NYC-Taxi-FHV-Project

In [1]:

```
import pandas as pd #DataFrame
import numpy as np #For array
import os #for os commands
from math import sin, cos, sqrt, atan2, radians, log #For calculation
import time           #to get the system time
import datetime       #for datetime operations
import holidays       #For extract date time of holidays
import calendar       #For calendar for datetime operations


pd.set_option('display.max_columns', 500)
os.environ["GOOGLE_APPLICATION_CREDENTIALS"]="E:/GitHub/NYU-Taxi-project/My First Proj
#os.environ["GOOGLE_APPLICATION_CREDENTIALS"]="./My Project 14295-223aab171173.json"
from google.cloud import bigquery
client = bigquery.Client()

#For geospatial data
import geopandas as gpd   #For geospatial data
import shapely
import pysal as ps
from fiona.crs import from_epsg
from shapely.geometry import Polygon
import geohash_hilbert as ghh # For geohash code
#import choroplethNYC as cp #For taxi zone map

#For machine learning models
import sklearn
from sklearn.linear_model import LinearRegression, Ridge,BayesianRidge #For lasso and
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error, mean_squared_log_error, r2_score, mak
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.cluster import MiniBatchKMeans
from sklearn.cluster import KMeans
from sklearn.neighbors import KNeighborsClassifier
import xgboost as xgb

#For visualization purpose
from scipy.misc import imread, imresize, imsave
from pandas.plotting import scatter_matrix
import scipy         #for other dependancies
import seaborn as sns #for making plots
from scipy.misc import imread, imresize, imsave
from bokeh.palettes import Spectral4
from bokeh.plotting import figure, output_notebook, show
from IPython.display import HTML
from matplotlib.pyplot import *
from matplotlib import cm
from matplotlib import animation
from scipy.misc import imread, imresize, imsave
import matplotlib.pyplot as plt
%matplotlib inline

plt.style.use('seaborn')
```

```
E:\Program Files\Anaconda3\lib\site-packages\pysal\model\spvcm\abstracts.py:10: UserWarning: The `dill` module is required to use the sqlite backend fully.
  from .sqlite import head_to_sql, start_sql
E:\Program Files\Anaconda3\lib\site-packages\sklearn\ensemble\weight_boosting.py:29: DeprecationWarning: numpy.core.umath_tests is an internal NumPy module and should not be imported. It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

1. Data Processing

1.1 Query Data from BigQuery

In [26]:

```
start = time.time()
query = (
"""
SELECT x.travel_time, x.date, x.month, x.day, pickup_hour, pickup_datetime, dropoff_da
    pickup_longitude, pickup_latitude, dropoff_longitude, dropoff_latitude,passenger_c
    temp,visib,mxpsd,wdsp,gust,prcp,sndp,fog,rain_drizzle,snow_ice_pellets,hail,thunde
FROM
(
      SELECT *,ROW_NUMBER() OVER(partition by date, pickup_hour) as row_number
      FROM
      (
            SELECT pickup_datetime, dropoff_datetime, pickup_latitude, pickup_longitud
            EXTRACT (HOUR FROM pickup_datetime) as pickup_hour,
            EXTRACT (DAY FROM pickup_datetime) as day,
            EXTRACT (MONTH FROM pickup_datetime) as month,
            EXTRACT (DATE FROM pickup_datetime) as date,
            TIMESTAMP_DIFF(TIMESTAMP(dropoff_datetime), TIMESTAMP(pickup_datetime), SE
            passenger_count
            FROM `bigquery-public-data.new_york_taxi_trips.tlc_yellow_trips_2016`
            WHERE pickup_latitude IS NOT NULL AND pickup_longitude IS NOT NULL and
                dropoff_longitude IS NOT NULL and dropoff_latitude IS NOT NULL
      ) x
      where x.travel_time >0
) x
JOIN
(
 select cast(mo as int64) as month,cast(da as int64) as day,temp,visib,mxpsd,wdsp,gust
 from `bigquery-public-data.noaa_gsod.gsod2016` where stn='725053'
) y on x.month = y.month and x.day = y.day
where x.row_number <= 500
"""
)
data = pd.io.gbq.read_gbq(query,dialect='standard')

end = time.time()
print("Time taken by above cell is {} mins.".format(round((end-start)/60,2)))
```

```
Time taken by above cell is 10.54 mins.
```

1.1.1 Define Trip Distance

1.1.1 Define Trip Distance

In [27]:
```
# great circle distance
def haversine_(lat1, lng1, lat2, lng2):
    """calculate haversine distance between two co-ordinates"""
    lat1, lng1, lat2, lng2 = map(np.radians, (lat1, lng1, lat2, lng2))
    AVG_EARTH_RADIUS = 6371  # in km
    lat = lat2 - lat1
    lng = lng2 - lng1
    d = np.sin(lat * 0.5) ** 2 + np.cos(lat1) * np.cos(lat2) * np.sin(lng * 0.5) ** 2
    h = 2 * AVG_EARTH_RADIUS * np.arcsin(np.sqrt(d))
    return(h)

# manhattan distance
def manhattan_distance_pd(lat1, lng1, lat2, lng2):
    """calculate manhatten distance between pick_drop"""
    a = haversine_(lat1, lng1, lat1, lng2)
    b = haversine_(lat1, lng1, lat2, lng1)
    return a + b

data['haversine_distance'] = round(haversine_(data.pickup_latitude,data.pickup_longitu
data['manhattan_distance'] = round(manhattan_distance_pd(data.pickup_latitude,data.pic
```

1.1.2 Define Day of Week

In [28]:
```
# create weekday
data["weekday"] = data['date'].dt.dayofweek
```

1.2 Remove Outlier

1.2.1 Remove Short & Large Distance

Some passengers get on taxi then get off immediately, so the time and distance is near zero. Many rows do have zero for pickup or drop off location or almost same location for pick up and drop off. Therefore, we are only considered the travel time is at least 60 second and no longer than 5 hours. And, we investage on the distance between 0 and 50 miles

In [5]:
```
data.loc[(data.haversine_distance == 0) & (data.travel_time <= 60), ['travel_time', 'h
```

Out[5]:

	travel_time	haversine_distance
286	2	0.0
1067	4	0.0
1201	7	0.0
1261	42	0.0
1914	12	0.0
2720	6	0.0
2750	54	0.0
3524	9	0.0
5528	6	0.0
5692	23	0.0

In [29]:
```
data = data.loc[(data['haversine_distance'] > 0.5) & (data['haversine_distance']<50)]
```

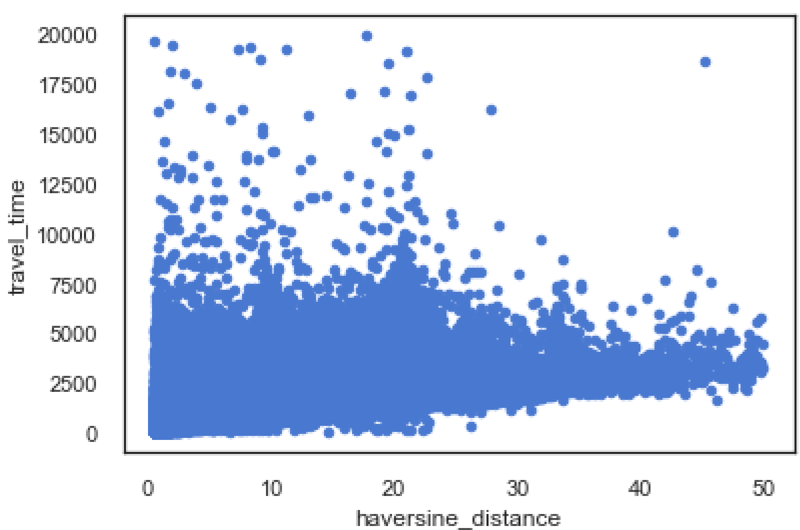
1.2.2 Remove Short & Large Travel Time

In NYC

In [30]:
```
data = data.loc[(data['travel_time'] > 60) & (data['travel_time'] < 20000)]
```

In [31]:
```
data.plot(x='haversine_distance',y='travel_time',kind='scatter')
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x558d4c82e8>



1.2.3 Clean GPS Coordinates

In [32]:

```
# clean any pickup not in the NYC
xlim = [-74.03, -73.77]
ylim = [40.63, 40.85]
data = data[(data.pickup_longitude> xlim[0]) & (data.pickup_longitude < xlim[1])]
data = data[(data.dropoff_longitude> xlim[0]) & (data.dropoff_longitude < xlim[1])]
data = data[(data.pickup_latitude> ylim[0]) & (data.pickup_latitude < ylim[1])]
data = data[(data.dropoff_latitude> ylim[0]) & (data.dropoff_latitude < ylim[1])]
```

1.2.4 Remove No Passenger Trip

In [33]:

```
data = data.loc[data.passenger_count > 0]
```

1.2.5 Clean Weather Data

In [34]:

```
# refill visib using forward or backward
data['visib'] = data['visib'].replace(999.9, np.nan).fillna(method='ffill')

# refill mxpsd using forward or backward
data['mxpsd'] = data['mxpsd'].replace(999.9, np.nan).fillna(method='ffill')

# refill wdsp using forward or backward
data['wdsp'] = data['wdsp'].replace(999.9, np.nan).fillna(method='ffill')

# refill gust as 0
data.loc[(data['gust'] == 999.9), 'gust'] = 0

# refit sndp as 0
data.loc[data['sndp'] == 999.9, 'sndp'] = 0
```

2. Exploratory Data Analysis & Process

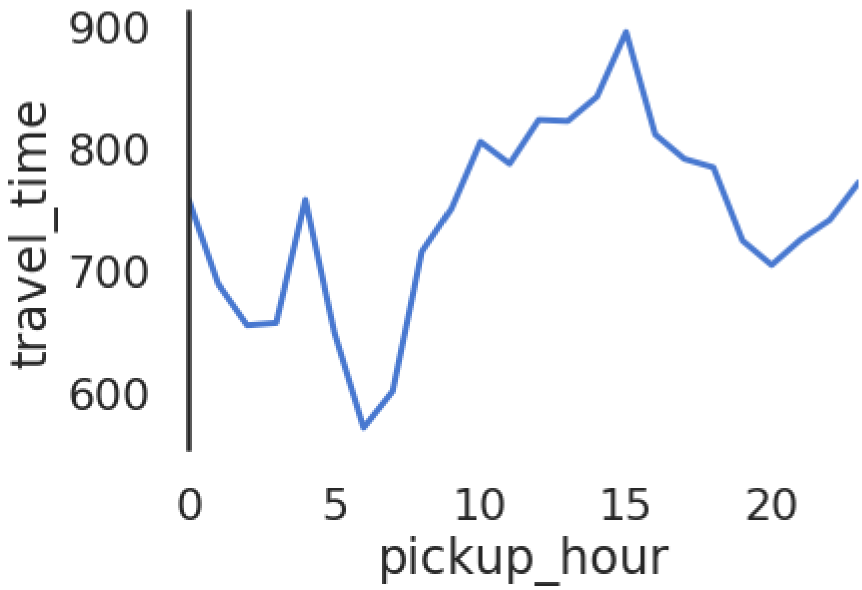
2.1 Trip Duration vs Hours, Day of Week and Month

2.1.1 Hourly Duration

In [12]:

```
summary_hour_duration = pd.DataFrame(data.groupby('pickup_hour')['travel_time'].median
summary_hour_duration.reset_index(inplace = True)
summary_hour_duration['unit']=1
sns.set(style="white", palette="muted", color_codes=False)
sns.set_context("poster")
sns.tsplot(data=summary_hour_duration, time="pickup_hour", unit = "unit", value="trave
sns.despine(bottom = True)
```

```
/Users/franceszhang/anaconda3/lib/python3.7/site-packages/seaborn/timeseries.py:183:
UserWarning: The `tsplot` function is deprecated and will be removed in a future rele
ase. Please update your code to use the new `lineplot` function.
  warnings.warn(msg, UserWarning)
```

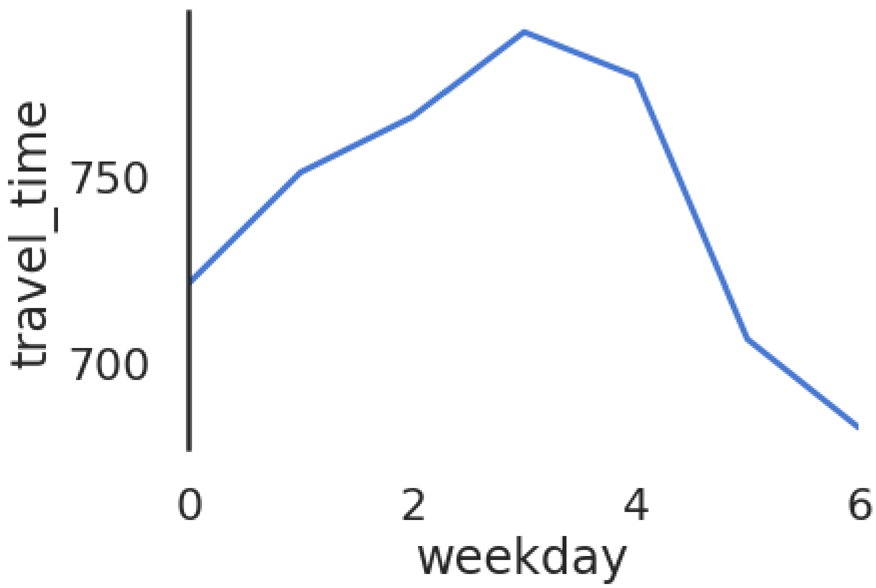


2.1.2 Weekly Durations

In [13]:

```
summary_week_duration = pd.DataFrame(data.groupby(['weekday'])['travel_time'].median()
summary_week_duration.reset_index(inplace = True)
summary_week_duration['unit']=1
sns.set(style="white", palette="muted", color_codes=False)
sns.set_context("poster")
sns.tsplot(data=summary_week_duration, time="weekday", unit = "unit", value="travel_ti
sns.despine(bottom = True)
```

```
/Users/franceszhang/anaconda3/lib/python3.7/site-packages/seaborn/timeseries.py:183:
UserWarning: The `tsplot` function is deprecated and will be removed in a future rele
ase. Please update your code to use the new `lineplot` function.
  warnings.warn(msg, UserWarning)
```

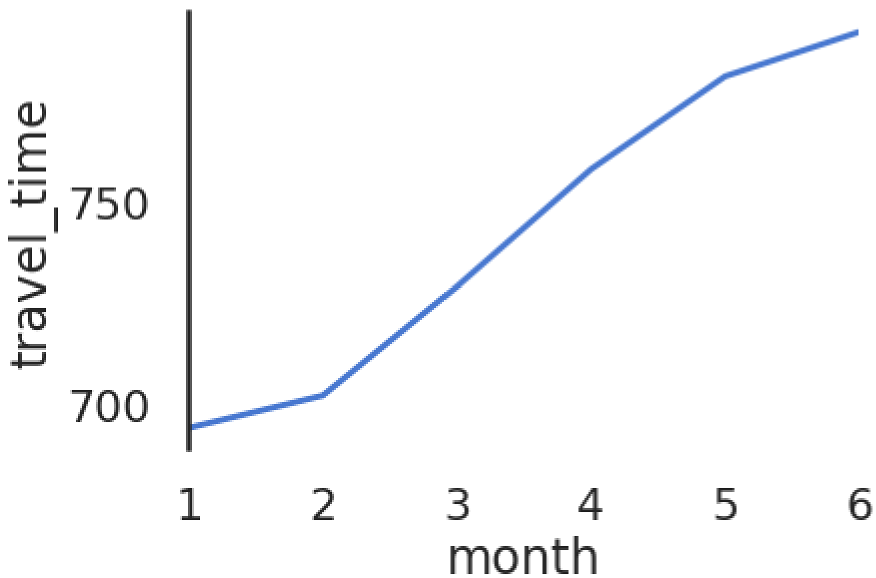


2.1.3 Monthly Duration

In [14]:

```
summary_month_duration = pd.DataFrame(data.groupby(['month'])['travel_time'].median())
summary_month_duration.reset_index(inplace = True)
summary_month_duration['unit']=1
sns.set(style="white", palette="muted", color_codes=False)
sns.set_context("poster")
sns.tsplot(data=summary_month_duration, time="month", unit = "unit", value="travel_tim
sns.despine(bottom = True)
```

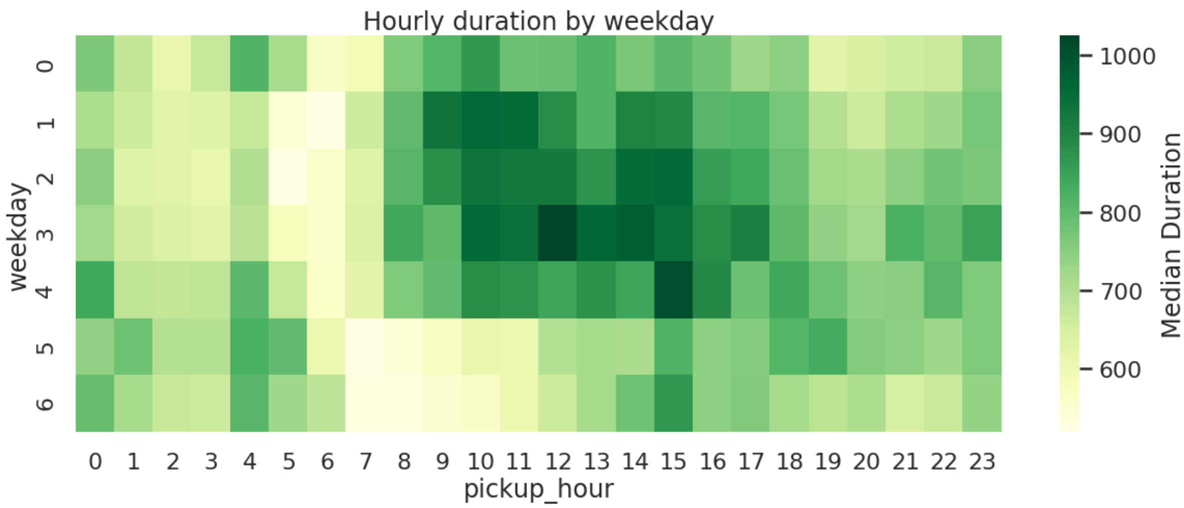
```
/Users/franceszhang/anaconda3/lib/python3.7/site-packages/seaborn/timeseries.py:183:
UserWarning: The `tsplot` function is deprecated and will be removed in a future rele
ase. Please update your code to use the new `lineplot` function.
  warnings.warn(msg, UserWarning)
```



2.1.4 Interaction of Hour, Day of Week and Month

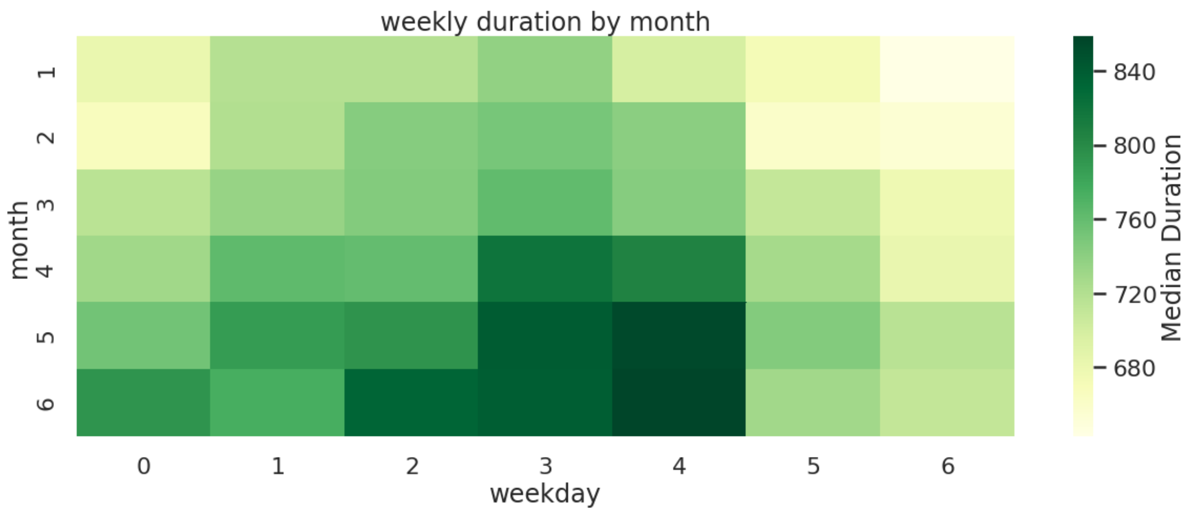
In [15]:
```
summary_hour_duration = pd.DataFrame(data.groupby(['weekday','pickup_hour'])['travel_t
summary_hour_duration.reset_index(inplace = True)
summary_hour_duration['unit']=1
heatmap_data1 = summary_hour_duration.pivot(index = 'weekday',columns = 'pickup_hour',
fig,ax=plt.subplots(figsize = (20,7))
plt.title('Hourly duration by weekday')
sns.heatmap(heatmap_data1, cbar_kws={'label': 'Median Duration'}, cmap="YlGn")
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1a23649b38>



In [16]:
```
summary_weekday_duration = pd.DataFrame(data.groupby(['weekday','month'])['travel_time
summary_weekday_duration.reset_index(inplace = True)
summary_weekday_duration['unit']=1
heatmap_data2 = summary_weekday_duration.pivot(index = 'month',columns = 'weekday',val
fig,ax=plt.subplots(figsize = (20,7))
plt.title('weekly duration by month')
ax.axis
sns.heatmap(heatmap_data2, cbar_kws={'label': 'Median Duration'}, cmap="YlGn")
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1a23b24780>



2.3 Weather Data

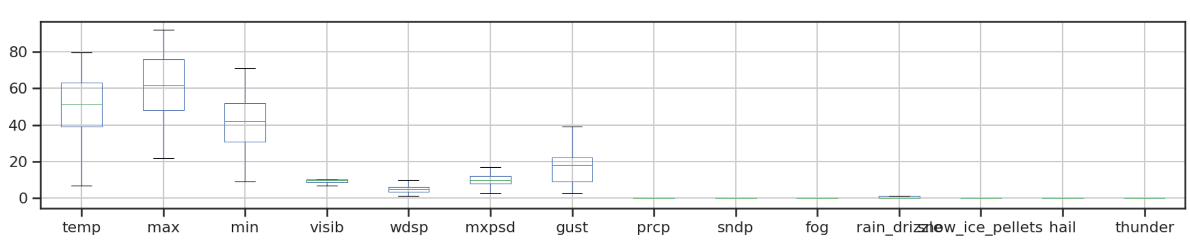
2.3.1 Load cleaned weather data

In [30]:
```
df_weather = pd.read_csv("./Data/tables/weather_2016_cleaned.csv")
```

2.3.2 Summary of weather data

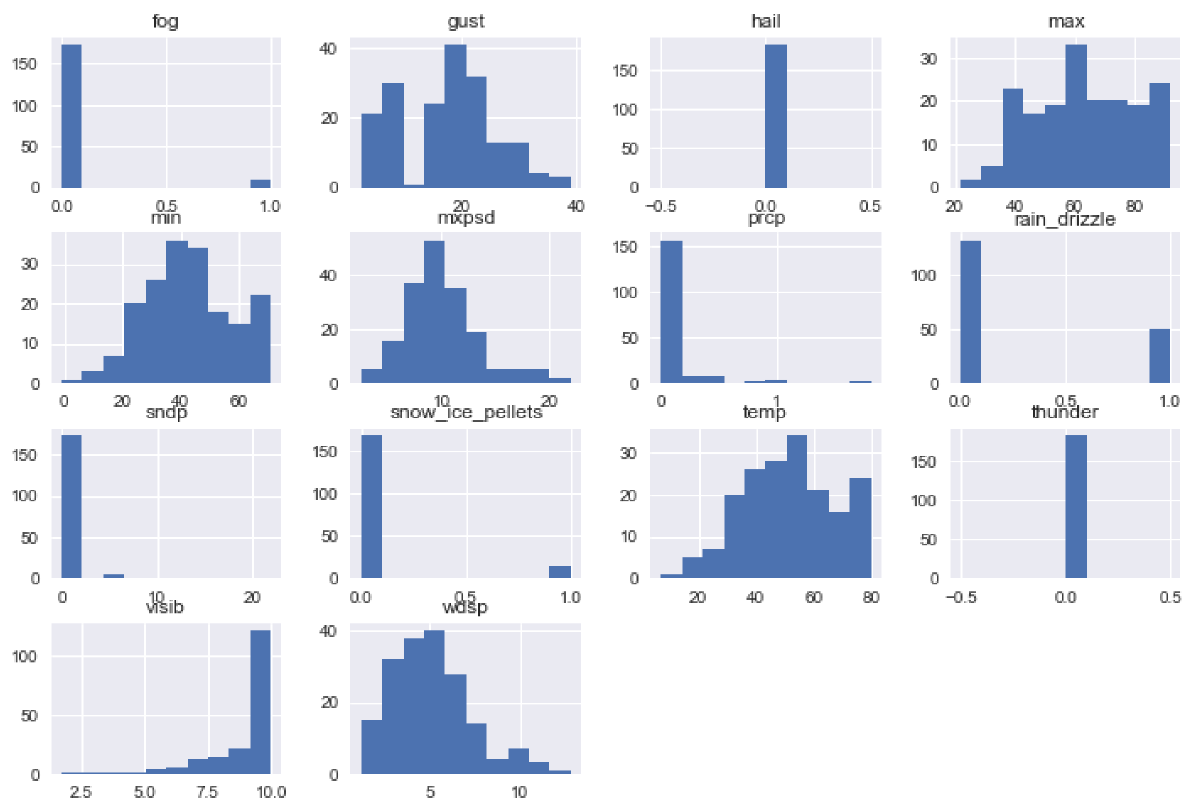
In [19]:
```
df_weather.boxplot(figsize=(30,5))
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x1a23a9f160>



In [33]:
```
df_weather.hist(figsize=(12,8))
```

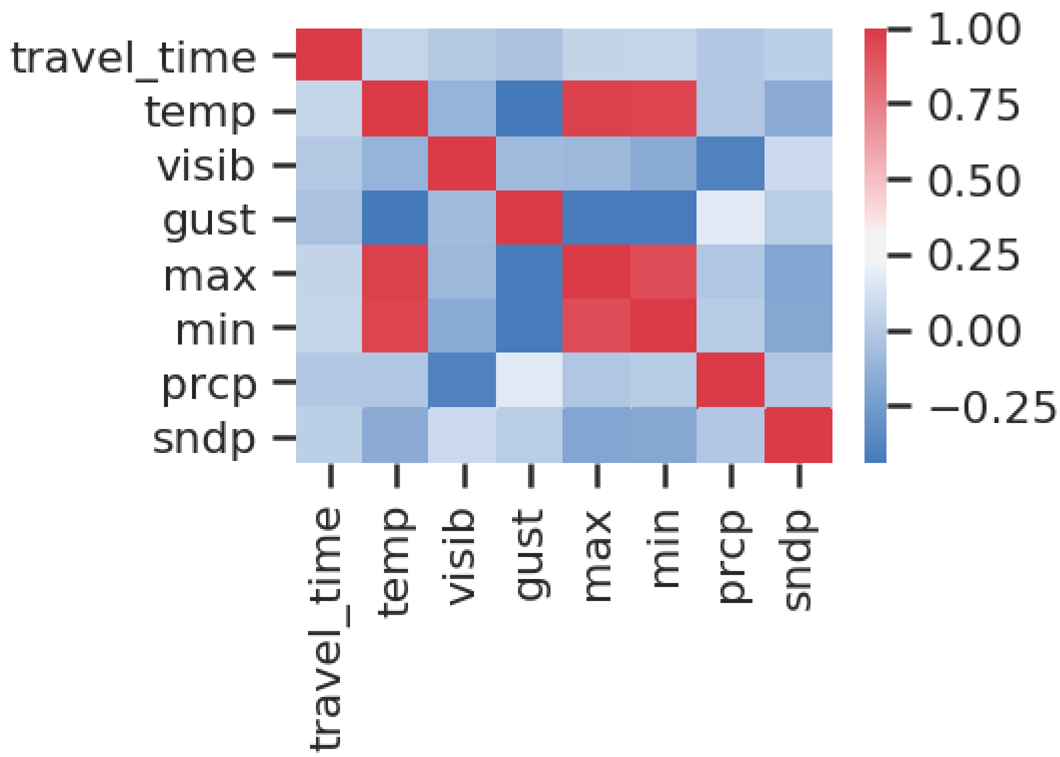
Out[33]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D44CB438>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D49D7CF8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D4027A90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D3CFABE0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D39C1CF8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D39C1978>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D3325278>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D30BA1D0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D2D2B278>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D28A97F0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D26C0E10>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D232F2B0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D20D5208>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D1E1BAC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D1C2B5C0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000D8D196B080>]],
      dtype=object)
```



2.3.3 Weather vs Trip Duration

In [21]:
```
df = data[['date','travel_time', 'temp','visib','mxpsd', 'wdsp', 'gust', 'max', 'min',
           'fog', 'rain_drizzle', 'snow_ice_pellets', 'hail', 'thunder']]
corr = df.corr()
cmap = sns.diverging_palette(250, 10, sep=20, as_cmap=True)
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns, cmap=cmap)
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x1a271a3780>

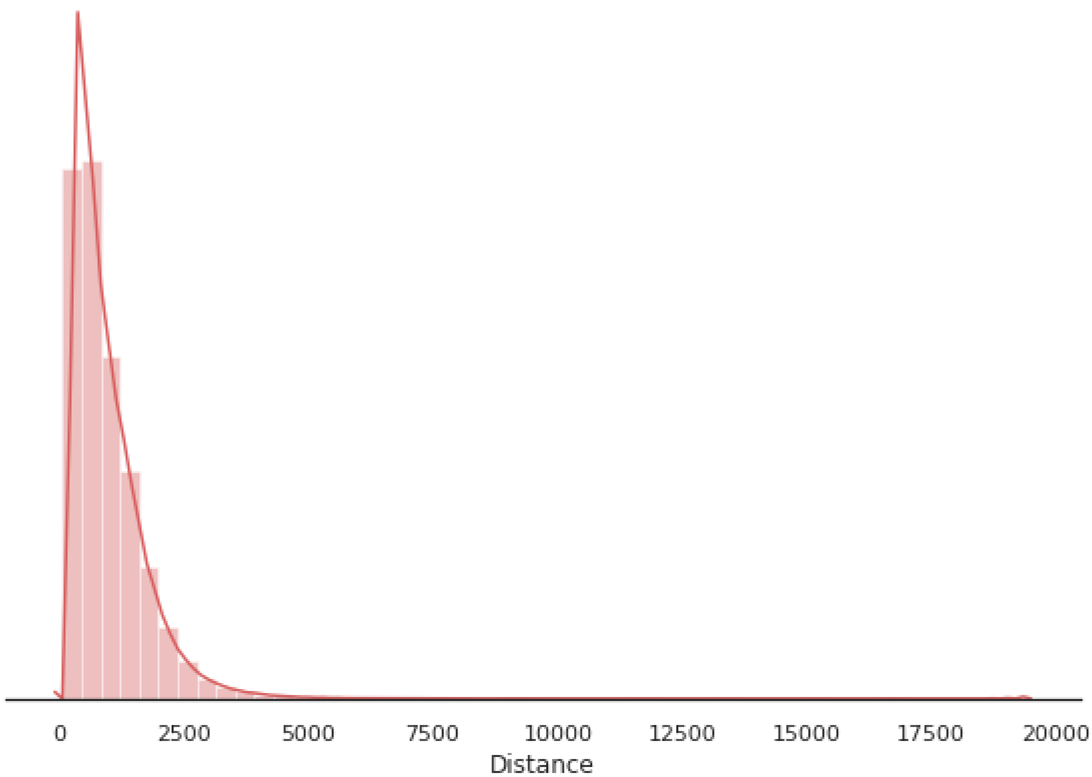


3. Feature Engineer

3.1 Transformation of Trip Duration

In [22]:

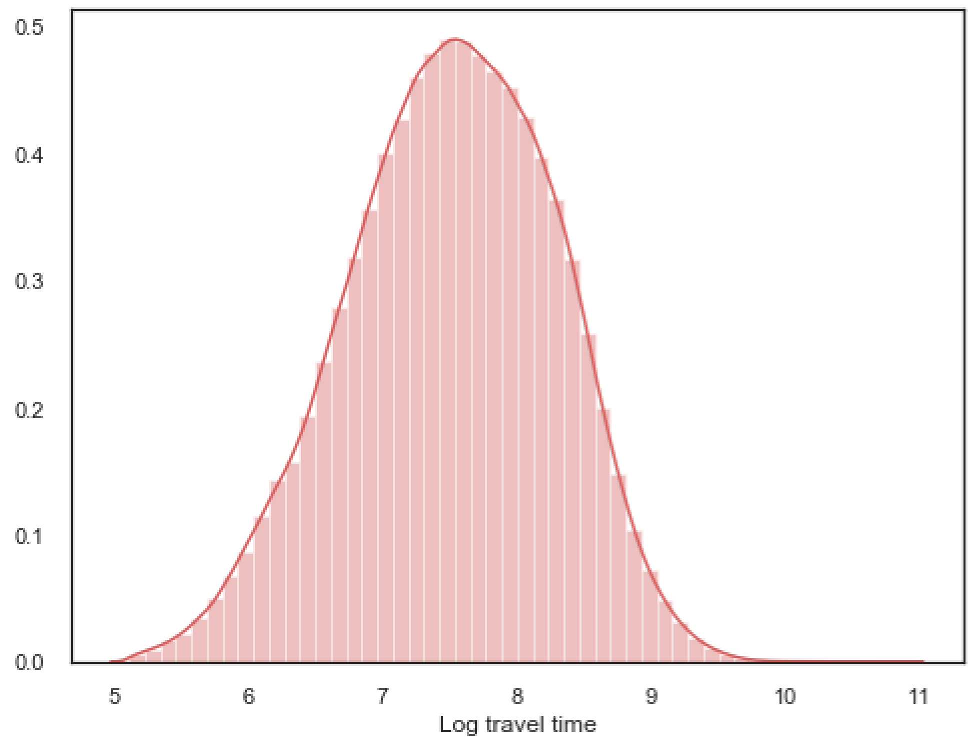
```
sns.set(style="white", palette="muted", color_codes=True)
ff, axes = plt.subplots(1,1, figsize=(8, 6), sharex=True)
sns.despine(left=True)

sns.distplot(data['travel_time'].values+1, axlabel = 'Distance', label = 'Histogrqm of
plt.setp(axes, yticks=[])
plt.tight_layout()
```



In [35]:
```
data['log_travel_time'] = np.log(data['travel_time']).values+1

sns.set(style="white", palette="muted", color_codes=True)
ff, axes = plt.subplots(1,1, figsize=(8, 6), sharex=True)
sns.distplot(data['log_travel_time'], axlabel = 'Log travel time', label = 'Histogrqm
```

```
E:\Program Files\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarnin
g: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[t
uple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array
index, `arr[np.array(seq)]`, which will result either in an error or a different resu
lt.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

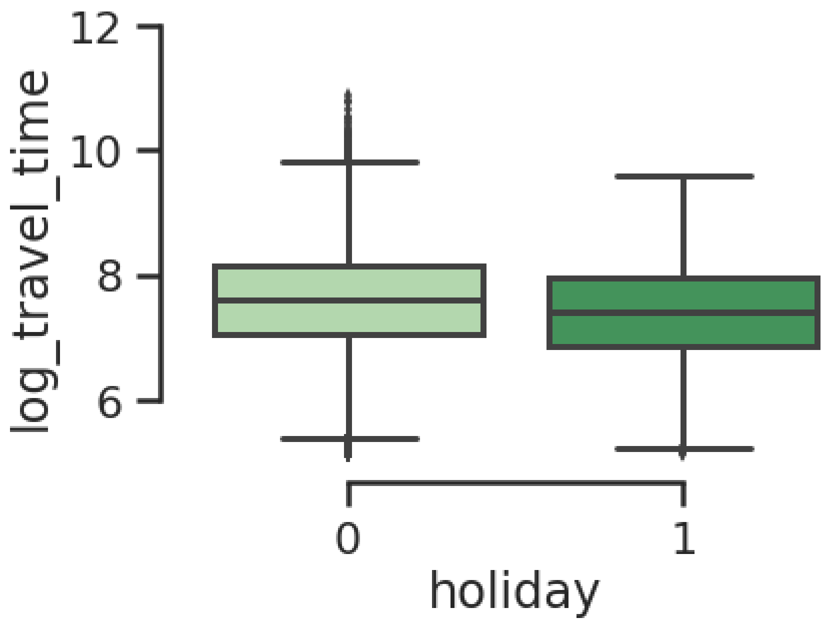
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x55f8b86e80>



3.2 Holiday

In [36]:
```
us_holidays = holidays.UnitedStates()
data['holiday'] = data['date'].apply(lambda x: 1 if x in us_holidays else 0)
```

In [25]:
```
sns.set(style = 'ticks')
sns.set_context("poster")
sns.boxplot(x = "holiday", y = "log_travel_time", data = data, palette = "Greens")
plt.ylim(5,12)
sns.despine(offset = 10, trim = True)
```

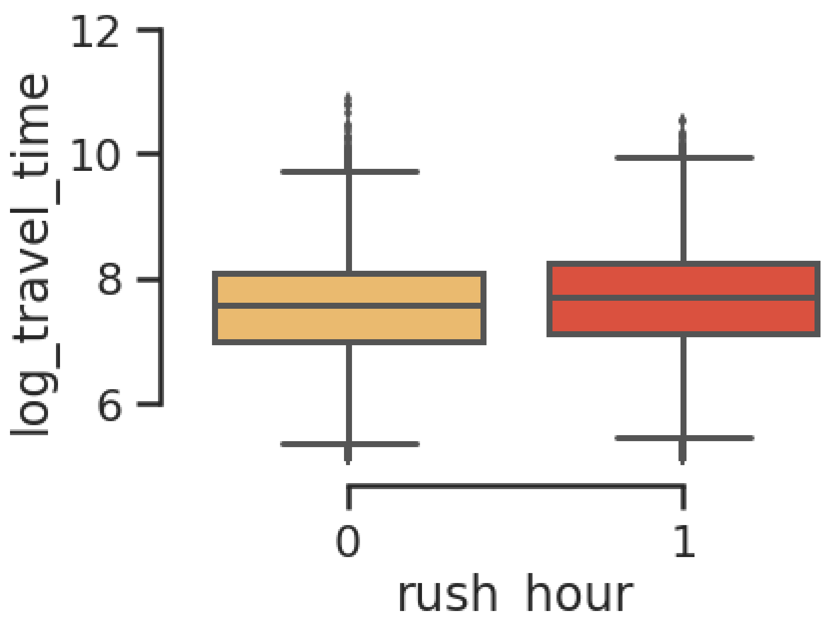


3.3 Rush Hour

In [37]:
```
# create dummy for rush hour
data["rush_hour"] = 0
data.loc[(data["pickup_hour"] >= 8) & (data["pickup_hour"] <= 16),"rush_hour"] = 1
```

In [27]:
```
sns.set(style="ticks")
sns.set_context("poster")
sns.boxplot(x="rush_hour", y="log_travel_time", data=data, palette="YlOrRd")
plt.ylim(5, 12)
sns.despine(offset=10, trim=True)
print(data.travel_time.max())
```

```
19341
```



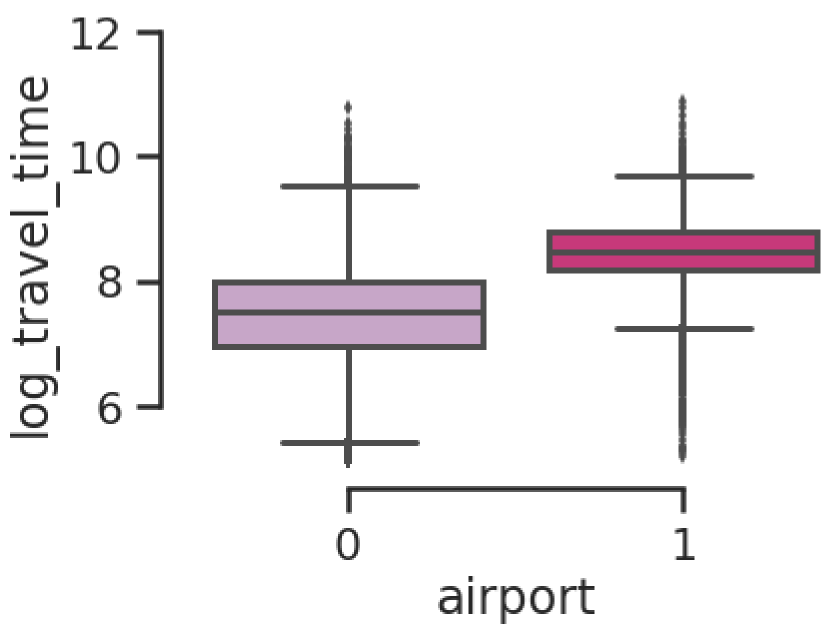
3.4 Bearing

In [38]:
```
def bearing_array(lat1, lng1, lat2, lng2):
    """calculate bearing for each trip"""
    AVG_EARTH_RADIUS = 6371  # in km
    lng_delta_rad = np.radians(lng2 - lng1)
    lat1, lng1, lat2, lng2 = map(np.radians, (lat1, lng1, lat2, lng2))
    y = np.sin(lng_delta_rad) * np.cos(lat2)
    x = np.cos(lat1) * np.sin(lat2) - np.sin(lat1) * np.cos(lat2) * np.cos(lng_delta_r
    return np.degrees(np.arctan2(y, x))

data['bearing'] = round(bearing_array(data.pickup_latitude,data.pickup_longitude,data.
```

3.5 Airport Trip

In [39]:
```
data['airport'] = 0
xlim = [-73.80, -73.77]
ylim = [40.63, 40.66]
data.loc[(data.pickup_longitude> xlim[0]) & (data.pickup_longitude < xlim[1]) &
         (data.pickup_latitude> ylim[0]) & (data.pickup_latitude < ylim[1]), 'airport'
data.loc[(data.dropoff_longitude> xlim[0]) & (data.dropoff_longitude < xlim[1]) &
         (data.dropoff_latitude> ylim[0]) & (data.dropoff_latitude < ylim[1]), 'airpor

xlim = [-73.88, -73.85]
ylim = [40.76, 40.78]
data.loc[(data.pickup_longitude> xlim[0]) & (data.pickup_longitude < xlim[1]) &
     (data.pickup_latitude> ylim[0]) & (data.pickup_latitude < ylim[1]), 'airport'] =
data.loc[(data.dropoff_longitude> xlim[0]) & (data.dropoff_longitude < xlim[1]) &
     (data.dropoff_latitude> ylim[0]) & (data.dropoff_latitude < ylim[1]), 'airport']
```

In [30]:
```
sns.set(style="ticks")
sns.set_context("poster")
sns.boxplot(x="airport", y="log_travel_time", data=data, palette="PuRd")
plt.ylim(5 , 12)
sns.despine(offset=10, trim=True)
```



3.6 Geohash

Add geohash to represent location

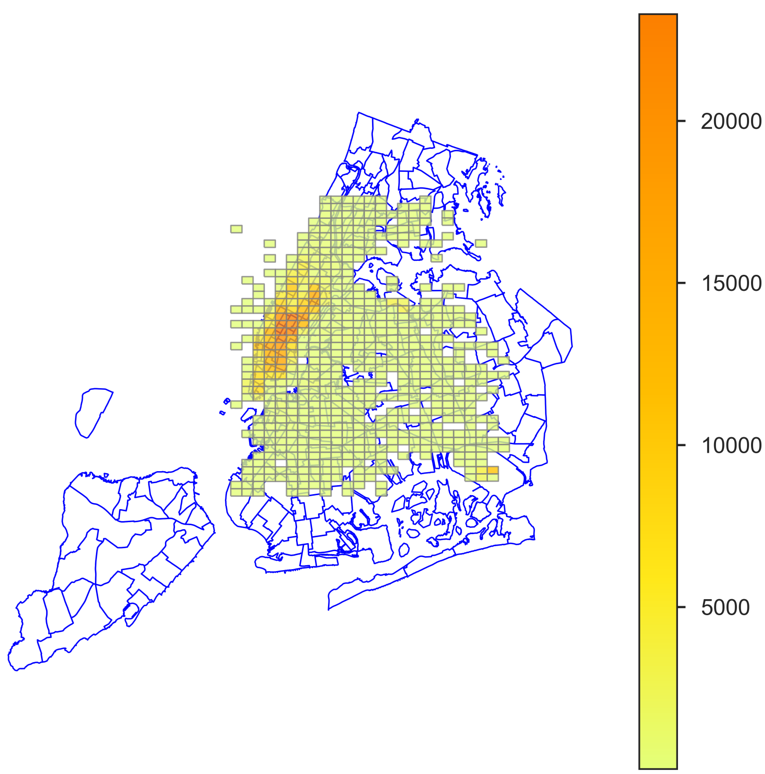
In [40]:
```
start = time.time()
pickup = []
dropoff = []
for i in range(len(data)):

    dropoff.append(ghh.encode(data.dropoff_longitude.iloc[i], data.dropoff_latitude.il


data['dropoff_geo'] = dropoff
data["dropoff_geo_recode"] = data["dropoff_geo"].astype('category').cat.codes

end = time.time()
print("Time taken by above cell is {}.".format(round((end-start)/60,2)))
```

```
Time taken by above cell is 2.0.
```

Plot geohash map

In [33]:
```
from IPython.display import Image
Image(filename='geohash_pickup.png', width=500, height=300)
```

Out[33]:



4. Optimize the memory usage

In [41]:
```
data = data.drop(['wdsp', 'gust', 'snow_ice_pellets', 'hail', 'thunder','dropoff_geo']
```

In [42]:
```
# Create a function to be calculating memory usage
def get_usage(obj):
    if isinstance(obj, pd.DataFrame):
        usage = obj.memory_usage(deep=True).sum()
    else:
        usage = obj.memory_usage(deep=True)
    return "{:03.2f} MB".format(usage / (1024**2))

# Convert object to int
obj = data.select_dtypes(include = 'object')
#obj = obj.iloc[:,0:7]
obj_f32 = obj.apply(pd.to_numeric, downcast='unsigned')

# Convert int64 to int8
obj = data.select_dtypes(include = 'int64')
obj_int = obj.apply(pd.to_numeric, downcast='unsigned')

# Convert float64 to float32
obj = data.select_dtypes(include = 'float64')
obj_f = obj.apply(pd.to_numeric, downcast='float')

# Calculated the memory we reduced by down grade int and float
print("Original memory usage: ", get_usage(data))
data[obj_f32.columns] = obj_f32
data[obj_int.columns] = obj_int
data[obj_f.columns] = obj_f
print("After converting int and float memory usage: ", get_usage(data))
```

```
Original memory usage:  735.38 MB
After converting int and float memory usage:  194.10 MB
```

In [21]:
```
data.head()
```

Out[21]:

	travel_time	date	month	day	pickup_hour	pickup_datetime	dropoff_datetime	pickup_longi
0	7.405229	2016-01-24	1	24	14	2016-01-24 14:01:14	2016-01-24 14:11:19	-73.97
1	7.949856	2016-01-24	1	24	14	2016-01-24 14:55:50	2016-01-24 15:13:13	-73.98
2	7.760415	2016-01-24	1	24	14	2016-01-24 14:45:06	2016-01-24 14:59:29	-73.97
3	6.966147	2016-01-24	1	24	14	2016-01-24 14:32:17	2016-01-24 14:38:47	-73.96
4	7.680855	2016-01-24	1	24	14	2016-01-24 14:51:23	2016-01-24 15:04:40	-73.97

Modeling

In [43]:

```
selected_features = ['month', 'pickup_hour', 'weekday', 'holiday','rush_hour',
                     'pickup_longitude', 'pickup_latitude', 'dropoff_longitude', 'drop
                     'temp','visib', 'mxpsd',  'prcp', 'sndp', 'fog', 'passenger_count
                     'bearing', 'airport','manhattan_distance','haversine_distance', '
                    ]

x = data[selected_features]
y = data['log_travel_time']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=
```

In [21]:

```
def train_test_model_performance(clf, x_train = x_train, y_train = y_train, x_test = 

    # Fit a model by providing X and y from training set
    clf.fit(x_train, y_train)
    print(clf)
    # Make prediction on the training data
    y_train_pred = clf.predict(x_train)

    # Make predictions on test data
    y_test_pred = clf.predict(x_test)

    # Evaluate
    R2_Train = clf.score(x_train,y_train)
    R2_Test = clf.score(x_test,y_test)
    RMSE_Train = sqrt(mean_squared_error(y_train, y_train_pred))
    RMSE_Test = sqrt(mean_squared_error(y_test, y_test_pred))
#     RMSLE_Train = sqrt(mean_squared_log_error(y_train, y_train_pred))
#     RMSLE_Test = sqrt(mean_squared_log_error(y_test, y_test_pred))

    metric_names = ['R2','RMSE']
    metric_values_train = [R2_Train, RMSE_Train]
    metric_values_test = [R2_Test, RMSE_Test]
    all_metrics = pd.DataFrame({'metrics':metric_names,
                                'train':metric_values_train,
                                'test':metric_values_test},columns=['metrics','train',
    print(all_metrics)
```

In [23]:
```
def cv_model_performance(clf, x_train = x_train, y_train = y_train, x_test = x_test, 

    # Fit a model by providing X and y from training set
    clf.fit(x_train, y_train)
    model = clf.best_estimator_
    print(model)

    # Make prediction on the training data
    y_train_pred = model.predict(x_train)

    # Make predictions on test data
    y_test_pred = model.predict(x_test)

    # Evaluate
    R2_Train = model.score(x_train,y_train)
    R2_Test = model.score(x_test,y_test)
    RMSE_Train = sqrt(mean_squared_error(y_train, y_train_pred))
    RMSE_Test = sqrt(mean_squared_error(y_test, y_test_pred))
    RMSLE_Train = sqrt(mean_squared_log_error(y_train, y_train_pred))
    RMSLE_Test = sqrt(mean_squared_log_error(y_test, y_test_pred))

    metric_names = ['R2','RMSE','RMSLE']
    metric_values_train = [R2_Train, RMSE_Train, RMSLE_Train]
    metric_values_test = [R2_Test, RMSE_Test, RMSLE_Test]
    all_metrics = pd.DataFrame({'metrics':metric_names,
                                'train':metric_values_train,
                                'test':metric_values_test},columns=['metrics','train',
    print(all_metrics)
```

Random Forest

Cross Validation

In [24]:
```
start = time.time()

# Choose the type of classifier. /
rf = RandomForestRegressor()

# Choose some parameter combinations to try
param_grid = {'n_estimators': [200,300,400],
              'max_features': ['auto'],
              'max_depth': [30,50,70],
              'min_samples_split': [50, 100,150],
              'n_jobs':[-1]
             }

# read theory
grid_obj = GridSearchCV(rf, param_grid, cv=3, n_jobs = 8, iid=False, verbose=10, scor
cv_model_performance(grid_obj)

end = time.time()
print("Time taken by above cell is {}.".format((end-start)/60))
```

```
Fitting 3 folds for each of 27 candidates, totalling 81 fits

[Parallel(n_jobs=8)]: Done   2 tasks      | elapsed:  4.8min
[Parallel(n_jobs=8)]: Done   9 tasks      | elapsed: 10.7min
[Parallel(n_jobs=8)]: Done  16 tasks      | elapsed: 17.7min
[Parallel(n_jobs=8)]: Done  25 tasks      | elapsed: 25.9min
[Parallel(n_jobs=8)]: Done  34 tasks      | elapsed: 33.4min
[Parallel(n_jobs=8)]: Done  45 tasks      | elapsed: 42.7min
[Parallel(n_jobs=8)]: Done  56 tasks      | elapsed: 51.6min
[Parallel(n_jobs=8)]: Done  75 out of  81 | elapsed: 69.3min remaining:  5.5min
[Parallel(n_jobs=8)]: Done  81 out of  81 | elapsed: 71.7min finished

RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=30,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=50,
           min_weight_fraction_leaf=0.0, n_estimators=400, n_jobs=-1,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
            train      test
metrics
R2       0.857622  0.796718
RMSE     0.270371  0.325117
RMSLE    0.032646  0.039328
Time taken by above cell is 73.63773880402248.
```

Train RF

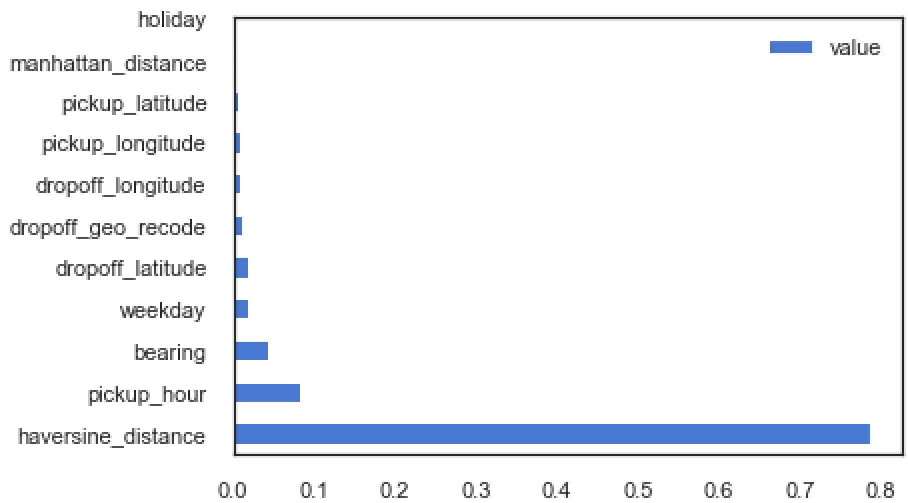
Feature Importance

In [78]:

```
start = time.time()
# parameters = {'n_estimators': 300,
#               'max_features': 'auto',
#                'max_depth': 50,
#                'min_samples_split': 40,
#                'random_state': 2,
#                'n_jobs': -1,
#                }
# 0.899009  0.839094 25

parameters = {'n_estimators': 300,
             'max_features': 'auto',
              'max_depth': 70,
              'min_samples_split': 150,
              'random_state': 2,
              'n_jobs': -1
              }

rf = RandomForestRegressor(**parameters)
train_test_model_performance(rf)

end = time.time()
print("Time taken by above cell is {}.".format(round(end-start)/60,2))
```

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=50,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=150,
           min_weight_fraction_leaf=0.0, n_estimators=200, n_jobs=-1,
           oob_score=False, random_state=2, verbose=0, warm_start=False)
            train      test
metrics
R2       0.852902  0.828674
RMSE     0.293303  0.316114
Time taken by above cell is 17.366666666666667.
```

In [69]:
```
features = pd.DataFrame(list(zip(selected_features, rf.feature_importances_))).sort_va
features.columns = ['feature', 'value']

ax = features.iloc[0:10].plot.barh()
t = np.arange(11)
ax.set_yticks(t)
ax.set_yticklabels(features['feature'])
plt.show()
```



Gradient Boosting Trees

Cross Validation

In [25]:
```
start = time.time()
GBDT = GradientBoostingRegressor()

# Choose some parameter combinations to try
param_grid = {'n_estimators': [200, 300],
              'max_depth': [7, 9],
              'learning_rate': [0.2],
              'min_samples_split': [50, 70],
              'subsample':[0.9],
              'random_state': [2]
             }

# read theory
grid_obj = GridSearchCV(GBDT, param_grid, cv=3, n_jobs=8, iid=False, verbose=10, scor
cv_model_performance(grid_obj)

end = time.time()
print("Time taken by above cell is {}.".format((end-start)/60))
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits

[Parallel(n_jobs=8)]: Done   2 tasks      | elapsed:  3.1min
[Parallel(n_jobs=8)]: Done   9 tasks      | elapsed:  6.1min
[Parallel(n_jobs=8)]: Done  12 out of  24 | elapsed:  7.5min remaining:  7.5min
[Parallel(n_jobs=8)]: Done  15 out of  24 | elapsed:  9.4min remaining:  5.7min
[Parallel(n_jobs=8)]: Done  18 out of  24 | elapsed: 12.1min remaining:  4.0min
[Parallel(n_jobs=8)]: Done  21 out of  24 | elapsed: 13.3min remaining:  1.9min
[Parallel(n_jobs=8)]: Done  24 out of  24 | elapsed: 14.2min remaining:    0.0s
[Parallel(n_jobs=8)]: Done  24 out of  24 | elapsed: 14.2min finished

GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
             learning_rate=0.2, loss='ls', max_depth=7, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=1,
             min_samples_split=70, min_weight_fraction_leaf=0.0,
             n_estimators=200, presort='auto', random_state=2,
             subsample=0.9, verbose=0, warm_start=False)
            train      test
metrics
R2       0.888072  0.819326
RMSE     0.239722  0.306506
RMSLE    0.028661  0.037110
Time taken by above cell is 15.195025777816772.
```

Train GBDT

In [33]:

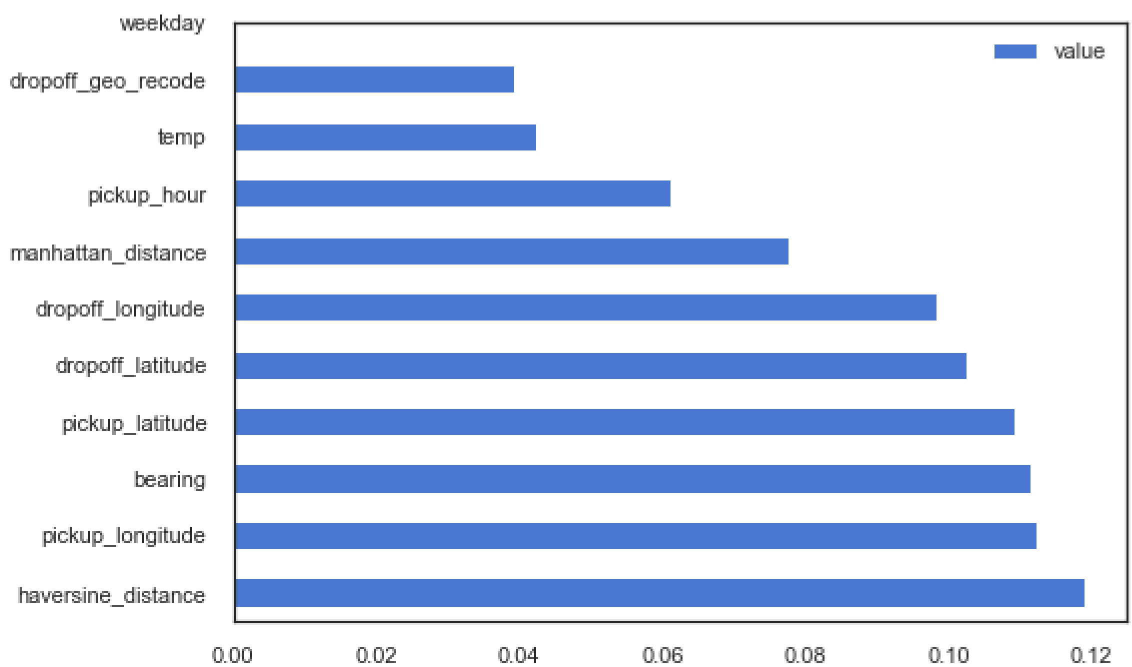
```
start = time.time()

#Choose some parameter combinations to try
# parameters = {
#     'n_estimators': 150,
#     'max_depth': 7,
#     'learning_rate': 0.2,
#     'min_samples_split': 30,
#     'max_features': 'auto',
#     'subsample': 0.7,
#     'random_state': 2
# }

#0.797
parameters = {
    'n_estimators': 300,
    'max_depth': 9,
    'learning_rate': 0.2,
    'min_samples_split': 50,
    'subsample': 0.9,
    'random_state': 2
}

GBDT = GradientBoostingRegressor(**parameters)
train_test_model_performance(GBDT)

end = time.time()
print("Time taken by above cell is {}.".format(round((end-start)/60),2))
```

```
GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
             learning_rate=0.2, loss='ls', max_depth=9, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=1,
             min_samples_split=50, min_weight_fraction_leaf=0.0,
             n_estimators=300, presort='auto', random_state=2,
             subsample=0.9, verbose=0, warm_start=False)
            train      test
metrics
R2       0.895770  0.857926
RMSE     0.244009  0.284756
Time taken by above cell is 80.
```

Feature Improtance

In [34]:

```
features = pd.DataFrame(list(zip(selected_features, GBDT.feature_importances_))).sort_
features.columns = ['feature', 'value']
features.head(10)

ax = features.iloc[0:10].plot.barh()
t = np.arange(11)
ax.set_yticks(t)
ax.set_yticklabels(features['feature'])
plt.show()
```



Extremely Gradient Boosting (XGB)

Spliting Train and Test Data

In [44]:

```
dtrain = xgb.DMatrix(x_train, label=y_train)
dvalid = xgb.DMatrix(x_test, label=y_test)
watchlist = [(dtrain, 'train'), (dvalid, 'valid')]
```

Grid Search CV for parameter selection

In [51]:

```
from sklearn.grid_search import GridSearchCV

parameters_for_testing = {
   'min_child_weight':[10,15],
   'max_depth':[15,17],
   'alpha':[10,15]

}

xgb_model = xgb.XGBRegressor(learning_rate =0.1, n_estimators=200, max_depth=12,
    min_child_weight=10, subsample=0.6, colsample_bytree=0.6, nthread= 8, scale_pos_we

gsearch1 = GridSearchCV(estimator = xgb_model, param_grid = parameters_for_testing, cv
gsearch1.fit(x_train,y_train)
print (gsearch1.grid_scores_)
print('best params')
print (gsearch1.best_params_)
print('best score')
print (gsearch1.best_score_)
```

Train model

In [45]:

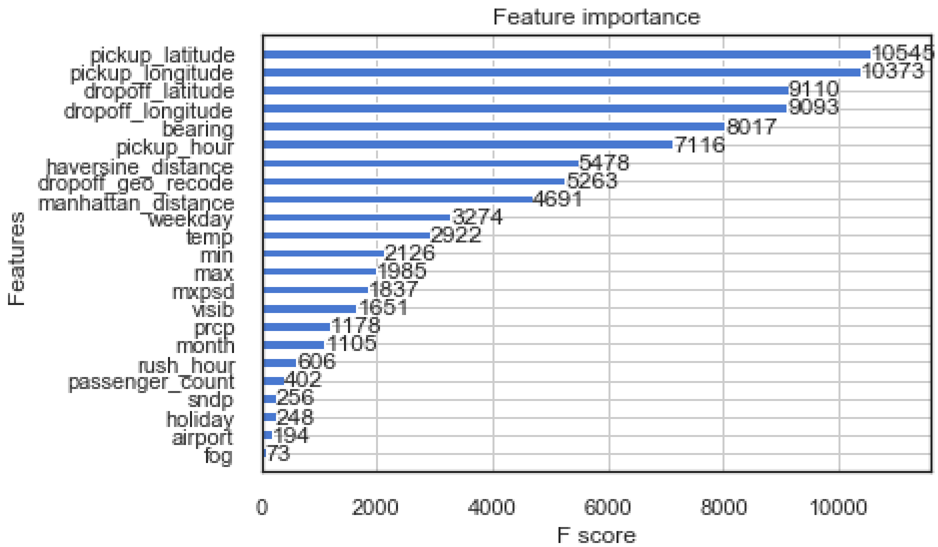
```
start = time.time()
xgb_pars = {'min_child_weight': 15, 'eta': 0.1, 'colsample_bytree': 0.7,
            'max_depth': 15, 'alpha' : 15,
            'subsample': 0.7,'nthread': -1, 'booster' : 'gbtree', 'silent': 1,
            'eval_metric': 'rmse', 'objective': 'reg:linear','lambda':1}
model = xgb.train(xgb_pars, dtrain, 250, watchlist, early_stopping_rounds=2,
      maximize=False, verbose_eval=1)
print('Modeling RMSE %.5f' % model.best_score)

end = time.time()
print("Time taken by above cell is {}.".format(round((end-start)/60),2))
```

```
[0]	train-rmse:6.34781	valid-rmse:6.34741
Multiple eval metrics have been passed: 'valid-rmse' will be used for early stoppi
ng.

Will train until valid-rmse hasn't improved in 2 rounds.
[1]	train-rmse:5.7157	valid-rmse:5.71532
[2]	train-rmse:5.14708	valid-rmse:5.14674
[3]	train-rmse:4.63691	valid-rmse:4.6365
[4]	train-rmse:4.17686	valid-rmse:4.17645
[5]	train-rmse:3.76306	valid-rmse:3.76268
[6]	train-rmse:3.39112	valid-rmse:3.39075
[7]	train-rmse:3.05643	valid-rmse:3.0561
[8]	train-rmse:2.75564	valid-rmse:2.75537
[9]	train-rmse:2.48588	valid-rmse:2.48563
[10]	train-rmse:2.24304	valid-rmse:2.24281
[11]	train-rmse:2.02494	valid-rmse:2.02476
[12]	train-rmse:1.82939	valid-rmse:1.82924
[13]	train-rmse:1.65383	valid-rmse:1.65374
[14]	train-rmse:1.49669	valid-rmse:1.49662
```

Feature Improtance

In [72]:
```
xgb.plot_importance(model, max_num_features=28, height=0.5)
```

Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0xd8ddc42eb8>



Evaluate model performance

In [46]:
```
# Make prediction on the training data
y_train_pred = model.predict(dtrain)

# Make predictions on test data
y_test_pred = model.predict(dvalid)

# Evaluate
R2_Train = r2_score(y_train_pred, y_train)
R2_Test = r2_score(y_test_pred, y_test)
RMSE_Train = sqrt(mean_squared_error(y_train, y_train_pred))
RMSE_Test = sqrt(mean_squared_error(y_test, y_test_pred))

metric_names = ['R2','RMSE']
metric_values_train = [R2_Train, RMSE_Train]
metric_values_test = [R2_Test, RMSE_Test]
all_metrics = pd.DataFrame({'metrics':metric_names,
                            'train':metric_values_train,
                            'test':metric_values_test},columns=['metrics','train','tes
print(all_metrics)
```

```
            train      test
metrics
R2       0.860991  0.848859
RMSE     0.266714  0.277860
```