

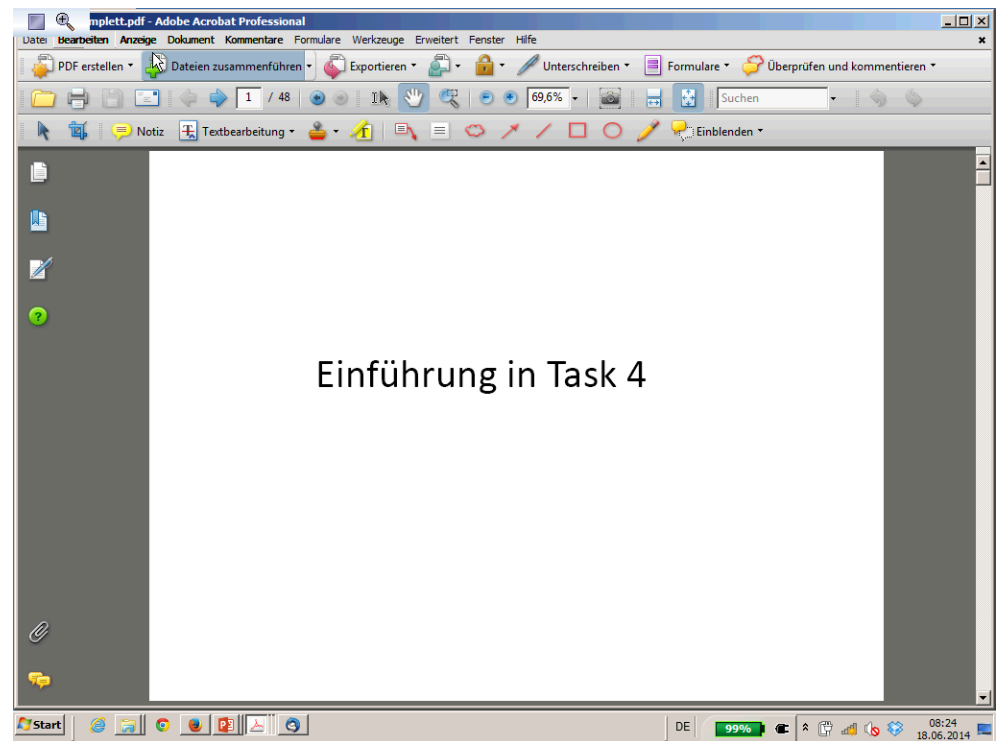
# Script generated by TTT

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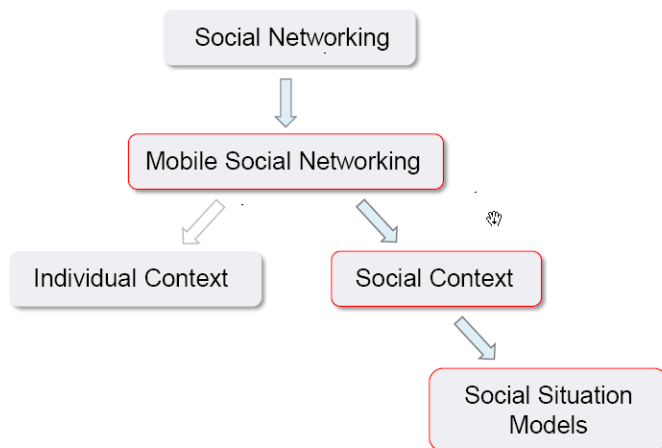
Date: Wed Jun 18 08:24:00 CEST 2014

Duration: 81:26 min

Pages: 32



## Social Situation Models as Models of Social Context



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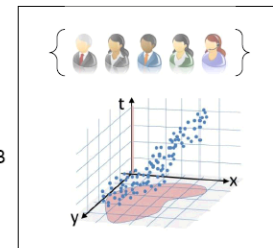
### Social Situation:

Co-located social interaction  
with full mutual awareness

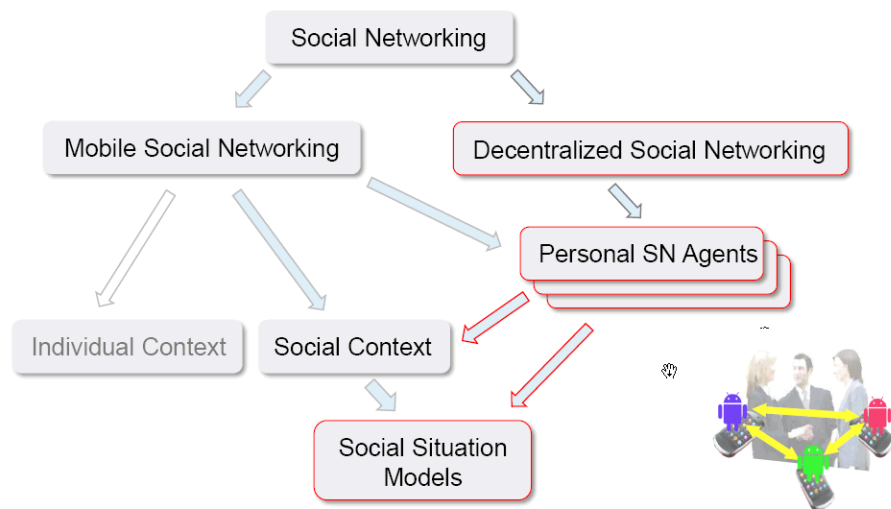


### Simplified Social Situation Model:

- Participating persons:  $P$ : set of IDs
- Spatio-temporal reference:  $X$ : sub-set of  $\mathbb{R} \times \mathbb{R}^3$
- $\rightarrow S = (P, X)$

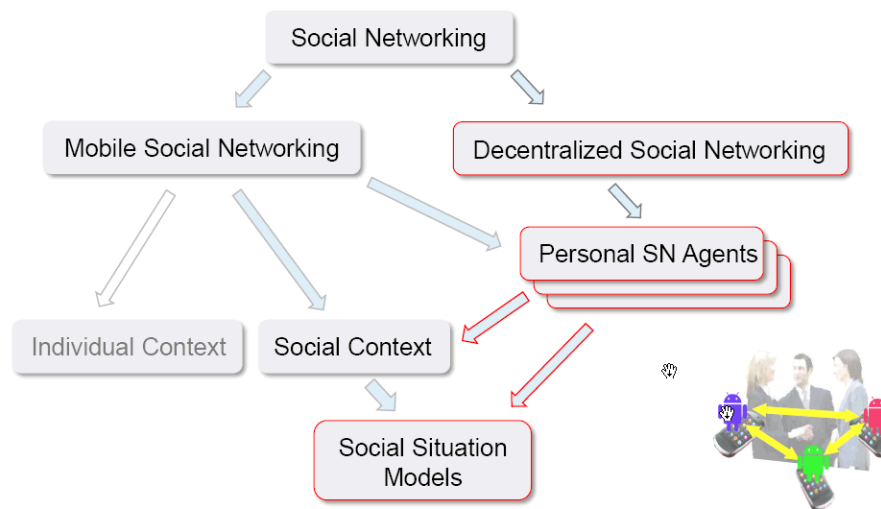


## Social Situation Models and Agents



4 / 25

## Social Situation Models and Agents



4 / 25

## Research Questions

- Method for **measuring** human **social interaction geometry** (mobile → live ; experiment → sociology model)
- **General, quantitative**, algorithmically processable **model** for human social interaction geometry
- Use of model to **detect Social Situations** (e.g. from mobile device measurements)
- Use as social context for **applications** maintaining **privacy**

7 / 18

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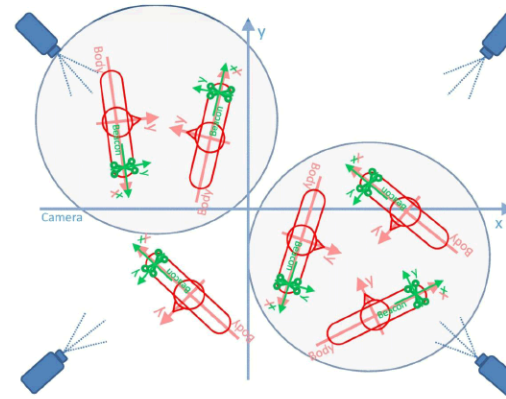
7 / 18

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7 / 18

## Experiment



8 / 18

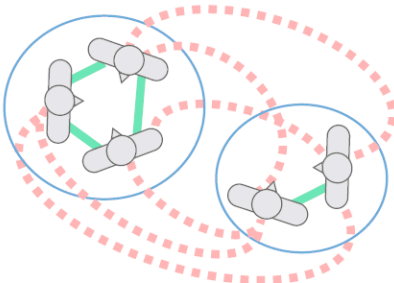
## Results

Experiment data: [Manual annotation](#)

$|S^{\oplus}| = 321307 (\delta\theta, \delta d)$  pairs corresponding to „in a social situation“  
 $|S^{\ominus}| = 398335 (\delta\theta, \delta d)$  pairs corresponding to „not in a social situation“

Example:

$|S^{\oplus}| = 4$   
 $|S^{\ominus}| = 6$



10 / 18

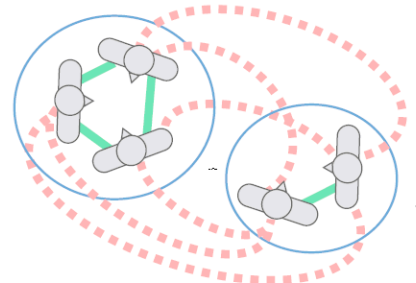
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10 / 18

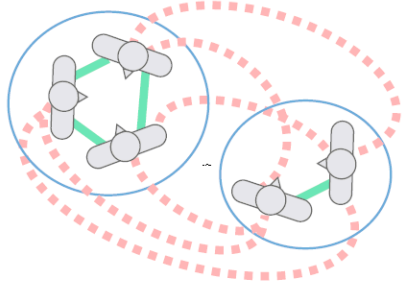
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10 / 18

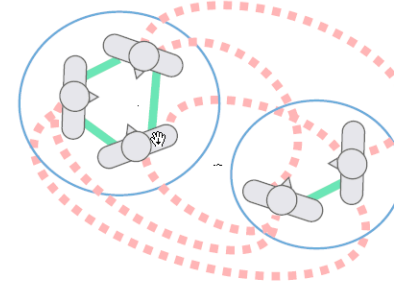
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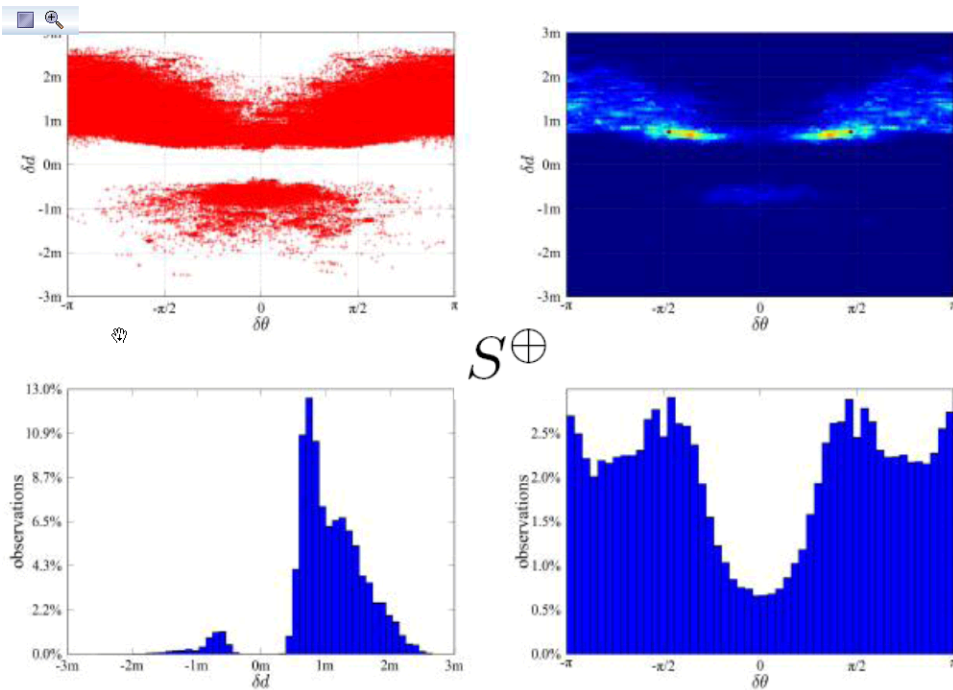
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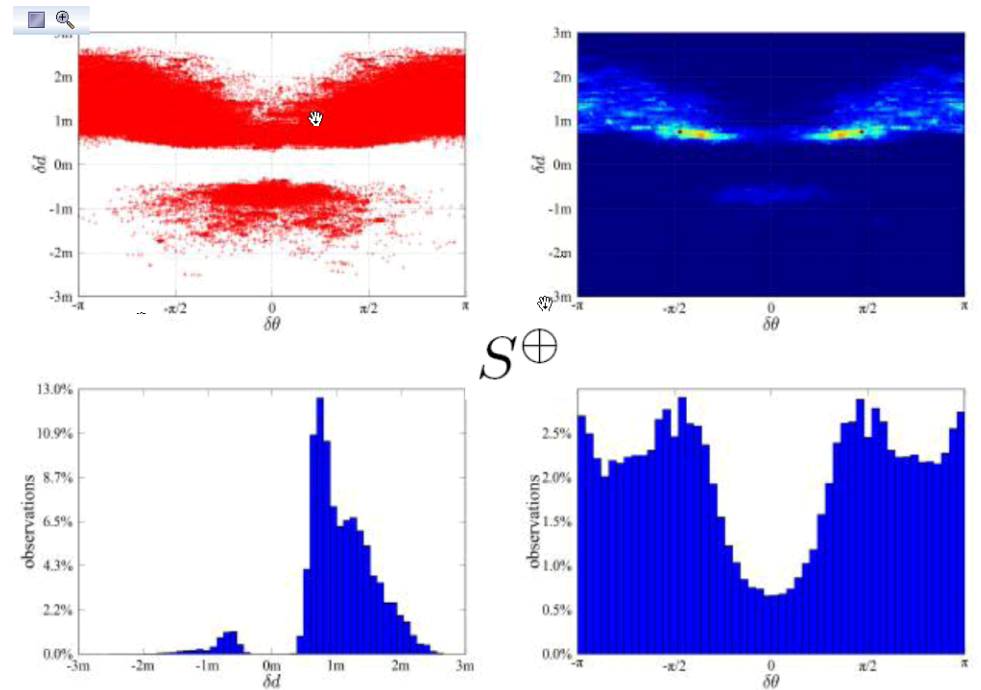
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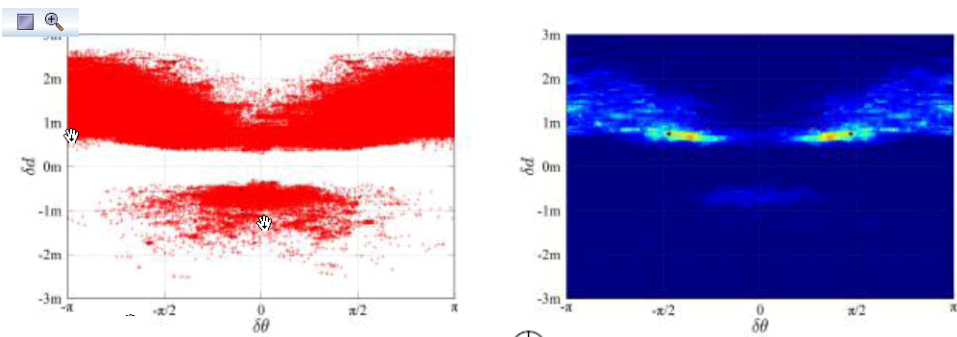
10 / 18



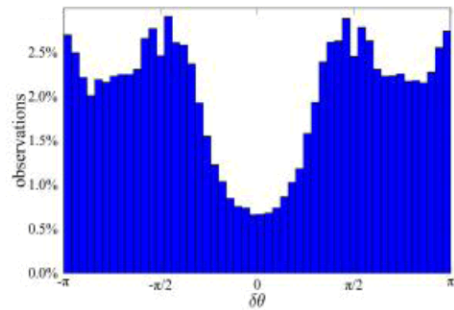
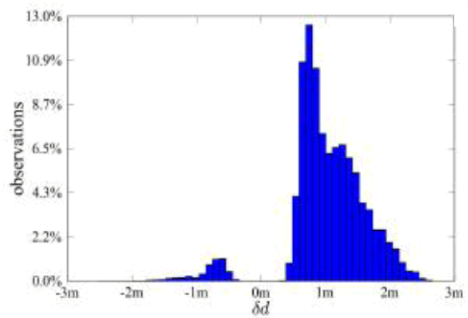
11 / 18



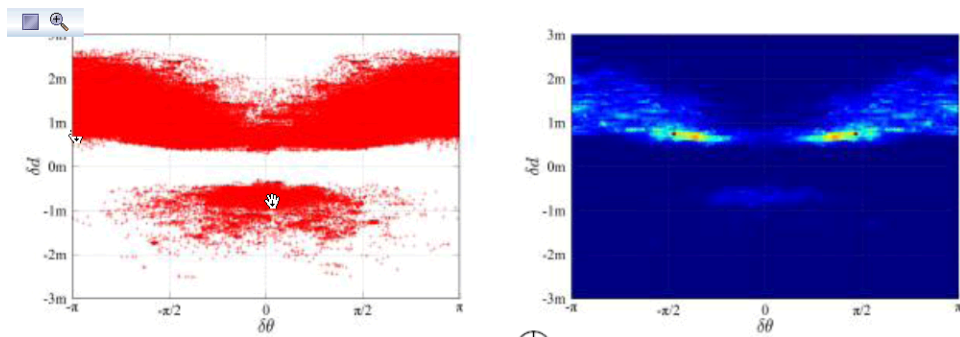
11 / 18



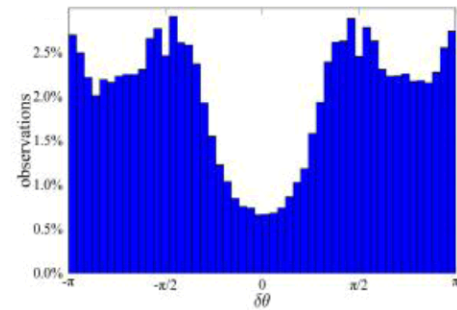
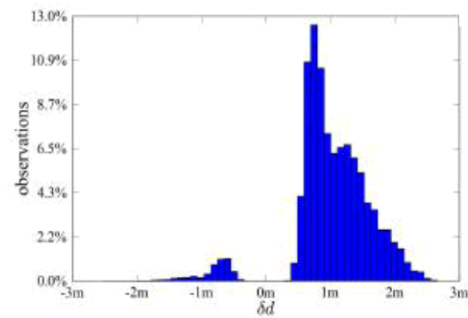
$S^{\oplus}$



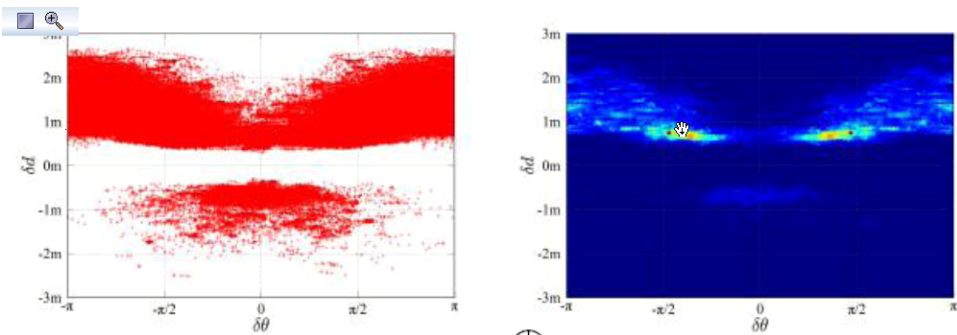
11 / 18



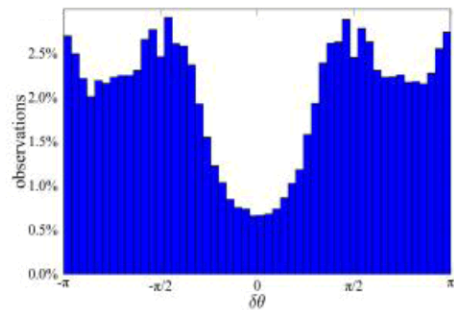
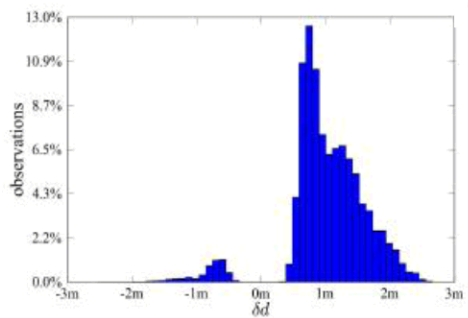
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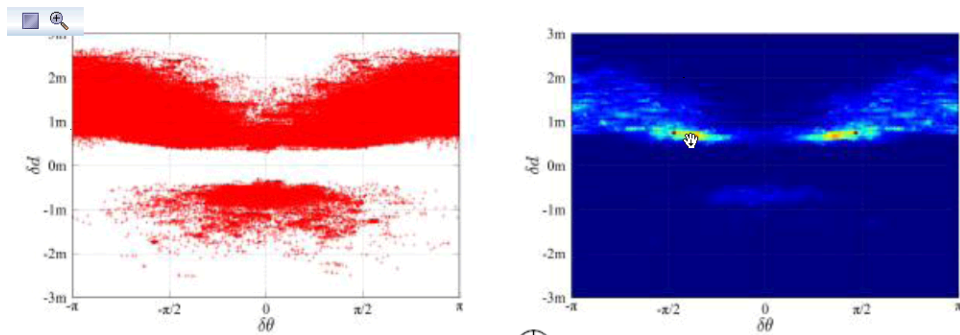
11 / 18



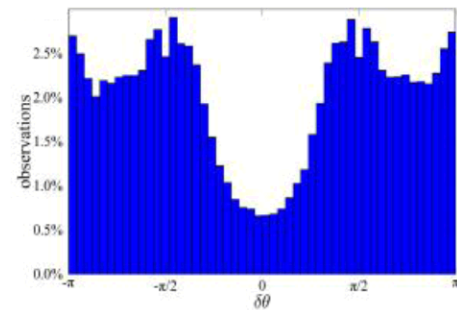
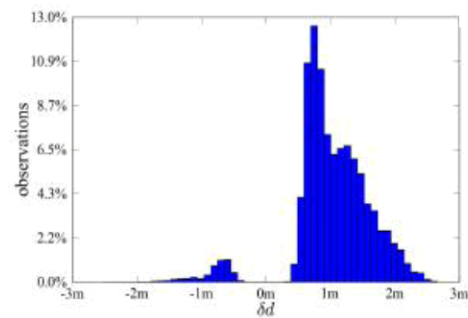
$S^{\oplus}$



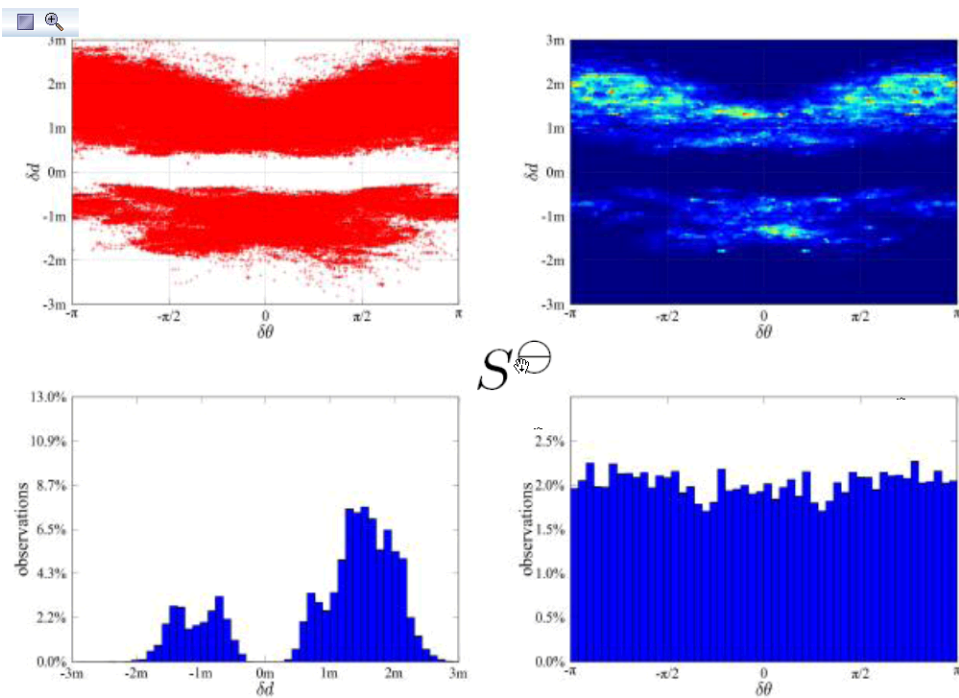
11 / 18



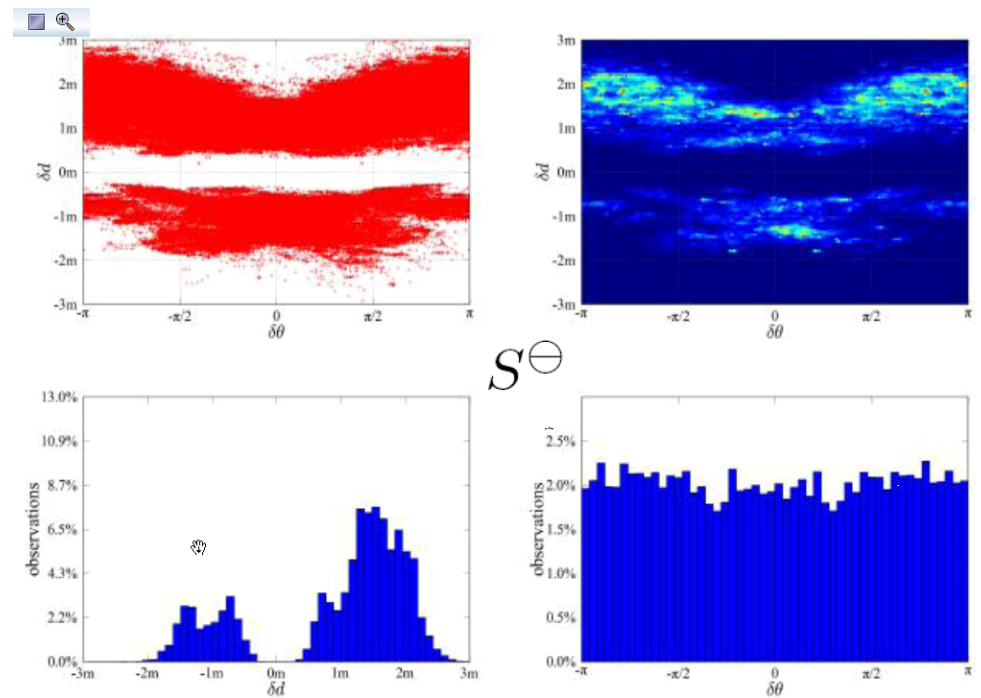
$S^{\oplus}$



11 / 18



12 / 18

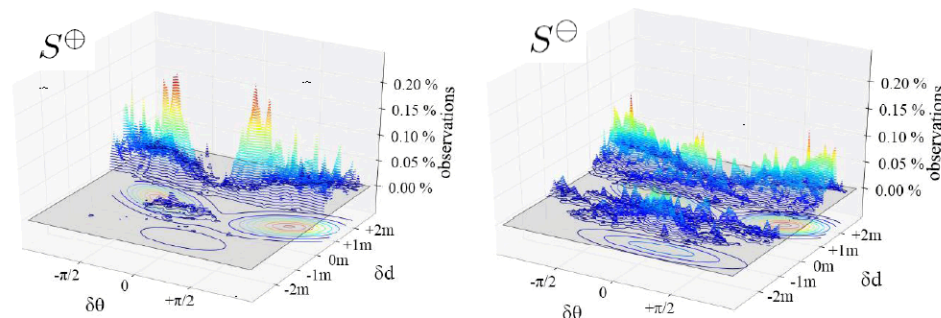


12 / 18

## Results

$S^{\oplus} = \{ (\delta\theta, \delta d) \}$  pairs in a social situation  
 $S^{\ominus} = \{ (\delta\theta, \delta d) \}$  pairs not in a social situation

→ train (EM-algorithm) one **Gaussian Mixture Model** for  $S^{\oplus}$  and one for  $S^{\ominus}$   
 →  $p^{\oplus}(\delta\theta, \delta d)$  and  $p^{\ominus}(\delta\theta, \delta d)$



13 / 18

## Classification Results

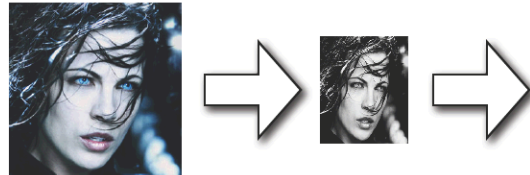
Classifier	Accuracy*
Gaussian Mixture Model (3 Gaussians)	74,34 %
Gaussian Mixture Model (5 Gaussians)	74,67 %
Gaussian Mixture Model (7 Gaussians)	74,59 %
Naive Bayes	65,45 %
Support Vector Machine (Polyn. Kernel)	77,81 %

(\*) w. 10-fold cross validation

14 / 18

# Preprocessing

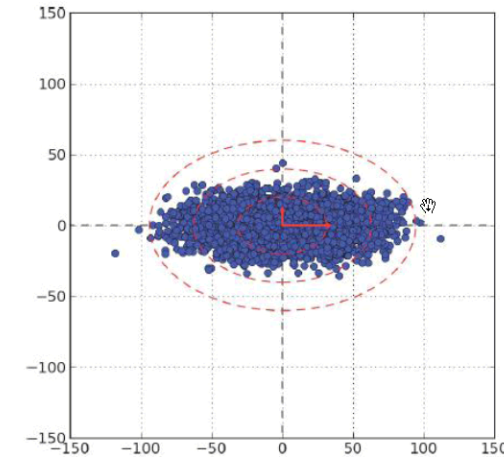
- Two-dimensional images correspond to one-dimensional vectors



Ⓜ			0.47
0.99	0.97	...	0.24
...	...	...	...

0.12	0.8	...	0.47	0.99	0.97	...
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# Example



# Derivation

- Eigenvalue decomposition of the covariance matrix

$$C = E\Lambda E^T = \begin{pmatrix} e_{11} & \dots & e_{1n} \\ \vdots & \ddots & \vdots \\ e_{m1} & \dots & e_{mn} \end{pmatrix} \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix} \begin{pmatrix} e_{11} & \dots & e_{m1} \\ \vdots & \ddots & \vdots \\ e_{1n} & \dots & e_{mn} \end{pmatrix}$$

where the columns of E denote the eigenvectors of C and each  $\lambda$  the respective eigenvalue

- In case of PCA, the principal components are the ones associated with the highest eigenvalues, hence

$$|\lambda_1| > |\lambda_2| > \dots > |\lambda_n|$$

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# Preprocessing

- Concatenation of the  $N_p$  images for each person  $p$  yields the final training dataset

$$X = \begin{pmatrix} i_{11} & i_{21} & \dots & i_{N_1} \\ i_{12} & i_{22} & \dots & i_{N_2} \\ \vdots & \vdots & \ddots & \vdots \\ i_{1d} & i_{2d} & \dots & i_{N_d} \end{pmatrix}$$

where  $i_{jk}$  denotes the  $k$ -th component of the  $j$ -th image (now represented as  $d$ -dimensional vectors) and  $N = \sum_{p \in P} N_p$

- A second data structure is mandatory to store the assignment of column indexes to persons

# Eigenfaces

- Reconsider the general form of the eigenvalue equation

$$\Sigma' x = \lambda x$$

- Substitute  $X^T X$  for  $\Sigma'$

$$X^T X x = \lambda x$$

- Multiply the above equation with  $X$

$$X X^T X x = \lambda X x$$

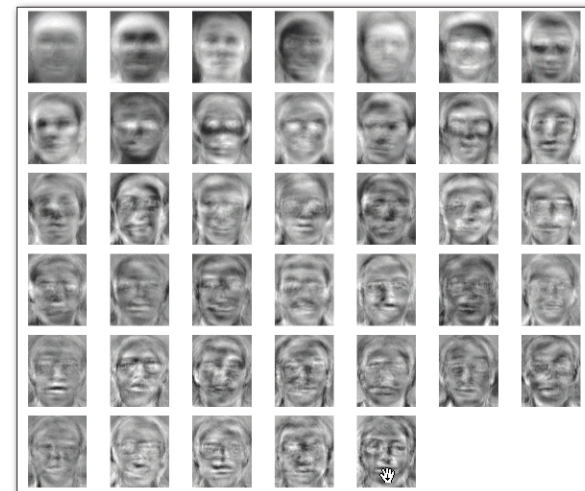
- Substitute  $\Sigma$  for  $X X^T$

$$\Sigma X x = \lambda X x$$

# Eigenfaces

- Next, PCA is used to determine the set of eigenfaces (typically  $\sim 40$ ) that are best fit to reconstruct the training data
- Beware:  
A  $92 \times 112$  image yields a 10304-dimensional vector.
- How can we deal with the eigenvalue decomposition of a  $10304 \times 10304$  covariance matrix?
- Actually only  $\sim 40$  eigenpairs need to be computed!

# Eigenfaces







## Task 2: Face Recognition

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main To Dos:

- built a database of face-images and detect faces with the help of Open-CV (given C++ class)
- understand and implement Principal Component Analysis
- implement a KNN classifier
- apply and test your implementation to the test-database.

