Preference Learning Labels by Anchoring on Consecutive Annotations

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MOTIVATION

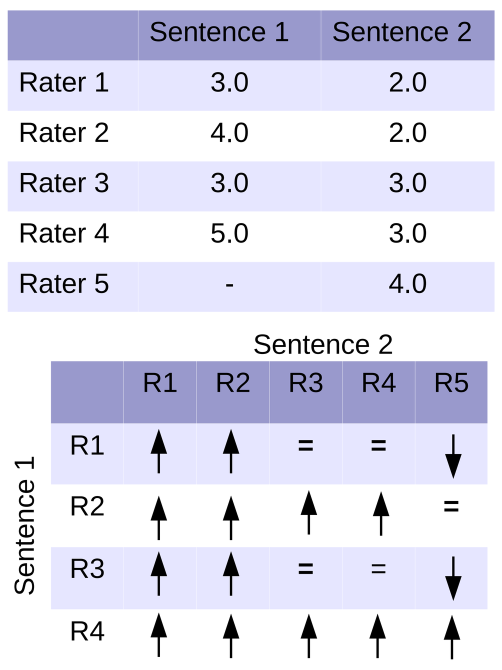
Background:

- An important task in human-computer interaction is to rank speech samples according to their expressive content.
- Preference learning framework is appropriate for obtaining emotional rank order for a set of speech samples.
- Challenge:
  - Obtaining reliable preference labels indicating preference between pair of speech samples

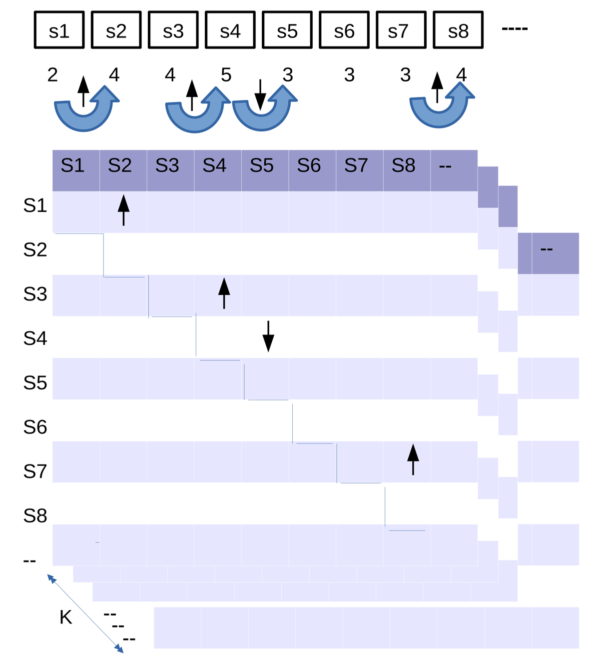
Our Work:

- We propose a method to obtain preference labels
  - That leverage the anchoring process by considering preference across consecutive annotations
  - The proposed consecutive labels (CL) are result of annotation trends assigned by a rater to consecutive samples
  - Achieved better performance with sparse set of relative labels

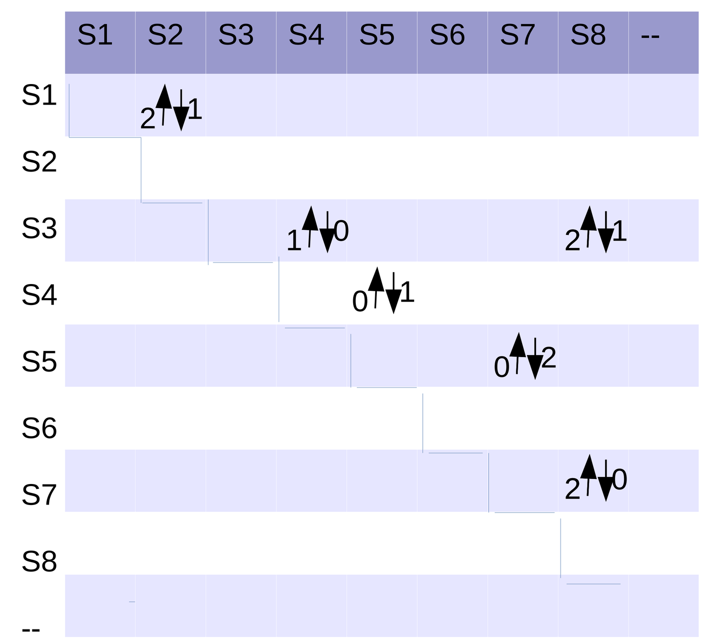
Proposed Anchor-based Ordinal Labels



Qualitative Agreement (Baseline)



individual CL matrix of annotators



Cumulative CL matrix

Step1:

- Obtained individual CL matrices for all k annotators indicating their consecutive preferences

Step2:

- Combined all individual CL matrices to obtain cumulative CL matrix.

CL1: All pairs

CL2: Pairs preferred by at least two annotators

CL3: Pairs preferred by at least three annotators

	CL1			CL2			CL3		
	A	V	D	A	V	D	A	V	D
Num. of Pairs in[K]	204	193	174	43	47	39	21	21	19
Coverage (%)	96.5	95.6	96.8	85.2	88.5	82.7	61.3	64.6	59.8

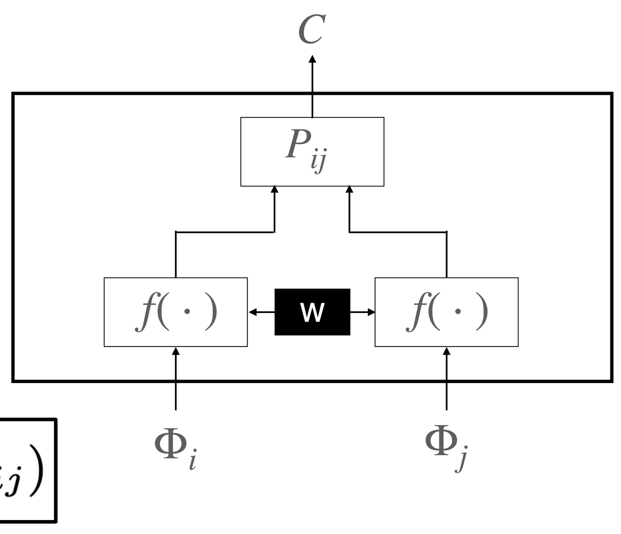
A: Arousal, V: Valence, D: Dominance, out of ~63K training samples

Preference Learning Framework and Performance Analysis for Speech Emotion Recognition

RankNet Framework[1]

This study relies on the RankNet-based implementation for preference learning

$$P_{ij} = \frac{1}{1+e^{-\sigma(s_i - s_j)}}$$



$$C = -\bar{P}_{ij}\log P_{ij} - (1-\bar{P}_{ij})\log(1-P_{ij})$$

Baseline ordinal labels:

- ABS (Baseline): Preference labels obtained using a difference between consensus score. Trained using all possible pairs.
- QA (Qualitative Agreement): Preference labels obtaining using QA method. Trained using randomly selected 200K pairs.

Experimental Results

KT: Kendall's Tau coefficient

Trained using (rows) / Tested using (columns)

KT	ABS	QA	CL1	CL2	CL3
	Arousal				
ABS	0.482	0.496	0.489	0.494	0.497
QA	0.491	0.512	0.481	0.486	0.485
CL1	0.501	0.521	0.526	0.534	0.535
CL2	**0.504**	**0.527**	**0.533**	**0.539**	0.537
CL3	0.498	0.513	0.518	0.535	**0.539**

KT	ABS	QA	CL1	CL2	CL3
	Valence				
ABS	0.301	0.292	0.284	0.289	0.292
QA	0.311	0.316	0.298	0.304	0.302
CL1	0.308	0.321	0.331	0.334	0.331
CL2	**0.315**	**0.330**	0.346	0.348	0.341
CL3	0.314	0.329	**0.349**	**0.351**	**0.345**

KT	ABS	QA	CL1	CL2	CL3
	Dominance				
ABS	0.380	0.376	0.364	0.369	0.373
QA	0.388	0.393	0.382	0.393	0.397
CL1	**0.398**	0.395	0.417	0.419	0.426
CL2	0.395	0.402	**0.428**	**0.430**	0.424
CL3	0.389	**0.406**	0.416	0.426	**0.432**

- ➢ Proposed CL resulted in a better performance, even on the test sets obtained using baseline label methods (ABS, QA).
- ➢ Among the proposed CL schemes, CL2 performed best for arousal, and dominance.
- ➢ CL3 leads to better performance in valence.

Corpora

The MSP-PODCAST corpus (Emotional corpus collected at UT Dallas)

- We used 1.10 version of the corpus, which is sourced from various audio-sharing websites with creative commons licenses
- Includes 63,076 segments of audio for training, (10,999, and 16,903) segments for development and testing
- We have only used attributes (arousal, valence, and dominance) labels in this work

Features

- We used pre-trained wav2vec2-large-robust[2] model from the HuggingFace library. We pruned top 12 transformer blocks and fine-tuned with MSP-PODCAST train set
- Considered average pooled vector across all frames as the sentence level representation

CONCLUSIONS

- Considered ordinal labels using consecutive annotations from annotators, resulting in less noisy and reliable labels.
- Explored trade-off between quality and quantity in the implementation of the proposed ordinal labels.

Future Work

- In the future, we want to explore similar strategies to deal with ordinal labels for categorical emotions.

References:
[1] C. Burges, T. Shaked, E. Renshaw, A. Lazier, M. Deeds, N. Hamilton, and G. Hullender, "Learning to rank using gradient descent," (ICML 2005)
[2] A. Baevski, Y. Zhou, A. Mohamed, and M. Auli, "wav2vec 2.0: A framework for self-supervised learning of speech representa- tions," (NeurIPS 2020)

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