Link to this file:
https://docs.google.com/document/d/1PuaGbsq-tfQrv1zzJjXac4k2JUx9aDcdwj5gj_bpcfI/edit?usp=sharing

Analysis Format:

Data Label

Similar words to specific keywords using Word2Vec and Doc2Vec in tabular format

List of similar words to ‘black’ using Word2Vec with the Gensim Phrases Package

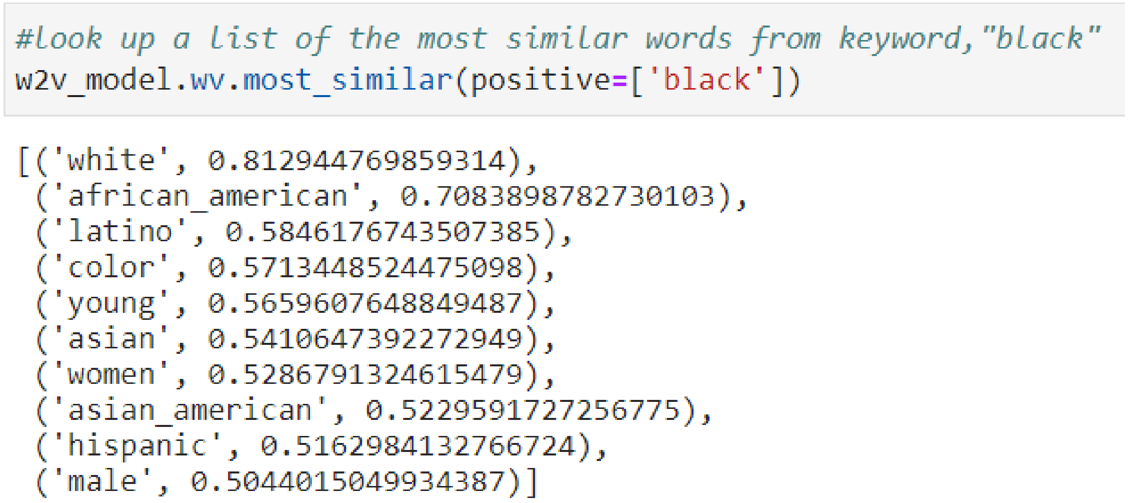
List of dissimilar words to ‘black’ using Word2Vec with the Gensim Phrases Package

Plot of dissimilar words to ‘black’ using Word2Vec with the Gensim Phrases Package (distance between any two words on the plot = dissimilarity between those two words)

Boston Globe 2018:

Word	Notable Similar Words from Word2Vec	Notable Similar Words from Doc2Vec
black	bullying, unaccountable	young
jamaican	---	disputing, autistic
dominican	emigrated	---
republic	emigrated	---
mano guay (Spanish slang)	outcountry, oozing, duality	---
emigrated	Sumbul (Muslim name), Mogadishu (capital of Somalia)	---

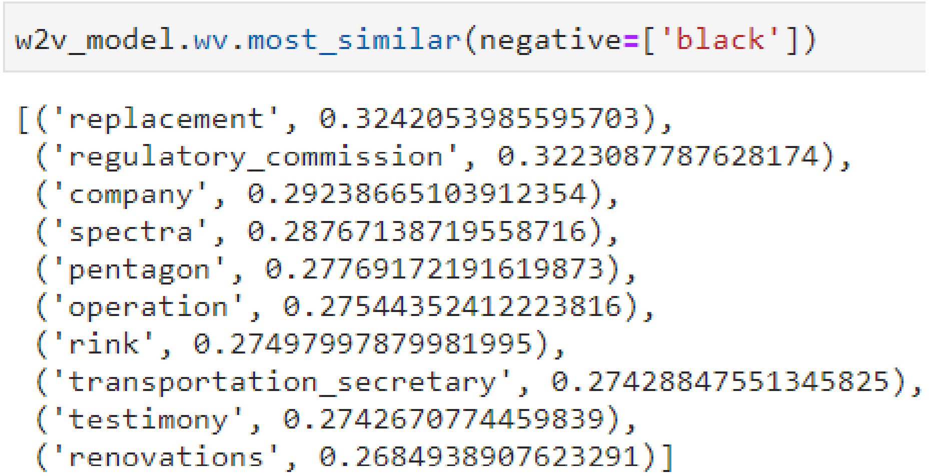
Below are the most similar words according to Word2Vec analysis using the Gensim Phrases Package (this package automatically detects common phrases used in a document); as opposed to earlier, when the models were trained on individual words, this time, the Word2Vec model was trained on the most common phrases appearing in the text data.



```
#look up a list of the most similar words from keyword,"black"
w2v_model.wv.most_similar(positive=['black'])
```

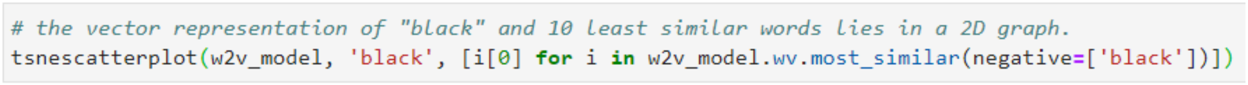
```
[('white', 0.812944769859314),
 ('african_american', 0.7083898782730103),
 ('latino', 0.5846176743507385),
 ('color', 0.5713448524475098),
 ('young', 0.5659607648849487),
 ('asian', 0.5410647392272949),
 ('women', 0.5286791324615479),
 ('asian_american', 0.5229591727256775),
 ('hispanic', 0.5162984132766724),
 ('male', 0.5044015049934387)]
```

Yet another interesting find using the Gensim Phrases package trained Word2Vec model were the least similar words.

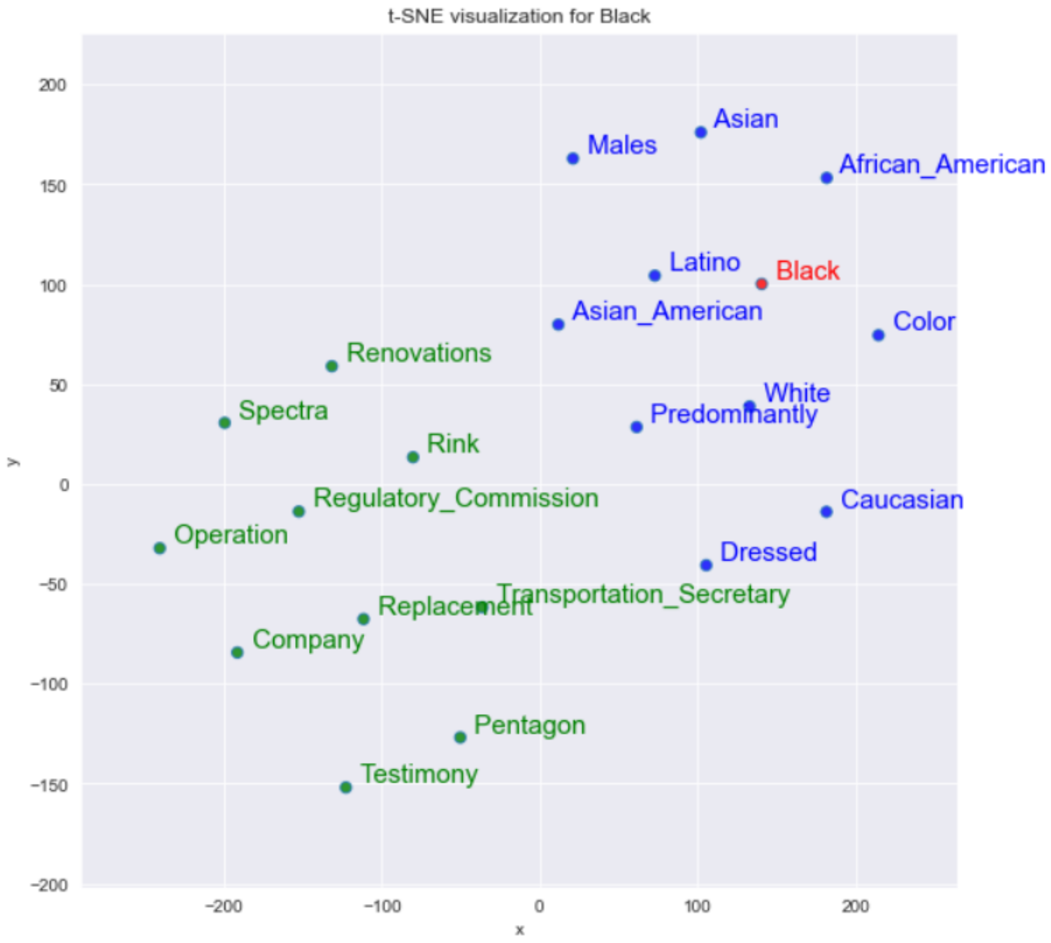


```
w2v_model.wv.most_similar(negative=['black'])
```

```
[('replacement', 0.3242053985595703),
 ('regulatory_commission', 0.3223087787628174),
 ('company', 0.29238665103912354),
 ('spectra', 0.28767138719558716),
 ('pentagon', 0.27769172191619873),
 ('operation', 0.27544352412223816),
 ('rink', 0.27497997879981995),
 ('transportation_secretary', 0.27428847551345825),
 ('testimony', 0.2742670774459839),
 ('renovations', 0.2684938907623291)]
```



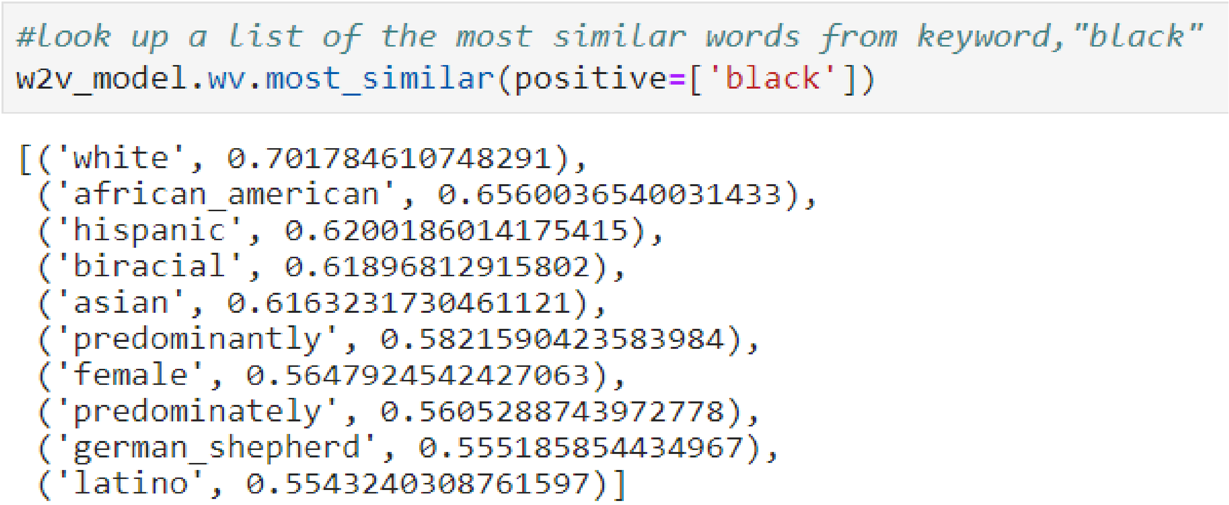
```
# the vector representation of "black" and 10 least similar words lies in a 2D graph.
tsnescatterplot(w2v_model, 'black', [i[0] for i in w2v_model.wv.most_similar(negative=['black'])])
```



Boston Globe 2017:

Word	Notable Similar Words from Word2Vec	Notable Similar Words from Doc2Vec
black	unarmed, vigilante, protagonist, white, deray	young, female
haitian	newness, learners, bold	modernist, champ
caribbean	gassed	stacked, holy
jamaican	immortalized	sciacca [city in Italy], lesbian
dominican	---	marching

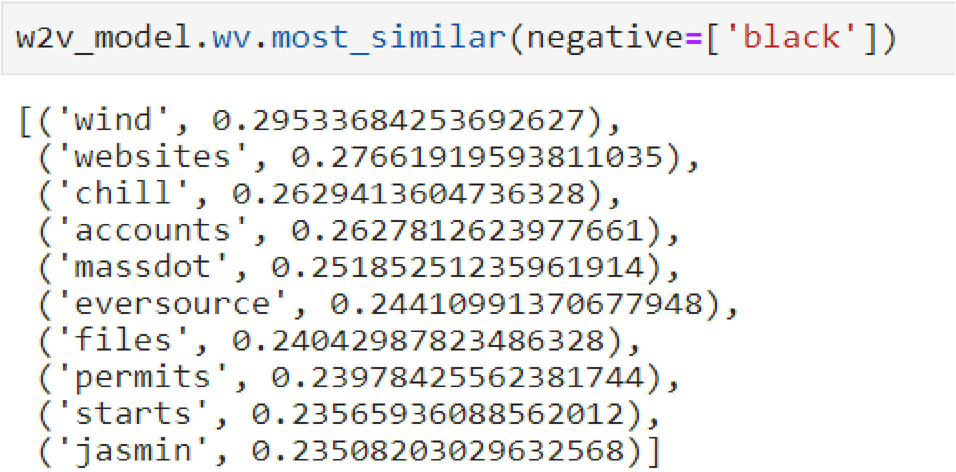
Most similar words according to Word2Vec + Gensim Phrases analysis:



```
#look up a list of the most similar words from keyword,"black"
w2v_model.wv.most_similar(positive=['black'])
```

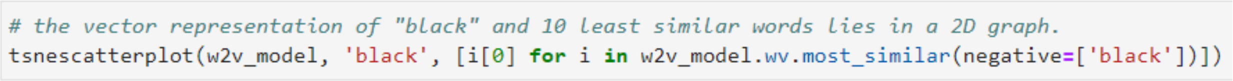
```
[('white', 0.701784610748291),
 ('african_american', 0.6560036540031433),
 ('hispanic', 0.6200186014175415),
 ('biracial', 0.61896812915802),
 ('asian', 0.6163231730461121),
 ('predominantly', 0.5821590423583984),
 ('female', 0.5647924542427063),
 ('predominately', 0.5605288743972778),
 ('german_shepherd', 0.555185854434967),
 ('latino', 0.5543240308761597)]
```

Least similar words according to Word2Vec + Gensim Phrases analysis:

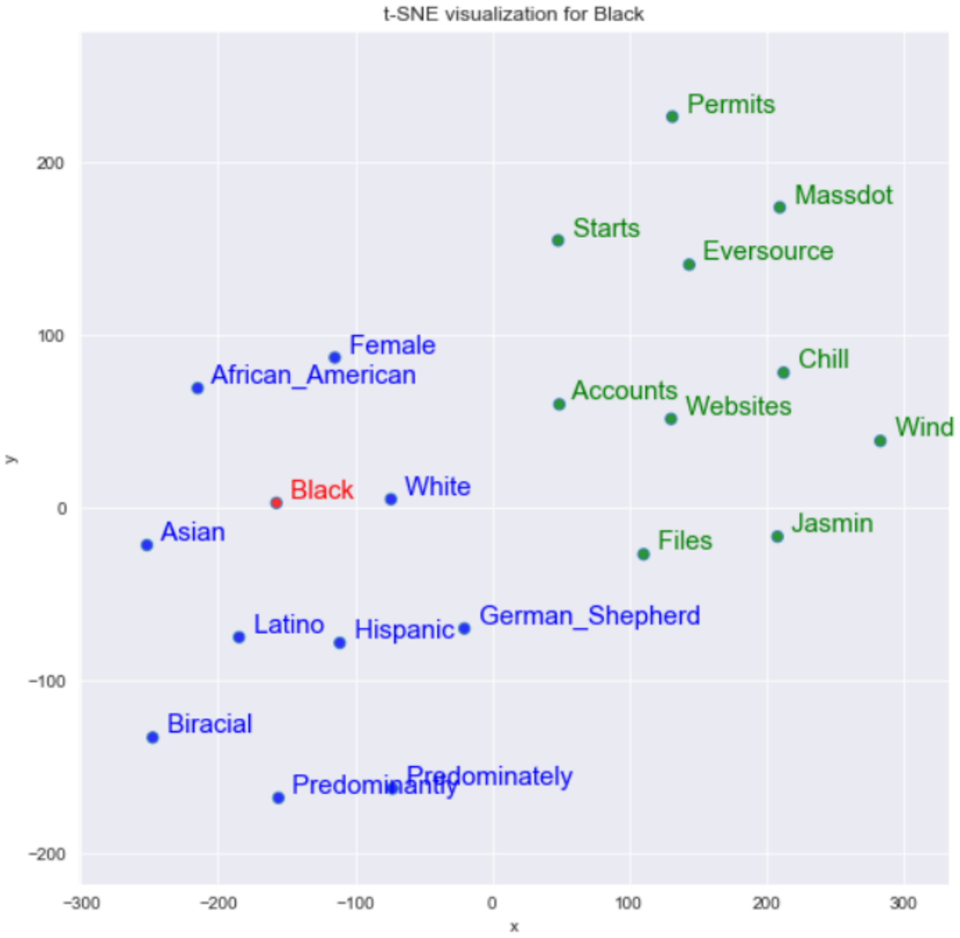


```
w2v_model.wv.most_similar(negative=['black'])
```

```
[('wind', 0.29533684253692627),
 ('websites', 0.27661919593811035),
 ('chill', 0.2629413604736328),
 ('accounts', 0.2627812623977661),
 ('massdot', 0.25185251235961914),
 ('eversource', 0.24410991370677948),
 ('files', 0.24042987823486328),
 ('permits', 0.23978425562381744),
 ('starts', 0.23565936088562012),
 ('jasmin', 0.23508203029632568)]
```



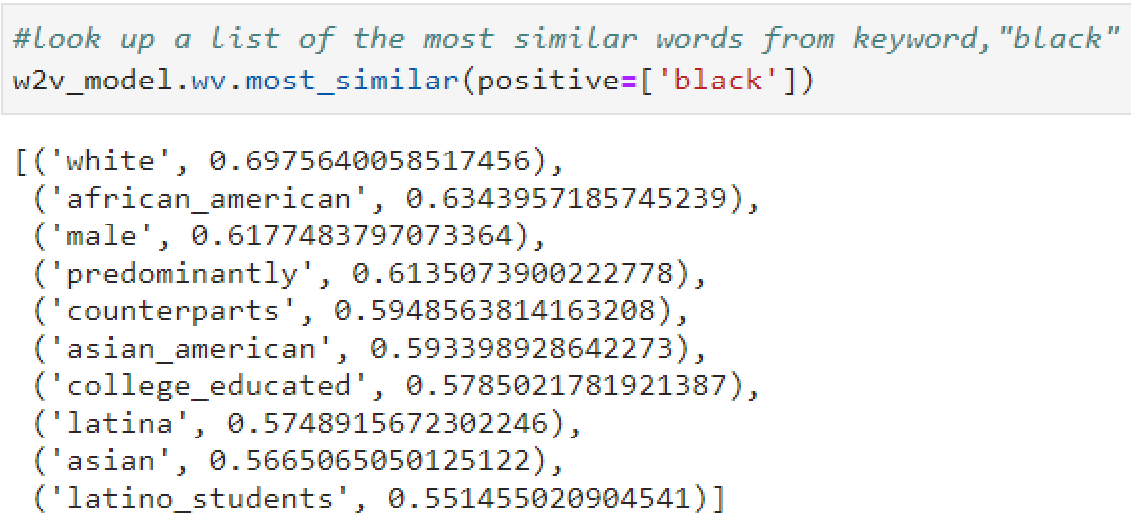
```
# the vector representation of "black" and 10 least similar words lies in a 2D graph.
tsnescatterplot(w2v_model, 'black', [i[0] for i in w2v_model.wv.most_similar(negative=['black'])])
```



Boston Globe 2016:

Word	Notable Similar Words from Word2Vec	Notable Similar Words from Doc2Vec
black	white, retaliated, resists, chosin [USS Chosin/Battle of Chosin Reservoir]	young
haitian	sauntering	immigrant
caribbean	sauntering	academy, poets, episcopal
republic	devolved	---

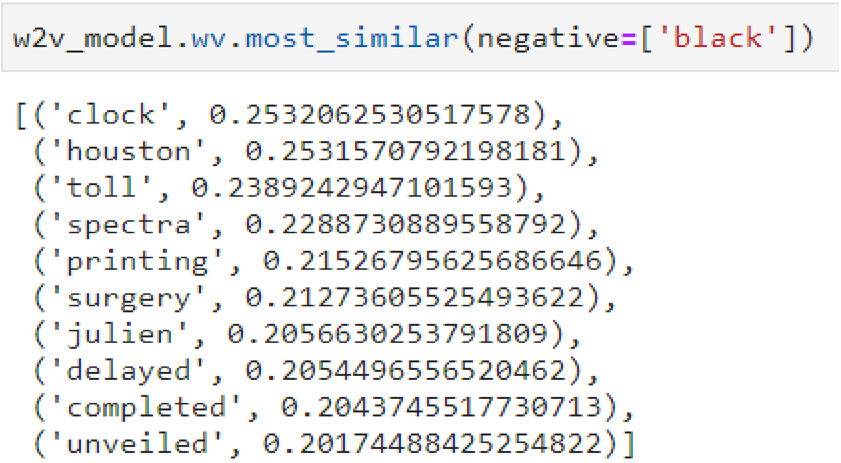
Most similar words according to Word2Vec + Gensim Phrases analysis:



```
#look up a list of the most similar words from keyword,"black"
w2v_model.wv.most_similar(positive=['black'])
```

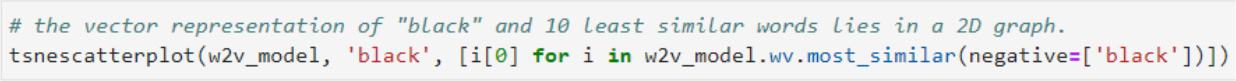
```
[('white', 0.6975640058517456),
 ('african_american', 0.6343957185745239),
 ('male', 0.6177483797073364),
 ('predominantly', 0.6135073900222778),
 ('counterparts', 0.5948563814163208),
 ('asian_american', 0.593398928642273),
 ('college_educated', 0.5785021781921387),
 ('latina', 0.5748915672302246),
 ('asian', 0.566506505012512 2),
 ('latino_students', 0.551455020904541)]
```

Least similar words according to Word2Vec + Gensim Phrases analysis:

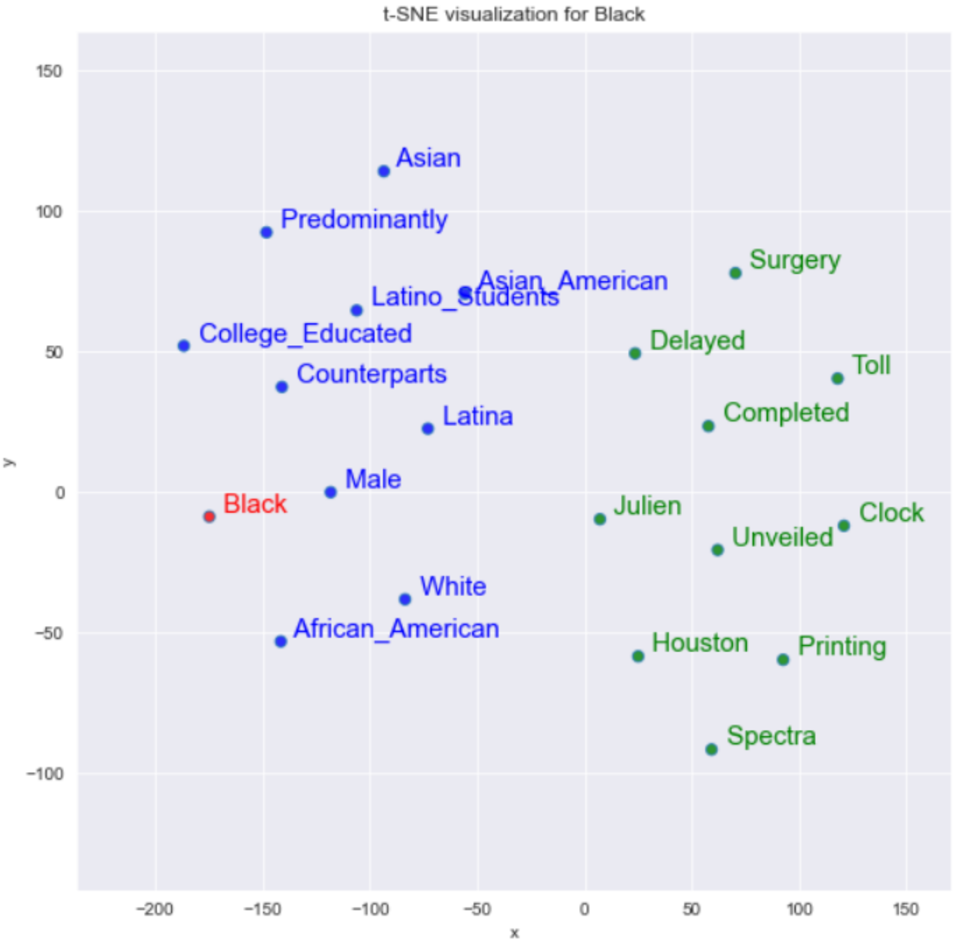


```
w2v_model.wv.most_similar(negative=['black'])
```

```
[('clock', 0.2532062530517578),
 ('houston', 0.2531570792198181),
 ('toll', 0.2389242947101593),
 ('spectra', 0.2288730889558792),
 ('printing', 0.21526795625686646),
 ('surgery', 0.21273605525493622),
 ('julien', 0.2056630253791809),
 ('delayed', 0.2054496556520462),
 ('completed', 0.2043745517730713),
 ('unveiled', 0.20174488425254822)]
```



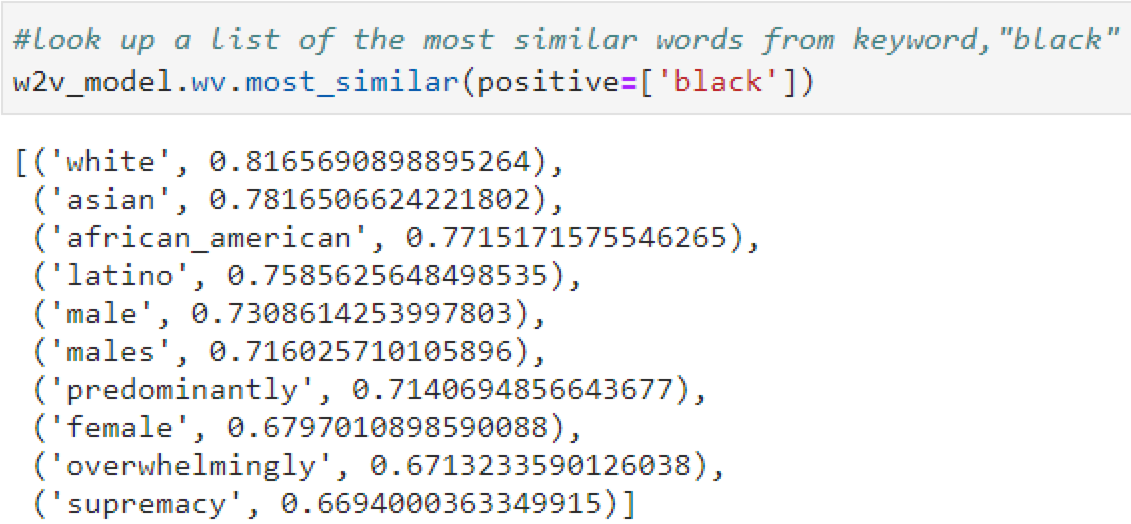
```
# the vector representation of "black" and 10 least similar words lies in a 2D graph.
tsnescatterplot(w2v_model, 'black', [i[0] for i in w2v_model.wv.most_similar(negative=['black'])])
```



Boston Globe 2015:

Word	Notable Similar Words from Word2Vec	Notable Similar Words from Doc2Vec
black	white, young, destitute	white, heighten, statistic, caucasian
haitian	bloc, majority, scientology, Armenian	cofounded
caribbean	---	mecca, masquerade, medieval
dominican	jewish, native, oldest	emigrated, journeyed

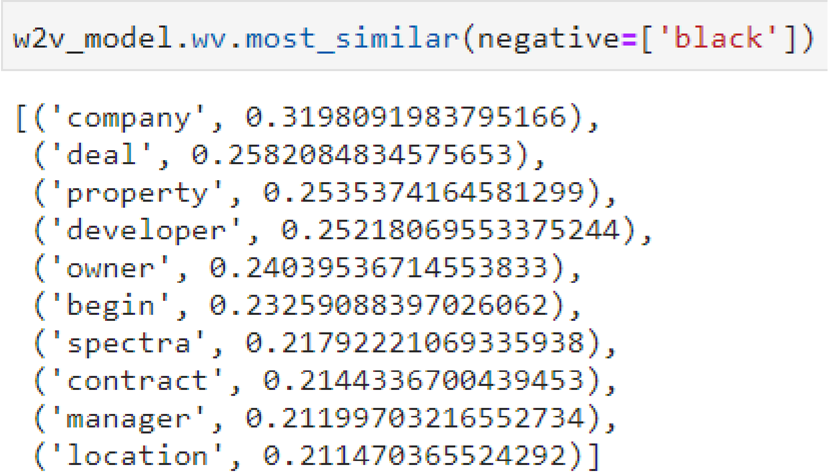
Most similar words according to Word2Vec + Gensim Phrases analysis:



```
#look up a list of the most similar words from keyword,"black"
w2v_model.wv.most_similar(positive=['black'])
```

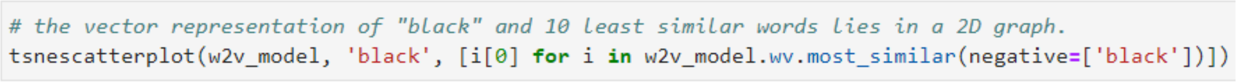
```
[('white', 0.8165690898895264),
 ('asian', 0.7816506624221802),
 ('african_american', 0.771517157546265),
 ('latino', 0.7585625648498535),
 ('male', 0.7308614253997803),
 ('males', 0.716025710105896),
 ('predominantly', 0.7140694856643677),
 ('female', 0.6797010898590088),
 ('overwhelmingly', 0.6713233590126038),
 ('supremacy', 0.6694000363349915)]
```

Least similar words according to Word2Vec + Gensim Phrases analysis:

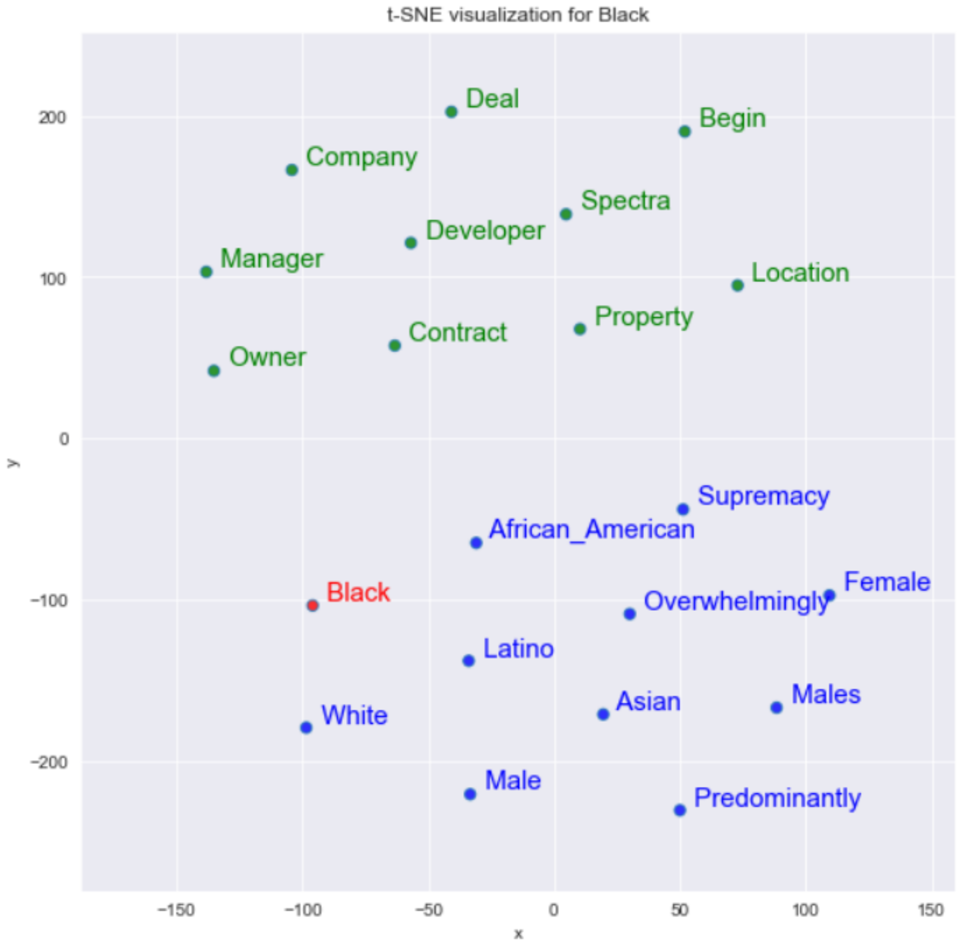


```
w2v_model.wv.most_similar(negative=['black'])
```

```
[('company', 0.3198091983795166),
 ('deal', 0.2582084834575653),
 ('property', 0.2535374164581299),
 ('developer', 0.25218069553375244),
 ('owner', 0.24039536714553833),
 ('begin', 0.23259088397026062),
 ('spectra', 0.21792221069335938),
 ('contract', 0.2144336700439453),
 ('manager', 0.21199703216552734),
 ('location', 0.211470365524292)]
```



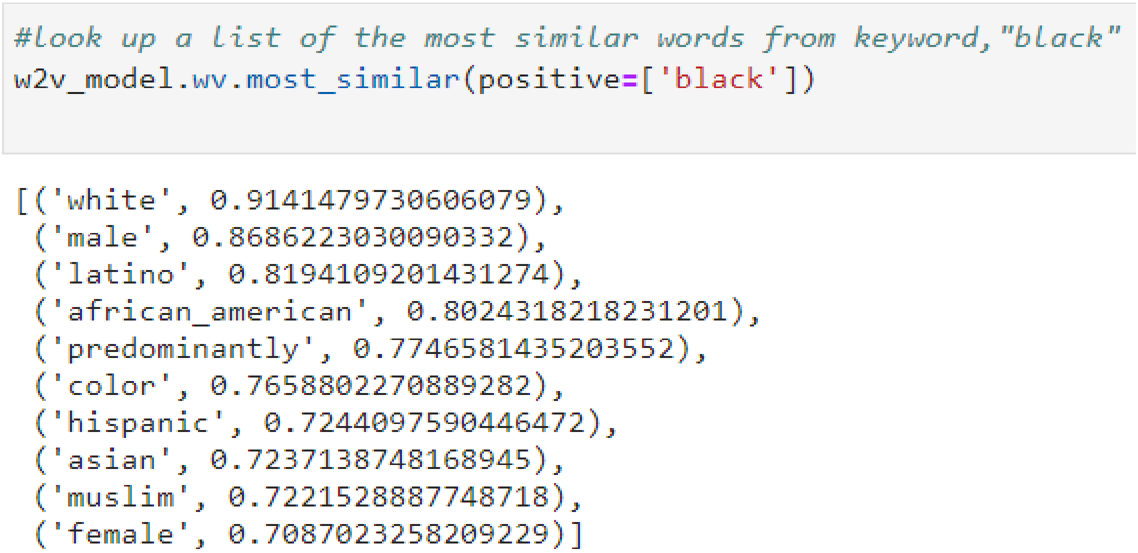
```
# the vector representation of "black" and 10 least similar words lies in a 2D graph.
tsnescatterplot(w2v_model, 'black', [i[0] for i in w2v_model.wv.most_similar(negative=['black'])])
```



Boston Globe 2014:

Word	Notable Similar Words from Word2Vec	Notable Similar Words from Doc2Vec
black	white	young, white, transgender, innocent
haitian	immigrant, lifelong	captive
caribbean	cultures	cottage
jamaican	earthy	rum
dominican	---	val

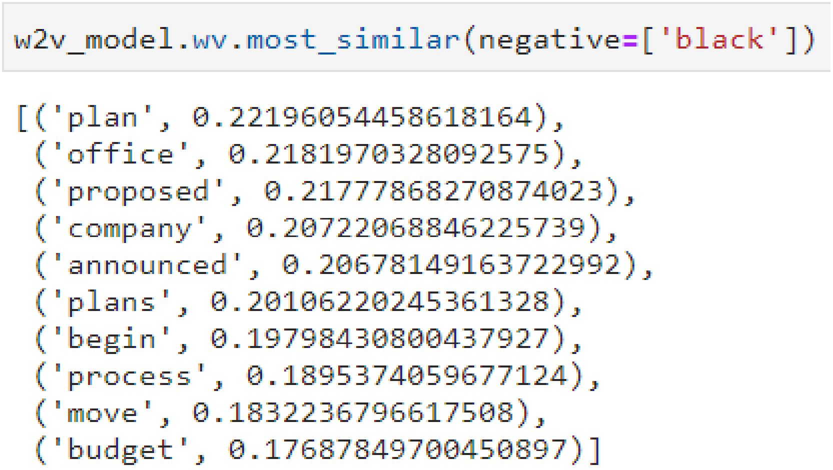
Most similar words according to Word2Vec + Gensim Phrases analysis:



```
#look up a list of the most similar words from keyword,"black"
w2v_model.wv.most_similar(positive=['black'])
```

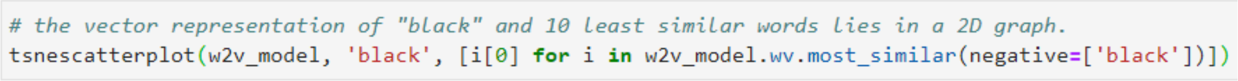
```
[('white', 0.9141479730606079),
 ('male', 0.8686223030090332),
 ('latino', 0.8194109201431274),
 ('african_american', 0.8024318218231201),
 ('predominantly', 0.7746581435203552),
 ('color', 0.7658802270889282),
 ('hispanic', 0.7244097590446472),
 ('asian', 0.7237138748168945),
 ('muslim', 0.7221528887748718),
 ('female', 0.7087023258209229)]
```

Least similar words according to Word2Vec + Gensim Phrases analysis:

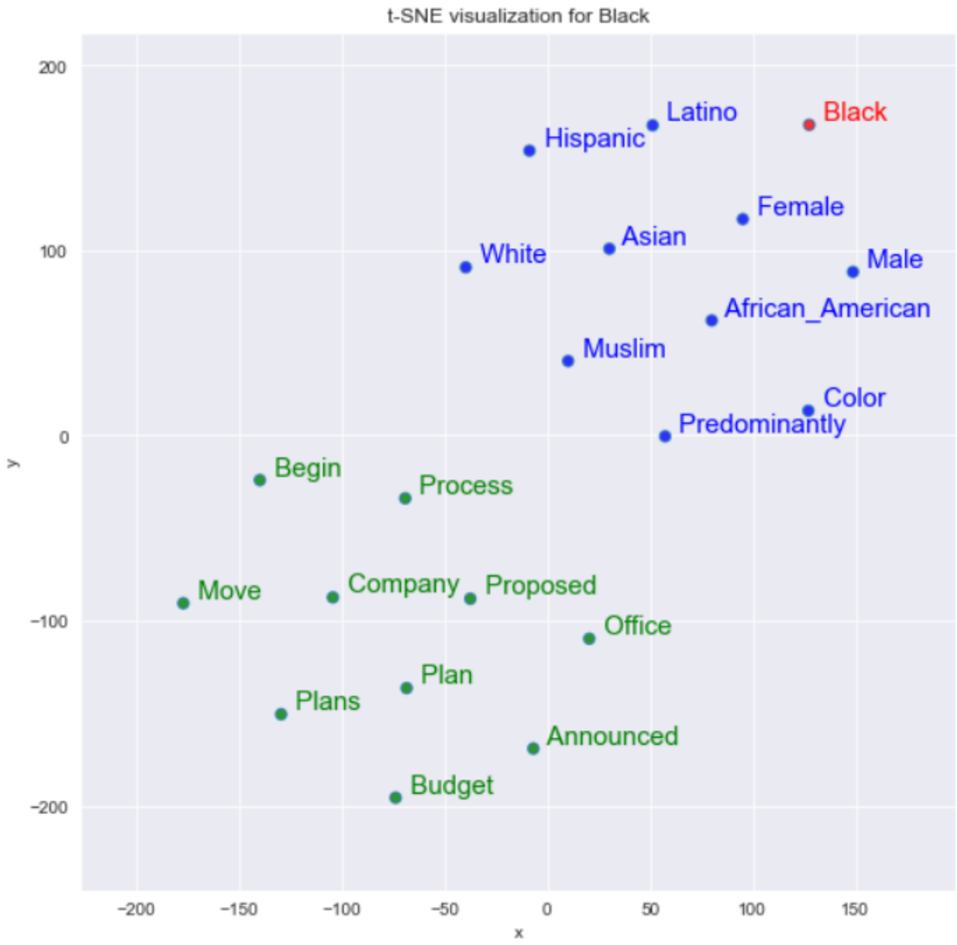


```
w2v_model.wv.most_similar(negative=['black'])
```

```
[('plan', 0.22196054458618164),
 ('office', 0.2181970328092575),
 ('proposed', 0.21777868270874023),
 ('company', 0.20722068846225739),
 ('announced', 0.20678149163722992),
 ('plans', 0.20106220245361328),
 ('begin', 0.19798430800437927),
 ('process', 0.1895374059677124),
 ('move', 0.1832236796617508),
 ('budget', 0.17687849700450897)]
```



```
# the vector representation of "black" and 10 least similar words lies in a 2D graph.
tsnescatterplot(w2v_model, 'black', [i[0] for i in w2v_model.wv.most_similar(negative=['black'])])
```



Insights upon using black/white-majority neighborhood names as keywords

Note: using the Word2Vec/Doc2Vec, we analyze text documents to generate word vectors for each word that occurs in the documents; these vectors are representative of the relationships of those words with all the other words in the documents (this is why we are able to find words that are "most similar" to a given word)

Representative Contexts:

1. Method: compute an average vector for a keyword using its 5 most similar words, and then get the word that is closest to the average vector.
2. Most of these representative vectors correspond either to other keywords or the same keywords.
3. It is interesting to note that the representative vectors for black-majority neighborhoods correspond to other black-majority neighborhoods, while those for white-majority neighborhoods correspond to other white-majority neighborhoods.
4. While this could be a potential hint of bias, there must be other factors at play, such as culture, politics, etc. which uniquely identify the two subsets of neighborhoods.

Similar Words:

1. Method: use Word2Vec's in-built Word2Vec.most_similar() method to generate 25 (this number was chosen because in the worst case, all 20 neighborhoods used as keywords will show up as the 20 most similar words to a given input word, so that even after filtering those out, we should have five other similar words) similar words to a given input word, and filter out any generated similar words which are also majority neighborhoods used as keywords.
2. While the method got rid of other neighborhood names, the remaining words do not seem to have much significance (I will push the results to Github regardless, so that the journalism team can take a second look).

Explanation of Results:

1. Word2Vec > similar_words_task consists of:
    a. all_similar_words - similar words to majority neighborhoods before filtering out other neighborhood names, the first word being the neighborhood name and the next five being the similar words
    b. neighborhood_filtered_similar_words - same as all_similar_words, but after filtering out other neighborhood names which may have been computed as similar words
    c. keyword_frequencies - the number of times each neighborhood name has occurred in each year in Boston Globe articles

   d. representative_words - the representative word for each majority neighborhood, as discussed under “Representative Contexts”, along with a similarity score (0 being completely different, 1 being exactly the same)
   e. older_keyword_results - similar words computed for the older set of keywords provided to us
2. Word2Vec > word_clouds_img consists of word clouds created from results obtained from the similar words analysis; in a word cloud, the size of a dot behind a word represents how frequently it has appeared, an edge/line between two dots/words represents that those two are similar, and the distance between two dots/words represents how similar those are (length of the edge/line is inversely proportional to the similarity of the connected words):
   a. all_similar_words_clouds
   b. neighborhood_filtered_word_clouds
   c. older_keyword_results_clouds