Predicting asthma exacerbations using personal sensor monitoring systems

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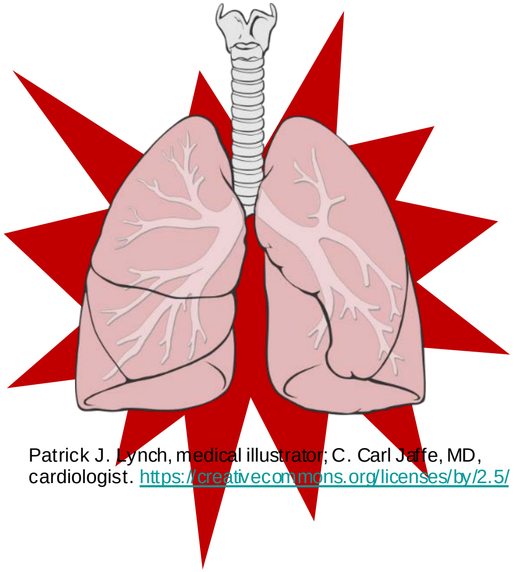
Support: NIBIB U24EB021996 (data center), U54EB022002 (informatics platform & epi study)

Motivation: improve asthma management

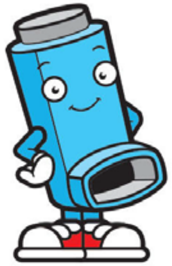
- 1 in 12 people have asthma in the US
  (25 million people)
- ~50% have an asthma attack each year
- Cost of $56 billion per year
  (medical costs, lost school & work days, early deaths)

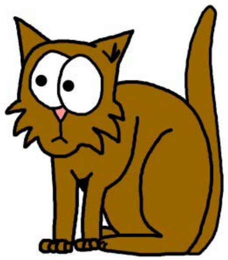


Patrick J. Lynch, medical illustrator; C. Carl Jaffe, MD, cardiologist. https://creativecommons.org/licenses/by/2.5/

- Many asthma attacks can be prevented by using long-term controller medications correctly and avoiding triggers

→ Mixed success of asthma management plans





Images: http://clipart-library.com/clipart/33171.htm
https://preview.tinyurl.com/yb6j8fn5

Data: https://www.cdc.gov/vitalsigns/asthma/index.html

PRISMS

Pediatric Research Using Integrated Sensor Monitoring Systems

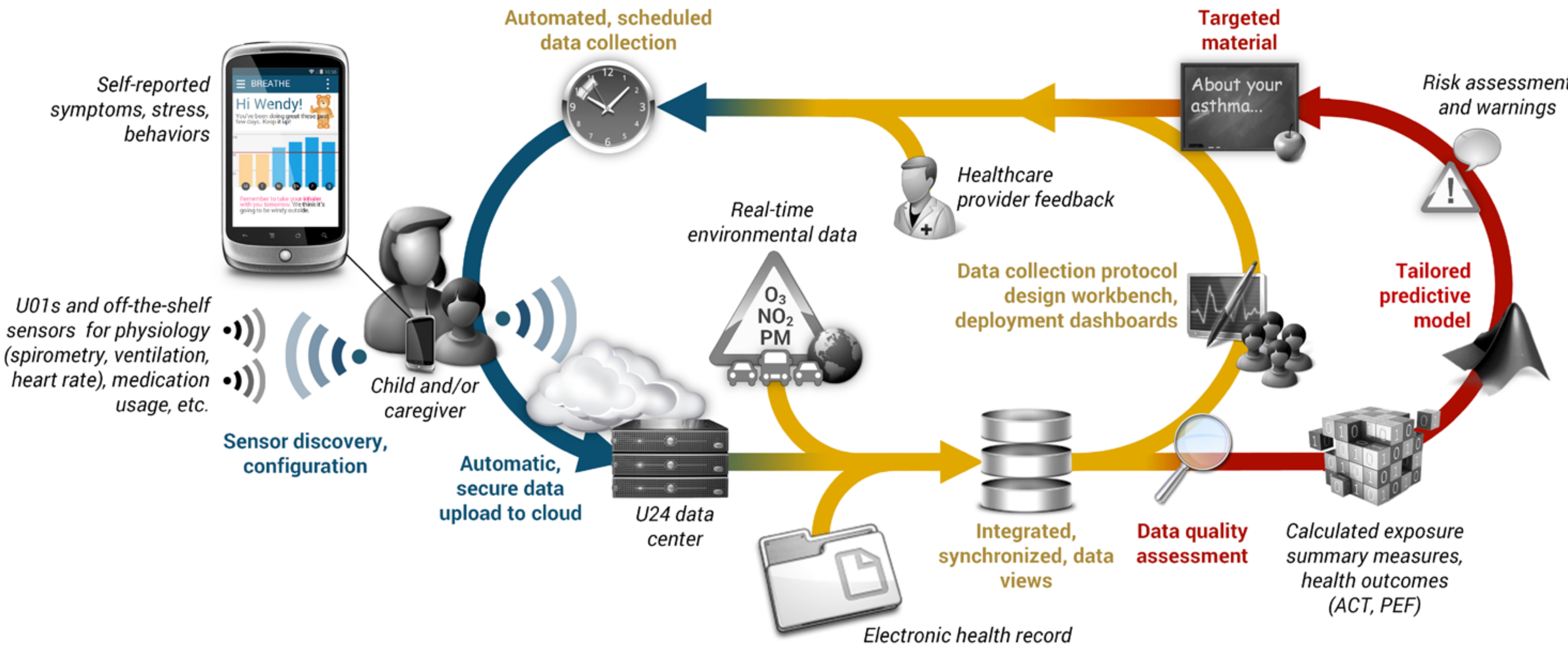
http://prisms-study.org/

- Launched in 2015 by the National Institute of Biomedical Imaging and Bioengineering (NIH/NIBIB)

- **Goal:** Develop sensor-based, integrated health monitoring systems for measuring environmental, physiological, and behavioral factors in pediatric epidemiological studies of asthma, and eventually other chronic diseases

- Three arms of PRISMS:
  - 6 Sensor Development Projects
  - 2 Informatics Platforms
  - 1 Data and Software Coordination and Integration Center

PRISMS ecosystem



(from UCLA/USC LA BREATHE U54 platform, PI: Bui)

Types of data to be collected

Typical data structure:

- Time stamp (GPS stamp)
- Multiple or single features (possibly pre-processed)
- Recorded continuously or on-demand, upload frequency to optimize power

Sensors

- GPS
- Accelerometer/gyroscope to classify physical activity
- Spirometry
- Inhaler use
- Environmental measures (PM, NO_2, near roadway pollution, etc.)

Real-time environmental data

- Weather
- Pollen
- Air quality indices
- Nearby traffic volumes
- Indoor/outdoor metrics

Self-reported measures

- Ecological momentary assessment (EMA) for asthma symptoms, inhaler usage, stress
- Validated questionnaires (health status, physical activity, etc.)

Electronic health record

- Demographics, vitals
- Medications
- Allergies and documented triggers
- Health status and comorbidities
- Pulmonary function tests, labs
- Past exacerbations (e.g., ER visits)

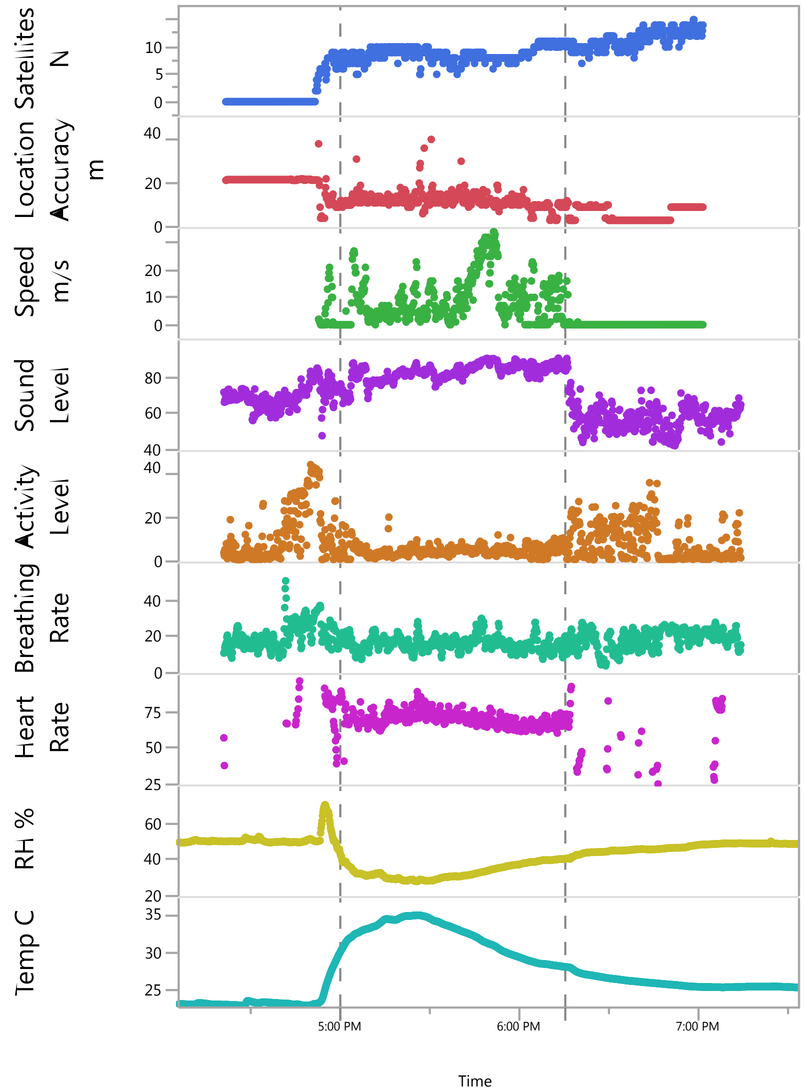
Example data: Contextual, real-time info

Evening Commute Example

Phone Sensors, including Geolocation Accuracy

Physiological Sensors

Meteorology Sensors



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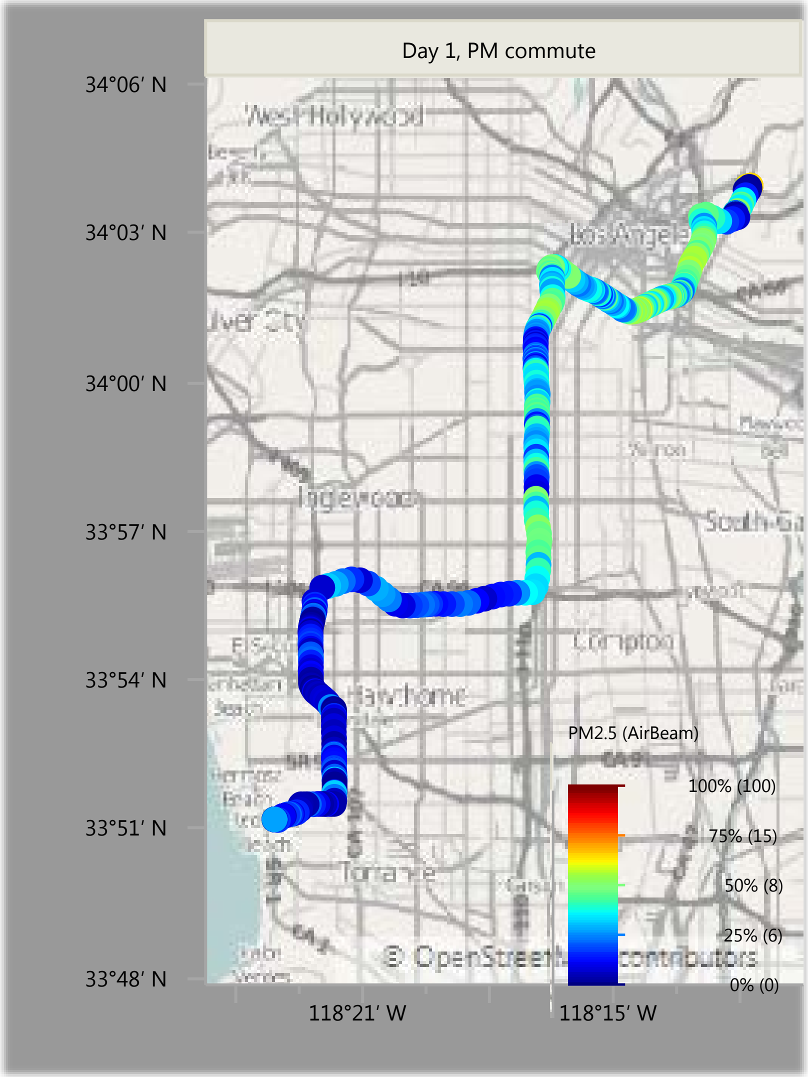
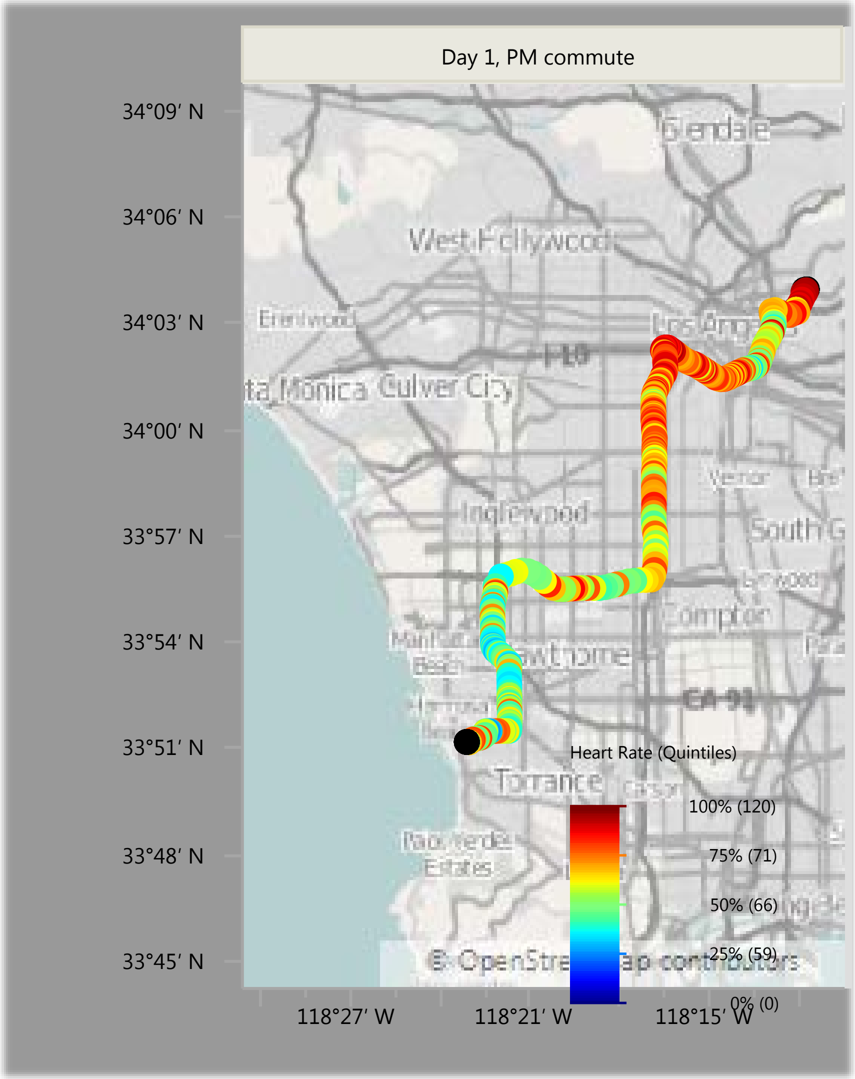
Example data: Spatial patterns, evening commute

Air Pollution



Heart Rate



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Conceptual overview of PRISMS data analysis

1. Evaluate sensors
[reliability, validity, etc.]

2. Data collection
- Baseline info
- Ongoing collection [user adherence]

[Metadata for data interpretation]

3. Key themes of planned PRISMS data analysis

- **Unsupervised cluster analysis/pattern detection**
  [e.g., identify asthma phenotype groupings]
- **Identify individual baselines** (e.g., Li et al *PLoS Biology* 15.1 (2017): e2001402)
- **Supervised prediction of deviations from typical patterns**
  A. Population-based models
  B. Cluster-specific population-based models
  C. Individualized prediction models

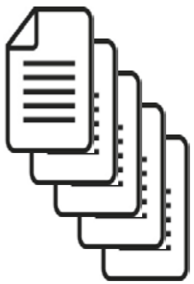
Personalization

Combine ensembles of models

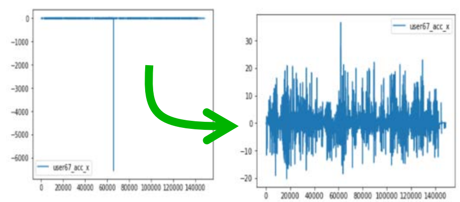
- **Real-time prediction**
  - Train models offline (nightly) and apply to real-time streaming data

Statistical analysis pipeline: raw data → health model

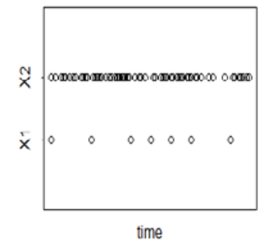
1. Data processing



Raw data files



Noise filters

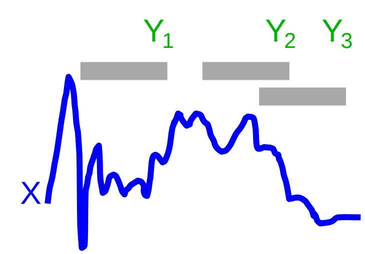


Temporal alignment

$$x \rightarrow \begin{matrix} f_1(x) \\ \vdots \\ f_k(x) \end{matrix}$$

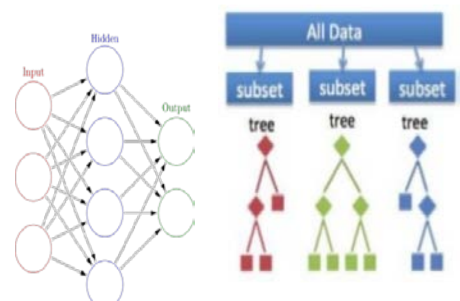
Transformation

2. Feature engineering

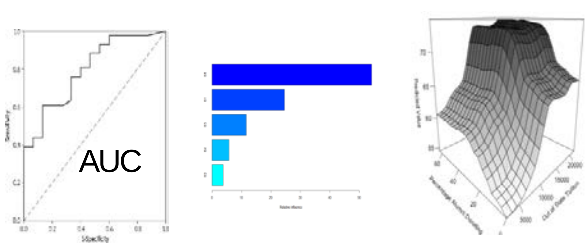


Summarize within windows

3. Modeling



Machine learning: model Y ~ **X**



Model performance, prediction, interpretation

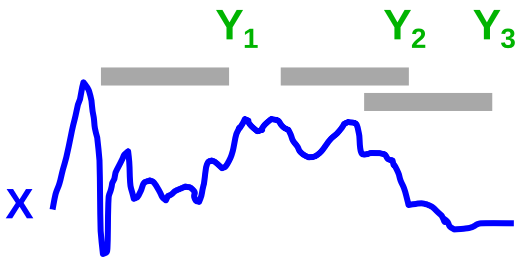
Broad challenge in health modeling: X→ Y

Summarizing/integrating exposures (X):

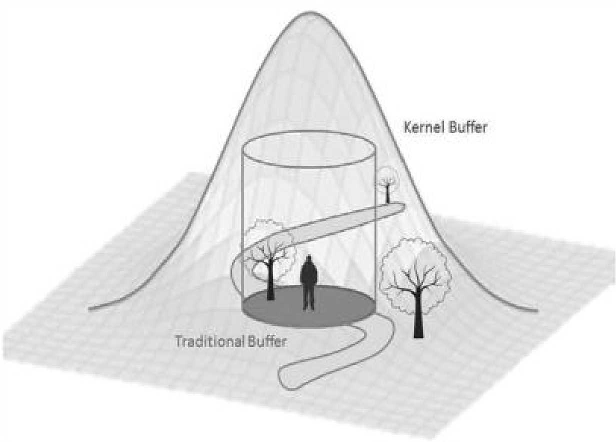
- Most assessed ~continuously
- At high spatial & temporal resolution

Matching to health outcomes (Y):

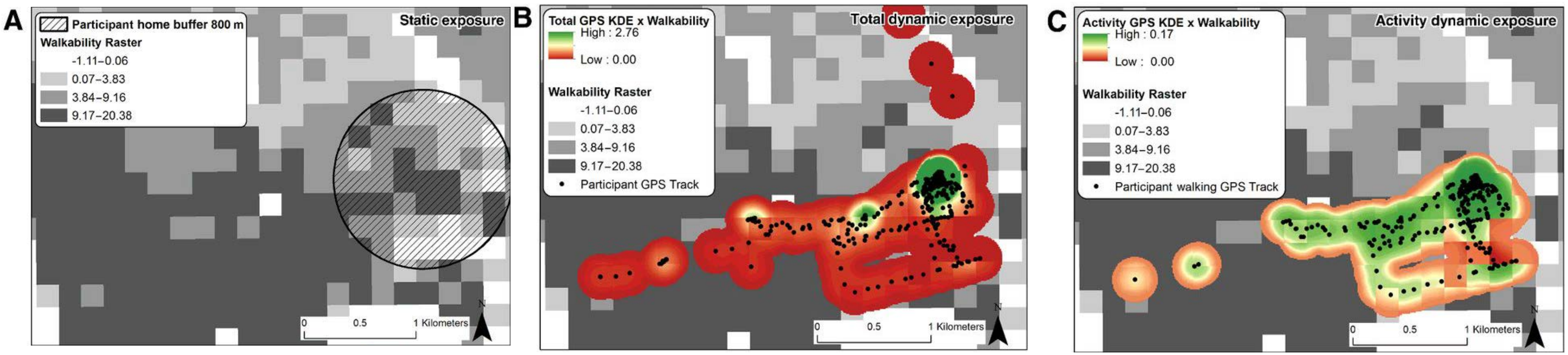
1. Assessed continuously (e.g., heart rate)
2. Assessed at regular intervals (e.g., twice daily peak flow, daily asthma control test score/symptoms diary, EMA symptoms)
3. Intermittent report of (rare) events (e.g., rescue use of smart inhaler, ER hospitalization)



Exposure assignment: GPS trajectories



Time-weighted kernel density smooth



Jankowska M, Natarajan L, Godbole S, Meseck K, Sears DD, Patterson RE, Kerr J. Kernel Density Estimation as a Measure of Environmental Exposure Related to Insulin Resistance in Breast Cancer Survivors. Cancer Epidemiol Biomarkers Prev. 2017 Jul; 26(7):1078-1084. PMID: 28258052.

Jankowska M, Schipperijn J, Kerr J. A framework for using GPS data in physical activity and sedentary behavior studies. Exerc Sport Sci Rev. 2015 Jan; 43(1):48-56. PMID: 25390297; PMCID: PMC4272622.

PRISMS can impact two major areas

1. **Environmental epidemiology research**
   - Understand environmental contributions to asthma exacerbations
   - New paradigm for exposure sciences (fine-scale personal exposures, with spatial and contextual info)

   → New public health policies

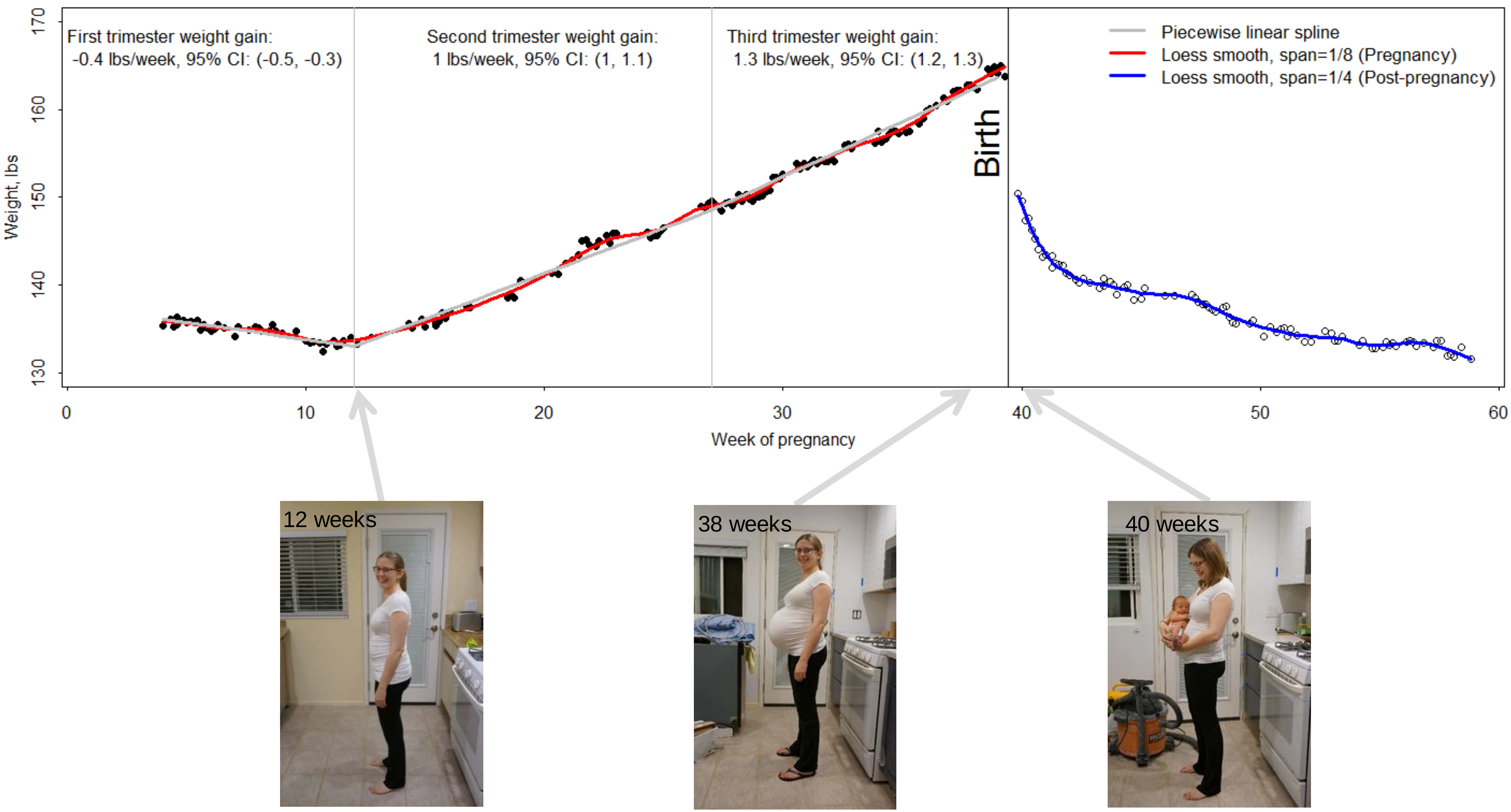
2. **Personalized medicine**
   - Trigger identification and avoidance
   - Personalized decision-making

   → Improved personal asthma management

What questions can these data answer? Policy implications?

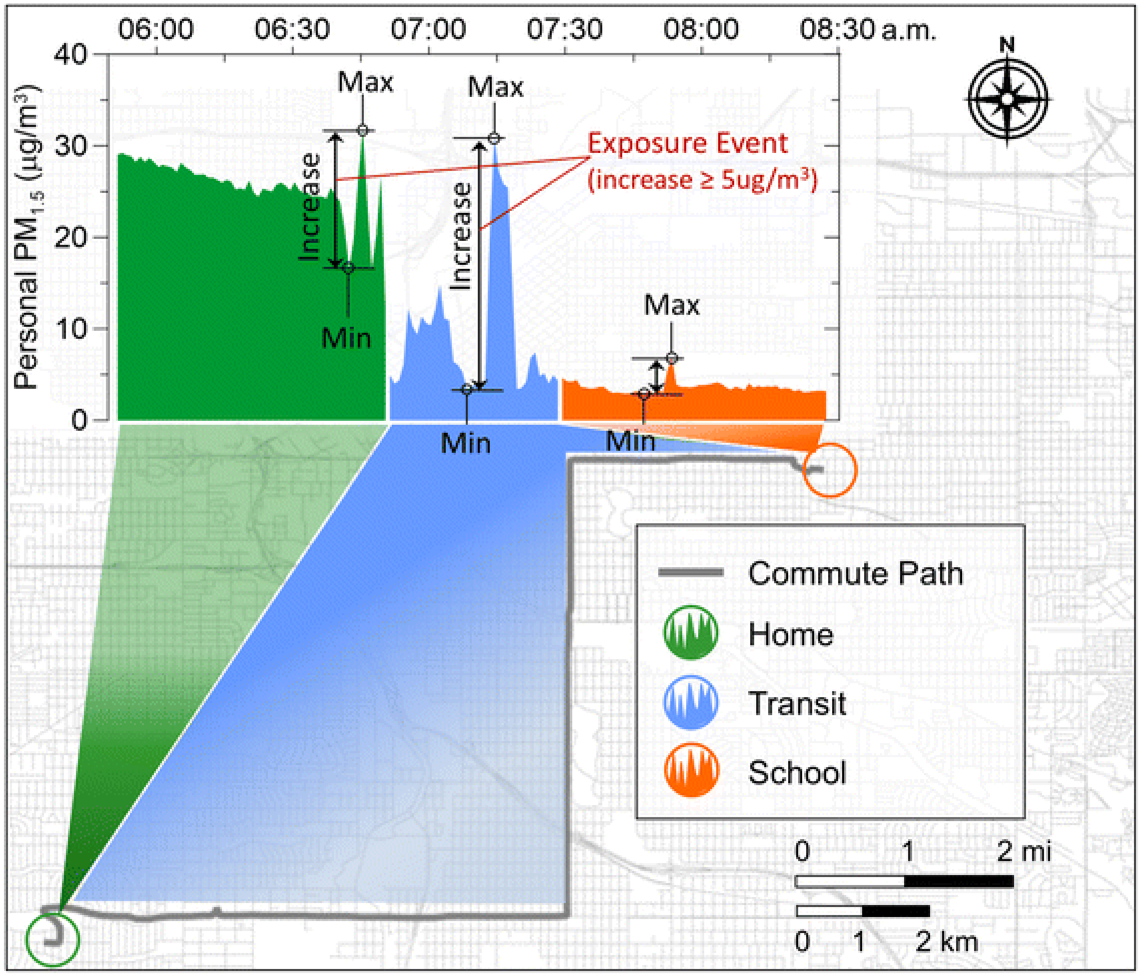
- Time course of exposure-response
  - Relevant averaging time for air quality standards
- Context: Health effects of personal vs ambient exposures
  - $PM_{2.5}$ from cooking or commuting: which is more toxic?
- Identify new sources/triggers
  - Are we missing a “smoking gun”?
- Heterogeneity of response to exposures (personal models)
  - Standards to protect health of vulnerable groups
- Can personalized data improve asthma management?
  - EMA questionnaires: symptoms, stress, etc. in context
  - Patient engagement and empowerment

Patient engagement: a personal example

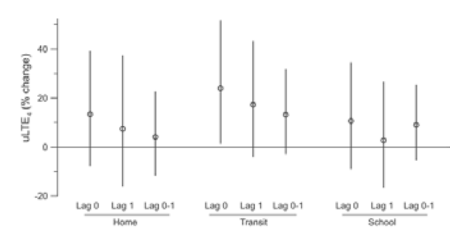


Eckel, S. (2017), The ups and downs of pregnancy. Significance, 14: 10–11. doi:10.1111/j.1740-9713.2017.01032.x
http://onlinelibrary.wiley.com/doi/10.1111/j.1740-9713.2017.01032.x/full#sign1032-fig-0001

Environmental epidemiology: PRISMS-like study



- 30 children, 8 days
- Personal exposure to fine particulate matter divided by microenvironment
- Exposure "spikes" during transit (vs. home or school) were most strongly related to biomarker of exposure



Rabinovitch, N., Adams, C.D., Strand, M., Koehler, K. and Volckens, J., 2016. Within-microenvironment exposure to particulate matter and health effects in children with asthma: a pilot study utilizing real-time personal monitoring with GPS interface. *Environmental Health*, *15*(1), p.96.

Challenges and open questions

- **Wearable sensors have to be *worn***
  - Compliance, missing data
  - How do specific sensors need to be worn? Is GPS enough?
- **Sensors *sense***
  - Will we measure the right things?
- **Cheap sensors are *cheap***
  - Requires calibration, more expensive QA/QC, processing
  - Incorporate data quality metrics in models?
- **Personal monitoring is *personal***
  - Privacy/Ethics issues: GPS trajectories, heart rate, etc..
- **Real-time sensors are *real-time***
  - Large volumes of data, potentially not relevant timescale
  - Feedback to user can influence behavior

Thank you!

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