# Chapter 4. Results

This chapter is divided into three sections, the first (4.1) examines general trends in the model inputs (detailed in section 3) and identifies key areas of analysis, the second (4.2) reviews the space, time and structures and interdependencies within the model inputs before the third reviews the trip purpose classification models and their outputs (4.3).

## 4.1 Overview of model inputs

### 4.1.1 Trip distance & duration

After calculating the distances and duration of the individual trips of the MTL Trajet survey, our analysis finds a total of 7,594 trips which are removed from the analysis based on the outlier strategy adopted in 3.4.3. As shown in **Table 4.1**, the majority (6,709) of these were from trips that were less than 50 m in length. These trips are potentially from cases where the app had switched on for slight movements or the user had mistakenly ended a trip while in traffic for more than 2 minutes (Patterson & Fitzsimmons, 2017b).

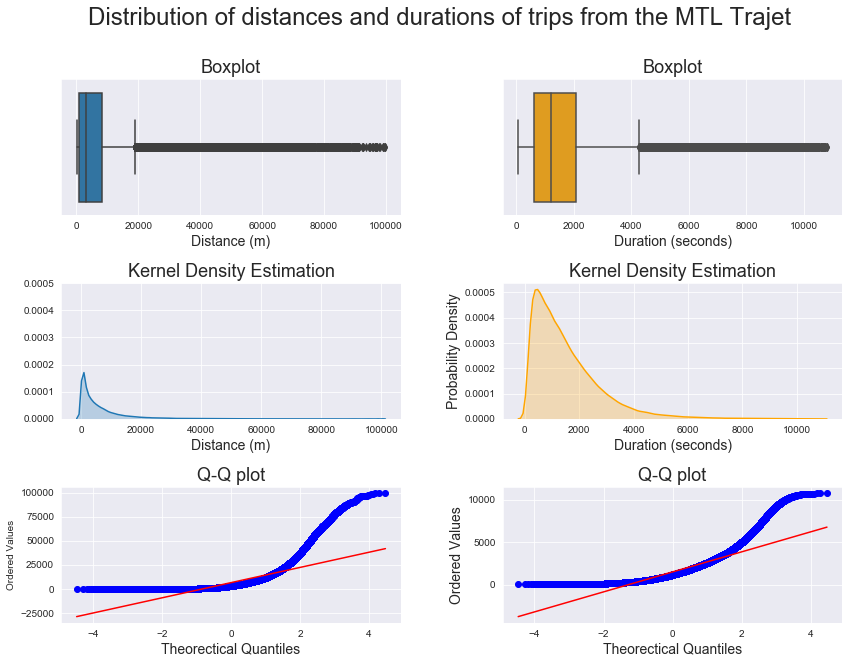
**Table 4.1** Outline of trips removed from the analysis

|  |  |  |
| --- | --- | --- |
| *Outlier Type* | | *Number removed* |
| *Distance below 50 m* | | 6,709 |
| *Distance above 100 km* | | 62 |
| *Duration below 60 seconds* | | 412 |
| *Duration above 3 hours* | | 411 |
| *Total* | 7,594 |

The resulting trips are shown to have a mean distance and duration of around 6.6 km and 26 mins, respectively (**Table 4.2**). Here, we see that both these variables are positively skewed, although distance is more so. The disparity between the mean and median in both trip distance and duration is indicative of both these variables exhibiting a long-tailed distributions, and this can be visually identified by examining the univariate kernel density estimations and Quantile-Quantile plots shown in **Figure 4.1**.

**Table 4.2** Summary statistics for distance and duration of trips from the 2017 MTL Trajet travel survey (converted to km and minutes; *N=177,938*)

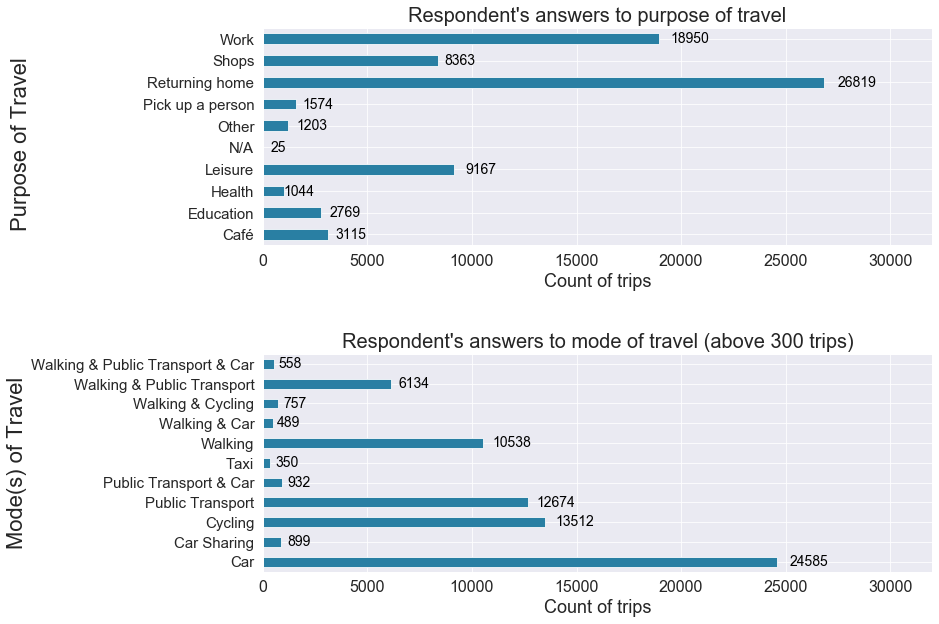
|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | *mean* | *STD* | *min* | *25%* | *Median* | *75%* | *95%* | *max* | *kurtosis* | *Skewness* |
| *Distance (km)* | 6.63 | 9.92 | 0.05 | 0.84 | 3.14 | 8.09 | 25.25 | 99.81 | 15.216 | 3.355 |
| *Duration (min)* | 25.62 | 21.42 | 1.00 | 10.27 | 20.07 | 34.68 | 65.81 | 179.98 | 6.097 | 1.967 |



**Figure 4.1** Boxplots (top), Kernel Density Estimation (middle) and Quantile-Quantile (bottom) plots showing the distribution of distance and duration of trips from the 2017 MTL Trajet travel survey.

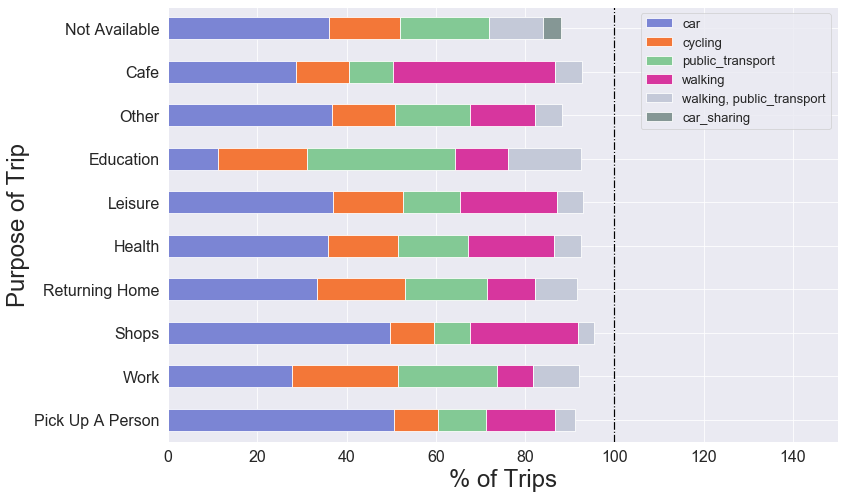
### 4.1.2 Travel purpose & mode

There are total of 73,029 trips from the MTL Trajet survey containing both a travel mode and purpose label. As shown in **Figure 4.2**, the categories of these variables have not been selected by the respondents in equal proportions. It is shown that severe class imbalance exists within both of these categories, with around 63.7% (45,769) of the trips that have been labelled as either trips to work and back to home, and 33.6% of the trips being taken by car. This finding is not unexpected for a survey that has taken place in North American city with a high level of employment, however, so we can argue that this study is relatively representative of trips occurring across Montréal (Meng *et al.*, 2019).



**Figure 4.2** Bar charts showing the type of trip purpose and travel mode selected by respondents to the 2017 MTL Trajet survey.

When the travel mode is broken down by purpose, in **Figure 4.3**, we see that there is higher usage of cars in trips for shopping and picking people up and lower usage of cars in trips for education.Notably, a higher proportion of respondent have walked or cycled when taking trips to work, cafés and places of education.



**Figure 4.3** Bar chart comparing the proportion of each unique trip purposes accounted for by each unique travel modes.

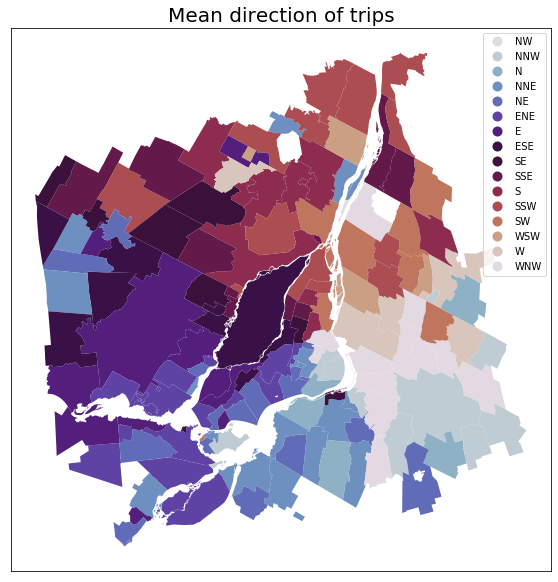
Comparing the distances and duration of the trips as grouped by trip purpose, in **Table 4.3**, we see that trips to cafés and shops are shorter in both mean distance (4.5 & 4.8 km) and duration (23 & 20 mins) compared to the other forms of trips such as work and returning home. When cross-referencing with travel mode (from **Figure 4.3**), it could be proposed that these values are a product of the fact that a higher proportion of these trips are walked.

**Table 4.3** Summary statistics of trip distance and duration per trip purpose (Note: trips that are classed as ‘Not Available’ have been omitted from this table)

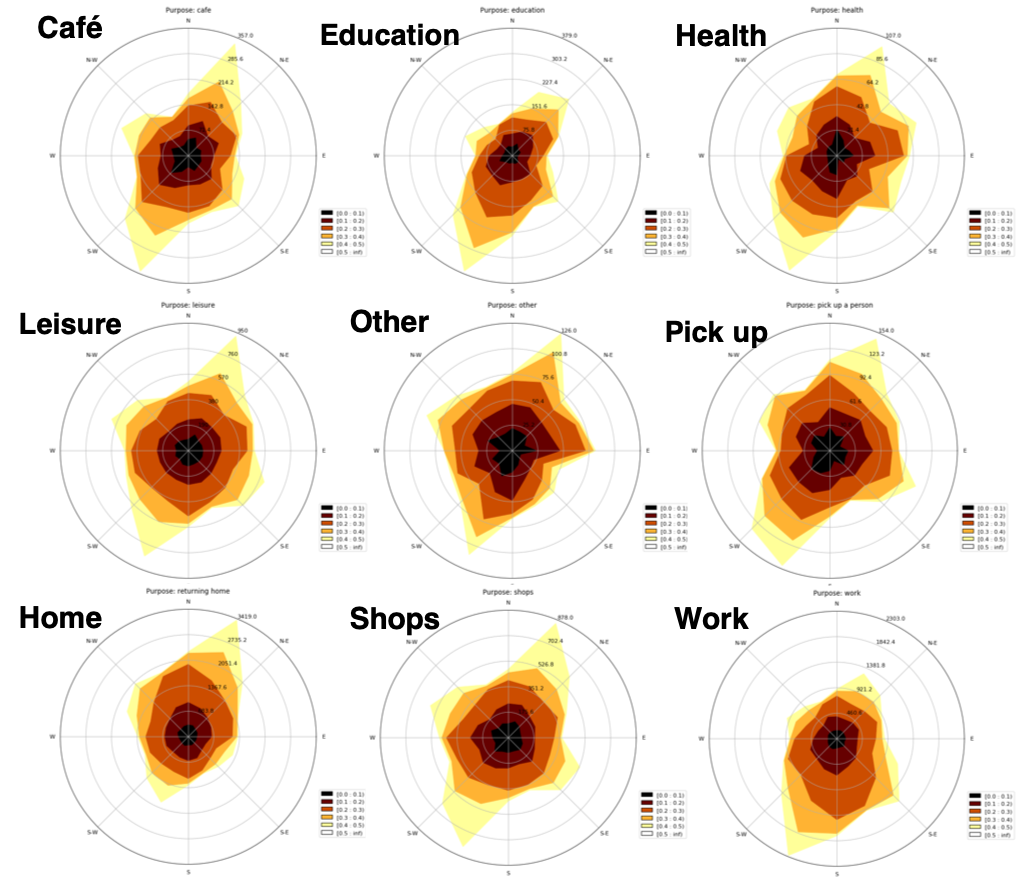
|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| *Trip Purpose* | *Trip distance (km)* | | | *Trip duration (mins)* | | |
|  | μ | σ | Skew | μ | σ | Skew |
| Café | 4.5 | 7.6 | +4.5 | 22.9 | 19.5 | +2.4 |
| Education | 5.8 | 6.8 | +3.5 | 28.9 | 19.4 | +1.3 |
| Leisure | 6.8 | 10.3 | +3.1 | 35.2 | 20.8 | +2.0 |
| Health | 6.2 | 8.0 | +2.8 | 25.2 | 19.7 | +2.0 |
| Other | 8.7 | 12.9 | +3.1 | 31.3 | 25.3 | +1.9 |
| Returning home | 7.5 | 9.8 | +3.2 | 29.0 | 22.2 | +1.7 |
| Pick up a person | 7.8 | 10.9 | +2.9 | 25.1 | 20.9 | +2.1 |
| Shops | 4.8 | 7.2 | +3.5 | 20.4 | 17.6 | +2.4 |
| Work | 7.6 | 8.3 | +2.6 | 28.8 | 19.8 | +1.5 |

### 4.1.3 Trip direction:

The mean direction of all trips taken across all 91 regions of Greater Montreal is shown in **Figure 4.4**.Here, we see that the direction is general towards the city of Montreal (see **Figure 3.2**) indicating we can be somewhat confident in assuming we have accounted for a some degree of the MAUP – with the directional dynamics of trips facing ‘inward’ towards downtown and the study area chosen versus out of the study area (ref). Across the individual purpose class, in **Figure 4.5,** the mean direction of the trips are generally shown to be in the NNE and SSW directions, something which is similar to the morphology of the island of Montreal. Notably, work and returning home trips shown to be more directionally dependent, in the SSW & NNE respectively, than the other purpose classes. Directional independence is shown in the trips categorized by other, café and purposes.



**Figure 4.4** Map showing the mean direction of trip within each region of Greater Montreal.



**Figure 4.5** Circular contour plot showing the mean direction of trips for each trip purpose.

### 4.1.4 Rush-hour & City Labels

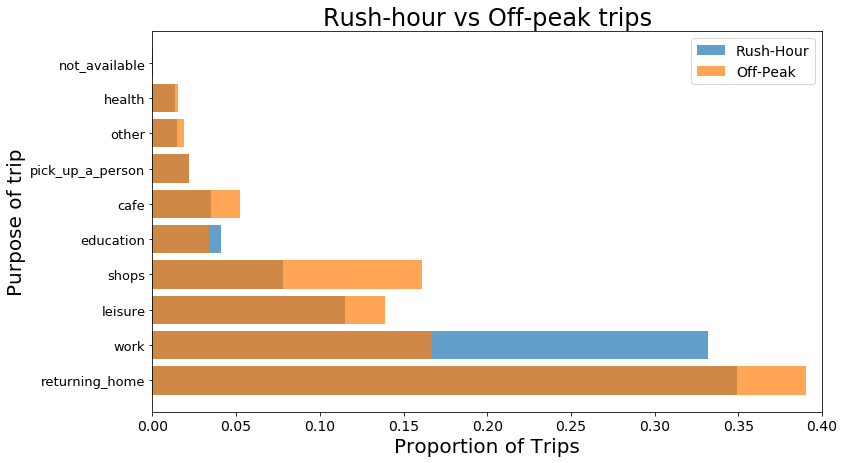
After applying city and rush hour labels to the origin and destination points (see 3.3.1), the majority of trips are found to have occurred within the City of Montreal (93.5%) and are evenly split between rush hour and off-peak (**Table 4.4**).

**Table 4.4** Results from the application of Rush-hour and City labels to the data.

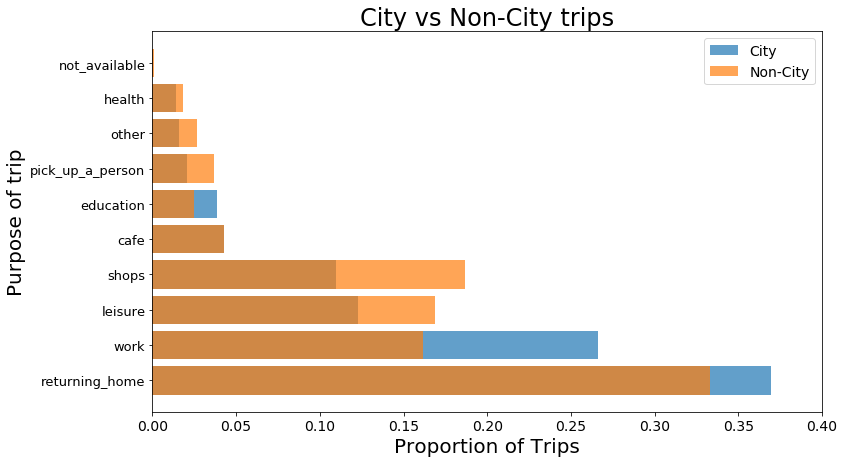
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Rush hour? | | City? | |
|  | Yes | No | Yes | No |
| Origin of trip | 36785 | 36244 | 63811 | 9218 |
| Destination of trip\* | 38650 | 34490 | 64136 | 8893 |

\* including trips that have passed through rush hour or city

When separated by purpose class, a higher proportion of trips are discovered to be carried out for work and education at rush-hour times versus trips to shops which are proportionally carried out at off-peak times (**Figure 4.6**). **Figure 4.7**, highlights that work and home-bound trips are disproportionately represented in trips occurring in the city as opposed to outside the city, where shopping and leisure trips are more proportionally represented.

**

**Figure 4.6** Bar chart showing the proportion of trips carried out during rush-hour and off-peak as grouped by purpose.

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**Figure 4.7** Bar chart showing the proportion of trips carried out within and outside the City of Montreal as grouped by purpose.

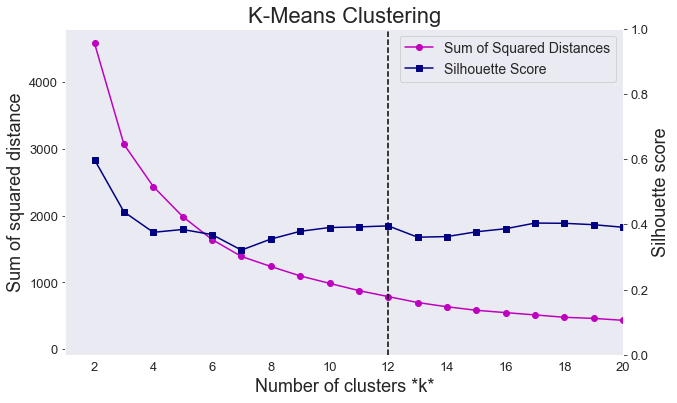
### 4.1.5 Land Use

Land use,

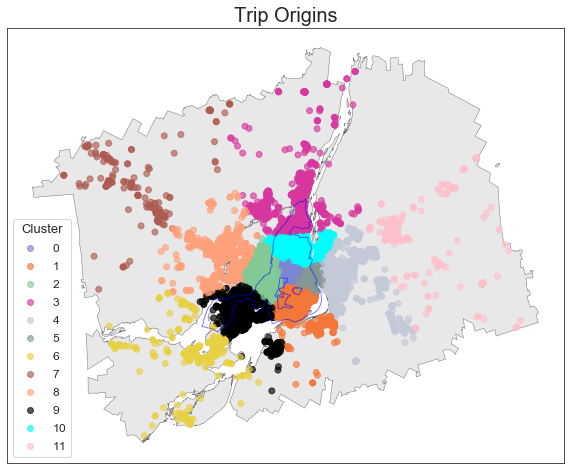
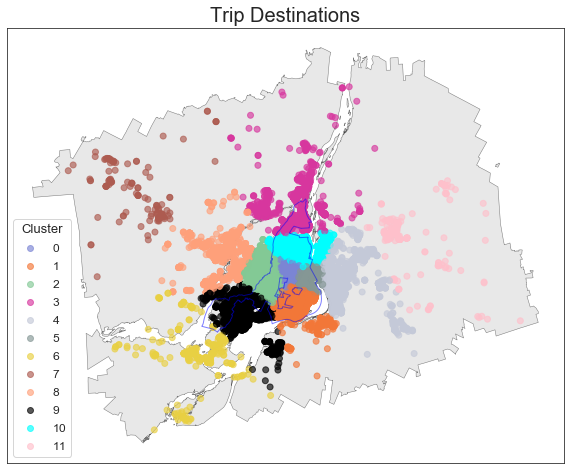
### 4.1.6 Clustering

### 4.1.6.1 Spatial

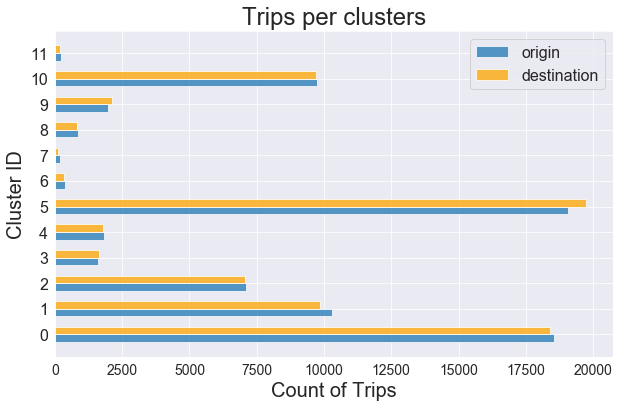
After fine-tuning values of *k* between 2-20 and evaluating the sum of squared distances and silhouette score within each k-number of clusters (**Figure 4.X**), we select a total of 12 for the k-means clustering algorithm to be built upon. These clusters mapped across the study region in **Figure 4.9** and a summary of how many trips have been assigned to each cluster is shown in **Figure 4.10**. Note that, the algorithm notably separates a region containing Downtown Montreal (*cluster-id=0*).



**Figure 4.8** Line graph comparing sum of squared distances and silhouette scores of k-means clustering algorithm for k between 2-20.



**Figure 4.9** Map of origin and destination points from the MTL Trajet trips coloured by cluster label across the study region.

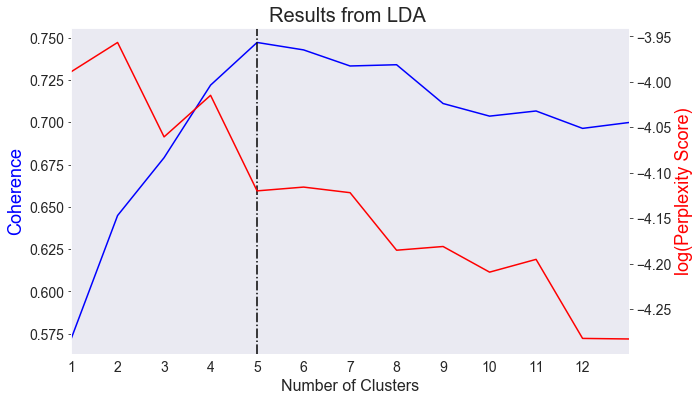


**Figure 4.10** Bar chart showing number of trips per spatial cluster identified by the k-mean clustering algorithm.

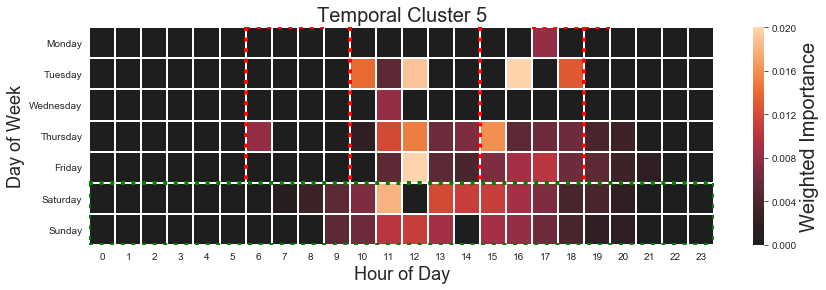
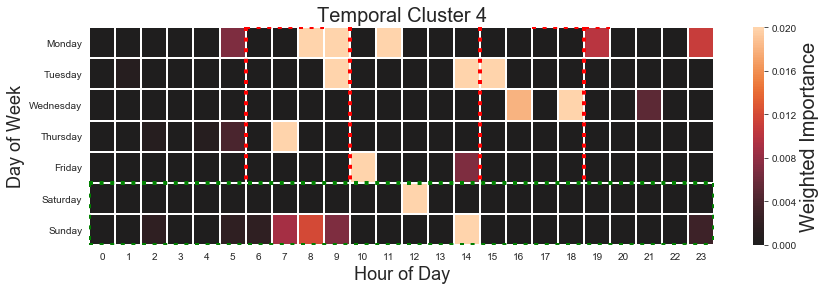
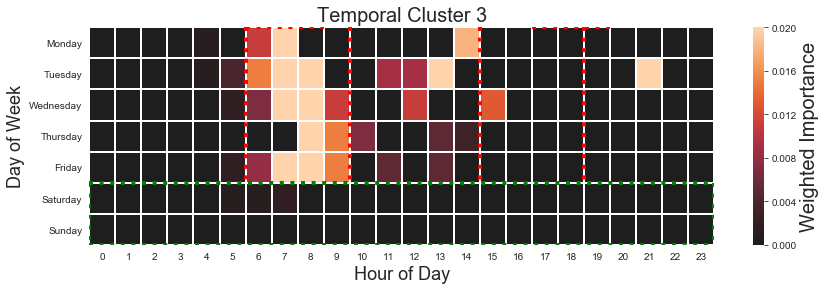
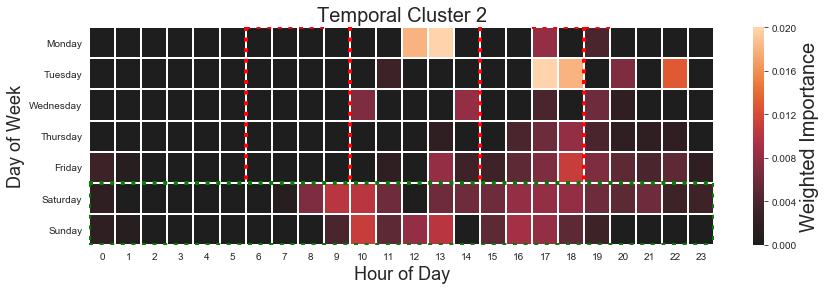
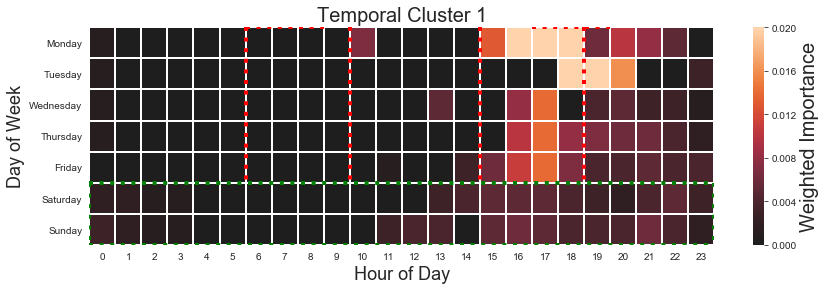
### 4.1.6.1 Temporal

We select

LDA (temporal clustering). Built with 50 passes through the data



**Figure 4.X**

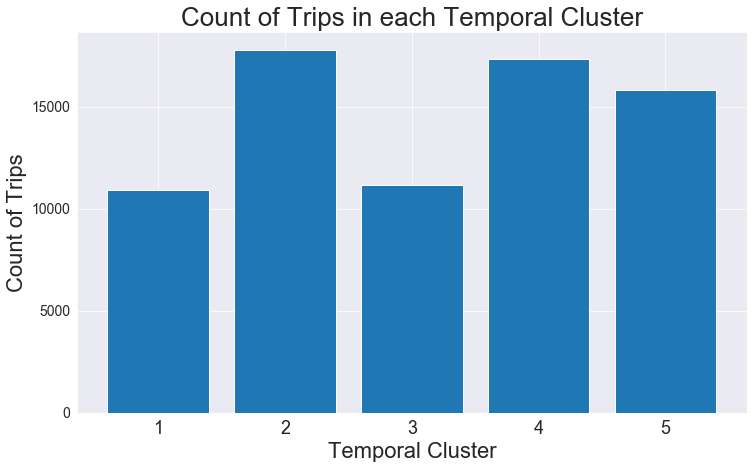


**Figure 4.X**

Notably the 5 clusters divide the data into individual purposes, indicating that are significant

|  |  |  |
| --- | --- | --- |
| *Temporal Cluster* | *Associated Trip Purposes* | *Weighted importance* |
| 1 | Returning Home | 0.549 |
| 2 | Leisure | 0.349 |
| Education | 0.111 |
| Other | 0.041 |
| 3 | Work | 0.488 |
| 4 | Work | 0.276 |
| Not Available | 0.002 |
| 5 | Shop | 0.306 |
| Café | 0.113 |
| Pick Up a Person | 0.060 |
| Health | 0.004 |

After joining these back to the data,



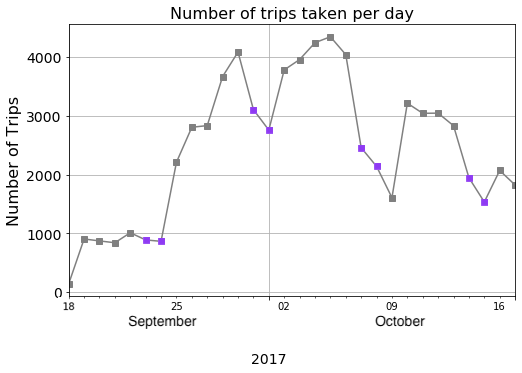
**Figure 4.X**

## 4.2 Exploratory Space and Time Data Analysis of Model Inputs

This section highlights the methods carried out to investigate space, time and space-time signatures in the data. It is hoped that the identification of these forms of trends will asses the ability for the purposes to be modelled inform the modelling process (detailed in 3.4).

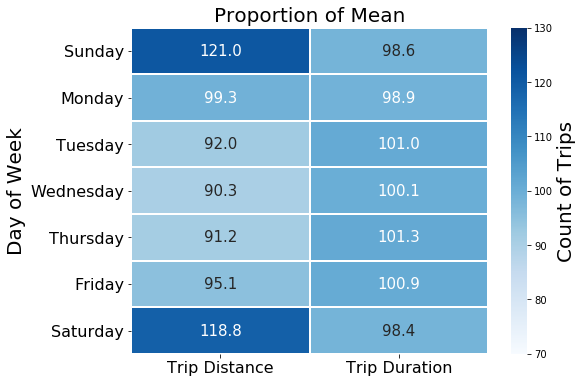
### 4.2.1 General

A total of 73,029 trips were recorded across the study period (18th September 2017– 17th October 2017), but there is significant variation in the amount of recorded trips per day. As shown in **Figure 4.X**, during the first 7 days of the study less than around 1000 trips were recorded per day compared with more than 1500 trips in the remaining days (with the most amount of trips being recorded on Thursdays/Fridays). Here, less trips are recorded on weekends versus weekdays, other than Monday 9th October, which was the day Thanksgiving was celebrated that year in Canada.



**Figure 4.X** Line plot showing the amount of recorded trips taken from the MTL Trajet app between 18th September 2019– 18th October 2019 (weekends indicated in **purple** ; data from PDO, 2017).

As broken down by week, on average, trips of longer distances are taken on the weekends versus weekday (**Figure 4.5**). Arguably this could result from the influence of work, with people travelling further into rural areas during weekends. Notably, there is no deviation from the mean travel duration across the week, on average in the trips



**Figure 4.3** Average trip distance and duration as proportion of the mean.

### 4.1.5 Weather

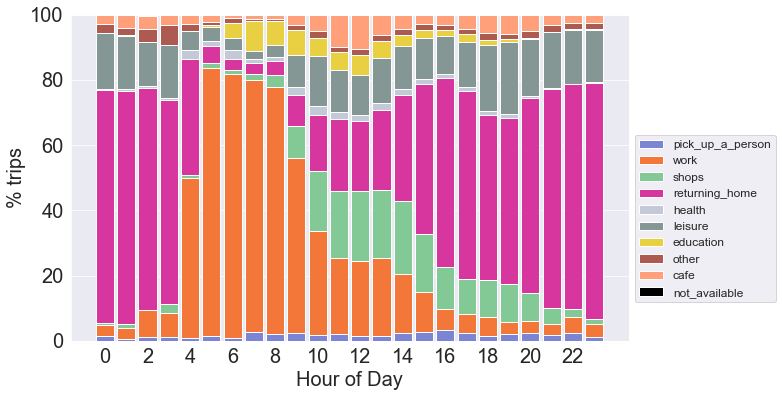
Across the study period, weather was shown to decrease. This may have an effect on our model (Gong *et al.*, 2018) Weather important (Xie *et al.*, 2016)

(3.2.2)

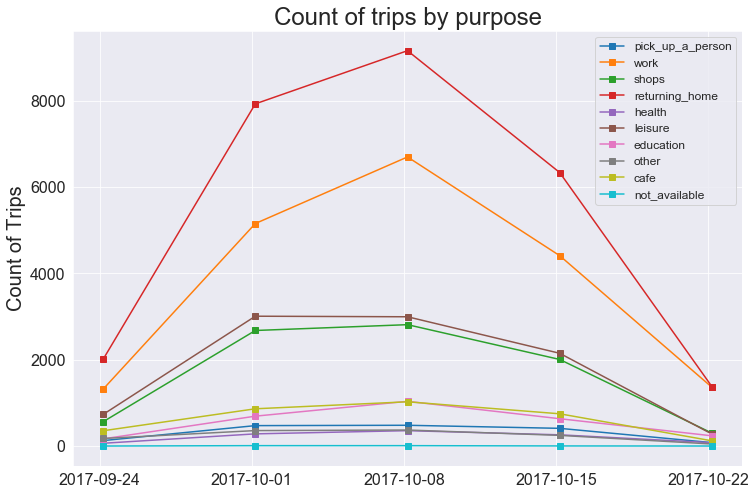
(Note, each week has 7 days apart from the last).

For this report, we divide this section into three main parts: spatial, temporal and spatial-temporal methods used to discern signal from the data.

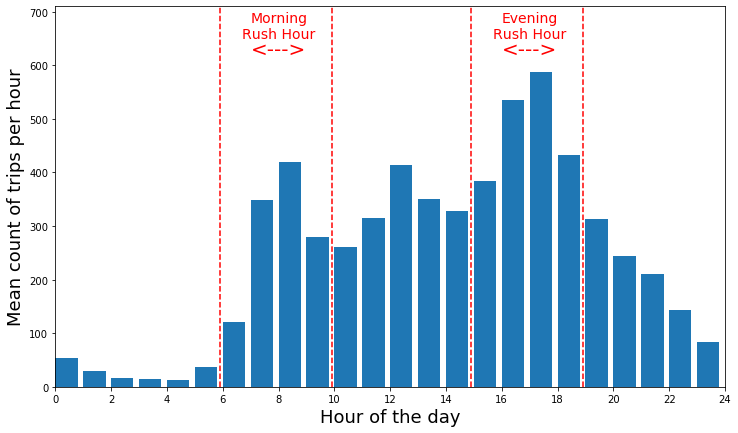
Temporal Analysis:



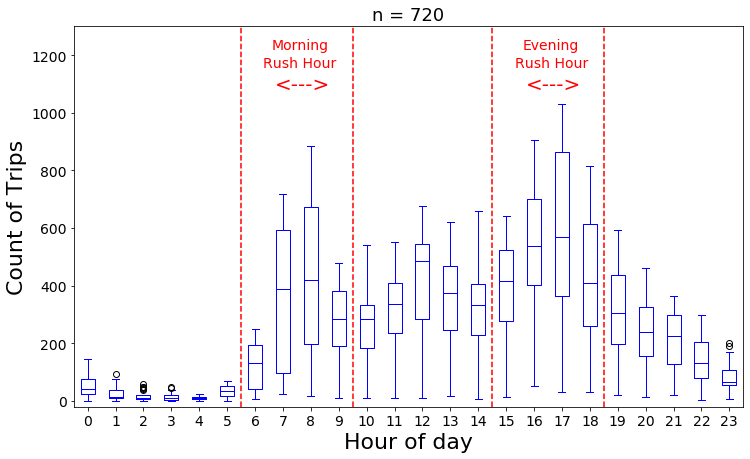
**Figure 4.X**



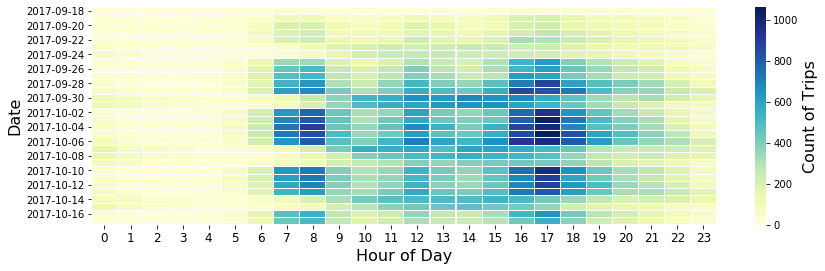
**Figure 4.X**



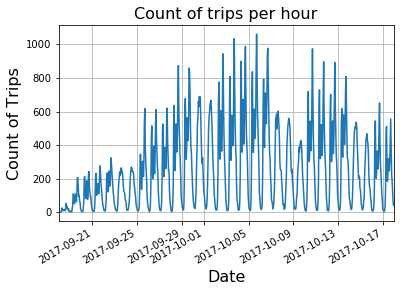
**Figure 4.X** (*n=720*)



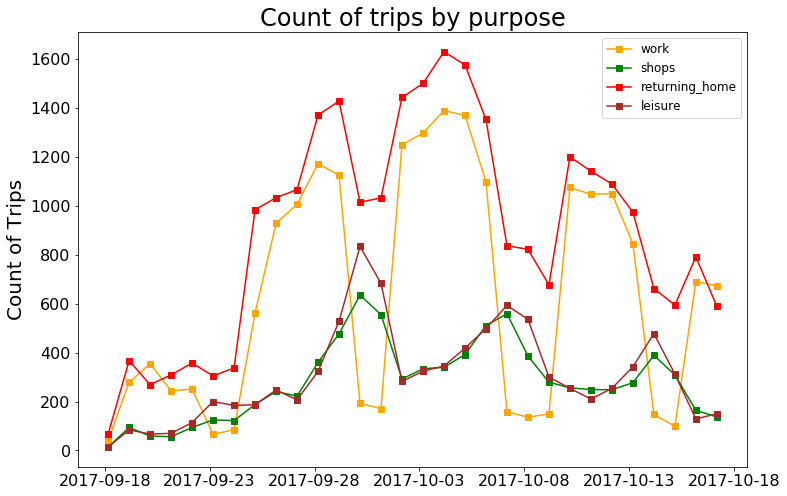
**Figure 4.X**



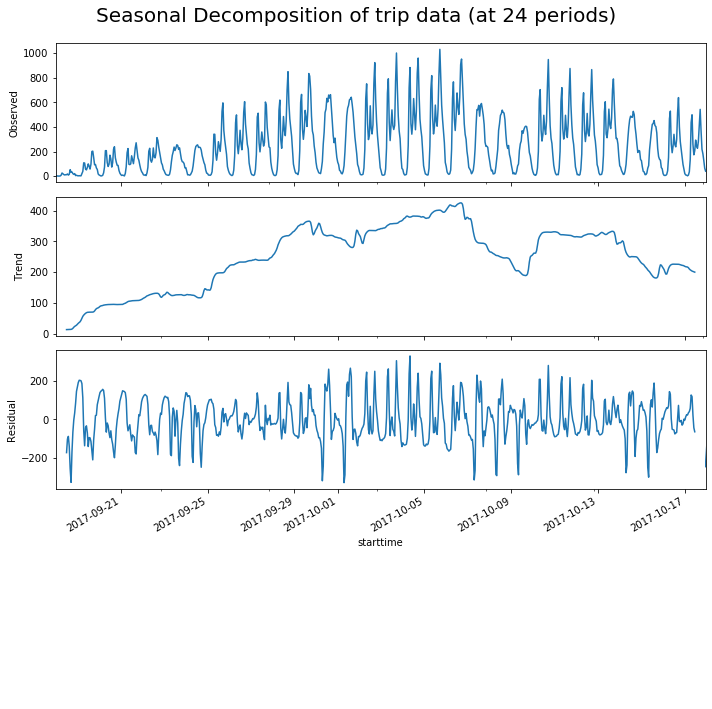
**Figure 4.X**



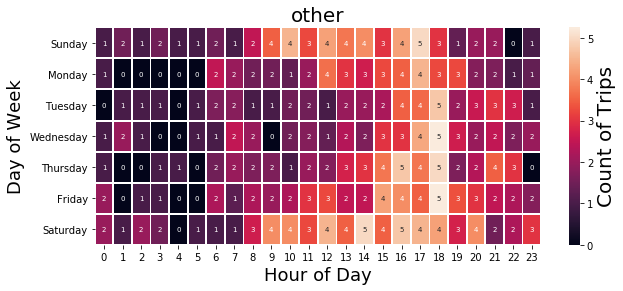
**Figure 4.X**



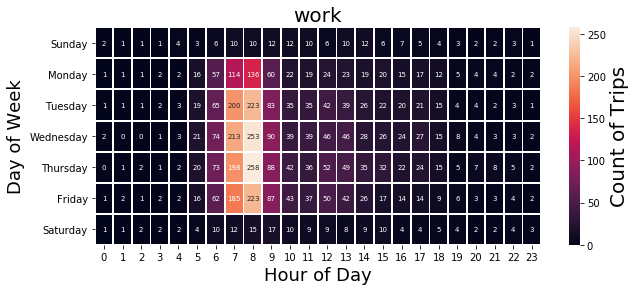
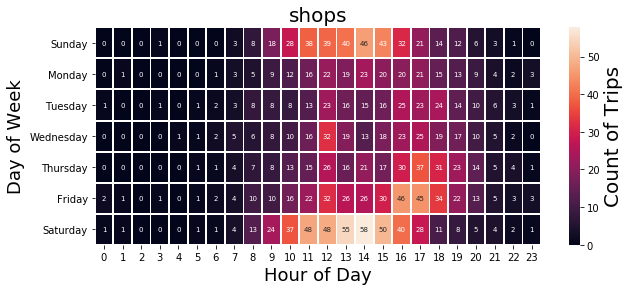
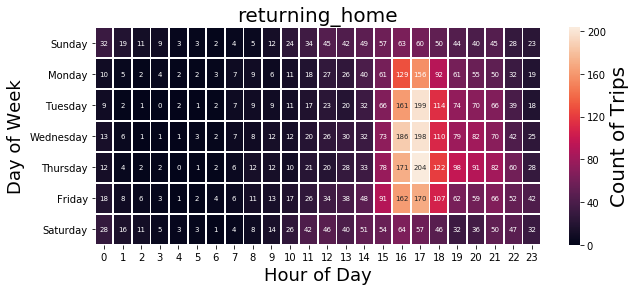
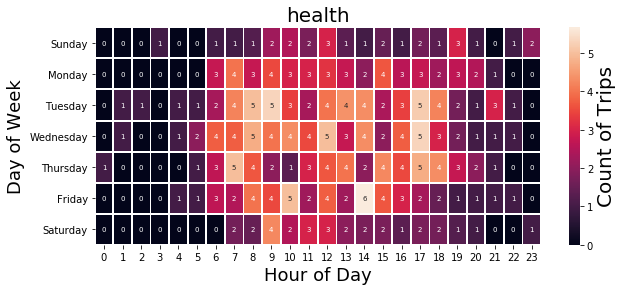
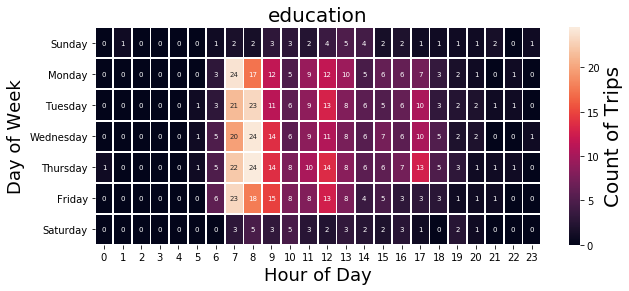
Clear diurnal a Temporal Decomposition



**Figure 4.X**

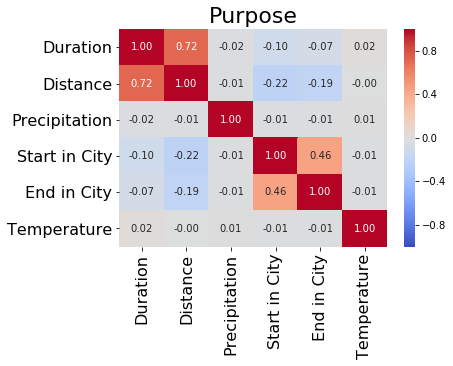
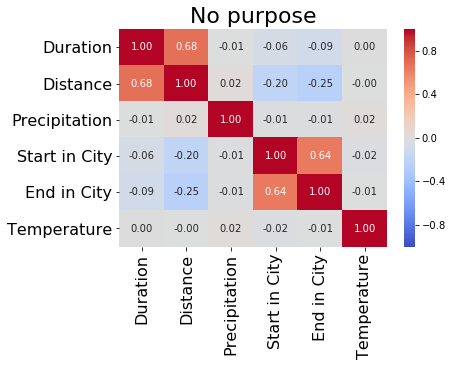
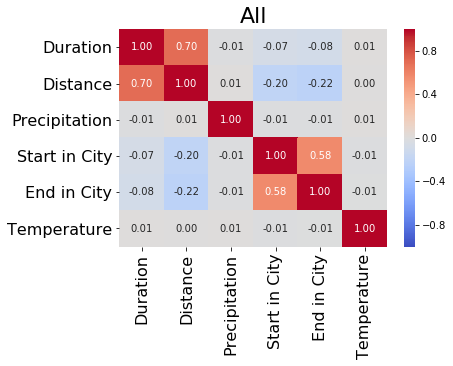






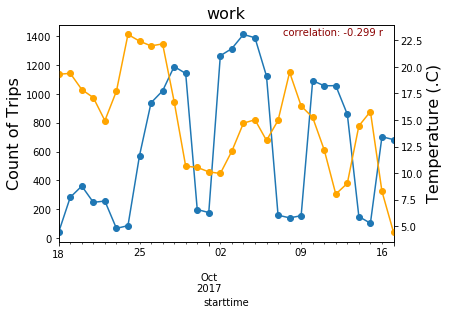
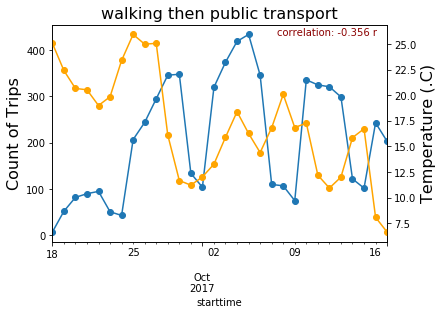
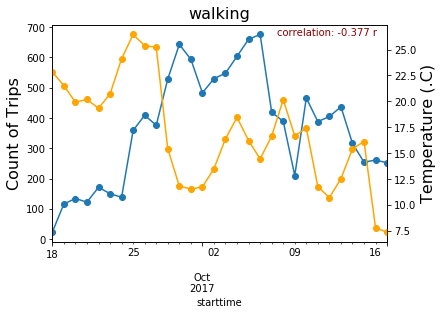
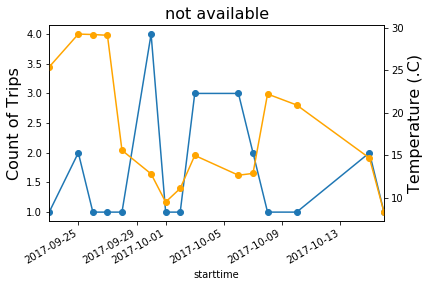
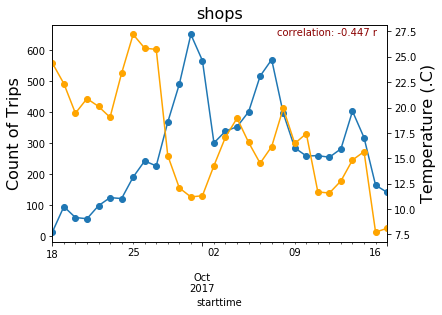
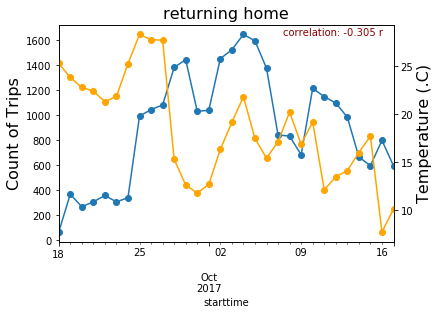
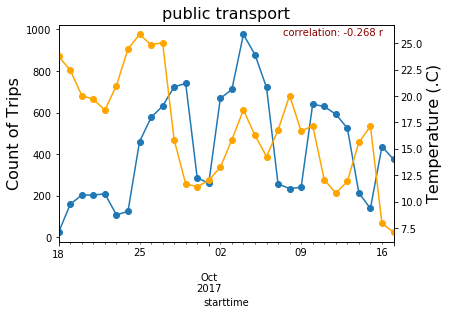
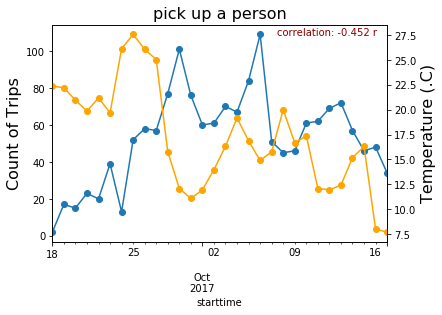
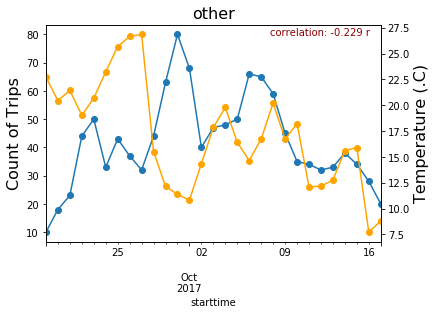
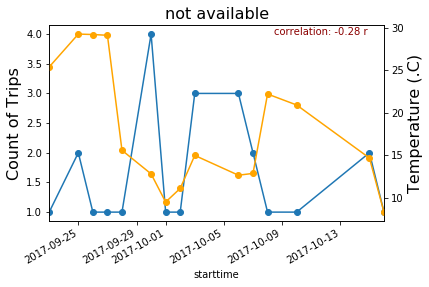
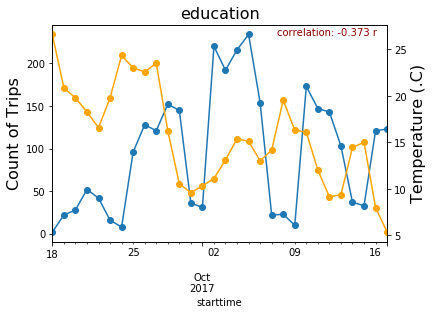
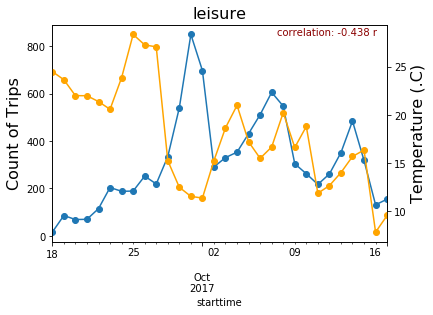
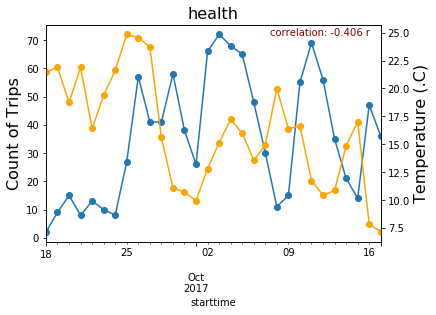
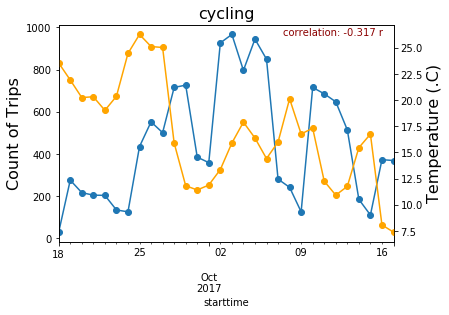
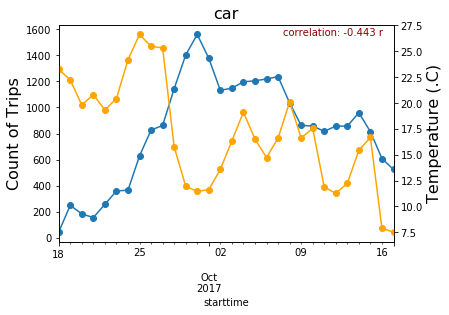
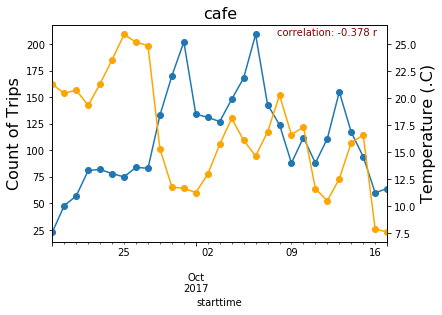
**Table 4.X** Augmented Dickey-Fuller Test (significant below 0.005 shown in **bold**)

|  |  |  |  |
| --- | --- | --- | --- |
| Purpose | ADF | p-value | n |
| All | -2.7261 | 0.0696 | 185285 |
| Cafe | -2.7386 | 0.0676 | 3189 |
| Education | -2.8689 | 0.0491 | 2830 |
| health | -4.1338 | **0.0009** | 1061 |
| Leisure | -1.8601 | 0.3511 | 9379 |
| Not available | -4.7958 | **0.0001** | 25 |
| Other | -2.4963 | 0.1164 | 1219 |
| Pick a person up | -2.8686 | 0.0491 | 1592 |
| Returning home | -2.8543 | 0.0509 | 27128 |
| Shops | -1.9669 | 0.3013 | 8554 |
| Work | -2.2594 | 0.1854 | 19241 |



**Figure 4.X**

### 4.1.7 Weather



Spatial Analysis:

Distribution:

Global Moran’s I

pick\_up\_a\_person 0.5629000152701666 0.0 0.001

work 0.5921787733479512 0.0 0.001

shops 0.5921624780237638 0.0 0.001

returning\_home 0.6169009566510006 0.0 0.001

health 0.547517193189426 0.0 0.001

leisure 0.5448749744913084 0.0 0.001

education 0.5872240653154563 0.0 0.001

other 0.5518371624439252 0.0 0.001

cafe 0.5733876521027782 0.0 0.001

not\_available 0.4356105321751141 0.0 0.001

Count of purpose per mtl trajet KS tests:

cafe KstestResult(statistic=0.5, pvalue=0.0)

education KstestResult(statistic=0.5, pvalue=0.0)

health KstestResult(statistic=0.5, pvalue=0.0)

leisure KstestResult(statistic=0.5, pvalue=0.0)

not\_available KstestResult(statistic=0.5, pvalue=0.0)

other KstestResult(statistic=0.5, pvalue=0.0)

pick\_up\_a\_person KstestResult(statistic=0.5, pvalue=0.0)

returning\_home KstestResult(statistic=0.5567048189947053, pvalue=0.0)

shops KstestResult(statistic=0.5, pvalue=0.0)

work KstestResult(statistic=0.5, pvalue=0.0)

### 4.1.4 Travel Purpose

Purpose Correlation:

KS test vs norm for grouped 1 hour

cafe KstestResult(statistic=0.5551535507713675, pvalue=3.287213099129875e-205)

education KstestResult(statistic=0.5, pvalue=9.82488208886262e-164)

health KstestResult(statistic=0.5, pvalue=9.82488208886262e-164)

leisure KstestResult(statistic=0.7251252221594695, pvalue=0.0)

not\_available KstestResult(statistic=0.5, pvalue=9.82488208886262e-164)

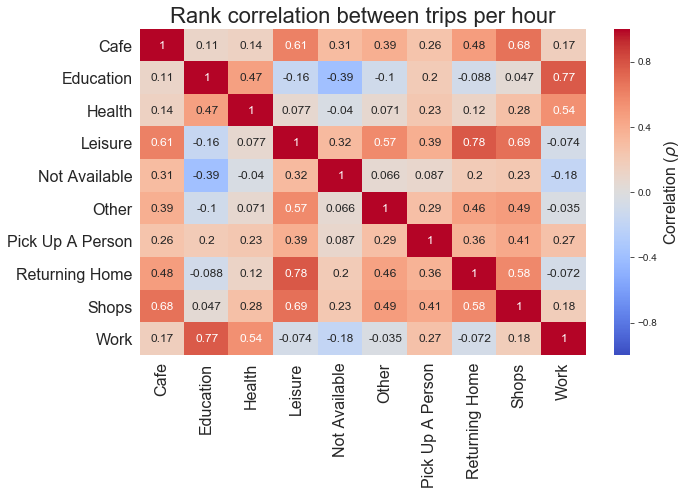
other KstestResult(statistic=0.5, pvalue=9.82488208886262e-164)

pick\_up\_a\_person KstestResult(statistic=0.5, pvalue=9.82488208886262e-164)

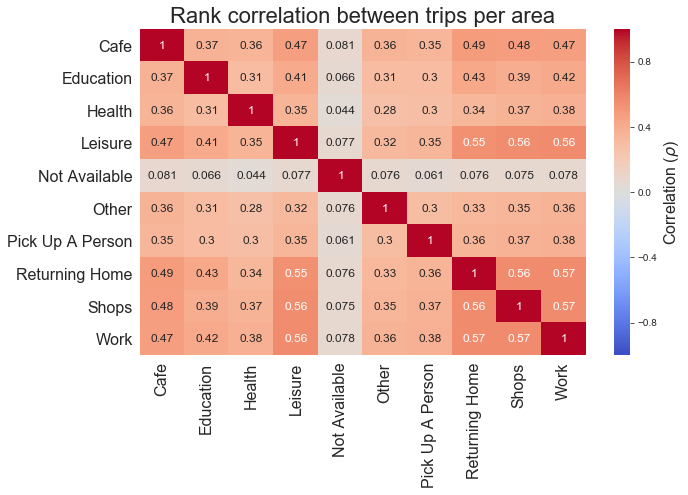
returning\_home KstestResult(statistic=0.8370232391566367, pvalue=0.0)

shops KstestResult(statistic=0.6061450521877981, pvalue=3.586226223248267e-249)

work KstestResult(statistic=0.749204542272784, pvalue=0.0)



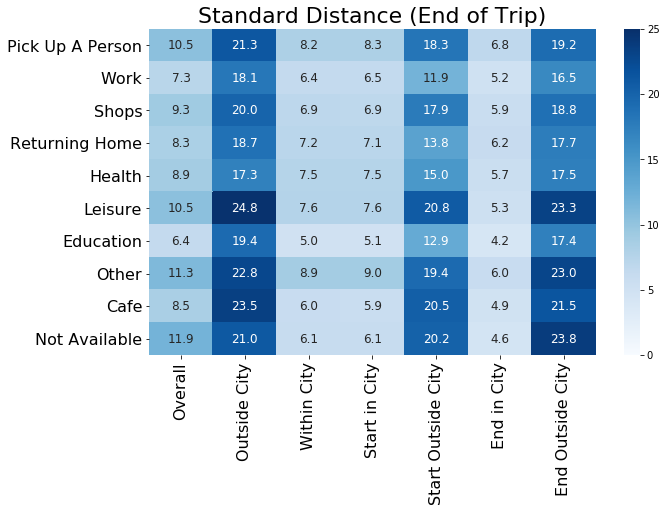
**Figure 4.X**



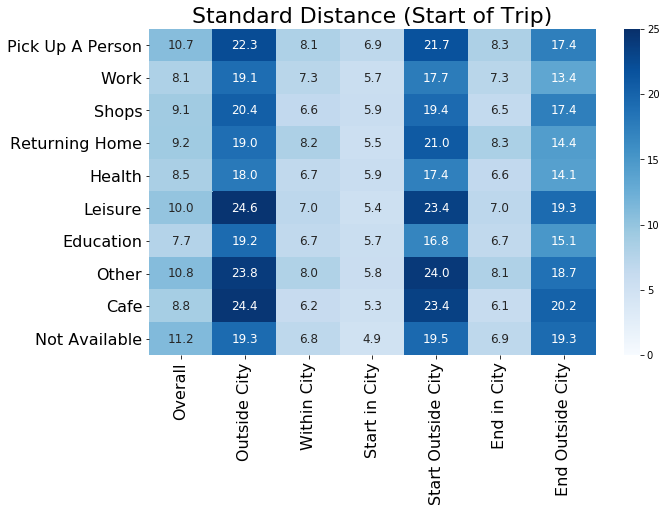
**Figure 4.X**

Start in the city cluster end

Start outside the city cluster end



**Figure 4.X**



**Figure 4.X**

Table of New Groups:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Label | Purpose Types |  |  |  |  |
| 0 |  |  |  |  |  |
| 1 |  |  |  |  |  |
| 2 |  |  |  |  |  |

## 4.3 Trip Purpose Classification Models

Examining the forecast-ability of the network: To build upon the structure and findings of the ESTDA.

- “omitted-variable bias (OVB) occurs when a statistical model leaves out one or more relevant variables” (i.e. purpose?)

**Table 4.X**

|  |  |  |
| --- | --- | --- |
| *Subset* | *N* | *% of total trips* |
| Rush Hour | 40,945 | 56.1 |
| Off-Peak | 32,084 | 43.9 |
| City | 68,275 | 93.5 |
| Non-city | 4,754 | 6.5 |

New Purpose labels:

Based on correlation

"1":["shops","leisure","cafe","returning\_home"],"2":["education"],\

"3":["health"],"4":["pick\_up\_a\_person"],"5":["work"]}

1 47464

5 18950

2 2769

4 1574

3 1044

*Classification of purpose of travel:*

Take 1st week -> predict then Take 2nd week -> predict then … compare accuracy scores

Sizes of data:

len(purp\_gdf), len(purp\_city), len(purp\_noncity), len(purp\_rush), len(purp\_nonrush), (71801, 66029, 5772, 39695, 32106)

CANT DO LSTM or RNN as time is not regular

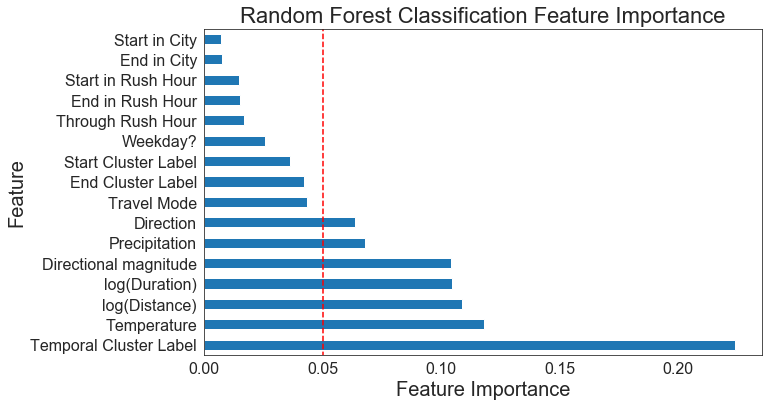
Can do CNN because of grid

*Random Forest:*

Random Forest:

ADD CONFUSION MATRIX OF PREDICTIONS FOR EACH CLASS WITH PROPER NAMES

* Feature importance
* Plot residuals



**Figure 4.X**

|  |  |  |  |
| --- | --- | --- | --- |
|  | RF |  | n |
| All | 0.8116480270099177 |  |  |
| City | 0.8131174162118273 |  |  |
| Non-City | 0.8086500655307994 |  |  |
| Rush | 0.8489446405768798 |  |  |
| Non-Rush | 0.7686380273550376 |  |  |

RF normal:

'purp\_gdf': array([0.80827185, 0.81544217, 0.8151112 , 0.81278586, 0.81742566]),

'purp\_city': array([0.81263883, 0.8150411 , 0.82103977, 0.80835463, 0.8143127 ]),

'purp\_noncity': array([0.80515298, 0.81320451, 0.80322581, 0.82200647, 0.82524272]),

'purp\_rush': array([0.84744822, 0.84464583, 0.84739179, 0.84680851, 0.84749213]),

'purp\_nonrush': array([0.76879298, 0.76944972, 0.76826376, 0.77100142, 0.77171334])

Cross-validated multi-class

{'purp\_gdf': array([0.73622947, 0.73838478, 0.73453903, 0.74275023, 0.74586841]),

'purp\_city': array([0.73694735, 0.74294601, 0.74016885, 0.72891901, 0.73780691]),

'purp\_noncity': array([0.70645161, 0.7516129 , 0.6983871 , 0.69789984, 0.73505654]),

'purp\_rush': array([0.79670736, 0.78838328, 0.7891232 , 0.80281169, 0.79278446]),

'purp\_nonrush': array([0.67220114, 0.66816888, 0.66500593, 0.67852906, 0.66476868])}

Predictions RF:

1.0 21108

0.0 2419

2.0 167

3.0 1

*Comparison of Models:*

Dimensions:

'purp\_gdf': (71801, 22),

'purp\_city': (67177, 22),

'purp\_noncity': (4624, 22),

'purp\_rush': (40342, 22),

'purp\_nonrush': (31459, 62)}

*SVC:*

cv\_scores\_rf

{'purp\_gdf': 0.7364844903988184,

'purp\_city': 0.7402228336866796,

'purp\_noncity': 0.7070773263433814,

'purp\_rush': 0.7959137684969578,

'purp\_nonrush': 0.6675014448083221}

cv\_scores\_svc

{'purp\_gdf': 0.6609411268200042,

'purp\_city': 0.6556903784564031,

'purp\_noncity': 0.7450851900393185,

'purp\_rush': 0.7543003079696537,

'purp\_nonrush': 0.7545752263533038}

cv\_scores\_nn

{'purp\_gdf': 0.7864950411479215,

'purp\_city': 0.7898867788353106,

'purp\_noncity': 0.7234600262123198,

'purp\_rush': 0.8369263126267558,

'purp\_nonrush': 0.7356963976112503}

num\_dims

{'purp\_gdf': (71801, 23),

'purp\_city': (67177, 23),

'purp\_noncity': (4624, 23),

'purp\_rush': (40342, 7),

'purp\_nonrush': (31459, 63)}

Hyper Parameter for SVC:

For the purposes of the classification models, the data is normalised for the purpose of the

Cs = [0.1, 1, 10]

gammas = [0.01, 0.1, 1]

Best == {'C': 0.1, 'gamma': 0.01}

SVC:

ADD CONFUSION MATRIX OF PREDICTIONS FOR EACH CLASS WITH PROPER NAMES

Results on the test set: RF:

precision recall f1-score support

0.0 0.00 0.00 0.00 0

1.0 0.85 0.89 0.87 15661

2.0 0.00 0.00 0.00 955

3.0 0.00 0.00 0.00 322

4.0 1.00 0.00 0.00 510

5.0 0.76 0.57 0.65 6247

accuracy 0.74 23695

macro avg 0.43 0.24 0.25 23695

weighted avg 0.78 0.74 0.74 23695

Results on the test set: SVC:

precision recall f1-score support

1.0 0.66 1.00 0.80 15661

2.0 0.00 0.00 0.00 955

3.0 0.00 0.00 0.00 322

4.0 0.00 0.00 0.00 510

5.0 0.00 0.00 0.00 6247

accuracy 0.66 23695

macro avg 0.13 0.20 0.16 23695

weighted avg 0.44 0.66 0.53 23695

Results on the test set: NN:

precision recall f1-score support

0.0 0.00 0.00 0.00 0

1.0 0.83 0.93 0.88 15661

2.0 0.00 0.00 0.00 955

3.0 0.00 0.00 0.00 322

4.0 0.00 0.00 0.00 510

5.0 0.73 0.64 0.68 6247

accuracy 0.79 23695

macro avg 0.26 0.26 0.26 23695

weighted avg 0.74 0.79 0.76 23695

NN:

10,000 iterations/epochs for NN

ADD CONFUSION MATRIX OF PREDICTIONS FOR EACH CLASS WITH PROPER NAMES

Best estimator:

ctivation='relu', alpha=0.1, batch\_size='auto', beta\_1=0.9,

beta\_2=0.999, early\_stopping=False, epsilon=1e-08,

hidden\_layer\_sizes=5, learning\_rate='constant',

learning\_rate\_init=0.001, max\_iter=500, momentum=0.9,

n\_iter\_no\_change=10, nesterovs\_momentum=True, power\_t=0.5,

random\_state=3, shuffle=True, solver='lbfgs', tol=0.0001,

validation\_fraction=0.1, verbose=False, warm\_start=False

'alpha': 0.01,

'hidden\_layer\_sizes': (50, 50, 50),

'max\_iter': 500,

'solver': 'lbfgs'

Predictions NN:

1.0 23136

0.0 559

CNN:

### 4.3.1 Spatial and Temporal Dependency in Error Terms:

After classification of trip purpose, we examine the spatial and temporal distribution of any mis-classified trips.

Error Terms & Scores

len(all\_true), len(no\_true), len(only\_svc), len(only\_rf), len(only\_nn), len(all\_but\_svc),len(all\_but\_rf),len(all\_but\_nn)

(13773, 3801, 857, 218, 588, 3427, 848, 183)

[Example results writing] “Most of the misclassified trip were …]

What I am trying to show:

* Idea about the MTL Trajet
* What specs for purposes (i.e. which modes, where, etc.)
* Space, time and space-time trends
* Classification results (how well we can classify purpose and most important things)