Mining and Modeling
Online Health Search

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In collaboration with many, including
Outline

• Online Health Search
  • Short- and Long-term health searching
  • “Cyberchondria”
  • “Web to World” transitions

• Searcher and Content Biases

• Mining Health Search Data
  • 3 applications: Nutrition Tracking, Pregnancy Prediction, Detection of Drug Interactions and Adverse Drug Reactions

• Opportunities and Challenges
Part I: Online Health Search
Health Seeking

- Healthcare websites for worried (un)well
  - Provide valuable information, address concerns, etc.

- 80% U.S. adults use search engines to find medical info (Pew, 2011)
  - Majority don’t verify quality (validity, date, etc.)

- Problem: Search engines for diagnostic reasoning
  - Link to pages with potentially-alarming content
  - More written about serious than benign explanations
  - Ranking algorithms use click logs; ignore likelihoods, reinforce alarming pages
Biased Health Content in Web Search

- Web search suffers from and amplifies biases of judgment
  - Base-rate neglect
  - Availability bias
  - Confirmation bias

→ Cyberchondria!!
(White and Horvitz, TOIS 2009)

% pages with co-occurrence of symptom and cause (circa 2007)

<table>
<thead>
<tr>
<th>Symptom</th>
<th>Cause</th>
<th>Web Crawl</th>
<th>Top 100 from Web Search</th>
<th>Top 100 from Domain Search (MSN Health)</th>
</tr>
</thead>
<tbody>
<tr>
<td>headache</td>
<td>caffeine withdrawal</td>
<td>29%</td>
<td>26%</td>
<td>25%</td>
</tr>
<tr>
<td></td>
<td>tension</td>
<td>68%</td>
<td>48%</td>
<td>75%</td>
</tr>
<tr>
<td></td>
<td>brain tumor</td>
<td>3%</td>
<td>26%</td>
<td>0%</td>
</tr>
<tr>
<td>muscle twitches</td>
<td>benign fasciculation</td>
<td>53%</td>
<td>12%</td>
<td>34%</td>
</tr>
<tr>
<td></td>
<td>muscle strain</td>
<td>40%</td>
<td>38%</td>
<td>66%</td>
</tr>
<tr>
<td></td>
<td>ALS</td>
<td>7%</td>
<td>50%</td>
<td>0%</td>
</tr>
<tr>
<td>chest pain</td>
<td>indigestion</td>
<td>28%</td>
<td>35%</td>
<td>38%</td>
</tr>
<tr>
<td></td>
<td>heartburn</td>
<td>57%</td>
<td>28%</td>
<td>52%</td>
</tr>
<tr>
<td></td>
<td>heart attack</td>
<td>15%</td>
<td>37%</td>
<td>10%</td>
</tr>
</tbody>
</table>

Co-occurrence of symptom & serious condition most common in Web search
Cyberchondria: Escalation in Health Concerns

- Users transition from common symptoms to rare, but serious diseases
  - *e.g.*, {headache, nausea, dizziness} → malignant brain tumor

**Escalation**

1. Query search engine for *[headache]*
2. Review results
3. Browse Web pages
4. Query for *[brain tumor]*

**Non-escalation**

4. Query for *[caffeine withdrawal]*
Survey to Understand Self-Diagnosis Online

• Survey of experiences with Web use for self diagnosis
• Self-report data from 500+ volunteers within Microsoft

• Web content increases anxiety (40% people), reduces anxiety (50% people)
  • Web can help, but can also cause distress, especially for those pre-disposed to anxiety
  • Key marginalizations (e.g., self-reported hypochondria) revealed larger effects

• Web helps patients understand conditions before and after diagnosis

• Escalation reported to occur frequently for 20% of respondents

(White and Horvitz, AMIA 2009; TOIS 2009)
Beyond Self-Reports: Mining Health Search Activity

- Mining insights from large-scale logs
  - Query sequences & page accesses
  - Content distribution & dynamics
  - Insights, predictive models, services

Search engine log analysis shows:
→ Given symptom query, transition to serious condition occurs 2x as often as transition to benign
→ ... even though, benign condition is often a lot more likely
Predicting Escalations From Page Content

Predict transition from common symptoms to rare, serious illnesses *based on features* of pages being viewed

Negatives = non-escalations
Query, click THEN no escalation, end session, etc.

Model accuracy = 73.4%
Baseline accuracy = 50%

<table>
<thead>
<tr>
<th>Query Outcome</th>
<th>Order of Presentation on Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Serious first</td>
<td>68.6%</td>
</tr>
<tr>
<td>Benign first</td>
<td>33.4%</td>
</tr>
<tr>
<td>Escalation</td>
<td>66.6%</td>
</tr>
<tr>
<td>Non-escalation</td>
<td>31.4%</td>
</tr>
</tbody>
</table>

(White and Horvitz, SIGIR 2010)
Web to World

• From our prior survey, **23.7% of respondents were put over the threshold to seek professional medical advice by Web content**

• Pursuit of in-world healthcare resources:
  • Healthcare Utilization Intention (HUI)
  • *E.g., [neurologist in seattle, wa], [evergreen hospital], [urgent care clinic]*

• Automated detection:
  • Appropriate medical specialty for the symptom (*e.g., neurologist* for symptom: muscle twitches)
  • Medical resource (*e.g., hospital, physician*)
  • Five-digit US zipcode, US city and state name pair (*e.g., Redmond, Washington*)

(White and Horvitz, AMIA 2010)
Studying Web to World

• Characterize and predict transitions to HUI in search logs

Session with healthcare utilization intent (HUI):

- q1
- q2 [chest pain]
- q3 [heart pain]
- P
- q4 [cardiologist]
- q5

Session without healthcare utilization intent (No HUI):

- q1
- q2 [chest pain]
- q3 [heart pain]
- P
- SESSION END

• Other methods for W2W identification, e.g.,
  • Visitation (via GPS tracking) (West et al., SIGIR 2013 – predicting geographic destinations)
  • Call medical facility (Mishra et al., SIGIR 2014 – time-critical search)
Characterizing Resource Pursuits

- HUI queries toward end of sessions
  - 36% of sessions, HUI was last query
- Mean: HUIs occur at 75% of session
Predicting HUIs

• Prediction task

  *Probability that user will next issue an initial HUI query given currently viewing page p.*

• Three classes of features

  • **Page:** Structure & content of current page.
  
  • **Session:** Attributes of search interaction in current session.
  
  • **User:** Aspects of users’ historic medical search interactions from the beginning of log data to start of current session.

<table>
<thead>
<tr>
<th>Features</th>
<th>HUI</th>
<th>No HUI</th>
</tr>
</thead>
<tbody>
<tr>
<td>SeriousBeforeBenign (Page)</td>
<td>59%</td>
<td>48%</td>
</tr>
<tr>
<td>IsWebForum (Page)</td>
<td>14%</td>
<td>9%</td>
</tr>
<tr>
<td>NumQueries (Session)</td>
<td>4.9</td>
<td>2.9</td>
</tr>
<tr>
<td>AvgQueryLength (Session)</td>
<td>4.5</td>
<td>4.1</td>
</tr>
<tr>
<td>NumUniqueSymptoms (User)</td>
<td>3.6</td>
<td>2.2</td>
</tr>
<tr>
<td>NumResourceQueries (User)</td>
<td>5.5</td>
<td>2.0</td>
</tr>
</tbody>
</table>

Logistic regression with five-fold CV

• **Accuracy:**
  
  - Page features = 59.3%
  
  - Page + session = 68.9%
  
  - Page + session + user = 77.7%
Long-term Health Searching

• Logs can provide lens on how medical concerns emerge over time and how concerns persist post onset

• Long-term needed to understand medical search
  • 60% of medical sessions start directly with a condition query
  • 95% of these sessions had medical query in prior session(s)

• Long-term helps us understand medical trajectories
  • Predict emerging concerns, personalize search, guide healthcare use

• Note: Long-term may be influenced by external events (e.g., diagnosis for oneself or others) – Web is not always the cause

(White and Horvitz, SIGIR 2012)
Condition Onset

• Explore search behavior before first occurrence of a condition

• Pre-onset history can contain other conditions
  • 83% searched for at most one other condition prior to onset
  • 61% searched for no conditions pre-onset

• 79.5% of prior symptoms were related to onset
  • Emergence of conditions extends back over time
Post-Onset Search Behavior

• Changes in search behavior **after the first onset condition query:**

<table>
<thead>
<tr>
<th>Feature</th>
<th>% or Avg (SD)</th>
<th>% change from pre-onset</th>
</tr>
</thead>
<tbody>
<tr>
<td>% URLs medical</td>
<td>4.9%</td>
<td>+88.5</td>
</tr>
<tr>
<td>% queries medical</td>
<td>4.2%</td>
<td>+31.3</td>
</tr>
<tr>
<td>% online time on medical pages</td>
<td>8.0%</td>
<td>+247.8</td>
</tr>
<tr>
<td># unique symptoms</td>
<td>0.50 (1.01)</td>
<td>−20.6</td>
</tr>
<tr>
<td>Symptom persistence (days)</td>
<td>2.46 (3.42)</td>
<td>−27.9</td>
</tr>
<tr>
<td># unique conditions</td>
<td>1.04 (1.29)</td>
<td>+40.5</td>
</tr>
<tr>
<td>Condition persistence (days)</td>
<td>7.57 (12.49)</td>
<td>+25.3</td>
</tr>
</tbody>
</table>

• Medical search increases, symptom searching decreases, and condition searching increases

• **Interesting future work:** Use combination of symptoms searched over time to **predict the onset condition** (early warning signs!)
Tracking HUIs and Related Activity over Time

Align all users based on first HUI query (hospital, physician, specialist, etc.):

Lift in searching over expected search activity on each day

(White and Horvitz, JAMIA 2014)
Applications

• Quantifying skewed content distributions online

• Identifying (and down-weighting?) pages that are likely to cause escalations – challenge: the escalation may be justified

• Predicting onset of conditions over time → earlier interventions

• Better supporting Web to World transitions
  • Directing people to the right healthcare professionals, summarizing long-term search histories for sharing with the HCP
Part II : Biases in Behavior and Content
Bias in IR and elsewhere

In IR, e.g.,
- Domain bias – People prefer particular Web domains
- Rank bias – People favor high-ranked results
- Caption bias – People prefer captions with certain terms

In psychology, e.g.,
- Anchoring-and-adjustment, confirmation, availability, etc.

- All impact user behavior
  - Opportunity to intersect psychology and IR
Biases and Search Behavior

- Bias can be observed in IR situations where searchers seek or are presented with information that significantly deviates from a known or accepted truth.

- Focus on set of Yes-No questions in Health Domain

(White, SIGIR 2013)
Initial Exploratory Questionnaire

- Gain early insight into possible biases in search
- **Focus on Yes-No questions (answered with “Yes” or “No”)**
  - Simplicity: Answers along single dimension (Yes → No)

- Microsoft employees; recall recent Yes-No query (in last 2 weeks)
- Asked about belief beforehand and afterwards
  - Multi-point scale: **Yes** / Lean Yes / **Equal** / Lean No / **No**

- 200 respondents. Recalled questions such as:
  - “Does chocolate contain caffeine?”
  - “Are shingles contagious?”
Survey Results

• Two main findings:
  1. Respondents kept strongly-held beliefs (Yes-Yes and No-No)
  2. If Before = Equal, then 2x as likely to believe Yes after search

Motivated us to:
Further explore possible impact of biases on behavior and outcomes
Log-Based Study of Yes-No Queries

• Queries, clicks, and results from Bing logs (2 weeks)
• Mined yes-no questions: start with “can”, “is”, “does”, etc.
• Focused on health since it’s important and we could get truth

• Randomly selected set of 1000 yes-no health questions
  • Each issued by at least 10 users, same top 10, same captions

• Examples include:
  • “Is congestive heart failure a heart attack?” (answer = No)
  “Do food allergies make you tired?” (answer = Yes)
Answer Labeling

Yes-No Answer labels for captions/results
Physician answers for the Yes-No questions

- Captions and result content
- Crowdsourced (Clickworker.com)
- 3-5 judges/caption (consensus)
- Task was to assign label of:
  - Yes only
  - No only
  - Both (Yes and No)
  - Neither (not Yes and not No)
- Agreement on 96% of captions
- Performed similar labeling for each top 10 search results
  - Crowdsourced judges, agreement on 92% of pages

Example Caption Labels

Suggests AFFIRMATIVE answer (Yes only):
Question: [can i take L carnitine while pregnant]
Is it safe to take L-Carnitine while pregnant - The Q&A wiki
http://wiki.answers.com/Q/Is_it_safe_to_take_L-Carnitine_while_pregnant
Is l-carnitine safe to take while pregnant? yes. Is it safe to take zithromax while pregnant? yes it is safe to take while pregnant. A doctor would not prescribe it ...

Suggests NEGATIVE answer (No only):
Question: [does robaxin show up on drug tests]
Does robaxin show up on drug tests? | Answerbag
http://www.answerbag.com/q_view/1239474
Does robaxin show up on drug tests? no . More Questions. Additional questions in this category. Can you have a DUI & work at a school in Pennsylvania?

Suggests BOTH affirmative and negative:
Question: [is tooth a bone]
Is tooth consider as a bone - The Q&A wiki
http://wiki.answers.com/Q/is_tooth_consider_as_a_bone
What does the bone in the tooth do? It helps u chew. Is a tooth a bone? Yes. Is your tooth a bone? No, teeth are not bones.

Suggests NEITHER affirmative nor negative:
Question: [does crestor cause bloating]
Does Crestor Cause Bloating? – HealthCentral
http://www.healthcentral.com/cholesterol/h/does-crestor-cause-bloating.html
Everything you need to know about does crestor cause bloating, including common uses, side effects, interactions and risks.
Physician Answers

- Two physicians reviewed the 1000 questions and gave answers
  - Inc. 50/50 = need more info, Don’t know = really unsure
  - Agreement between physicians on Yes-No was 84% (κ=0.668)

Focused on the 680 questions where both agreed Yes or No
- Distribution: 55% Yes and 45% No (used as TRUTH in our study)
Result Ranking

- Volume of Yes-No content in the results

<table>
<thead>
<tr>
<th>Source</th>
<th>Yes only</th>
<th>No only</th>
<th>Both</th>
<th>Neither</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caption</td>
<td>28.7%</td>
<td>8.4%</td>
<td>2.7%</td>
<td>60.2%</td>
</tr>
<tr>
<td>Result</td>
<td>35.0%</td>
<td>12.7%</td>
<td>6.3%</td>
<td>41.0%</td>
</tr>
</tbody>
</table>

→ More Yes content in top-10 than No content

- Relative ranking of **top** Yes-No content when both in top 10

<table>
<thead>
<tr>
<th>Source</th>
<th>Yes above No</th>
<th>No above Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caption</td>
<td>65.1%</td>
<td>34.9%</td>
</tr>
<tr>
<td>Result</td>
<td>62.4%</td>
<td>37.6%</td>
</tr>
</tbody>
</table>

→ Yes content ranked above No more often (when both shown)
User Behavior (Clickthrough rate)

- Studied **clickthrough rates** on captions containing answers
- Controlled for rank by just considering top result (r=1)

SERP click likelihoods for different captions given variations in answer presence in SERPs/captions, and rank

<table>
<thead>
<tr>
<th>Condition(s)</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>SERP&lt;sub&gt;Y&lt;/sub&gt;</td>
<td>80.0%</td>
</tr>
<tr>
<td>SERP&lt;sub&gt;N&lt;/sub&gt;</td>
<td>75.9%</td>
</tr>
<tr>
<td>SERP&lt;sub&gt;BOTH&lt;/sub&gt;, Caption&lt;sub&gt;Y&lt;/sub&gt;</td>
<td>45.6%</td>
</tr>
<tr>
<td>SERP&lt;sub&gt;BOTH&lt;/sub&gt;, Caption&lt;sub&gt;N&lt;/sub&gt;</td>
<td>14.2%</td>
</tr>
<tr>
<td>Caption&lt;sub&gt;Y&lt;/sub&gt;</td>
<td>41.1%</td>
</tr>
<tr>
<td>Caption&lt;sub&gt;N&lt;/sub&gt;</td>
<td>16.3%</td>
</tr>
<tr>
<td>Caption&lt;sub&gt;Y,r=1&lt;/sub&gt;</td>
<td>47.4%</td>
</tr>
<tr>
<td>Caption&lt;sub&gt;N,r=1&lt;/sub&gt;</td>
<td>12.6%</td>
</tr>
</tbody>
</table>

3-4x as likely to click on captions with Yes content, even though TRUTH = 55% Yes / 45% No
User Behavior (Result skipping)

- Studied result **skipping** behavior
- Frequency with which people skipped caption w/answer to click other caption

<table>
<thead>
<tr>
<th>Click</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes only</td>
<td>33.3%</td>
<td>41.5%</td>
</tr>
<tr>
<td>No only</td>
<td>8.5%</td>
<td>16.7%</td>
</tr>
</tbody>
</table>

- Users more likely (4x) to skip No to click Yes than vice versa
Answer Accuracy

- Examined accuracy of the top search result, as well as first click and last click in session

<table>
<thead>
<tr>
<th>Answer defn.</th>
<th>All</th>
<th>Physician Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top result</td>
<td>45.0%</td>
<td>57.1%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>22.9%</td>
</tr>
<tr>
<td>First click</td>
<td>50.0%</td>
<td>59.1%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>27.9%</td>
</tr>
<tr>
<td>Last click</td>
<td>52.3%</td>
<td>66.2%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>29.4%</td>
</tr>
</tbody>
</table>

- Findings show:
  1. Top result accurate only 45% of time, less when truth is No
  2. Users improve accuracy, but only slightly (limited by top 10)

- Potential cause for low accuracy ➔ bias in retrieved content
Content Biases

• Content bias in search results describes a deviation from a known or accepted truth that negatively affects result accuracy

• Used Cochrane reviews as ground truth (cochrane.org)
  • “Systematic reviews of the effects of health care” (interventions)

• Selected 3 outcomes: Helps, Does not help, Inconclusive (1/3 each)

• Matched queries, Hand-labeled content in top 10 and search index (top 1000)

Example queries:
Does green tea help with weight loss?
Can cranberries cure UTIs?
Can echinacea treat the common cold?

Contribute to positive skew in search engine results

(White and Hassan, TWEB 2014)
Impact on Search Behavior

- Potentially-alarming content in captions drives clickthrough behavior, leading to changes in CTR distributions including click inversions.

Click inversions (Clarke, Agichtein, Dumais, White, 2007)

Lauckner and Hsieh (CHI 2013) serious conditions in captions
→ Negative emotional outcomes for users

(White and Horvitz, TWEB 2013)
Building Click Prediction Models

- Features associated with clickthrough inversion caption pairs
- Learn models to predict clickthrough

Table V. Results corresponding to the features listed in Table IV with $\chi^2$ and p-values ($d.f = 1$). Features related to inversions and supported at 95% confidence level are bold. In rows with any cell count < 5 we use a Fisher’s exact test.

Click perplexity, lower = better

Presence of following is likely to cause inversions:
- Acute
- Severe
- Malignant
- Deadly
- Escalations
- Cancer
- ...

Fig. 4. Perplexity curves for DBN-model variants. Lower perplexity represents better prediction. Error bars denote standard error.
Part III: Mining Health Search Data

3 example applications:

1. Nutrition monitoring in populations
2. Pregnancy
3. Detecting adverse drug reactions and interactions
Example 1:
Nutrition Monitoring in Populations

(Robert West, White, Horvitz, WWW 2013)
“From Cookies to Cooks: Insights on Dietary Patterns via Analysis of Web Usage Logs”
Nutrition is a Major Health Factor

• For example, annual cost of morbidity and mortality of obesity in United States and Canada: $300 billion

• Who eats what, when, and where?

• Answer usually obtained via phone surveys, medical records, diary studies, etc.

• Explored the use of logs and online recipe accesses for population-scale nutrition monitoring

(West, White, Horvitz, WWW2013)
# Log Analysis – Recipe Users

## Consenting IE users, 18 months

<table>
<thead>
<tr>
<th>URL</th>
<th>Referrer</th>
<th>Timestamp</th>
<th>Anonym. UID</th>
<th>Geolocation</th>
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</thead>
<tbody>
<tr>
<td>yahoo.com?q=the+onion</td>
<td>yahoo.com</td>
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<td>theonion.com</td>
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<td>1283769640</td>
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<td>Hackensack, NJ, USA</td>
</tr>
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<td>theonion.com/Area-Man-Sad</td>
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</tr>
<tr>
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<td>Blumenau, SC, Brazil</td>
</tr>
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<td>Hfd5eRfKoP</td>
<td>Montreal, QC, Canada</td>
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**Nutrition**

- Calories: 359 kcal
- Cholesterol: 44 mg
- Fiber: 7.3 g
- Sodium: 299 mg

*Percent Daily Values are based on a 2,000 calorie diet.*
Nutritional time series

- 6 nutrients: total kcal, protein, fat, sodium, cholesterol
- For each nutrient: average by day of year
Online Recipes for Approximating Food Popularity

- **Fundamental assumption**: Searched online recipes ≈ eaten food
- Reality check: user survey among Microsoft employees
- “Recall last time you used an online recipe.”
  - “Did it represent well what you normally eat? 75% yes”
  - “Did you search for the specific dish you ended up cooking?” 81% yes

Other factors:
- Population bias: online recipe users may not be representative of population
- False positives: “look but don't cook”
- False negatives: “cook but don't look”
Anatomy of Nutritional Time Series

Discrete Fourier Transform

(a) Spectral density
(b) Annual frequency
(c) Weekly frequency
(d) Residual
Anatomy of Nutritional Time Series

Low-freq. period

Non-periodic anomalies

High-freq. period

Discrete Fourier Transform

Christmas
Thanksgiving
St. Patrick’s Day
...

(a) Spectral density
(b) Annual frequency
(c) Weekly frequency
(d) Residual

Time series

Calories per serving
Nutritional time series: Annual variation

- Calories per serving
- Calories from protein
- Calories from carbs
- Sodium [mg]
- Calories from fat
- Cholesterol [mg]
Nutritional time series: Annual variation

Effects are seasonal!
Correlations with Population Health

- Congestive heart failure (CHF): chronic condition that is dangerous and costly
- Increased sodium intake can cause acute exacerbation of symptoms
- Anecdotal reports by health practitioners:
  - Salty holiday meals with family → higher rates of CHF exacerbation

Idea:
- Approximate sodium intake via recipe clicks
- Correlate with hospital admission records

Data: All CHF admissions to emergency department for time period of our logs (Washington Hospital Center, Washington, D.C.)
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Pearson correlation: $r = 0.62$, $p = 0.0028$
Applications

Estimating nutritional intake from logs enables:

• Insights about public health via online activities
• Cheap and fast tracking of population-wide dietary preferences
• Guide targeted public-health campaigns
• Understand and intervene on chronic conditions
• Support of users interested in changing eating habits
Example 2: Exploring Time-Dependent Concerns about Pregnancy and Childbirth from Search Logs

(Adam Fourney, White, Horvitz, SIGCHI 2015)
Pregnancy

• Last year, 3,957,577 babies were born to parents in the United States

• Many of those parents searched online for information about their pregnancy or their newborns

• Their queries tell, in exquisite detail, the very human and personal story of pregnancy and childbirth

• Advertisers know this
  • A person’s attention becomes 220 times more valuable to advertisers if it is known they are pregnant*

Pregnancy

Can this data also be of value as a tool for public health research? e.g., studying querying for self-induction of labor over 40 weeks:

- Interest in self-induction of labor peaks at week 38.
- Induction not recommended before week 39.

- Can tackle questions such as:
  - How do the experiences of pregnancy & childbirth manifest in the logs?
  - Can we predict who is pregnant, how far along they are, and when they give birth?

(Fourney, White, Horvitz, SIGCHI 2015)
Leveraging Self-Report Queries

“I am N weeks pregnant”

- ~13,000 users searched this phrase on Bing.com, between June 2012 and December 2013
- Assume are as reliable as survey responses, especially since unprompted
- Places users on a well-known timeline

1st day of last menstrual period

i am 12 weeks pregnant

i am 20 weeks pregnant

i am 35 weeks pregnant

and feel nauseous

and want to be done
Characterizing and Predicting

Compute temporal distributions of key query terms

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<th>Term</th>
<th>Due date</th>
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<td>missed</td>
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<tr>
<td>period</td>
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<td>labor</td>
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<tr>
<td>newborn</td>
<td></td>
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<tr>
<td>sleep</td>
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</table>

**Predict** for non self-report users

1. Fit features to a linear model via linear regression
2. If line slope 0.85-1.15, user → (likely to be) pregnant

Improves coverage beyond self-reporting searchers
(8x increase in coverage)

Prediction error = ±0.685 weeks on average
(median: 0 weeks)
Validation With External Data

Comparison with CDC data on birth @ weeks gestation

Many tests performed during pregnancy:

Compare spikes in query interest against **when tests are performed**

**Differences in population, delays in querying (e.g., unlikely to search during labor or soon thereafter!)**

Figure 5: Histograms detail about how interest in three standard prenatal screening procedures vary over 40 gestational weeks. Bars show the proportion of searchers who have searched at least once for the bigram of interest in the associated week. Red bars report weeks in which each test is typically performed, as reported in [2], [18], and [24] respectively.
Applications

• Supporting mothers through personalized search
  • Tailoring search experience to stage or first time moms
  • Providing advice or guidance during related activities (e.g., flying when pregnant)

• Providing support via signals mined from logs
  • Quantifiable data to support assertions about pregnancy experiences
  • [back pain] → “Many expectant mothers query for this in Tri. 1, drops off in Tri. 2”

• Public health research
  • Studying sensitive issues, e.g., early induction of labor or drug abuse while pregnancy via search activity
Example 3: Identifying Drug Interactions and Adverse Drug Reactions from Search Logs

(White et al., JAMIA 2013)
(White et al., Nature CPT 2014)
Signals on Medication Adverse Effects

→ Web search as sensor for side effects?
  1 in 250 of people query on top-100 drugs

• Adverse drug effects – 4th leading cause of preventable death in U.S.
Signals on Medication Adverse Effects

• Pharmacovigilence: spontaneous reports FDA Adverse Event Reporting System (AERS) – reports from patients, clinicians, drug companies

• 2011 finding in AERS analysis (Tattonetti, et al.):
  • \( Paxil + Pravachol \rightarrow \checkmark \) Hyperglycemia
  • \( Pravachol \rightarrow \times \) Hyperglycemia
  • \( Paxil \rightarrow \times \) Hyperglycemia

(Tattonetti et al., Nature CPT 2011)
Web-Scale Pharmacovigilance

- Disproportionality analysis **using logs pre 2011**
- Reporting ratios (RR) -- observed vs. expected: \( RR = \frac{a}{b} \overline{c} \overline{d} \)

Hyperglycemia-related terms:
- polydipsia
- thirst
- thirstiness
- thirsty
- polyphagia
- appetite increase
- increased appetite
- hungry
- polyuria
- frequent urinating
- frequent urination
- increased urination
- hyperglycaemia
- hyperglycemia
- high glucose
- glucose high
- high blood glucose
- blood glucose high
- high blood sugar
- blood sugar high
- increase blood sugar
- blood sugar increase

\( RR >> 1 \rightarrow \text{drug interaction} \)

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<tr>
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<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>RR</th>
<th>95% CI (Lower, Upper)</th>
<th>p-value (one-tailed)</th>
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<tr>
<td>Expected (pravastatin)</td>
<td>342</td>
<td>2716</td>
<td>2581</td>
<td>56302</td>
<td>2.747</td>
<td>2.438, 3.094</td>
<td>&lt; 0.0001</td>
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<tr>
<td>Expected (paroxetine)</td>
<td>342</td>
<td>2716</td>
<td>3645</td>
<td>71243</td>
<td>2.461</td>
<td>2.189, 2.767</td>
<td>&lt; 0.0001</td>
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(White et al., JAMIA 2013)
Characterizing Sensor Error

- Test on known interactions
- 31 true positives for hyperglycemia (TP)
- 31 true negatives for hyperglycemia (TN)

Focused = Subset of terms with clearer connection to hyperglycemia
Users as their Own Control

• Use search logs to detect adverse drug reactions not drug interactions

• Using ground truth from drug safety community (OMOP): 400 drugs + outcomes
  - Four outcomes: renal failure, GI bleed, liver injury, MI

• Within-user analysis: before and after first instance of drug

Exclusion periods to reduce effect of web on search behavior

→ More “experiential” signal
Rare, Serious Adverse Effects

FDA uses AERS & Multi-item Gamma Poisson Shrinker algorithm (DuMouchel and Pregibon, KDD)

## Complementarity of Signals (AUROC)

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<th>Search</th>
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<td>0.93</td>
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<td>Acute Liver Injury</td>
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<tr>
<td>Acute Myocardial Infarction</td>
<td>0.70</td>
<td>0.73</td>
<td>0.75</td>
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<tr>
<td><strong>Average</strong></td>
<td>0.81</td>
<td>0.83</td>
<td>0.86</td>
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AUROC improvements over separate are statistically significant (p < 0.05)
Applications

- Prediction of **unknown** drug interactions and adverse drug reactions
- Inform follow-on studies and clinical trials
- BLAERS (internal MSR tool)
- Prospective analysis
  - Needs time-indexed ground truth
- Impact through:
  - Early alerting for patients
  - Partnerships with government agencies
  - Partnerships with drug companies
Part IV: Opportunities and Challenges
(Some of the) Limitations of Log Analysis

• Logs offer **SCALE** but should be used in combination with more traditional instruments (intake logs, surveys, clinical studies)
  • Logs provide information about the “what”, not the “why”
  • Opportunities for log-survey linking methodologies, **in-situ** monitoring of behavioral rationales via focused surveys →
• Experiential vs. exploratory
  • Difficult to distinguish those affected from those interested
• Multiple people using the same machine (intertwined behavioral signals for 50%+ of userids)
  • Recent research on **activity attribution** may help (White et al., WWW2014)
Opportunities and Challenges

• Health information seeking → Important, prevalent
• Clear benefit to people (in surfacing reliable content), could save lives!
• Mixed methods important to fully understand observed behavior

• Searchers need help in finding reliable content, learning and managing decisions about self-treatment & pursuing professional care.

• Significant ethics and privacy implications – health is personal
• Need clearer paths to impact – connections with companies/agencies

• Emphasized big data – “small data” is important too
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• Emphasized big data—”small data” is important too
Opportunities and Challenges

• Sensor systems for public health monitoring
  - Search is a limited lens on online behavior – also tweets, social media posts, etc.

• Need to understand biases in data – validate data against known truth

• Mining can’t occur in isolation – needs partnerships for impact

• Small data mining → personal health management
  - Triangulate signals from many sources, devices, EHR, etc. (with informed user consent!), logs as memory aid
Thanks for listening!

Thanks to the BCS-IRSG and Microsoft Research for the KSJ Award. I’m deeply honored.