# Data-driven modeling

## APAM E4990

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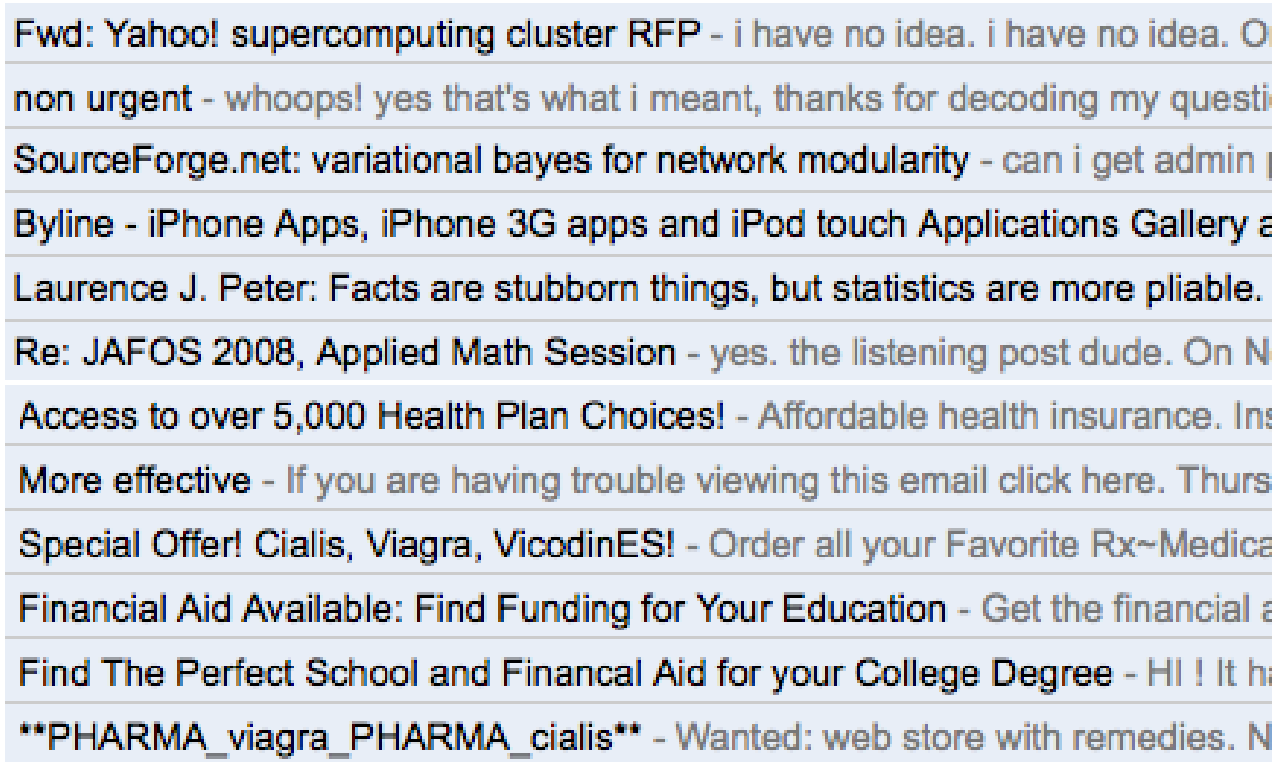
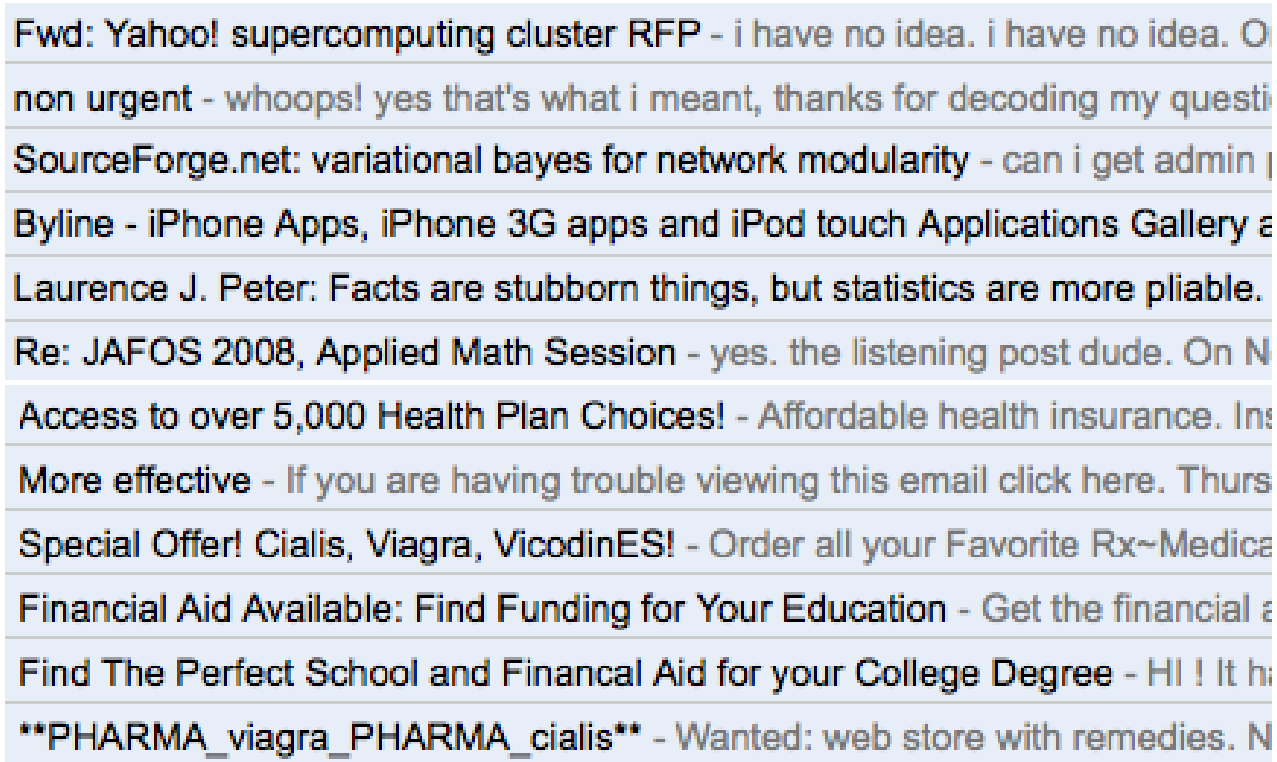
# Data-dependent products

- Effective/practical systems that learn from experience impact our daily lives, e.g.:
  - Recommendation systems
  - Spam detection
  - Optical character recognition
  - Face recognition
  - Fraud detection
  - Machine translation
  - ...

# Learning by example



# Learning by example




- How did you solve this problem?
- Can you make this process explicit (e.g. write code to do so)?

# Learning by example


- We learn quickly from few, relatively unstructured examples ... but we don't understand *how* we accomplish this
- We'd like to develop algorithms that enable machines to learn by example from large data sets

# Got data?

- Web service APIs expose lots of data

programmableweb

Subscribe | Register / Login

Home | News | APIs | Mashups | Members | How-To

Dashboard | Directory | Newest | Most Popular | By Category | API Scorecard | Add API

## Web Services Directory

Subscribe to get the latest APIs

**Filter APIs**

Keywords:

Category:

Company:

Protocols / Styles:

Data Format:

Managed By:

Date: All

Reset

**View by Category**

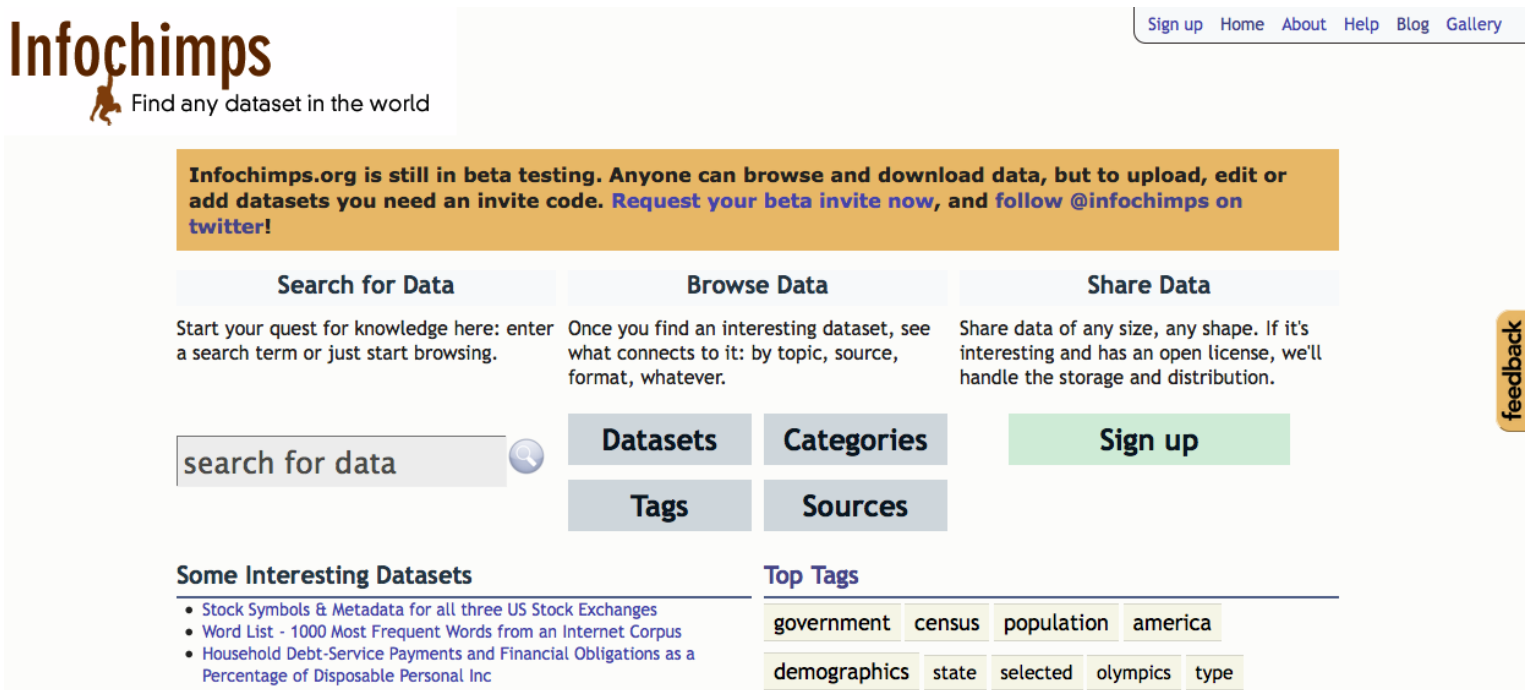
Sort by: Name | Date | Popularity | Category

Viewing 1 to 1446 of 1446 APIs

| API | Description | Category | Mashups |
|---|---|---|---|
| Google Maps | Mapping services | Mapping | 1799 |
| Flickr | Photo sharing service | Photos | 476 |
| YouTube | Video sharing and search | Video | 413 |
| Amazon eCommerce | Online retailer | Shopping | 315 |
| Twitter | Microblogging service | Social | 260 |
| eBay | Online auction marketplace | Shopping | 178 |
| Microsoft Virtual Earth | Mapping services | Mapping | 173 |
| del.icio.us | Social bookmarking | Bookmarks | 139 |
| Google Search | Search services | Search | 135 |
| Yahoo Maps | Mapping services | Mapping | 131 |
| Yahoo Search | Search services | Search | 126 |
| 411Sync | SMS, WAP, and email messaging | Messaging | 120 |
| Last.fm | Online radio service | Music | 120 |
| Facebook | Social networking service | Social | 107 |

# Got data?

- Many free, public data sets available online



# Black-boxified?

Google code labs e.g. "ajax apis" or "open source" Search

Watch Google I/O keynotes live on May 19 and 20!

**Google Prediction API (Labs)** Home Docs FAQ Forum Terms

### What is the Google Prediction API?

The Prediction API enables access to Google's machine learning algorithms to analyze your historic data and predict likely future outcomes. Upload your data to Google Storage for Developers, then use the Prediction API to make real-time decisions in your applications. The Prediction API implements supervised learning algorithms as a RESTful web service to let you leverage patterns in your data, providing more relevant information to your users. Run your predictions on Google's infrastructure and scale effortlessly as your data grows in size and complexity.

### How do I start?

- Learn more about Google Prediction API.
- Request access.
- Try out the sample code.

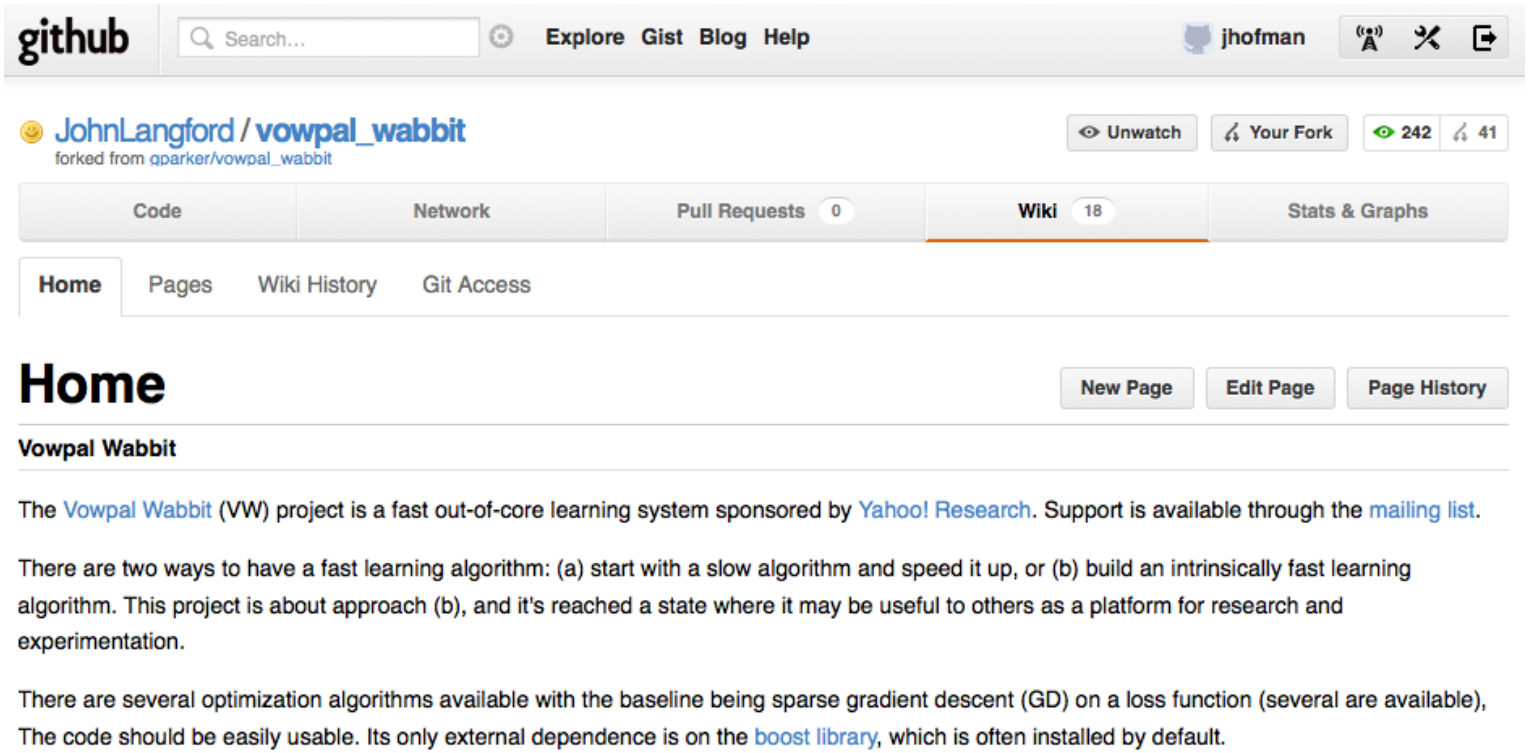

### Features

- Lightweight RESTful API
- Asynchronous training
- Automatically selects from several available machine learning techniques
- Supported inputs: numeric data or unstructured text
- Outputs hundreds of discrete categories
- Accessible from many platforms: Google App Engine, Apps Script (Google Spreadsheets), web & desktop apps, and command line

### Uses

- Language identification
- Customer sentiment analysis
- Product recommendations & upsell opportunities
- Message routing decisions
- Diagnostics
- Document and email classification
- Suspicious activity identification
- Churn analysis
- And many more...

# Black-boxified?



# Roadmap?

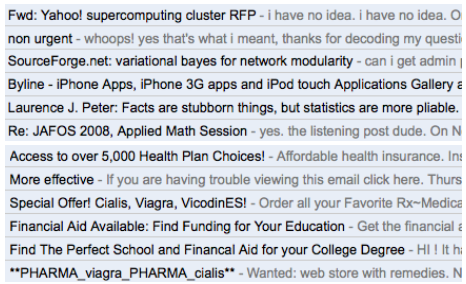
Step 1: Have data

Step 2: ???

Step 3: Profit

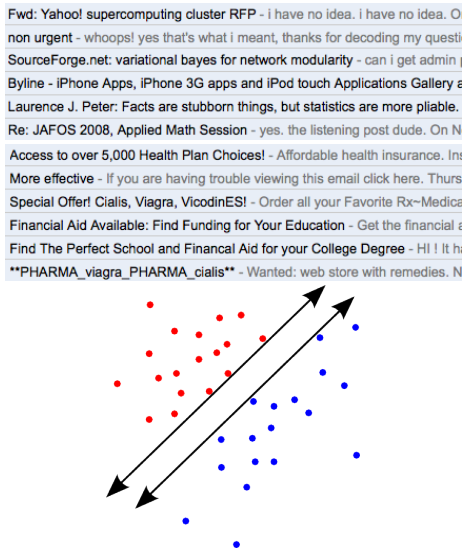
# Roadmap, take two

1. Get data



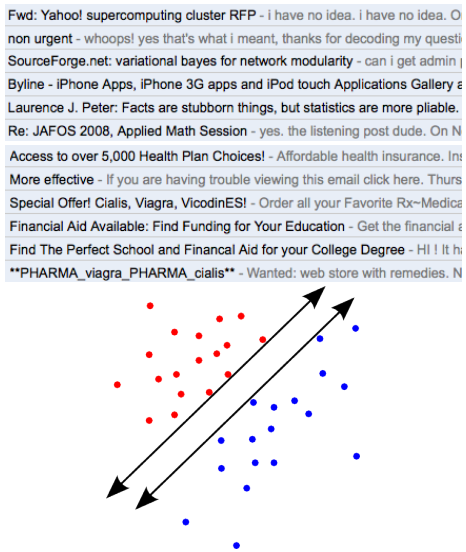
# Roadmap, take two

1. Get data
2. Visualize/perform sanity checks
3. Clean/filter observations
4. Choose features to represent data



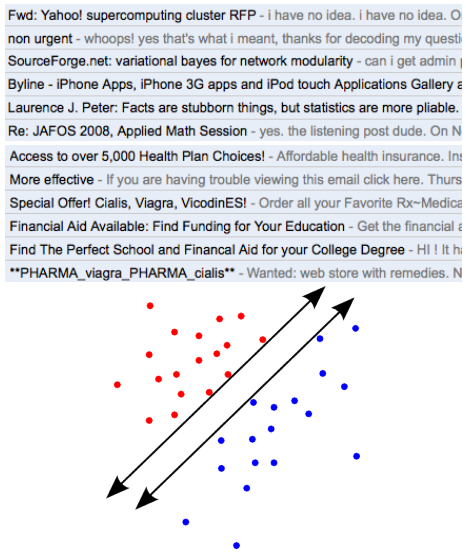
# Roadmap, take two

1. Get data
2. Visualize/perform sanity checks
3. Clean/filter observations
4. Choose features to represent data
5. Specify model
6. Specify loss function



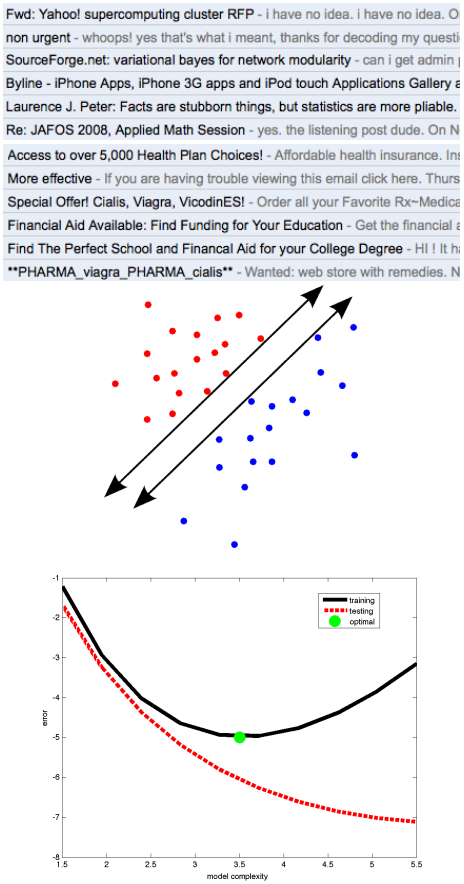
# Roadmap, take two

1. Get data
2. Visualize/perform sanity checks
3. Clean/filter observations
4. Choose features to represent data
5. Specify model
6. Specify loss function
7. Develop algorithm to minimize loss



# Roadmap, take two

1. Get data
2. Visualize/perform sanity checks
3. Clean/filter observations
4. Choose features to represent data
5. Specify model
6. Specify loss function
7. Develop algorithm to minimize loss
8. Choose performance measure
9. "Train" to minimize loss
10. "Test" to evaluate generalization



# Topics

- Supervised
  - k-nearest neighbors
  - Naive Bayes
  - Linear regression
  - Logistic regression
  - Support vector machines
  - Collaborative filtering
  - Matrix factorization
- Unsupervised
  - K-means
  - Mixture models
  - Principal components analysis
  - Topic models

- Data representation: feature space, selection, normalization
- Model assessment: complexity control, cross-validation, ROC curve, Bayesian Occam's razor
- Large-scale learning

# Everything old is new again[1]

- Many fields ...
  - Statistics
  - Pattern recognition
  - Data mining
  - Machine learning
- ... similar goals
  - Extract and recognize patterns in data
  - Interpret or explain observations
  - Test validity of hypotheses
  - Efficiently search the space of hypotheses
  - Design efficient algorithms enabling machines to learn from data

[1] http://cbcl.mit.edu/publications/theses/thesis-rifkin.pdf

# Statistics vs. machine learning[2]

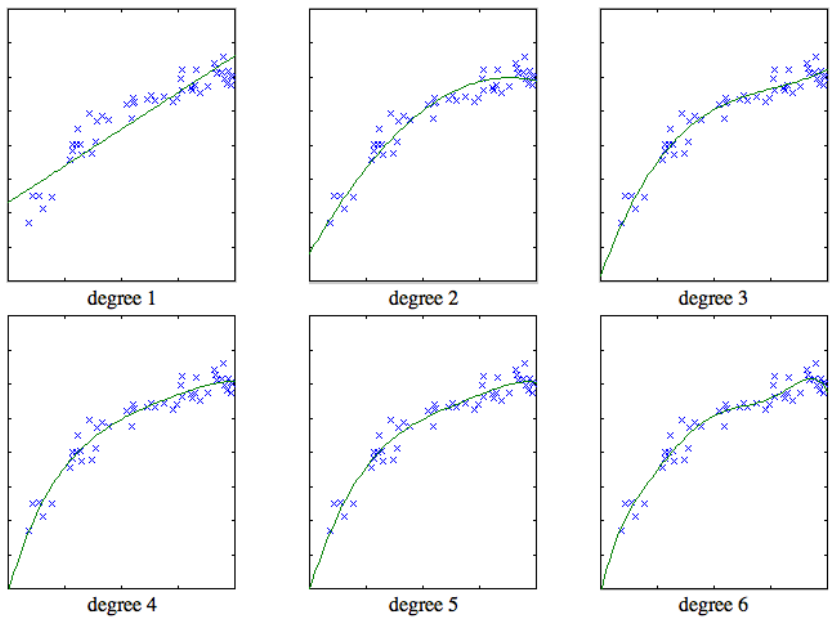
**Glossary**

| Machine learning | Statistics |
|---|---|
| network, graphs | model |
| weights | parameters |
| learning | fitting |
| generalization | test set performance |
| supervised learning | regression/classification |
| unsupervised learning | density estimation, clustering |
| large grant = \$1,000,000 | large grant= \$50,000 |
| nice place to have a meeting: Snowbird, Utah, French Alps | nice place to have a meeting: Las Vegas in August |

[2] http://anyall.org/blog/2008/12/statistics-vs-machine-learning-fight/

# Philosophy

- We would like models that:
  - Provide predictive and explanatory power
  - Are complex enough to describe observed phenomena
  - Are simple enough to generalize to future observations



# Example: Netflix Prize


Not Interested

Our best guess for Jake: **5 stars**

Average of 4,275,920 ratings: **3.8 stars**

## The Big Lebowski

1998 R 117 minutes

Slacker Jeff "The Dude" Lebowski (Jeff Bridges) gets involved in a gargantuan mess of events when he's mistaken for another man named Lebowski, whose wife has been kidnapped and is being held for ransom. All the while, Dude's friend, Walter (John Goodman), stirs the pot. Brothers Joel Coen and Ethan Coen write and direct this cult comedy classic that also stars Steve Buscemi, Philip Seymour Hoffman, Julianne Moore and John Turturro.

**Cast:** Jeff Bridges, John Goodman, Philip Seymour Hoffman, Steve Buscemi, Julianne Moore, Tara Reid, Peter Stormare, David Huddleston, Philip Moon, Mark Pellegrino, Flea, Torsten Voges, Jimmie Dale Gilmore, Jack Kehler, John Turturro, James G. Hoosier, Richard Gant, Christian Clemenson, David Thewlis, Peter Siragusa, Sam Elliott, Ben Gazzara, Jon Polito, Asia Carrera, Paris Themmen

**Director:** Joel Coen

**Genres:** Comedy, Cult Comedies, Universal Studios Home Entertainment, Blu-ray

**This movie is:** Quirky, Witty

**Format:** DVD and streaming (Blu-ray availability date unknown) (HD available)

Play

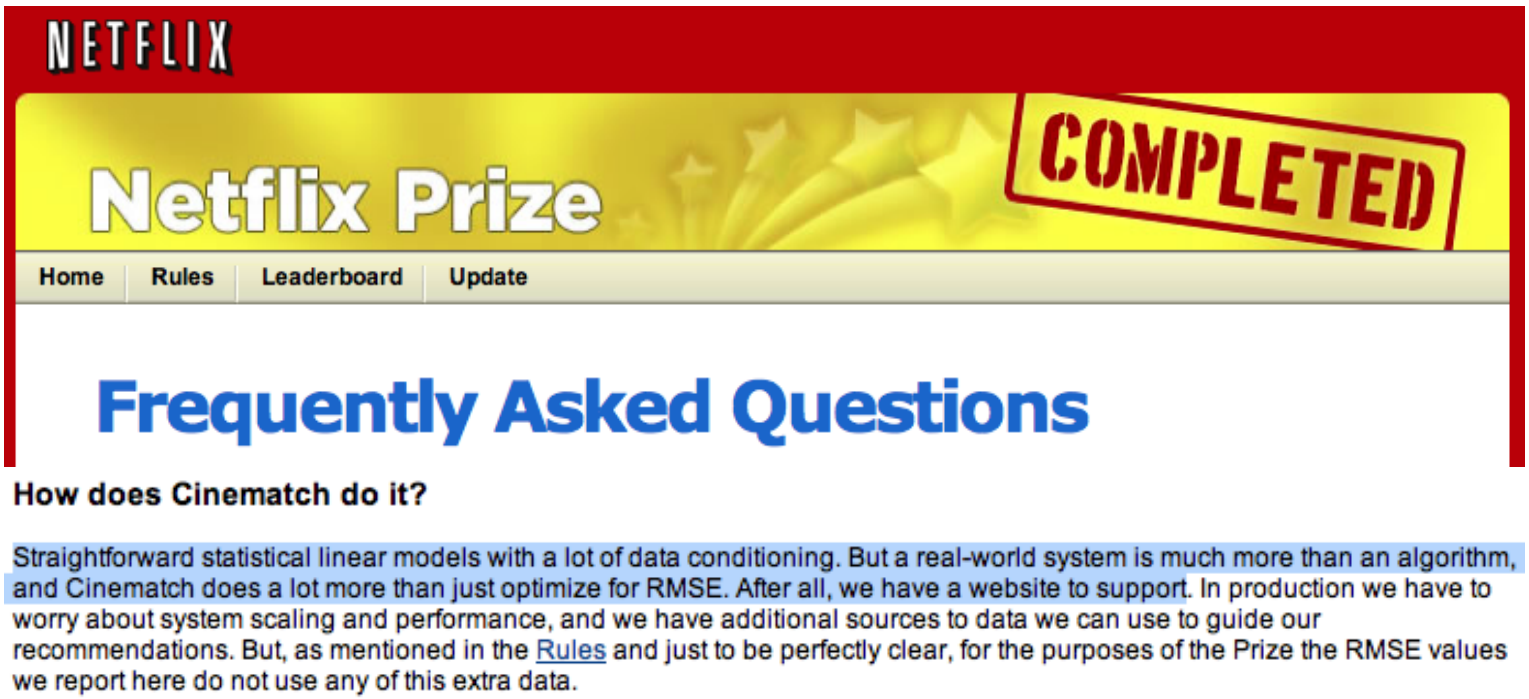
Add to Instant Queue

Add to DVD Queue

Play Trailer

Recommended based on your interest in: Fargo, O Brother, Where Art Thou? and No Country for Old Men

# Example: Netflix Prize



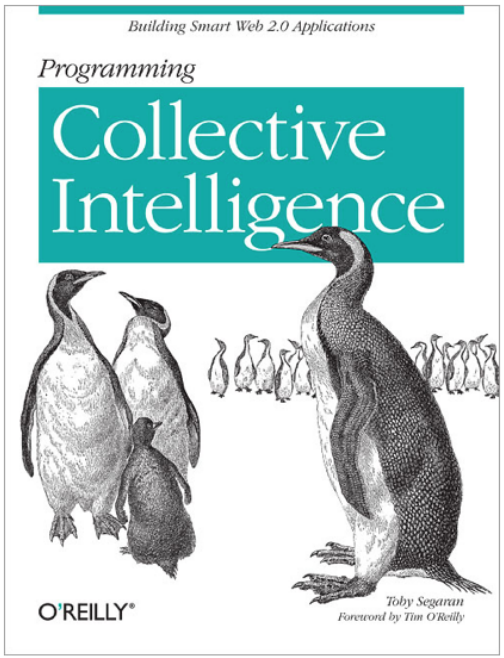
# Shipping = Feature

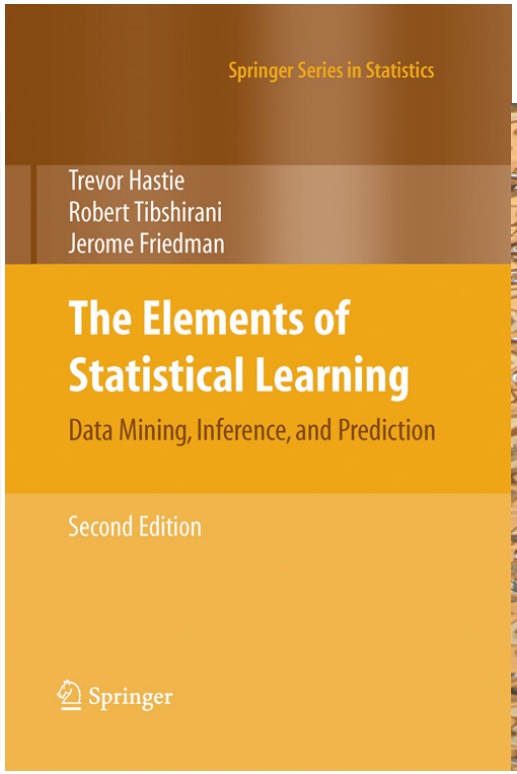
Add an asymmetric frequency feature $\mathbf{y}^{(3)}_{j,f_{ut}}$: **SBRAMF-UTB-UTF-MTF-ATF-MFF-AFF**

$$\widehat{r_{uit}} = \mu_i + \mu_u + \mu_{u,t} + \mu_{i,\text{bin}(t)} + \left(\mathbf{p}^{(1)}_i + \mathbf{p}^{(2)}_{i,\text{bin}(t)} + \mathbf{p}^{(3)}_{i,f_{ut}}\right)^T \left(\mathbf{q}^{(1)}_u + \mathbf{q}^{(2)}_{u,t} + \frac{1}{\sqrt{|N(u)|}} \sum_{j \in N(u)} \left(\mathbf{y}^{(1)}_j + \mathbf{y}^{(2)}_{j,\text{bin}(t)} + \mathbf{y}^{(3)}_{j,f_{ut}}\right)\right) \tag{34}$$

| Model extension (+) | epoch time | #epochs | probeRMSE, $k = 50$ features |
|---|---|---|---|
| **SBRMF** - SVD with biases | 17[s] | 69 | 0.9054 |
| **SBRAMF** - asymmetric part | 50[s] | 30 | 0.8974 |
| **+UTB** - user time bias | 61[s] | 50 | 0.8919 |
| **+UTF** - user time feature | 62[s] | 38 | 0.8911 |
| **+MTF** - movie time feature | 74[s] | 37 | 0.8908 |
| **+ATF** - asymmetric time feature | 74[s] | 44 | 0.8905 |
| **+MFF** - movie frequency feature | 149[s] | 46 | 0.8900 |
| **+AFF** - asymmetric frequency feature | 206[s] | 45 | 0.8886 (0.8846 with $k = 1000$) |

# References


Building Smart Web 2.0 Applications
Programming
Collective Intelligence
O'REILLY
Toby Segaran
Foreword by Tim O'Reilly


Springer Series in Statistics
Trevor Hastie
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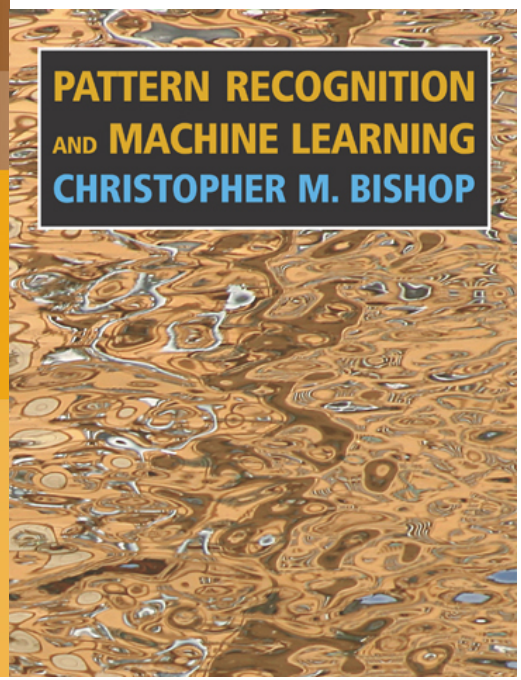

PATTERN RECOGNITION
AND MACHINE LEARNING
CHRISTOPHER M. BISHOP

# Disclaimer

You may be bored if you already know how to ...

- Acquire data from APIs
- Clean/explore/visualize data
- Classify and cluster various types of data (e.g., images, text)
- Code in Python, R, SciPy/NumPy, etc.
- Scale solutions to large data sets (e.g. Hadoop, SGD)
- Script with unix tools on the command line, e.g.

```
$ sed -e 's/<[^>]*>//g' < page.html > page.txt
```

# Themes

## Data jeopardy

Regardless of scale, it's difficult to find the right questions to ask of the data

# Themes

## Data hacking

Cleaning and normalizing data is a substantial amount of the work (and likely impacts results)

# Themes

## Data hacking

The ability to iterate quickly, asking and answering many questions, is crucial

# Themes

## Data hacking

Hacks happen: sed/awk/grep are useful, and scale

# Themes

"Data science"

Simple methods (e.g., linear models) work surprisingly well, especially with lots of data

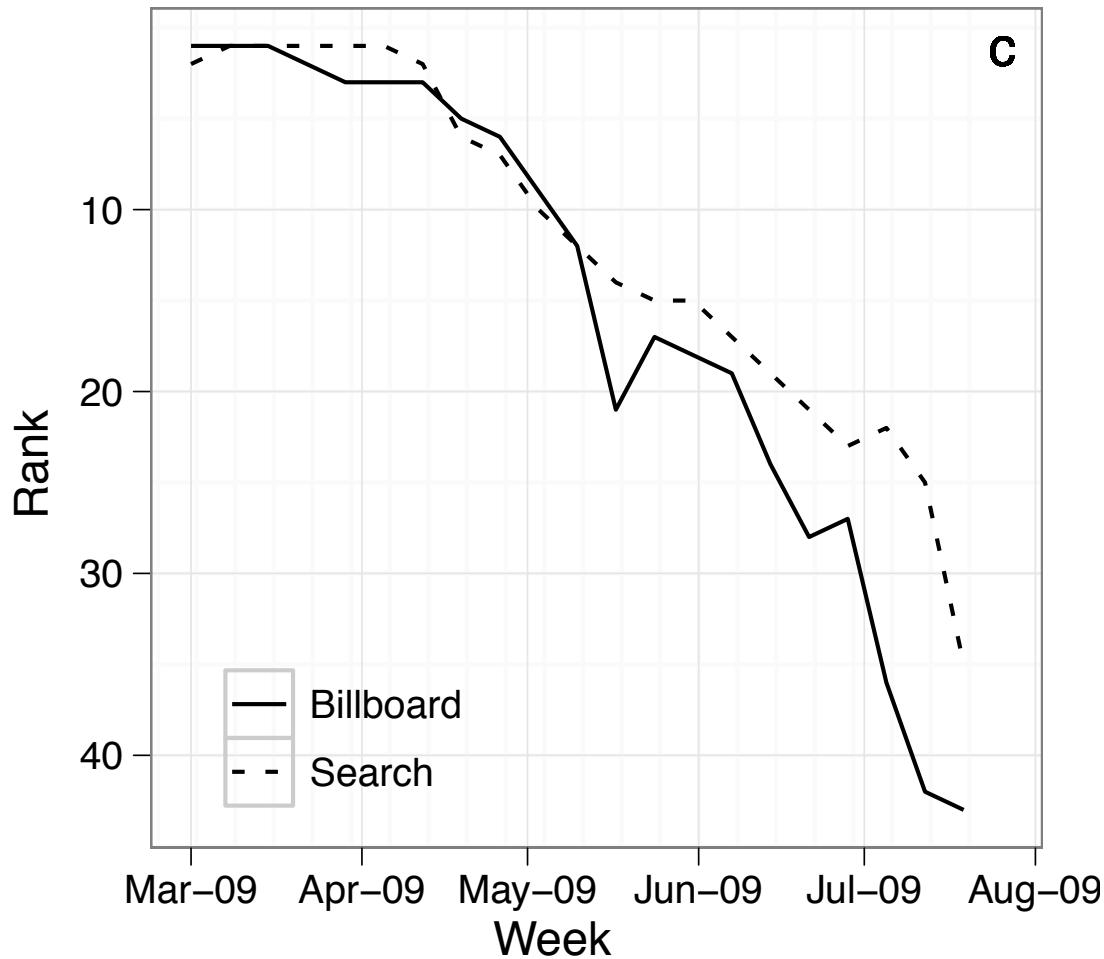
# Themes

"Data science"

It's easy to cover your tracks—things are often much more complicated than they appear

# Predicting consumer activity with Web search

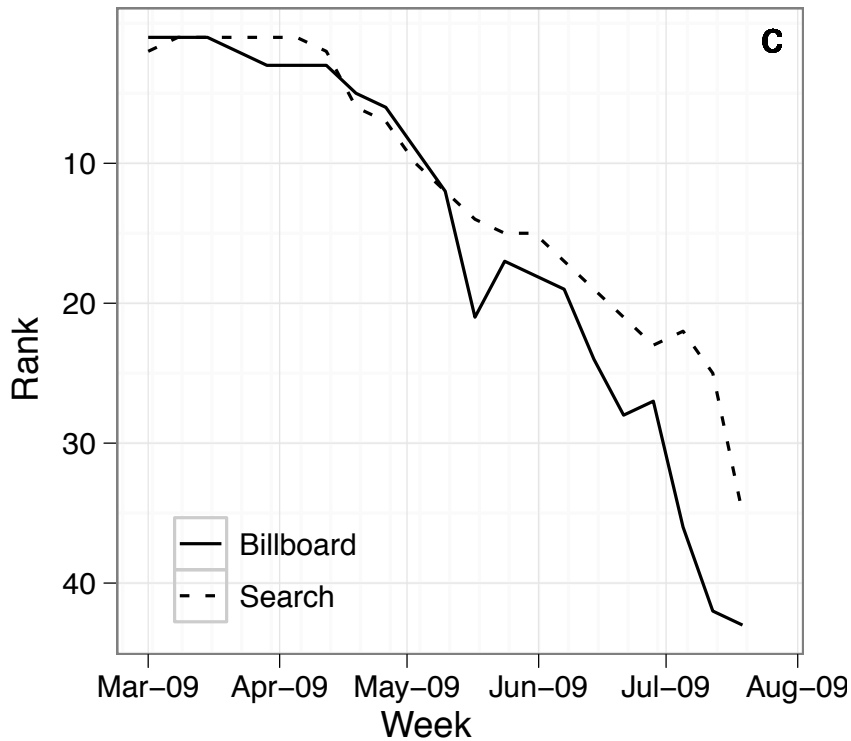
with Sharad Goel, Sébastien Lahaie, David Pennock, Duncan Watts



# Search predictions

## Motivation

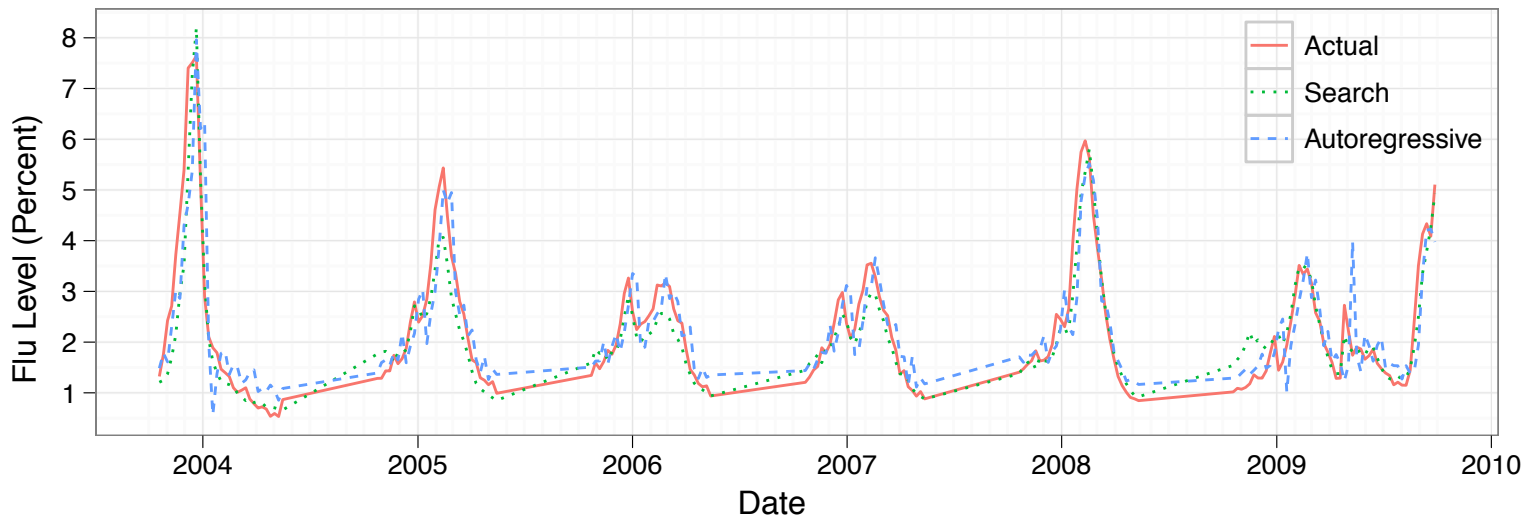
Does collective search activity provide useful predictive signal about real-world outcomes?



# Search predictions

## Motivation

Past work mainly focuses on predicting the present[1] and ignores baseline models trained on publicly available data

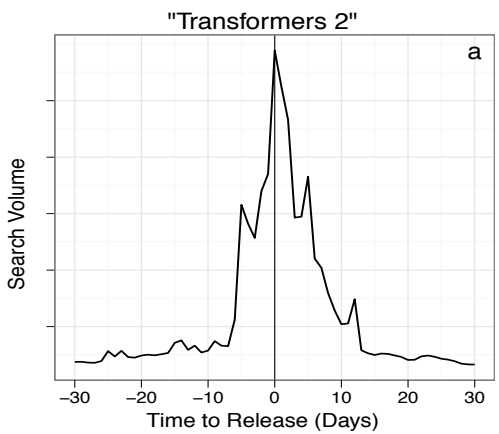


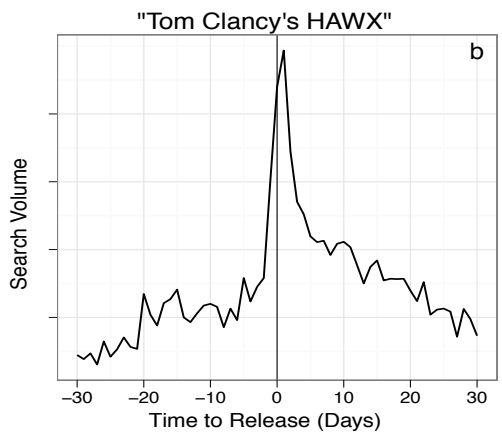

[1] Varian, 2009

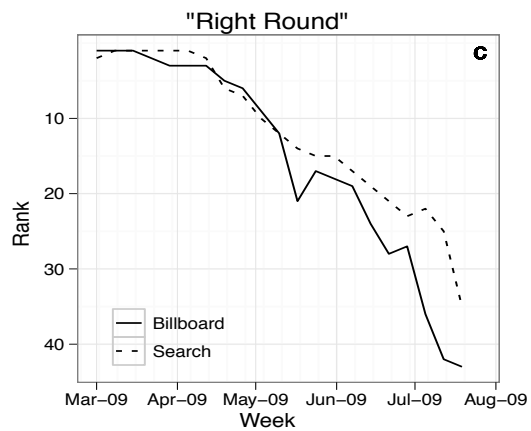
# Search predictions

## Motivation

We predict future sales for movies, video games, and music



# Search predictions

## Search models

For movies and video games, predict opening weekend box office and first month sales, respectively:

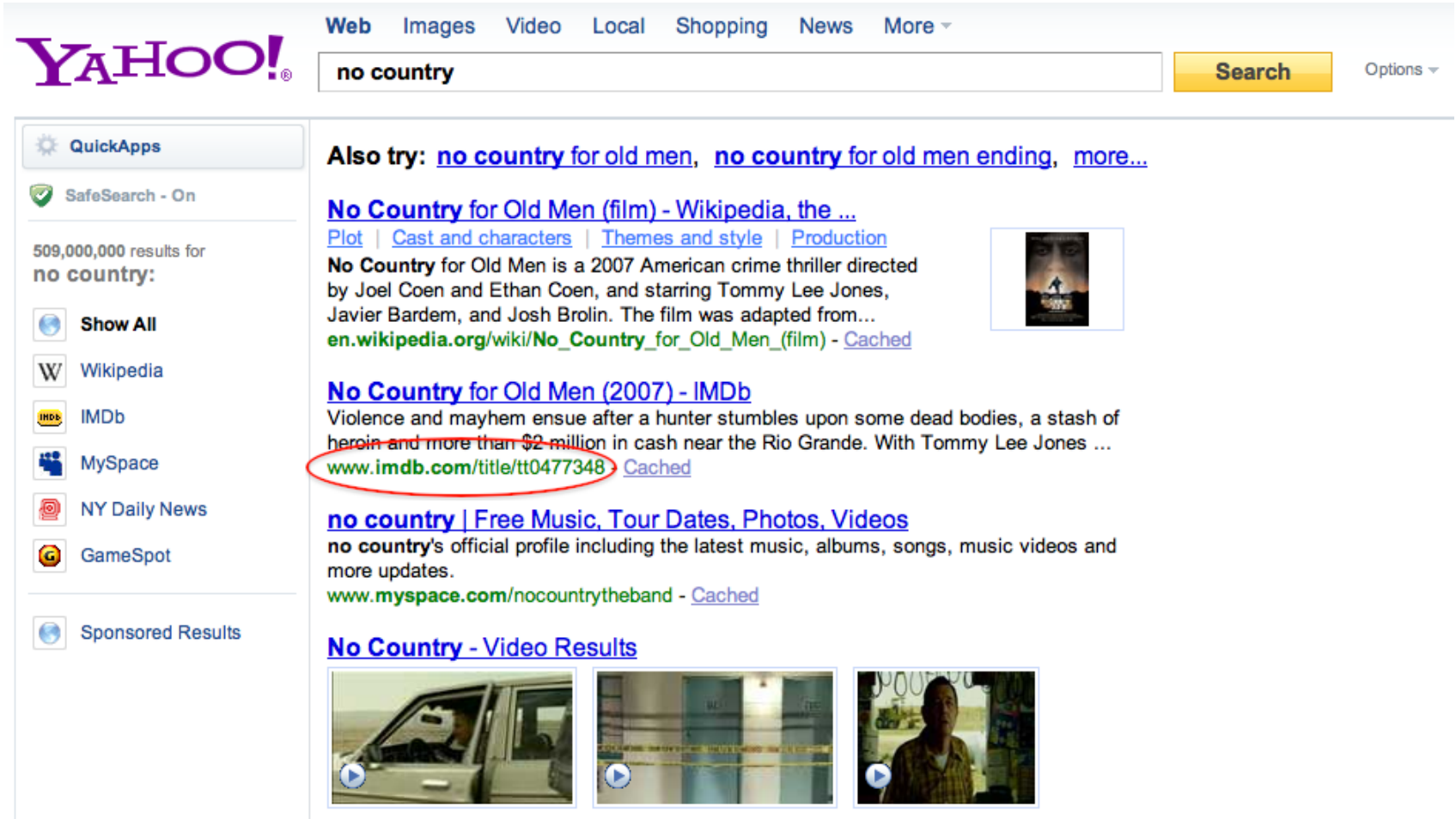
$$\log(\textbf{revenue}) = \beta_0 + \beta_1 \log(\textbf{search}) + \epsilon$$

For music, predict following week's Billboard Hot 100 rank:

$$\textbf{billboard}_{t+1} = \beta_0 + \beta_1 \textbf{search}_t + \beta_2 \textbf{search}_{t-1} + \epsilon$$

# Search predictions

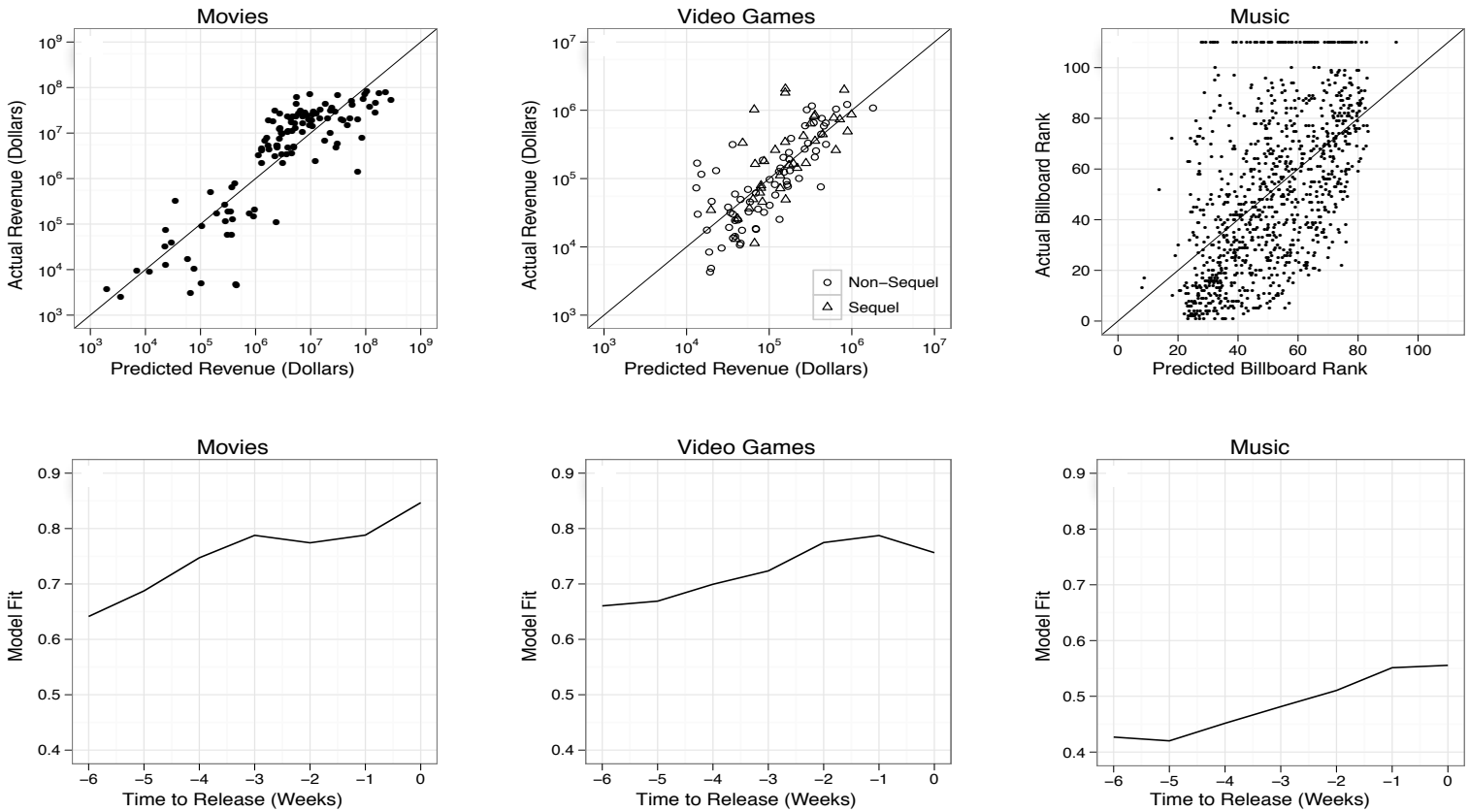
## Search volume



# Search predictions

## Search models

Search activity is predictive for movies, video games, and music weeks to months in advance



# Search predictions

## Baseline models

For movies, use budget, number of opening screens and Hollywood Stock Exchange:

$$\begin{aligned} \log(\textbf{revenue}) &= \beta_0 + \beta_1 \log(\textbf{budget}) + \beta_2 \log(\textbf{screens}) + \\ &\quad \beta_3 \log(\textbf{hsx}) + \epsilon \end{aligned}$$

# Search predictions

## Baseline models

For video games, use critic ratings and predecessor sales (sequels only):

$$\log(\textbf{revenue}) = \beta_0 + \beta_1 \textbf{rating} + \beta_2 \log(\textbf{predecessor}) + \epsilon$$

# Search predictions

## Baseline models

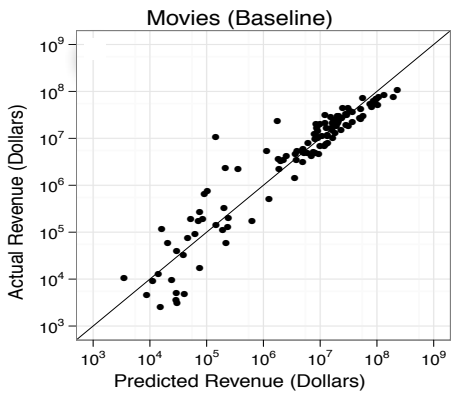
For music, use an autoregressive model with the previously available rank:

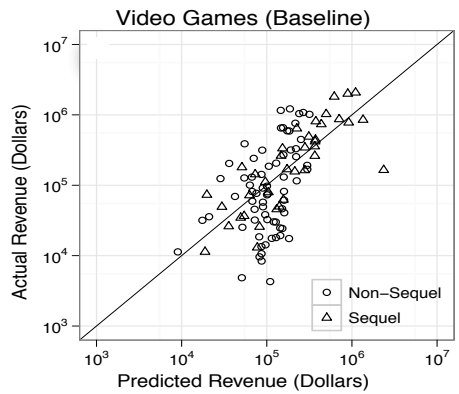
$$\textbf{billboard}_{t+1} = \beta_0 + \beta_1 \textbf{billboard}_{t-1} + \epsilon$$

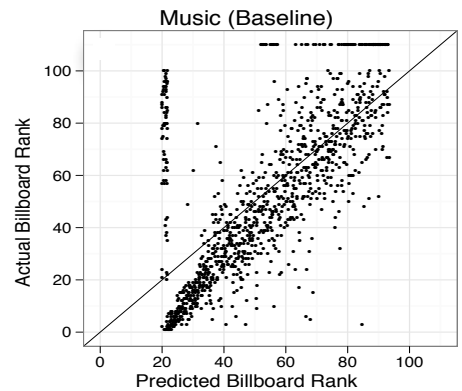
# Search predictions

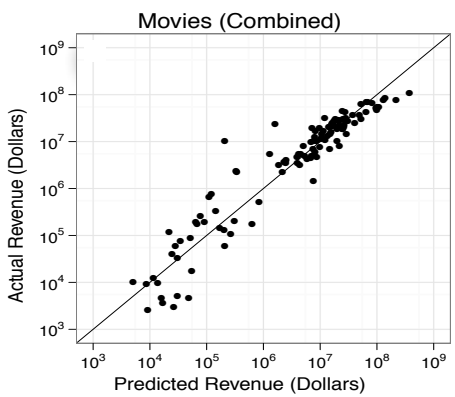
## Baseline + combined models

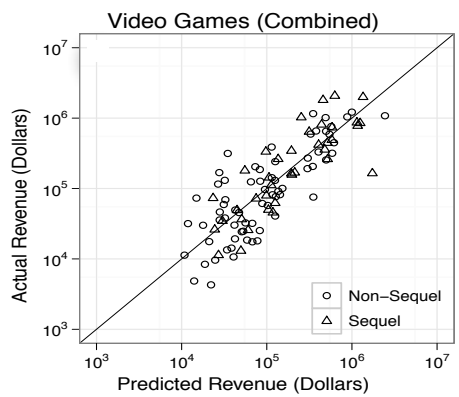
Baseline models are often surprisingly good

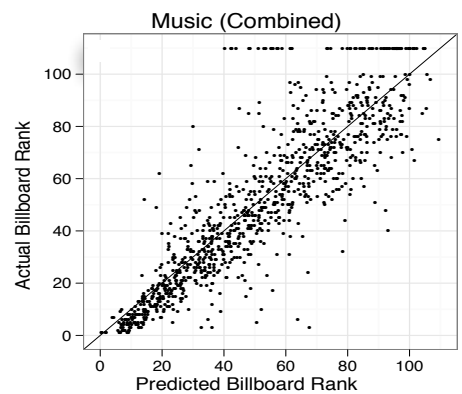


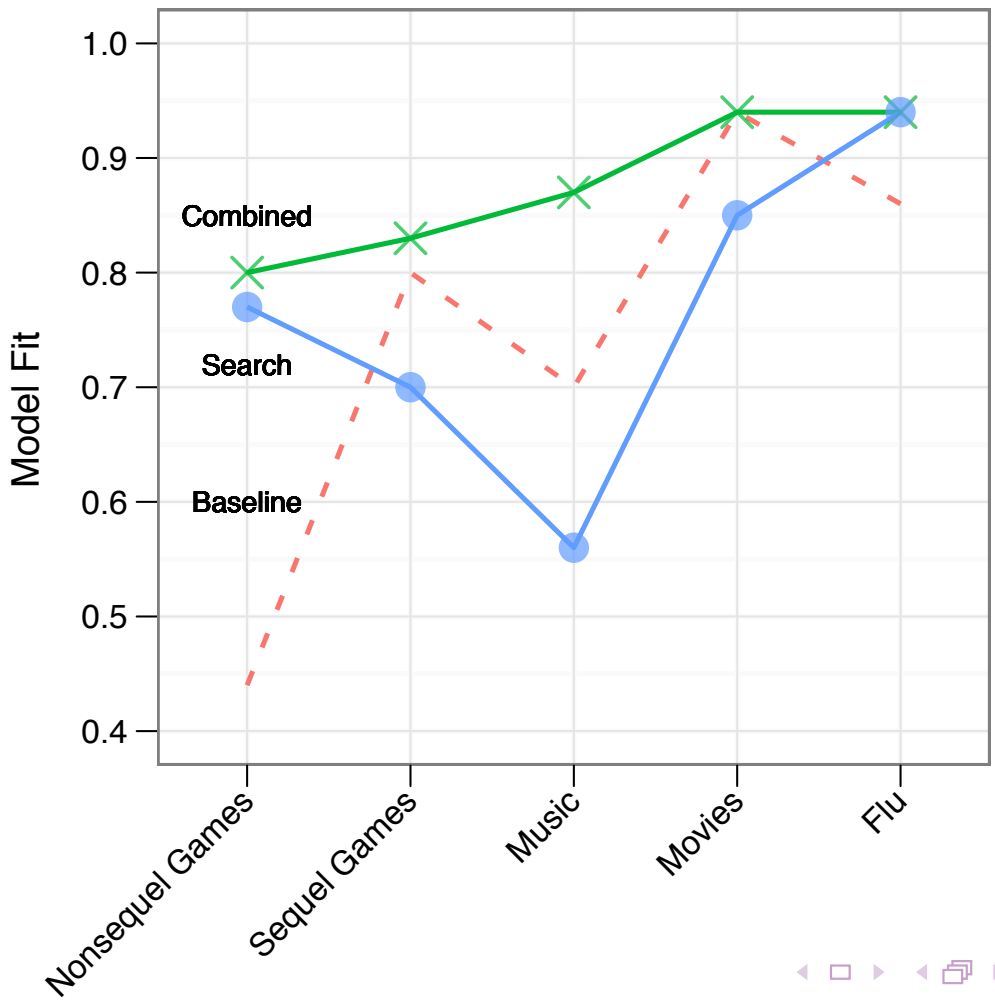



# Search predictions

## Model comparison

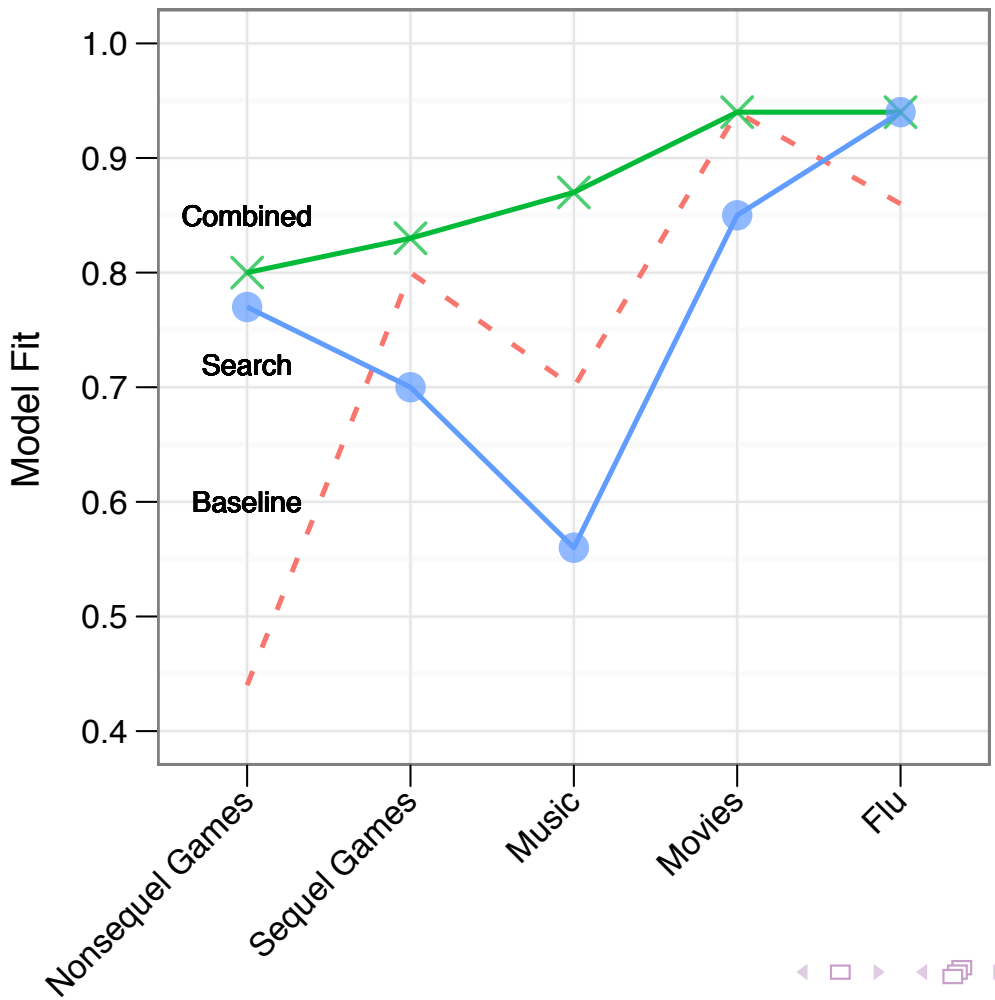
For movies, search is outperformed by the baseline and of little marginal value



# Search predictions

## Model comparison

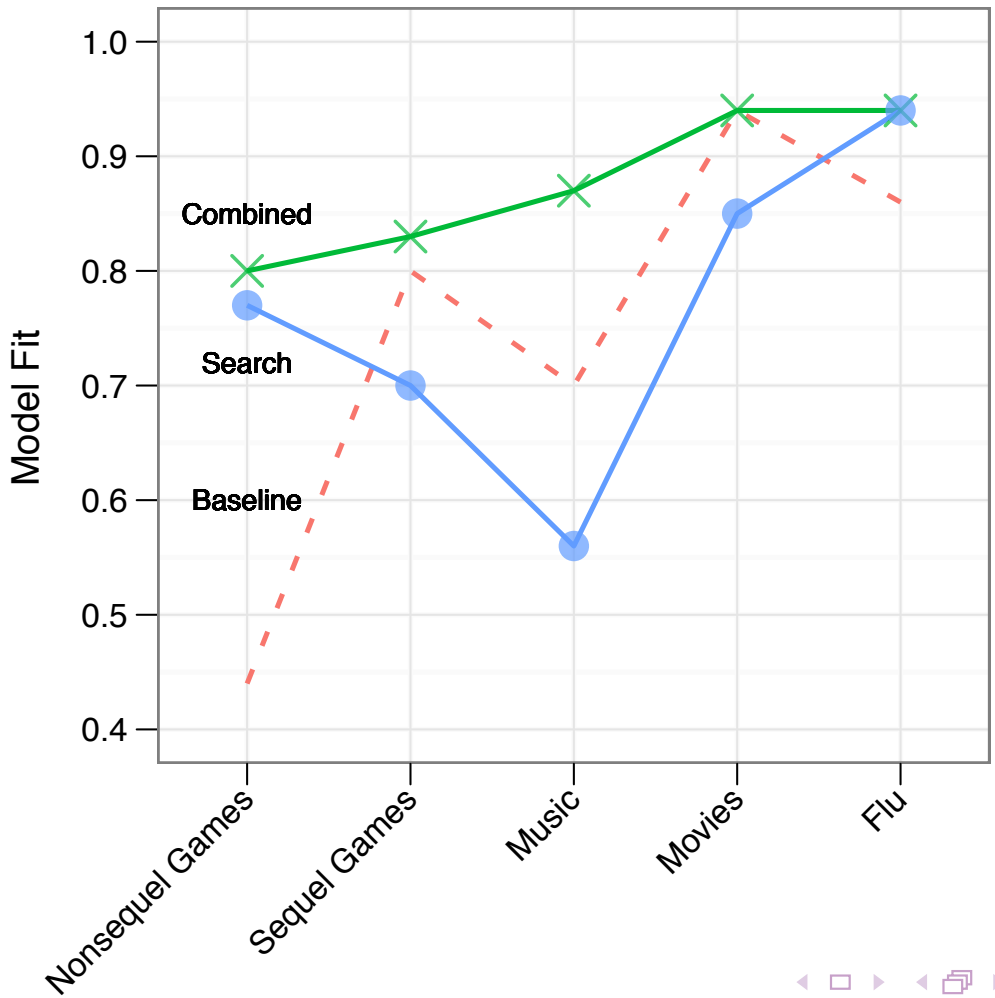
For video games, search helps substantially for non-sequels, less so for sequels



# Search predictions

## Model comparison

For music, the addition of search yields a substantially better combined model



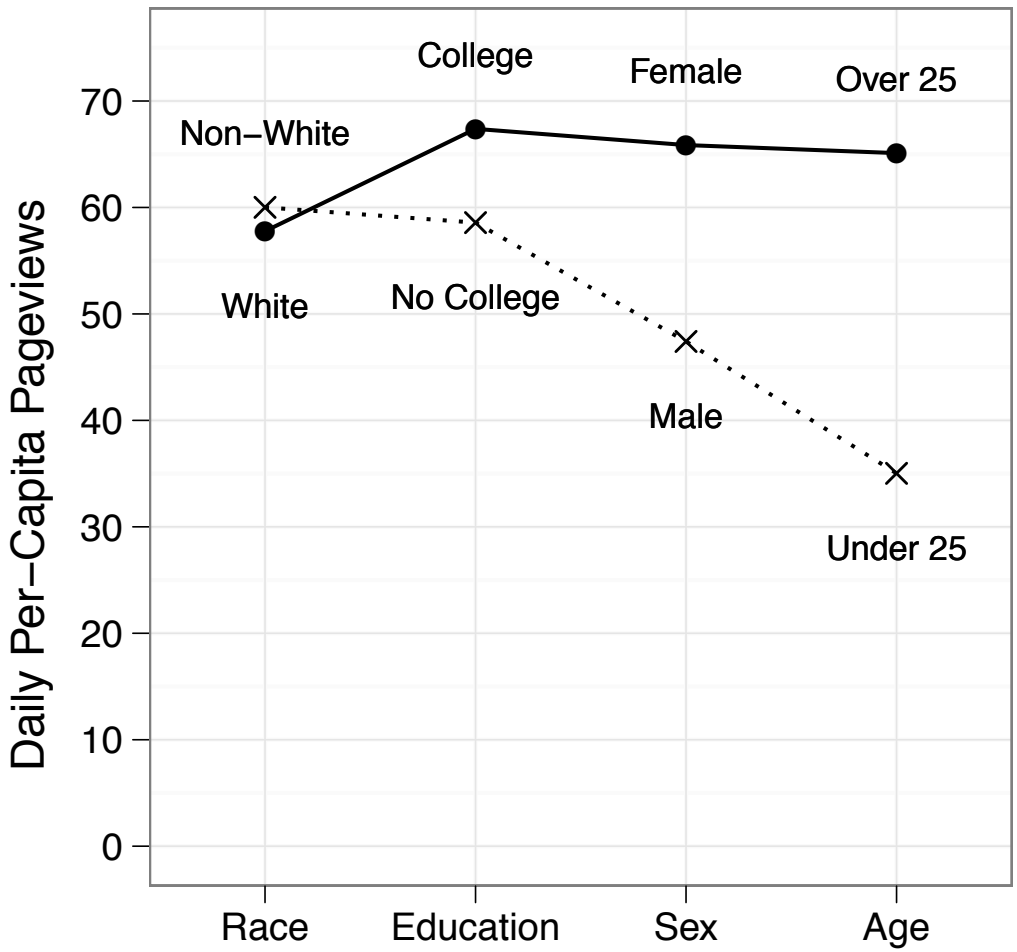
# Search predictions

## Summary

- Relative performance and value of search varies across domains
- Search provides a fast, convenient, and flexible signal across domains
- "Predicting consumer activity with Web search"
  Goel, Hofman, Lahaie, Pennock & Watts, PNAS 2010

# Demographic diversity on the Web

with Irmak Sirer and Sharad Goel



# Motivation

*Science* 17 April 1998:
Vol. 280 no. 5362 pp. 390-391
DOI: 10.1126/science.280.5362.390



POLICY

INFORMATION ACCESS

## Bridging the Racial Divide on the Internet

**Donna L. Hoffman and Thomas P. Novak**

+ Author Affiliations

The Internet is expected to do no less than transform society (1); its use has been increasing exponentially since 1994 (2). But are all members of our society equally likely to have access to the Internet and thus participate in the rewards of this transformation? Here we present findings both obvious and surprising from a recent survey of Internet access and discuss their implications for social science research and public policy.

Previous work is largely survey-based and focuses and group-level differences in online access

# Motivation

*"As of January 1997, we estimate that 5.2 million African Americans and 40.8 million whites have ever used the Web, and that 1.4 million African Americans and 20.3 million whites used the Web in the past week."*

-Hoffman & Novak (1998)

# Motivation

Focus on activity instead of access

How diverse is the Web?

To what extent do online experiences vary across demographic groups?

# Data

nielsen MegaPanel

- Representative sample of 265,000 individuals in the US, paid via the Nielsen MegaPanel[2]
- Log of anonymized, complete browsing activity from June 2009 through May 2010 (URLs viewed, timestamps, etc.)
- Detailed individual and household demographic information (age, education, income, race, sex, etc.)

[2] Special thanks to Mainak Mazumdar

# Data

```
# ls -alh nielsen_megapanel.tar
-rw-r--r--  100G Jul 17 13:00 nielsen_megapanel.tar
```

# Data

- Transform all demographic attributes to binary variables
  e.g., Age $\rightarrow$ Over/Under 25, Race $\rightarrow$ White/Non-White, Sex $\rightarrow$ Female/Male

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  e.g. `www.yahoo.com` $\rightarrow$ `yahoo.com`, `us.mg2.mail.yahoo.com/neo/launch` $\rightarrow$ `mail.yahoo.com`

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- Restrict to top 100k (out of 9M+ total) most popular sites (by unique visitors)
- Aggregate activity at the site, group, and user levels

# Hadoop + Pig (+ awk)

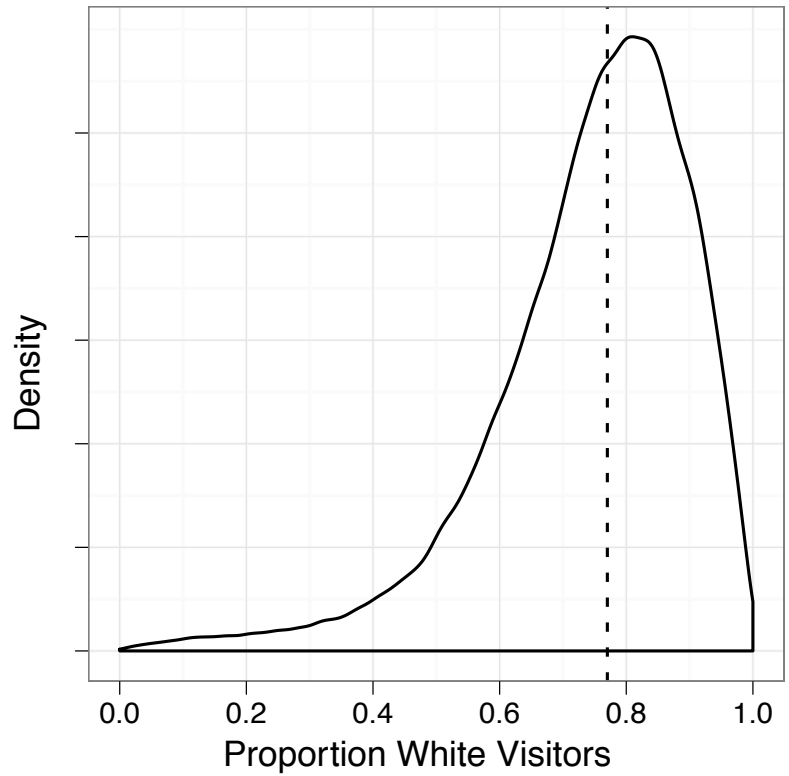
## 100GB → ∼1GB

```
-- define streaming command for normalizing urls
DEFINE add_star_domains `awk 'n=split($2,a,"."); (n==3) {print $1"\t*."a[2]"."a[3]"\t"$3}'`;

-- flatten user histories
user_pageviews = FOREACH users GENERATE
        uid,
        FLATTEN(history) AS (did, pageviews, weight);

-- join user pageviews against top domains
user_pageviews = JOIN user_pageviews BY did, top_domains BY did USING 'replicated';
user_pageviews = FOREACH user_pageviews GENERATE
        user_pageviews::uid AS uid,
        top_domains::domain AS domain,
        user_pageviews::pageviews AS pageviews;

-- stream through awk to extract two-level domains (e.g. *.yahoo.com)
user_pageviews = STREAM user_pageviews THROUGH add_star_domains AS (uid:long, domain:chararray, pageviews:int);

-- regroup and count pageviews by normalized domains
-- (userid, normalized_domain, num_pageviews)
user_pageviews = GROUP user_pageviews BY (uid, domain) PARALLEL 10;
user_pageviews = FOREACH user_pageviews GENERATE
        group.uid AS uid,
        group.domain AS domain,
        SUM(user_pageviews.pageviews) AS pageviews;
```

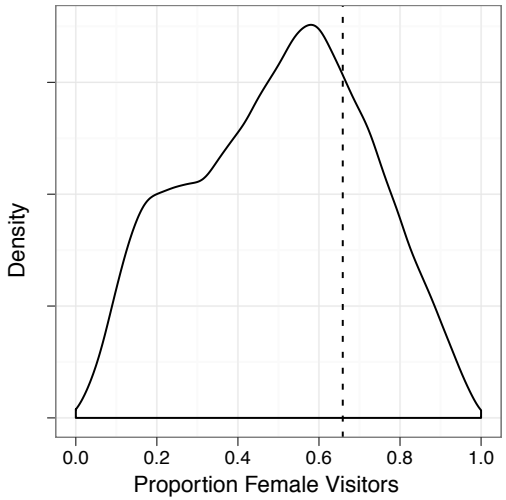
# Site-level skew

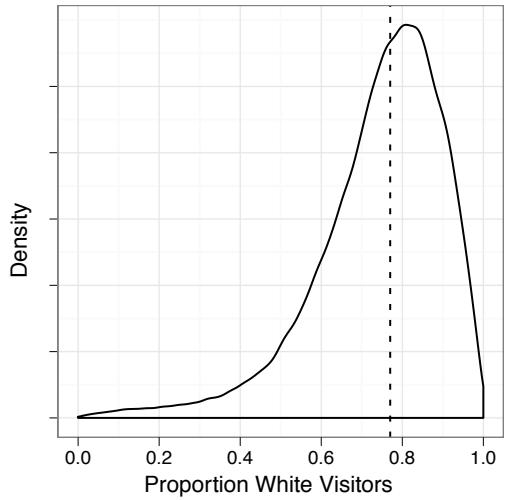
How diverse are site audiences?

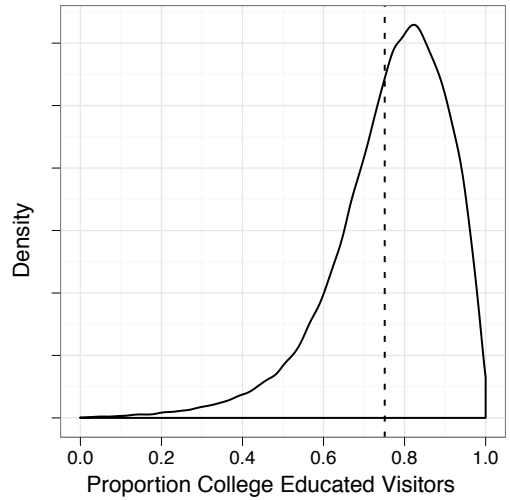
- For each site and attribute, calculate the skew in visitors (e.g., 93% of pageviews on `foxnews.com` are by White users)
- For each attribute, plot the distribution of visitor skew across all sites

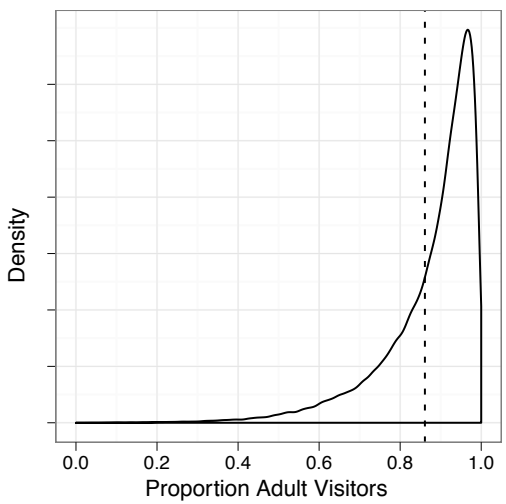


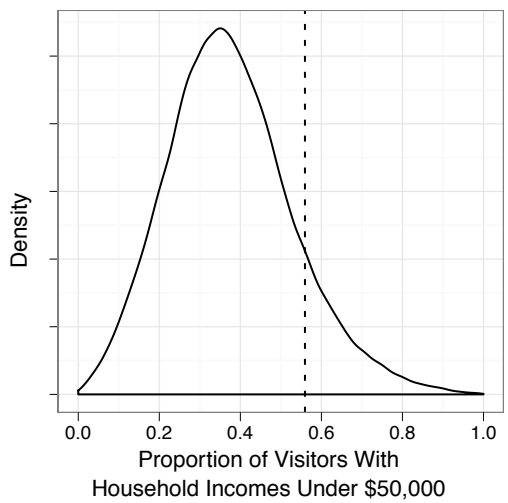
# Site-level skew



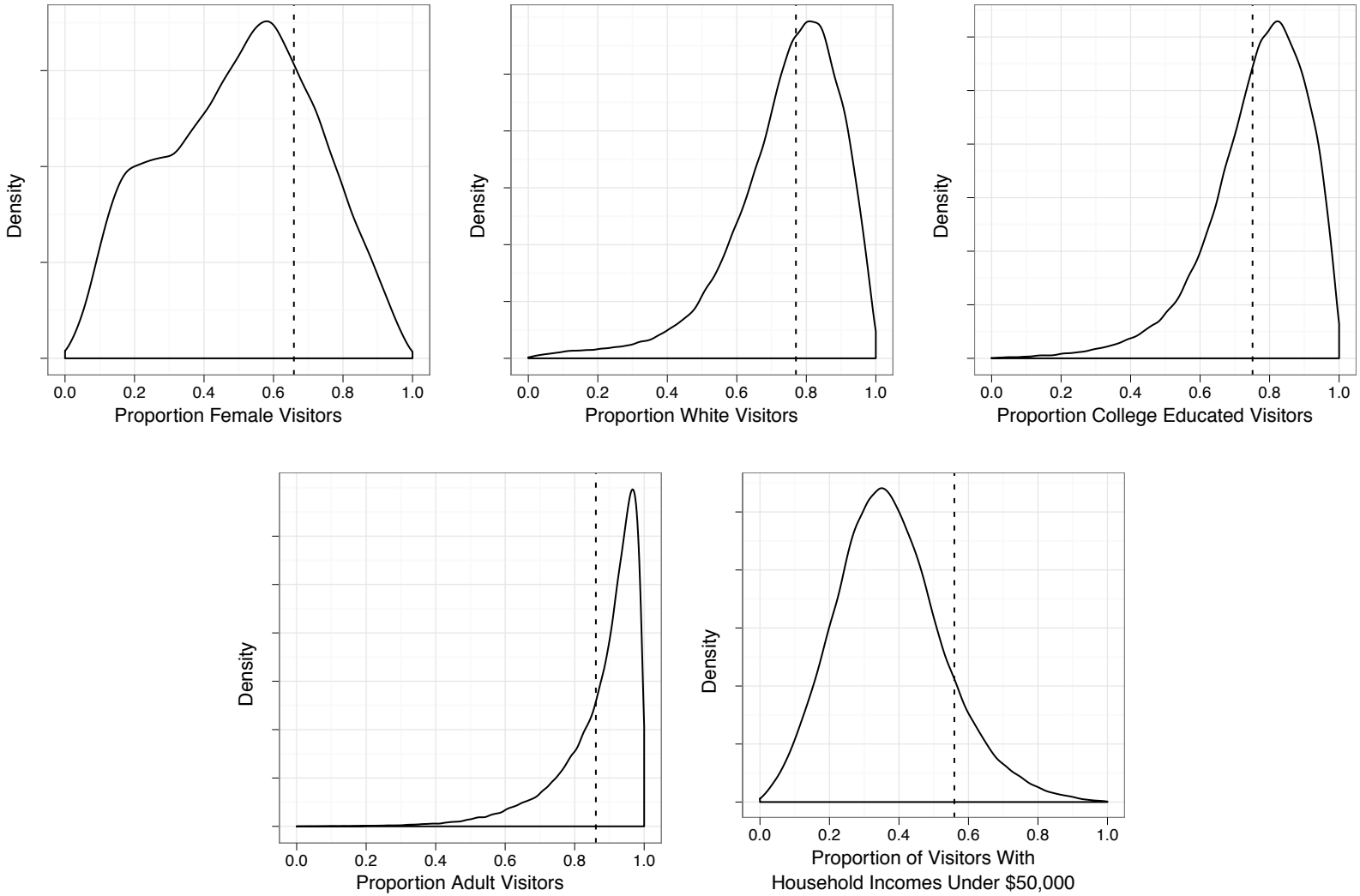



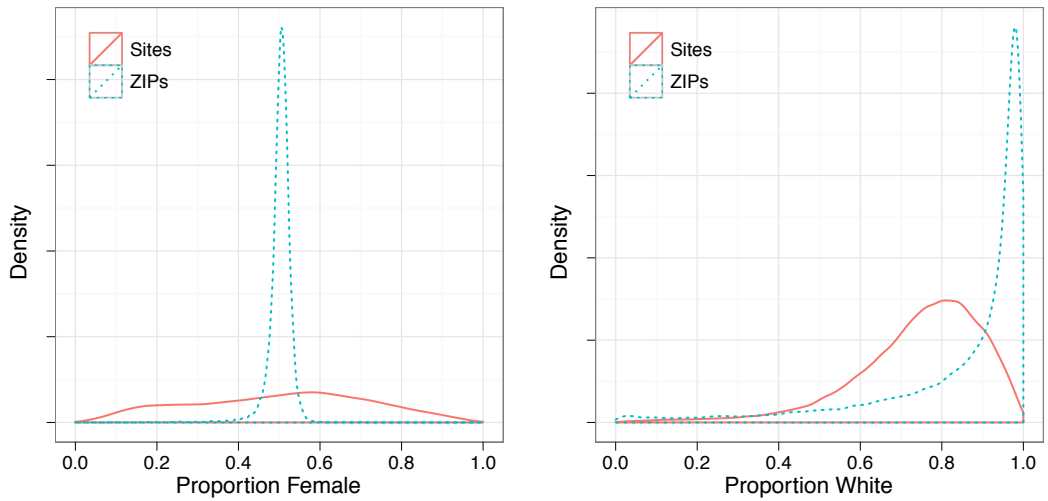
# Site-level skew




Many sites have skew close the overall mean, but there also popular, highly-skewed sites

# Sites vs. ZIPs

How do diversity of the online and offline worlds compare?



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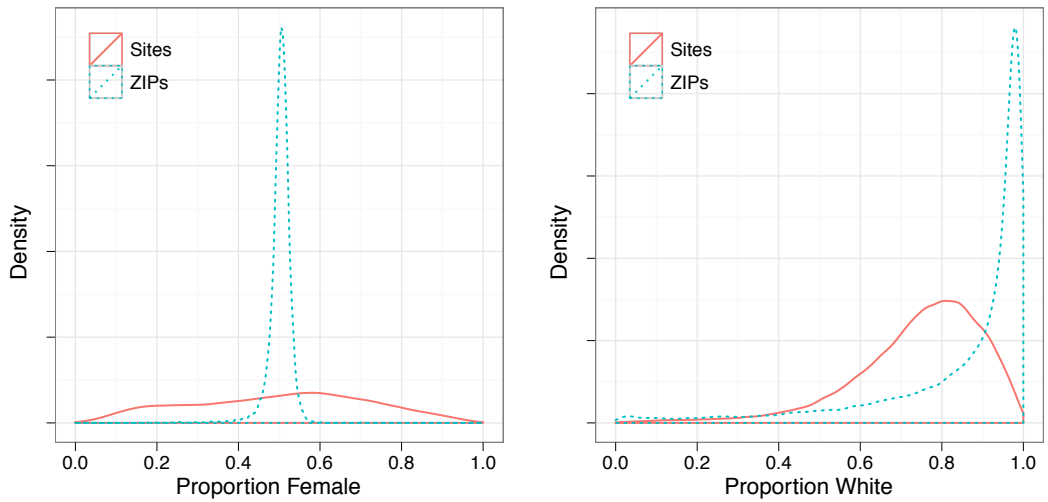


As expected, neighborhoods are more gender-balanced than sites

# Sites vs. ZIPs

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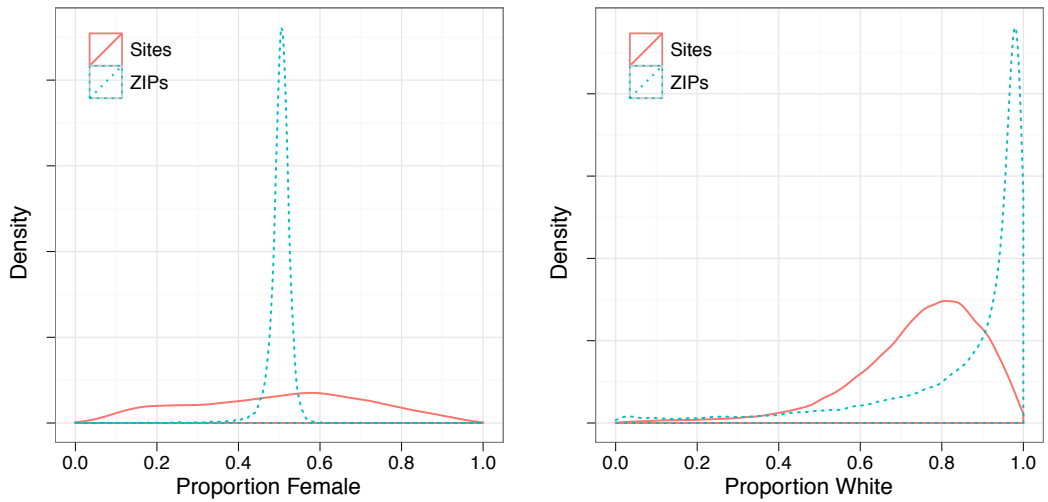
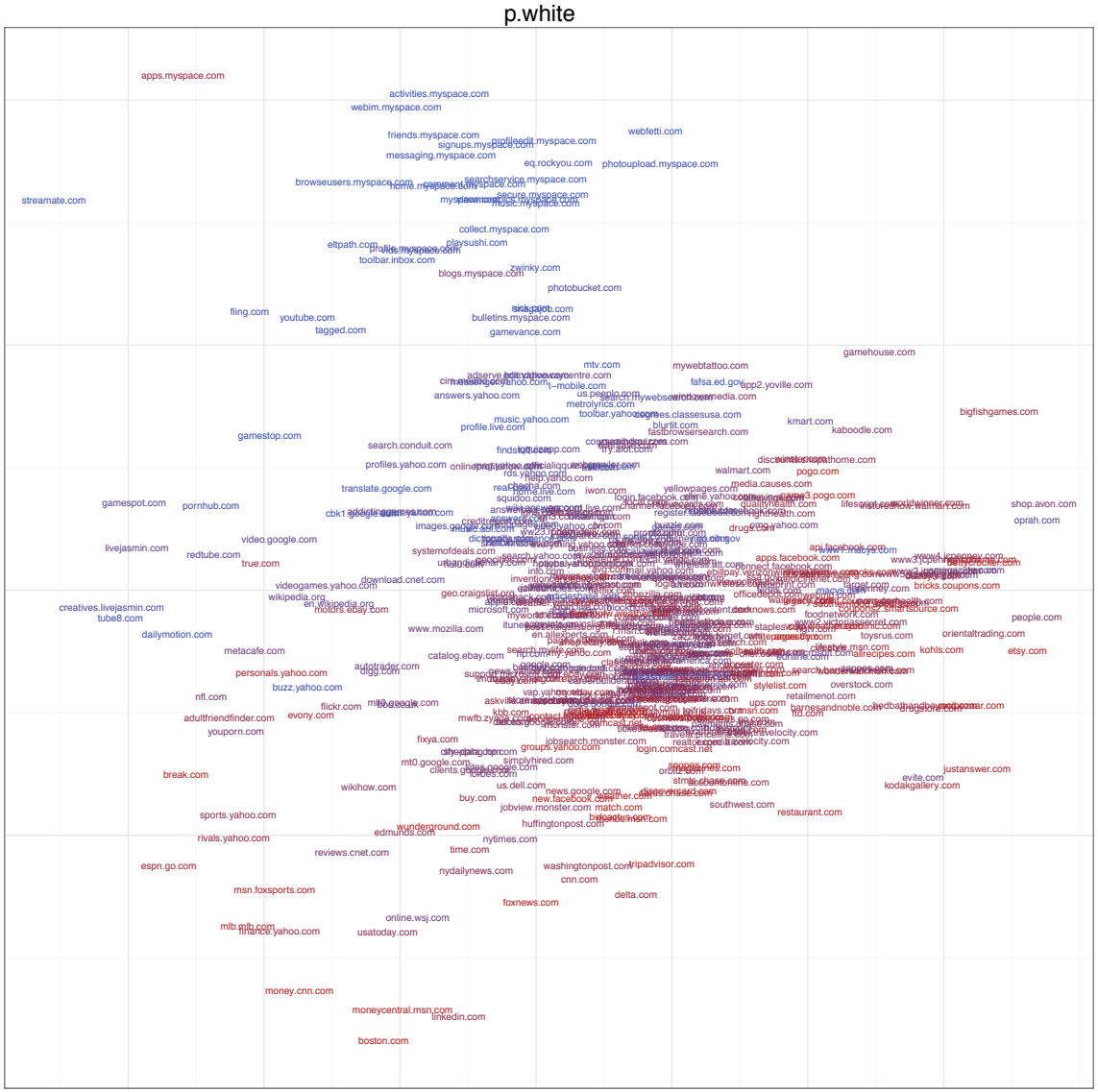


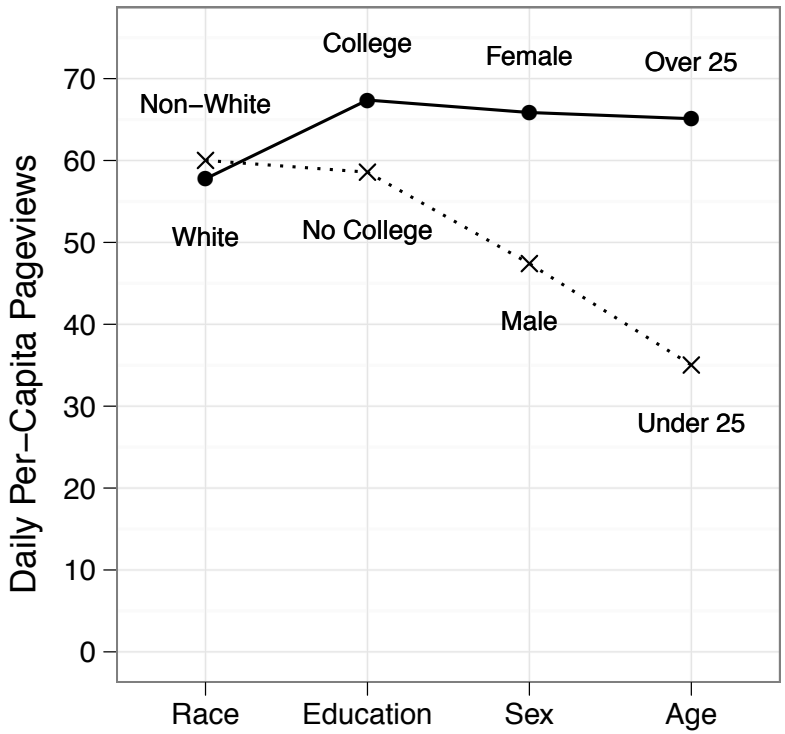

But sites typically have more racially diverse audiences than neighborhoods have residents

# Site-level skew



# Group-level activity

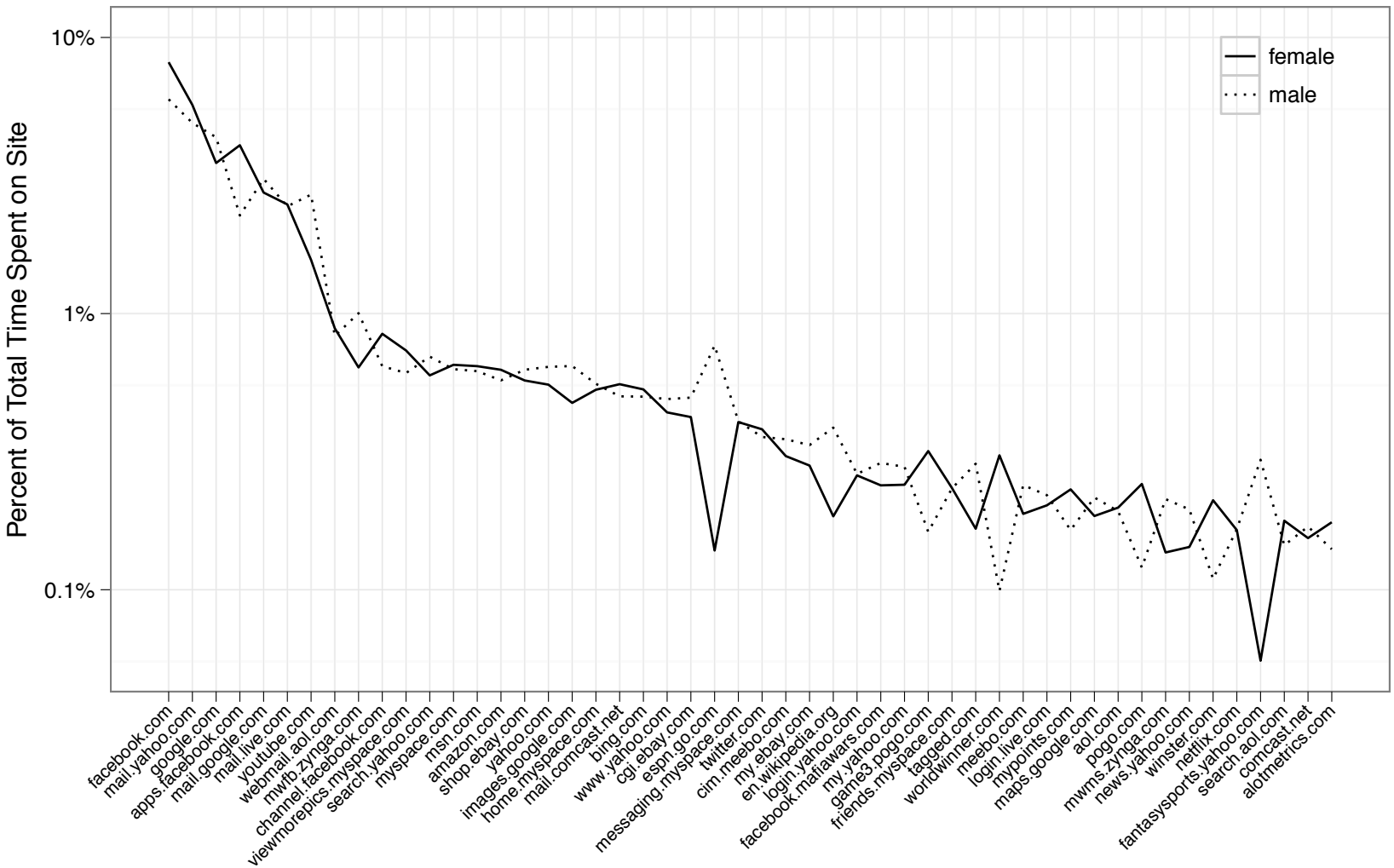
How does browsing activity vary at the group level?




Large differences exist even at the aggregate level
(e.g. women on average generate 40% more pageviews than men)

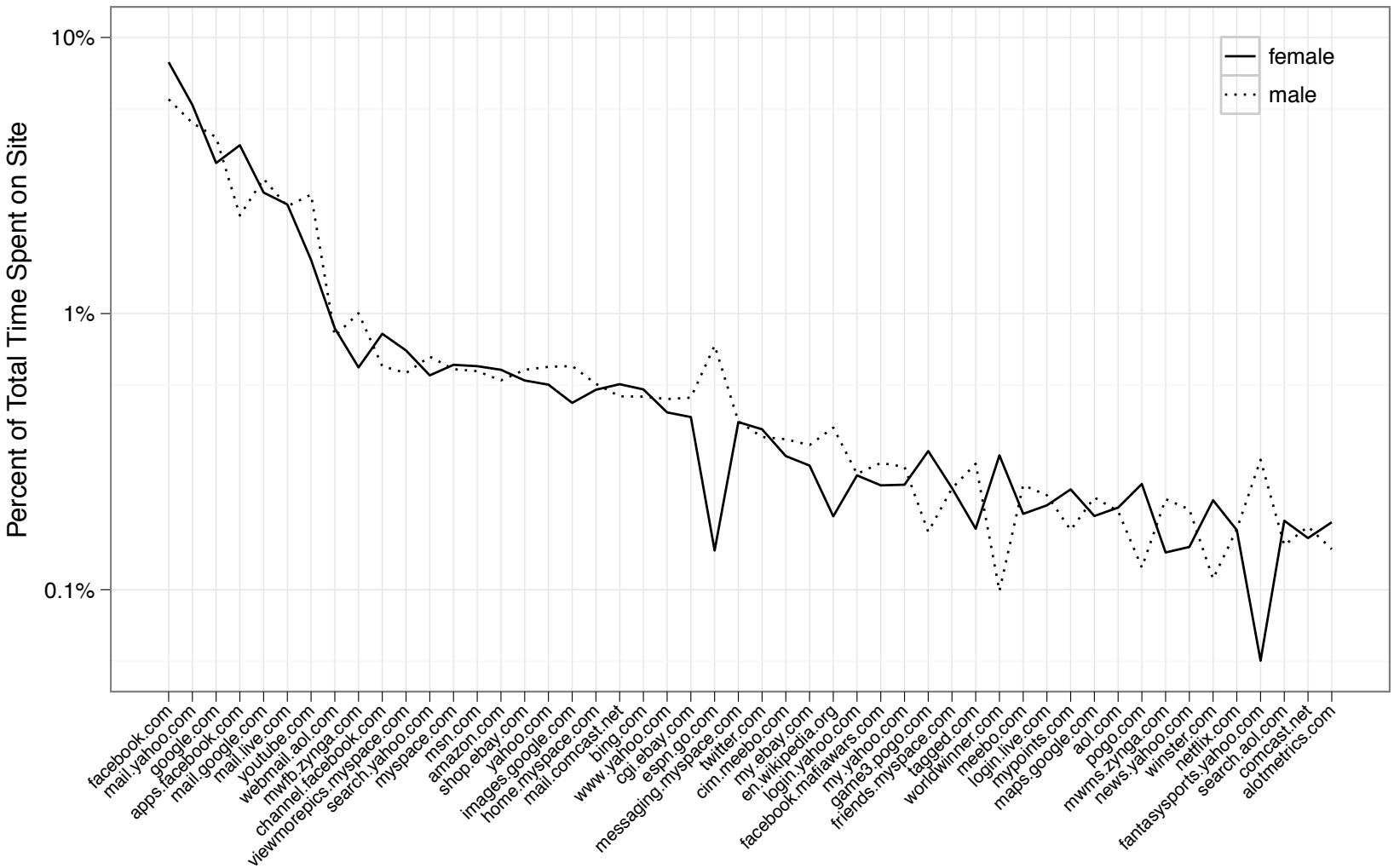
# Group-level activity

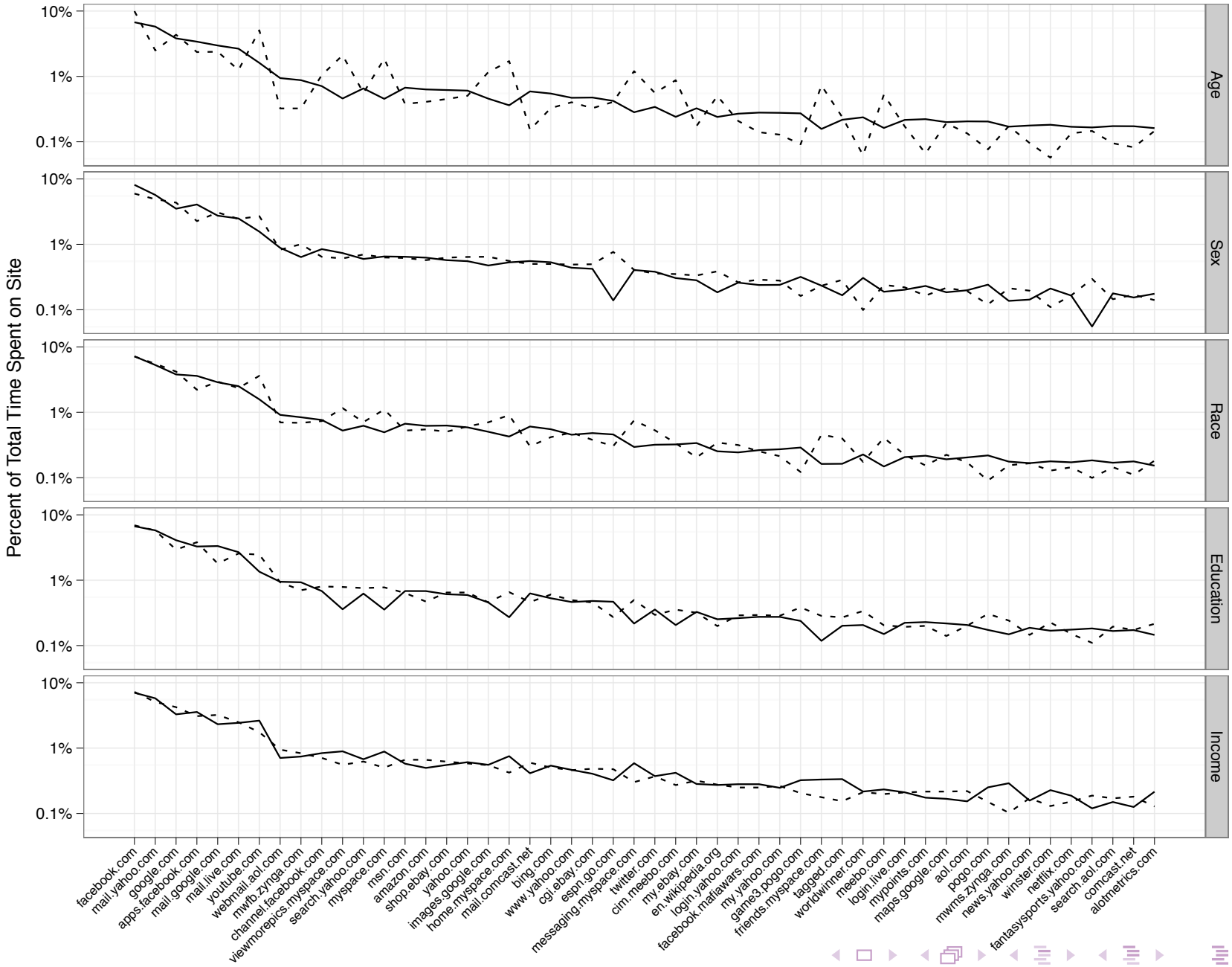
All groups spend more than a third of their time on a handful of email, search, and social networking sites



# Group-level activity

But different groups distribute their time differently, both on universally popular and on more niche sites




Percent of Total Time Spent on Site
10%
1%
0.1%
Age
Sex
Race
Education
Income
facebook.com
mail.yahoo.com
google.com
apps.facebook.com
mail.google.com
mail.live.com
youtube.com
webmail.aol.com
mwfb.zynga.com
channel.facebook.com
viewmorepics.myspace.com
search.yahoo.com
myspace.com
msn.com
amazon.com
shop.ebay.com
yahoo.com
images.google.com
home.myspace.com
mail.comcast.net
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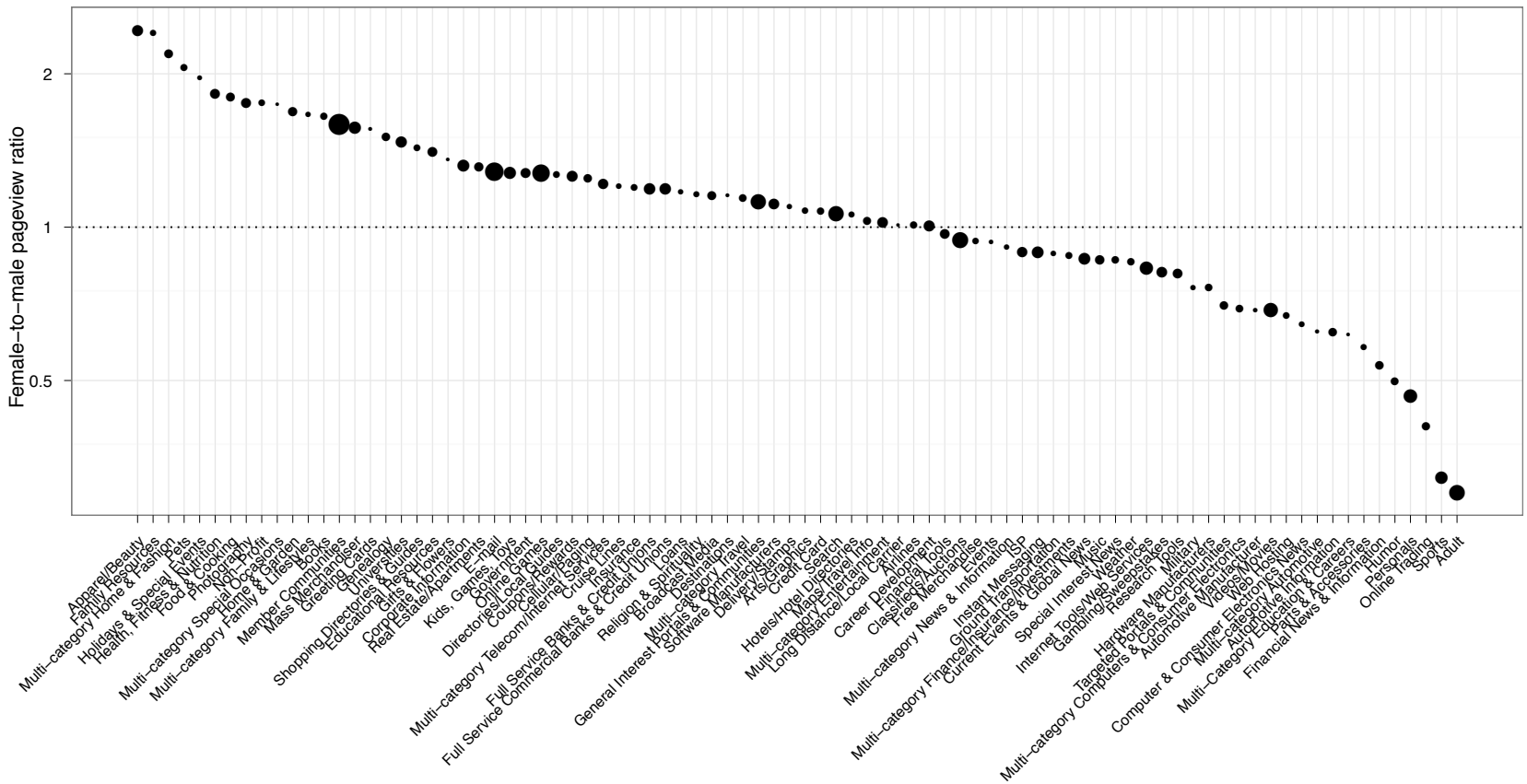
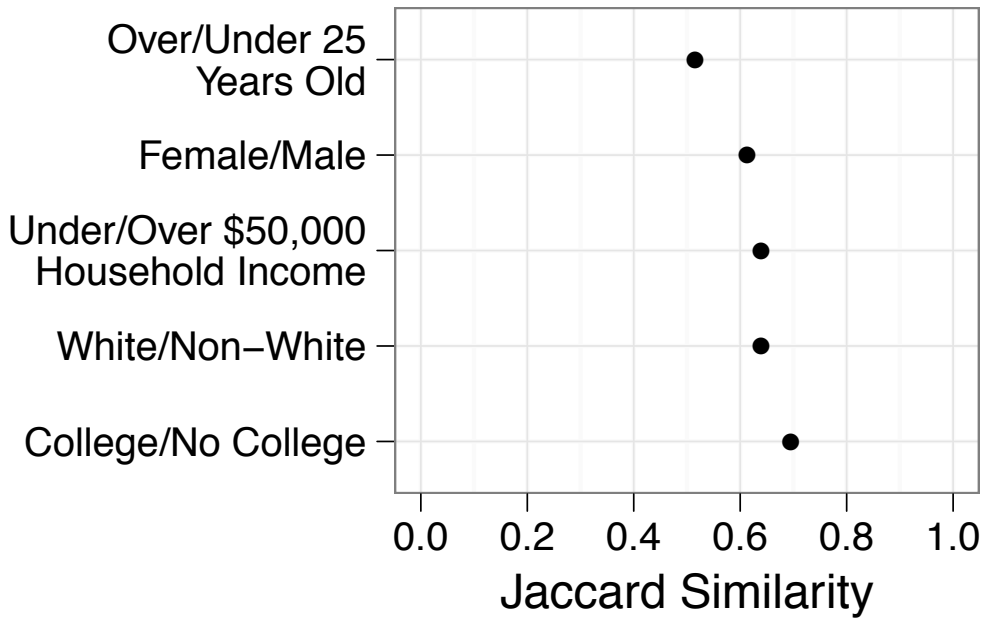
www.yahoo.com
cgi.ebay.com
espn.go.com
messaging.myspace.com
twitter.com
cim.meebo.com
my.ebay.com
en.wikipedia.org
login.yahoo.com
facebook.mafiawars.com
my.yahoo.com
game3.pogo.com
friends.myspace.com
tagged.com
worldwinner.com
meebo.com
login.live.com
mypoints.com
maps.google.com
aol.com
pogo.com
mwms.zynga.com
news.yahoo.com
winster.com
netflix.com
fantasysports.yahoo.com
search.aol.com
comcast.net
alotmetrics.com

# Group-level activity



# Group-level activity

There is both reasonable overlap and variation amongst the most popular sites within groups



# Individual-level prediction

How well can one predict an individual's demographics from their browsing activity?

- Represent each user by the set of sites visited
- Fit linear models to predict majority/minority for each attribute on 80% of users
- Tune model parameters using a 10% validation set
- Evaluate final performance on held-out 10% test set

# Individual-level prediction

```
model <- glm(is.female ~ ., data=nielsen, family=binomial)
```

???

# Individual-level prediction

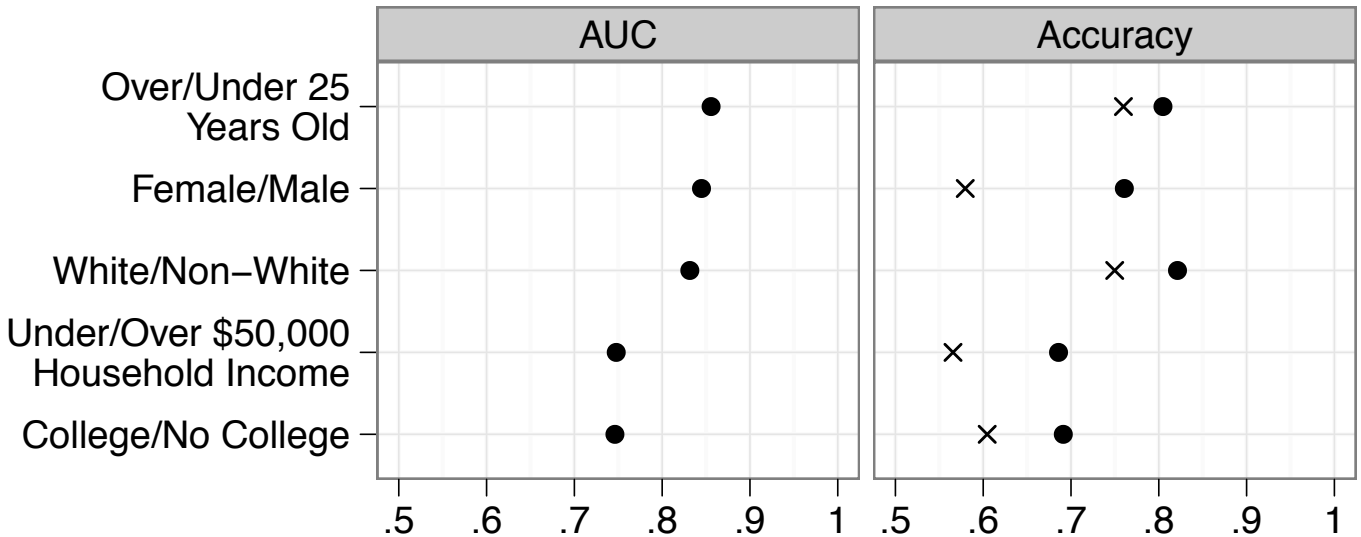
$$\hat{y}(x_i) = w \cdot x_i + b$$

$$\text{Support Vector Machine}^3: \quad L(y, \hat{y}) = C \sum_i [1 - y_i \hat{y}(x_i)]_+ + ||w||^2$$

[3] `http://bit.ly/svmperf`

# Individual-level prediction

Reasonable (∼70-85%) accuracy and AUC across all attributes



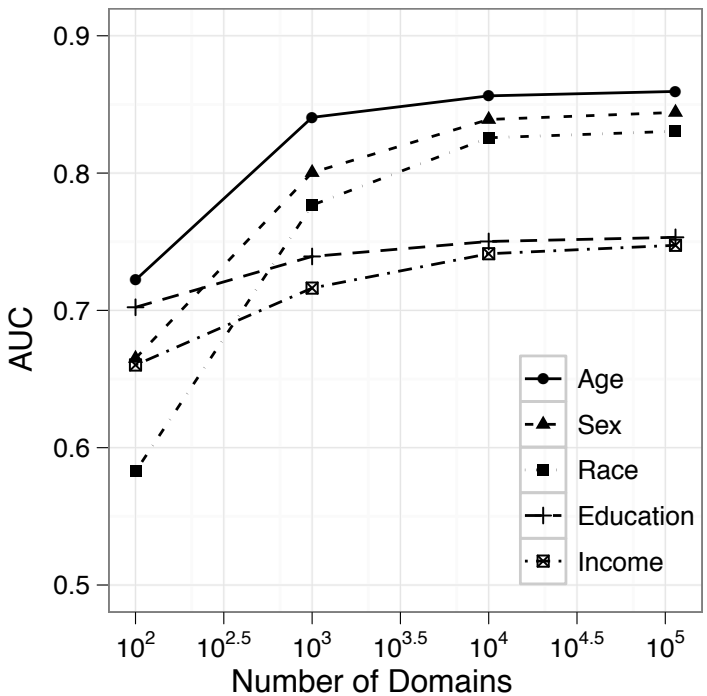
# Individual-level prediction

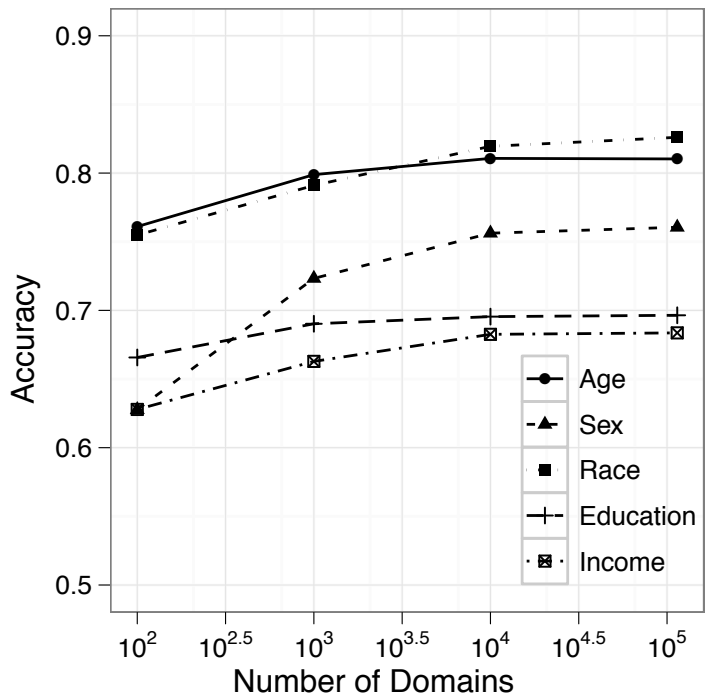
## Highly-weighted sites under the fitted models

| | Large positive weight | Large negative weight |
|---|---|---|
| **Female** | winster.com<br>lancome-usa.com | sports.yahoo.com<br>espn.go.com |
| **White** | marlboro.com<br>cmt.com | mediatakeout.com<br>bet.com |
| **College Educated** | news.yahoo.com<br>linkedin.com | youtube.com<br>myspace.com |
| **Over 25 Years Old** | evite.com<br>classmates.com | addictinggames.com<br>youtube.com |
| **Household Income Under $50,000** | eharmony.com<br>tracfone.com | rownine.com<br>matrixdirect.com |

# Individual-level prediction

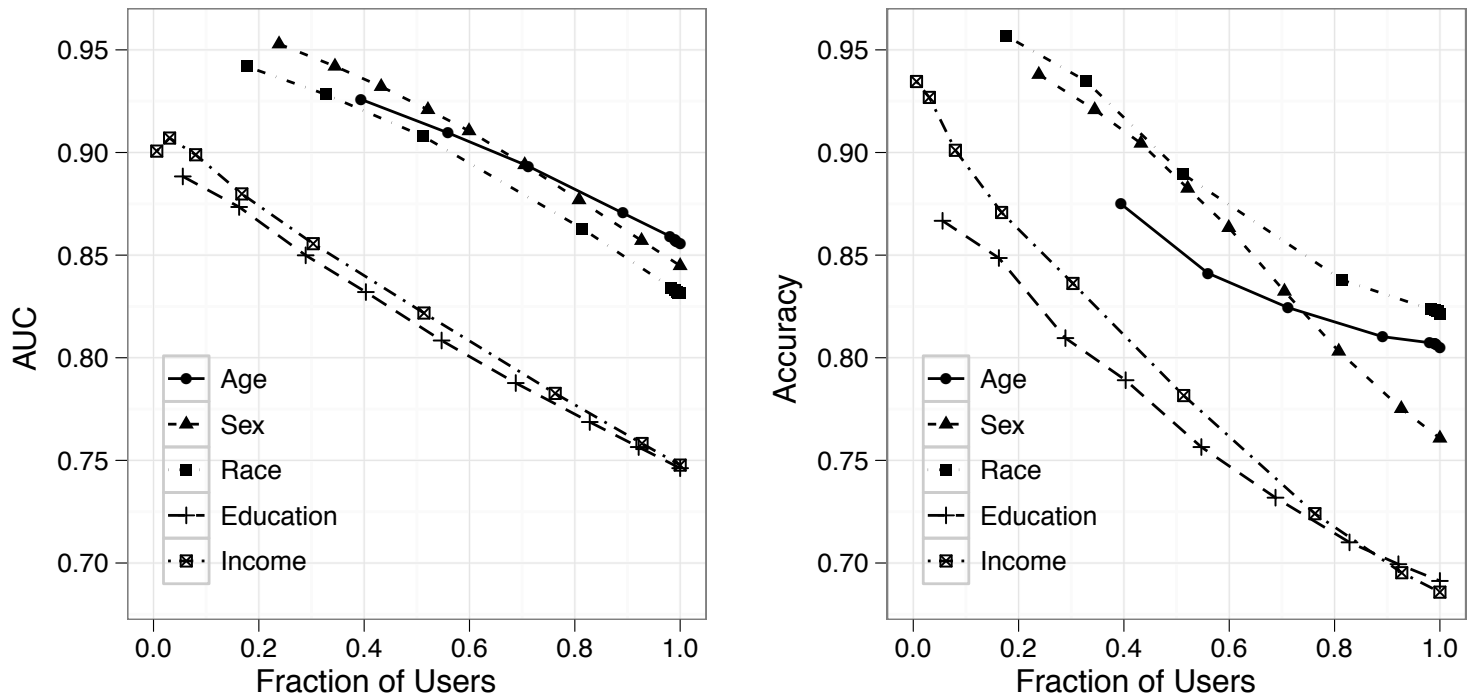
Similar performance even when restricted to top 1k sites



# Individual-level prediction

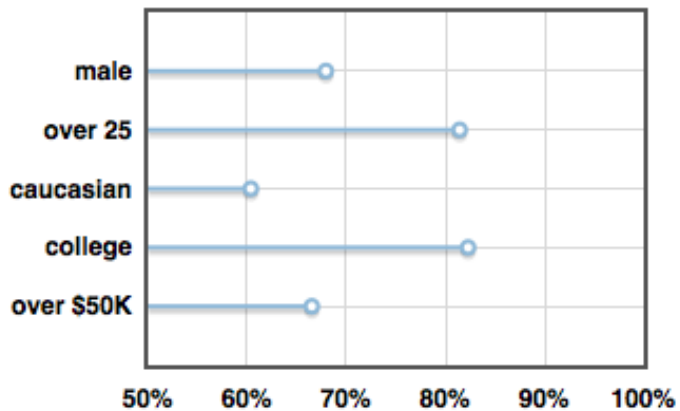
Substantially better performance when restricted to "stereotypical" users (∼80-90%)



# Individual-level prediction

## Proof of concept browser demo

From the 28 sites we found in your browser history, it appears that you're a **caucasian male** who is **over 25** years old with a **college** education earning **over $50K** per year.




`http://bit.ly/surfpreds`

# Summary

- Notable differences in online and offline diversity
- Large group-level differences in how users distribute their time
- User demographics can be inferred from browsing activity with reasonable accuracy