Traffic flow analysis from Uber movement data

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Contents

Introduction

Travelling from one place to another is a hard task in big cities. For that reason, some companies like Uber provide their users with cars, so they can easily travel in exchange of some money. Also, users can take the role of the drivers and get payed. This service is specially important for tourists, because they do not own a vehicle in the city and using the public transport may take a long time; but also for people living in the city, who do not own a car, or who do not want to waste time finding a parking place. There are many advantages and disadvantages about services of this kind, but it is not the main objective of this document to discuss them.

Uber provides some datasets related with the use of their services in different cities around the world. It is possible to use that data in order to create a graph, where city areas are the nodes and their adjacencies are the edges. Next, we can analyze the traffic flow between different parts of a city. By doing that, it is the objective of this document to detect congested areas (meaning areas where the Uber traffic flow is very dense). Once that metric is calculated, it would be possible to use different criteria to find out the most congested area. That would mean that it is the area where most cars drive in and out, and so it is an important area. Moreover, some community detection algorithms can also be applied to this scenario. By performing this type of analysis, it is possible to identify groups of congested areas (or, in the same way, non congested areas). Note that there is one assumption made here: the Uber traffic is representative of the general traffic flow, meaning that if a particular area is traversed by many Uber cars, then it is likely that the same happens with ordinary traffic.

Those results could be used to identify which route can be followed to avoid dense traffic, or to identify important parts of the city (assuming that cars tend to drive to areas where most of the people activity is focused).

Once different criteria are used for each kind of annalysis, some discussion will be made regarding how robust or accurate are the used methods, together with some possible future improvements.

The code used during all the process can be found attached at the end of this document.

Dataset

We can find a huge amount of information in the Uber website. Once there, we can get datasets which gather information on different big cities around the world, such as London, Paris, Amsterdam, Chicago, Los Angeles, New Dheli or Sydney. The only difference between datasets of different cities is the amount of data, because all of them are characterized by the same information. We chose to analyze the traffic flow in Amsterdam. Hence, every piece of information from this point on was analyzed for this city.

There are two types of files in the datasets: geographical data (a GeoJSON file), and trips data (a CSV file).

GeoJSON is a format used for describing geographical data using JSON. It allows to define many different areas, shapes or others, using spatial objects (points, lines, polygons. . .) to do so. These objects are created from points, which are characterized by coordinates. In the case of the Uber dataset, GeoJSON is used to define areas of a city. An area is defined by a polygon, which can belong to one of the three cathegories below.

- **Simple polygon:** the area is enclosed into an ordinary polygon.
- **Simple polygon with holes:** the area is enclosed into a simple polygon, but there are parts inside that polygon which do not belong to the original area. In this case, The area is represented as an array of polygons. The first one defines the outer ring, while the rest of them define the holes.
- **Multipolygon:** the area is formed by different islands. In this case, it is represented by several polygons, each one of them corresponding to one island.

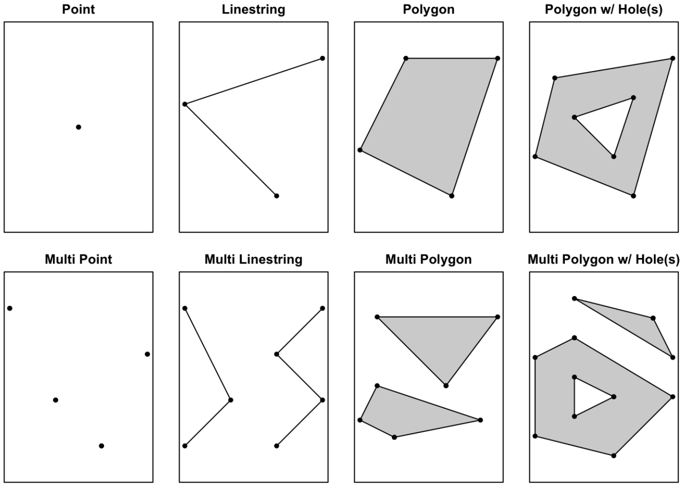
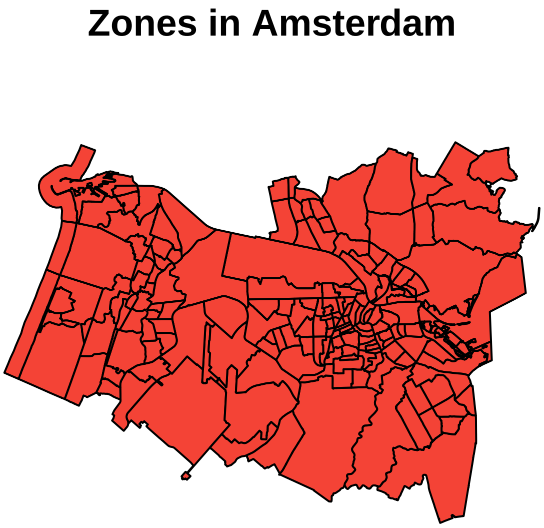


Figure 1: Different types of spatial objects, used in GeoJSON

Each area is a polygon, and is identified by an ID. In the case of Amsterdam, there are 181 of them, where the IDs are numbers from 0 to 180. Since GeoJSON is a well kown format, there are different tools to read data from the previous file, such as the *readOGR* function. The geographical representation of the zones in Amsterdam can be found below. Recall that a zone can be formed by different polygons, or have holes. However, the vast majority of zones are defined by simple polygons, and those cases could barely be seen. Hence, all of them are shown using the same color in the figure below. Note that the city center of Amsterdam is located where most of the small areas are, and they tend to be larger when their distance to the city center increases (even tough there are some exceptions).



The other type of file in the dataset is the Uber related one. It is a CSV file where each row corresponds to a single trip. A trip has an origin and a destination, it occured at a time and it has a duration, represented by several statisticals. An example of this kind of data can be found below. Note that the dataset only provides the origin and destination zone ID of the trip, and we do not know the route followed by the car. This will be a problem in the future.

Table 1: Uber data (columns 1 to 4)

sourceid	dstid	hod	mean_travel_time
143	141	7	258.90
132	12	7	662.86
130	32	7	584.99
8	173	11	870.56
172	176	10	289.16

Table 2: Uber data (columns 5 to 7)

standard_deviation_travel_time	geometric_mean_travel_time	geometric_standard_deviation_travel_time
213.93	205.88	2.09
283.84	623.17	1.38
306.62	511.66	1.68
407.70	807.46	1.42
216.32	229.97	1.97

We can slightly tune the information which is gathered in the CSV file, by the following parameters: only week days, only weekends or both; data hourly, weekly or monthly aggregated; data belonging to the first, second, third or forth quarter of a given year. The information analyzed in this document will be from the first quarter of 2018, hourly aggregated and from week days only. Hourly, because it is the most granulated option. Week days only, because we assume that those are the most busy days, and weekends could lower the average traffic flow in some areas. And first quarter of 2018, because it seemed updated enough.

That means that we will know the time in which the annalyzed trips happened. Hence, we can treat sepparately trips at different times, obtaining the average evolution of the traffic during the day.

Graph

The purpose of this project is to obtain a graph from the traffic flow dataset of Uber and perform different analyses on it. Specifically, centrality measures will be carried out to determine the areas where there is more traffic flow per time interval, at the same time that community detection algorithms are applied to know how the zones of the city can be grouped in clusters according to the traffic analyzed.

The first step is to build the graph from the dataset. The package used for creating and manipulating the graph is *igraph*. As mentioned in the previous section, the dataset is structured with a GeoJSON format. The idea is to create a graph from these data in which each node represents a predefined geographical area of the map and each edge represents a connection between adjacent zones. In addition, the graph is intended to be weighted and undirected. With a weighted graph we can represent how many trips have crossed each of the edges, increasing the weight by 1 for each time a user of Uber has crossed that area. On the other hand, the choice to create an undirected graph is due to the fact that each predefined zone can contain a set of roads, of which we do not know their direction (that is, the area is a black box), so we can not know if a particular road is congested only in one direction. Therefore, with an undirected graph, only the times a user traverses each road, either in one direction or in another, are represented.

To sum up the previous paragraph, we aim to create a weighted undirected graph. From *rgeos* package the function *gTouches* allows us to obtain the adjacency matrix from a GeoJSON object, i.e. a $n \times n$ matrix A where

$$A_{ij} = \begin{cases} true & \text{if} \quad \text{i and j are adjacent} \\ false & \text{otherwise} \end{cases}$$

.

Thus, this matrix defines which zones are adjacent to each other, so we can directly create a simple graph from it with the function *graph_from_adjacency_matrix*, from *igraph* package. This graph only contains the zones (nodes) and the connections (edges) among all of them.

Once you have the simple graph, the second step is to calculate the weights of each of the edges to represent the traffic that circulates from one area to another. As seen in the previous section, this information can not be taken out from the dataset directly, since only the source and destiny zones of each of the travels are provided. Hence, a priori, the route followed in each trip is unknown to us, so we must make an approximation on this path to be able to define complete routes.

The first approach was to use an API that provides the shortest route between two geographical points, such as Project OSRM (Open Source Routing Machine) or Google Maps Platform, in such a way that you can obtain a real approximation of each route. However, there are certain limitations in these APIs that do not allow the calculation of all the routes of the dataset in a reasonable time (e.g. number of queries per second), so this option has been discarded.

The alternative that has been followed is to find the shortest path between the source and destination zones in the graph, which may not be as accurate as the first option (since in the graph each node represents a large area, with lots of possible routes, so the shortest path is calculated at a higher level of abstraction) but that is also a good approximation. Therefore, the shortest path is calculated for each trip and the weight of those edges that make up that path is increased by one unit.

With these steps, a weighted undirected graph is obtained. However, we aim to analyze the traffic flow in the city for each hour interval throughout the day. As the dataset provides information about hourly averaged Uber trips throughout three months, then 24 different graphs are created and trips made within the same interval of time are collected in the same graph.

The analysis performed over these 24 graphs is explained in the following sections. Since there are lots of graphs and multiple algorithms, the results are represented in GIF format attached to this documents, where the evolution of the traffic flow during the day is shown dynamically. Both in the GIFs and in the images, the darker the color of an area, the higher the value of the measure.

Centrality measures

Once the graph is created, it is time to perform some calculations with different criteria in order to find out the most important areas of the city. The meaning of *important* may differ from one approache to another, and will determine the interpretation from the information obtained in the results. In this section, different centrality measures will be applied on the graph. Each one of them will be explained, and the results will be shown with some images.

Recall that the graph is actually a dynamic graph, were each node evolves in intervals of one hour of time. This behaviour is better shown in movement, rather than in a static image. That is why some GIFs are attached to this document. Each one of them shows the evolution of the graph depending on the time and the centrality used.

Degree centrality

The degree centrality determines that the importance of a node is directly proportional to the number of edges between that node and the others. Since in the graph used for modelling the zones in the city of

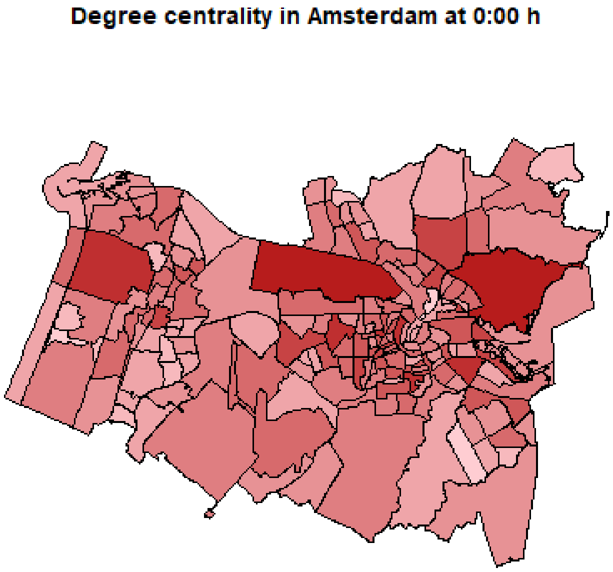


Figure 2: Degree centrality in Amsterdam

Amsterdam a pair of nodes can only have one (or none) edge, then this means that the most important area in the city is the one with more neighbours. In other words, an area is very important if it is possible to reach many areas from there.

Before showng the results, let's discuss this measure. If an area has many adjacent areas, then it is true that the zone is potentially traversed by many cars, because it is possible to reach many places from there. However, reacall that not all zones are similar to each other. There are some huge zones, while other areas are tiny. In the case of Amsterdam, large areas tend to be far from the city center, while small areas tend to be in the city center. A large area has a large perimeter, meaning that it will normally have many neighbors. However, before performing any calculations, we can predict that the most important areas will tend to be in the city center, because it is where most of the human activity is concentrated. Actually, Z may be the reason why those geographical areas are divided into smaller zones.

While the graph is a dynamic one, this measure do not depend on the Uber trips, but only in the adjacencies. Hence, one single image is enough to show the results of this measure, because it will not change over time (the zones have always the same neighbours).

It can be seen in the figure that the most important areas are the big ones, as expected. The darker colors are present in huge areas close to small ones. That means, large areas close to the city center. This makes sence, because if a large area is surrounded by small ones, then the number of potential neighbors can be higher. Also, there are some small areas in the city center with a dark color, meaning that the number of neighbors is high, and therefore its importance is high as well.

Using this centrality, we get a low number of important areas, which are located in or near the city center, which makes sense. Also, there is another important area in the outskirts of the city. However, except for these few cases, the rest of the areas in the graph have a similar color, meaning a similar importance.

To sum up, this centrality does not seem to be a good aproach, because it does not take into account the

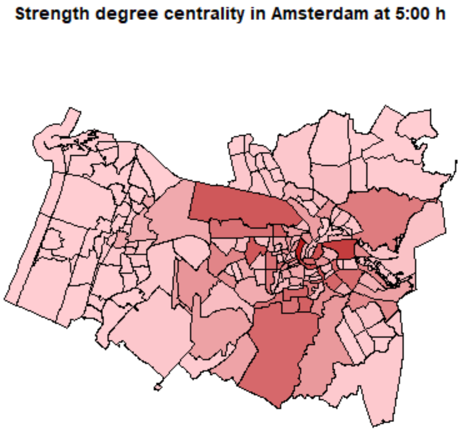
Uber trips. However, the results do not differ too much from the expected ones, being most of the important areas located near the city center.

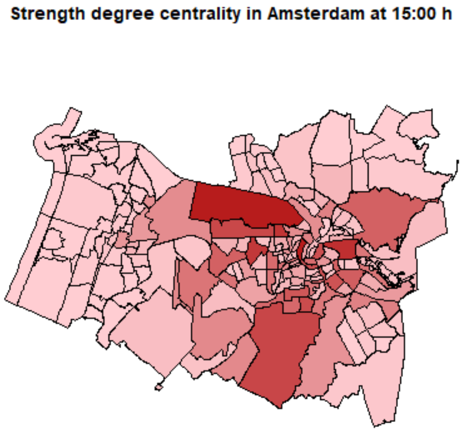
Strength degree centrality

This one is a similar measure to the previous one. However, there is a very important difference: now, the importance of a node is determined not by its number of edges, but by the weighted sum of its edges. Recall that the weight of an edge between two nodes is the number of Uber cars which drove for a given time between both nodes, assuming that the route is the shortest path between origin and destination.

This centrality seems to be a very good one for this scenario. As said in the introduction of this document, the annalisys is performed in order to find out congested (or not congested) areas. Since the importance of a node is directly proportional to the number of cars which traspass that zone, then this one seems to be a good approach.

Recall that we are working with a dynamic graph. Hence, the number of trips between zones vary with time, obtaining a different value of the strength degree centrality for every hour. This evolution can be better seen in the attached GIF.


Strength degree centrality in Amsterdam at 5:00 h


Strength degree centrality in Amsterdam at 15:00 h

Two images corresponding to different times are provided. First, the traffic flow at 5:00h. Second, the traffic flow at 15:00h. In both cases the most important areas are the same ones. Those are big areas close to the city center, and many small areas in the city center. That means that those are the areas traspassed by most cars.

The areas in the outskirts of the city are barely used by cars, while the closer to the city center an area is, the more cars drive there. There is an important fact that may explain why the small areas in the city center are less congested that the ones surrounding. Amsterdam is a beautiful city full of canals in the city center. There are small roads in both sides of the canals, but those are both full of people and bicicles. Hence, it makes sense for people to finish or begin their Uber trips in streets close to the city center (where most of the activity is concentrated), but close enough not to be far from where they are. In other words, it makes sense that there are many areas in the city senter where the traffic is not dense.

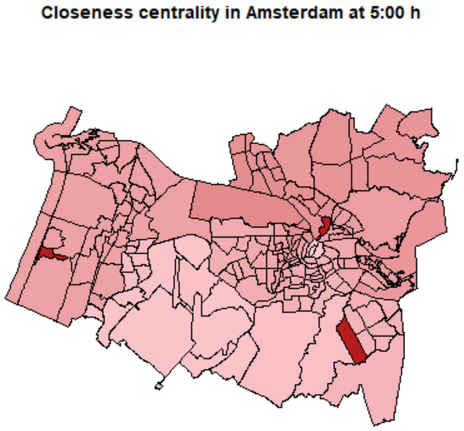
Now, let's compare both times in the figure. As said before, the most important areas are the same ones in both cases. However, at 5:00h there are much less traffic than at 15:00h, which is predictible; most of the activity in a city take place during the day. However, there is still traffic at 5:00h, when it seems reasonable to assume that some people start to go to work.

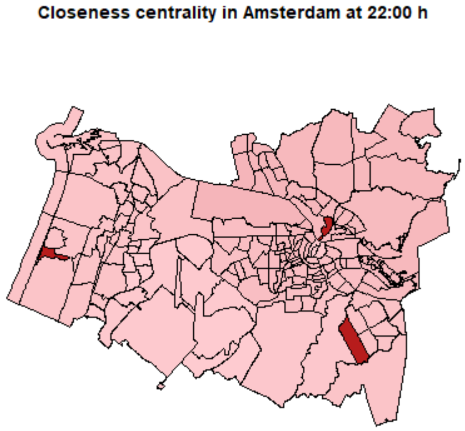
In the GIF attached to this document, it is possible to observe that the peak of traffic flow is obtained during the day, but there is still a lot of traffic until 2 or 3 am. The lowest amount of cars is obtained at 5:00h. From that point on, it starts to increase again.

Note that the assumption made in the degree centrality is shown to be correct: big areas, which have many neighbors, tend to be traspassed by many cars.

Closeness centrality

The importance of a node (in a weighted graph) in the closeness centrality is inversely proportional to the sum of the weights of the shortest paths between that node and all the others. In other words, the most central node is the one from which it is possible to reach all the others avoiding as much traffic as possible. So, the higher the measure is, the better that node is for travelling to other nodes avoiding traffic jams.

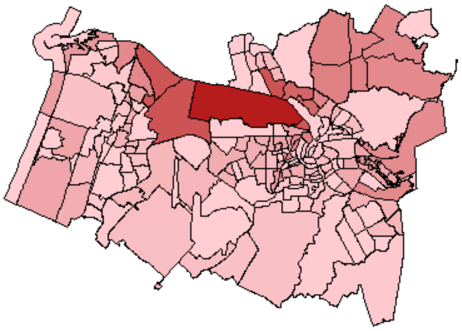

Closeness centrality in Amsterdam at 5:00 h

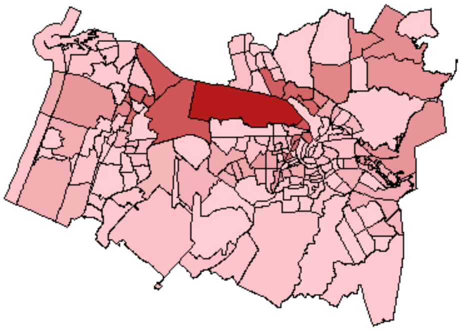

Closeness centrality in Amsterdam at 22:00 h

There are three nodes which remain very important all the time, by this metric. Those are small areas outside the city center. The rest of the nodes remain low in this metric, meaning that it is more likely to follow a congested route from those nodes. While the magnitude (or color, in the figures) remain more or less static, there is a slightly difference between day and night. For example, at 5:00h all the nodes seem to increase this metric. As seen in the strength degree centrality, at that time the traffic is very low, so it is more likely to avoid traffic jams from any node. However, during the day the traffic generaly increases, and the closeness centrality of the nodes decrease. This is an expected result.

Betweenness centrality

In a weighted graph like this one, the betweenness centrality of a node A measures how many paths between all pairs of other nodes traverse the node A, where that paths are the ones which minimize the sum of weights of the route between origin and destination. In other words, if a node is rated high by this centrality, it means that there are many traffic-free routes which traverse that node. Hence, that node is important for drivers who want to avoid traffic congestions.


Betweenness centrality in Amsterdam at 3:00 h


Betweenness centrality in Amsterdam at 14:00 h

Again, there are differences between day and night times, even though those are slightly ones. As said before, there is less traffic during the night, so there will be more important nodes by this metric at night. On the contrary, there are less important nodes during the day, because the traffic is higher and so the sum weight of the path also increases. Overall, there is a most important node highlighted all times. That one is a big area close to the city center.

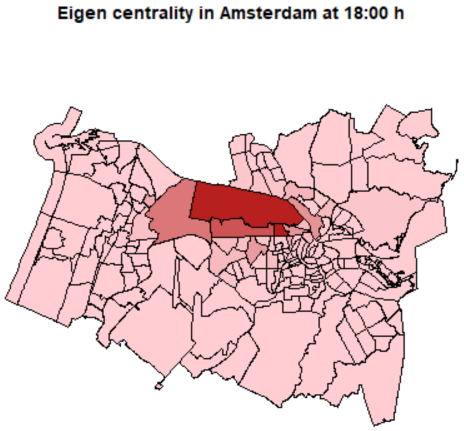
To sum up, high rated nodes by betweenness centrality are important nodes for those drivers who want to avoid traffic, and one node is highlighted over the others.

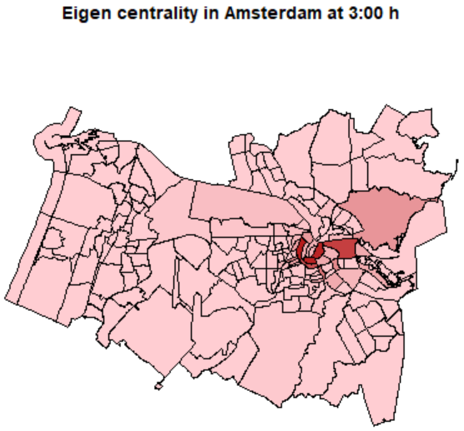
Eigenvector centrality

Eigenvector centrality (or just eigen centrality) measures the influence of a node in the network. It is similar to the Page Rank centrality, which will be analyzed later (actually, Page Rank is a variation of eigen centrality). This measure rates higher those nodes who are connected with high rated neighbors. Since this is a weighted graph, the importance of a node is proportional to the sum of weights of their edges, and their neighbors'. In other words, a node becomes more important if the traffic is dense both in that area and in the adjacent ones.

Note that this is a recursive definition: first node's neighbors are rated high by eigen centrality if the traffic is dense both in them and in their neighbors. Let A -> B -> C be a graph where node A is connected to node B, and B is connected to node C. If the traffic in C is dense, then the importance of B increases, which means that the importance of A also increases. Hence, it can be seen that all nodes indirectly connected to other nodes affect their eigen centrality.

This measure fits for our scenario, because it is expected that if the traffic is dense in an area, then it will also be dense in close areas. First, because people tend to drive to that geographical places. Second, because if an area is congested, then it is expected that people take alternative routes avoiding that area, meaning that they would drive though close areas (neighbor nodes in the graph). Hence, it is clear that an important node has an influence on their neighbors.


Eigen centrality in Amsterdam at 18:00 h


Eigen centrality in Amsterdam at 3:00 h

In this case, the most congested areas are very different depending on whether it is day or night time. As shown in the images, eigen centrality for the areas in Amsterdam at 18:00h rates high those nodes located in the Northwest of the city center. This is true for most of the day (see the correspondent GIF attached to this document). However, between 2:00h and 6:00h, this is completely different. The most congested areas are those located just in the city center.

While the amount of cars can vary depending on the time, the expected result would be that the most congested areas would remain more or less the same for all the day, even though the traffic would be denser during day time. However, in this case there is a great shift in the importance of nodes depending on the already discussed periods of time. That change happens between 1:00 and 2:00h, and no transition phase is appreciated. However, the important areas are close in both cases, so this is not a radical difference.

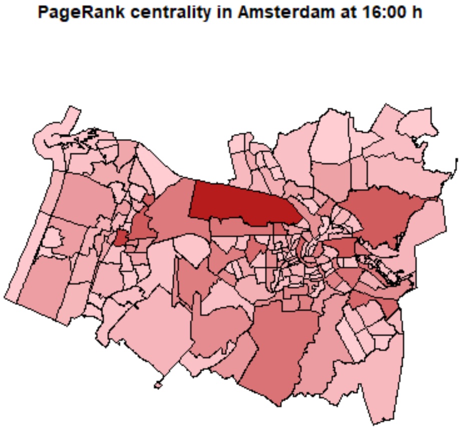
Also, note that the important nodes tend to be close from each other for a given time. This is an expected result, because the importance of a node depends on the importance of their neighbors. Hence, it is expected to find that an important node is surrounded by important neighbors.

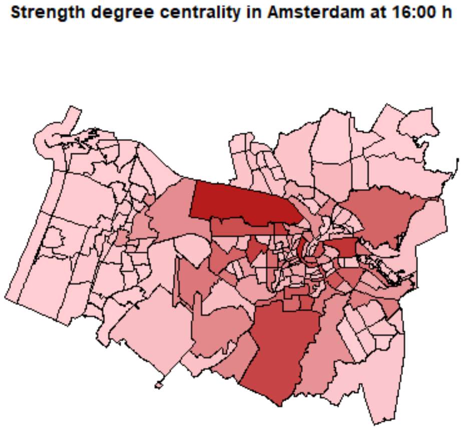
This centrality is a very good one for our scenario. Together with the strength degree centrality, eigenvector centrality is a good tool to look for congested areas.

Page Rank centrality

The last analyzed centrality is Page Rank. As said before, Page Rank is a variation of the eigenvector centrality, so it is expected that the results here would be similar to the previous ones. However, Page Rank is originaly designed for directed graphs. Since we are working with an undirected graph, then the results can be not as accurate as expected.

In the case of undirected and weighted graphs, Page Rank is supposed to behave similarly as the strength degree distribution, discussed previously in this document. The only difference is that neighbors' rates have a small effect on a given node. Recall that attached to this document there are GIFs which make the comparation easier, but here some images will be shown comparing both centralities.


PageRank centrality in Amsterdam at 16:00 h


Strength degree centrality in Amsterdam at 16:00 h

As seen in the figures, it is true that both centralities behave very similarly. The differences are very small ones, so no special discussion will be made here. The interpretation of the results for Page Rank in this case (an undirected, weighted graph) is the same one as for the strength degree centrality: the congested areas are those which get a high rate by this metric.

Communities detection

The analysis of community detection in the graph allows us to know which areas of the city show similar behavior at certain times of the day. The zones that are within the same community tend to connect with a greater probability than with zones of other communities, what, in our case, indicates which zones have similar traffic flow in a certain interval of time.

There are multiple community detection algorithms. We will only focus this analysis on the following ones: Edge-Betweenness, Fast-Greedy, Label Propagation and Walktrap. All of these algorithms take into account the weights of the edges, so they are good approaches for this case. It is worth mentioning that Spinglass and Optimal Modularity algorithms were also used during the tests. However, they were discarded: the first, because it does not work with unconnected networks, and the second, because it used too much computation time for a single graph, so using it in each of the 24 graphs would not entail finishing the analysis in a reasonable time.

Edge-Betweenness

This algorithm uses the weight of the edges of the graph to detect communities. It is based on the idea that two nodes connected by an edge with a relatively high weight means that this edge is more likely to connect two different communities than one with a low weight. The algorithm iteratively eliminates those edges that have a high weight until some criterion is reached, thus obtaining communities of nodes separated from each other.

The results obtained with this algorithm for each graph are represented in the attached file *betweenness.com.gif*. As an example, the following figure shows the different communities detected in Amsterdam at 9am. It should be mentioned that, in these images, two colors that may seem the same at first glance represent different communities. In this case the algorithm finds 15 (VER ESTO PARA PONERLO CON CODIGO!!!!!!!!!!!) different communities in the range of 9am to 10am.

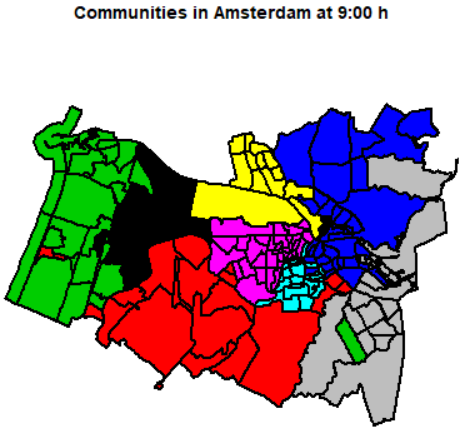


Figure 3: Betweenness comunnities from 9:00h to 10:00h

Observing the evolution of the communities detected throughout the day, it can be seen that the communities that vary the most are those farthest from the center, in the east and west, although they are not very substantial variations. This may happen because these zones are more likely to suffer big variations in traffic flow during the day. On the other hand, the communities that vary least in size correspond to central and more busy areas, with a more constant traffic flow than the outskirts.

Fast-Greedy

Fast-Greedy is an iterative algorithm that is based on optimizing the value of a quality function called modularity. The algorithm begins considering each node as an independent community. Subsequently, the communities are merged in such a way that this fusion is locally optimal, i.e. that the merge causes the greatest increase of all in the modularity. It is completed once this value can not be increased further.

The results over all the graphs can be observed in figure *fast.greedy.com.gif*. With this algorithm it can be observed that fewer (larger) communities are detected than with the previous algorithm. At the same time, the results obtained in terms of variation are similar to the ones from the previous algorithm: the sizes of the most central communities practically do not vary throughout the day, while the areas further east and west vary a little more.

Label Propagation

This is a very fast and simple algorithm. Label propagation is based on assigning one label out of k in the initial configuration. Then, iteratively each node takes the most frequent label of all its neighbours in a synchronous way until each node has one of the most frequent labels in its neighbourhood.

The results obtained from this algorithm can be seen in figure *label.prop.com.gif*. The evolution in time of the communities vary much more than with the previous algorithms. During rush hours, the city center constains multiple small communities and the zones around it also vary in size. During the rest of the time, mainly at night, there are fewer communities and the variation is not very accused. Given that the central areas are the busiest, it is possible that the differences in traffic (weights) between edges of the city center are greater at peak hours, so, for each zone near the city center, the direct contact with zones out of the

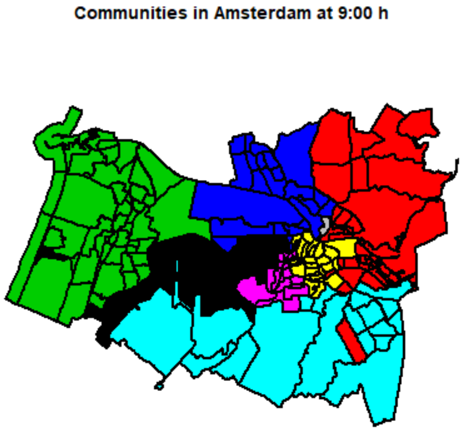


Figure 4: Fast-greedy comunnities from 9:00h to 10:00h

center with very low traffic and multiple zones inside the center with different traffic peaks can cause the formation of multiple communities in this part of the city.

Walktrap

This is the last algorithm used for detecting communities. The idea of Walktrap is that performing random walks on the graph lead to stay within the same community, since walking to other community is more unlikely due to the lower number of paths that exist among communities. This idea can be extended to weighted edges, assuming that it is more likely to walk through the edges with higher weights.

This algorithm obtains the largest number of communities of all the algorithms analyzed. The larger communities are close to the center, while in the eastern and western areas there are more and smaller communities. This can happen because near the city center the probability of following a path that leads to the zone with more traffic flow is higher than going other way, so the random walks cover a longer area when performed near the center.

Conclusion and future work

The analysis of traffic in a city can be very important to detect areas which are usually more congested, the time at which this occurs and for how long. Being able to estimate these three variables with precision would be very useful to carry out better urban planning. With this project we intend to make an approximation to this analysis using the traffic flow of Uber users as data.

Although the results obtained allow us to get an idea about how traffic in the city behaves by zones, the truth is that there are a number of restrictions that make it very difficult to perform a more robust analysis. First of all, Uber offers information about the origin and destination areas of the trips, but not of the intermediate zones that it crosses. Hence, trying to infer the route using the shortest path technique does not represent reality. The map of the city only includes zones, which cover several roads. That means that the shortest path in the graph may not be the same as the real route of the trip. That causes a great inaccuracy to perform a more precise analysis.

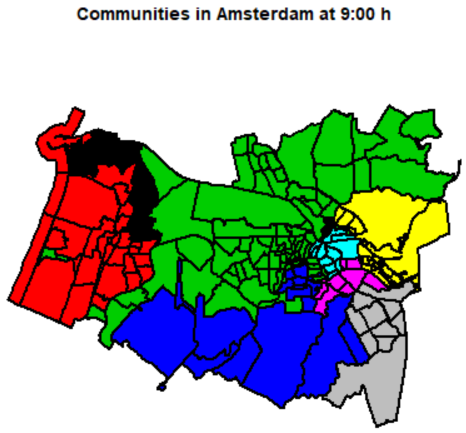


Figure 5: Label propagation comunnities from 9:00h to 10:00h

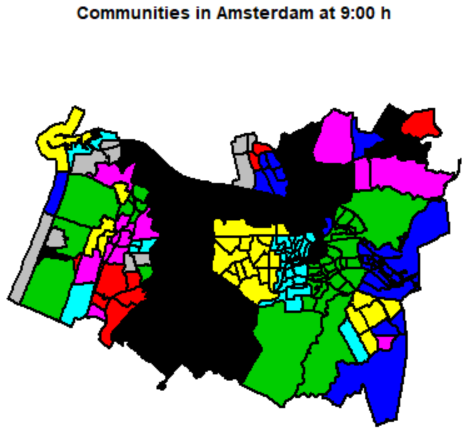


Figure 6: Walktrap comunnities from 9:00h to 10:00h

Moreover, in the graph all the nodes are treated as equal, because the size and distances in meters are not taken into account. However, areas on the map vary greatly in size, and distances are important for a driver. Suppose, for example, a case in which there are 5 areas adjacent to each other: 4 small zones and a relatively large area. If the shortest path between two of the small zones is through the other two small zones on the map, the graph will consider that the shortest route will be through the large zone, since the number of jumps would be 2 instead of 3 and. Therefore, an error would be made.

Indeed, the main problem of the presented method is the calculation of shortest paths in the graph. As said before, the route may not be the same as the real one. However, some good points about it is that it is a simple and fast method, which do not require great computing resources. An altertative for this method would be to use some API for calculating trip routes, such as Google Maps API or OSRM (Open Source Routing Machine). Using those, it the calculated route would be much more precise, and it would be necessary to analyze which zones it traverses.

Despite these drawbacks and the improvements that could be made in the analysis, the results presented in this project may coincide with reality and are valid for knowing the behavior of a city at the zone level, not only of the city of Amsterdam but of any other city that Uber offers in its datasets repository.

Code used

```r
library(rgeos)
library(igraph)
library(rgdal)
library(rgl)
library(sp)
library(ggplot2)
library(knitr)

setwd("C:\\Users\\Usuario\\TELECO\\Master Tec Teleco\\2º CURSO\\Redes Sociales y Economicas\\Project\\G
amsterdam <- read.csv("data\\amsterdam-wijk-2018-1-OnlyWeekdays-HourlyAggregate.csv", header = TRUE, sep
polys <- readOGR("data\\amsterdam_wijk.json")

#Adjacency matrix
adj_matrix <- gTouches(polys, byid = TRUE)

#Print zones
plot(polys, main = "Zones in Amsterdam", col="#f44336",border="black", lwd=2)

#Template graph: undirected and weighted (value 1 by default). Some centralities may fail for weight=0
g_original <- graph_from_adjacency_matrix(adj_matrix, weighted=TRUE, mode="undirected") %>% set_edge_at

#Calculate all shortest paths
sp <- list()
for (i in 1:nrow(adj_matrix)){
  sp[[length(sp) + 1]] <- get.shortest.paths(g_original, i)
}

#g is a list of graphs, one per hour of day
g <- list()

#Centralities:
degree.cent <- list()
degree.str.cent <- list()
closeness.cent <- list()
betweenness.cent <- list()
eigen.cent <- list()
page.rank.cent <- list()

#Communities
betweenness.com <- list()
fast.greedy.com <- list()
label.prop.com <- list()
spinglass.com <- list()
walktrap.com <- list()
optimal.com <- list()

for (hour in 1:24){
  current_data <- subset(amsterdam, hod==hour-1)
  g[[length(g) + 1]] <- g_original

  for(i in 1:nrow(current_data)) {
    trip <- current_data[i,]
    #Zone ID = position in matrix
    from <- trip$sourceid
    to <- trip$dstid

    #Path A->B->C becomes vector (A, B, B, C)
    route <- as.vector(sp[[from]]$vpath[[to]])
    EP = rep(route, each=2)[-1]
    EP = EP[-length(EP)]

    #Take edges IDs for accesing E(g[[hour]]))
    edge_ids <- get.edge.ids(g[[hour]], EP)

    #Increase weight of edges with previous IDs
    E(g[[hour]])$weight[edge_ids] = E(g[[hour]])$weight[edge_ids] + 1

  }

  #CENTRALITIES
  degree.cent[[length(degree.cent) + 1]] <- centr_degree(g[[hour]], mode = "all")
  degree.str.cent[[length(degree.str.cent) + 1]] <- strength(g[[hour]], mode = "all")
  betweenness.cent[[length(betweenness.cent) + 1]] <- betweenness(g[[hour]], directed = FALSE)
  eigen.cent[[length(eigen.cent) + 1]] <- eigen_centrality(g[[hour]], directed = FALSE)
  closeness.cent[[length(closeness.cent) + 1]] <- closeness(g[[hour]], mode = "all")
  page.rank.cent[[length(page.rank.cent)+1]] <- page_rank(g[[hour]])

  #COMUNITIES
  betweenness.com[[length(betweenness.com) + 1]] <- cluster_edge_betweenness(g[[hour]])
  fast.greedy.com[[length(fast.greedy.com) + 1]] <- cluster_fast_greedy(g[[hour]])
  label.prop.com[[length(label.prop.com) + 1]] <- cluster_label_prop(g[[hour]])
  walktrap.com[[length(walktrap.com) + 1]] <- cluster_walktrap(g[[hour]])

}
#Colors for centralities
rbPal <- colorRampPalette(c('#ffcdd2','#b71c1c'))

#Strength
png(filename="img\\degree.str.cent\\%02d.png")
for (hour in 1:24){
  Colores <- rbPal(100)[as.numeric(cut(degree.str.cent[[hour]],breaks = 100))]
  plot(polys, main = paste("Strength degree centrality in Amsterdam at ", (hour-1), ":00 h", sep=""), c
}
dev.off()
system("\"C:\\Program Files\\ImageMagick-7.0.8-Q16\\magick.exe\" -delay 80 img\\degree.str.cent\\*.png


#Degree
png(filename="img\\degree.cent\\%02d.png")
for (hour in 1:24){
  Colores <- rbPal(100)[as.numeric(cut(degree.cent[[hour]]$res,breaks = 100))]
  plot(polys, main = paste("Degree centrality in Amsterdam at ", (hour-1), ":00 h", sep=""), col=Colores
}
dev.off()
```

```r
system("\"C:\\Program Files\\ImageMagick-7.0.8-Q16\\magick.exe\" -delay 80 img\\degree.cent\\*.png img\


#Closeness
png(filename="img\\closeness.cent\\%02d.png")
for (hour in 1:24){
  Colores <- rbPal(100)[as.numeric(cut(closeness.cent[[hour]],breaks = 100))]
  plot(polys, main = paste("Closeness centrality in Amsterdam at ", (hour-1), ":00 h", sep=""), col=Colo
}
dev.off()
system("\"C:\\Program Files\\ImageMagick-7.0.8-Q16\\magick.exe\" -delay 80 img\\closeness.cent\\*.png in


#Betweenness
png(filename="img\\betweenness.cent\\%02d.png")
for (hour in 1:24){
  Colores <- rbPal(100)[as.numeric(cut(betweenness.cent[[hour]],breaks = 100))]
  plot(polys, main = paste("Betweenness centrality in Amsterdam at ", (hour-1), ":00 h", sep=""), col=Co
}
dev.off()
system("\"C:\\Program Files\\ImageMagick-7.0.8-Q16\\magick.exe\" -delay 80 img\\betweenness.cent\\*.png


#Eigen
png(filename="img\\eigen.cent\\%02d.png")
for (hour in 1:24){
  Colores <- rbPal(100)[as.numeric(cut(eigen.cent[[hour]]$vector,breaks = 100))]
  plot(polys, main = paste("Eigen centrality in Amsterdam at ", (hour-1), ":00 h", sep=""), col=Colores
}
dev.off()
system("\"C:\\Program Files\\ImageMagick-7.0.8-Q16\\magick.exe\" -delay 80 img\\eigen.cent\\*.png img\\


#PageRank
png(filename="img\\page.rank.cent\\%02d.png")
for (hour in 1:24){
  Colores <- rbPal(100)[as.numeric(cut(page.rank.cent[[hour]]$vector,breaks = 100))]
  plot(polys, main = paste("PageRank centrality in Amsterdam at ", (hour-1), ":00 h", sep=""), col=Colo
}
dev.off()
system("\"C:\\Program Files\\ImageMagick-7.0.8-Q16\\magick.exe\" -delay 80 img\\page.rank.cent\\*.png in

#Communities
png(filename="img\\betweenness.com\\%02d.png")
for (hour in 1:24){
  plot(polys, main = paste("Communities in Amsterdam at ", (hour-1), ":00 h", sep=""), col=membership(be
}
dev.off()
system("\"C:\\Program Files\\ImageMagick-7.0.8-Q16\\magick.exe\" -delay 80 img\\betweenness.com\\*.png


png(filename="img\\fast.greedy.com\\%02d.png")
for (hour in 1:24){
  plot(polys, main = paste("Communities in Amsterdam at ", (hour-1), ":00 h", sep=""), col=membership(fa
}
dev.off()
system("\"C:\\Program Files\\ImageMagick-7.0.8-Q16\\magick.exe\" -delay 80 img\\fast.greedy.com\\*.png i


png(filename="img\\label.prop.com\\%02d.png")
for (hour in 1:24){
  plot(polys, main = paste("Communities in Amsterdam at ", (hour-1), ":00 h", sep=""), col=membership(la
}
dev.off()
system("\"C:\\Program Files\\ImageMagick-7.0.8-Q16\\magick.exe\" -delay 80 img\\label.prop.com\\*.png in


png(filename="img\\walktrap.com\\%02d.png")
for (hour in 1:24){
  plot(polys, main = paste("Communities in Amsterdam at ", (hour-1), ":00 h", sep=""), col=membership(wa
}
dev.off()
system("\"C:\\Program Files\\ImageMagick-7.0.8-Q16\\magick.exe\" -delay 80 img\\walktrap.com\\*.png img
```