From Team Intelligence to Social Intelligence

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A Festschrift for Richard Volz

Research Collaborators

- **Human Agent Teams**
  - TAMU: **R. Volz**, T. Ioerger, J. Wall, M. Miller, Y. Zhang, S. Cao
  - PSU: M. McNeese, X. Fang, S. Sun, R. Wang, S. Oh, H. Kim, D. Minotra,
  - SA Tech: M. Endsley, L. Strater, H. Cuevas,
  - ARL: L. Allender, T. Hanratty
- **Cyber SA**
  - PSU: P. Liu, M. McNeese, D. Hall, P. Chen, T. Mullen
  - CMU: C. Gonzalez
- **Network Growth**
  - PSU: L. Giles, H. Foley, K. Ivanova, B. Qiu, H. Wang
- **DARPA Network Challenge**
  - Penn State (D. Hall, N. Giacobe, H. Kiim et al), J. Unsworth, M. Reilly (UIUC), G. Marchionini (UNC), M. Weiss (Pitt), J. Stanton (Syracuse)

- **EMERSE:** P. Mitra, A. Tapia, J. Jansen, L. Giles, H. Kim, A. J.

Motivation: Team Training for NASA Space Shuttle Control Center

Problem: Training teams and subteams for effective teamwork are costly.

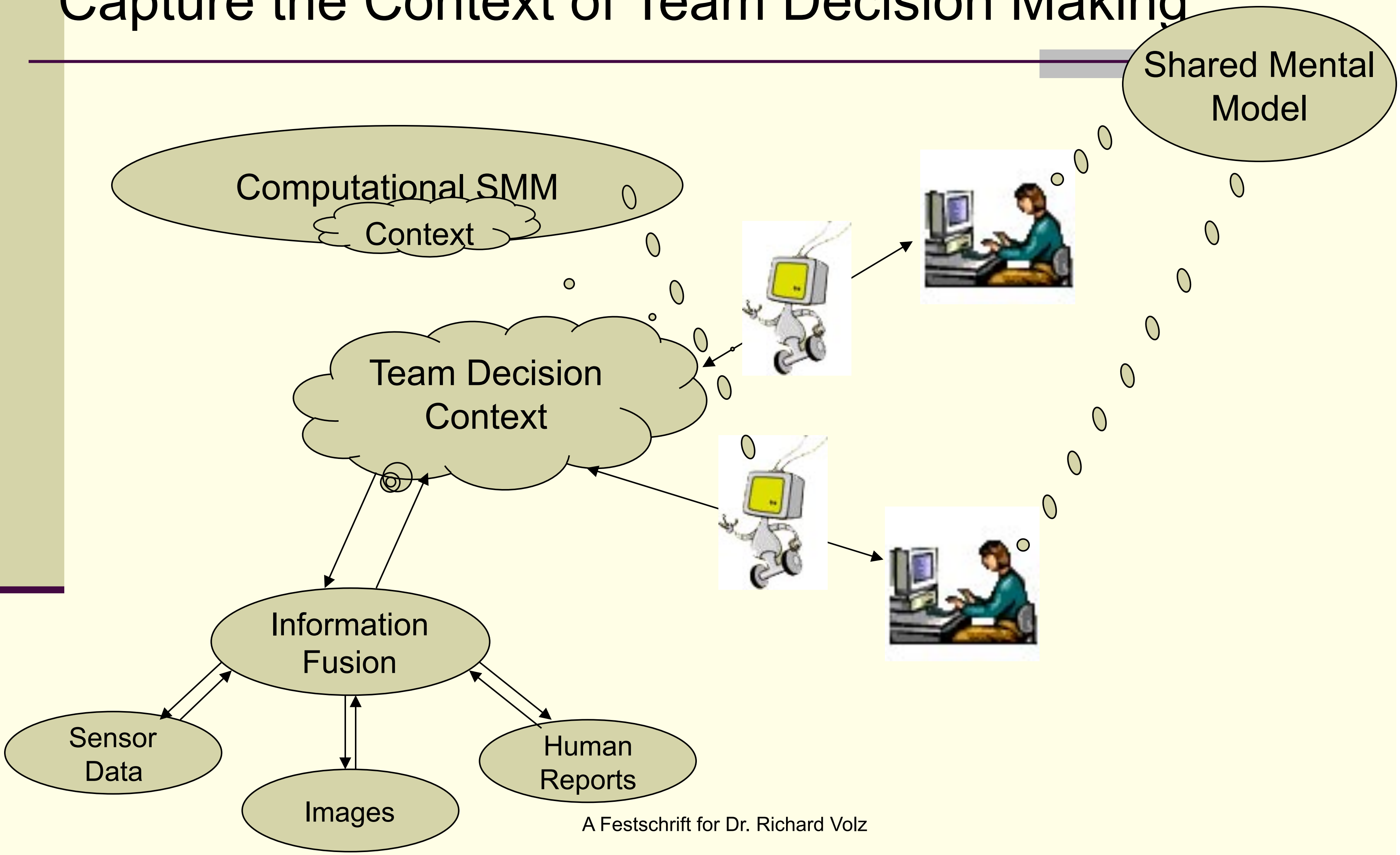
Goal: Improve the cost-effectiveness of training teams using intelligent coach and “virtual teammates”.

Psychological Studies about Effective Human Teamwork

Indicated that

- Team members can anticipate needs of team mates
- Team members can offer information proactively.
- These teamwork behaviors are due to an overlapping shared mental model.

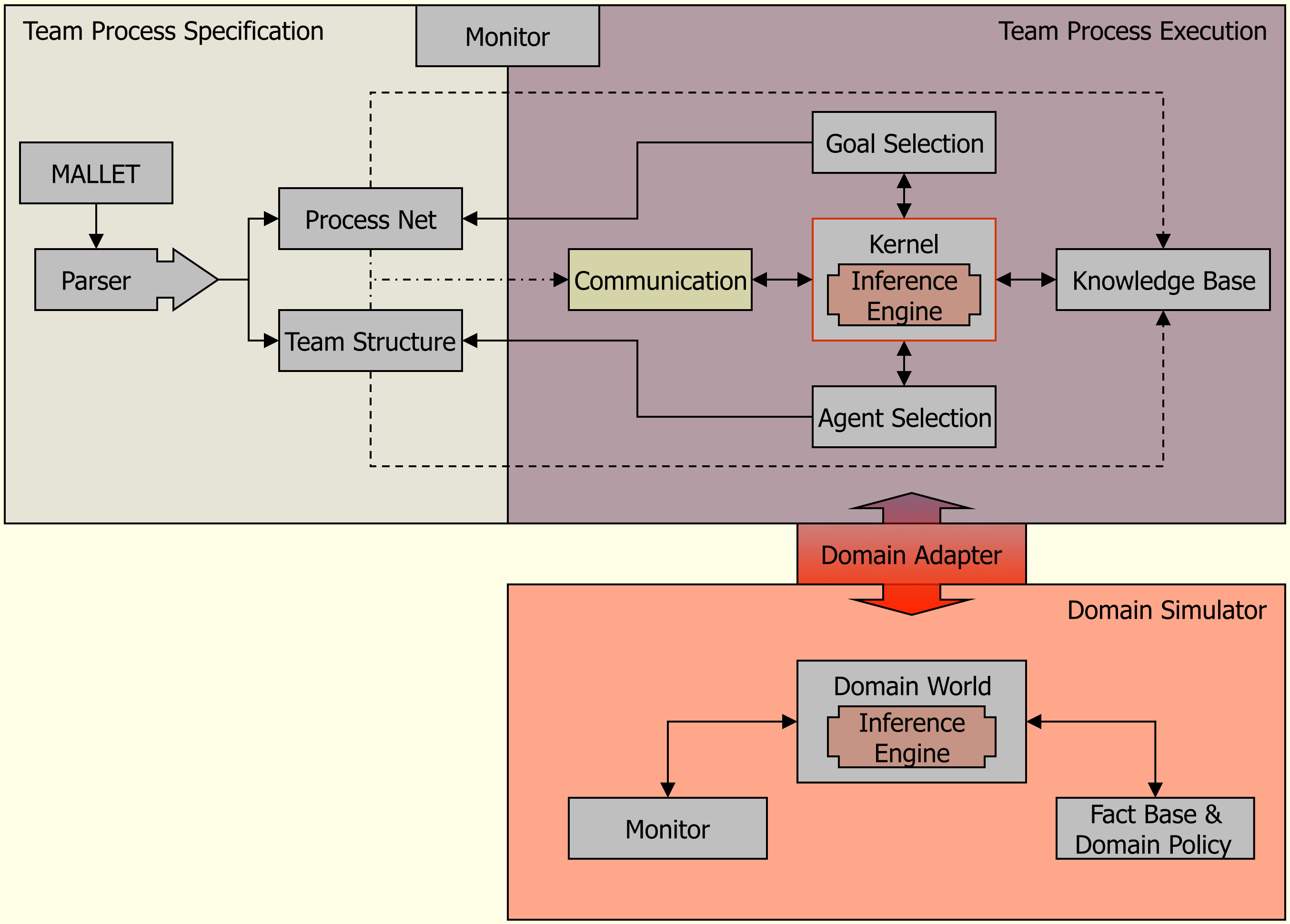
A Computational Shared Mental Model Can Capture the Context of Team Decision Making



CAST: Agents Anticipating Information Needs from A Team Process

- Capture the shared team process using a high-level language (MALLET).
- Infer needs of teammates from the team process.
- Agents generates proactive exchanges of information relevant to the needs.

CAST Software Architecture



Formal Foundations of CAST

- Joint Intention Theory (Cohen & Levesque)
  - Ensures agents inform teammates about the success, failure, or abort of joint intentions.
- SharedPlan Theory (Kraus & Grosz)
  - Agents collaborate with a shared global plan.
- A Theoretical Framework of ProInform
  - Introduced a new communication performative (ProInform).
  - Proactive inform behavior is derived from assist axiom in SharedPlan Theory

Fan, Yen, and Volz, "A Theoretical Framework on Proactive Information Exchange in Agent Teamwork", AI Journal, 169 (1), pp. 23-97, 2005.

Using CAST for Teamwork Simulation

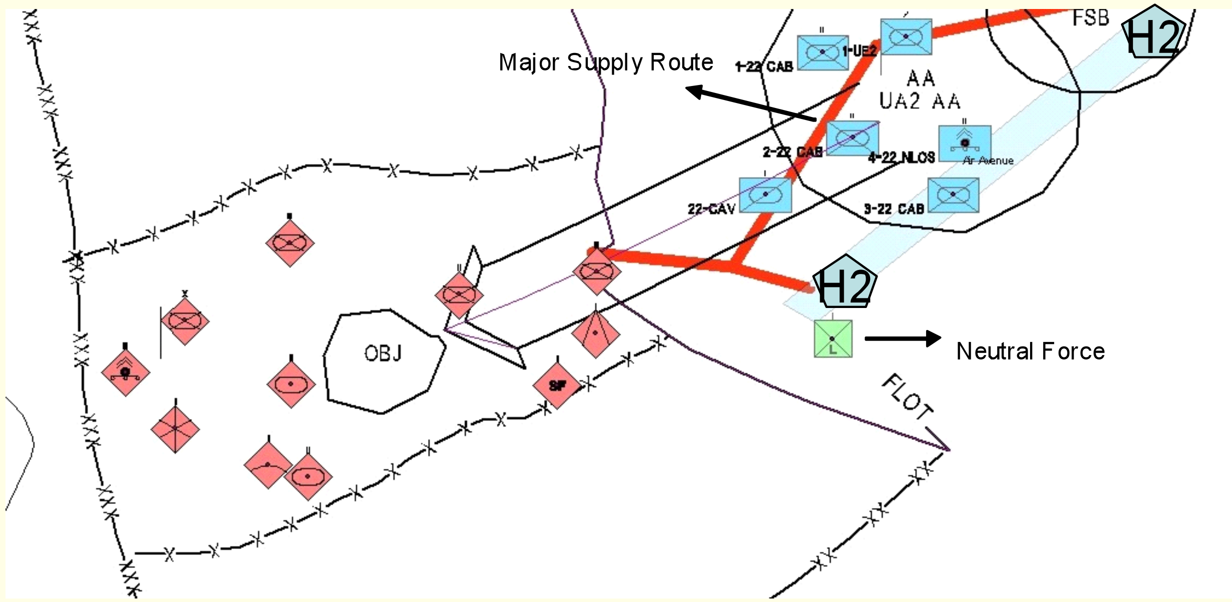
- University 21 (with Jim Wall, Dick Volz, Tom Ioerger)
  - Used CAST agents to develop “virtual teammates” for training Army’s Digital Brigade.
  - Army 101 (learned the jargon and symbols)
- MURI on Intelligent Team Training (PI: Dick Volz)
  - Developed a intelligent training framework for SA crews on AWACS.
  - PhD’s: Sen Cao, Yu Zhang, Mike Miller, and J. Yin.

Command and Control Team

S2: Intel Officer

S3: Maneuver Officer (Assign units to tasks)

S4: Logistic Officer



An Exemplar Scenario

S2: Access the actions, locations and intents of enemy entities.

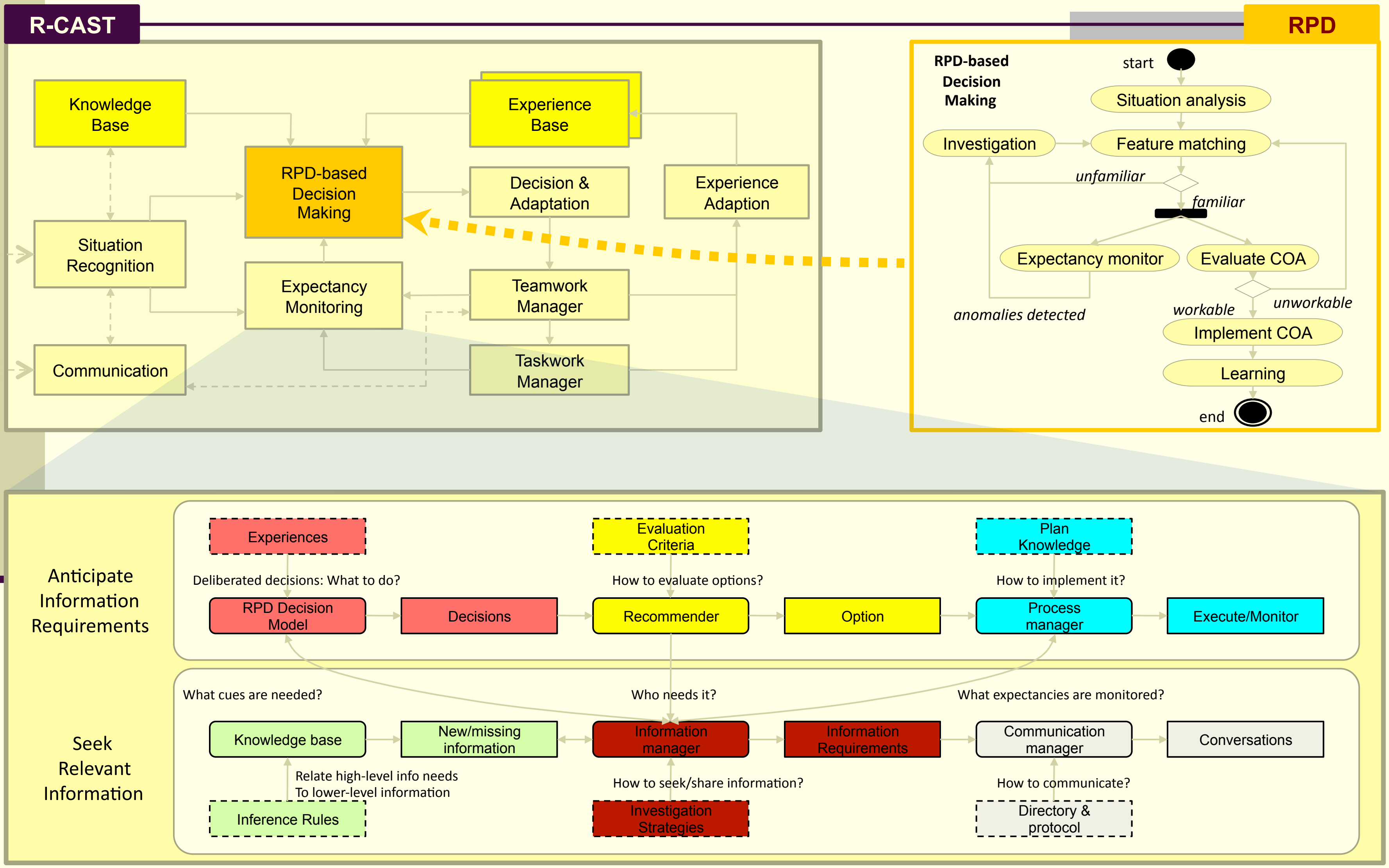
S3: Defeat enemy and protect the supply route.

S4: Identify alternative supply route and sustain supplies.

Can we have a reusable decision-making process?

- Implemented a decision-making process (RPD) in CAST
  - RPD models naturalistic decision making under time stress
  - Compare current situation with previous experiences to find a “satisfiable” solution/decision.
- Adopted RPD as the decision-making process of agents
  - Resulted in the second generation of agents: R-CAST

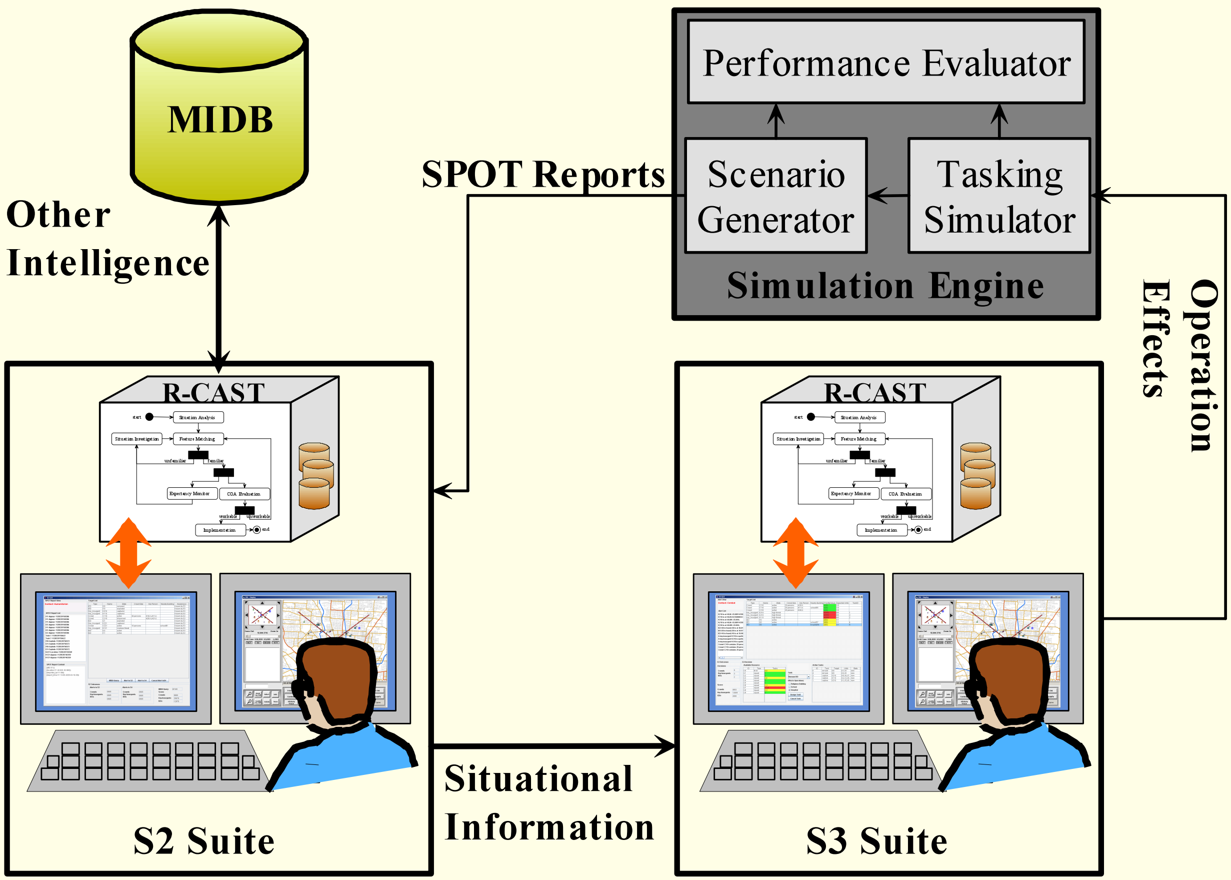
R-CAST Anticipates Information Needs of Multiple Types



Agent as Teammates to Agents as Decision Aids

- Design a synthetic C2 team task involving multiple dimensions: The Three-Block Challenge
  - Combat
  - Peace keeping (crowd control)
  - Logistic support (IED on MSR)
- Study factors that affect human-agent team collaboration and trust through a series of experiments.

The Three Block Challenge Simulation Environment



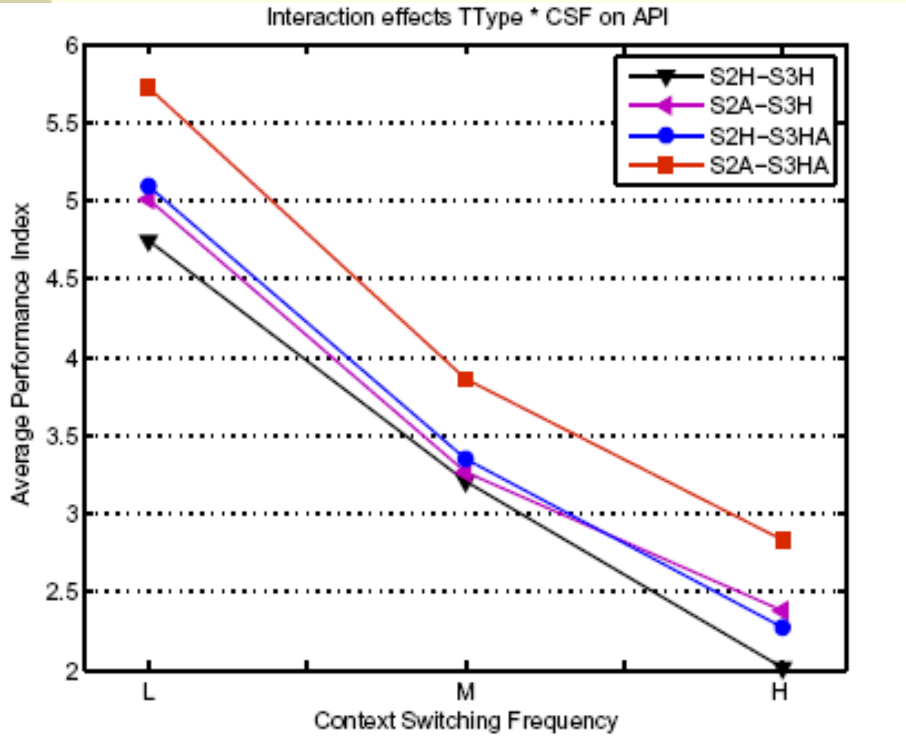
Decisions of S2-S3 Team

- S2: Access the threat level of targets (key insurgents, crowds, and IED)
  - Needs information about friendly/foe status of key persons in crowds.
- S3: Allocate 9 platoons (including an EOD unit for IED) to remove threats based on
  - Levels and types of threats of targets
  - Distance of units to targets
  - How long has the target appeared (Target disappears after a time, determined stochastically)
  - Combat readiness of units

Four Human-Agents Experiments

- **Experiment 1:** Supporting Multiple-Context Decision Making
- **Experiment 2:** Trust on Cognitive Aids
- **Experiment 3:** Agent Error Patterns and Human Trust Calibration
- **Experiment 4:** Visualization of Agents Decision Space(VADS) of RPD Agents

Experiment 1: Supporting Multi-Context Decision Making



- Context switching frequency was varied in the experiments.
- C2 Performance in decision making was improved with R-CAST Agents.
- Performance improved by 40% under high context switching frequency.
- S2 agents and S3 agents both are needed.

Experiment 2: Human Trust on Agents

- A systematic-error was introduced into the agents recommendation.

- Experiment Group: knew the source of error,
- Control Group: did not know the source of error. (Both knew about the agents reliability.)

- Experiment Group had

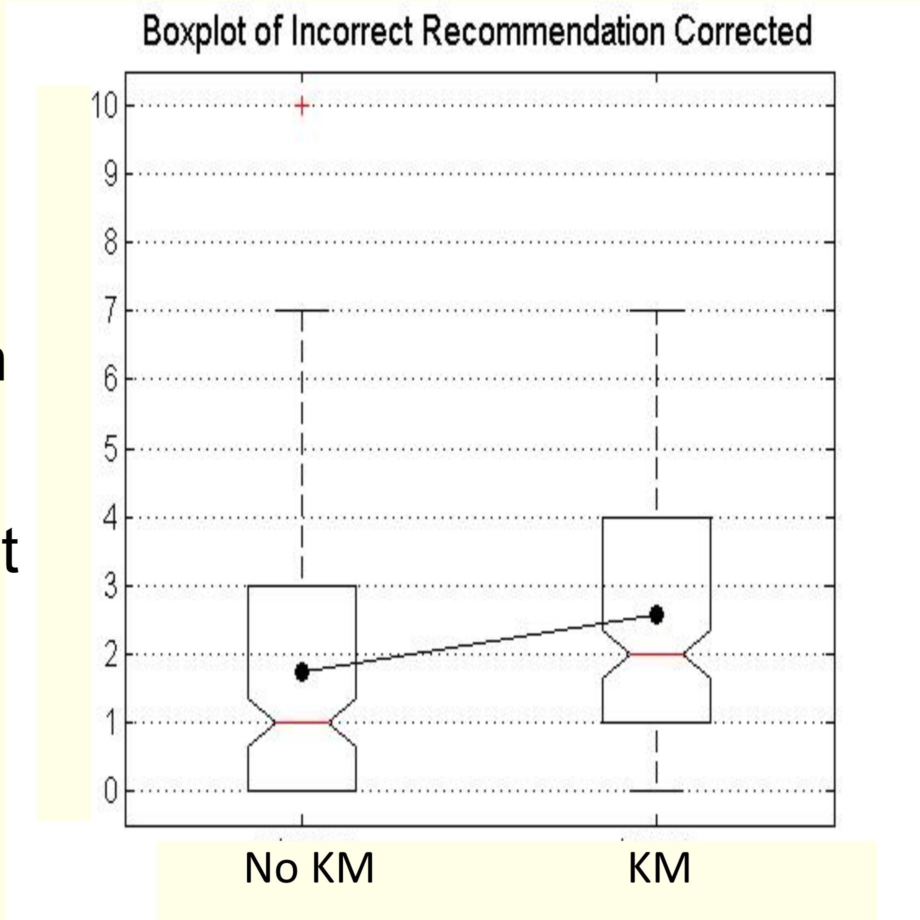
  + Better Automation Usage Decisions (AUDs)

  + Better Trust

Experiment 2 Results

With knowledge about the factors that affect agent reliability, subjects showed

- More suitable automation usage decisions.
- More suitable level of trust on the agents

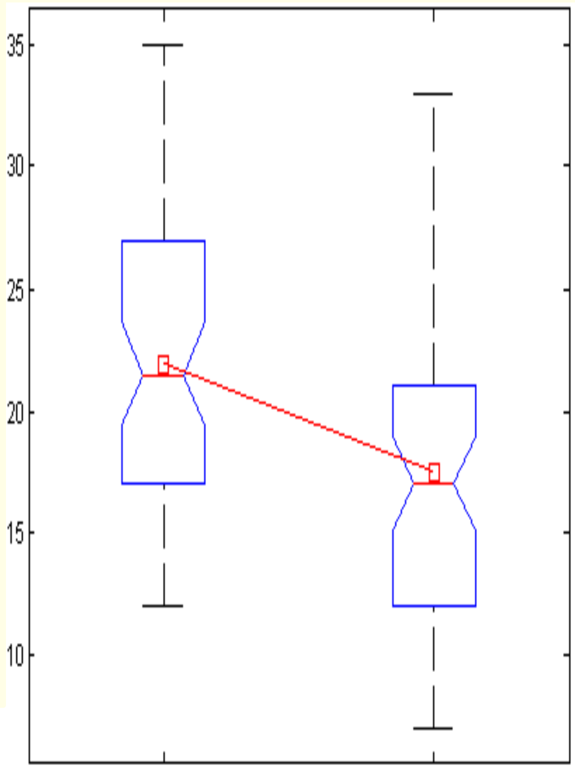


Experiment 3: Does Agent Error Patterns Affect Human Trust?

- Research Question: Does the pattern of error affect the human trust on agents?
- This study consisted of two conditions:
  - agents with random-errors and
  - agents with systematic-errors.
- Result: Participants in the systematic-error condition made better automation usage decisions.

Experiment 3 Results

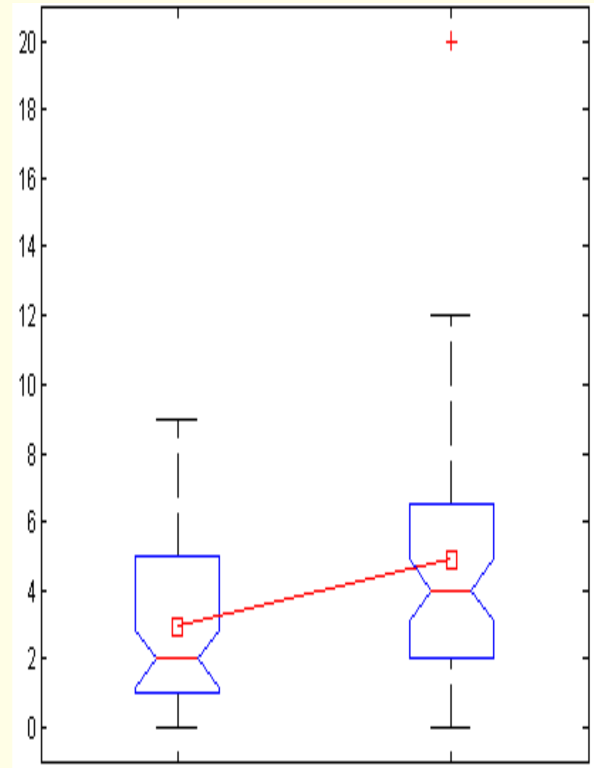
The number of
correct recommendations accepted



Systematic Error | Random Error

Systematic errors vs. Random errors

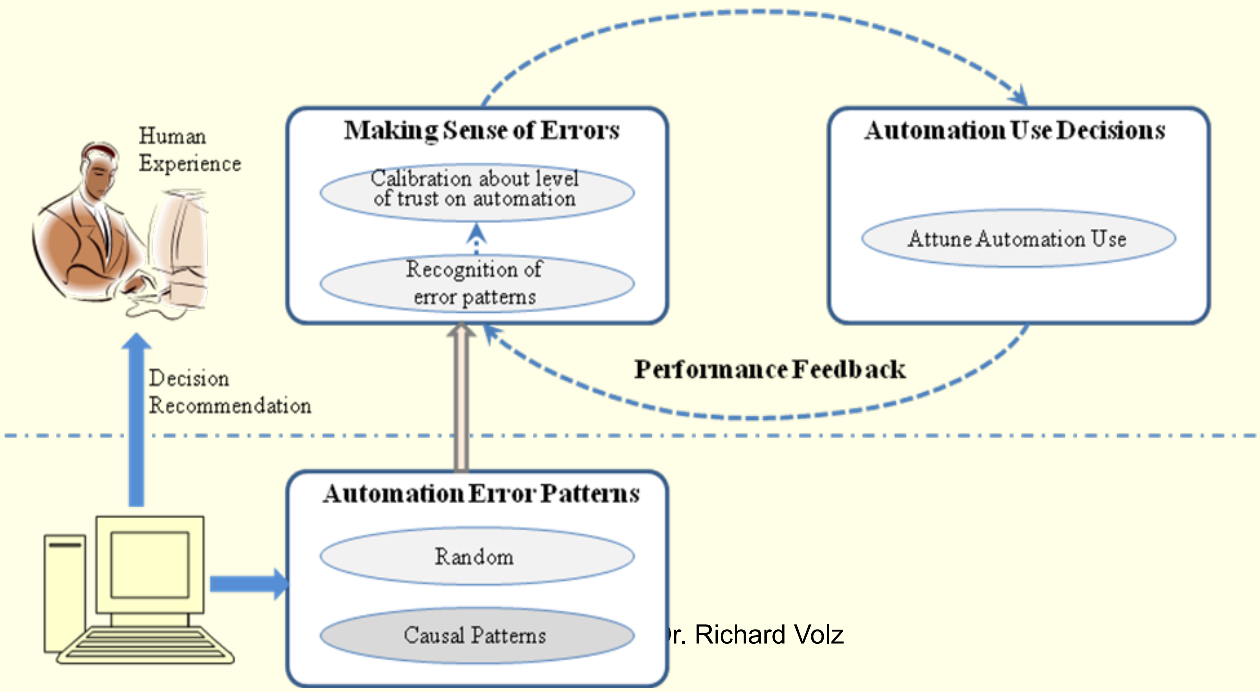
The number of correct
Recommendations changed correctly



Systematic Error | Random Error

A Cognitive Model about Human-Agent Trust (Experiment 2 and 3)

- For understandable error patterns, knowledge manipulation on the cause of automation error does improve automation usage decisions.
- Human trusts the agent less when it is hard to recognize the pattern of errors.



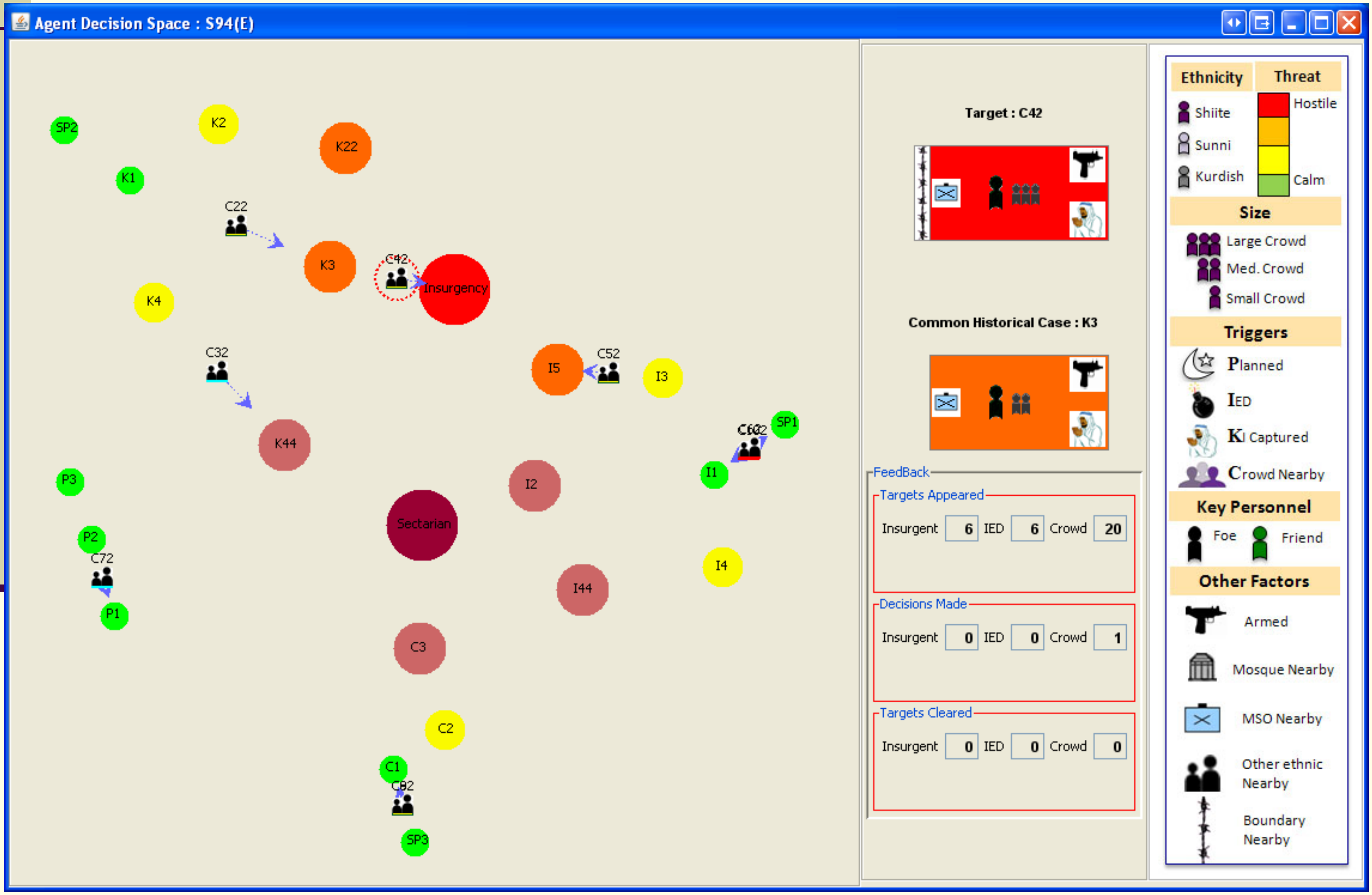
Experiment 4: Visualization of Agent Decision Space (VADS)

PENNSTATE 1855

- Can it enhance war fighter's global situation awareness (i.e., tracking change of threats of multiple targets)?

- Can it assist war fighters to project change of threats?

R-CAST Visualization of Agent Decision Space (VADS)♪



Experiment 4 Design

- 32 (16x2) participants recruited for this experiment.
- The display condition was a between subjects factor.
- One group used the VADS, and the other used an Agent-Decision Table (ADT).

Data Analysis

- Differences in scores in scenarios involving high-workload (3 and 4) is more significant than the ones involving low-workload (1 and 2).
- Difference in scores for scenario-3 is notably significant (p = .024). However, differences in scores were not as significant for scenario-4.
- The hypotheses about the possible effectiveness on scenario-3 can be tested in future experiments.

From Teams to Networks

- Real-world problems often require people and agents (robots or software) form large-scale complex networks
  - Communication networks
  - Transportation networks
  - Information networks
  - Energy networks
  - Social networks
- These networks have shown common properties:
  - Long-tail degree distributions
  - Scale-free networks

Research Agenda

- How to establish meaningful metrics about macro-level properties of networks?
  - Resilient of networks
- How to extract and/or identify patterns hidden in the networks?
  - Community Discovery
  - Cyber Security
- How to model the dynamic behaviors of networks?
  - Network evolution
  - Spreading of influence

Modeling Network Growth

Nano-technologist Co-authorship Network

- **Rapid growth in short period**
- **The field started in recent years**
- **Can be used to predict trends of nanotechnology to analyze spread of ideas in the network**

Table 1. Number of scientists and number of papers in different nanoscience communities as of year 2006

Dataset	*Scientists*	*Papers*
NanoSCI	292393	368511
NanoTube	31688	25285
NanoWire	86234	80645
NanoParticle	81734	69530
Fullerene	97641	96331

Characterize network growth

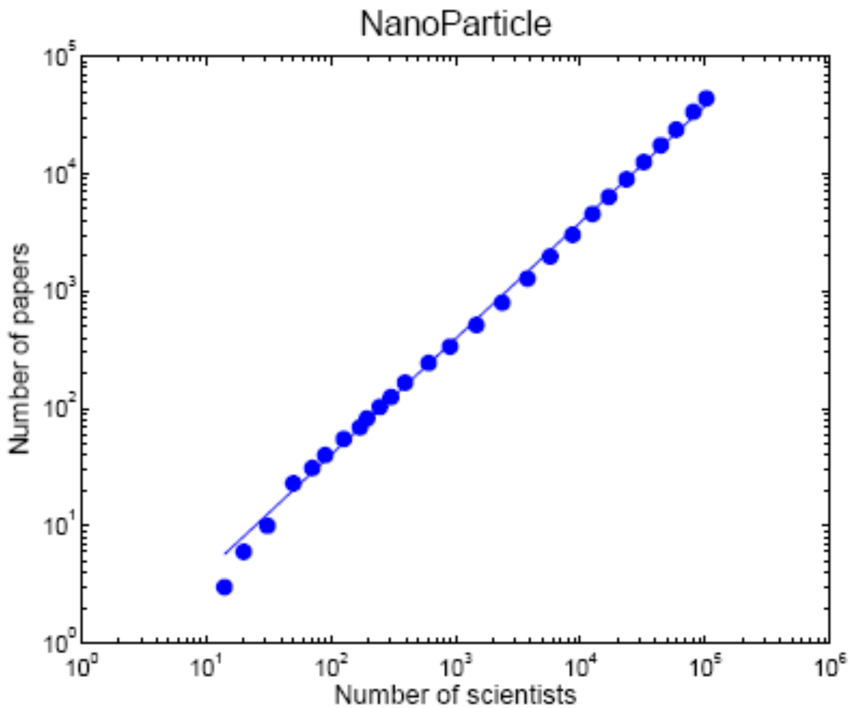


Figure 1. Growth rate of the *NanParticle* network for the period from 1980 to 2006 expressed as the number of papers versus the number of scientists that wrote the papers.

densification rate $\Delta\chi(t)$

$$|E(t)| = 3.0459 * |V(t)|^{1.1141}$$

$$\Delta\chi(t) = \frac{\Delta E}{\Delta V}.$$

A Hybrid Growth Model

A **growth** model that combines
- Preferential Attachment
- Locality-based Growth

- Model: At each time step
  - A new node is added
  - Several new edges are added (based on edge/node ratio)
  - The start node of a new edge is selected randomly and the end node is selected with probability
    - proportional to the degree of the node and
    - inversely proportional to the distance between the two nodes

$$p_t(v_p) = \frac{\frac{d'_t(v_p)}{r'_t(v_p, v_s)}}{\sum_p \frac{d'_t(v_p)}{r'_t(v_p, v_s)}}$$

Compare the Model with the Data

Properties of network structure that may affect the function of the networked system

- **Degree distribution P(k)**

$$P(k) \sim k^{-\gamma}$$

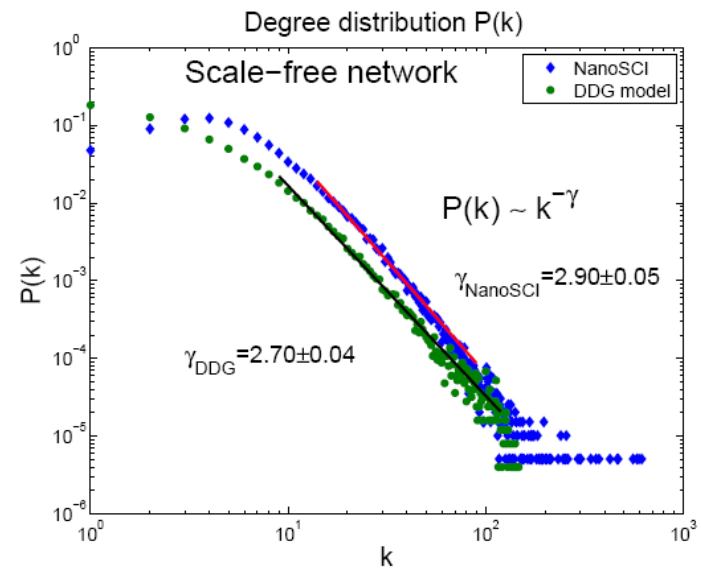


Figure 4. Degree distributions of the *NanoSCI* **network (diamonds) and of the DDG model data (circles). Each set of symbols is fitted with a power law with exponent** $\gamma_{NanoSCI} = 2.90 \pm 0.05$ **for** *NanoSCI* **and** $\gamma_{DDG} = 2.70 \pm 0.04$ **for DDG model data.**

Assortative mixing

- Assortative mixing on networks
  - Assortativity coefficient **r** – describes the correlation between the degrees of adjacent nodes

r>0 implies assortative network

Assortative network is a network with dense hubs sparsely connected between each other.

r<0 implies dissassortative network

$$r = \frac{N^{-1}\sum_i j_i k_i - [N^{-1}\sum_i (j_i + k_i)/2]^2}{N^{-1}\sum_i (j_i^2 + k_i^2) - [N^{-1}\sum_i (j_i + k_i)/2]^2} \quad (3)$$

where j_i, k_i are the degrees of the nodes at the ends of the ith edge, with $i = 1, 2, \ldots, N$.

Dataset	**Assortativity coefficient r**
NanoSCI (all)	0.04
NanoTube	0.12
NanoWire	0.06
NanoParticle	0.04
Fullerene	0.09
NanoFabrication	0.66
DDG model	**0.30**

Degree-dependent clustering coefficient

- Network transitivity or Clustering (hierarchical structure)
  - Degree-dependent clustering coefficient **C(k)** – a quantitative measure of intrinsic hierarchy

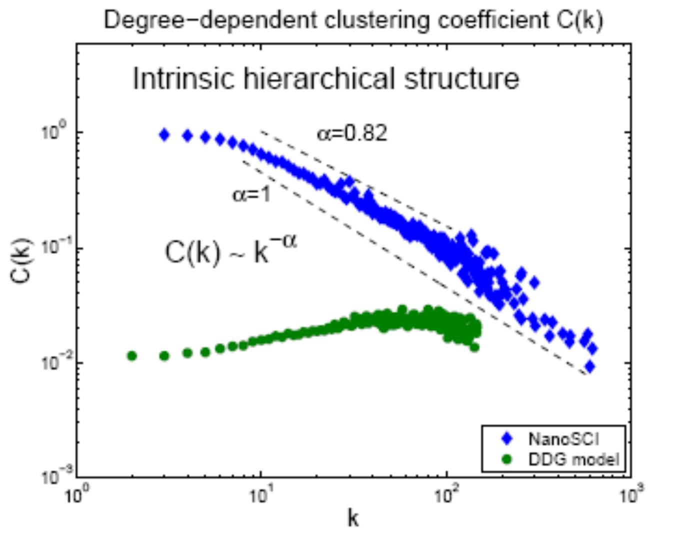


Figure 2. Degree-dependent clustering coefficient of the *NanoSCI* network (diamonds) and of the DDG model data (circles).

$$C(k) \sim k^{-\alpha}$$

$\alpha=1$ Implies intrinsic hierarchical structure of the network

Deterministic scale-free network [Dorogovtsev et al., 2001]

Average degree of the nearest neighbors

Average degree of the nearest neighbors $\mathbf{<k_{nn}(k)>}$ characterizes the assortativity of the network

$$<k_{nn}(k)> \sim k^{\beta}$$

For assortative networks: $<k_{nn}(k)>$ is a monotonically increasing function of k.

$\beta>0$ Assortative network

For disassortative networks: $<k_{nn}(k)>$ is a monotonically decreasing function of k.

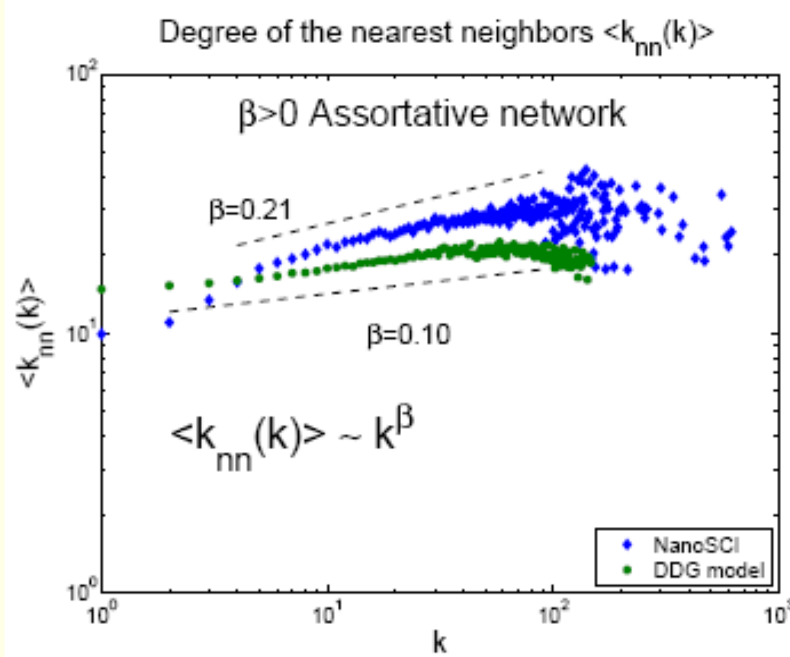
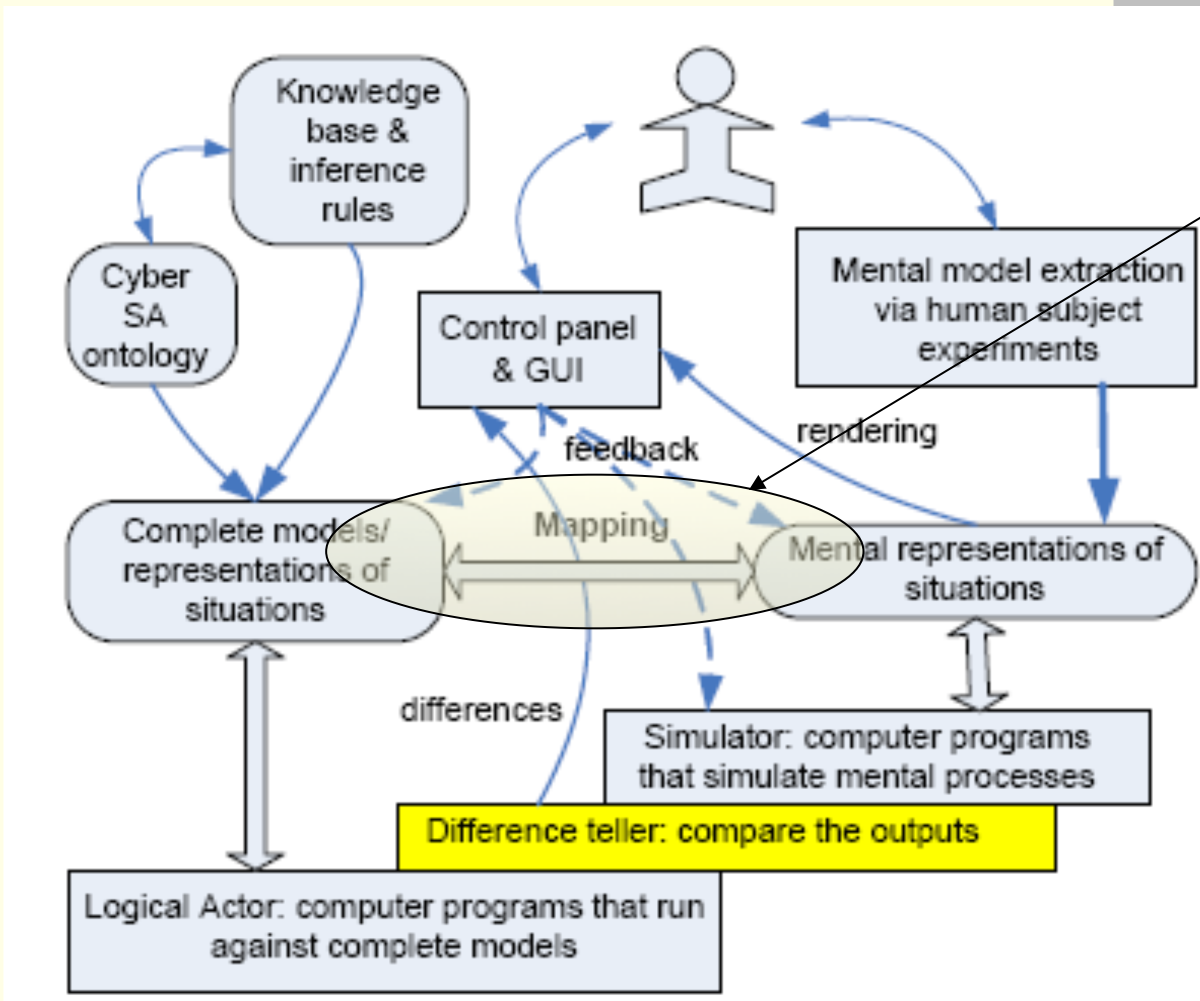


Figure 3. Average degree of the nearest neighbors of the *NanoSCI* network (diamonds) and of the DDG model data (circles).

Research Questions

- How to establish meaningful metrics about macro-level properties of networks?
  - Resilient of networks
- How to extract and/or identify patterns hidden in the networks?
  - Community Discovery
  - Cyber Security
- How to model the dynamic behaviors of networks?
  - Network evolution
  - Spreading of influence
- Ultimately, design networks, optimize networks, adapt networks in real-time.

MURI: Cyber Situation Awareness



R-CAST

and

Relational

Networks

Goal: Social Intelligence

- Design, optimize, and adapt networks in real-time to achieve social intelligence (i.e., intelligence that can not be achieved by people or machines alone)
  - Cyber Situation Awareness
  - Detecting and Responding to Extreme Events
  - Smart Space for Aging in Place

Networks for Extreme Events (Emergency Informatics)

- How people use social media during Extreme Events?
- How to develop social computing technology to support the coordination of first responders and NGO's for disaster relief?

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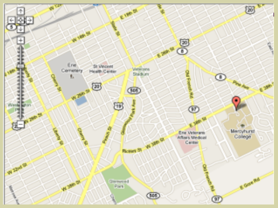
iSchool Team for DARPA Network Challenge (3rd among academic teams)



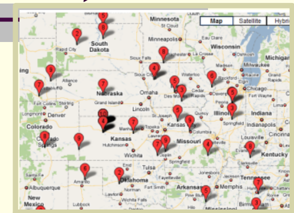
Erie, PA
Competitor Site
Observer

Albany, NY
Twitter w/ picture
Observer/Photo Analysis

Royal Oak, MI
Twitter w/ picture
Observer - Fake

Providence, RI
Twitter w/picture
Observer/Photo Analysis

Seattle, WA
Twitter w/o Picture
Observer



Champaign, IL
Competitor Site
Observer

Des Moines, IA
Twitter
Self Recant

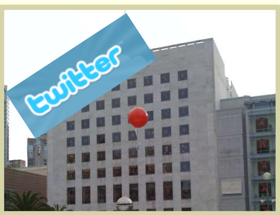
Christiana (Glascow), DE
Twitter w/ Photo
Detail /Photo Analysis

Bithlow , FL
Custom Cralwer
Observer

Charlottesville, VA
Observer Report
Conf.Details / Call Back

Scottsdale, AZ
Competitor Site
Detail /Photo Analysis

Portland, OR
Twitter w/ Picture
Observer



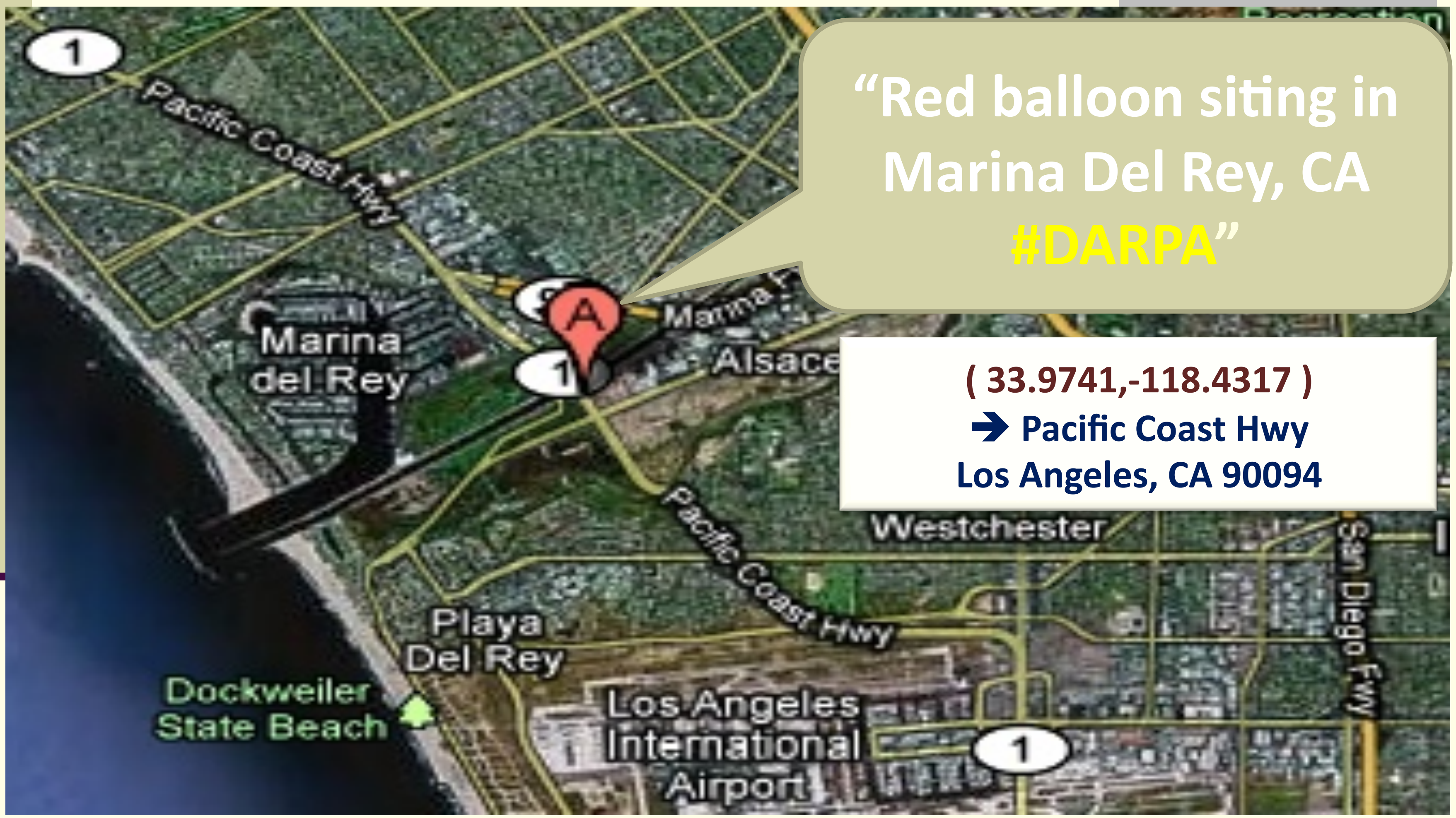
San Francisco, CA
Twitter/Blog
Detail/Photo Analysis

Santa Barbara, CA
Twitter
Detail/Photo Analysis

Westfield, NJ
Twitter w/o Picture
Conflicting Data

Memphis , TN
Competitor Trade Offer
Never Confirmed

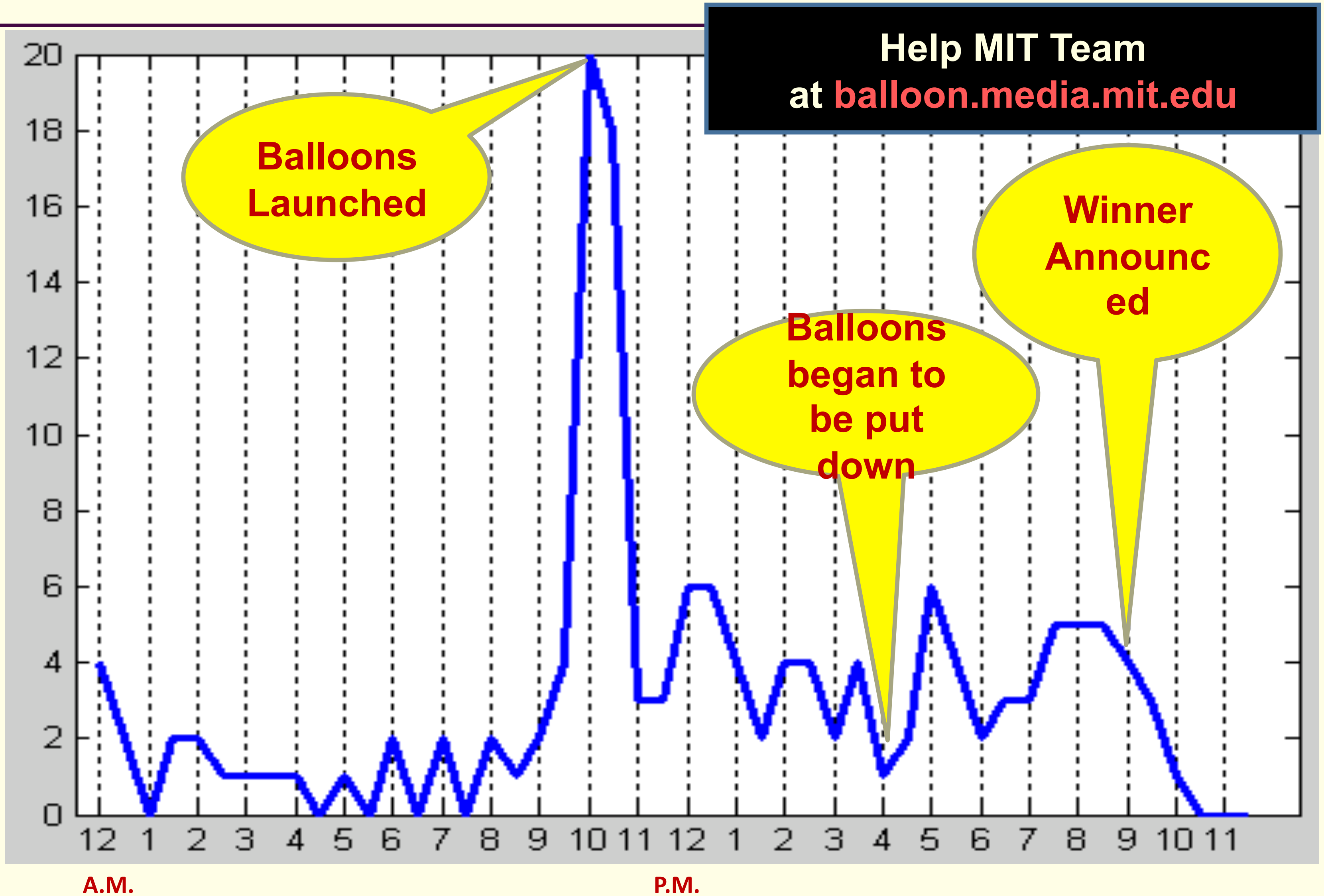
Geotag of Tweets are Important



Map from maps.google.com

Validate Information Source

Tweets can be useful for Crowd Sourcing



EMERSE:

Enhanced Messaging for Emergency Response SErvices

- NSF RAPID project to support the relief of Haiti (Chile, and others)
- Automate
  - Topic Classification of Tweets
  - Geotagging of Tweets
  - Translation of Tweets
- Subscription by topic and regions
- Collaboration with NetHOPE, a coordination body of NGO's.

Summary

- Certain aspects of team intelligence can be first class behavior of “agents”
- A suitable “trust” relationship between human and agents can improves the performance of human-agent teams.
- The studies of properties, patterns, and behaviors of large-scale networks formed by human and agents (physical robots or software agents) are keys for enhancing social intelligence.