Uber Movement - Data Wrangling

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Version: 1.0

Environment: Python 3.6.0 and Anaconda 4.3.0 (64-bit)

Libraries used:

- pandas 0.22.0 (for data frame, included in Anaconda Python 3.6)
- numpy 1.14.0 (for data manipulation, included in Anaconda Python 3.6)
- datetime (for datetime formats , included in Anaconda Python 3.6)
- math (for mathematical functions, like sin, radians, etc., included in Anaconda Python 3.6)
- sklearn.linear_model (for Linear Regression, included in Anaconda Pyhton 3.6)
- sklearn.metrics (for accuracy tests, like r2_score, included in Anaconda Pyhton 3.6)
- networkx has (for creation and manipulation of complex networks, included in Anaconda Pyhton 3.6)
- seaborn (for data visualisation and creating plots, included in Anaconda Pyhton 3.6)
- matplotlib (for data visualisation, included in Anaconda Pyhton 3.6)

Introduction

This project is about exploring and understanding the data, by performing both graphical and non-graphical EDA methods to first understand the data and then find the data problems. It enables us to practice on the most important process of Data Wrangling. It is devided into three tasks, with three different files, which are:

1. Detecting and fixing errors in 38KB file `dirty_data.csv` , comprising of 309 rows .
2. Impute the missing values in 15KB file `missing_value.csv` , comprising of 120 rows.
3. Detecting and removing outliers in 14KB file `outliers.csv` , comprising of 100 rows.

The dataset provided is about Uber Ridesharing data in Victoria, Australia. This data set contains the following variables:

- Id: A unique id for the journey
- Uber type: A categorical attribute for the type of the journey.
- Origin region: Region for the origin of the journey
- Destination region: Region for the destination of the journey
- Origin latitude: Latitude of the origin
- Origin longitude: Longitude of the origin
- Destination latitude: Latitude of the destination
- Destination longitude: Longitude of the destination
- Journey Distance: The shortest path, in meters, between the origin and the destination
- Departure date: Date of the departure
- Departure time: Time of the departure
- Travel time: Travel time (i.e., duration) of the journey in seconds
- Arrival time: The time of the arrival
- Fare$: The fare of the journey

Two other data files are provided which are `nodes.csv` , which contains data about the latitude and longitude position of any node, and `edges.csv` , which contains information about distance and speed limit between two nodes.

These data set contains the following variables: `nodes.csv` :

- id: A node id for the locations
- lat: Latitude of the node
- long: Longitude of the node

`edges.csv` :

- u: Node id for origin location
- v: Node id for destination location
- distance(m): Distance from the origin to the destination node in metres
- street type: A categorical varibale representing street type between two nodes
- speed(km/h): Speed limit from the origin to the destination node in Kilometres per hour

More details for each task will be given in the following sections.

We are assuming all data files are kept in the current working directory. If this is not the case, following code can be used to change the working directory. One can put in the desired path in the given quotes.

In [1]:
```
# Setting working directory
# import os
# os.chdir('/Users/reyash/Downloads/FIT5196/Assignment-2')
```

Importing libraries

In [2]:
```
# importing libraries

import pandas as pd
import numpy as np
import datetime
from math import radians, atan2, sin, cos,sqrt

from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

import networkx as nx

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Task 1 - Cleaning Dirty Data

This task is to detect and rectify `Semantic` and `Syntactical` anomalies, including formats, integrity constraints, etc. We will begin exploring dirty data now!

Reading Data

In [3]:
```
# reading dirty data
data = pd.read_csv('29895405_dirty_data.csv')

# saving column names of dataframes
header = data.columns.to_list()

# reading data about nodes & edges
nodes = pd.read_csv('nodes.csv')
edges = pd.read_csv('edges.csv',index_col = 0)

data = data.rename(columns = {'Unnamed: 0':'Id'})
nodes = nodes.rename(columns = {'Unnamed: 0':'node'})

# renaming columns for easy access while operations
data.columns = data.columns.str.strip().str.lower().str.replace(' ', '_').str.replace('\(s\)', '').str.replace('\(m\)', '')
```

In [4]:
```
data.describe()
```

Out[4]:

	uber_type	origin_region	destination_region	origin_latitude	origin_longitude	destination_latitude	destination_longitude	journey_distance	travel_time	fare$
count	309.000000	309.000000	309.000000	309.000000	309.000000	309.000000	309.000000	309.000000	309.000000	309.000000
mean	0.705502	5.058252	5.012945	-36.619492	144.937018	-36.637928	144.917716	17159.584142	4429.433722	94.252589
std	0.747725	2.459379	2.684702	9.562921	0.100922	9.566080	0.121151	17587.588475	4240.886697	253.780360
min	0.000000	1.000000	1.000000	-38.110916	144.654173	-38.110916	144.654173	537.000000	153.540000	2.710000
25%	0.000000	3.000000	3.000000	-37.823450	144.927414	-37.861835	144.905716	4534.000000	1210.180000	11.650000
50%	1.000000	5.000000	5.000000	-37.814464	144.960728	-37.814796	144.955328	8722.000000	2530.320000	17.400000
75%	1.000000	7.000000	7.000000	-37.804417	144.990059	-37.805850	144.985865	41560.000000	9972.900000	29.330000
max	3.000000	9.000000	9.000000	37.861835	145.046450	37.861835	145.046450	51061.000000	13204.980000	1315.170000

Some anomalies found upon inspection are,

- **Syntactic Anomalies**
  - `uber_type` has minimum value of 0 and maximum of 3, which contradicts its description of having three type values.
  - `origin_latitude` and `destination_latitude` has maximum value of 37.861835, which contradicts the fact of data being about uber rides in Victoria, since Victoria is in southern hemishpere, which corresponds to negative latitude values.

In [5]:
```
# Looking at the information about the dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 309 entries, 0 to 308
Data columns (total 14 columns):
id                       309 non-null object
uber_type                309 non-null int64
origin_region            309 non-null int64
destination_region       309 non-null int64
origin_latitude          309 non-null float64
origin_longitude         309 non-null float64
destination_latitude     309 non-null float64
destination_longitude    309 non-null float64
journey_distance         309 non-null float64
departure_date           309 non-null object
departure_time           309 non-null object
travel_time              309 non-null float64
arrival_time             309 non-null object
fare$                    309 non-null float64
dtypes: float64(7), int64(3), object(4)
memory usage: 33.9+ KB
```

Let's have a look at few values of the dataset.

In [6]:
```
# Priting first 5 elements in the dataset
data.head()
```

Out[6]:

	id	uber_type	origin_region	destination_region	origin_latitude	origin_longitude	destination_latitude	destination_longitude	journey_distance	departure_date	departure_time	travel_time	arrival_time	fare$
0	ID3487635877	1	8	4	-37.815834	145.046450	-37.810009	144.995790	4510.0	2018-03-09	07:24:43	1411.44	7:48:14	9.04
1	ID1553159484	0	3	4	-37.810907	144.988892	-37.808068	144.991715	537.0	2018-05-08	08:22:56	153.54	8:25:29	3.91
2	ID3397114293	1	8	6	-37.815834	145.046450	-37.790797	144.985865	7470.0	2018-04-20	21:25:59	2302.38	22:04:21	25.32
3	ID3646335243	1	5	6	-37.799047	144.935588	-37.790797	144.985865	7771.0	2018-07-14	10:44:36	2060.88	11:18:56	16.15
4	ID3427629663	1	7	4	-37.861835	144.905716	-37.814118	145.009281	11869.0	2018-07-26	11:59:45	3714.66	13:01:39	17.24

Uber Type

Upon inspecting the data more carefully, it is apparent that there is a pattern between `id` and `uber_type` , which is, ID's strating with 'ID1' corresponds to uber type '0', ID's strating with 'ID3' corresponds to uber type '1', and ID's strating with 'ID5' corresponds to uber type '2'.

Using the information about the presence of three uber types and aforementioned pattern we can correct the rows with uber type as 3!

In [7]:
```
uber_types = {0,1,2} # Acceptable uber types

print('Number of rows with unacceptable uber types are',data[~data.uber_type.isin(uber_types)].shape[0],'.')
```

```
Number of rows with unacceptable uber types are 6 .
```

In [8]:
```
# Fetching indexes of rows with unacceptable uber types
uber_indexes = data[~data.uber_type.isin(uber_types)].index.to_list()

# Following loop compares the ID string with the patterns passed and updates the uber type accordingly
for index in uber_indexes:
    if data.loc[index,'id'].startswith('ID1'):
        data.loc[index,'uber_type'] = 0
    elif data.loc[index,'id'].startswith('ID3'):
        data.loc[index,'uber_type'] = 1
    else:
        data.loc[index,'uber_type'] = 2
```

In [9]:
```
print('Number of rows with unacceptable uber types after correction are',data[~data.uber_type.isin(uber_types)].shape[0],'.')
```

```
Number of rows with unacceptable uber types after correction are 0 .
```

Latitude values

Since the data is about uber rides in victoria, where latitude values are negative and longitude are postive. Therefore, positive latitude and negative longitudes are unacceptable. We will correct it by simply negating wrong latitude and longitude values.

In [10]:
```
print('Number of rows with postive latitudes are', data[(data.origin_latitude > 0) | (data.destination_latitude > 0)].shape[0],'.')
print('Number of rows with negative longitudes are', data[(data.origin_longitude < 0) | (data.destination_longitude < 0)].shape[0],'.')
```

```
Number of rows with postive latitudes are 10 .
Number of rows with negative longitudes are 0 .
```

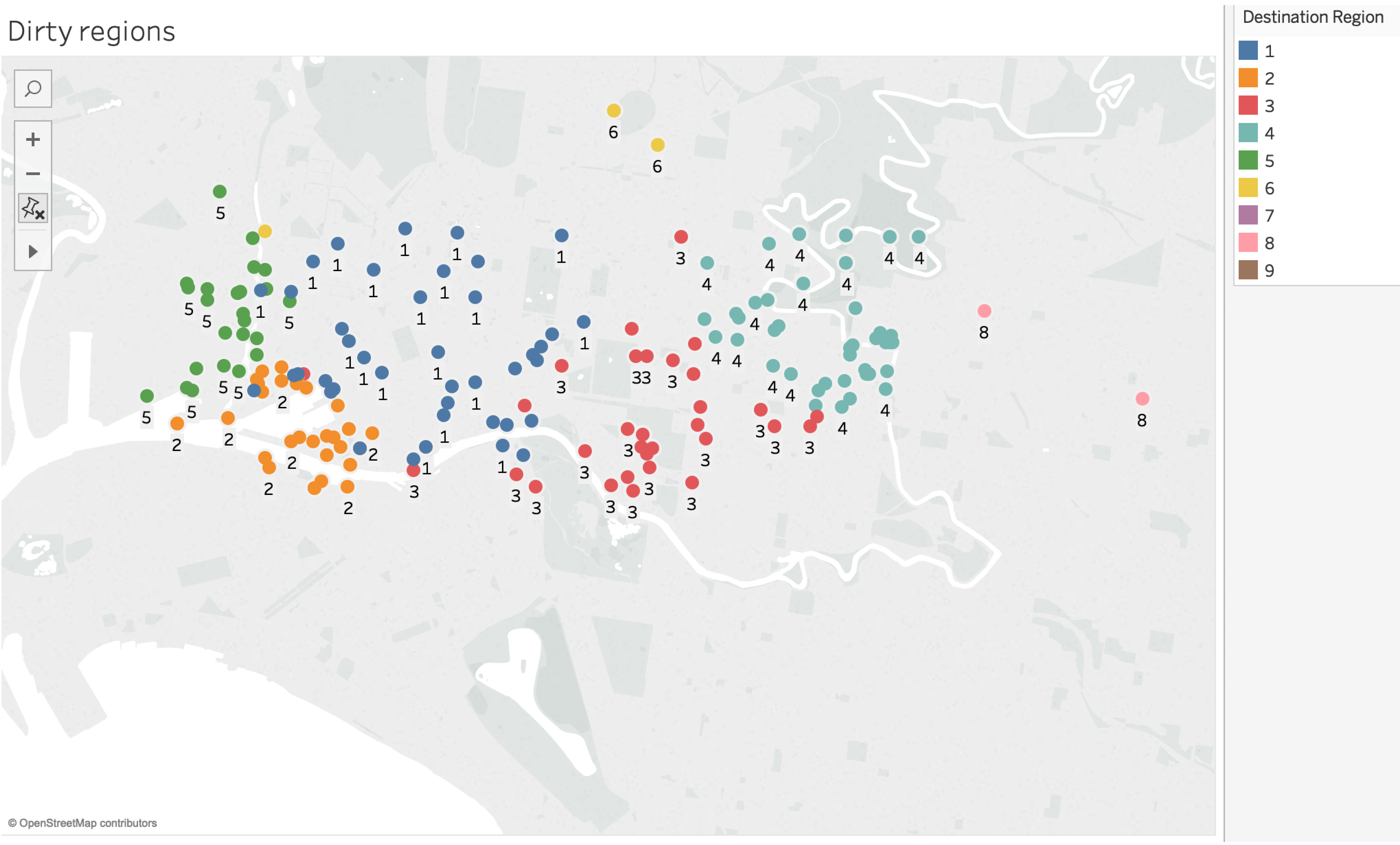
In [11]:
```
# Fixing latitudes

# Fetching indexes of positive latitudes
origin_indexes = data[(data.origin_latitude > 0)].index
dest_indexes = data[(data.destination_latitude > 0)].index

# Storing indexes of rows with wrong latitude values
lat_indexes = data[(data.origin_latitude > 0) | (data.destination_latitude > 0)].index.to_list()

# Negating wrong latitude values in 'origin_latitude' and 'destination_latitude'
data.loc[(data.origin_latitude > 0), 'origin_latitude'] = data[(data.origin_latitude > 0)].origin_latitude.apply(lambda x: -x)
data.loc[(data.destination_latitude > 0), 'destination_latitude'] = data[(data.destination_latitude > 0)].destination_latitude.apply(lambda x: -x)
```

In [12]:
```
print('Number of rows with postive latitudes after correction are', data[(data.origin_latitude > 0) | (data.destination_latitude > 0)].shape[0],'.')
```

```
Number of rows with postive latitudes after correction are 0 .
```

Regions

Now we will explore the region of origin and destination nodes.



We can see from the figure above that regions are overlapping, which is wrong.

We will be using haversine distance to compute distance between two locations of earth, which is explained as follows.

Haversine formula

The distance between any two points on the earth, can be calculated through haversine formula, given their logitude and latitude details, which is,

$d = 2R.\,atan2(\sqrt{h}, \sqrt{1-h})$, where,

h is the haversine formula given by,

$h = sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + cos(\phi_1).\,cos(\phi_2).\,sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)$,

R = Radius of Earth,
ϕ_1 = Latitude of point 1,
ϕ_2 = Latitude of point 2,
λ_1 = Longitude of point 1,
λ_2 = Longitude of point 2

In [13]:
```python
print(data.groupby(['origin_latitude','origin_longitude']).origin_region.unique().head())
print(data.groupby(['destination_latitude','destination_longitude']).destination_region.unique().head())
```

```
origin_latitude  origin_longitude
-38.110916       144.654173          [9, 6]
-37.861835       144.905716          [7, 1]
-37.826364       144.951835             [2]
-37.826175       145.008375             [3]
-37.825421       144.980994             [3]
Name: origin_region, dtype: object
destination_latitude  destination_longitude
-38.110916            144.654173               [9, 3]
-37.861835            144.905716                  [7]
-37.825002            144.982767                  [3]
-37.824725            144.943005                  [2]
-37.824703            144.942872                  [2]
Name: destination_region, dtype: object
```

Apparently, some nodes corresponds to two regions, which violates integrity constraint. This is a '**Semantic Anomaly**'.

We can correct this by exploring all the occurances of nodes in origin and destination region, and selecting the common/frequent value of region . If no value is common, we can select any for now.

In [14]:
```python
# Checking integrity constraints

# Fetching origin and destination nodes
origin_regions = dict(data.groupby(['origin_latitude','origin_longitude']).origin_region.unique())
destination_regions = dict(data.groupby(['destination_latitude','destination_longitude']).destination_region.unique())

# Filtering common occurances of nodes in origin and destination regions
common_nodes = list(set(origin_regions.keys()).intersection(set(destination_regions.keys())))

# Following loop interates over all the common nodes and find the common value for region, if any.
# If it finds any common value of region, it assigns common value of the region to both origin region and destination region.
# If no common value is found, it assigns the first occurance values in origin to all.

for node in common_nodes:
    common_region = list(set(origin_regions[node]).intersection(set(destination_regions[node])))
    if common_region:
        origin_regions[node] = common_region
        destination_regions[node] = common_region
    else:
        destination_regions[node] = origin_regions[node]

# Assigning region values to origin region and destination region.
for key,value in origin_regions.items():
    data.loc[((data.origin_latitude == key[0]) & (data.origin_longitude == key[1])),'origin_region'] = value[0]

for key,value in destination_regions.items():
    data.loc[((data.destination_latitude == key[0]) & (data.destination_longitude == key[1])),'destination_region'] = value[0]
```

Now we will compute centres of regions using both origin regions and destination regions. We will combine information about all nodes and compute median values of latitude and longitude for each region, which will correspond to centre of regions.

In [15]:
```python
# Fetching relevant columns
origin_data = data[['origin_region','origin_latitude','origin_longitude']]
destination_data = data[['destination_region','destination_latitude','destination_longitude']]
regions_cols = ['region','latitude','longitude']

# Renaming columns uniformly, for concatenation
origin_data.columns = regions_cols
destination_data.columns = regions_cols

# Computing medians on concatenated dataframe of both, origin and destination region, for each region
# Concatenated data is grouped by region values. Median is computed on the grouped data
region_centre = (pd.concat([origin_data,destination_data]).groupby(['region']).median()).T.to_dict('list')  # storing as a dictionary
region_centre
```

Out[15]:
```
{1: [-37.81182145, 144.9566952],
 2: [-37.819409949999994, 144.94080205],
 3: [-37.818959400000004, 144.98421405],
 4: [-37.8099899, 145.00706280000003],
 5: [-37.8054636, 144.9322708],
 6: [-37.7874325, 144.98364660000001],
 7: [-37.8618349, 144.90571599999998],
 8: [-37.8158343, 145.04645],
 9: [-38.1109156, 144.65417250000002]}
```

Now we will define, functions to compute haversine distance, calculate closest region centre and clusters of all nodes.

In [16]:
```python
# Following function accepts latitude and longitudes of two locations and returns haversine distance between them
def haversine_distance(lat1, lon1, lat2, lon2):
    R = 6378 # radius of the earth in KMs

    lat_diff = radians(lat2 - lat1)
    long_diff = radians(lon2 - lon1)

    rad_lat1 = radians(lat1)
    rad_lat2 = radians(lat2)

    h = (sin(lat_diff/2) ** 2)+(cos(rad_lat1) * cos(rad_lat2) * (sin(long_diff/2) ** 2))

    polar = atan2(sqrt(h), sqrt(1-h))

    distance = (2*R*polar)*1000 # Distance is in KMs, multiply by 1000 to get meters

    return round(distance, 3)
```

In [17]:
```python
# Following function accepts latitude and longitude of a position, alongwith details of region centres, and returns the closest region corresponding to that node.
def closest_region(lat, long, centre):
    '''
    This function accepts latitude and longitude of a node, compute its distance from all the centres of the region.
    It returns the value of closest region
    '''
    distance_from_regions = {}
    # Calculating distances from all centres
    for region, coordinates in centre.items():
        distance_from_regions[region] = haversine_distance(lat, long,coordinates[0], coordinates[1] )
    shortest = min(distance_from_regions, key = distance_from_regions.get) # returing the region index, based on the distances computed above
    return shortest
```

In [18]:
```python
# Following function is basic K-Means implementation for computing optimal clusters of region
# It returns optimal region values for each node

def Kmeans_region(centre, region_type):

    '''
    This function accepts region centres and the type of region (destination/origin).
    It assigns new region values to nodes, according to shortest distance from centres, and compute new centres iteratively.
    It repeats aforementioned process until the centres stop moving, and have achieved an optimal state
    '''

    new_centres = centre
    old_centres = {} # for storing current centres for next iteration
    counter = 0
    while (new_centres != old_centres): # runs until centres stop changing
#         print(counter)
        old_centres = new_centres.copy()

        # Calculating new centres
        centre_lat = dict(data.groupby('calc_{}_region'.format(region_type))['{}_latitude'.format(region_type)].median())
        centre_long= dict(data.groupby('calc_{}_region'.format(region_type))['{}_longitude'.format(region_type)].median())
        regions = sorted(data['{}_region'.format(region_type)].unique().tolist())
        new_centres = {}
        for region in regions:
            new_centres[region] = [centre_lat[region], centre_long[region]]

        # Assigning region according to new centres generated
        data['calc_{}_region'.format(region_type)] = data[['{}_latitude'.format(region_type),'{}_longitude'.format(region_type)]].apply(lambda t: closest_region(t['{}_latitude'.format(region_type)],t['{}_longitude'.format(region_type)],new_centres), axis=1)

        counter += 1
```

In [19]:
```
# Computing Optimal region values for each node

# Assigning nodes to nearest region centers initially
data['calc_origin_region'] = data[['origin_latitude','origin_longitude']].apply(lambda t: closest_region(t.origin_latitude,t.origin_longitude,region_centre), axis=1)
data['calc_destination_region'] = data[['destination_latitude','destination_longitude']].apply(lambda t: closest_region(t.destination_latitude,t.destination_longitude,region_centre), axis=1)

# Iteratively computing for optimal region
Kmeans_region(region_centre,'origin')
Kmeans_region(region_centre,'destination')
```

In [20]:
```
print('Number of origin region values changed are',data[data.origin_region != data.calc_origin_region].shape[0],'.')
print('Number of destination region values changed are',data[data.destination_region != data.calc_destination_region].shape[0],'.')
```

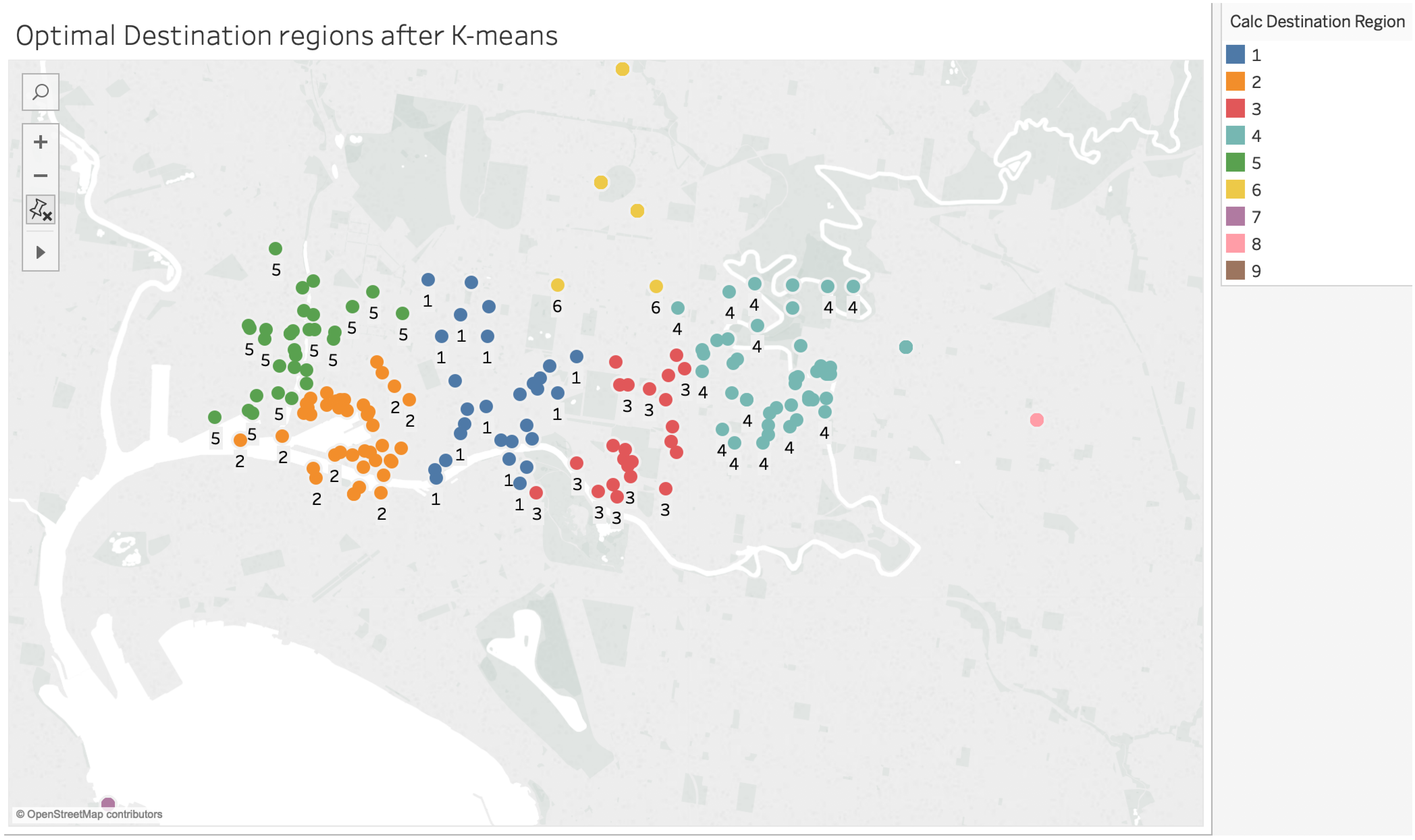
```
Number of origin region values changed are 46 .
Number of destination region values changed are 37 .
```

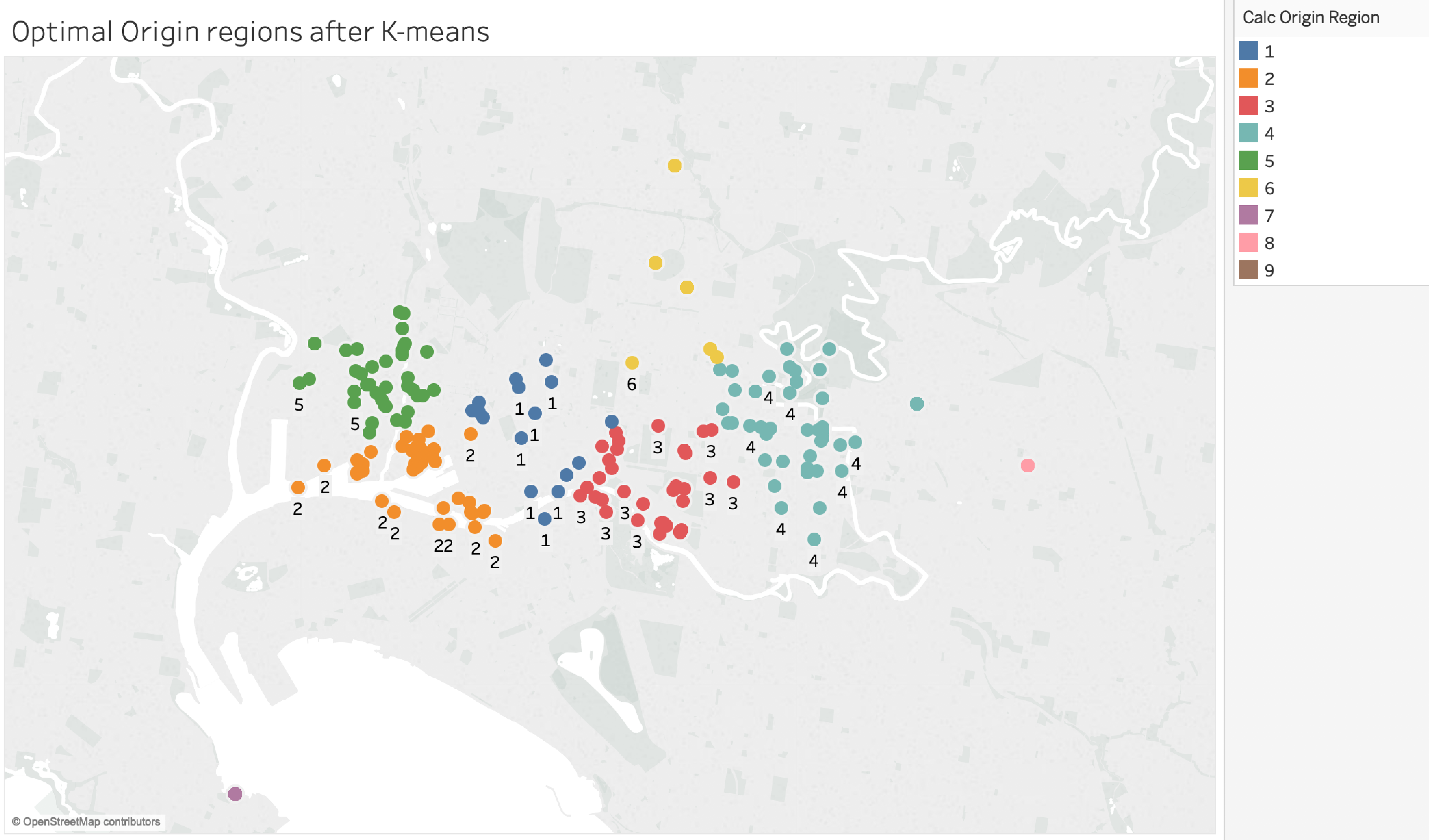
In [21]:
```
# Updating final optimal values
data.loc[data.origin_region != data.calc_origin_region,'origin_region'] = data[data.origin_region != data.calc_origin_region].calc_origin_region
data.loc[data.destination_region != data.calc_destination_region,'destination_region'] = data[data.destination_region != data.calc_destination_region].calc_destination_region
```

In [22]:
```
data.to_csv('region.csv', index = False)
```

Regions after correction

We can see that regions are properly segregated after K-means!





Correcting date format

Two types of date formats are detected, which are:

1. `%Y-%m-%d` : Year-month-day
2. `%d/%m/%y` : Day-month-year
3. `%Y-%d-%m` : Year-day-month

Out of these first one is the most common one, so it would be thw right format and the other ones would be errors. We will correct it and bring it in a common format. This is another kind of **Syntactical Anomaly** where uniform format is not followed.

Upon careful inspection, another **Semantic error** identified in this column are few dates out of the month constraint, like, month of february has day of 31 in the date ('2018-02-30). Other wrong dates include,'2018-06-31' and '2018-04-31'.

In [23]:
```
# defining wrong dates
wrong_dates = {'2018-06-31','2018-04-31','2018-02-30'}
data['correct_date'] = pd.to_datetime(data.departure_date , format = '%Y-%m-%d', errors = 'coerce')
date_indexes = data[((data.correct_date.isnull()) | (data.departure_date.isin(wrong_dates)))].index.to_list()
data.drop(['correct_date'], axis=1, inplace = True)
```

In [24]:
```
# Separating months according to days in months
months_30 = {'04','06','09','11'}
months_31 = {'01','03','05','07','08','10','12'}

# Following function accepts a date, and returns the right form of those dates, I chose the last day of that month to correct that
def fix_dates(date):
    '''
    This function accepts a date, and split the day part, and checks its values, and set its to the last day of that month.
    '''
    date = date.split('-')
    date_day =  date[2]
    date_month = date[1]
    if date_month in months_30 and not (int(date_day) <= 30):
        date[2] = '30'
    elif date_month == '02' and not (int(date_day) <= 28):
        date[2] = '28'
    return ('-').join(date)
```

In [25]:
```
# Following function accepts a date string and returns the parsed date
def parse_date(date_string):
    '''
    This function accepts the a date and try parsing it from any of the given formats, and returns the parsed value
    '''
    formats = ['%Y-%d-%m','%d/%m/%y','%Y-%m-%d']
    for frmt in formats:
        if frmt == '%Y-%m-%d':
            date_string = fix_dates(date_string)
        try:
            return datetime.datetime.strptime(date_string, frmt)
        except ValueError:
            pass
```

In [26]:
```
# fixing date formats
data.departure_date = data['departure_date'].apply(lambda t: parse_date(t.strip()))
```

In [27]:
```python
nat = np.datetime64('NaT')
print('Number of rows with no dates after parsing are',data[np.isnat(data.departure_date)].shape[0],'.')
```

```
Number of rows with no dates after parsing are 0 .
```

In [28]:
```python
data.head()
```

Out[28]:

	id	uber_type	origin_region	destination_region	origin_latitude	origin_longitude	destination_latitude	destination_longitude	journey_distance	departure_date	departure_time	travel_time	arrival_time	fare$	calc_origin_region	calc_destination_region
0	ID3487635877	1	8	4	-37.815834	145.046450	-37.810009	144.995790	4510.0	2018-09-03	07:24:43	1411.44	7:48:14	9.04	8	4
1	ID1553159484	0	3	3	-37.810907	144.988892	-37.808068	144.991715	537.0	2018-08-05	08:22:56	153.54	8:25:29	3.91	3	3
2	ID3397114293	1	8	6	-37.815834	145.046450	-37.790797	144.985865	7470.0	2018-04-20	21:25:59	2302.38	22:04:21	25.32	8	6
3	ID3646335243	1	5	6	-37.799047	144.935588	-37.790797	144.985865	7771.0	2018-07-14	10:44:36	2060.88	11:18:56	16.15	5	6
4	ID3427629663	1	7	4	-37.861835	144.905716	-37.814118	145.009281	11869.0	2018-07-26	11:59:45	3714.66	13:01:39	17.24	7	4

Now the dates have been parsed, and can be put in a proper format in the output file.

Now we will move towards fixing distances travelled in trips. For this task we will fetch node ID's of origin and destination from the `nodes.csv` file, on the basis of the latitude and longitude values provided in the dirty data.

Merging dirty data with nodes data

In [29]:
```python
# merging nodes data accroding to the longitude and latitude details
df = pd.merge(data, nodes, left_on = ['origin_latitude','origin_longitude'], right_on = ['lat','lon'], how='left')
df = df.rename(columns = {'node':'origin_node'})
df = df.drop(['lat','lon'], axis = 1)

df2 = pd.merge(df, nodes, left_on = ['destination_latitude','destination_longitude'], right_on = ['lat','lon'], how='left')
df2 = df2.rename(columns = {'node':'destination_node'})
df2 = df2.drop(['lat','lon'], axis = 1)
```

In [30]:
```python
df2.head()
```

Out[30]:

	id	uber_type	origin_region	destination_region	origin_latitude	origin_longitude	destination_latitude	destination_longitude	journey_distance	departure_date	departure_time	travel_time	arrival_time	fare$	calc_origin_region	calc_destination_region	origin_node	destination_node
0	ID3487635877	1	8	4	-37.815834	145.046450	-37.810009	144.995790	4510.0	2018-09-03	07:24:43	1411.44	7:48:14	9.04	8	4	1889485053	4061053476
1	ID1553159484	0	3	3	-37.810907	144.988892	-37.808068	144.991715	537.0	2018-08-05	08:22:56	153.54	8:25:29	3.91	3	3	241807193	681285284
2	ID3397114293	1	8	6	-37.815834	145.046450	-37.790797	144.985865	7470.0	2018-04-20	21:25:59	2302.38	22:04:21	25.32	8	6	1889485053	4307007286
3	ID3646335243	1	5	6	-37.799047	144.935588	-37.790797	144.985865	7771.0	2018-07-14	10:44:36	2060.88	11:18:56	16.15	5	6	2185303474	4307007286
4	ID3427629663	1	7	4	-37.861835	144.905716	-37.814118	145.009281	11869.0	2018-07-26	11:59:45	3714.66	13:01:39	17.24	7	4	1390575046	2481930759

We have succesfully merges the data!

Calculating shortest distances

Now we will be computing shortest distance with the help of Dijisktra's Algorithm. We will be using `edges.csv` file, which contains information after distance ad speed limit between two nodes.

We will use `networkx` library to build a graph of nodes using distance as the weights. This graph will later be used to apply Dijikstra's and compute shortes distance between my origin nodes and destination nodes.

In [31]:
```python
# Building Graph between nodes using distance as weights
Graph = nx.from_pandas_edgelist(edges, 'u', 'v', ['distance(m)'])

short_dist = {}
paths = {}
travel_times = {}

df2['calc_distance'] = np.NaN

# Following loop iterates upon all the rows of my dataset and calculate shortest distance and all paths with shortest distance between origin and destination nodes.
# 'single_source_dijkstra()' is used to calculate the shortest distance
# 'all_shortest_paths()' is used to generate paths with shortest distance for all trips

for index in range(df2.shape[0]):

    src = df2.loc[index,'origin_node']
    des = df2.loc[index,'destination_node']

    dist, path = nx.single_source_dijkstra(Graph,source=src, target=des, weight = 'distance(m)')
    df2.loc[index,'calc_distance'] = dist

    short_dist[(src,des)] = dist
    # Generating all shortest paths for all trips
    paths[(src,des)] = list(nx.all_shortest_paths(Graph,source=src, target=des, weight='distance(m)'))

# Storing indexes where calculate distance is not equal to given distance.
distance_indexes = df2[(df2.journey_distance != df2.calc_distance)].index.to_list()
```

Now we will update distances for trips, where the distance provided is not the shortest one.

In [32]:
```python
print('The number of rows in which distance are not shortest are',df2[df2.journey_distance != df2.calc_distance].shape[0],'.')
df2.loc[(df2.journey_distance != df2.calc_distance),'journey_distance'] = df2[(df2.journey_distance != df2.calc_distance)].calc_distance
```

```
The number of rows in which distance are not shortest are 5 .
```

In [33]:
```python
print('The number of rows in which distance are not shortest, after correction are',df2[df2.journey_distance != df2.calc_distance].shape[0],'.')
```

```
The number of rows in which distance are not shortest, after correction are 0 .
```

Travel time and Arrival time

Now we will check the integrity constaraint on travel times and arrival time based on the formula `Departure time + Travel time = Arrival time`. Any rows where this property violates leads to the presence of another **'Semantic Anomaly'** in our dataset.

Firstly, we will check for rows where `Departure time > Arrival time`.

In [34]:

```
df2[['departure_time','travel_time','arrival_time']][df2.departure_time > df2.arrival_time]
```

168	12:27:25	3859.50	11:23:06
169	13:16:17	380.64	13:09:57
171	16:58:37	12976.50	13:22:21
173	20:46:36	11702.10	17:31:34
174	3:19:49	10941.96	00:17:28
175	23:13:36	2552.82	22:31:04
178	6:04:56	973.02	05:48:43
181	20:11:14	1891.86	19:39:43
182	22:07:30	11407.86	1:17:37
183	22:30:31	11065.68	19:26:06
259	23:43:11	2302.38	0:21:33
288	23:47:38	2090.46	0:22:28

We can see that some trips ends on the next day of the departure date. However, some rows like index 167, has departure time after arrival time. Since every row can only have one error, we can assume travel time is correct and will correct arrival and departure times, with the help of formula,

` Arrival time + Travel time = Departure time`

In [35]:

```
# Checking for rows whcih satisfies above condition
df2[['departure_time','travel_time','arrival_time']][(pd.to_datetime(df2.arrival_time) + pd.to_timedelta(df2.travel_time, unit = 's')).astype('datetime64[s]').dt.time == pd.to_datetime(df2.departure_time).dt.time]
```

Out[35]:

	departure_time	travel_time	arrival_time
167	20:23:42	580.86	20:14:02
168	12:27:25	3859.50	11:23:06
169	13:16:17	380.64	13:09:57
171	16:58:37	12976.50	13:22:21
173	20:46:36	11702.10	17:31:34
174	3:19:49	10941.96	00:17:28
175	23:13:36	2552.82	22:31:04
178	6:04:56	973.02	05:48:43
181	20:11:14	1891.86	19:39:43
183	22:30:31	11065.68	19:26:06

Now, we will swap departure and arrival times in the above rows.

In [36]:

```
# Swapping departure and arrival times
swap_indexes = df2[(pd.to_datetime(df2.arrival_time) + pd.to_timedelta(df2.travel_time, unit = 's')).astype('datetime64[s]').dt.time == pd.to_datetime(df2.departure_time).dt.time].index
df2.loc[swap_indexes,['departure_time','arrival_time']] = df2.loc[swap_indexes,['arrival_time','departure_time']].values
```

Now we will look for the rows which violates our integrity equation of `Departure time + Travel time = Arrival time`.

If any such rows are found, then by assuming the departure time is correct we can safely assume some anomalies in travel time and arrival times.

In [37]:

```
# rounding off time to two decimal places
df2['travel_time'] = df2.travel_time.apply(lambda t: round(t,2))

# calculated arrival time = departure time + travel time given
df2['calc_arrival'] = (pd.to_datetime(df2.departure_time) + pd.to_timedelta(df2.travel_time, unit = 's')).astype('datetime64[s]').dt.time

print('Number of rows with wrong arrival time is',df2[pd.to_datetime(df2.arrival_time).dt.time != df2.calc_arrival].shape[0],'!')
df2[['departure_time','travel_time','arrival_time','calc_arrival']][pd.to_datetime(df2.arrival_time).dt.time != df2.calc_arrival]
```

```
Number of rows with wrong arrival time is 20 !
```

Out[37]:

	departure_time	travel_time	arrival_time	calc_arrival
74	07:08:59	1262.98	7:28:45	07:30:01
75	01:01:54	1875.88	1:31:56	01:33:09
77	07:10:39	830.46	7:24:14	07:24:29
78	08:07:38	10738.72	11:06:05	11:06:36
79	07:32:58	1483.90	7:57:46	07:57:41
82	04:13:58	1210.18	4:33:52	04:34:08
85	09:38:06	2276.70	10:14:38	10:16:02
86	09:08:02	10940.46	12:09:49	12:10:22
91	13:07:12	973.84	13:22:30	13:23:25
94	07:14:40	945.16	7:29:21	07:30:25
99	23:14:18	982.56	4:45:16	23:30:40
101	11:33:11	3729.06	12:18:58	12:35:20
107	19:01:25	3523.02	19:04:52	20:00:08
108	13:23:49	1797.36	18:44:55	13:53:46
110	16:59:43	1939.02	20:57:48	17:32:02
116	16:31:28	718.80	20:11:58	16:43:26
117	12:13:08	2214.60	15:43:56	12:50:02
119	11:18:26	13204.98	12:30:57	14:58:30
122	20:56:14	3535.56	1:49:38	21:55:09
123	19:32:22	1785.18	22:31:34	20:02:07

Now we will correct these 20 rows found! We will compute travel time on the shortest paths returned by Dijikstra's.

In [38]:

```
def traveltime(path, edges):
    '''
    This function accepts any paths, which is a list of nodes vistied in the order, and returns the travel time taken on that.
    'edges.csv' is used to compute time by using distance and speed between any two nodes.
    '''
    tt = 0
    for i in range(len(path)-1):
        tt = tt + (edges[((edges.u==path[i]) & (edges.v == path[i+1])) | ((edges.v==path[i]) & (edges.u== path[i+1]))]['distance(m)'].values[0] * 1.0 * 3600) / (edges[((edges.u==path[i]) & (edges.v== path[i+1])) | ((edges.v==path[i]) & (edges.u== path[i+1]))]['speed(km/h)'].values[0] * 1000)
    return tt
```

In [39]:
```
# Following function will be used to filter large dataset of edges, to the the dataset containing details about nodes visited in my paths.
def relevant_nodes(paths):
    '''
    This function accepts a dictionary of paths, and returns all the visited nodes in all the paths.
    '''
    visited_nodes = set()

    for key,path in paths.items():
        for p in path:
            visited_nodes = visited_nodes|set(p)
    return visited_nodes
```

In [40]:
```
# Following function filters edges dataset and returns trimmed dataset for the nodes required.
def filter_edges(visited_nodes):
    return edges[(edges.u.isin(visited_nodes) | edges.v.isin(visited_nodes))]
```

Since the `edges.csv` contains more than 250,000 rows, we can filter it for the nodes that are traversed in our paths, with the help of above two functions.

In [41]:
```
filtered_edges = filter_edges(relevant_nodes(paths))
print('Number of rows in filtered edges are',filtered_edges.shape[0])
```

```
Number of rows in filtered edges are 19386
```

Now we will be computing travel times in the rows which violated integrity constraint by using `traveltime()` function. Then we will check whether the time calculated is same as one of the times computed for the shortest paths by Dijikstra's. If it is true, then we can infer that the problem is in 'Arrival Time' and fix that using `Arrival time = Departure time + Travel time` , and if it is false, then the travel time given is wrong and can be corrected by using the formula `Travel time = Arrival time - Departure time` .

In [42]:
```
# filtering relevant indexes
relevant_index = df2[pd.to_datetime(df2.arrival_time).dt.time != df2.calc_arrival].index.to_list()

# Iterating over all indexes
for index in relevant_index:
    # Getting ride details, i.e. 'origin_node' and 'destination_node'
    ride = tuple(df2.loc[index,['origin_node','destination_node']].to_list())
    current_time = df2.loc[index, 'travel_time']

    travel_times = []

    # Iterating over all paths computed by Dijikstra's for every ride
    for path in paths[ride]:
        # Computing travel times for all rides
        travel_times.append(round(traveltime(path, filtered_edges),2))

    # Checking if the time provided is in the travel times of shortest paths
    if current_time in travel_times:
        # Fixing Arrival time, if condition satisfies
        calc_arrival_time = (pd.to_datetime(df2.loc[index, 'departure_time']) + pd.to_timedelta(df2.loc[index, 'travel_time'], unit='s')).strftime(format="%H:%M:%S")
        df2.loc[index, 'arrival_time'] = calc_arrival_time
    else:
        # Fixing Travel time, if condition is False
        df2.loc[index, 'travel_time'] = (df2.loc[index, 'arrival_time'] - pd.to_timedelta(df2.loc[index, 'departure_time'])).seconds
```

In [43]:
```
# Checking if all violations have been tackeled
df2['calc_arrival'] = (pd.to_datetime(df2.departure_time) + pd.to_timedelta(df2.travel_time, unit = 's')).astype('datetime64[s]').dt.time

print('Number of rows with wrong arrival time is',df2[pd.to_datetime(df2.arrival_time).dt.time != df2.calc_arrival].shape[0],'!')
```

```
Number of rows with wrong arrival time is 0 !
```

In [44]:
```
df2.head()
```

Out[44]:

	id	uber_type	origin_region	destination_region	origin_latitude	origin_longitude	destination_latitude	destination_longitude	journey_distance	departure_date	departure_time	travel_time	arrival_time	fare$	calc_origin_region	calc_destination_region	origin_node	destination_node	calc_distance	calc_arrival
0	ID3487635877	1	8	4	-37.815834	145.046450	-37.810009	144.995790	4510.0	2018-09-03	07:24:43	1411.44	7:48:14	9.04	8	4	1889485053	4061053476	4510.0	07:48:14
1	ID1553159484	0	3	3	-37.810907	144.988892	-37.808068	144.991715	536.0	2018-08-05	08:22:56	153.54	8:25:29	3.91	3	3	241807193	681285284	536.0	08:25:29
2	ID3397114293	1	8	6	-37.815834	145.046450	-37.790797	144.985865	7470.0	2018-04-20	21:25:59	2302.38	22:04:21	25.32	8	6	1889485053	4307007286	7470.0	22:04:21
3	ID3646335243	1	5	6	-37.799047	144.935588	-37.790797	144.985865	7771.0	2018-07-14	10:44:36	2060.88	11:18:56	16.15	5	6	2185303474	4307007286	7771.0	11:18:56
4	ID3427629663	1	7	4	-37.861835	144.905716	-37.814118	145.009281	11869.0	2018-07-26	11:59:45	3714.66	13:01:39	17.24	7	4	1390575046	2481930759	11869.0	13:01:39

We are done handling all the errors, and its time to get the output file!

In [45]:
```
# Getting proper formats of dates and times
df2.departure_date = df2.departure_date.apply(lambda t : t.strftime(format = '%Y-%m-%d'))

df2 = df2.rename(columns = {'id':''})
header[0] = ''
```

In [46]:
```
# Dropping irrelevant columns
cols = ['calc_origin_region','calc_destination_region','origin_node','destination_node','calc_distance','calc_arrival']
df2.drop(cols,axis=1,inplace=True)
```

In [47]:
```
# writing to csv file
df2.to_csv('29895405_dirty_data_solution.csv',index = False, header = header)
```

Task 2 - Missing Data

This data majorly covers the **'Coverage Anomalies'** of missing data.

Reading data

We will read data file with missing values into a dataframe using `read_csv()` function from pandas library. We will using cleaned data file generated from Task - 1 and rows with non-null values in missing dataset, for training our models to impute the missing data.

In [48]:
```
missing_df = pd.read_csv('29895405_missing_value.csv')

training_df = pd.read_csv('29895405_dirty_data_solution.csv')

header = missing_df.columns.to_list()
missing_df = missing_df.rename(columns = {'Unnamed: 0':'id'})
training_df = training_df.rename(columns = {'Unnamed: 0':'id'})

# Changing colummn names for easy access in later stages
missing_df.columns = missing_df.columns.str.strip().str.lower().str.replace(' ', '_').str.replace('\(s\)', '').str.replace('\(m\)', '').str.replace('$','')
training_df.columns = training_df.columns.str.strip().str.lower().str.replace(' ', '_').str.replace('\(s\)', '').str.replace('\(m\)', '').str.replace('$','')
```

Let's check the missing values in the `missing_df` dataframe.

In [49]:
```
missing_df.isnull().sum()
```

Out[49]:
```
id                        0
uber_type                20
origin_region             0
destination_region        0
origin_latitude           0
origin_longitude          0
destination_latitude      0
destination_longitude     0
journey_distance          0
departure_date            0
departure_time            0
travel_time               0
arrival_time              0
fare                     19
dtype: int64
```

There are 20 missing values in `uber_type` and 19 missing values in `fare` .

Uber type

We can easily correct the `uber_type` in the same way we did in Task - 1, with the pattern between `id` and `uber_type` , which is, ID's strating with 'ID1' corresponds to uber type '0', ID's strating with 'ID3' corresponds to uber type '1', and ID's strating with 'ID5' corresponds to uber type '2'.

In [50]:
```
# Storing indexes of rows with missing uber_type values
missing_indexes = missing_df[missing_df.uber_type.isnull()].index

# Correcting Uber Type
for index in missing_indexes:
    if missing_df.loc[index,'id'].startswith('ID1'):
        missing_df.loc[index,'uber_type'] = 0
    elif missing_df.loc[index,'id'].startswith('ID3'):
        missing_df.loc[index,'uber_type'] = 1
    else:
        missing_df.loc[index,'uber_type'] = 2

missing_df.head()
```

Out[50]:

	id	uber_type	origin_region	destination_region	origin_latitude	origin_longitude	destination_latitude	destination_longitude	journey_distance	departure_date	departure_time	travel_time	arrival_time	fare
0	ID1175692122	0.0	9	8	-38.110916	144.654173	-37.815834	145.046450	51032.0	2018-05-16	08:09:23	12681.06	11:40:44	24.93
1	ID1203782189	0.0	2	5	-37.816940	144.931554	-37.805029	144.931230	3420.0	2018-06-03	01:07:30	950.04	1:23:20	14.93
2	ID1771871365	0.0	8	9	-37.815834	145.046450	-38.110916	144.654173	51032.0	2018-06-18	22:00:40	12681.06	1:32:01	31.54
3	ID5801114100	2.0	4	3	-37.801044	145.008336	-37.824059	144.973518	5386.0	2018-03-04	18:19:54	1294.20	18:41:28	151.79
4	ID1391587949	0.0	6	9	-37.790818	144.985793	-38.110916	144.654173	47186.0	2018-05-13	18:01:28	11418.06	21:11:46	29.73

We have fixed the error in Uber types!

Now, let's check the types of objects in dataframe.

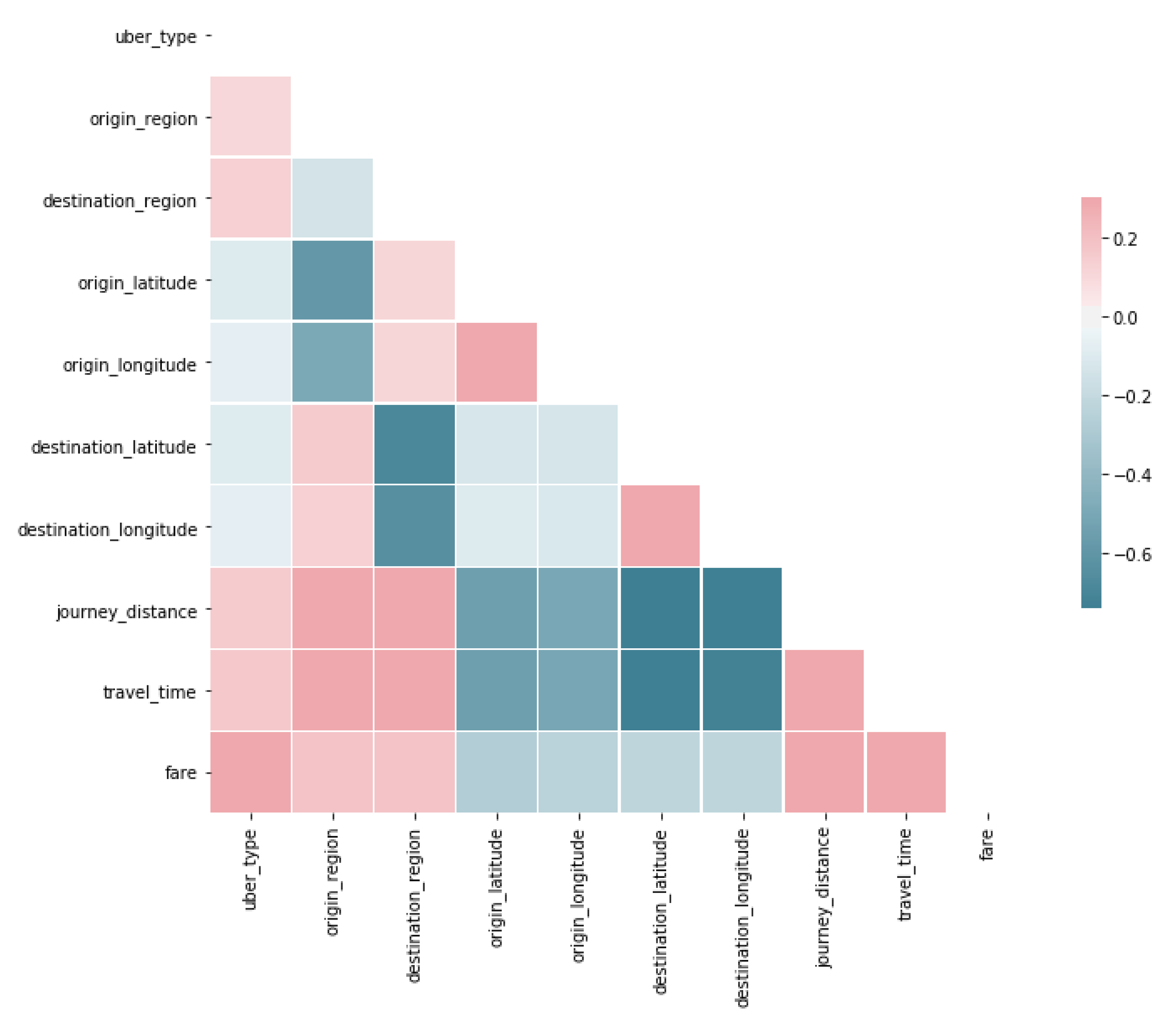
In [51]:
```
missing_df.dtypes
```

Out[51]:
```
id                        object
uber_type                float64
origin_region              int64
destination_region         int64
origin_latitude          float64
origin_longitude         float64
destination_latitude     float64
destination_longitude    float64
journey_distance         float64
departure_date            object
departure_time            object
travel_time              float64
arrival_time              object
fare                     float64
dtype: object
```

Fares

Now we will select and generate features to predcit fares. We can plot the correlation plot and use the most relevant one.

In [52]:
```
corr = training_df.corr()
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0, square=True, linewidths=.5, cbar_kws={"shrink": .5});
```



Upon observing this corelation plot, we can see that `uber_type` has a very strong relationship with fare. Other relevant features can be `journey_distance` and `travel_time`.

We will now engineer some other features.

Feature 1 - `Departure Day` : Since, we know that uber charges extra on weekends than on weekdays. We will build a feature from departure date, telling whether it's a weekday or weekend.

Feature 2 - `Time Zone` : Uber has segregated its charges on the basis of time the ride starts. We know that the Uber company has a specific rule to define a discrete number for morning (i.e. 0)(6:00:00 - 11:59:59), afternoon (i.e. 1,) (12:00:00 - 20:59:59), and night (i.e. 2) (21:00 - 5:59:59) to calculate the fare.

In [53]:
```python
missing_df.departure_date = pd.to_datetime(missing_df.departure_date)
missing_df['departure_day'] = missing_df.departure_date.dt.weekday

training_df.departure_date = pd.to_datetime(training_df.departure_date)
training_df['departure_day'] = training_df.departure_date.dt.weekday

# We use 0 for for weekdays and 1 for weekend
def is_weekend(day):
    '''
    This function returns whether the passed day is weekend or weekday
    '''
    if day <= 5:
        return 0
    else:
        return 1

missing_df.departure_day = missing_df.departure_day.apply(lambda d: is_weekend(d))
training_df.departure_day = training_df.departure_day.apply(lambda d: is_weekend(d))
```

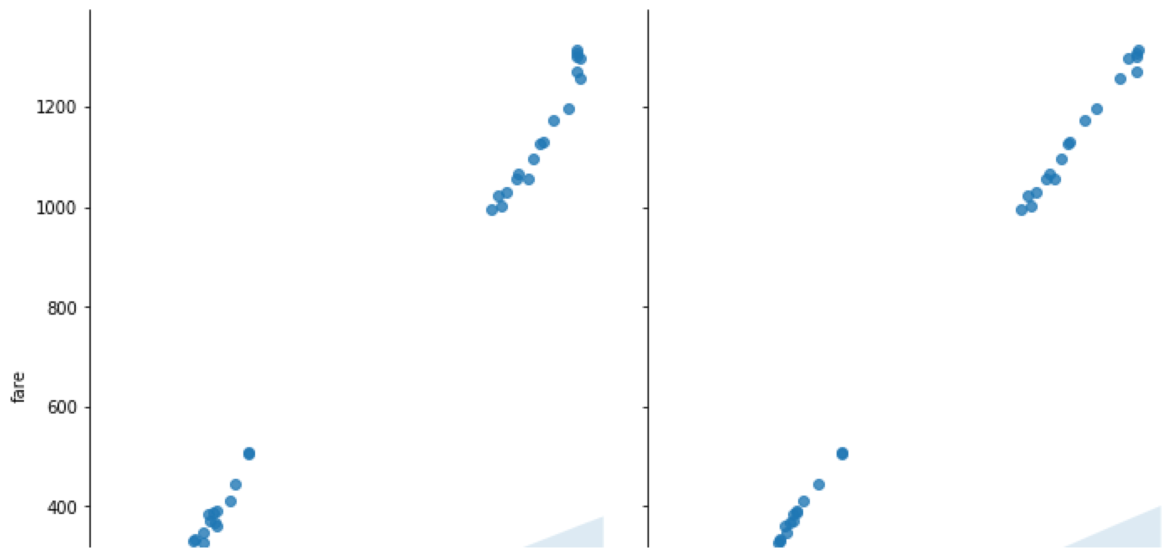
In [54]:
```python
#  Calculating departure time

def time_zone(date):
    '''
    This function calculates the the departure time category set by uber
    '''
    hr = date.hour
    if hr >= 6 and  hr <= 11:
        return 0
    elif hr >= 12 and hr <= 20:
        return 1
    else :
        return 2

# Calcuating departure time zone
missing_df['time_zone'] = missing_df.departure_time.apply( lambda t: time_zone(pd.to_datetime(t)))
training_df['time_zone'] = training_df.departure_time.apply( lambda t: time_zone(pd.to_datetime(t)))
```

Let's drop null values from the missing data!

In [55]:
```python
# Dropping null rows
dropped_df = missing_df.copy()
dropped_df.dropna(subset=['fare'], axis=0, inplace = True)

dropped_df.uber_type = dropped_df.uber_type.astype('int64')
# merging training data with non-null values of missing data
training_df = pd.concat([training_df,dropped_df],ignore_index = True)
```

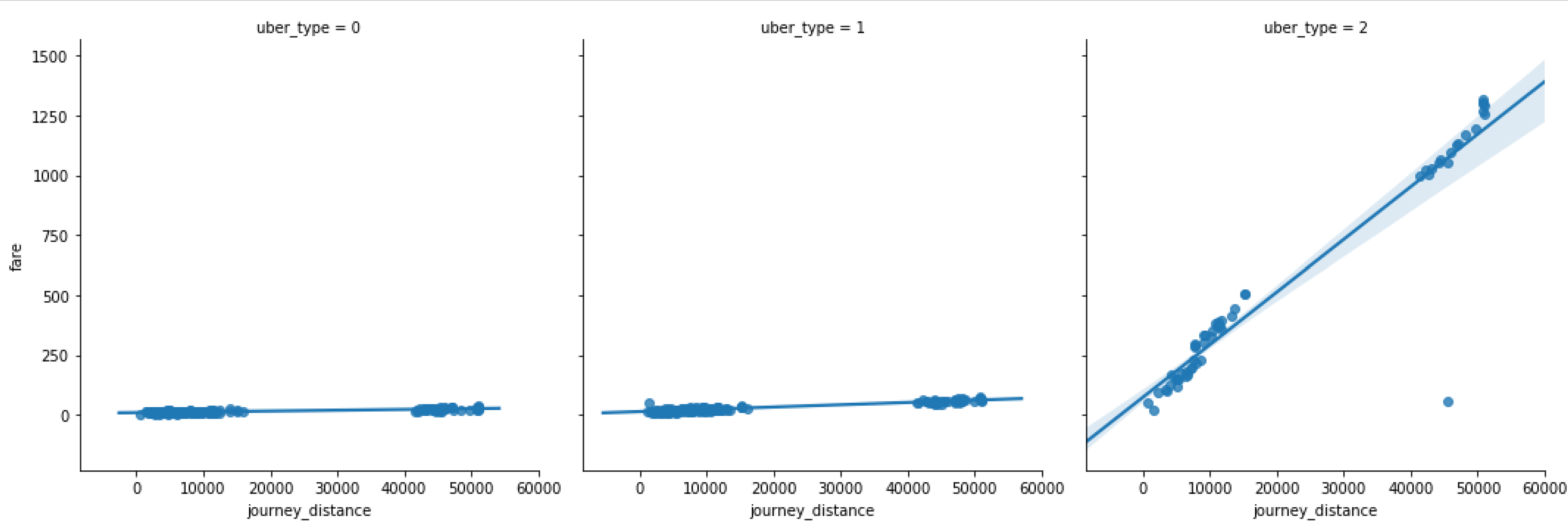
Let's look at how well the `travel_time` and `journey_distance` are co-related to fare! Let's also try fitting a linear regression model to these.

In [56]:
```python
sns.pairplot(training_df, x_vars=['journey_distance','travel_time'], y_vars='fare', height=7, aspect=0.7, kind='reg');
```

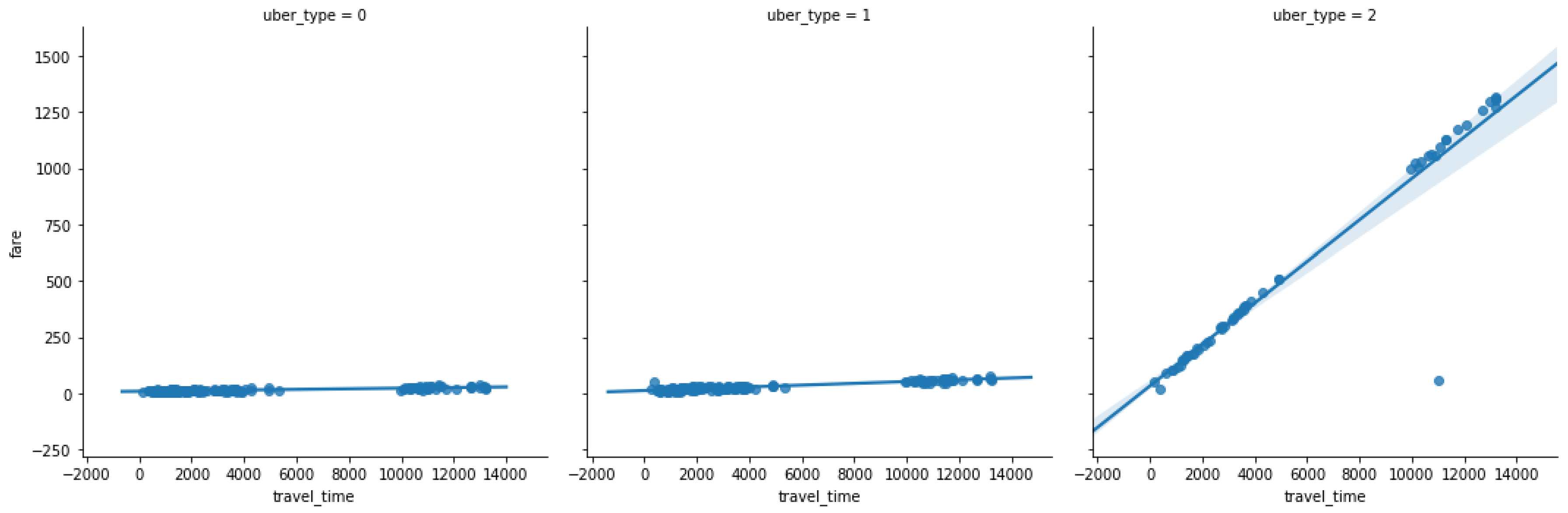


From the graph above we can see that we can't fit one linear model to all of our dataset, since the `uber_types` are forming different clusters, because of their different scale.
We will try fitting three linear models to our dataframe, according to three uber types.

In [57]:
```python
sns.lmplot('journey_distance','fare', col = 'uber_type',data = training_df);
```



In [58]:
```python
sns.lmplot('travel_time','fare', col = 'uber_type',data = training_df);
```



We can see that, linear model gives a best fit to this data, when devided by their Uber types.

Now, we will devide our data into three parts and fit three linear models to it.

We can also see that there are few outliers in our `training_df` . First, we will remove those by using linear model outlier detection, since they can itroduce bias in our results.

Methodology:

1. **Rectifying the training data:** First we will fit a linear model on the training data, and predict fares on the same. After that, we will compute residuals on the training data `(Given Fare - Fare predicted)` , and perform Inter-Quantile based detection on the residuals and remove the outliers.
2. **Predicting missing fares:** Then, we will train linear model again on the training dataset wihtout outliers, and predict fares for the missing data

In [59]:
```python
# Inter-quantile outlier detection
def iqr_detect_outlier(dataset):
    '''
    This function accepts any data series and returns the index of the outliers found in that series.
    '''
    q1, q3= np.percentile(dataset,[25,75]) # computing percentile
    iqr = q3 - q1 # Inter-Qunatile range
    median = dataset.median()
    outlier_index = []
    indexes = dataset.index.to_list()
    cutoff = 1.5*iqr
    for index in indexes:
        if np.absolute(dataset[index] - median) > cutoff:
            outlier_index.append(index)
    return outlier_index
```

In [60]:
```python
# Deviding missing  and training data according to the uber types
uber_0 = missing_df[missing_df.uber_type == 0].copy()
uber_1 = missing_df[missing_df.uber_type == 1].copy()
uber_2 = missing_df[missing_df.uber_type == 2].copy()

uber_0_train = training_df[training_df.uber_type == 0].copy()
uber_1_train = training_df[training_df.uber_type == 1].copy()
uber_2_train = training_df[training_df.uber_type == 2].copy()
```

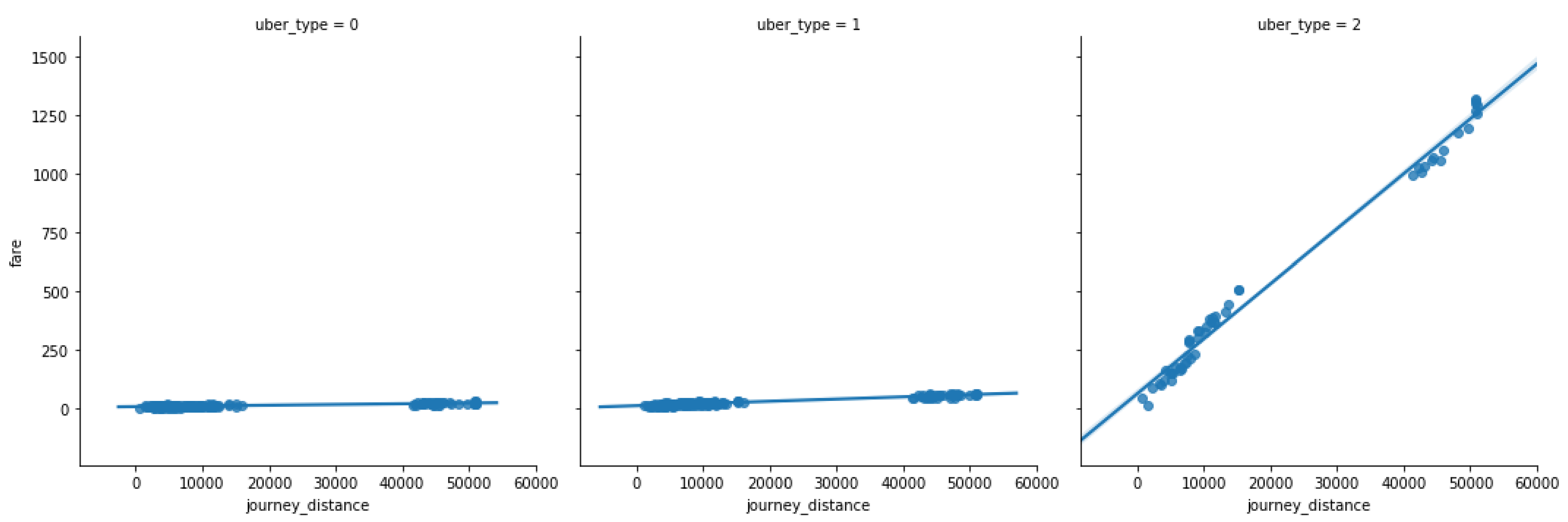
In [61]:
```python
# Defing Linear Regression models
lm_for_uber0 = LinearRegression()
lm_for_uber1 = LinearRegression()
lm_for_uber2 = LinearRegression()

# Defining features
features = {'journey_distance','travel_time','departure_day','time_zone'}

# Fitting all three models using indicidual's training dataset
lm_for_uber0.fit(uber_0_train[[x for x in uber_0_train.columns if x in features]],uber_0_train.fare)
lm_for_uber1.fit(uber_1_train[[x for x in uber_1_train.columns if x in features]],uber_1_train.fare)
lm_for_uber2.fit(uber_2_train[[x for x in uber_2_train.columns if x in features]],uber_2_train.fare)
```

Out[61]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [62]:
```python
# Outlier removal in training dataframe

# Predicting fares on the training dataset
uber_0_train['fare_predicted'] = lm_for_uber0.predict(uber_0_train[[x for x in uber_0.columns if x in features]])
uber_1_train['fare_predicted'] = lm_for_uber1.predict(uber_1_train[[x for x in uber_0.columns if x in features]])
uber_2_train['fare_predicted'] = lm_for_uber2.predict(uber_2_train[[x for x in uber_0.columns if x in features]])

#  Concating the splitted training data
uber_train = pd.concat([uber_0_train,uber_1_train,uber_2_train])

# Computing residuals
uber_train['residuals'] = uber_train.fare - uber_train.fare_predicted

# Finding outliers using IQR outlier detection on residuals computed
train_outliers_index = set()
print('OUTLIERS IN TRAINING DATA')
for uber in range(3):
    train_outliers_index = train_outliers_index|(set(iqr_detect_outlier(uber_train[uber_train.uber_type == uber].residuals)))
    print('For Uber Type',uber,', outliers found:',len(iqr_detect_outlier(uber_train[uber_train.uber_type == uber].residuals)))

train_outliers_index = list(train_outliers_index)

# Dropping all the outliers form the dataset
training_df.drop(train_outliers_index, inplace = True)
```

```
OUTLIERS IN TRAINING DATA
For Uber Type 0 , outliers found: 11
For Uber Type 1 , outliers found: 6
For Uber Type 2 , outliers found: 3
```

In [63]:
```python
sns.lmplot('journey_distance','fare', col = 'uber_type',data = training_df);
```



Now we can see the outliers are removed from training data!

Now, we will compute missing fares after training Linear Regression model on the filtered training data.

In [64]:
```
# Re-defining uber training sets with new training_df
uber_0_train = training_df[training_df.uber_type == 0]
uber_1_train = training_df[training_df.uber_type == 1]
uber_2_train = training_df[training_df.uber_type == 2]

# Defing Linear Regression models
lm_for_uber0 = LinearRegression()
lm_for_uber1 = LinearRegression()
lm_for_uber2 = LinearRegression()

# Fitting all three models using indicidual's training dataset
lm_for_uber0.fit(uber_0_train[[x for x in uber_0_train.columns if x in features]],uber_0_train.fare)
lm_for_uber1.fit(uber_1_train[[x for x in uber_1_train.columns if x in features]],uber_1_train.fare)
lm_for_uber2.fit(uber_2_train[[x for x in uber_2_train.columns if x in features]],uber_2_train.fare)
```

Out[64]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

Now, we have trained our model on new training set without outliers and will generate our predictions further!

In [65]:
```
# Predicitng fares for all missing rows in each uber type data
uber_0['fare_predicted'] = lm_for_uber0.predict(uber_0[[x for x in uber_0.columns if x in features]])
uber_1['fare_predicted'] = lm_for_uber1.predict(uber_1[[x for x in uber_0.columns if x in features]])
uber_2['fare_predicted'] = lm_for_uber2.predict(uber_2[[x for x in uber_0.columns if x in features]])

# Concating all the data together
uber = pd.concat([uber_0,uber_1, uber_2])
```

We have predicted the values of fares using all the features we selected and engineered. Now we will put those in `missing_df` .

In [66]:
```
# Merging the predicted values with the original missing data
missing_df = pd.merge(missing_df,uber[['id','fare_predicted']], on = 'id', how = 'left')

# Rounding off predicted fares upto two decimal places
missing_df.fare_predicted = missing_df.fare_predicted.apply(lambda f: round(f,2))
```

Let's check the accuracy of our predicted values.

We will be using RMSE and R-squared values to quantify and compare our predictions. We will use `mean_squared_error()` and `r2_score()` functions from 'sklearn.metrics' library.

In [67]:
```
# Dropping rows with missing values to check accuracy
dropped_df = missing_df.copy()
dropped_df.dropna(subset=['fare'], axis=0, inplace = True)
dropped_df.head()

print('ACCURACY\n')
# Prinitng Accuracy for each Uber type
for i in range(3):

    rmse = mean_squared_error(dropped_df[dropped_df.uber_type == i].fare, dropped_df[dropped_df.uber_type == i].fare_predicted)
    r2 = r2_score(dropped_df[dropped_df.uber_type == i].fare, dropped_df[dropped_df.uber_type == i].fare_predicted)

    print('For Uber-Type',i,',')
    print('Root mean squared error: ', rmse)
    print('R2 score: ', r2,'.\n')

# Printing the accuracy for all dataset
rmse_uber = mean_squared_error(dropped_df.fare, dropped_df.fare_predicted)
r2_uber = r2_score(dropped_df.fare, dropped_df.fare_predicted)
print('For complete dataset')
print('Root mean squared error: ', rmse_uber)
print('R2 score: ', r2_uber,'.\n')
```

```
ACCURACY

For Uber-Type 0 ,
Root mean squared error:  12.467496296296295
R2 score:  0.8402943221846536 .

For Uber-Type 1 ,
Root mean squared error:  26.262710714285713
R2 score:  0.9293480230760919 .

For Uber-Type 2 ,
Root mean squared error:  59.92375263157876
R2 score:  0.9994795327859336 .

For complete dataset
Root mean squared error:  25.219326732673228
R2 score:  0.9993590499303966 .
```

'R-squared' values looks fairly good for all uber types, especially for Uber type 1 and Uber type 2.

Let's now fill the blanks with predicted values.

In [68]:
```
# Filling missing rows with predicted fares
missing_df.loc[missing_df.fare.isnull(),'fare'] = missing_df[missing_df.fare.isnull()].fare_predicted
```

In [69]:
```
# Dropping irrelvant columns
cols = ['departure_day','time_zone','fare_predicted']
missing_df.drop(cols, axis = 1, inplace = True)

header[0] = ''
# Saving dataframe as csv file
missing_df.to_csv('29895405_missing_data_solution.csv',index = False, header = header)
```

Task 3 - Outlier

This task deals with the **`Coverage Anomalies`** of outliers.

Reading data

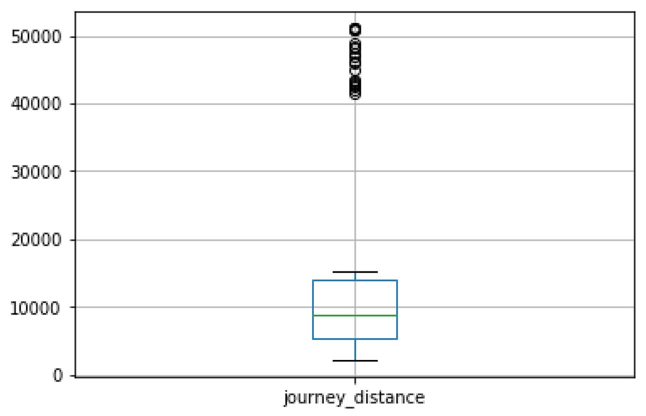
In [70]:
```
outliers = pd.read_csv('29895405_outliers.csv', index_col = 0)

# Saving the column names of the data
header = outliers.columns.to_list()

# Changing column names for easy access
outliers = outliers.rename(columns = {'Unnamed: 0.1':'id'})
outliers.columns = outliers.columns.str.strip().str.lower().str.replace(' ', '_').str.replace('\(s\)', '').str.replace('\(m\)', '').str.replace('$','')

outliers['fare_predicted'] = np.NaN

outliers.head()
```

Out[70]:

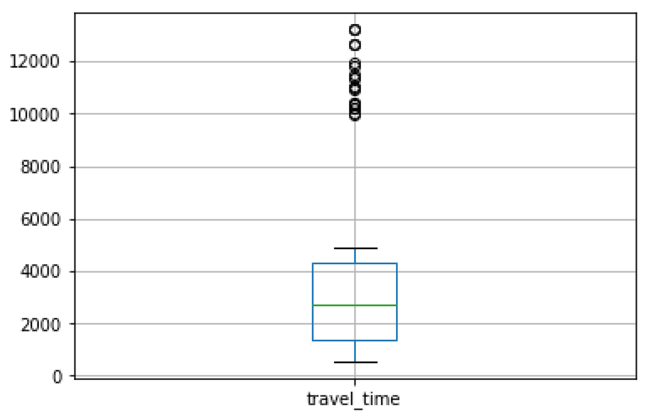
	id	uber_type	origin_region	destination_region	origin_latitude	origin_longitude	destination_latitude	destination_longitude	journey_distance	departure_date	departure_time	travel_time	arrival_time	fare	fare_predicted
0	ID3984160279	1	5	9	-37.799905	144.934745	-38.110916	144.654173	46061.0	2018-01-21	00:40:13	11069.52	3:44:42	62.98	NaN
1	ID1504197634	0	2	9	-37.813653	144.937020	-38.110916	144.654173	42677.0	2018-02-04	22:25:38	10225.74	1:16:03	31.32	NaN
2	ID1810289714	0	9	1	-38.110916	144.654173	-37.813177	144.962828	43425.0	2018-02-07	01:10:52	10439.28	4:04:51	25.73	NaN
3	ID1223605929	0	2	6	-37.817973	144.932053	-37.787433	144.980377	6602.0	2018-05-12	06:56:11	1661.76	7:23:52	9.41	NaN
4	ID5639243507	2	7	2	-37.861835	144.905716	-37.823281	144.938265	9701.0	2018-02-22	19:30:25	3187.32	20:23:32	243.55	NaN

Plotting data

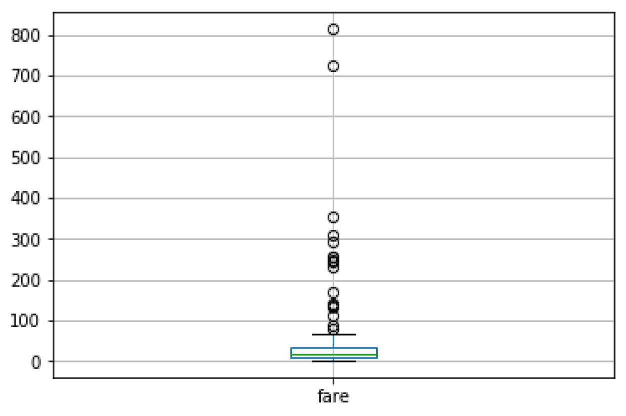
In [71]:
```
distance = outliers.boxplot(column = 'journey_distance')
```



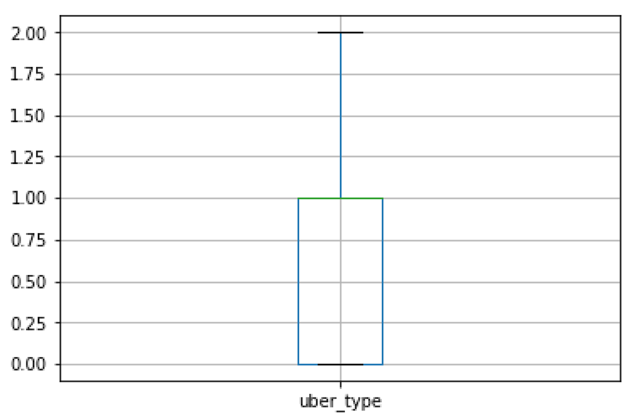
In [72]:
```
travel = outliers.boxplot(column = 'travel_time')
```



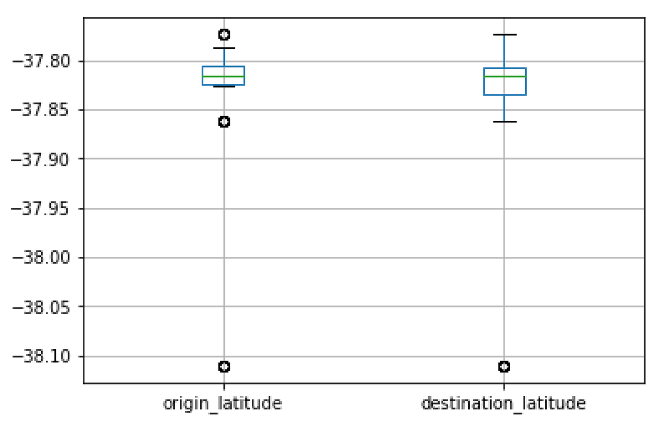
In [73]:
```
fare = outliers.boxplot(column = 'fare')
```



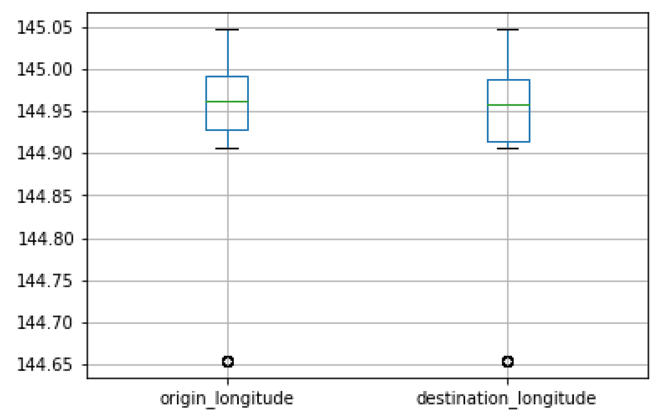
In [74]:
```
uber_type = outliers.boxplot(column = 'uber_type')
```



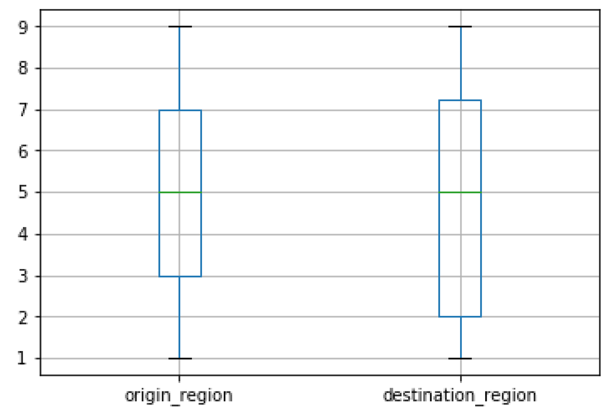
In [75]:
```
lat_cols = ['origin_latitude','destination_latitude']
origin = outliers.boxplot(column = lat_cols)
```



In [76]:
```python
long_cols = ['origin_longitude','destination_longitude']
destination = outliers.boxplot(column = long_cols)
```



In [77]:
```python
regions = outliers.boxplot(column = ['origin_region','destination_region'])
```



Predicting fares

Since the data is co-related we will use multivariate outlier detection technique to detect and remove outliers. We will use linear models to detect outliers in this dataset.

First, we will predict fares for the rows, using the same model we used in Task 2 of missing data, compute residuals, and use Inter-Quantile outlier detection technique on residuals to filter out the outliers.

To use the model generated, we need to generate the features we used, i.e. `journey_distance` , `travel_time` , `departure_day` , `time_zone` .

In [78]:
```python
# Creating features in outliers
outliers.departure_date = pd.to_datetime(outliers.departure_date)
outliers['departure_day'] = outliers.departure_date.dt.weekday
outliers.departure_day = outliers.departure_day.apply(lambda d: is_weekend(d))
outliers['time_zone'] = outliers.departure_time.apply( lambda t: time_zone(pd.to_datetime(t)))
```

In [79]:
```python
# Following function predict fares for outliers data, by fitting three models on the training dataset, for each uber type
def predict_fare(uber_type):
    '''
    This function accepts a uber type, and predicts fares for that uber types in outliers data.
    It fits linear regression models on the training data, for the passed uber type and compute fares through the same.
    '''
    features = {'journey_distance','travel_time','departure_day','time_zone'}

    # Filtering data for one uber type
    uber = outliers.query("uber_type == {}".format(uber_type))
    training_uber = training_df.query("uber_type == {}".format(uber_type))

    # Defining and training linear regression model for particular uber type
    lm_for_uber = LinearRegression().fit(training_uber[[x for x in training_uber if x in features]], training_uber["fare"])

    # Predicting fares
    fare_predicted = lm_for_uber.predict(uber[[x for x in uber if x in features]])

    # Updating outliers data
    counter = 0
    for index in uber.index.to_list():
        outliers.loc[index,'fare_predicted'] = fare_predicted[counter]
        counter += 1

# Calling function 'predict_fare'  for each uber type
for types in sorted(outliers.uber_type.unique()):
    predict_fare(types)

# Computing residuals
outliers['residual'] = outliers.fare - outliers.fare_predicted
```

Detecting and removal of outliers

In [80]:
```python
print('OUTLIERS')
outliers_indexes = set()
for uber_type in range(3):
    print('For Uber Type {}:'.format(uber_type), outliers.iloc[iqr_detect_outlier(outliers[outliers.uber_type == uber_type].residual),].shape[0])
    outliers_indexes = outliers_indexes|set(outliers.iloc[iqr_detect_outlier(outliers[outliers.uber_type == uber_type].residual),].index.to_list())

outliers_indexes = list(outliers_indexes)
```

```
OUTLIERS
For Uber Type 0: 7
For Uber Type 1: 6
For Uber Type 2: 4
```

In [81]:
```
outliers.iloc[outliers_indexes,]
```

Out[81]:

	id	uber_type	origin_region	destination_region	origin_latitude	origin_longitude	destination_latitude	destination_longitude	journey_distance	departure_date	departure_time	travel_time	arrival_time	fare	fare_predicted	departure_day	time_zone	residual
97	ID1506691518	0	3	7	-37.821937	144.968322	-37.861835	144.905716	7819.0	2018-04-16	16:43:26	2737.56	17:29:03	4.375	11.545407	0	1	-7.170407
34	ID5414191154	2	9	2	-38.110916	144.654173	-37.823506	144.943146	42561.0	2018-04-09	06:44:39	10231.62	9:35:10	725.940	1005.967955	0	0	-280.027955
68	ID3170987893	1	7	6	-37.861835	144.905716	-37.787433	144.980377	11633.0	2018-06-11	20:33:32	3645.30	21:34:17	12.035	25.280446	0	1	-13.245446
70	ID5364577724	2	6	9	-37.773845	144.983689	-38.110916	144.654173	48197.0	2018-05-10	09:19:31	11519.40	12:31:30	814.610	1130.907953	0	0	-316.297953
7	ID1267848442	0	6	9	-37.787433	144.980377	-38.110916	144.654173	47033.0	2018-03-13	20:26:27	11350.50	23:35:37	12.015	22.495251	0	1	-10.480251
71	ID5327186310	2	7	6	-37.861835	144.905716	-37.787442	144.980409	11630.0	2018-04-19	20:52:50	3678.54	21:54:08	139.440	380.013263	0	1	-240.573263
41	ID3676086034	1	9	3	-38.110916	144.654173	-37.823646	144.975031	44850.0	2018-04-22	02:05:46	10904.22	5:07:30	31.075	60.811850	1	2	-29.736850
10	ID1332655308	0	6	3	-37.773803	144.983647	-37.817141	144.996180	9815.0	2018-01-22	16:37:03	3028.50	17:27:31	4.985	11.886488	0	1	-6.901488
50	ID3534272956	1	9	7	-38.110916	144.654173	-37.861835	144.905716	50797.0	2018-06-26	21:51:23	13204.98	1:31:27	34.935	68.118550	0	2	-33.183550
19	ID3429790887	1	2	3	-37.813922	144.940449	-37.821332	144.993451	5370.0	2018-07-21	15:54:47	1264.32	16:15:51	19.870	15.833195	0	1	4.036805
52	ID1982613153	0	8	7	-37.807202	145.026637	-37.861835	144.905716	13986.0	2018-07-04	01:20:13	4298.28	2:31:51	8.285	17.772000	0	2	-9.487000
84	ID5307103614	2	9	2	-38.110916	144.654173	-37.813900	144.944226	41926.0	2018-06-26	06:07:50	10049.22	8:55:19	356.430	988.144094	0	0	-631.714094
57	ID3490088517	1	9	7	-38.110916	144.654173	-37.861835	144.905716	50797.0	2018-06-09	14:11:51	13204.98	17:51:55	66.580	62.108928	0	1	4.471072
90	ID1555435418	0	3	9	-37.820337	144.990252	-38.110916	144.654173	45890.0	2018-07-28	20:58:27	11011.62	0:01:58	14.530	22.047271	0	1	-7.517271
27	ID3526501634	1	6	2	-37.787442	144.980409	-37.819083	144.946569	5498.0	2018-04-23	13:22:35	1377.42	13:45:32	8.090	16.295283	0	1	-8.205283
62	ID1652357581	0	9	7	-38.110916	144.654173	-37.861835	144.905716	50797.0	2018-04-11	08:19:56	13204.98	12:00:00	11.370	20.851472	0	0	-9.481472
95	ID1470993605	0	5	7	-37.806163	144.934776	-37.861835	144.905716	10756.0	2018-03-07	16:56:04	3451.98	17:53:35	5.565	12.467208	0	1	-6.902208

In [82]:
```
# Dropping all outliers
outliers.drop(outliers_indexes, axis = 0, inplace = True)

# Dropping irrelevant columns
cols = ['departure_day','time_zone','fare_predicted', 'residual']
outliers.drop(cols, axis = 1, inplace = True)

# writing outliers data
header[0] = ''
outliers.to_csv('29895405_outliers_solution.csv',index = False, header = header)
```

Conclusion & Summary

This assignment measured the understanding of basic tools of Data Wrangling and Manipulation in Python programming language. The main outcomes achieved while applying these techniques were:

- **Detecting and correcting data anomalies.** It helped us understand the various types of anomalies in the data, and learn efficient techniques to correct it.
  - By using `to_datetime()` function we were able to parse dates from different formats.
  - By using `groupby()` function, we were able to group data according to nodes, computed centres of region. Then by using `radians()` , `sin()` , and etc., we computed haversine distance between two nodes, and computed optimal region values for all nodes.
  - By using `from_pandas_edgelist()` , we were able to create a network between all nodes, and we were able to compute shortest distances and paths between two nodes by using `single_source_dijikstra()` and `all_shortest_paths()` respectively.
- **Data manipulation.** By using the `pandas` package, importing dictionaries from data frames was quite straightforward. Additional operations like filtering, enumerating, slicing, droppinng and combining also made data transformation tasks more manageable.
- **Imputing missing values.** It helped us understand the use of Linear Regression models for imputing missing data. By using `LinearRegression()` from sklearn library, we were able to impute missing data by using training data and also compared the accuracy of our predictions by using function like `r2_score()` from 'sklearn.metrics'.
- **Data visualisation.** We were able to visualise various properties of data, by using functions like `boxplot()` , `lmplot()` , `heatmap()` and `pairplot()` from 'seaborn' library. It aided us to detect outliers and correctly monitor the corelations between various attributes in the data.
- **Detecting and removing outliers.** It aided us in learning about using linear models for outlier detection in multivariate data. We computed residuals on the 'fare' column from the linear regerssion model we trained on trainig dataset, viz, cleaned dirty data and non-null rows of missing data, and performed inter-quantile range outlier detection technique, by using `median()` and `quantile()` function in 'numpy' library, on residuals to detetct and remove outliers.

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