Social Behavior Prediction Through Reality Mining

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Outline

- Introduction and Motivation
- Corpora
- Identification Based on Reality Mining
- Tensor Analysis of Reality Mining Data
- Other Efforts
- Conclusions & Future Potential

Acknowledgement:
Sandy Pentland, MIT Media Lab

Overview & Motivation

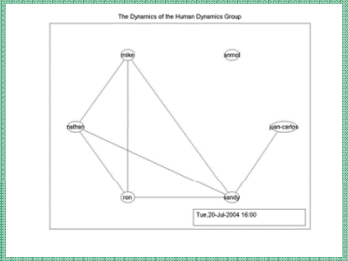
Sociometric Badges (microphone, IR, accelerometer, …)

Bluetooth

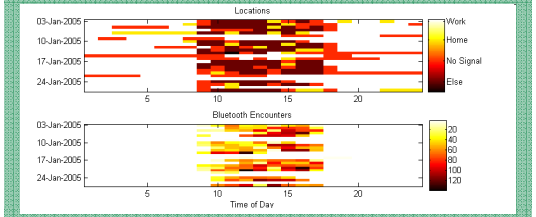
Smart Phones

- *Surveys*
- *Patient Records*
- *Call Info*

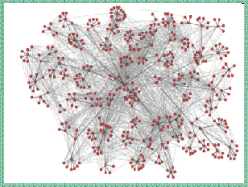
Sensors & Data



Dynamic Network Analysis



Anomalous Behavior



Group Behavior Prediction

Analytics

Focus:
- **Dynamic, real-time analysis of networks and behavior prediction**
- **Sensor rich multi-INT data**

MIT LL Applications:
- **Correlation of Multiple INTs (cyber, cell, etc.)**
- **Persistent Surveillance**
- **Urban Warfare**
- **Blue force tracking**
- **Cognitive Radio**
- **CT**

Potential Future Sponsors:
- **DoD/IC**
- **DHS**

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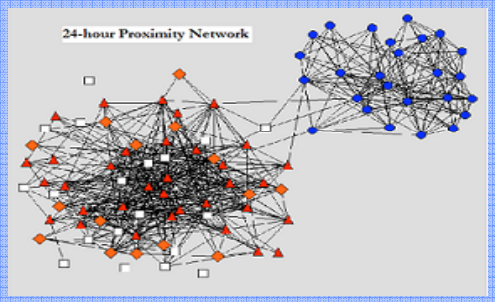
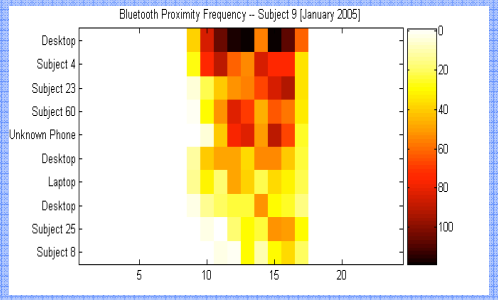
Recognition and Prediction

Multi-INT Fusion Produces Noisy Group Data

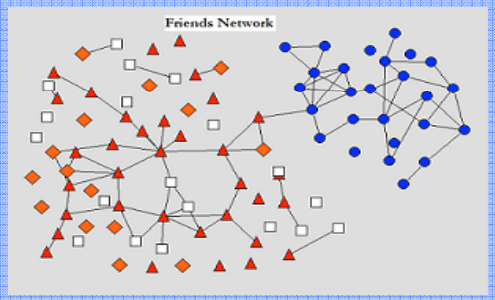


Single Devices Produce Fine-Grained Temporal Dynamics

Social Network Analysis Extracts High-Level Features



Proposed Effort: Real-Time Analysis of Network Features



Corpora

- 94 students were given Nokia 6600 smart cell phones [1]
- Sensor data collected 09/04 – 06/05
  - Cell phone location
  - Phone activity
  - Bluetooth scans
- Data anonymized for release
- Additional data:
  - Student surveys on health
  - Surveys on social network

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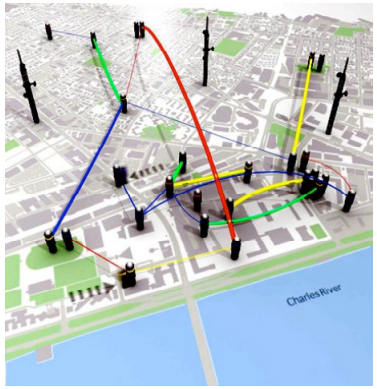
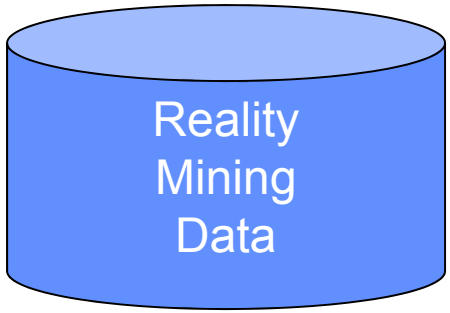
Reality Mining Data

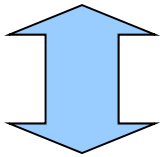
- **Raw data is Bluetooth Addresses, Cell Phone calling, and Cell Phone location**
- **No content—voice or message**
- **Typical Query of Location Data**

```
select * from locs where (myhn=44) order by d, t limit 4;
-----------------------------------------------
| myhn | date       | time     | areaid | cellid|
+------+------------+----------+--------+-------+
| 44   | 2004-11-01 | 18:25:30 | 5119   | 40813 |
| 44   | 2004-11-01 | 18:26:01 | 5119   | 40332 |
| 44   | 2004-11-01 | 18:26:18 | 5119   | 40811 |
| 44   | 2004-11-01 | 18:27:13 | 5119   | 40332 |
```





MySQL DB



Algorithms
& Experiments

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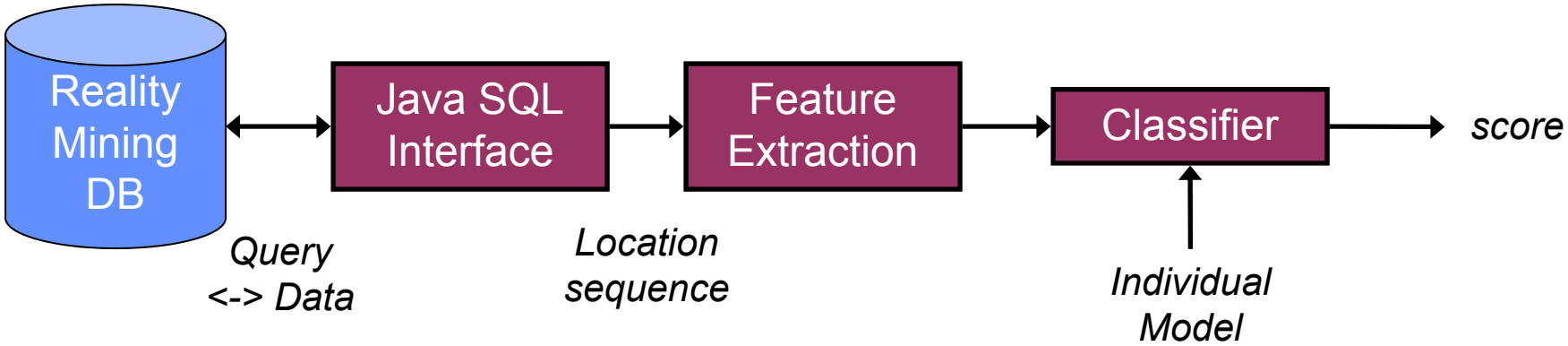
Identification via Reality Mining Data



- **Typical Testing Scenario**
- **Location sequence is over a period of time—typically 1-5 days**
- **Feature extraction summarizes location information as a vector**
- **Classifier used for detection of the individual**

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Features for Recognition

Input Stream

..... 5119_40811 5119_40811 5119_40811 5188_60241 5188_40811 5188_40813 5188_40811 5188_42171 5188_40811 5188_40332 5188_40811 5188_40332 5188_40811 5188_40332 5188_40811 5188_40811 5188_40811 5188_40811 5188_42171 5188_40811 5182_43861 5182_43861 5188_40811 5188_40332 5188_40811 5188_40332 5188_40811 5188_40332 5188_43032 5188_40333 5188_43032 5188_43033 5188_40333 5188_43033 5188_43031 5188_43033 5188_40333 5188_43031 .....

Window over k days

5119_40811 5188_60241 5188_40811 5188_40813 5188_40811 5188_42171 5188_40811 5188_40332

N-grams

5119_40811| 5188_60241 5188_60241| 5188_40811 5188_40811|5188_40813 5188_40813| 5188_40811
5188_40811|5188_42171 5188_42171| 5188_40811 5188_40811|5188_40332

Probabilities

P(5119_40811| 5188_60241) = 1/7
P(5188_60241| 5188_40811) = 1/7
…

Vector

V = [0 … 0 1/7 0 … 0 1/7 0 … 0 …]

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Experimental Setup

- N-gram Features weighted with log of inverse frequency in "background"
- SVM Classifier, Linear Kernel
- Training Set 1 (TR1)
  - Data collected between September 2004 and December 1, 2004
- Training Set 2 (TR2)
  - Data collected between March 1, 2005 and March 31, 2005
- Test sets at about 1 month intervals:
  - TST1, Jan 1–Feb 1, 2005
  - TST2, Feb1–March 1, 2005
  - TST3, March 1–April 1, 2005
  - TST4, April 1–June 1, 2005

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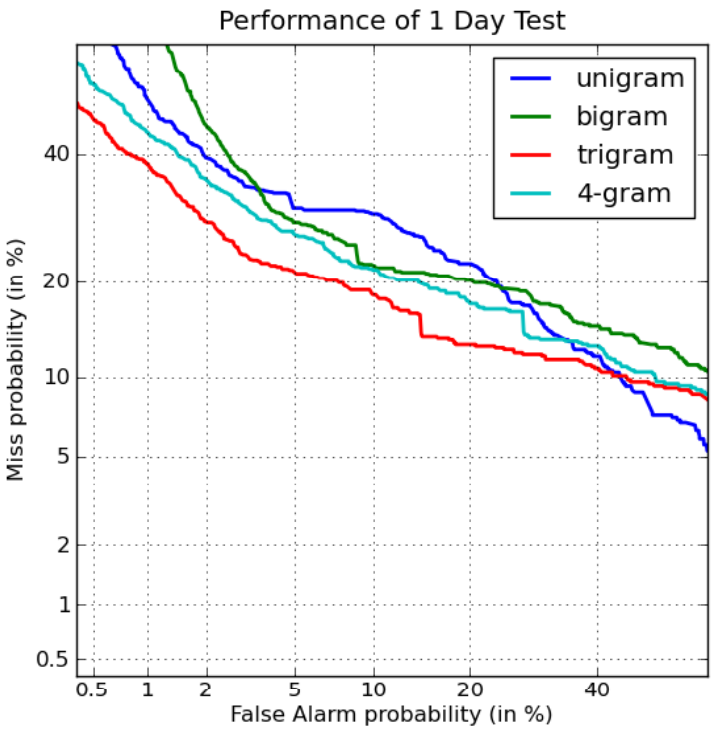
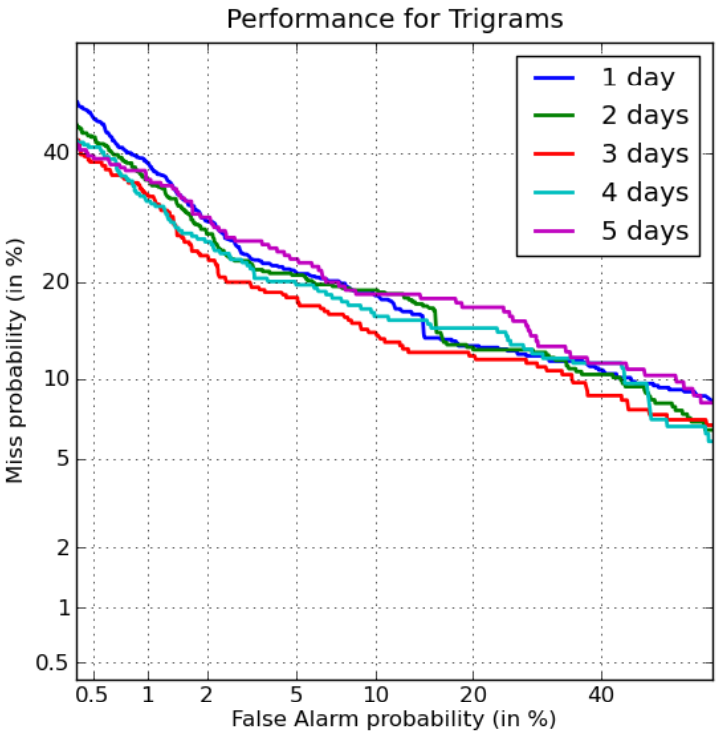
Identification Experimental Results #1

- Initial experiments looked TRN1 and TST1
- Varied *n*-gram order
- Varied window for accumulating statistics from 1-5 days





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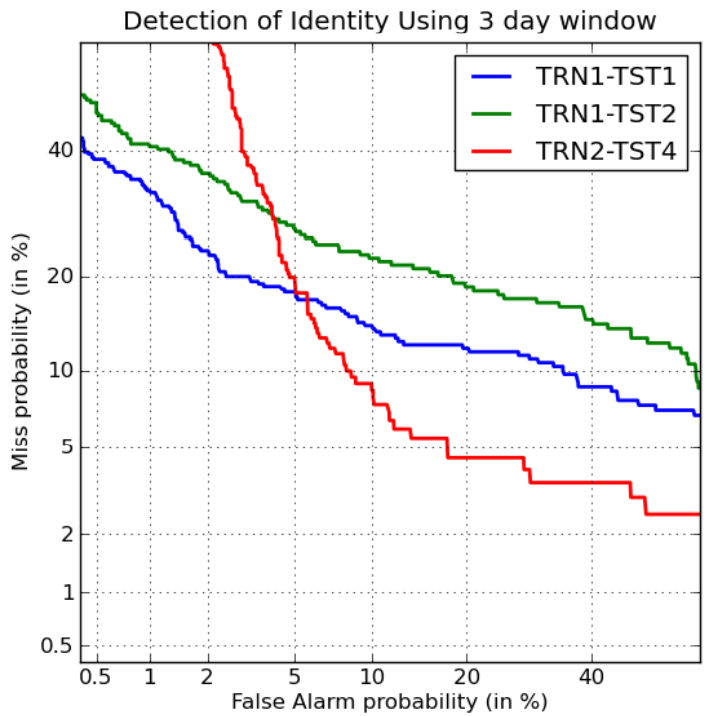
Identification Experimental Results #2

- **Considered training duration:**
  - **1 month versus 3 months**
- **More months of training data changes curve shape—better results at low Pfa**
- **Equal Error rates < 10% !**



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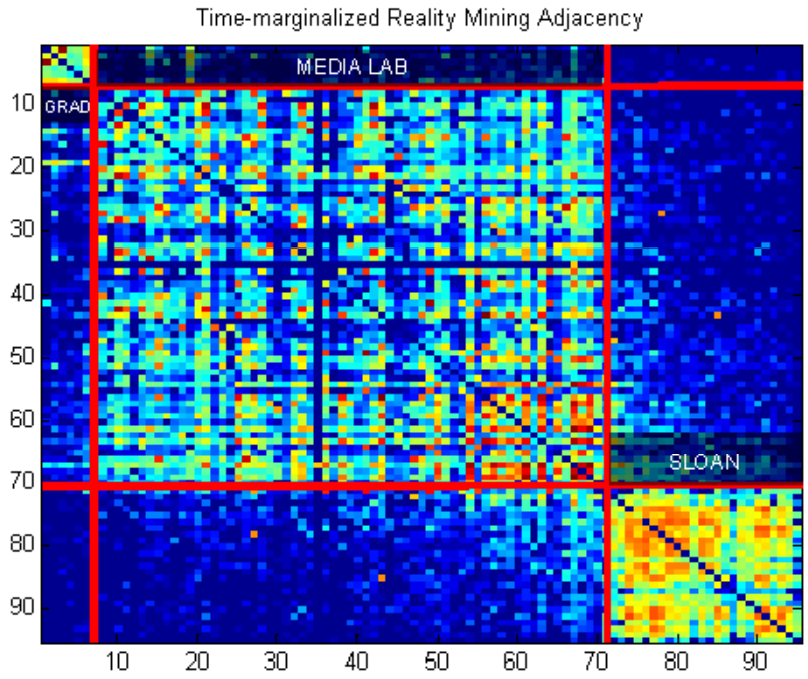
Tensor Representation and Analysis

- Dynamic social network (DSN) [2] as a 3-dimensional data cube (node x node x time)
- Corresponds to 3-mode *tensor* (multi-way array) [3]
- Can use *tensor analysis* tools to gain meaningful insights into DSNs [4]
- Why these tools are useful, what can they do?
  - Give high-order, meaningful summarizations of input data
  - Computationally fast
  - Find co-clusters in multiple dimensions when they exist



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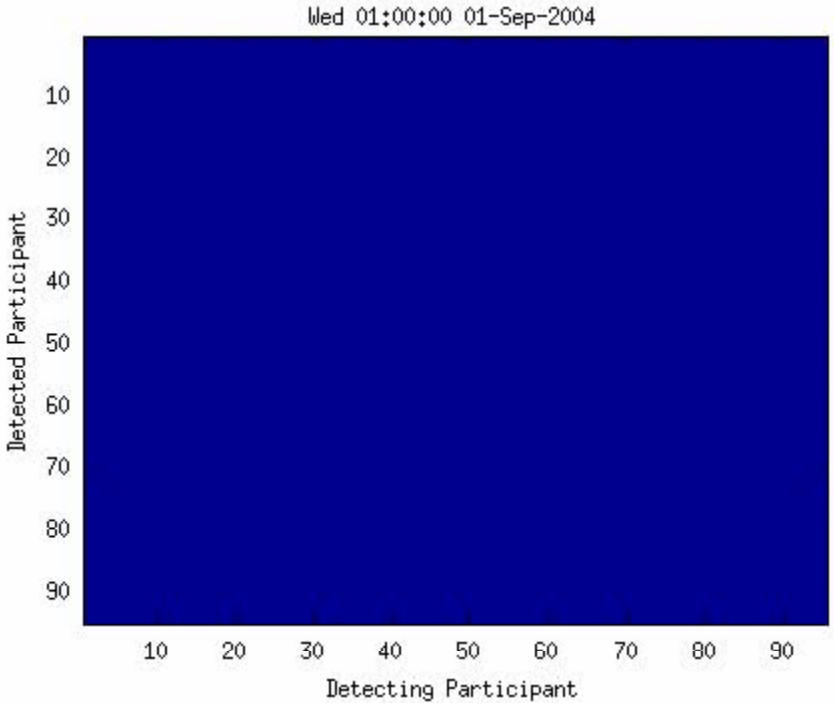

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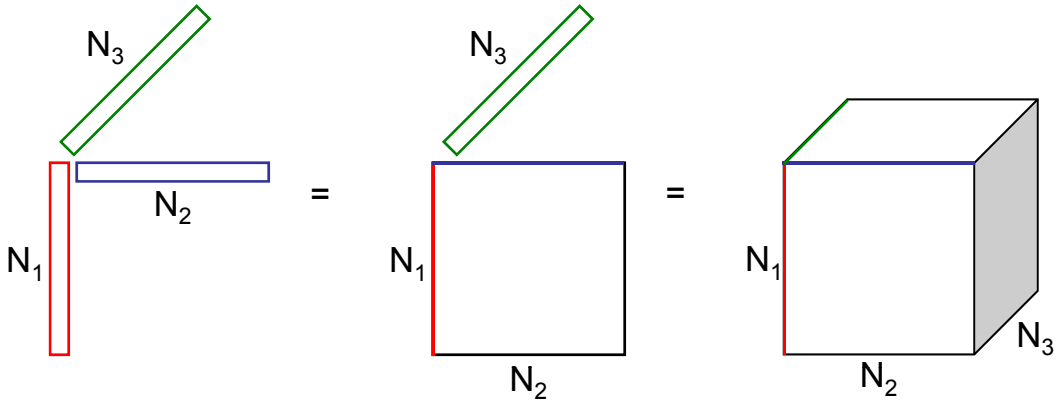
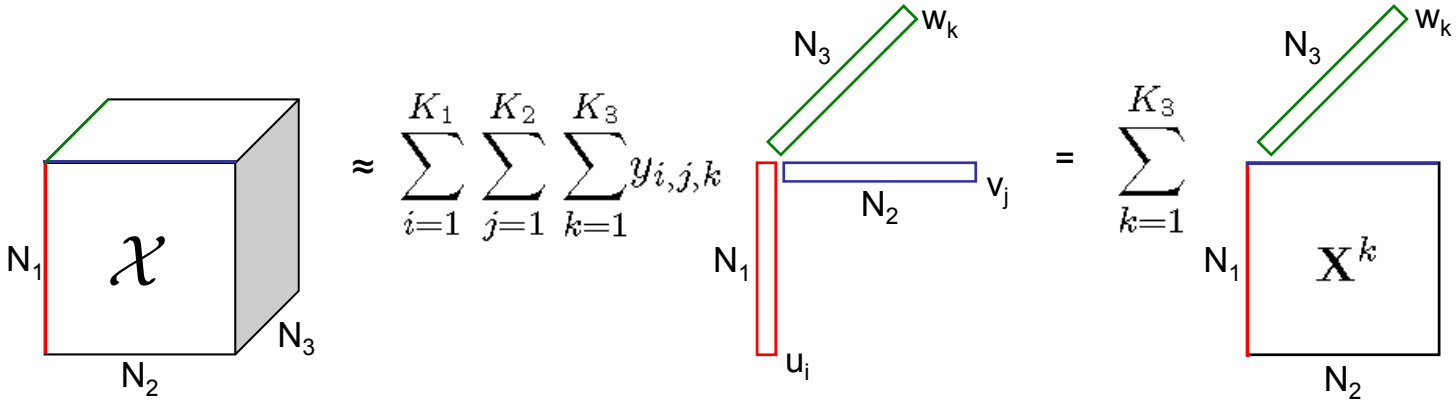
Multi-linear (Tensor) Algebra



Rank-1 Tensor



Rank-(K_1,K_2,K_3) Approximation

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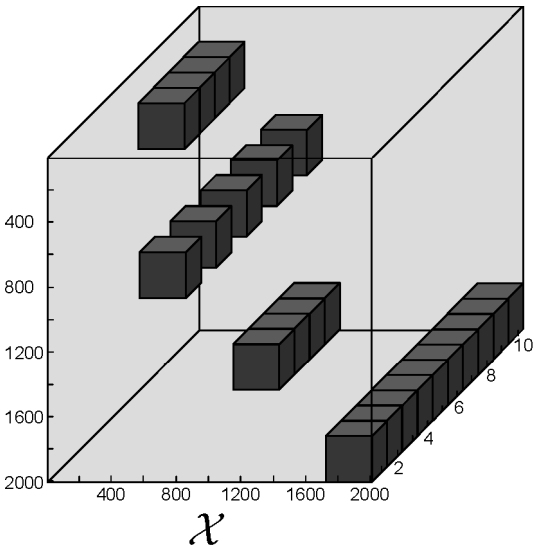
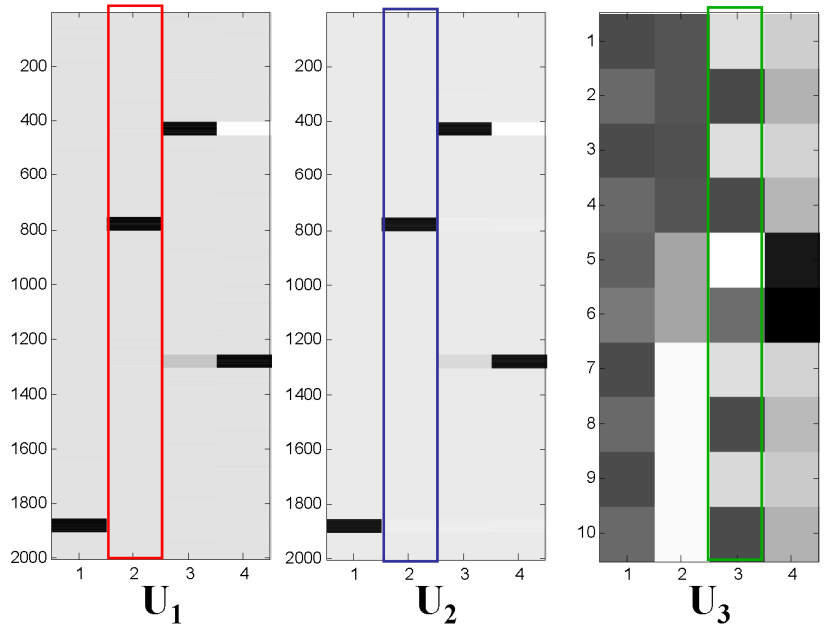
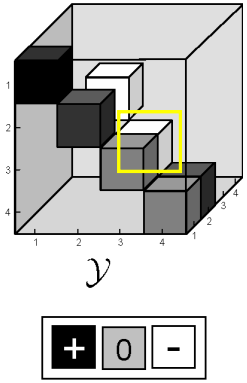
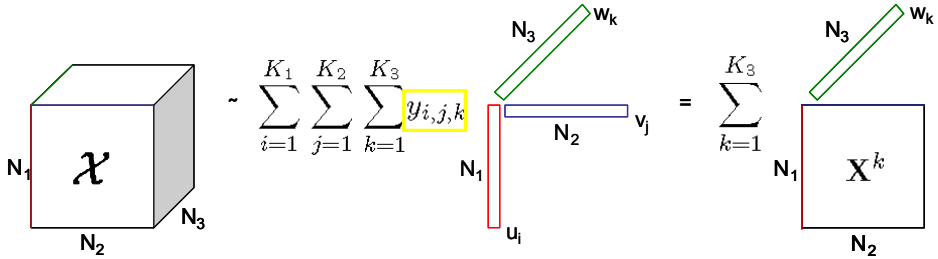
Toy Problem









Rank-(K_1,K_2,K_3) Approximation

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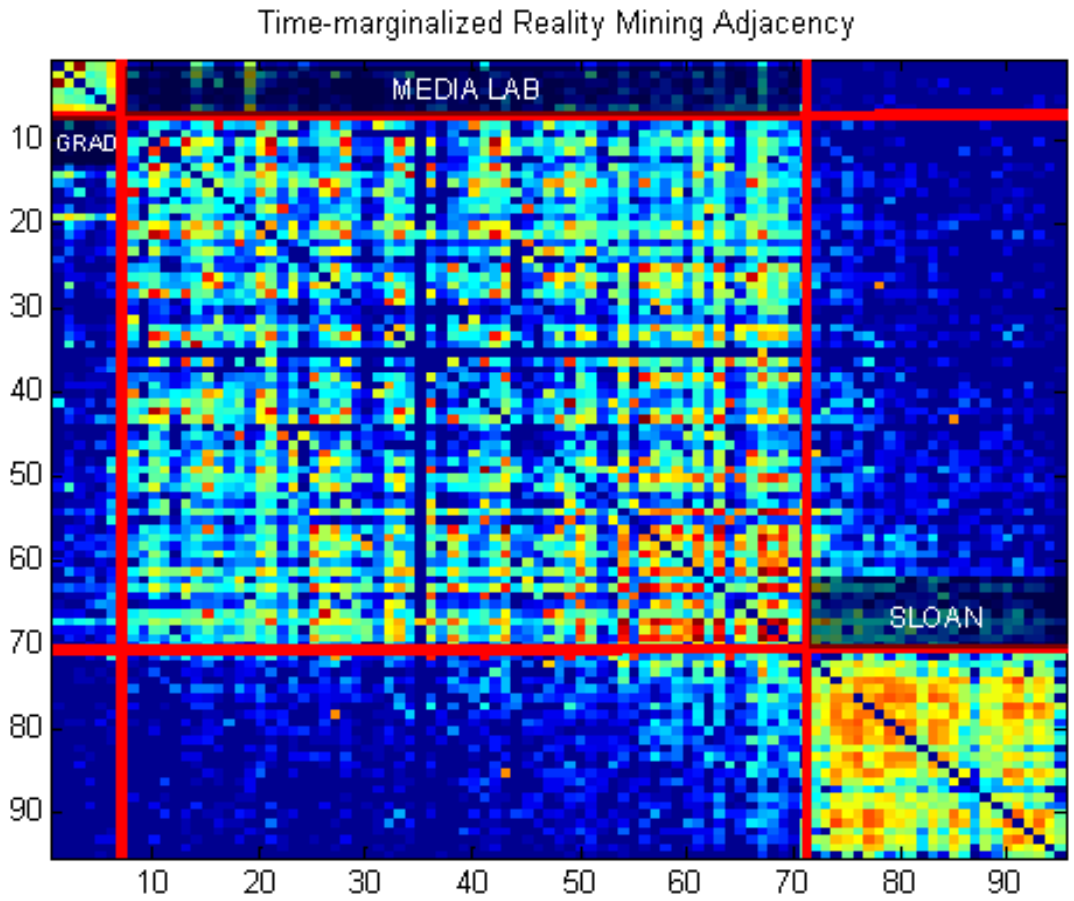
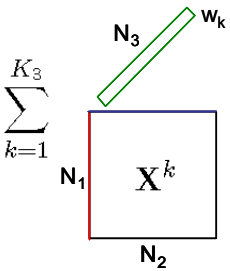
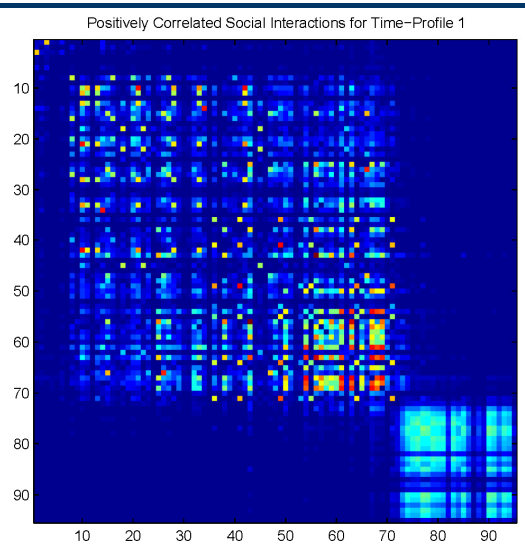
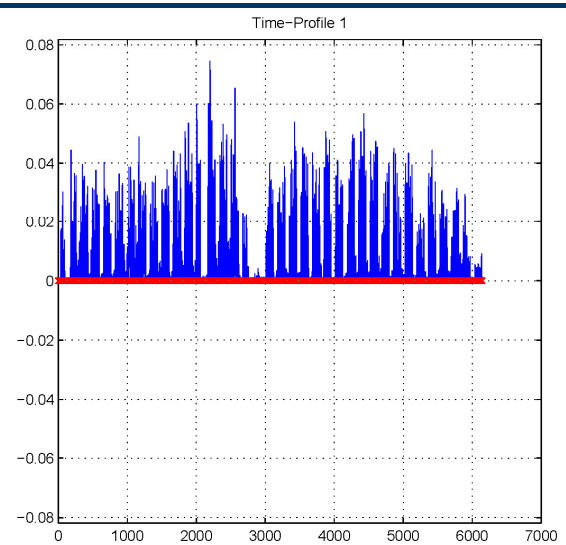
Reality Mining – Bluetooth Proximity

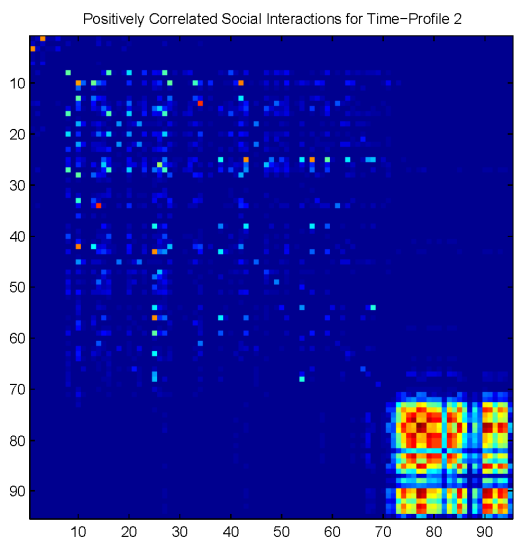


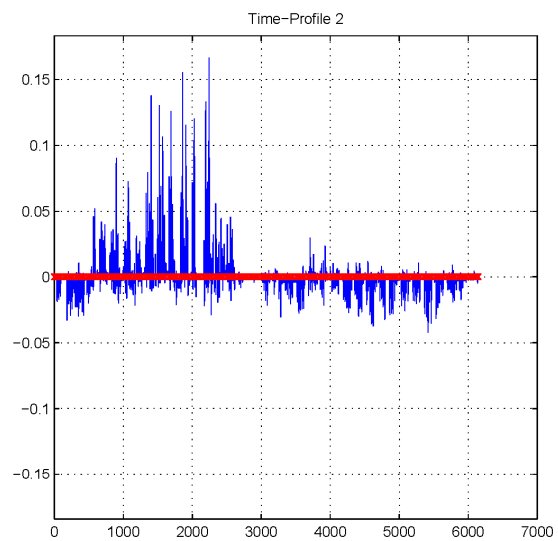
Reality Mining











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Course-Attending Behavior

```
Thu 11:00:00 07-Oct-2004
Thu 16:00:00 14-Oct-2004
Tue 10:00:00 26-Oct-2004
Thu 11:00:00 28-Oct-2004
Tue 11:00:00 02-Nov-2004
Thu 10:00:00 04-Nov-2004
Tue 11:00:00 09-Nov-2004
Tue 11:00:00 16-Nov-2004
Thu 11:00:00 18-Nov-2004
Tue 11:00:00 23-Nov-2004
Tue 11:00:00 30-Nov-2004
Thu 11:00:00 02-Dec-2004
Mon 10:00:00 06-Dec-2004
```

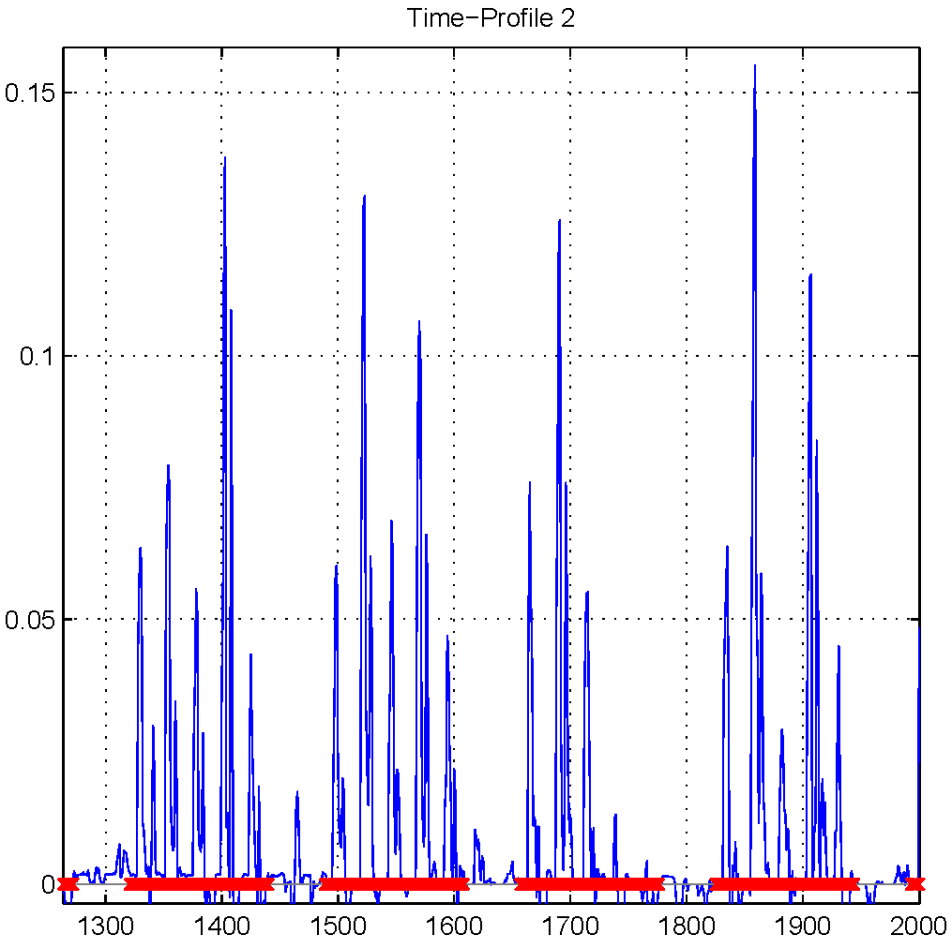
```
15.515 L01 E51-395 TR8.30-10
15.515 L02 E51-325 TR8.30-10
15.515 L04 E51-395 TR10.30-12
15.515 L05 E51-325 TR10.30-12
15.515 L06 E51-315 TR10.30-12
15.515 R01 E51-151 R3
15.515 R02 E51-085 R1
15.515 R03 E51-057 R1
15.515 R04 E51-085 R3
15.515 R05 E51-085 R4
15.515 R06 E51-315 R4
```

[5]

15.515 Financial Accounting
Prereq: —
G (Fall)
4-0-5

An intensive introduction to the preparation and interpretation of financial information. Adopts a decision-maker perspective on accounting by emphasizing the relation between accounting data and the underlying economic events generating them. Class sessions are a mixture of lecture and case discussion. Assignments include textbook problems, analysis of financial statements, and cases. Restricted to first-year Sloan Master's students. *R. Frankel, G. Plesko*

[6]



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Conclusion & Future Potential

- *Dynamic* social network analysis:
  - Interesting and "new" area at the tactical level
  - Amenable to many standard techniques in Machine Learning, Signal Processing, Social Network analysis

- Analysis Methods:
  - Good accuracy for detection of identity from network data
  - Tensor methods provide insight into patterns of life
  - Other analysis methods provide rules and generative models for dynamic data

- Future Potential:
  - Numerous applications for dynamic network data analysis
  - Fusion with other modalities
  - Large opportunity for doing novel work in this area

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References

[1] N. Eagle and A. Pentland, “Reality mining: sensing complex social systems,” Personal and Ubiquitous Computing, vol. 10, no. 4, pp. 255–268, 2006.

[2] K. Carley, “Dynamic network analysis,” in Dynamic social network modeling and analysis: Workshop summary and papers, 2003, pp. 133–145.

[3] L. De Lathauwer, B. De Moor, J. Vandewalle et al., “A multilinear singular value decomposition,” SIAM Journal on Matrix Analysis and Applications, vol. 21, no. 4, pp. 1253–1278, 2000.

[4] J. Sun, D. Tao, and C. Faloutsos, “Beyond streams and graphs: dynamic tensor analysis,” in Proceedings
of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2006, pp. 374–383.

[5] MIT Fall 2004-2005 Class Schedule, Online, 2004. [Online]. Available: http://replay.waybackmachine.org/20041124034024/http:/web.mit.edu/registrar/www/schedules/csbindex.shtml#15

[6] MIT 2004-2005 Course Catalog, Online, 2004. [Online]. Available: http://web.mit.edu/catalog/archive/2004-2005/part 3.pdf

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