Stage3 - The Implementation Stage.

- Novelty

Users can already find tweets related to their topic by searching for keywords or hashtags related to their topic. However, this project will allow users to find tweets that are both semantically and structurally similar to their tweets, not just related to the topic of those tweets. Users will also be recommended hashtags, such as those of 'intermediate popularity', which users do not include in their tweets, but which are topically related to their tweets.

- Usefulness

This project will allow users to find which tweets and hashtags are similar to their own tweets. Thus, this project aims to bridge different Twitter communities by finding 'hidden' connections between them based on different measures of similarity. This will facillitate communication between previously isolated communities.

- Development Environment

This project is developed with Python language and the Linux operating system.
The deliverables for this stage include the following items:

Section 1. Evaluation of tweet dissimilarity by Extended Edit Distance integrated Word2Vec (EDW), and clustering by the distance value (Implemented and written by Lingfei Zeng)

- Sample small data snippet.
  The input data are plain text of tweet contents. The plain text can be converted by Json file scraped from the webpage. In this section, the sample data are the scraped tweets in csv file, downloaded from http://followthehashtag.com/datasets/, named "USA Geolocated tweets". It contains 20,000 tweets and here is the sample of the data are in Table 1:

- Sample small output
  In the distance evaluation job, the output of the system is distance value of two tweets, ranging from 0 to 1 . After clustering by k-medoids or hierarchical clustering method, the output are the clusters of tweets.

- Working code

```
# Disimilarity evaluation algorithm Extended Edit
# Distance integrated Word2Vec (EDW)

def sentence_to_word(sentence):
    sentence = re.sub("[^a-zA-Z]", " ", sentence.lower())
```

```
    words = WORD.findall(sentence)
    return words

def edit_distance(s1, s2):
    words_1 = sentence_to_word(s1)
    words_2 = sentence_to_word(s2)

    m=len(words_1)+1
    n=len(words_2)+1

    tbl = {}
    bestMove={}
    for i in range(m):
            tbl[i,0]=i
            bestMove[i, 0] = 'D'

    for j in range(n):
        tbl[0,j]=j
        bestMove[0, j] = 'I'

    for i in range(1, m):
        for j in range(1, n):
            if words_1[i-1] == words_2[j-1]:
            cost = 0
            minVal = 10000000
                if tbl[i, j - 1] + 1 < minVal:
                    minVal = tbl[i, j - 1] + 1
                    bestMove[i, j] = 'D'
                if tbl[i - 1, j] + 1 < minVal:
                    minVal = tbl[i - 1, j] + 1
                    bestMove[i, j] = 'I'
                if tbl[i - 1, j - 1] + cost < minVal:
                    minVal = tbl[i - 1, j - 1] + cost
                    bestMove[i, j] = ' '

            else:
                try:
                    word2vec_cost = 1 - model.similarity(
                    words_1[i - 1],
                     words_2[j - 1])
                except KeyError, e:
                    word2vec_cost = 1

                cost = 2*word2vec_cost
```

```
            minVal = 10000000
            if tbl[i, j - 1] + 1 < minVal:
                minVal = tbl[i, j - 1] + 1
                bestMove[i, j] = 'D'
            if tbl[i - 1, j] + 1 < minVal:
                minVal = tbl[i - 1, j] + 1
                bestMove[i, j] = 'I'
            if tbl[i - 1, j - 1] + cost < minVal:
                minVal = tbl[i - 1, j - 1] + cost
                bestMove[i, j] = 'R'

            tbl[i, j] = minVal

iTmp = i
jTmp = j
counting = 0
while True:
    if bestMove[iTmp, jTmp] == 'R' or bestMove[iTmp, jTmp] =
        if bestMove[iTmp, jTmp] == 'R':
        counting += 1
        iTmp -= 1
       jTmp -= 1
    elif bestMove[iTmp, jTmp] == 'D':
        jTmp -= 1
    elif bestMove[iTmp, jTmp] == 'I':
        iTmp -= 1
    if iTmp == 0 or jTmp == 0:
        break

counting += max(m-1,n-1)
return tbl[i,j]/counting
```

- Demo and sample findings
  The performance of EDW algorithm is evaluated by published paired-wised benchmark data set [1] first. Several benchmarking paired sentences with different similarities were tested with our algorithm. The results together with the comparison of the similarities reported in the literature are shown in Table 2. Since the benchmarking uses different scale of core system, the table lists the levels of similarities of each sentence pairs directly. Besides are the distance score generated by EDW, ranging from 0-1, from least similar to identical. From the comparison we can see that the EDW calculated the distance between benchmarking sentences in high accuracy.

Table 1: Data Snippet

Index	Tweet contents
1	I'm at,@DunkinDonuts in Lithonia, GA https://t.co/d6IU15ig5J
2	Cleared:,Closure on #US1 SB at South of Olden Ave
3	Want to,work in #Burlington, MA? View our latest opening: https://t.co/qwwWQt0DMj,#Healthcare #Job #Jobs #Hiring #CareerArc

Table 2: Distance score generated by EDW, compared with reported benchmarking

Sentence pair	Semantic similarities reported by [1]	Distance sore by EDW
Midday is 12 o'clock in the middle of the day. Noon is 12 o'clock in the middle of the day.	Identical	0.081319882
A boy is a child who will grow up to be a man. A lad is a young man or boy.	Related	0.59221011
A hill is an area of land that is higher than the land that surrounds it. A mound of something is a large rounded pile of it.	Vaguely similar	0.76921332
Cord is strong, thick string. A smile is the expression that you have on your face when you are pleased or amused, or when you are being friendly.	Unrelated	0.91587261

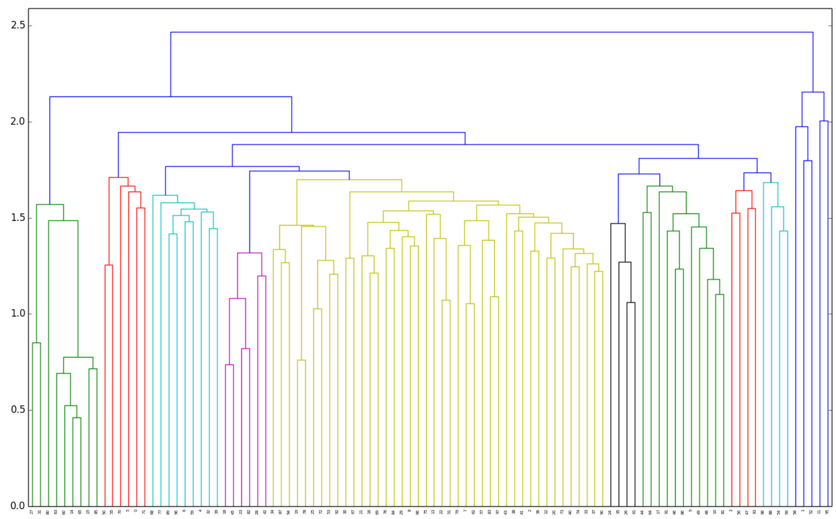
Table 3: Sample result of tweet clusters

Tweet contents	Cluster label
I'm at,@DunkinDonuts in Lithonia, GA https://t.co/d6IU15ig5J	0
I'm at,@InNOutBurger in Long Beach, CA https://t.co/uqmEomzVKZ	0
I'm at Home,https://t.co/fDCP5atErT	0
I'm at Los Angeles,International Airport (LAX) - @flylaxairport in Los Angeles, CA,https://t.co/rCVIJrXCMX	0
I'm at Twerk in,Horsham, PA https://t.co/VRmWIJssIC	0
Cleared:,Closure on #US1 SB at South of Olden Ave	1
Cleared:,Incident on #I87NYSThruway NB at Exit 21 (I-87) - Catskill (Rte 23)	1
Want to,work in ? View our latest opening: https://t.co/47mSniYiPU #Hospitality,#Veterans #Job #Jobs #Hiring #CareerArc	2
Want to,work in #Burlington, MA? View our latest opening: https://t.co/qwwWQt0DMj,#Healthcare #Job #Jobs #Hiring #CareerArc	2
Want to,work in #Charlotte, NC? View our latest opening: https://t.co/nkrJjulisQ,#BusinessMgmt #insurance #Job #Jobs #Hiring	2
Want to,work in #FALLSCHURCH, VA? View our latest opening: https://t.co/sgxNmVAkQl,#Healthcare #Job #Jobs #Hiring #CareerArc	2

Then using the tweet data set, a pair-wised distance matrix was generated based on the score calculated by EWD. This distance matrix was utilized to do the clustering with k-medoids or hierarchical clustering method. The functions are available in related Python packages Kmedoids and Scipy. For k-medoids method, the outputs are index of tweets in different clusters. For hierarchical clustering method, the outputs are tweet clusters and a dendrogram. A sample output by the k-medoids method were shown in the Table 3. The tweets have been grouped into 3 clusters and the similarities of tweets in the same clusters are very high. A sample output of dendrogram of 100 tweets generated by hierarchical clustering are shown in Figure 1.

After clustering the tweets, we can also find the representative tweet in each clustering. The method is as follows: for each tweet in one cluster, sum the distance between it and every other tweets, and find the one tweet with the minimal summed distance. This tweet is the representative of this cluster. Thus we can find a representative for every cluster. Later, when user input a new tweet, it is compared with the representatives. Whichever cluster with the representative has the shortest distance with the new tweet, the cluster is the new tweet to be assigned to. Then if we would like to find similar tweets to the new tweets, we just need to compare every tweets in this cluster and return the highest hits. Since we can maintain a relative high number of clusters so the number of tweets

Figure 1: Dendrogram generated by EDW and hierarchical clustering)



in one cluster is limited (or else the classification would not be accurate), the computation time is small.

Section 2. Evaluation of tweet similarity by TF-IDF based document2vec and Hierarchical Clustering (Implemented by Xunjie Zhu and written by Michael Lan)

- Sample Small Data Snippet (This is a subset 3 tweets out of thousands of tweets used)

211 : RT @KCONTV: Fans dancing in front of the @HondaCenter before the #BTSinAnaheim concert! #TWTinAnaheim #BTS https://t.co/QAVEt0uqYn
212 : RT @BTS_V_sana: 02line(01)ARMY all #ARMY #BTSRT #RT https://
213 : RT @bangtanitl: #BTS was mentioned on Kangnam Style, 170331 https://t.co/uL8yrSGBJB https://t.co/qJ0IINaTrH

- Sample Small Data Output

The word and paragraph vectors, along with the document-term frequency matrix, are huge, so we did not include them in Phase 3 write-up. Additionally, they are only intermediate outputs. The dendrogram of the clustering results is the final output, and a visual and description of it is given below the pipeline description in this section.

- Pipeline Description

Since it would be quite lengthy to include all the code used, only the hierarchical clustering algorithm code has been given at the end of this section. Also, the bipartite graph and Simrank code was completed but are not part of the main pipeline yet, so only a histogram of their output is given; the code is not included. The rest of the code can be given upon request, and may be included in the final report. The pipeline is briefly described:

The data crawler uses a listener to find new tweets that contain certain keywords or hashtags, collectively called a 'filter'. To find tweets that are related to certain topics but do not necessarily contain the hashtags of those topics, we first gathered tweets containing initial keywords. New keywords, hashtags, and topics were found from in this first iteration of tweets, and were added to the filter. Then, we ran the data crawler again using this new filter, and repeated this multiple times. Essentially, we used previous iterations of keywords or hashtags to find new topics, and we only ran clustering on the tweets found in the final iteration. Each iteration is called a 'generation'.

There were two separate methods we used to find new topics: 1)We took the 10 most frequent new, non-trivial keywords hashtags found in this first iteration of tweets and added them to the filter 2) We used LDA to find new topics. IE) Filter in Gen 1: music, concerts Filter in Gen 2: music, concerts, classical, metal Filter in Gen 3: music, concerts, classical, metal, bach

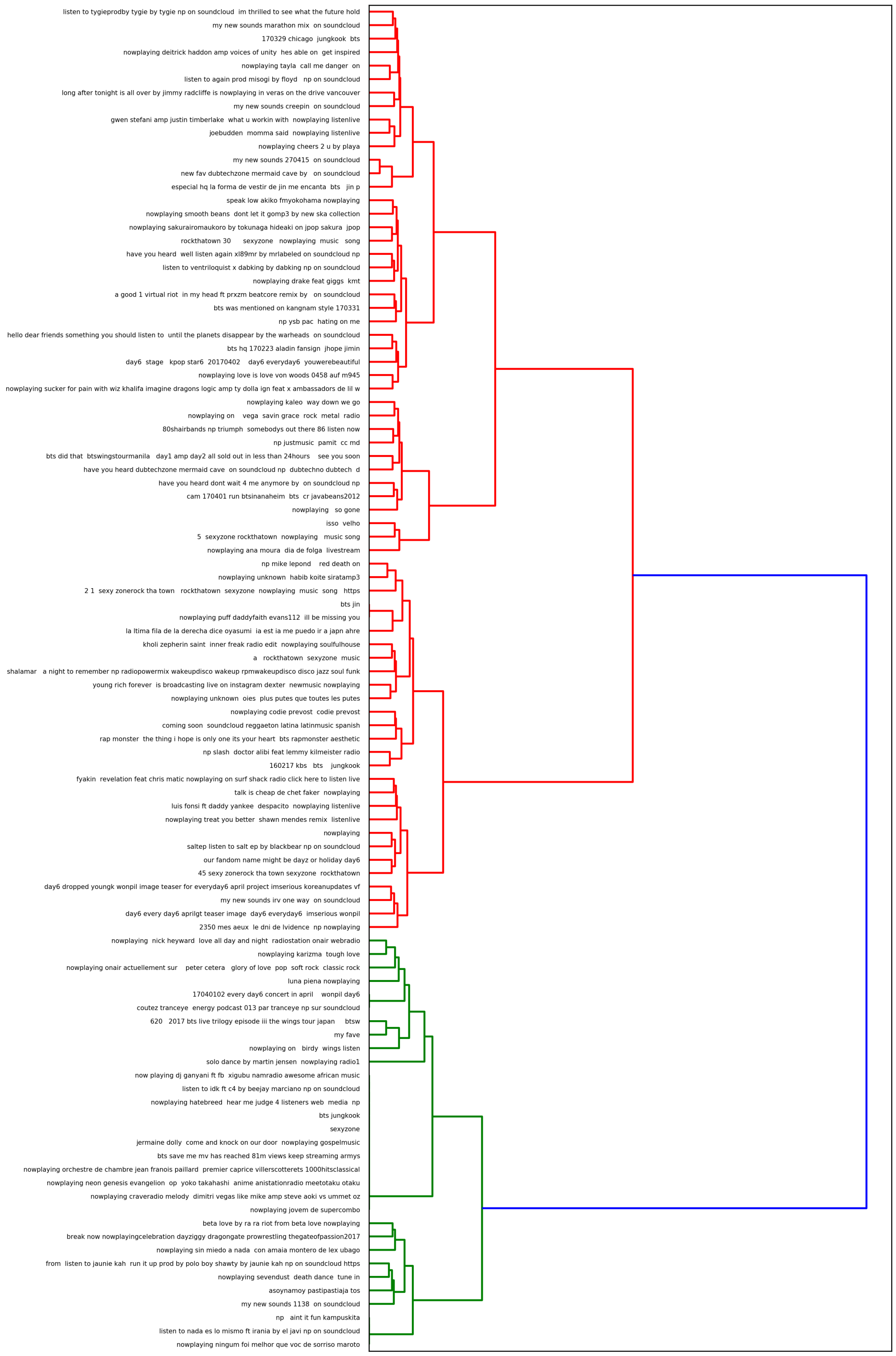
Later, the crawler and topic finding scripts will be deployed to a linux server to be run periodically. This will be implemented by crontab.

The pipeline is described as follows:

1. Start up a listener of incoming tweets. Uses the Tweepy library to connect to Twitter Streaming API. Outputs a JSON text file of data
2. Read a JSON text file and outputs a file of tweets
3. Use term frequency and latent dirichlet allocation respectively to find new topics from existing tweets
4. Read file of tweets and uses regular expressions to do some preprocessing
5. Train word vector and tf-idf weighted sum of word vector to form document vector. Computes similarity between tweets. Outputs word and paragraph vectors
6. Cluster the tweets into topics and outputs a dendrogram

- Interesting findings in Dendrogram

Since there were thousands of tweets that were gathered, we created a dendrogram for 100 tweets. There appear to be two main groups, and within the red group, there were 4 main subgroups. This sample shows that our algorithms work. However, since we did not input in meaningful data yet, and since this dendrogram only shows 100 of thousands of tweets, we do not expect this sample to give meaningful results. Later, we will gather better data and perform an analysis.


listen to tygieprodby tygie by tygie np on soundcloud im thrilled to see what the future hold
my new sounds marathon mix on soundcloud
170329 chicago jungkook bts
nowplaying deitrick haddon amp voices of unity hes able on get inspired
nowplaying tayla call me danger on
listen to again prod misogi by floyd np on soundcloud
long after tonight is all over by jimmy radcliffe is nowplaying in veras on the drive vancouver
my new sounds creepin on soundcloud
gwen stefani amp justin timberlake what u workin with nowplaying listenlive
joebudden momma said nowplaying listenlive
nowplaying cheers 2 u by playa
my new sounds 270415 on soundcloud
new fav dubtechzone mermaid cave by on soundcloud
especial hq la forma de vestir de jin me encanta bts jin p
speak low akiko fmyokohama nowplaying
nowplaying smooth beans dont let it gomp3 by new ska collection
nowplaying sakurairomaukoro by tokunaga hideaki on jpop sakura jpop
rockthatown 30 sexyzone nowplaying music song
have you heard well listen again xl89mr by mrlabeled on soundcloud np
listen to ventriloquist x dabking by dabking np on soundcloud
nowplaying drake feat giggs kmt
a good 1 virtual riot in my head ft prxzm beatcore remix by on soundcloud
bts was mentioned on kangnam style 170331
np ysb pac hating on me
hello dear friends something you should listen to until the planets disappear by the warheads on soundcloud
bts hq 170223 aladin fansign jhope jimin
day6 stage kpop star6 20170402 day6 everyday6 youwerebeautiful
nowplaying love is love von woods 0458 auf m945
nowplaying sucker for pain with wiz khalifa imagine dragons logic amp ty dolla ign feat x ambassadors de lil w
nowplaying kaleo way down we go
nowplaying on vega savin grace rock metal radio
80shairbands np triumph somebodys out there 86 listen now
np justmusic pamit cc md
bts did that btswingstourmanila day1 amp day2 all sold out in less than 24hours see you soon
have you heard dubtechzone mermaid cave on soundcloud np dubtechno dubtech d
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nowplaying unknown habib koite siratamp3
2 1 sexy zonerock tha town rockthatown sexyzone nowplaying music song https
bts jin
nowplaying puff daddyfaith evans112 ill be missing you
la ltima fila de la derecha dice oyasumi ia est ia me puedo ir a japn ahre
kholi zepherin saint inner freak radio edit nowplaying soulfulhouse
a rockthatown sexyzone music
shalamar a night to remember np radiopowermix wakeupdisco wakeup rpmwakeupdisco disco jazz soul funk
young rich forever is broadcasting live on instagram dexter newmusic nowplaying
nowplaying unknown oies plus putes que toutes les putes
nowplaying codie prevost codie prevost
coming soon soundcloud reggaeton latina latinmusic spanish
rap monster the thing i hope is only one its your heart bts rapmonster aesthetic
np slash doctor alibi feat lemmy kilmeister radio
160217 kbs bts jungkook
fyakin revelation feat chris matic nowplaying on surf shack radio click here to listen live
talk is cheap de chet faker nowplaying
luis fonsi ft daddy yankee despacito nowplaying listenlive
nowplaying treat you better shawn mendes remix listenlive
nowplaying
saltep listen to salt ep by blackbear np on soundcloud
our fandom name might be dayz or holiday day6
45 sexy zonerock tha town sexyzone rockthatown
day6 dropped youngk wonpil image teaser for everyday6 april project imserious koreanupdates vf
my new sounds irv one way on soundcloud
day6 every day6 aprilgt teaser image day6 everyday6 imserious wonpil
2350 mes aeux le dni de lvidence np nowplaying
nowplaying nick heyward love all day and night radiostation onair webradio
nowplaying karizma tough love
nowplaying onair actuellement sur peter cetera glory of love pop soft rock classic rock
luna piena nowplaying
17040102 every day6 concert in april wonpil day6
coutez tranceye energy podcast 013 par tranceye np sur soundcloud
620 2017 bts live trilogy episode iii the wings tour japan btsw
my fave
nowplaying on birdy wings listen
solo dance by martin jensen nowplaying radio1
now playing dj ganyani ft fb xigubu namradio awesome african music
listen to idk ft c4 by beejay marciano np on soundcloud
nowplaying hatebreed hear me judge 4 listeners web media np
bts jungkook
sexyzone
jermaine dolly come and knock on our door nowplaying gospelmusic
bts save me mv has reached 81m views keep streaming armys
nowplaying orchestre de chambre jean franois paillard premier caprice villerscotterets 1000hitsclassical
nowplaying neon genesis evangelion op yoko takahashi anime anistationradio meetotaku otaku
nowplaying craveradio melody dimitri vegas like mike amp steve aoki vs ummet oz
nowplaying jovem de supercombo
beta love by ra ra riot from beta love nowplaying
break now nowplayingcelebration dayziggy dragongate prowrestling thegateofpassion2017
nowplaying sin miedo a nada con amaia montero de lex ubago
from listen to jaunie kah run it up prod by polo boy shawty by jaunie kah np on soundcloud https
nowplaying sevendust death dance tune in
asoynamoy pastipastiaja tos
my new sounds 1138 on soundcloud
np aint it fun kampuskita
listen to nada es lo mismo ft irania by el javi np on soundcloud
nowplaying ningum foi melhor que voc de sorriso maroto

- Working Code

```
class HierarchicalClusterer(object):
    def __init__(
            self,
            distance_matrix,
            linkage_function,
            minium_clusters=2):
        self.distance_matrix = distance_matrix
        self.linkage_function = linkage_function
        self.minium_clusters = minium_clusters

    def build_clusters(self):
        print 'a'

    def do_link_clustering(self, cluster_id_list, cluster_nodes):

        def small_big(first, second):
             if first < second else (second, first)

        def merge(cluster1,
                  cluster2,
                  distance,
                  cluster_ids,
                  cluster_nodes):
            cluster1, cluster2 = small_big(cluster1, cluster2)
            cluster_ids[cluster1].extend(cluster_ids[cluster2])
            cluster_ids[cluster2] = []
            node = Node()

            if cluster_nodes[cluster1]:
                node.left = cluster_nodes[cluster1]
                cluster_nodes[cluster1].parent = node
            else:
                node.left_instance = cluster1

            if cluster_nodes[cluster2]:
                node.right = cluster_nodes[cluster2]
                cluster_nodes[cluster2].parent = node
            else:
                node.right_instance = cluster2

            node.set_height(distance, distance)
            cluster_nodes[cluster1] = node

        length = self.distance_matrix.shape[0]
```

```
cluster_number = self.distance_matrix.shape[0]
distance_list = [
    ClusterPair(first,
    second,
    self.distance_matrix[first][second], 1, 1)
    for first in range(length) for second in range(first +
    length)]

distance_queue = MyHeap(
    initial=distance_list,
    key=lambda x: x.distance)

while cluster_number - self.minium_clusters > 0:
    pair = distance_queue.pop()
    if not pair:
        break

    if not valid_pair(pair, cluster_id_list):
        continue

    merge(pair.cluster1, pair.cluster2,
     pair.distance, cluster_id_list, cluster_nodes)

    for index in range(length):
        if index != pair.cluster1 \
                and cluster_id_list[index]:
    cluster1, cluster2 = \
        small_big(cluster1, cluster2)

            new_distance = self.linkage_function(
                self.distance_matrix,
                cluster_id_list[smaller],
                cluster_id_list[bigger])

            distance_queue.push(ClusterPair(
                smaller,
                bigger,
                new_distance,
                len(cluster_id_list[smaller]),
                len(cluster_id_list[bigger])))

    cluster_number -= 1
```

Section 3. Evaluation by SimRank (Implemented by Michael Lan) This was written in Python 2.7, using the Sublime Text Editor. We gathered data, called 'Dataset 8', which belongs to 2 very different communities: Music and Politics. This dataset uses the initial filter:

$$\#music, \#concert, \#politics, \#trump, \#russia, \#brexit$$

The Gaming hashtags #gaming, #gamers, #pc, and #xbox were also included, but they did not yield many tweets.

Sample Findings: We tested to see if the system would say that tweets or hashtags about music would be similar to music-related tweets and hashtags, and did the same with politics. The Demo Video in Phase 4 shows that the system was able to do this.

Since the rest of the code has many lines, it is not included in this report. The small data snippet (around 37 Mb), small sample output and the code are uploaded on Github: https://github.com/circlefive05/SimRank-on-Twitter-UI

Some more information can be found on the file 'More on SimRank.doc' on [...]

Implementation Steps:

1. Using the Tweepy API, start up a listener of incoming tweets. Two iterations: first iteration uses a set of 'initial hashtags'. Second iteration uses the top 25% most frequent hashtags from the previous iteration's tweets, plus the hashtags from the previous iteration's filter, to filter tweets in the second iteration. A JSON file is outputted, and tweets, in plain text, are extracted from this using the Pandas library.

2. Create bipartite graph G. Use positive ID integers for tweets, and negative ID integers for hashtags. Create an adjacency matrix M such that each node is assigned an index id.

3. Compute M^k for even numbers up to k = Kmax. Assuming sparsity, choose Kmax = 4. Sum up these M^k. Take the nonzero entries, the chosen pairs, of the sum. Run SimRank on the chosen pairs. Use pickle to store the graph, the ID-to-node hash tables, and the scores hash table.

The iterative gathering approach obtains tweets which are structurally similar to the filter, but does not restrict the data to only finding tweets that contain hashtags in the filter. This is better than blindly gathering Listener. We only demonstrate a sample with a small amount of data, so the results are not as strong. Also, since the data consists of new tweets, the results depends on what's trending at the time of collection.

References

[1] J. O'shea, Z. Bandar, and K. Crockett. A new benchmark dataset with production methodology for short text semantic similarity algorithms. *ACM Trans. Speech Lang. Process.*, 10(4):19:1–19:63, Jan. 2014.