Transport modal split prediction using Artificial Neural Networks

Ivo Cornelis de Geus

ABSTRACT

Cycling as a means of transport has gained significant international attention as a means to deal with increasing urbanisation and societal costs of urban automotive use, promising to reducing automotive use and its related socio-environmental impacts. The factors influencing individuals' choices to choose the bike are not yet fully understood, nor are they well-defined for estimation. This can lead to difficulties when estimating facility requirements for urban neighborhoods, such as traffic separation using separate lanes and bicycle parking. Literature shows that mobility choices depend on a multitude of factors, both local and regional, along with socio-economic and demographic factors. The aim of this study is to combine existing mobility diary logs to make predictions of cycling mobility activity on a local scale based on the accessible facilities surrounding the local area. Since this study is more about data estimation and less about explainability, a custom implementation of a back-propagating neural network is implemented to make these predictions. The results of the implementation show a promising but initially limited accuracy based on only access to facilities, with an accuracy of 55% based on categorical cross-entropy over the 7 main transport modes. For future projects, we recommend an increase of data which should happen over time and possibly an agent-based simulation approach, instead of the area-based approach in this project.

KEYWORDS

Infrastructure, Land Use, Spatial Planning, Cycling, Travel Mode, Travel Time, Machine Learning, Neural Networks

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2 INTRODUCTION

In both the Netherlands and in international contexts, cycling as a mode of transport is receiving increasing recognition as a sustainable alternative to private car use, and as a complementary option to public transport use (Dekoster & Schollaert, 1999; Næss & Strand, 2012; Pucher & Buehler, 2008; Romanillos & Gutiérrez, 2020). Nevertheless, there is still an active topic of research to understand the urban contexts in which cycling could serve as a viable alternative to car use.

This is reinforced by the fact that the expensive investment necessary to ensure high-quality infrastructure for cyclists is an important requirement for increasing its modal share (Buehler & Dill, 2016; Goodwin, 2012; Pucher & Buehler, 2008). This issue is further complicated as active mode choice is influenced by spatial, infrastructural, socio-economic, cultural, habitual, as well as demographic influences (Félix et al., 2019; Næss, 2015; Oldenziel & Albert de la Bruhèze, 2011; Snellen, 2001; Ton, 2019).

In order to understand which areas should receive priority in making cycling attractive, it is critical for transport planners and policy makers to model travel preferences, see possible potential missed, and being able to predict future choices. The approach taken in this project is studying the direct relationship between land use and mobility patterns.

Travel behaviour is commonly examined using either Revealed Preference studies, or Stated Preference studies (Aditjandra et al., 2013; Handy et al., 2005). In the Netherlands, a national ongoing study implementation of a Revealed Preference study is known as "Onderweg in Nederland", collecting a representative sample of a large amount of randomly selected participants (CBS, 2022). This research uses research travel diaries to record trips, aims and movements, allowing researchers to determine local mobility behaviour. These responses can be further expressed as modal split, and can be different depending on the category and aim of specific travels. The ODiN project has a long history, starting in another shape as early as 1978, at that time in the form of the Research on Mobility Behaviour (Onderzoek Verplaatsingsgedrag, OVG). Due to methodological changes in research methods and data shapes, the current data is available from 2018 onwards.

Using these data, transport behaviour research is able to calculate significant predictive factors in regressions, expressing the explanatory power of different features using elasticities, like in the meta-analysis (e.g. see Ewing and Cervero, 2010) or in meta-regressions (e.g. see Stevens, 2017). Several meta-analysis employ similar techniques, building further on similar data (Næss, 2022). When focusing on active modes, we can even see that meta-analysis in land-use cycling interactions seem to focus disproportionately on context with lower cycling levels, particularly the USA (Nello-Deakin & Harms, 2019).

One industry-standard method of further capturing discrete mobility choices is using Random Utility Modelling (RUM), more specifically logit models, to predict movements. These logit models are popular as they have a simple mathematical foundation while having the possibility to deal with unobserved explanatory variables, such as stochastic variables (Lee et al., 2018). See for a good introduction on logit models the works by **mcfadden<empty citation>**.

Mobility is often seen as a form of derived demand, instead of a direct demand. This means that a user is usually assumed to have a negative utility from the travel itself, such as a loss in time due to travel duration, costs due to tariffs, taxes, fares, insurances, tolls and depreciation, and other costs such as inconvenience. These factors can be quantified in the form of an abstract utility value, which would more often than not be negative for the travel part. The reason why the travel would still happen is because of the positive value of the destination, which why this is commonly described as a derived demand: the demand and value of the travel is derived from it's destination.

The previously described logit models have to be built on expert opinion with domain knowledge and underlying assumptions on choice order and importance (such as the 4-step demand model). Each choice is impacted by the utility derived from all parts in the mobility equation, including the utility from both the travel and the destination.

Logit models (and their versions such as multinomial logit and nested logit models) are based on the assumption that every choice is independent and identically distributed (IID-property). If this is not the case, choices can be nested, which is one of the advantages of a nested logit model, where similar choices are grouped. A next step is the step towards the inclusion of mixed logit, which relaxes the assumption if independence of irrelevant attributes. These systems however still suffer from the assumptions of linear characteristics of underlying model and the assumptions of the creator on the order and importance of different factors.

Taking non-parametric methods as an alternative for logit modeling could prove a valuable addition to the field. Existing research shows the potential of using an implementation of an artificial neural network (ANN), more specifically a basic back-propagating neural network (BPNN) to study urban systems (Bakri et al., 2023; Chang et al., 2019; Lee et al., 2018; Van Cranenburgh & Alwosheel, 2019). In contrast to structured versions of logit models, these networks are able to capture specific non-linear patterns from data using different layers of activation. This contributes to the research field of estimation of mobility behaviour analysis using neural networks.

While these networks seem to outperform logit models in some existing literature examples, a common counter-argument against their use is the lack of intrinsic understanding on the formation of mobility decisions it provides the creator. By combining and dispersing the signal of the input variables through several layers of hidden units in a neural network, it becomes very challenging to find the variables of higher explanatory power. This in turn makes it difficult to create take-away conclusions on the decision-making of travellers on an individual level.

These counter-arguments are valid points, and show that the need exists for continuation of explainable models in transport decision analytics. In this project, however, we focus on only making a prediction, and do not zoom in further on how these decisions are made. This is based on the need of this project (as explained in subsection 2.1), and the scale of the dataset.

Another approach gaining momentum is including preference studies and habitual studies as an addition to random utility theory. De Vos et al. (2022) and De Vos (2015) show that habits, past satisfactory experiences and attitudes are a great predicting factor, which itself is "a cyclical process between travel mode choice and travel satisfaction seems to occur". This aligns with the active mode choice studies done by Ton (2019), where the "experienced choice set" is set by both rational factors, and by habits and attitudes. This study considers consonant (use of preferred mode) and dissonant users (use of non-preferred mode) where land-use or facilities offered do explain choices, but habits impact the switching tendency people have, reinforcing the concept of non-rational choices.

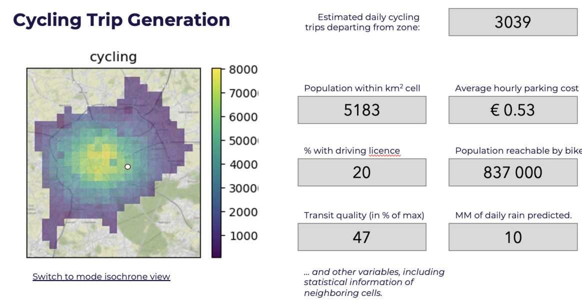

Figure 1: Prototype tool setup with viewing parameters.

2.1 Project purpose & desired outcome

In this project, we investigate the ability to extrapolate from existing transportation modal split known in regions with enough responses to mobility surveys to fill in the regions for which this information is not known. The modal split is to be estimated based on land-use variables, such as ease of access to facilities, either by mobility or proximity. We implement the first part of a land-use transport feedback-circle as defined by Bertolini (2017), aiming to correlate and predict modal split based on the access to different facilities. The desired outcome is a map with, for every region, an estimated modal split.

2.2 Thesis Structure

This thesis is divided into the introduction on the relevancy and need for the topic at hand, background and further elaboration on the research gap, research questions with elaboration on what the research should answer concretely, methodology including data gathering and processing, results of the performance of the model and presentation online, and discussion of the results.

3 BACKGROUND

3.1 Cycling for Mobility

Globally increasing urbanisation, combined with an increasing expectation of urban transport quality and urban living standards have put governments under pressure to enact policy changes encouraging more sustainable travel (UN, 2018). Defining sustainable mobility, or just sustainability itself, is already quite challenging, and this lack of standardised definition can often lead to confusion at best or green-washing at worst (Banister, 2008; Holden et al., 2013). One way to define sustainable mobility is to see it as a part of general broad prosperity ("brede welvaart"), and as a "way to improve living quality using mobility". This definition departs from a more traditional utility-based understanding of mobility, and reinforces social effects of mobility, both internal and external, individual and societal. (Snellen et al., 2021; Wilmink et al., 2021).

Encouraging active mobility, such as walking or biking, has increasingly become mainstream, with the 2020 pandemic acting as a catalyst for change (Nikitas et al., 2021). Both in the Netherlands and internationally, an increasing awareness for the power and potential for cycling as a dominant form of urban mobility is appearing. Advantages include increased physical and mental health

(Avila-Palencia et al., 2018; Bassett et al., 2008; Sallis et al., 2004), decreased urban emissions, equitable mobility, increase in social contact, optimising urban space utilisation, daily commercial spending, and general decrease use of energy consumption for enabling movement.

The advantages of cycling as a transport method are contrasted with automotive institutional dominance as a large player in mobility space. While automotive use has driven general prosperity and individual well-being to the levels we expect currently, its omni-presence and contemporary institutional dominance as an incumbent in policy-making is currently hindering adoption and recognition of other options (Kanger & Schot, 2016; Smink et al., 2015). Given the omnipresence and societal expectations of automotive focus, it has the structural and argumentative power to keep itself important by setting policy, setting policy agendas and creating societal expectations Brisbois, 2020. This institutional power extends to incumbent government institutions, and therefore to marked demand for transport models for with a focus on automotive transport, under-representing active, public and multi-modal transport options in these models (Kębłowski & Bassens, 2018; Te Brömmelstroet & Bertolini, 2011).

3.2 Predicting Modal Split

The concept of researching land-usage as an explanatory variable for mobility behaviour is a well-researched topic (see Bertolini, 2017 for a system-perspective overview), yet definitive conclusions about its impact are still debated. In a large study in the context of the Netherlands, Snellen (2001) shows that, when controlled for socio-demographic factors, land-use alone seems to show low predictive power on active mode selection, something we see in other studies as well (Nello-Deakin & Harms, 2019).

Individual studies on the impact of facilities and land-use can be compiled in a meta-analysis (e.g. see Ewing and Cervero, 2010; Gim, 2012, with bike focus Buehler and Dill, 2016; Muhs and Clifton, 2015), and in meta-regressions (e.g. see Stevens, 2017). We can take inspiration from what seem to be significant predictors to include in this research.

The external validity and repeatability of most of these results have been subject to extensive professional debate. The use of this cross-sectional analysis has been discussed as these meta-analyses can be seen as flawed in lack of controlling variables (such as self-selection or owning a driving licence), wrongfully assuming causality and integration and understanding of contexts (Handy et al., 2005; Næss, 2015, 2022; Van Wee, 2009).

4 RESEARCH QUESTIONS

The main research question is shown here, and subdivided in sub-questions.

RQ How can we accurately estimate the local transport modal split for all postcode-4 areas in the Netherlands using a backward-propagating neural network, and how can the results be effectively presented in an online tool for urban planning and decision-making?

The first part of the research question revolves around the development and implementation of a backward-propagating neural network (BPNN) for the estimation of transport modal split. Traditional methods for estimating modal split often rely on linear models and revealed preference studies. However, this research aims to push the boundaries of prediction accuracy by utilizing a neural network, which has the potential to capture complex non-linear relationships in the data.

The neural network's training and validation processes will involve feeding the network with a substantial amount of data, learning from it, and optimizing its weights and parameters to minimize errors. The research will explore the convergence of the model's performance and determine how well it aligns with actual modal split data.

The second part of the research question emphasizes the practical application of the obtained results. It addresses the challenge of translating complex predictive models into actionable information for urban planning and decision-making. The development of an online tool becomes crucial in this regard, as it bridges the gap between data analysis and practical use. The online tool will serve as a user-friendly interface for urban planners, policymakers, and stakeholders to access the estimated modal split data.

4.1 SQ1: How do we process and clean ODiN data to ensure its accuracy and reliability?

As we will explore later, the ODiN dataset contains a large number of trips as surveyed over the total population. These will have to be summarized, extracted and pre-processed to serve as training material for our model.

4.2 SQ2: How can we use accessibility and mobility performance to determine access to facilities from postal code zones?

Isochrones by themselves do not convey so much information about the actual reach and attractiveness of specific modes. The goal is to extend beyond the initial area for which we have enough data, and make accurate predictions for the areas with less available data.

4.3 SQ3: How to we adapt a back-propagating neural network to our dataset?

We expect that the final base dataset will be relatively small, especially given the requirements of a neural network. For this, we have to take extra considerations. There are many strategies to work around small sample sizes of training data, and we explore several methods to deal with this, and work around the limited set.

4.4 SQ4: How can we present and use the insights gained from the estimated modal split in the Netherlands?

There are many methods of dissemination. One central point will be how to show the gained knowledge and insights, and make them available to other projects, given that the results seem to be worth sharing.

5 METHODOLOGY

The aim of this study is to estimate mobility modal split for individual areas, enabling a fast heuristic for a motivated investment in new infrastructure for cycling, and possibly finding underrepresented areas of investment, where higher cycling use could be expected.

This study combines several different data sources to generate dependent features to estimate the modal split for each area. This paragraph explains the order of preparation of these data-sources. An oversight and schematic view of the data preparation process is shown in **??** and **??**.

5.1 ODiN Mobility Diaries

In the Netherlands, mobility diary surveys have been conducted nationally in several different forms, starting in 1978 with the Project Research on Mobility Behaviour (Onderzoek Verplaatsingsgedrag, OVG). From 2018 forward, the latest methodological version of the research method has been used, which is called Onderweg in Nederland (Travelling in the Netherlands, from now on called ODiN) research (CBS, 2022). This dataset contains the total amount of trips, ordered in trips, movements and movement-chains, made by respondents on one specified day in the Netherlands. This dataset is in wide use in both governmental, academic and commercial applications, see Bakri et al., 2023; Boonstra et al., 2022.

The main limitation, and at the same time one of the reasons for the existence of this study, is the spatial resolution of the results from the Onderweg in Nederland mobility survey, which reports data of journeys made on a resolution level of postal codes. In the Netherlands, postal codes differ in size quite a bit, which can impact the accuracy of our study. For the sake of simplicity, we will assume that the facilities accessible from the geometric centroid of a postal code area is representative for the whole area.

In the ODiN dataset, every journey can consist out of several legs with different modes, so that a single journey can be made for the first part by car, middle part by public transit, and the final part by bike. In the data, this is simplified to the main travel class, which is the one covering the largest time-span in the trip. Using this main travel class, we calculate the fraction of each mode and merge this with each postal code area. To increase the amount of data available, we will stack all compatible research data created by the ODiN project, with the exception of 2020, as its mobility patterns have been significantly changed due to pandemic restrictions in that year.

5.2 Calculating Reach: Isochrones

After we have determined a relative modal split for each area, we now take the centroid of the area, and determine the number of facilities available per mode. To determine this, we first take the nearest road from the area centroid of each postcode-4 area as a departure point for our isochrones.

To find the the facilities within reach for each area, we will calculate the facility reach for the modes below. Reach can be expressed in many different ways, and a standard one is to generate the area accessible within a maximum of a specified time. These areas are known as isochrones, which can be literally translated as keeping time (chrome) the same (iso). In this research, we take a maximum of 30 minutes from the nearest road from centroids of the postcode-areas.

- Walking
- Cycling
- Public Transit with walking as access/egress
- Public Transit with cycling as access/egress
- Driving in off-peak hours

To calculate these isochrones, there are many options available in forms of paid, free and open-source versions. In this case, we have chosen to create a custom implementation of the GraphHopper Route Generator, GH for short. GraphHopper has the advantage that it is open-source, has support for publicly accessible OpenStreetMap files and for public transport schemes in the form of standardised GTFS-files. The source material is available in readily extracted form in the shape of OpenStreetMap ProtoBuf files, available on GeoFabrik. The Public Transport Feeds in the form of GTFS-files can be found in the national data access point, on TransitLand.

In order to make the non-standard implementation of combining cycling with transit, where cycling is used instead of walking for both the access and egress parts of journeys, a small modification has to be made in the GraphHopper Java source-code.

For all isochrones, the departure time is set for Tuesday 3 October 2023, 8:30am. Isochrones for public transit will have a time-departure window of 30 minutes from the set departure time, meaning that a route has to start before 9:00am and take at most 30 minutes from departure.

Gathering
Prison
Healthcare
Industry
Office
Accommodation
Education
Miscellaneous
Sport
Retail
Residential

Table 1: Categories of land use as defined in the Base Registry of Addresses and Buildings (BAG).

5.3 Converting Reach to Facilities

In order to further process the geospatial reach of the isochrones into a quantification of actual facilities accessible by specific modes, we use the Base Registry for Adresses and Buildings (Basisregistratie Adressen en Gebouwen, BAG). The BAG is a national database service in the Netherlands which exposes all buildings and their functions in 11 different categories, as noted in Table **??**, as points. Points can have multiple different purposes, so each point is assigned a list of boolean true/false values for every category. Using an export service by GeoParaat, we extract all these points in the form of a single GeoPackage-file, and cross-section these with the generated isochrones.

5.4 Final Data Merging

As Isochrones normally tend to create quite irregular shapes, even after simplifying, the spatial join to calculate which points fall

Dependent variables	Example area 1741
sted_1	False
sted_2	True
sted_3	False
sted_4	False
sted_5	False
omgevingsadressendichtheid	2126
stedelijkheid	2
kmarea	0.743158
driving_off_bijeenkomst	7125
driving_off_cel	19
driving_off_gezondheidszorg	5573
driving_off_industrie	25729
driving_off_kantoor	19655
driving_off_logies	5395
driving_off_onderwijs	1820
driving_off_overige_gebruiks	36607
driving_off_sport	1191
driving_off_winkel	15618
driving_off_woon	650193
transit_off_bijeenkomst	337
...	...
walking_woon	15210

Table 2: Independent spatial variables as input for the artificial neural network. Repetition of facility reach by transit, cycling and walking has been removed for brevity.

Independent variables	Example area 1741
Bus/tram/metro	0.000000
Fiets	0.310141
Overig	0.010955
Personenauto - bestuurder	0.310673
Personenauto - passagier	0.114983
Te voet	0.174129

Table 3: Dependent modal split as output for the artificial neural network.

within which isochrone will require some significant computing power. To perform this join-operation, we will use 6 virtual private computers in the cloud, which should streamline this operation significantly. After these preparation steps, we end up with a single dataset with both the dependent and independent variables. One example we will use throughout this paper is for postcode area 1741, with the independent spatial variables shown in Table **??**, and dependent modal-split variables shown in Table **??**.

5.5 Preparation & Processing

The accessible facilities for each point are first pre-processed by taking the natural logarithm of the sum-value of facilities accessible. This value is then normalised to standardized z-scores from the mean fit for training the artificial neural network. After this normalisation step, the value of the accessibility per area is input input into the ANN, joined with the one-hot-encoded label of urbanity, and the size of the postcode-area in square kilometers. These are matched with the modal split data as dependent variables.

We have designed a standard backwards-propagating neural network implementation in TensorFlow, an industry standard library developed by Google. The model is composed of the input layer, 3 hidden layers of 64 neurons each, a dropout layer of 20% between the hidden layers, and a Rectified Linear Unit activation function, with a soft-max output function. The complete setup of the model is seen in Figure 9.

In order to compensate for the limited dataset after filtering, we have performed a 10-fold cross-validation based on the dataset to ensure consistent test results and avoid over-fitting on the data as much as possible.

The soft-max output function resembles a familiar S-shaped logistic function. In this case, instead of a normal Utility index similar to logit models, the ANN outputs a similar abstract utility index, which is evaluated in the logistic function to come to a probability for each modality to be chosen from that specific area. This score is then evaluated with a cross-entropy loss function. We split the input data into a training and validation dataset, for which we will provide metrics of training accuracy. Afterwards, we compare the accuracy of the output compared to the actual known modal split for each area.

6 RESULTS

To gain insights into the modal split patterns in the Netherlands, we analyzed the data from the ODiN mobility diaries. The modal split analysis provides a comprehensive understanding of travel behavior across different regions. In Figure 3, we present the percentage of trips made mainly by bike, highlighting distinct peaks at 0% and 100%. These extreme values signify areas where cycling as a mode of transportation is either entirely absent or dominant. The distribution of the number of trips registered per postcode area is depicted in Figure 5. The mean percentage of bike trips is approximately 58%, with a median of 35%. The areas which have less than 40 responses over the stacked years is shown in Figure 4. In the following results, only areas with at least this minimum response rate is included in training, such as shown in Figure 6.

For all the approved areas, we have taken the described isochrones of 30 minutes, which results in an isochrone such as shown in Figure 7 for every zone. Cross-sectioning this with the Base Registry of Addresses and Buildings and their functions, we get a result such as shown in Figure 8. This view is simplified, as some points might have two or more functions simultaneously, such as in the case of mixed development.

After making the necessary changes and tweaks for training the model, our most optimal result comes out on a average accuracy over 10 cross-validations of 46.048, with a mean deviation over the folds of +- 12.5809. The development of the model over the training epochs is visible in Figure 10

7 CONCLUSIONS & RECOMMENDATIONS

Following extensive experimentation with the dataset and various configurations of the model, it is evident that the predictive efficacy of the modeled functions is notably limited. This is substantiated by

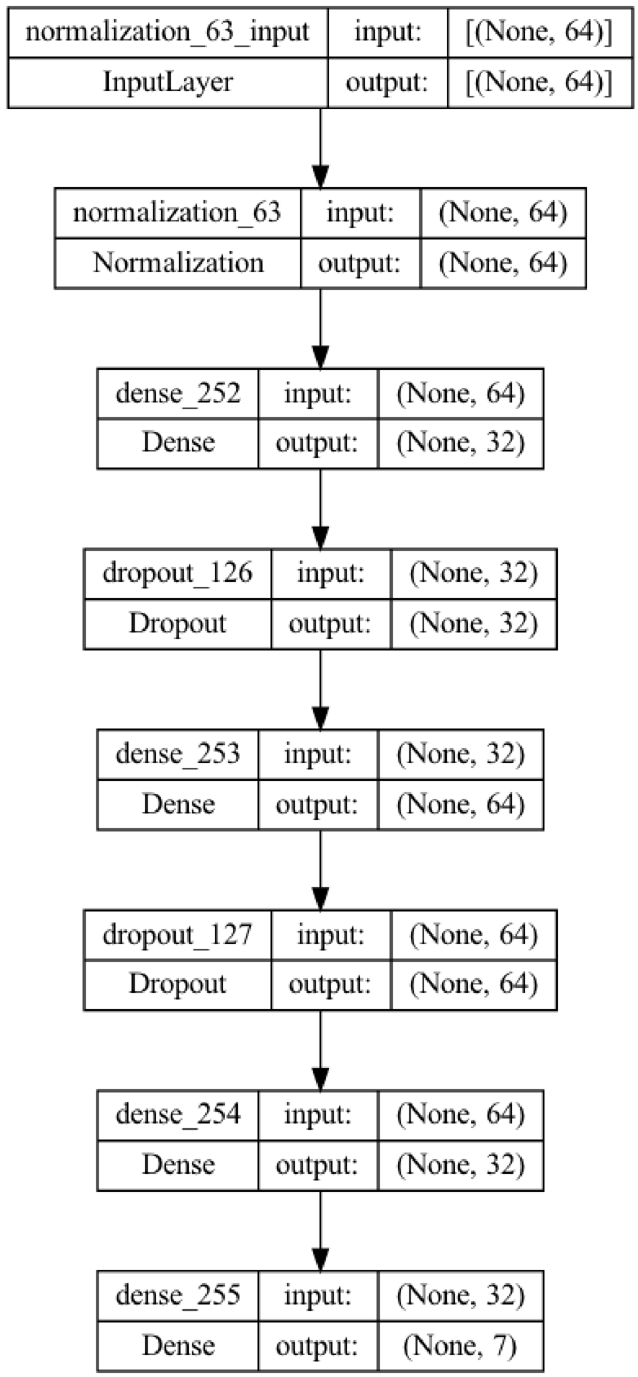

Figure 2: Layout of the backwards-propagating neural network as implemented in this projectx.

the model's recurrent tendency to converge toward the expected values, such as the mean of the variables. These observations suggest that the model is predominantly adapting to the data rather than effectively forecasting it based on the provided dependent variables.

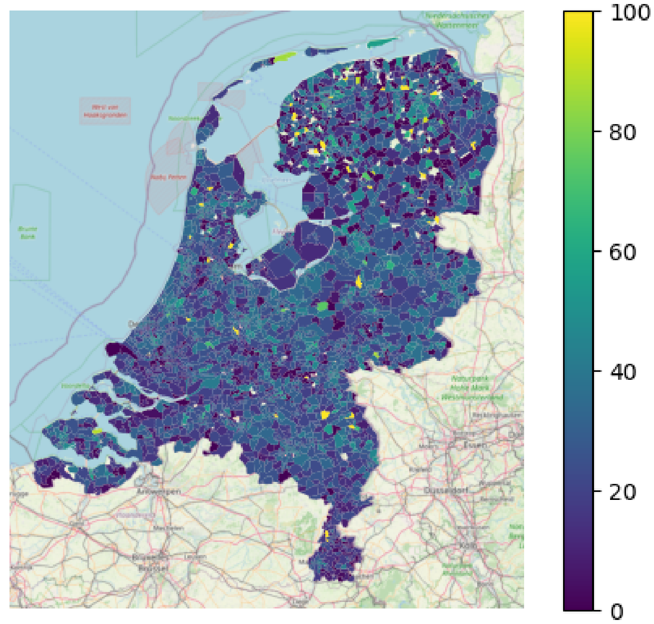

Figure 3: Naive modal split: percentage of trips made by bike, with large spikes to 0 and 100% visible.

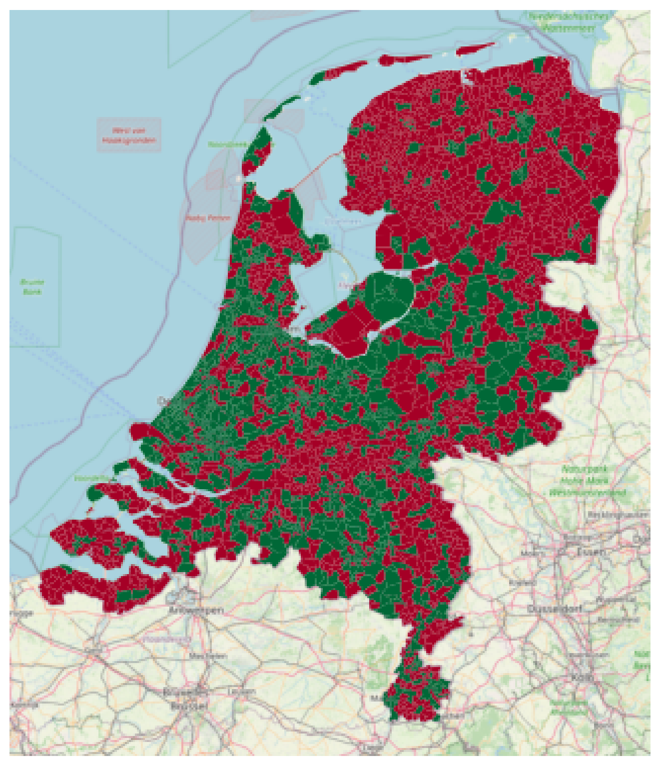

Figure 4: Areas with at least 50 responses, green areas to be included in training dataset.

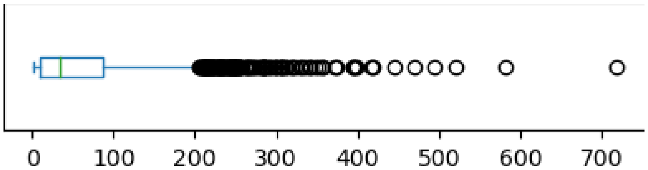

Figure 5: Distribution of amount of trips registered per postcode area, mean=58%, median=35%.

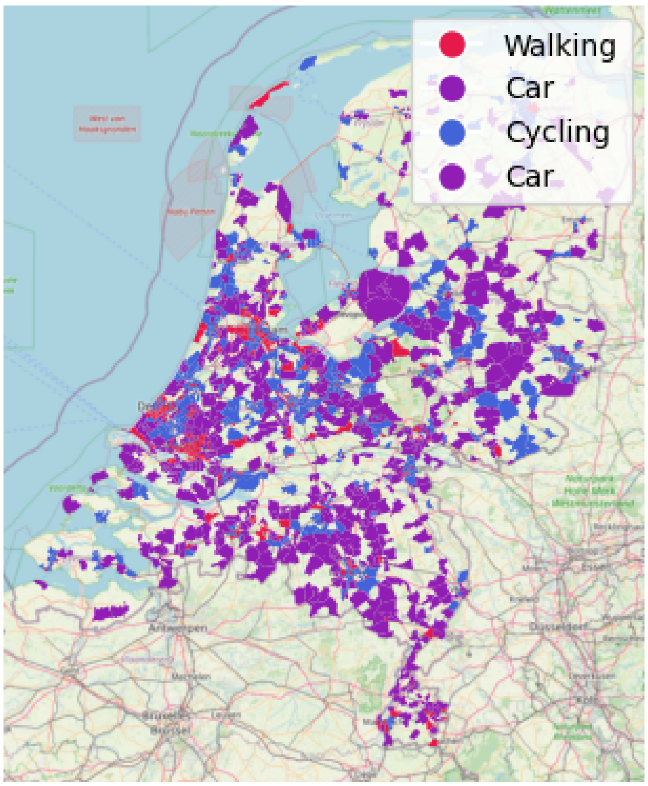

Figure 6: Dominant transport mode in the areas that comply to the minimum response rate of 40 stacked responses.

For future research, it is imperative to discern the independent variables with more predictive power, make the necessary adjustments, and make further enhancements to to improve the resultant outcomes. Given that our findings fell considerably short of our initial expectations, we have decided against providing these results in a tool online, as they might have conveyed a deceptive impression of precision, which, regrettably, is not reflective of accuracy.

One strong take-away from this study is that, while we can assume a strong link between land-use and mobility, one does not immediately lead to the other, and further study would be required to find better automated ways of estimating modal split from generally available data, such as implemented here.

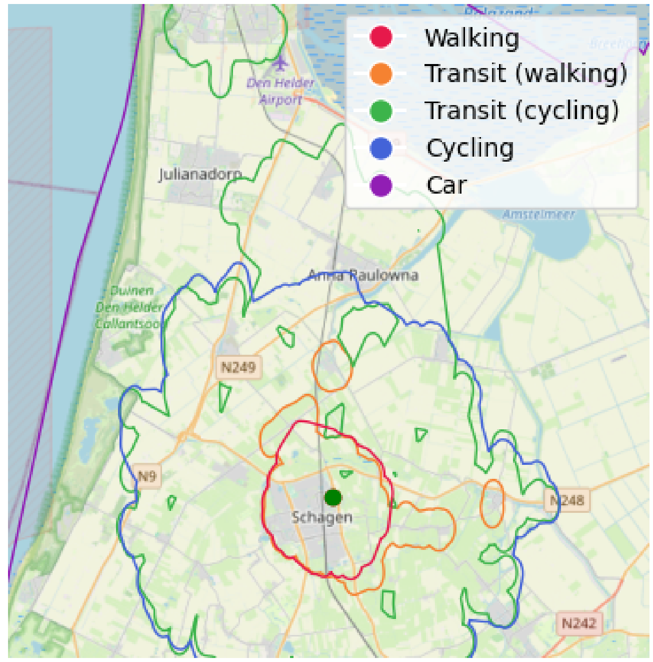

Figure 7: Areas accessible within 30 minutes from centroid of postcode-area 1741 using walking, transit (combined with walking or cycling), cycling, and car.

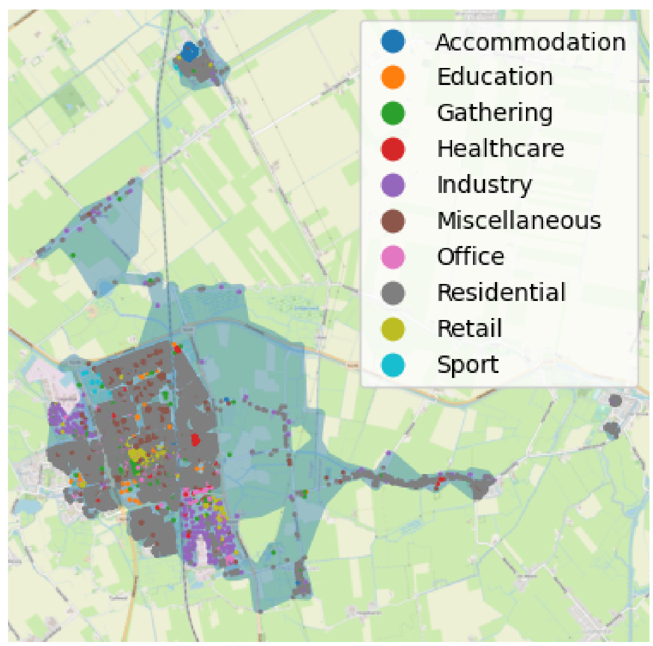

Figure 8: Facilities available within area accessible by combining transit and walking from centroid of postcode-area 1741 according to BAG-registry.

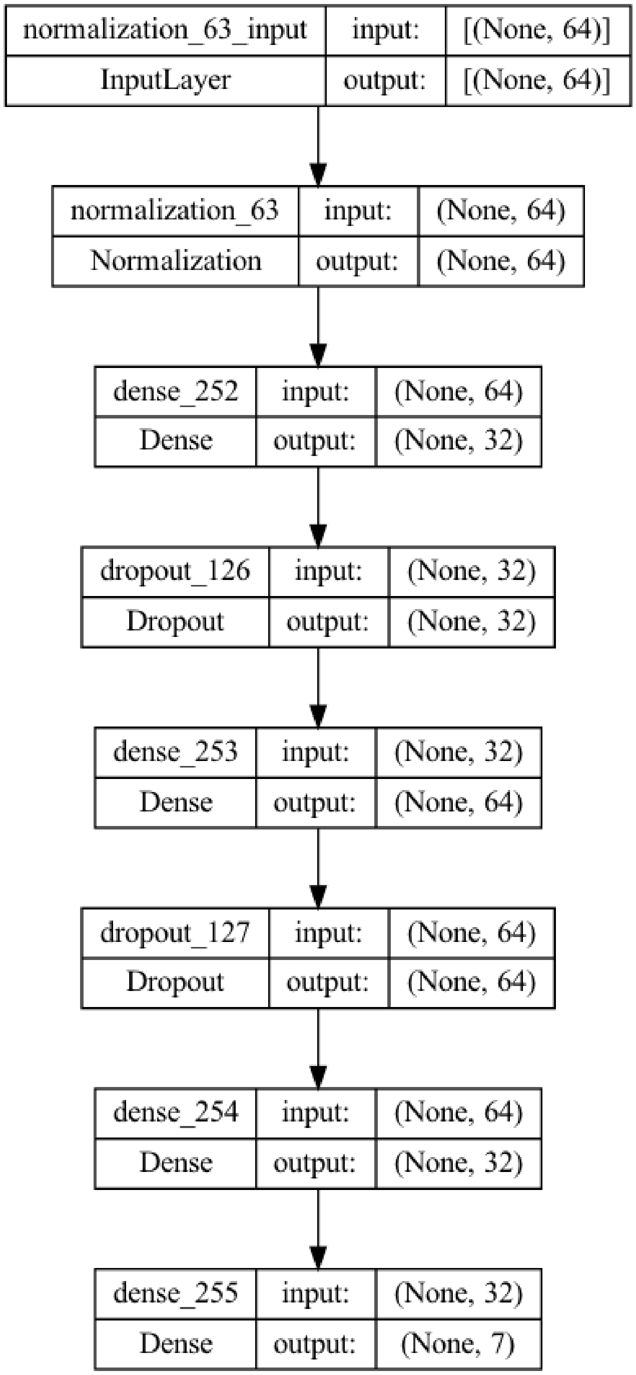

Figure 9: Implementation of the final model used to train and estimate modal split over the different areas, with normalised spatial access info as input, and estimated fractions of modal split as output.

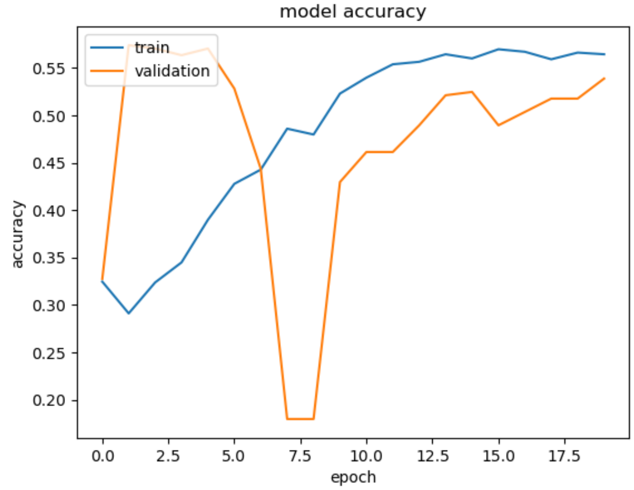

Figure 10: Accuracy of the model while training the 10th cross-validation.

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