Institute of Transport Economics
Norwegian Centre for Transport Research

Towards activity-based demand modelling for the Greater Oslo Area

Using machine learning to predict travel mode choice and activity plans

Stefan Flügel, Christian Weber, Simen Sørbøe Klommestein, Johan Korsmo, Anders Kielland

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Summary

This report documents the R&D efforts conducted as part of the PRELONG project between 2022 and 2024, focusing on generating activity plans for a synthetic population in the Greater Oslo Area. At the core of our approach are two neural network models that predict the characteristics of all trips made on a typical weekday. These machine learning models are trained on travel survey data from RUTER-MIS (2017–2024) and are applied to population and commuting data.
Among the many potential applications of these datasets are agent-based simulation models that use this data as input. Furthermore, additional analyses explore the influence of level-of-service variables on the prediction of travel mode choices, highlighting certain challenges associated with a purely data-driven approach.

Kort sammendrag

Denne rapporten dokumenterer FoU-arbeidet som ble utført som en del av PRELONG-prosjektet mellom 2022 og 2024, med fokus på å generere aktivitetsplaner for en syntetisk befolkning i Stor-Oslo-området. Kjernen i tilnærmingen vår er to nevrale nettverksmodeller som forutsier egenskapene til alle reiser som foretas på en typisk ukedag. Disse maskinlæringsmodellene er trent på reisevanedata fra RUTER-MIS (2017–2024) og anvendes på befolknings- og pendlerdata.
Blant de mange potensielle anvendelsene av disse datasettene er agentbaserte simuleringsmodeller som bruker dataene som input. I tillegg undersøker analyser påvirkningen av tilbudsvariabler (LoS) på prediksjonen av valg av reisemiddel, og fremhever visse utfordringer knyttet til en rent datadrevet tilnærming.

Preface

In this report, we introduce a method to generate activity plans for applications in transport models and transport planning. Our generation of activity plans is similar in output to the prediction of activity plans in so-called activity-based demand models (ABDMs), a class of models going back to the 1970s. In comparison to classical ABDM, that are rule-based or estimated with classical statistical methods of inference, we are using techniques within machine learning, in particular deep neural networks. The models are trained on travel survey data from Ruter AS and are applied to a representative set of agents for the Greater Oslo Area.

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The analysis and writing of this report was led by Stefan Flügel (TØI). Stefan's colleagues at TØI, Christian Weber, Simen Sørbøe Klommestein and Anders Kielland have contributed to development, programming, analysis and/or writing of the report. In addition has Johan Korsmo (former Epigram) contributed to the development and programming of the original data flow and model. Quality insurance of the report was done by Frants Gundersen. We also want to thank all participants of the PRELONG project for valuable comments and Ruter AS for donating their travel survey data.

Oslo, December 2024
Institute of Transport Economics

Bjørne Grimsrud	Frants Gundersen
Managing Director	Director of Research

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ENGLISH **Summary**

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This report documents the R&D efforts conducted as part of the PRELONG project between 2022 and 2024, focusing on generating activity plans for a synthetic population in the Greater Oslo Area. At the core of our approach are two neural network models that predict the characteristics of all trips made on a typical weekday. These machine learning models are trained on travel survey data from RUTER-MIS (2017–2024) and are applied to population and commuting data.

Transport modelling is evolving to address the challenges of urbanization, technological advancements, and complex travel behavior. Traditional four-step travel demand models, while foundational, often fail to capture the dynamic nature of travel patterns in urban areas.

Activity-based travel demand (ABDM) models offer a more detailed and dynamic representation of travel behavior, which accounts for the complexities of daily schedules, individual preferences and environmental constraints. This is achieved by: 1) The aggregated data structure is replaced with a disaggregated one, i.e. individuals (rather than population segments within geographic areas) are the unit of analysis. 2) Transport demand is derived from the demand to perform activities, with an emphasis on sequences of tours or all-day travel plans rather than individual (round) trips. 3) Time (clock time) is explicitly modelled (start/end times and activity planning are important).

To bridge the gap the towards activity-based and agent-based transport models, this report documents the generation of activity plans (first documented in Flügel 2022) using a machine learning approach, specifically deep neural networks.

Figure S1 gives a schematic overview of the main data, methods and concepts and how they are related in our overall approach to transport modelling. This report describes the four squares on the left side of the figure, which a specific focus on the demand model that in our case are two neural network models (model 1 and model 2).

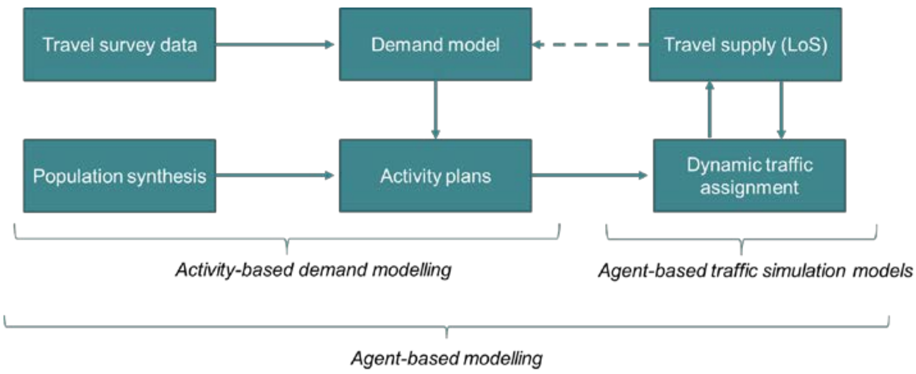


Figure S1: High level overview over related data and methods in this report.

As Figure S2 illustrates, model 1 does predict overall characteristics of the trip diary (activity plans): Start time of first trip, Start time of last trip, Number of trips and the Sequence of trips before and after the work activity. Model 2 predicts characteristics of trips: Travel mode, Purpose, End zone and Time duration since previous trip.

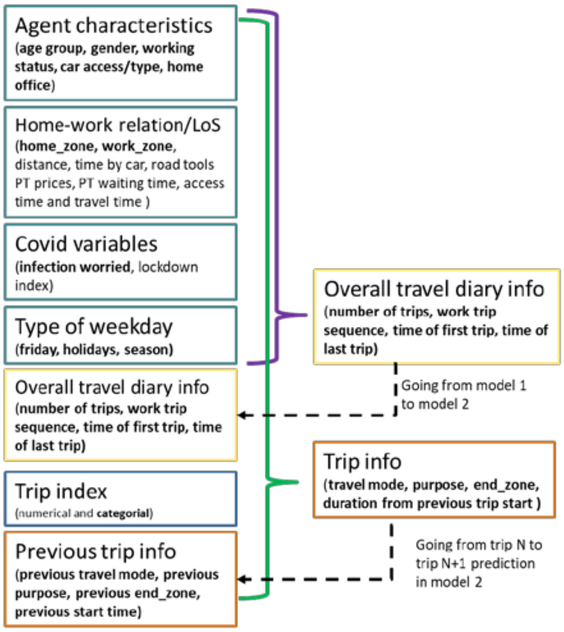


*Figure S2: Input and output variables of the two neural network models. The purple brackets indicate model 1 and the green bracket model 2. Categorical variables in **bold** font.*

The dotted arrows indicated that outputs are transformed into inputs when applying it to new data. Our approach captures correlations between multiple trip characteristics (trip purpose, travel mode, departure time, destination choice). For example, the output "purpose: picking up" will be strongly correlated with the output of "travel mode: car".

The neural network models are trained on travel survey data, more specifically a random sample of 75% of the respondents in Ruter-MIS from January 2017 to September 2024. The models are validated against the remaining 25% of the sample (validation data). Overall the models seem to capture the correlation pattern on the validation data as exemplified by the next two figures.

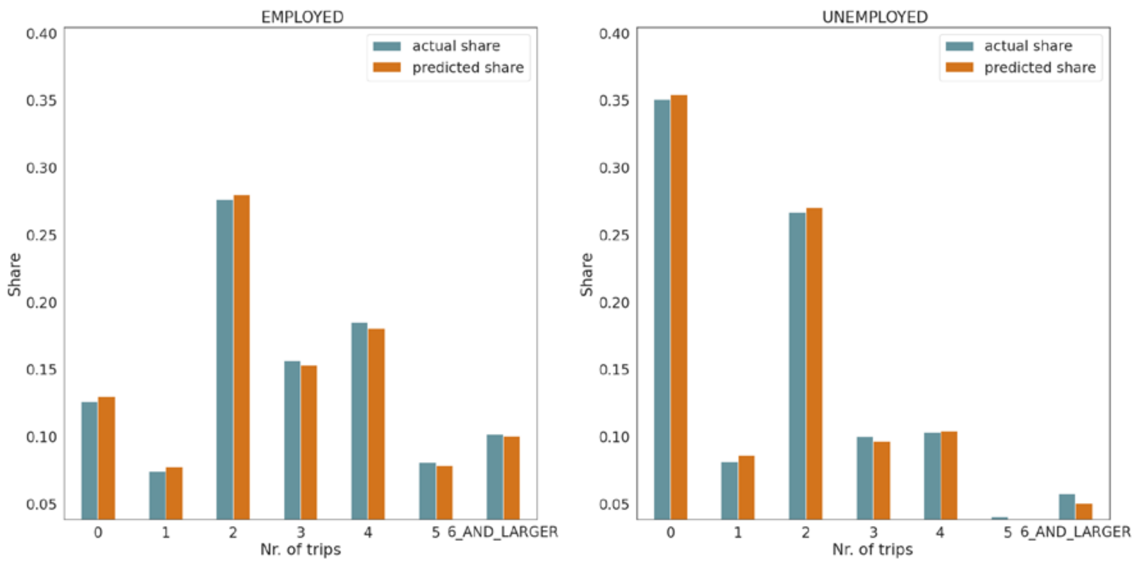


Figure S3: Actual share (in Ruter-MIS) and predicted share (from model 1) on the validation data for the Number of trips by occupation status.

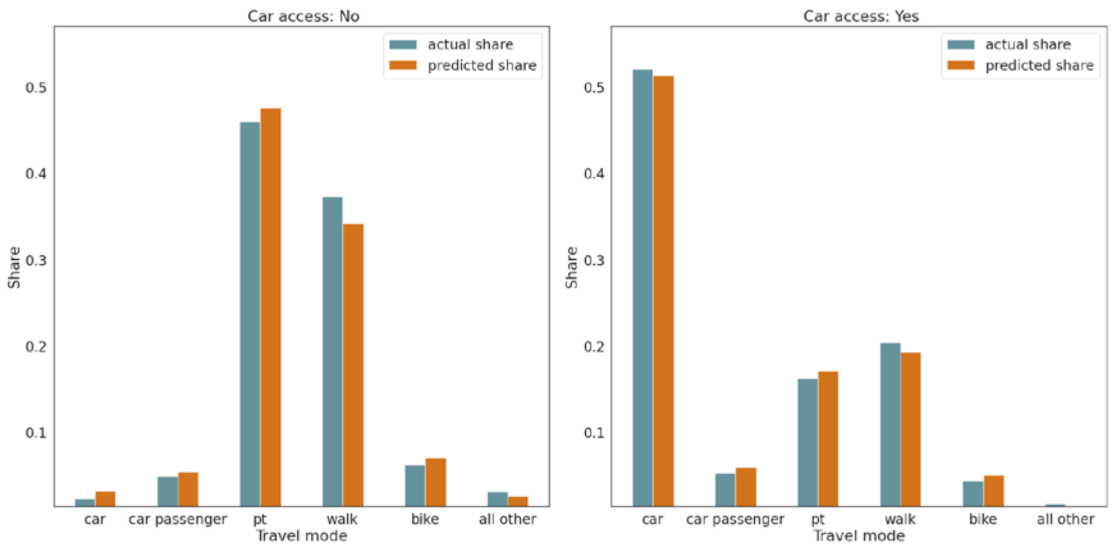


Figure S4: Actual share (in Ruter-MIS) and predicted share (from model 2) on the validation data for the travel mode choice; segmented by car access.

The models are than applied to a synthetic population that is assembled from various data sources (population data, commuting data, zonal data etc.).

Figure S5 shows the geographical location of different types of activities at 12 o'clock.

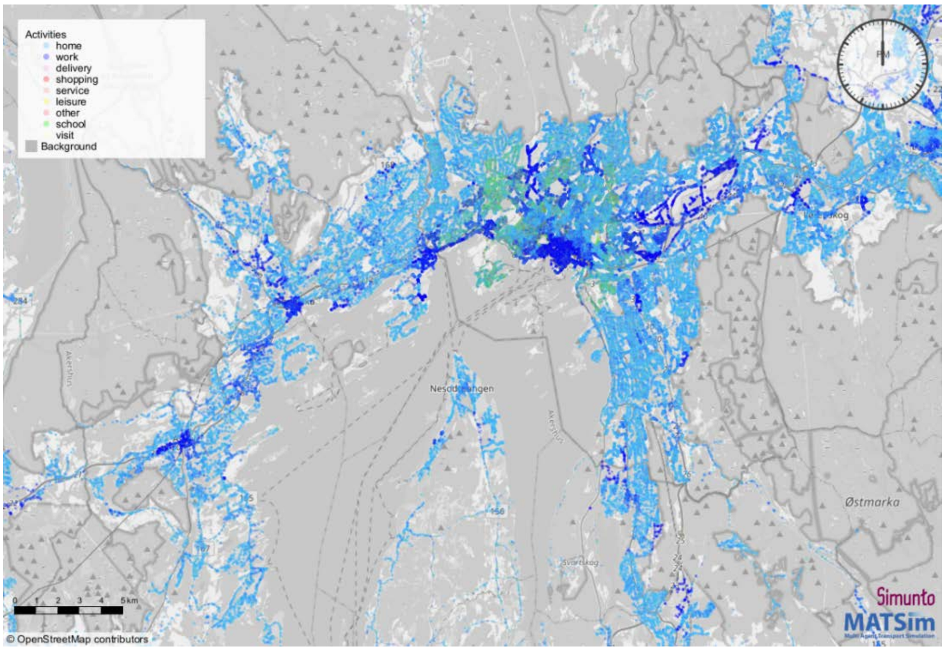


Figure S5: Geographical location of generated activities at timestamp 12:00:00.

The report includes some additional analysis regarding the effects of Level-of-Service on the prediction of travel model choice. We find that elasticities of demand, as implied by the neural network predictions, depend strongly on the model formulation and are in general on the lower side.

Our overall approach has several known limitations requiring further refinement. First, the coarse zonal system used for destination prediction results in imprecise non-work trip destinations, potentially leading to illogical or excessively long trips. Future versions should incorporate predictive travel distance models or geography-conditioned sampling to address these issues. Additionally, population synthesis could benefit from richer data inputs, such as microdata.no, and leveraging machine learning or generative AI to enhance agent characteristics like household type, education, and income.

Despite improvements since earlier versions, the model generates too many trips in the afternoon, likely due to the trip-by-trip prediction method. Exploring advanced architectures like recurring neural networks or attention-based models may help resolve this issue. Validation of synthetic activity plans remains challenging due to limited external data, with mobile data or MATSim-validated traffic simulations offering potential solutions. Lastly, the current backend implementation, relying on Python scripts and notebooks, is user-unfriendly, and a front-end interface is planned for 2025 to improve functionality and facilitate scenario testing.

Despite these challenges, the approach demonstrates significant promise. Its compatibility with dynamic transport models and applicability in agent-based modeling enables downstream applications, such as the MATSim transport simulation model. Moreover, the spatial-temporal data structure holds potential beyond transport, for example, in epidemiological simulations.

The method's adaptability for future synthetic populations (e.g., for 2030 or 2050) ensures relevance for long-term predictions, provided input data remains representative. Importantly, the approach can bridge future agent-based land-use models predicting long-term behavior and transport simulation models capturing detailed network-dependent behavioral adjustments, marking an important step toward advancing state-of-the-art transport models in Norwegian cities.

NORSK Sammendrag

Mot aktivitetsbasert etterspørsels-modellering

Bruk av maskinlæring for prediksjon av transportmiddel-valg og aktivitetsplaner

TØI rapport 2065/2024 • Forfattere: Stefan Flügel, Christian Weber, Simen Sørbøe Klommestein, Johan Korsmo, Anders Kielland • Oslo, 2024 • 62 sider

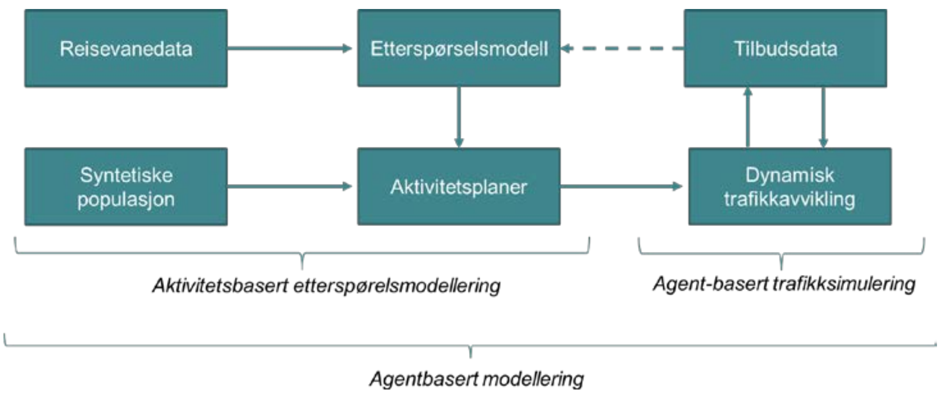
Denne rapporten dokumenterer FoU-arbeidet som ble utført som en del av PRELONG-prosjektet mellom 2022 og 2024, med fokus på å generere aktivitetsplaner for en syntetisk befolkning i Stor-Oslo-området. Kjernen i tilnærmingen vår er to nevrale nettverksmodeller som forutsier egenskapene til alle reiser som foretas på en typisk ukedag. Disse maskinlærings-modellene er trent på reisevanedata fra RUTER-MIS (2017–2024) og anvendes på befolknings- og pendlerdata.

Transportmodellering utvikler seg for å møte utfordringene knyttet til urbanisering, teknologiske fremskritt og komplekse reisemønstre. Tradisjonelle firetrinnsmodeller for transport-etterspørsel, selv om de er grunnleggende, klarer ofte ikke å fange opp den dynamiske naturen til reisemønstre i urbane områder.

Aktivitetsbaserte reiseetterspørselsmodeller (ABDM) gir en mer detaljert og dynamisk representasjon av reisemønstre, som tar hensyn til kompleksiteten i daglige tidsplaner, individuelle preferanser og miljømessige begrensninger. Dette oppnås ved: 1) Den aggregerte datastrukturen erstattes med en disaggregeret struktur, dvs. individer (i stedet for befolkningssegmenter innenfor geografiske områder) er analyseenheten. 2) Transportetterspørsel er avledet fra etterspørselen etter å utføre aktiviteter, med fokus på sekvenser av turer eller hele-dagen-reiseplaner i stedet for individuelle (tur-retur) reiser. 3) Tid (klokkeslett) modelleres eksplisitt (start-/sluttidspunkter og aktivitetsplanlegging er viktige).

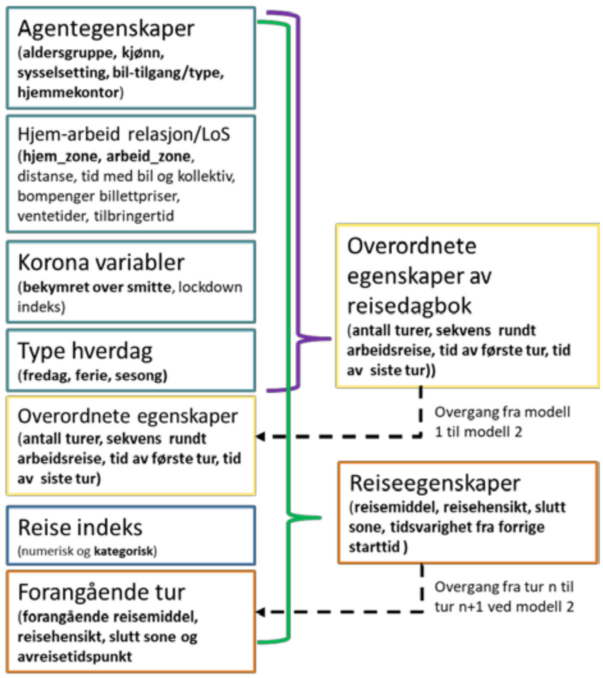
For å bygge bro mot aktivitetsbaserte og agentbaserte transportmodeller dokumenterer denne rapporten genereringen av aktivitetsplaner (først dokumentert i Flügel 2022) ved bruk av en maskinlæringstilnærming, spesielt dype nevrale nettverk.

Figur S1 gir en skjematisk oversikt over hoveddataene, metodene og konseptene, og hvordan disse henger sammen i vår overordnede tilnærming til transportmodellering. Denne rapporten beskriver de fire rutene på venstre side av figuren, med spesielt fokus på etterspørselsmodellen, som i vårt tilfelle består av to nevrale nettverksmodeller (modell 1 og modell 2).



Figur S1: Oversikt over relaterte data og metoder i denne rapporten.

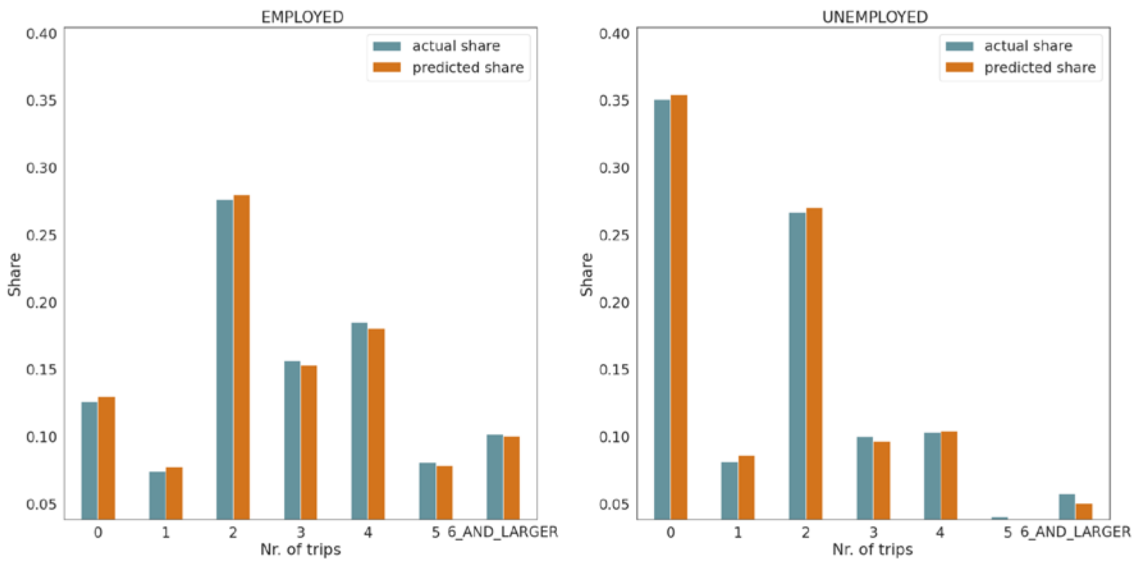
Som illustrert i Figur S2 forutsier modell 1 de overordnede egenskapene til reisedagboken (aktivitetsplaner): Starttidspunkt for første reise, starttidspunkt for siste reise, antall reiser og rekkefølgen av reiser før og etter arbeidsaktiviteten. Modell 2 forutsier egenskaper ved reisene: Reisemåte, formål, endesone og tidsvarighet siden forrige reise.



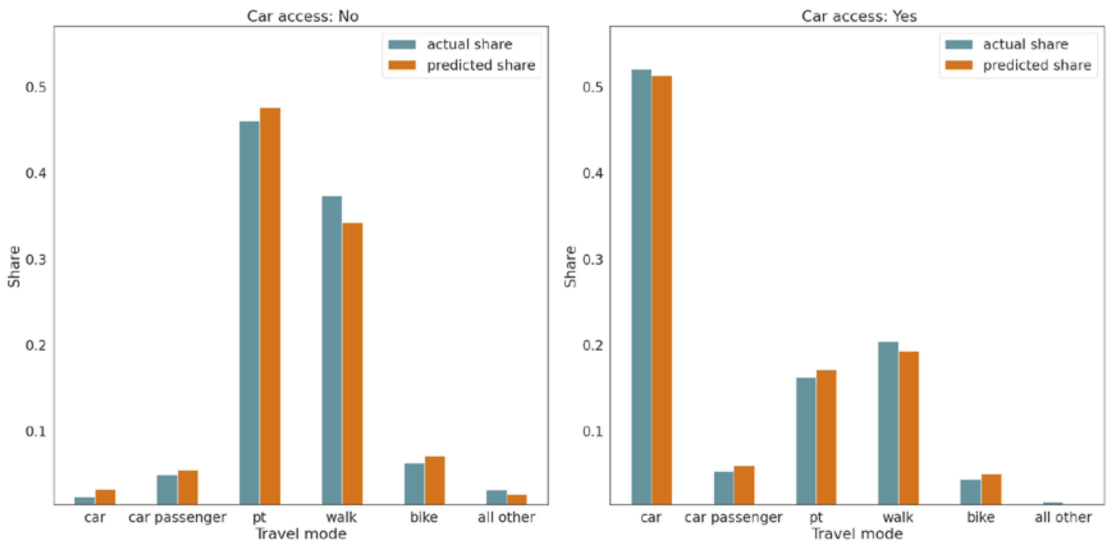
Figur S2: Inndata- og utdata-variabler for de to nevrale nettverksmodellene. De lilla klammene indikerer modell 1, og den grønne klammen indikerer modell 2. Kategoriske variabler er i ***fet*** *skrift.*

De stiplete pilene indikerer at utdata blir transformert til inndata når modellene brukes på nye data. Vår tilnærming fanger opp korrelasjoner mellom flere reiseegenskaper (reisehensikt, transportmiddel, avreisetidspunkt, destinasjonsvalg). For eksempel vil «hensikt: hente» være sterkt korrelert med resultatet «transportmiddel: bil».

De nevrale nettverksmodellene er trent på et tilfeldig utvalg av 75 % av respondentene i Ruter-MIS fra januar 2017 til september 2024. Modellene er validert mot de øvrige 25 % av utvalget (valideringsdata). Samlet sett ser modellene ut til å fange korrelasjonsmønstrene i valideringsdataene, som vist i de neste to figurene.



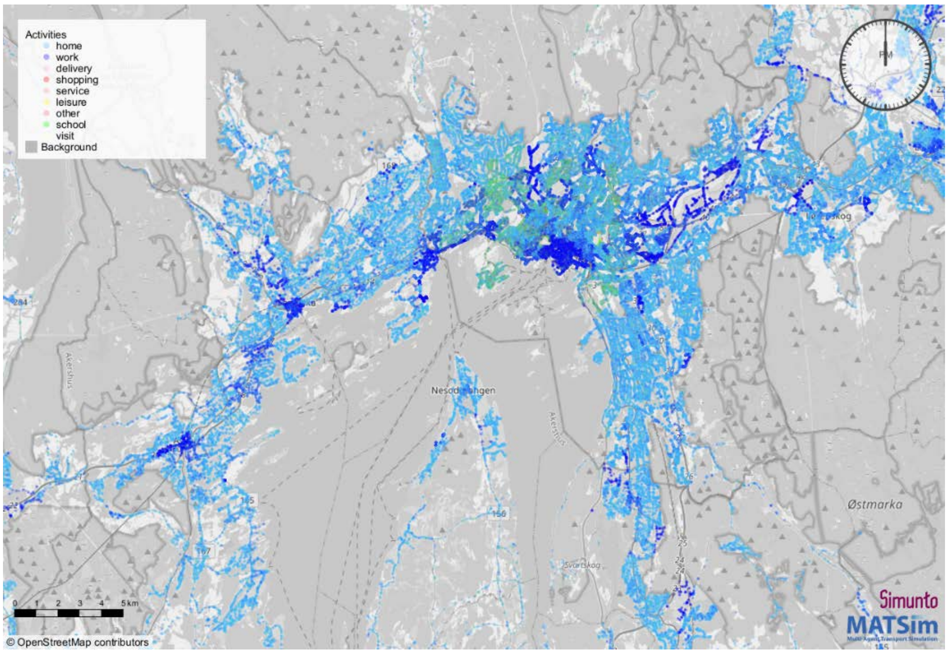
Figur S3: Faktisk andel (i Ruter-MIS) og forutsagt andel (fra modell 1) på valideringsdataene for antall turer gitt yrkesstatus.



Figur S4: Faktisk andel (i Ruter-MIS) og forutsagt andel (fra modell 1) på valideringsdataene for transportmiddelvalg gitt biltilgang.

Modellene er så anvendt på en syntetisk befolkning som er sammensatt av forskjellige data kilder (registerdata, pendlerstatistikk og sonedata fra transportmodeller).

Figur S5 viser den geografiske fordelingen av ulike aktiviteter klokka 12.



Figur S5: Geografisk fordeling av genererte aktiviteter ved klokkeslett 12:00:00.

Rapporten inkluderer noen tilleggsanalyser om effektene av Level-of-Service på prediksjonen av transportmiddelvalg. Vi finner at etterspørselselastisitetene, slik de er implisert av predikeringer av de nevrale nettverksmodeller, avhenger sterkt av modellformuleringen og er generelt noe lave.

Vår overordnede tilnærming har flere kjente begrensninger som krever videre utvikling. For det første fører det grove sonesystemet som brukes til destinasjonsprediksjon til upresise destinasjoner for ikke-arbeidsreiser, noe som potensielt kan resultere i ulogiske eller altfor lange turer. Fremtidige versjoner bør inkludere prediktive modeller for reiselengde, geografisk betinget utvalg eller grunnkrets-spesifikke destinasjonsvalgmodeller for å adressere disse problemene. I tillegg kan populasjonssyntese dra nytte av rikere datainnganger, som mikrodata.no, og bruk av maskinlæring eller generativ AI for å forbedre agentkarakteristikker som husholdstype, utdanning og inntekt.

Til tross for forbedringer siden tidligere versjoner genererer modellen fortsatt for mange turer på ettermiddagen, sannsynligvis på grunn av prediksjonsmetoden som predikerer tur-for-tur. Utforskning av avanserte arkitekturer som rekursive nevrale nettverk kan muligens bidra til å løse dette problemet. Validering av syntetiske aktivitetsplaner forblir utfordrende på grunn av begrensede eksterne data, der mobildata eller MATSim-validerte trafikksimuleringer kan tilby potensielle løsninger. Til slutt er den nåværende backend-implementasjonen, som er avhengig av Python-skript og notatbøker, lite brukervennlig. En front-end-grensesnitt er planlagt for 2025 for å forbedre funksjonaliteten og lette scenariotesting.

Til tross for disse svakheter viser tilnærmingen betydelig potensial. Dens kompatibilitet med dynamiske transportmodeller og anvendelighet i agentbasert modellering muliggjør videre anvendelser, som transportsimuleringer i MATSim. Videre har den romlig-temporale datastrukturen potensiale utover transport, for eksempel i epidemiologiske simuleringer.

Metodens anvendbarhet til fremtidige syntetiske populasjoner (f.eks. for 2030 eller 2050) sikrer relevans for langsiktige prediksjoner, forutsatt at inngangsdata forblir representative. Tilnærmingen kan bygge bro mellom fremtidige agentbaserte arealbruksmodeller som forutsier langsiktig atferd og transportsimuleringsmodeller som fanger opp detaljerte atferdsjusteringer i transportnettverket. Dette markerer et viktig steg mot å fremme avanserte transportmodeller i norske byer.

1 Introduction

1.1 Background

Traditionally, transport planning in Norway and internationally has relied on the four-step travel demand modelling approach (Ortuzar and Willumsen 2024). This approach offers a broad framework for various modelling methods, with great success over the years. However, it has not been optimal, particularly in highly dynamic and densely populated areas. The current rapid technologically driven advancements in transportation modes and work patterns, along with urbanization, are causing an increasing complexity in travel patterns.

In this report, we are moving towards activity-based demand models (ABDMs) for transport planning by introducing methods to generate activity plans for a synthetic population of the greater Oslo Area. ABDMs employ agents to represent individuals, each characterized by a set of demographic and socioeconomic attributes. The individual, agent-based, data structure relates ABDM to general framework of agent-based modelling. ABDMs operate on the principle that travel demand originates from the actual activities that require traveling, such as work, shopping and leisure. These models predict detailed individual travel patterns, including the type, sequence, location, timing and duration of activities, along with the travel modes to accomplish them.

ABDMs offer a more detailed and dynamic representation of travel behavior, which accounts for the complexities of daily schedules, individual preferences and environmental constraints. Thus, ABDMs provide a nuanced and adaptable framework for analyzing travel behavior, offering insights into how transport systems can be designed and modified to meet the evolving needs.

Modern ABDMs are more data-intensive than the traditional modelling approaches. Even though the emergence of big data has made these models more feasible, there is still a significant lack of real data to build such models, which in most situations necessitate the need for synthetic data. Synthetic data is artificially generated and not derived from real-world events but designed to closely resemble actual data at a level suitable for the analysis of interests. We introduce a machine learning approach to generate synthetic data. Our model is trained on a sample of population data obtained from the Ruter customer survey (Ruter-MIS). It is then employed to generate synthetic travel plans for a complete population in urban settings.

This study is part of efforts towards establishing new transport models in cities. As suggested in the seminar "Transport Models for the Future", these long-term efforts start with a clean slate and are decoupled from the traditional transport models in Norway (Meland, 2021).

We focus on the demand side of personal transport and only briefly touch on issues related to the coupling of demand models with traffic assignment models. In particular, the study investigates the possibility to establish ABDM have a microscopic (agent-based) and dynamic representation of travel demand in form of all-day activity plans.

Current trends – like urban densification, increased congestion, active transport, micro-mobility and new modes of transportation resulting from further automation and sharing economies – make the transport markets and networks more dense and dynamic. Capturing individual constraints and temporal dependencies are arguably getting more important and the need for activity-based models in cities is therefore likely to increase. Furthermore, taking an individual and activity-based approach to demand modelling has arguably increased during and after the COVID-19 pandemic. The effects of home office on travel demand are an example for that.

1.2 Objectives

The objective of this report is to discuss approaches to ABDMs and to document the generation of a dynamic and agent-based travel demand representation of an average weekday in the greater Oslo region. A thematic introduction and motivation is given in chapter 2.

1.3 Comparison with previous work

(this section is most relevant for readers that are familiar with the first model presented in Flügel 2022)

The work was initiated in the PRELONG project (Flügel 2021) and was further developed in the project for the NPRA. The first generation of traveling plans in the PRELONG project had several weaknesses that are addressed in this report. Table 1.1 gives a comparative overview of the improvement over the first model (presented in Flügel 2022) and in the model presented in this report).

Table 1.1: Improvements over the initial model from the PRELONG project (Flügel 2022).

Weakness of initial model	Further addressed in this report	Section
Activity plan generation not sensitive to Level-of-Service (LoS) data (except travel distance)	Evaluating LoS data as explanatory variables for prediction of travel mode choice in Ruter-MIS	3.1 and chapter 5
Limited and outdated training data	Include 4.5 more years of training data, now covering Ruter-MIS from January 2017 to September 2024	3.2
Included only agents that did at least one trip (agents staying at home all day where generated based on exogenous information)	Include the prediction of Number of trips as an endogenous part of the modelling approach.	4.1 and 4.2
The number of travels is skewed towards later traveling time points compared to true distribution	A more direct prediction of the time of the first trip and the total amount of trips	4.1, 4.2 and 4.6
Unrealistic activity chains are predicted	Improvements by a more direct prediction of number of trips and the trip sequence of trips around work trips	4.1 and 4.2
No possibility to account of home office for future scenarios	Extent of home office is now an explanatory variable that can be defined for future scenarios	4.1 and 6.3
No seasonal variation and no difference between weekday	We have introduced seasonal effects in the model and accounting for that Fridays may have a slightly different activity pattern that Mondays to Thursdays	4.1

By inclusion of the 2020 and 2021 data, the possible field of application of the modelling approach extended. As results in section 6 indicate, the model can now be used to predict mobility patterns for future pandemic scenarios (compare analysis in chapter 6).

1.4 Structure of the report and disclaimer

Chapter 2 presents a review of relevant methodology. Chapter 3 documents the data sources used in this study. Chapter 4 describes the methods for generating activity plans and some results. Chapter 5 contains an investigation of how including LoS data effects prediction of travel mode in neural network models. Chapter 6 presents the result of the generation of activate plans, and the effect of COVID on travel choices. Chapter 7 discusses weaknesses in the current approach and possibilities for further model development.

The language model GPT-4o (GPT-4o System Card | OpenAI) has been occasionally used as a writing assistant in this report. GPT4 was also used to generate summaries chapters (in both English and Norwegian). The authors have carefully checked and, if needed, revised all text generated by GPT-4.

2 Methodological overview

2.1 High level overview

Figure 2.1 gives a schematic overview of the main data, methods and concepts and how they are related in our overall approach to transport modelling. The concept of agent-based modelling and activity-based modelling are further described in section 2.2.

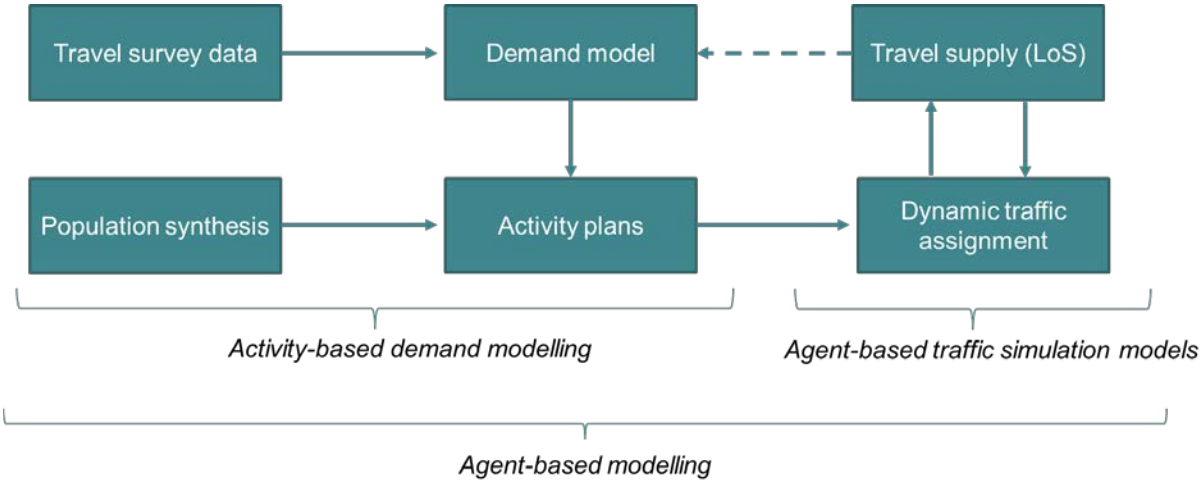


Figure 2.1: High level overview over related data and methods in this report.

A central part of overall approach are activity plans which are generated by the demand model and used as input in the agent-based traffic simulation model. An typical example of an activity plan in the MATSim-xml format is given below:

```
<person id="0001000" age="50-66" gender="female" , occupation status = 1 ,access_car "e-car" >
        <plan selected="yes">
                <activity type="home" x="271184.762022" y="6669835.18865" end_time="06:50:52">
                </activity>
                <leg mode="car">
                </leg>
                <activity type="work" x="271795.602597" y="6669520.14361" end_time="16:03:15">
                </activity>
                <leg mode="car">
                </leg>
                 <activity type="shopping" x="271795.602597" y="6669520.14361" end_time="16:40:15">
                </activity>
                <leg mode="car">
               </leg>
                <activity type="home" x="271184.762022" y="6669835.18865">
                </activity>
        </plan>
</person>
```

The set of all activity plans in the synthetic population represent the total travel demand of persons above the age of 15 years, in our case for an average weekday.[1]

Our overall approach can be divided into these 6 main steps (Figure 2.2):

1. Train a neural network model using travel survey data. We are using Ruter-MIS combined with additional data.
2. Generate a synthetic population
3. Use neural network models to predict individual activity plans for the agents in the synthetic population
4. Fed the activity plans into an agent-based simulation models and simulate congestion and LoS data
5. Adjust activity plans within the simulation model given congestion / LoS until equilibrium is approximated
6. Optional: Feedback LoS into demand model (not implemented yet)

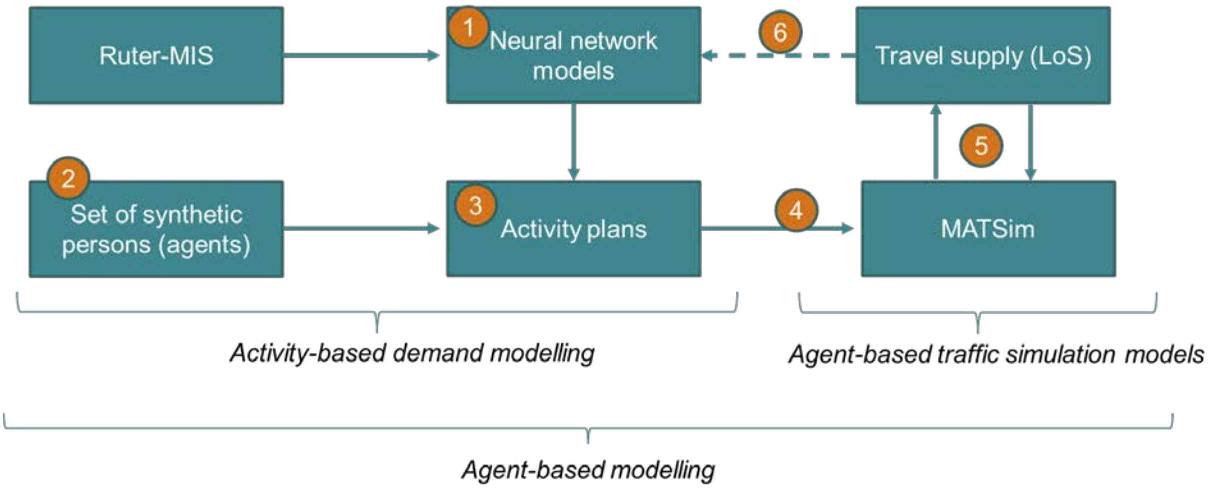


Figure 2.2: The specific contribution of our approach to elements in the schema presented in Figure 2.1.

This report describes the steps 1-3. Step 4 and 5 are performed in the PRELONG project with the MATSim modelling framework (Horni et al 2016) and not described here in detail, but will rather be covered in future reports. Step 6 is not yet performed, but is expected to play an important role in a future transport model system. As for now, the LoS entering the demand model (the neural networks) comes exogenously from the RTM23+ model, and not from the agent-based simulation model.

In order to place our approach in the broader context of transport modelling, Figure 2.3 shows the corresponding elements of Figure 2.1 for the regional transport models (e.g. RTM23+). The demand model TraModBy (Rekdal et al 2021) is applied on population segments and produces origin-destination (OD) matrices which quantify the aggregated transport flow between and within geographical regions, called basic statistical units (BSU). The OD matrices are fed into a static assignment model, that outputs LoS-data, which then are fed back into the demand model TraModBy.

[1] The current model can distinguish between two types of workdays, 1) Mondays to Thursdays and 2) Fridays.

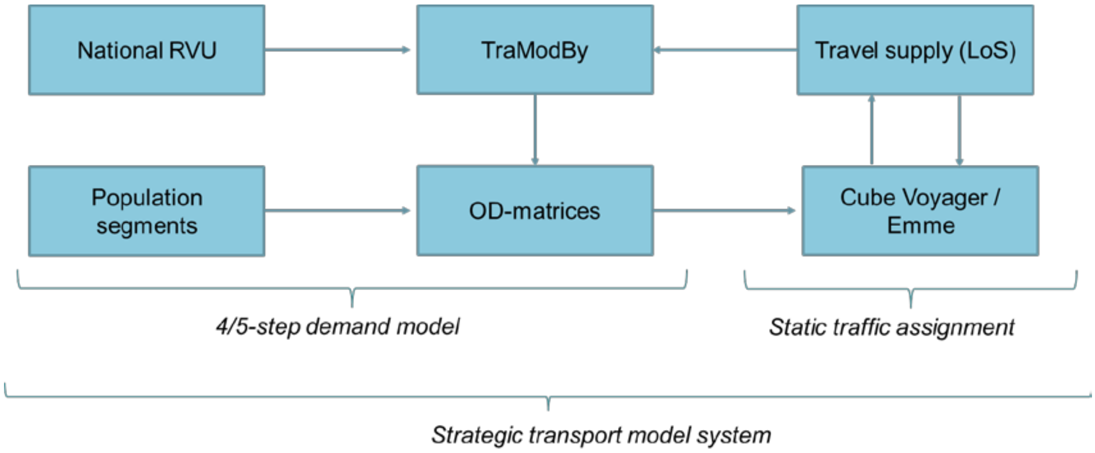


Figure 2.3: In comparison to Figure 2.1, the high level overview of the regional transport models (RTM).

In comparison to the aggregated and static OD-matrices, the activity plans generated in this project are disaggregated and contain a clock-time dimension. This is in accordance with the activity-based and agent-based modelling approach as further described below.

2.2 Agent-based modelling

The overall approach in the previous section falls generally under agent-based modelling.

Agent-based modelling is a computational algorithmic approach used to simulate the behavior of individual agents and their interactions with each other. In an agent-based model, each agent is defined as an autonomous entity that has its own behavior and decision-making rules. In the case of activity-based demand models, agents have agency over their activity plan and can adjust these plans given changes in environment.

Agent-based models can be applied to various fields, including social sciences, economics, biology, and engineering. In transportation and traffic engineering, agent-based models are used to simulate the behavior of individual vehicles, drivers, and pedestrians in a road network. These models are called agent-based traffic simulation models.

Agent-based traffic simulation models are used to analyze the performance of traffic networks under different scenarios, such as changes in traffic volume, road capacity, traffic control strategies, and travel behavior. These models consider the interactions between the individual agents and their surroundings, including other agents, infrastructure, and traffic regulations.

An popular agent-based traffic simulation framework is MATSim (Horni et al 2016). MATSim is reported among the most used agent-based simulation algorithms in transport modelling (see Figure 2.4). Agents in MATSim have agency in the sense that they can choose its own route through the network and adjust some dimensions in their initially activity plans through departure time choice and transport mode choice. Note that this behavior is sensitive to the LoS including changes in travel time caused by congestion.

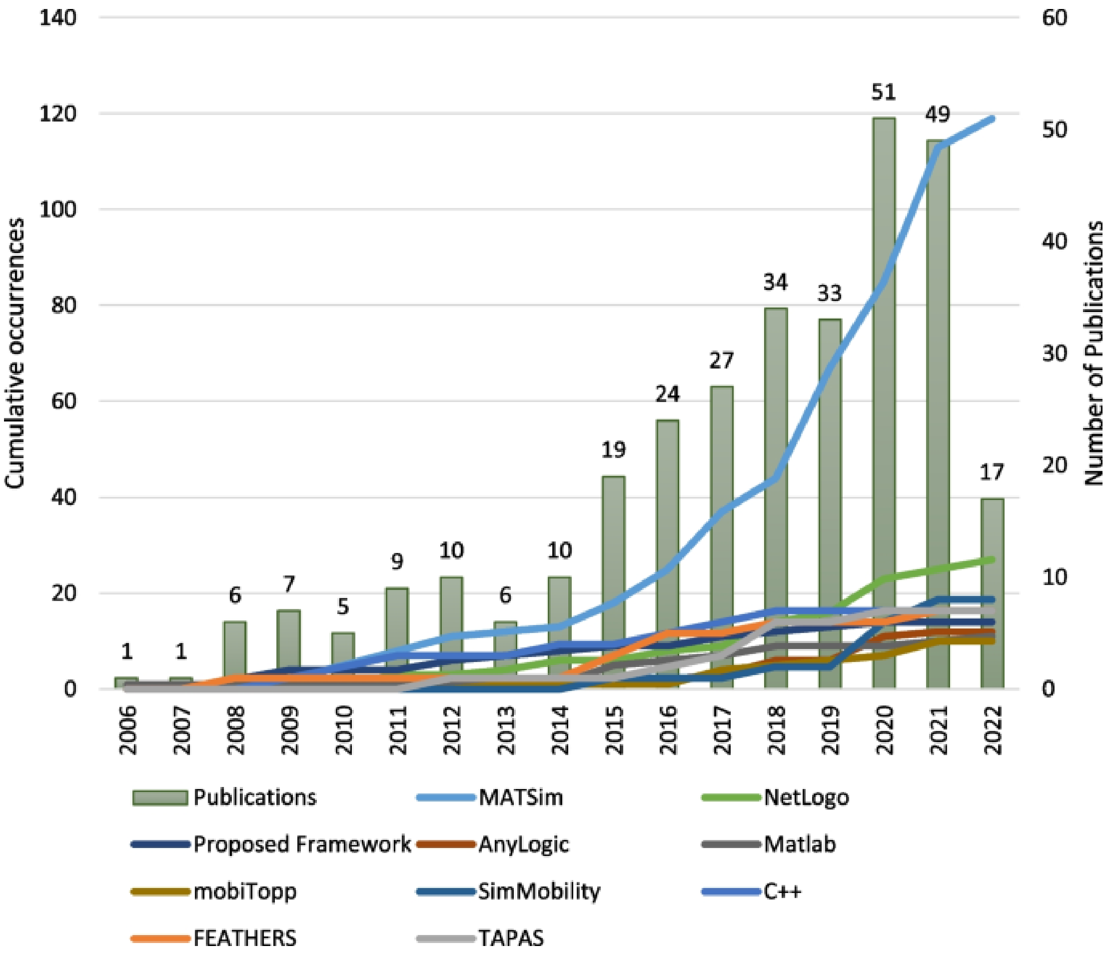


Figure 2.4: Number of publications using different agent-based transport simulation models based on recent literature review; source Bastarianto et al 2023.

2.3 Activity-based demand modelling

In this section we give a short overview of activity-based demand models.[2]

As described by Jones (2012), the formal development of traffic and transport modelling began in the 1950s and 1960s with a vehicle-based approach. The first expansion of the vehicle-based paradigm came in the 1970s, motivated by economists who introduced central concepts such as the value of time, generalized travel costs, utility, and discrete choice of travel options. The perspective was on a person's choice of trips (rather than the vehicles themselves) and is referred to as a tour-based perspective. Several central model types based on the maximization of utility or the minimization of generalized travel costs were introduced. Trip generation, destination choice, and mode choice were along with traffic assignment linked together into the so-called four-step models.

The next expansion that Jones (2012) describes is activity-based modelling. The paradigm shift lies in the interpretation that transport demand is derived from the demand to perform activities, rather than minimizing travel costs as in tour-based models/classical four-step models. The activity-based approach tries to "understand" why individuals travel and how the individual plans their trips based on their all-day activity plans. So-called activity-based demand models (ABDM) were developed.

[2] The overview is partly based on the outline of activity based demand models in Flügel et al (2021)

Compared to the traditional four-step models, ABDM involve three fundamental changes in methodology:[3]

1. The aggregated data structure is replaced with a disaggregated one, i.e. individuals or households (rather than population segments within geographic areas) are the unit of analysis.
2. Transport demand is derived from the demand to perform activities and the emphasis is on sequences of tours or all-day travel plans instead of single (round) trips.
3. Time (clock time) is explicitly modelled (start/end times and activity planning are important).

I combination with traffic assignment models and simulations models ABDM also can include dynamic interactions and feedback mechanisms within the system.

ABDM promises the following improvements compared to classical four-step models:

1. Realism in behavioral modelling is improved as individual decisions are subject to person-specific constraints.
2. Choice behavior is based on all-day activity plans and is modelled/simulated to achieve consistency between dependent trips.
3. Higher resolution in time and space.
4. Includes multiple behavioral dimensions (choice of departure time), and some ABDM also consider household decisions (coordinating trips for multiple household members).

In recent years, ABDM have become increasingly popular in the transportation research field for their ability to provide detailed insights into individual travel behavior. The brief literature review below aims to provide an overview of the key developments in this area, focusing on both early and recent contributions.

A foundational precursor to this line of research is Hägerstrand's time-geography framework (Hägerstrand 1970), which emphasized the spatial and temporal constraints shaping individual activity and travel patterns. This work laid the conceptual groundwork for later developments by highlighting the interplay between time, space, and human behavior.

Building on these early ideas, Adler and Ben-Akiva (1979) introduced a theoretical and empirical model to analyze trip chaining behavior, focusing on sequences of trips but without explicitly considering departure times. Recker (1995) expanded this approach with the Household Activity Pattern Problem (HAPP), which provided an explicit representation of time in both the formulation and solution, thereby addressing one of the key limitations of earlier work.

[3] For a more detailed discussion see Resouli og Timmermans (2014)

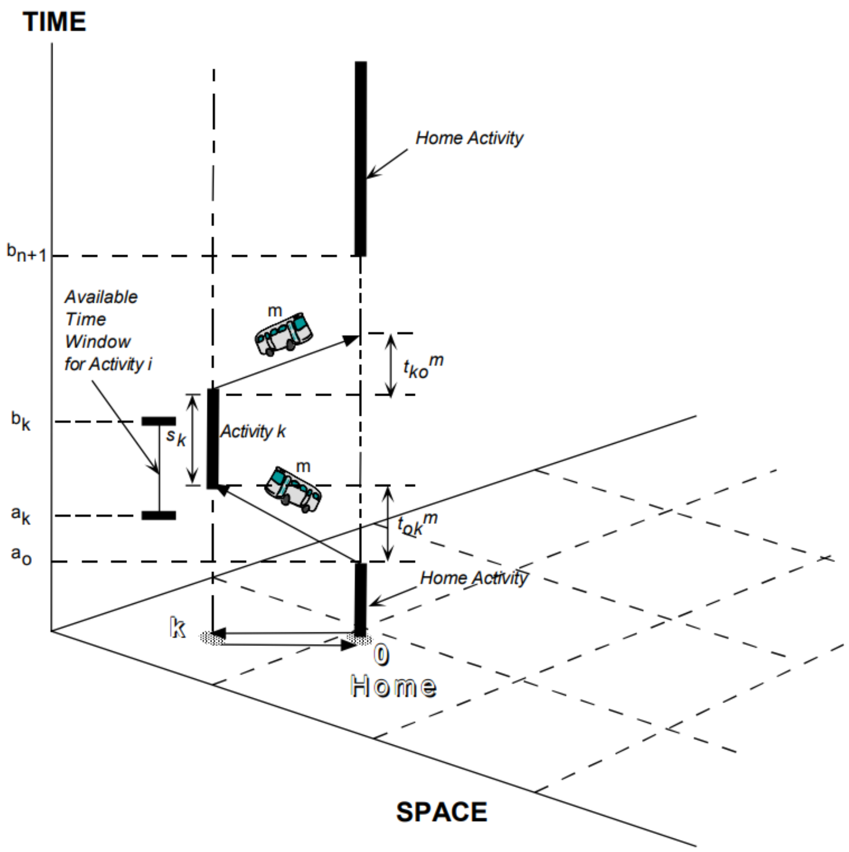


Figure 2. Optimal Space-Time Path for Simple Destination/Mode Choice Example

Figure 2.5: Illustration of explicit representation of time in the activity based demand models (Source: Recker 1995)

Some of the early and well-known ABDM models include AMOS (Kitamura 1993), Albatross (Arentze and Timmermans 2000), and CEMDAP (Bhat et al., 2004). These models have been influential in shaping the field and paved the way for future developments in activity-based modeling.

More recently, Västberg et al. (2020) presented a dynamic discrete choice activity-based travel demand model in the Swedish context. This work demonstrates the continued evolution of ABDM approaches and the growing interest in incorporating more advanced techniques to better understand travel behavior.

A novel approach in the field leverages generative machine learning models, as illustrated by Badu-Marfo et al. (2022). Their study introduces the Composite Travel Generative Adversarial Networks for Tabular and Sequential Population Synthesis, which showcases the potential of incorporating advanced machine learning techniques to improve the accuracy and flexibility of activity-based models. A machine learning modelling approach trained an Danish travel survey data to predicting trip plans and travel modes was recently presented in Arkoudi et al (2023).

2.4 Machine learning as a discipline

Machine learning (ML) sits at the intersection of computer science and mathematics/statistics. ML algorithms learn from data and make predictions or decisions based on patterns and insights they derive from that data. While domain knowledge can be helpful in certain cases, it is not a strict requirement for developing and implementing machine learning models. E.g. ML-based chess programs do not need the developers to be good chess players or input a lot of human chess knowledge.

Domain knowledge is required in software development, where technical skills are applied to create programs and tools tailored to specific industries or areas of expertise. And in research, which involves utilizing analytical and quantitative methods to explore and understand specialized topics. Data science combines elements of computer science, mathematics/statistics, and domain knowledge to extract insights, create models, and make data-driven decisions in a specific context or industry. In contrast to classical decision processes where the rules are predefined and then programmed into the machine, in ML data is used to learn the rules.

The deep learning revolution within ML began around 2012 and has since transformed the field, leading to significant advancements in various applications. Deep learning, a subset of machine learning, involves the use of artificial neural networks with multiple layers to model complex patterns and representations in data. These deep neural networks are particularly adept at handling large, high-dimensional datasets. The revolution was ignited in 2012 when Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton developed a deep convolutional neural network (Krizhevsky et al 2012) showing that model size (given enough training data) is essential in making good predictions on complex tasks. Since then, deep learning has rapidly progressed and has been applied to various domains, such as natural language processing, speech recognition, image synthesis, game playing, and medical diagnostics, among others.

2.5 Machine learning in the PRELONG-project

The ongoing PRELONG project (2021-2026) aims for a proof-of-concept of reliable and fast prediction of the level of congestion in the Greater Oslo Area using deep learning (Flügel 2021). The main idea is to train a neural network using the input data to a MATSim model in addition to the simulated output of the model. In that case, the neural net can be used as substitute for the severely time-consuming MATSim simulation (Figure 2.6).

Machine learning enters the PRELONG project at three stages.

1. Machine learning is used to generate activity plans and initial travel mode choice of agents representing the population.
2. Within the simulation model MATSim, agent can adjust travel choices (route, mode choice and departure time choice) by “learning” some the aggregate outcomes of the simulation (e.g. delays cause by congestion). This resembles mechanisms of reinforcement learning without being related to deep learning.
3. An AI-meta model that predicts level of congestion on a link-hour level given in different scenario (road capacity, speed limit, road toll and demand effects).

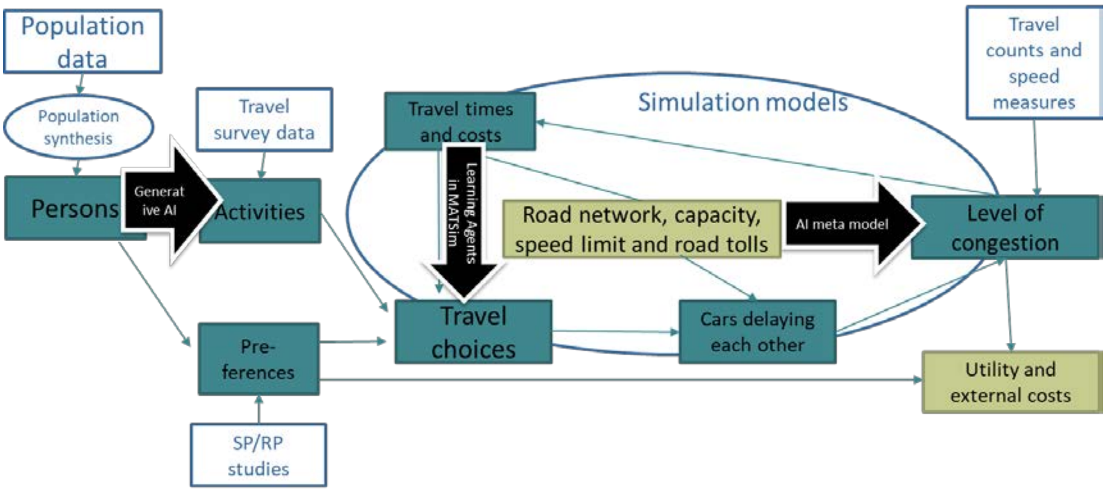


Figure 2.6: Illustration of the conceptional information flow in the project, highlighting with black arrows the three types of machine learning stages.

In this report, we focus on 1), i.e. the generation of activity plans including travel mode choice. The generation of activity plans is done trip-by-trip in an autoregressive way, not too different from large language model producing text in a token-by-token approach. We refer the approach described in this report as "generative AI" as discussion in a bit more detail in the next section.

2.6 Synthetic data and the use of generative AI

In this study, we generated two synthetic data sets. The first dataset is a synthetic population of agents in the Oslo area and the second is composed of synthetic travel diaries for the agents. The travel diaries were predicted using ML with the synthetic populations as input data. Machine learning models used to generate content (here activity plans) are referred to as generative AI. Within the context of activity-based transport modelling, the synthetic travel diaries are referred to as agent's activity plans.

In the first test of agent-based traffic simulation with MATSim for the city of Oslo from 2018 (later documented in Flügel et al 2021), the activity plans were taken directly ("bootstrapped") from observed travel plans in Ruter-MIS survey. The observations were replicated to reach population size with only random changes to coordinates of home locations (to avoid the possibility to match back to actual respondents) and departure times (to avoid the clumping of agents). Thus, with this first approach, the synthetic agents and travel diaries were directly connected to real people and travel plans. This approach had several disadvantages:

1) Even though Ruter-MIS is a large-scale survey, the number of observations compared to the total population is small. Accordingly, our simple upscaling strategy is prone to so-called "sampling zeros", i.e. plausible but unobserved activity plans. See Figure 2.7 of a conceptional illustration of sampling zeros.
2) Sample selection biases in Ruter-MIS will carry over to the synthetic population.
3) Ruter-MIS is limited to Oslo Akershus while the RTM23+ area includes also the cities Drammen and Moss and surrounding areas.

The generation of agents and activity plans in the approach of this report is done in four steps (described in more detail in chapter 4):

1) Deriving basic agent groups defined by home location (BSU-level), gender and age group based on official population statistics from statistics Norway.

2) Adding additional variables describing agents, Level-of-Service (LoS) and variables controlling the scenario:
    a. Car access, occupation status and remote working are derived from geographic data (based on zonal data from the RTM model system) and/or demographic data (based on shares in Ruter-MIS),
    b. Sampling of agent's work location given home location based on commuting statistics,
    c. LoS-variables describing the transport supply on the home-work relation are added to all agents with a valid work location.
3) Setting scenario variables:
    a. Corona variables (personal perceived infection risk and lock-down stringency) are assigned,
    b. Defining the type of weekday (Monday-Thursday versus Friday, Holiday versus Off-holiday and season (winter, summer and spring/autumn).
4) Applying the trained machine learning models to generate activity plans given the data from step 1-3).

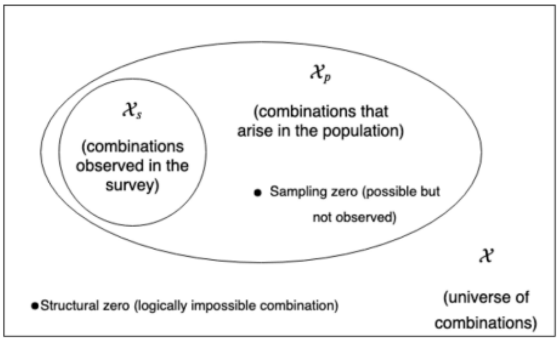


Fig. 1. Representation of the sampling zeros, the structural zeros and the different sets of combinations that arise in population synthesis.

Figure 2.7: Illustration of "sampling zeros", source: Garrido et al 2020.

Generation of agent's characteristics representative of the real population is the core challenge of population synthesis. As described by Garrido et al 2020, one can divide methods used for population synthesis into deterministic and simulation-based methods. Deterministic methods, as matrix fitting or sample expansion (as used in the earlier approach), require very large samples to approximate high-dimensional data. Simulation-based approaches include Gibbs sampling (Farooq et al 2013), Bayesian network approach (Sun and Erath 2015), Hidden Markov Models (Saadi et al 2016), and deep generative models such as Variational Auto-Encoder (Borysos et al 2019) and Generative Adversarial Networks (GAN, Garrido et al 2020).

In this study, we are using a simplified Gipps sampling for step 2 and deep generative models for step 4. Gibbs sampling is a Markov Chain Monte Carlo (MCMC) method used for generating samples from conditional probability distributions. In our case, the distributions are based on observed shares in Ruter MIS, regional zonal data and commuting statistics. For the deep generative models, we are using a fully connected neural network where output of the previous prediction is used (autoregressively) in the consecutive prediction. This is the same idea as in large language models predicting the next token (word) with input of the previous words. However, instead of forming a sentence word-by-word, we are generating all-day activity plans trip-by-trip.

Our approach captures correlations between multiple trip characteristics (trip purpose, travel mode, departure time, destination choice). For example, the output "purpose: picking up" will be strongly correlated with the output of "travel mode: car". This is achieved as the different sets of output nodes in the neural network share common hidden layers. The sequential generation of trips captures dependencies between consecutive trips (e.g. travel mode of previous trip effects travel mode of current trip). In addition to being able to capture these correlations, the neural networks are also able to capture potential interaction between explanatory variables. This is in contrast to more structural modelling in logit models, where the coding of all interaction effects would often be impractical and difficult to estimate numerically.

Activity plans can be generated with our neural networks for arbitrary agents, such that different demand representations can be generated for different sets of agents, e.g. for future populations or populations with different scenario variables (as in our case different corona scenarios).

2.7 Neural network versus logit models

In this section, we discuss neural networks in light of the topic of this report, i.e. with respect of predicting characteristics of trips (such as travel mode choice). Since many readers of the report might be more familiar with logit models, that are traditionally used for such tasks, we compare the modelling aspects of neural networks and logit models.

Table 2.1 gives and an overview of the main differences between logit models and deep learning.

Table 2.1: Comparison of concepts and properties of neural networks and logit models.

	Model input and output (in our application in chapter 5)	**Internal model to produce output**	**Optimization to find best parameters in the internal model**	**Data to train/estimate parameters and validation**
Neural network (NN)	Agent characteristics and LoS → probabilities of trip characteristics Probabilities are interpreted as the NN “beliefs” (assigned likelihood) in its predictions	Layers with activation functions calculated from weights and biases; parameters not interpretable (typically >10^4)	Gradient descent such to minimize the loss function (typically no explicit assumption made about the distribution of the errors). Loss function “cross-entropy” has great resembling with negative log-likelihood	Split in training and validation data. Model validation via predictive performance on validation data No direct calculation of standard errors of parameters
(nested) logit models	Agent characteristics and LoS → probabilities of trip characteristics Probabilities are interpreted as probabilities from the researcher's perspective	Utility functions with predefined structure and interpretable parameters (typically, 10-100 parameters)	Gradient descent to find parameters that maximize the likelihood function given distributional assumptions	Typically, no split in estimation and validation data. Validation often based on sign and significance of the parameters of the estimated model Inference of parameters and estimation of standard errors (taking into account size of the given sample)

The neural network (NN) model uses agent characteristics and LoS to predict probabilities of trip characteristics. The probability distributions produced by the neural network are interpreted as the beliefs assigned by the model to its predictions. The internal model consists of layers with activation functions that contain weights and biases, but these parameters are not easily interpretable. The optimization uses gradient descent to minimize a loss function, which in the case of classification is mathematically equivalent to negative log-likelihood used in logit models.

The typical nested logit model also uses agent characteristics and LoS to predict probabilities of trip characteristics. As such it can have identical inputs and output as neural network models. However, the interpretation of the output probabilities is different. In the case of logit models the probabilities produced by the model are interpreted from the researcher's perspective due to incomplete information, imperfect modelling and measurement errors. The core of logit models typically consists of utility functions with a predefined structure and interpretable parameters. The optimization method used to find the values of the parameters is gradient descent, but – in contrast to neural network models - gradient descent here applied such to maximize the likelihood function given assumptions about the distribution of error terms.

Logit models are compatible with economic theory (RUM) and choice behavior is interpretable as economic behavior. Thus, parameters have an economic interpretation, which can be used in further analysis, such as Cost-benefit analysis. Researchers can evaluate the reasonableness of the parameter signs, and it is straightforward to conduct hypothesis testing.

NNs on the other hand pick merely up the correlations between input and output, and learn functions that best map the given input to the output. Indeed, deep neural networks are very good function approximators. Neural networks are highly flexible and can be used to approximate a wide range of functions, from simple linear functions to highly complex, non-linear functions. In many applications, neural networks can be trained to be robust to noise in the input data, making them well-suited for problems where the data is noisy or unreliable. However, researchers applying neural networks have limited possibilities to interpret the parameters in machine learning models, and in many ways, they act as engineers (not scientists) in applying machine learning.

Machine learning is best suited when 1) the data is large and complex 2) there is no a priori theory or intuition about the relationships, and 3) when the goal is to generate the best possible predictions (and not necessarily the best understanding). Additionally, generative AI can be used to generate more data points, which is another important application of machine learning.

2.8 Motivation for using neural networks for our application

The choice of method (neural networks) for the generation of activity plans in this report can be explained by the overall methodological approach in PRELONG project which was set out to combine machine learning techniques with agent-based simulation models.

As described in section 2.6. neural networks do – by design – account for possible interaction effects of explanatory variables. This comes handy for models with various explanatory variables.

The lack of interpretability of parameters was not deemed as crucial for our overall approach. This is partly because travel mode choice and departure time choice is later also simulated within MATSim based on utility (scoring function) that are readable interpretable by well-defined parameters. Thus, the argument that the initial travel plans are generated by models that lack some interpretability was less important. Note also that by performing model comparisons (as done in chapter 4) one can get a pretty good idea about what drives the accuracy of the neural networks. Furthermore, plotting output probabilities input variables (as than for instance in chapter 5) gives a good understanding on that explains certain pattern in model results.

3 External data sources

In the chapter we give a brief overview over the data used in training the neural networks models and predicting synthetical trip diaries.

3.1 Level-of-Service data

The Level-of-Service (LoS) variables are imported from the RTM23+ model. LoS include several variables describing the distance, travel time, cost and other factors for different transport modes between all pairs of basic statistical units (BSU). Some variables are segmented into rush-period and non-rush period.

These LoS data are intendent to reflect the transportation network and public transport supply as of years 2019- 2020.

The LoS-files are imported in omx-format and combined into a Pandas dataframe using a custom Python script.

3.2 Ruter-MIS

In this study, we use Ruter-MIS as the training data for our machine learning models. We include data from January 2017 until September 2024. The model originally presented in Flügel (2022) used data from March 2017 to March 2020 only.

Ruter-MIS is an travel survey data administrated by the Ruter AS, the public transport provider in the Oslo and surrounding municipality Akershus. This does notably not include the cities Drammen and Moss as indicated in the map below.

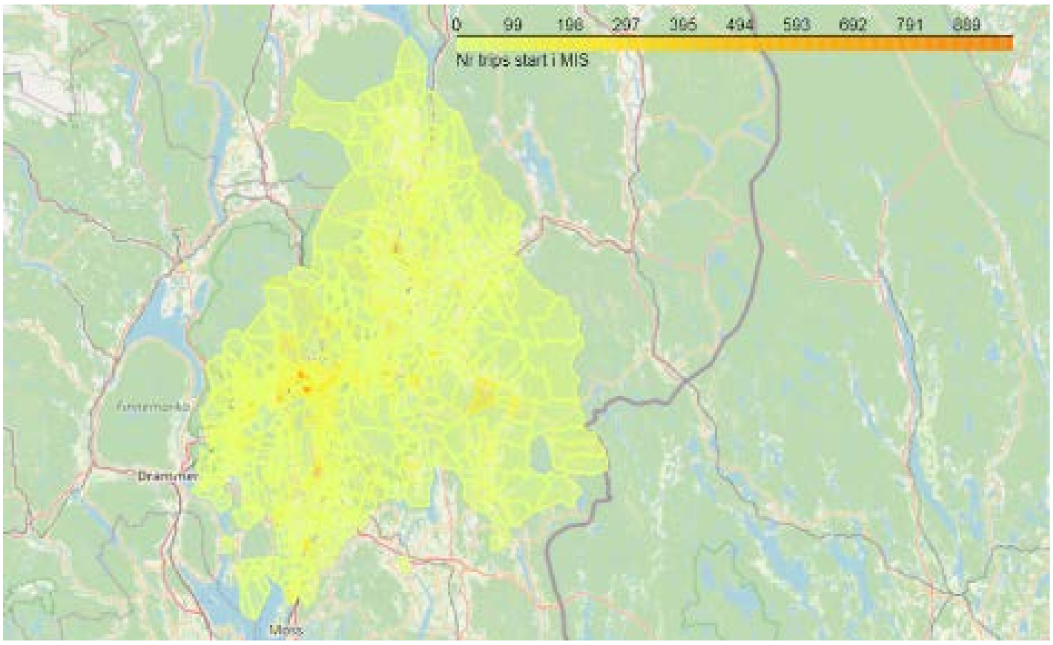


Figure 3.1: Geographical area of survey Ruter-MIS, colors indicating the number of reported trips starting in each BSU.

Ruter-MIS is conducted by computer assistant telephone interviews (CATI). The respondents reply to the demographic questions and questions related to use, attitudes and habits around use of public transport. The core of Ruter-MIS is travel diaries which the respondence report by listing all trips (including start time, destination, purpose and mode choice) of the day prior the interview. As interviews are conduced Tuesday to Saturday, most trips relate to weekdays. Respondents have a minimum age of 15 years.

Figure 3.2 plots the number of questionnaires in our data set. Note that the data comes in two files: A person-file containing all respondents (one line per person), also does that did not make any trips, and a trip-file that reports characters of trips for those that respondent that reported a trip diary (one line per trip).

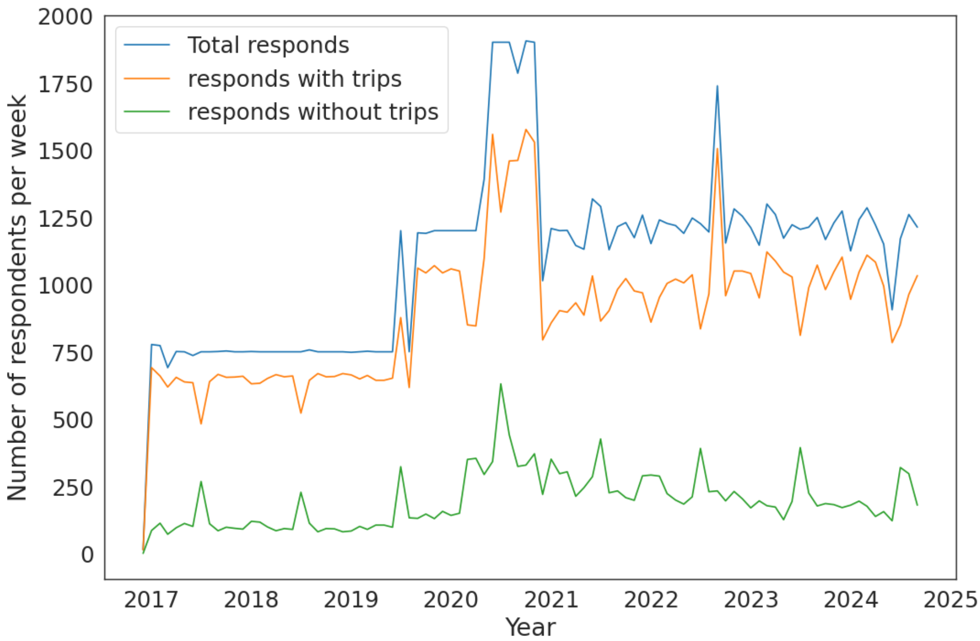


Figure 3.2: Number of complete questionnaires from Ruter-MIS over time. The green line indicates the number of questionaries where no trip diary is reported as the respondent did not make any trips on the previous day.

Note that for the first weeks in January, we only have data from the persons with no trips.

3.3 Lock-down stringency index

The lock-down stringency index is included in our improved model (section 4.1) as an explanatory variable. The main reason for that being that travel behaviour data from the covid-period is included in the training of the model. The variable is meant to "control" for this specific period. In most application and prediction purposes, the stringency index will be set such to represent a normal ("non-pandemic") situation. However, the inclusion expands the scope of the model as it stringency index can also be used to simulate new pandemic scenarios.

Hale et al (2021) established a Stringency Index, ranging from 0 to 100, based on the following metrics: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls.

The stringency index differs per date and country and is publicly available. The dataset does not contain the single metrics behind the index. For some countries, the index is also divided in an index for nonvaccinated and vaccinated. However, this information is not available for Norway (compare Figure 3.3).

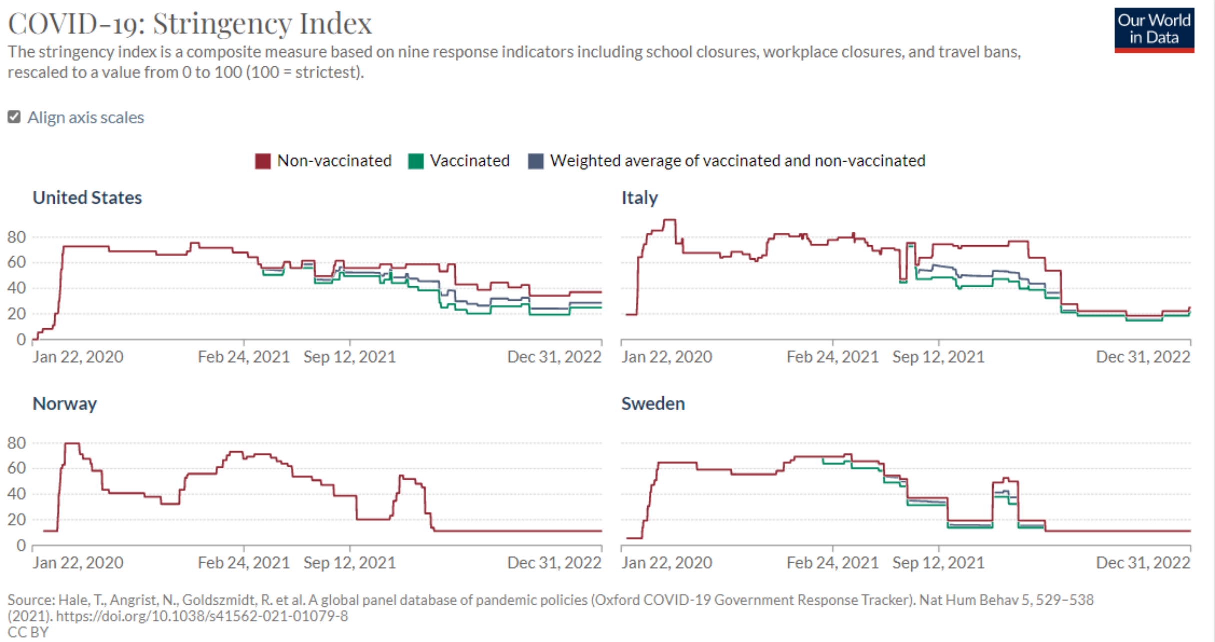


Figure 3.3: Stringency index in some countries Source: https://ourworldindata.org/explorers/coronavirus-data-explorer?uniformYAxis=0&hideControls=true&Metric=Stringency+index&Interval=7-day+rolling+average&Relative+to+Population=true&Color+by+test+positivity=false&country=USA~ITA~NOR~SWE

Figure 3.4 shows the stringency index in Norway in direct comparison to Sweden and Germany. Norway had initially a rather high index, at least compared to Sweden, but then reduced measures in summer/autumn 2020, before increasing again late 2020. From there, the index for Sweden and Norway are rather similar. In comparison, Germany had in general a somewhat higher index than Norway.

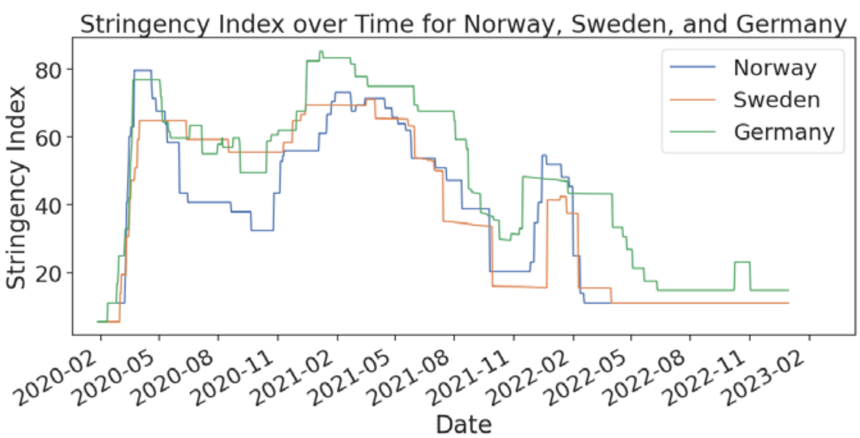


Figure 3.4: Comparison of the stringency index in Germany, Norway and Sweden.

It is noteably that the stringency index is correlated with the number of COVID-related deaths especially troughout 2020-2021; however, most death occured in the period after Februar 2022 when all COVID-19 related restrictions where removed (Figure 3.5).

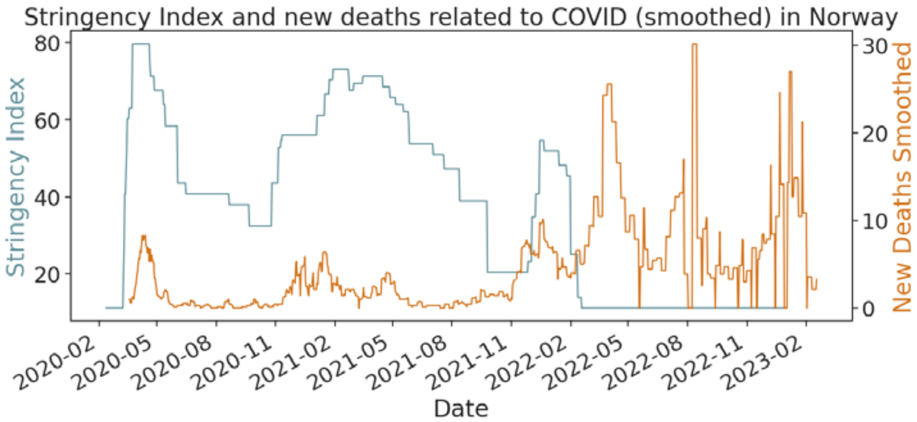


Figure 3.5: Stringency index and new COVID-related death in Norway.

3.4 External data used for synthetic population

The population synthesis done in this project uses following external data sources:

- Population data
    - This data contains the number of persons living in each BSU as of year 2020, segmented by gender and age group. The data comes originally from SSB but is taken out of the RTM23+ model system (file: "sdat_1_def_2020_dbh")
- Commuting statics
    - This data gives the conditional probability of the location (BSU) of the work place given each home-BSU. The data is based on register-based commuting statistics of year 2019. In this project, we only had access to conditional probabilities (not absolute values).
- Data on employment status
    - This data contains information on the number of employed and unemployed persons in each BSU. The data is taken from the RTM23+ model (file: "sdat_3_utd_innt_g2020_uforandret"
- Data on car types
    - Includes information about the share of different car types (electric car, hybrid and "fossil") for each home BSU. The data is taken from the RTM23+ model (file: "sdat_71_kjtandel_NB2021_gk2020_2024.dbf"). This files is the projection for 2024 and is used in the latest version of the synthetic population (chapter 4 and 6) while the corresponding file for 2020 was used for the analysis in chapter 5.
- Data on car access
    - In includes the share of different car access categories as modelled by the RTM23+ model (file: "tb2-biltilgang-soner-5segs-18up.txt")

As described in section 4.5, the methods to generate our synthetic population also involves data from Ruter-MIS. This is mainly because the zonal data mentioned above for employment status, car types and car access, does not include sociodemographic variation (only geographic variation). Ruter-MIS is also used to create variation in shares for use of home-office / working remotely, which is a variable in the synthetic population but for which we do not have zonal data on a BSU level from RTM23+.

4 Generation of activity plans with neural network models

This chapter explains the generation of activity plans, starting with the training of two neural network models. We refer section 2.6 for an methodological discussion and overview over our approach.

4.1 Overview neural network models

While the original version of our approach (as described in Flügel et al 2022) uses a single neural network model to predict trip characteristics, the current version of our approach, we use two different neural network models. We refer to the two new models as model 1 and model 2. Model 2 is similar to the original model and includes 4 of the original 5 output variables, i.e. trip purpose, trip end region, trip start time and travel mode. The variable that is omitted in the new approach is a variable called "last trip" which was in the original model used to determine when to stop generating new trips for a given synthetic person/agent.

The original model had several weaknesses which motivated the new approach with two neural networks. These weaknesses included:

- Did only apply to agents that make at least one trip (the split in agents that do travel and do not travel was determined exogenously prior to the neural network predictions
- Did predict the characteristics of the next trip without knowing how many trips there where to make in total
- Did not control for Fridays and seasonal effects, and observations in holidays where excluded
- Did not included Level-of-Service variables (besides the distance by car from home to work)
- Did not include the extent of home-office in prediction

In the new approach, model 1 predicts overall characteristics of the trip diary (activity plans): Start time of first trip, Start time of last trip, Number of trips and the Sequence of trips before and after the work activity. These variables can respectively take 11, 11, 7 and 5 categorial values (see next section). As shown the Appendix the underlying neural network is a dense network with 2 hidden layers, with respectively 180 and 90 nodes, and a total number of trainable parameters of 31084. The activation function for the output layers is a so-called Softmax such that output variables can be interpreted as probabilities.

Model 2 predicts characteristics of trips: Travel mode, Purpose, End zone and Time duration since previous trip, with respectively 7, 10, 9 and 15 categories variables (see section 4.3). The model has the same overall architecture as model 1, but input variables resulting in a higher number of trainable parameters (43781, see appendix).

An overview over input variables to model 1 and model 2 are given in Figure 4.1.

The prediction of Number of trips (model 1) is than used to determine the number of trips that are generated in model 2 (making the original binary "is last" variable from the previous model version redundant).

These three other variables of model 1 give prediction of the activity and trip plans in model 2 some more contextual framing.

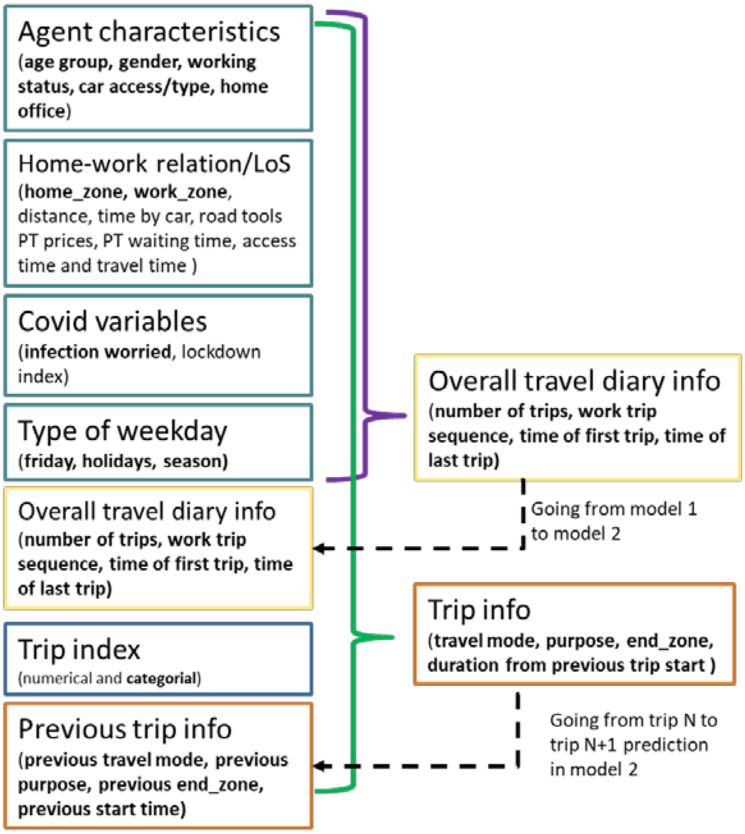


Figure 4.1: Input and output variables of the two neural network models. The purple brackets indicate model 1 and the green bracket model 2. Categorical variables in ***bold*** *font.*

The dotted arrows indicated that outputs are transformed into inputs when applying it to new data. The procedure his is further described in the next section 4.4. The next two section illustrate the predictions of the models on the validation data. Note that in the training and validation data the input variables are given by the data and do not need to be produced iteratively as illustrated in the figure above.

4.2 Model 1's prediction on the validation data

Model 1 is trained on 75% of Ruter MIS, while a random 25% of the sample of respondents is saved for validation. The validation data for model 1, which is on a person level, has 14165 observations.

Figure 4.2 to Figure 4.5 show the average predicted probability from model 1 ("predicted share") against to actual share in the validation data. All figures are segmented by the occupation status which is input into the model.

Figure 4.2 shows that employed persons are less likely to have no travel (Nr of trips = 0) a given weekday compared to unemployed persons (including students and retired people). We also see that 2 trips (typically one trip from home and one trip back to home) are most common for those travelling. From the comparison of the blue and red pillars, the seems that model 1 is able to reproduce the overall pattern in the validation data.

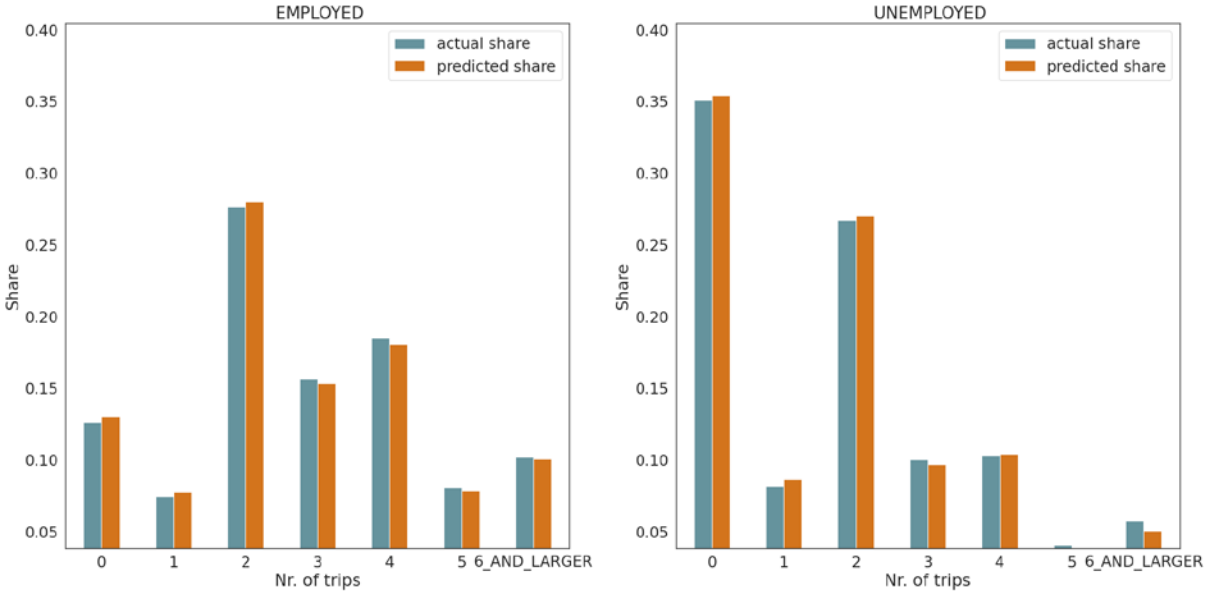


Figure 4.2: Actual share (in Ruter-MIS) and predicted share (from model 1) on the validation data for the Number of trips by occupation status.

Figure 4.3 shows that a significant share of employed people do not have a work trip on the given weekday. Note that this is affected by the inclusion of the covid period (see more in chapter 6).

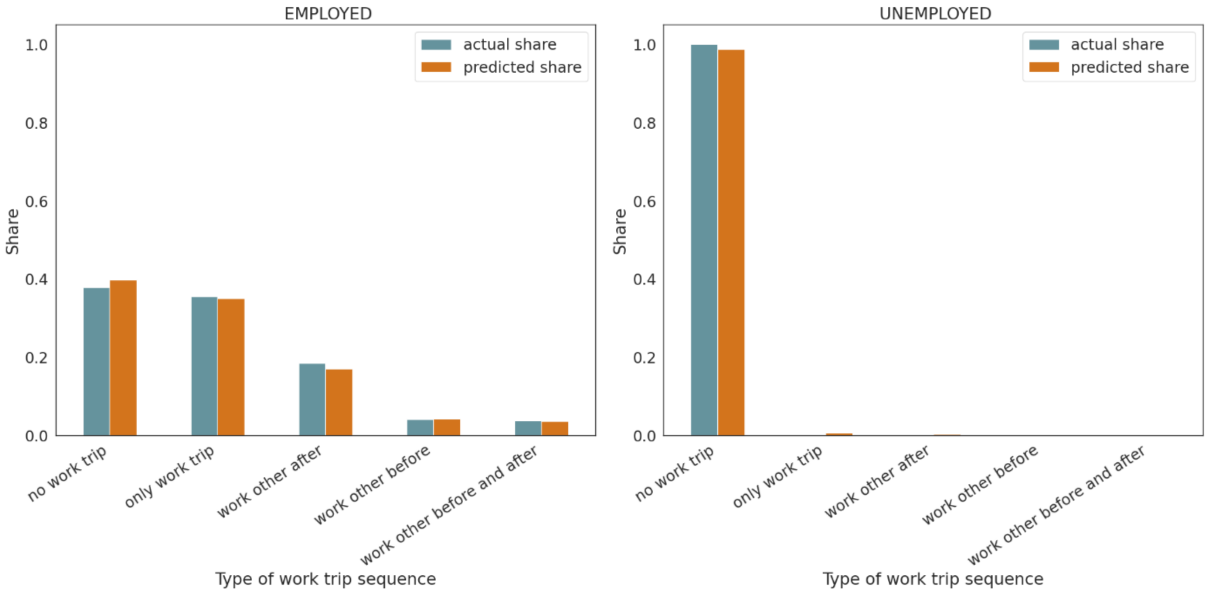


Figure 4.3: Actual share (in Ruter-MIS) and predicted share (from model 1) on the validation data for the sequence of trips around the work trip; segmented by occupation status.

Figure 4.4 gives the start time of the first trip. It is revealed that unemployed persons have their first trip typically later in the day.

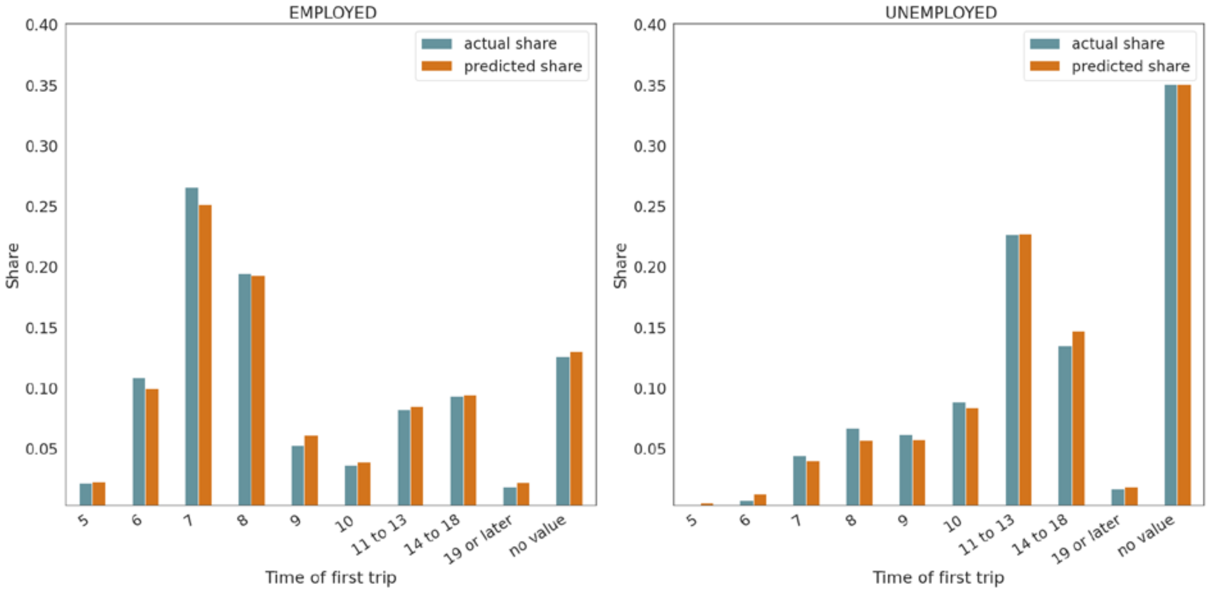


Figure 4.4: Actual share (in Ruter-MIS) and predicted share (from model 1) on the validation data for the time of first trip; segmented by occupation status.

Figure 4.5 gives the start time of the last trip of the trip diary. As for the other predictions, it seems again model 1 makes reasonable good predictions at this level of aggregation.

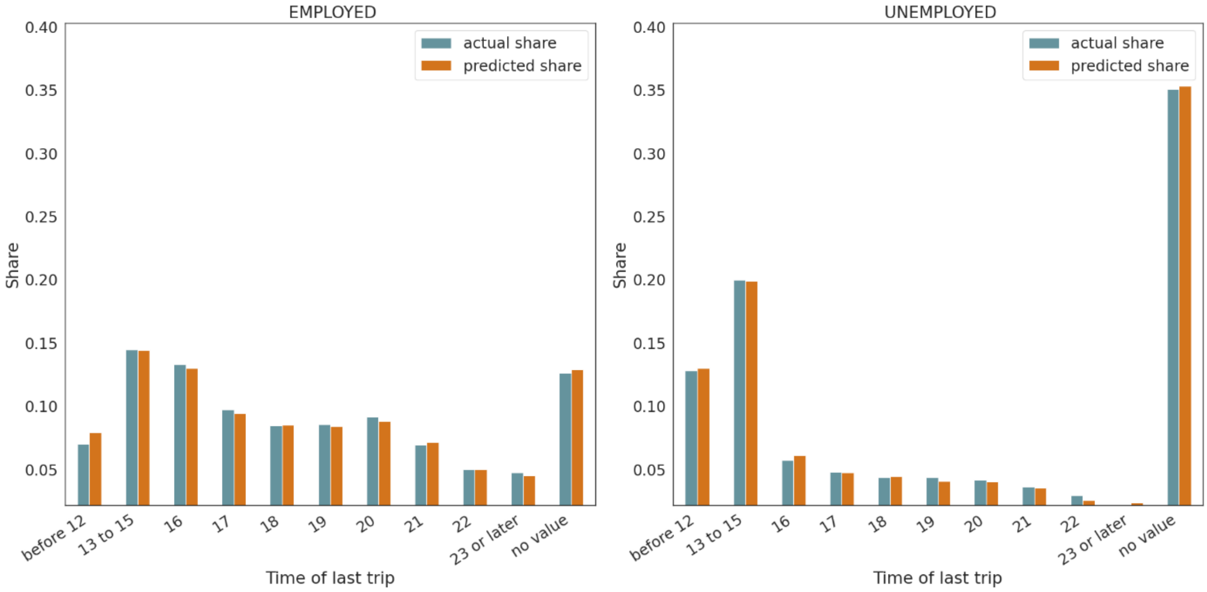


Figure 4.5: Actual share (in Ruter-MIS) and predicted share (from model 1) on the validation data for the time of last trip; segmented by occupation status.

The bar diagrams above do not show that individual probabilities greatly vary and that there is correlation among the individual probabilities. For illustration, Figure 4.6 plot individual probabilities for 3 and 0 trips as predicted by model 1. The model seems not vary capable of distinguishing probabilities for 3 trips as all predicted probabilities lie between 6 and 18%. The models seems more capably to distinguish zero trip though, where probabilities vary between (close to) 0% and 50%. We clearly see that the two probabilities are negativity correlated. From the marginal distribution function at the top and the right side of the joint plots (where colors indicate distribution given the true label), we see that the model tentatively predicts the correct pattern, as the distribution function for 0 trips (greenish blue) clearly has a different shape from the other marginal distribution functions.

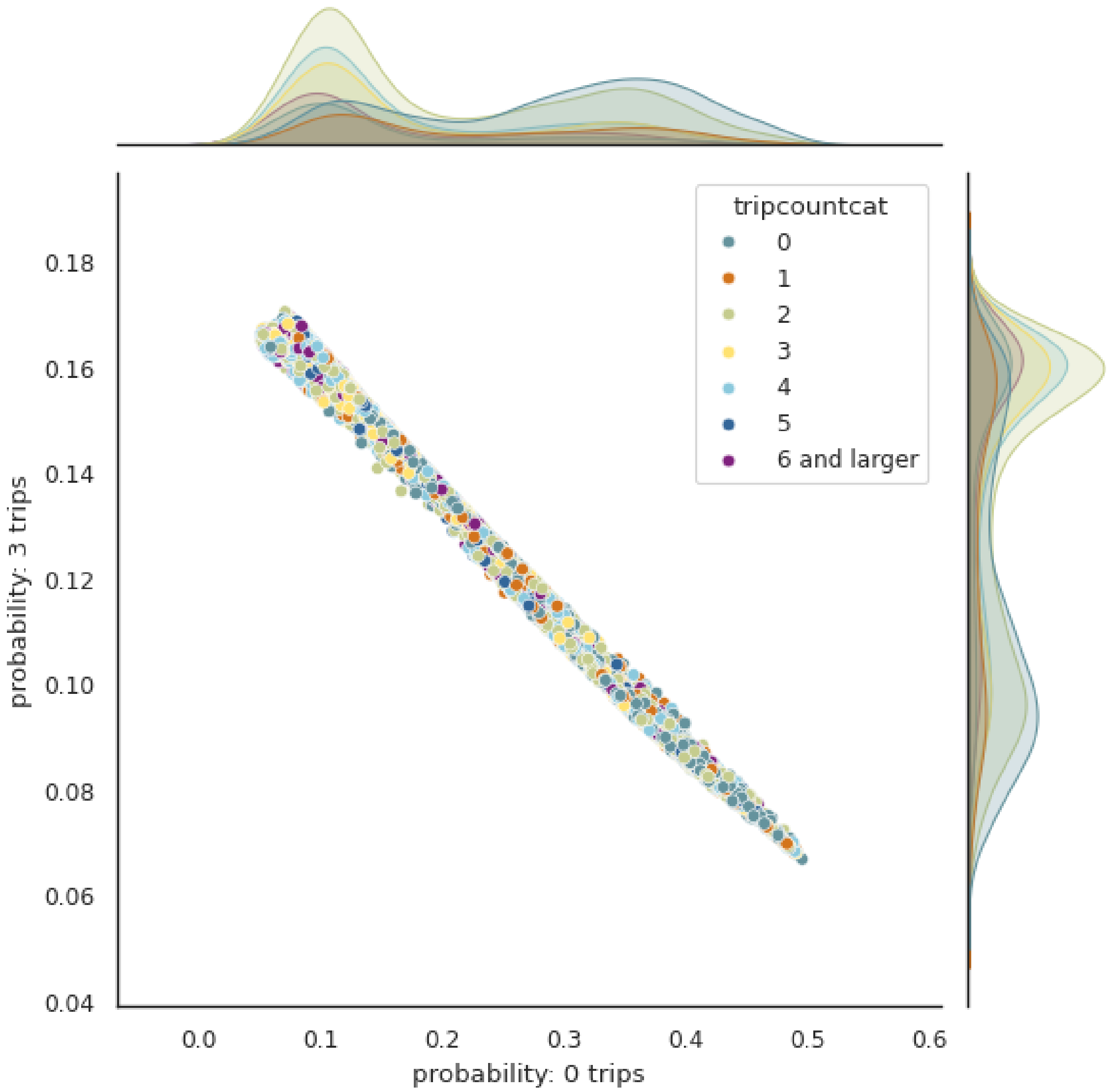


Figure 4.6: Joint plot of the individual probability for 3 trips (Y-axis) and 0 trips (X-axis); color codes indicate true number in validation data.

For comparison, there seems to be a slight positive correlation between the probabilities of 3 and 2 trips (Figure 4.7).

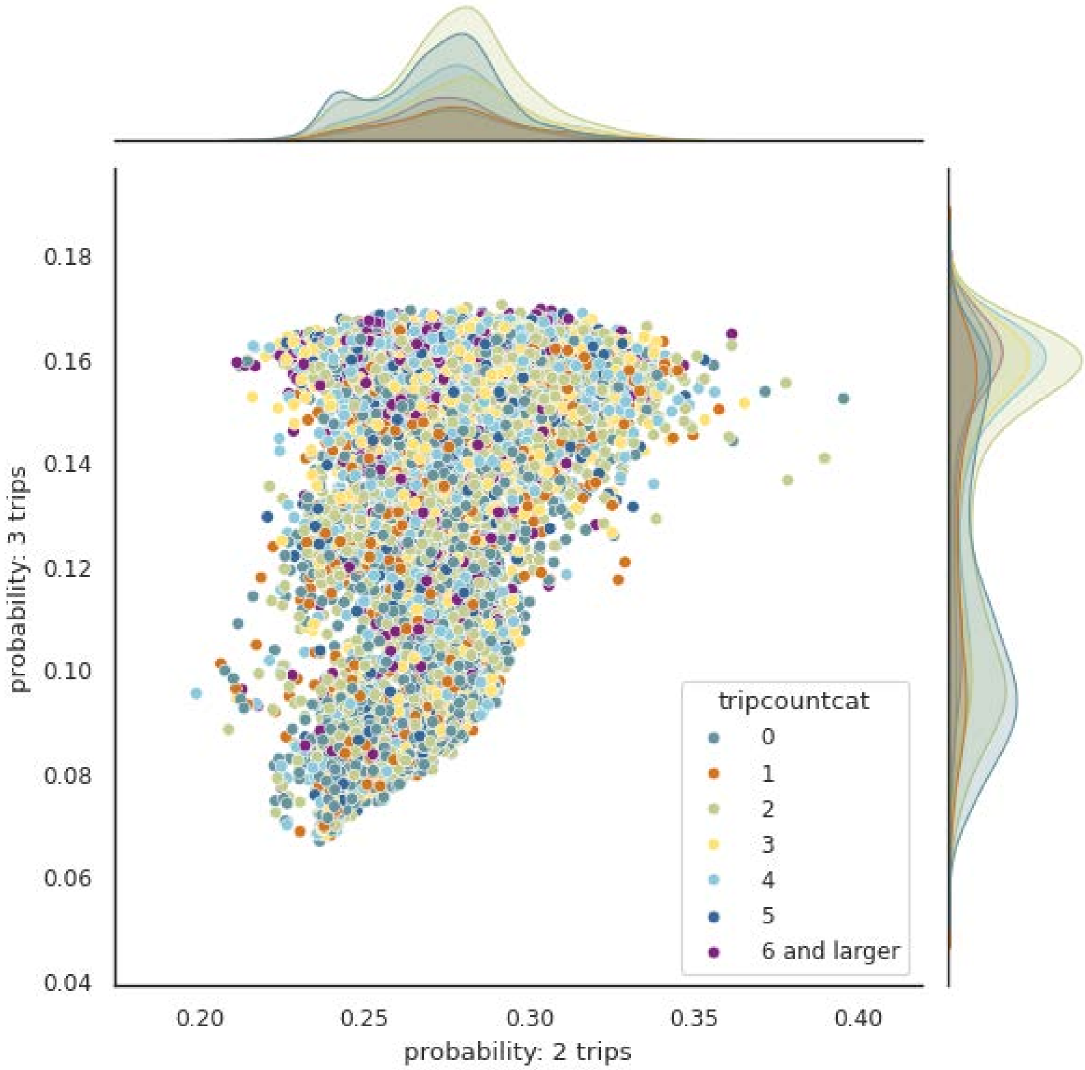


Figure 4.7: Joint plot of the individual probability for 3 trips (Y-axis) and 2 trips (X-axis); color codes indicate true number in validation data.

4.3 Model 2's prediction on the validation data

Model 2 is trained on a trip-level and includes only respondents of Ruter-MIS that did make at least one trip.

Figure 4.8 gives the actual and predicted probabilities for different categories of the travel mode variables, segmented by those persons have not car access and the respondents that have car access (either an electric car or combustion engine car. The model slightly underpredict the probability of walk on the validation data, but seems otherwise to pick up fine on the differences in travel mode choice given information about car access.

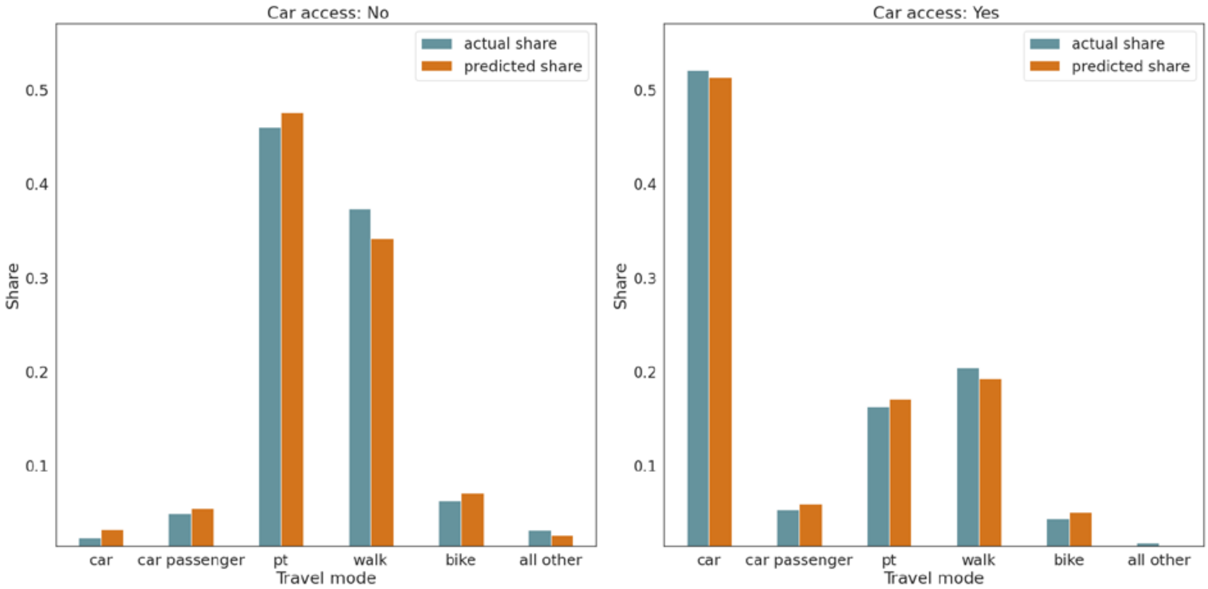


Figure 4.8: Actual share (in Ruter-MIS) and predicted share (from model 2) on the validation data for the travel mode choice; segmented by car access.

Figure 4.9 shows the results for trip purpose. We see that delivery (which assumable is often related to children) has higher probability for persons with car access. Model 2 is predicting this pattern correctly, but seems to slightly overpredict work trips and underpredict travel back home.

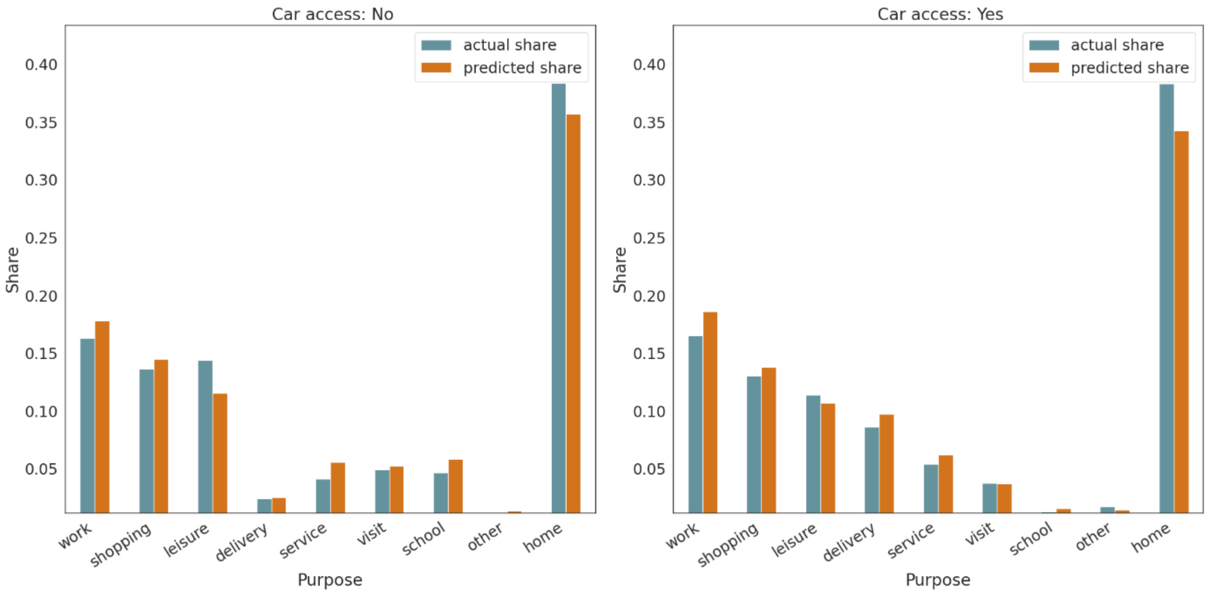


Figure 4.9: Actual share (in Ruter-MIS) and predicted share (from model 2) on the validation data for the travel purpose; segmented by car access.

Figure 4.10 give the corresponding diagram for the time duration of the start of the trip and the previous trip. It measures the duration of the previous trip and the activity performed at departure. We see that most durations are under 1 hour (which is slightly underpredict by model 2). We see that 8 and 9 hours (typically commuting + work durations) are slightly more common compared to 7 hours and 10 hours.

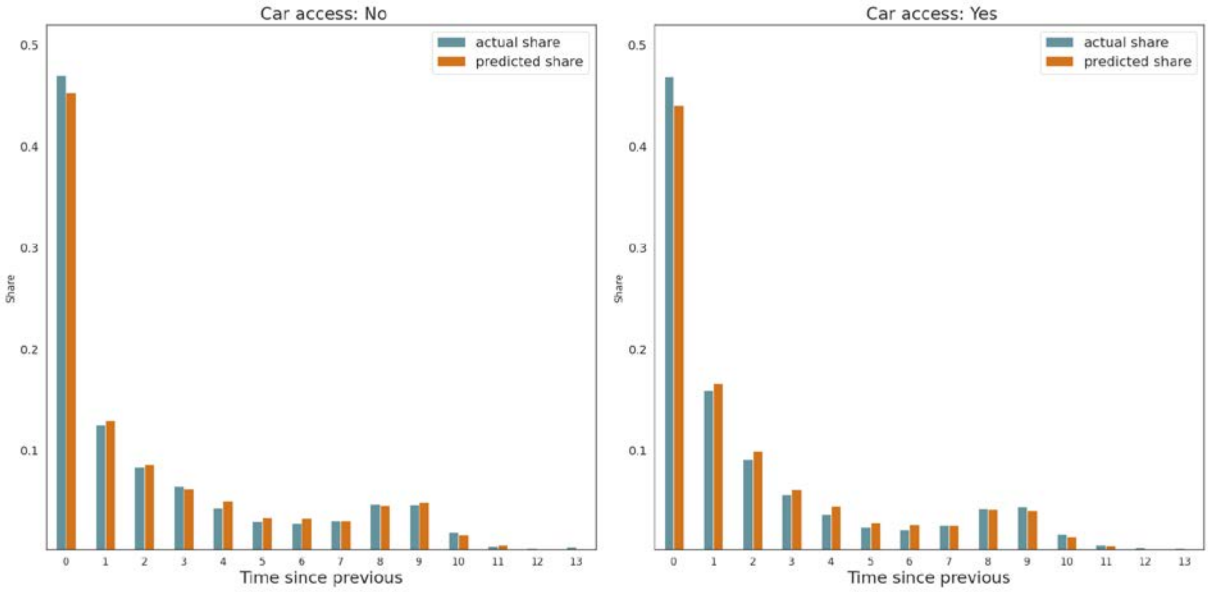


Figure 4.10: Actual share (in Ruter-MIS) and predicted share (from model 2) on the validation data for the duration relative to the previous trip start; segmented by car access.

Finally, Figure 4.11 gives actual and predicted shares for the predicted end zones. The models seems to catch the overall pattern satisfactory. The “IN” zones are within the Oslo-municipality will “Out” refers to sones outside Oslo (compared Figure 4.12 below).

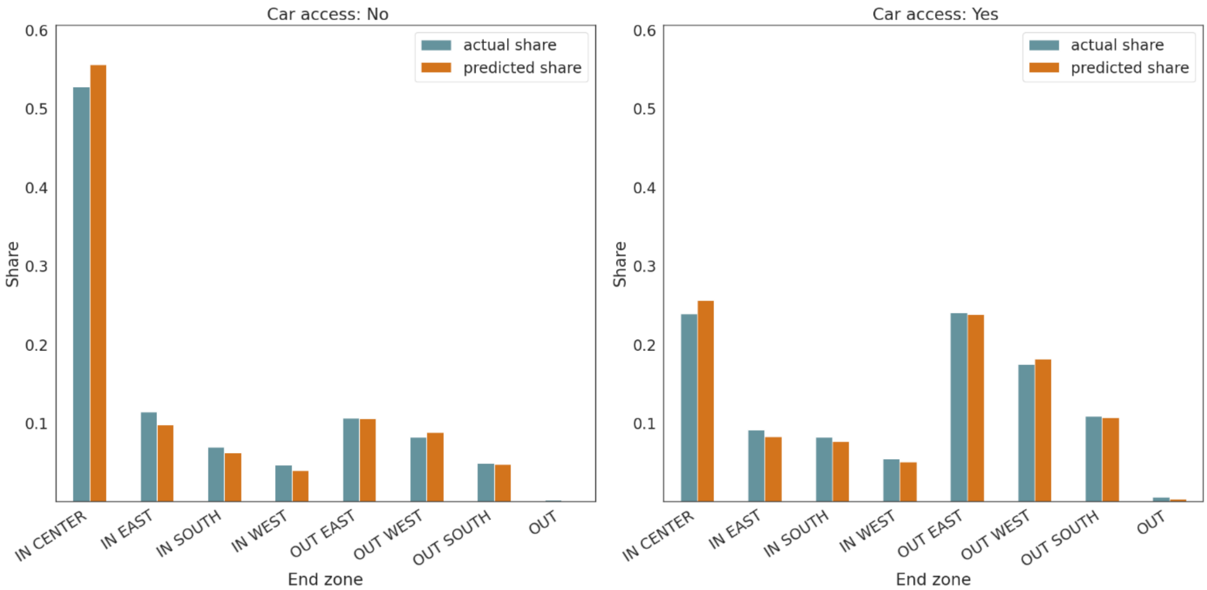


Figure 4.11: Actual share (in Ruter-MIS) and predicted share (from model 2) on the validation data for the destination choice to aggregated sones; segmented by car access.

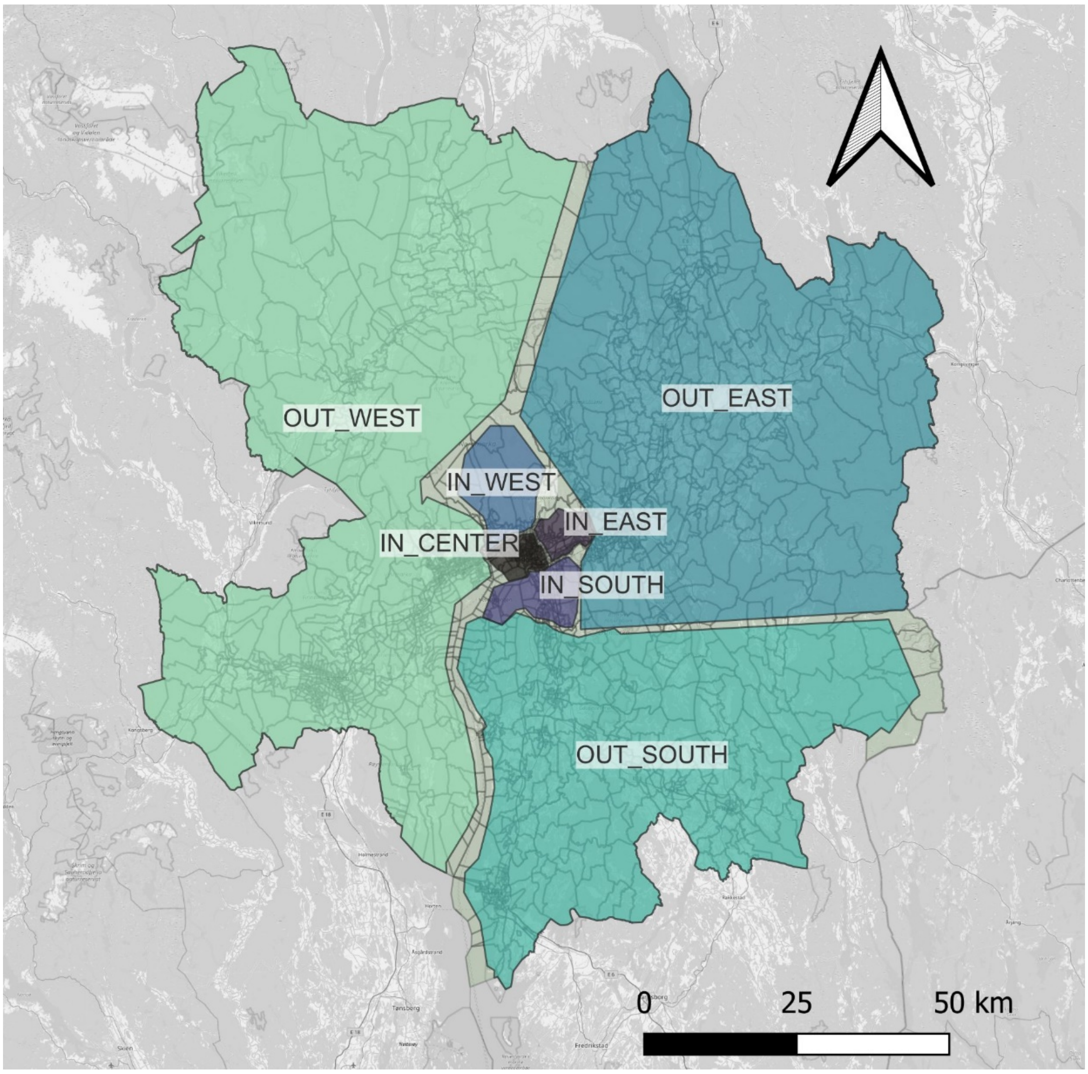


Figure 4.12: Applied zones (aggregation from basic statistical units).

Note that the "IN_CENTER" zone comprises all BSU that lie within the "Ring 3" roads circle. Note also that the sone are defined for the whole area of RTM23+, not "just" the Oslo/Akerhus region covered by Ruter-MIS.

As in the previous section, we take a look at correlations of individual probabilities of some variables. Figure 4.13 shows that there is a great variation (And an expected negative correlation) in the assigned probabilities for taking public transport (PT) and being car driver. From the marginal distribution, where again the true travel mode in the validation data is given by color codes, we see that model 2 is capably to give - in general - a high (low) probability for car driver for observations that actually were car drivers (actually took PT). The model is also able to assign a high probability for PT for observations that actually took PT (seen by the light blue dots in the upper left corner of the joint plot.

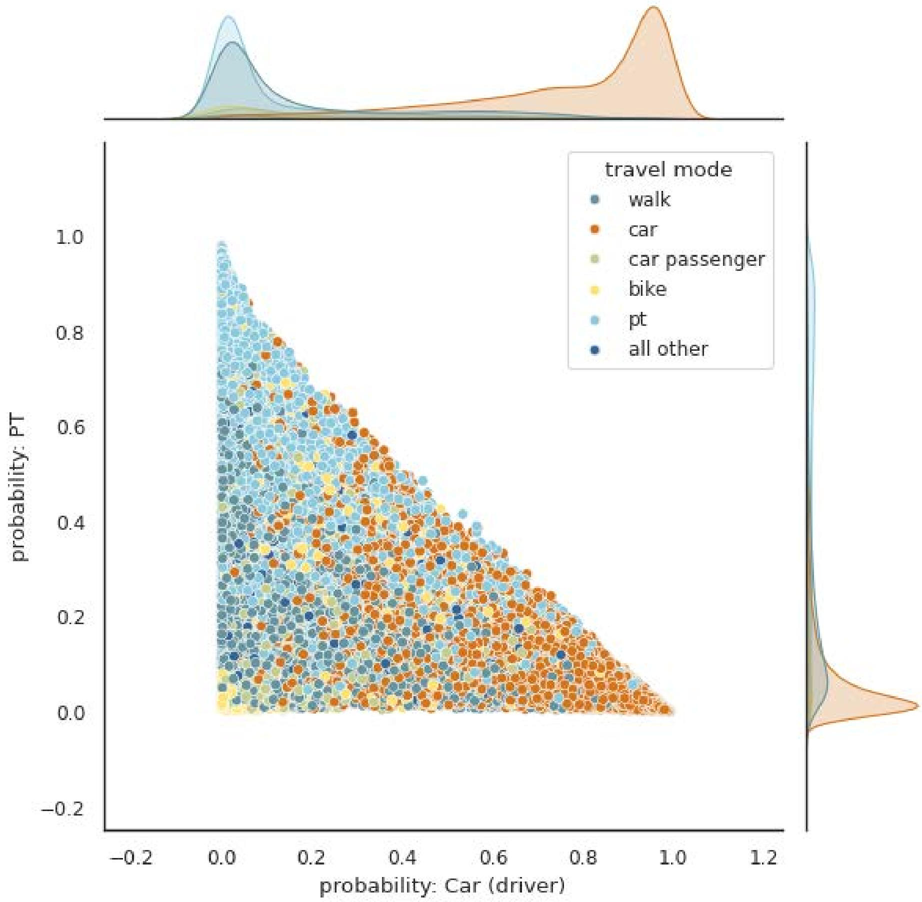


Figure 4.13: Joint plot of the individual probability for public transport (Y-axis) and car driver (X-axis); color codes indicate true travel mode in validation data.

Note that the of travel mode by model 2 is somewhat "easier" for trips where information about the previous travel mode are available. This is further investigated by dedicated model runs in chapter 5.

Figure 4.14 shows a similar plot for the two most frequent trip purpose (Home and Work). Compared the PT and car, the marginal probability functions given true label are even more distinct, indicating that the model 2 reliably distinguished these two trip purposes on a individual level.

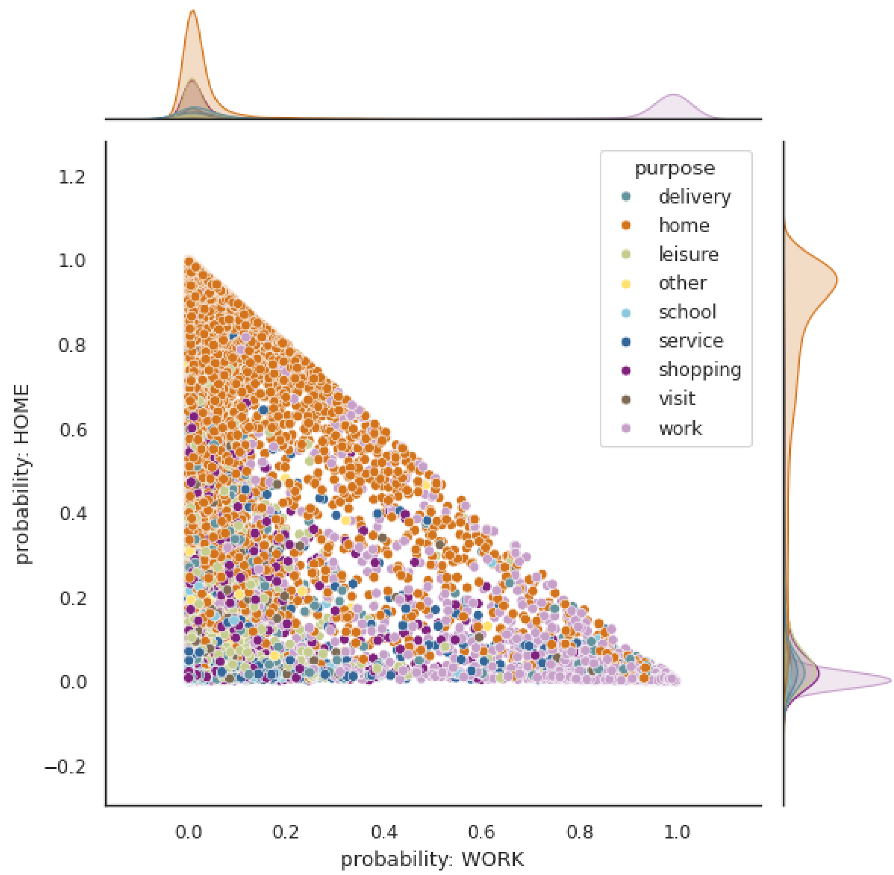


Figure 4.14: Joint plot of the individual probability for travel purpose Home (Y-axis) and travel purpose Work (X-axis); color codes indicate true travel purpose in validation data.

4.4 Overall data flow in generation

After the two neural network models are trained and validated, the models can be applied for the generation of activity plans on external data. Figure 4.15 gives an overview overall data flow.

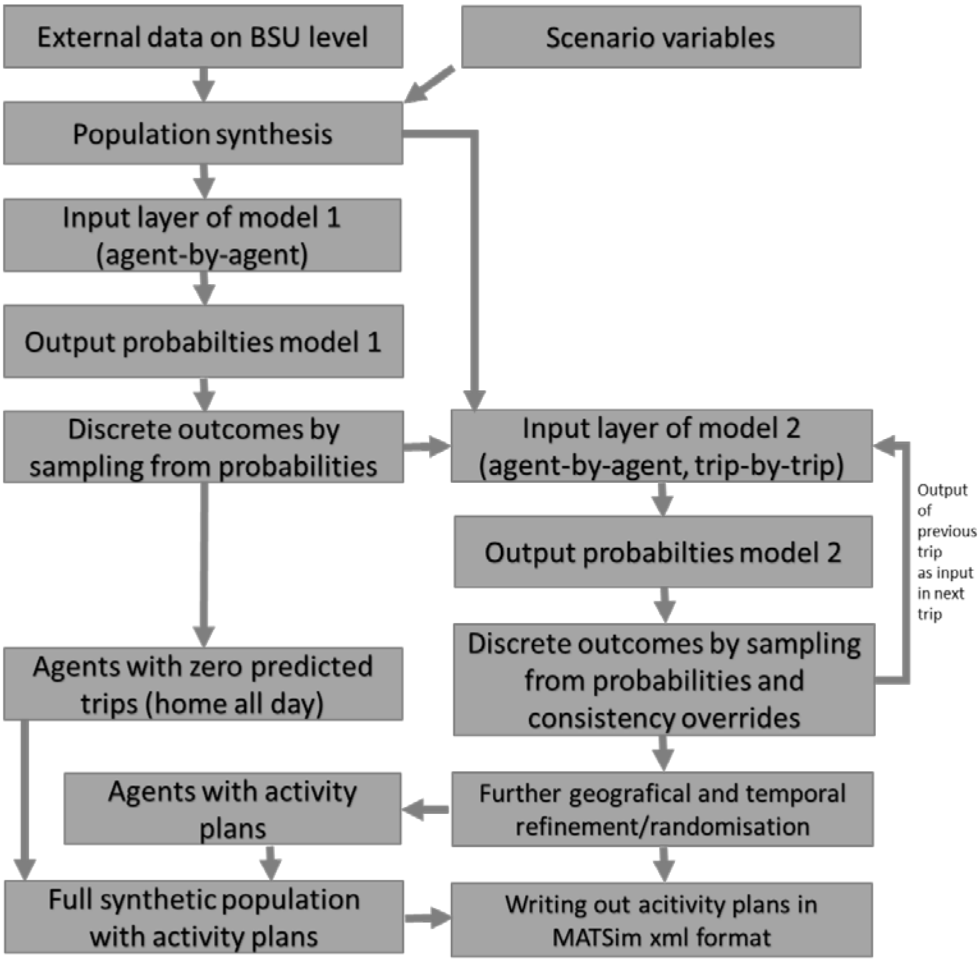


Figure 4.15: Data flow in Generation of activity plans in PRELONG project.

The approach takes external data on a BSU level (population data and zonal data (inkl LoS-data from the RTM23+ model) and scenario variables (type of weekday and Corona variables) as input and goes through a process of population synthesis which produces a set of agents with agent types and home-workplace locations. This part is described further in section 4.5.

For each agent, model 1 then predicts the choice probabilities of the four output variables (compare section 4.2). We are then sampling discrete outcomes from the individual output probabilities. The discrete outcomes from model 1 are added to the input layer going into model 2. Respondent for which the discrete outcome of Number of trips is “0” are jumping over model 2. Model 2 then predicts the 4 trips characteristic (compare previous section) of the first trip and the same sampling procedure as for model 1 is applied. The discrete outcomes of model 2 are then added to the input layer of next prediction (e.g. the prediction of the first trips. The four input variables are called “previous travel model”, “previous purpose”, “previous end zone” (which is the start zone of the new trip) and “previous start time”. For the second trip “previous start time” is taken from the discrete outcome of the “Time of first trip” (from model 1). For the third and all consecutive trips of each agent, “previous start time” is calculated as the sum of earlier start time and the discrete outcome of the prediction of “time since previous start time”.

For each agent, model 2 predicts (iteratively) as many trips as the discrete outcome of “Number of Trips” (from model 1) predefines.

Note that sampling from individual probabilities can result in a work trip (or home trips) to an end zone that is not consistent with the work zone (or home zone) given from the input data to the model. In this case, we overwrite the prediction of the end zone and replace it with the value of the input data. This only is done in application of the model on the external data (i.e. not in the validations data in section 4.2 and section 4.3). The overwritten values is used in the prediction of the consecutive trips (if applicable) as the “previous end zone”.

Another inconsistency that can emerge is that trips are predicted that have a start time that is later than the “Time of last trip” from model 1. We do currently not correct for this and allow for that trips happen after that point of time (which also may be after 24:00).

As Figure 4.15 illustrates, the next step after model 2 is iteratively applied is to refine the geographical and temporal information. Data coming out of model 2 have a geographical refinement of BSU-level for home and work trips and zonal-level for all remaining purposes. For later application in MATSim the location of activities is placed on the MATSim network links by randomly drawing a link from within the current BSU /zone. For zones, especially the different “OUT”-zones (compare Figure 4.12), this comes with some arbitrariness and may results in some illogical geographical patterns. Ways to improve upon this are discussed in section 7.2.

4.5 Population synthesis

In this section, we give an overview over how the input data for model 1 is established in the process of generating activity plans for the whole population of the RTM23+ area. The main part relates to generation the agents and their characteristics. This process is referred to as population synthetic. As discussed in section 2.6, the of the process is not done with machine learning in this project, but is instead based on sampling characteristics given conditional probabilities from zonal data (for geographic variation) and Ruter MiS (for sociodemographic variation). As indicated in section 3.4, we applied the 2020 population data but assumed car type data for 2024 to account for the increase share of electric vehicles.[4]

Figure 4.16 illustrates how the different data sets (introduced in chapter 3) are combined to establish the agents characteristic (age group, gender, occupation status, car access/type and working remotely.

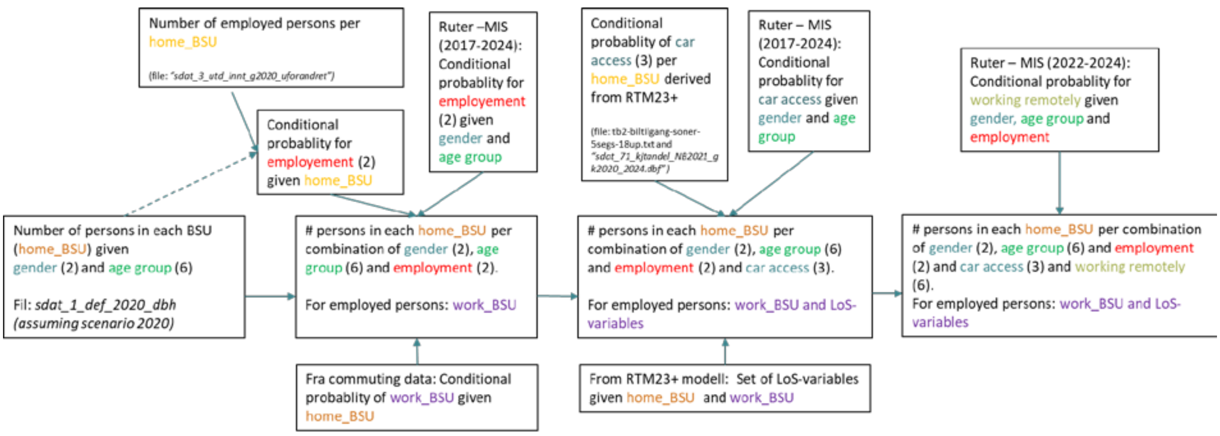


Figure 4.16: Schematic overview over population synthesis (actual data flow is more involved).

[4] We did not have direct access to the 2024 population data. In interpolation between the available 2020 and 2030 data should be considered in real-world application for year 2024.

The outcome of the population synthesis are around 1.3 million agents (for age 15 or above) corresponding to the population in the RTM23+ area, i.e. Oslo, Aksershus, plus some additional areas in and around Drammen and Moss.

Figure 4.17 gives some shares for agent characteristics of these 1.3 million agents. Note that the age information is given from the original population files while the working remotely ("home office") variables is based on the post covid data from Ruter-MIS (compared Figure above). The information on the employment status is given from a combination of zonal data and Ruter-MIS.

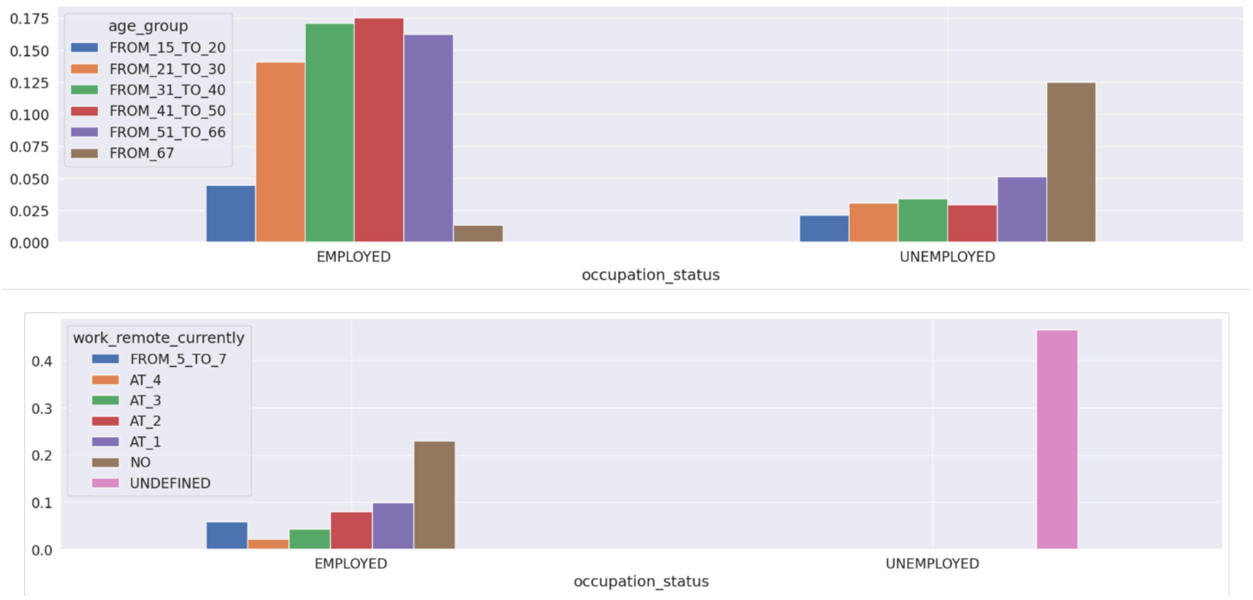


Figure 4.17: Age group (upper panel) and home office (lower panel) by employment status in the synthetic population. AT_X means that respondents works X days a week from home currently.

A central part of the population synthesis is to sample a work place location on a BSU level based on commuting data and home-BSU. Based on the home-work relation, we can import Level of Service (LoS) data (see section 3.1 and for some analysis chapter 5). The LoS-data is direct input into model 1 while the geographical information of home (and work) place is aggregated into zones as indicated by the map presented earlier (Figure 4.12).

Figure 4.18 gives the number of agents for each home-work zone combinations (only agents that are employed and have gotten assigned a work BSU are included here).

work_zone	IN_CENTER	IN_WEST	IN_EAST	IN_SOUTH	OUT_WEST	OUT_EAST	OUT_SOUTH	OUT
home_zone								
IN_CENTER	91148	5420	12340	3916	13151	5668	2236	375
IN_WEST	22100	4946	2562	568	4676	1152	378	89
IN_EAST	29410	2594	17219	2426	3756	5575	1032	108
IN_SOUTH	35017	1934	8413	12423	4283	2946	3195	183
OUT_WEST	47237	3594	6832	1427	141115	4511	2116	11225
OUT_EAST	30034	1514	16947	1932	4819	72282	2334	17227
OUT_SOUTH	25854	997	5507	4378	3988	4554	64597	4136
OUT	0	0	0	0	0	0	0	137

Figure 4.18: Total amount of agents with the following home and work zone in the synthetic population.

4.6 Resulting synthetical activity plans

Finally, we take a look at the resulting synthetic activity plans. The following figures are based on the following assumptions (scenario variables).

** the variable "infection worried" are set to "no" for all agents*

** Lockdown-stringency index is set to zero*

** week day: Non-holiday, non-Friday weekday in spring/autumn*

The generated synthetic activity plans include 3.61 million trips (from 1.08 agents with at least one trip). Of those trips, 1.62 million trips are mode with car.

Figure 4.19 shows the distribution of trips on an hourly level for all start locations. The color indicates the trip purpose, e.g. the activity performed at destination. We see a plausible distribution trip purposes, where the most of the trips in the morning hours end at work activity while most trips in the afternoon/evening end at home.

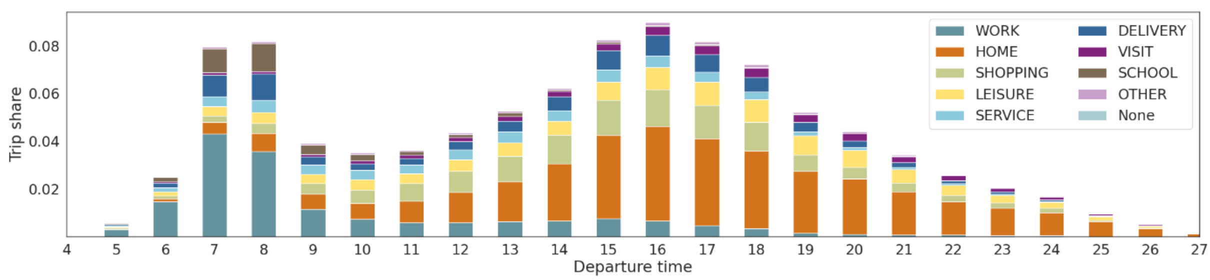


Figure 4.19: Distribution over departure times (all start locations) by trip purpose (type of activity at destination).

Figure 4.20 gives the same distribution but segmented into travel models used. Of course, the propensity for different travel mode varies with the location. Trips starting in the OUT_WEST zone, for instance have a higher share of car compared to trips starting in the Oslo city center (IN_CENTER) as illustrated in Figure 4.21 and Figure 4.22.

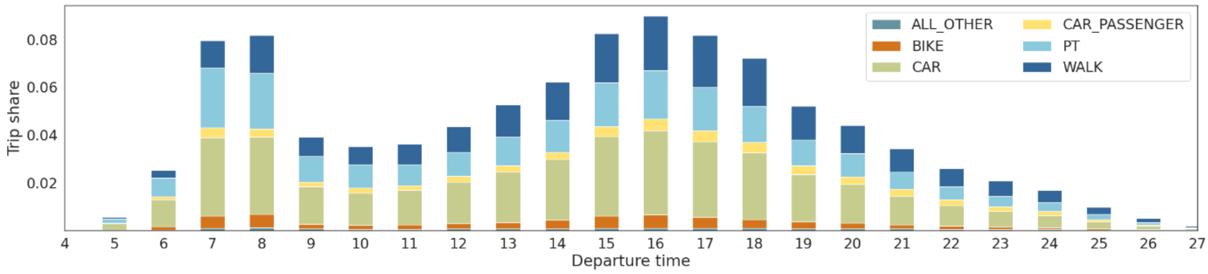


Figure 4.20: Distribution over departure times (all start locations) by travel mode.

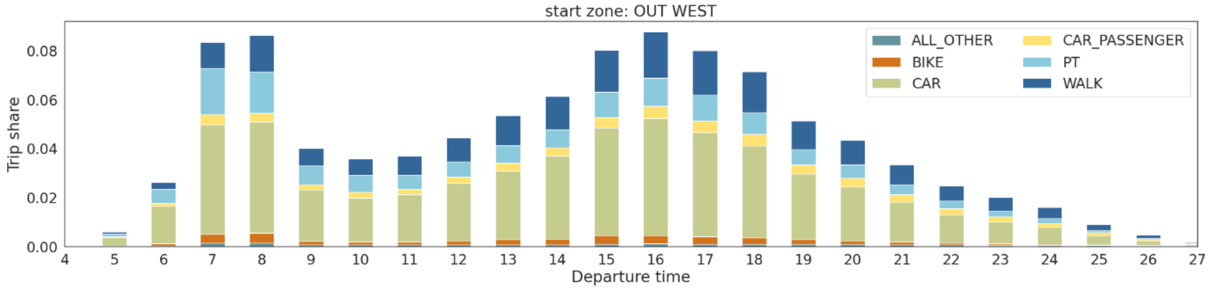


Figure 4.21: Distribution over departure times from the OUT_WEST zone, by travel mode.

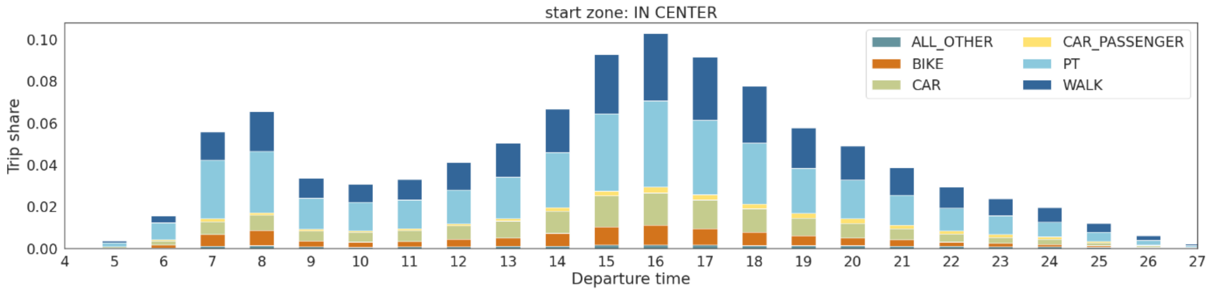


Figure 4.22: Distribution over departure times from the IN_CENTER zone, by travel mode.

From the last two figures, we also see that the distribution of departure times is different start location. Comparing Figure 4.22 with Figure 4.21 we see that trips starting in the Oslo city center have a greater peak in the afternoon than trips starting in OUT-WEST.

With Figure 4.23 to Figure 4.26 we can take a closer look at the geographical distribution of activities throughout the day. Activities are on

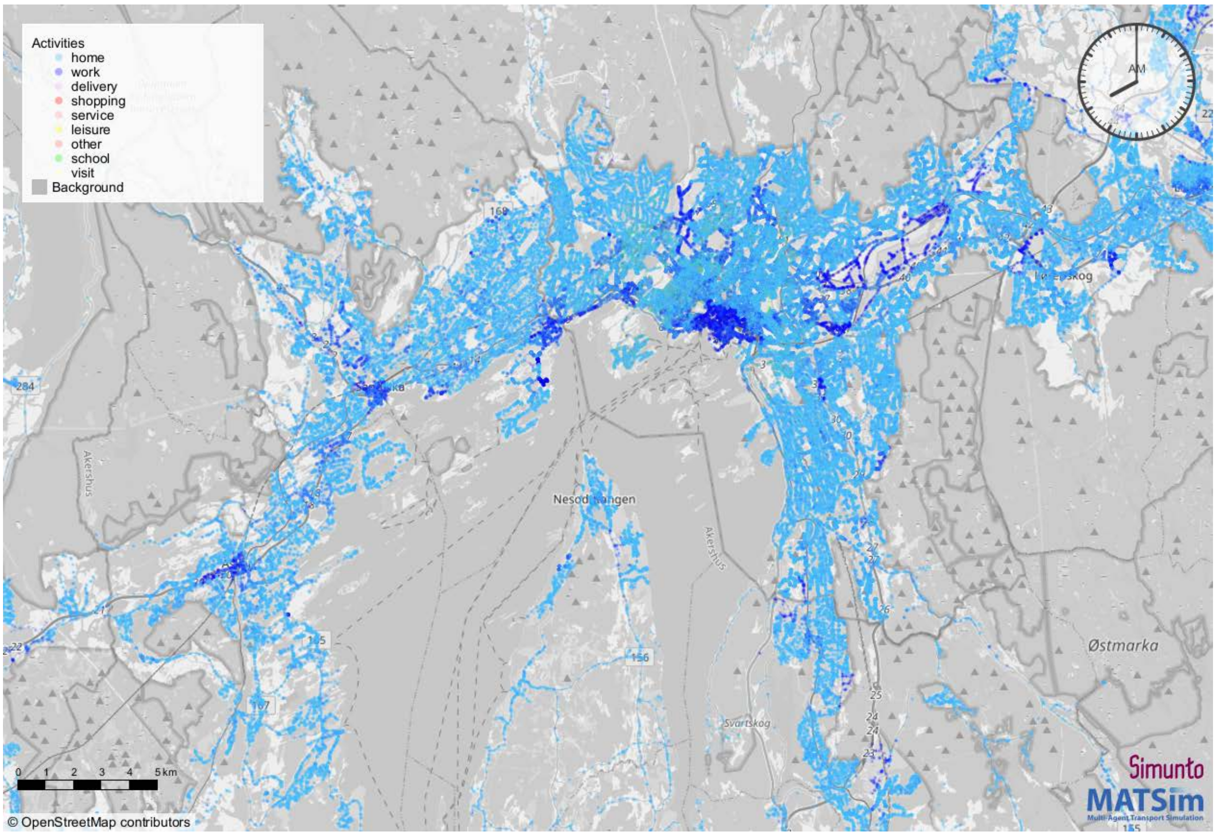


Figure 4.23: Generated activities at timestamp 08:00:00.

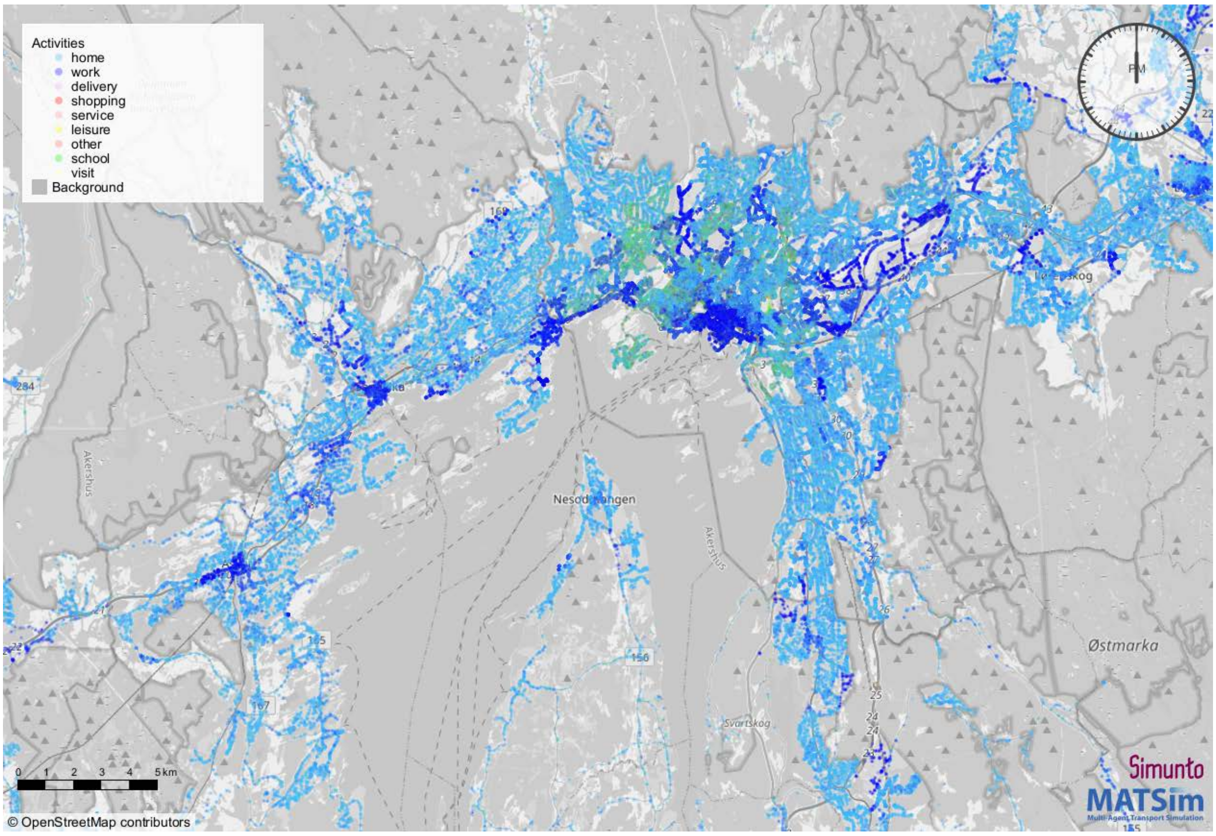


Figure 4.24: Generated activities at timestamp 12:00:00.

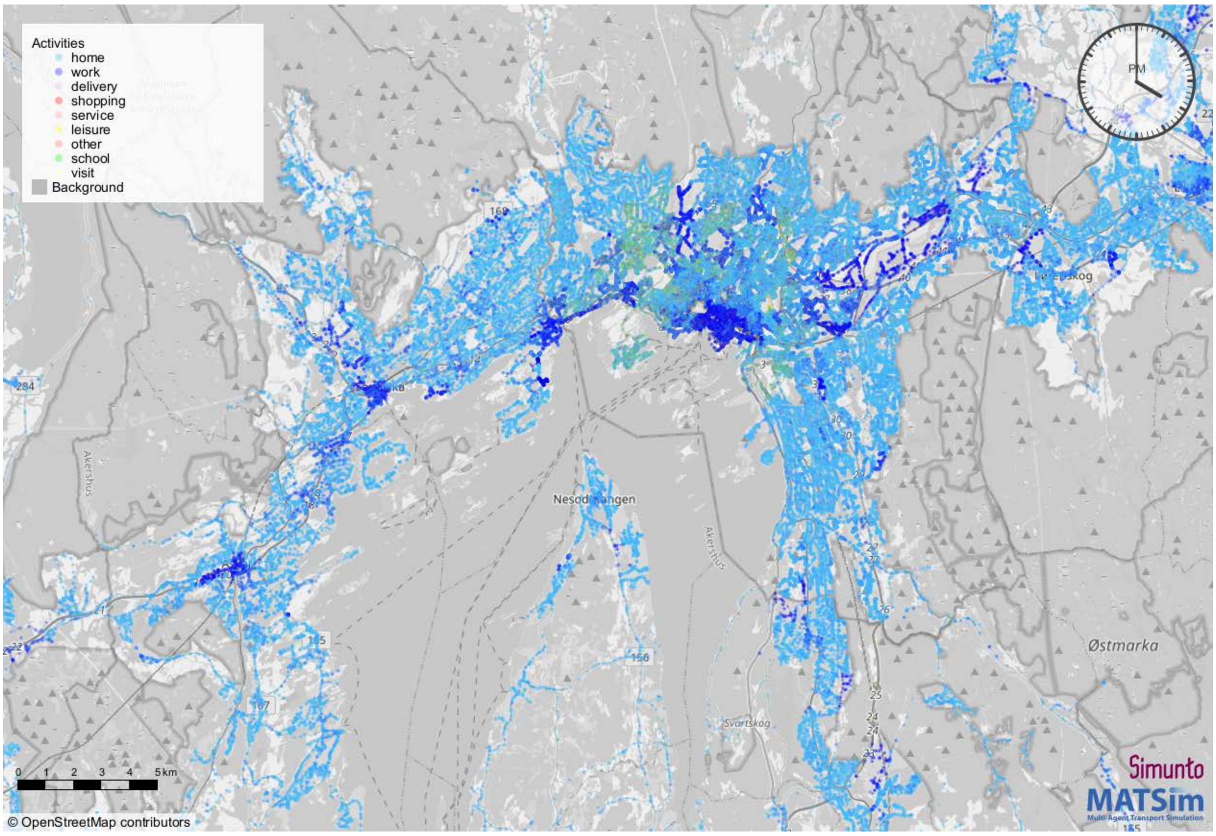


Figure 4.25: Generated activities at timestamp 16:00:00.

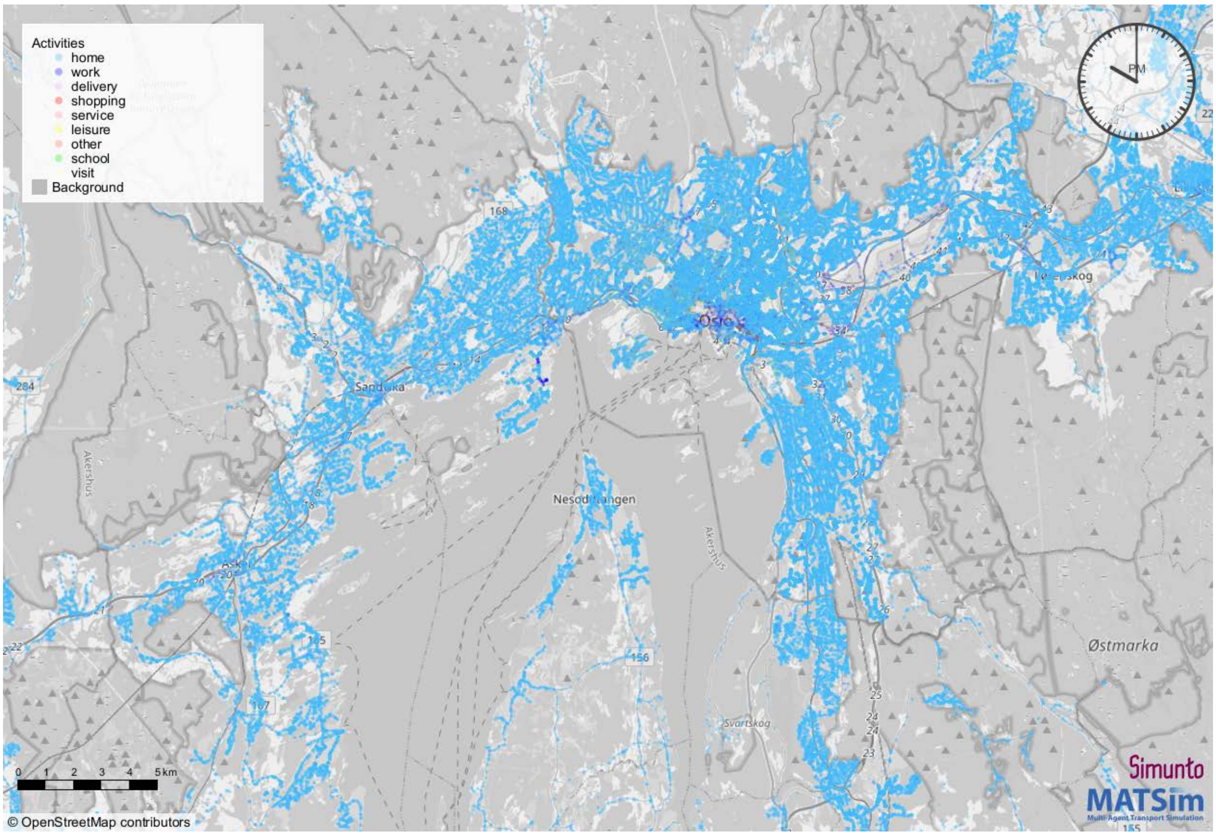


Figure 4.26: Generated activities at timestamp 22:00:00.

5 Additional topic 1: Predicting travel mode choice with neural networks with and without Level of Service

In this section, we investigate the effect of Level-of-Service (LoS) on the neural network based prediction of travel mode choice. This analysis was executed before we got updated data from Ruter-MIS, and was therefore conducted on data from March 2017 to March 2020.

In the generation of activity plans (previous chapter) LoS entered in the model (both model 1 and model 2) on the home-work relation, i.e. not on a single trip level. The reason for this is that destination choice is an endogenous variable and can therefore not be calculated as an input to the model.[5] In our overall approach (Section 2.1), the impact of LoS on travel mode choice (as well as route and departure time choice) on a trip level is handled in the downstream MATSim model.

In this chapter, we only considering travel mode choice and not the other elements of activity plans. We only using a single neural network and not two as for full activity plans (previous chapter). This chapter offers therefore limited insights on the inclusion of LoS in activity based demand models in general. However, in this section we point to some challenges in using LoS for travel mode predictions. As discussed in section 2.1 and section 7.1, in out overall modelling approach the effects of LoS on mode, departure time and route choice are handled in the downstream agent-based simulation model.

5.1 The predictive power of LoS-data

In this study, predictive ability is measured using the proportion of observations where the model assigns the highest probability to the actual chosen travel mode. This metric is commonly referred to as accuracy.

It is important to note that accuracy is dependent on the number of categories being predicted. For instance, transitioning from predicting five to six travel modes will generally reduce the overall accuracy. This was the case in the project after we divided the options “car” in to “car driver” and “car passenger”. Assuming a naïve model with no predictive power (pure random guessing), one would expect an accuracy of 0.2 with 5 categories (100/5) and of 0.1667 (100/5) with 6 categories.

However, neural networks are not trained specifically on accuracy but rather on a loss function, which represent the deviation between all probabilities and the actual outcome. Note, that this loss metric correspondents well to our approach where we sample from all probabilities to determine the outcome of the prediction.

Despite its limitations, accuracy is used as a performance metric in this section because it is easy to interpret. However, one should avoid placing too much emphasis on this metric alone.

All models evaluated in this section contain the same architecture (2 hidden layers with respectively 64 and 32 nodes), learning rate (0.001) and number of epochs (100). All models are trained on the same training data from Ruter-MIS (N= 66333).

[5] An alternative approach would have been to include the LoS of a (random) selection of possible destination and than predict destination choice among those sample destination. This approach, which would have been similar to the way the RTM model models destination choice was not implemented.

As long as not specified otherwise, we refer to the accuracy as measured on the test data set (N= 13267).[6]

Table 5.1 reports on the obtained accuracy given different sets on input data. The fields marked in light orange involve explanatory variables that were used in the original model presented in the PRELONG project (Flügel et al 2022). The green marked fields involve LoS-variables (see section 3.1).

Table 5.1: Accuracy with different sets of explanatory variables.

	S1	S2	S3	S4	S5	S6	S7	S8	S9
Gender	X								
Age group	X								
Occupation status	X								
Car access	X								
Home region		X							
Work region		X							
Work distance			X						
Previous travel mode				X					
Previous purpose					X				
Previous start time					X				
Activity index (numerical)					X				
Activity index (categorical)					X				
Previous region					X				
Distance walk						X			
Invehicle time (IV) car							X		
Dummy IV time PT missing							X		
Invehicle time PT							X		
Waiting time PT								X	
Access time PT								X	
Boardings PT								X	
Cost singleTicket PT									X
Cost saisonTicket PT									X
Cost road tolls									X
Accuracy (test data)	0.592	0.525	0.476	0.676	0.524	0.5	0.49	0.537	0.545

As one reading example, the model where only agent characteristics (gender, age group occupational status and car access) enter the model (S1) obtained an accuracy of 0.592. That is in 59.2% of the observations in the test-data, the S1-model assigned the highest probability to the actual travel mode.

We see from **Feil! Fant ikke referansekilden.** that the model with only previous travel mode (S4) has the single highest accuracy. This should not be a surprise given that there is typically a high correlation between previous travel mode and current travel mode within a given day. Note that the accuracy given that are is a previous travel mode (that trips besides trip 1), the accuracy is even higher (while it is low without this information).

[6] In this analysis we divided the data into training-, validation- and test data. While for the full models in the PRELONG project, we only divided in training and validation.

The accuracy for the different LoS-variables is quite similar. Note that many LoS within and across S6-S9 are strongly correlated.

Table 5.2 gives the obtained accuracy for different combination of sets 1-9 from Table 5.1.

Table 5.2: Accuracy with different combination of sets of explanatory variables.

	S11	S12	S13	S14	S15	S16	S17	S-all
S1 - agent types	X	X	X	X		X	X	X
S2 - home and work region		X	X	X		X	X	X
S3 - working distance		X	X	X		X	X	X
S4 - previous travel mode			X	X			X	X
S5 - previous other trip information		X	X	X		X	X	X
S6 - distance walk	X			X	X	X	X	X
S7 - travel time car and PT	X				X	X	X	X
S8 - PT-service	X				X	X	X	X
S9 - costs car and PT	X				X	X	X	X
Info on current trip (purpose, end region and departure time)								X
Accuracy (test data)	0.666	0.622	0.74	0.766	0.6	0.677	0.779	0.789

From the two tables, we can investigate the effect of adding LoS to the neural network model.

Comparing S1 (a model with only agents characteristics) with S11 (adding LoS), we obtain an increase of accuracy of by 7.4 percent points (0.666-0.592=0.074).

Comparing S12 with S16, we get the effect of adding LoS to a model with the PRELONG variables minus previous travel model. Here the increase is 5.5 percent points.

Using the full PRELONG model this increase is 3.9 percent points (comparing S13 with S17).

The observed decrease in added precision with increased size of the base model is expected as LoS is correlated with the geographical information at least for commuting trips (home-work region and work distance). In case of including previous travel mode it also appears that that variables takes away “explanatory power” from LoS.

Note that the models S-11 to S-17 in Table 5.2, include no information about end region, departure time and purpose of given trip as these are outputs variables in the model for predicting activity plans (compare chapter 4). However, in the context of predicting only travel mode choice of a given trip they can be used as input into the neural network. This model referred to as “S-all” and obtained a accuracy of 0.789 on the test data (and 0.7923 on the validation data).

5.2 A closer look at predicted market shares

In the previous section, we defined and explored the accuracy of different model variants.

We emphasize that we are not interested in highest possible accuracy in the context of generating activity plans for agent-based modelling. Rather we are interested in predicting current level and variation in market shares; therefore we are interested in getting all probabilities correct.

Table 5.3 gives the accuracy and average assigned probabilities for different groups of observations obtained by the “S-all” model on the test data. Average probabilities represent the market shares of the 6 transport modes.

From the upper section of the table showing results for the first trip of a day, we see that the accuracy of the neural network model is strongly dependent of the actual travel mode. If the actual travel mode Car Driver, the neural network is able to assign the highest probability to Car Driver in 82% of the observations in the test data. On the other hand, the corresponding value for Bike is 0%, e.g. for the first trip, the model does never assign the highest probability to the bike alternative.

Table 5.3: Accuracy and (average) predicted probabilities given previous transport mode.

Trip number	Actual travel modes		Accuracy	Average probabilities on test data					
	Previous travel mode (known to model)	Travel mode (not known to the model)		CAR DRIVER	CAR PASSENGER	PUBLIC TRANSPORT	BIKE	WALK	OTHER
For first trip	Not available	CAR DRIVER	0.820	0.662	0.067	0.140	0.035	0.084	0.012
		CAR PASSENGER	0.059	0.484	0.127	0.244	0.042	0.084	0.018
		PUBLIC TRANSPORT	0.736	0.201	0.060	0.582	0.056	0.077	0.023
		BIKE	0.000	0.337	0.041	0.305	0.086	0.212	0.019
		WALK	0.605	0.220	0.043	0.162	0.063	0.498	0.014
		OTHER	0.029	0.324	0.061	0.394	0.043	0.133	0.046
For con-secuative trips	CAR DRIVER	CAR DRIVER	0.985	0.934	0.016	0.022	0.006	0.020	0.002
		CAR PASSENGER	0.000	0.848	0.044	0.041	0.011	0.052	0.004
		PUBLIC TRANSPORT	0.162	0.670	0.034	0.200	0.021	0.069	0.006
		BIKE	0.000	0.730	0.014	0.061	0.034	0.157	0.004
		WALK	0.348	0.604	0.013	0.012	0.027	0.341	0.004
		OTHER	0.000	0.829	0.046	0.083	0.010	0.019	0.012
	CAR PASSENGER	CAR DRIVER	0.080	0.210	0.589	0.107	0.006	0.077	0.011
		CAR PASSENGER	0.941	0.101	0.761	0.095	0.003	0.028	0.012
		PUBLIC TRANSPORT	0.393	0.098	0.474	0.370	0.007	0.037	0.014
		BIKE	0.000	0.266	0.400	0.009	0.006	0.314	0.005
		WALK	0.500	0.046	0.460	0.052	0.010	0.422	0.009
		OTHER	0.000	0.140	0.365	0.370	0.002	0.064	0.060
	PUBLIC TRANSPORT	CAR DRIVER	0.678	0.565	0.083	0.209	0.017	0.120	0.006
		CAR PASSENGER	0.063	0.184	0.147	0.540	0.010	0.110	0.009
		PUBLIC TRANSPORT	0.897	0.055	0.066	0.781	0.010	0.080	0.009
		BIKE	0.000	0.127	0.092	0.525	0.026	0.218	0.011
		WALK	0.610	0.086	0.044	0.333	0.028	0.500	0.009
		OTHER	0.000	0.132	0.058	0.724	0.006	0.071	0.009
	BIKE	CAR DRIVER	0.595	0.470	0.047	0.053	0.358	0.066	0.006
		CAR PASSENGER	0.000	0.286	0.069	0.053	0.541	0.035	0.016
		PUBLIC TRANSPORT	0.400	0.026	0.031	0.350	0.537	0.050	0.006
		BIKE	0.869	0.070	0.015	0.036	0.769	0.105	0.005
		WALK	0.304	0.073	0.026	0.017	0.565	0.312	0.006
		OTHER	0.000	0.004	0.010	0.115	0.826	0.035	0.009
	WALK	CAR DRIVER	0.509	0.471	0.060	0.198	0.029	0.237	0.005
		CAR PASSENGER	0.032	0.306	0.104	0.417	0.030	0.133	0.010
		PUBLIC TRANSPORT	0.648	0.091	0.058	0.556	0.028	0.259	0.009
		BIKE	0.000	0.143	0.020	0.301	0.065	0.463	0.008
		WALK	0.909	0.065	0.019	0.093	0.016	0.804	0.003
		OTHER	0.000	0.341	0.029	0.318	0.072	0.225	0.015
	OTHER	CAR DRIVER	0.444	0.363	0.060	0.101	0.018	0.151	0.307
		CAR PASSENGER	0.000	0.258	0.064	0.160	0.009	0.004	0.504
		PUBLIC TRANSPORT	0.167	0.044	0.018	0.222	0.009	0.027	0.680
		BIKE	0.000	0.160	0.045	0.149	0.035	0.127	0.483
		WALK	0.167	0.082	0.020	0.067	0.018	0.227	0.586
		OTHER	0.769	0.102	0.038	0.108	0.012	0.106	0.634

While these might be seen as shortcomings, it is important to notice that the model gives meaningful level of markets share and a variations in markets shares that goes in the expected direction. E.g. for cases the actual mode was car, the model assigns a probability for bike of 3.5%, while it assigns as probability of on average 8.6% for choices where the actual travel mode is bike. Note again that the model is not aware of what the actual choice in the test data is prior to prediction. Thus, the model seems to capture some variation across observation.

This pattern gets even more clear when looking at trips where there is a previous trip. In this case, the model has knowledge of the previous travel mode and will use this information in the prediction of the travel mode. Given that the previous travel mode was bike, the model assign – on average – a probability for bike of 76.9% for observations when indeed bike was chosen (and a significant lower probability of 35.8% when car as actually chosen).

It is important to note that great variation in probabilities on an individual level. This is illustrated in Figure 5.1, that shows predicted probabilities for Car Driver and Public Transport (this Figure is similar to Figure 4.13 in capture 4 that was based on the model 2 from the generation of full activity plans). Each dot represents one observation in the test data and the color code indicates the actual travel model.

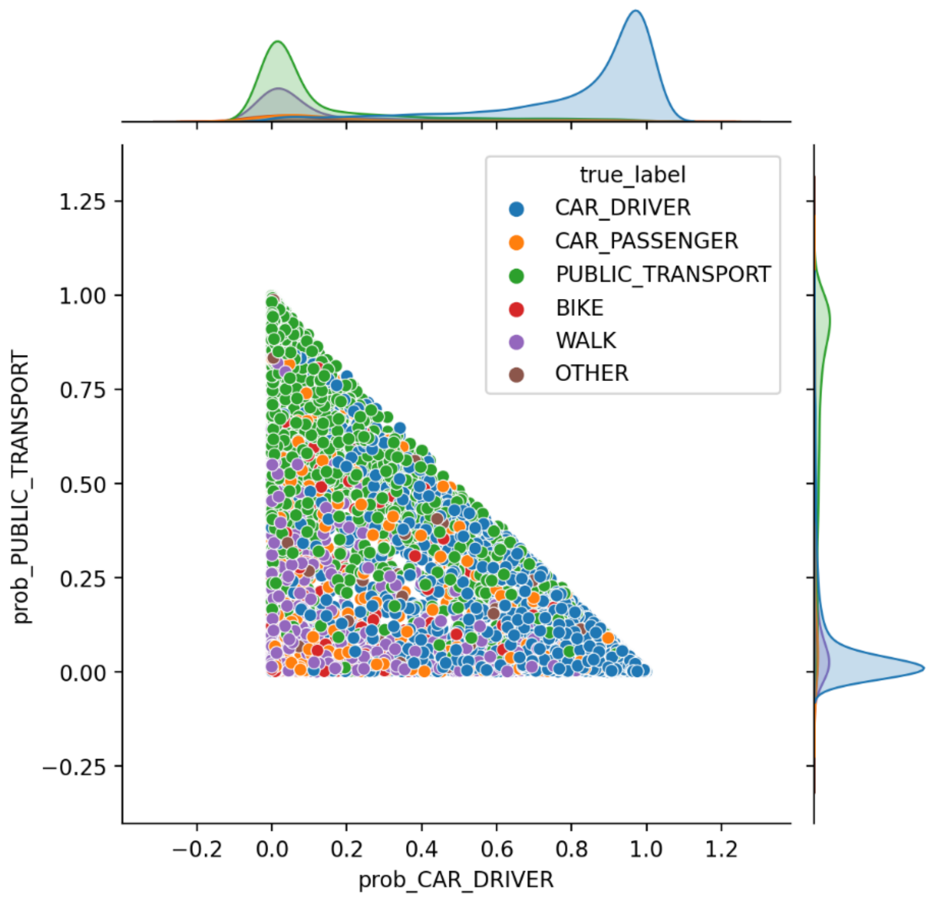


Figure 5.1: Joint plot of assigned probabilities of Car Driver versus Public Transport on test-data. Colors indicate true travel mode.

Obviously, markets share vary across geographical relations, which can be demonstrated by aggregating probabilities into relations on a zone level (Figure 5.2). All dots in Figure 5.2, that share the same color have the some end zone. There are 7 dots of each color, one dot for each start zone. Figure 5.2: Joint plot of average predicted probabilities (i.e. market share) for Car Driver and Public Transport aggregated over groups defined by start- and end region. Color code indicate end region.

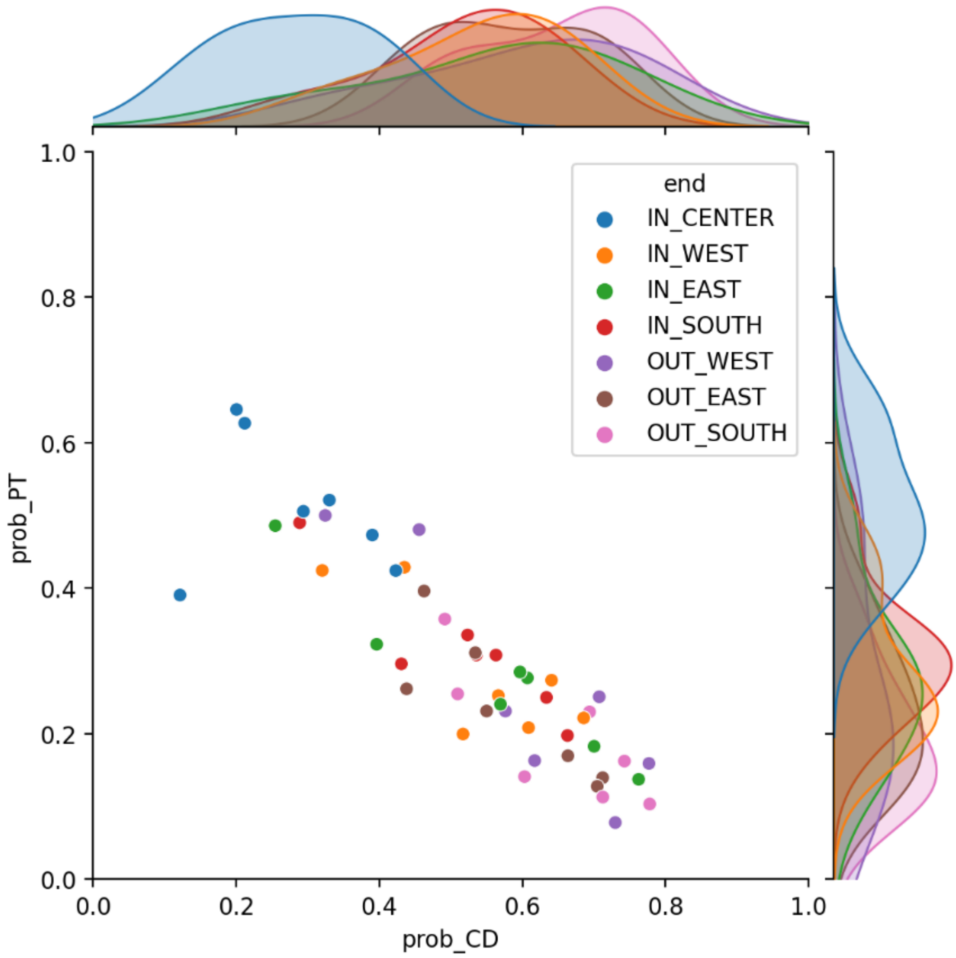


Figure 5.2: Joint plot of average predicted probabilities (i.e. market share) for Car Driver and Public Transport aggregated over groups defined by start- and end region. Color code indicate end region.

The blue dot most left in the joint plot is the relation “from IN_CENTER to IN_CENTER” and indicated that the predicted marked for Car Driver within Ring 3 is rather low.

We can also compare the predicted market shares against the market shares as observed from Ruter-MIS. In this connection it is important to note that some relations (e.g. Out_WEST to OUT EAST) do not have that many observations in Ruter-MIS. This makes same comparison somewhat unstable. The comparison gets more stable when including the whole Ruter-MIS data (March 2017-March 2020), i.e. also the training data.

Figure 5.3 shows the joint plot of predicted and observed market shares for both data sets.

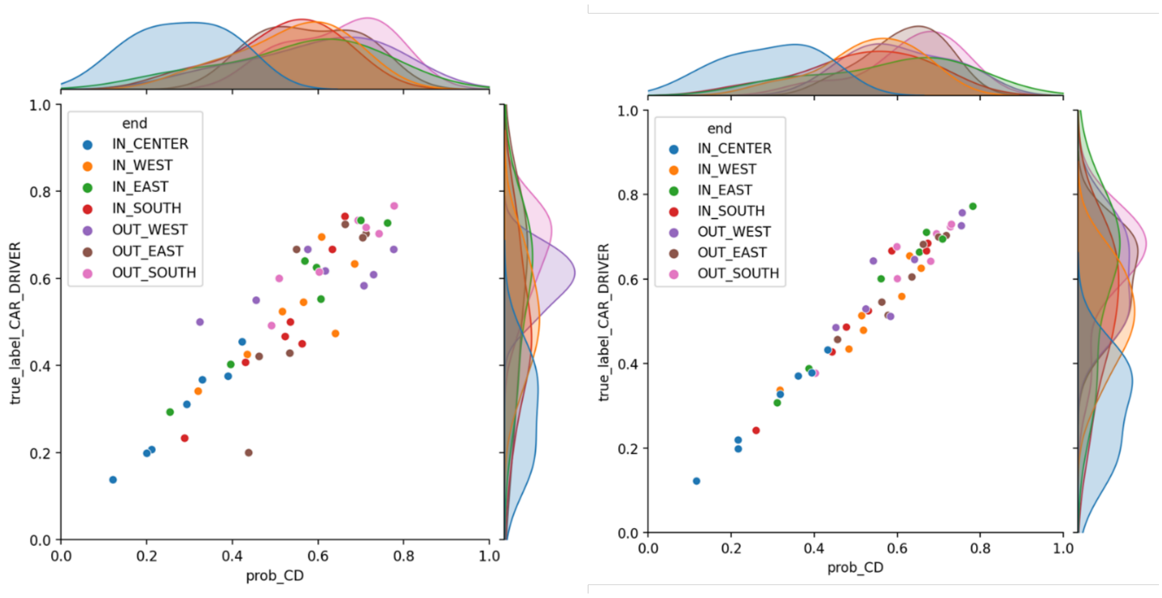


Figure 5.3: Scatterplot of predicted market share and market share in Ruter-MIS for Car Driver. Left-panel only on test-data, Right panel on whole data from March 2017- March 2020.

The improved fit on the whole data is primary true to more stable markets shares in Ruter-MIS (in addition the neural network is slightly better to predict on observations that are included in the training data).

Figure 5.4 shows the corresponding comparison for the market shares for public transport.

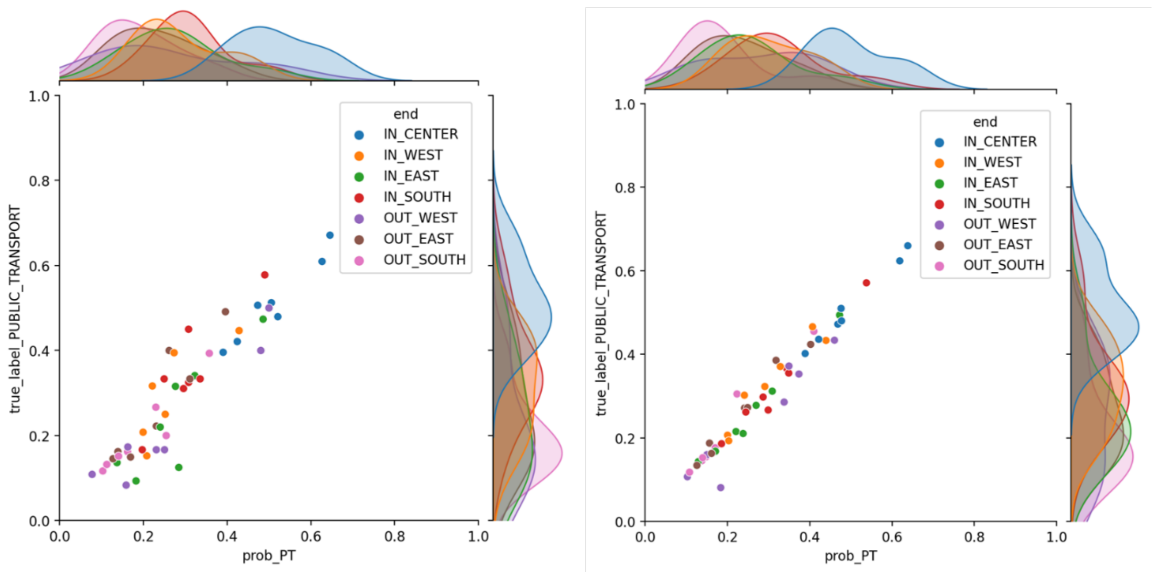


Figure 5.4: Scatterplot of predicted market share and market share in Ruter-MIS for Public Transport. Left-panel only on test-data, Right panel on whole data from March 2017- March 2020.

For more details, Figure 5.5 gives the numbers behind the right panel of Figure 5.4 on a OD-level and also provides the relative deviation for each OD-pair.

Predicted	IN_CENTER	IN_WEST	IN_EAST	IN_SOUTH	OUT_WEST	OUT_EAST	OUT_SOUTH
IN_CENTER	38.9%	44.0%	47.3%	53.8%	46.0%	40.2%	41.0%
IN_WEST	46.8%	20.1%	22.1%	34.4%	10.3%	31.8%	22.4%
IN_EAST	61.9%	32.9%	30.9%	34.9%	33.8%	15.7%	14.8%
IN_SOUTH	63.8%	40.7%	27.0%	28.7%	37.4%	24.2%	13.8%
OUT_WEST	47.7%	20.4%	23.8%	29.9%	15.0%	24.9%	17.1%
OUT_EAST	42.2%	24.2%	13.0%	24.5%	35.0%	12.6%	10.8%
OUT_SOUTH	47.6%	29.1%	17.1%	18.6%	18.4%	16.2%	14.0%

MIS (2017-2020)	IN_CENTER	IN_WEST	IN_EAST	IN_SOUTH	OUT_WEST	OUT_EAST	OUT_SOUTH
IN_CENTER	40.2%	43.3%	49.4%	57.1%	43.4%	42.4%	45.5%
IN_WEST	47.2%	20.7%	21.5%	36.6%	10.7%	38.6%	30.5%
IN_EAST	62.4%	37.1%	31.2%	35.5%	28.6%	18.8%	15.5%
IN_SOUTH	66.0%	46.6%	27.8%	29.8%	35.3%	27.2%	14.5%
OUT_WEST	48.0%	19.3%	21.1%	26.7%	16.0%	27.3%	17.6%
OUT_EAST	43.6%	30.2%	14.3%	26.2%	37.2%	13.4%	11.8%
OUT_SOUTH	51.0%	32.3%	16.8%	18.6%	8.1%	16.3%	15.3%

Relative differences	IN_CENTER	IN_WEST	IN_EAST	IN_SOUTH	OUT_WEST	OUT_EAST	OUT_SOUTH
IN_CENTER	-3.2%	1.5%	-4.3%	-5.8%	6.1%	-5.0%	-9.8%
IN_WEST	-0.8%	-2.9%	2.7%	-6.0%	-3.8%	-17.5%	-26.8%
IN_EAST	-0.8%	-11.4%	-0.9%	-1.7%	18.3%	-16.3%	-4.0%
IN_SOUTH	-3.3%	-12.7%	-2.9%	-3.6%	5.9%	-11.0%	-4.9%
OUT_WEST	-0.5%	5.3%	13.2%	12.2%	-5.9%	-8.5%	-3.4%
OUT_EAST	-3.2%	-20.1%	-9.5%	-6.4%	-6.0%	-6.0%	-8.2%
OUT_SOUTH	-6.6%	-9.9%	1.9%	-0.1%	127.0%	-0.8%	-8.1%

Figure 5.5: Predicted (upper left) and observed (upper right) market shares for Public transport and relative deviation (bottom). The color coding follows the share percentages with dark green representing the highest value and dark red the lowest value.

Overall, we see that the neural network model captures well the overall pattern in markets shares across OD-pairs. It captures, for instance that, Public Transport is more popular in the south corridor compared to the west corridor.

5.3 Sensitivity analysis and derived elasticity parameters for LoS data

In this section, we perform sensitivity analysis by manipulating the input data and applying it on the trained neural networks. In particular, we increase the Level-of-service variables by 10% in the following 6 sensitivity tests:

- Car travel time
- Road toll
- PT in-vehicle time
- PT access time
- PT waiting time
- PT ticket prices (both single tickets and seasonal tickers)

We can then derive the value of *elasticity of demand* (relative change in demand of given mode/ relative change in LoS) from the average changes in the probability for different travel models. As all LoS are costs for the user we expect own elasticities (the demand effect relates to the change of LoS of the same mode) to be negative and cross-elasticities to be positive (the demand effects relates to the change of LoS of another transport mode.

Our initial tests revealed that the results (the size of the derived elasticity parameter) depend strongly on the model version. From the models from section 5.1 with the whole set of LoS variables (S15, S16, S17 and S-all) we summaries the main results (elasticity with respect to car and PT) in Table 5.4.

Table 5.4: Elasticity derived from different sensitivity tests on different neural networks (own elasticity values color coded; green: expected result, orange: unexpected result.

Sensitivity test	Modell S15 (only LoS)		Modell S16		Modell S17		Modell S-all	
	Elast. Car	Elast. PT	Elast. Car	Elast. PT	Elast. Car	Elast. PT	Elast. Car	Elast. PT
Car travel time	-0.234	0.479	-0.06	0.327	-0.039	0.21	-0.004	0.166
Road toll	0.124	-0.28	-0.059	0.14	-0.038	0.089	-0.022	0.058
PT invehicle	0.194	-0.302	0.171	-0.226	0.105	-0.116	0.092	-0.098
PT access time	0.286	-0.32	0.135	-0.15	0.084	-0.079	0.061	-0.042
PT waiting time	0.11	-0.208	0.051	-0.104	0.031	-0.06	0.021	-0.043
PT ticket prices	0.341	-0.364	0.23	-0.129	0.136	-0.039	0.101	0.03

From Table 5.4, we see that elasticity values decrease with larger models (going from S15, to S-all). This likely relates to that the neural network puts less weight in LoS-variables when the input factor includes other variables (like work distance) that are correlated with LoS. Modell S15 yields elasticity parameters that seem most consistent with the literature while M16 yields in general low – and S17 and S-all very low – values. However, S15 gives the “wrong” size for the sensitivity analysis where road tolls are increased. Note that road tolls are sparsely distributed in the training data such that the neural network will have a hard time to predict that will happen with marginal changes in that attribute.

While model S16, S17 and S-all give correct sign of elasticities (own- and cross-elasticities) for the two main mode of transport (car and PT), some of the cross-elasticities with respect to Walk, Bike and Others got wrong size (Table 5.5).

Table 5.5: Own- and cross-elasticities for sensitivity tests with model S-all.

	Elast. car Total	Elast. public transport	Elast. bike	Elast. walk	Elast. other
Car travel time	-0.004	0.166	-0.071	-0.285	-0.006
Road toll	-0.022	0.058	0.009	-0.029	-0.008
PT invehicle	0.092	-0.098	-0.112	-0.13	0.002
PT access time	0.061	-0.042	-0.016	-0.154	0.021
PT waiting time	0.021	-0.043	0.018	-0.004	0.018
PT ticket prices	0.101	0.03	-0.14	-0.403	-0.032

In the reminder of this section, we take a closer look at scenario where we alter the waiting time in public transport. The own elasticity based on model “S-all” was derived as -0.043 (compare Table 5.5). This is the overall elasticity for the whole area covered by Ruter-MIS.

It is important to note that there is variation in the elasticity across different sub-markets. Table 5.6 shows derived elasticity values on a OD level.

Table 5.6: Derived own elasticity of demand of changes in waiting time for public transport (model: S-all).

Own elasticity	IN_CENTER	IN_WEST	IN_EAST	IN_SOUTH	OUT_WEST	OUT_EAST	OUT_SOUTH
IN_CENTER	-0.012	-0.034	-0.029	-0.029	-0.042	-0.062	-0.082
IN_WEST	-0.037	-0.037	-0.079	-0.086	-0.122	-0.101	-0.153
IN_EAST	-0.020	-0.053	-0.020	-0.048	-0.075	-0.092	-0.108
IN_SOUTH	-0.025	-0.086	-0.069	-0.027	-0.120	-0.159	-0.161
OUT_WEST	-0.043	-0.115	-0.130	-0.114	-0.045	-0.115	-0.221
OUT_EAST	-0.068	-0.141	-0.188	-0.103	-0.108	-0.085	-0.180
OUT_SOUTH	-0.049	-0.113	-0.126	-0.134	-0.131	-0.095	-0.069

From Tabell 5-5, we see that elasticities for waiting time differ between -0.012 (In_Center to In_Center) to -0.221 (Out_West to Out_South). The latter is close to a factor 20 higher than the former. That the lowest value is observed within Oslo city center (Ring 3), can be expected as waiting time is not that high of a burden within Ring 3 as services have a rather high frequency. On other relations, where waiting times are high already, one would expect higher changes, also in relative terms.

Overall, the pattern in elasticity for waiting time seems reasonable, but the absolute values are rather on the lower side of what would be expected.

5.4 Market share prediction of trips from home to work on the population level

In this section, we apply the trained neural networks from section 5.1 to our generated synthetic population. Note however that the population used for this analysis is the version established in 2022 (Flügel et 2022) that have minor difference to the latest version described in in section 4.5..

As the neural networks model in this chapter only predict travel mode choice, we can apply the model only to trips where we know the origin and destination. Only in this cases we can extract the LoS variables as defined in these modes. Challenges related to applying LoS in activity-based demand models are discussed further in chapter 7.

From the population synthesis, we have BSU ("grunnkrets") for home (all agents) and for the work place (for those agents that are working). We can assign LoS-variables for all agents that do work. There are two sets of LoS, one for rush and one for non-rush.

In the following, we predict travel mode choice for the (direct) trip from home to work in (morning) rush for all agents that have a home and work place (N=783063). We use model version S17 for this purpose and set all variables related to the previous trip to "missing value".

Figure 5.6 illustrates the predicted probabilities for Car Driver and Public Transport by home and work region.

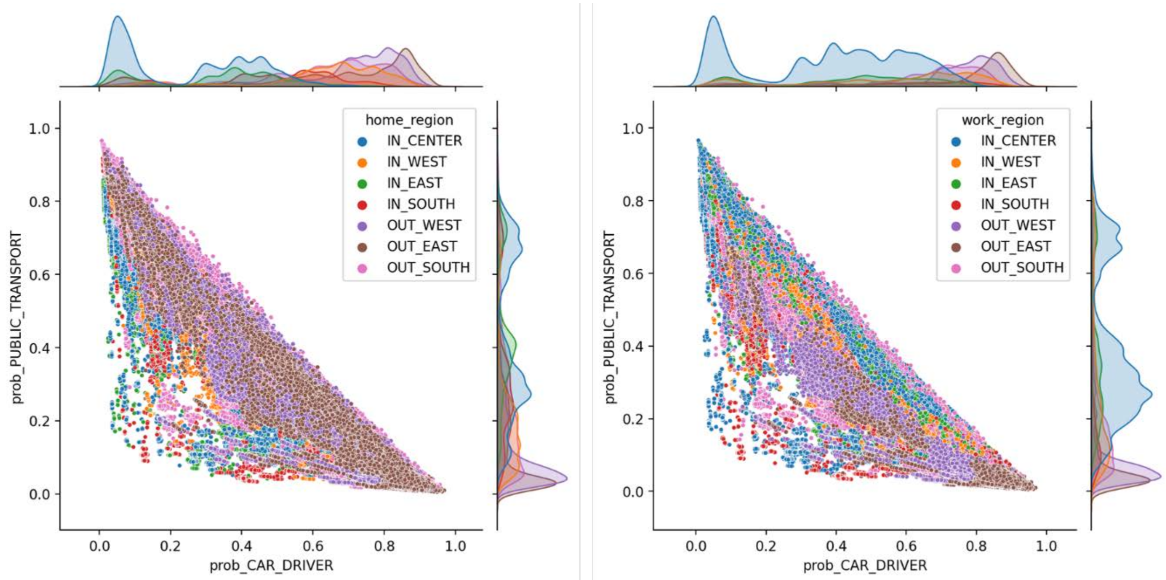


Figure 5.6: Predicted probability of Car Driver and Public transport by home region (left panel) and work region (right panel). Each point is an (working) agent in the population.

We clearly see that the outer-regions, in particular “Out_West” and “Out_East” have lowe probabilities for public transport, while the best probabilities for public transport for those relations with work place in Inner city center (“In_Center”).

Comparing the marginal distribution for the probability of Car Driver, we see a asymmetric patters. People living in “In_Center” have a lower probability for Car Driver compared to people that work in “In_Center”. This relates to the differences in car access.

The effect of car access is also illustrated in Figure 5.7 that shows the relative probability of public transport relative to car on the y-axis and the relative travel time (access, waiting and invehicle time) in public transport relative to travel time by car on the x-axis. Note that the scales are in logs and that 10^0 equals 1 (meaning 50%-50% chances). We see that the public transport options is slower (“RelTime_PR>1”) for almost all OD-pairs (the ones on the left are presumable relations from Nesoddtangen to Oslo city center).

We see a negative correlation between the relative probability of PT and the relative travel time. More than differences in travel time, however, it seems that the relative probability of PT is largely explained by car access.

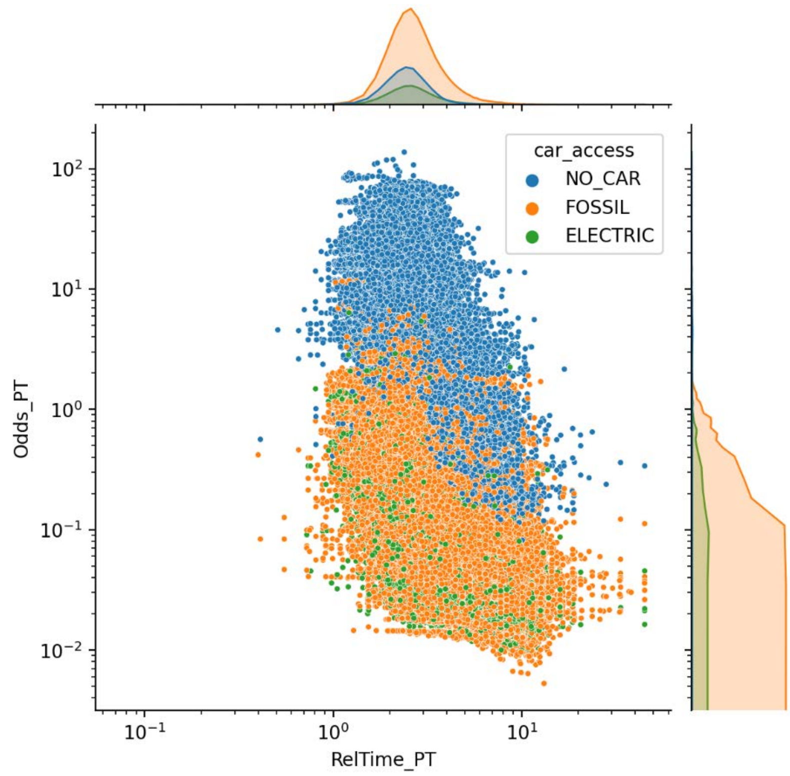


Figure 5.7: Relative probability (odds) of PT as a function of relative travel time of PT compared to time by car Colors indicate car access.

Figure 5.8 to Figure 5.10 show the predicted market for public transport shares on a map for respectively trip below 5 km, between 5-25 km and over 25km.

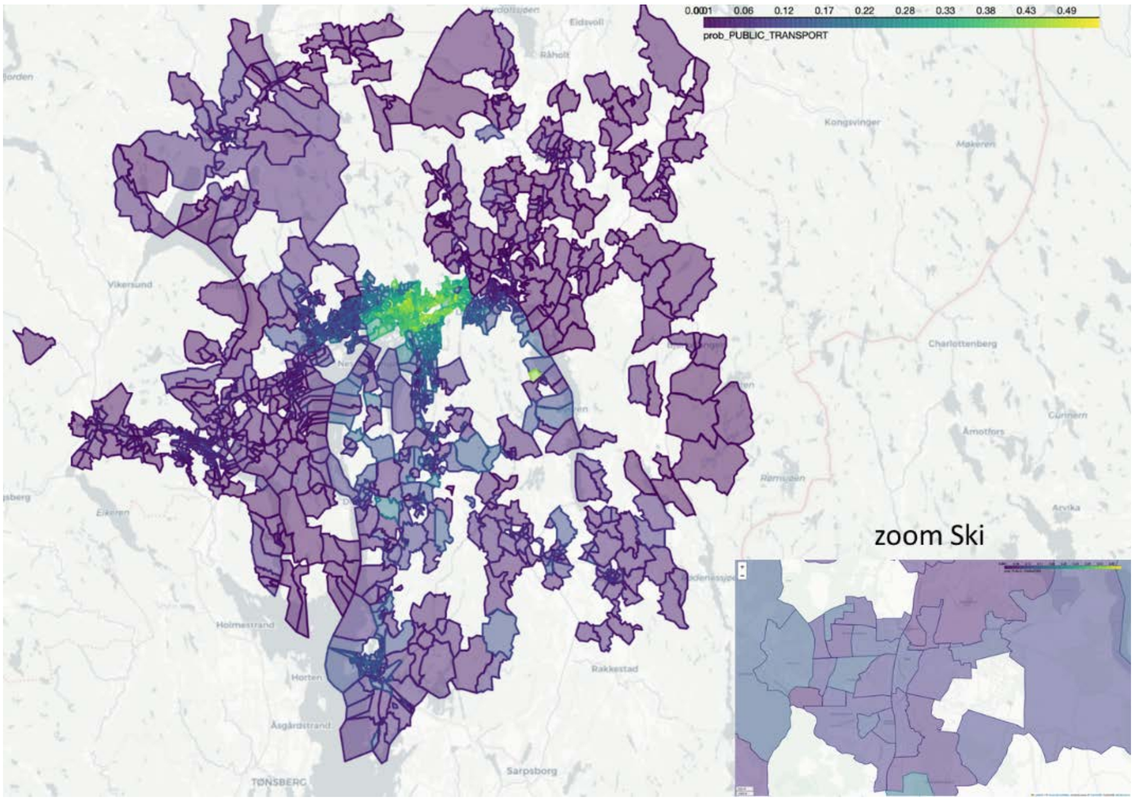


Figure 5.8: Predicted market shares for public transport by home BSU for trip from home to work of under 5 km.

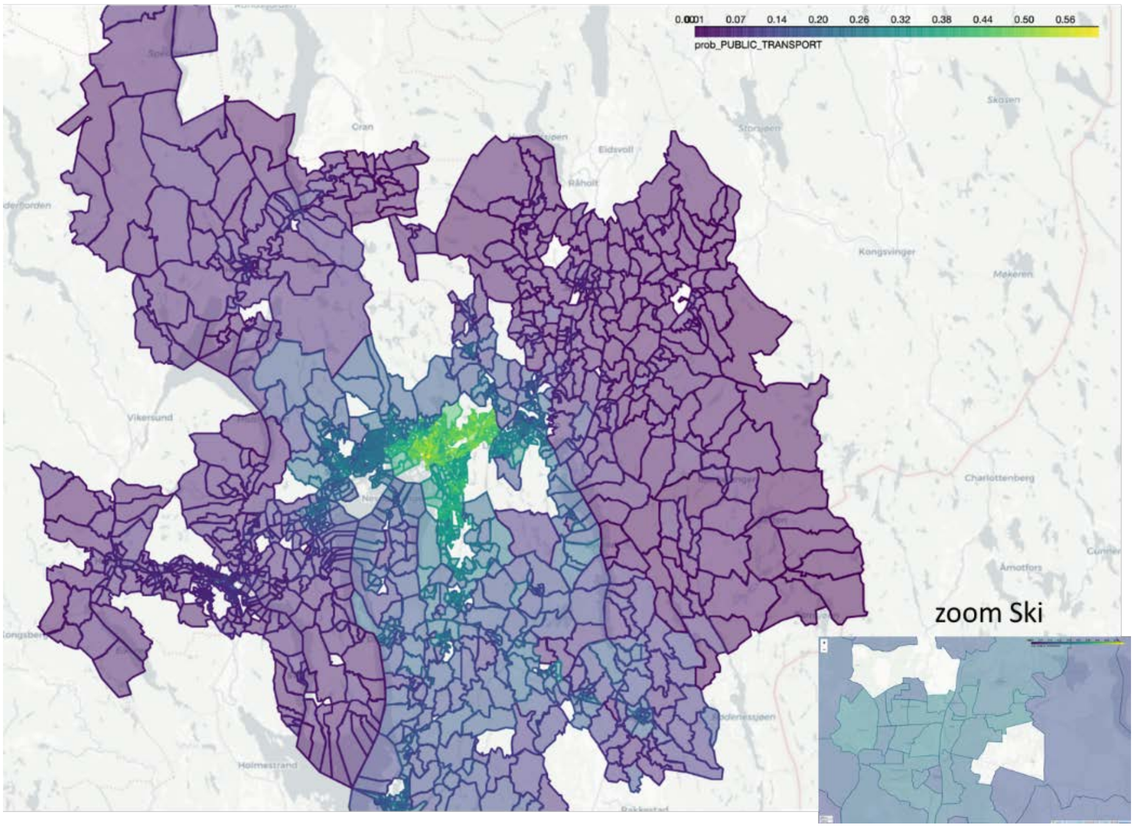


Figure 5.9: Predicted market shares for public transport by home BSU for trip from home to work of between 5 and 25 km.

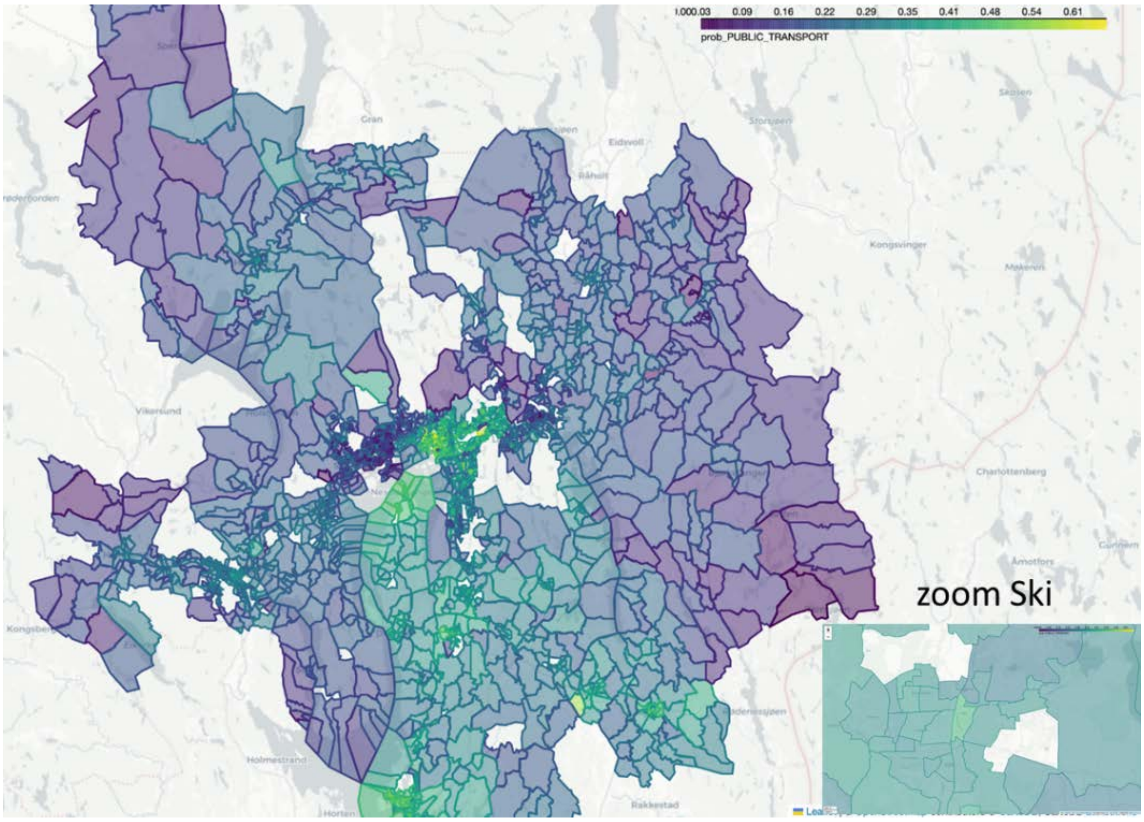


Figure 5.10: Predicted market shares for public transport by home BSU for trip from home to work of over 25 km.

We can see that markets shares for public transport are greatest in Oslo City center, at Nesoddtangen and along the railway lines (in case of trip over 25 km). Looking closer on the BSU in Ski, we can see that the market share for PT (in this case train) is highest in the BSU around the train station of Ski (see right-lower panel in Figure 5.10).

6 Additional topic 2: Effects of covid and working remotely

In this chapter, we return to the prediction of all-day activity plans where travel mode choice is one of several predicted output variables. In contrast to the empirical analysis in Chapter 5, this includes data January 2017 to September 2024 and the two neural networks (mode 1 and model 2) presented in Chapter 4. In this chapter, we take a closer look at the covid variables “infection worried” and “lock-down stringency index” as well as “working remotely”. This is motivated by the specific goal within the CAPSLOCK project is to be able to model behavior before, during and after the COVID pandemic.

6.1 The models ability to predict the travel patterns before, during and after Covid in the validation data

Figure 6.1 shows actual and predicted shares of "no trips" (i.e. a “0” for the variable Number of Trips) from January 2017 to September 2024. The plot is based on average monthly data.

There is a clear seasonal effect in the June month which is common holiday period in Norway, which seems well captured by model 1. We also see a clear increase in the share of people not leaving home in the covid period (February 2020- February 2022). Note also that the date itself is not a input in the model and has itself not explanatory power.

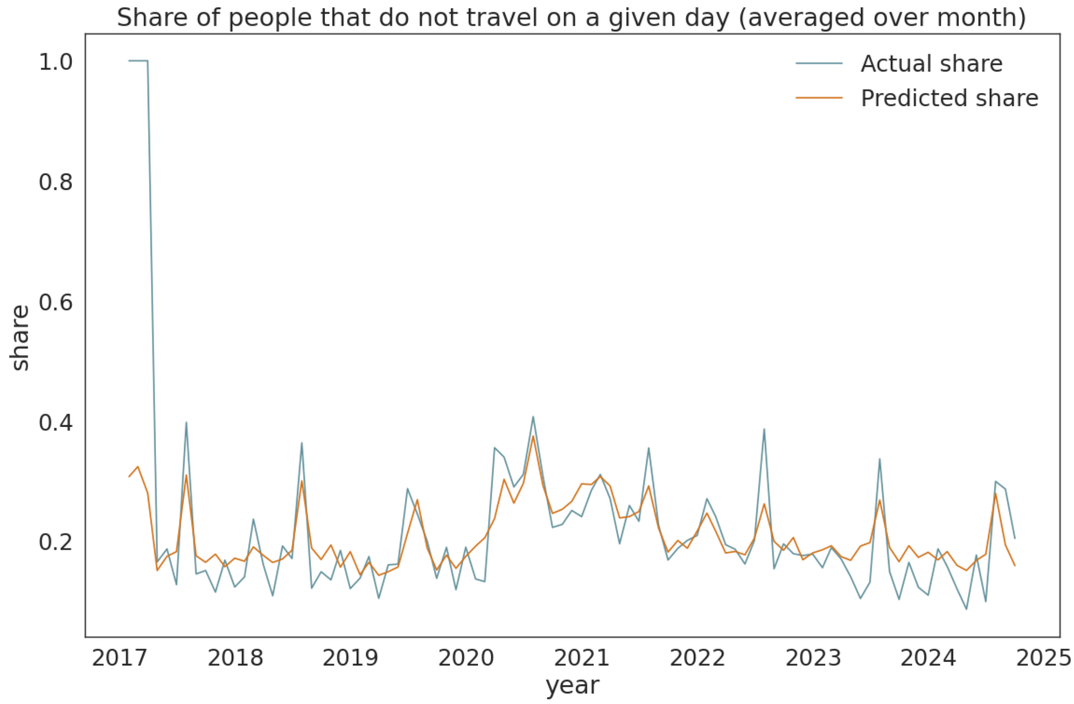


Figure 6.1: Actual and predicted shares of "no trips" on a given weekday over time as predicted by model 1 on the validation data.

As pointed on in section 3.2, we only have persons without trips in the first weeks of January. For those respondents the model is not able to assign the correct probability. In general, we see that variance over time in the predicted outcome is lower than the actual variance in the validation data. This illustrates that neural networks, besides being more flexible still do “average out” to some degree (however to a lower degree as in classical regression models).

Figure 6.2 gives a similar plot but for “no work trip”. Comparing the blue and orange plots, we see again a good correspondence between actual and predicted shares. Besides the tops in the June-month, we see three tops within the COVID period. As shown by a secondary axis in the figure, this corresponds with the three lockdown periods, i.e. spring 2020 (initial lockdown), winter 2020/2021 (lockdown prior to first vaccination campaign) and November/December 2021 (short “omicron-lockdown”).

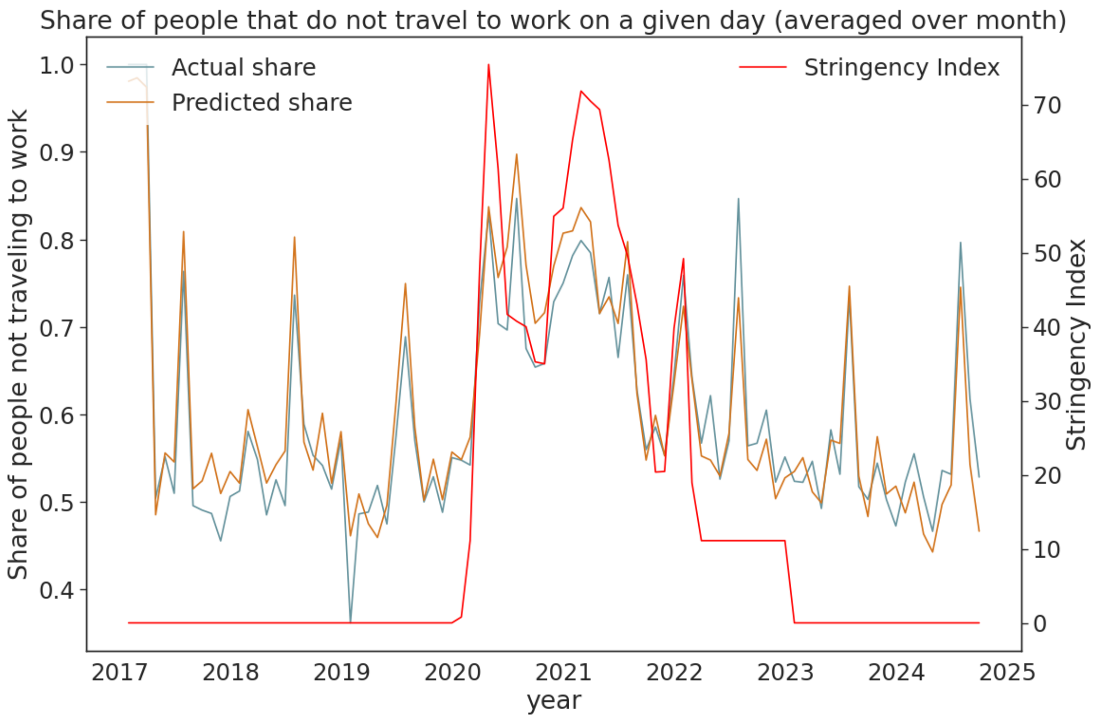


Figure 6.2: Actual and predicted shares of "no trips" on a given weekday over time as predicted by model 1 on the validation data; secondary axis shows stringency index.

Turning to some results on a trip level (model 2), Figure 6.3 gives the share of trips per month being done by public transport. As we can see, model 2 is capturing the sharp drop at the beginning of the pandemic fine. It also correctly predict the recovery of market share for public transport in 2022 and 2023.

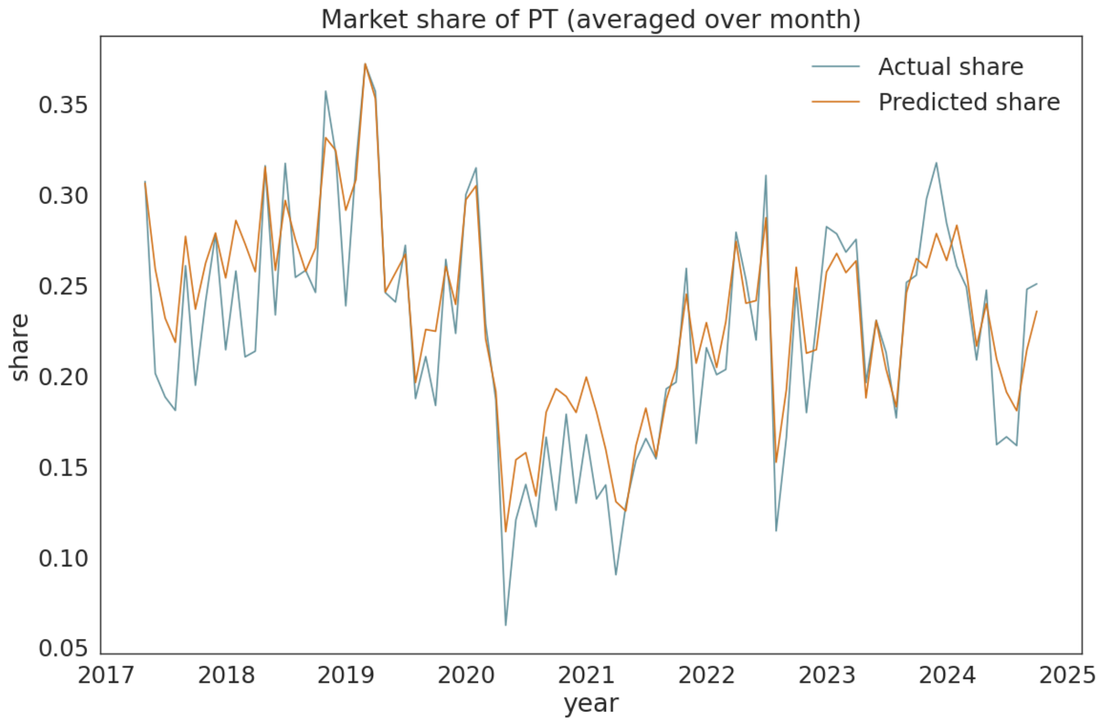


Figure 6.3: Actual and predicted market share of public transport over time as predicted by model 2 on the validation data.

Figure 6.4 shows share for trips ending in Oslo city center (within Ring 3) over time. The connection with the COVID pandemic is somewhat unclear. In any case, model 2 seems to make a decent job in getting the correct time trend in the actual shares.

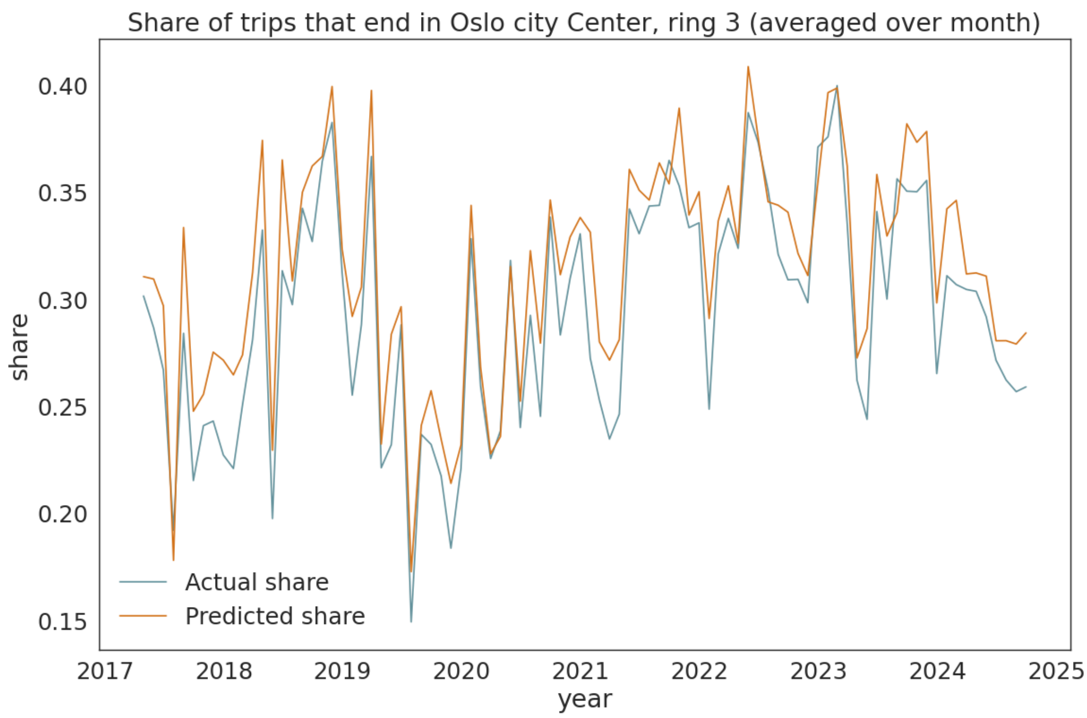


Figure 6.4: Actual and predicted market share of trips ending in Oslo City center over time as predicted by model 2 on the validation data.

6.2 The effects of the “covid variables”

Let’s take a look at the effect of the person’s subjective worry about getting infected and the lock-down stringency index. The former variable is reported in Ruter-MIS on an individual level, while the other variable is attached to observations in Ruter-MIS given the date of the interview and the external data described in section 3.3.

Figure 6.5 shows how the predicted average probability of not having a trip depends on the infection worried variable (controlled for age). We see that in each age group, the probability of not travelling increases with the worried of getting infected. Note that this variables not available (set to “undefined”) for observation before and after the covid period. In this periods the propensity to not travel is generally lower (as also seen from Figure 6.1).

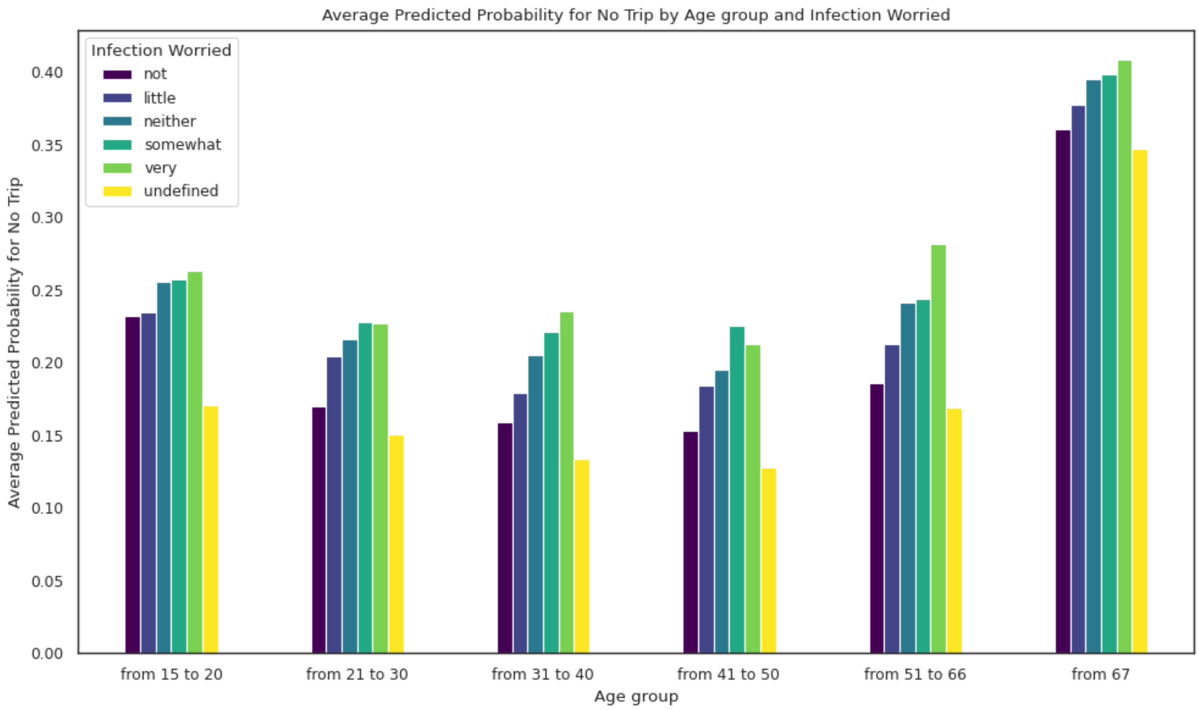


Figure 6.5: Predicted share of persons doing no trip on a given weekday by age group and infection worried (model 1).

Figure 6.6 shows a similar figure but on the y-axis we now have the (average) probability to choose Public Transport (PT), based on model 2. We generally see, that younger persons are more likely to take PT and that the effect of infection worried I somewhat more unclear, compared to older persons where there seems to be a trend that higher worries give less use of PT.

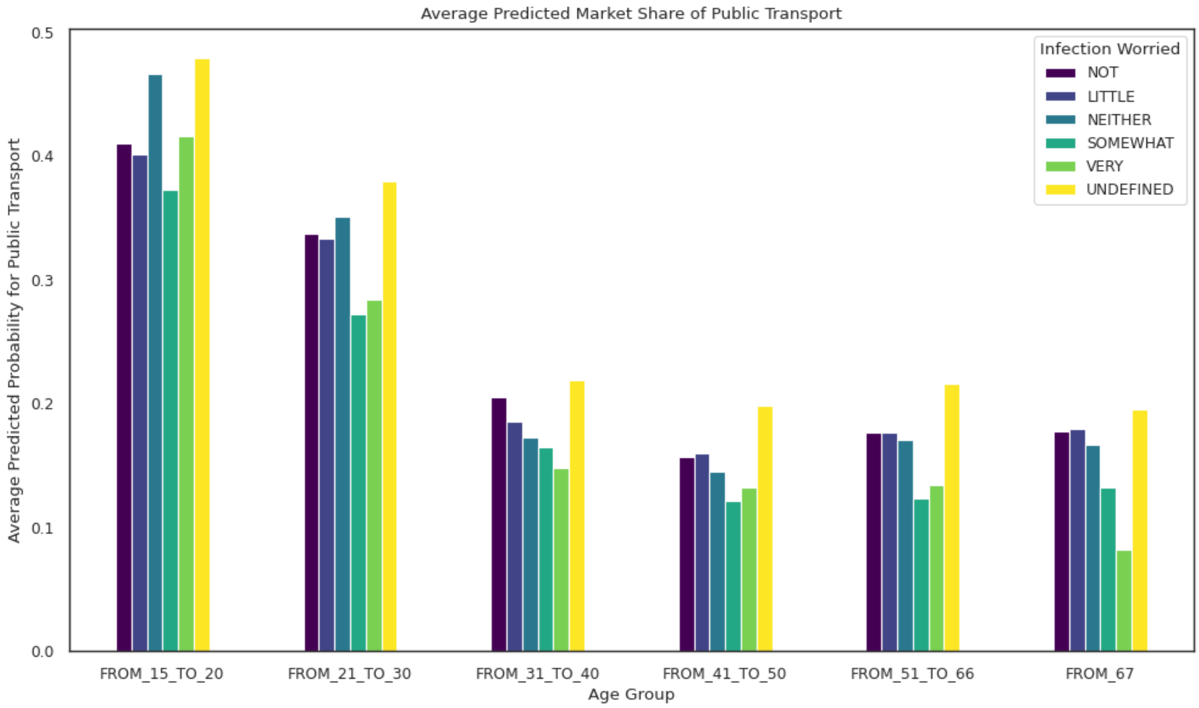


Figure 6.6: Predicted share of trips being done by public transport by age group and infection worried (model 2).

Figure 6.7 and Figure 6.8 give corresponding figures, only that age group is replaced by buckets for the stringency index. We see a clear effect of the stringency index at least for the bucket.

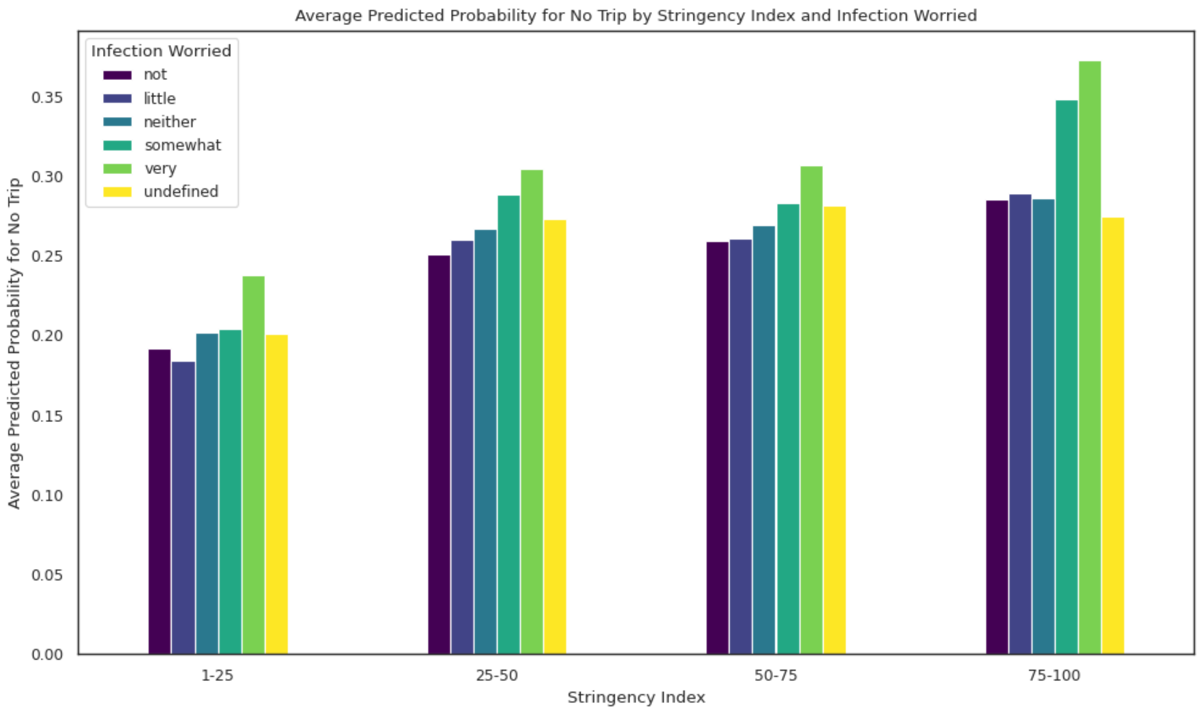


Figure 6.7: Predicted share of persons doing no trip on a given weekday by buckets of stringency index and infection worried (model 1).

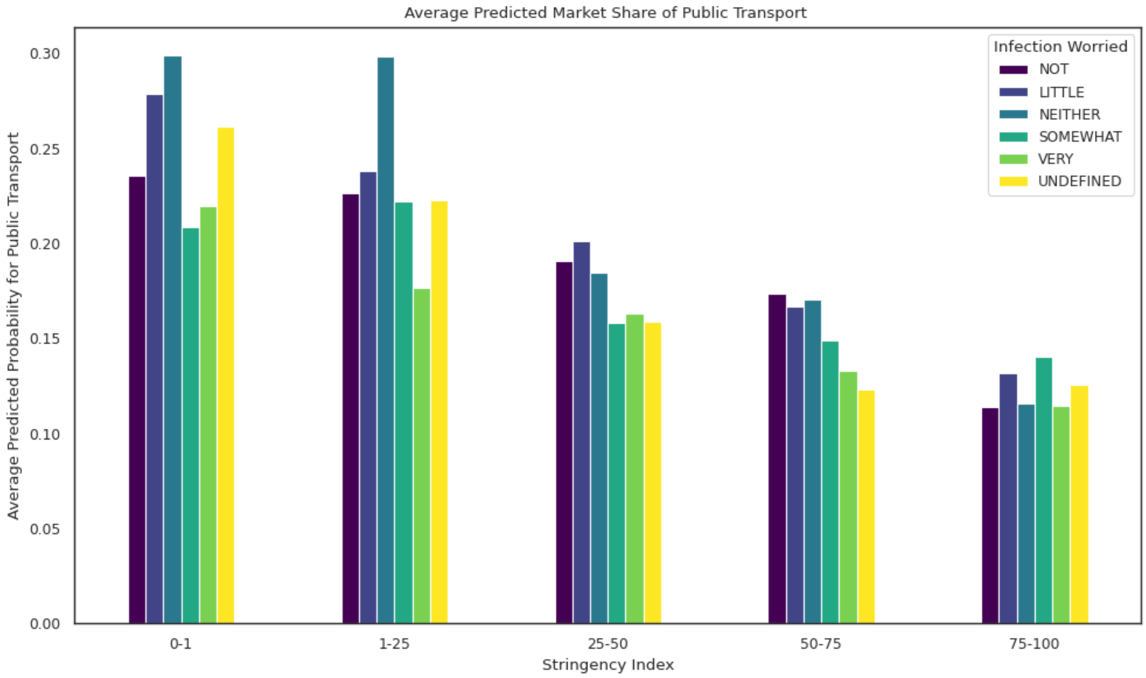


Figure 6.8: Predicted share trips being done by public transport by buckets of stringency index and infection worried (model 2).

6.3 The effect of the home-office

Lastly, we take a look at the effect of home office (variable "work_remote_currently"). The propensity to not have a trip at all is expectedly affected by the extent (days per week) of use of home-office. This is shown in Figure 6.9, which also shows some variability with respect to the variable infection worried.

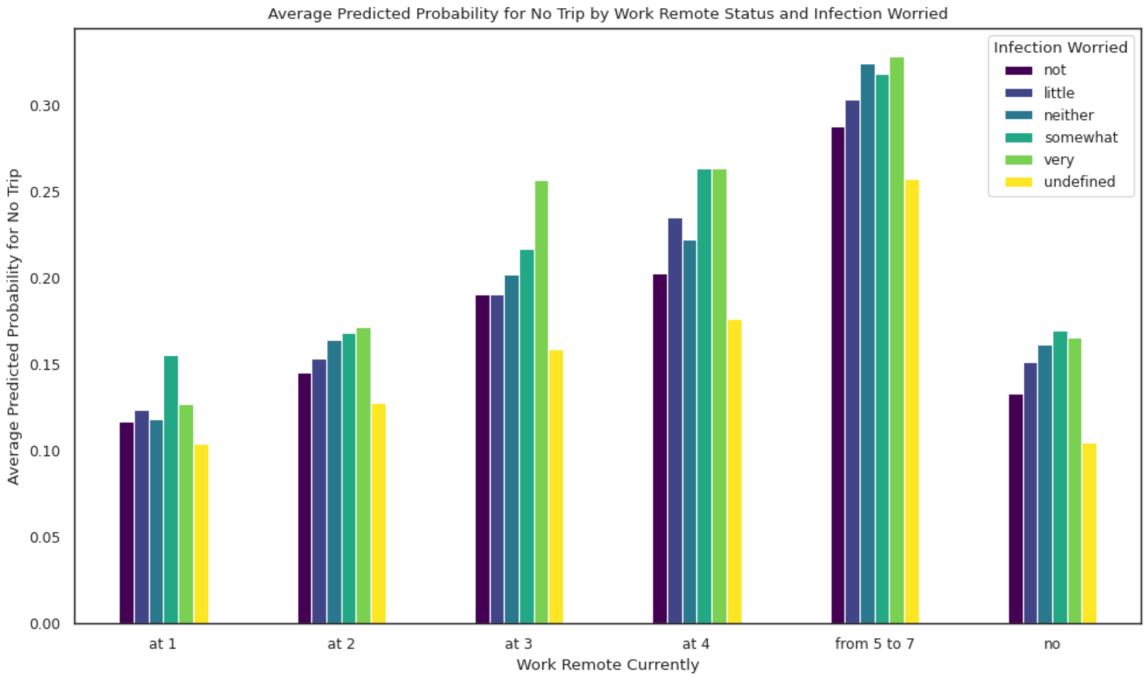


Figure 6.9: Predicted share of persons doing no trip on a given weekday by extent of working remotely infection worried (model 1). Observations with work_remote_currently == UNDEFINED are excluded. AT_X means that respondent has X day per week in home office.

We can also look at the distribution of some individual probabilities. Figure 6.10 plots the probabilities of “no work trip” and “only work trip”. The latter meaning that the main activity sequence is “home-work-home”, i.e. straight to work and home without stops in between. Note that the colour codes in this figure is related to the amount of days (in the current week) of working from home, and that values “undefined” (largely observation prior to covid) are not included. From the figure we see a clear effect of the amount of home office, and the model assigned largely high probability (between 80-100%) for “no work trip” for respondents that work 5+ days a week from home. Logically, probabilities for ”straight to work and back” are low for this group.

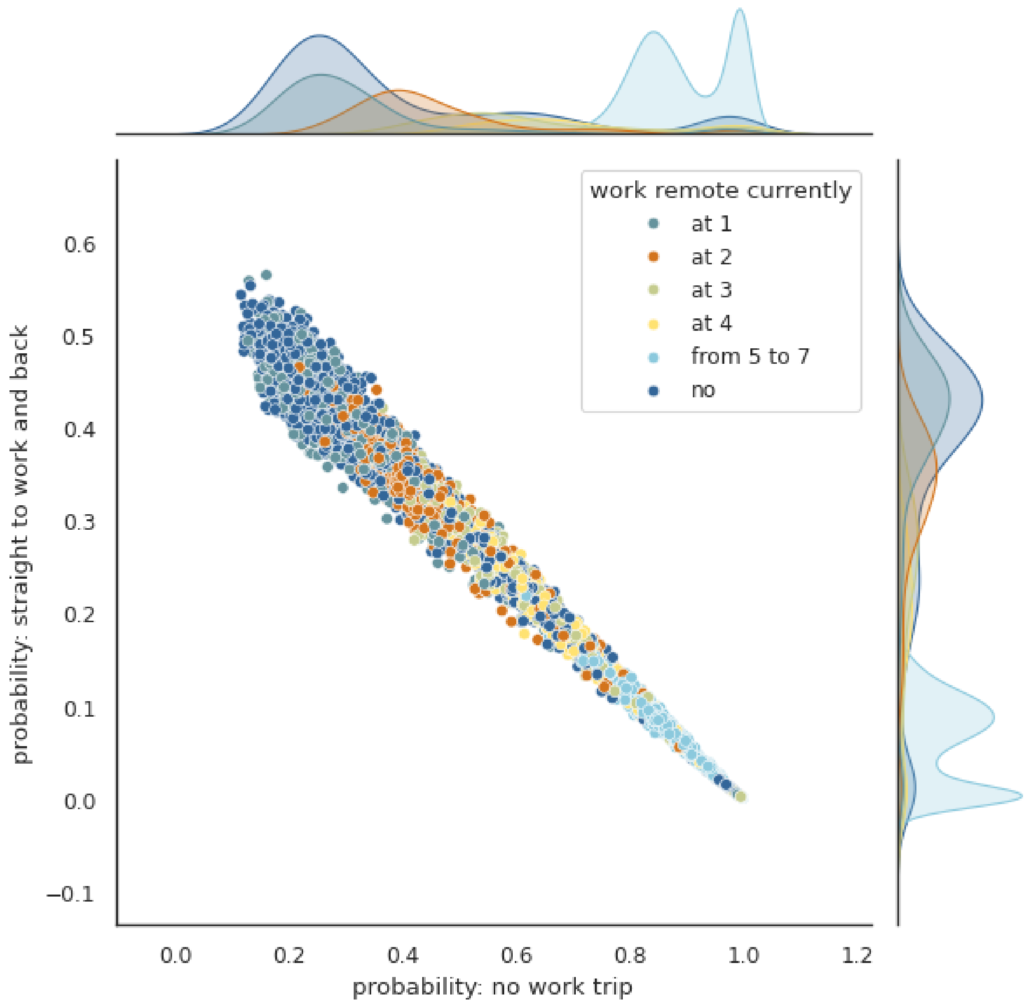


Figure 6.10: Joint plot between the probability of going straight to work and home (home-work-home sequence) an no work trip with in variable "work trip sequence". Color indicate current status of home office. Observations with work_remote_currently == UNDEFINED are excluded.

Figure 6.11 below is similar to Figure 6.10, but has the probability of “no trip at all” on the Y-axis. Not surprisingly, we a positive correlation here. Not that none of the individual probability gives a higher value for “no work trip” than for “no trip at all”; this is reassuring. As for the previous figure, we also see a clear effect of working remotely as indicated by the colors of the points.

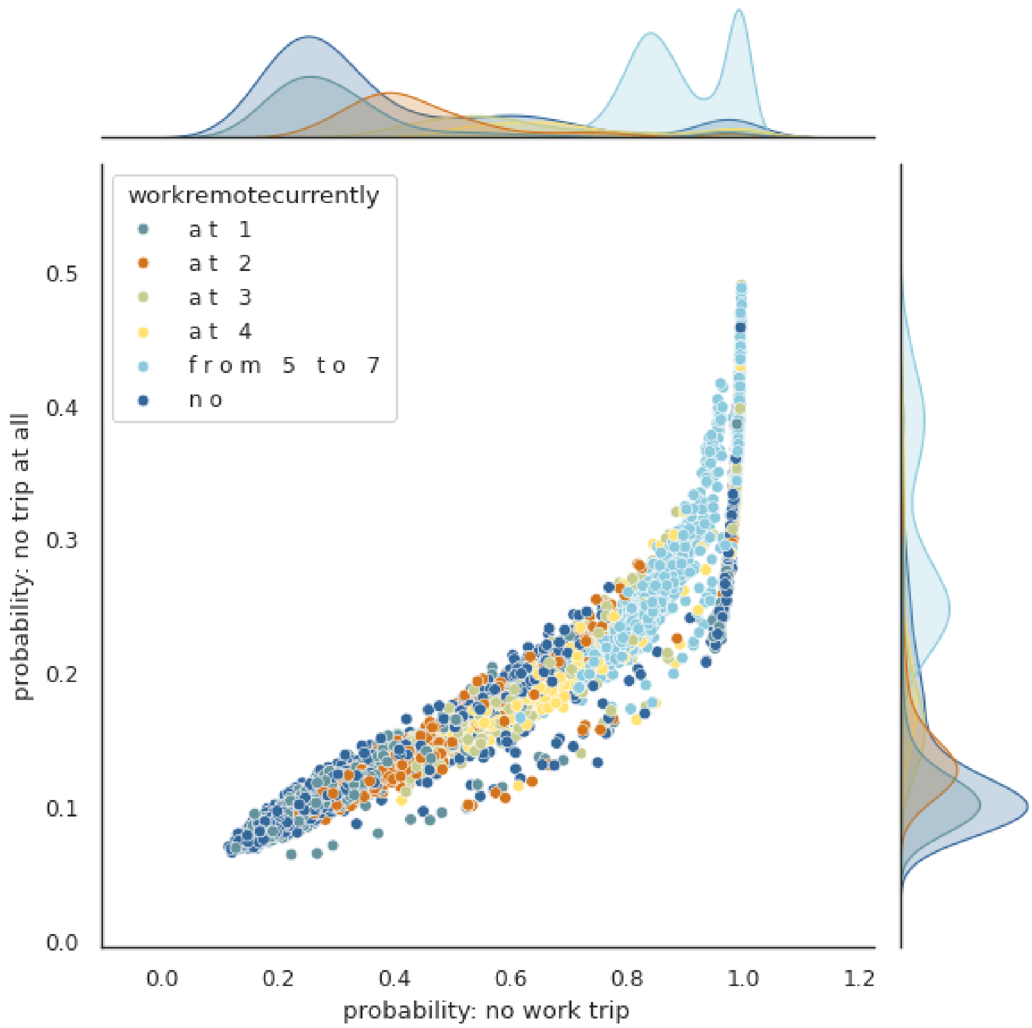


Figure 6.11: Joint plot of predicted probabilities for "not trip" and "no work trip" (model 1) by extent of home office in the current week. Observations with work_remote_currently == UNDEFINED are excluded.

7 Discussion and further work

7.1 Discussion

In this report, we documented a method and some first results of a generation of synthetic trip diaries / activity plans given agent characteristics and geographical home-work relation with a machine learning approach using neural networks. Our machine learning modelling approach was trained on travel survey data from Ruter-MIS covering the Greater Oslo area and predicts first overall characteristics of activity plans (as the number of trips) and then characteristics of trips in an autoregressive way where the characteristics of the previous trips enter the prediction of the next trip. Overall the models seem capable to capture correlations pattern between different input and output variables resulting in plausible activity plans and overall statistics.

An overview, discussion and motivation for the methodological is provided in chapter 2.

Despite several weaknesses (see next section), we believe our approach is an important step towards new and improved transport models in cities as discussed in Flügel et al (2021), Flügel et al (2023) and Kristensen et al (2024). The clock-time dimension (the prediction of departure times and activity duration) makes our resulting data compatible with dynamic transport models and the microscopic data structure enables agent-based modelling in downstream applications. The agent-based transport simulation model MATSim was described as one of this potential downstream applications. The resulting data might also be interesting for other applications where one needs spatial-temporal information about the location and movements of all citizens over the course of a weekday. This information makes our data also interesting for simulation models outside of transportation domain (e.g. simulating spreading of viruses).

We consider our approach not to be a full activity-based demand model in the traditional sense and mechanism of travel demand should be handled endogenously in the downstream application. The sensitive of behavioral dimension (such as travel mode choice and departure time) for changes in travel costs (congestion and Level-of-Service) is not included in our model, at least not on a trip-level. Level of Service variables enter only on a home-work relation in our neural network model. Behavioral adjustments on a trip level are in our overall approach handled in the downstream MATSim model.

While our approach of adding synthetic activity plans to agents is applicable on future populations (e.g. synthetic populations established for year 2030 or 2050), the use of our approach for long-term predictions rests on the assumption that behavioral patterns trained based on 2017-2024 data remain valid and that input data can be generated that is represented for the future. In this connection, we should repeat that we do not predict destination choice for trips to work and use commuting statistics based on register-data instead. Commuting statistics can in our approach be replaced by projected/predicted home-work relations. Such data could be predicted by external land use models.

Considering future state-of-the-art transport models in (Norwegian) cities, we believe that our approach could be an import link between agent-based land use models (that predict long-term behavior and location choices) and agent-based transport simulation models (predicting detailed behavioral adjustments given network conditions).

7.2 Known weaknesses and further research

In this last section of the report, we list some known weaknesses and ways to improve upon in later versions/iteration of the approach.

- The zonal systems (aggregations of BSU) is coarse, which makes prediction of destination of non-work trips imprecise. As a consequence, the random selection of coordinates within zones prior to MATSim may lead to some illogical destination and too long trips).
    - In upcoming versions, we should test one or several of the following:
        - Predicting travel distance as an output variables and base the sampling of coordinates on those predictions.
        - Introduce selection of coordinates conditioned on the geography of home and work relation (for which we know the BSU), e.g. that a shopping activity should with greater likelihood be at a location "between" home and work
        - Included a model that samples BSU for trips (besides those that go home and to work) with an additional model that considers zonal data
            - E.g. visiting trips should go to BSU in proportion to number of inhabitants in the BSU; picking-up trips should relate to the number of kindergarten and elementary schools etc.
- The population synthesis can be improved, both in terms of data input and method.
    - We should consider using data from microdata.no to get information about correlation of agent characteristics (unfortunately, in its current form, microdata.no does not offer a detailed geographical segmentation of the data).
    - We should consider using machine learning /generative AI also for the establishment of agents characteristics (not just the activity plans)
    - Some agent characteristics such as household type, education and income would be nice to include. The possibility for this dependent on the availability in the training data (e.g. income is not reported in Ruter-MIS).
- Even though much improved compared to 2022-version, our current models still generates to many trip in the afternoon. This may be caused by the successive "trip-for-trip" prediction that may still "press" additional trips into the trip diary the end of a day. Changes to the model architecture possible utilizing recurring neural networks (RNN) are attention based models might therefore be tested out.
- Validation of the synthetic activity plans is not obvious given a lack of external data sources on a population level. Extensive mobile data (which we do not have access to) might be best method for temporal-spatial distributions pattern, but would not have given us information about trip purpose / activity types. After the activity plans have been input into MATSim we can compare the resulting simulated traffic with traffic count data. This was done with the original generated approach (Flügel et al 2022) but was not been done latest version.
- Our current implementation (back-end code) is via a bunch of python files and notebook and is not very user-friendly. In 2025, we plan to work on a user-interface (front-end) that effortless connects with the back-end. Improved functionality and flexibility via the front-end program will make scenario testing more straightforward.

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Appendix A: Technical model summary of neural network models

```
____________________________________________________________________________________________
 Layer (type)                Output Shape                 Param #   Connected to
============================================================================================
 input (InputLayer)          [(None, 64)]                 0         []

 dense_1 (Dense)             (None, 180)                  11700     ['input[0][0]']

 dense_2 (Dense)             (None, 90)                   16290     ['dense_1[0][0]']

 time_of_first_trip_cat_nac  (None, 11)                   1001      ['dense_2[0][0]']
 at (Dense)

 time_of_last_trip_cat_naca  (None, 11)                   1001      ['dense_2[0][0]']
 t (Dense)

 trip_count_cat (Dense)      (None, 7)                    637       ['dense_2[0][0]']

 work_trip_cat (Dense)       (None, 5)                    455       ['dense_2[0][0]']

============================================================================================
Total params: 31084 (121.42 KB)
Trainable params: 31084 (121.42 KB)
Non-trainable params: 0 (0.00 Byte)
```

Figure A-0.1: Model summary of model 1.

```
____________________________________________________________________________________________
 Layer (type)                Output Shape                 Param #   Connected to
============================================================================================
 input (InputLayer)          [(None, 131)]                0         []

 dense_1 (Dense)             (None, 180)                  23760     ['input[0][0]']

 dense_2 (Dense)             (None, 90)                   16290     ['dense_1[0][0]']

 travel_mode (Dense)         (None, 7)                    637       ['dense_2[0][0]']

 purpose (Dense)             (None, 10)                   910       ['dense_2[0][0]']

 end_zone (Dense)            (None, 9)                    819       ['dense_2[0][0]']

 time_since_prev_cat (Dense  (None, 15)                   1365      ['dense_2[0][0]']
 )

============================================================================================
Total params: 43781 (171.02 KB)
Trainable params: 43781 (171.02 KB)
Non-trainable params: 0 (0.00 Byte)
____________________________________________________________________________________________
```

Figure A-0.2: Model summary of model 2.

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