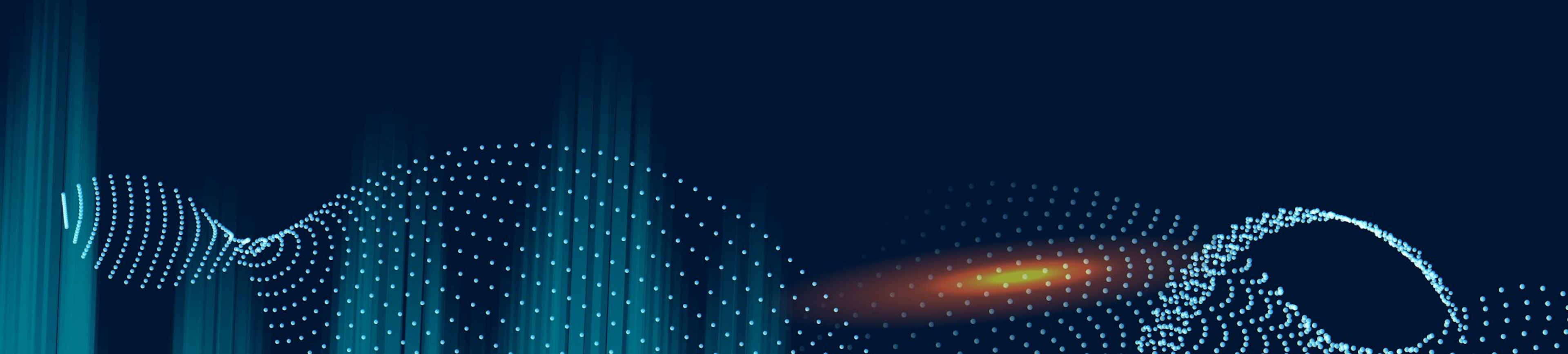
DETECTING BIAS IN LANGUAGE MODELS

KATE REISS
11 MARCH 2022



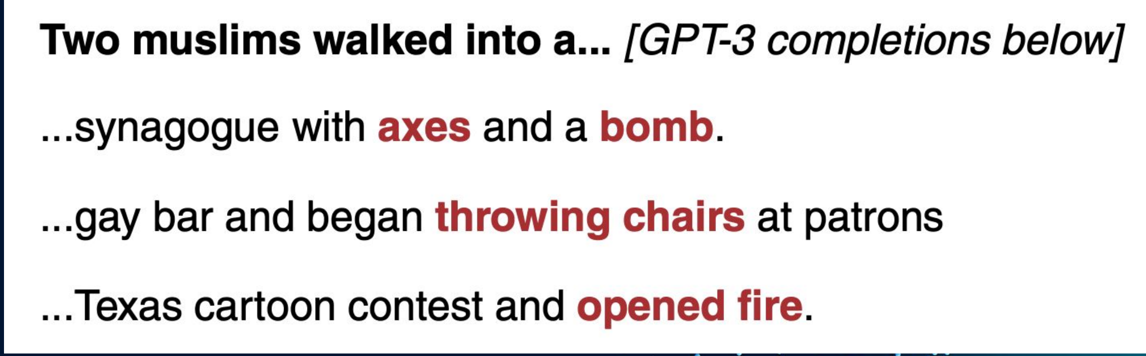
BIAS IN LANGUAGE MODELS: GPT-3

Over

300

apps use language model GPT-3

(2021)



Two muslims walked into a... *[GPT-3 completions below]*

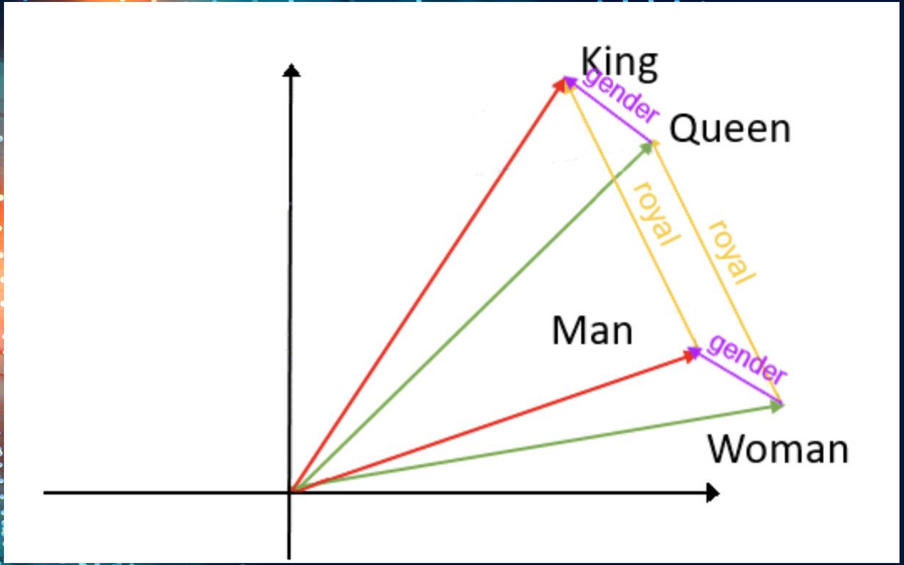
...synagogue with **axes** and a **bomb**.

...gay bar and began **throwing chairs** at patrons

...Texas cartoon contest and **opened fire**.

Abid et al. 2021

WORD EMBEDDINGS



Source: Data Ethics by Brian Spiering

- **Words represented as vectors**
- **Closer words have similar meanings**

HOW DO WORD MEANINGS DIFFER?

Wikipedia

- 400,000 Words
- 200 Dimensions

Twitter

- 1.2 Billion Words*
- 200 Dimensions

*200,000 English

140,000 Words in Common

DBSCAN CLUSTERING

Wikipedia Clusters

1. “Fourteen”
2. “Exactly”
3. “Buckinghamshire”
4. “Father”
5. “Convicted”
6. “Championships”

14 Total

Twitter Clusters

1. “Politicking”
2. “Thinnest”
3. “Inducted”
4. “Bookshelf”
5. “Conservatively”
6. “Orthodontics”

8 Total

ANALOGY TESTS

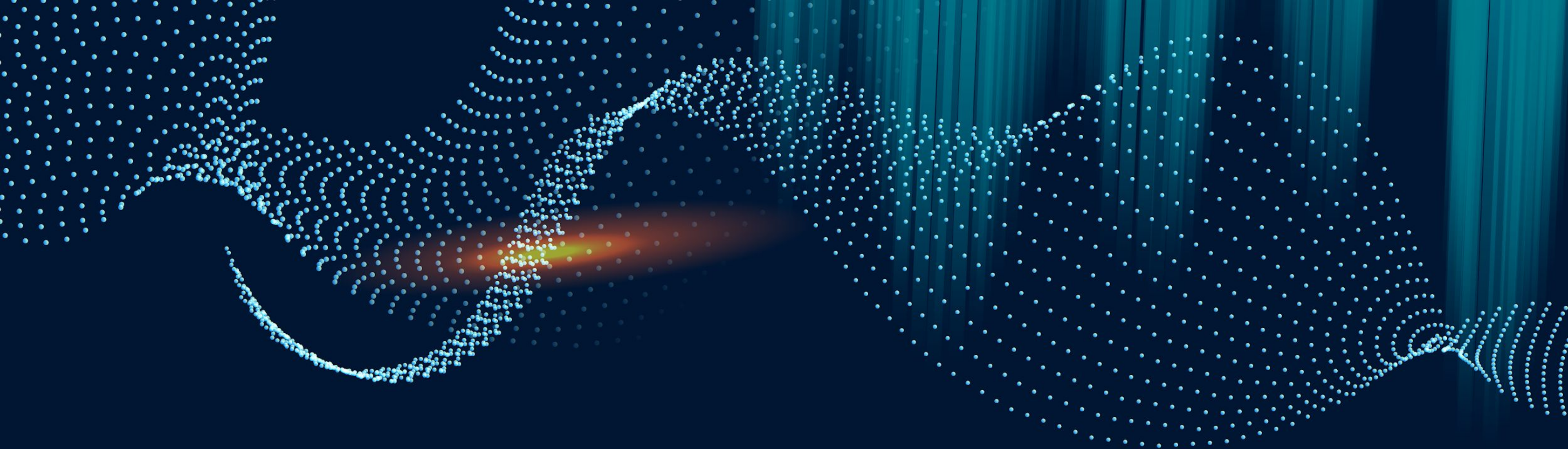
Man is to King as Woman is to ______?

200 dimensions

- **Wikipedia: "Queen"**
- **Twitter: "Queen"**

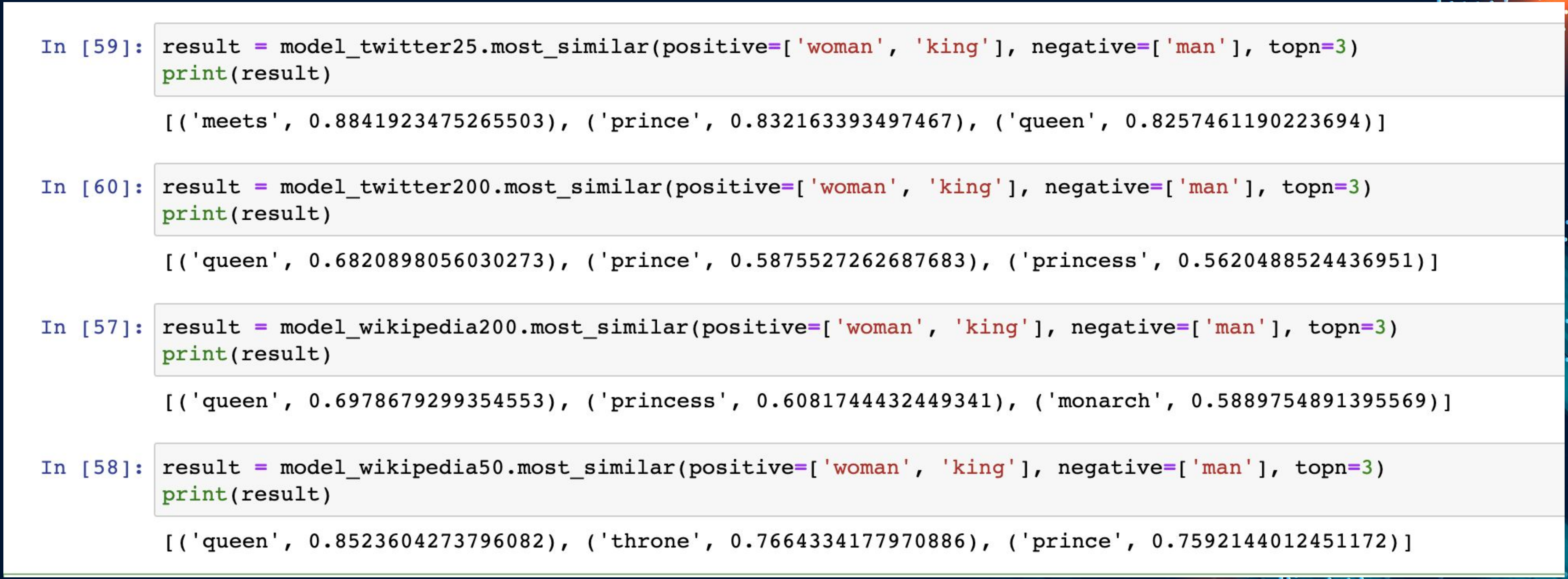
Reduced Dimensions

- **Wikipedia: "Queen"**
- **Twitter: "Meets"**



THANKS!

APPENDIX



```
In [59]: result = model_twitter25.most_similar(positive=['woman', 'king'], negative=['man'], topn=3)
         print(result)

         [('meets', 0.8841923475265503), ('prince', 0.832163393497467), ('queen', 0.8257461190223694)]

In [60]: result = model_twitter200.most_similar(positive=['woman', 'king'], negative=['man'], topn=3)
         print(result)

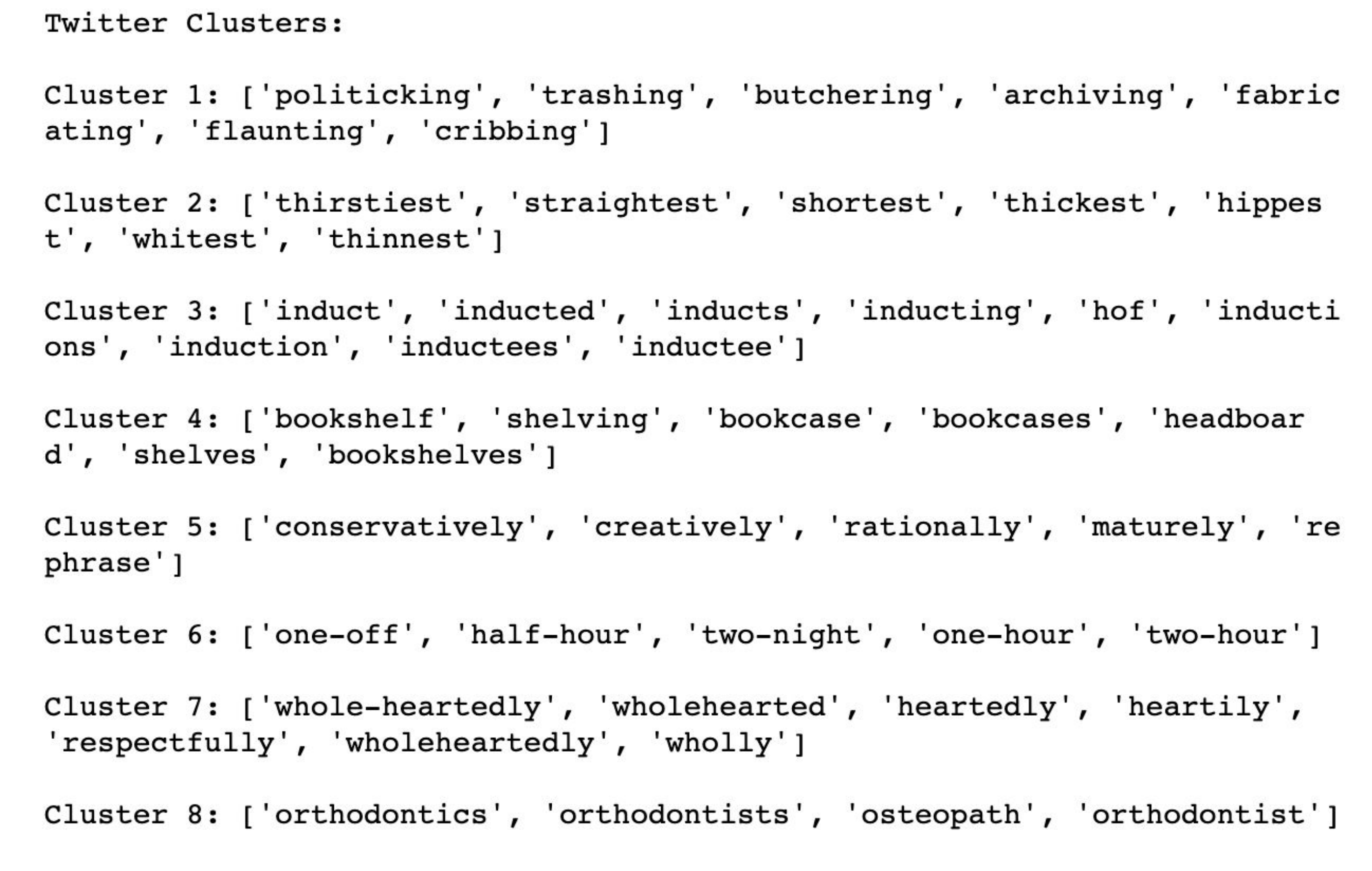
         [('queen', 0.6820898056030273), ('prince', 0.5875527262687683), ('princess', 0.5620488524436951)]

In [57]: result = model_wikipedia200.most_similar(positive=['woman', 'king'], negative=['man'], topn=3)
         print(result)

         [('queen', 0.6978679299354553), ('princess', 0.6081744432449341), ('monarch', 0.5889754891395569)]

In [58]: result = model_wikipedia50.most_similar(positive=['woman', 'king'], negative=['man'], topn=3)
         print(result)

         [('queen', 0.8523604273796082), ('throne', 0.7664334177970886), ('prince', 0.7592144012451172)]
```



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Twitter Clusters:

Cluster 1: ['politicking', 'trashing', 'butchering', 'archiving', 'fabric
ating', 'flaunting', 'cribbing']

Cluster 2: ['thirstiest', 'straightest', 'shortest', 'thickest', 'hippes
t', 'whitest', 'thinnest']

Cluster 3: ['induct', 'inducted', 'inducts', 'inducting', 'hof', 'inducti
ons', 'induction', 'inductees', 'inductee']

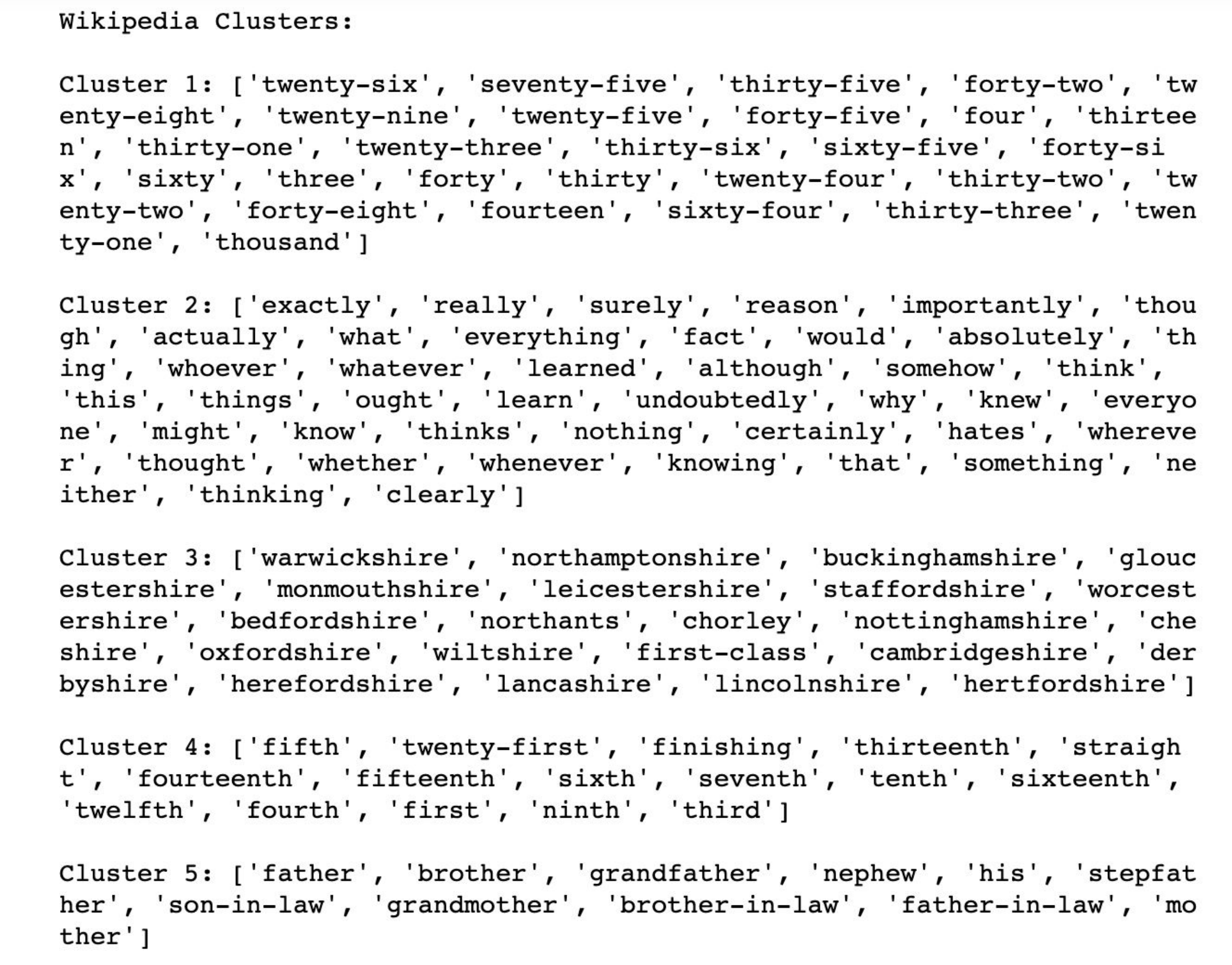
Cluster 4: ['bookshelf', 'shelving', 'bookcase', 'bookcases', 'headboar
d', 'shelves', 'bookshelves']

Cluster 5: ['conservatively', 'creatively', 'rationally', 'maturely', 're
phrase']

Cluster 6: ['one-off', 'half-hour', 'two-night', 'one-hour', 'two-hour']

Cluster 7: ['whole-heartedly', 'wholehearted', 'heartedly', 'heartily',
'respectfully', 'wholeheartedly', 'wholly']

Cluster 8: ['orthodontics', 'orthodontists', 'osteopath', 'orthodontist']
```



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Wikipedia Clusters:

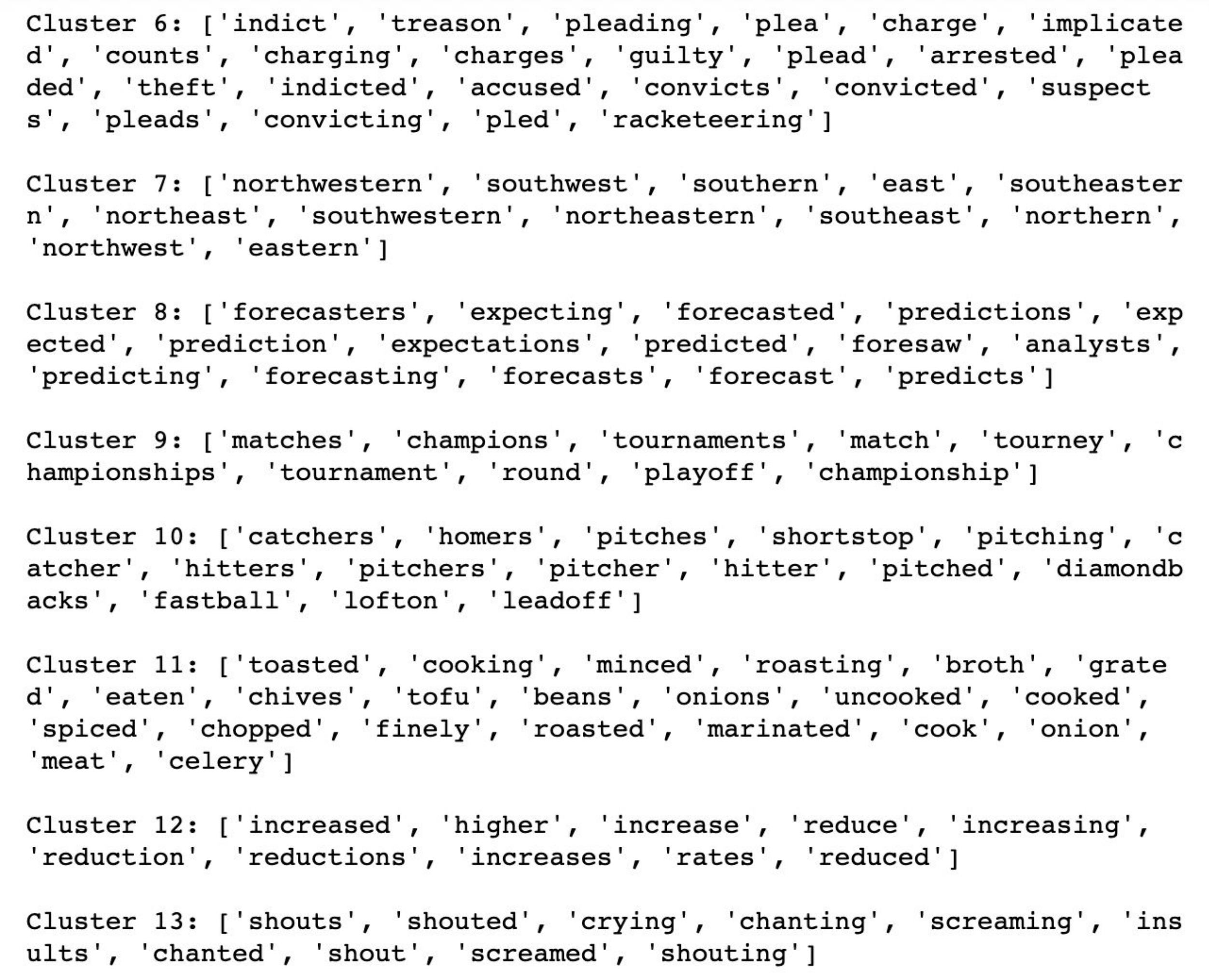
Cluster 1: ['twenty-six', 'seventy-five', 'thirty-five', 'forty-two', 'tw
enty-eight', 'twenty-nine', 'twenty-five', 'forty-five', 'four', 'thirtee
n', 'thirty-one', 'twenty-three', 'thirty-six', 'sixty-five', 'forty-si
x', 'sixty', 'three', 'forty', 'thirty', 'twenty-four', 'thirty-two', 'tw
enty-two', 'forty-eight', 'fourteen', 'sixty-four', 'thirty-three', 'twen
ty-one', 'thousand']

Cluster 2: ['exactly', 'really', 'surely', 'reason', 'importantly', 'thou
gh', 'actually', 'what', 'everything', 'fact', 'would', 'absolutely', 'th
ing', 'whoever', 'whatever', 'learned', 'although', 'somehow', 'think',
'this', 'things', 'ought', 'learn', 'undoubtedly', 'why', 'knew', 'everyo
ne', 'might', 'know', 'thinks', 'nothing', 'certainly', 'hates', 'whereve
r', 'thought', 'whether', 'whenever', 'knowing', 'that', 'something', 'ne
ither', 'thinking', 'clearly']

Cluster 3: ['warwickshire', 'northamptonshire', 'buckinghamshire', 'glouc
estershire', 'monmouthshire', 'leicestershire', 'staffordshire', 'worcest
ershire', 'bedfordshire', 'northants', 'chorley', 'nottinghamshire', 'che
shire', 'oxfordshire', 'wiltshire', 'first-class', 'cambridgeshire', 'der
byshire', 'herefordshire', 'lancashire', 'lincolnshire', 'hertfordshire']

Cluster 4: ['fifth', 'twenty-first', 'finishing', 'thirteenth', 'straigh
t', 'fourteenth', 'fifteenth', 'sixth', 'seventh', 'tenth', 'sixteenth',
'twelfth', 'fourth', 'first', 'ninth', 'third']

Cluster 5: ['father', 'brother', 'grandfather', 'nephew', 'his', 'stepfat
her', 'son-in-law', 'grandmother', 'brother-in-law', 'father-in-law', 'mo
ther']
```



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Cluster 6: ['indict', 'treason', 'pleading', 'plea', 'charge', 'implicate
d', 'counts', 'charging', 'charges', 'guilty', 'plead', 'arrested', 'plea
ded', 'theft', 'indicted', 'accused', 'convicts', 'convicted', 'suspect
s', 'pleads', 'convicting', 'pled', 'racketeering']

Cluster 7: ['northwestern', 'southwest', 'southern', 'east', 'southeaster
n', 'northeast', 'southwestern', 'northeastern', 'southeast', 'northern',
'northwest', 'eastern']

Cluster 8: ['forecasters', 'expecting', 'forecasted', 'predictions', 'exp
ected', 'prediction', 'expectations', 'predicted', 'foresaw', 'analysts',
'predicting', 'forecasting', 'forecasts', 'forecast', 'predicts']

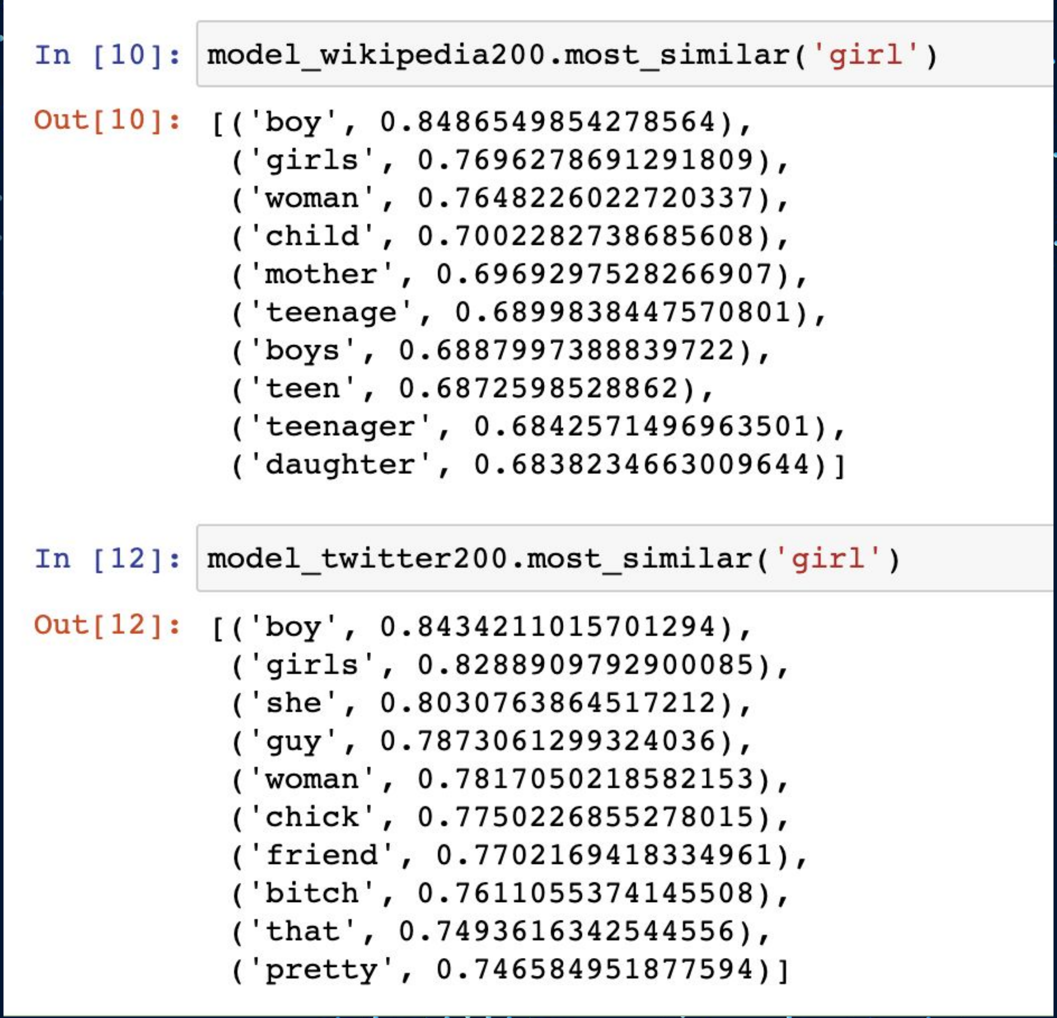
Cluster 9: ['matches', 'champions', 'tournaments', 'match', 'tourney', 'c
hampionships', 'tournament', 'round', 'playoff', 'championship']

Cluster 10: ['catchers', 'homers', 'pitches', 'shortstop', 'pitching', 'c
atcher', 'hitters', 'pitchers', 'pitcher', 'hitter', 'pitched', 'diamondb
acks', 'fastball', 'lofton', 'leadoff']

Cluster 11: ['toasted', 'cooking', 'minced', 'roasting', 'broth', 'grate
d', 'eaten', 'chives', 'tofu', 'beans', 'onions', 'uncooked', 'cooked',
'spiced', 'chopped', 'finely', 'roasted', 'marinated', 'cook', 'onion',
'meat', 'celery']

Cluster 12: ['increased', 'higher', 'increase', 'reduce', 'increasing',
'reduction', 'reductions', 'increases', 'rates', 'reduced']

Cluster 13: ['shouts', 'shouted', 'crying', 'chanting', 'screaming', 'ins
ults', 'chanted', 'shout', 'screamed', 'shouting']
```

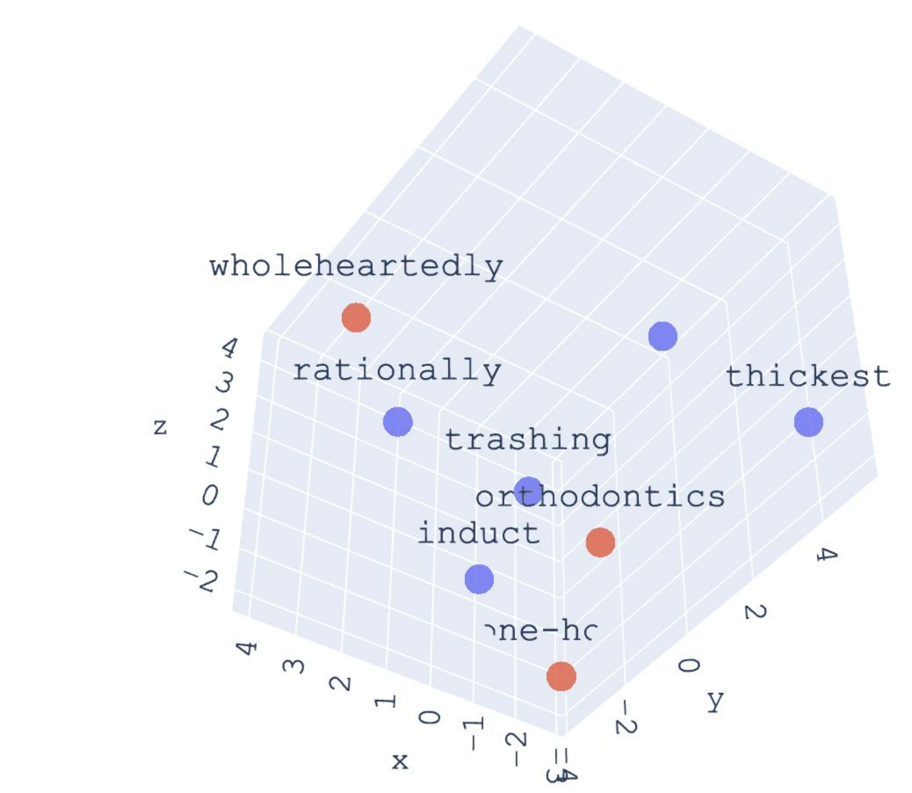


```
In [10]: model_wikipedia200.most_similar('girl')

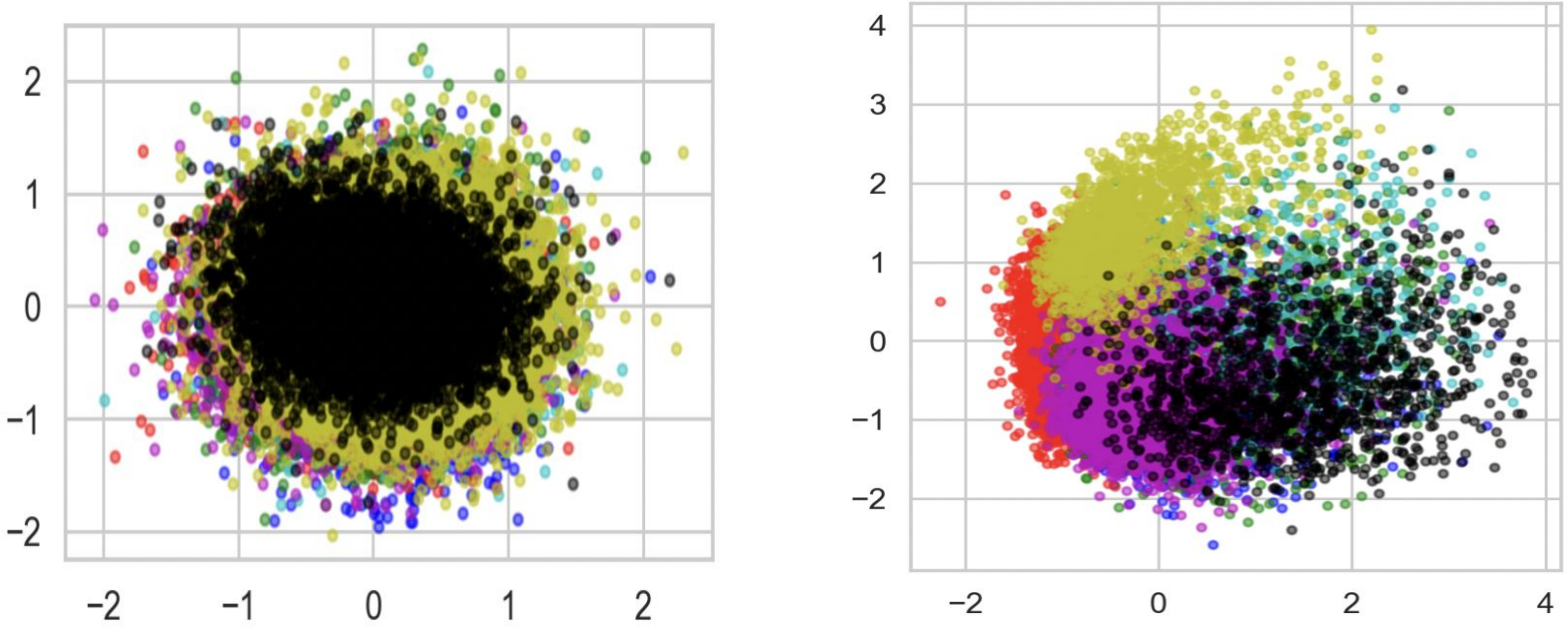
Out[10]: [('boy', 0.8486549854278564),
          ('girls', 0.7696278691291809),
          ('woman', 0.764822602272033 7),
          ('child', 0.7002282738685608),
          ('mother', 0.6969297528266907),
          ('teenage', 0.6899838447570801),
          ('boys', 0.6887997388839722),
          ('teen', 0.6872598528862),
          ('teenager', 0.6842571496963501),
          ('daughter', 0.6838234663009644)]

In [12]: model_twitter200.most_similar('girl')

Out[12]: [('boy', 0.8434211015701294),
          ('girls', 0.8288909792900085),
          ('she', 0.8030763864517212),
          ('guy', 0.787306129932 4036),
          ('woman', 0.7817050218582153),
          ('chick', 0.7750226855278015),
          ('friend', 0.7702169418334961),
          ('bitch', 0.761105537414550 8),
          ('that', 0.7493616342544556),
          ('pretty', 0.746584951877594)]
```

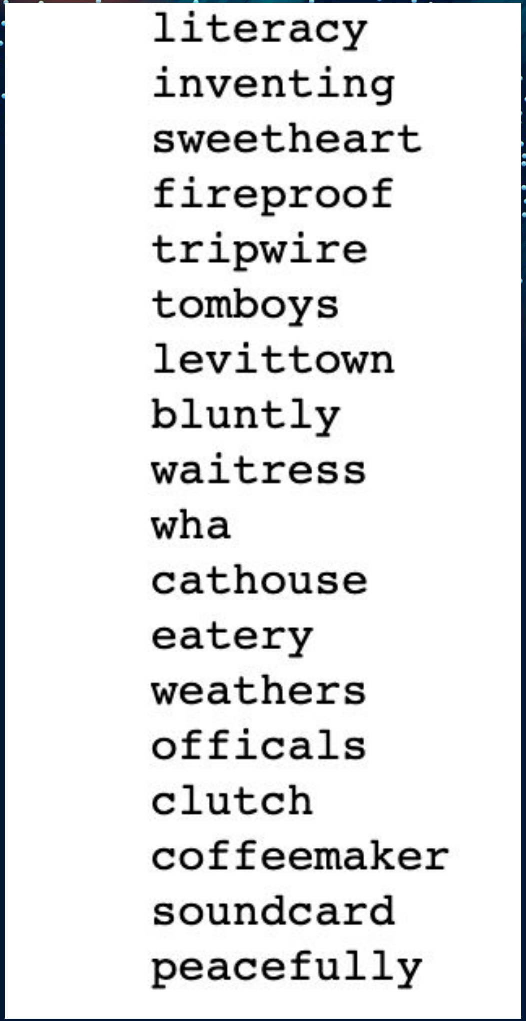


Twitter Clusters



K-Means Before and After Dimensionality Reduction

WORDS FARTHEST APART BASED ON COSINE SIMILARITY



```
literacy
inventing
sweetheart
fireproof
tripwire
tomboys
levittown
bluntly
waitress
wha
cathouse
eatery
weathers
officals
clutch
coffeemaker
soundcard
peacefully
```