Modeling Uncertainty in Predicting Emotional Attributes from Spontaneous Speech

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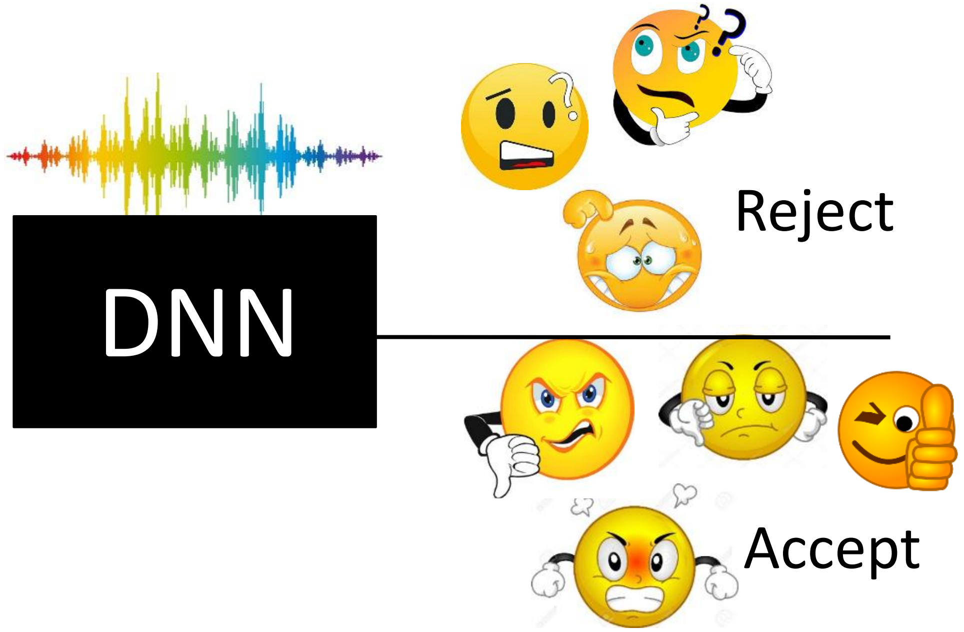
Motivation

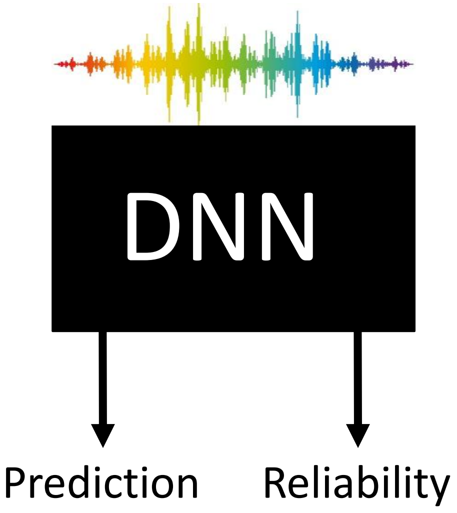
- **Speech emotion recognition is a hard problem**
  - Prediction are not always reliable
- **Wide application domains – accurate and confident recognition using DNNs**
- **The key challenge is to define mechanisms to quantify reliability to accept or reject an instance**
  - e.g., Softmax Response
  - Monte Carlo Dropout



First study on reject option using uncertainty modeling for speech emotion recognition

Reliability of SER Models

- **Ambiguous emotional content leads to low SER performance**
- **Its is important to know what the model does not know**
  - Abstain from predicting when in doubt, reducing the risk of error
  - Involve human-in-the-loop
- **SER models should provide a prediction score along with its confidence**
  - We can use confidence to achieve a low error rate while still maintaining coverage as high as possible (reject option)
  - Reliable SER models can be helpful in mission critical applications in (e.g., healthcare and security)
  - Uncertainty prediction facilitates human-in-the-loop solutions



Related Work

- **Speech and Image Tasks**
  - Selective guaranteed risk algorithm for Imagenet and CIFAR-10 classification tasks [Geifman et. al. 2017]
  - Capturing uncertainty from text transcriptions and word error rates to solve ASR task [Dey et. al. 2019, Vyas et.al. 2019]

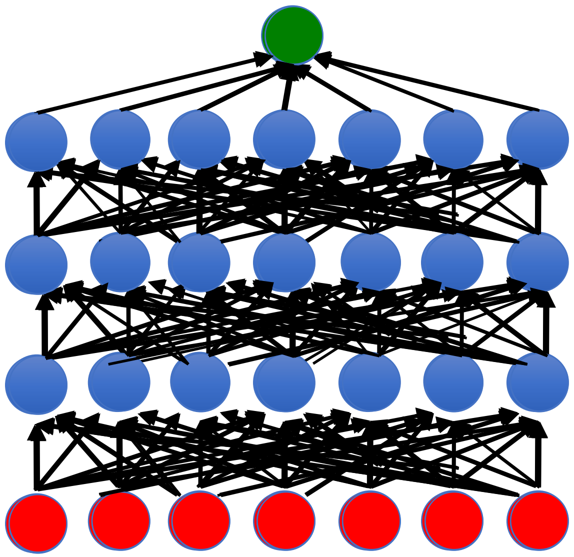
- **Speech Emotion Recognition**
  - Use human labelers' agreement to build emotion scoring models [Deng et. al. 2012]
  - Include samples from target domain in a semi-supervised fashion based on confidence levels achieved from multi-corpora training [Deng et. al. 2012]
  - Applying reject option to emotion classification under a risk minimization framework: learning thresholds based on softmax response and difference between two highest predictions [Sridhar and Busso 2018]
  - Use MC dropout as a sampling technique for active learning to train autoencoder with unlabeled data selected based on their posterior probability estimates [Abdelwahab and Busso 2019]

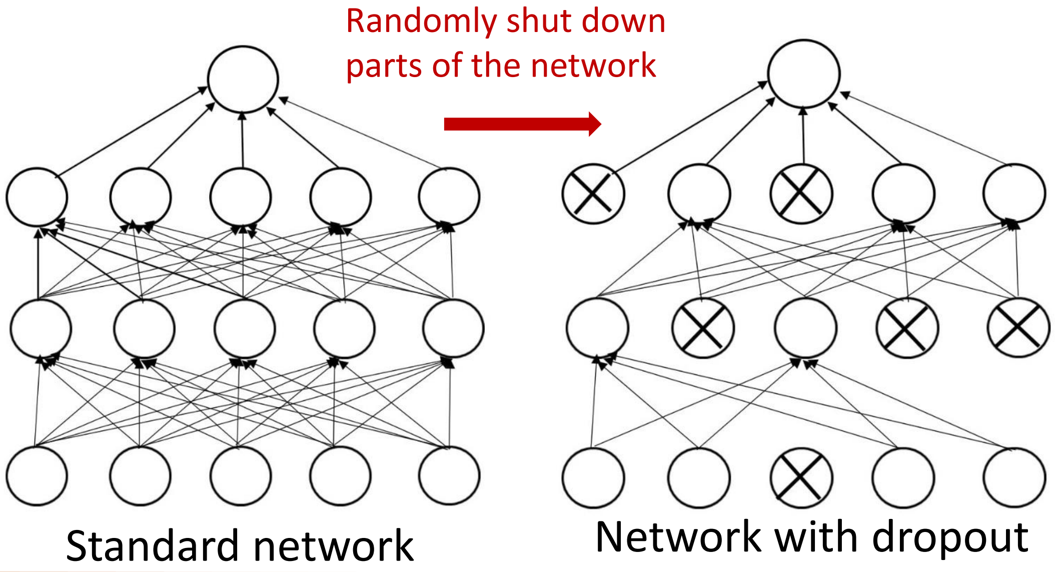
Outline

1. Dropout for Confidence Estimation
2. Database
3. Analysis
4. Application for Reject Options

Monte Carlo Dropout

- **DNNs with dropout regularization can be used to quantify prediction uncertainty [Gal et al., 2016]**
  - We can represent the models' uncertainty
  - Use different configurations of dropout, analyzing predictions per sample
  - We can estimate the posterior distribution on the predictions during inferences by sampling weights in a Monte Carlo fashion





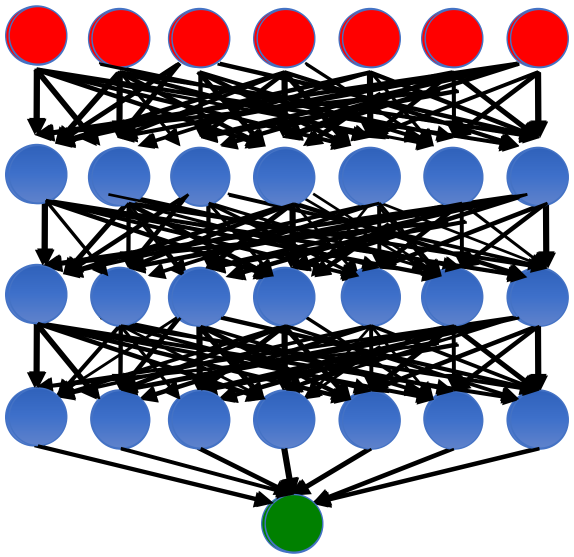
Uncertainty Estimation: Monte Carlo Dropout

- **Dropout can approximate a Bayesian Inference in deep Gaussian processes** **[Gal et al., 2016]**

Posterior predictive distribution

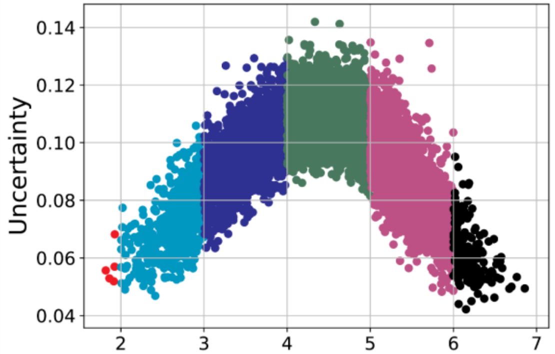
$$p(x_{test}|X) \approx \int p(x_{test}|\omega)p(\omega|X)d\omega$$

  - Change the weights setup randomly by applying dropout
  - As such, different configurations of the network lead to slightly different prediction
  - Prediction Uncertainty will be the variance of N step predictions
  - Multiple iterations through a network with dropout is analogous to obtaining predictions form an ensemble of thinner networks.



Goal: Learn the confidence of the model in each of its predictions

Sample ordered binwise according to uncertainty in prediction



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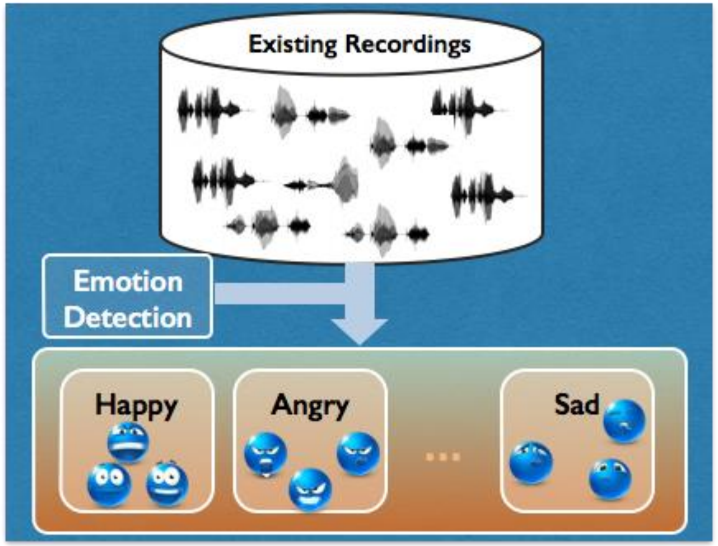
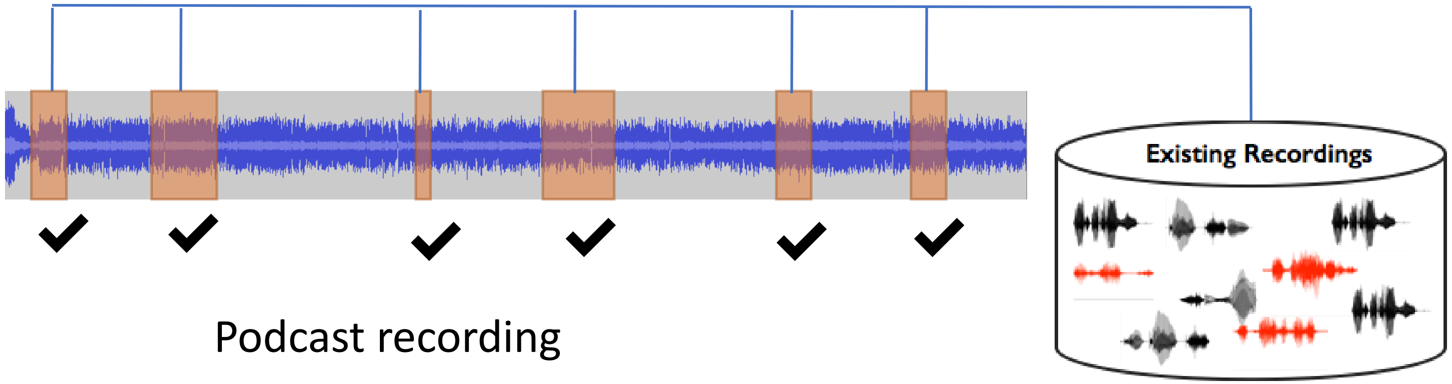
The MSP-Podcast Database

- Use existing podcast recordings
- Divide into speaker turns
- Emotion retrieval to balance the emotional content
- Annotate using crowdsourcing framework

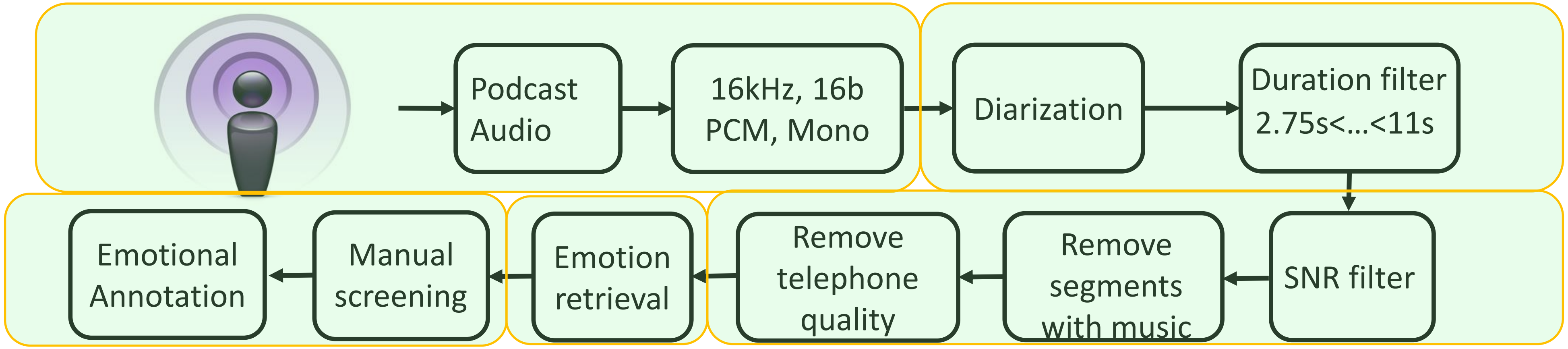




Reza Lotfian and Carlos Busso, "Building naturalistic emotionally balanced speech corpus by retrieving emotional speech from existing podcast recordings," IEEE Transactions on Affective Computing, vol. 10, no. 4, pp. 471-483, October-December 2019..

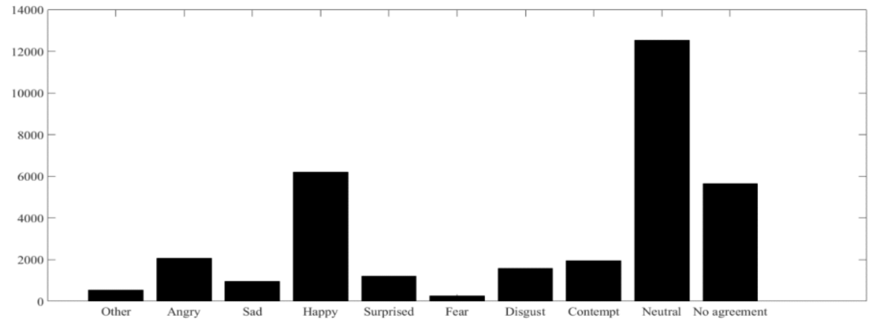
The MSP-Podcast Database

- **MSP-Podcast**
  - Collection of publicly available podcasts (naturalness and the diversity of emotions)
    - Interviews, talk shows, news, discussions, education, storytelling, comedy, science, technology, politics, etc.
  - Creative Commons copyright licenses
  - Single speaker segments, High SNR, no music, no phone quality
  - Developing and optimizing different machine learning framework using existing databases
    - Balance the emotional content
  - Emotional annotation using crowdsourcing platform

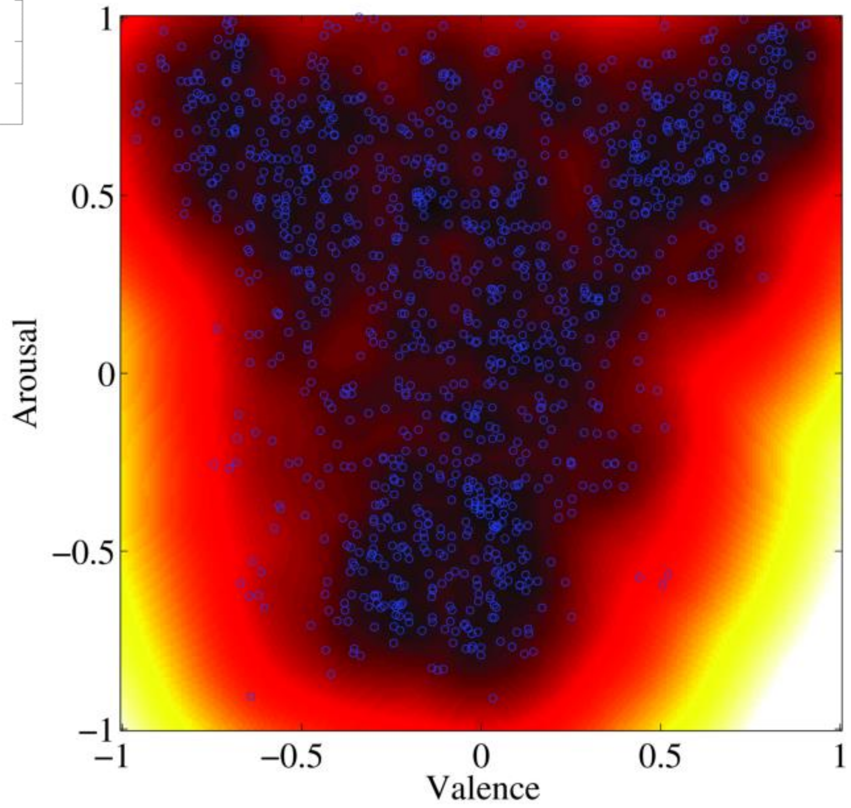


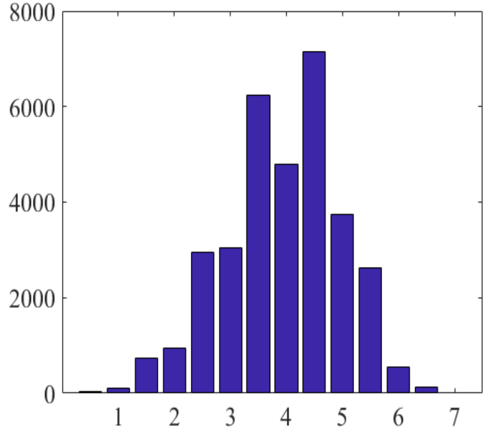
MSP-Podcast corpus version 1.4

With emotion labels:
33,262 sentences
(56h, 29m)

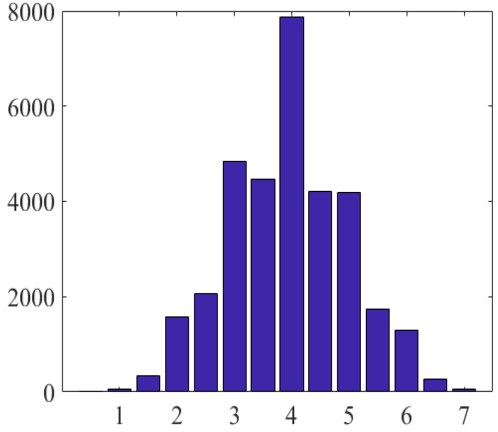


Primary emotional classes

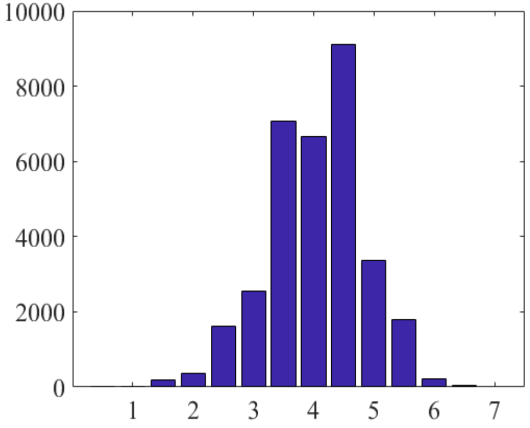




Arousal



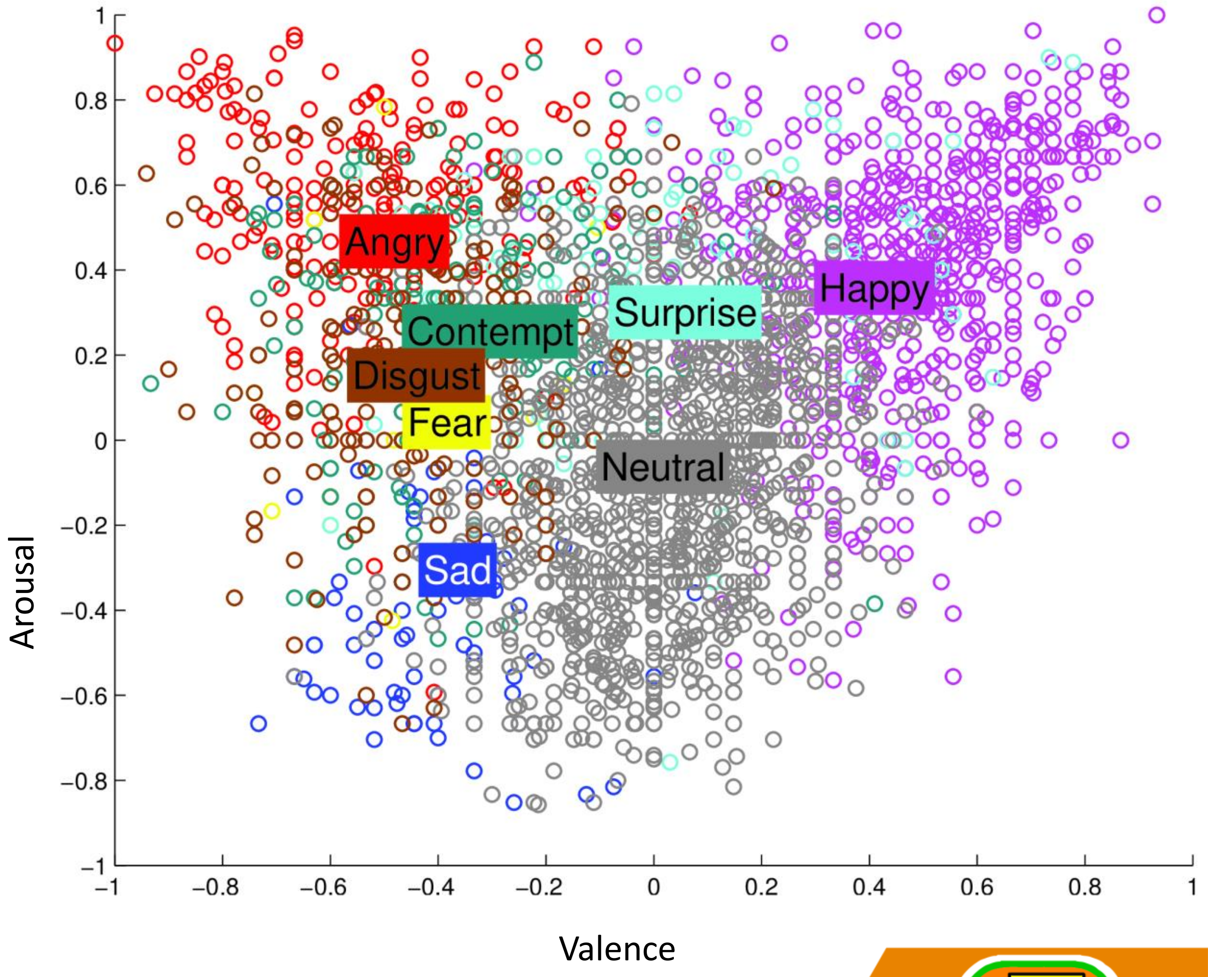
Valence



Dominance

MSP-Podcast database

- Version 1.4 of the **MSP-Podcast** corpus
  - 33,262 (56h,29m)
- Corpus partition with minimal speaker overlap sets:
  - Test data
    - 9,255 samples from 50 speakers (25 males, 25 females)
  - Validation data
    - 4,300 samples from 30 speakers (15 males, 15 females)
  - Train data
    - Remaining 19,707 samples



Acoustic Features

- **Interspeech 2013 Feature set**
  - 65 low level descriptors (LLD)
  - High Level Descriptors (HLDs) are calculated on LLDs resulting in total of 6,373 features
  - HLDs include:
    - Quartile ranges
    - Arithmetic mean
    - Root quadratic mean
    - Moments
    - Mean/std. of rising/ falling slopes

4 energy related LLD	**Group**
Sum of auditory spectrum (loudness)	prosodic
Sum of RASTA-filtered auditory spectrum	prosodic
RMS Energy, Zero-Crossing Rate	prosodic
55 spectral LLD	**Group**
RASTA-filt. aud. spect. bds. 1–26 (0–8 kHz)	spectral
MFCC 1–14	cepstral
Spectral energy 250–650 Hz, 1 k–4 kHz	spectral
Spectral Roll-Off Pt. 0.25, 0.5, 0.75, 0.9	spectral
Spectral Flux, Centroid, Entropy, Slope	spectral
Psychoacoustic Sharpness, Harmonicity	spectral
Spectral Variance, Skewness, Kurtosis	spectral
6 voicing related LLD	**Group**
F_0 (SHS & Viterbi smoothing)	prosodic
Prob. of voicing	voice qual.
log. HNR, Jitter (local & δ), Shimmer (local)	voice qual.

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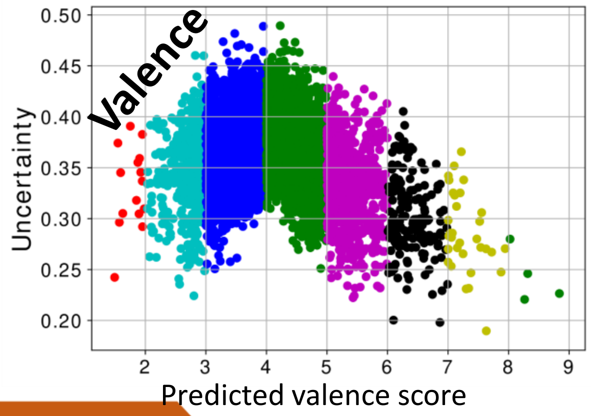
Implementation Details

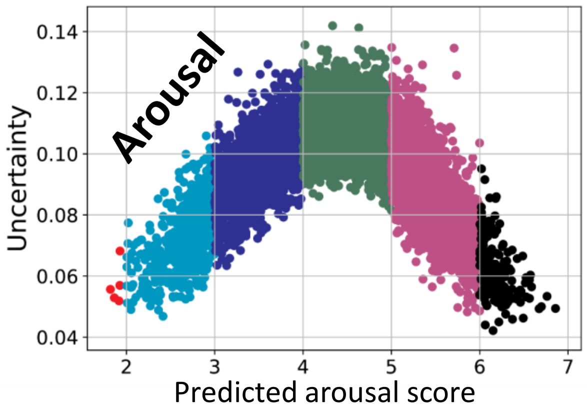
- **Train separate regression model each for arousal, valence and dominance**
  - DNN with 3 dense layers, 512 nodes per layer
  - SDG optimizer with a learning rate of 0.001
  - Cost function: 1-CCC
  - Input: 6,373D feature vector
  - Output: Prediction score for arousal, valence and dominance
- **Activation functions:**
  - Tanh activation at the hidden layers give the best performance across emotional attributes
  - We also compare reject option performance with tanh and ReLU as activation functions.
- **Evaluation metric: CCC**

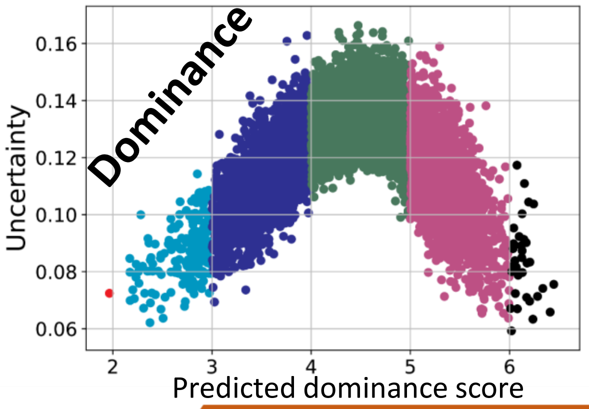
$$\rho_c = \frac{2\rho\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2 + \left(\mu_x - \mu_y\right)^2}$$

Analysis of Uncertainty Prediction - 1

- **Prediction uncertainty as a function of emotional attributes:**
  - Train models each for arousal, valence, dominance with dropout and weight regularization
  - Obtain test predictions with corresponding uncertainties for each sample
  - Design a scatter plot to visualize uncertainty estimates for each test sample – create uniform bins using prediction scores
- **Observations:**
  - More ambiguous emotional content observed among neutral samples (middle samples – high uncertainty)
  - Samples with extreme emotional content are predicted more confidently

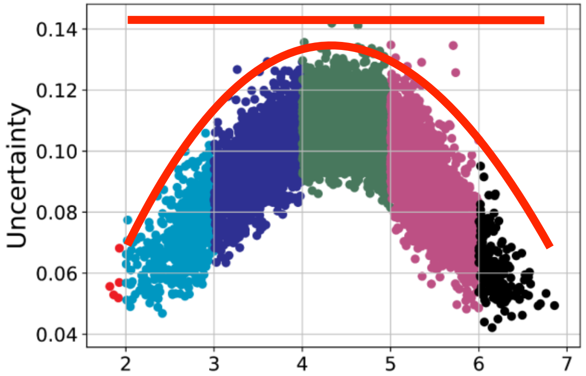


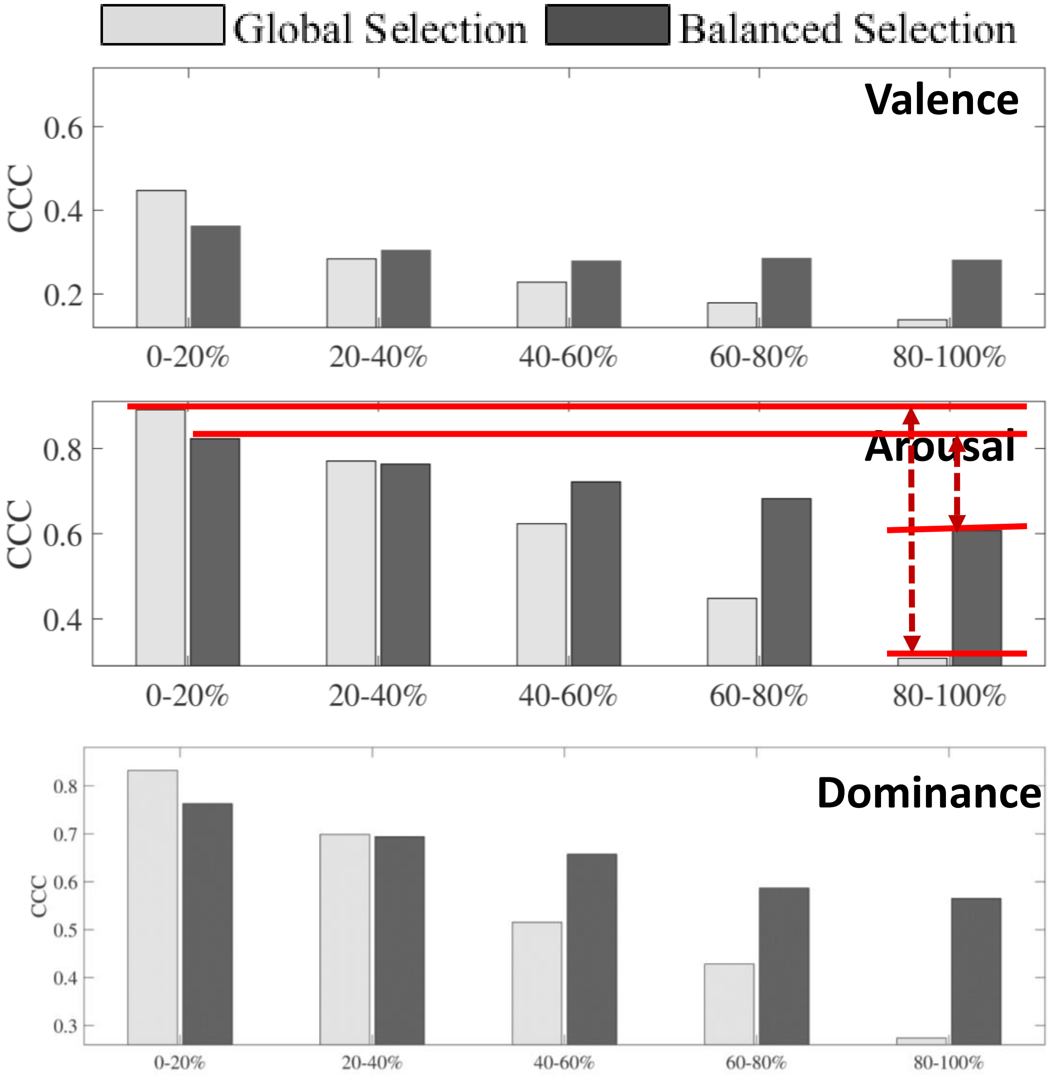




Analysis of Uncertainty Prediction - 2

- **Performance as a function of uncertainty**
  - Create five subsets according to uncertainty
    - 0-20%: lower uncertainty
    - 80-100% more uncertainty
  - Global Selection
  - Balanced Selection





- **Observations:**
  - Regression performance decreases as uncertainty increases. Ranges of performance are broader for global selection, creating large performance gaps across sets

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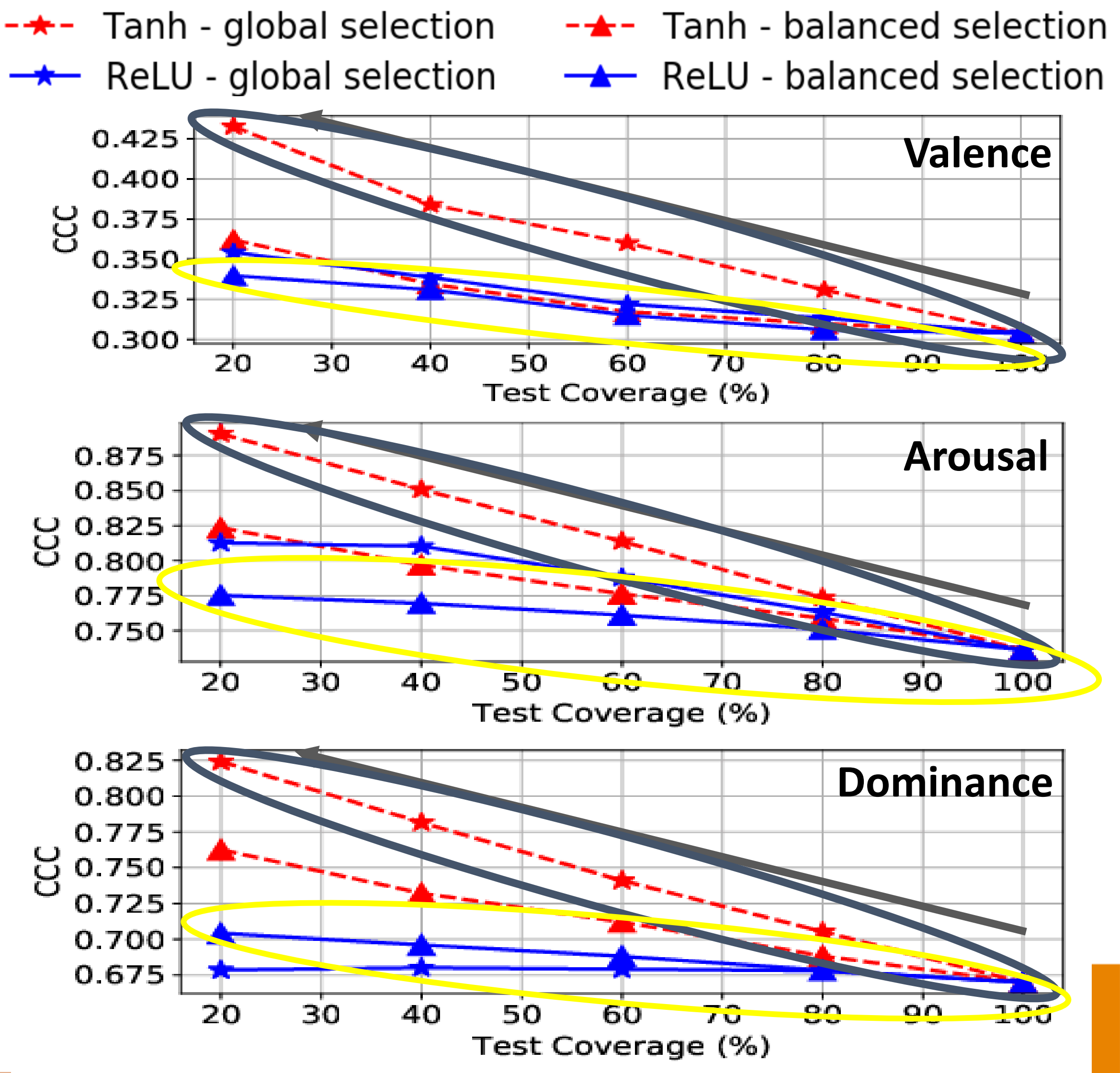
Application in Rejection Option for SER

- **Accepting or rejecting samples based on prediction uncertainty**
  - Rejecting ambiguous samples improves prediction performance of the model but at the same time reduces test coverage
- **Experiment:**
  - DNN performance optimized on the validation set with a fixed dropout of 0.5 for all emotional attributes. Here dropout *is not used* during inference.
  - Accept or reject a test sample based on prediction uncertainty achieved from MC dropout models. Here dropout *was used* during inference
- **Performance reported with tanh and ReLU activations at the hidden layers**

Reject Option Results

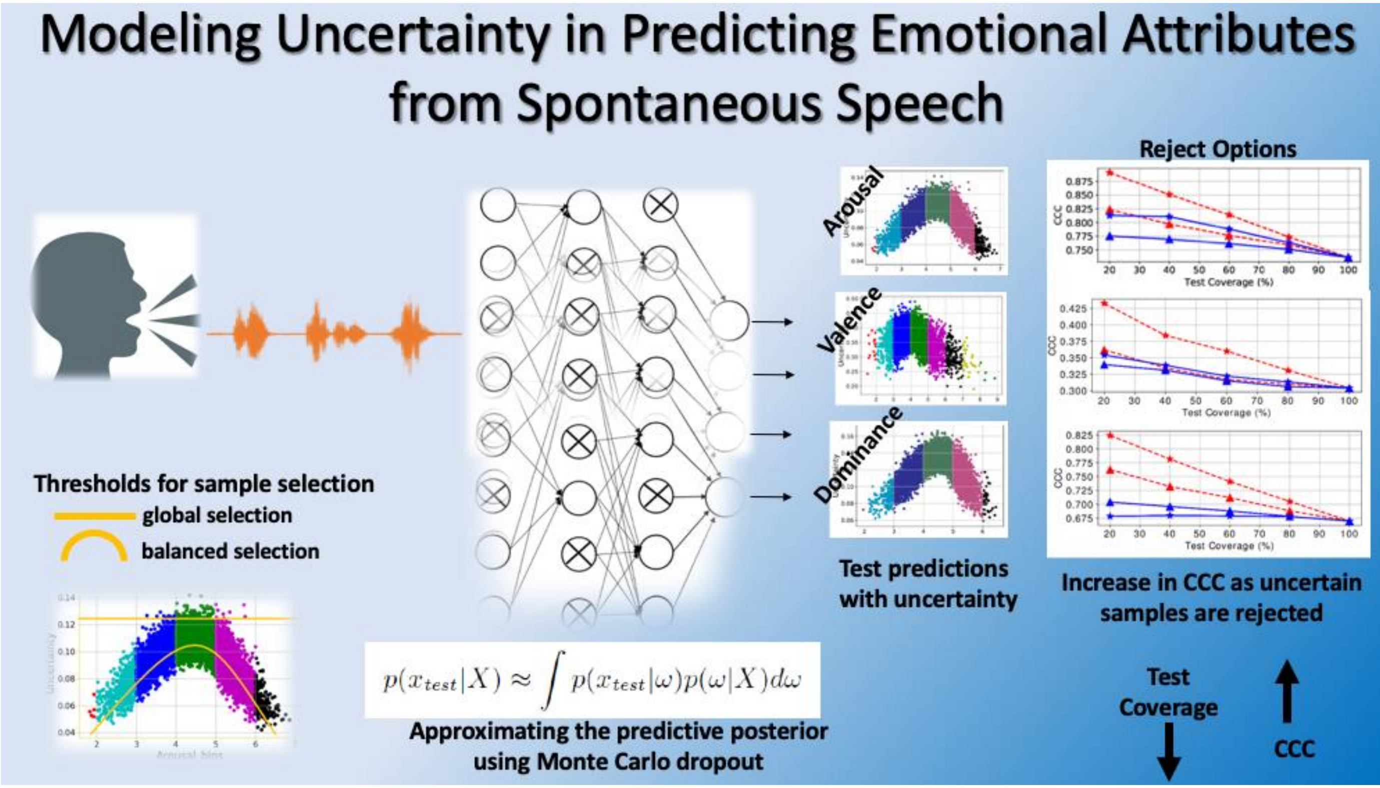
- **Baseline: CCC at 100% test coverage without MC dropout**

- **Observations**
  - CCC improves as more uncertain samples are rejected, leading to decrease in coverage
  - Reject Option leads to gains in CCC across emotional attributes without compromising too much on coverage
  - Rejecting samples without attempting to balance their emotional content is better



Conclusions

- **MC dropout is an effective method to quantify uncertainty in SER systems**
- **Confidence of SER models is higher for samples with extreme emotional values**
- **Rejecting samples with low confidence/high uncertainty increases the regression performance**
- **At a test coverage of 75%, relative gains in CCC was observed up to:**
  - 7.34% (arousal); 13.73% (valence); 8.79% (dominance)
- **Future Work**
  - Understanding the impact of different activation functions
  - Uncertainty modeling in semi-supervised and unsupervised cases



Thank you

- **This work was funded by NSF CAREER Grant IIS-1453781**

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