Carnegie Mellon University
School of Computer Science

Friendship and proximity in a fraternity cohort with mobile phone sensors

http://mominmalik.com/sunbelt2018.pdf

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Sunbelt XXXVIII, 01 July 2018

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Sunbelt
2018 Utrecht

Key points

Theory:

- RFID and Bluetooth sensors *measure* proximity, which can be a proxy for the *construct* of interaction
- But proximity is also important as a construct

Practice:

- Compare sensors to other data (e.g., survey data)
- Reduce sensor data by “feature extraction” and variable selection, done with careful cross-validation

Sensors + social network studies

Study	Sensor	Collection
Sociometric badge	Infrared	2002, 2007
Reality Mining	Bluetooth	2004
Social Evolution	Bluetooth	2008-2009
SocioPatterns	RFID	2008-2018
Lausanne	Bluetooth	2009-2010
SocialfMRI	Bluetooth	2010-2011
Copenhagen Networks Study	Bluetooth	2012-2013

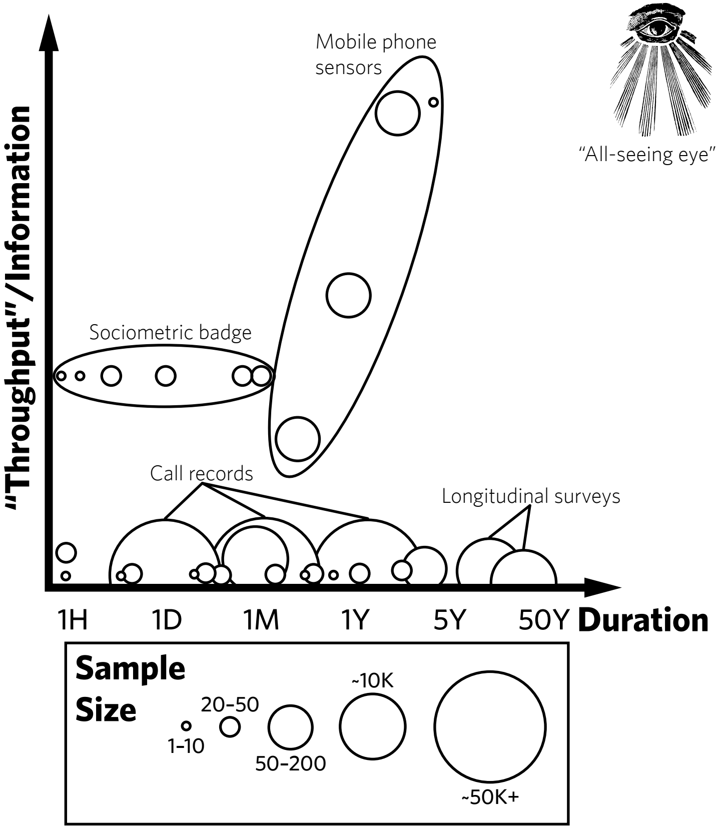
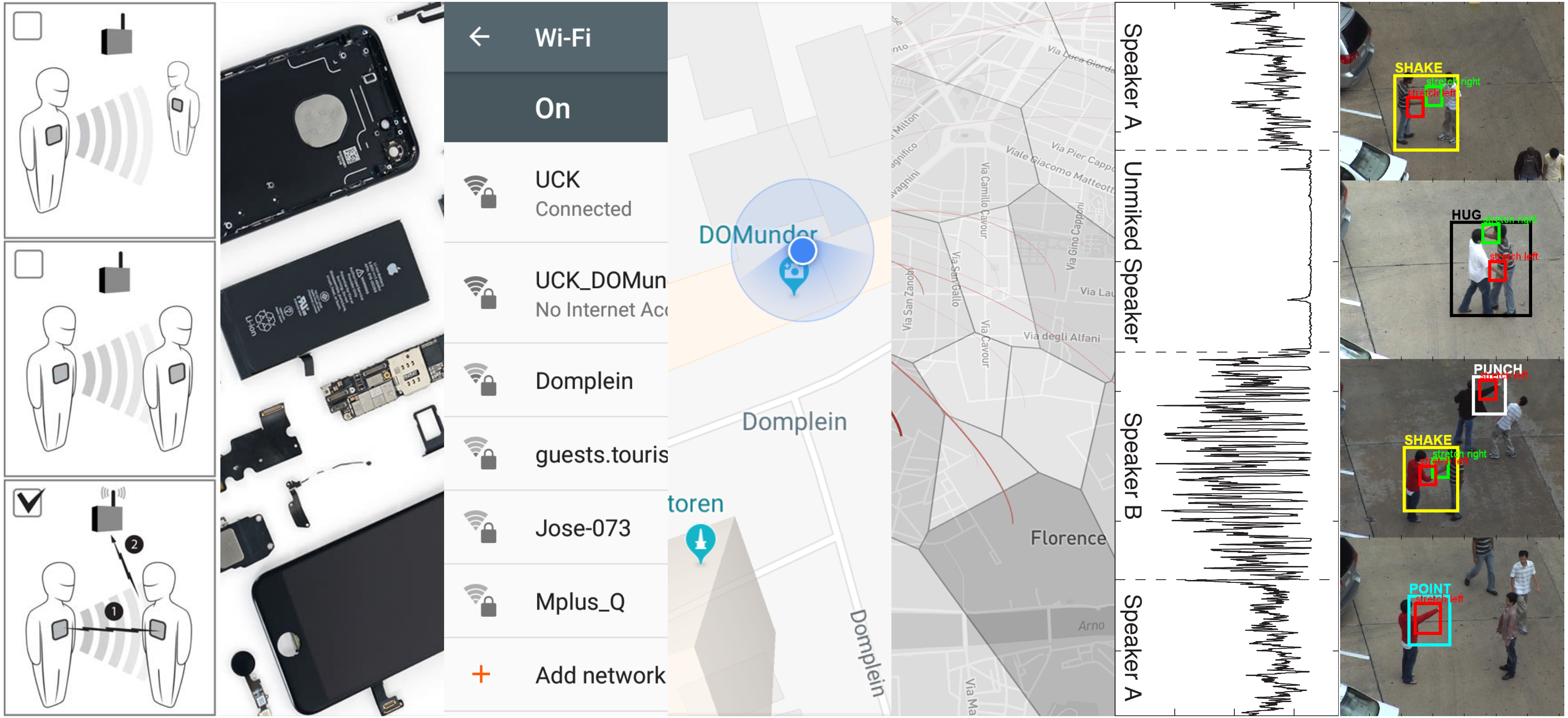


Diagram reproduced from Nadav Aharony, Wei Pan, Cory Ip, Inas Khayal, and Alex Pentland (2011). "Social fMRI: Investigating and shaping social mechanisms in the real world". *Pervasive and Mobile Computing* 7(6), 643–659. doi: [10.1016/j.pmcj.2011.09.004](https://doi.org/10.1016/j.pmcj.2011.09.004).

Relational sensor data

RFID[1] | Bluetooth | WiFi | GPS | Cell towers | Audio[2] | Video[3]



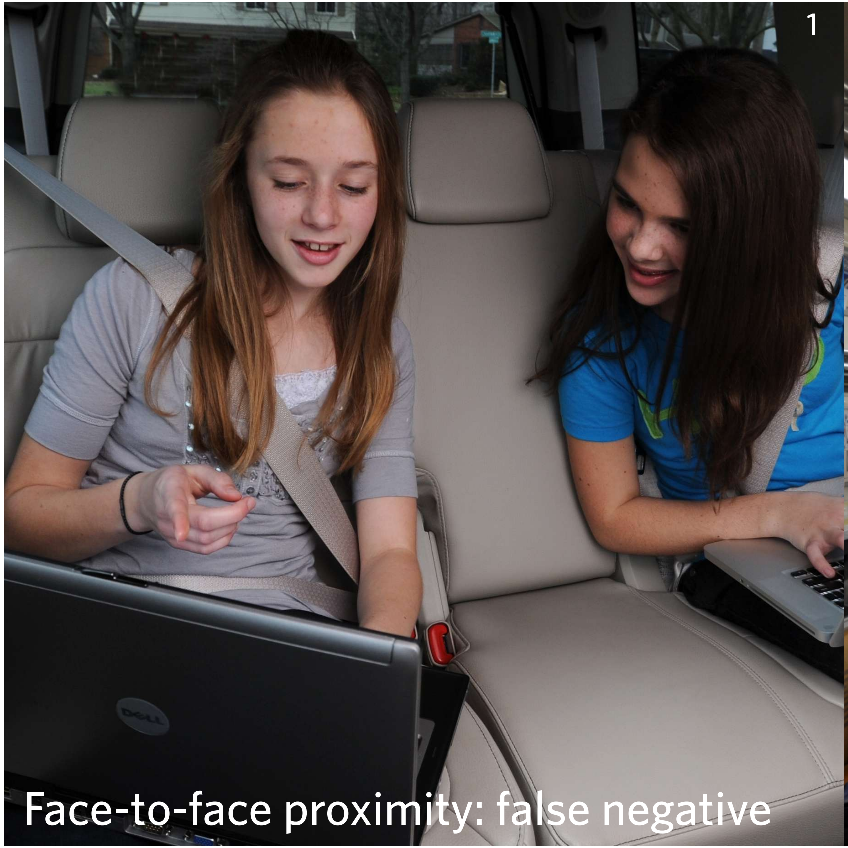
Inconsistent terminology suggests confusion

- Copenhagen Networks Study (Bluetooth):
  - "Proximity data"[1]
  - "Face-to-face interactions"[2]
  - "Close proximity interactions"[3]
  - "Face-to-face contacts"[4]
  - "Physical contacts"[5]
- SocioPatterns papers (RFID):
  - "Person-to-person interaction"[6]
  - "Face-to-face contacts"[7]
  - "Close-range interactions"[8]
  - "Face-to-face interactions"[9]
  - "Face-to-face proximity"[10]
- Audio:
  - "Face-to-face conversation"[11]

Back to basics: *Constructs.*

- *Constructs*: primitives of social science
  - A measurement might be a *proxy* for an non-observable construct (e.g., multiple choice questions and intelligence)
  - Proxies always give errors (binary construct: false negatives and false positives)
  - (Criterion-related ["predictive"] validity)
- Face-to-face interaction: neither the measure nor the construct

In-person interaction is the true construct


1
Face-to-face proximity: false negative

2
Face-to-face proximity: false positive

(*Conversation* is a separate construct)

Constructs have their own importance

- What construct do we care about?
- Depends on what we want to study/investigate.
  - Disease transmission? Directional proximity and/or physical contact.
  - Persuasion? Conversation.
  - Mimicry? Interaction.
  - Latent homophily, expressed geographically? Proximity.
  - Environmental exposure? Proximity.

Survey data, too, has its own importance

- "Objective" sensor data is not superior to survey data
  - Yes, informant inaccuracy, social desirability bias, ambiguous questions...
- But they are measuring *different things*
  - Surveys better measure the *psychological perceptions* that may ultimately be causal for behavior[1] (e.g., memorability[2])
- So, discrepancies must not be resolved in favor of the "objective" data
- Discrepancies are exactly the interesting thing to study!!
- Propinquity is an example (discrepancy is "close strangers, distant friends"[3])

Proximity is itself interesting (propinquity!)

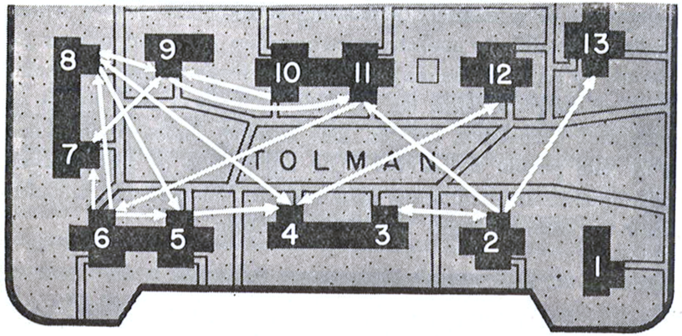


FIG. 9a. Pattern of Sociometric Connections in Tolman Court

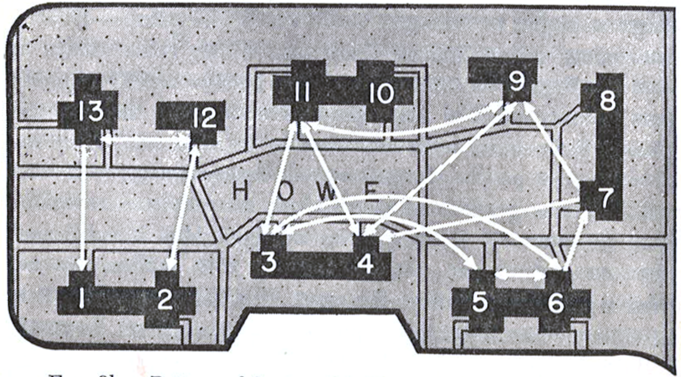
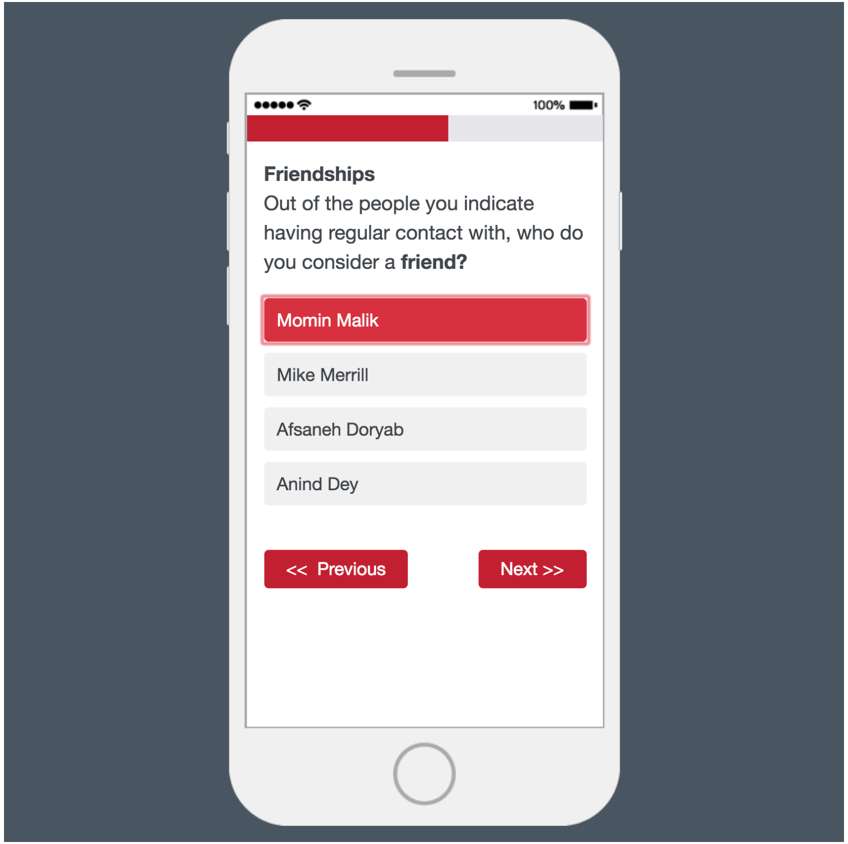


FIG. 9b. Pattern of Sociometric Connections in Howe Court

Study

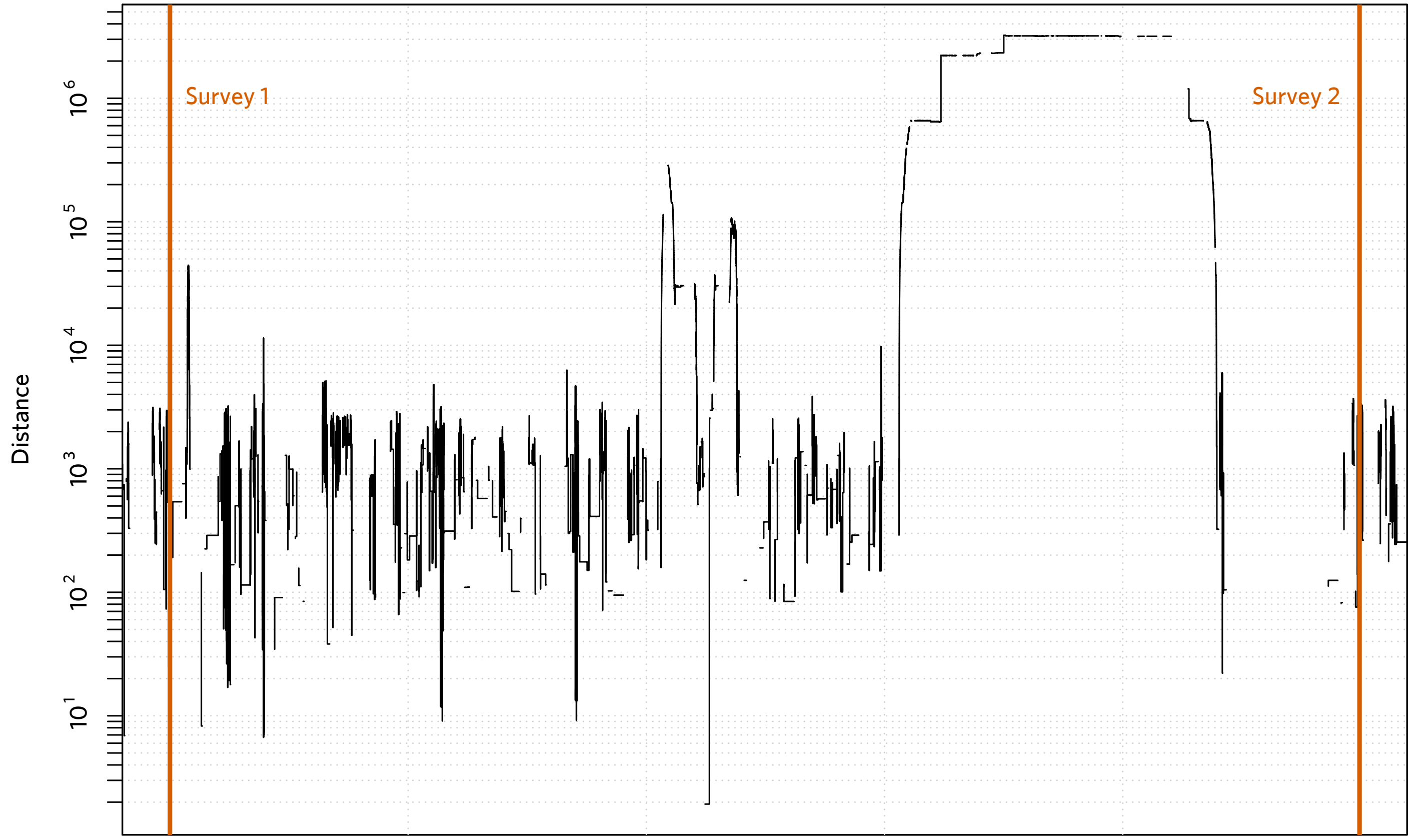
Data: Surveys + mobile phone tracking



Goal: Study propinquity

- Not proximity as proxy for interaction, but proximity itself
- Compare proximity (via “location”, WiFi) to longitudinal sociometric choice
- Look at proximity at scales larger than that of interaction
  – Small scales (proximity at <10m): underlying causal mechanism might still be interaction.
  – Large scales (proximity >20m): will capture other mechanisms, e.g. latent homophily, common environmental exposure, etc.

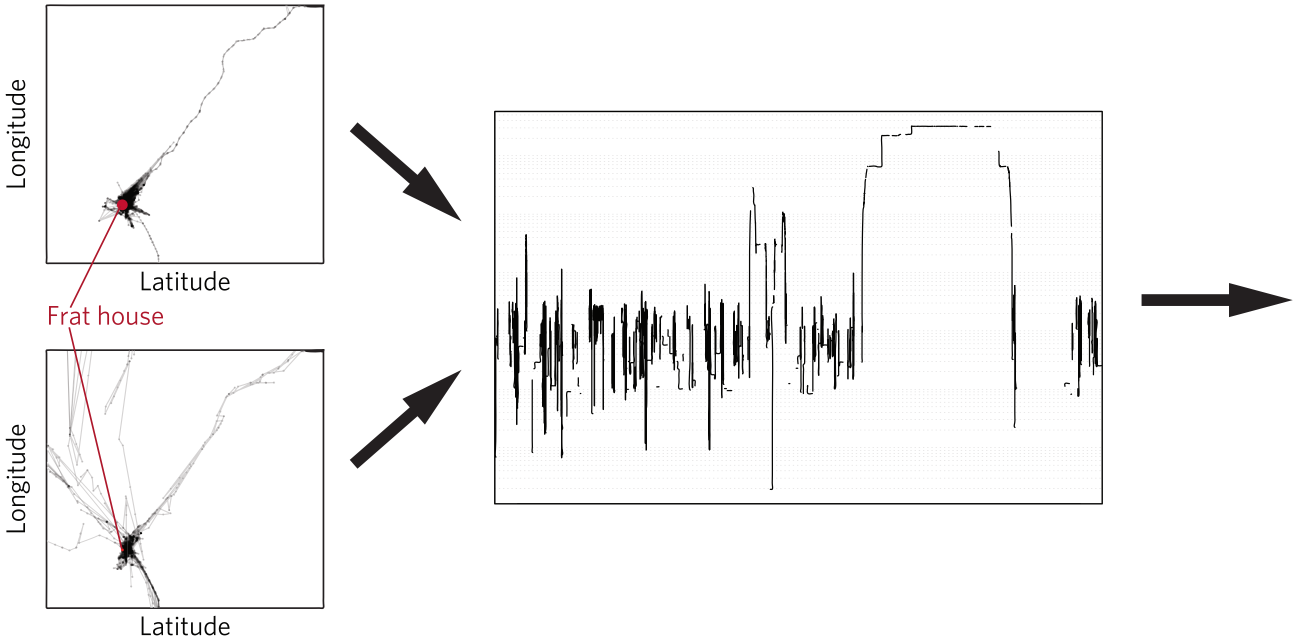
Core problem: *Different resolutions*



Approach: First do machine learning

- Step 1: Find out how to meaningfully characterize the association of proximity and friendship
- Step 2: Using this characterization, model co-evolution

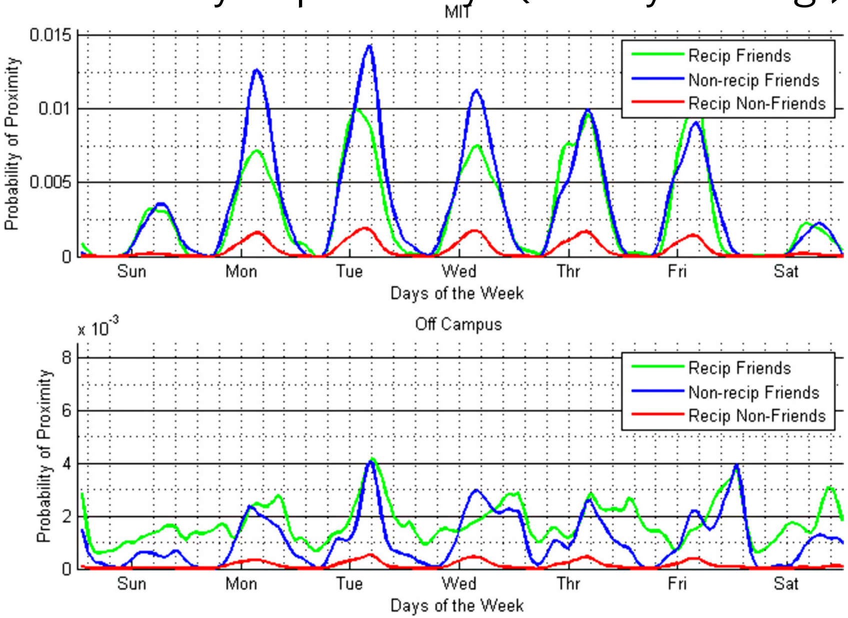
Data processing and “feature extraction”



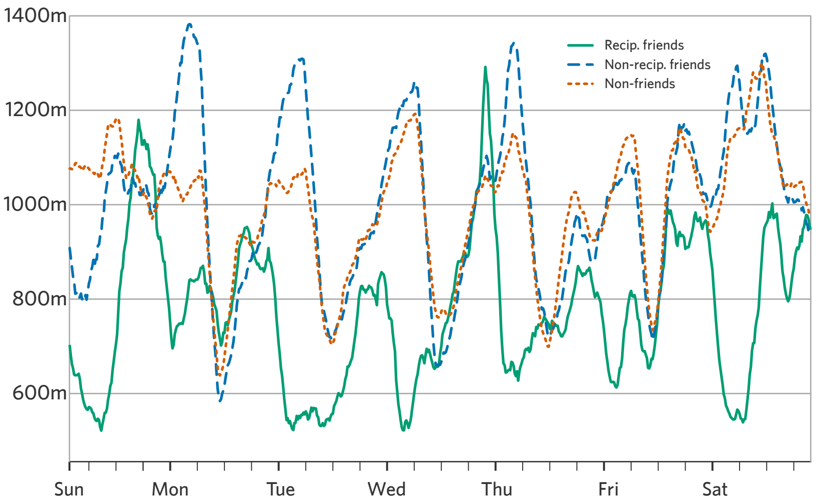
0.086	0.281	0.0793	0.079	
0.005	0.073	0.0054	0.005	
0.057	0.234	0.0547	0.054	…
0.007	0.086	0.0074	0.007	
0.071	0.258	0.0669	0.066	
0.024	0.154	0.0238	0.023	
	⋮			

Caution: Aggregates can mislead. Better test of an association is its predictive performance

“Probability of proximity” (Reality Mining[1])



Median pairwise distance (our study)

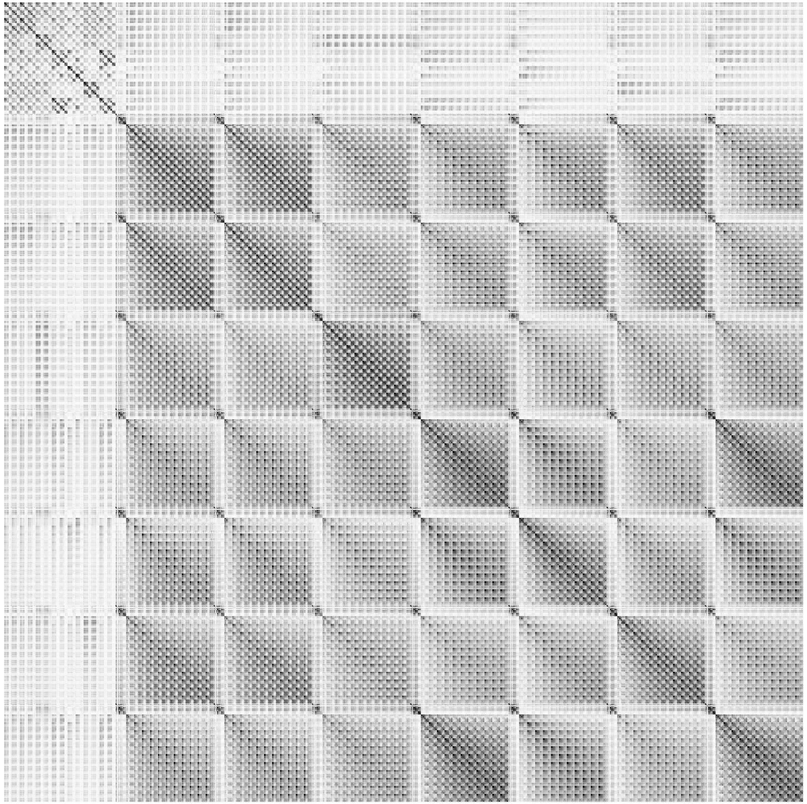


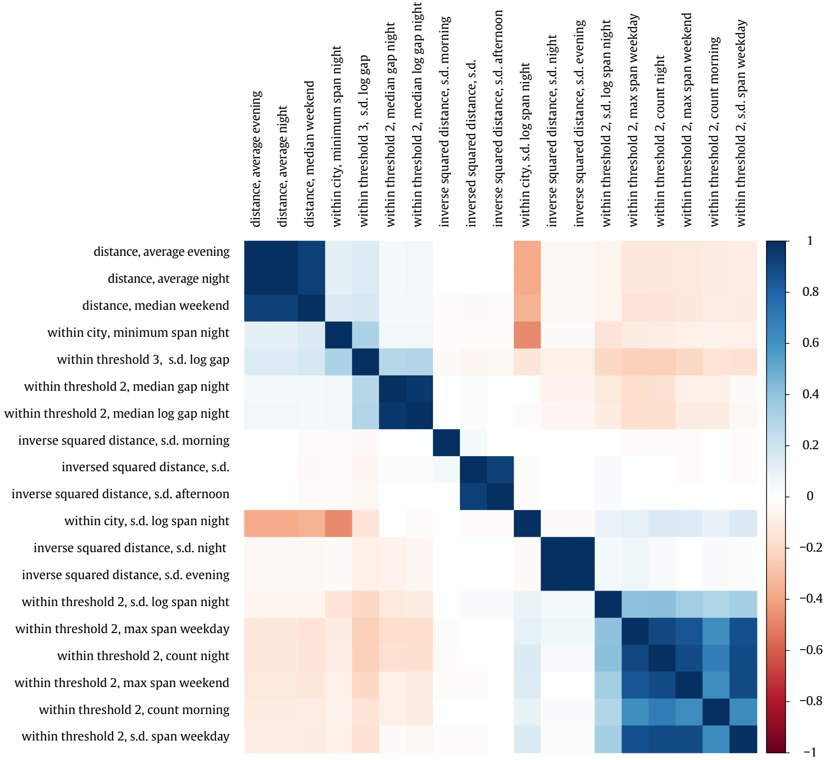
We found what looked like a compelling pattern as well, but it proved ineffective for prediction when tested with cross-validation. Why? Aggregate trends obscure between-dyad and week-to-week variance.

Test the performance via *cross-validation*

- Split data into “training” and “test”
- Fit model on training, evaluate on test
- Done correctly, simulates out-of-sample data, thereby directly establishing external validity
- But dependencies (e.g. time, networks) can complicate cross-validation
- We use multiple cross-validation schema to control for this (details in forthcoming work)

Result: ~30% association. Can get with 2.5K features… or 19, after feature selection.





Summary: How we *should* use sensors

- If using Bluetooth, RFID proxies for interaction, do more testing against human-coded benchmarks
- But *proximity* is also inherently interesting
- Compare proximity other forms of data (e.g., friendship for propinquity/influence vs. exposure)
- Comparing sensor data and survey data, e.g. via SAOMs, is a good framework
- Reduce/summarize rich signals through feature extraction + selection, not naïve aggregation

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Thank you!

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Work with Jürgen Pfeffer, Afsaneh Doryab. Michael Merrill, and Anind K. Dey

Thanks also to Yuvraj Agarwal and Nynke Niezink.

Endnotes/references (1 of 2)

Slide 4

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