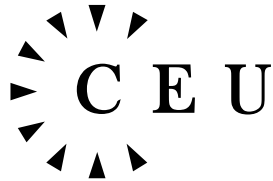# Networks and Cities

CEU

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2020

RESEARCHER DECLARATION

I Luis Guillermo Natera Orozco certify that I am the author of the work Networks and Cities. I certify that this is solely my own original work, other than where I have clearly indicated, in this declaration and in the thesis, the contributions of others. The thesis contains no materials accepted for any other degrees in any other institutions. The copyright of this work rests with its author. Quotation from it is permitted, provided that full acknowledgement is made. This work may not be reproduced without my prior written consent.

Statement of inclusion of joint work

Signature of PhD Candidate:

September, 2020

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September, 2020

Signature of Dr. Michael Szell, endorsing statement of joint work:

September, 2020

Signature of Dr. Orsyola Vásárhelyi , endorsing statement of joint work:

September, 2020

ABSTRACT

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EXTRACTING THE MULTIMODAL FINGERPRINT FOR TRANSPORTATION NETWORKS

Urban mobility increasingly relies on multimodality, combining the use of bicycle paths, streets, and rail networks. These different modes of transportation are well described by multiplex networks. Here we propose the overlap census method which extracts a multimodal profile from a city's multiplex transportation network. We apply this method to 15 cities, identify clusters of cities with similar profiles, and link this feature to the level of sustainable mobility of each cluster. Our work highlights the importance of evaluating all the transportation systems of a city together to adequately identify and compare its potential for sustainable, multimodal mobility.

1.1   Prelude

The infrastructure of different modes of transportation can be described as a mathematical object, the multiplex transport network [1, 2, 3, 4, 5, 6, 7, 8, 9]. A city's multiplex transport network contains the layer of streets and other coevolving network layers, such as the bicycle or the rail networks, which together constitute the multimodal transportation backbone of a city. Due to the car-centric development of most cities [10], streets form the most developed layers [11, 12] and define or strongly limit other layers: For example, sidewalks are by definition footpaths along the side of a street and make up a substantial part of a city's pedestrian space [11]. Similarly, most bicycle paths are part of a street or are built along the side. Yet, the different layers of a multimodal network typi-

cally serve as diverse channels to permeate a city. Here we consider the transport networks of 15 world cities and develop an urban fingerprinting technique based on multiplex network theory to characterize the various ways in which transport layers can be interconnected, identifying the potential for multimodal transport. Using clustering algorithms on the resulting urban fingerprints, we find distinct classes of cities, reflecting their transport priorities.

1.2   METHODS AND DATA

We acquired urban transportation networks from multiple cities around the world, defined by their administrative boundaries, using OSMnx [13]. These data sets are of high quality [14, 15] in terms of correspondence with municipal open data [16] and completeness [17]. The various analyzed urban areas and their properties are reported in Table 1.1. Figure 1.1 shows the different network layers for Manhattan, one of our analyzed cities.

	Pedestrian			Bicycle			Rail			Street			Population
	Nodes	Links	$\langle k \rangle$	Nodes	Links	$\langle k \rangle$	Nodes	Links	$\langle k \rangle$	Nodes	Links	$\langle k \rangle$	
Amsterdam	23,321	33,665	2.89	34,529	35,619	2.06	1,096	1,655	3.02	15,125	21,722	2.87	872,680
Barcelona	20,203	30,267	3.00	7,553	7,647	2.02	249	249	2.00	10,393	15,809	3.04	1,600,000
Beihai	2,026	2,978	2.94	0	0	0.00	59	62	2.10	2,192	3,209	2.93	1,539,300
Bogota	81,814	121,038	2.96	9,760	9,651	1.98	166	165	1.99	62,017	91,197	2.94	7,412,566
Budapest	73,172	106,167	2.90	10,494	10,318	1.97	1,588	1,964	2.47	37,012	52,361	2.83	1,752,286
Copenhagen	30,746	41,916	2.73	13,980	13,988	2.00	276	369	2.67	15,822	20,451	2.59	2,557,737
Detroit	47,828	78,391	3.28	3,663	3,626	1.98	20	21	2.10	28,462	45,979	3.23	672,662
Jakarta	140,042	191,268	2.73	248	231	1.86	58	54	1.86	138,388	188,637	2.73	10,075,310
LA	89,543	128,757	2.88	14,577	14,428	1.98	173	221	2.55	71,091	101,692	2.86	3,792,621
London	270,659	351,824	2.60	62,398	60,043	1.92	2,988	3,535	2.37	179,782	219,917	2.45	8,908,081
Manhattan	13,326	21,447	3.22	3,871	3,777	1.95	349	436	2.50	5,671	9,379	3.31	1,628,701
Mexico	108,033	158,425	2.93	5,218	5,278	2.02	370	364	1.97	95,375	140,684	2.95	8,918,653
Phoenix	111,363	157,075	2.82	35,631	35,979	2.02	105	138	2.63	73,688	102,139	2.77	1,445,632
Portland	50,878	72,958	2.87	24,252	24,325	2.01	230	340	2.96	35,025	49,062	2.80	583,776
Singapore	82,808	110,612	2.67	12,981	12,947	1.99	683	740	2.17	50,403	66,779	2.65	5,638,700

Table 1.1. *Measures for the administrative area of analyzed cities. The number of nodes, links and average degree ($\langle k \rangle$) for each layer in all cities of our dataset are highly diverse due to the varying developmental levels and focus of transport. The range of population in the analyzed cities goes from half million people to ten million people living in Jakarta, this allows to have a range of different sizes and cover different developmental stages.*

Data and code to replicate the results are available in: (`https://doi.org/10.7910/DVN/GSOPCK`), and: (`https://github.com/nateraluis/Multimodal-Fingerprint`).

We characterize each city as a multiplex network [18, 19, 20] with M layers and N nodes that can be active in one or more layers in the system. Layers follow a primal approach [21] where nodes represent intersections (that may be
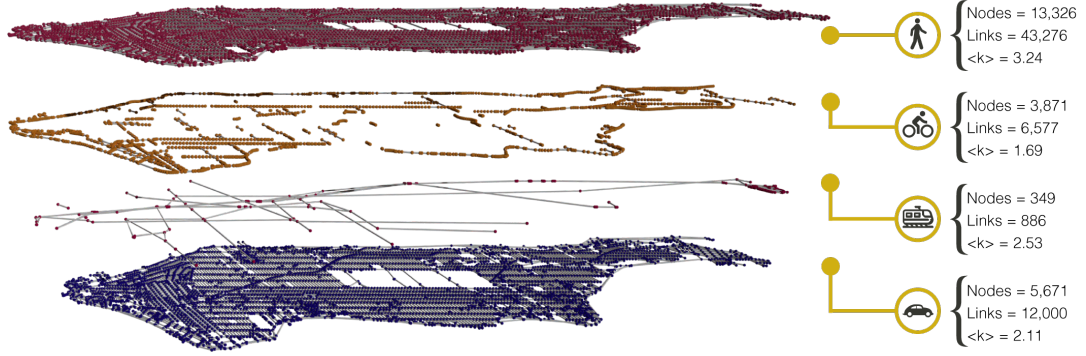
Figure 1.1. *(Map plot left) Multiplex network representation of Manhattan with the four analyzed layers of transport infrastructure (pedestrian paths, bicycle paths, rail lines, and streets), with data from OpenStreetMap. (Right) Network information for each layer, number of nodes, links and average degree $\langle k \rangle$.*

present in one or more layers), and links represent streets (denoted by s), bicycle paths and designated bicycle infrastructure (b), subways, trams and rail infrastructure (r), or pedestrian infrastructure (p). Construction of these intersection nodes follows the topological simplification rules of OSMnx [13].

In a multimodal city, we expect to find many transport hubs that connect different layers, such as train stations with bicycle and street access, i.e. nodes that are active in different multiplex configurations. Here we propose a method to assess all such combinations of node activities in the system, helping us to learn how well connected different modes are. For each city, we build a profile based on the combinations of node activities, and refer to it as *overlap census* (Figure 1.2). The overlap census captures the percentage of nodes that are active in different multiplex configurations and provides an "urban fingerprint" of its multimodality [8]. To define the overlap census formally, given a multiplex transport network with M layers the overlap census is a vector of $(2^M) - 1$ components, which accounts for the fractions of nodes that can be reached through at least one layer.

In Fig. 1.2(a) we show a schematic of how the overlap census is built: taking the multiplex network, and calculating the percentage of nodes that overlap in different configurations. The multiplex approach addresses the multimodality of a city: it not only counts how many nodes or links there are in each layer, but it shows how they are combined, revealing the possible multimodal mobility combinations in the city. Understanding the possibilities for interchange between mobility layers provides us with a better understanding of urban systems, showing us the complexity and interplay between layers.
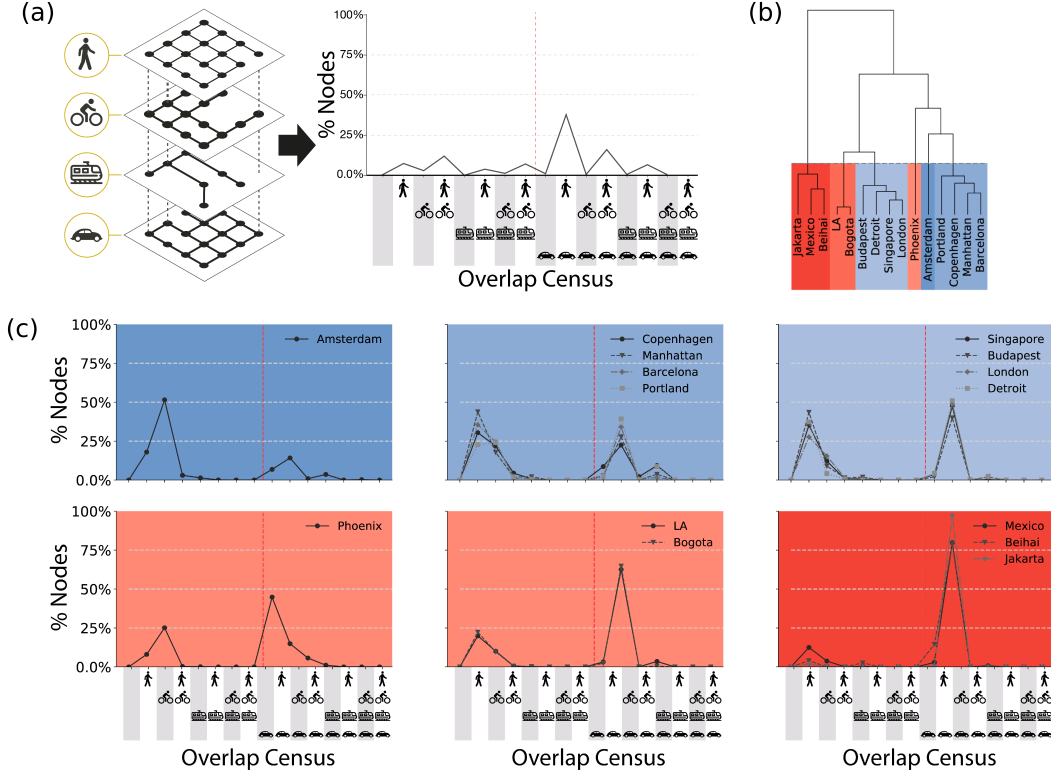
Figure 1.2. *(a) Schematic of multiplex layers in a city (left) and its transformation to the overlap census (right). In the overlap census, the vertical red line gives a visual separation of the left from the right half where nodes become active in the street layer. High spikes in the right half indicate car-centricity. (b) Clusters of cities based on similarity of their overlap census. We find six different clusters using a k-means algorithm (coloured areas), which explain more than 90% of the variance. (c) Overlap census for cities in each cluster. The first one corresponds to Amsterdam (the city with most active nodes in bicycle-only configurations). The Copenhagen-Manhattan-Barcelona-Portland city cluster has many active nodes in pedestrian-only and bicycle-only configurations, representing an active mobility city. The clusters of Los Angeles-Bogota and Mexico-Beihai-Jakarta are car-centric.*

1.3 FINDINGS

Even in a multimodally "optimal" city there will be a high heterogeneity of node activities due to the different speeds and nature of transport modes, implying, for example, a much lower density of nodes necessary for a train network than for a bicycle network. Therefore, a good way to assess a city's over-

lap census is by comparing it with the overlap census of other cities. We find similarities between cities via a k-means algorithm fed with fifteen vectors (one per city), where each vector contains the percentages of nodes active in each possible configuration. The algorithm separates the 15 analyzed cities into six different clusters [Fig. 1.2(b)].

On the left half of the overlap census, we show the configurations in which nodes are not active in the street layer, while the right half contains car-related configurations [Fig. 1.2(c)] . These clusters of cities are useful to explain similarities in infrastructure planning in different transport development paths [22, 23], with clusters of car-centric urbanization (like Mexico, Beihai, and Jakarta) opposed to clusters that show a more multimodal focus in their mobility infrastructure (like Copenhagen, Manhattan, Barcelona, and Portland). In the extreme cluster that contains only Amsterdam, close to 50% of nodes are active in the bicycle layer, whereas in the Mexico-Beihai-Jakarta cluster more than 50% of nodes are active in the street-pedestrian configuration. The concentration of nodes in just one configuration informs not only about the mobility character of the city, i.e. Amsterdam being a bicycle-friendly city, but unveils the importance of explicitly considering overlooked layers and their interconnections. For example, Singapore, Budapest, London, and Detroit have two main peaks indicating that most of their nodes are either active in the street-pedestrian or only in the pedestrian configuration. This is not the case in Los Angeles and Bogota, where the majority of nodes are active in the car-pedestrian combination, i.e. the pedestrians have to share most of the city with cars. Our multimodal fingerprint unravels how different transport modes are interlaced, helping identifying which layer (or set of layers) could be improved to promote multimodal, sustainable mobility.

To summarize, we propose the new "overlap census" method based on multiplex network theory allowing to rigorously identify and compare the multimodal potential of cities.

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