This notebook chronicles my major learnings from the Uber traffic prediction competition hosted on Zindi.

Initial Preprocessing

In this competition, the target value was not explicitly given in the training set so we needed to an initial preprocessing to obtain it. Special thanks to the community for providing us with the initial processing code. The code is replicated below.

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pylab as plt
```

In [2]:

```
uber = pd.read_csv(r'''C:\Users\ADEBAYO\Desktop\Current DS\Uber\train_revised.csv''', low_m
test = pd.read_csv(r'''C:\Users\ADEBAYO\Desktop\Current DS\Uber\test_questions.csv''', low_
```

In [3]:

```
uber.head()
```

Out[3]:

	ride_id	seat_number	payment_method	payment_receipt	travel_date	travel_time	travel_fron
0	1442	15A	Mpesa	UZUEHCBUSO	17-10-17	7:15	Migoı
1	5437	14A	Mpesa	TIHLBUSGTE	19-11-17	7:12	Migoı
2	5710	8B	Mpesa	EQX8Q5G19O	26-11-17	7:05	Keroka
3	5777	19A	Mpesa	SGP18CL0ME	27-11-17	7:10	Homa Ba
4	5778	11A	Mpesa	BM97HFRGL9	27-11-17	7:12	Migoı

In [4]:

```
ride_id_dict = {}
for ride_id in uber["ride_id"]:
    if not ride_id in ride_id_dict:
        ride_id_dict[ride_id] = 1
    else:
        ride_id_dict[ride_id] += 1
```

In [5]:

```
uber = uber.drop(['seat_number', 'payment_method', 'payment_receipt', 'travel_to'], axis=1)
```

In [6]:

```
uber.drop_duplicates(inplace=True)
uber.reset_index(drop= True, inplace=True)
```

In [7]:

```
uber["number_of_tickets"]= np.zeros(len(uber))
```

In [8]:

```
for i in range(len(uber)):
    ride_id = uber.loc[i]["ride_id"]
    uber.at[i,"number_of_tickets"] = ride_id_dict[ride_id]
```

In [9]:

```
uber.head()
```

Out[9]:

	ride_id	travel_date	travel_time	travel_from	car_type	max_capacity	number_of_tickets
0	1442	17-10-17	7:15	Migori	Bus	49	1.0
1	5437	19-11-17	7:12	Migori	Bus	49	1.0
2	5710	26-11-17	7:05	Keroka	Bus	49	1.0
3	5777	27-11-17	7:10	Homa Bay	Bus	49	5.0
4	5778	27-11-17	7:12	Migori	Bus	49	31.0

EXPLORATORY DATA ANALYSIS

In this step, we aim to understand the provided data to see if there are patterns, structures, etc. that could be useful in our modelling phase.

N.B: There is another EDA provided through the community. You can also check it out in the Uber Discussion.

In [10]:

```
uber.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6249 entries, 0 to 6248
Data columns (total 7 columns):
ride_id              6249 non-null int64
travel_date          6249 non-null object
travel_time          6249 non-null object
travel_from          6249 non-null object
car_type             6249 non-null object
max_capacity         6249 non-null int64
number_of_tickets    6249 non-null float64
dtypes: float64(1), int64(2), object(4)
memory usage: 341.8+ KB
```

In [11]:

```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1111 entries, 0 to 1110
Data columns (total 7 columns):
ride_id         1111 non-null int64
travel_date     1111 non-null object
travel_time     1111 non-null object
travel_from     1111 non-null object
travel_to       1111 non-null object
car_type        1111 non-null object
max_capacity    1111 non-null int64
dtypes: int64(2), object(5)
memory usage: 60.8+ KB
```

From the above codes, we can see that there are no null values meaning this dataset is 'super-clean'. This is not the usual scenerio. Data-cleaning is usually an important step developing a good model.

We can also see that our travel dates is treated as an object. We should reconsider changing it to datetype.

In [12]:

```
uber['travel_date'] = pd.to_datetime(uber['travel_date'])
test['travel_date'] = pd.to_datetime(test['travel_date'])
```

In [13]:

```
print(uber['travel_date'].dtypes)
print(test['travel_date'].dtypes)
```

```
datetime64[ns]
datetime64[ns]
```

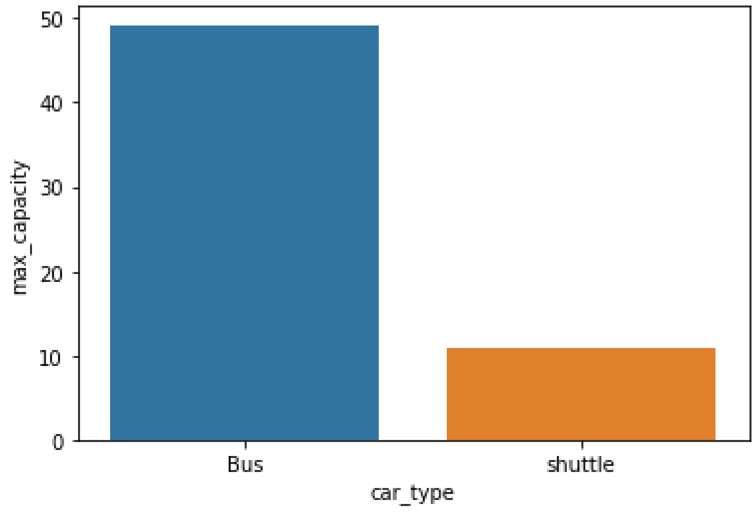
Let us start our exploration proper.

In [14]:

```
sns.barplot(x='car_type',y='max_capacity',data=uber)
```

Out[14]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6c93e2e8>
```

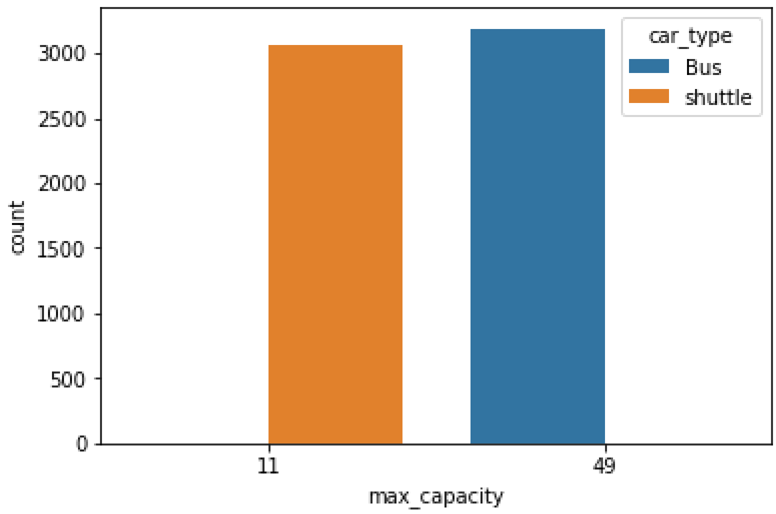


In [15]:

```
sns.countplot(x='max_capacity',data=uber,hue='car_type')
```

Out[15]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6cee3f98>
```



From the data description, we already know that all buses and shuttles have the same maximum capacity. That was easily confirmed using the seaborn barplot.

Another thing we explored was the numbers of buses and shuttles in the dataset using seaborn's countplot. We can see that they are rougly the same.

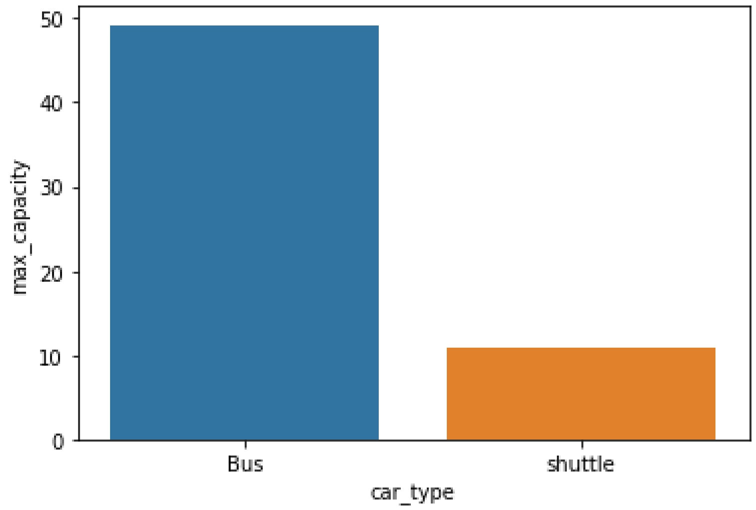
We can confirmed if this holds true for the test set too

In [16]:

```
sns.barplot(x='car_type',y='max_capacity',data=test)
```

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6ca44400>
```

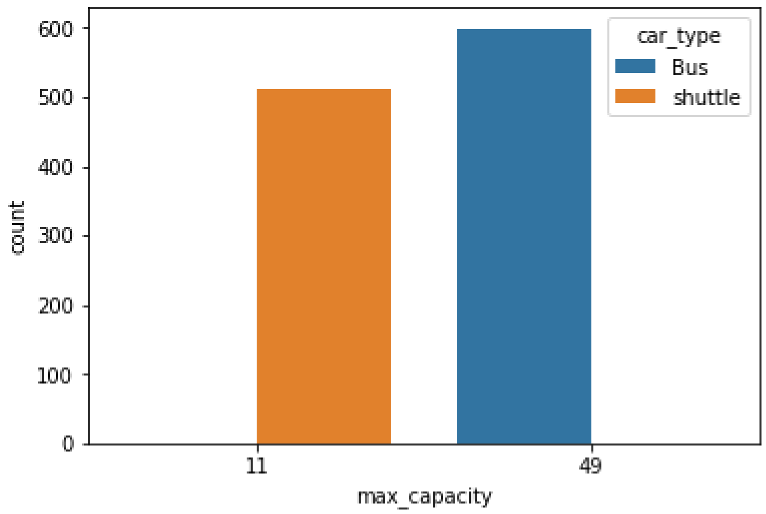


In [17]:

```
sns.countplot(x='max_capacity',data=test,hue='car_type')
```

Out[17]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6cab2278>
```



It can be seen that the training is fairly representative of the test set. This is important as we want our unseen scenerios to be similar to the seen scenerios to make our models as accurate as possible

Another thing that is worth exploring is the travel times. Are they horly in nature? Are they just morning journeys? etc. To do this, we have to convert the travel times to meaning numerical data. One way will be to just extract the hour term. Another way is to convert is to minutes from midnight (another valuable insight provided by the community).

In [18]:

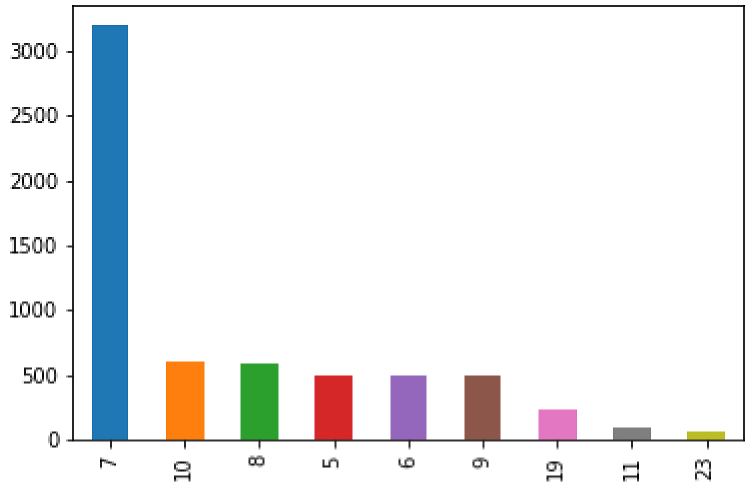
```
#Extracting the hour term
uber['hour_booked'] = pd.to_numeric(uber['travel_time'].str.extract(r'(^\d*)').loc[:,0])
test['hour_booked'] = pd.to_numeric(test['travel_time'].str.extract(r'(^\d*)').loc[:,0])
```

In [19]:

```
uber['hour_booked'].value_counts().plot.bar()
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6cab21d0>
```

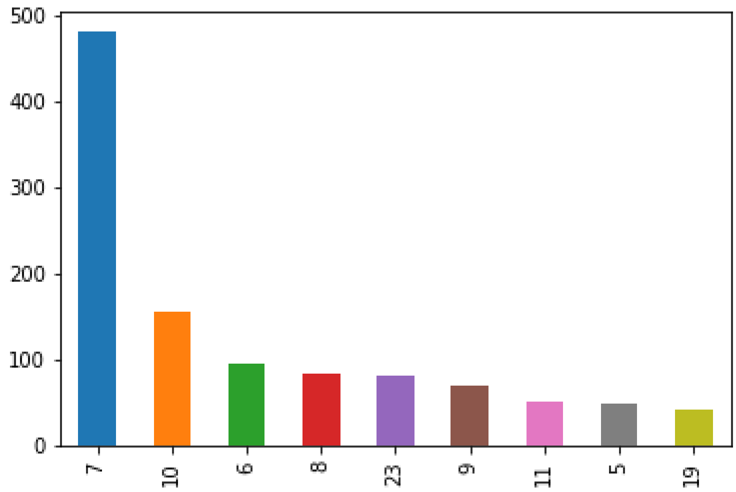


In [20]:

```
test['hour_booked'].value_counts().plot.bar()
```

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6cefccf8>
```



In [21]:

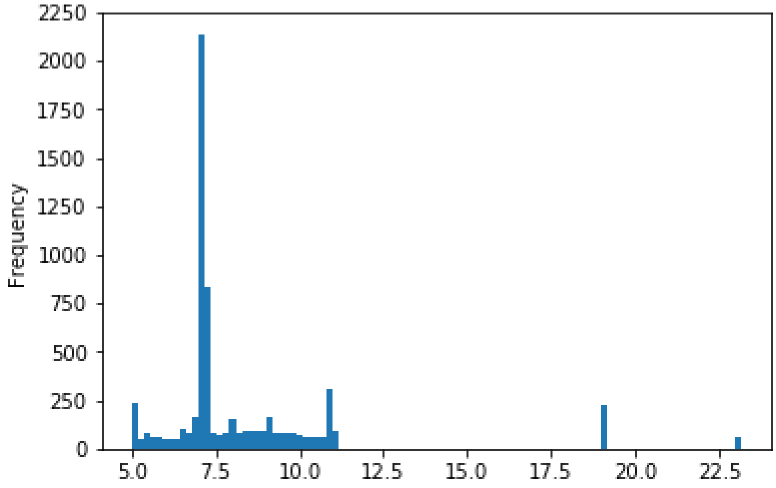
```
#express travel time in minutes from midnight
test["travel_time"] = test["travel_time"].str.split(':').apply(lambda x: int(x[0]) * 60 + i
uber["travel_time"] = uber["travel_time"].str.split(':').apply(lambda x: int(x[0]) * 60 + i
```

In [22]:

```
(uber["travel_time"]/60).plot.hist(bins=100)
```

Out[22]:

<matplotlib.axes._subplots.AxesSubplot at 0x20d6d1214a8>

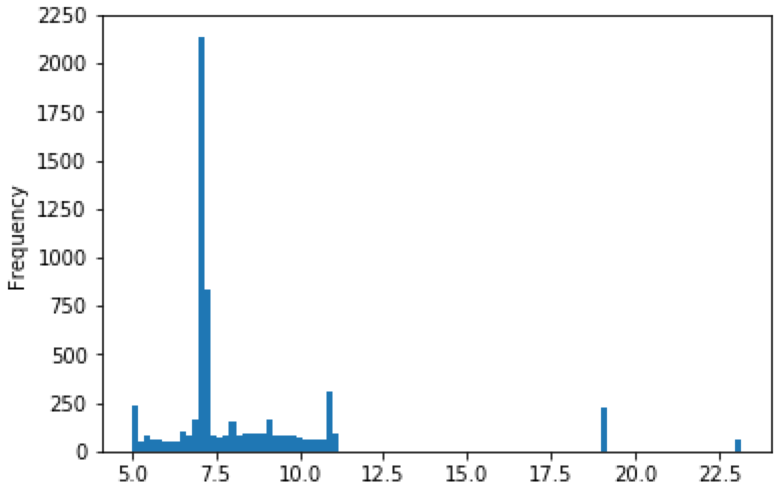


In [23]:

```
(uber["travel_time"]/60).plot.hist(bins=100)
```

Out[23]:

<matplotlib.axes._subplots.AxesSubplot at 0x20d6d044c88>

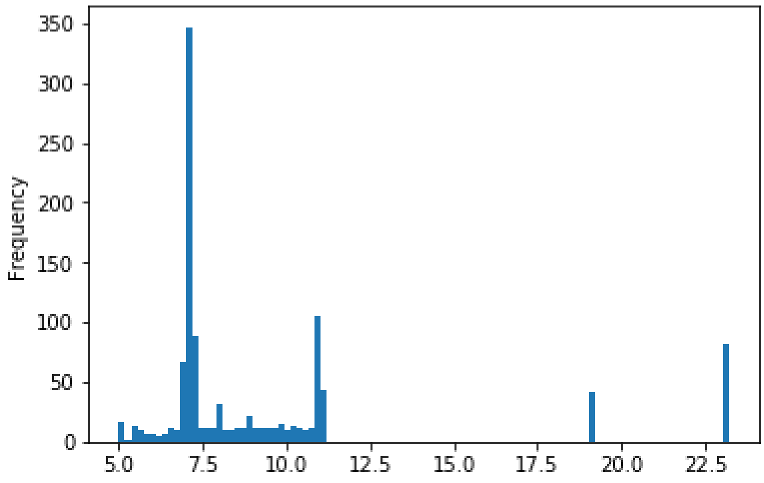


In [24]:

```
(test["travel_time"]/60).plot.hist(bins=100)
```

Out[24]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d1b5f28>
```



Both methods gave us almost the same information about the data. The most frequent travel time is around 7am and most of the journeys take place before noon with some journeys at 7pm and 11pm.

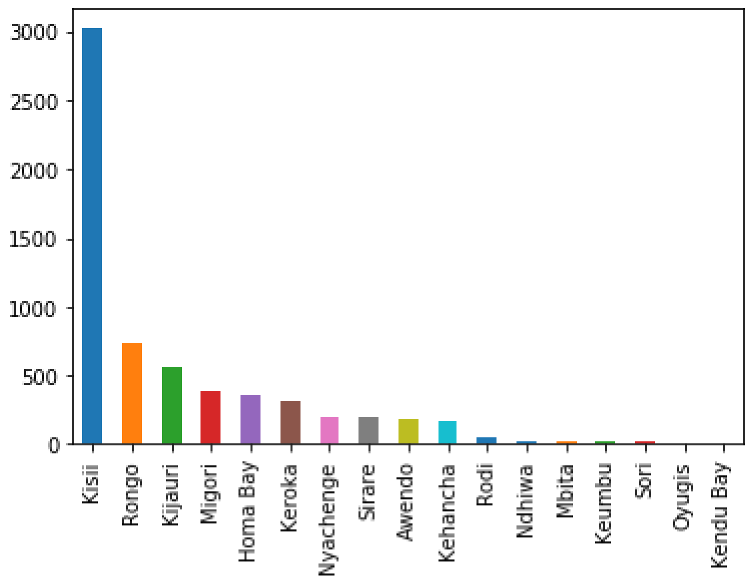
Another column to explore is travel from i.e where do most of our customers come from?

In [25]:

```
uber['travel_from'].value_counts().plot.bar()
```

Out[25]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d315d68>
```

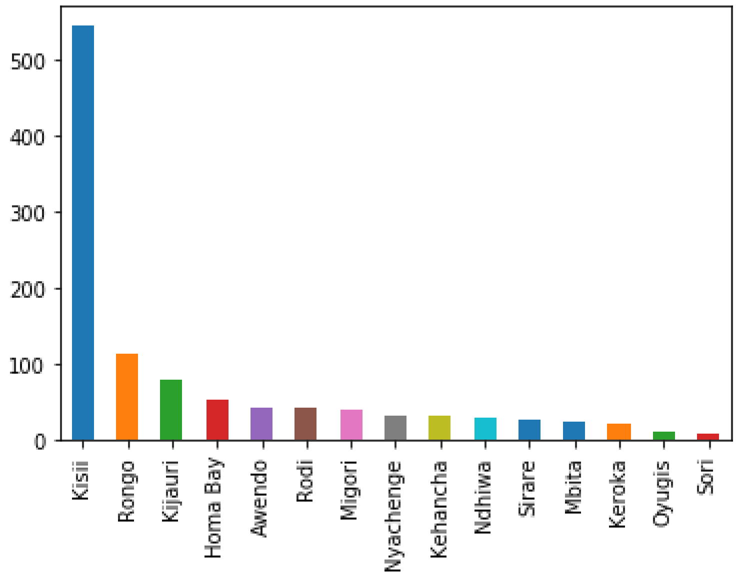


In [26]:

```
test['travel_from'].value_counts().plot.bar()
```

Out[26]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d446128>
```



So many of our customers are actually coming from Kisii. The training set is fairly representative of the test set too.

We can also explore to see if people are likely to travel on a particular day of the week more than the rest.

In [27]:

```
uber["travel_day"] = uber["travel_date"].dt.day_name()
test["travel_day"] = test["travel_date"].dt.day_name()
```

In [28]:

```
uber["travel_yr"] = uber["travel_date"].dt.year
test["travel_yr"] = test["travel_date"].dt.year
```

In [29]:

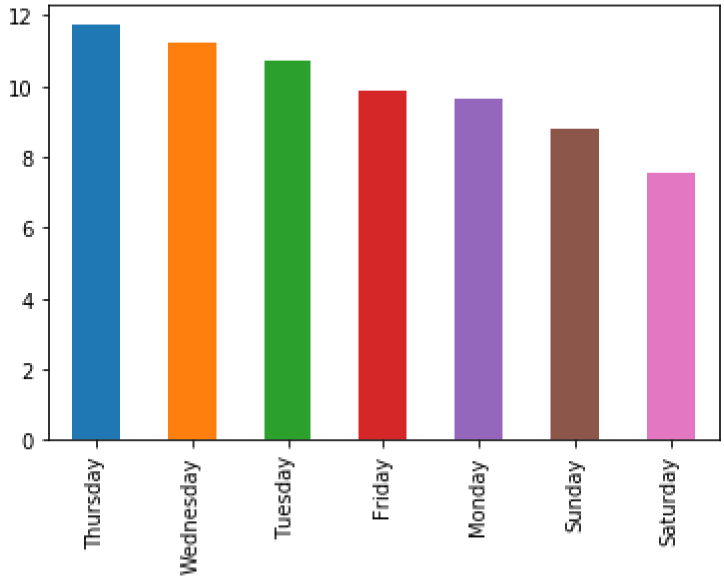
```
#Calculating the number of weeks in the dataset we have data for
a=uber[uber["travel_yr"]==2018]["travel_date"].dt.week.nunique() + uber[uber["travel_yr"]==
b=test[test["travel_yr"]==2018]["travel_date"].dt.week.nunique() + test[test["travel_yr"]==
```

In [30]:

```
(uber[uber['car_type']=='shuttle']["travel_day"].value_counts()/a).plot.bar()
```

Out[30]:

<matplotlib.axes._subplots.AxesSubplot at 0x20d6d5880f0>

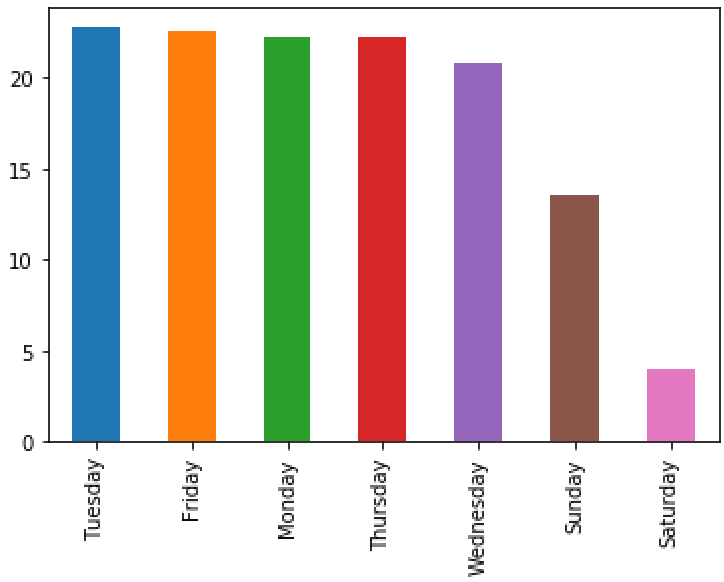


In [31]:

```
(test[test['car_type']=='shuttle']["travel_day"].value_counts()/b).plot.bar()
```

Out[31]:

<matplotlib.axes._subplots.AxesSubplot at 0x20d6d58b5c0>

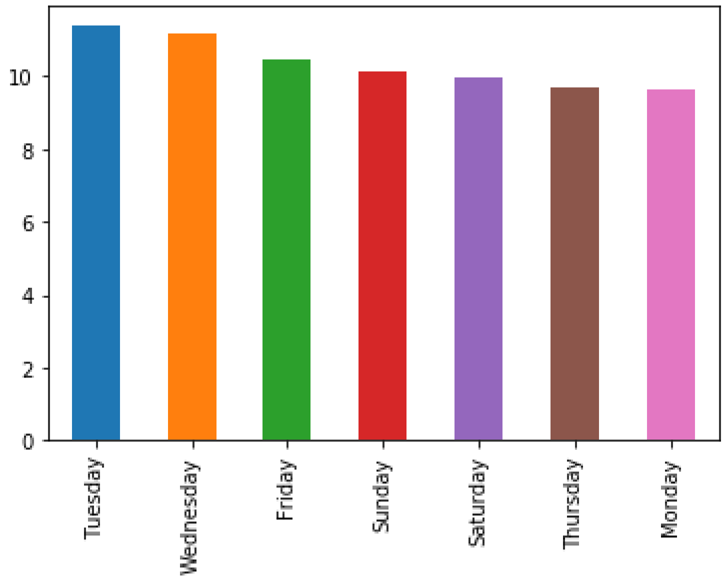


In [32]:

```
(uber[uber['car_type']=='Bus']["travel_day"].value_counts()/a).plot.bar()
```

Out[32]:

<matplotlib.axes._subplots.AxesSubplot at 0x20d6d61b470>

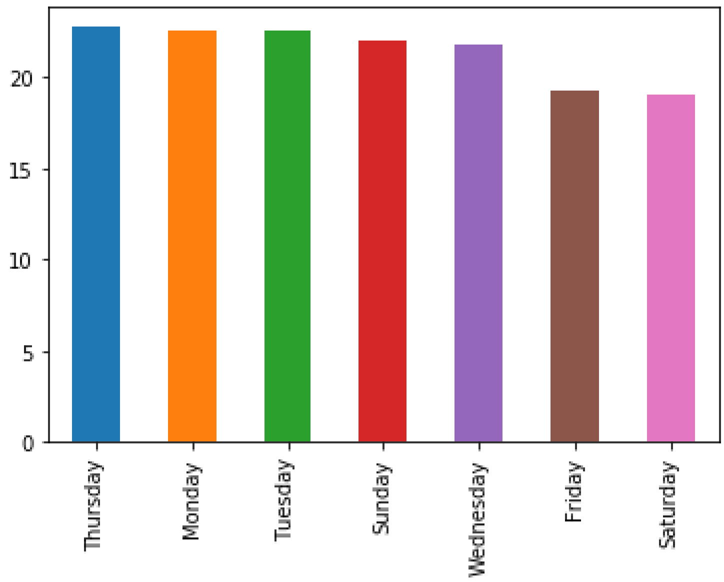


In [33]:

```
(test[test['car_type']=='Bus']["travel_day"].value_counts()/b).plot.bar()
```

Out[33]:

<matplotlib.axes._subplots.AxesSubplot at 0x20d6d643e10>

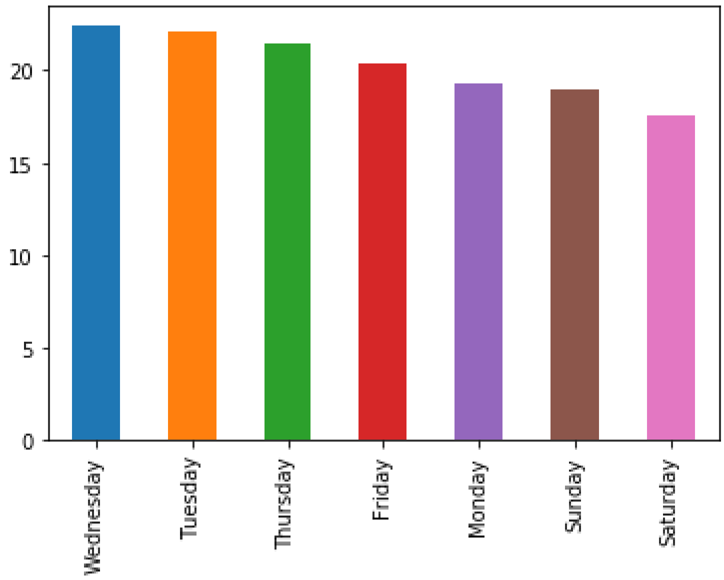


In [34]:

```
(uber["travel_day"].value_counts()/a).plot.bar()
```

Out[34]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d68f5c0>
```

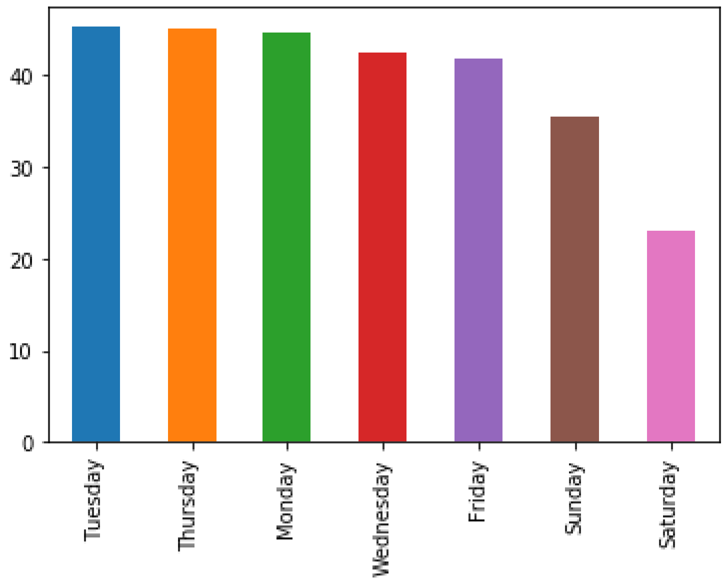


In [35]:

```
(test["travel_day"].value_counts()/b).plot.bar()
```

Out[35]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d753748>
```



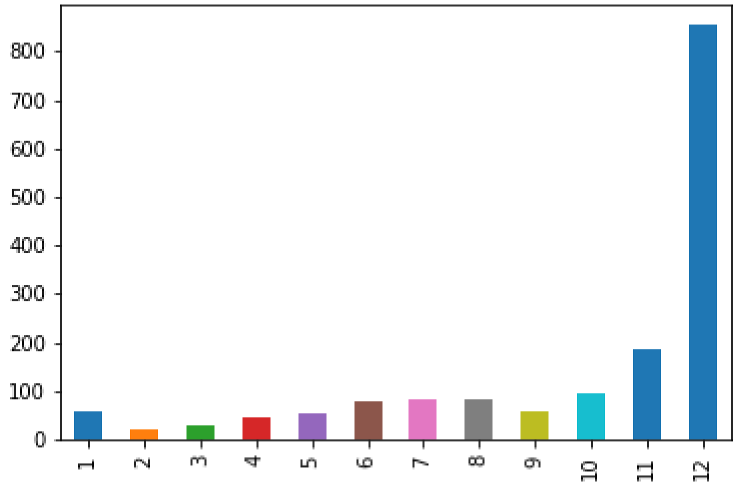
From the above analysis, there seem to be no clear indication that the day of the week matters as the average people that travel on a particular day seems to change with context.

In [36]:

```
uber[uber["travel_yr"]==2017]["travel_date"].dt.month.value_counts().sort_index().plot.bar(
```

Out[36]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d7c01d0>
```

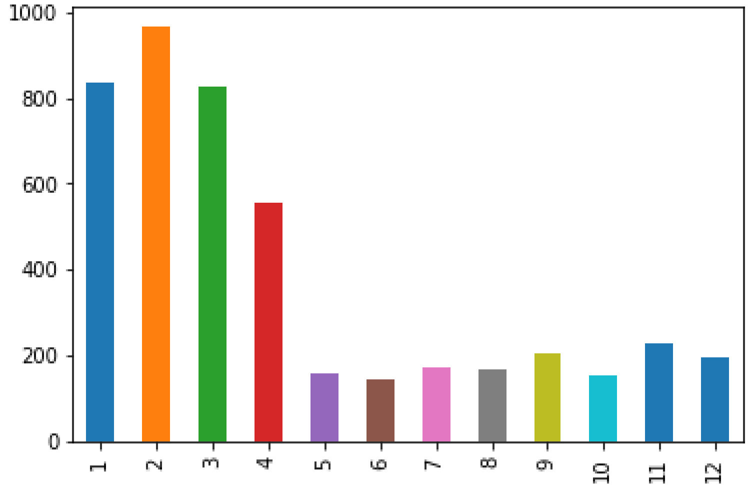


In [37]:

```
uber[uber["travel_yr"]==2018]["travel_date"].dt.month.value_counts().sort_index().plot.bar(
```

Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d77eeb8>
```



In [38]:

```
try:
    test[test["travel_yr"]==2017]["travel_date"].dt.month.value_counts().sort_index().plot.
except:
    print('No data point to plot.')
```

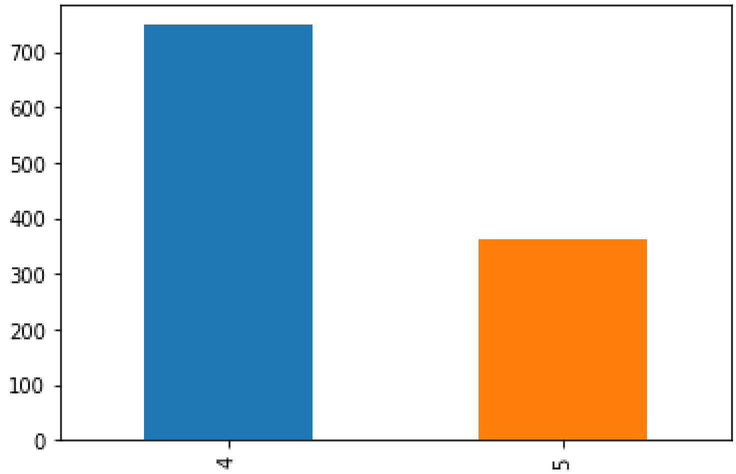
```
No data point to plot.
```

In [39]:

```
test[test["travel_yr"]==2018]["travel_date"].dt.month.value_counts().sort_index().plot.bar(
```

Out[39]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d84afd0>
```



It is clear that from the exploration above that there is something inconsistent about the travel date in the training set. There shouldn't be data for anytime earlier time earlier than Oct 2017 and later than April 2018. This make the date an unreliable indicator. Thus, any date-related feature is unnecessary for modelling.

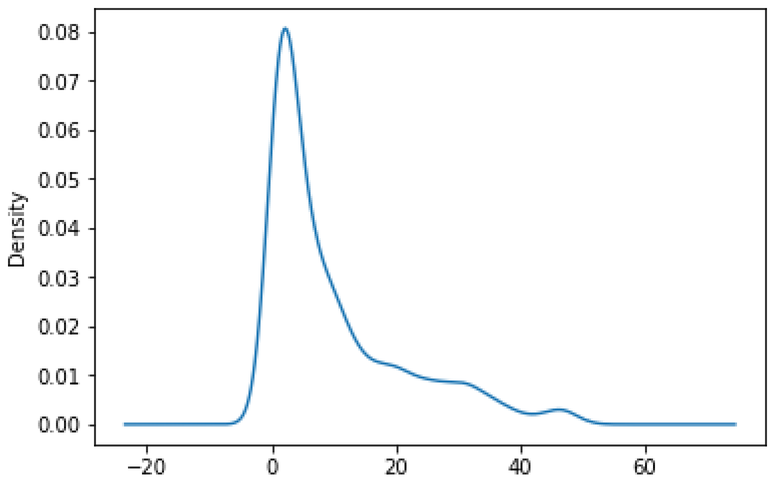
Lastly we can check to see the distribution for ticket sales.

In [40]:

```
((uber[uber['car_type']=='Bus']['number_of_tickets'])).plot.density()
```

Out[40]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d4e34e0>
```

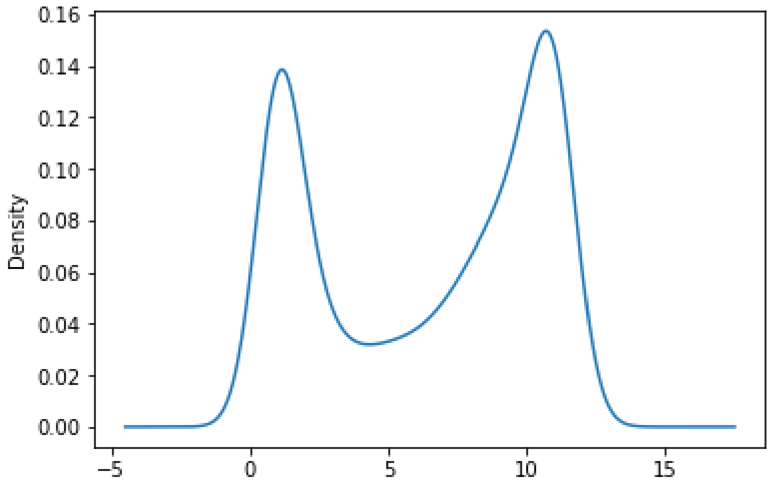


In [41]:

```
((uber[uber['car_type']=='shuttle']['number_of_tickets'])).plot.density()
```

Out[41]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d9182b0>
```



It can be seen that for buses, the bus is usually almost empty while for the shuttles, they are almost always full or empty.

In [42]:

```
uber = uber[['travel_time','travel_from','car_type','number_of_tickets','hour_booked']]
uber.head()
```

Out[42]:

	travel_time	travel_from	car_type	number_of_tickets	hour_booked
0	435	Migori	Bus	1.0	7
1	432	Migori	Bus	1.0	7
2	425	Keroka	Bus	1.0	7
3	430	Homa Bay	Bus	5.0	7
4	432	Migori	Bus	31.0	7

Feature Engineering

In [43]:

```
#Trying to linearize the travel time feature for better prediction
uber['travel_time_log']=np.log(uber['travel_time'])
test['travel_time_log']=np.log(test['travel_time'])
```

We proceed to create two features: late night and early morning based on our EDA.

In [44]:

```
uber['early_morning']=uber['hour_booked']<8
test['early_morning']=test['hour_booked']<8
uber['late_night']=uber['hour_booked']>18
test['late_night']=test['hour_booked']>18
```

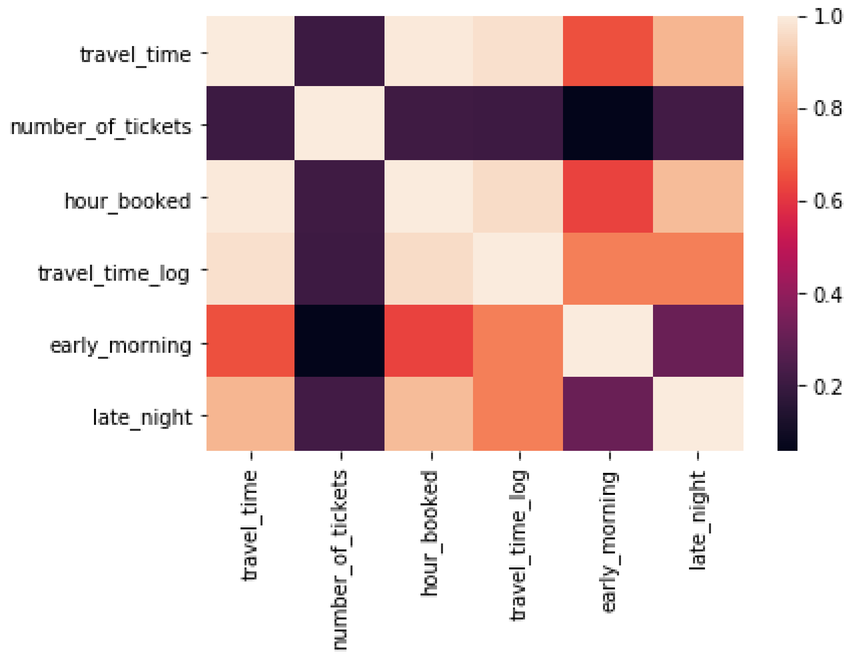
We use the uber .corr function and seaborn's heatmap to see if there is any linear relationships between our features and targets

In [45]:

```
sns.heatmap(abs(uber.corr()))
```

Out[45]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6d5711d0>
```



There seem to be no strong relationship between all of our features and target.

We now try to incoporate an external data - distance from town to Nairobi.

In [46]:

```
distance={'Migori':370.9,'Keroka':279.8,'Kisii':305.5,'Homa Bay':305.5,'Keumbu':294.0,
        'Rongo':330.3,'Kijauri':276.6,'Oyugis':331.1,'Awendo':349.5,
        'Sirare':391.9,'Nyachenge':322.8,'Kehancha':377.5,
        'Kendu Bay':367.5,'Sori':392,'Rodi':349.1,'Mbita':399.4,
        'Ndhiwa':369.6}
```

In [47]:

```
uber['distance']=uber['travel_from'].map({k:v for k,v in distance.items()})
test['distance']=test['travel_from'].map({k:v for k,v in distance.items()})
```

In [48]:

```
test=pd.get_dummies(test,prefix=['car_type','travel_from'],columns=['car_type','travel_from
uber=pd.get_dummies(uber,prefix=['car_type','travel_from'],columns=['car_type','travel_from
```

MODELLING

In [49]:

```
print("Original features:\n", (list(uber.columns)), "\n")
```

```
Original features:
 ['travel_time', 'number_of_tickets', 'hour_booked', 'travel_time_log', 'ear
ly_morning', 'late_night', 'distance', 'car_type_Bus', 'car_type_shuttle',
'travel_from_Awendo', 'travel_from_Homa Bay', 'travel_from_Kehancha', 'trave
l_from_Kendu Bay', 'travel_from_Keroka', 'travel_from_Keumbu', 'travel_from_
Kijauri', 'travel_from_Kisii', 'travel_from_Mbita', 'travel_from_Migori', 't
ravel_from_Ndhiwa', 'travel_from_Nyachenge', 'travel_from_Oyugis', 'travel_f
rom_Rodi', 'travel_from_Rongo', 'travel_from_Sirare', 'travel_from_Sori']
```

In [50]:

```
feature_cols=['travel_time', 'hour_booked', 'travel_time_log', 'early_morning', 'late_night
         'car_type_Bus', 'car_type_shuttle', 'travel_from_Awendo', 'travel_from_Homa Bay',
         'travel_from_Kendu Bay', 'travel_from_Keroka', 'travel_from_Keumbu', 'travel_from_
         'travel_from_Kisii', 'travel_from_Mbita', 'travel_from_Migori', 'travel_from_Ndhiw
         'travel_from_Oyugis', 'travel_from_Rodi', 'travel_from_Rongo', 'travel_from_Sirare
```

In [51]:

```
predicted_col=['number_of_tickets']
```

In [52]:

```
X_train=uber[feature_cols].values
Y_train=uber[predicted_col].values

#Reshaping target column to avoid Sklearb throwing in a warning
Y_train=Y_train.ravel()

split_test_size=0.30

from sklearn.model_selection import train_test_split
Xtrain, Xtest, Ytrain, Ytest= train_test_split(X_train,Y_train, test_size=split_test_size,
```

In [53]:

```
from sklearn.metrics import mean_squared_error,mean_absolute_error
from sklearn.model_selection import cross_val_score,KFold,StratifiedKFold
kfold=KFold(n_splits=5)
from sklearn.preprocessing import PolynomialFeatures,MinMaxScaler,StandardScaler
poly=PolynomialFeatures(degree=1).fit(Xtrain)
```

In [54]:

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
```

In [55]:

```
Utrain=(poly.transform(Xtrain))
Utest=(poly.transform(Xtest))
scaler=StandardScaler().fit(Utrain)
Utrain=scaler.transform(Utrain)
Utest=scaler.transform(Utest)
```

First Model

In [56]:

```
gbrt = GradientBoostingRegressor(criterion='mse',random_state=10,n_estimators=100).fit(Utra
cv = cross_val_score (gbrt,Utrain,Ytrain,cv=5)
print(" Average CV is: ", cv.mean())
Ypred=gbrt.predict(Utest)
MAE=mean_absolute_error(Ytest,Ypred)
MSE=mean_squared_error(Ytest,Ypred)
print("GBR MAE:", MAE)
print("GBR Training set score: {:.5f}".format(gbrt.score(Utrain,Ytrain)))
print("GBR Test set score: {:.5f}".format(gbrt.score(Utest,Ytest)))
```

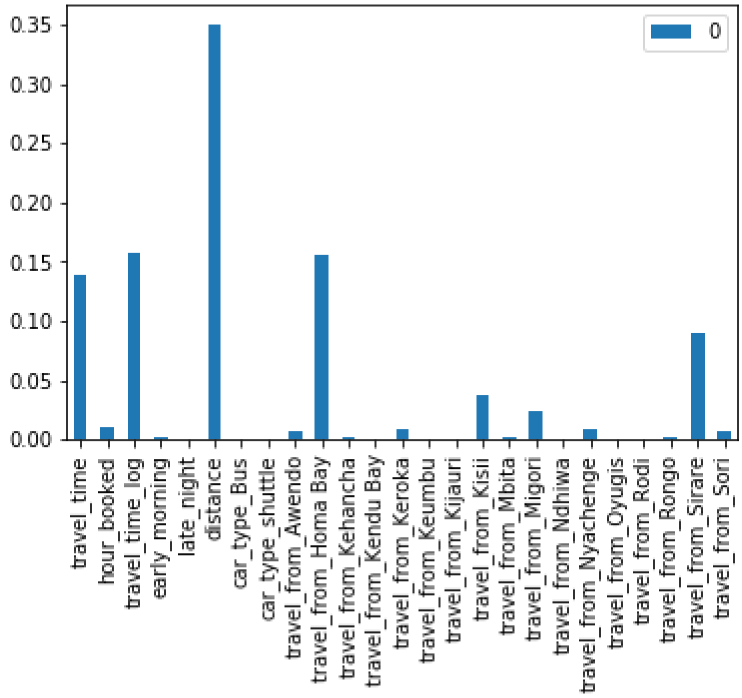
```
 Average CV is:  0.5413819387042605
GBR MAE: 3.92390830743937444
GBR Training set score: 0.56234
GBR Test set score: 0.54731
```

In [57]:

```
b=list(gbrt.feature_importances_[1:])
pd.DataFrame(index=feature_cols,data=b).plot.bar()
```

Out[57]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20d6e2f74e0>
```



We can clearly see that some features are far more important than some others. While we can just minually remove them. It is better we use the sklearn.feature_selection recursive feature selection with or without cross validation tool (it is better with cv).

In [58]:

```
from sklearn.feature_selection import SelectFromModel
from sklearn.feature_selection import RFE,RFECV
select = RFECV(gbrt,cv=5)
select.fit(Utrain,Ytrain)
```

Out[58]:

```
RFECV(cv=5,
   estimator=GradientBoostingRegressor(alpha=0.9, criterion='mse', init=Non
e,
             learning_rate=0.1, loss='ls', max_depth=3, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=1,
             min_samples_split=...te=10, subsample=1.0, tol=0.0001,
             validation_fraction=0.1, verbose=0, warm_start=False),
   min_features_to_select=1, n_jobs=None, scoring=None, step=1, verbose=0)
```

In [59]:

```
select.n_features_
```

Out[59]:

```
13
```

We see that the feature selection tool reduced the features from about 25 to 13

In [60]:

```
cv = cross_val_score (select,Utrain,Ytrain,cv=5)
print(" Average CV is: ", cv.mean())
Ypred=select.predict(Utest)
MAE=mean_absolute_error(Ytest,Ypred)
print("GBR MAE:", MAE)
print("GBR Training set score: {:.5f}".format(select.score(Utrain,Ytrain)))
print("GBR Test set score: {:.5f}".format(select.score(Utest,Ytest)))
```

```
 Average CV is:  0.5434639649815292
GBR MAE: 3.9347467695573606
GBR Training set score: 0.56809
GBR Test set score: 0.54587
```

It can be seen that the metrics are almost the same for both sets of features but we prefer the select model because according to Ockham razor principle, you always want to the simplest model that performs best.

Other implementation

While I tried out other implementations like xgboost, Adaboost, Light GBM, Decision trees, Extra trees and Random Forest, I didnt pay much attention to them as I started the challenge late and didnt have the time to tune every model. I also tried out tricks like PCA but the results were not better off than using just select.I focused only on Gradient Boosting. In hindsight, that may not have been the best decision.

I will however be sharing one other implementation I tried out with alongside gradient boosting (after heavy parameter tuning using Grid Search). Because of the time it took to grid-search, I will just be implementing the best model I obtained in my first grid-search range. To learn more about Grid Search ()

In [61]:

```
gbr = GradientBoostingRegressor(learning_rate=.3,random_state=100,n_estimators=220,subsampl
                                loss='lad').fit(Utrain,Ytrain)
select2 = RFECV(gbr,cv=5)
select2.fit(Utrain,Ytrain)
```

Out[61]:

```
RFECV(cv=5,
   estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse',
init=None,
             learning_rate=0.3, loss='lad', max_depth=3, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=1,
             min_samp...=100, subsample=0.75, tol=0.0001,
             validation_fraction=0.1, verbose=0, warm_start=False),
   min_features_to_select=1, n_jobs=None, scoring=None, step=1, verbose=0)
```

In [62]:

```
cv = cross_val_score (select2,Utrain,Ytrain,cv=5)
print(" Average CV is: ", cv.mean())
Ypred=select2.predict(Utest)
MAE=mean_absolute_error(Ytest,Ypred)
print("GBR MAE:", MAE)
print("GBR Training set score: {:.5f}".format(select2.score(Utrain,Ytrain)))
print("GBR Test set score: {:.5f}".format(select2.score(Utest,Ytest)))
```

```
 Average CV is:  0.5159643614441931
GBR MAE: 3.53976801371126
GBR Training set score: 0.54808
GBR Test set score: 0.53017
```

In [63]:

```
import mlxtend
```

In [64]:

```
#You will need to install mlxtend
from mlxtend.regressor import StackingCVRegressor
```

Since we cant use the stackingCVRegressor with the RFECV select model, we need to redefine our inputs such that the only the most informative features are used. (There is a slight increase from 13 - 19) because I choose to include all the categories of the travel_from.

In [65]:

```
feature_cols=['travel_time_log', 'travel_from_Awendo', 'distance','car_type_shuttle',
                   'travel_from_Homa Bay', 'travel_from_Kehancha', 'travel_from_Kendu Bay',
                   'travel_from_Keumbu', 'travel_from_Kijauri', 'travel_from_Kisii', 'trave
                   'travel_from_Ndhiwa', 'travel_from_Nyachenge', 'travel_from_Rodi',
                   'travel_from_Rongo', 'travel_from_Sirare', 'travel_from_Sori']
```

In [66]:

```
predicted_col=['number_of_tickets']
```

In [67]:

```
X_train=uber[feature_cols].values
Y_train=uber[predicted_col].values

Y_train=Y_train.ravel()

split_test_size=0.3

from sklearn.model_selection import train_test_split
Xtrain, Xtest, Ytrain, Ytest= train_test_split(X_train,Y_train, test_size=split_test_size,
```

Stacking is a type of ensembling that combines the results of two or more estimators using another estimator. Please note that my implementation may not be the best. Stacking is supposed to be used when you are trying to merge the results of three very good estimators. I didn't optimize the decision tree and random forest models.

However, it can be seen that stacked model is not so far off from my best model (imagine the potential if I had used it on many highly tuned models).

In [68]:

```
lr=LinearRegression()
dt = DecisionTreeRegressor(criterion='mae',random_state=100)
rf = RandomForestRegressor(random_state=10,n_estimators=100)
gb = GradientBoostingRegressor(learning_rate=.3,random_state=100,n_estimators=220,subsample
                               loss='lad')
stack = StackingCVRegressor(regressors=(gb, dt, rf),
                            meta_regressor=lr,cv=5)
stack.fit(Utrain,Ytrain)
```

Out[68]:

```
StackingCVRegressor(cv=5,
          meta_regressor=LinearRegression(copy_X=True, fit_intercept=True, n
_jobs=None,
         normalize=False),
          refit=True,
          regressors=(GradientBoostingRegressor(alpha=0.9, criterion='friedm
an_mse', init=None,
             learning_rate=0.3, loss='lad', max_depth=3, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=1,
             min_sa...imators=100, n_jobs=None,
           oob_score=False, random_state=10, verbose=0, warm_start=False)),
          shuffle=True, store_train_meta_features=False,
          use_features_in_secondary=False)
```

Below I will be slightly changing my implementation. I am using the mean_absolute_error as the scorer so I can easily see whether my model is generalizing well since mae is the objective metric is the challenge.

In [69]:

```
from sklearn.metrics import make_scorer
```

In [70]:

```
cv = cross_val_score (stack,Utrain,Ytrain,cv=5,scoring=make_scorer(mean_absolute_error))
print("Average CV is:", round(cv.mean(),3),cv.std())
Ypred=stack.predict(Utest)
Ypred_t=stack.predict(Utrain)
MAE=mean_absolute_error(Ytest,Ypred)
MAE_t=mean_absolute_error(Ytrain,Ypred_t)
print("GBR Training set score: {:.3f}".format(MAE_t))
print("GBR Test set score: {:.3f}".format(MAE))
```

```
Average CV is: 3.757 0.20927656236807862
GBR Training set score: 3.604
GBR Test set score: 3.742
```

After another set of gridsearch (ran for about five hours), my winning I came up with my best solution which ended out in the top 25% of all the submitted entries. My model ended up about 0.5 MAE behind winning model in the public leaderboard. I ran out of time to try out other grid search parameters unfortunately.

Below I will contrasting my model to a model of a friend that ended in the top 5% of all submitted entries (about 0.2 MAE behind the winning model).

In [71]:

```
gb=GradientBoostingRegressor(learning_rate=.5,random_state=100,n_estimators=250,subsample=0
                            max_depth=4).fit(Xtrain,Ytrain)
cv = cross_val_score (gb,Utrain,Ytrain,cv=5,scoring=make_scorer(mean_absolute_error))
print("Average CV is:", round(cv.mean(),3),cv.std())
Ypred=gb.predict(Xtest)
Ypred_t=gb.predict(Xtrain)
MAE=mean_absolute_error(Ytest,Ypred)
MAE_t=mean_absolute_error(Ytrain,Ypred_t)
print("GBR Training set score: {:.3f}".format(MAE_t))
print("GBR Test set score: {:.3f}".format(MAE))
```

```
Average CV is: 3.617 0.2584669864383674
GBR Training set score: 3.425
GBR Test set score: 3.512
```

The major difference between the two implementation is the range of Grid Search. While I constrained myself, his grid search was more extensive but it took about 3 days for these parameters to be obtained. His implementation is available in the folder.

Finally, I will be sharing something I learnt from a friend after I shared this concern with him after the competition ended: Randomized Search. Randomized Search is similar to Grid Search. The only difference is not available permutations are tested. It randomly picks a specified amount of permutations as defined by you. This could save you a lot of time and helps you choose a more extensive range of search parameters.

In [72]:

```
from sklearn.model_selection import RandomizedSearchCV
```

In [73]:

```
#There are about 300,000 different combinations in the grid defined below. We would be usin
#and see how our model fairs (we do tgis using n_iter)

estimator = GradientBoostingRegressor(random_state=12)
param = {'learning_rate':[0.001, 0.003,.01,0.03,0.05,0.1,0.3,0.5,1,3,5 ],
        'n_estimators':[i for i in range(50,550,10)],
        'subsample':[i/100 for i in range(50,100,5)],
        'loss':['lad','ls','huber'],
        'max_depth':[i for i in range(1,20)]}
rs=RandomizedSearchCV(estimator, param_distributions = param,
                      n_iter=10, n_jobs=-1, random_state=81,cv=3,
                     return_train_score=True)
rs.fit(Xtrain,Ytrain)
```

```
C:\Users\ADEBAYO\Anaconda3\lib\site-packages\sklearn\model_selection\_searc
h.py:791: RuntimeWarning: overflow encountered in square
  array_means[:, np.newaxis]) ** 2,
```

Out[73]:

```
RandomizedSearchCV(cv=3, error_score='raise-deprecating',
          estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman
_mse', init=None,
             learning_rate=0.1, loss='ls', max_depth=3, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=1,
             min_sampl...te=12, subsample=1.0, tol=0.0001,
             validation_fraction=0.1, verbose=0, warm_start=False),
          fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
          param_distributions={'learning_rate': [0.001, 0.003, 0.01, 0.03,
0.05, 0.1, 0.3, 0.5, 1, 3, 5], 'n_estimators': [50, 60, 70, 80, 90, 100, 11
0, 120, 130, 140, 150, 160, 170, 180, 190, 200, 210, 220, 230, 240, 250, 26
0, 270, 280, 290, 300, 310, 320, 330, 340, 350, 360, 370, 380, 390, 400, 41
0, 420, 43...', 'ls', 'huber'], 'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10,
11, 12, 13, 14, 15, 16, 17, 18, 19]},
          pre_dispatch='2*n_jobs', random_state=81, refit=True,
          return_train_score=True, scoring=None, verbose=0)
```

In [74]:

```
a=pd.DataFrame(rs.cv_results_)
a.sort_values('rank_test_score').head().transpose()
```

Out[74]:

	8	1	2	4	9
mean_fit_time	9.46327	18.5958	4.23771	20.7244	0.421857
std_fit_time	0.454136	0.103495	0.241539	0.899712	0.0127586
mean_score_time	0.046871	0.0520789	0.0260406	0.0572892	0.00520714
std_score_time	0.022094	0.0073653	0.00736547	0.00736648	0.00736401
param_subsample	0.75	0.5	0.6	0.65	0.5
param_n_estimators	330	230	350	450	100
param_max_depth	7	18	4	10	1
param_loss	lad	lad	lad	lad	lad
param_learning_rate	0.01	0.05	0.1	0.1	0.3
params	{'subsample': 0.75, 'n_estimators': 330, 'max_...	{'subsample': 0.5, 'n_estimators': 230, 'max_d...	{'subsample': 0.6, 'n_estimators': 350, 'max_d...	{'subsample': 0.65, 'n_estimators': 450, 'max_...	{'subsample': 0.5, 'n_estimators': 100, 'max_d...
split0_test_score	0.582917	0.584482	0.583257	0.581858	0.383814
split1_test_score	0.518422	0.518844	0.51689	0.516053	0.358329
split2_test_score	0.481112	0.468336	0.463358	0.457859	0.330896
mean_test_score	0.527484	0.523888	0.521168	0.51859	0.35768
std_test_score	0.042053	0.0475503	0.0490421	0.0506545	0.0216084
rank_test_score	1	2	3	4	5
split0_train_score	0.532657	0.548755	0.532041	0.546197	0.36262
split1_train_score	0.562201	0.576943	0.566888	0.572449	0.382529
split2_train_score	0.571901	0.586415	0.569794	0.579995	0.386988
mean_train_score	0.555587	0.570704	0.556241	0.566214	0.377379
std_train_score	0.0166902	0.0159952	0.017153	0.0144853	0.0105941

In [*]:

```
cv = cross_val_score (rs,Utrain,Ytrain,cv=5,scoring=make_scorer(mean_absolute_error))
print("Average CV is:", round(cv.mean(),3),cv.std())
Ypred=rs.predict(Xtest)
Ypred_t=rs.predict(Xtrain)
MAE=mean_absolute_error(Ytest,Ypred)
MAE_t=mean_absolute_error(Ytrain,Ypred_t)
print("GBR Training set score: {:.3f}".format(MAE_t))
print("GBR Test set score: {:.3f}".format(MAE))
```

```
C:\Users\ADEBAYO\Anaconda3\lib\site-packages\sklearn\model_selection\_searc
h.py:841: DeprecationWarning: The default of the `iid` parameter will change
from True to False in version 0.22 and will be removed in 0.24. This will ch
ange numeric results when test-set sizes are unequal.
  DeprecationWarning)
C:\Users\ADEBAYO\Anaconda3\lib\site-packages\sklearn\model_selection\_searc
h.py:791: RuntimeWarning: overflow encountered in square
  array_means[:, np.newaxis]) ** 2,
C:\Users\ADEBAYO\Anaconda3\lib\site-packages\sklearn\model_selection\_searc
h.py:841: DeprecationWarning: The default of the `iid` parameter will change
from True to False in version 0.22 and will be removed in 0.24. This will ch
ange numeric results when test-set sizes are unequal.
  DeprecationWarning)
C:\Users\ADEBAYO\Anaconda3\lib\site-packages\sklearn\model_selection\_searc
h.py:791: RuntimeWarning: overflow encountered in square
  array_means[:, np.newaxis]) ** 2,
```

It can be seen that while the implementation above is somewhat simple and time-efficient. The metrics are not particularly bad. One can rerun the search a few number of times and see whether there is a trend in the chosen parameter and then grid search based on the smaller range. One could also random search for a larger number of times.

Conclusion

I heard that a top 5 model used Genetic Algorithm for its parameter tuning. Apparently, the person had a lot of time for the tuning as GA is very time-consuming like Grid Search. This may not be possible in a short hackathons or even in some real life scenerios where time is severly limited.

This notebook have taken us through some very important concepts in data science (EDA, Feature Selection, Stacking, HypperParameter Tuning) using the uber data from Zindi. It is specifically desined for those who are just starting their data science journey especially as regards working with real-life data. I hope you find it informative.

P.S: Any other top solution could just clone this notebook and mention one or two two things that made their model stand out if they dont have the time to share an extensive notebook like this.

In [ ]:

```
```