

# Trump\_Word2Vec

December 11, 2019

```
[ ]: https://github.com/QuantCS109/TrumpTweets/blob/master/notebooks\_features/  
     ↪ Trump_Word2Vec.ipynb
```

## 1 Word2Vec Algorithm

This is an implementation of the [Word2Vec algorithm](#) using the skip-gram architecture. I'm adapting code from a course in Udacity to our problem. The original code is here: <https://github.com/udacity/deep-learning-v2-pytorch/tree/master/word2vec-embeddings>

```
[1]: import sys  
      sys.path.append('..') #to add top-level to path  
      sys.path.append('../modules') #to add top-level to path  
  
      from modules.project_helper import TweetData  
      from modules.skipgram import get_batches, SkipGramNeg, NegativeSamplingLoss,   
      ↪ subsampling  
      from modules.skipgram import cosine_similarity, plot_similar_words  
      import numpy as np  
  
      import torch  
      import torch.optim as optim  
  
      %matplotlib inline  
      %config InlineBackend.figure_format = 'retina'  
      import matplotlib.pyplot as plt  
      from sklearn.manifold import TSNE  
  
      import warnings  
      warnings.filterwarnings("ignore")
```

### 1.1 Loading data

```
[2]: # time series of trump archives to be able to train the model sequentially  
      data = TweetData('../data/intermediate_data/trump_archive_ts/  
      ↪ trump_archive_db_1910.csv')  
      # full data set
```

```
# data = TweetData('data/trump_archive_db.csv')
```

```
[3]: # get list of words
```

```
words = data.words
```

```
print(words[:30])
```

```
['while', 'the', 'do', 'nothing', 'democrats', 'fail', 'the', 'american',  
'people', 'and', 'continue', 'the', 'impeachment', 'scam', 'my',  
'administration', 'will', 'continue', 'to', 'deliver', 'real', 'results', 'as',  
'seen', 'over', 'the', 'past', 'month', 'below', 'the']
```

```
[4]: print("Total words in Trump's tweets: {}".format(len(words)))
```

```
print("Unique words: {}".format(len(set(words))))
```

Total words in Trump's tweets: 395944

Unique words: 4583

```
[5]: # These are two dictionaries to convert words to integers and back again  
      ↪(integers to words).
```

```
# The integers are assigned in descending frequency order, so the most frequent  
      ↪word ("the")
```

```
# is given the integer 0 and the next most frequent is 1, etc.
```

```
vocab_to_int, int_to_vocab = data.vocab_to_int, data.int_to_vocab
```

```
int_words = data.int_words
```

```
print(int_words[:30])
```

```
[253, 0, 47, 140, 75, 1451, 0, 104, 33, 2, 402, 0, 686, 713, 32, 279, 10, 402,  
1, 1381, 306, 559, 39, 505, 107, 0, 698, 1061, 3512, 0]
```

## 1.2 Training

```
[6]: #device = 'cuda' if torch.cuda.is_available() else 'cpu'
```

```
device = 'cpu'
```

```
# Get our noise distribution
```

```
threshold = 1e-4 #lowered threshold as used in Word2Vec algorithm since we have  
      ↪smaller sample
```

```
freqs, train_words = subsampling(threshold, int_words)
```

```
word_freqs = np.array(sorted(freqs.values(), reverse=True))
```

```
unigram_dist = word_freqs/word_freqs.sum()
```

```
noise_dist = torch.from_numpy(unigram_dist**(0.75)/np.sum(unigram_dist**(0.75)))
```

```
#original is 5, skipgram paper suggests up to 20 for small data sets
```

```
N_negative_sampling = 7
```

```

# instantiating the model
embedding_dim = 100
model = SkipGramNeg(len(vocab_to_int), embedding_dim, noise_dist=noise_dist).
    ↪to(device)

# using Negative Sampling Loss as our loss function
criterion = NegativeSamplingLoss()

# Choosing optimizer
optimizer = optim.Adam(model.parameters(), lr=0.003)

# train for some number of epochs
print_every = 200
steps = 0
epochs = 20

for e in range(epochs):

    # get our input, target batches
    for input_words, target_words in get_batches(train_words, 512):
        steps += 1
        inputs, targets = torch.LongTensor(input_words), torch.
        ↪LongTensor(target_words)
        inputs, targets = inputs.to(device), targets.to(device)

        # input, output, and noise vectors
        input_vectors = model.forward_input(inputs)
        output_vectors = model.forward_output(targets)
        noise_vectors = model.forward_noise(inputs.shape[0],
        ↪N_negative_sampling)

        # negative sampling loss
        loss = criterion(input_vectors, output_vectors, noise_vectors)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # loss stats
    if steps % print_every == 0:
        print("Epoch: {}/{}".format(e+1, epochs))
        print("Loss: ", loss.item()) # avg batch loss at this point in
        ↪training
        valid_examples, valid_similarities = cosine_similarity(model.
        ↪in_embed, device=device)
        _, closest_idxs = valid_similarities.topk(6)

```

```

        valid_examples, closest_idx = valid_examples.to('cpu'),
→closest_idx.to('cpu')
        for ii, valid_idx in enumerate(valid_examples):
            closest_words = [int_to_vocab[idx.item()] for idx in
→closest_idx[ii][1:]]
            print(int_to_vocab[valid_idx.item()] + " | " + ', '.
→join(closest_words))
            print("...\n")

```

Epoch: 1/20

Loss: 8.298316955566406

much | swing, sarah, the, length, motto  
s | chance, yesterday, session, sell, express  
their | poll, prayer, recover, version, forum  
what | march, going, pages, ultimately, instead  
big | anniversary, terrorists, play, comments, taken  
will | together, letting, should, corrupt, days  
our | billions, products, met, point, ask  
new | ever, prayers, heather, abe, kemp  
award | true, regardless, referred, schiff, however  
outside | barely, spirit, nick, comcast, cup  
king | security, minneapolis, opinions, setbacks, south  
colorado | cable, baseball, technology, fortune, mails  
standing | across, israeli, n, responsibility, dropping  
rating | returned, near, study, thrown, camp  
follow | farmers, un, greatly, birth, blood  
lied | officially, donation, build, someday, deadline  
...

Epoch: 2/20

Loss: 4.9751057624816895

all | seek, voters, pressure, properly, general  
has | interesting, rick, departing, killing, court  
for | ryan, soon, putting, brett, syria  
be | encourage, to, he, of, my  
no | see, supported, democrats, is, responsibility  
big | new, anniversary, terrorists, badly, from  
get | put, a, from, newly, hope  
will | together, should, new, pageant, days  
mainstream | tougher, suites, meddling, strassel, disaster  
sleepy | oreilly, landed, stage, obamas, un  
terrorism | facebook, ready, nafta, opposes, sacrifice  
created | between, phil, interest, language, state  
b | positions, victory, probe, attitude, keep  
follow | farmers, greatly, un, june, monday  
king | security, this, never, setbacks, must

known | entire, public, countries, loans, membership  
...

Epoch: 3/20

Loss: 3.9950668811798096

get | put, a, from, push, newly  
people | wear, problems, away, republicans, get  
but | association, article, solidarity, p, unfair  
up | party, end, stuff, highly, money  
news | roads, mobile, briefed, even, turned  
have | very, interests, weak, dollars, including  
me | steps, law, weak, wind, the  
back | players, view, off, airlines, went  
fine | reminds, actually, ive, ago, relief  
turned | even, news, hoping, administrations, audience  
month | broadcast, leave, who, hacking, because  
changed | o, univision, soldier, appreciate, lawyers  
concerning | news, truly, got, companies, defeat  
nyc | obamas, worthless, losers, lessons, born  
victims | opposed, clue, drone, benghazi, texas  
st | finished, days, story, japan, beyond  
...

Epoch: 3/20

Loss: 3.654520034790039

can | started, moore, fired, that, off  
his | ever, points, duty, higher, should  
only | is, know, the, syrian, long  
people | wear, problems, our, republicans, beaten  
never | product, process, chairman, the, part  
a | late, post, hosting, from, w  
my | partner, be, reported, hillarys, states  
for | the, and, soon, putting, jeff  
rating | study, crazy, best, served, example  
named | mike, character, thomas, words, reasons  
don | inflation, prior, army, lot, bilateral  
biden | photo, dumbest, to, aware, opposition  
death | time, opposition, which, iranian, machine  
concerning | news, got, dems, companies, truly  
funding | talk, last, drugs, taking, thoughts  
anymore | looks, doj, legitimate, up, to  
...

Epoch: 4/20

Loss: 3.302253484725952

one | been, good, regime, me, times  
today | congratulate, reducing, wife, no, alabama  
big | new, from, anniversary, badly, will

dont | ideal, chairman, recovery, size, will  
but | solidarity, non, article, association, out  
u | des, better, rated, thomas, hope  
a | from, post, environment, w, hosting  
now | display, change, i, broken, that  
victims | opposed, drone, benghazi, texas, clue  
coverage | james, pollster, hostages, peace, congressman  
list | exactly, gop, endure, n, fires  
weeks | culture, harbor, requirements, them, detention  
concerning | news, got, companies, dems, despite  
soldiers | piece, drugs, shoot, disease, donors  
spirit | outside, lack, heritage, brussels, politicians  
involved | protected, estate, luck, sometimes, testimony  
...

Epoch: 5/20

Loss: 3.262411594390869

big | from, badly, new, will, anniversary  
our | congratulations, looking, people, the, met  
them | response, fight, u, great, fixing  
be | to, of, justice, my, the  
by | is, restaurant, know, barriers, are  
again | seems, the, season, holes, team  
president | or, should, giving, millions, she  
he | abuse, be, looking, from, the  
twitter | himself, everything, afraid, higher, period  
known | entire, countries, operations, society, says  
disgusting | lovely, blue, newly, girl, get  
terrorism | decades, exactly, facebook, amp, black  
nato | beaten, endorse, am, kids, made  
within | commitment, second, korea, negotiators, embassy  
received | amp, house, pm, friends, role  
don | inflation, army, prior, bilateral, lot  
...

Epoch: 5/20

Loss: 3.096003770828247

very | have, a, blowing, they, amp  
about | is, lifted, great, k, by  
fake | im, wage, long, speech, oh  
we | of, commitment, to, america, believe  
at | the, it, lower, a, they  
there | seat, issue, do, usa, kong  
back | players, you, off, commander, is  
one | been, good, me, washington, regime  
involved | protected, estate, sometimes, on, be  
funding | talk, last, drugs, sun, in  
social | response, destination, the, never, amp

charge | gee, attacks, know, good, businesses  
defense | leaders, totally, for, work, it  
death | opposition, time, pledged, iranian, god  
often | same, president, others, dems, really  
officials | anthony, topics, negative, investigate, today  
...

Epoch: 6/20

Loss: 3.06138014793396

by | is, know, are, the, in  
in | and, the, to, that, for  
get | from, people, put, a, bernie  
an | to, yes, now, unhinged, superior  
obama | you, obamacare, i, gets, become  
our | the, congratulations, people, for, based  
s | spend, other, you, lower, then  
so | its, and, you, years, will  
rep | vote, follow, freedom, military, patient  
victims | opposed, drone, texas, benghazi, cap  
turnberry | half, growth, loan, investigating, chiefs  
executive | may, amp, republican, many, favorite  
negotiations | anyway, caucus, missiles, bad, dinner  
n | standing, birthday, obamas, asking, across  
known | countries, entire, operations, says, turnout  
signing | waste, demand, medicaid, finest, changes  
...

Epoch: 7/20

Loss: 2.990067958831787

but | solidarity, out, non, unfair, church  
not | that, i, of, time, and  
of | be, i, we, to, not  
never | the, chairman, he, part, deadly  
when | place, impeachment, by, win, mess  
has | supreme, your, trying, historic, before  
is | by, the, are, and, just  
them | they, response, fight, u, great  
necessary | future, m, things, weve, w  
month | leave, broadcast, both, priority, children  
staff | underlying, away, perfectly, my, well  
group | at, went, cold, force, thank  
troops | in, lindsey, early, suggested, consequences  
lied | failing, build, picks, unrelated, starting  
immigrants | flooding, apology, entitled, figure, harbor  
closely | meeting, file, inspire, looking, scam  
...

Epoch: 7/20

Loss: 2.8556125164031982

that | not, i, it, just, in  
never | he, chairman, deadly, the, ted  
make | on, beat, washington, thank, tough  
your | gave, has, are, history, soon  
fake | long, can, oh, im, turn  
who | right, should, justice, do, since  
do | or, there, who, and, donald  
i | you, that, all, not, time  
sleepy | twitter, national, how, oreilly, salaries  
announce | mid, began, incorrectly, garbage, newsmax  
disgusting | lovely, get, blue, girl, newly  
received | house, friends, amp, pm, role  
troops | lindsey, in, suggested, early, sacred  
outside | spirit, russia, tariffed, comcast, barely  
views | third, th, world, white, simple  
officials | negative, topics, anthony, club, today  
...

Epoch: 8/20

Loss: 2.936371088027954

me | guy, you, statements, read, polls  
country | trade, much, open, wall, first  
out | the, people, am, from, general  
democrats | no, every, the, want, i  
time | not, media, i, the, only  
fake | long, which, turn, oh, when  
now | that, it, i, for, they  
the | and, for, in, is, a  
named | thomas, delayed, see, words, reasons  
executive | may, premiums, republican, amp, so  
beach | airport, rampant, pageant, int, trip  
staff | away, underlying, fair, happy, night  
senators | pennsylvania, allegiance, hilton, ambassador, worked  
colorado | mails, nervous, giant, including, victory  
tune | scene, producing, weekend, tomorrow, at  
st | story, japan, going, prosecutor, positive  
...

Epoch: 9/20

Loss: 2.869204044342041

now | i, that, it, they, display  
it | that, even, dnc, they, now  
just | that, is, nice, him, to  
out | people, am, from, the, just  
not | that, the, time, of, stop  
his | he, works, against, dont, amp  
one | else, been, good, washington, brand



country | trade, much, open, wall, first  
lyin | acknowledging, jury, stated, david, celebrating  
clue | usual, everything, crazy, deficit, and  
n | obamas, asking, standing, across, birthday  
officials | topics, negative, club, anthony, says  
spirit | outside, haters, lack, returned, paso  
short | proven, issues, is, standing, matters  
king | minneapolis, this, playing, security, the  
nato | am, made, endorse, beaten, flying  
...

Epoch: 9/20

Loss: 2.730422258377075

is | like, just, know, about, the  
when | didnt, by, is, mess, about  
fake | report, incorrect, presidency, when, long  
get | disgusting, people, getting, a, really  
been | for, and, else, the, one  
for | the, in, and, will, c  
country | trade, much, wall, our, open  
very | a, well, good, and, energy  
sanctuary | strong, guilty, law, borders, position  
head | something, pageant, idea, see, however  
gang | asked, gangs, ms, limbaugh, subsidize  
changed | o, a, lawyers, know, rebuilt  
coverage | pollster, concentration, agent, fast, granted  
fire | modern, protecting, not, saved, completely  
signing | demand, order, will, rule, very  
lied | picks, unrelated, asked, failing, even  
...

Epoch: 10/20

Loss: 2.8310461044311523

when | didnt, by, about, dumb, is  
today | honor, tomorrow, great, bless, thank  
country | trade, much, our, wall, open  
been | for, and, the, else, hunt  
make | beat, on, thank, also, all  
to | in, the, americans, we, people  
should | president, or, brought, not, will  
new | big, will, great, crowds, baton  
shortly | fireworks, arizona, remain, to, inner  
turned | predicted, watergate, hoping, audience, legitimate  
follow | june, greatly, demand, farmers, tremendous  
son | door, saw, terminated, amp, cont  
often | same, dems, others, does, believe  
nato | am, made, endorse, beaten, flying  
fine | actually, game, albert, hospital, profits

head | something, pageant, however, idea, subpoena  
...

Epoch: 11/20  
Loss: 2.6983354091644287  
thank | you, great, cleveland, tomorrow, rally  
it | even, that, bad, they, over  
there | obstruction, do, seat, no, ridiculous  
never | he, inquiry, hunt, bob, opinions  
all | could, i, on, not, we  
even | it, that, bad, they, wanted  
one | else, reviews, brand, washington, focus  
amp | the, obamacare, a, and, from  
biden | opposition, plans, heavily, fill, abolish  
human | hell, military, nd, vets, help  
sanctuary | borders, strong, law, guilty, position  
losers | away, natl, thanks, driving, dopey  
death | god, pledged, abe, mission, tougher  
fine | albert, game, actually, hospital, profits  
rating | approval, crazy, according, in, wrong  
works | his, after, knows, failed, rock  
...

Epoch: 11/20  
Loss: 2.3760986328125  
hillary | clinton, crooked, she, email, server  
trump | donald, intl, tower, by, hotel  
many | so, s, sold, mexico, deals  
if | that, confidence, crazy, can, they  
amp | the, via, a, trump, obamacare  
this | life, case, back, is, so  
so | many, totally, much, now, sources  
the | in, at, to, for, being  
tune | tomorrow, at, great, tonight, newly  
human | hell, fights, vets, help, military  
whats | interviewed, committee, there, cartels, on  
received | friends, pm, house, agent, five  
clue | everything, crazy, raised, card, marco  
officials | local, club, negative, got, topics  
head | something, however, cold, subpoena, starting  
senators | working, worked, replace, raise, so  
...

Epoch: 12/20  
Loss: 2.7435519695281982  
i | that, you, am, have, prove  
as | and, is, thing, know, bob  
been | for, and, hunt, the, else

do | there, or, and, they, no  
years | access, improve, we, but, presidency  
should | brought, not, or, against, fbi  
about | when, lied, is, mainstream, lifted  
even | that, it, bad, wanted, they  
soldiers | disadvantage, drugs, broken, syria, floods  
involved | truly, closely, protected, holiday, ivanka  
presidency | but, years, does, number, its  
charge | peter, entirely, own, doj, totally  
mainstream | news, about, media, disaster, write  
lied | picks, asked, about, comey, unrelated  
anymore | legitimate, rest, looks, purposely, been  
received | friends, pm, agent, house, purpose

...

Epoch: 13/20

Loss: 2.5673794746398926

with | all, of, from, north, up  
this | life, back, case, is, employed  
what | know, true, allies, real, lot  
good | very, things, looks, trading, headquarters  
country | much, our, trade, open, the  
be | will, tonight, rally, pme, crowd  
time | more, is, telling, only, media  
like | kellyanne, would, is, chance, do  
non | but, etc, went, later, made  
soldiers | syria, drugs, disadvantage, isis, floods  
reserve | fed, deficit, borrow, quantitative, germany  
mainstream | news, media, write, disaster, about  
sanctuary | borders, crimes, law, californias, strong  
warming | global, trans, cold, cannot, called  
short | proven, add, is, think, victorious  
blue | monster, championship, rated, palmer, departing

...

Epoch: 14/20

Loss: 2.6829850673675537

do | or, there, and, they, seat  
is | stewart, disaster, isnt, time, dumb  
america | again, lets, together, make, we  
we | must, will, america, commitment, us  
country | our, much, trade, open, working  
back | love, this, commander, boycott, done  
new | crowds, ill, pm, pme, dinner  
up | had, results, story, end, they  
announce | pensacola, hotels, economies, planning, capital  
reserve | fed, deficit, borrow, quantitative, germany  
changed | lawyers, o, same, a, didnt

beach | palm, pageant, excited, tonight, golf  
fire | concerned, conversation, wayne, testimony, completely  
mainstream | news, write, media, perhaps, piece  
involved | truly, train, with, closely, informant  
rep | version, aoc, committed, waiting, debbie  
...

Epoch: 14/20

Loss: 2.687187910079956

obama | obamacare, gets, isnt, cia, any  
america | again, lets, together, you, we  
years | six, ago, improve, access, most  
our | country, military, vets, strong, and  
up | had, they, falsely, story, end  
great | thank, evening, fantastic, crowd, love  
trump | donald, tower, intl, by, trumps  
with | all, of, north, and, from  
soldiers | syria, drugs, disadvantage, troops, broken  
himself | comey, report, fool, disgraced, lover  
twitter | winner, bad, imagination, baker, cpac  
known | wrong, looking, says, wheres, perfect  
named | resort, club, former, patrick, beach  
non | etc, being, amazon, unfair, later  
presidency | number, has, its, best, total  
b | can, rolling, palos, elite, ireland  
...

Epoch: 15/20

Loss: 2.611232042312622

border | southern, immigration, security, wall, drug  
from | the, embassy, and, people, with  
being | fighters, the, many, luxurious, direct  
years | ago, six, improve, access, taken  
out | am, fiction, people, just, really  
i | that, am, have, prove, you  
u | s, tariffs, countries, trade, billions  
be | will, tonight, pme, proud, classic  
follow | june, loaded, demand, please, respond  
nato | pay, u, dollars, reciprocal, billions  
st | th, unemployment, hopefully, susan, young  
clue | puts, everything, crazy, raised, waste  
immigrants | allow, caravans, security, must, immigration  
officials | local, heed, got, law, former  
social | daca, carolina, dishonesty, johnson, because  
son | book, saw, door, innocent, ill  
...

Epoch: 16/20

Loss: 2.6353986263275146

on | m, at, p, tonight, enjoy  
about | questions, exist, lied, when, cnn  
he | his, against, total, him, picked  
s | u, pay, dollars, now, billions  
of | hanoi, with, great, a, top  
they | nothing, no, them, only, little  
must | loopholes, laws, we, secure, security  
much | country, so, things, ballots, given  
fine | albert, unparalleled, game, government, skyline  
executive | premiums, amp, owners, sole, rule  
r | faster, holidays, friday, dedication, bay  
concerning | already, moon, speech, hosting, pageant  
don | prior, eric, bilateral, hold, asked  
troops | home, captured, soldiers, libya, tens  
spirit | outside, optimism, army, unbelievable, you  
mitt | romney, bush, shouldnt, newsmx, quit

...

Epoch: 16/20

Loss: 2.625612497329712

than | far, more, higher, despite, news  
want | dems, once, can, democrats, formula  
so | totally, many, bad, now, reports  
that | i, if, manafort, just, false  
all | on, with, urging, again, in  
they | nothing, no, them, only, do  
get | mess, smart, cant, streaming, dont  
again | america, lets, make, join, let  
victims | families, prayers, accident, god, responders  
negotiations | china, un, deal, deals, testing  
announce | pleased, chief, hotels, nominated, shortly  
nato | pay, u, reciprocal, billions, countries  
turned | whistleblowers, watergate, predicted, hoping, legitimate  
troops | home, captured, soldiers, libya, ironic  
fine | unparalleled, albert, government, game, traitor  
beach | palm, florida, pageant, tonight, airport

...

Epoch: 17/20

Loss: 2.4947333335876465

by | despite, trump, via, course, the  
dont | but, ig, do, know, yourself  
president | meeting, xi, administration, handle, pres  
not | the, does, that, allowing, responsible  
was | election, took, job, senior, panel  
one | reviews, else, focus, achievement, political  
this | is, back, so, employed, life

must | loopholes, laws, we, secure, finally  
school | qvc, killings, philadelphia, fellow, chain  
blue | monster, doral, rated, gary, courses  
loser | dummy, church, hell, cover, ny  
funding | drugs, emergency, not, immigration, lottery  
list | luxurious, palos, topic, call, yet  
concerning | already, recent, kingdom, low, hosting  
troops | home, soldiers, captured, libya, ironic  
himself | fool, comey, report, disgraced, ohr  
...

Epoch: 18/20

Loss: 2.655994415283203

to | the, will, tomorrow, i, start  
about | questions, lied, sources, when, exist  
now | lottery, so, southern, luther, they  
and | their, as, only, do, the  
only | they, and, their, cost, self  
as | and, j, for, yourself, demands  
u | s, tariffs, countries, trade, pay  
but | does, dont, hope, always, longer  
received | cpac, pm, philippines, honored, agent  
soldiers | syria, troops, broken, home, isis  
terrorism | islamic, individuals, khan, thinking, solidarity  
create | midas, heard, features, somebody, building  
necessary | border, creative, strong, whats, democrats  
lyin | ted, cruz, investigating, oath, leaking  
senators | replace, leadership, working, repeal, raise  
tom | brady, pa, hes, salt, holes  
...

Epoch: 18/20

Loss: 2.4753682613372803

media | news, fake, corrupt, lamestream, cnn  
many | so, jinning, eu, comparison, being  
up | had, they, shifty, elections, results  
not | that, of, does, the, highly  
do | they, or, perhaps, and, improve  
never | why, inquiry, either, trumper, opinions  
or | they, do, yourself, passion, else  
even | it, they, try, very, little  
twitter | winner, bad, imagination, cpac, wash  
rep | education, aoc, version, israel, help  
anymore | rest, journalism, credibility, news, purposely  
blue | monster, doral, rated, courses, performance  
dem | podesta, hillary, acid, debates, voter  
award | offers, exceptional, hotel, memory, luxurious  
himself | fool, comey, ohr, exposed, disgraced

offers | rooms, signature, star, architectural, luxury  
...

Epoch: 19/20

Loss: 2.5002264976501465

the | to, in, which, from, not  
only | their, they, and, cost, all  
border | southern, immigration, drugs, security, drug  
do | perhaps, improve, they, want, or  
going | nevada, let, accept, payer, again  
when | didnt, then, dumb, hated, about  
out | people, am, has, flights, just  
must | loopholes, we, laws, secure, and  
executive | cycle, owners, premiums, signed, sign  
clue | puts, quantitative, stimulus, waste, marco  
weeks | two, universe, east, africa, season  
presidency | has, number, visit, unparalleled, upward  
blue | monster, doral, rated, courses, miami  
outside | massive, crowd, preparing, shortly, unbelievable  
rest | anymore, strongly, poland, journalism, patriots  
r | senate, william, abortion, faster, dedication  
...

Epoch: 20/20

Loss: 2.5455482006073

if | that, it, says, they, else  
have | report, i, which, they, compete  
fake | media, news, incorrect, russian, mainstream  
with | had, amp, on, of, conde  
going | nevada, let, hey, accept, fun  
get | smart, mess, cant, must, dont  
their | and, only, boxing, eu, which  
are | those, cases, brutal, we, these  
non | achievers, buy, fires, bank, tariffed  
anymore | rest, journalism, credibility, news, they  
dem | podesta, hillary, debates, acid, is  
beach | palm, airport, florida, golf, tonight  
doubt | powerful, you, compared, young, watergate  
biden | joe, sleepy, shifty, heavily, side  
turnberry | scotland, ireland, resort, aberdeen, wind  
named | resort, former, club, top, located  
...

Epoch: 20/20

Loss: 2.270085573196411

and | their, as, all, is, for  
media | fake, corrupt, news, bad, packed  
is | stewart, and, disaster, dumb, this

```

so | totally, many, bad, reports, ratings
very | good, little, id, a, ocare
america | again, make, lets, together, video
good | very, things, xi, trading, epa
years | ago, six, manufacturing, boy, broken
created | safer, tool, gained, u, hired
presidency | visit, has, unparalleled, letting, resolution
views | rooms, luxurious, designed, offers, acres
twitter | winner, cpac, tonight, imagination, bad
executive | cycle, signed, owners, interview, sign
dem | podesta, debates, hillary, acid, dems
soldiers | syria, troops, died, trained, home
b | rolling, questions, peninsula, she, ireland
...

```

```

[7]: #If you wanna save the model
      #torch.save(model, '../models/tweet_embeddings/trump_rnn_1910.net')

```

### 1.3 Visualizing the word vectors

Below we'll use T-SNE to visualize how our high-dimensional word vectors cluster together. T-SNE is used to project these vectors into two dimensions while preserving local structure. Check out [this post from Christopher Olah](#) to learn more about T-SNE and other ways to visualize high-dimensional data. Wiki on T-SNE, a bit complicated! [https://en.wikipedia.org/wiki/T-distributed\\_stochastic\\_neighbor\\_embedding](https://en.wikipedia.org/wiki/T-distributed_stochastic_neighbor_embedding)

```

[8]: # getting embeddings from the embedding layer of our model, by name
      embeddings = model.in_embed.weight.to('cpu').data.numpy()

```

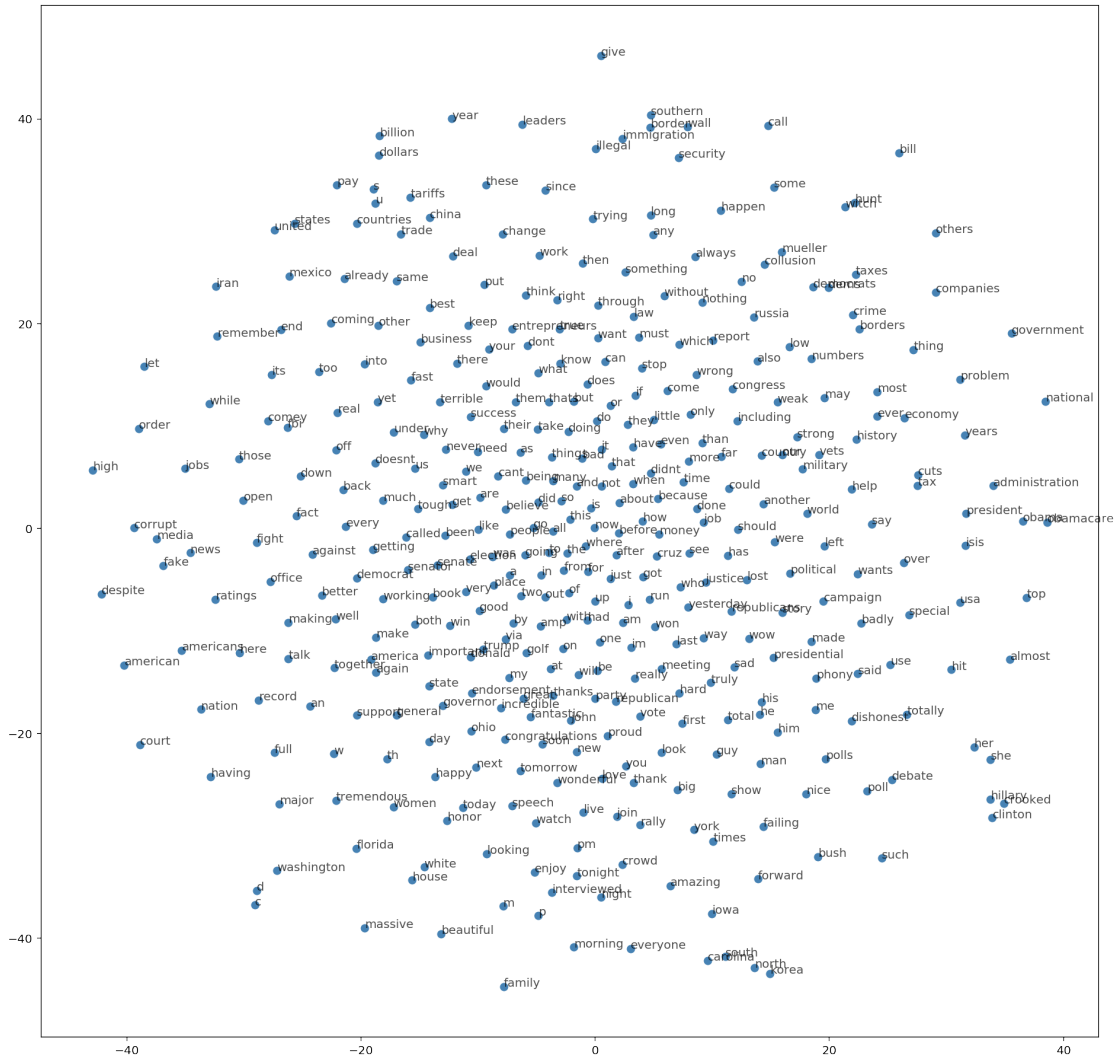
```

[9]: viz_words = 400
      tsne = TSNE()
      embed_tsne = tsne.fit_transform(embeddings[:viz_words, :])

      fig, ax = plt.subplots(figsize=(16, 16))
      for idx in range(viz_words):
          plt.scatter(*embed_tsne[idx, :], color='steelblue')
          plt.annotate(int_to_vocab[idx], (embed_tsne[idx, 0], embed_tsne[idx, 1]),
                      ↪alpha=0.7)

```





```
[10]: # If you wanna load a pre-trained model
model = torch.load('./models/tweet_embeddings/trump_rnn_1911.net')
keys = ['collusion', 'hillary', 'hotel', 'democrats', 'campaign', 'fed', 'china', 'mexico', 'tariffs', 'tax']
embeddings = model.in_embed.weight.to('cpu').data.numpy()

[11]: plot_similar_words(keys, model, vocab_to_int, int_to_vocab, num=20, file=None)
```

'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.

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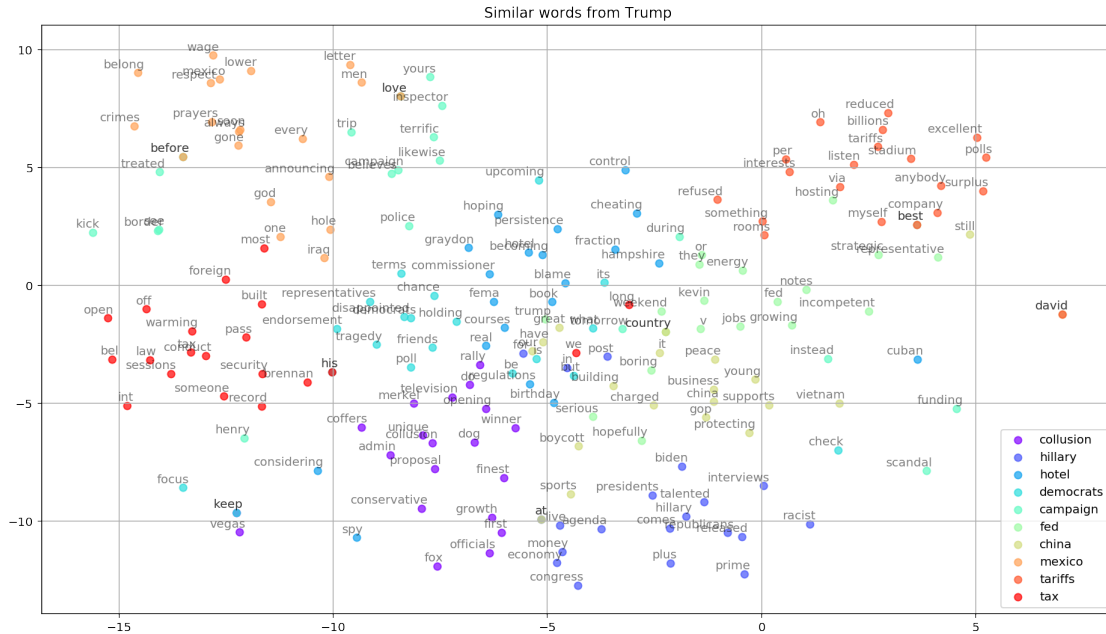
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```
[12]: trump_returns_words = ['getting',
    'happy',
    'paying',
    'against',
    'support',
    'farmers',
    'pelosi',
    'spending',
    'just',
    'billion']
plot_similar_words(trump_returns_words, model, vocab_to_int, int_to_vocab,
    ↪num=20, file=None)
```

'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.

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