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Person Detection from Audio

"Speaker Diarization / Segmentation": given multi-party audio data (possibly with background noise):

→ who talks when?

- Typically 3 steps:
  - --segmentation into speech / non-speech
  - --detection of speaker transitions
  - --clustering of speaker segments (+ classification of speaker)
- Segmentation into speech / non-speech:
  - -- Generate features:
    - ++ digital signal (pre-) processing (involving e.g. sub-division signal into overlapping samples of typically several ms, Fourier-transform etc.)
    - ++ MEL filters → MEL cepstrum coefficients
    - ++ Further Fourier- and other transformations
    - ++ additional features: zero-crossing rates, energy statistics etc.

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Person Detection from Audio

- Clustering of segments:
  -- e.g. use hierarchial bottom up clustering:
  merge segments with most similar models (e.g. Gaussians);
  cut dendrogram at maximum total likelihood

- Numerous systems integrate or split several of the aforementioned steps or use other ML techniques (DBN approaches etc.) → difficult business ☺

Person Detection from Video

- First step: Face detection
  - Naive apprach: simple pixel based binary classifier.
    Problem: too many possibilities for non-faces
  - Other approaches:
    - detect correct relatively positioned patches of skin, eyes or other face elements. Advantage; relatively robust against rotations
    - Approach [6]: Use special features instead of pixels (advantage: domain knowledge can be encoded into features), Intelligent feature selection / combination of simple binary classifiers that work on single features (AdaBoost)
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Person Detection from Video

- Human figure detection:
  - Main problem: too many options (clothes, accessoires)→ pixels as features won‘t work
  - Approaches:
    - features: histograms of directions of detected edges

Fig. 8. People detection. Examples of people detection in public spaces (pictures from [216]).

[1]

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Detecting Social Signals: Gestures and Posture

- Gestures:
  --not many studies yet interpreting them as social signals
  --several studies: gestures as means of input
  (special example: touch interfaces)
  --other study: automatic interpretation of sign language
- Gesture recognition: main challenges:
  --detecting gesture-relevant body parts: select feature spaces, e.g. via
  ++histograms of oriented gradients
  ++etc.
  --modeling temporal dynamic e.g. using:
  ++Hidden Markov Models (HMMs)
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Detecting Social Signals: Gaze and Face

- Features for facial expression recognition:
  - geometric (shapes of facial components, locations of focal points etc.)
  - appearance (skin texture in different areas)

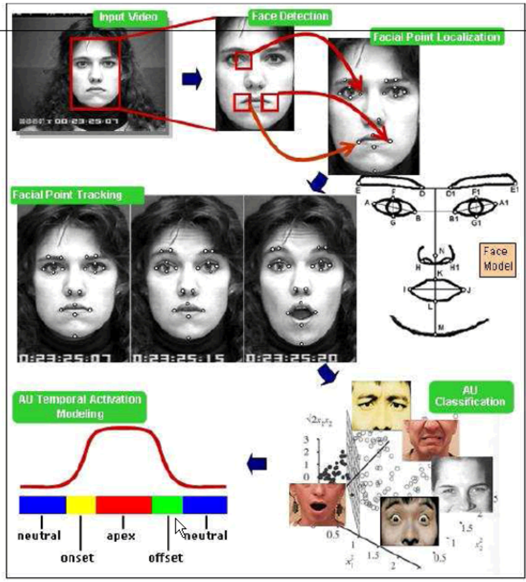

Fig. 9. AU detection. Outline of a geometric-feature-based system for detection of facial AUs and their temporal phases (onset, apex, offset, neutral) proposed in [196].

[1]

Detecting Social Signals: Gaze and Face

- AU: smallest discernable temporal feature sequence: sequence of geometry or appearance features (modeled e.g. via Dynamic Bayesian Networks (DBN))

- Detection: example: basic integrative methods based on optical flow on detected faces:
  --optical flow: motion pattern of picture elements (e.g. pixels):
  represented by vector field of velocity V(x,y,t) of intensity:

$$I(x+dx, y+dy, t+dt) = I(x,y,t) + \frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt + O(d^2)$$

$$\rightarrow \frac{\partial I}{\partial x}V_x + \frac{\partial I}{\partial y}V_y + \frac{\partial I}{\partial t} = 0 \quad \text{(optical flow equation)}$$

use numeric methods to compute solutions

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Detecting Social Signals: From Audio

- Vocal features: up to now: mostly investigated for speech detection
- Prosody: pitch, tempo, energy
  --pitch: first fundamental frequency (1st maximum in Fourier transform (e.g. 30ms frames)
  --tempo: vowels / sec. ; vowel: phonetically relevant unit
  --energy E of signal s(t): $E = \sum_i s(t_i)^2$
- Few efforts so far in analysis of non-linguistic vocalizations
  --example: laughter detection (e.g. via SVMs)
  and linguistic vocalizations
- silence detection: e.g. via energy as feature (often as by-product of speaker diarization)

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Context

- Important issue: behavioral cues can have different meaning if happening in different outer contexts
- Example: temporal dynamics of behavioral cues / social signals (e.g. relative person–person timing, person-environment timing etc.)
- Other important issue: multi-modal combination / fusion of social signals (e.g. audio and interaction geometry)

Applications

- Predict outcome of dyadic interaction (selling, dating etc.) via audio and derived via social signals such as
  - --activity (via energy),
  - --influence (via stat. analysis of influence of A's speaking patterns on B's speaking patterns)
  - --consistency (stability of person's speaking patterns)
  - --mimicry (mirroring)
- Eigenbehaviors (via PCA on features such as location, co-presence etc.)
- Analyzing interactions in small groups (e.g. meetings), role structures and detection of user interest via audio and video:

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Applications

- Interactions in small groups: dominance of persons, recognition of collective actions
- recognition of roles and extraction of small social networks (e.g. via analyzing meetings or broadcast TV shows)
- analyze reaction of users to embodied conversational agents (ECAs)

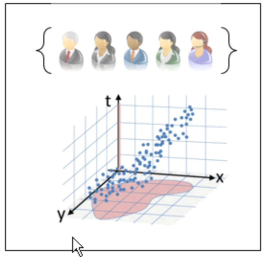
Social Situation Models as Models of Social Context

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 $\mathbb{R} \times \mathbb{R}^3$
- → S = (P, X)



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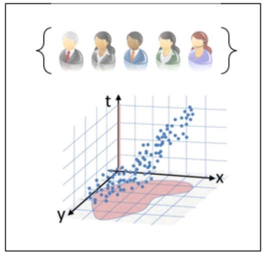

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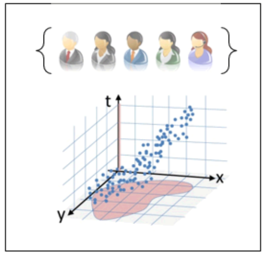

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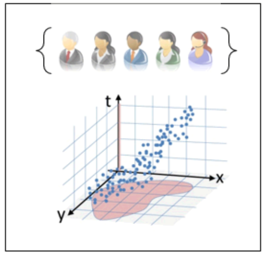

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Detecting Social Situations: Mobile Social Signal Processing

Social Situation detection

- Example: microphone → audio-signals → speaker diarization → set of interacting persons
- Example: gyroscope, accelerometer, ultrasound-s. → relative body distance & orientation → set of interacting persons

Social Situation understanding

- Example: microphone → audio-signals → analysis of prosody → emotion detection → model of state of mind of person(s)

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Geometry of Social Interaction

Interpersonal distances

- Hall: „general quality“ of social relation → 4 personal zones
- Other influences (?):
  social context:
  architectural environment (socio-petal, socio-fugal forces (Watson)), density, gender, etc.
  individual context:
  culture, age, self-esteem, disabilities,

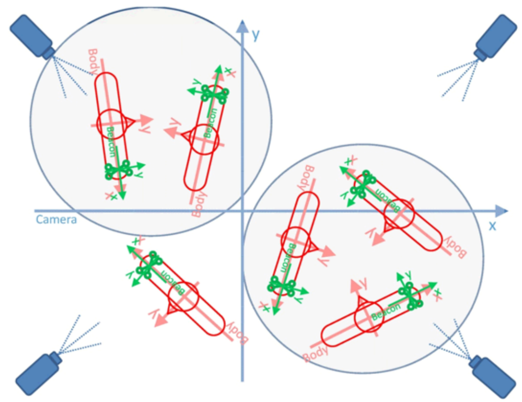
Body angles

- Kendon: F-Formations [8]

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

Experiment



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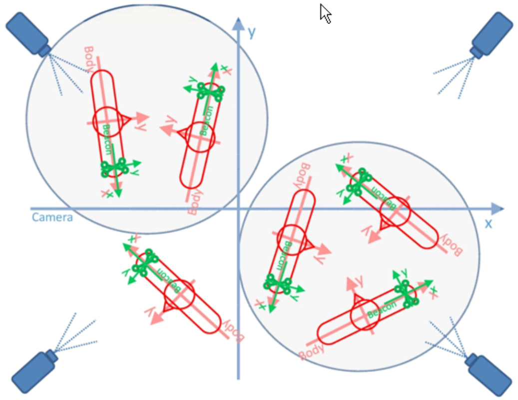

Model for Human Social Int. Geometry: Function $p(\delta\theta, \delta d)$

- Idea: Reduce n-ary social interaction to binary; infer n-ary by graph clustering
- Binary: $p(\delta\theta, \delta d)$
  - $\delta d(t) = \pm |P_{x,y}\ s_1(t)\ -\ P_{x,y}\ s_2(t)|$
  - $\delta\theta(t)\ = \theta_z\,(R_{12}(t)) = \theta_z\,\left((R_1(t)\,(R_2(t))^T\right)$
- Optional: $p(\delta\theta,\ \delta d,\ \overline{\delta d})$

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Results

Experiment data: Manual annotation

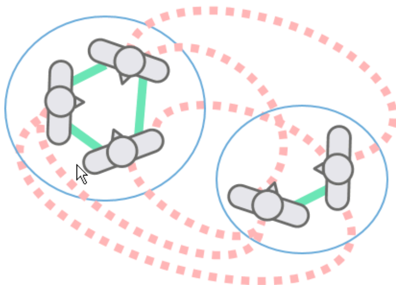
$|S^{\oplus}|\ =$ 321307 $(\delta\theta,\ \delta d)$ pairs corresponding to „in a social situation“

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

Example:

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

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



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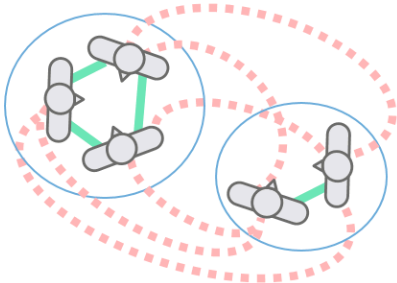

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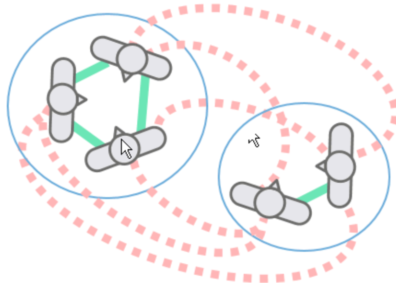

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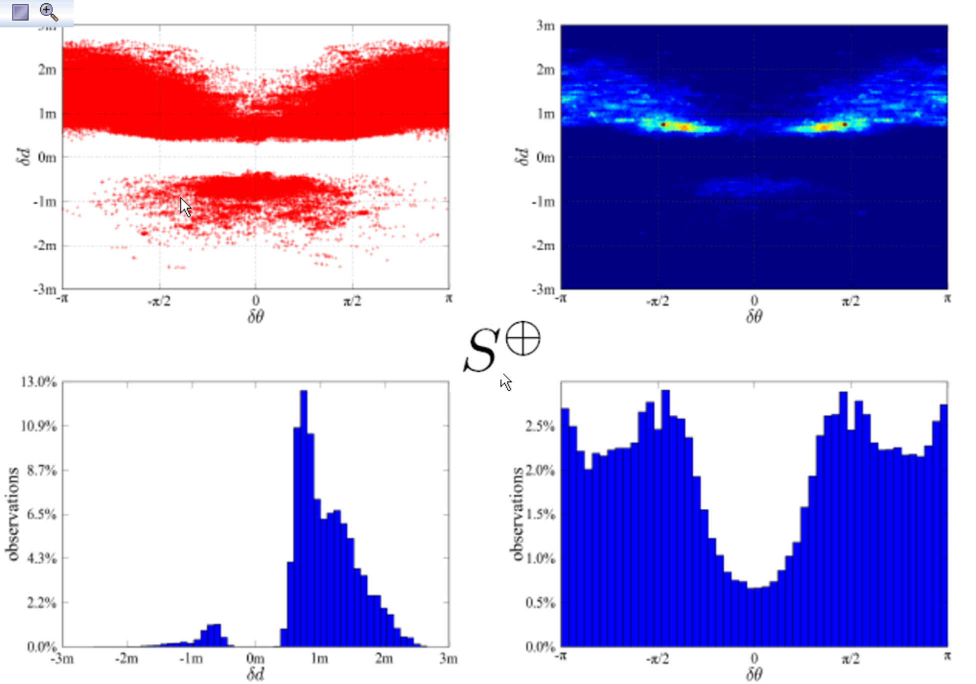

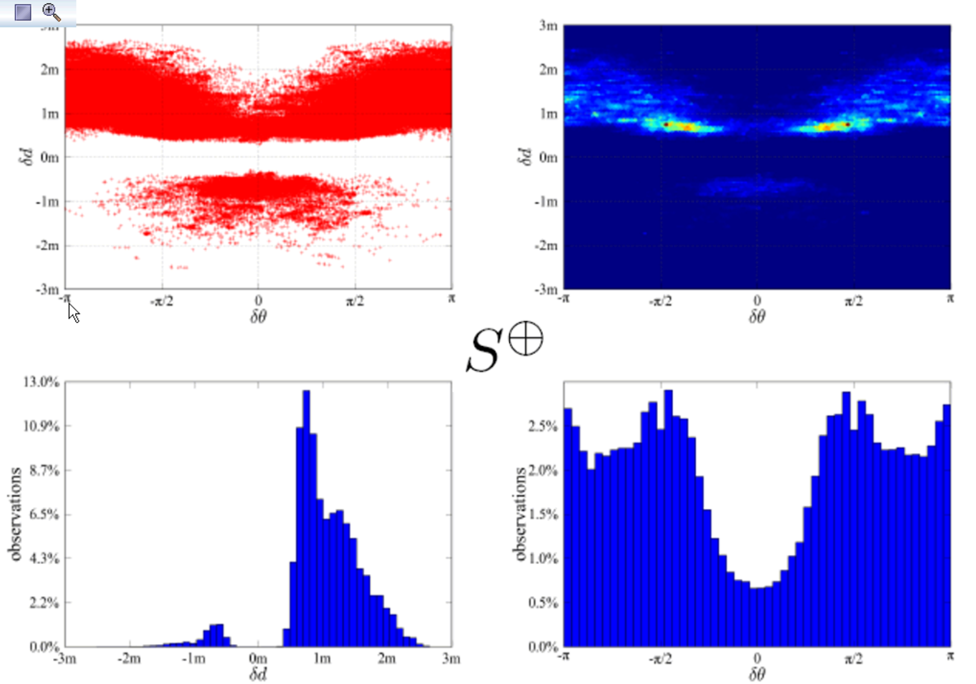

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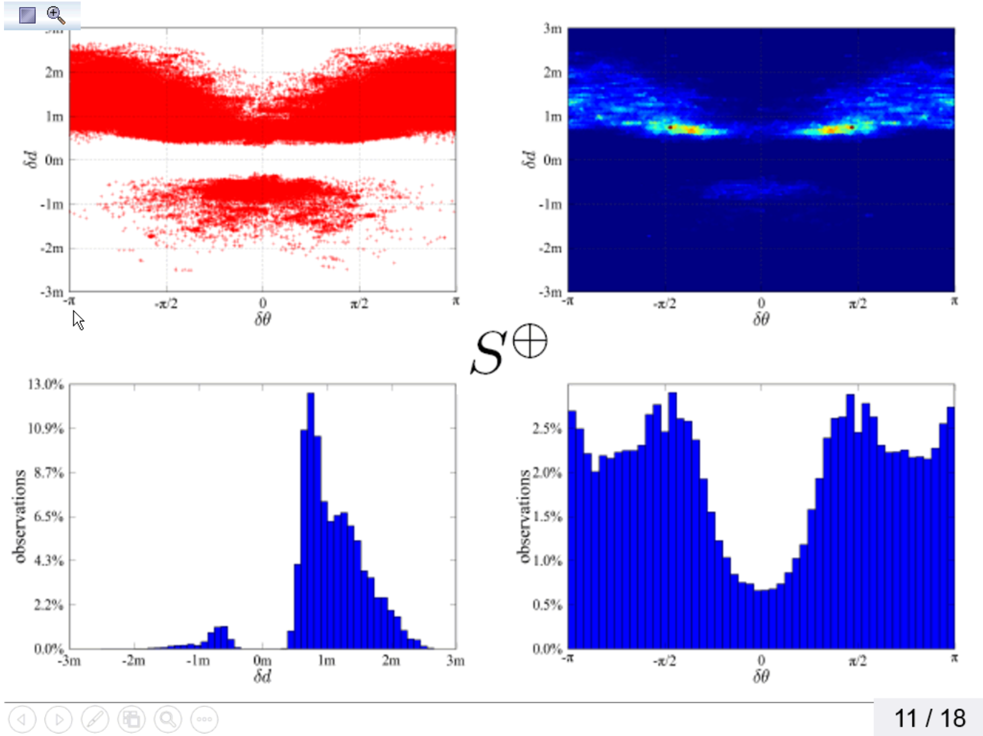
$S^{\oplus}$
δd
δθ
observations
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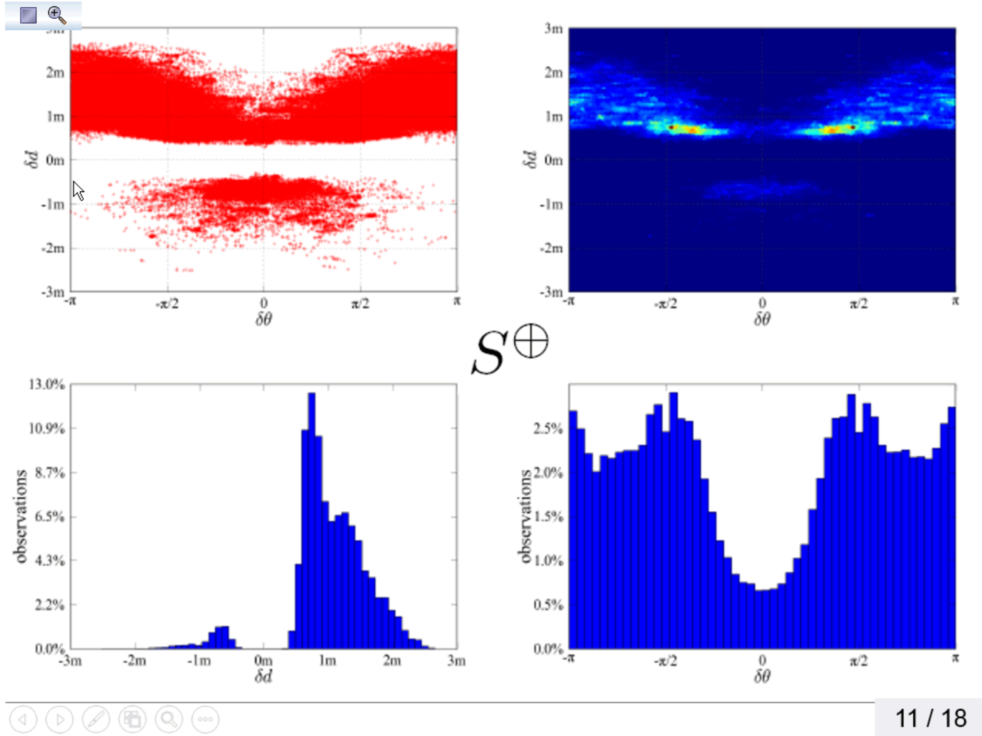
$S^{\oplus}$
δd
δθ
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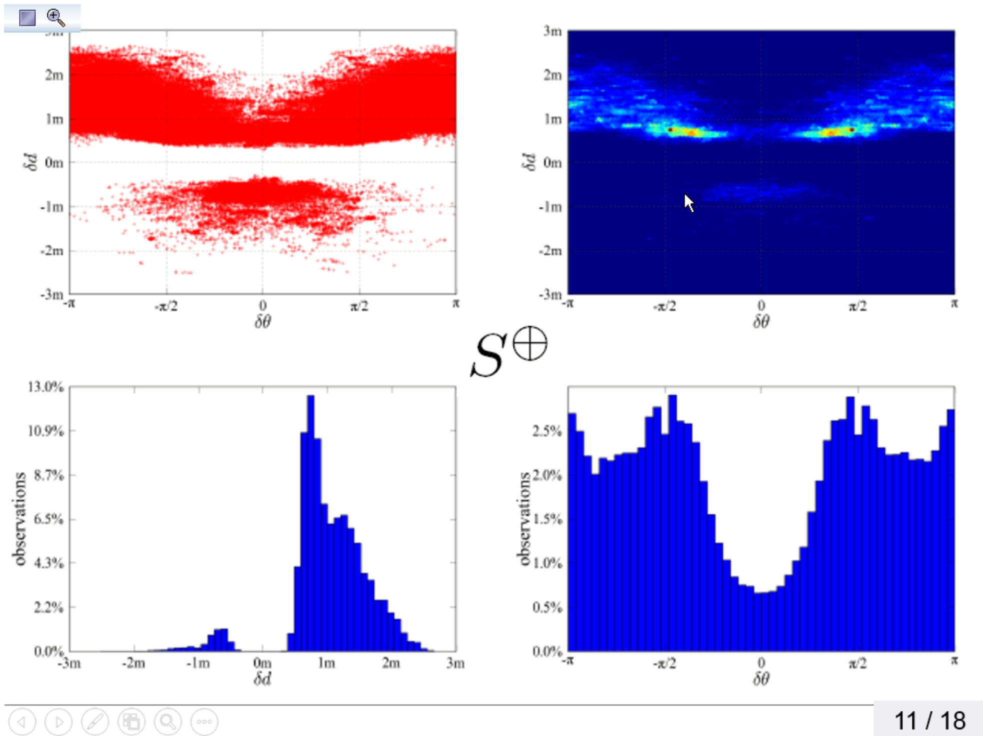
11 / 18


$S^{\oplus}$
δd
δθ
observations
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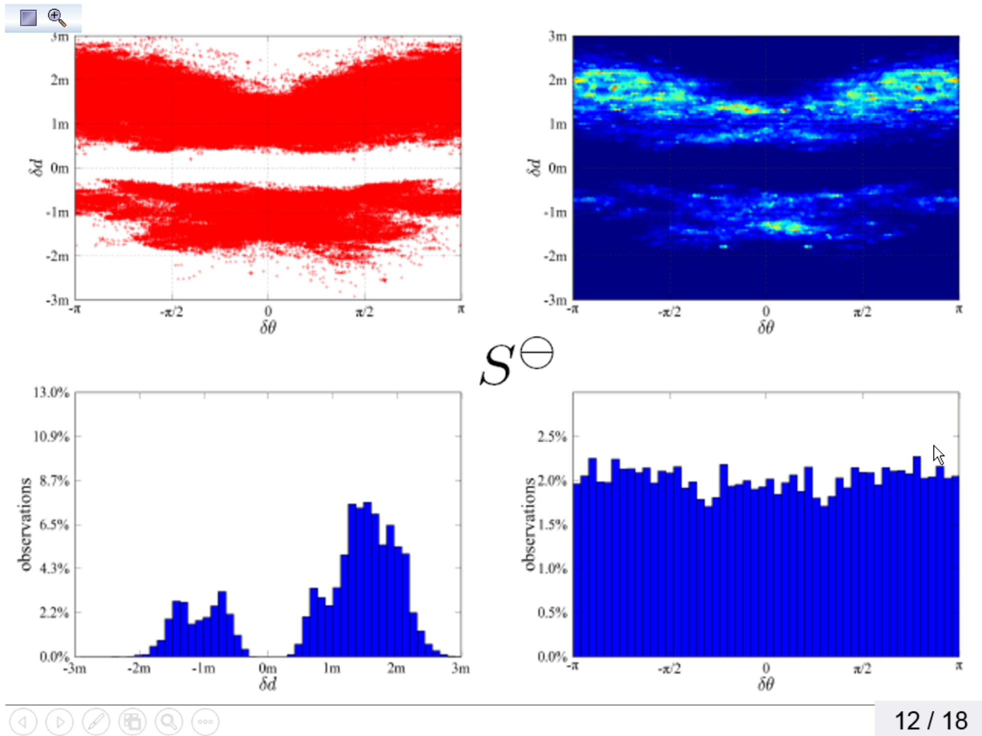
$S^{\ominus}$
δd
δθ
observations
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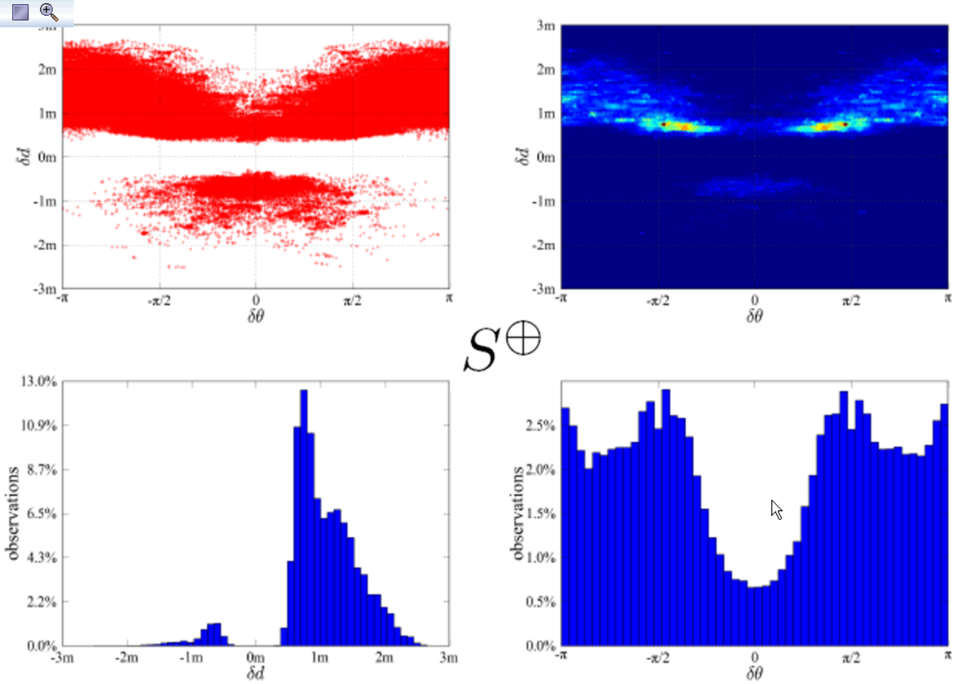

Classification Results

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

Reconstructing Social Situations

- For each t : complete weighted Graph $G(V,E,w,t)$ with V=set of persons,

$$w((s_1,s_2)) = \frac{p^{\oplus}(\delta\theta_{s_1s_2}, \delta d_{s_1s_2})}{p^{\oplus}(\delta\theta_{s_1s_2}, \delta d_{s_1s_2}) + p^{\ominus}(\delta\theta_{s_1s_2}, \delta d_{s_1s_2})}$$

- Average Link Clustering of $G(V,E,w,t)$ + Maximum Modularity Dendrogram Cut → Partition X of V
- Compare X with annotation X' via $RAND(X,X')$ → Accuracy of Social Situation Detection for each t
- Average over all t : RAND ~ 0.76 Adj.Rand ~0.529

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