SI 544 Final Paper

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< Investigating the Effect of Trump's Election on Hate Crimes Using Twitter API >

Abstract

This research was designed to analyze the effect of Trump's presidential win on the average number of hate crimes nationwide. It was hypothesized that there would be a higher mean of hate incidents after the 2016 presidential election compared to before the election. The data was extracted from Twitter, where the number of tweets reporting hate crimes before the election was compared to the number of hate crime-reporting tweets after the election. Contradictory to the speculated increase of incidents implied by the vast media coverage of hate crimes, the results of this research show that there is no significant difference between the average number of hate incident-reporting tweets before and after the election.

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I. Introduction

Research Topic

Since the presidential election of Donald Trump on November 9th, 2016, there has been an uproar on social media over the aftermaths of the election. The day after the election, a collection of tweets called “Day 1 in Trump’s America” circulated the Internet. These viral tweets reported hate speech and hate crimes faced by women, Muslims, and people of color throughout the United States, inciting fear and anger towards Trump supporters. The immediate surge in racist and sexist attacks following the election implied the impacts of Trump’s xenophobic, Islamophobic, and misogynistic remarks that had gained widespread attention during his campaign. The series of tweets highlighting racist acts throughout the nations alluded to the increased likelihood for women, Muslims, and people of color to be subject to instances of harassment. This trend has inspired us to carry out further research of the effects of Trump’s presidential win on the instances of hate speech and hate crimes on college campuses throughout the U.S.

The impact of Trump’s presidential win on hate crimes is a topic of current interest because of the debate surrounding the true cause for the apparent increase in hate crimes. On the one hand, some believe that Trump has truly caused an increase in hateful sentiments and actions among his followers. It can be argued that his presidential win has given his supporters permission to carry out acts of hate, thus causing the number of incidents to rise. On the other hand, some believe that Trump’s presidential win has not necessarily changed the number of hate crime incidents; it has simply raised the awareness of them. They argue that the level of focus and attention towards hate incidents had suddenly heightened after the presidential election, making it seem as if the number of incidents has actually increased. Our research will explore this argument of whether or not there is indeed a difference in the number of hate crimes before and after Trump’s presidential win.

Research Speculation

We used the concepts of mean, standard deviation, and hypothesis testing to extract meaningful findings from our dataset. The null hypothesis and the alternative, as well as the t-statistics for the hypothesis testing in this research are as follows:

$$Y_{before} = tweets\ about\ hate\ crime\ before\ election$$

$$Y_{after} = tweets\ about\ hate\ crime\ after\ election$$

$$\bar{y}_{before} = sample\ mean\ of\ hate\ crime\ reporting\ tweets\ before\ election$$

$$\bar{y}_{after} = sample\ mean\ of\ hate\ crime\ reporting\ tweets\ after\ election$$

$$\mathrm{T} \sim N(0, sd^2)$$

$$\mathrm{sd} = \sqrt{\frac{(sd_{before})^2}{N_{before}} + \frac{(sd_{after})^2}{N_{after}}}$$

$$H_0 : \mu_{before} = \mu_{after}$$

$$H_1 : \mu_{before} \neq \mu_{after}$$

$$\mathrm{t} = \frac{\bar{y}_{before} - \bar{y}_{after}}{sd}$$

We expect to find a higher number of hate crime reporting tweets after Trump's win compared to before. For each of the two groups Y_{before} and Y_{after}, we came up with the probability of each Twitter account having tweets about hate crimes and calculated the mean and standard deviation values of these probabilities. The following report will discuss the methodology used for our data collection and analysis, the results of our research, the limitations, and some directions for further research.

II. Methodology

Dataset used in research

The dataset we used in this research are the Twitter tweets posted by 2,258 colleges and universities in the United States. The list of accounts was scraped from a Twitter account @Stamats, which posted the accounts of all colleges and universities in the United States, including public, private, community, for-profit, etc. We then wrote a Python program to retrieve the tweets posted by these accounts in a date range of one month before and after the election. The code also filtered tweets based on target words related to the topic of hate crime. We referred to a Crime Vocabulary Word List provided by MyVocabulary.com to come up with the list of target words.[1] To make these target words more relevant to our research purpose, we retrieved some sample tweets, went through the results, and filtered out the irrelevant words.

Data collection strategy

First of all, we gathered all tweets using a Python module 'tweepy.' After that, we divided these tweets into two groups - tweets before the Election Day and after. We set the same range of time - one month - for the two groups. We also came up with a list of 'target_words' that included possible words relevant to hate crimes, such as 'hate crime', 'sexual harassment' and 'racial discrimination.' Then, for each group of tweets, we checked if the tweet contained the words in the

[1] MyVocabulary.Com (12.06.16) Retrieved from https://myvocabulary.com/

‘target_words’ list, grabbed the tweets that did, and saved them into separate csv files. In this process, we lemmatized each word in the tweets to figure out if the tweet was actually dealing with the incidents we were looking for. The biggest advantage of lemmatizing is that it enables us to find all possible tenses and parts of speech for each target word. Also, this process was necessary because if we were to not lemmatize the words and were to simply check whether the target words were in the tweets, tweets like ‘I like grapes’ would have been counted as addressing incidents about ‘rape.’ We used a Python module ‘nltk’ for this. As a result, we had two datasets of tweets that were related to hate crimes, and calculated the mean and standard deviation for each group as mentioned in the earlier part of the report. We were then able to investigate the null hypothesis using these values.

The advantage of this data collection strategy is that more than 2,000 Twitter accounts were used, enabling us to have a large number of datasets for analysis that would raise the validity of this research. Another advantage is that this method can be applicable to other types of Twitter accounts to figure out different perspectives of this research topic. However, the disadvantage of this strategy is the use of a target word list. Selecting tweets based on keywords rather than content may lead to the inclusion of some irrelevant tweets. Thus, the number of tweets retrieved according to the current strategy may not be 100% accurate.

III. Results

<u>Hypothesis summary</u>

We tested the null hypothesis that there is no significant difference between the mean of hate crime-reporting tweets before Trump’s presidential win and the mean after his win. The alternative hypothesis is that there is a significant difference between the two means.

$$H_0 : \mu_{before} = \mu_{after}$$

$$H_1 : \mu_{before} \neq \mu_{after}$$

Research results

Statistics:

Before Group	mean	0.03496074
	standard deviation	0.08794605
After Group	mean	0.03259604
	standard deviation	0.04217888
T-statistics	mean difference	-0.0529853
	standard deviation	0.00351381
	T	0.67297201
	p-value	0.5009651

Sample Tweets:

(Before)

UMich, 2016-10-13 13:02:05, b'RT @umichdpss: Still time to sign up for the #PurpleRun this Sat! Support domestic violence victims & survivors @SafeHouseCenter.\n\nhttps://\xe2\x80\xa6'

(After)

UMich, 2016-11-12 23:06:11, b'RT @umichdpss: We are very concerned & disturbed by the reported intimidation crime. Local officers are investigating & conducting addition.

In retrieving the data, there were some authentication errors, and some universities had no retrievable data in their accounts. The ‘Before Group’ and ‘After Group’ refer to the number of accounts that had data in each date range. Then, we retrieved the number of total tweets and the target tweets from each 'Before Group' and 'After Group.' In the statistics, we calculated the values of the average and standard deviation, and then calculated the p-value with those values. According to our calculation, we cannot reject the null with 95% confidence, since the T statistic of 0.67297201 is much less than 1.96.

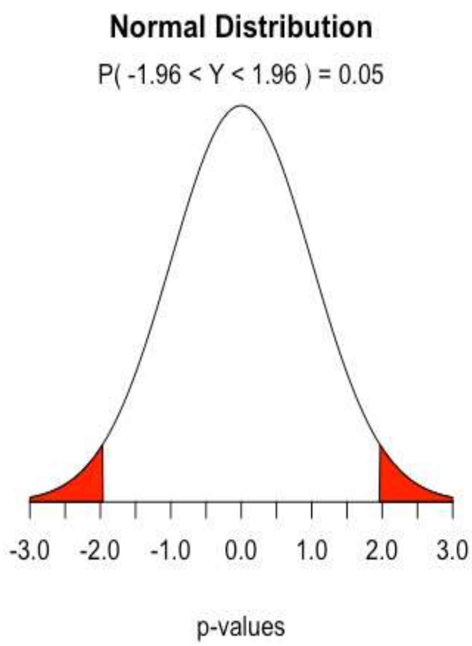

Figure 1. 95% confidence interval plot

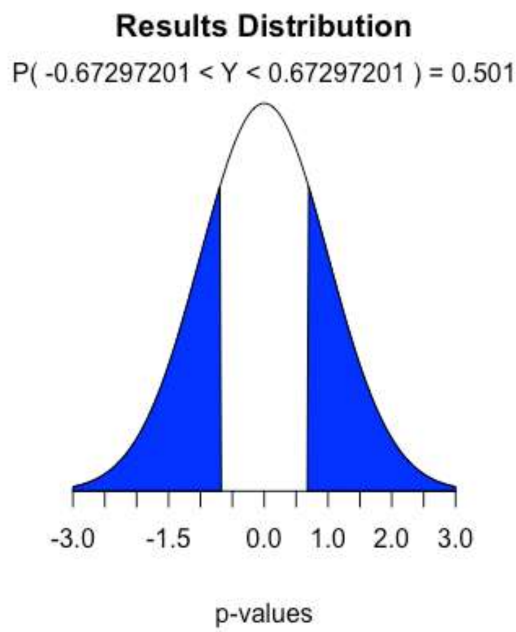

Figure 2. Result plot

The result of our research was surprising because we expected a large increase in the mean number of hate crime-reporting tweets after the presidential election compared to before the election. We had assumed that the vast media coverage on hate crime incidents shortly after Trump's presidential win represented the actual increase in the number of hate crimes nationwide.

However, the result of this research showed that there is no significant difference between the mean number of hate crime-reporting tweets before and after the election.

IV. Conclusion

Findings

Based on our results, we cannot say that there has been an increase in hate crime-related tweets after Trump's presidential win. We came up with three possible interpretations for the research findings. First of all, it is possible that an increase in the media coverage on hate crimes affected people to think that there has been an actual increase in the number of tweets mentioning hate crimes. Second, the result could have been affected by how the research is limited to the college and university population. Since college and university students tend to be more liberal, we speculated that the racial/sexual discrimination tendency is more likely to be exposed. Lastly, since the election campaign had been going on for over a year, the tweets retrieved within a month before and after the Election Day may not be enough of a date range for inspecting the differences.

Limitations and points of improvement

While the tweets posted by college and university Twitter accounts were the main dataset in this research, this may lack representativeness in conducting a research to test a hypothesis on a national level. The results from analyzing this dataset cannot be generalized to all populations and are somewhat limited to the student population. Thus, further studies should consider retrieving tweets from accounts that are more related to the general public, such as accounts of police departments in each city (e.g. @NYPDnews). This will improve representativeness of the dataset and improve the reliability of hypothesis analysis. Moreover, the use of tweets as the dataset can also be a limitation of the research. Due to the lack of reliability of social media, it is difficult to ensure the validity of our data. To improve this point, future studies should consider using official police reports that contain verified information regarding hate crimes.

Another limitation is that we filtered tweets based on keywords related to crimes. However, some tweets may have been irrelevant to our topic of interest, since they were chosen based only on keywords. Further studies should use context analysis techniques to filter tweets based on content rather than relying on keywords so that data accuracy can be improved.

Strong points of the research

One of the best parts of conducting this research is that we applied what we learned from several different courses to tackle real-world issues. According to an article from Quartz, "there is no dataset that can tell us whether hate crimes have surged on a national level in the short span of time between the election and today."[2] Our research is an attempt to provide a meaningful dataset regarding whether there has been an increase in the number of tweets related to hate crimes post-2016 presidential election. Conducting this research by writing our own python program allowed us to run the program as many times as needed, increasing the accuracy of the result. Furthermore, this would also enable us to update our dataset periodically if further research is deemed necessary.

[2] Quartz (12.06.16) Retrieved from http://qz.com/843834/are-hate-crimes-really-on-the-rise-in-america-heres-a-guide-to-the-data/

V. References

MyVocabulary.Com (12.06.16) Retrieved from https://myvocabulary.com/

Quartz (12.06.16) Retrieved from http://qz.com/843834/are-hate-crimes-really-on-the-rise-in-america-heres-a-guide-to-the-data/

VI. Appendix

i. Raw Data

Date Range:

Before	2016-10-10 ~ 2016-11-07
After	2016-11-08 ~ 2016-12-07

Numbers:

Universities	Try	2,258
	Actual	2,231
	Before Group	2,088
	After Group	2,089
	Before Target	793
	After Target	686
Before Group	Total tweets	180,650
	Target tweets	2,380
After Group	Total tweets	163,840
	Target tweets	1,970

ii. Crime Vocabulary Word List

A)	Abuse, Accessory, Accomplice, Accused, Accuser, Activists, Adversary, Affect, AFIS, Against, Agency, Aggravated assault, Alarm, Alcohol, Alert, Alias, Alibi, Alienate, Allegation, Ammunition, APB, Appeal, Armed, Arraignment, Arrest, Arsenal, Arson, Art forgery, Assailant, Assault, Attack, Authority, Autopsy
B)	Background check, Backup, Bail, Ballistics, Battery, Beat, Behavior, Behind bars, Belligerence, Big house, Blackmail, Bloodstain, Bombing, Brawl, Breach, Break-in, Breaking and entering, Bribery, Brutality, Bullying, Burden of proof, Burglary, Bystander
C)	Capture, Case, Caution, Chase, Cheat, Civil, Claim, Coercion, Collusion, Combat, Commission, Commit, Complaint, Complication, Conduct, Confession, Connection, Conspiracy, Contact, Contacts, Contempt, Control, Controversial, Conviction, Cops, Coroner, Corruption, Counsel, Counterfeit, Court, Credit theft, Crime, Criminal, Criminal justice system, Criminology, Cuffs, Custody
D)	Damage, Danger, Dangerous, Dark side, Data base, Deadly, Deal, Dealings, Death, Deed, Defendant, Defense, Deliberate, Delinquency, Democratic, Denial, Department, Deputy, Detail, Detain, Detection, Detective, Deter, Determination, Deviant, Direct, Discovery, Dismember, Disobedience, Disorderly, Dispatch, Disregard, Disruption, District attorney, DNA, Documentation, Documents, Domestic, Dossier, Drill, Drugs, Duty
E)	Educate, Education, Effect, Elusive, Embezzle, Emergency, Enable, Encumber, Enforce, Entail, Equality, Escape, Ethical, Evasive, Eviction, Evidence, Evil, Examination, Execute, Exonerate, Expert, Explosives, Expunge, Extort, Extradition, Extreme
F)	Failure, Fairness, Family, Fatality, Fault, FBI, Federal, Felony, Ferocity, Fight, Fighting, Fine, Fingerprint, Firebombing, First-degree, Flee, Footprints, Forbidden, Force, Forensics, Forgery, Formal charge, Frantic, Fraud, Freedom, Full-scale, Fundamental, Furtive
G)	Good guys, Gory, Government, Grief, Grievance, Guarantee, Guard, Guilty, Gun, Gunrunning
H)	Hand-to-hand, Handcuffs, Handle, Harassment, Harm, Harmful, Headquarters, Heinous, Helicopter, Help, Helpful, High-powered rifle, High-profile, Hijack, Hire, Holding cell, Holster, Homicide, Honesty, Honor, Hostage, Hot-line, Humanity
I)	Identification, Illegal, Immoral, Immunity, Impeach, Impression, Imprison, Improper, Incarceration, Incompetent, Incriminating, Indictment, Influence, Informant, Information, Initiative, Injury, Inmate, Innocence, Innocent, Inquest, Instruct, Integrity, Intelligence, Interests, Interference, International, Interpol, Interpretation, Interrogate, Interrogate, Interstate, Intervention, Interview, Intrastate, Intruder, Invasive, Investigate, Investigation, Irregular, Irresponsible, Issue
J)	Jail, John Doe, Judge, Judgment, Judicial, Judiciary, Jurisdiction, Jury, Justice, Juvenile
K)	Kidnapping, Kill, Killer, Kin
L)	Laboratory, Larceny, Law, Law-abiding, Lawfully, Lawsuit, Lawyer, Leaks, Lease, Legal, Legislation, Legitimate, Lethal, Libel, Liberty, License, Lie detector, Lien, Lieutenant, Limits, Long hours, Lowlife, Loyalty, Lynch
M)	Mace, Maintain, Majority, Malice, Malpractice, Manacled, Manslaughter, Marshal, Mayhem, Metal detector, Minor, Minority, Miscreant, Misdemeanor, Missing person, Mission, Model, Money laundering, Moratorium, Motorist, Murder, Murderer
N)	National, Negligent, Negotiable, Negotiate, Neighborhood, Network, Nine-one-one, Notation, Notification, Nuisance
O)	Oath, Obey, Obligation, Offender, Offense, Officer, Official, On-going, Open case, Opinion, Opportunity, Order, Organize, Ownership
P)	Partner, Partnership, Pathology, Patrol, Pattern, Pedestrian, Peeping Tom, Penalize, Penalty, Perjury, Perpetrator, Petition, Petty theft, Phony, Plainclothes officer, Plea, Plead, Police, Policy, Power, Precedent, Precinct, Preliminary findings, Prevention, Principle, Prior, Prison, Private, Probable cause, Probation, Probation officer, Procedure, Professional, Profile, Prohibit, Proof, Property, Prosecute, Prosecutor, Prostitution, Protection, Protocol, Provision, Public, Punishment
Q)	Quake, Qualification, Quality, Quantify, Quantity, Quarrel, Quell, Question, Quickly, Quirk, Quiver
R)	Radar, Raid, Rank, Rap sheet, Rape, Reason, Reckless endangerment, Record, Recovery, Recruit, Redress, Reduction, Refute, Register, Regulations, Reinforcement, Reject, Release, Repeal, Reported, Reports, Reprobate, Reputation, Requirement, Resist, Responsibility, Restitution, Restraining order, Restriction, Revenge, Rights, Riot, Robbery, Rogue, Rough, Rules, Rulings
S)	Sabotage, Safeguard, Sanction, Scene, Sealed record, Search and rescue team, Secret, Seize, Seizure, Selection, Sentence, Sergeant, Serial killer, Seriousness, Services, Sex crimes, Shackles, Sheriff, Shooting, Shyster, Sighting, Situation, Skillful, Slander, Slashing, Slaying, Smuggling, Sorrow, Speculation, Spying, Squad, Stabbing, Stalking, Statute, Statute of limitation, Stigma, Stipulation, Subdue, Subpoena, Successful, Summons, Supervise, Suppress, Surveillance, Survivor, Suspect, Suspected, Suspicion, Suspicious, Sworn, System
T)	Tactic, Task force, Terrorism, Testify, Testimony, Theft, Threatening, Three-strikes law, Thwart, Tire-slashing, Torture, Toxicology, Trace, Traffic, Trafficking, Tragedy, Transfer, Trauma, Treatment, Trespass, Trial, Trooper, Trust
U)	Unacceptable, Unauthorized, Unclaimed, Unconstitutional, Undercover, Underpaid, Understaffed, Unexpected, Unharmed, Uniform, Unintentional, Unit, Unjust, Unknown, Unlawful, Unsolved, Uphold
V)	Vagrancy, Vandalism, Viable, Vice, Victim, Victimize, Victory, Vigilance, Vigilante, Violate, Violation, Violence, Volunteer, Vow, Voyeurism, Vulnerable
W)	Wanted poster, Ward, Warning, Warped, Warrant, Watch, Weapon, Will, Wiretap, Wisdom, Witness, Worse, Wrong
X)	
Y)	Youth
Z)	Zeal, Zealous

iii. Python Codes

```
import tweepy
import csv
import time
import nltk
from datetime import date
from nltk.stem import WordNetLemmatizer
from auth_key import *

today = date.today()
election_day = date(2016, 11, 8)
date_from = election_day - (today - election_day)

wordnet_lemmatizer = WordNetLemmatizer()

id_dict = {}
target_words = ['intimidation', 'sexual', 'discrimination', 'hate', 'racial', 'ethnicity',
'crime', 'assault', 'attack', 'abuse', 'arrest', 'caution', 'emergency', 'fight', 'harassment',
'harm', 'improper', 'investigate', 'threat', 'offender', 'misdemeanor', 'offense', 'perpetrator',
'rape', 'violate', 'violation', 'violence', 'suspect', 'suspected', 'victim']

total_num = 0

def pos_converter(upenn_pos):
        if upenn_pos =='MD' or upenn_pos =='VB' or upenn_pos =='VBD' or upenn_pos =='VBG' or upenn_pos =='VBN' or
            upenn_pos =='VBP' or upenn_pos =='VBZ':
                return 'v'
        elif upenn_pos =='JJ' or upenn_pos =='JJR' or upenn_pos =='JJS':
                return 'a'
        elif upenn_pos == 'RB' or upenn_pos =='RBR' or upenn_pos =='RBS':
                return 'r'
        else:
                return 'n'

def get_2000_univ():
        twitter_list_file = open('twitteraccount_list.txt', 'r')
        indicator = 0
        global total_num
        id_list = []
        for row in twitter_list_file:
                if indicator == 1:
                        id_list.append(row)
                        indicator = 0
                        total_num += 1
                if row.startswith(" Follow"):
                        indicator = 1

        for item in id_list:
                try:
                        name, account = item.split(' @')
                        id_dict[name[1:]] = account[:-1]
                except:
                        continue

def get_all_tweets(screen_name):
        auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
        auth.set_access_token(access_key, access_secret)
        api = tweepy.API(auth, wait_on_rate_limit=True)

        loopCond = True
        alltweets = []

        try:
                new_tweets = api.user_timeline(screen_name = screen_name,count=200)
                if len(new_tweets)>0 and new_tweets[-1].created_at.date() < date_from:
                        for tweet in new_tweets:
                                if tweet.created_at.date() < date_from:
                                        new_tweets.remove(tweet)
                        loopCond = False

        except:
                new_tweets = []
                print(screen_name, "is in trouble.")

        alltweets.extend(new_tweets)

        if len(alltweets)>0:
                oldest = alltweets[-1].id - 1

        while len(new_tweets) > 0 and loopCond:
                try:
                        new_tweets = api.user_timeline(screen_name = screen_name,count=200,max_id=oldest)
                        if len(new_tweets)>0 and new_tweets[-1].created_at.date() < date_from:
                                for tweet in new_tweets:
                                        if tweet.created_at.date() < date_from:
                                                new_tweets.remove(tweet)
                                alltweets.extend(new_tweets)
                                loopCond = False
                                break

                except:
                        new_tweets = []
                        print(screen_name, "is in trouble.")

                alltweets.extend(new_tweets)

                if len(alltweets)>0:
                        oldest = alltweets[-1].id - 1
        print(len(alltweets) ,"tweets appended")
        return alltweets
```

```
def write_count(inputfile, outputfile):
	count_dic = {}
	input_file = csv.reader(open(inputfile, newline=''), delimiter=',', quotechar='"')

	for row in input_file:
		if row[0]=='id':
			continue
		if row[0] not in count_dic:
			count_dic[row[0]] = 1
		else:
			count_dic[row[0]] += 1

	new_out = list(count_dic.items())

	with open(outputfile, 'w', newline='') as f:
		writer = csv.writer(f, delimiter=',', quotechar='"')
		writer.writerow(["id"]+["count"])
		writer.writerows(new_out)
	pass

def tweet_match(all_writer, before_writer, after_writer, before_target_writer, after_target_writer):
	pos_list = nltk.pos_tag(target_words)
	target_words_lemma = [wordnet_lemmatizer.lemmatize(words[0], pos_converter(words[1])) for words in pos_list]

	for key in id_dict:
		print("Retrieving all tweets from", key, "(", counter , "of", total_num, ")")
		all_items = get_all_tweets(id_dict[key])
		all_out = []
		before_out = [[tweet.user.screen_name, tweet.created_at, tweet.text.encode("utf-8")]
		    for tweet in all_items if (tweet.created_at.date()<election_day and tweet.created_at.date() >= date_from)]
		after_out = [[tweet.user.screen_name, tweet.created_at, tweet.text.encode("utf-8")]
		    for tweet in all_items if (tweet.created_at.date()>=election_day)]
		all_out.extend(after_out)
		all_out.extend(before_out)

		print("Writing files...")
		before_writer.writerows(before_out)
		after_writer.writerows(after_out)
		all_writer.writerows(all_out)

		print("Matching target words...")
		before_lem, after_lem = [], []
		for row in before_out:
			text_list = nltk.pos_tag(nltk.word_tokenize(str(row[2]).lower()))
			before_lem.append([row[0], row[1], row[2],
			     [wordnet_lemmatizer.lemmatize(words[0], pos_converter(words[1])) for words in text_list] ])
		for row in after_out:
			text_list = nltk.pos_tag(nltk.word_tokenize(str(row[2]).lower()))
			after_lem.append([row[0], row[1], row[2],
			    [wordnet_lemmatizer.lemmatize(words[0], pos_converter(words[1])) for words in text_list] ])

		before_lem_out, after_lem_out = [], []
		for row in before_lem:
			for word in target_words_lemma:
				if word in row[3]:
					before_lem_out.append([row[0], row[1], row[2]])

		for row in after_lem:
			for word in target_words_lemma:
				if word in row[3]:
					after_lem_out.append([row[0], row[1], row[2]])

		print("Writing",len(before_lem_out),"and",len(after_lem_out),"filtered results...")
		before_target_writer.writerows(before_lem_out)
		after_target_writer.writerows(after_lem_out)

		counter += 1
		pass

def call_writer(filename):
	f = open(filename, 'w', newline='')
	fw = csv.writer(f, delimiter=',', quotechar='"')
	fw.writerow(["id"]+["created_at"]+["text"])
	return fw

def main():
	counter = 1
	print("Today is", today, "and the election day was", election_day)
	print("Therefore, we retrieved data from", date_from)

	get_2000_univ()

	all_writer = call_writer('alltweets.csv')
	before_writer = call_writer('before_refine.csv')
	after_writer = call_writer('after_refine.csv')
	before_target_writer = call_writer('before_refine_target.csv')
	after_target_writer = call_writer('after_refine_target.csv')

	tweet_match(all_writer, before_writer, after_writer, before_target_writer, after_target_writer)

	write_count('before_refine.csv', 'before_counter.csv')
	write_count('after_refine.csv', 'after_counter.csv')
	write_count('before_refine_target.csv', 'before_counter_target.csv')
	write_count('after_refine_target.csv', 'after_counter_target.csv')

	print("Done")

if __name__ == '__main__':
	main()
```

iii. Geographical location of the colleges and universities

All versus Target (After election)

Before versus After (Target tweets)