PADUA15: A NETWORK APPROACH FOR 15-MINUTE CITY EXPANSION

LFN 2023/24 Final Report

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ABSTRACT

This study explores practical solutions for urban challenges arising from long journeys and uncontrolled city growth. Inspired by the 15 Minute City idea, we focus on making essential services accessible within a 15-minute walk (or bike ride) in Padua. Using a network-based approach, we analyze the current state of the city and propose ways to expand the coverage of services within this timeframe. Our goal is to create a more convenient and sustainable urban living experience, addressing issues like traffic, air quality and time waste. The code to reproduce the results can be found at `https://github.com/danielcharles0/LFN2324`.

1 INTRODUCTION

In 1994, a physicist named Cesare Marchetti proposed theorized the Marchetti Constant [1], which states that in general, people have been always been willing to commute for about a half-hour, one-way. The immediate consequence is that even if there is vast amount of land available, that land has no value in an urban context, unless transportation makes it quickly accessible to the urban core. With the advancement of faster modes of transport, the city boundaries exploded as we can see in Figure 1. The introduction of cheap cars combined with the low cost of farmland paved the way for the urban sprawl era. But this car-centric planning caused several problems including biodiversity, decrease in citizen's quality of life caused by increased traffic congestions, low quality of air and increasing financial burdens and social inequalities.
In this landscape, Carlos Moreno proposed a new way of planning cities: the **15 Minute City framework** [3]. The basic idea is that people should be able to access essential urban services in 15 minutes by bike or walking. The framework highlights four characteristics:

- *Proximity*, which can be viewed in spatial or temporal terms. Within the 15-min quickly accessible radial nodes, residents in a given neighborhood can readily access basic services
- *Diversity*, use of mixed-use neighborhoods and diversity in culture and people
- *Density*, consider the optimal number of people that an area can comfortably sustain

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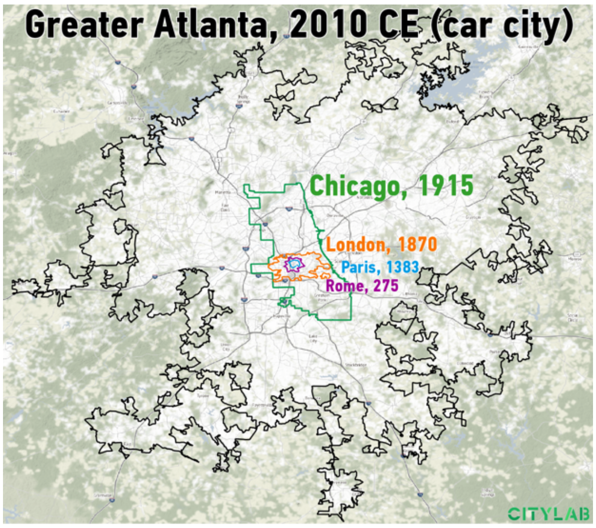


Figure 1: Rome (275) and Paris (1383) are examples of city of foot. London (1870) expands the city boundaries as railways are introduced. Finally, Chicago (1915) and Atlanta (2010) represent the boundaries in the era of cars. Source [2]

- *Digitalization*, smart city is essential to ensure the actualization of the concept

In our project, we emphasized the proximity aspect within a network-based approach, leveraging the inherent network structure of cities. This was explored through a case study centered around the city of Padua, first analyzing the current state of the city and then expanding the area covered by all services in 15 minutes.

2 DATASET

The dataset we have used is the Padua's street network extracted from OpenStreetMap using the OSMnx library [4]. OSMnx models the data as a NetworkX [5] MultiDiGraph, which is a nonplanar directed graph with possible self-loops and parallel edges. After cleaning the data, nodes represent intersections or dead-ends and edges represent the walking connection.
The count of nodes and edges after cleanup is 5462 nodes and 10496 edges.

3 METHOD

The analysis of the city's coverage was a fundamental task since we needed to know how much the city already respected this 15-minute concept. The first step was to prepare the data for the analysis, by getting the pedestrian street network from OpenStreetMap. However, this network lacked the required Point of Interest (POI) data. To address this gap, we extracted the existing POIs, represented as geographical points not integrated into the network, from the OpenStreetMap database using OSMnx. Subsequently, attempts were made to link these POIs to the network, by making new nodes to connect to the nearest edge but this resulted in numerous flawed connections which we couldn't solve, so a solution was devised where we designated the nearest node to each POI as its representative on the network, effectively treating it as a POI. The approximation doesn't alter significantly the results, since the real position of the POIs is in a radius of around 1 minute time.
At this point, we set the walking speed to 5 km/h, which is the average walking speed according to Wagnild and Wall-Scheffler [6], rounded down. We generated the ego-graph from every POI and tagged all the nodes in the subgraph, so that

each node would have a flag for each service that identifies if the node is covered in 15 minutes by the service or not. Thanks to the flags, we could plot which zones of Padua are all served in a 15 minute walk, as shown in Figure 2a.
Now, the positioning of brand new POIs is a sort of Facility Location Problem (FLP), but with less constraints. We focused on walking as travelling method, since it is the slowest form of travelling, and we considered a node to satisfy the 15 minutes condition if it can reach all grouped services in Table 1.

group	**type**	**OpenStreetMap tag**
education	school	amenity=school
	kindergarten	amenity=kindergarten
	library	amenity=library
healthcare	clinic	amenity=clinic
	doctor	amenity=doctors
	hospital	amenity=hospital
	pharmacy	amenity=pharmacy
transportation	public transport stop	public_transport=True
food	food	shop=food

Table 1: List of POIs with relative OSM tag

Subsequently, our objective was to identify groups of unreached nodes characterized by a diameter (maximum distance between two nodes within the group) of less than 30 minutes. This would enable us to position the new facility at the centroid of each node set. Unfortunately, this challenge proved unsolvable using the initial approach, as we couldn't locate a suitable algorithm for graph clustering based on this specific constraint. Consequently, we chose to employ a community detection algorithm, specifically the Louvain method [7] implemented in the NetworkX library, to identify distinct communities within the graph. Exploring the community structure in the street network reveals intriguing parallels to the complex dynamics inherent in urban landscapes. A city is composed of unique communities or neighborhoods, each possessing its distinct internal relationships and defining characteristics, so the community view could work well.

After finding the communities for each category and removing the components with a small number of nodes, we computed the most central node, hoping that it could expose the most influential node. We considered two different measures, Closeness Centrality and Betweenness Centrality. The newly positioned Point of Interest (POI) was then located at these points. Finally, we evaluated their performances based on the improvement on the coverage they brought. In Section 4 we show the coverage results we got with each measure.

4 RESULTS

4.1 Before adding new POIs (facilities)

After having obtained which nodes in the graph are near to at least one POI of a certain category for all the categories we are analyzing, we can evaluate some measurements. First we consider the initial coverage of each category in Table 2. While

Category	Number of POIs	Number of covered nodes	Percentage of coverage
Education	94	3124	57.13%
Healthcare	64	2491	45.56%
Transportation	454	4299	78.62%
Food	120	3543	64.8%

Table 2: Table of covered nodes for each category.

transportation in Padua is well-established, there is a noticeable gap in healthcare coverage, which is mainly concentrated around the center of the city. Similarly, the food and education categories also have limited coverage in the outskirts of the city, emphasizing a disadvantage for individuals with lower economic means.

It is interesting to evaluate the number of nodes that are covered by at least one POI of each category, since it is a good measure of how much a city is close to be a 15 minutes city. Another good measure is the number of isolated nodes, so nodes that are not close to any POI. This measures in the original network can be found in Table 3 and also graphically in Figure 2a.

Total Nodes	Total POIs	Covered Nodes	Coverage (%)	Isolated Nodes	Isolation (%)
5468	732	1917	35.06%	436	7.97%

Table 3: Initial coverage and isolation.

4.2 After adding new POIs (facilities)

After having selected which nodes for each community detected are the ones with highest value of closeness centrality and betweenness centrality, the analysis of coverage have been repeated but this time considering (separately) these new sets of nodes as POIs for the category they belong to and here are the results.

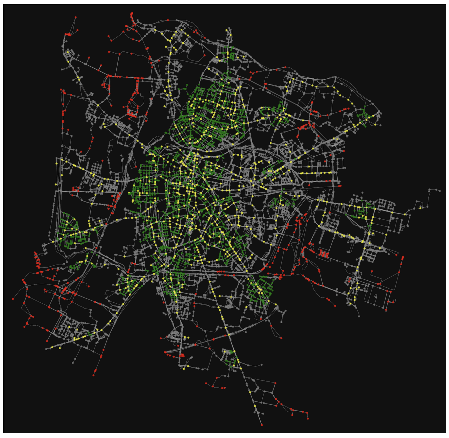
Using Closeness Centrality

The results reported in the following table can be seen graphically in Figure 2b.

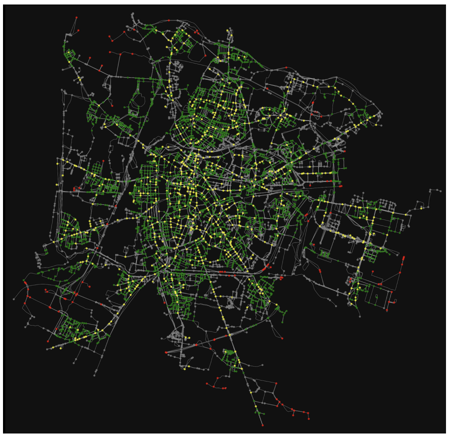
Total Nodes	Total POIs	Covered Nodes	Coverage (%)	Isolated Nodes	Isolation (%)
5468	913	3534	64.63%	123	2.25%

Table 4: Results with Betweenness centrality.

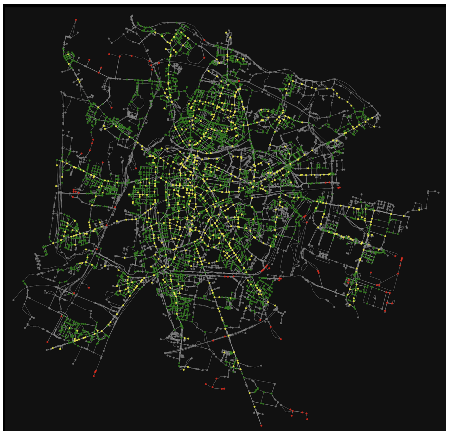
Using Closeness centrality improves the coverage of all categories by $29,57\%$ while also bringing down the percentage of isolated nodes by $5,72\%$.



(a) Initial coverage.



(b) Coverage with Closeness centrality.



(c) Coverage with Betweenness centrality.

Figure 2: Coverage progress.
Green nodes: covered by all categories.
Red nodes: isolated nodes.
Grey nodes: covered by at least one category, but not all.

Using Betwenness Centrality

The results reported in the following table can be seen graphically in Figure 2c.

Total Nodes	Total POIs	Covered Nodes	Coverage (%)	Isolated Nodes	Isolation (%)
5468	913	3643	66.62%	90	1.65%

Table 5: Results with Betweenness centrality.

Using Betweenness centrality improves the coverage of all categories by 31, 56% while also bringing down the percentage of isolated nodes by 6, 32%. Note that betweenness performs slightly better than closeness, in particular by approximately 2% in terms of coverage.

5 CONCLUSIONS

As reported in the tables in Section 4, at the same total number of POIs, the ones obtained through Betweenness Centrality lead to a higher coverage, i.e. 66.62%, and lower percentage of isolated nodes, i.e. 1.65%, than the ones obtained through Closeness Centrality. Our explanation of the better performance of the Betweenness Centrality is that it is inherent in its definition, because, roughly, the score is proportional to the number of shortest paths that pass through a node v s.t. v is not an endpoint of those. This means that a node gets an higher value if it is crucial for the network viability, i.e. through which a lot of people need to pass to get to another point, and this would be a perfect spot for placing a POI.

Even if the total coverage would not get to 100%, with our method it increases considerably from the initial one, from 35.06% to 66.62%. What is more noteworthy is that this improvement is possible by introducing only 181 brand new POIs, which is just less than a quarter of the initial ones. Note that the provided solution is not optimal; there is room for improvement by incorporating elements of the Facility Location Linear Programming problem to achieve an optimal outcome.

Future efforts could involve incorporating population data based on zones, a piece of information that we weren't able to find. This would enable a more precise analysis by correlating coverage not with the number of nodes, which may consider sparsely populated areas such as industrial zones, but rather with the population served by the services.

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CONTRIBUTIONS

Every member has actively participate to solve problems of any entity faced while developing the project, helping the rest of the team when they had issues in their code. In the end, the overall work was split in this way:

Member	Work	Fraction of work
Enrico Bolzonello	Community detection approach, dataset setup, refactoring and report	33%
Daniel Carlesso	Passage from POIs connection to approximation, analysis post community detection and report	33%
Michele Zadro	Coverage analysis before adding POIs and report	33%

Table 6: Table of contribution of each member.

Overall we worked together for the most part, communication was strong from the beginning when we had to decide what project to develop. Once we established the general area of interest, our team immersed into literature regarding 15 minute cities, both in network science approaches and in urbanism, to gain a preliminary knowledge on how to approach the problem.

Then, since several problems arose, we engaged in discussion on which path to take, as all members actively expressed their ideas to converge to the best one. Nonetheless, when we had difficulties with the code we helped each other to overcome them.