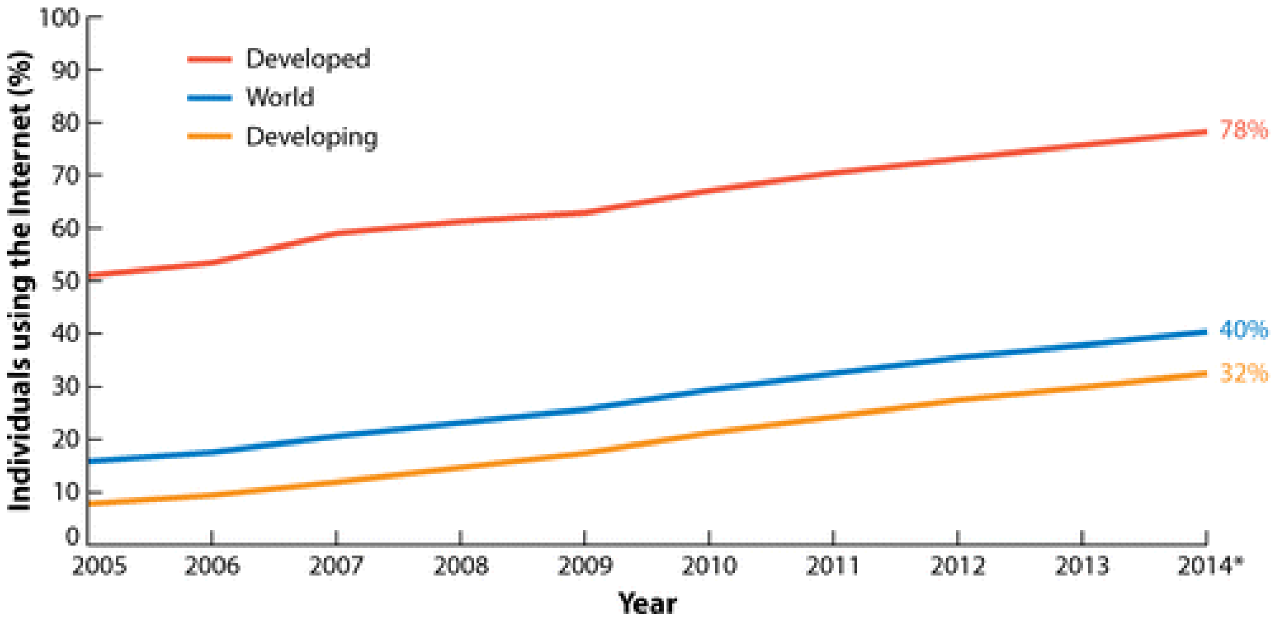
Affective computing

Nisheeth

Overview of this module

- Interesting research questions
  - Reality mining project
- Sentiment analysis
  - Recommended reading: Pang & Lee (2008) Opinion mining and sentiment analysis
- Affect, emotion and trait determination
- Affective computing
  - BCI
  - Emotive responding
  - Gamification
- Reinforcement learning
  - Explore-exploit dilemma
  - Artificial curiosity
  - Alternative models of preference learning

Internet access is near universal



Gosling SD, Mason W. 2015.
Annu. Rev. Psychol. 66:877–902

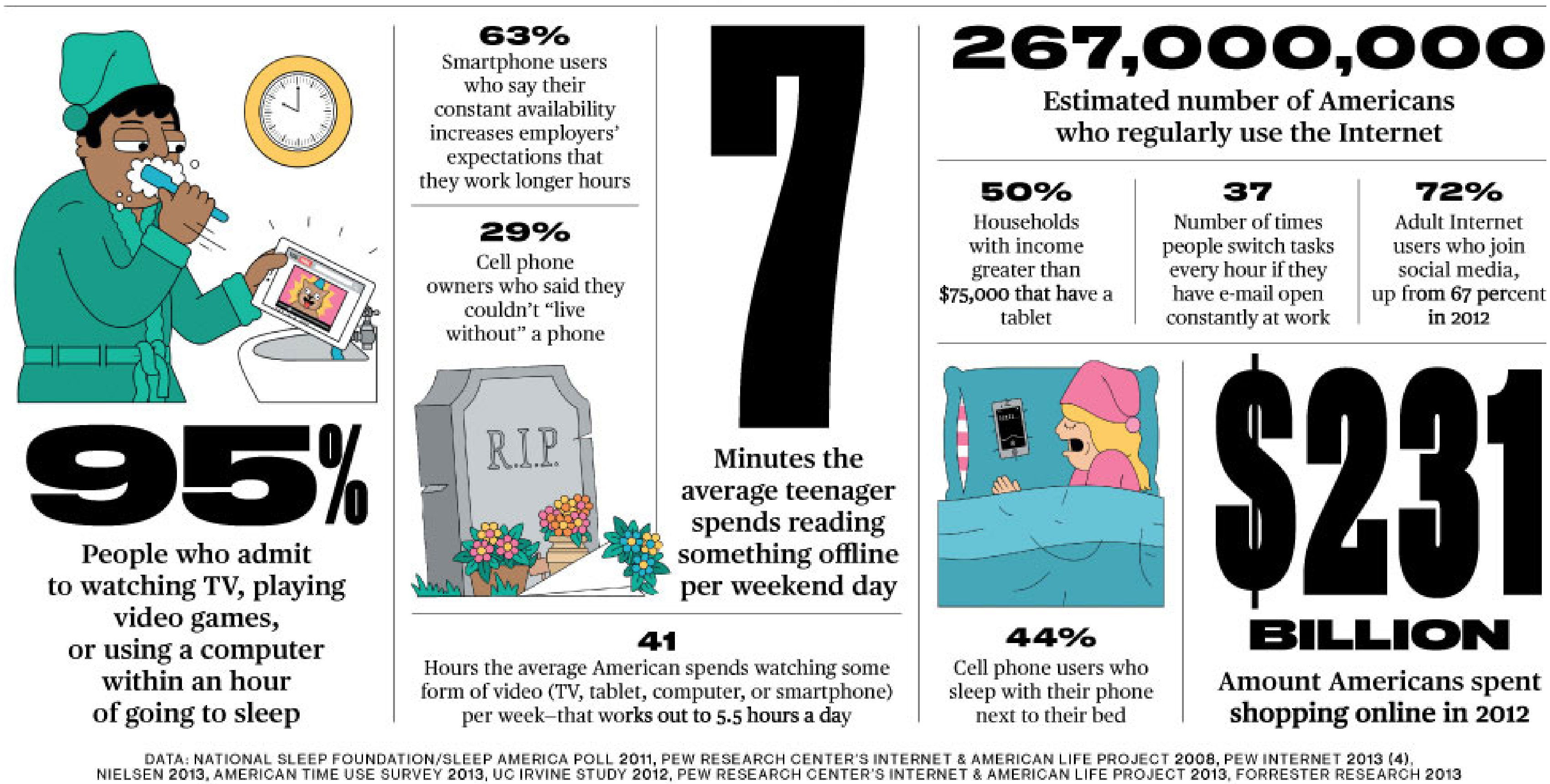
Potential in behavior research

- Scale
- Efficiency
- Granularity
- Ecological validity

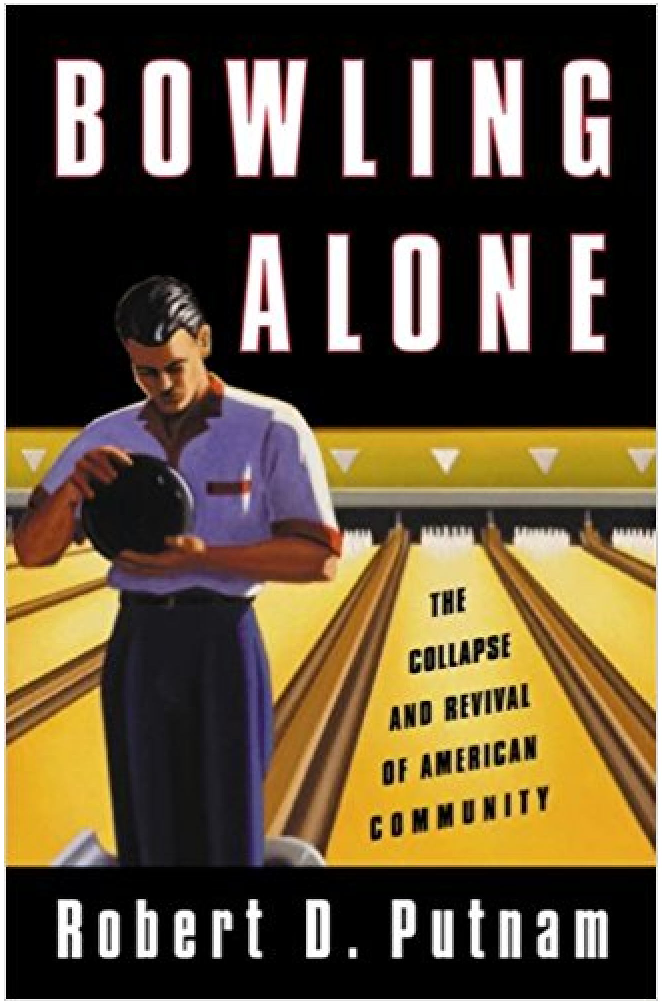
Category 1

PSYCHOLOGY OF THE INTERNET

Common research themes



Important questions



Rise and Decline of League Bowling

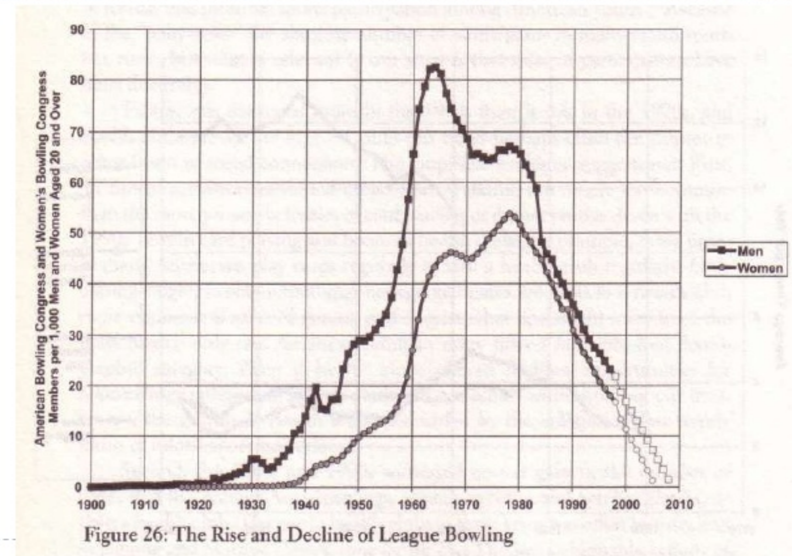
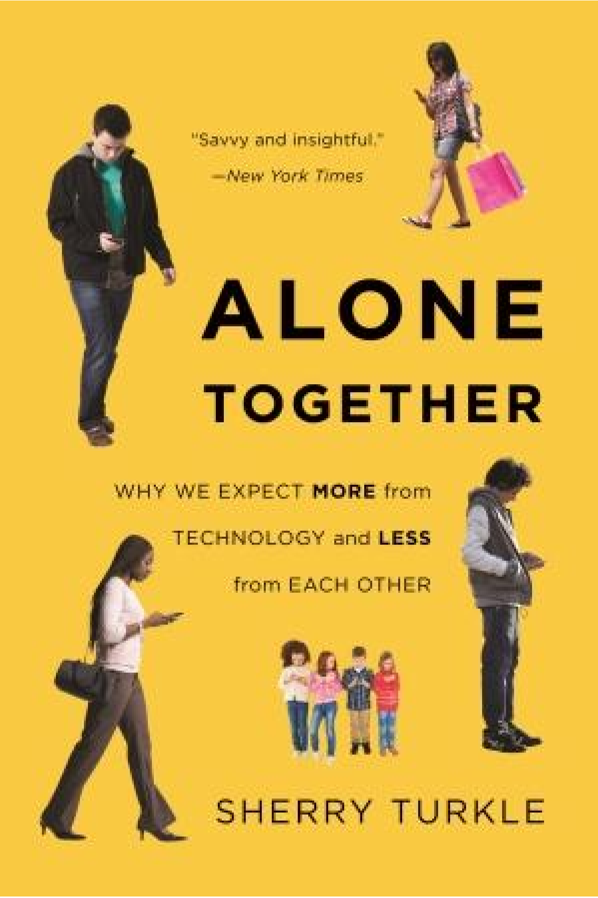
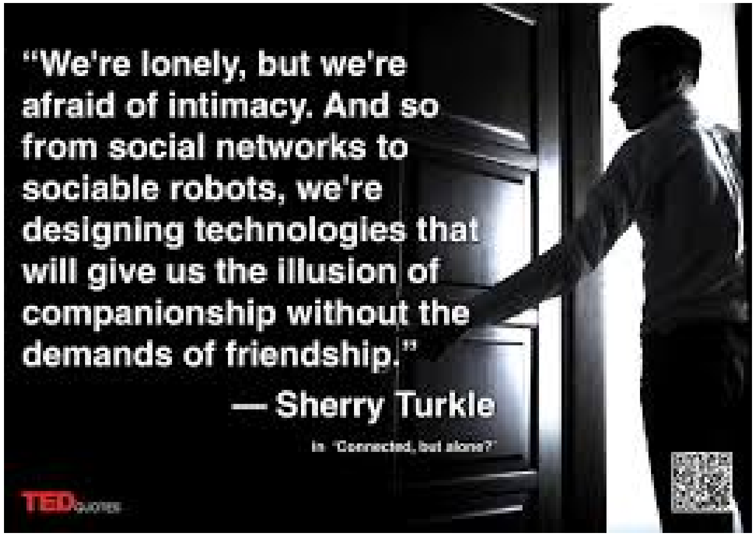


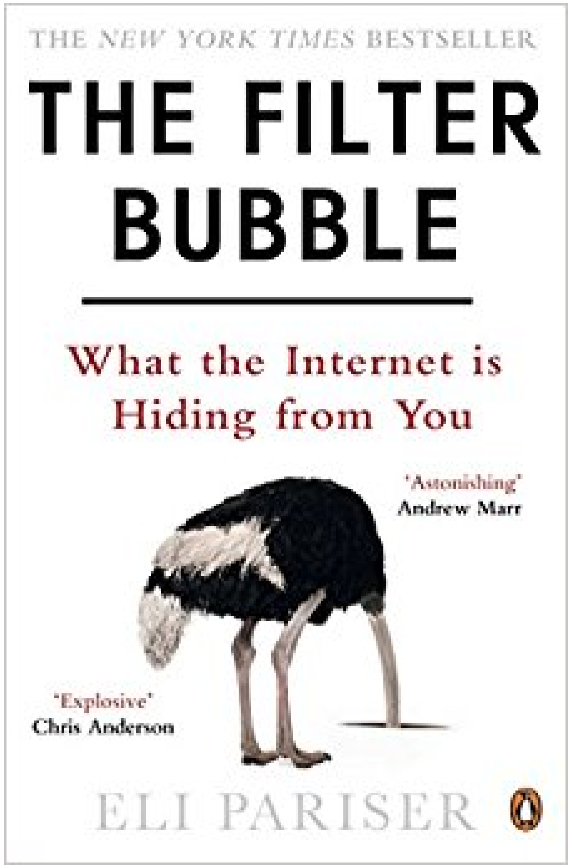
Figure 26: The Rise and Decline of League Bowling

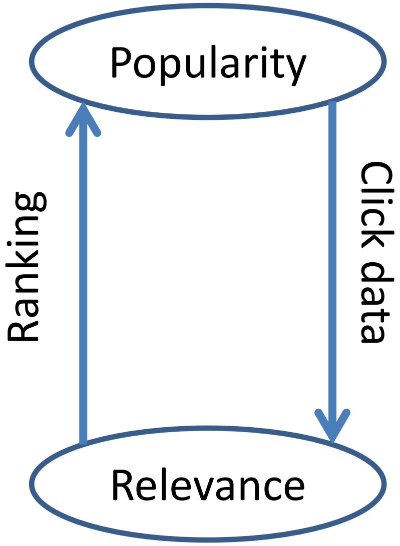
Important questions





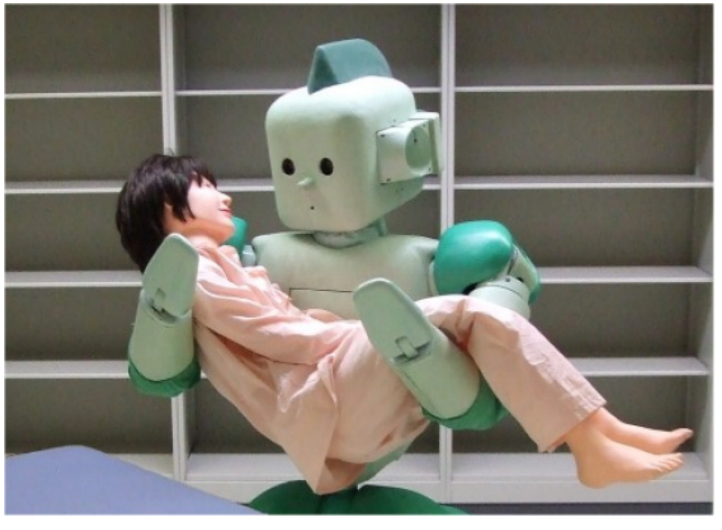
Important questions

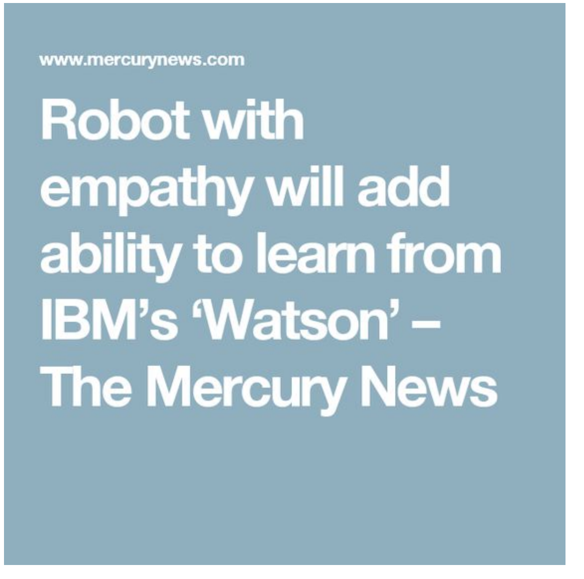




No convincing data

- Hard to quantify central constructs
- Hard to attribute causality
- Hard to collect representative data
- But answering these questions is crucial!

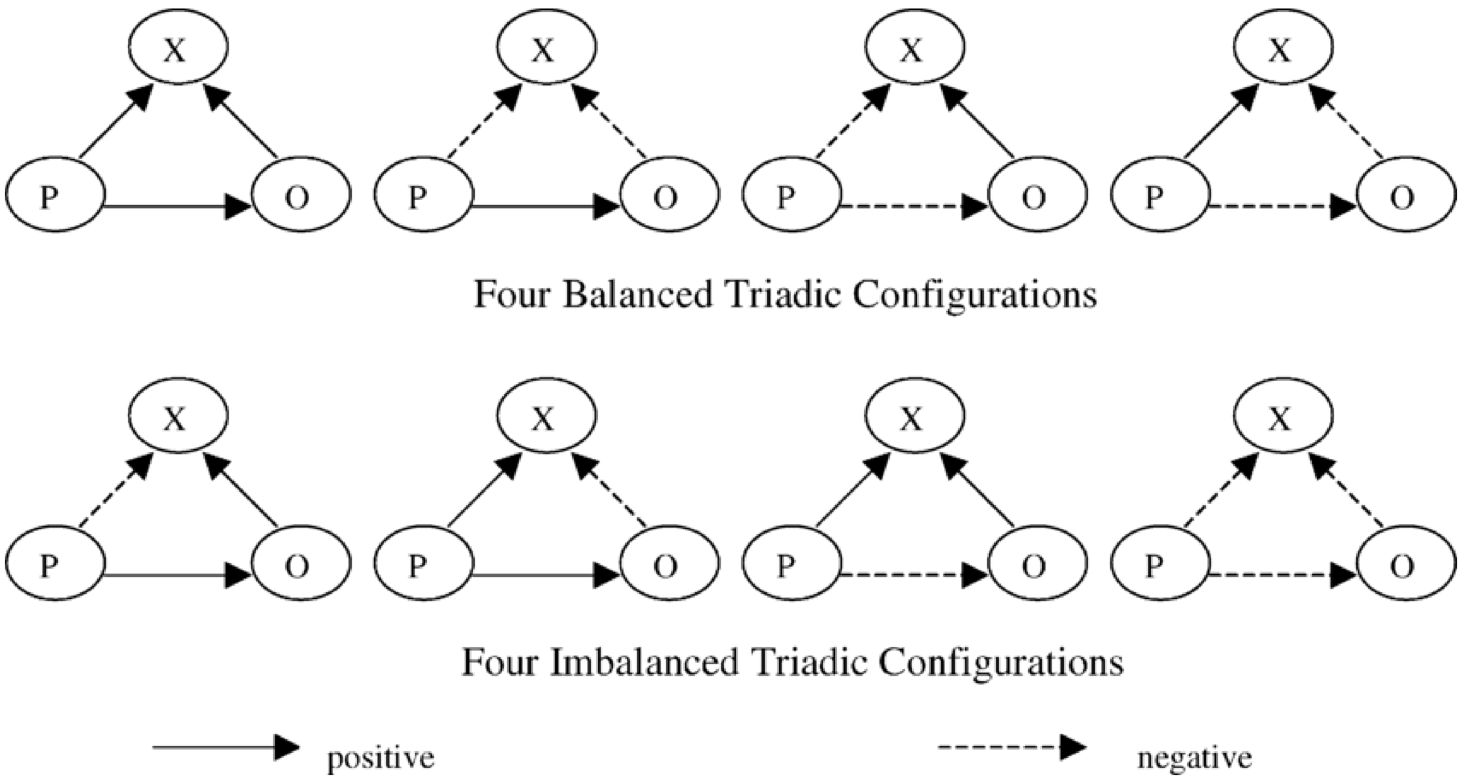




Category 2

PSYCHOLOGY VIA THE INTERNET

Triadic relationship interactions



Convincing evidence this account holds for reciprocal web relationships (Leskovec, 2010)

Word-trait associations

Trait	No. of words sig. at p <.001	Top 20 words
Neuroticism	24	awful (0.26), though (0.24), lazy (0.24), worse (0.21), depressing (0.21), irony (0.21), road (-0.2), terrible (0.2), Southern (-0.2), stressful (0.19), horrible (0.19), sort (0.19), visited (-0.19), annoying (0.19), ashamed (0.19), ground (-0.19), ban (0.18), oldest (-0.18), invited (-0.18), completed (-0.18)
Extraversion	20	bar (0.23), other (-0.22), drinks (0.21), restaurant (0.21), dancing (0.2), restaurants (0.2), cats (-0.2), grandfather (0.2), Miami (0.2), countless (0.2), drinking (0.19), shots (0.19), computer (-0.19), girls (0.19), glorious (0.19), minor (-0.19), pool (0.18), crowd (0.18), sang (0.18), grilled (0.18)
Openness	393	folk (0.32), humans (0.31), of (0.29), poet (0.29), art (0.29), by (0.28), universe (0.28), poetry (0.28), narrative (0.28), culture (0.28), giveaway (-0.28), century (0.28), sexual (0.27), films (0.27), novel (0.27), decades (0.27), ink (0.27), passage (0.27), literature (0.27), blues (0.26)
Agreeableness	110	wonderful (0.28), together (0.26), visiting (0.26), morning (0.26), spring (0.25), porn (-0.25), walked (0.23), beautiful (0.23), staying (0.23), felt (0.23), cost (-0.23), share (0.23), gray (0.22), joy (0.22), afternoon (0.22), day (0.22), moments (0.22), hug (0.22), glad (0.22), fuck (-0.22)
Conscientiousness	13	completed (0.25), adventure (0.22), stupid (-0.22), boring (-0.22), adventures (0.2), desperate (-0.2), enjoying (0.2), saying (-0.2), Hawaii (0.19), utter (-0.19), it's (-0.19), extreme (-0.19), deck (0.18)

(Yarkoni, 2010)

Social contagion

By the end of the experiment, Facebook data scientists noted that the number of users who had seen the notification & voted had increased from

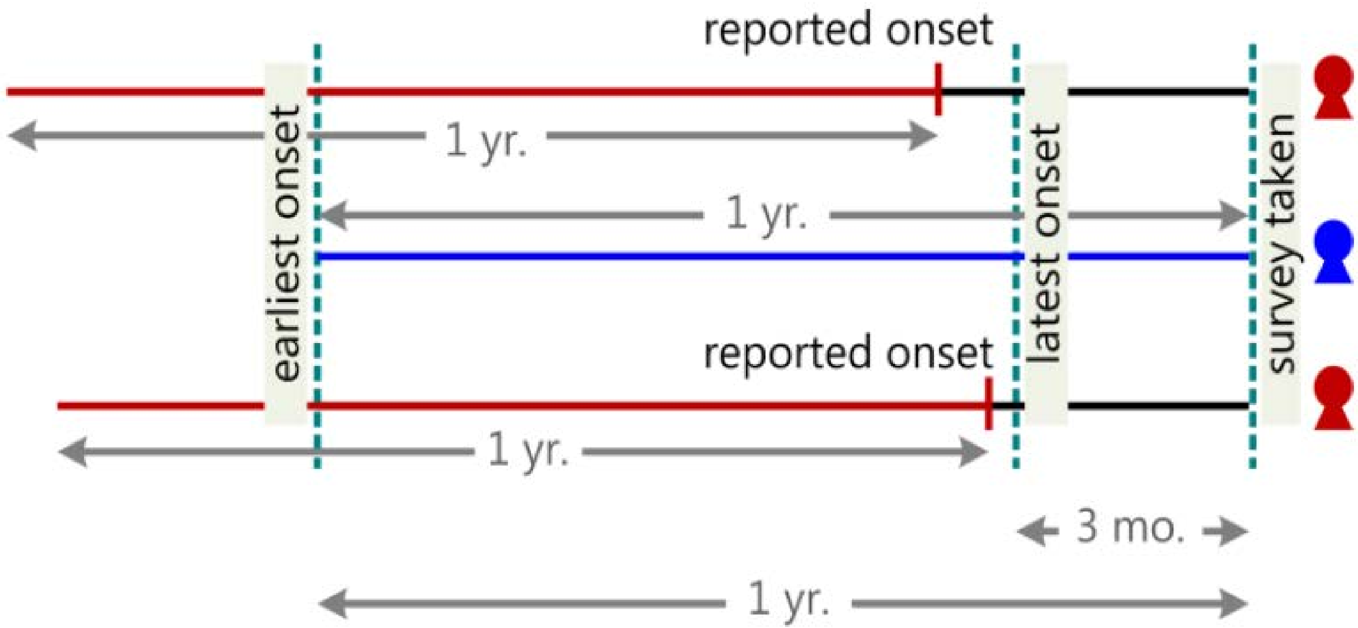
63% to **67%**

Which equated to approximately

340,000

additional votes being placed

Track depression via Twitter



~ 500 participants

Diurnal patterns

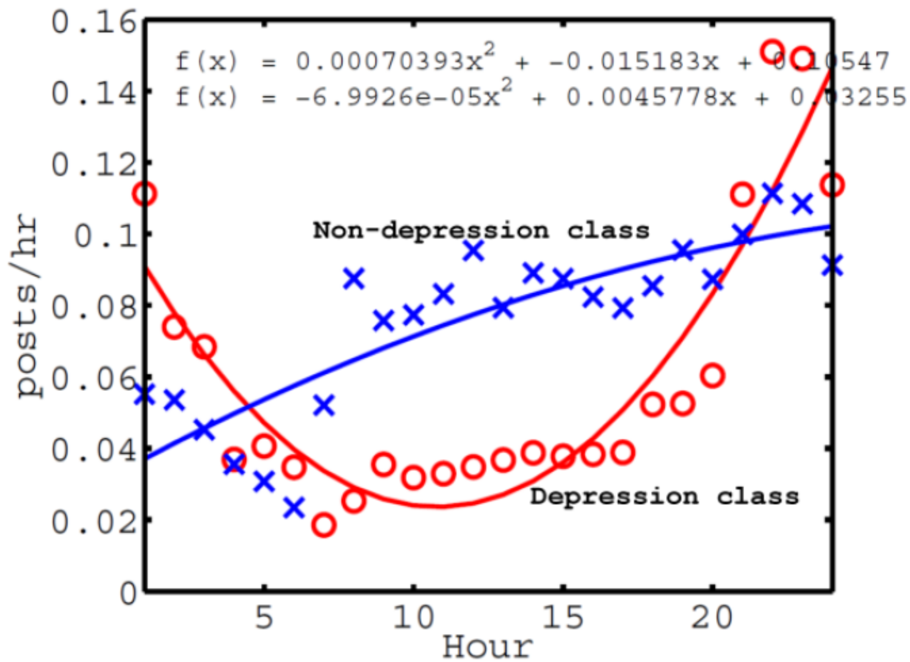
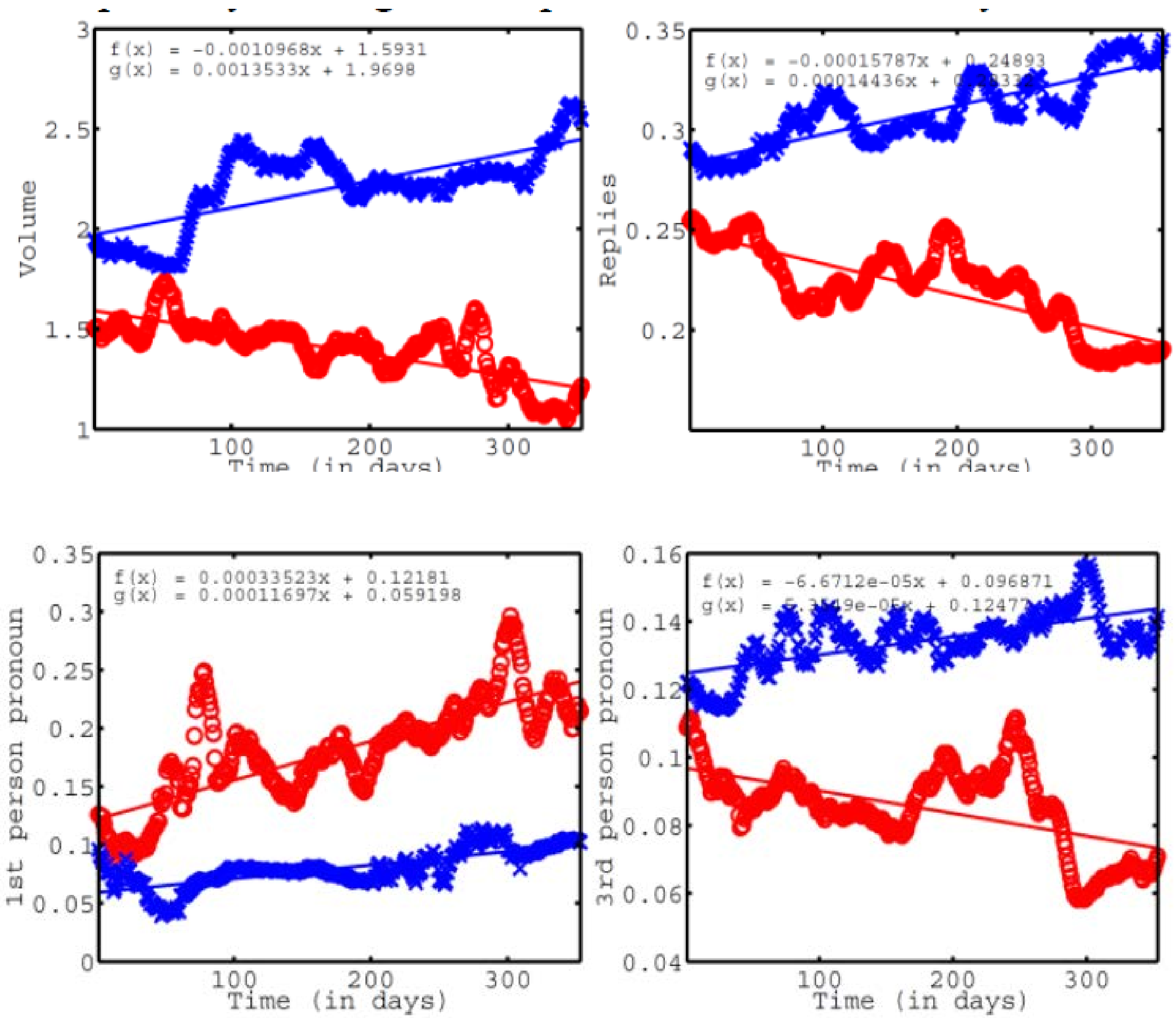


Figure 2: Diurnal trends (i.e. mean number of posts made hourly throughout a day) for the two classes. The line plots correspond to least squares fit of the trends.

Evolution of situation



Common methodology

- Surveys
- Personality tests, commonly the Big Five
- Simple statistics on digital data

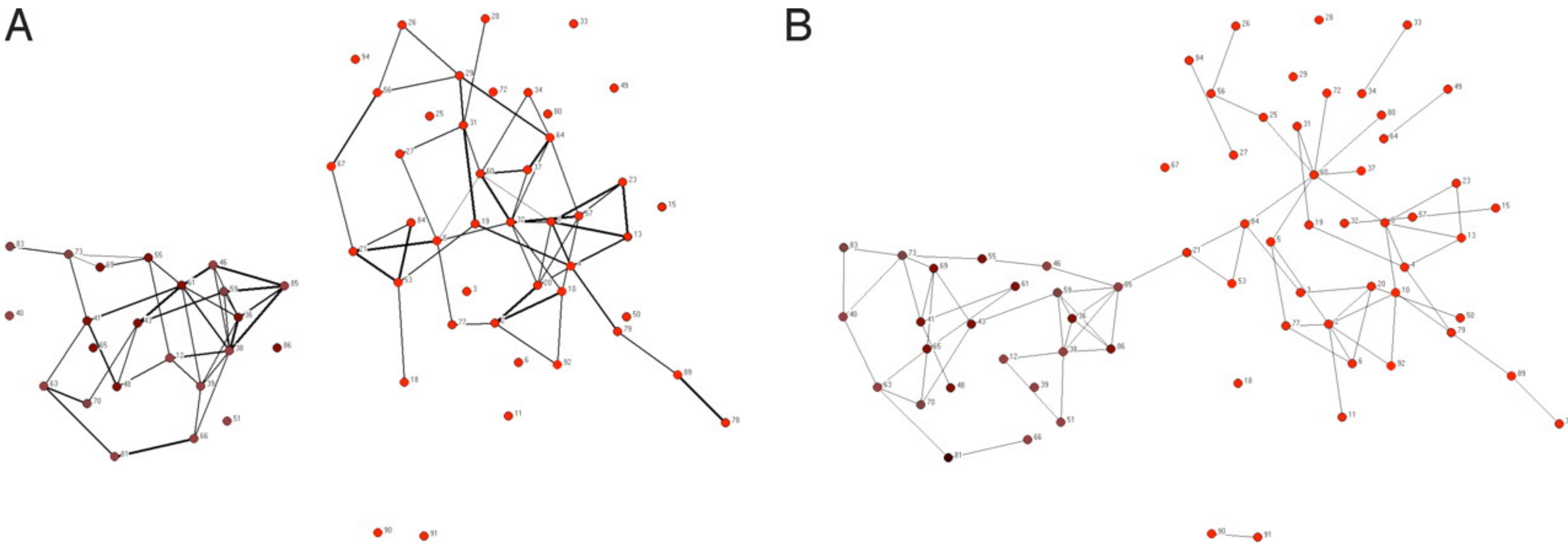
New project

REALITY MINING

Dataset

- 100 Nokia 6600 phones equipped with custom apps to track
  - Call logs
  - Nearby phones
  - Nearby cell towers
  - App usage
- Participants were also surveyed about their social life halfway through the tracking period (one semester)

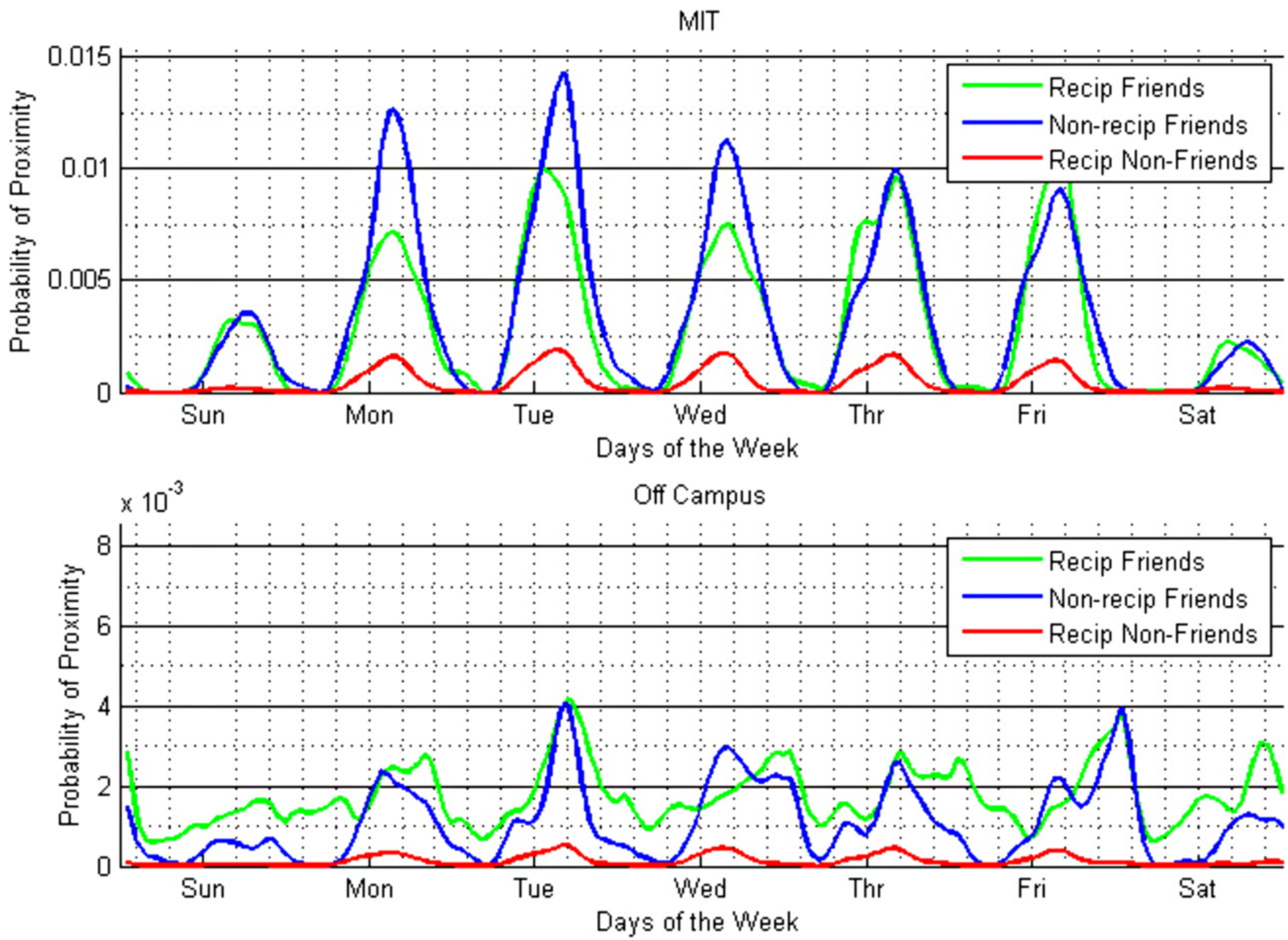
Inferring friendship structure



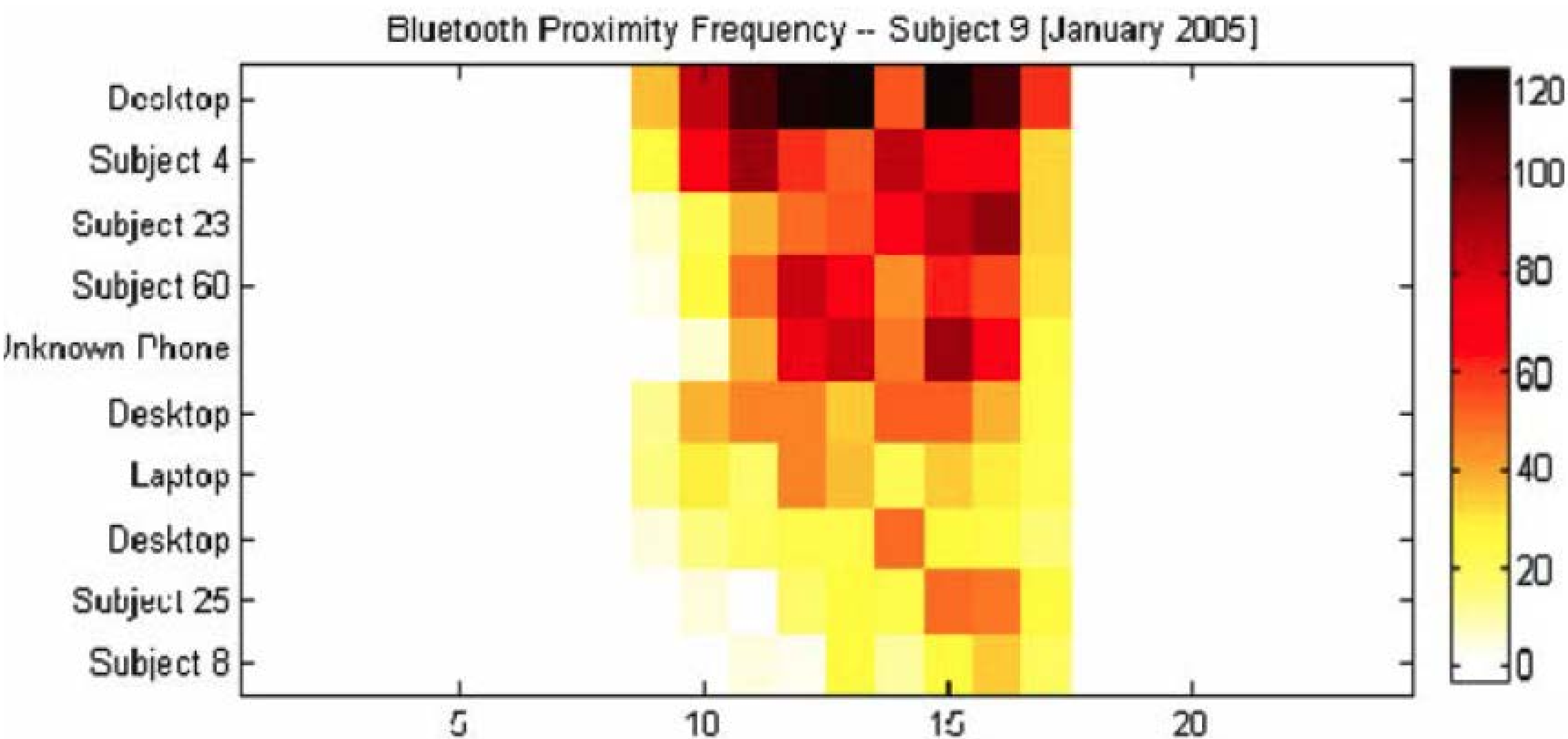
Inferred

Self-reported

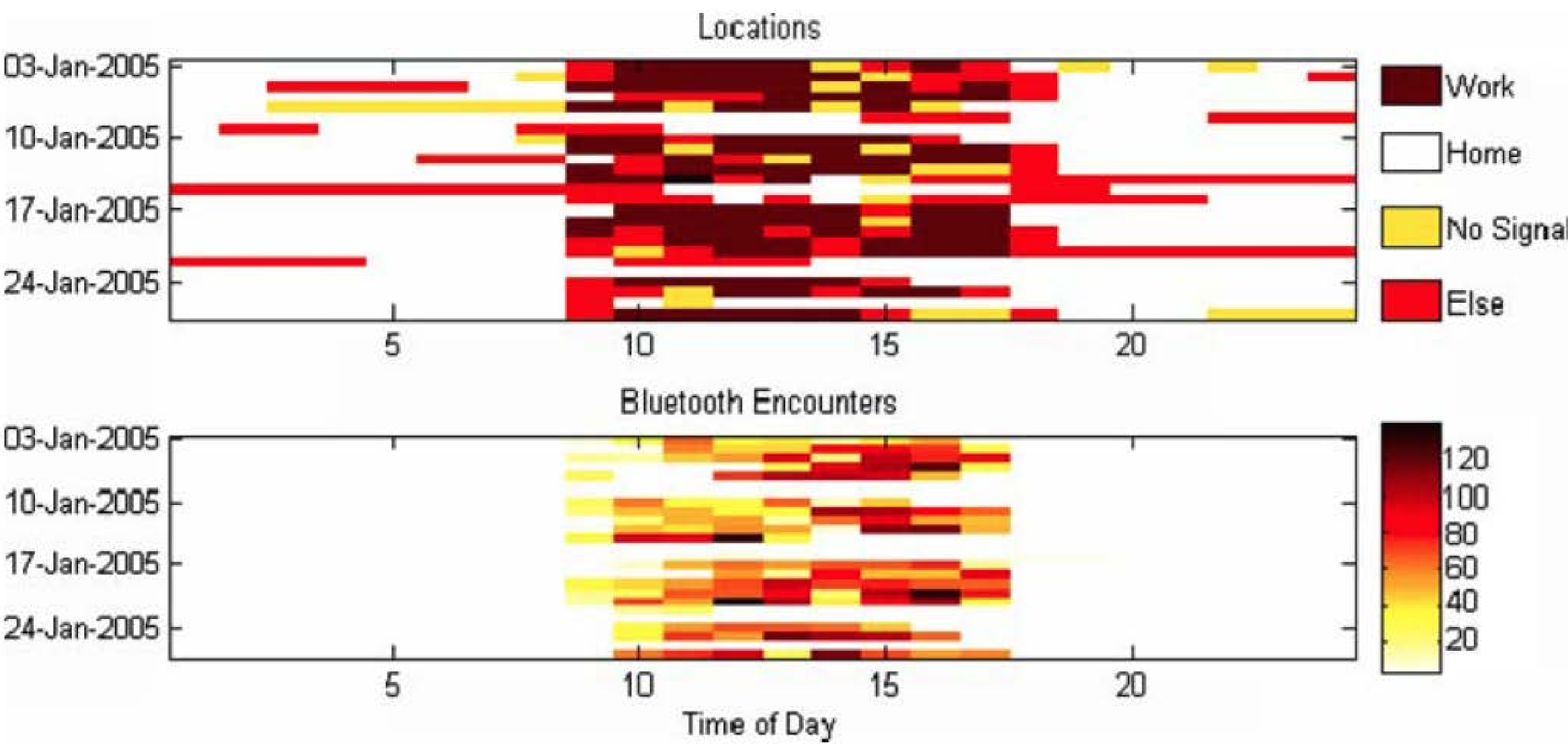
Dynamics of proximity and relationship



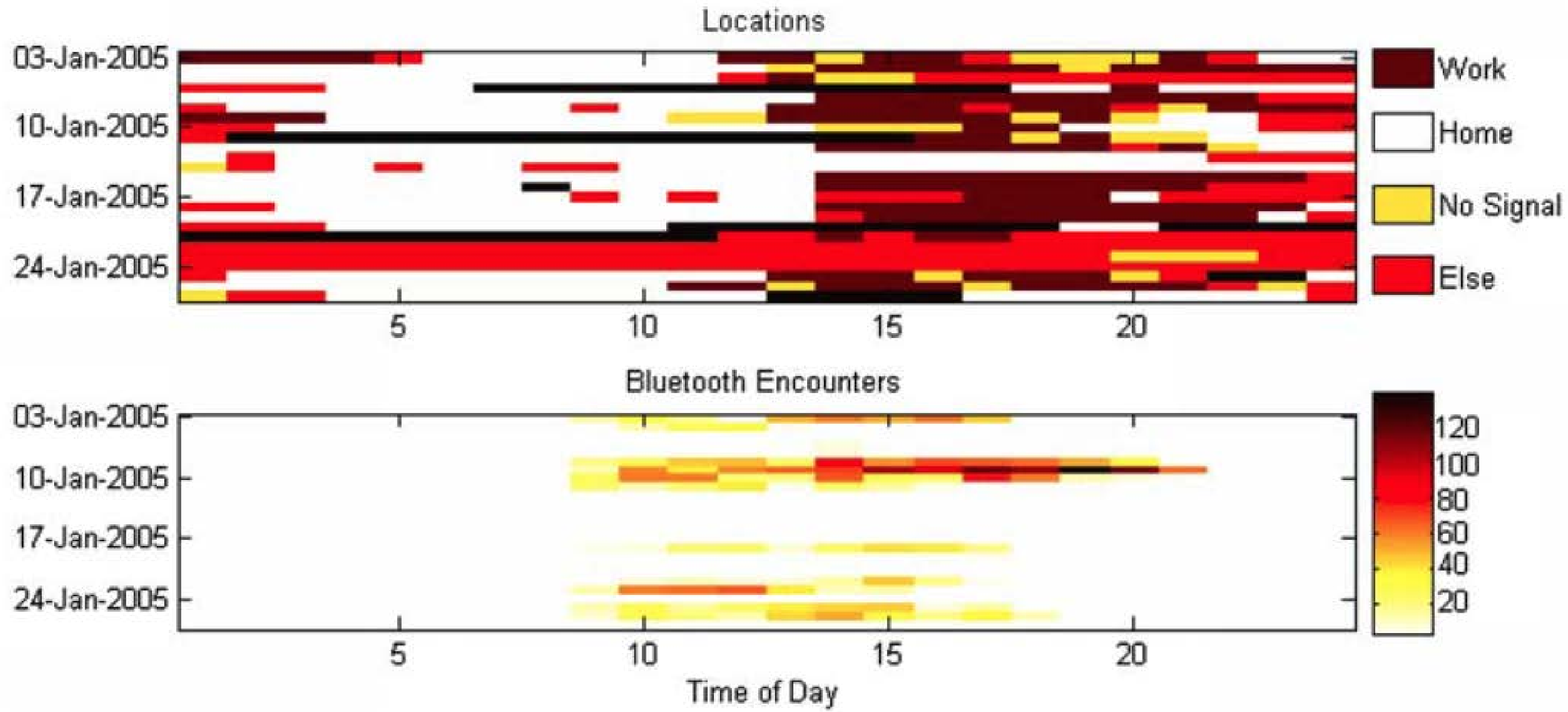
Localization



Entropy


Locations
03-Jan-2005
10-Jan-2005
17-Jan-2005
24-Jan-2005
5
10
15
20
Work
Home
No Signal
Else
Bluetooth Encounters
03-Jan-2005
10-Jan-2005
17-Jan-2005
24-Jan-2005
5
10
15
20
Time of Day
120
100
80
60
40
20

Entropy



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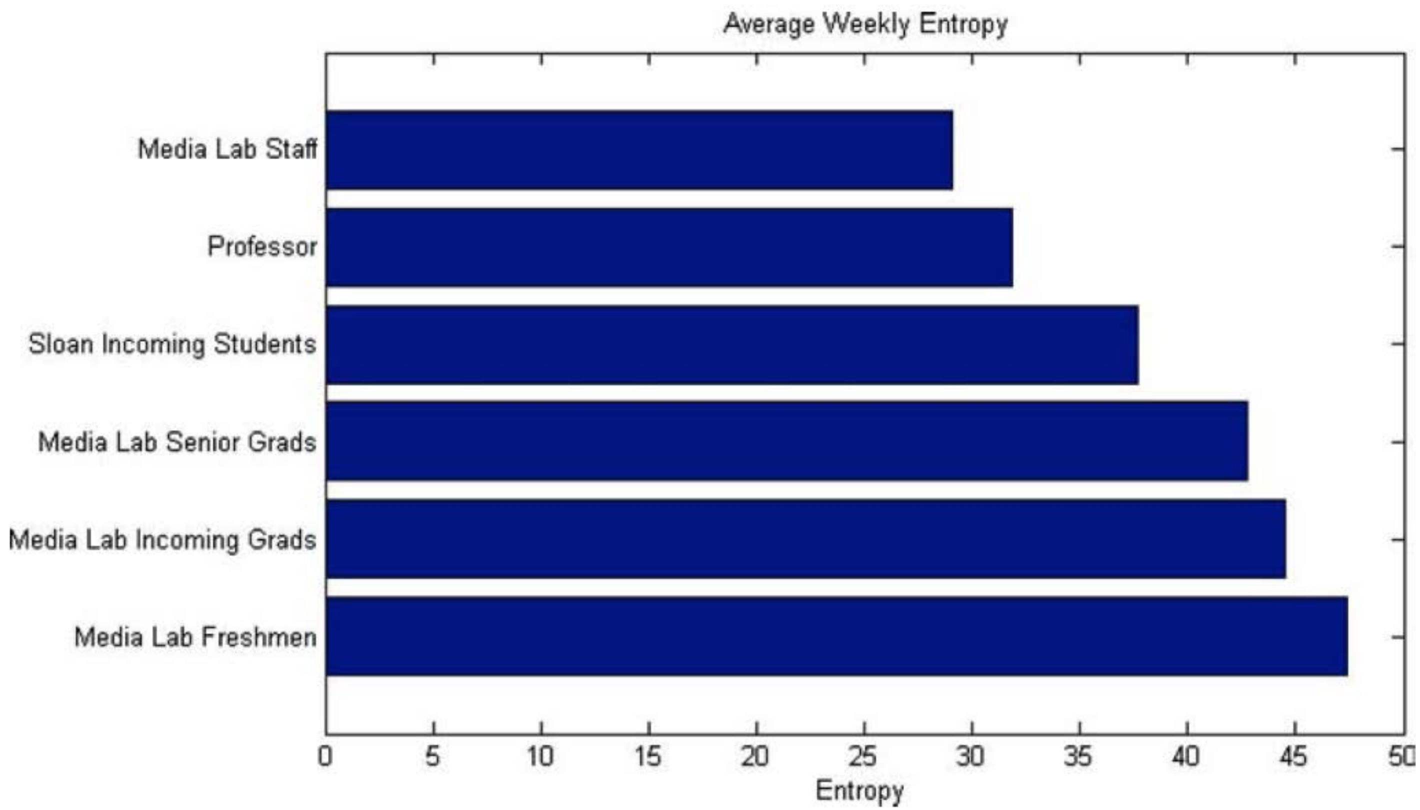
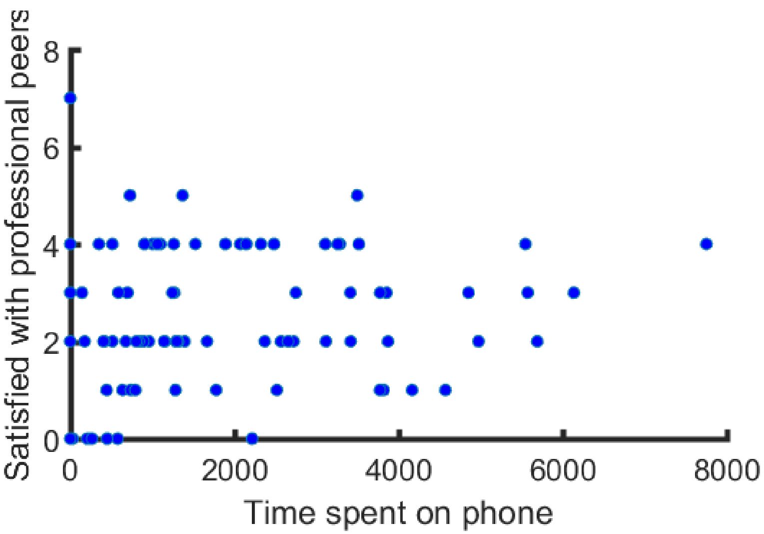
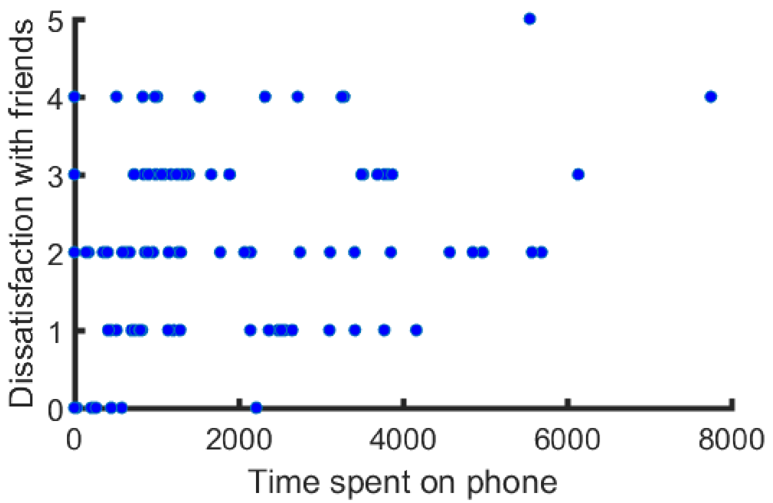
Entropy



Average Weekly Entropy
Media Lab Staff
Professor
Sloan Incoming Students
Media Lab Senior Grads
Media Lab Incoming Grads
Media Lab Freshmen
0
5
10
15
20
25
30
35
40
45
50
Entropy

Low-hanging fruit





Value of the original study

- Showed that regular phones could be used to infer location using cell tower ID pretty well
- Showed that Bluetooth could be used to detect interpersonal proximity fairly well
- Showed that interpersonal relationships could be predicted quite well using physical proximity off work

Desirable directions

- What can we infer from the call logs themselves?
  - Can we infer location? (***)
  - Can we infer physical proximity? (***)
  - Can we infer relationship structure? (****)
  - Can we infer personality traits? (*****, have to use own data)
- I'm looking for
  - **creative** theories of how call patterns might correlate with these factors, and
  - **competent** operationalization of these theories in your formal models
- Due 28th April