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

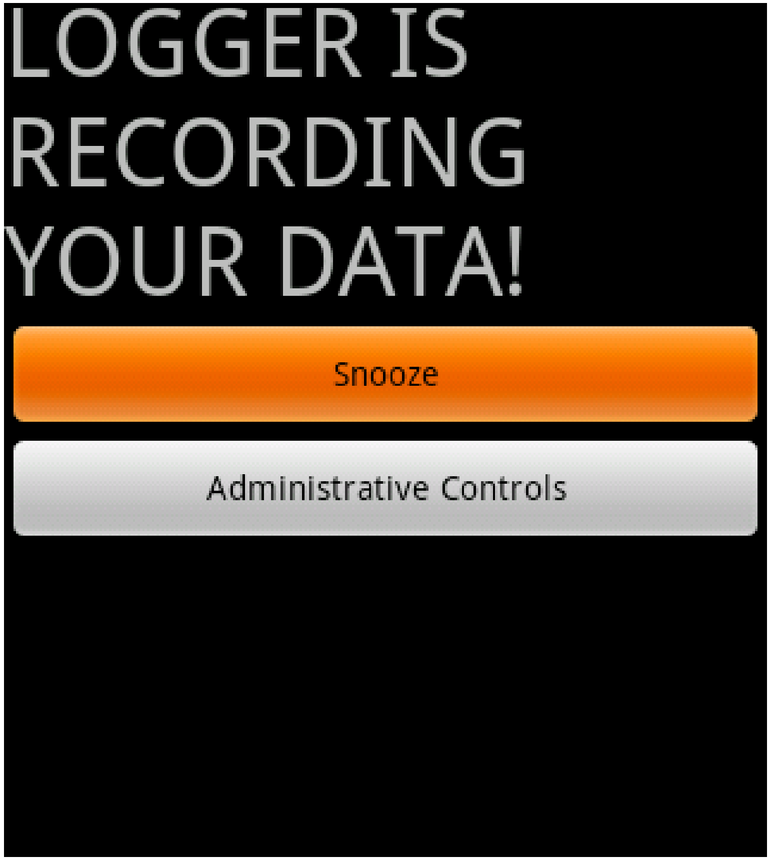
- Alert you to nearby attractions .
- Detect & deactivate when battery is too hot

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

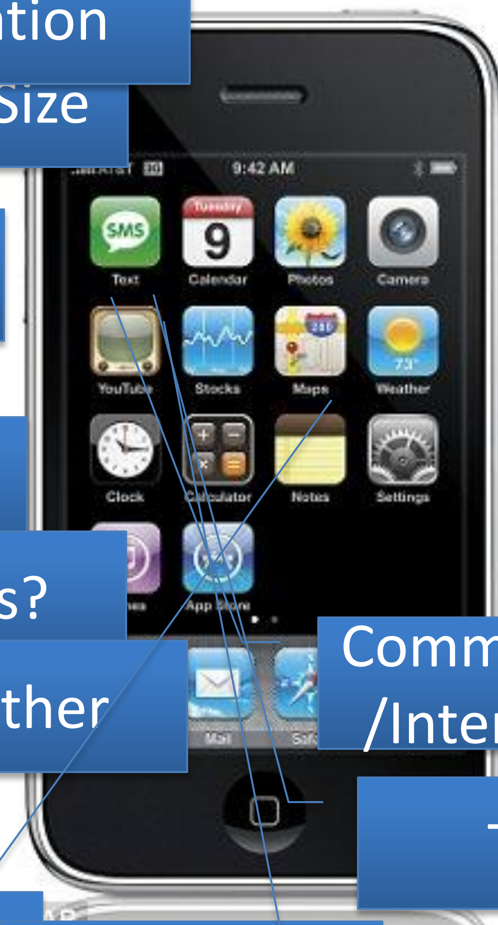


Key Health Considerations

- 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

Location

Indoors?

Communication /Interruptions

Weather

Automation

Environment

Time?

Recording

Survey?

Scheduled?

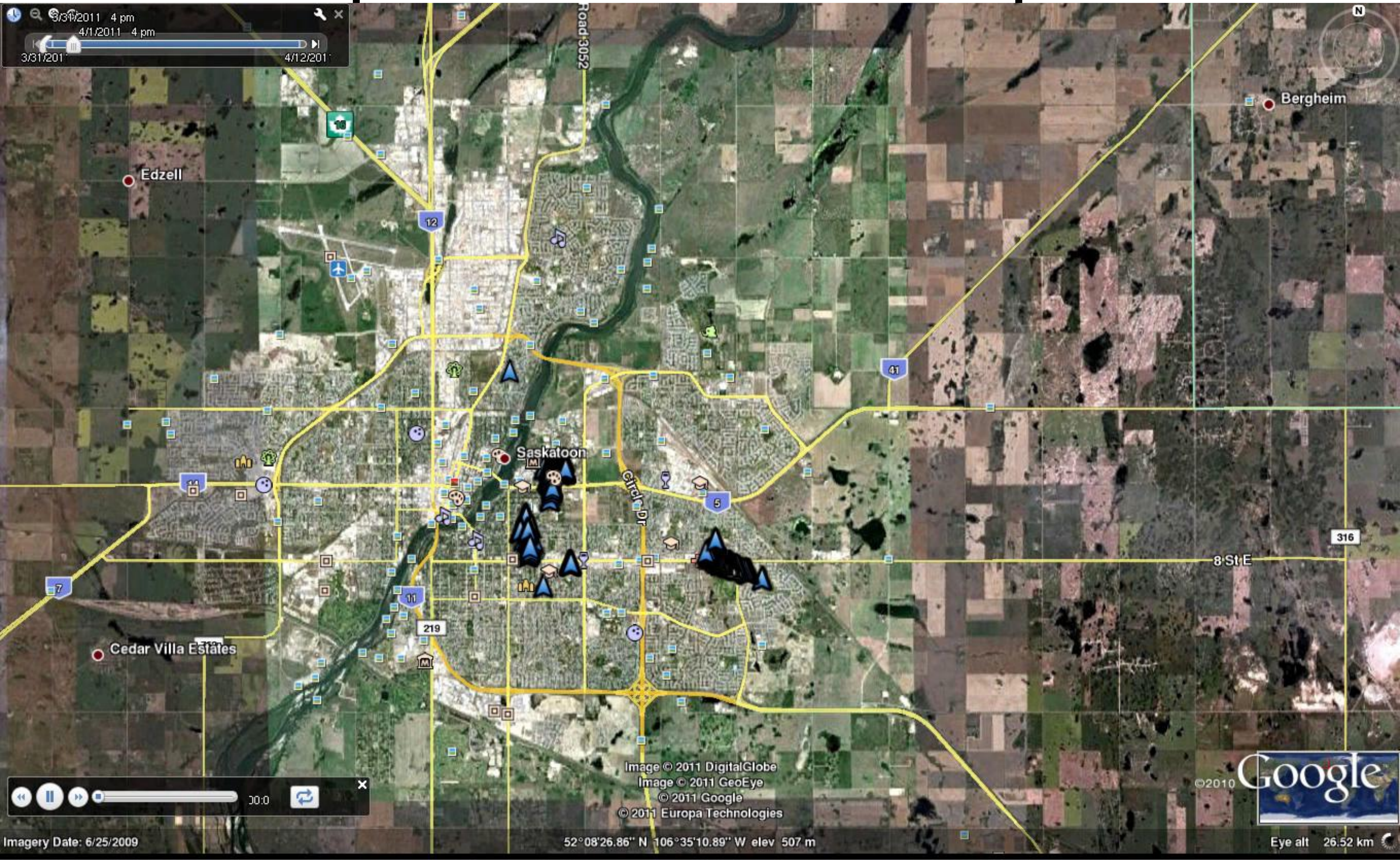
Contact

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)

Next

Example of GPS Data Sequence



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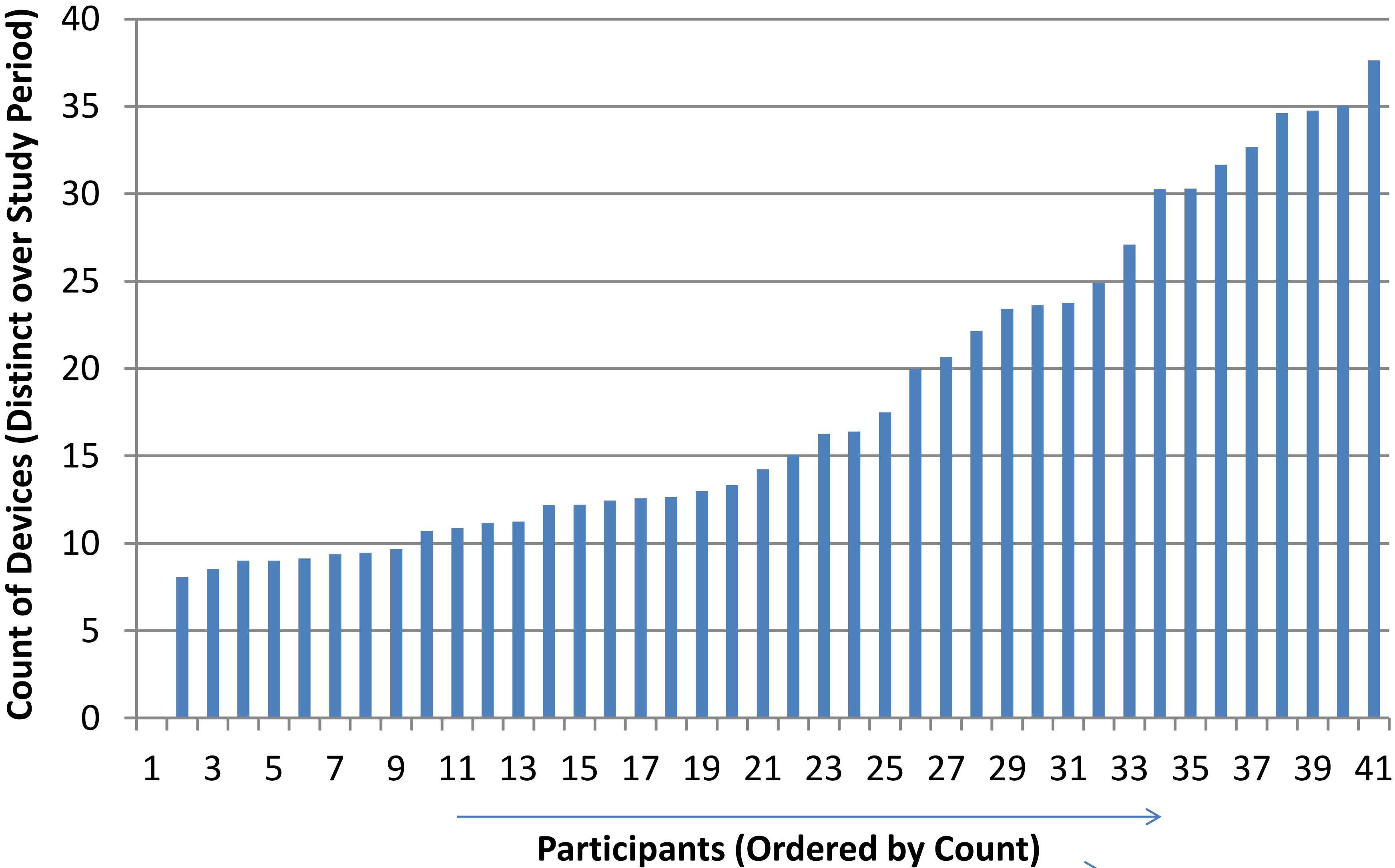
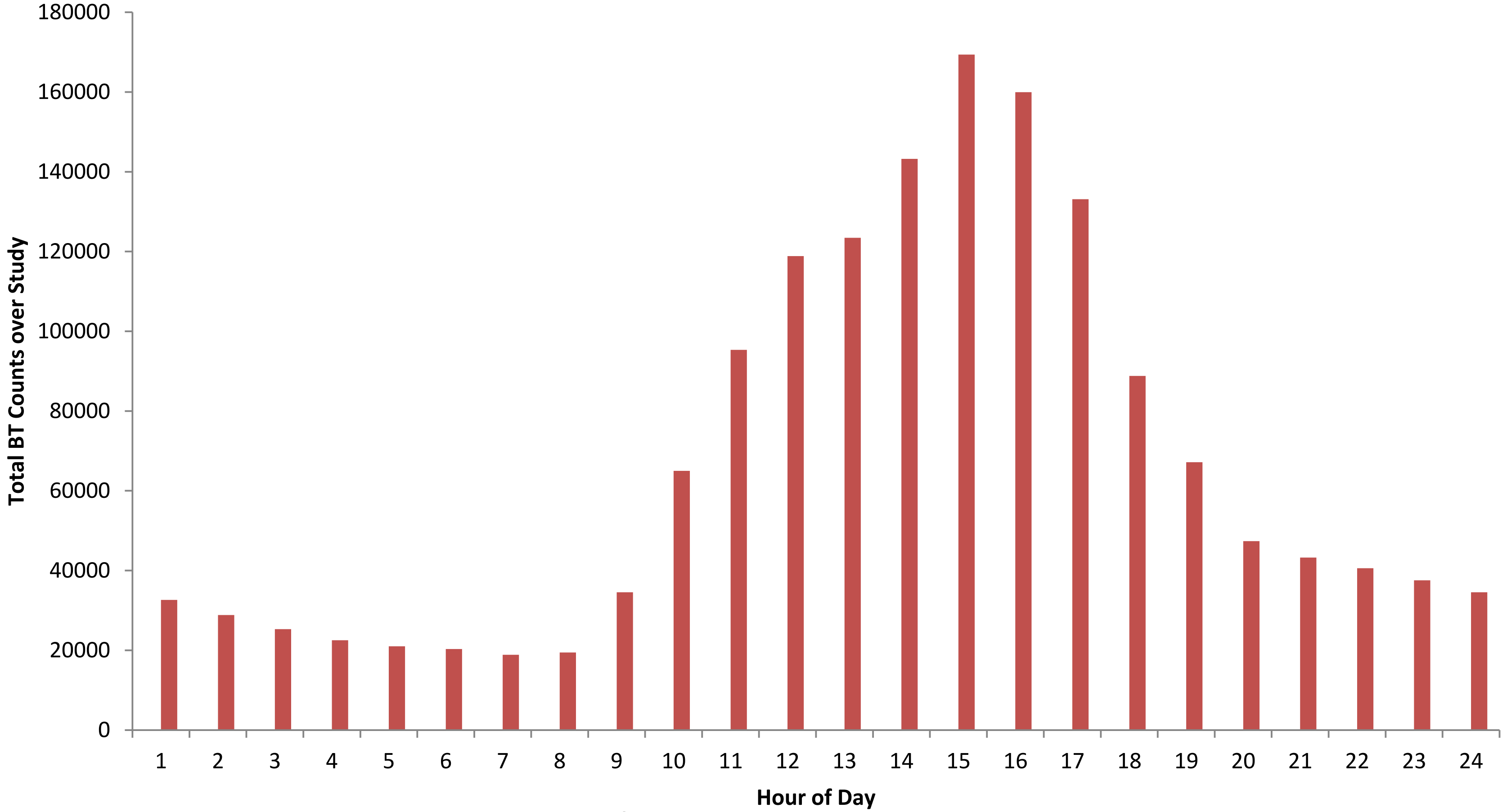
Daily Average Distinct Bluetooth Devices Encountered by Participants

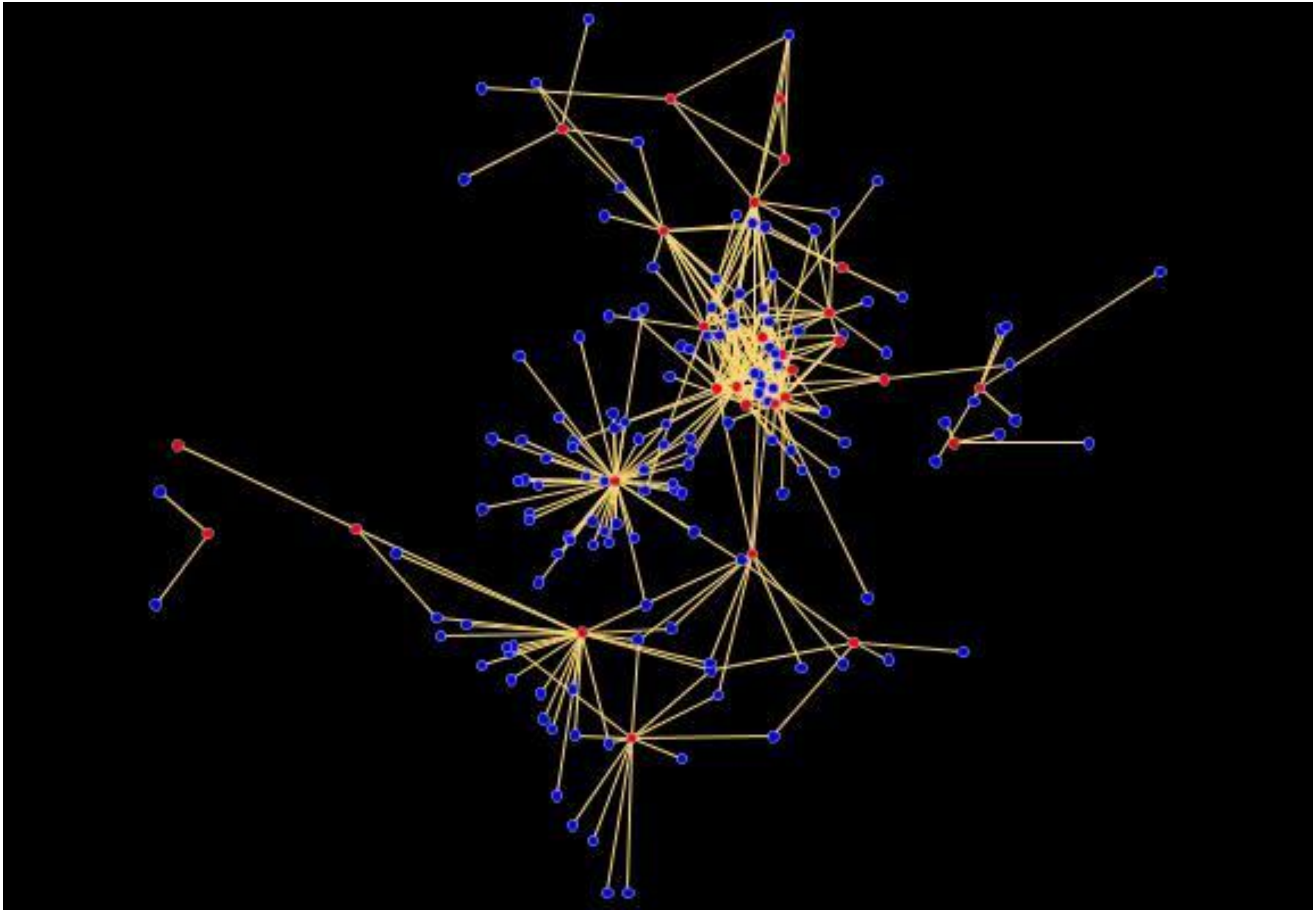


Bluetooth Contacts by Hour of Day

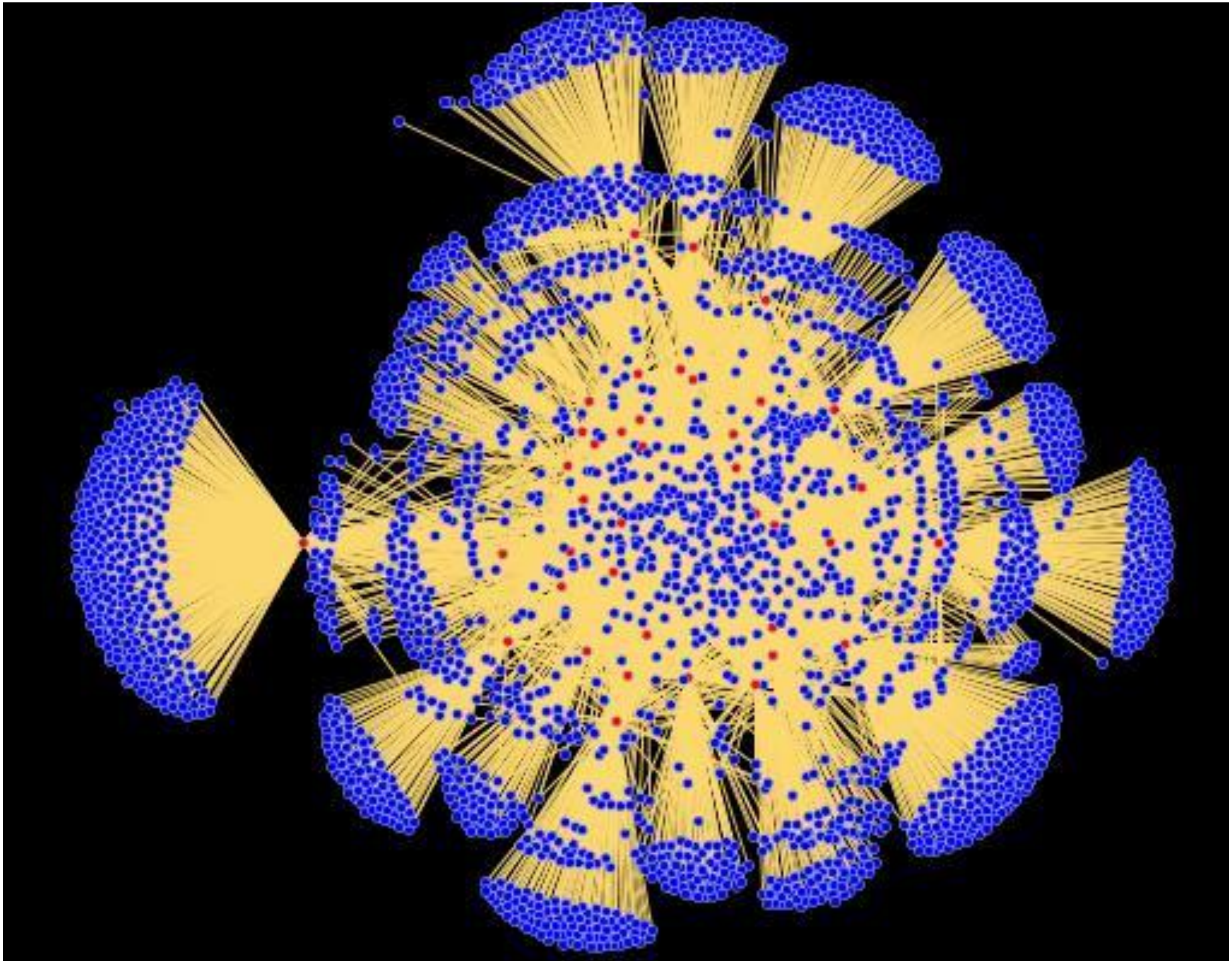


Hour of Day

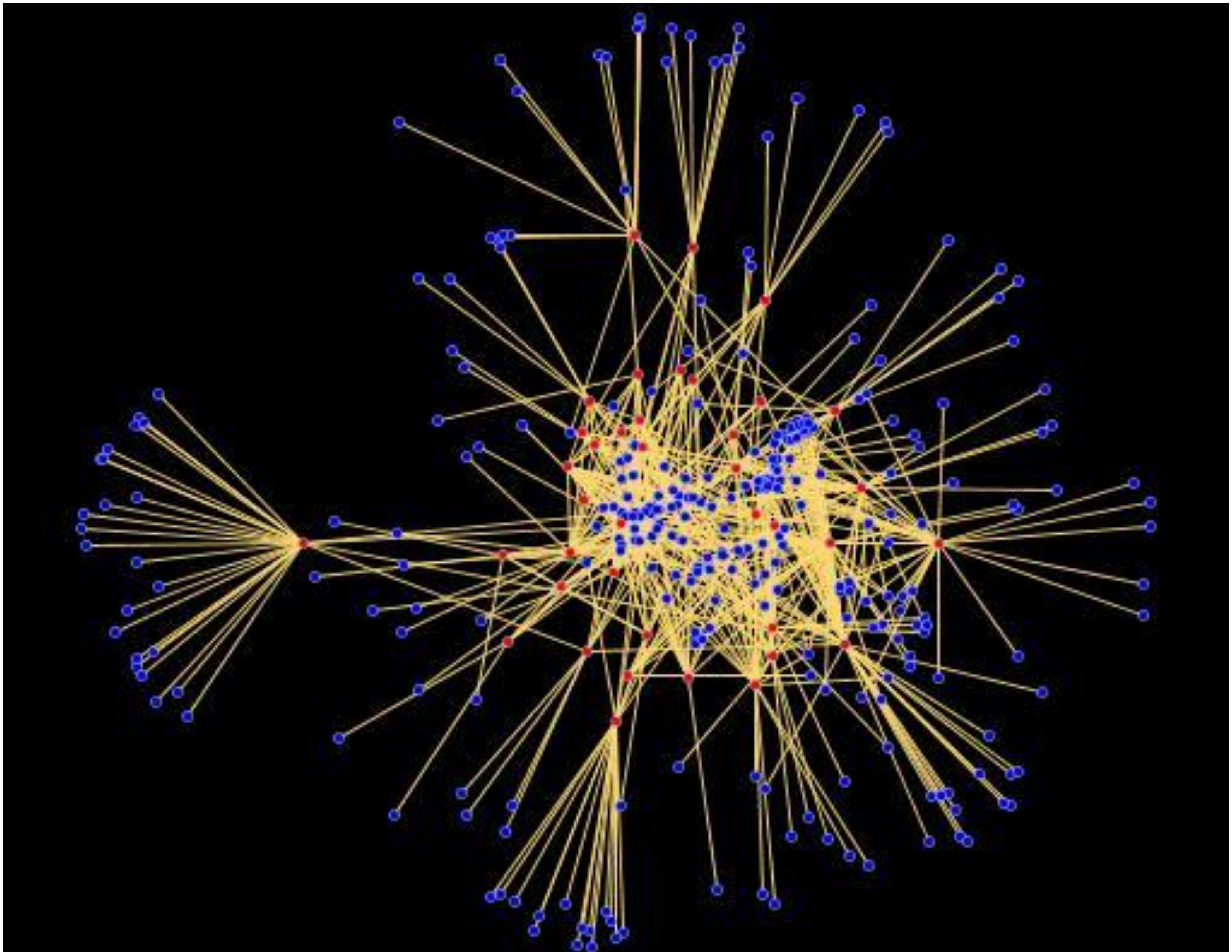
Participants (Red) contacts with All Bluetooth Contacts (Blue) over 1 day



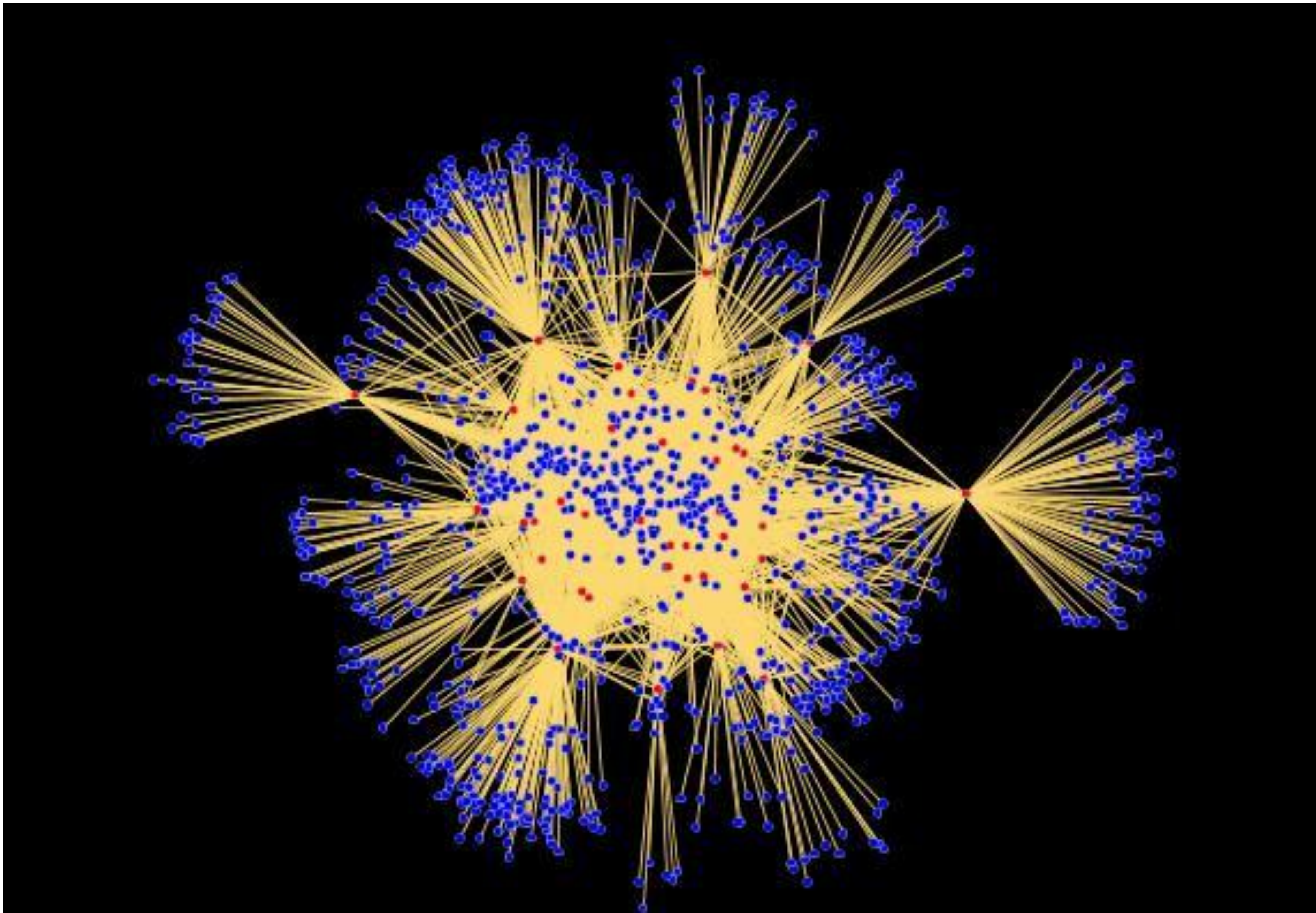
All Bluetooth Contacts over 1 Week



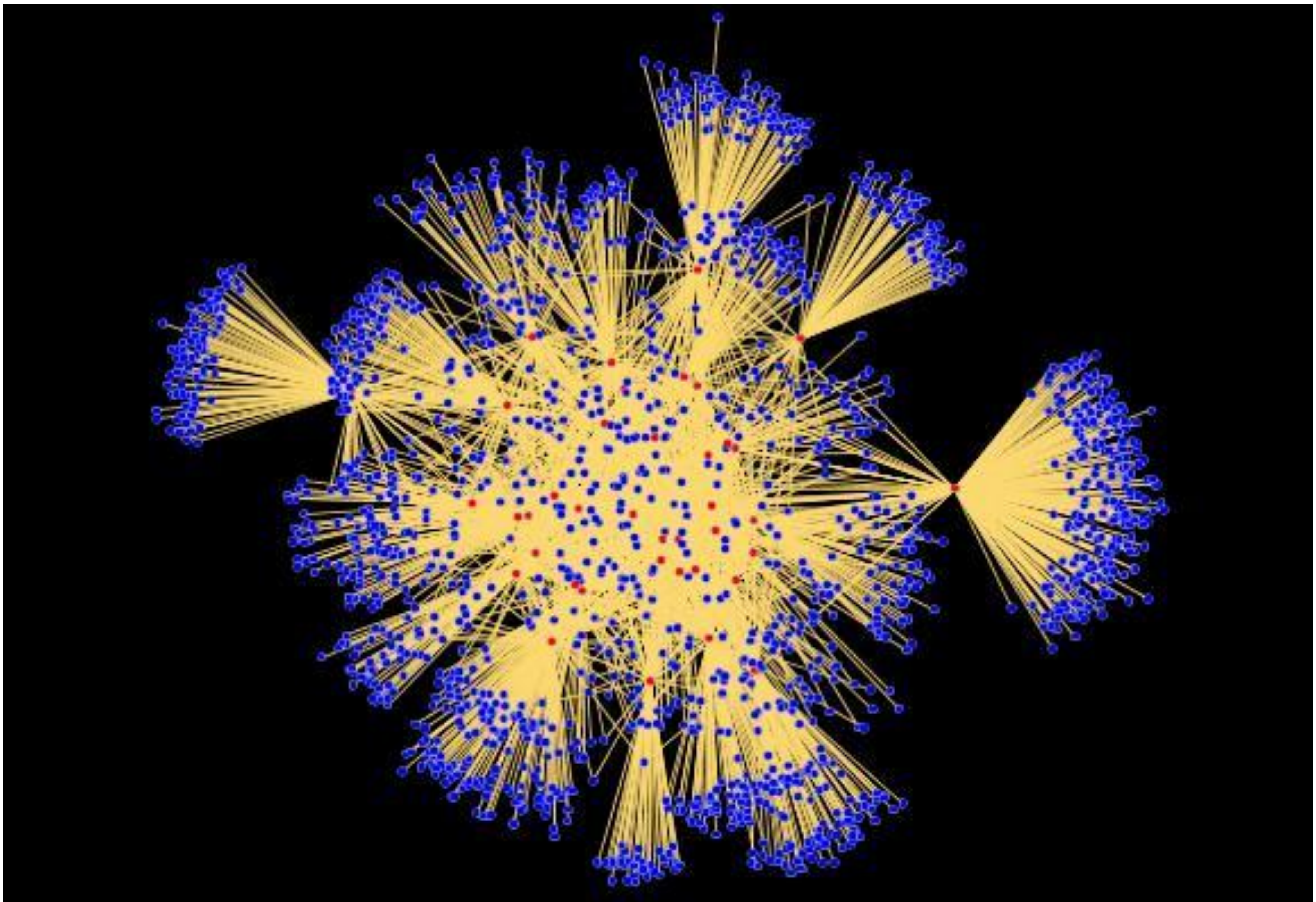
Close Proximity Bluetooth Contacts over 1 Week



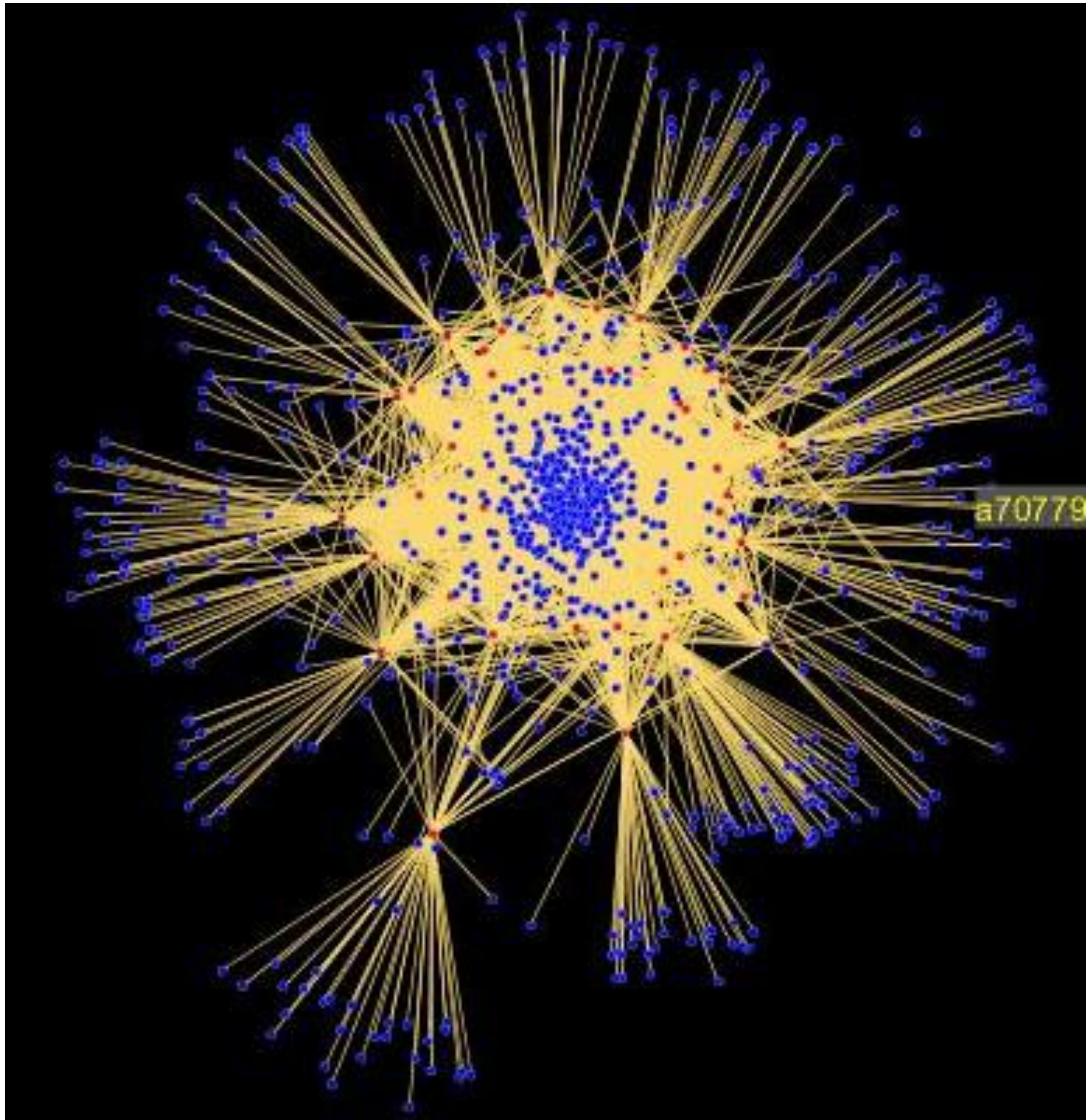
Participant Contacts with Stationary Bluetooth Devices over 1 Week



Participant Contacts with Mobile Bluetooth Devices over 1 Week

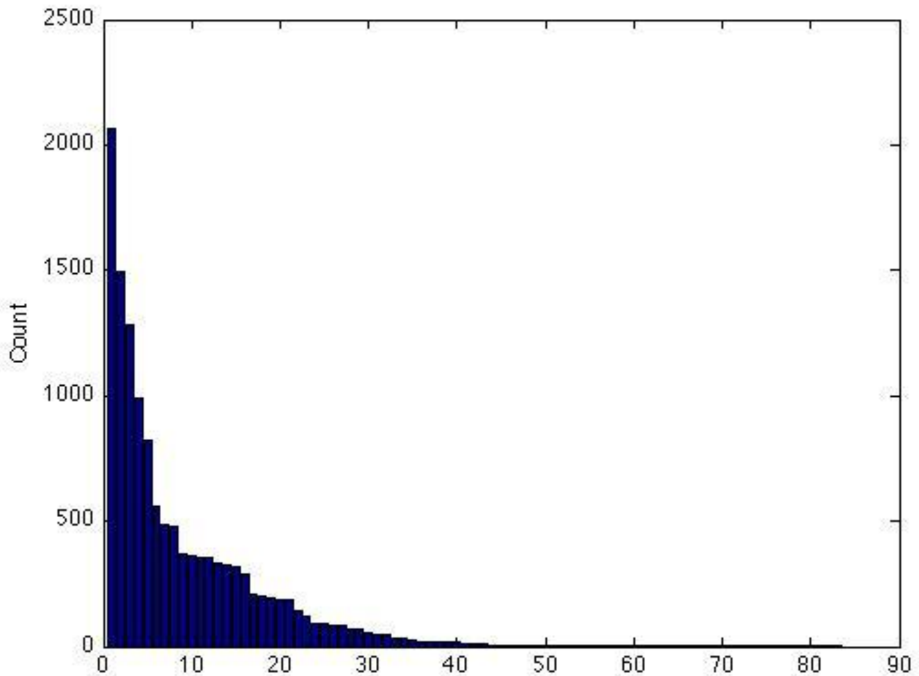


Participant Contacts with Mobile Bluetooth Devices over Entire Study



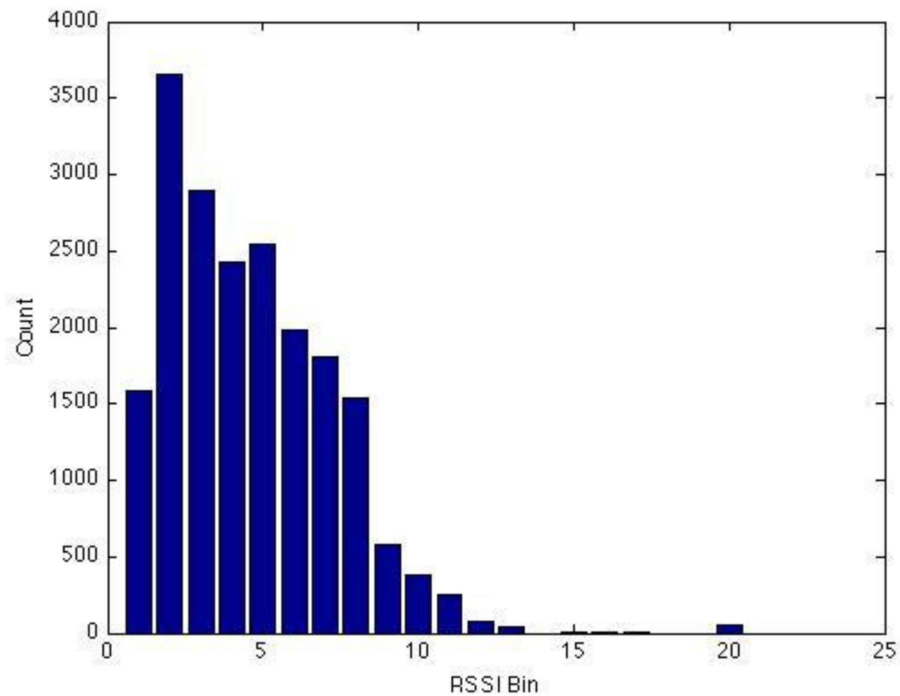
Bluetooth Contacts

Histogram: Contact count with different devices



Distinct Bluetooth Devices

Histogram: Signal Strength



Weaker Signal => More distant

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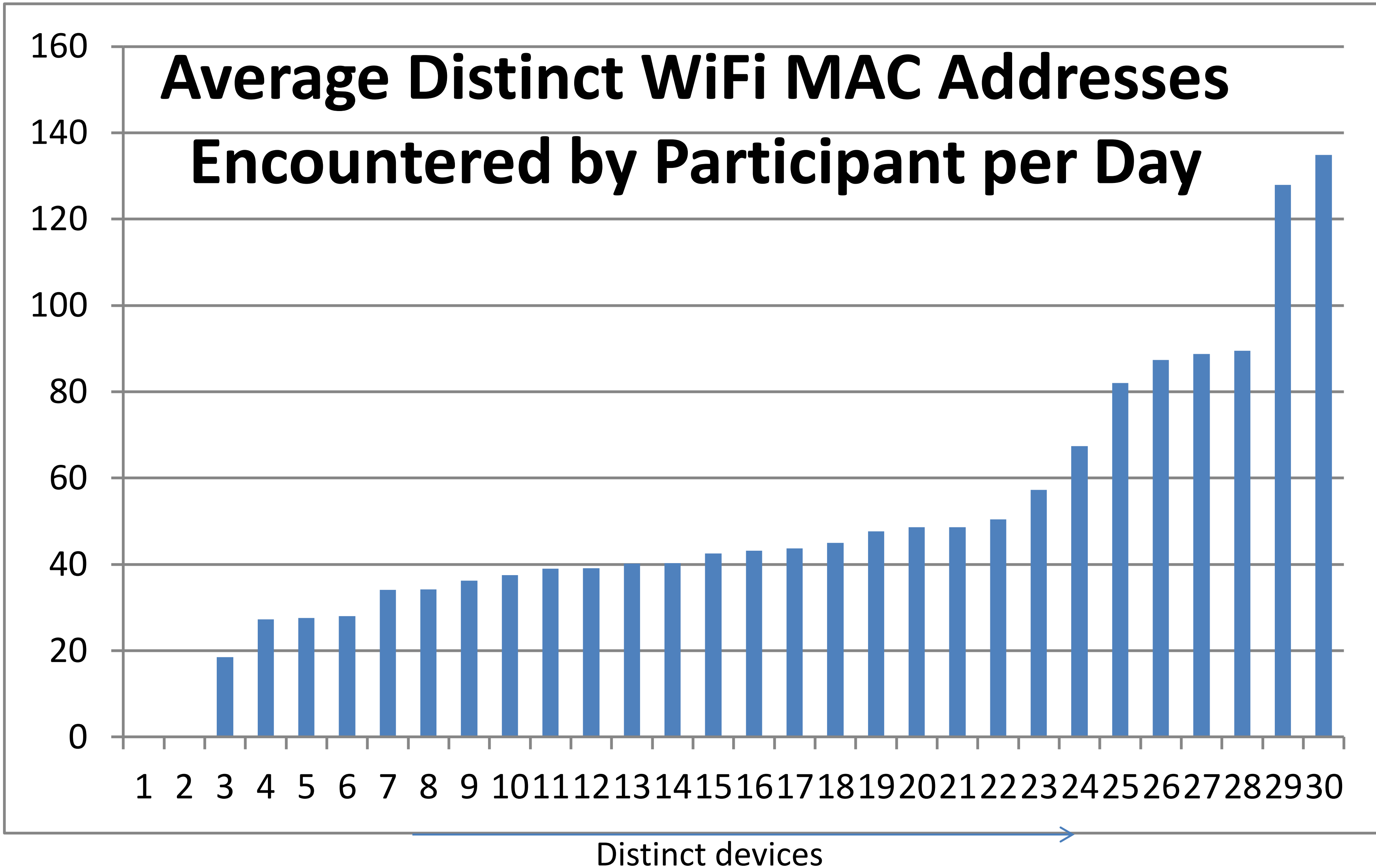
Daily Contact with Distinct WiFi Routers

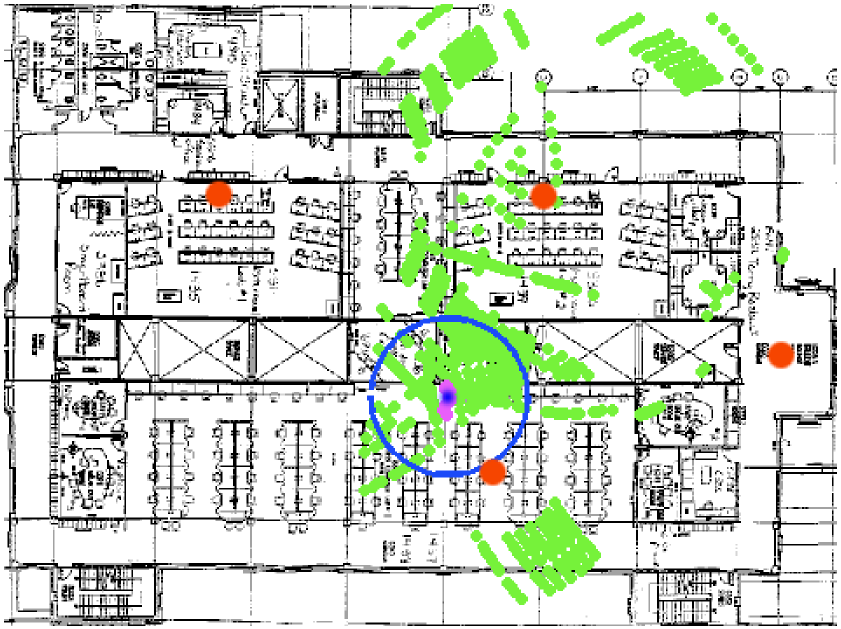


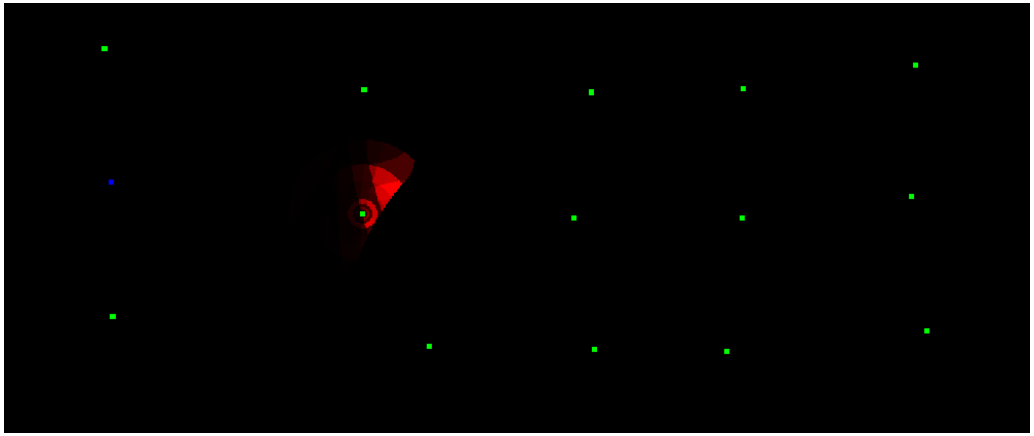
WiFi/Bluetooth As a Location Marker

- 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





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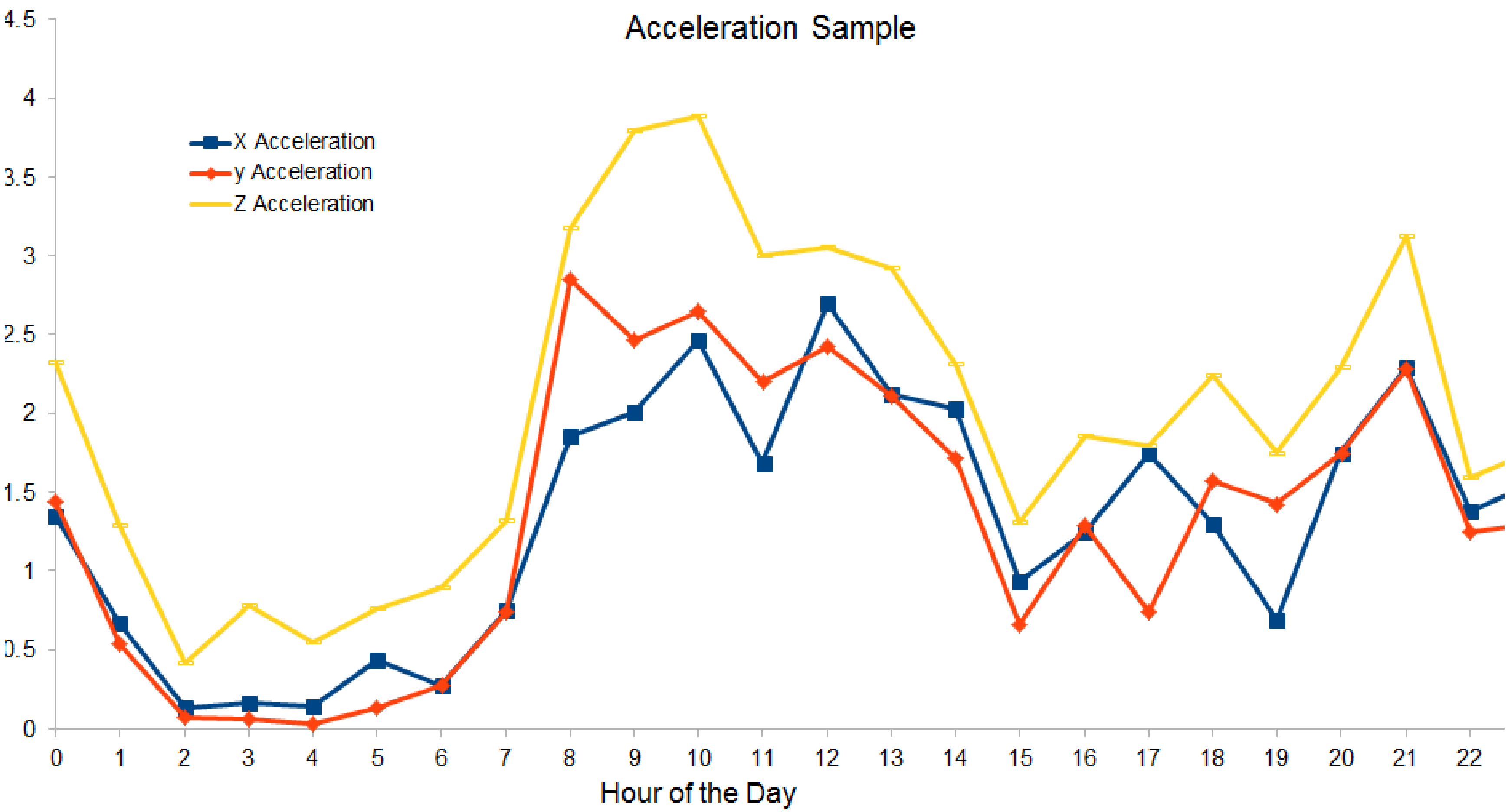
Accelerometer



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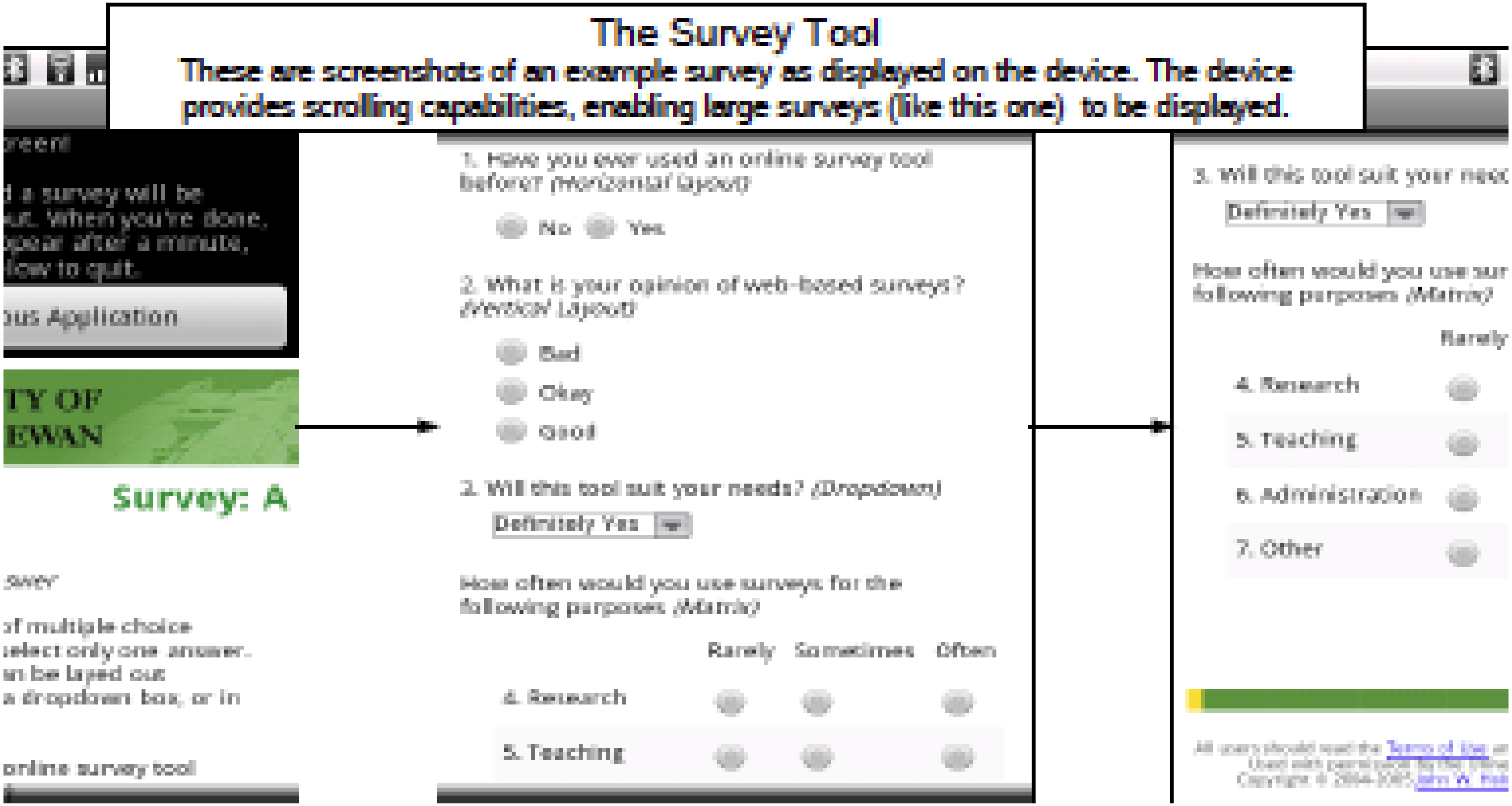
Surveys



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
  - Proximity
  - GPS
  - Accelerometer
  - Microphone
- Communications
  - Cellular
  - Wifi
  - Bluetooth

Location

Portion Size

Activity

Location

Indoors?

Weather/Flu watch/etc.

Communication /Interruptions

Automation

Environment

Time?

Recording

Survey?

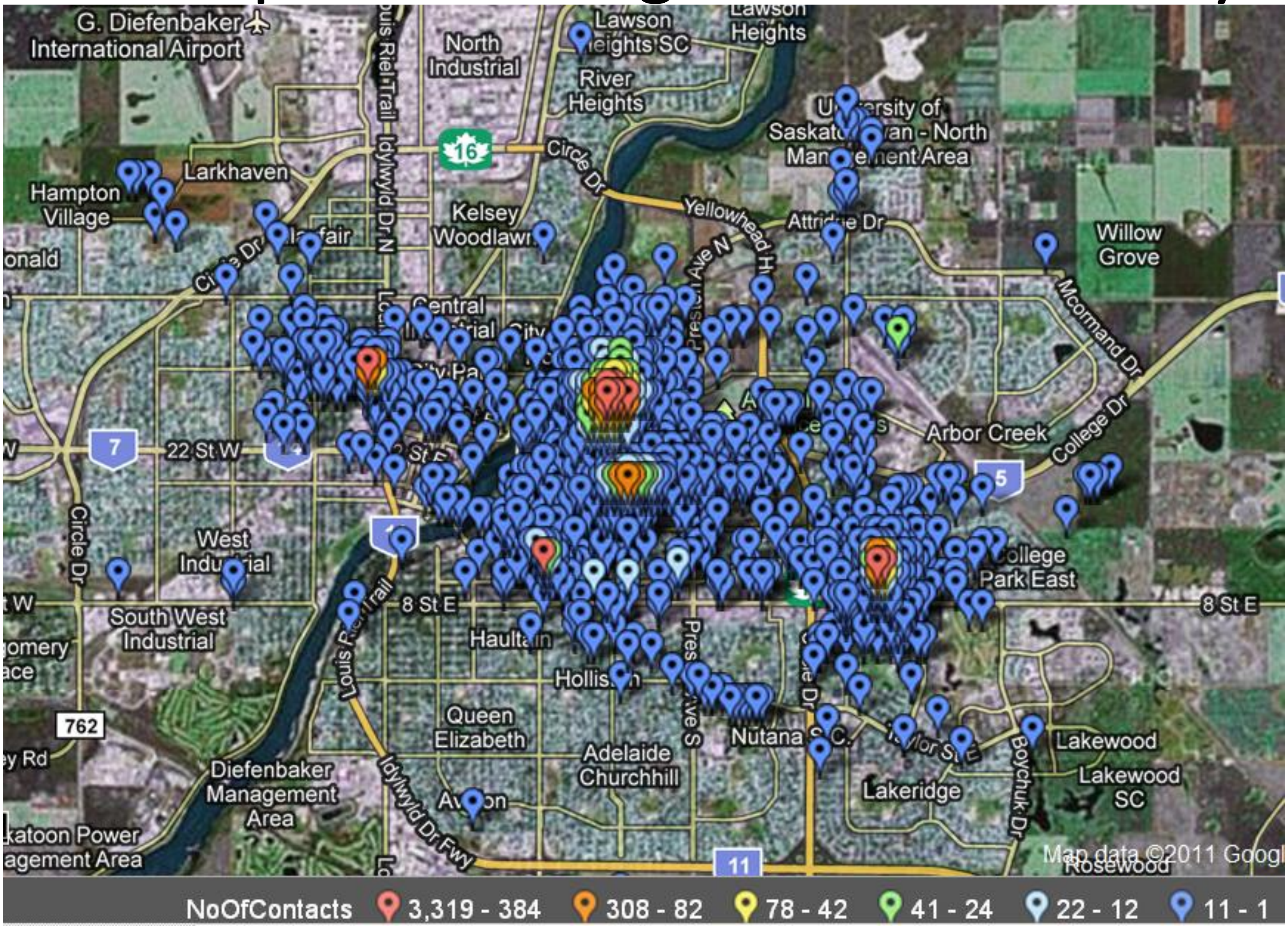
Scheduled?

Contact

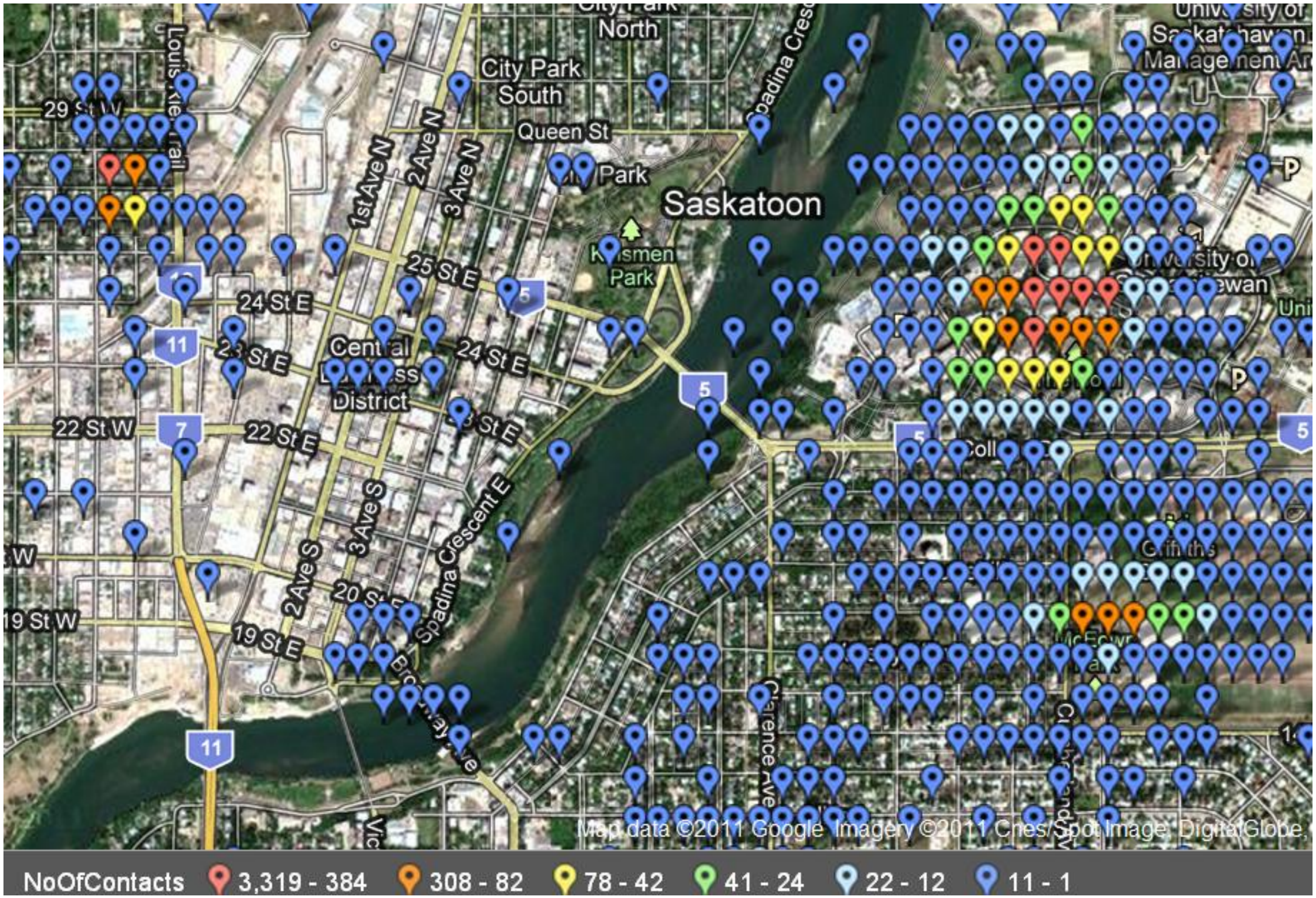
Example: Importance of Place

- Incorporating place can lend understanding of
  - Transmission of norms (cf Madan et al 2009/2010)
  - 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

Back

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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- ✓ Sensor Platforms
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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

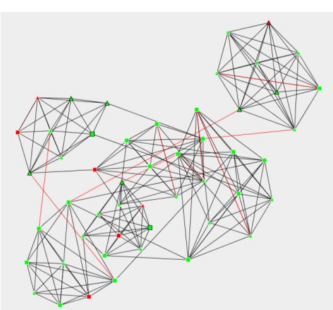
Modelers as Buzzards: Lofty Goals

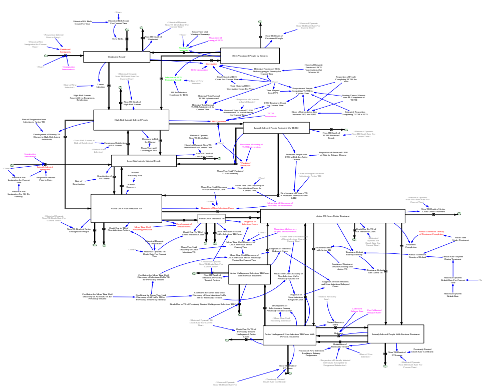
Modelers as Buzzards: Lowly Meals of Data

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

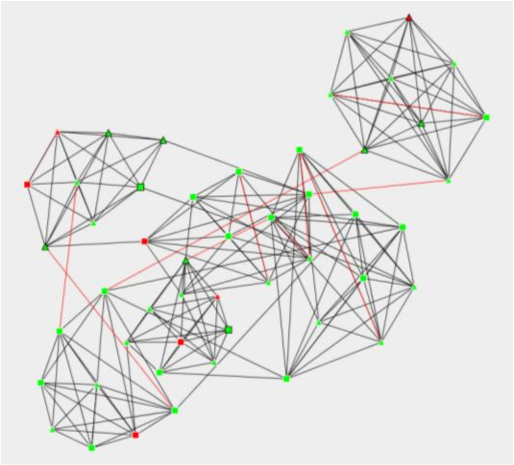
- “Filling the gaps” between sensor data
- Capturing regularities that underlie sensor data
- “Filtering” of noisy sensor data
  - Arriving at “consensus” estimates combining measured data & model predictions
- Generalizing observed behavioral patterns
- Understanding proximal & distal implications of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

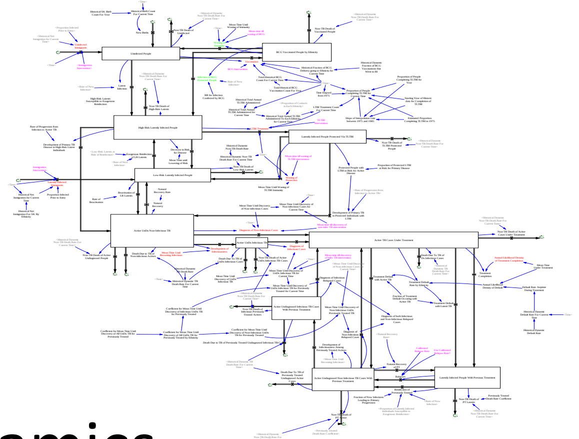
Motivation

Replacing… Or…

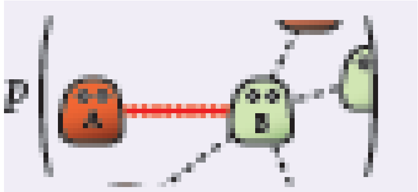
Relevant Modeling Types

- 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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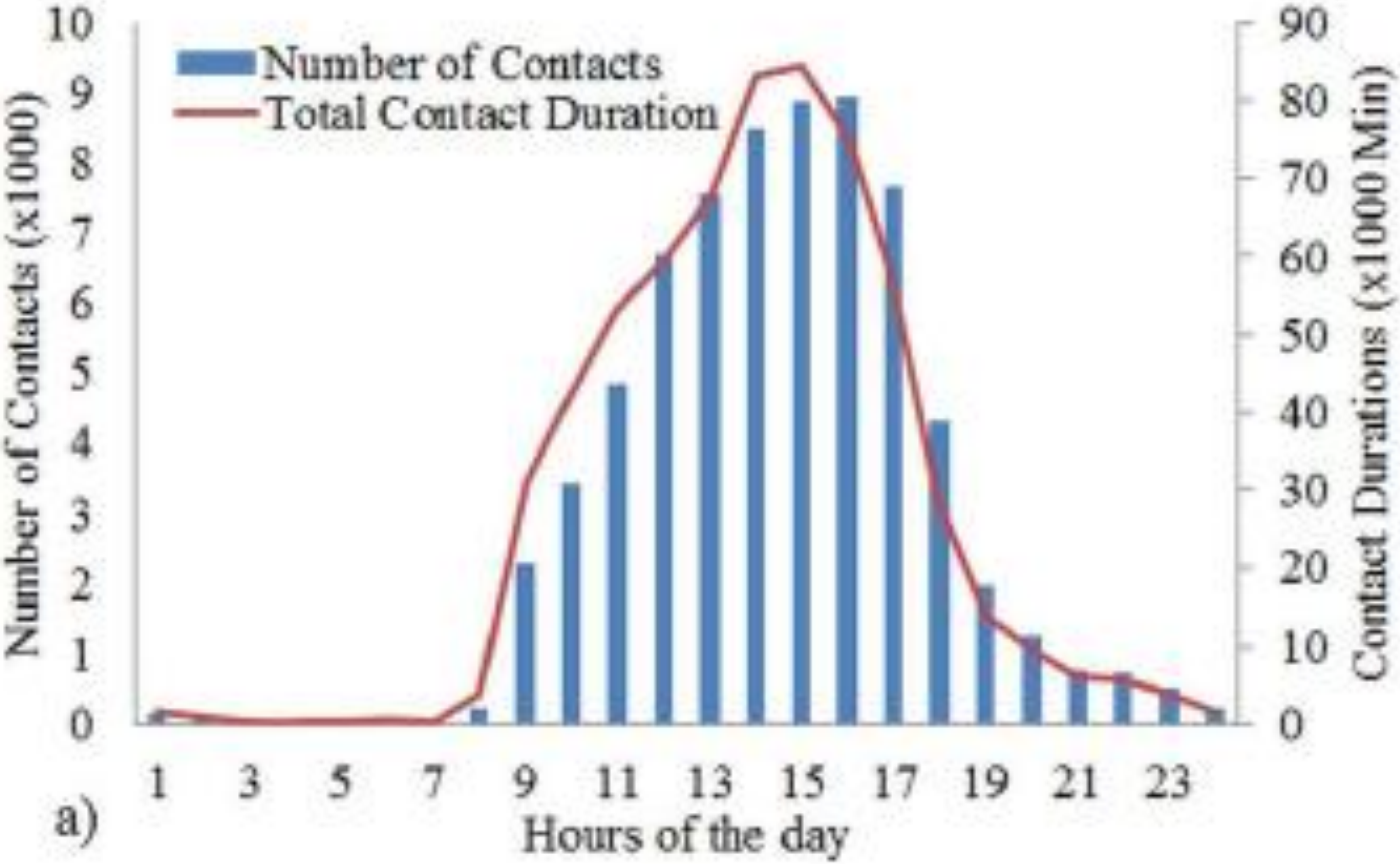
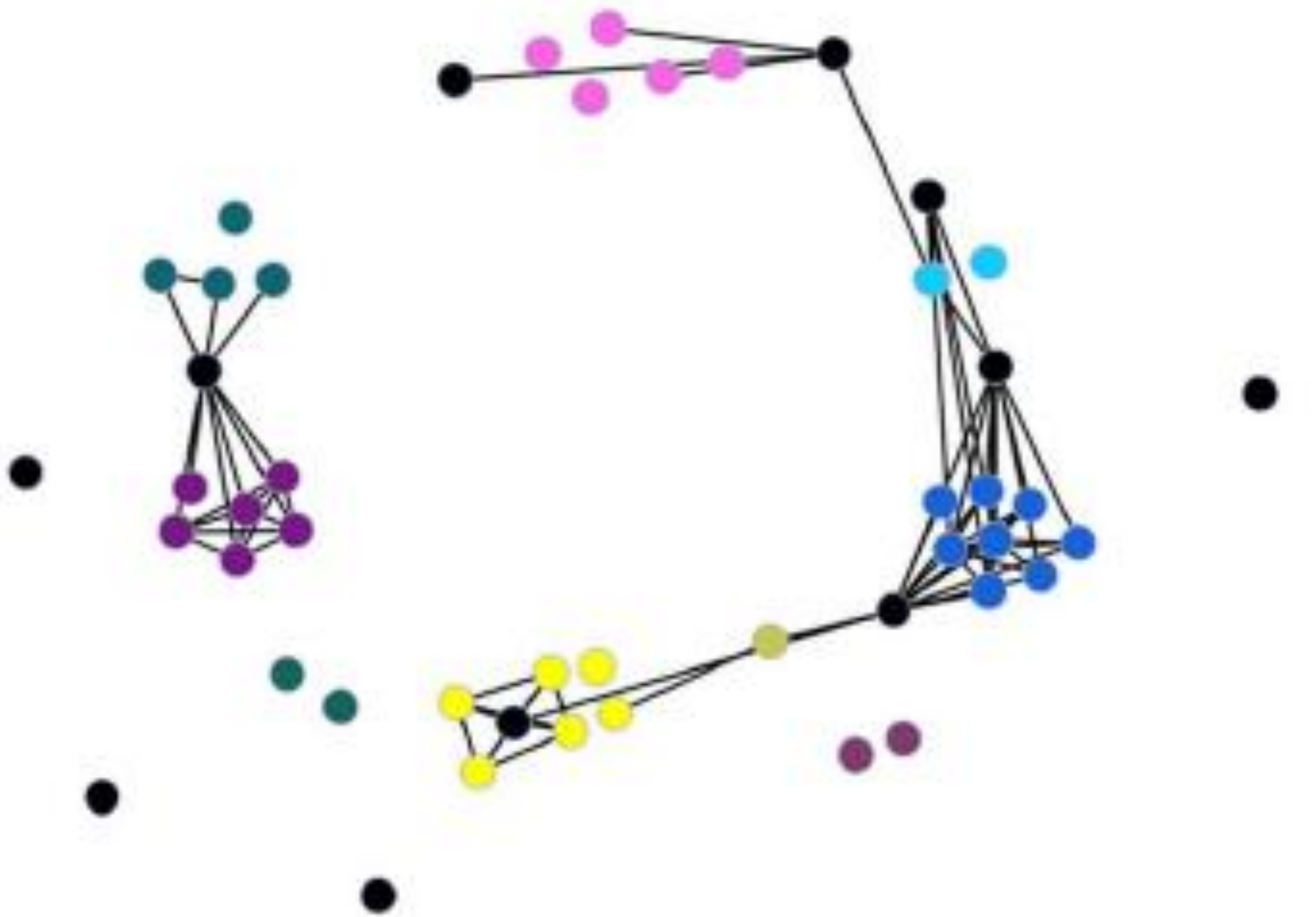
Flunet Study

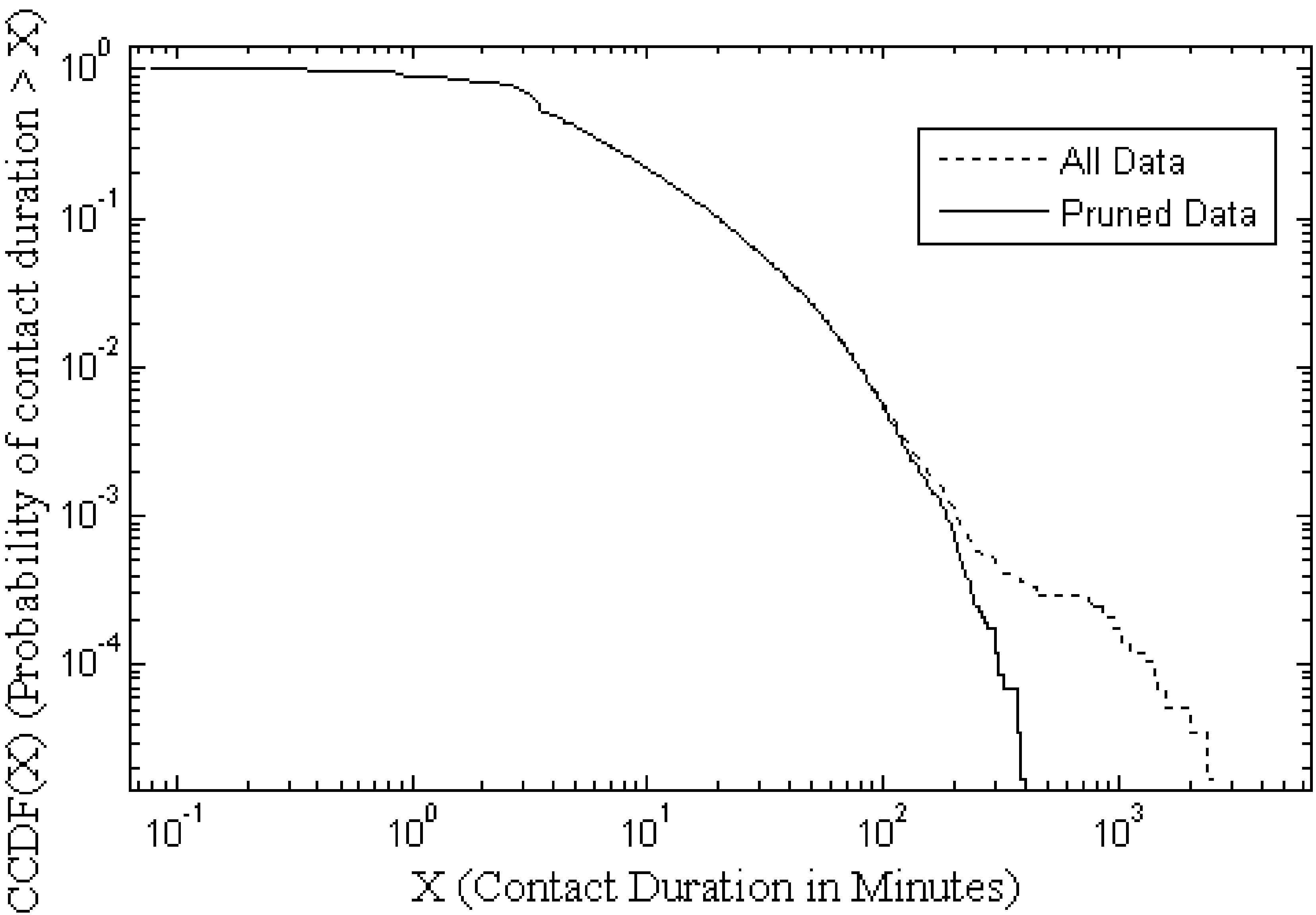
- Small scale study
  - People: 36 participants
  - Places: 9 “beacons” at fixed locations
- Information collected
  - Proximity
    - Each sensor recorded every 30 seconds
    - 3 RSSI proximity categories: Close (<5m), Medium (5-15m), far (>15m)
    - Proximity resolution 1-2 minutes
  - **Cross-linked 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



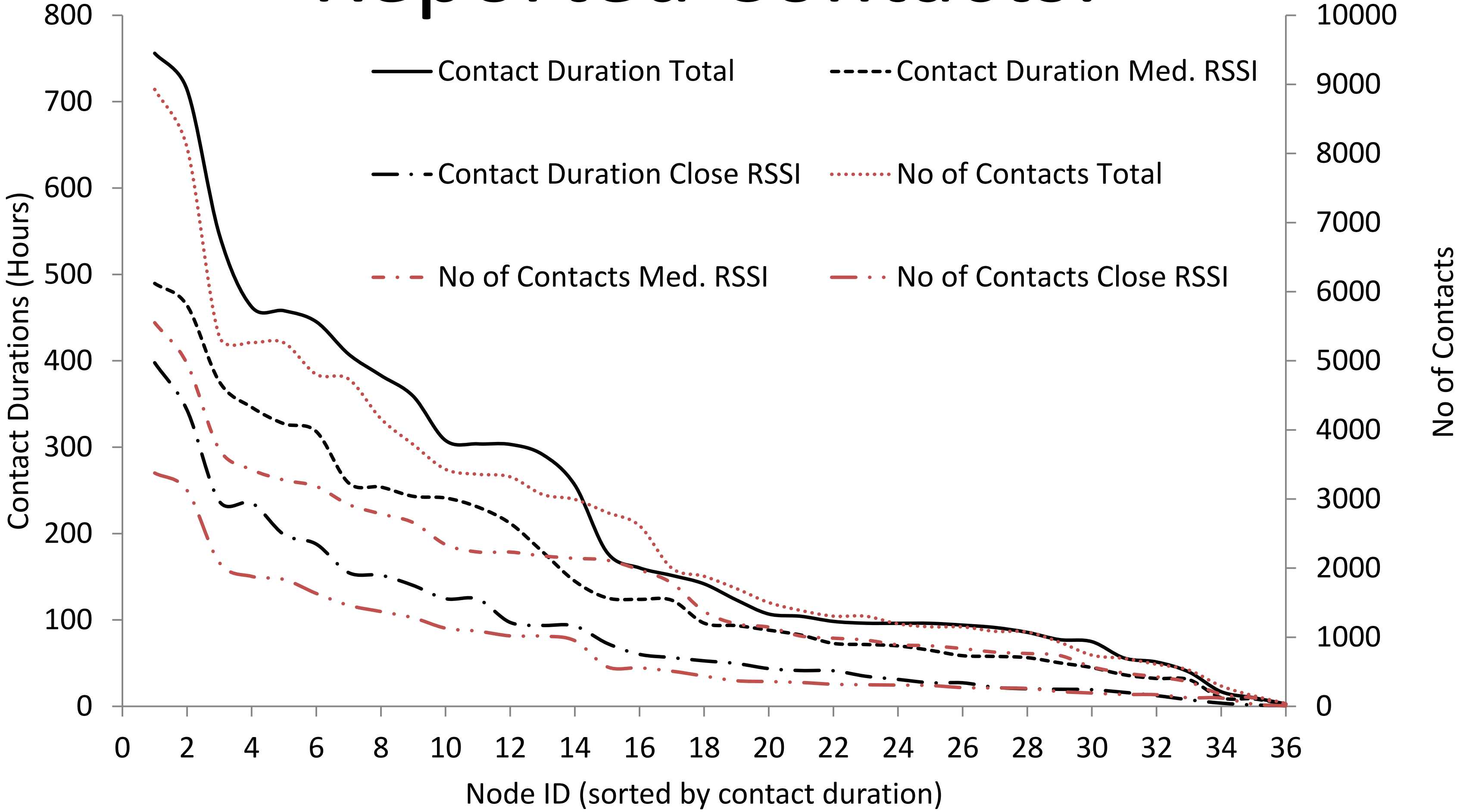
Aggregated Contact Graph





CCDF(X) (Probability of contact duration > X)
X (Contact Duration in Minutes)
All Data
Pruned Data
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-1}
10^0
10^1
10^2
10^3

Reported Contacts:



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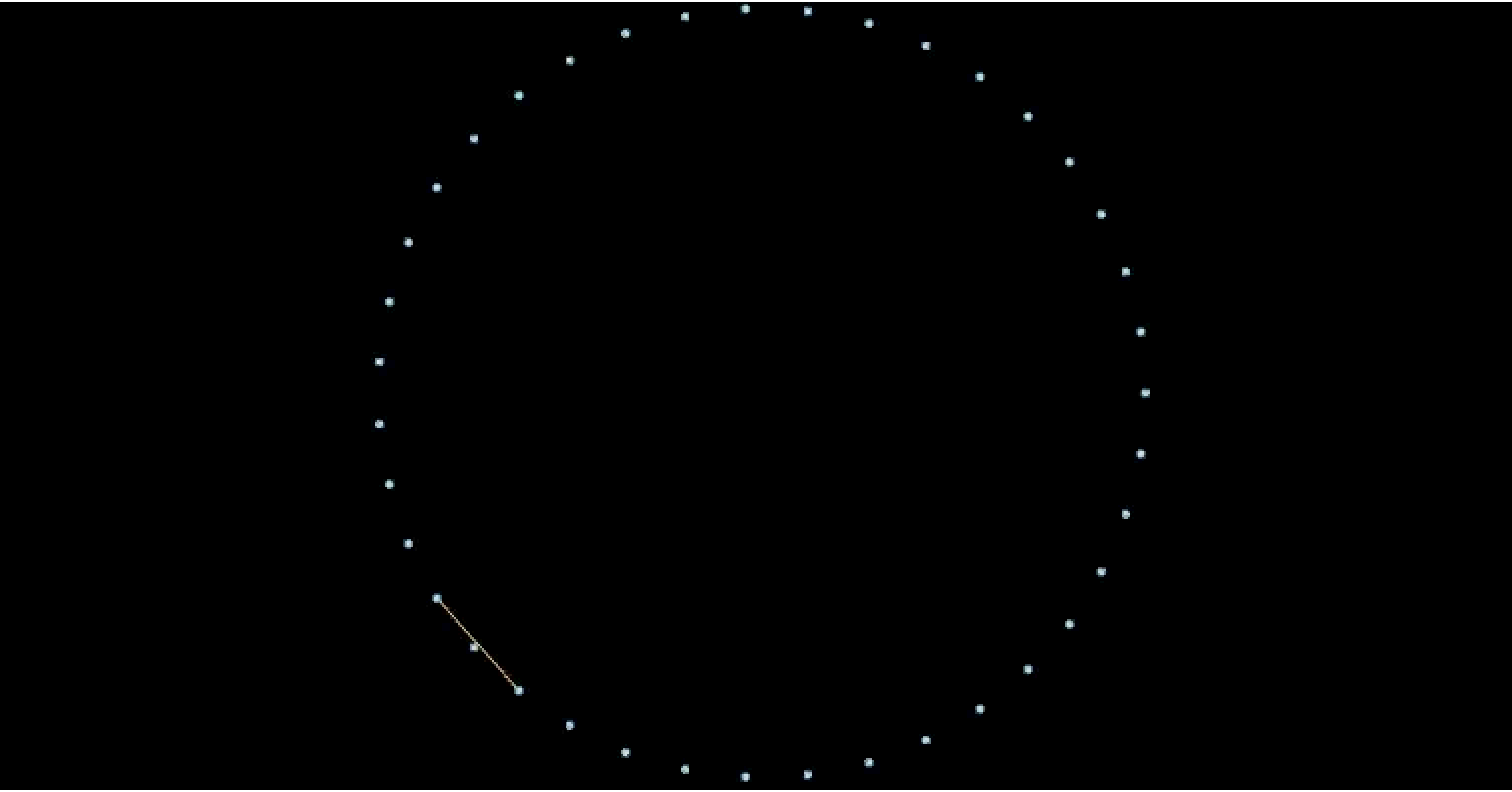
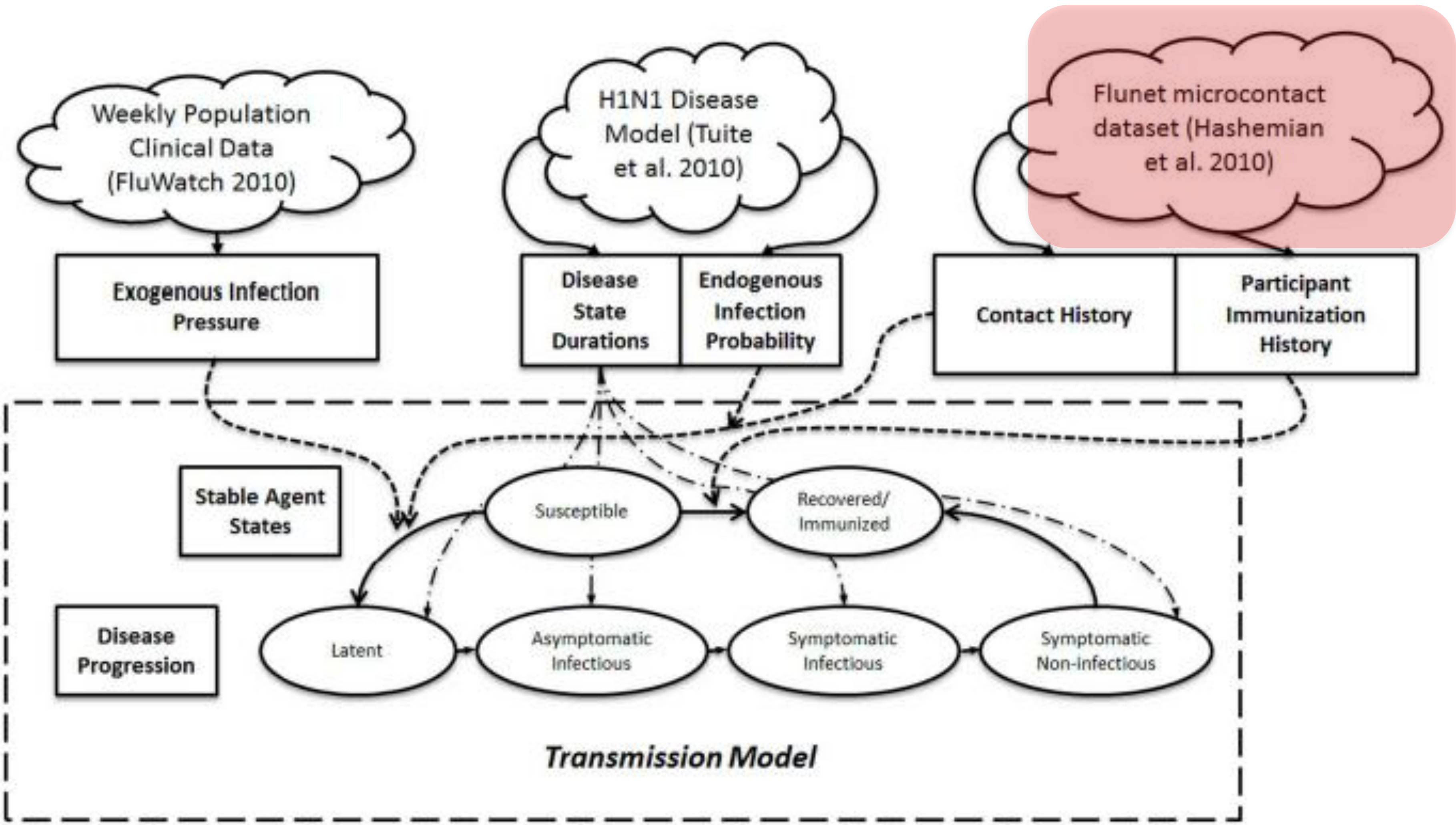
Video: Aggregated Hourly Contact Data



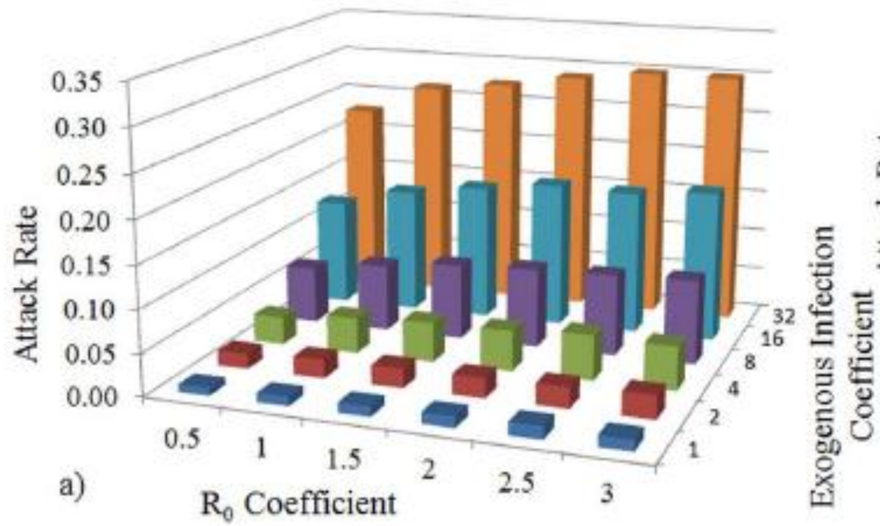
Integration of Model & Data Sources

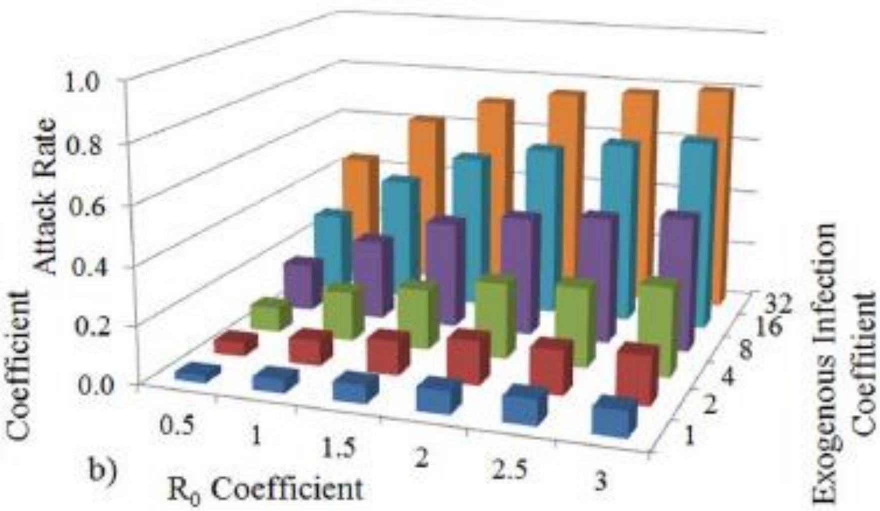


Dealing with Stochastics

- Uncertainties $\Rightarrow$ 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



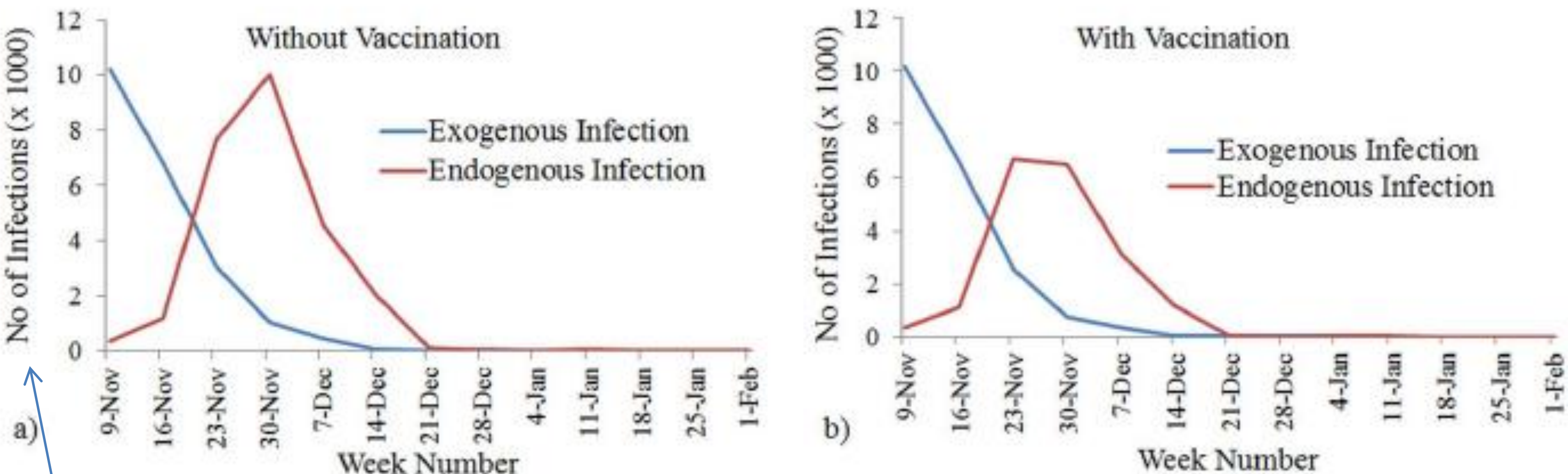


Close distance required for transmission

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

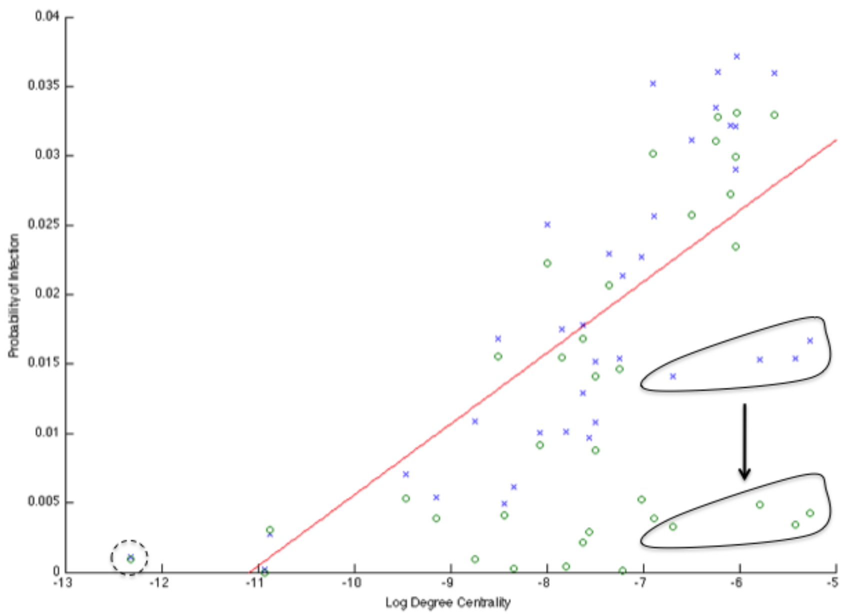
Results consistent with count of self-reports of symptoms of influenza-like illness

Number of Infections



Infections spread over 100,000 realizations

Results



Correlation between centrality measures & model-derived likelihood of infection

	Without Vaccination		With Vaccination	
	ρ	p	ρ	p
Betweenness	0.172	0.316	0.110	0.522
Degree	0.415	0.012	0.296	0.080
Time Degree	0.514	0.001	0.344	0.040
Log Time Degree	0.740	<0.001	0.503	0.002

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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”

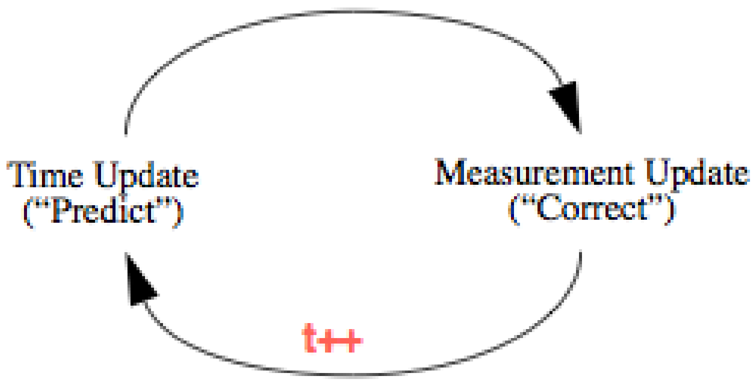
Benefits to Data

- 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

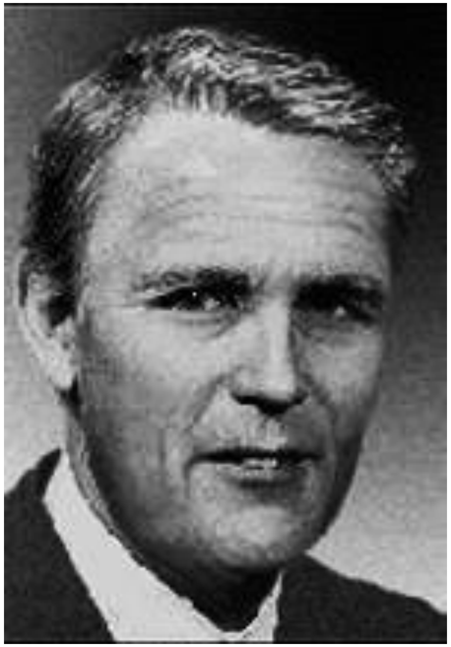
Benefits to Models

- 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 Kalman Filter (R. E. Kalman 1960)



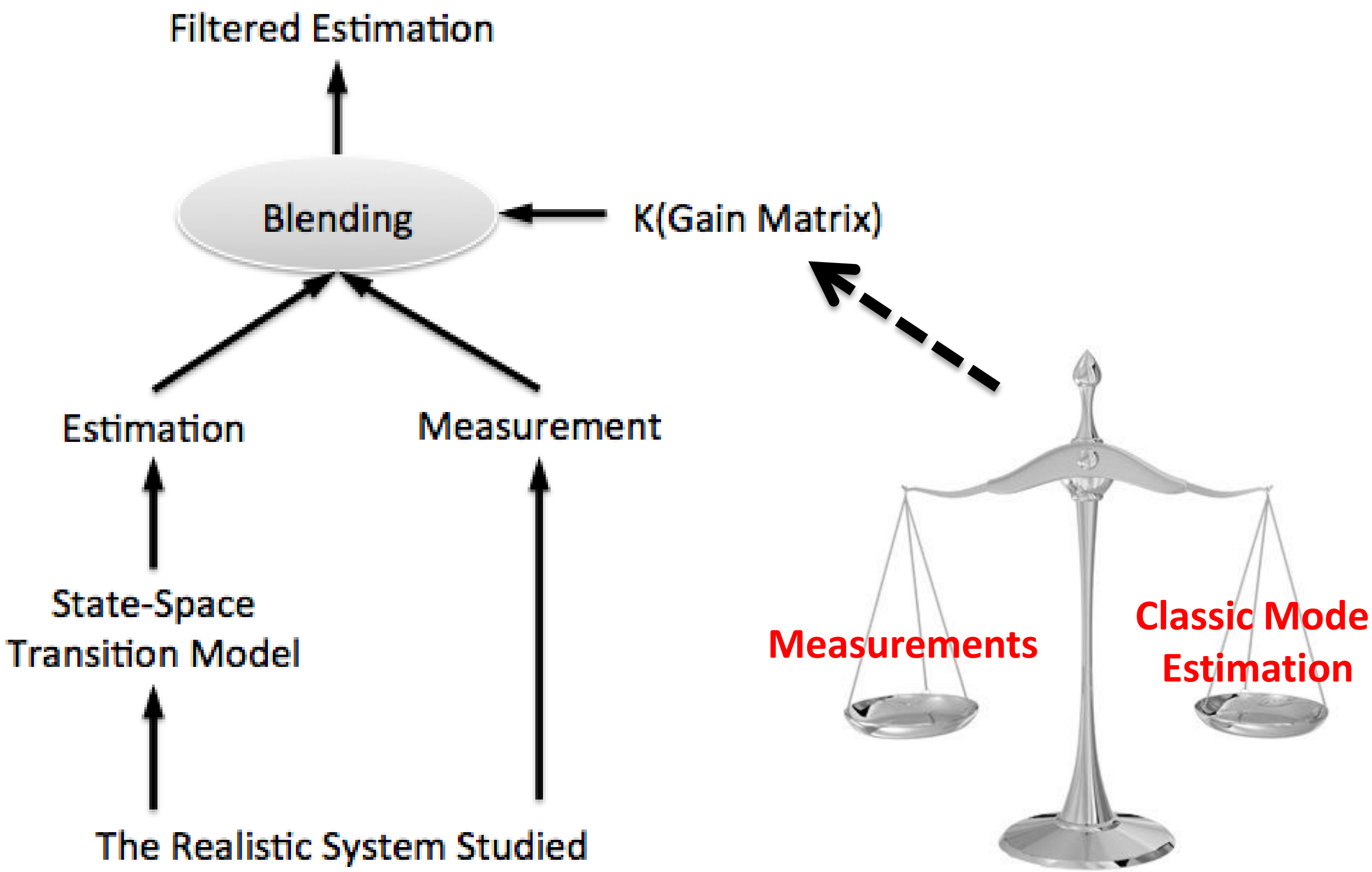
The ongoing discrete Kalman filter cycle. The *time update* projects the current state estimate ahead in time. The *measurement update* adjusts the projected estimate by an actual measurement at that time. (Welch, G. and Bishop, G. 2006)



Rudolf Emil Kalman
(1930-)

Slide courtesy of Weicheng Qian

The Dissected Kalman Filter



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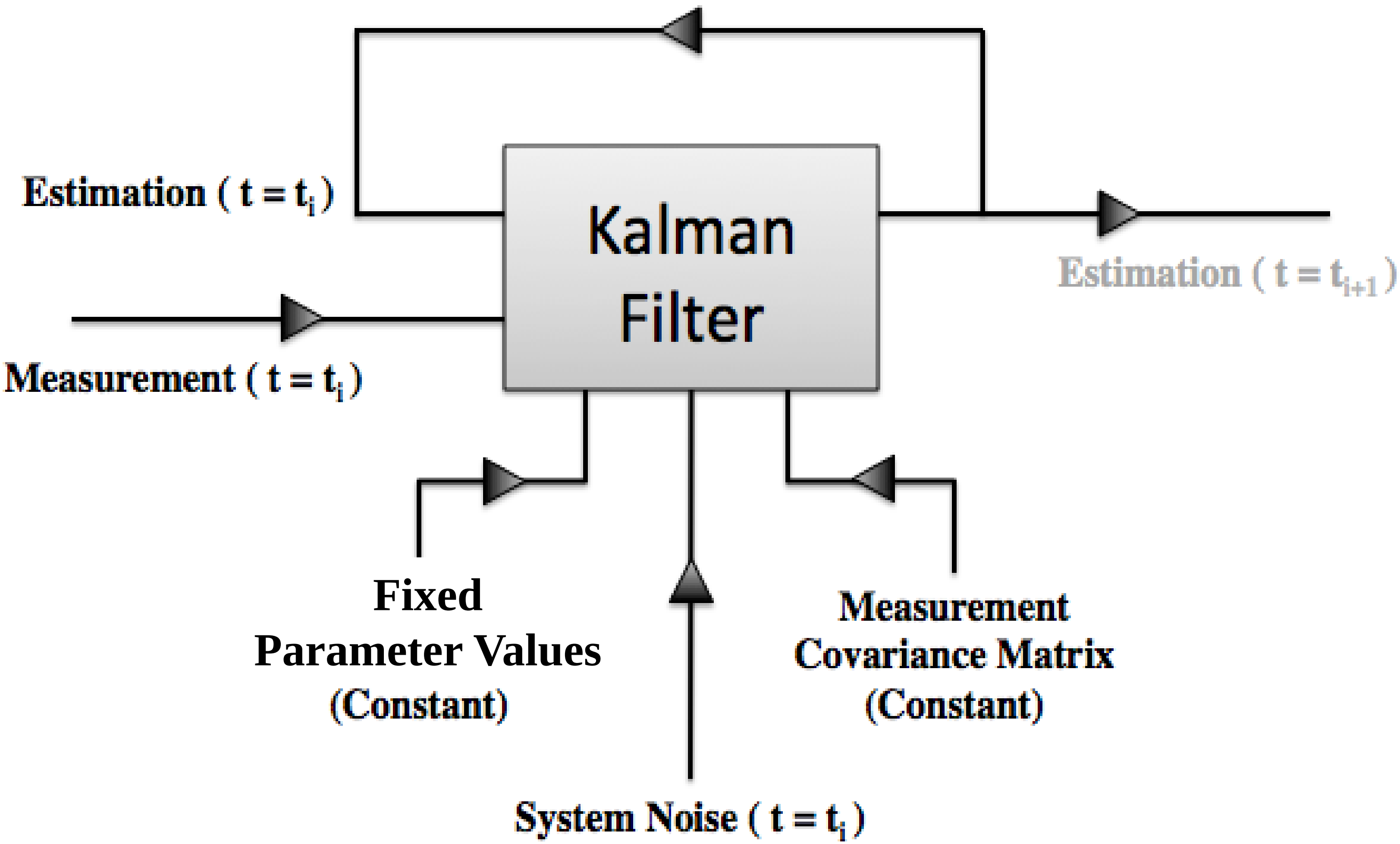
Higher level view of Kalman Filter



Slide courtesy of Weicheng Qian

Kalman Filter Equations

$$\dot{X}(t) = f(X(t), t) + w(t)$$

$$\dot{Y}(t = k_i) = h_i(X(t = k_i)) + v(t = k_i)$$

System Theory

$$\hat{x}_k(+) = \hat{x}_k(-) + K_k[z_k - h_k(\hat{x}_k(-))]$$

$$P_k(+) = [I - K_k H_k(\hat{x}_k(-))]P_k(-)$$

Measurement Update Equations

$$H_k(\hat{x}_k(-)) = \left.\frac{\partial h_k(x(t_k))}{\partial x(t_k)}\right|_{x(t_k)=\hat{x}_k(-}$$

$$K = \frac{PH^T}{HPH^T + R}$$

'Gain' (Weighting) Matrix

$$F(\hat{x}(t), t) = \left.\frac{\partial f(x(t), t)}{\partial x(t)}\right|_{x(t)=\hat{x}(t)}$$

$$\dot{\hat{x}}(t) = f(\hat{x}(t), t)$$

$$\dot{P}(t) = F(\hat{x}(t), t)P(t) + P(t)F^T(\hat{x}(t), t) + Q(t)$$

System evolutio between measurements

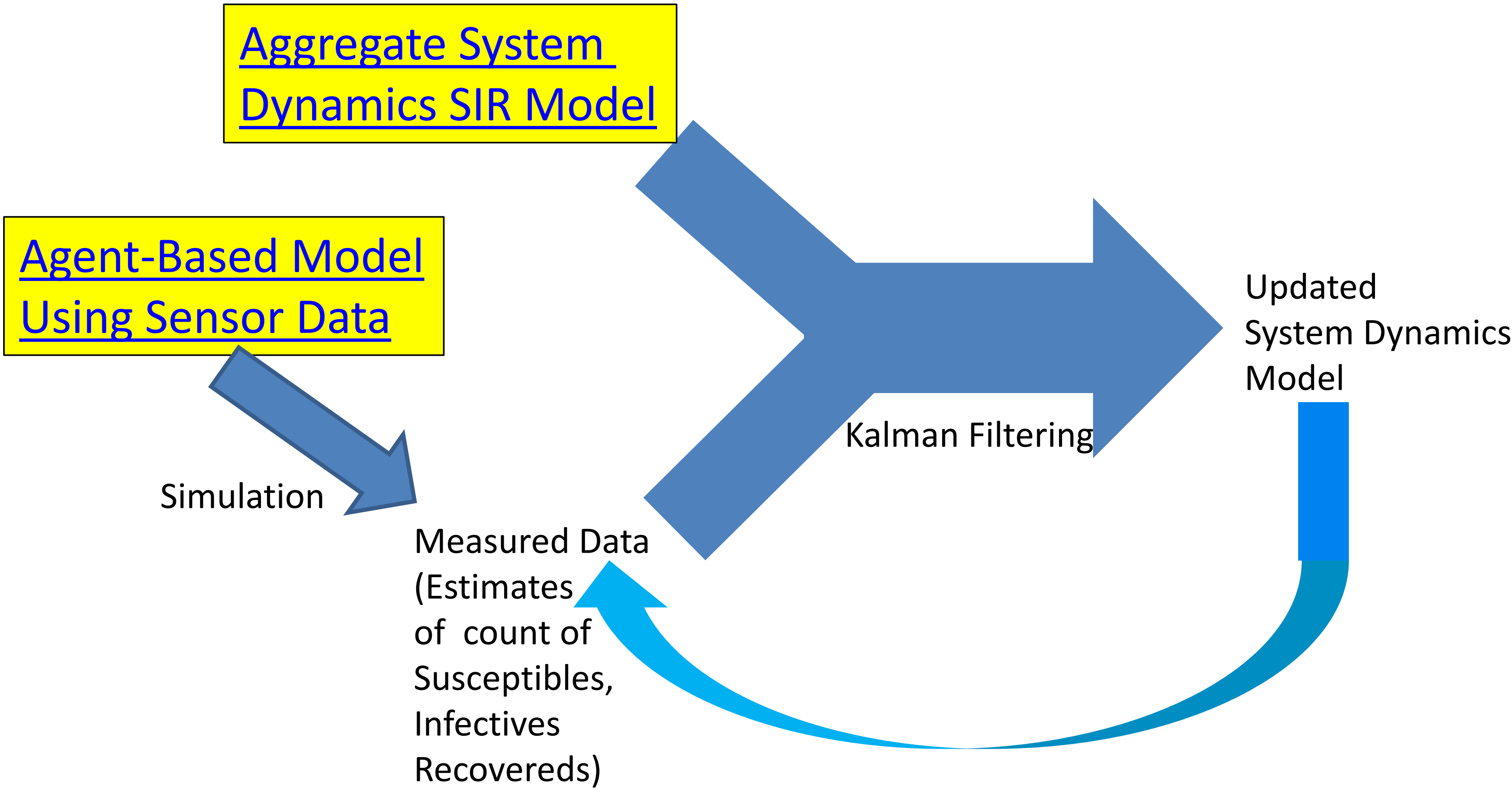
Evaluating Using a Synthetic Population

- 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

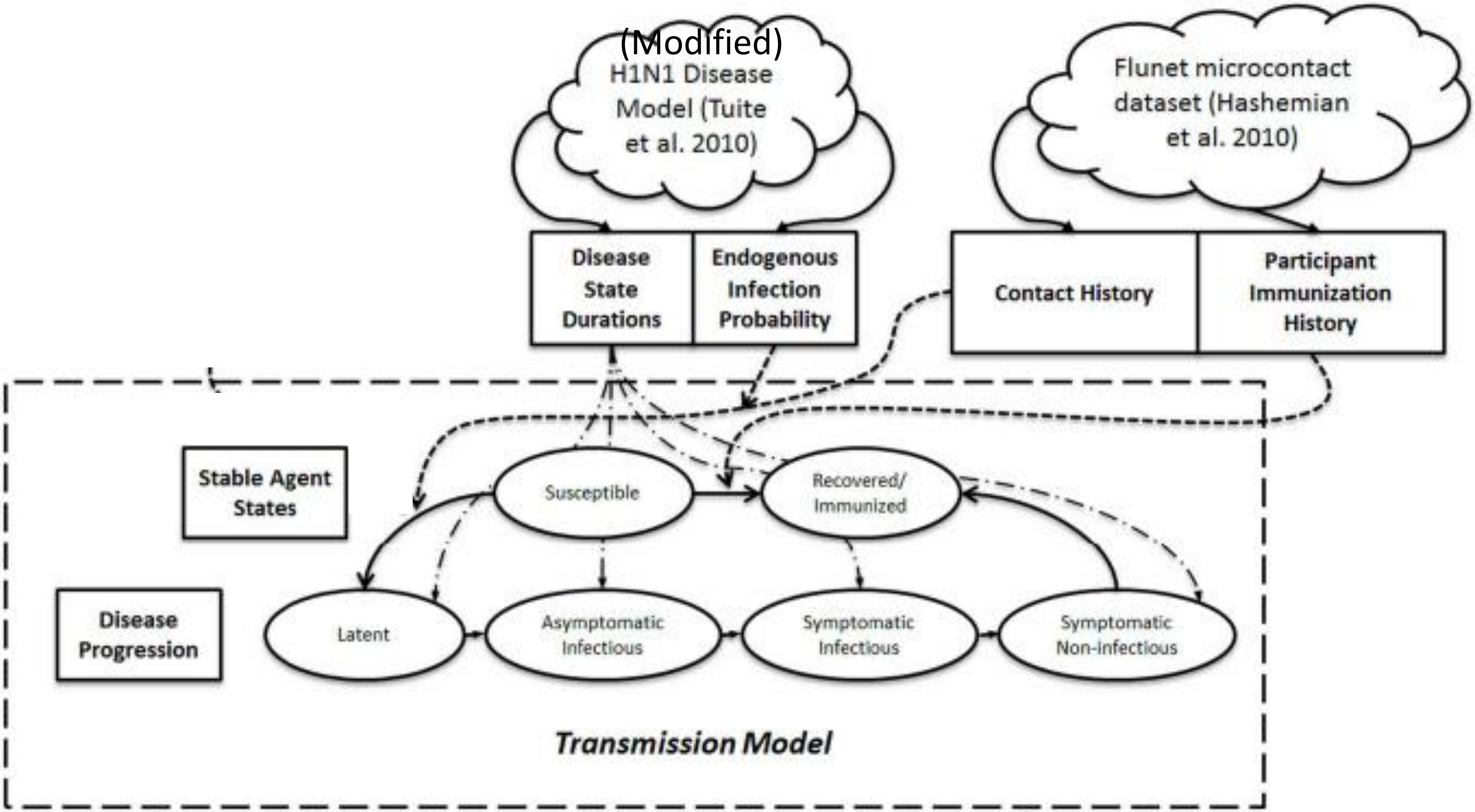
Synthetic Population Studies

- 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

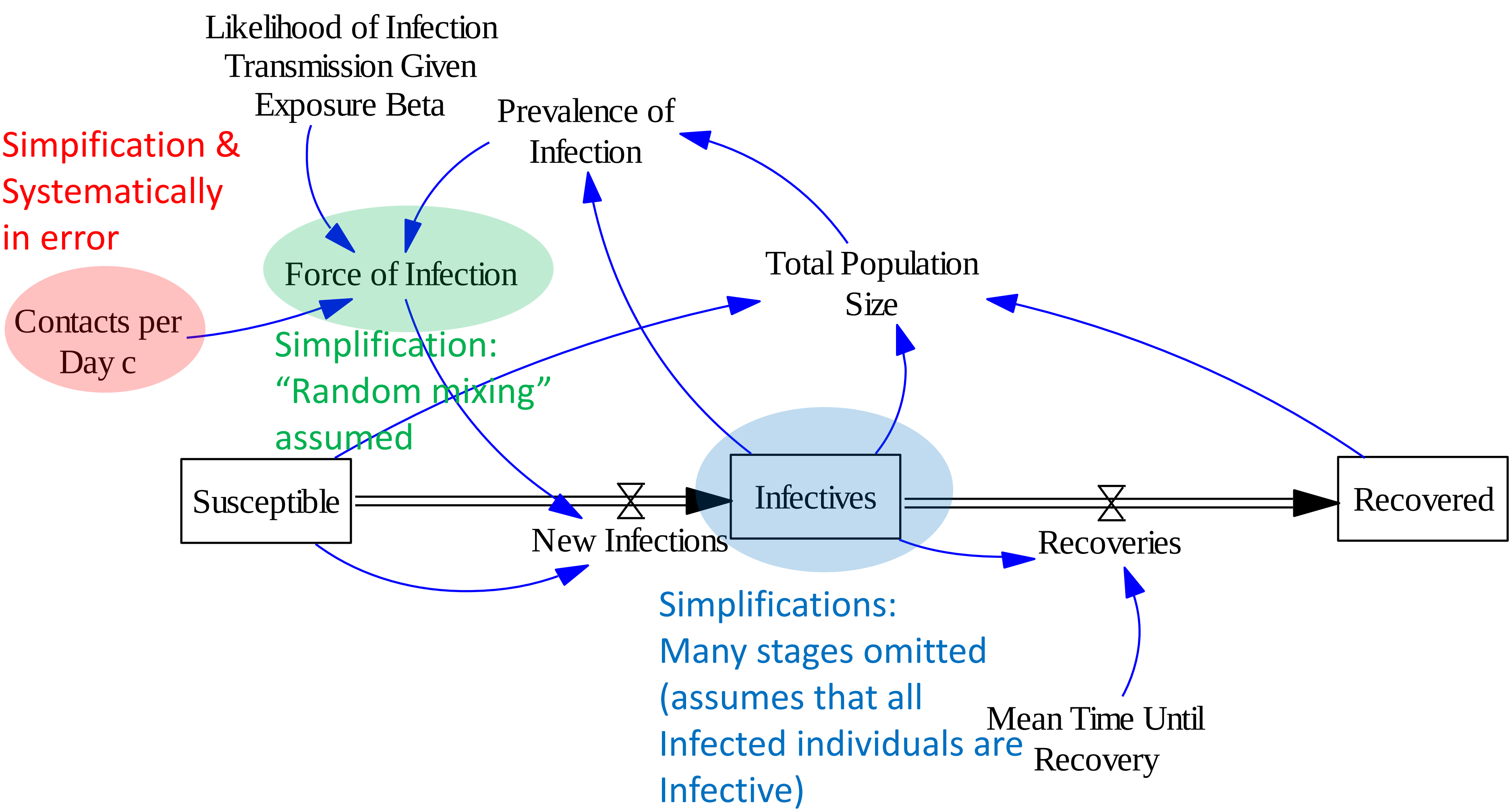


The Underlying Transmission Model



Back

Aggregate System Dynamics SIR Model



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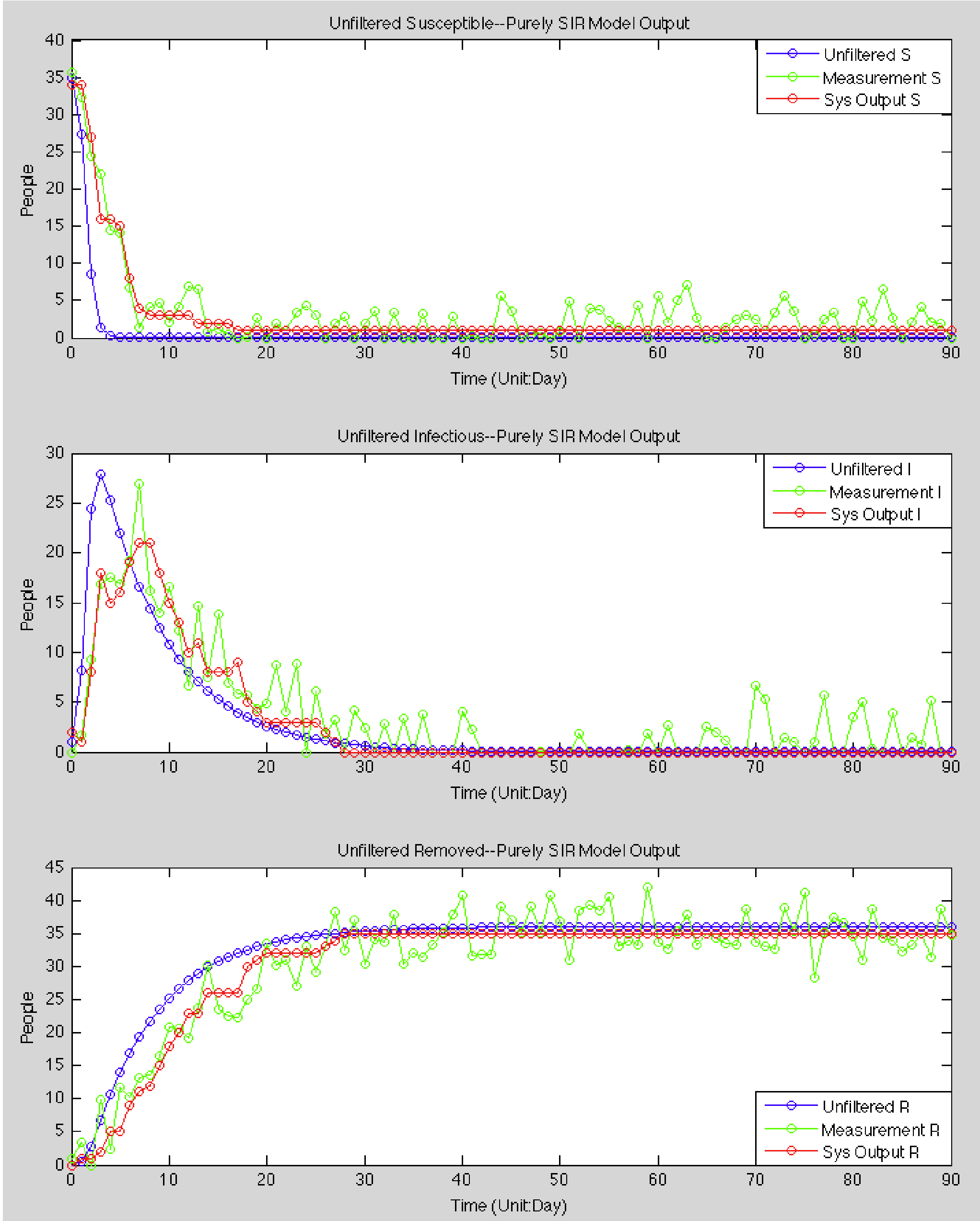
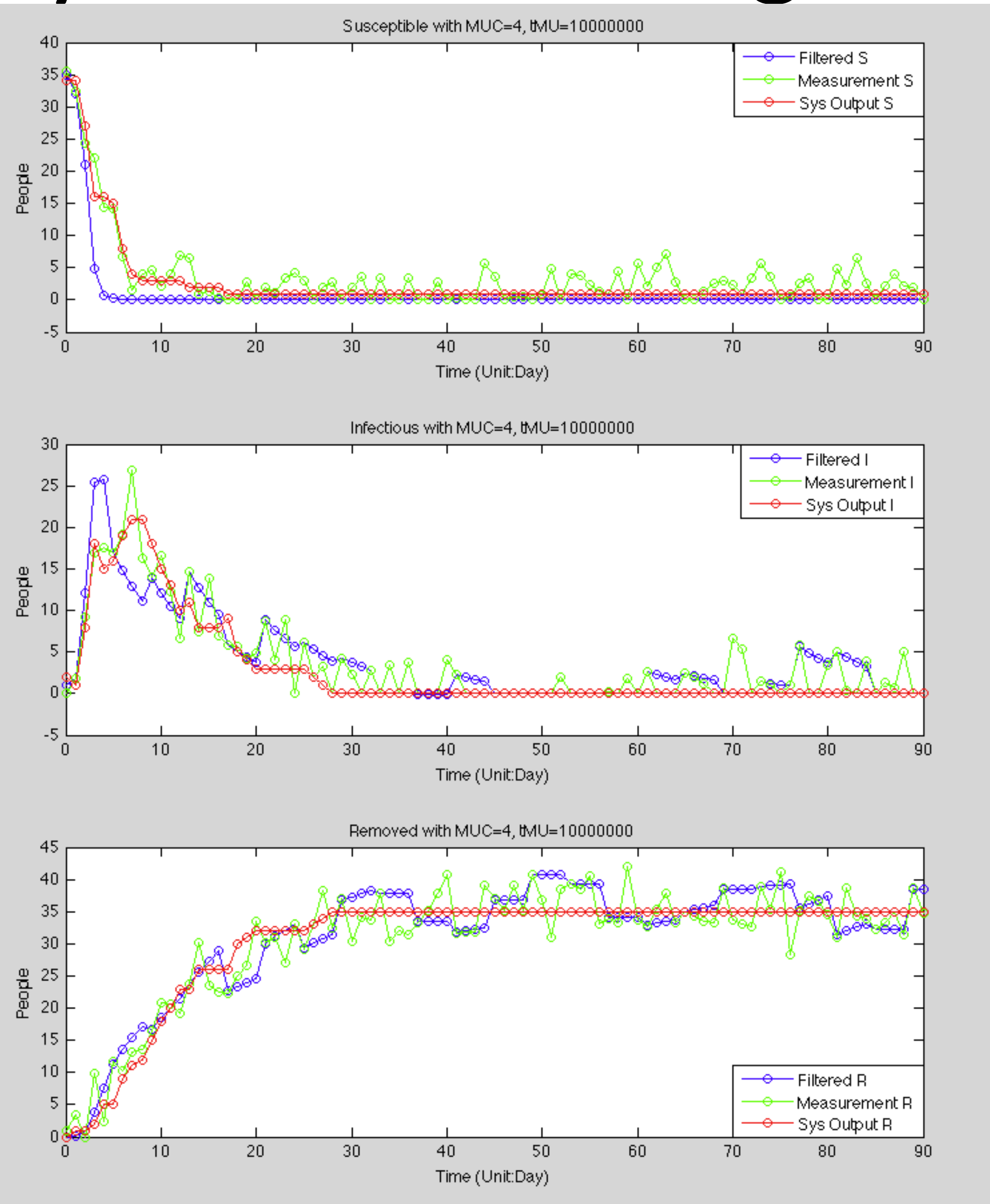
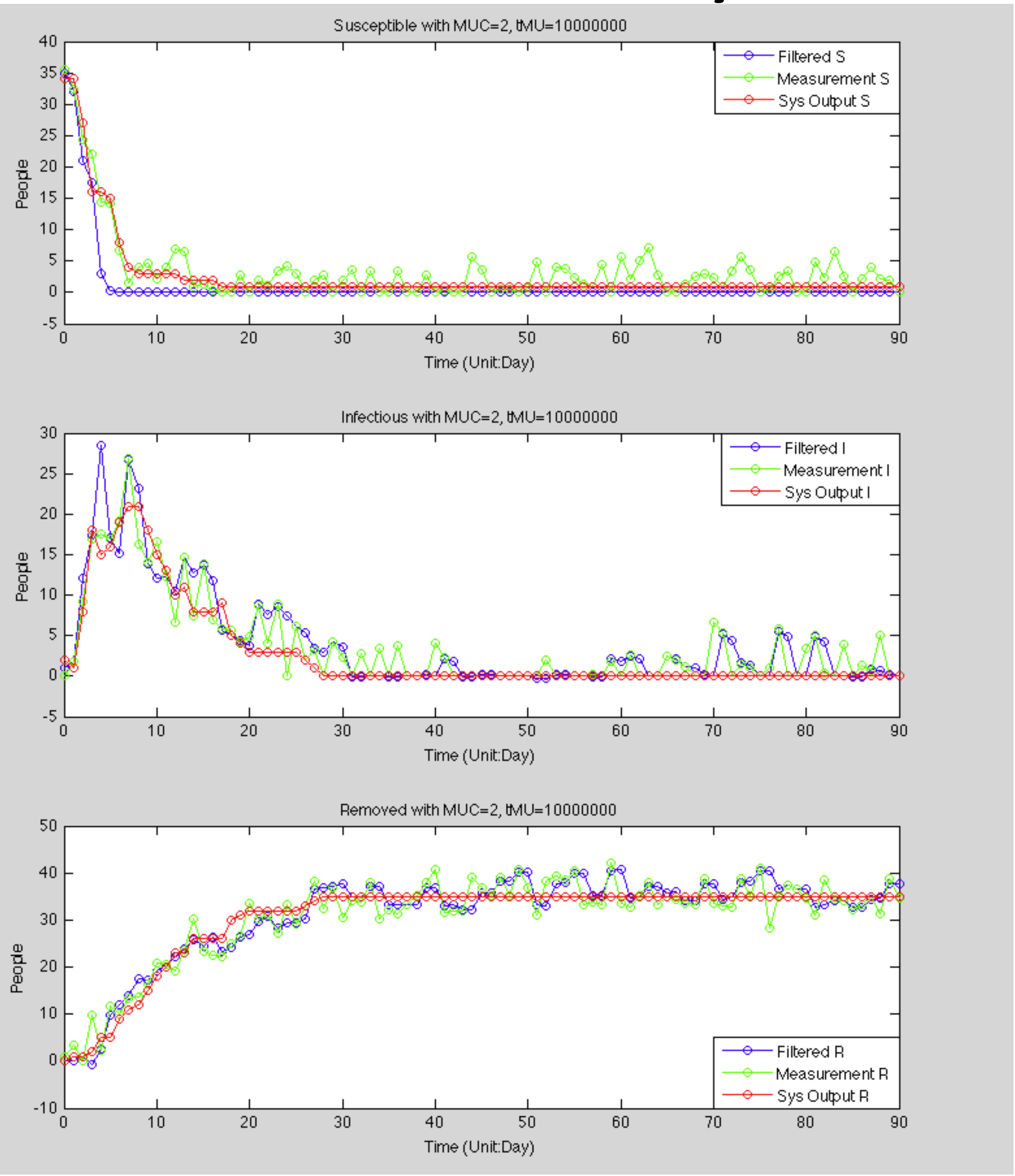
“Open Loop” Model



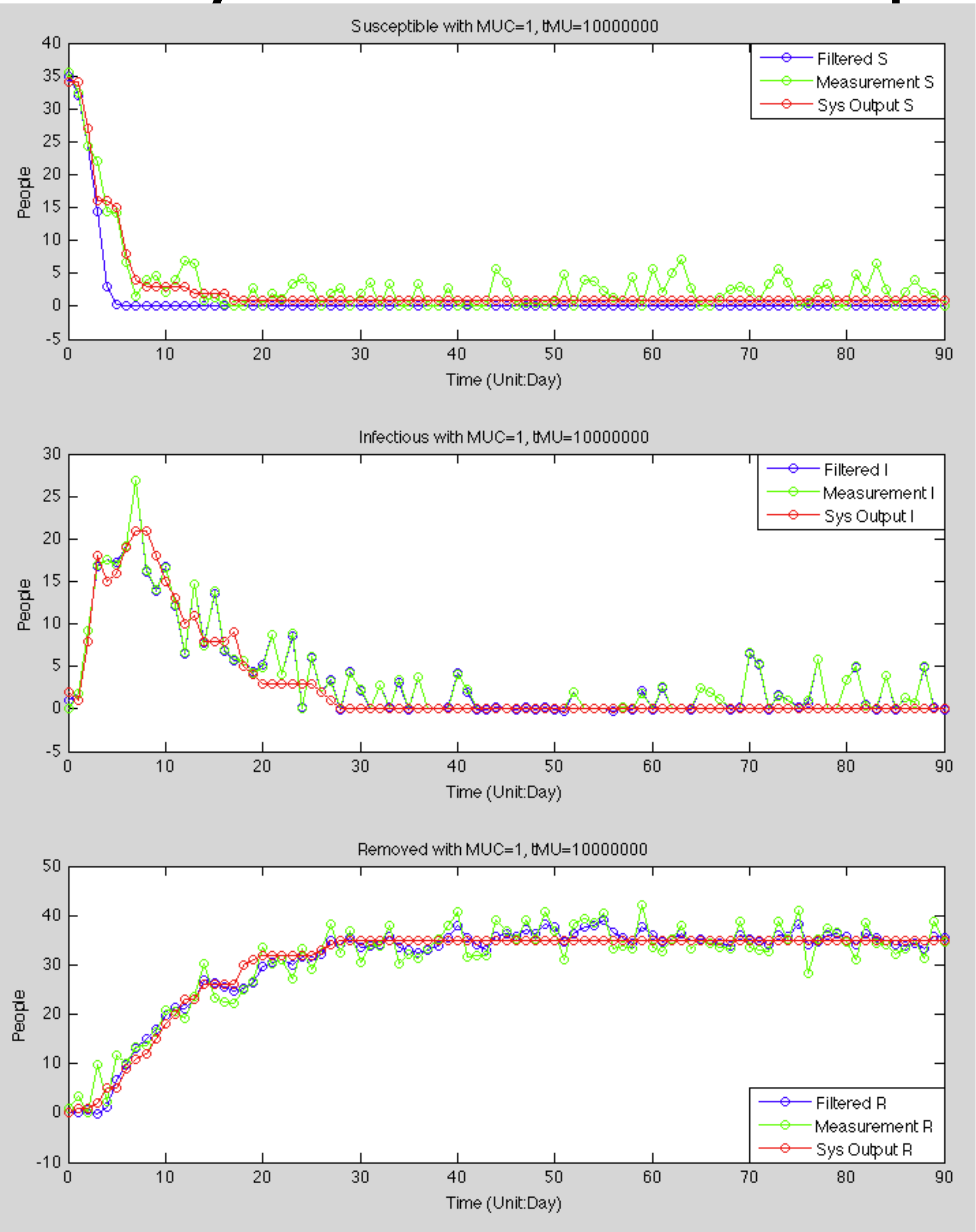
4 Days Between "Regroundings"



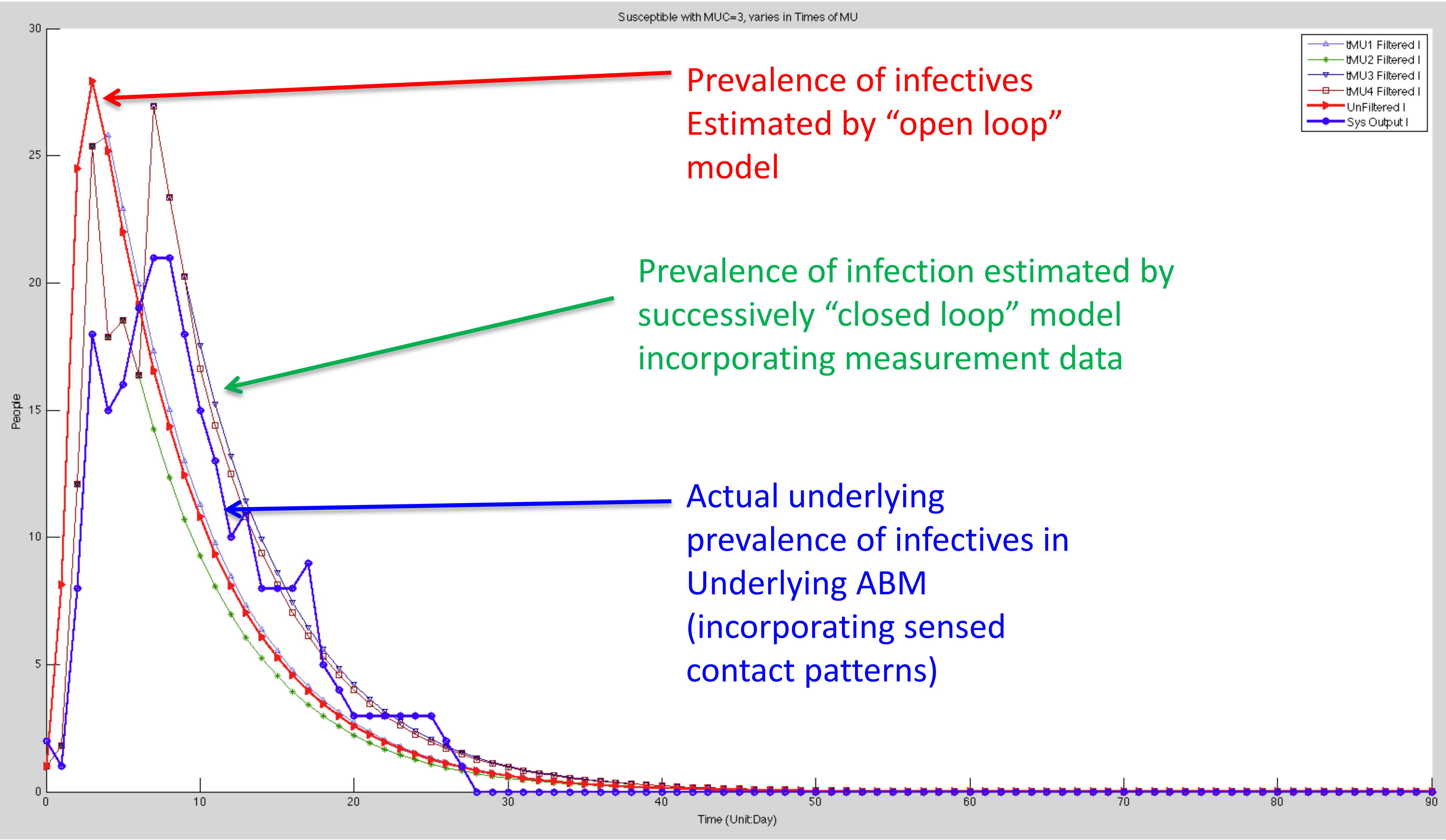
Simplest Case: Only State Updates Measurement Every Other Day



Simplest Case: Only State Updates Daily Measurement Updates



Projecting Forward from Updates



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

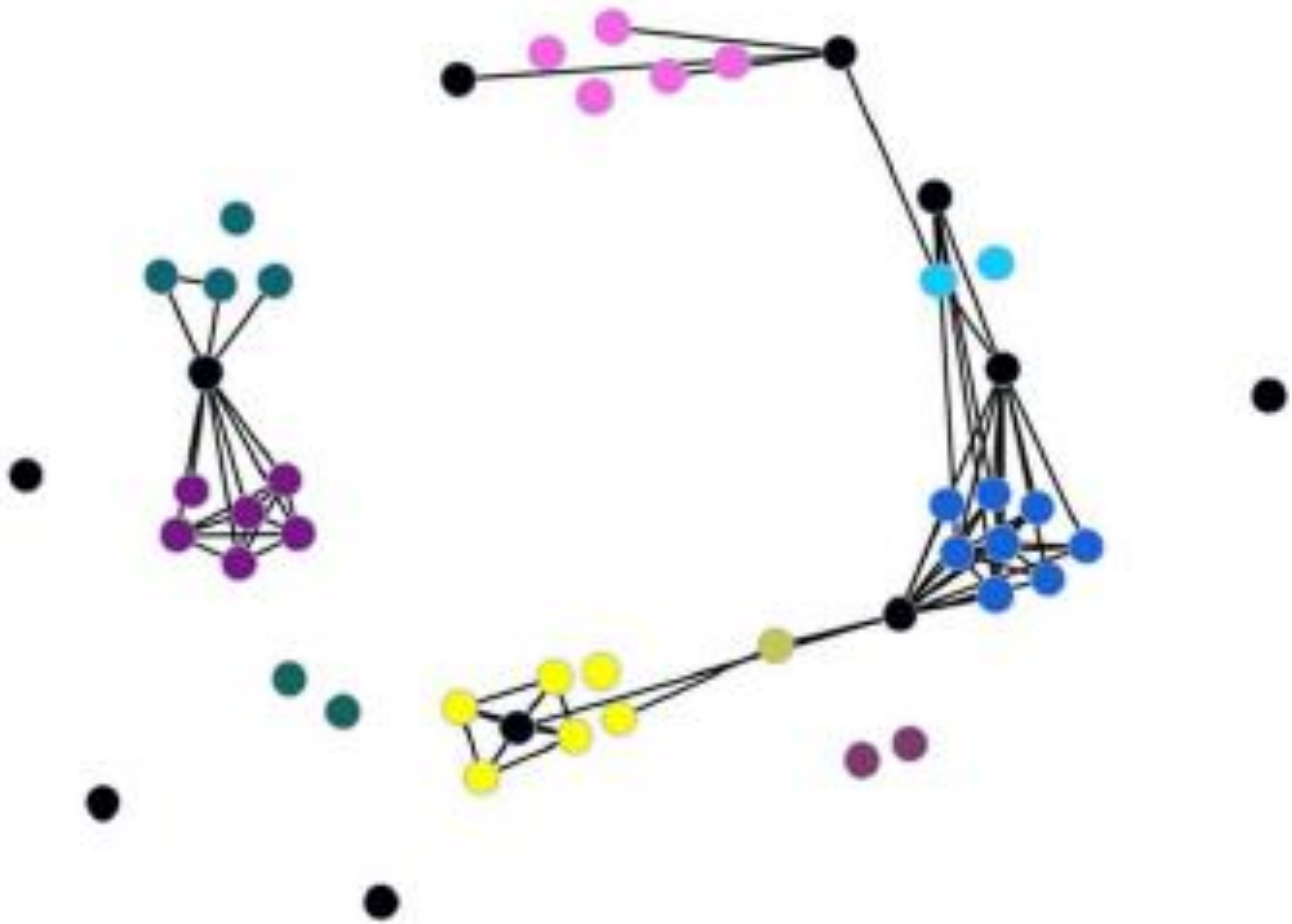
Not Shown Here

- Updating parameters
- Updating estimates of non-observables
- Finer-grained data updates

Outline

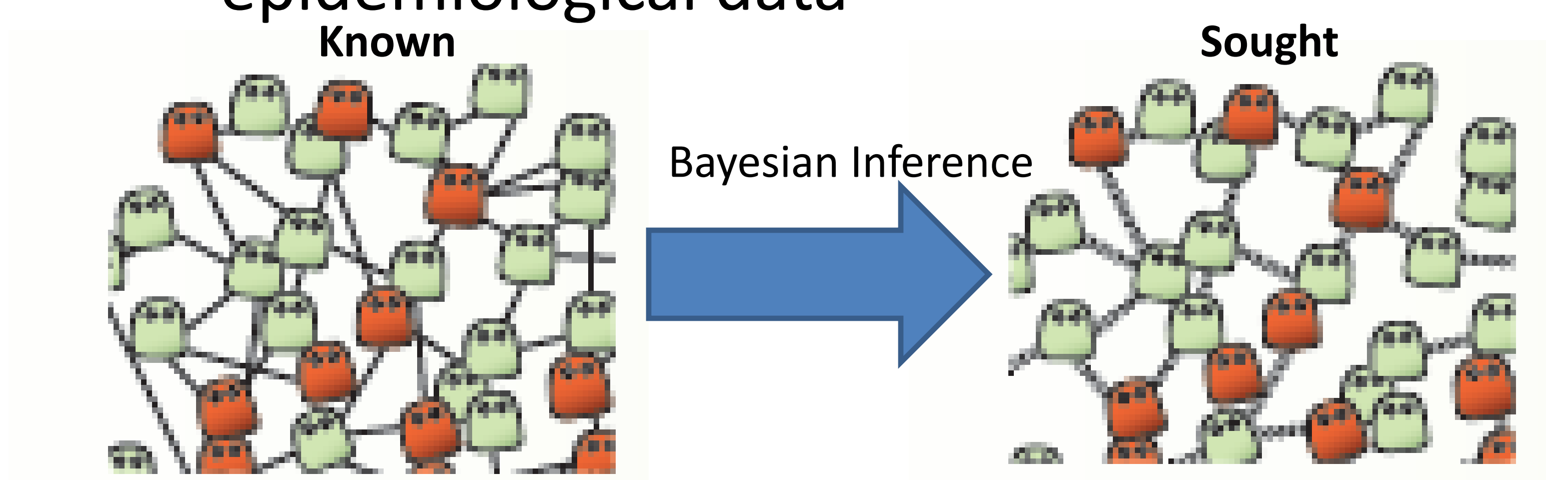
- ✓ Motivations
- ✓ Sensor Platforms
- ✓ "Greater than the sum of its parts": Synergizing models & sensor data
- Vignettes
  - ✓ The role of contact characteristics in the spread of pandemic influenza (ABM & sensor data)
  - ✓ "Self-correcting" models: Synergizing models & ongoing measurement data (SD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

Contact Data can Permit Static or Dynamic Network Reconstruction

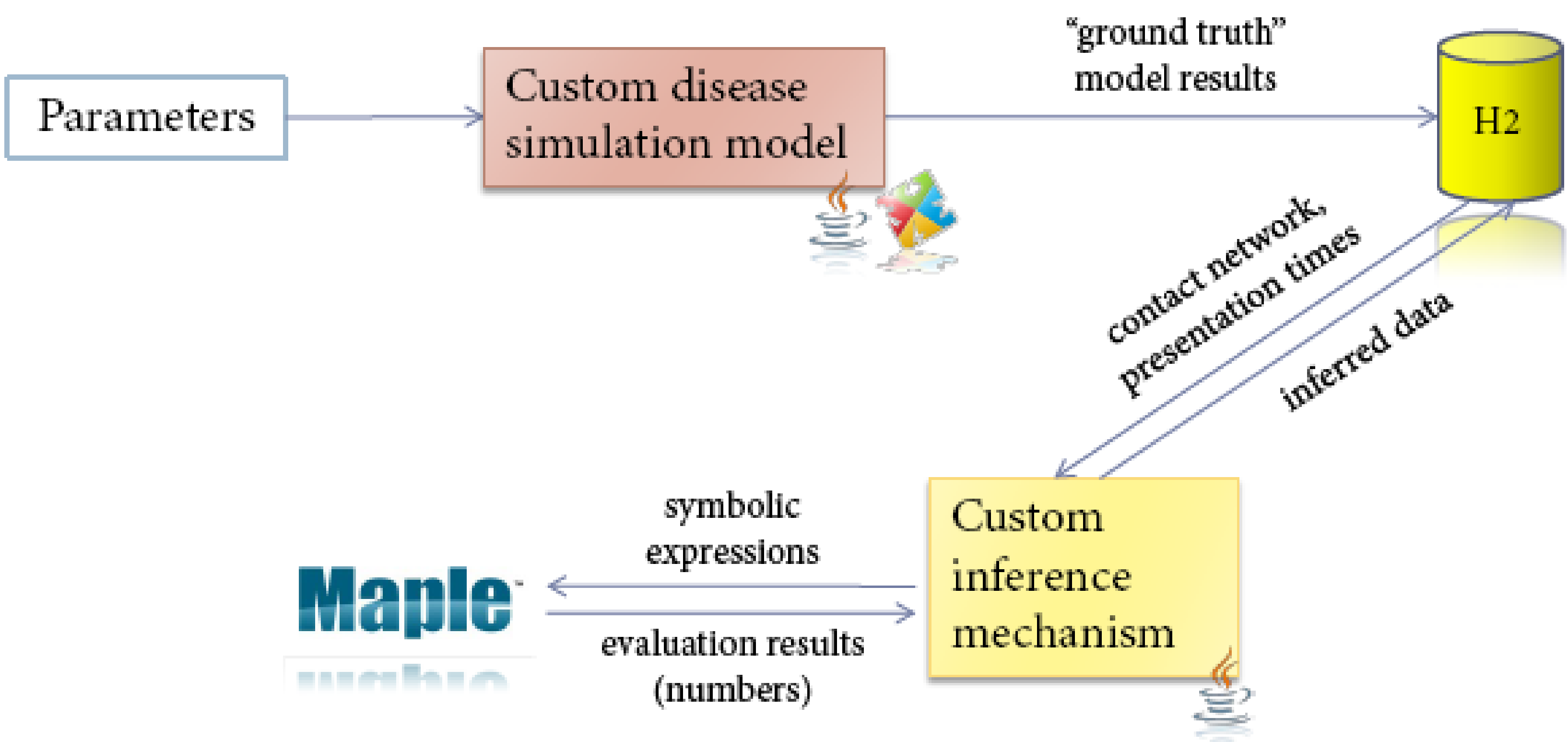


Inferential Models

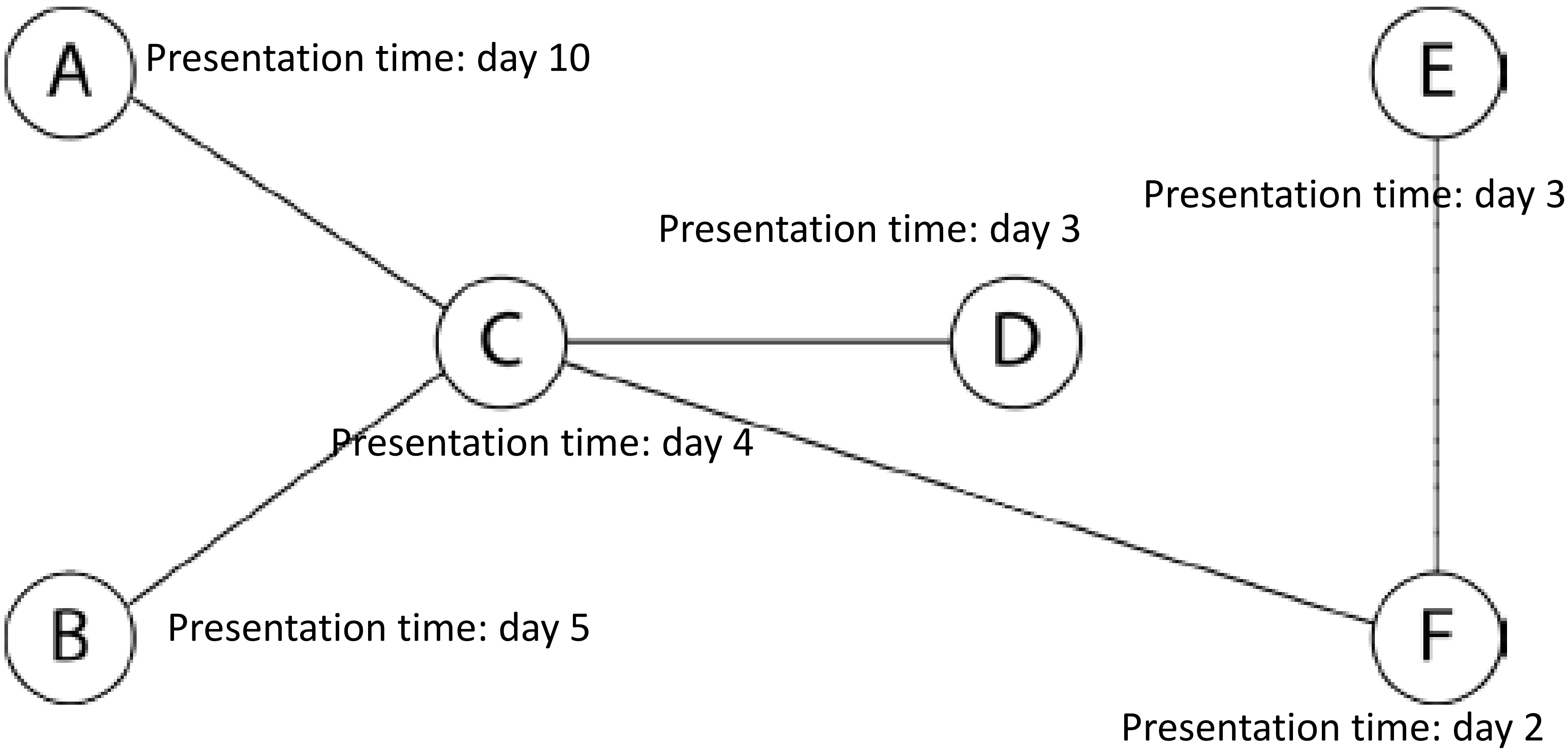
- Can use mathematical formulation of dynamics to express distributions on regarding events
- These formulations can then be used to estimate likelihood of given underlying factor (e.g. A transmitted to B) in light of available data
  – Available data might include molecular epidemiological data



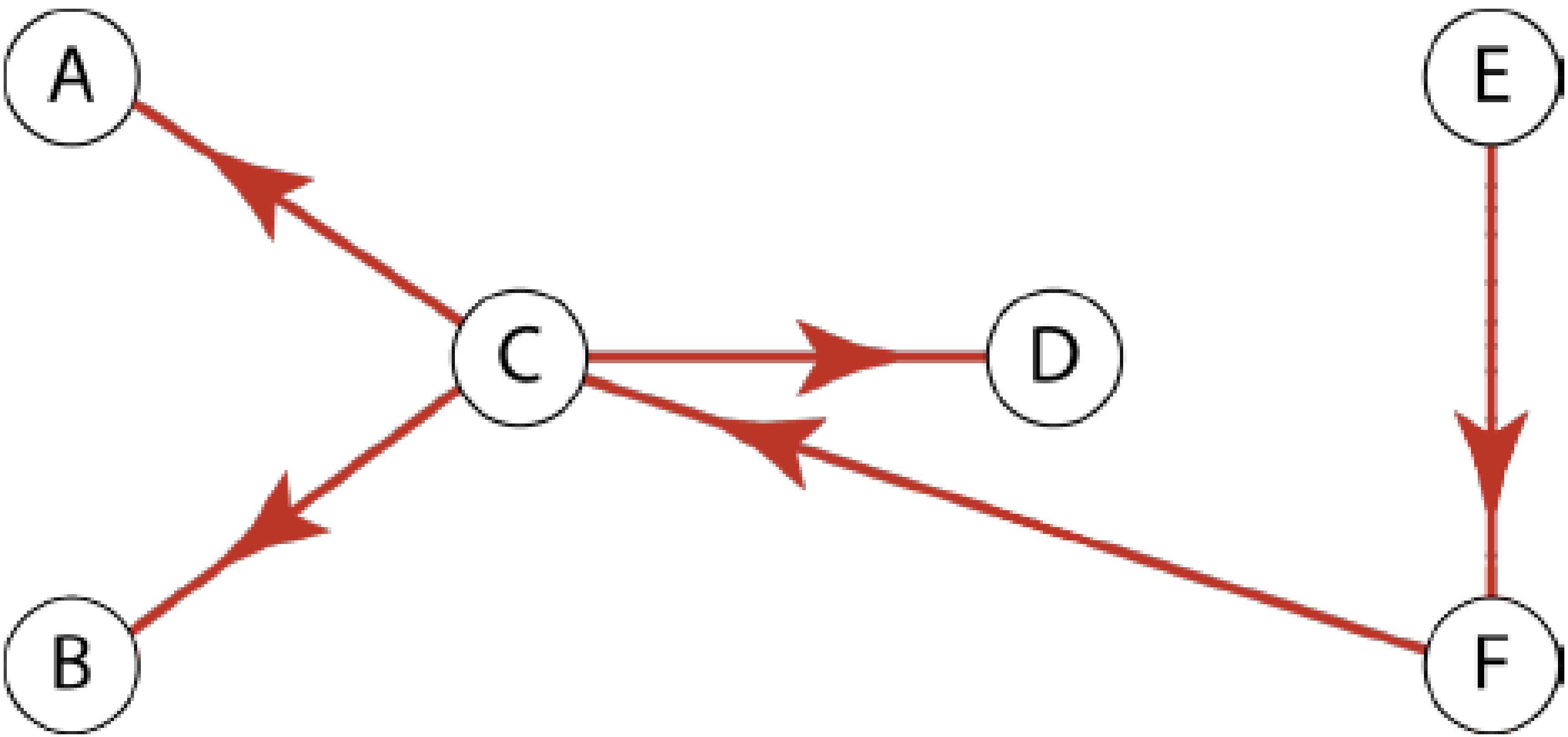
Sensing and Feedback for Epidemiological Modeling to help Evaluate Analysis Strategies



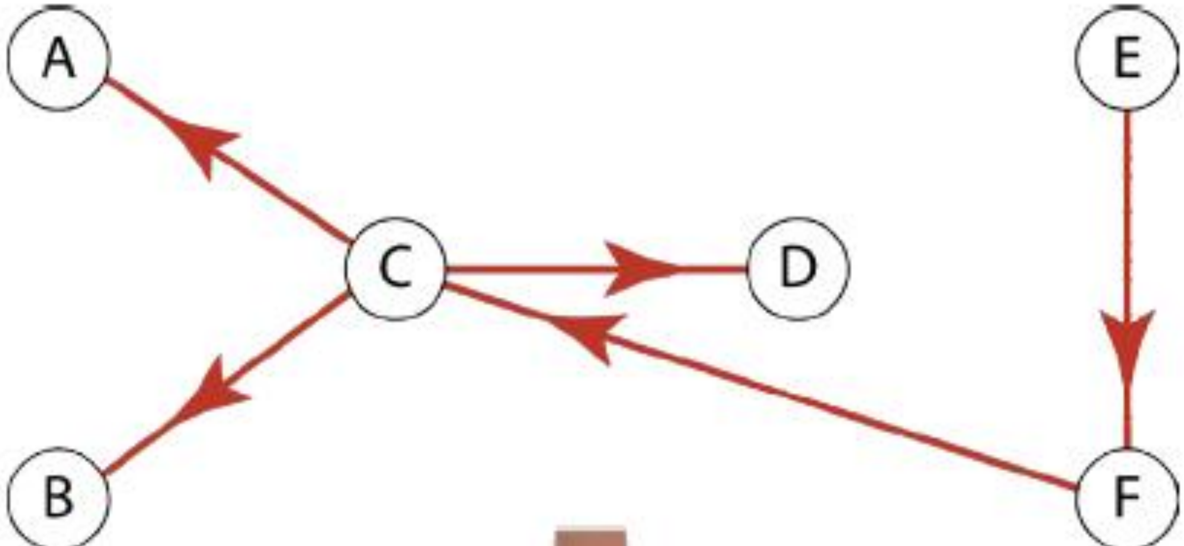
A Simple Contact Network (e.g.Gathered via Sensed proximity)



A Hypothesis for Pathways of Infection Spread



Determination of Expression for Likelihood of Hypothesized Infection Spread Pathway



$$\int_j^{t_B} P(i_E)P(t_E|i_E)\int_{iE}^{t_B} P(i_F|i_E)P(t_F|i_F)\int_{iF}^{t_B} P(i_C|i_F)P(t_C|i_C)\left(\int_{ic}^{t_A} P(i_A|i_C)P(t_A|i_A)\,di_A\right)$$

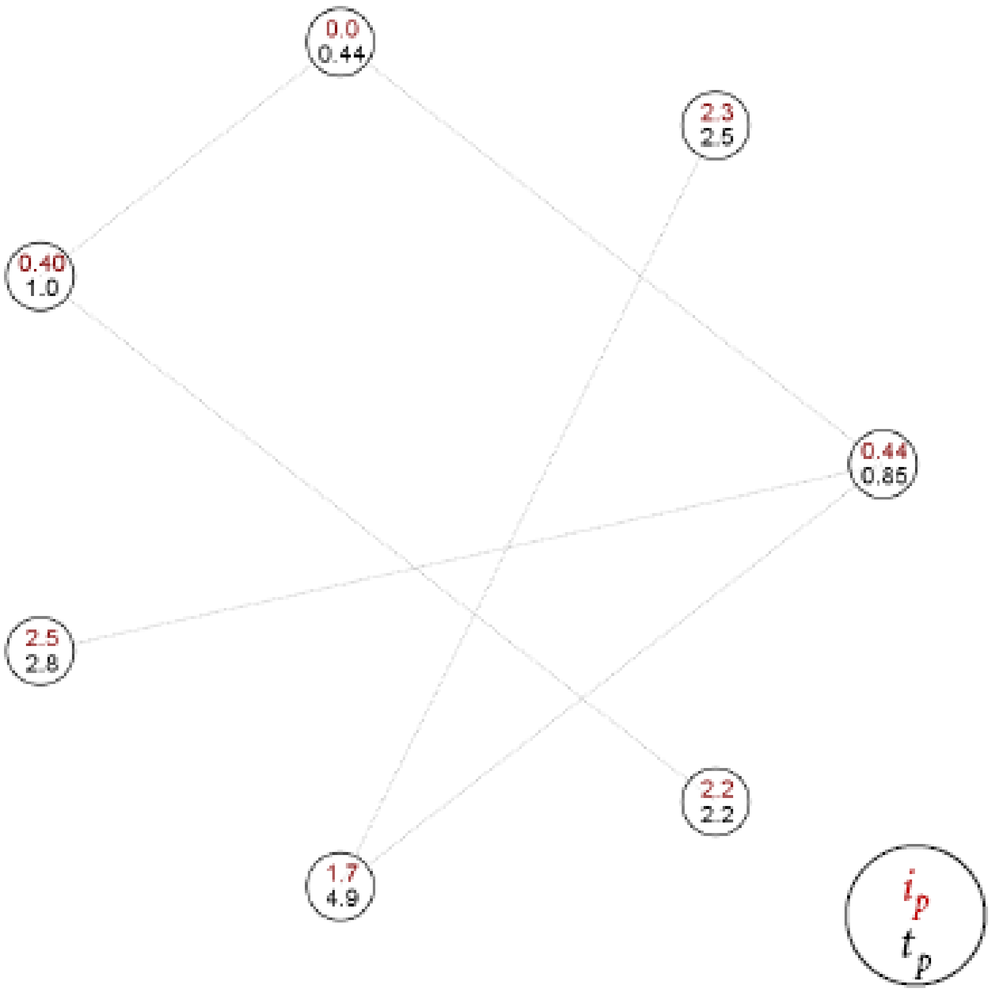
$$\left(\int_{iC}^{t_B} P(i_B|i_C)P(t_B|i_B)\,di_B\right)\left(\int_{iC}^{t_D} P(i_D|i_C)P(t_D|i_D)\,di_D\right) di_C\,di_F\,di_E$$

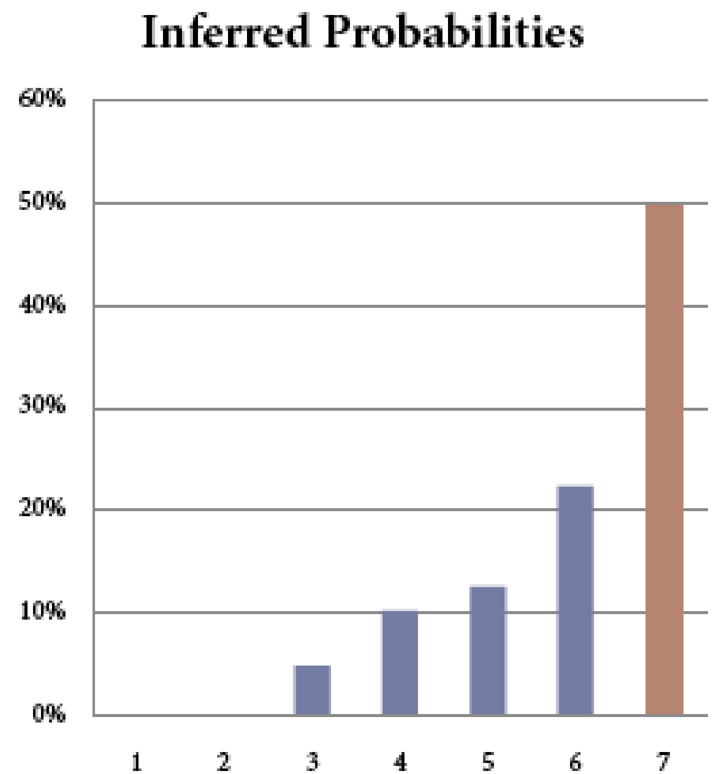
Evaluation of Likelihood

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

$$\int_j^{t_B} \frac{1}{j}\frac{e^{-\frac{t_E-i_E}{\tau_p}}-e^{-\frac{t_E-i_E}{\tau_s}}}{\tau_p-\tau_s}\int_{iE}^{t_B}\alpha e^{-\alpha(i_F-i_E)}\frac{e^{-\frac{t_F-i_F}{\tau_p}}-e^{-\frac{t_F-i_F}{\tau_s}}}{\tau_p-\tau_s}\int_{iF}^{t_B}\alpha e^{-\alpha(i_C-i_F)}\frac{e^{-\frac{t_C-i_C}{\tau_p}}-e^{-\frac{t_C-i_C}{\tau_s}}}{\tau_p-\tau_s}$$
$$\left(\int_{i_C}^{t_A}\alpha e^{-\alpha(i_A-i_C)}\frac{e^{-\frac{t_A-i_A}{\tau_p}}-e^{-\frac{t_A-i_A}{\tau_s}}}{\tau_p-\tau_s}\,di_A\right)\left(\int_{iC}^{t_B}\alpha e^{-\alpha(i_B-i_C)}\frac{e^{-\frac{t_B-i_B}{\tau_p}}-e^{-\frac{t_B-i_B}{\tau_s}}}{\tau_p-\tau_s}\,di_B\right)$$
$$\left(\int_{iC}^{t_D}\alpha e^{-\alpha(i_D-i_C)}\frac{e^{-\frac{t_D-i_D}{\tau_p}}-e^{-\frac{t_D-i_D}{\tau_s}}}{\tau_p-\tau_s}\,di_D\right)\,di_C\,di_F\,di_E$$

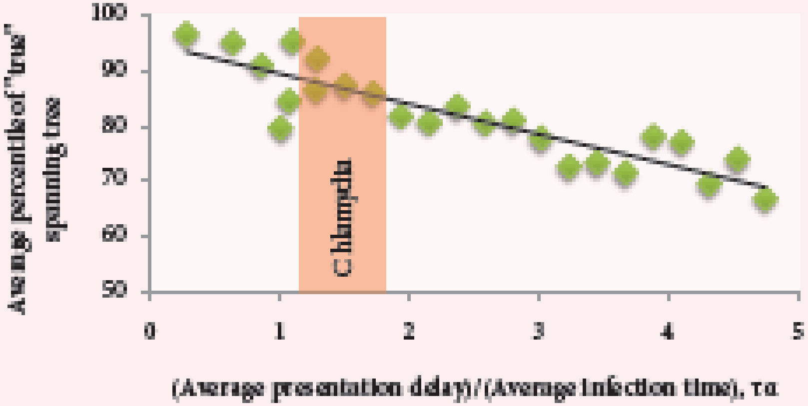
$$= 1.47\%$$



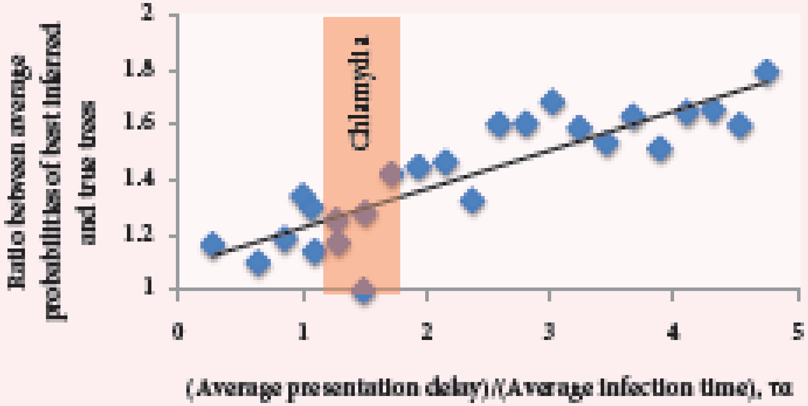


Highlighted bar represents computational model's tree.

Inferring of Complete Infection Pathways (Assessed via Synthetic Data from ABM)

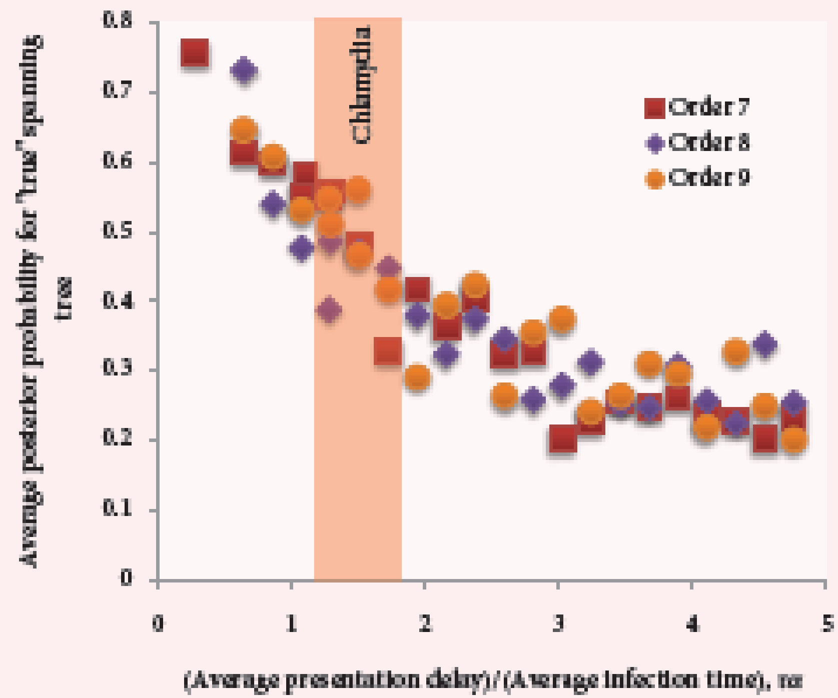


Plot 3: The average percentile of the true tree, as a function of the relative presentation delay.



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's metric is important: the probability of the "true" spanning tree (the underlying pathway of infection that produced a given set of data from the simulation model) demonstrates how much "validity" the inference assigns to it.



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?