

Sentiment Analysis

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Today's Agenda

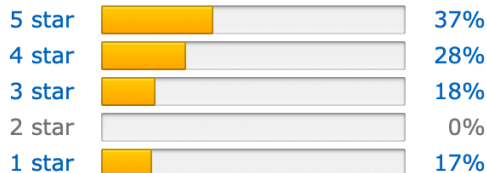
1. Guest Lecture (6:00-6:50PM)
2. Mini-Lecture and Lab Tutorial (7:20-8:20 PM)

Why Should We Care About Sentiment Analysis?

Customer reviews

★★★★☆ 3.7 out of 5

9 global ratings



▼ [How are ratings calculated?](#)

Top reviews



Top reviews from the United States



Troy summers



How u set up 3 Alexas 5 show. And 5 smart plugs. Help me

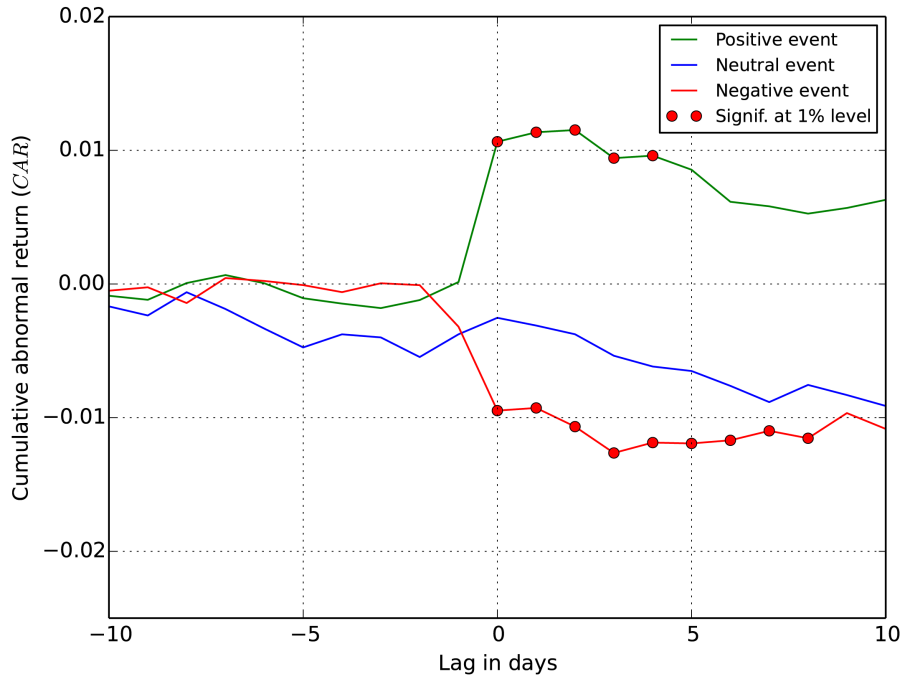
Reviewed in the United States on April 26, 2020

How u set it up, do I set it up with a smart plug, have 5, 3 Alex's and 5 show. Do I put in each room.

Helpful

| [Comment](#)

| [Report abuse](#)



Ranco, Gabriele, Darko Aleksovski, Guido Caldarelli, Miha Grčar, and Igor Mozetič. 2015. “The Effects of Twitter Sentiment on Stock Price Returns.” *PLOS ONE* 10(9):e0138441. doi: [10.1371/journal.pone.0138441](https://doi.org/10.1371/journal.pone.0138441).

Do Anti-Immigrant Laws Shape Public Sentiment? A Study of Arizona's SB 1070 Using Twitter Data¹

René D. Flores
University of Washington

Scholars have debated whether laws can influence public opinion, but evidence of these “feedback” effects is scant. This article examines the effect of Arizona’s 2010 high-profile anti-immigrant law, SB 1070, on both public attitudes and behaviors toward immigrants. Using sentiment analysis and a difference-in-difference approach to analyze more than 250,000 tweets, the author finds that SB 1070 had a negative impact on the average sentiment of tweets regarding immigrants, Mexicans, and Hispanics, but not on those about Asians or blacks. However, these changes in public discourse were not caused by shifting attitudes toward immigrants but by the mobilization of anti-immigrant users and by motivating new users to begin tweeting. While some scholars propose that punitive laws can shape people’s attitudes toward targeted groups, this study shows that policies are more likely to influence behaviors. Rather than placating the electorate, anti-immigrant laws may stir the pot further, mobilizing individuals already critical of immigrants.

TABLE A3
EXAMPLES OF TWEET SENTIMENT CLASSIFICATION

Sentiment Score	Message	Polarity
-1.65	URL illegal aliens are criminals . . .	Negative
-1.01	deport illegal aliens. what example are we giving our children?	Negative
-.96	trespass invasion robbery cheat murder rape get amnesty i detest playing soccer against beaners . . . dirty mexicans	Negative
0	immigration and commerce with mexico. on both, arizona politicians should consider the broader economic impact	Neutral
0	news service (via @username): immigration measures bring reactions from both sides, URL	Neutral
0	advocacy groups say obama continues committed to immigration reform, groups . . . URL	Neutral
.51	it is great to see young successful black people . . . yo check out awesome writer @username	Positive
.75	Inlovewithimmigrants, i love soccer!	Positive
1.25	asians are awesome :)	Positive

NOTE.—Tweets were modified slightly to protect the anonymity of Twitter users.

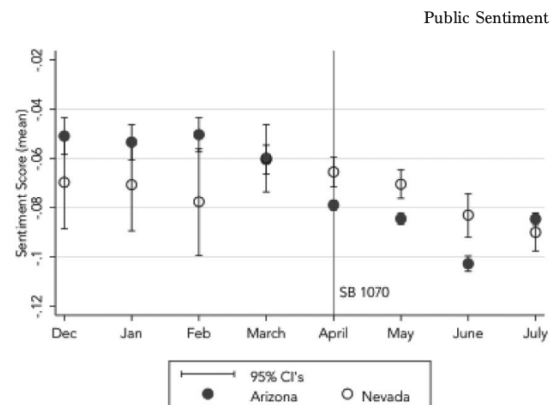


FIG. 3.—Average sentiment score of tweets about immigrants. The vertical lines represent 95% confidence intervals. The vertical line on April 2010 indicates when the Arizona governor approved SB 1070.



Article

Sentiment Analysis Based on Deep Learning: A Comparative Study

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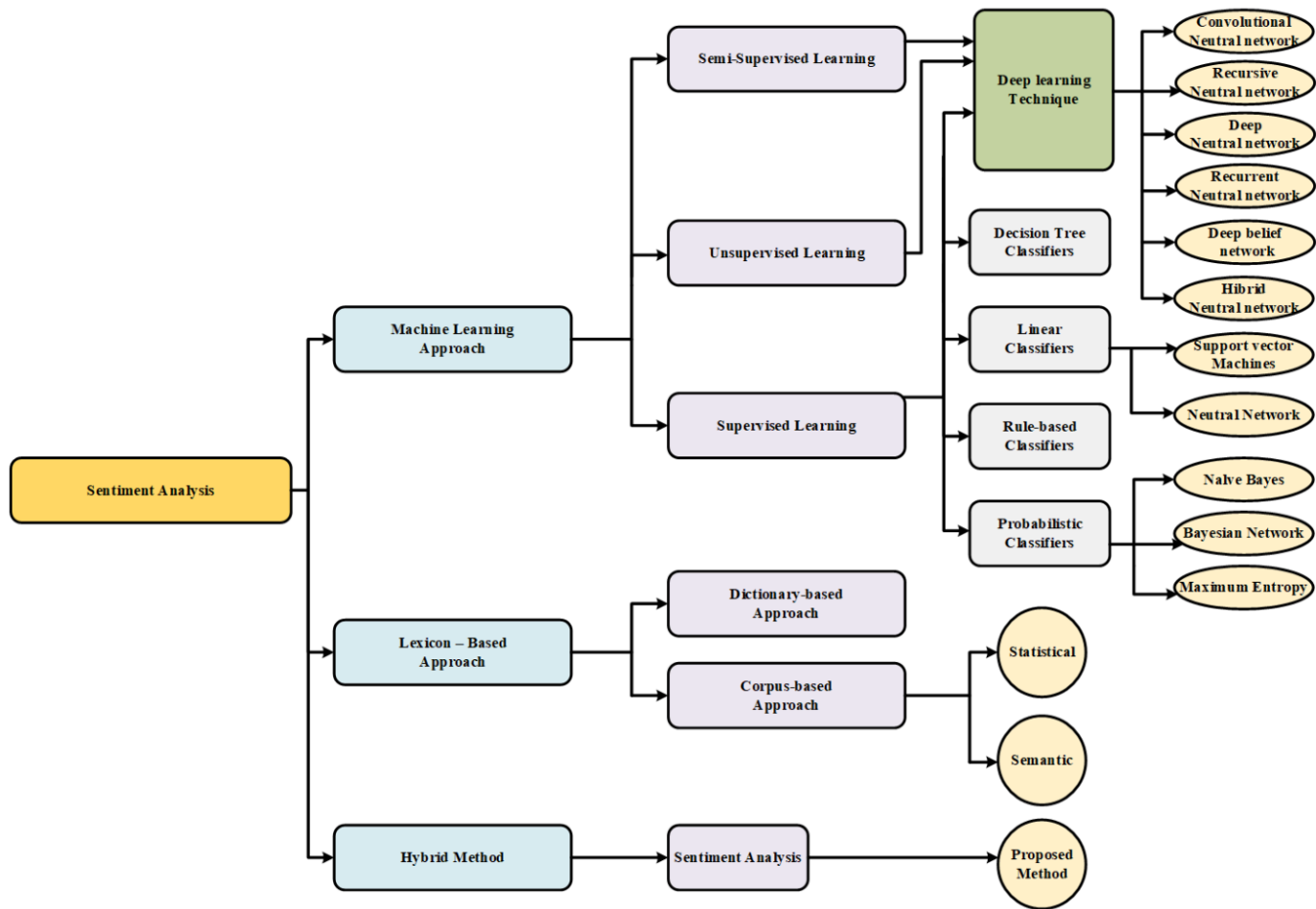
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Sentiment Lexicons

The General Inquirer

<http://www.wjh.harvard.edu/~inquirer/>

LIWC (Linguistic Inquiry and Word Count)

Pennebaker, J.W., Booth, R.J., & Francis, M.E. (2007). Linguistic Inquiry and Word Count: LIWC 2007. Austin, TX

<http://liwc.wpengine.com/>

MPQA Subjectivity Cues Lexicon

Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. Proc. of HLT-EMNLP-2005.

Riloff and Wiebe (2003). Learning extraction patterns for subjective expressions. EMNLP-2003.

https://mpqa.cs.pitt.edu/lexicons/subj_lexicon/

Bing Liu Opinion Lexicon

<https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html>

Loughran and McDonald Sentiment Word Lists

Tim Loughran and Bill McDonald, 2011, When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks, *Journal of Finance*, 66:1, 35-65. (Available at SSRN: <http://ssrn.com/abstract=1331573>.)

QDAP Dictionary

http://trinker.github.io/qdap/vignettes/qdap_vignette.html

A Review of Sentiment Analysis in R

Naldi, Maurizio. 2019. “A Review of Sentiment Computation Methods with R Packages.” *ArXiv:1901.08319 [Cs]*.

1. syuzhet;
2. Rsentiment;
3. SentimentR;
4. SentimentAnalysis

Movie Review Data

<http://www.cs.cornell.edu/people/pabo/movie-review-data/>

Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan, [Thumbs up? Sentiment Classification using Machine Learning Techniques](#), *Proceedings of EMNLP 2002*.

Bo Pang and Lillian Lee, [A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts](#), *Proceedings of ACL 2004*.

Bo Pang and Lillian Lee, [Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales](#), *Proceedings of ACL 2005*.

Moving Toward Deep Learning Approaches

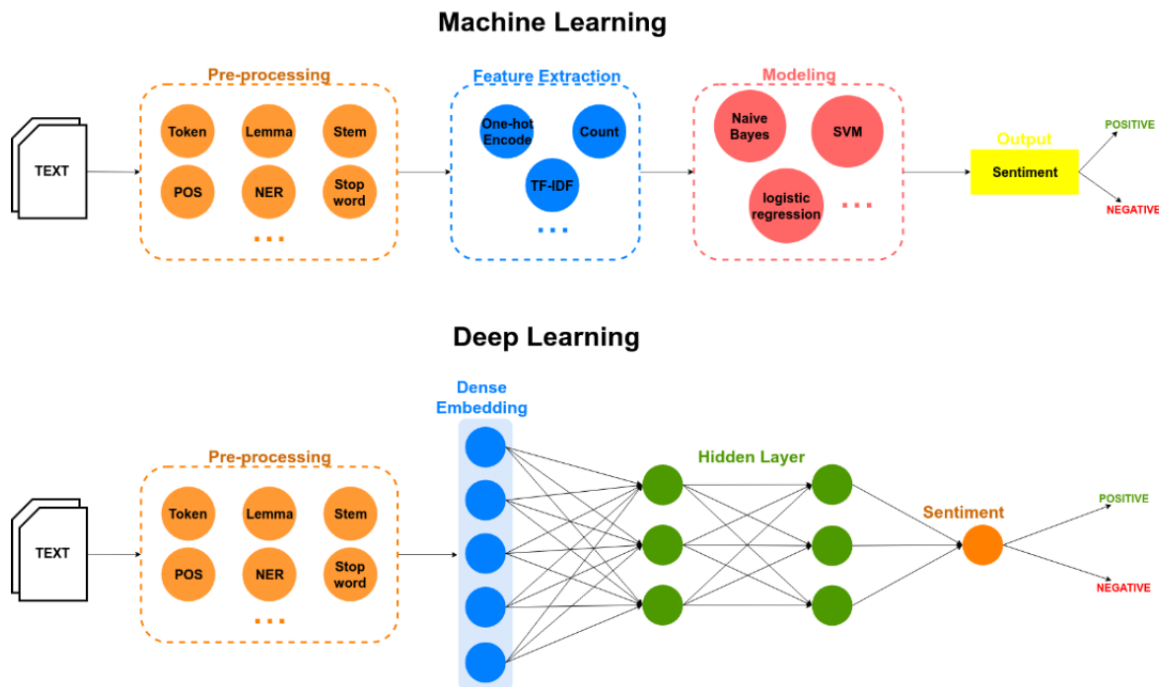


Figure 1. Differences between two classification approaches of sentiment polarity, machine learning (top), and deep learning (bottom). Part of Speech (POS); Named Entity Recognition (NER); Term Frequency-Inverse Document Frequency (TF-IDF).

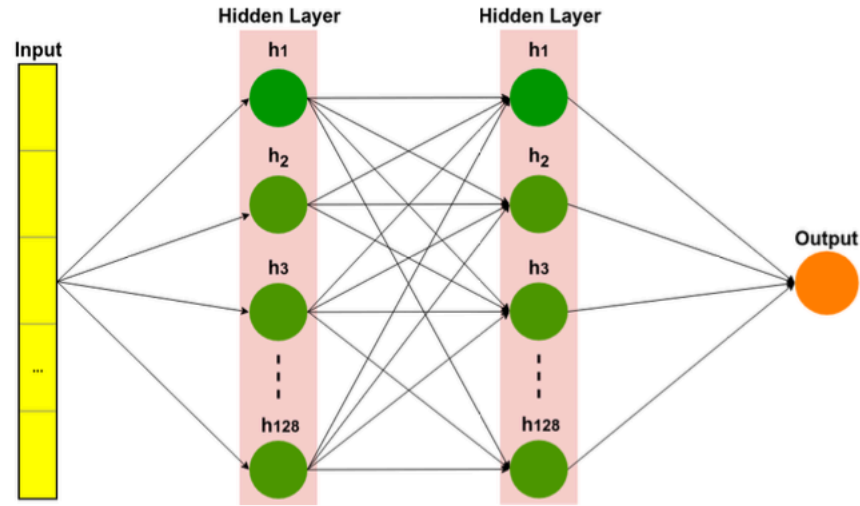


Figure 2. Deep neural network (DNN).

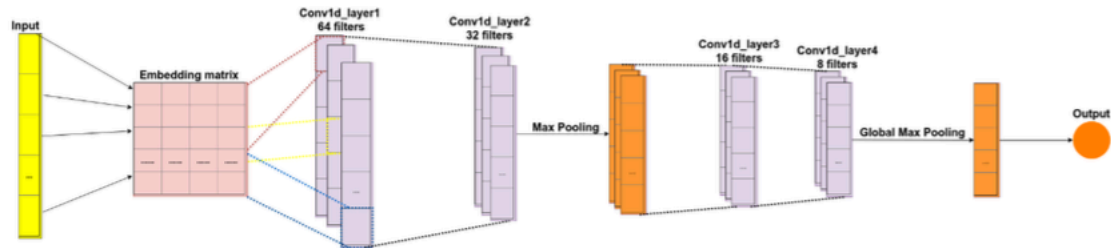


Figure 3. A convolutional neural network.

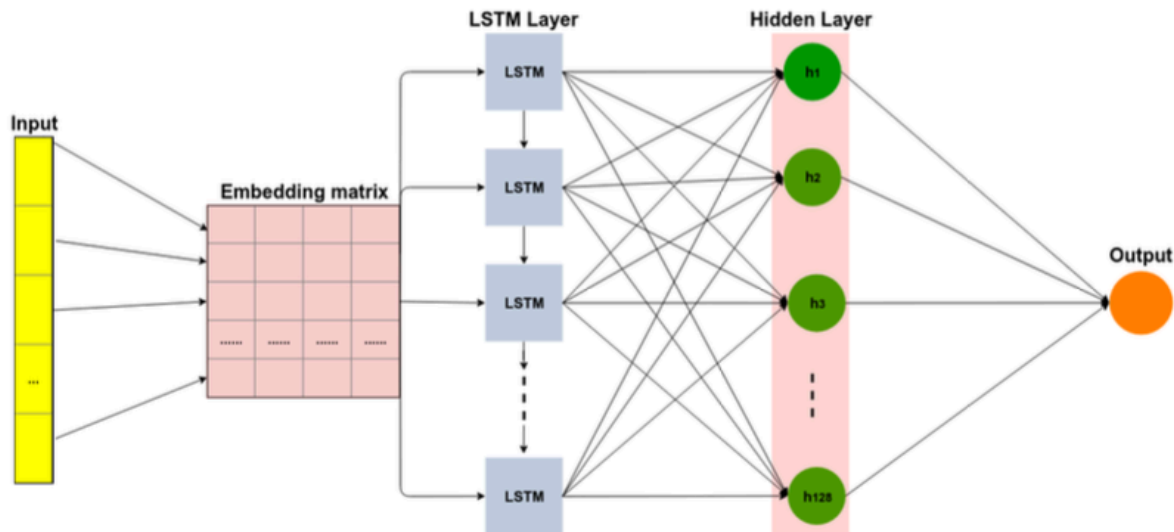


Figure 4. A long short-term memory network. LSTM, long short-term memory.

Moving toward a Deep Learning Approach

https://tensorflow.rstudio.com/guide/keras/examples/imdb_fasttext/

https://github.com/rstudio/keras/blob/master/vignettes/examples/imdb_fasttext.R

https://tensorflow.rstudio.com/guide/keras/examples/imdb_lstm/

https://github.com/rstudio/keras/blob/master/vignettes/examples/imdb_lstm.R

Sentiment Analysis API

Google Cloud NLP Sentiment API

<https://cloud.google.com/natural-language/docs/sentiment-tutorial>

Microsoft Azure Text Analytics API

<https://docs.microsoft.com/en-us/azure/cognitive-services/text-analytics/>

<https://docs.microsoft.com/en-us/azure/cognitive-services/text-analytics/quickstarts/text-analytics-sdk?pivots=programming-language-python&tabs=version-3-1#sentiment-analysis>

Thank you!

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