# Chapter 5. Discussion

## 5.1 Evaluation of research objectives

### 5.1.1 Main research question: Can we effectively classify trip purpose?

Overall, the classifiers struggled with comprehensive predictions across the unique trip-purpose classes within from the 2017 MTL Trajet. We do find that the models were quite effective in the classification of trips for the purposes of *work* and *returning home*, so we can infer to some extent about the types of urban movement patterns that these classes exhibit. Indeed, trips detailing both these classes were found to be very regular in both space and time.

The models struggled with the classification of shopping and leisure activities, something also found within the literature (Attard *et al.*, 2016). One factor for this, may simply be that a multi-class classification model is not an effective strategy for studying trip purpose of such heterogeneity. For example, we do not separate purposes that are time invariant and time variant and this may have been very problematic for the classifiers.

Instead a better strategy may have been to create broad categorisation for some of the trip purposes and individualised for other models. Indeed, it is likely that the space-time controls on each of these purposes will be vastly different and ignoring this may have led to a degree of omitted variable bias (OVB).

Correspondingly, we omit spatial cluster labels, city vs non-city and rush hour for the classification. These may be more important in the prediction for certain trip purpose. For example, it is likely that a completely different set of dynamics govern *how* and *why* people travel within the suburbs of Montreal vs downtown i.e. people being able to walk to shops downtown versus having to drive in the suburbs. Notably in 4.1.4, a greater proportion of leisure, shops and café trips are outside of rush hour and the city.

Moreover the discovery of effective classification in *work* and *home* trips is not something that serves as a new insight in mobility research as we expect to be able to characterise these (Meng *et al.*, 2019). Further, this trend may simply be a function of these trip purposes being the predominant class within the data set.

We also make an argument that the study area itself is unfeasible for effective classification as we see indications of both spatial and temporal non-stationarity across the study region and study period. This make the modelling procedure somewhat redundant, and may be an explanation as to why we see more errored trips in the suburbs of Montreal and towards the latter part of the study period (**Figure 4.28+29**).

### 5.2.2 Sub-Question: Which indicators were the most useful?

Broadly from the results of the analyses we do not overwhelmingly find one primary indicator for trip-purpose, although temporal clusters are found to be most important determined by *feature importance*. Notably, these highlighted temporal dependencies in the various purpose classes and were broadly found to be more important in the classifier performance of time-invariant trip purpose classes (*work*, *education*).

Direction and magnitude of direction (4.1.3) were also discovered to be an important predictor. Indeed, we see some purpose classes that have some identifiable directional dependence (work and returning home – as people travel to and from suburbs). And some activities with directional independence (cafés – as people may simply head to nearest and not head for a specific café).

### 5.2.3 Sub-question: Which models performed the best?

There is clear difference in the types of trips that each classifier was able to identify.

Notably, each of the models discovered different trends suggesting they each able to mapped onto different non-linear trends within the data. The SVM and MLP were similar in terms of the trips that they predicted which the RF could not. These models which rely on the conversion of feature space into higher dimension to find trends, may have found non-linear patterns that inherently probabilistic methods (such as RF) may not have. Then again, we have no way of comprehensively knowing this as both SVM and MLP are ‘black boxes’.

We find over-sampling to improve the performance of the RF (which reached an accuracy close to 80%), but unexpectedly the over- and under-sampling was ineffective for the SVM and MLP. Arguably, this may have been due to these model being been underfitted and so would have perhaps benefitted from further hyperparameter tuning (Semanjski *et al.*, 2017).

## 5.3 Uncertainty

The modelling set-up itself focuses on movements in Montreal, something which is specific to the city and its unique network topology. As such, we cannot be overly confident in transferring any findings from this report to other cities. Indeed, we can argue that the spatial and temporal trends from the results are ‘frozen’ in time and space.

Further, it is inaccurate to assume that what is examined in Montreal at the time of the study period can even be reapplied to Montreal at different points in time (i.e. to Winter or 5 years in the future or past), let alone to another city (Gong *et al.*, 2019). For real world decision-making in urban environments, we cannot comprehensively use too much of the information from the MTL Trajet to analyse movements outside of the realm of the study area.

Due to the types of model used (i.e. machine learning methods are non-linear) we still have a lack of understanding over the unique govern principles of why people make trips – a major gap also noted in other research of trip purpose classification (Meng *et al.*, 2019).

## 5.3 Further research

Although no explicit metric was discovered to be overwhelmingly important in classification models in this study, more research is needed to evaluate the potential of a wider range of metrics which could be used in combination with each other. Proposedly, accounting for the spatio-temporal interdependencies within the MTL Trajet could be used for to more effect that way that space and time separately (as in this report; Aslger *et al.*, 2018).

Finally, more work is needed to account for space-time, arguably the use convolutional neural networks may be used to solve this problem, as they could represent the MTL Trajet trips as spatial images. Additionally, combining a CNN with models which account for temporal memory (i.e. CNN–Long-Short Term Memory; Shi *et al.*, 2015) may be used to represent the trips as videos which these networks can study patterns in.

# 6. Conclusion:

In conclusion, we present an in-depth analysis into the feasibility of using space and time indicators in trip purpose classification modelling and find that they offer some degree of explanation in seemingly chaotic trip purposes.

Despite this, the modelling approach used in this report only focuses on Montreal and only for one month in September. And to this extent the research is *frozen* in time and *limited* by space. We can thus assume, this modelling procedure may have a completely different result for other cities. Moving forward, it is clear that trip purpose classification models will need include more contextual information if we hope to correctly identify key indicators of travel purpose. But, indicators themselves will need to be individualised to specific activities and cities.

Also, trend of movement are chaotic as that transport networks are complex systems (ref). Nevertheless, there is an emergence of pattern in the chaos of transport that researchers can tap into and study (Li *et al.*, 2016). VGI collected from travel surveys are particular hindered by this, as we do not ultimately know who each one of the individual participants are and whether they have (Shi *et al.*, 2018).

Further, if some attempt to add other external qualitative forms of information such as in mobility studies (Bantis & Haworth, 2017)

Notes

1st order effect

2nd order effect

There may still be spatial randomness also

*On Neighbourhood effect ->* People often traverse neighbourhoods and boundaries throughout one day (Kwan, 2018)

Understanding the interactions within complex system such as a city is a prerequisite for predicting changes within it… big data offers us an opportunity to study this (Cheng *et al.*, 2017)

VGI requires rethinking of geographical concepts (Elwood *et al.*, 2012).

\* Nevertheless, some trips will always be car-dependent [Health?], due to their nature or their spatio-temporal location (Sioui *et al.*, 2012)

Overall, it has mostly been found that socio-demographic features are less important in the improvement of purpose classification (Montini et al., 2014; ref). Arguably, this finding in the literature may relate is a as when people travel they often pass through and by a range of areas, POI and neighbourhoods (Kwan, 2018). Notably, socio-demographic data has been used as key identifiers in other areas of mobility studies i.e. in mode classification and the predicting of when and how people travel around cities (Xie *et al.* 2016; Bantis & Haworth, 2017).

- Aslger *et al.* (2018) break down influence of individual temporal and spatial indicators of the trips and highlights temporal features to be importance in the classification accuracy across a range of trip purposes.

(fractal) emergence in patterns of travel (Li *et al.*, 2016)

Insight into those spatial and temporal trends can improve the performance of Intelligent Transportation Systems (ITS). (Taayab *et al.*, 2014)

Oversampling can cause overfitting (Buda et al., 2018)

Flows generate change immediately whereas the ultimate locational redistribution takes longer to work itself out. [In reality] this process of working out is implicit and the ultimate equilibrium that occurs is a product of both fast and slow processes with no explicit time scale. (Batty, 2013)

Moreover, ML methods, as opposed to probabilistic and rule-based methods, are generally better at accounting for hidden relationships in the data (Li *et al.*, 2016).

Other models:

CANT DO LSTM or RNN as time is not regular

Can do CNN because of grid

CNN-LSTM using videos of each trip could prove important

If we are able to discern the activities in individual’s travel movement (hereafter, ‘*trip purpose’*) between an origin and destination along a transport network, we can use this information to inform the planning of essential (e.g. health & educational services) and non-essential (e.g. leisure & commercial) services. Indeed, improving our understanding of the context surrounding human mobility in a city can even be used in the estimation of travel demand in the longer term (Meng *et al.*, 2019). This is as, the modes of travel that people use around a city are often tied to socio-demographic charactersitics of the underlying population (). Through shifts in these characterstics, such as through gentrification, this may have an effect on the activities that people partake in and how they travel to them (Bricka *et al.*, 2015).

This is as, the modes of travel that people use around a city are often tied to socio-demographic characteristics of underlying populations such as employment and (Zhang & Cheng, 2019

Space-Time:

Primarily the movement of people is of concern to time-space analysis.

Paradigm shift (Brunsdon, 2015)

Li *et al.* (2016) challenges in dealing with big geospatial data, reviews if those traditional methods still useful for data

Spatial statistics is well suited to handle big data. It offers capabilities to summarize the data, and express measures of variation and uncertainty. (Li *et al.*, 2016)

### 5.2.2 Sub-Question: Which indicators were the most useful?

Actual

notes

We discover the models less accurate with the Indeed, it may be that different spatial dynamics govern the processes in further regions.

Spatial disparity/diversity in the mis-classified. It could be argued that understanding where this occurs across space may help improve the classification accuracy and the understanding of the general processes.

LDA clusters were very effective in seperating the data classes (figure with LDA PCA)

In general, representing space and time and machine learning models has been a difficult notion. It is difficult to account for the combination of space and time structure cannot be accounted for (Cheng *et al.*, 2011), and this study is no exception to that.

### 5.2.3 Sub-Question: Which models performed the best?

The multi-class models

When considering that a total 13,378 of correct trips are identified by any one of the models, the fact that only ~7000 trips have been identified by all of them suggests that each of the models have mapped onto relatively different non-linear patterns within the data.

## 5.3 Uncertainty

Actual

Indeed, it can become very difficult to find any sample that is representative enough to truly account for all dynamics involved with movement, as ultimately there will always be people who do not want to be studies (Goodchild, 2013)

We must be sceptical of spatial and temporal trends seen within the data. Indeed it may be a produce of underlying trends in population (or a 1st order effect)

2nd order effect

There may still be spatial randomness also

notes

We cannot represent space-time in models, because by models, by their very definition are an abstraction or generalisation of reality. Because everything is different across space, we will always mis-represent it (Tobler’s first law of geography; Tobler, 1970).

We can also be uncertain about our models, which may be overfitted

Correlation doesn’t mean causality, especially with the Class-imbalance in the trip purposes

“Virtually Impossible to create a representive sample in geographic space (Goodchild, 2013)

“methodologies originally developed to analyse small data and are not necessarily equipped to tackle some of the distinctive features of newer sources (Gorman, 2013; Arribas-Bel, 2017).

An *et al.* (2015). Problem is that one is often taken in expense of the other with spatial and temporal data An *et al.* (2015).

”

\*\*Problems with training and testing on different parts of the year -> ﻿However, the “feasibility and effects of choosing these data from dif- ferent periods of the year are still unknown” Gong *et al.* (2018) [i.e. can’t apply to other parts of the year]

Ultimately, the value of SBD (Spatial big data analysis) relies on uncertainty handling (Shi *et al.*, 2018)

We are still missing real information (~20%)

“flows generate change immediately whereas the ultimate locational redistribution takes longer to work itself out” Batty *et al.* (2013) maybe go on about fractals and chaos

Furthermore, in order to be able to predict transport demand or traffic, not only are real-time data required but also historic data. (Li *et al.*, 2016 -> find another ref, but basically trying to say that historical is needed as well).

Schwanen, T. (2018) -> many forms of uncertainty that cannot be dealt with using better techniques [i.e. with VGI and general space time]

Weather important (Xie *et al.*, 2016), shown to decrease and more precip in later study. We know this affects transport mode, and transport mode may affect transport purpose (ref).

We discover both directional dependence and indendence in the data, thus we may see different things in different directions (anistrophy and isotrophy; see <https://en.wikipedia.org/wiki/Anisotropy>)

Problem ﻿-> “development of explicit, formal, and computable representations of geographic knowledge” (Miller & Goodchild, 2014)

“People ﻿in rural areas tend to use technology differently than people who live in cities.” (Hetch & Stephens, 2014)

“Virtually Impossible to create a representive sample in geographic space (Goodchild, 2013)

Data has been routed (Patterson & Fitzsimmons, 2017b; Ville de Montréal, 2019)

Although, it must not be forgotten that this study primarily focusses in on Montréal and this may not be transferred to other cities (Ergodoic and Ecological Fallacy).

[Complex!] Transportation is a classic social dilemma where individually rational behaviour (being mobile) leads to collectively irrational outcomes such as congestion (Miller, 2013)

“methods developed for smaller data sets being used on 'big data' is problematic” (Gorman, 2013)

No consideration of space-time metrics -> clusters -> but harder to include

Land use

As shown in **Figures 3.3** and **Table 3.2**, the land use categories are fairly unbalanced with the majority of land use being residential and employment (27% + 18%, respectively).

## 5.3 Further Research

actual

Although no explicit metric was discovered to be overwhelmingly important in classification models in this study, more research is needed to evaluate the potential of a wider range of metrics which could be used to classify trip intention. Proposedly, accounting for the spatio-temporal interdependencies within the trip intentions from labelled travel survey data.

notes

More intensive methods of ML such as CNN used in the mode classification could also be used in

Dabiri, S., & Heaslip, K. (2018) use CNN for mode classification

[Better modelling] “there are uses of machine learning methods that have been extended to account for the limitations of working with spatio-temporal data (such as the integration of convolutional neural networks and LSTM methods (Shi *et al*., 2015; Yu *et al.*, 2017; Han *et al.*, 2019)“. Using a better model that accounts for space-time (CNN-LSTM) -> which you input a video of trip.

demographic shifts [through gentrification] creates changing travel demands and employment rate

Liu *et al.* (2016) predicting the next step with mode -> maybe applied to purpose

\* Jahromi *et al.* (2016) try to simulate GPS movement/mobility that infer about interactions of people with a city and its services [Mention about ABM and simulating interactions -> could act as a scaled up version]. The understanding of human mobility in an urban space has become crucial to optimize the network management (Jahromi *et al.*, 2016). ABM a great tool but ABMs could be very data demanding and sometimes too complex without offering much additional insight (An *et al.*, 2015).

Train ML method to look for uncertainty and outliers (Shi *et al.* 2018). Deep learning requires huge datasets (Shi *et al.*, 2018)

Visualisation and Interactivity:

Can we make big geospatial data analysis and visualisation available to an end-user through interactivity? (maybe Li *et al.*, 2016) -> currently not

Videos of change over time may be needed for space-time investigation

Batty *et al.* (2012) smart cities of the future -> integration of trip purpose and other integrated network.

\*\*\*\* (fractal) emergence in patterns of travel (Li *et al.*, 2016)

People behave irrationally with transport (Miller, 2013)

# 6. Conclusion:

EXTRA:

## 2.3. Representation of space and time in mobility modelling

Difficulty in space, time and space-time metrics in models

1. Models can’t handle

The broader use of space and time metrics in models has been a challenging concept.

machine learning is the unable to directly handle spatio-temporal structure (Cheng *et al.*, 2011)

“Space–time analysis seeks to understand when and where (and sometimes why) things occur.” An *et al.* (2015). Problem is that one is often taken in expense of the other with spatial and temporal data An *et al.* (2015).

Spatio-temporal modeling has always been of interest to researchers in geographical information science (GIS) (Ren *et al.*, 2019).

there is not a close coupling between big data and space-time methods used to analyse them (An *et al.*, 2015)

Mathematical models being employed without regard of space, often including problems that are inherently tied to spatial considerations (O'Sullivan & Manson, 2015)

However, methods to assess quality assurance of the geospatial data still relevant on big geospatial data as they still describe the same processes (Li *et al.*, 2016)

network and topological models not well suited for handling geospatial big data (Li *et al.*, 2016)

1. Things Change

Size of space-time neighbourhoods change (Cheng *et al.*, 2014)

[Problem with time sampling] -> ﻿different patterns can be observed for different temporal resolutions (Zhao *et al.*, 2019).

Determining threshold of time and space (Adepeju & Evans, 2018)

(Ren *et al.*, 2019)\* Need to account for local trends with models, a lot of papers use models that don’t consider local, but still do space-time analytics (i.e. with locally-weighted CNN layers on a network)