Decoding Istanbul's Vehicular Veins: A Network Science Exploration of Metropolitan Traffic Dynamics

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1. Abstract

This project employs the techniques of network science to investigate and discern the underlying patterns of traffic flow in Istanbul, one of the world's busiest cities. Using the data collected by the Istanbul Metropolitan Municipality, we seek to identify and analyze the major traffic nodes and intersections that exert a significant influence on the city's overall traffic dynamics. The objective of our research is to understand the complex and interrelated systems that contribute to the unique traffic behavior of Istanbul and identify critical points of congestion. With a network science approach, we propose a model that incorporates spatial correlation and linear diffusion across different locations, drawing on various traffic parameters. The results from this investigation include an identification of the key locations on overall traffic flow and a better understanding of traffic pattern variations. The insights from this research will not only address Istanbul's traffic congestion issues but will also enrich the broader field of urban traffic systems, aiding strategic transportation planning in other metropolitan cities grappling with similar challenges.

Keywords: network science, road networks, diffusion, traffic, congestion propagation, urban traffic systems, traffic dynamics, istanbul, metropolitan systems

2. Introduction

Traffic congestion in metropolitan cities has emerged as a pressing issue in the face of rapid urbanization and globalization (Bull, 2003). The implications of this problem extend beyond mere transportation inefficiency, permeating into the quality of life of residents, and sustainability. Studies have also shown that congestion can have an adverse impact on economic productivity, slowing job growth and affecting productivity per worker. These impacts are particularly noticeable when there are approximately 4.5 minutes of delay per one-way auto commute and 11,000 average daily traffic per lane on average across the regional freeway networks (Sweet, 2014). A comprehensive understanding of traffic network congestion levels is therefore crucial, as it directly influences land use, productivity, and environmental policy-making processes, thereby affecting the lives of city residents.

Istanbul, a bustling metropolis renowned for its heavy traffic, presents a unique and complex case for investigating the underlying patterns of vehicular flow. The city's distinctive traffic dynamics, shaped by its unexampled geographical, cultural, and infrastructural characteristics, necessitate a dedicated exploration.

Previous research has significantly contributed to our understanding of urban traffic dynamics. For instance, studies have delved into macroscopic traffic dynamics and analyzed spatio-temporal congestion propagation at the network level (Jiang et al., 2017). These investigations have offered valuable insights into traffic patterns and congestion management in various urban contexts. However, they often fall short in addressing the unique challenges posed by Istanbul's traffic dynamics.

In this study, we aim to fill this gap by leveraging the extensive data collected by the Istanbul Metropolitan Municipality (IMM), which includes the impact of the Covid-19 lockdowns in 2020 and 2021. Our primary objectives are:

1. Identify and analyze the major traffic nodes and intersections that play a pivotal role in shaping Istanbul's overall traffic dynamics.
2. Understand the relationship between these nodes and their influence on network.
3. Establish a traffic network model that accurately represents and mimics Istanbul's traffic dynamics.
4. Come up with a model to quantify diffusion that can be used in real test scenarios.

By identifying these influential locations and their interrelationships, we aim to gain insights into the complex systems contributing to Istanbul's unique traffic behavior. This research not only targets the difficulties of Istanbul's distinctive traffic patterns but also enriches the extensive discipline of urban traffic systems. It propels our understanding and informs strategic transportation initiatives, thereby benefiting other densely populated metropolises tussling with similar issues.

3. Data Description

The data that was used is collected and made publicly available by IMM in their Open Data Portal (Açık Veri Portalı). IMM collects hourly data from over 2400 locations, composed of the following metrics for each location, with the descriptions:

- DATE_TIME: Contains date and time information. The data is in YYYY-MM-DD HH24:MI:SS format, and the date break is hourly.
- LATITUDE: Latitude of the point that the data is collected from.
- LONGITUDE: Longitude of the point that the data is collected from.
- GEOHASH: The hashed geo-location of the point that the data is collected from.
- MINIMUM_SPEED: Minimum speed (in km/h) for the respective geohash area for a given hour.
- MAXIMUM_SPEED: Maximum speed (in km/h) for the respective geohash area for a given hour.
- AVERAGE_SPEED: Average speed (in km/h) for the respective geohash area for a given hour.
- NUMBER_OF_VEHICLES: The number of different vehicles in the relevant geohash area in the given hour.

The published data covers the time frame starting from January 2020 and is published up to April 2023, monthly. For each month, there exist some gaps, where no data was available for a few of the stations at most for two hours, but overall, the data is homogeneous in the sense that most of the data points have the similar number of timestamps. The gaps in the data have pushed the team to make the decide to average the data out over a full day's span to overcome the difficulties of not being able to compare data points based on timestamps.

The data concerns the roads starting from the west end of Istanbul, where there are roads in the border between Tekirdağ and Istanbul, and spans until the roads that border Gebze, Kocaeli. The points are located as follows, according to IMM's portal:

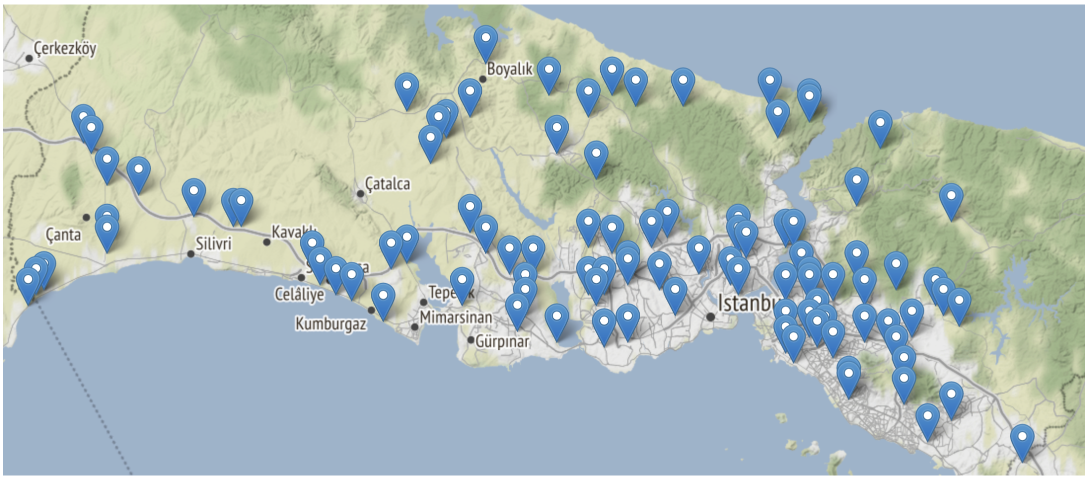


Figure 1: Some of the data points for January 2020

4. Results and Analysis

4.a. Network's Structural Analysis

Network analysis enables us to gain insights into the traffic of Istanbul. By analyzing networks, we can depict the static configuration of roads in Istanbul, while also capturing changes and developments over time by utilizing data from different time intervals. For this purpose, we created a correlation network for each month from January 2020 to April 2023 in Istanbul, which was derived from the hourly traffic density dataset that Istanbul Metropolitan Municipality publishes. Correlation between the points was measured using the Spearman Correlation, specifically focusing on the average speed (in km/h) recorded.

The Spearman Correlation is particularly effective for this type of analysis because it is a non-parametric measure of rank correlation. It assesses how well the relationship between two variables can be described using a monotonic function. In other words, if the rankings of one variable increase, whether or not the rankings of the other variable also increase can be examined with Spearman Correlation. This is especially helpful when analyzing traffic data, where we expect that as traffic intensity increases in one area (higher ranking), it may also increase in another area (higher ranking), or conversely, decrease in another area (lower ranking).

Furthermore, the choice to utilize average speed instead of other metrics, such as the number of vehicles, is driven by several reasons. Firstly, average speed provides a more comprehensive and meaningful measure of traffic conditions as it takes into account the overall flow and movement of vehicles within a specific area. In the background, it captures the collective experience of drivers in terms of the time it takes to traverse a particular distance, reflecting the level of congestion and efficiency of the transportation network. Furthermore, average speed allows for easier comparison and analysis across different locations and time intervals. This information is valuable for understanding the dynamic nature of traffic and assessing the impact of various factors on the overall traffic flow.

After calculating the Spearman correlation for each pair of nodes, we filtered out the pairs with less significant results based on their p-values to focus on a more connected network. We chose the p-value of 0.01 to maintain a strict level of statistical significance. This choice helps us to reduce the likelihood of false positives. In other words, by choosing 0.01 as a p-value, we ensure that the correlations we focus on are both statistically significant and practically meaningful, thereby enabling us to construct a better view of the connected nodes of Istanbul's traffic network.

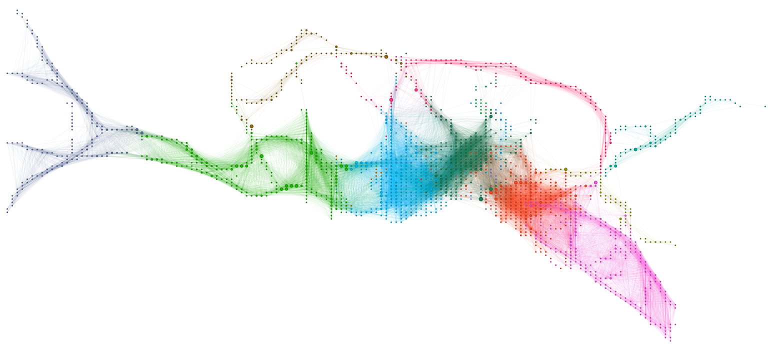


Figure 2: An Example Network - January 2020

The above illustration (Figure 2) showcases an example network we synthesized, reflecting data from January 2020, utilizing the visualization software Gephi. To optimize the visual representation, we chose to display only the largest connected component of the graph, effectively encapsulating approximately 90 % of the original nodes. Leveraging Gephi's Modularity feature, we were able to determine communities within the network, clarifying the interrelations among distinct road clusters. Specifically, we employed the Louvain algorithm, a well-known community detection method that facilitates the identification of node clusters exhibiting higher-density connections relative to the rest of the network. Such communities frequently display an elevated level of organization within the network and offer insights into the infrastructure of the traffic system. For instance, roads consolidated within the same community might be components of the same district, or they may concurrently be impacted by certain traffic conditions. Therefore, the Louvain algorithm allows for a more profound comprehension of these structural interconnections and associations, enabling us to derive more meaningful interpretations of the network. To detect critical nodes, we scaled node sizes proportional to their betweenness centralities. This strategy was instrumental in highlighting focal points that significantly impact the flow within the network. Finally, we deployed the GeoLayout plugin of Gephi to plot the nodes onto a grid, based on their respective latitudes and longitudes. This further enhanced our ability to visually represent the shape and structure of traffic intensities with greater fidelity.

4.a.1. 2020 March vs. 2020 April

Firstly, we wanted to study the alterations in the traffic network structure of Istanbul during the Covid-19 pandemic. We chose the specific period of interest to observe these structural changes in March and April, a time of evolving health guidelines and regulations.

On March 11, 2020, the first case of Covid-19 was detected in Turkey, and until April, there were not many restrictions on Covid-19 ("Turkey confirms first case of coronavirus," 2020). However, a remarkable transformation occurred in early April when an encompassing curfew was instituted. This curfew, in essence, acted as an external disruptor to the traffic network, allowing us to explore the transformations and adaptability of Istanbul's traffic infrastructure under extreme conditions ("8 Nisan İtibariyle Karantina Uygulamaları,", 8.04.2020).

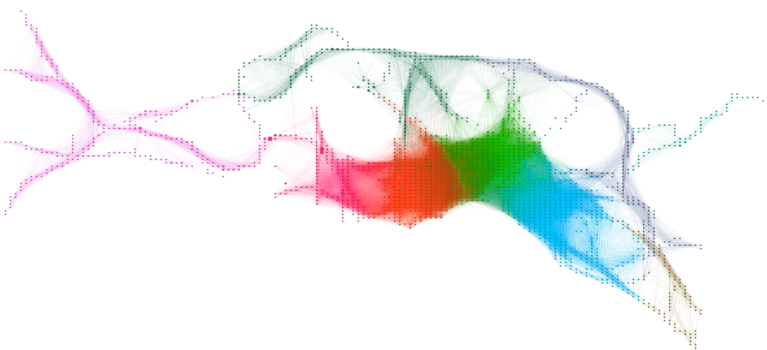


Figure 3: Correlation Network for March 2020

In March 2020 (Figure 3), the network is more connected, as evident by the darker shaded regions, which point out the fact that the edge-weights, thus correlation, between the points are high. Also, the points with higher betweenness centrality are to the outside of the center of Istanbul, which is probably due to the fact that there are many roads connecting the center, but a few roads connecting the outskirts to the center. The clusters are well-separated, meaning that a good separation of roads is possible and major traffic conjunctions can be identified with ease.

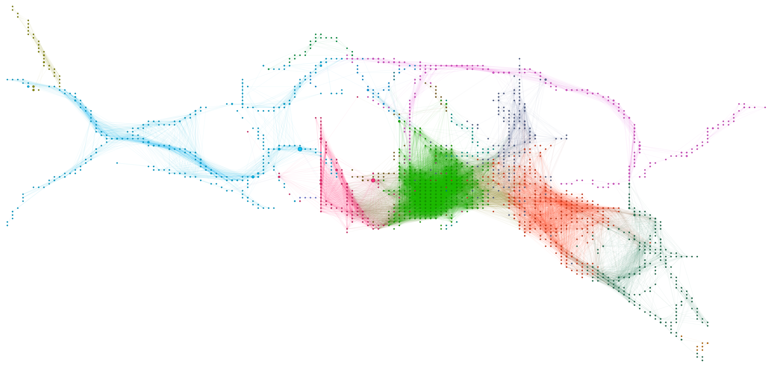


Figure 4: Correlation Network for April 2020

However, in April 2020 (Figure 4), there are major differences to what we could call a 'normal network'. Firstly, there seems to be more division in the network, which can be identified by the fact that there are more clusters in the network than in March 2020. The correlation between the points is less, which we believe is due to the nationwide curfews and restrictions on travel. Furthermore, the points with higher betweenness centrality have moved closer to the center of the city, which can be attributed to the shorter distance traveled during strict measures, and people choosing to stay at home instead of going out. This inherent characteristic of the month is also visible when we examine the green area, that spans from Eminönü to Bakırköy, which is colored in green. The edge weight of that region indicates that a lot of the car traffic has happened within that cluster, which is a compelling argument for the case of short-distance travel.

4.a.2. 2022 January vs. 2022 February

We are also interested in studying the changes in Istanbul's traffic network during another significant period in the Covid-19 pandemic, specifically between January and February 2022. When we look at the dashboard prepared by WHO, we can observe the critical changes in Covid-19 cases nationwide. More specifically, the end of January 2022 and the beginning of February 2022 marks the peak of COVID in Turkey (World Health Organization, 2023).

In January 2022, the country faced strict Covid-19 restrictions once again as the number of cases shot up quickly. This sudden increase in cases led to changes in how people traveled, which in turn, could have impacted Istanbul's usual traffic patterns. Then in February 2022, the number of infections rapidly escalated even more, effectively doubling by February, leading to the pandemic's peak in Turkey (World Health Organization, 2023).

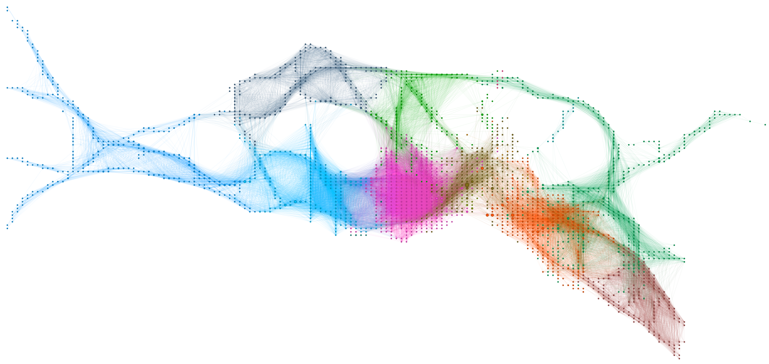


Figure 5: Correlation Network for January 2022

In January 2022 (Figure 5), the effect of lockdowns is visually present. We can observe that, compared to January 2020, the intensity of the traffic is less. However, we see that the nodes with higher betweenness centrality have moved closer and closer to the center of the city. One of the most prominent nodes, colored with brown is in the Şişli district, which shows that the model is compliant with our real-world expectations. Another node in orange with high centrality is the Avrasya (Eurasia) Tunnel, which connects the two sides of Istanbul. As one might expect, many of the shortest paths from the Asian side to the European side would go through the tunnel. This means that, if one were to disrupt the travel through the Avrasya Tunnel, its effects would be profoundly felt by the whole network.

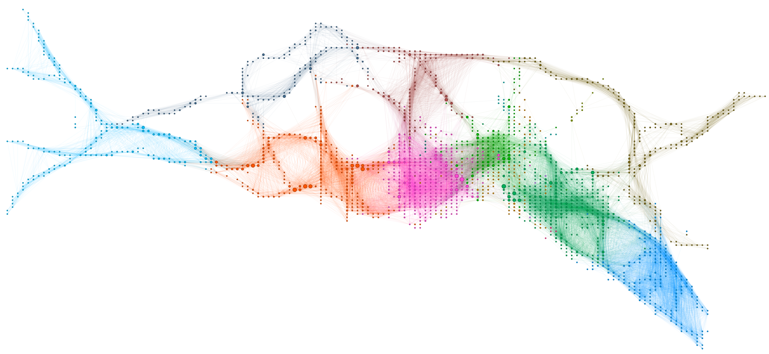


Figure 6: Correlation Network for February 2022

During the next month (Figure 6), with the rise of another wave of Covid-19, and with new regulations, we can see the changes reflected in the network as well. Firstly, the intensity of the colors, which indicate the strong relationship between the points, has been washed away. This means that there seem to be fewer cars around Istanbul. Secondly, the number of points with high betweenness centrality has increased, shining light on the fact that the distance of travel has again been shortened and hence more nodes had shortest paths going over them. Another observation is that the Asian side of Istanbul has a more unified structure, which is reflected by the decrease in the number of different clusters.

4.a.3. 2022 September vs. 2022 October

Lastly, we want to focus on the influence of the academic calendar on Istanbul's traffic patterns, with a particular focus on September and October. In Turkey, the academic year for primary, secondary, high school, and university students typically commences at the end of September. Consequently, there is a distinct contrast in traffic conditions between these two months. September, being the final stretch of the summer break, sees comparatively quieter roads in Istanbul. However, with the onset of the academic year in October, the city generally experiences a significant increase in road traffic. We expect to see a change in the structure since the city undergoes a substantial increase in road traffic, as students return to their educational institutions. For those reasons, to study the impact of the school calendar on Istanbul traffic, the period of September and October 2022, which marks the first school opening after the COVID-19 effects, holds significant value for observation.

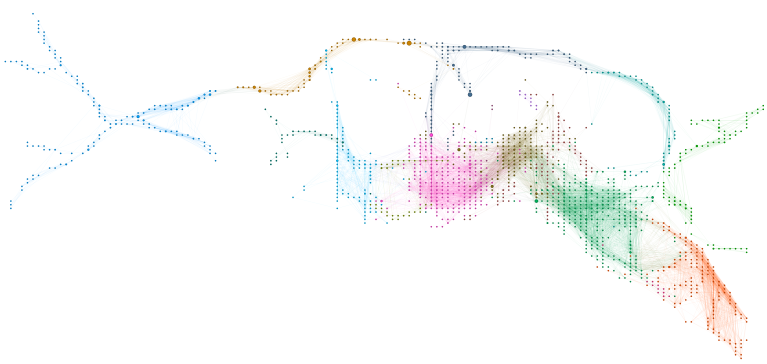


Figure 7: Correlation Network for September 2022

In September 2022 (Figure 7), we see that with the schools not in session for half of the month, many of the connections in the previous networks that we have analyzed are not there, which is probably due to the summer break. As before, the network has more clusters, and the cluster regions are not strictly defined. We also see that the nodes with the most centrality have shifted to the outskirts, one possibly closer to Istanbul, which could be attributed to the air traffic that the Istanbul Airport gets. Overall, we see that Avrasya Tunnel has a great influence on the network, serving as an underground bridge for the city.

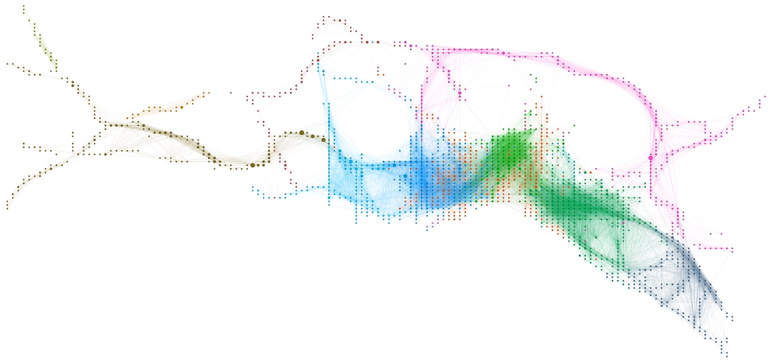


Figure 8: Correlation Network for October 2022

Moving onto the next month (Figure 8), October 2022, there exists a different scenario. We now see a more connected network in terms of correlation between the points. However, the clusters are very scrambled, and a good separation is not achieved. The points with higher betweenness centrality are now closer to the center of the city, with one connecting Çekmeköy to Yavuz Sultan Selim Bridge. Another particularly interesting case occurs near Esenyurt and Büyükçekmece, where the points around there colored brown are connecting a lot of different roads. This might be attributed to the inflow of people to Istanbul from the cities in the west at the beginning of the educational year.

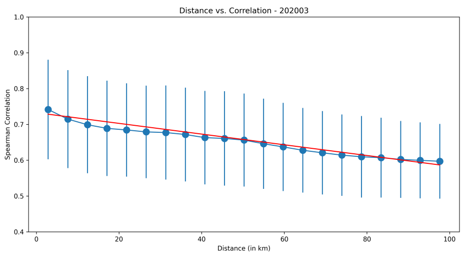
4.b. Distance vs. Correlation

For all pairs of nodes in each month, we calculated a correlation. We hypothesized that with increasing distance, the correlation between the points would decrease as a natural consequence of spatial constraints and the intricate web of urban development. For instance, nodes far apart in geographical space, belonging to different city sectors, might demonstrate unique traffic patterns, influenced by local factors such as road layouts, land use, and population density. These localized traffic patterns might not necessarily correlate with the traffic characteristics of other distant locations.

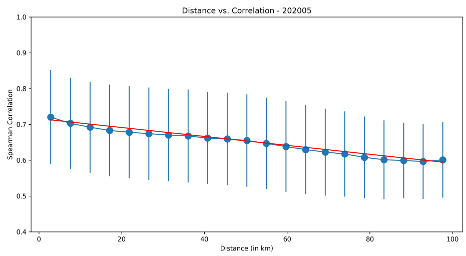
In order to validate this hypothesis and identify any deviations from the expected trend, we plotted the relationship between the geographical distance and the absolute Spearman correlation coefficient. While building this plot, we chose to bin the distance variable, as there are many pairs of points that have the same distance to each other, which would give us a better overall view of the correlation at that distance. We came up with the optimal bin number as 21, which allowed for good separation between the points, and for each bin, we averaged out the Spearman correlation metric. This plot served as a visual tool for inspecting the influence of distance on the correlation between traffic speeds at different locations. We also did not consider the pair of points that were more than 100 kilometers away, as they would likely cause noise in our analysis.

Although we observed some variation in the correlation patterns for different months, the overall trend indicated a decrease in correlation as the distance between pairs of nodes increased, which supports our hypothesis. It is important to note that while the correlation generally decreases, there were instances where the correlation remained relatively constant over varying distances. These observations highlight the complex nature of traffic dynamics in Istanbul, where certain factors may lead to localized similarities in traffic patterns even across significant distances.

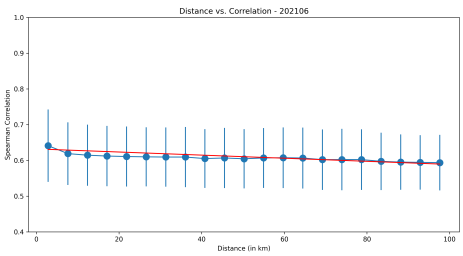
We see that for most of the months, the average correlation of the closest points is around 0.7, while the most distant points are approximately 0.6. There are some deviations from these observations, which should be explored in the future with a more in-depth analysis of singular pairs. Below are four figures, the upper half of which represents the regular behavior of average correlation with increasing distance, and the bottom half represents a weaker relationship between the variables' distance and average correlations, which can be considered as outlier months.



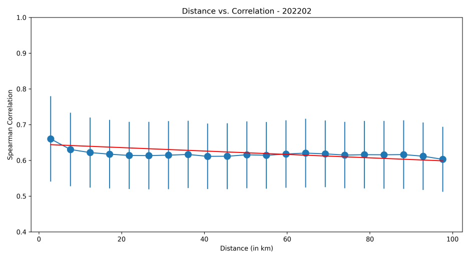
(a) Distance vs. Correlation Plot for March 2020



(b) Distance vs. Correlation Plot for May 2020



(c) Distance vs. Correlation Plot for June 2021



(d) Distance vs. Correlation Plot for February 2022

Figure 9: Distance vs. Correlation Plots for Various Months

Even though the relationship seems weak for some months (Figure 9c, 9d), we are able to identify a negative relationship between distance and the average correlation metric. The presence of a negative relationship, albeit varying in strength across different months, indicates a certain level of spatial heterogeneity in the traffic patterns across Istanbul. This observation aligns with the intuitive notion that traffic flow and congestion may be affected by location-specific factors such as the types and levels of activity occurring in different parts of the city.

Interestingly, in certain months like June 2021 and February 2022 (Figure 9c, 9d), the expected negative correlation is less pronounced, suggesting the influence of other possible factors. For instance, this could be due to seasonal changes, large-scale events, or alterations in transportation infrastructure. These findings invite further exploration into the interactions between geographical distance and traffic patterns in the city.

4.c. Centrality Analysis - Critical Points

In network analysis, the concept of betweenness centrality plays a crucial role in identifying the most important nodes in a network. In our case, these nodes correspond to the most significant regions in Istanbul that bear the most significant impact on the city's traffic flow. Simply put, a region with high betweenness centrality implies that it lies on many of the shortest paths traversed by commuters, acting as a critical connection between various areas. Therefore, such regions can be seen as 'bottlenecks' or 'critical points' in the overall traffic network of Istanbul.

Our last analysis focuses on identifying these critical points, taking into consideration the monthly fluctuations in Istanbul's traffic flow. First of all, we took the traffic networks that we analyzed in the previous sections as a basis. We hypothesize that the region exhibiting the highest betweenness centrality for a particular month emerges as the most critical region for that month. This stems from the assumption that regions with a high degree of betweenness centrality play a central role in the transmission of traffic and can greatly affect flow efficiency, causing delays when congested.

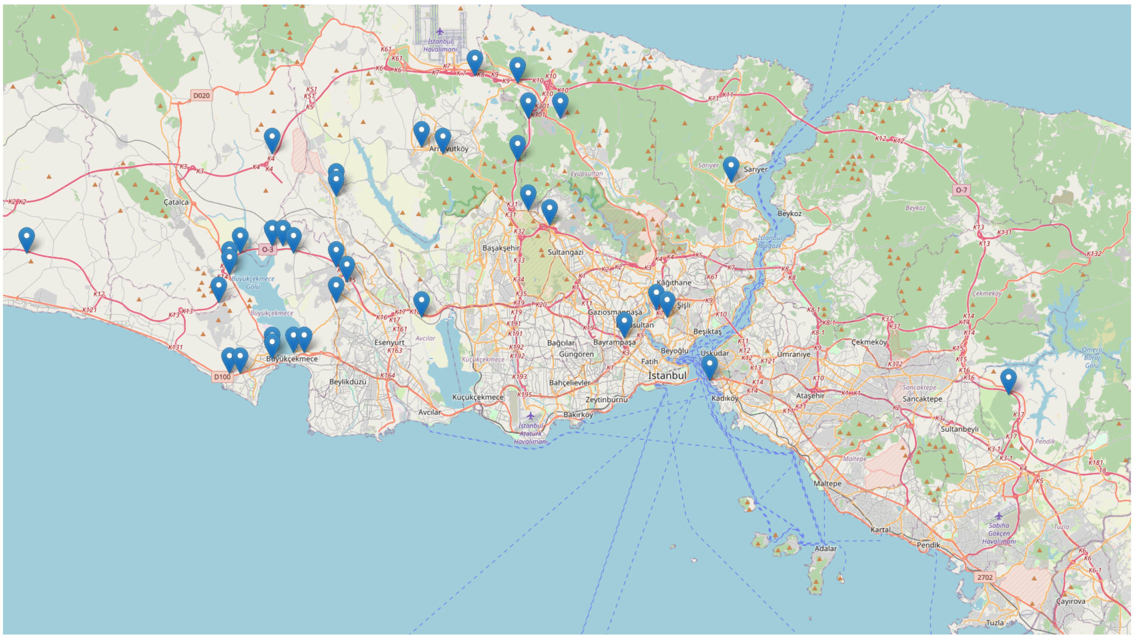


Figure 10: Points with highest betweenness centrality for all 40 months

When we examine the map for the distribution of the points with the highest centralities (Figure 10), we see a clear divergence in the European side of Istanbul. The only two points on the Asian side are located in Avrasya Tunnel near Kadıköy and North Marmara Highway near Sultanbeyli. The rest of them are scattered around the European side, mainly clustering around Büyükçekmece and Beylikdüzü. The points clustered around these two districts are most likely to have the highest centralities due to the lack of roads connecting that area to the city center, and thus many of the shortest paths go through those nodes. We also have seen the effect of Covid-19, on the structure and the clustering of the network, which has also affected the centralities. Conversely, we believe that the nodes that have the highest centralities in their respective months that are located near Şişli have achieved those metrics as they have an intrinsic importance, being a part of the road that is either leading to a bridge or coming from the bridge. It is also important to highlight the criticality of the Avrasya Tunnel, about which was mentioned before.

4.d. Diffusion model for congestion propagation

Significant insights concerning the behaviour of a network can be gained through the use of reaction-diffusion models (Bellocchi & Geroliminis, 2020). Here, the "reaction" term refers to a non-linear function which corresponds to the arbitrary choices employed by drivers, such as deciding to use a less-optimal road because the optimal one is congested. The "diffusion" term quantifies the natural linear flow between roads, which would be the sole contributor to flow in the ideal case. Essentially, "reaction" can be defined as describing all non-linear effects other than "diffusion" that cause deviations within the ideal flow of a road network.

Here, in an effort to quantify the diffusion within the road network we formulate the problem as follows. Consider the directed weighted graph $G = (V, E)$, where V is the set of stations that fall within the borders of Istanbul and $E = \{ (v_i, v_j) \in V^2 \mid d_H(v_i, v_j) < 1 \}$ where d_H is the Haversine distance. Note that the definition allows us to put two diffusion coefficients between sufficiently close nodes. The corresponding adjacency matrix for G will have diffusion weights $\sigma_{ij} > 0$ to quantify the diffusion from v_i to v_j.

Using the definitions above, for a node v_i having number of cars C_i diffusion can be modelled as the differential equation:

$$\frac{\partial C_i}{\partial t} = \Big(\sum_{v_k \in N(v_i)} \sigma_{ki} C_k \Big) - \Big(\sum_{v_k \in N(v_i)} \sigma_{ik} C_i \Big) \tag{1}$$

where the terms stand for incoming and outgoing flow respectively, depending on the weight of the edge and the number of cars at given t. A descriptive explanation for this would be: "The change in cars with respect to time at a given node is the sum of all cars entering the node minus all cars exiting from the node."

To find the diffusion weights, we iterate through time intervals and consider the change in number of cars for each node, $\Delta C = C_t - C_{t-1}$. At each iteration, given two neighbouring nodes, we predict the change for one node from the other by multiplying the other node's change with the current weight, and comparing it with the real change to improve the weight. As an example, consider $\Delta C_i^{true}, \Delta C_j^{true}$ for two neighbouring nodes v_i, v_j. We predict the change in v_j from v_i as $\Delta C_j^{pred} = \Delta C_i^{true} \sigma_{ij}$ and update the weight as $\sigma_{ij}^{next} = \sigma_{ij} + \theta(\Delta C_j^{pred} - \Delta C_j^{true})$ if and only if $sgn(\Delta C_j^{true}) = sgn(\Delta C_j^{pred})$ so as to improve on the prediction for the next iteration.

The underlying assumption here is that if the changes are reflected similarly for two nodes, then there is a high chance that the flow is directed through those nodes consecutively, which implies diffusion. The weights here reflect the magnitude of diffusion, as a high change in a given node would mean there are more nodes diffusing towards that particular node. With the definition of a flow parameter, the learned model can be used in experimental testing of congestion flow.

4.d.1. Main diffusion pathways

Employing the proposed approach with all available data points, it was possible to use the weights/degrees to observe nodes where the diffusion behaviour converged to either local or city-wide congestions. Figure 11 was generated by first including all nodes on the map and then filtering out nodes with zero degrees, which are essentially those that were learned to be ineffective. Node colors correspond to the districts the nodes belonged to.

With the knowledge of these pathways, it becomes possible to foresee an expected scenario between two nodes on the map. Especially when two nodes are connected with a bridge of single nodes, the model can be extended to measure propagation between distant nodes as well, by considering further derivatives for the differential equation. Note that this would most likely be unfeasible on the general scale and could be partially feasible for single nodes, as the calculation of the second derivative would be much more expensive than the first derivative.

Finally, it might be worthwhile to generate different diffusion networks from multiple months and then arrive at a consensus by averaging or taking the median from the obtained distribution, especially since we are aware that some months of the data used include extreme conditions. However, for a general baseline, we decided to make use of all data points regardless of these considerations.

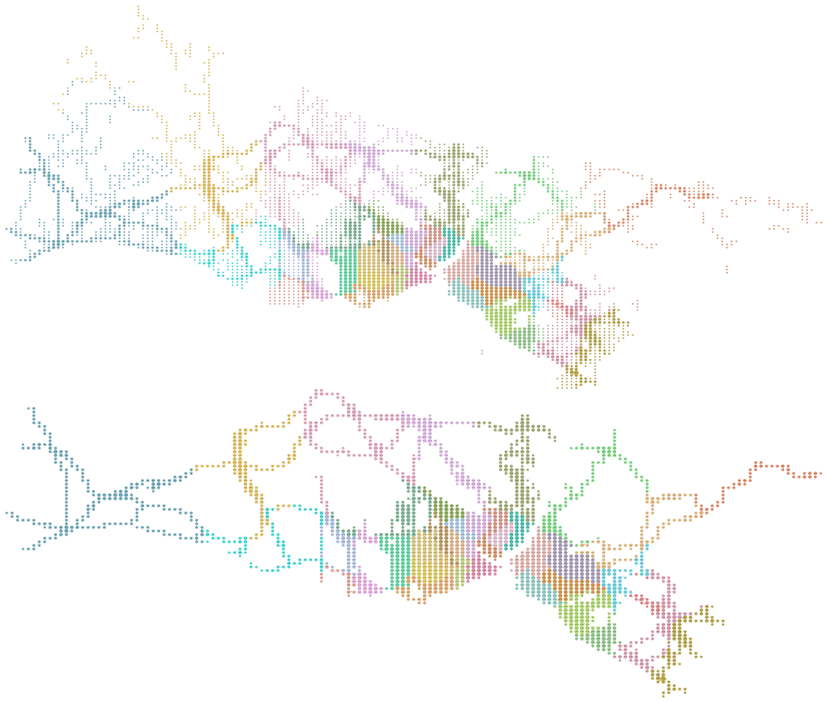


Figure 11: Learned diffusion paths for Istanbul

4.d.2. Experimental testing

With the learned model, it is possible to conduct extensive experimental testing by initializing two parameters:

- **Flow Magnitude:** The percentage of cars that exit from the node at a given time. It is used to determine the speed of diffusion. Higher speeds mean less accuracy but but also less time to convergent behaviour (either local or global spreading).
- **Starting Position:** How many nodes each car has at $t = 0$.

The results from an example diffusion test from a random central node in Beşiktaş can be found in Figure 12. Here, the row above has a flow magnitude of 1, while the row below has a flow magnitude of 5.

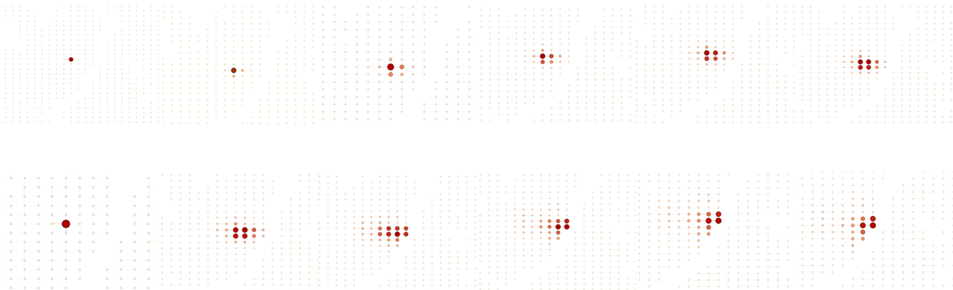


Figure 12: Example diffusions - Beşiktaş

As expected, the diffusion converges much more rapidly at higher flow speeds, but the diffusion for intermediate nodes on the way up to the convergent state becomes much less stable. Additionally, the flow speed itself is expected to affect the convergence state, as with the case we have presented.

Extending the observations, we conclude that by considering the two parameters we have discussed, it becomes possible to simulate scenarios of diffusion under different conditions. Particularly, the flow speed is vital to understand. This model operates under the scenario that flow speed is independent; meaning that the number of cars observed at a station does not affect the flow speed. The logical justification would be that the increased amount of cars, with decreased average speed, would balance out the flow.

On a final note, while not all experimental scenarios could be tested due to time constraints, one can expect nodes to form certain groups by their behaviour. Specifically, some set of local "sink" nodes pull nearby diffusion, while other "source" nodes consistently push out what they have, with most nodes taking place somewhere in the middle of this spectrum. The nodes with "sink" behaviour become particularly important in this case, as they will probably merit most of the infrastructure expenditure; while the "source" nodes do not require further intervention.

5. Conclusion

In this study, we used rich traffic data and network analysis techniques to explore and understand the spatio-temporal traffic patterns in the complex and dynamic city of Istanbul. Our main findings are summarized as follows:

- Through a comprehensive analysis of the temporal dynamics of the traffic network in Istanbul, we have observed that the structure of traffic flow varies significantly according to different months and social events. Notably, a marked change in traffic network was observed starting from March 2020, a change that can be directly attributed to the Covid-19 pandemic. The change in the network structure related to both Covid-19 and the school calendar shows the dynamic nature of Istanbul traffic that is prone to change.
- The correlation analysis showed a generally decreasing trend of correlation with increasing distance between nodes, suggesting a spatial heterogeneity in the traffic patterns across Istanbul. However, there were exceptions to this pattern, highlighting the complexity of traffic dynamics and the influence of local factors.
- The centrality analysis identified key regions or 'critical points' that bear significant impacts on the city's traffic flow. These regions, including Beylikdüzü, Şişli, and the Avrasya Tunnel, are characterized by high betweenness centrality and thus serve as crucial connections in the traffic network.
- By employing a diffusion model, we were able to identify the main diffusion pathways and conduct experimental testing to simulate congestion propagation scenarios. The model enabled us to predict the behavior of traffic flow, offering potential value for traffic management strategies.

These findings provide valuable insights for urban planners, policymakers, and transportation authorities to understand the city's traffic dynamics and devise strategies to improve traffic conditions. Furthermore, the methodologies and models employed in this study could be extended and applied to other cities or regions, contributing to the broader field of urban traffic analysis and management.

It is worth noting that while our study provides a detailed analysis of Istanbul's traffic patterns, there are several potential directions for future research. These could include a more in-depth analysis of the factors contributing to the observed traffic patterns, such as road infrastructure, land use, and socio-economic factors, as well as the exploration of other types of centrality measures and network analysis techniques. Moreover, additional datasets such as vehicle counts, population density, and public transportation usage could be integrated to enrich the analysis. Finally, the development of more sophisticated models to predict traffic conditions and simulate various traffic management scenarios would be a valuable contribution to the field.

In conclusion, our work highlights the value of applying network analysis techniques to traffic data to understand complex urban traffic patterns. Through this approach, we can gain insights that help to manage traffic more effectively, plan infrastructure development, and ultimately, contribute to more sustainable and livable cities.

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