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Using crowdsourcing for labelling emotional speech assets*

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Abstract

The success of supervised learning approaches for the classification of emotion in speech depends highly on the quality of the training data. The manual annotation of emotion speech assets is the primary way of gathering training data for emotional speech recognition. This position paper proposes the use of crowdsourcing for the rating of emotion speech assets. Recent developments in learning from crowdsourcing offer opportunities to determine accurate ratings for assets which have been annotated by large numbers of non-expert individuals. The challenges involved include identifying good annotators, determining consensus ratings and learning the bias of annotators.

1 Introduction

The automatic recognition of emotion from speech recordings uses supervised machine learning techniques which requires labelled training data in order to operate effectively. The performance of these supervised learning techniques depends on the quality of the training data and therefore on the quality of the labels. For many real life tasks, manual annotation by an expert is the primary way of getting the labels, but it can be an expensive and time-consuming process [20, 23, 4]. In some cases it can be impossible to get the actual label (also known as the ground truth or gold standard) and it is estimated from the subjective opinion of a small number of experts who can often disagree on the labels [14, 29]. It can be argued that emotional expertise does not necessarily correlate with emotional experience [11] suggesting that wider non-expert annotators can provide equally valid labels.

Recently with the availability of crowdsourcing [19] services such as Mechanical Turk¹, reCAPTCHA² and Games with a Purpose³ it has become inexpensive to acquire labels from multiple non-expert annotators. This has led to significant research into learning from crowdsourcing including comparing labels from non-expert annotators with the ground truth [20, 33], analysing consensus versus coverage requirements [7] and investigating methods and techniques for determining the ground truth and learning the bias of annotators [28, 29, 32].

In this position paper we propose the use of crowdsourcing for acquiring emotional labels in the domain of emotion recognition from speech. The rest of the paper is organized as follows—Section 2 presents a review of the techniques that are currently used for labelling emotional speech assets that are to be used as training data. Section 3 discusses crowdsourcing and its main challenges and includes some practical experiences of using crowdsourcing, while Section 4 concludes with a use case for an EmotionML which is appropriate for the usage being presented in this paper.

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¹www.mturk.com

²recaptcha.net

³www.gwap.com

2 Rating Emotional Assets for Training

Although current research in emotion recognition from speech has used both expert [2, 26, 36] and non-expert [9, 31] annotators for labelling the emotion in speech assets, most of the research does not indicate explicitly what expertise the annotators have.

Various numbers of annotators have been used—from two [2, 13, 36] up to between three to nine [9, 24, 26]. Odd numbers are often used to ensure a majority decision and five has been proposed as a good compromise [6]. There are a few exceptions when larger numbers of annotators have been used [1, 3, 21, 22, 27] but in these cases the annotated assets are not used for training an emotion recognition system so a consensus emotional rating is not required.

The methods used to determine a single rating from the different annotators depend on whether the annotation is categorical or dimensional. Majority voting is regularly used to select a categorical label [36]. With assets rated on a dimensional scale the mean of all annotators' values for each dimension is usually used [18].

Determining which assets are used as training data is generally based on some measure of annotator agreement. In categorical rating, often a requirement is for a certain proportion of annotators to agree [5, 24] before an asset can be considered as training data. This requirement can be complemented with a strength scale, requiring agreement from a certain proportion of annotators who consider the emotion to be at least of a required strength [12, 30, 31]. However, the most popular measure of agreement between categorical annotators in this area is the κ -statistic [16]. There is no consensus on what value denotes a high level of agreement, although Fleiss [16] suggests values smaller than 0.4 indicate low agreement, values between 0.4 and 0.7 indicate good agreement and values higher than 0.7 indicate excellent agreement. However, others suggest that values above 0.75 [35] or above 0.80 [10] indicate good agreement and below 0.4 [35] or below 0.67 [10] indicate bad agreement. A significant amount of research in this area report κ values between 0.3 and 0.5 [2, 9, 25] which overall does not support strong agreement among annotators, although there are some rare exceptions with very high κ values around 0.8 [8, 26]. This high agreement may be explained by the nature of the annotation task undertaken in these cases, requiring the annotator to select from a small number of distinctive categories. For the much more rarely dimensionally rated assets Grimm and Kroschel [17] use the standard deviation of all ratings on a dimension as a measure of agreement between annotators.

There have been limited efforts in the literature into estimating the bias of annotators and generally statistical techniques are used. Grimm et al. [18] calculates a correlation coefficient between the individual ratings and the mean of all ratings for dimensionally rated assets and uses this to determine the reliability of the annotator.

There has been limited research also into comparing non expert annotations with 'ground truth' in emotion recognition in speech. Engberg et al. [15] investigated how well people could recognize emotions in acted speech assets using 20 listeners. Their results revealed that the emotions were identified correctly in 67% of the cases indicating significant room for improvement.

Overall, there is little evidence in the literature of the usage of the recent phenomenon known as crowdsourcing in the labelling of emotional speech assets for use as training data. A limited number of annotators is generally used and, although it is often not often stated in the literature, the expectation is that these annotators are perceived to be experts. Generally, relatively simple statistical techniques are used to determine the actual label for the asset and thresholds on measures of inter-annotator agreement determine the most suitable training data.

3 Crowdsourcing

Crowdsourcing is the use of tasks outsourced to a large group of non-expert individuals [19]. One of the recent applications of crowdsourcing has been to label training data for a wide range of supervised learning application domains. It has been successfully used in machine translation [4], natural language tasks [33], computer aided diagnosis [28, 29], computer vision [32, 34] and sentiment analysis [7, 20].

Practical experiences with crowdsourcing has found that it can offer a fast and effective way to get labels

[20] that are of the same quality as those from experts [33] and usually very cheaply—Ambati et al. [4] report that it is possible to get 20 hours of annotation for only US\$45. Many researchers also note that it is possible to get a large number of labels very quickly—Snow et al. [33] obtained 300 ratings from 10 annotators in just 11 minutes using Amazon’s Mechanical Turk.

There are a number of challenges with using crowdsourcing to label speech assets, including (i) how to select which assets are presented for rating, (ii) how to estimate the reliability or bias of the annotators, (iii) how to derive the ground truth or actual rating for the asset and (iv) maintaining the balance between data coverage and data quality.

A recent development in this area is to use active learning to address the first of these concerns, that is selecting the appropriate assets for rating [4, 7, 14]. Active learning proposes techniques for selecting the more informative unlabelled examples to present for labelling. Brew et al. [7] recommend including a clustering-based step which results in identifying a sufficiently diverse set of clusters that represent dominant example types from which to select exemplars for labelling.

Both Donmez et al. [14] and Smyth et al. [32] propose learning approaches for determining the bias of the annotators whereas Brew et al. [7] have found that good annotators are valuable for training and defines good annotators as those that have the highest agreement with the consensus rating. There have also been considerable directions into addressing the challenge of learning the ground truth from multiple possibly noisy labels [28, 29, 32]. Raykar et al.’s [29] approach is to learn a classifier from the multiple annotations using maximum likelihood estimation and estimating the ground truth and the annotator performance is a byproduct of their proposed algorithm. From the point of view of getting annotations, the challenge of balancing the coverage of the assets with the quality of the labels is investigated by Brew et al. [7] who conclude that fewer annotators are needed in domains with high consensus.

A practical issue with using crowdsourcing services such as Mechanical Turk is to analyse the trustworthiness of the users who perform the tasks. Current research shows that the numbers of untrustworthy users is not large, normally a small subset produces most of the invalid input [23]. There is evidence of a number of different techniques used to guard against malicious or lazy users. Some research requires users to show some degree of accuracy on a small test subset [4] while other work uses the percentage of previously accepted submissions from a user in order to determine his or her trustworthiness and motivation [4, 20]. Kittur et al. [23] recommends including explicitly verifiable questions to reduce invalid responses and increase time-on-task.

4 Conclusions

In this position paper we have proposed using crowdsourcing as a mechanism for rating emotional speech assets. The use of crowdsourcing is relatively novel in domains where it can be impossible or too expensive to get the actual label or ground truth and there has been significant research into using machine learning techniques to address the challenges of learning the ground truth labels and learning annotator bias in crowdsourced data. The subjectivity of rating emotional assets offers opportunities for use of these techniques to create datasets of quality labelled speech assets for use in a number of research areas. The area that is of most interest to the authors of this position paper is the use of these quality assets in the classification and prediction of emotion in speech. Below we have included a use case that reflect our requirements of an emotion markup language.

Seán has a set of speech assets extracted from recordings of experiments using mood induction procedures. He wants to get these assets rated on a number of different scales, including activation and evaluation, by a large number of non-expert annotators. He wants to use a micro-task system such as Mechanical Turk to get these ratings. Active learning will be used to select the most appropriate assets to present for labels from the annotators. He will then analyse and evaluate different techniques for identifying good annotators and determining consensus ratings for the assets which will be used as training data for developing prediction systems for emotion recognition.

References

- [1] Å. Abelin and J. Allwood. Cross Linguistic Interpretation of Emotional Prosody. In *Proc. of the ISCA ITRW on Speech and Emotion*, pages 110–113, 2000.
- [2] H. Ai, D. J. Litman, K. Forbes-Riley, M. Rotaru, J. Tetreault, and A. Pur. Using System and User Performance Features to Improve Emotion Detection in Spoken Tutoring Dialogs. In *Proc. of Interspeech 2006*, pages 797–800, 2006.
- [3] K. Alter, E. Rank, S.A. Kotz, U. Toepel, and M. Besson. Accentuation and Emotions—Two Different Systems? In *Proc. of the ISCA ITRW on Speech and Emotion*, pages 138–142, 2000.
- [4] V. Ambati, S. Vogel, and J. Carbonell. Active Learning and Crowd-Sourcing for Machine Translation. In *Proc. of LREC '10*, pages 2169–2174, 2010.
- [5] A. Batliner, S. Steidl, B. Schuller, D. Seppi, K. Laskowski, T. Vogt, L. Devillers, L. Vidrascu, N. Amir, L. Kessous, and V. Aharonson. Combining Efforts for Improving Automatic Classification of Emotional User States. In *Proc. of IS-LTC 2006*, pages 240–245, 2006.
- [6] A. Batliner, S. Steidl, C. Hacker, and E. Nöth. Private Emotions Versus Social Interaction: a Data-driven Approach Towards Analysing Emotion in Speech. *User Modeling and User-Adapted Interaction*, 18(1-2):175–206, 2007.
- [7] A. Brew, D. Greene, and P. Cunningham. Using Crowdsourcing and Active Learning to Track Sentiment in Online Media. In *Proc. of PAIS 2010*, pages 1–11. IOS Press, 2010.
- [8] F. Burkhardt, J. Ajmera, R. Englert, J. Stegmann, and W. Burlison. Detecting anger in automated voice portal dialogs. In *9th Int. Conf. on Spoken Language Processing*, pages 1–4, 2006.
- [9] Z. Callejas and R. Lopezcozar. Influence of Contextual Information in Emotion Annotation for Spoken Dialogue Systems. *Speech Communication*, 50(5):416–433, 2008.
- [10] J. Carletta. Assessing Agreement on Classification Tasks: the Kappa Statistic. *Computational Linguistics*, 22(2):249–254, 1996.
- [11] R. Cowie and R. Cornelius. Describing the emotional states that are expressed in speech. *Speech Communication*, 40(1-2):5–32, 2003.
- [12] T. Danisman and A. Alpkocak. Emotion Classification of Audio Signals Using Ensemble of Support Vector Machines. *Perception in Multimodal Dialogue Systems, LNCS*, 5078:205–216, 2008.
- [13] L. Devillers and L. Vidrascu. Real-life Emotion Recognition in Speech. *Speaker Classification II, LNCS*, 4441:34–42, 2007.
- [14] P. Donmez, J.G. Carbonell, and J. Schneider. Efficiently Learning the Accuracy of Labeling Sources for Selective Sampling. In *Proc. of the 15th ACM SIGKDD*, pages 259–268, 2009.
- [15] I.S. Engberg, A.V. Hansen, O. Andersen, and P. Dalsgaard. Recording and Verification of a Danish Emotional Speech Database. In *Proc. of Eurospeech '97*, pages 1695–1698, 1997.
- [16] J. L. Fleiss. *Statistical methods for rates and proportions*. Wiley, 2nd edition, 1981.
- [17] M. Grimm and K. Kroschel. Evaluation of Natural Emotions Using Self Assessment Manikins. In *Proc. of IEEE Automatic Speech Recognition and Understanding Workshop*, pages 381–385, 2005.
- [18] M. Grimm, K. Kroschel, E. Mower, and S. Narayanan. Primitives-based Evaluation and Estimation of Emotions in Speech. *Speech Communication*, 49(10-11):787–800, 2007.

- [19] J. Howe. *Crowdsourcing: Why the Power of the Crowd Is Driving the Future of Business*. Crown Business, 2008.
- [20] P.Y. Hsueh, P. Melville, and V. Sindhwani. Data Quality from Crowdsourcing: a Study of Annotation Selection Criteria. In *Proc. of the NAACL HLT 2009 Workshop on Active Learning for Natural Language Processing*, pages 27–35, 2009.
- [21] A. Iida, N. Campbell, F. Higuchid, and M. Yasumura. A Corpus-based Speech Synthesis System with Emotion. *Speech Communication*, 40(1-2):161–187, April 2003.
- [22] I. Iriondo, R. Guaus, A. Rodríguez, P. Lázaro, N. Montoya, J.M. Blanco, D. Bernadas, J.M. Oliver, D. Tena, and L. Longhi. Validation of an Acoustical Modelling of Emotional Expression in Spanish Using Speech Synthesis Techniques. In *ISCA Workshop on Speech & Emotion*, pages 161–166, 2000.
- [23] A. Kittur, E. Chi, and B. Suh. Crowdsourcing for Usability: Using Micro-Task Markets for Rapid, Remote, and Low-cost User Measurements. *Proceedings of CHI 2008*.
- [24] K. Komatani, R. Ito, T. Kawahara, and H.G. Okuno. Recognition of Emotional States in Spoken Dialogue with a Robot. *Innovation in Applied Artificial Intelligence, LNCS*, 3029:413–423, 2004.
- [25] D. Litman and K. Forbes-Riley. Recognizing Student Emotions and Attitudes on the Basis of Utterances in Spoken Tutoring Dialogues with Both Human and Computer Tutors. *Speech Communication*, 48(5): 559–590, 2006.
- [26] D. Neiberg, K. Elenius, and K. Laskowski. Emotion Recognition in Spontaneous Speech Using GMM. In *Proc. of Interspeech '06*, pages 809–812, 2006.
- [27] C. Pereira. Dimensions of Emotional Meaning in Speech. In *Proceedings of the ISCA Workshop on Speech and Emotion*, pages 25–28, 2000.
- [28] V.C. Raykar, S. Yu, L.H. Zhao, A. Jerebko, C. Florin, G.H. Valadez, L. Bogoni, and L. Moy. Supervised Learning from Multiple Experts: Whom to trust when everyone lies a bit. In *Proc. of ICML-2009*, pages 889–896, 2009.
- [29] V.C. Raykar, S. Yu, L.H. Zhao, G.H. Valadez, C. Florin, L. Bogoni, and L. Moy. Learning from Crowds. *Journal of Machine Learning Research*, 11:1297–1322, 2010.
- [30] M. Shami and W. Verhelst. Automatic Classification of Expressiveness in Speech: A Multi-corpus Study. *Speaker Classification II, LNCS*, 4441:43–56, 2007.
- [31] M. Slaney and G. McRoberts. Baby Ears: a Recognition System for Affective Vocalizations. *Proc. of ICASSP '98*, pages 985–988, 1998.
- [32] P. Smyth, U. Fayyad, M. Burl, P. Perona, and P. Baldi. Inferring Ground Truth from Subjective Labelling of Venus Images. *Advances in neural information processing systems*, 7:1085–1092, 1995.
- [33] R. Snow, B. O'Connor, D. Jurafsky, and A.Y. Ng. Cheap and Fast - But is it Good? Evaluating Non-Expert Annotations for Natural Language Tasks. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pages 254–263. ACL, 2008.
- [34] A. Sorokin and D. Forsyth. Utility data annotation with Amazon Mechanical Turk. In *Proc. of CVPR 2008*, pages 1–8, 2008.
- [35] S. Steidl. *Automatic Classification of Emotion-Related User States in Spontaneous Childrens Speech*. Phd, Universitat Erlangen-Nurnberg, 2009.
- [36] L. Vidrascu and L. Devillers. Annotation and Detection of Blended Emotions in Real Human-Human Dialogs Recorded in a Call Center. In *Proc. of ICME 2005*, pages 944–947, 2005.