Regression Modeling

Prediction of travel time for flights from Taiwan to Hong Kong

Overview

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Problem Statement

To predict the estimated time taken for an aircraft, plying the route from from Taiwan Taoyuan International Airport (IATA: TPE) to Hong Kong International Airport (IATA: HKG), at any point in time at which it is detected on the flight radar to arrive to Hong Kong.

Exploratory Data Analysis

Summary flight info

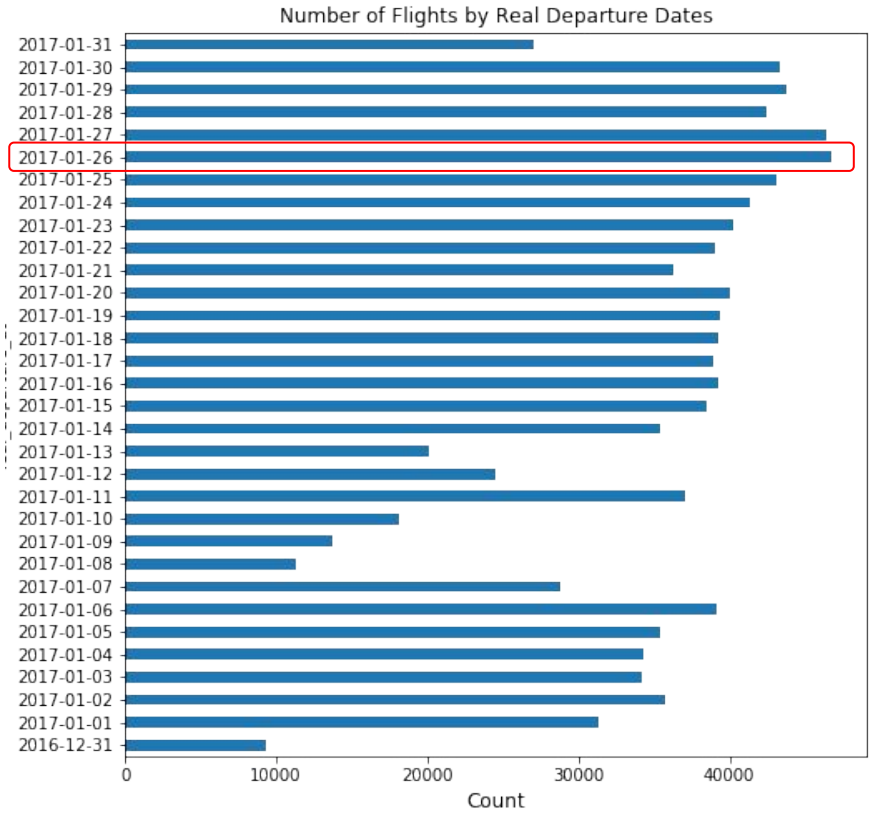
Feature	Type	Description
flight_id	*object*	Unique identifier for every flight record
flight_callsign	*object*	Used by Air Traffic Control to denote a specific flight
aircraft_model	*object*	Aircraft model of the flight
aircraft_registration	*object*	Each aircraft is assigned a registration number—often called a tail number—that is unique to the aircraft. Registration numbers are based on the country of registration, with the United Kingdom employing 'G' as their first letter identifier, followed by a hyphen and four further letters e.g. G-STBA. In the United States 'N' is used as the first letter followed by either letters or numbers e.g. N463UA.
airline	*object*	Airline operating the flight
origin	*object*	Country which the flight departed from
destination	*object*	Country which the flight arrived at
scheduled_departure_utc	*float*	Scheduled departure in Unix Time (UTC); elapsed seconds since January 1st 1970 00:00:00 UTC (Universal Time)
scheduled_arrival_utc	*float*	Scheduled arrival in Unix Time (UTC); elapsed seconds since January 1st 1970 00:00:00 UTC (Universal Time)
real_departure_utc	*float*	Real departure in Unix Time (UTC); elapsed seconds since January 1st 1970 00:00:00 UTC (Universal Time)
estimated_arrival_utc	*float*	Estimated arrival in Unix Time (UTC); elapsed seconds since January 1st 1970 00:00:00 UTC (Universal Time)
real_flight_duration	*float*	Duration in which the plane is in the air (in seconds)

Flight radar info

Feature	Type	Description
flight_id	*object*	Unique identifier for every flight record
timestamp_utc	*int*	Time of observation in Unix Time (UTC); elapsed seconds since January 1st 1970 00:00:00 UTC (Universal Time)
timestamp_dt	*int*	Timestamp of observation (YYYY-MM-DD HH:MM)
latitude	*float*	Latitude of aircraft's coordinate (WGS 84) at time of observation
longitude	*float*	Longitude of aircraft's coordinate (WGS 84) at time of observation
altitude	*int*	Altitude of aircraft (feet above mean sea level) at time of observation
heading	*int*	Compass heading of aircraft, denoted as 0-359
speed	*int*	Speed of the aircraft over the ground, measured in Knots (nautical miles per hour)

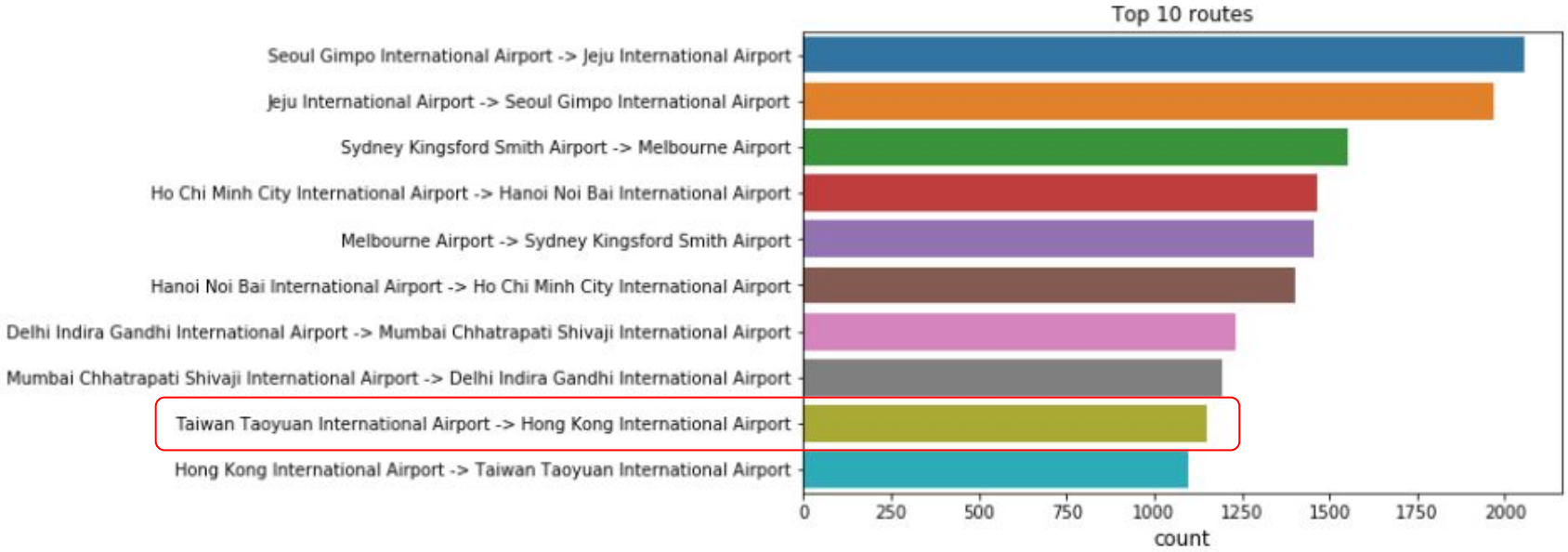
Exploratory Data Analysis

- Most number of departures happen to be on 2017-01-26



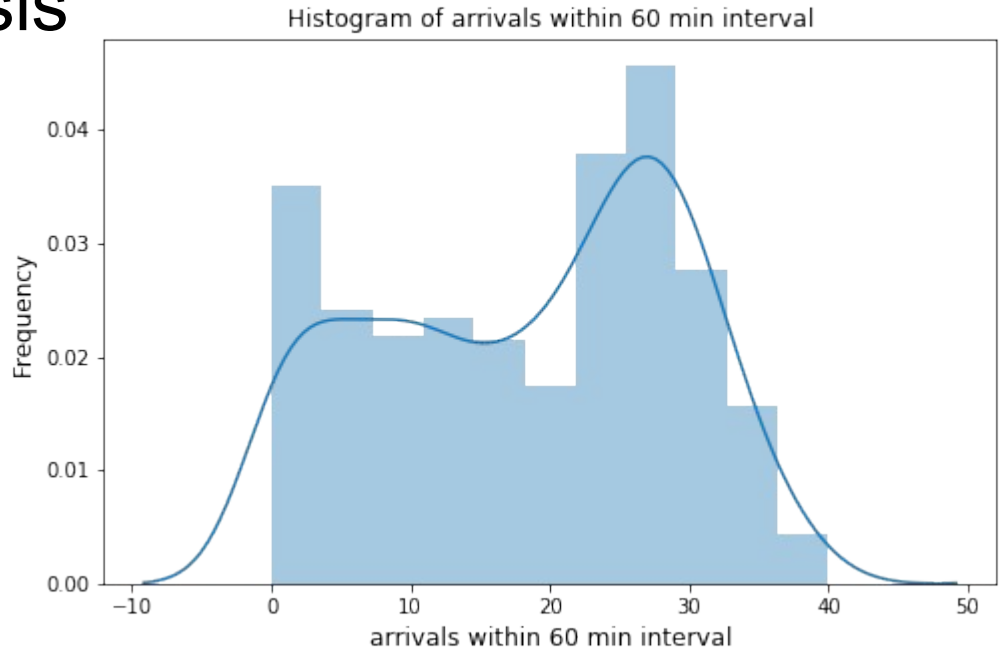
Exploratory Data Analysis

- Top international route in Jan 2017



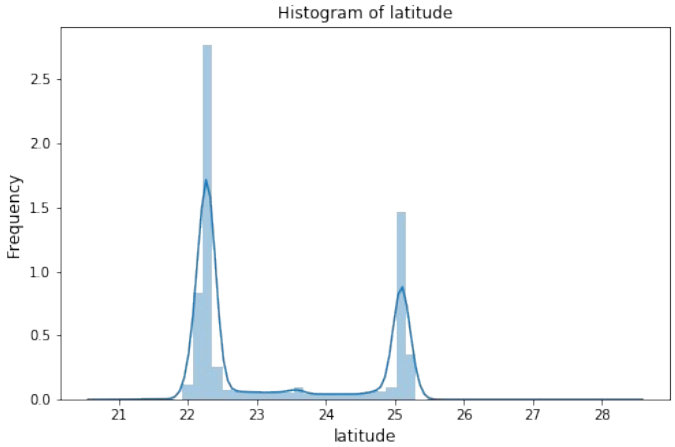
Exploratory Data Analysis

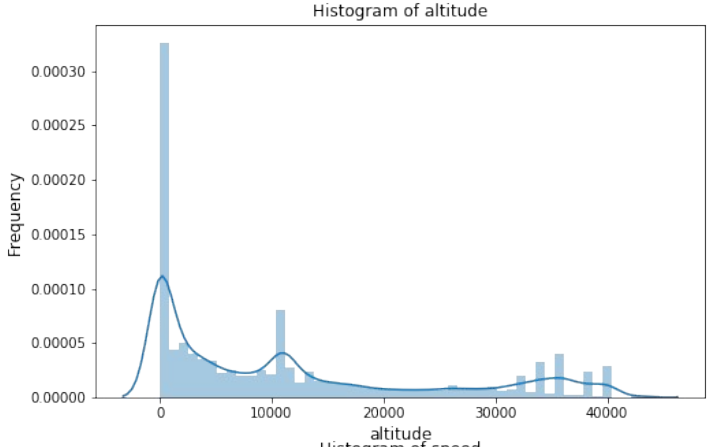
- Not normally distributed
- Bi-modal

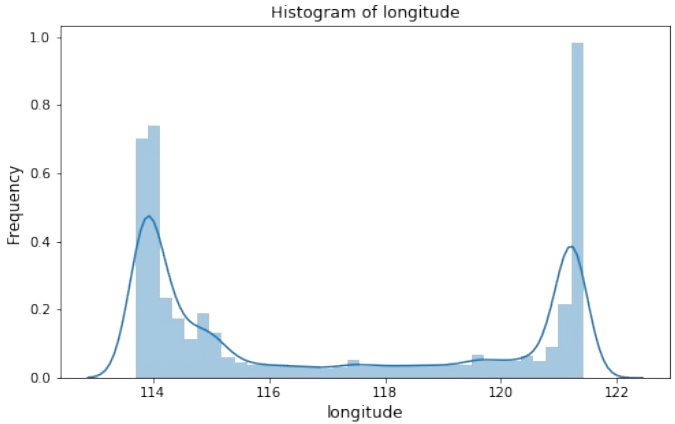


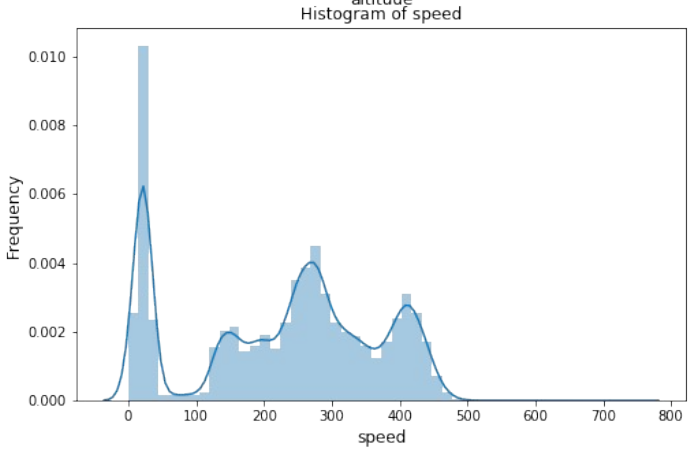

```
df_arrivals_at_hkg['forecasted_arrival_dt'] = \
(df_arrivals_at_hkg['real_departure_dt'] + pd.to_timedelta(df_arrivals_at_hkg['real_flight_duration'], unit='s'
.fillna(df_arrivals_at_hkg['real_departure_dt'] + pd.to_timedelta(df_arrivals_at_hkg['scheduled_flight_duration
.fillna(df_arrivals_at_hkg['scheduled_departure_dt'] + pd.to_timedelta(df_arrivals_at_hkg['real_flight_duration
.fillna(df_arrivals_at_hkg['scheduled_arrival_dt'])\
.fillna(df_arrivals_at_hkg['estimated_arrival_dt'])
```

Exploratory Data Analysis

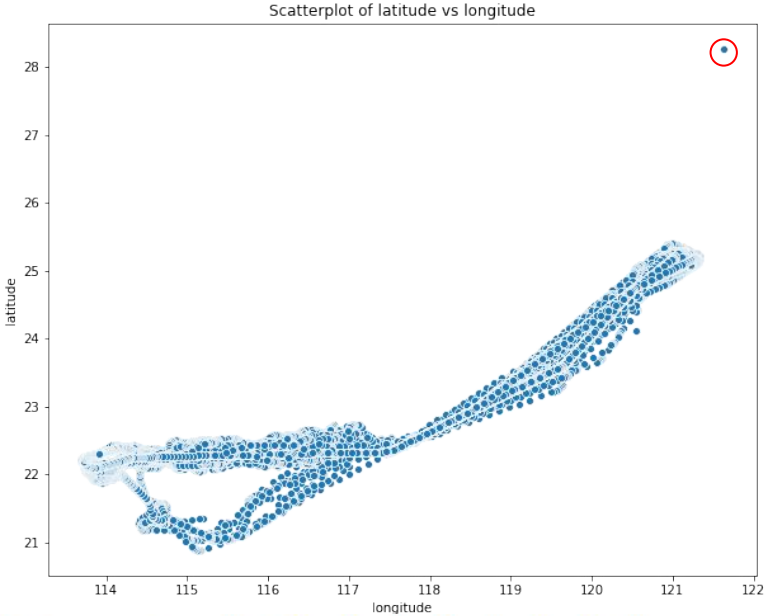








Exploratory Data Analysis



	flight_id	timestamp_utc	latitude	longitude	altitude	heading	speed	timestamp_dt
27371	c31cf95	1484662603	28.258541	121.633163	11600	8	0	2017-01-17 14:16:43
27372	c31cf95	1484662641	24.921299	120.893318	19450	256	0	2017-01-17 14:17:21
27373	c31cf95	1484662667	24.853016	120.848541	20684	230	390	2017-01-17 14:17:47
27374	c31cf95	1484662677	24.837517	120.830132	21338	219	454	2017-01-17 14:17:57
27375	c31cf95	1484662694	24.831850	120.808067	22190	258	329	2017-01-17 14:18:14

Feature Engineering

	flight_id	timestamp_dt	real_departure_dt	time_since_real_departure	latitude	longitude	altitude	heading
152164	c33e9e8	2017-01-18 11:53:40	2017-01-18 11:53:45	-5.0	25.067184	121.244965	0	49
152165	c33e9e8	2017-01-18 11:53:46	2017-01-18 11:53:45	1.0	25.070297	121.248878	50	48
152166	c33e9e8	2017-01-18 11:53:54	2017-01-18 11:53:45	9.0	25.076294	121.256813	525	50
152167	c33e9e8	2017-01-18 11:54:00	2017-01-18 11:53:45	15.0	25.079367	121.260925	775	51

	flight_id	timestamp_dt	real_departure_dt	time_since_real_departure	latitude	longitude	altitude	heading
152445	c33e9e8	2017-01-18 13:29:27	2017-01-18 11:53:45	5742.0	22.287163	113.872627	450	74
152446	c33e9e8	2017-01-18 13:29:33	2017-01-18 11:53:45	5748.0	22.288513	113.876900	375	70
152447	c33e9e8	2017-01-18 13:30:01	2017-01-18 11:53:45	5776.0	22.294333	113.895111	50	71
152448	c33e9e8	2017-01-18 13:30:10	2017-01-18 11:53:45	5785.0	22.296242	113.900909	0	69

Feature Engineering

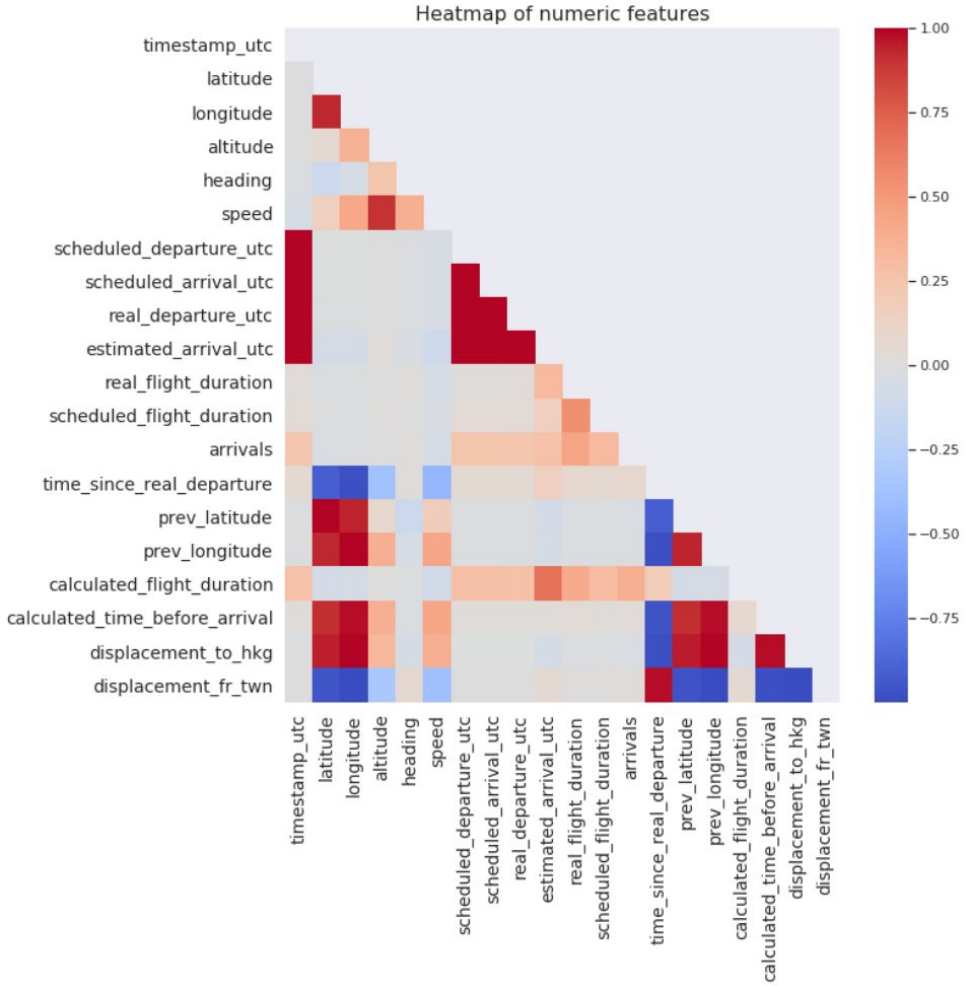
```
# Filter to get records where
# plane has taken off; i.e. speed > 0
# plane's time_since_real_departure >= 0
temp = merged_df.loc[(merged_df['flight_id'] == unique_flight_id) &
                     (merged_df['time_since_real_departure'] >= 0) &
                     (merged_df['speed'] > 0)].sort_values(by='timestamp_utc')


# time_since_real_departure after arrival
# where altitude = 0

possible_arrival_df = temp.loc[(temp['altitude'] == 0) &
                               (temp['time_since_real_departure'] > 11)]
if possible_arrival_df.shape[0] > 0:
    complete_flights.append(unique_flight_id)
    calculated_flight_duration = possible_arrival_df.iloc[0]['time_since_real_departure']
    temp = temp[temp['time_since_real_departure'] <= calculated_flight_duration]
    temp = temp.assign(calculated_flight_duration=calculated_flight_duration)
    filtered_df = filtered_df.append(temp, ignore_index=True)
else:
    incomplete_flights.append(unique_flight_id)
```

Feature Engineering

- Heatmap was plotted to investigate multicollinearity
- There are features in the dataset that describe a common attribute of the displacement_to_hkg, displacement_fr_twn, latitude, longitude.
- These features tend to exhibit high correlation among themselves



Baseline Regression Modeling

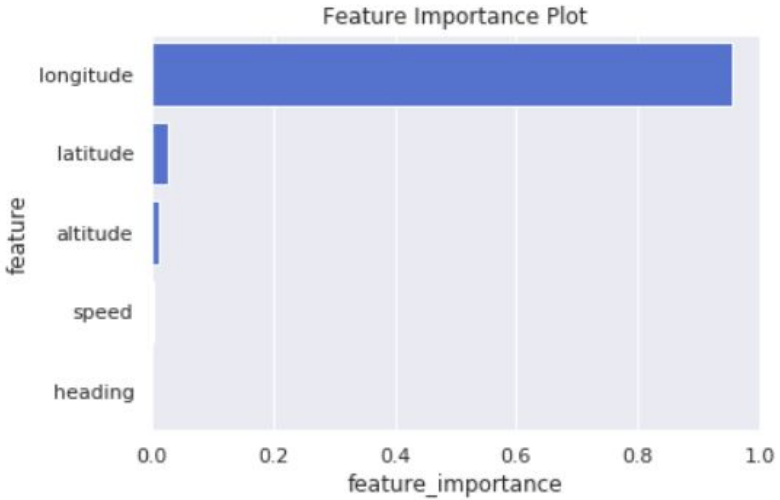
- Features: latitude, longitude, altitude, heading, speed
- RMSE value: 1909.991128
- Adjusted R2: 0

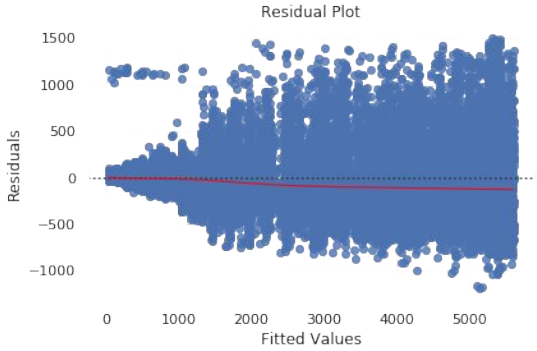
More Regression Modeling

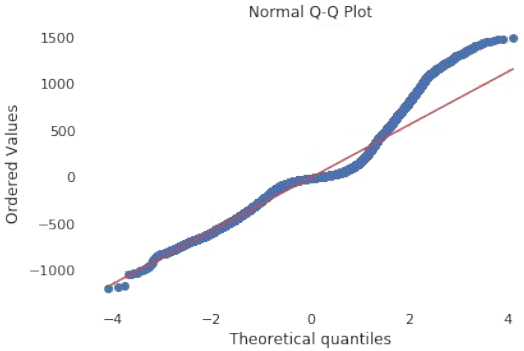
	model_name	mse	rmse	mae	r2	r2_adjusted
0	Random Forest Regression	8.970662e+04	299.510628	86.043145	0.975403	0.975399
1	Linear Regression	1.307992e+05	361.661743	184.162588	0.964136	0.964130
2	Lasso Regression	1.307993e+05	361.661815	184.162983	0.964136	0.964130
3	Ridge Regression	1.307998e+05	361.662606	184.201100	0.964135	0.964130
4	AdaBoost Regression	1.695393e+05	411.751498	322.838671	0.953513	0.953506
5	ElasticNet Regression	2.524455e+05	502.439582	311.995118	0.930781	0.930771
6	Baseline	3.648066e+06	1909.991128	1666.500000	-0.000281	-0.000427

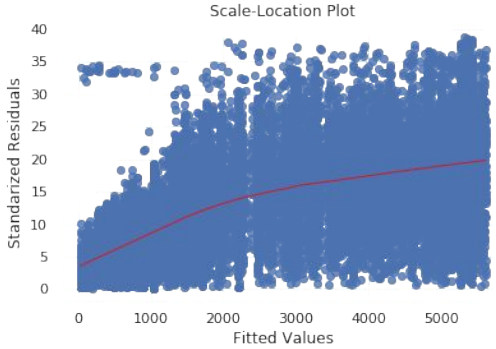
Regression Modeling

- Random Forest Regression









Conclusion and Recommendation

- The Random Forest Regressor had the lowest RMSE
- This model may not necessarily be reliable when predicting outside the time periods of Jan 2017, as this model omits potentially important time-dependent variables such as enroute weather information
- Obtain more information of the flight journey if financially feasible