Thank You for Organizing the Seminar!

University of Münster

- Ann-Kathrin Meyer
- Prof. Tobias Brandt

University of Koblenz and Landau

- Prof. Patrick Delfmann
- Jun. Prof. Dennis Riehle

- Develop a deeper understanding of data analytics especially in the domains of urban analytics and artificial intelligence.
- Boost our productivity with fresh mountain air and fun on the ski slope.

Popularity and Controversy

A Location-Based Twitter Sentiment Analysis of Donald Trump and Boris Johnson

Popularity and Controversy: A Location-Based Twitter Sentiment Analysis of Donald Trump and Boris Johnson

Leo Giesen

Agenda

Motivation and Relevance


TRUMP

The data analysis improves the understanding of the geographic impact on public perception.

Motivation and Relevance

OBJECTIVE

- Understand the **role** and **factor** of the geographic location on public perception of political leaders.

MOTIVATION

- Explore the nuanced **interplay** between **geographic location** and **public perception** of political leaders.

RELEVANCE

- Growing importance of **social media** in political discourse. Especially Trump has instrumentalized Twitter for his political agenda.
- **Technological advancements** in sentiment analysis provide more accurate results.
- Important to understand the **public opinion** in the context of global political climate.

The effect of events on the geographical public opinion shapes political behavior.

Motivation and Relevance

IMPACT

- This offers valuable insights for a range of stakeholders. E.g., **researchers** can form certain statements about Trump and Johnson supported by a solid data foundation.
- **Political figures** get insights into what role the **geographic factor** plays in the reaction to political or social **events** and how people from different cities voice their opinion and emotions affecting their **political agenda**, policy and strategy (crisis management).

- One can learn from events and sentiment development from the past.
- Politicians can adjust their political behavior against the background of the local perception.
- A researcher can estimate how the public reacts to a certain event.

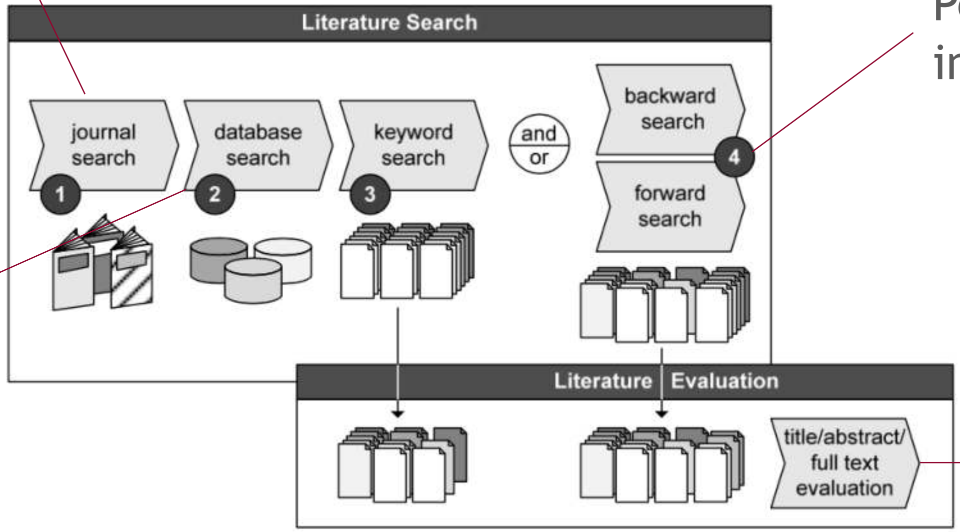
Research Background & Methodology

The research method consists of the literature search and evaluation.

Research Background and Methodology | Methodology

Considered journals:
All (No limitation to
Senior Scholar Basket)

Database: Scopus



Performed if further insights are necessary

See next slide

(vom Brocke et al. 2015, p. 12)

The literature search determines which papers are inspected for relevance.

Research Background and Methodology | Literature Search

LITERATURE

- The search query comprises the three criteria for relevance including the synonyms and other forms of the word stem for each word.
- First focus on Senior Scholar Basket and then extending it to further publication outlets.
- The Senior Scholar Basket research yielded 0 results and the all-outlet query put out 6 results.

SEARCH QUERY

TITLE-ABS-KEY ("sentiment analysis" OR "opinion mining") AND

TITLE-ABS-KEY ("Donald Trump" OR "Trump" OR "Boris Johnson" OR "Johnson") AND

TITLE-ABS-KEY ("location" OR "geospatial" OR "regional" OR "geographic" OR "geo-tagged") AND

AND (EXACTSRCTITLE("European Journal of Information Systems")
OR EXACTSRCTITLE("Information Systems Journal")
OR EXACTSRCTITLE("Information Systems Research")
OR EXACTSRCTITLE("Journal of the Association for Information Systems")
OR EXACTSRCTITLE("Journal of Information Technology")
OR EXACTSRCTITLE("Journal of Management Information Systems")
OR EXACTSRCTITLE("Journal of Strategic Information Systems")
)

CRITERIA FOR RELEVANCE

S.A.

Presi-dent

Location

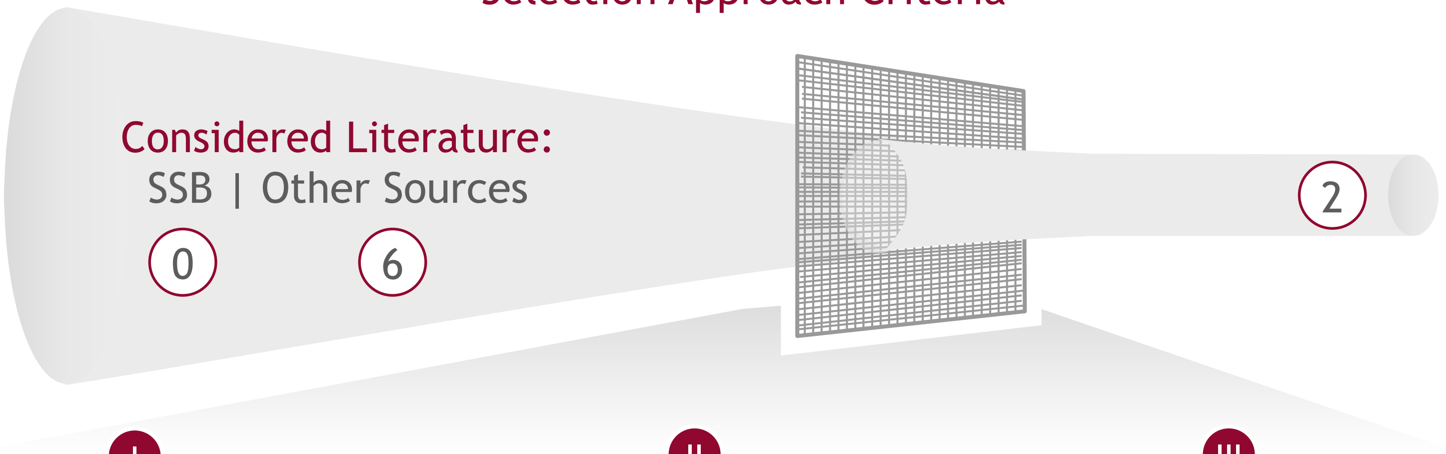
Filtering of SBB

S.A. = Sentiment Analysis; SSB = Senior Scholar Basket

The literature evaluation step determines, which sources are relevant for the thesis.

Research Background and Methodology | Literature Evaluation

Selection Approach Criteria



I — Sentiment Analysis
→ Is any type of sentiment analysis implemented?

II — Political Leader
→ Is the sentiment analysis focused on any of the two political leaders?

III — Location-Specific Data
→ Does the analysis take any location into consideration for the analysis?

Result

- Two relevant scientific paper have been identified. Further information about the **learnings** are in the backlog.
- Nevertheless, **insights** from the other five papers can also be incorporated and build upon, such as data visualization techniques.

SSB = Senior Scholar Basket

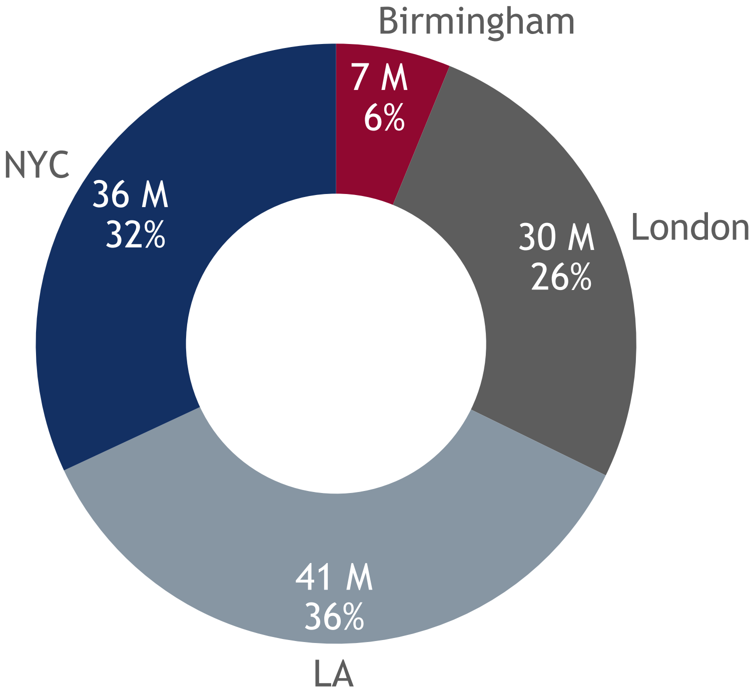
Analysis, Results and Discussion

Data Overview

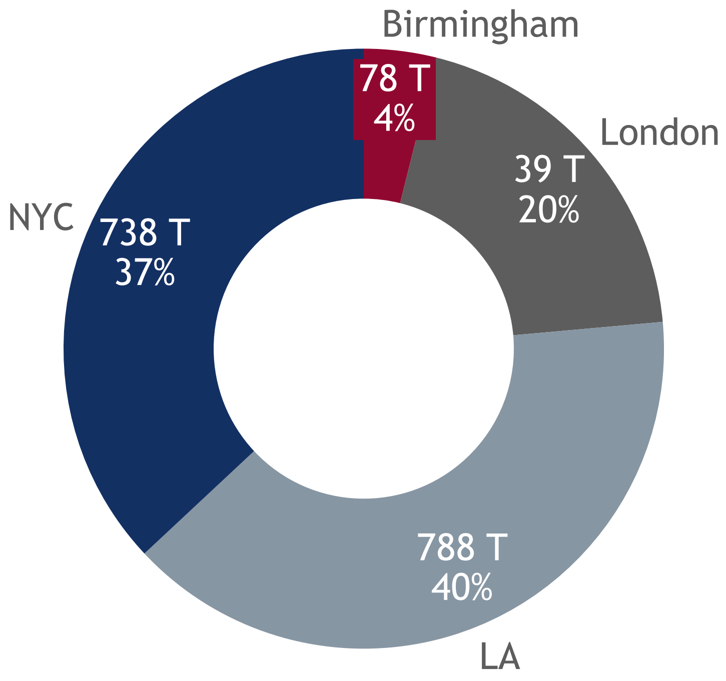
The US generated almost 88% of the relevant data.

Data Overview

A third of the Tweets come from the **GB.**



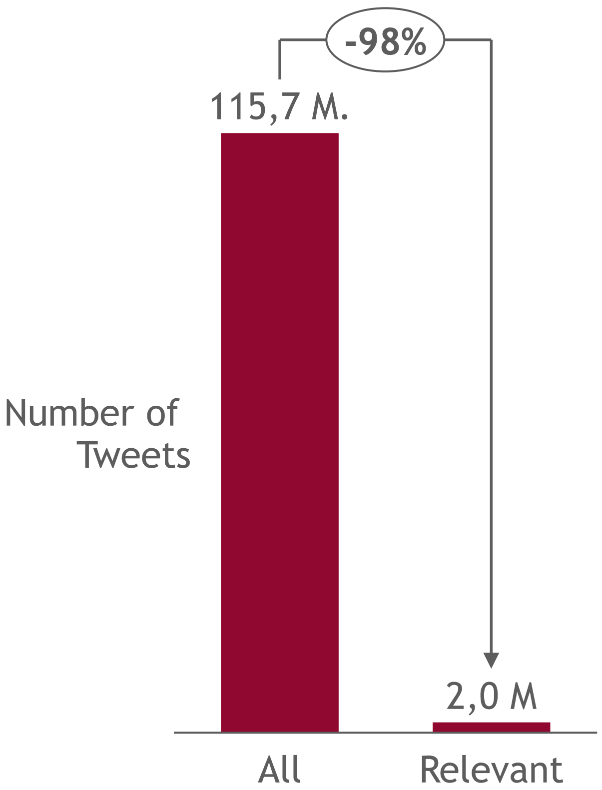
The **relevant data** comprises primarily the US. **Time frame** (08-2018;07-2022) ensures the existence of sentiment and LIWC* data.



*Linguistic Inquiry and Word Count

The large dataset is filtered to ~2 million relevant Tweets.

Data Overview



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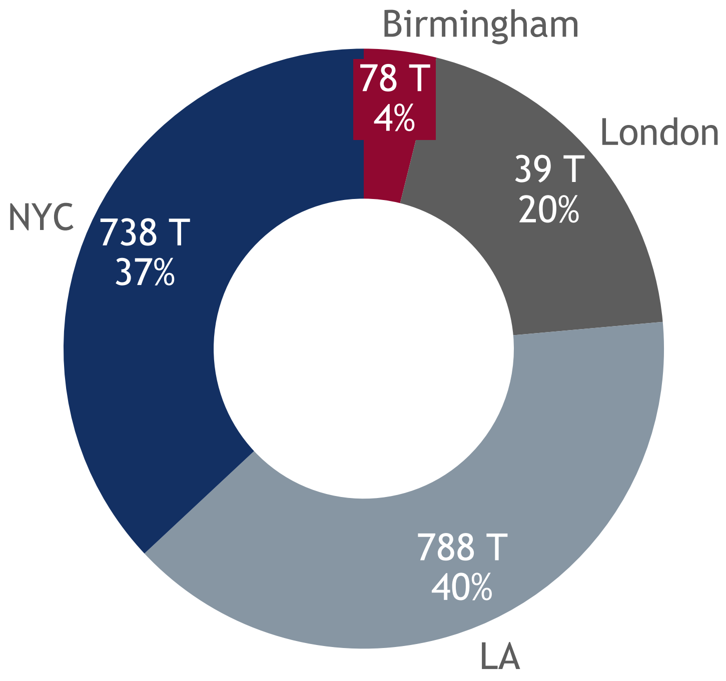
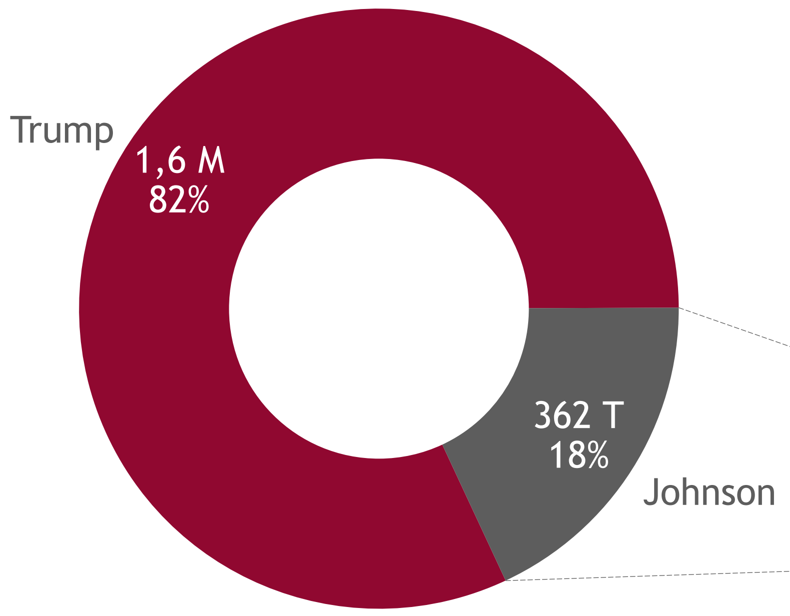
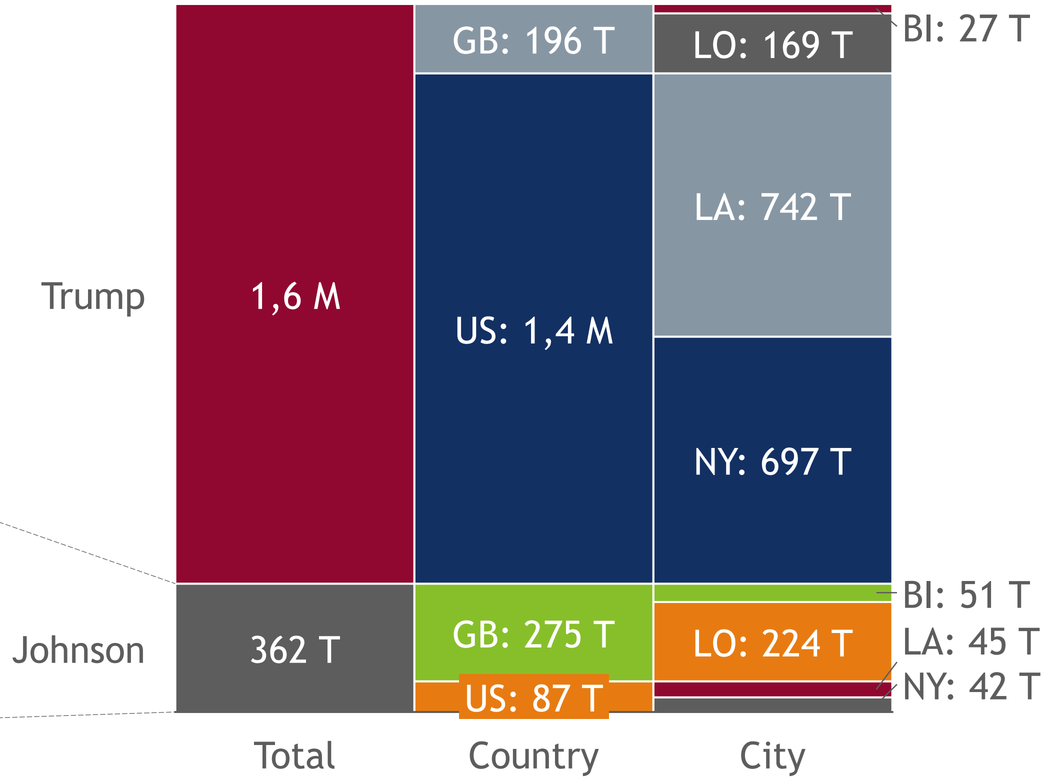


Trump has significantly more public attention than Johnson.

Data Overview

President: There are more than four times as many Tweets are about Trump than about Johnson.





Birmingham (BI), London (LO), Los Angeles (LA), New York City (NY)

Analysis, Results and Discussion

Sentiment Analysis

There are three central types of sentiment analysis.

Analysis, Results and Discussion | Types of Sentiment Analysis

SCOPE

Sentiment Scoring or Graded Sentiment Analysis

- Based on the **level** of positivity.

Neutral

Negative ⟷ Positive

- Realized with **VADER** (Valence Aware Dictionary and sEntiment Reasoner).

Emotion Detection

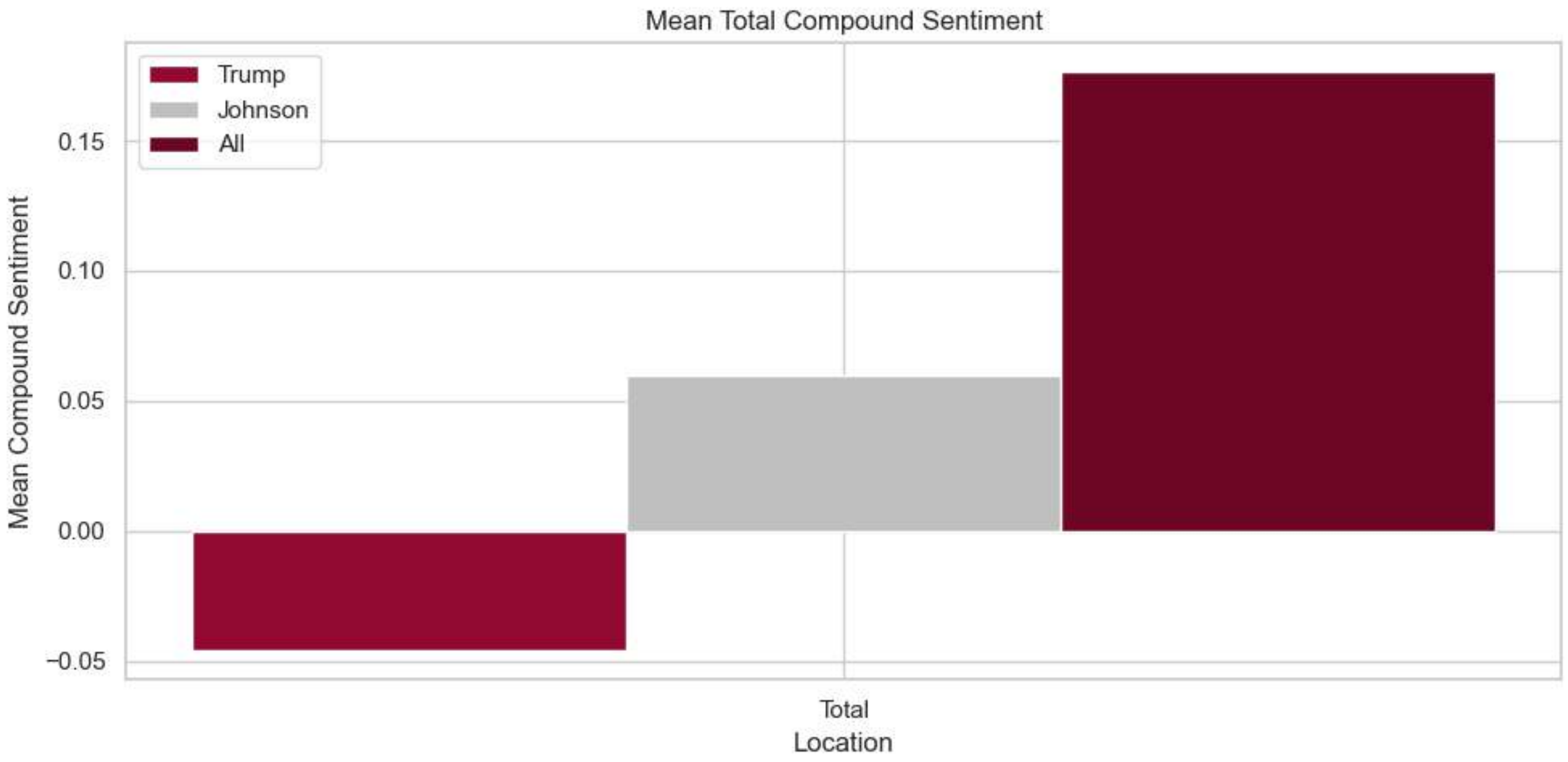
- Identify the which emotions are expressed in a text, such as happiness, frustration, anger, and sadness
- Realized with a **machine learning** or **lexicon-based** approach.
- Here the lexicon-based **LIWC** (Linguistic Inquiry and Word Count) is applied.

Aspect-based Sentiment Analysis

- Granular sentiment understanding by outlining detailed opinions
- For instance, “the product is too small” judges the size aspect of the product.

Sentiment Score Location

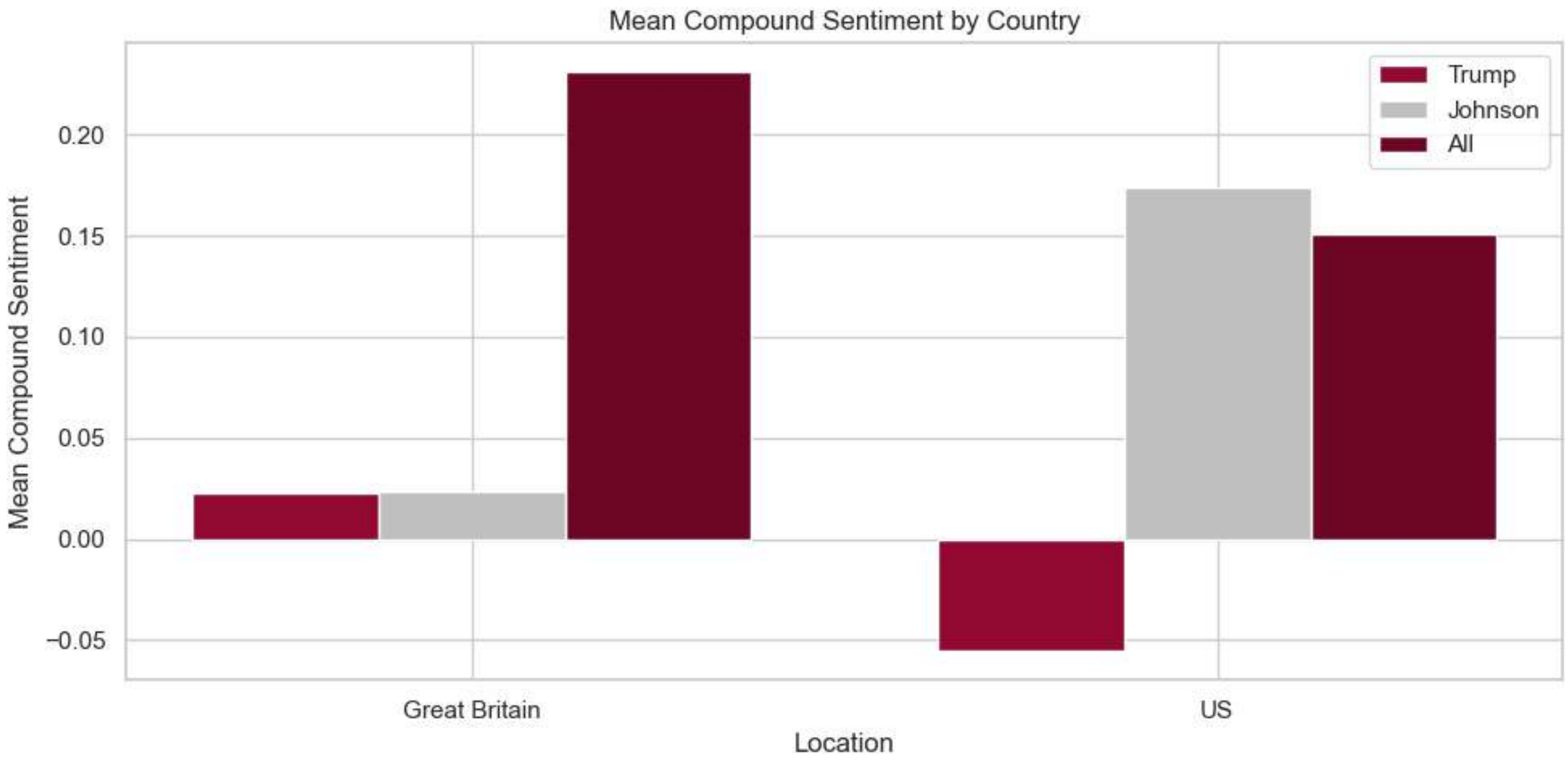
Analysis, Results and Discussion | Mean Location Sentiment



Daily analysis of the bar charts including the daily development is in the backlog.

Sentiment Score Location

Analysis, Results and Discussion | Mean Location Sentiment



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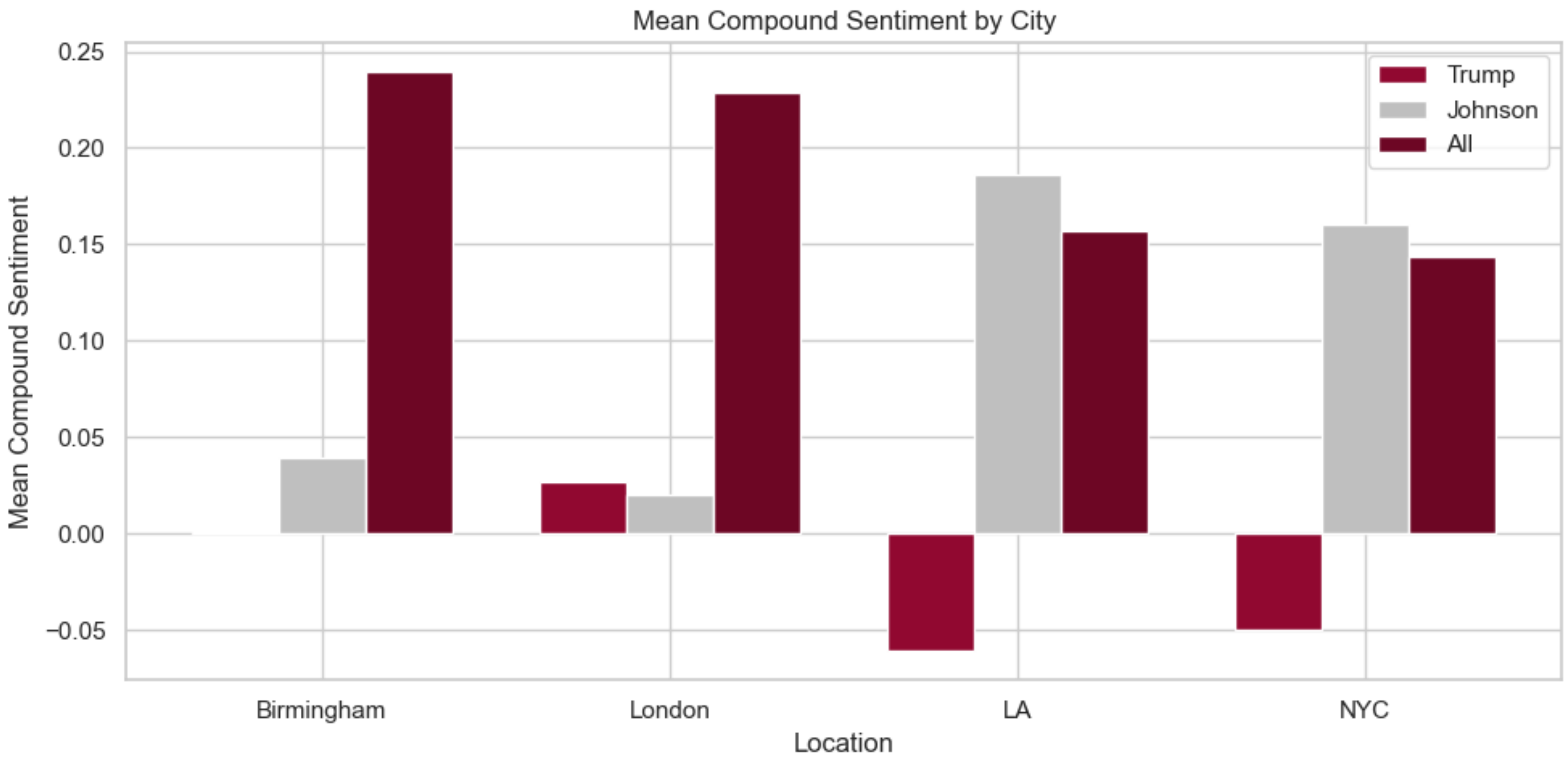
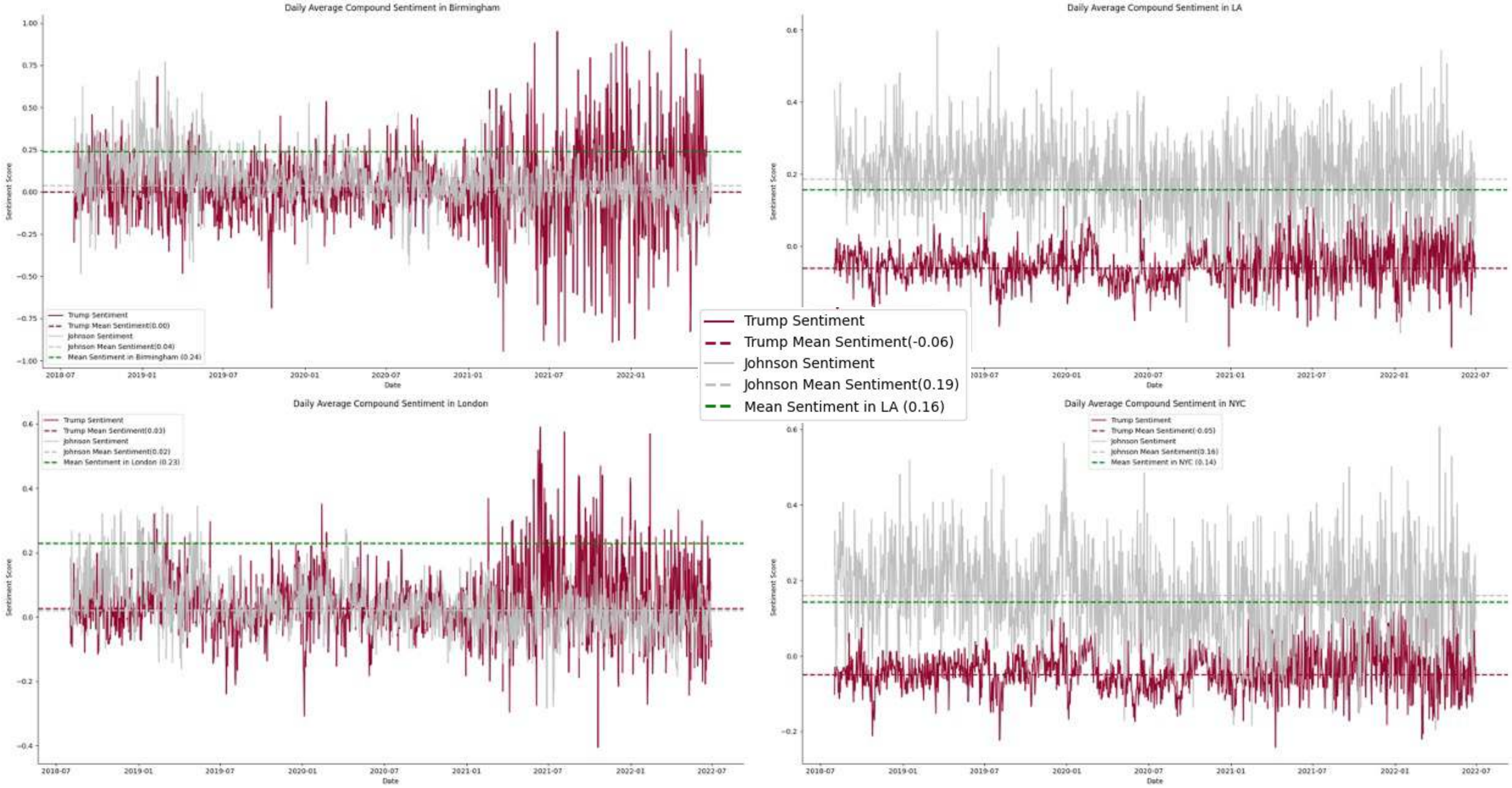
Sentiment Score Location

Analysis, Results and Discussion | Mean Location Sentiment

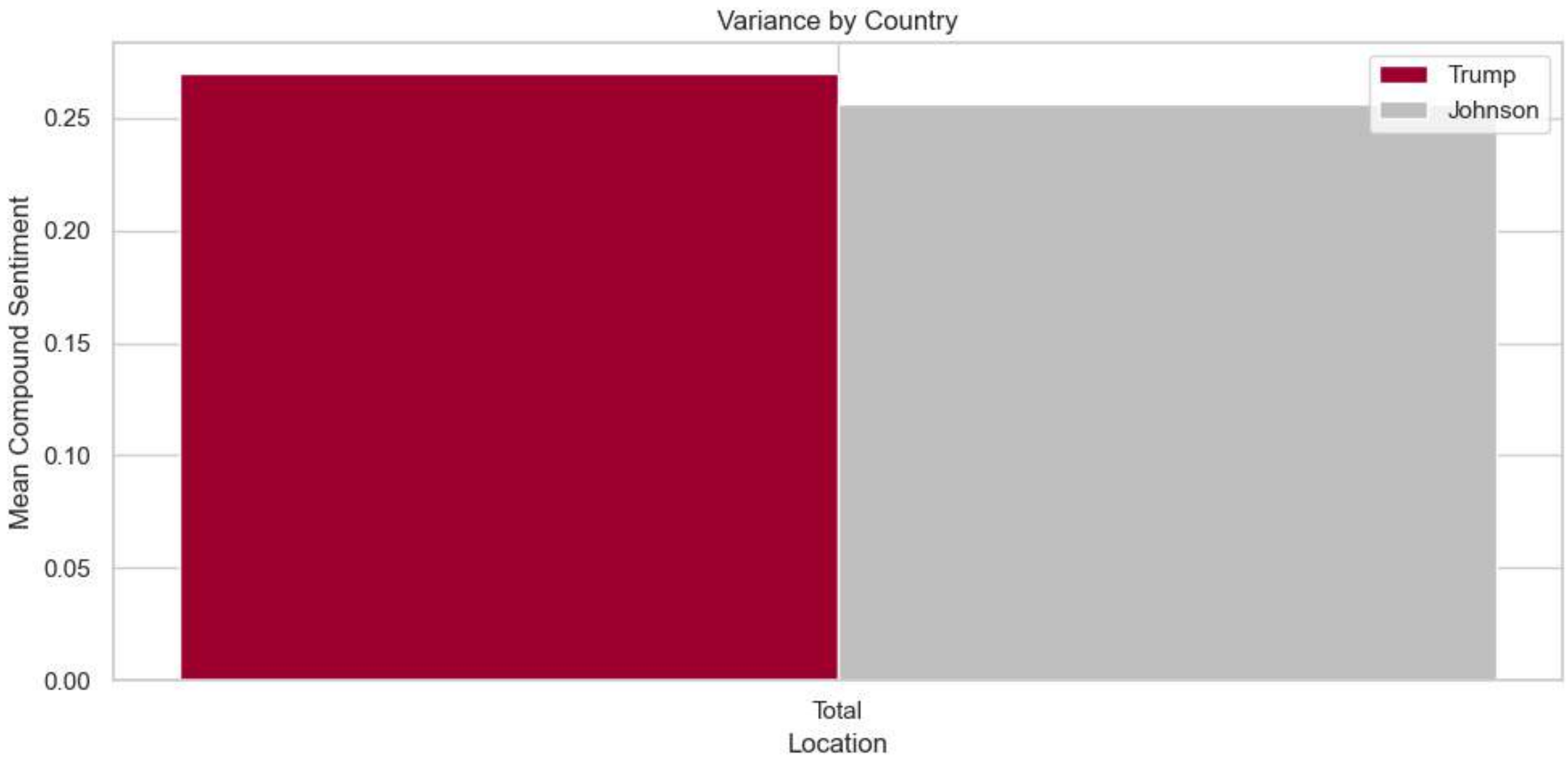


Daily analysis of the bar charts including the daily development is in the backlog.

Daily Sentiment Development per City

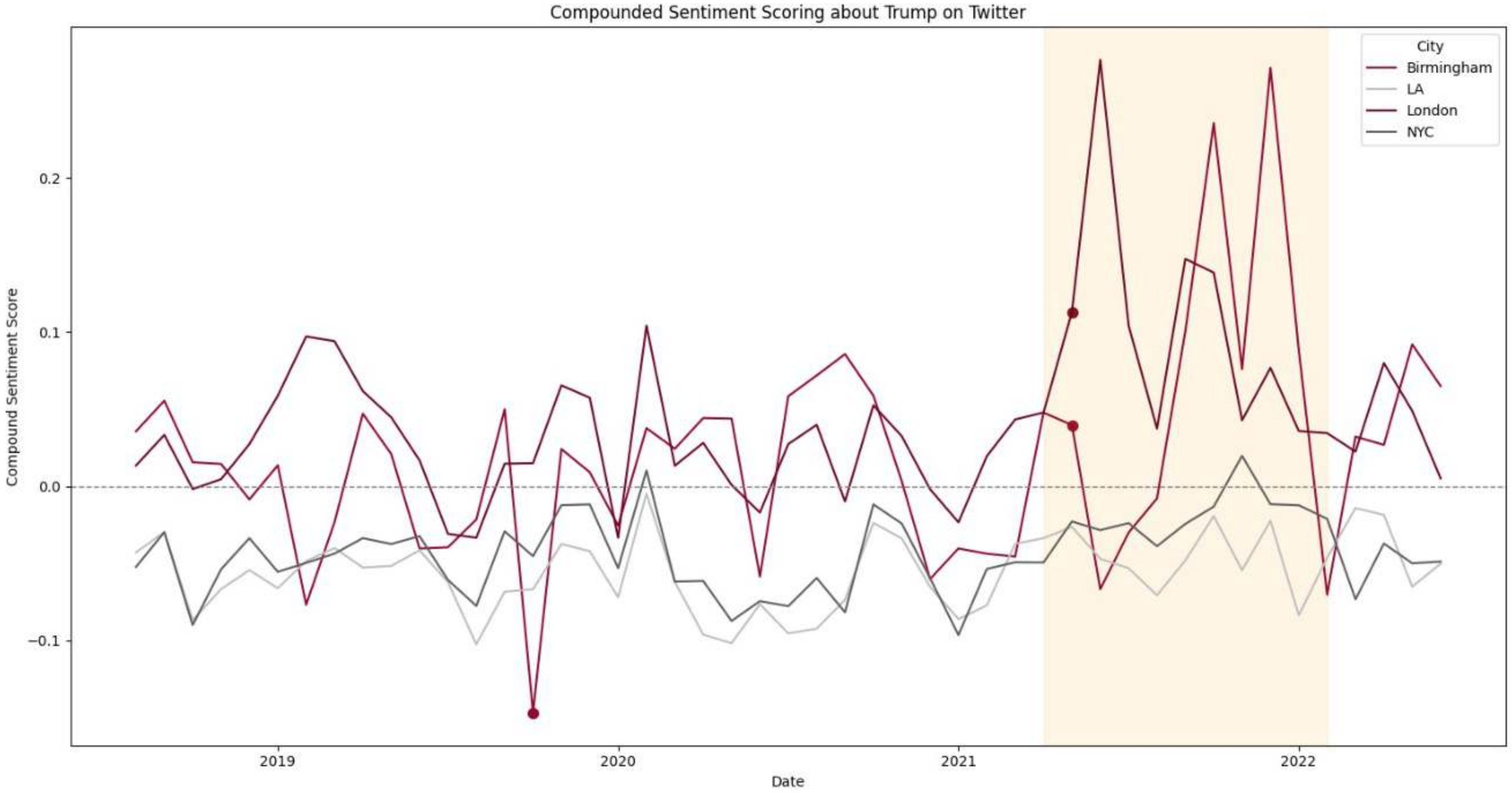


Trump has a higher overall variance.



Events Outlier Analysis: Trump

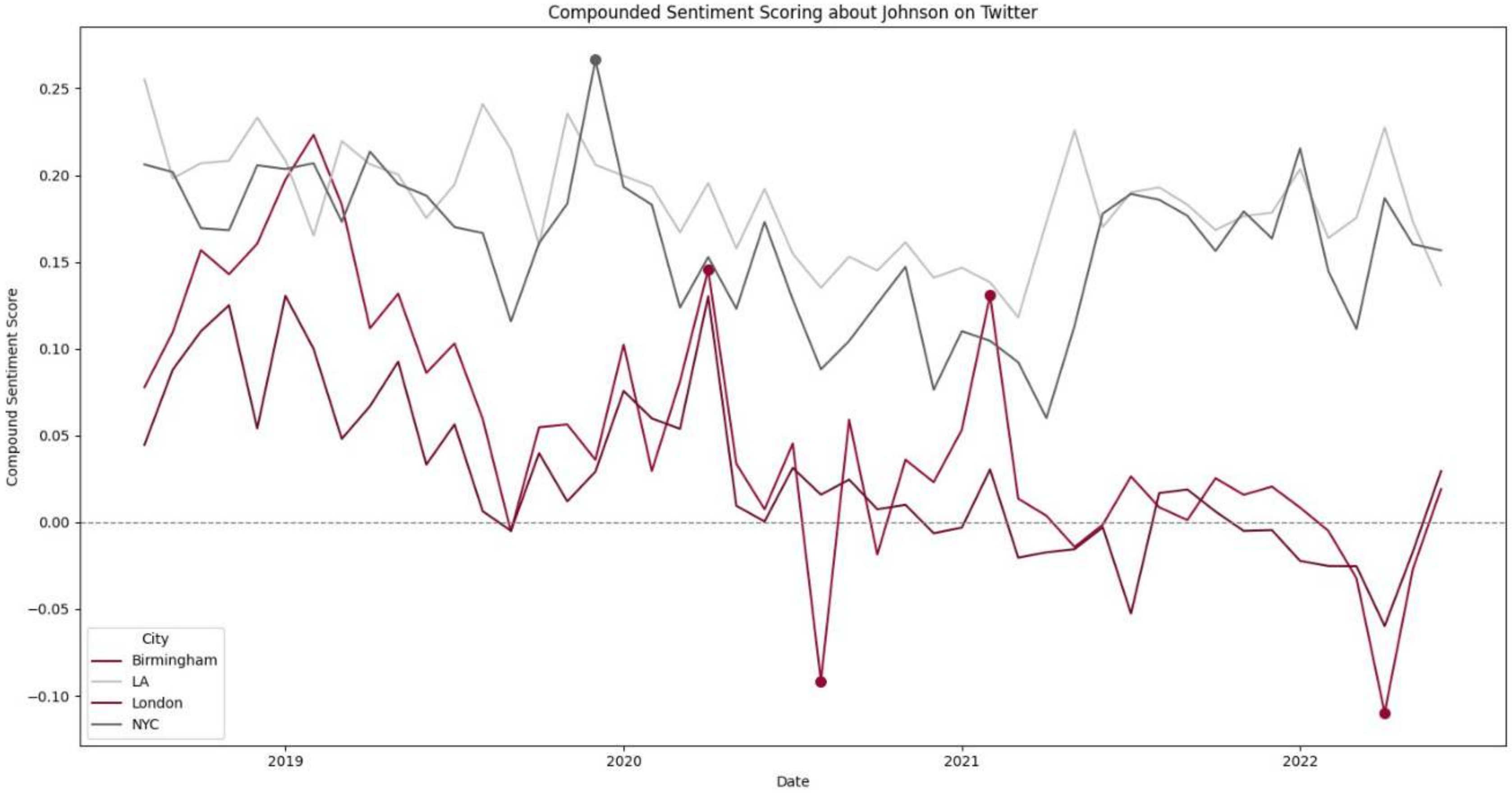
Analysis, Results and Discussion



The visualizations are on a monthly basis. The daily development is in the backlog. The monthly view is clearer.

Events Outlier Analysis: Johnson

Analysis, Results and Discussion



The visualizations are on a monthly basis. The daily development is in the backlog. The monthly view is clearer.

Outlook

Next Steps and Out of Scope Ideas

There are four central next steps.

Outlook

NEXT STEPS

Research Event

- Research city **characteristics**, local **developments** to explain sentiment trends, high and low points.

High Participation Event

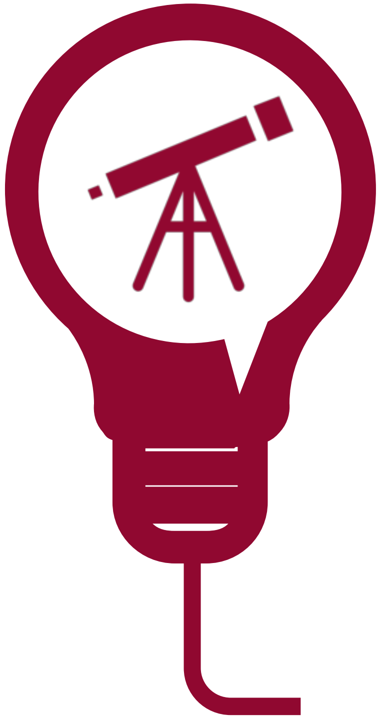
- Plot **daily number** of Tweets and identify peaks due to events (election).

Fine-Grained Analysis

- Group sentiment into **segments** to identify opposing views.

LIWC

- What emotions are associated with the presidents or which emotions do they trigger?
- Do people react differently (→ controversy, opposing opinions)? Understand variables in LIWC, e.g., what does emo_pos =22.22 mean?



OUT OF SCOPE IDEAS

User Analysis

- User analysis in each city and country to understand their **sentiment deviation** when they talk about the presidents.

Compare Predictions

- Non-scientific, but fun: ChatGPT as a prediction for Twitter sentiment and emotion detection. Check the deviation to the given values.

Borrow-Level Analysis

- A more fine-grained location analysis could be performed.

Closing Remarks

Outlook

TAKEAWAYS

- In contrast to Johnson, Trump is overall negatively regarded.
- The presidents are more popular in other countries compared to their home country.
- Nevertheless, both presi-dents are not as popular as the average Tweet and a negative shift of public perception since 2018.

LIMITATIONS

- The sentiment score and emotion detection might not be able to determine an accurate value in complex sentence constructs. E.g., a negative Tweet with the word "Trump" might not focus on Trump.
- Birmingham has a very high variance due to a limited amount of data, preventing the generation of insights.

IMPLICATIONS FOR RESEARCH

- The analysis offers valuable insights contributing to the broader academic discourse in urban analytics and political sentiment analysis.
- Other research can build upon the sentiment analysis insights and have data to back their statements.
- Researchers can develop a model to predict the public sentiment after an event.

ChatGPT speeds up coding and theory. It also improves writing and aids in thinking.

AI Usage

CODE	THEORY	THINKING & WRITING
▪ **Realization and implementation**: Quickly generate code, especially for visualizations. ▪ **Quality Control**: Quickly enhance code by enforcing coding best practices, increase performance, etc. ▪ **Assistant and Teacher**: Explain, debug and solve errors.	▪ **Researcher**: Provide a basic understanding of the theoretical background, e.g. relations of different fields ▪ **Research Assistant**: Summarize papers. Evaluation of papers can be faulty. Best to double check everything!	▪ **Inspiration**: Provides ideas for brainstorming and aids in divergent thinking. ▪ **Revisor**: Check your research approach and find mistakes you made on the way. ▪ **Language Support**: Improves low quality sentences and helps to find fitting words.

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Backlog

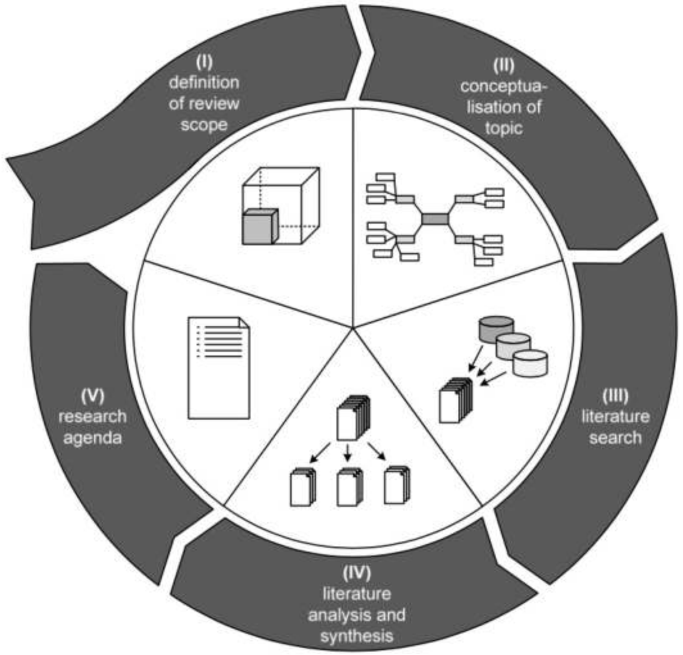
General

- Previously filtered by English language; not necessary as sentiment was determined this way
- Repository can be found here: https://github.com/lgiesen/twitter-sentiment-analysis-politicians

Literature Research: Research Method

Literature Research

Framework for Literature Reviewing



(Brocke et al. 2009, p. 10)

Taxonomy of Literature Reviews

Characteristic	Categories			
(1) focus	research outcomes	research methods	theories	applications
(2) goal	integration	criticism		central issues
(3) organisation	historical	conceptual		methodological
(4) perspective	neutral representation		espousal of position	
(5) audience	specialized scholars	general scholars	practitioners/politicians	general public
(6) coverage	exhaustive	exhaustive and selective	representative	centralpivotal

adjusted from vom Brocke et al. (2009, p. 10)

(vom Brocke et al. 2015)

Literature Research: Paper Criteria

Literature Research

Paper	Sentiment Analysis	Political Leader	Location-Specific Data	Relevant
East Meets West: Sentiment Analysis for Election Prediction	x	x		
Sentiment Analysis between VADER and EDA for the US Presidential Election 2020 on Twitter Datasets	x	x		
Location-based Sentiment Analyses and Visualization of Twitter Election Data	x	x	x	x
Collection and Sentiment Analysis of Twitter Data on the Political Atmosphere	x	x		
Location-based Twitter Sentiment Analysis for Predicting the U.S. 2016 Presidential Election	x	x	x	x
Detecting Shifts in Public Opinion: A Big Data Study of Global News Content	x	x		

Literature Research: Exemplary Insights From Relevant Paper

- **Title**: “Location-based Sentiment Analyses and Visualization of Twitter Election Data”
- **Goal**: “evaluate similarity between sentiment of location-based tweets and on-ground public opinion reflected in election results”
- **Data**: “two case studies: US presidential elections of 2016 and UK general elections of 2017”
- **Focus**: “state-wise user sentiment towards Hillary Clinton and Donald Trump”
- **Result**: “Twitter location sentiment does indeed corroborate with the election result in both cases”

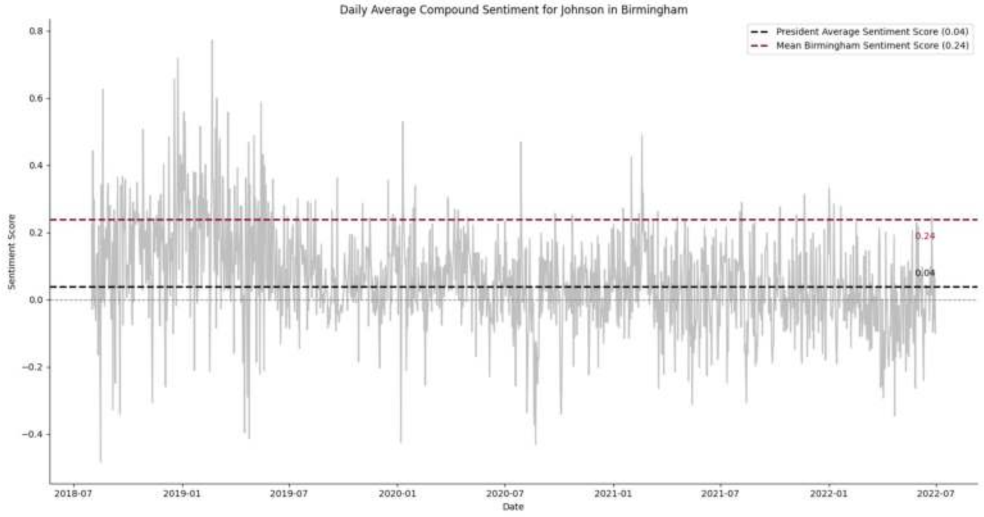
- **Learning**:
  - Understand **sentiment analysis methods** better and see the implementation
  - To find out: Since it deals with location-based data, the paper might offer insights into how sentiment varies **geographically**, which can be crucial in political analysis.
  - The study covers two different elections (US and UK), offering a **comparative perspective** on sentiment analysis in different political contexts.
  - Improve my **data visualization** based on how they effectively presented the sentiment analysis results.
  - Understand how sentiment on social media **correlates** with election results.

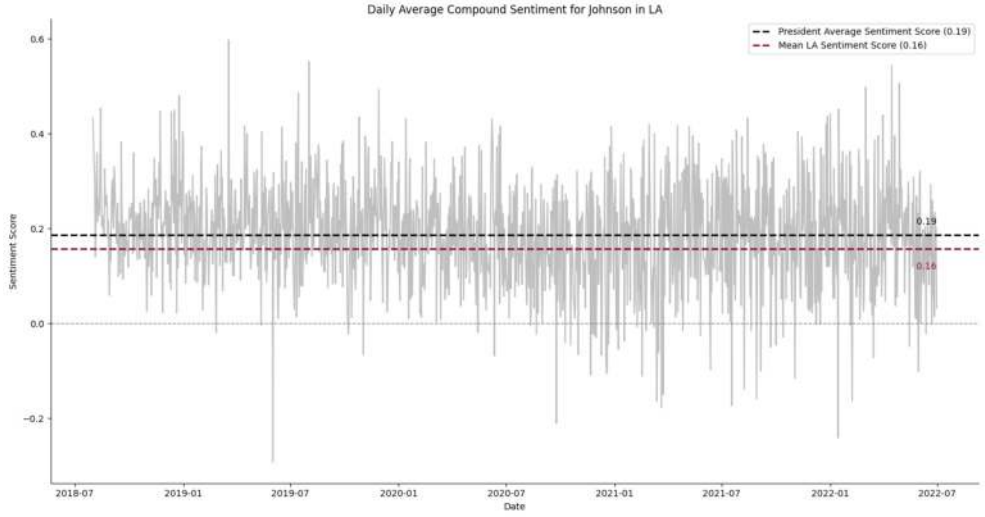
LIWC variables that are considered relevant upon first sight.

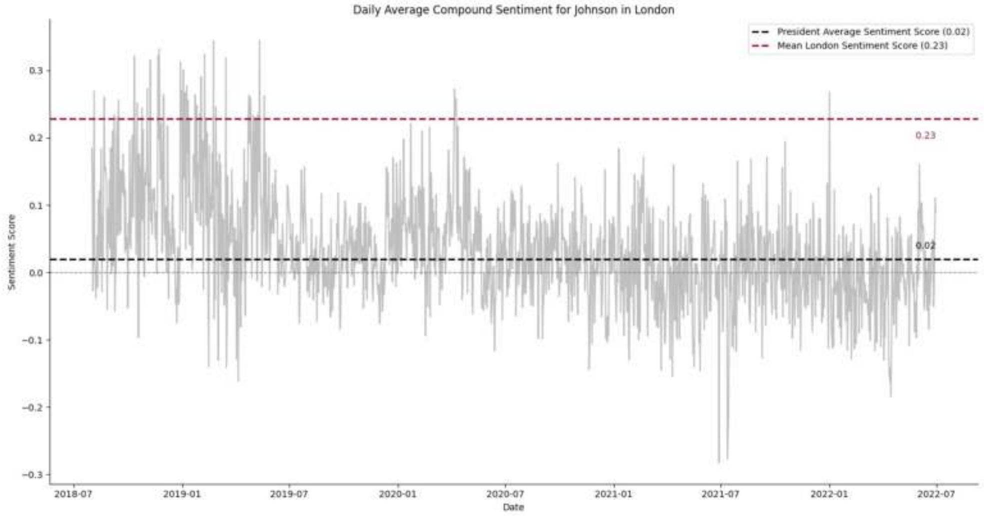
Analysis, Results and Discussion | LIWC

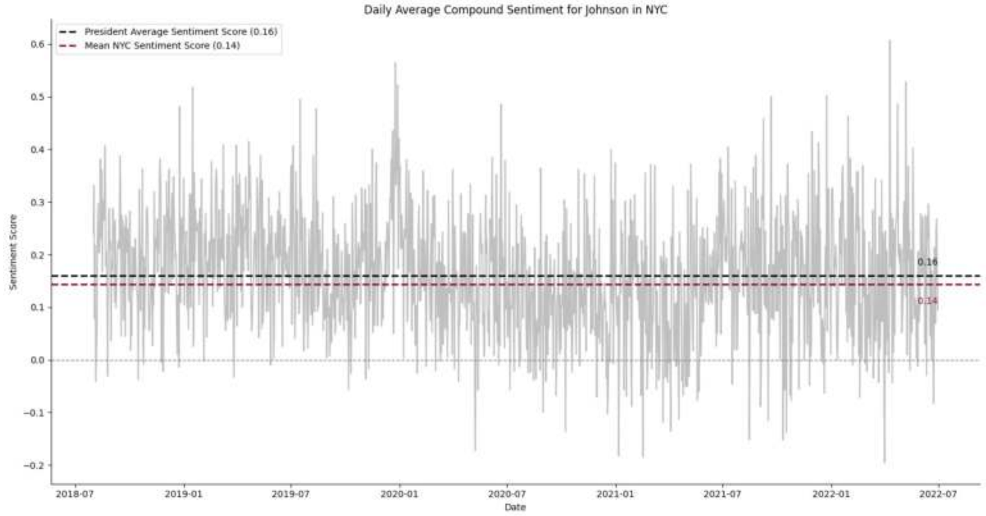
1. **Sentiment Analysis Columns:**
   - Tone, tone_pos, tone_neg: These columns might provide additional insights into the emotional tone of the tweets.
   - Affect, emotion, emo_pos, emo_neg, emo_anx, emo_anger, emo_sad: Specific emotional dimensions that can give a more nuanced view of the sentiments.
2. **Engagement Metrics (Optional):**
   - quote_count, reply_count, retweet_count, favorite_count: The gravity and reach of the Tweets can be considered for a more representative result.
3. **Language and Demographics (Optional):**
   - lang: The language of the tweet, if you're focusing on tweets in specific languages.
   - Culture, politic, ethnicity: Get insights into cultural or political contexts.

President City Analysis: Johnson

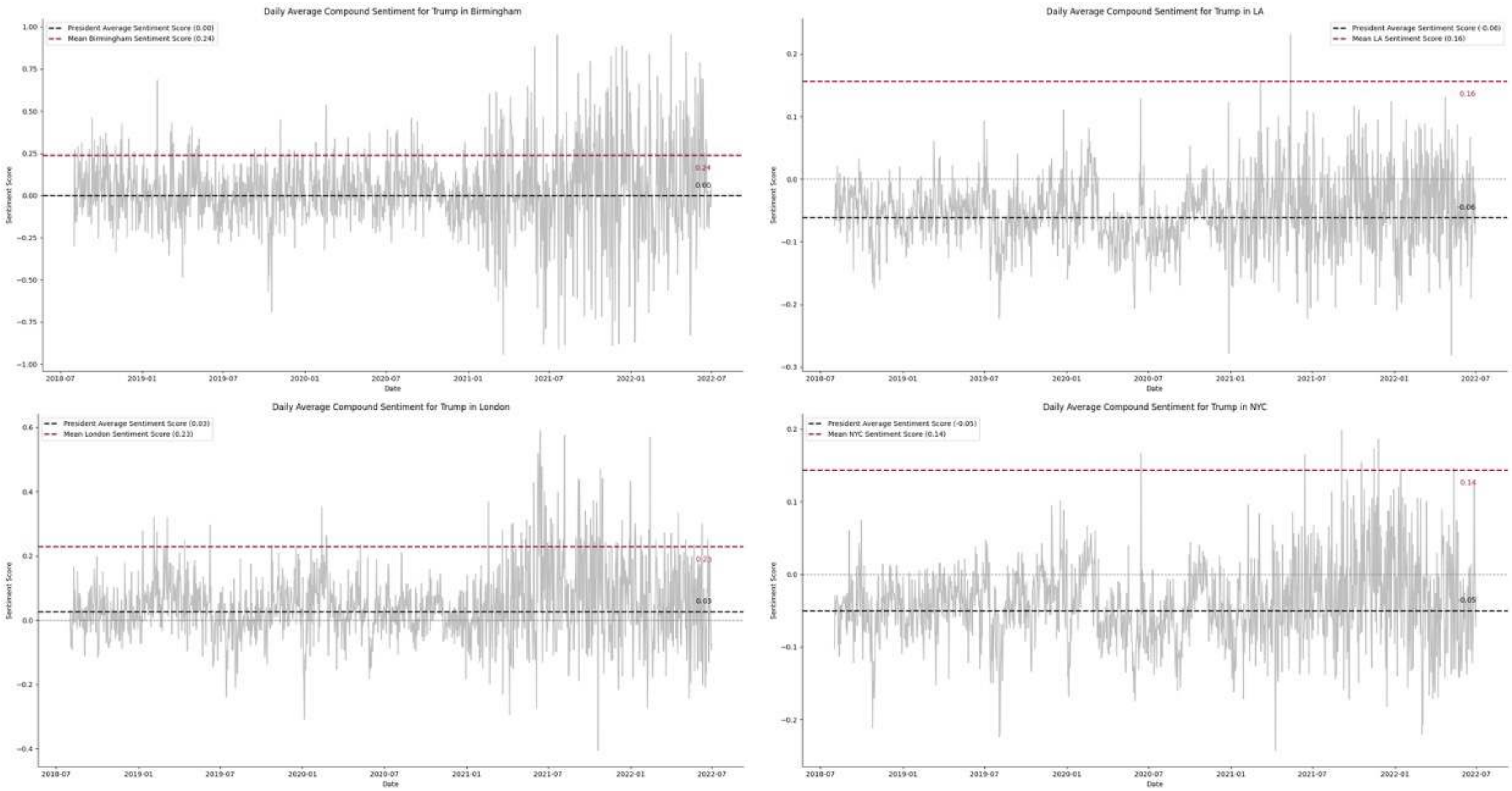








President City Analysis: Trump



Data: Query

- Query with parameter of the presidents' last name:

```
SELECT *
FROM tweets
INNER JOIN sentiment USING (item_number)
INNER JOIN LIWC USING (item_number)
LEFT JOIN place USING (place_id)
WHERE text LIKE ? AND (country_code = 'GB' OR country_code = 'US' OR
country_code IS NULL OR country_code = '')
```

Data: Mean Sentiment and Number of Tweets

- Mean Sentiment

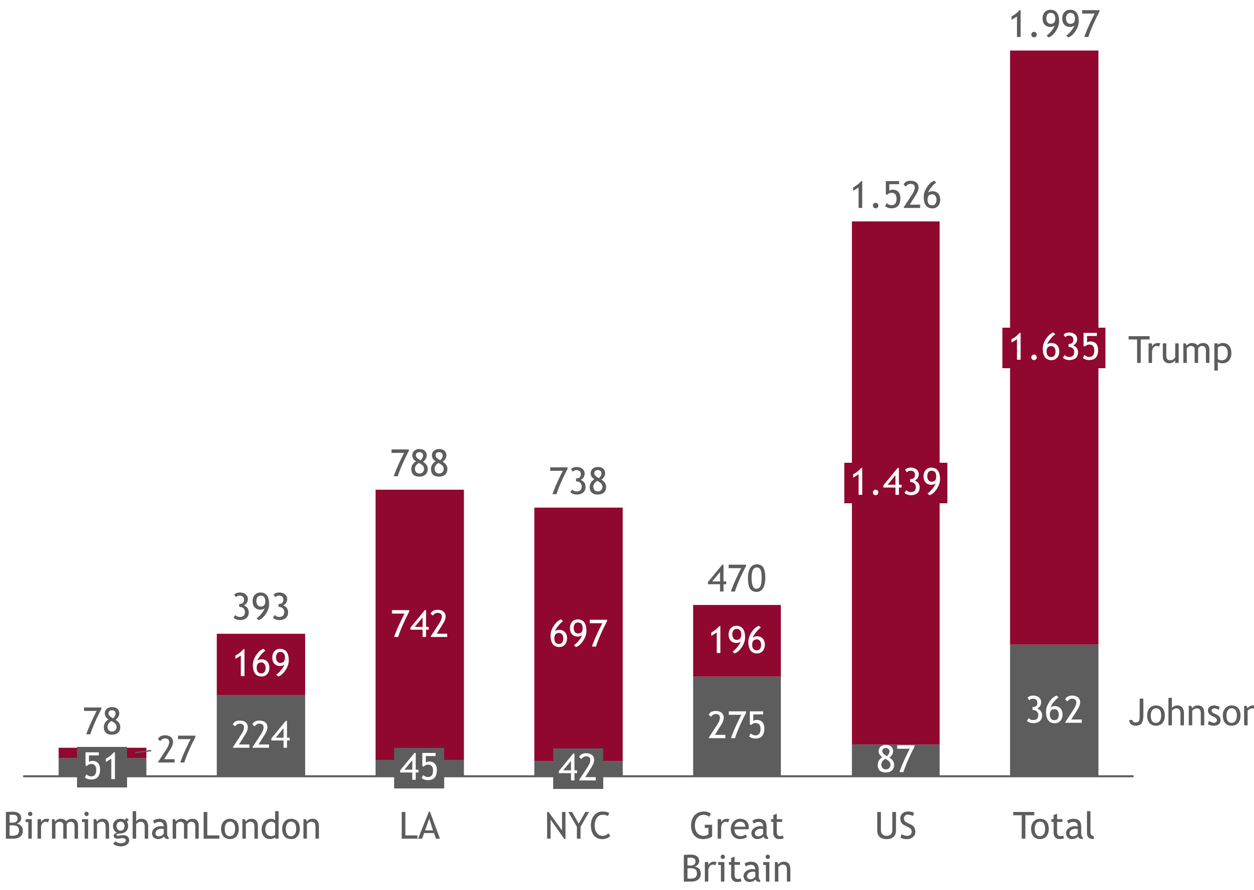
	Birmingham	LA	London	NYC	Great Britain	US	Total
trump	0.000941	-0.061045	0.026475	-0.049612	0.022986	-0.05551	-0.046108
johnson	0.039323	0.186258	0.019903	0.160315	0.023505	0.173843	0.059622
All	0.239253	0.156903	0.228856	0.143292	0.230849	0.150487	0.176390

- Number of Tweets

	Birmingham	LA	London	NYC	Great Britain	US	Total
trump	26758	742399	169071	696803	195829	1439202	1635031
johnson	50952	45289	223714	41560	274666	86849	361515
President Total	77710	787688	392785	738363	470495	1526051	1996546
All	7148908	41449103	30145037	36959351	37293945	78408454	115702399

- Variance

	Birmingham	LA	London	NYC	Great Britain	US	Total
trump	0.290855	0.270334	0.276585	0.264865	0.278612	0.267719	0.269673
johnson	0.263458	0.227933	0.25853	0.229428	0.259501	0.228816	0.256254



The row “All” reflects the unfiltered tweets.