Using Open Data to Derive Local Amenity Demand Patterns for Walkability Simulations and Amenity Utilization Analysis

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Understanding human behavior and preferences are important for urban planning and the design of walkable neighborhoods. However, it remains challenging to study human activity patterns because significant efforts are required to collect the relevant data, convert unstructured data into useful knowledge, and take into consideration different urban contexts. In the context of the heated discussion about urban walkability and amenities, as well as the need of identifying a feasible approach to analyze human activities, this paper proposes a simple and effective metric of the amenity demand patterns, which demonstrates the spatiotemporal distribution of human activities according to the activeness in urban amenities. Such metric has the potential to support the urban study about people, mobility, and built environment, as well as other relevant design thinking. Further, a case study illustrates the data and the new metric can be used in walkability simulations and amenity utilization analysis, thus informing the design decision-making process.

Keywords: *Big Data, Urban Amenity, Walkability, Human Activity*

INTRODUCTION

Understanding human behavior is crucial for studying mobility-related issues in urban planning and design (Huang and Wong 2016). It not only supports decision-making in road network design, real estate development, and architecture programming but also relates to interdisciplinary topics such as healthy and sustainable cities (Nieuwenhuijsen and Khreis 2019). However, it remains challenging to study human activities because significant efforts are required to collect the relevant data, convert unstructured data into useful knowledge, and take into con-

sideration different urban contexts.

Large efforts have been made to empower urban study about human activities with data-based methods. Some of them are used to describe the aggregated commuting pattern and characterize the built environment. For example, Grauwin et al (2015) clustered mobile network signatures and used them to characterize human dynamic behavior on the city and local scale. Dashdorj and Sobolevsky (2016) classified geographical areas based on their amenity distribution, such as working or shopping oriented areas and proved the similarity between such activity

categorical profiles and human activity timeline categories estimated through cell phone data records. Frias-Martinez et al. (2012) identified urban land uses and landmarks from geolocated Twitter data. Besides, there are also more specific metrics proposed to support planning decision-making from different aspects. Yoshimura et al. (2016) uncovered customers' spatial distributions by analyzing their consecutive transactions, which can help improve spatial arrangements of retail shops. Wang et al. (2015) defined linked activity spaces among social groups by analyzing call dataset, which may relate to demands for amenities for social life. Despite new perspectives in understanding the urban environment, none of these researches have directly shown the way of implementing the proposed methods in the planning or design process, or how these data can practically influence the decision making.

Meanwhile, current planning paradigms promote high density, walkable neighborhoods as one solution for many challenges. Studies have shown that walkable neighborhoods can significantly reduce traffic-related pollution and lower the risk for chronic diseases (Frank et al. 2006; Lee and Buchner 2008), promote economic growth and prosperity (Claris and Scopelliti 2016), and foster an increase in social capital and political participation (Leyden 2003). Walkable amenities, as one of the most important factors towards a walkable city, have also become a heated topic in urban planning and design. It has been associated with socioeconomic growth (Clark et al. 2002; Zandiatashbar and Hamidi 2018), urban environment (Carlino and Saiz 2019) and quality of life (Mulligan and Carruthers 2011; Carr et al. 2011).

In the context of the discussion about urban walkability and amenities, as well as the need of identifying a feasible approach to analyze human activities, this paper proposes a simple and effective metric of the amenity demand patterns, which demonstrates the spatiotemporal distribution of human activities according to the activeness in urban amenities. More specifically, we regard the utility of ameni-

ties as the indicator of human activity (e.g. going to a restaurant, going to a cinema) because (1) urban amenities basically refer to all the services, functions and infrastructures that residents use in their daily lives (Allen 2015), which makes it a viable measure of what people usually do; (2) the amenity-based metric explicitly specifies people's destinations so that it can be interpreted and employed in mobility-related researches more effortlessly.

Also, this paper introduces a case study about the way of utilizing this metric in the design process. Based on Urbano (Dogan et al., 2018), an independently researched and developed plugin toolbox for Rhinoceros3D & Grasshopper, this metric proves to be valuable input data that can help promote mobility-aware urban design.

METHODOLOGY

We consider Lower Manhattan as our test ground because it is one of the most walkable regions worldwide with a high density of urban amenities. For other cities, although details of data processing may vary due to the difference in available open data, the foundational information needed to derive the result stays the same.

Data Sources
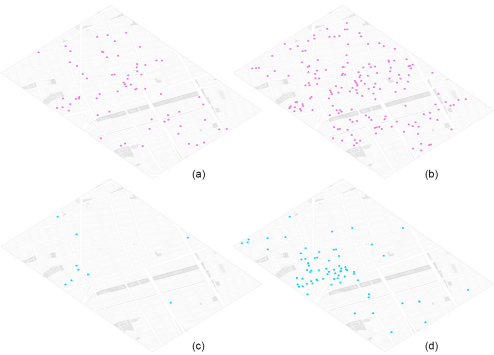
The datasets are retrieved from NYC open data and map data platforms, including Open Street Maps and

Figure 1
OSM has fewer amenity data points compared to Google Maps. The presented region is the same as the following case study region. (a) Cafe in OSM; (b) Cafe in Google Maps; (c) Pharmacy in OSM; (d) Pharmacy in Google Maps.

Google Places API.

Firstly, the PLUTO dataset from NYC Department of City Planning is an extensive land use dataset at the tax lot level. It contains fields about building floor area of different land uses including commercial, residential, office, retail, garage, storage, factory, and other use. Secondly, the Overpass API of Open Street Maps (OSM) provides geographical data of urban fabrics and building footprints. It also contains information about urban amenities as nodes with metadata telling its coordinates, name, amenity type, opening hours, rating, etc. Although OSM data has reasonably high quality and is comparatively easy to obtain, its amenity data is not as comprehensive as Google Places data (Figure 1). Furthermore, Google's data provides a critical dataset called popular times, which presents the utility of a specific place using a 24/7 matrix with each popularity number of any given hour relative to the typical peak popularity (100) for the business for the week (Table 3). To infer occupant density in the amenities we refer to ASHRAE Standard 62.1-2013: Ventilation for Acceptable Indoor Air Quality that provides standardized occupancy assumptions per architectural use case (ASHRAE 2015).

Data Processing

In general, the necessary information to derive the result consists of amenity type, location, capacity, and temporal utility of each amenity in the studied region. The process is introduced here by steps (Figure 2).

Step 1 is to map out the primary data, including PLUTO data and all the amenity information from OSM and Google Maps. The latter one is straightforward, while the first one needs additional processing. In PLUTO data, The location of a lot is depicted by the coordinate of a point near its center, expressed in the New York-Long Island State Plane coordinate system. Also, the commercial area refers to all the allocated area for commercial use in a lot, including but not limited to office and retail use. Hence, we use commercial area subtracting office area as the equivalence of the total indoor amenity area in each tax lot and then map them onto the lat-long coordinate system.
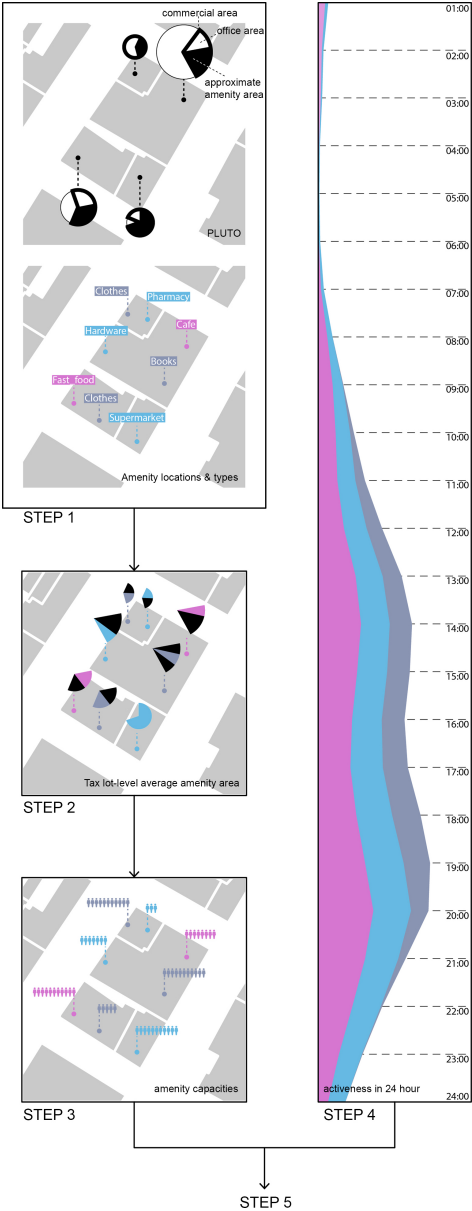
Step 2 is to derive amenity areas in preparation for calculating amenity capacities since there is no official open data directly containing such information. We divide the total amenity area on tax lot level equally between all amenities in that lot. This step introduces inaccuracy as amenities may differ in size. Nonetheless, it is an approximate measurement and can obtain desirable results when we apply it to a larger region (e.g. the whole Lower Manhattan Area) and introduce some descriptive statistics such as the interquartile range (IQR) to filter the outliers (Figure 3). The median value, perceived as the normal amenity area of each type, can be assigned to all the outliers as well as amenities with an unknown area in the same region (Table 2).

Step 3 is to calculate amenity capacities based on its type and area. The amenity capacity is the outcome of multiplying the amenity area the standardized occupant densities described by ASHRAE (2015). With regard to the choice of study types (Table 1), we first choose the most common amenity types in the city so that there is sufficient data to retrieve from maps platforms. Among them, we then select important types of walkable amenities as reported by the sample data sheet from Walk Score so that they are valuable for the discussion.
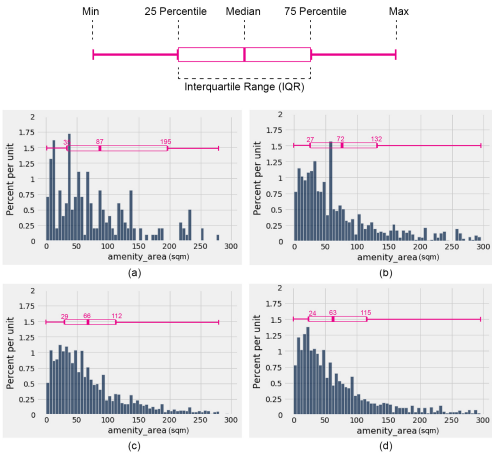
OSM Node Tag	Google Amenity Type	Walkscore Category	Study Type
amenity=post_office	type=post_office	errands	post_office
amenity=bank	type=bank		bank
amenity=cinema	type=movie_theater	culture_entertainment	cinema
amenity=theatre			theatre
amenity=arts_centre	type=arts_centre		arts_centre
shop=department_store	type=department_store	grocery	department_store
shop=supermarket	type=grocery_or_supermarket		supermarket
shop=convenience	type=convenience_store		convenience
shop=hardware	type=hardware_store		hardware
amenity=pharmacy	type=pharmacy		pharmacy
amenity=restaurant	type=restaurant	dining	restaurant
amenity=fast_food	type=restaurant and name include "Fast		fast_food
amenity=café	type=café		café
amenity=bar or amenity=pub	type=bar or type=night_club	drinking	bar_pub
shop=clothes	type=clothing_store	shopping	clothes
shop=books	type=book_store		books
shop=beauty or shop=hairdresser	type=beauty or type=haircare		beauty
shop=shoes	type=shoes		shoes

Study Type	Area Lower Boundary (sqm)	Area Upper Boundary (sqm)	General Area (sqm)	Area Per Person (sqm)	General Capacity (person)
post_office	19.56	199.4	88.02	4.65	15
bank	24.35	178.35	89.45	4.65	15
cinema	25.11	421.63	186.15	0.6	248
theatre	26.09	358.6	161.02	0.6	215
arts_centre	23.89	133.65	70.99	2.78	20
department_store	26.02	364.02	134.67	1.39	78
supermarket	35.56	149.28	80.81	2	32
convenience	29.49	118.55	67.16	1.39	39
hardware	35.21	192.48	87.58	1.39	50
pharmacy	27.21	133	72.68	1.39	42
restaurant	29.52	112.64	66.29	2	35
fast_food	28.24	70.62	44.52	1.39	36
café	24.63	115.33	62.71	1.39	50
bar_pub	30.645	147.52	81.55	1.39	47
clothes	13.7	102.8	51.45	1.5	21
books	11.3	93.4	45.31	1	26
beauty	19.415	78.01	46.79	1	27
shoes	20.41	123.75	66.04	1.39	38

Table 1
Study types of amenities are selected concerning different datasets.

Table 2
General statistics generated from step 2 and 3 are used to depict the average area and capacity information of each study type.

Step 4 is to explore temporal utility data from Google popular times. For each amenity with available popular time data, we calculate the average activeness of each hour in a week, which results in an array of 24-hour data expressing the specific utility patterns of this place in a general day. Since the urban mobility pattern differs from weekday to weekend, we also treat them separately (Table 3).

The final step is to combine all the previous results so as to convert the temporal utility pattern to the user pattern. Under an assumption that the peak activeness in amenity (100) is equivalent to the utility of full capacity, the temporal amenity utility can be directly transformed into the temporal user population by multiplying its capacity. Ideally, the user population should be calculated for each amenity in the studied region and then be summed up for each type in order to derive the result. However, to limit the computational burden, we instead use a sampling method (300 samples for each type), derive average statistics for each type, and finally multiply them with the total number of amenities in each kind. The even-

Figure 3
Use the interquartile range (IQR) to analyze the distribution of the deriving amenity area (sqm). (a) Hardware stores; (b) Pharmacies; (c) Restaurants; (d) Cafes.

Amenity type: café
Name: Orens Coffee
Phone: +1 212-717-3907
Address: 985 Lexington Ave, New York
Coordinate: 40.769769, -73.962482
Rating: 4.2
Rating Number: 60

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Mon	0	0	0	0	0	0	0	29	90	87	48	58	80	93	90	70	45	25	0	0	0	0	0	0
Tue	0	0	0	0	0	0	0	45	87	90	70	67	77	80	74	61	41	25	0	0	0	0	0	0
Wed	0	0	0	0	0	0	0	51	77	74	58	61	80	100	96	77	48	22	0	0	0	0	0	0
Thu	0	0	0	0	0	0	0	22	58	90	87	61	54	67	83	80	58	32	0	0	0	0	0	0
Fri	0	0	0	0	0	0	0	51	77	67	61	67	74	74	64	54	38	25	0	0	0	0	0	0
Weekday Average	0	0	0	0	0	0	0	39.6	77.8	81.6	64.8	62.8	73	82.8	81.4	68.4	46	25.8	0	0	0	0	0	0
Sat	0	0	0	0	0	0	0	22	38	51	61	58	58	67	87	93	80	48	0	0	0	0	0	0
Sun	0	0	0	0	0	0	0	0	51	61	51	61	67	61	61	67	61	0	0	0	0	0	0	0
Weekend Average	0	0	0	0	0	0	0	11	44.5	56	56	59.5	62.5	64	74	80	70.5	24	0	0	0	0	0	0

tual datasheet for amenity demand patterns is presented in Table 4.

Result

Using Table 4, the amenity demand patterns can be represented by a 24-hour timeline graph (Figure 4). The total height of the graph refers to the overall amount of activities in the studied region, which peaks during the day and dips in the early morning. Each layer in the graph represents the demand pattern of a particular amenity, some of which are not quite consistent with the overall pattern due to unique functionality. For example, banks and post offices tend to stop service early in the afternoon, while bar and pub become dominant activities during midnight.

Intuitively, human activities demonstrate diverse patterns in distinct spatial and temporal contexts. By separating the weekday and weekend data and making comparative graphs, it is shown that, during the weekend, both daytime and nightlife are more active, and the peak hour of overall activities shifts several hours earlier. Regarding the spatial difference, we conduct our deriving method for Lower Manhattan and Downtown Paris and compare the results using the same graph. It turns out that the urban pulse de-

picted by amenity demand patterns in the two cities also have significant differences.

CASE STUDY

To examine the value of amenity demand data in design practice, this case study aims to use the derived data to inform an urban mobility model and discuss how it can influence the design decisions in urban design and program allocation.

Case Setup and Tool Description

Urbano (Urbano.io) is a tool that allows designers to interactively modify the model according to urban mobility simulation results (Figure 5). It streamlines the workflow of importing data, model setup, simulating iteratively and modifying designs in order to promote the mobility-aware urban design process. Moreover, it provides the ability to customize people's different preferences and demands for urban amenities. Taking advantage of these features of Urbano, we embed into the initial model all the relative data of driving the mobility simulation, including amenity locations, building-level population, amenity capacities, and amenity demand patterns in weekdays of Lower Manhattan, along with the automatically downloaded geographical metadata of ur-

| Study Type	Amenity Count	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
post_office	82	0	0	0	0	0	0	0	82	246	410	574	656	738	820	820	902	902	738	492	164	164	82	0	0
bank	1183	0	0	0	0	0	0	0	0	2366	5915	7098	8281	9464	10647	10647	10647	9464	5915	1183	1183	1183	1183	0	0
cinema	165	0	0	0	0	0	0	0	0	0	1980	3465	5280	7095	9075	11880	16005	22440	28545	30360	26070	18315	10395		
theatre	253	0	0	0	0	0	0	0	0	0	0	506	759	2530	3289	3289	3289	3036	4301	12144	29348	13915	13156	8349	5566
arts_centre	2109	0	0	0	0	0	0	0	0	0	2109	2109	2109	2109	2109	4218	6327	10545	10545	10545	8436	0	0	0	
restaurant	6314	6314	0	0	0	0	0	0	6314	12628	18942	25256	44198	75768	88396	75768	56826	50512	69454	94710	1E+05	1E+05	75768	44198	18942
fast_food	585	585	585	0	0	0	585	1755	3510	4095	2925	2925	6435	11700	13455	9945	7605	7605	8190	9360	9360	7605	4680	2340	1170
cafe	1697	0	0	0	0	0	1697	8485	23758	33940	33940	32243	30546	32243	33940	33940	32243	28849	25455	22061	16970	10182	5091	3394	0
bar_pub	3133	18798	12532	9399	3133	0	0	0	0	0	0	0	6266	12532	12532	15665	15665	25064	37596	53261	62660	62660	59527	53261	43862
department_store	201	0	0	0	0	0	0	0	201	1005	2211	4221	6231	8040	9045	9045	9045	9648	10251	9849	7638	4824	1809	201	0
supermarket	1304	2608	1304	0	0	0	1304	1304	2608	5216	10432	14344	18256	22168	26080	27384	27384	26080	27384	29992	29992	27384	20864	14344	9128	5216
convenience	370	1850	1480	1480	1110	1480	1850	2590	3700	4810	5180	5180	5550	5920	6290	6660	5920	5180	4440	4070	3700	3700	3700	3330	2590
hardware	258	0	0	0	0	0	0	0	2838	6708	8772	8514	9030	9288	8772	7998	5934	3354	1806	1032	774	516	516	258	
pharmacy	1665	6660	3330	3330	1665	1665	1665	4995	9990	18315	24975	29970	34965	38295	41625	43290	44955	46620	46620	43290	36630	29970	24975	18315	11655
clothes	6742	0	0	0	0	0	0	0	0	0	6742	20226	33710	40452	47194	47194	47194	53936	60678	53936	33710	13484	0	0	0
books	480	0	0	0	0	0	0	0	0	0	960	1440	2880	4320	4800	5280	4800	5280	6240	6720	5280	1440	480	0	0
shoes	943	0	0	0	0	0	0	0	0	0	1886	5658	8487	11316	12259	13202	14115	15088	16031	15088	9430	3772	943	0	0
beauty	1963	0	0	0	0	0	0	0	0	1963	3926	7852	11778	13741	17667	17667	17667	17667	21593	21593	15704	7852	3926	1963	0
Sum		36815	19231	14209	5908	4449	7101	20433	52771	92638	1E+05	2E+05	2E+05	3E+05	3E+05	3E+05	3E+05	4E+05	4E+05	4E+05	3E+05	2E+05	2E+05	3E+05	99654
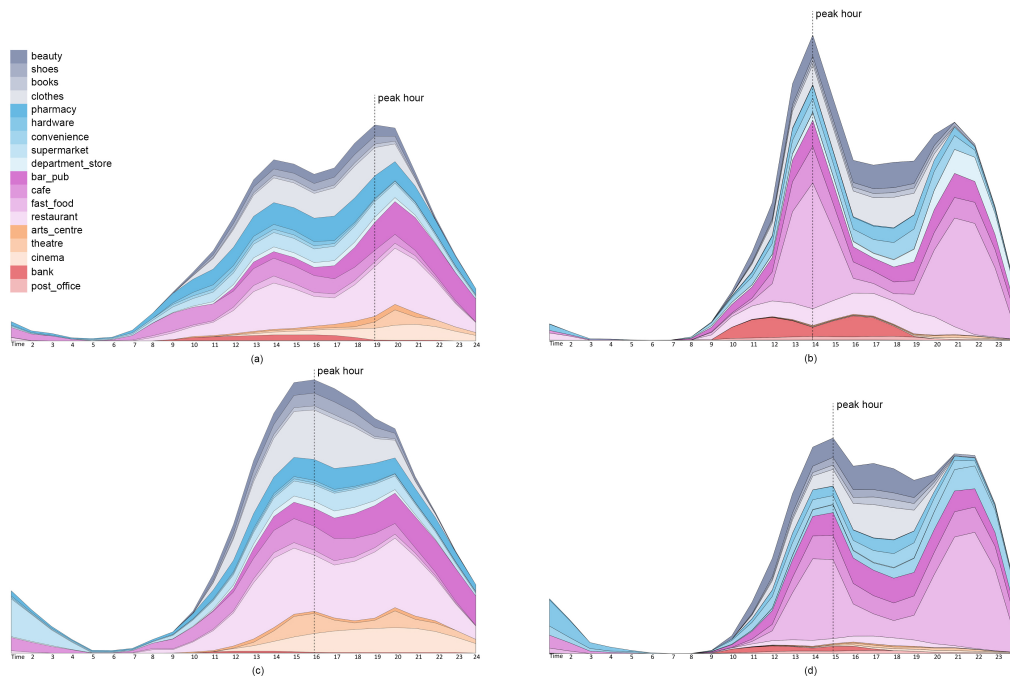
Figure 4
Timeline graph for amenity demand patterns reveals spatiotemporal differences in urban pulse. (a) Weekday pattern in Lower Manhattan; (b) Weekday pattern in Paris; (c) Weekend pattern in Lower Manhattan; (d) Weekend pattern in Paris.

ban networks. These inputs construct a contextual model with abundant metadata that enables designers to get a more profound perception of urban mobility environment.

We select a rectangle area in Lower Manhattan as the study region to carry out the general simulation based on the 24-hour matrix of the generated amenity demand patterns input. Additionally, we choose a block in the center of this region to test how a new project would affect the current condition in the sense of pedestrians and amenities (Figure 6).
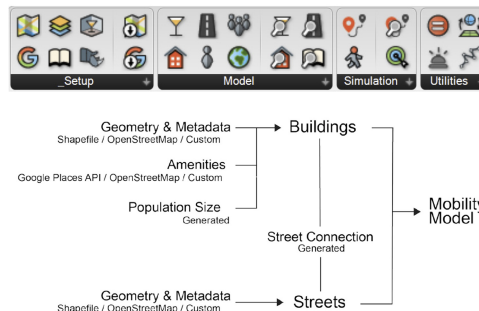
Figure 5
Framework of Urbano.io

Figure 6
Study regions

Lower Manhattan area used to derive human activity pattern

Simulation region

Site for case study

amenities and help decide the appropriate program under the context.

Furthermore, in the selected block as the test site for the new project, we run the same simulation with different program scenarios to explore their variance in the performances, including self-interests in receiving pedestrian hits and regional impact on nearby businesses (Figure 8). Accordingly, we can make decisions in the program selection with custom criteria.

In pursuit of a more explicit illustration of how the derived data works, we plot each amenity's activity pattern from the simulation result and compare them with the real data from the original Google popular times (Figure 9). Regardless of the different height, which represents the overall activeness of the business and is totally driven by the routing simulation and population data, the shapes of the lines that are variant in different amenity types are indeed determined by the amenity demand data derived in the previous chapter. The comparison confirms that the data is overall representative and can be concerned as a workable proxy for measuring human activities regarding amenity utilities, especially for the types with less variance in the business pattern, such as restaurants and banks. Nevertheless, this derived data depicts a general pattern over the whole Lower Manhattan region. If one would like to get a more

Result and Analysis

There are 24 simulation results each of which represents the mobility state of an hour in a weekday (Figure 7). Though Urbano is able to calculate various mobility metrics such as walk score and street utility, we will only focus on the simulation of amenity usage, which is called "amenity hits", referring to pedestrian hits that an amenity received in a round of simulation. This metric is mainly driven by the shortest-path routing system of Urbano, with the building-level population data deciding the population coming from all origins and the data of amenity demand patterns deciding the population going to all destinations. It can measure local demands for different

Figure 7
Simulation results
in a 24-hour matrix
for the selected
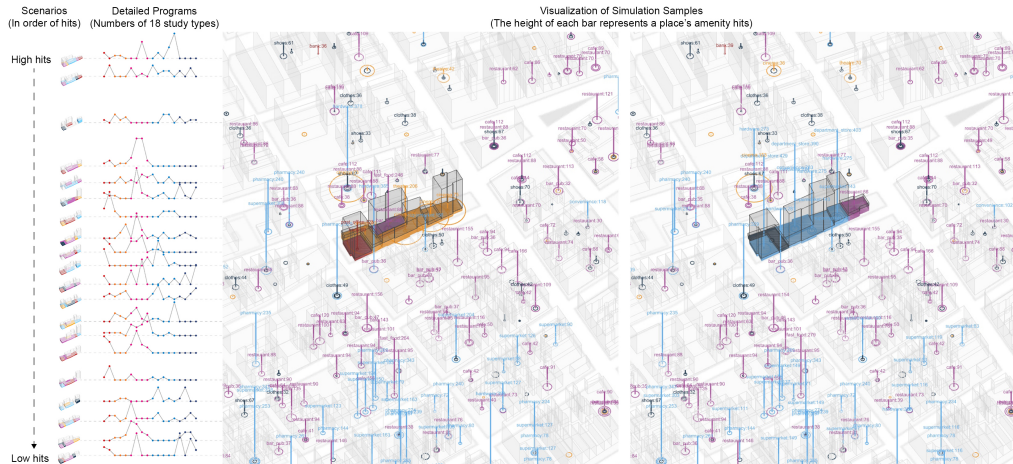rectangle region in
Lower Manhattan
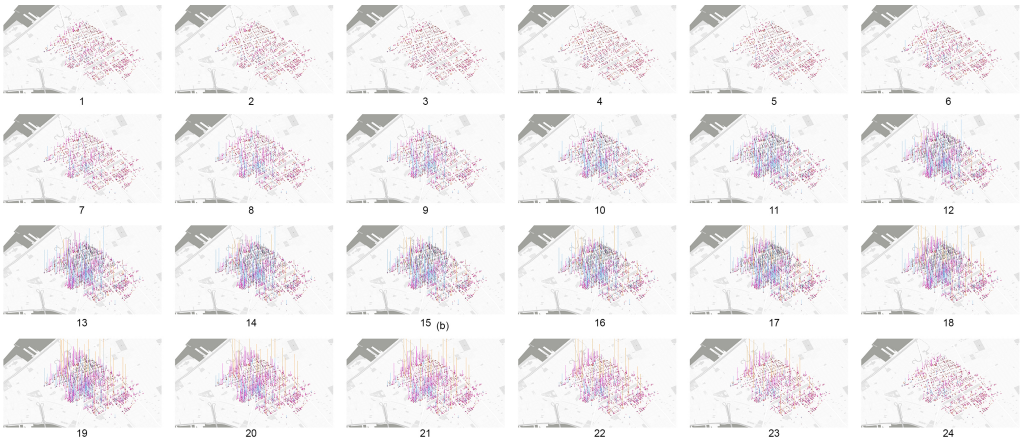
Figure 8
Impacts and
Performances of
different scenarios
in the site context

precise simulation result resembling the truth, it will be helpful to incorporate more detailed local metadata into the model, such as opening hours. However, this is usually not the case in early-stage site analysis and urban design thinking.
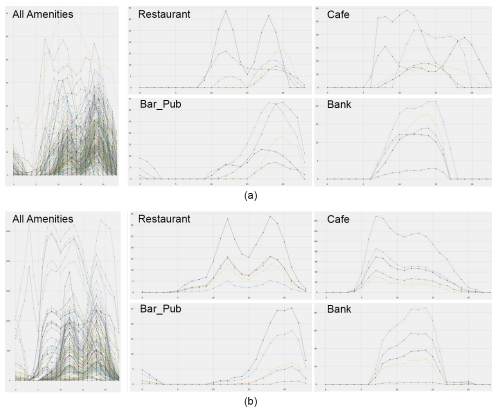

Figure 9
Comparison of
amenity demand
patterns between
simulation and real
data. For each type,
we randomly select
5 samples. (a)Real
data; (b)Simulation
result.

DISCUSSION AND CONCLUSION
Scale of the study area
Caution is needed about choosing the scale of the study area, both for deriving the amenity demand

patterns and for running the simulation as the case study. Under the first circumstance, there is a risk in misinterpreting the existing situation as implicit needs, which is especially problematic if we only consider a relatively small area. For example (Figure 10), if we only compute the data from the case region, the amenity demand patterns remain similar. But after downsizing the computing area into the quarter of the region, the result starts to change drastically, and some amenity types even start to have zero demands, which is questionable. Under the latter circumstance, since there is a cut-off border for the selected region and the simulation result near the border is less reliable, it is also inappropriate to use a too-small study area.

Limitation in data sources
The accessibility and contents of open data largely differ among countries and cities, and there certainly exist other possibilities in processing data. For example, the dataset like PLUTO may not be available outside of NYC, while other cities may provide data that is not available for Manhattan as well (e.g. the city of Melbourne provides an open dataset of seating capacity of cafes and restaurants). Besides, some data has not been updated for years and may deviate from

Figure 10
Amenity demand
patterns of 6
sample types
derived from
different scales of
the study area
express significant
variance.

the most recent fact. Moreover, the user-generated data mostly relies on GPS on mobile phones (e.g. Google popular times data), which has the problem of coverage and bias.

While more efforts are being made to empower the urban database in the era of big data and smart city, the metric of amenity demand pattern and its deriving method proposed in this paper should also evolve with more advanced data in the future. However, intellectual merits will remain as it develops a new way of quantifying and measuring people's behavior in the city and links it closely to urban function and built environment so that it is more useful to urban planning and design.

Conclusion

"Cities have the capability of providing something for everybody, only because, and only when, they are created by everybody" (Jacobs, 1992). Urban planners and designers have long pursued a human-centric urban environment. The accelerated technical development and increased access to urban data are providing us a profound opportunity to better understand human preferences and behavior in cities. This paper aims to propose a data-driven metric of amenity demand patterns to help measure human activities in the local context. Constructed from the local data and user-generated contents, such metric has the potential to support the urban study about people, mobility, and built environment, as well as other relevant design thinkings.

Also, under the bigger technological context of extraordinary advancements in areas like big data and smart city, and emerging paradigms about empowering planners and architects with computational techniques, this paper shows how amenity demand data can be utilized and leveraged in active mobility simulation workflows and how these simulations can be used in the design decision-making process to achieve "better" design outcomes.
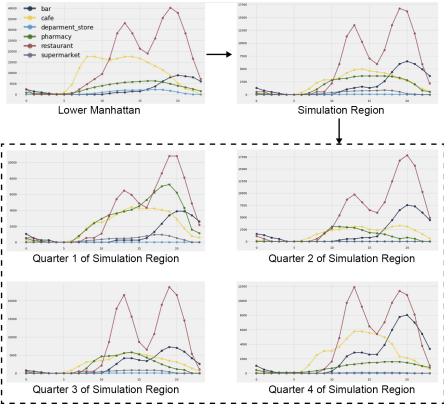
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[1] https://urbano.io/

[2] https://www.walkscore.com/