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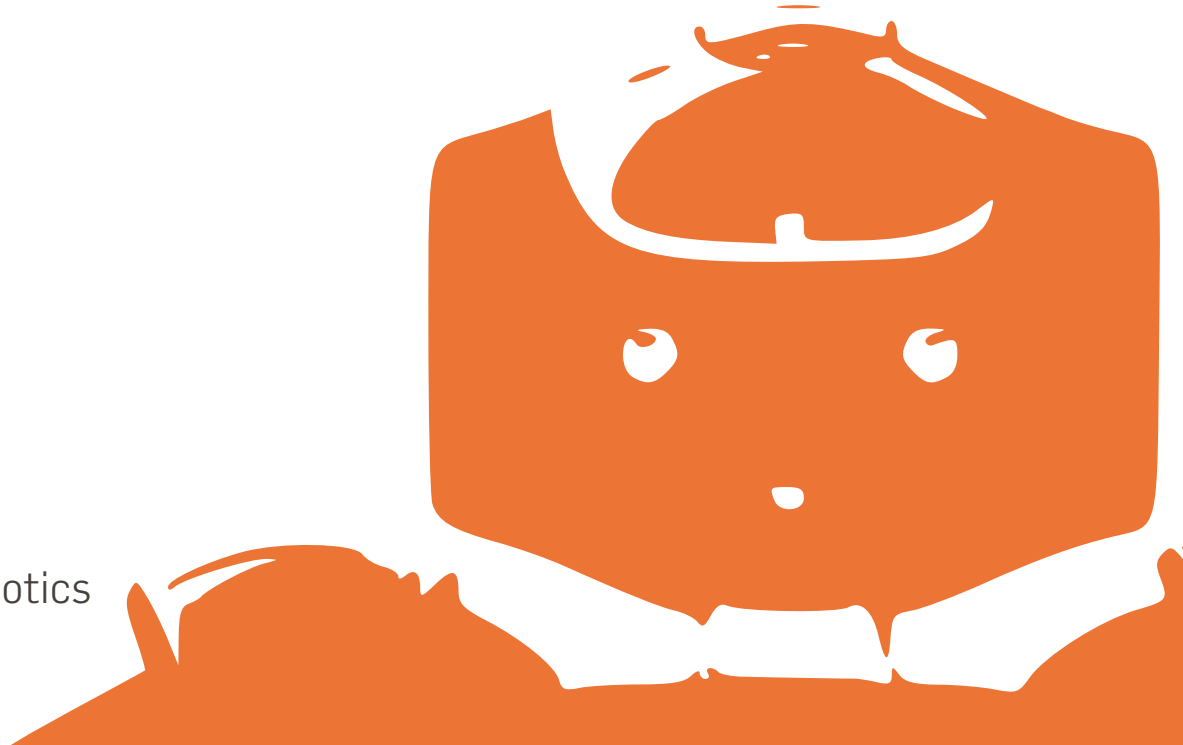
You can download the sources of this presentation here:

github.com/severin-lemaignan/lecture-hri-emotions

ROBOTICS WITH PLYMOUTH UNIVERSITY

Automatic Processing of Emotions

AINT512



Séverin Lemaignan

Centre for Neural Systems and Robotics
Plymouth University

THIS WEEK

This week, we are looking at the automatic processing of emotions:

- models of emotions
- action units
- emotion classification
- emotion generation

MODELS OF EMOTION

PAUL EKMAN AND BASIC EMOTIONS

Paul Ekman, a psychologist, found that when shown facial expressions people across the world all recognised six **basic emotions**.

Source: emotionresearcher.com

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Anger, disgust, fear, happiness, sadness and surprise.

Some other emotion are less universally recognised, e.g. contempt.

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Anger, disgust, fear, happiness, sadness and surprise.

Some other emotion are less universally recognised, e.g. contempt.

In 1990 Ekman extended his list of basic emotion to include other emotions: *Amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame*

EMOTION AND MACHINES

Computer and robots should be able to read emotions

- This is crucial in understanding the social world around the robot and responding appropriately.
- This has a large number of applications, e.g. sentiment analysis to predict what the stock market will do based on emotional content of tweets.

EMOTION AND MACHINES

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Should machines express emotions?

- Due to the **media equation** we cannot help attributing emotions to robots and other technology.
- As we expect machines to express emotions, it would be good as a robot designer to take control of the unconscious attribution of emotion by the user.
- + cf Serge's slides

EMOTION AND MACHINES

Why would representing emotion be useful?

- You can model the emotional state of the user and respond appropriately. For example, the user is bored, if the robot knows this it can do something to entertain the user.
- You can use a model to let the robot express emotions. For example, this can be used for “emotion contagion”. If the robot is happy, this will influence how the user feels.

HOW TO REPRESENT EMOTIONS?

Several approaches (or **models**):

ON/OFF approach to basic emotions:

- Anger : ON/OFF
- Disgust : ON/OFF
- Fear : ON/OFF
- Happiness : ON/OFF
- Sadness : ON/OFF
- Surprise : ON/OFF

Why is this a poor approach to representing emotion?

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- Surprise : ON/OFF

Why is this a poor approach to representing emotion?

$\Rightarrow$ no representation of gradual emotions; all is just “on” or “off”

HOW TO REPRESENT EMOTIONS?

Several approaches (or **models**):

Gradual representation of emotion would be better:

- Anger : $[0; 1]$
- Disgust : $[0; 1]$
- Fear : $[0; 1]$
- Happiness : $[0; 1]$
- Sadness : $[0; 1]$
- Surprise : $[0; 1]$

What is the problem with this representation?

HOW TO REPRESENT EMOTIONS?

Several approaches (or **models**):

Gradual representation of emotion would be better:

- Anger : $[0; 1]$
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- Fear : $[0; 1]$
- Happiness : $[0; 1]$
- Sadness : $[0; 1]$
- Surprise : $[0; 1]$

What is the problem with this representation?

$\Rightarrow$ can lead to contradicting emotion representation, for example Happiness = 1 and Sadness = 1.

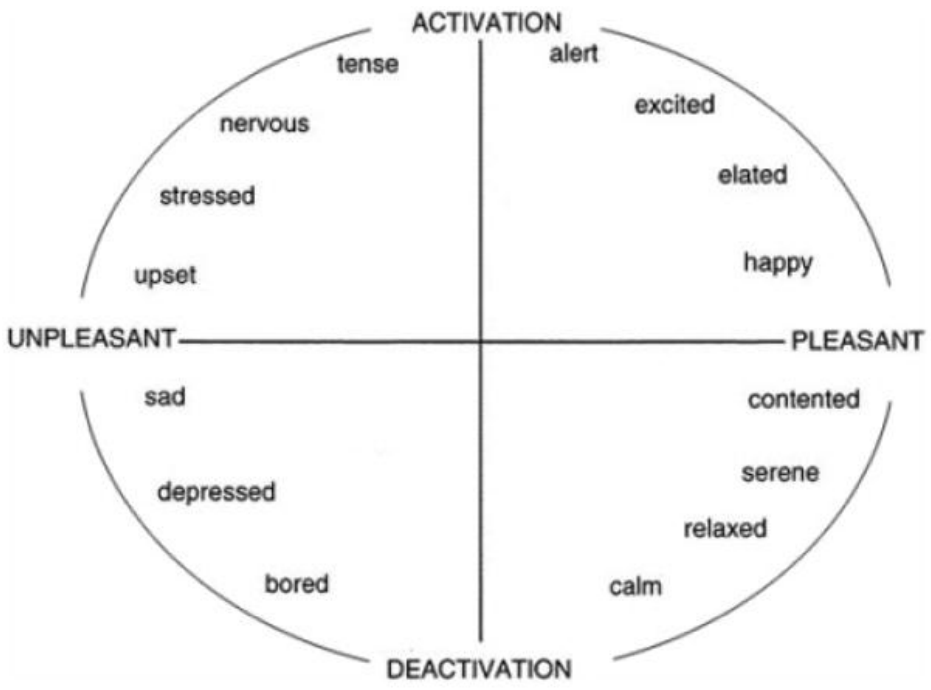
HOW TO REPRESENT EMOTIONS?

$\Rightarrow$ continuous representations of emotions in space

CIRCUMPLEX MODEL

Two-dimensional space (**arousal** and **valence** on x and y dimensions)

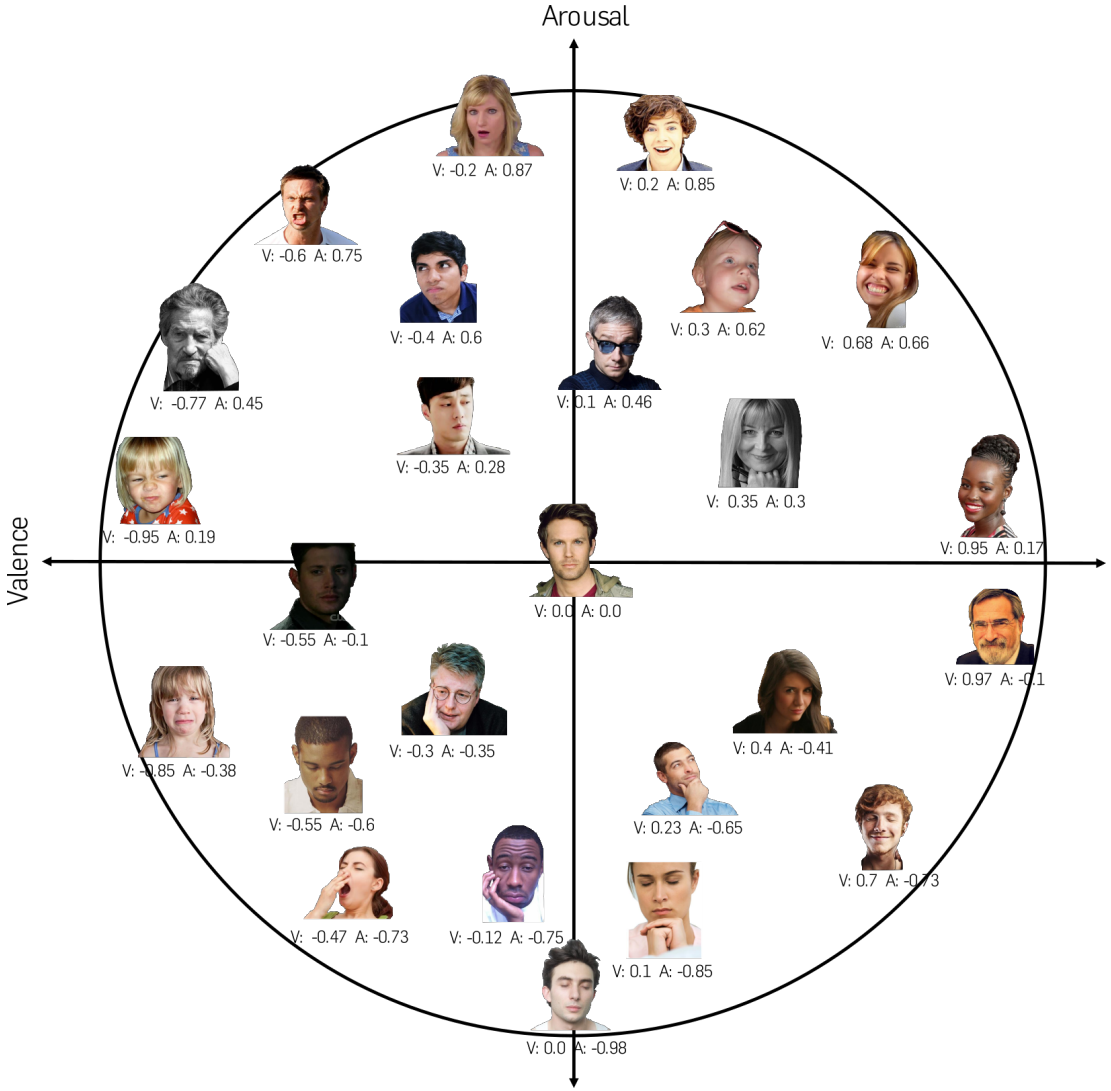
- emotions are noted on circumference of the circle.
- middle of circle (0,0) is **neutral**
- the further from the centre, the stronger the emotion.



Source: Posner et al., 2005

[Russell J. **A circumplex model of affect** 1980]

CIRCUMPLEX MODEL



[Mollahosseini et al. **Affectnet: A database for facial expression, valence, and arousal computing in the wild** 2017]

P-A-D MODEL

By Albert Mehrabian and James A. Russell (1974)

Three-dimensional representation of emotion.

- **Pleasure, Arousal and Dominance**.
- Most used model in robotics and Human-Machine Interaction

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Arousal: intensity of an emotion. Anger and rage are unpleasant emotions, but rage has a higher intensity or a higher arousal state. However boredom, which is also an unpleasant state, has a low arousal value.

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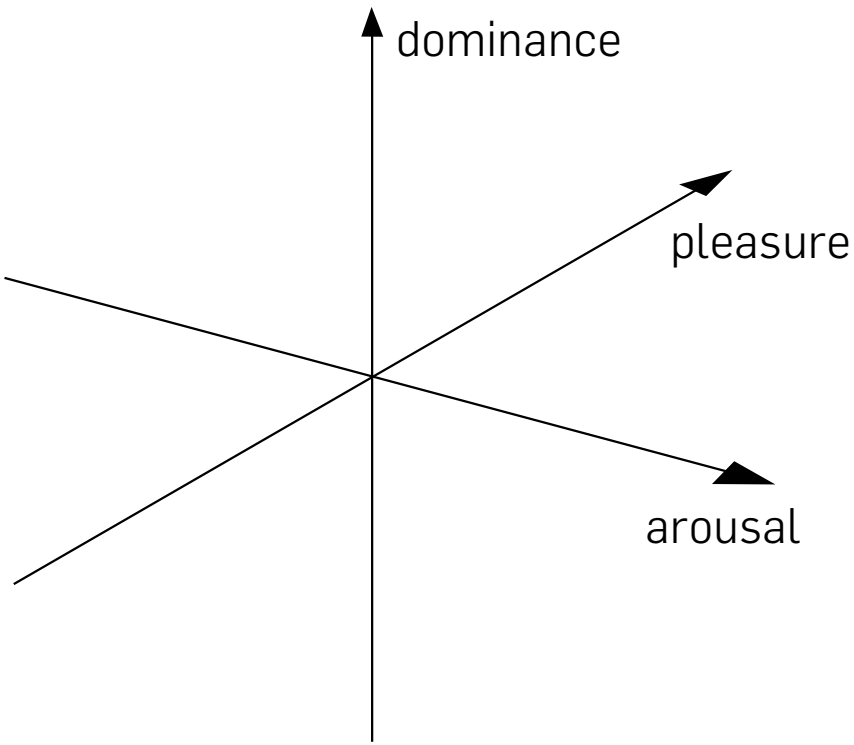
Arousal: intensity of an emotion. Anger and rage are unpleasant emotions, but rage has a higher intensity or a higher arousal state. However boredom, which is also an unpleasant state, has a low arousal value.

Dominance: controlling and dominant nature of the emotion. For instance while both fear and anger are unpleasant emotions, anger is a dominant emotion, while fear is a submissive emotion.

PAD MODEL



Emotion	Pleasure	Arousal	Dominance
Admiration	.49 (.27)	-.19 (.42)	.05 (.50)
Gloating	.08 (.47)	.11 (.45)	.44 (.50)
Gratification	.39 (.43)	-.18 (.46)	.41 (.43)
Gratitude	.69 (.24)	-.09 (.58)	.05 (.55)
Happy for	.75 (.21)	.17 (.51)	.37 (.49)
Hope	.22 (.33)	.28 (.52)	-.23 (.52)
Joy	.82 (.18)	.43 (.54)	.55 (.43)
Love	.80 (.22)	.14 (.58)	.30 (.52)
Pride	.72 (.25)	.20 (.48)	.57 (.43)
Relief	.73 (.21)	-.24 (.59)	.06 (.53)
Satisfaction	.65 (.26)	-.42 (.47)	.35 (.47)
Anger	-.62 (.23)	.59 (.38)	.23 (.58)
Disappointment	-.64 (.22)	-.17 (.54)	-.41 (.49)
Distress	-.75 (.16)	-.31 (.52)	-.47 (.45)
Fear	-.74 (.19)	.47 (.56)	-.62 (.43)
Fears confirmed	-.74 (.22)	.42 (.59)	-.52 (.48)
Hate	-.52 (.26)	.00 (.45)	.28 (.45)
Pity	-.27 (.29)	-.24 (.37)	.24 (.51)
Remorse	-.42 (.33)	-.01 (.54)	-.35 (.54)
Reproach	-.41 (.28)	.47 (.38)	.50 (.45)
Resentment	-.52 (.26)	.00 (.51)	.03 (.49)
Shame	-.66 (.22)	.05 (.55)	-.63 (.46)

[H. Hoffmann, A Scheck, T. Schuster, H. Kessler **Mapping discrete emotions into the dimensional space: An empirical approach** 2012]

Now, how to map automatically a face onto one of these models?

ACTION UNITS

FACIAL ACTION CODING SYSTEM

The **Facial Action Coding System** (FACS) aim is to **taxonomize human facial movements** by their appearance on the face.

Facial movements are encoded as **action units**.

Wikipedia has a large list of action units.

[Ekman, **The Facial Action Coding System**, 1977]

ACTION UNITS

AU	Description	Facial muscle	Example image
1	Inner Brow Raiser	*Frontalis, pars medialis*	
2	Outer Brow Raiser	*Frontalis, pars lateralis*	
4	Brow Lowerer	*Corrugator supercilii, Depressor supercilii*	
5	Upper Lid Raiser	*Levator palpebrae superioris*	
6	Cheek Raiser	*Orbicularis oculi, pars orbitalis*	

[*Source: Automated Face Analysis group, CMU*]

ACTION UNITS

AU	Description	Facial muscle	Example image
7	Lid Tightener	*Orbicularis oculi, pars palpebralis*	
9	Nose Wrinkler	*Levator labii superioris alaquae nasi*	
10	Upper Lip Raiser	*Levator labii superioris*	
11	Nasolabial Deepener	*Zygomaticus minor*	
12	Lip Corner Puller	*Zygomaticus major*	

[*Source: Automated Face Analysis group, CMU*]

ACTION UNITS

AU	Description	Facial muscle	Example image
13	Cheek Puffer	*Levator anguli oris (a.k.a. Caninus)*	
14	Dimpler	*Buccinator*	
15	Lip Corner Depressor	*Depressor anguli oris (a.k.a. Triangularis)*	
16	Lower Lip Depressor	*Depressor labii inferioris*	

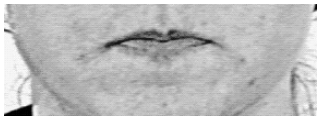
[*Source: Automated Face Analysis group, CMU*]

ACTION UNITS

AU	Description	Facial muscle	Example image
17	Chin Raiser	*Mentalis*	
18	Lip Puckerer	*Incisivii labii superioris and Incisivii labii inferioris*	
20	Lip stretcher	*Risorius w/ platysma*	
22	Lip Funneler	*Orbicularis oris*	
23	Lip Tightener	*Orbicularis oris*	

[*Source: Automated Face Analysis group, CMU*]

ACTION UNITS

AU	Description	Facial muscle	Example image
24	Lip Pressor	*Orbicularis oris*	
25	Lips part	*Depressor labii inferioris or relaxation of Mentalis, or Orbicularis oris*	
26	Jaw Drop	*Masseter, relaxed Temporalis and internal Pterygoid*	
27	Mouth Stretch	*Pterygoids, Digastric*	

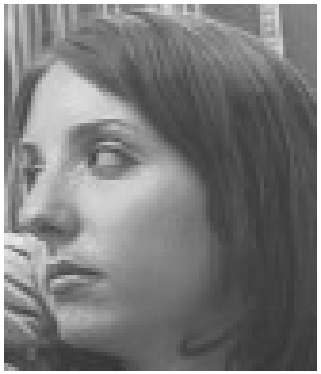
[*Source: Automated Face Analysis group, CMU*]

ACTION UNITS

AU	Description	Facial muscle	Example image
28	Lip Suck	*Orbicularis oris*	
41	Lid droop	*Relaxation of Levator palpebrae superioris*	
42	Slit	*Orbicularis oculi*	
43	Eyes Closed	*Relaxation of Levator palpebrae superioris; Orbicularis oculi, pars palpebralis*	
44	Squint	*Orbicularis oculi, pars palpebralis*	

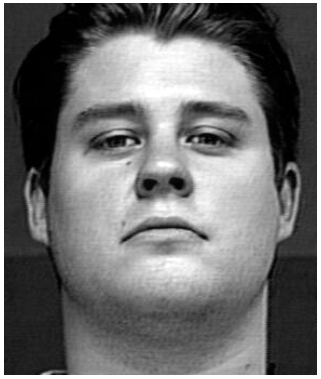
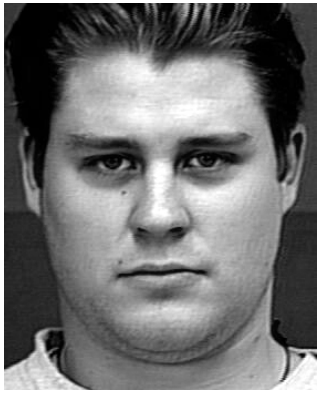
[*Source: Automated Face Analysis group, CMU*]

ACTION UNITS

AU	Description	Facial muscle	Example image
45	Blink	*Levator palpebrae superioris; Orbicularis oculi, pars palpebralis*	
46	Wink	*Levator palpebrae superioris; Orbicularis oculi, pars palpebralis*	
51	Head turn left		
52	Head turn right		

[*Source: Automated Face Analysis group, CMU*]

ACTION UNITS

AU	Description	Facial muscle	Example image
53	Head up		
54	Head down		

[*Source: Automated Face Analysis group, CMU*]

ACTION UNITS

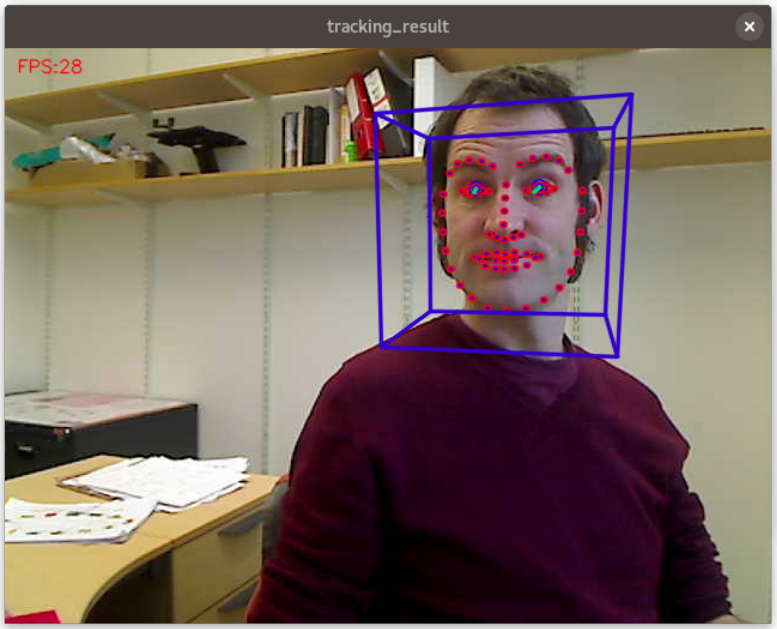
AU	Description	Facial muscle	Example image
61	Eyes turn left		
62	Eyes turn right		
63	Eyes up		
64	Eyes down		

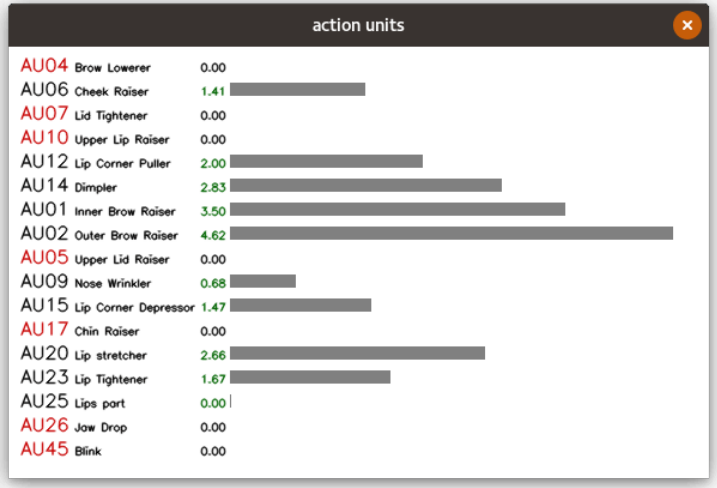
[*Source: Automated Face Analysis group, CMU*]

OPENFACE ACTION UNITS

OpenFace is an open-source library that recognises 17 action units.

github.com/TadasBaltrusaitis/OpenFace





(not to be confused with this other CMU OpenFace)

OPENFACE 17 ACTION UNITS

AU	Description	Example image
1	Inner Brow Raiser	
2	Outer Brow Raiser	
4	Brow Lowerer	
5	Upper Lid Raiser	
6	Cheek Raiser	

AU	Description	Example image
7	Lid Tightener	
9	Nose Wrinkler	
10	Upper Lip Raiser	
12	Lip Corner Puller	

OPENFACE 17 ACTION UNITS

AU	Description	Example image
15	Lip Corner Depressor	
17	Chin Raiser	
20	Lip stretcher	
23	Lip Tightener	

AU	Description	Example image
14	Dimpler	
25	Lips part	
26	Jaw Drop	
45	Blink	

LET'S BUILD OUR OWN EMOTION CLASSIFIER FROM SCRATCH

SHOPPING LIST

What do we need?

SHOPPING LIST

What do we need?

- a dataset of labelled faces

SHOPPING LIST

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- a dataset of labelled faces
- some pre-processing faces to normalise them

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What do we need?

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- a classifier

Google

human face happiness

All | Images | Videos | Shopping | News | More | Settings | Tools | View saved | SafeSearch

smile | cartoon | male | boy | grandpa | black and white | real | happiness | joy | sad | gratitude | beauty | emotional | smiley | hawaiian

Disgust
wered brow
rrowed eyes
arrowed nostrils
Closed mouth

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	emotion	AU01	AU02	AU04	AU05	AU06	AU07	AU09	AU10	AU12	AU14	AU15	AU17	AU20	AU23	AU25	AU26	AU45	face
2	0	1.07	0	0.05	2.95	0	0	0	0	0	0	0	0	0	0	1.36	0	0	fear/processed/aligned/fear-041_aligned.bmp
3	0	1.57	0	0.63	0	1.02	1.39	0	0.45	0	0	0	0	0	0	0.45	1.35	0	fear/processed/aligned/fear-053_aligned.bmp
4	0	1.38	0	1.17	0	1.36	0	1.85	1.21	0	0	0	0	0.05	0	0	0	0	fear/processed/aligned/fear-035_aligned.bmp
5	0	0	0.97	0.87	2.48	0	0	0	0	0	0	0.31	0	0.71	0.32	1.41	0.24	0	fear/processed/aligned/fear-018_aligned.bmp
6	0	3.79	2.52	0	4.61	0	0	0	0	0	0	0	0	0	0	1.53	0.67	0	fear/processed/aligned/fear-043_aligned.bmp
7	0	2.55	0	0	1.2	1.58	0	0	1.27	0.64	0	0.93	1.14	0	0	0	0	0	fear/processed/aligned/fear-044_aligned.bmp
8	0	1.93	2.72	0	3.86	0	0	0	0	0	0	1.38	0.67	1.23	0	0.15	0.83	0	fear/processed/aligned/fear-006_aligned.bmp
75	1	0	1	0	0	1.79	3.94	0	2.96	2.62	0	0.79	0	0	0.36	0	0	1.08	happiness/processed/aligned/happiness-098_aligned.bmp
76	1	0	0	0	1.78	0	0	0	0	0	0	0	0	0	0	2.14	1.55	0	happiness/processed/aligned/happiness-093_aligned.bmp
77	1	0	0	0	0	2.17	2.74	1.8	1.83	1.91	1.23	0	0	0.61	0	3.24	0	0.04	happiness/processed/aligned/happiness-095_aligned.bmp
78	1	0	0	2.91	0	1.38	0	2.71	2.11	1.04	1.38	0.15	0.71	1.4	0.23	0.56	0	0.65	happiness/processed/aligned/happiness-046_aligned.bmp
79	1	0.51	0	0	0	1.23	2.38	0.82	0.33	2.21	0.99	0.03	0	0	0	1.5	0.39	0.07	happiness/processed/aligned/happiness-025_aligned.bmp
80	1	0.51	0.76	0	0	1.56	0	0	1.23	2.56	1.12	0	0	0	0	0	0	0	happiness/processed/aligned/happiness-024_aligned.bmp
81	1	0	0	0	0	3.22	3.45	0	2.84	3.37	0	0	0	0	0	0	0	0	happiness/processed/aligned/happiness-075_aligned.bmp
196	2	0	0.1	3.45	1.14	0	0	1.75	0.65	0	0	0.11	1.04	2.05	0	0.67	0	0.12	anger/processed/aligned/anger-051_aligned.bmp
197	2	0	0.92	0	0	0.43	1.79	0	0.24	0	0	0	0	0	0	0	0	0	anger/processed/aligned/anger-027_aligned.bmp
198	2	1.27	0	2.58	0	0	0	0	0.39	0	0	1.35	2.39	1.28	0.28	0	0	0	anger/processed/aligned/anger-057_aligned.bmp
199	2	4.5	1.72	0	1.24	1.54	0	0	1.63	0	0	0.22	0	0	0	2.29	0	0	anger/processed/aligned/anger-047_aligned.bmp
200	2	0	0	0	0.29	0	0	0.56	0	0	0	0	0	0	0	1.5	0	0	anger/processed/aligned/anger-008_aligned.bmp
201	2	0	0	0	0.93	0.86	0	0.8	1.35	0.85	0	0	0	0	0.5	0	0	0	anger/processed/aligned/anger-031_aligned.bmp
202	2	2.73	0	0	1.11	1.55	0.32	3.07	1.75	1.21	1.34	1.15	0	0	0.03	2.07	0	0	anger/processed/aligned/anger-019_aligned.bmp
203	2	0	1.1	3.59	0	2.33	3.16	2.56	3.38	0	1.34	0	0	1.92	0	3.03	0	0	anger/processed/aligned/anger-016_aligned.bmp
280	3	0	0	0	0.33	0	0	0	0	0	0	0	0	0	0.59	0	0	0	surprise/processed/aligned/surprise-077_aligned.bmp
281	3	0.34	0	0	1.38	1.24	0	0	1.48	2.05	0	0.57	0	0	0.12	3.27	0	0	surprise/processed/aligned/surprise-079_aligned.bmp
282	3	1.44	0	0	0.59	0	0	0	1.66	0.76	0	0.49	0	0	0.08	1.31	0	0	surprise/processed/aligned/surprise-040_aligned.bmp
283	3	0.24	0	0.9	1.43	0	0.89	0	1.23	0	0	1.29	0	0.56	0.11	0	0	0	surprise/processed/aligned/surprise-004_aligned.bmp
284	3	0.95	0	0	0	0	0	1.04	0	0	0.13	0	1.07	2.53	0.36	0	0	0	surprise/processed/aligned/surprise-062_aligned.bmp
285	3	0.69	0.91	0	1.87	0	0	0	1.34	0	0	1.09	0	0	0	2.94	1.45	0	surprise/processed/aligned/surprise-005_aligned.bmp
286	3	1.19	0.68	0	2.03	0.33	0	0	0.58	1.73	1.65	0.22	0	0	0	1.92	0.7	0	surprise/processed/aligned/surprise-029_aligned.bmp
287	3	3.88	2.83	0	4.25	0	0	0	0.52	1.14	0	1.09	0	0	0.1	1.49	1.64	0	surprise/processed/aligned/surprise-017_aligned.bmp
288	3	0	0	0	1.48	1.46	0.79	0	2.65	1.39	0	1.08	0.4	0	0.89	0.11	0	0	surprise/processed/aligned/surprise-080_aligned.bmp
289	3	0	0	0.79	1.62	0	2.49	0	0	0	0	0	0	0	0.01	1.62	1.87	0	surprise/processed/aligned/surprise-060_aligned.bmp
290	3	1.87	0.79	0	2.75	0	0	0	0	0	0	0	0	0	0.56	1.76	0.58	0	surprise/processed/aligned/surprise-002_aligned.bmp
368	4	0	0	1.58	0.84	0	0	0	0	0	0.59	0	0	0	0	0	0	0	sadness/processed/aligned/sadness-025_aligned.bmp

OUR TINY 'EMOTIONS' DATASET

- A couple of Google queries
- a bit of manual filtering
- 558 faces, between 70 and 130 per emotion
- split into 2 datasets: a **training** dataset (50 face per emotion) and a **testing** dataset
- for each face, OpenFace pre-processing to:
  - extract facial landmarks
  - normalise and mask out the faces
  - extract action units

The dataset is available for you to play with on the lecture's GitHub repo.

CLASSIFICATION?

We want to train a classifier with our training dataset, and then check whether the emotions in the test faces can be properly recognised.

What are our options here?

CLASSIFICATION?

We want to train a classifier with our training dataset, and then check whether the emotions in the test faces can be properly recognised.

What are our options here?

1. 'eigenfaces' (PCA) on the training dataset; then project test faces + kNN/SVM (i.e. face recognition with 6 possible classes)

CLASSIFICATION?

We want to train a classifier with our training dataset, and then check whether the emotions in the test faces can be properly recognised.

What are our options here?

1. 'eigenfaces' (PCA) on the training dataset; then project test faces + kNN/SVM (i.e. face recognition with 6 possible classes)
2. LDA instead of PCA to improve inter-class discrimination

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4. PCA, then kNN/SVM on the action units?

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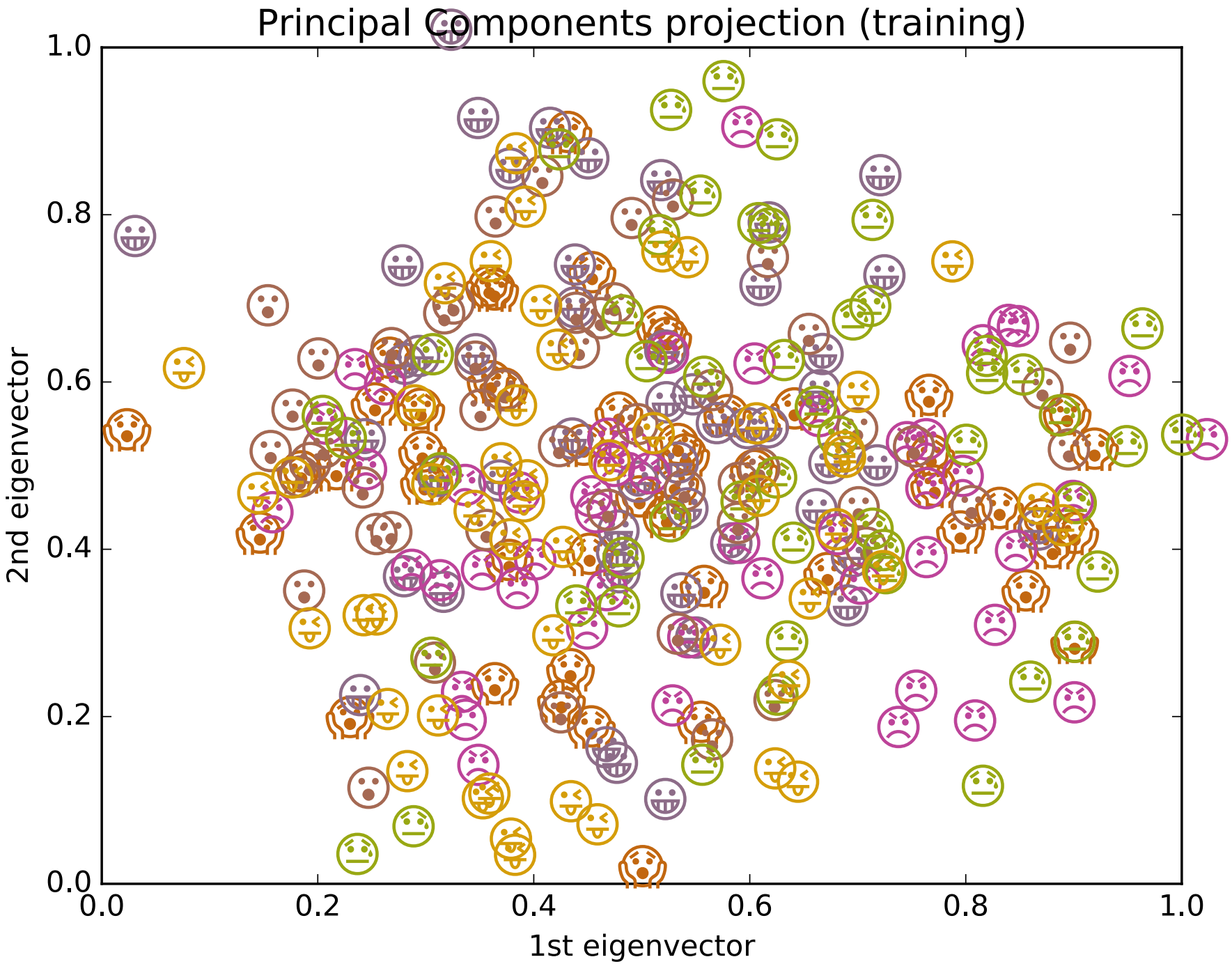
3. kNN/SVM on the action units directly?
4. PCA, then kNN/SVM on the action units?
5. LDA, then kNN/SVM on the action units?

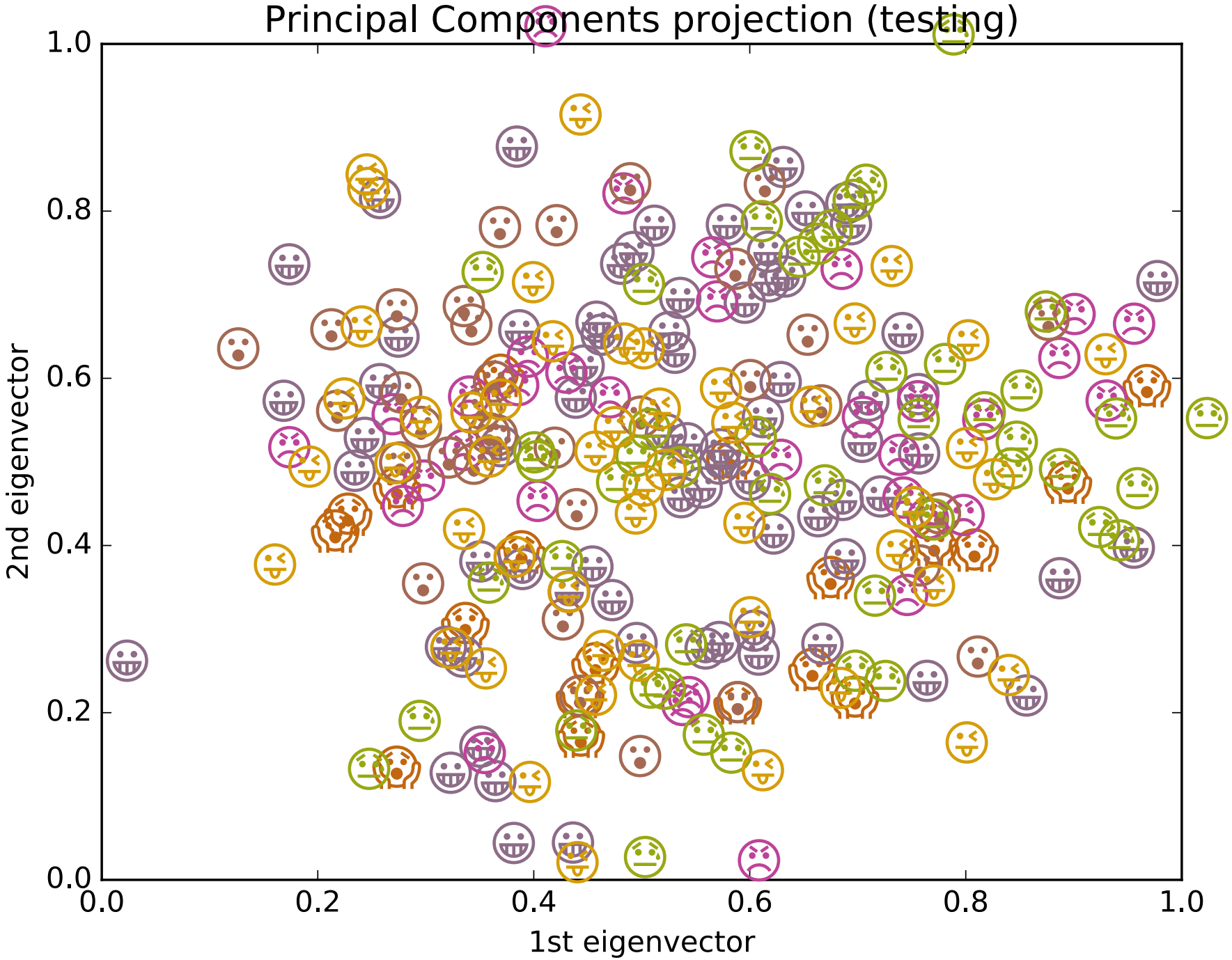
PYTHON HELPERS

```
import numpy as np
import PIL.Image as Image
import matplotlib.pyplot as plt

def read_image(path):
    im = Image.open(path)
    im = im.convert("L") # to grayscale
    return np.asarray(im, dtype=np.uint8).flatten()

def plot_embedding(X, labels):

    x_min, x_max = np.min(X, 0), np.max(X, 0)
    X = (X - x_min) / (x_max - x_min)

    plt.figure()
    ax = plt.subplot(111)
    for i in range(X.shape[0]):
        plt.text(X[i, 0], X[i, 1], str(labels[i])],
                 color=plt.cm.Dark2((int(labels[i]) + 1) / 8.))
```

PCA ON THE DATASET

```
import csv
from sklearn.decomposition import PCA

training_images = []
training_categories = []
with open("training.csv", 'r') as csvfile:
    details = csv.DictReader(csvfile, skipinitialspace=True)
    for row in details:
        training_images.append(read_image(row["face"]))
        training_categories.append(row["emotion"])

# same for testing set
testing_images = ...
testing_categories = ...

pca = PCA(n_components=20)
pca.fit(training_images)

# plots only the 2 first coordinates in PCA space
plot_embedding(pca.transform(training_images), training_categories)
plot_embedding(pca.transform(testing_images), testing_categories)
```


Principal Components projection (training)
2nd eigenvector
1st eigenvector
0.0
0.2
0.4
0.6
0.8
1.0


Principal Components projection (testing)
2nd eigenvector
1st eigenvector
0.0
0.2
0.4
0.6
0.8
1.0

CLASSIFICATION RESULTS, PCA

% of successful emotion prediction out of 258 test faces

kNN:

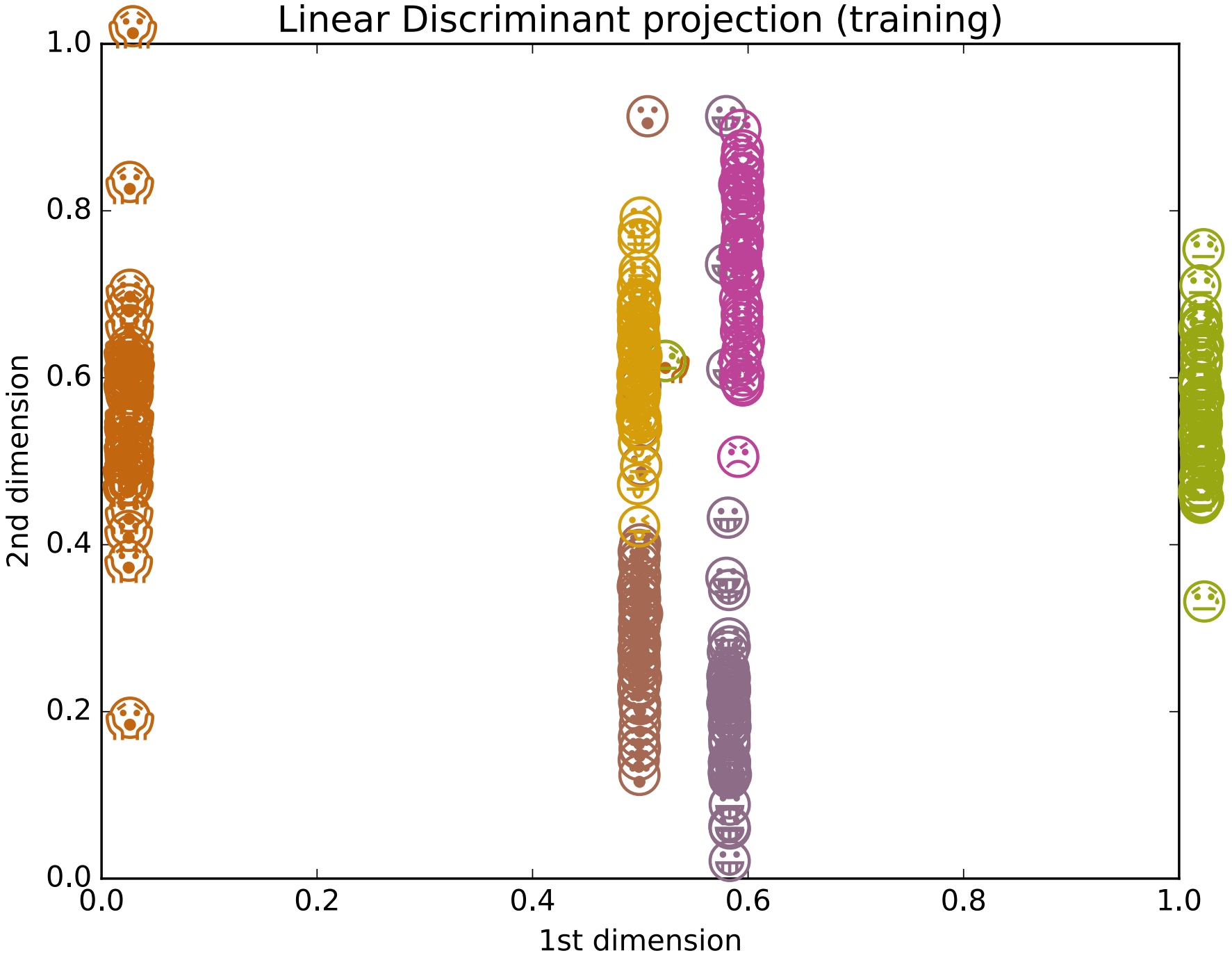
- k=1: 30.2%
- k=2: 26.0%
- k=4: 28.3%
- k=6: 30.2%
- k=9: 33.7%

SVM:

- kernel: rbf: 19.4%

LDA ON THE DATASET

```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

lda = LinearDiscriminantAnalysis(n_components=20)

lda.fit(training_images, training_categories)

plot_embedding(lda.transform(training_images), training_categories)
plot_embedding(lda.transform(testing_images), testing_categories)
```


Linear Discriminant projection (training)
2nd dimension
1st dimension
0.0
0.2
0.4
0.6
0.8
1.0

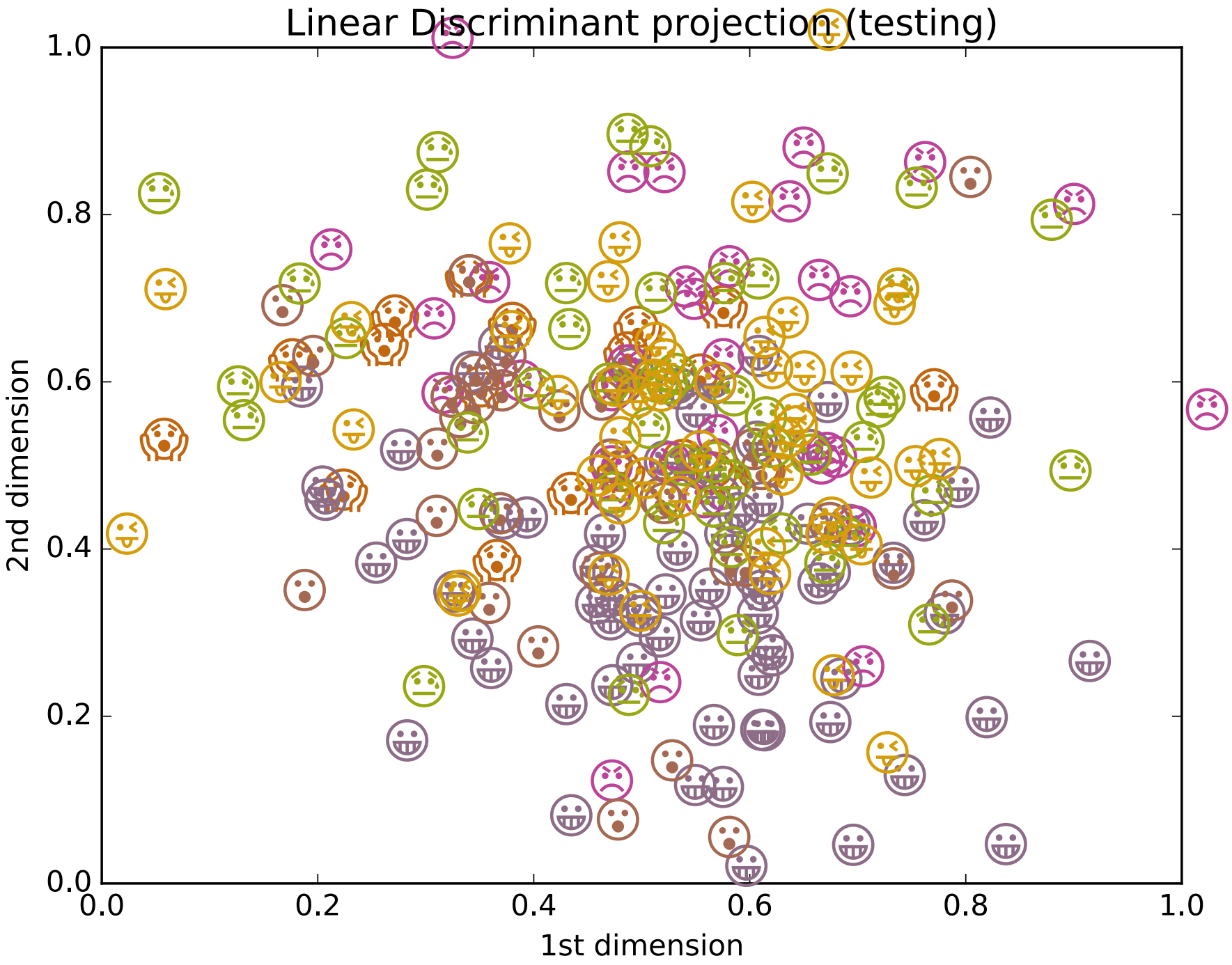
LINEAR DISCRIMINANT ANALYSIS OVERFITTING

Great result? No! Massive overfitting!

LDA requires the number of samples per class n (i.e. number of faces per emotion, 50 here) to be much larger than the number of features p (in our case, 112×112 px $= 12544$!)

Rule of thumb: $n > 3 \cdot p$

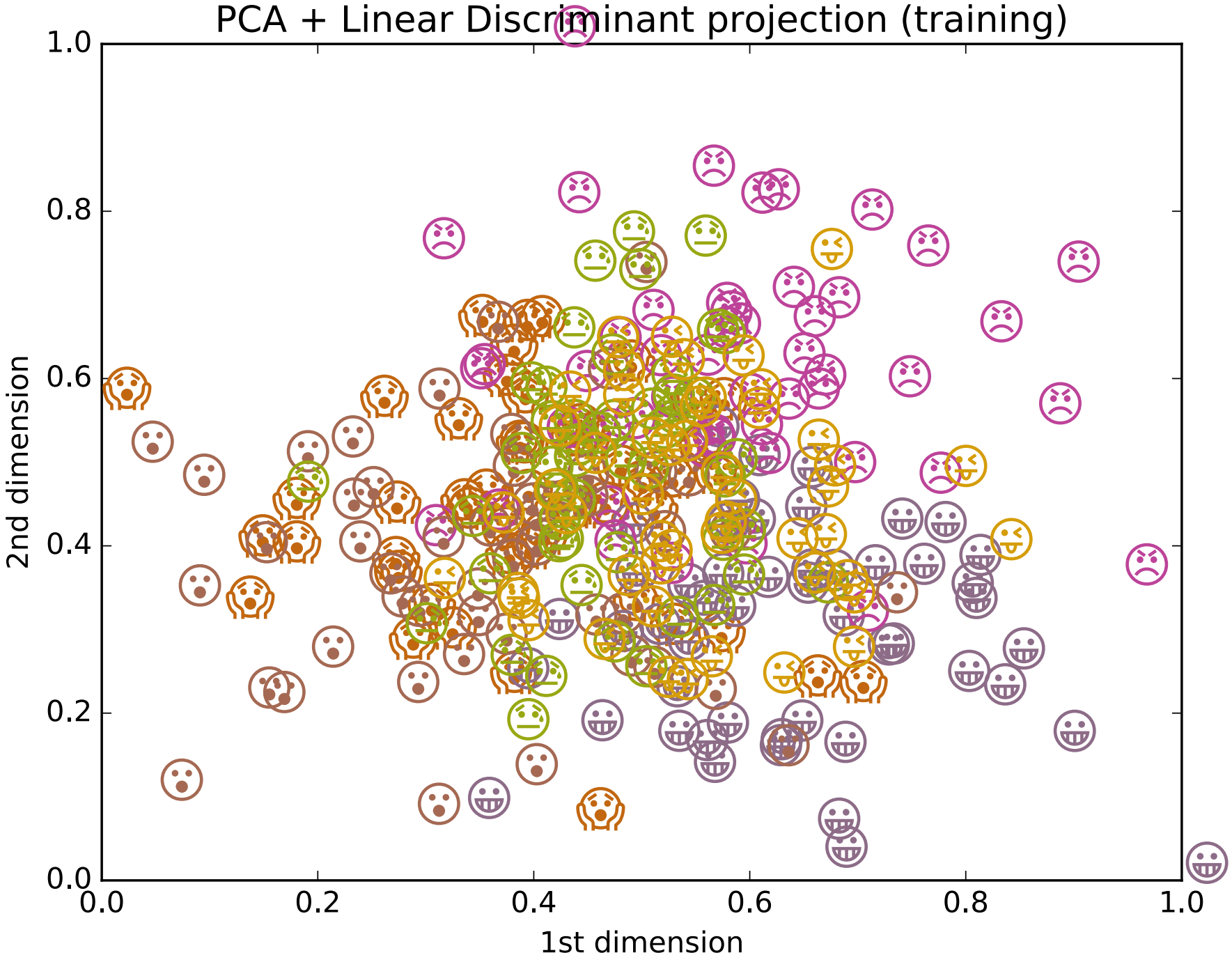
...not going to work if we use the pixels directly.

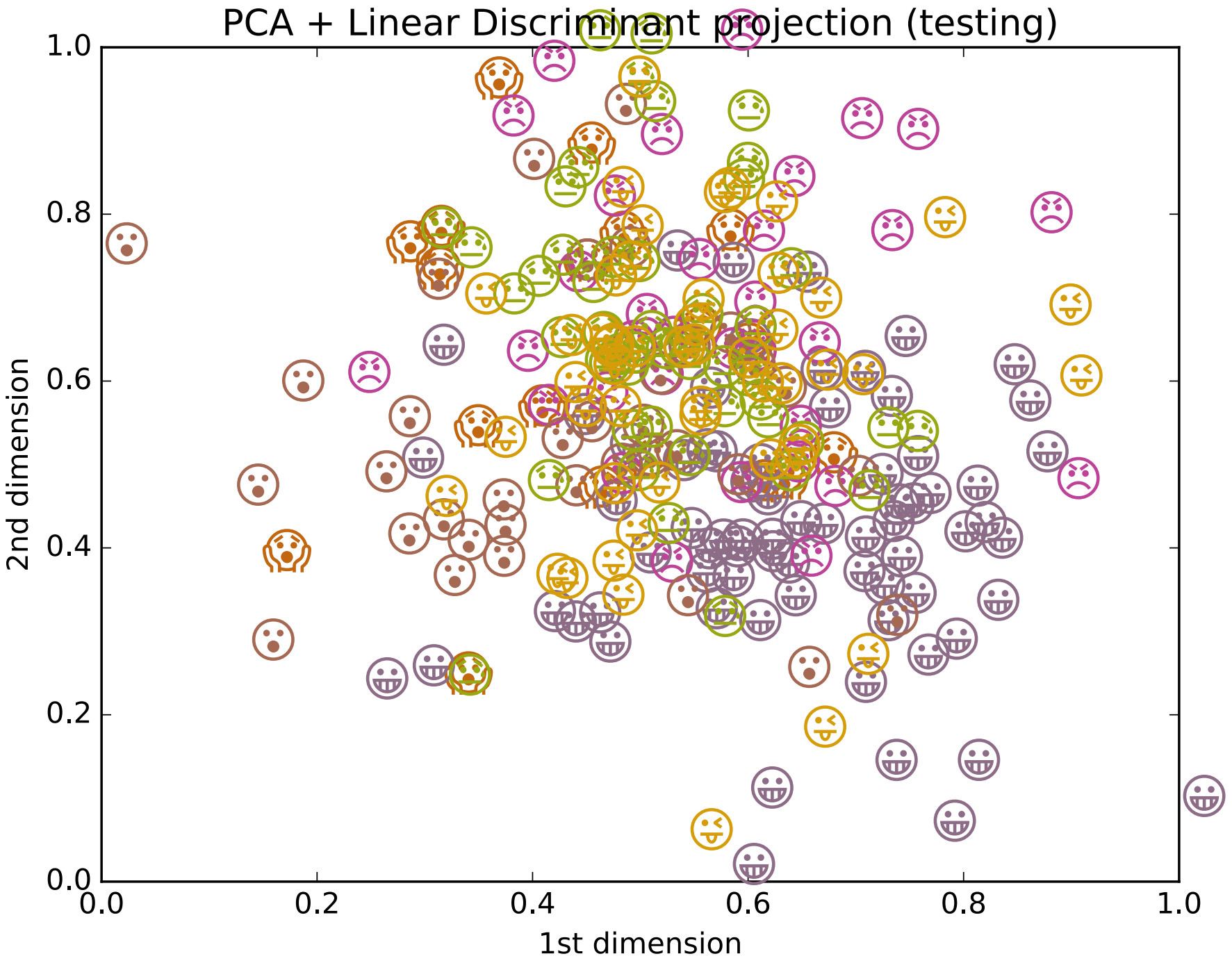

Linear Discriminant projection (testing)
2nd dimension
1st dimension
0.0
0.2
0.4
0.6
0.8
1.0

Idea: first, reduce dimensionality (using PCA for instance), and then, perform a LDA on the lower dimensionality representation.

PCA + LDA ON THE DATASET

```
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

# first, PCA on 12544-D observations
pca = PCA(n_components=20)
pca.fit(training_images)

# then LDA on 20-D observations
lda = LinearDiscriminantAnalysis(n_components=10)
lda.fit(pca.transform(training_images), training_categories)

# apply the transform...
lda_pca_training_images = lda.transform(pca.transform(training_images))
lda_pca_testing_images = lda.transform(pca.transform(testing_images))

# and plot!
plot_embedding(lda_pca_training_images, training_categories)
plot_embedding(lda_pca_testing_images, testing_categories)
```


PCA + Linear Discriminant projection (training)
2nd dimension
1st dimension
0.0
0.2
0.4
0.6
0.8
1.0


PCA + Linear Discriminant projection (testing)
2nd dimension
1st dimension
0.0
0.2
0.4
0.6
0.8
1.0

CLASSIFICATION RESULTS, PCA FOLLOWED WITH LDA

% of successful emotion prediction out of 258 test faces

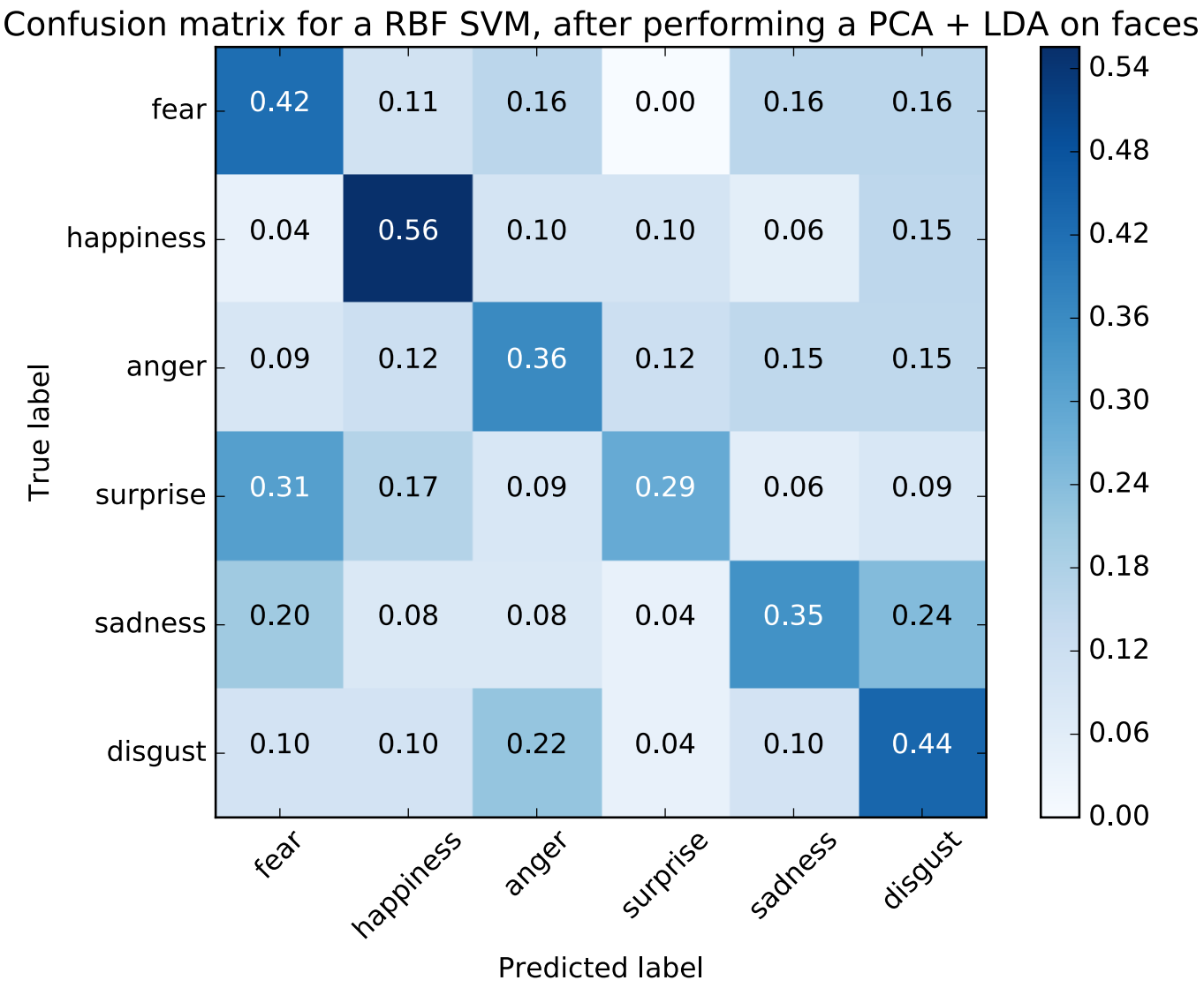
kNN:

- k=1: 39.5%
- k=2: 33.3%
- k=4: 36.4%
- k=6: 35.7%
- k=9: 36.8%

SVM:

- kernel: rbf: 41.9%
- kernel: linear: 38.4%
- kernel: poly: 26.0%

CONFUSION MATRIX



CLASSIFICATION RESULTS, ACTION UNITS

What about classifying using the 17 action units directly?

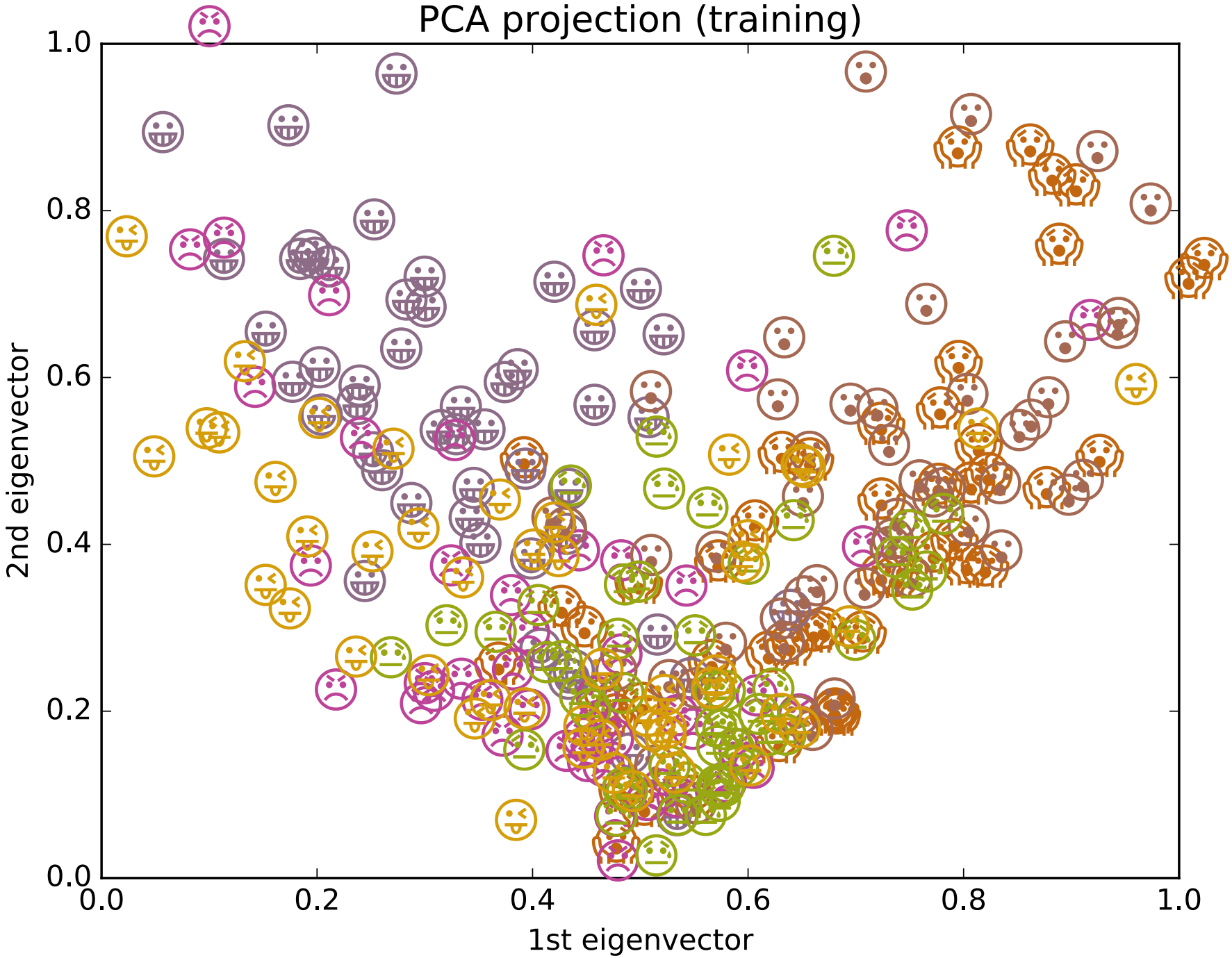
kNN:

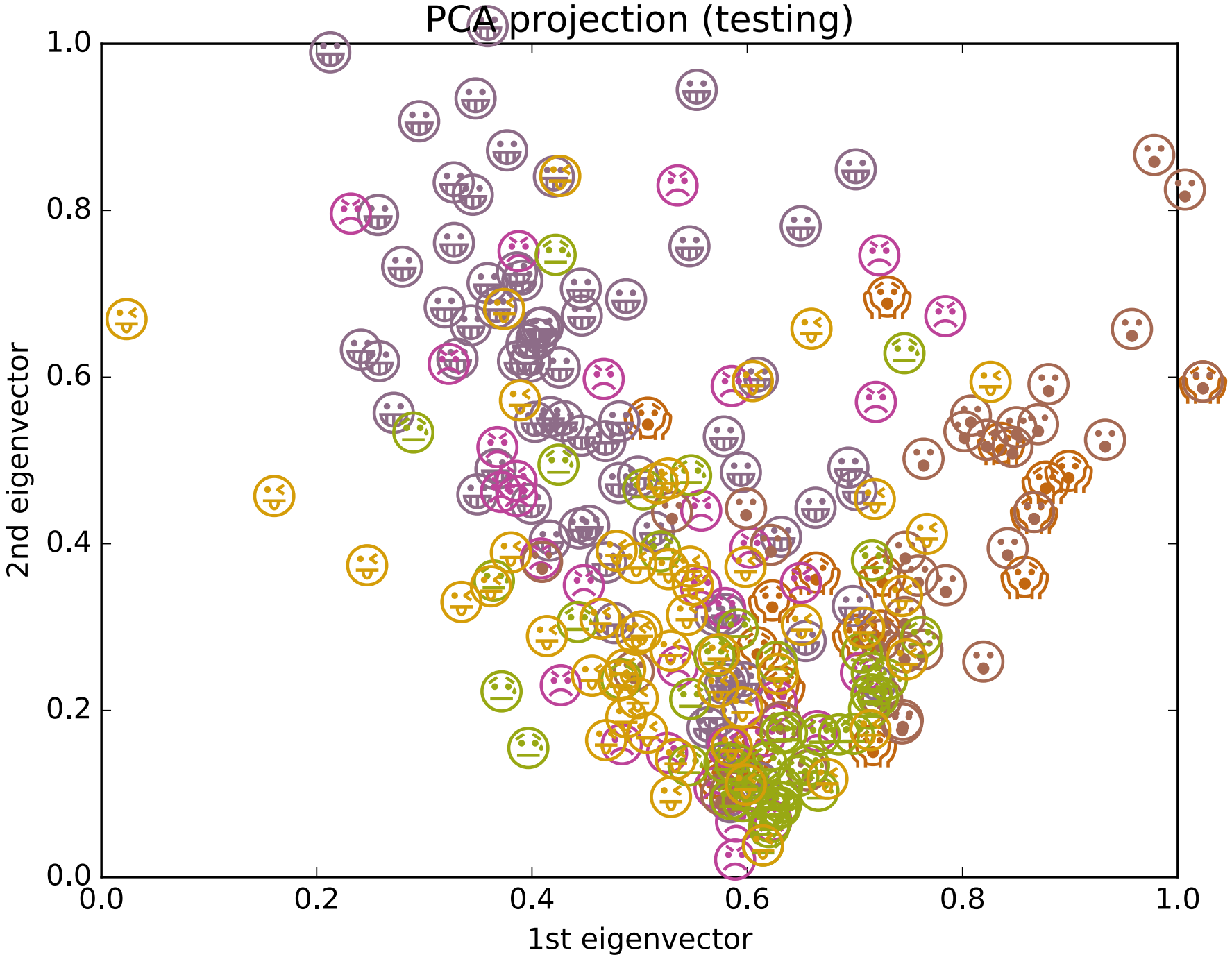
- k=1: 46.9%
- k=2: 42.2%
- k=4: 50.8%
- k=6: 46.1%
- k=9: 52.3%

SVM:

- kernel: rbf: 48.8%
- kernel: linear: 52.3%
- kernel: poly: 38.0%

```
from numpy import genfromtxt
from sklearn import neighbors, svm

csv_train = genfromtxt('training.csv')
training = csv_train[:,1:-1]
training_categories = csv_train[:,0]

csv_test = genfromtxt('testing.csv')
testing = csv_test[:,1:-1]
testing_categories = csv_test[:,0]

clf = neighbors.KNeighborsClassifier(k)
clf.fit(training, training_categories)
knns_predictions = clf.predict(testing)

clf = svm.SVC(kernel=kernel)
clf.fit(training, training_categories)
svm_predictions = clf.predict(testing)
```


PCA projection (training)
2nd eigenvector
1st eigenvector
0.0
0.2
0.4
0.6
0.8
1.0


PCA projection (testing)
2nd eigenvector
1st eigenvector
0.0
0.2
0.4
0.6
0.8
1.0

CLASSIFICATION RESULTS, PCA ON AUS

Classification on the first 5 eigen components.

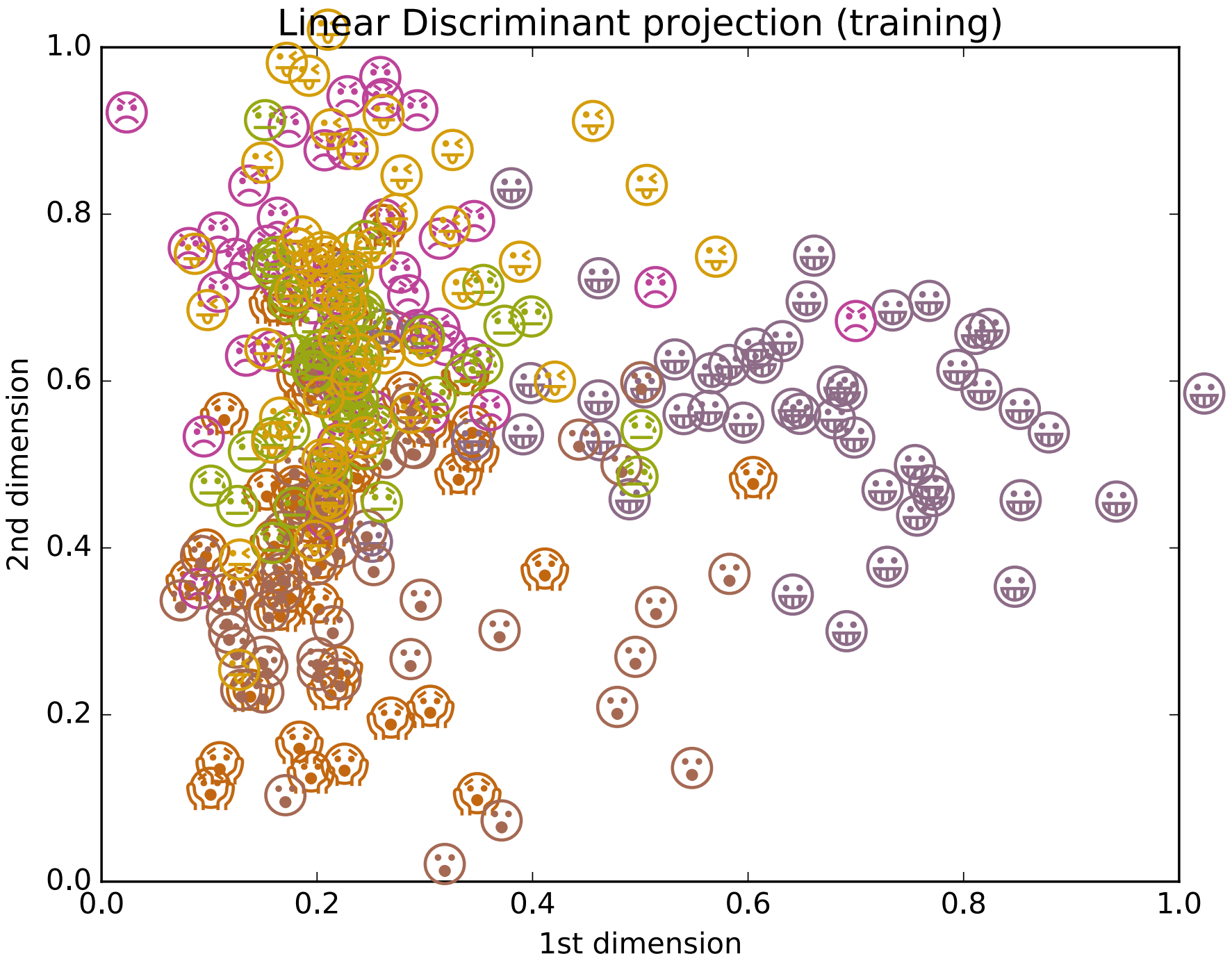
kNN:

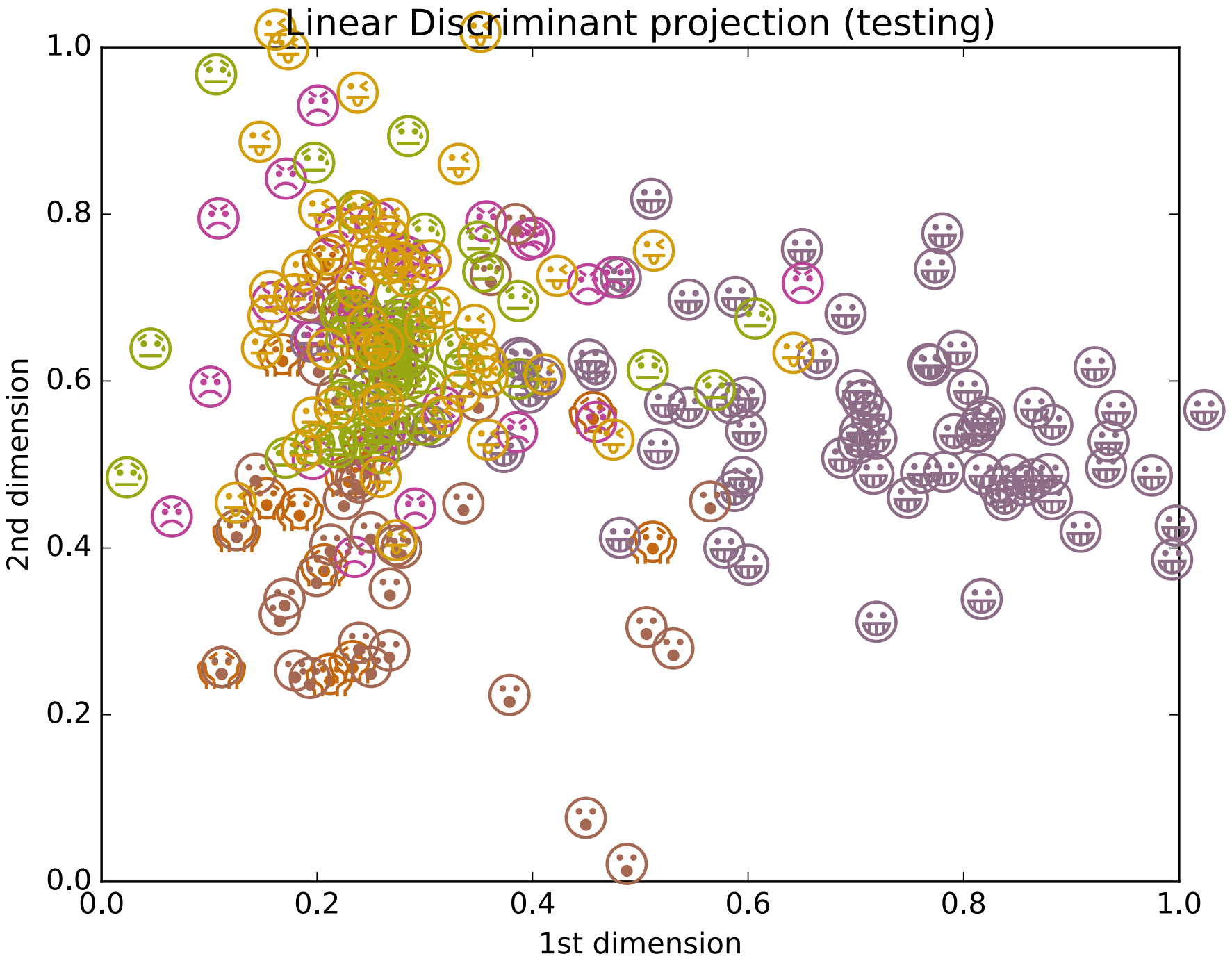
- k=1: 45.7%
- k=2: 39.1%
- k=4: 45.0%
- k=6: 43.8%
- k=9: 47.3%

SVM:

- kernel: rbf: 50.8%
- kernel: linear: 47.7%
- kernel: poly: 39.9%

$\Rightarrow$ no improvement


Linear Discriminant projection (training)
2nd dimension
1st dimension
0.0
0.2
0.4
0.6
0.8
1.0


Linear Discriminant projection (testing)
2nd dimension
1st dimension
0.0
0.2
0.4
0.6
0.8
1.0

CLASSIFICATION RESULTS, LDA ON AUS

Classification on the first 5 components.

kNN:

- k=1: 45.7%
- k=2: 43.0%
- k=4: 45.7%
- k=6: 46.9%
- k=9: 52.3%

SVM:

- kernel: rbf: 53.1%
- kernel: linear: 51.9%
- kernel: poly: 40.3%

⇒ same as direct, better than PCA

CLASSIFICATION RESULTS, LDA ON AUS

With only **2 components**:

kNN:

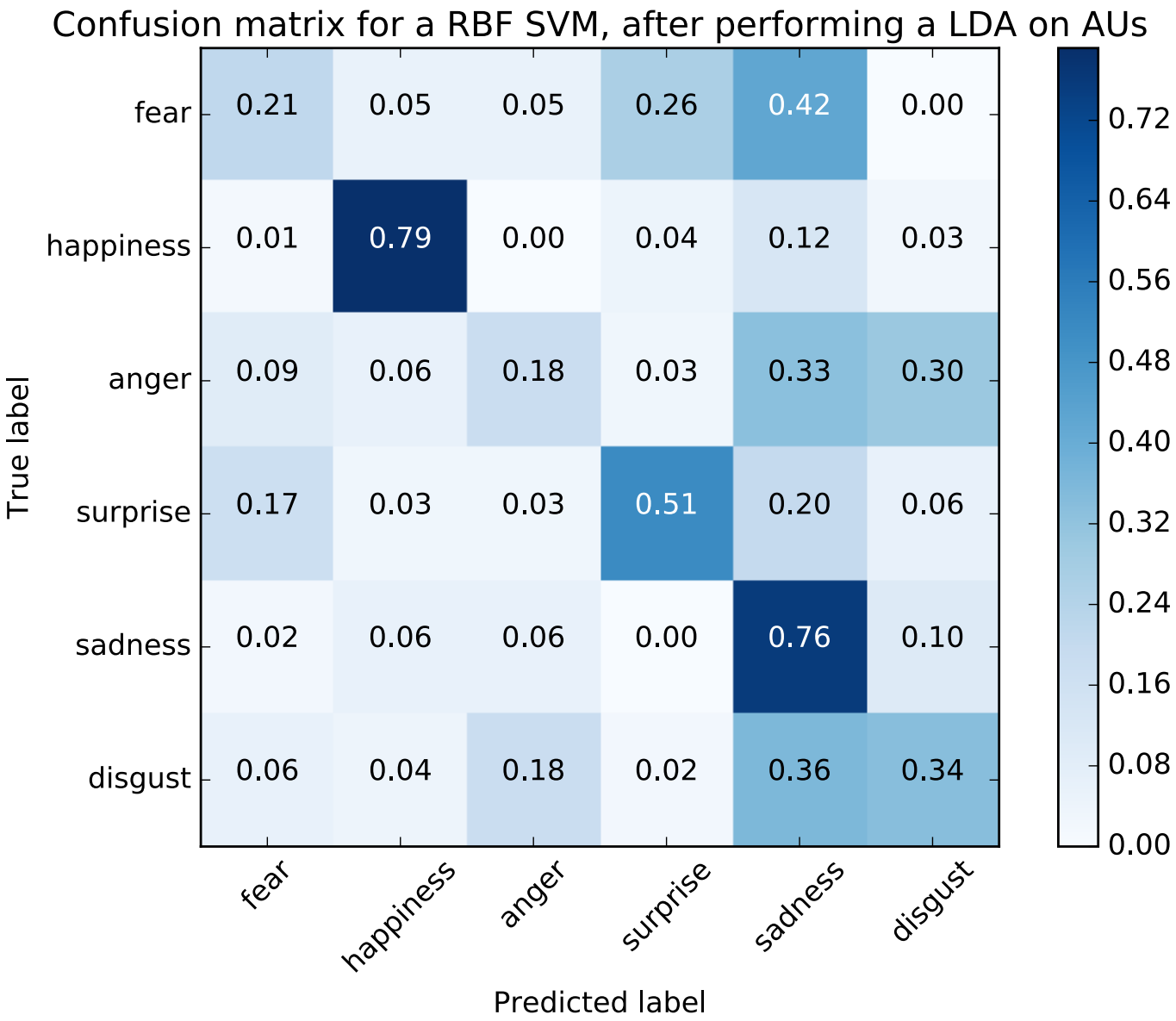
- k=1: 43.4%
- k=2: 42.6%
- k=4: 49.2%
- k=6: 51.2%
- k=9: 49.2%

SVM:

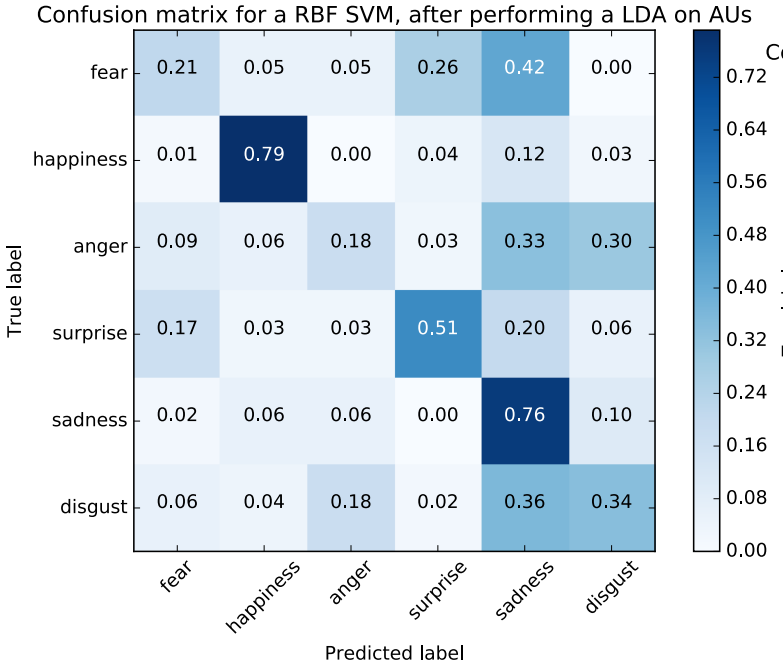
- kernel: rbf: 53.9%
- kernel: linear: 48.8%
- kernel: poly: 39.9%

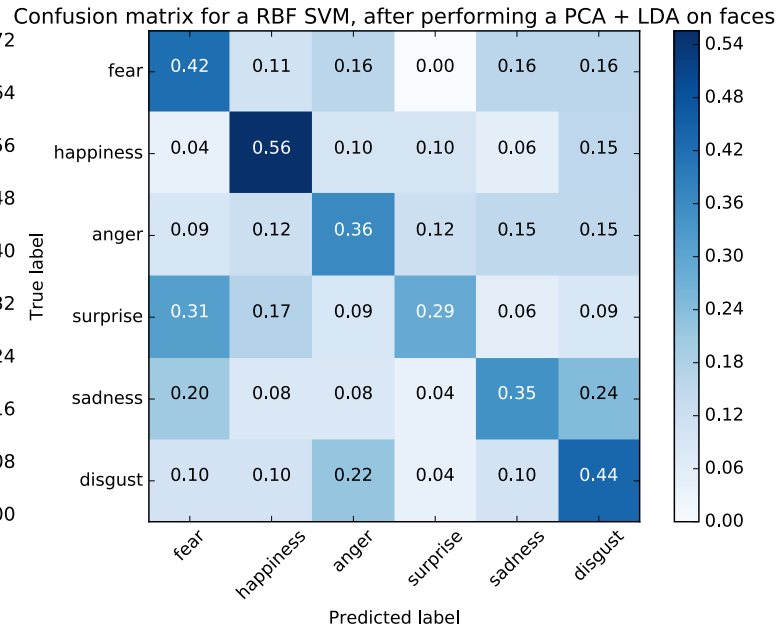
$\Rightarrow$ **2 values, extracted from the faces, are sufficient to recognise an emotion** $\approx$ 54**% of the time.**

CONFUSION MATRIX



CONFUSION MATRIX





HOW TO IMPROVE IT FURTHER?

Ideas?

HOW TO IMPROVE IT FURTHER?

Ideas?

- better dataset (wider range of facial expressions)
- larger dataset
- use the facial landmark directly?
- different classifier → neural network (deep or not)?

Natural emotions are much harder

GENERATING EMOTIONAL RESPONSES

SOLAR CHARGE LEVEL
WALL·E

HOW TO EXPRESS THE ROBOT'S INTERNAL STATE?

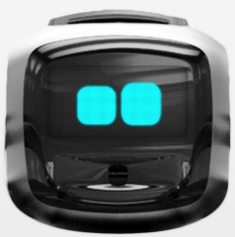
- facial expressions (when available!)
- Gestures/postures
- non-verbal utterances, sounds
- dynamics of motion
- proxemics
- ...

HOW EXPRESSIVE A ROBOT CAN BE?

Anki's Cozmo

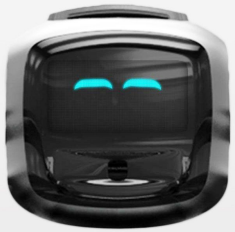
Cozmo wants to be upright.

COZMO


Neutral

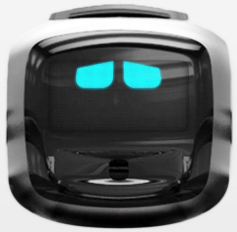
Blink (high)

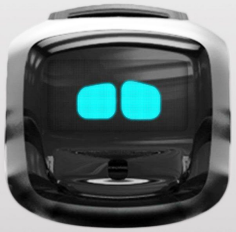
Happy


Glee

Blink (low)

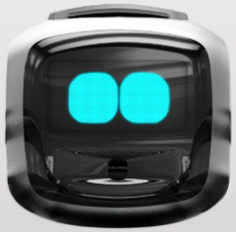
Sad (looking down)

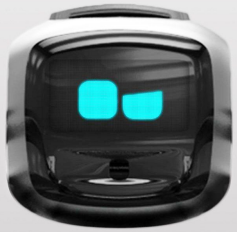

Sad (looking up to user)


Worried

Focused/Determined

Annoyed


Surprised


Skeptic

Frustrated/Bored

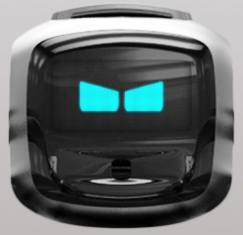
Unimpressed

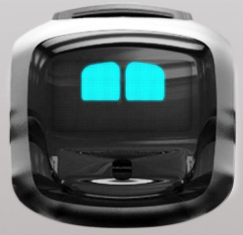
Sleepy Eyes

Suspicious

Squint

Angry


Furious


Scared

Awe

anki

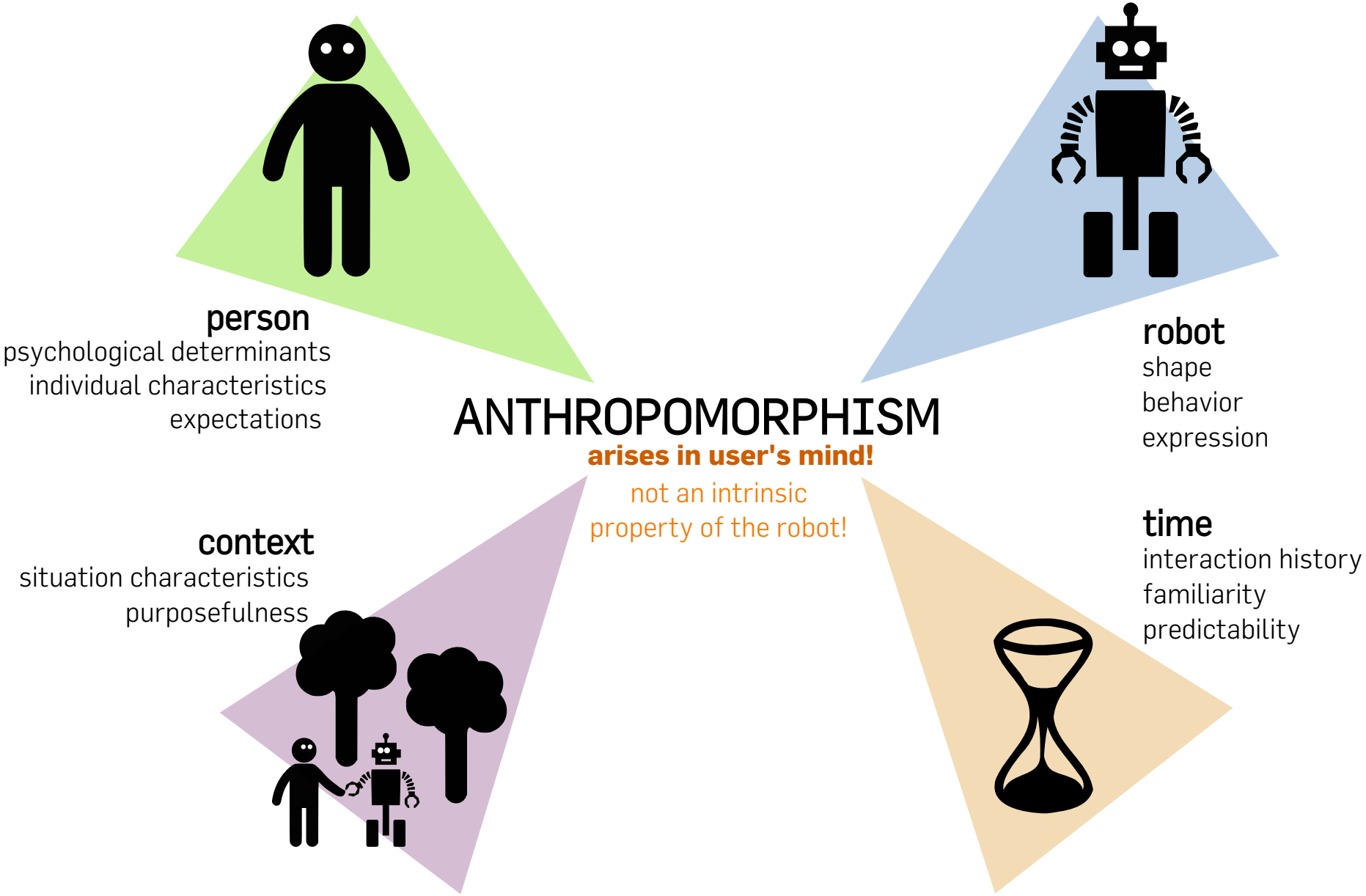
R2-D2 Reloaded: A Flexible Sound Synthesis System for Sonic Human-Robot Interaction Design

Markus Schwenk **Kai O. Arras**

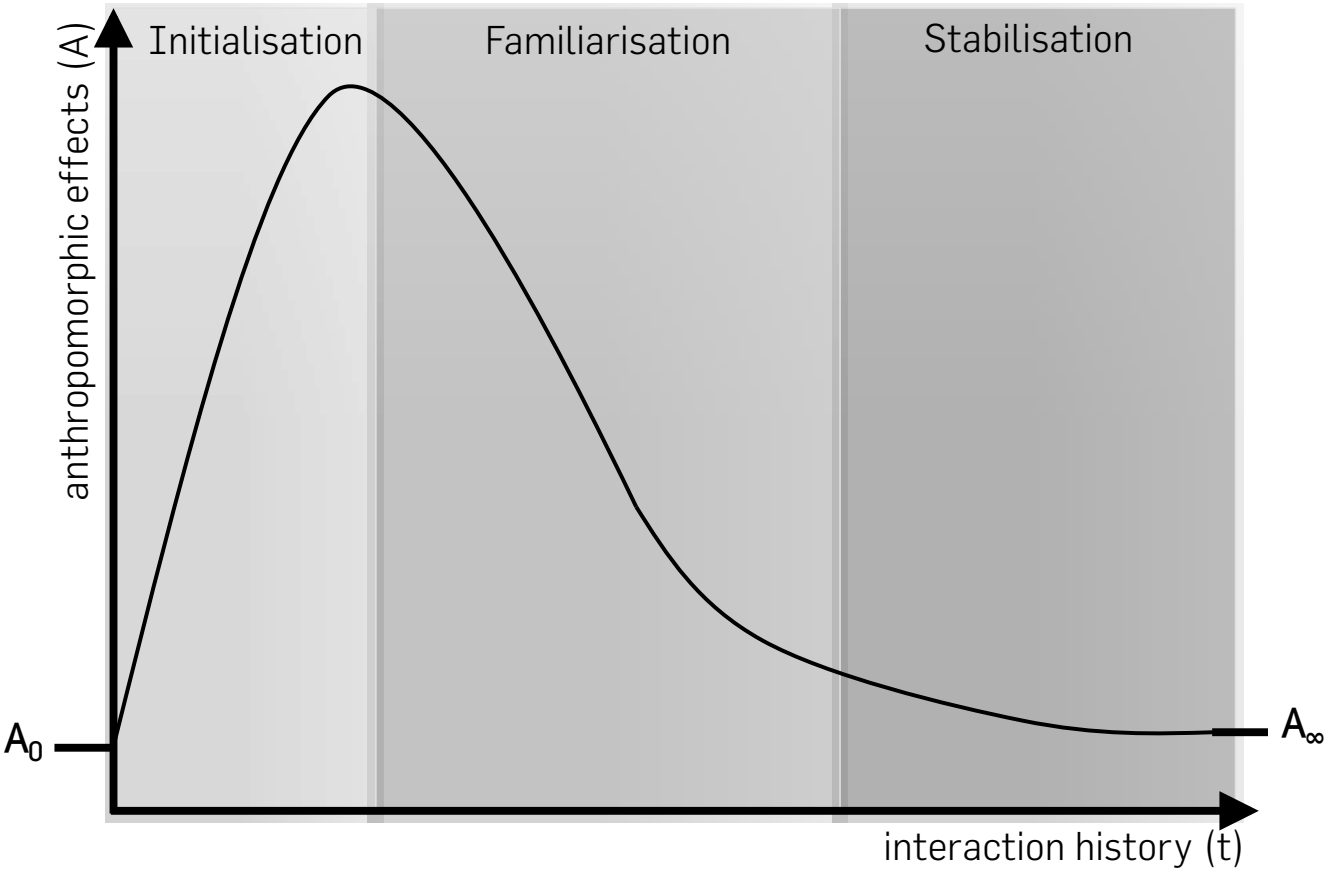
Social Robotics Lab University of Freiburg, Germany

ANTHROPOMORPHISM

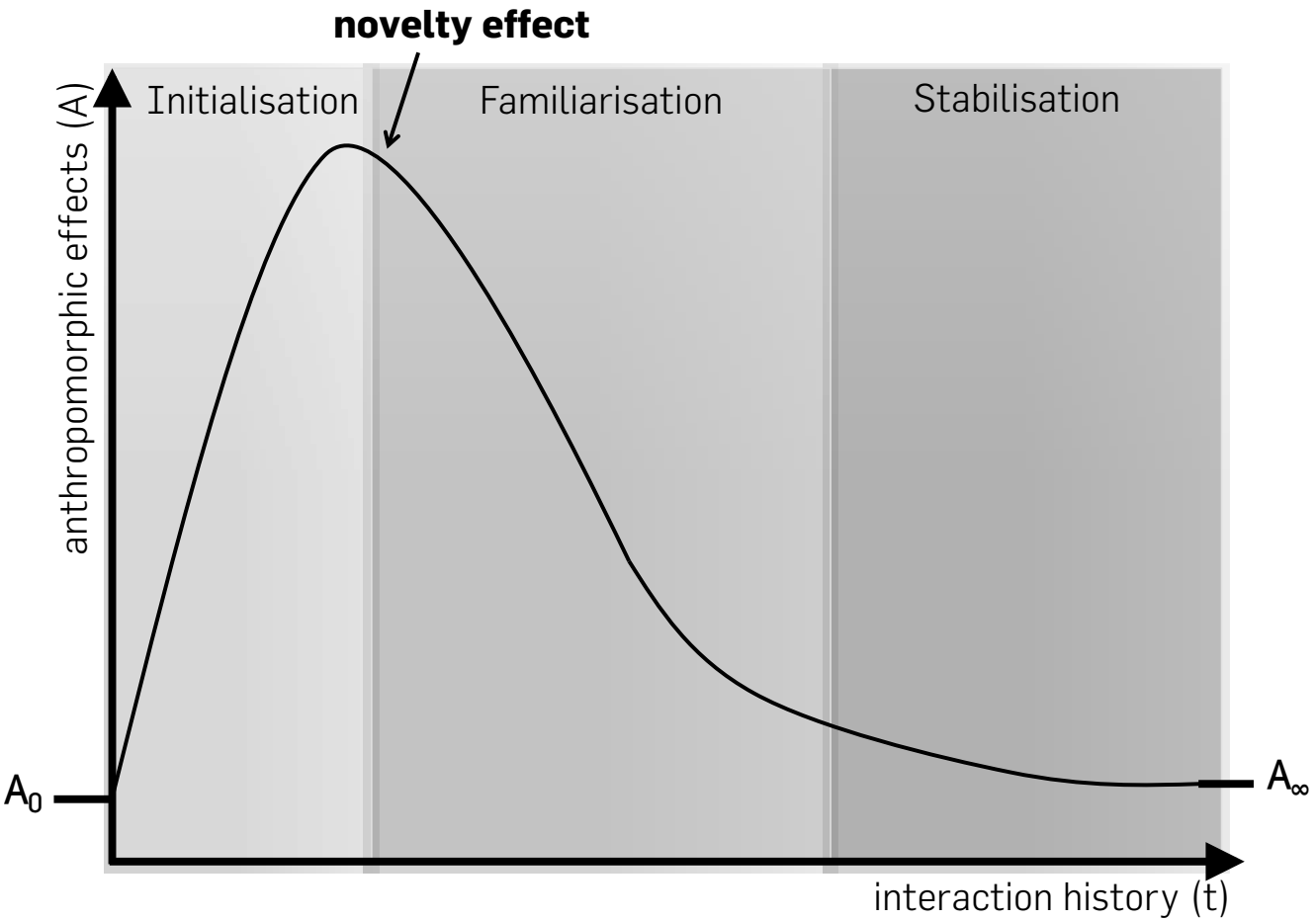
Source: Christoph Bartneck


person
psychological determinants
individual characteristics
expectations
robot
shape
behavior
expression
ANTHROPOMORPHISM
arises in user's mind!
not an intrinsic
property of the robot!
context
situation characteristics
purposefulness
time
interaction history
familiarity
predictability

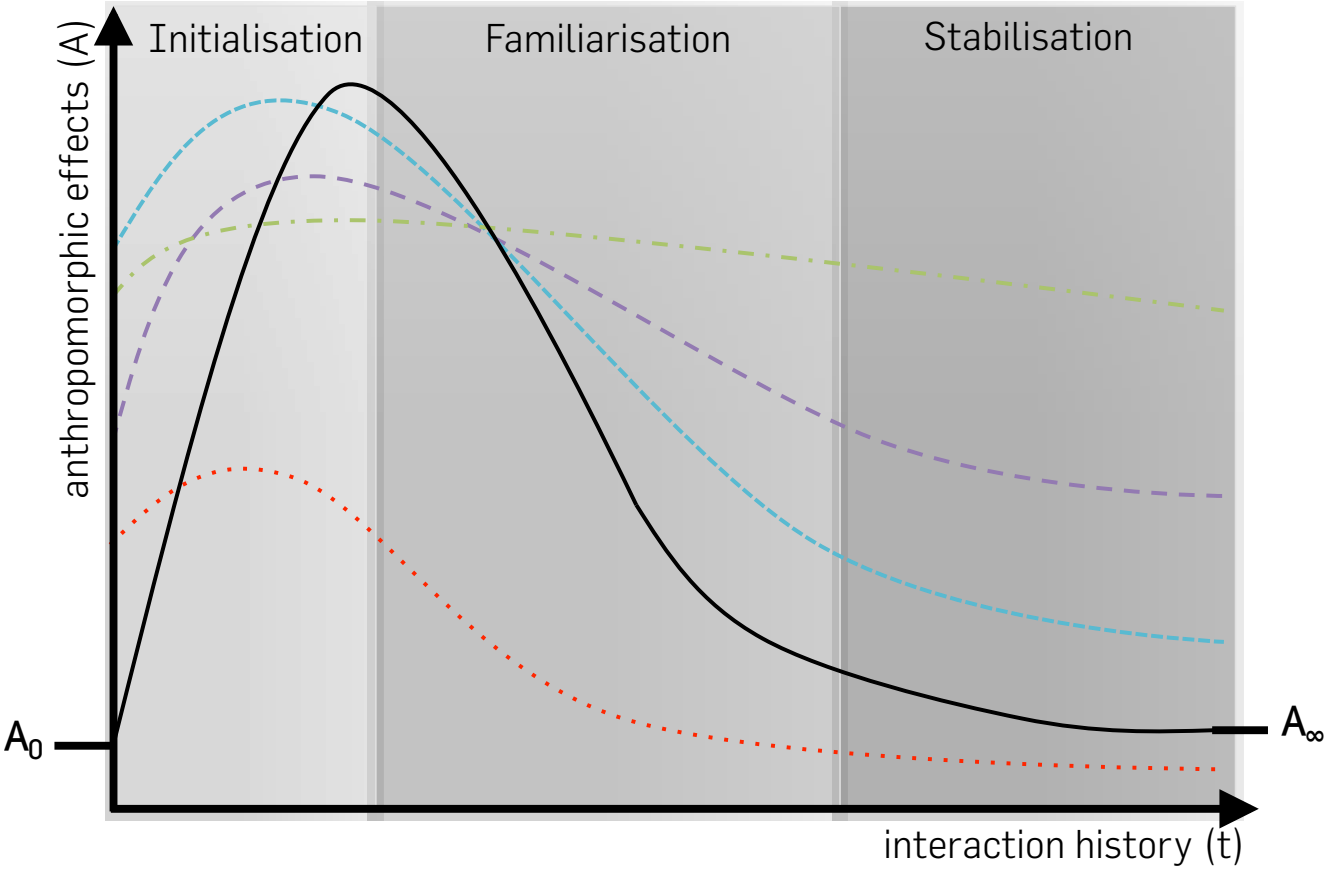
DYNAMICS OF ANTHROPOMORPHISM



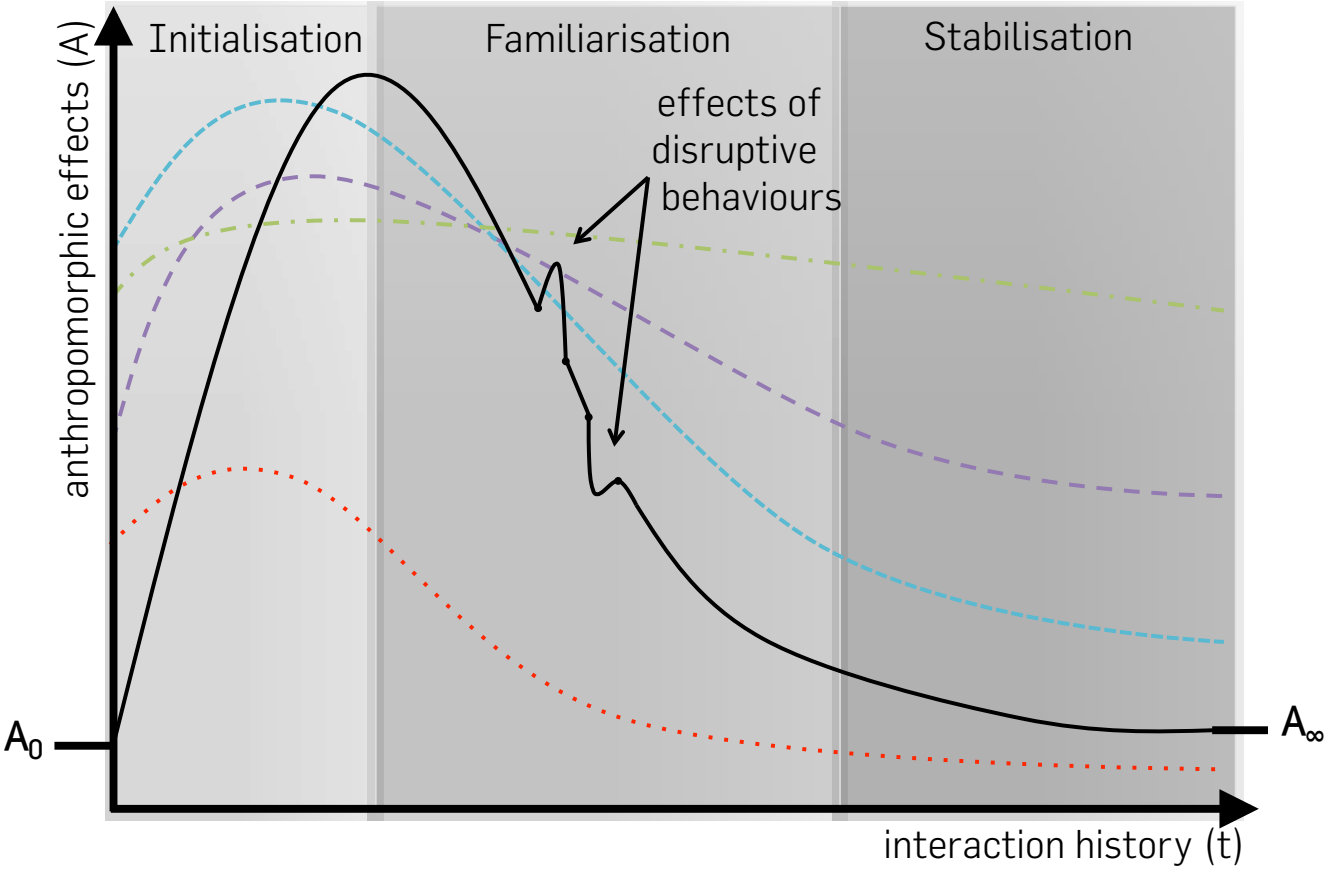
DYNAMICS OF ANTHROPOMORPHISM



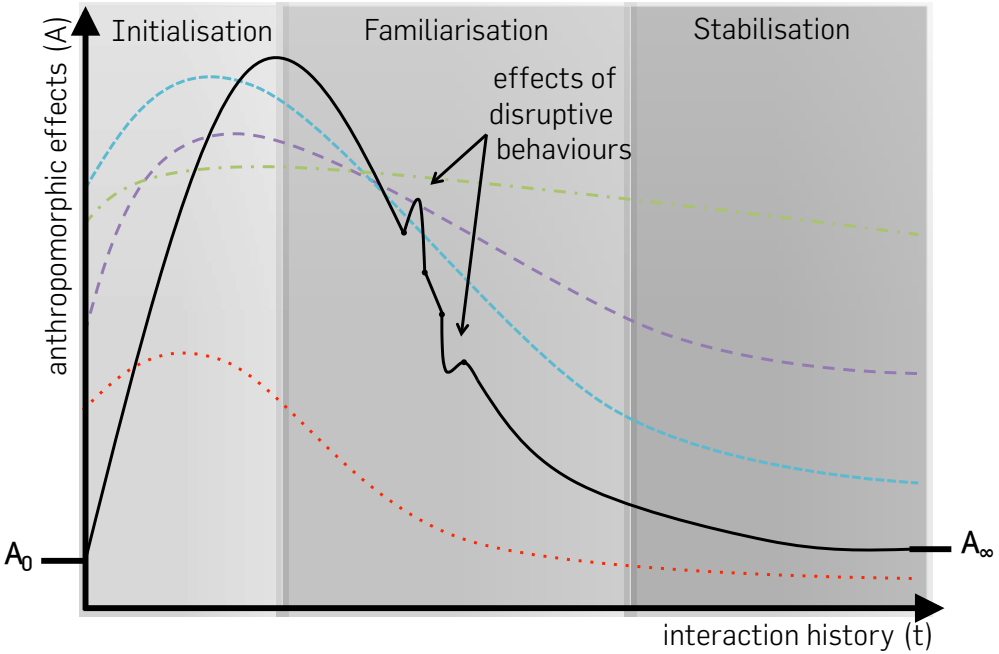
DYNAMICS OF ANTHROPOMORPHISM



DYNAMICS OF ANTHROPOMORPHISM

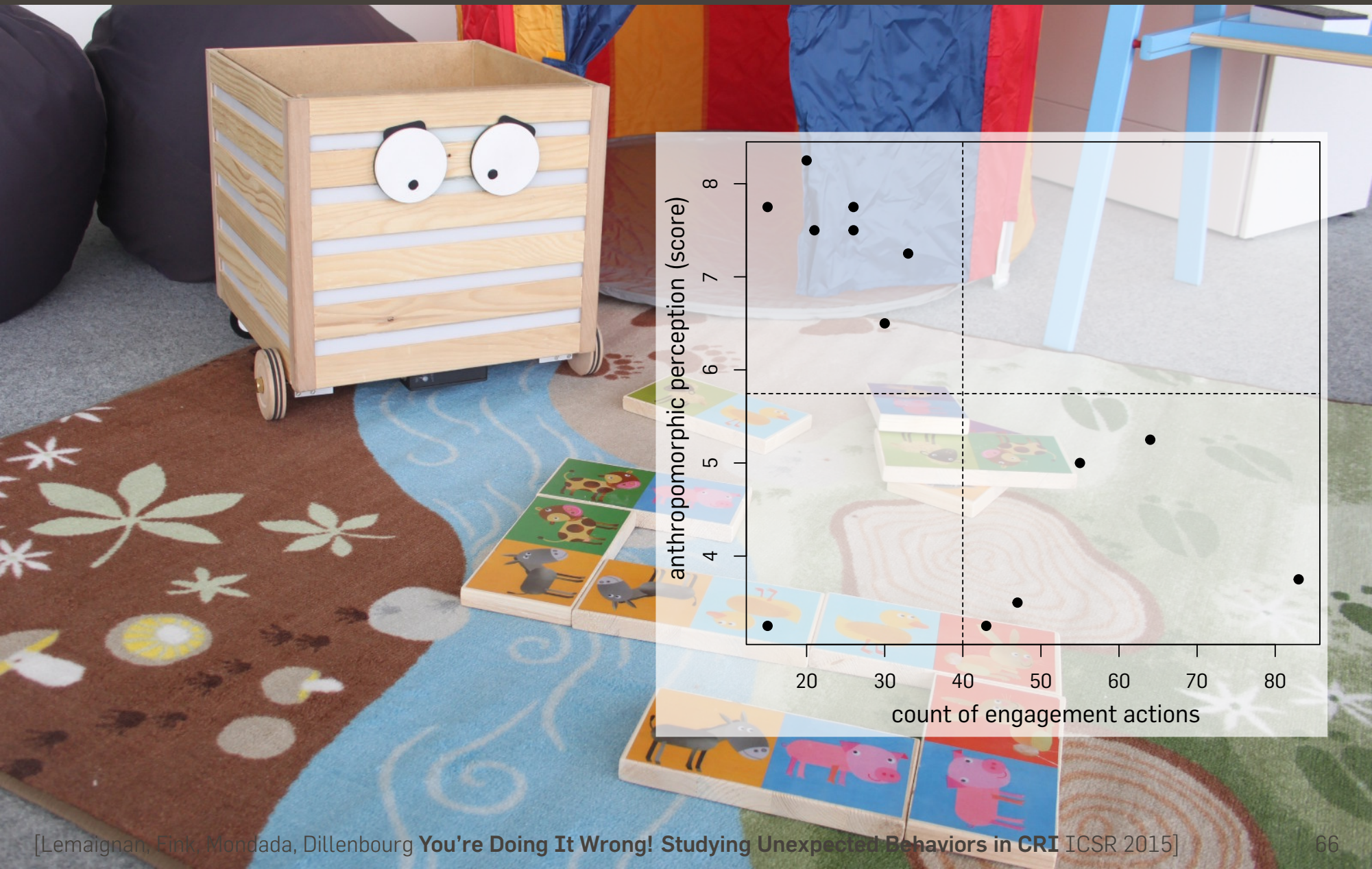


COZMO?


Initialisation
Familiarisation
Stabilisation
effects of disruptive behaviours
anthropomorphic effects (A)
A_0
A_∞
interaction history (t)

DISRUPTIVE BEHAVIOURS TO ELICIT ENGAGEMENT?

ANTHROPOMORPHISM != ENGAGEMENT



[Lemaignan, Fink, Mondada, Dillenbourg **You're Doing It Wrong! Studying Unexpected Behaviors in CRI** ICSR 2015]

That's all for today, folks!

Questions:
Portland Square B316 or **severin.lemaignan@plymouth.ac.uk**

Slides:
github.com/severin-lemaignan/lecture-hri-emotions