Politecnico di Torino

Department of Electronics and Telecommunications

Department of Telecommunications, Electronics and Physics

ICT for SMART MOBILITY

Laboratory Report

Laboratory 2

Academic Year 2025/2026

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1 Analysis of Carsharing Data and OD Matrix for Torino

In the first part of the analysis, car-sharing booking records for the city of Turin are examined to construct an Origin–Destination (OD) matrix. Each trip is assigned to specific urban zones using geospatial filters. A temporal filter was applied to the dataset, however, no data points were removed, and no outliers were detected.

1.1 OD Matrix Computation and Visualization

The analysis started by loading the zoning data for Turin from the `TorinoZonescol.geojson` file, which divides the city into different zones based on their geographic boundaries.

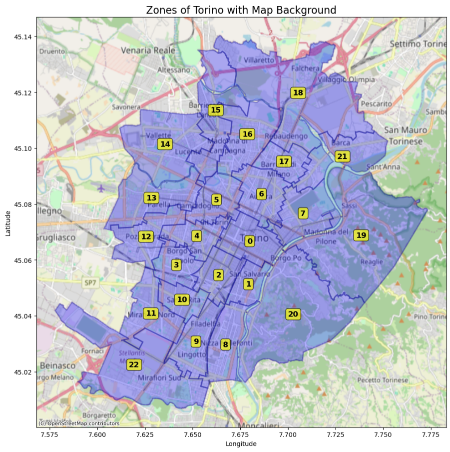


Figure 1: Numbered of zones examined in Turin

Booking records were then selected from the `ictts_PermanentBookings` collection in MongoDB. To focus only on meaningful trips, a geographic filter was applied: a trip was considered valid only if both its starting location (`init_loc`) and ending location (`final_loc`) were located within one of the predefined city zones. This check was performed using a `$geoWithin` query, which verifies whether a point lies inside a given area.

After filtering the data, a 23×23 Origin–Destination (OD) matrix was created to count the number of trips between each pair of zones (see Figure 12). OD matrix were normalized using this equation:

$$\text{Normalized Value} = \frac{\text{Value}}{\sum_{i,j} \text{Value}_{ij}}. \tag{1}$$

1.2 OD Matrices for Different Time Periods

1.2.1 Weekdays vs Weekends & Days vs Nights

The analysis of carsharing activity using Car2Go and Enjoy in Torino reveals clear differences in trip flows between zones on weekdays and weekends. By contrasting these patterns, it becomes possible to understand how mobility demand varies across days, supporting better planning by identifying peak usage times and zones with higher activity. For this part of the study, the comparison is between weekdays against weekend.

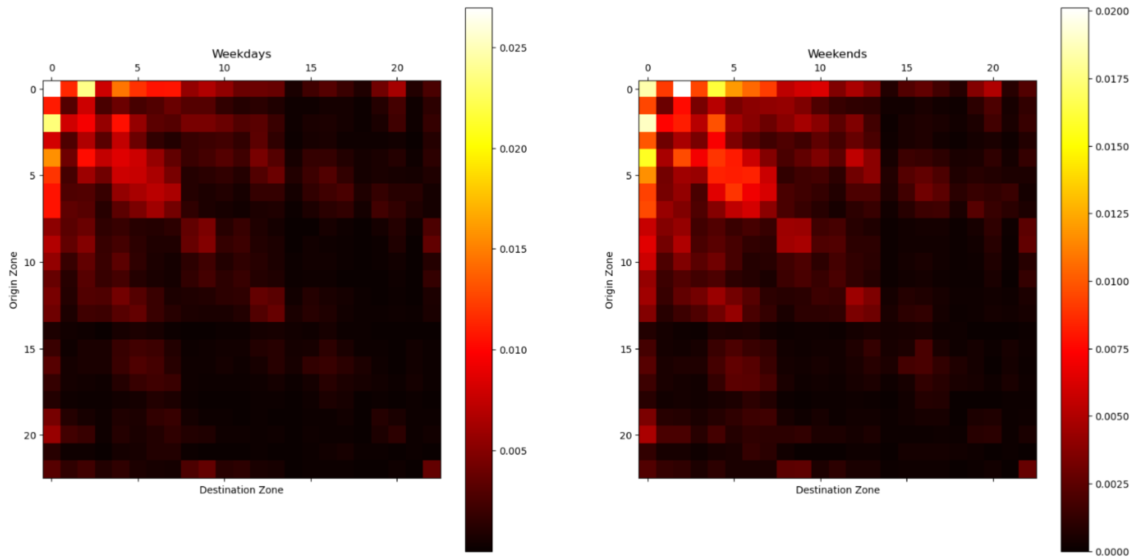


Figure 2: OD Matrices for Car Sharing Trips in Torino: weekdays and weekends

Figure 2 presents the normalized OD (Origin–Destination) matrices for weekdays and weekends, where lighter colors correspond to stronger trip flows. During weekdays the pattern is quite well distributed, with trips in the center, this leads probably to the presence of different workplaces in the center of the city. During weekends the pattern shifts numerically toward areas associated with leisure and recreation, like zone 5 which is the center of the city with all shops and coffees, lighter color means more movements towards these zones, for example is possible to see a lot of trips to San Salvario (zone 3), the young center of the city with a lot of pubs, is possible to see all the columns linked to the center with a lighter color. This change in increasing of trips towards zones 3,4,5 and 6 is likely linked to weekend social activities, outings, and reduced work-related travel.

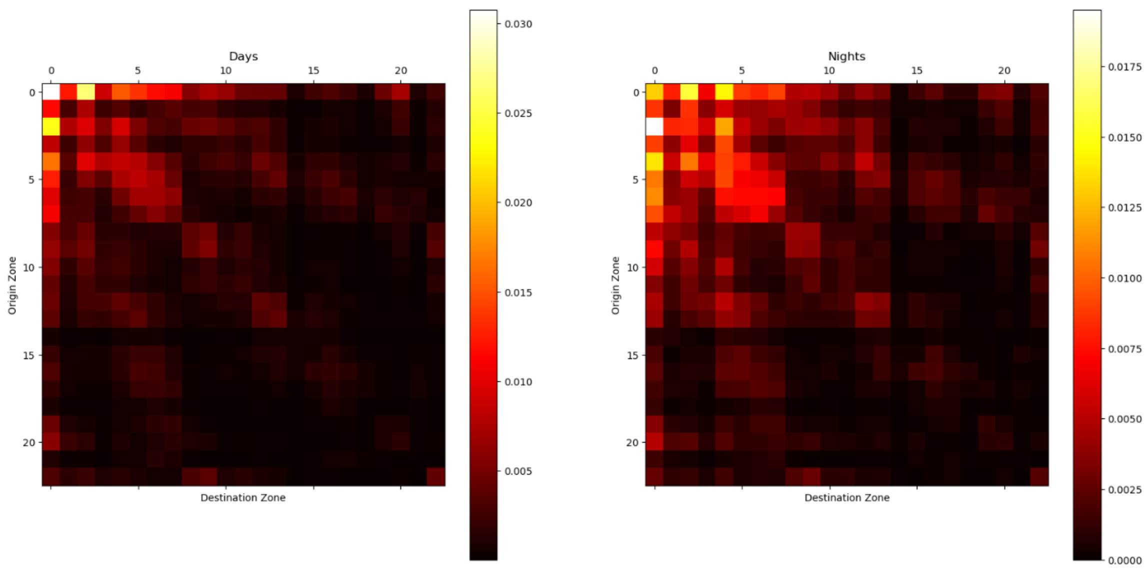


Figure 3: OD Matrices for Car Sharing Trips in Torino: days vs nights

Figure 3 shows the difference between the day time and the night time, also in this case is clear that during night we have peaks related to the nightlife, all zones in the center of the city looks lighter, mainly from zone 3 to zone 7. Similar consideration can also be found in the comparison between Sunday vs Monday rentals, in which during Sundays city center zones looks lighter (Figure 13).

1.2.2 Two Different Weeks

The presented OD matrices analyze weekday travel patterns for two weeks: September 5–12, 2017, and October 24–31, 2017. The normalized OD matrices for each week are shown below.

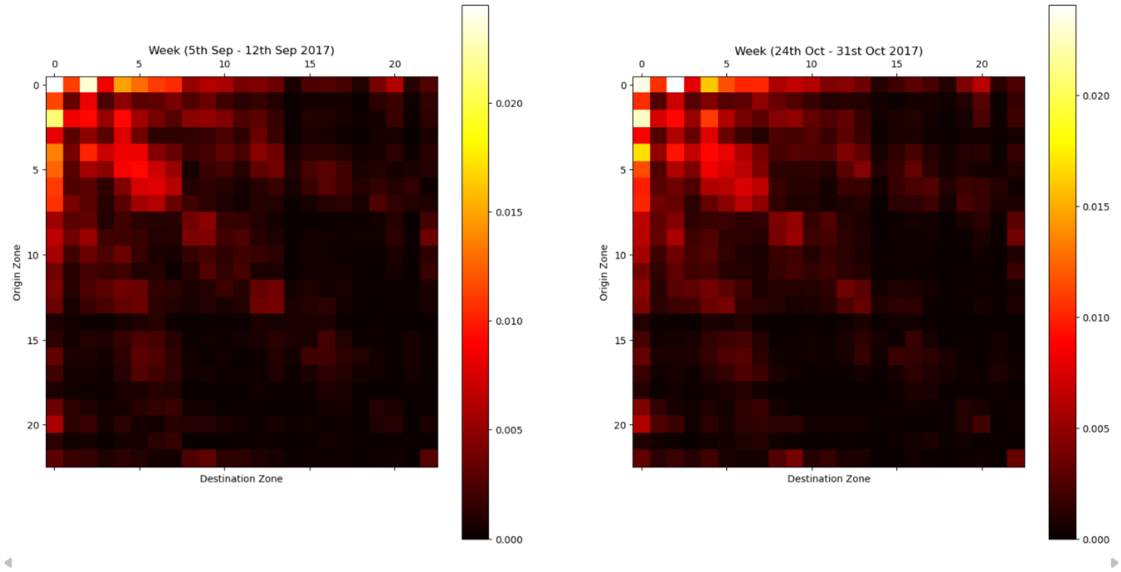


Figure 4: OD matrices for Car Sharing Trips in Torino: 5-12 Sep 2017 vs 24-31 Oct 2017

A comparison of the two OD matrices shows clear differences in mobility patterns. The average normalized values are slightly reduced in Week 2, which may suggest a general decline in travel demand or a change in commuting habits. Additionally, Week 2 displays a narrower spread of values for several origin–destination pairs, indicating more uniform travel behavior than in Week 1. Such variations may stem from seasonal factors, local events, or shifts in daily routines.

In both matrices, the highest values correspond to a few OD pairs with particularly strong travel flows, revealing key zones of concentrated activity. Recognizing these patterns is essential for tracking how mobility demand changes over time and for informing more effective transportation planning.

1.3 OD Matrices for Car2GO and Enjoy

In this part of the analysis, the Car2Go and Enjoy services were observed over different time periods. A comparison between daytime and nighttime usage is shown in Figure 5 for Enjoy and in Figure 6 for Car2Go. Comparing the OD matrices of Enjoy and Car2Go shows that Enjoy is more widely used across the city, as indicated by a lighter OD matrix extending across many zones outside the city center. The comparison continues between weekdays and weekends in the appendix (Figure 14, Figure 15).

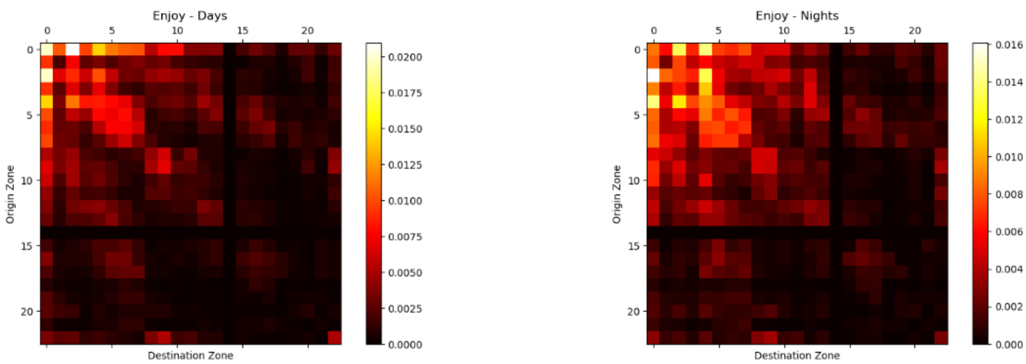


Figure 5: OD Matrices for Enjoy Car sharing Trips in Torino: days vs nights

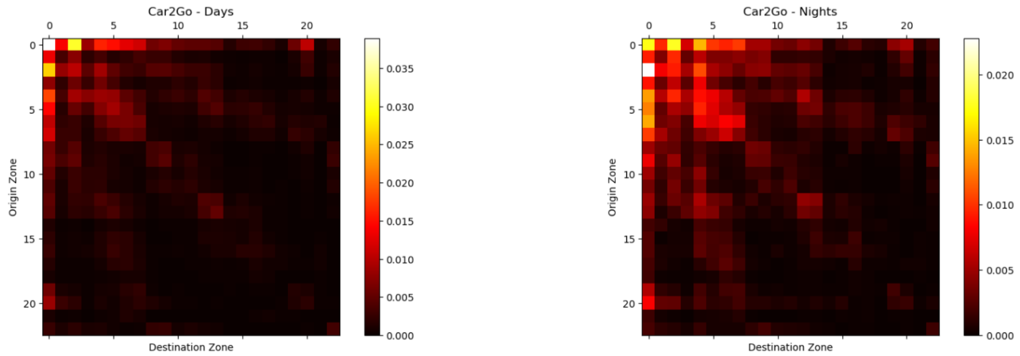


Figure 6: OD Matrices for Car2Go Car sharing Trips in Torino: days vs nights

2 Similarity Metrics for OD Matrices

This section evaluates D-1 (Manhattan), D-2 (Euclidean), D-inf (Maximum) and A (spectral) distances to measure similarity between normalized OD matrices from Car2Go, Enjoy, and other scenarios. These distances are defined as follows:

$$\boldsymbol{D_1(a,b)} = \sum_{i=1}^{n} |a_i - b_i|\,, \quad \boldsymbol{D_2(a,b)} \;\; = \sqrt{\sum_{i=1}^{n}(a_i - b_i)^2}\,, \quad \boldsymbol{D_\infty(a,b)} = \max_{i=1,\ldots,n} |a_i - b_i|\,, \quad \|\boldsymbol{A}\|_{\boldsymbol{2}} \;\; = \sqrt{\lambda_{\max}(A^\top A)}\,. \tag{2}$$

These metrics capture cumulative, squared, and maximum deviations. D_1 is recommended for its balance and interpretability. The table below summarizes the results for five scenarios:

Table 1: Comparison of similarity metrics under different scenarios.

Scenario	**D1**	**D2**	**D∞**	**Spec.**
Day Time vs Night Time	0.2467	0.0270	0.0176	0.0236
Weekday vs Weekends	0.1515	0.0142	0.008	0.0115
Car2Go vs Enjoy (Day Time)	0.3074	0.0304	0.0191	0.0269
Car2Go vs Enjoy (Night Time)	0.3322	0.0245	0.0088	0.0182
Week Sep vs Week Oct	0.1573	0.0103	0.0032	0.0056
31st Oct 2017 vs 5th Sep 2017	0.4638	0.0339	0.0134	0.0224

Table 1 summarizes the behavior of the four distance metrics across all scenarios.

The comparison between daytime and nighttime shows moderate dissimilarity: the Manhattan and Euclidean distances are the highest in the table, indicating structural changes between daytime and nighttime mobility patterns, likely reflecting a shift from commuting-related flows to leisure or residential movements.

When comparing weekdays with weekends, all distance metrics decrease, revealing that weekend mobility patterns are more similar to weekday ones than those observed in the daytime–nighttime comparison. This suggests that daily activity structures, although reduced in intensity, retain a similar spatial distribution during weekends.

The comparison between Car2Go and Enjoy exhibits higher distances, reflecting marked differences in user bases and service coverage. The Euclidean, maximum, and spectral distances further confirm distinct OD usage profiles between the two operators.

The two-week comparison (September vs. October) indicates strong temporal stability in aggregated OD patterns over longer periods, with mobility structures remaining highly consistent across months.

Finally, the comparison between specific days (31 Oct vs. 5 Sep) shows the largest dissimilarity, suggesting the presence of strong day-to-day fluctuations that are smoothed out when considering weekly trip distributions.

3 Analysis of IMQ and UnipolTech data for Torino

IMQ and UnipolTech data for the city of Torino are analyzed to derive the OD matrix, and the similarity using the metrics of the previous task is:

$$\boldsymbol{Manhattan(D-1)} = 0.547927\,, \quad \boldsymbol{Euclidean(D-2)} = 0.054731\,, \quad \boldsymbol{Maximum(D-inf)} = 0.021646 \tag{3}$$

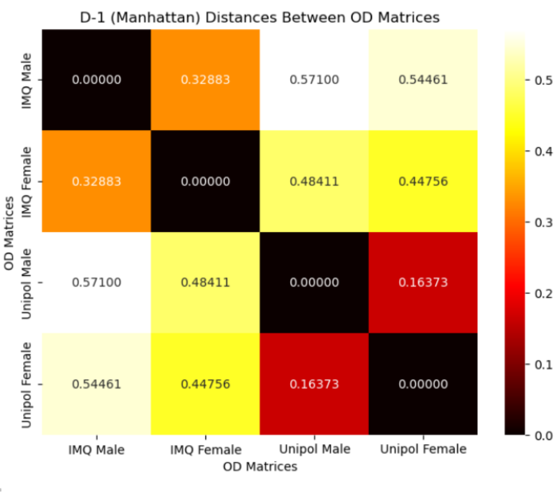
3.1 People with Similar Profiles Analysis

A comparison of the Origin–Destination (OD) matrices from the IMQ and UnipolTech datasets using the D-1 (Manhattan) similarity metric in Figure 7 shows that, although users with similar demographic or functional profiles present some moderate similarities, the strongest consistency always appears within each dataset, not across them.

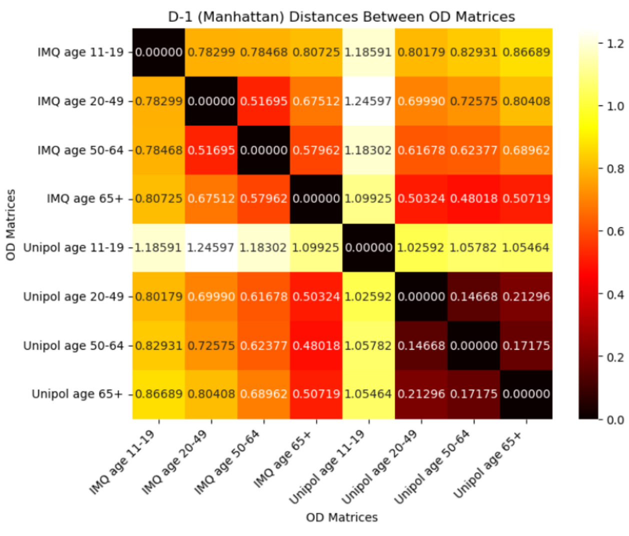
For example, *IMQ Male* vs. *IMQ Female* yields a much smaller distance (~ 0.33) compared to *IMQ Male* vs. *Unipol Male* (~ 0.57). Likewise, IMQ age groups display closer internal similarity relative to any cross-dataset pair. This pattern indicates that profile similarity does not fully translate into behavioural similarity across datasets.

The largest Inconsistencies occur between the most distinct demographic groups across datasets. For instance, IMQ users aged 11–19 differ substantially from Unipol users of the same age group (distance = 1.18). This suggests that differences in data collection context, population type, and trip purposes strongly influence the resulting mobility patterns.

Overall, while demographic categories (gender, age, purpose, commercial vs. non-commercial) retain some explanatory value, the dataset itself remains the dominant factor, meaning that individuals with "similar profiles" behave similarly within the same dataset, but not necessarily across different datasets such as IMQ and UnipolTech. Therefore, The appendix includes Unipol,IMQ OD and the comparison of other distances(D-inf and D-2)



(a) OD matrix Unipol/IMQ related to gender



(b) OD matrix related to age groups

Figure 7: Manhattan Distance For Male-Female and Age Group

3.2 Gender with greater differences in behaviour across age groups IMQ

From the distance values in the table, women show larger differences in mobility behaviour across age groups than men. This is visible across all three metrics (D-1, D-2, and D-inf): For every age-pair comparison, the female distances are consistently higher than the male distances for the same two age groups.

The largest behavioural change in the entire dataset occurs for women aged 11–19 vs. 65+ with a D-1 value of 0.905279.Men show their maximum change across the same age groups, but the value (0.807247) is smaller.

These results suggest that women's mobility behaviour evolves more significantly as they age, while men's mobility patterns remain comparatively more stable across life stages.

In other words, female mobility varies more across age, whereas male mobility is more consistent from one age bracket to another.

Table 2: Distance Gender–Age Comparisons.

Gender	Age Group 1	Age Group 2	D-1	D-2	D-inf
Male	11–19	20–49	0.782993	0.051432	0.012837
Male	11–19	50–64	0.784683	0.057447	0.021511
Male	11–19	65+	0.807247	0.069179	0.026411
Male	20–49	50–64	0.516950	0.036412	0.012766
Male	20–49	65+	0.675122	0.061495	0.021943
Male	50–64	65+	0.579617	0.050709	0.022469
Female	11–19	20–49	0.743353	0.059710	0.020027
Female	11–19	50–64	0.842493	0.066739	0.025719
Female	11–19	65+	0.905279	0.085466	0.033935
Female	20–49	50–64	0.474796	0.035164	0.010676
Female	20–49	65+	0.559627	0.052934	0.020255
Female	50–64	65+	0.541398	0.045011	0.016747

3.3 IMQ Users More Likely to Use Car2GO and Enjoy

The comparison between IMQ users and the OD matrices of Car2Go and Enjoy using the D-1, D-2 and D-inf distances reveals clear and consistent behavioural patterns across demographic groups. For Car2Go, the closest match is obtained for male users aged 20–49, who achieve the lowest dissimilarity values across all distances (D-1 = 0.6722, D-2 = 0.0544, D-inf = 0.0188), followed by men aged 50–64 and women aged 20–49. This indicates that Car2Go's mobility structure aligns most strongly with working-age adults, with a noticeable male dominance in similarity strength. In contrast, Enjoy shows the highest similarity with both men and women aged 20–49, with D-1 values of 0.6741 and 0.7751 respectively. Although Enjoy maintains a similar adult-user profile, its similarity scores are more balanced across genders, suggesting a more inclusive and diversified user base than Car2Go. Across all age groups, women consistently show higher dissimilarity than men for Car2Go, while Enjoy exhibits a reduced gender gap, indicating that women's mobility behaviour aligns more closely with Enjoy's OD patterns. Overall, the results show that Car2Go best reflects male adult mobility behaviour, whereas Enjoy captures a broader and more gender-balanced segment of the population, particularly within the 20–49 age range.

Gender	**Age Group**	**Platform**	**D-1**	**D-2**	**D-inf**
male	11–19	Car2Go	0.9906538	0.0748558	0.0168201
male	11–19	Enjoy	0.9781858	0.0702806	0.0141345
male	20–49	Car2Go	0.6722109	0.0544453	0.0187956
male	20–49	Enjoy	0.6741020	0.0493725	0.0151879
male	50–64	Car2Go	0.7695887	0.0640014	0.0254829
male	50–64	Enjoy	0.7835397	0.0633979	0.0249497
male	65+	Car2Go	0.9284343	0.0904636	0.0284661
male	65+	Enjoy	0.9597933	0.0889551	0.0289996
female	11–19	Car2Go	0.8985716	0.0738707	0.0325104
female	11–19	Enjoy	0.9171258	0.0714945	0.0338812
female	20–49	Car2Go	0.7370865	0.0684142	0.0265992
female	20–49	Enjoy	0.7750980	0.0679756	0.0265036
female	50–64	Car2Go	0.8395558	0.0757492	0.0220400
female	50–64	Enjoy	0.8470544	0.0719232	0.0215517
female	65+	Car2Go	0.9553166	0.0983795	0.0295372
female	65+	Enjoy	0.9757471	0.0978632	0.0308556

Table 3: Distance IMQ users - Carsharing

3.4 All Dataset Comparison

The mobility patterns, represented by Origin-Destination (OD) matrices, were compared across three datasets: IMQ, UnipolTech, and CarSharing. The greatest similarity was found between IMQ and UnipolTech (Manhattan distance: 0.5479), suggesting comparable user behaviors. The IMQ and CarSharing comparison showed moderate dissimilarity (distance: 0.6779), but patterns were still broadly similar. However, the largest difference was observed between UnipolTech and CarSharing (distance: 0.9107), indicating markedly different mobility dynamics. These variations underscore the influence of user demographics, travel intent, and geographical scope on observed mobility patterns.

Table 4: Distance: All datasets.

Comparison	Manhattan (D-1)	Euclidean (D-2)	Maximum (D-inf)
IMQ vs Unipol	0.5479	0.05473	0.0216
IMQ vs CarSharing	0.6779	0.0583	0.01875
Unipol vs CarSharing	0.9107	0.0962	0.02966

4 Alternative Zone Division Methods for Mobility Analytics in Turin

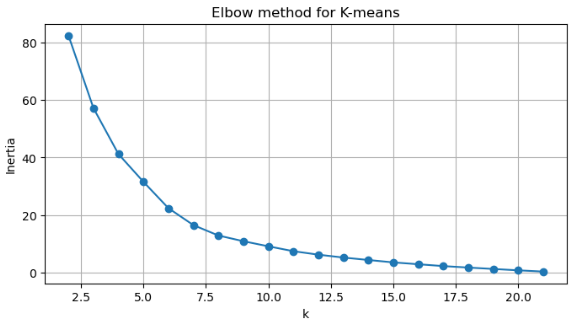
The existing subdivision of Turin into fixed quarters is simple to apply but may fail to capture the full complexity of mobility flows within the city. More advanced data-driven approaches—such as K-Means or Hierarchical Clustering—enable the creation of zones that emerge directly from observed travel behavior. By grouping areas according to trip intensity, spatial proximity, and movement patterns, these clustering methods produce a more flexible and realistic zoning structure that better reflects the city's actual mobility dynamics.

4.1 K-Means Clustering

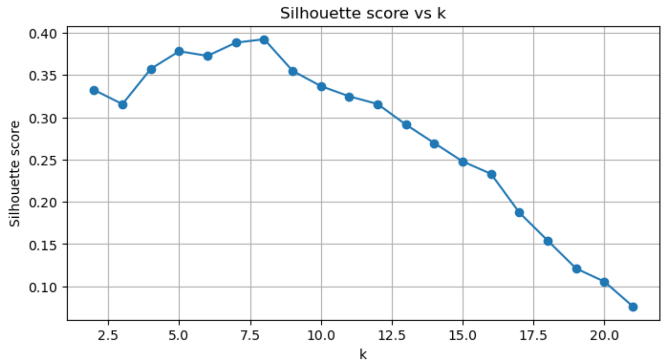
The K-means clustering is based on a multidimensional representation of each zone combining spatial information (longitude and latitude of the centroid) and mobility indicators from both datasets: CarSharing trip departures and arrivals (`cs_out`, `cs_in`) and UnipolTech trip departures and arrivals (`unipol_out`, `unipol_in`). All features were standardised to ensure a balanced contribution to the clustering process.

4.2 Choice of the Number of Clusters (k)

The optimal number of clusters was identified through the Elbow Method (Fig. 8a) and Silhouette Scores (Fig. 8b). Inertia shows diminishing improvements beyond $k = 8$, while silhouette values peak between $k = 5$ and $k = 8$, indicating that $k = 8$ provides a good balance between compactness and separation.



(a) Elbow Method



(b) Silhouette Method

Figure 8: Methods for selecting the number of clusters.

4.3 Clustering the City with $k = 8$

With $k = 8$, K-means groups zones according to similarities in both spatial position and mobility behaviour. The resulting clusters (Fig. 9) show distinct demand profiles. Cluster 0 represents the highest-activity areas, with $\texttt{cs\_out} = 35991$, $\texttt{cs\_in} = 36115$, $\texttt{unipol\_out} = 25836$, and $\texttt{unipol\_in} = 25776$, clearly identifying major mobility hubs. In contrast, Cluster 2 exhibits low demand ($\texttt{cs\_out} \approx 2479$, $\texttt{unipol\_out} \approx 3098$), while Cluster 7 shows low carsharing activity but moderate Unipol inflow ($\texttt{unipol\_in} \approx 14455$). These differences confirm that the clustering captures meaningful behavioural structures across the city. The cluster labels were then mapped back onto the geographic shapefile to obtain a mobility-driven zoning.

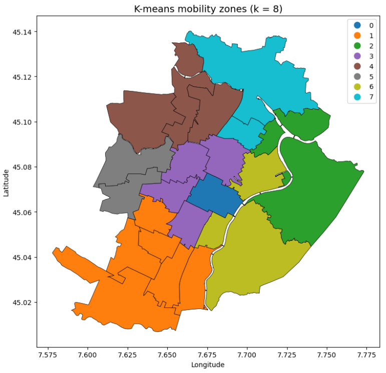


Figure 9: Mobility-based zoning of Turin for $k = 8$.

Clust.	cs_out	cs_in	unipol_out	unipol_in
0	35991.0	36115.0	25836.0	25776.0
1	7771.2	7753.7	21872.5	21789.2
2	2479.5	2519.5	3098.0	3117.0
3	17594.8	17617.8	25164.8	25118.0
4	3458.0	3435.7	20096.3	20079.3
5	7678.5	7636.0	29267.5	29318.5
6	9462.3	9479.3	12870.7	12848.0
7	2529.5	2484.5	14356.0	14455.5

Table 5: Cluster-wise Mobility Flows for CarSharing and UnipolTech.

5 Comparison of Trip Generation and Trip Distribution for UnipolTech and CarSharing

Continuous densities for trip generation and trip distribution were estimated for UnipolTech and CarSharing using kernel density estimation. In both datasets, origin and destination densities are strongly concentrated in the central area of Turin, confirming the role of the city center as the main mobility hub. The similar spatial patterns of origins and destinations indicate predominantly short-distance trips.

Bandwidth selection based on log-likelihood and train–validation analysis ensures robust density estimates. Compared to CarSharing, UnipolTech exhibits more compact and smoother density surfaces, reflecting more regular mobility behavior, while CarSharing shows a wider spatial spread, indicating greater flexibility in trip patterns.

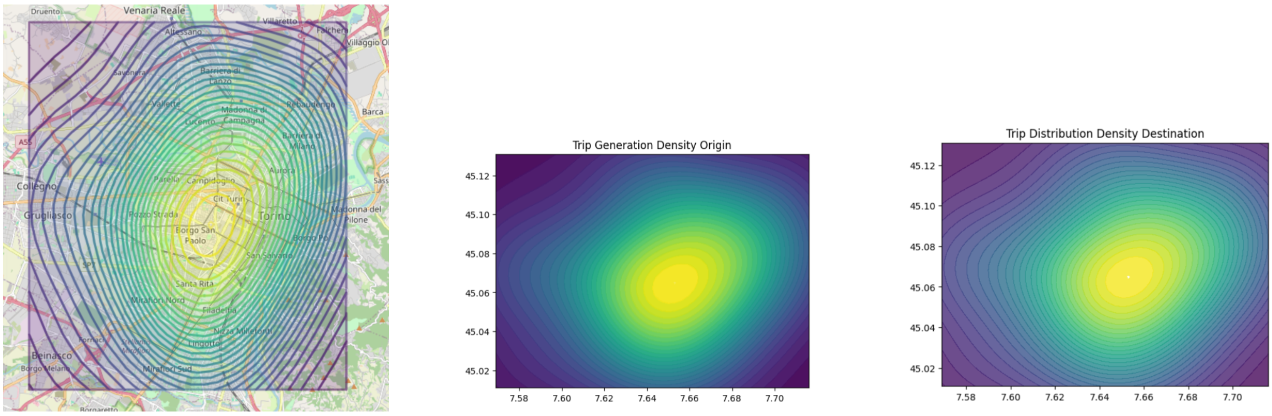


Figure 10: Contour Plot in Turin, Travel Generation Density for Origins, and Travel Generation Density for Destinations for the Unipol Database.

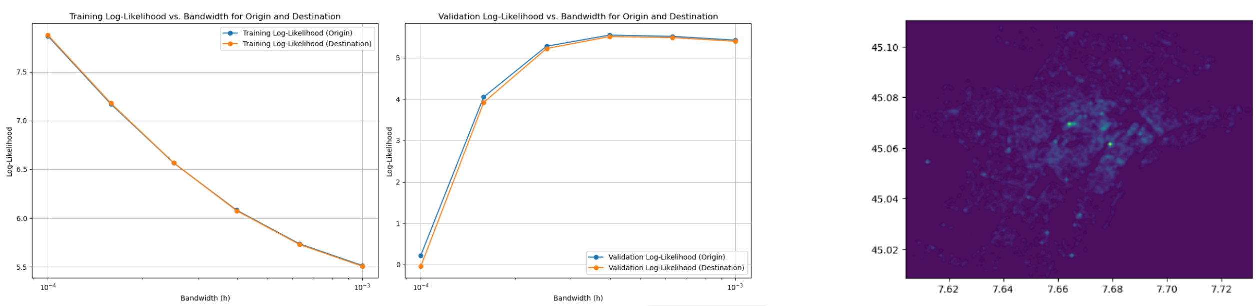


Figure 11: Comparison of Destinations Density, Log-Likelihood Plots, and Origins Density for CarSharing Database.

6 Appendix

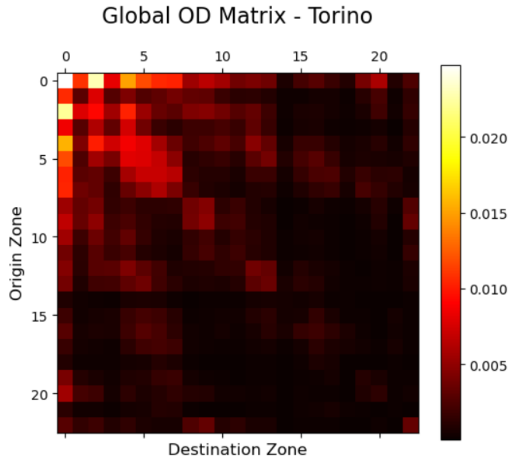


Figure 12: Global OD Matrix for Car sharing Trips in Torino

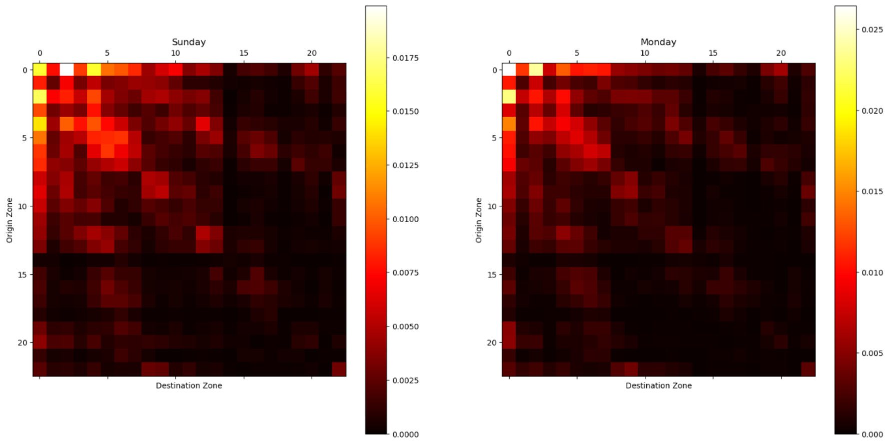


Figure 13: OD Matrices for Car sharing Trips in Torino: Sunday vs Monday

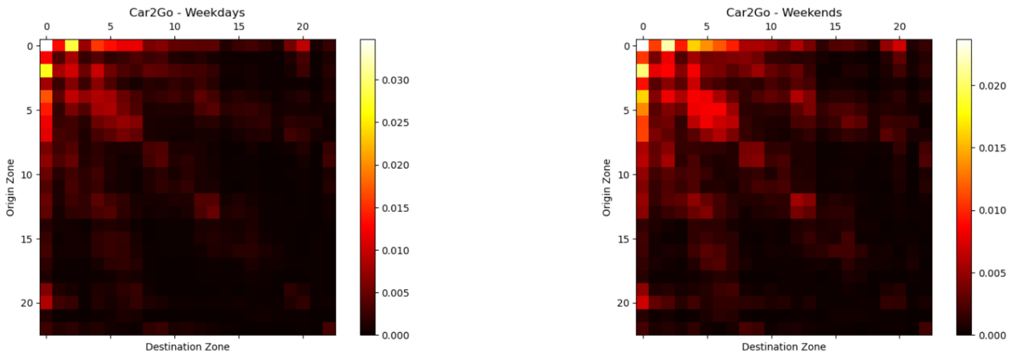


Figure 14: OD Matrices for Car2Go Car sharing Trips in Torino: weekdays vs weekends

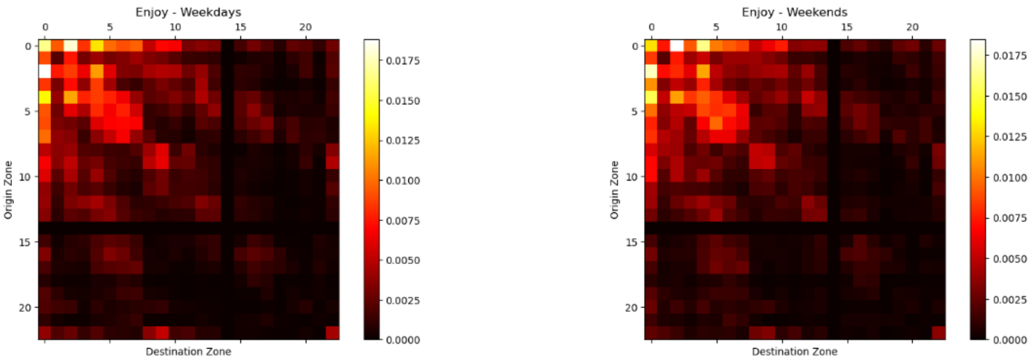


Figure 15: OD Matrices for Enjoy Car sharing Trips in Torino: weekdays vs weekends

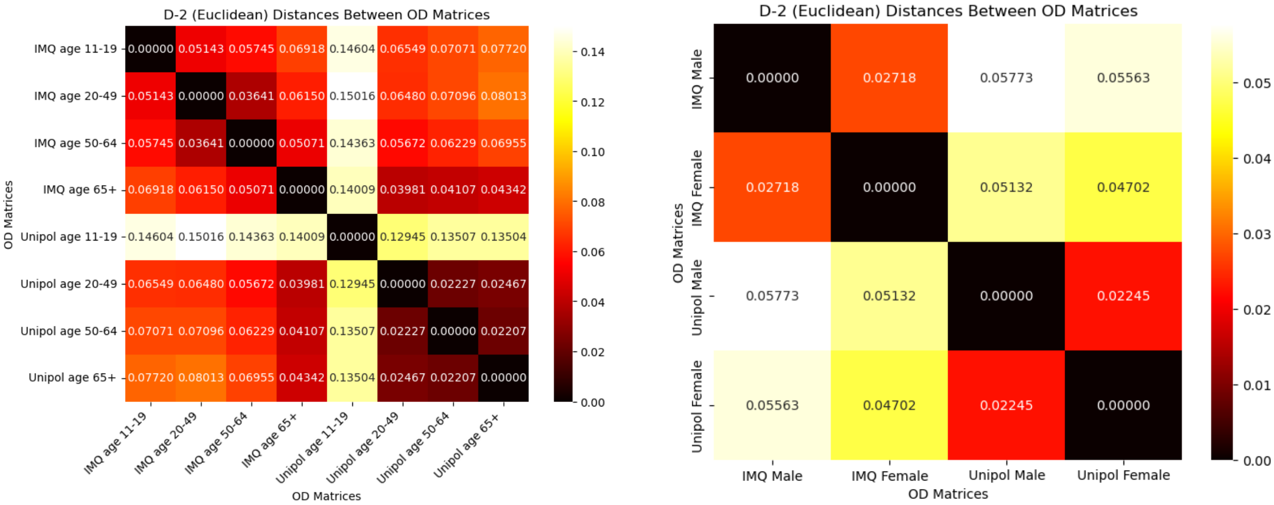
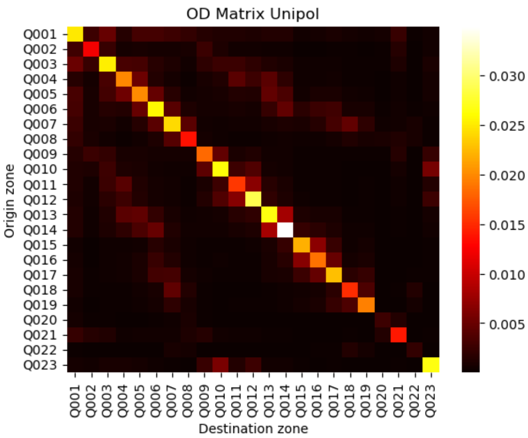
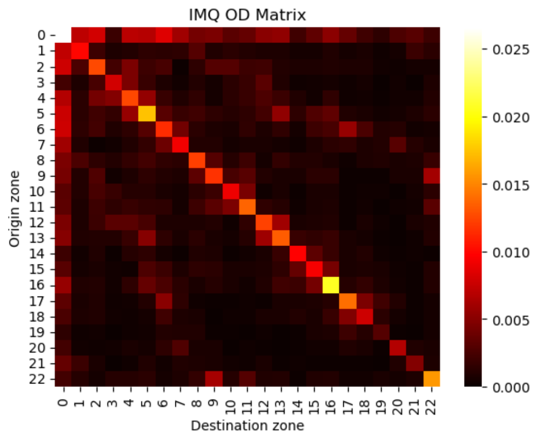


Figure 16: Comparison of Euclidean distances by age group and by gender.



(a) Unipol OD Matrix



(b) IMQ OD Matrix

Figure 17: OD matrices for UnipolTech and IMQ datasets.

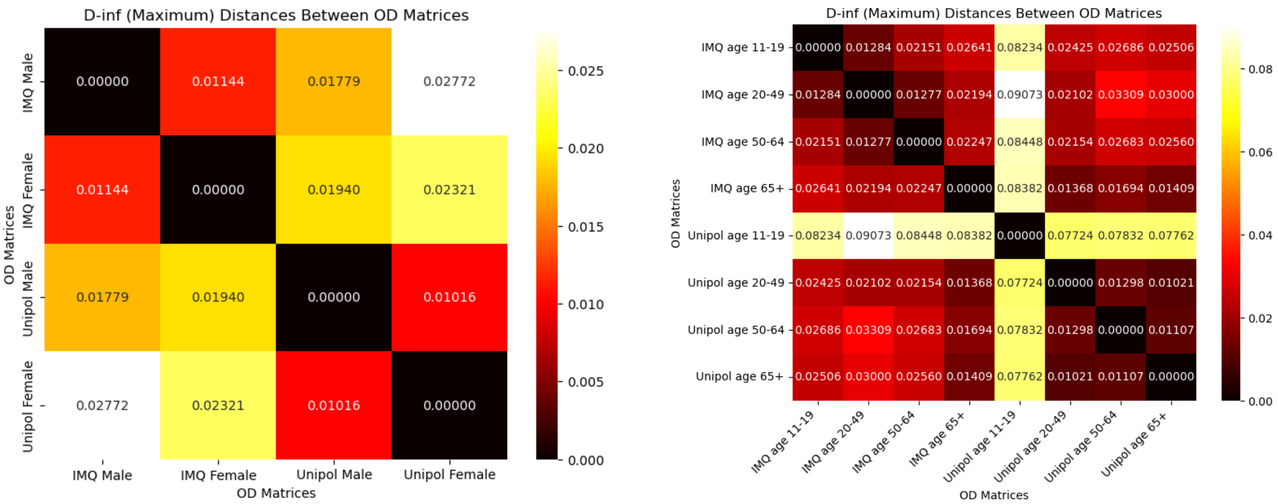


Figure 18: comparison of D-inf by Age group and by gender