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Machine Learning for Land Use Scenarios and Urban Design

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1 ABSTRACT

Geographic Information Systems (GIS) are becoming a more common tool in the practice of urbanism and urban design. Usually, GIS is used to visualize geo-located data to gain inside into the urban fabric, to either plan interventions within it, restructure it, or extend it. One problem for a data-driven planning process with GIS is how to turn the gained data into knowledge to drive a project.

This paper discusses the use of super- and unsupervised machine learning to develop land-use scenarios for a vacant site within the city parameters of Berlin. Unsupervised learning is used to find cluster which shares certain characteristics. This interpretation of the data helps to make more informed decisions.

As an example, for supervised learning, a neural network was trained to develop land-use scenarios fully autonomously. Autonomously generated land-use scenarios are an essential step to bridge the gap between the analysis and the design phase of urban development and enable the use of artificial intelligence in the planning process.

Keywords: Land-Use Scenarios, Urban Design, Neurnal Networks, Machine Learning, GIS

2 INTRODUCTION

The topic of "Big Data" or the handling of a multitude of digital resources in urban planning is a long-standing discussion that first emerged in the course of the "Smart City" movements (Batty 2012a; Batty et al. 2012b). The interaction of different disciplines such as planning but also computer science is essential for this phenomenon. On the other hand, the application of these new technologies also scares off many "old-established" planners, the entry hurdle in the application of these new methods was and is partly very high, administrations were not technologically prepared for this trend. The discussion about who has power over the data and who can and may process it has not stopped at urban planning (Streich 2018). Holistic data collection approaches in the smart city context have always relied on the collection of GIS datasets (Exner 2014). 3D city models, on the other hand, attempted to represent the topology of the city in its three-dimensionality (Döllner et al. 2006) and provided the first platforms for simulations in a three-dimensional urban context (Zeile 2010; Mach and Petschek 2006). With the approach of digital twins - coming from product development, transferred to urban planning (Batty 2018), simulation in the urban context is experiencing a renaissance (Dembski et al. 2019).

Using the possibility of parametric design, form-finding processes can be quickly integrated into urban situations. In König et al. (Koenig et al. 2017), "cognitive design" also uses contextual data such as GIS repositories to create and verify designs. In combination with methods of "artificial intelligence" or the "machine learning" assigned to the domain, various international research groups are trying to enrich novel, design methods with "intelligent" algorithms to make faster (and more transparent) statements about (urban) designs like relational urbanism in their approach for the Baishizhou Shanghai study (Ilaria Di Carlo 2016; Llabres and Rico 2016; Cantrell and Mekies 2018). While others generated the land use pattern with cellular automata such as KPF UI (KPF UI 2019, 2018). But some issues have still not been resolved:

How can the data be interpreted correctly in an urban context? Can planners and programmers go beyond the visual feedback of the single layer and analyse them?

In this contribution, we propose 1) a new method for organising land use plans (semi-)automatically out of urban land use datasets and 2) additionally give an outlook on how typological AI can be used to integrate the implementation of different land-use scenarios into generative urban planning processes.

3 MACHINE LEARNING FOR LAND-USE SCENARIOS

In this section we introduce the notion of "land use" used for us in the context of machine learning - it is solely about how we can use a meaningful approach to classify “use” / “land-use” on an urban district level. Land use represents the link between the land cover and the actions people take in their environment (Di

Gregorio 2005). Therefore in planning, the challenge is to find a suitable link between those two, so that the land is suitable for the actions people take and vice versa. While land use is relevant in different scales like the regional, city, district or quarter and parcel or building scale (Curdes 1995), in the following we will focus on the district scale.

In the following, we consider the search for suitable land use as a classification problem, while classification is assigning objects to a group based on several observed attributes. (Sathya and Abraham 2013)

If we use this logic to identify a suitable land use for a specific area, the object becomes a certain area of land which can be assigned to a group of potential land uses, based on its attributes. Following this approach implies that not merely the intention of the planner – but the characteristic of the land itself becomes the driver for the pursued use. Whereas the use can become the driver of the design itself.

The case study for the use of machine learning for land use scenarios was conducted and discussed for the Berlin Pankower Tor site, a flat conversion area of a former freight station. Both super-supervised and unsupervised machine learning were used to interpret geodata.

3.1 Methodology: Land-Use – from Vector to Grid Cell

With the help of machine learning algorithms, we aim to go beyond the representation of geospatial data to a (semi-) automated or first interpretation of it. To apply the algorithms, we first have to prepare the geospatial data for it.

Within GIS the form of raster GIS and vector GIS or the mixture of both are commonly used to represent geospatial data (Winter 1998). To link areas as "objects" for classification with geospatial data, the objects need to be geometrically defined. Therefore, we chose a region-based grid GIS approach, in which we divided the site into grid cells.

Afterwards, we scaled the data to make them relatively comparable to each other. So instead of focusing on absolute values, we interpreted the interplay of relative values of certain data categories with the help of two different machine learning algorithms. Thereby we achieved with the unsupervised learning method we achieved different clusters of areas of a site based on the characteristics whereas with the help of a supervised learning method we assigned land use to specific grid cells based on the characteristics of the cell.

3.2 Data

Various data can be linked to the grid cells of the raster GIS. For example, they could be structured according to the order of the city structure in categories like the constructive spatial structure, land use structure, infrastructure, social and economic structures (Streich 2011).

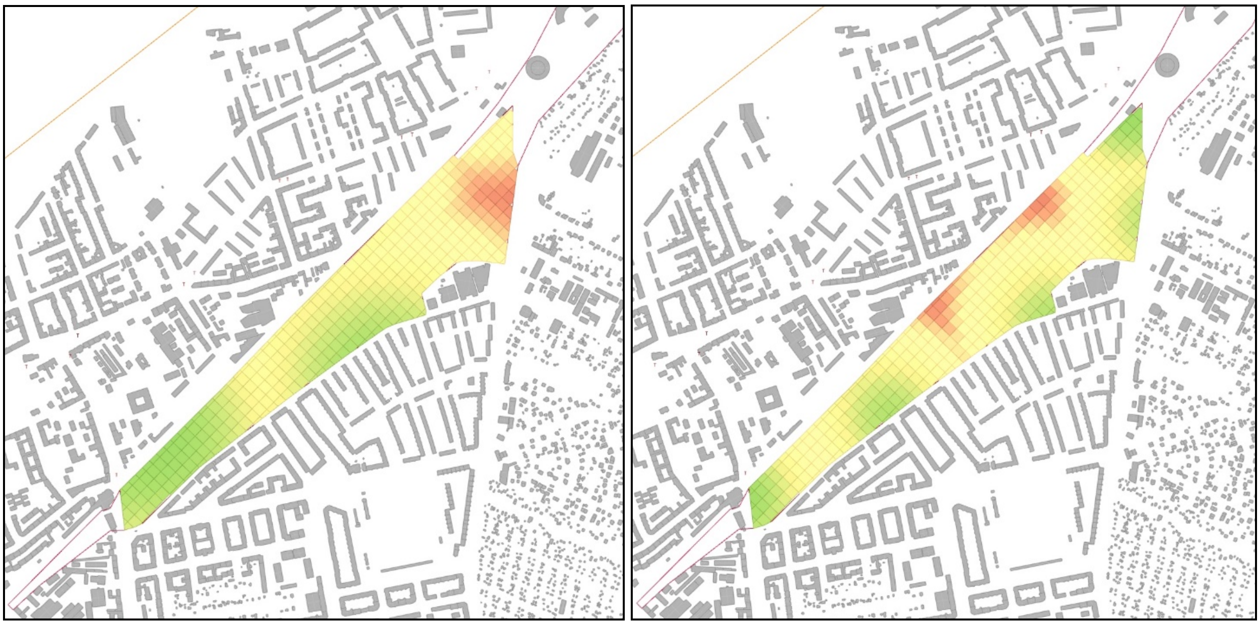

Fig. 1 (left): relative proximity to schools (green high proximity to red low proximity). Fig. 2 (right): relative proximity to public transportation (green high proximity to red low proximity)

The way we implemented geospatial data was by distinguishing distance-based data from environmental and morphological data. If this method would be implemented for analysis of an urban district, other categories such as performance, cadastral and socio-demographic data would matter as well. Distance-based data includes social, cultural or other amenities, local supplies, communal uses, transportation especially public transportation etc. measured in either the shortest or street network distance to the related cell. Environmental data focuses on aspects such as sun exposure, noise pollution ventilation and wind comfort, soil conditions and similar. Less relevant for the case study site as an even and cleared site was morphological data which would include the topology, landscape and existing build structures. Also performance data such as walkability, cadastral data and socio-demographic data didn't play a role in this case. We set a residential mix-use as a specific desire for land use. Therefore, qualitative measures of which land use is best for the site is less relevant. But relative measures like which areas on the site are better for land use x compared to other areas help to place a suitable use. In other words comparing the values of all categories between all cells.

For the task presented in the case study, distance-based and environmental data were the most relevant decision criteria. As an example of distance-based data, we implemented educational facilities (see figure 1), public transport (see figure 2), general accessibility of the site, local amenities, as well as commercial uses based on agglomeration advantages. In the area of environmental data, information on relative noise pollution was used. Therefore we used geospatial data provided by OpenStreetMap (OpenStreetMap Contributors 2020) and the city of Berlin (Senatsverwaltung Berlin 2017).

3.3 Unsupervised and supervised machine learning

To explore the potential of machine learning for land use in the realm of classification, we tested different approaches within machine learning, namely supervised and unsupervised learning.

3.3.1 Unsupervised machine learning for land-use scenarios

As an example, for unsupervised learning, we implemented a k-means clustering algorithm in python with the help of the sklearn library.

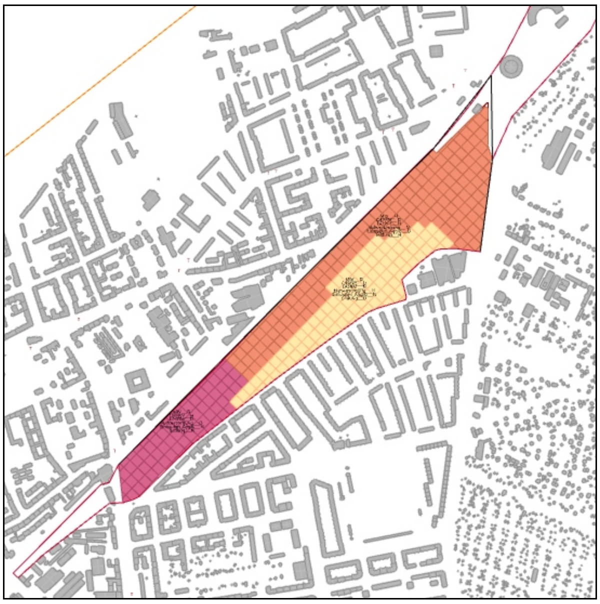
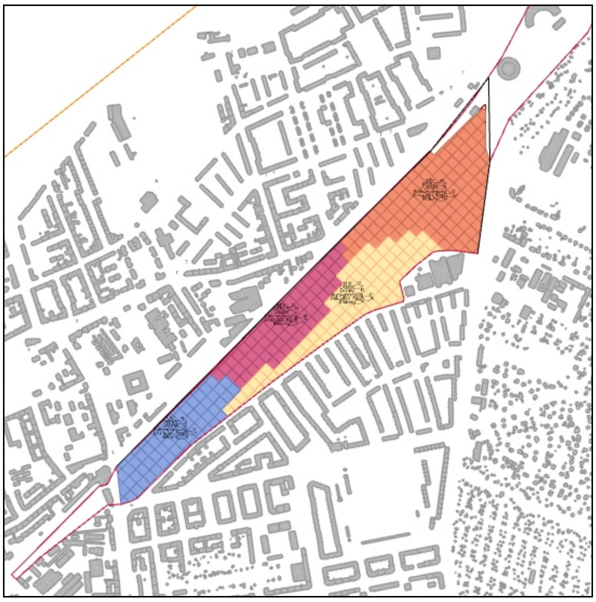

Fig. 3 (left): Clustering with three cluster. Fig. 4 (right): Clustering with four cluster.

orange	Education demand: high; motorized private transport: high; public transport: average; noise pollution: high; local amenities demand; low; shopping demand:low
red	Education demand: average; motorized private transport: low; public transport: high; noise pollution: average; local amenities demand; average; shopping demand:high
yellow	Education demand: average; motorized private transport: average; public transport: average; noise pollution: low; local amenities demand; high; shopping demand:low

orange	Education demand: high; motorized private transport: high; public transport: average; noise pollution: average; local amenities demand; average; shopping demand:average
red	Education demand: average; motorized private transport: average; public transport: low; noise pollution: high; local amenities demand; low; shopping demand:low
yellow	Education demand: low; motorized private transport: average; public transport: average; noise pollution: low; local amenities demand; high; shopping demand:low
blue	Education demand: low; motorized private transport: low; public transport: average; noise pollution: average; local amenities demand; average; shopping demand:high

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Clustering aims to find subsets or clusters within the dataset that are related in terms of their data. The k-means clustering algorithm clusters the data by relating the data points to k sets of clustering centroids (James et al. 2017). This method is best compared to the planner overlaying different analysis layers to search for a pattern that may emerge from it. With the use of the k-means algorithm, this task is automated. The algorithm returns descriptive characteristics for certain clusters of the site. For instance, the description for the yellow cluster in fig. 3 is average values for access to education, motorized private transport, and public transport; low values for noise pollution and high demand for local amenities including a grocery store, while providing relatively low values for shopping. Clustering, therefore, allows to go beyond the visual feedback of a single layer and shows how clusters with similar characteristics emerge on the site. Looking at a different number of clusters helps to get a better grasp of how the site can be organized by relating the values of each cell to one another. This can help the planner make informed decisions while assigning land use. Determining the optimal number of clusters into which the data may be clustered is the popular elbow method (James et al. 2017). In this case, the elbow method suggests five clusters (see fig. 5).

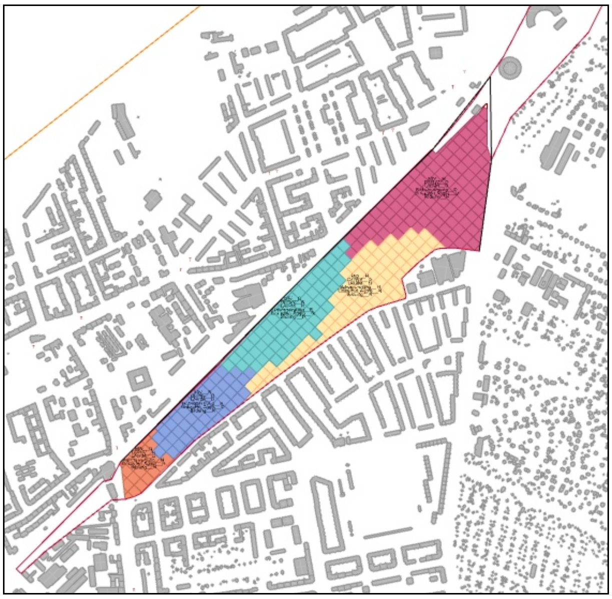
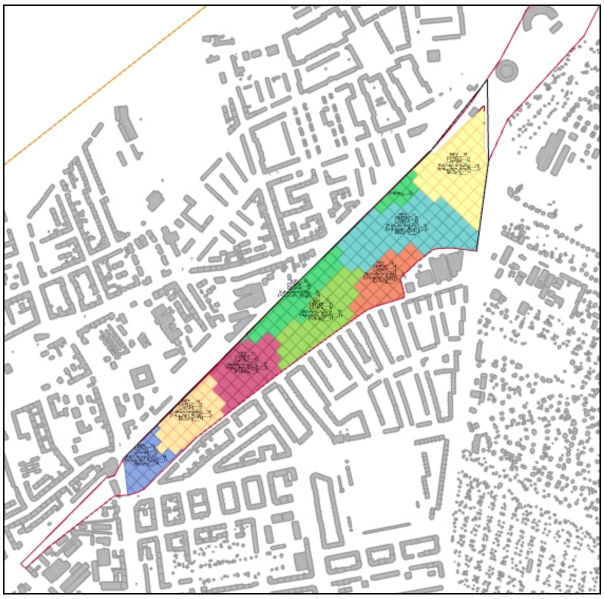

Fig. 5 (left): Clustering with five cluster (optimal acc. to elbow). Fig. 6 (right): Clustering with eight cluster.

orange	Education demand: low; motorized private transport: low; public transport: high; noise pollution: average; local amenities demand; low; shopping demand: high
red	Education demand: high; motorized private transport: high; public transport: average; noise pollution: average; local amenities demand; average; shopping demand: average
yellow	Education demand: low; motorized private transport: high; public transport: average; noise pollution: low; local amenities demand; high; shopping demand: low
blue	Education demand: low; motorized private transport: low; public transport: average; noise pollution: average; local amenities demand; high; shopping demand: average
light blue	Education demand: average; motorized private transport: average; public transport: low; noise pollution: high; local amenities demand; low; shopping demand: low

orange	Education demand: low; motorized private transport: high; public transport: high; noise pollution: low; local amenities demand; high; shopping demand: low
red	Education demand: average; motorized private transport: low; public transport: high; noise pollution: average; local amenities demand; average; shopping demand: average
yellow	Education demand: low; motorized private transport: low; public transport: average; noise pollution: average; local amenities demand; high; shopping demand: low
blue	Education demand: low; motorized private transport: low; public transport: average; noise pollution: average; local amenities demand: low; shopping demand: high
light blue	Education demand: high; motorized private transport: high; public transport: low; noise pollution: average; local amenities demand: high; shopping demand: low
green	Education demand: average; motorized private transport: average; public transport: low; noise pollution: high; local amenities demand: low; shopping demand: low
light green	Education demand: low; motorized private transport: average; public transport: low; noise pollution: low; local amenities demand: average; shopping demand: low
light yellow	Education demand: high; motorized private transport: high; public transport: high; noise pollution: high; local amenities demand; low; shopping demand: low

Since the planner still has to transfer the cluster to meaningful land use himself, this algorithm could be used as a semiautomatic approach, helping the planner to make more informed decisions.

3.3.2 Supervised machine learning for land-use scenarios

The aim of supervised learning differs from the one of unsupervised learning we discussed before. Instead of trying to find clusters on how the site could be organized based on the underlying characteristics, supervised learning relates a specific pre-defined land use to each cell based on how it learned to interpret its data.

So supervised learning depends on a training source with labelled data to train on and to classify the test data accordingly. We used an Artificial Neural Network (ANN) as an example for supervised learning. An ANN uses error signals to adjust its interconnection with weight combinations and thereby learns how to classify cells according to the training data (Sathya and Abraham 2013). We implemented the ANN with the sklearn and tensorflow python library.


Fig. 7 (left): Suggested land use by ANN for the ground floor: 0 – local amenities, grocery, 1 – no specific ground floor use, 2 – commercial (work), 3 – educational amenities, 4 – commercial (retail). Fig. 8 (right): Suggested land use by ANN for upper floors: 0 – residential, 1 – commercial.

As a training set, we generated a pseudo database of land use relating to the categories we use. Therefore, we described each land use how it relates to the categories. For example, a site for a grocery store is described as follows: rather good access to road infrastructure, for better coverage of local supplies a rather high distance to other grocery stores, a medium to high proximity to public transport, proximity to other stores is preferred but not required, proximity to educational facilities, noise pollution or other environmental factors are rather irrelevant. Commonly land use is classified into types such as residential, commercial, industrial, recreational, institutional, various types of green and open space, infrastructural and transportation land use (Reicher 2017). While the method introduced here can be used to assist a classification in such a way, we focused on the usage related to the following planning steps namely educational amenities, local supplies, commercial and residential land use. We differentiated between the use of the ground floor and the upper floors.

Green spaces and infrastructure were considered in a later step. Green spaces and infrastructure were then to the morphology of the urban design rather than to the characteristics of the site itself, even though in a different context, especially green spaces might be more related to the site characteristics and context influences.

In the training process of the ANN, we followed a conventional approach (Hastie et al. 2017). After we trained the ANN and filterd the results, we gained slightly related land-use scenarios for the site which could serve as a base for generating various urban design schemes. In a later stage, we double-checked the average shortest walking distance from each parcel to the amenities in various generated street networks to get

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feedback on whether it is well-positioned regarding walking distances. The amenities were mostly in their ideal location regarding their walking distance or only off by a parcel.

4 TYPOLOGICAL AI: IMPLEMENTATION OF LANDUSE SCENARIOS FOR GENERATIVE URBAN DESIGN

For a better understanding of what typological AI is and what approaches have been used in the context of urban planning, we start this paragraph by introducing similar approaches.

In addition to the more familiar approaches in architecture, parametric design and generative design have also found their way into urban planning (Fusero et al. 2013). Parametric models, applied for example by Zaha Hadid Architects (Rico 2011; Schumacher 2008) or relational urbanism (Cantrell and Mekies 2018; Ilaria Di Carlo 2016; Llabres and Rico 2016), are used for form-finding, scenario development and optimization of certain aspects of a design (Fusero et al. 2013). Generative approaches like from Nagy et al. represent more or less fully automated design generation to optimize development for profit and solar energy (Nagy et al. 2018). More recently, Design Space Exploration started to be used for multi-criteria and stakeholder optimization in urban design like suggested by Wilson et al. (Wilson et al. 2019, KPF UI 2019;) and implemented also by sidewalk labs and others (Ikhena 2020; Margrave 2020). The proposed method enables the generation of design variants via procedural geometry generation and statistical analysis of the variants. This allows a systematic search for designs based on performance criteria to find reasonably good trade-offs for multiple criteria and multiple stakeholders.

But how can the design space be generated to represent a rather extensive field of possibilities? And how can a generated design relate to its surrounding?

4.1 Methodology: land use to typological design generation

The already discussed ANN land-use scenarios require as input contextual, environmental and other influences as well as desired land-uses. Those land-use scenarios serve as a base for the procedural design generation of variants. The generation of the design variants is built up as follows: first, the structure of the district is generated based on the district typology, based on the construction fields of the district typology building typologies are generated and complete the urban design.

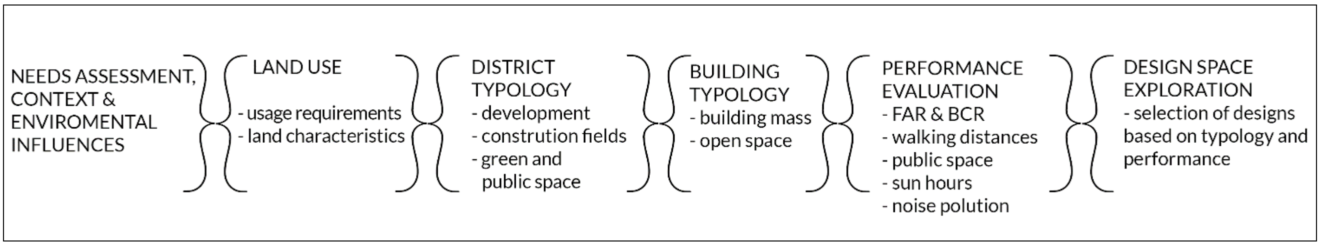

Fig. 9: Proposed workflow

The design versions are evaluated for floor area ratio (FAR) and building coverage ratio (BCR), real walking distances to key amenities, quantities of land usage, sun hours and noise pollution. After the design versions are exported including their performance data, they are imported into a design space explorer (DSE) to make them easily selectable based on their performance values and morphological criteria like the district typology, the building typology and the average building height.

4.1.1 District Typologies

There had been various approaches on how to generate urban design variants. A common way is to start with the street network and then to implement other morphological elements like green spaces and buildings (Schumacher 2008; Rico 2011; Cantrell and Mekies 2018; Fink and Koenig 2019; Wilson et al. 2019). In urban design also other approaches had been discussed, for example, to start with the green and public spaces and then to develop all other aspects according to it (Bott et al. 2014; Sheppard 2015). One of the key benefits of working with DSE is the ability to make different design approaches comparable and include them in the design space in which the planner and stakeholder can search for a suitable design scheme. To offer a design space that incorporates different approaches, we developed typologies for urban districts in the German context. Like building typologies also district typologies can benefit from the "inherent knowledge" (Curdes 1995) of the typology due to the "shared formula" derived from repetitive construction (Luna et al.

2010). The district typology incorporates the street network, construction fields, as well as the public and green space system. Following typologies had been developed, described algorithmically and were implemented in the generative process: the grid district, the irregular grid district, the fluent district, the cluster district, the central district and hybrid forms with the free shaped public space, overriding open spaces and various exceptions.

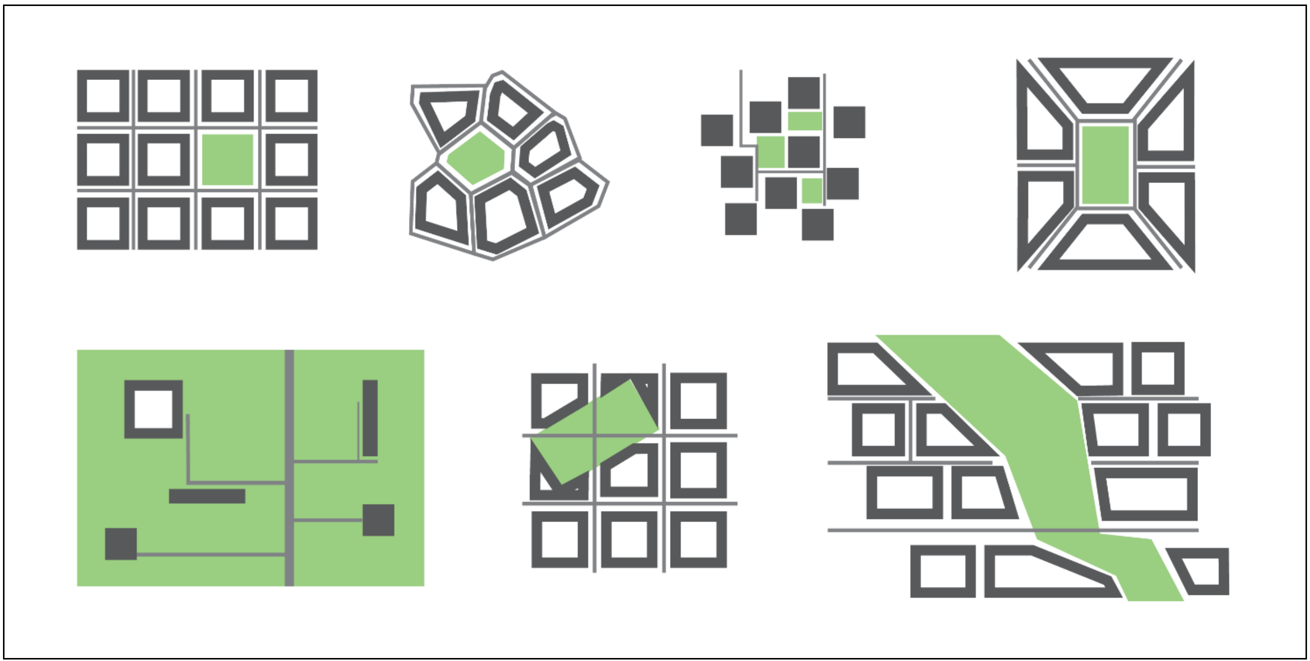

Fig. 10: District typologies: grid district, irregular grid district, cluster district, central district, fluent district, free shaped public space, overriding open spaces.

4.1.2 Building Typologies

Based on the construction fields and the land use, the construction fields are further divided into parcels suiting the land use. Based on the parcels and the land use, different building typologies are generated.

There are various suggestions for typologies on the building level (Bürcklin and Peterek 2016; Reicher 2017; Korda 2005). In this context, we implemented the perimeter block, the dissolved perimeter, linear buildings, detached houses including multifamily, the box and hybrid typologies.

4.1.3 Performance Evaluation and Design Space Exploration

After an urban massing is generated, it is evaluated on different performance criteria. Following the process of geometry generation like shown in figure 11, preliminary urban designs were generated based on the land-use scenarios derived from the Artificial Neural Network, district typologies and building typologies. At the point of the analysis (Fig. 11, 8) over a thousand variants were generated. For each land use scenario (figure 11, 3), the different district typologies (figure 11, 4-5) were applied in certain variants of the typologies, like different orientations or grid sizes etc. Based on the district typologies different building typologies (figure 11, 6-7) were applied again enriching the solution space. These generate urban massings are now calculated in quantities, like area usage of public versus private areas, FAR, BCR etc. and performance characteristics. We implemented a sunlight analysis (Ladybug 2013), real walking distances with a*search algorithm and noise exposure. Many other evaluations could be applied, like cost estimates etc.. But with each evaluation the time required for the computation increases. Based on these criteria, the choice of various typologies and their comparability with help of DSE makes them selectable for various interest groups like investors, cyclist activists, environmental activists, administration and others. We also found with a small study group, that the way the design variants are selectable with the DSE can be used to help also non-professionals to express their desires and priorities for the site based on a preliminary design. This could make this workflow interesting for more interactive participation methods like the Charette (Nanz and Fritsche 2012).

With this heuristic approach based on land use scenarios urban designs could be found, that outperformed an urban design study for the site in all areas (Christ et al. 2017). This means, that versions were found, that

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provided more open space as well as more build square meters, shorter real walking distances to all key amenities, more sun hours per façade square meter and less noise pollution.

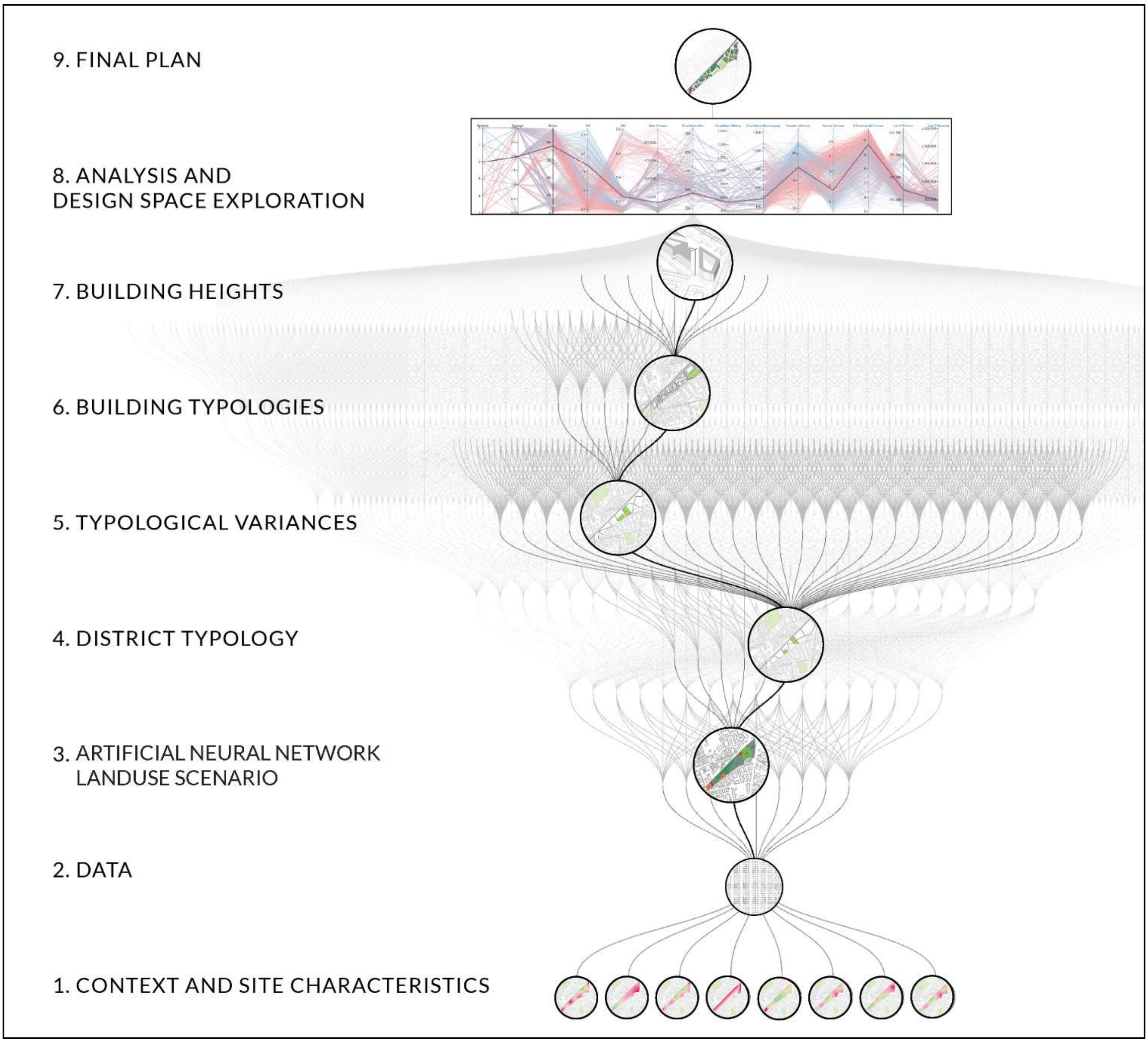

Fig. 11: Integration of the land-use scenarios in a generative typological approach

5 CONCLUSION

While both machine learning algorithms - supervised and unsupervised - aim to find hidden patterns in geospatial data referred to a site the way they do this differs. The fundamental difference between those two classes of machine learning is the existence of labelled training data (Wah and Berry 2020; Alloghani et al. 2020).

In supervised learning, with the existence of labelled training data, the data pattern or characteristics of a grid cell as data are directly transferred to a specific label from the training set in this case a land use. Whereas in unsupervised learning, the hidden pattern in the analysed geospatial data is related to each other as clusters. While the cluster emerge from the characteristics of the geospatial data of each grid cell. This makes each approach suitable for different use scenarios.

The supervised learning method, which was discussed with the example of an Artificial Neural Network for classification, is suitable for directly generating land-use scenarios and use these as a design basis for generative urban design. It comes with the upside of directly performing a task for the planner of placing the land use in a way that suits the labelled training set. This makes supervised learning suitable to at least partially automate the task to develop land-use scenarios.

But the training of the Artificial Neural Network and the description for the land use for generating the training data is a relatively time-consuming matter - especially if the requirements for the land-use change. Also, the ability to control the quantity in which each land use is assigned is rather limited.

Unsupervised learning on the other side does not directly transfer the information of the geospatial data to pre-defined land use or label. It rather provides an analysis of the relationship of the geospatial data, or the analysed characteristics of each cell, to each other. Therefore, it can be used as a helpful tool for analysis to show the planner patterns or better clusters which emerge from different combinations of geospatial data.

This approach is rather flexible and relatively easy to implement and can give the planner a first overview and inform the decision of where to place which use. The performance evaluation of the generated preliminary design based on the land-use scenarios shows that this method can help to find high-performance designs (s. 4.1.3) and especially DSE makes these design variants comparable and selectable based on structural or performance criteria.

In general, the presented AI mechanisms in combination with the design space exploration fits very well in the context of urban workshops, initial brainstorming, starting discussions and the first approaches with quantitative data to an area and the spatial grasping of the proposed uses and dimensions. It is intended to be a useful addition to the planning process at a very early stage - in the so-called preliminary draft, in which important urban planning parameters are set and checked for their effect. The tool still needs to be tested in real life situations to further evaluate the effectiveness for planning and participation.

The proposed concept is not intended to replace the actual planning work in the sense of plan elaboration and plan realization; rather, we see it as a useful addition to be able to "explore" variants more quickly, better and more transparently and to be able to better grasp not only qualitative design work but also quantitative urban development designs. Used sensibly, it helps to be able to quickly examine variants at an early stage. Artificial intelligence is not intended to replace the planner's profession, but to better prepare the basis for decision-making.

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