

Executive Summary

This report analyzes Airbnb listing descriptions to uncover how language supports pricing strategies and influences perceived property value. Listings were categorized as cheap, normal, or expensive based on a price-per-guest metric. Key findings show that expensive listings use more positive sentiments and luxurious vocabulary to justify premium pricing, while cheaper listings emphasize location and functionality. Expensive listings highlight service, prestige, and exclusivity; cheap listings often include non-English words and terms that suggest practical benefits or safety cues. Sentiment analysis confirms positive sentiments across all listings, with luxury properties using the most optimistic language. Visualizations like TF-IDF, correlograms, sentiment scoring, and bigram networks support these insights in a dashboard. These findings offer actionable strategies for hosts, like tailoring descriptions to signal appropriate value for each pricing tier, balancing positivity with practical information to optimize listing performance.

TF-IDF Analysis

The first visualization in this study uses a TF-IDF analysis (Figure 1) to uncover the most distinctive words for each property type. This visualization clearly illustrates how language varies with price. Cheap listings are often filled with Chinese characters, other nationalities like 'Mexican', or time spams that maybe are to places potentially close to famous sightings, and even the word 'police', potentially indicating that cheap properties are in dangerous areas, and police is a token to make customers think that the area is safer. In contrast, expensive listings use words like 'kapalua' and other Hawaiian words, suggesting that most expensive listings are in Hawaii, 'generous', and 'management', which are service-related, and 'gold', indicating luxury and expensive things. These words not only indicate exclusivity but also prestige and status. Normal listings use functional but less emotionally powerful words like 'toddler', 'lodge', and 'vacation'. This tier appears to focus on practical descriptions over showing luxury, and also indicates more like properties more made for families and tourists.

Correlogram analysis

The correlogram (Figure 2) compares word frequency proportions between cheap, normal, and expensive listings. We can see some clear outliers like ‘villa’, ‘resort’, ‘pool’ for expensive properties, suggesting more exclusivity. For cheap, we can see ‘basement’ or ‘24h’, which may indicate properties that are in a house and that are for the short term. And in normal we can find ‘Astoria’ which indicates possibly a neighborhood with many normal price properties or ‘cute’ which may be a good adjective to identify the property type, in contrast to expensive that might be looking for adjectives like luxurious or prestigious. Both cheap and normal have a high frequency in tokens with minutes, potentially indicating that tourists choose those properties because they want to be near famous landmarks.

Sentiment Analysis AFINN, Bing, and NRC

The sentiment analysis (Figure 3) applies three lexicons to evaluate the emotional tone of listings. All three price categories display positive sentiment across all lexicons, affirming that Airbnb descriptions are written with the intent to persuade and attract. Expensive listings, however, exhibit the highest sentiment scores, particularly in the AFINN lexicon, where numeric intensity plays a key role. The dominance of positive words like ‘beautiful’, ‘enjoy’, and ‘quite ’ in all listing types reflects a marketing orientation. Having more emotion in expensive listings suggests an effort to match premium pricing with premium appeal.

Bigram Analysis

The bigram network graph (Figure 4) reveals that listings form dense clusters such as ‘short’, ‘walk’, ‘minutes’, and numbers between 5 and 20 that confirm our initial hypothesis that descriptions that are considered cheap or normal prioritize sinilazing that it is in a location walking distance and nearby tourist places. Another interesting cluster is ‘view’, ‘ocean’ and ‘mountain’,

indicating that clients value property with some kind of views, either the ocean if it is on the beach or the mountain. Lastly, an assumption that was 'village' is a token referring to 'East Village', which is a neighborhood in New York, not a property in a village.

Price Setting through Correlation Analysis

Using correlation (Figure 5), it was found that cheap listings had a correlation coefficient of 0.744 between cleaning fee and price, normal listings 0.758, and expensive listings 0.628. These results suggest that for affordable and mid-range listings, cleaning fees are strongly tied to the overall cost. In contrast, luxury listings show a weaker correlation, potentially because pricing is less itemized and more influenced by bundled services or brand prestige.

Additional Analytical Insights

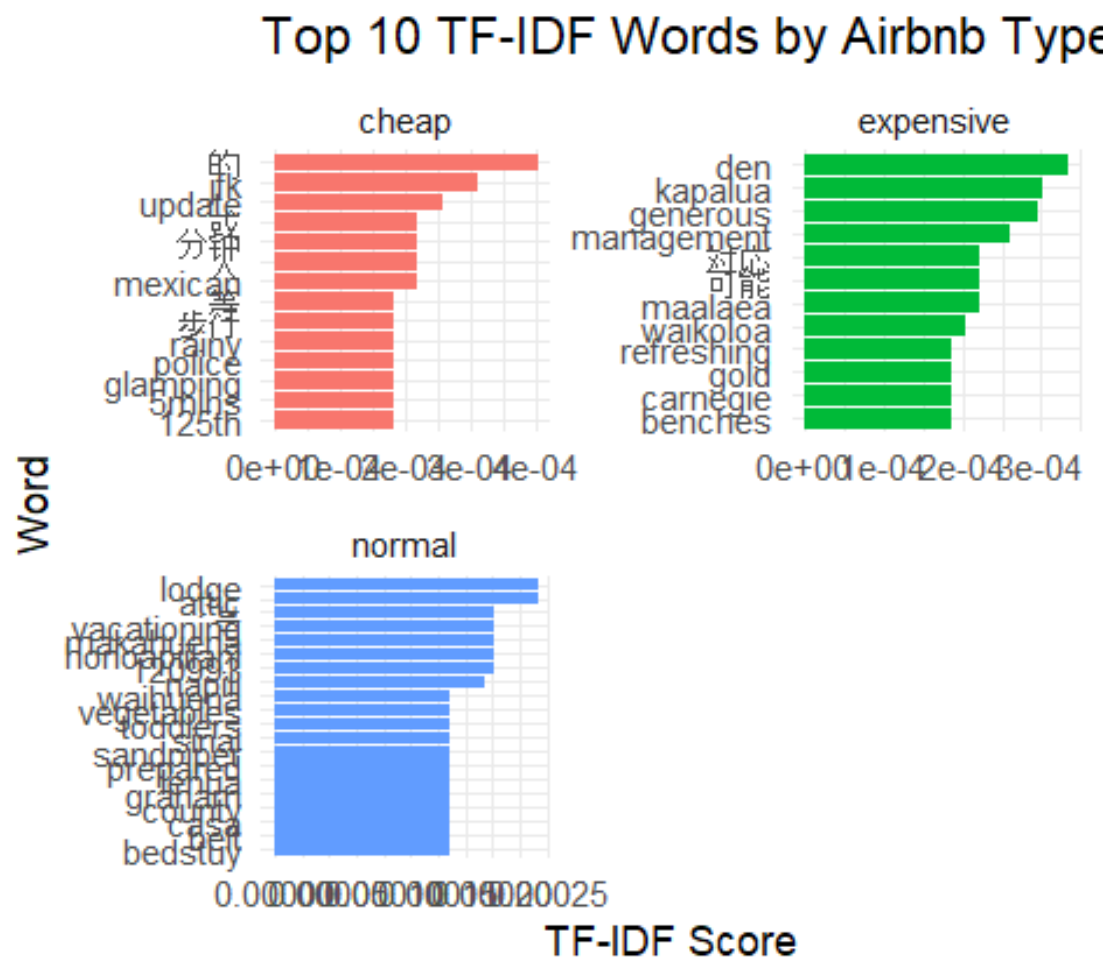
A Zipf's Law plot (Figure 6) confirms that all Airbnb listing types follow a common linguistic distribution, but normal ones have more unique tokens. Additionally, topic modeling through LDA (Figure 7), I found topics like nature, functional space, and convenience. These themes show that Airbnb listings focus on common user needs but are weighted differently according to the listing type.

Conclusion and dashboard

The Airbnb dashboard (Figure 8) brings together key visualizations that reveal how listing language aligns with pricing strategy. The TF-IDF/Quadrogram panel shows that expensive listings use exclusive, luxury-related tokens. The correlogram compares word proportions. The sentiment score chart shows that expensive listings are written in more emotionally positive tones. Finally, the bigram network shows clusters around walkability, scenic views, and convenience. The dashboard supports the conclusion that expensive listings benefit from persuasive, optimistic language, while value-tier listings are best served by emphasizing location and practical benefits.

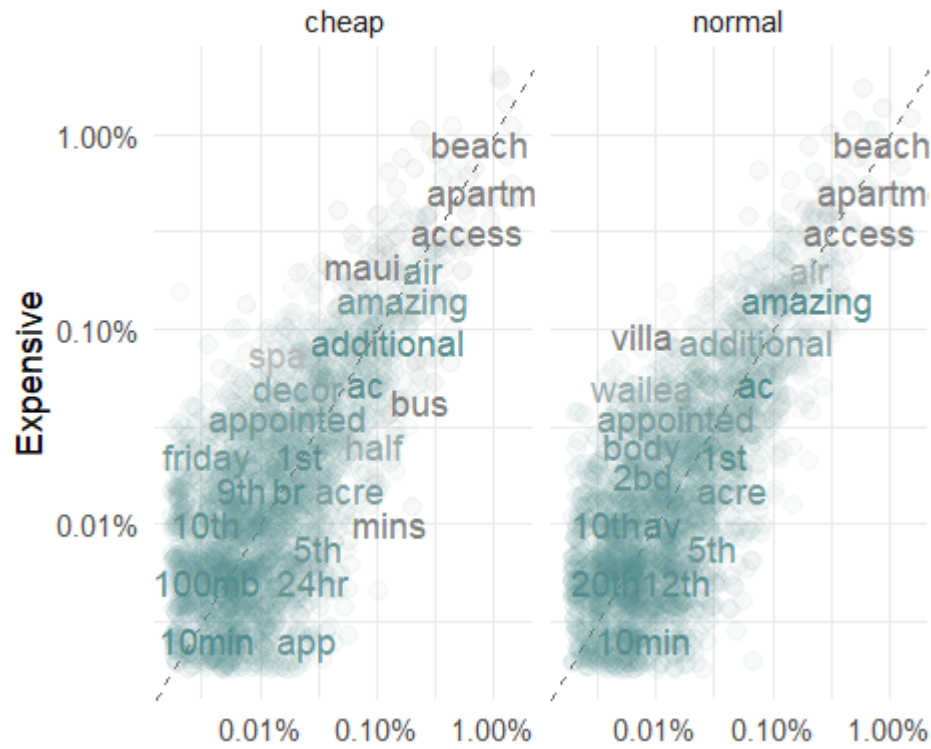
Appendix

(1)



(2)

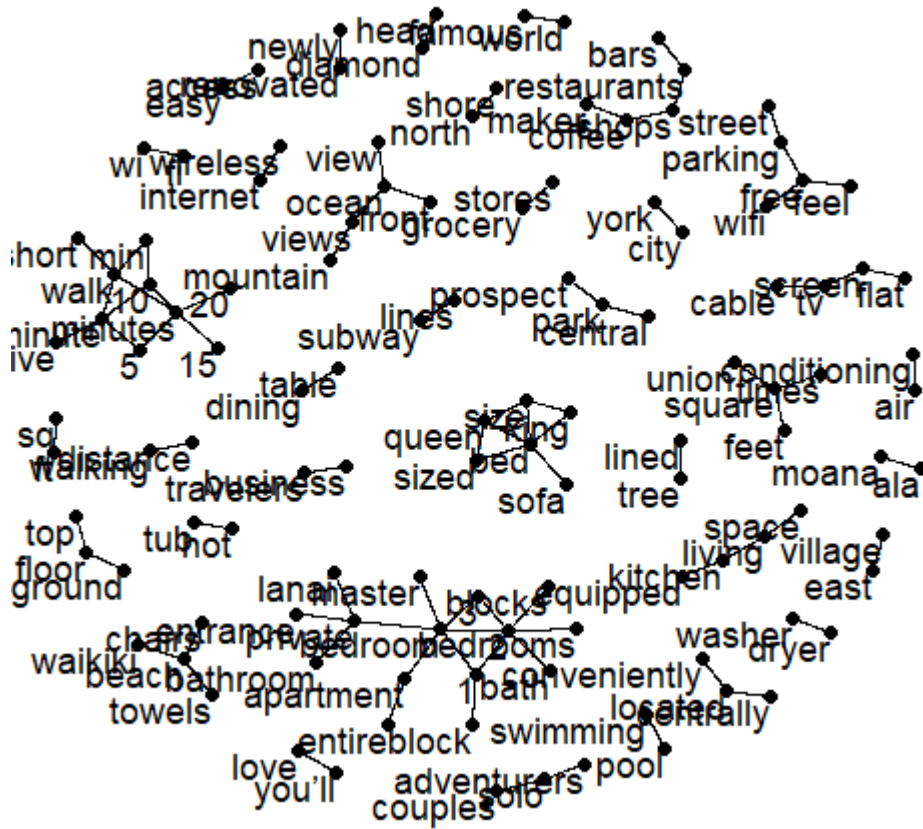
Comparing expensive with cheap and normal



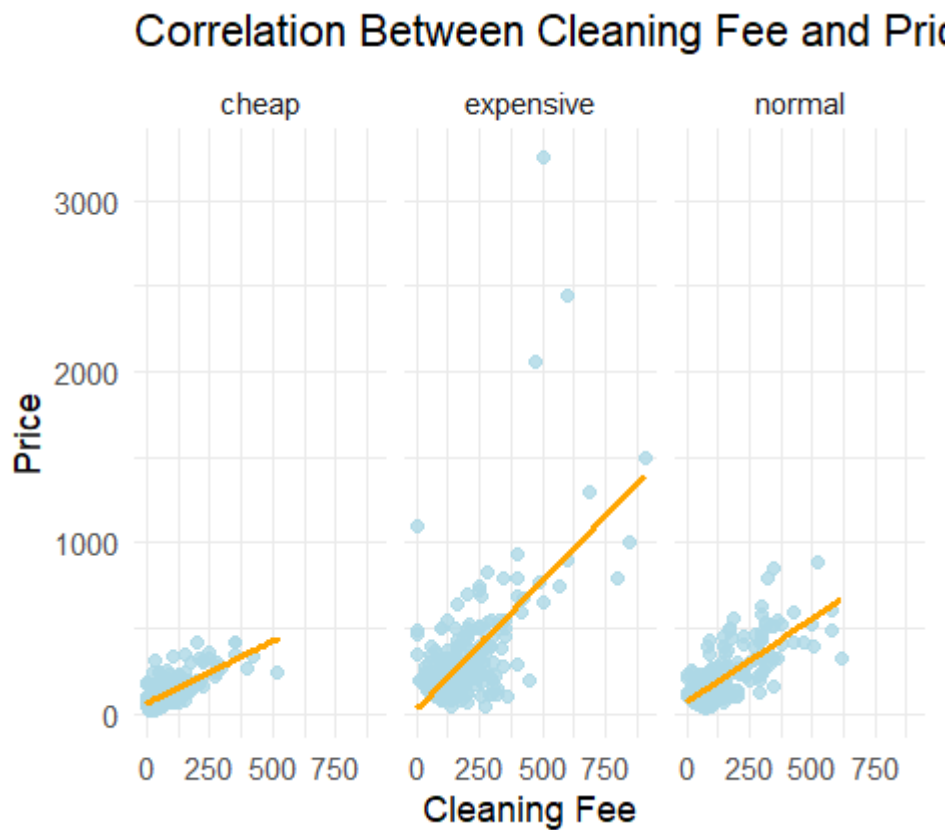
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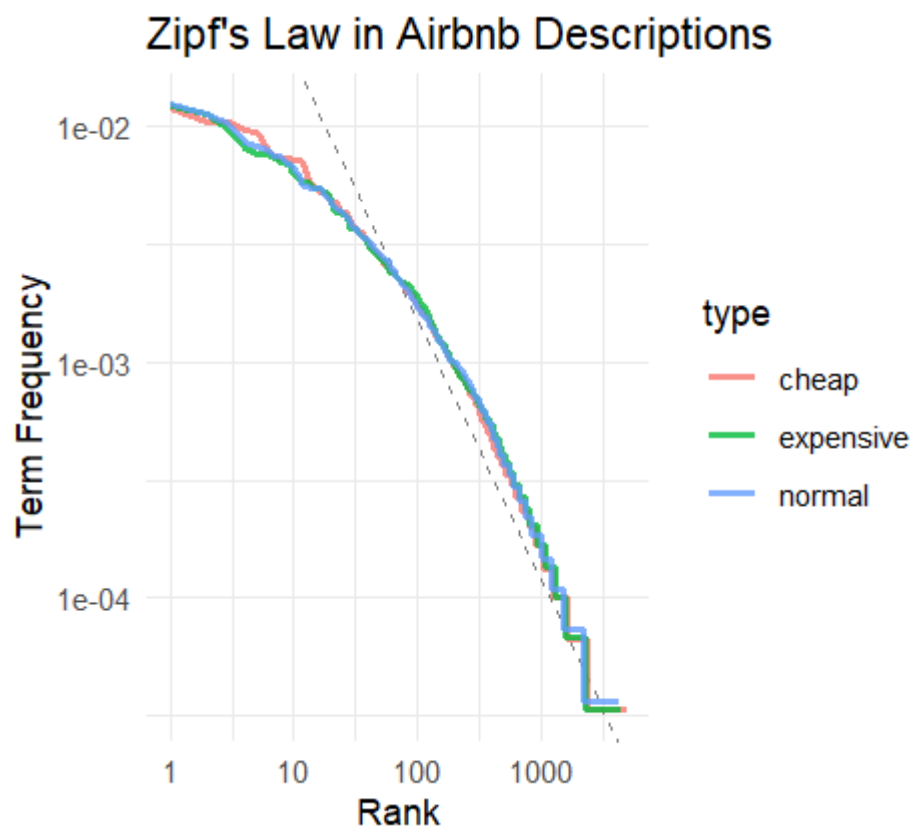
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(5)

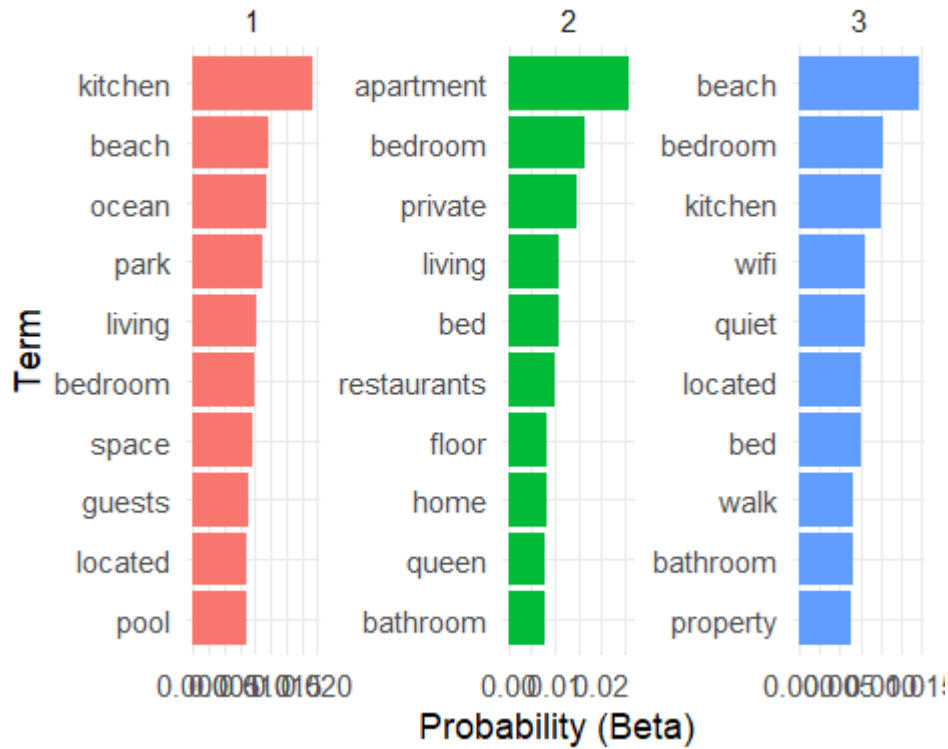


(6)



(7)

Top Terms per Topic in Airbnb Descript

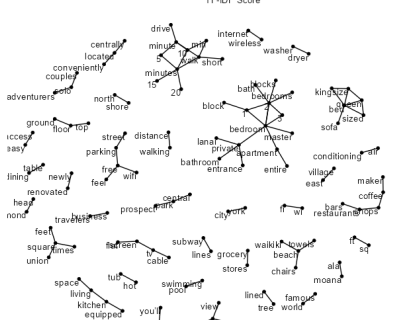
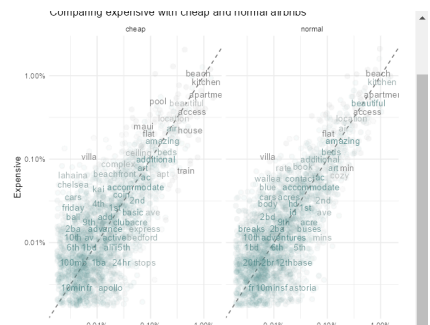
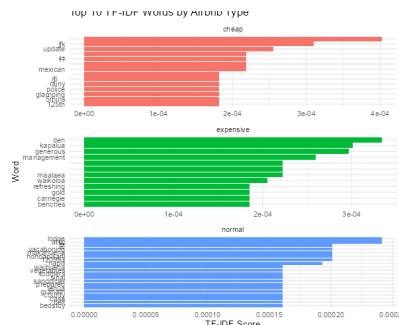


(8)

Select Airbnb Type:
All

Select Text View:
TF-IDF

Select Sentiment Graph:
Sentiment Score



(9)

Airbnb Property category Analysis

Select Airbnb Type:

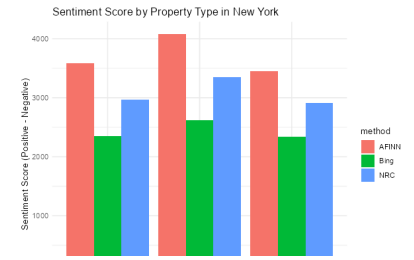
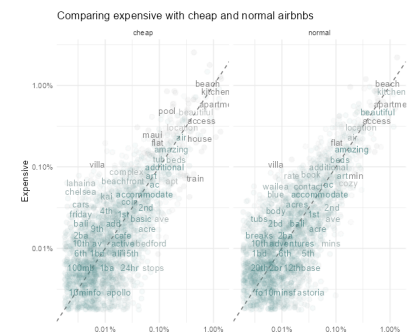
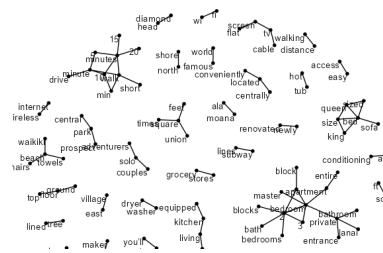
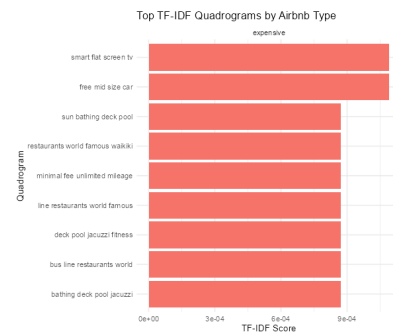
expensive

Select Text View:

Quadrogram

Select Sentiment Graph:

Sentiment Score



(10)

Select Airbnb Type:

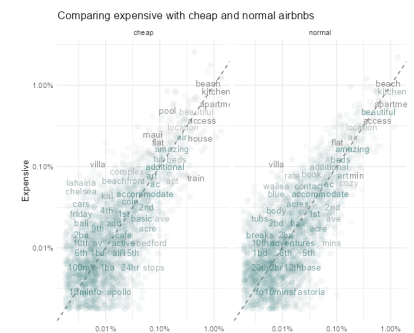
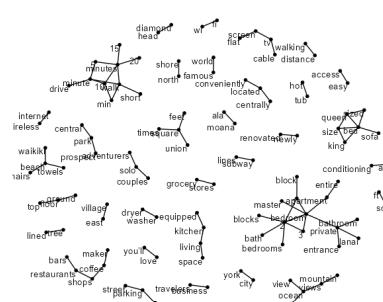
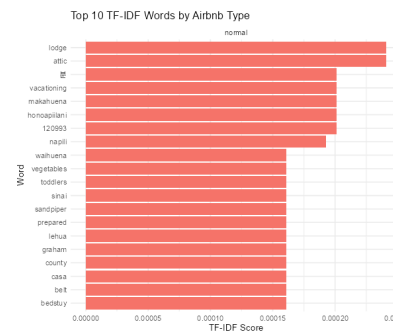
normal

Select Text View:

TF-IDF

Select Sentiment Graph:

Top Words



References

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