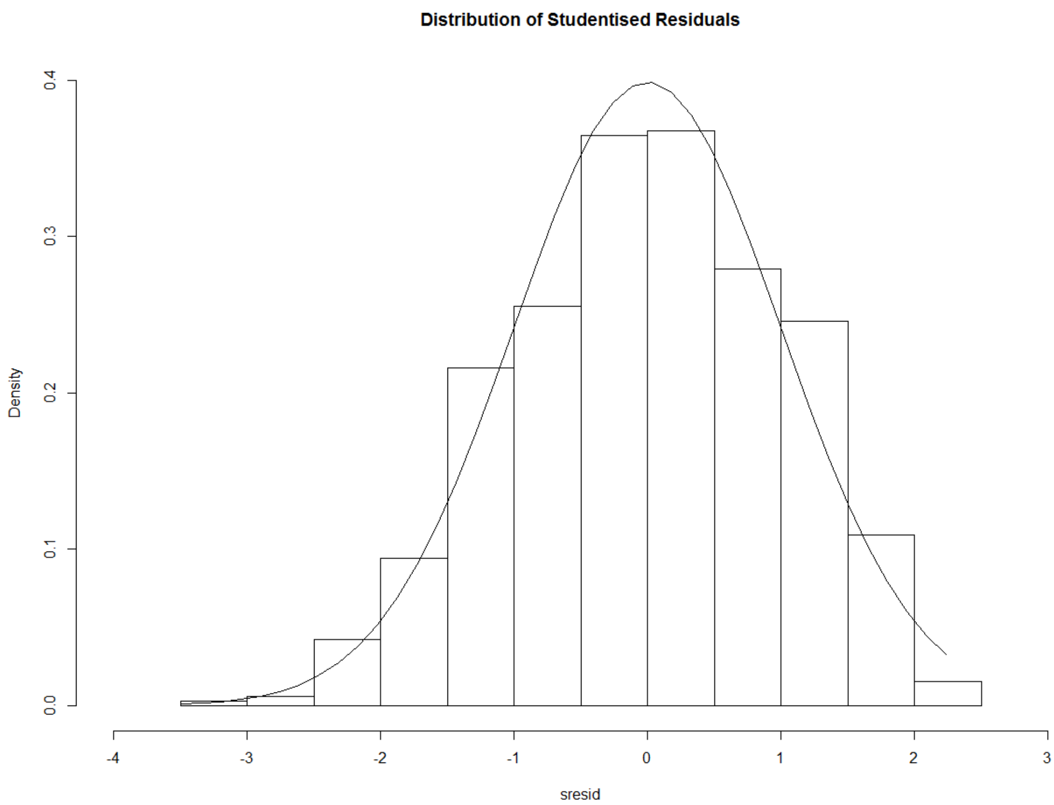

Figure 4.12 – Histogram of Studentised Residuals for Combined Vote Model

Anderson Darling Test of Normality	
Test Statistic	**P-value**
0.97527	0.014 *

Table 4.20 – Anderson Darling Test for Combined Vote Model

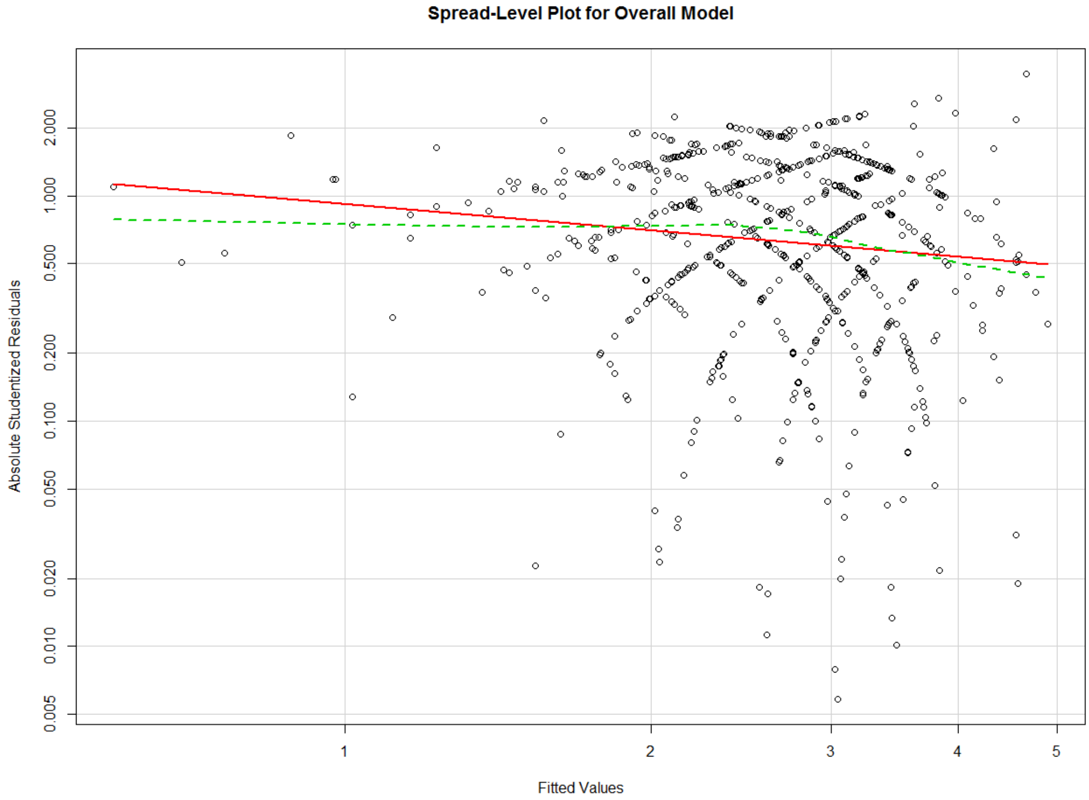

Figure 4.13 – Spread-Level Plot for Combined Vote Model

Non-Constant Variance Test	
Test Statistic	**P-Value**
0.4536413	0.5

Table 4.21 – Non-Constant Variance Test for Combined Vote Model

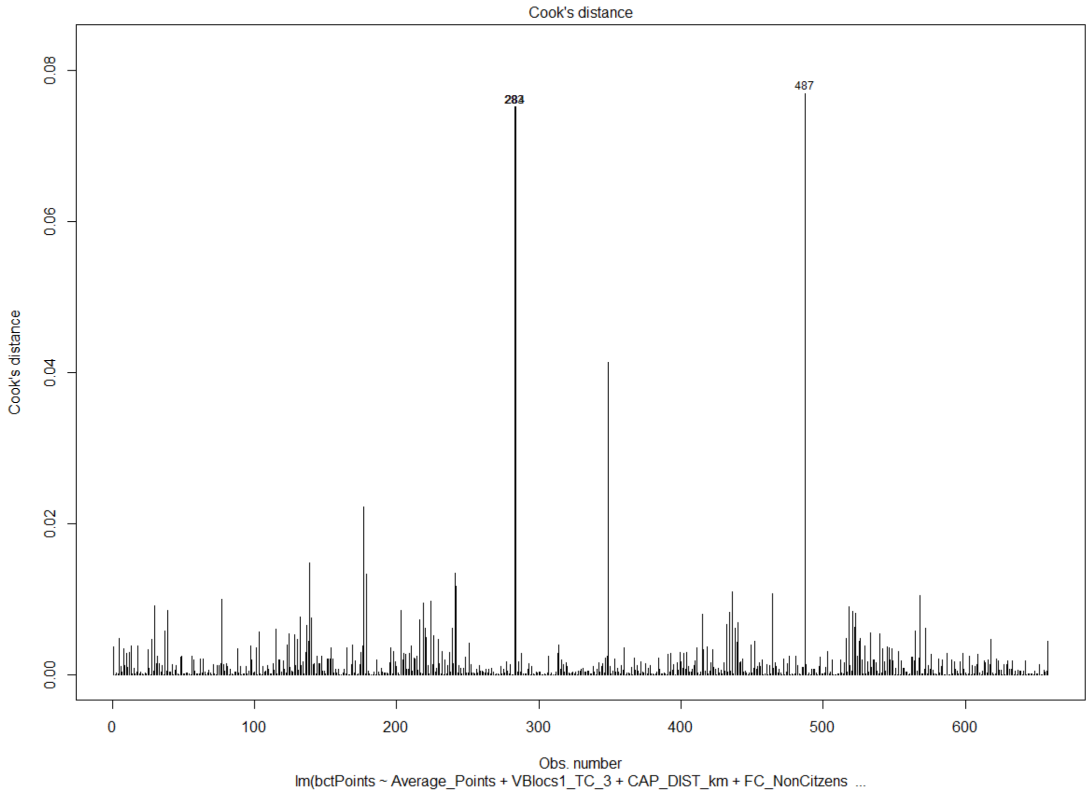

Figure 4.14 – Crook's Distance for Combined Vote Model

VIF for Combined Vote Model			
Variable	**VIF**	**Variable**	**VIF**
Average Points	1.347773	Key 2	1.072051
VBlocs1 TC 3	1.616008	VBlocs1 TC 13	1.180607
CAP DIST km	1.329094	Key 6	1.317441
FC NonCitzens	1.595067	Time signature 4	1.547969
Com LANGFAM y	1.195970	Com VBlocs1 y	1.581708
Liveness	1.467950	VBlocs1 TC 1	2.280827
Key 3	1.752130	Key 5	1.407898
METRIC Citizens	1.479909	OOA	1.526073
TC PerfType Solo	1.159431	Speechiness	1.424888

Table 4.22 – VIF for Combined Vote Model

Adjusted R-Squared and F-Test for Televote Model			
Adj. R-squared	Degrees of freedom	F-statistic	P-value:
0.2946	314	12.35	0 ***

Table 4.23 – Adjusted R-Squared and F-Test for Televote Model

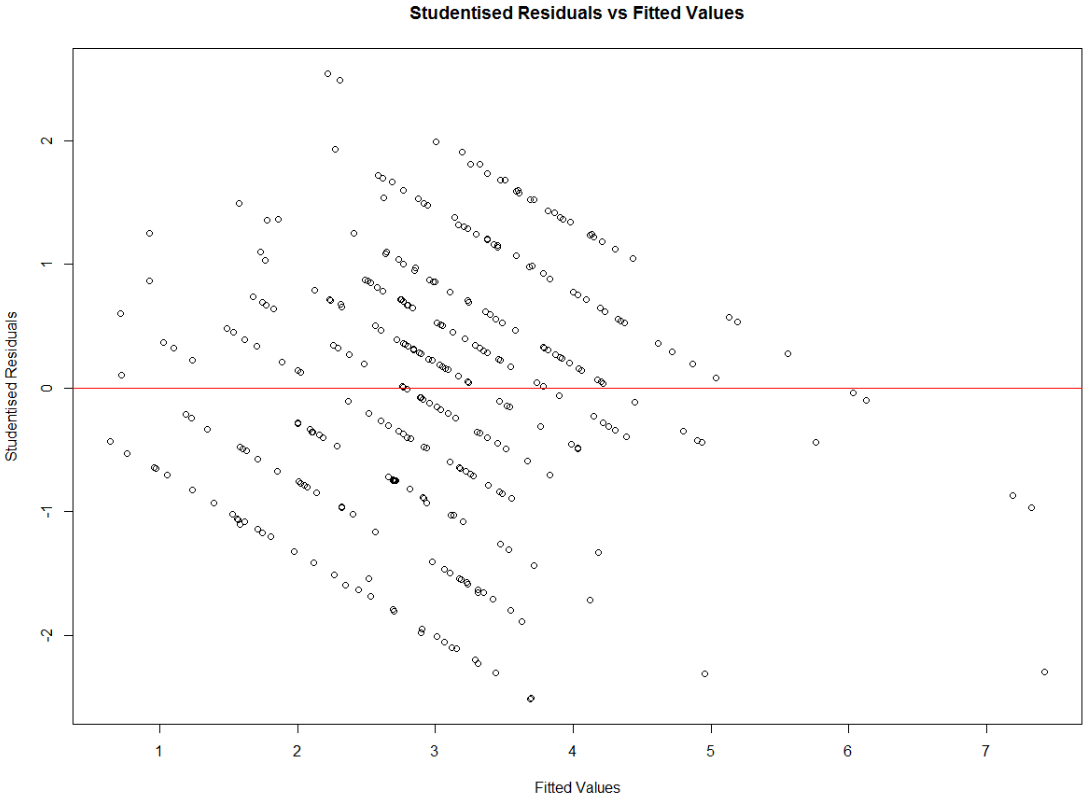

Figure 4.15 – Residual vs Fitted Values Plot for Televote Model

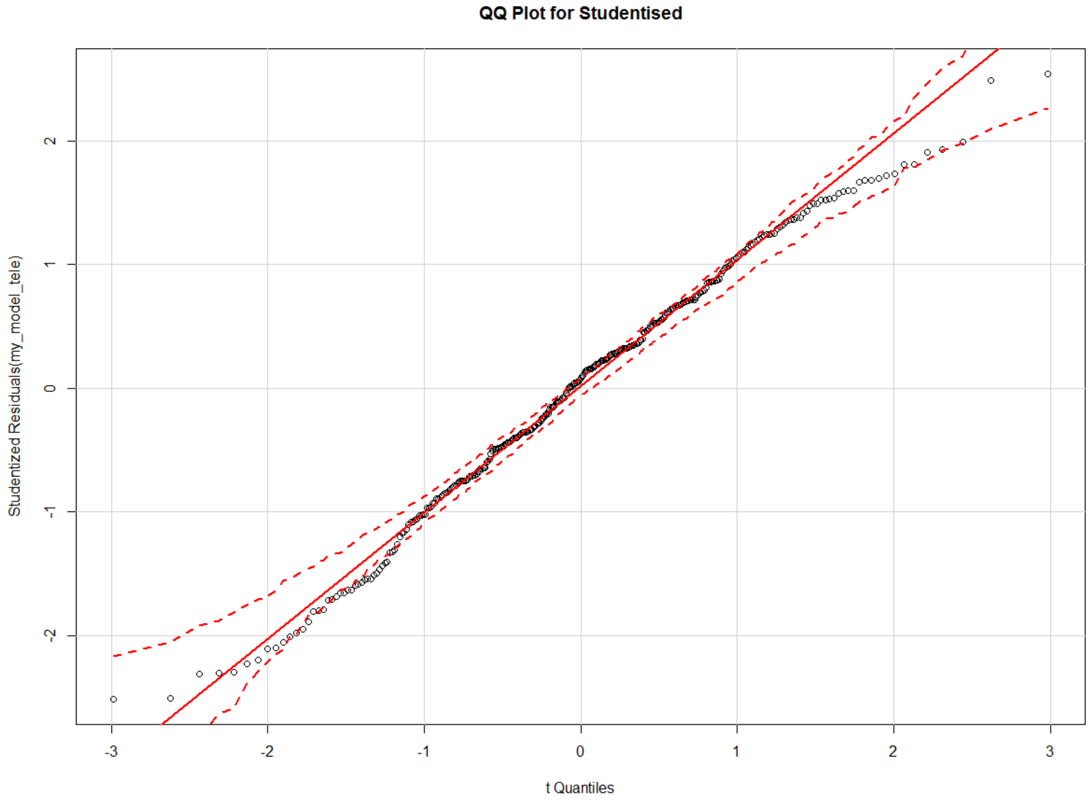

Figure 4.16 – QQ-Plot of Studentised Residuals for Televote Model

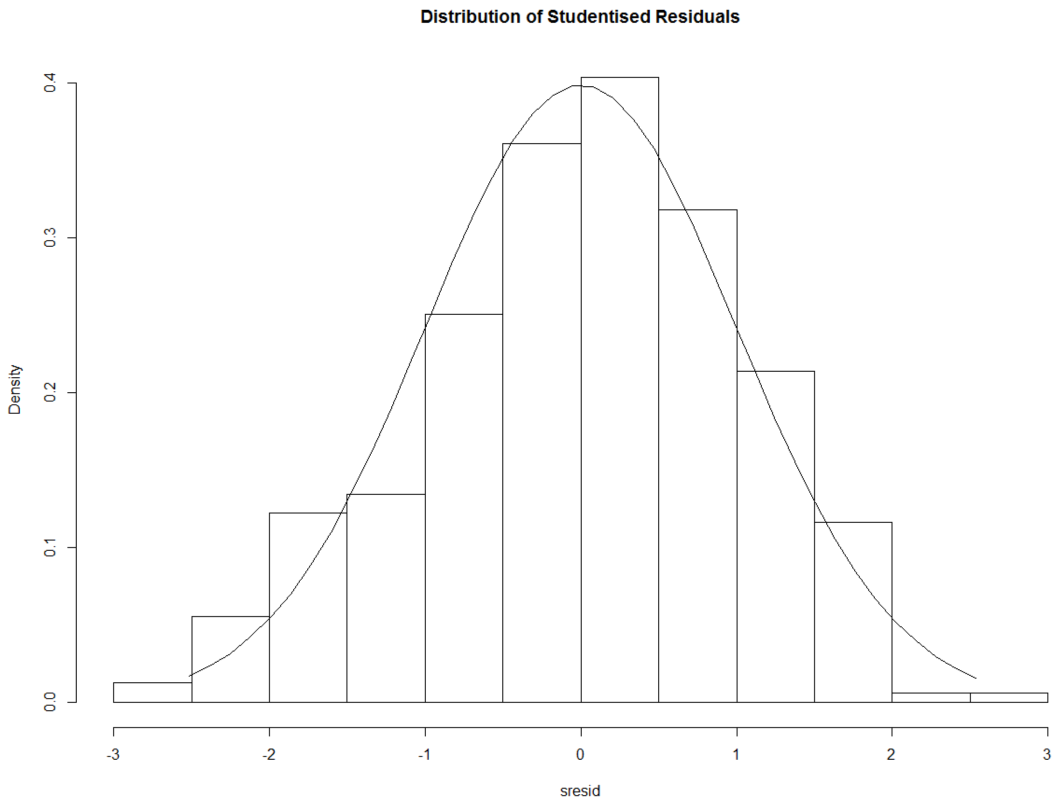

Figure 4.17 – Histogram of Studentised Residuals for Televote Model

Anderson Darling Test of Normality	
Test Statistic	**P-value**
0.61791	0.107

Table 4.24 – Anderson Darling Test for Studentised Residuals

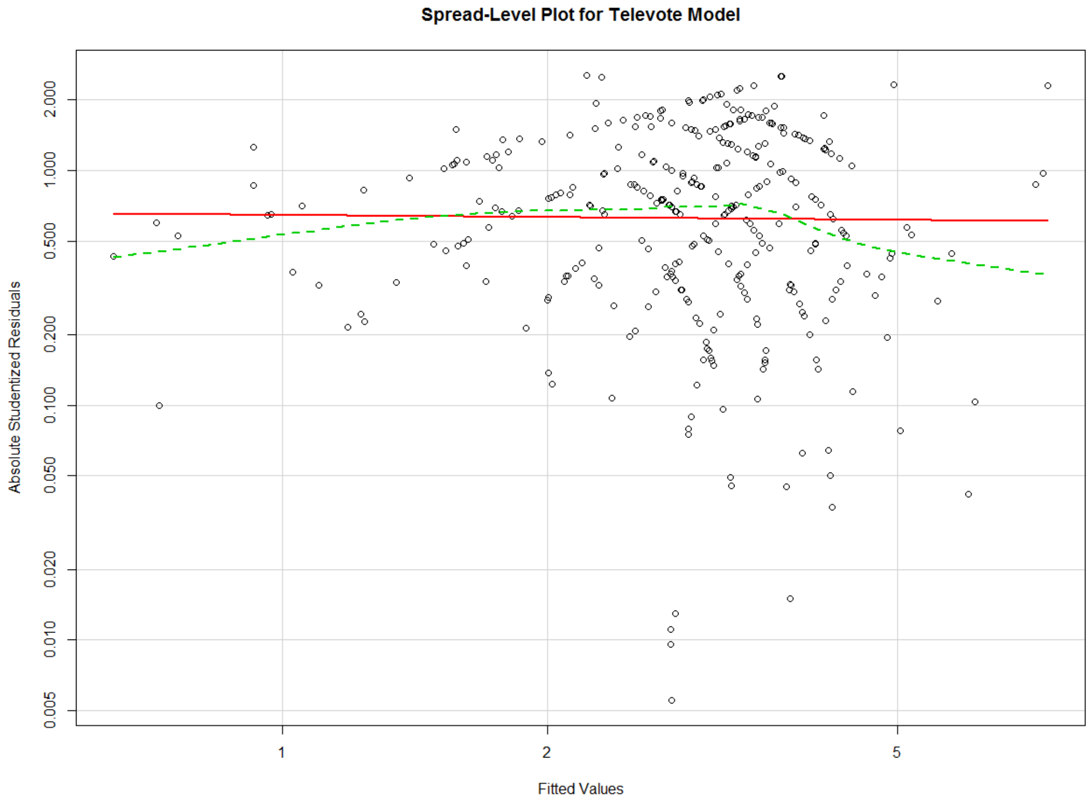

Figure 4.18 – Spread Level Plot for Televote Model

Non-Constant Variance Test	
Test Statistic	**P-Value**
0.8763709	0.349

Table 4.25 – Non-Constant Variance Test for Overall Model

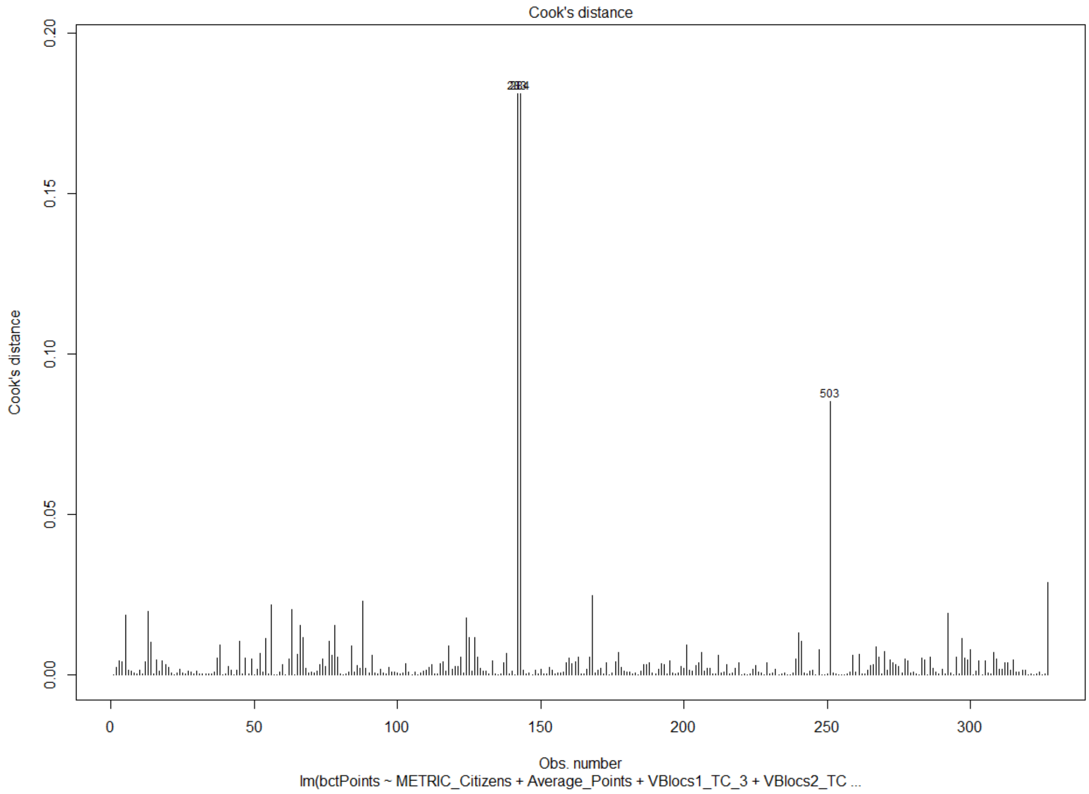

Figure 4.19 – Crooks Distance Plot for Televote Model

VIF for Televote Model			
Variable	**VIF**	**Variable**	**VIF**
METRIC Citizens	1.193334	OOA	1.338632
Average Points	1.101302	Acousticness	2.292494
VBlocs1 TC 3	2.888167	Danceability	1.979577
VBlocs2 TC 1	2.081586	Key 7	1.773117
Mode 1	1.267619	VBlocs1 TC 13	1.120414
Key 11	1.535410	Com LANGFAM y	1.205597

Table 4.26 – VIF for Televote Model

Adjusted R-Squared and F-Test for Jury Model			
Adj. R-squared	Degrees of freedom	F-statistic	P-value:
0.1942	324	14.26	0 ***

Table 4.27 – Adjusted R-Squared and F-Test for Jury Model

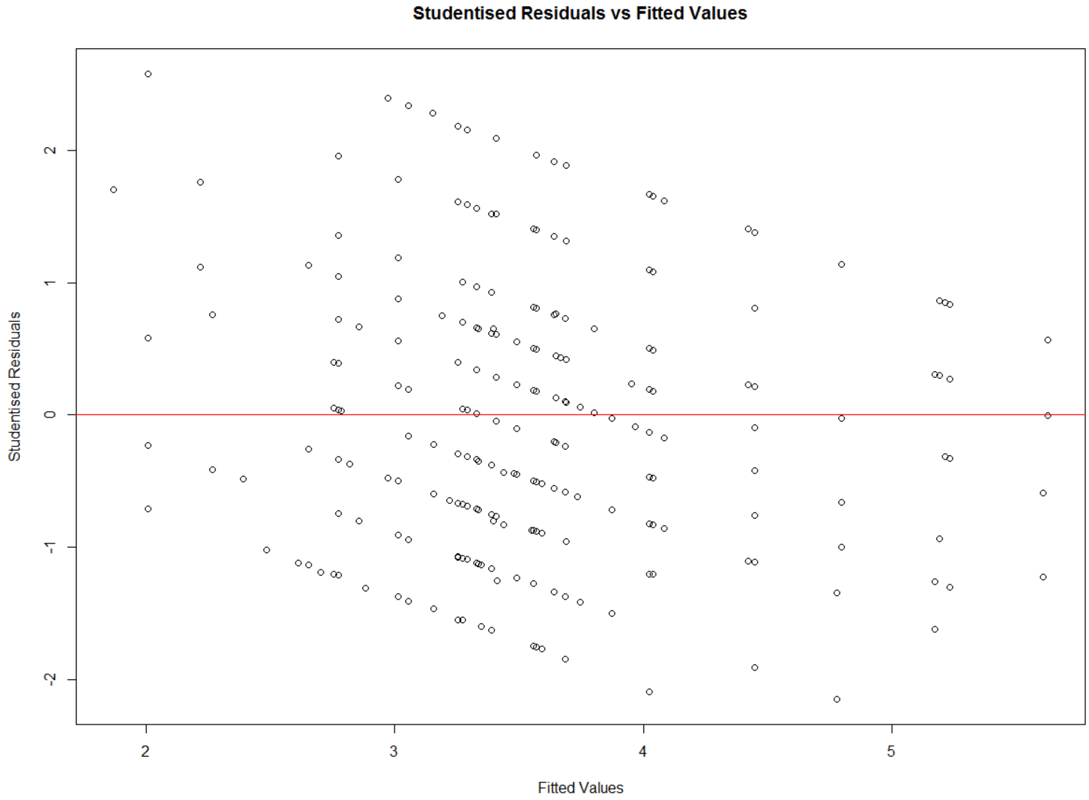

Figure 4.20 – Residual vs Fits for Jury Model

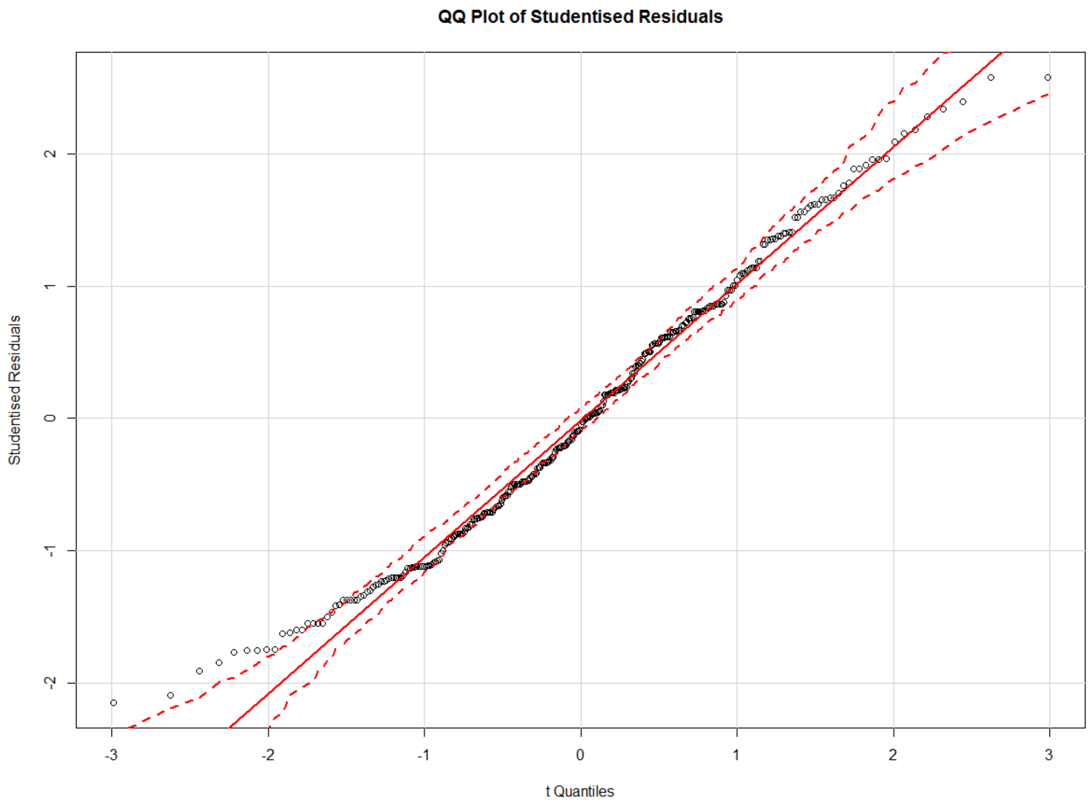

Figure 4.21 – QQ-Plot of Studentised Residual for Jury Vote Model

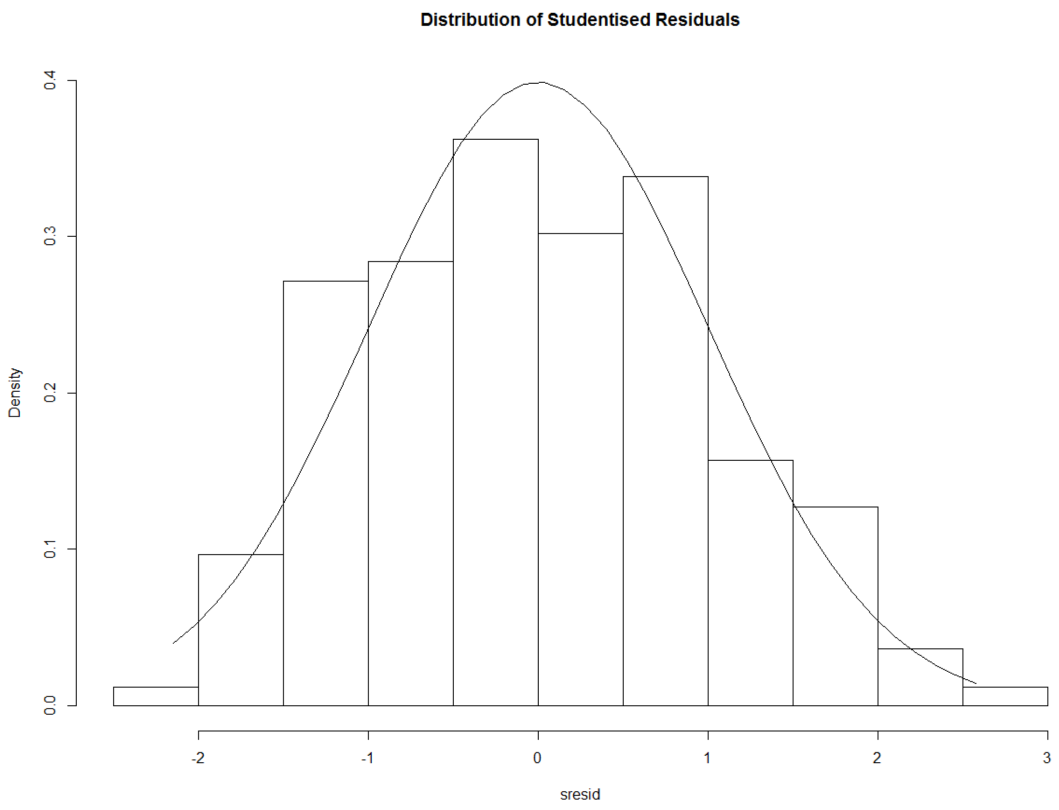

Figure 4.22 – Histogram of Studentised Residual for Jury Vote Model

Anderson Darling Test of Normality	
Test Statistic	**P-value**
1.2686	0.003 **

Table 4.28 – Anderson Darling Test for Jury Vote Model

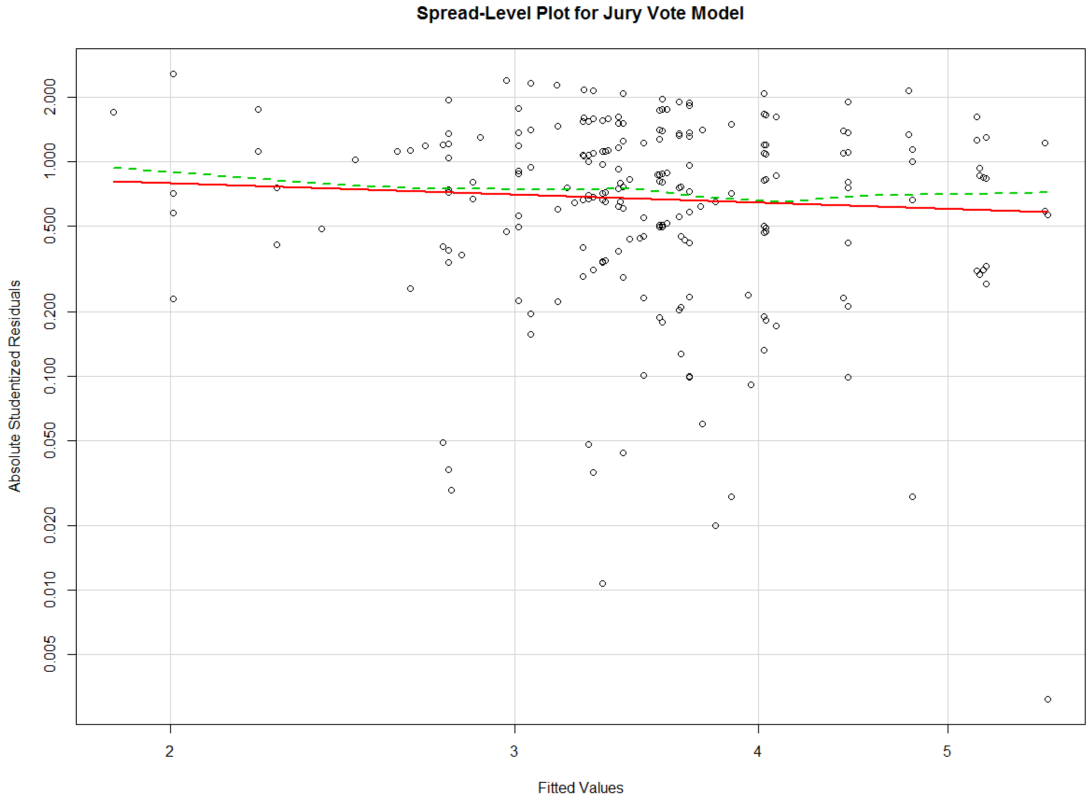

Figure 4.23 – Spread-Level Plot for Jury Vote Model

Non-Constant Variance Test	
Test Statistic	**P-Value**
3.267453	0.071

Table 4.29 – Non-Constant Variance Test for Jury Vote Model

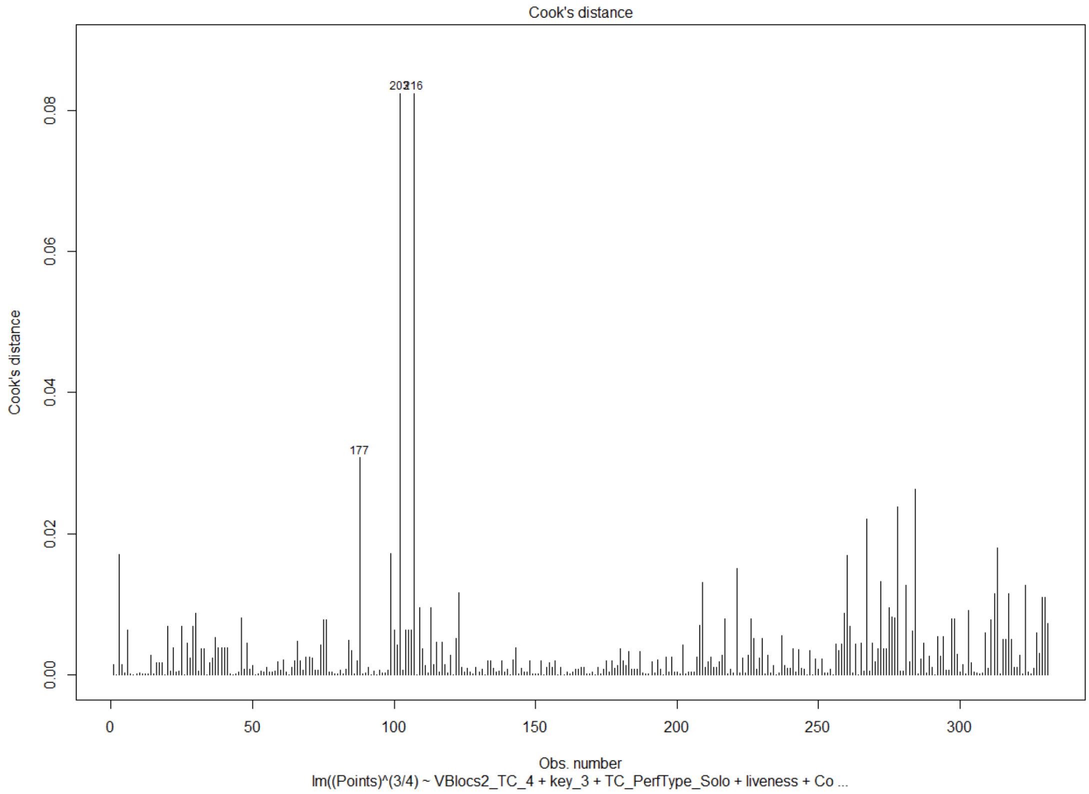

Figure 4.24 – Crooks Distance for Jury Vote Model

VIF for Jury Model			
Variable	**VIF**	**Variable**	**VIF**
VBlocs2 TC 4	1.208411	Liveness	1.068208
Key 3	1.058692	Com VBlocs1 y	1.134866
TC PerfType Solo	1.020516	Com LANGFAM y	1.069148

Table 4.30 – VIF for Jury Vote Model

4.7 Conclusions

The research problem was answered using three methods. Firstly, the significance of the predictor variables in explaining the response variable points was examined using T-tests. Secondly, the effect the predictor variables have on the response variable points was identified by examining the signs of the estimated coefficients of the predictor variables. Thirdly, the additional amount of variation explained by the inclusion of predictor variables was examined by observing the increase in R-squared with the addition of the corresponding predictor variables.

Note that the combined vote and jury vote models will be used to make approximate conclusions as they failed to satisfy the normality assumptions required for linear regression. However, the Televote model passed the normality assumptions and shall be used to make precise conclusions.

4.7.1 T-tests for Predictor Variables

4.7.1.1 Combined Vote Model

Table 4.14 on page 62 shows the T-tests for the predictor variables of the combined vote model. Some of the factors previously identified in the literature review, specifically Average_Points, CAP_DIST_km, ComLANGFAM_y, TC_PerfType_Solo and OOA are significant in explaining the points and voting patterns of the 2016 ESC.
Furthermore, the two voting blocs VBlocs1_TC_3 and VBlocs1_TC_1 are significant in explaining the points. ComVBlocs1_y is also a significant predictor variable in the combined vote model.
Although the migration measure METRIC_Citizens is not significant in explaining the points, FC_NonCitizen is significant in explaining the ESC scores.
A collection of the Echo Nest music factors are also significant in explaining the points of the 2016 ESC; most notably liveness, key_3, key_2, time_signature_4 and key_5.

4.7.1.2 Televote Model

Table 4.16 on page 64 shows the T-tests for the televote model predictor variables. Similar to the combined vote model, Average_Points is significant in explaining the scores. However, in contrast to the combined vote model; CAP_DIST_km, OOA, ComLANGFAM and TC_PerfType_Solo are not.
Furthermore, like the combined vote model, the televote model has two significant voting blocs; VBlocs1_TC_3 and VBlocs2_TC_1. Note, VBlocs1_TC_3 is also significant in the combined vote model, while VBlocs2_TC_1 is not.
The migration measure METRIC_Citizens is significant in explaining the points of the televote, while FC_NonCitizens is not.
Finally a handful of Echo Nest music factors are significant in explaining the televote, specifically mode_1, key_7, key_11, acousticness and danceability. It should be noted

that these Echo Nest music factors are completely different from those in the combined vote model.

4.7.1.3 Jury Model

Table 4.18 on page 65 shows the T-test results for the predictor variables of the jury vote model. These results further contrast the findings of both the combined vote and televote models.

The only previously identified factors from the literature review that are significant in explaining the jury vote are TC_PerfType_Solo and ComLANGFAM_y. This is in contrast to the two other models, where among other factors, Average_Points was significant in explaining the voting patterns.

Furthermore, the only voting bloc significant in explaining the jury vote is VBlocs2_TC_4, which is not a significant predictor variable in either of the other two models. Similar to the combined vote model, ComVBlocs1_y is also significant in explaining the jury vote scores.

None of the migration based factors are significant in explaining the jury vote. This contrasts with the other two models, where FC_NonCitizens and METRIC_Citizens are significant.

4.7.2 Sign Effects of Predictor Variables

4.7.2.1 Combined Vote Model

The signs of the estimated coefficients (Table 4.14 on page 62) in the combined vote model show the effect the predictor variables have on the points of the combined vote. The majority of predictor variables; specifically Average_Points, OOA, VBlocs1_TC_3, VBlocs1_TC_1, FC_NonCitizens, key_3, TC_PerfType_Solo, and speechiness all have a positive impact on the voting patterns of the combined vote. The remaining predictor variables VBlocs1_TC_1, key_5, key_2, key_6, time_signature_4 and liveness have a negative effect on the points.

4.7.2.2 Televote Model

Table 4.16 on page 64 displays the signs of the estimated coefficients for the televote model. These signs show the effects the predictor variables have on the scores from the televote data. The predictor variables Average_Points, METRIC_Citizens, VBlocs1_TC_3, mode_1, key_11, acousticness and danceability have a positive effect on the scores. These results complement the combined vote model, where Average_Ponts, VBlocs1_TC_1 and the migration patterns also have a positive impact on the scores. In contrast, the remaining predictor variables; specifically VBlocs2_TC_1, danceability, key_7 and VBlocs1_TC_13 all have a negative effect on the voting pattern.

4.7.2.3 Jury Vote Model

The signs of the estimated coefficients for the jury vote model can be found in Table 4.18 on page 65. The signs show the directional effect the predictor variables have on the points from the jury vote. The predictor variables VBlocs2_TC_4, key_3, and TC_PerfType_Solo have a positive effect on the points of the jury. The remaining predictor variables liveness and ComVBlocs1_y have a negative impact on the voting patterns.

4.7.3 Additional Variance Explained by Predictor Variables

4.7.3.1 Combined Vote Model

The adjusted R-squared (Table 4.19 on page 69) value for the combined vote model is 0.1867. In contrast, the adjusted R-squared value for the combined vote model excluding all voting blocs is 0.1659. Therefore the incorporation of the voting blocs corresponds to an additional increase of 2.08% in the amount of variation explained by the model.

The adjusted R-squared value for the combined vote model excluding all Echo Nest music factors is 0.1336. Thus with the incorporation of the Echo Nest features, the combined vote model explains an additional 5.31% of the variation in the data.

Finally the adjusted R-squared value for the combined vote model excluding the migration patterns is 0.1732. Therefore the inclusion of the migration patterns explains an additional 1.35% of variation in the data.

It is interesting to see that out of these three groups of variables it is the Echo Nest features that explain the most variation in the data.

4.7.3.2 Televote Model

The adjusted R-squared value (Table 4.23 on page 74) for the final Televote model is 0.2946. In comparison, the adjusted R-squared value for the Televote model excluding all voting blocs is 0.2679. Therefore the incorporation of the voting blocs corresponds to an additional increase of 2.67% in the amount of variation explained by the model.
The adjusted R-squared value for the Televote model excluding all Echo Nest music factors is 0.257. Thus with the incorporation of the Echo Nest features, the Televote model explains an additional 3.76% of the variation in the televote data.
Finally the adjusted R-squared value for the Televote model excluding all features based migration patterns is 0.2526. Thus the inclusion of features based on migration data explains an additional 4.2% of the televote data.
It is interesting to see that out of these three groups of variables it is the migration based variables that explain the most variation in the data. This is in contrast to the overall vote model, where the Echo Nest features explain the most variation.

4.7.3.3 Jury Model

The adjusted R-squared value (Table 4.27 on page 77) for the final Jury vote model is 0.1981. In contrast the adjusted squared value for the Jury vote model excluding all voting blocs is 0.1038. Therefore the incorporation of the voting blocs corresponds to an additional increase of 9.43% of the amount of variation explained by the model.
Furthermore the adjusted R-squared value for the Jury vote model excluding all Echo Nest features is 0.1442. Thus with the incorporation of the Echo Nest Features, the Jury vote model explains an additional 5.39% of the variation in the jury data.
It is interesting to see that out of the groups of variables it is the voting blocs that explain the most variation in the jury vote data. This is in contrast to both the combined vote model and the televote model, where the Echo Nest features and migration patterns explained the most variation respectively.

4.8 Summary

This chapter outlined the results from the methodologies described in the previous chapter. There were six sections to this chapter; data collection, exploratory analysis, data processing, data modelling, model evaluation and conclusions.

The data collection section outlined the sources of the data used in the research, as well as the results for some of the variables that required derivation; such as the voting blocs. The data for the migration patterns and Echo Nest music factors were collected from the Eurostat website and Spotify Web API respectively. The exploratory analysis mostly consisted of constructing visualisations and descriptive statistics for the collected variables. The migration factors were found to be correlated with the points of the 2016 ESC. Similarly the voting blocs were found to have an association with the points. However there was little association or correlation found between the Echo Nest music factors and the points. Notably, the exploratory analysis informed the data processing tasks needed prior to the data modelling stage.

In total, there were four tasks required in the data processing stage in order to facilitate the data modelling stage. All the incomplete observations were removed from the data which resulted in a dataset of 658 observations. The nominal variables were dummy encoded to facilitate the modelling of the categories, this resulted in 132 binary variables. As some factors such as OOA and FC_Citizens were not on a comparable scale or magnitude, all the numeric variables were standardised to have mean 0 and standard deviation 1. Finally a data reduction removed 83 variables from the dataset, resulting in a final processed dataset of 79 variables.

The data modelling sections give the results of modelling the data. Three models were iteratively fitted to the data based on the stratified approach described in chapter three. Furthermore the response variables of each model were transformed in an attempt to normalise the residuals. A Box-Cox power transformation of 0.5454 and 0.6262 was performed on the combined vote model and the televote model respectively. Although a Box-Cox transformation was not efficient on the jury vote model, through trial and error a power transformation of ¾ was found to result in near normality and constant error variance.

The model evaluation section assessed both the model assumptions and fit of the three final models. As the normality assumptions were not satisfied for the combined vote and jury vote models, these results were interpreted as approximations. However, the Televote model satisfied all the assumptions required for linear regression and could be used to derive precise solutions. Furthermore the fit for all three of the final models was found to be satisfactory. The crooks distance for all observations from the three models were less than 1. There was no signs of multi-collinearity being an issue, as all of the VIF were less than 10.

The conclusion section outlined the results for the research hypothesis. For the most part the voting blocs, migration patterns and Echo Nest music factors were significant in explaining the points and voting patterns of the 2016 ESC. Notably, the migration patterns were significant in explaining the scores of the combined vote and the televote. With regards to the Echo Nest music factors, acousticness had a positive affect and danceability had a negative effect on the televote scores. Furthermore the migration patterns had a positive impact on the points. The variables were most effective at explaining the scores from the televote, as the televote model returned the highest adjusted R-squared value of 0.2946.

5. ANALYSIS, EVALUATION AND DISCUSSION

5.1 Introduction

This chapter discusses the results from the previous chapter in the broader context of the research problem. The discussion will also suggest possible reasons for the results. This chapter will be split into four sections; literature review factors, voting blocs, and migration patterns and Echo Nest music factors.

5.2 Literature Review Factors

A number of factors were incorporated into this dissertation based on past research. Notably, the average number of points exchanged between countries is a good predictor of the voting patterns of the 2016 ESC combined vote and televote, but not the jury vote. Overall, this is in keeping with Clerides and Stengos' (2006) research on the ESC, and makes intuitive sense as historic voting patterns should give some indication of the current trends, give or take some degree of error. If two countries have consistently exchanged a high magnitude of points throughout the competition, it is likely that they will continue this pattern.

The order of appearance in which the participants performed can also explain the voting patterns of the competition. This dissertation determined that the participants who performed later on in the competition scored higher than the participants who performed earlier on in the competition. This is understandable, as the audience is more likely to remember the performances at the end of the competition than at the beginning of the competition. This is in keeping with previous research, such as Spierdijk and Vellekoop's (2006) paper, which also found similar results. However, they also determined that performers who performed at the very start and end of the competition scored higher than performers who performed in the middle of the competition.

5.3 Voting Bloc

Throughout the research on the ESC, the presence of voting blocs has been continuously identified. Voting blocs are communities of countries who systematically trade votes

regardless of performance quality. These voting blocs are thought to be driven mostly by geographical, cultural and political factors.
The results showed that the effects of voting blocs were present in the 2016 ESC. In particular, the voting blocs were significant in explaining the scores from the combined vote, televote and jury vote. However, the voting blocs were found to be more prolific in the televote and combined vote. It is possible that the significant voting blocs of the televote carried over into the combined vote, and as such had a significant impact on the final scores and rankings of the competition. This is in keeping with previous research, which found the televote to be more susceptible to biased voting. The jury as a panel of music experts, are expected to distribute points without being biased by irrelevant factors. As such it could be the audience at home who are the underlying cause of the voting blocs, due to biased voting bias due to geographical, cultural and political factors.
The results show that being a member of a voting bloc has both a positive and negative impact on the scores, in that some voting blocs increase the magnitude of points, while others decrease the magnitude of points. Possible reasons for this could be the size of the voting bloc and the influence of the voting bloc members. In relation to this research, it should be noted that the voting blocs in this dissertation varied substantially in size and members.

5.4 Migration Patterns

Similarly, there has been a persistent insinuation that migration patterns influence the scores of the competition. It is thought that migrants consistently and systematically vote for their home country, regardless of the quality of the performance.
The results concluded that the migration patterns did in fact explain the points and voting patterns of the 2016 contest. This is in keeping with previous research which concluded that Turkish migrants abroad consistently vote for Turkey in the competition. Similarly, Blangardo and Baio found in their 2015 paper that population stock counts could explain the points and scores of the ESC. Interestingly, the migration patterns were found to be most influential in the televote, which in turn may have carried over to the combined vote. Furthermore, it is interesting to note that the the effects of migration could not be found at all in the jury vote. This is once again in keeping with the idea of having expert judges to determine the results of music competitions, whereby they are less likely to be biased by irrelevant factors in comparison to the general public.

The results found the migration patterns to have a positive effect on the points, as such the higher the proportion of migrants living abroad, the greater the chance of an increase in points for their home country. It is understandable that people are likely to vote for their home country due to a special connections they associate with it; such as the country of their birth or citizenship.

5.5 Echo Nest Music Factors

Unlike the voting blocs and migration patterns, there has not been any research into modelling the ESC scores using music features derived from Echo Nest services. In relation to previous research, the Echo Nest music factors have been predominantly utilised in the context of hit song classification, with varying degrees of success. Most research into performance factors of the ESC relate to the performance type, the gender of the singer and the language of the song. There has not been any research into quantifying music concepts such as key, tempo and energy.

The results showed that Echo Nest music factors such as energy, tempo and valance could not explain the points and voting patterns of the ESC. This is in keeping with Borg and Hokkanen's research on pop hit classification, which concluded that the Echo Nest music factors alone were insufficient to predict a hit song. However a number of Echo Nest music factors were found to be significant in explaining the points and voting patterns of the 2016 ESC; most notably danceability, acousticness and the keys of the songs. Interestingly danceability had a negative effect on the televote scores, while acousticness had a positive effect on the televote scores. This could be interpreted as the factors that describe the current fashionable trend in pop music both in the competition and in the general public. Parallels can be drawn between these effects and the musical features of the most pop artists today, such as Ed Sheeran, whose predominant musical style is very acoustic based in nature and less dance music orientated. A degree of caution should be taken with the keys, as the keys might actually be more representative of certain countries and not the actual key of the song. For example key 3 was found to be significant in explaining the scores of the jury vote and televote. However, upon closer inspection, there are only three countries that performed a song in key 3; Malta, Bosnia and Herzegovina, and the winning country Ukraine. Thus key three may be significant purely because the winning country Ukraine performed in the key.

5.6 Summary

In summary, this chapter has sought to apply the results of the previous chapter to the research problem and the broader context of the ESC. Leading to the conclusion that the voting blocs, the migration patterns and some of the Echo Nest music factors were significant in explaining the points and voting patterns of the 2016 ESC. Interestingly the influence of migration patterns and voting blocs was found to be more prevalent in the televote data, which in turn may have contributed to the combined vote. This makes intuitive sense, as the televote is more susceptible to bias than the jury vote, as the jury is designed as a collection of music experts who judge the performances purely based on the music and songs. Furthermore acousticness and danceability were also found to be significant in explaining the scores. This could be interrupted as the current and preferred music trend in the competition, whereby the songs which are more acoustic and less dance orientate score higher. Finally, the findings and concepts present here can be further applied to other competitions and structures that rely on either opinion polls or expert judges, such as BBC's strictly come dancing or ITV's X-Factor.

6. CONCLUSION

6.1 Research Overview

The ESC has become a cultural phenomenon in the twenty first century. It is now a multi-continental song competition encompassing up to 42 countries. Each participating country sends an artist and original song to be performed. Winning the competition offers brief exposure and air time for performers to progress their music career to the next level. Furthermore the winning country gets to host the competition the following year, in turn benefiting from exposure and increased tourism. In order to be successful at the ESC, a performer must appeal to a wide proportion of the audience. There are a lot of factors involved in determining such a performance. Some of these factors may be in the control of the performer, such as the type of song and music being performed. Other factors are in the control of the competition, such as the order of appearance and rounds. However there are external factors such as migration patterns and voting blocs that are outside the control of both the performer and the competition.

6.2 Problem Definition

This research focused on exploring whether the points and voting patterns of the 2016 ESC could be explained using a combination of competition, external and performance factors. It is important to note that the voting structure of the 2016 ESC differs significantly from much earlier competitions. The final scores are a combined total and equal weighting of the televote and jury vote scores. From an analytical standpoint, the jury vote can be viewed as the judgements of music experts and the televote can be viewed as the opinion of the general public. This research concentrated on investigating whether voting blocs, migration effects and Echo Nest music factors could explain the voting patterns of the combined vote, the televote and the jury vote.

6.3 Design / Experimentation, Evaluation & Results

The design of the research followed the six stages of the CRISP-DM life cycle; research understanding, data understanding, data preparation, data modelling, model evaluation and research conclusions. The research problem was explored and then converted into a multiple linear regression problem, whereby the significance of the predictor variables in explaining the response variable points was tested. The predictor variables were formed from a combination of the performance, competition and external factors.

Data was collected on these factors, from freely available resources and websites. The data for the migration patterns and Echo Nest music factors were collected from the Eurostat website and Spotify Web API. The data was initially stored and wrangled in a Microsoft Excel spreadsheet. A number of factors including the voting blocs and migration effects required additional derivation. The voting blocs were derived using two clustering techniques; edge betweenness clustering and short random walks clustering. Once the data was finally collected, it was saved as a .csv file and analysed using R studio and a variety of external R packages including ggplot2, igraph and car.

An exploratory analysis was initially performed in order to understand the patterns and structures of the collected data. A variety of descriptive statistics and visualisations were derived from the data. Notably the voting blocs and migration patterns were found to have an association or correlation with the points of the 2016 ESC. The exploratory analysis also highlighted some data processing tasks required prior to fitting the model. These steps included handling missing observations, dummy encoding the levels of the nominal variables, standardising the numeric variables and performing a data reduction.

A stratified analysis approach was taken to analyse the data, whereby models were built upon the combined vote, the televote and the jury vote. The processed data and variables were fitted iteratively using stepwise fitting and the AIC criterion to assist in variable selection. Each of the three variable blocs; competition, external and performance variable blocs were fitted independently and variables found to be significant continued on to the final stage where they were fitted altogether.

The fit and model assumptions were evaluated using a variety of techniques including visualisations such as residual plots, QQ-plots, histograms and statistical tests such as Anderson-Darling normality tests and non-constant variance tests. The televote model was the only model to fully satisfy the model assumptions. Unfortunately the combined vote model and the jury vote model failed to satisfy the normality assumptions and were used for approximations. Overall the fit of the models was satisfactory with no signs of extreme outliers or multi-collinearity.

The research problem was answered using a variety of methods. The significance of the predictor variables in explaining the response variable points were evaluated using T-tests. The effects of the predictor variables on the response variables were determined by observing the sign of the corresponding estimated coefficient. Finally the amount of variation explained by each group of factors was examined by interpreting the difference in the adjusted R-squared value between the models with and without the corresponding predictor variables.

Overall the results showed that the migration patterns had a positive impact on points and were significant in explaining the voting patterns of the 2016 ESC. Similarly, the voting blocs were also significant in explaining the scores of the competition. However, the voting blocs had both positive and negative effects on the points. Certain Echo Nest music factors such as the keys, danceability and acousticness were found to be significant in explaining the scores of the 2016 ESC. In particular songs that were more acoustic and less danceable were significant in explaining the voting patterns of the televote.

6.4 Contributions and Impact

This research aimed to add a number of contributions to the already existing body of research on the ESC. It appears that no previous research has attempted to model the scores of the 2016 ESC using a combination of migration patterns, voting blocs and Echo Nest music factors. The research gives an update on the effects of voting blocs in the 2016 competition. The presence of voting blocs has consistently been identified throughout the history of the ESC. This research establishes that the presence and effects of voting blocs can still be seen today. In particular there appears to be no research that modelled the scores of the ESC using music features derived from Echo Nest music services. Furthermore, the effects of migration patterns on the ESC has only ever been examined in terms of stock counts or specific countries, such as Turkey. No research has attempted the effects of migration patterns on the ESC using proportion measures of foreign nationals and citizens living abroad.

6.5 Future Work & Recommendations

Throughout this research a number of problems and limitations arose. These limitations can be taken note of and investigated within any future research on this topic. Overall, it is a great challenge to model data that is the product of personal tastes and opinions. As personal taste and opinion incorporates a lot of variation that is difficult to quantify in numeric or structured way. Possible suggestions for reducing this variation include the usage of more dynamic models and better data that captures the patterns and information more effectively.

Data from other competitions could be utilised, especially the 2015 and 2017 competition. In particular these competitions share the same voting structure and have a similar size.

The voting blocs themselves could also be derived using the more recent years of the competition. This research derived the voting blocs from the 1975 competition to the 2015 competition. This could be inducing bias as the voting blocs have developed throughout the years.

In terms of data processing, the handling of missing migration data could be an area of improvement. The migration data for the research came from the Eurostat website, however a large number of countries did not have any migration data available. Alternative sources or imputation techniques could be used generate a complete set of data for the 2016 ESC.

In terms of experimentation, natural language processing techniques could be implemented to quantify the nature of the lyrics. Alongside the music, the words of the song have great weight on the reception of the song.

Finally a more flexible and efficient model could be used to model the complexities in the voting patterns of the ESC. This research utilised a multiple linear regression which is possibly too simplistic give the nature of the ESC problem. A more flexible regression model such as MARS or Elastic Nets could be used to overcome this issue.

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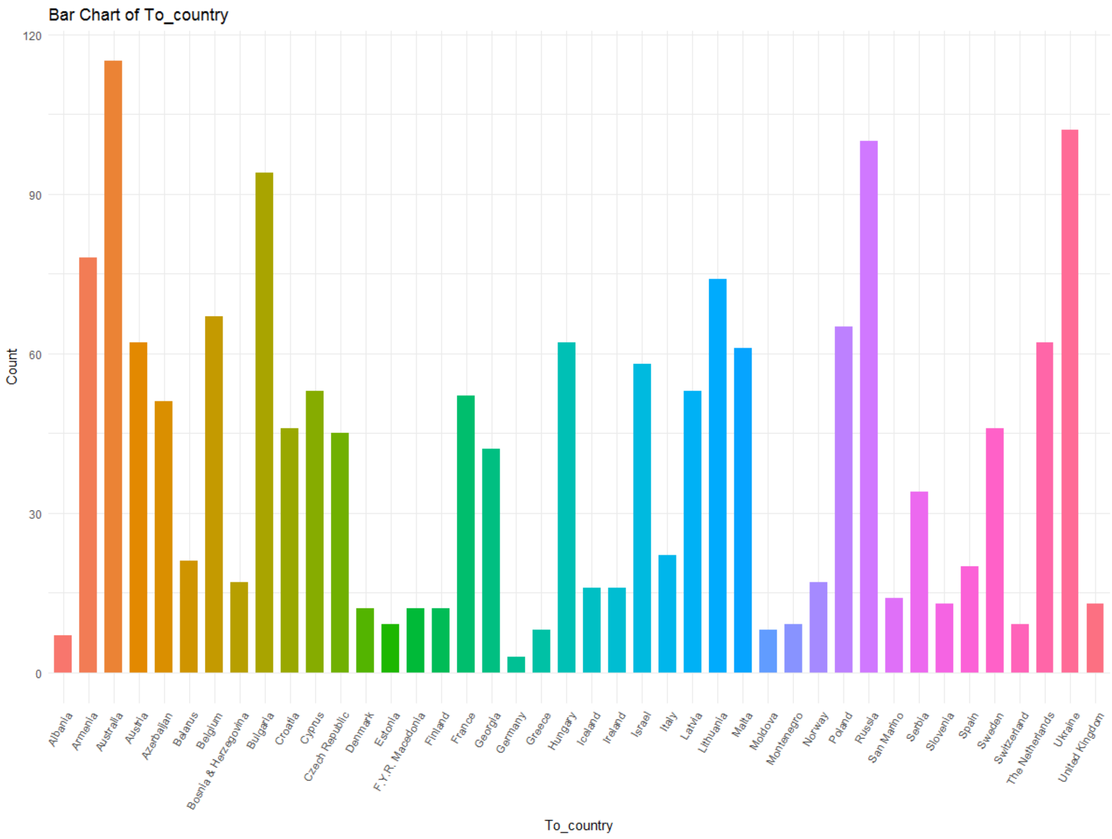
APPENDIX A

Semi-Final 1 Results							
Draw	**Country**	**Place**	**Points**	**Draw**	**Country**	**Place**	**Points**
1	Finland	15	51	10	Czech Republic	9	161
2	Greece	16	44	11	Cyprus	8	164
3	Moldova	17	33	12	Austria	7	170
4	Hungary	4	197	13	Estonia	18	24
5	Croatia	10	133	14	Azerbaijan	6	185
6	The Netherlands	5	197	15	Montenegro	13	60
7	Armenia	2	243	16	Iceland	14	51
8	San Marino	12	68	17	Bosnia and Herzegovina	11	104
9	Russia	1	342	18	Malta	3	209

Semi-Final 2 Results							
Draw	**Country**	**Place**	**Points**	**Draw**	**Country**	**Place**	**Points**
1	Latvia	8	132	10	Australia	1	330
2	Poland	6	151	11	Slovenia	14	57
3	Switzerland	18	28	12	Bulgaria	5	220
4	Israel	7	147	13	Denmark	17	34
5	Belarus	12	84	14	Ukraine	2	287
6	Serbia	10	105	15	Norway	13	63
7	Ireland	15	46	16	Georgia	9	123
8	Macedonia	11	88	17	Albania	16	45
9	Lithuania	4	222	18	Belgium	3	274

Final Results							
Draw	**Country**	**Place**	**Points**	**Draw**	**Country**	**Place**	**Points**
1	Belgium	10	181	14	Cyprus	21	96
2	Czech Republic	25	41	15	Serbia	18	115
3	Netherlands	11	153	16	Lithuania	9	200
4	Azerbaijan	17	117	17	Croatia	23	73
5	Hungary	19	108	18	Russia	3	491
6	Italy	16	124	19	Spain	22	77
7	Israel	14	135	20	Latvia	15	132
8	Bulgaria	4	307	21	Ukraine	1	534
9	Sweden	5	261	22	Malta	12	153
10	Germany	26	11	23	Georgia	20	104
11	France	6	257	24	Austria	13	151
12	Poland	8	229	25	United Kingdom	24	62
13	Australia	2	511	26	Armenia	7	249

APPENDIX B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90
60
30
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Australia
Austria
Azerbaijan
Belarus
Belgium
Bosnia & Herzegovina
Bulgaria
Croatia
Cyprus
Czech Republic
Denmark
Estonia
F.Y.R. Macedonia
Finland
France
Georgia
Germany
Greece
Hungary
Iceland
Ireland
Israel
Italy
Latvia
Lithuania
Malta
Moldova
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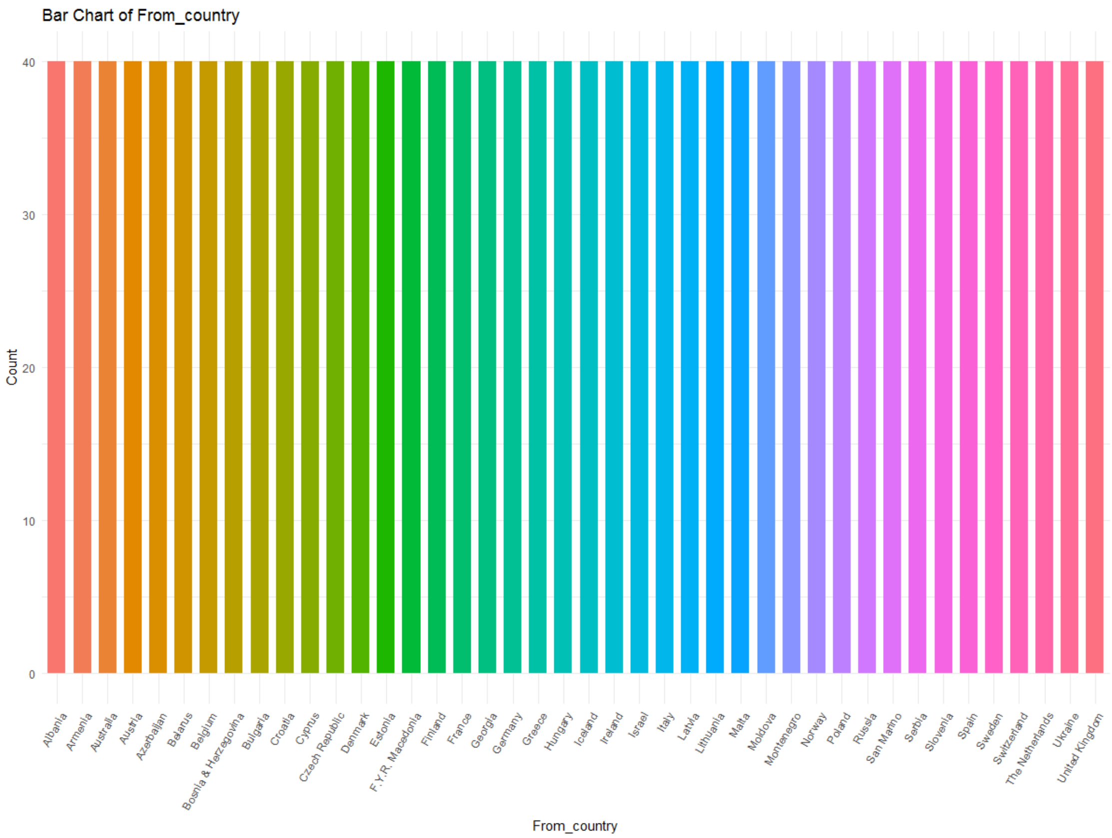
Russia
San Marino
Serbia
Slovenia
Spain
Sweden
Switzerland
The Netherlands
Ukraine
United Kingdom
To_country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Australia
Austria
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Belarus
Belgium
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Bulgaria
Croatia
Cyprus
Czech Republic
Denmark
Estonia
F.Y.R. Macedonia
Finland
France
Georgia
Germany
Greece
Hungary
Iceland
Ireland
Israel
Italy
Latvia
Lithuania
Malta
Moldova
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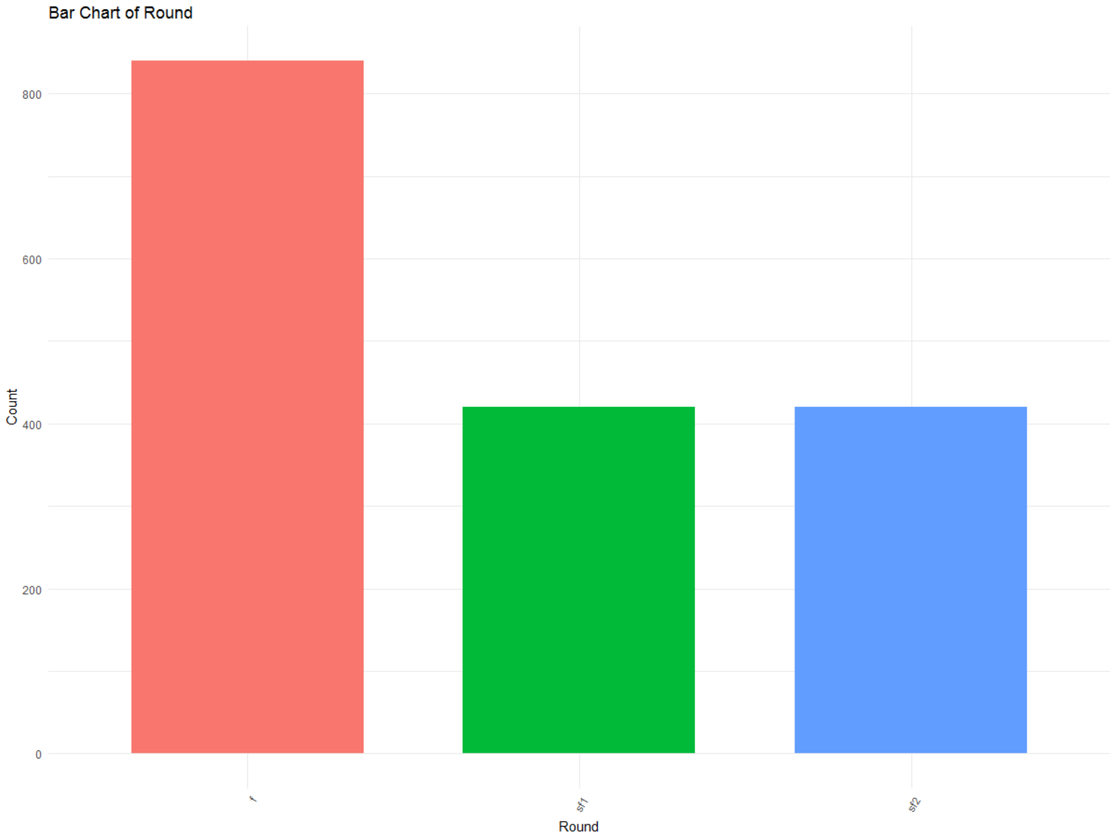
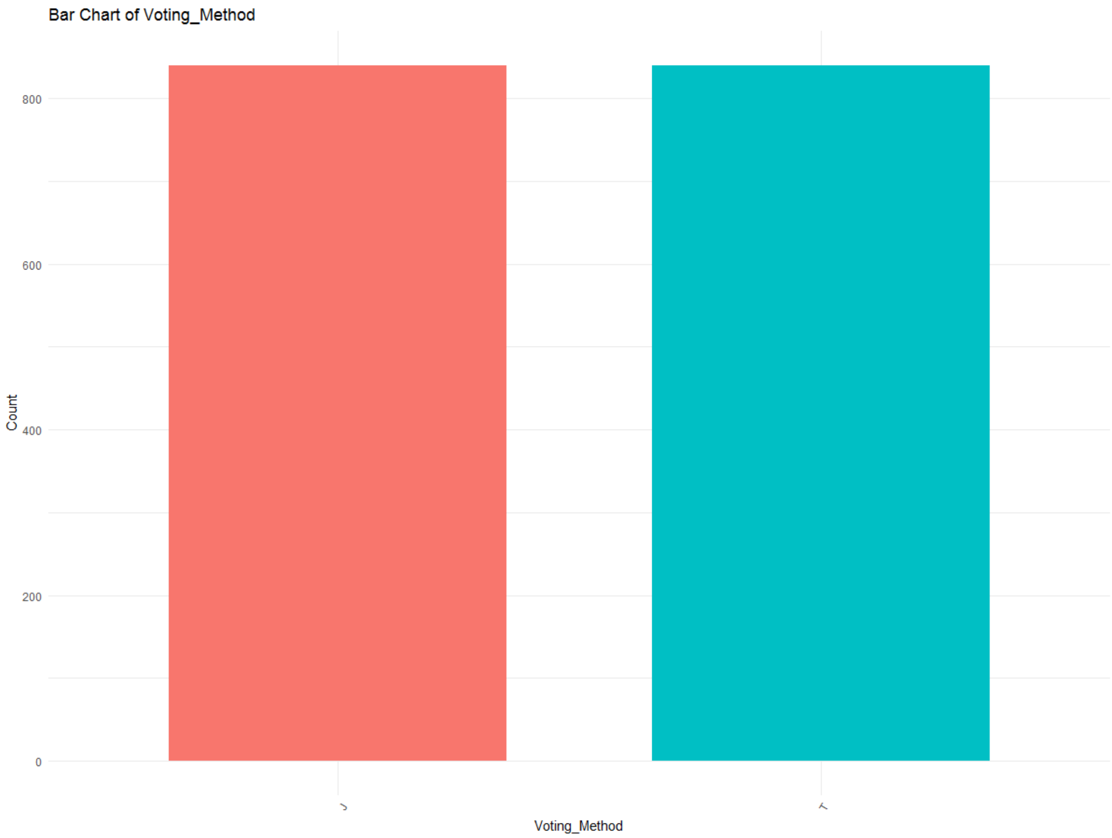
Slovenia
Spain
Sweden
Switzerland
The Netherlands
Ukraine
United Kingdom
From_country


Bar Chart of Round
800
600
400
200
0
Count
f
sf1
sf2
Round


Bar Chart of Voting_Method
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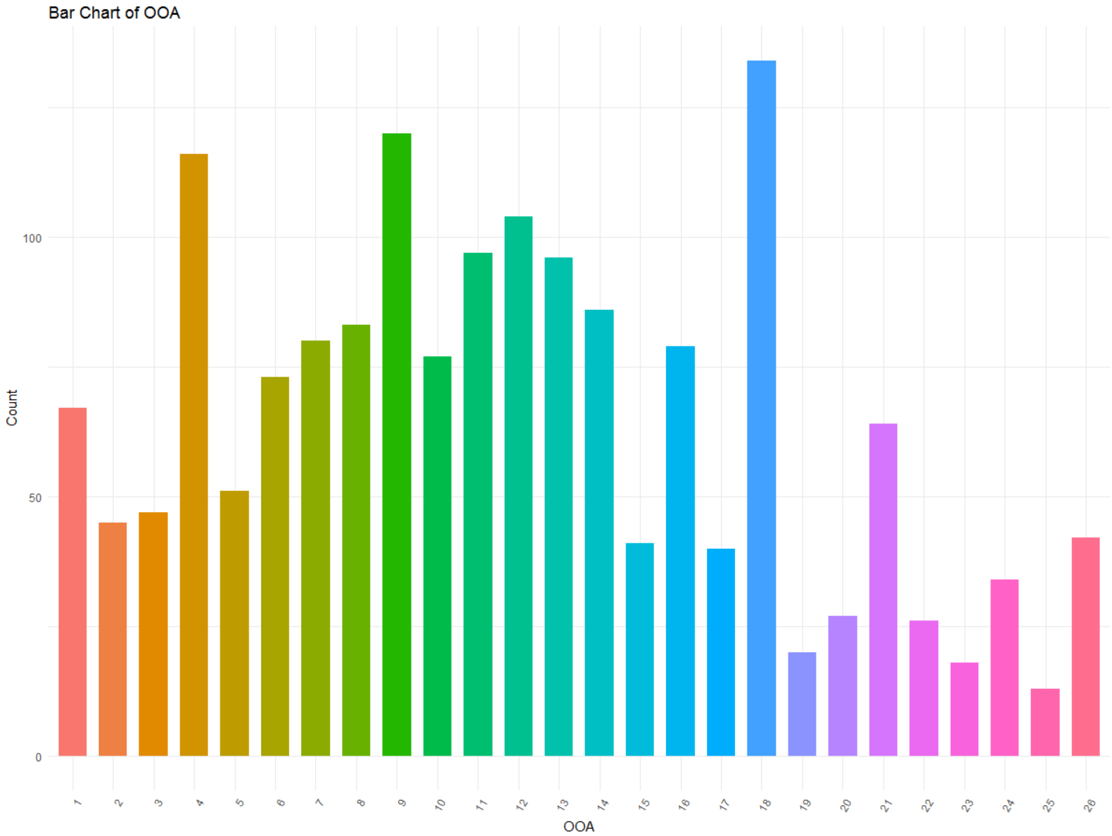
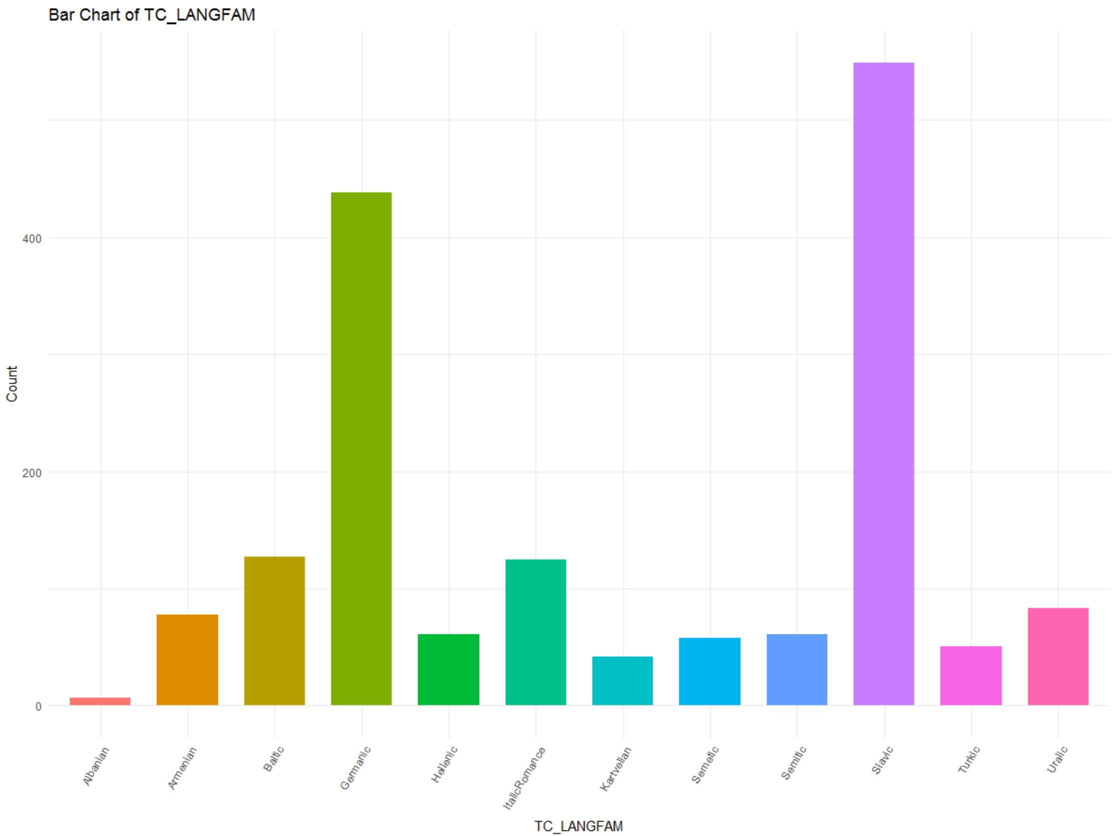
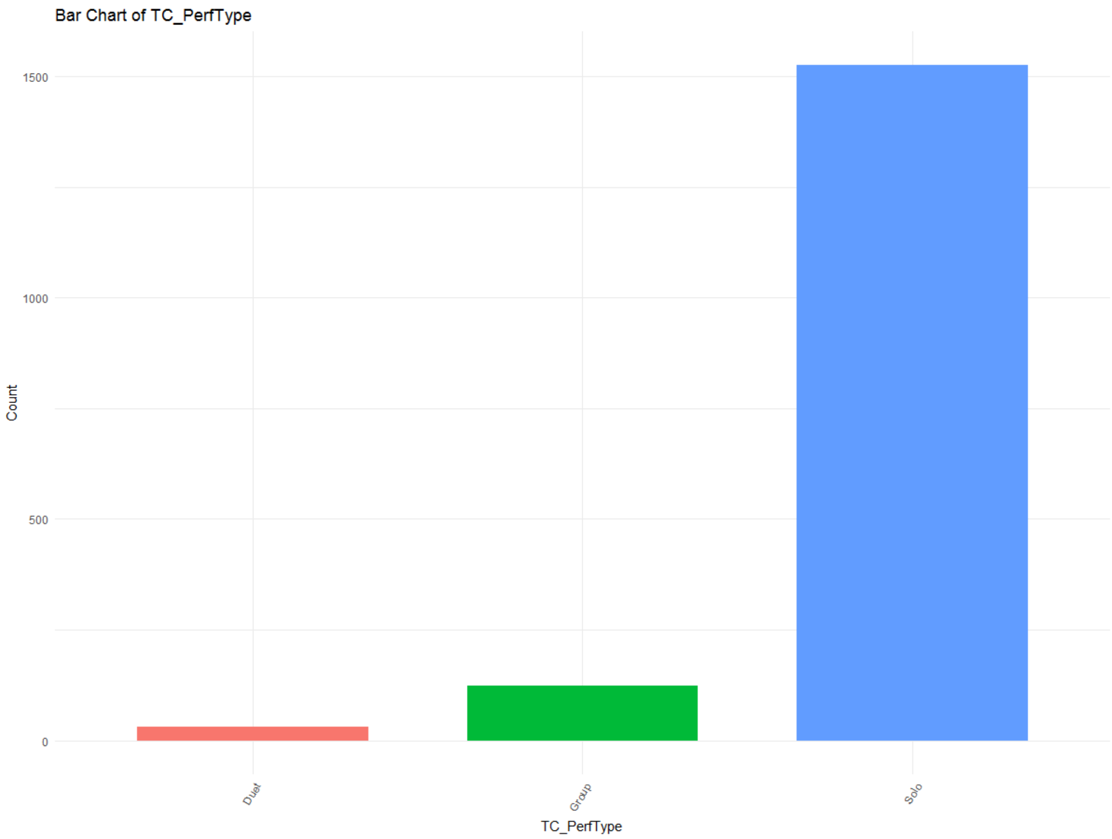
600
400
200
0
Count
Voting_Method



Bar Chart of OOA
Count
0
50
100
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
OOA



Bar Chart of TC_LANGFAM
Count
0
200
400
Albanian
Armenian
Baltic
Germanic
Hellenic
ItalicRomance
Kartvelian
Semetic
Semitic
Slavic
Turkic
Uralic
TC_LANGFAM


Bar Chart of TC_PerfType
Count
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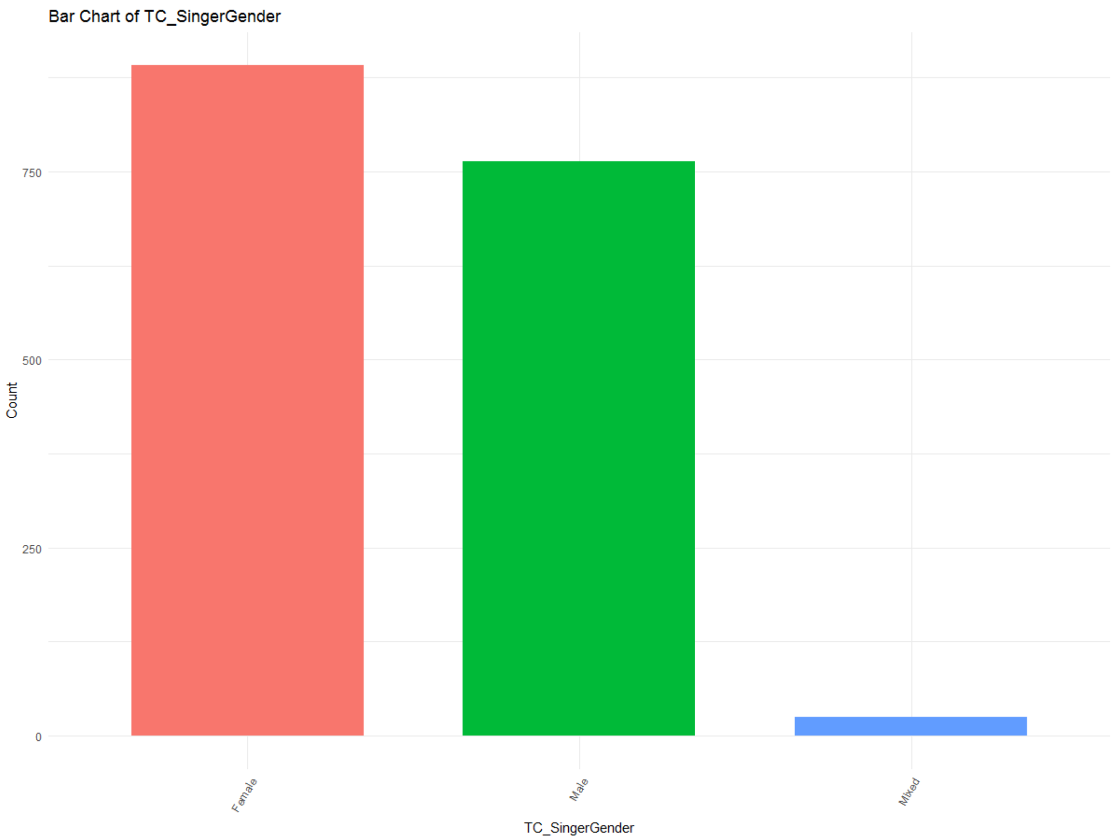
1000
500
0
Duet
Group
Solo
TC_PerfType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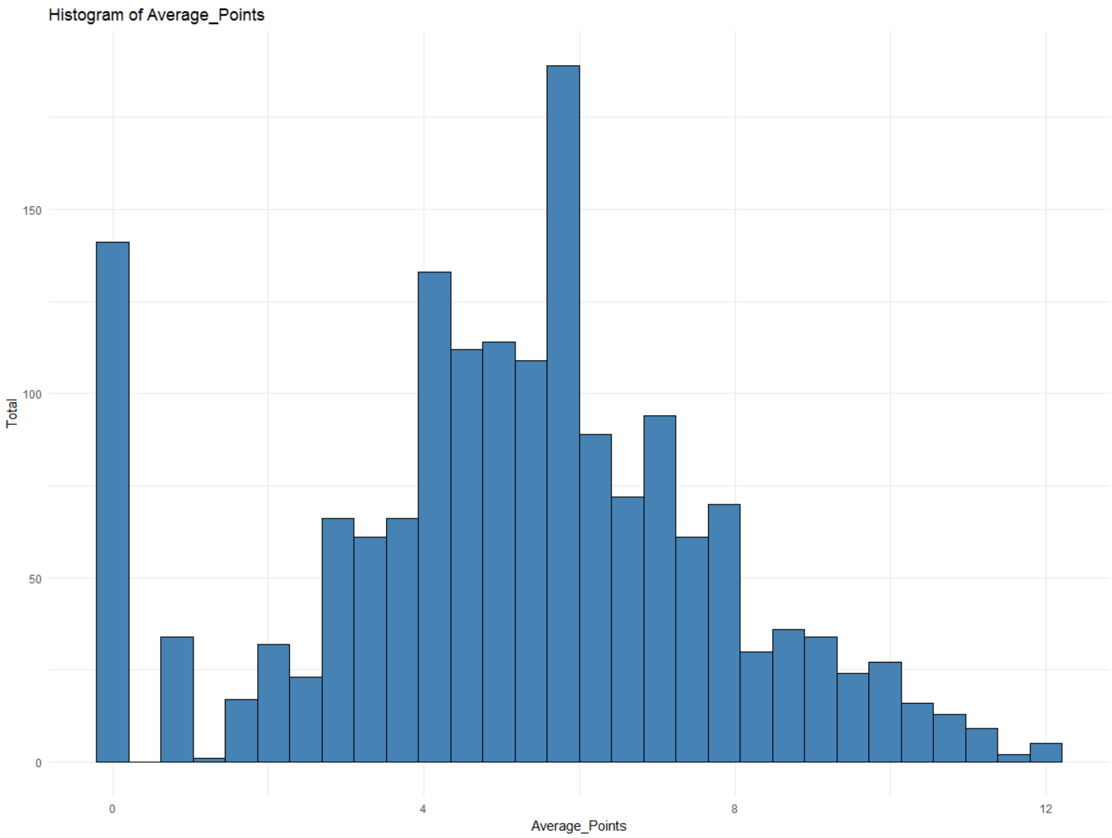
500
250
0
Female
Male
Mixed
TC_SingerGender


Histogram of Average_Points
Total
Average_Points
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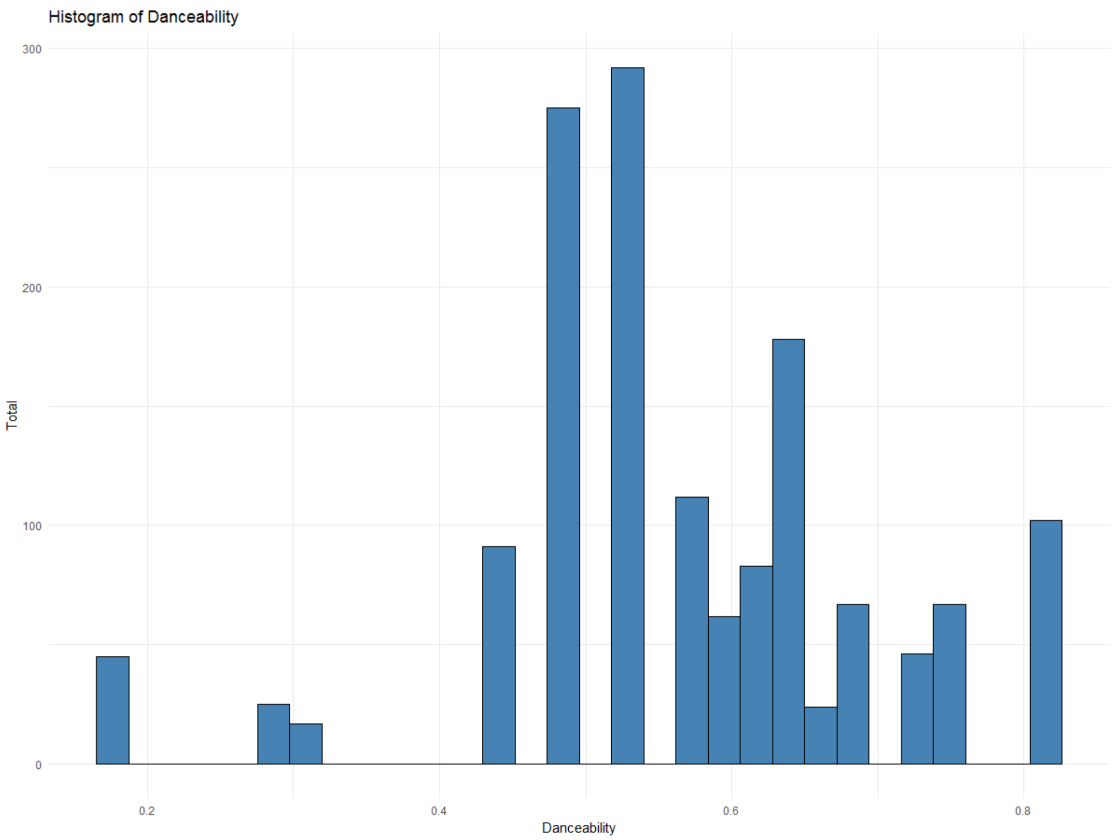
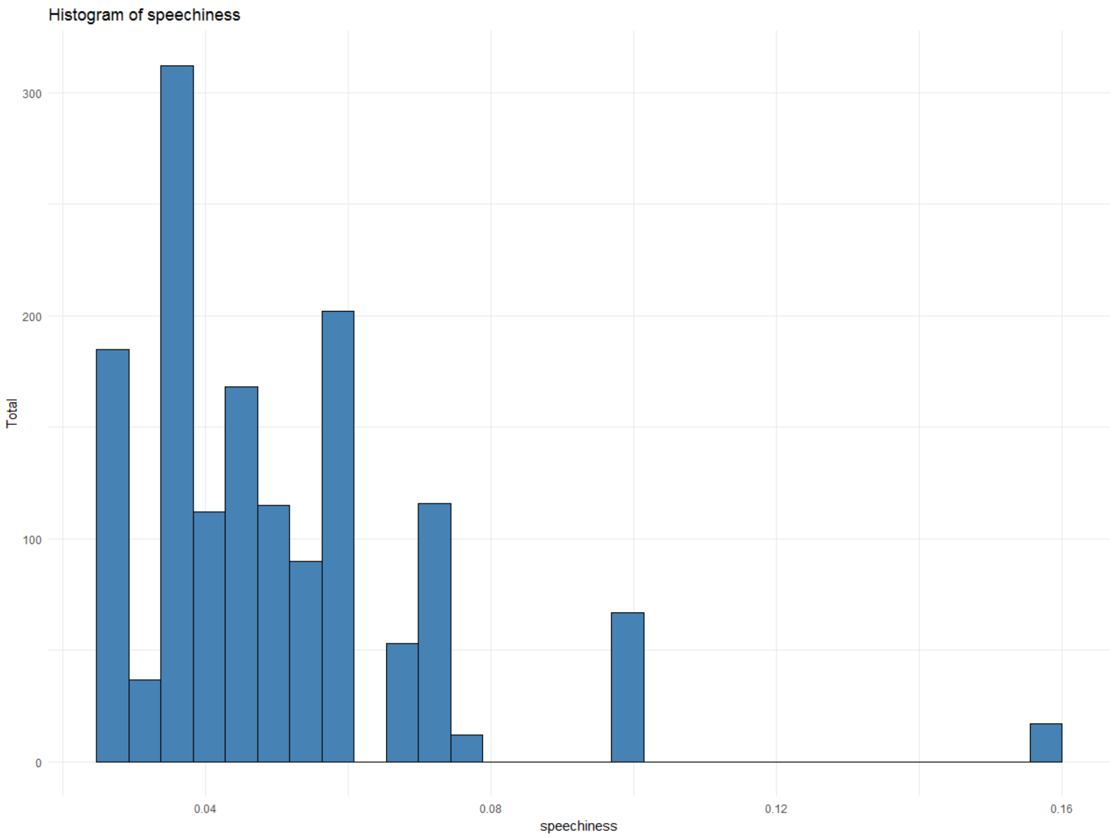
50
100
150
0
4
8
12


Histogram of Danceability
Total
Danceability
0
100
200
300
0.2
0.4
0.6
0.8


Histogram of speechiness
Total
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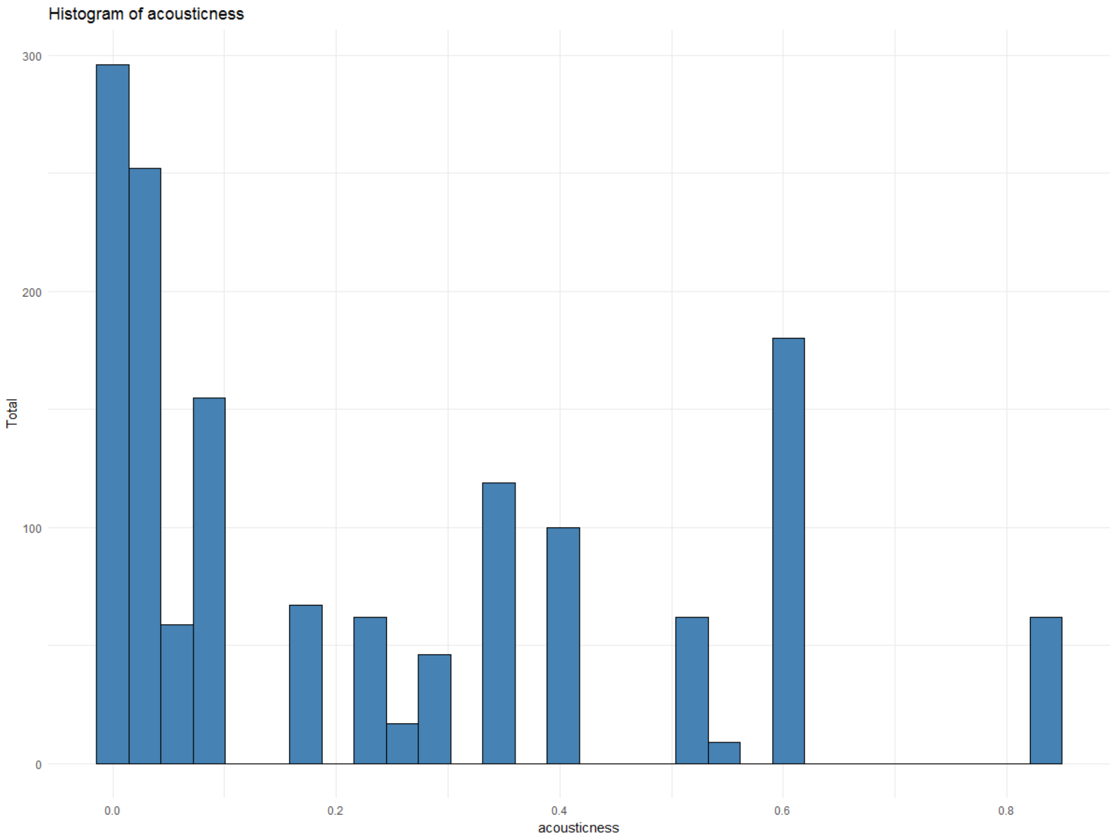
200
100
0
0.04
0.08
0.12
0.16
speechiness


Histogram of acousticness
Total
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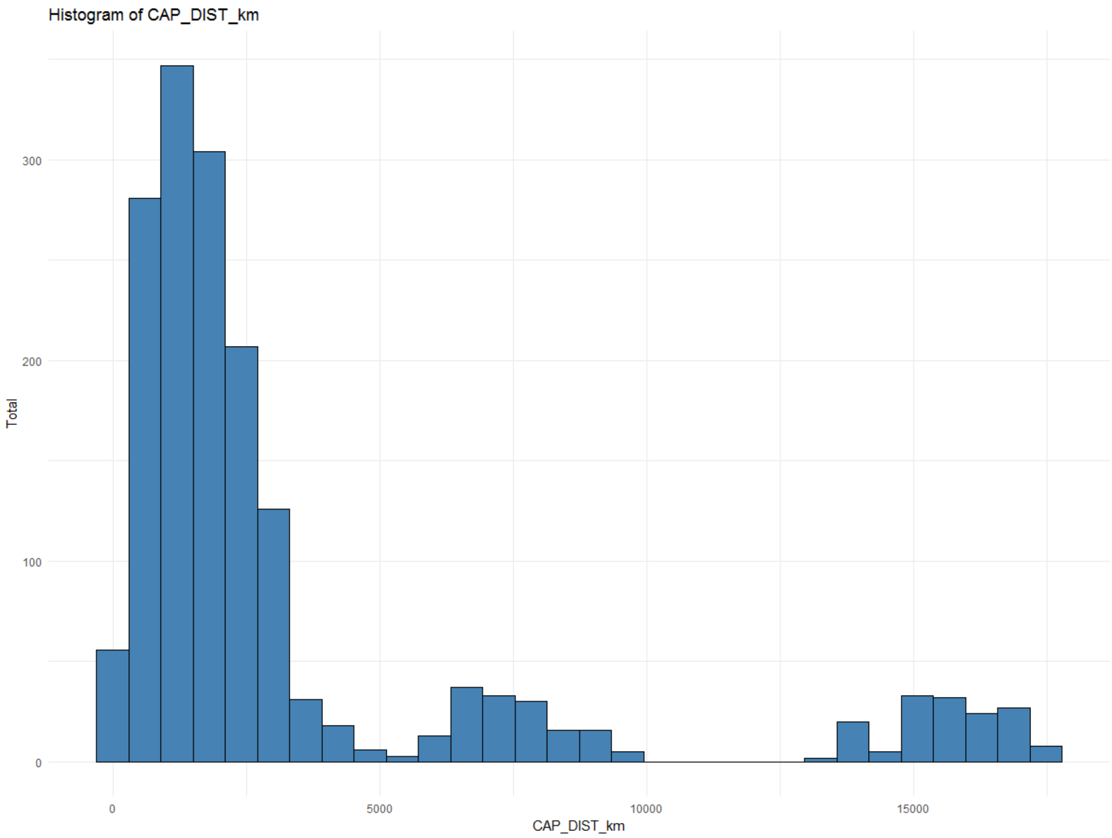
200
100
0
0.0
0.2
0.4
0.6
0.8
acousticness


Histogram of CAP_DIST_km
Total
CAP_DIST_km
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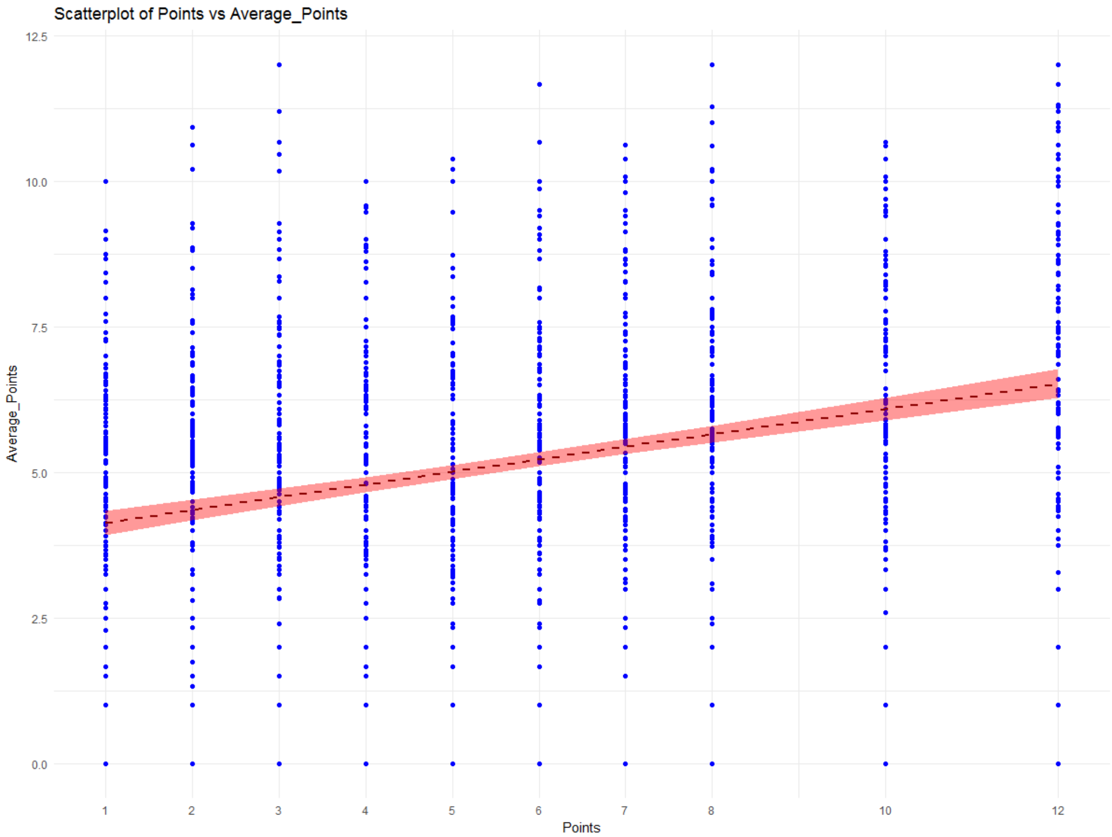
100
200
300
0
5000
10000
15000


Scatterplot of Points vs Average_Points
Average_Points
Points
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5.0
7.5
10.0
12.5
1
2
3
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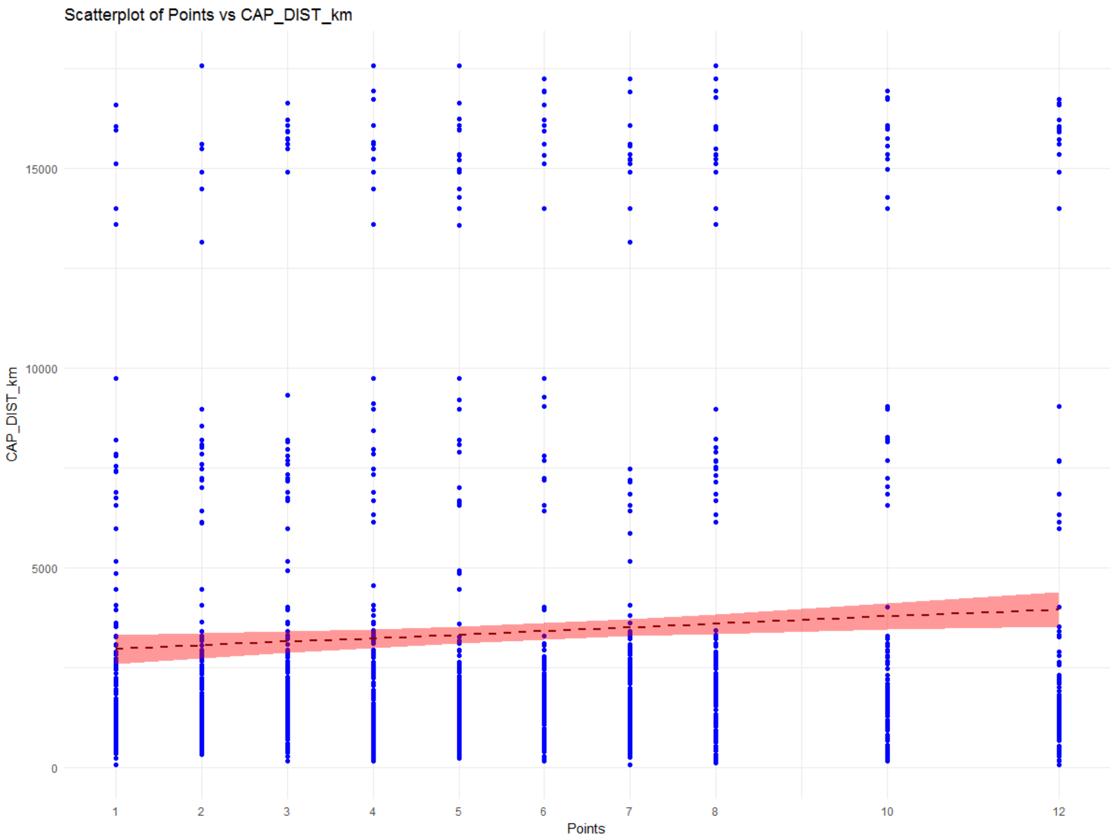
6
7
8
10
12


Scatterplot of Points vs CAP_DIST_km
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10000
5000
0
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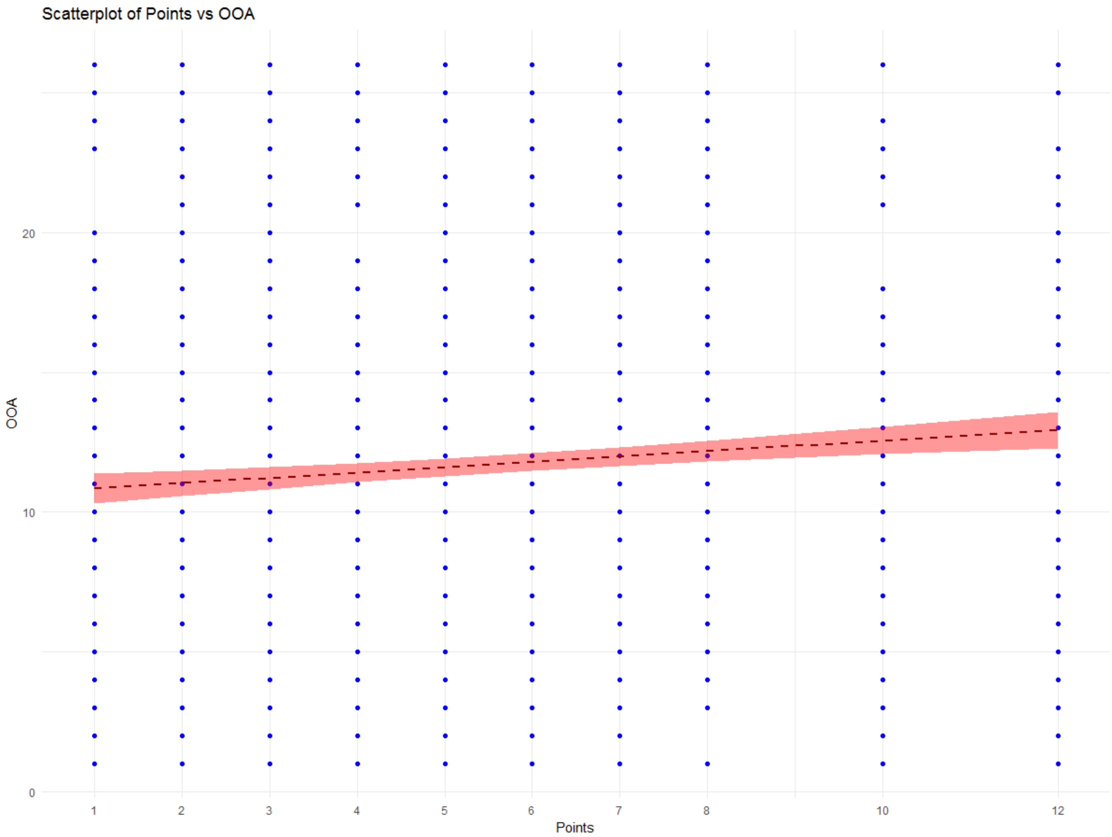
2
3
4
5
6
7
8
10
12
Points


Scatterplot of Points vs OOA
OOA
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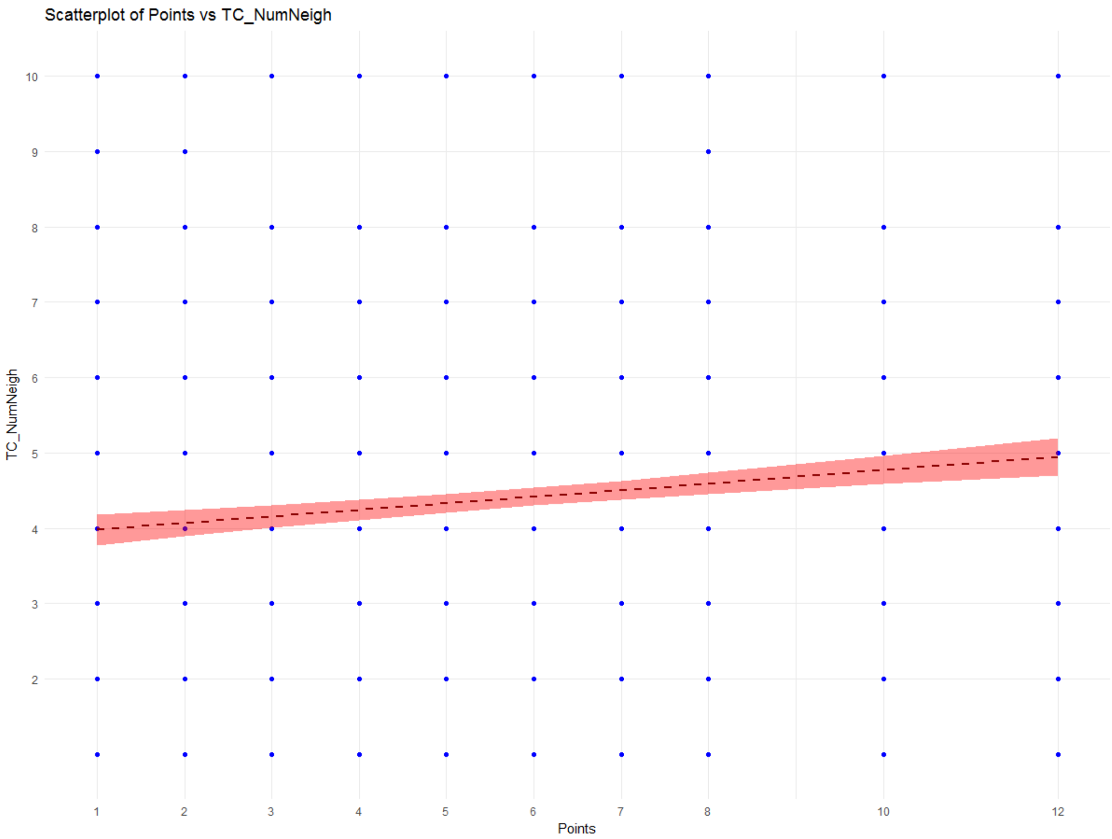
8
10
12
Points


Scatterplot of Points vs TC_NumNeigh
TC_NumNeigh
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6
5
4
3
2
1
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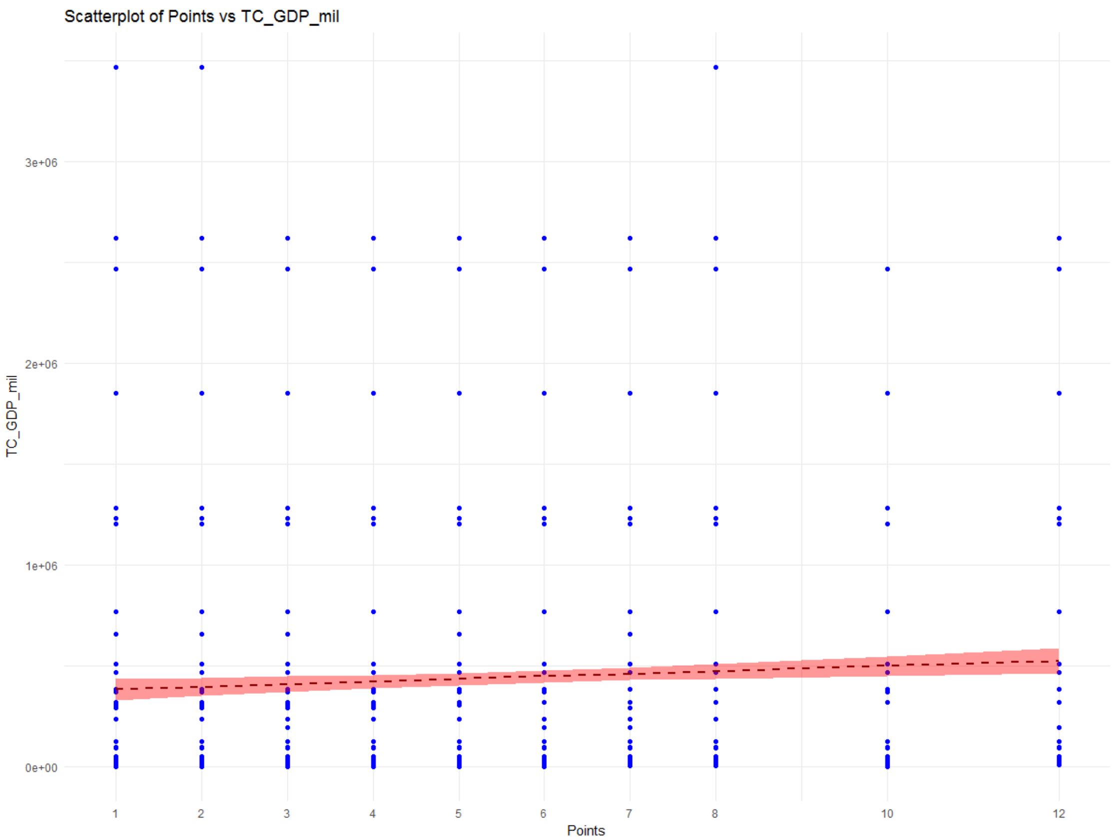
6
7
8
10
12


Scatterplot of Points vs TC_GDP_mil
TC_GDP_mil
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2e+06
1e+06
0e+00
1
2
3
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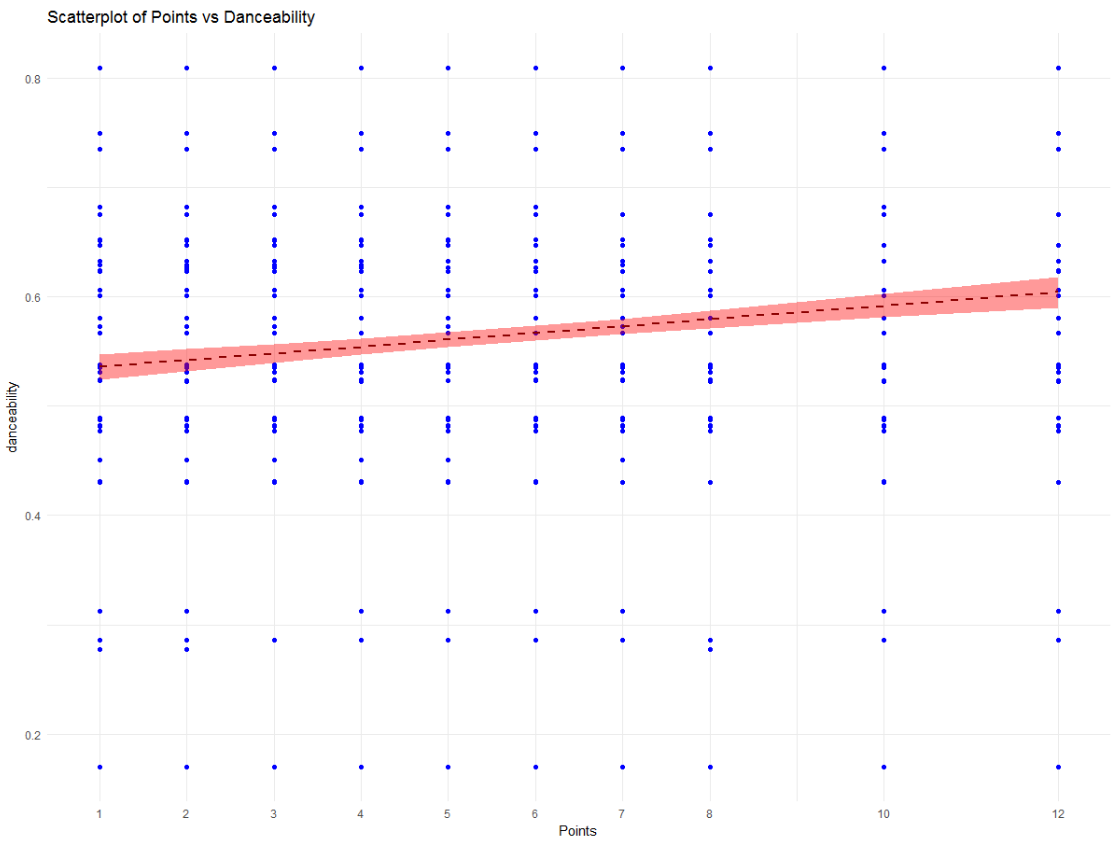
6
7
8
10
12


Scatterplot of Points vs Danceability
danceability
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0.4
0.6
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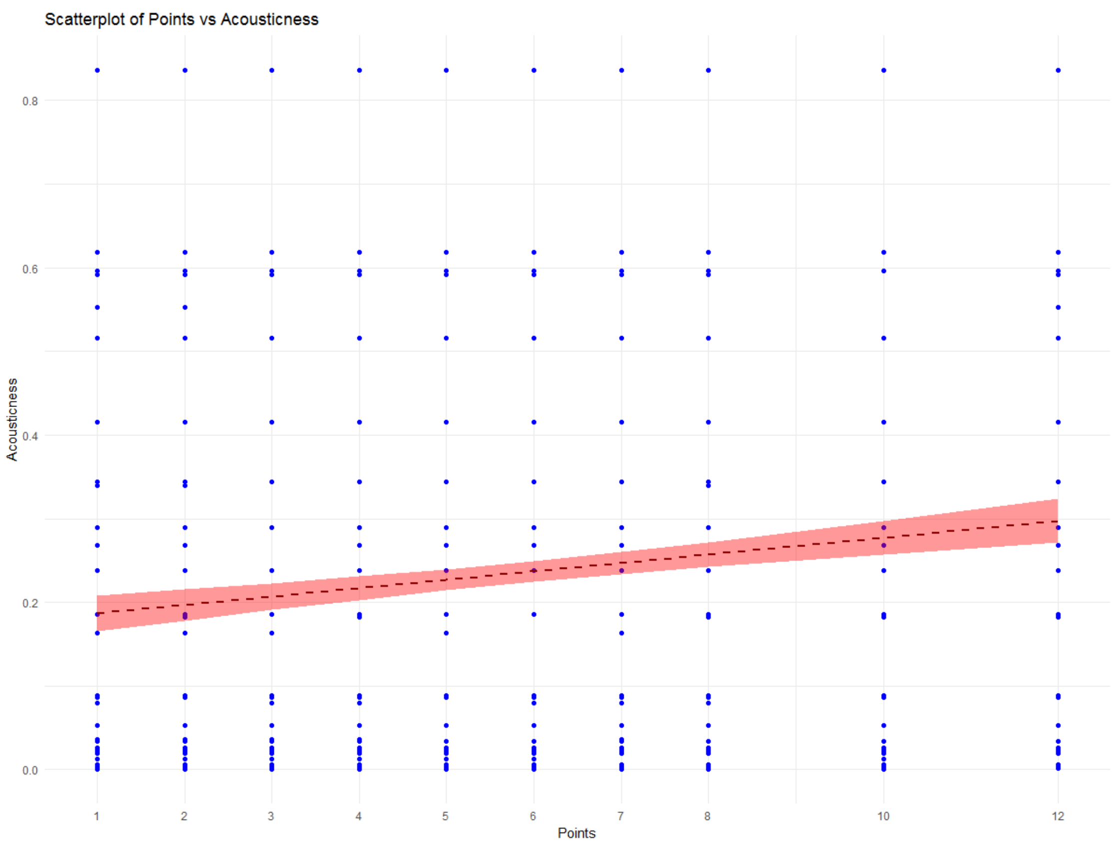
1
2
3
4
5
6
7
8
10
12
Points


Scatterplot of Points vs Acousticness
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2
3
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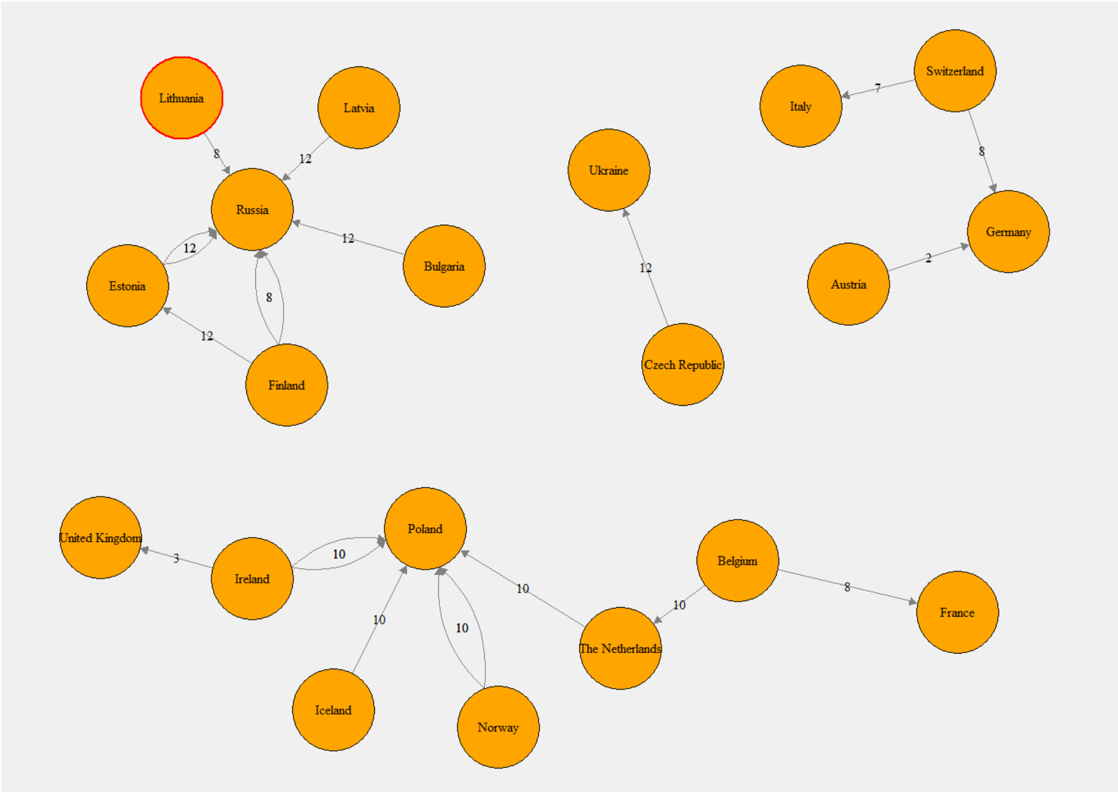
7
8
10
12
Points



Televote network with High METRIC_Citizens

Jury vote network with High METRIC_Citizens