Semi-automatic parametrization of social context cognition model (for personality and affect generation)

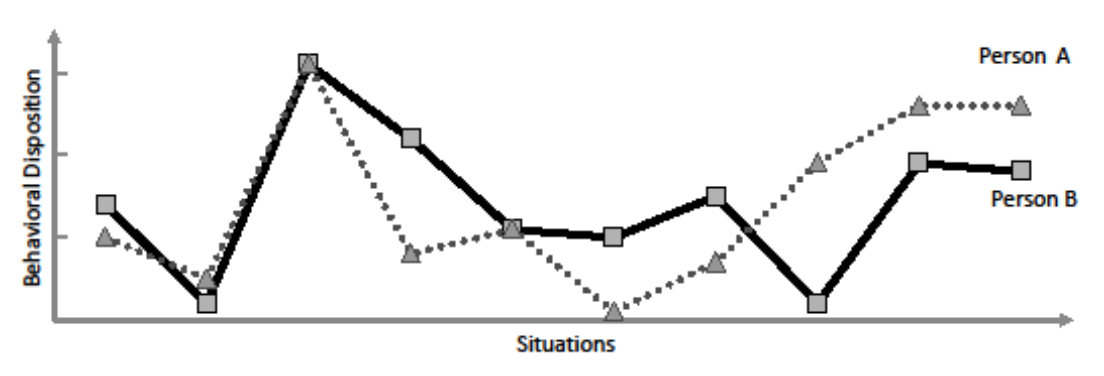
Jaroslaw Kochanowicz
Tan Ah Hwee
Daniel Thalmann

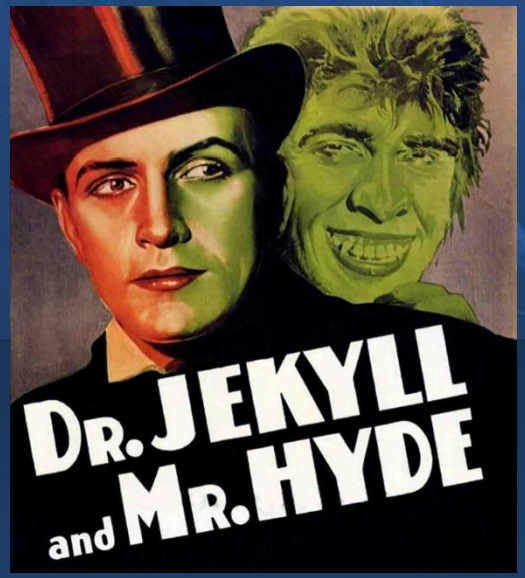
Original Problem

Personality models like 'Big Five' attribute features (e.g. openness, conscientiousness, extraversion, agreeableness, and neuroticism) that remain static over all contexts

But in fact, those features change significantly!

- difference between contexts = difference between people
- 50-50 person-situation rule

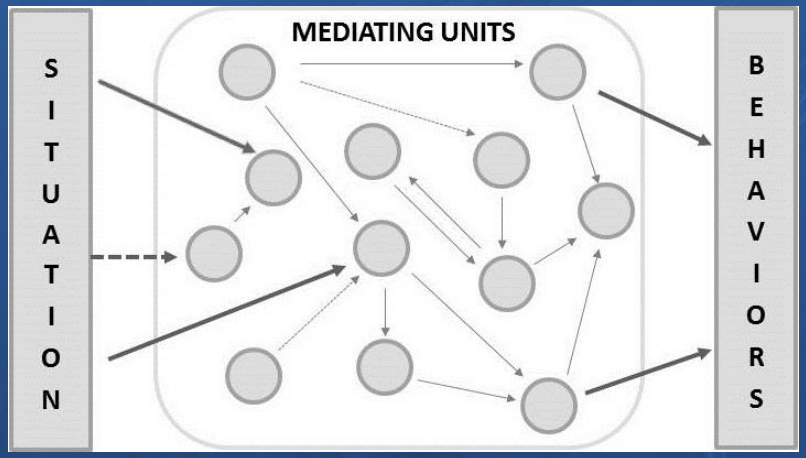




Psychological framework and proposed model

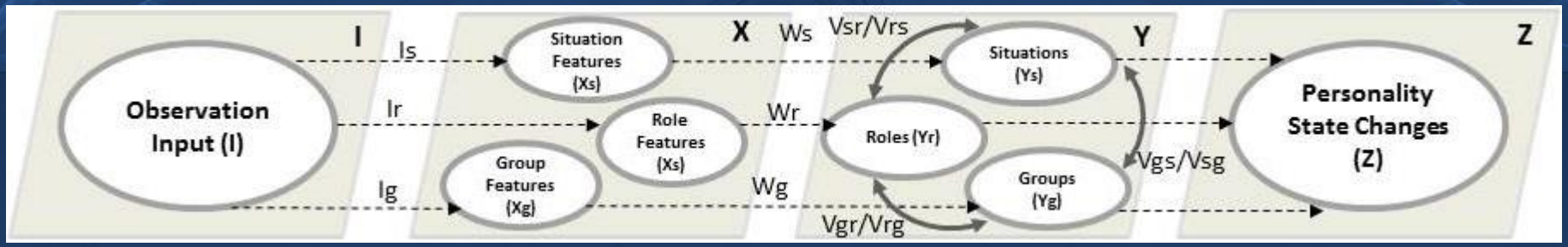
Cognitive-Affective Personality System (CAPS). W. Mischel and Y. Shoda. 1995

- mediating units
- very little detail

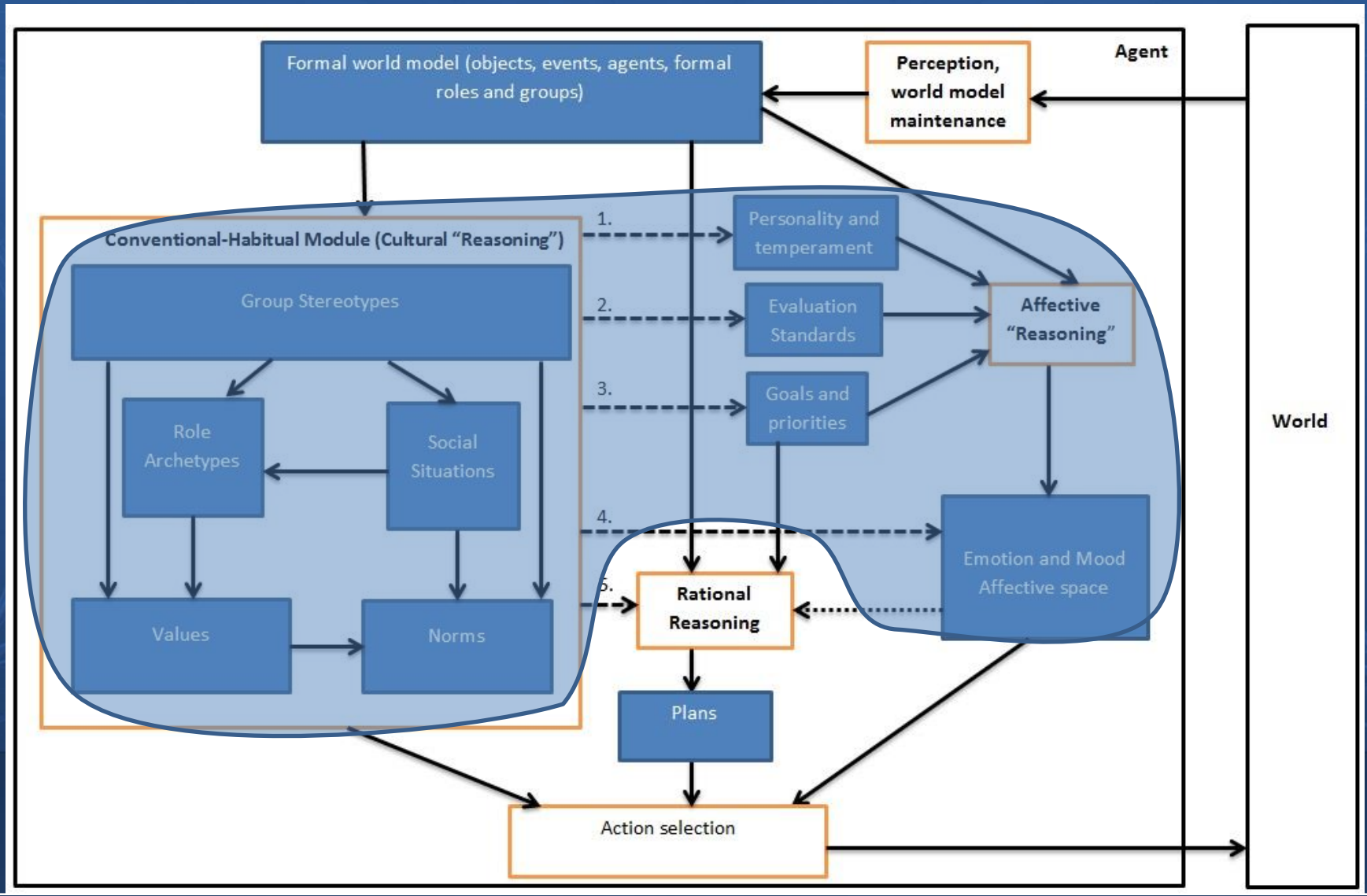


Solution: social Context based Personality(SCP)

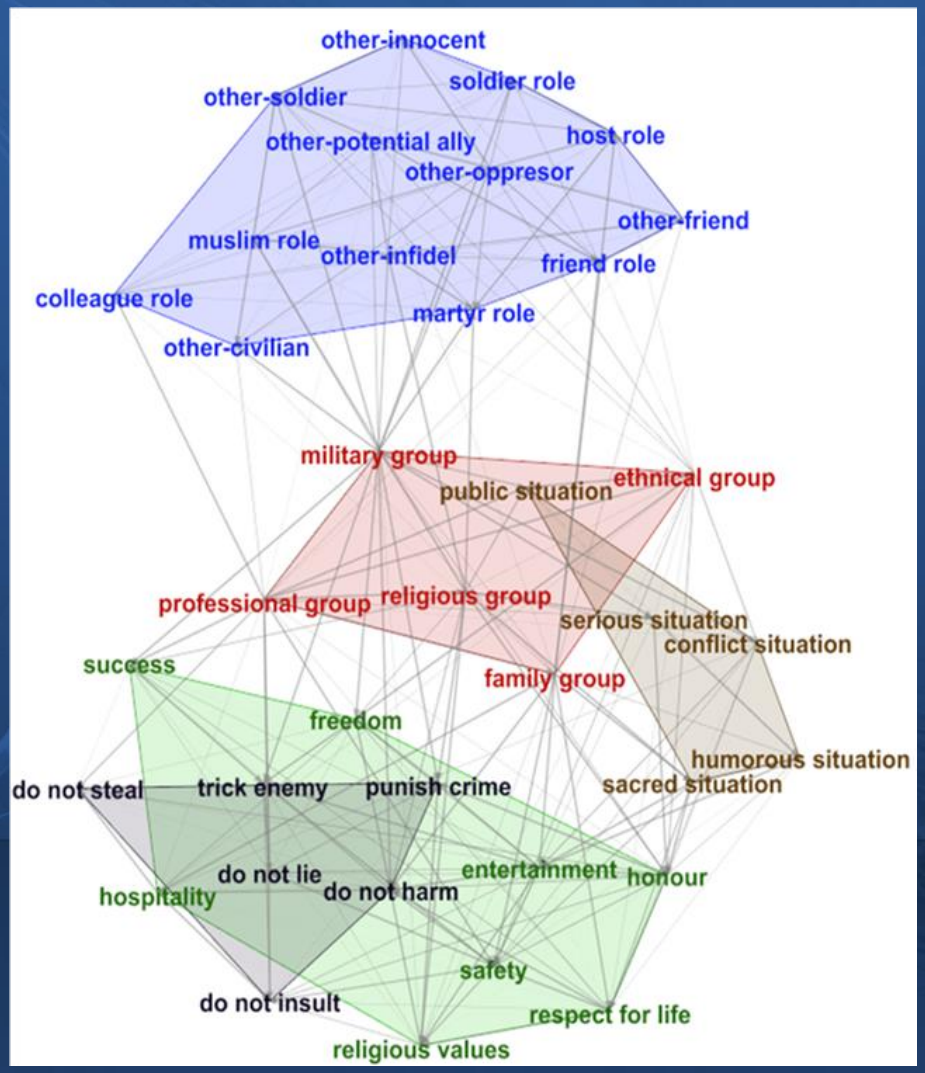
- specification of CAPS
- connectionist model of social context cognition



New personality



Problem with the developed characters



Complex. Many parameters.

How do we get good parameters?

Solution: offline crowdsourcing of the social context cognition

Literature study: crowdsourcing affective and socio-cognitive data

-VidL, a distributed video-labeling tool specifically designed for labeling affective data.
[Micah Eckhardt and Rosalind Picard. 'A more effective way to label affective expressions'. In Affective Computing and Intelligent Interaction and Workshops, 2009. ACII 2009. 3rd International Conference on, pages 1–2. IEEE, 2009.]

-'Guess What?' game crowd-sourcing affective video data labeling of social situations.
[Laurel D Riek, Maria F Oconnor, and Peter Robinson. Guess what? a game for affective annotation of video using crowd sourcing. In Affective computing and intelligent interaction, pages 277–285. Springer, 2011]

System often have problems with 'no objective ground-truth'

- the agreement between the subjects is low,
- this reflects the subjective, culture variant elements

Serious differences to SCP

- SCP extracts precisely the above interpretation differences
- SCP not only probes labels, but also their quantitative relations

There is no real parallel system to compare against

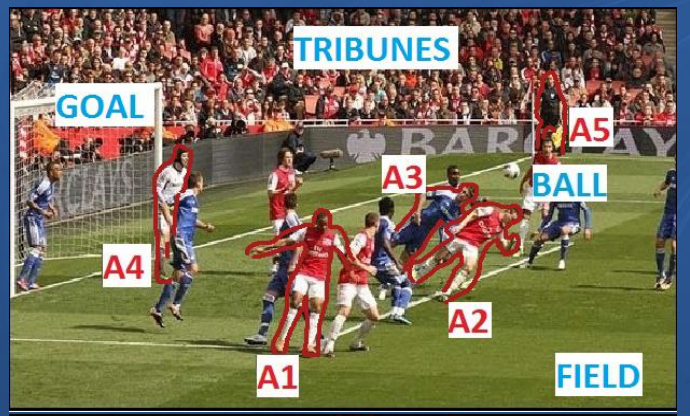
Method overview

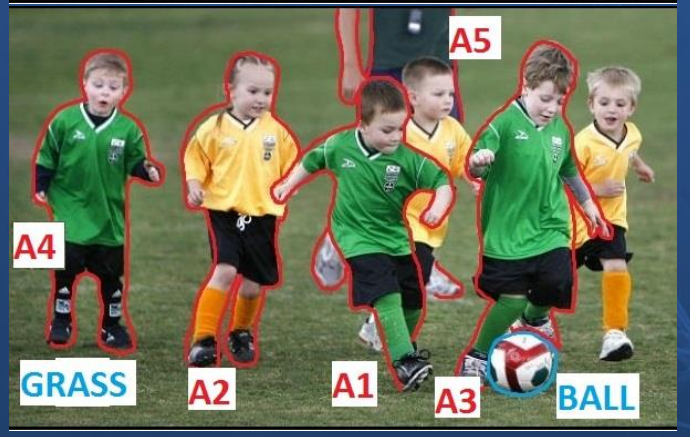
Domain specific sample preparation
- selection to reflect domain
- preprocessing (relevant labeling: ‘ball’ etc.)
- initial set feature selection

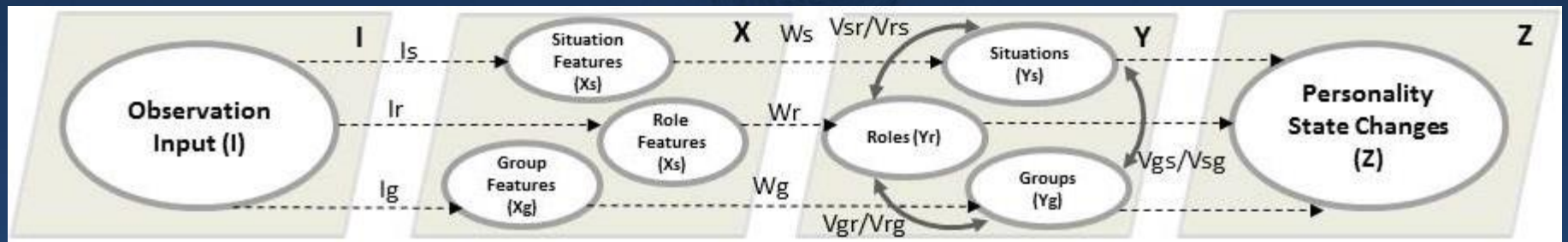
Obtaining parameters
- discrete (mediating unit labels)
- continuous (degree of their presence)

Parameter processing
- correlation/link estimation
- duplicate elimination

SCP generation







Some details, duplicate merging

Duplicate merging procedure

- when are the two terms identical? ‘Football player’ vs ‘goalkeeper’
- domain dependent, not lexical!
- calculate correlations between mediating units, e.g:

$$C_{AP,RC}(ap,rc) = \sum_{\substack{a \in A \\ q \in \mathrm{QA}_{\mathrm{RC}}(rc,a)}} \frac{\overline{V}_{\mathrm{AP}}(ap,a,q) * \overline{V}_{\mathrm{RC}}(rc,a,q)}{\sqrt{U_{\mathrm{AP}}(ap) * U_{\mathrm{AC}}(ac)}}$$

$$U_{\mathrm{X}}(x) = \sum_{QA(n) \in \mathrm{QA}_{\mathrm{X}}(x)} \overline{V}_{\mathrm{X}}(x,n)^2$$

- calculate the differences in correlation patterns
- propose merging when c. patterns of two terms < proximity tolerance
- system designer knows the domain, has the last call

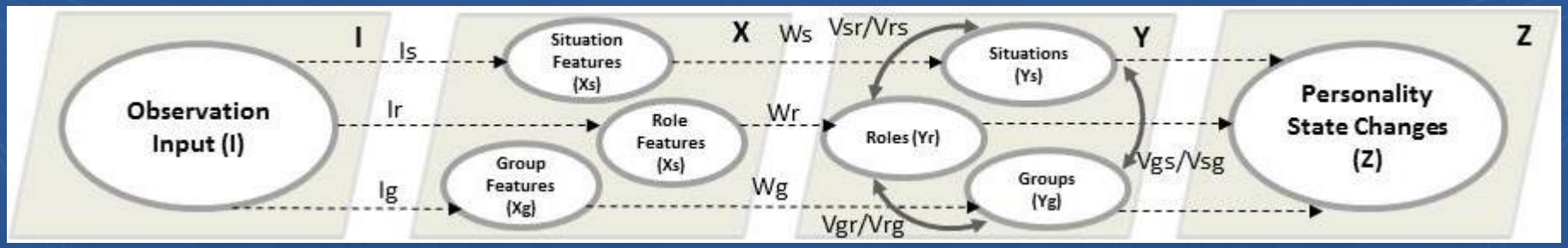
ROLE COMPONENT	BASE SIZE
referee	89 QA
player	95 QA
goalkeeper	72 QA
father	110 QA
child	78 QA
spectator	99 QA
mother	80 QA

MERGER PAIRS — Proximity tolerance parameter: 0.2

COMP 1	COMP 2	STATUS	Distance
referee	ref	duplicate	0.08
referee	arbiter	duplicate	0.13
player	footbal player	duplicate	0.18
referee	assistant referee	duplicate (user set)	0.28
player	goalkeeper	distinct(user set)	0.13
father	dad	distinct	0.23

See Scene Correlations | See Group Correlations | Set as automanaged | Set as distinct | Set as duplicate | See samples | See question-answer sets | Generate Model

Some details, feature evaluation



Feature evaluation

- use percepts to estimate features in linear regression:

$$\tilde{V}_{SF}(f,s) = \sum_{p \in \mathrm{OP}} (\alpha(p,f) + \beta(p,f) V_{OP}(p,s))$$

$$\beta(p,f) = \frac{\sum_{QA(n) \in \mathrm{QA_{SF}}(f)} \overline{V}_{\mathrm{OP}}(p,n) * \overline{V}_{SF}(f,n)}{\sum_{QA(n) \in \mathrm{QA_{SF}}(f)} \overline{V}_{\mathrm{OP}}(p,n)^2},$$

$$\alpha(p,f) = \overline{p} - \overline{f} * \beta_{SP,SF}(p,f)$$

- compare human data with SCP's output:
- difference between the two estimates feature quality (feature and component errors)

$$\tilde{V}_{SC}(c,n) = exp\left(- \sum_{f \in SF} \frac{(V_{SF}(f,n) - \overline{f})^2}{2 D_{SC,SF}(c,f)^2} \right)$$

$$E_{SF}(f) = \sum_{QA(n) \in \mathrm{QA_{SF}}(f)} \frac{\tilde{V}_{SF}(f,n) - \overline{V}_{SF}(f,n)}{|\mathrm{QA_{SF}}(f)|}$$

$$E_{SC}(c) = \sum_{QA(n) \in \mathrm{QA_{SC}}(c)} \frac{\tilde{V}_{SC}(c,n) - \overline{V}_{SC}(c,n)}{|\mathrm{QA_{SC}}(c)|}$$

Testing

Domain: family life and sport. Facial expressions analyzed using emotion extraction software and used as percepts.

Test included 50 preprocessed samples, 10 subjects.

System obtained:

-18 role components (auto-merged to 9)
-11 situation components (auto-merged to 7)
-8 group components (auto-merged to 6)

Validation of feature and component 'errors':

a) in training samples. e = 0.19, 0.12 (sd = 0.08, 0.03)
b) in unused samples e = 0.27, 0.19 (sd = 0.07, 0.03)
avr. human error: e = 0.16, 0.13
c) SCP performance under data stream: e = 0.25, 0.22 with (sd = 0.08, 0.03)

- in trained samples: similar to humans
- in unused samples: decent performance for components. Features are harder.
- under stream of data: system is stable, potentially usable for social agents

Summary

Problem of static-personality issue was presented.

Socio-cognitive model was discussed and its shortcomings discussed

Semi-automatic socio-cognitive model parametrization method was presented

Validation shows promise, but issues with features must be addressed

Thank you!