@ NYC Data Science Academy

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Senti-Meter

by

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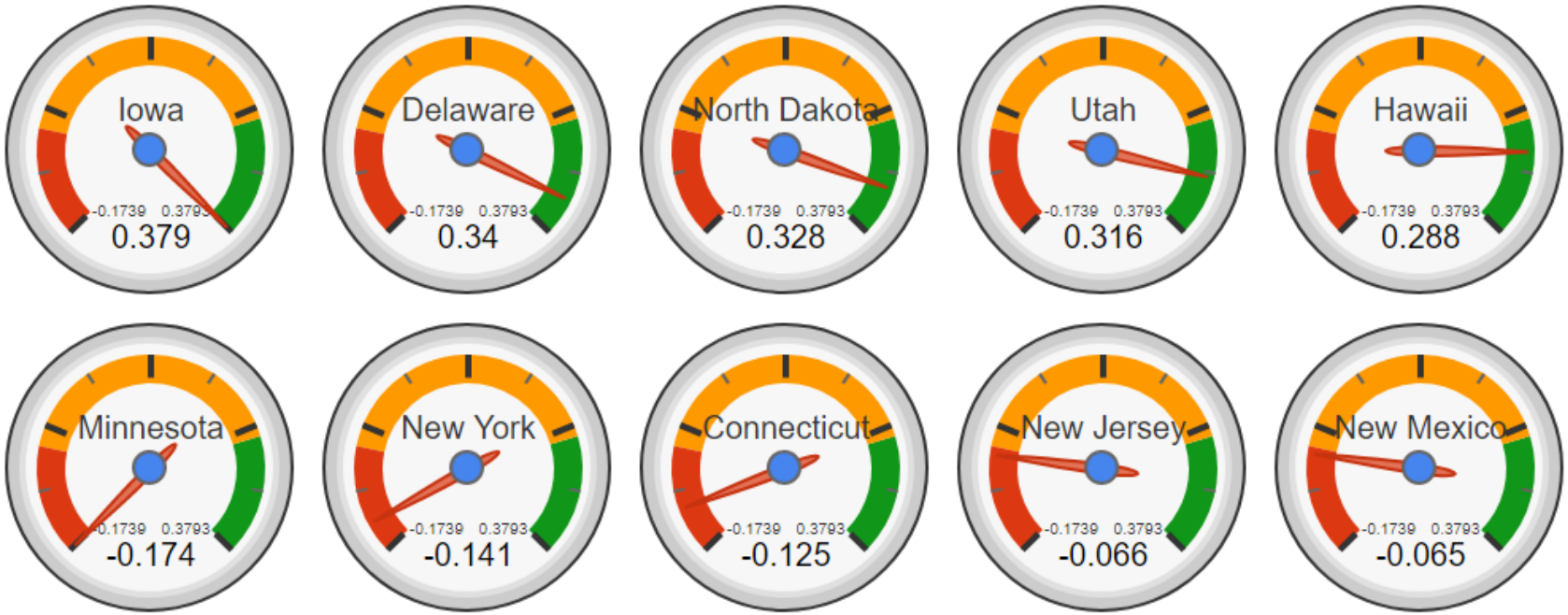
1 Overview

- Senti-Meter=Sentiments (tweets) + Measurement (use of positive and negative words)



1 Overview

- Objective(s)—

  a) **Scrape** tweets using **Selenium**

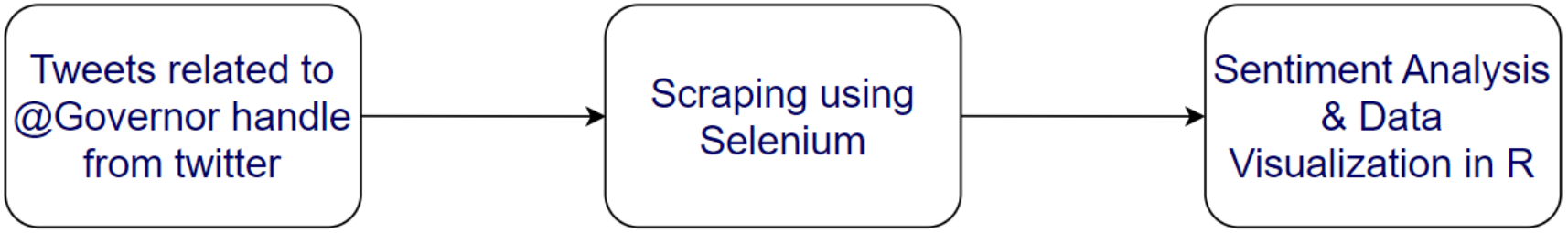
  b) **Quantify** the **sentiment** of people towards **governors** of all 50 States in US.

  c) **Rank** the Governors based on a sentiment analysis of the tweets and **compare** the **rankings** with the recently published Morning Consult Governor Approval rankings[1]

  d) Provide **insight** on **performance** that pertain to **age**, **party affiliation** and **gender** of governors

[1] https://morningconsult.com/governor-approval-ratings-july-2017/

2 Methodology



- Web scraping—

  a) **Selenium** used to scrape 43,737 tweets [target was to extract 1000 tweets for each governor]

  b) All **sampled tweets** had **reference** to @Governor (twitter verified account) handle. This kept out irrelevant tweets and tweets from people with similar names as the Governors

2 Methodology

- Sentiment Analysis & Data Visualization—
  a) **R-Studio** was used for postprocessing the scraped data

  b) Each tweet was cleaned up (using 'gsub', 'tolower', 'str_split') and the individual words were matched with a **word repository** to obtain a sentiment score [+1 if positive, 0 if neutral and -1 if negative]. For example—

```
> score = as.integer(unlist(score.sentiment("Web scraping
is exciting and fun", pos, neg)))

> score
[1] 2

> score = as.integer(unlist(score.sentiment("Web scraping
is okay", pos, neg)))

> score
[1] 0
> score = as.integer(unlist(score.sentiment("Web scraping
can be challenging at times", pos, neg)))

> score
[1] -1
```

2 Methodology

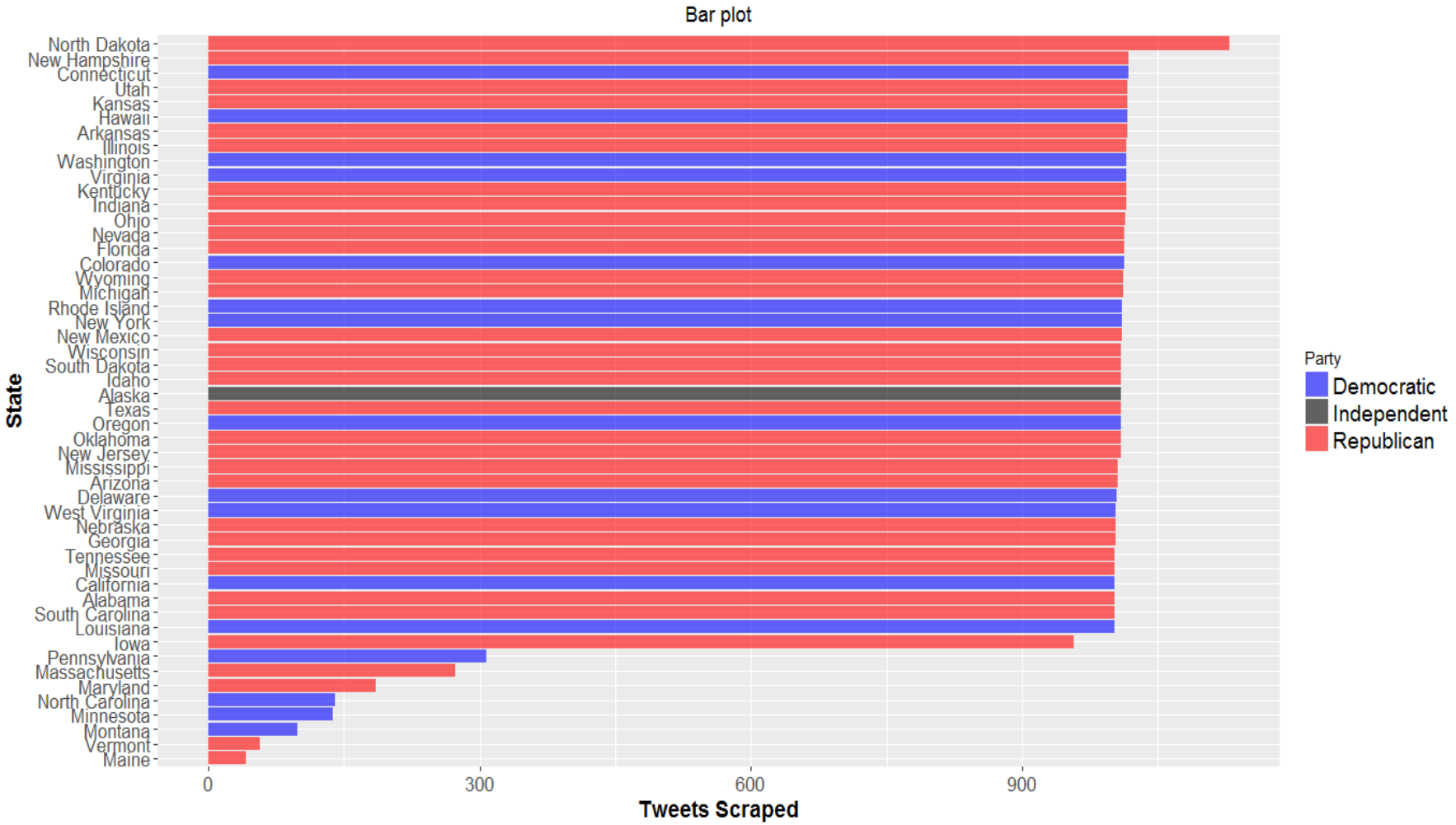
c) The word repository contains a list of 2006 positive words and 4784 negative words[23] and can be downloaded from—
https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#lexicon

[2] Hu, Minqing, and Bing Liu. "Mining and summarizing customer reviews." Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2004.

[3] Liu, Bing, Minqing Hu, and Junsheng Cheng. "Opinion observer: analyzing and comparing opinions on the web." Proceedings of the 14th international conference on World Wide Web. ACM, 2005.

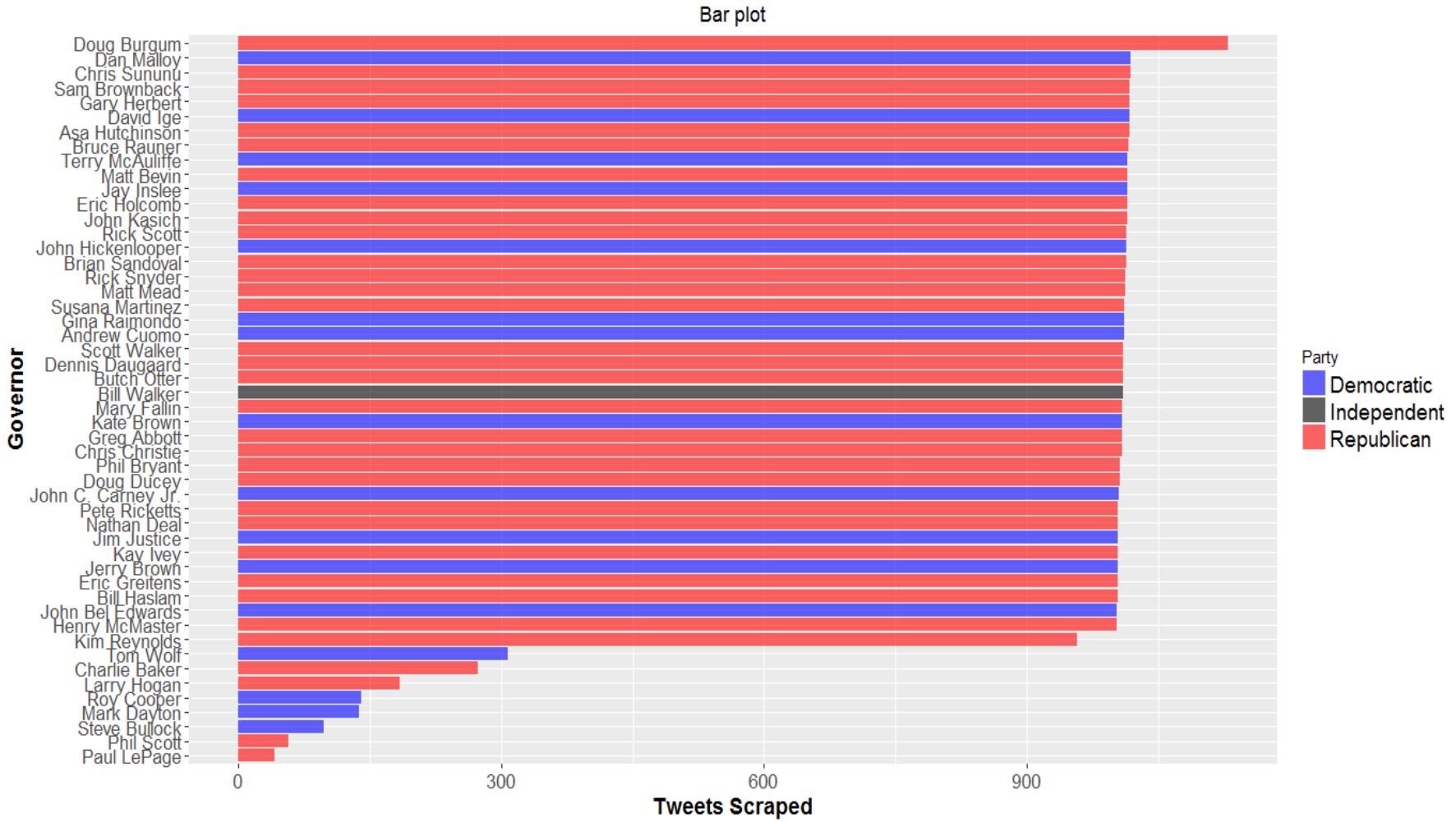
3 Data Visualization & Analysis

- Tweets scraped listed by **state** (43,737 tweets in total)



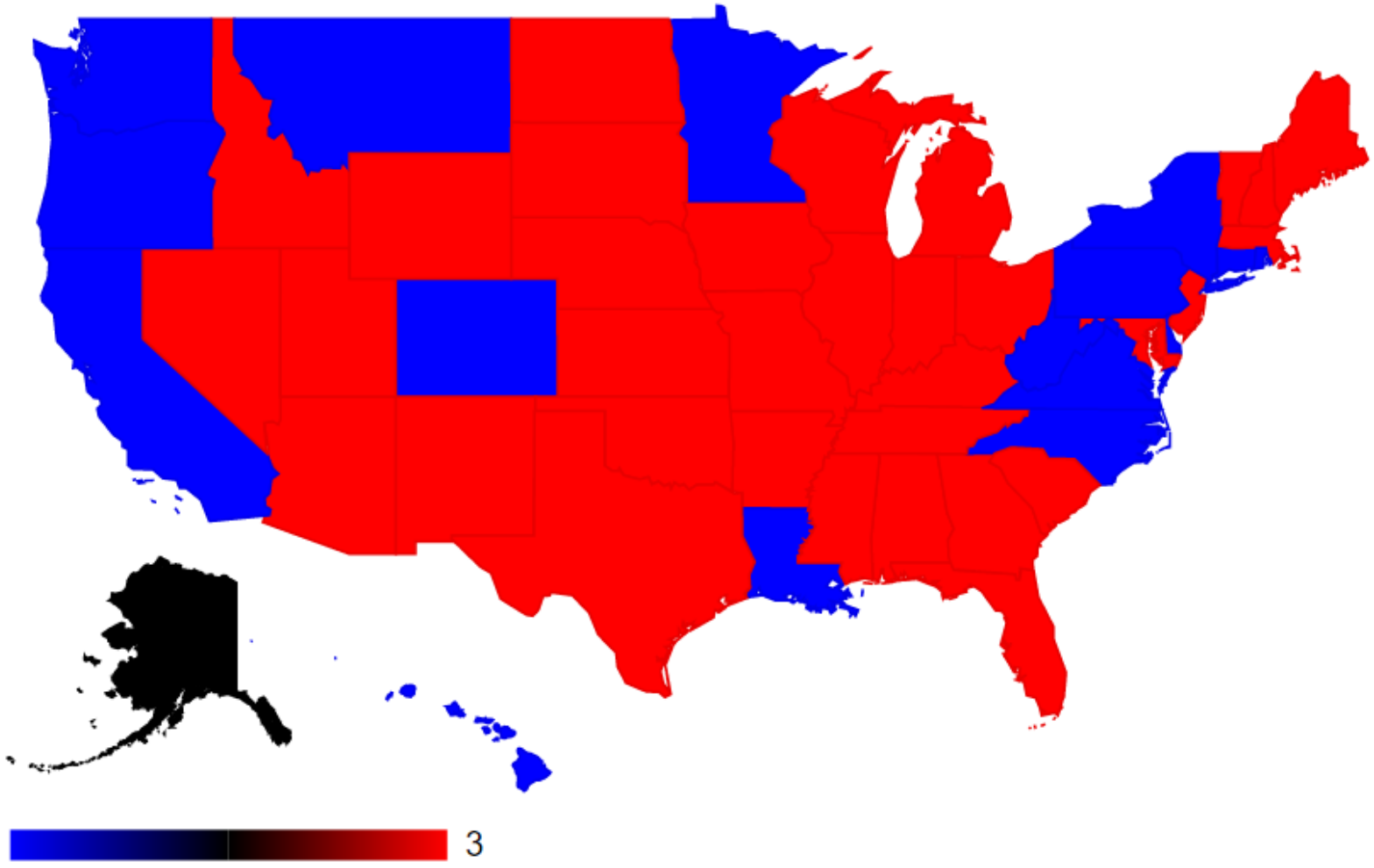
3 Data Visualization & Analysis

- Tweets scraped by name of **governor** (43,737 tweets in total)



3 Data Visualization & Analysis

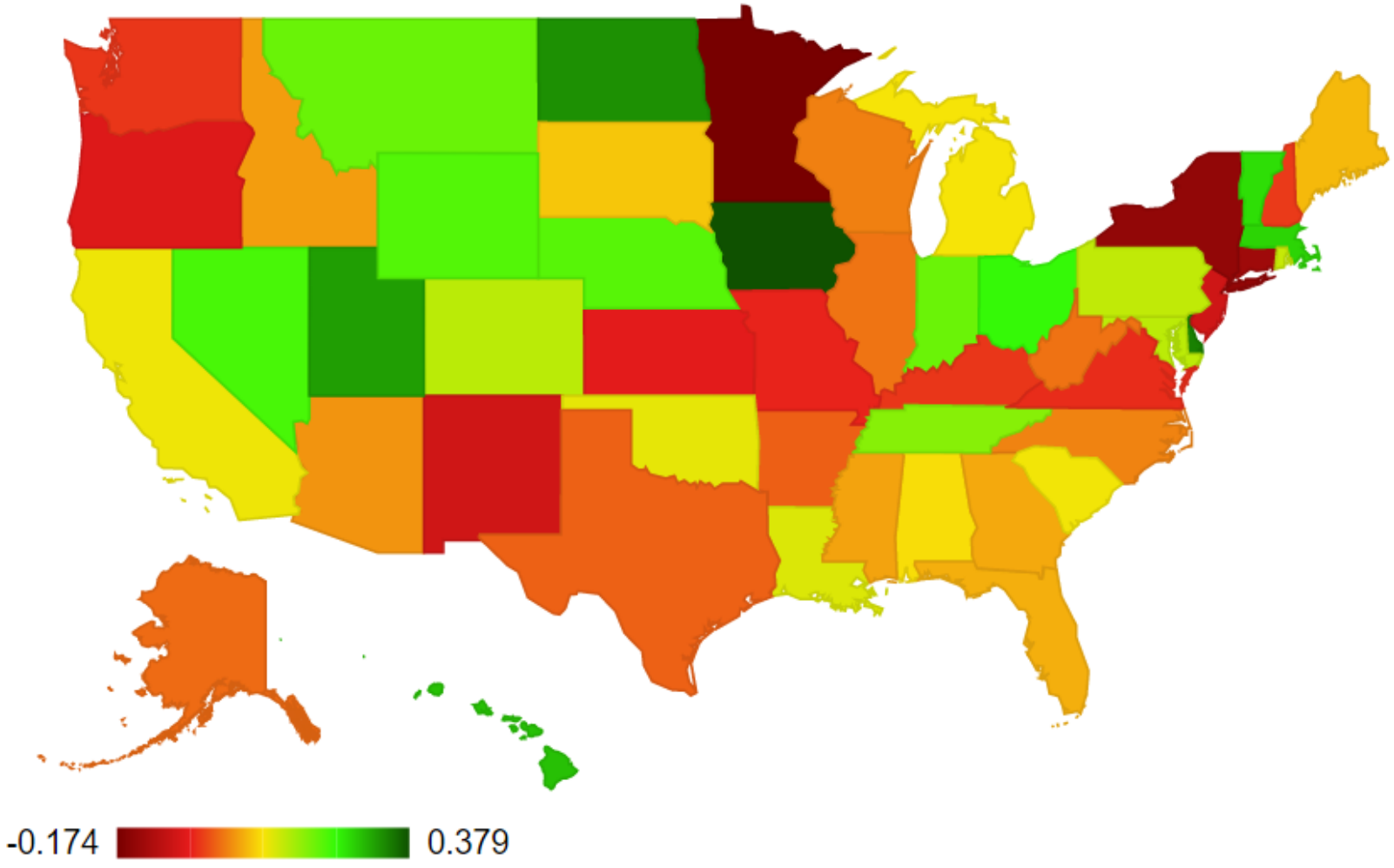
- **Party** affiliation of current **governors** [Republican, Democrat, Independent]



Data: score_analysis • Chart ID: GeoChartID22243a82102 • googleVis-0.6.2
R version 3.4.0 (2017-04-21) • Google Terms of Use • Documentation and Data Policy

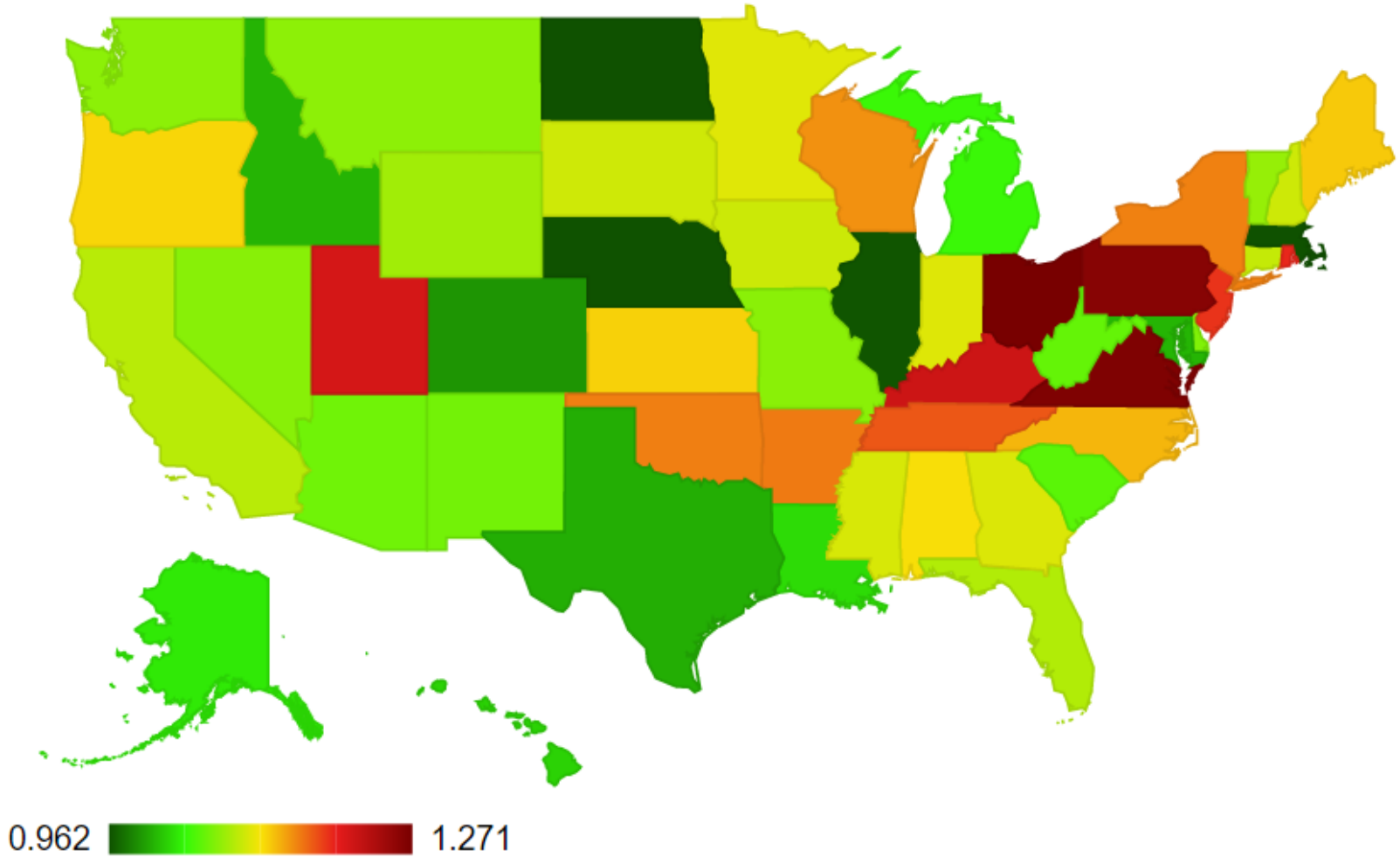
3 Data Visualization & Analysis

- **Mean** sentiment score of **governors**



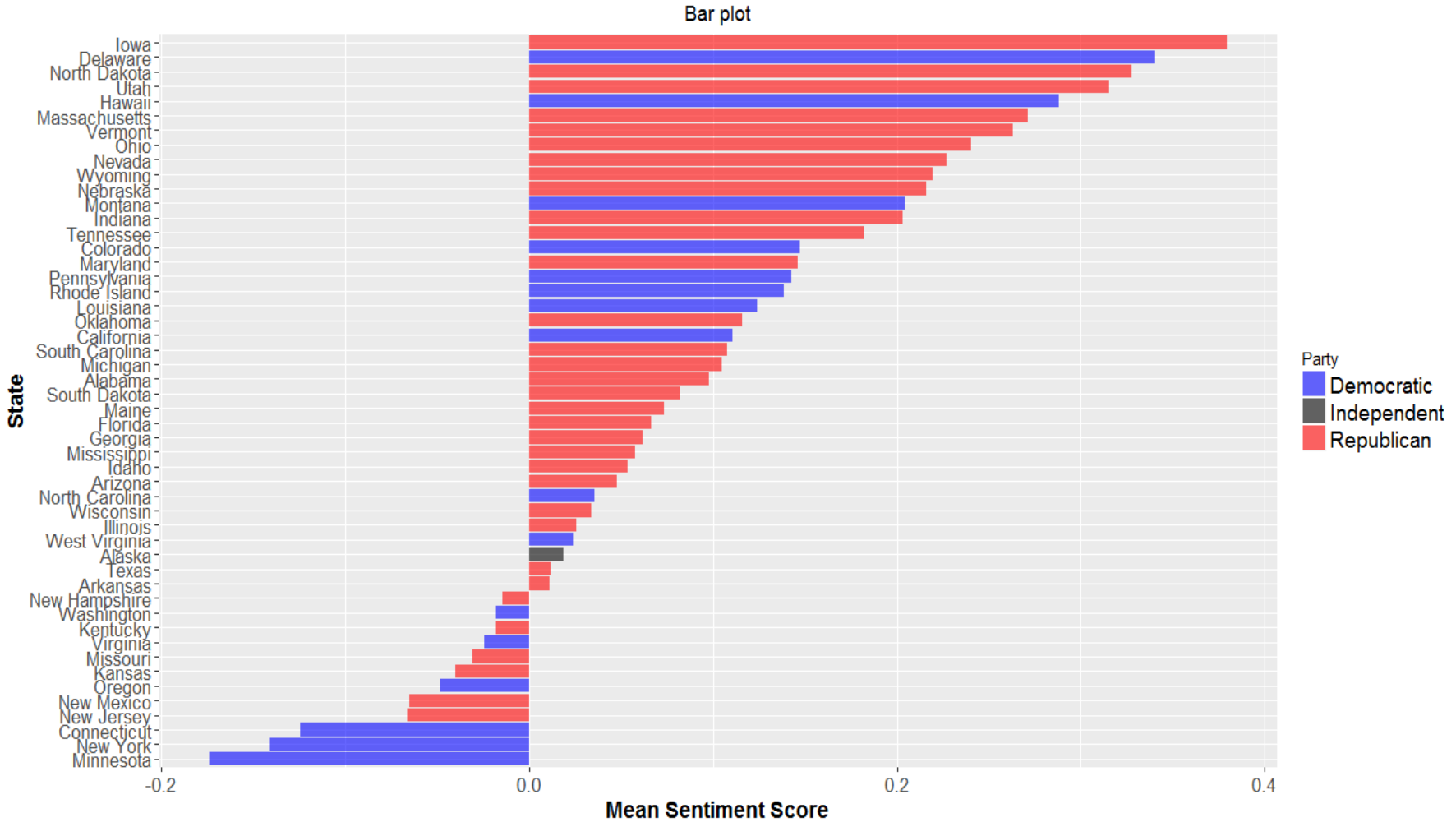
3 Data Visualization & Analysis

- **Standard deviation** on sentiment score of **governors**



3 Data Visualization & Analysis

- **Bar plot** with mean sentiment score for each **state**



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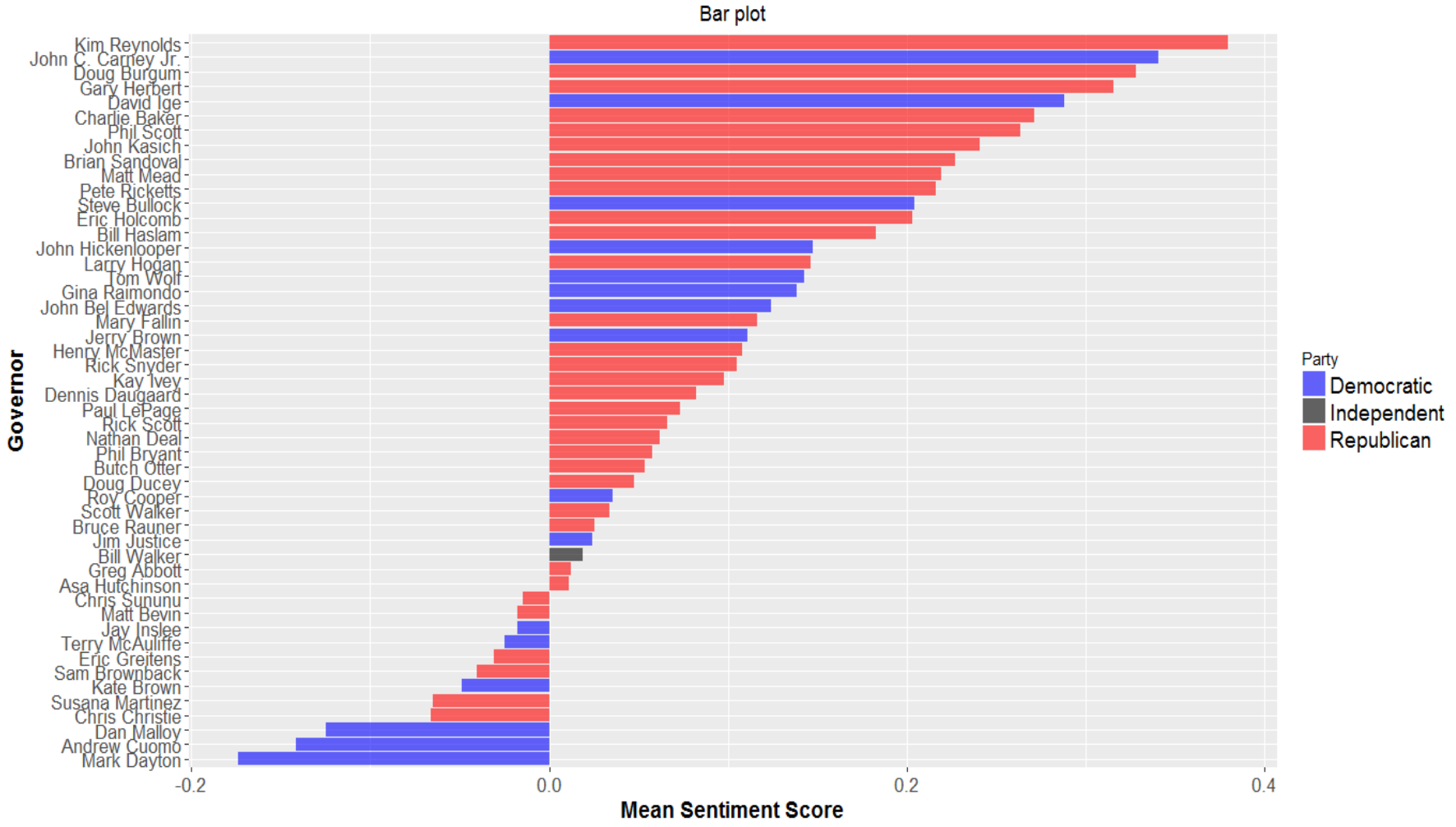
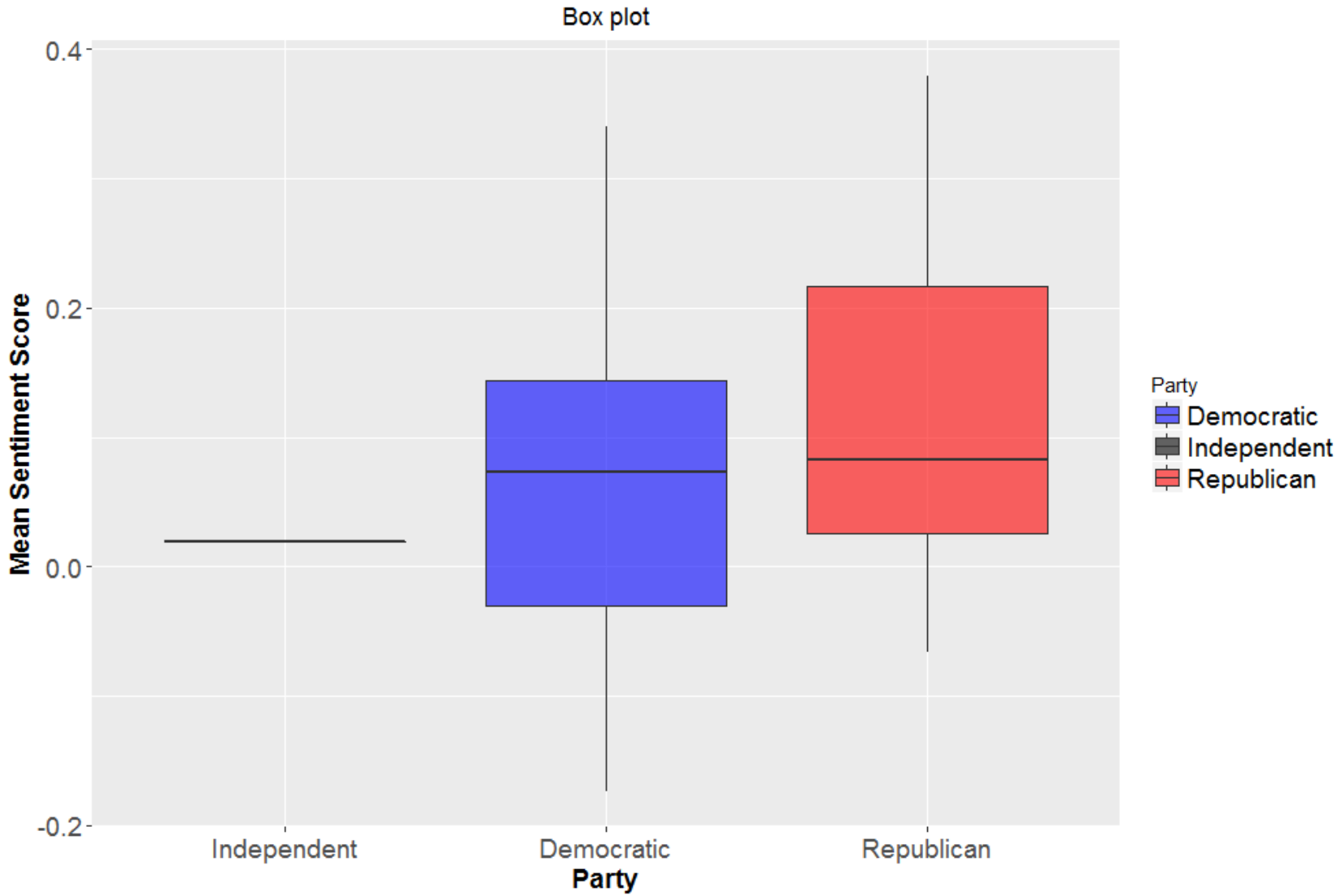


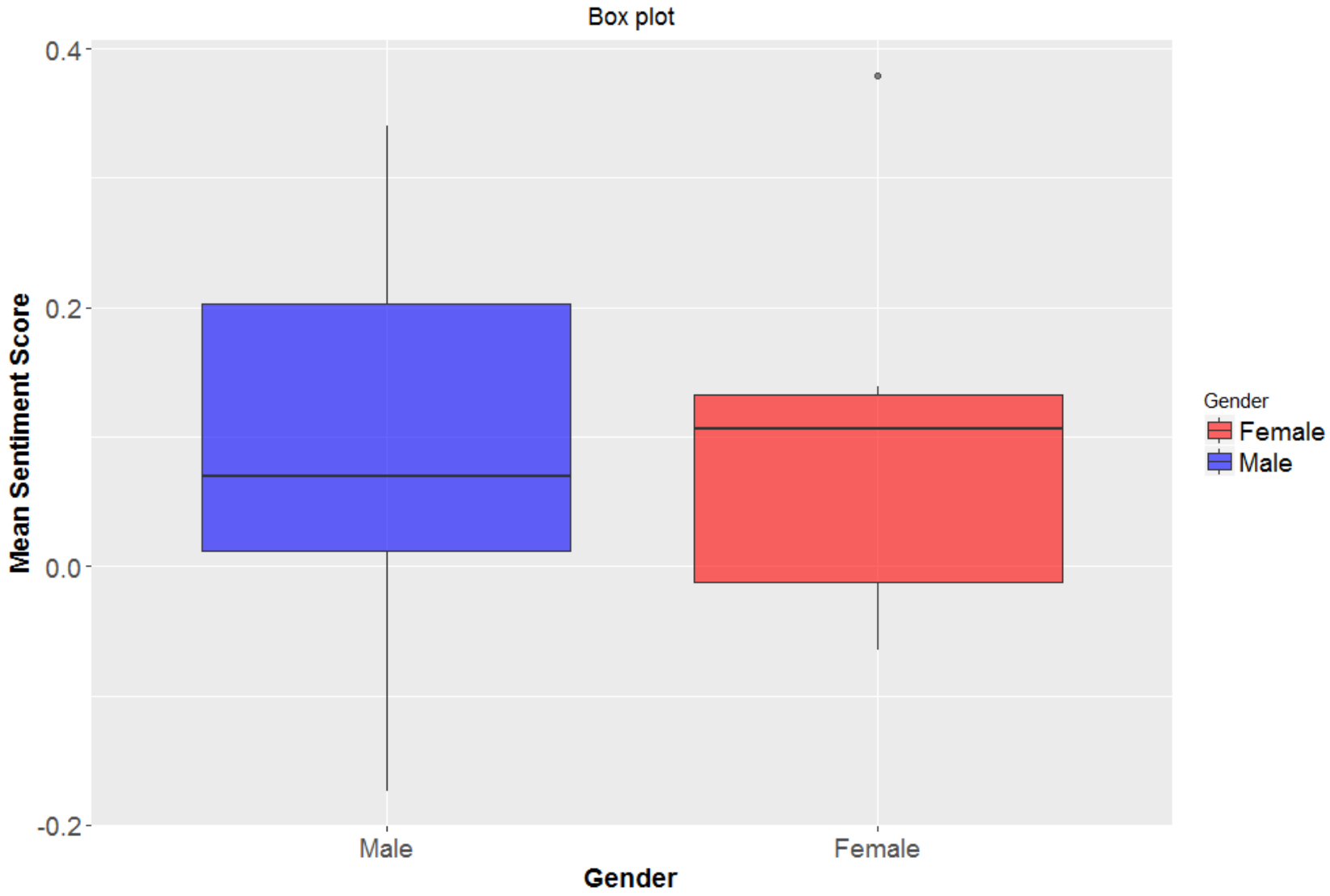
3 Data Visualization & Analysis

- **Box plot** with **mean** sentiment score and **party** affiliation



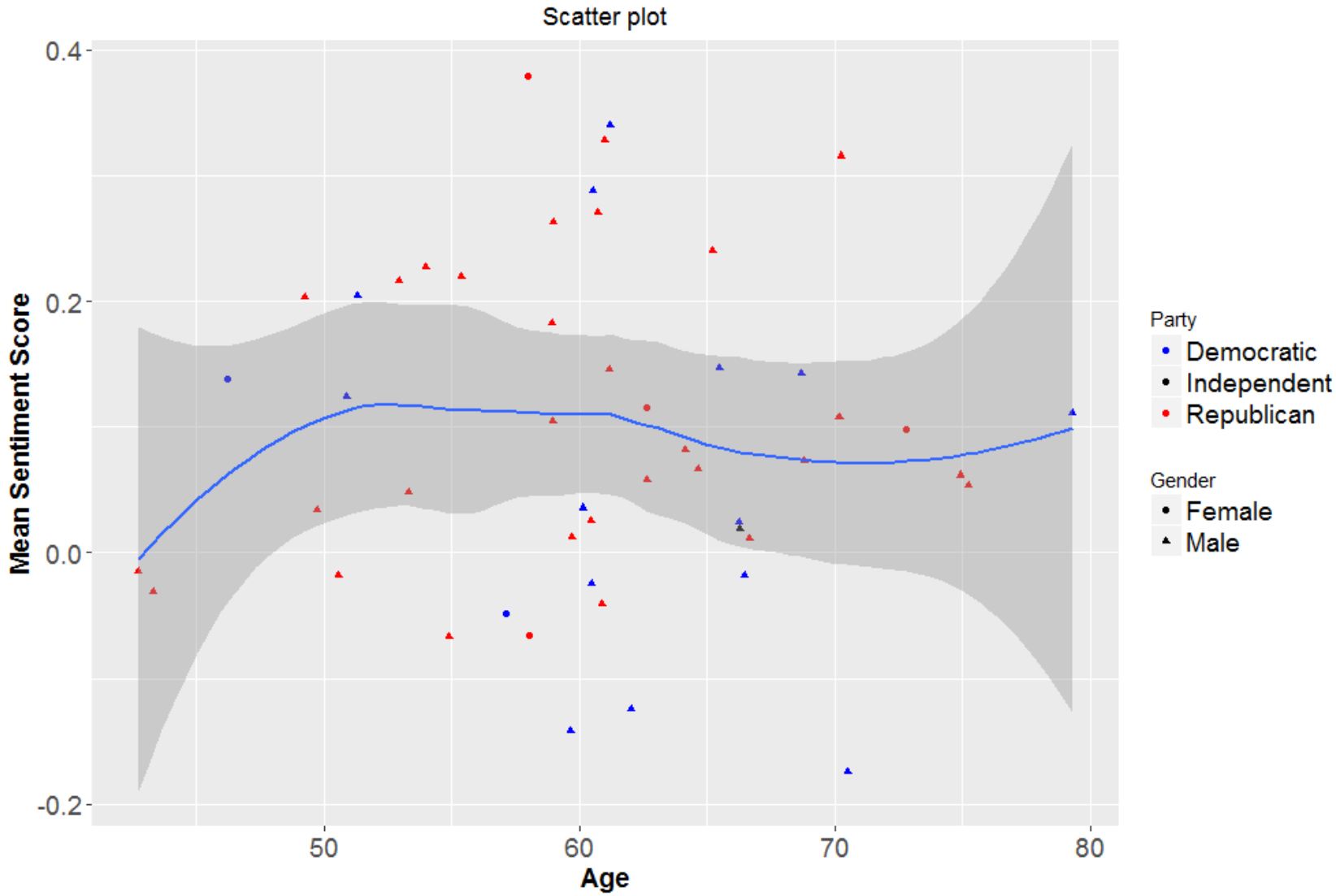
3 Data Visualization & Analysis

- **Box plot** with **mean** sentiment score and **gender** of governor



3 Data Visualization & Analysis

- **Scatter plot** with **mean** sentiment score and **age** of governor



3 Data Visualization & Analysis

- **ANOVA Test**

H_0: $\mu_1 = \mu_2$

Analysis of Variance Table

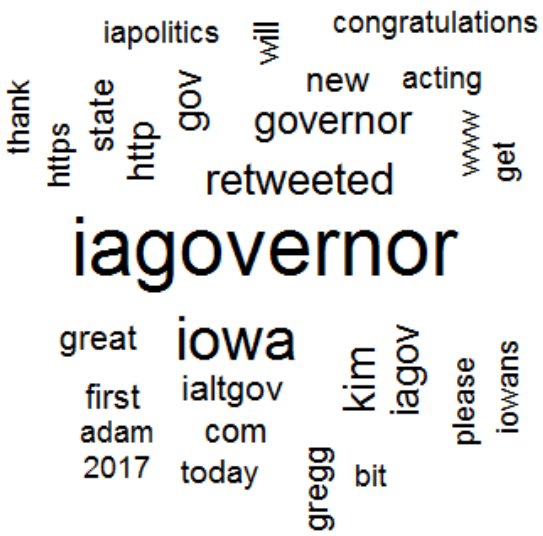
Response: Mean_Sentiment_Score

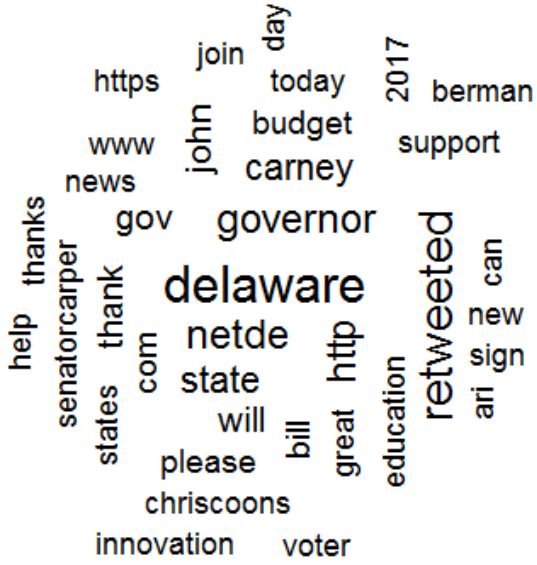
	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Gender	1	0.00043	0.0004314	0.0243	0.8769
Party	2	0.03095	0.0154772	0.8708	0.4255
Age	1	0.00017	0.0001658	0.0093	0.9235
Residuals	45	0.79979	0.0177731		

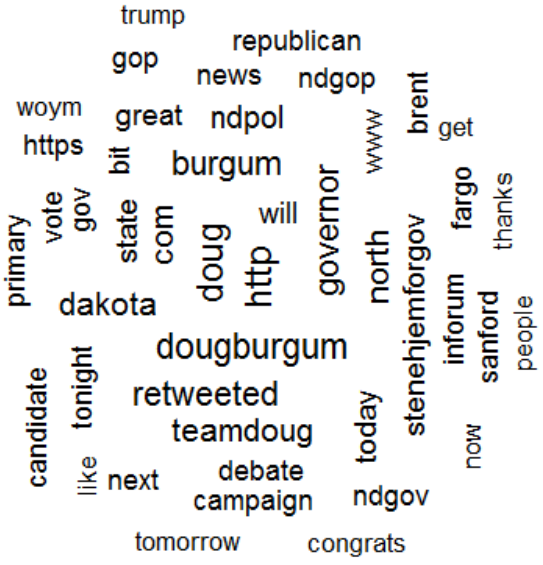
Fail to reject H_0

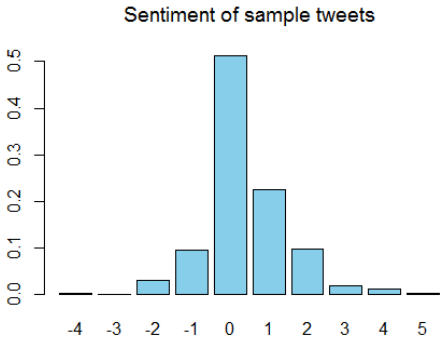
3 Data Visualization & Analysis

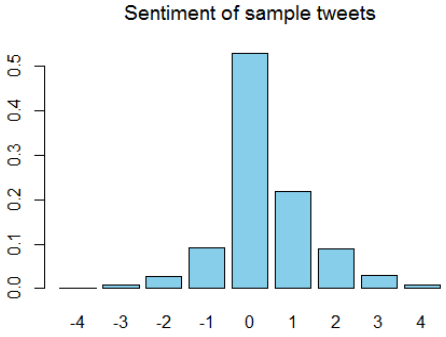
- **Word cloud** of **top** three governors (min. frequency= 25)

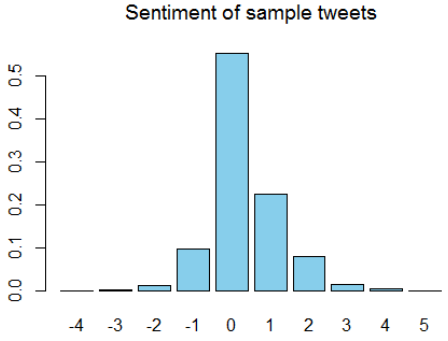








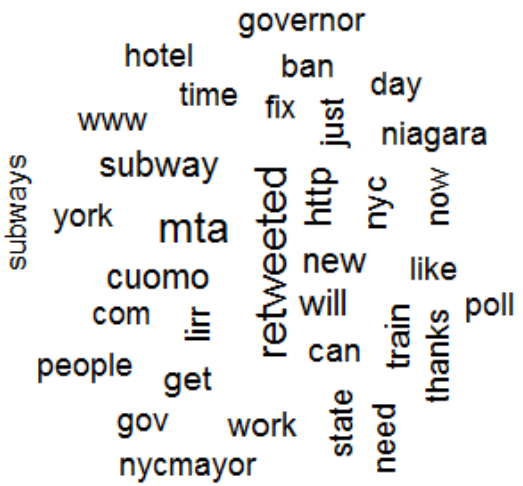


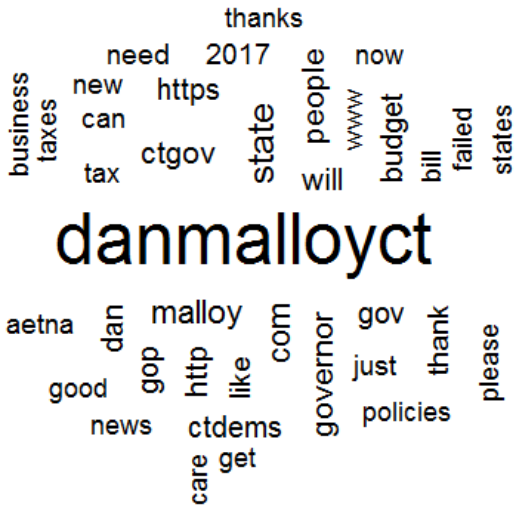


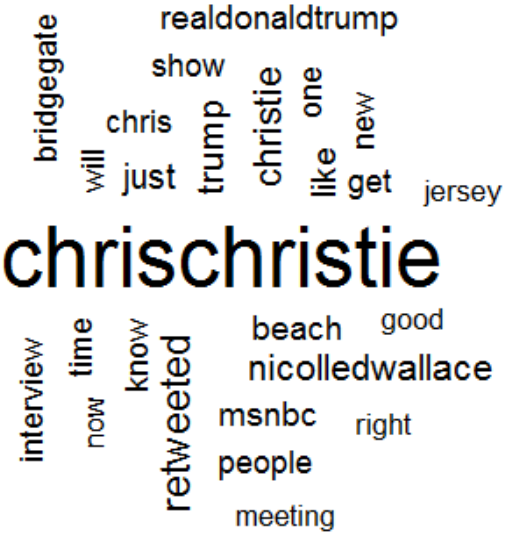
IOWA **DELAWARE** **NORTH DAKOTA**

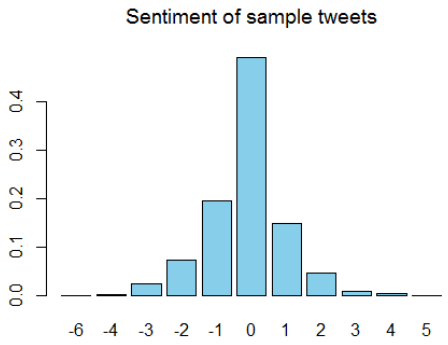
3 Data Visualization & Analysis

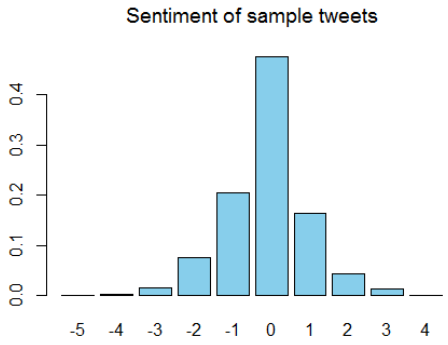
- **Word cloud** of **bottom** three governors (min. frequency= 25)

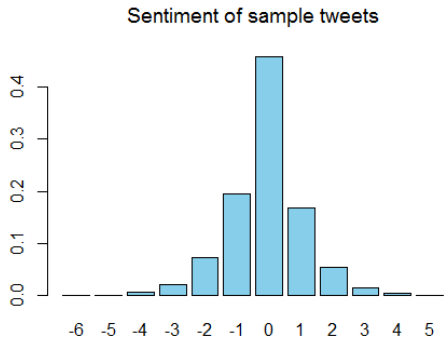












NEW YORK **CONNECTICUT** **NEW JERSEY**

3 Data Visualization & Analysis

- **Rankings** based on **mean sentiment score** and **comparison** with **Morning Consult**

State	Governor	Party	Tweets Scraped	Twitter Rank (from top)	Morning Consult (from top)
Iowa	Kim Reynolds	Republican	957	1	-
Delaware	John Carney Jr.	Democratic	1005	2	28
North Dakota	Doug Burgum	Republican	1129	3	4
Utah	Gary Herbert	Republican	1017	4	9
Hawaii	David Ige	Democratic	1017	5	36
Massachusetts	Charlie Baker	Republican	273	6	1
Vermont	Phil Scott	Republican	57	7	8
Ohio	John Kasich	Republican	1014	8	20
Nevada	Brian Sandoval	Republican	1013	9	7
Wyoming	Matt Mead	Republican	1012	10	3

State	Governor	Party	Tweets scraped	Twitter Rank (from bottom)	Morning Consult (from bottom)
Minnesota	Mark Dayton	Democratic	138	1	17
New York	Andrew Cuomo	Democratic	1011	2	23
Connecticut	Dan Malloy	Democratic	1018	3	3
New Jersey	Chris Christie	Republican	1009	4	1
New Mexico	Susana Martinez	Republican	1011	5	11
Oregon	Kate Brown	Democratic	1009	6	21
Kansas	Sam Brownback	Republican	1017	7	2
Missouri	Eric Greitens	Republican	1003	8	29
Virginia	Terry McAuliffe	Democratic	1015	9	23
Kentucky	Matt Bevin	Republican	1015	10	13

5 Conclusions and Future Outlook

- **Tweets** can be used as a **quick way to gauge** the approval of governors. It only takes few hours of coding and data processing when compared to conventional polling techniques that require significant $$ and resources.

- The **analysis** can be **improved** by taking **inputs** from **multiple social media** platforms (facebook ,…).

- Sentiment analysis can be **improved** by constantly **updating the list** of positive and negative words as the society evolves with time.

- There is always a **segment of population** who **do not use social media** platforms to express emotions. This will have an impact on the data analysis.

- It would be interesting to study how predictions change as a function of the **sample size** of tweets.

- This study can be extended to gauge the sentiment towards **President and Presidential Candidates** as well.

- With the **right imagination**, sky is the limit!

THANK YOU