1 Data Description

We are working with the Taxi Dataset from before. A Proposition from my last investigation involved dropping all erroneous rows before feature generation began. At this point we have 4566 rows. There are only two erroneous rows still in the dataset which have now been removed so we have 4564 rows. We also drop the missing values leaving 4433 rows.

Next we should drop columns that are irrelevant to clustering. These include:

1. X
2. X.1
3. error_count
4. outlier_count
5. missing_values_count
6. not_store_and_fwd

2 Data cleaning

to prepare for PCA we need to make sure that data is comparable, some features will not be able to be normalized.

2.1 Lpep Times

We should convert this to Unix time, as our algorithm may not be able to correctly interpret this date-time format.

2.2 One Hot encoding

For PCA to work well we should one hot encode any remaining text fields. The fields:

1. VendorID
2. RateCodeID
3. Payment_type
4. Trip_type

3 Feature Generation

Next we need to generate a handful of features.

3.1 Actual Velocity

A very simple value for velocity can be calculated from the distance divided by the journey time in seconds.

3.2 Price from distance only

a factor of price without things like added tax and etc, the price only generated from distance. This can be calculated from Total_amount. As I investigated this i found that Fare_amount already represents this variable.

3.3 Normalization

It is good practice to normalize numerical data where possible before starting PCA so that components are only weighted by value and variance and not size. We need to normalize the following:

1. Pickup_longitude
2. Pickup_latitude
3. Dropoff_longitude
4. Dropoff_latitude
5. Passenger_count
6. Trip_distance
7. Fare_amount
8. Tip_amount
9. Tolls_amount
10. Total_amount
11. pickup_unix
12. dropoff_unix
13. trip_time_seconds
14. velocity

The following were not not normalized:

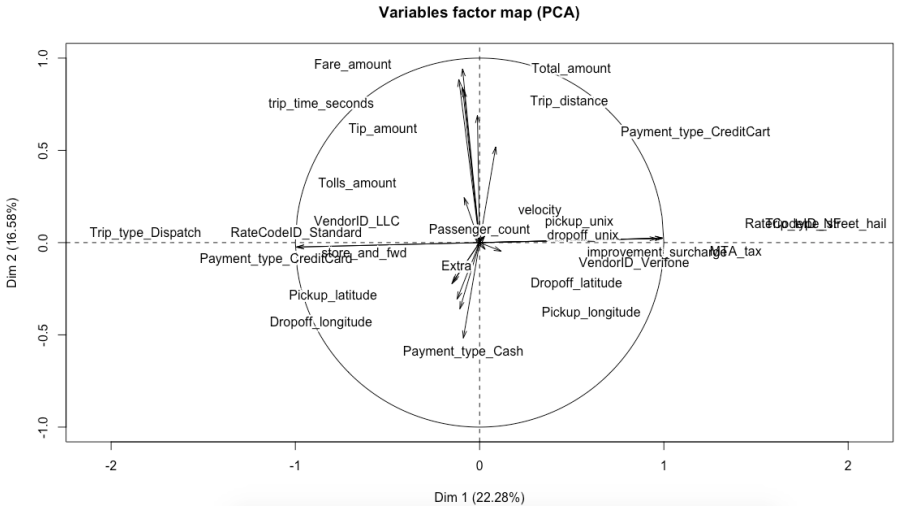
1. Pickup_longitude
2. Pickup_latitude
3. Dropoff_longitude

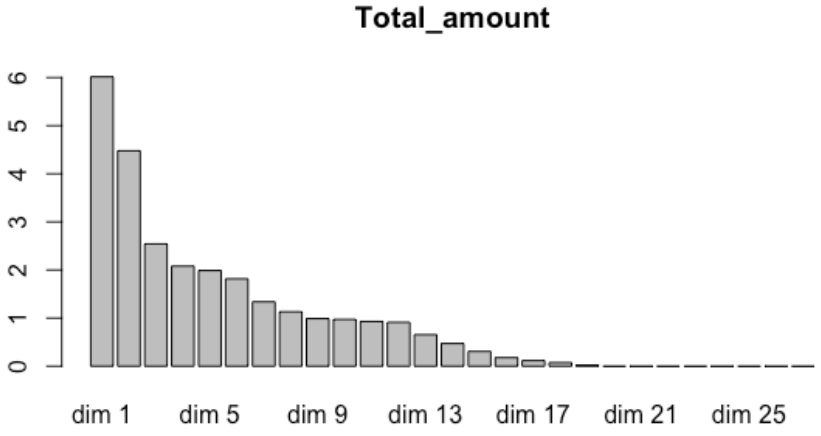
4. Dropoff_latitude
5. Trip_distance
6. velocity

4 PCA Analysis

4.1 Eigenvalues and dominant axes

At this point we have a total of 27 variable.





test	eigenvalue	percentage of variance	cumulative percentage of variance
comp 1	6.015	22.278	22.278
comp 2	4.478	16.585	38.862
comp 3	2.543	9.419	48.281
comp 4	2.079	7.699	55.979
comp 5	1.987	7.361	63.340
comp 6	1.816	6.725	70.065
comp 7	1.337	4.952	75.017
comp 8	1.131	4.189	79.206
comp 9	0.988	3.658	82.863
comp 10	0.972	3.599	86.462
comp 11	0.929	3.441	89.904
comp 12	0.911	3.374	93.278
comp 13	0.655	2.425	95.703
comp 14	0.470	1.742	97.445
comp 15	0.306	1.132	98.577
comp 16	0.177	0.655	99.232
comp 17	0.115	0.425	99.657
comp 18	0.074	0.273	99.930
comp 19	0.019	0.070	100.000
comp 20	0.000	0.000	100.000
comp 21	0.000	0.000	100.000
comp 22	0.000	0.000	100.000
comp 23	0.000	0.000	100.000
comp 24	0.000	0.000	100.000
comp 25	0.000	0.000	100.000
comp 26	0.000	0.000	100.000
comp 27	0.000	0.000	100.000

5 Variables point of view

PCA has reduced our dataset down to 3 dimensions. The below tables describe the strength of these values in each dimension.

5.1 dimension descriptions Dim 1

	correlation	p.value
Trip_type_street_hail	0.99386177	0.000000e+00
RateCodeID_NF	0.99386177	0.000000e+00
MTA_tax	0.99386177	0.000000e+00
improvement_surcharge	0.96381202	0.000000e+00
Extra	0.11819145	2.909115e-15
Payment_type_CreditCart	0.08758005	5.197305e-09
VendorID_Verifone	0.02957182	4.897721e-02
VendorID_LLC	-0.02957182	4.897721e-02
Tolls_amount	-0.08399587	2.133242e-08
trip_time_seconds	-0.08553300	1.172330e-08
Payment_type_Cash	-0.08830664	3.876594e-09
Total_amount	-0.09260283	6.528726e-10
Trip_distance	-0.09336012	4.729037e-10
Dropoff_longitude	-0.10726733	8.032696e-13
Fare_amount	-0.11297777	4.551051e-14
Pickup_longitude	-0.12201843	3.571623e-16
Pickup_latitude	-0.14405064	5.492807e-22
Dropoff_latitude	-0.15081861	5.719633e-24
Trip_type_Dispatch	-0.99386177	0.000000e+00
RateCodeID_Standard	-0.99386177	0.000000e+00

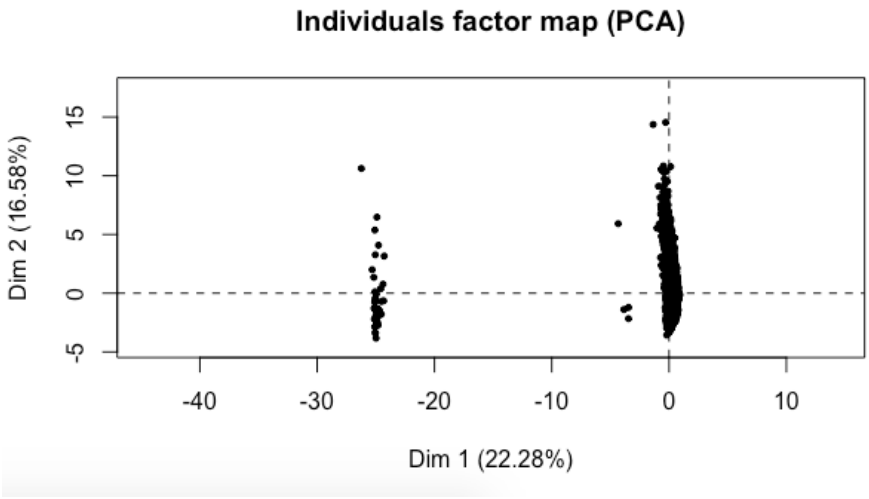
5.2 dimension descriptions Dim 2

	correlation	p.value
Total_amount	0.94170106	0.000000e+00
Fare_amount	0.88510140	0.000000e+00
Trip_distance	0.84263052	0.000000e+00
trip_time_seconds	0.82937540	0.000000e+00
Tip_amount	0.68927040	0.000000e+00
Payment_type_CreditCart	0.51899701	2.517581e-304
Tolls_amount	0.24407175	3.920809e-61
velocity	0.09570332	1.715496e-10
dropoff_unix	0.03630055	1.564755e-02
VendorID_LLC	0.03628322	1.569728e-02
pickup_unix	0.03571890	1.739360e-02
VendorID_Verifone	-0.03628322	1.569728e-02
Extra	-0.04686357	1.802089e-03
Pickup_latitude	-0.21081067	1.030527e-45
Dropoff_latitude	-0.22326882	3.369714e-51
Pickup_longitude	-0.30618860	7.467424e-97
Dropoff_longitude	-0.35943140	2.640413e-135
Payment_type_Cash	-0.51766731	1.643092e-302

5.3 dimension descriptions Dim 3

	correlation	p.value
Pickup_latitude	0.66033394	0.000000e+00
Dropoff_latitude	0.65588453	0.000000e+00
Pickup_longitude	0.63457647	0.000000e+00
Dropoff_longitude	0.56083152	0.000000e+00
Payment_type_Cash	0.37844790	5.873443e-151
Fare_amount	0.34750409	5.105259e-126
Trip_distance	0.34747262	5.394929e-126
trip_time_seconds	0.31007265	2.103999e-99
Total_amount	0.27702659	6.403979e-79
VendorID_Verifone	0.25296029	1.114903e-65
Tolls_amount	0.16545742	1.407720e-28
dropoff_unix	0.13784620	2.988764e-20
pickup_unix	0.13763443	3.414776e-20
Trip_type_street_hail	0.08729253	5.832857e-09
RateCodeID_NF	0.08729253	5.832857e-09
MTA_tax	0.08729253	5.832857e-09
improvement_surcharge	0.08520073	1.335469e-08
Extra	-0.03243589	3.080629e-02
Payment_type_CreditCard	-0.03482829	2.039805e-02
store_and_fwd	-0.04593107	2.221673e-03
Trip_type_Dispatch	-0.08729253	5.832857e-09
RateCodeID_Standard	-0.08729253	5.832857e-09
Tip_amount	-0.13598540	9.569774e-20
VendorID_LLC	-0.25296029	1.114903e-65
Payment_type_CreditCart	-0.37431545	1.822935e-147

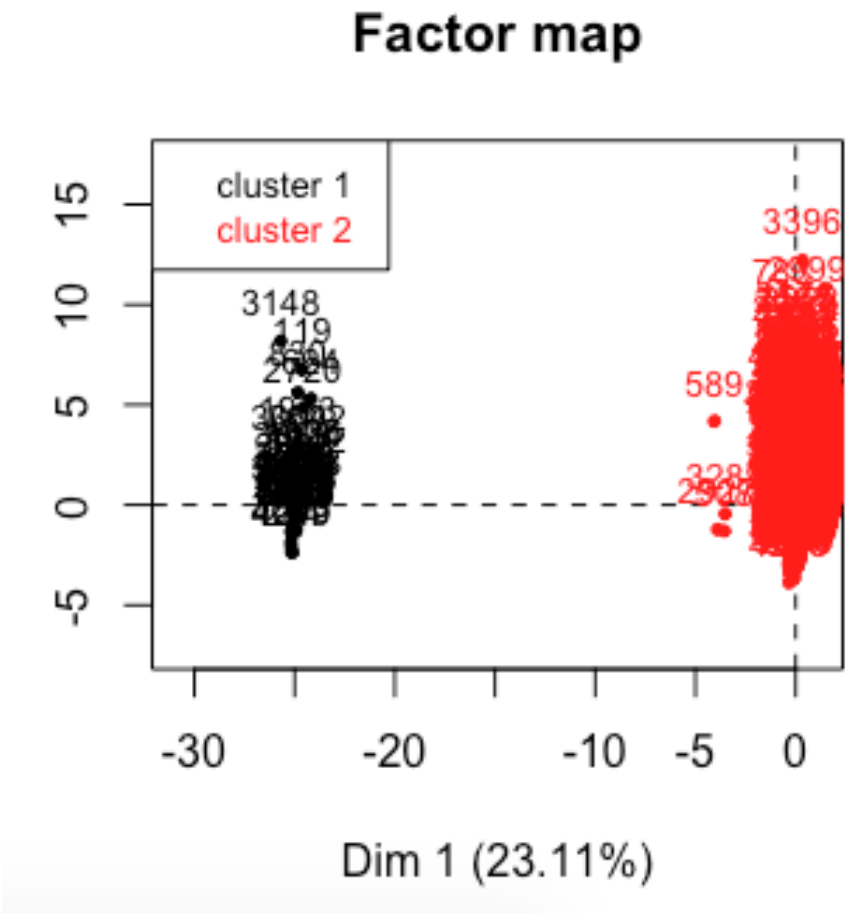
By running the command *plot.PCA(res.pca,choix=c("ind"),cex=0.8,label=c('none'))*, we can see the following graph of two very distinct groups.



6 Perform a PCA taking into account also supplementary variables

Supplementary variables and individuals are not used for the determination of the principal components. Their coordinates are predicted using only the information provided by the performed principal component analysis on active variables/individuals.

The clustering looks pretty clear from this.



42 points belong to cluster 1, with 4391 in the 2nd cluster. This is forcing the clear two clusters. This 1st cluster is very small and could be considered unhelpful, unless these refer to outliers.

	Eta2	P-value
Dim.1	0.9890591535	0.00000000
Dim.2	0.0008660378	0.05008404

7 More supplements

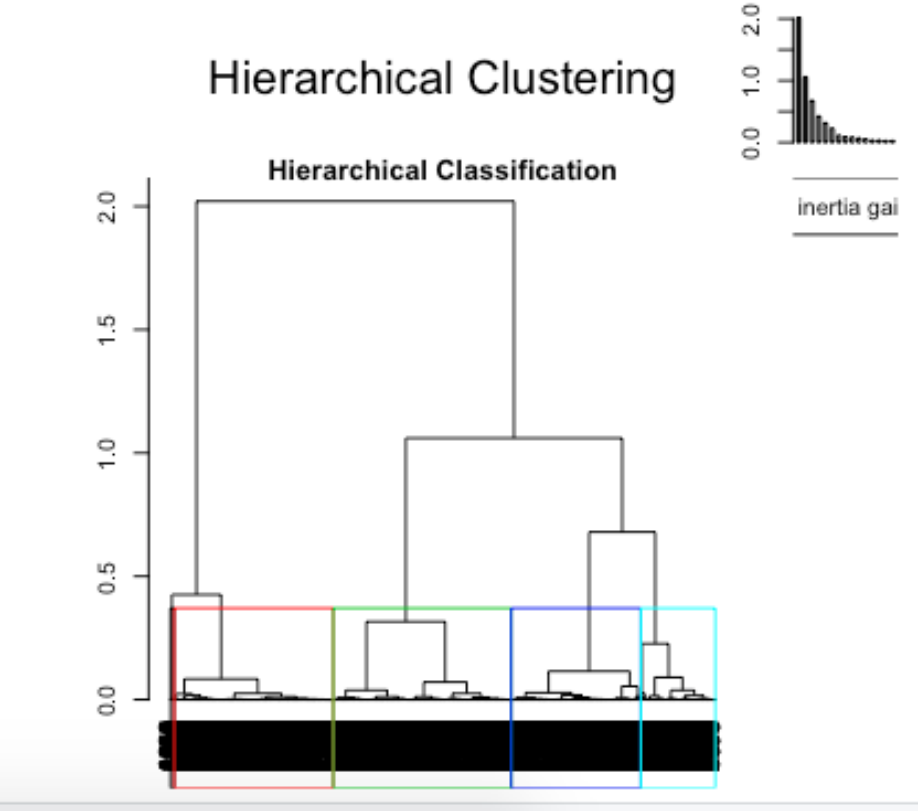
The following variables correlate strongly with Fare_Amount without being directly related to the fare amount.

- Fare_Amount - 7
- Trip_time_seconds - 17
- RateCodeNF - 21

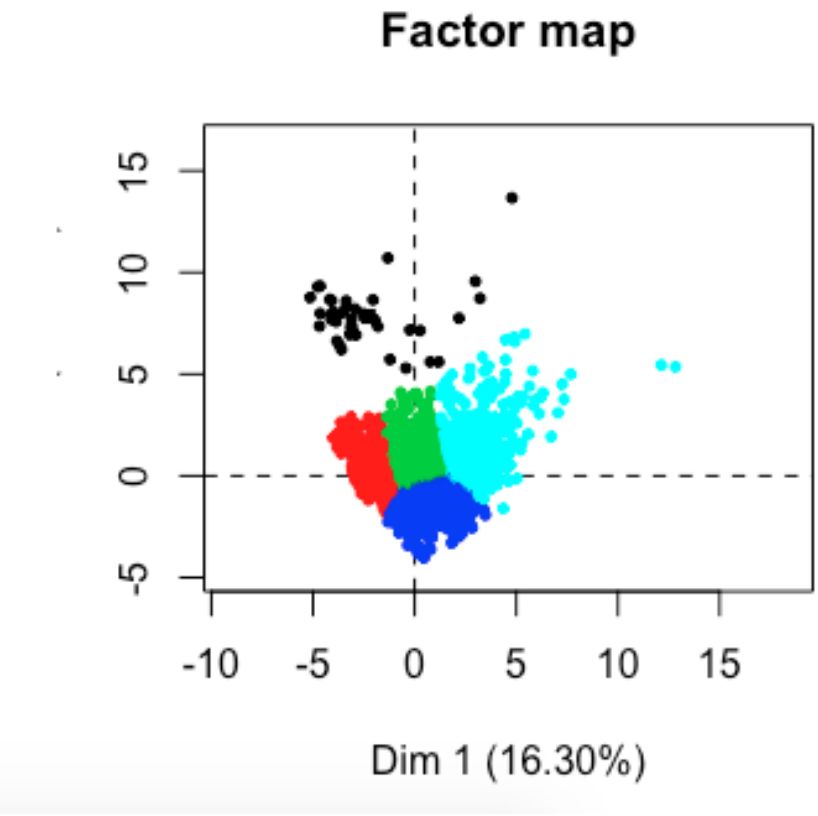
- RateCodeStandard - 22
- Trip_type_Dispatch - 26
- Trip_type_street_hail - 27

From my early investigation I only found two clusters, one cluster representing what I believe to be outliers, and the other normal data.

My mistake before was not involving other supplementaries in the clustering.



The colored boxes in the above graph represent the 5 different clusters, it is difficult to see the narrow black square on the far left, these are the outliers we clustered before. You can also see the clear different collections of data. And the graph below shows the new clusters.



The below table shows the split of clusters, with black, red, green, dark blue, light blue corresponding to 1,2,3,4,5. As you can see from our previous clustering we still have 42 outliers so the outliers class is still classified.

1	2	3	4	5
42	1424	1069	1378	520

Next I have tried to come up with 5 plain English ways of describing these clusters. I have come up with the following.

- 1 - Outliers
- 2 - Cheap Street hail, Negotiated Fares
- 3 - Average trips
- 4 - Expensive Street hail, Negotiated Fares
- 5 - Expensive ,long, trips