



# Finding the optimal location for a new parking lot

COURSERA CAPSTONE PROJECT

# Introduction

## ► Background

- This project takes place in the city of Grenoble (capital of french Alpes).
- People refrain to go shopping or dining down town because of the difficulty to find a parking lot. They prefer to go outside of the city for this reason.
- Owners of shops and restaurants are starting to complain to the city mayor because the business is suffering from this situation.

## ► Stakeholders

- Owners of down town venues are impacted because the lack of parking lots is pushing customers outside of the city and they are losing money.
- The city of Grenoble's administration is interested because it is its duty to make sure all venues of the city are easily accessible

## ► Objective

- Determine the best place to construct a new underground parking lot considering the density of the different areas of the city in terms of popular venues and the location of the currently existing parking lots

# Data

## ► Dataset 1

- Dataset from Foursquare API
- Provides the top 100 venues of Grenoble along with their categories and location

## ► Dataset 2

- Dataset from Grenoble city web site
- Provides the location of all currently existing parking lots of the city

Dataset 1

	name	categories	lat	lng
0	Jardin du thé	Tea Room	45.188788	5.727536
1	Place Victor Hugo	Plaza	45.188994	5.724607
2	L'Ardoise	French Restaurant	45.190558	5.725346
3	Okko Hotels Grenoble Jardin Hoche	Resort	45.184859	5.726299
4	Amorino	Dessert Shop	45.191037	5.727638

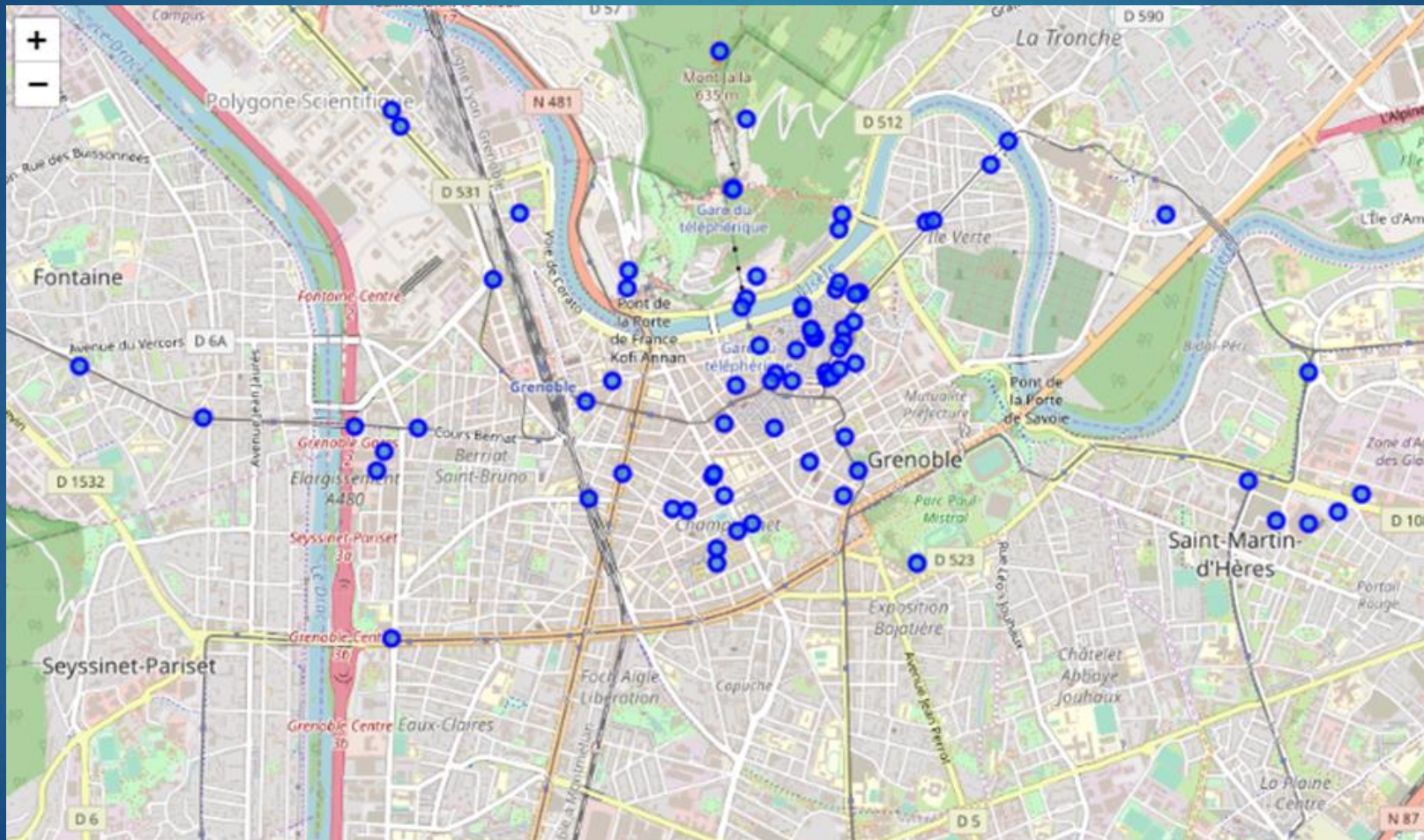
Dataset 2

_id	CODE	LIBELLE	ADRES...	TYPE	TOTAL	type	id	lon	lat
1	EFF_PK...	BERRIA...	RUE DE...	PKG	578	PKG	EFF_PK...	5.716033	45.18878
2	EFF_PK...	EUROP...	2, AVEN...	PKG	1055	PKG	EFF_PK...	5.712008	45.191959
3	PVP_PK...	HOICHE	RUE FR...	PKG	677	PKG	PVP_PK...	5.726327	45.185748
4	EFF_PK...	LAFAYE...	RUE RA...	PKG	311	PKG	EFF_PK...	5.729321	45.190778
5	PVP_PK...	MUSÉE	50, AVE...	PKG	770	PKG	PVP_PK...	5.732239	45.194399
6	PVP_PK...	PHILIPP...	PLACE ...	PKG	519	PKG	PVP_PK...	5.725235	45.191835
7	EFF_PK...	TERRAY	33 BIS, ...	PKG	106	PKG	EFF_PK...	5.712443	45.185621
8	PVP_PK...	VERDUN	PLACE ...	PKG	110	PKG	PVP_PK...	5.732018	45.18897
9	QPA_PK...	CHAVANT	17, BD ...	PKG	394	PKG	QPA_PK...	5.731463	45.185612



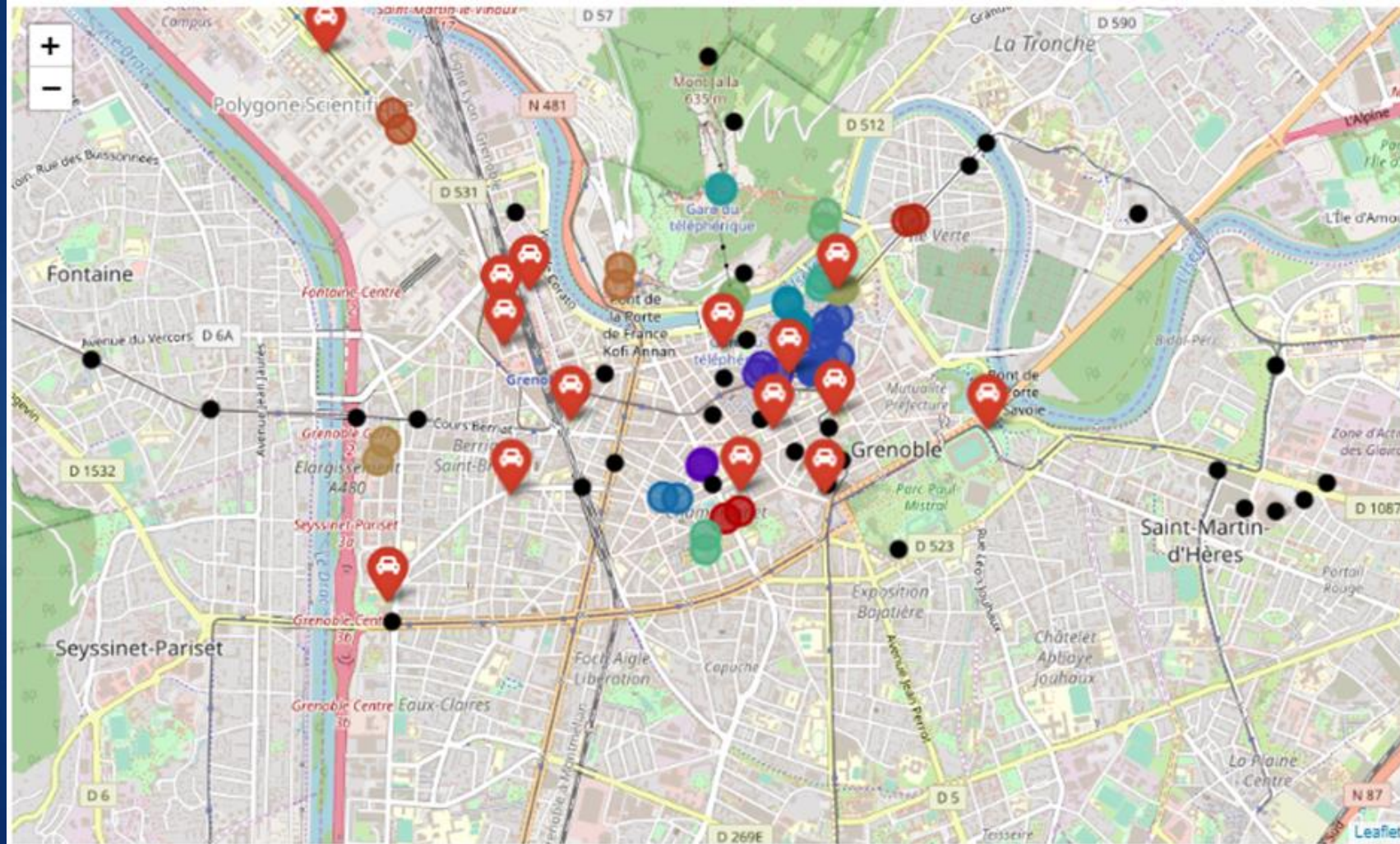
# Methodology

- Folium map showing the top venues of Grenoble from Foursquare API





# Methodology



- DBSCAN density-based clustering of top venues (colored circles)
- Removal of outliers (black dots)
- Addition to the map of parking lots from dataset 2 (red car icons)

# Methodology

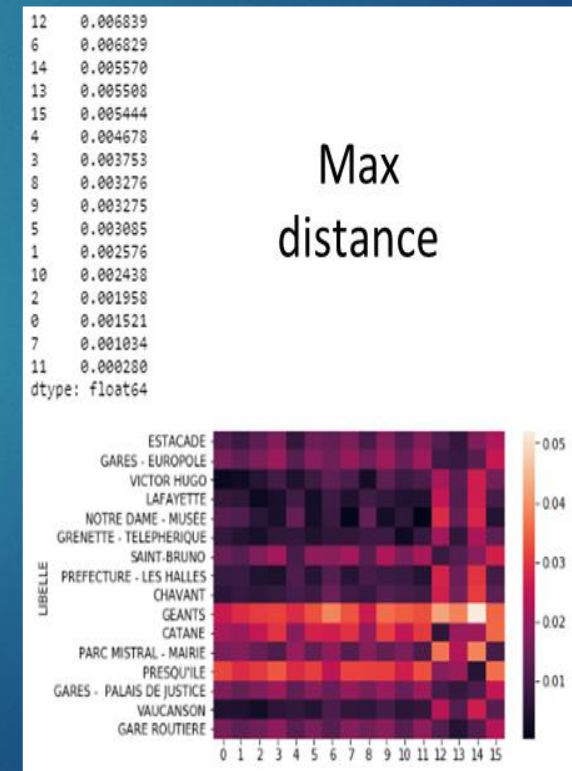
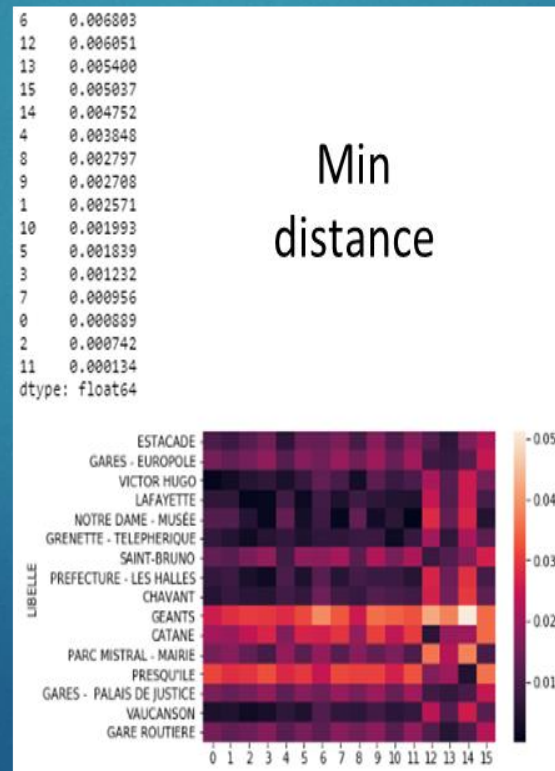
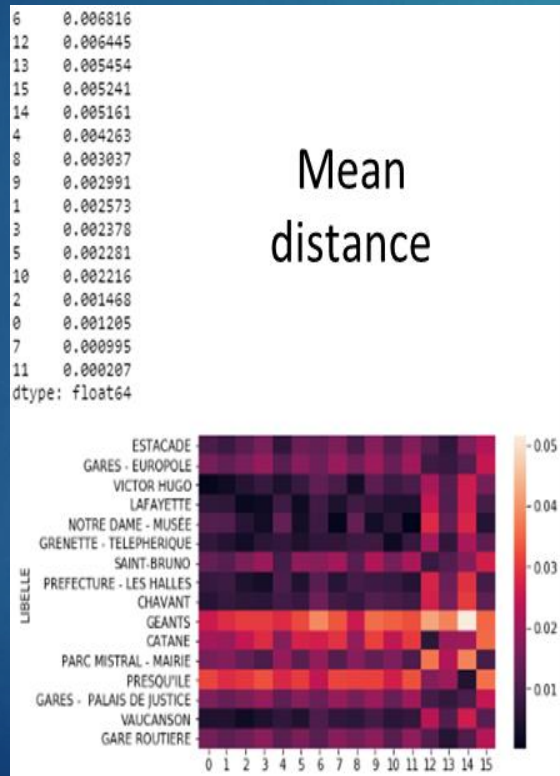
- Computation of euclidean distances from all venues to all existing parking lots

	0	1	2	3	4
LIBELLE					
ESTACADE	[0.010988811909196714, 0.010256769090738317]	[0.008190057029457626, 0.00821529824562055]	[0.01182214704948849, 0.012701893328585687, 0....	[0.014684040527354189, 0.016051330807739503, 0...	[0.006520639781295689, 0.007292746094546028]
GARES - EUROPOLE	[0.01595701498417506, 0.01528398021329736]	[0.013037646612879865, 0.01303861434517998]	[0.01565691119585124, 0.01661369796391712, 0.0...	[0.01854080049910506, 0.019571259534978076, 0....	[0.011622396536212594, 0.012369489922641672]
VICTOR HUGO	[0.0008891416155753296, 0.0015209362324787783]	[0.00257050064217306, 0.0025761912001632573]	[0.0054488478551531876, 0.005499529585897249, ...	[0.006819070629408433, 0.008823957819029251, 0...	[0.0046779541637528566, 0.003848416964458193]
LAFAYETTE	[0.006645740356982084, 0.007363580507160417]	[0.006665675849305872, 0.006538287412896047]	[0.0017030547347651076, 0.0007423400511354474, ...	[0.001255626053944763, 0.0030522353573527003, ...	[0.009317354413987396, 0.00869131042475026]
NOTRE DAME - MUSÉE	[0.011238068726585922, 0.011995607723742445]	[0.011229538320205507, 0.01109501101084856]	[0.005698748087748, 0.005157548602985889, 0.00...	[0.0036995423134355988, 0.0016884094763119457, ...	[0.013839745781103637, 0.013265070794577637]



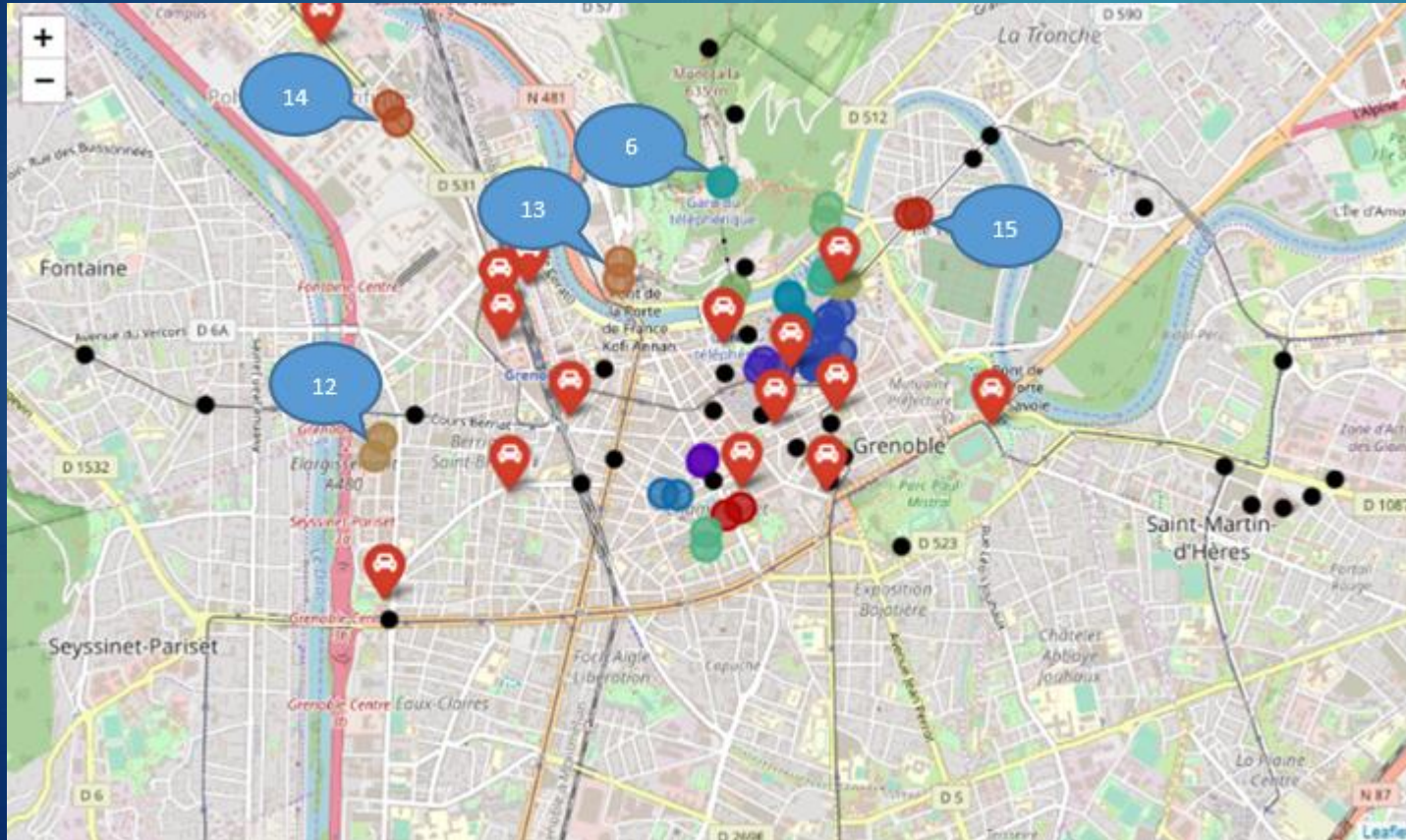
# Methodology

- ▶ Computation of aggregated distances from clusters to existing parking lots
- ▶ Use of 3 different distance metrics to rank the clusters according to their distance to the nearest parking lot
- ▶ Visualization using Seaborn heatmaps



# Results

- ▶ The 3 different distance metrics give similar results although the ranking of the top 5 clusters in terms of distance to the nearest parking lot is slightly different
- ▶ Clusters 6 and 13 should be excluded for geographical reasons independent of this analysis



- ▶ Our recommendation is to choose the areas of clusters 12, 14 or 15 to build a new parking lot. These areas are pretty dense in terms of popular venues and the nearest parking lot is quite further away compared to the other clusters.



# Discussion and conclusion

- ▶ Difficulties encountered:
  - ▶ The number of venues returned by the Foursquare API is quite poor compared to large US cities. Having more venues would certainly help to identify the high density clusters in terms of popular venues leading to the need of parking lots.
- ▶ Ideas for further improvement of the model:
  - ▶ Use additional features about the existing parking lots like their total capacity in terms of parking spaces
  - ▶ Use additionnal datasets like the location of all bus and tramway stations as the need of parking lots is certainly less relevant in areas that are well served by public transports

The background of the slide features a dark blue field filled with numerous bright blue, diagonal light streaks that create a sense of motion and depth. In the top right corner, there is a solid yellow rectangle.

# Thank you!

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