SOCIAL SIGNAL PROCESSING

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 social signals are observable behaviors that people display during social interactions

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- social signals from an individual produces changes in others (like creating a belief about the person, generating an appropriate social response, perform any actions)
- the changes are not random, they follow *principles and laws* (in particular *social norms*)

WHY DO WE NEED SSP?

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3 MAIN PROBLEMS

- *Modeling:* identification of the principles and laws
- Analysis: automatic detection and interpretation
- Synthesis: automatic generation of artificial social signals

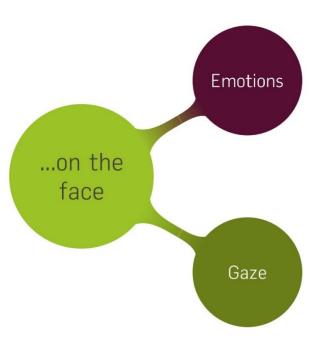
IS IT HARD?

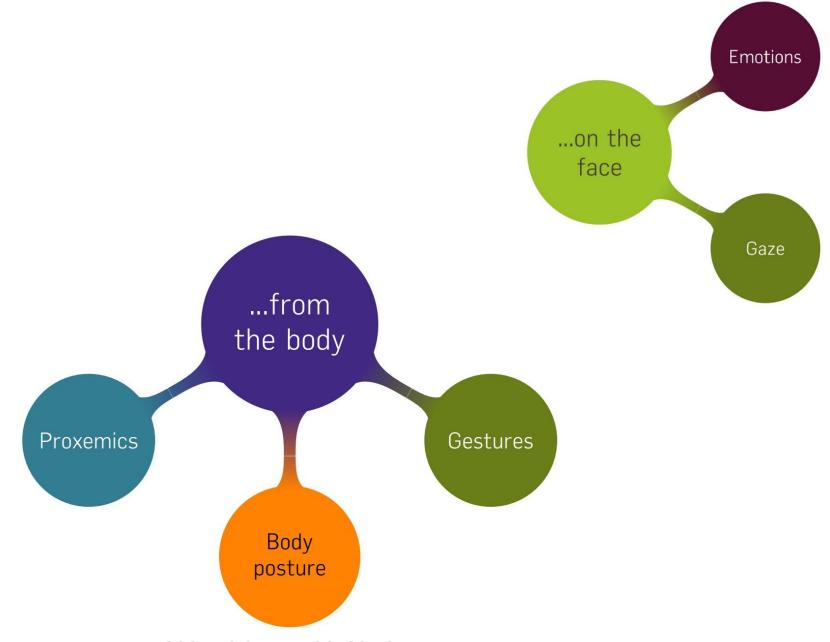
- as with most human activities that seems easy to us, social signal processing is tremendously hard
- often broken down in smaller, sometimes more manageable tasks:

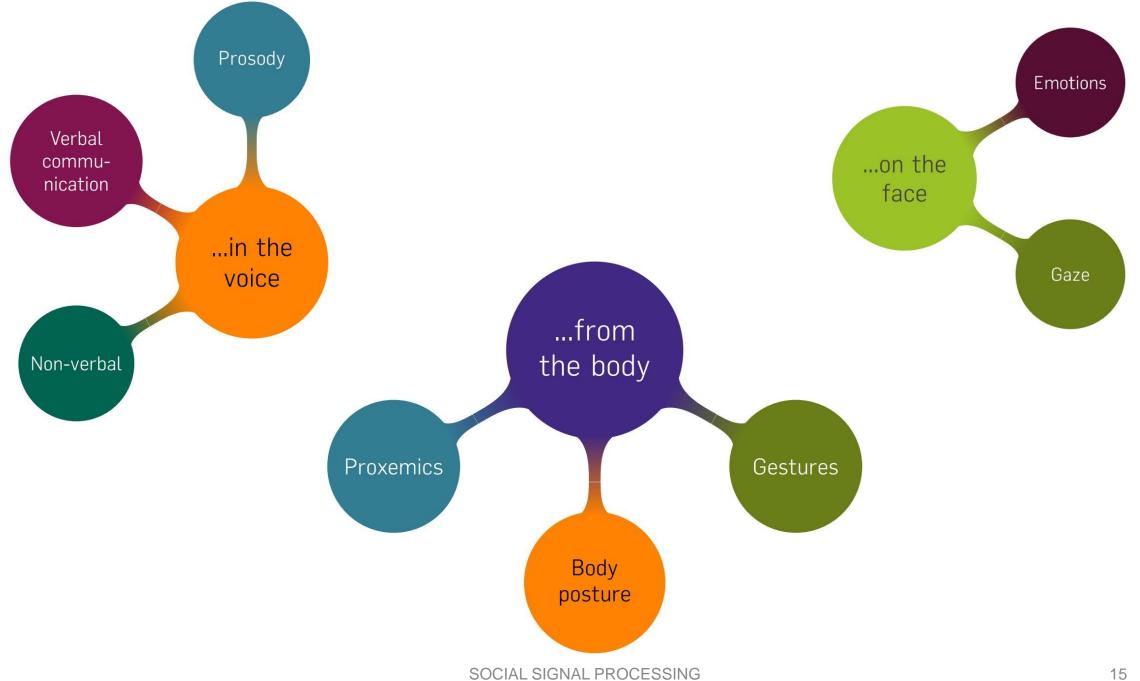
IS IT HARD?

- as with most human activities that seems easy to us, social signal processing is tremendously hard
- often broken down in smaller, sometimes more manageable tasks:
 - people detection
 - face detection
 - face recognition
 - gesture recognition
 - gaze detection
 - facial expression reading (wink, blink, talking, ...)
 - detection of social signals from verbal communication
 - emotion recognition (from faces, movement, speech, ...)

• ...



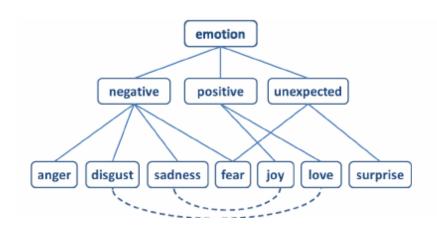




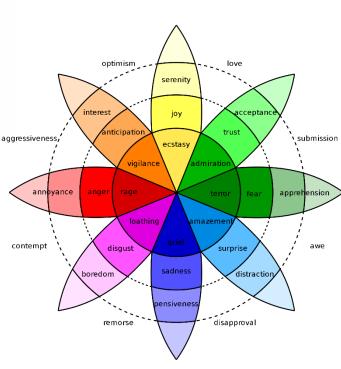
EMOTION RECOGNITION

- Emotions are connected to
 - feeling
 - mood
 - affect
- Components of emotions
 - cognitive
 - physiological
 - behavioral

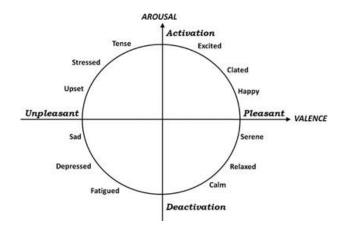
EMOTION MODELS



discrete emotion models



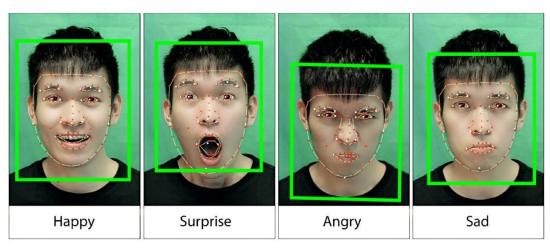
hybrid emotion models



dimensional emotion models

FACIAL EMOTION RECOGNITION

- 1) face detection
- 2) landmark identification
- 3) facial expression classification
- 4) mapping expressions to emotions



EMOTION RECOGNITION SERVICES

- Affectiva (anger, contempt, disgust, fear, joy, sadness, surprise)
- Amazon Rekognition (anger, calmness, confusion, disgust, happiness, sadness, surprise)
- Face++ (anger, disgust, fear, happiness, neutral, sadness, surprise)
- Google Vision (anger, joy, sorrow, surprise)
- Kairos (anger, disgust, fear, joy, sadness, surprise)
- Microsoft Face (anger, contempt, disgust, fear, happiness, neutral, sadness, surprise)
- Sightcorp F.A.C.E. (anger, disgust, fear, happiness, sadness, surprise)
- Sighthound Cloud (anger, disgust, fear, happiness, neutral, sadness, surprise)

IMAGE DATASET

- Karolinska Directed Emotional Faces
 - 973 frontal images with 2 sets of 70 individuals expressing 7 emotions



- Radboud Faces Database
 - 1,608 frontal images with 3 gaze directions from 67 models expressing 8 emotions



EVALUATION RESULTS

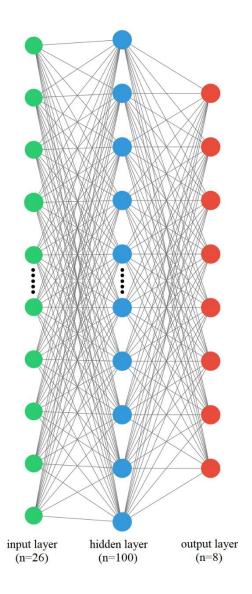
API	KDEF (%)	RaFD <i>(%)</i>	Overall <i>(%)</i>	
Affectiva	54.57	64.68	60.87	
F.A.C.E.	63.21	61.32	62.03	
Kairos	45.74	26.99	34.06	
Rekognition	52.62	39.74	44.60	
Face++	77.08	71.33	73.50	
Google	43.47	36.63	39.21	
MS Face	75.33	76.24	75.90	
Sighthound	62.18	72.33	68.50	

VOTING SYSTEM

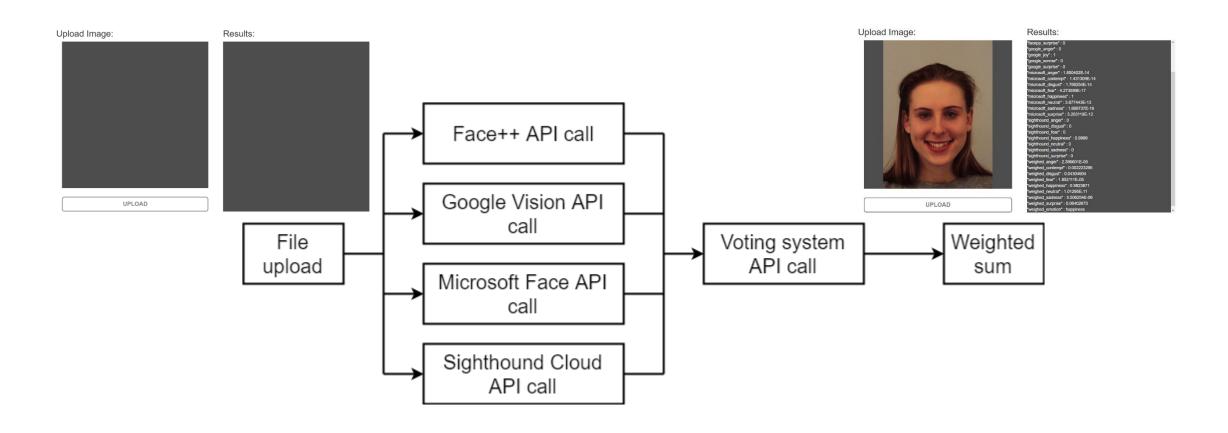
- Input is the result from multiple emotion recognition services
- Neural network computes weighted average of confidence values
- Output are confidence values for each emotion category

VOTING SYSTEM

- Online service created in MS Machine Learning Studio
 - multiclass neural network
 - 100 hidden nodes
 - learning rates: 0.01, 0.02, 0.04
 - number of iterations: 164-500, number of points: 3
 - initial learning weight: 0.1
 - momentum: 0
 - min-max normalizer
- 75% training set, 25% testing set (non-stratified sampling)



WORKFLOW



WORKFLOW

Upload Image:



UPLOAD

Results:

```
"facepp_surprise" : 0
"google_anger" : 0
"google_joy" : 1
"google_sorrow" : 0
"google_surprise" : 0
"microsoft_anger" : 1.850402E-14
"microsoft_contempt": 1.431309E-14
"microsoft disgust": 1.768254E-14
"microsoft_fear" : 4.273599E-17
"microsoft_happiness" : 1
"microsoft_neutral" : 3.877443E-13
"microsoft_sadness" : 1.899737E-16
"microsoft surprise": 3.203119E-12
"sighthound_anger" : 0
"sighthound_disgust": 0
"sighthound fear" : 0
"sighthound_happiness" : 0.9999
"sighthound_neutral" : 0
"sighthound_sadness" : 0
"sighthound_surprise" : 0
"weighed_anger" : 2.396601E-05
"weighed_contempt": 0.002223295
"weighed disgust" : 0.04304604
"weighed_fear" : 1.852111E-05
"weighed_happiness" : 0.9823871
"weighed neutral" : 1.01295E-11
"weighed_sadness" : 5.506254E-06
"weighed_surprise" : 0.06402673
"weighed_emotion" : happiness
```

VOTING SYSTEM ACCURACY

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Voting system	90.75	97.08	94.69	

VOTING SYSTEM ACCURACY

	Actual class							Precision		
		Α	С	D	F	Н	N	Sa	Su	(%)
Predicted class	Α	303	0	3	3	0	0	6	0	96.19
	С	3	188	0	0	0	0	1	0	97.92
	D	7	0	327	5	0	0	3	0	95.61
	F	4	0	2	298	0	0	7	6	94.01
	Н	0	0	0	1	340	0	0	0	99.71
	N	10	13	0	1	0	340	7	2	91.15
	Sa	13	0	8	12	0	0	316	0	90.54
	Su	0	0	0	20	0	0	0	332	94.32
	ecall (%)	89.12	93.53	96.18	87.65	100	100	92.94	97.65	

HOW TO CLASSIFY SOCIAL SIGNALS?

- raw signals will in most cases require pre-processing to extract features
- the raw social signal (audio or video) requires pre-processing to extract between 10 and over 1000 features
 - a raw signal contains too much data, and cannot be fed to the classifier immediately
 - pre-processing extracts feature data which is relevant for the information which we are after (pitch, volume/energy, duration, ...)
 - these features then form the input for the classifier

EXAMPLE: RECOGNIZING GENDER FROM SPEECH

- can we automatically recognize someone's gender from speech?
- 3168 recorded voice samples, collected from male and female speakers







 the voice samples are pre-processed by acoustic analysis and 20 features are extracted

EXAMPLE: RECOGNIZING GENDER FROM SPEECH

- performance
 - kNN (k=7): 97,8% classified correctly
 - SVM: 97,5% classified correctly
- recognizing gender from speech is easy and robust
- all classification algorithms can deal with this problem