

Google Tools for Data

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Google

March 28, 2014

What day of the week are there the most searches for [hangover]?

1. Sunday
2. Monday
3. Tuesday
4. Wednesday
5. Thursday
6. Friday
7. Saturday

Searches for [hangover]

Explore trends

Hot searches

Search terms ?

hangover

+ Add term

Other comparisons

Limit to

Web Search

United States

December
2007 - January
2008

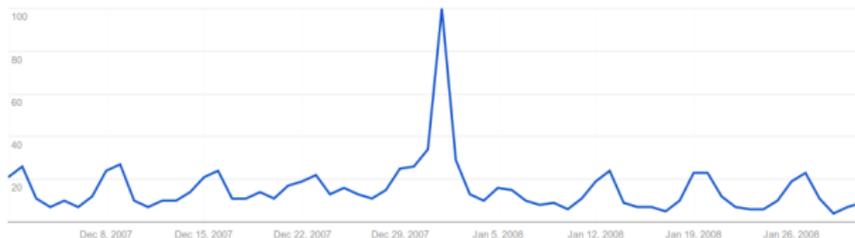
All Categories

Interest over time ?

The number 100 represents the peak search volume

News headlines ?

Forecast ?



Embed

Regional interest ?

Worldwide > United States



0 100

Subregion | Metro | City

Related terms ?

Top

Rising

cure hangover

100

hangover cures

65

hangover remedies

35

Searches for [hangover] and [vodka]

Explore trends

Hot searches

Search terms

✕ hangover

✕ vodka

+ Add term

▸ Other comparisons

Limit to

Web Search

United States

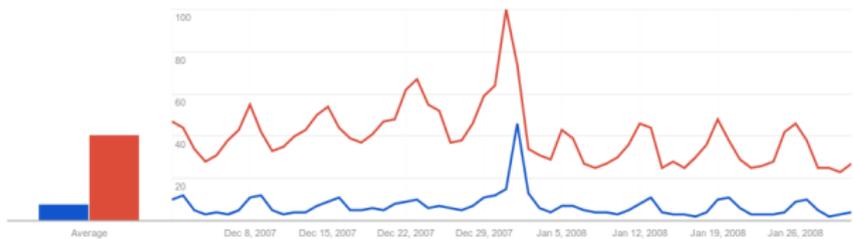
December
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All Categories

Interest over time

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News headlines Forecast



Embed

hangover

vodka

Regional interest

Worldwide > United States



Related terms

Top

Rising

cure hangover

100

hangover cures

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hangover remedies

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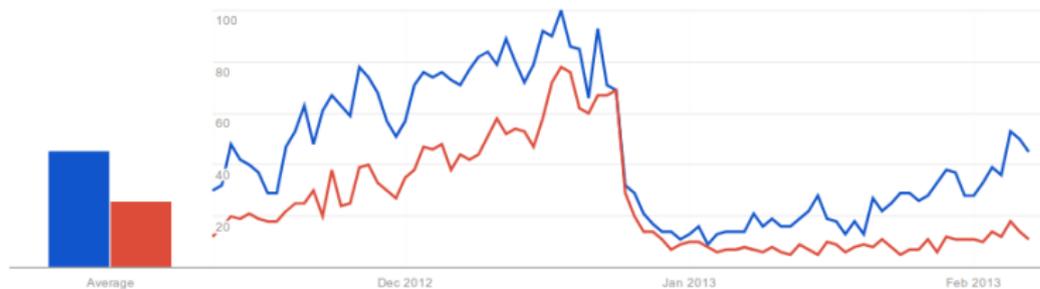
Looking for gifts when single

1. [gift for boyfriend]
2. [gift for girlfriend]

Interest over time [?](#)

The number 100 represents the peak search volume

News headlines [?](#) Forecast [?](#)



Looking for gifts when married

1. [gift for husband]
2. [gift for wife]

Web Search Interest: gift for husband, gift for wife. United States, Past 90 days. 

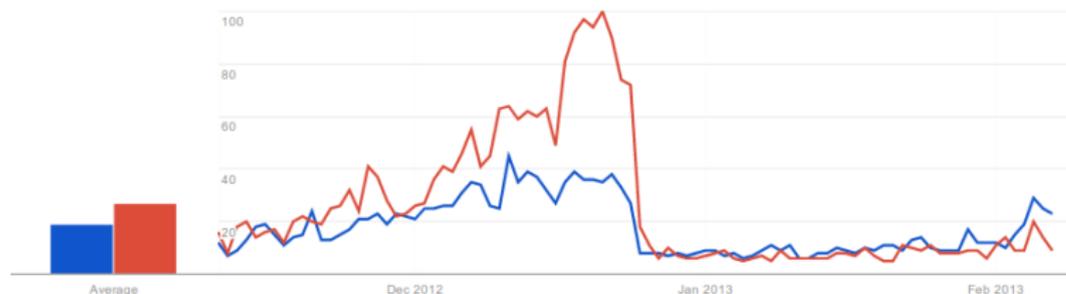


Interest over time

The number 100 represents the peak search volume

News headlines 

Forecast 

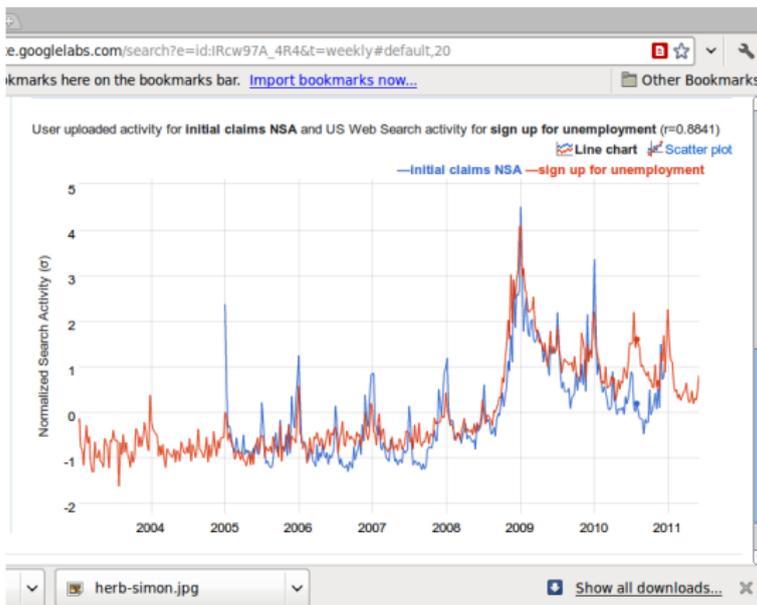


Problem motivation

- ▶ Want to use Google Trends data to nowcast economic series
 - ▶ unemployment may be predicted by “job search” queries
 - ▶ auto purchases may be predicted by “vehicle shopping” queries
 - ▶ often a contemporaneous relationship, hence “nowcasting”
 - ▶ useful due to reporting lags and revisions
- ▶ Fat regression problem: there are many more predictors than observations
- ▶ Millions of queries, hundreds of categories
 - ▶ number of observations ~ 100 for monthly economic data
 - ▶ number of predictors ~ 150 for “economic” categories in Trends
- ▶ How do we choose which variables to include?

Example: unemployment

- ▶ Sometimes Google Correlate works
- ▶ Load in: data on initial claims for unemployment benefits
- ▶ Returns: 100 queries, including [sign up for unemployment]



Build a simple AR model

- ▶ Use deseasonalized initial claims (y_t)
- ▶ Use deseasonalized, detrended searches for [sign up for unemployment] (x_t)

$$\text{base: } y_t = a_0 + a_1 y_{t-1} + e_t$$

$$\text{regr: } y_t = a_0 + a_1 y_{t-1} + b x_t + e_t$$

- ▶ Estimate regressions using rolling window
- ▶ One-step-ahead MAE during recession is about 8.7% lower when [sign up for unemployment] query is included

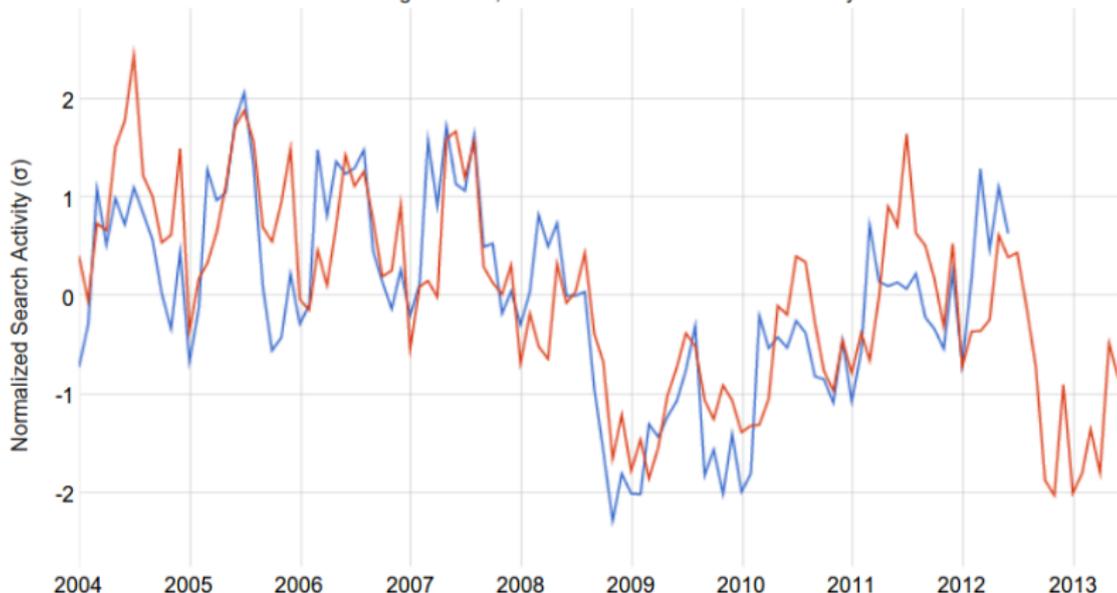
But simple correlation has limits . . .

User uploaded activity for **Auto Sales NSA (corrected)** and United States Web Search activity for **indian restaurants**
($r=0.7848$)

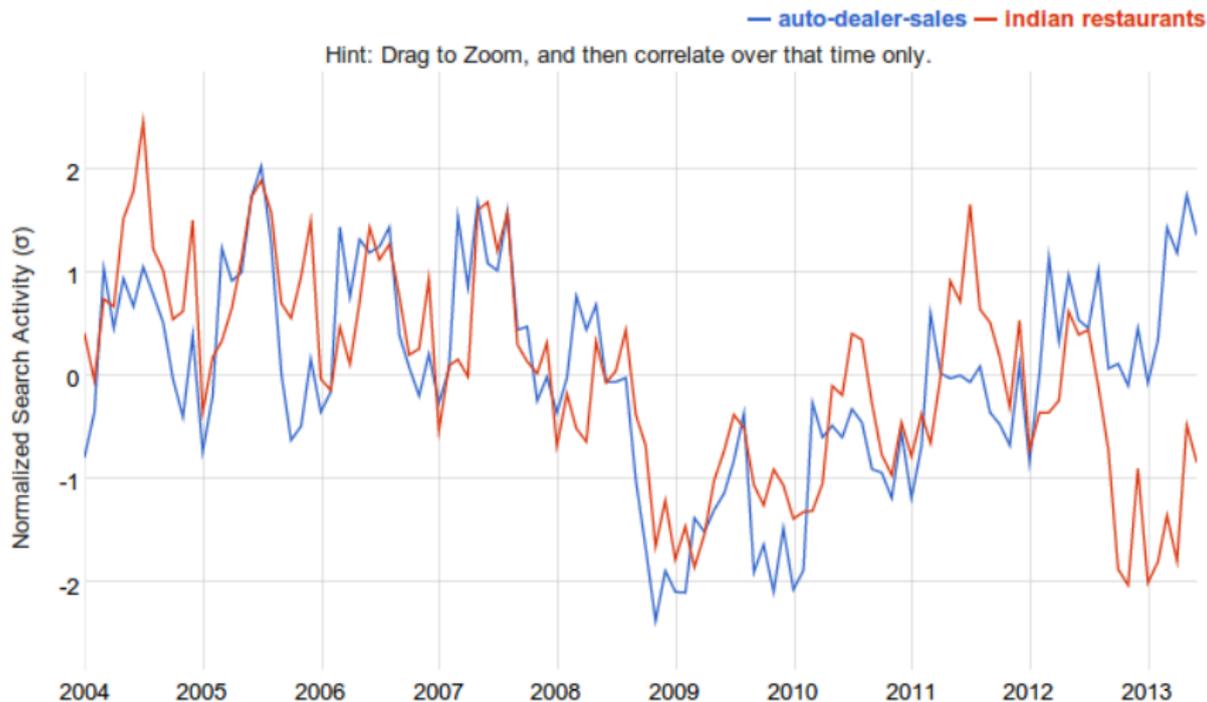
 Line chart  Scatter plot

— Auto Sales NSA (corrected) — indian restaurants

Hint: Drag to Zoom, and then correlate over that time only.



Spurious correlation is a danger



How to avoid spurious correlation?

- ▶ Control for trend and seasonality
 - ▶ Build a model for the *predictable* (trend + seasonality) part of time series
 - ▶ In time series this is called *whitening* or *prewhitening*
 - ▶ Find regressors that predict the *residuals* after removing trend and seasonality
- ▶ How to choose regressors?
 - ▶ Simple correlation is too limited
 - ▶ Human judgment doesn't scale

Some approaches to variable selection

- ▶ Human judgment: what we mostly do
- ▶ Significance testing: forward and backward stepwise regression
- ▶ Complexity criteria: AIC, BIC, etc
- ▶ Dimensionality reduction: principle component, factor models, partial least squares
- ▶ Machine learning: Penalized regression, lasso, LARS, ridge regression, elastic net

- ▶ Bayesian Structural Time Series (BSTS)
 - ▶ Decompose time series into trend + seasonality + regression
 - ▶ Use Kalman filter for trend + seasonality (whiten time series)
 - ▶ Spike and slab regression for variable selection
 - ▶ Estimate via Markov Chain Monte Carlo simulation of posterior distribution
 - ▶ Bayesian model averaging for final forecast

How BSTS helps reduce overfitting

- ▶ Kalman filter used to whiten the series
 - ▶ Remove common seasonality and trend, regressors chosen to predict residuals
 - ▶ Estimation of (seasonality, trend, regression) is simultaneous
 - ▶ Same spirit as Granger causality
- ▶ Overfitting due to spurious correlation with regressors
 - ▶ Remove “one time” events (can be automated)
 - ▶ Apply human judgment
- ▶ Overfitting due to many regressors
 - ▶ Informative prior to suggest likely number of regressions or regressor categories
 - ▶ Bayesian model averaging over many small regressions (“ensemble estimation”)

Basic structural model with regression

- ▶ Consider classic time series model with *constant* level, linear time trend, and regressors
 - ▶ $y_t = \mu + bt + \beta x_t + e_t$
- ▶ “Local linear trend” is a stochastic generalization of this
 - ▶ Observation: $y_t = \mu_t + z_t + e_{1t} = \text{level} + \text{regression}$
 - ▶ State 1: $\mu_t = \mu_{t-1} + b_{t-1} + e_{2t} = \text{random walk} + \text{trend}$
 - ▶ State 2: $b_t = b_{t-1} + e_{3t} = \text{random walk for trend}$
 - ▶ State 3: $z_t = \beta x_t = \text{regression}$
- ▶ Parameters to estimate: regression coefficients β and variances of (e_{it}) for $i = 1, \dots, 3$
- ▶ Use these variances to construct optimal Kalman forecast:
$$\hat{y}_t = \hat{y}_{t-1} + k_t \times (y_{t-1} - \hat{y}_{t-1}) + x_t \beta$$
- ▶ k_t depends on the estimated variances

Intuition for Kalman filter

- ▶ Consider simple case without regressors and trend
 - ▶ Observation equation: $y_t = \mu_t + e_{1t}$
 - ▶ State equation: $\mu_t = \mu_{t-1} + e_{2t}$
- ▶ Two extreme cases
 - ▶ $e_{2t} = 0$ is constant mean model where best estimate is sample average through $t - 1$: $\bar{y}_{t-1} = \sum_{s=1}^{t-1} y_s$
 - ▶ $e_{1t} = 0$ is random walk where best estimate is current value y_{t-1}
- ▶ For general case take weighted average of current and past observations, where weight depends on estimated variances

Nice features of Kalman approach

- ▶ No problem with unit roots or other kinds of nonstationarity
- ▶ No problem with missing observations
- ▶ No problem with mixed frequency
- ▶ No differencing or identification stage (easy to automate)
- ▶ Nice Bayesian interpretation
- ▶ Easy to compute estimates (particularly in Bayesian case)
- ▶ Nice interpretation of structural components
- ▶ Easy to add seasonality
- ▶ Good forecast performance

Spike and slab regression for variable choice

- ▶ Spike
 - ▶ Define vector γ that indicates variable inclusion
 - ▶ $\gamma_i = 1$ if variable i has non-zero coefficient in regression, 0 otherwise
 - ▶ Bernoulli prior distribution, $p(\gamma)$, for γ_i
 - ▶ Can use an informative prior; e.g., expected number of predictors
- ▶ Slab
 - ▶ Conditional on being in regression ($\gamma_i = 1$) put a (weak) prior on β_i , $p(\beta|\gamma)$.
- ▶ Estimate posterior distribution of (γ, β) using MCMC

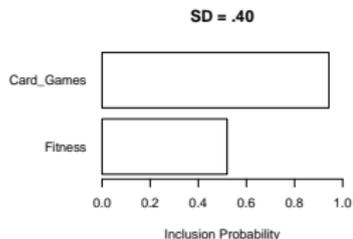
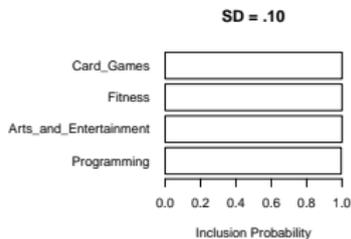
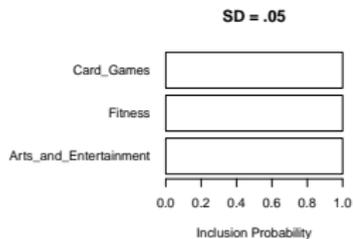
Bayesian model averaging

- ▶ We simulate draws from posterior using MCMC
- ▶ Each draw has a set of variables in the regression (γ) and a set of regression coefficients (β)
- ▶ Make a forecast of y_t using these coefficients
- ▶ This gives the posterior forecast distribution for y_t
- ▶ Can take average over all the forecasts for final prediction
- ▶ Can take average over draws of γ to see which predictors have high probability of being in regression

Torture test simulation for BSTS

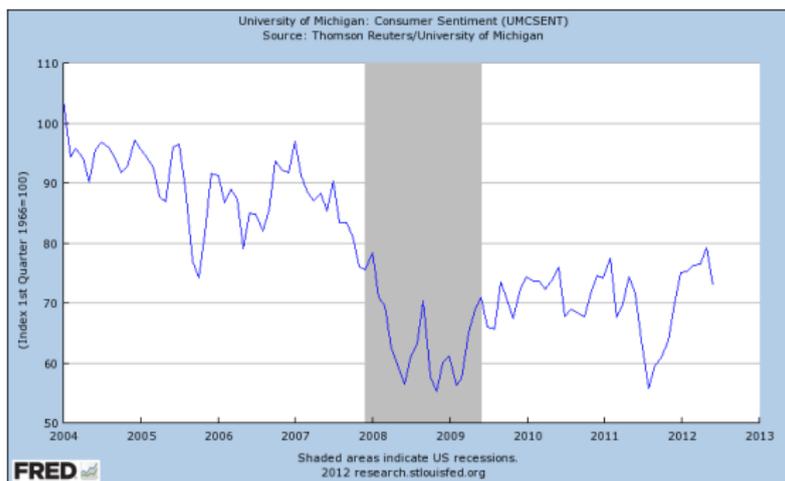
- ▶ Pick $k = 3$ categories (out of 150) and their associated time series
- ▶ Construct artificial time series = sum of these k + noise
- ▶ See if BSTS picks the right categories
 - ▶ 0 noise = perfect
 - ▶ 5% noise = perfect
 - ▶ 10% noise = misses one, but still does good forecast
 - ▶ performance deteriorates for higher noise levels
 - ▶ ... but it degrades gracefully

Example of torture test



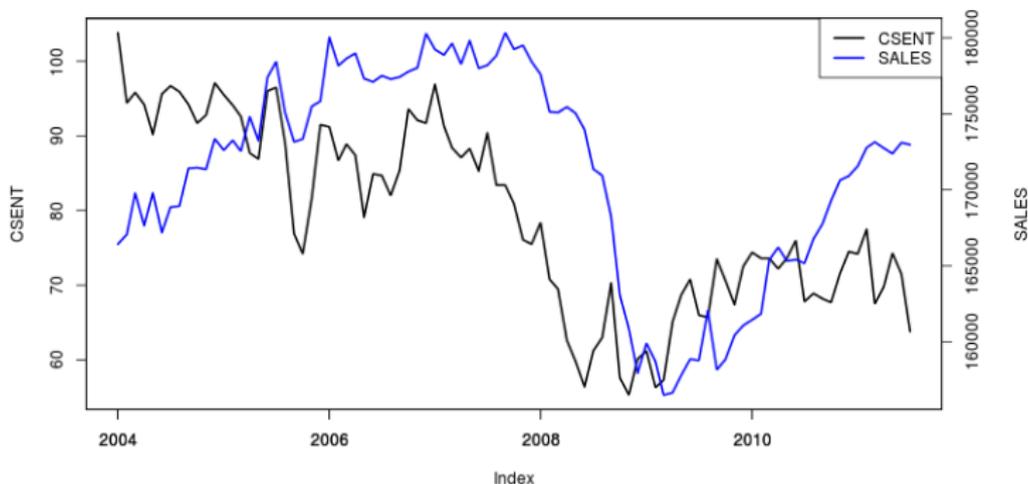
Example 1: Consumer Sentiment

- ▶ Monthly UM Consumer sentiment from Jan 2004 to Apr 2012 ($n = 100$)
- ▶ Google Insights for Search categories related to economics ($k = 150$)
- ▶ No compelling intuition about what predictors should be



Consumer sentiment as leading indicator

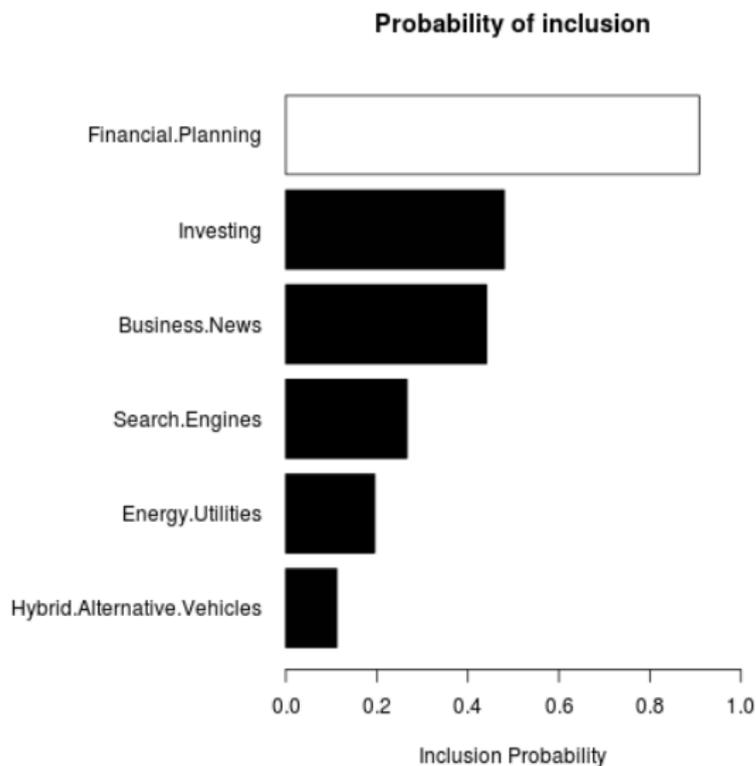
- ▶ Leading indicator of retail sales in last recession



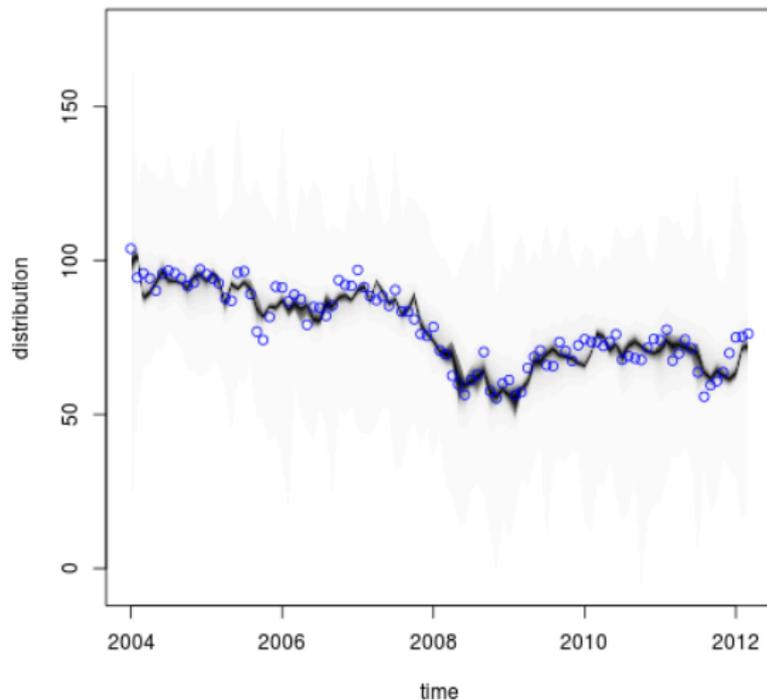
Variable selection

- ▶ Google Insights for Search categories related to economics ($k = 150$)
- ▶ Deseasonalize predictors using R command `stl`
- ▶ Detrend predictors using simple linear regression
- ▶ Let `bsts` choose predictors

UM Consumer Sentiment Predictors



Posterior distribution of one-step ahead forecast



State decomposition

Recall observation equation:

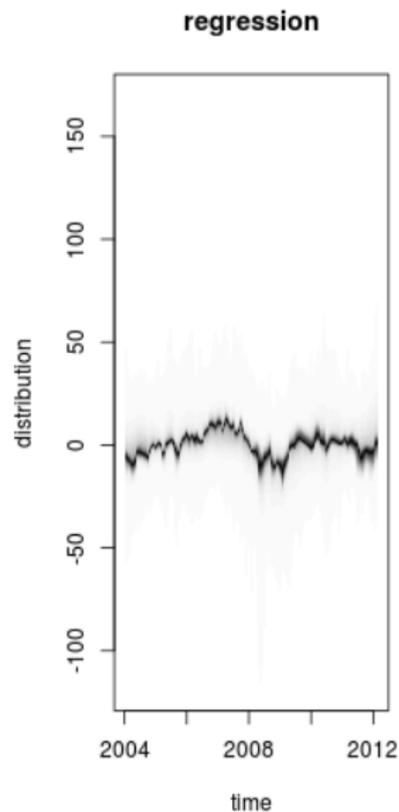
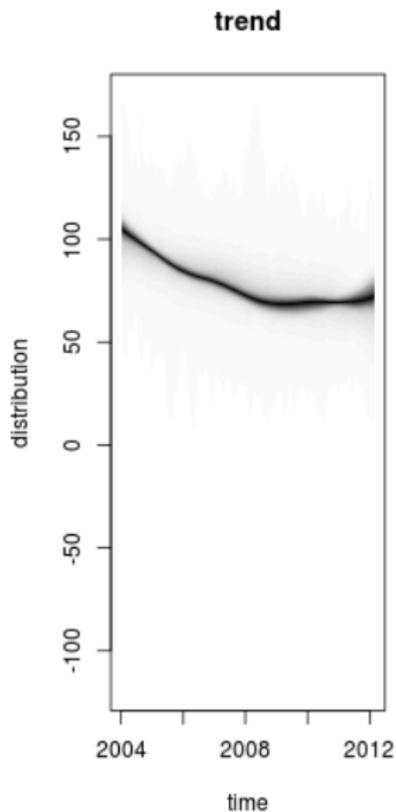
$$y_t = \mu_t + x_t\beta + e_{1t}$$

We can plot the posterior distribution of each of these components. The regression component can be further expanded

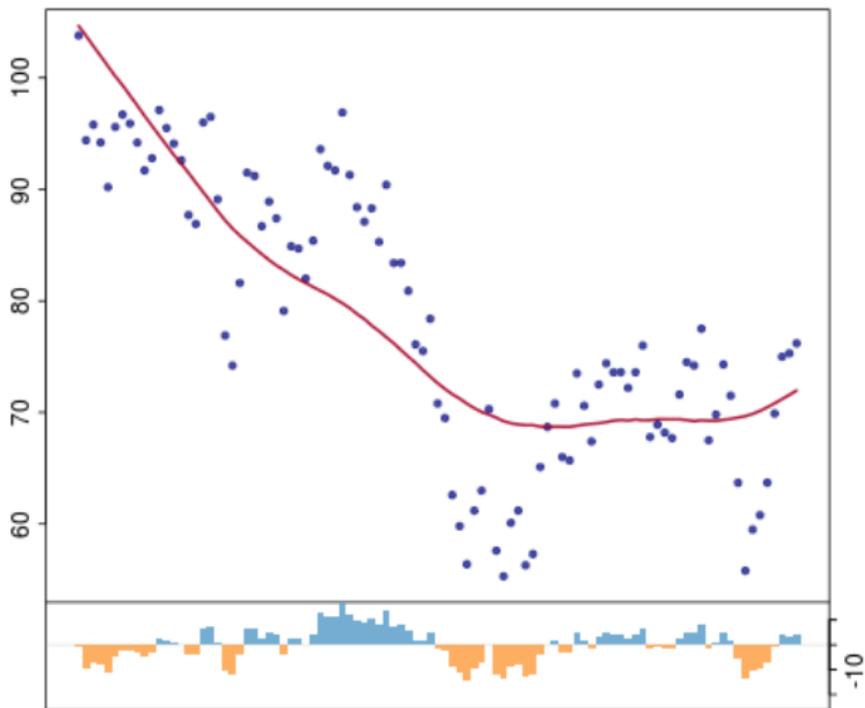
$$y_t = \mu_t + x_{1t}\beta_1 + \cdots + x_{pt}\beta_p + e_{1t}$$

Natural to order predictors by probability of inclusion and look at cumulative plot.

Trend and regression decomposition

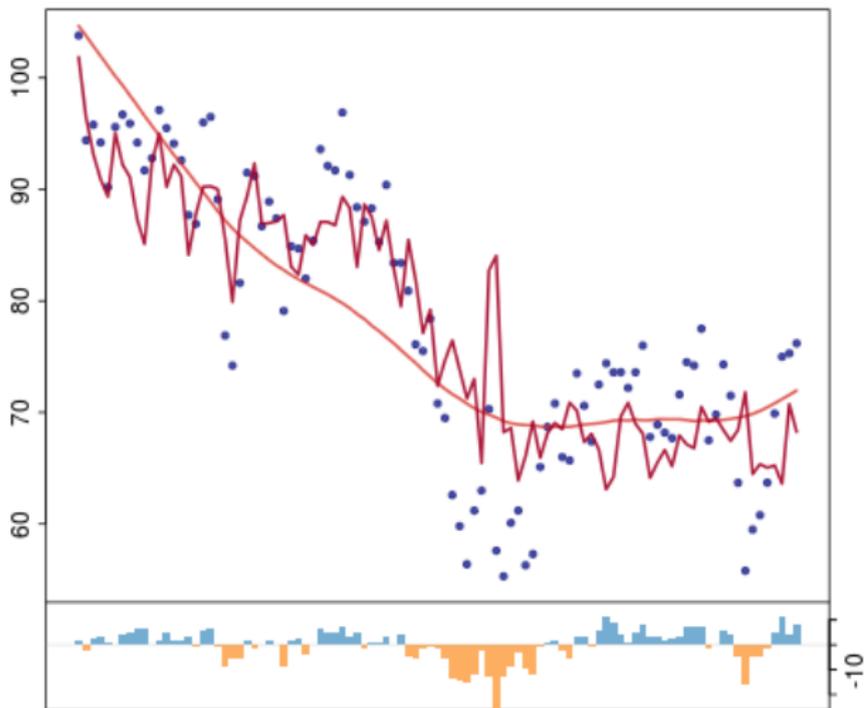


1. trend (mae=5.6656)

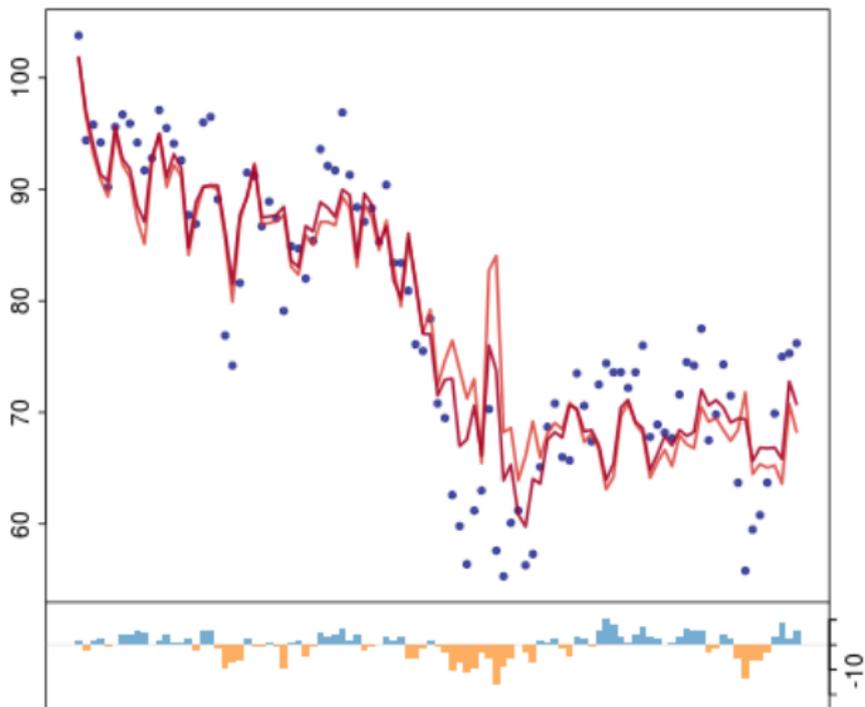


add Financial Planning

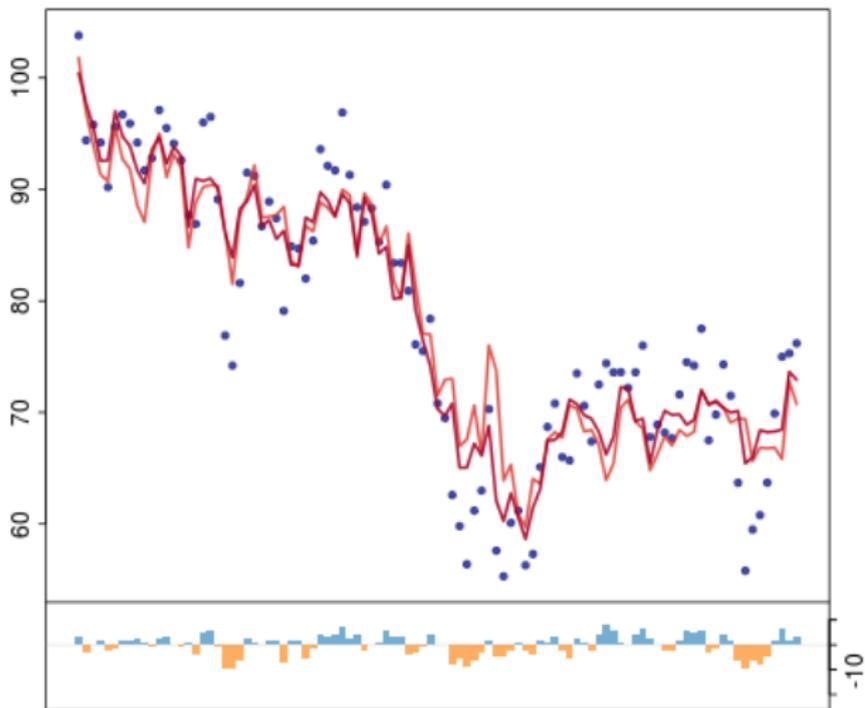
2. add Financial.Planning (mae=4.8529)



3. add Business.News (mae=3.9888)

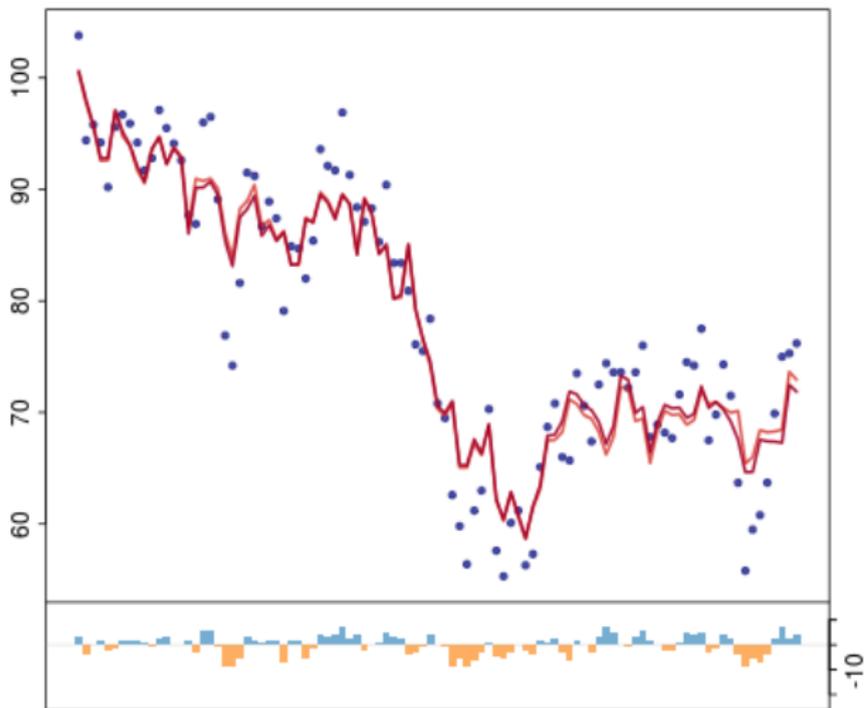


4. add Investing (mae=3.3511)



add Search Engines

5. add Search.Engines (mae=3.2748)



Example 2: gun sales

Use FBI's National Instant Criminal Background Check

The screenshot shows a Google Correlate search for 'FBI NICS data' in the United States. The search results show a strong correlation with 'stack on' (0.9356). Other correlated terms include 'bread', '44 mag', 'buckeye outdoors', 'mossberg', 'g star', 'ruger 44', 'baking', '.308', and 'savage 22'. The interface includes navigation options like 'Compare US states', 'Compare weekly time series', and 'Compare monthly time series'. The 'Compare monthly time series' option is selected. The 'Country' is set to 'United States'. The 'Shift series' is set to '0' months. The 'Documentation' section includes links for 'Comic Book', 'FAQ', 'Tutorial', and 'Whitepaper'. The 'Correlate Labs' section includes a link for 'Search by Drawing'. The 'User uploaded activity' section shows 'FBI NICS data' and 'United States Web Search activity for stack on' with a correlation coefficient of $r=0.9356$.

www.google.com/trends/correlate/search?e=id:pwAHca4H6em&t=m

Google correlate FBI NICS data Search correlations

Edit this data

Compare US states
Compare weekly time series
Compare monthly time series

Shift series 0 months
Country: United States

Documentation
[Comic Book](#)
[FAQ](#)
[Tutorial](#)
[Whitepaper](#)

Correlate Labs
[Search by Drawing](#)

Correlated with FBI NICS data

- 0.9356 **stack on**
- 0.9329 bread
- 0.9326 44 mag
- 0.9317 buckeye outdoors
- 0.9307 mossberg
- 0.9273 g star
- 0.9267 ruger 44
- 0.9264 baking
- 0.9254 .308
- 0.9242 savage 22

Show more Export data as CSV | Share: Tweet

User uploaded activity for **FBI NICS data** and United States Web Search activity for **stack on** ($r=0.9356$)

Google Correlate Results

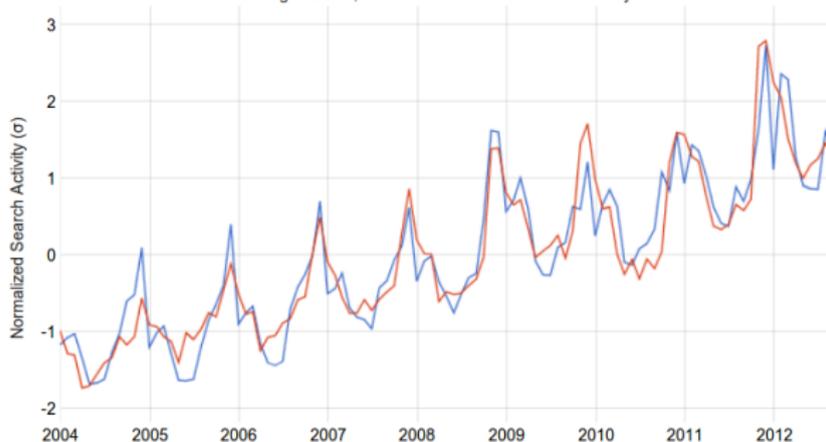
- ▶ [stack on] has highest correlation
- ▶ [gun shops] is chosen by bsts
- ▶ Regression model gives 11% improvement in one-step ahead MAE

User uploaded activity for **FBI NICS data** and United States Web Search activity for **stack on** ($r=0.9356$)

Line chart Scatter plot

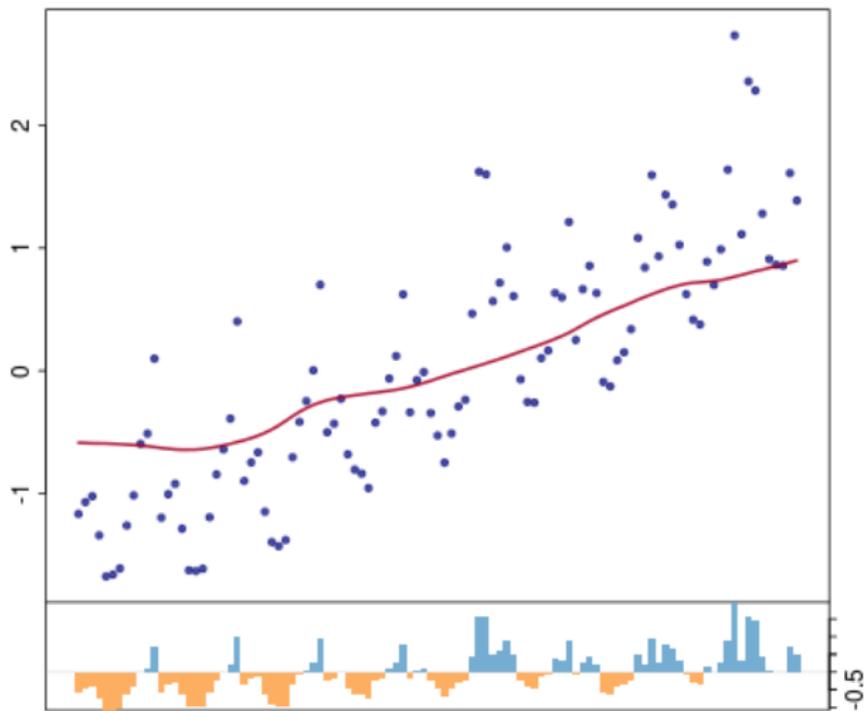
— FBI NICS data — stack on

Hint: Drag to Zoom, and then correlate over that time only.

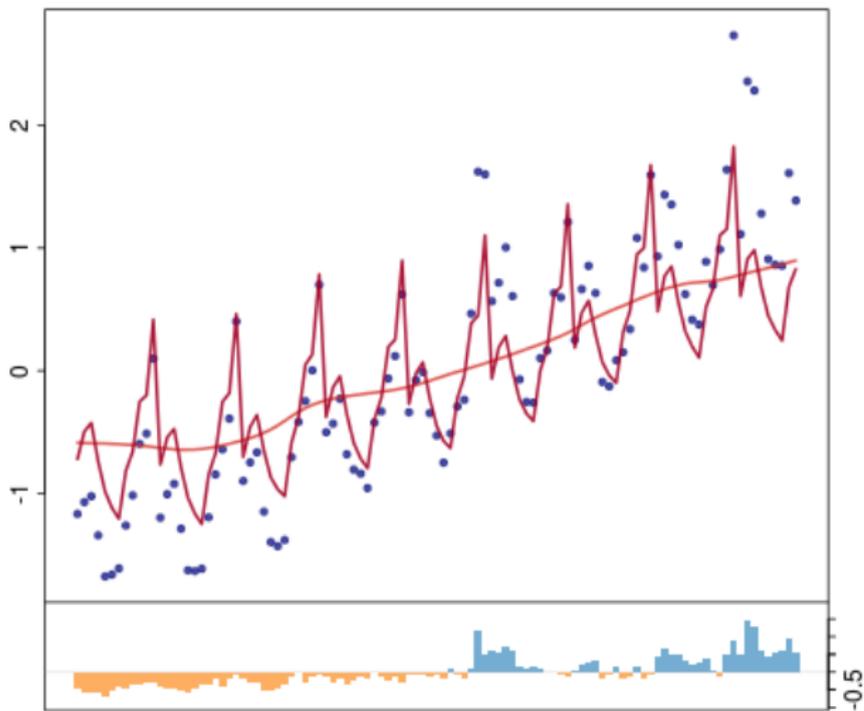


Trend

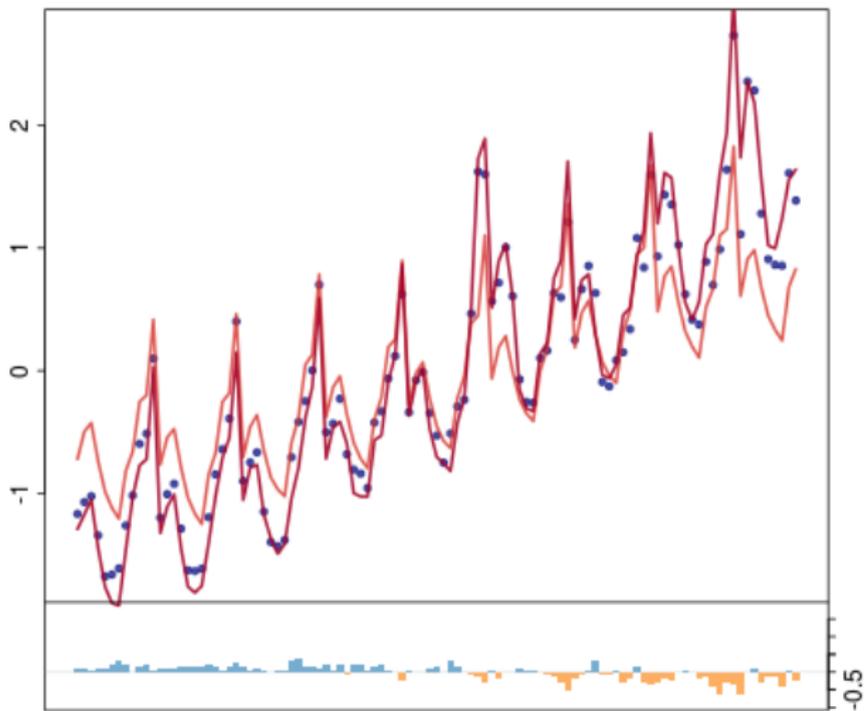
1. trend (mae=0.49947)



2. add seasonal (mae=0.33654)



3. add gun.shops (mae=0.15333)



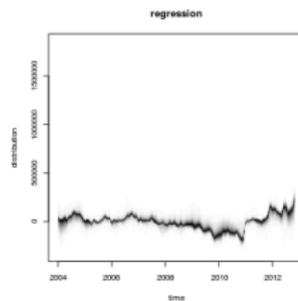
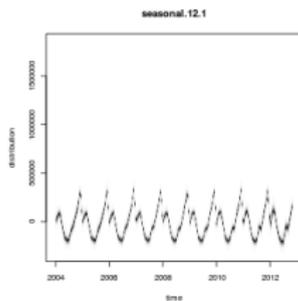
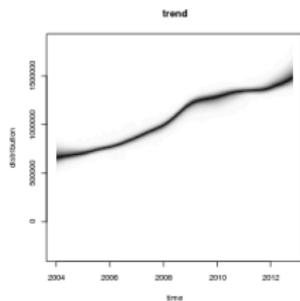
Google Trends predictors

- ▶ 586 Google Trends verticals, deseasonalized and detrended
- ▶ 107 monthly observations

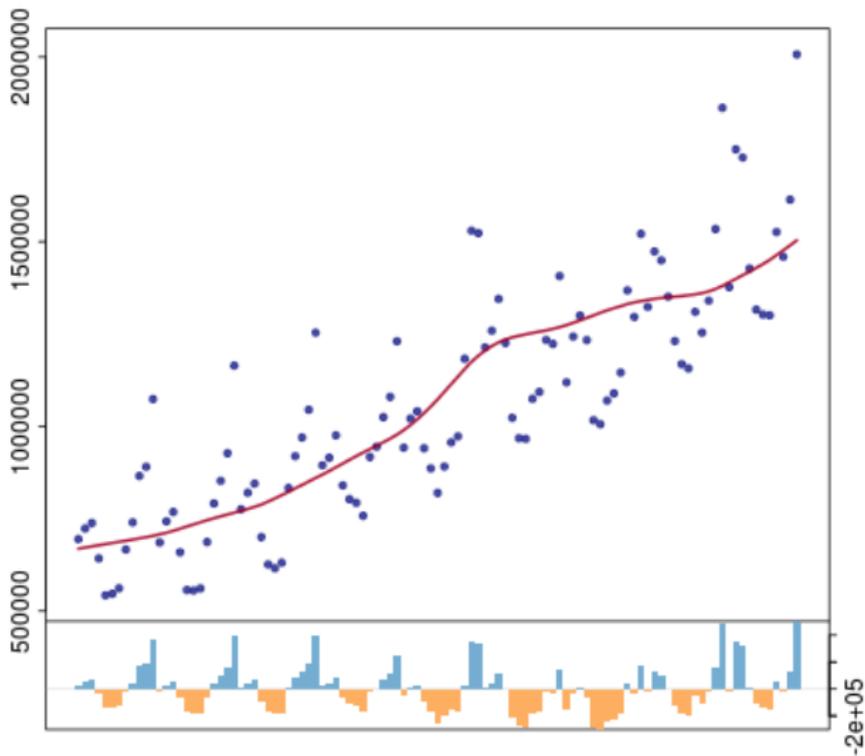
Category	mean	inc.prob
Recreation::Outdoors::Hunting:and:Shooting	1,056,208	0.97
Travel::Adventure:Travel	-84,467	0.09

Table: Google Trends predictors for NICS checks.

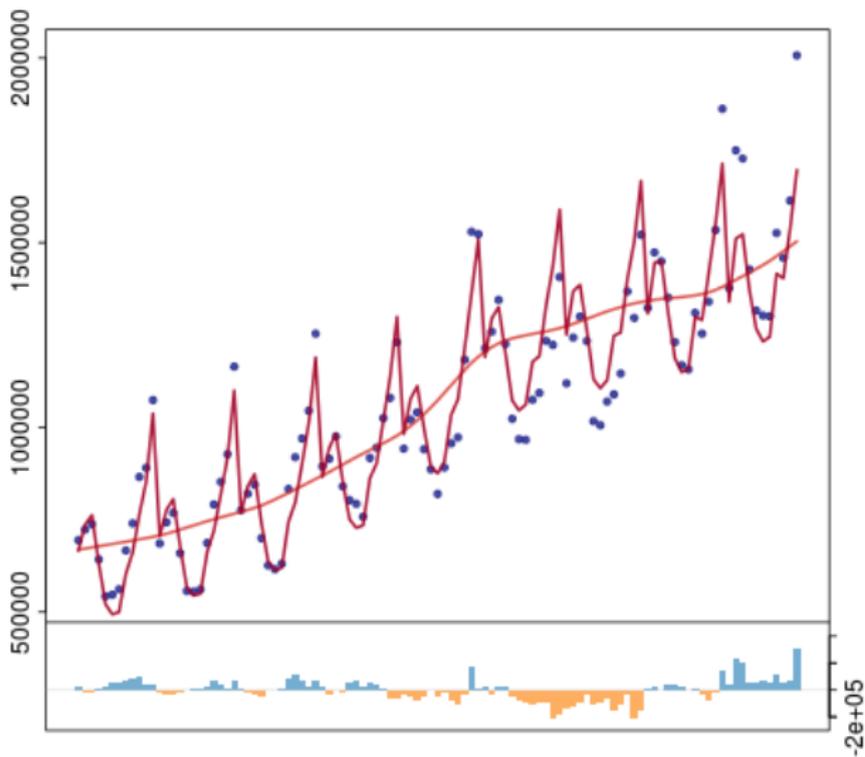
State decomposition



1. trend (mae=130270)

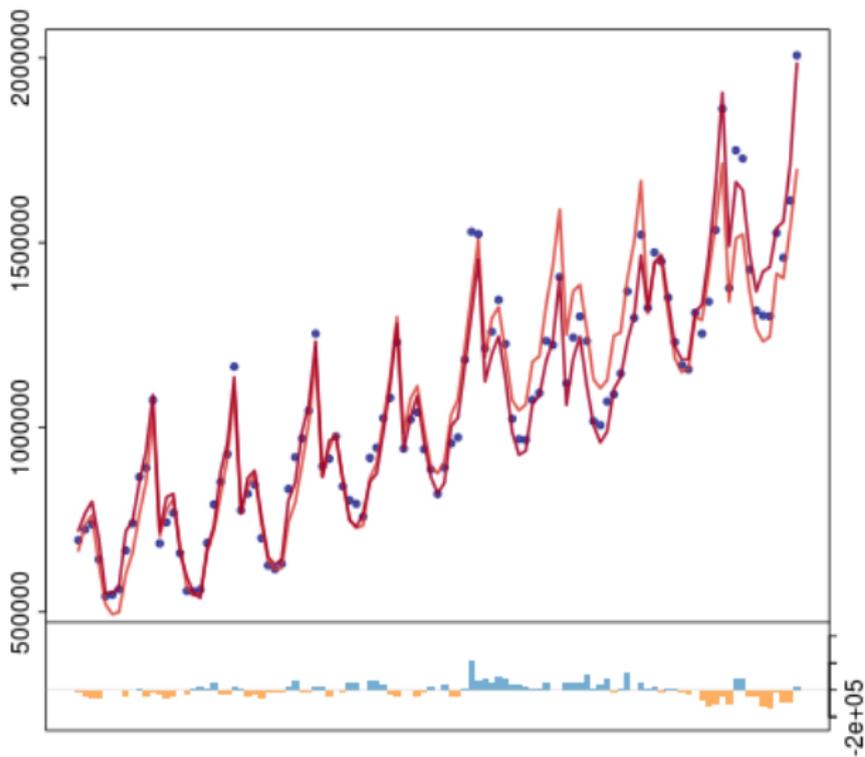


2. add seasonal (mae=61094)



Hunting and Shooting

3. add recreation_shooting (mae=43128)



Searches for [gun shop]

Explore trends

Hot searches

Search terms

gun shop

+ Add term

Other comparisons

Limit to

Web Search

United States

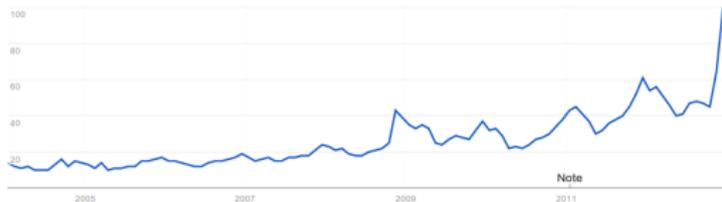
2004 - present

All Categories

Interest over time

The number 100 represents the peak search volume

News headlines Forecast



Embed

Regional interest

Worldwide > United States



0 100

Subregion | Metro | City

View change over time

Embed

Related terms

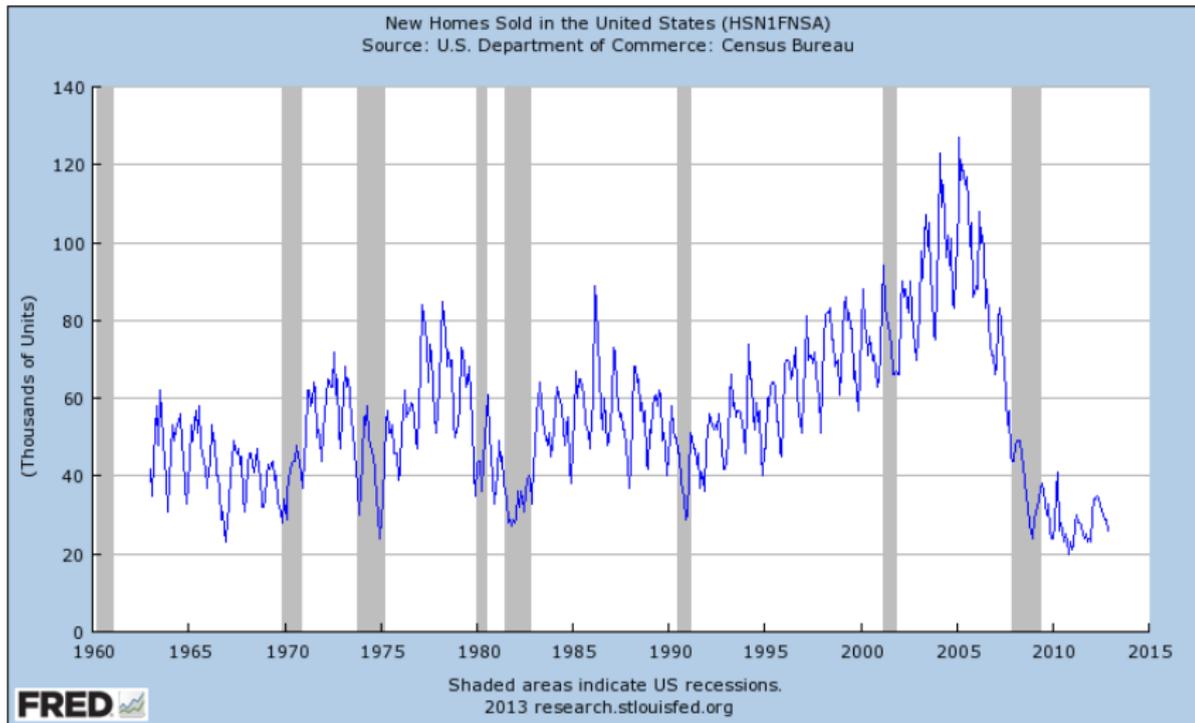
Top Rising

Term	Interest
buds gun shop	100
the gun shop	20
gun shops	15
bass pro	15
bass pro shop	15
pawn shop	15
gun store	10
buds guns	5
online gun shop	5
bills gun shop	5

Embed

- ▶ Can use prior to improve estimate of trend component
 - ▶ Google data starts in 2004, only one recession
 - ▶ Can estimate parameters of trend model with no regressors
 - ▶ Use this as prior for estimate of trend in estimation period
- ▶ Can use prior to influence variable choice in regression
 - ▶ Influence the expected number of variables in regression (parsimony)
 - ▶ Give higher weight to certain verticals (e.g., economics related)
 - ▶ Exclude obvious spurious correlation (e.g., pop song titles)

New Homes Sold in the US



Run correlate



HSN1FN5A Search correlations [Edit this data](#)

[Compare US states](#)

[Compare weekly time series](#)

Compare monthly time series

Shift series months

Country: United States

Documentation

[Comic Book](#)

[FAQ](#)

[Tutorial](#)

[Whitepaper](#)

Correlate Labs

[Search by Drawing](#)

Correlated with **HSN1FN5A**

0.9819 [tahitian noni juice](#)

0.9809 [exhaust sound](#)

0.9802 [traderonline.com](#)

0.9789 [www.kbb.com](#)

0.9786 80/20 mortgage

0.9782 [appreciation rate](#)

0.9776 [home appreciation](#)

0.9759 [help-u-sell](#)

0.9759 [planned community](#)

0.9758 [new home builder](#)

[Show more](#) | [Export data as CSV](#) | Share: [Google+](#) [Twitter](#) [Facebook](#) [LinkedIn](#) [Print](#)

User uploaded activity for **HSN1FN5A** and United States Web Search activity for **80/20 mortgage** ($r=0.9786$)

[Line chart](#) [Scatter plot](#)

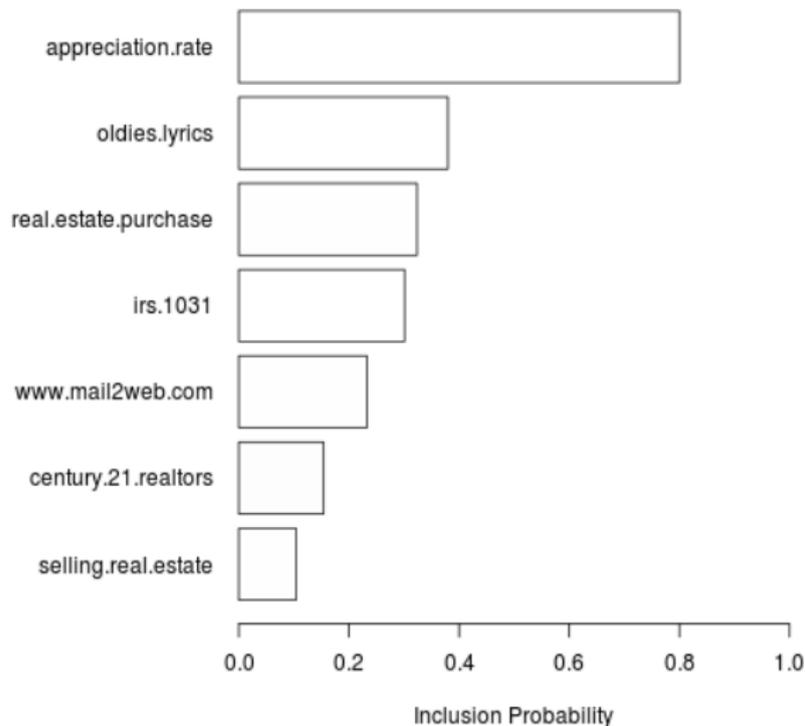
— HSN1FN5A — 80/20 mortgage

Hint: Drag to Zoom, and then correlate over that time only.

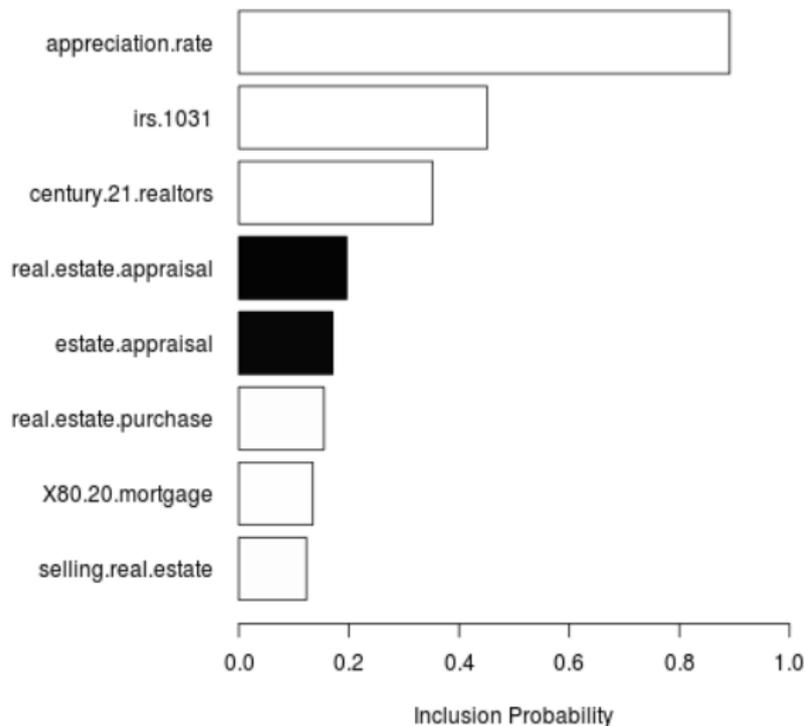


BSTS variable selection

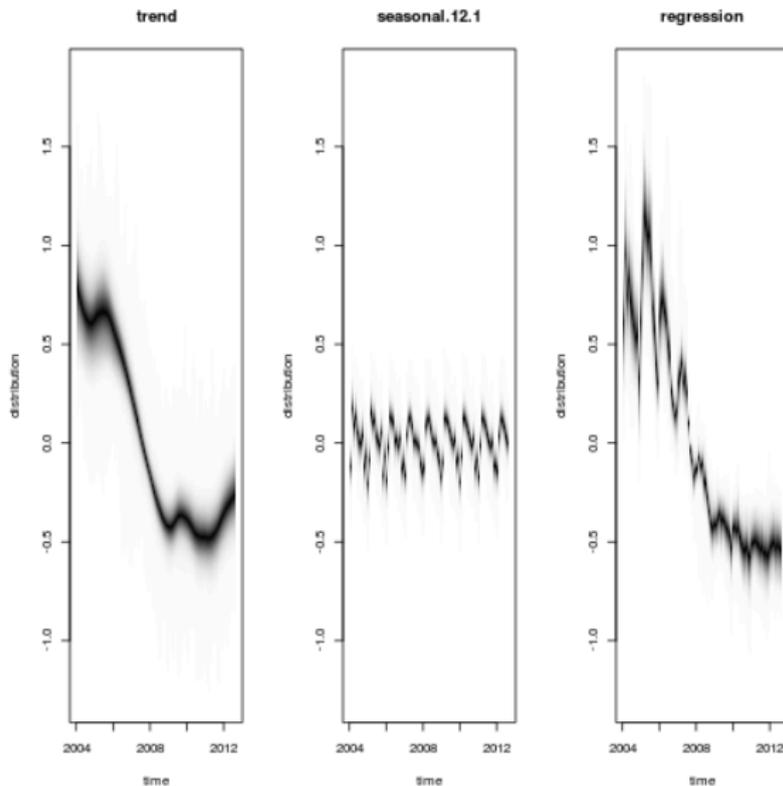
With all correlates



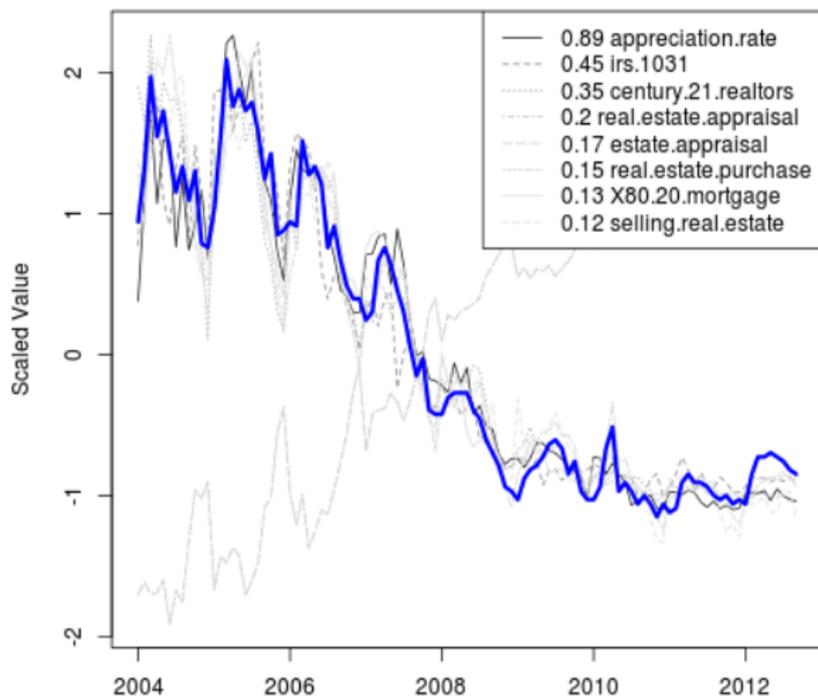
Eliminate spurious correlates



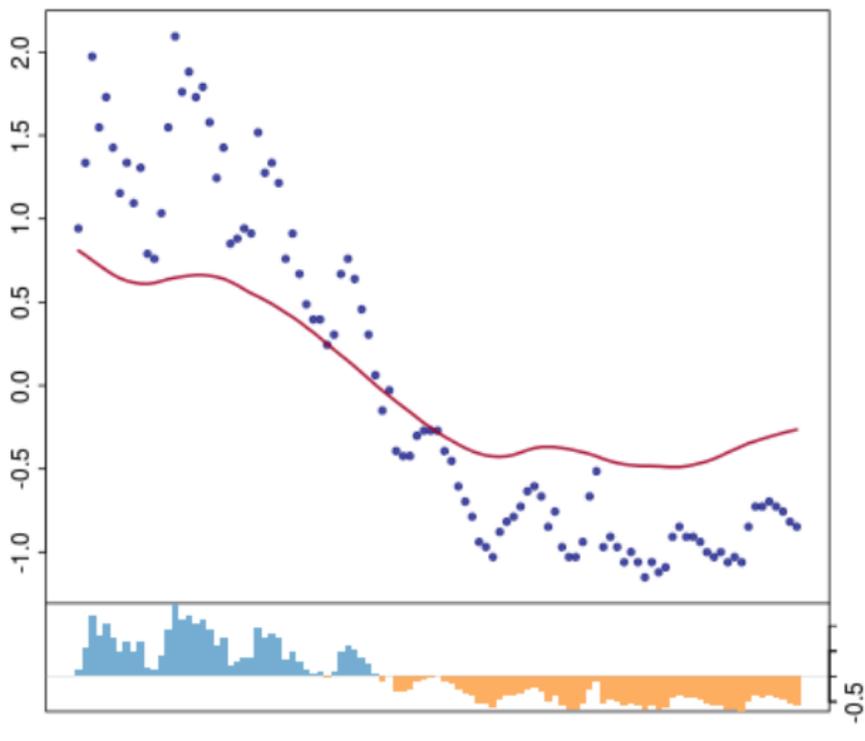
State decomposition



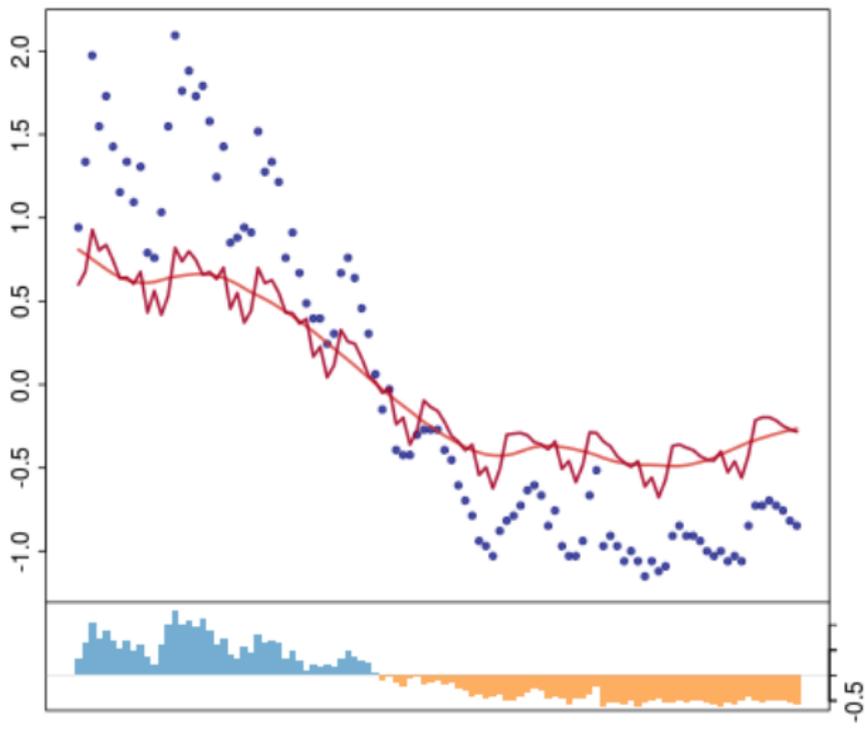
Predictors



1. trend (mae=0.48054)

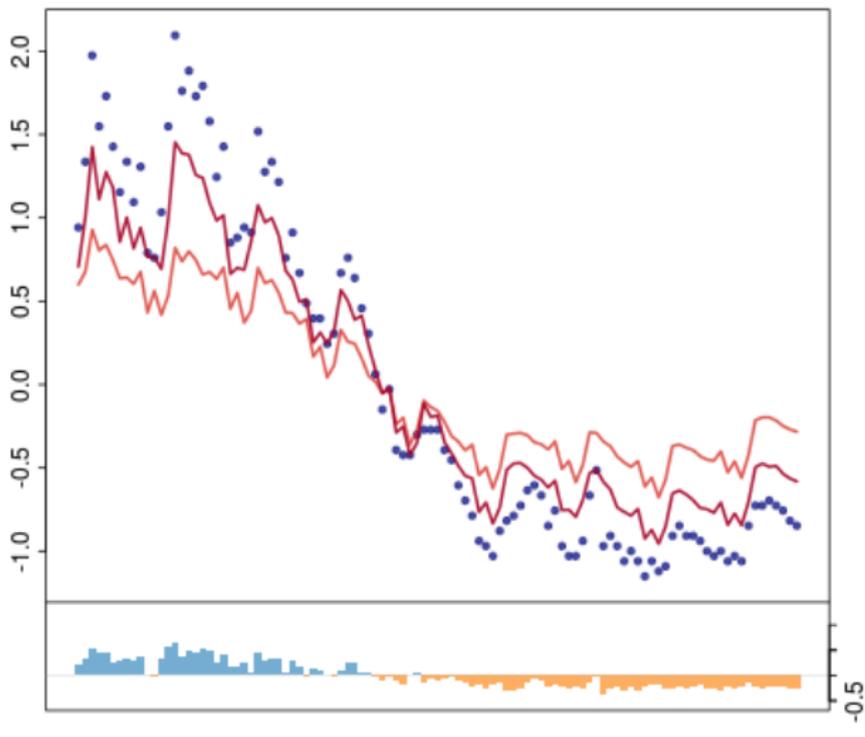


2. add seasonal (mae=0.47767)

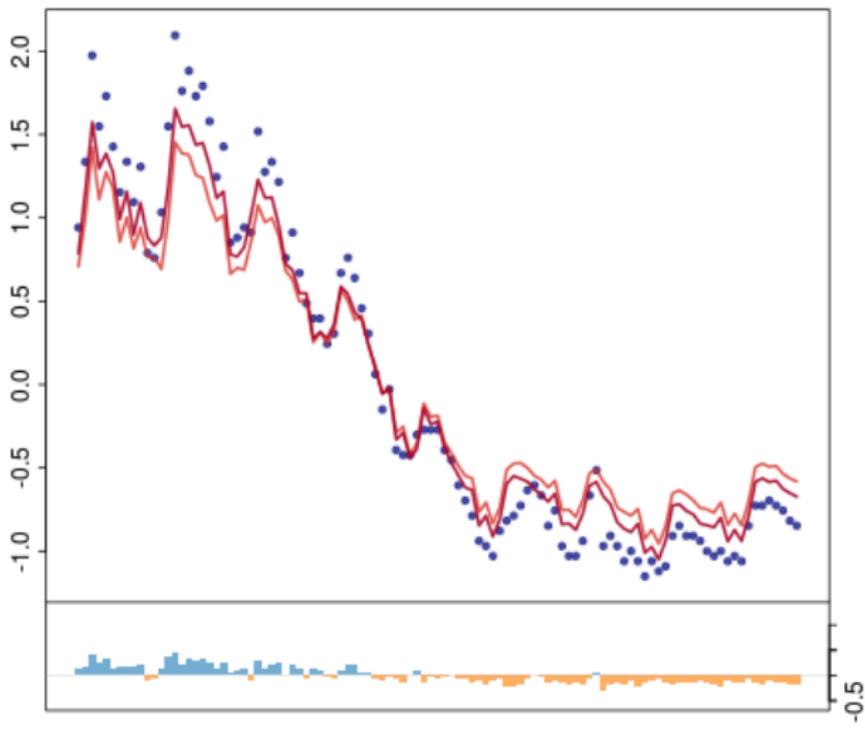


Appreciation rate

3. add appreciation.rate (mae=0.2241)

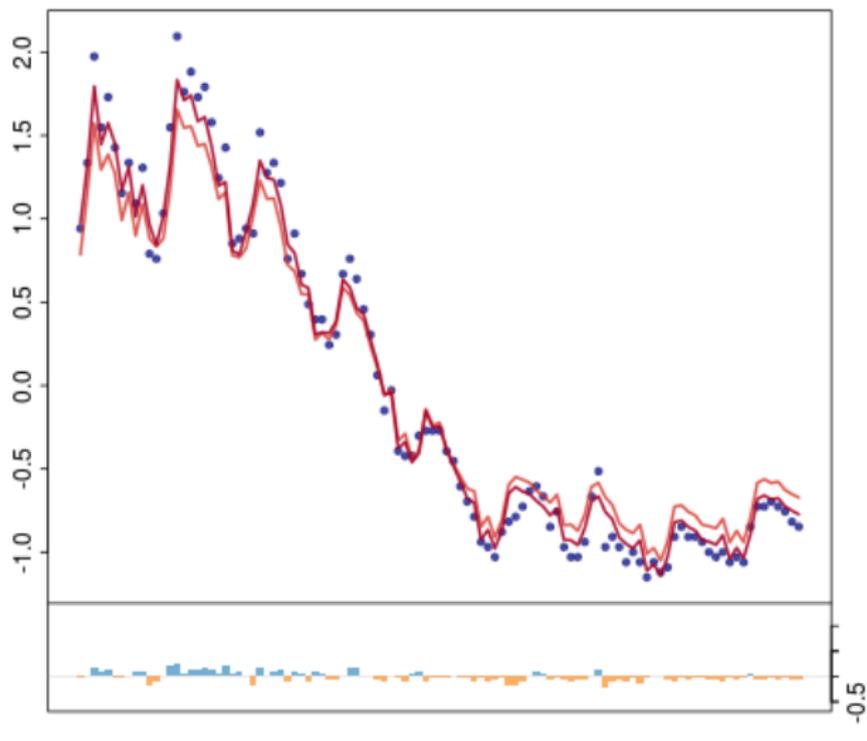


4. add irs.1031 (mae=0.14654)



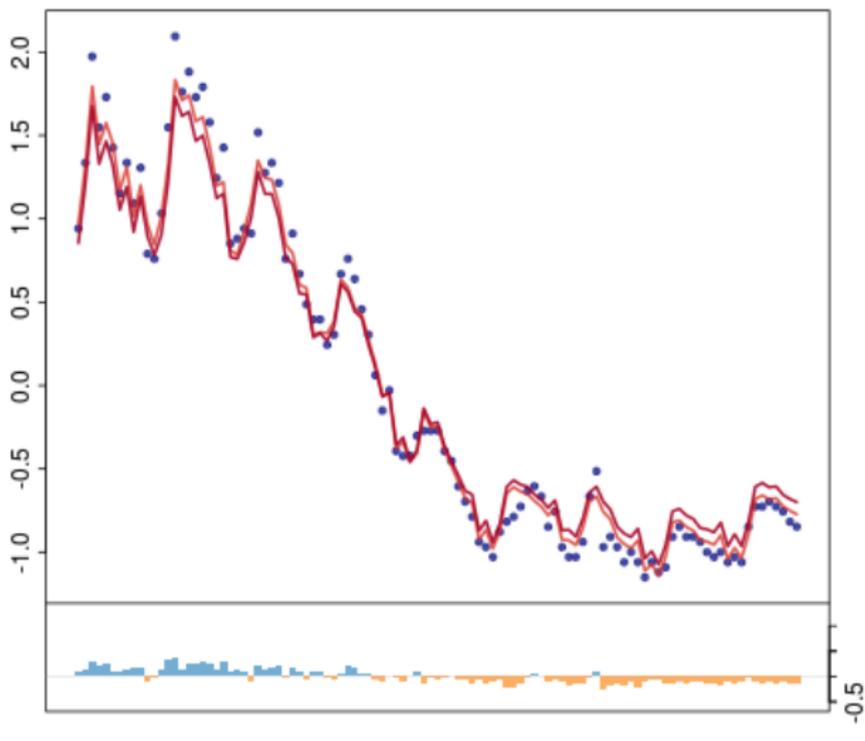
Century 21 realtors

5. add century.21.realtors (mae=0.077138)

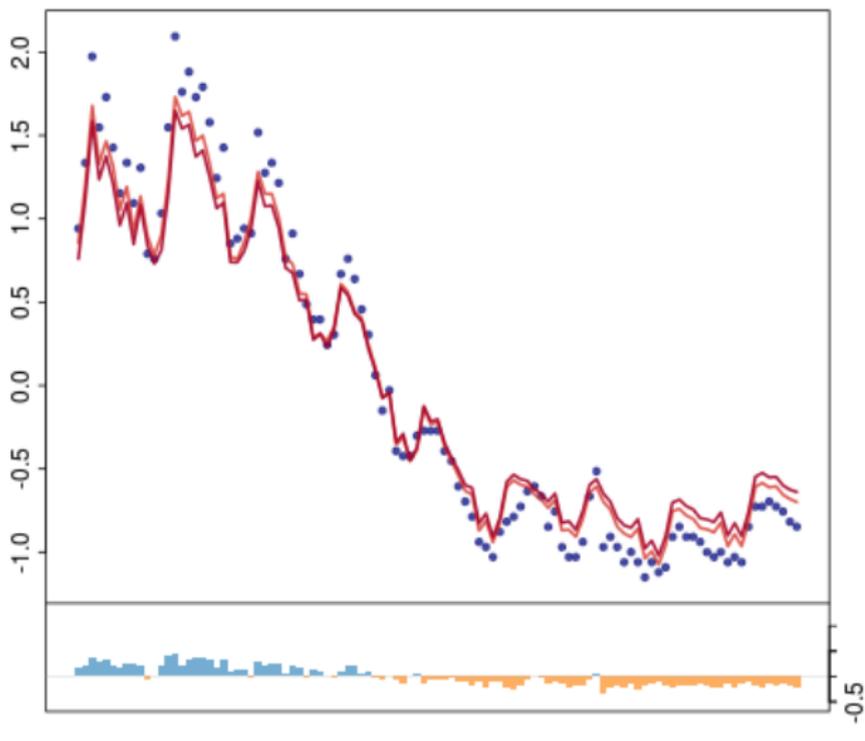


Real estate appraisal

6. add real.estate.appraisal (mae=0.12315)

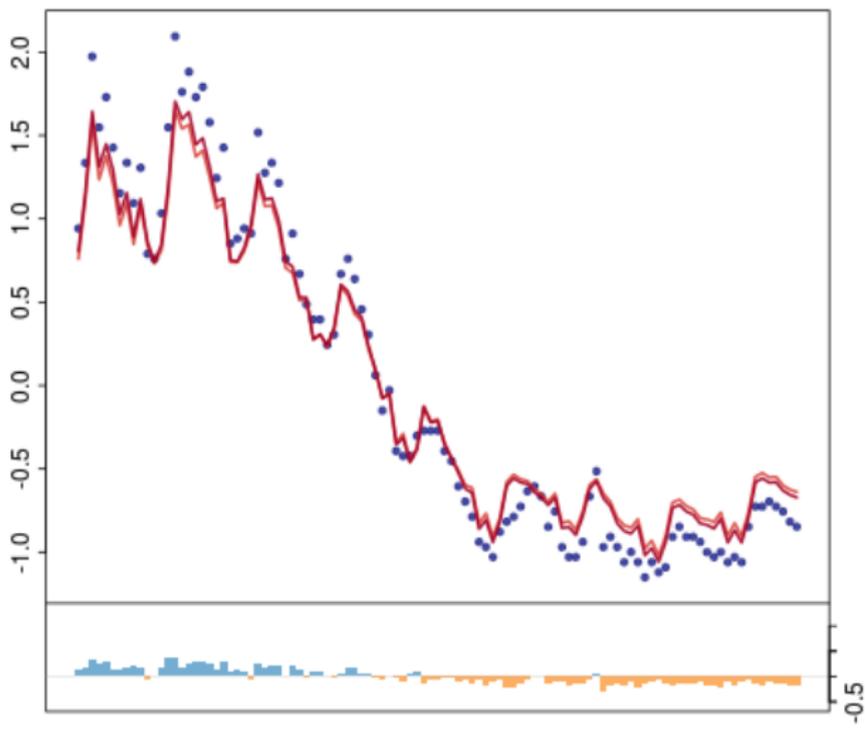


7. add estate.appraisal (mae=0.16587)

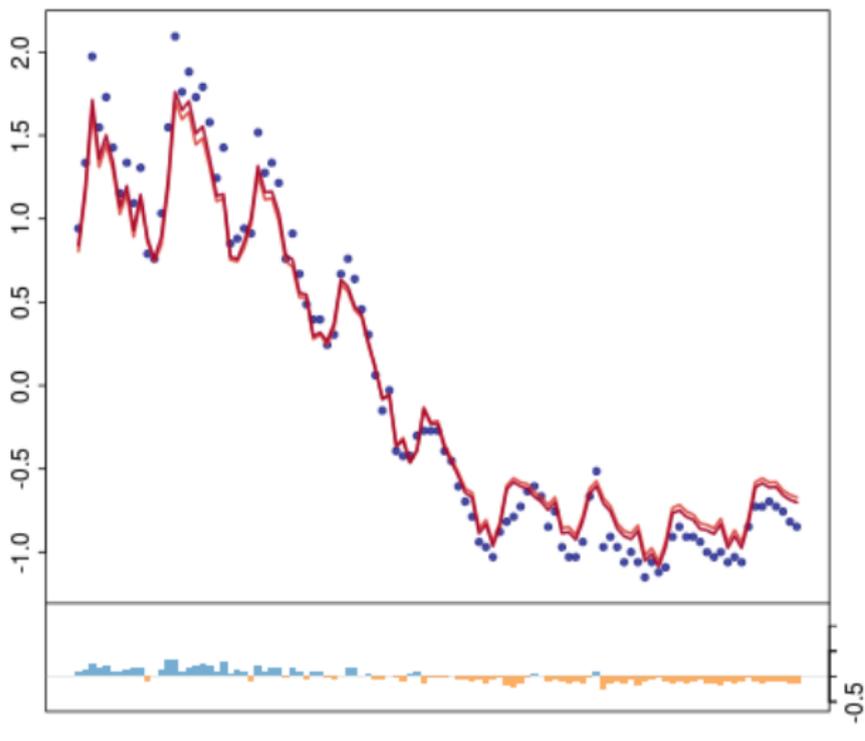


Real estate purchase

8. add real.estate.purchase (mae=0.13757)



9. add X80.20.mortgage (mae=0.11207)

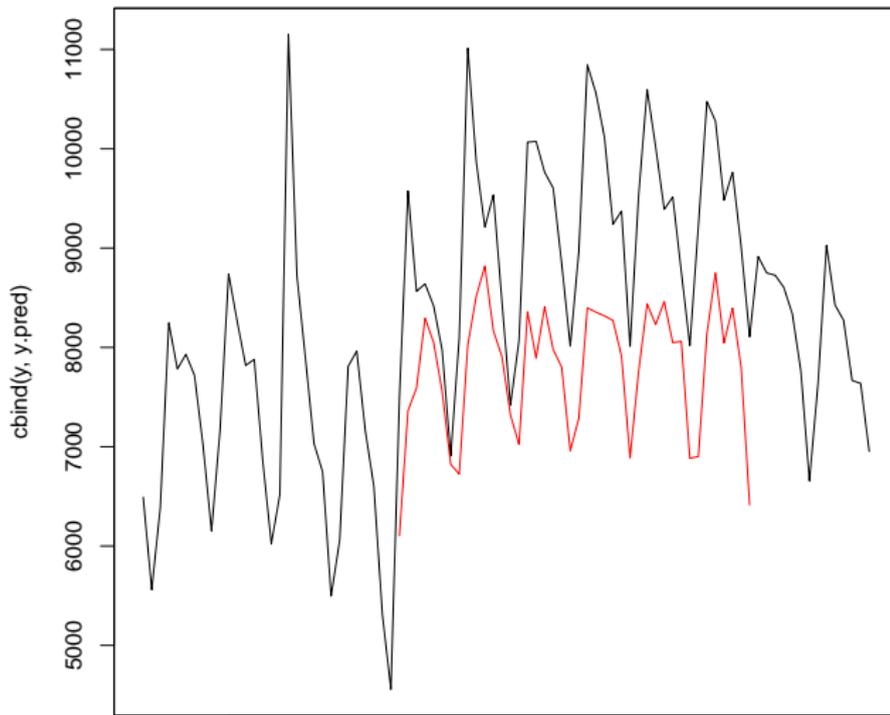


- ▶ In order to determine the causal impact of an intervention
 - ▶ Estimate what would have happened without the intervention (“the counterfactual”)
 - ▶ Compare counterfactual to actual outcome
- ▶ We can use BSTS (and related tools) to build predictive model for counterfactual

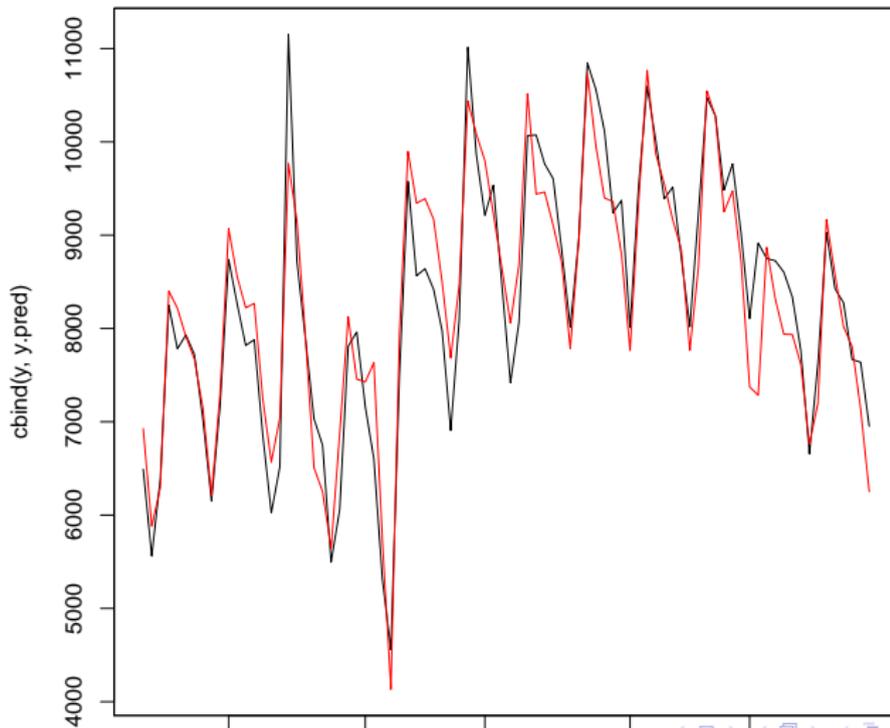
Example: impact of ad spend

- ▶ An online advertiser increased ad spending for 6 weeks. What was the impact on visitors to its web site? Two approaches:
 1. Extrapolation
 - ▶ Use BSTS to determine best predictors using Trends categories.
 - ▶ Turned out to be Photo and Video Sharing and Photo and Video Services.
 - ▶ Build predictive model of counterfactual using these predictors
 2. Dummy variable for campaign period

Extrapolation



Dummy variable



Survey Amplification

- ▶ Google Consumer Surveys uses an online survey in place of an ad
- ▶ User completes survey to get access to online content
- ▶ Win, Win, Win
 - ▶ Survey writer: pays about 10 cents a survey
 - ▶ Publisher gets 5 cents per response
 - ▶ User gets access to premium content

Example of survey

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- A YouTube video
- An ad on your mobile phone
- An ad on your tablet
- None of the above

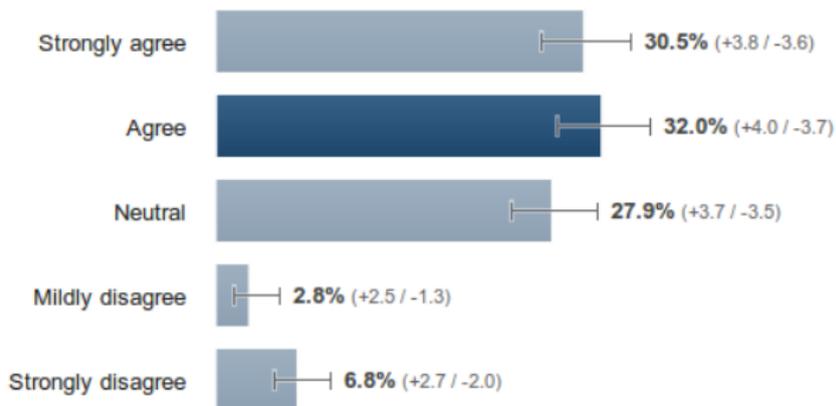
Assembled in America?

SINGLE ANSWER

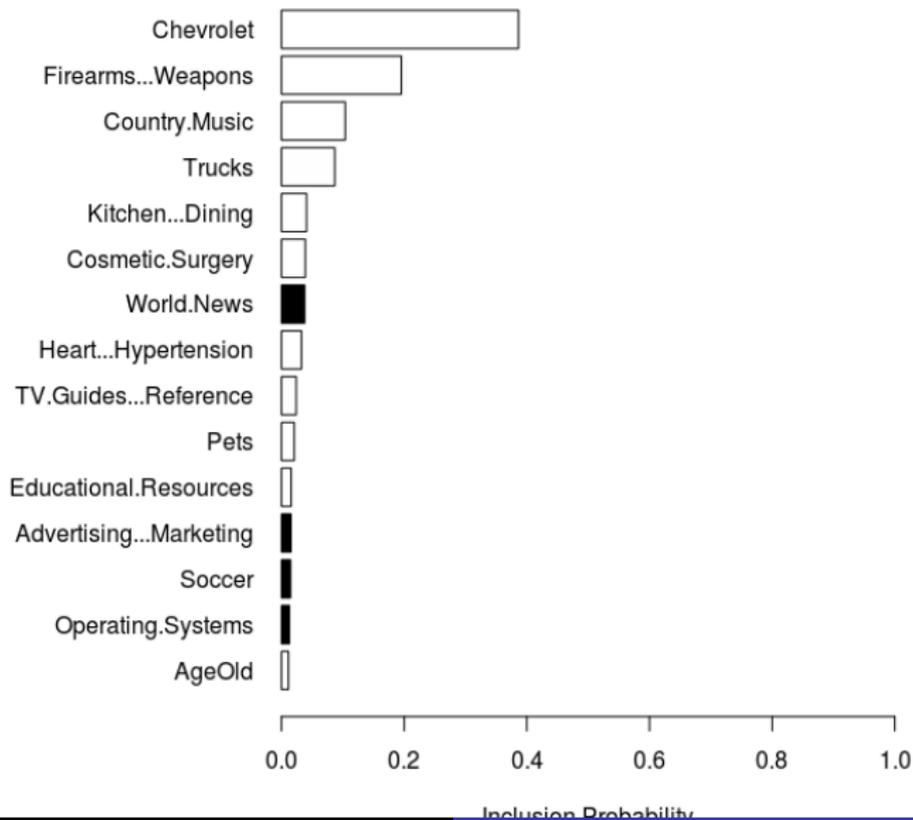
I prefer to buy products that are assembled in America

Results for respondents with demographics. Weighted by Age, Region. (694 responses) ?

Confidence too close to call. ?



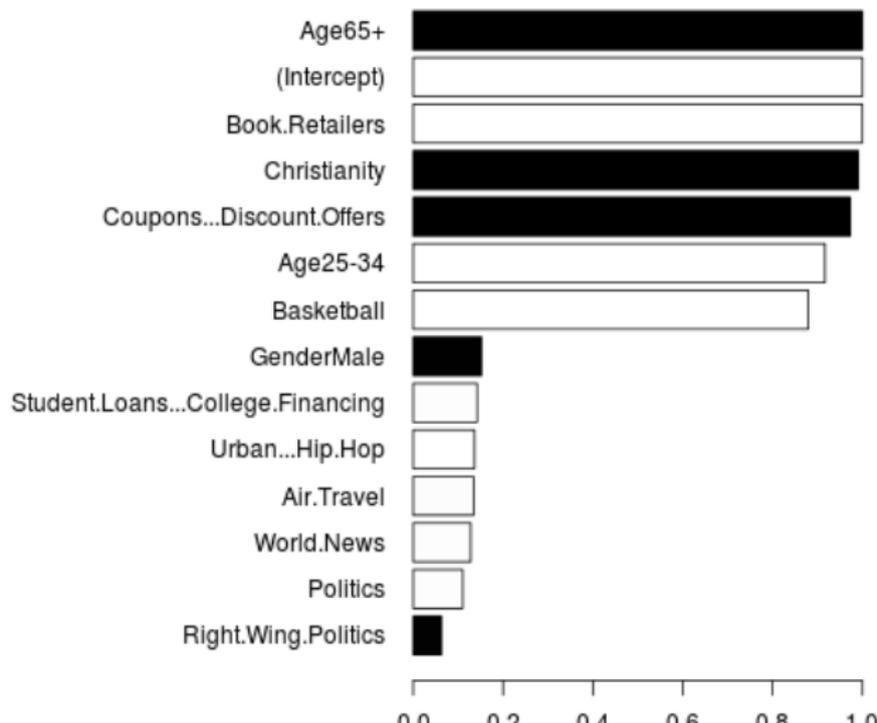
Predictors from Trends



Where to advertise

Top cities		Bottom cities	
1. Kershaw, SC	83.2	Calipatria, CA	40.2
2. Summersville, WV	82.8	Fremont, CA	40.2
3. Grundy, VA	82.8	Mountain View, CA	40.8
4. Chesnee, SC	82.7	San Jose, CA	41.4
5. Duffield, VA	82.5	Berkeley, CA	41.4
6. Norton, VA	82.3	Redmond, WA	41.5
7. Jonesville, VA	82.2	Glendale, CA	41.5
8. Walnut Cove, NC	82.2	Cupertino, CA	41.6

Predictors of Obama Vote



Survey Amplification: Obama Support

