Customer Segmentation

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The goal

"NutrientH20" (pseudonym) wants to understand its social-media audience a little bit better, so that it could hone its messaging a little more sharply.

Assumptions

For the sake of this analysis (based on the pseudonym) we will **consider NutrientH20 as a nutrient water brand which is entering the market of flavoured electrolytes**.

Approach

1. Identify scope+context of problem (goal+assumptions)
2. Data normalisation
3. Hypotheses creation
4. Hypotheses testing
    a. KNN Clustering
    b. PCA
    c. Cluster Identification
5. Recommendation

Data pre-processing

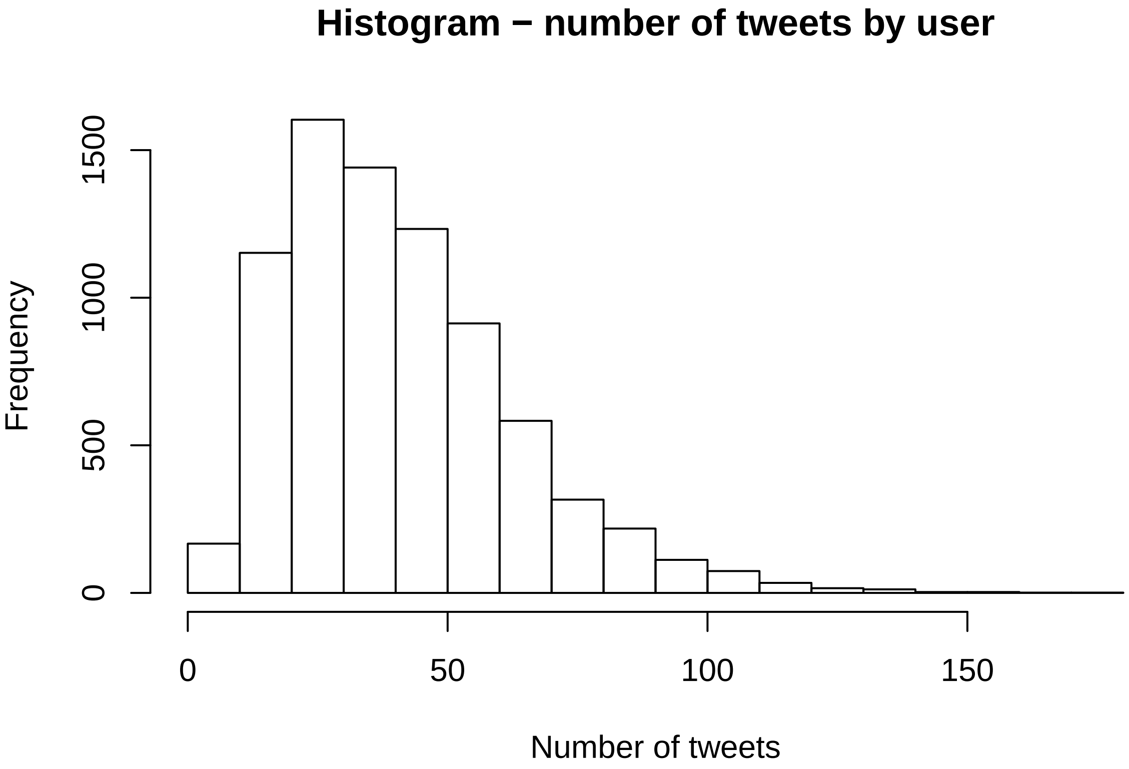
We have a dataset that includes 36 tweet categories for 7882 users, where each cell represents how many times each user has posted a tweet that can be tagged to that category. Categories include the following:

x
adult
art
automotive
beauty
business
chatter
college_uni
computers
cooking
crafts
current_events
dating
eco
family
fashion
food
health_nutrition
home_and_garden

x
music
news
online_gaming
outdoors
parenting
personal_fitness
photo_sharing
politics
religion
school
shopping
small_business
spam
sports_fandom
sports_playing
travel
tv_film
uncategorized

Data normalisation

As with any problem where the columns are similar items with values as frequency of occurence (typical text analytics base data), we calculate the term frequencies as % of tweets tagged to a category per user. This normalises for the difference in number of tweets per user, giving us an intuition of weightage of a category in the tweet profile for the user.



Outlier removal

We look at the 4 unwanted categoies - **chatter**, **uncategorized**, **adult** and **spam** and see the % of data filtered when we set a range of cutoffs on the term frequency of that particular category for every user.

1. Chatter

```
## Warning in cbind(seq(10, 40, 5), chatter_outlier): number of rows of result
## is not a multiple of vector length (arg 1)
```

TF_Chatter	% Data
10	30.4237503
15	17.2925653
20	9.0332403
25	4.2375032
30	1.8015732
35	0.6470439

2. Adult

TF_Adult	% Data
10	3.9583862
15	2.5881756
20	1.5478305
25	0.8754123
30	0.4694240
35	0.1776199
40	0.0380614
45	0.0253743
50	0.0000000

3. Spam

```
## Warning in cbind(seq(1, 70, 5), spam_outlier): number of rows of result is
## not a multiple of vector length (arg 1)
```

TF_Spam	% Data
1	0.5962954
6	0.0380614
11	0.0000000

4. Uncategorized

TF_Uncat	% Data
10	2.4993656
13	1.0910936
16	0.5709211
19	0.2537427
22	0.1268714
25	0.0507485
28	0.0380614
31	0.0253743
34	0.0253743

TF_Uncat	% Data
37	0.0126871
40	0.0000000

We identified the following cutoffs dfor outliers our base data:

1. chatter>0.25 (9%)
2. adult>0.20 (1.5%)
3. spam>0.01 (0.6%)
4. uncategorized>0.16 (0.57%)

We also checked for mutual exclusivity of these rows (max data loss if all are Mutually Exclusive) and for that if we remove rows with these features, we lose about 12-13% of the data, which seems like a practical enough trade off for removing a lot of noise from the, mainly due to these 4 columns

Why these columns?

1. Chatter and uncategorized tweets will anyway not help in clustering, their correlation with any field is being assumed as a coincidence
2. Spam and adult are categories that we do not want in our clusters

Customer Segments - Intuition (Hypothesis)

Correlated categories

When we looked at the set of categories, we expected some categories to have a strong correlation - eg. personal_fitness & health_nuitrition seem intuitively correlated. To set a cutoff, we looked at the number of pairs that made the different cutoffs for correlation.

Correlation Cutoff	Pair Counts
0.50	23
0.55	17
0.60	11
0.65	6
0.70	3
0.75	2
0.80	1
0.85	0
0.90	0

Var1	Var2	Freq
personal_fitness	health_nutrition	0.8099024
college_uni	online_gaming	0.7728393
fashion	cooking	0.7214027
beauty	cooking	0.6642389
politics	travel	0.6602100
parenting	religion	0.6555973
religion	sports_fandom	0.6379748
fashion	beauty	0.6349739
outdoors	health_nutrition	0.6082254
parenting	sports_fandom	0.6077181

Var1	Var2	Freq
computers	travel	0.6029349

Shown above are the number of unique pairs of categories that made the cut above a certain correlation value. 11 seems to be a reasonable number to compare - let's take a look at the categories with correlation>0.60, which we can expect to see together as the features of the clusters we are going to create.

By looking at these pairs, we feel that we should look for 5 broad clusters of customers:

1. The fit ones

personal_fitness, **health_nutrition** come with the highest correlation of 0.8, followed by the pair of **health_nutrition** and **outdoors** with a correlation of 0.6. We expect our first category to be populated by people who are fitness-oriented and focus on keeping a healthy lifestyle.. We are not sure about any age-based demographics for this cluster as of now.

2. Gen X

parenting, **religion** and **sports_fandom** - all 3 categories have correlation of ~0.60 between them (all 3 unique pairs) which hint at a uniform association among all three. We are assuming Gen X (people aged 39-54) to fall in this category.

3. The Instagrammers

Beauty, **Cooking** and **fashion** - all 3 categories are correlated reasonable well with each other with values ranging from 0.63-0.72, hinting at an association among the 3. While these people might not be focused on a healthy lifestyle in terms of exercise and eating right, they are focused on how they look, what they eat - which in this day and age of social media hints at the one stop shop for sharing the perfect reel life.

4. The centennial gamer

We see one particular pair (**college_uni** and **online_gaming**) with a high correlation of 0.77, which hits at the age group between later teens and early 20s.

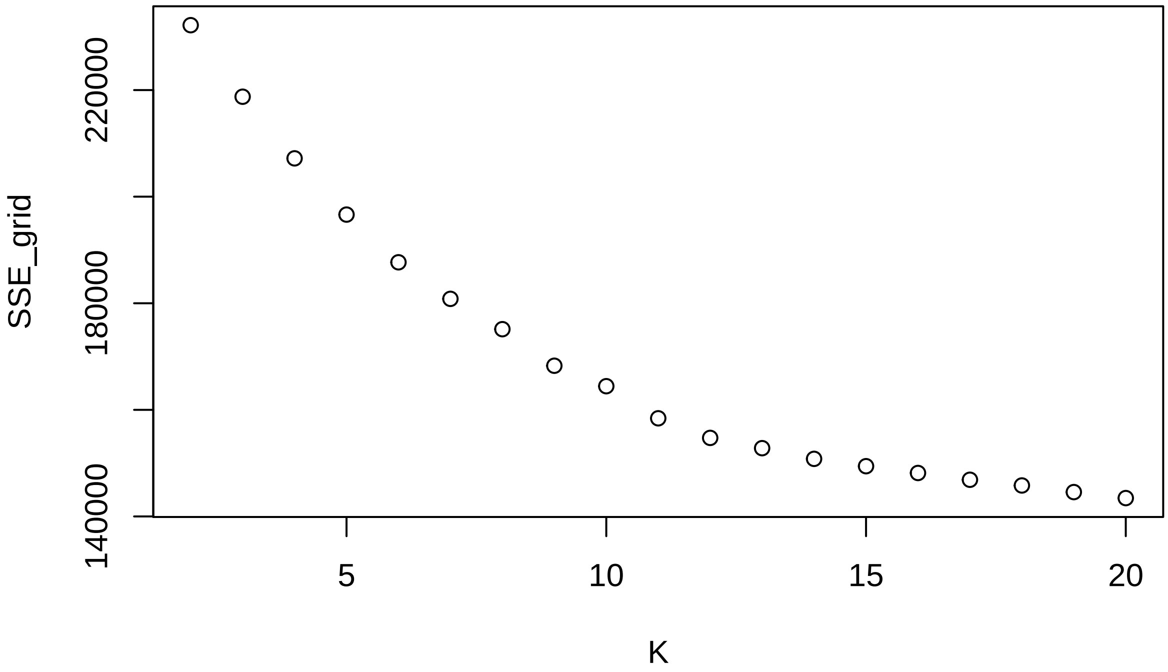
5. Politics and Travel?

We don't know what to call this category yet - the intersection of politics and travel is unique yet not uncommon. Politically aware people who like to travel, social workers, stand-up comedians, legal consultants, management consultants - there are many people who are likely to tweet about both of these categories. Let's hope our clustering exercise helps us understand these people better.

Hypothesis testing

Clustering using KNN

We perform z-scoring on our TF dataset and create a grid for number of clusters in KNN to see where the elbow comes in our curve (to decide k for KNN)



Clearly, there is no clear edge - we will go ahead with our range of k in [3,6] for clustering based on our hypothesis. Clustering will help us put our individual customers in separate groups based on similarities in their tweeting patterns.

Principal Component Analysis

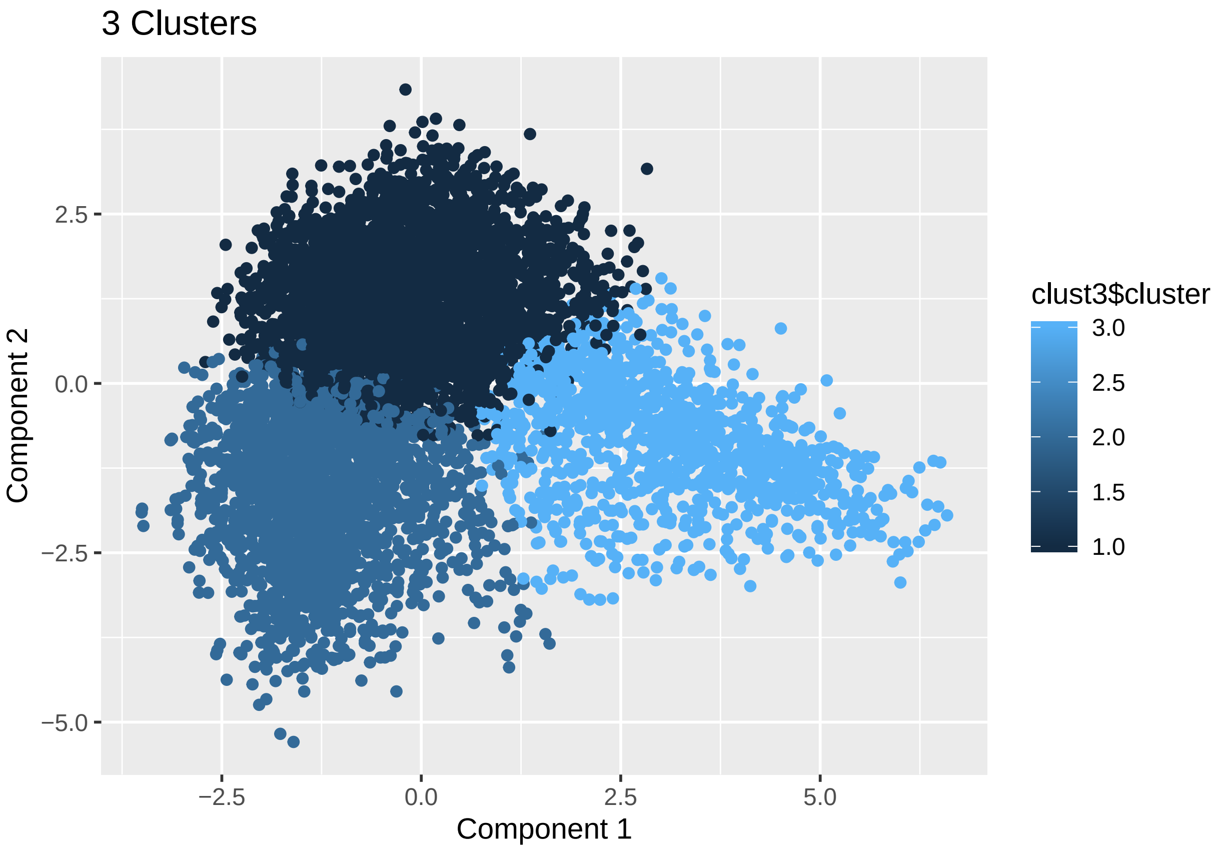
Principal Component Analysis (PCA) will help us understand the composition of each point as an aggregation of the different numbers and types of tweets made by each point. We will consider only the first two pricipal components.

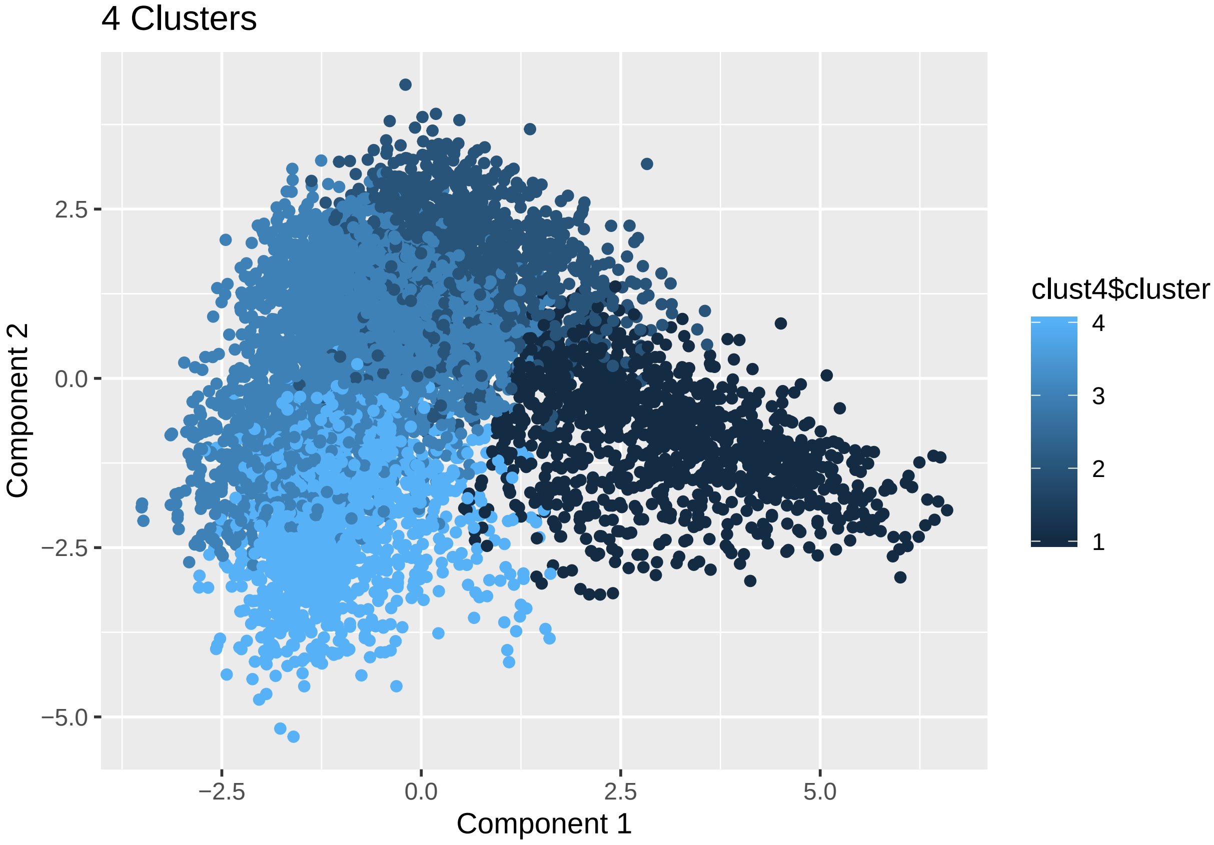
PCA and KNN

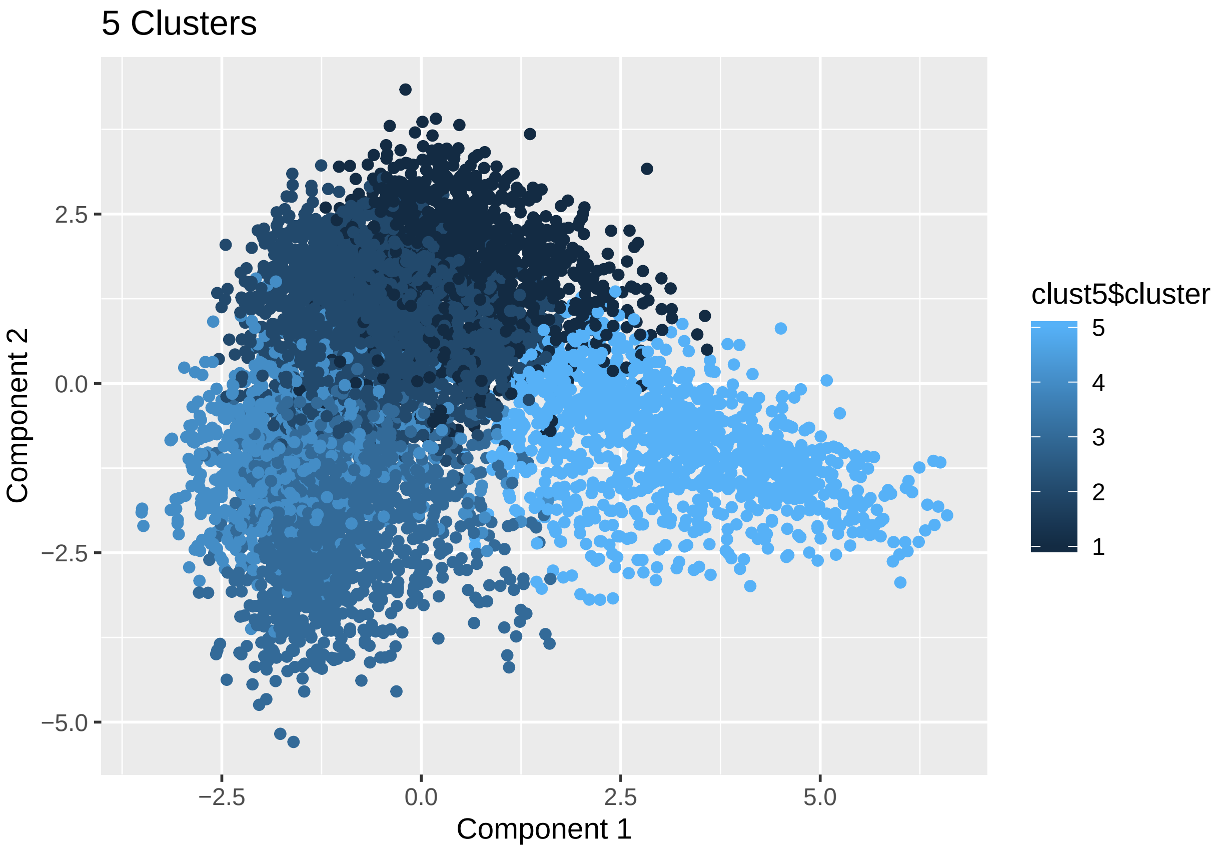
We will now compare the results of KNN and PCA. Steps:

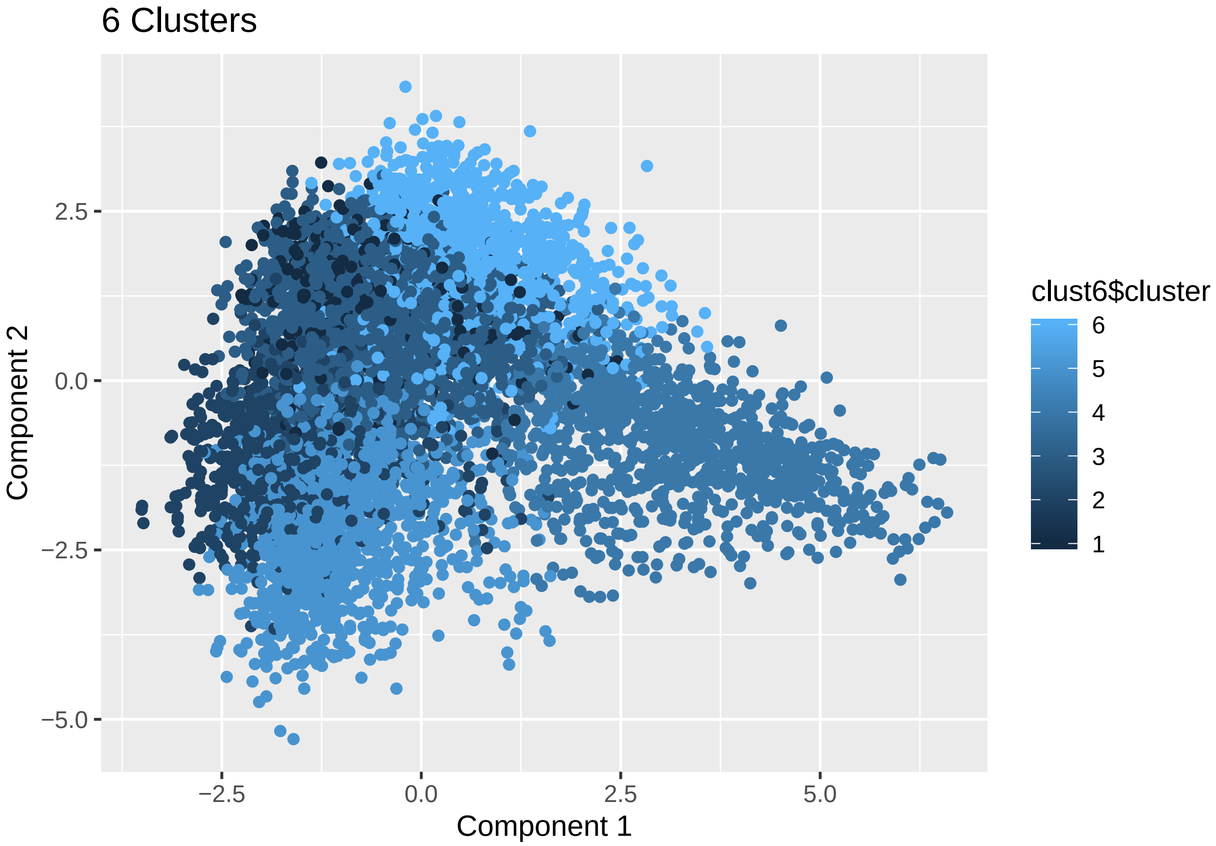
1. Plot each point on the PCA plot - the plot will tell us where each point lies based on it's composition of different number and types of tweets.
2. Color of each point will be displayed based on cluster assigned to that point in KNN
3. This will help us understand if customers from a particular cluster tend to tweet more about any specific topic(s).

Different plots from KNN look like:

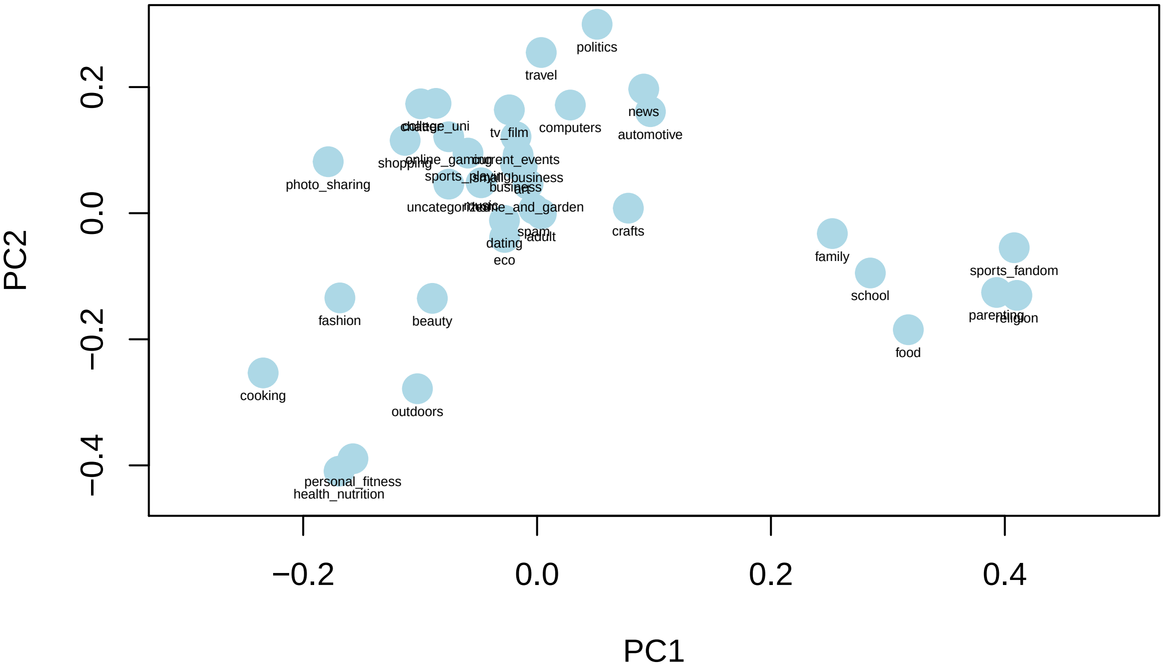

3 Clusters


4 Clusters

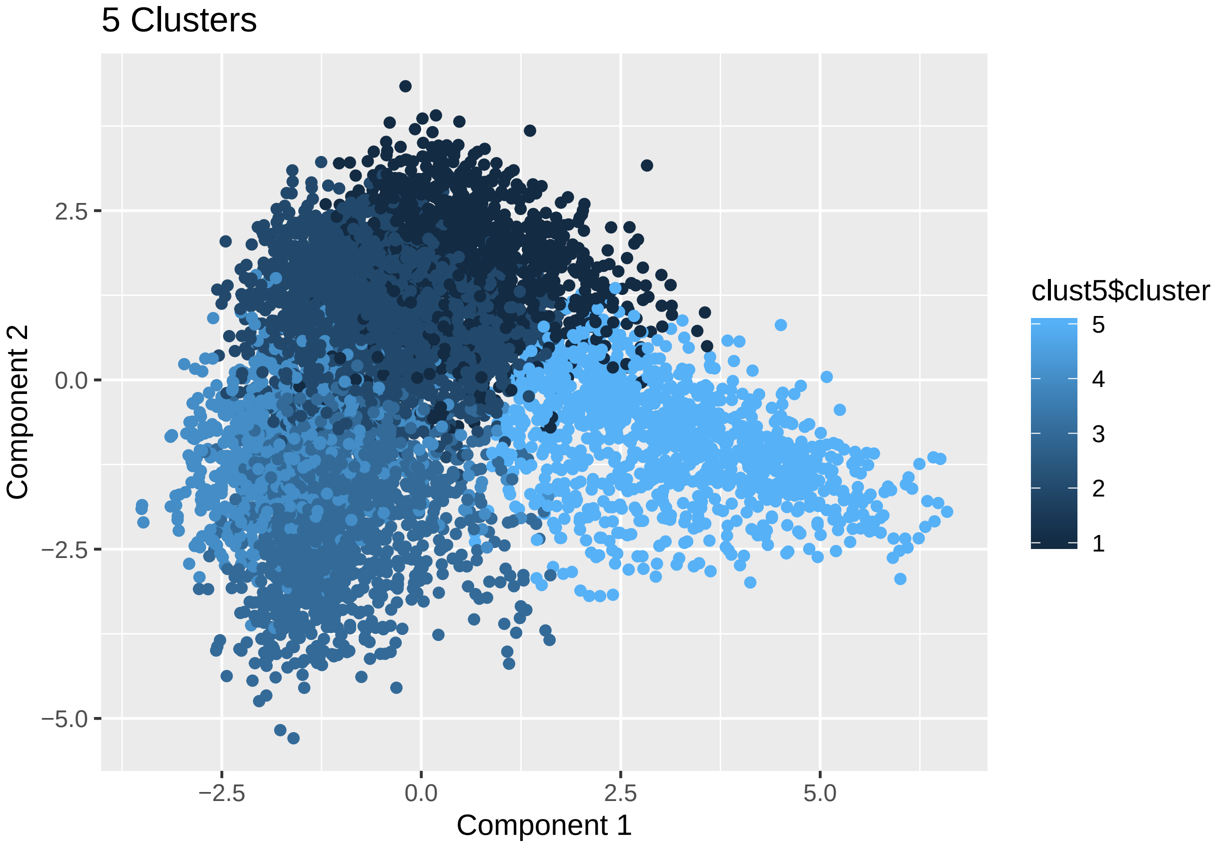

5 Clusters
Component 2
2.5
0.0
−2.5
−5.0
−2.5
0.0
2.5
5.0
Component 1
clust5$cluster
5
4
3
2
1


6 Clusters
Component 2
2.5
0.0
−2.5
−5.0
−2.5
0.0
2.5
5.0
Component 1
clust6$cluster
6
5
4
3
2
1

Looking at how PC1 and PC2 are formed in terms of categories:



We can see 5 clusters - let's look at our data points coloured in 5 clusters again:



Cluster Identification

Comparing plots for both categories along PC1 and PC2, we can identify the 5 segments

1. The fit ones

personal__fitness, **health__nutrition** and **outdoors** appear close by between PC1=[-0.2,-0.1] and PC2=[-0.45,-0.3]

2. The Instagrammer

Going slightly wider on PC1 and a little up on PC2, we reach **Beauty**, **Cooking** and **fashion** - all 3 categories lying between the younger age reflecting categories like **college__uni**, **online__gaming**, **photo__sharing** and fitness focused **personal__fitness**, **health__nutrition**, **outdoors**. We can consider these people active on social media and aware of their looks and food.

3. The net-savvy student

Further up PC2 on similar PC1 range as the 2 clusters above, **college__uni** and **online__gaming** interact with other categories that net-savvy high school and college students are likely to tweet about like **shopping**, **tv__film**, **sports__playing** etc.

4. The aware traveller

After observing **politics** and **travel** land near **news**, we can take 1 step closer to identifying this cliuster as aware travellers who keep up with current events, tv, film and computers. These are likely to be working professionals that have travelling jobs.

5. The homely parents (Gen X)

parenting, **religion** and **sports__fandom** - all 3 categories appear on the far right along PC1, right after **food**, **school** and **family**. Reflects traits and interests of traditional American parents - sports, religion, food, family, school and the most obvious, parenting.

Recommendations

1. The fit ones

Appeal to the importance of electrlytes in a balanced diet and how they help achieve fitness goals.

2. The Instagrammer

These people can be approached for collabs as marketing opportunities where both parties end-up in a win-win situation.

3. The net-savvy student

Appeal to this being as an easy, all-in-one solution to carry around campus to stay hydrated and enjoy flavoured, non-fattening drinks at the same time.

4. The aware traveller

Travelling takes a toll on the body - place this item at popular ports of travel and advertise the advantages of staying hyrated while travelling. These can include better sleep, prevention of ear-blockage during take-offs and landings or change in altitude in general.

5. The homely parents (Gen X)

Display the product in the light of a healthy alternative to sodas for their children - delivering great taste AND replacement. This is the new party drink!

Appendix

Data collection and preparation

The data in social_marketing.csv was collected in the course of a market-research study using followers of the Twitter account of a large consumer brand that shall remain nameless—let's call it "NutrientH20" just to have a label.

A bit of background on the data collection: the advertising firm who runs NutrientH20's online-advertising campaigns took a sample of the brand's Twitter followers. They collected every Twitter post ("tweet") by each of those followers over a seven-day period in June 2014. Every post was examined by a human annotator contracted through Amazon's Mechanical Turk service. Each tweet was categorized based on its content using a pre-specified scheme of 36 different categories, each representing a broad area of interest (e.g. politics, sports, family, etc.) Annotators were allowed to classify a post as belonging to more than one category. For example, a hypothetical post such as "I'm really excited to see grandpa go wreck shop in his geriatic soccer league this Sunday!" might be categorized as both "family" and "sports." You get the picture.

Each row of social_marketing.csv represents one user, labeled by a random (anonymous, unique) 9-digit alphanumeric code. Each column represents an interest, which are labeled along the top of the data file. The entries are the number of posts by a given user that fell into the given category. Two interests of note here are "spam" (i.e. unsolicited advertising) and "adult" (posts that are pornographic, salacious, or explicitly sexual). There are a lot of spam and pornography "bots" on Twitter; while these have been filtered out of the data set to some extent, there will certainly be some that slip through. There's also an "uncategorized" label. Annotators were told to use this sparingly, but it's there to capture posts that don't fit at all into any of the listed interest categories. (A lot of annotators may used the "chatter" category for this as well.) Keep in mind as you examine the data that you cannot expect perfect annotations of all posts. Some annotators might have simply been asleep at the wheel some, or even all, of the time! Thus there is some inevitable error and noisiness in the annotation process.