Speech Emotion

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Motivation

- Speech: primary form of communication, especially with a machine
- Goal: make interaction with machines more human-like
- Detecting speech emotion can be helpful for smart assistants





Overview of Speech Emotion Field (Schuller)

- Speech emotion detection has been a challenging problem to tackle
- An accurate representation of the emotions needs to be created
- Complex networks and large amounts of data are typically required for an accurate model
- Challenges
    - Cross-cultural differences in emotions
    - Complex inflections like irony and sarcasm

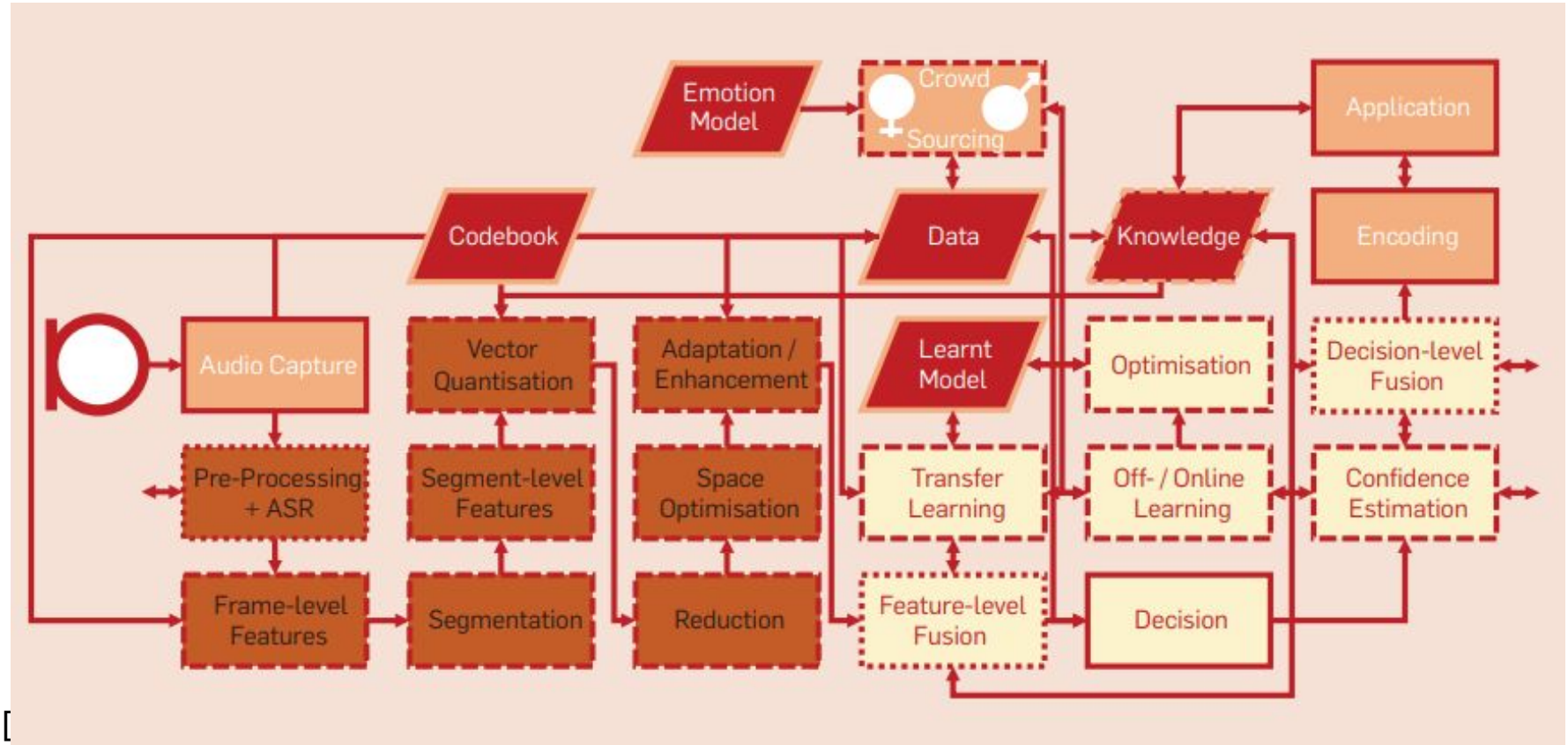
[8]

Standard Approach (Schuller)

- Modeling
  - Representing emotion so it can well be handled by a machine
  - Discrete classes
    - Happy, sad, etc.
  - Continuous dimension
    - Activation/Arousal
    - Valence
- Annotation
  - Acquisition of labelled data
- Features
  - Audio
    - MFCC, spectral flux, etc.
  - Textual
    - Identifying meaning
    - Can be combined with audio feature analysis

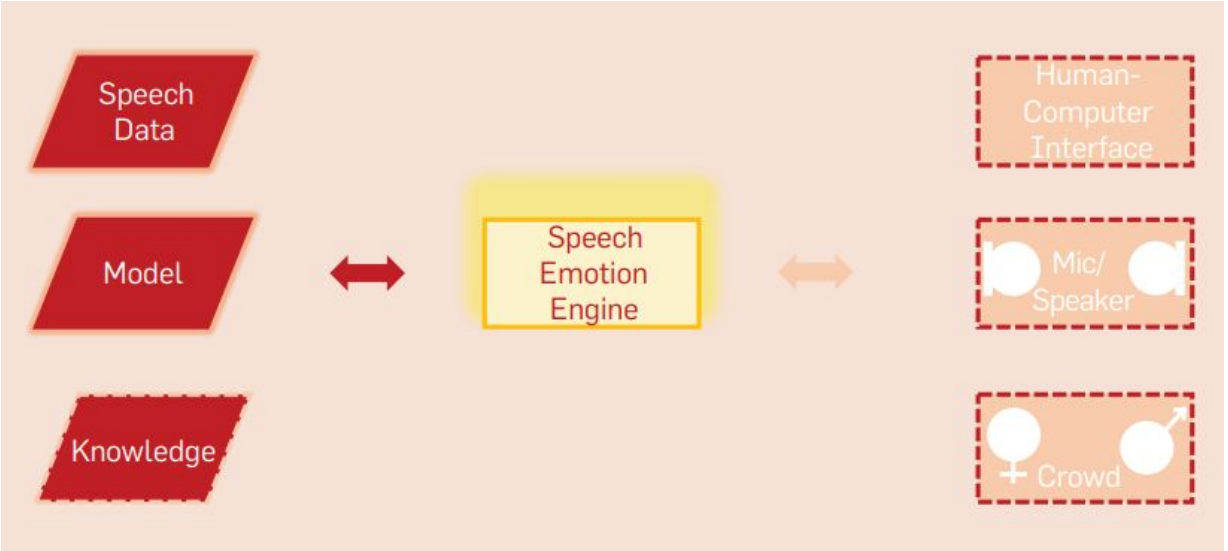
[8]

Standard Approach (Schuller)



Current State-of-the-Art (Schuller)

- Neural nets are popular because they have the ability to learn complex patterns like those that indicate emotion in speech
- Depends on large amounts of data



Busso et al.: Analysis of Emotion Recognition

Methods:

- Acted speech for happy, sad, angry and neutral
- Acoustical features:
  - Mean, standard deviation, range, maximum/minimum, and median of pitch and energy
  - Ratio of voiced and unvoiced speech
- SVM classifier

Results:

	Anger	Sadness	Happiness	Neutral
Anger	0.68	0.05	0.21	0.05
Sadness	0.07	0.64	0.06	0.22
Happiness	0.19	0.04	0.70	0.08
Neutral	0.04	0.14	0.01	0.81

[1]

Busso et al.: Analysis of Emotion Recognition

Criticism

- The authors generally see the downfall of their experiments
  - Not enough features for input
- Limitation of global pitch and energy features
  - Recognize MFCC - don't use it
- Database was only one voice actress

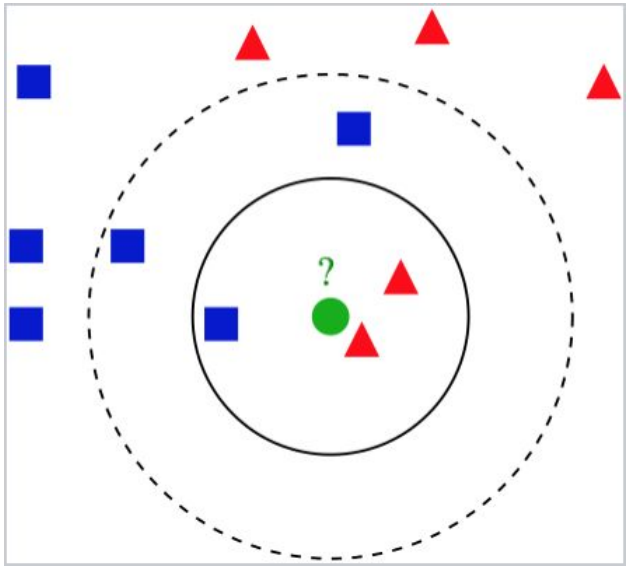
SVM

- Effective for more complex (non-linear) data
- Used for high-dimensional spaces
- Long training time

Aun and Rajoo: Influence of Languages

Methods:

- Malay, English and Mandarin
- Acted speech for happy, sad, angry and neutral used to compare languages
- Acoustical features:
  - MFCC
  - Pitch
  - Energy
  - Zero-Crossing Rate
- kNN classifier
  - Euclidean Distance



$$d(\mathbf{p}, \mathbf{q}) = d(\mathbf{q}, \mathbf{p}) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2}$$

$$= \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}.$$

[2]

Aun and Rajoo: Influence of Languages

Results:

- First experiment:

Language	Classification Rate				
	Happiness	*Sadness*	*Anger*	*Neutral*	*Average*
English	75	86	83	70	78.5
Malay	70	75	74	65	71.0
Mandarin	75	71	74	70	72.5
Average	73.3	77.3	77	68.3	74.0

- Second experiment:

Language	Classification Rate				
	Happiness	*Sadness*	*Anger*	*Neutral*	*Average*
Malay	73	78	77	71	74.75
Mandarin	78	80	77	69	76
Average	75.5	79	77	70	75.4

Aun and Rajoo: Influences of Languages

Criticism

- Use the same sentence
- Small set of data

kNN

- Effective with large training sets
- Robust to noisy data
- Computation time is large due to distance calculations
- Determine k and hand-pick features

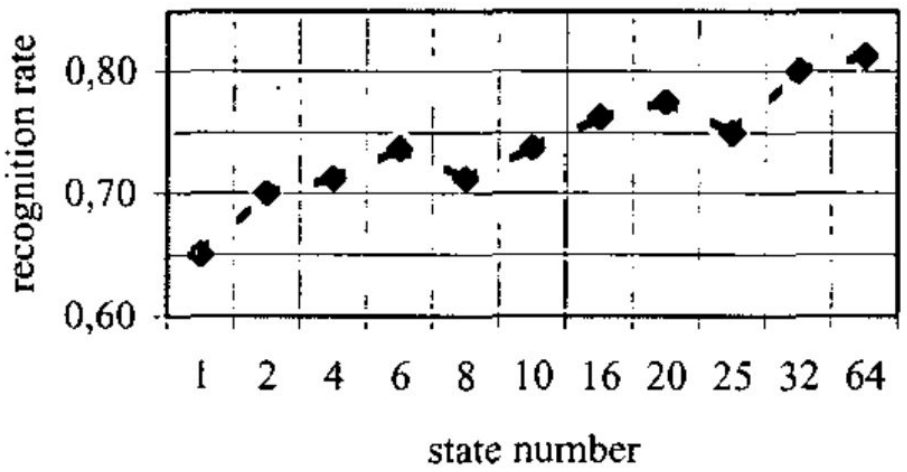
[3]

Feature Based Approach: Hidden Markov Models (Schuller et al.)

- Energy related features
  - Relative maximum and position of maximum of derivation of energy
  - Average and standard deviation of derivation of energy
- Pitch related features
  - Mean duration of voiced sounds
  - Average pitch, relative pitch minimum/maximum
- Hand pick optimal features and vectorize after modeling probabilities with Gaussian Mixture Models (GMM's) [4]

Schuller et al. Results:

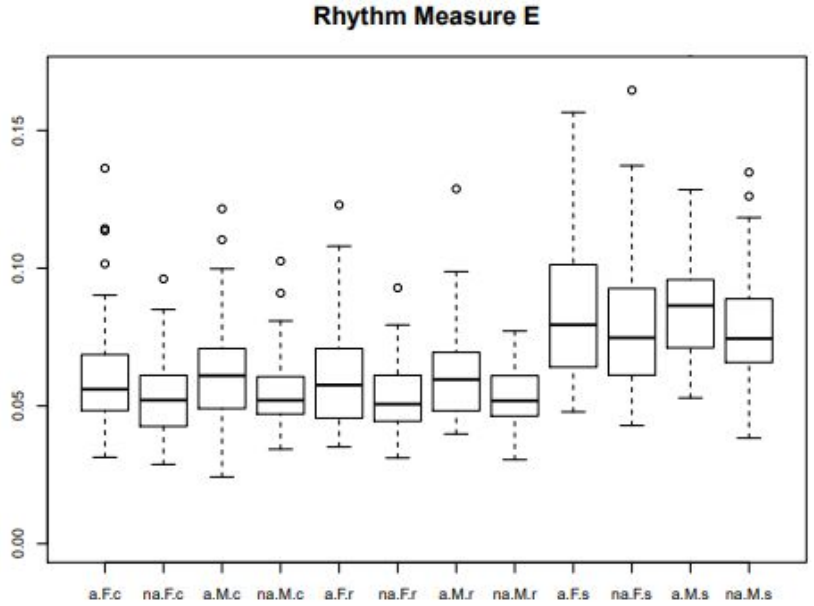
- Each emotion represented by one GMM
- Results dependent on number of states used
- Generally derived features give better results for less states
- **Results:**



Labeled emotion	Recognized emotion						
	ang	dis	fea	sur	joy	ntl	sad
ang	**68.5**	12.7	2.6	**1.8**	2.7	8.4	3.3
dis	12.8	**84.7**	2.1	0.3	0.0	0.1	0.0
fea	1.8	0.1	**95.4**	0.2	2.0	0.4	0.1
sur	6.3	6.7	6.3	**73.5**	6.1	0.9	0.2
joy	10.1	11.8	7.9	**1.2**	**68.0**	0.5	0.5
ntl	10.4	0.9	1.0	0.1	1.9	**79.6**	6.1
sad	5.9	10.1	2.8	2.1	2.2	1.8	**75.1**

Rhythm and Formant Features for Automatic Alcohol Detection (Schiel et al.)

- RMS rhythmicity and formant frequencies F1-F4 analyzed
- Alcohol Language Corpus dataset
- RMS measure primarily based on the median of the absolute value of the differences of the RMS values between maxima



[7]

Formant Analysis (Schiel et al.)

- Track vowels without any manual correction to the speech recordings
- Formant tracker configured to use a nominal F1 frequency
    - 531 Hz for male, 595 Hz for female
- Median formant frequencies F1 – F4 derived from the middle 30% of each vowel segment

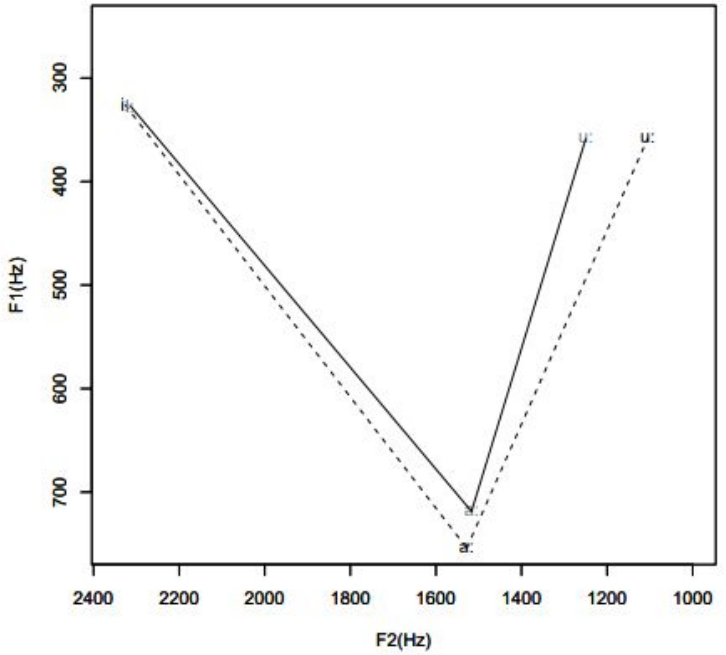


Figure 2: *Vowel triangle in the F1/F2 plane. The solid line combines vowel centroids of sober speech, the dashed line those of alcoholized speech.*

Schiel et al. Results and Opinions

- Significant differences between drunk and sober speech were found with formant based methods
- Even still, usefulness is limited for our desired applications
    - No prognosis rate is given by paper
- Differences detected likely too subtle for accurate detection

	$F1_m$	$F1_{qq}$	$F4_{qq}$	ED
alc	⇑	⇑	⇑	⇑
score	p<0.0001	p=0.046	p=0.004	p<0.0001
sex	F,M	F,M	F,M	F
vow	/a:/	/u:/	/a: i: u:/	/u:/
sty	r,s,c	r,s,c	r,s,c	r,s,c

	A	B	C	D, E
alc	⇑	⇑	⇑	⇑
score	p<0.0001	p<0.0001	p<0.001	p<0.0001
sty	r,s	r,s	c	r,s,c

	F	G	H	I
alc	⇑	⇑	⇑	⇑
score	p<0.0001	p<0.0001	p<0.0001	p<0.0001
sty	r,s,c	r,s	r,s	r

Neural Network Approaches

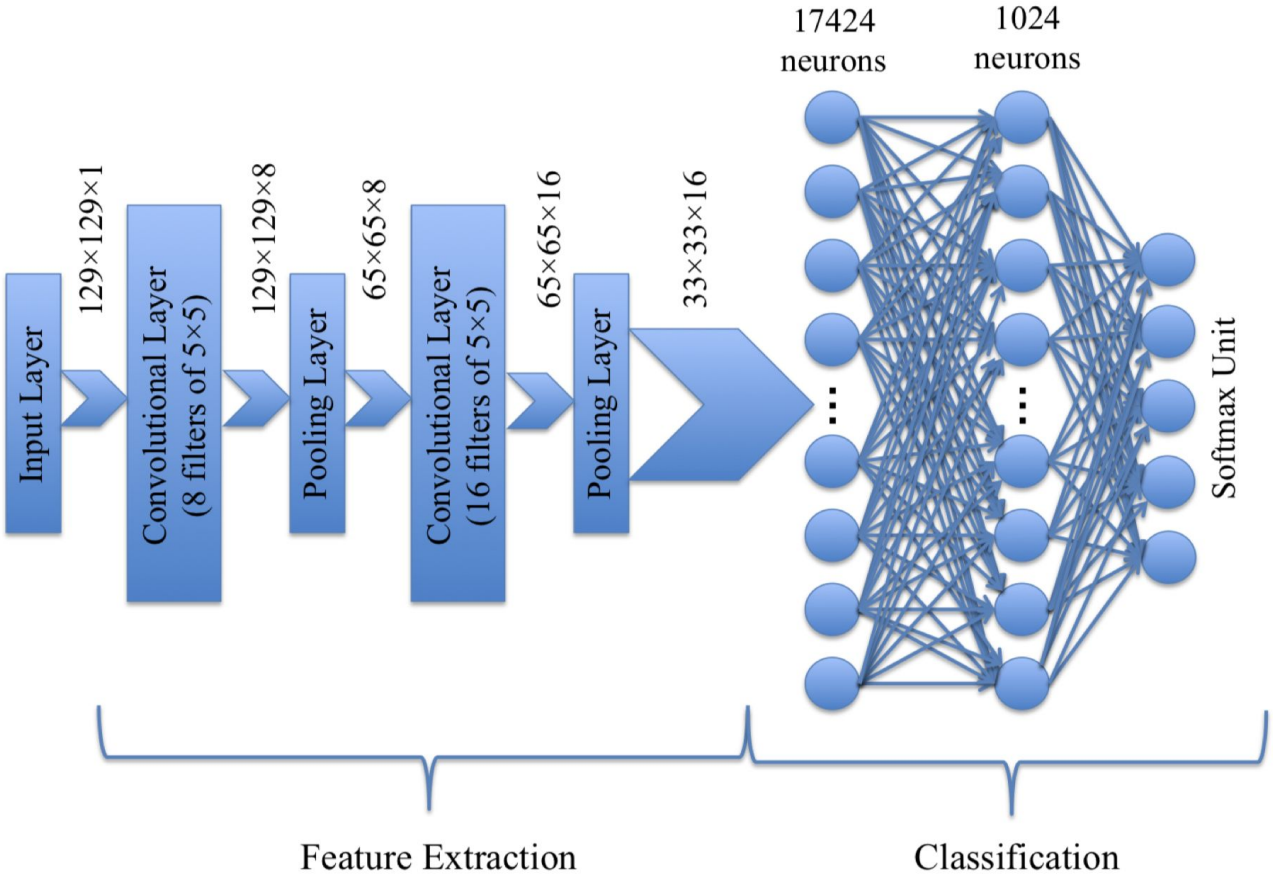
- Valence and arousal vs. direct labels
- Spectrogram as input data (no need to select features)
- May require more training data than other approaches
- Curriculum Learning may improve accuracy of model (Lotfian & Busso) [5]
    - Emulates human learning
    - Use disagreement on emotion from human evaluators as measure of difficulty
    - Minimax Conditional Entropy to account for noisy annotations

	Aro. [F-score]	Val. [F-score]
w/o curriculum	0.779	0.592
With random curriculum	0.771	0.590
Criterion 1-Error of predicted label	0.783	0.607*°
Criterion 2-Disagreement between annotators	0.789*°	0.615*°
Criterion 3-Minmax entropy	0.791*°	0.616*°

Speech Emotion Detection Using Convolutional Neural Networks (Shahsavarani)

- Large databases with varying emotional speech data
- Audio preprocessing
  - Wide band spectrogram data below 4 kHz, normalized and resized to 129 x 129
- Used data augmentation and dropout to reduce overfitting
- K-fold cross validation for training/testing network
  - Randomly divide data into K folds
  - K-1 folds used for training, remaining fold for testing
  - Repeat this process K times so that each fold is tested on once [6]

Convolutional Neural Network Architecture



Shahsavarani Results:

- Results for an American English Database dependent on convolution filter dimensions, pooling type, dropout probability, data augmentation, and epochs
- High accuracy potentially due to speech data

f_1	f_2	pooling	$p_{dropout}$	augmentation	epoch	CV accuracy (%)
5×5	5×5	Max	0	10x	100	66.36
5×5	5×5	Max	0.5	10x	100	73.81
10×10	5×5	Max	0.5	10x	100	73.38
10×10	5×5	Average	0.5	10x	100	75.55
5×5	5×5	Max	1	20x	100	63.64
5×5	5×5	Max	0.5	20x	100	72.91
10×10	5×5	Max	0.5	20x	100	68.9
10×10	5×5	Max	0.2	20x	100	78.17
10×10	**5×5**	**Average**	**0.2**	**20x**	**100**	**88.91**
10×10	**5×5**	**Average**	**0.2**	**20x**	**800**	**92.63**
10×10	**5×5**	**Average**	**0.2**	**20x**	**4000**	**94.51**

Summary of Findings

- Neural network methods are the cutting edge for speech emotion detection
- Drunkenness detection has a small pool of research mostly based on bag-of-features models
- Combining a neural net drunkenness detector with a general emotion detector could prove very useful for applications like AI assistants

References

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[3] G. Xiao, C. Zha, X. Zhang & L. Zhao. 2015. “A Speech Emotion Recognition Method in Cross-Languages Corpus Based on Feature Adaptation.” In Proceedings of the International Conference on Information Technology Systems and Innovation (ICITSI ‘15). pp. 1-4. DOI: 10.1109/ICITSI.2015.7437680

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[6] Shahsavarani, B. S. (2018). Speech Emotion Recognition using Convolutional Neural Networks (Master thesis, The University of Nebraska-Lincoln).

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[8] Bjorn W. Schuller (2018). Speech Emotion Recognition: Two Decades in a Nutshell, Benchmarks,and Ongoing Trends (Communications of the ACM).