Retrieving Categorical Emotions using a Probabilistic Framework to Define Preference Learning Samples

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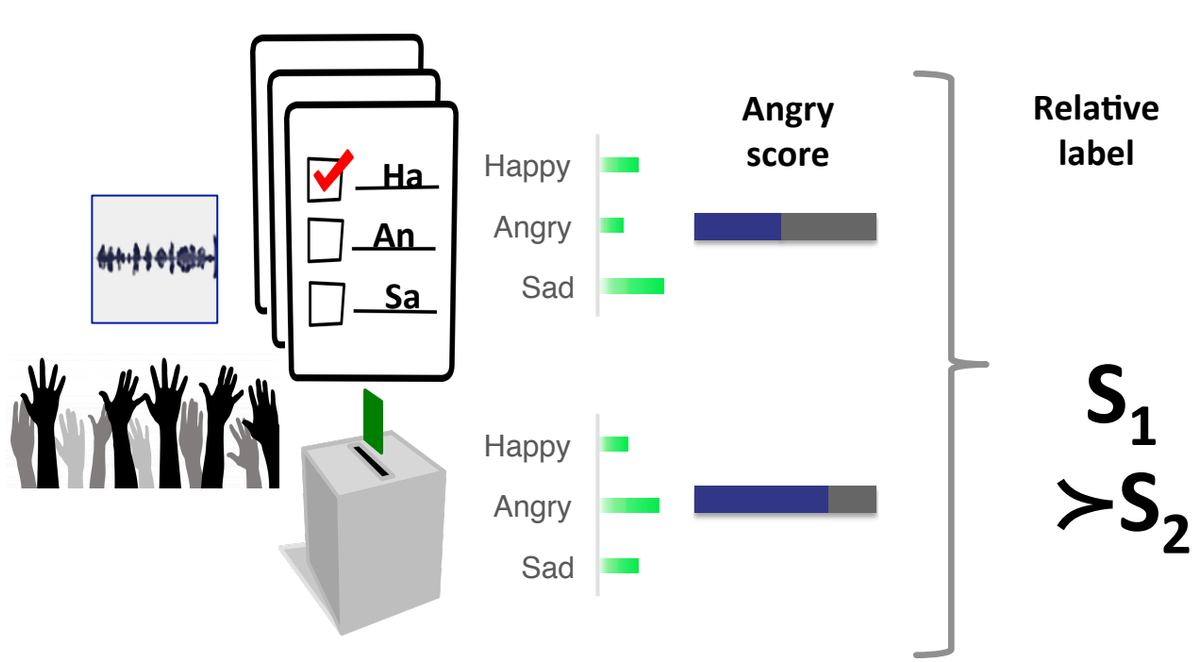

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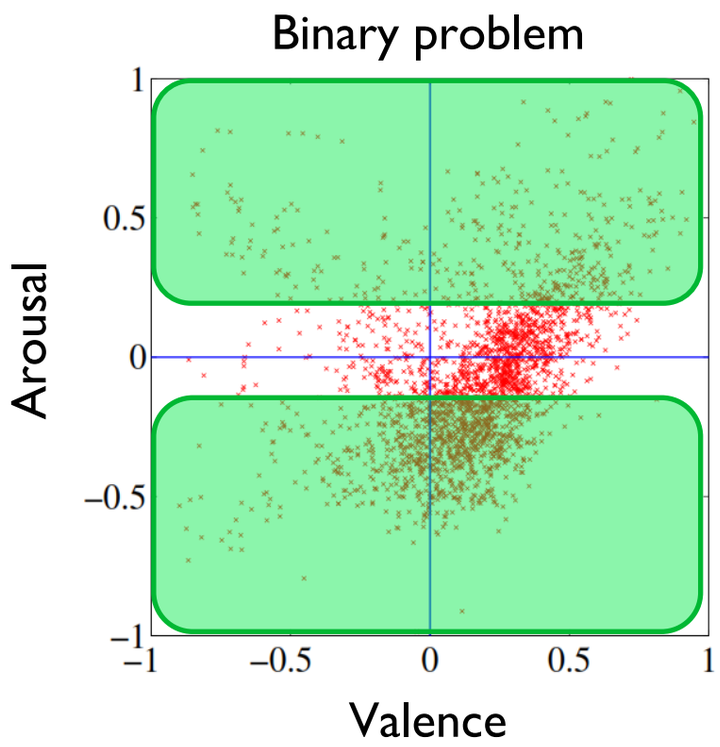
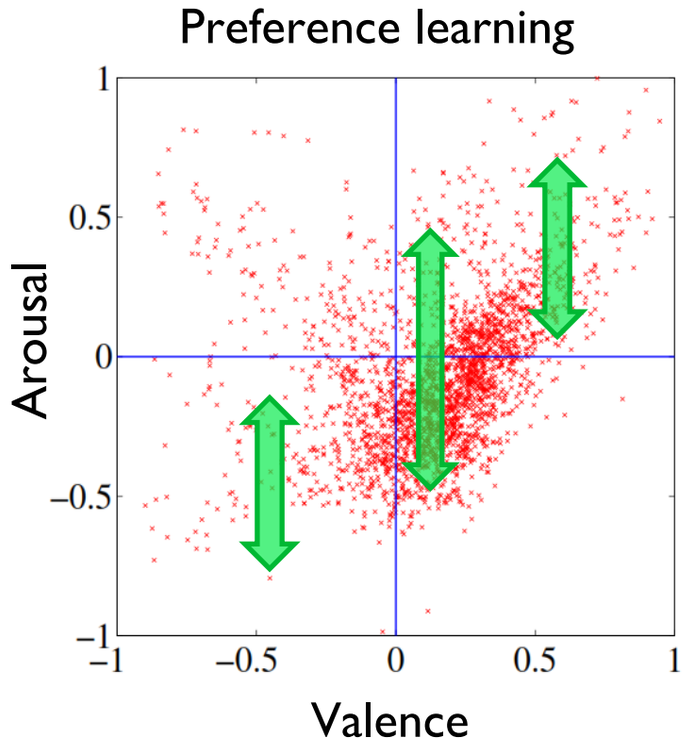
Motivation

- Retrieving speech conveying target emotion
  - Surveillance, call center
- Binary and multi-class
  - Focus of most previous studies
  - Few studies on preference learning on continuous attributions (arousal, valence,…) [Lotfian et.al, 2016]
- This study: Preference learning on categorical emotions (Happy, Sad,….)
  - E.g., “is sample A happier than sample B”

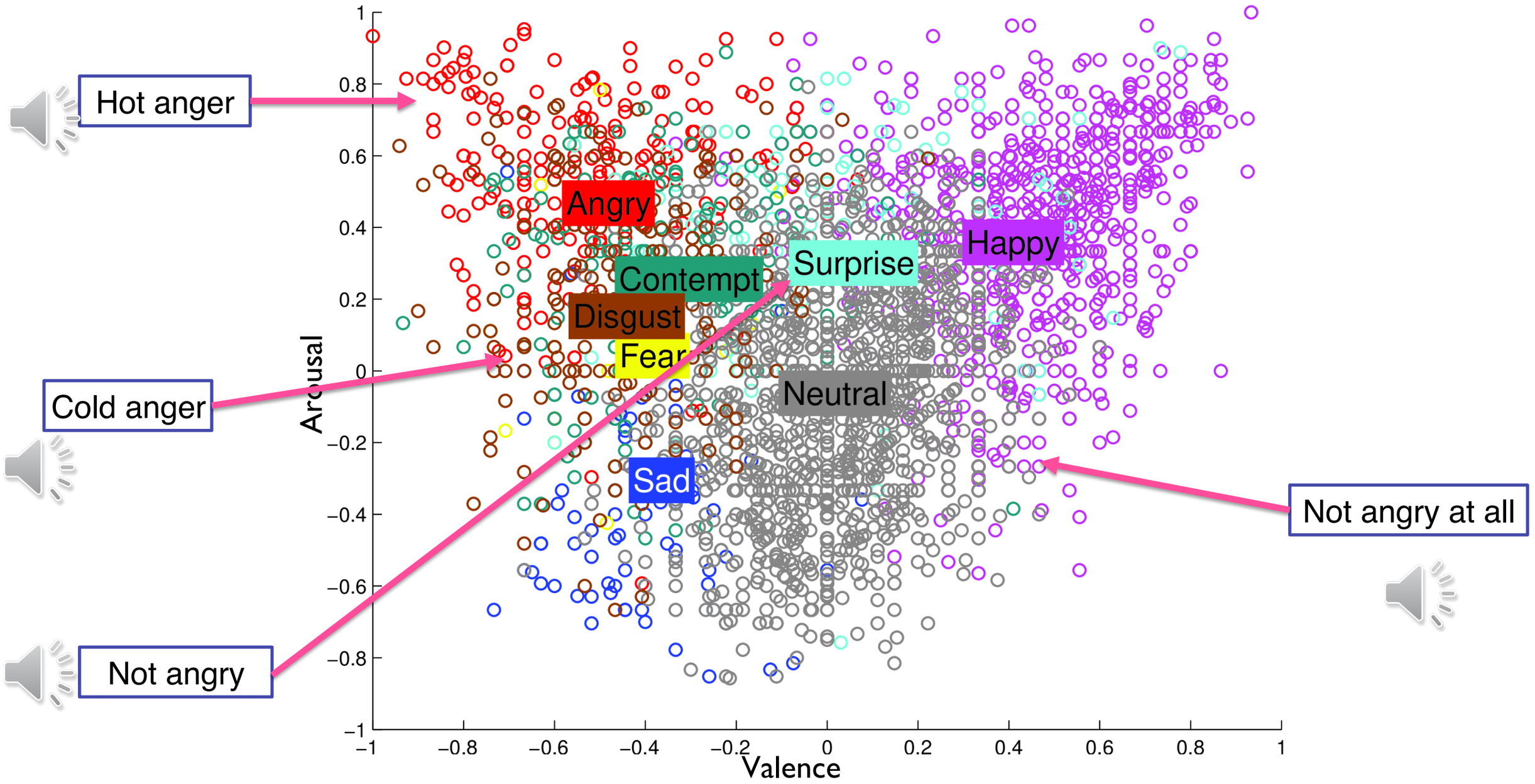
Preference Learning-Ranking

- Multiclass classification
  - Assign a class label to each sample (High versus low arousal)
- Preference learning
  - For each class rank samples based on relevance to the class (Intensity of emotion)
- More reliable training examples without sacrificing training size





Categorical Emotion Ranker



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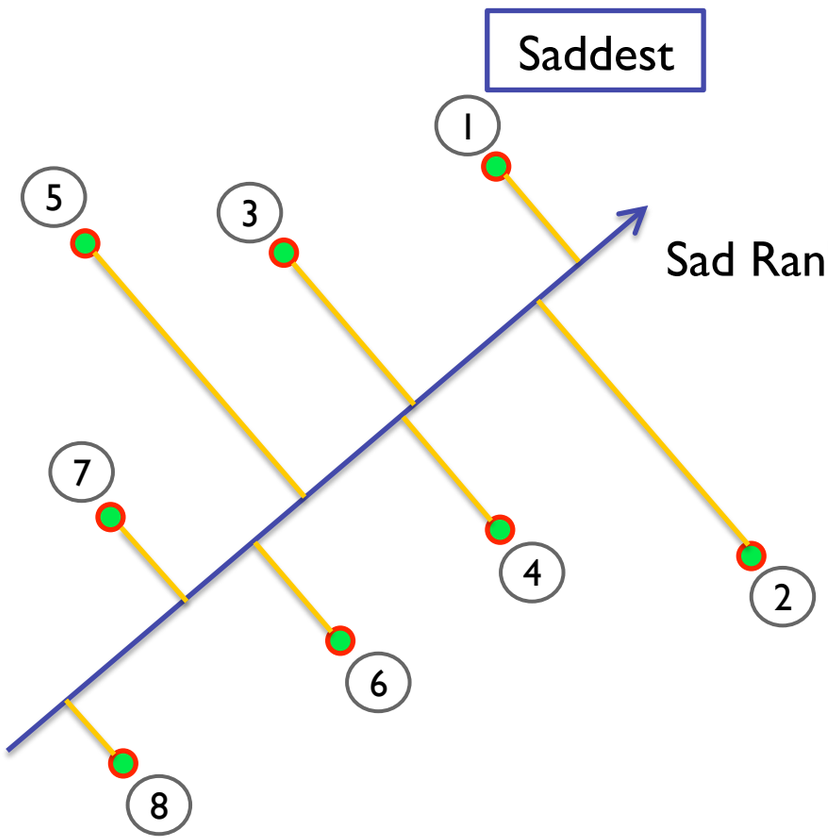
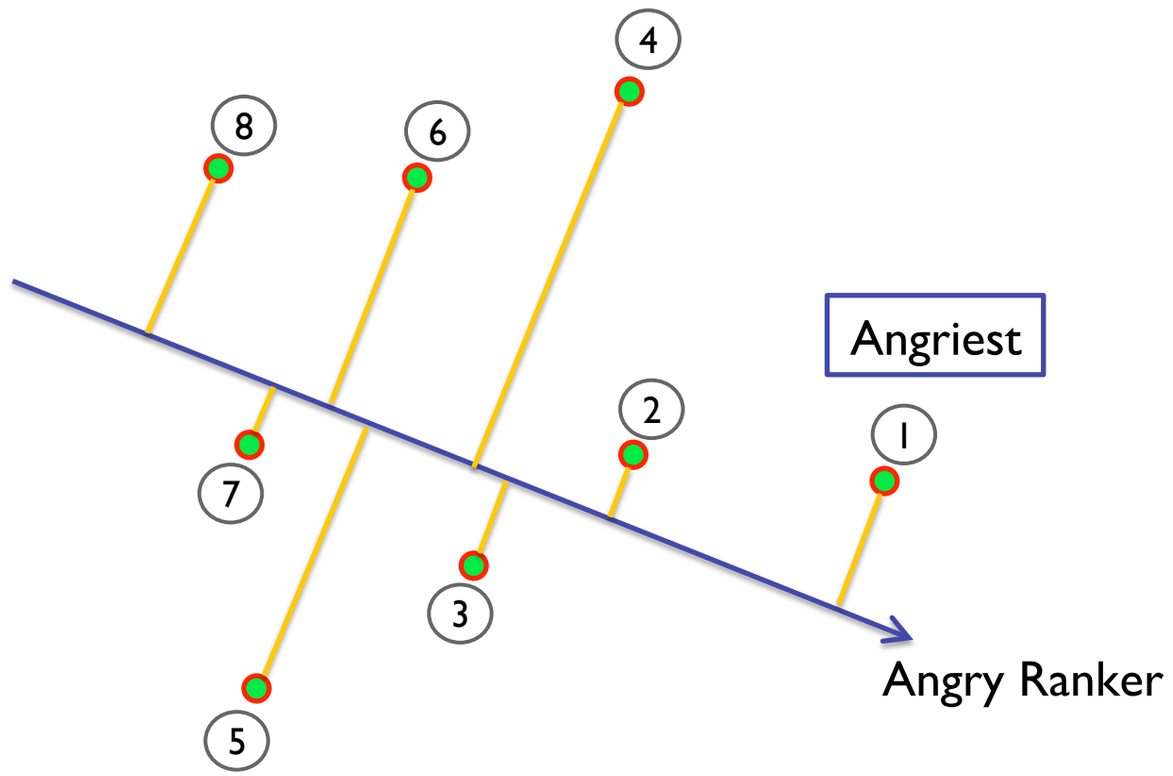




Training Preference

- Preference learning needs a set of ordered pairs of samples for training
  - Arousal, Valence, Dominance: interval variables

$$e^{s_1}_{arousal} - e^{s_2}_{arousal} > margin \longrightarrow s_1 \succ_{arousal} s_2$$

- Happiness, Sadness … binary (happy – not happy)

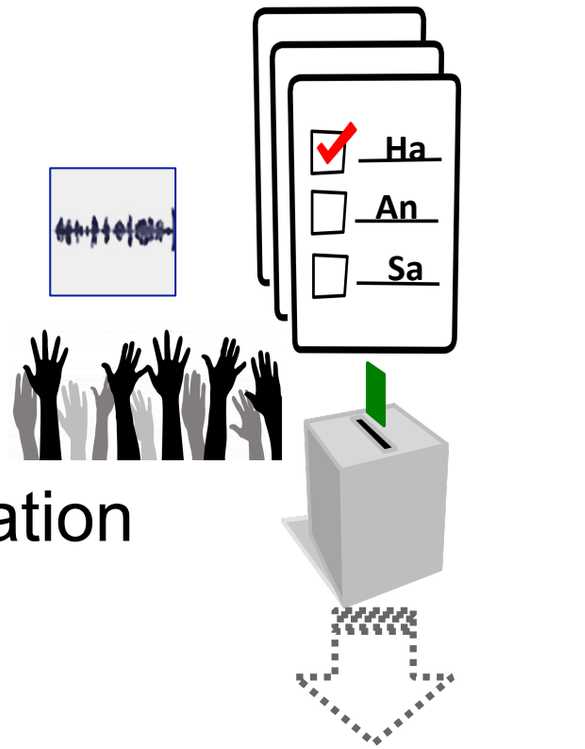
$happy \succ_{happiness} sad$ ✓ [Cao et.al, 2014]

$angry \succ_{happiness} sad$?

$happy_1 \succ_{happiness} happy_2$?

Definition of the Problem

- What we have for training:
  - Audio sample & set of subjective evaluations
    $s_1(happy, happy, happy)$
    $s_2(happy, happy, sad)$
- Hypothesis:
  - Individual annotations provides more information than majority vote



- s_1 is more likely to be happy than s_2

$$s_1 \succ_{happiness} s_2$$

- s_2 is more likely to be sad than s_1

$$s_2 \succ_{sadness} s_1$$

$$P(Happy|happy, happy, happy) > P(Happy|happy, happy, sad)$$

$$P(Sad|happy, happy, sad) > P(Sad|happy, happy, happy)$$

Quantifying Categorical Emotion Preference

- Set of R annotations $x_1, x_2, ..., x_R$
- Emotion class $w_j, j \in \{1, ..., E\}$
- Posteriori probability (choose the class that maximize)

$$P(w_k|x_1, x_2, x_3) = \frac{P(w_i)\prod_{i=1}^{R} p(x_i|w_k)}{\sum_{j=1}^{m} P(w_j)\prod_{i=1}^{R} p(x_i|w_k)}$$

- Sum rule [Kittler,1998]

$$\nu_j = (1-R)P(w_j) + \sum_{i=1}^{R} P(w_j|x_i)$$

Relevance s
core

Databases

- IEMOCAP (Feature selection and Training)
  - 5 sessions, 10 trained actors
  - Script and spontaneous improvisations
  - 12 hours of recording, manually segmented, transcribed and annotated by 3 independent evaluators

- MSP-IMPROV (Testing)
  - Collected under dyadic improvisation
  - Natural scenarios
  - 4 emotions: anger, sadness, happiness, neutral
  - 9 hours of recording, at least annotated by 5 independent evaluators through crowd-sourcing

Database	Angry	Happy	Sad	Neutral	Other	No Agreement	Total
IEMOCAP	289	284	608	1099	1704	800	4784
MSP-IMPROV	792	2644	885	3477	85	555	8438

Experimental Evaluation

- Learning preference from sum rule (relevance score)

$$\nu_j = (1 - R)P(w_j) + \sum_{i=1}^{R} P(w_j|x_i)$$

- Estimate $P(w_j)$ and $P(w_j|x_i)$ using training database

- Annotation labels: $x\downarrow i \in$ {Happy, Excited, Surprised, Fear, Angry, Frustrated, Disgusted, Sad, Neutral and Other}

- Target emotions: $\omega\downarrow j \in$ {Happiness, Anger, Sadness}

- Learning $P(w_j|x_i) \rightarrow$ assume majority vote consensus label is true label (w_j)

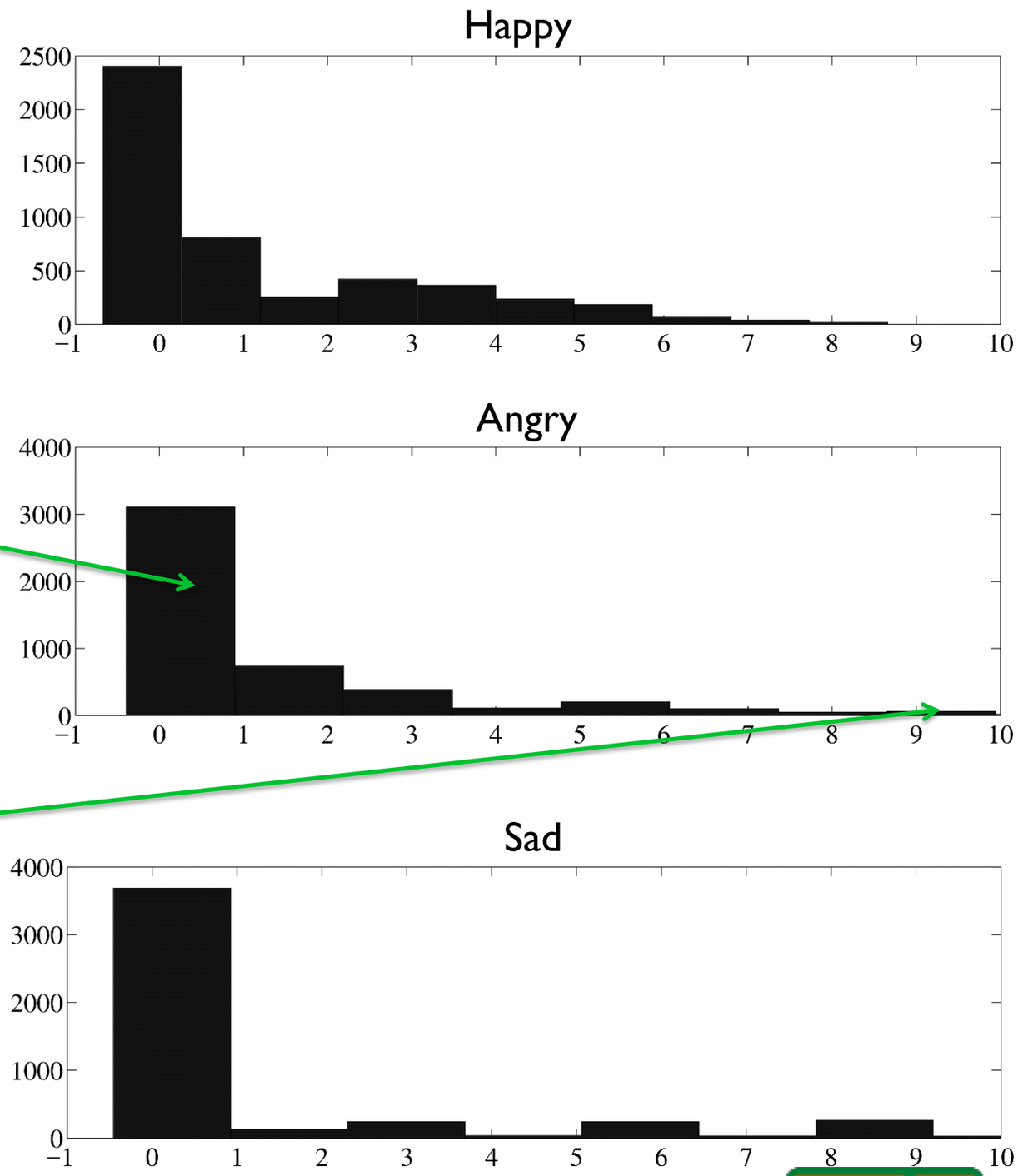
Experimental Evaluation

- Histogram of relevance score estimated on the training set

$$\nu_j = (1 - R)P(w_j) + \sum_{i=1}^{R} P(w_j|x_i)$$

Unlikely to be angry

Likely to be angry



IEMOCAP corpus

Acoustic features

- Speaker state challenge feature set at INTERSPEECH 2013
  - 6308 high level descriptors
  - OpenSMILE toolkit
- Feature selection (separate for each emotion)
  - Step 1: 6308→500
    - Information gain separating target emotion (e.g., Happy vs. other)
  - Step 2: 500→100
    - Floating forward feature selection
    - Maximizing the precision of retrieving top 10%

Preference Learning Methods

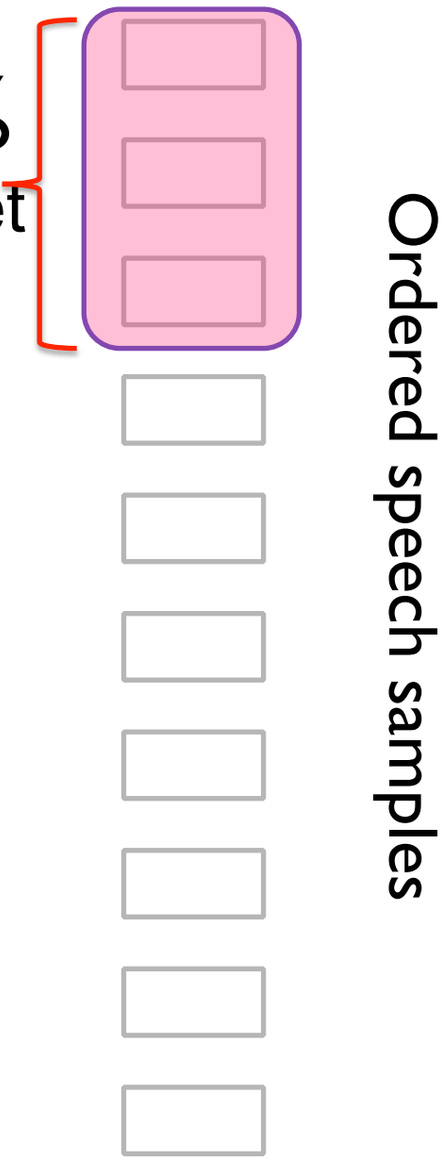
- Rank-SVM: LibSVM toolkit [Joachims, 2006]
- Gaussian Process (GP) preference learning toolkit [Chu & Ghahramani, 2005]
- Training: IEMOCAP database
- Testing: MSP-IMPROV database
- Relative labels:
  - Relevance score (proposed method)
  - Baseline:
    - Label based (Cao et al. [2014])

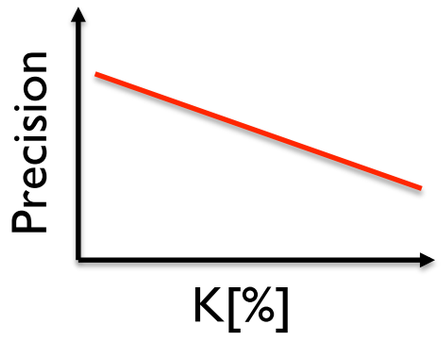
$$happy \succ_{happiness} sad$$

Measure of Retrieval Performance

Precision at K (P@K)

- Speech samples ordered by a rank method
- Select K that we know has target emotion in the test set
  - Example: P@30 → 2644 Happy samples in test set
    retrieve 2644*0.30=793 samples of highest rank
- Success if the sample is from target emotion class (Happy)
  - We can compare this approach to other machine learning algorithm





Comparing Precision @ K

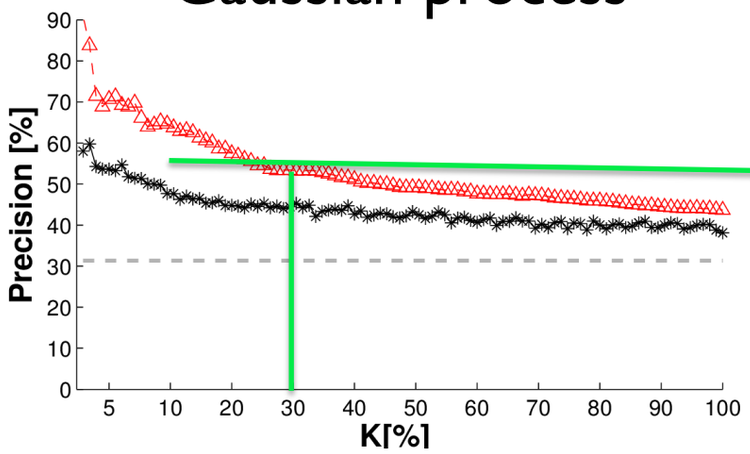
Relevance score

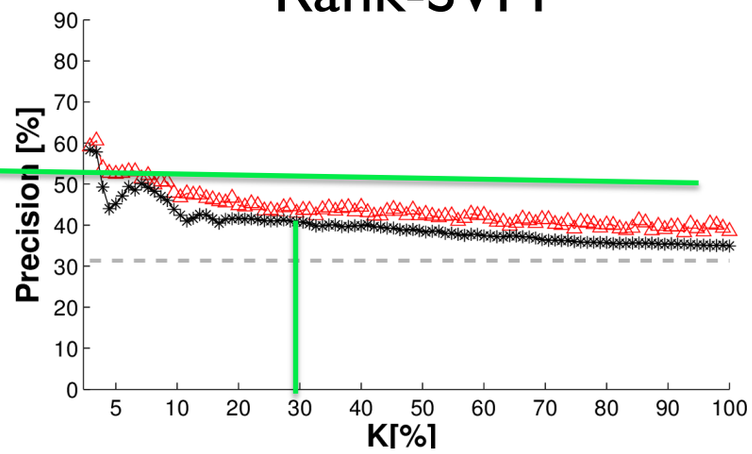
Cao et al

Gaussian process

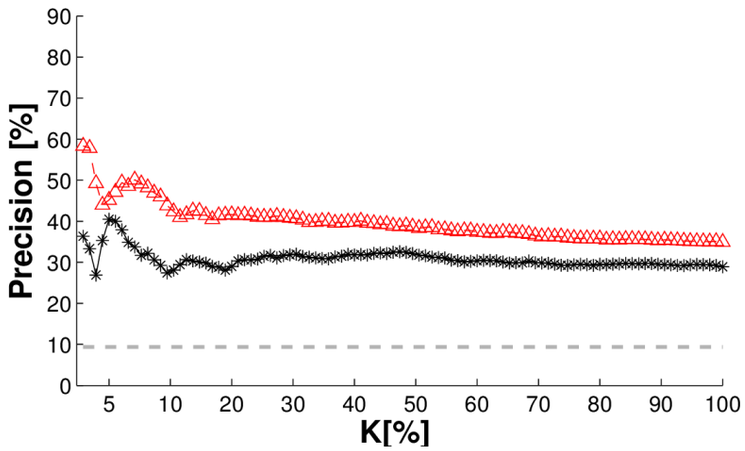
Rank-SVM

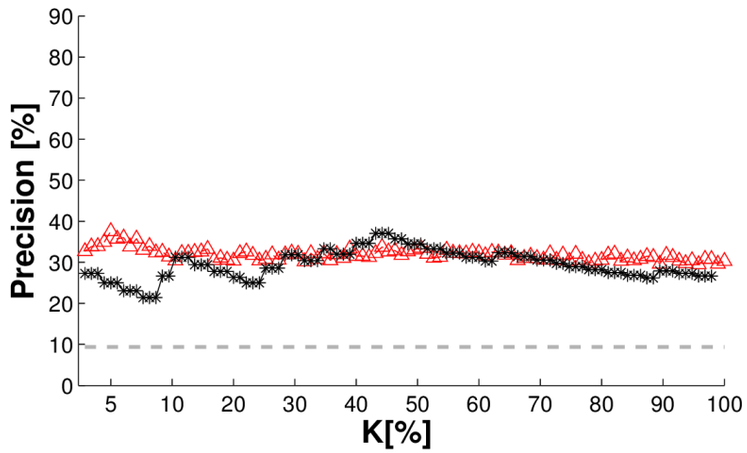
Happy



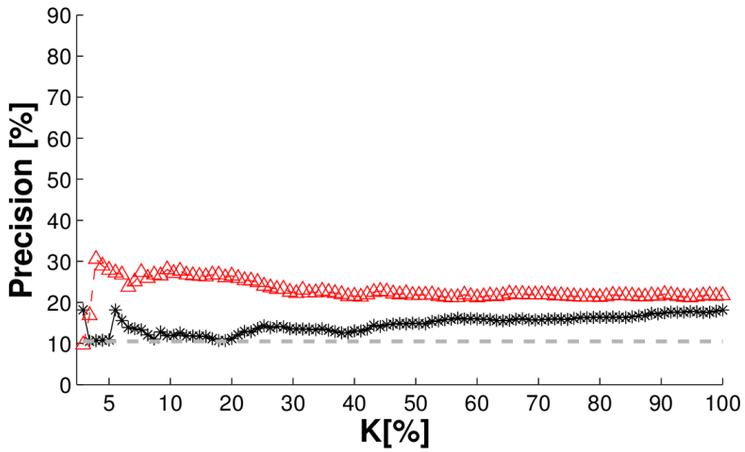


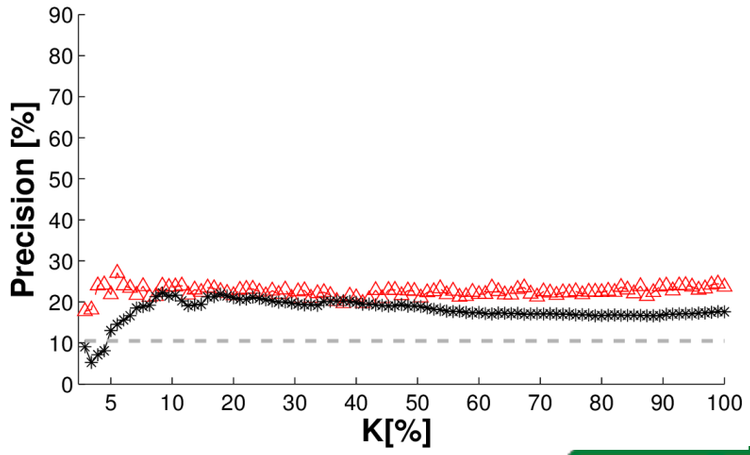
Angry



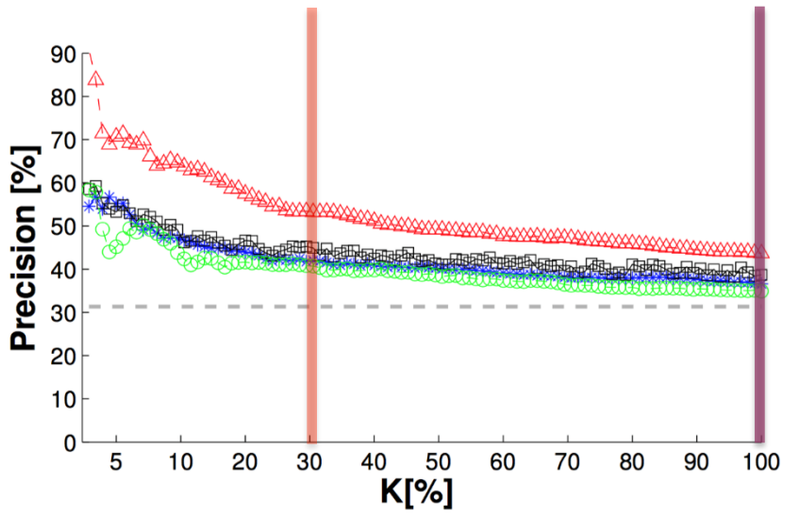


Sad

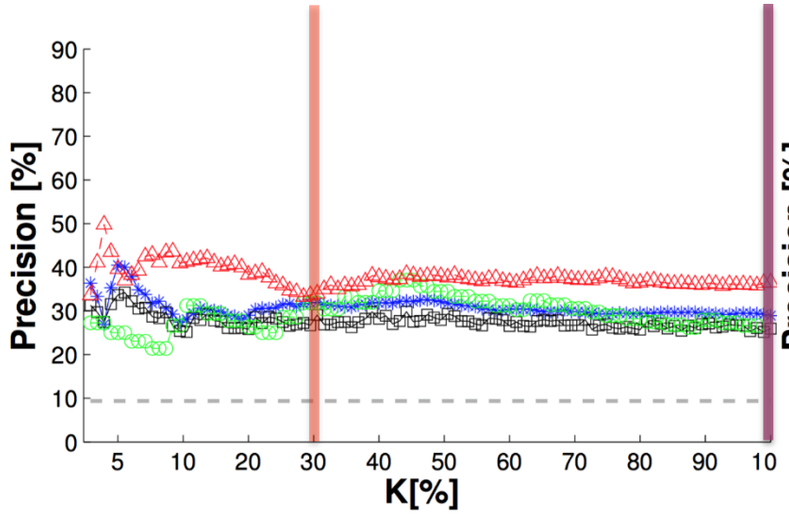




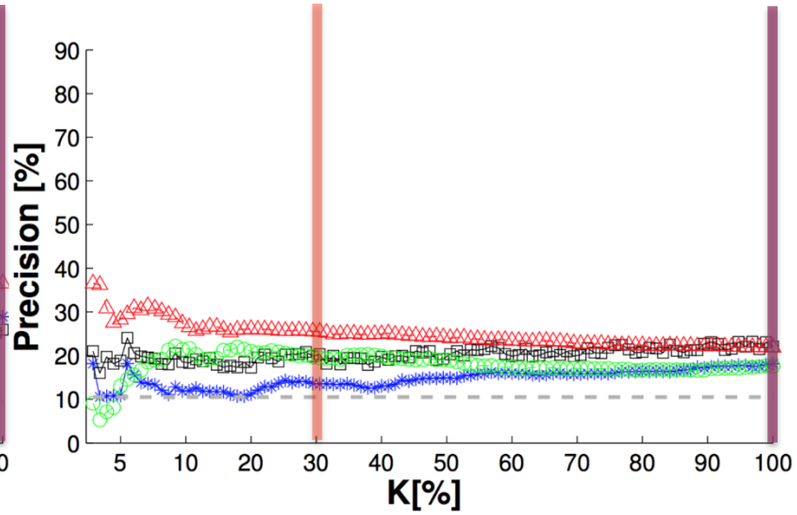
Accuracy of Retrieval



Happy



Angry



Sad

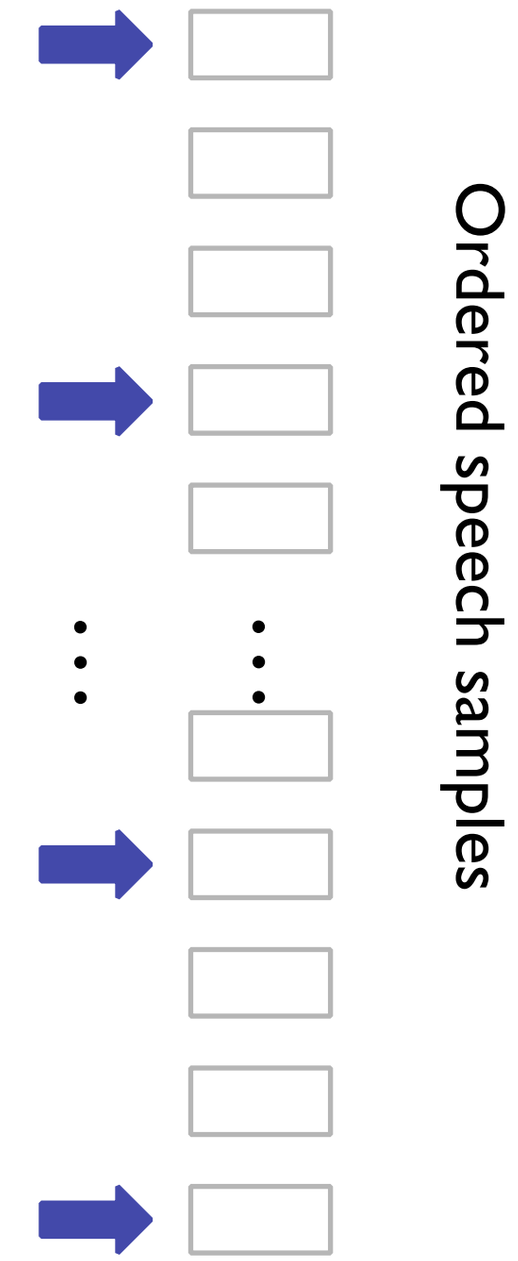
Cao et al. 2015(SVM) — Cao et al. 2015(GP) — Relevance score(SVM) — Relevance score(GP) — Random

- Label based ranking
- Relevance score ranking

Emotion Category	Cao et al. [2015] P@30	Cao et al. [2015] P@100	Relevance score P@30	Relevance score P@100
Happy	42.4	37.1	53.4*	43.7*
Angry	31.8	28.9	36.5	33.6*
Sad	20.1	22.0	25.6	21.9

Performance of Ranking

- Select 20 sample
- Find if the order is correct
  - Baseline: relevant score estimated for test set



Kendall rank correlation coefficient for Gaussian process preference learning

Emotion Category	Cao et al. [2015]	Relevance score
Happy	0.194	0.242
Angry	0.118	0.126
Sad	0.158	0.194

Conclusion and Future Work

- We proposed relative labels used in preference learning for categorical emotions
  - Using raw annotations instead of only consensus labels
- Higher precision than consensus label based ranking and binary classification

We have better relative labels!!!

- Future work:
  - Consider reliability of annotators in relevance score
  - Deep neural network based preference learning
  - Consider arousal and valence (Multi-task learning)

References

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Thanks for your attention!

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