Ranking Emotional Attributes With Deep Neural Networks

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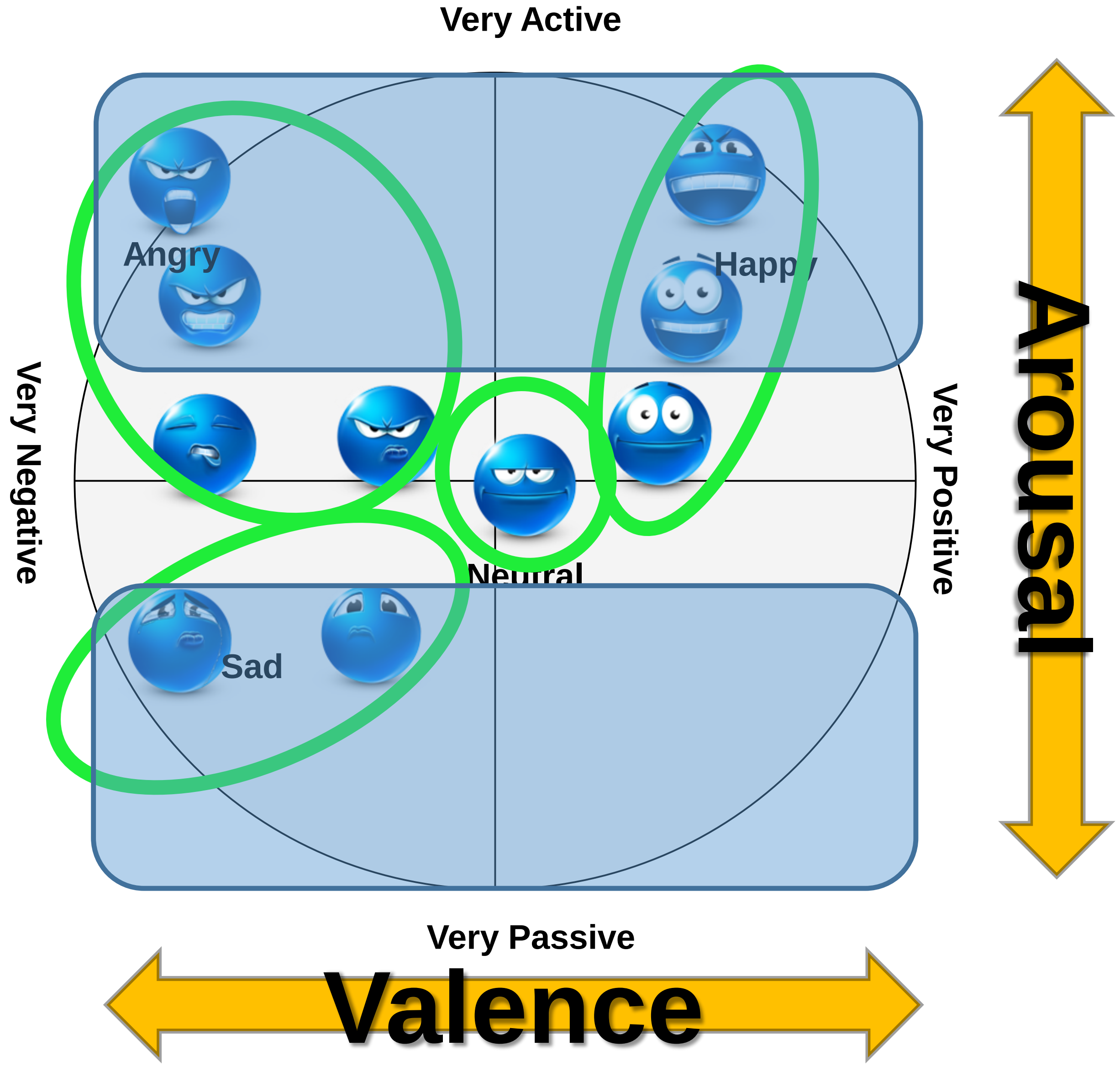
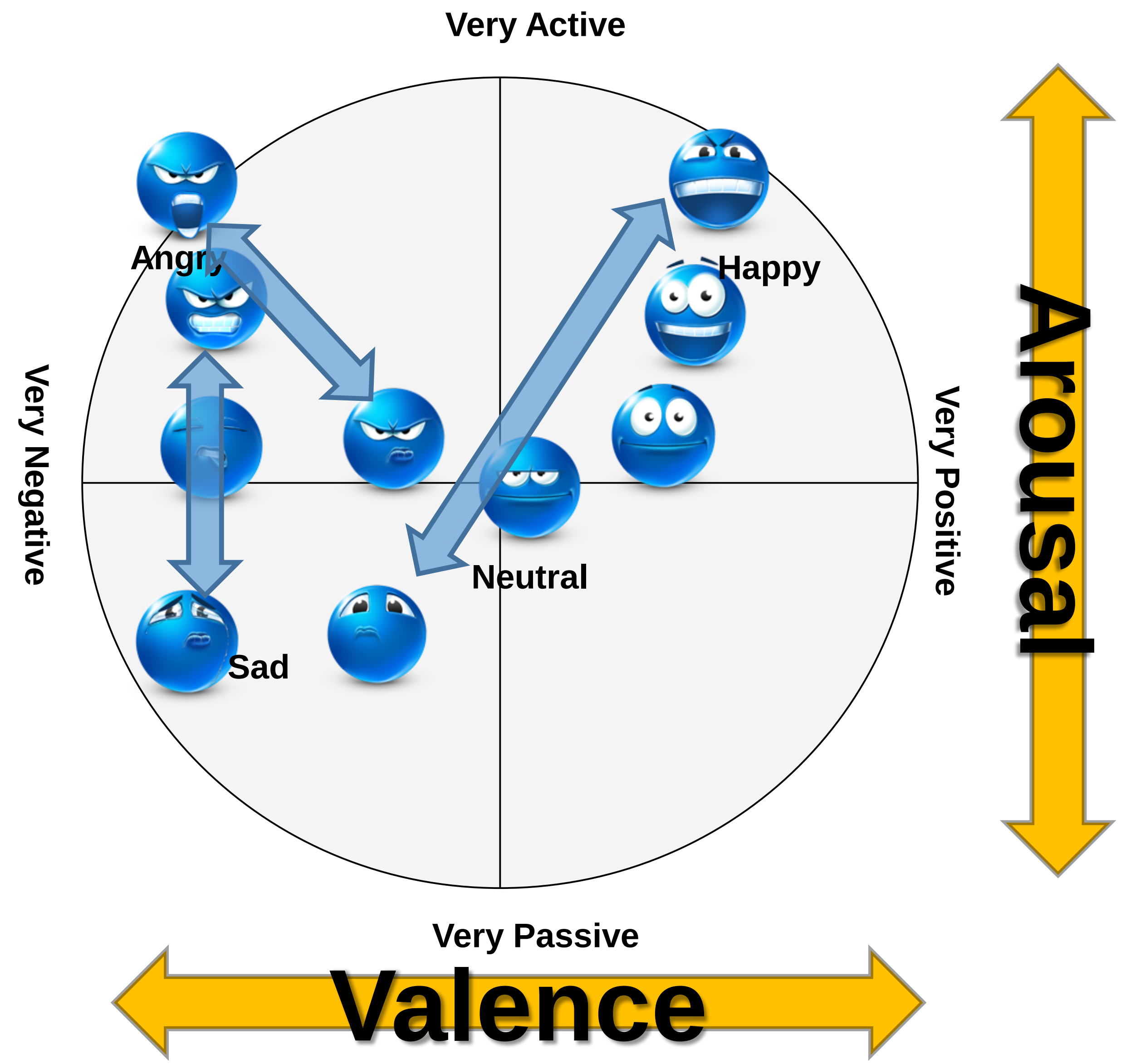
Motivation

- Emotion recognition systems can be trained to
  - Classify discrete categories such as Happy, Neutral, Angry etc.
  - Classify or predict values of emotional attributes such as
    - Arousal (passive vs active)
    - Valence (positive vs negative)



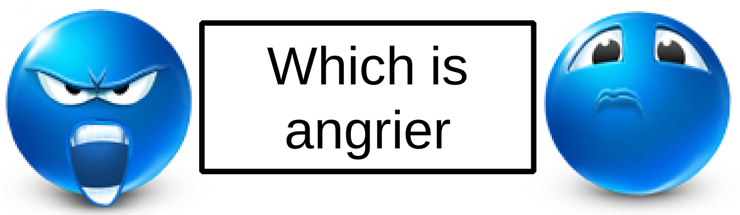
Motivation

- Humans are better at relative comparisons than absolute values
- Rank emotional attributes rather than absolute classification/regression
- Appealing for Emotional Retrieval tasks
  - Rank order aggressive behavior
  - Retrieve target behaviors with given emotions

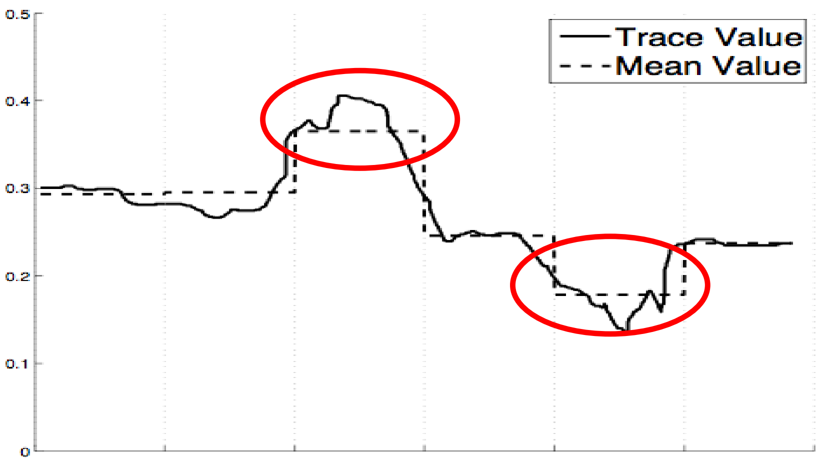


Related Work

- Commonly formulated as comparisons between pairs of samples
- Rankers for categorical emotions (e.g. angry rankers) [Cao et al. 2012, 2014]
    - Pairs formed between preferred emotion and other emotion



- Preference learning methods were used to learn from continuous ratings [Martinez et al. 2014]
- Alternative framework to study trends where raters agreed [Parthasarathy et al. 2016]

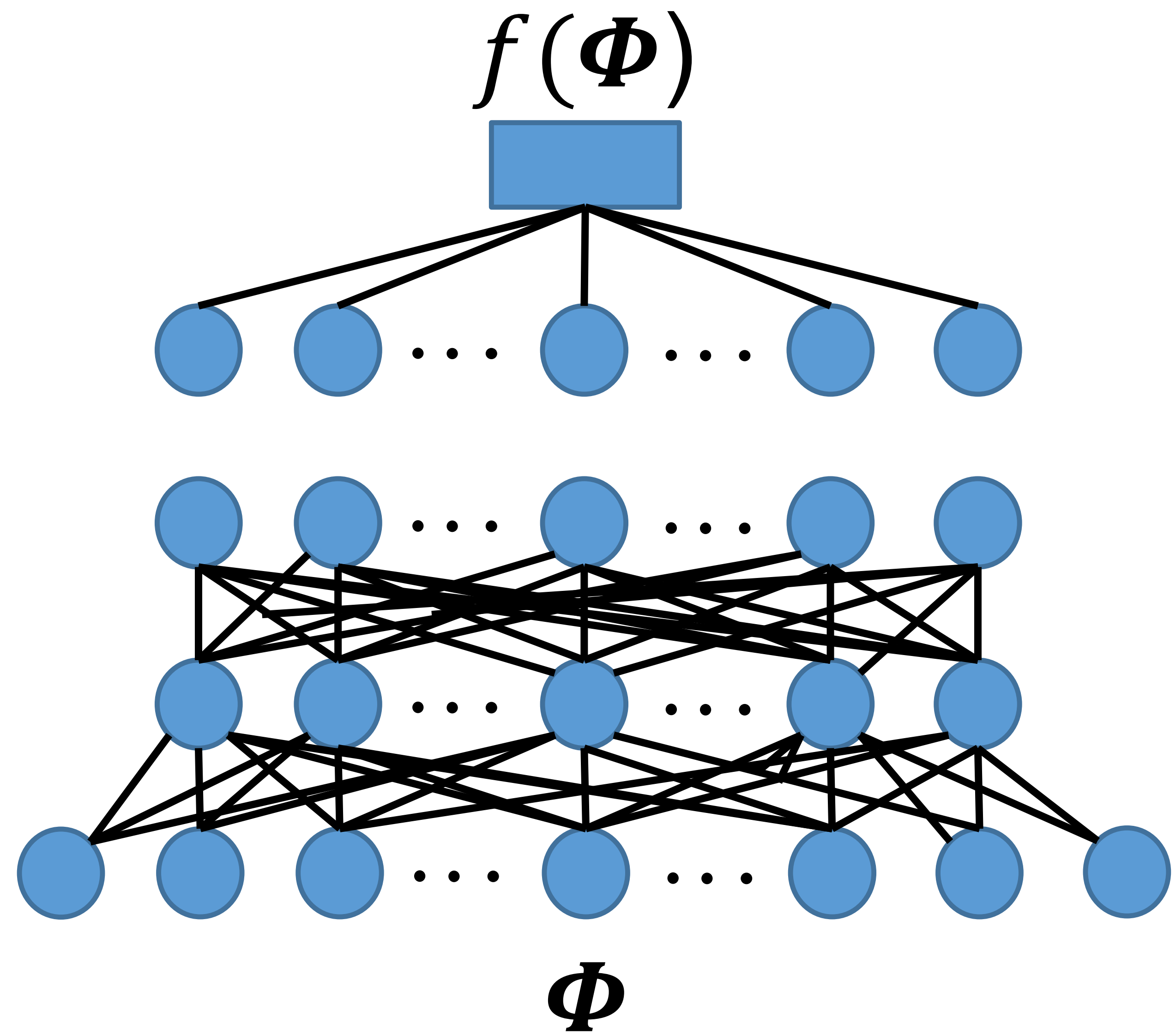


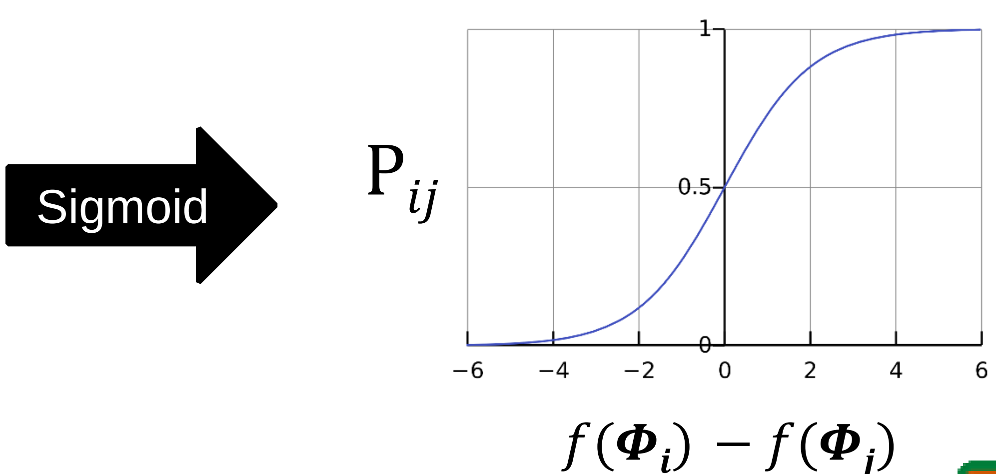
Contributions

- We rank order emotional attribute
- None of the previous studies have focused on using neural net learning techniques for preference learning
- We utilize a neural network framework for preference learning – RankNet
- To our knowledge, this is the first study that uses neural networks for ranking emotional attributes

RankNet

- Given: samples i, j, with features $\boldsymbol{\Phi}_i, \boldsymbol{\Phi}_j$
- Goal: Find f that learns the probability, P_{ij}, that $i \gg j$
- Neural network learns the function f, which maps feature vector $\boldsymbol{\Phi}$, to $f(\boldsymbol{\Phi})$
- Probabilistic framework
  - $\mathrm{P}_{ij} \equiv \dfrac{1}{1+e^{-\sigma(f(\boldsymbol{\Phi}_i)-f(\boldsymbol{\Phi}_j))}}$





RankNet

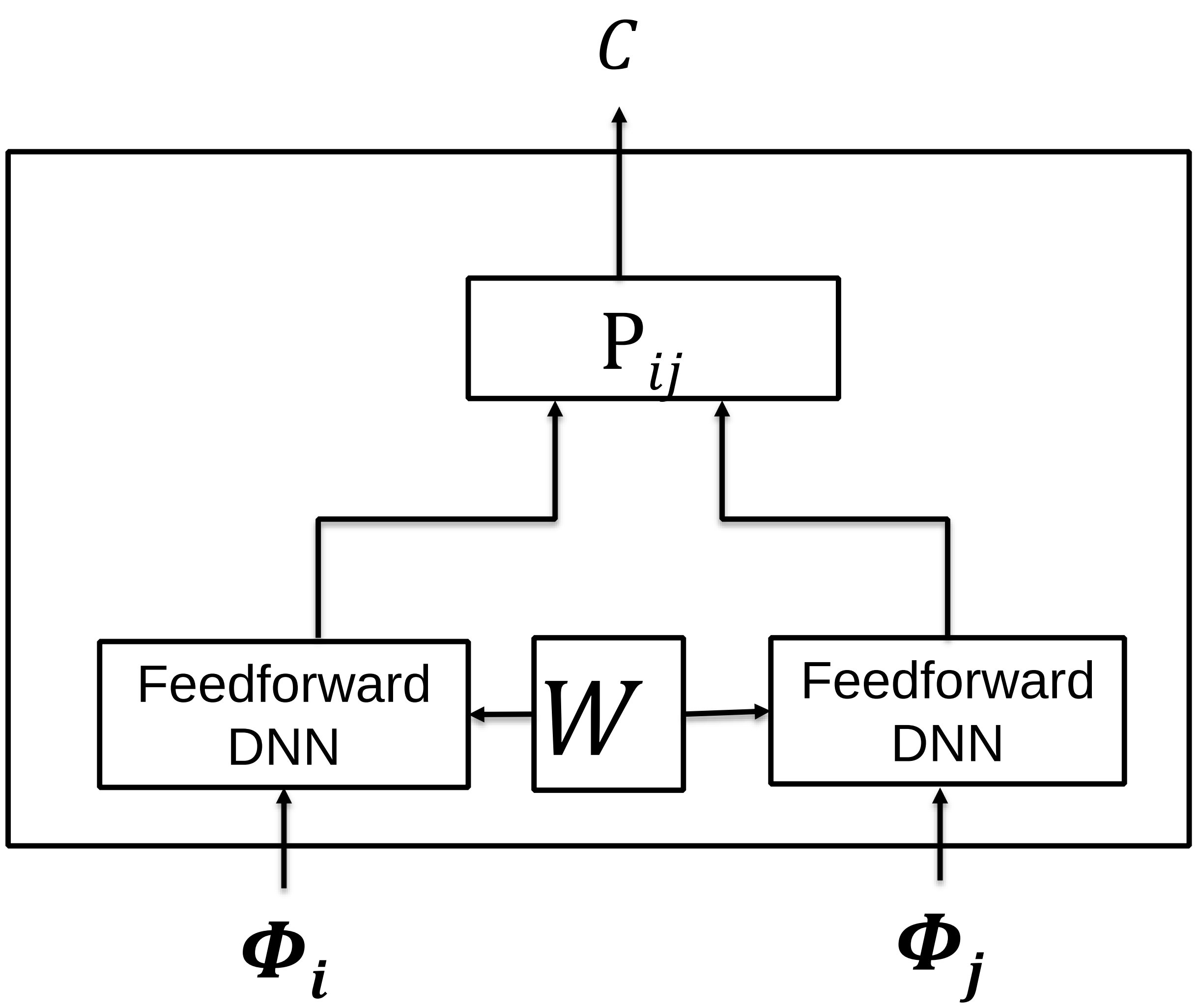
- Ideal probabilities $\overline{\mathrm{P}_{ij}}$ is set according to the preference in pairs of samples.
  - $\overline{\mathrm{P}_{ij}}$ = 0 if $j \gg i$
  - $\overline{\mathrm{P}_{ij}}$ = 1 if $i \gg j$
- Cross entropy is then used as the cost function to measure deviation of model

$$\boxed{C = -\overline{\mathrm{P}_{ij}} log(\mathrm{P}_{ij}) - (1 - \overline{\mathrm{P}_{ij}}) log(1 - \mathrm{P}_{ij})}$$

- Simplifies to
  - $C = log\left(1 + e^{-\sigma(f(\boldsymbol{\Phi}_i) - f(\boldsymbol{\Phi}_j))}\right)$ when $\overline{\mathrm{P}_{ij}}$ = 1
  - $C = log\left(1 + e^{-\sigma(f(\boldsymbol{\Phi}_j) - f(\boldsymbol{\Phi}_i))}\right)$ when $\overline{\mathrm{P}_{ij}}$ = 0

RankNet Framework

- The neural network for RankNet can be modeled with a **Siamese** architecture
- Features of pairs of samples are fed at the input
- Train two identical neural networks that share all parameters



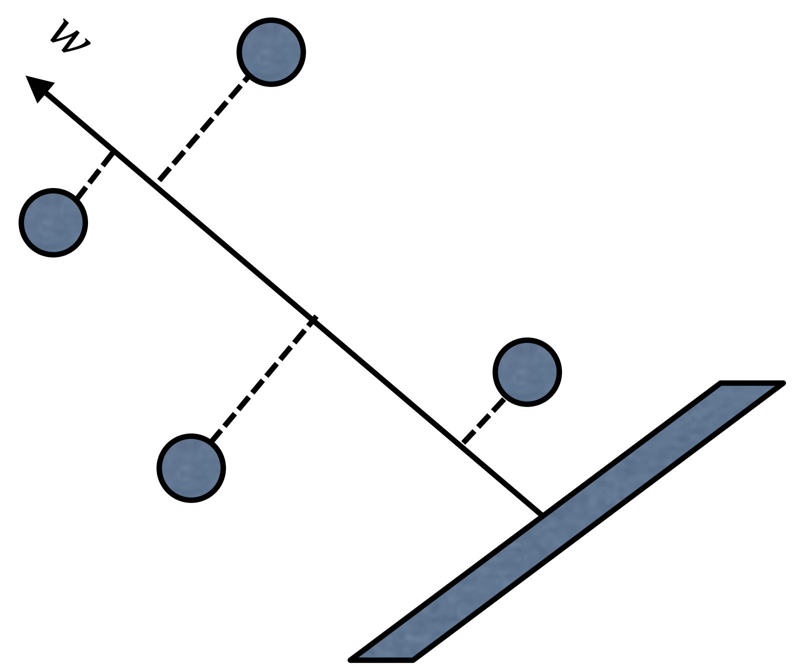
Baselines

- RankSVM framework for recognizing emotional attributes [Lotfian & Busso 2016]

- Given: $i \gg j$ goal is to

$$\min_{w,\xi} \frac{1}{2} \|w\|^2 + C \sum_{i,j} \xi_{i,j}$$

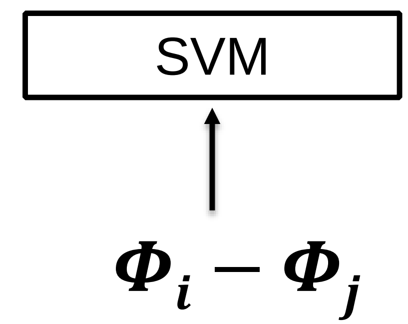
$$s.t\ \langle w, (\boldsymbol{\Phi}_i - \boldsymbol{\Phi}_j) \rangle \geq 1 - \xi_{i,j}\ and\ \xi_{i,j} \geq 0$$



- Reduced to binary classification with $\boldsymbol{\Phi}_i - \boldsymbol{\Phi}_j$

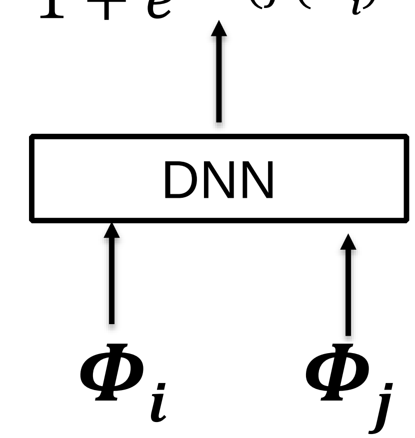
Differences

- RankSVM
  - Input is restricted to difference between features $\boldsymbol{\Phi}_i - \boldsymbol{\Phi}_j$
  - Large margin classifier
    - Redundant data can be removed
    - Performance does not increase with data [Lotfian & Busso 2016]
  - Kernel methods for non-linear classification



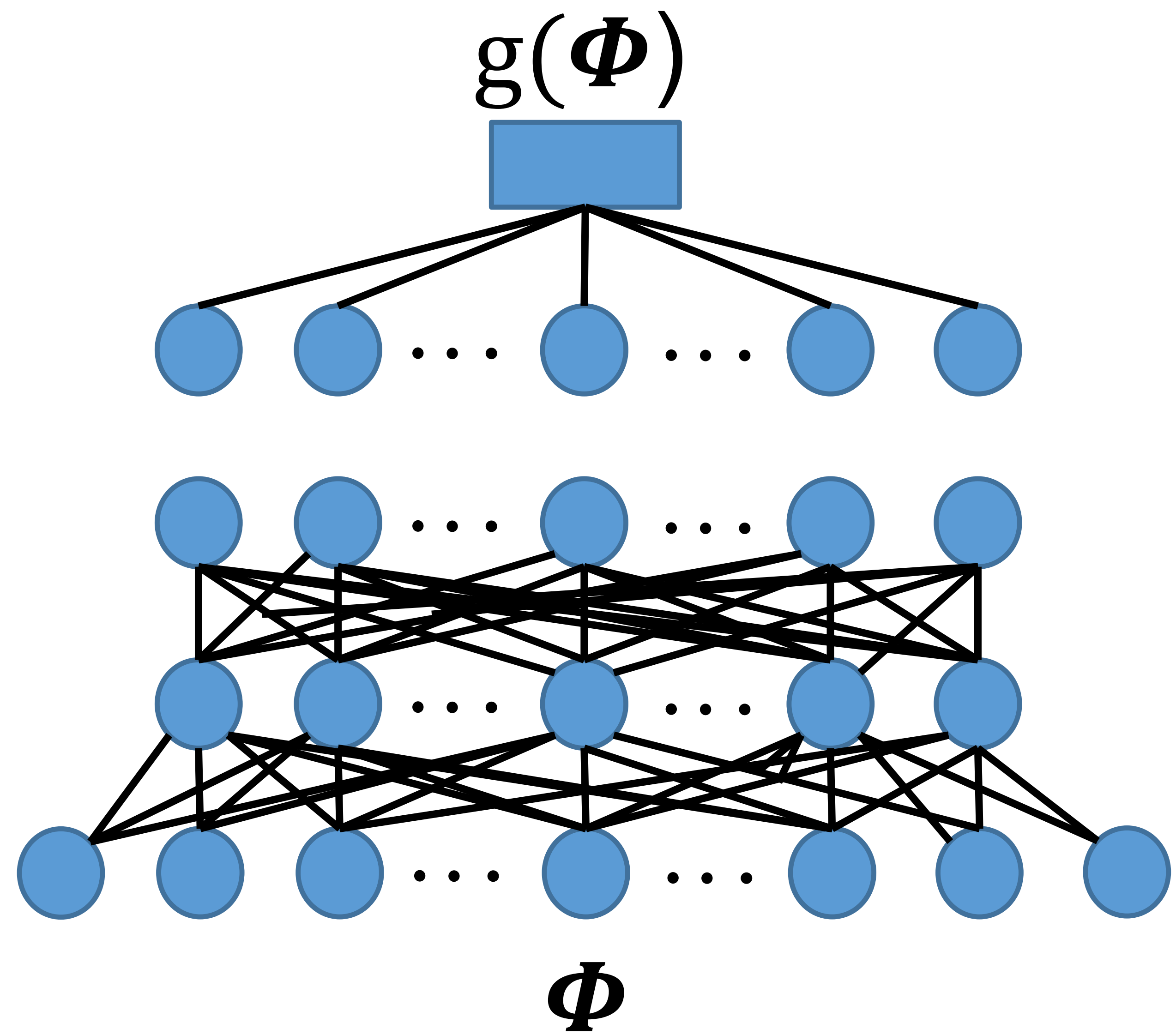
- RankNet
  - Features $\boldsymbol{\Phi}$ individually fed with no restrictions
  - Learns a non-linear mapping $f(\boldsymbol{\Phi})$
    - Optimized for pairs of samples
  - Highly data and parameter dependent

$$\mathrm{P}_{ij} \equiv \frac{1}{1 + e^{-\sigma(f(\boldsymbol{\Phi}_i) - f(\boldsymbol{\Phi}_j))}}$$



Baselines

- DNNRegression: Regression using DNNs
- No relative comparisons
- Use scores, $g(\boldsymbol{\Phi})$ to rank order sentences



Databases

- <u>Train:</u> USC-IEMOCAP
  - 12 hours of conversational recordings from 10 actors in dyadic sessions
  - Sessions consists of emotional scripts as well as improvised interactions
  - All speaking turns annotated for emotional attributes by two raters on a scale of 1-5
  - Arousal, Valence and Dominance
- <u>Test:</u> MSP-IMPROV
  - Improvisation between actors (12 actors)
  - Contains 8,438 speaking turns
  - Annotated by novel crowdsourcing methods on a scale of 1-5 by at least 5 raters
  - Arousal, Valence and Dominance

IEMOCAP

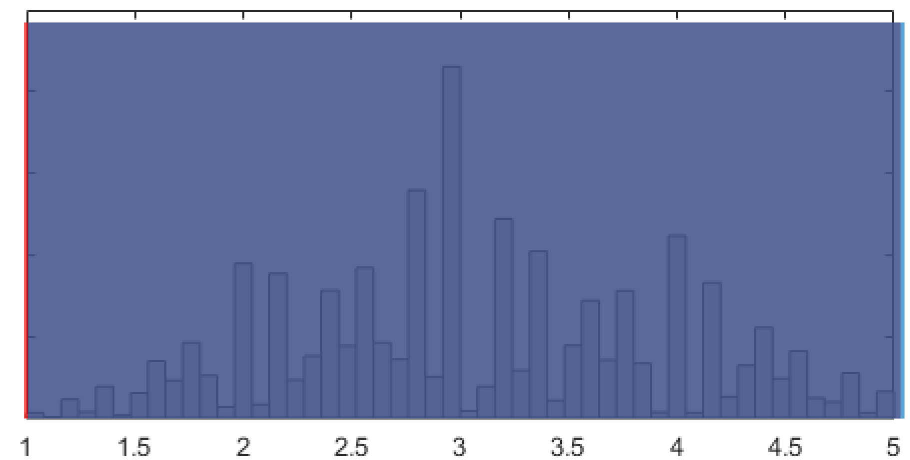
MSP-IMPROV

Experimental Settings

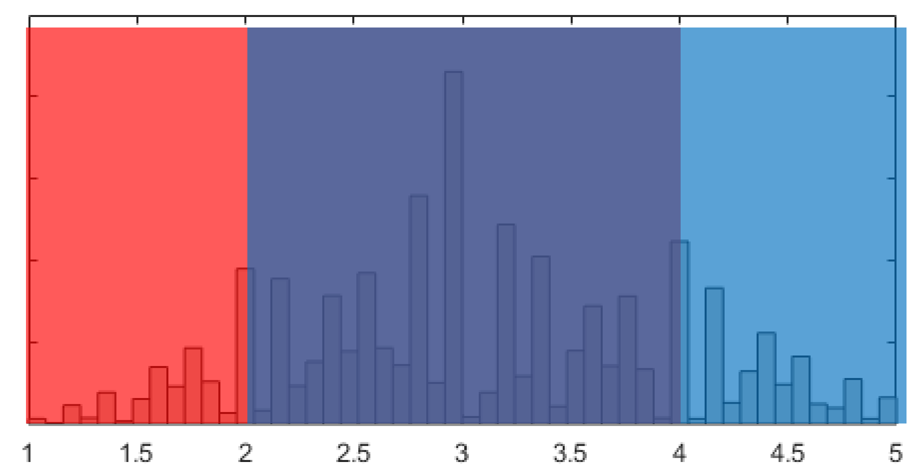
- Acoustic Features
  - Geneva Minimalistic Acoustic Parameter Set [Eyben et al. 2016]
    - Minimalistic features selected based on their performance in previous studies
    - Extended set – 88 features
    - Reproducibility (no feature selection)
    - Theoretical significance
- All DNN architectures include
  - 2 hidden layer, feed forward architecture 256 nodes each
  - Sigmoidal activation function
  - Stochastic Gradient Descent, learning rate of 10^{-4} for 100 epochs

Experimental Settings

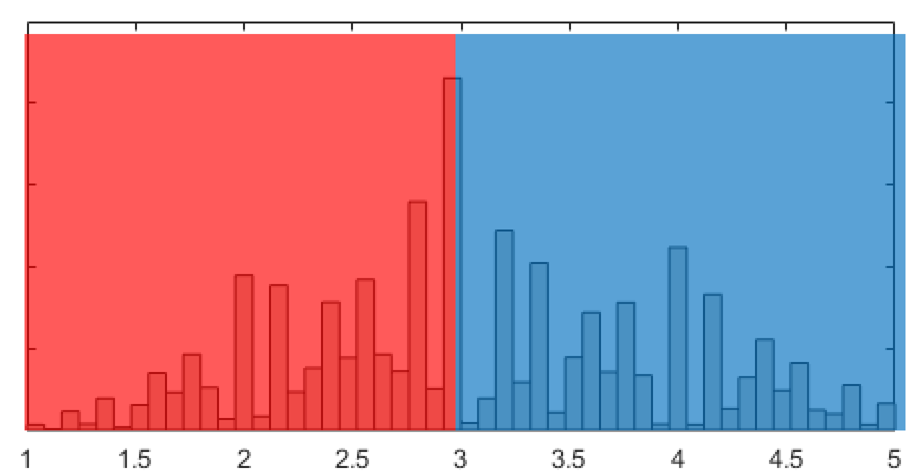
- Relative labels: consider samples separated by margin t
- $|S1_{arousal} - S2_{arousal}| > t$
- Tradeoff between t and data size
  - $\overset{\text{increase}}{\Uparrow} t \Leftrightarrow \overset{\text{increase}}{\Uparrow}$ reliability $\Leftrightarrow \overset{\text{decrease}}{\Downarrow}$ data
- RankSVM: $t = 1.0$ for arousal and dominance $t = 0.9$ for valence[Lotfian & Busso 2016]
- For RankNet we study the performance for $t \in \{0,1,2,3\}$
- Regression has no relative scores



t = 0



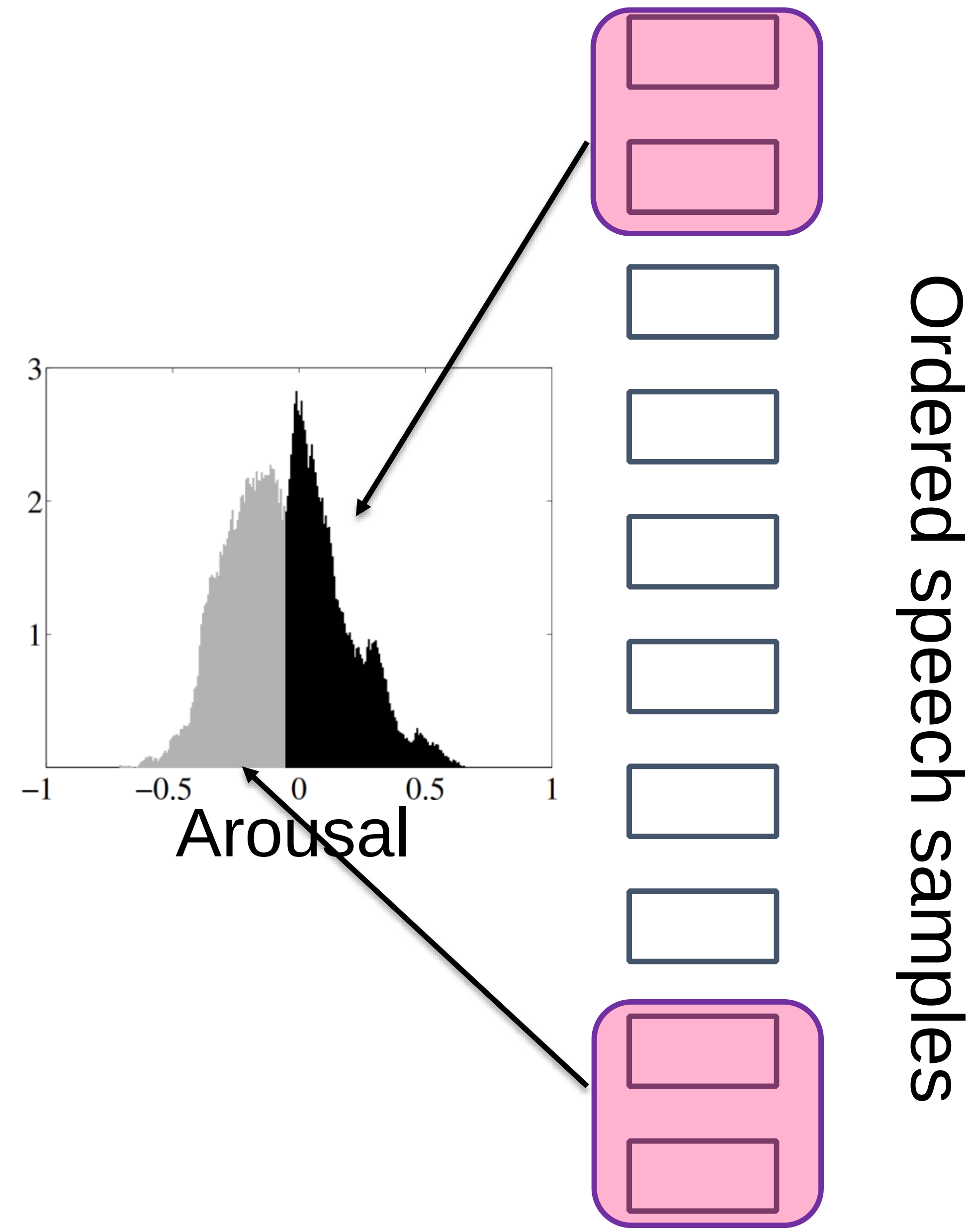
t = 1



t = 2

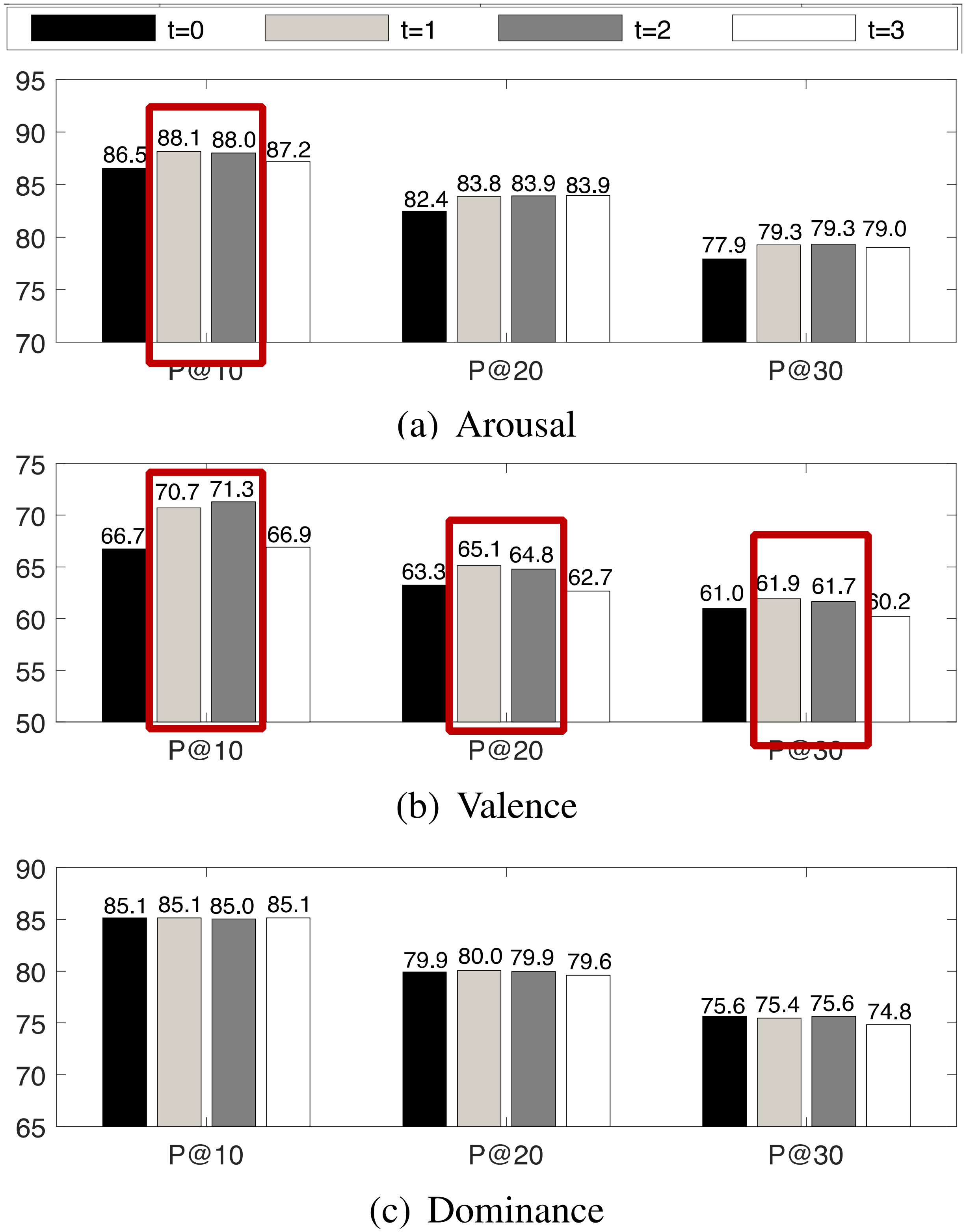
Evaluation

- Precision at k ($P@k$)
  - Measures the precision at retrieving k % of the samples from top and bottom
  - Ground truth is split into high and low classes about the median
  - Evaluate success in retrieving samples on the correct side of the split



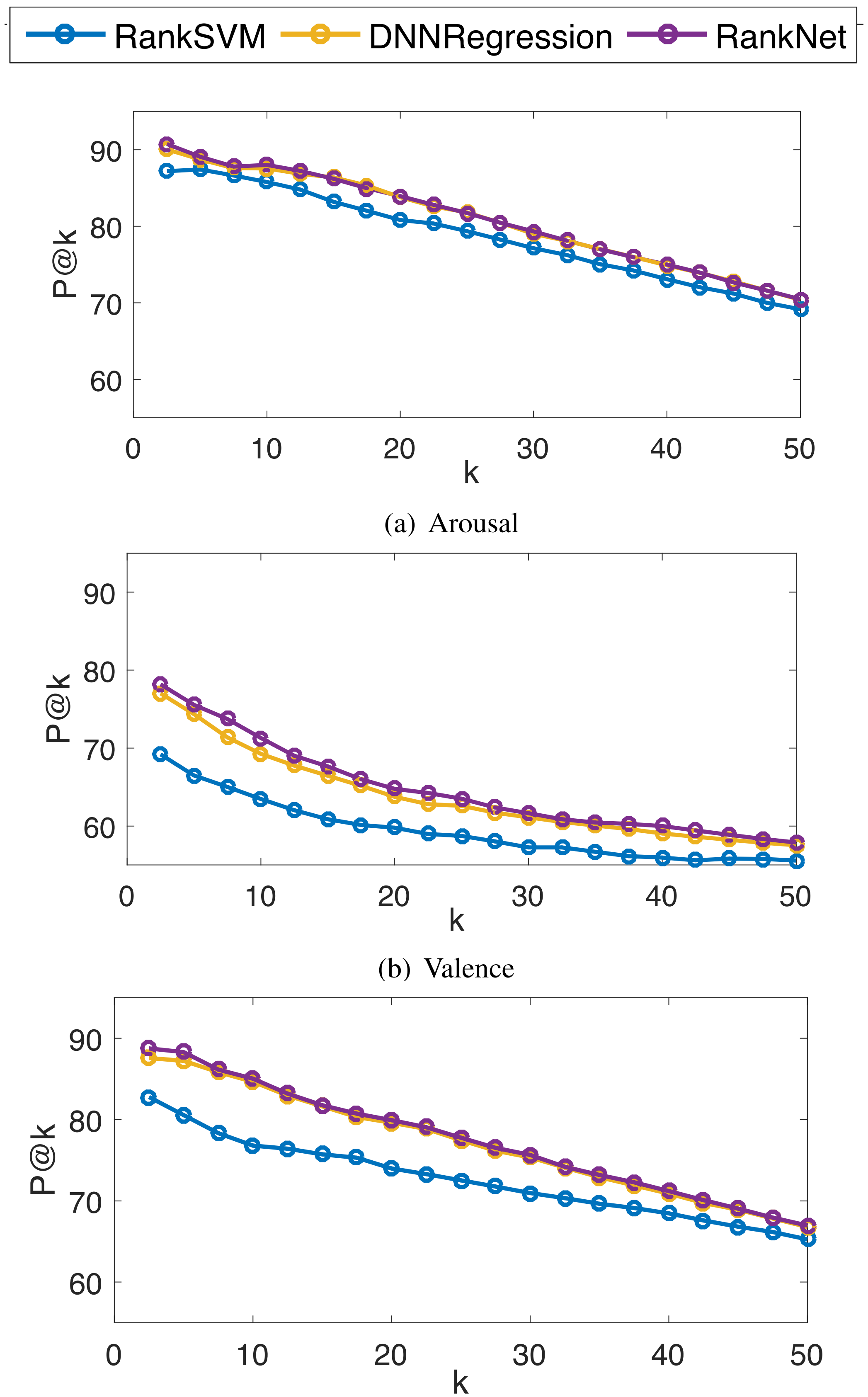
Effect of Margin on RankNet

- Attributes annotated on scale of 1-5
- P@10, P@20, P@30
- We see improvement for $t = 1{,}2$ but decrease $t = 3$.
- Use $t = 2$ for RankNet



Comparisons

	RankSVM	**RankNet**	DNNRegression
Arosual			
P@10	85.77	**88.02**	87.54
P@20	80.81	**83.93***	83.72*
P@30	77.15	**79.32***	79.02*
Valence			
P@10	63.46	**71.29***	69.28*
P@20	59.79	**64.77***	63.76*
P@30	57.26	**61.66***	61.13*
Dominance			
P@10	76.79	**86.15***	84.67*
P@20	73.97	**79.94***	79.61*
P@30	70.95	**75.65***	75.33*



(a) Arousal

(b) Valence

(c) Dominance

* Denotes Statistical Significance over RankSVM (population proportion)

Results

- Kendall's Tau Coefficient τ
  - Correlation between the two ordered lists [-1,1]

	RankSVM	**RankNet**	DNNRegression
Arousal	0.36	**0.41***	0.41*
Valence	0.08	**0.14***	0.13*
Dominance	0.28	**0.35***	0.34*

- RankNet and DNNRegression outperform RankSVM in all cases for $P@k$ and Kendall's τ
- Kendall's τ values are better than those reported in previous studies
  - τ values $\approx$ 0.02 for Arousal, 0.05 valence$_{\text{[Martinez et al. 2014]}}$

Conclusions

- Benefits of using deep neural network architectures for ranking emotional attributes
- Cross – corpora evaluations show that RankNet algorithms outperform RankSVM algorithms for $P@k$, τ
- Future Work
  - Use of other architectures (RNN-LSTMs) for preference learning to outperform DNNRegression
  - Ranking for emotional classes
  - Role of training data size in performance
    - Will we see better performance with increase in data size?

Thanks for your attention!

Questions?