Personal Health Companion

Technical Documentation

Group 3

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This documentation is written to explain how the main function works from a programmer's perspective. We'll assume the programmer has a working knowledge of Java, Python, PHP, HTML, JavaScript and CSS and will only serve to show the programmer where to find and edit each portions of the code and what they do.

1. Function requirements

Following are the requirements for the system-to-be:

Identifier	Brief Description	PW
REQ1a	The system shall attain real time tweets from twitter using stream API	**5**
REQ1b	The system shall acquire the historical health-related tweets the users sent in a certain period. (e.g. in a month or two)	**5**
REQ1c	The system shall attain basic information from tweets of users which are health-related. (E.g. location, personal tweets numbers related, followers,	**5**
REQ2	The system shall be able to access geographic information associating with Google Map.	**4**
REQ3	The system shall have a database to store whole stream of data from twitter	**4**
REQ4a	The system shall filter out irrelevant tweets in database	**5**
REQ4b	The system shall classify relevant tweets data from database by different sets. (E.g. types of exercise, locations, genders, types of foods, etc.)	**5**
REQ4c	The system shall estimate twitter users workout calories by approximate calculation.	**3**
REQ5a	The system shall provide graph to display the exercising trends.	**3**
REQ5b	The system shall provide graph to display the smoking trends.	**3**
REQ5c	The system shall provide graph to display the alcohol consumption trends.	**3**
REQ5d	The system shall provide graph to display the dietary habit trends.	**3**
REQ6	The system shall provide approximate real time tweets rolling the screen.	**3**
REQ7	The system shall do the sentiment analysis by evaluating corresponding mood state the tweets show.	**2**
REQ8	The system shall provide graphs based on geographic information and show the dietary, smoking alcohol and exercise trends	**4**
REQ9	The system shall provide dynamic hashtag cloud to show tweets users are interested in.	**3**
~~**REQ10a**~~	~~The system shall provide an approximately real time leader board on community basis.~~	~~**2**~~
~~**REQ10b**~~	~~The system shall be able to show top 10 ranks for work out aggregated for 3days.~~	~~**2**~~
REQ11	The system shall have the ability to draw information of big events correlating the themes users care about from twitter and present on a calendar.	**2**
~~REQ12~~	~~The system shall provide a calculator for users to show their calories loss.~~	~~3~~

REQ13a	The system shall allow user to sign up and provide an alternative option of sign up using a third party API.	**5**
REQ13b	The system shall allow registered user to login.	**5**
REQ13c	The system shall allow guest users to visit.	**5**
REQ13d	The system shall allow login users to edit/delete their profile.	**5**
REQ13e	The system shall allow user to stay login status in a moment for convenience.	**1**
REQ14	The system shall define authorizations for different class of users. (e.g. Registered user, Guests, Administrators)	**5**
~~REQ15~~	~~The system shall allow user to invite their friends to join the community.~~	**~~2~~**
~~REQ16~~	~~The system shall provide a platform (like BBS) for users to share experiences and their comments as well as making friends.~~	**~~2~~**
REQ17a	The system shall provide users database to store user information and retrieve data from them.	**3**
REQ17b	The system shall separate users according to their public information like ages and form groups of common interest.	**3**
REQ18a	The system should be able to collect and save relevant comments.	**2**
REQ18b	The system should be able to analyze the comments and categorize them for correlation purposes.	**2**

The above table with RED Fonts is actually the things we fail to show on the Demo2, and some with ~~DELETE~~ signs is the things we won't implement in future job.

All functional requirements are listed in three aspects as mentioned above. Some requirements divided into several parts with suffix like "a" or "b" are associated with each other.

REQ1 to REQ3 are requirements for data collections. In this part, the system needs to attain less more relevant information from tweets and associate the data with geographical information from google map.

REQ4 concerns all the data processing and analysis. The method we use for classification is a kind of learning machine and for data sifting part we use another algorithm for recognition of tweets' language.

REQ5 to REQ12 are basically our form of data output to users. As mentioned in the table, the functionalities include graph display from analyzing big data(REQ5), real time relevant tweets displaying what people are talking about(REQ6), recommendations from estimating the average level(REQ7), heat map for users to get what they concern about associating their own location(REQ8), tag cloud to show up some hashtags which users can simply select as their wish and get relevant tweets(REQ9), leaderboard displaying ranks listing with various themes and it would be additional to this system(REQ10), a calendar which provides information of big events abstracted from tweets' data (REQ11) and a calculator for calculating calories loss in convenience(REQ12).

The remaining (**REQ13 to REQ18**) represents the way we design for users to easily get the hang of our system as well as the interactions between system and users. What's needed to be note is **REQ14** which provide our design of authorization for different classes of users. Detailed speaking, as for guest users, they can get access to data analytic graphs and tag cloud for tweets; as for login users, they are allowed to get into BBS to share information and dig deeper in data mining results so as private recommendations. They are also permitted to build their own database and save their own workout with highly security; as for administers, they have the privilege such as locking users account which are under suspension and maintaining the running of system but no access to private database.

Temporarily, we focus more on the statistical analysis and show some interesting result integrating with different themes, period and geographic locations which results in the inadequate implementation on website session and bunch of REQs related to website have not been finished yet. Also we consider the significance of various part of data analysis and leave over a few of them we proposed previously.

2. Non-function requirement:

Identifier	Brief Description	PW
NF-REQ1	System must be easily run with few maintenance and quickly recovered if it is broke down for some reasons.	5
NF-REQ2	System must have a proper schedule for regular maintenance.	5
NF-REQ3	System should entirely protect privacy issues of users and anyone should never be allowed to access others detailed information.	5
NF-REQ4	System should be aesthetically designed in order to attract more users or stoppers-by.	5
NF-REQ5	The system server should have the ability to handle overload in site visits.	5
NF-REQ6	System should provide FAQ & efficient response for users (aka User-Friendly Design). In this part, users should be at ease when getting information and explanations about their concern.	5

In the above table, **NF-REQ1** interpret the reliability of system; **NF-REQ2** shows requirements in supportability;**NF-REQ3** is most important thing for users and it applies the standard of functionality.**NF-REQ4** concerns demand for usability; **NF-REQ5** is supportability;**NF-REQ6** represents the performance. The main idea in this section is to make users willing to stay with safety and comfort and what is worth noting is that all the rules should be applied to all stages of design and be pursued carefully.

3. Use Cases

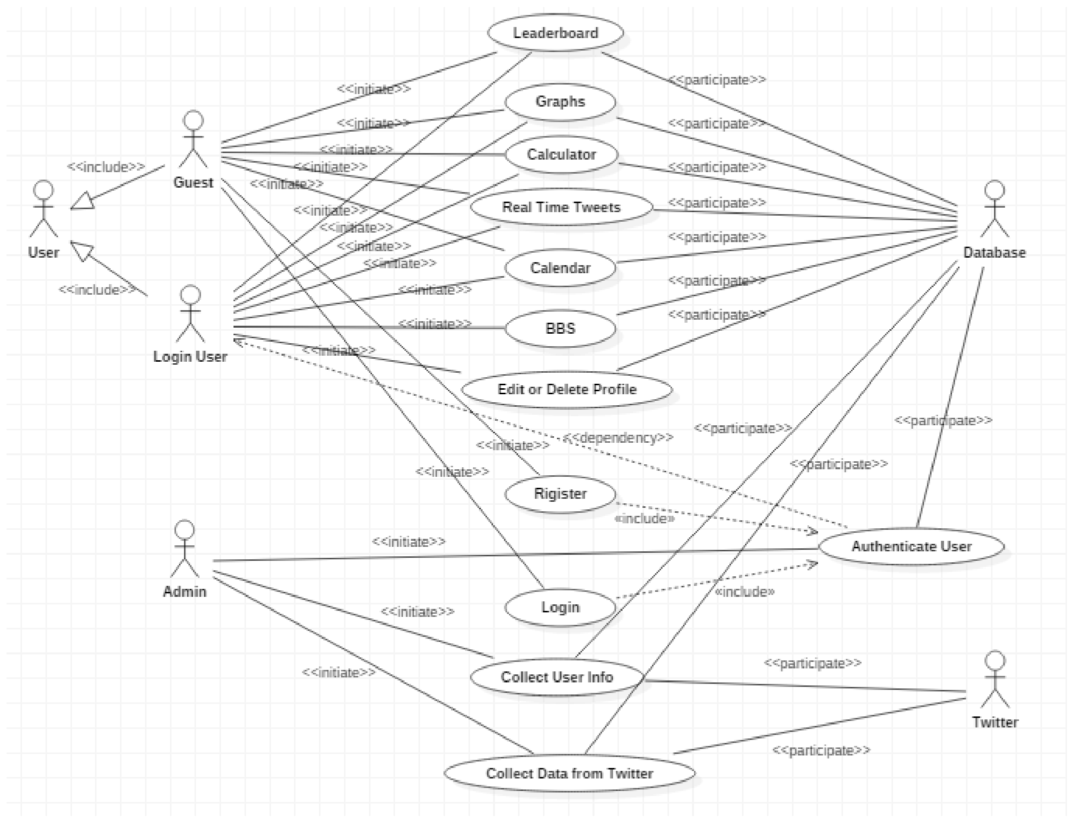
Use Cases Casual Description The summary of use cases is as follows:

Use Case	Case Name	Description	Requirements
UC-1	Register	The system shall allow user to register, and create his profile	REQ13ab REQ14,REQ17a
UC-2	View/Edit Personal Profile	System shall display the personal profile for the logged in user.	REQ13c
UC-3	Show Graphs	System shall show users graphs of several aspects(e.g. heat map, tweet numbers in a period)	REQ2, REQ4ab, REQ5abcd,REQ8,REQ9, REQ10ab
UC-4	Display Calendar	System shall be able to support a calendar and allow uses to register for events.	REQ4ab, REQ11
UC-5	Show Calculator	System shall be able to support workout calculator on the home tab.	REQ4abc, REQ12
~~**UC-6**~~	~~Show Leaderboard~~	~~System shall calculate # of tweets collected per user and show the leaderboard in the UI~~	~~REQ4ab~~ ~~REQ10a,10b~~
UC-7	Show real-time Tweets	System shall be able to show real-time tweets with tags provided by user	REQ4ab, REQ6
~~**UC-8**~~	~~A BBS section~~	~~System shall provide users a platform for communication~~	~~REQ16~~ ~~REQ18ab~~
UC-9	Collect Twitter Information	System shall collect and store the tweets with a given region.	REQ1abc REQ3, REQ4ab

UC-10	Collect User Information	System shall collect User Information to perform draw the necessary conclusion.	REQ17ab
UC-11	Validate User Login Information	System shall validate when a user attempts to login.	REQ14
UC-12	Login	Once authenticated by system, User's status shall change.	REQ3
UC-13	Comparison based on geo Info	The system shall be able to show the comparison for different geographic information.	REQ2, REQ4ab, REQ5abcd,REQ8,REQ9, REQ10ab

We only show the most key part on Demo2, the UC3.

The use case diagram is on below:



The traceability matrix between UCs and REQs is on below:

REQs	PW	UC1	UC2	UC3	UC4	UC5	UC6	UC7	UC8	UC9	UC10	UC11	UC12
REQ1a	**5**									**X**			
REQ1b	**5**									**X**			
REQ1c	**5**									**X**			
REQ2	**4**			**X**									
REQ3	**4**									**X**			**X**
REQ4a	**5**			**X**	**X**	**X**	**X**	**X**		**X**			
REQ4b	**5**			**X**	**X**	**X**	**X**	**X**		**X**			
REQ5a	**3**			**X**									
REQ5b	**3**			**X**									
REQ5c	**3**			**X**									
REQ5d	**3**			**X**									
REQ6	**3**							**X**					
REQ7	**3**												
REQ8	**2**			**X**									
REQ9	**4**			**X**									

REQ10a	3			X			X						
REQ10b	2			X			X						
REQ11	2				X								
REQ12	2					X							
REQ13a	3	X											
REQ13b	5	X											
REQ13c	5		X										
REQ13d	5		X										
REQ13e	5												
REQ14	1	X										X	
REQ15	5												
REQ16	2								X				
REQ17a	2	X									X		
REQ17b	3										X		
REQ18a	3								X				
REQ18b	2								X				
	2												

Max PW	**5**	**5**	**4**	**2**	**3**	**2**	**5**	**2**	**5**	**3**	**5**	**4**
Total PW	**18**	**10**	**37**	**12**	**16**	**14**	**13**	**6**	**29**	**6**	**5**	**4**

4. Use Cases Fully Dressed Description

To further develop the detailed specification of use cases, we start by drafting usage scenarios.

We thought of two possible approaches to develop use cases. One is that we first start at the data collection and another is that we start at the user functionalities like register, login, etc.

The primary goal of the system is to display data we collected to the user intuitively, but the data analytic would be fundamental to all the features. Henceforth, we decided to begin with data collection and getting the data would be the first logical step to begin data analysis too. We start from Use Case 9.

USE CASE: UC9 **Collect Twitter Information**
Related Requirements: REQ-1abc, REQ-3, REQ-4ab **Initiating Actor:** Administrator **Actor's Goal:** To collect tweets from Twitter. **Participating Actors:** Database, Twitter. **Preconditions:** The number of API calls made should not have exceeded the limit and the administrator must be successfully authenticated by Twitter. **Success End Condition:** The tweets are successfully collected and stored in the database. **Failed End Condition:** The tweets are not collected from Twitter.

Extension Points: NA

Flow of Events for Main Success Scenario:

→1. Administrator makes a request to the API to get tweets. Relevant hashtags are also entered in order to get the related tweets.

←2.Twitter sends the tweets relative to the hashtags to the administrator which is stored in the database.

USE CASE: UC10 **Collect User Information**

Related Requirements: REQ-17a, REQ-17b

Initiating Actor: Administrator

Actor's Goal: To collect user information extracted from the user profile from Twitter using the corresponding user id and store it in the database.

Participating Actors: Database, Twitter.

Preconditions: Successful execution of UC9; Administrator should have a valid user ID for the profile to be retrieved.

Success End Condition: The user information is successfully collected and stored in the database.

Failed End Condition: The user information is not collected from Twitter.

Extension Points: NA

Flow of Events for Main Success Scenario:

→1. Administrator searches for the user id relative to the user profile to be retrieved from the tweets received from Twitter.

→2. Administrator sends an API request to Twitter to get the user profile. The user id is also entered in this request.

←3.Twitter sends in the required user profiles, which are stored in the database.

The data collected through the above two use cases shall be further used in mathematical model section. The mathematical model section shall further identify the key attributes required to develop the necessary analytics. Now, we proceed with the use cases which are defined to display our data analysis intuitively.

USE CASE: UC3 **Show Graphs**

Related Requirements: REQ-4ab, REQ-5abcd, REQ-8, REQ-9, REQ-10ab

Initiating Actor: User

Actor's Goal: To view any graph of data.

Participating Actors: Database.

Preconditions: Data Connectivity and instantaneity.

Success End Condition: User can view any graph of data.

Failed End Condition: The graph is not visible because of un-availability of required workout data.

Extension Points: NA

Flow of Events for Main Success Scenario:

→1. User enters the website.

←2. System show all graphs of data to user.

→3. User selects location on heat map by inputting the name of location or pointing it on the map.

←4. System show a more specific data of chosen location to user.

USE CASE: UC4	**Display Calendar**
Related Requirements: REQ-4ab, REQ-11	
Initiating Actor: User	
Actor's Goal: To view any upcoming event and RSVP	
Participating Actors: Database	
Pre-Conditions: Data Connectivity	
Success End Condition: User can view and RSVP for events.	
Failed End Condition: NA	
Flow of Events for Main Success Scenario:	
Include: Login (UC12)	
→1.User inputs events type he/she want to learn about.	
← 2. System will request events information from Database.	
←3. System will retrieve the events information according to interests and input from users, then display the events on the calendar.	
→ 4. User can view the events and click on RSVP.	

← 5. System will add the user name to the participants list in the database.
← 6. System will display confirmation message and mark the event as "Attending".

USE CASE: UC7 **Display Real-Time Tweets**
Related Requirements: REQ-4ab, REQ-6
Initiating Actor: User
Actor's Goal: To view real time tweets related to different tags
Participating Actors: Database
Pre-Conditions: Data Connectivity
Success End Condition: User can view interested tweets rolling the side screen.
Failed End Condition: NA
Flow of Events for Main Success Scenario:
→1.User inputs the tags or themes he/she want to see.
← 2. System will request relevant tweets information from Database.
←3. System will retrieve the tweets information according to the tags input from user and display the events on the side screen.
→ 4. User can view the tweets and link to twitter.

All these Use Cases above are concerning about how we collect data and display to users. Now we respect user to interact with our system. The interaction design can be found on some use cases listed above, i.e. BBS section has the option for login users to post some experiences, and UC4 allows login users to add their personal event to the calendar. All these interactions result in use cases designed only for users other than data. The following use cases are for users.

Use Case UC1: **Register**

Related Requirements:REQ-13ab, REQ-14, REQ-17a

Initiating Actor: User

Actor's Goal: To register onto the system & create a profile on system.

Participating Actors: Database.

Preconditions: (a) User must be an unregistered user. (b) System displays the homepage.

Post conditions: User success to register, database store the profile

Failed End Condition: The user have registered, and fail to register.

Flow of Events for Main Success Scenario:

→1. User clicks "Sign Up" option on home page.

←2. System displays the profile page (user type (general user, governor)twitter ID, password, confirm password, gender….), and let user to fill in

→3. User type valid ID which has not registered in the system, and type same password twice, provide all mandatory information, and click bottom "save"

←4. System (a) prepares a database query to verify that ID has not registered in system; (b) signs to twitter to verify the twitter ID is a valid ID; (c) checks whether the two password are same; (d) check all mandatory information provided

←5. Database signs the ID has not registered in the system

←6. Twitter signs the twitter ID provided is valid

← 7. System (a) stores the profile in the Database； (b) prompts a message that " Registered successfully"

Flow of Events for Extensions (Alternate Scenarios)

3a. User type a valid ID which has registered in the system, and click "SAVE"

←1. System (a) detects error, (b) prompts a message "You have registered ", (c) directs to Homepage

3b. User type an invalid twitter ID, and click “SAVE”

←1. System (a) detects error, (b) prompts a message “Invalid twitter ID, please type again”

→2. User supplies a valid twitter ID

←3. Same as in Step 4

3c. User type different passwords, and click “SAVE”

←1. System (a) detects error, (b) prompts a message “Passwords do not match each other, please type again”

→2. User supplies same passwords twice

←3. Same as in Step 4

3d. User only provides part of mandatory information

←1. System (a) detects error, (b) prompts a message “You have to provide all the mandatory information, please type the rest.”

→2. User supplies all the mandatory information

← 3. Same as in Step 4

3e. User click cancel option

← 1. System (a) doesn’t store the profile; (b) redirects to Homepage

Use Case UC2:	**View/Edit Personal Profile**

Related Requirements: REQ-2c

Initiating Actor: Login User

Actor’s Goal: To edit his/her profile information.

Participating Actors: Database.

Preconditions: The system displays the profile page

Post conditions: User edit his profile successfully, Database updated user’s profile

Failed End Condition: profile failed to updated

Flow of Events for Main Success Scenario:

→ 1. User clicks “Edit” bottom

← 2. System display the profile page in editing condition, and let user change

→ 3. User type information that need be updated, and click “Save”

← 4. System (a) stores the updated profile to Database, (b) prompts a message ”updated successfully”

Flow of Events for Extensions (Alternate Scenarios)

3a. User type an invalid twitter ID, and click “SAVE”

← 1. System (a) detects error, (b) prompts a message “Invalid twitter ID, please type again”

→2. User supplies a valid twitter ID

←3. Same as in Step 4

3b. User type different passwords, and click “SAVE”

←1. system (a) detects error, (b) prompts a message “Passwords do not match each other, please type again”

→2. User supplies same passwords twice

←3. Same as in Step 4

3c. User click cancel option

← 1. System (a) doesn’t update the profile; (b) redirects to profile page in cannot-editing condition

Use Case UC2:	**Twitter Graphs**

Related Requirements: REQ-5a,REQ-5b, REQ-5c
Initiating Actor: User
Actor’s Goal: To achieve twitter histograms on the web page.
Participating Actors: Database.
Preconditions: The twitter histogram is available and is up to date.
Success End Condition: The twitter histogram is updated based on recent data and is available on website when a user logs in.
Failed End Condition: The histogram is not visible because of unavailability of required twitter data.

Extension Points: NA 3a. User type an invalid twitter ID, and click “SAVE”

← 1. System (a) detects error, (b) prompts a message “Invalid twitter ID, please type again”

→2. User supplies a valid twitter ID

←3. Same as in Step 4

3b. User type different passwords, and click “SAVE”

←1. system (a) detects error, (b) prompts a message “Passwords do not match each other, please type again”

→2. User supplies same passwords twice

←3. Same as in Step 4

3c. User click cancel option

← 1. System (a) doesn’t update the profile; (b) redirects to profile page in cannot-editing condition

Flow of Events for Main Success Scenario:
→ 1. User clicks the kind of twitter histogram (exercise, smoke, dietary and alcohol).Similar analysis for colder and warmer places.
→ 2. System sends request about the twitter data of histogram to database.
← 3. Database checks and sends back the twitter data of histogram.
← 4. System calculates the twitter data of histogram.
← 5. System displays data on website.

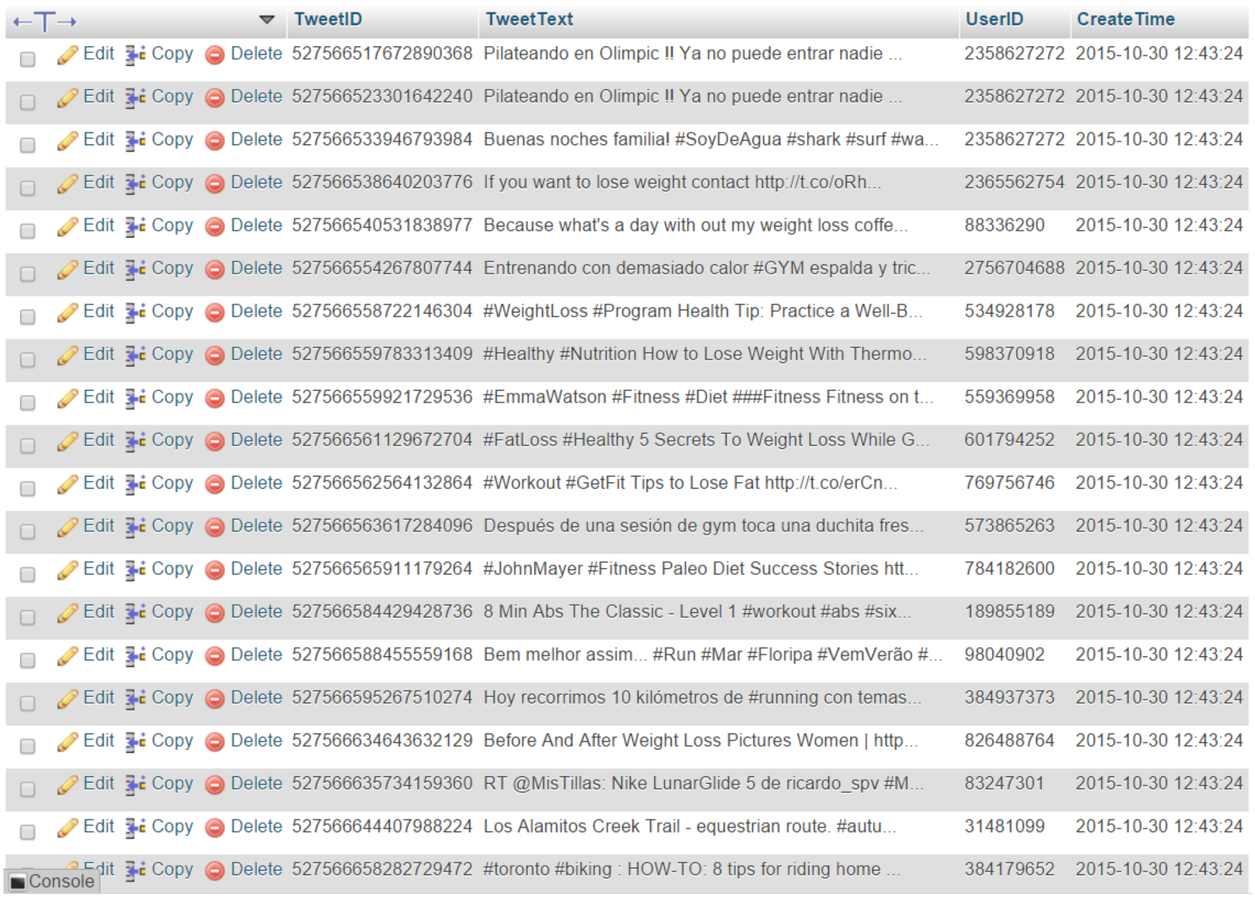
According to the table, we mainly derive the use cases which are directly interacting with actors. These use cases might not be detailed enough, but they fully covered the features which we would like to implement.

5. Technical Implementation

1. Data Collection Part

The data is originally collected from twitter and what we are using is streaming API which is nothing fancy. After listening to the API, we formulate the data in JSON files and import them into database.

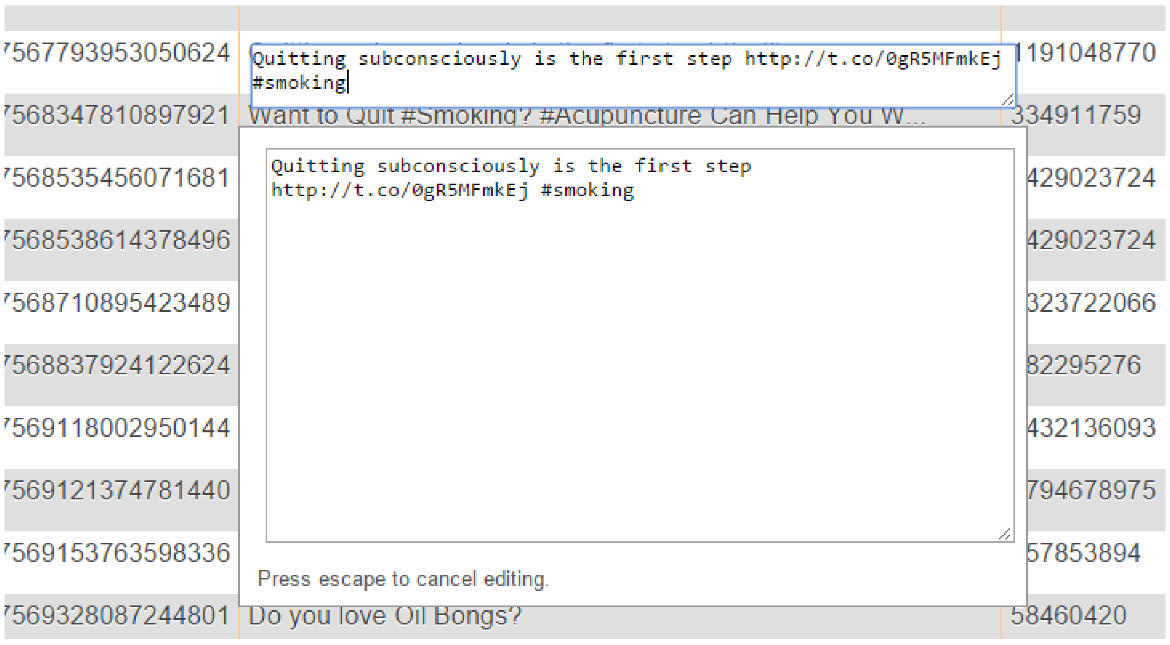
Some of the data collection snapshots are displayed here: (according to the hashtags we shortlisted)



←T→	TweetID	TweetText	UserID	CreateTime
Edit Copy Delete	527566517672890368	Pilateando en Olimpic !! Ya no puede entrar nadie ...	2358627272	2015-10-30 12:43:24
Edit Copy Delete	527566523301642240	Pilateando en Olimpic !! Ya no puede entrar nadie ...	2358627272	2015-10-30 12:43:24
Edit Copy Delete	527566533946793984	Buenas noches familia! #SoyDeAgua #shark #surf #wa...	2358627272	2015-10-30 12:43:24
Edit Copy Delete	527566538640203776	If you want to lose weight contact http://t.co/oRh...	2365562754	2015-10-30 12:43:24
Edit Copy Delete	527566540531838977	Because what's a day with out my weight loss coffe...	88336290	2015-10-30 12:43:24
Edit Copy Delete	527566554267807744	Entrenando con demasiado calor #GYM espalda y tric...	2756704688	2015-10-30 12:43:24
Edit Copy Delete	527566558722146304	#WeightLoss #Program Health Tip: Practice a Well-B...	534928178	2015-10-30 12:43:24
Edit Copy Delete	527566559783313409	#Healthy #Nutrition How to Lose Weight With Thermo...	598370918	2015-10-30 12:43:24
Edit Copy Delete	527566559921729536	#EmmaWatson #Fitness #Diet ###Fitness Fitness on t...	559369958	2015-10-30 12:43:24
Edit Copy Delete	527566561129672704	#FatLoss #Healthy 5 Secrets To Weight Loss While G...	601794252	2015-10-30 12:43:24
Edit Copy Delete	527566562564132864	#Workout #GetFit Tips to Lose Fat http://t.co/erCn...	769756746	2015-10-30 12:43:24
Edit Copy Delete	527566563617284096	Después de una sesión de gym toca una duchita fres...	573865263	2015-10-30 12:43:24
Edit Copy Delete	527566565911179264	#JohnMayer #Fitness Paleo Diet Success Stories htt...	784182600	2015-10-30 12:43:24
Edit Copy Delete	527566584429428736	8 Min Abs The Classic - Level 1 #workout #abs #six...	189855189	2015-10-30 12:43:24
Edit Copy Delete	527566588455559168	Bem melhor assim... #Run #Mar #Floripa #VemVerão #...	98040902	2015-10-30 12:43:24
Edit Copy Delete	527566595267510274	Hoy recorrimos 10 kilómetros de #running con temas...	384937373	2015-10-30 12:43:24
Edit Copy Delete	527566634643632129	Before And After Weight Loss Pictures Women | http...	826488764	2015-10-30 12:43:24
Edit Copy Delete	527566635734159360	RT @MisTillas: Nike LunarGlide 5 de ricardo_spv #M...	83247301	2015-10-30 12:43:24
Edit Copy Delete	527566644407988224	Los Alamitos Creek Trail - equestrian route. #autu...	31481099	2015-10-30 12:43:24
Edit Copy Delete	527566658282729472	#toronto #biking : HOW-TO: 8 tips for riding home ...	384179652	2015-10-30 12:43:24

Console

Figure: Extracted Tweets

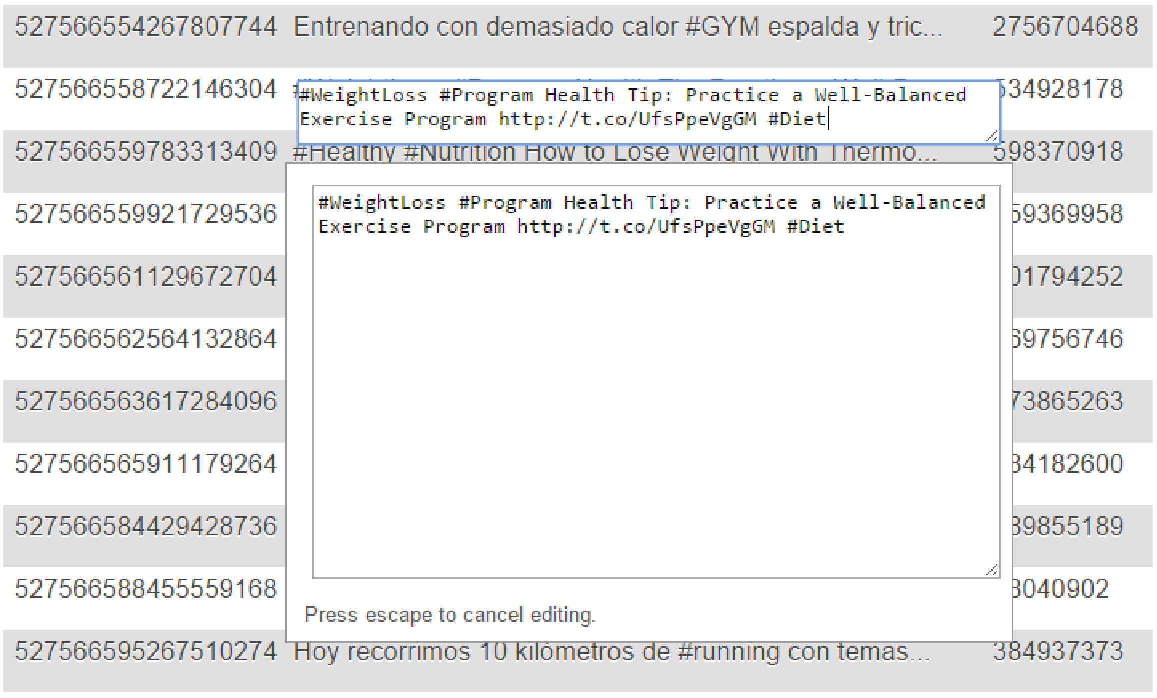


7567793953050624	Quitting subconsciously is the first step http://t.co/0gR5MFmkEj #smoking	1191048770
7568347810897921	Want to Quit #Smoking? #Acupuncture Can Help You W...	334911759
7568535456071681		429023724
7568538614378496		429023724
7568710895423489		323722066
7568837924122624		82295276
7569118002950144		432136093
7569121374781440		794678975
7569153763598336		57853894
7569328087244801	Do you love Oil Bongs?	58460420

```
Quitting subconsciously is the first step
http://t.co/0gR5MFmkEj #smoking
```

Press escape to cancel editing.

Figure: Sample tweet depicting how people tweet about being motived to quit smoking.

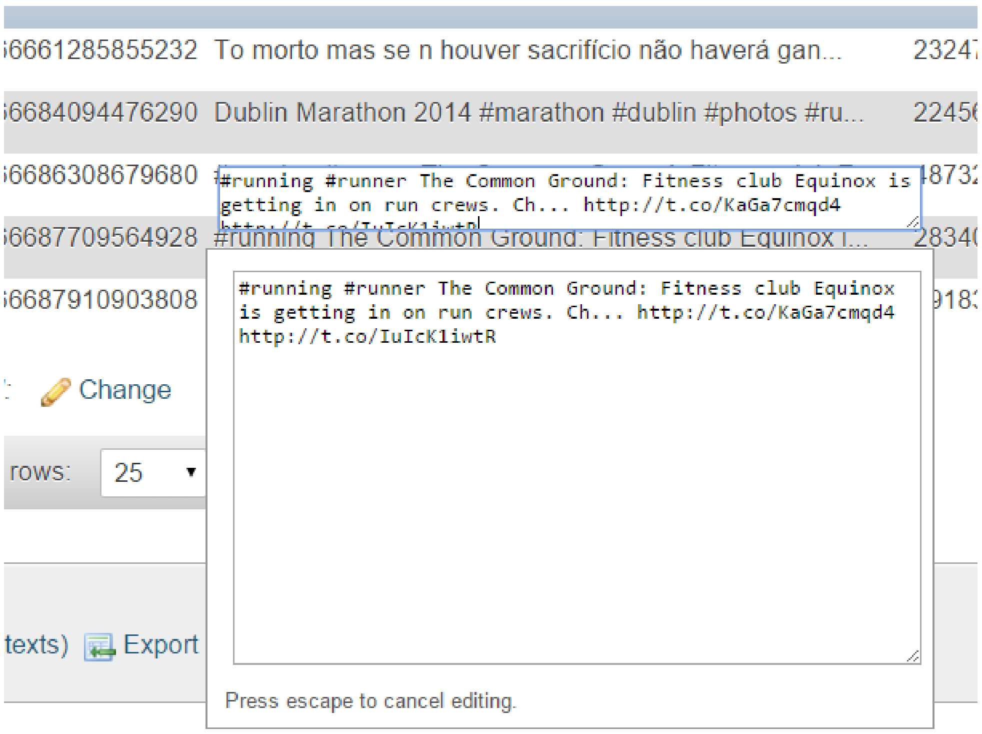


527566554267807744	Entrenando con demasiado calor #GYM espalda y tric...	2756704688
527566558722146304	#WeightLoss #Program Health Tip: Practice a Well-Balanced Exercise Program http://t.co/UfsPpeVgGM #Diet	34928178
527566559783313409	#Healthy #Nutrition How to Lose Weight With Thermo...	598370918
527566559921729536		59369958
527566561129672704		01794252
527566562564132864		59756746
527566563617284096		73865263
527566565911179264		34182600
527566584429428736		39855189
527566588455559168		3040902
527566595267510274	Hoy recorrimos 10 kilómetros de #running con temas...	384937373

```
#WeightLoss #Program Health Tip: Practice a Well-Balanced
Exercise Program http://t.co/UfsPpeVgGM #Diet
```

Press escape to cancel editing.

Figure: Sample tweet depicting how people tweet about being motivated to lose weight.



66661285855232	To morto mas se n houver sacrifício não haverá gan...	23247
66684094476290	Dublin Marathon 2014 #marathon #dublin #photos #ru...	22456
66686308679680	#running #runner The Common Ground: Fitness club Equinox is getting in on run crews. Ch... http://t.co/KaGa7cmqd4	48732
66687709564928	#running The Common Ground: Fitness club Equinox i...	28340
66687910903808		9183

Change

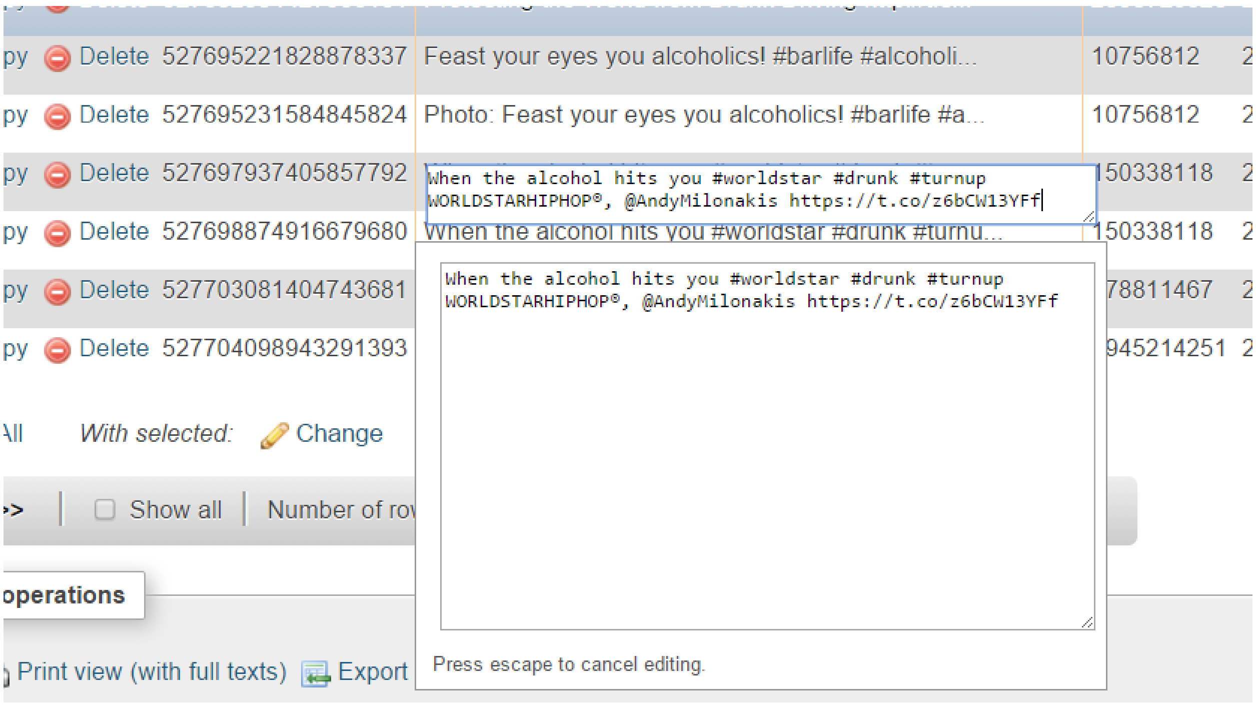
rows: 25

texts) Export

```
#running #runner The Common Ground: Fitness club Equinox
is getting in on run crews. Ch... http://t.co/KaGa7cmqd4
http://t.co/IuIcK1iwtR
```

Press escape to cancel editing.

Figure: Tweet regarding fitness


py Delete 527695221828878337 Feast your eyes you alcoholics! #barlife #alcoholi... 10756812 2
py Delete 527695231584845824 Photo: Feast your eyes you alcoholics! #barlife #a... 10756812 2
py Delete 527697937405857792 When the alcohol hits you #worldstar #drunk #turnup WORLDSTARHIPHOP®, @AndyMilonakis https://t.co/z6bCW13YFf 150338118 2
py Delete 527698874916679680 When the alcohol hits you #worldstar #drunk #turnu... 150338118 2
py Delete 527703081404743681 78811467 2
py Delete 527704098943291393 945214251 2

All With selected: Change

-> | Show all | Number of rov

operations

Print view (with full texts) Export

```
When the alcohol hits you #worldstar #drunk #turnup
WORLDSTARHIPHOP®, @AndyMilonakis https://t.co/z6bCW13YFf
```

Press escape to cancel editing.

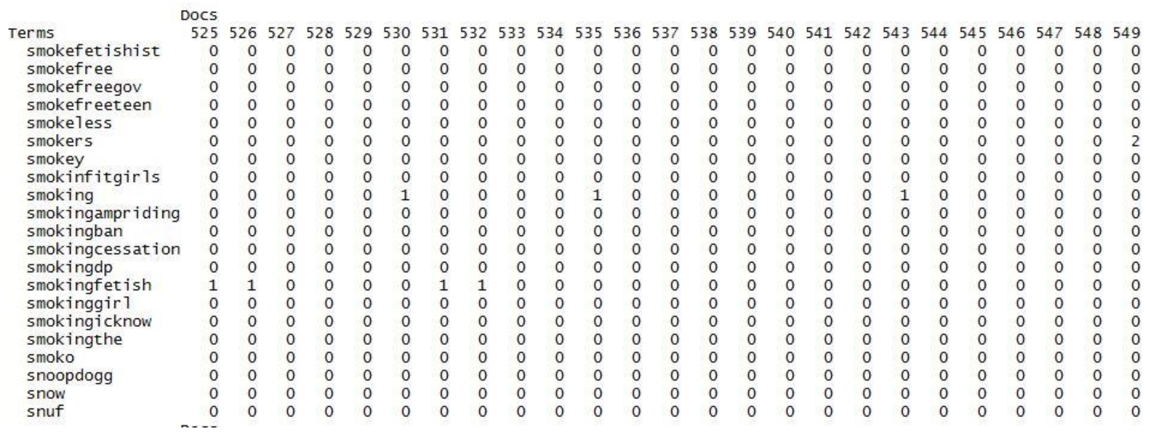
Figure: Tweet by a person who is into drinking.

2. Data filtering Algorithms

For the data filtering part, we use two kinds of clustering methods: Hierarchical Clustering methods and K-means Clustering method, but before use these method we have to preprocess these data (tweets).

2.1 Data Pre-process

We convert all data to lower case, remove punctuation, numbers, URLs, and do stemming first. After than we can make sure all data in Tweets are unique meaning words. Then use these cleaned tweets, we can get a term-document matrix which row label is the words (terms), column label is the tweet numbers (documents), and the content is the term frequency. Once we get the matrix, we can do the clustering. The sample term-document matrix (1980-2000 terms, 500-550 tweets) is as following:



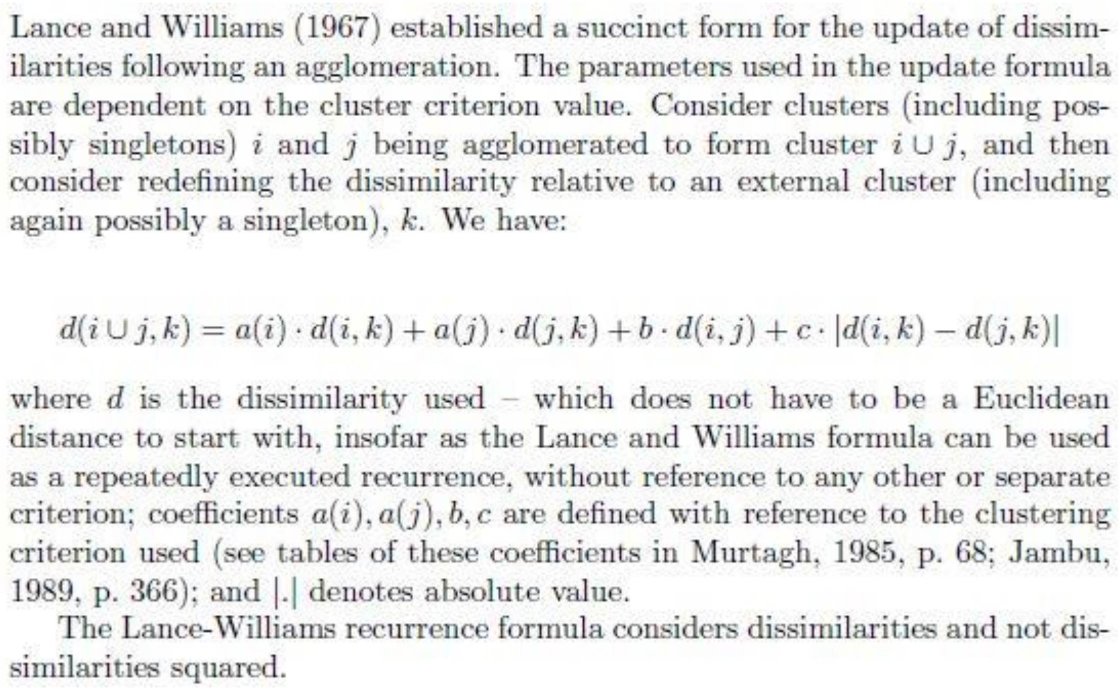
```
                   Docs
Terms              525 526 527 528 529 530 531 532 533 534 535 536 537 538 539 540 541 542 543 544 545 546 547 548 549
  smokefetishist     0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokefree          0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokefreegov       0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokefreeteen      0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokeless          0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokers            0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   2
  smokey             0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokinfitgirls     0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smoking            0   0   0   0   0   1   0   0   0   0   1   0   0   0   0   0   0   0   1   0   0   0   0   0   0
  smokingampriding   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokingban         0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokingcessation   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokingdp          0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokingfetish      1   1   0   0   0   0   1   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokinggirl        0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokingicknow      0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smokingthe         0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  smoko              0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  snoopdogg          0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  snow               0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
  snuf               0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
```

When we get the matrix, it is easy to get the frequency of terms, just the sum of the row numbers.

Then after removing sparse (we set sparsity as 0.95), we can cluster terms.

2.1.1 Hierarchical Clustering

For the hierarchical clustering, we use Wald's method using a set of dissimilarities for the n objects being clustered. Initially, each object is assigned to its own cluster and then proceeds iteratively, at each stage joining the two most similar clusters, continuing until there is just a single cluster. At each stage distances between clusters are recomputed by the Lance–Williams dissimilarity update formula, which is as following:



Lance and Williams (1967) established a succinct form for the update of dissimilarities following an agglomeration. The parameters used in the update formula are dependent on the cluster criterion value. Consider clusters (including possibly singletons) i and j being agglomerated to form cluster $i \cup j$, and then consider redefining the dissimilarity relative to an external cluster (including again possibly a singleton), k. We have:

$$d(i \cup j, k) = a(i) \cdot d(i,k) + a(j) \cdot d(j,k) + b \cdot d(i,j) + c \cdot |d(i,k) - d(j,k)|$$

where d is the dissimilarity used – which does not have to be a Euclidean distance to start with, insofar as the Lance and Williams formula can be used as a repeatedly executed recurrence, without reference to any other or separate criterion; coefficients $a(i), a(j), b, c$ are defined with reference to the clustering criterion used (see tables of these coefficients in Murtagh, 1985, p. 68; Jambu, 1989, p. 366); and $|.|$ denotes absolute value.

The Lance-Williams recurrence formula considers dissimilarities and not dissimilarities squared.

A number of different clustering methods are provided. *Ward's* minimum variance method aims at finding compact, spherical clusters. Two different algorithms are found in the literature for Ward clustering. We implement the criterion Murtagh (1985) and Legendre (2012).

We start with (let us term it) the Ward1 algorithm as described in Murtagh (1985).

It was initially Wishart (1969) who wrote the Ward algorithm in terms of the Lance-Williams update formula. In Wishart (1969) the Lance-Williams formula is written in terms of squared dissimilarities, in a way that is formally identical to the following.
Cluster update formula:

$$\delta(i \cup i', i'') =$$

$$\frac{w_i + w_i''}{w_i + w_{i'} + w_{i''}}\delta(i, i'') + \frac{w_i' + w_i''}{w_i + w_{i'} + w_{i''}}\delta(i', i'') - \frac{w_i''}{w_i + w_{i'} + w_{i''}}\delta(i, i')$$

$$\text{and } w_{i \cup i'} = w_i + w_{i'} \tag{3}$$

We now look at the Ward2 algorithm described in Kaufman and Rousseeuw (1990) and Legendre and Legendre (2012).

At each agglomerative step, the extra sum of squares caused by agglomerating clusters is minimized, exactly as we have seen for the Ward1 algorithm

above. We have the following.
Cluster update formula:

$$\delta(i \cup i', i'') =$$

$$\left(\frac{w_i + w_i''}{w_i + w_{i'} + w_{i''}}\delta^2(i, i'') + \frac{w_i' + w_i''}{w_i + w_{i'} + w_{i''}}\delta^2(i', i'') - \frac{w_i''}{w_i + w_{i'} + w_{i''}}\delta^2(i, i')\right)^{1/2}$$

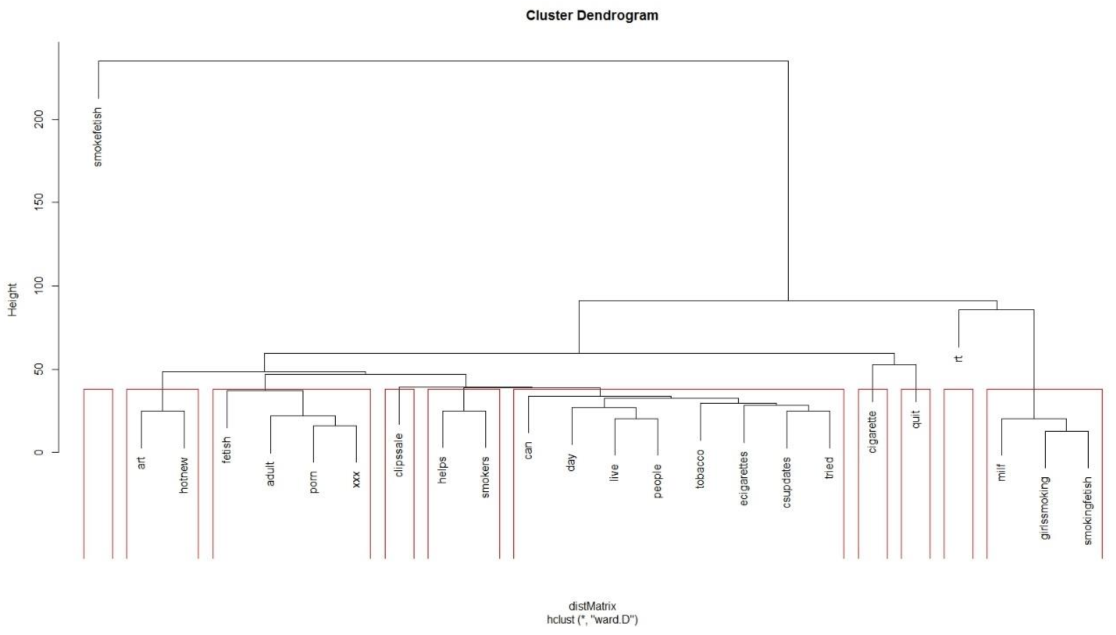
$$\text{and } w_{i \cup i'} = w_i + w_{i'} \tag{4}$$

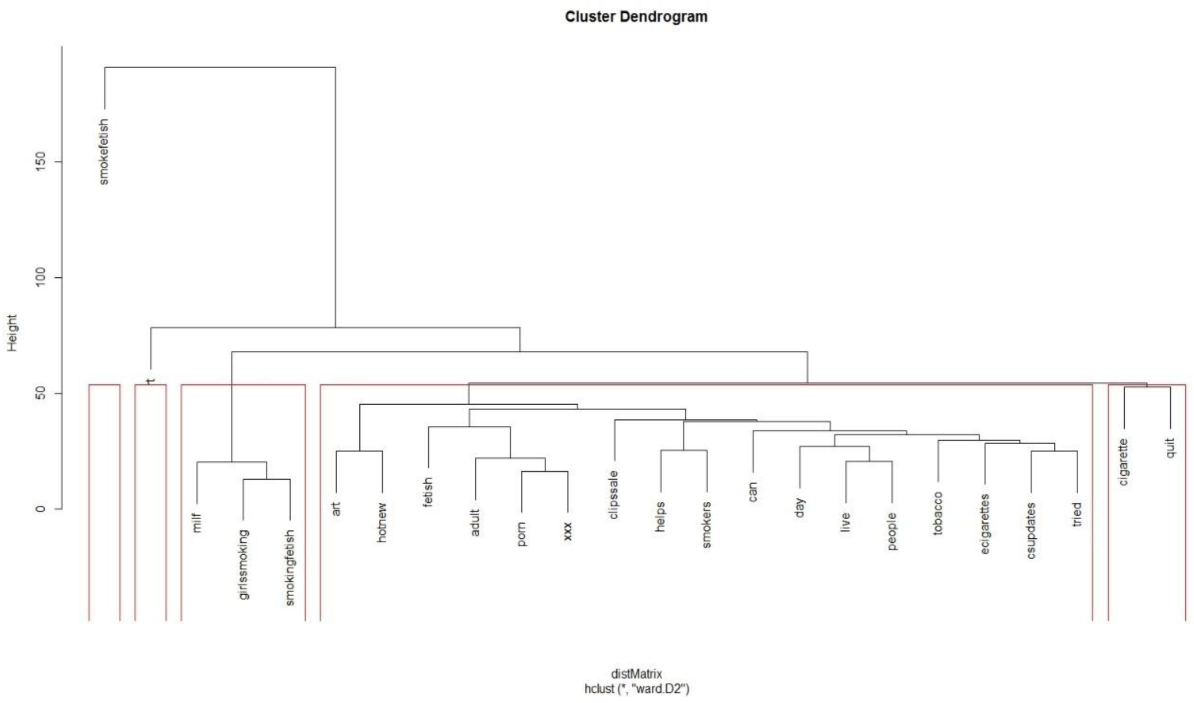
Contrary to Ward1, the input dissmilarities are Eucludean distances (not squared). They are squared within equation (4): $\delta^2(i, i') = \sum_j (x_{ij} - x_{i'j})^2$. It is such squared Euclidean distances that interest us, since our motivation arises from the error sum of squares criterion.

If members != NULL, then d is taken to be a dissimilarity matrix between clusters instead of dissimilarities between singletons and members gives the number of observations per cluster. This way the hierarchical cluster algorithm can be 'started in the middle of the dendrogram', e.g., in order to reconstruct the part of the tree above a cut. Dissimilarities between clusters can be efficiently computed only for a limited number of distance/linkage combinations, the simplest one being *squared* Euclidean distance and centroid linkage. In this case the dissimilarities between the clusters are the squared Euclidean distances between cluster means.

In hierarchical cluster displays, a decision is needed at each merge to specify which subtree should go on the left and which on the right. Since, for n observations there are n-1 merges, there are 2^{(n-1)} possible orderings for the leaves in a cluster tree, or dendrogram. After ordering the subtree so that the tighter cluster is on the left (the last, i.e., most recent, merge of the left subtree is at a lower value than the last merge of the right subtree). Single observations are the tightest clusters possible, and merges involving two observations place them in order by their observation sequence number.

We use R to implement these methods, two of results are as following, the first using Murtagh (1985) and the second using Legendre (2012):





2.1.2 K-means clustering with R

K-means clustering is the most popular partitioning method. It requires the analyst to specify the number of clusters to extract. A plot of the within groups sum of squares by number of clusters extracted can help determine the appropriate number of clusters. Conceptually, the K-means algorithm:

Selects K centroids (K rows chosen at random)

Assigns each data point to its closest centroid

Recalculates the centroids as the average of all data points in a cluster (i.e., the centroids are p-length mean vectors, where p is the number of variables)

1. Assigns data points to their closest centroids
2. Continues steps 3 and 4 until the observations are not reassigned or the maximum number of iterations (R uses 10 as a default) is reached.

3. Implementation details for this approach can vary.
4. R uses an efficient algorithm by Hartigan and Wong (1979) that partitions the observations into k groups such that the sum of squares of the observations to

their assigned cluster centers is a minimum. This means that in steps 2 and 4, each observation is assigned to the cluster with the smallest value of:

$$SS(k) = \sum_{i=1}^{n} \sum_{i=0}^{p} (x_{ij} - \bar{x}_{kj})^2$$

5. Where k is the cluster,xij is the value of the jth variable for the ith observation, and xkj-bar is the mean of the jth variable for the kth cluster.
6. K-means clustering can handle larger datasets than hierarchical cluster approaches. Additionally, observations are not permanently committed to a cluster. They are moved when doing so improves the overall solution. However, the use of means implies that all variables must be continuous and the approach can be severely affected by outliers. They also perform poorly in the presence of non-convex (e.g., U-shaped) clusters.
7. The format of the K-means function in R is kmeans(x, centers) where x is a numeric dataset (matrix or data frame) and centers is the number of clusters to extract. The function returns the cluster memberships, centroids, sums of squares (within, between, total), and cluster sizes.

Since K-means cluster analysis starts with k randomly chosen centroids, a different solution can be obtained each time the function is invoked. Use the set.seed() function to guarantee that the results are reproducible. Additionally, this clustering approach can be sensitive to the initial selection of centroids. The kmeans() function has an nstart option that attempts multiple initial configurations and reports on the best one. For example, adding nstart=25 will generate 25 initial configurations. This approach is often recommended.

3. Data Analysis Part

The goal of analysis of tweets is to cluster them and accurately label each one. The analysis is based on two parts.

First, we do Natural Language analysis on each tweets in two different properties. We consider that a tweet can be identify on the words which are most informative. We implement this in Term Frequency & Inverse Document Frequency (TFIDF). Here are some mathematical definition of TFIDF.

Term Frequency:

In the case of the term frequency tf(*t*,*d*), the simplest choice is to use the *raw frequency* of a term in a document, i.e. the number of times that term *t* occurs in document *d*. If we denote the raw frequency of *t*by $f_{t,d}$, then the simple tf scheme is tf(*t*,*d*) = $f_{t,d}$. Other possibilities include

- Boolean "frequencies": tf(*t*,*d*) = 1 if *t* occurs in *d* and 0 otherwise;
- Logarithmically scaled frequency: tf(*t*,*d*) = 1 + log $f_{t,d}$, or zero if $f_{t,d}$ is zero;
- augmented frequency, to prevent a bias towards longer documents, e.g. raw frequency divided by the maximum raw frequency of any term in the document:

$$\mathrm{tf}(t,d) = 0.5 + \frac{0.5 \times f_{t,d}}{\max\{f_{t,d} : t \in d\}}$$

Inverse Document Frequency:

The inverse document frequency is a measure of how much information the word provides, that is, whether the term is common or rare across all documents. It is the logarithmically scaled fraction of the documents that contain the word, obtained by dividing the total number of documents by the number of documents containing the term, and then taking the logarithm of that quotient.

$$\mathrm{idf}(t,D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

With

- N: total number of documents in the corpus $N = |D|$
- $|\{d \in D : t \in d\}|$: Number of documents where the term t appears (i.e. $\mathrm{tf}(t,d) \neq 0$). If the term is not in the corpus, this will lead to a division-by-zero. It is therefore common to adjust the denominator to $1 + |\{d \in D : t \in d\}|$.

(From Wikipedia: https://en.wikipedia.org/wiki/Tf%E2%80%93idf)

In order to adapt this method with the clustering, we apply TFIDF along with cosine-similarity calculation.

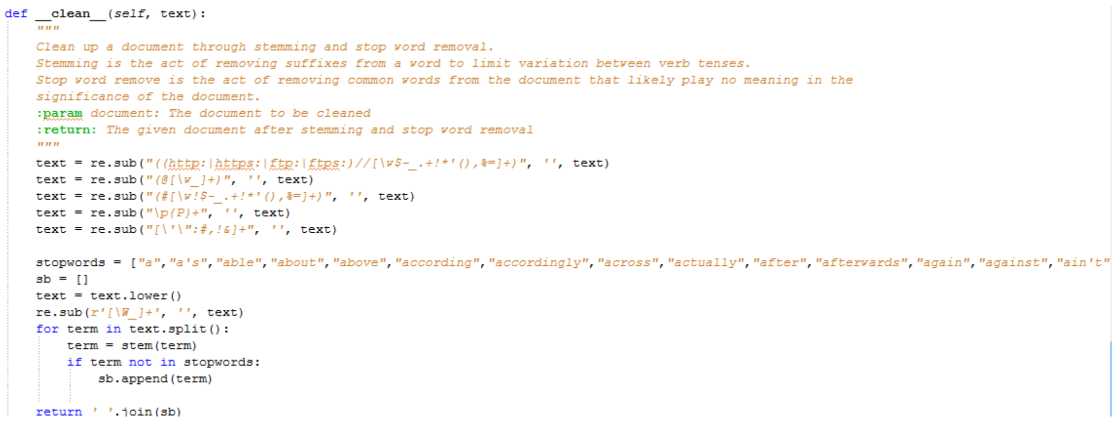
The cosine of two vectors can be derived by using the Euclidean dot product formula:

$$\mathbf{a} \cdot \mathbf{b} = \|\mathbf{a}\| \, \|\mathbf{b}\| \cos\theta$$

Given two vectors of attributes, *A* and *B*, the cosine similarity, *cos(ϑ)*, is represented using a dot product and magnitude as

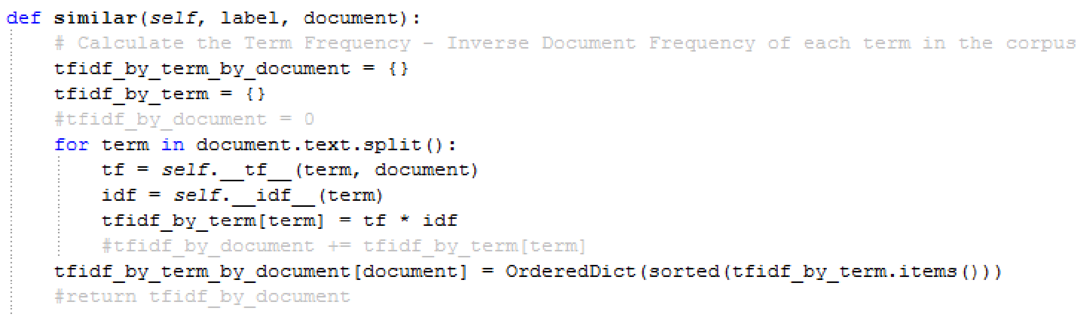
$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Source code is shown in python:



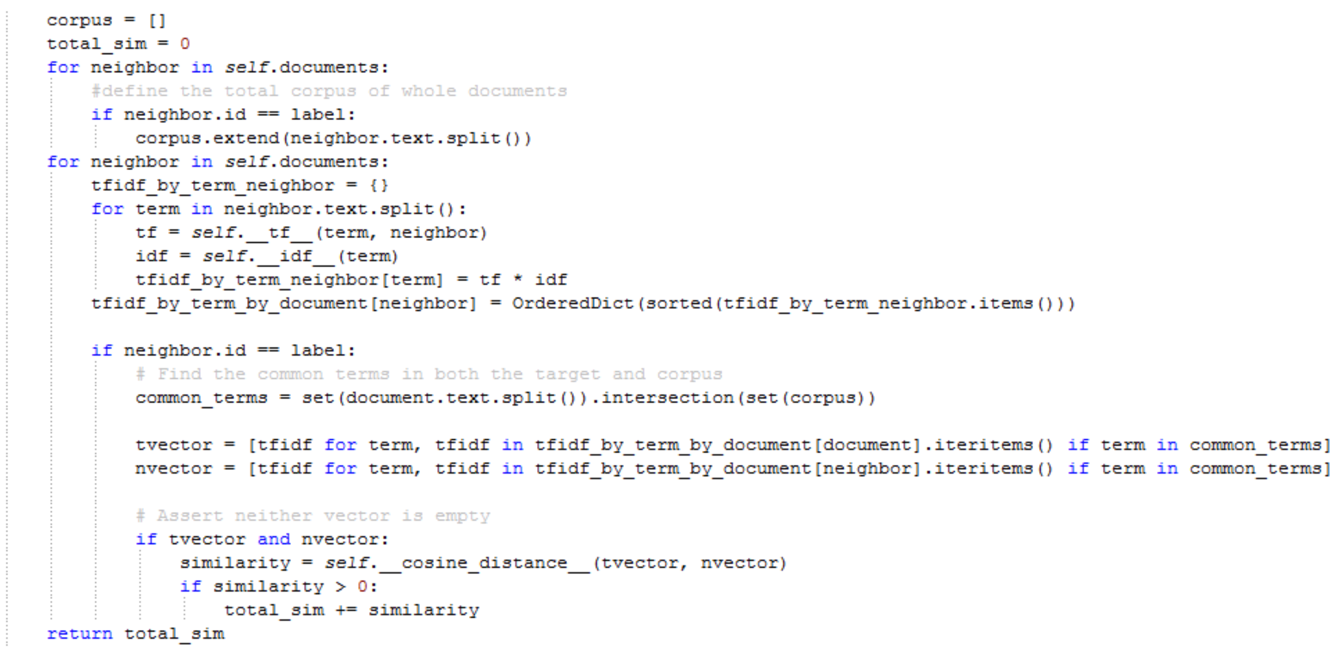
```python
def __clean__(self, text):
    """
    Clean up a document through stemming and stop word removal.
    Stemming is the act of removing suffixes from a word to limit variation between verb tenses.
    Stop word remove is the act of removing common words from the document that likely play no meaning in the
    significance of the document.
    :param document: The document to be cleaned
    :return: The given document after stemming and stop word removal
    """
    text = re.sub("((http:|https:|ftp:|ftps:)//[\w$-_.+!*'(),%=]+)", '', text)
    text = re.sub("(@[\w_]+)", '', text)
    text = re.sub("(#[\w!$-_.+!*'(),%=]+)", '', text)
    text = re.sub("\p{P}+", '', text)
    text = re.sub("[\'\":#,!&]+", '', text)

    stopwords = ["a","a's","able","about","above","according","accordingly","across","actually","after","afterwards","again","against","ain't"
    sb = []
    text = text.lower()
    re.sub(r'[\W_]+', '', text)
    for term in text.split():
        term = stem(term)
        if term not in stopwords:
            sb.append(term)

    return ' '.join(sb)
```

As can be seen from the code, we test a tweet after retrieving the most identical terms. Cleaned text will be used to calculate the TF and IDF for each term left.



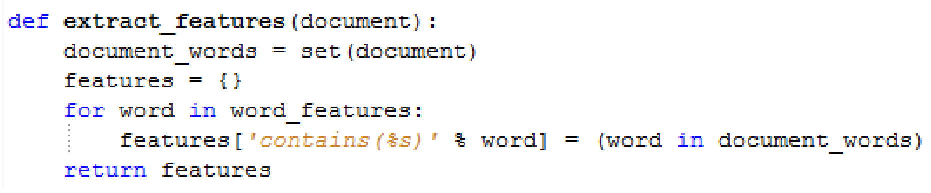
```python
def similar(self, label, document):
    # Calculate the Term Frequency - Inverse Document Frequency of each term in the corpus
    tfidf_by_term_by_document = {}
    tfidf_by_term = {}
    #tfidf_by_document = 0
    for term in document.text.split():
        tf = self.__tf__(term, document)
        idf = self.__idf__(term)
        tfidf_by_term[term] = tf * idf
        #tfidf_by_document += tfidf_by_term[term]
    tfidf_by_term_by_document[document] = OrderedDict(sorted(tfidf_by_term.items()))
    #return tfidf_by_document
```

The TFIDF evaluation will now formulate as a vector to test the cosine similarity between tweets to be tested and tweets in certain training set containing group of labeled tweets. If a tweet contains the identical terms belonging to certain group, it will show trend of larger similarity evaluation to that group.



```
corpus = []
total_sim = 0
for neighbor in self.documents:
    #define the total corpus of whole documents
    if neighbor.id == label:
        corpus.extend(neighbor.text.split())
for neighbor in self.documents:
    tfidf_by_term_neighbor = {}
    for term in neighbor.text.split():
        tf = self.__tf__(term, neighbor)
        idf = self.__idf__(term)
        tfidf_by_term_neighbor[term] = tf * idf
    tfidf_by_term_by_document[neighbor] = OrderedDict(sorted(tfidf_by_term_neighbor.items()))

    if neighbor.id == label:
        # Find the common terms in both the target and corpus
        common_terms = set(document.text.split()).intersection(set(corpus))

        tvector = [tfidf for term, tfidf in tfidf_by_term_by_document[document].iteritems() if term in common_terms]
        nvector = [tfidf for term, tfidf in tfidf_by_term_by_document[neighbor].iteritems() if term in common_terms]

        # Assert neither vector is empty
        if tvector and nvector:
            similarity = self.__cosine_distance__(tvector, nvector)
            if similarity > 0:
                total_sim += similarity
return total_sim
```

Second, we will move on to the sentimental analysis of feelings of twitterers when posting tweet. Since our categories are based on extent of positive, motive and negative, the sentiment of certain training set like positive smoking and quit smoking will definitely show differences. We implement the sentimental analysis by using Natural Language Toolkit based on Naïve Bayes Classifier. We need to extract features from the original text rather than cleaned text.



```
def extract_features(document):
    document_words = set(document)
    features = {}
    for word in word_features:
        features['contains(%s)' % word] = (word in document_words)
    return features
```

Then we build up Naïve Bayes Classifier. Also we have definition here in Wikipedia:

Naïve Bayes Classifier:

Abstractly, naive Bayes is a conditional probability model: given a problem instance to be classified, represented by a vector $\mathbf{x} = (x_1, \ldots, x_n)$ representing some *n* features (independent variables), it assigns to this instance probabilities

$$p(C_k|x_1, \ldots, x_n)$$

For each of *K* possible outcomes or *classes*.

The problem with the above formulation is that if the number of features *n* is large or if a feature can take on a large number of values, then basing such a model on probability tables is infeasible. We therefore reformulate the model to make it more tractable. Using Bayes' Theorem, the conditional probability can be decomposed as

$$p(C_k|\mathbf{x}) = \frac{p(C_k)\ p(\mathbf{x}|C_k)}{p(\mathbf{x})}.$$

We apply the mathematical model in python:

```
pos_tweets = []
neg_tweets = []
f = open('sentiment_training.txt', 'r')
line = f.readline()
while line != '':
    pos_pattern = re.compile('1\t')
    while pos_pattern.match(line):
        line = pos_pattern.sub('', line)
        pos_tweets.append([line, 'positive'])
        line = f.readline()
    neg_pattern = re.compile('0\t')
    while neg_pattern.match(line):
        line = neg_pattern.sub('', line)
        neg_tweets.append([line, 'negative'])
        line = f.readline()
    line = f.readline()
f.close()

# extract the word features out from the training data
word_features = get_word_features(get_words_in_tweets(tweets))


# get the training set and train the Naive Bayes Classifier
training_set = nltk.classify.apply_features(extract_features, tweets)
classifier = NaiveBayesClassifier.train(training_set)


def classify_tweet(tweet):
    return classifier.prob_classify(extract_features(tweet.split()))
```

Then we get the evaluation of the positive sense of a tweet. We import the probability as another dimension for tweets in case we can categorize tweets in the way we want.

Finally we apply the properties which have already been abstracted on numbers to k-Nearest Neighbor (kNN) Algorithm for classification of new tweet input. Description of kNN from Wikipedia:

K-Nearest Neighbor:

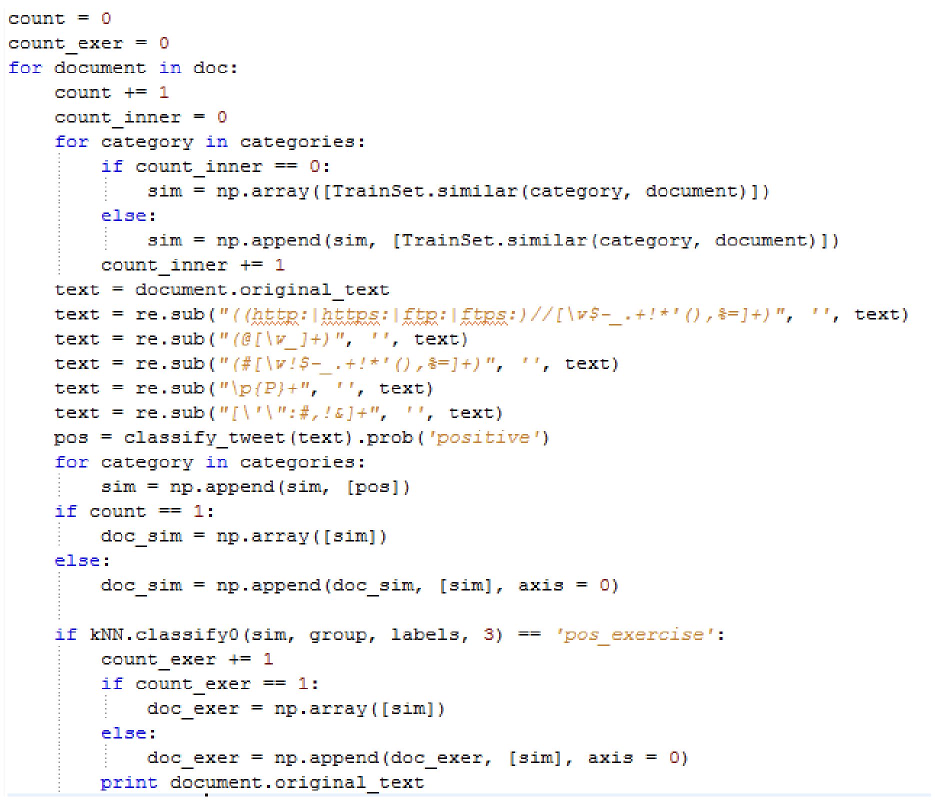
The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples.

In the classification phase, *k* is a user-defined constant, and an unlabeled vector (a query or test point) is classified by assigning the label which is most frequent among the *k* training samples nearest to that query point.

A commonly used distance metric for continuous variables is Euclidean distance. For discrete variables, such as for text classification, another metric can be used, such as the overlap metric (or Hamming distance).

As we have been able to build up mathematical model, we use Euclidean distance for kNN. Implementations are done in Python:

```python
def classify0(inX, dataSet, labels, k):
    dataSetSize = dataSet.shape[0]
    diffMat = tile(inX, (dataSetSize, 1)) - dataSet
    sqDiffMat = diffMat**2
    sqDistances = sqDiffMat.sum(axis=1)
    distances = sqDistances**0.5
    sortedDistIndicies = distances.argsort()
    classCount={}
    for i in range(k):
        voteIlabel = labels[sortedDistIndicies[i]]
        classCount[voteIlabel] = classCount.get(voteIlabel,0) + 1
    sortedClassCount = sorted(classCount.iteritems(),
    key=operator.itemgetter(1), reverse=True)
    return sortedClassCount[0][0]
```



```python
count = 0
count_exer = 0
for document in doc:
    count += 1
    count_inner = 0
    for category in categories:
        if count_inner == 0:
            sim = np.array([TrainSet.similar(category, document)])
        else:
            sim = np.append(sim, [TrainSet.similar(category, document)])
        count_inner += 1
    text = document.original_text
    text = re.sub("((http:|https:|ftp:|ftps:)//[\w$-_.+!*'(),%=]+)", '', text)
    text = re.sub("(@[\w_]+)", '', text)
    text = re.sub("(#[\w!$-_.+!*'(),%=]+)", '', text)
    text = re.sub("\p{P}+", '', text)
    text = re.sub("[\'\":#,!&]+", '', text)
    pos = classify_tweet(text).prob('positive')
    for category in categories:
        sim = np.append(sim, [pos])
    if count == 1:
        doc_sim = np.array([sim])
    else:
        doc_sim = np.append(doc_sim, [sim], axis = 0)

    if kNN.classify0(sim, group, labels, 3) == 'pos_exercise':
        count_exer += 1
        if count_exer == 1:
            doc_exer = np.array([sim])
        else:
            doc_exer = np.append(doc_exer, [sim], axis = 0)
        print document.original_text
```

It will show result of classify for tweets of positive exercise. For now we have not integrate the result of analysis model with database or user interface. We are facing problem of curse of dimensionality. We are still optimizing the model and improving accuracy of analysis.

There are two parts in this tweet analysis – K-NN algorithm being the first level of removal of garbage tweets which is implemented in R. The algorithm is discussed in the previous section. The second step is the tweet analysis which is performed by the language analysis. The tweets are classfied into different categories. In our project, our main motive is to categorize the tweets into the following categories:

1. A separate category for garbage(garbage)
2. People who follow a positive a diet (pos.diet)
3. People who follow a negative diet (neg.diet)
4. People who need motivation for following a positive diet (mot.diet)
5. People who drink liquor (pos.alcohol)
6. People who want to quit drinking alcohol (quit.alcohol)
7. People who smoke (pos.smoking)
8. People who want to quit smoking (quit.smoking)
9. People who workout (pos.exercise)
10. People who require motivation for workout (mot.exercise)

Text Classification with NGRAM:

Tweet classification involves assigning a document to category by human means. The analysis tool provides a classification facility that takes training tweets for each of the above mentioned categories which is generated by us. The analysis tool learns how to classify the tweets that is in the SQL database based on what it learnt with the training tweets given by us.
For each category, around 50 training tweets are manually given. The training tweets are taken from Twitter using input from a website called Hashtagify which actually mentions the most related hashtags.
Using the training tweet dataset we train a set of character based language models for each category. This training process processes the data in 12 character sequences as specified by the NGRAM_SIZE. We initially chose an NGRAM_SIZE of 6 , but it was insufficient to get satisfactory results.

For example,
Tweet 1- I do not like running
From this example, one can see that with an NGRAM size of 6 , we get two sequence of characters that are,
1. I do not
2. like r
3.unning
Tweet 2- I like running.
1. I like
2. runnin
3. g

With this size, Tweets 1 and 2 will have almost 50% probability of being placed in both categories. But, we know that Tweet 1 goes into motivational exercise and Tweet 2 goes into positive exercise. So we need a larger NGRAM_SIZE. We chose an NGRAM_SIZE of 12. Though we could use a larger size, 12 proved to give a better classification and performance level in terms of the time it takes to classify a million tweets. The training is done on this data set provided by us for each category and then classification happens based on the training received.

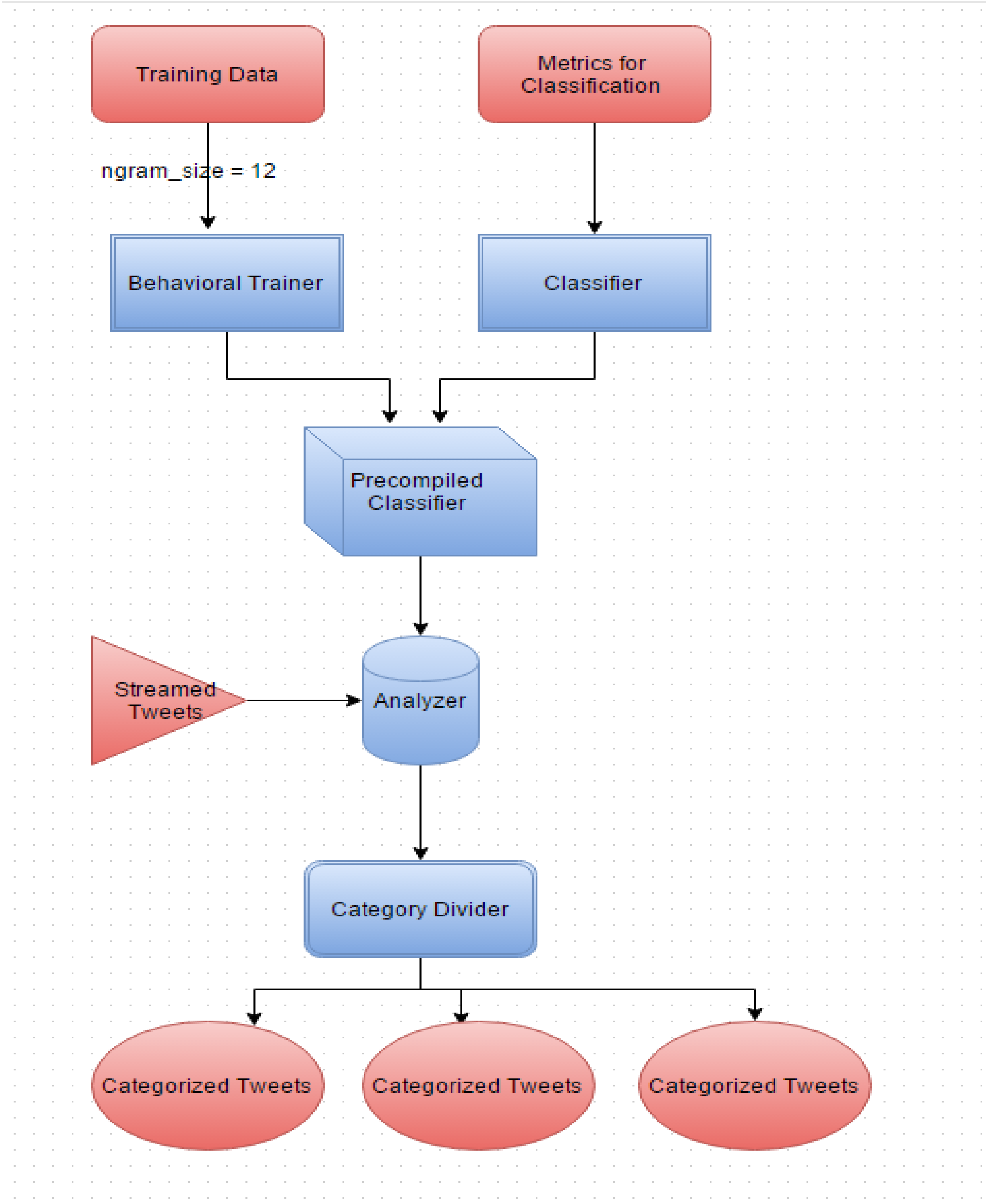
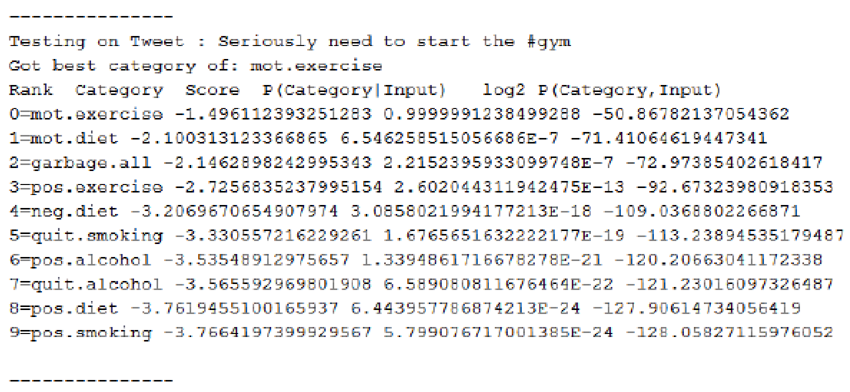


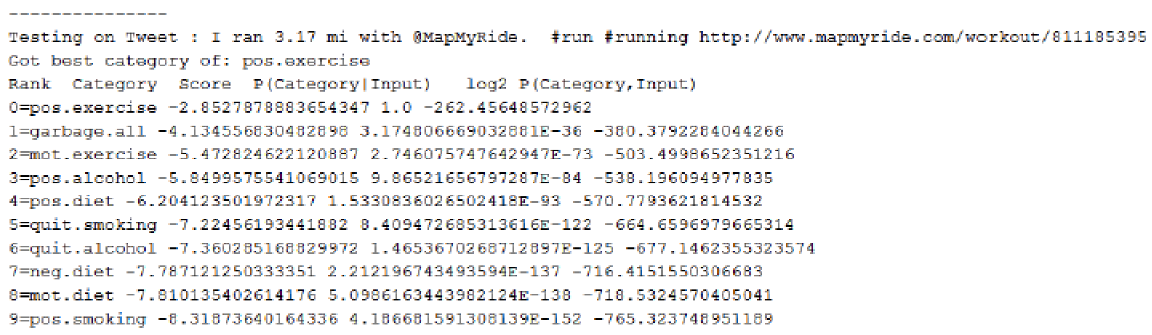
Figure: Text Classification of Tweets

Dynamic Classification:

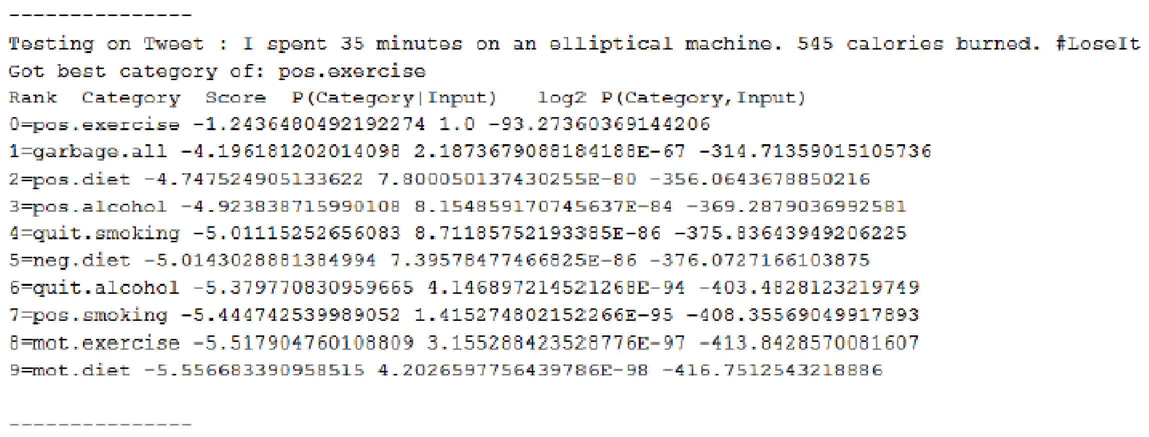
Before using the trained classification, we pre-compile the classifier to produce the more efficient compile version which is pretty fast in the classification process. The code takes more time to compile so already compiled binaries prove much efficient. Classification is actually classifying the tweet based on our categories, it takes the training tweets as a comparison matrix and runs the comparison on the input tweets. The following output shows the categorization of a tweet with respect to all the categories.



```
---------------
Testing on Tweet : Seriously need to start the #gym
Got best category of: mot.exercise
Rank  Category  Score  P(Category|Input)   log2 P(Category,Input)
0=mot.exercise -1.496112393251283 0.9999991238499288 -50.86782137054362
1=mot.diet -2.10031312336686 6.546258515056686E-7 -71.41064619447341
2=garbage.all -2.1462898242995343 2.2152395933099748E-7 -72.97385402618417
3=pos.exercise -2.7256835237995154 2.602044311942475E-13 -92.67323980918353
4=neg.diet -3.2069670654907974 3.0858021994177213E-18 -109.0368802266871
5=quit.smoking -3.330557216229261 1.6765651632222177E-19 -113.23894535179487
6=pos.alcohol -3.53548912975657 1.3394861716678278E-21 -120.20663041172338
7=quit.alcohol -3.565592969801908 6.589080811676464E-22 -121.23016097326487
8=pos.diet -3.7619455100165937 6.443957786874213E-24 -127.90614734056419
9=pos.smoking -3.7664197399929567 5.799076717001385E-24 -128.05827115976052

---------------
```



```
---------------
Testing on Tweet : I ran 3.17 mi with @MapMyRide.  #run #running http://www.mapmyride.com/workout/811185395
Got best category of: pos.exercise
Rank  Category  Score  P(Category|Input)   log2 P(Category,Input)
0=pos.exercise -2.8527878883654347 1.0 -262.45648572962
1=garbage.all -4.134556830482898 3.174806669032881E-36 -380.3792284044266
2=mot.exercise -5.472824622120887 2.746075747642947E-73 -503.4998652351216
3=pos.alcohol -5.8499575541069015 9.86521656797287E-84 -538.196094977835
4=pos.diet -6.204123501972317 1.5330836026502418E-93 -570.7793621814532
5=quit.smoking -7.22456193441882 8.409472685313616E-122 -664.6596979665314
6=quit.alcohol -7.360285168829972 1.4653670268712897E-125 -677.1462355323574
7=neg.diet -7.787121250333351 2.212196743493594E-137 -716.4151550306683
8=mot.diet -7.810135402614176 5.0986163443982124E-138 -718.5324570405041
9=pos.smoking -8.31873640164336 4.186681591308139E-152 -765.323748951189
```



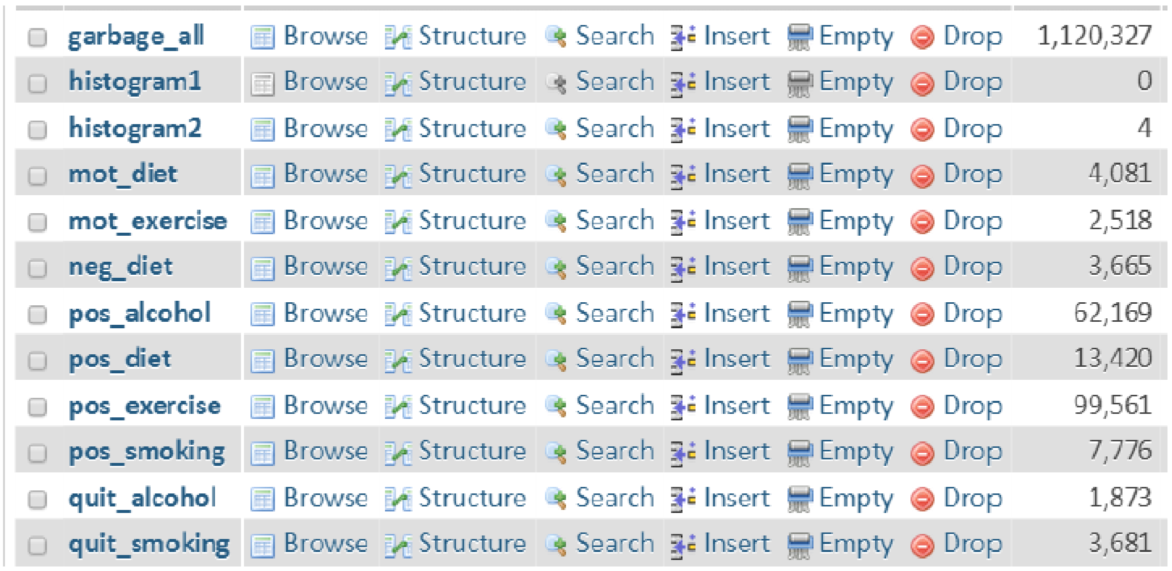
```
---------------
Testing on Tweet : I spent 35 minutes on an elliptical machine. 545 calories burned. #LoseIt
Got best category of: pos.exercise
Rank  Category  Score  P(Category|Input)   log2 P(Category,Input)
0=pos.exercise -1.2436480492192274 1.0 -93.27360369144206
1=garbage.all -4.196181202014098 2.187367908818418 8E-67 -314.71359015105736
2=pos.diet -4.747524905133622 7.800050137430255E-80 -356.0643678850216
3=pos.alcohol -4.923838715990108 8.154859170745637E-84 -369.2879036992581
4=quit.smoking -5.01115252656083 8.711857521933 85E-86 -375.8364394920622 5
5=neg.diet -5.0143028881384994 7.395784774668 25E-86 -376.0727166103875
6=quit.alcohol -5.379770830959665 4.146897214521268E-94 -403.4828123219749
7=pos.smoking -5.444742539989052 1.415274802152266E-95 -408.3556904991789 3
8=mot.exercise -5.517904760108809 3.155288423528776E-97 -413.842857008160 7
9=mot.diet -5.556683390958515 4.202659775643978 6E-98 -416.7512543218886

---------------
```

The above figure shows a sample tweet and the output of classifier. The classifier actually tests that tweet for all the categories and gives the expected probability of each category. All the categories are given ranks, and the tweets are finally categorized belonging to the classification which has lowest rank i.e.; Rank 0. For the sake of garbage collection and to maintain correctness and accuracy of the data analysis we have a category ***"Garbage"***, if the classifier has no matching category it puts that tweet into the garbage category.

The introduction of garbage category proves to be beneficial not only to improve correctness of analysis but also provides us with a metrics to calculate the fractional useful tweets. We can use total no. of tweets and garbage tweets to find out what fraction of the total tweets are not useful.

Once the classification is done we move on to tagging tweets to their categories. This tag is used later on for the purpose of analysis. As soon as the Rank is determined, the tweet is tagged and is moved to the corresponding category table in SQL Database.

For the sake of convenience and dependable tagging process, we have introduced tables in SQL Database. Each category has its own table. The below figure clearly depicts our DB arrangement for tagging process.



☐	garbage_all	Browse	Structure	Search	Insert	Empty	Drop	1,120,327
☐	histogram1	Browse	Structure	Search	Insert	Empty	Drop	0
☐	histogram2	Browse	Structure	Search	Insert	Empty	Drop	4
☐	mot_diet	Browse	Structure	Search	Insert	Empty	Drop	4,081
☐	mot_exercise	Browse	Structure	Search	Insert	Empty	Drop	2,518
☐	neg_diet	Browse	Structure	Search	Insert	Empty	Drop	3,665
☐	pos_alcohol	Browse	Structure	Search	Insert	Empty	Drop	62,169
☐	pos_diet	Browse	Structure	Search	Insert	Empty	Drop	13,420
☐	pos_exercise	Browse	Structure	Search	Insert	Empty	Drop	99,561
☐	pos_smoking	Browse	Structure	Search	Insert	Empty	Drop	7,776
☐	quit_alcohol	Browse	Structure	Search	Insert	Empty	Drop	1,873
☐	quit_smoking	Browse	Structure	Search	Insert	Empty	Drop	3,681

As soon as the categorization id finished, copying of tweets into corresponding table takes place at the same time, while the tweet is getting copied to SQL DB the java analyzer takes the next tweet in queue and starts its analysis.

Is classification Legitimate?

For the process of classification, asking a question about its legitimate output is crucial for data analysis. Our Analysis process gets into jeopardy once the classifier starts segregation of tweets in unexpected manner. To make sure that the classification is done properly we use probabilistic determination of tweets provided categories. Each tweet is given the probability for each category. The probabilistic determination is described below:

A JointClassification is a conditional classification derived from a joint probability assignment to each category and the object being classified. The conditional probabilities are computed from the joint probabilities, but an additional score may be provided for ordering. These scores must be ordered in the same way as the joint probabilities. For example, the language model classifiers implement the score as an entropy rate to allow between-document comparisons.

In addition to the score and conditional probability methods, this interface adds a method to retrieve joint log (base 2) probability by rank, jointLog2Probability(int).

The conditional probability estimate of the category given the input is derived from the joint probability of category and input:

P(category|input) = P(category,input) / P(input)

where the joint probability P(category,input) is determined by the joint probability estimate and the input probability P(input) is estimated by marginalization:

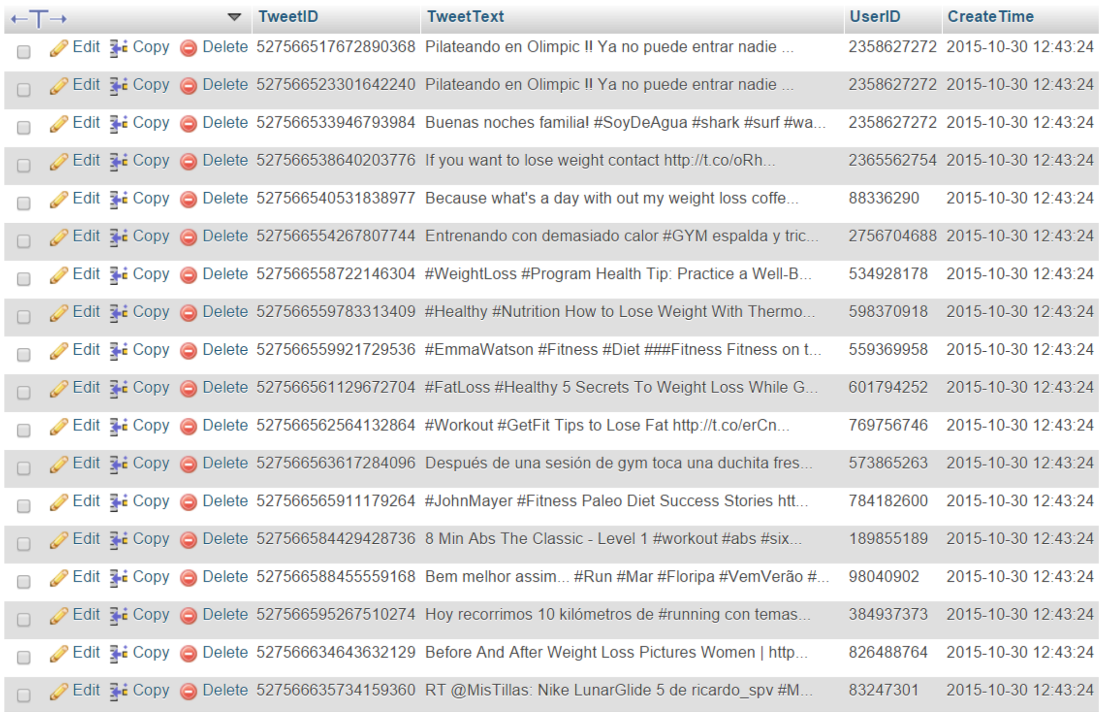
P(input) = Σcategory P(category,input)

In the study of probability, given at least two random variables X, Y, ..., that are defined on a probability space, the joint probability distribution for X, Y, ... is a probability distribution that gives the probability that each of X, Y, ... falls in any particular range or discrete set of values specified for that variable.

4. Database Design

Then we are transmitting the tweets in MongoDB to MySQL. So far we have collected around 50000 tweets. Tweets relevant to our hashtags in consideration are stored in MongoDB initially. These tweets are later extracted into MySQL since it's easy to data analysis if the data is stored in a relational database. Also, It's easy to extract information unto User Interface if we have our data stored in MySQL. The UserID, TweetID, TweetText and CreationTime are stored in these tables.

Here is the snapshot of our database:



←T→	TweetID	TweetText	UserID	CreateTime
☐ Edit Copy Delete	527566517672890368	Pilateando en Olimpic ‼ Ya no puede entrar nadie ...	2358627272	2015-10-30 12:43:24
☐ Edit Copy Delete	527566523301642240	Pilateando en Olimpic ‼ Ya no puede entrar nadie ...	2358627272	2015-10-30 12:43:24
☐ Edit Copy Delete	527566533946793984	Buenas noches familia! #SoyDeAgua #shark #surf #wa...	2358627272	2015-10-30 12:43:24
☐ Edit Copy Delete	527566538640203776	If you want to lose weight contact http://t.co/oRh...	2365562754	2015-10-30 12:43:24
☐ Edit Copy Delete	527566540531838977	Because what's a day with out my weight loss coffe...	88336290	2015-10-30 12:43:24
☐ Edit Copy Delete	527566554267807744	Entrenando con demasiado calor #GYM espalda y tric...	2756704688	2015-10-30 12:43:24
☐ Edit Copy Delete	527566558722146304	#WeightLoss #Program Health Tip: Practice a Well-B...	534928178	2015-10-30 12:43:24
☐ Edit Copy Delete	527566559783313409	#Healthy #Nutrition How to Lose Weight With Thermo...	598370918	2015-10-30 12:43:24
☐ Edit Copy Delete	527566559921729536	#EmmaWatson #Fitness #Diet ###Fitness Fitness on t...	559369958	2015-10-30 12:43:24
☐ Edit Copy Delete	527566561129672704	#FatLoss #Healthy 5 Secrets To Weight Loss While G...	601794252	2015-10-30 12:43:24
☐ Edit Copy Delete	527566562564132864	#Workout #GetFit Tips to Lose Fat http://t.co/erCn...	769756746	2015-10-30 12:43:24
☐ Edit Copy Delete	527566563617284096	Después de una sesión de gym toca una duchita fres...	573865263	2015-10-30 12:43:24
☐ Edit Copy Delete	527566565911179264	#JohnMayer #Fitness Paleo Diet Success Stories htt...	784182600	2015-10-30 12:43:24
☐ Edit Copy Delete	527566584429428736	8 Min Abs The Classic - Level 1 #workout #abs #six...	189855189	2015-10-30 12:43:24
☐ Edit Copy Delete	527566588455559168	Bem melhor assim... #Run #Mar #Floripa #VemVerão #...	98040902	2015-10-30 12:43:24
☐ Edit Copy Delete	527566595267510274	Hoy recorrimos 10 kilómetros de #running con temas...	384937373	2015-10-30 12:43:24
☐ Edit Copy Delete	527566634643632129	Before And After Weight Loss Pictures Women | http...	826488764	2015-10-30 12:43:24
☐ Edit Copy Delete	527566635734159360	RT @MisTillas: Nike LunarGlide 5 de ricardo_spv #M...	83247301	2015-10-30 12:43:24

5. User Interface Section

When you click into our website, you will see the flowing home page:

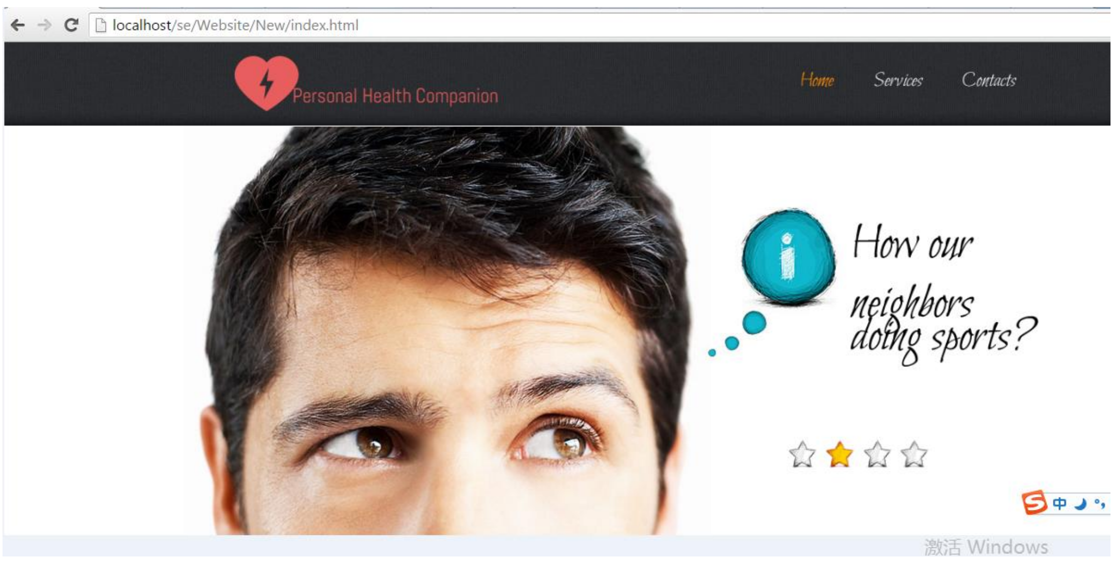

localhost/se/Website/New/index.html
Personal Health Companion
Home
Services
Contacts
How our neighbors doing sports?
激活 Windows

Figure 1. Home page

when user click into the service, which you can find in the navigation part:

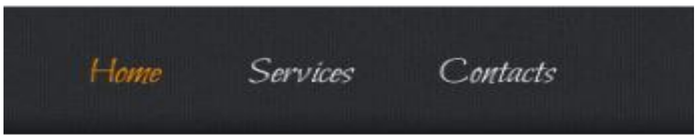


Figure 2. Homepage navigation

User will see such a table for our features. And User can choose any of the features that they are interested in and click the button "Read More", and it will jump into the corresponding html file.

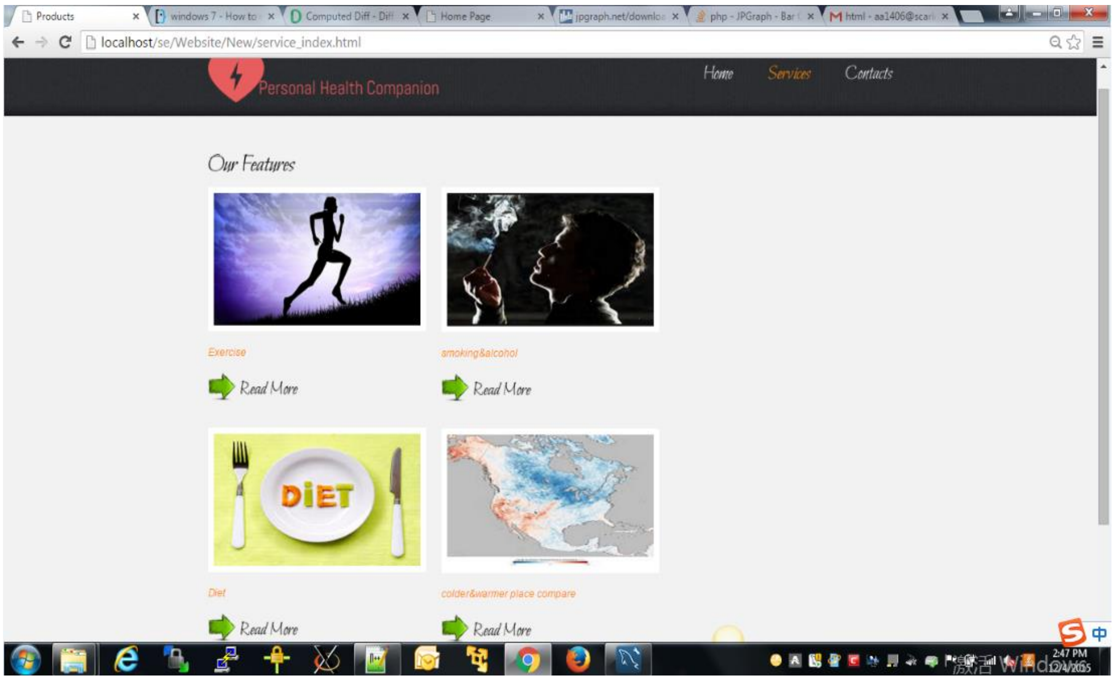

localhost/se/Website/New/service_index.html
Personal Health Companion
Home
Services
Contacts
Our Features
Exercise
Read More
smoking&alcohol
Read More
Diet
Read More
colder&warmer place compare
Read More

Figure 3. Features page

If I click "Exercise", the website will goes into the exercise.html, showing the weekly exercise trends.

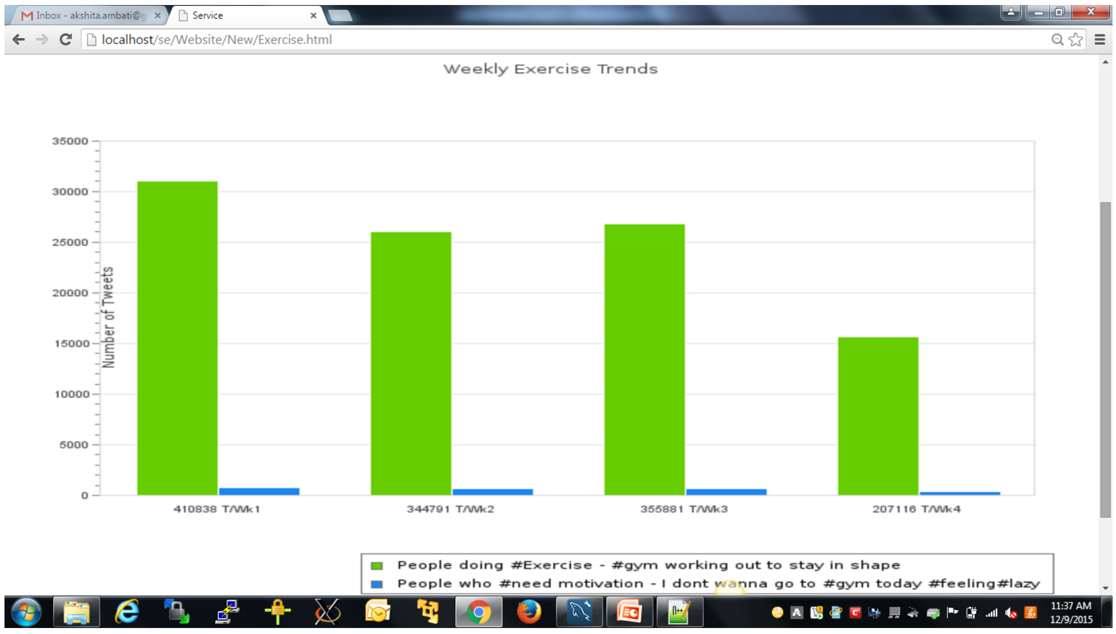


Figure 4.1 Weekly Trends for exercise

Similarly we have diet and Smoking & Alcohol weekly trends as below:

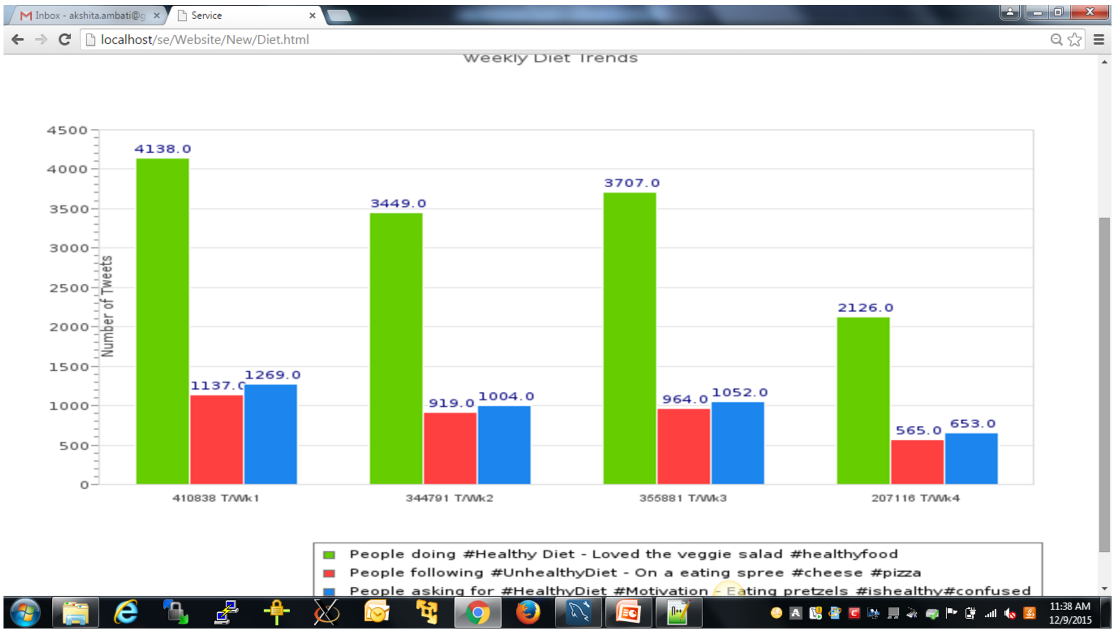


Figure 4.2 Weekly Trends for Diet

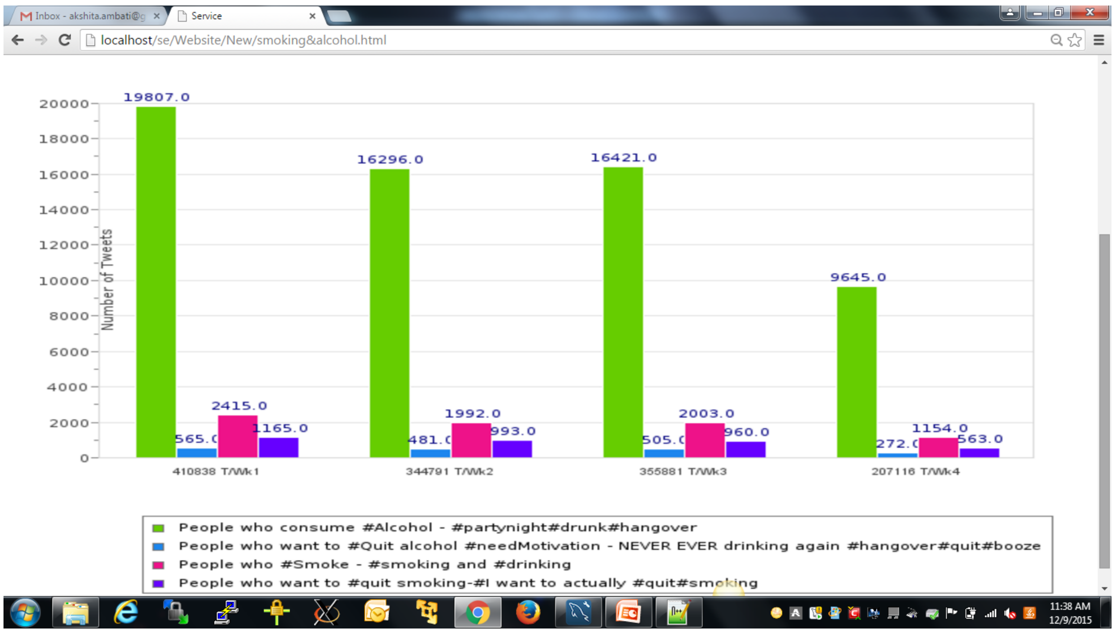


Figure 4.3 Weekly Trends for Smoking & Alcohol

As you can see, there is a navigation part too. And when you click into certain feature, it will show a drop-down list based on our different features.

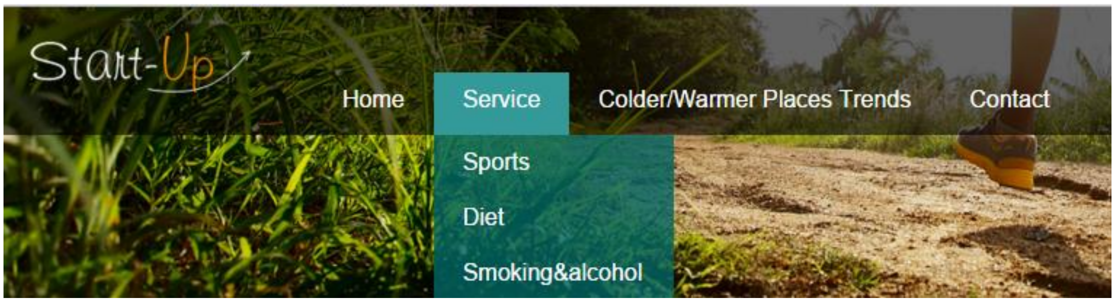


Figure 4.4. Navigation for features

When I want to know the difference trend between the warm and cold place, you can click any of the features as you like. For example, I will click “ diet ”.

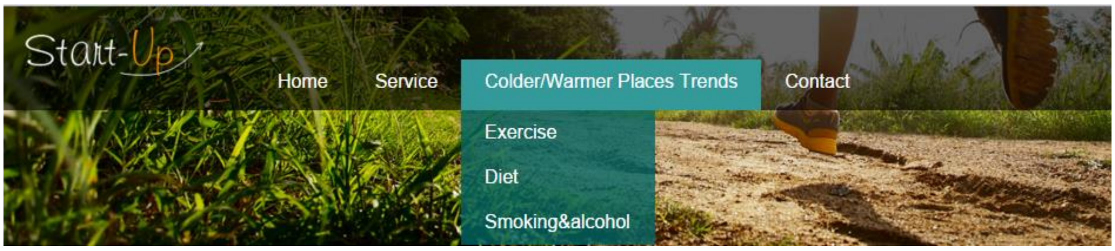


Figure 4.5. Navigation for features

The following three screenshots are the Exercise, Diet and Smoking & Alcohol trends for the Colder and Warmer places

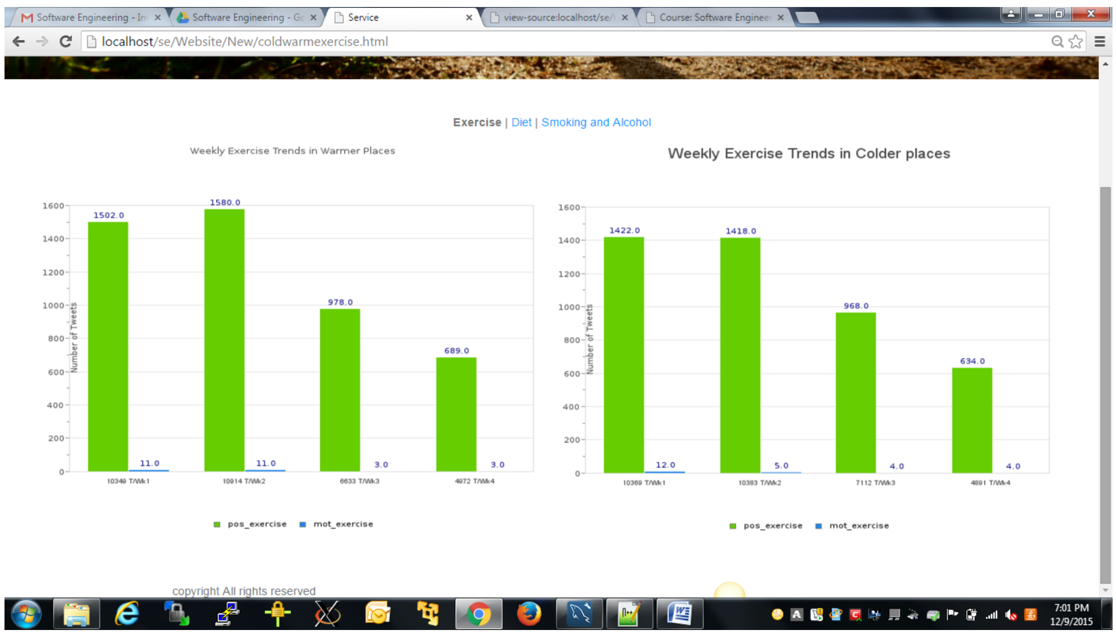

Software Engineering - In
Software Engineering - Gc
Service
view-source:localhost/se/
Course: Software Enginee
localhost/se/Website/New/coldwarmexercise.html
Exercise | Diet | Smoking and Alcohol
Weekly Exercise Trends in Warmer Places
Number of Tweets
1502.0
1580.0
978.0
689.0
11.0
11.0
3.0
3.0
10349 T/Wk1
10914 T/Wk2
6633 T/Wk3
4972 T/Wk4
pos_exercise
mot_exercise
Weekly Exercise Trends in Colder places
1422.0
1418.0
968.0
634.0
12.0
5.0
4.0
4.0
10369 T/Wk1
10383 T/Wk2
7112 T/Wk3
4891 T/Wk4
copyright All rights reserved
7:01 PM
12/9/2015

Figure 4.6. Weekly Exercise Trends for Colder/Warmer places

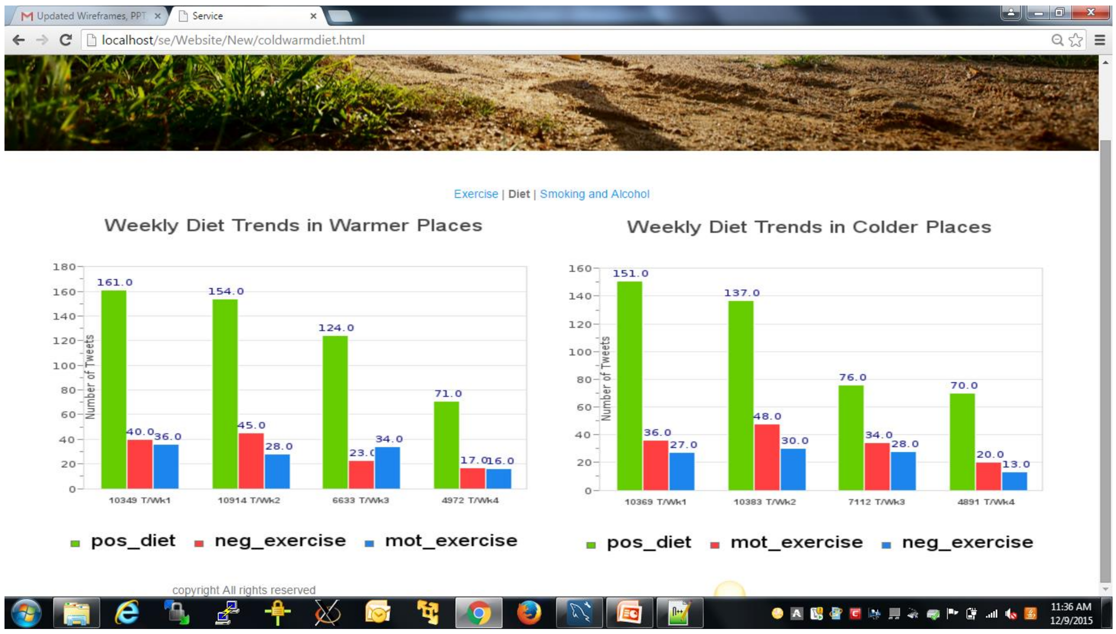


Figure 4.7. Weekly Diet Trends for Colder/Warmer places

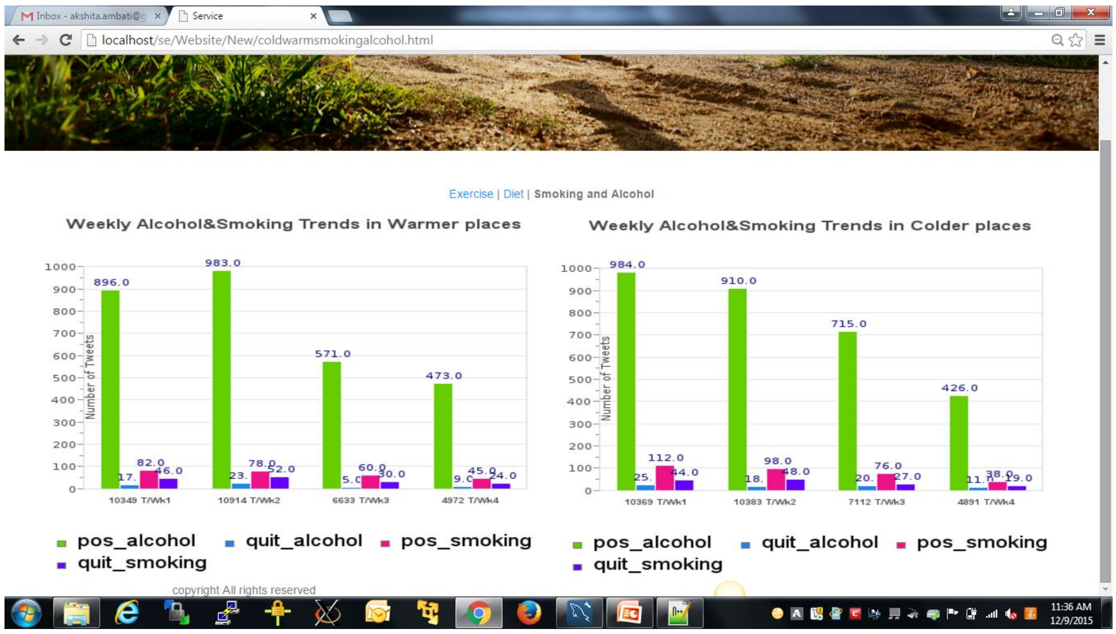
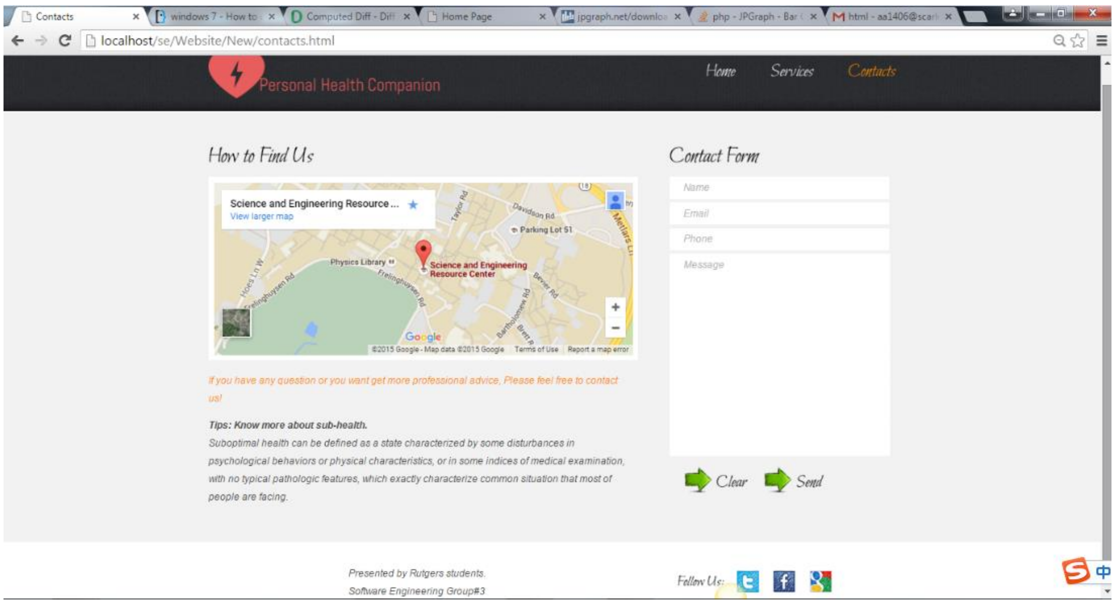


Figure 4.8. Weekly Smoking & Alcohol Trends for Colder/Warmer places

Users will enter this below page after clicking “Contacts” and they can easily find the location of our team from the map.



If you have any question or you want get more professional advice, Please feel free to contact us!

Tips: Know more about sub-health.
Suboptimal health can be defined as a state characterized by some disturbances in psychological behaviors or physical characteristics, or in some indices of medical examination, with no typical pathologic features, which exactly characterize common situation that most of people are facing.

Presented by Rutgers students.
Software Engineering Group#3

Figure4. 9. Contact page

And they can also write down advises about our project on the contact form showed at the right of this website.