Data Science for Human Well-being

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Science Is Revolutionized By Data
Lessons from Online Social Networks

Network structure
- Small-World [Watts & Strogatz, 1998]
- Powerlaw topology [Faloutsos, 1999]
- Bowtie structure [Broder et al., 2000]

Network behavior
- Communication patterns [Leskovec & Horvitz, 2008]
- Information diffusion [Romero et al., 2011]

Lessons limited to Online Behavior

But how to capture offline behavior?

Wearable and Mobile Devices

69% adults own smartphones in developed countries
46% in developing economies (rapidly growing)

Wearable and mobile devices generate massive digital traces of real-world behavior and health
What did we learn from these data?

- Treasure of data with great promise
  - Data available for many years (e.g. Fitbit founded in 2007)
  - Data is regularly thrown away and overlooked

Today: How can we gain well-being insights from these data?

Physical Activity  Sleep  Mental Health

How to gain insights from these data?

Data Experts
Don’t know what questions to ask & scientific impact

Domain Experts
Don’t know data and how new methods could address their big questions

Gaining insights requires intersection of
- Knowing CS methods to extract insights from massive data
- Knowing data, its limitations, and how to address them
- Knowing big questions and how to find new ways to address them
My Research

New computational methods for digital activity traces to understand and improve human well-being

- Work with terabyte-scale data
- Conduct massive observational studies
- Generate actionable insights
- Impact health applications

Digital Activity Traces: The Data

- Multimodal data about our behaviors and health
  - Sensor data
  - Device usage data
  - Social interactions
  - Language

- Activity and health data across millions of people
  - Massive scale
  - Granular detail
  - Continuous & Long-term
  - Low cost
Impact of Digital Activity Traces: Health & Domain Experts

Limitations of health research today:

- Confined to laboratories
- Short-term (≤5 days), small scale (≤50 subjects), (binary) resolution
- Biases from self-reports/surveys (up to 700% off!)
- High cost

➔ We know very little about our behavior & health
  - How much do people exercise? What do people eat? What do they struggle with?

• Opportunity: Improve human well-being
  - Advance science: Better understanding of human behavior and health
  - Improving healthcare: Actionable insights

However...

...there is lack of computational models and large-scale analyses of digital activity traces for human well-being
Why is it hard to build a bridge?

Computational Challenges

Need new methods to address data limitations and model domain knowledge and questions.

1. How to integrate anecdotal and qualitative domain knowledge into computational models for empirical validation at scale

2. How to infer well-being from noisy raw data, or multimodal data sources

3. How to turn observational, biased, scientifically “weak” data into strong scientific results

Research Overview

• Methods
  • Data Mining  
    WWW’18a, WWW’18b, WWW’18c, WWW’17a, WWW’15, KDD’15
  • Social Network Analysis  
    WSDM’17, WWW’17b
  • Natural Language Processing  
    TACL’16, ICWSM’14

• Application Domains
  • Health, Medicine and Psychology  
    Nature’17, JMIR’16, NPJ DigMed’18, Pervasive Health’17
This Talk

Data Science Methods for Human Well-being

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Research Impact

My methods and insights are used at...

Physical Activity
- Under Armour
- azumio
- NASA

Sleep
- Microsoft
- Bing

Mental Health
- CRISIS TEXT LINE
- talkspace
- THERAPY FOR HOW WE LIVE TODAY
In This Part…

1. **How do patterns of activity vary globally?**
   [Althoff, Sosic, Hicks, King, Delp, Leskovec - Nature, 2017]
   - **Macro-scale:** Leverage ubiquitous smartphone usage to study physical activity at planetary scale
   - Defined & studied new measure: **Activity Inequality** (unevenly distributed activity)

2. **How can we model everyday behavior?**
   [Kurashima, Althoff, Leskovec - WWW, 2018]
   - **Micro-scale:** New machine learning methods to combat activity inequality by learning when to encourage individual users
Activity Tracking

Tracking actions
• Steps (automatic)
• Runs
• Walks
• Workouts
• Biking
• Weight
• Heart rate
• Food
• Drinks
• And many, many others

The Data

• Industry collaboration: Azumio freely shared data for open academic research

Azumio Dataset Statistics
• 5.6 million users
• Users from over 120 countries
• 791 million actions recorded
• 160 million days of steps tracking
  • >230 billion data points (3TB)

Challenge: How to connect data to long-standing domain questions?
Physical activity is extremely important for health [Lee et al., 2012]. But we do not know how much physical activity people get!

According to WHO:
• 5-54% of Germans don’t get enough activity
• No data for Switzerland and Israel

Health research limitations today:
• High cost, short-term, limited scale
• Biases from self-reporting

Worldwide Activity

But, how is activity distributed within the population?
Result 1: Inequality of Physical Activity

Difference in means

For the first time, sufficient data to estimate tails of distribution

- How (un)evenly is activity distributed?
- Gini index of the activity distribution:
  - Activity rich vs. activity poor people

\[ G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2 \sum_{i=1}^{n} \sum_{j=1}^{n} x_j} \]

Result 2: Activity Inequality Predicts Obesity

Tails/extremes matter more than the mean

\[ R^2 = 0.64 \] (vs. 0.47 for avg. activity)

Massive digital traces uniquely enable studying tails!
The Challenge: Convincing Domain Experts

• New concept + new instrument = skepticism
• Domain experts know that these data are ...
  • Noisy
  • Sometimes inaccurate
  • Observational
  • Biased and full of selection effects
• That is why data have been thrown out before
• Designed and conducted over 20 reweighting, resampling, stratification, and simulation experiments to demonstrate validity of results

Demonstrating Validity of Results

...in light of valid concerns
• Flawed sensor?
• But women wear phones less?
• Obesity data inaccurate?
• Biased population?
• Due to rich people?
• Missing data? Outliers?
• Inaccuracy of location inference?
• Reproducible: Released analyses and data at http://activityinequality.stanford.edu
Research Implications

- Pioneered new paradigm for monitoring populations
- Working with public health researchers on implications for obesity, policy, urban planning

How to improve health by combating activity inequality?

- **Next:** Moving from macro to micro level
  - How to target notifications and reminders for each individual to encourage healthy behavior?

Modeling Everyday Behavior

- Apps tracks everyday behaviors: drink, food, sleep, weight, heart rate, running, walking, stretching, biking, workout, …

How can we model this behavior?

Kurashima, Althoff, Leskovec - WWW, 2018
Modeling Task

• **Task:** Model *what* action user will take next and *when*

Why is this useful?
• **Predictions** useful as interventions if they are **timely** and **explainable**
  • Timeliness: Diet support – send diet reminder *just before* meal choice
  • Explainability: “Hey, we saw you missed your weekly run this morning. How about tomorrow morning?”

Why Is This Task Hard?

• **Human behavior is highly complex**
  • Actions vary *over time*
  • Interdependencies in short- & long-term
  • Creatures of habit with *periodic behaviors*
  • Individual preferences

• **Model requirements**
  • Predict *action* and *continuous time*
  • Need **timely** and **explainable** predictions
Background: Temporal Point Processes

- **Definition**: Random process whose realization consists of a list of discrete events localized in time \( \{t_n\}_{n \in \mathbb{N}} \) with \( t_n \in \mathbb{R}^+ \)

- **Benefits**
  - Generative process that predicts both action and time
  - Flexible through *conditional intensity function* \( \lambda(t'|H_t) \) where \( H_t \) represents the history of actions until \( t \)

- Conditional density that **an event occurs** at time \( t' \)

\[
f(t'|H_t) = \lambda(t'|H_t) \exp\left(-\int_t^{t'} \lambda(\tau|H_t)\,d\tau\right)
\]
Real Activity Data

Color denotes activity type

Short-term dependencies between actions. Workout → Heart rate
Real Activity Data

My Approach: Three Components

1. **Short-term interdependencies** between actions
2. **Long-term periodic effects**
3. **Time-varying action propensity**
1. Short-term Interdependency

**Empirical Evidence**

Model: Exponential Distribution

\[ \text{ShortTerm}_u(t, a) = \sum_{(t', a') \in H_{ut}} \theta_{a' a} \omega_{a' a} \exp(-\omega_{a' a} \Delta t' t) \]

- **Exponential** \( \omega_{a' a} > 0 \) Rate parameter – Shape
- **Importance** Sum over all previous events

2. Long-term Periodicity

**Empirical Evidence**

Model: Weibull Distribution

\[ \text{LongTerm}_u(t, a) = \sum_{t' \in H_{ut}^a} \phi_{c_t' a} \gamma_{c_t' a} \kappa_{c_t' a} \Delta t' t^{\kappa_{c_t' a} - 1} \exp(-\gamma_{c_t' a} \Delta t' t) \]

- **Weibull** \( \kappa_{c_t' a} > 0 \) Shape \( \gamma_{c_t' a} > 0 \) Scale
- **Importance** All previous events of same type

[WWW’18a]
3. Time-varying Action Propensity

### Empirical Evidence

![Graph showing time of day (hours) vs. fraction of events (biking)]

<table>
<thead>
<tr>
<th>Time of day (hours)</th>
<th>Fraction of events (biking)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>0.04</td>
</tr>
<tr>
<td>4</td>
<td>0.08</td>
</tr>
<tr>
<td>6</td>
<td>0.04</td>
</tr>
<tr>
<td>8</td>
<td>0.00</td>
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<tr>
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<td>18</td>
<td>0.04</td>
</tr>
<tr>
<td>20</td>
<td>0.08</td>
</tr>
<tr>
<td>22</td>
<td>0.04</td>
</tr>
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</table>

#### Model: Mixture of Gaussians

\[
Time_u(t, a) = \sum_{z \in Z} \frac{\beta_{az}}{\sqrt{2\pi}\sigma_{az}^2} \exp\left(-\frac{(l_t - \mu_{az})^2}{2\sigma_{az}^2}\right)
\]

- **Gaussian**
- **Importance:** How likely does Gaussian trigger event?

#### Model Inference

\[
\lambda_u(t, a) = \alpha_{ua} + Time_u(t, a) + ShortTerm_u(t, a) + LongTerm_u(t, a)
\]

- **Personalization factor**

- Learn parameters via **Expectation-Maximization algorithm**
**Prediction Results**

- Action prediction (10)
- Time prediction

**Model Explainability**

- Few model parameters (~500)
- Can visualize inferred distributions to see what TIPAS model learned from data

*Earlier lunches mean earlier dinners! (~5h period)*

*Not obvious! Does not hold for dinners!*

*Important for interventions (e.g. diet reminder)*

---

[WWW’18a]
Modeling Summary

- **Generative model** that encodes empirical insights on human behavior
  - Takes previous actions into account (early lunch)
  - Models interdependencies between actions
- **Predictions** enable personalized health interventions
  - Timely and explainable predictions tell us when & how to notify users


Next

**Data Science Methods for Human Well-being**

**Physical Activity**

1. How do patterns of activity vary around the world?
2. How can we model & predict everyday behavior?

**Sleep**

3. How to use search engines for sleep insights?

**Mental Health**

4. How to use natural language processing to improve mental health care?
In This Part…

• **Q:** How does sleep affect cognitive performance?
• **Bridge:** Search logs studied for a decade, domain experts never thought of looking there
  • First-ever combination of web search and wearable data
  • Statistical model encoding biological domain knowledge

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Key Insight: Cognitive Performance through Search Engine Interactions

• Search engines are used repeatedly every day, awake or sleepy, by billions of people

• **Key insight:** Reframe everyday interactions with web search engine as series of performance tasks
  • Query typing speed (or click on search result)

\[
\Delta t(c) = 237\text{ms} \quad \Delta t(e) = 219\text{ms}
\]
Result: Real-World Performance Variation

Factors affecting performance at 4am
(1) Awake for many hours
(2) Humans are always slow at 4am
(3) Just got up and slow afterwards

• Performance far from constant (31% variation)

How can we distinguish these three factors?

Modeling Challenges

How to disentangle the three effects?
• Many factors, highly correlated
• Current approach: Forced desynchrony protocol in sleep lab & active sleep deprivation at tiny scale

My approach
• Leverage existing variation of real-world interactions with web search engines across millions of people
• Develop statistical model to disentangle effects
Biologically-inspired Statistical Model

- Bridge: Generative model encoding multiple biological processes to disentangle effects (domain knowledge)

- **Generalized Additive Model** [Hastie & Tibshirani, 1990]
  \[ y \sim N(\mu(x), \sigma^2) \]
  - Keystroke timing
  - Keystroke features
  - Gaussian noise

\[
\mu(x) = \alpha + f(key(x)) + g(timeofday(x)) + h(timeawake(x))
\]
- Intercept
- Keystroke (control for key pressed: “A”, “a”, “@”, …)
- Time of day
- Time since wakeup (wearable sleep measurement)

Model: Why Time of Day?

- Lab studies: Several biological processes drive performance variation
  1. **Circadian rhythm (C):** behavior-independent, near 24h oscillations that is time-dependent
  \[ g(timeofday(x)) \]
  \[ \Rightarrow \text{model time of day} \]

\[
\text{Habitual sleep time}
\]

\[
\text{Reaction time}
\]

\[
\text{Time of day}
\]

\[
0h \quad 12h \quad 24h
\]
Model: Why Time Since Wakeup?

- Two additional biological processes impact performance
  2. Homeostatic sleep drive (H): the longer awake, the more tired you become
  3. Sleep inertia (I): performance impairment experienced immediately after waking up

![Graph showing reaction time over time since wakeup]

Model: Parameter Learning

$$\mu(x) = \alpha + f(key(x)) + g(timeofday(x)) + h(timeawake(x))$$

- No assumptions about functional form!
- Convex optimization problem
  (~1000 parameters, ~75M observations)
**Result: Time Since Wakeup**

- **Validation:** Model identifies homeostatic sleep drive and sleep inertia consistent with lab-based studies.
- **New insights:** It was impossible to measure cognitive performance at scale and outside lab. Now we can!

**Research Impact**

**New science**

[Althoff, Horvitz, White, Zeitzer – WWW, 2017]

1. Used my method to estimate impact of sleep deprivation on real-world performance
   - Largest-ever study by 400x

**Reducing vehicle accidents**

[Althoff, Horvitz, White – NPJ Digital Medicine, 2018]

2. Used my method at US population scale to predict vehicle accident risk
   - 16 billion keystrokes across ~2700 US counties
   - Technology could help reduce vehicle accidents
NLP for Mental Health

- **Question:** How to talk to someone to help them feel better?

- **Mobile devices** enable counseling conversations wherever you are
  - **Massive scale:** >56M messages to date
  - **Daily(!) active rescues for danger of suicide**
Leveraging Data to Improve Treatment

- Text-based counseling enables quantitative study of conversation strategies (IRB approved)
  - Full conversation transcripts
  - Conversation outcomes

- Helps answer important questions
  - Why are some counselors much better than others?

Data-driven Conversation Strategies

Developed computational models and provided quantitative evidence for five conversation strategies:

1. Adaptability: Language model comparison
   - Best counselors adapt to conversation
2. Dealing with ambiguity: Clustering
   - Best counselors react differently to identical situations
3. Creativity: Subspace analysis
   - Best counselors use less generic/templated language
4. Making progress: HMM extension
   - Best counselors understand problem quickly & solve
5. Change in perspective: Coordination analysis
   - Best counselors change people’s perspective

Mental Health: Impact

- Insights concretely improved counseling training

Summary
• Digital traces capture behavior and health at scale
• New methods needed to unlock insights
• Developed new methods in Data Mining, Social Network Analysis, Natural Language Processing
  • Concrete impact on understanding of human well-being
  • My methods and insights have been used at Microsoft, Under Armour, Crisis Text Line, and many other orgs.

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Thank you!

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