Multimodal Signal Processing (MSP) lab
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Predicting Categorical Emotions by Jointly Learning Primary and Secondary Emotions Through Multitask Learning

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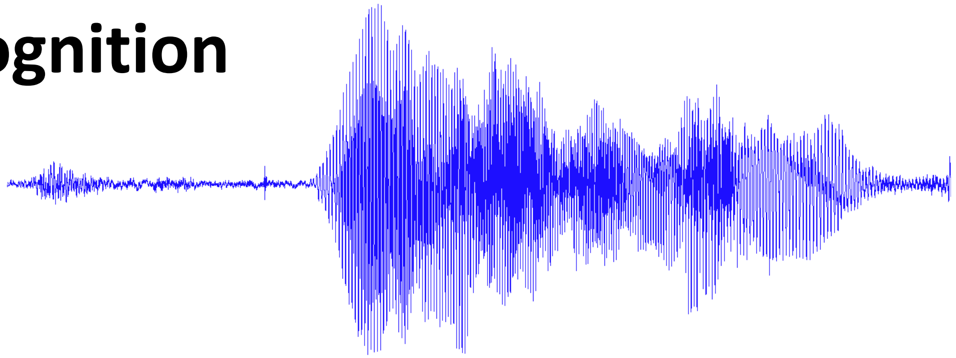
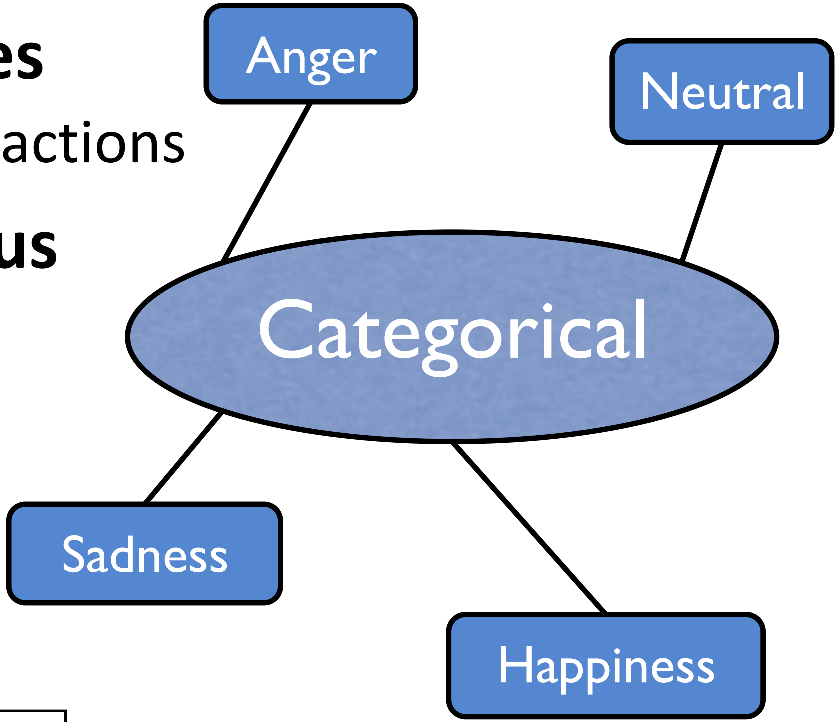
Introduction

- **Increasing interest in speech emotion recognition**
- **Emotion recognition from speech**
  - Call centers
  - Healthcare
  - Education
  - Entertainment
  - Creating emotions aware human computer interaction

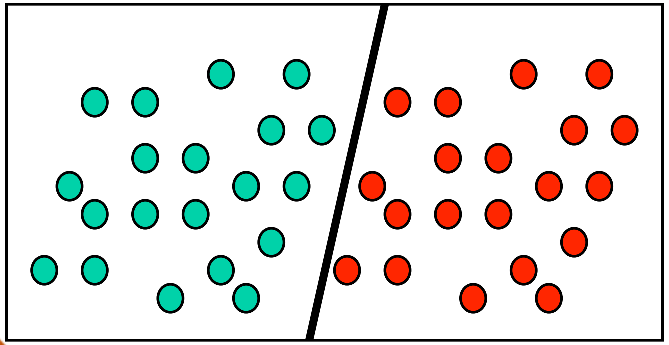


Motivation

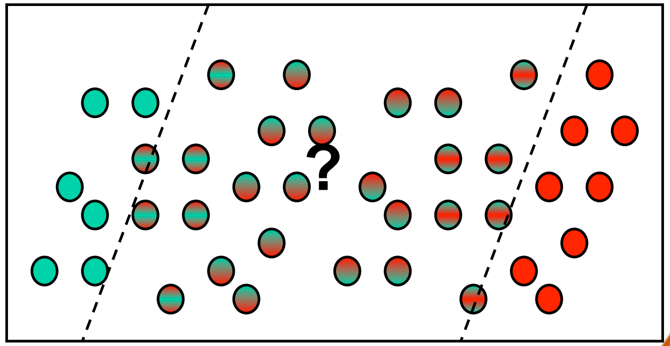
- **Interest in the recognition of discrete categories**
  - Useful in human-human and human-computer interactions
- **Spontaneous human interactions are ambiguous**
  - The boundary between categories are not clear
  - Difficult machine learning problem



Conventional machine learning problem



Emotion recognition



Motivation: Annotation of Emotions

- **Spontaneous corpora**
  - Emotions are not predetermined during recording
  - Need to be emotionally annotated
- **Emotional labels often come from perceptual evaluations from multiple evaluators**
  - Compensate for outlier and individual variations
- **Aggregating annotators' votes (consensus label)**
  - Majority vote

- Hap
- Hap
- Sur
- Ang
- Neu

Noise

Hap

Motivation: Annotation of Emotions

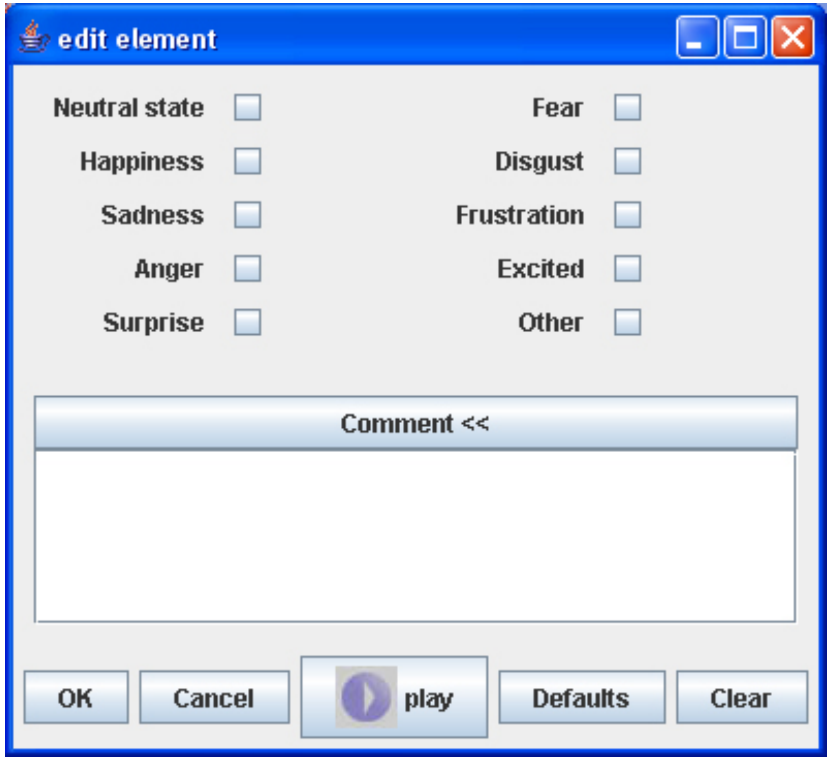
- **Evaluators often disagree on the perceived emotion**
  - Noise or information?
- **Assigning a single emotion per sentence oversimplifies the subjectivity in emotion perception**
  - More than one label can be relevant
- **Evaluator should identify as many emotions as they perceived**
  - Concept of major emotion versus minor emotion [Devillers et al., 2005]

Expression of Emotion

- **Mock subjective evaluation**

✦Sample 1: [fru; ()] [ang; ()] [neu; ()]

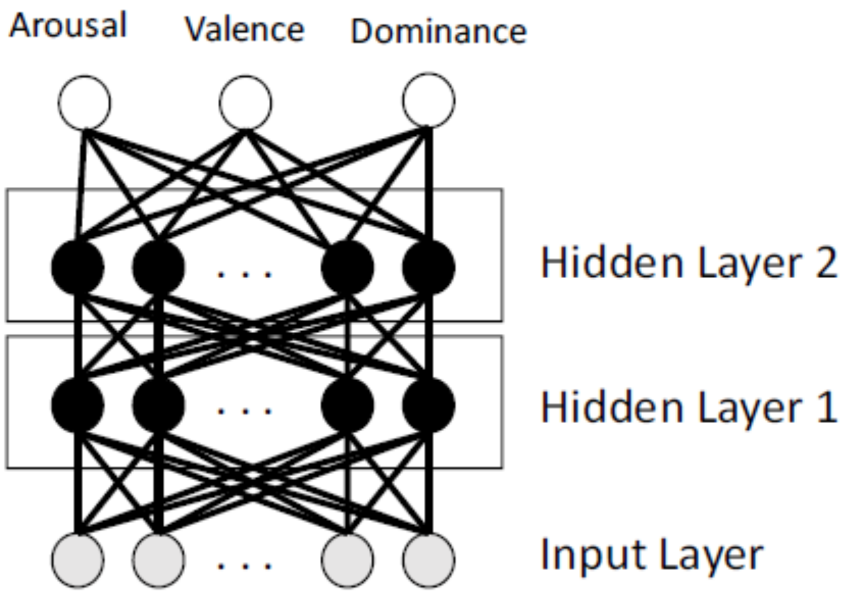
☑ Angry	☐ Sad	☐ Happy	☐ Amused	☑ Neutral
☑ Frustrated	☐ Depressed	☐ Surprise	☐ Concerned	
☑ Disgust	☑ Disappointed	☐ Excited	☐ Confused	
☐ Annoyed	☐ Fear	☐ Contempt	☐ Other	



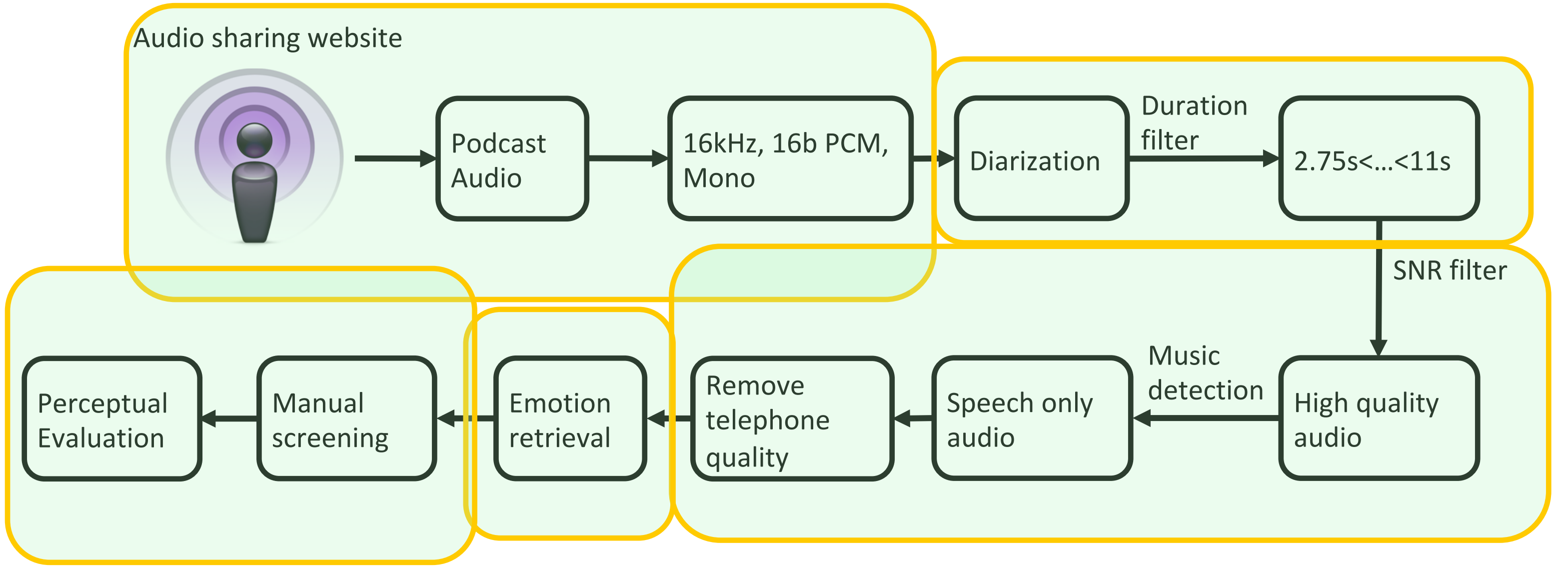
We hypothesize that secondary emotions provide useful information, even to predict the dominant emotion

Related Work

- **Better use of emotional annotations collected from multiple raters**
  - Consider the disagreement between multiple annotators as measure of difficulty [Lotfian and Busso, 2018a]
  - Soft label: instead of 1-hot ground truth [Fayek et al., 2016]
  - Ensembles: Train multiple classifiers, aggregate outcomes [Lotfian and Busso, 2018b]
- **Multitask learning in emotion recognition**
  - Use of multiple emotional attributes (arousal, valence, dominance) [Parthasarathy and Busso, 2017]
  - Gender and emotion [Ververidis 2004, Vogt 2006]
  - Attributes and emotional classes [Xia & Liu, 2016]



MSP-Podcast corpus



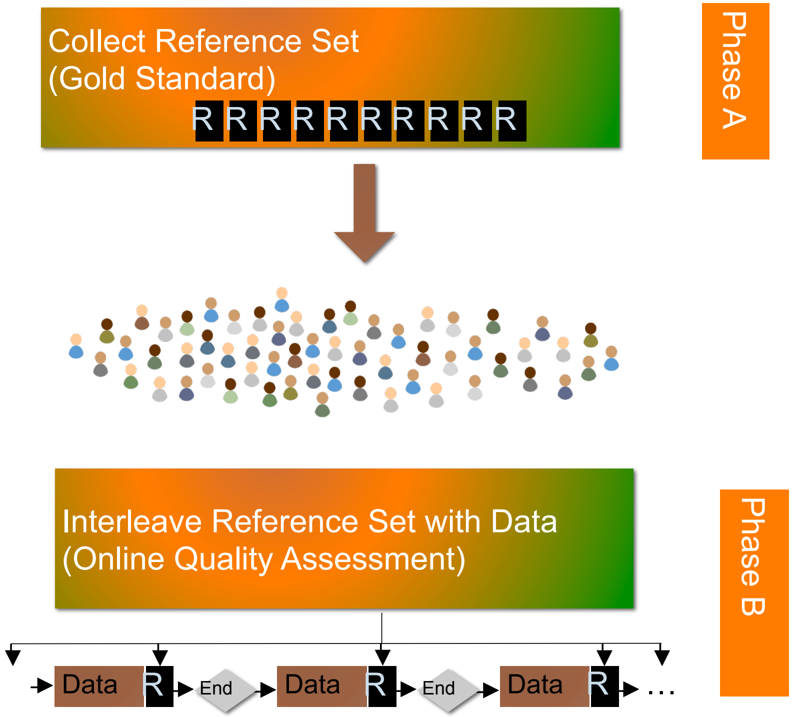
- **Collection of audio recordings[1] (Podcasts)**
  - Naturalness and the diversity of emotions
  - Creative Commons copyright licenses
  - Duration between 2.75s – 11s
  - Perceptive evaluation of emotional content

[1] Reza Lotfian and Carlos Busso, "Building naturalistic emotionally balanced speech corpus by retrieving emotional speech from existing podcast recordings," IEEE Transactions on Affective Computing

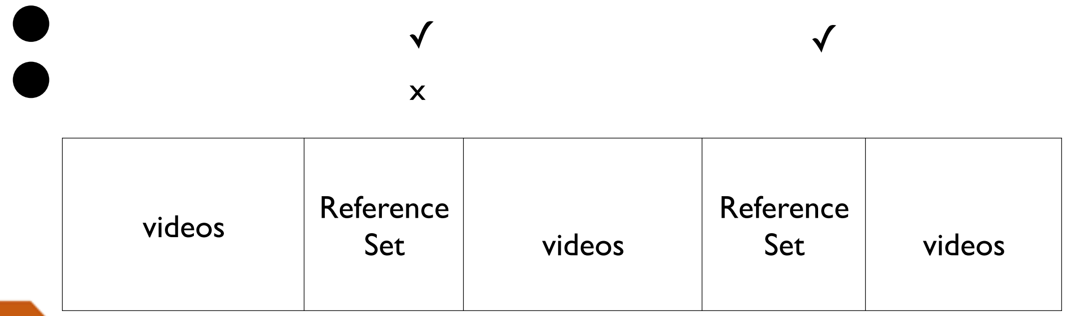
MSP-Podcast corpus

- **Study uses version V1.1 (22,630 sentences – 39hrs,12min)**
  - Test: 7,181 sentences (50 speakers)
  - Development: 2,614 (20 speakers)
  - Train: 12,835 (rest of the speakers)
- **Evaluated through Amazon Mechanical Turk**
  - At least 5 evaluations per sentence

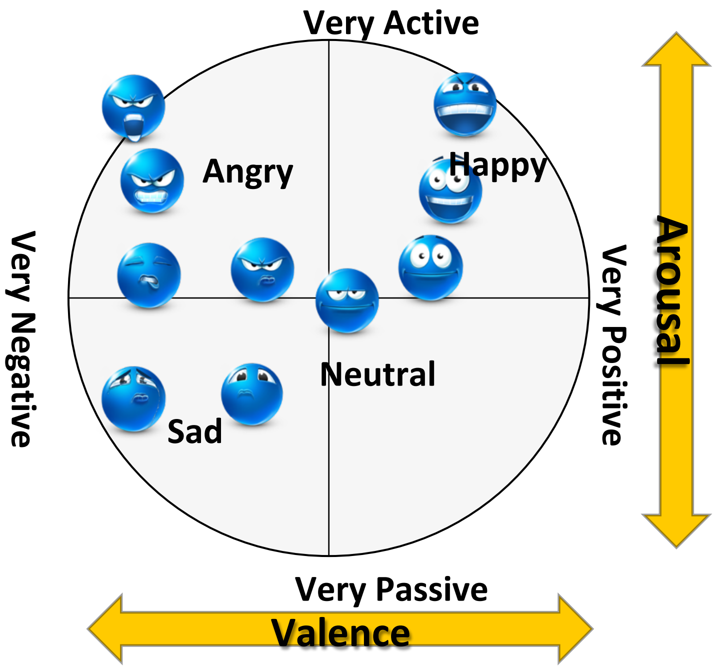
Collect reference set



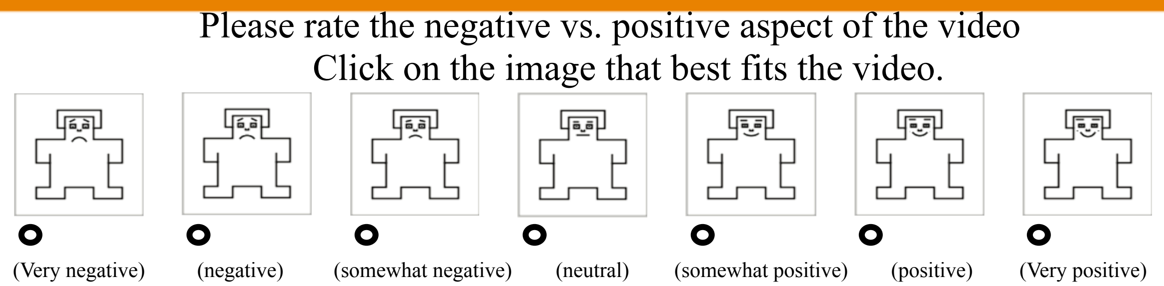
Trace performance in real time



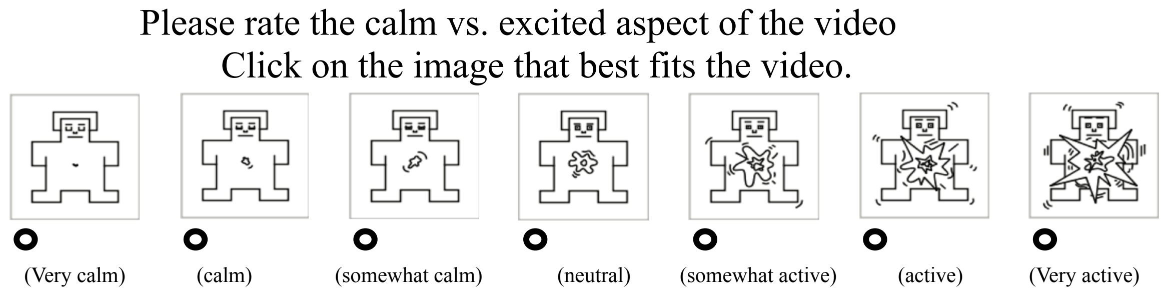
MSP-Podcast corpus



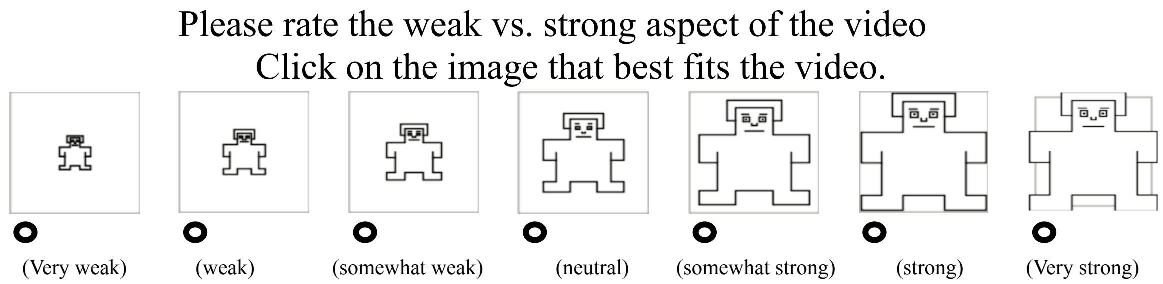
Valence



Arousal



Dominance



MSP-Podcast corpus

Primary emotion

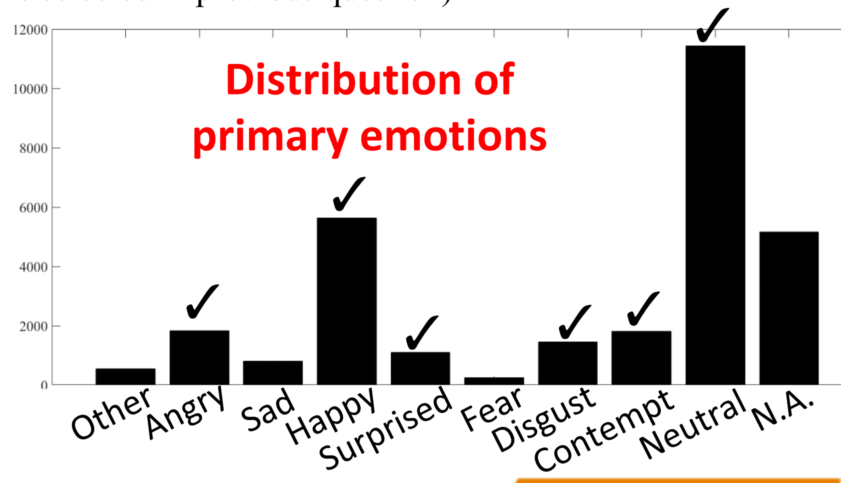
Is any of these emotions the primary emotion in the audio? If not, select **Other** and specify the emotion.

○ Angry ○ Sad ○ Happy ○ Surprise ○ Fear ○ Disgust ○ Contempt ○ Neutral ○ Other ☐

Secondary emotion

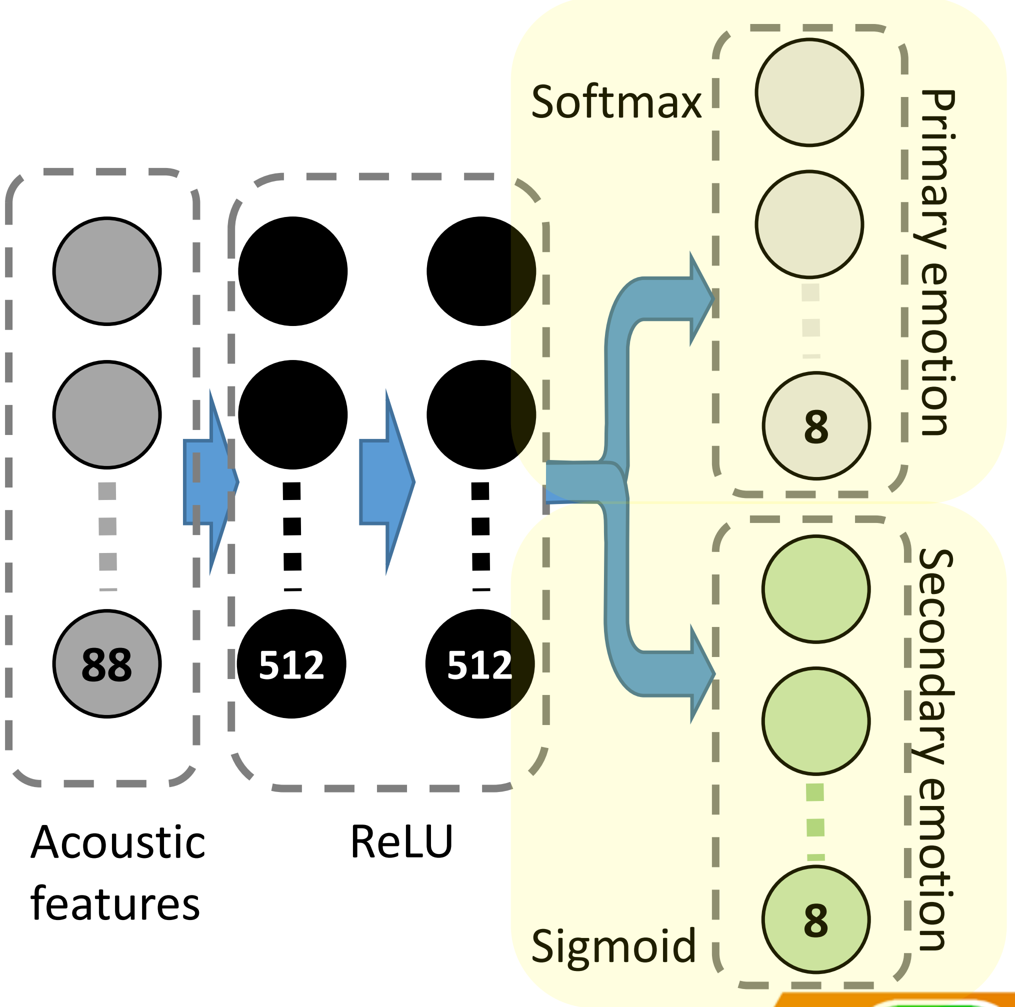
Please pick all the emotional classes that you perceived in the audio(Include the primary emotions selected in previous question)

☐ Angry	☐ Sad	☐ Happy	☐ Amused	☐ Neutral
☐ Frustrated	☐ Depressed	☐ Surprise	☐ Concerned	
☐ Disgust	☐ Disappointed	☐ Excited	☐ Confused	
☐ Annoyed	☐ Fear	☐ Contempt	☐ Other ☐	



Multitask Learning Network

- **Learning two different tasks**
  - Primary emotion
  - Secondary emotion
- **Two shared layers**
- **Primary emotion**
  - Eight class problem
  - Softmax layer with cross-entropy function
- **Secondary emotion**
  - Find all the emotional categories that are relevant to the speaking turn
  - Distance between true and predicted classes
  - Kullback-Leibler divergence (KLD)

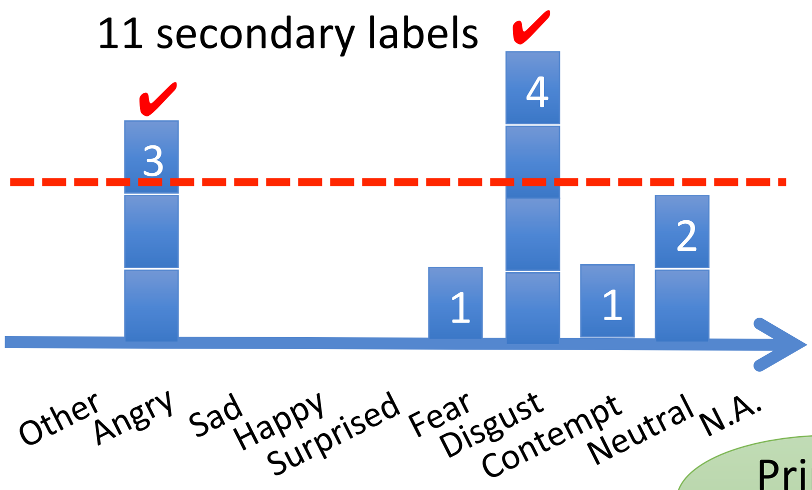


$$L_{ov} = (1-\alpha) \times L_{primary} + \alpha \times L_{secondary}$$

Labels for Secondary Emotions

- **Vector for secondary emotions**
  - We remove primary class
  - We remove the expanded list of emotions
    - Same 8 classes as primary emotion
  - *k* is the average number of secondary emotions for sentence *l*
  - A class is a secondary emotion if its votes are more than *k*
  - Add primary emotion

Example: Primary emotion: sadness
5 evaluators
11 secondary labels

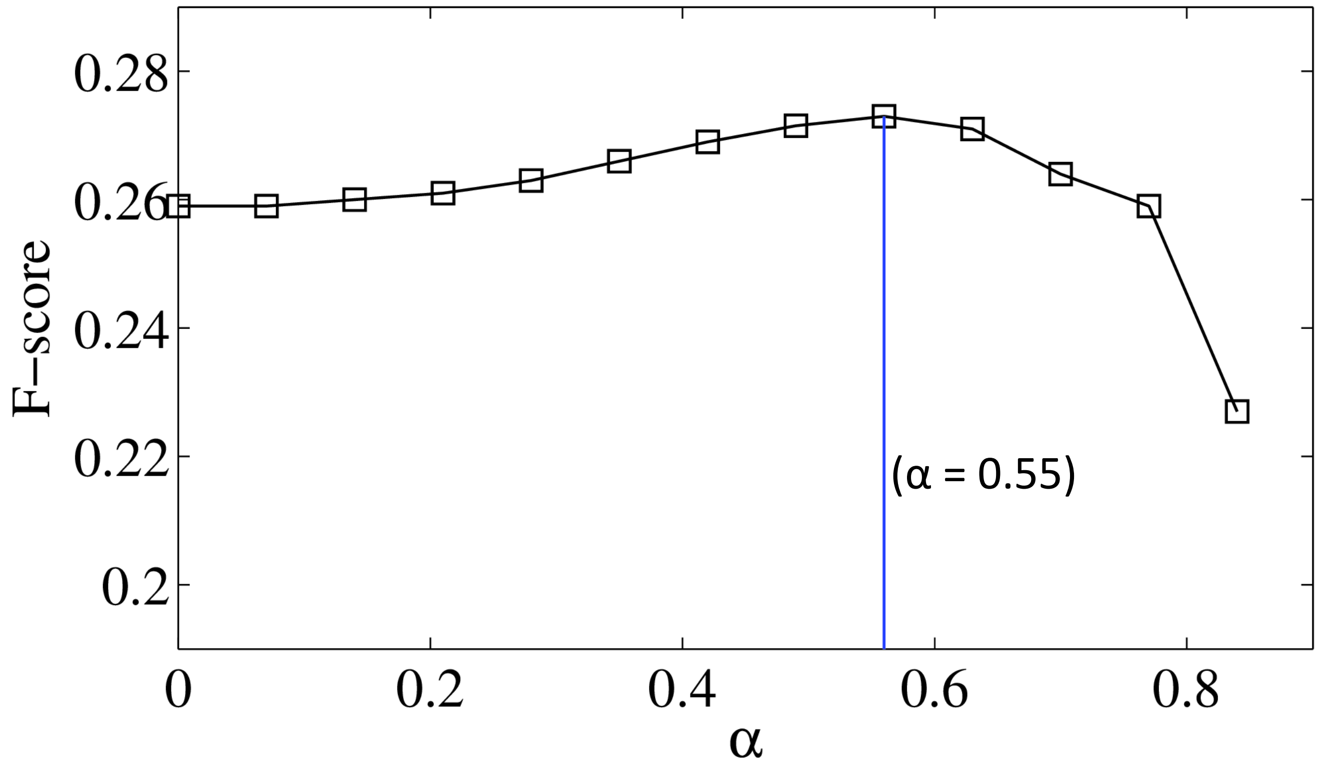


$$\begin{bmatrix} \text{Anger} \\ \text{Sadness} \\ \text{Happiness} \\ \text{Surprise} \\ \text{Fear} \\ \text{Disgust} \\ \text{Contempt} \\ \text{Neutral} \end{bmatrix} = \begin{bmatrix} \mathbf{1} \\ 0 \\ \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \\ \mathbf{1} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix}$$

Primary emotion

Experimental Results

- **Acoustic features**
  - eGeMAPS set [Eyben et al., 2016]
  - 88 acoustic features
- **Hyperparameter optimization:**
  - Tradeoff between primary and secondary task in cost function (α)
- **Parameter optimization on development set**
  - More weight to secondary emotion
  - F-score of primary emotion classification increases by including secondary emotion in training



$$L_{ov} = (1 - \alpha) \times L_{primary} + \alpha \times L_{secondary}$$

Baselines

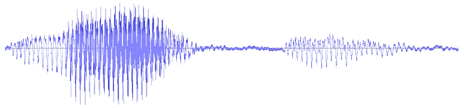
- **Hard label primary emotion (Hard label PE)**

- Hap
- Hap
- Sur
- Ang
- Neu

$\rightarrow$ Hap

Majority vote

Softmax (8 nodes)
Fully connected (512 nodes)
Fully connected (512 nodes)



- **Soft label derived from primary emotion (Soft label PE)** **[Fayek et al.2016]**

Sentence A { Hap, Hap, Sur, Ang, Neu } →

$$\begin{bmatrix} \text{Anger} \\ \text{Sadness} \\ \text{Happiness} \\ \text{Surprise} \\ \text{Fear} \\ \text{Disgust} \\ \text{Contempt} \\ \text{Neutral} \end{bmatrix} = \begin{bmatrix} 0.2 \\ 0.0 \\ 0.4 \\ 0.2 \\ 0.0 \\ 0.0 \\ 0.0 \\ 0.2 \end{bmatrix}$$

Results: Cross-entropy loss

- **Average cross-entropy loss on test set**
  - Use of auxiliary task helps reducing the cross-entropy loss
  - Considering secondary emotions lead to better generalization

	Cross-entropy Loss
Hard label PE	1.391
Soft label PE	1.350
MTL (PE+SE)	**1.339**

Results: Primary Emotions

- **Detecting primary emotion**
  - Human performance is only F1-score=38.9
    - Compare labels from one rater with consensus labels from rest of the raters
    - Difficult task (spontaneous speech)
  - Chances performance is 12.5%
  - Proposed approach achieves 2.3% absolute improvements (9.6% relative gain)

	Precision	Recall	F1-score
Hard label PE	23.1%	24.9%	24.4
Soft label PE	24.9%	25.8%	25.3*
MTL (PE+SE)	26.4%	26.1%	26.3**
Human performance	40.8%	37.2%	38.9

(*) approach outperforms the Hard-label PE baseline
(**) approach outperforms other alternative methods

Results: Secondary emotions

- **Results on detecting secondary emotions**
  - MTL framework is optimized to maximize the classification performance of the primary task
  - Binary classification tasks
    - Does the sentence convey the detected emotional class?
    - multiple emotions are possible
  - Baseline: single-task learning that recognizes secondary emotions (*Hard label SE*)
  - Proposed method outperforms baseline by 5.1%

	Accuracy
Hard label SE	61.7%
MTL (PE+SE)	66.8%*

(*) approach outperforms the Hard-label SE baseline

Shared representation learned by MTL model is discriminative for both tasks

Final Remarks

- **Categorical emotions are more convenient but prototypical classes can be ambiguous**
- **Secondary emotion labels convey complementary and useful information that a classifier should leverage**
- **Multitask (Primary + Secondary emotion) improves the classification performance**
  - Efficient framework to leverage annotation of secondary labels
- **Future directions**
  - Attribute based emotions (arousal-valence) as auxiliary task
  - Investigate the optimum criteria to accept a class as a secondary emotion

Questions?

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