Predicting cab booking cancellation

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Springboard Data Science Career Track

Capstone Project- I

2019

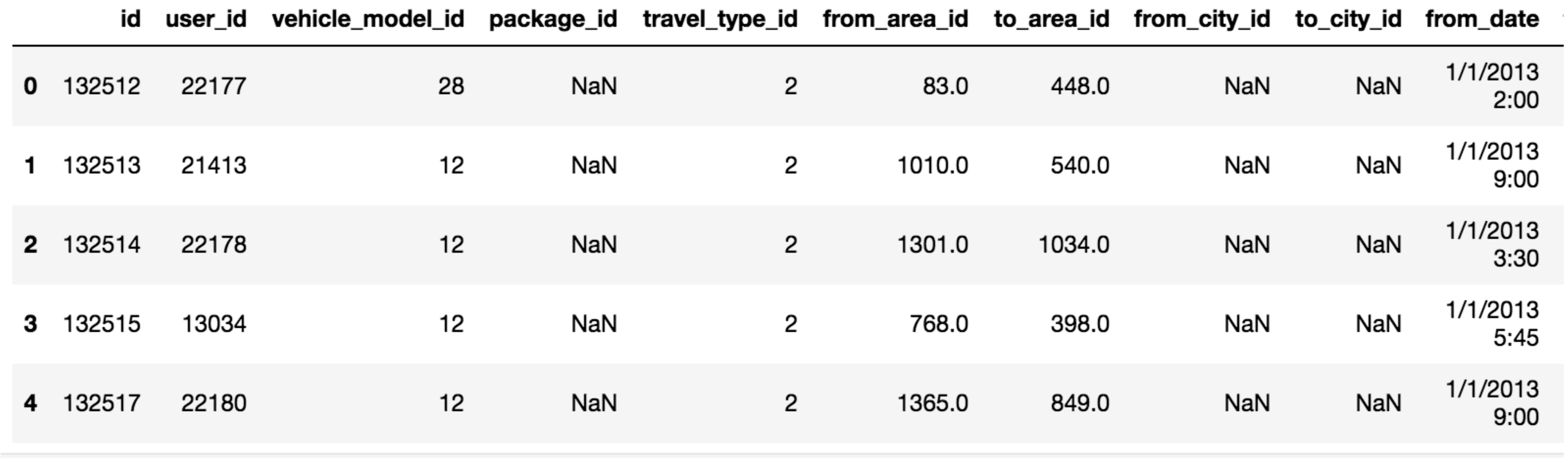
The Problem Statement

- To improve the customer service for Bangalore (India) based cab company called ’**YourCabs’**.
- A certain percentage of booking gets canceled by the company due to the unavailability of a car.
- So, the challenge is to **build a predictive model**, which would classify the upcoming bookings as, if they would eventually get cancelled due to car unavailability, or not.
- So this is a **classification** problem.

The Dataset

- Originally listed as a ‘Kaggle’ challenge.
- Downloaded as ‘csv file’ from the following : https://www.kaggle.com/c/predicting-cab-booking-cancellations2/data
- 43431 rows and 20 columns
- All the variables/data columns are categorical. The target variable/column is 'Car_cancellation', which takes the value "1", if the ride gets canceled, otherwise "0".

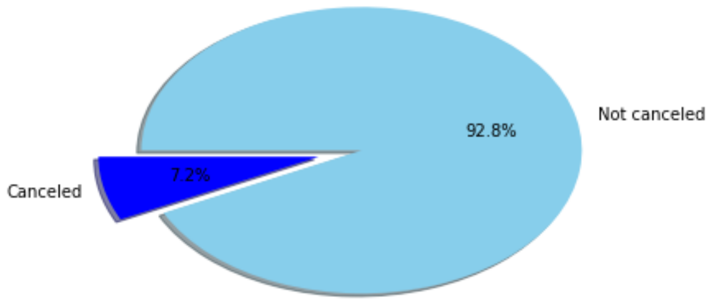
The first 5 lines of the data

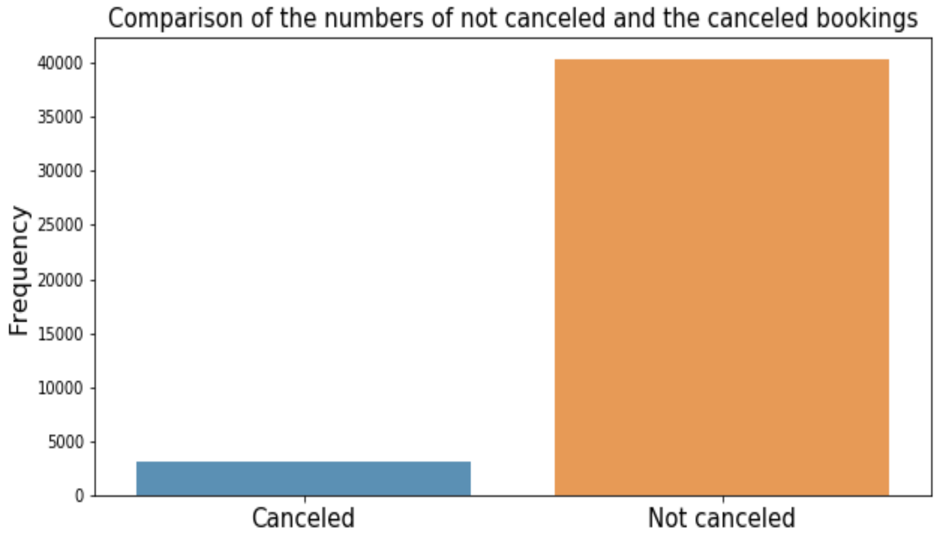


	id	user_id	vehicle_model_id	package_id	travel_type_id	from_area_id	to_area_id	from_city_id	to_city_id	from_date
0	132512	22177	28	NaN	2	83.0	448.0	NaN	NaN	1/1/2013 2:00
1	132513	21413	12	NaN	2	1010.0	540.0	NaN	NaN	1/1/2013 9:00
2	132514	22178	12	NaN	2	1301.0	1034.0	NaN	NaN	1/1/2013 3:30
3	132515	13034	12	NaN	2	768.0	398.0	NaN	NaN	1/1/2013 5:45
4	132517	22180	12	NaN	2	1365.0	849.0	NaN	NaN	1/1/2013 9:00

Data Wrangling:

- Python packages used: **NumPy**, **Pandas**, **Scikit-learn**, **Matplotlib**, **Seaborn**
- **Data/column engineering: 'Booking_created'**: timestamp of the ride booking information . **'from_date'**: timestamp of the actual trip start information. We have split those ’DateTime' objects into separate day of the week, date, month and hour columns.
- **Class imbalance:** Only ~7% (only 3132, in total 43,431) of the total booking has been canceled.

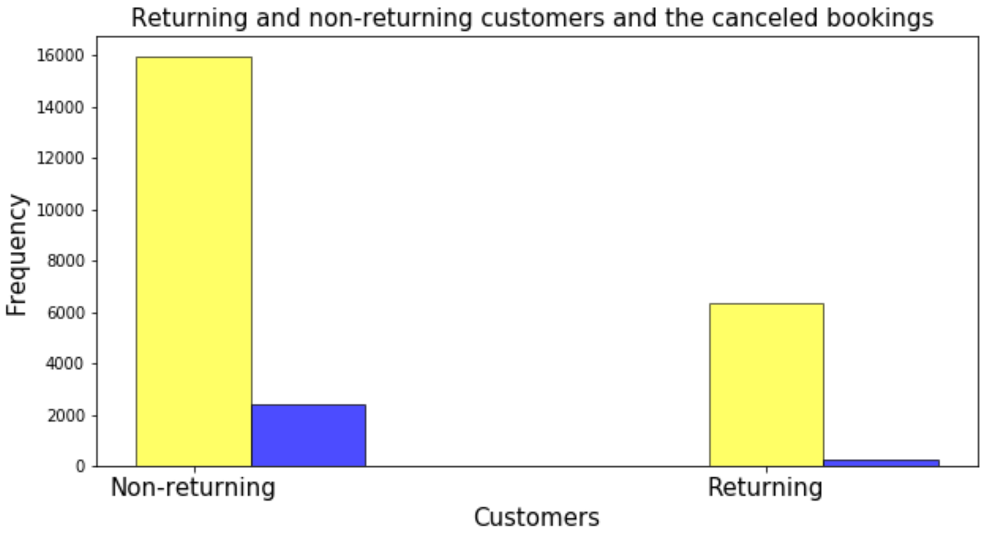


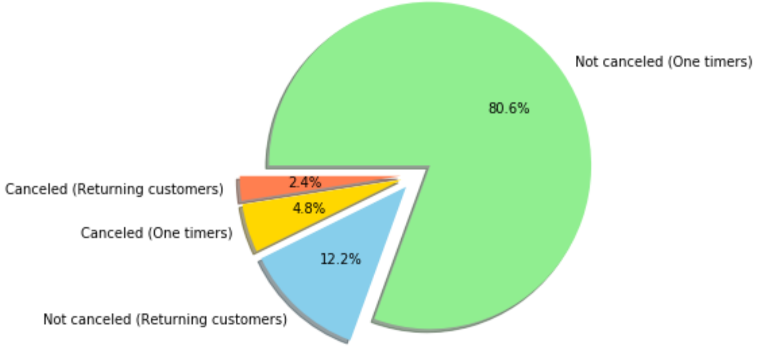


Exploratory Data Analysis (EDA)

User ID:

- Each user has been assigned a unique ‘User ID’
- Total 22267 user IDs.
- ‘user_id '29648' is the most frequent user (frequency 471).
- The no. of one-time users (non returning) are: 15935 and that of the returning customers are: 6332.
- ~16.6% of the total returning customers got their trips canceled.

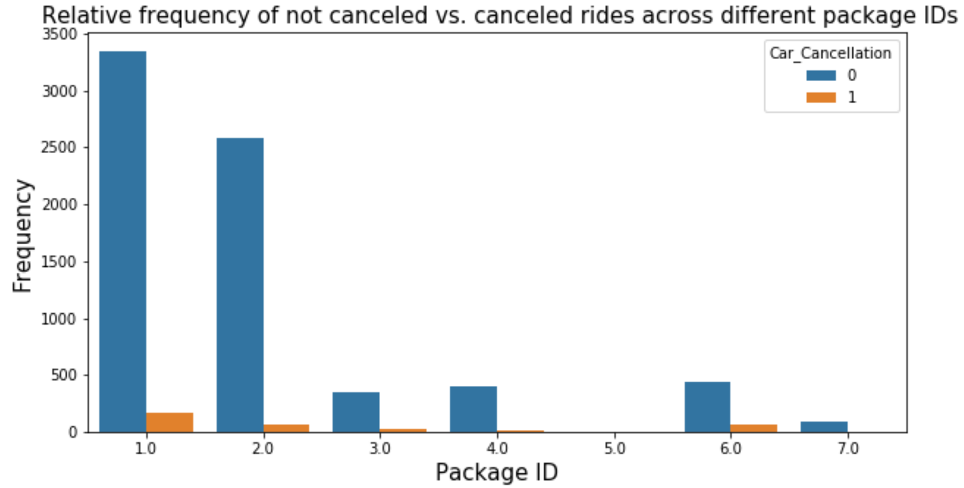




EDA – continued:

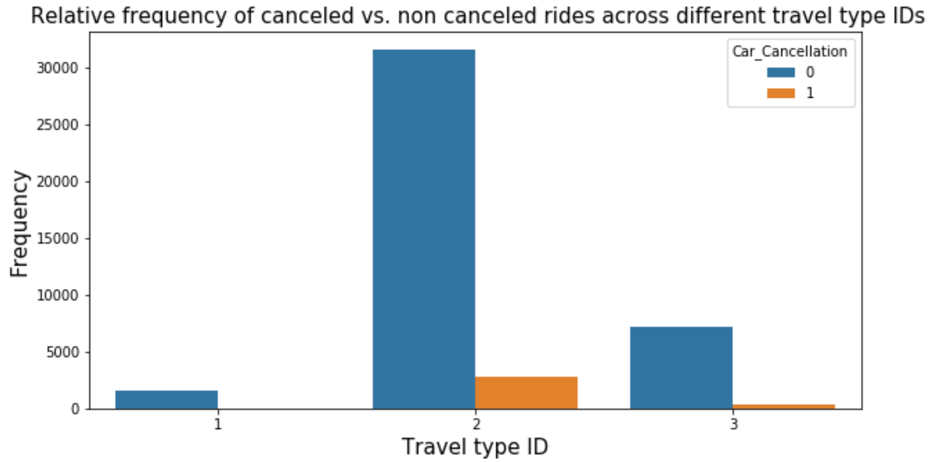
Package ID:

- Different package IDs are the various travel (booking) plans, from which customers can choose theirs.



Travel type ID:

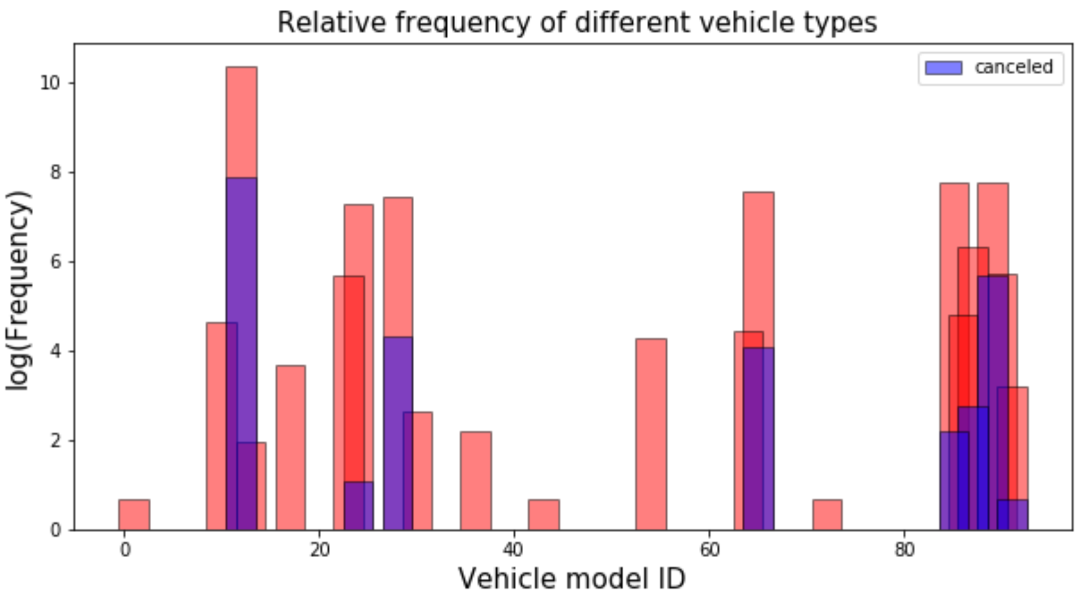
- Three different travel types are available to choose.
- Travel type '2' (i.e. for point to point travel) is the most popular.



EDA – continued:

Vehicle model ID:

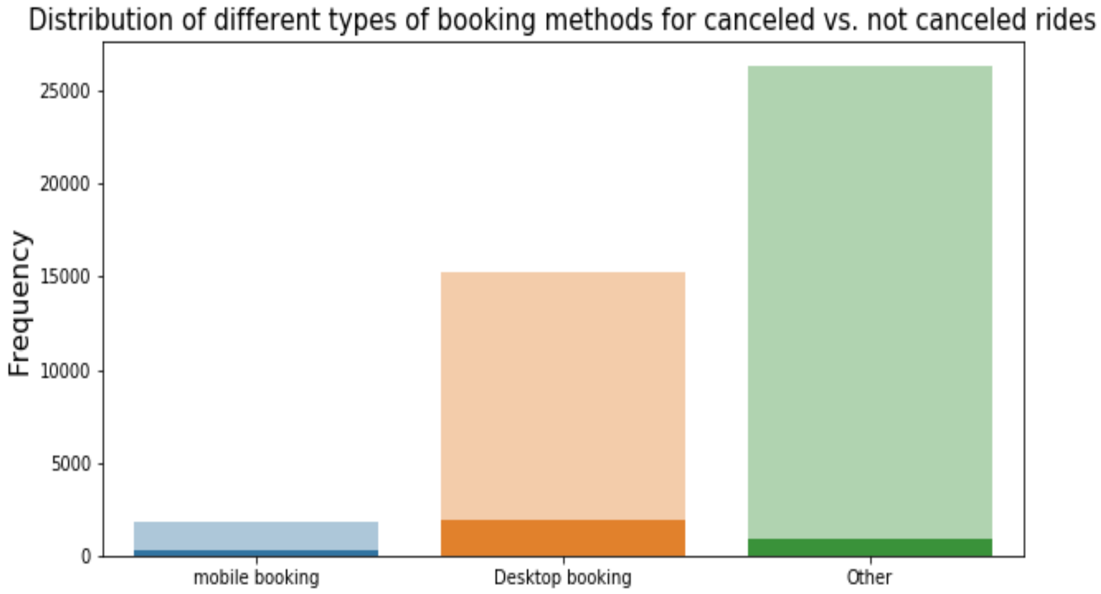
- 27 different types of vehicles have been listed.
- The most popular one is the vehicle with the vehicle ID no '12 (used 31859 times.)
- Got the maximum number of cancellations (2668 times) too.
- Y-axis has been resized by using logarithmic operation, to get a clear picture of the entire data.



EDA – continued:

Booking methods:

- Three different types of 'Booking methods.' : 'mobile booking' ,'desktop/website booking.' So, the remaining portion as 'other method' of booking.
- 1878 bookings have been made from mobile websites, 15270 bookings from desktop websites, so, 26283 bookings have been made differently! So, other methods of booking are mostly favored
- maximum cancellations correspond to the bookings made from the desktop websites.



EDA – continued:

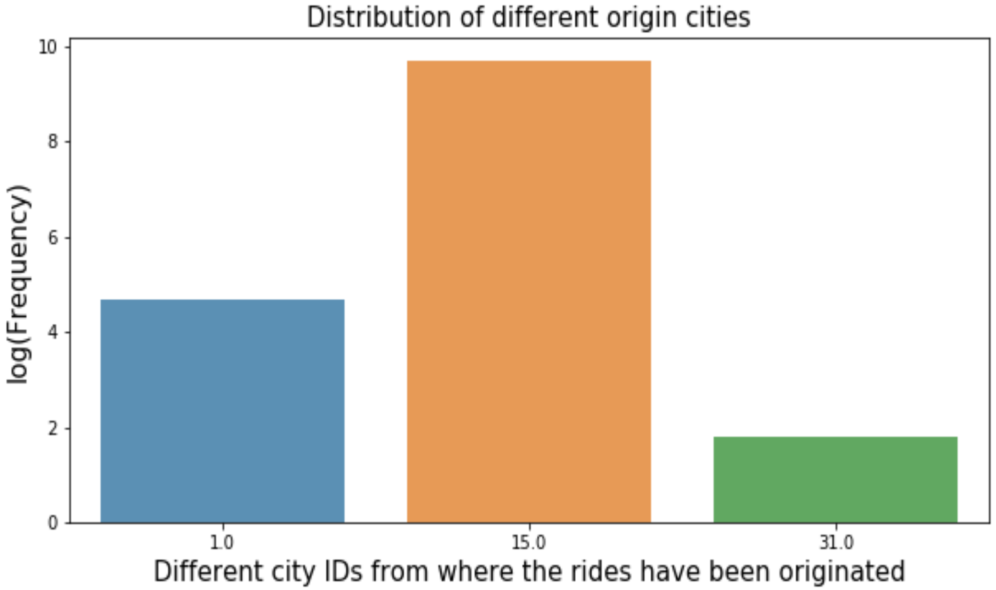
Pick-up/Destination Area ID:

- 598 unique origin and 568 destination area information have been listed.
- The most popular origin area is the area with ‘area_id’ no. '393', which is eventually the most popular destination area as well.
- 559 area IDs are common to both as the pick-up and drop-off locations.
- There are specific pick-up and drop-off areas for which more than 50% of the bookings were canceled.
- Moreover, some routes (from specific pick-up to some drop-off areas) are there for which more than 90% of bookings were canceled.
- This is very interesting to see that some routes are infamous in terms of cancellations; the cancellation rate for them is pretty high.
- As an example, the route from area ID: 626 to area ID: 122, almost 91% of the bookings were canceled.

EDA – continued:

Origin/Destination city ID :

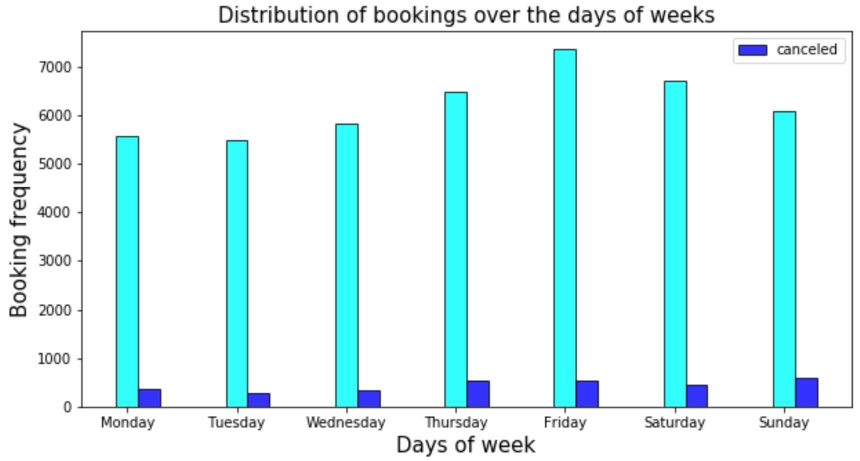
- Only 3 origin cities have been recorded.
- The most popular origin city is the city with the ID no: '15'. Whereas, 116 unique destination cities are there.
- The most popular destination city is the city with the ID no: '32' (475 rides have their destinations to this city.)
- However, most of the information is missing.

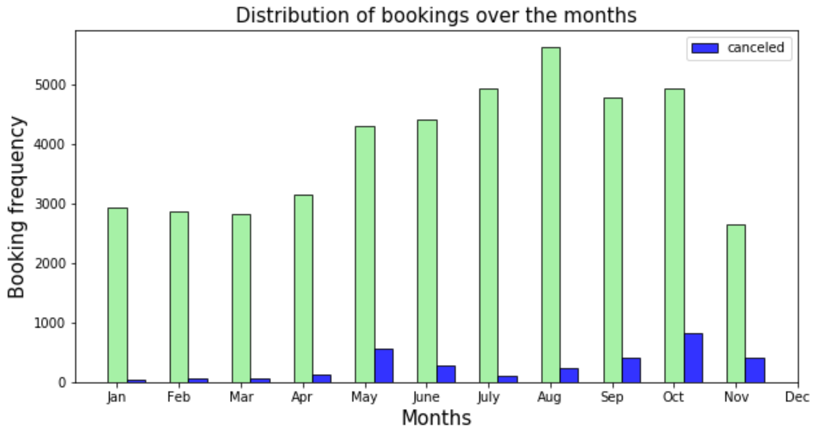


EDA – continued:

Booking time:

- Timestamp of the booking (when somebody booked the cab).
- Maximum no. of bookings made at a given timestamp is, 18. Corresponding date-time is 2013-10-31 10:30:00.
- Maximum bookings were made on Fridays.
- Bookings were made almost equally throughout the month.
- Maximum bookings were made in August.

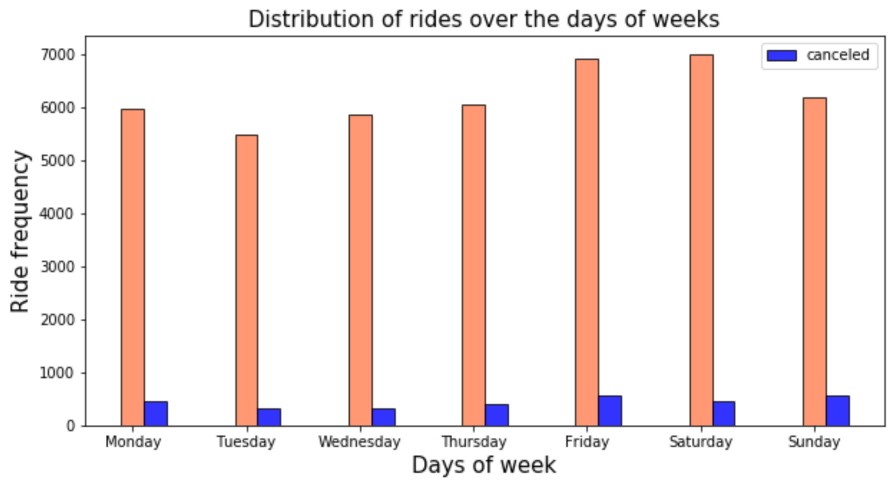


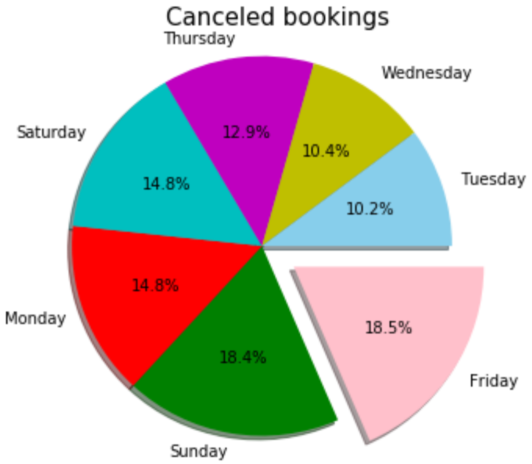


EDA – continued:

Timestamp of the actual ride:

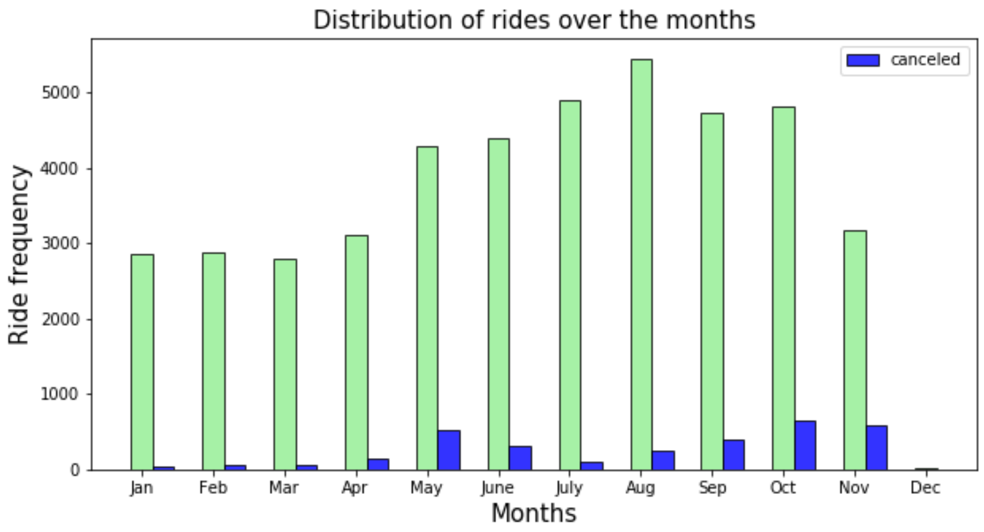
- Timestamp of the actual rides.
- Maximum no. of trips started at a given timestamp is, 20 and the corresponding date-time is: 2013-10-12 06:00:00 and 2013-07-04 22:15:00.
- Maximum frequency (6990) of rides correspond to Saturday,' followed by 'Friday.'
- The maximum cancellations (578) correspond 'Friday,' followed 'Sunday.'

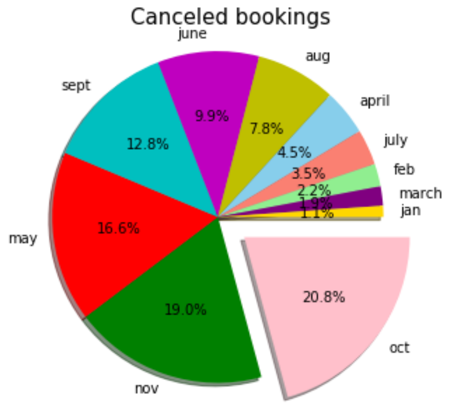




EDA – continued:

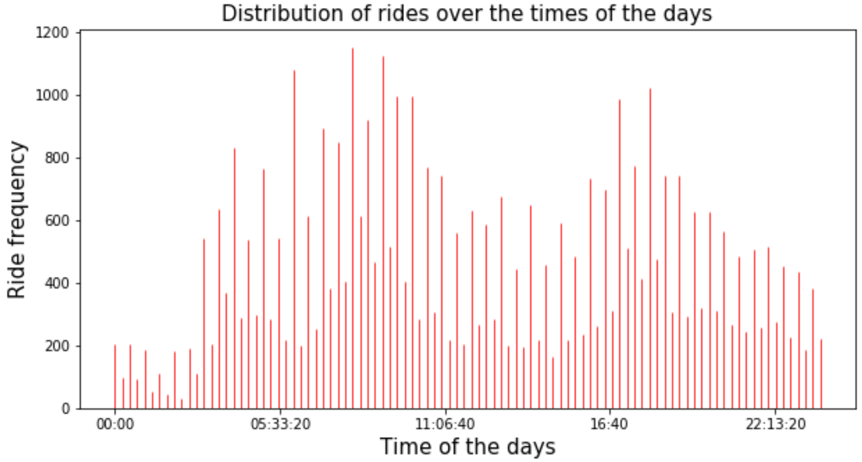
- Extracted the ride frequency over the months of the year.
- Maximum frequency (5445) corresponds to the month of 'August,' followed by 'July.’
- On the same figure, we have plotted the canceled ride frequencies. Maximum cancellation (650) correspond to the month of 'October,' followed by 'November.'

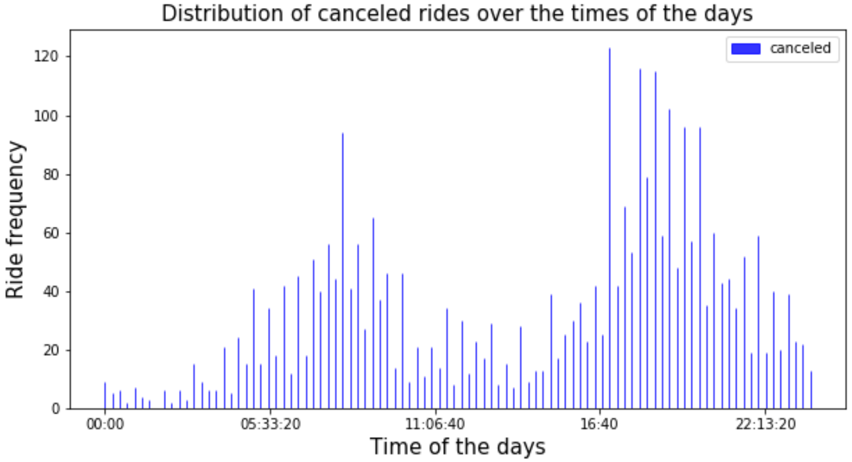




EDA – continued:

- These are the frequencies of the rides across different times of the day.
- The two humps/clusters in the distributions of the ride frequencies. One is around the morning and another for the evening time.
- The ride cancellation distribution also follows the same trend. Maximum numbers of rides got canceled in these two peak hours.

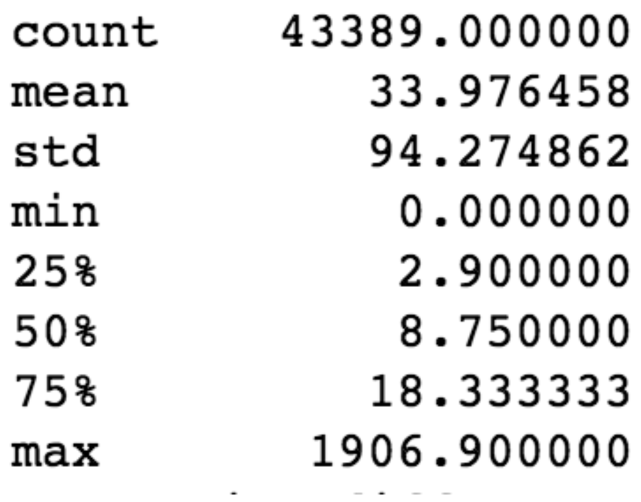




EDA – continued:

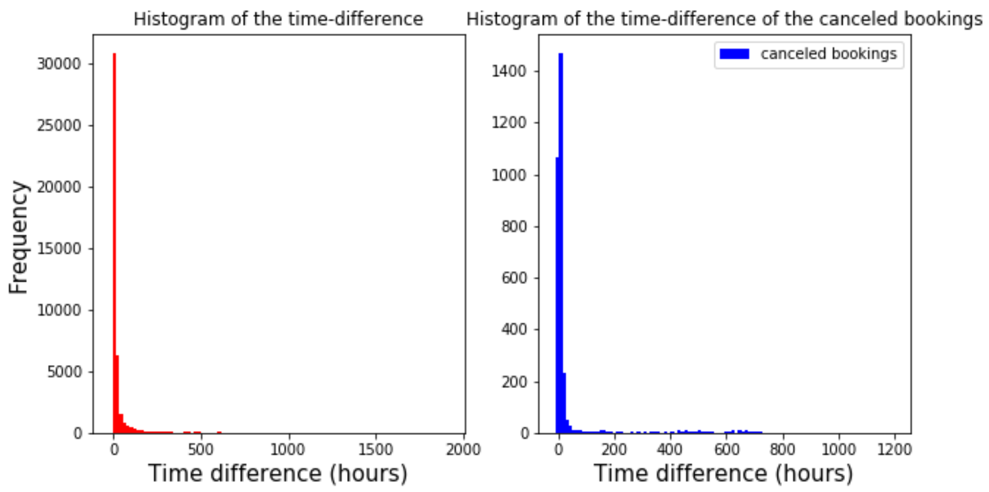
Time difference:

- This is the numerical feature created.
- This is the difference in the timestamps (in hours) between the ‘booking created’ and the ‘trip start time’.
- There are 42 entries of the dataset, for which the time difference is negative, which is unphysical. – Dropped.

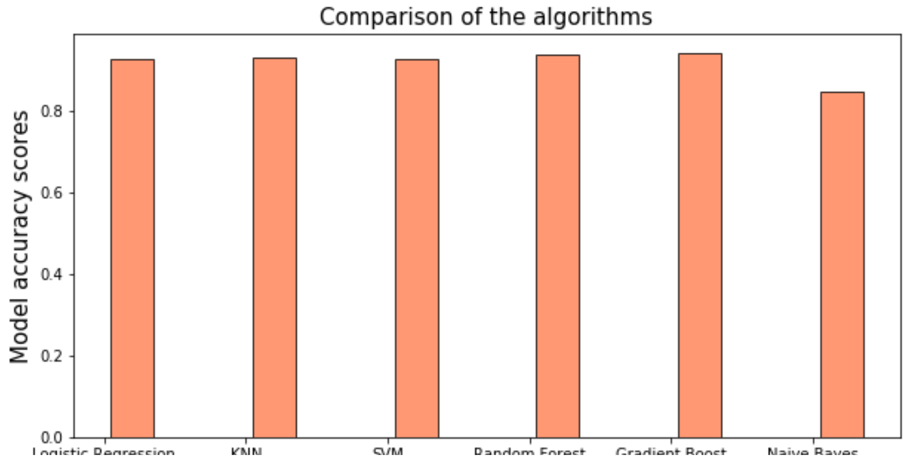


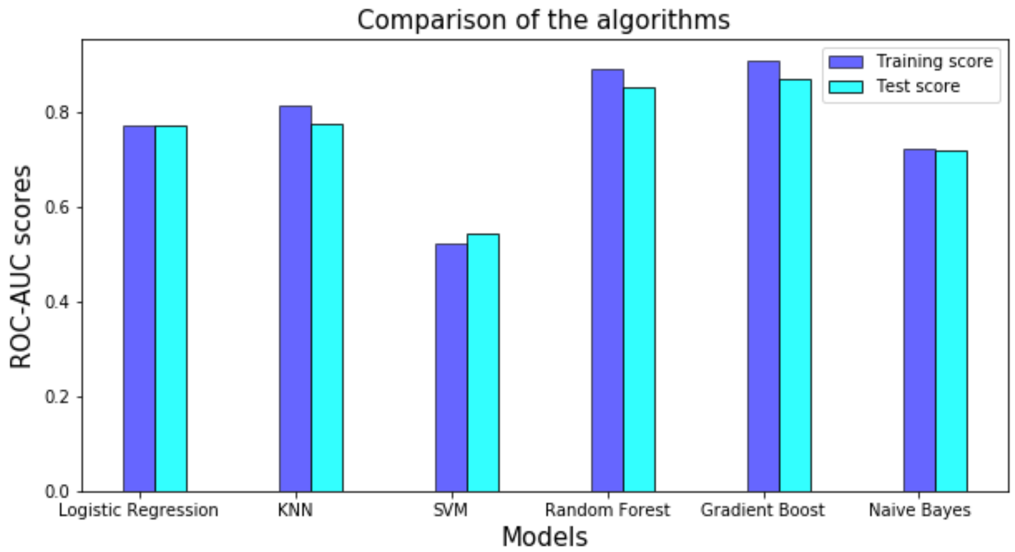
```
count    43389.000000
mean        33.976458
std         94.274862
min          0.000000
25%          2.900000
50%          8.750000
75%         18.333333
max       1906.900000
```

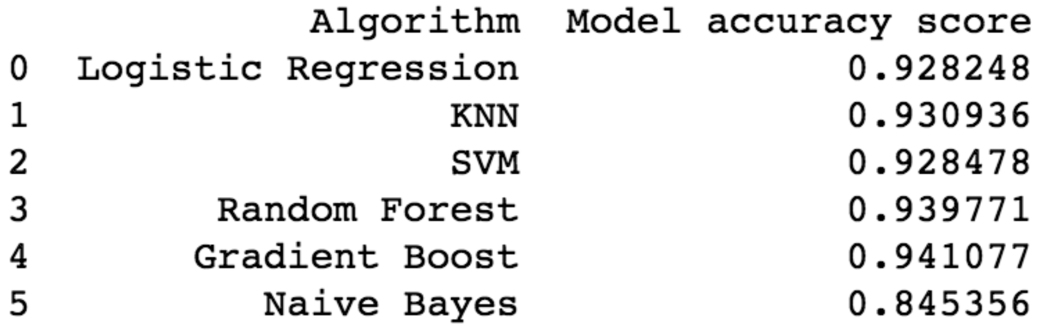
Descriptive Statistics



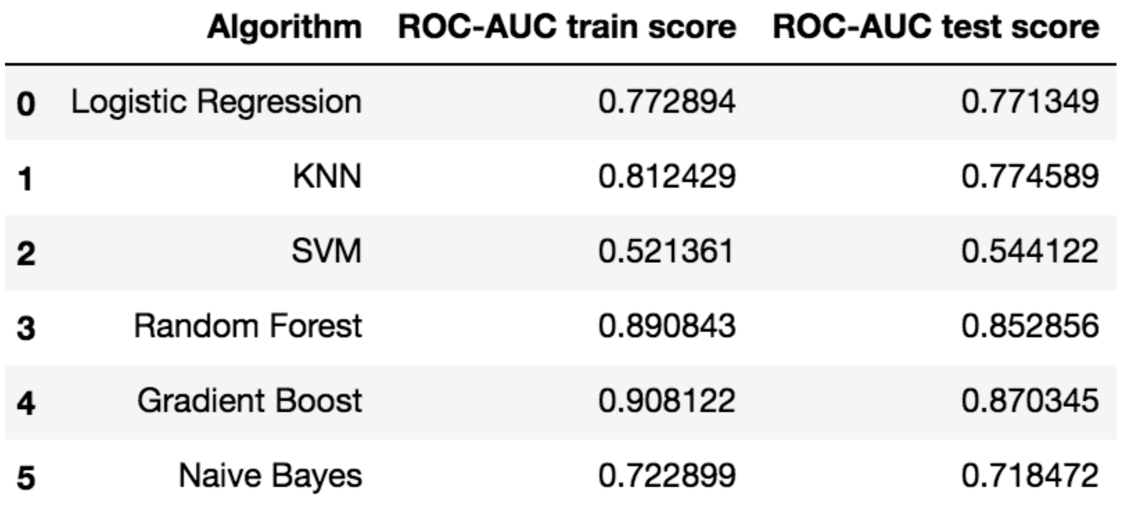
Applying Machine Learning models and comparing their performances:







```
             Algorithm  Model accuracy score
0  Logistic Regression              0.928248
1                  KNN              0.930936
2                  SVM              0.928478
3        Random Forest              0.939771
4       Gradient Boost              0.941077
5          Naive Bayes              0.845356
```

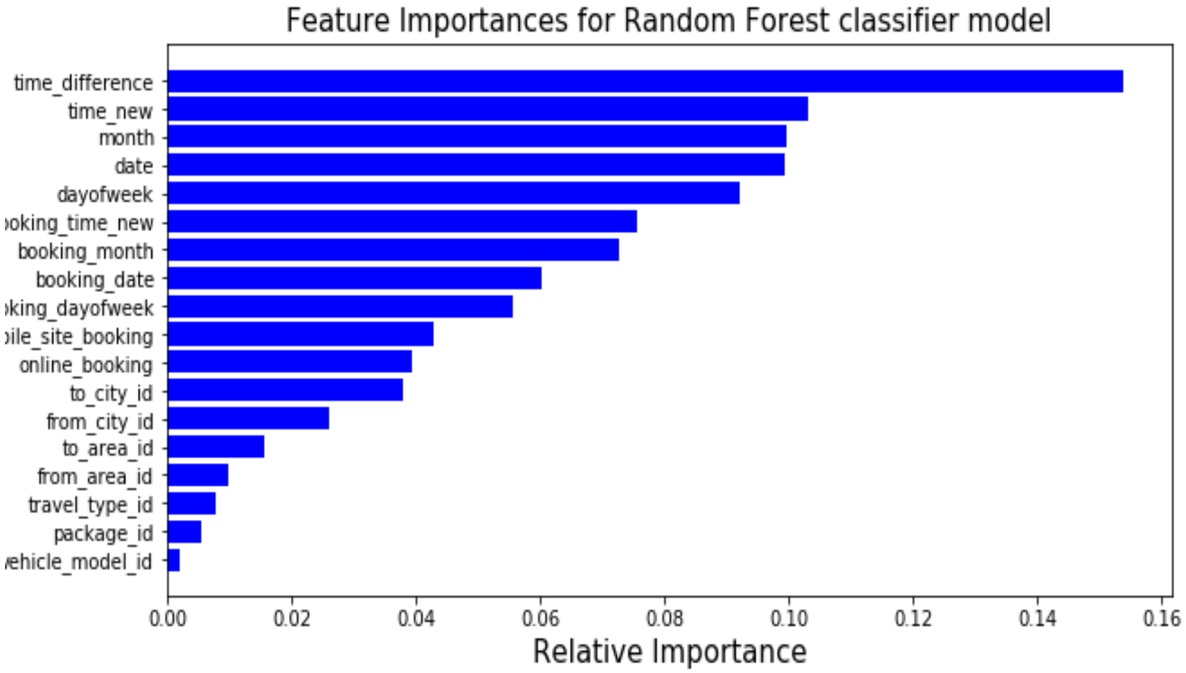


	Algorithm	ROC-AUC train score	ROC-AUC test score
0	Logistic Regression	0.772894	0.771349
1	KNN	0.812429	0.774589
2	SVM	0.521361	0.544122
3	Random Forest	0.890843	0.852856
4	Gradient Boost	0.908122	0.870345
5	Naive Bayes	0.722899	0.718472

Hyperparameter Tunning:

- the **Gradient Boost**, and the **Random Forest** are the two best performing models.
- Performed the hyperparameter tuning, through the gridsearch, for the two ML models.
- Fitting these models with optimized hyperparameters (found through the grid search), we evaluated the model performance in terms of **ROC-AUC** score.

Model	ROC-AUC Score
Random Forest (RF)	0.8860217314758018
Gradient Boost (GB)	0.8987293089109146



Future Direction:

- Here we have used only the data of one year. The model can be improved, if we can use the data from at least another year.
- Use ensembles of the machine learning models to average out bias and improve performance.
- Try to use more feature engineering. Especially, here we have neglected the Latitude/longitude (GPS data) info. We could have extracted the route information out of them, and use that as a feature.
- Try to fit and predict using the Extreme Gradient boost classifier model.

Acknowledgement:

- Mentor: Max Sop
- Kaggle
- Springboard Team

For detailed analysis:
https://github.com/debisree/Springboard_Debisree/tree/master/Capstone_1_predicting_cab_booking_cancellation

Thank you!