From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series

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Measuring public opinion
through social media?

People in U.S.

Query

Can we derive a similar measurement?

Write

facebook

twitter

Query

Aggregate Text Sentiment Measure

Contributions

- Correlations between
  1. Very simple text sentiment analysis
  2. Telephone public opinion polls
     - Consumer confidence and Presidential job approval
- Time-series smoothing is a critical issue
- Also
  - Topic selection, topic volumes, text leads polls, stemming, election polling

Rest of talk

- Data Overview
- Analysis
- Discussion and Related Work

- New Results!

Text Data: Twitter

- Twitter is large, public, and all in one place
- Sources
  1. Archiving Twitter Streaming API

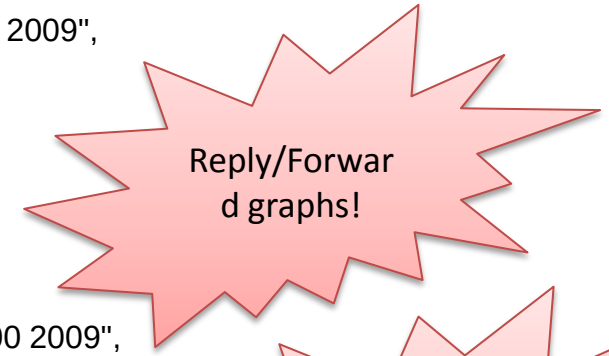
     "Gardenhose"/"Sample": ~15% of public tweets
  2. Scrape of earlier messages via API

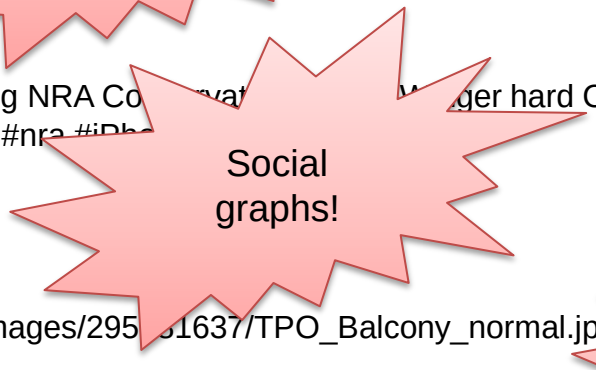
     thanks to Brendan Meeder
- Sizes
  - 0.7 billion messages, Jan 2008 – Oct 2009
  - 1.5 billion messages, Jan 2008 – May 2010

Message data

{
"text": "Time for the States to fight back !!! Tenth Amendment Movement: Taking On the Feds http://bit.ly/14t1RV #tcot #teaparty",
"created_at": "Tue Nov 17 21:08:39 +0000 2009",
"geo": null,
"id": 5806348114,
"in_reply_to_screen_name": null,
"in_reply_to_status_id": null,

"user": {
"screen_name": "TPO_News",
"created_at": "Fri May 15 04:16:38 +0000 2009",
"description": "Child of God - Married - Gun carrying NRA Co[illegible]ger hard Core Anti Obama (Pro America), Parrothead - www.ABoldStepBack.com #tcot #nra #iPh[illegible]
"followers_count": 10470,
"friends_count": 11328,
"name": "Tom O'Halloran",
"profile_background_color": "f2f5f5",
"profile_image_url": "http://a3.twimg.com/profile_images/295[illegible]1637/TPO_Balcony_normal.jpg",
"protected": false,
"statuses_count": 21147,
"location": "Las Vegas, Baby!!",
"time_zone": "Pacific Time (US & Canada)",
"url": "http://www.tpo.net/1dollar",
"utc_offset": -28800,
}
}





Message data we use


```
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```

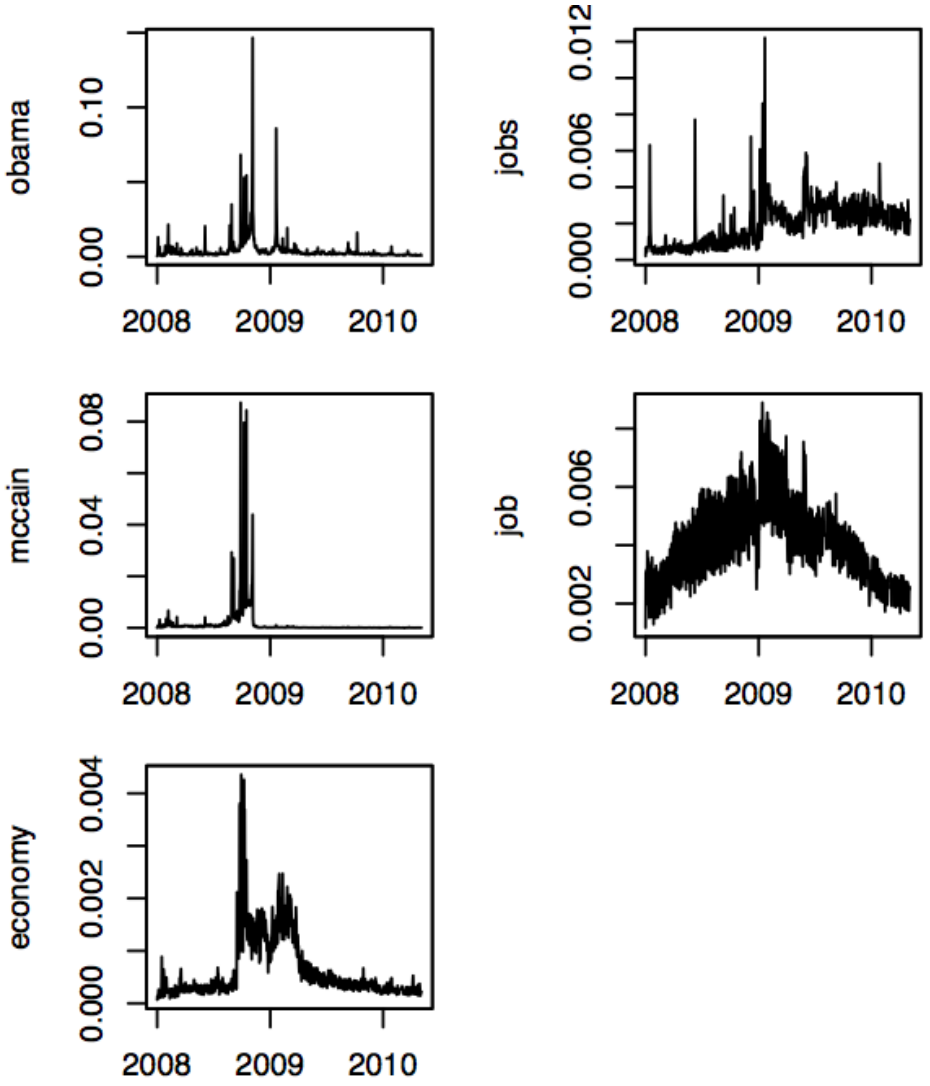

1. Text
2. Timestamp

Poll Data

- Consumer confidence, 2008-2009
  - Index of Consumer Sentiment (Reuters/Michigan)
  - Gallup Daily (free version from gallup.com)
- 2008 Presidential Elections
  - Aggregation, Pollster.com
- 2009 Presidential Job Approval
  - Gallup Daily
- Which tweets correspond to these polls?

Message selection via topic keywords

- Analyzed subsets of messages that contained manually selected topic keyword
  - “economy”, “jobs”, “job”
  - “obama”
  - “obama”, “mccain”
- High day-to-day volatility
  - Fraction of messages containing keyword
  - Nov 5 2008: 15% contain “obama”



Sentiment analysis: word counting

- Subjectivity Clues lexicon from OpinionFinder / U Pitt
  - Wilson et al 2005
  - 2000 positive, 3600 negative words

- Procedure
  1. Within topical messages,
  2. Count messages containing these positive and negative words

A note on the sentiment list

- This list is not well suited for social media English.
  - “sucks”, “ :) ”, “ :(”

- Examples for one day.

(Top examples)

word	*valence*	*count*
will	positive	3934
bad	negative	3402
good	positive	2655
help	positive	1971

(Random examples)

word	*valence*	*count*
funny	positive	114
fantastic	positive	37
cornerstone	positive	2
slump	negative	85
bearish	negative	17
crackdown	negative	5

Sentiment Ratio over Messages

For one day *t* and topic word, compute score

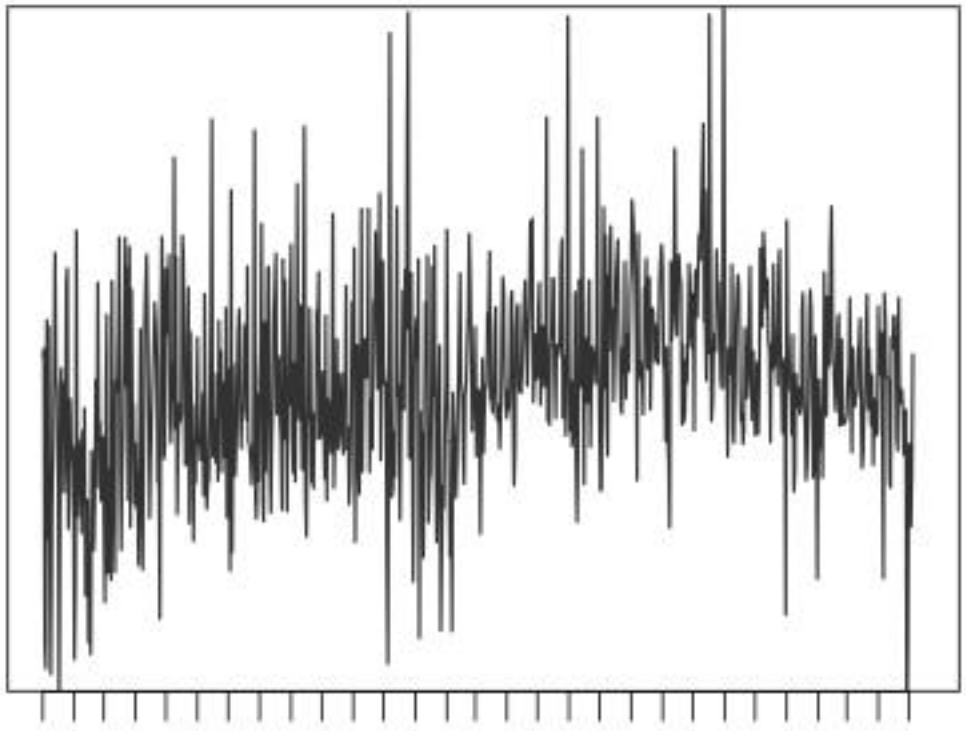
$$\frac{\text{MessageCount}_t(\text{pos. word AND topic word})}{\text{MessageCount}_t(\text{neg. word AND topic word})}$$

$$= \frac{p(\text{pos. word} \mid \text{topic word}, t)}{p(\text{neg. word} \mid \text{topic word}, t)}$$

Sentiment Ratio Moving Average

- High day-to-day volatility.
- Average last *k* days.
- Keyword “jobs”,

  k = 1, 7, 30
- (Gallup tracking polls: 3 or 7-day smoothing)



$$MA_t = \frac{1}{k}\left(x_{t-k+1} + x_{t-k+2} + \ldots + x_t\right)$$

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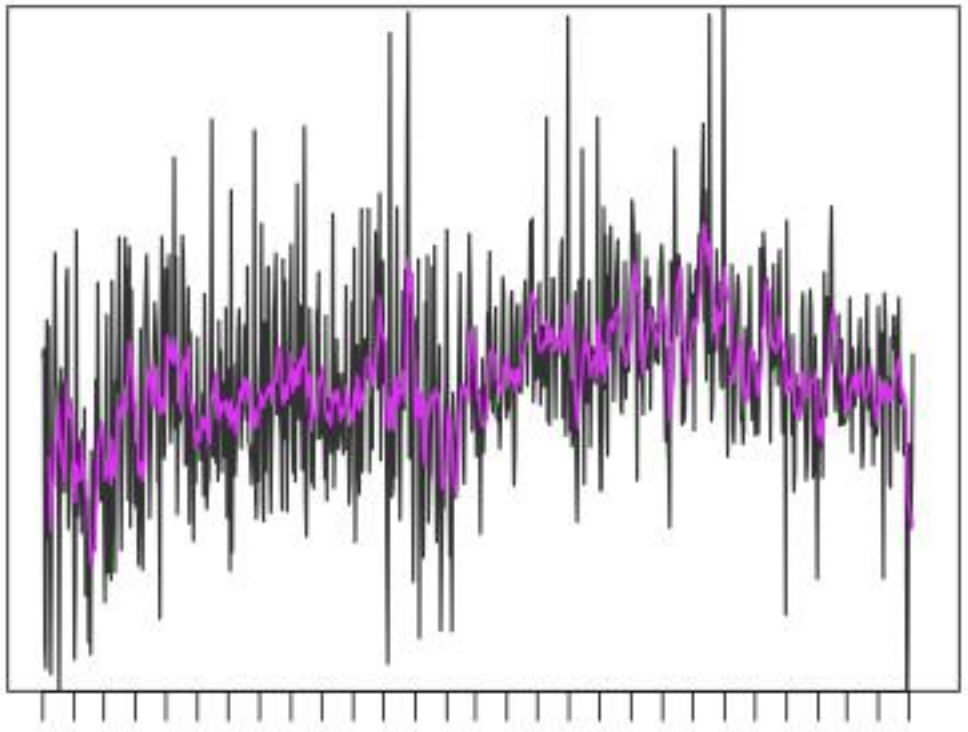

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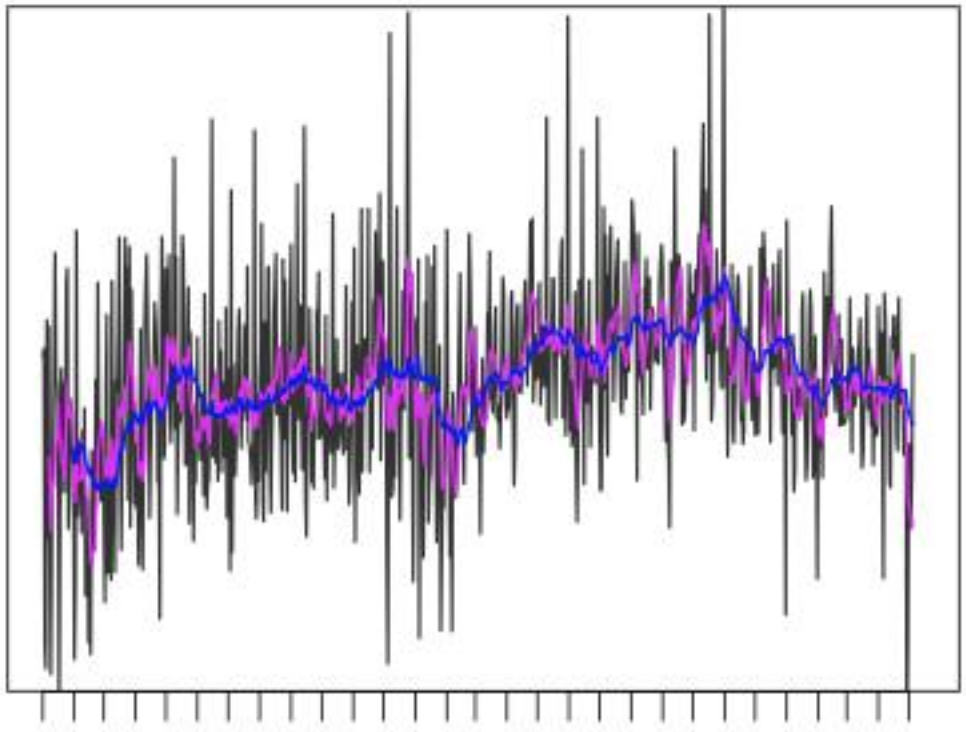

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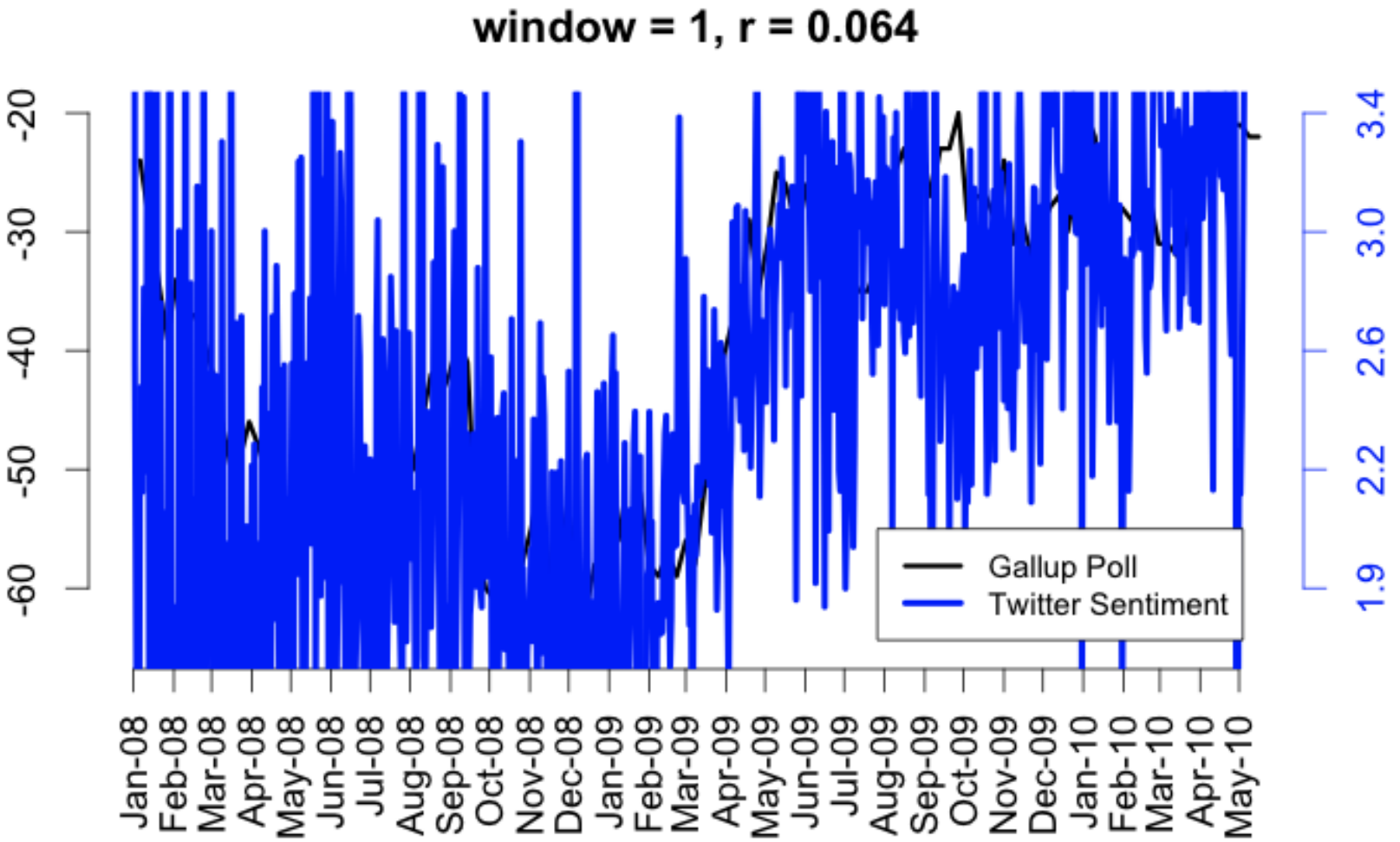
Smoothed comparisons

“jobs” sentiment



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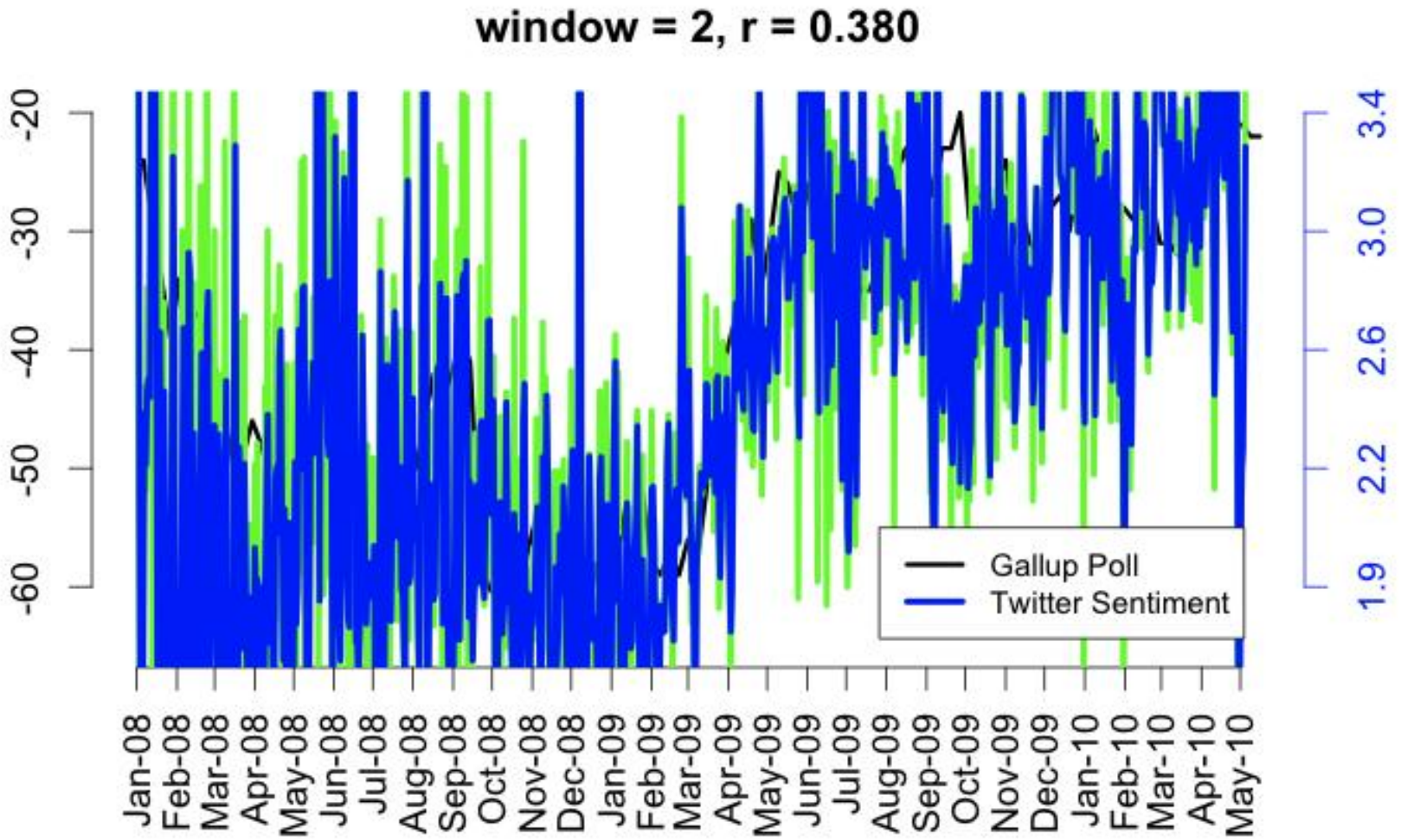

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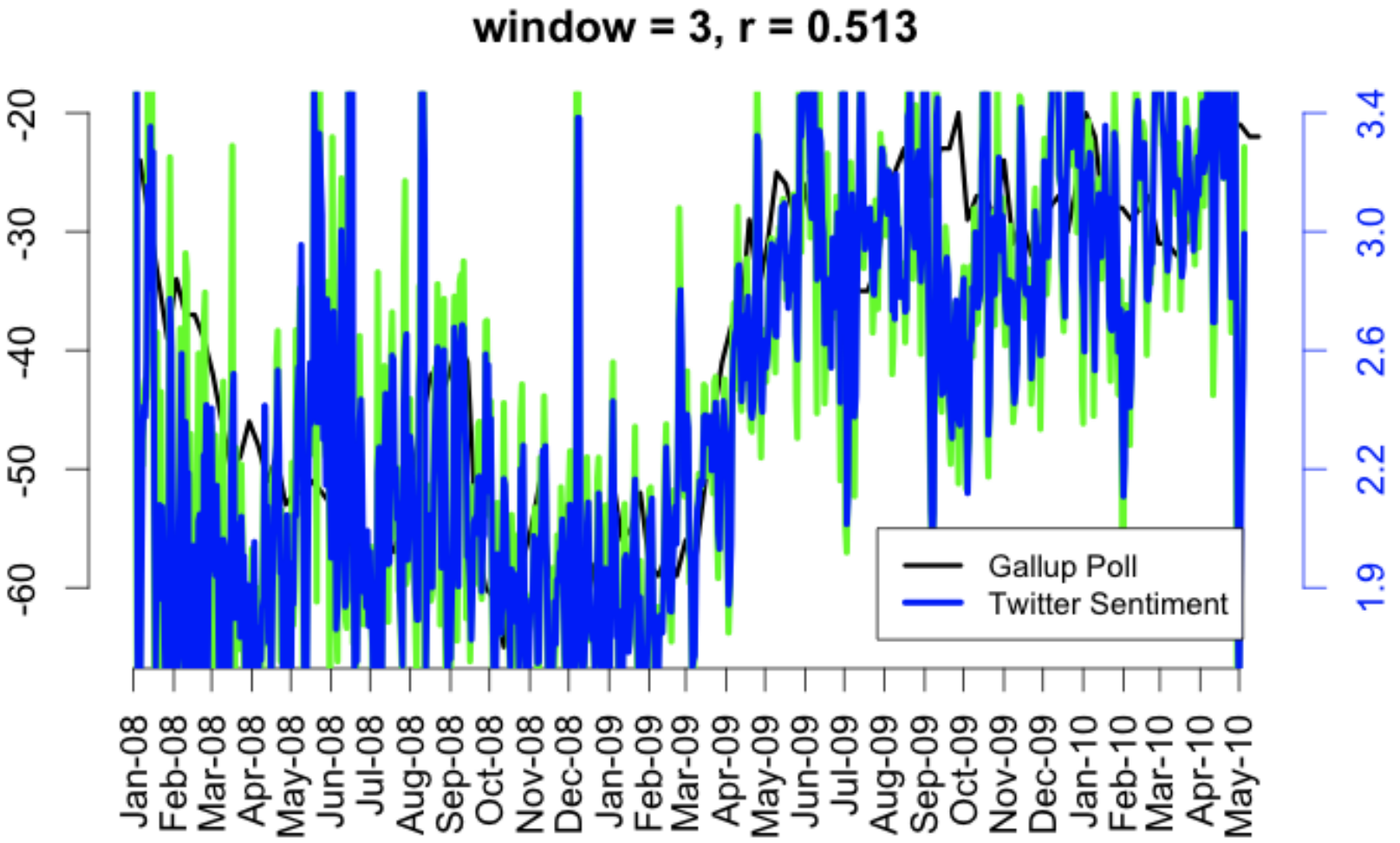

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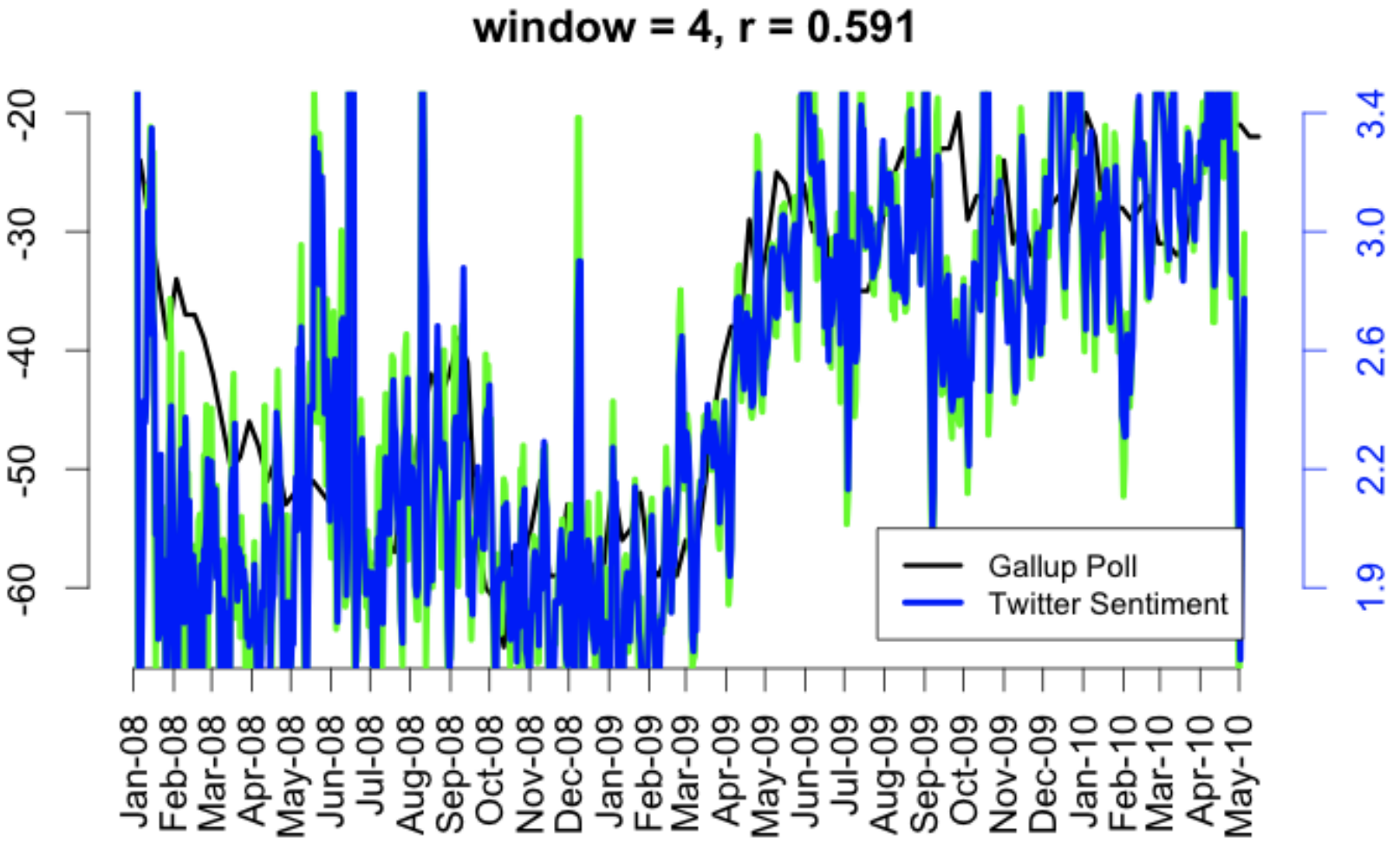

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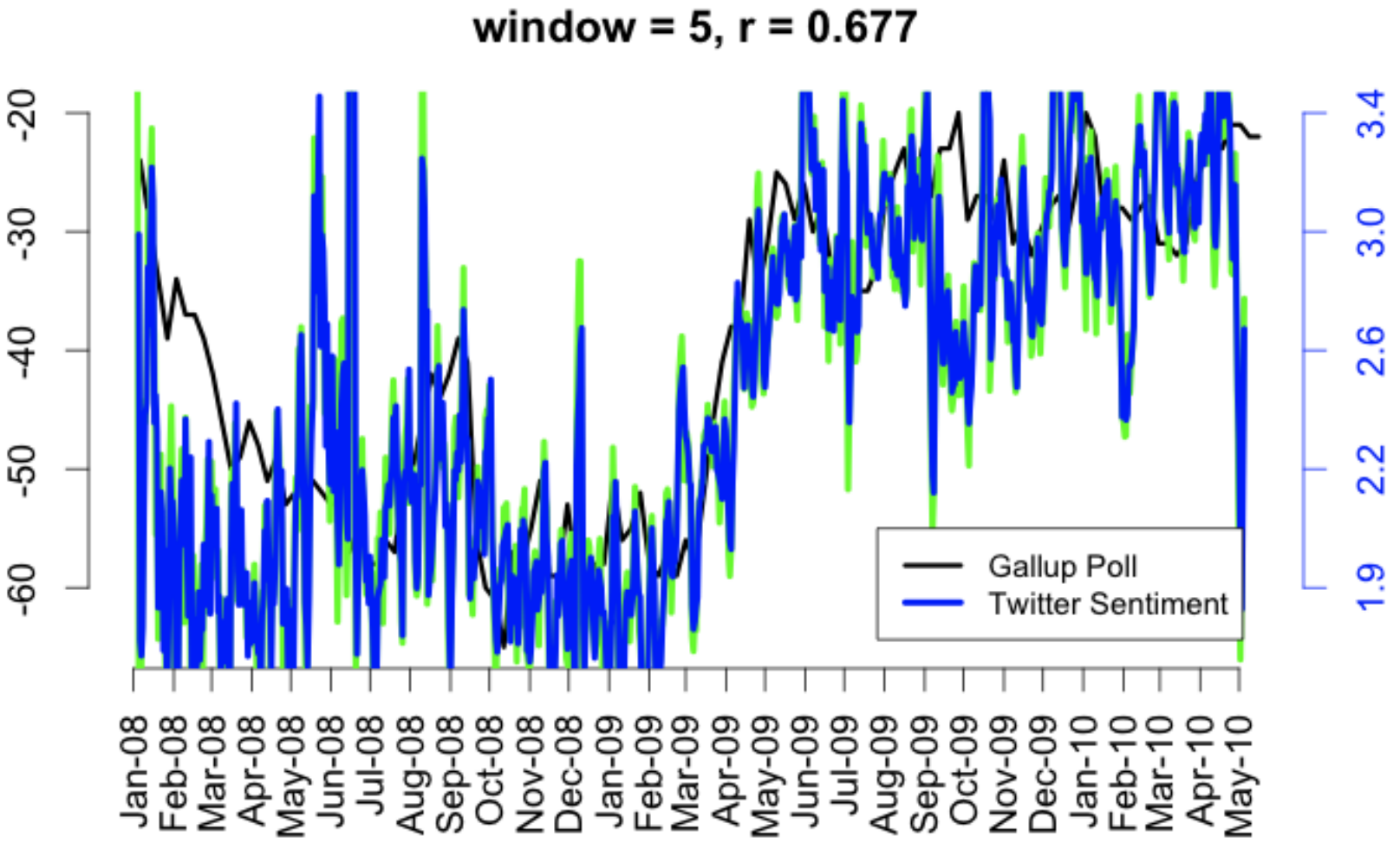

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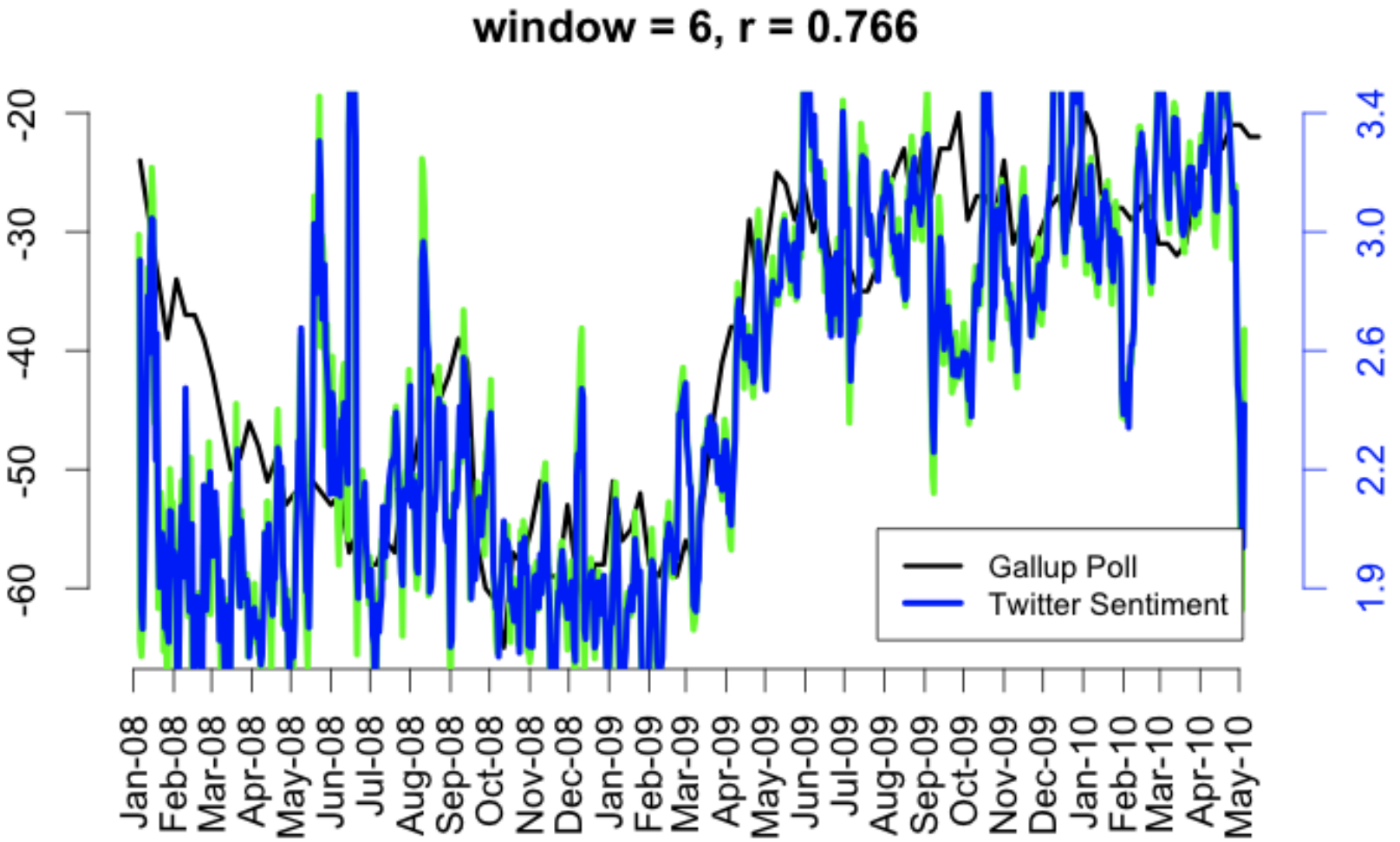

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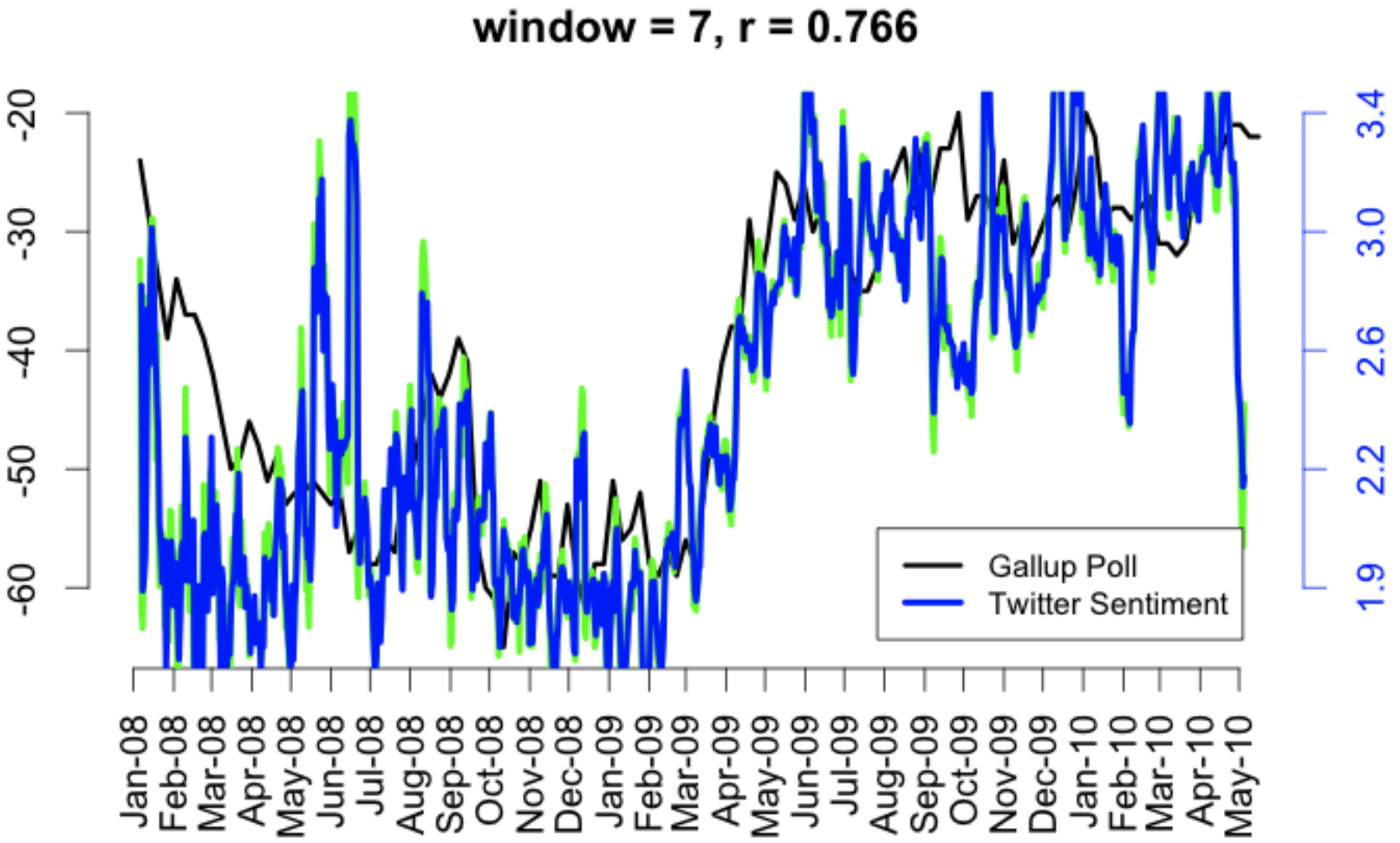

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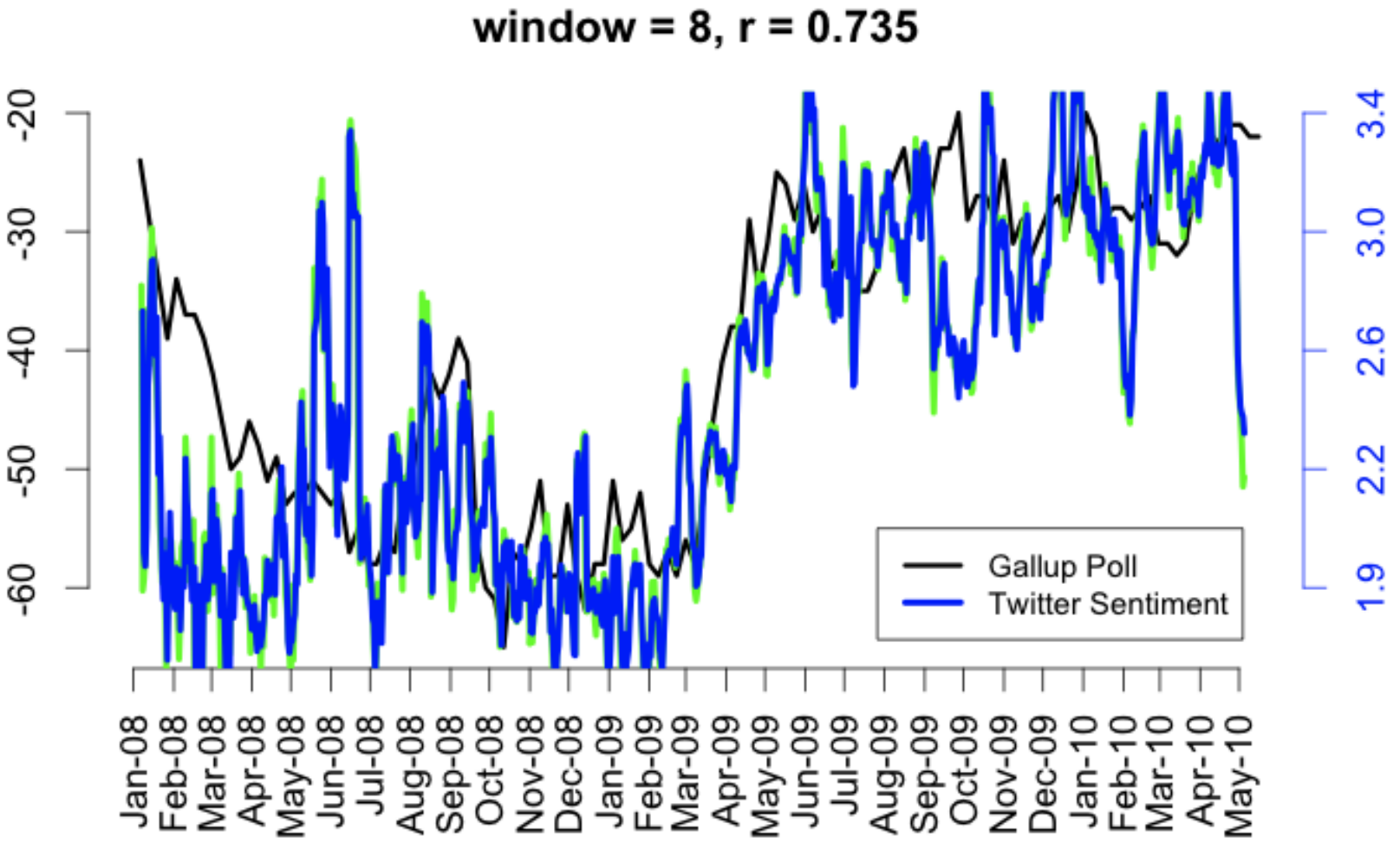

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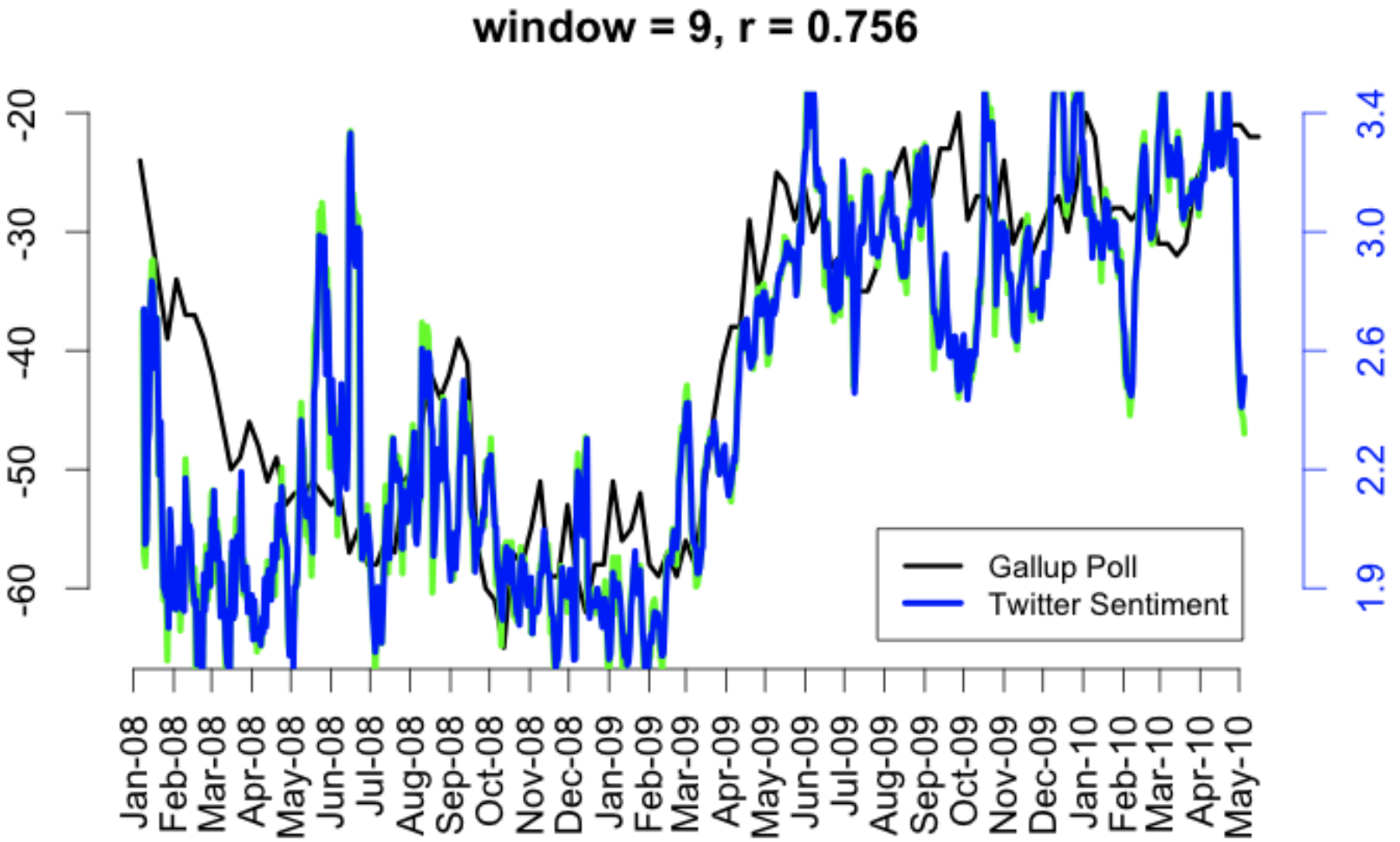

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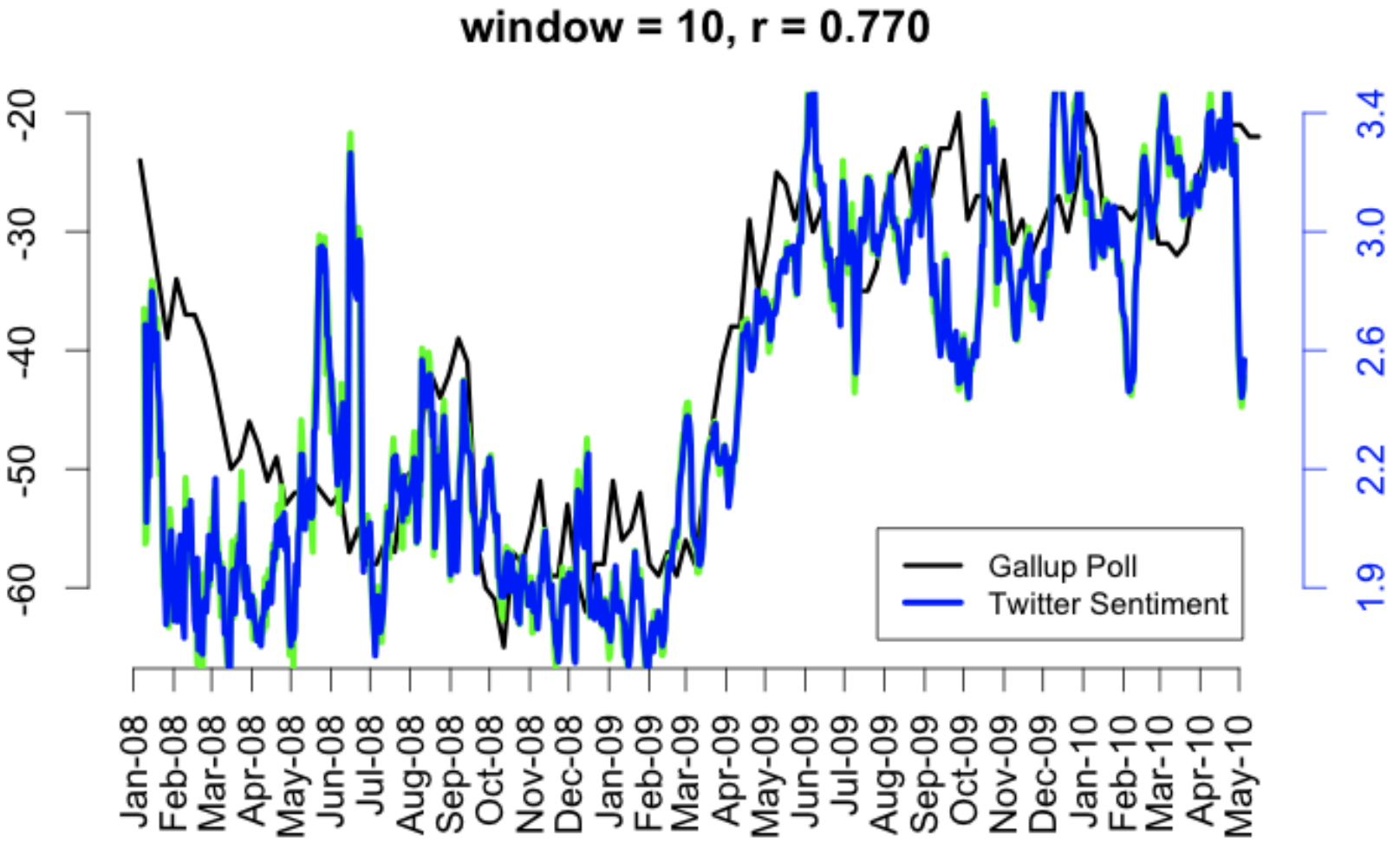

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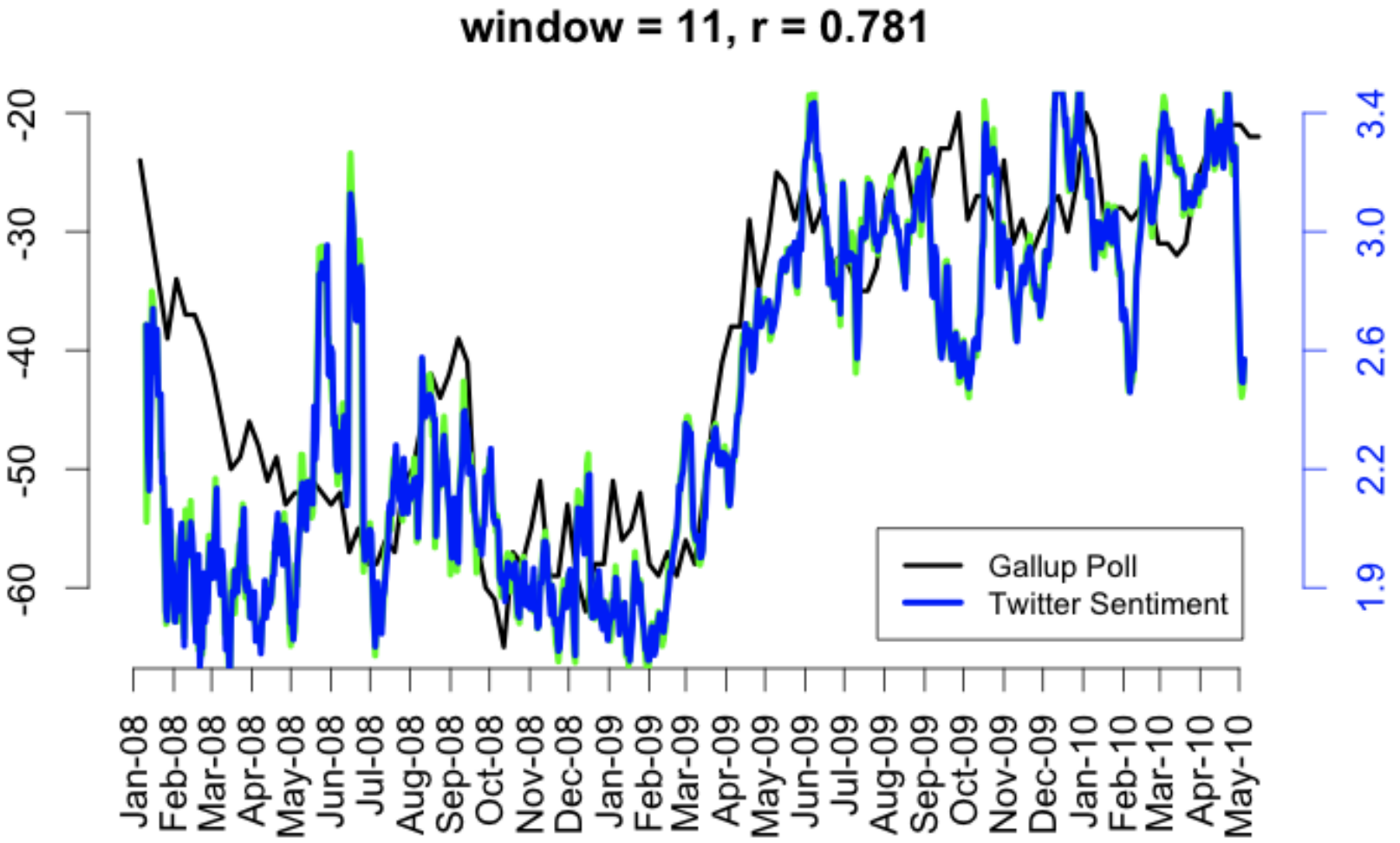

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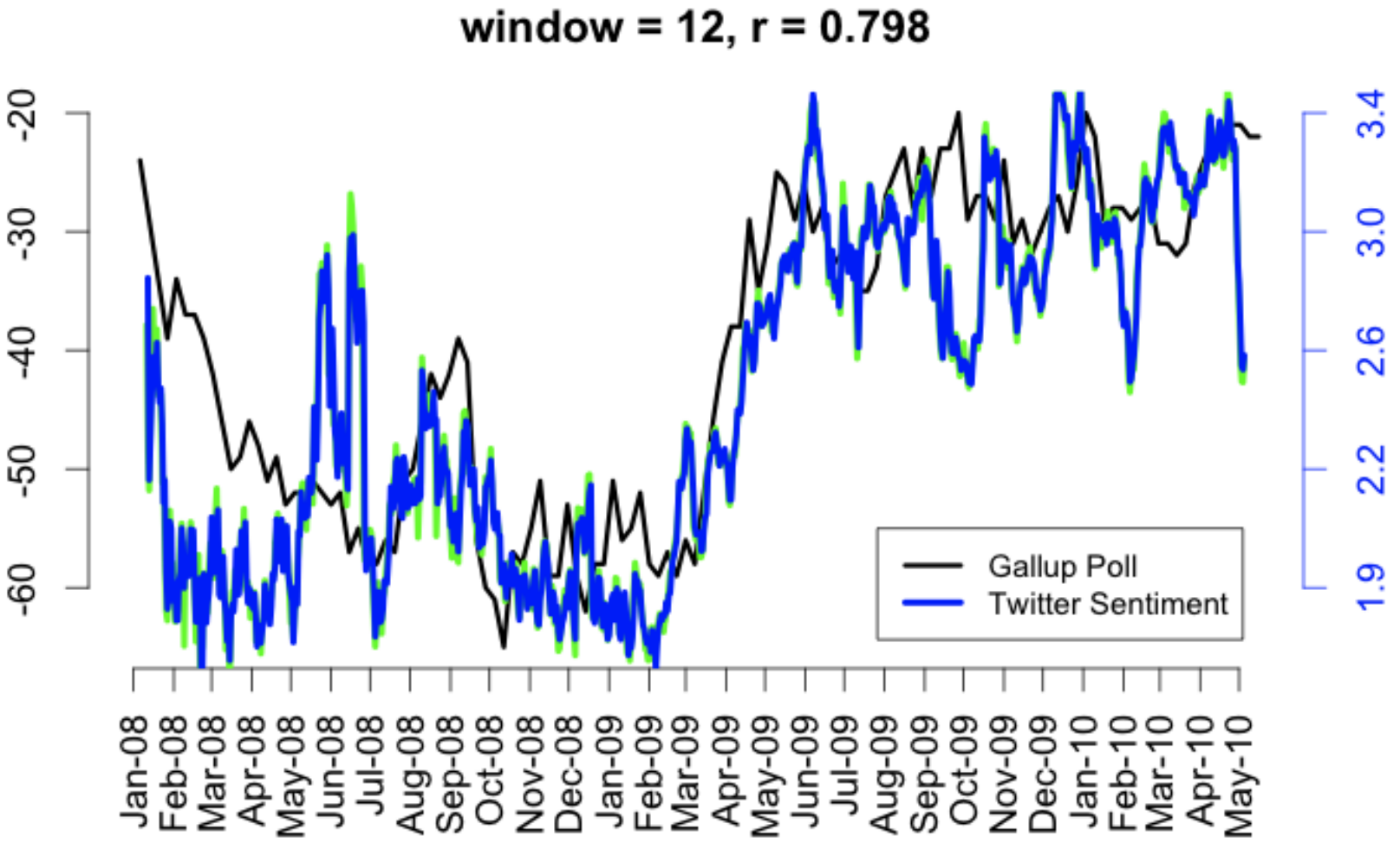

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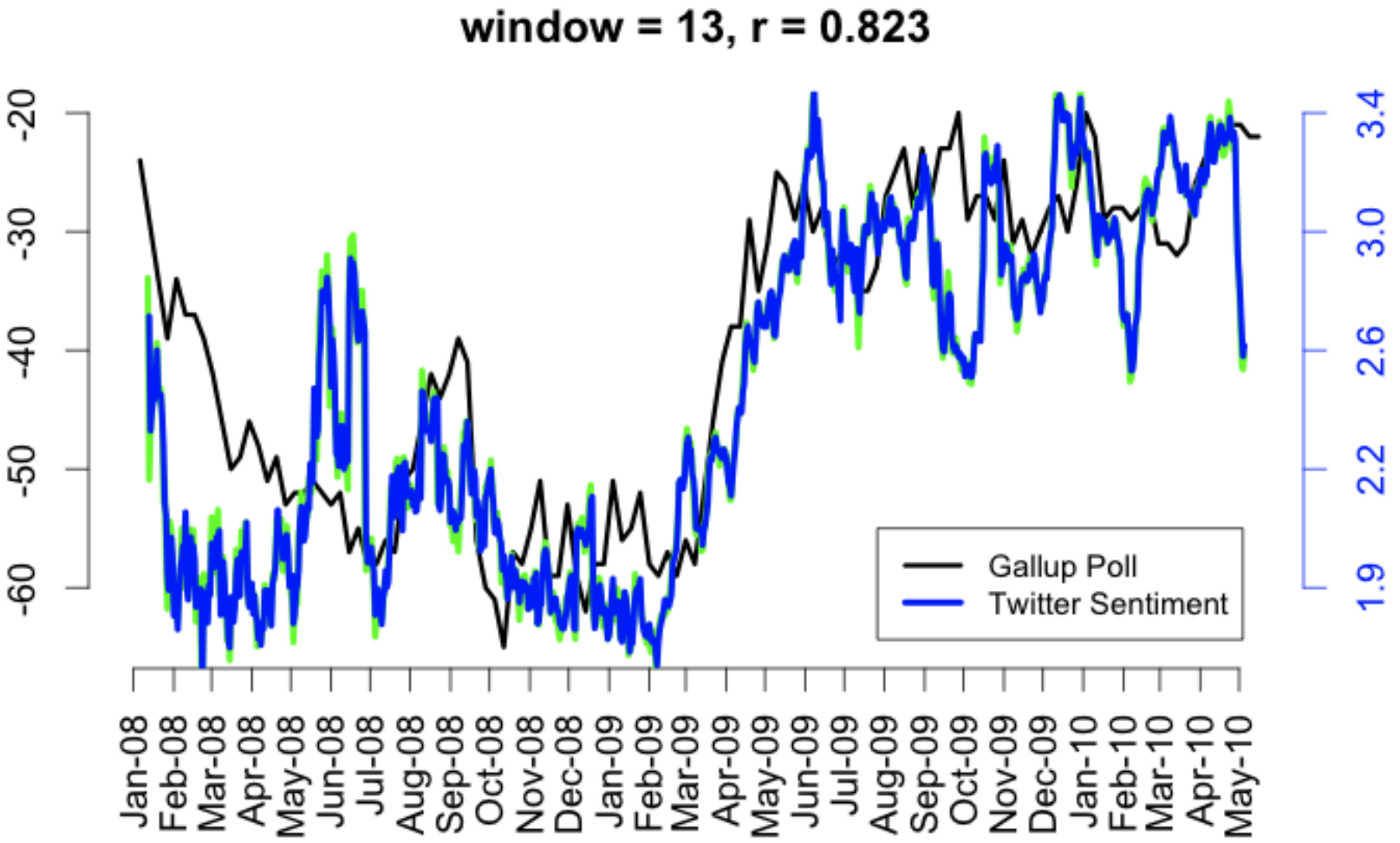

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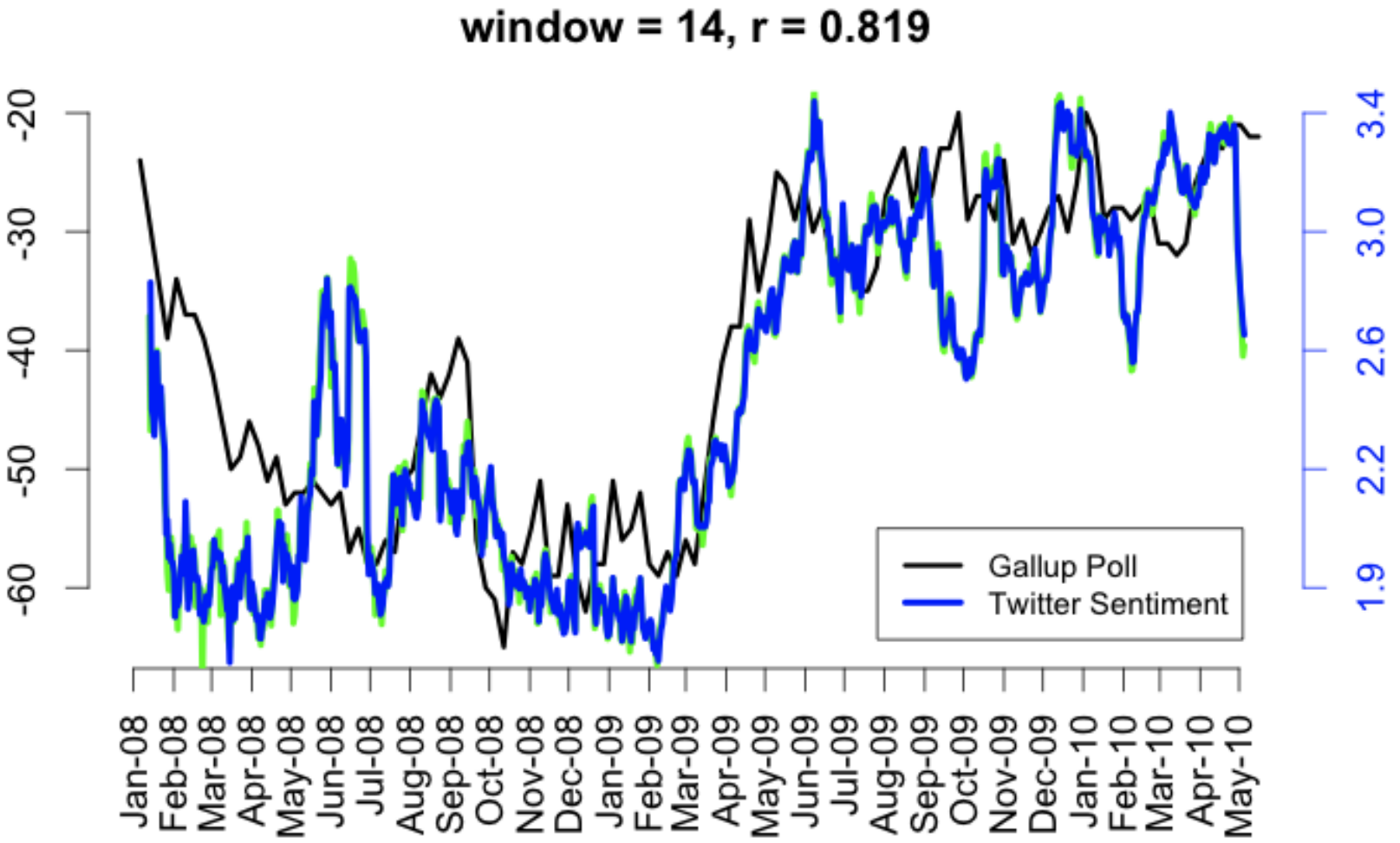

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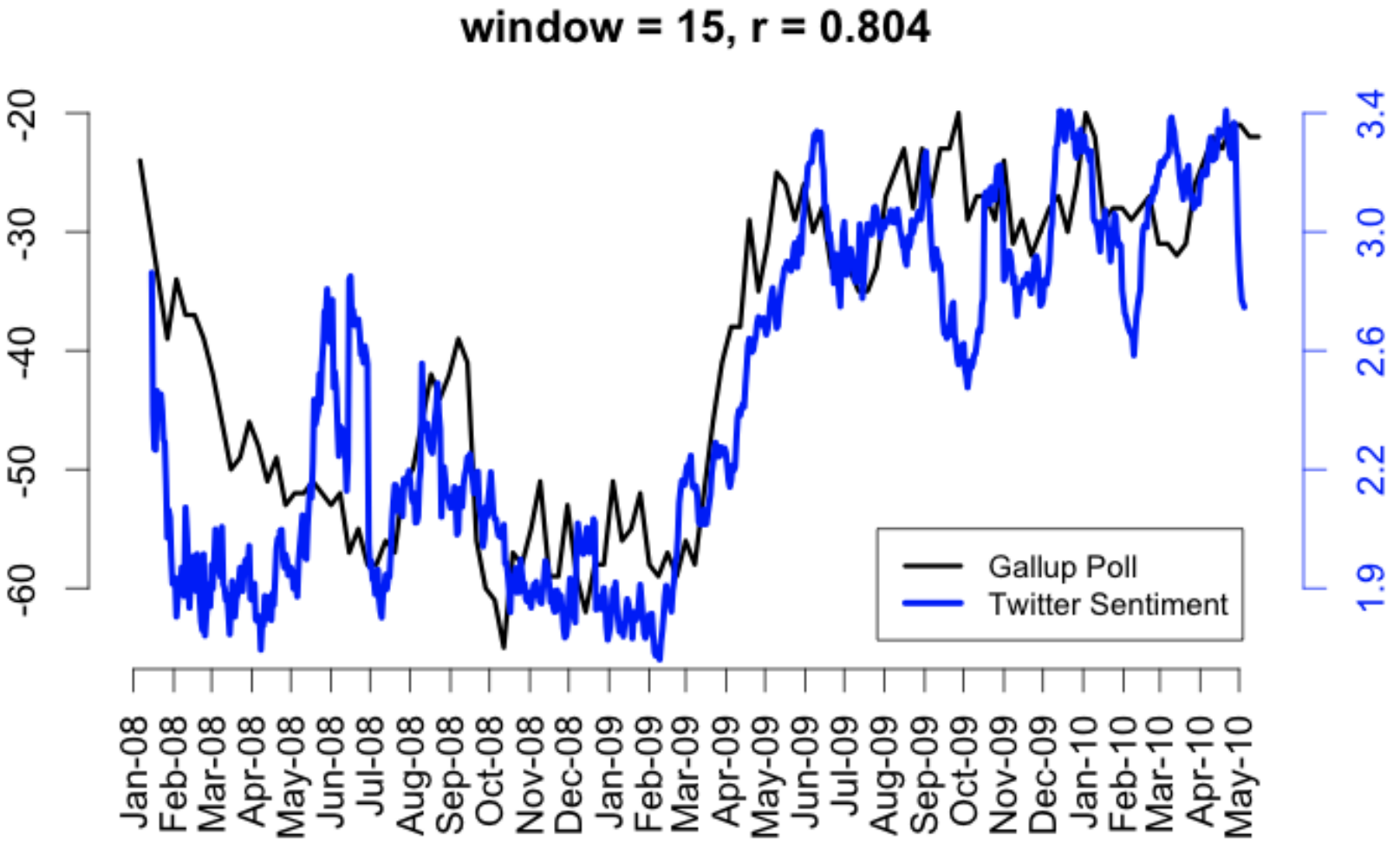

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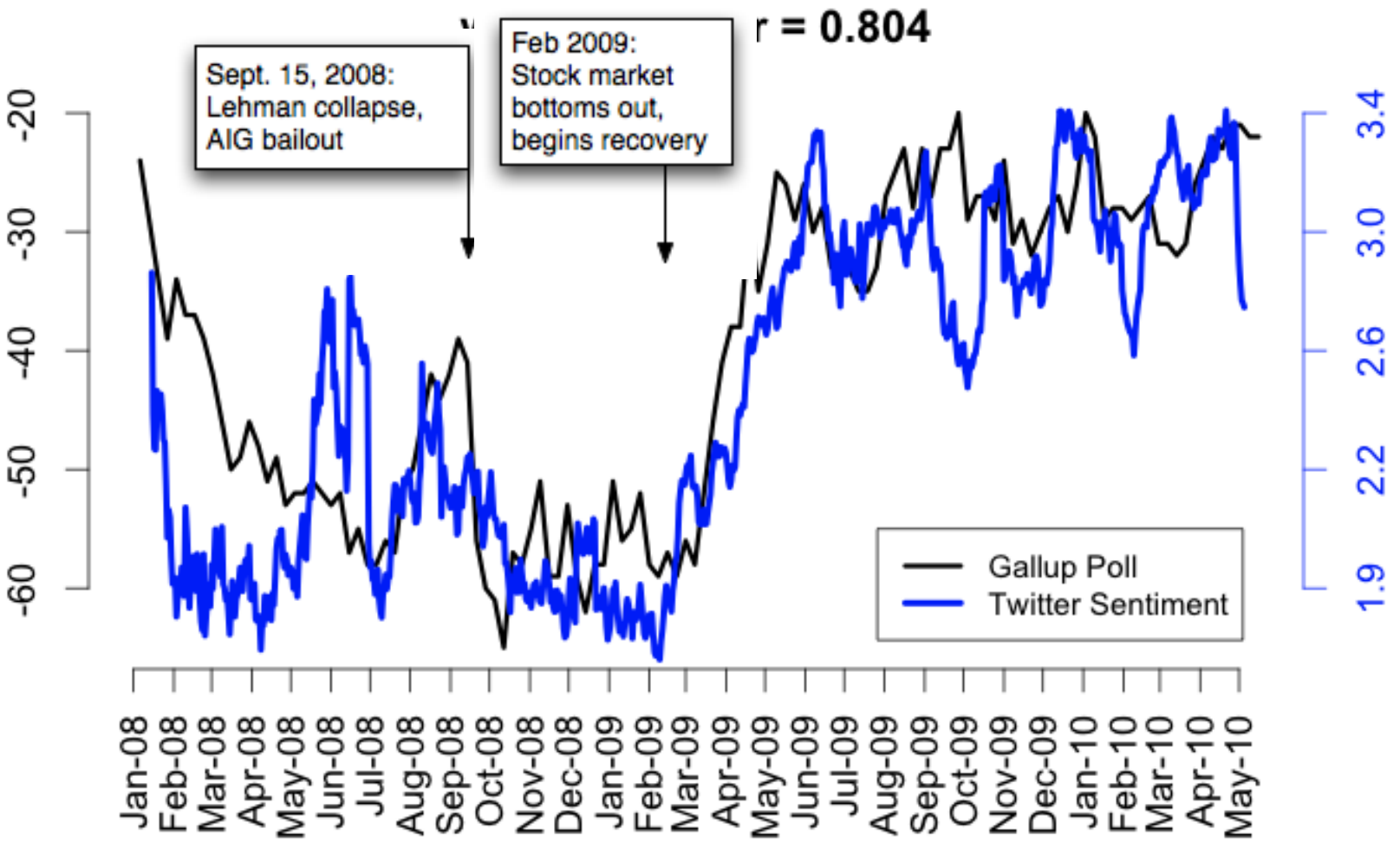
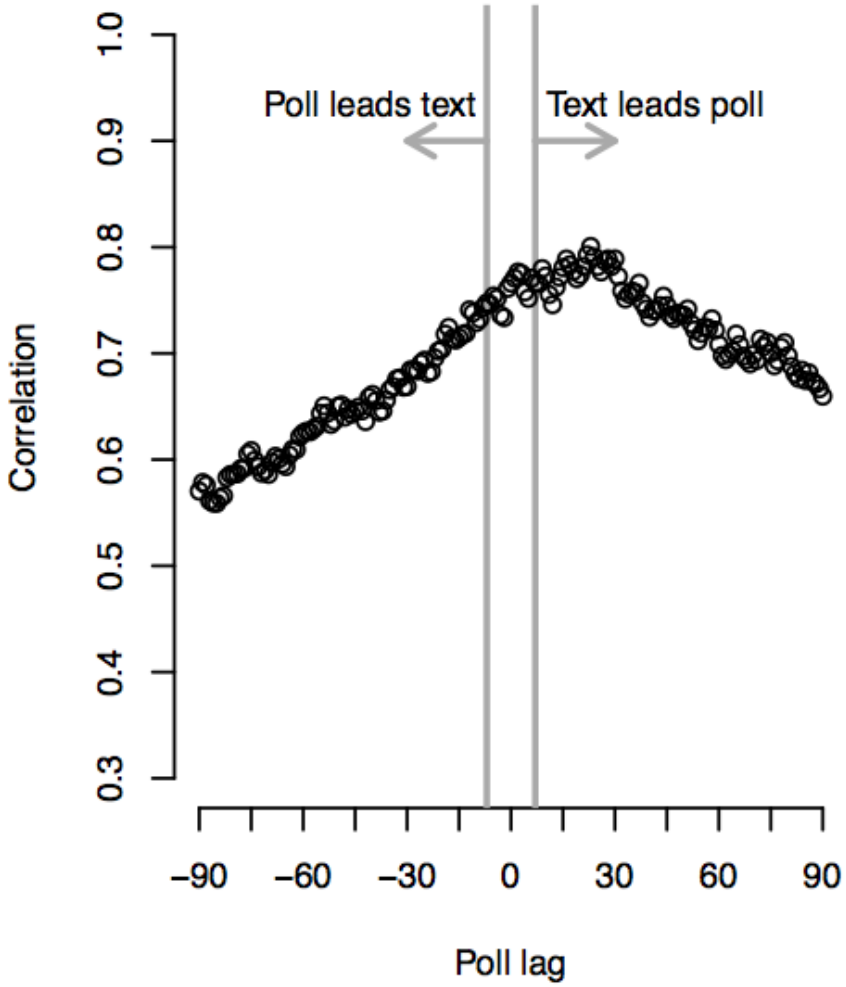


Which leads, poll or text?

- Cross-correlation analysis: between
  - Sentiment score for day *t*
  - Poll for day *t+L*

- "jobs" leading indicator for the poll
- (Can turn into forecasting model: see paper)



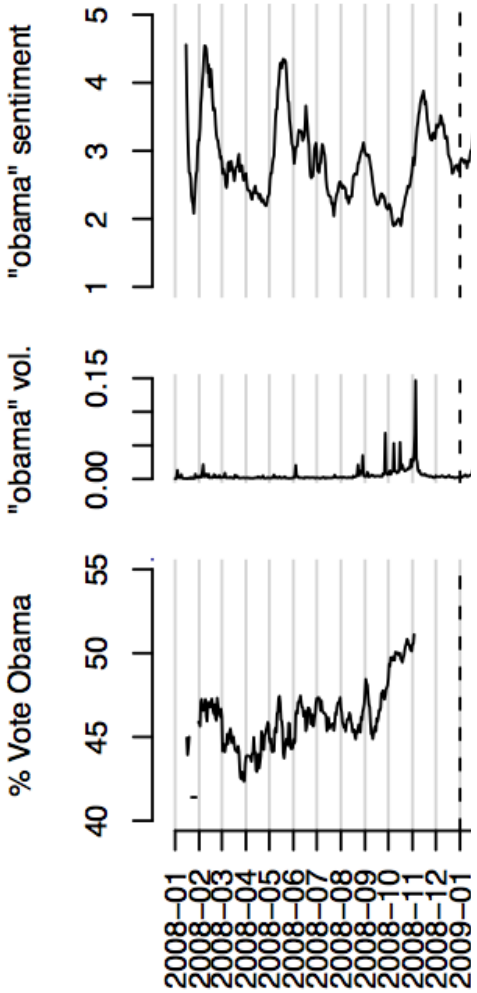
Keyword message selection

- 15-day windows, no lag
  - “jobs” r = 80%
  - “job” r = 7%
  - “economy” r = -10%

- Look out for stemming
  - (“jobs” OR “job”) r = 40%

Presidential elections and job approval

- 2008 elections
  - “obama” and “mccain” sentiment do not correlate
  - But, “obama” and “mccain” volume => 79%, 74% (!)
  - Simple indicator of election news?



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  - But, “obama” and “mccain” volume => 79%, 74% (!)
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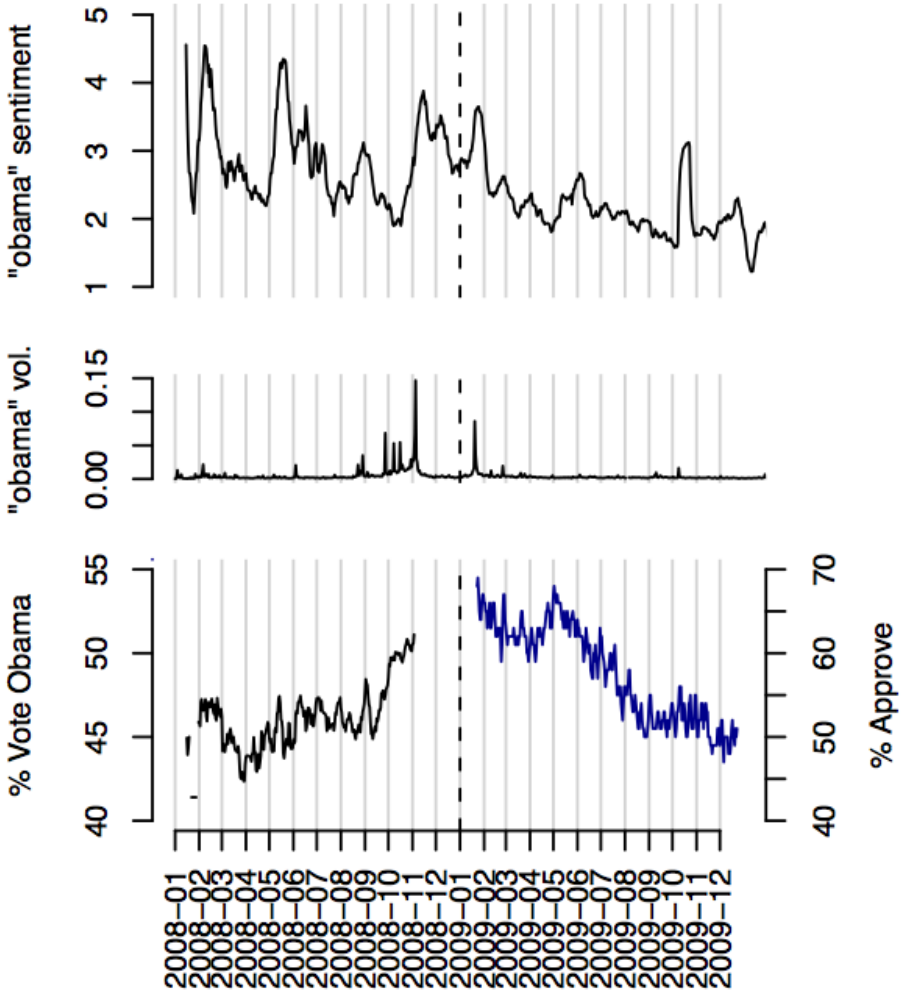
- 2009 job approval
  - “obama” => r = 72%
  - Looks easy: simple decline



Related work: aggregate sentiment

	Text	Message Selection	Opinion Estimation	External Correlate
This work – O'Connor et al ICWSM-2010	Microblogs (Twitter)	Keywords related to poll	Word counting (OpinionFinder)	Opinion polls
Mishne and de Rijke 2006	Blogs (Livejournal)	N/A	Linear model (words, time)	Mood labels
Dodds and Danforth 2009	Blogs, Speeches, Songs	N/A	Word counting (LIWC)	Exploratory (mostly)
Gilbert and Karahalios ICWSM-2010	Blogs (Livejournal)	N/A	Decision tree + NB (words)	Stocks
Asur and Huberman 2010	Microblogs (Twitter)	Movie name	NB-like model (char. n-grams)	Movie sales
Bollen et al 2010	Microblogs (Twitter)	N/A	Word counting (POMS)	Stocks, politics
Tumasjan et al ICWSM-2010	Microblogs (Twitter)	Party name	Word counting (POMS)	Elections
Kramer 2010	Microblogs (Facebook Wall)	N/A	Word counting (LIWC)	Life satisfaction answers
… many more!				

Conclusions

- Preliminary results that sentiment analysis on Twitter data can give information similar to traditional opinion polls
  - But, still not well-understood
  - Twitter bias?
  - News vs. opinion?
- Issues
  - Relevant message selection
  - Time series smoothing
- Replacement for polls?
  Promising but not quite yet