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A METHOD FOR GENERATING A NON-MANUAL FEATURE MODEL FOR SIGN LANGUAGE PROCESSING

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ABSTRACT

While recent approaches to sign language processing have shifted to the domain of Machine Learning (ML), the treatment of Non-Manual Features (NMFs) remains an open question. The principal challenge facing this method is the comparatively small sign language corpora available for training machine learning models.

This study produces a statistical model which may be used in future ML, rules-based, and hybrid-learning approaches for sign language processing tasks. In doing so, this research explores the emerging patterns of non-manual articulation concerning grammatical classes in Irish Sign Language (ISL). The experimental method applied here is a novel implementation of an association rules mining approach to a sign language dataset consisting of NMF and grammatical class data from the Signs of Ireland corpus.

Our analysis of association rules has identified patterns between grammatical classes and various non-manual articulations. One such pattern discovery is the strong correlation between various NMFs and depicting verbs. Indeed, this study reports that the less lexicalised a sign is, the more likely it is to use NMFs.

Findings from this work will inform future research on NMF treatment in sign language processing, while the statistical model may be utilised by such systems in the future.

Index Terms— Natural Language Processing, Sign Language Processing, Association Rules, Non-Manual Features, Grammatical Class

1. INTRODUCTION

Over a decade ago, [1] identified a *"small subset of the constructs of sign language...that pose significant challenges to the field of SLR [Sign Language Recognition]"*. This subset exclusively lists the following challenging constructs; adverbs, Non-Manual Features (NMFs), placement, classifiers, directional verbs, positional signs, body shift, iconicity, and finger spelling. It may be argued that these challenges are transferable to other sign language processing applications such as sign language generation and sign language machine translation.

Many of these challenges, including the treatment of NMFs, are yet to be adequately addressed [2]. [2] take the position that such challenges can be overcome, for sign language generation, if researchers in linguistics and computer graphics work together. A similar position is held by the authors. Indeed, a computational approach to sign language processing, that is informed by linguistic understanding, is central to the work presented here. As reported later in this paper, this work has uncovered new linguistic insights regarding the relationship between NMFs and grammatical classes. Further, the method, now proven, may be applied to uncover new insights for other constructs such as those listed in [1].

In recent years, Machine Learning (ML) methods have been applied to the problem of sign language processing. This approach may be considered the state-of-the-art for sign language recognition, e.g., [1, 3, 4] but is rather new in the context of sign language generation, e.g., [5, 6].

The Association Rules Mining (ARM) method employed in this study has the potential to produce a statistical model that may inform sign language processing applications, as an automated resource, or as a tool to help focus efforts towards the most pertinent problems. In this study, that statistical model is comprised of data pertaining to NMFs and grammatical classes for Irish Sign Language (ISL). The approach, however, may be deployed to generate models for any sign language data, including but not limited to the constructs listed in [1].

2. METHOD

This work has drawn upon data mining methodologies, as defined in [7] and [8], to discover useful patterns and trends from the Signs of Ireland (SOI) corpus. The novelty of this study is in the application of a data mining approach known as ARM to identify patterns between the physical movements of NMFs and grammatical units in ISL.

At a macro level, this work follows the Knowledge Discovery in Databases (KDD) process, where data mining is a single step in the process. Initially proposed as a unified process in [9] and [10], the KDD process includes several steps. How these steps are applied to this study is described in subsequent sections and illustrated in Figure 1.

3. DATA SELECTION

This study leverages content from the SOI corpus [11]. Alternative ISL corpora do exist but these do not contain natural/authentic ISL utterances by native, or near-native, signers, e.g., those reported in [12] and [13]. Corpora also exist that contain authentic utterances from native signers using sign languages other than ISL. However, given that this study relates specifically to ISL, and because insights from language are best garnered from natural/authentic use of the language, the SOI corpus is the most compatible dataset available, and is thus, the dataset selected for this study.

The SOI corpus was compiled to document how ISL was used at the turn of the twenty-first century in the Republic of Ireland. Ini-

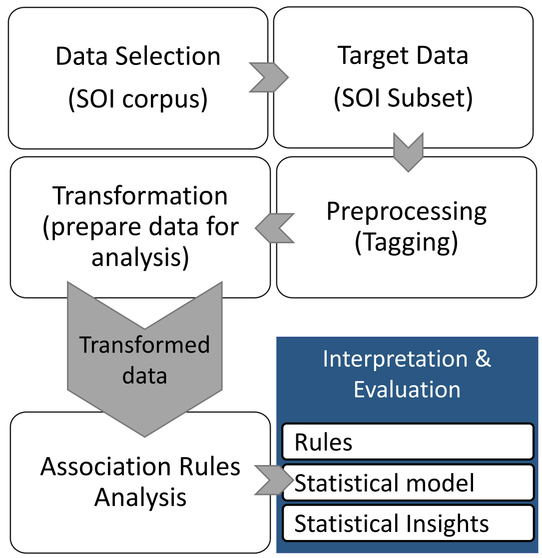

Fig. 1. The KDD process as applied to this research

tially developed in 2004 at Trinity College Dublin, the SOI corpus is a digital multi-modal corpus of ISL utterances comprising a demographic range of signing across 40 signers and multiple language registers. The most recent count puts the total number of annotated tokens in the SOI corpus at 51,753, including all annotation tokens on all tiers. Of those, 11,161 are tokens from the *Lexical Gloss* tier. These figures are inclusive of the 5,372 annotation tokens added in this study. Readers are directed to [11] for details of the SOI corpus provenance and composition.

4. TARGET DATA

The target data, for this study, is a randomly selected subset of the SOI corpus which is representative of the SOI corpus demographic. The subset consists of 2,989 lexical gloss tokens from 11 annotation files. Participants include 6 females and 5 males aged between 20 and 79, from 4 geographical areas. All data is of the narrative language register. Specific details of how the subset was selected are discussed in [14].

The subset selection, and indeed, the entirety of the SOI corpus, consists of multiple tiers/layers of time series video annotations, including annotations for multiple NMFs. These multiple layers of NMFs form one part of the data for analysis in this research. Another part, the grammatical class data, is added during the preprocessing stage. The subset is limited to the narrative language register, having been elicited through a picture-based narrative task, and a personal experience narrative task.

The non-manual articulators considered in this study are head, body, eyegaze, eye aperture, eyebrows, and cheeks. NMFs such as eyegaze squint and head-nod, are distinguished from non-manual articulators in this paper. Mouthings are outside the scope of this study. Readers are directed to [15] and [16] for comprehensive works on Mouthing in ISL.

This work has leveraged the Auslan corpus annotation guidelines [17] to guide the grammatical class annotation in the SOI subset. This framework was selected for the high-volume classes, which offer a granular level of annotation which may be grouped into more abstract categories for analysis where required.

5. PREPROCESSING

Preprocessing begins with the creation of additional annotation tiers containing grammatical class data. This allows patterns to be identified between the grammatical class annotation layers and the existing NMF layers. Corpus annotation is an arduous and time-consuming process and the time requirements of this process have had a material impact on the size of the subset available for analysis.

6. TRANSFORMATION

ARM algorithms discussed later in this paper, require the data to be cleaned and formatted in tabular form, or as transactional data. Therefore, there is a requirement to refactor the corpus data from its existing state in the ELAN annotation tool to one compatible with the algorithm. This process requires the manual resolution of various time alignment issues that occur across multiple tiers. In such cases, it must be determined manually which of the NMF annotations are pertinent to the lexical gloss. Where possible, each lexical gloss is considered out of context. With this approach there is no requirement to distinguish between the linguistic levels at which an NMF exists, instead, it is simply a matter of recording that data in a manner true to the source material.

7. ASSOCIATION RULES MINING

Association Rules Mining (ARM) is an unsupervised rule-based machine learning method which aims to identify interesting patterns or affinities between items in a dataset. A modern approach to ARM was proposed in a seminal paper by [18]. [19] reports that ARM is a method used in domains such as bioinformatics, intrusion detection, medical diagnosis, web mining, scientific data analysis, and retail. This work represents the first application of this method to sign language data.

[18] posits the following formal definition for association rules: I is an itemset of i to n values; $I = \{i_1, i_2, \ldots, i_n\}$. D is a database of transactions t, where transactions are comprised of a subset of I; $D = \{t_i, t_{i+1}, ..., t_n\}$. The rule $A \rightarrow B$ (If A then B) is valid when A and B are a subset of I ($A, B \subseteq I$) and A intersection B is equal to an empty set ($A \cap B = \emptyset$).

7.1. Measures of Interestingness

Interestingness Measures (IMs) are metrics designed to identify, rank, and filter rules that are of potential interest to a given study. [20] compare over 50 IMs while reporting their property-based framework for analysing IMs. One theme that is common amongst literature pertaining to IMs, is that there is no best measure of interestingness. Ultimately, the nature of the dataset should define the IMs [21, 22]. This study utilises the following IMs:

7.1.1. Support-Confidence Framework

The modern approach to ARM, published in [18], includes two user-specified evaluation metrics, as defined in Equation 1. Support ($supp$) is a measure of significance. It is the fraction of transactions that contain both item A and item B. Confidence ($conf$) is a measure of interestingness and expresses how often items in B appear in transactions that contain A. In other words, confidence is the conditional probability that if item A is found then item B will be found also.

A $\rightarrow B$ if $supp(A \cup B) \geq minsupp$
and

$$conf(A \rightarrow B) = \frac{supp(A \cup B)}{supp(A)} \geq minconf \quad (1)$$

Strong rules may be generated by high-frequency items. In this regard, many grammatical classes occur too infrequently in the dataset to generate any significant rules. Given this, frequency count is not necessarily the most appropriate metric for establishing a rule's interestingness. Often, high-frequency rules present obvious affinities, e.g., *[if verb, then not noun]*, or *[if head forward, then not head backward]*. Affinities such as these are already known and may be considered uninteresting or spurious.

7.1.2. Lift

lift [23,24] is a bidirectional IM that provides a mechanism to reduce the probability of finding patterns that appear due to chance alone by comparing the confidence of the rule $A \rightarrow B$ with the prior confidence of B alone. Therefore, lift will only include rules whereby the $conf(A \rightarrow B) > conf(B)$. Thus, resolving many shortfalls of the Support-Confidence framework. A formal definition of the lift metric is:

$$\text{lift (A} \rightarrow B) = \frac{conf(A \rightarrow B)}{supp(B)} = \frac{supp(A \cup B)}{supp(A) \times supp(B)} \quad (2)$$

Generally, the value of lift may indicate dependencies and correlation. Strong associations are identified by a higher lift value. Lift is sensitive to low support rules which makes it good for spotting niche trends but this capability also makes lift susceptible to noise [25]. As such, lift offers some resolution to the rare item problem which is unresolved by the Support-Confidence framework.

7.1.3. Fisher's Exact Test

Fisher's exact test [26] is a statistical test to assess associations between categorical variables. [25] describe it as a probabilistic IM that calculates the p-value of a one-sided Fisher's exact test using simple permutation tests on 2×2 contingency tables (see [26]).

With regards to the application of Fisher's exact test to ARM, it may be assumed that the null hypothesis (H_0) is: there is no statistical significance between items in the rule tested. P-value may range from 0 to 1, where 0 implies a higher significance level between the antecedent and consequent. Rules with a p-value lower than a predefined significance level will result in rejection of H_0, and therefore, there is a statistical significance between items in the antecedent and consequent.

$$\text{p-value} = \text{P}(\text{C}_{AB} \geq c_{AB}) \quad (3)$$

Equation 3 shows how the p-value may be calculated, where C_{AB} represents the number of transactions which contain all items in A and B, and c_{AB} represents the observed co-occurrence count.

Significance testing with Fisher's exact test may be used to filter spurious rules generated with support and confidence, and resolves lift's problem of noise in lower-frequency items.

7.2. Algorithms

Classic ARM implementations such as Apriori [18, 27], FP-Growth [28], and Eclat [29, 30] employ an exhaustive approach to producing correlations between all frequent itemsets to be found in a given dataset. Such an approach generates a large volume of rules which may be inhibitive for larger datasets but can be advantageous for smaller datasets such as those commonly seen in sign language corpora.

Other algorithms such as [31–37], have endeavoured to reduce the number of rules produced to include only interesting rules. Such approaches run the risk of excluding important rules. Therefore, the research in this area has endeavoured to strike a balance between avoiding false discoveries, while also including all interesting rules.

7.3. Experimental Setup

This study utilises the *aRules* implementation of the *Apriori* algorithm using the R programming language.

The SOI corpus subset was organised into a number of datasets, consisting of primarily binary data, with varying degrees of abstraction. The IMs and parameters were set for each experiment as follows: $supp > 0.001(.1\%)$, $conf > 0.01(1\%)$, $p\text{−}value < 0.5$, $lift > 1.2, minlen = 2, maxlen = 4, maxtime = 10$

Support and confidence were set quite low to capture low-frequency items, while the values set for lift and p-value filter out rules which may be considered statistically insignificant. The parameters *minlen* and *maxlen* refer to the minimum and maximum number of items allowed in a rule, while *maxtime* allows a time limit for the algorithm to execute.

8. INTERPRETATION AND EVALUATION

8.1. Distribution

An exploratory analysis found that plain nouns and depicting verbs were the most frequent grammatical classes observed in the dataset at 18.6% and 19.2% respectively. The next most common classes, approximately 50% less frequent than depicting verbs, were pronouns and plain verbs. Despite plain nouns being counted amongst the most frequent grammatical classes, further analysis showed that, at 45%, fully lexical signs account for less than half of the signs in the dataset. Partly lexical signs were observed in 46% of the dataset, while non-lexical signs were observed at a rate of 4%.

8.2. Association Rules

Given the page limit of this paper, it is only possible to report some selected findings of this study. Readers are directed to [14] for reported correlations between grammatical classes and NMFs, as well as inter-NMF correlations, and correlations observed with Constructed Actions.

The SOI data generated 4.4 million statistically significant rules after filtering through the experiment parameters. Below, is an example of a single 2-item rule. Note that rules may be 2-item, 3-item, or 4-item, and are of the format [if *antecedent*, then *consequent*].

[if *body lean*, then *depicting verb*], supp=11.7%, conf=61%

Throughout the dataset, the strongest correlation with NMFs can be observed with depicting verbs. This correlation is evident in the high volume of rules across all NMFs, the high frequency of rules, and in many cases, the high confidence values for rules. The strength of these correlations lends support to the argument in [38] for American sign language and Catalan sign language, and later in [39] for ISL, which assert that NMFs are prevalent in metonymic signs such as *brush-teeth* and *smoke-a-cigarette*. Metonymic signs are categorised under depicting verbs in the Auslan annotation guidelines [17].

Rules indicate that depicting verbs are most likely to occur with body lean, head forward, eyegaze down or right, eye aperture squint, and eyebrows furrowed. These rules broadly conform to findings reported for ASL in [40] and [41], which suggest that upper parts of the face and head are utilised for syntax.

After depicting verb, the next most frequently observed grammatical class in the dataset is plain noun. Plain nouns and verbs account for 59% of all fully lexical signs in the dataset. Of the grammatical classes that constitute the fully lexical category, plain verbs and determiners present with no affinity to NMFs. Plain nouns, adjectives, and prepositions are observed to have a weak affinity with most NMFs. That is, based on their occurrence in this dataset, it is feasible that these will occur again with NMFs, though the probability of this is low.

NMFs were observed across multiple grammatical classes in the fully lexical category but in low frequency. Although not all grammatical classes occur frequently enough in the dataset to generate significant rules; what has been observed of plain nouns, plain verbs, and adjectives, indicates a pattern in which the more lexicalised a sign is, the less likely it is to be articulated through NMFs. Non-lexical signs were observed to correlate with NMFs but, like many fully lexical signs, they occur in low frequency. Non-lexical signs show the strongest affinity with NMFs, while fully lexical signs show the lowest affinity. This supports the assertion that more lexicalised signs are observed with fewer NMFs. This argument is strengthened by the observation that partly lexical signs have a particularly strong affinity with NMFs. The strong affinity between NMFs and partly lexical signs was found to be driven by depicting signs, and of those, depicting verbs were most frequently observed with a wide variety of NMFs. These findings align with [15] who reports that morphologically complex signs in ISL, such as verbs, were found to correlate with mouth gestures, while morphologically simple signs, such as nouns, correlate with mouthings.

9. CONCLUSIONS

This work has proven that the ARM method can successfully identify patterns in a sign language dataset. Such patterns may be utilised to identify new knowledge based on quantitative scientific principles. In addition, rules generated by the ARM algorithm, and the measures of interestingness which accompany them, are useful tools which may be utilised by future sign language processing applications.

Supplementary annotations to the SOI corpus, the transformed dataset, and the statistical model contribute a collection of assets to future research in various areas of sign language linguistics and processing. The distribution analysis and association rules analysis of the data provide previously unknown linguistic insights about ISL while, in some cases, re-enforcing previously reported findings. For example, this study found that the more lexicalised a sign is, the less likely it will be observed with NMFs, and that partly-lexical signs are most likely to occur with NMFs.

This paper has reported that the *"small"* subset of challenging constructs reported in [1] actually accounts for approximately half of the lexical items in our dataset. The distribution analysis identified 46% of signs in the dataset as partly lexical. While it was acknowledged that depicting signs are documented as frequent in narrative text types, this evidence not only confirms that the lexicon of ISL includes a portion of signs which are phonetically unconstrained, it also identifies the productive lexicon as somewhat proportionate to the established lexicon concerning usage frequency. Given this, by not processing partly lexical signs, many sign language processing applications are missing a significant portion of the sign language lexicon.

This research was undertaken to fill a knowledge gap that exists between the linguistic understanding of sign languages and the computational processing of sign languages. Until now, the linguistic study of ISL has not quantified how NMFs or grammatical classes have been deployed in the language. Indeed, no sign language has been documented in the manner used in this study. A statistical description, such as this, is required by a computational approach to sign language processing. Given this, the statistical description developed as part of this work contributes some bridging of that knowledge gap, while the now-proven ARM method provides a framework to further fill that gap in the future across languages and linguistic phenomena such as those listed in [1].

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