Sensing and Feedback for Epidemiological Modeling
Cross-Leveraging Sensors & Systems Models

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Institute for Systems Science & Health 2011
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Outline

• Motivations
• Sensor Platforms
• “Greater than the sum of its parts”: Synergizing models & sensor data
• Vignettes
  – The role of contact characteristics in the spread of pandemic influenza (ABM & sensor data)
  – “Self-correcting” models: Synergizing models & ongoing measurement data (SD & sensor data)
  – Inferring pathways of infection spread over contact networks (SNA & sensor data)
• Conclusions
Motivating Observations

• Many uses of computational models involving human health and behavior require copious data.
• Effective selection, throttling, fusion, filtering, interpretation of sensor data is aided by models.
• Rich sensor platforms are increasingly embedded in commodity consumer electronic devices.
  – These sensors are predominantly designed for usability (e.g. to change screen orientation, adjusting volume, transferring data), but can often be repurposed.
  – Cross-linking of sensor data is readily accomplished.
• We are immersed in a growing cacophony of wireless communication signals.
  – WiFi, Bluetooth, GPS, GPRS/GSM, Infrared, RFID, etc.
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iEpi
Smartphones are Amazing Devices

• Seamlessly connect/failover to whatever network is available
• Track path of morning run or in car
• Take pictures
• Record a lecture
• Reorient when orientation changed
• Interact with printers, computers, TVs, etc.
• Slow down when battery is getting low

• Alert you to nearby attractions
• Detect & deactivate when battery is too hot
Smartphones are Amazing Devices (Key Enabling Technology: Sensors)

• Seamlessly connect/failover to whatever network is available (WiFi/GPRS/GSM receivers)
• Track path of morning run or in car (GPS)
• Take pictures (Camera)
• Record a lecture (Microphone)
• Reorient when orientation changed (Accelerometers)
• Interact with printers, computers, TVs, etc. (Bluetooth)
• Slow down when battery is getting low (battery voltage)
• Alert you to nearby attractions (GPS & Internet access)
• Detect & deactivate when battery is too hot (battery temperature)
Generation 2 Platform: iEpi

• Google Android Smartphone
  – Customized version of Android 2.1
  – Commodity hardware (HTC) => Lower price

• Multiple sensor modalities (including surveys)

• Episodic bursts of data collection optimize battery life

• Richly functional smartphone
  – external incentives to carry & chart device
Key Health Considerations

- Location (access to care, access to resources, barriers to activity, environmental risks)
- Physical activity (obesity, T2DM & GDM, risk of falls)
- Spatial proximity (transmission of pathogens, interpersonal communication)
- Social context (norms, imitative behavior, communication, perception of safety)
- Communication: Person & mass media (risk perception, norms, beliefs, social cues)
Potential of Convergence

- Sensors on the iPhone
  - Battery temp & level
  - Touch interface
  - Camera
  - Proximity
  - GPS
  - Accelerometer
  - Microphone

- Communications
  - Cellular
  - Wifi
  - Bluetooth

Location

Portion Size

Activity

Indoors?

Weather

Automation

Environment

Recording

Survey?

Communication / Interruptions

Time?

Scheduled?
iEpi: Multi-Purposed Multi-Sensor Data Collection

- **GPS**
  - Outdoor location (& uncertainty est)
  - Distinguishing indoors & outdoors

- **Bluetooth**
  - Proximity to participants or other ‘discoverable’ bluetooth devices (including device class)
  - Indoor location

- **Accompanying:** Network (TCP) use: Browsing, movie viewing, &c

- **Future:** Audio, Camera/light, Compass, phone calls, context specific monitoring, federated sensors, p2p transmission, webservice data collections

- **WiFi**
  - Indoor location estimation
  - Data transport to server

- **Accelerometer**
  - Physical activity
  - Compliance

- **Battery**
  - Monitor/Regulate power consumption
  - Compliance
  - Temperature

- **Surveys** (time & context specific)
Example of GPS Data Sequence
Daily Average Distinct Bluetooth Devices Encountered by Participants

Count of Devices (Distinct over Study Period)

Participants (Ordered by Count)
Bluetooth Contacts by Hour of Day

The graph above shows the total Bluetooth contacts counted over the study period, grouped by hour of the day. The y-axis represents the total number of contacts, while the x-axis indicates the hour of the day. The data suggests a peak in the number of contacts around midday, with a decline in the early morning and evening hours.
Participants (Red) contacts with All Bluetooth Contacts (Blue) over 1 day
All Bluetooth Contacts over 1 Week
Close Proximity Bluetooth Contacts over 1 Week
Participant Contacts with Stationary Bluetooth Devices over 1 Week
Participant Contacts with Mobile Bluetooth Devices over 1 Week
Participant Contacts with Mobile Bluetooth Devices over Entire Study
Bluetooth Contacts

Histogram: Contact count with different devices

Histogram: Signal Strength

Weaker Signal => More distant
Daily Contact with Distinct WiFi Routers

Average Distinct WiFi MAC Addresses Encountered by Participant per Day

Distinct devices
WiFi/Bluetooth As a Location Marker

• Presence & strength of one or more WiFi or bluetooth signal can indicate location (cf Skyhook)
  – “Trilateration” can identify location from these signal strengths

• Participants in a study will commonly pass through signals of hundreds of WiFi routers and discoverable Bluetooth devices e.g. in 1 month study in Saskatoon, participants saw approximately
  – 19,000 distinct routers (range 554-4393/participant)
  – 9700 distinct BT devices (range 242-1129/participant)
Indoor Localization

- Where am I (inside)?
  - GPS unreliable
  - Data exists from WiFi and BT devices
- How do we use it?
- Sensor fusion techniques for managing error
The Survey Tool
These are screenshots of an example survey as displayed on the device. The device provides scrolling capabilities, enabling large surveys (like this one) to be displayed.

1. Have you ever used an online survey tool before? (Horizontal Layout)
   - No
   - Yes

2. What is your opinion of web-based surveys? (Vertical Layout)
   - Bad
   - Okay
   - Good

3. Will this tool suit your needs? (Dropdown)
   - Definitely Yes

How often would you use surveys for the following purposes (Marina)?

4. Research
5. Teaching
6. Administration
7. Other

Key Use: Disambiguation, Affect
Cross-Linking of Sensor Data: Metcalf’s Law

• Opportunities for cross-linking of sensor data => values rises as square of number of sensors

• Example cross linking (BT=Bluetooth):
  – Accelerometer/GPS (with GIS)/BT (how does physical activity level change near parks? In high crime areas? How do these change around other people? weather?)
  – BT/GPS/Wifi (estimates of contact location, understanding of social context/capacity of contacts)
  – BT/Wifi/GPS (indoor & outdoor positioning)
  – GPS & Accelerometer: Triggering more rapid measurement of accelerometer if moving quickly
  – Triggered surveys and any sensor: Disambiguation
Potential of Convergence

• Sensors on the iPhone
  – Touch interface
  – Camera
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  – GPS
  – Accelerometer
  – Microphone

• Communications
  – Cellular
  – Wifi
  – Bluetooth

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- Location
- Portion Size
- Activity
- Automation
- Environment
- Recording
- Survey?
- Contact
- Indoors?
- Communication/Interruptions
- Time?
- Scheduled?
Example: Importance of Place

• Incorporating place can lend understanding of
  – Mobility patterns giving rise to contacts
  – Resources that may be exploited by visitors
  – Impact of environment
    • On Risks (surface accumulation of pathogens)
    • On behavior
  – Character/capacity of interaction
  – Status of users
  – External parties
Density of Contact Durations Between Study Participants During a 1 Month Study
Finer Spatial Resolution
Example Questions that Can be Investigated Now: Epidemiology

• How do physical activity levels vary by proximity to parks? By social context? By neighborhood safety index?
• Which grocery stores do participants visit? And how often? How do they get there? With whom?
• How much time do particular family members spend together? Where do they spend this time?
• How (quickly) does a change in physical activity by parents affect kids’ activity levels?
• How (long) do socialization, mobility and eating patterns of newcomers differ from established residents?
• How often do participants visit restaurants? Which restaurants? With others, or alone?
• Where do participants get info (browsing/youtubing/skyping)
Example Questions that Can be Investigated Now: Health Services Delivery

• How much time are nurses able to spend with patients? How does this vary by shift?
• Is proper time being taken for handwashing?
• Where are nurses kept waiting in a facility?
• What sets of staff need to meet most frequently?
• Are patients being visited according to schedule?
• What areas are requiring most of the time of nurses & doctors?
Short-Term Extensions

• **Surveys triggered based on current & past context**
• Calling behavior
• More flexible interface
• Data from peered bluetooth devices
  – Weight, respiration & pulse sensors, galvanic skin response, etc.
• Proximity to an ‘on’ TV
• Barcode scanning
• Third-party opt-in
Example (Remembered) Triggered Survey Information

- **Activity**
  - “What are you doing right now?”
  - “Have you come outside to smoke?”
  - “For what sort of purpose have you just left home?”
  - “In what sort of physical activity are you engaged?”
- **Location:** “Give a brief name to your location”
- **In kitchen:** “Are you currently or about to eat? If so, let me see!”
- **Who just called you?”

- **Relationship (to participants/other recurrently contacted non-participants)**
  - “What is the relationship of the people currently around you?”
  - “What is the relationship of the people who have just arrived?”
- **“What TV channel are you watching?”**
- **“Describe your mood”**
- **“Why are you up so early?”**
- **“Are you in a taxi? In a bus? In a car?”**

Once answered, much information can be applied automatically for future disambiguation.
Long Term Possibilities

• Detailed stochastic mobility, activity, interaction models
• Affect detection (voice/touch/keyboard)
• Greater flexibility in query rates
  – Contingent data collection
  – Model-informed adaptive sensor sample rate adjustment
• Monitoring environmental risk (cough/sneeze, mosquito frequency classification detection)
• Link to point-of-sale data
• Bar code scanning (e.g. food ingredient information)
• Automatic cross-device overdetermined trilaterialization & from arbitrarily placed WiFi/BT locations
• Measurement from federated devices (BT scales, respiration & heart rate sensors, galvanic skin response, etc.)
• Convenient food photodiarying
• Automatic activity classification
• Study of risk perception via controlled experiments ‘health games’ w/info feedback
• Richer “self-calibrating” predictive models
• Closer integration of communication monitoring
• Environmental risk inference
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Limitations of Sensor Data

• Taken in isolation, sensor data offers limited insight
  – Limited generalizability
  – Unclear implications for decision making or future behavior
  – Unclear what “happens between” the sensor measurements
  – Noise data obscure analyses
Limitations of Models

• For certain questions, gluttonous need for data
• Fragility due to assumptions
  – Dependence on assumptions regarding exogenous factors
  – Systematic errors
  – In even best models, risk of rapid obsolescence & divergence from actual situation
• Overconfidence in anticipated state
Modelers as Buzzards: Lofty Goals
Modelers as Buzzards: Lowly Meals of Data
Ubiquitous Sensors and Dynamic Models: A Natural Synergy

**Sensor Data**
- Rich grounding in observations
- Providing databases for model parameterization & calibration
- Stimulating dynamic hypotheses

**Dynamic Models**
- “Filling the gaps” between sensor data
- Capturing regularities that underlie sensor data
- “ Filtering” of noisy sensor data
  - Arriving at “consensus” estimates combining measured data & model predictions
- Generalizing observed behavioral patterns
- Understanding proximal & distal implications of observed behavior
- Determining adaptive sampling rates
Motivation

Replacing... Or...
Relevant Modeling Types

• Agent-based models
  – Generalizing individual behavior (e.g. mobility)
  – Replay observed patterns
  – Simulating implications of individual level patterns
  – Generating probability distributions

• System Dynamics models
  – “Self-correcting” models: Online “filtering” identifies “consensus” understanding of situation
  – Hybrid continuous models of agent dynamics

• Social Network Analysis
  – Inferencing models (e.g. Reconstructing transmission chains)
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Flunet Study

• Small scale study
  – People: 36 participants
  – Places: 9 “beacons” at fixed locations

• Information collected
  – Proximity
    • Each sensor recorded every 30 seconds
    • 3 RSSI proximity categories: Close (<5m), Medium (5-15m), far (>15m)
    • Proximity resolution 1-2 minutes
  – Cross-linked health survey data

• Time: 13 weeks during 2009 pandemic influenza season
  – Study duration: November 9, 2009 – February 9, 2010
  – Approximately 262K 30-second timeslot samples
Contacts by Time of Day

![Contacts by Time of Day Graph](image-url)
Video: Aggregated Hourly Contact Data
Integration of Model & Data Sources

- Weekly Population Clinical Data (FluWatch 2010)
  - Exogenous Infection Pressure

- H1N1 Disease Model (Tuite et al. 2010)
  - Disease State Durations
  - Endogenous Infection Probability

- Flunet microcontact dataset (Hashemian et al. 2010)
  - Contact History
  - Participant Immunization History

Transmission Model

- Stable Agent States
  - Disease Progression
  - Susceptible
  - Latent
  - Asymptomatic Infectious

- Recovered/Immunized
  - Symptomatic Infectious
  - Symptomatic Non-Infectious
Dealing with Stochastics

• Uncertainties ⇒ many “Groundhog Day” like realizations required

• Ensemble size
  – Baseline scenarios: 100,000 realizations
  – Alternative scenarios for different parameter values: 2,500 realization

• Sensitivity analyses: Different ensembles carried out for
  – With and without considering vaccination
  – Closeness of proximity required to transmit
  – With and without behavioral removal
Results

Transmission possible even for longer range (e.g. 10-15m) contacts

Close distance required for transmission

Results consistent with count of self-reports of symptoms of influenza-like illness
Number of Infections

Infections spread over 100,000 realizations
Results

Correlation between centrality measures & model-derived likelihood of infection

<table>
<thead>
<tr>
<th></th>
<th>Without Vaccination</th>
<th>With Vaccination</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\rho$</td>
<td>$p$</td>
</tr>
<tr>
<td>Betweenness</td>
<td>0.172</td>
<td>0.316</td>
</tr>
<tr>
<td>Degree</td>
<td>0.415</td>
<td>0.012</td>
</tr>
<tr>
<td>Time Degree</td>
<td>0.514</td>
<td>0.001</td>
</tr>
<tr>
<td>Log Time Degree</td>
<td>0.740</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>
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Reflection on Models

Ongoing measurements

• Pros
  – Glimpse of elements of recent situation
  – Confidence in actual trends

• Cons
  – Delays
  – Noisy
  – Unclear Implications for
    • Decision making
    • Underlying situation

Models

• Pros
  – All models are approximations, but some are useful for short-term anticipation
  – Interpretation of current underlying situation
  – Linkage to decision making: Understanding consequences of choices

• Cons
  – Absent correction
    • Even the most detailed model is almost certain to eventually diverge from reality
      – Systematic errors
      – Omissions
      – Particular uncertainties
    • Models start to become “stale”
Benefits of Synergizing Models & Ongoing Measurement via “Closed Loop Models”

**Benefits to Data**
- Interpreting for implications to other areas of the system not directly measured
- Understanding implications for decision making
- Separating signal from noise: Avoiding overconfidence in measurements
- Generalization/abstraction to broader dynamic patterns of behavior

**Benefits to Models**
- Preventing model state divergence from actual situation
- Maintaining model “freshness” by repeated re-grounding in measured data
- Better understanding of current situation
- More reliable prospective simulation with the model
- Avoiding overconfidence in model output
The ongoing discrete Kalman filter cycle. The *time update* projects the current state estimate ahead in time. The *measurement update* adjusts the projected estimate by an actual measurement at that time. (Welch, G. and Bishop, G. 2006)
The Dissected Kalman Filter

Slide courtesy of Weicheng Qian
Higher level view of Kalman Filter

Slide courtesy of Weicheng Qian
Kalman Filter Equations

\[ \dot{X}(t) = f(X(t), t) + w(t) \]
\[ \dot{Y}(t = k_l) = h_l(X(t = k_l)) + v(t = k_l) \]
\[ \hat{x}_k(+) = \hat{x}_k(-) + K_k[z_k - h_k(\hat{x}_k(-))] \]
\[ P_k(+) = [I - K_k H_k(\hat{x}_k(-))] P_k(-) \]
\[ K = \frac{PH^T}{HPH^T + R} \]
\[ H_k(\hat{x}_k(-)) = \left. \frac{\partial h_k(x(t_k))}{\partial x(t_k)} \right|_{x(t_k) = \hat{x}_k(-)} \]
\[ F(\hat{x}(t), t) = \left. \frac{\partial f(x(t), t)}{\partial x(t)} \right|_{x(t) = \hat{x}(t)} \]
\[ \dot{\hat{x}}(t) = f(\hat{x}(t), t) \]
\[ \dot{P}(t) = F(\hat{x}(t), t)P(t) + P(t)F^T(\hat{x}(t), t) + Q(t) \]

System Theory

Measurement Update Equations

‘Gain’ (Weighting) Matrix

System evolution between measurements
Evaluating Using a Synthetic Population

• Analytic approaches (and study designs) are often challenging and costly to test in the real world
  – Expensive to establish study
  – Time consuming
  – Ethical barriers
  – Lack of definitive knowledge of how conclusions compare to some “ground truth”

• We can often evaluate such approaches using “synthetic populations” drawn from simulation models
  – Here, the simulation model helps to identify potential weaknesses of study designs & analysis approaches
Synthetic Population Studies

- Establish a “synthetic population” for a “virtual study”
- Perform simulation, simulating study design of interest
  - Actual underlying situation is blinded from researcher
  - Collect data from the synthetic population similar to what would collect in the external world
  - Optionally, may actually simulate roll out and dynamic decision protocols
- Analysis procedures being evaluated are applied to the data from the synthetic population
- We compare the findings from those analysis procedures to the underlying “ground truth” in the simulation model
Performing the Filtering

**Aggregate System Dynamics SIR Model**

**Agent-Based Model Using Sensor Data**

Simulation

Measured Data (Estimates of count of Susceptibles, Infectives, Recovereds)

Kalman Filtering

Updated System Dynamics Model
The Underlying Transmission Model

(Modified)

H1N1 Disease Model (Tuite et al. 2010)

Disease State Durations
Endogenous Infection Probability

Contact History
Participant Immunization History

Flunet microcontact dataset (Hashemian et al. 2010)

Stable Agent States

Disease Progression

Transmission Model

Susceptible
Recovered/Immunized
Latent
Asymptomatic Infectious
Symptomatic Infectious
Symptomatic Non-Infectious
Aggregate System Dynamics SIR Model

Simplication & Systematically in error

Contacts per Day c

Likelihood of Infection Transmission Given Exposure Beta

Prevalence of Infection

Total Population Size

Simplification: “Random mixing” assumed

Simplifications: Many stages omitted (assumes that all Infected individuals are Infective)

Mean Time Until Recovery

Back
“Open Loop” Model
4 Days Between “Regroundings”
Simplest Case: Only State Updates
Measurement Every Other Day
Simplest Case: Only State Updates

Daily Measurement Updates
Projecting Forward from Updates

Prevalence of infectives
Estimated by “open loop” model

Prevalence of infection estimated by successively “closed loop” model incorporating measurement data

Actual underlying prevalence of infectives in Underlying ABM (incorporating sensed contact patterns)
Why Aggregate Models?

• Typically the state in dynamic models involve both observable & non-observable elements
• We can make limited inference on non-observable components from observable
• Many observations are often required to “triangulate” non-observables
• Inferring non-observables is far easier if there are fewer of them => more aggregate models
  – Almost always required for aggregate measurement
• Ubiquitous sensing does raise the intriguing potential for inferring state at the individual level
Not Shown Here

• Updating parameters
• Updating estimates of non-observables
• Finer-grained data updates
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Contact Data can Permit Static or Dynamic Network Reconstruction
Inferential Models

• Can use mathematical formulation of dynamics to express distributions on regarding events

• These formulations can then be used to estimate likelihood of given underlying factor (e.g. A transmitted to B) in light of available data
  – Available data might include molecular epidemiological data
Sensing and Feedback for Epidemiological Modeling to help Evaluate Analysis Strategies
A Simple Contact Network (e.g. Gathered via Sensed proximity)

Presentation time: day 10
A

Presentation time: day 3
C

Presentation time: day 4
B

Presentation time: day 3
day 3
D

Presentation time: day 2
F

Presentation time: day 3
E
A Hypothesis for Pathways of Infection Spread
Determination of Expression for Likelihood of Hypothesized Infection Spread Pathway

\[
\int_{t_B}^{t_A} P(i_E)P(t_E|i_E) \int_{i_E}^{t_F} P(i_F|i_E)P(t_F|i_F) \int_{i_F}^{t_B} P(i_C|i_F)P(t_C|i_C) \left( \int_{i_C}^{t_A} P(i_A|i_C)P(t_A|i_A) \, di_A \right) \\
\left( \int_{i_C}^{t_B} P(i_B|i_C)P(t_B|i_B) \, di_B \right) \left( \int_{i_C}^{t_D} P(i_D|i_C)P(t_D|i_D) \, di_D \right) \, di_C \, di_F \, di_E
\]
Evaluation of Likelihood

\[
\int_j^{t_B} P(i_E)P(t_E|i_E) \int_j^{t_B} P(i_F|i_E)P(t_F|i_F) \int_j^{t_B} P(i_C|i_F)P(t_C|i_C) \left( \int_{i_C}^{t_A} P(i_A|i_C)P(t_A|i_A) di_A \right) \\
\left( \int_{i_C}^{t_B} P(i_B|i_C)P(t_B|i_B) di_B \right) \left( \int_{i_C}^{t_D} P(i_D|i_C)P(t_D|i_D) di_D \right) di_C di_F di_E
\]

\[
\int_j^{t_B} \frac{e^{-\frac{t_E-i_E}{\tau_p}} - e^{-\frac{t_E-i_E}{\tau_s}}}{\tau_p - \tau_s} \int_{i_E}^{t_B} \alpha e^{-\alpha(t_F-i_E)} \frac{e^{-\frac{t_F-i_F}{\tau_p}} - e^{-\frac{t_F-i_F}{\tau_s}}}{\tau_p - \tau_s} \int_{i_F}^{t_B} \alpha e^{-\alpha(i_C-i_F)} \frac{e^{-\frac{t_C-i_C}{\tau_p}} - e^{-\frac{t_C-i_C}{\tau_s}}}{\tau_p - \tau_s} \int_{i_C}^{t_B} \alpha e^{-\alpha(i_B-i_C)} \frac{e^{-\frac{t_B-i_B}{\tau_p}} - e^{-\frac{t_B-i_B}{\tau_s}}}{\tau_p - \tau_s} \int_{i_C}^{t_B} \alpha e^{-\alpha(i_D-i_C)} \frac{e^{-\frac{t_D-i_D}{\tau_p}} - e^{-\frac{t_D-i_D}{\tau_s}}}{\tau_p - \tau_s} di_A di_B di_C di_F di_E
\]

\[= 1.47\%\]
Highlighted bar represents computational model’s tree.
Inferring of Complete Infection Pathways (Assessed via Synthetic Data from ABM)

Plot 3: The average percentile of the true tree, as a function of the relative presentation delay.

Plot 4: The ratio between the average probabilities of the best inferred tree and the true tree, as a function of the relative presentation delay.

Plot 5: The average calculated posterior probability of the true spanning tree, as a function of relative presentation delay. Contact networks with different orders (numbers of patients) were considered.
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Conclusions

• Sensors are increasingly ubiquitous
• Commodity sensor-bearing devices can serve a dual use as versatile sensor platforms
• Diverse communication signals permit creative repurposing
• Coupled with models, sensor data can offer significant and complementary health insights
• Each systems science modeling type presented at ISSH can support compelling – and often unique – insights when coupled with sensed data
Thank You!

Questions?