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Synthetic and Tangible Agents for an Activity-based Urban Planning Tool

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1 ABSTRACT

AI is on the rise. Powerful cloud platforms and networked software components can perform increasingly complex data evaluations and simulations. Recent research and development projects[1] show how great the potential of artificial intelligence is for urban planning. However, despite the impressive, technical possibilities, it currently remains unclear how planning stakeholders and the affected population can be meaningfully involved in the intelligent processes of the "black box". The authors are of the opinion that sustainable urban development planning not only requires acceptance of the spatial planning result, as has been the case up to now, but also requires acceptance of the increasingly digitally supported planning process. For this reason, it must also be possible for laypersons to understand the digital analysis and evaluation processes and to comprehend their relevance and spatial interactions. Consequently, simulations must not only run in the computers of the respective planning or engineering offices, but require a simple, haptic analog translation that can also be used in participation processes as already shown in the CityScope projects[2].

For this project, the big revitalization project of Deutzer Hafen in Cologne to a future district with more than 9.500 daily users is used as a case study in building a decision support system for urban planning. It is composed of three parts: an agent-based model, a tangible user interface and a synthetic population. The project enables users to get in touch with an agent-based model (ABM) without any knowledge in coding or even interacting with computers. It connects physical objects to digital information. Based on the theories of Castiglione et.al.[3] , Gehl[4] , Shannon[5] and Jacobs[6] this project shows how to use an artificial and analog simulation model to measure the urban vitality of the public spaces in the district, based on the activity and travelling patterns of the population. This is done by testing different scenarios in which we change interactive parameters of the model: the use of the buildings and the demographics of the population. We can then determine which scenarios benefit the most life in the public spaces of the district, by finding areas of interest or problematic ones.

Keywords: Smart Cities, Agent-based modelling, KI/AI, Participation, Tangible Data

2 INTRODUCTION

The revitalization project of Deutzer Hafen aims to transform the old industrial harbor district of Cologne into a new, vibrant neighborhood. Designed by the danish architecture firm COBE[7], the project was chosen in a competition organized by the city in 2016. The mixed-use buildings are supposed to house 5.000 people and serve as workspace for another 4.500.

We use the future district as case study for a decision support system for urban planning, that is composed of three parts: an agent-based model (a), a synthetic population (b) and a tangible user interface (c).

a.) As the district Deutzer Hafen is not build yet and not even populated by now, this project takes simulation methods to help in order to describe future possible conditions. Therefore agent-based-models give a particularly good setup, because this technology is able to simulate multiple different scenarios of spatio-temporal relations. Agent-based models (ABMs) are used in multiple fields to simulate complex systems through a set of independent agents that follow certain rules and react on an environment. In urban planning,

[1] PLANERIN 1/2019: Künstliche Intelligenz: Die Transformation gestalten, SRL - Vereinigung für Stadt-, Regional- und Landesplanung e.V.
[2] https://www.media.mit.edu/projects/cityscope/overview/
[3] Gehl, J., Life Between Buildings: Using Public Space, 2012
[4] Castiglione, J. et al.: Activity-BasedTravel Demand Models: A Primer, 2014
[5] Shannon C.E.; A mathematical theory of communication; SIGMOBILE Mob Comput Commun; 2001
[6] JACOBS, J. The life and death of great American cities. New York, 1961.
[7] https://www.cobe.dk/idea/deutzer-hafen

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activity-based travel demand models (ABTDM) are used to estimate the demand for travel in a region and the resulting performance of the transportation system, according to different scenarios and policy, economic, demographic or land use changes, as i.e., defined by Castiglione et. al in "Activity-Based Travel Demand Models: A Primer". They also define the focus of these models as "whether, when, and where to participate in activities and for how long. Travel is a derived demand resulting from the need for people to engage in activities outside the home"[8]. This need for traveling and engaging in activities has also been connected to quality of urban spaces. In "Life Between Buildings", Gehl describes that in public spaces of poor quality, people only pass by on the way to necessary activities that they must do, like going to work or shopping. On the other hand, if the public space is of good quality, people start engaging in more optional activities, such as taking a walk or sitting on a bench. People attract more people, and so social activities, that result from the presence of others, such as just watching people passing by, also arise[9]. Jacobs, in "The Death and Life of Great American Cities", connects urban vitality to diversity in the built environment. Successful street life is described by her as "An intricate sidewalk ballet"[10] where a diversity of people, with different purposes and during different times of the day pass by.

b.) Based on these theories, we aim to use an ABTDM to measure the urban vitality of public spaces in the district, based on the activity and traveling patterns of the future population. To simulate the activity and traveling patterns, the model needs a *synthetic* population, which is a virtual representation of the community of the modeled area. Commonly this population is built by combining census data and travel or time use survey data. But this leads often to problems, because the data may not always be up to date, because of the amount of time and resources taken to make appropriate surveys. To bypass this an experimentation with a new approach is made: building a synthetic population based on metadata of social media. The present constant flow of user generated content is mostly coming from location based social networks (LBSN), where people share where they are when and what they are doing. Mining this data makes it possible to produce a sort of digital census, that is cheaper and fresher than traditional surveys. According to this project social media posts inside the city of Cologne were collected from Twitter and Instagram. The used profiles are kept anonymous and have their activity patterns inferred, resulting in a population that reflects a sample of the city. These profiles are then used to populate the model. The model will enable more innovative and broader user participation in urban planning.

c.) The interaction with the model is done through a tangible user interface (TUI), that connects the digital information of the ABTDM with a physical model of the district. The TUI makes interaction with the complex system more feasible and intuitive. The participation in the design process gets much easier and includes all stakeholders, not only the specialists. In a game-like experience, the user can change the use of buildings in the model by moving tags around or adjust the demographics of the population with a slider. Visual statistics give immediate feedback to the user's actions, making complex relationships become clearer.

3 RELATED WORK

As shown in the CityScope Projects of the City Science Group (CSG) at the Media Lab/Massachusettes Institute of Technology (MIT), a tangible user interface (TUI) can increase the purpose of a rapid prototyping urban design tool. The CityScope model has been used in several cities and projects to simulate scenarios with the participation of all stakeholders involved. With its open-source approach, the CSG tries to encourage people to use CityScope as a platform and also develop it further, in order to keep this network growing. One particular project worth mentioning is Finding Places[11], developed by the City Science Lab at Hafencity University Hamburg, a sister lab of the MIT CSG. The project aimed to help finding locations for accommodating the enormous number of refugees that were coming to Germany in 2015. The CityScope table with its TUI always serves as a hub for participation. The content that is shown, varies depending on the projects from daylight analysis[12] to complex agent-based models[13].

[8] Castiglione, J. et al.: Activity-BasedTravel Demand Models: A Primer, 2014; page 76
[9] Gehl, J., Life Between Buildings: Using Public Space, 2012; page 11
[10] JACOBS, J. The life and death of great American cities. New York, 1961.
[11] Noyman, A. et al.: Finding Places: HCI Platform for Public Participation in Refugees' Accommodation Process.
[12] Cody M., R.: Towards interactive sustainable neighborhood design: combining a tangible user interface with real time building simulations.

The tangible user interface used in this project builds up on the technology developed by the MIT for the earlier stages of the CityScope table, which is available as opensource on Github[14]. For the building process of our table, the focus was on easy fabrication with commonly in FabLabs available digital fabrication tools.

Our modified table is connected to an activity-based travel demand model based on a synthetic population. For this model, the Urban Vitality benchmark was introduced, as a way of measuring and predicting street life. This Benchmark goes back to Jacob's theories of Urban Vitality through diversity.

4 METHODOLOGY

4.1 Synthetic

The synthetic population is created following a series of steps described in the upcoming sub-sections. The steps range from data collection and preparation to geolocated points classification over pattern mining and finally user profiling and classification.

4.1.1 Data Collection and Preparation

The data collection and preparation was segmented into three steps, with the goal of finding users that could be profiled for the population.

First collection: between May 27 and August 09, 2020, 31.817 posts were collected from Twitter and Instagram, using the Tweepy[15] and Instaloader[16] Python libraries. Tweets were filtered by a bounding box around the city of Cologne and Instagram posts by hashtags with the city name.

Filtering users: First, all posts without coordinates or with coordinates outside of Cologne are discarded. Posts are then grouped by authors and every user that posted from less than two different locations is deleted. This step already discards a good number of bots or business profiles. Twitter has a self-proclaimed location field for each user's profile, so all users with a location different from Cologne are discarded. Both Twitter and Instagram have a description text field for each profile, which businesses usually use to describe their activities. A list of business key words is used to try and filter these profiles. Instagram also has an extra "is business account" tag, so those with "true" values are also discarded. After this filtering process, 163 unique users remain.

Collecting users' timelines: In the next step, all posts from each of the users' profiles are collected, to determine their individual mobility patterns. Some profiles could not be found, likely because they were deleted by the users in between the data collection period. In total, 115.967 posts from 122 users were collected. After going through the same filtering process of deleting posts without coordinates and outside of Cologne, the total amount of posts goes down to 9.305, as seen in Table 1.

Step	First collection	Posts Geo-tagged	Posts Inside Cologne	Users	Filtered Users	Found users	Timeline Posts	After Filtering
Twitter	21.117	1.010 (4,78%)	817	241	63		103.835	6.637
Instagram	10.700	6.642 (62%)	4.628	2.642	100		12.132	2.668
Total	31.817	7.652	5.445	2.883	163	122	115.967	9.305

Table 1: Overview of collected data from social media.

4.1.2 Geolocated Points Classification and Pattern Mining

For the agent-based model, each agent must have an activity table for the day, so all the geolocated points from each user's posts are categorized in activities, which is done in three steps:

Clustering of spatially redundant points: the points are clustered to filter out points that represent the same place, but with slightly different coordinates values. We use Python and its scikit-learn implementation of the DBSCAN density-based clustering, as done by Boeing[17]. A function from Boeing's paper is used to calculate

[13] Grignard, A. et al.: The Impact of New Mobility Modes on a City: A Generic Approach Using ABM.
[14] https://github.com/CityScope
[15] https://www.tweepy.org/
[16] https://instaloader.github.io/
[17] Boeing G., Clustering to Reduce Spatial Data Set Size.

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the coordinates of the cluster's centroid and find the member of the cluster closest to it, that will be categorized.

Reverse geocoding and tagging: To classify the points into one of the activity categories, an approach similar to the one from Swier et al.[18] is followed. We use the Overpass API[19] to return information from OpenStreetMaps[20]. The around filter finds all elements within a radius around the input coordinates. The elements returned by the API are tagged with numerous keys and values, describing their location or use. To fit each point in one of our categories, a dictionary with tags separated by categories is used. For points that return multiple elements, with multiple tags, the category is defined as the one in where most of the tags fit. This "location-based" method of classification of the posts only through their coordinates was chosen over "content-based" methods, because, as observed by Rout et al.[21], when someone writes about an event, they might just be talking about it and not necessarily be there.

Defining home and work location: Home and work location can be determined by finding the locations from where the user generates more content, like shown by Cui et al.[22]. The home location is defined as the most repeated point in the "WOHNEN" category. As mentioned by Swier et al., "this is a bold assumption" that might not always be right but "seems reasonable" [p. 28]. The work or study location is defined as the user's most repeated point, that is different from the home point and belongs to any category other as "WOHNEN", "FREIZEIT" or "KULTUR".

Pattern mining: Before deriving each user's mobility pattern, it is necessary to filter those that have enough information to do so, meaning a minimum number and variety of activities. To define these requirements, we look into two main references. Gehl simplifies outdoor activities in public spaces in three categories: necessary, optional and social activities [Ibid., p. 9]. Castiglione et al. present, on the other hand, four general categories in which activities are grouped for models: mandatory, maintenance, discretionary and at-home [Ibid., p. 79]. Similar with Gehl's categories, they are also influenced by their priority in the daily activity pattern schedule. It is defined then that to be considered a valid activity schedule, each user must have at least three necessary activities (one mandatory, one of maintenance and one at-home) and one optional/discretionary activity. From the total of 122 users, 83 ended up being profiled. For each user two tables with 24 slots corresponding to each hour of the day are created, one for weekdays and one for weekends. Every geolocated point is appended to the slot corresponding to the time when the person posted from that location, in the appropriate table depending if the post was created on a weekday or weekend. The plot in Fig. 1 of the most repeated activity for each hour shows potential in using geolocated social media posts to infer activity patterns. We can see that, on weekdays, ARBEIT occurs consistently during working hours. SCHULE has a peak in the morning and another one after lunch, probably reflecting the time when kids go first to school in the morning and then the time they come back from lunch. GASTRO has also peaks during lunch and dinner hours. And ZUHAUSE appears as the major activity during the whole day, which might be reflective of the period when the data was collected, during the COVID-19 pandemic, when a great part of the population was quarantining in compliance to the social distancing rules and because most commercial places were closed.

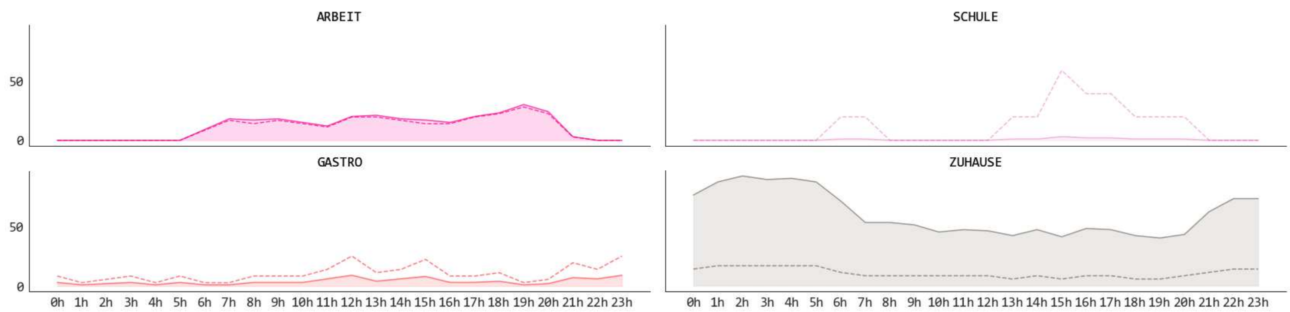

Figure 1: Activity frequency on weekdays. - (% total of all activities) - - (% total of each activity)

[18] Swier N, Komarniczky B, Clapperton B (2015) Using geolocated Twitter traces to infer residence and mobility
[19] http://overpass-api.de/
[20] https://www.openstreetmap.org
[21] Rout, D. et al. Where's @wally? A Classification Approach to Geolocating Users Based on their Social Ties.
[22] Cui, Y. et al. Social Media and Mobility Landscape: Uncovering Spatial Patterns of Urban Human Mobility with Multi Source Data.

These tables represent a fraction of a typical weekday and weekend for each user, but of course, they are not complete since it is impossible for even very active users to collect posts for every hour of the day. Additional to gaps in the timetable with no activities, some anomalies could also be observed, such as particular activities happening in unlikely hours, like GESUNDHEIT at 1:00 am or NACHTL in the middle of the day. These seemingly mistakes are probably related to the reverse geotagging done with OSM, that could sometimes retrieve wrong activity tags for the buildings. The anomalies are deleted, and gaps are filled with activities in the close slots.

4.1.3 User Profiling and Classification

Besides the activity table, the synthetic population needs at least two other characteristics to simulate travel patterns in the model, which are type of person and type of vehicle owned. In our model the population is divided in six different types of people, adapted from CityScope [Ibid.]. These are Student, Young professional, Executives, Mid-career workers and home maker. Types of vehicles are none, bike and car.

Similar to existing approaches[23] a Bayesian Network model is used to predict these missing characteristics. A Bayesian Network is a "Probabilistic Graphical Model (PGM) that represents conditional dependencies between random variables through a Directed Acyclic Graph (DAG)"[24]. These dependencies can be defined initially or can also be learned from data. In our case, we want to find out what is the relationship between activity table, type and vehicle ownership, so we train the model with a time use survey dataset from IPUMS[25] that contains more than 15.428 time use diaries with all three variables present. The model is built in Python with the pomegranate library[26]. To avoid bias in the training dataset, we use an equal number of types of people and an even distribution of vehicle types per type of people in the dataset.

As seen in the structure of the learned graph model in Fig. 2, type is influenced by the amount of time people spend at school and at work, which on the other hand is influenced by the amount of time one spends at home. Vehicle is influenced by school, because the students are the ones that tend to have more bikes. Leisure activities, on the other hand, are independent of the other variables, which could make sense, considering that all types of people have some type of leisure activity.

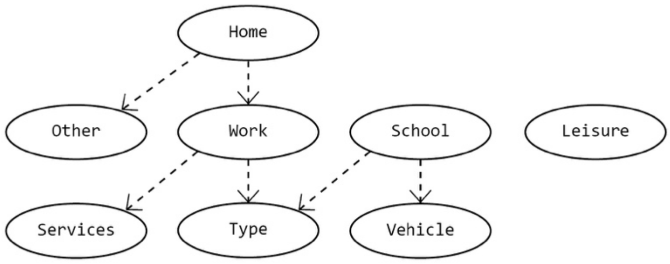

Figure 2: Network structure of trained model.

The model predicts that our users are divided in the following groups: 9 Students, 12 Young professionals, 23 Home makers, 20 Mid-career workers and 19 Executives. But the vehicle ownership prediction did not work as expected, with only students having bikes and all the other types having cars. That might be because the size of the profiles samples is too small to make a realistic prediction for each type of person. For this reason, we decide to attribute vehicles to each person inside the agent-based model, as explained in 4.4.2.

The sample reconstruction, which is the final step of creating the synthetic population, is also done inside the agent-based model. It consists in drawing samples of people profiles until the distribution matches the desired demographics. Since this will be an interactive parameter, that can be adjusted to visualize different scenarios, the sample reconstruction is made alongside with the running of the model, as necessary.

[23] https://medium.com/sidewalk-talk/a-first-step-toward-creating-a-digital-planning-laboratory-is-populating-it-beeb87d485f1
[24] https://towardsdatascience.com/introduction-to-bayesian-belief-networks-c012e3f59f1b
[25] Fisher et al., Multinational Time Use Study Extract System: Version 1.3 [dataset].
[26] https://github.com/jmschrei/pomegranate

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4.2 Tangible

The tangible user interface spans the bridge between digital and analogue world. From a technical point of view, the TUI is based on a pipeline that detects physical change of a model, translates it to a digital equivalent that triggers an action and connects the resulting digital information back to the physical object. The objective is to mirror the physical model into a digital twin, that updates almost in real time.

4.2.1 Hardware

Instead of Lego bricks as done by CityScope, the model was built from plywood and 3d printed, custom made components. These materials were easily approachable, and fabrication was possible in the local FabLab. The hardware consists of three main layers, as visualised also in Fig. 3:

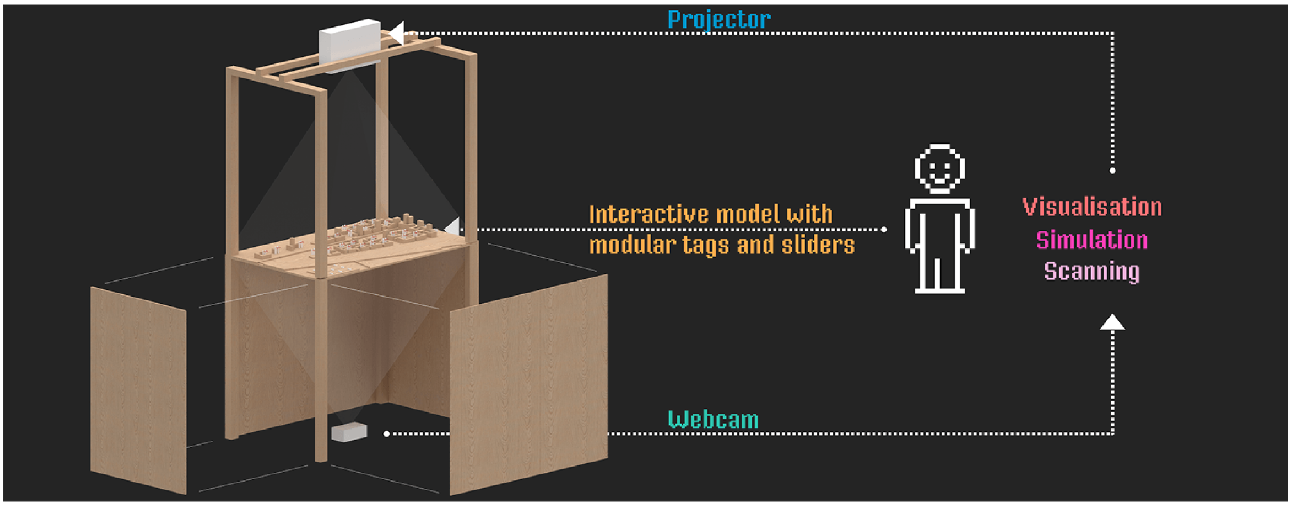

Fig. 3: Interface overview

On top, the projector that visualises the simulation on top of the model and gives near real time feedback to the user's action. Another projector gives more detailed, complex information and statistics of the simulation.

In the middle, the 1:1000 representation with its tags and sliders serves as interface for the user. The way of interaction is explained more in detail in 4.3.3.

On the bottom, two webcams capture a real time picture from the downside of the model and stream the current model configuration to the computer. The final setup is visible also in Fig. 5.

4.2.2 Software

This process can be divided in two parts and was developed in Grasshopper, a visual programming interface for the 3d modelling software Rhinoceros[27]:

The scanning process, a basic computer vision framework. This is an adoption of the script shared by Cityscope on Github. During this process, the incoming picture from the webcams is translated into digital information about the current table configuration. The special challenge here was, that unlike the CityScope model, this model is not based on a regular grid, where one tangible element comes after the other, always with the same distance. And in addition, it was necessary to use very small elements that are able to represent the specific city scale.

The data exchange. After successfully reading the webcam picture, the information has to be sent to GAMA[28], the programming environment used for the simulation. For this, the Google Firebase realtime database was used. After organizing the data in Grasshopper in a JSON format (JavaScript Object Notation) it can be streamed to the database. From GAMA, it is possible to directly access that database and deconstruct the JSON file.

[27] https://www.rhino3d.com/de/
[28] https://gama-platform.github.io/

4.2.3 Interaction

After connecting hard- and software and enabling the bridge to the simulation in GAMA, the final setup, as seen in Fig. 5 is ready and interaction with the model is possible. There are two ways of interacting with the simulation:

Through so called tags (on the left in Fig. 4). Each building of the model has two of these tags, representing lower and upper-level use of the building. Through these tags, the use of the building can be changed.

Through so called sliders (on the right in Fig. 4). The model also has five sliders integrated. Through those, different parameters such as demographics of the district or simulation speed, can be changed.

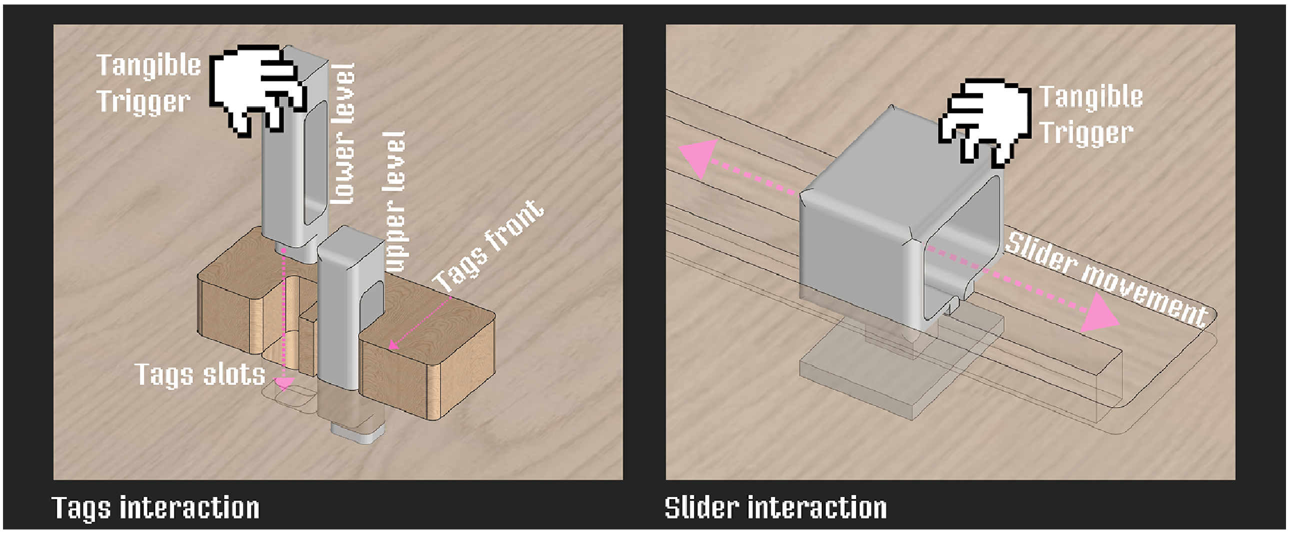

Fig. 4 Ways of interaction with the model

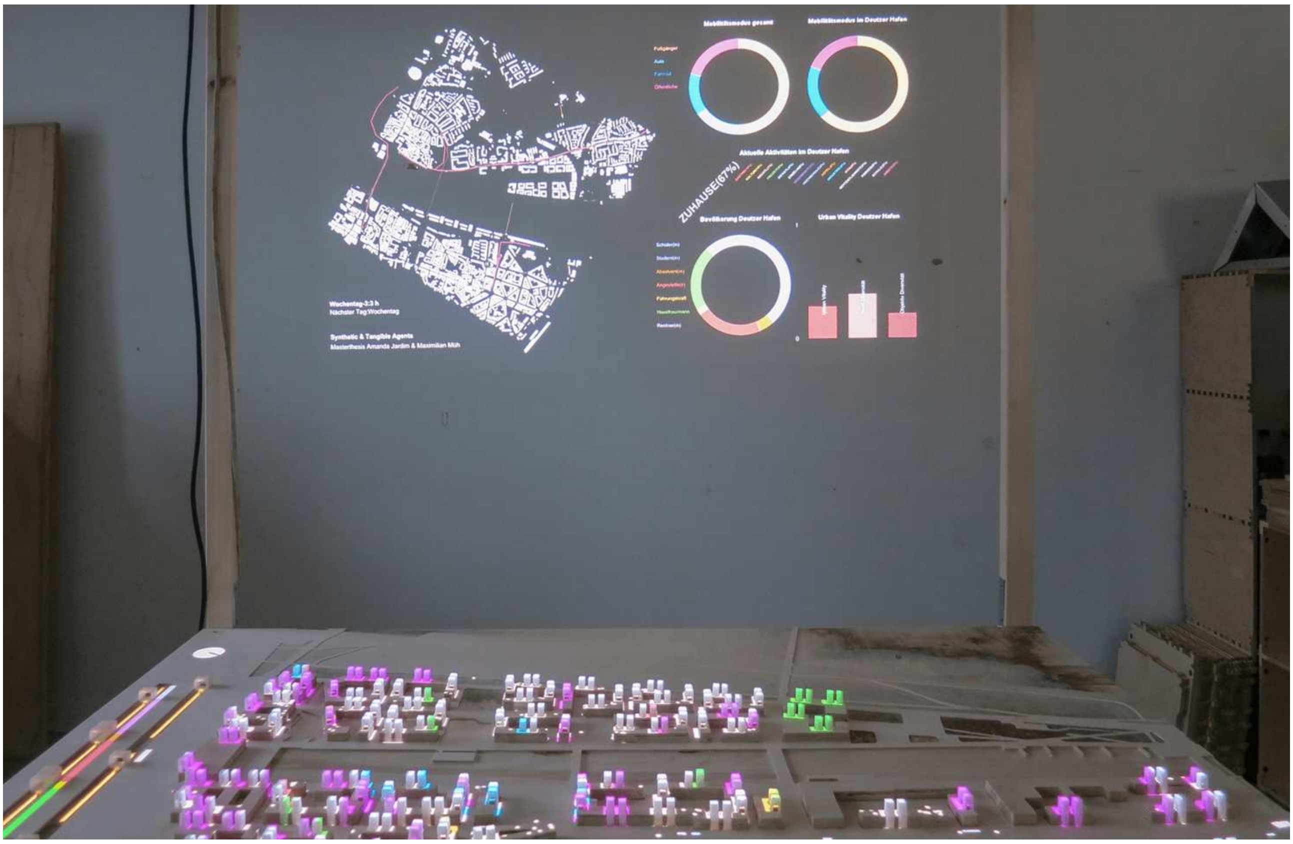

Fig. 5: Final setup with projection on top of the model and second screen projection with extra information in the back

4.3 Agents

GAMA is an open-source project, available and well documented on Github. Along with the available examples from CityScope on Github, this helped in developing the here described model.

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4.3.1 Environment

Before building the actual Agent Based Model, the environment and the agents to populate, must be defined, and built. The environment is centred on the Deutzer Hafen district and includes the surrounding city in a radius of 1,3 km around it. The necessary data such as buildings and their use, streets, nature, but also population and households, was collected from OSM (Open Street Maps) and combined with demographics data from Offene Daten Köln[29], an open-source data initiative from the city of cologne.

4.3.2 Agent: People

The agents in the model take on the role of the future residents of Deutzer Hafen and the residents of the surrounding districts. To optimize the simulation speed, a percentage of 8% is used to populate the district and the surrounding area, otherwise it would be impossible to run the model with our resources. Through optimizing the code, this percentage should be increased in the future. As mentioned by Castiglione et al., it may not be necessary to run the full-scale model, in order to get representative results, though.

People attributes such as type and activity table are imported for each agent from the CSV files with the profiles created before in 4.1. Other attributes such as living or working place are defined in the model. The distribution of different profiles relates to the demographics gathered in 4.4.1. While this is fixed for all people agents living in the surrounding city, the demographics in the Deutzer Hafen district are changeable. The people agents get vehicles (car and/or bike) assigned according to statistics from the German Ministry of Transport[30].

During the simulation, the people agents follow their individual activity table. While the positions for living and working are fixed, the headed locations for other activities such as shopping, etc. get defined by special distance and proximity. Depending on the agent's profile, its assigned vehicles and the distance to the next activity, the people agents choose the mode of transportation and plan their next trip, with a maximum of four different modes available (walking, public transport, bike, car).

4.3.3 Agent: Public transport

The public transport network of Cologne was also integrated in the simulation, using the data collected in 4.4.1. A number *n* of vehicles is created at the beginning of the simulation, each one in a different stop, so there is an interval in between them. The vehicles move from stop to stop according to their schedule and embark and disembark people. When a people agent chooses public transport as mode for a trip, they find the next stop and walk until there. They also find the stop closest to their target location and save that information. When the vehicle arrives at the stop where the people agent is waiting, the people agent 'embarks' on the vehicle and is added to the list of people who will disembark at their target stop. As soon as the vehicle arrives at the target stop of that people agent, they 'disembark' and walk the rest of the way until their target building. This agent is of course a simplification of the public transport available in the district and represents only the tram.

4.3.4 Agent: Building

Using the data that was collected in 4.4.1, the buildings are generated in GAMA. These building agents then carry information such as building use, available living space and number of residents. This information is then accessible for the people agents, which interact with the buildings.

4.3.5 Agent: Urban Vitality cell

Jane Jacobs defines urban vitality as an essential factor in terms of street life [Ibid.]. As part of this project, an urban vitality benchmark is implemented as a high resolution, real time heat map. This benchmark should be based on the diversity of people currently moving, their current objective, and the pedestrian flow related to time. Desired is a diverse, continuous pedestrian flow with little peaks or valleys in public places.

As mentioned, Jacobs defines three main drivers for street life: (a) diversity of people (b) different purposes and (c) during different times of the day [Ibid.]. This can be interpreted as diversity of agent profile, agent objective diversity and diversity in time.

[29] https://www.offenedaten-koeln.de/
[30] https://www.bmvi.de/SharedDocs/DE/Artikel/G/mobilitaet-in-deutschland.html

Diversity itself is a measurable value and can be calculated using the Shannon entropy Index H_S (Equation 1). This index was introduced by Shannon as part of his paper "A mathematical theory of communication"[31]. H_S describes the variety of different species in a dataset, considering the number of different species *(i)* and the number of individuals from each species *(n)*. *N* is defined as the total number of individuals in the dataset.

$$H_S = -\sum_{i}^{S} p_i * \log p_i \; where \; p_i = \frac{n_i}{N}$$

Equation 1 Shannon entropy index

Commonly used in ecology to describe the diversity of species, it is also applied to describe diversity in an urban context as done by Cerrone et al.[32] or the diversity of people in cities[33].

The grid cells with a resolution of 50 x 50 m evaluates the urban vitality of this space in real time and gives a visual feedback. Therefore, every round of the simulation, the people agents that overlap the cell, give two information values to the cell: profile and current objective. Along with those two, the current time stamp is saved. H_S is then used to calculate the diversity of each of those three values. Since we always know the number of different species (*i* in Equation *1*) we can calculate the maximum H_S and from that the amount of diversity that is reached depending on that maximum. The result is a value between 0 and 1. Combining diversity of profiles, current objectives and time stamps, the urban vitality of each cell is calculated in real time. The current value is then translated in colours which indicate the quality of the public space as a heat map on the model. Black stands for no vitality, values in the red area indicate a bad vitality with little diversity and blue is rpresenting high urban vitality (see Fig.6).

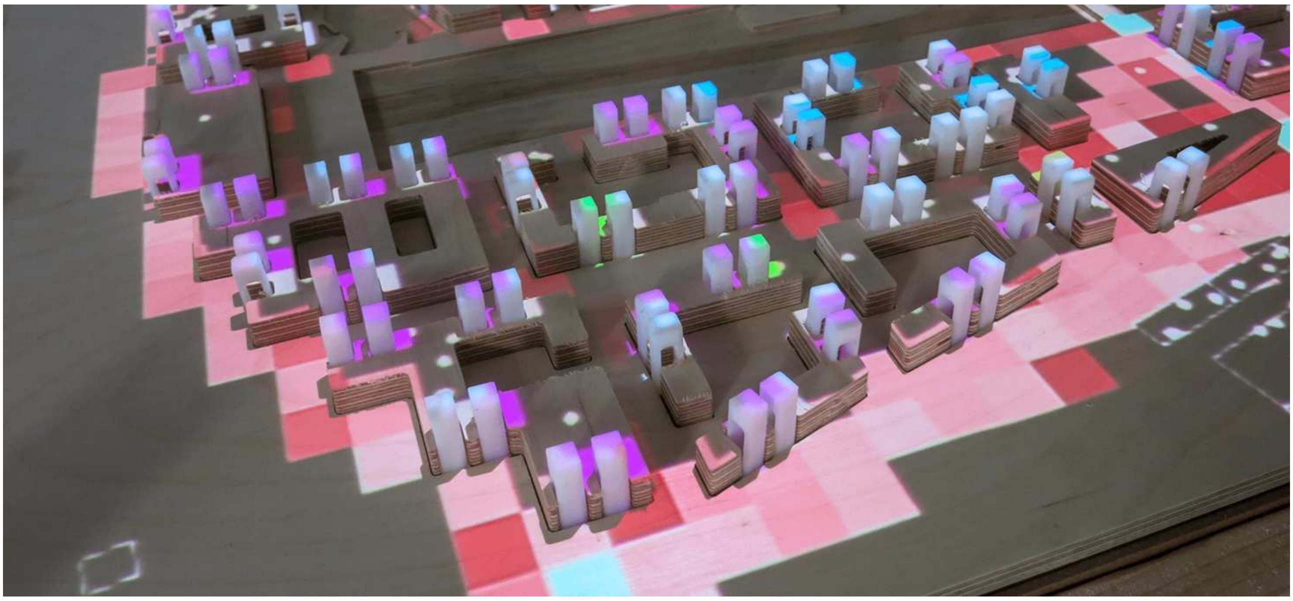

Fig. 6 Urban Vitality Cell projected on the model

5 LIMITATIONS AND FUTURE DEVELOPMENT

Time limitations and limited range of accessed user profiles lead unfortunately to larger gaps in the streamed social media content. In favour of building the profiles for the agent-based model, the social media data had to be enriched to fit the needed purposes for a trouble-free simulation process. Additionally, some technical issues might have affected the accuracy of the obtained profiles. First, gaps and anomalies in the activity table could be solved with a bigger volume of data and using a different service for the reverse geocoding,

[31] SHANNON, C.E.; A mathematical theory of communication; SIGMOBILE Mob Comput Commun; page 36

[32]Cerrone, D. et al.: Integrative Urbanism: Using Social Media to Map Activity Patterns for Decision-Making Assessment.

[33] Kemeny, T.: Immigrant diversity and economic development in cities: a critical review.

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like the Google Places API[34], or even by building context for the activity from the user's posts with text analysis or image classification. More data, maybe from phone location, would also mean more users profiles, that would make a better sample of the city than the limited number of profiles integrated now.

While using the interface, it became clear that the scanning process used now is heavy in computational power and not precise enough. Therefore, future processes should be written in Python, using a computer vision library such as OpenCV[35]. This is also done now by CityScope in recent projects and could be adopted from the Code available on Github. This could speed the process up and make it more precise. Another way of increasing the speed of interaction but also of the agent-based model would be to change from an online database to a local solution. Especially promising here is the use of UDP (User Datagram Protocol)[36].

For the ABM, a big limitation was computational power. The simulation could run only with 8% of the 70.000 people agents, that inhabit the investigated area. Since GAMA is generally able to run simulations with many agents, this could probably be improved by a further optimizing of the source code. While running the ABM, it also became obvious, that the model is a closed system, meaning the influence of the surrounding investigated area is not considered in any decision. This is especially visible when looking at the mode of transportation, where most of the agents chooses "walking". This is mostly because of the lack of long-distance trips since the radius of the investigated area is 1.3 km only. Introducing households and their members travel relationships would also result in a more realistic model.

6 CONCLUSION

The simulation of different scenarios in the district, by changing parameters of population demographics and building use, resulted in a big impact on the calculated urban vitality of the public spaces. This response of the model not only highlights some obvious assumptions but also shows surprising results in different settings – like how easy it is to lose visitors when removing certain commercial buildings. Many uncertainties remain due to simplifications in the agent-based model and limited data and technical resources. Despite still not have been tested in a bigger group due to the current social distancing rules, the tangible user interface performed well between a small group of real estate and urban planning experts. The model performed easily understandable, intuitive and gave almost immediate feedback to the user while interacting with it. A constructive note was the suggestion to calibrate the simulation by testing it with already existing districts, which should be a next step for further development. Built with a much more affordable set-up than similar tools such as touchscreen tables, it still has the potential of being reused for different projects, just by replacing the tabletop and keeping the rest of the hardware. Also approachable was the concept of the agents in the simulation being based on real people from social media, as noted by a guest who interacted with the table. Such feedback hints at the potential of making citizens feeling recognized in urban design decisions, since social media is so familiar to almost everybody nowadays. Even with the possibility of privacy concerns raising, people tend to feel comfortable in having their data used when they know how, why and for what it will be computed. So, the combination of (blackbox-)simulations with an interactive tangible user interface is a powerful tool in clarifying some of these questions and showing to what individual data could be contributing to. The project was presented as part of the Detmold Conference Week 2020[37] and experts from building industry, real estate management and urban planning gave valuable feedback.

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