Sensing, Inference, and Intervention in Support of Mental Health

Eric Horvitz
Microsoft Research
HCI + AI: Growth in Resources & Competencies

Data & computation

Learning, inference, representation

Causal inference

Perception

NLP
HCI + AI: Growth in Resources & Competencies

Data & computation
Learning, inference, representation
Causal inference
Perception
NLP

Tools & platforms
Data to Predictions to Interventions

- Sensed data
- Predictive model
- Decision model

Data $\rightarrow$ Predictions $\rightarrow$ Actions

- Treatment
- Prevention
- Promotion
Data to Predictions to Interventions

Sensed data → Predictive model → Predictions → Actions

Active learning
Experience sampling
Ideal experimentation

- Treatment
- Prevention
- Promotion
Revolution Brewing

Computational social science

Data
Devices
Life-centricity of web

Representations & models
Learning & inference
Perception, predictions, decisions
Revolutions Brewing

Computational social science
Public health & epidemiology

Data
Devices
Life-centricity of web

Representations & models
Learning & inference
Perception, predictions, decisions
Revolutions Brewing

Computational social science
Public health & epidemiology
Social psychology & personality
Clinical psychology & psychiatry

Data
Devices
Life-centricity of web

Representations & models
Learning & inference
Perception, predictions, decisions
Revolution Brewing

Mental health & wellbeing

Data
Devices
Life-centricity of web

Representations & models
Learning & inference
Perception, predictions, decisions
Evidential Streams & Inferences from Populations

e.g., Search, Twitter, Facebook, Reddit, TalkLife, Crisis Txt Line, Apps

Health insights & diagnosis

Mental health & wellness
Wrestling with (the Wild West of) Population Data

**Supervised learning**: experts, crowd, participants

**Unsupervised learning**: clustering, topic modeling

**Causal modeling**: propensity, Neyman-Rubin
Wrestling with (the Wild West of) Population Data

Sensitivity, robustness, error modeling
Statistics of rare events
Sequence alignment
NL psych models: LIWC, ANEW, etc.
NL topics/sentiment: Emolex, SentiWordNet, Empath
Wrestling with Large-Scale Population Data

Experimental design
Matched sets for studies
  - Control
  - Test/intervention

Example:

*Rare serious adverse effects of medications*
Wrestling with Large-Scale Population Data

Detect rare adverse effects of drugs

Self-controlled study
Query rate ratio

Query Timeline

$D$: query for drug of interest
$C$: query for condition of interest
$S$: query for symptom of $C$

surveillance window post $D_{\text{First}}$

surveillance window pre $D_{\text{First}}$

ignored $C$ or $S$

$\alpha = D_{\text{Last}} - D_{\text{First}}$
$\beta = 7$ days
$\gamma = 60$ days
$\theta = (\alpha + \beta + \gamma)$

Wrestling with Large-Scale Population Data

Wrestling with Large-Scale Population Data

Alignment

Machine learning to align

Example:

*Pregnancy info needs*
Wrestling with Large-Scale Population Data

Alignment

Machine learning to align

Example:

Pregnancy info needs

A. Fourney, R. White, E. Horvitz, CHI 2015
Wrestling with Large-Scale Population Data

Alignment

Machine learning to align

Example:

*Pregnancy info needs*

A. Fourney, R. White, E. Horvitz, CHI 2015
Wrestling with Large-Scale Population Data

Alignment

Episodic structure

Example:

Breast cancer

<table>
<thead>
<tr>
<th>Time</th>
<th>Query</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nov 13 2013 7:40pm</td>
<td>feels like lump in breast</td>
</tr>
<tr>
<td>Dec 1 2013 11:21am</td>
<td>pain after biopsy</td>
</tr>
<tr>
<td>Dec 1 2013 11:31am</td>
<td>what happens after breast biopsy</td>
</tr>
<tr>
<td>Dec 9 2013 6:33pm</td>
<td>how often are breast lumps cancer</td>
</tr>
<tr>
<td>Dec 9 2013 6:45pm</td>
<td>does cancer make you thirsty</td>
</tr>
<tr>
<td>Dec 9 2013 6:49pm</td>
<td>how long does it take for biopsy results</td>
</tr>
<tr>
<td>Dec 12 2013 12:08pm</td>
<td>stage 2a breast cancer</td>
</tr>
<tr>
<td>Dec 12 2013 12:15pm</td>
<td>invasive ductal carcinoma</td>
</tr>
<tr>
<td>Dec 12 2013 12:17pm</td>
<td>poorly differentiated idc breast cancer</td>
</tr>
<tr>
<td>Dec 12 2013 12:29pm</td>
<td>breast cancer survival rate</td>
</tr>
<tr>
<td>Dec 12 2013 12:32pm</td>
<td>stage 2 breast cancer survival rate</td>
</tr>
<tr>
<td>Dec 12 2013 7:44pm</td>
<td>breast reconstruction surgery</td>
</tr>
<tr>
<td>Dec 12 2013 7:46pm</td>
<td>breast reconstruction after cancer</td>
</tr>
<tr>
<td>Dec 13 2013 8:05am</td>
<td>breast cancer treatment</td>
</tr>
<tr>
<td>Dec 13 2013 8:16am</td>
<td>recovering from breast cancer</td>
</tr>
<tr>
<td>Dec 15 2013 09:20am</td>
<td>breast cancer surgeon</td>
</tr>
<tr>
<td>Dec 15 2013 10:22am</td>
<td>full mastectomy</td>
</tr>
<tr>
<td>Dec 15 2013 10:23am</td>
<td>mastectomy pros and cons</td>
</tr>
<tr>
<td>Dec 15 2013 10:29am</td>
<td>do you need chemo after mastectomy</td>
</tr>
</tbody>
</table>

Paul, White, Horvitz, TWEB 2016
Wrestling with Large-Scale Population Data

Alignment  Key pivot points

Episodic structure  Diagnosis date
                  Screening
                  Surgery
                  Chemotherapy

Example:

*Breast cancer*
Wrestling with Large-Scale Population Data

Alignment

Episodic structure

Example: Breast cancer

Paul, White, Horvitz, TWEB 2016
Wrestling with Large-Scale Population Data

Alignment

Episodic structure

Example:

*Breast cancer*
Wrestling with Large-Scale Population Data

Alignment

Episodic structure

Example:

*Breast cancer*
Propensity: Normalizing cohorts to understand influences

$u_1$ timeline

$u_2$

$u_3$

Learning outcome of action
Propensity: Normalizing cohorts to understand influences

Kiciman and Richardson, KDD 2015
Propensity: Normalizing cohorts to understand influences
Propensity: Normalizing cohorts to understand influences
Pharmacy/Lorazepam, outcome: medication
Max. exp. tweets: 1.00

Pharmacy/Tramadol, outcome: pain
Max. exp. tweets: 1.61

Pharmacy/Tramadol, outcome: painkiller
Max. exp. tweets: 0.12

Pharmacy/Xanax, outcome: weed
Max. exp. tweets: 0.51

no. days before and after treatment

Kiciman and Richardson, KDD 2015
Opportunity: Major Life Changes

Understand, support through difficult life changes

Major illness
Loss
Death
Divorce
Birth

Example: Birth of child
Postpartum depression (PPD)
CDC: ~15%
50% cases unreported
Identifying Multiple Dimensions of a Life Change

Identify tweets about births: Twitter Firehose

2,929 new mother candidates

Gender classifier

10 tweets per candidate & profile

376 new mothers

-3 months

Birth!

+ 3 months

1st person pronoun
Structure & Dynamics of Engagement on Social Graph

**Engagement.**
Volume: mean normalized number of posts per day
Replies, retweets, questions, shared links

**Ego network**
#inlinks; #outlinks

De Choudhury, Counts, Horvitz. CSCW 2013, CHI 2013
Linguistic Analysis

1) [high NA] Ugh, my daughter hates her bassinet. I hate disappointing her. What a miserable day.

2) [low activation] My baby is only catnapping during the day. That’s so sad and depressing. I feel helpless.

3) [low dominance] Anxiety/panic attacks need to eff off!!!!!!!!!!! I’m trying to lead a somewhat normal life with my baby!!! #frustrated #miserable

4) [high 1st person pronoun use] No lie I fuckin’ miss all socializing..... my daughter keeps me occupied and exhausted. I have all my moments of the day.

De Choudhury, Counts, Horvitz. CSCW 2013, CHI 2013
Linguistic analysis

Volume
PA
NA
Activation
Dominance
1st pronouns
3rd pronouns
2nd pronouns
Indefinite pronouns
Articles
Verbs
Aux-verbs
Adverbs
Tentative
Func. Words
Negation
Inhibition
Assent
Certainty
Conjunction
Preposition
Inclusive
Exclusive
Swear
Quantifier
Non-fluency
Filler

3°

1°

Neg. Affect
Patterns and Outcomes

~15% of new mothers: severe changes
- Activity level down,
- Language usage: 1st person up, 3rd person down,
- Negative affect up, positive affect down
Predicting Postnatal Outcomes

Predicting postpartum changes with data drawn before birth.

Exciting family of results

Human subjects + online:
New mothers w/ FB timeline, Twitter
Major depressive episodes

Prenatal evidence

De Choudhury, Gamon, Counts, Horvitz. ICWSM 2013
De Choudhury, Counts, Horvitz, Hoff. ICWSM 2014
Major Life Challenges: Major Illness

Grappling with diagnosis & treatment

Queries before & after inferred breast CA diagnoses

Proxy for understanding if, how, and when life may return to normal?
MOURNING AND MELANCHOLIA

Dreams having served us as the prototype in normal life of narcissistic mental disorders, we will now try to throw some light on the nature of melancholia by comparing it with the normal affect of mourning. This time, however, we must begin by making an admission, as a warning against any over-estimation of the value of our conclusions. Melancholia, whose definition fluctuates even in descriptive psychiatry, takes on various clinical forms the grouping together of which into a single unity does not seem to be established with certainty; and some of these forms suggest somatic rather than psychogenic affections. Our material, apart from such impressions as are open to every observer, is limited to a small number of cases whose psychogenic nature was indisputable. We shall, therefore, from the outset drop all claim to general validity for our conclusions, and we shall console ourselves by reflecting that, with the means of investigation at our disposal to-day, we could hardly discover anything that was not typical, if not of a whole class of disorders, at least of a small group of them.

The correlation of melancholia and mourning seems justified by the general picture of the two conditions. Moreover, the exciting causes due to environmental influences are, so far as we can discern them at all, the same for both conditions. Mourning is regularly the reaction to the loss of a loved person, or to the loss of some abstraction which has taken the place of one, such as one’s country, liberty, an ideal, and so on. In some people the same influences produce melancholia instead of mourning and we consequently suspect them of a pathological disposition. It is also well worth notice that, although mourning involves grave departures from the normal attitude to life, it never occurs to us to regard it as a pathological condition and to
It is remarkable that this painful unpleasure is taken as a matter of course by us.
Major Life Challenges: Grieving

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Normally, respect for reality gains the day.

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Normally, respect for reality gains the day.

In reality, however, this presentation is made up of innumerable single impressions (or unconscious traces of them), and this withdrawal of libido is not a process that can be accomplished in a moment, but most certainly, as in mourning, be one in which progress is long-drawn-out and gradual.
Opportunity: Assist with Complicated Grief

Unusually severe & prolonged grieving that impairs function
2 to 3% of population worldwide

Death: Child or life partner, sudden violent death
High rates of suicidal ideation, risk-taking
Value of psychotherapy

M. Katherine Shear, M.D.
Opportunity: Assist with Complicated Grief

<table>
<thead>
<tr>
<th>Component</th>
<th>Description</th>
<th>Evidence from Randomized, Controlled Trials</th>
</tr>
</thead>
<tbody>
<tr>
<td>Establishing lay of the land</td>
<td>Discussion of the nature of loss, grief, and adaptation to loss; description of complications of grief and their effects; description of the treatment and rationale for procedures in the treatment</td>
<td>Shear et al.,³⁰ Shear et al.,³⁵ Boelen et al.,³⁶ Acierno et al.,³⁷ Rosner et al.,³⁸ Bryant et al.,³⁹ Kersting et al.,⁴⁰ Litz et al.,⁴¹ Wagner et al.,⁴² Papa et al.,⁴³ Shear et al.⁴⁴</td>
</tr>
<tr>
<td>Promoting self-regulation</td>
<td>Self-monitoring, self-observation, and reflection; reappraisal of troubling thoughts and beliefs; extending compassion to oneself; “dosing” emotional pain by confronting it and setting it aside</td>
<td>Shear et al.,³⁰ Shear et al.,³⁵ Boelen et al.,³⁶ Rosner et al.,³⁸ Bryant et al.,³⁹ Kersting et al.,⁴⁰ Litz et al.,⁴¹ Wagner et al.,⁴² Rosner et al.⁴⁵</td>
</tr>
<tr>
<td>Building connections</td>
<td>Strategies for meaningful connections with others; sharing pain and letting others help</td>
<td>Shear et al.,³⁰ Shear et al.,³⁵ Rosner et al.,³⁸ Kersting et al.,⁴⁰ Wagner et al.,⁴² Rosner et al.⁴⁵</td>
</tr>
<tr>
<td>Setting aspirational goals</td>
<td>Exploring ambition for personal goals and activities that engender eagerness and hope; generating enthusiasm and other positive emotions in ongoing life; creating sense of purpose and possibilities for future happiness</td>
<td>Shear et al.,³⁰ Shear et al.,³⁵ Acierno et al.,³⁷ Bryant et al.,³⁹ Litz et al.,⁴¹ Papa et al.⁴³</td>
</tr>
<tr>
<td>Revisiting the world</td>
<td>Strategies for confronting or revisiting avoided situations</td>
<td>Shear et al.,³⁰ Shear et al.,³⁵ Boelen et al.,³⁶ Acierno et al.,³⁷ Rosner et al.,³⁸ Bryant et al.,³⁹ Kersting et al.,⁴⁰ Rosner et al.⁴⁵</td>
</tr>
<tr>
<td>Storytelling</td>
<td>Recounting and reflecting on the story of the death in order to create an acceptable account; practice in confronting pain and setting it aside</td>
<td>Shear et al.,³⁰ Shear et al.,³⁵ Boelen et al.,³⁶ Rosner et al.,³⁸ Bryant et al.,³⁹ Wagner et al.,⁴² Rosner et al.⁴⁵</td>
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<tr>
<td>Using memory</td>
<td>Reviewing positive memories of the deceased and inviting reminiscence of negative memories; describing an imagined conversation with the deceased</td>
<td>Shear et al.,³⁰ Shear et al.,³⁵ Rosner et al.,³⁸ Bryant et al.,³⁹ Wagner et al.,⁴² Rosner et al.⁴⁵</td>
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Opportunity: Assist with Complicated Grief

Table 3. Core Components of Treatment for Complicated Grief

<table>
<thead>
<tr>
<th>Component</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Establishing lay of the land</td>
<td>Discussion of the nature of loss, grief, and loss; description of complications and their effects; description of the treatment goals and procedures in the treatment.</td>
</tr>
<tr>
<td>Promoting self-regulation</td>
<td>Self-monitoring, self-observation, and self-reflection; appraisal of troubling thoughts and emotions; building resilience and setting it aside.</td>
</tr>
<tr>
<td>Building connections</td>
<td>Strategies for meaningful connection with others; sharing pain and letting others in.</td>
</tr>
<tr>
<td>Setting aspirational goals</td>
<td>Exploring ambition for personal goals and growth that engender eagerness and homeostasis; engaging in meaningful activities; creating a sense of purpose and hope for future happiness.</td>
</tr>
<tr>
<td>Revisiting the world</td>
<td>Strategies for confronting or revisiting traumatic experiences.</td>
</tr>
<tr>
<td>Storytelling</td>
<td>Recounting and reflecting on the stories of grief, loss, and recovery, in order to create an acceptable account of the events.</td>
</tr>
<tr>
<td>Using memory</td>
<td>Reviewing positive memories of the deceased, including reminiscence of negative memories and an imagined conversation with the deceased.</td>
</tr>
</tbody>
</table>

Areas of Uncertainty

Data are lacking on risk factors for complicated grief, its frequency among bereaved persons in various age groups, and its natural history. Consensus is needed regarding diagnostic criteria. Data are also lacking on associated sleep disturbance and its treatment, as are data from randomized, double-blind trials evaluating the effects of antidepressants and other medications (e.g., oxytocin) on patients with complicated grief. A multicenter trial (ClinicalTrials.gov number, NCT01179568) is under way to assess the efficacy of antidepressant medication alone or in combination with therapy for complicated grief.
On Sensitivity, Ethics, Disclosure

Seeking Insights About Cycling Mood Disorders via Anonymized Search Logs

Elad Yom-Tov\textsuperscript{1}, PhD; Ryen W White\textsuperscript{2}, PhD; Eric Horvitz\textsuperscript{2}, MD, PhD

\textsuperscript{1}Microsoft Research, Herzeliya, Israel
\textsuperscript{2}Microsoft Research, Redmond, WA, United States
On Sensitivity, Ethics, Disclosure

Data, privacy, and the greater good

Eric Horvitz* and Deirdre Mulligan*

Large-scale aggregate analyses of anonymized data can yield valuable results and insights that address public health challenges and provide new avenues for scientific discovery. These methods can extend our knowledge and provide new tools for enhancing health and wellbeing. However, they raise questions about how to best address potential threats to privacy while reaping benefits for individuals and society as a whole. The use of machine learning to make leaps across informational and social contexts to infer health conditions and risks from nonmedical data provides representative scenarios for reflections on directions with balancing innovation and regulation.

What if analyzing Twitter tweets or Facebook posts could identify new mothers at risk for postpartum depression (PPD)? Despite PPD’s serious consequences, early identification and prevention remain difficult. Absent a history of depression, detection is largely dependent on new mothers’ self-reports. But researchers found that shifts in sets of activities and language usage on Facebook are predictors of PPD (1) (see the photo). This is but one example of ongoing research that uses machine learning to identify health-related indicators.

Although digital nudging shows promise, a recent flare-up in the United Kingdom highlights the privacy concerns it can ignite. A Twitter suicide-prevention application called Good Samaritan monitored individuals’ tweets for words and phrases indicating a potential mental health crisis. The app notified the person’s followers so they

Horvitz & Mulligan, Science 2015