Bias in News Headlines

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Introduction

- News contain stereotypes
- Find biases towards minorities
    - refugees
    - politics
    - anything controversial
- Topic detection
- Detecting biases for selected topics
    - domain classifier
    - sentiment analysis

Definition of Bias

- “Bias in cognitive science is generally defined as a *deviation from a norm*, deviation from some true or objective value.”
- Deviation from *mean topic sentiment*
- Deviation from *mean topic flavour*
- Domain classification

Data

- Get data from Newspaper APIs
- First: Kaggle News Aggregator Dataset
  - small timespan in 2014
  - limited number of categories
  - no politics
- Then: Reddit API (r/worldnews)
  - selected most occurring domains
  - about 43,000 news headlines from 2016 and 2017
  - over 200 frequently occurring domains

General Sentiment Analysis Results

- Sentiment Analysis for each headline, value between -1 and 1.
- The average sentiments of the respective domains differ a lot, e.g.:
  - domains with very negative average sentiment (around -0.3):
    - alertnet.org
    - antiwar.com
    - generally world news outlets
  - domains with relatively positive average sentiment (around -0.1):
    - bloomberg.com
    - economist.com
    - generally newspapers about economy or science

Topic Detection

- We want to find possibly controversial topics
- LDA
- Biterm Topic Model [1]

[1] Yan, X., Guo, J., Lan, Y., & Cheng, X. (2013, May). A biterm topic model for short texts. In Proceedings of the 22nd international conference on World Wide Web (pp. 1445-1456). ACM.

Biterm Topic Model

- Better for smaller texts than LDA
- LDA: model a document as a mixture of topics
- BTM: model whole corpus as a mixture of topics

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Topics

- Cluster the 2017 dataset into 20 topics
- Determine the topic from the 20 top words for that topic
- Validate using small study
  - Ask participants to determine the topic, and to rate how coherent the topic was on a 7 point scale
- Use the most coherent & controversial topics for analysis

Topics

Keywords	Topic	Average Rating
election, EU, Brexit, vote, party, president, minister, UK, parliament, presidential, Theresa, May, says, prime, European, Le, Pen, government, would, French	EU Politics	5.66
Russian, Russia, US, intelligence, Trump, hacking, hackers, attack, cyber, CIA, FBI, security, government, former, ex, spy, data, says, officials	Cyber security/Russian interference with US elections	6
Germany, party, Trump, right, says, German, Nazi, world, anti, social, pope, new, election, far, Brexit, leader, president, French, speech, saying	Right-wing politics/populism	4.33

Topics

Keywords	Topic	Average Rating
first, flight, china, flights, new, jet, air, London, passengers, airport, India, service, aircraft, plane, passenger, longest, flying, queen, test, year	Flights?	5
billion, oil, million, china, energy, year, world, record, company, tax, new, percent, 2016, India, market, government	Asian economy/energy market	3.66
Korea, navy, south, china, u, military, japan, sea, Korean, aircraft, north, missile, carrier, Chinese, US, force, air, Russian, missiles, Japanese	Asian military activity	3

Sentiment Analysis

- Sentiment analysis doesn’t work well to detect bias on its own
  - Some topics (e.g. war, crime) are more negative in general
- However, it still works if we check if news outlets deviate from the *mean topic sentiment*

- VADER (Valence Aware Dictionary and sEntiment Reasoner)
  - Takes negations into account (“not good”)

Sentiment analysis

Deviation from mean topic sentiment

	EU Politics	Cyber Security & Russian Hacking	Right-wing politics/populism	Middle East conflicts	Israel
Mean topic sentiment	-0.041	-0.111	-0.111	-0.128	0.215
washingtonpost.com	0.048	-0.021	0.150	0.063	0.093
rt.com	-0.035	0.009	-0.030	0.013	-0.281
nytimes.com	0.039	-0.084	0.226	-0.032	0.100
theguardian.com	-0.009	-0.055	-0.075	-0.071	-0.008
independent.co.uk	-0.064	0.063	-0.105	-0.082	-0.089
dw.com	-0.039	-0.045	0.038	0.020	0.030
cbc.ca	0.019	-0.089	0.109	-0.062	0.047
cnn.com	-0.029	0.020	-0.160	0.038	0.043
reuters.com	0.088	0.035	0.120	0.079	0.089
bloomberg.com	0.121	-0.011	-0.031	-0.070	0.034
bbc.com	-0.039	-0.004	-0.038	-0.070	-0.033
foxnews.com	-0.043	0.076	-0.132	-0.026	-0.217

Red = statistically significant with $p < 0.05$ according to two-sided T-test

Flavour

- Idea: news outlets that use flavourful words (adjectives and adverbs) can induce more bias in the reader
- Detect adjectives, adverbs, comparatives and superlatives using NLTK
- Count the number of flavour words, normalize by sentence length
- Compute the deviation from the *mean topic flavour*

Flavour analysis

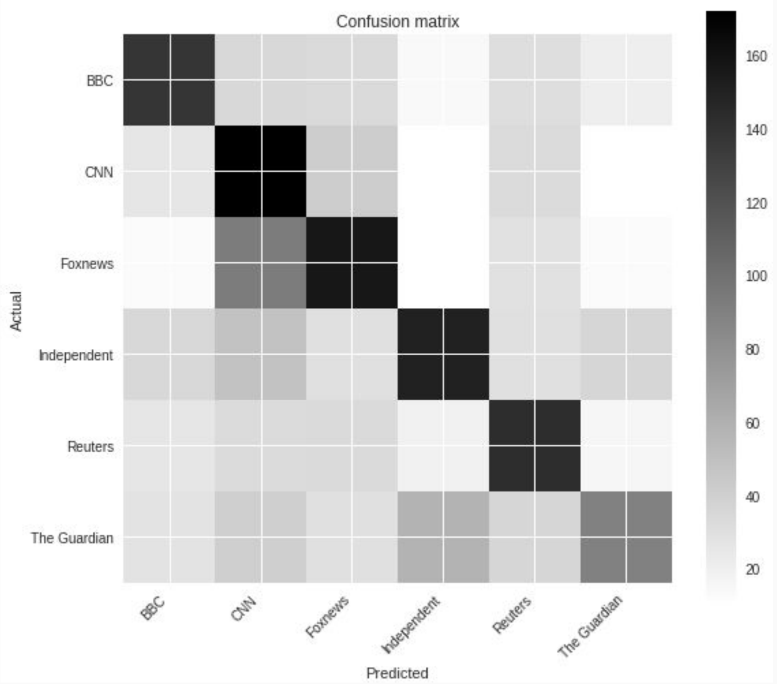
Deviation from mean topic flavour

	EU Politics	Cyber Security & Russian Hacking	Right-wing politics/populism	Middle East conflicts	Israel
Mean topic flavour	0.099	0.099	0.095	0.095	0.118
washingtonpost.com	0.011	-0.026	0.040	0.015	0.132
rt.com	0.028	0.040	-0.014	0.014	-0.028
nytimes.com	-0.051	-0.062	-0.073	-0.060	0.007
theguardian.com	0.009	-0.003	-0.016	-0.001	-0.002
independent.co.uk	-0.002	0.018	0.024	0.011	0.001
dw.com	0.026	-0.000	0.027	0.014	-0.037
cbc.ca	0.021	0.050	0.003	0.007	-0.060
cnn.com	-0.007	0.009	-0.020	-0.006	0.124
reuters.com	0.018	0.010	0.015	0.006	-0.032
bloomberg.com	-0.050	-0.080	-0.077	-0.052	-0.087
bbc.com	-0.018	-0.009	-0.013	-0.003	0.001
foxnews.com	0.023	0.044	0.031	0.005	-0.119

Red = statistically significant with $p < 0.05$ according to two-sided T-test

Domain Classification

- Bag of Words model with a Random Forest Classifier
- 6 selected domains
- F1-Score: 0.4815



Domain Classification

Most indicative words:

- **BBC**: festival, became, part, football, children, sues, injures
- **CNN**: ISIS, US, enough, Erdogan, Christmas, revenge, NASA, mosul, hotel, apartment, Aleppo, USS, team
- **Foxnews**: reportedly, Venezuelan, latest, Iran
- **Reuters**: oil, speed
- **The Guardian**: land, Erdo, soar, project
- **The Independent**: refugees, trade, UK, green, Corbyn

Conclusion

- There are measurable biases in newspaper headlines
- Classification goes surprisingly well
- Differences are significant

Discussion

- How suitable is our approach for news bias detection?
  - Is Sentiment Analysis accurate enough?
  - Does it become accurate on average for a big number of headlines?
  - What kind of bias does Flavour Analysis indicate? How do we interpret the flavour matrix?
- Do you think we could prove a bias for certain domains?
- What could we have done better?

Thank you for your attention!