# Large-Scale, Computationally Intensive Forecasting in R

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# Overview

## "Large-Scale" = Lots of time series

- Manual analysis impractical
- Diversity of time series
  - Growth
  - Seasonality
  - Shocks, regime change, emergence
- Automatic and robust methods needed
  - Ensemble method (a.k.a., "Many Models" approach)



## "Computationally Intensive"....

- Two sources
  - Thousands of forecasts every day
  - Arising from statistical method
    - Fitting the "many models"
    - Quantifying statistical uncertainty
      - Simulation-based confidence intervals (requiring 1K to 10K forecasts per time series)



# "Forecasting in R"

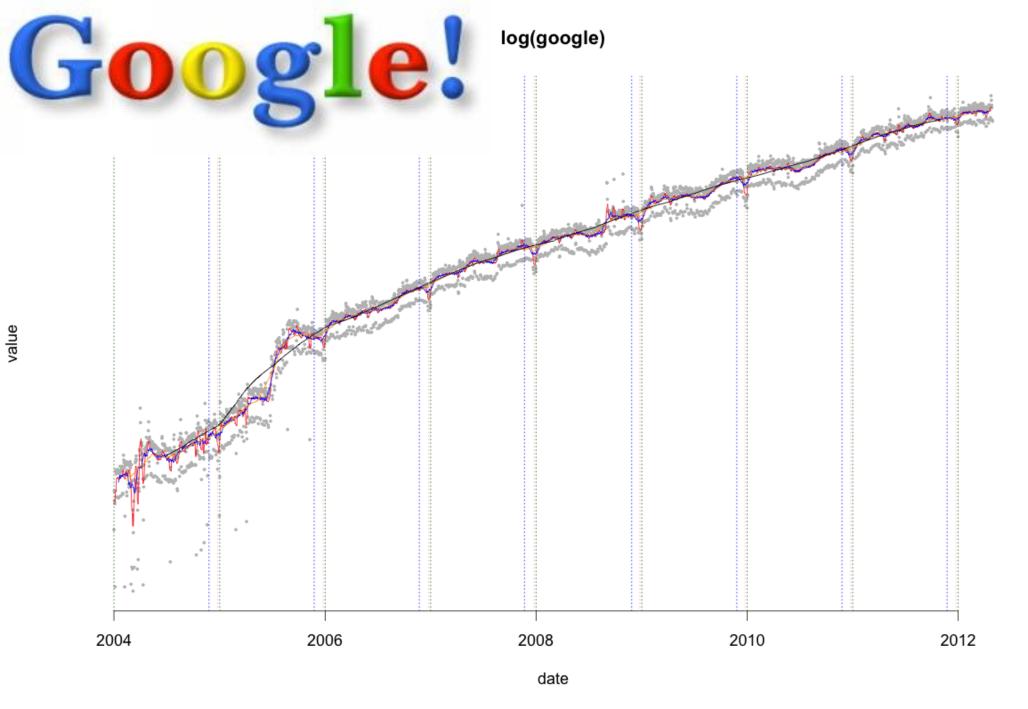
Just what it sounds like! :-)



# Data

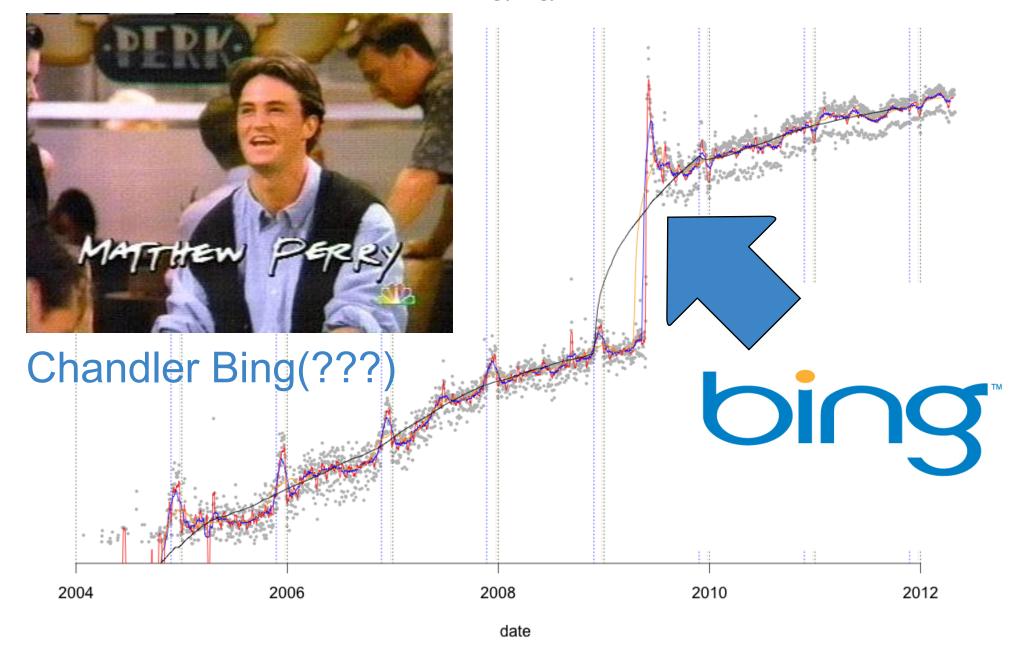
#### The Data

- 1000 time series from Google Trends:
  - Looked at past 5 years of data
  - Hence, persistently popular queries
  - Forecasts based on subset of 5 years
- Let's look at some of them...
  - o Data since 2004, not just 5 years
  - Shown on logarithmic scale (y-axis)
  - Grey is data, 7-/31-/91-/365-day moving averages shown too
  - T-giving, New Years marked

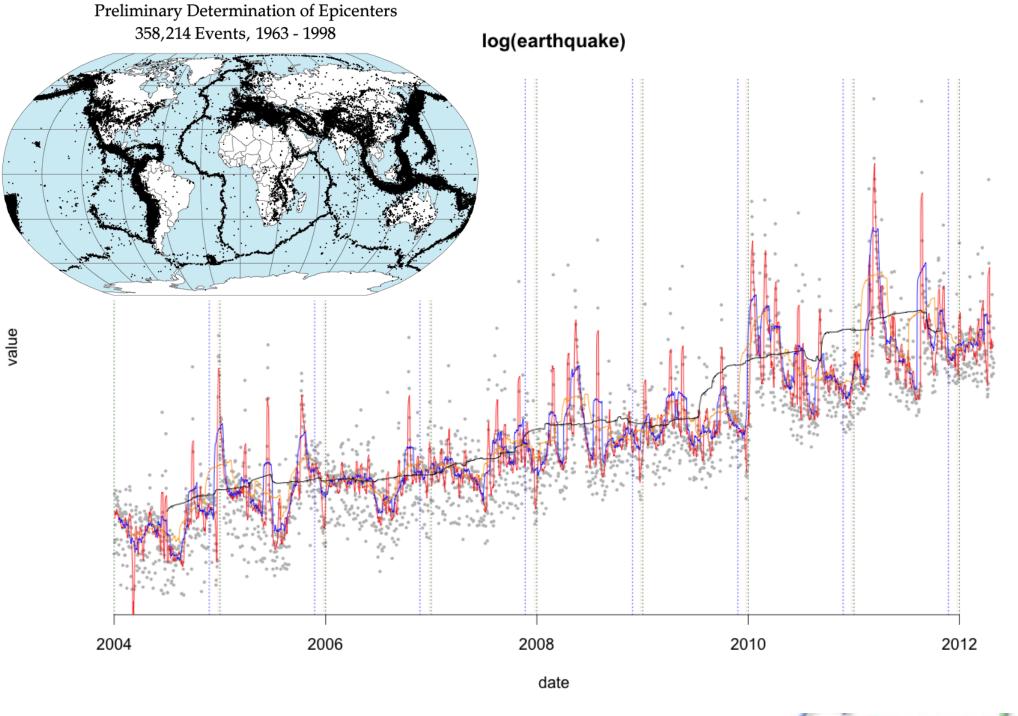




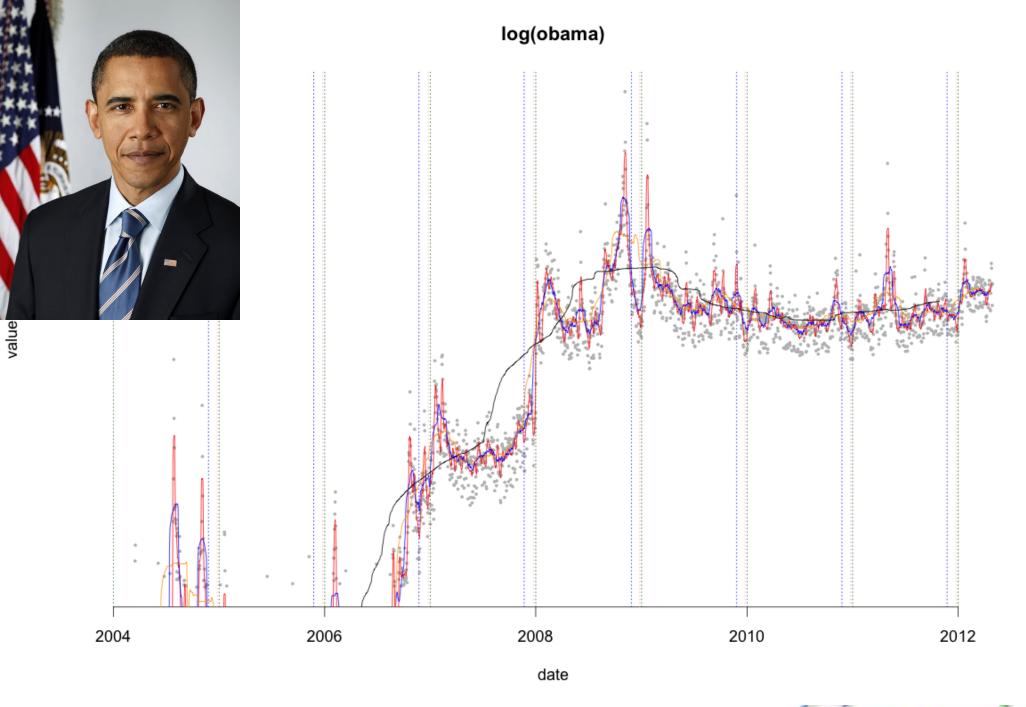
#### log(bing)



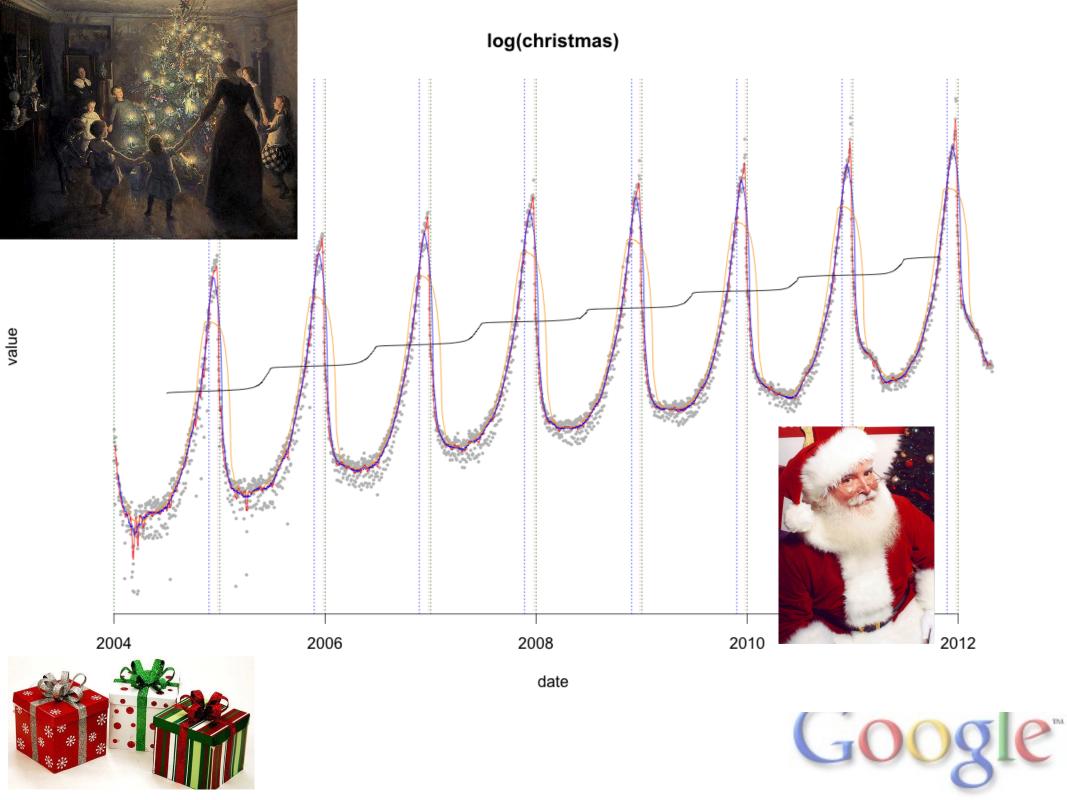




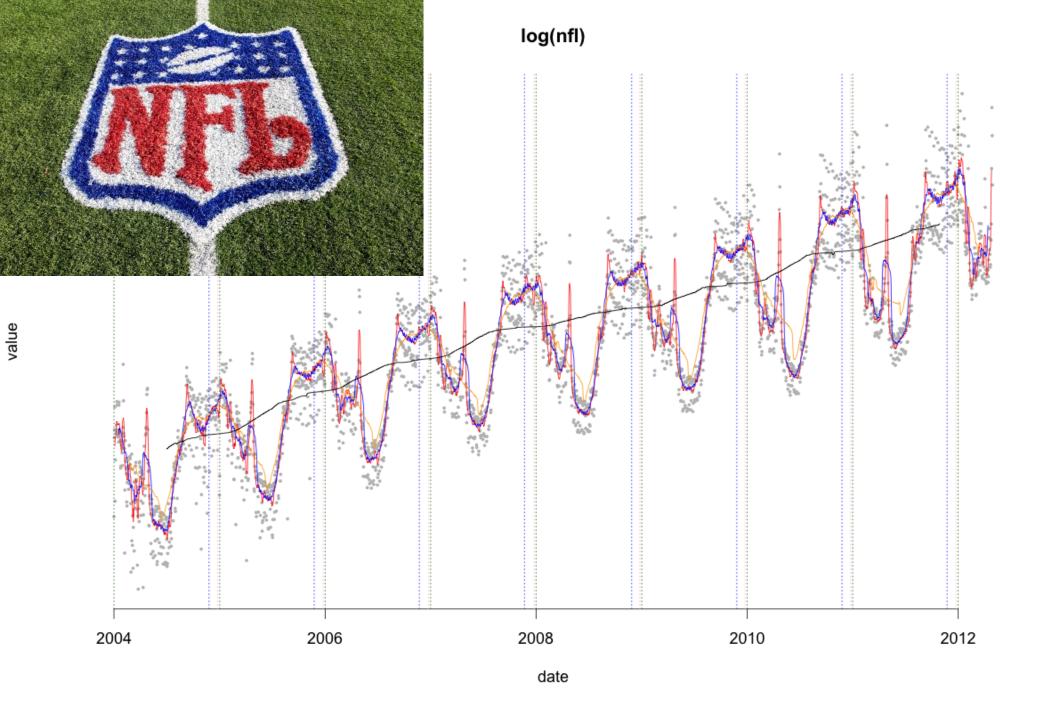




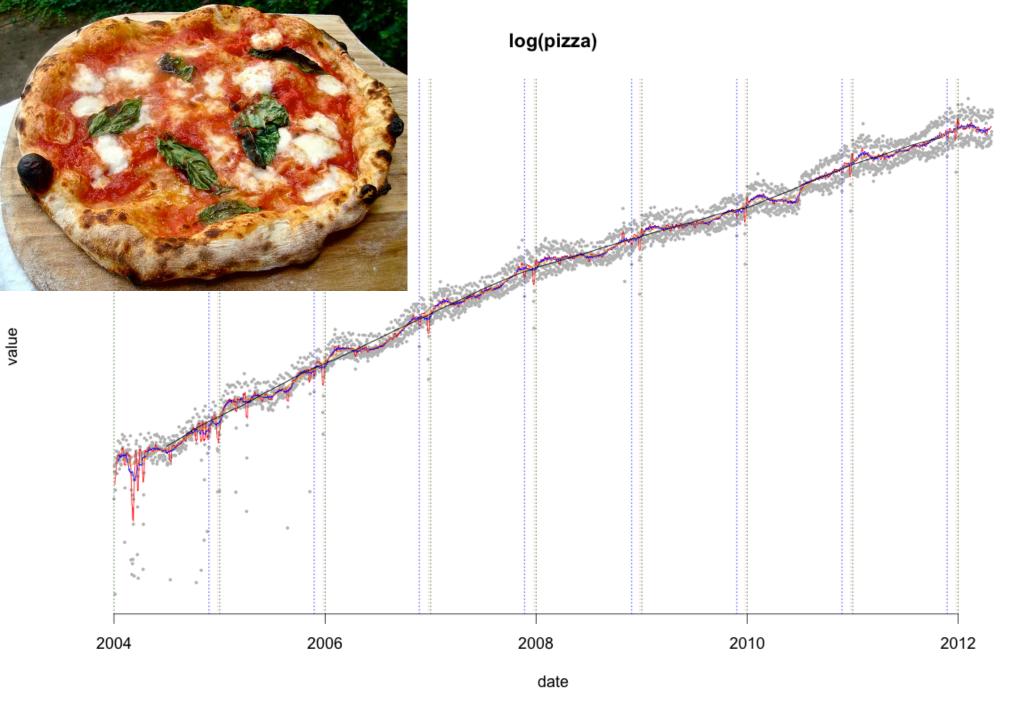










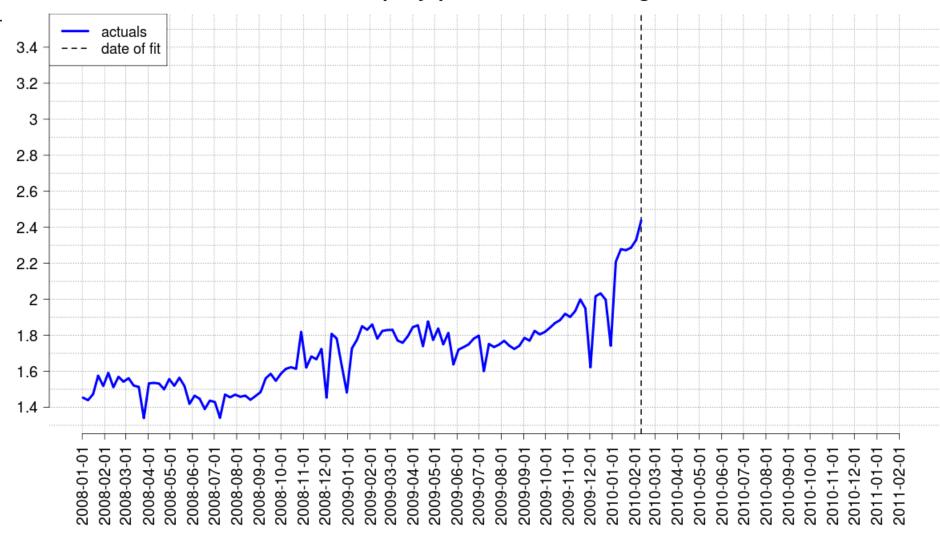




# Methods



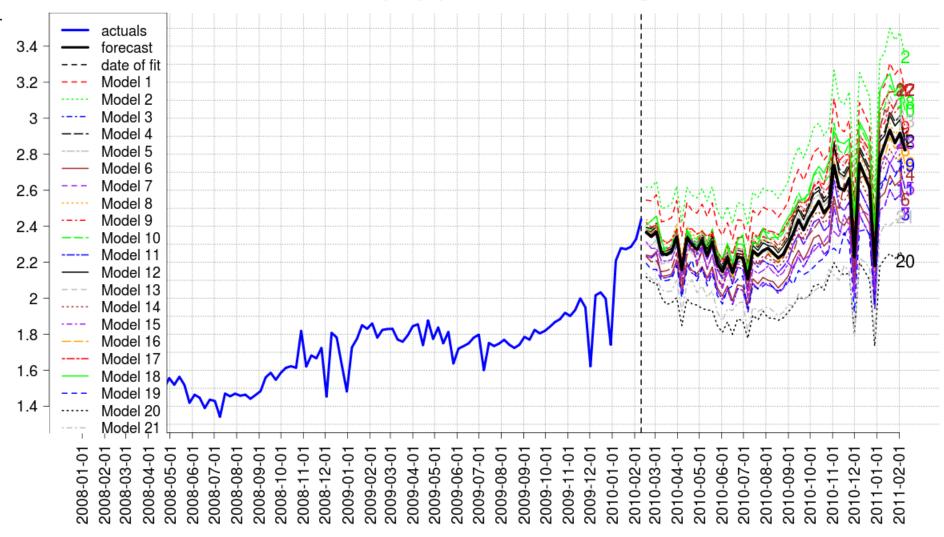
#### The trend for query 'pizza' in US from Google Trends







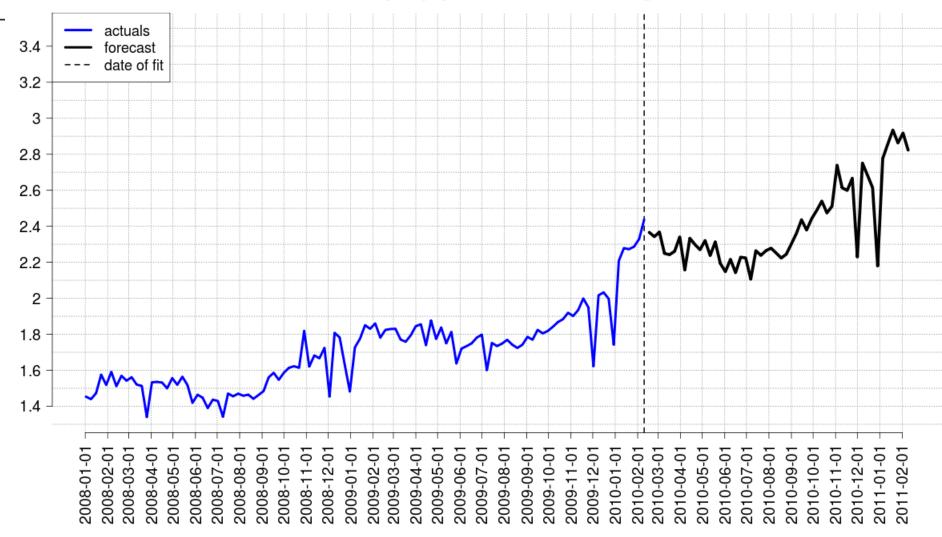
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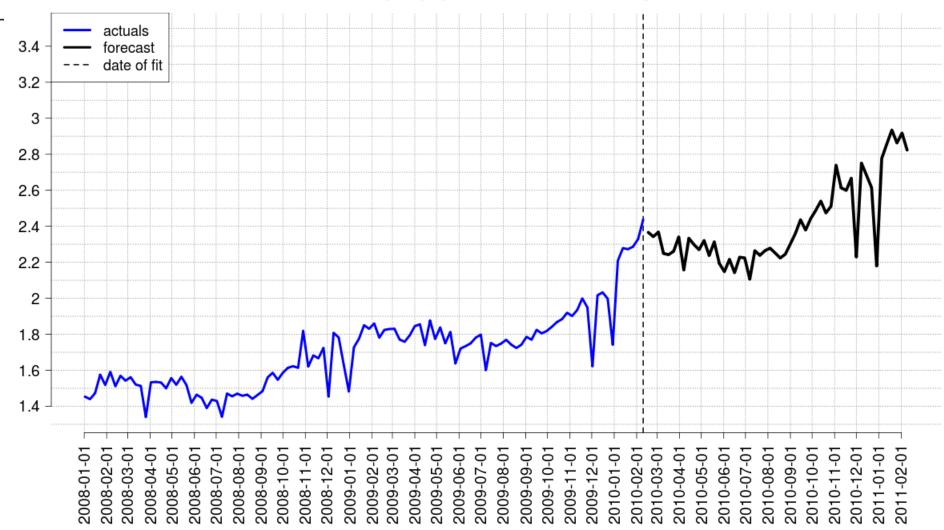
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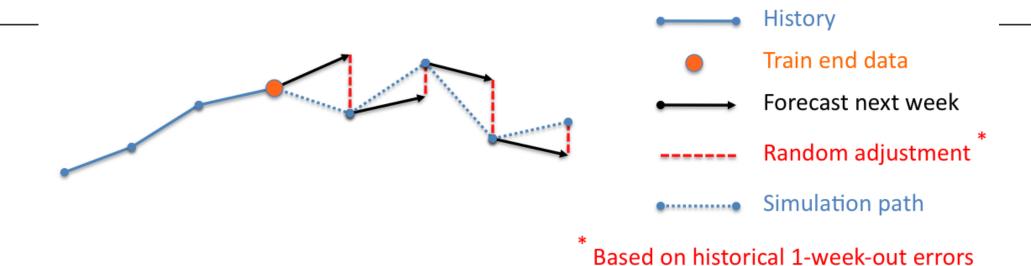
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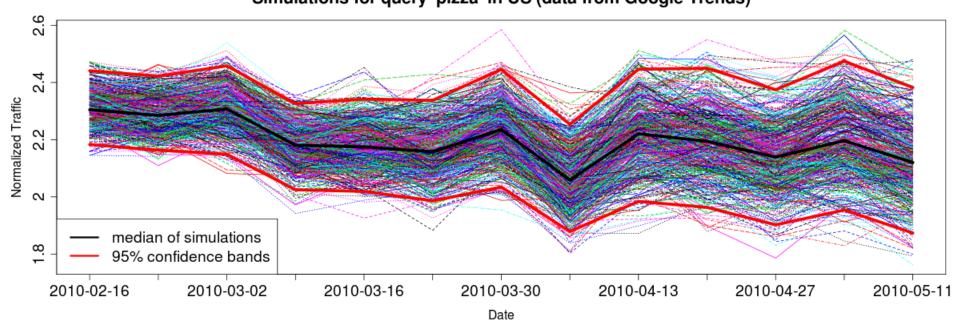
Armstrong, J. S. Combining forecasts. Principles of forecasting: A handbook for researchers and practitioners, 417–439.

Clemen, R. Combining forecasts: A review and annotated bibliography. International Journal of forecasting 5, 559-583

#### Confidence Intervals



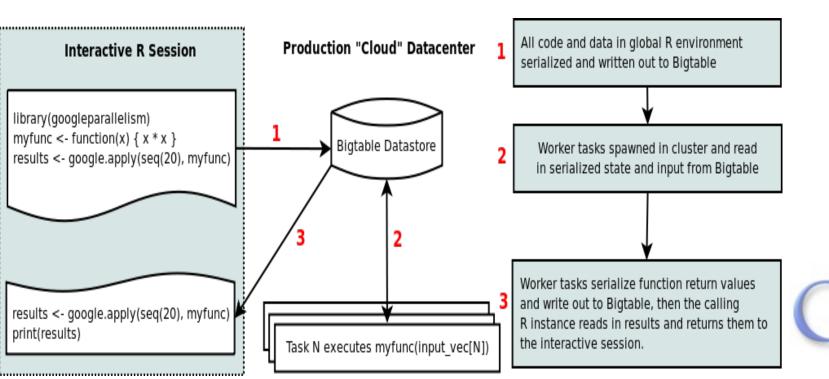
#### Simulations for query 'pizza' in US (data from Google Trends)



# Parallelization in R: Why?

- 1,000 Trends t.s. X
- 1,000 realization/t.s. X
  - ~10 sec/realization = 10^7 sec ~ 4 months

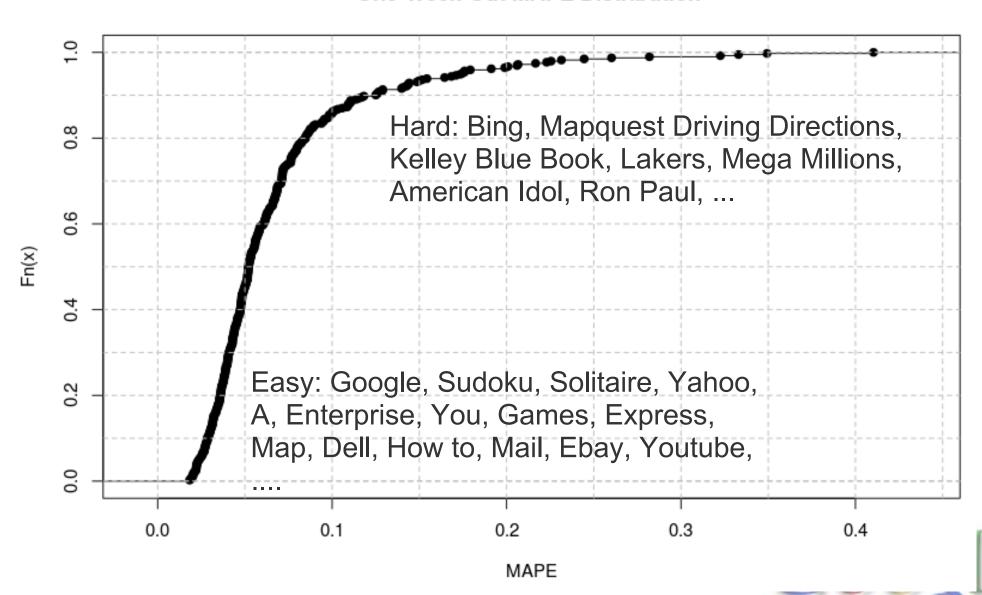
But 9 hours in parallel, cut by factor of ~300



## Overall Performance

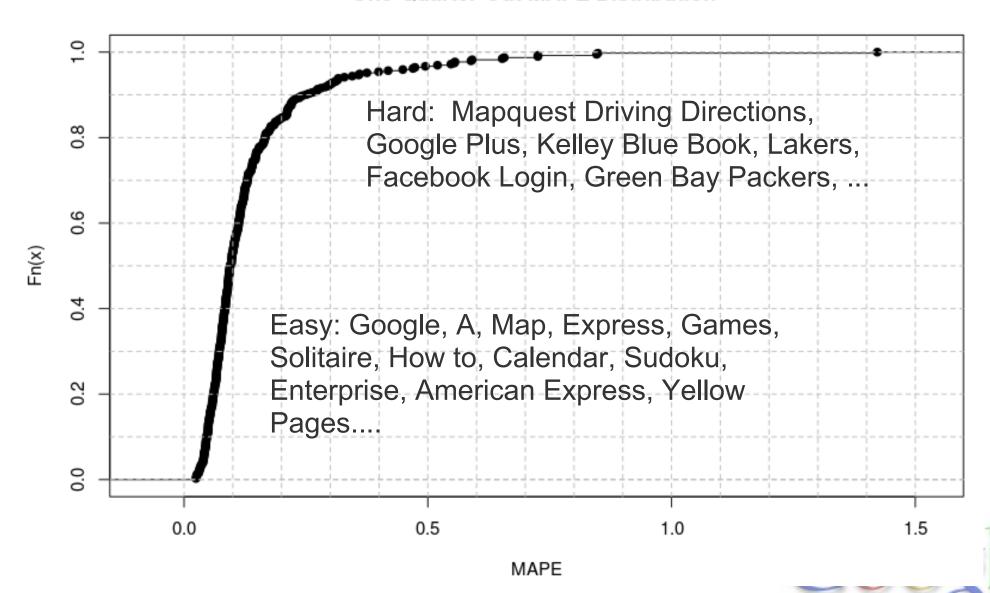
#### One-Week-Out MAPE

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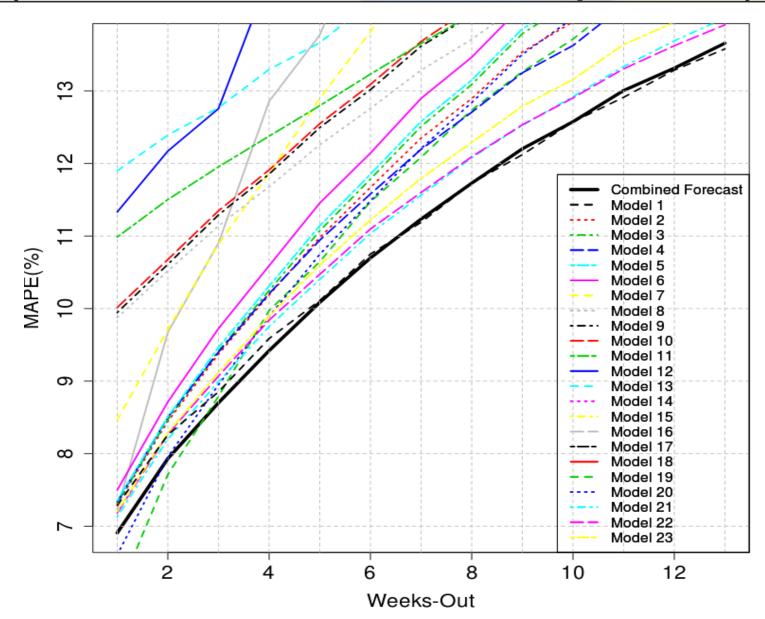


#### One-Quarter-Out MAPE

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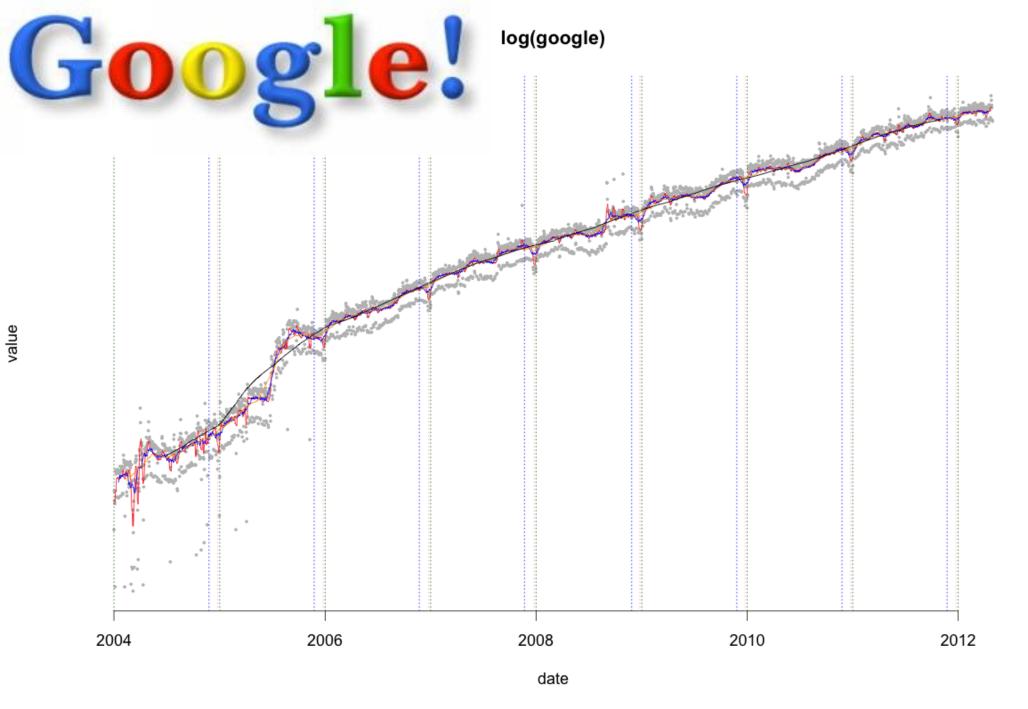


# Performance of Individual Models (Overall, based on all queries)



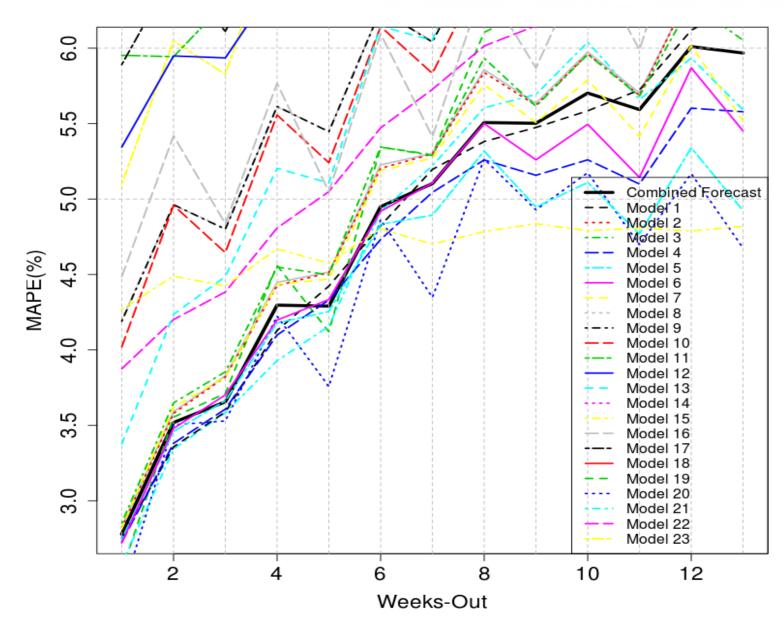


# Performance on Individual Time Series



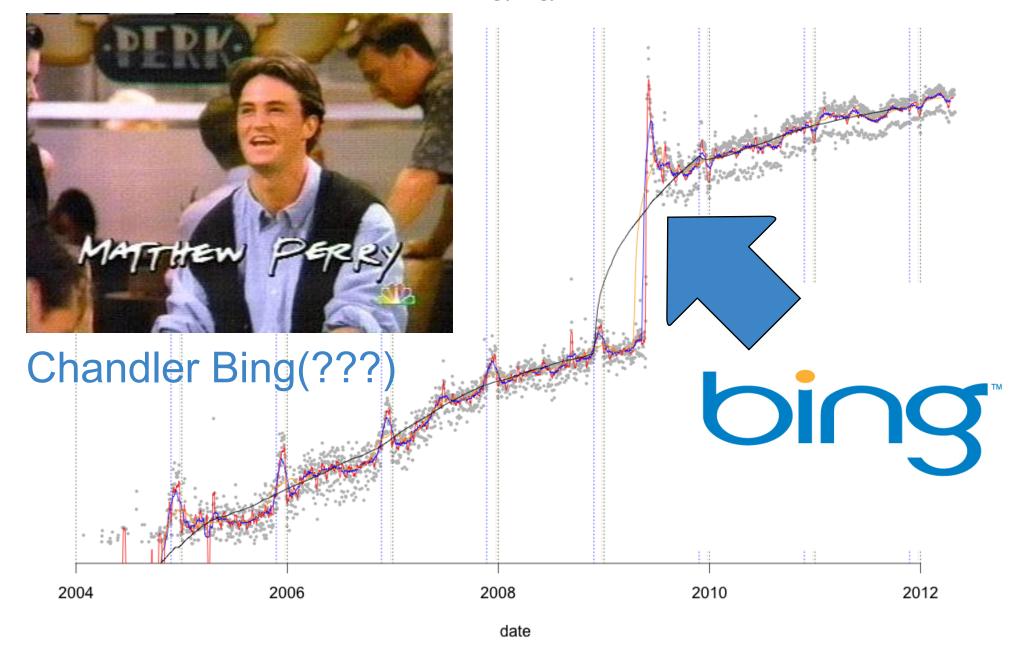


# Performance on query "google"



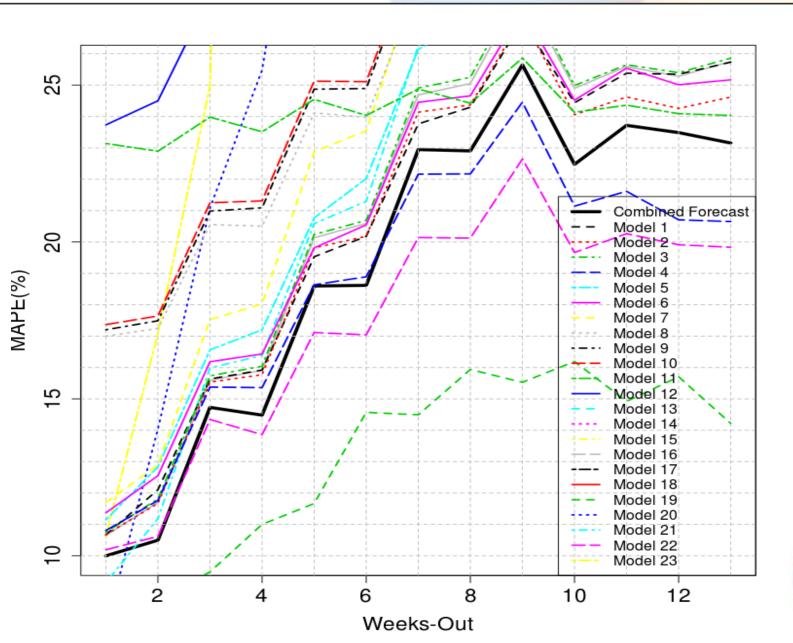


#### log(bing)



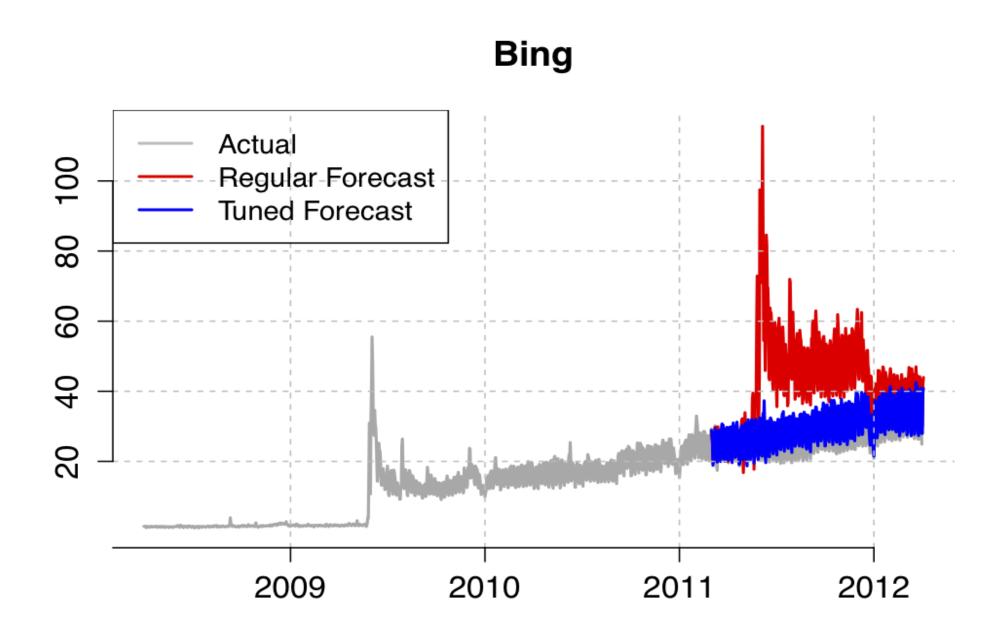


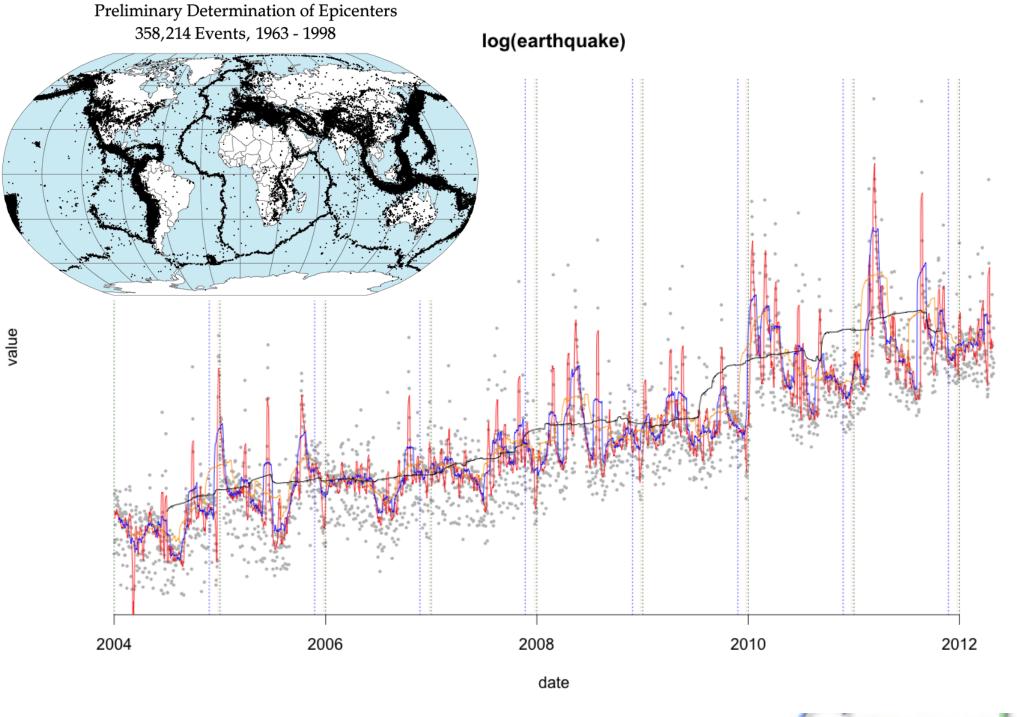
# Performance on query "bing"





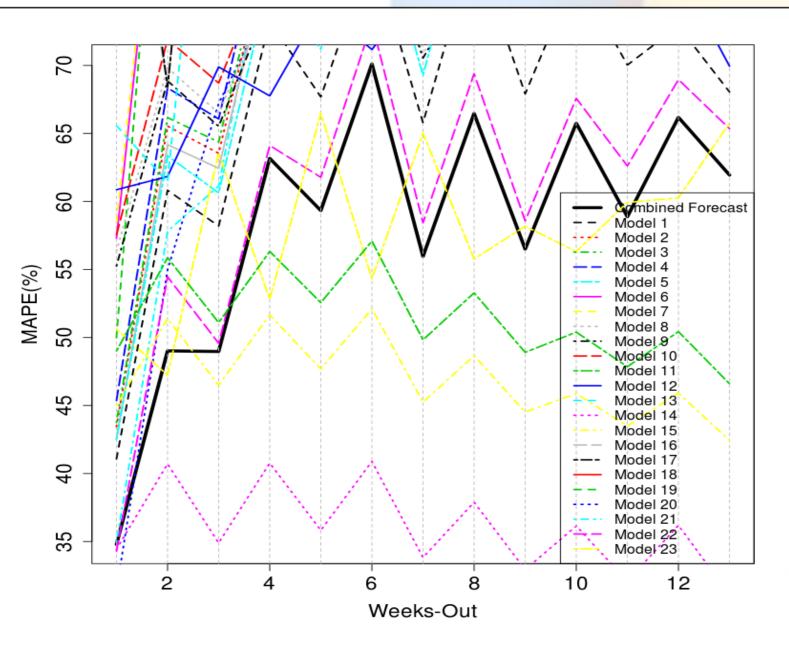
# Tuned forecast (normalized values)



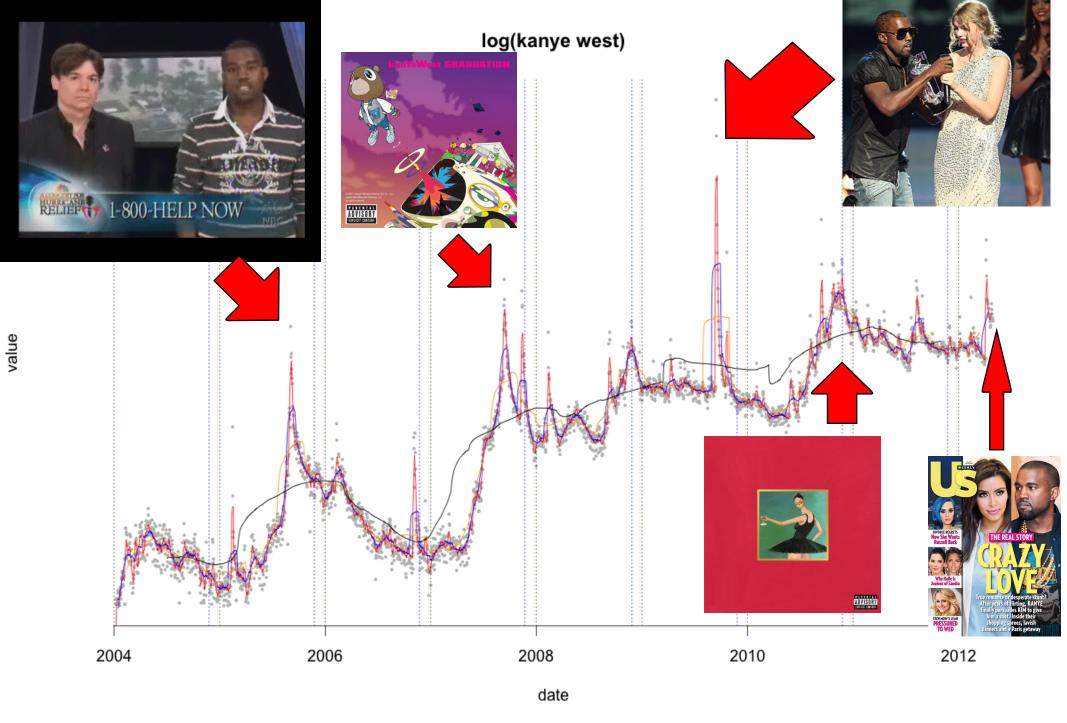




# Performance on query "earthquake"









Celebrity earthquakes

# Wrapping Up...

## Conclusions, Statistical Methods

- Automatic, robust method needed for large number of diverse time series
- Many Models (MM) approach does well for large percentage of 1000 Trends queries
- Overall, MM beats individual models
- Some models do better on particular queries, but how to know a priori?

## Conclusions, Computing

- Large number of time series & statistical method => large number of forecasts
- Number of forecasts => parallelization
- Parallelization: google.apply() internally, external options available
- Our version cut run time by factor of 300 (4 months -> 9 hrs)

#### See also:

JSM2011 Paper, http://research.google.com/pubs/pub37483.html) & JSM2012 Presentation (K. Millar, "Scaling R to Internet Scale Data", upcoming 8/1/12 @ 11:05am)

#### **Future Work**

- Classification?
- Correlations / multivariate methods?
- Aggregate / disaggregate forecasting?
- Dimension reduction? Then forecast?
- More models?



# That's All, Folks!