

# **COMP 3647**

## **Human-AI Interaction Design**

### **Topic 7**

### ***Affective Computing: Basics***

**Prof. Effie L-C Law**

# Quiz #1

**“Humans are feeling machines that think rather than thinking machines that feel”**

***Who said that?***

- A. Antonio Damasio, neuroscientist**
- B. Rosalind Picard, computer scientist**
- C. Paul Ekman, psychologist**
- D. Lisa Feldman Barret, psychologist**



# Quiz #2

**Who proposed six basic emotions:**

**Angry, Disgust, Fear, Happy, Sad, Surprise**

***Who said that?***

- A. Antonio Damasio, neuroscientist**
- B. Rosalind Picard, computer scientist**
- C. Paul Ekman, psychologist**
- D. Lisa Feldman Barrett, psychologist**



# Quiz #3

## Who proposed Theory of Constructed Emotion?

*Who said that?*

- A. Antonio Damasio, neuroscientist
- B. Rosalind Picard, computer scientist
- C. Paul Ekman, psychologist
- D. Lisa Feldman Barret, psychologist



# Quiz #4

**Who coined the term and found the field “Affective Computing”?**

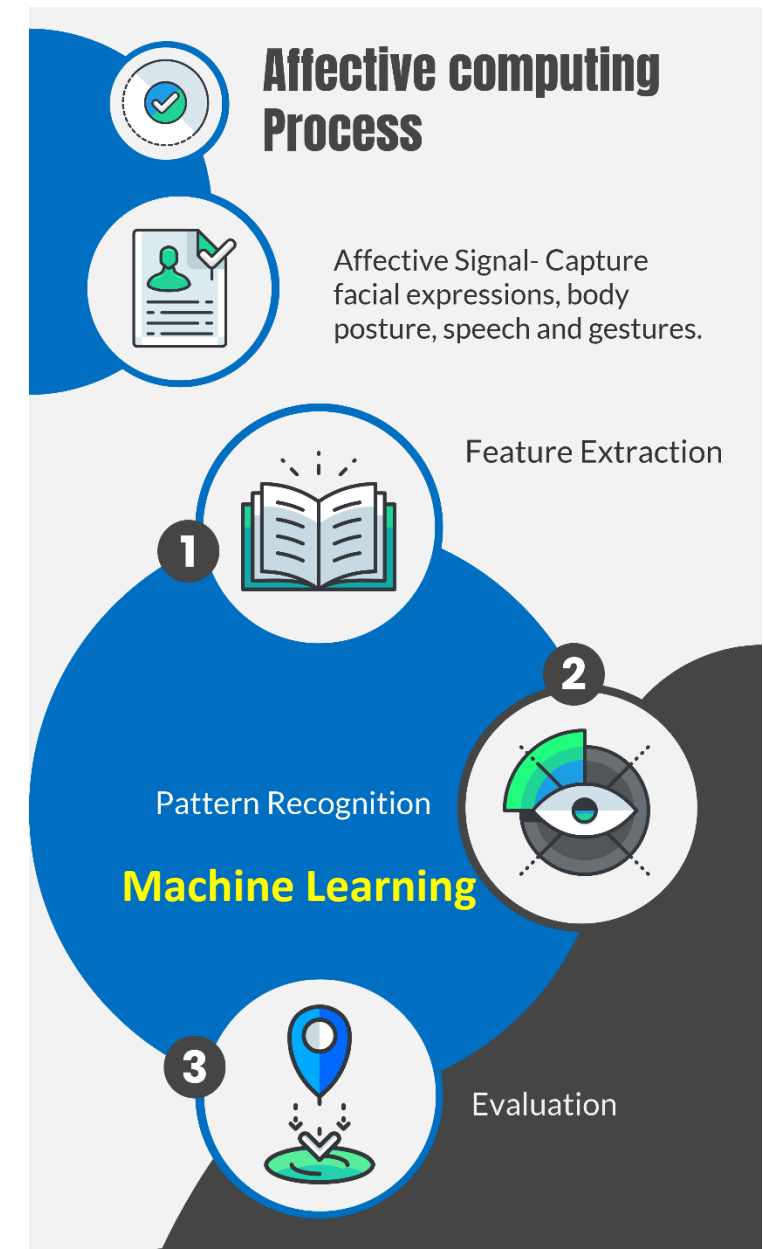
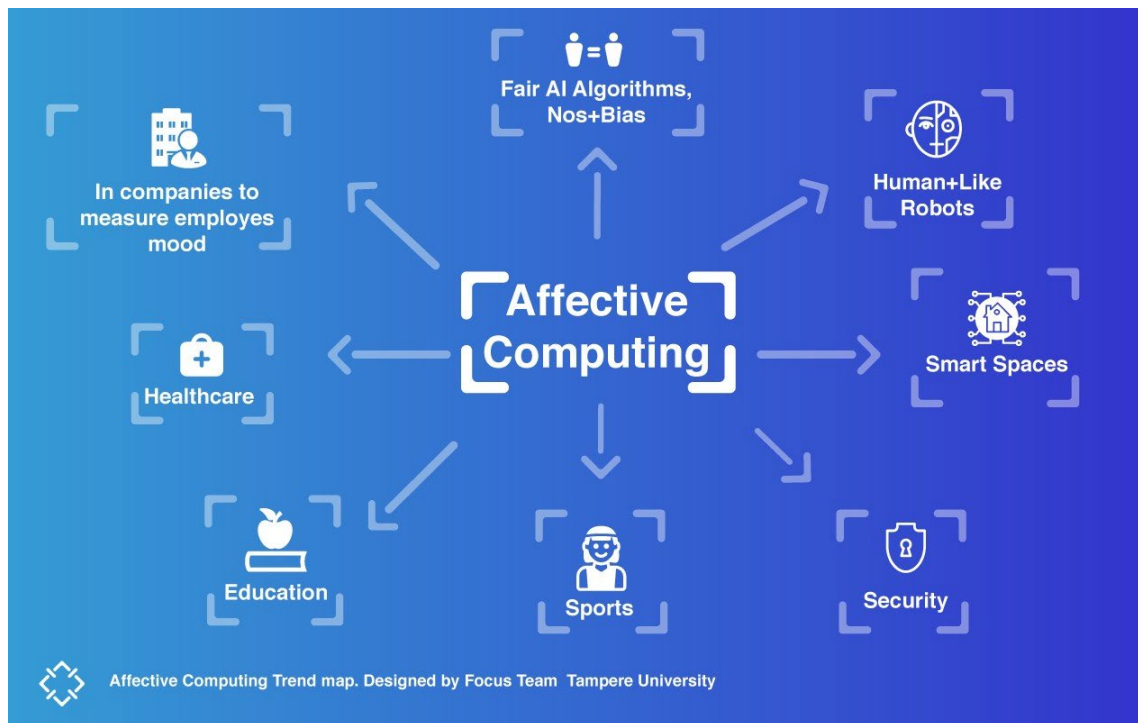
***Who said that?***

- A. Antonio Damasio, neuroscientist**
- B. Rosalind Picard, computer scientist**
- C. Paul Ekman, psychologist**
- D. Lisa Feldman Barret, psychologist**

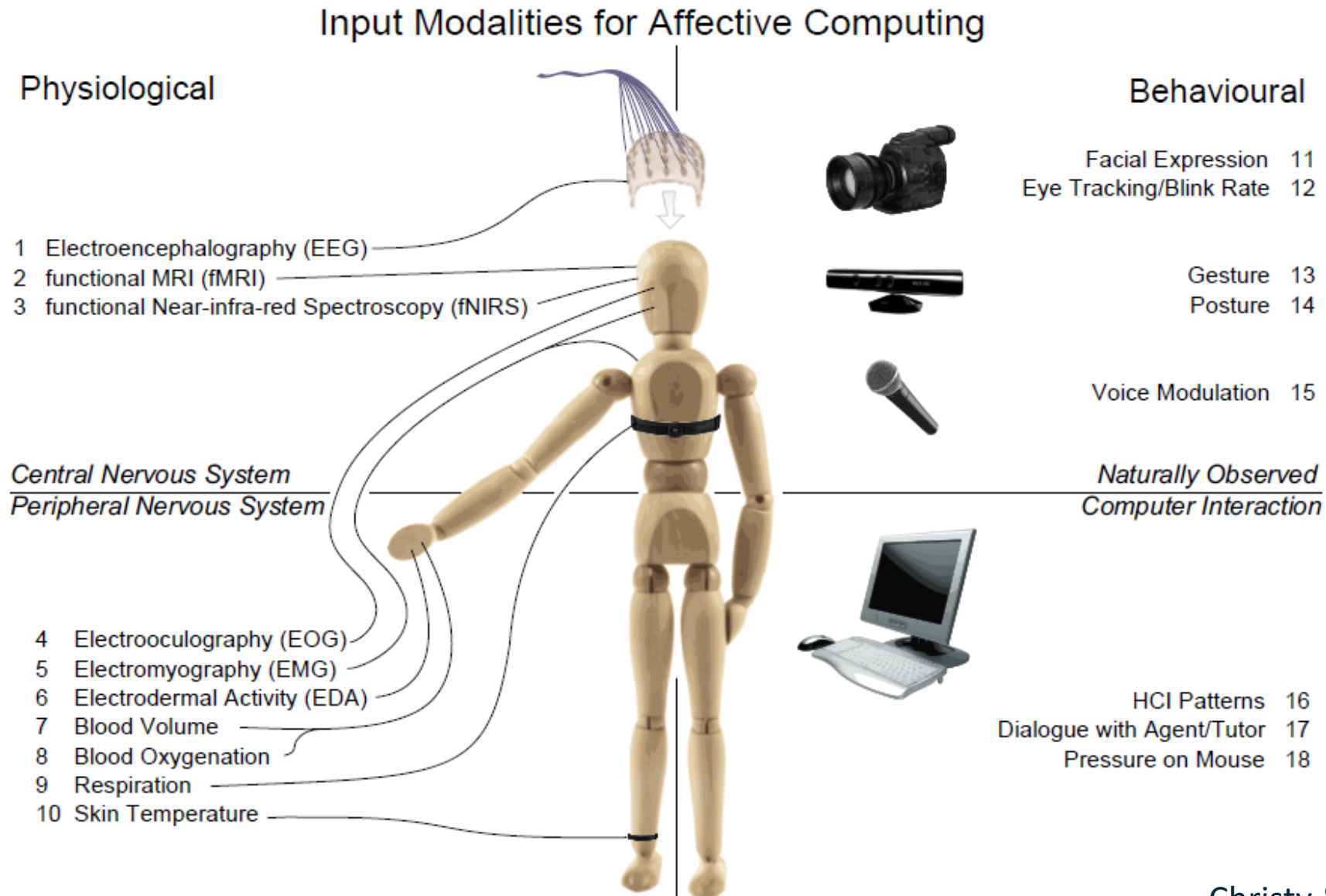


# What is Affective Computing?

Affective Computing is the study and development of systems and devices that can **recognize, interpret, process, and simulate** human affects/emotions. It is an interdisciplinary field spanning computer science, psychology, and cognitive science.



# Automatic Multimodality Emotion Recognition (AMER)

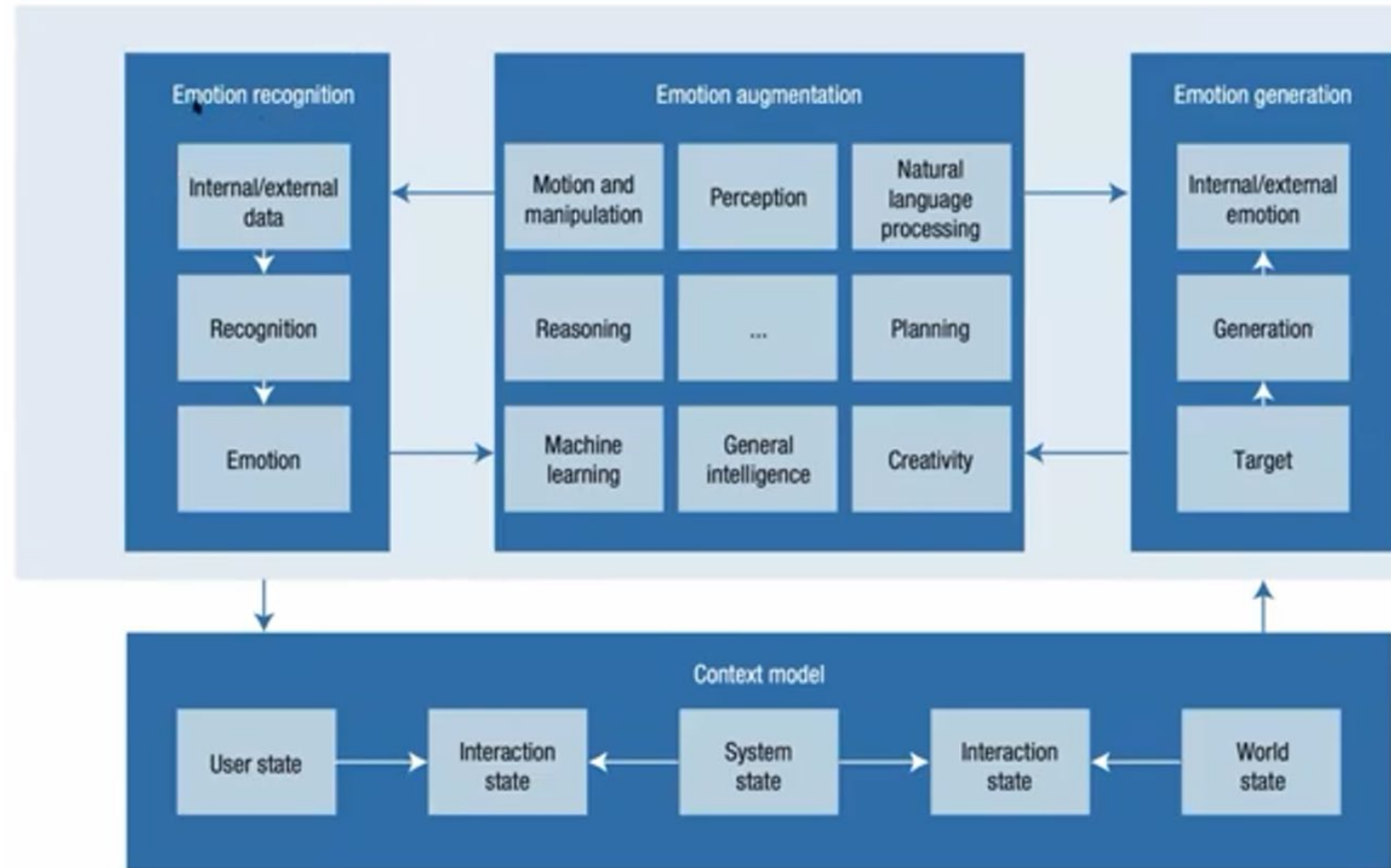


# Emotion + AI Research

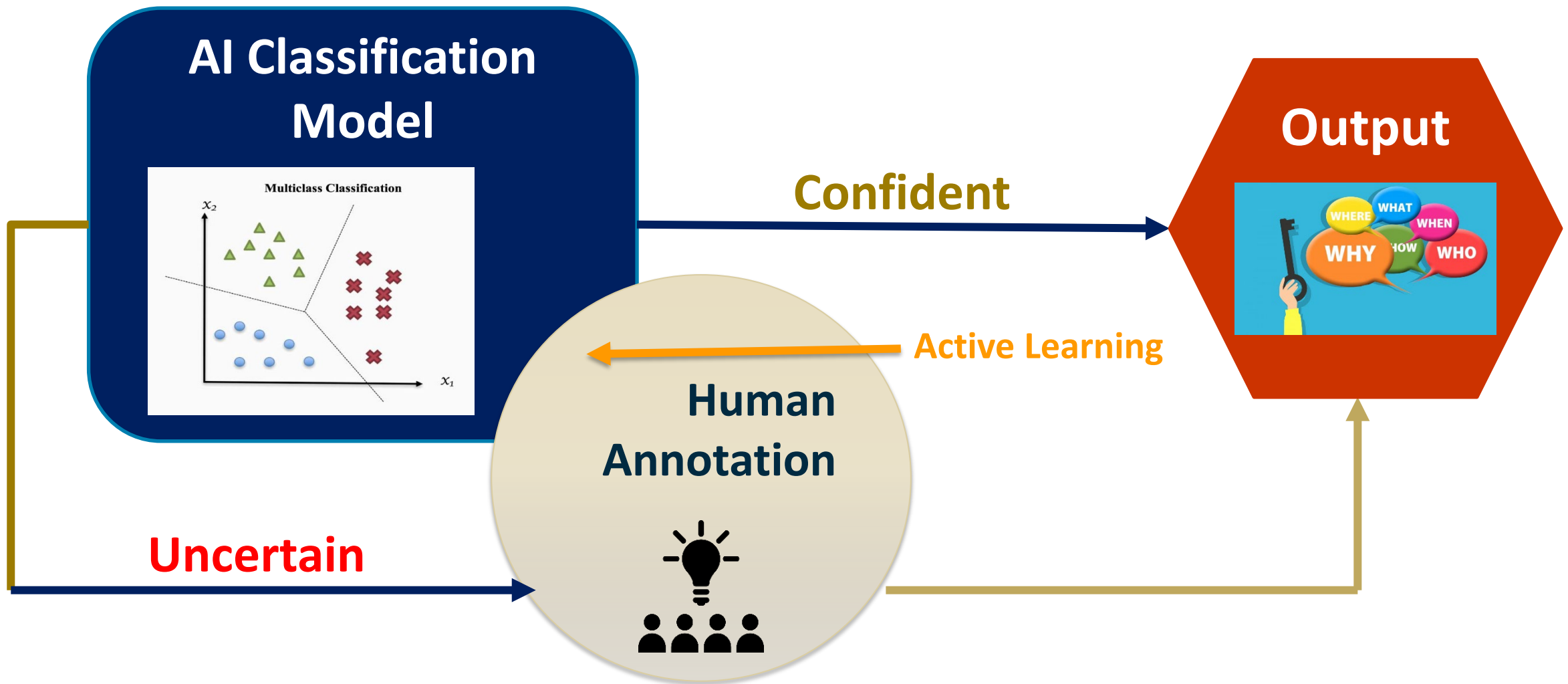


# Artificial Emotional Intelligence (AEI)

(Bjorn Schuller, Imperial College London)



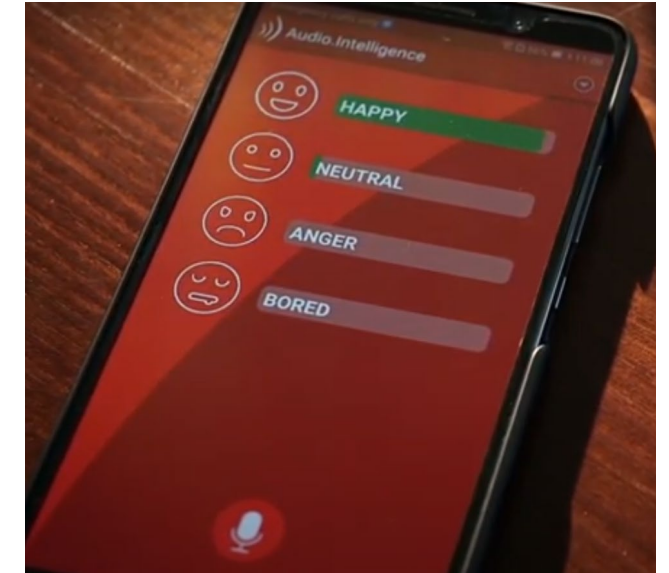
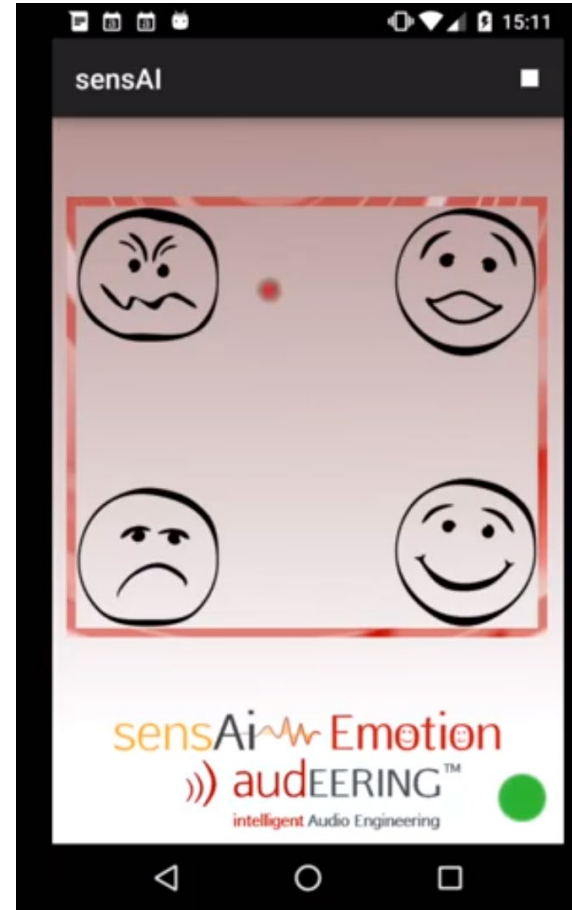
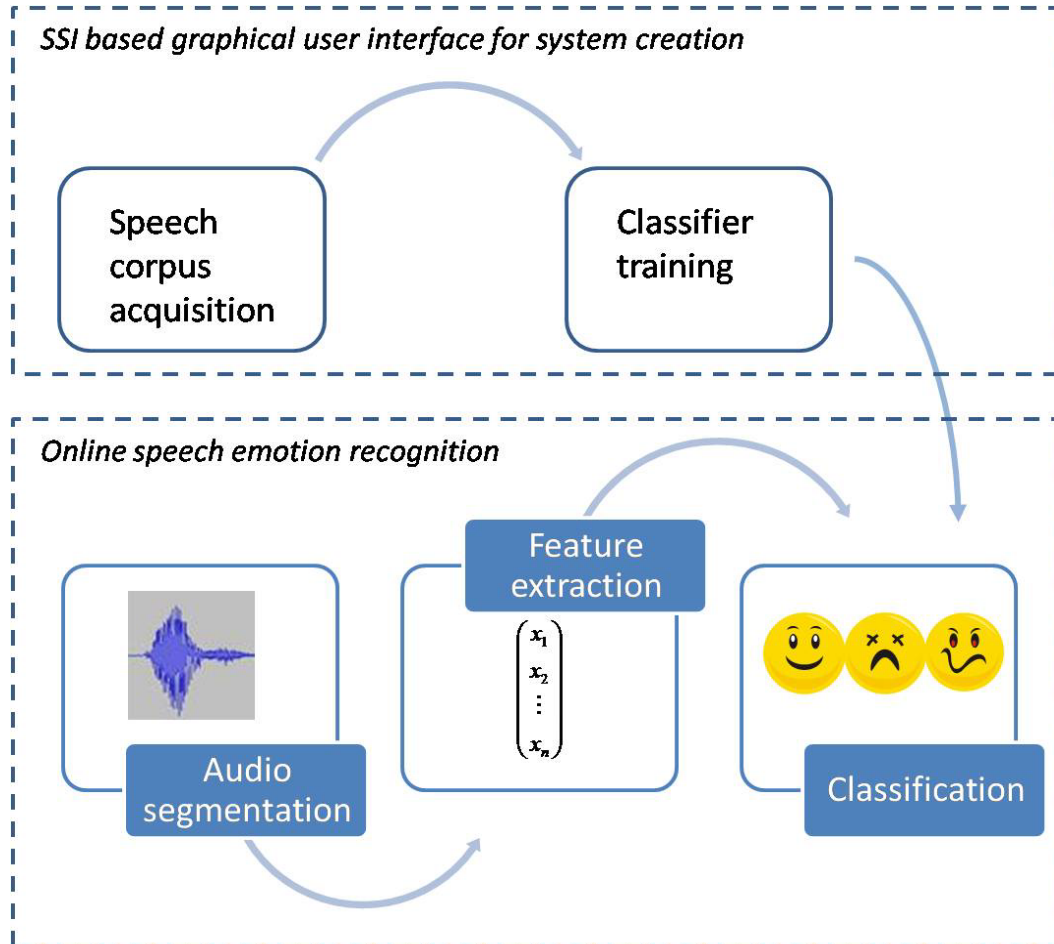
*"The Age of Artificial Emotional Intelligence", IEEE Computer, 2018.*



### Human-in-the-Loop:

(1) **Annotate a *subset* of data**; (2) Train a model with labelled data; (3) Make predictions on unlabelled data; (4) **Validate *uncertain* predictions**; (5) Revise the model to improve prediction.

# Speech Emotion Recognition: Emotion + AI

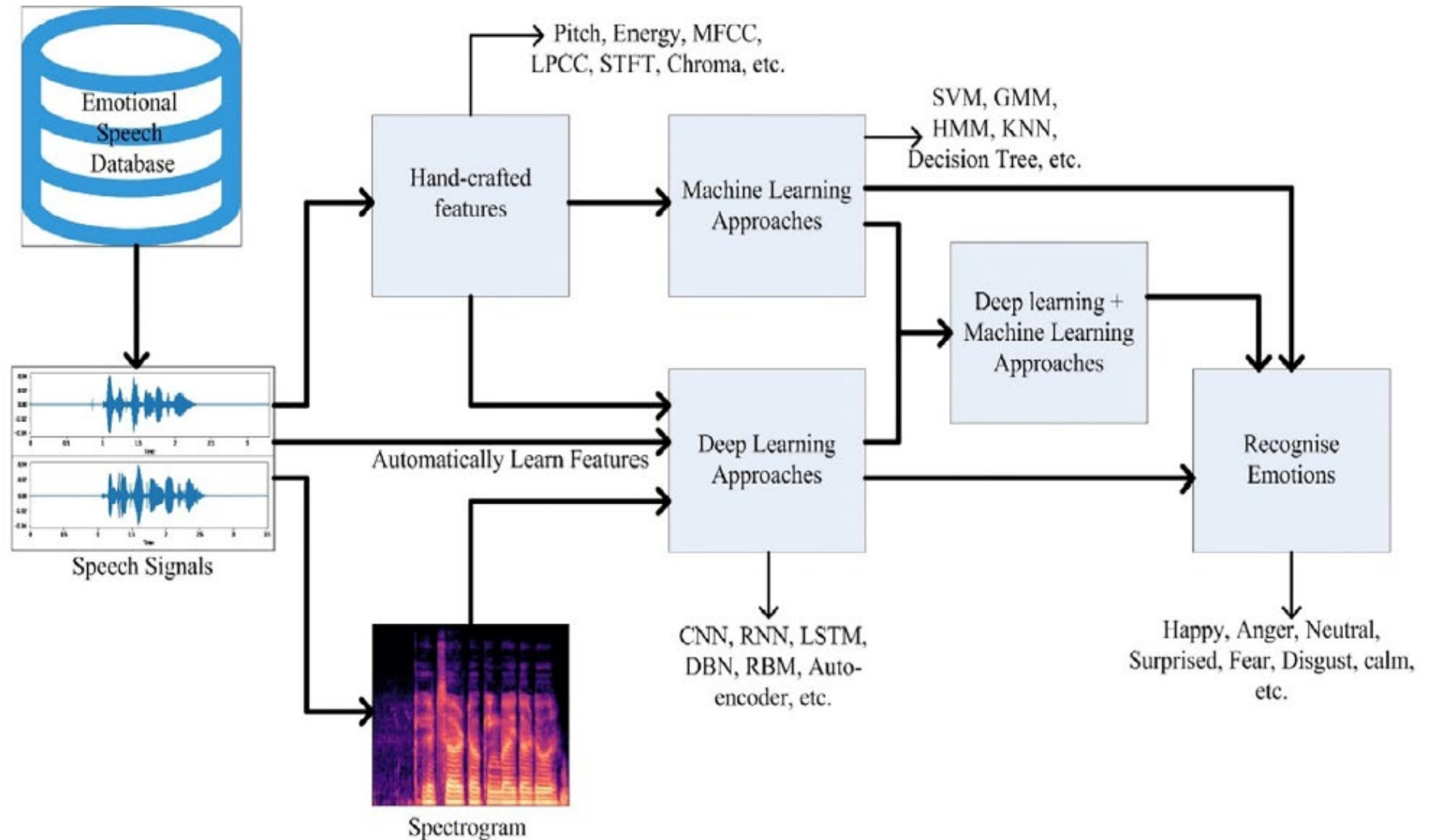


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University of Augsburg

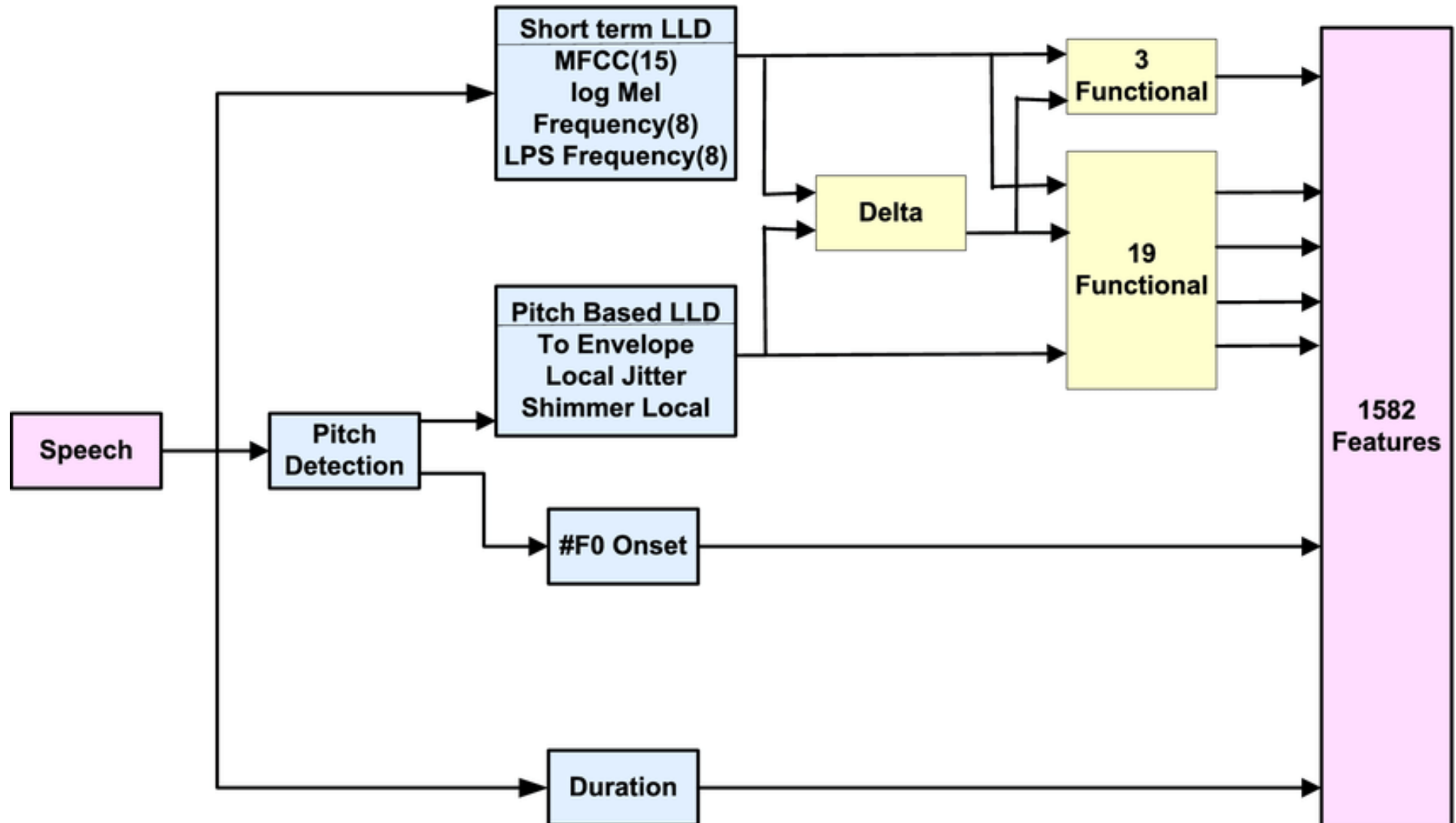
<https://www.informatik.uni-augsburg.de/lehrtstuehle/hcm/projects/tools/emovoice/>

Law, E. L. C., Soleimani, S., Watkins, D., & Barwick, J. (2020). Automatic voice emotion recognition of child-parent conversations in natural settings. *Behaviour & Information Technology*, 1-18.

# Speech Emotion Recognition (SER)



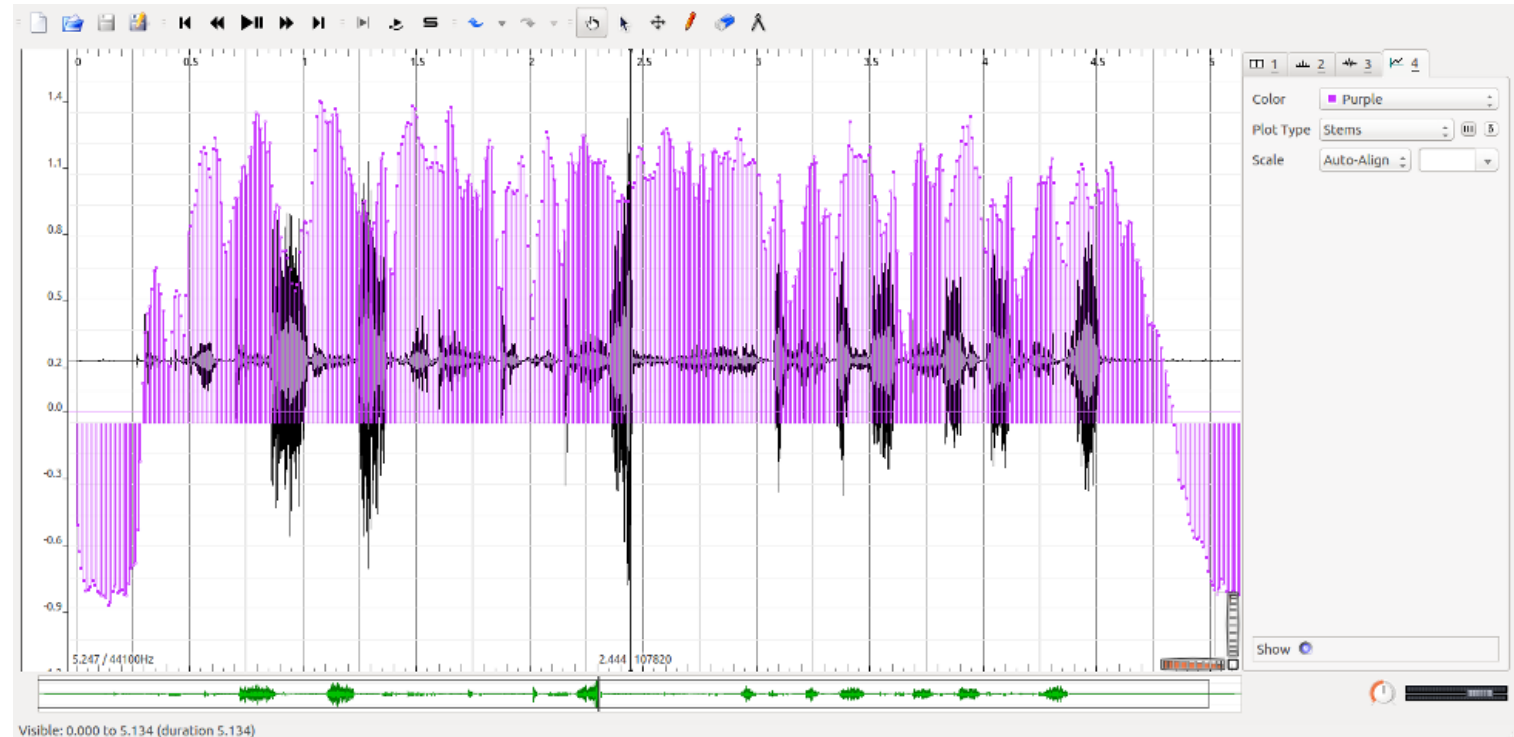
# OpenSMILE: Open-source Speech and Music Interpretation by Large-space Extraction



# OpenSMILE 3.0: Speech Features

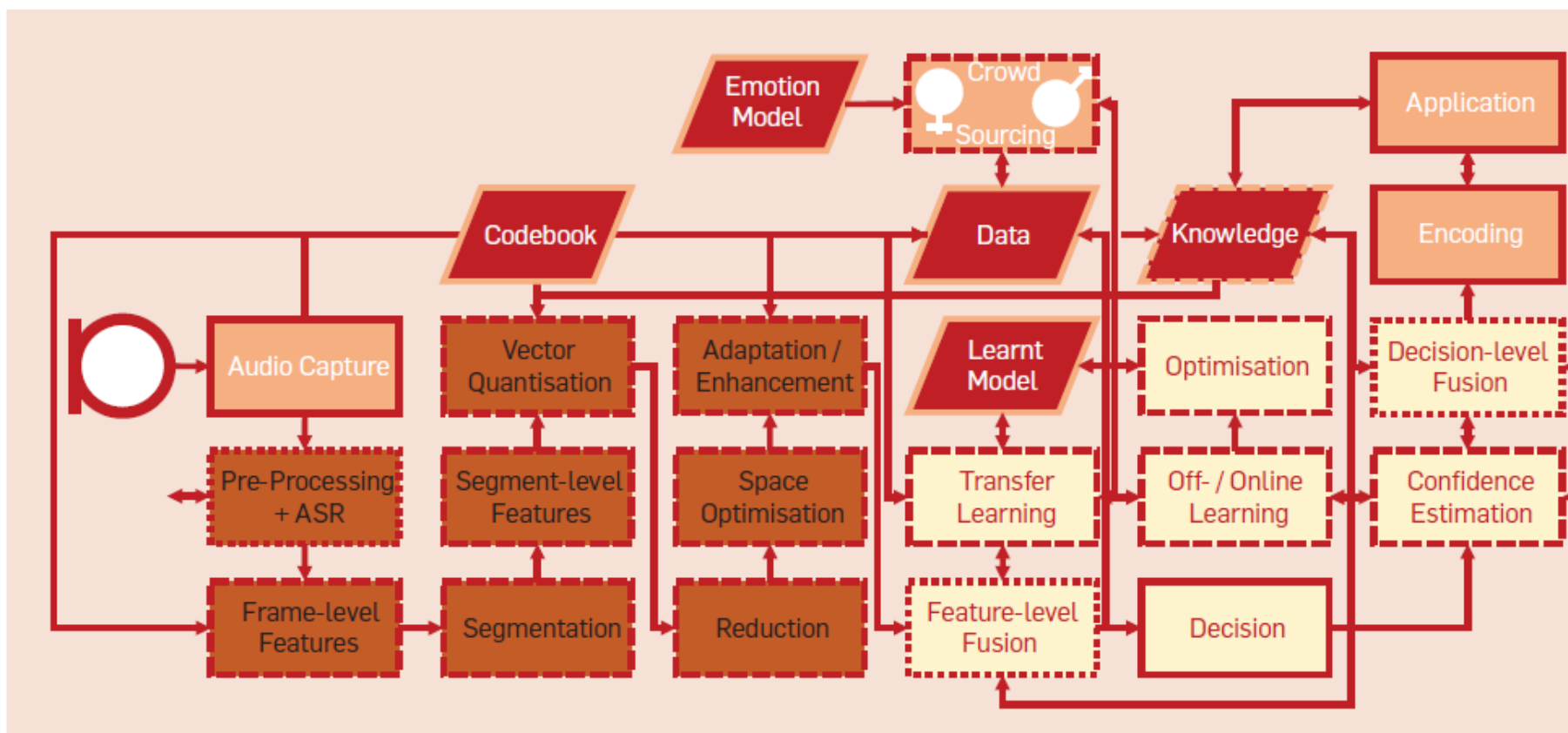
<https://www.audeering.com/research/opensmile/>

- Signal energy
- Loudness
- Mel-/Bark-/Octave-spectra
- MFCC (Mel-frequency cepstral coefficient)
- PLP-CC (perceptual linear prediction cepstral coefficient)
- Pitch
- Voice quality (Jitter, Shimmer)
- Formants
- LPC (linear predictive coding)
- Line Spectral Pairs (LSP)
- Spectral Shape descriptors



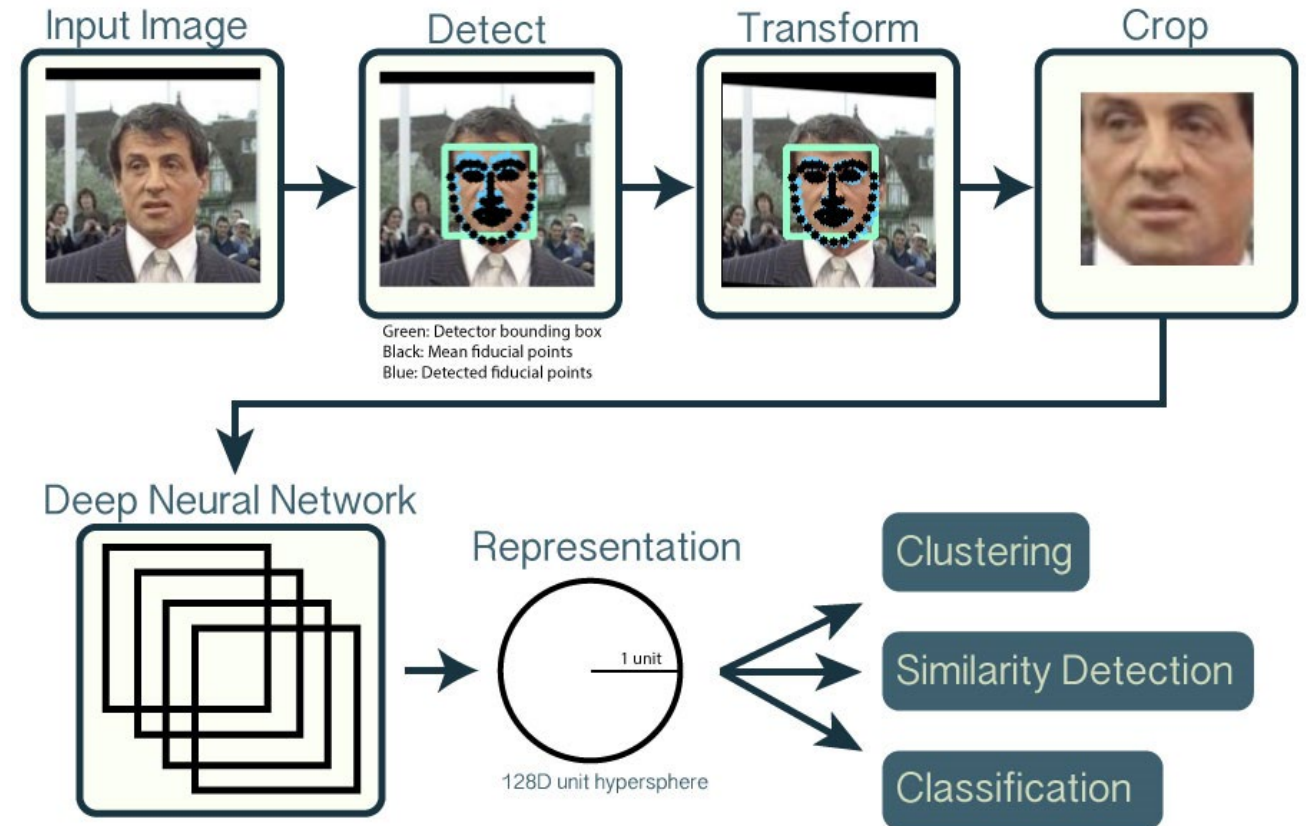
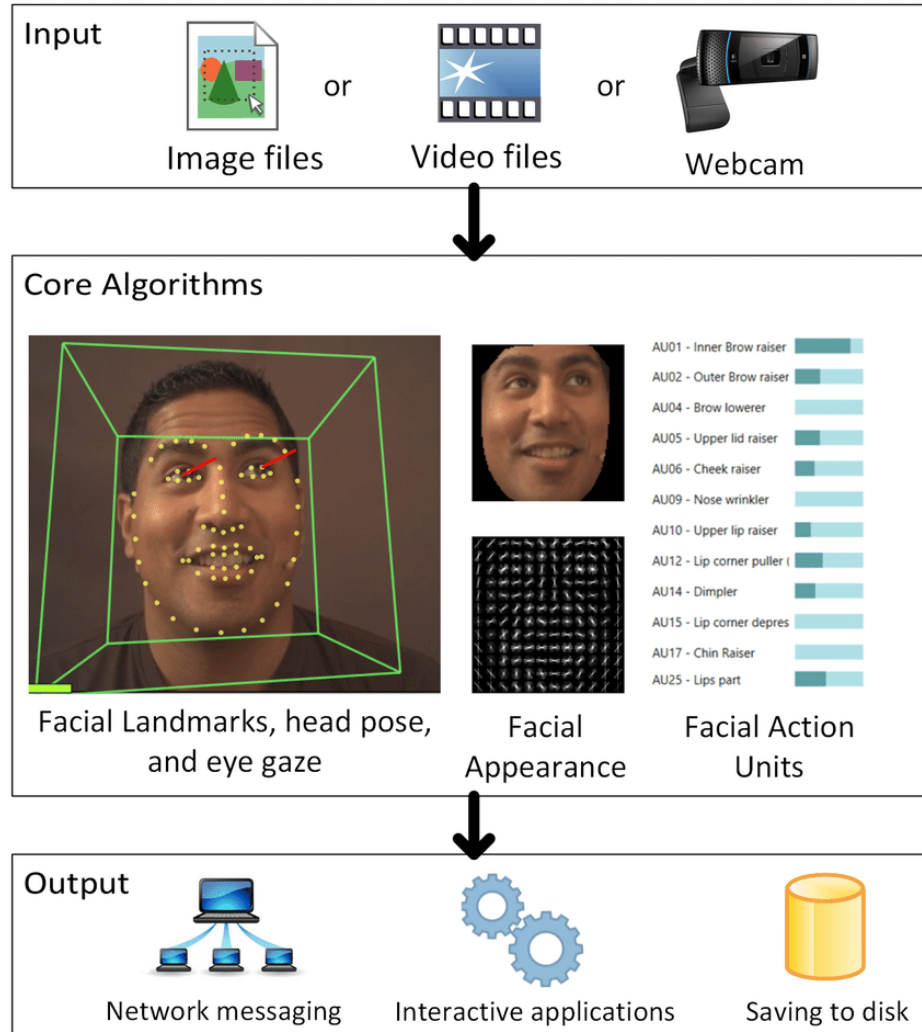
# SER: Challenges (Schuller, 2018)

- Automatic SER requires an appropriate **emotion representation (modelling)**
- Robustness of prediction requires accurate data labelling (**annotation**) considering **states and traits** (i.e. context-awareness)



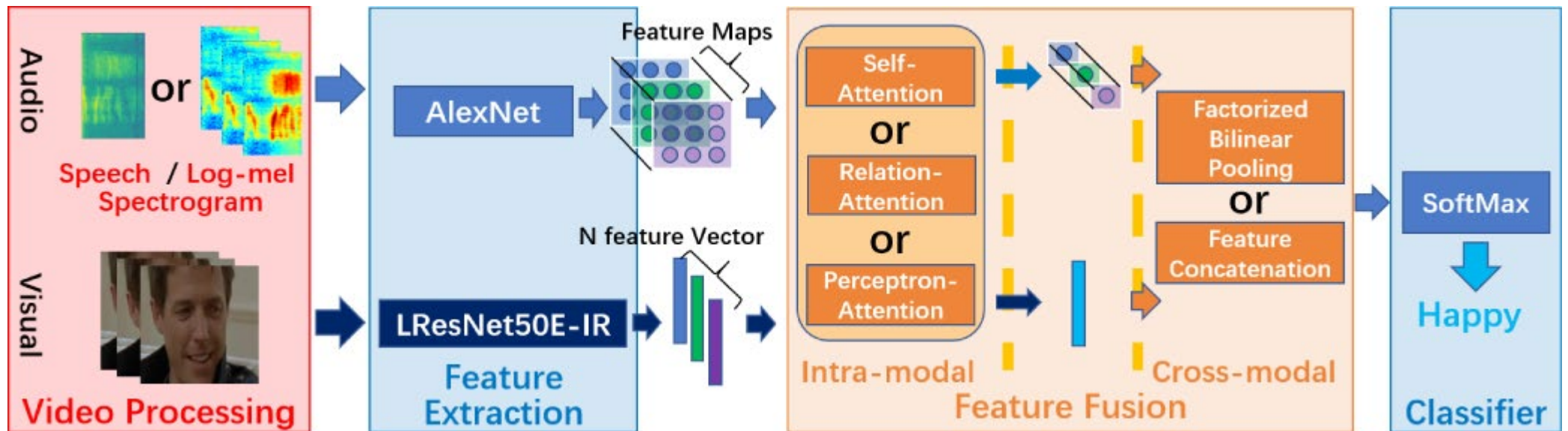
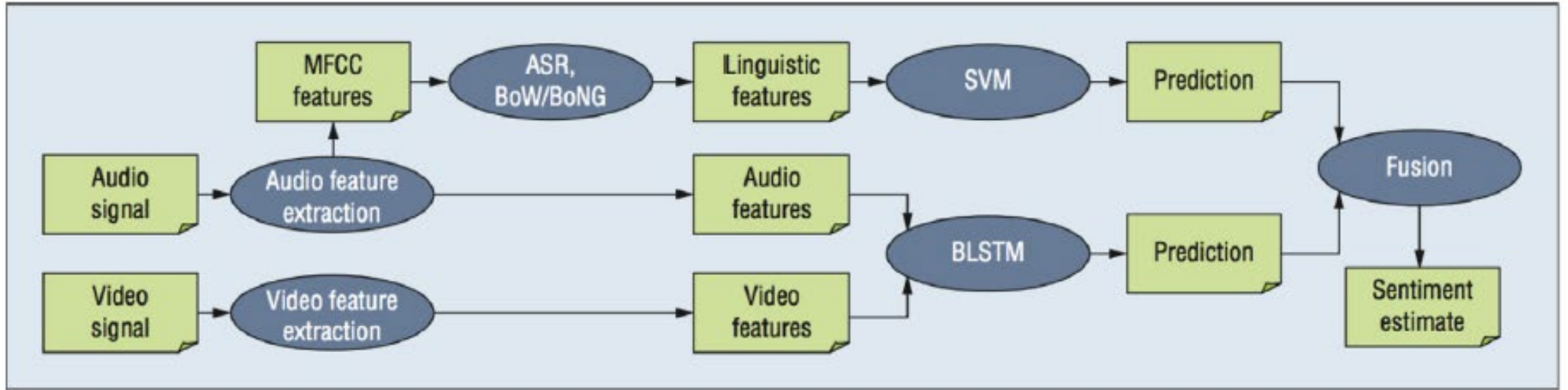


# OpenFace



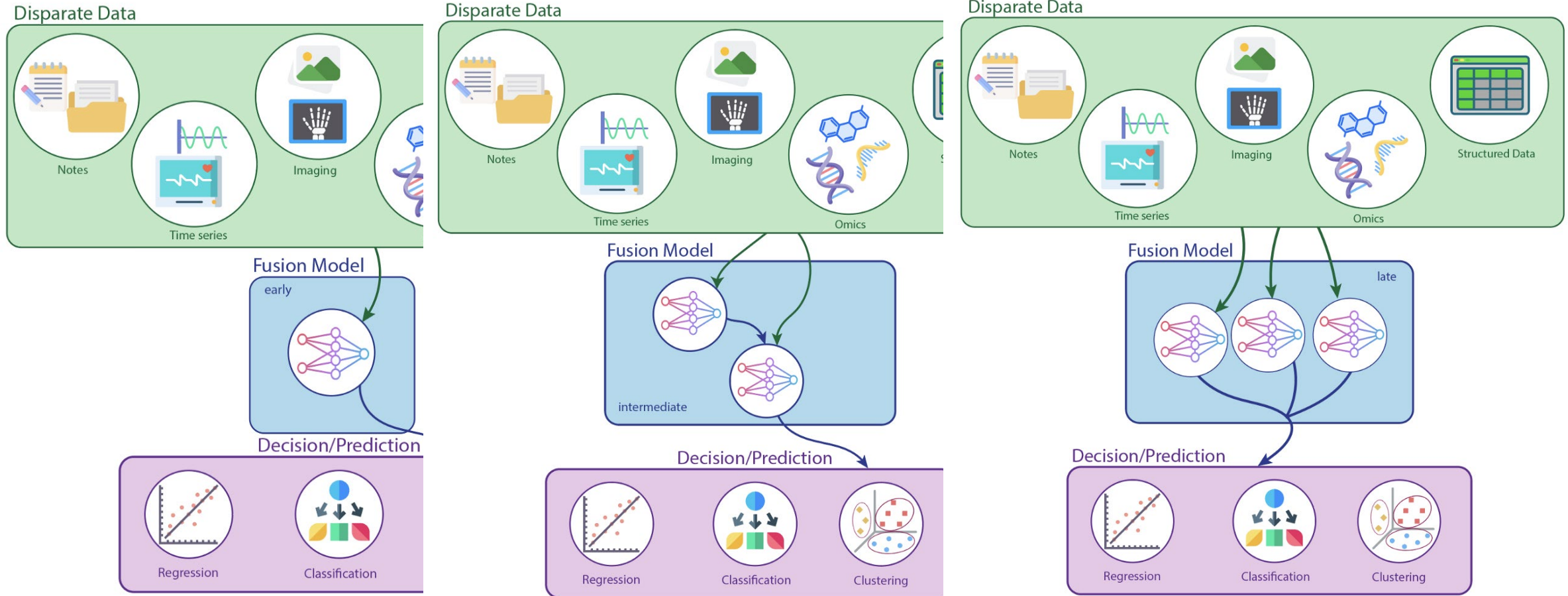


# Data Fusion



# Three Types of Fusion:

## Early (Feature), Intermediate (Joint), Late (Decision)



# Björn Schuller's Invited Talk (2022)

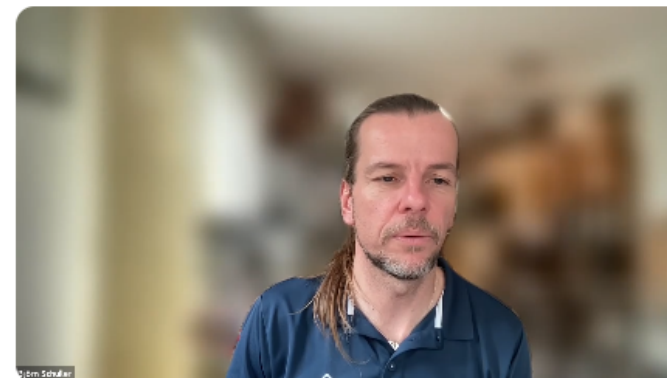
Björn Schuller

Imperial College  
London

SER



- **Intro** Patent in 1970ies
- **Chapter 1** First real papers in mid 1990ies  
Expert Features, mostly acted,  
mostly categories, noise robustness,  
low comparibility
- **Chapter 2** Late Naughties  
Systematic Brute Forcing & standardised  
features (openSMILE), spontanous  
realistic data, challenges (Interspeech '09)
- **Chapter 3** Deep Learning – 2010s  
End-2-End Learning (2016), AutoML (2018),  
Dimensions
- **Chapter 4** 2020ies... Several Companies, Application



Audio Transcript

Chat Messages

Search transcript

...  
interesting. But then, after um that,  
it's really degrading for most of the  
most challenging database on the

# Emotion Corpora/ Databases/ Datasets

Database	Type	Size [hrs]	Speakers
eNTERFACE'05 [23]	Acted	-	42
CREMA-D [10]	Acted	-	91
RAVDESS [19]	Acted	-	24
IEMOCAP [5]	Acted	$\approx 12$	10
MSP-IMPROV [8]	Acted	$\approx 9.5$	12
CreativeIT [25, 26]	Acted	$\approx 8$	16
SEMAINE [24]	Natural	$\approx 75$	150
MAHNOB-HCI [41]	Natural	-	27
RECOLA [35]	Natural	$\approx 3.75$	46
SEWA [18]	Natural	44	398
CMU-MOSEI [45]	Natural	$\approx 65$	1,000
MSP-Face	Natural	$\approx 24.7 (+46)$	302



# CREMA-D (Cao et al. 2014, IEEE Transaction on Affective Computing)

Code	Sentence
DFA	Don't forget a jacket.
IEO	It's eleven o'clock,
IOM	I'm on my way to the meeting.
ITH	I think I have a doctor's appointment.
ITS	I think I've seen this before.
IWL	I would like a new alarm clock.
IWW	I wonder what this is about.
MTI	Maybe tomorrow it will be cold.
TAI	The airplane is almost full.
TIE	That is exactly what happened.
TSI	The surface is slick.
WSI	We'll stop in a couple of minutes.



12 sentences of emotionally neutral content

6 emotions: Anger, Disgust, Fear, Happy, Sad +  
**Neutral**

IEO: 3 intensity levels (low, medium, high) for each  
emotions but NOT neutral:  $3 \times 5 + 1 = 16$   
Each of 11 sentences:  $11 \times 6 \text{ Emotions} = 66$

91 Actors \*  $(16 + 66) = 7462 \rightarrow 7442 \text{ video}$   
Each video split: audio-only, visual-only, mixed

$7442 \times 3$  clips. Each annotated by 10 raters  
 **$223,269 \text{ clips} / \sim 90 \text{ clips} = 2443 \text{ raters}$**

# CREMA-D: Inclusivity and Diversity of Database (Bias in AI)

Actors' Age Distribution

Age	# actors
20-29 YRS	34
30-39 YRS	23
40-49 YRS	16
50-59 YRS	12
60-69 YRS	5
OVER 70 YRS	1

Race/Ethnicity Distribution

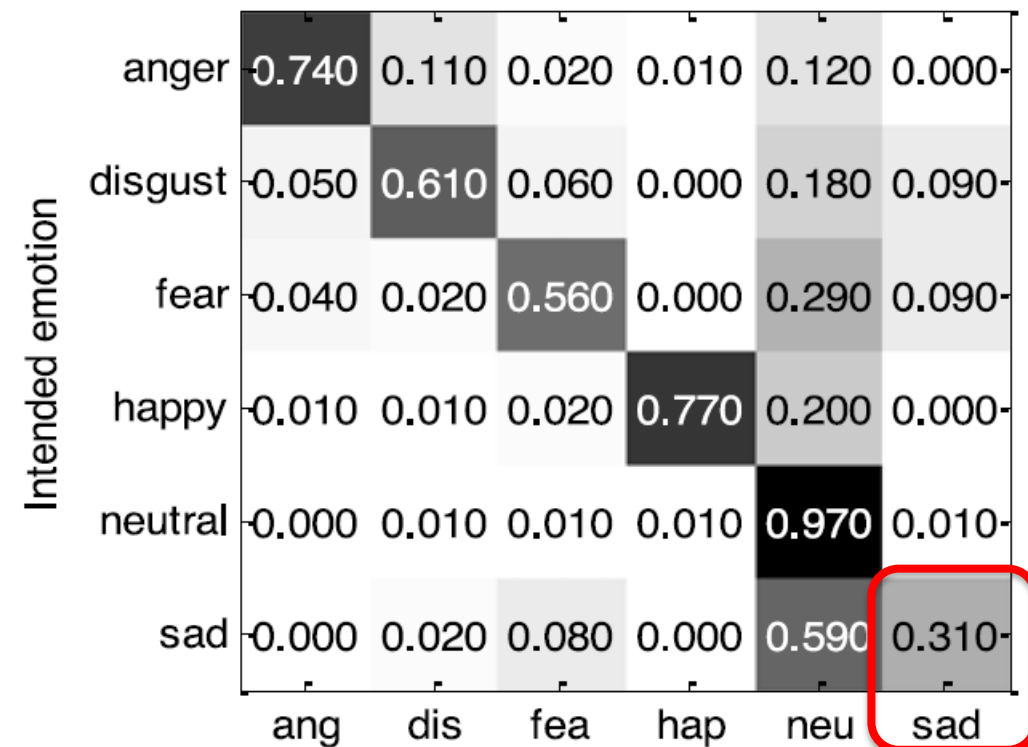
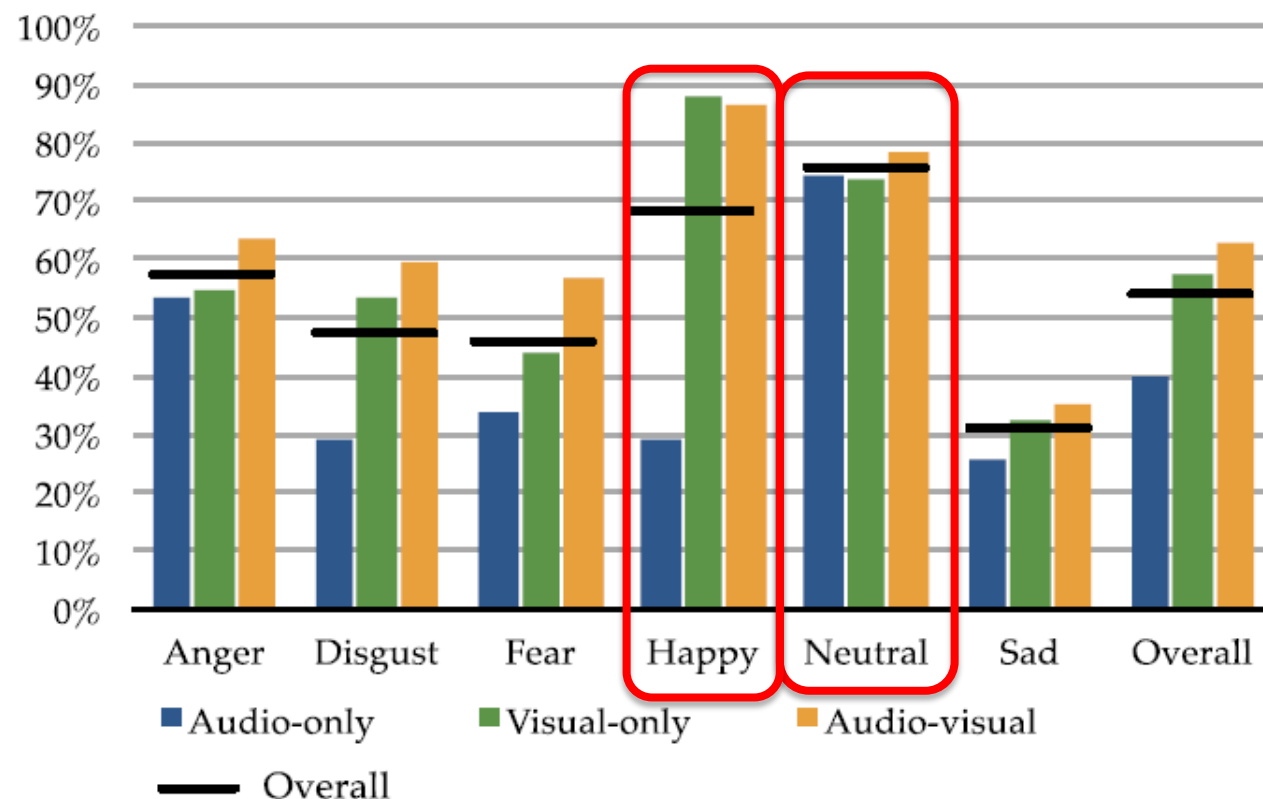
Race/Ethnicity	Raters	Actors
Caucasian	73.60%	58.24%
Hispanic	10.80%	10.99%
African American	8.10%	23.08%
Asian	4.50%	7.69%
Other/No Answer	3.00%	0.00%

**Test your Emotional Intelligence!**  
**Google Form**



# CREMA-D: Emotion Recognition Rates

Recognition Rates



# CMU-MOSEI (Multimodal Opinion Sentiment and Emotion Intensity)

Dataset	# S	# Sp	Mod	Sent	Emo	TL (hh:mm:ss)
CMU-MOSEI	23,453	1,000	{l, v, a}	✓	✓	65:53:36
CMU-MOSI	2,199	98	{l, v, a}	✓	✗	02:36:17
ICT-MMMO	340	200	{l, v, a}	✓	✗	13:58:29
YouTube	300	50	{l, v, a}	✓	✗	00:29:41
MOUD	400	101	{l, v, a}	✓	✗	00:59:00
SST	11,855	—	{l}	✓	✗	—
Cornell	2,000	—	{l}	✓	✗	—
Large Movie	25,000	—	{l}	✓	✗	—
STS	5,513	—	{l}	✓	✗	—
IEMOCAP	10,000	10	{l, v, a}	✗	✓	11:28:12
SAL	23	4	{v, a}	✗	✓	11:00:00
VAM	499	20	{v, a}	✗	✓	12:00:00
VAM-faces	1,867	20	{v}	✗	✓	—
HUMAINE	50	4	{v, a}	✗	✓	04:11:00
RECOLA	46	46	{v, a}	✗	✓	03:50:00
SEWA	538	408	{v, a}	✗	✓	04:39:00
SEMAINE	80	20	{v, a}	✗	✓	06:30:00
AFEW	1,645	330	{v, a}	✗	✓	02:28:03
AM-FED	242	242	{v}	✗	✓	03:20:25
Mimicry	48	48	{v, a}	✗	✓	11:00:00
AFEW-VA	600	240	{v, a}	✗	✓	00:40:00

Total number of sentences	23453
Total number of videos	3228
Total number of distinct speakers	1000
Total number of distinct topics	250
Average number of sentences in a video	7.3
Average length of sentences in seconds	7.28
Total number of words in sentences	447143



# CMU-MOSEI: Rationale & Sources

- Diversity in the training samples
- Variety in the topics
- Diversity in speakers

## Sources:

- Social multimedia: **monologue** videos of opinions
  - language in the form of spoken text
  - visual via perceived gestures and facial expressions
  - acoustic through intonations and prosody
- 5000 videos, 14 experts quality check → 3228 videos
- Automatic check: facial feature extraction confidence
- 57% male vs. 43% female
- Tokenisation: Punctuation marks rather than Stanford CoreNLP tokenizer



# Summary

- Humans are NOT good emotion recognisers
- AI-powered emotion recognition applications (ERA) may (not) be better in terms of accuracy, which in general remains moderate.
- The ground truth of ERA is based on human annotators → paradox?!
- More research on Affective Computing is MUCH needed!

# Suggested Reading

Christy, T., & Kuncheva, L. I. (2014). Technological advancements in affective gaming: A historical survey. *GSTF Journal on Computing (JoC)*, 3(4), 1-10.

Gandhi, A., Adhvaryu, K., Poria, S., Cambria, E., & Hussain, A. (2022). Multimodal sentiment analysis: A systematic review of history, datasets, multimodal fusion methods, applications, challenges and future directions. *Information Fusion*.

Picard, R. W. (2000). *Affective computing*. MIT press.

Poria, S., Cambria, E., Bajpai, R., & Hussain, A. (2017). A review of affective computing: From unimodal analysis to multimodal fusion. *Information Fusion*, 37, 98-125.

Schuller, B. W. (2018). Speech emotion recognition: Two decades in a nutshell, benchmarks, and ongoing trends. *Communications of the ACM*, 61(5), 90-99.

Tomar, P. S., Mathur, K., & Suman, U. (2022). Unimodal approaches for emotion recognition: A systematic review. *Cognitive Systems Research*.

Zhao, S., Yao, X., Yang, J., Jia, G., Ding, G., Chua, T. S., ... & Keutzer, K. (2021). Affective image content analysis: Two decades review and new perspectives. *IEEE Transactions on Pattern Analysis and Machine Intelligence*.