An Intelligent Tree Planning Approach Using Location-based Social Networks Data

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Abstract. How do we make sure that all citizens in a city can enjoy the necessary amount of green space? While an increasing part of the world's population lives in urban areas, contact with nature remains important for human well-being. As optional tree planting sites and resources are limited, the best site to plant must be determined. Can we locate these sites based on the popularity of nearby venues? How can we detect groups of people who tend to spend time in tree deprived areas?

Currently, tree location sites are chosen based on criteria from spatial-visual, physical and biological, and functional categories. As these criteria do not give any insights into the number of people benefiting from the tree placement, we propose a new data-driven criterion taking socio-cultural aspects into account. We combine an LBSN mobility data set with a tree location data set, both of New York, as a case study. Using the mobility data we create a venue interaction network from which we extract venue communities. These communities are then scored based on the number of trees in the vicinity of their venues. Applying multi-objective optimization theory, we combine the popularity of venues with the tree density of venue communities to identify locations where planting a tree can benefit the highest number of people and make the largest impact. [1]

Keywords: Urban computing · tree planning · social network analysis · community detection algorithms · mobility data · multi-objective optimization

1 Introduction

As of 2018, 55% of the world's population lives in urban areas, a number which is projected to grow to 68% by 2050 [5]. The North-American continent stands out in particular, where this number is already at 82%. While it is easy to point

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[1] This work earlier participated and was selected for the Future Cities Challenge co-organised by Foursquare at NetMob 2019. The work has not been published elsewhere.

out the economical reasons for moving to the city – at least at the first sight [8] – there are certainly downsides attached to urban life. One of them is the inescapable fact that cities, by definition [7], have a higher population density, leading to more built-up areas and thus a scarcer supply of nature than in rural areas. However, as Rohde and Kendle put it, "it is obvious from any casual observation that many human beings do not like to be dissociated from the natural world; as a nation we spend millions of pounds every year on garden and household plants" [21]. Indeed, contact with nature does seem to be linked to human well-being and positive emotional effects and is even said to strengthen urban communities [13, 19]. Apart from socio-cultural benefits, urban greenery can help to mitigate two characteristically urban problems: air pollution due to traffic [14] and (extreme) warmth due to the urban heat island effect [17]. The inclusion of parks and street trees in city landscapes is, therefore, an important aspect of the urban planning process.

To date, socio-cultural arguments play a marginal if not non-existent role in formal frameworks describing criteria for selecting potential tree planting sites. The criteria in these frameworks do not account for the amount of people that are accommodated by the newly planted trees. When following the established criteria, trees may end up in places where they are beneficial to some people, but its effects may not serve the majority of people, or may never reach the people yearning for them most.

To tackle this problem, we propose taking a data-driven approach based on available mobility data which allows considering an additional tree planning criterion. Popular adoption of Location-Based Social Networks (LBSNs) has allowed the collection of valuable data representing the movement of people between venues. Data from the location technology platform Foursquare can be used to construct a network of venues, with users moving between those venues. Priority should be given to sites visited by many people and specifically by people who tend to move between areas lacking trees.

We identify such locations by combining two ways of analyzing the structure of a venue interaction network. By combining the knowledge about (i) venue popularity, and (ii) venue communities with a low tree density, we can detect popular venues within tree deprived communities and thus provide a prioritization that can be used for site selection in the tree planning process, as schematically shown in Figure 1. This prioritization can be embedded within the criteria of established tree planning frameworks that currently lack this socio-cultural value and insight.

Our paper makes the following contributions:

- We describe a novel criterion for potential tree planting site selection based on network communities within a venue interaction network;
- We apply a concept from multi-objective optimization theory to combine this criterion with venue popularity, based on network analysis of venue interaction data from an LBSN;
- We apply this method to prioritize venues as potential tree planting sites in New York City.

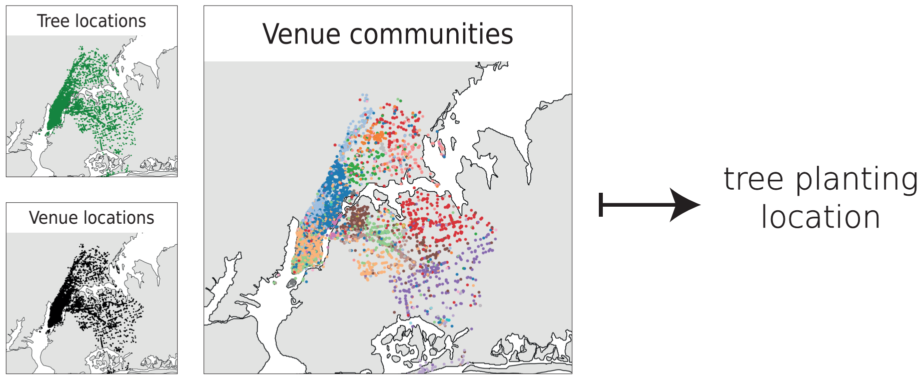


Fig. 1: We combine three types of data (tree locations, venue locations, venue communities) to determine a new criterion which can be used in selecting potential tree planting sites.

The rest of this paper is organized as follows. Section 2 presents the related work. We present our proposed data-driven tree-planning methodology in Section 3. In Section 4 we experiment with the method by implementing it for a specific case in New York City. The results for this are discussed in Section 4.2. Finally, Section 5 presents a number of concluding remarks.

2 Related work

Most of the work in the field of tree planning revolves around selecting appropriate tree species for predetermined planting sites [23, 24]. This reflects the observations by Spellerberg [24] and Pauleit [20] that tree planning is often – or at least has been for some time – an afterthought in the urban design process and characterised by pragmatism. According to an Australian survey, while the visual aesthetic of trees and socio-cultural function of green spaces in the city seem to be important motives for planting trees, the first motive only plays a small role in the tree planning process [22] and the second motive is not reflected in the sparse body of site selection criteria that we could find. The work by Amir and Misgav [2], in which they aim to describe a complete tree planning decision framework, does incorporate criteria on site selection. They define three useful criterion categories, which are *spatial-visual*, *physical and biological* and *functional*. Criteria relating to the socio-cultural function of green spaces, however, are missing. We observed several works describing site selection criteria [10, 20], but those fall within the category of *physical and biological* criteria that are essential for the survival of the tree. Moriani [14] did use population density in their planting priority index, but as they focused on the air pollution-reducing quality of trees, this still falls within the category of *functional* criteria. We believe then, that the body of site selection criteria is still incomplete and that we can contribute to this framework by introducing a new socio-cultural criterion which takes people movement into account.

As a way to capture the general movement patterns of people within cities, we utilize data collected by LBSNs. As defined by Zheng [25], social networks are social structures that consist of individuals connected to each other via specific types of interdependencies. In LBSNs these individuals are connected through their shared experience interacting with the locations in the network. Oftentimes, in LBSNs users announce their visit to venues through a so-called check-in option. The check-in data can provide information about the movement of people between a network of venues. The structure of such a network can be explored to find underlying patterns. For instance, locations can be grouped based on the similarity between user profiles [12]. Hung et al. [9] use these user profile similarities to find user communities. Girvan and Newman [6], however, use clustering algorithms on the full network to detect communities, eliminating the need for individual trajectories. Noulas et al. in [18] has studied the spatial network of venues derived from such data and proposed a variant of gravity mobility models using inter-venue connectivity information. Most of these approaches have considered studying the network properties of LBSN data without considering how such information can be used in improving urban aspects. Recently, Arp et al. [3] have shown how such data can be used in optimising the state of traffic within the city. In this paper, we aim to study whether such data can be used for improving decision making regarding the optimal allocation of resources, notably in this case the green space, throughout the city.

3 Methods

In this section, we introduce our proposed method. First, we describe two separate possible indicators and how they can be used to define objectives for planting trees (Sections 3.1 and 3.2). Then, we argue that the best way to use them is by combining them using multi-objective optimization theory (Section 3.3), thereby forming the method we propose in this paper.

3.1 Venue popularity

A first possible approach to maximize the impact of planting a tree, is to plant it near a place where many people pass by. From this perspective, the goal is to find the venue that is maximally popular among visitors. To find this place we compute the degree of all nodes in the undirected network graph $G = (V, E, W)$, where nodes $v \in V$ are venues and edges $e = (v_1, v_2), e \in E$ movements of people between two venues v_1 and v_2, with weight $w_e \in W$ as the number of movements between the pair of venues. The degree of a node v is then defined as the sum of the weights of the edges that are connected to it:

$$\deg(v) = \sum_{e \in \{(u,v) | u \in \mathrm{adj}(v)\}} w_e \tag{1}$$

3.2 Venue community tree density

Although trees near popular venues may reach many people, we will still be missing those who visit other venues. Naively, one might say that an additional, or: parallel, objective could be to then look for venues that have the least trees in the vicinity. This approach would, however, discard the reality that people move about and that people are thus prone to visit multiple venues. A single venue that has few trees in its vicinity might not be a major problem if the usual crowd for this venue also regularly visits other venues that do have more trees in the neighbourhood. Using LBSNs, we can actually use this observation in our objective. To this end, we introduce a measure we call the *tree density coefficient*. This measure intends to highlight *groups* of *related* venues that have a low tree density, instead of *single* venues that have a low tree density. A relation between venues, in this sense, is determined by people travelling often between those venues.

Using graph theory parlance, these related venues can be discovered through the task called *community detection*. A community is a group of nodes of which the nodes are densely connected with each other, but much less with the rest of the network [6]. To detect the communities, we use the Louvain community detection algorithm [4]: a fast algorithm that is able to find communities with high quality. The algorithm performs based on the optimization of modularity, a measure that compares the density of connections within a community with the density between communities. Modularity, as defined by Newman et al. [16], is computed as in Equation 2:

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \tag{2}$$

Here, A_{ij} is the adjacency matrix holding the number of edges between nodes i and j, m the number of edges in the network, k_i the degree of node i and $\delta(c_i, c_j)$ a delta function that returns 1 if i and j are assigned to the same community and 0 otherwise.

As it is computationally heavy to compute the modularity of a community, the Louvain algorithm uses heuristics to approximate it. Therefore, it does not necessarily return the best community layout. To gain confidence in the robustness of our communities, we choose to run the algorithm 1,000 times in our own experiments, to create a large number of community layouts.

To compute the tree density coefficient for a venue, we first count the number of trees in the vicinity of the venues. We approximate this vicinity by creating a grid of the city, thereby discretizing the geographic space into grid cells, where each grid cell is 50 by 50 meters, calculated using Universal Transverse Mercator coordinate system [11]. Each venue v_i is mapped to a cell in the grid and is assigned the number of trees in the cell as its *venue tree density* vtd_i.

We compute the *community tree density* ctd_i for a venue v_i by averaging the vtd_i with the venue tree densities of all the other venues in its community C_i, over multiple iterations k of the community detection algorithm:

$$\mathrm{ctd}_i^k = \frac{1}{|C_i|} \sum_{v_j \in C_i} \mathrm{vtd}_j, \quad 0 < k \leq k_{\max} \tag{3}$$

In the end, the *tree density coefficient* c_i for a venue v_i is its average community tree density value over all iterations of the community detection algorithm:

$$c_i = \frac{1}{k_{\max}} \sum_{t=1}^{k_{\max}} \mathrm{ctd}_i^k \tag{4}$$

3.3 Joining both objectives through multi-objective optimization

The two objectives discussed above, venue popularity and venue tree density, can both be important in discovering the most suitable location(s) for one or more new trees. Indeed, a venue with a low tree density coefficient could have only one visitor, whereas other venues in the same community that have a similarly low tree density coefficient could have many visitors. In this case, the latter venue(s) would be more appropriate as a tree planting site. It is therefore important to take both objectives into account. To achieve this, we borrow a method from multi-objective optimization theory, namely the Pareto front.

We join the venue degrees, i.e. the popularity of venues, with community-based tree density coefficients by detecting the set of venues that are Pareto efficient, i.e., the venues that are found by minimizing the tree density coefficient and maximizing the influence of the venue: the optimal trade-offs between the two measures. Also called the Pareto frontier, the venues in this set meet our criterion of helping most people needing trees. Tree planners could choose any of the venues along the Pareto frontier, depending on their preference towards either of the two measures.

4 Experiments

4.1 Data sources

City of choice: New York We conducted a case study to investigate the implementation and workings of our criterion using real data. For this, we chose to focus on New York City as data on both venue interactions and tree locations were richly available.

We used two data sets to construct our criterion. We used venue interaction data of New York, provided by Foursquare as part of the Future Cities Challenge 2019, to create the venue interaction network. To assign tree density scores, we used a Street Tree Census data set [1]. In the remainder of this section we describe the properties of the venue interaction data and street tree data set, respectively, and how we processed them to implement our methods.

Table 1: Description of New York data set (Foursquare).

	Original	**After pre-processing**
no. of venues (nodes)	17,975	15,803
no. of interactions (edges)	7,919,999 (directed, parallel)	248,597 (undirected)

Venue interaction data Foursquare City Guide is a mobile app that recommends places to its users based on their likes or check-ins. The Foursquare venue interaction data set comprises of two parts: venues and movements between them. Venues in this set are locations people can visit. Venue coordinates are recorded, as well as their name and a category. Movements are recorded when individuals make consecutive check-ins at different locations.

The data set contains information on ten different cities around the world. As we focused on New York in this case study, we used the New York data, but it should be noted this study is applicable to any of the other nine cities, provided we have access to a corresponding tree location data set. The data was collected between April 2017 and March 2019.

As not all venues found in the movement data occur in the venue information data, we considered only the venues with known locations for the construction of the network. Additionally, we observed that some venues were only connected within small subgraphs, 'connected components', of less than 3 venues and did not have any edges to the large, main connected component in the graph. These 86 venues were omitted. In the end, we were able to use 15,803 of the 17,975 venues in our analysis. We used this data to create a network where nodes were represent venues and the edges represent movements between them. We combined the many parallel interactions between venues into singular weighted edges between the venues, where the edge weight denotes the number of interactions between two given venues. Later, we used this data as input for both the detection of nodes with high node degrees (see Section 3.1) as well as the Louvain algorithm (see 3.2). In Table 1, we provide a comparison between the original data set and the pre-processed data set.

Street Tree Census The Tree Census data set contains information on street trees in New York City and surrounding cities. It contains information on among others the *species* and *health* of the trees, as well as their *longitude* and *latitude*. As only street trees were counted, trees in parks were not taken into account in the tree survey and are therefore not present in the data set.

As discussed in Section 3.2, we discretized the geographic space into a grid, counting the number of trees per cell to obtain a measure for the tree density around the location of each venue. To provide insight into the data, we show the tree counts over grid cells in Figure 2.

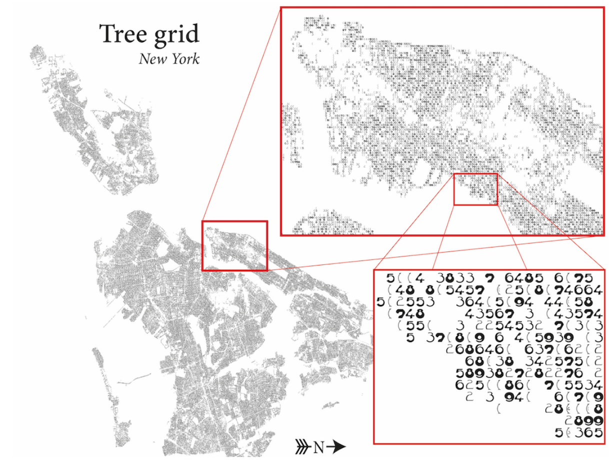
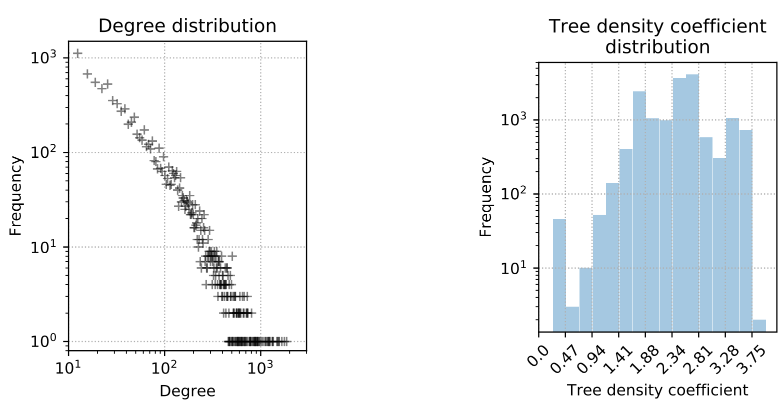


Fig. 2: The trees within part of the New York street tree dataset, discretized into grid cells of 50 by 50 meters. Shown as a heatmap-like data plot using 'FatFonts' [15].

4.2 Results

Venue popularity We computed the venue popularity as the degree of each node and observed that the distribution follows a power law (see Figure 3a), as is generally the case in scale-free networks modeling natural phenomena. To decide which venues would be interesting as a tree planting site according to this method, one should prioritize venues with higher degrees.



(a) (b)

Fig. 3: The power law distribution of venue degrees (a) and distribution of tree density coefficients (b).

Venue community tree density We used the Louvain community detection algorithm as implemented in the Python `NetworkX` package. We set the resolution to 0.5 to find decently small communities. One such community lay out is shown in Figure 5a.

As the communities are detected using the heuristic Louvain algorithm, we averaged the community tree density of the venues over 1,000 runs of the algorithm, each time possibly detecting slightly different communities in the network, to obtain their tree density coefficients.

To find tree-deprived communities, we combined the locations of the venues within the communities with the tree locations in the street tree data set. First, we calculated the tree density for each venue. Then, the average tree density of the venues in the community was computed and returned to each of those venues as its community tree density.

We show the distribution of the tree density coefficient values in Figure 3b. The distribution is slightly skewed to the right, which means most communities are filled with trees. Some, however, would still benefit from planting more. Prioritization for tree planting sites using this method should be given to the venues with the lowest coefficients.

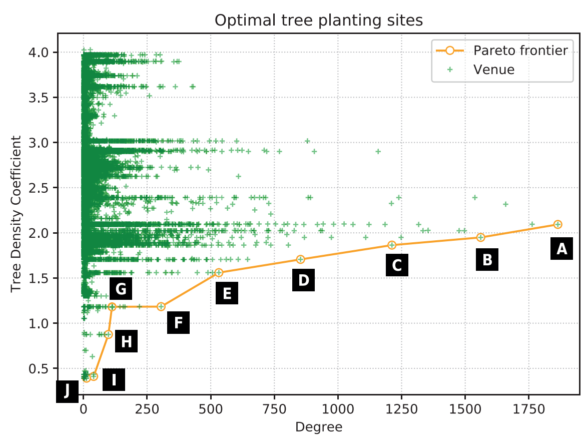
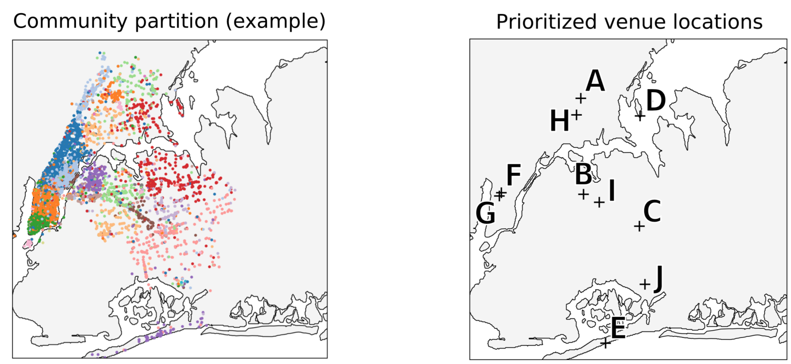


Fig. 4: The distribution of venues according to degree and tree density coefficient. The Pareto frontier shows the venues with the optimal tree planting location according to our criterion. Venue labels correspond with Figure 5b and Table 2.

Joining both objectives through multi-objective optimization To select the most impactful planting locations, we combined both measures. This results in the distribution of venues and associated Pareto frontier as shown in Figure 4. Here we minimize the tree density coefficient of the venues while maximizing their degree. These venues are highlighted by the Pareto frontier and should be prioritized according to our new criterion. To indicate the locations of the venues on the Pareto frontier, we show the venues on a map in Figure 5b and provide additional insights into the data in Table 2.

It is noteworthy that one of the selected venues (venue H) is a rose garden, amidst a park lush with trees. This is explained by the fact that the tree data set contains only street trees and no park trees. Additionally, we found upon inspection using Google Street View that some of the venues (most notably venues A, B, D, G and H) do seem to be near a considerate amount of trees. When inspecting these locations in the tree data base[2], we see that there are either only a few (venues B and G) or no trees (venues A, D, E and H) recorded in the immediate vicinity of the venues. We see that along with park trees, trees on private grounds are also not recorded.



(a) One of the 1,000 community partitions.

(b) Optimal tree planting locations (see Table 2).

Fig. 5: Map of New York City showing the optimal tree planting locations based on community structures.

5 Conclusion

In this paper, we propose a novel criterion that can be used when selecting potential tree planting sites. The nature of the criterion is socio-cultural, capturing people movement between venues and tree-lacking (social) communities into one measure. Having implemented the measure for a case study on New York City, we show that the measure is applicable in the field and can be used to support decision-makers by providing them with optional planting sites along a Pareto frontier.

[2] The tree database can be explored on a map at `https://tree-map.nycgovparks.org/`, last visited 9 September 2020.

We want to note that our approach depends heavily on the quality of the available data. Regarding the tree data, we see that some venues indicated by our criterion as tree lacking seem to actually be in a green area. We believe that the application of our method can be improved with a more detailed tree location data set. Then, the criterion proposed in this paper can be a meaningful addition to the established site selection criteria.

Regarding the venue communities, we are aware that the used data set includes only venues selected and listed by Foursquare. Amongst those venues are major train stations, schools and other public buildings. The movements between the venues and hence also the venue communities used to find optimal planting locations only represent people that are using Foursquare, other inhabitants are not represented in the data. Unfortunately, full movement data is almost always proprietary. We would like to mention that the venue network could also be estimated based on other, more representative data.

We conclude that the newly introduced socio-cultural approach to finding a tree planting site that benefits different communities of city dwellers is feasible and can be easily implemented by urban planning organizations. Integration of this approach depends on the availability of detailed records of existing trees and movement data of city inhabitants.

Acknowledgments

We thank Foursquare and the organisation of Netmob for organising the Future Cities Challenge and providing us with access to Foursquare's venue interaction data set.

Table 2: The venues that are, according to the Pareto analysis, the most efficient to place trees next to.

Degree	Tree density coefficient	Venue ID	Venue Name	Latitude	Longitude	Venue Category
A 1864	2.09323399	4b637f59f964a5207b7e2ae3	MTA Subway - West Farms Square/E Tremont Av (2/5)	40.8402	-73.8800	Metro Stations
B 1561	1.94936904	4f940fe7e4b059d7da88be53	Junction Blvd	40.7491	-73.8694	Miscellaneous Shops
C 1212	1.86431926	4e7647cffa76059701632021	MTA Subway - 179th St (F)	40.7125	-73.7846	Metro Stations
D 853	1.70625431	4bace08af964a520cf143be3	Sammy's Fish Box Restaurant	40.8390	-73.7836	Seafood Restaurants
E 532	1.55978734	4cc86db294e1a0933e6c978b	Rockaway Beach - 116th Street	40.5779	-73.8359	Beaches
F 305	1.18353191	4abcfe4bf964a520fa8720e3	Hulu Theater	40.7509	-73.9941	Music Venues
G 112	1.18192331	4c516433d2a7c9b6c4c61911	Bean & Bean Organic Coffee	40.7472	-73.9971	Coffee Shops
H 98	0.87556379	4debdb6b52b11677f060802e	Peggy Rockefeller Rose Garden	40.8592	-73.8735	Gardens
I 40	0.41121454	4d93a4489ef2721e6bffc3d2	I-495 / Grand Central Parkway Interchange	40.7400	-73.8455	Intersections
J 12	0.39198899	4e26fd0f1f6eb1ae139ad929	TSA Security Screening	40.6457	-73.7762	General Travel

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