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This paper provides a new perspective of looking at emoji: Users. On 100 Twitter users represented by emojis from 200 tweets, an exploratory analysis is conducted to find patterns of emoji use for individual users. We use k-means clustering, principal component analysis and hierarchical clustering on different distance measures, with special focus on outlying users with unique using patterns. Our findings could give insights of how the ways people use emoji converge and diverge, show hidden connections between emojis, and help people better understand this novel language in the digital era.

Headings:

Digital communications

Social media

PATTERNS OF EMOJI USE FOR INDIVIDUAL TWITTER USERS: AN EXPLORATORY ANALYSIS

by
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Table of Contents

Introduction

For the first time ever, the Oxford Dictionaries Word of the Year is not a word consisting of English letters – it's a word made of Unicode and represented as a picture: 😂, which can be identified either by its codepoint as U+1F602 or its official name as "FACE WITH TEARS OF JOY", that "best reflected the ethos, mood, and preoccupations of 2015"[1].

This probably is the best indicator of the popularity of emoji, the pictograms that have ruled the world of digital communications. This paper tries to look at this new group of "letters" from users' perspective: to find patterns in the use of emoji across tweets by individual users, a way of modeling twitter users with respect to their emoji use.

About Emoji

The revolution of the modern pictograms starts from emoticon, the elder sibling of emoji, which is a short sequence of characters, typically punctuation symbols. The use of emoticons in the digital era dates back to 1982, where a professor at Carnegie Mellon University proposed to use :-) and :-(to distinguish jokes from more serious posts on their computer-science message board. Within a few months, the use of emoticons had spread, and the set of emoticons was extended with hugs and kisses, by using characters found on a typical keyboard. A few decades later, emoticons have found their way into

[1] http://blog.oxforddictionaries.com/2015/11/word-of-the-year-2015-emoji

everyday digital communications. They allow authors to express their feelings, moods and emotions, augmenting a written message with non-verbal elements. They help to draw the reader's attention, enhancing and improving the understanding of the message (Hogenboom et al., 2015).

Emoji, the younger sibling, is a step further, developed with modern communication technologies that facilitate more expressive messages. It is a graphic symbol that represents not only facial expressions, but also animals and plants, food and drink, vehicles and buildings, and concepts and ideas. Literally translated as "picture character" in Japanese, emoji were first provided in Japan by the three major mobile carriers (NTT DoCoMo, KDDI au and Softbank) at the end of the 20th century to facilitate digital communication. However, Apple's support for emojis on the iPhone, in 2010, led to global popularity (Novak, Smailović, Sluban, & Mozetič, 2015). Emoji were first standardized in Unicode 6.0 consisting of 722 characters. As of August 2015, Unicode 8.0 defines a list of 1281 single- or double-character emoji symbols[2].

These pictograms have grown to be an indispensable non-verbal part in what used to be considered as pure-verbal communications, providing what used to be exclusive for face-to-face communications. And the step from emoticons to emoji is not only the change of the way of expression, but also the establishment of a global convention. Unlike emoticons that can be arbitrarily "spelled" by users, emoji have standards regardless of users and regardless of culture. They are a common set of meaningful symbols shared by all human kind.

Their prevalence and popularity gain attention not only from the dictionaries, but also from geeks and scholars. Over the past few years we saw the emergence of tools and applications like emojitracker[3], emojipedia[4] and emoji translate[5], and we saw emoji being scrutinized by linguists, psychologists and computer scientists. One particular favorite context for these studies is the social media. Facebook, Twitter and Instagram all have introduced (and enjoyed popularity of) emoji to their system, where tons of data can be retrieved by the public. Since different platforms have different features and factors, this study is focused on the emoji use on Twitter due to its high accessibility and more structured/normalized text content.

User as a New Perspective

Both Twitter and Instagram have been used as corpora for analysis of emoji use. However, these studies have treated their data merely as giant collection of text without much metadata, and the analysis has been limited to single tweets/Instagram posts. But social media is a far more fertile ground than traditional corpora and there are the most important metadata – the contents are generated by its users. Tweets expressing different ideas, talking about different topics and having different tones can be associated by their common creator, thus possibly exposing certain patterns. In such way the relatively novel world of emoji can be linked to the areas of stylistics and user modeling on social media.

Stylistics is the study and interpretation of texts in regard to their linguistic and tonal style. Sources of study in stylistics may range from canonical works of writing to popular texts, and non-literary texts may be of just as much interest as literary ones[6]. Stylistics as a conceptual discipline may attempt to establish principles capable of explaining particular choices made by individuals and social groups in their use of language, and can be applied to areas such as discourse analysis.

The idea of user modeling on social media comes from the need for personalization inspired by the widespread of social media websites where a huge number of users generate infinite number of contents. As one of the major issues in personalization, building users' profiles has been a challenging yet attractive subject for researchers. Researchers aim to provide solid user models which can be used by applications to enhance user experiences in social media websites (Abdel-Hafez & Xu, 2013). In this way the traditional area of stylistics is applied to the textual analysis of digital contents generated by users.

This study intends to incorporate ideas from both the pioneering studies on emoji and the more developed areas of stylistics and user modeling on social media, conducting an exploratory analysis on users represented by the emojis they used in their Twitter feeds. What to be found could give some insights of how the ways people use emoji converge or diverge, show "hidden" connections between emojis, and help people better understand this novel language in the digital era.

[2] http://www.unicode.org/versions/Unicode8.0.0/
[3] http://www.emojitracker.com/
[4] http://emojipedia.org/
[5] http://emojitranslate.com/
[6] https://en.wikipedia.org/wiki/Stylistics_(field_of_study)

Literature review

The key purpose of user modeling is to build a user profile “by acquiring, extracting and representing the features of users” (Zhou et al, 2012). The profile can be used for presenting more relevant content to each user. It usually contains the user’s basic information (age, gender, country etc.), keywords representing his/her interest, as well as more sophisticated information such as that of the user’s behavior like sequence of clicks and time spent on pages (Kim, Ha, Lee, Jo, & El-Saddik, 2011). Moreover, the user’s social information, such as connections with other users, social behaviors like likes and shares, may also be used for building the profile. This kind of information can be used to enhance the performance of many predictive applications (Yu, Pan, & Li, 2011).

Data

Data collection depends on the nature of the social media and the target application. These data can be classified into explicit, implicit and social ones. Explicit data are given directly by the user, such as demographic information, comments, posts, queries, and ratings. Researchers extract keywords from users’ comments and posts and use them to represent their interests (Lu, Lam, & Zhang, 2012). Tags are also commonly used as keywords of interest directly when they are attached by users to some web content (Hannon, Mccarthy, O’mahony, & Smyth, 2012). Meanwhile, implicit data are those inferred from users’ behavior and can be acquired by studying users’ clicks, navigations and transactions. For example, when a user opens a webpage by clicking link, the page title can be extracted as his/her interest, or keywords can be extracted from the page's content if the user dewell on it for time larger than some pre-defined threshold (Das, Datar, Garg, & Rajaram, 2007). Finally, social data represents relationships and interactions between users. These relationships can be bidirectional, requiring acceptance of both users connected, or unidirectional without such acceptance. Classic cases of these two types are friending on Facebook and following/followers on Twitter. Such social network data can be represented as undirected and directed graph, where we can use graph analysis to detect communities in the network. Researchers (Ma, Zhou, Liu, Lyu, & King, 2011) used social network graphs to find "trusted communities", or in other words "like-minded groups" for a user. It may also be used simultaneously with, or replace, the nearest neighbor method that finds like-minded users using similarities between users.

User Representation

A user is usually represented by a vector based on keywords. It's simple and common to represent a user as pairs of concepts and related weights. The concepts correspond to the user's interests and the weights correspond to the degree of interest. The weights can be binary (0 or 1) numbers or integers such as items' ratings or term frequency (Tf) (Barla, 2011). They can also be real numbers which can be calculated using several methods such as term frequency multiplied by inverse document frequency (Tf-Idf). Here Tf is the frequency of the concept, while Idf is the total number of documents divided by the number of documents that contains the concept.

Other representations for users' profiles include graph-based and hierarchy-based profiles. These two kinds of profiles consist of nodes and edges. The nodes usually represent the keywords and the edges represent the relationships between these nodes. In some cases it was proposed that these edges be associated with weights, representing the strength of the relationship between any two nodes (Abdel-Hafez & Xu, 2013).

Profile Construction

A simple method to generate keywords for representing a user is traditional Bag of Words (BOW), which is typically used in cases of explicit data. BOW is a collection of words used in the user's text, ignoring their order, weighted by their frequency or the more complex Tf-Idf weighting. Hannon et al. (2012) used this method to represent Twitter users' profiles. Similarly, Chen et al. (2010) did the same to construct profiles using Tf-Idf weighting, but also built a followee profile by collecting words from followees' tweets, using terms with the highest 20% Tf values and excluding words occurring in one followee's profile only. Words resulted from this filtering are termed high-interest words. They also modeled URLs by the words used to describe them in users' tweets, and determined whether a URL is of the user's interest or not using cosine similarity.

Some social media websites enable its users to use social tagging to annotate items with chosen tags. These annotations can be modeled as quadruples of user-tag-resource-relations. Hannon et al. (2012) used a category database which maintain twitter curated lists, hand-annotated by users with topical tags, to extract a set of tags representing all the lists the user belongs to. Abel et al. (2011) implemented a cross-system user model that collects tags from various social tagging services and maps them to each other, thus converting system-specific vocabularies to a common vocabulary. To connect different user accounts from different websites, they used Google social graph for users linking their accounts through their Google profiles.

Some researchers use concepts extracted from users' data to construct user profiles. Wikipedia was used by Lu et al. (2012) as a rich external source of data for extracting concepts from users' tweets. They used Explicit Semantic Analysis (ESA) to compute semantic relatedness between a Wikipedia concept and a tweet, both vectorized as pairs of terms and Tf-Idf weights. In addition, they vectorized each users' social connections as pairs of other users and corresponding "affinity scores" computed based on replies, retweets and mentions between them. Kim et al. (2011) used a text mining method consisting of three steps: term extraction, frequent pattern mining, and pattern pruning. In the first step, they extract terms from implicit data such as clicks, views and bookmarks. Then they weight these terms using Tf-Idf values and find frequent patterns. Finally, they pruned the patterns by removing unnecessary terms from frequent patterns.

Topic modeling is another way to represent user interest, which represents it as topics rather than keywords. Ahmed et al. (2011) modeled users' interests as latent topics based on Latent Dirichlet Allocation (LDA), with two distributions: users' distributions over topics and topics' distributions over terms. User queries were used to collect words of interest for the user for advertising targeting. They presented a fixed-dimensional hierarchical model of user actions divided into epochs. They indicated that previously expressed interests are more likely to be expressed. They assumed external effects were not part of users' interests and aimed to filter them out of the users' profiles. Another model, proposed by Zhong et al. (2012), transfers user's behavior over composite social networks. A Users' distribution over networks was introduced to indicate how much a user is influenced by a given network. They draw a network for each user from a Dirichlet distribution, and then a social network from a Multinomial distribution for every interaction of a given user. Based on their similarities to others, each user adopts relationship from different sub-networks individually.

Methods

In this exploratory study, we used the explicit data of emoji occurring in one's twitter feed, in a Bag-of-Emoji approach, to represent each user as a vector of emojis weighted by Tf-Idf value, and performed analysis started from k-means clustering, hierarchical clustering and principal component analysis. The data collection and transformation part was done with Python while the analysis part was done with R.

Data Collection and Transformation

The data we conducted analysis on is from the 200 most recent tweets containing emojis from each of the 100 sampled users. Thus in total there are 20,000 "emoji tweets" published by 100 users.

The reference data for this study is the Emoji Sentiment Ranking table[7] made available online by the Sentiment of Emojis study (Novak, Smailović, Sluban, & Mozetič, 2015), having 969 emojis ranked by total occurrence in their collection of tweets. The top 60 emojis were used by us as keywords to catch live tweet streams, using Tweepy, a python library to access the Twitter API. Retweets were excluded in this process. In this way we can get sampled Twitter users that mentions the most popular emojis in real time.

Next we use Tweepy to access the timeline of the users retrieved in the previous

[7] http://kt.ijs.si/data/Emoji_sentiment_ranking/

step. Starting from each user's most recent tweets, we tried to find 200 tweets (again retweets were excluded) that contained any emojis from our reference table, until the user's tweets were exhausted. Those who had at least 200 "valid tweets" were "valid" users to be included in our sample. It took 141 users retrieved from the first step to reach our proposed size of 100 users.

During the previous step we also parsed the valid tweets and kept counts of each emoji. In such way, after reaching 100 valid users we also got the count of each emoji for each user, also known as the "term frequency" (tf), and the number of users who used each emoji, treated as the "document frequency" (df) in our Tf-Idf weighting. Then using these two quantities we computed the Tf-Idf value of each emoji for each user, using the formula:

$$Tf.Idf = 1 + \mathrm{tf} \cdot \ln \frac{N}{df}.$$

Here N is the number of documents which is 100, the number of users in our case, and add-one smoothing is used to separate low weighted terms from never-used ones.

As a result, now each user in our sample is a vector of Tf-Idf values for 969 emojis, or a point in a space of 969 dimensions.

Glitches

There are a few glitches during the data collection and transformation process. First, for retweet exclusion, some say the "retweeted" Boolean field in a status (tweet) object indicates whether it's a retweet or not, and conditioning on it could eliminate retweets, which turns out to be a myth. We tried on it by experimenting with our own Twitter accounts, and finally found what it really means: it's basically the "retweet" button on each tweet when viewed in a Twitter feed, between “Reply” and “Like”, whose “on” status indicates it has been retweeted by the viewing account. In the case of Tweepy, it means whether the tweet has been retweeted by the account that’s authorized to use the API. Two viable ways to identify a retweet would be to test if it starts with “RT ” (two capital letters followed by a space) and if the embedded “retweeted status” field is empty, although in both cases some non-retweets (manually adding “RT ” at the beginning or quoting other tweets with one’s own words) might be misjudged. But since we need only non-retweets, both can give a guarantee. The latter is used in our study.

Second, Twitter has limits on the volume of information accessed in certain timeframe by each user through its API, which led to a deny of access after about 20 users’ timelines were scanned in our data collection. Thus a sleep of the program after a while was needed to enable full access to all the sampled users.

The third one is a little bit silly, but still worth reporting. When looking at some of the summary information after the first round of computation, we found many emojis having a Tf-Idf value of 1, implying their $df = N$, i.e. they were used by all the users. But it was not the case, although those emojis were fairly popular ones. This turned out to be due to a very basic rule in most programming languages: arithmetic calculations on integers result in integers, including division. Thus any emojis that were used by more than half of the users would have $\ln \frac{N}{df} = \ln 1 = 0$. A simple floating number conversion fixed this problem.

Analysis Tools

In our exploratory study we will use K-Means Clustering, Hierarchical Clustering and Principal Component Analysis as our major analysis tools.

To cluster vectorized samples in to K clusters, K-means starts from K initially, sometimes randomly assigned "means" and assign each point to its nearest mean, thus partitioning the data into K clusters. Then it computes the centroid of points in each of the clusters as an updated mean. With K new means it reassign data to their nearest means. It iterates between these two steps until the difference between the new and the old means are relatively small, or a pre-defined number of iterations is reached.

Hierarchical Clustering tries to build a hierarchy of clusters in either a bottom-up or a top-down approach. In this study we used the bottom up approach, where each data point is in its own singleton cluster at the bottom and the pair of clusters that are closest to each other is merged as we move up the hierarchy. Here "closest" can be subject to two choices of measures: it depends on the distance metric specified for comparing data points, which we will further explore in one of the analysis sections; it also depends on the way the distances between clusters are calculated based on distances between points in the clusters, where single linkage, complete linkage and average linkage, among many others, can be used. We started with Euclidean Distance which is the most widely used distance measure, defined by:

$$Dist(a,b) = \sqrt{\sum_{i=1}^{n}(a_i - b_i)^2}.$$

We used complete linkage in this study, which uses the maximum distances between points in one cluster and points in the other as the distance between the two clusters. The results of hierarchical clustering will be visualized in dendrograms.

Principle Component Analysis tries to find “directions” that best separates the data points. It transforms the data into a set of orthogonal directions, called principal components (PCs) in an order such that the projections of data points on each PC have the greatest variance among PCs excluding the previous ones. In fact, the principal components are the orthonormal eigenvectors of the covariance matrix of the data, ordered by their corresponding eigenvalues, so these two terms will be used interchangeably.

Analysis

Global Summary

Before conducting more complex analysis on user vectors, we first made a global summary of our data of emoji counts, regardless of differences among users. We started with three charts of the top emojis, by different measures of popularity:

Table 1: Top Emojis by Total Count

##		Unicode.name	Count
##	1	FACE WITH TEARS OF JOY	7780
##	4	SMILING FACE WITH HEART-SHAPED EYES	2538
##	5	LOUDLY CRYING FACE	2531
##	2	HEAVY BLACK HEART	2053
##	15	WEARY FACE	815
##	7	SMILING FACE WITH SMILING EYES	715
##	24	UNAMUSED FACE	713
##	36	SPARKLES	712
##	6	FACE THROWING A KISS	670
##	9	TWO HEARTS	660

Table 2: Top Emojis by User Count

##		Unicode.name	User.count
##	1	FACE WITH TEARS OF JOY	92
##	4	SMILING FACE WITH HEART-SHAPED EYES	91
##	5	LOUDLY CRYING FACE	77
##	2	HEAVY BLACK HEART	76
##	6	FACE THROWING A KISS	74
##	24	UNAMUSED FACE	70
##	7	SMILING FACE WITH SMILING EYES	69
##	18	SMIRKING FACE	67
##	8	OK HAND SIGN	61
##	11	GRINNING FACE WITH SMILING EYES	59

Table 3: Top Emojis by Tweet Count

##		Unicode.name	Tweet.count
##	1	FACE WITH TEARS OF JOY	3632
##	4	SMILING FACE WITH HEART-SHAPED EYES	1505
##	2	HEAVY BLACK HEART	1485
##	5	LOUDLY CRYING FACE	1244
##	15	WEARY FACE	585
##	24	UNAMUSED FACE	566

## 16	PERSON WITH FOLDED HANDS	507
## 9	TWO HEARTS	492
## 8	OK HAND SIGN	488
## 7	SMILING FACE WITH SMILING EYES	479

Not surprisingly FACE WITH TEARS OF JOY is leading in number of total occurrences, number of users and number of tweets. But unlike being far ahead in number of total occurrences and tweets, it edges SMILING FACE WITH HEART-SHAPED EYES by only one in number of users, which will be directly used by our Tf-Idf weighting as the document frequency. The difference also extends to the leading group: despite forming a "Big 4" (or indeed "3+1") in total counts and tweet counts, LOUDLY CRYING FACE and HEAVY BLACK HEART fail to catch up with the leading duo in number of users and has a slim lead over others.

With these three quantities we can make division to get the following charts:

Table 4: Top Emojis by Count per User (Unfiltered)

##	Unicode.name	Count.per.user	User.count
## 1	FACE WITH TEARS OF JOY	84.565	92
## 573	LEFTWARDS BLACK ARROW	74.000	1
## 563	WHITE DOWN-POINTING TRIANGLE	55.500	2
## 934	CLOCK FACE SIX OCLOCK	36.000	1
## 5	LOUDLY CRYING FACE	32.870	77
## 906	REGIONAL INDICATOR SYMBOL LETTER K	31.000	1
## 13	WHITE HEART SUIT	30.455	11
## 385	HEAVY PLUS SIGN	30.000	1
## 634	ENVELOPE	30.000	1
## 769	CLOCKWISE DOWNWARDS AND UPWARDS OPEN CIRCLE ARROWS	30.000	1

Table 5: Top Emojis by Count per Tweet (Unfiltered)

##	Unicode.name	Count.per.tweet	Tweet.count
## 634	ENVELOPE	30.0000	1
## 472	SQUARED COOL	7.0000	8
## 799	GLOBE WITH MERIDIANS	5.5000	2
## 934	CLOCK FACE SIX OCLOCK	5.1429	7
## 729	PEACE SYMBOL	5.0000	2
## 180	BLACK RIGHT-POINTING TRIANGLE	4.0000	1
## 100	WHITE STAR	3.5000	2
## 814	LADY BEETLE	3.5000	2
## 650	CHEERING MEGAPHONE	3.3333	3
## 75	HOT BEVERAGE	3.3158	19

With the denominators of each division listed here, we can see that the leading emojis in terms of per-user and per-tweet counts are mostly rare ones, which encouraged us to filter the emojis.

We picked 20 for number of users and 50 for number of tweets as the non-inclusive threshold, resulting in 86 and 98 "popular" emojis respectively.

Table 6: Top Emojis by Count per User (Filtered)

##	Unicode.name	Count.per.user	User.count
## 1	FACE WITH TEARS OF JOY	84.565	92
## 5	LOUDLY CRYING FACE	32.870	77
## 4	SMILING FACE WITH HEART-SHAPED EYES	27.890	91
## 2	HEAVY BLACK HEART	27.013	76
## 67	SKULL	21.833	24
## 36	SPARKLES	20.941	34
## 53	HUNDRED POINTS SYMBOL	14.500	30
## 15	WEARY FACE	14.052	58
## 9	TWO HEARTS	11.786	56
## 49	MULTIPLE MUSICAL NOTES	11.409	44

Now these two charts show popular emojis that are most repeatedly used, by individual users and in individual tweets. In the count-per-user chart, again, we see the "Big 4" - their huge lead in total count is not cancelled too much by division. Their popularity could be illustrated this way: lots of people use them; people using them do it frequently. Probably more blatant is the "Big One" - if we need a classification of emojis based on popularity, the best could be dichotomous: FACE WITH TEARS OF JOY, and the rest.

Table 7: Top Emojis by Count per Tweet (Filtered)

##	Unicode.name	Count.per.tweet	Tweet.count
## 108	FEARFUL FACE	2.8261	69
## 67	SKULL	2.5314	207
## 1	FACE WITH TEARS OF JOY	2.1421	3632
## 42	POUTING FACE	2.1099	91
## 52	FIRE	2.0792	101
## 5	LOUDLY CRYING FACE	2.0346	1244
## 36	SPARKLES	1.8351	388
## 76	WAVING HAND SIGN	1.7593	54
## 44	CRYING FACE	1.7446	184
## 3	BLACK HEART SUIT	1.7344	128

Things are a little different when tweet count goes to the denominator. The Big Four's dominance is over and only two of them make it into the top ten. Interestingly it seems that faces with a negative sentiment are more repeated in tweets.

Another interesting fact is the presence of SKULL and SPARKLES. They make it into both charts and even form a "second tier" just behind the Big Four. They are neither too popular nor too unpopular, having user counts in the 20s and 30s. But their medium-sized fanbase seem to be crazy about them - they use them frequently and repeatedly.

We can do yet another division to compute the number of tweets containing each emoji per user, filtered with the same threshold, getting 79 users. This time we get the familiar squad of a Big 4, or "Big 1+3":

Table 8: Top Emojis by Tweet Count per User (Filtered)

##	Unicode.name	Tweet.count.per.user	User.count	Tweet.count
## 1	FACE WITH TEARS OF JOY	39.4783	92	3632
## 2	HEAVY BLACK HEART	19.5395	76	1485
## 4	SMILING FACE WITH HEART-SHAPED EYES	16.5385	91	1505
## 5	LOUDLY CRYING FACE	16.1558	77	1244
## 53	HUNDRED POINTS SYMBOL	11.8667	30	356
## 36	SPARKLES	11.4118	34	388
## 15	WEARY FACE	10.0862	58	585
## 49	MULTIPLE MUSICAL NOTES	9.6818	44	426
## 16	PERSON WITH FOLDED HANDS	9.2182	55	507
## 9	TWO HEARTS	8.7857	56	492

Next we moved to Tf-Idf weighting. We looked at the "top emoji" for each user, the one with the highest Tf-Idf value. Out of the 100 top emojis, there are 80 distinct ones. Then we looked at those emojis that are at the top for multiple users, with SKULL at the "top of the top":

Table 9: Emojis atop Multiple Users

##	Emoji	Users
## 31	SKULL	4
## 2	HEAVY BLACK HEART	3
## 4	LOUDLY CRYING FACE	3
## 24	MULTIPLE MUSICAL NOTES	3
## 51	MUSICAL NOTE	3
## 3	BLACK HEART SUIT	2

```
## 10          THUMBS UP SIGN      2
## 18                SPARKLES      2
## 19           GROWING HEART      2
## 20             POUTING FACE     2
## 25         REVOLVING HEARTS     2
## 26   HUNDRED POINTS SYMBOL      2
## 48          SLEEPING SYMBOL     2
## 62               PEDESTRIAN     2
```

With these findings we are ready to move to the next step of our analysis, on users each represented by a vector of Tf-Idf values of emojis.

K-Means Clustering and Principal Component Analysis

We started clustering using the k-means clustering method, with arbitrarily picked values of k. But then we found some very weird pattern, shown with the following bar plot of the sizes of the clusters with respect to k:

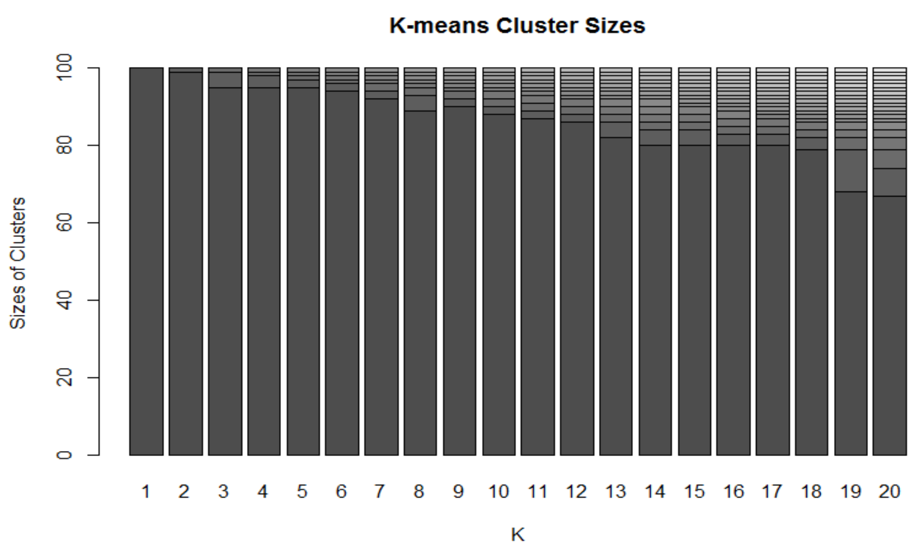


Figure 1: Sizes of Clusters over K

In most cases there is a giant cluster accompanied by several mini clusters, mostly singletons. This prompted us to try hierarchical clustering using Euclidean distance as a reference to k-means clustering, getting the following dendrogram (larger and clearer dendrograms will be included in the appendix):

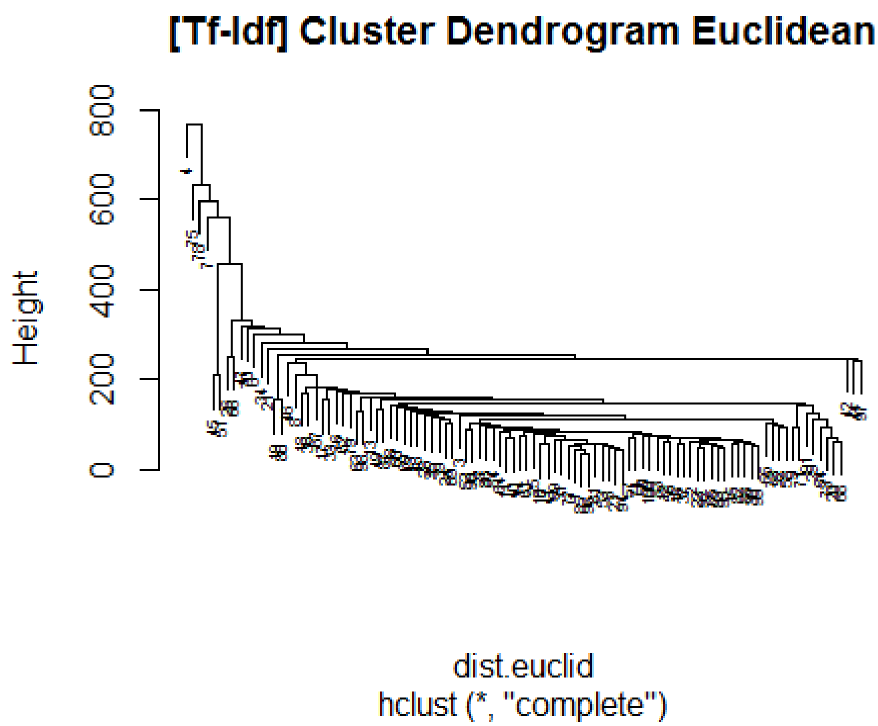


Figure 2: Hierarchical Clustering Dendrogram (Euclidean)

For convenience, we labeled the users with the order in which they were retrieved, instead of their irrelevant screen names. We can identify 4 wildly outlying users from this dendrogram: user 4, 75, 78, and 7. So naturally we expected a 5-means clustering algorithm would yield a giant cluster and 4 singletons. But what we actually got is <95, 2, 1, 1, 1>. It turned out instead of getting No.7, the 4th outlier, it found the pair of No.45 and No.51, which can be seen in the dendrogram lying on the left, one level deeper than No.7 but still quite far from the giant. Then when we tried 6-means, as expected we got a giant of 94, a duet, and 4 singletons. We kept getting this partition from multiple runs, suggesting it's quite stable. This choice of number can also be supported by the following plot of within cluster sum of squares (WCSS) across K from 1 to 50:

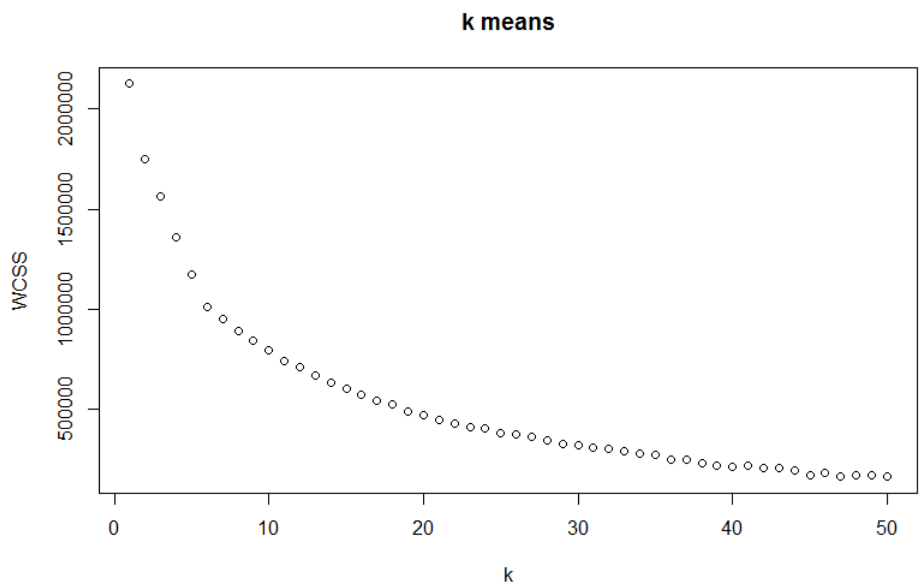


Figure 3: Within Cluster Sum of Squares across K

This shows that 6 is likely the best choice for K: the improvement of WCSS has a significant drop beyond k=6. Next we turned to Principal Component Analysis:

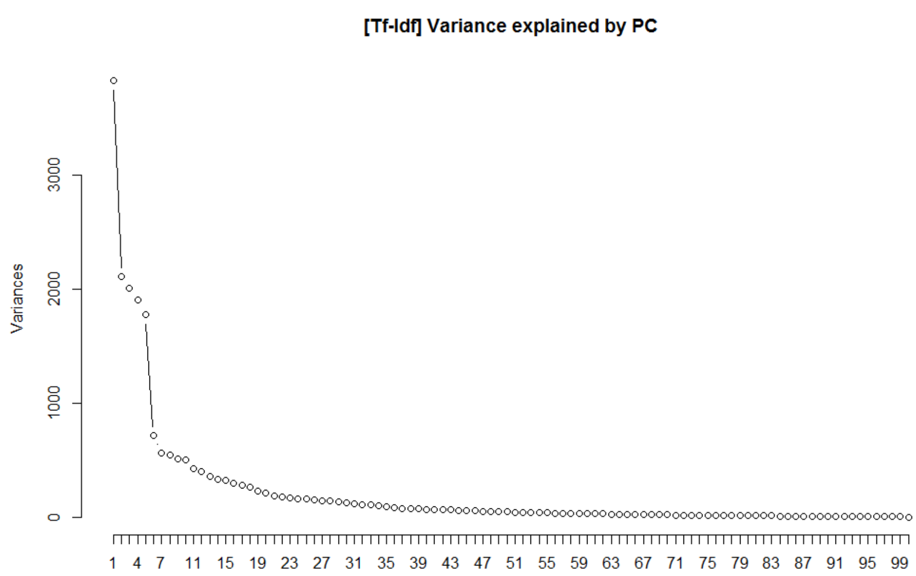


Figure 4: Screeplot of Variances Explained by PC

Based on the screeplot above (most variance is explained by the first 5 PCs) we looked at the paired plot among PC1 to PC5. With the users labeled by their cluster number, we can see a giant cluster 6, a pair of 5s extracted by PC3, and singletons 3, 1, 4 and 2 extracted by PC1, PC2, PC4 and PC5 respectively:

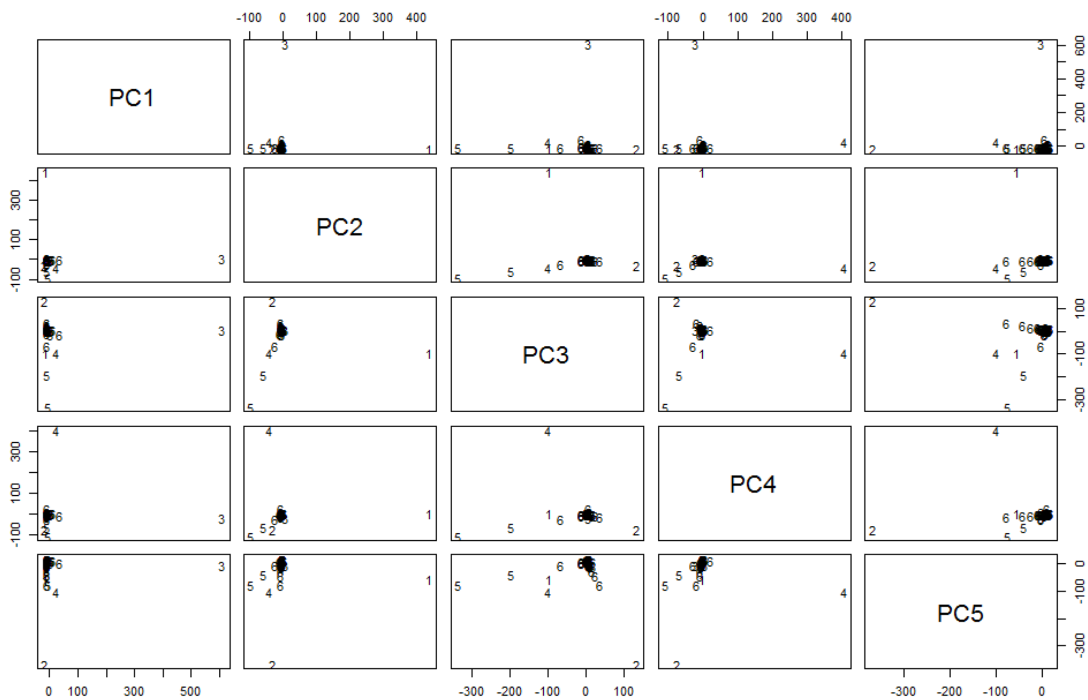


Figure 5: Pair-wise Plot of the First 5 PCs

At this point we are tempted to take a deeper look at these outliers. For each of them, their leading emojis (with highest Tf-Idf values) will be listed, together with leading emojis in each PC, i.e. those with largest/smallest values in the corresponding eigenvector (this can be interpreted as the emojis having largest “weights” in defining the direction, as the eigenvectors are normalized), and some interesting findings from their actual Twitter feeds.

Analysis of Outliers: Mini Case Studies

Outlier along PC1: Aunty White Heart (User.4)

According to the plots of PC1, most people are squeezed at 0, with a lone ranger hanging around 600. It's User.4, who, for the reason we'll see, are nicknamed Aunty White Heart. We wrote a function in R to show all emojis used by a designated user, sorted by Tf-Idf value and for each emoji, its actual count (Tf), tweet count (which we termed Twf), and user count, and run it with 4 as input :

Table 10: Leading Emojis of Aunty White Heart

##	Tf-Idf	Tf	Twf	Users
## WHITE HEART SUIT	616.83	279	200	11

That "s" should be scratched since as we see above, User.4 only used one emoji – "WHITE HEART SUIT", for a total of 279 times over all the 200 tweets retrieved, while only 11 users in our sample used it, resulting in a bursting Tf-Idf of 616.8.

Unsurprisingly, when we look at the emojis with largest values in the eigenvector for PC1, we can see below "WHITE HEART SUIT" is absolutely dominating.

Table 11: Leading Emojis along PC1

##	Loading
## WHITE HEART SUIT	0.9977202
## WHITE DOWN-POINTING TRIANGLE	0.0265481
## WHITE STAR	0.0026388

The easier, and probably better way to know about this user might be to just look at the actual timeline page. As far as we can tell, this middle-aged lady (according to the profile picture) appears to be a quite average user, with the exception that she might not be a fan of emoji: "WHITE HEART SUIT" actually looks more like a plain-text character (♡) than a colorful image (e.g. "HEAVY BLACK HEART": ❤), as most emojis, or what we would expect emojis, do.

Compared to others, as we will see later, this lady is the only “true outlier”, since she’s the only one that perhaps should not be in our sample of “emoji users”. Its impact is huge: the most significant PC is dedicated to her and doesn’t really separate our points as it should do. In this sense however, Aunty White Heart, the lone ranger, is not alone.

Outlier along PC2: Devout Lefty (User.75)

According to the plots, there is a lone ranger along almost every significant PC, whose impacts are not too different from each other. The second one, nicknamed Devout Lefty, is User.75.

Table 12: (Top 7) Leading Emojis of Devout Lefty

##	Tf-Idf	Tf	Twf	Users
## LEFTWARDS BLACK ARROW	341.7826	74	74	1
## CLOCK FACE SIX OCLOCK	166.7861	36	7	1
## THOUGHT BALLOON	136.8525	59	44	10
## ELECTRIC LIGHT BULB	106.1967	30	10	3
## BOUQUET	90.8720	30	3	5
## CHERRY BLOSSOM	85.8105	40	30	12
## HERB	63.9104	21	12	5

Unlike Aunty White Heart this user has a pretty long list of used emoji, and only the top 7 are listed here. Yet we can still identify the distinguishing factor: the first four emojis all have a Tf-Idf value over 100, with the leading one, "LEFTWARDS BLACK ARROW", being 341.8.

What Aunty could find resonance in is this lefty’s domination in PC2. As shown with the listing of the top 10 emojis in the second eigenvector below, they are exactly the same as the top-10-TfIdf emojis, with “LEFTWARDS BLACK ARROW” leading the way:

Table 13: Leading Emojis along PC2

##	Loading
## LEFTWARDS BLACK ARROW	0.71889
## CLOCK FACE SIX OCLOCK	0.35081
## THOUGHT BALLOON	0.28761
## ELECTRIC LIGHT BULB	0.22339
## BOUQUET	0.19140
## CHERRY BLOSSOM	0.17760

## HERB	0.13425
## YELLOW HEART	0.12324
## SEEDLING	0.12014
## BLACK UNIVERSAL RECYCLING SYMBOL	0.10082

This user's use of left arrow, spread over 74 tweets, is partly easy to interpret, when we look at his/her account and those tweets: s/he appears to be a devout Muslim who tweets mostly about his/her religious belief (according to what Twitter translated, of course), in Arabic, which is written from right to left. In fact, the left arrow seems to appear only in tweets from du3a.org, "an application for Twitter accounts that public automatically time tweets in hour by hour with blessings (in Arabic) of Allah".

The perplexing part, however, is that the application doesn't automatically add left arrows to its tweets, suggesting they're manually added by this devout guy. Further, according to the chart above, s/he is the only one in our sample that uses this emoji, which is the reason for the huge Tf-Idf value. Language cannot well explain it here, considering there're others in our sample who tweets in right-to-left scripts. And it's even harder for our little knowledge (and Twitter's translation capability) of Arabic and Islam to explain the use of the other three leading emojis - a clock, a balloon and a bulb.

Outliers along PC3: the Sparkling Duet (User.51 & User.45)

Along PC3, there are a pair of outliers: user 51 and 45.

In order to find what makes them far from the others and what makes them linked early in hierarchical clustering and constantly got clustered together in K-means, again, we need to look at their leading emojis, and the eigenvector for PC3:

Table 14: (Top 5) Leading Emojis of User.51

##	Tf-Idf	Tf	Twf	Users
## SPARKLES	378.5834	350	70	34
## SPARKLING HEART	33.8103	33	11	37
## FIREWORK SPARKLER	29.9699	9	2	4
## PERSON RAISING BOTH HANDS IN CELEBRATION	21.5777	39	12	59
## RAINBOW	20.2636	8	2	9

Table 15: Leading Emojis of User.45

##	Tf-Idf	Tf	Twf	Users
## SPARKLES	216.76	200	200	34
## HEAVY BLACK HEART	110.77	400	200	76

Table 16: Leading Emojis along PC3

##	Loading
## SPARKLES	-0.871082
## WHITE DOWN-POINTING TRIANGLE	-0.230698
## LEFTWARDS BLACK ARROW	-0.166068
## HEAVY BLACK HEART	-0.111753
## CLOCK FACE SIX OCLOCK	-0.081039
## FEARFUL FACE	-0.078951
## THOUGHT BALLOON	-0.065032
## SPARKLING HEART	-0.050885
## ELECTRIC LIGHT BULB	-0.050770
## FIREWORK SPARKLER	-0.049761

The lists of the duet don't have many items in common. In fact, User.45 only used 2 emojis. But they both have a leading "SPARKLES" with a huge Tf-Idf. Despite having as many as 34 users, it was used 350 and 200 times respectively.

We also see some suspicious number: the emoji was used 350 times over 70 tweets by User.51 and 200 times over 200 tweets by User.45. Plus the only other emoji from User.45 was used 400 times over 200 tweets. It is very likely that each of his/her sampled tweets contains exactly one “SPARKLES” and two “HEAVY BLACK HEART”.

In fact, like what we learned from Devout Lefty, both cases are indication of "the inhuman".

User.51 is the more human one, as s/he used many of the popular emojis. The SPARKLES tweets seem to be auto-generated by an application called Statusbrew, which publishes a welcome tweets, with a “SPARKLES”, to each of his/her new friends.

User.45, however, is probably a robot. This account tweets super frequently the same text content containing a link, one SPARKLES and two HEAVY BLACK

HEARTs, and directions on how to watch porn videos, accompanied by different short porn clips.

Outlier along PC4: Hanryu Hama (User.78)

User.78, the outlier along PC4, is self-introduced to be an addicted Japanese fan of a Korean pop star and tweeted mostly about her idol, among other Korean entertainment topics. We nickname her Hanryu Hama (in Japanese, Korean Wave Addict, literally).

Her leading emojis, along with the ones in the eigenvector for PC4, are a little surprising:

Table 17: Leading Emojis of Hanryu Hama

##	Tf-Idf	Tf	Twf	Users
## WHITE DOWN-POINTING TRIANGLE	423.4985	108	99	2
## SPLASHING SWEAT SYMBOL	65.8817	33	25	14
## TWO HEARTS	61.8809	105	76	56
## BOX DRAWINGS LIGHT ARC UP AND LEFT	19.4207	4	3	1
## BOX DRAWINGS LIGHT ARC UP AND RIGHT	19.4207	4	3	1
## BEAMED SIXTEENTH NOTES	19.4207	4	3	1
## HEAVY BLACK HEART	19.1128	66	55	76
## WHITE HEART SUIT	18.6582	8	7	11
## DROPLET	18.5328	5	5	3
## BOX DRAWINGS LIGHT ARC DOWN AND RIGHT	14.8155	3	3	1
## HEAVY HEART EXCLAMATION MARK ORNAMENT	12.0364	5	3	11
## WHITE LEFT POINTING INDEX	10.2103	2	1	1
## BLACK HEART SUIT	9.5740	5	3	18
## EIGHTH NOTE	6.9915	2	1	5
## WHITE FOUR POINTED STAR	5.6052	1	1	1
## BOX DRAWINGS LIGHT HORIZONTAL	5.6052	1	1	1
## BOX DRAWINGS LIGHT DOWN AND LEFT	5.6052	1	1	1
## BOX DRAWINGS LIGHT DOWN AND RIGHT	5.6052	1	1	1
## WHITE STAR	4.9120	1	1	2

Table 18: Leading Emojis along PC4

##	Loading
## WHITE DOWN-POINTING TRIANGLE	0.902486
## SPLASHING SWEAT SYMBOL	0.156476
## TWO HEARTS	0.131075
## BOX DRAWINGS LIGHT ARC UP AND LEFT	0.041722
## BOX DRAWINGS LIGHT ARC UP AND RIGHT	0.041722
## BEAMED SIXTEENTH NOTES	0.041722
## DROPLET	0.039597
## BOX DRAWINGS LIGHT ARC DOWN AND RIGHT	0.031829
## HEAVY HEART EXCLAMATION MARK ORNAMENT	0.023928
## BLACK HEART SUIT	0.022349

The easy part is those hearts which she used for her idol, and the splashing sweat which, according to the actual tweets, was used to show greeting/regards (typically followed by "otsukaresama deshita") to her hard-working idol when she tweeted about him shooting for TV shows.

But when it comes to the down-pointing triangle with a stunning 423 Tf-Idf, and those weird box drawings which she is the only user of, things are not that easy. We won't know from their Unicode names, but when looking at what those symbols actually are and her tweets, we realized they indicate trouble: they are actually part of emoji's fraternal twin - kaomoji, which is as popular in Japan. The downing-pointing triangle is used as an open mouth in any smiling faces, while those box drawing arcs and lines are arms swinging in different directions, sometimes followed by musical notes to show happiness (for example, (´▽`)ﾉ♬).

So while Hanryu Hama did use emojis, her use of kaomojis, along with the inclusion of those symbols in our emoji set, makes her another outlier and costs PC4.

By the way, the only other user in our sample that used WHITE DOWN-POINTING TRIANGLE is User.51, the “Sparkler” (whose top 3 emojis are all sparkles) along PC3 (only three times in one tweet, preventing it from thriving in PC4). The interesting part is, tweeting in Russian, s/he is also a fan of some Korean idols. Actually, some kaomojis can also be found in his/her tweets – it could possibly be something spread with fandom.

Outlier along PC5: Skull Girl (and the Gang) (User.7)

Table 19: (Top 7) Leading Emojis of Skull Girl

##	Tf-Idf	Tf	Twf	Users
## SKULL	407.7282	285	74	24
## LOUDLY CRYING FACE	39.1593	146	96	77

## HUNDRED POINTS SYMBOL	22.6715	18	14	30
## FACE WITH STUCK-OUT TONGUE	9.5627	6	4	24
## NEW MOON WITH FACE	5.9822	3	2	19
## HEAVY BLACK HEART	5.1166	15	8	76
## NEUTRAL FACE	4.5135	3	3	31

Table 20: Leading Emojis along PC5

##	Loading
## SKULL	-0.920427
## WHITE DOWN-POINTING TRIANGLE	-0.249340
## SPARKLES	-0.215568
## LEFTWARDS BLACK ARROW	-0.108319
## LOUDLY CRYING FACE	-0.070818
## CLOCK FACE SIX OCLOCK	-0.052858
## THOUGHT BALLOON	-0.042930
## HUNDRED POINTS SYMBOL	-0.038891
## SPLASHING SWEAT SYMBOL	-0.033834
## ELECTRIC LIGHT BULB	-0.033079

Similar to User.51, this girl (according to her profile picture) appears to be an average user, whose emojis are all quite popular ones. But she still gets the certificate to our club: a striking Tf-Idf of 407.7, for SKULL. It’s not a particularly rare emoji, but the fact that Skull Girl used it 285 times over 74 tweets (so almost 4 times per tweet) is definitely “outlying”.

This reminds us of the earlier section showing that 4 users have SKULL as their top emoji. Thus we then looked at "the Gang": user 5, 59, and 98. But their lists of leadig emojis won’t be here, not only because they are too long but more importantly, they appears to be irrelevant. Although all are crowned with SKULL, the tf-idf values of those skulls are far from the lead. This is also supported by their projections along PC5:

Table 21: Projections of Users Topped by SKULL

##	7	5	59	98
##	-369.8622	-8.0044	-24.8582	-77.0860

Then we tried to measure the similarity/distance within this likely subgroup. We used the Euclidean distance, which is implicitly used in K-means and PCA, because of the involvement of sum of squares in both cases, and explicitly used in our first run of hierarchical clustering:

Table 22: Euclidean Distances between Users Topped by SKULL

##	7	5	59
## 5	391.588	/	/
## 59	375.274	52.748	/
## 98	325.221	104.973	96.524

The first column above shows how distant Skull Girl (User.7) is from her Gang, which also corresponds to the heights in the cluster.

But this part actually prompted a later section: although here the Gang don't seem to belong to their leader at all, it's only in the case of Euclidean distance. In exploring this, we will try other distance measures, in one of which they do belong.

Now as our lengthy accounting of outliers finished, we can make a naive summarization: we found that each of them have at least one emoji with an extremely large Tf-Idf value. On the other hand, in the sense of picking outliers, it's not the end. What we just listed are merely "more significant" outliers. But if we kick them out of our party, the underbosses will seize power. That is what we will do in the next section.

Analysis of Outliers and Insiders: Gradual Elimination (“Unwrapping”)

To get a look at more outliers more quickly, we wrote a function to eliminate the most outlying user along the first PC (which is assumed to be the extreme point along PC1 that is farther from the median), i.e. “unwrap” the outermost “layer”, book-keep information of the eliminated outlier, then run PCA on the remaining data, and plot the first 2 PCs of the new sample.

Then in a brute-force manner, we run it repeatedly to gradually eliminate outliers and printed the plot of each “layer”, from the original data all the way down. There was at least one apparent outlier at every layer until 20 user were eliminated. Even when there are multiple outlying points, they never appear to be in a common cluster compared to the huddle. The plots of the first two PCs from with all the users to without 19 outlying users are placed in the appendix for reference due to its length. Below is the final plot, with 20 users eliminated:

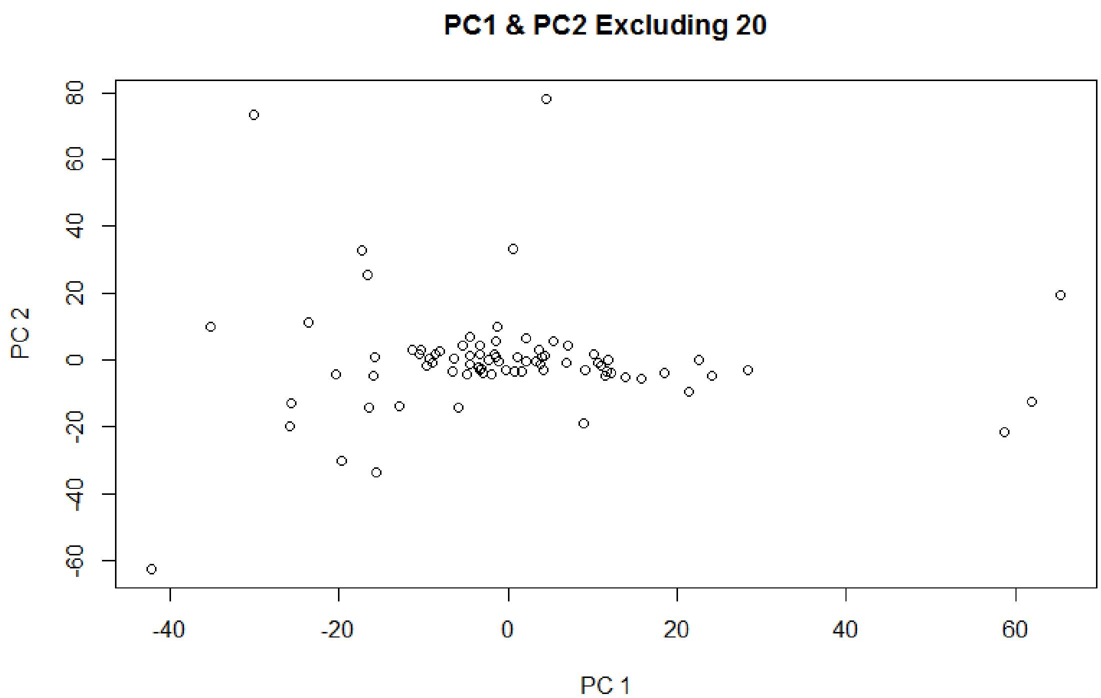


Figure 6: Plot of the First 2 PCs with 20 Users Eliminated

This plot looks a lot better than the earlier ones. Nevertheless, it's still hard to detect any specific subgroup here, except for the trio on the right.

Before looking at the trio, we first checked our book-kept list of outliers (indexed by layer). The list also include the "most influential" emoji of the most significant PC along the direction each outlier is heading, its loading in the eigenvector, its Tf-Idf value for the outlier, its rank for the user, and his/her maximum Tf-Idf value:

Table 23: Eliminated Outliers and Leading Emojis at PC1

##	Layer	User	Leading.Emoji.PC	Loading	TfIdf	Rank	Max.TfIdf
##	0	4	WHITE HEART SUIT	0.99772	616.830	1	616.830
##	1	75	LEFTWARDS BLACK ARROW	0.71849	341.783	1	341.783
##	2	51	SPARKLES	0.89940	378.583	1	378.583
##	3	78	WHITE DOWN-POINTING TRIANGLE	0.91731	423.498	1	423.498
##	4	7	SKULL	0.98987	407.728	1	407.728
##	5	26	HUNDRED POINTS SYMBOL	0.61021	127.417	2	143.760
##	6	45	SPARKLES	-0.81811	216.762	1	216.762
##	7	80	BLACK HEART SUIT	-0.73327	174.195	1	174.195
##	8	47	PENGUIN	0.47952	127.236	1	127.236
##	9	70	HEAVY PLUS SIGN	-0.57969	139.155	1	139.155
##	10	6	HEAVY MULTIPLICATION X	-0.54281	126.536	1	126.536
##	11	34	FEARFUL FACE	0.63356	174.819	1	174.819
##	12	66	HUNDRED POINTS SYMBOL	-0.63232	129.825	1	129.825
##	13	97	MUSICAL NOTE	0.64900	149.844	1	149.844
##	14	21	CROWN	0.39902	86.107	1	86.107
##	15	19	BLACK HEART SUIT	0.47973	124.465	1	124.465
##	16	42	SQUARED COOL	0.70948	158.795	1	158.795
##	17	46	ENVELOPE	-0.72427	139.155	1	139.155
##	18	44	REGIONAL INDICATOR SYMBOL LETTER S	0.35293	83.152	2	83.893
##	19	8	THUMBS UP SIGN	0.78843	144.172	1	144.172

We see some familiar user numbers here, along with their featured emojis: Aunty White Heart (4) at Layer 0, Devout Lefty (75) at Layer 1, the Sparkling Duet (51 & 45) at Layer 2 and 6, Hanryu Hama (78) with her triangle mouth at Layer 3, and Skull Girl at Layer 4, interrupted by an uninvited guest User.26, whom, soon we will see in the next section, rises from the concrete jungle of Manhattan (distance).

There are 19 different leading emojis for the first PCs of the 20 layers (the only exception goes to the two layers where the duet is outlying). Yet what stays constant is their domination along almost each layer, large Tf-Idf values and high rank. Even the two emojis ranked 2nd (at layer 5 and 18) for their corresponding users is quite close to the leader. Again, this shows how a large Tf-Idf could cause the outlying.

What it really means is here: the first PC is the “direction” that best separates the samples; thus the emoji leading the way the outlier is heading should best differentiate it from the others – it should have a not only “large”, but “remote” Tf-Idf. But the largeness and remoteness of a Tf-Idf is inherently related: this can be illustrated by the following contour plot of the formula we used ($Tf.Idf = 1 + \text{tf} \cdot \ln \frac{N}{df}$, where $N = 100$):

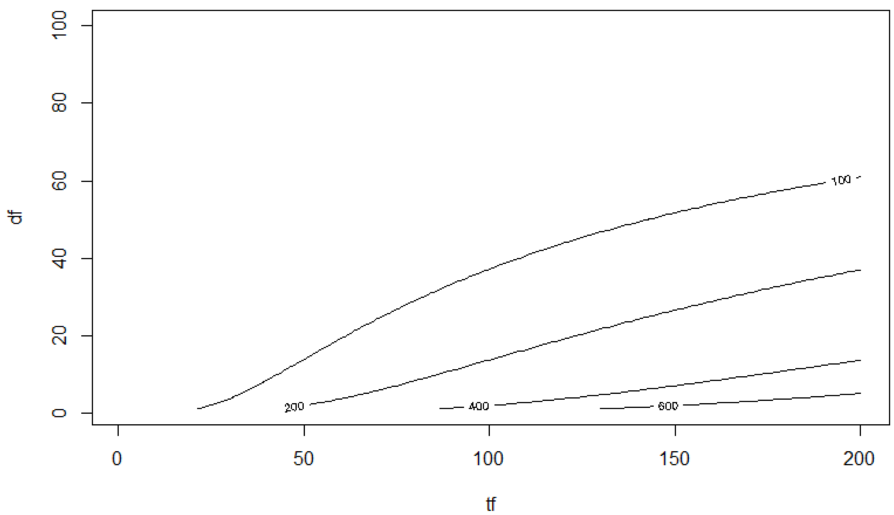


Figure 7: Contour Plot of Tf-Idf

As shown by the contour lines, for a value to be as large as 100, even an emoji with a 200 term frequency needs have a document frequency as small as 60, meaning 40 of the users have a value of 0. Thus a large Tf-Idf itself would suggest remoteness.

This can also be supported by looking at the “insiders”, who remain in the sample after unwrapping. Their max tf-idf values are sorted and shown in the bar plot below:

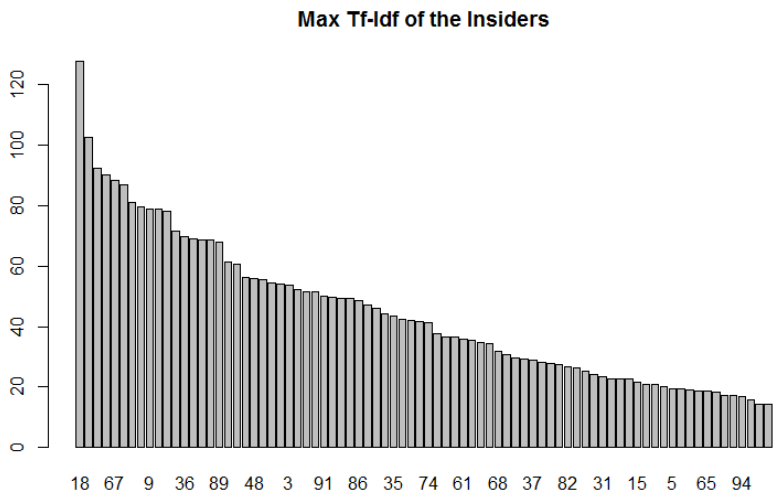


Figure 8: Contour Plot of Tf-Idf

Now back to the PCA plot of the insiders. We saw there is a trio traveling to the far east. This can be illustrated by their projection along PC1 (for comparison, that of the 4th guy is also included):

Table 24: Projection of Users along PC1

##	63	17	98	54
##	65.274	61.885	58.630	28.367

So all the three (63, 17, 98) have a projection around 60 while the closest "westerner" (54) from them is merely 28.

Then the following two tables were made to show the loadings and the Tf-Idf values for the four (the trio + the first westerner) of the top 10 leading emojis on both sides of PC1:

Table 25: Emojis Leading the Positive Side of PC1

##	Loading	63	17	98	54
## SKULL	0.50968	53.8033	19.5525	92.3354	10.9898
## WEARY FACE	0.29201	9.7156	31.5047	6.4473	29.3258
## LOUDLY CRYING FACE	0.21522	26.3524	8.8409	10.1478	9.6250
## BLACK SMILING FACE	0.17429	0.0000	71.4164	0.0000	0.0000
## HEAVY HEART EXCLAMATION MARK ORNAMENT	0.15512	0.0000	58.3891	0.0000	0.0000
## HUNDRED POINTS SYMBOL	0.15133	9.4278	9.4278	2.2040	19.0596
## PERSEVERING FACE	0.15037	18.3302	30.7090	0.0000	0.0000
## POUTING FACE	0.14573	54.4646	0.0000	0.0000	3.5459

## TONGUE	0.12255	6.7085	20.9796	0.0000	39.5321
## FIRE	0.12163	13.5979	27.2456	0.0000	0.0000

Table 26: Emojis Leading the Negative Side of PC1

##		63	17	98	54
## NEW MOON WITH FACE	-0.218521	0.0000	0	0	2.6607
## PERSON WITH FOLDED HANDS	-0.181126	4.5870	0	0	0.0000
## MUSICAL NOTE	-0.169683	0.0000	0	0	0.0000
## PEDESTRIAN	-0.167152	0.0000	0	0	0.0000
## MULTIPLE MUSICAL NOTES	-0.135252	0.0000	0	0	0.0000
## SLEEPING SYMBOL	-0.123894	0.0000	0	0	6.7085
## RAISED HAND	-0.112195	0.0000	0	0	0.0000
## WHITE DOWN POINTING BACKHAND INDEX	-0.110983	0.0000	0	0	0.0000
## CLAPPING HANDS SIGN	-0.099583	0.0000	0	0	1.5798
## TWO HEARTS	-0.094689	3.3193	0	0	1.5798

A few things can be learned from these tables. First, no single emoji could explain the ordering and distance of the four listed users; in fact, it's not even clear how a combination (with loadings considered) of "featured" emojis could explain it. Second, there's not a clear-cut separation between the two directions: even the most "positve" user (63) has a non-zero entry in one of the leading emojis at the negative side. Besides, we may also infer a possible inverse relation between emojis at different ends (e.g. SKULL & NEW MOON WITH FACE). This could lead to another direction of exploration: Transpose the data frame and analyze on emojis as vectors of users.

Hierarchical Clustering: Comparing Distance Measures

In earlier sections we tried K-means Clustering, Principle Component Analysis and Hierarchical Clustering on Euclidean distance. Although the former two methods do not explicitly use Euclidean distance, the fact that both cases involve sum of squares – K-means uses it to calculate the centroids and measure distance of points to them, and PCA finds the direction that maximize the variance which is a sum of squares (in fact it is equivalent to minimizing the sum of squared distances) – suggests Euclidean distance is implicitly used. As a result, we've already seen connections between results of these three methods.

But there are other distance and similarity measures, and these measures may sometimes yield different results. Thus we turned to try hierarchical clustering with some of them and had some interesting findings.

Cosine Similarity and Angular Distance

We start from cosine similarity, which is often used along with Tf-Idf weighting in Information Retrieval to measure similarity of the query with documents and thus compare candidate documents. Since we don't have a query here and what we are going to do is clustering, we need to convert it to a distance metric. The more intuitive way, $Dist = 1 - Sim$ would yield an improper distance metric that does not satisfy the triangular inequality property. To maintain the property while keeping the ordering, we use Angular Distance defined by:

$$Ang.Dist = \frac{2 \cdot \cos^{-1}(Sim)}{\pi}.$$

Here Sim is the original cosine similarity. In this way we computed cosine similarity and transformed it to angular distance in R, and then conducted hierarchical clustering (all the larger and clearer dendrograms will be included in the appendix):

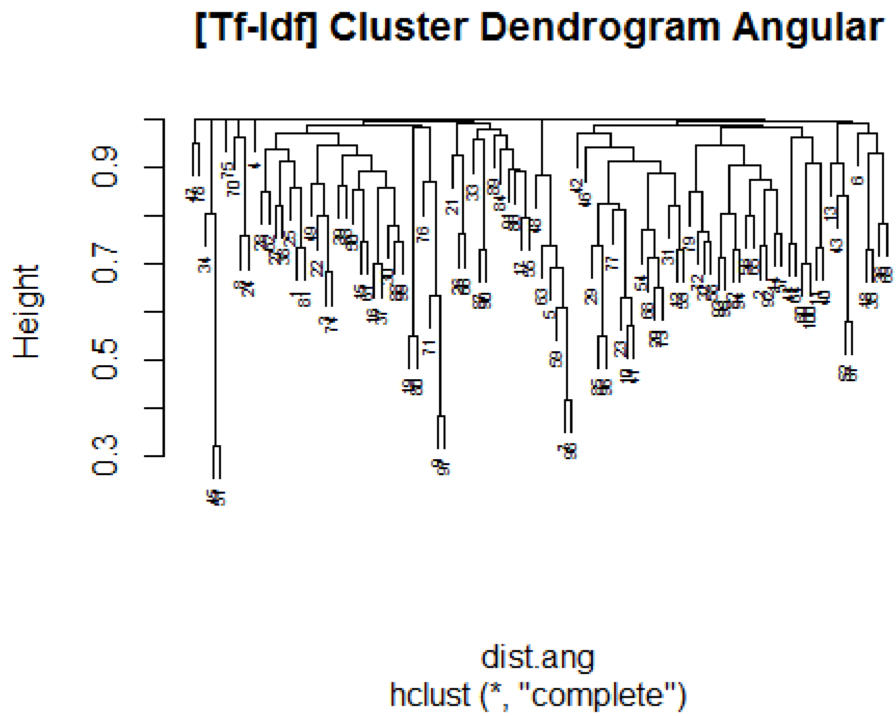


Figure 9: Hierarchical Clustering Dendrogram (Angular)

This is a very different dendrogram. The distance is “normalized”: it’s the ratio of the angle between the two vectors to $\frac{\pi}{2}$. Thus the “length” or norm of the vector doesn’t matter. Two vectors that are superposed over each other but vary a lot in length now have a distance of 0. The fact that it takes value in $[0, 1]$ also has the effect that the distances are bounded: as shown in the dendrogram more users are linked together as the height approaches 1.

Therefore, what we can learn from this dendrogram is also very different: we won’t find outliers as we did with Euclidean, but instead we can do quite the opposite: we can find small groups of users that are close to each other, at the lower height levels. We have met some of them before: the Sparkling Duet (45 & 51) are actually the closest pair; Skull Girl and the Gang (7 & 98, 59, 5) finally form a team.

Manhattan Distance

Next we turn to Manhattan Distance, which is another widely used distance measure that is often compared to Euclidean. It is defined by:

$$Dist(a,b) = \sum_{i=1}^{n} |a_i - b_i|.$$

Sometimes both generate similar results in clustering when there is a clear partition, but that's not the case here. And the case here turns out to be a good example to show the difference between them:

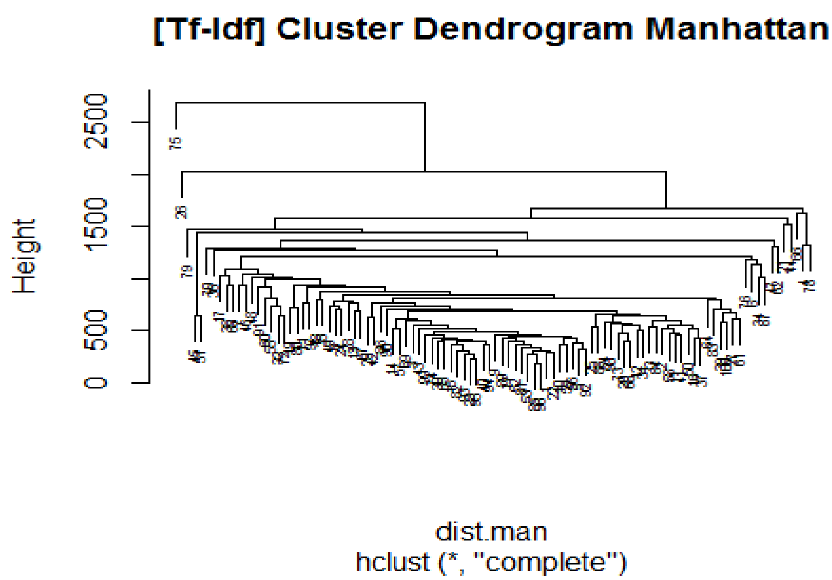


Figure 10: Hierarchical Clustering Dendrogram (Angular)

In some way this is similar to the Euclidean one: a few outliers hanging in the highland with the hoi polloi floundering at lower levels (and the Sparkling Duet are still together). But in most sense it's different: we got different outliers.

We know one of them, Devout Lefty (75), who's also in the highland in Euclidean Distance, but the other one, User.26 seems strange. This user, who also interrupted the queue of Euclidean outliers in the unwrapping process, is actually an all-rounder: s/he is the one who used the most number of distinct emojis in the 200 sampled tweets, notching 126 different emojis.

And this actually shows the difference between Euclidean and Manhattan: the former encourages “professionals” – a user having one emoji with very large Tf-Idf value would be distant from others and become an outlier, while the latter encourages “generalists” – one who have more high-Tf-Idf emojis is more likely to be an outlier. This is supported not only by the all-rounder, User.26, but also by Devout Lefty, who have three emojis with Tf-Idf over 100.

Binary Distance

Finally, we went on a very different approach: ignoring the Tf-Idf weights and term frequencies, we convert the vectors to binary ones and cluster based on binary distance, defined as:

$$Dist(a,b) = \frac{\sum_{i=1}^{n} \mathbb{I}\{a_i=1 \wedge b_i=1\}}{\sum_{i=1}^{n} \mathbb{I}\{a_i=1 \vee b_i=1\}}.$$

So the distance is also normalized: it’s the ratio of the number of emojis two users both use to the number of emojis that either of them used.

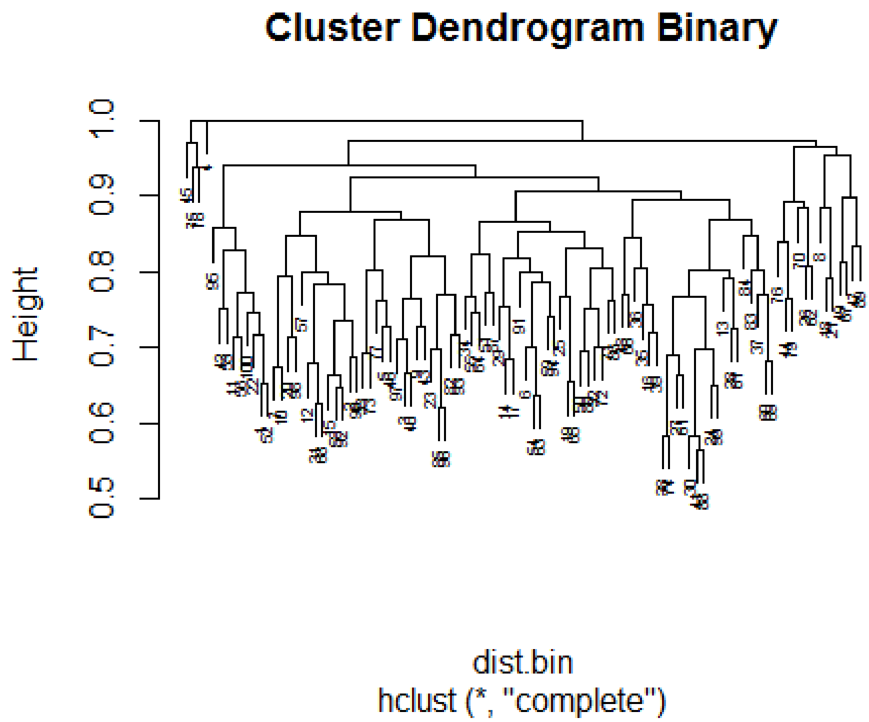


Figure 10: Hierarchical Clustering Dendrogram (Angular)

Similar to the case of angular distance, another normalized distance, more users are linked near the top. But unlike the previous analysis this one is done without considering how much a user uses each emoji: it only cares about whether someone uses an emoji or not. This seems to be the reason that, unlike what we've found so far but like what we were expecting when doing clustering, there do appear to be a few number of clusters of "reasonable" sizes at certain height levels. Further exploration would be needed to show what links users in each cluster.

Discussions

This exploratory study has been filled with surprising findings, resulting in a somewhat disorganized analysis part. But this is what exploration could lead to, and motivates us to make further exploration in the future.

Started with clustering, we were expecting an ideal result: the whole user sample is partitioned to several groups of similar sizes, with group members exposing similar patterns of emoji use – similarly high frequency of certain emojis, typically – and easy-to-distinguish patterns from groups to groups. But instead of groups we ended up spending most of our time on individuals: every outlier is outlying in its own, weird but fascinating way. Some of them don't intend to use emojis; some of them are results of auto-tweeting applications; some of them just uses too much different emojis. Despite only looking at some of them, we believe each of the remaining has a unique and as interesting reason to be outlying.

Even the groups we actually found are not really similar to each other as expected. We didn't expect a Russian fan of Korean idols would be closely paired with a porn robot, constantly, in Euclidean, Manhattan and Angular distances, not to say why and how SPARKLERS are used to welcome new friends in one case but to promote porn videos in the other, as the only tie between the pair.

We didn't expect the most widely used, sometimes default Euclidean distance that are connected to the two methods we first tried might not be the "best" choice for our data. As explained in the previous section, it gets greater when the difference is concentrated, meaning that one “outlying” emoji could single-handedly push a user to be an outlier. On the other hand, Manhattan distance which encourages difference to be spread over multiple dimensions, is able to pick out outliers not as easily identified: it is usually easier to recognize high frequency and uniqueness (the two factors of Tf-Idf) of a certain emoji than differences accumulated across emojis. In such way, this distance measure is more tolerant if someone has special craving for a certain emoji but also use ones that are common to others. Angular distance, which might not be appropriate for finding large clusters due to its normality, is also useful because of its normality. It is able to find groups whose members’ emojis are similar in proportions but vary in “volume”, or frequency. This is particularly useful in the case of Tf-Idf weighting, as those emojis used by few users (small df, thus large idf) would have large difference even when their actual term frequencies vary a little. We do found the Gang of Skulls who all love skulls but have different frequencies using this distance measure.

There are also unexpected findings from the global summary, such as that SMILING FACE WITH HEART-SHAPED EYES is almost as ubiquitous as FACE WITH TEARS OF JOY, that FEARY FACE is most repeated in single tweets among popular emojis, and that SKULL is the most widely “featured” emoji among our sample of users.

These unexpected findings prompts us to expect more: this is the end of the paper but really, like most exploratory analysis, is just a start.

The setting of our study is fairly simple compared to what we had reviewed from the literature. We’ve only used the explicit data of emoji occurrence, treated each user’s

200 tweets as a “Bag of Emojis”, and represent s/he as a vector of emojis’ Tf-Idf values. We could certainly try more from what we’ve learned from previous studies on user modeling, such as using social interaction data like retweets, replies, likes and lists where emojis are involved, representing sample of users as a graph having edges as their emoji-involved relationship, extracting concepts from emojis, and inferring distributions of emojis in topic modeling.

Throughout this process we also found many new directions of exploration, such as using text data as context/background of emoji occurrences, weighting emojis on different metrics like binary (which we already tried in hierarchical clustering), term frequency (i.e. ignoring number of users/document frequency), “Twf” (termed for “tweet frequency” i.e. number of tweets containing each emoji by each user) and “Twf-Idf” with a new unit, introducing categories, including Unicode blocks, faces/shapes/items and sentiments (from the reference table we used) of emojis, and transpose the data frame and conduct analysis on emojis vectorized by users.

After all, we will continue to work on this fun topic and post updates on a blogsite[8]. We also encourage those who get a chance to read this paper try with their own ideas, probably more advanced technical skills and larger and more scientifically sampled data.

[8] http://ngaeghy.web.unc.edu/category/emoji/

Bibliography

Abdel-Hafez, A., & Xu, Y. (2013). A survey of user modelling in social media websites. *Computer and Information Science*, *6*(4), 59.

Abel, F., Gao, Q., Houben, G. J., & Tao, K. (2011). Cross-system user modeling and personalization on the social web. *User Modeling and User-Adapted Interaction (UMUAI), Special Issue on Personalization in Social Web Systems*, 22(3), 1-42.

Ahmed, A., Low, Y., Aly, M., Josifovski, V., & Smola, A. J. (2011). Scalable distributed inference of dynamic user interests for behavioral targeting. *Paper presented at the ACM Conference on Knowledeg Discovery and Data Mining (KDD)* (pp. 373-382).

Barla, M. (2011). Towards social-based user modeling and personalization. *Information Sciences and Technologies Bulletin of the ACM Slovakia*, 3(1), 52-60.

Chen, J., Nairn, R., Nelson, L., Bernstein, M., & Chi, E. H. (2010). Short and tweet: experiments on recommending content from information streams. *Paper presented at the Proceedings of the 28th international conference on Human factors in computing systems* (pp. 1185-1194).

Das, A. S., Datar, M., Garg, A., & Rajaram, S. (2007). Google news personalization: scalable online collaborative filtering. *Paper presented at the 16th International Conference on World Wide Web* (pp. 271-280).

Hannon, J., Mccarthy, K., O'mahony, M. P., & Smyth, B. (2012). A multifaceted user model for twitter. *User Modeling, Adaptation, and Personalization*, 303-309.

Hogenboom, A., Bal, D., Frasincar, F., Bal, M., De Jong, F., & Kaymak, U. (2015). Exploiting Emoticons in Polarity Classification of Text. *J. Web Eng.*,*14*(1&2), 22-40.

Kim, H. N., Ha, I., Lee, K. S., Jo, G. S., & El-Saddik, A. (2011). Collaborative user modeling for enhanced content filtering in recommender systems. *Decision Support Systems*, 51(4), 772-781.

Lu, C., Lam, W., & Zhang, Y. (2012). Twitter User Modeling and Tweets Recommendation Based on Wikipedia Concept Graph. *Paper presented at the Twenty-Sixth Conference on Artificial Intelligence Workshops (AAAI)*.

Ma, H., Zhou, D., Liu, C., Lyu, M. R., & King, I. (2011). Recommender systems with social regularization. *Paper presented at the Fourth ACM International Conference on Web Search and Data Mining* (pp. 287-296).

Novak, P. K., Smailović, J., Sluban, B., & Mozetič, I. (2015). Sentiment of emojis. *PloS one*, 10(12), e0144296.

Yu, L., Pan, R., & Li, Z. (2011). Adaptive social similarities for recommender systems. *Paper presented at the Proceedings of the fifth ACM conference on Recommender systems*, Chicago, Illinois, USA.

Zhong, E., Fan, W., Wang, J., Xiao, L., & Li, Y. (2012). *ComSoc: adaptive transfer of user behaviors over composite social network.* Paper presented at the 18th ACM International Conference on Knowledge Discovery and Data Mining (KDD)696-704.

Zhou, X., Xu, Y., Li, Y., Jøsang, A., & Cox, C. (2012). The state-of-the-art in personalized recommender systems for social networking. *Artif. Intell. Rev.*, 37(2), 119-132

Appendix

Sample Python Code for Data Collection and Transformation

```
emoji_sent_table = pd.read_csv('Emoji_Sentiment.csv', encoding='utf-8',
index_col=0)
emoji_track_list = emoji_sent_table[0:59].index.tolist() #60 most popular
emojis
users_names = set()
N_streamed_users = 50

class MyStreamListener(tweepy.StreamListener):

    def on_status(self, tweet):
        if len(users_names) < N_streamed_users:
            if not tweet.text.startswith("RT "):
                print tweet.user.screen_name
                users_names.add(tweet.user.screen_name)
            return True
        else:
            return False

    def on_error(self, status):
        print status
        if status == 420:
            return False

def main():
    auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
    auth.set_access_token(access_token, access_token_secret)

    myStream = tweepy.Stream(auth, MyStreamListener())
    myStream.filter(track=emoji_track_list)

    with open('users_names_6.txt','w') as f:
        for name in users_names:
                f.write(name+'\n')

def computeAverageCount():
    emoji_table["count_per_user"] =
emoji_table["count"]/emoji_table["users_count"]
    emoji_table.to_csv('Emoji_Count.csv', encoding='utf-8')
    return

def computeTwtAverageCount():
    emoji_table["count_per_tweet"] =
emoji_table["count"]/emoji_table["tweet_count"]
```

```
    emoji_table.to_csv('Emoji_Count.csv', encoding='utf-8')
    return

class User(object):
    def __init__(self, screen_name):
        self.screen_name = screen_name
        self.emojis = {}

def connectMongo(db_key, col_key):
    client = MongoClient()
    db = client[db_key]
    collection = db[col_key]
    return collection

def emojiParse():
    #users_collection = connectMongo('users_twitter_db', 'users_collection')
    users_collection = connectMongo('users_twitter_db', 'users_collection_8')
    emoji_collection = connectMongo('users_twitter_db', 'emoji_collection')
    #emoji_collection.drop()

    cursor = users_collection.find()
    #Parse and Count Emoji Instances
    for user_doc in cursor:
        someone = User(screen_name=user_doc['screen_name'])
        for tweet in user_doc['timeline']:
            for emoji_key in emoji_table.index.tolist():
                count = tweet['text'].count(emoji_key)
                if count>0:
                    if someone.emojis.has_key(emoji_key):
                        someone.emojis[emoji_key] += count
                    else:
                        someone.emojis[emoji_key] = count
                        emoji_table.loc[emoji_key, 'users_count'] += 1
                    emoji_table.loc[emoji_key, 'count'] += count
        #Store Back to MongoDB
        emoji_collection.insert({"screen_name":someone.screen_name,
"emoji_values":[]})
        for emoji_key in someone.emojis.keys():
            emoji_collection.update({"screen_name":someone.screen_name},
                                  {
                                   "$push":{
                                            "emoji_values":{

"$each":[{"emoji":emoji_key, "count":someone.emojis[emoji_key]}],
                                                            "$sort":{"count":-1}
                                            }
                                    }
                                   }
                               )

    emoji_table.to_csv('Emoji_Count.csv', encoding='utf-8')
    return

def computeTfIdf(emoji_collection):
```

```
    cursor = emoji_collection.find()
    for user_doc in cursor:
        emoji_collection.update({"screen_name":user_doc['screen_name']},
                                {
                                 "$set":{
                                         "emoji_tfidf":[]
                                         }
                                 }
                                )

        for emoji_tuple in user_doc["emoji_values"]:
            tfidf=
1+emoji_tuple['count']*math.log(N_user/float(emoji_table['users_count'][emoji_
tuple['emoji']]))

            emoji_collection.update({"screen_name":user_doc['screen_name']},
                                {
                                 "$push":{
                                          "emoji_tfidf":{

"$each":[{"emoji":emoji_tuple['emoji'], "tfidf":tfidf}],
                                                       "$sort":{"tfidf":-1}
                                          }
                                 }
                                }
                            )

    return
```

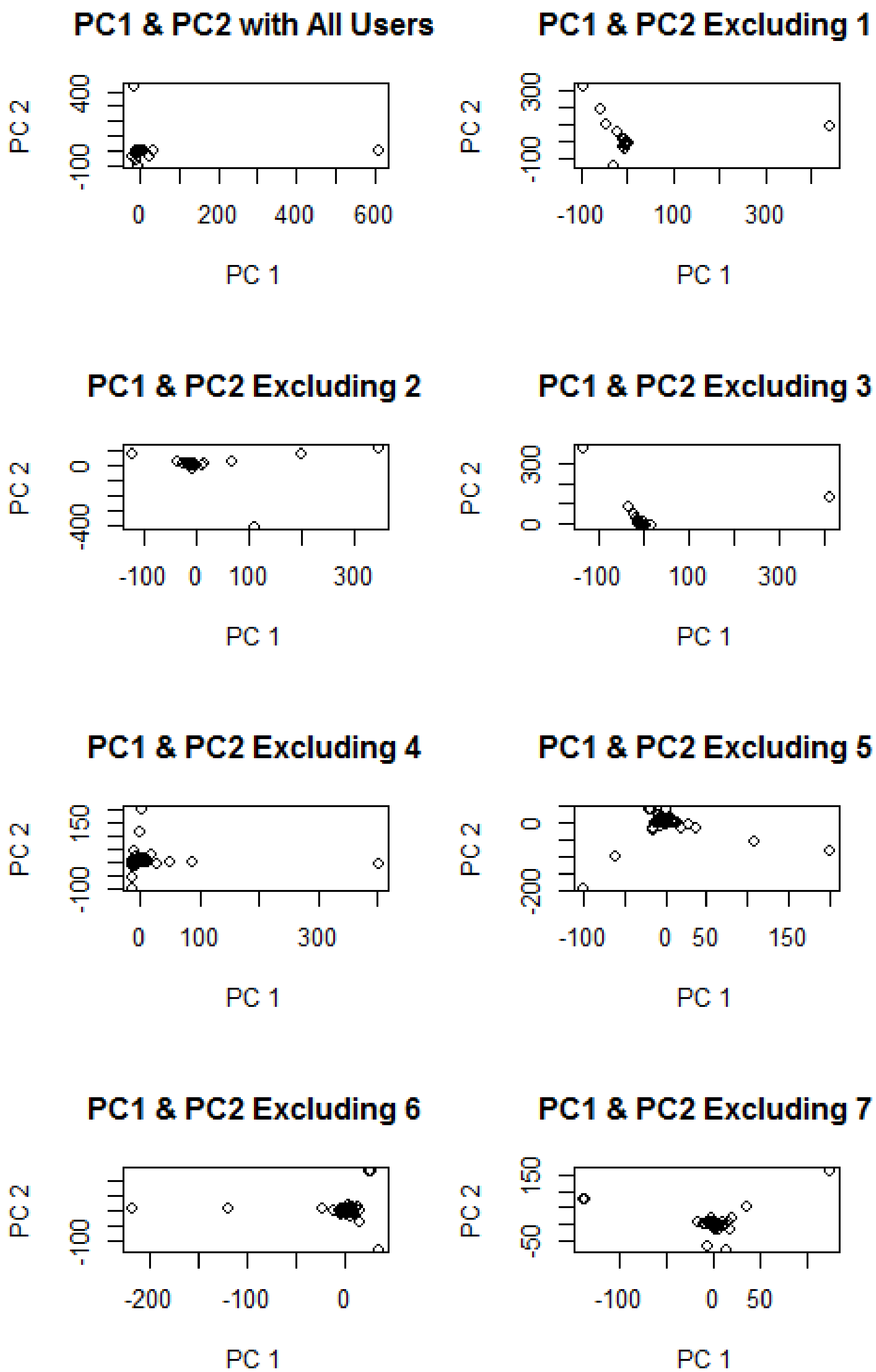
Sample R Code for Analysis

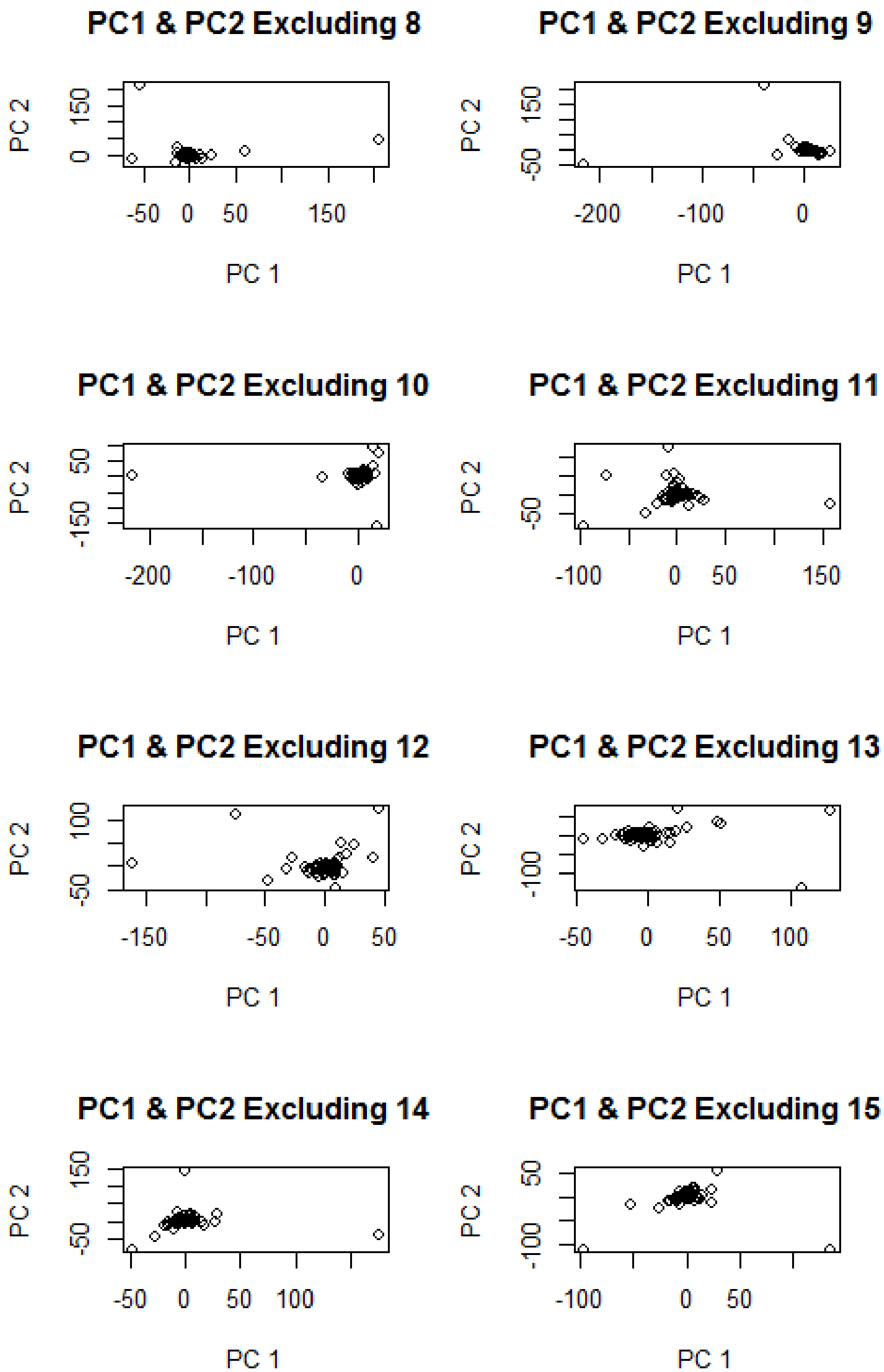
```
leading.emojis = function(User.num){
personal.top =
data.frame(cbind(emoji.tfidf[User.num,],emoji.count[User.num,],emoji.tw
count[User.num,],emoji.list[,5]))
colnames(personal.top) = c("Tf-Idf","Tf","Twf", "Users")
personal.top = personal.top[order(emoji.tfidf[User.num,],
decreasing=TRUE),]
personal.top[personal.top[,1]>0,]
}
```

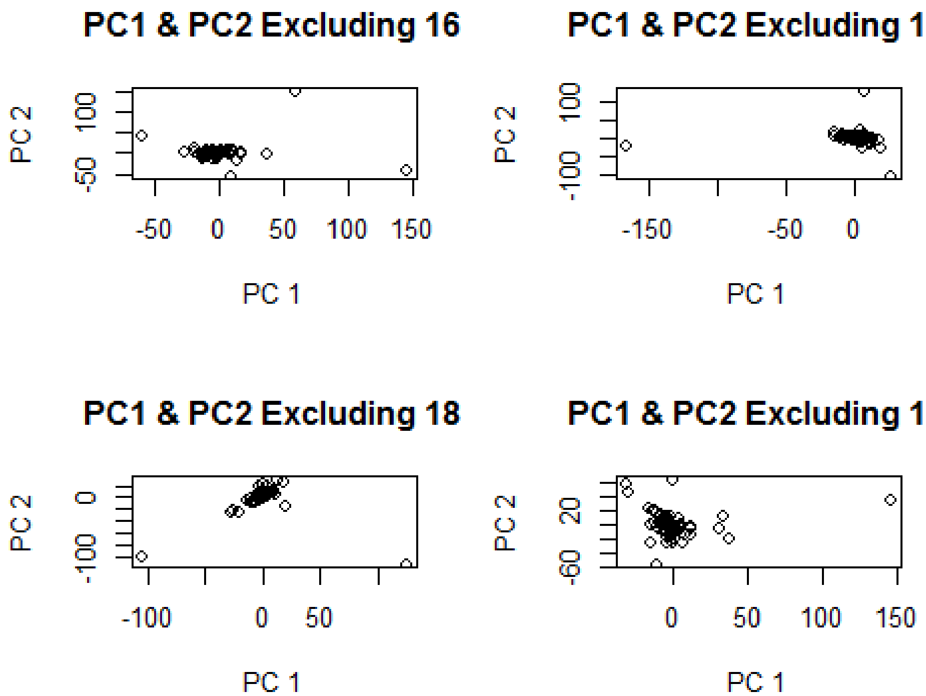
```
unwrappping = function(k){
  if (max(pc.tfidf.new$x[,1])-median(pc.tfidf.new$x[,1])
      >median(pc.tfidf.new$x[,1])-min(pc.tfidf.new$x[,1])){
    outlier.num = which.max(pc.tfidf.new$x[,1])
    my.end = function(x){max(x)}
    which.end = function(x){which.max(x)}
  }else{
    outlier.num = which.min(pc.tfidf.new$x[,1])
    my.end = function(x){min(x)}
    which.end = function(x){which.min(x)}
  }

  locator = as.integer(names(outlier.num))
  exiles[nrow(exiles)+1,] <<- data.frame(locator,
    names(which.end(pc.tfidf.new$rotation[,1])),
    my.end(pc.tfidf.new$rotation[,1]),
    emoji.tfidf[locator,which.end(pc.tfidf.new$rotation[,1])],
    rank(-emoji.tfidf[locator,],ties.method="min")[which.end(pc.tfidf.n
ew$rotation[,1])],
    max(emoji.tfidf[locator,]), row.names=k-1,
    stringsAsFactors=FALSE)

  emoji.tfidf.new <<- emoji.tfidf.new[-outlier.num,]
  pc.tfidf.new <<- prcomp(emoji.tfidf.new)
  plot(pc.tfidf.new$x[,1:2],
       main = paste0("PC1 & PC2 Excluding ",k),
       xlab = "PC 1", ylab = "PC 2")
}
```

```
cos.sim <- function(matx){
  (matx%*%t(matx))/sqrt(rowSums(matx^2)%*%t(rowSums(matx^2)))
}
cos.sim.tfidf = cos.sim(emoji.tfidf)
dist.ang = as.dist(2*acos(cos.sim.tfidf)/pi)
```

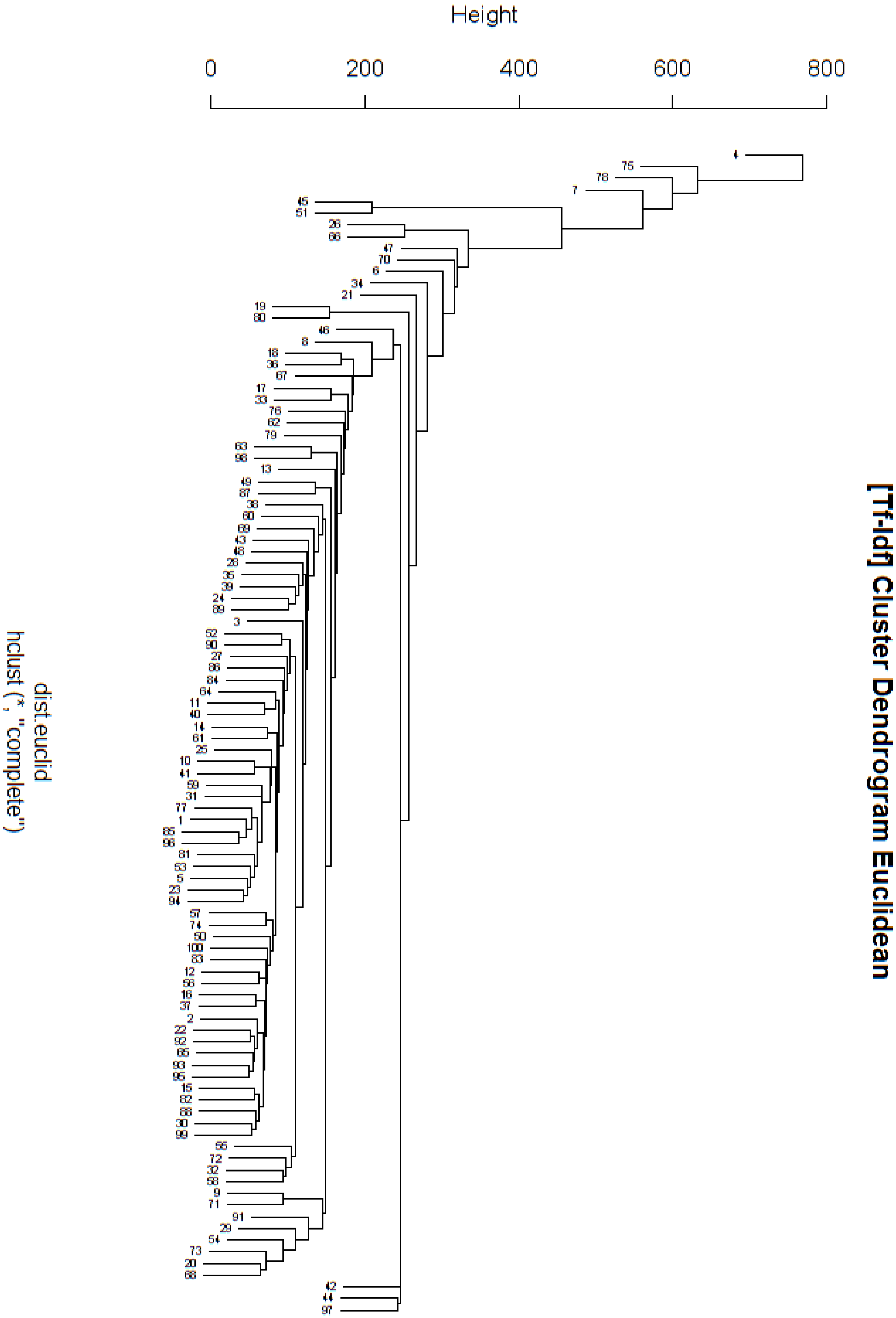
PCA Plots during Unwrapping

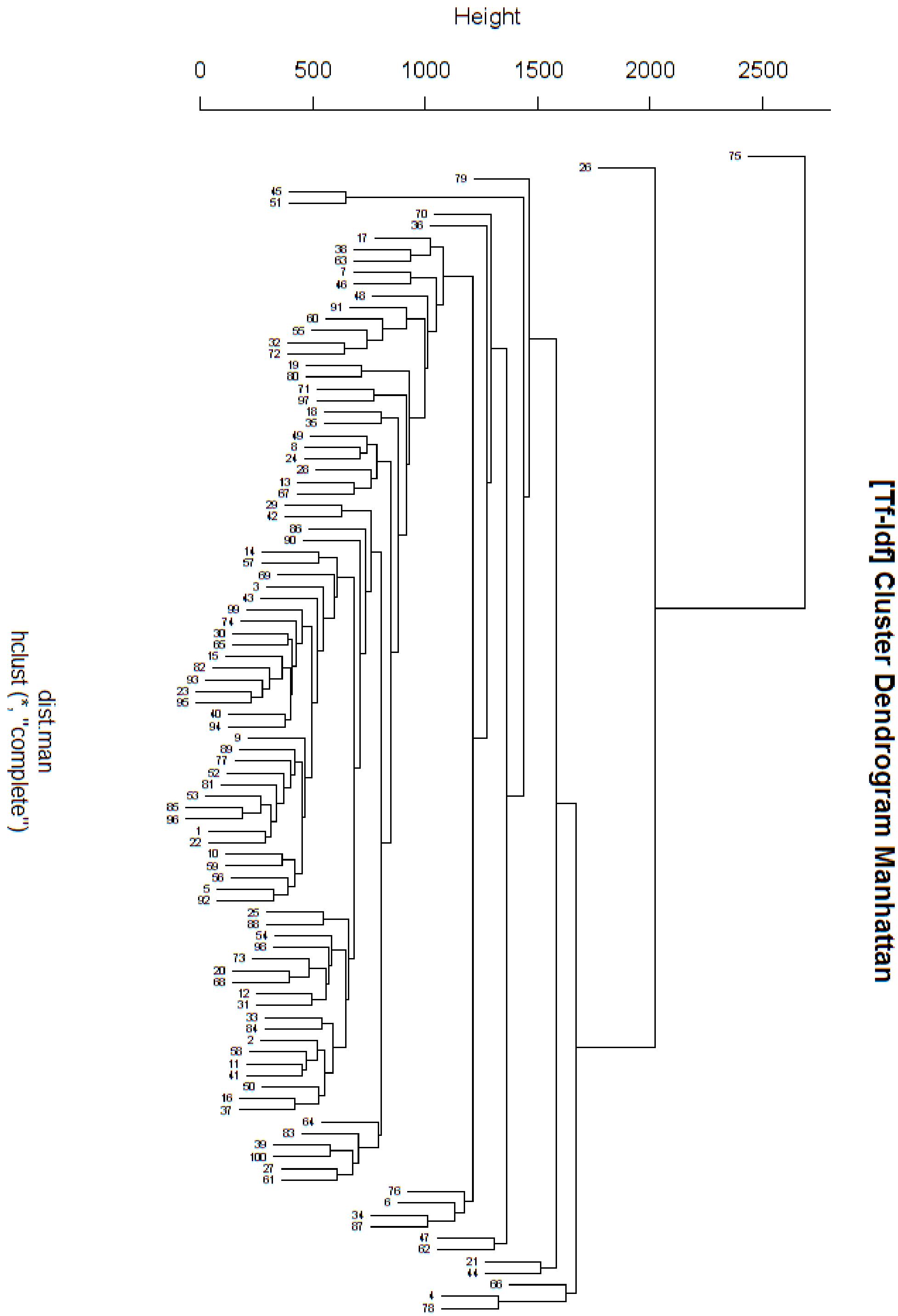



PC1 & PC2 Excluding 8
PC 2
0
150
-50
0
50
150
PC 1
PC1 & PC2 Excluding 9
PC 2
-50
150
-200
-100
0
PC 1
PC1 & PC2 Excluding 10
PC 2
-150
50
-200
-100
0
PC 1
PC1 & PC2 Excluding 11
PC 2
-50
-100
0
50
150
PC 1
PC1 & PC2 Excluding 12
PC 2
-50
100
-150
-50
0
50
PC 1
PC1 & PC2 Excluding 13
PC 2
-100
-50
0
50
100
PC 1
PC1 & PC2 Excluding 14
PC 2
-50
150
-50
0
50
100
PC 1
PC1 & PC2 Excluding 15
PC 2
-100
50
-100
0
50
PC 1

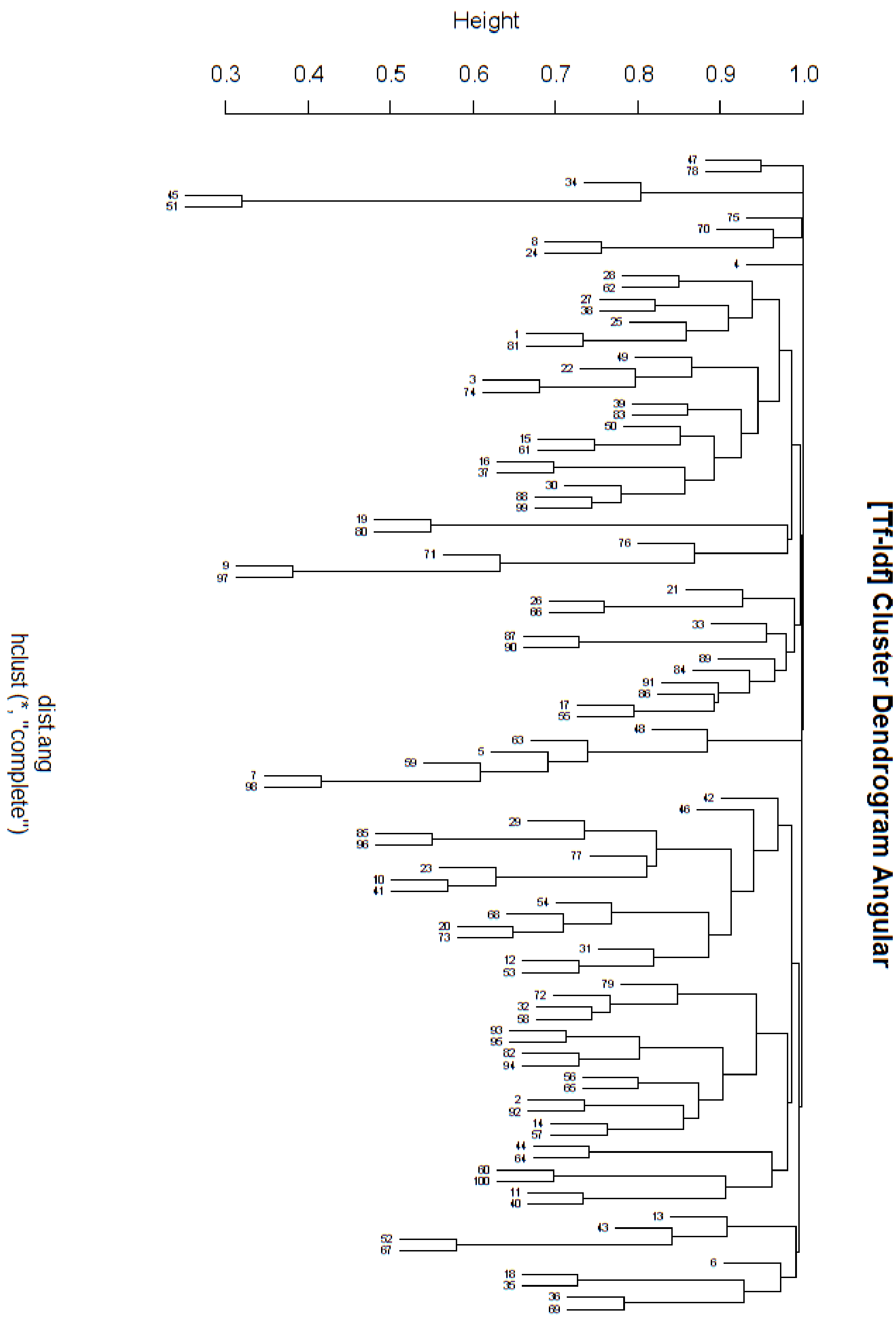

PC1 & PC2 Excluding 16
PC 2
PC 1
-50
0
50
100
150
PC1 & PC2 Excluding 17
PC 2
PC 1
100
-100
-150
-50
0
PC1 & PC2 Excluding 18
PC 2
PC 1
0
-100
50
PC1 & PC2 Excluding 19
PC 2
PC 1
20
-60

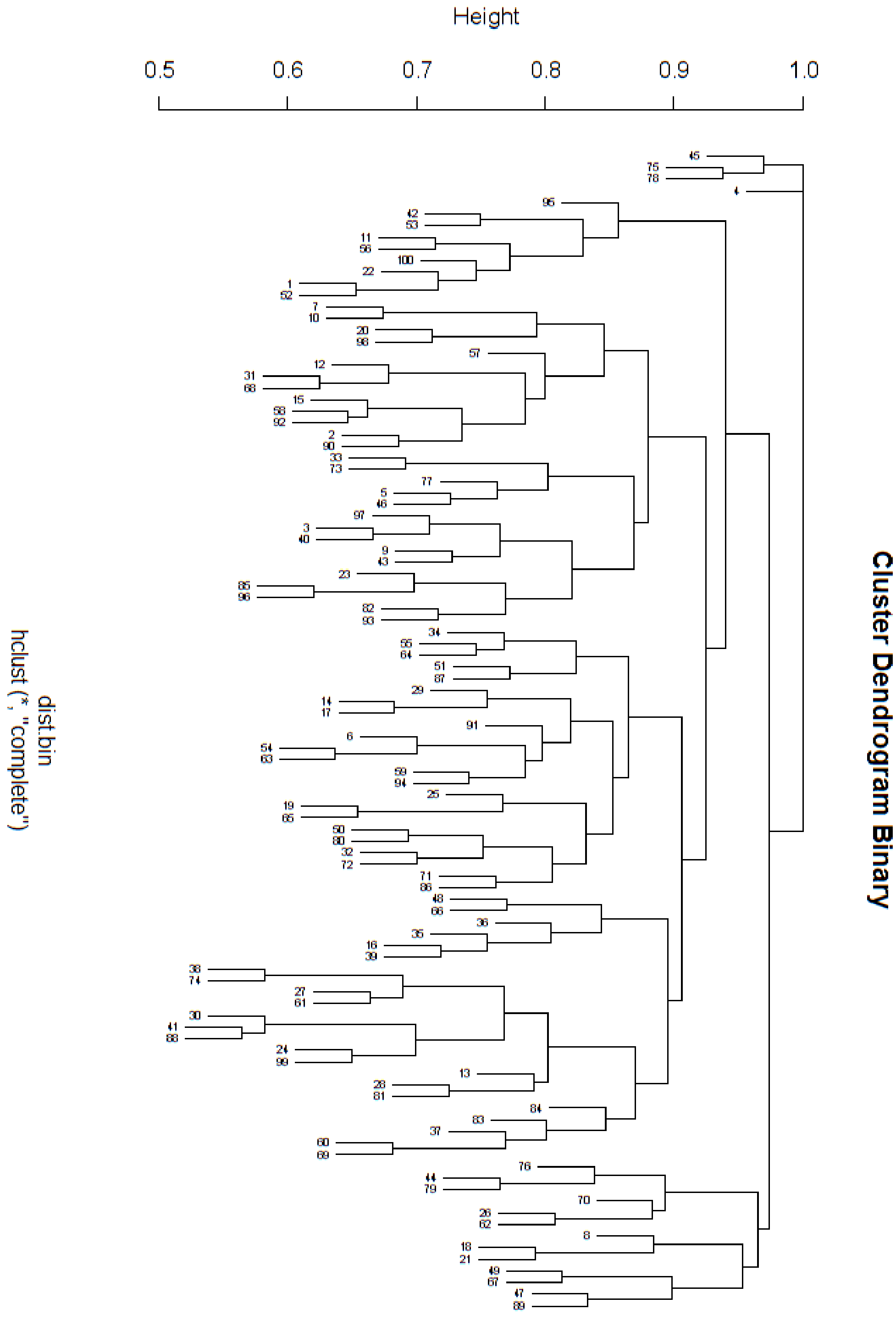
Cluster Dendrograms with Different Distance Measures





[Tf-Idf] Cluster Dendrogram Manhattan
Height
0
500
1000
1500
2000
2500
dist.man
hclust (*, "complete")


[Tf-Idf] Cluster Dendrogram Angular
Height
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
dist.ang
hclust (*, "complete")


Cluster Dendrogram Binary
Height
0.5
0.6
0.7
0.8
0.9
1.0
dist.bin
hclust (*, "complete")