Emotion Research

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ICT
INSTITUTE FOR CREATIVE TECHNOLOGIES

Mind reading

Well, Guy Cuny is the editor of the technology website, news wireless...

Mind reading

Why care about emotion?

Why care about emotion?

- **Explosion of interest across traditional scientific disciplines**
  Neuroscience, Economics, Organizational Behavior, Psychology
- **Growing interest in computer science and engineering**
  - NSF Human-Centered Computing Initiative
  - 2007: founding of 1st research society on emotion in human-computer interaction
    - Leadership council: Cowie, Gratch, Pelachaud
- **Why?**
  - Dissatisfaction with rational models
    - Eg. Findings popularized by Damasio
  - Broadening of computer applications into the social domain
    - Learning, HCI, Computer Games, Social surveilance

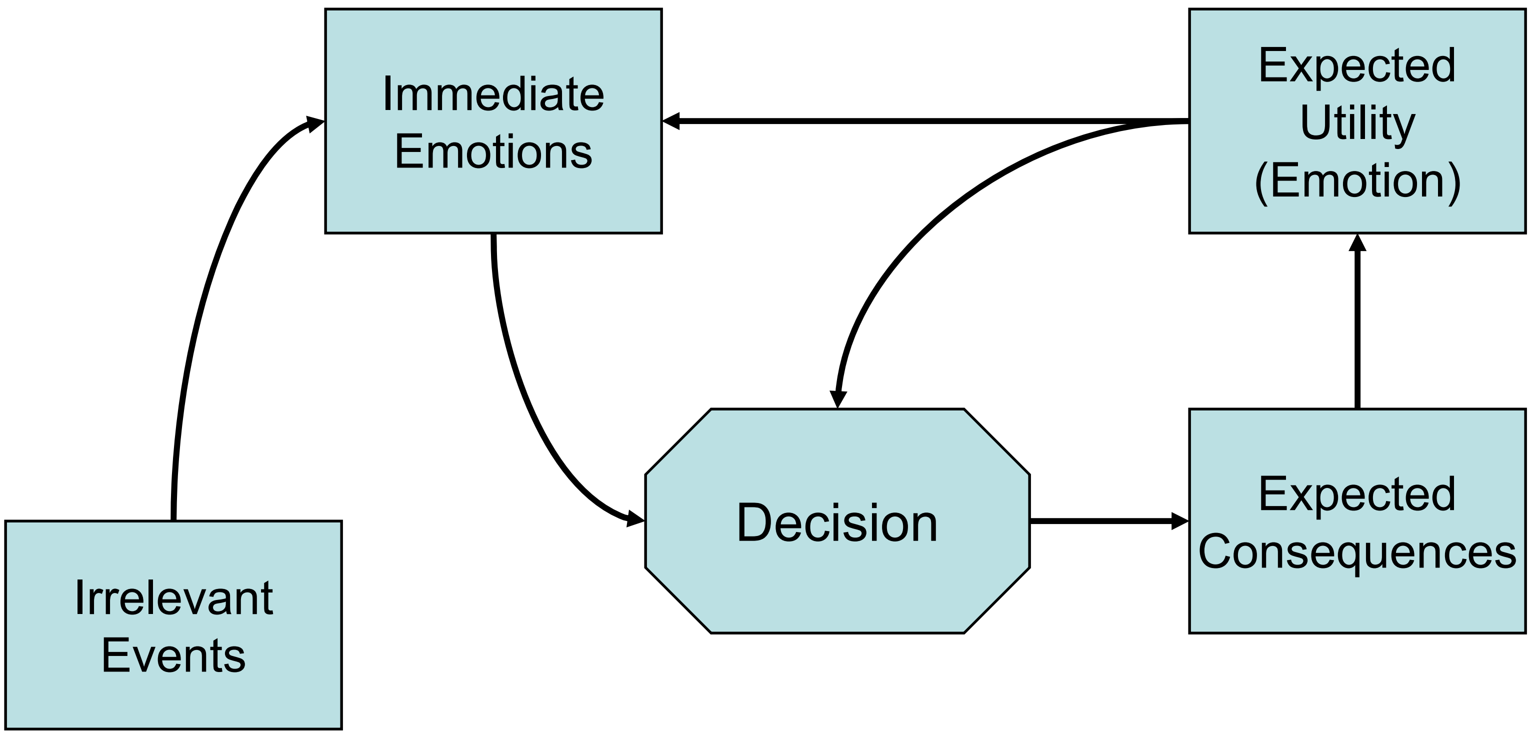
Why care about emotion?

Very different potential goals

- **Modeling goal:**
  - Focus on accurately modeling how emotion works in people
  - Application: User modeling, social simulations, cognitive science
  - Criteria: contrast model predictions against human data
- **Influence goal:**
  - Focus on using emotional displays to achieve social effects
    - Persuasion, entertainment/believability,
  - Unnecessary to accurately model how emotion works in humans
  - Application: Games, HCI, Tutoring
  - Criteria: measure social effects
- **General Intelligence goal: (biomemetic)**
  - Focus on understanding function of emotions in human intelligence
  - Application: improve general models of artificial intelligence
  - Criteria: better problem solving

Emotions change how we think (Loewenstein and Lerner. 2003)

Emotion research highlights limitations of Classical Decision Models

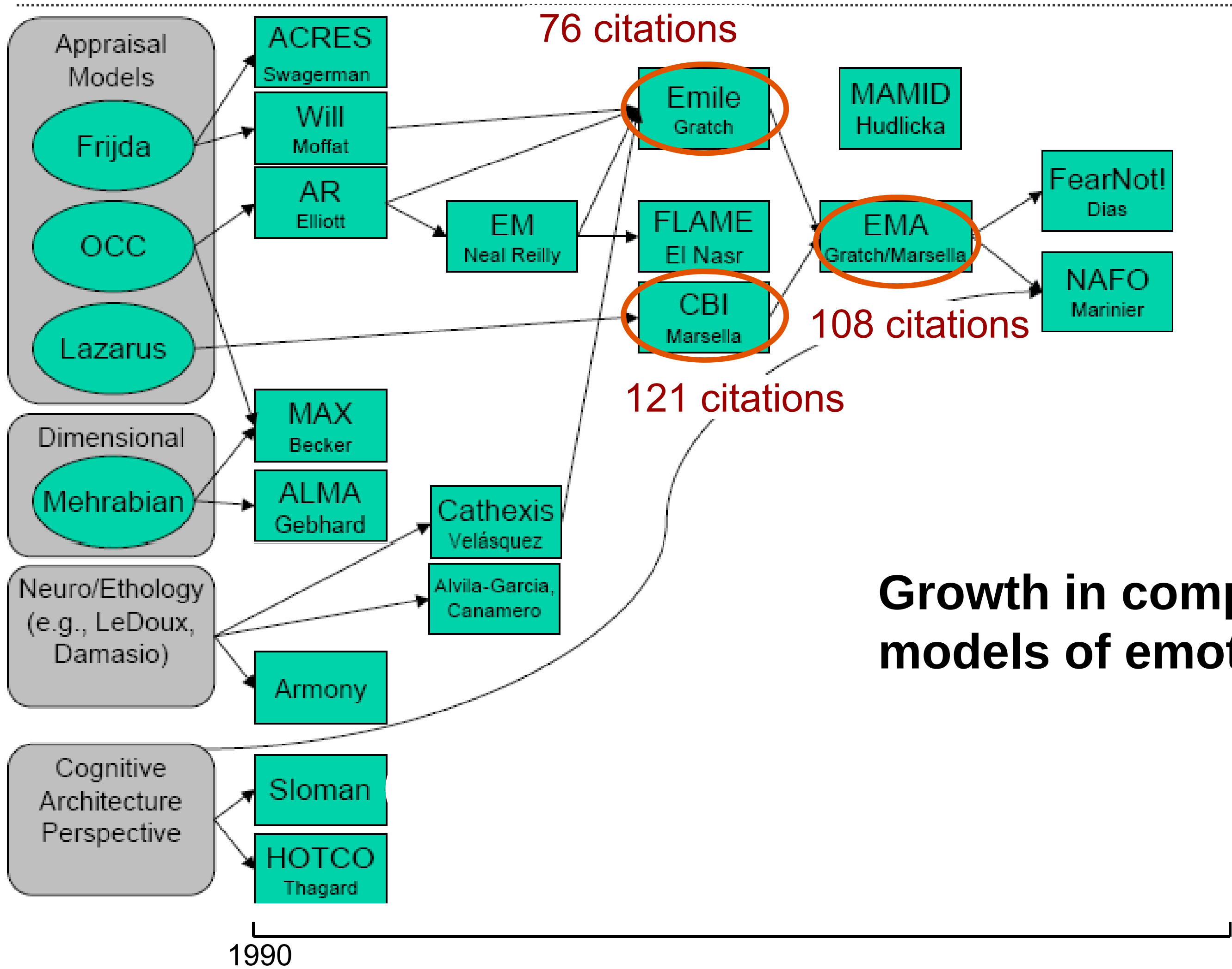


Change nature of social interactions (e.g. Anger)

Lerner & Tiedens 2006

- **Cognitive biases**
  - Greater tendency to blame others/outgroups (Keltner et al 93; Mackie et al 00)
  - Optimistic perception of future risk (Lerner & Keltner 2000/2001)
  - Quicker (mis)perception of angering events (DeSteno et al 2000/2004)
  - Shallower/stereotypical reasoning (Bodenhausen et al 1994)
- **Behavioral changes**
  - Physiological preparation for aggressive responses (Keltner & Haidt 1999)
  - Characteristic facial and bodily displays (Spoor&Kelly04, Parkinson01, Ekman)
- **Changes in social partners**
  - Elicits fear-related responses (even subliminal presentation) (Dimberg&Ohman96)
  - Serves as demand for someone to change course of interaction (Emde et al. 76)

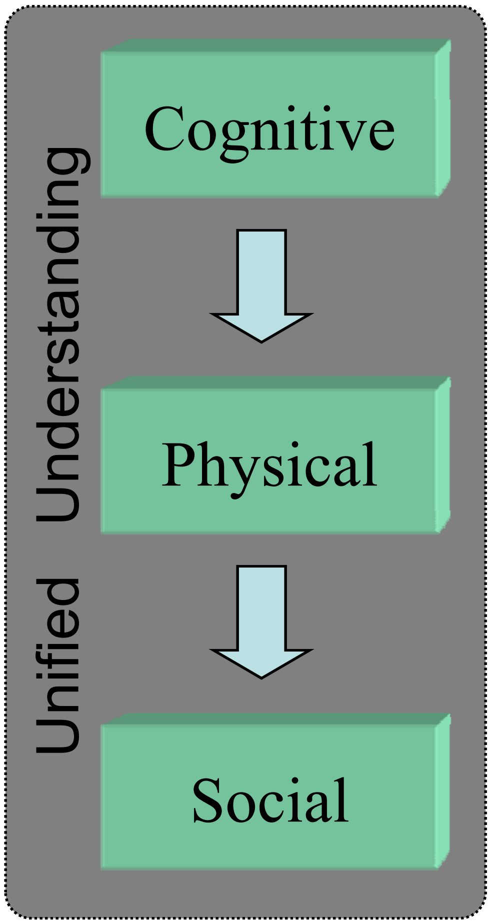
and these changes can be modeled computationally



Growth in computational models of emotion

Specific interest

Computational models of socio-emotional processes



Central questions:

- what are the underlying cognitive mechanisms
- how can they be modeled computationally

- what is the link between cognition and behavior
- how is emotion physically expressed

- how do emotional displays impact the cognition and behavior of observers/partners

Cognitive

How does an agent know what emotion it should have?

Theory → Interactive Models → User Studies

Theories of cognitive emotion


Magda Arnold

- Top down theories
  - Cognition influences emotion
  - Appraisal Theory (Arnold, Lazarus, Frijda, Scherer, Ortony et al.)
    Emotion arises from an *evolving subjective interpretation* of person's relation to their environment and informs cognitive and physical acts

Appraisal Theory

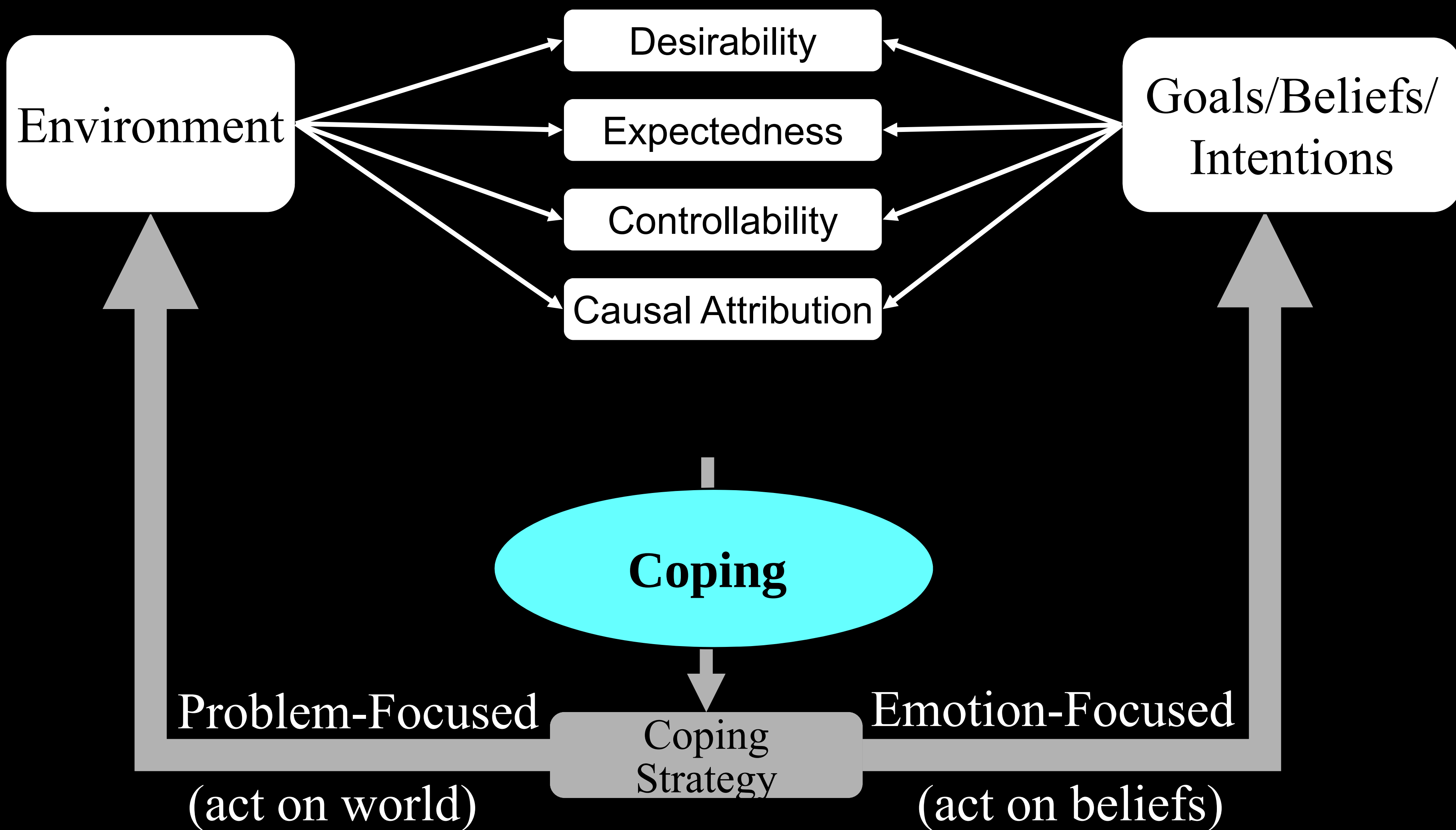
(Arnold, Lazarus, Frijda, Scherer, Ortony et al.)

Magda Arnold

- Emphasizes cognitive antecedents of emotion
  - Emotion arises from an *evolving subjective interpretation* of person's relation to their environment
  - Well-suited to computational realization
    - Emotion arises from inference over representations

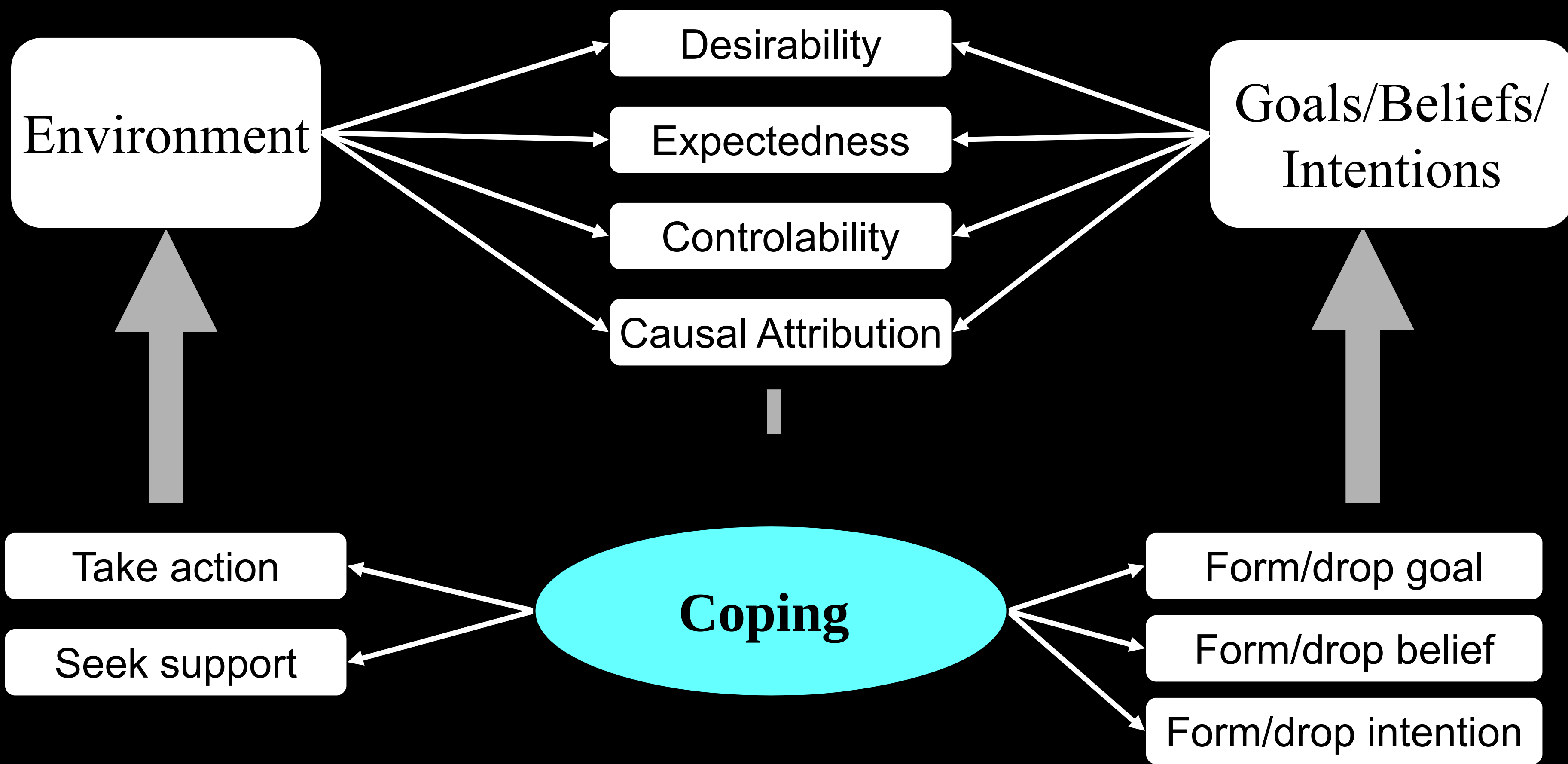
Appraisal Theory

Smith and Lazarus91 cognitive-motivational-emotive system



Appraisal Theory

Smith and Lazarus91 cognitive-motivational-emotive system

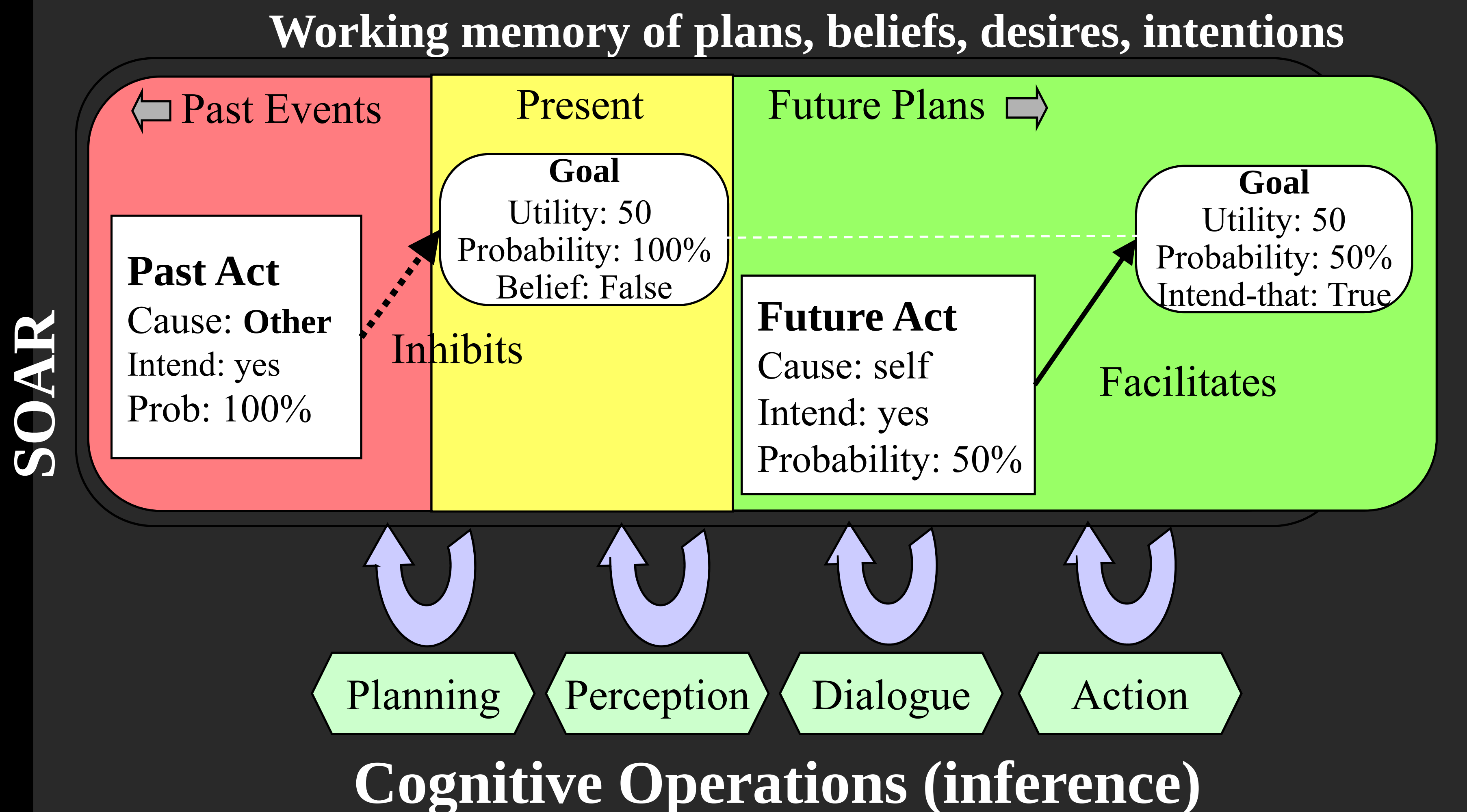


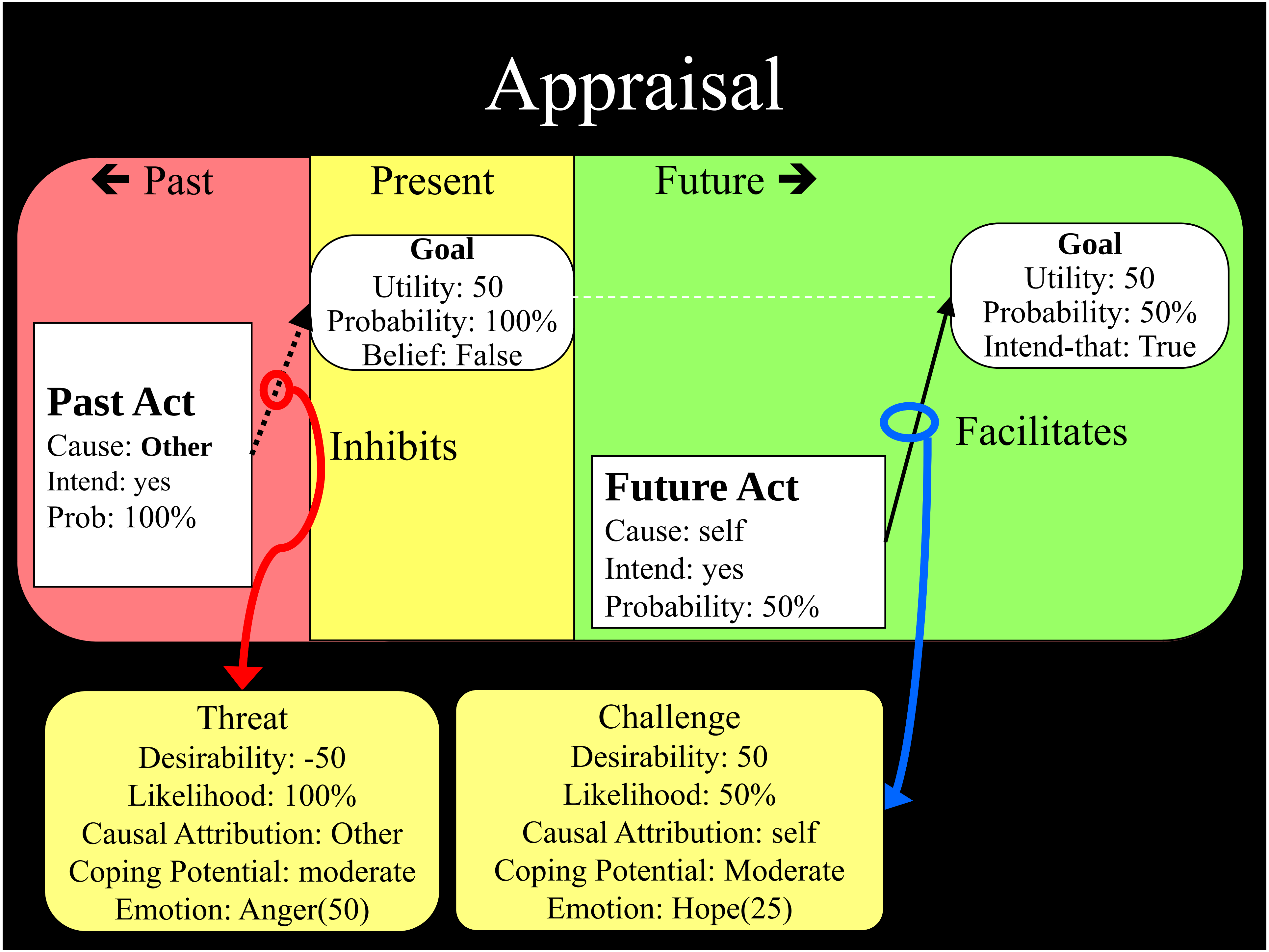
Computational appraisal theory

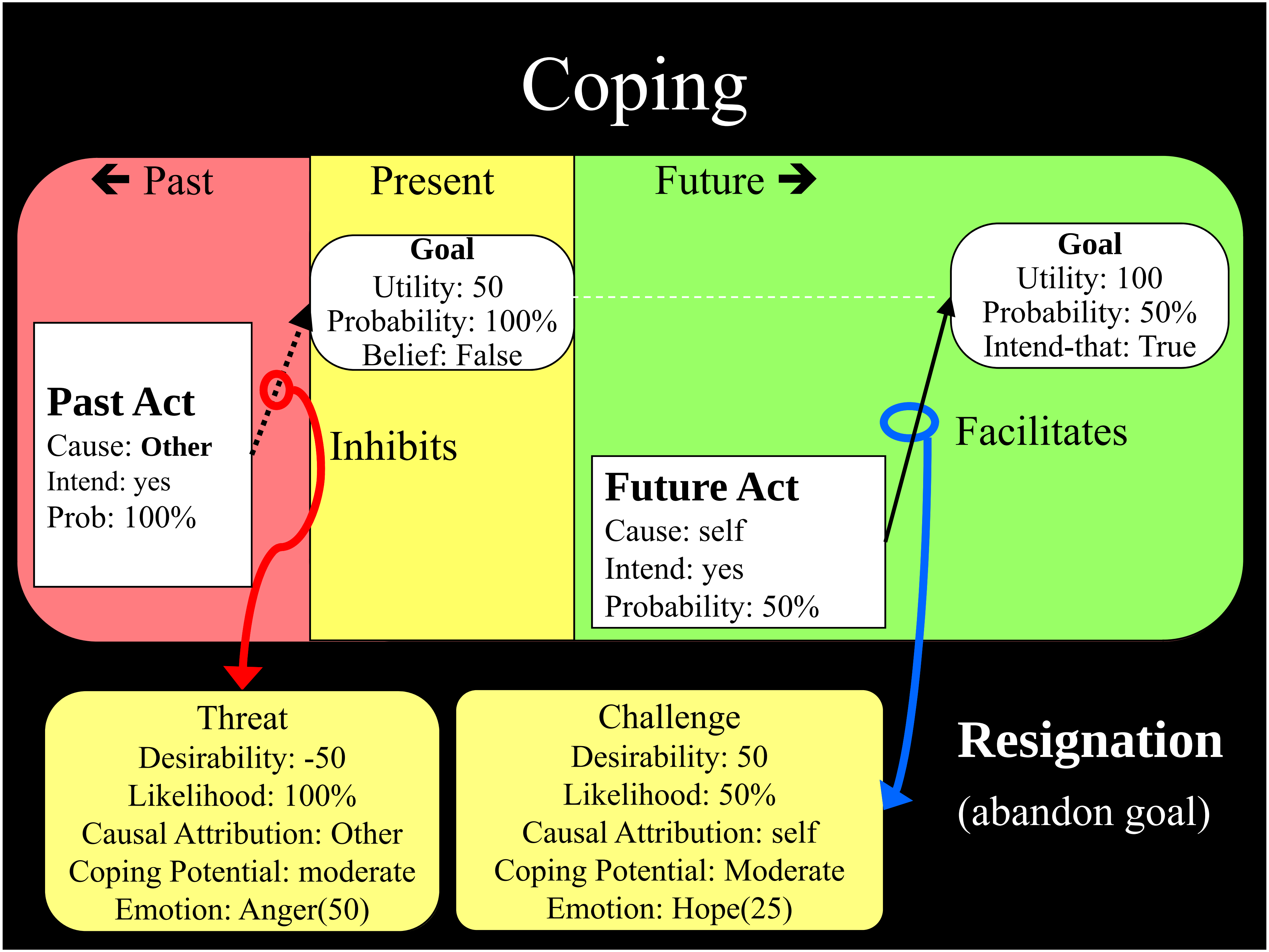
- Theory provides only high-level requirements
  - How do we represent the person-environment relation?
  - How do appraisal processes operate over representation?
  - How do appraisal, cognition, coping interact/unfold over time?
- Methods differ on how they model cognition
  - Gratch and Marsella's EMA
  - Hudlicka's MAMID – belief nets
  - El Nasr's FLAME – based on markov decision processes
  - Neal Reilly's EM – based on reactive planning
  - Marinier – based on Newell's PEACTIDM

EMA Model of Appraisal and Coping

Cognition as multiagent planning/envisionment




Appraisal
Past
Present
Future
Goal
Utility: 50
Probability: 100%
Belief: False
Goal
Utility: 50
Probability: 50%
Intend-that: True
Past Act
Cause: Other
Intend: yes
Prob: 100%
Inhibits
Facilitates
Future Act
Cause: self
Intend: yes
Probability: 50%
Threat
Desirability: -50
Likelihood: 100%
Causal Attribution: Other
Coping Potential: moderate
Emotion: Anger(50)
Challenge
Desirability: 50
Likelihood: 50%
Causal Attribution: self
Coping Potential: Moderate
Emotion: Hope(25)


Coping
Past
Present
Future
Goal
Utility: 50
Probability: 100%
Belief: False
Goal
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Intend-that: True
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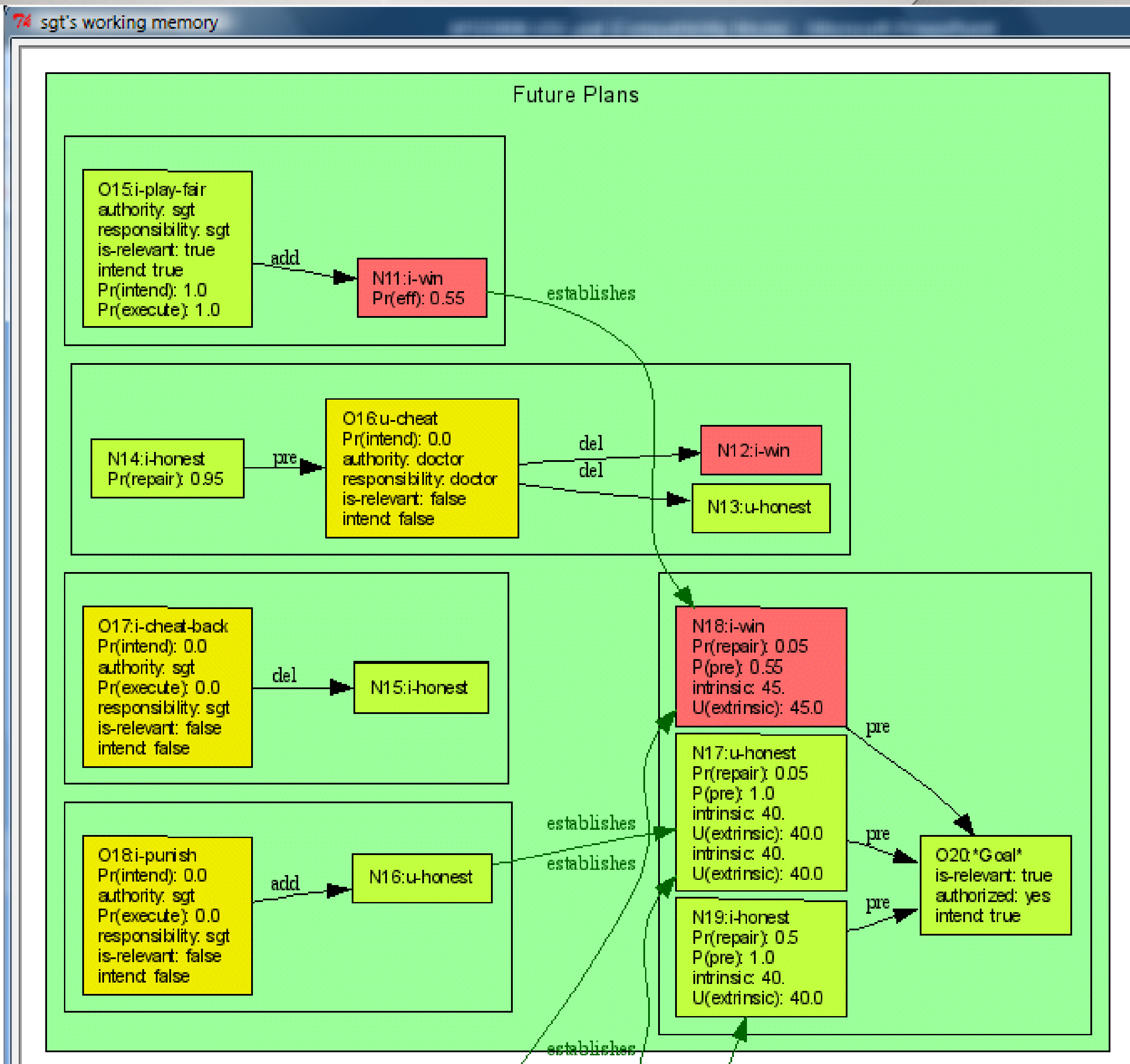
Desirability: 50
Likelihood: 50%
Causal Attribution: self
Coping Potential: Moderate
Emotion: Hope(25)
Resignation
(abandon goal)

Study (third iteration)

- **Competitive Turn-based strategy game**
  - Partial Observability
  - Opportunities for deception
  - Social emotions
  - Dynamic: situation shifts over time

OBJECTIVE: examine dynamics of appraisal & coping responses as goal of WINNING facilitated or threatened

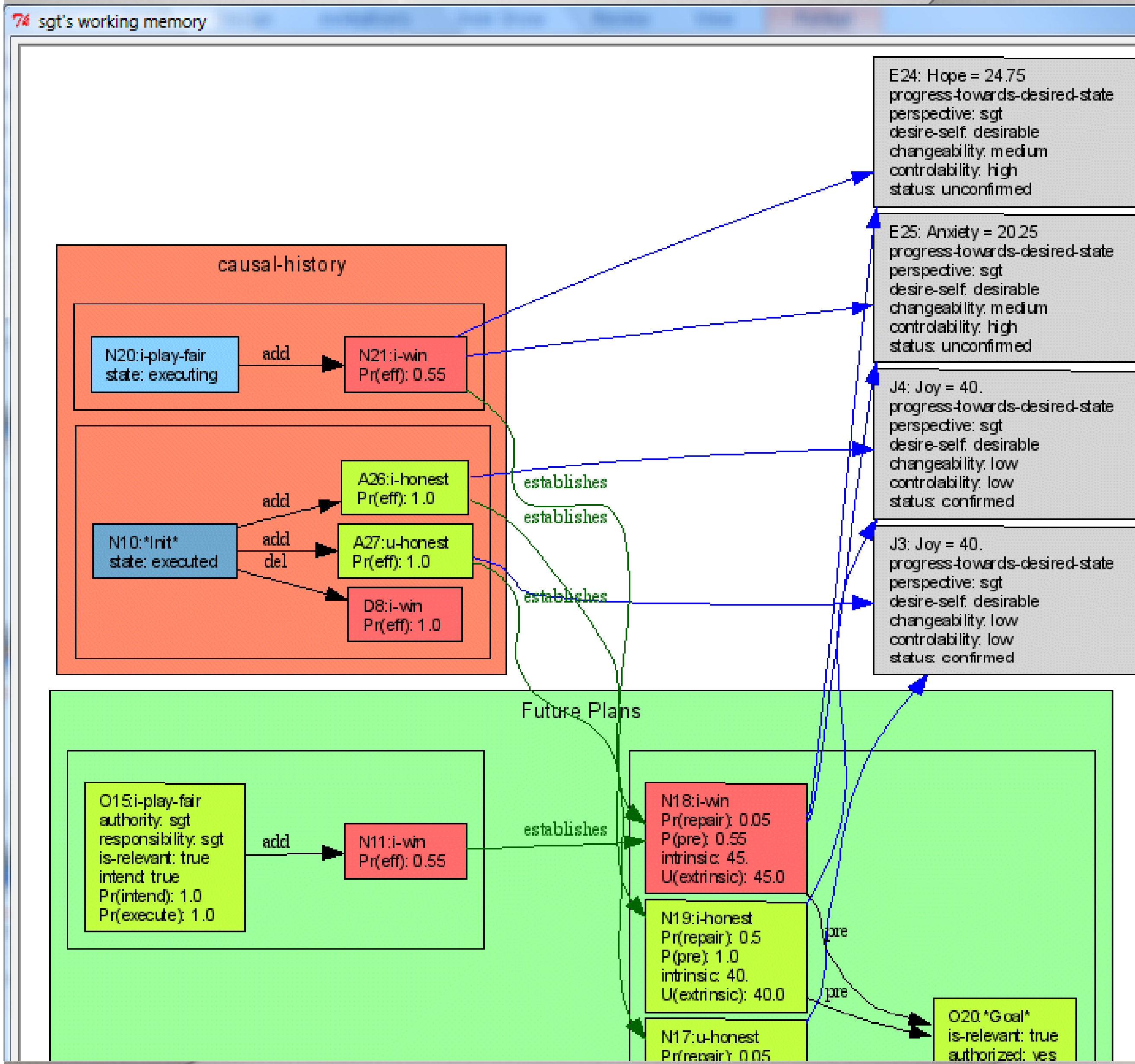
- **Q1: How do appraisals relate to intensity of emotional response over time**
- **Q2: How do people cope with the emotions wining or losing gives rise to?**
- **Q3: Do appraisals uniquely determine emotional response?**
- **Do results corroborate EMA model predictions?**



EMA Predictions

Task Model

- Developed and validated in 2 pilot studies
- People have two goals
  - Winning
  - Fairness
- Most subjects assume the game is fair
  - Can ignore cheating/fairness for main analysis



EMA Predictions

EMA

- Automatically derives emotion and coping tendencies from task model
- Automatically updates in response to game events
- Appraisals and coping tendencies constitute a set of predictions that can be tested against data

Prior Expectations

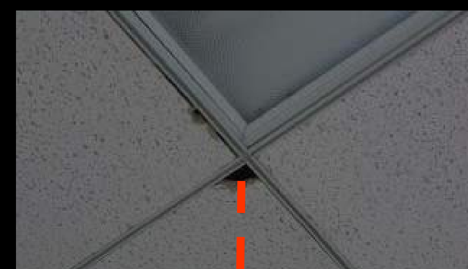
WINNING

WON GAME

Prior Expectations

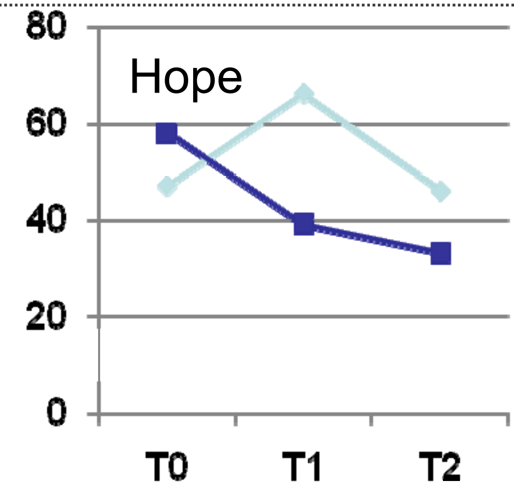
LOSING

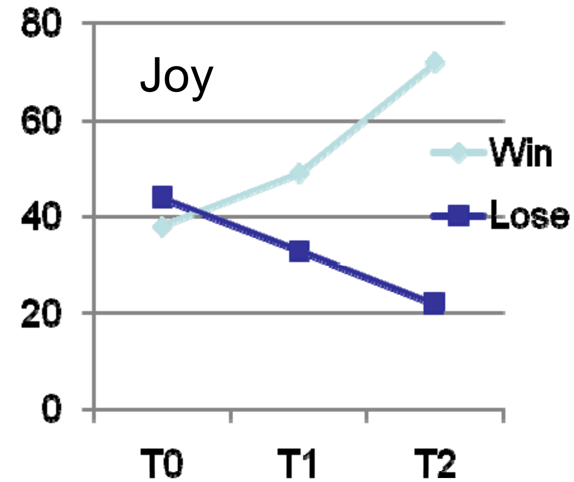
LOST GAME



Qualitative Results: Positive Emotions

- **Hope predictions from model**
  - Hope increases while winning
  - Hope drops after won
  - Hope drops while losing
  - Hope drops if lost
- **Joy predictions from model**
  - Joy flat if winning
  - Joy raises if won
  - Joy flat if losing (nonsig declining trend)
  - Joy flat if lost (nonsig declining trend)
- **Results:**
  - Predictions supported at p≤0.0





Q1: Emotion Intensity Predictions

	Hope	Joy	Fear	Sadness	Anger
Realization Model	EM. PEACTIDM	ParleE, PEACTIDM	EM, PEACTIDM	ParleE, PEACTIDM	ParleE, PEACTIDM
Expected Utility	EMA, ParleE, FearNot!		EMA		EMA
Threshold Model		EMA, EM		EMA, EM	
Additive Model	Cathexis. FLAME	Cathexis, FLAME	Cathexis, FLAME	Cathexis, FLAME	Cathexis, FLAME
Hybrid Model	Price et al85	Price et al85	Price et al85	Price et al85	EM, Price et al85

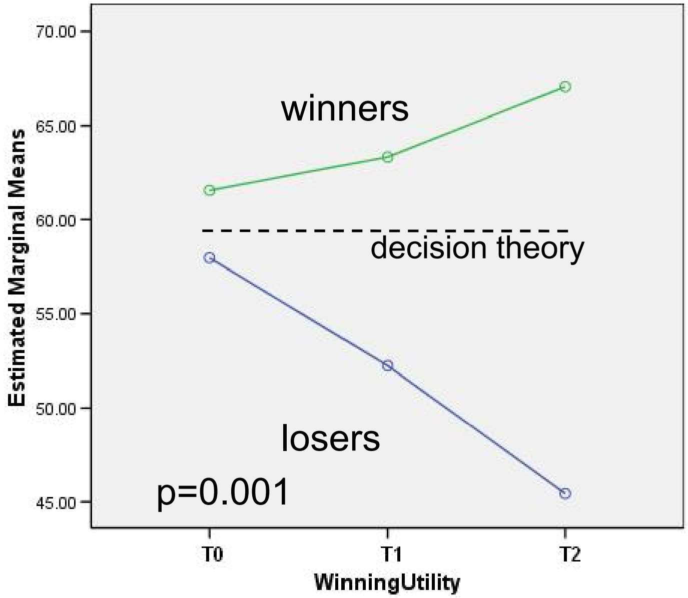
Q2: Fixed Utility Results

- **Decision theory predicts winning utility *constant* over time**
- **EMA predicts winning utility *will change* in response to emotion**
  - **losers will assign less utility to winning (distancing)**

RESULTS: Clear support for EMA

- **Losers assign less utility to winning**
- **ALSO Winners assign more utility to winning**

- **NOTE: Contradicts fundamental assumption of decision theory**

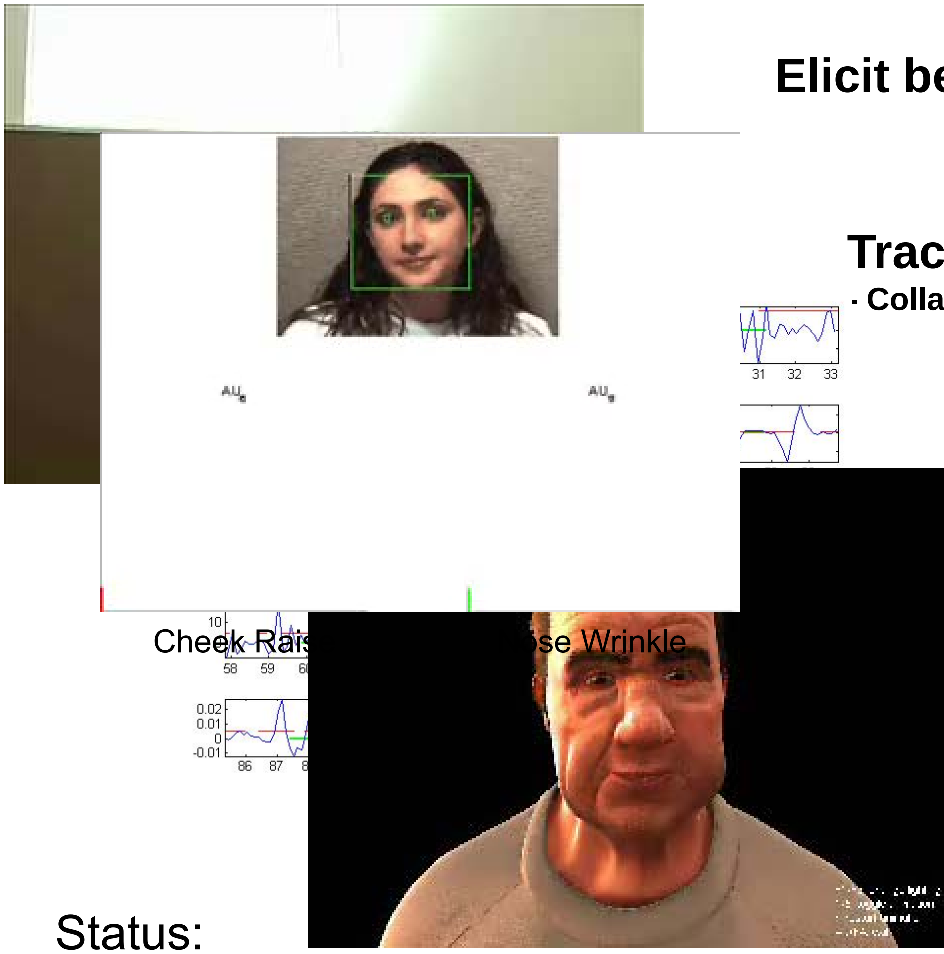


Physical

Behavioral Expression of Emotion

- **Data driven approaches to behavior generation**

Accomplishment: Learning to Express Behavior



Elicit behavior from user studies

Track using machine vision techniques
- **Collaboration with Movellan (UCSD), Morency (MIT/USC)**

Cluster and recognize with machine learning techniques
- **Using LDCRF (Morency)**
- **Collaboration with French Military Academy**

Synthesize behavior
- **Collaboraion with Filmakademie Baden-Wuerttember**

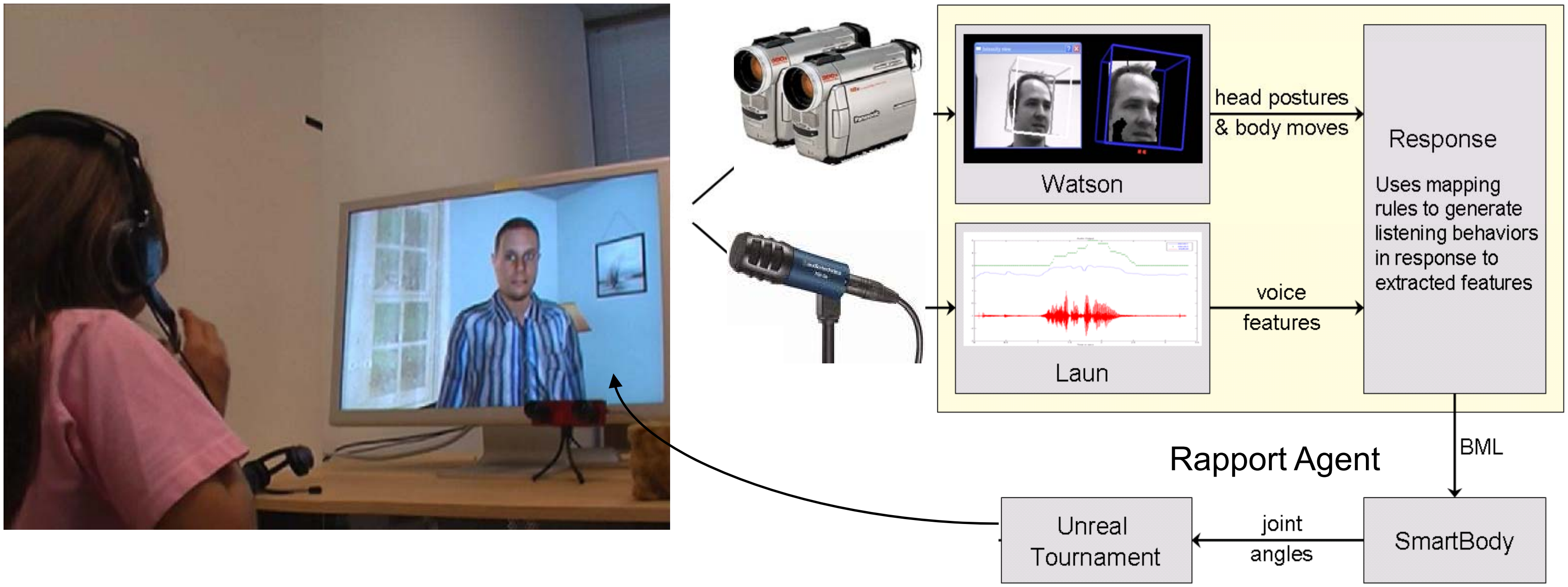
Status:

preliminary results with learning to produce head nods

Emotion and Social Influence

Accomplishment: Emotionally responsive agents

- **Agents that can sense and respond to nonverbal signals**

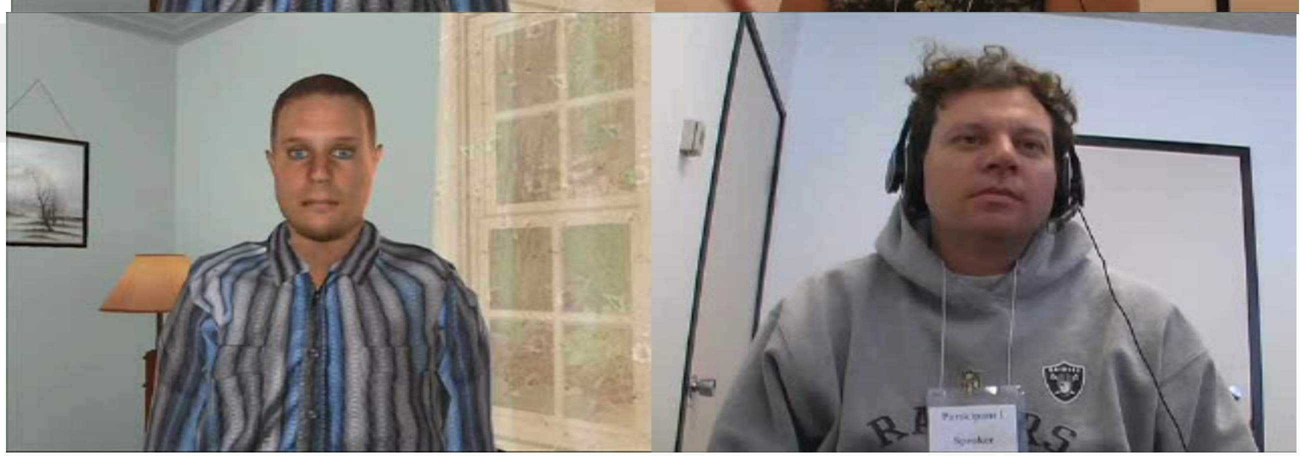


- **Emphasis on “dyadic” tasks**
  – Rapport
  – Negotiation (in collaboration with USC Marshall School)

- Face-to-face

- Responsive

- Non-contingent



Accomplishment: Empirical Findings

- **Responsive virtual humans can produce more engagement than speaking face-to-face with a stranger** (Gratch et al HCI07)
- **Negative or ill-timed feedback causes more speech disfluency**
  - e.g., stutters, filled pauses – Gratch et al IVA07
- **Shy subjects more sensitive to timing of nonverbal cues**
  - With ill-timed feedback, shy subjects report (Kang et al AAMAS08)
    Greater embarrassment
    Poorer performance

- **Take away message**
  - Virtual Humans can sometimes be better than real ones
  - Virtual Humans can't just look and move realistically, behavior must be appropriately responsive to and coordinated with the user

Summary

- **Emotion multilayered phenomenon**
  - Influences Thinking
  - Virtual humans can simulate some of this influence

  - Influences Behavior
  - Virtual humans can generate realistic behavior
  - May be utility in using cognitive models to trigger these behaviors

  - Influences Observers
  - Important for variety of social computing applications