```
#Taxi Fare Prediction
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
pd.set_option('display.float_format', lambda x: '%.3f' % x)
RSEED = 100
%matplotlib inline
plt.style.use('fivethirtyeight')
plt.rcParams['font.size'] = 18
palette = sns.color_palette('Paired', 10)
```

+ Code + Markdown

[2]:
```
data = pd.read_csv('../input/train.csv', nrows = 50000)
data.head()
```

[2]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	2009-06-15 17:26:21.0000001	4.500	2009-06-15 17:26:21 UTC	-73.844	40.721	-73.842	40.712	1
1	2010-01-05 16:52:16.0000002	16.900	2010-01-05 16:52:16 UTC	-74.016	40.711	-73.979	40.782	1
2	2011-08-18 00:35:00.00000049	5.700	2011-08-18 00:35:00 UTC	-73.983	40.761	-73.991	40.751	2
3	2012-04-21 04:30:42.0000001	7.700	2012-04-21 04:30:42 UTC	-73.987	40.733	-73.992	40.758	1
4	2010-03-09 07:51:00.000000135	5.300	2010-03-09 07:51:00 UTC	-73.968	40.768	-73.957	40.784	1

[3]:
```
data.describe()
```

[3]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
count	50000.000	50000.000	50000.000	50000.000	50000.000	50000.000
mean	11.364	-72.510	39.934	-72.505	39.926	1.668
std	9.686	10.394	6.225	10.408	6.015	1.289
min	-5.000	-75.424	-74.007	-84.654	-74.006	0.000
25%	6.000	-73.992	40.735	-73.991	40.734	1.000
50%	8.500	-73.982	40.753	-73.980	40.753	1.000
75%	12.500	-73.967	40.767	-73.964	40.768	2.000
max	200.000	40.783	401.083	40.851	43.415	6.000

[4]:
```
data['pickup_datetime'] = pd.to_datetime(data['pickup_datetime'])
data = data.drop(columns = 'key')
# Remove null attributes
data = data.dropna()
```

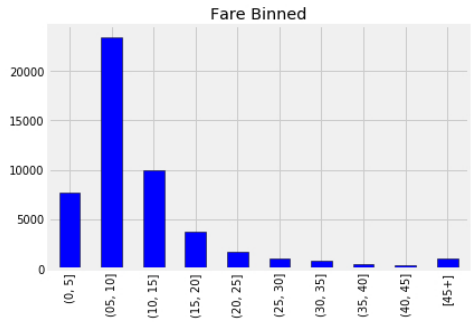
[5]:
```
print(f"There are {len(data[data['fare_amount'] < 0])} negative fares.")
print(f"There are {len(data[data['fare_amount'] == 0])} $0 fares.")
print(f"There are {len(data[data['fare_amount'] > 100])} fares greater than $100.")
```

```
There are 6 negative fares.
There are 3 $0 fares.
There are 16 fares greater than $100.
```

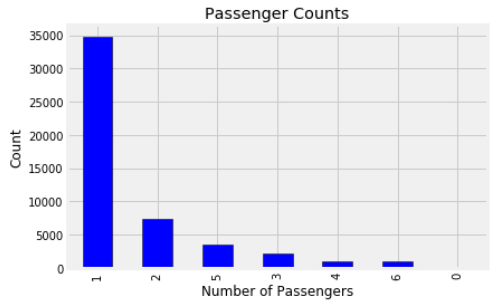
[6]:
```
data = data[data['fare_amount'].between(left = 2.5, right = 100)]
```

[7]:
```
# Bin the fare and convert to string
data['fare-bin'] = pd.cut(data['fare_amount'], bins = list(range(0, 50, 5))).astype(str)

# Uppermost bin
data.loc[data['fare-bin'] == 'nan', 'fare-bin'] = '[45+]'

# Adjust bin so the sorting is correct
```

```
data.loc[data['fare-bin'] == '(5, 10]', 'fare-bin'] = '(05, 10]'

# Bar plot of value counts
data['fare-bin'].value_counts().sort_index().plot.bar(color = 'b', edgecolor = 'k');
plt.title('Fare Binned');
```



[8]:
```
data['passenger_count'].value_counts().plot.bar(color = 'b', edgecolor = 'k');
plt.title('Passenger Counts'); plt.xlabel('Number of Passengers'); plt.ylabel('Count');
```



[9]:
```
data = data.loc[data['passenger_count'] < 6]
```

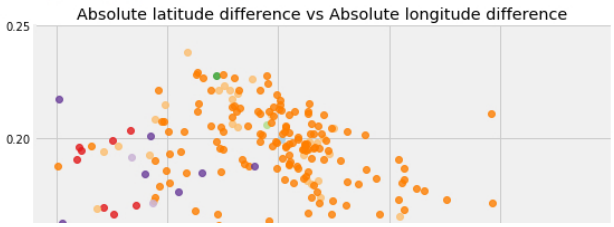
[10]:
```
print(f'Initial Observations: {data.shape[0]}')
# Remove latitude and longtiude outliers
data = data.loc[data['pickup_latitude'].between(40, 42)]
data = data.loc[data['pickup_longitude'].between(-75, -72)]
data = data.loc[data['dropoff_latitude'].between(40, 42)]
data = data.loc[data['dropoff_longitude'].between(-75, -72)]

print(f'New number of observations: {data.shape[0]}')
```

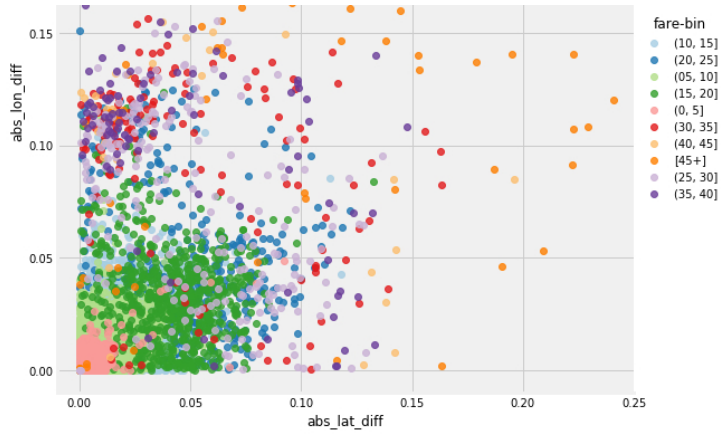
```
Initial Observations: 48985
New number of observations: 47953
```

[11]:
```
# Absolute difference in latitude and longitude
data['abs_lat_diff'] = (data['dropoff_latitude'] - data['pickup_latitude']).abs()
data['abs_lon_diff'] = (data['dropoff_longitude'] - data['pickup_longitude']).abs()
```

[12]:
```
sns.lmplot('abs_lat_diff', 'abs_lon_diff', hue = 'fare-bin', size = 8, palette = palette,
           fit_reg = False, data = data.sample(10000, random_state=RSEED));

plt.xlim((-0.01, .25)); plt.ylim((-0.01, .25))
plt.title('Absolute latitude difference vs Absolute longitude difference');
```

```
/opt/conda/lib/python3.6/site-packages/seaborn/regression.py:546: UserWarning: The `size` paramter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```





[13]:

```
#TEST

test = pd.read_csv('../input/test.csv', parse_dates = ['pickup_datetime'])

# Create absolute differences
test['abs_lat_diff'] = (test['dropoff_latitude'] - test['pickup_latitude']).abs()
test['abs_lon_diff'] = (test['dropoff_longitude'] - test['pickup_longitude']).abs()

# Save the id for submission
test_id = list(test.pop('key'))
```

[14]:

```
# Radius of the earth in kilometers
R = 6378

def haversine_np(lon1, lat1, lon2, lat2):
    # Convert latitude and longitude to radians
    lon1, lat1, lon2, lat2 = map(np.radians, [lon1, lat1, lon2, lat2])

    # Find the differences
    dlon = lon2 - lon1
    dlat = lat2 - lat1

    # Apply the formula
    a = np.sin(dlat/2.0)**2 + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2.0)**2
    # Calculate the angle (in radians)
    c = 2 * np.arcsin(np.sqrt(a))
    # Convert to kilometers
    km = R * c

    return km
```

[15]:

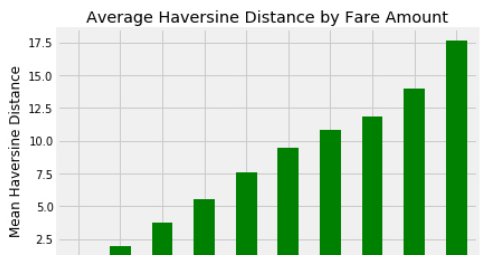
```
data['haversine'] =  haversine_np(data['pickup_longitude'], data['pickup_latitude'],
                          data['dropoff_longitude'], data['dropoff_latitude'])

test['haversine'] = haversine_np(test['pickup_longitude'], test['pickup_latitude'],
                          test['dropoff_longitude'], test['dropoff_latitude'])
```

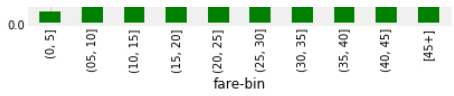
[16]:

```
subset = data.sample(10000, random_state=RSEED)
```

[17]:

```
data.groupby('fare-bin')['haversine'].mean().sort_index().plot.bar(color = 'g');
plt.title('Average Haversine Distance by Fare Amount');
plt.ylabel('Mean Haversine Distance');
```





[18]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

lr = LinearRegression()
```

[19]:
```
# Split data
X_train, X_valid, y_train, y_valid = train_test_split(data, np.array(data['fare_amount']),
                                                      stratify = data['fare-bin'],
                                                      random_state = RSEED, test_size = 10000)
```

[20]:
```
lr.fit(X_train[['abs_lat_diff', 'abs_lon_diff', 'passenger_count']], y_train)
```

[20]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

[21]:
```
from sklearn.metrics import mean_squared_error
import warnings
warnings.filterwarnings('ignore', category = RuntimeWarning)

def metrics(train_pred, valid_pred, y_train, y_valid):
    """Calculate metrics:
       Root mean squared error and mean absolute percentage error"""

    # Root mean squared error
    train_rmse = np.sqrt(mean_squared_error(y_train, train_pred))
    valid_rmse = np.sqrt(mean_squared_error(y_valid, valid_pred))

    # Calculate absolute percentage error
    train_ape = abs((y_train - train_pred) / y_train)
    valid_ape = abs((y_valid - valid_pred) / y_valid)

    # Account for y values of 0
    train_ape[train_ape == np.inf] = 0
    train_ape[train_ape == -np.inf] = 0
    valid_ape[valid_ape == np.inf] = 0
    valid_ape[valid_ape == -np.inf] = 0

    train_mape = 100 * np.mean(train_ape)
    valid_mape = 100 * np.mean(valid_ape)

    return train_rmse, valid_rmse, train_mape, valid_mape

def evaluate(model, features, X_train, X_valid, y_train, y_valid):
    """Mean absolute percentage error"""

    # Make predictions
    train_pred = model.predict(X_train[features])
    valid_pred = model.predict(X_valid[features])

    # Get metrics
    train_rmse, valid_rmse, train_mape, valid_mape = metrics(train_pred, valid_pred,
                                                             y_train, y_valid)

    print(f'Training:   rmse = {round(train_rmse, 2)}')
    print(f'Validation: rmse = {round(valid_rmse, 2)}')
```

[22]:
```
evaluate(lr, ['abs_lat_diff', 'abs_lon_diff', 'passenger_count'],
        X_train, X_valid, y_train, y_valid)
```

```
Training:   rmse = 5.37
Validation: rmse = 6.56
```

[23]:
```
train_mean = y_train.mean()

# Create list of the same prediction for every observation
train_preds = [train_mean for _ in range(len(y_train))]
valid_preds = [train_mean for _ in range(len(y_valid))]

tr, vr, tm, vm = metrics(train_preds, valid_preds, y_train, y_valid)
```

```
print(f'Baseline Training:   rmse = {round(tr, 2)}')
print(f'Baseline Validation: rmse = {round(vr, 2)}')
```

```
Baseline Training:   rmse = 9.36
Baseline Validation: rmse = 9.37
```

[24]:
```
preds = lr.predict(test[['abs_lat_diff', 'abs_lon_diff', 'passenger_count']])

sub = pd.DataFrame({'key': test_id, 'fare_amount': preds})
sub.head(10)
```

[24]:

	key	fare_amount
0	2015-01-27 13:08:24.0000002	8.740
1	2015-01-27 13:08:24.0000003	9.354
2	2011-10-08 11:53:44.0000002	6.284
3	2012-12-01 21:12:12.0000002	8.518
4	2012-12-01 21:12:12.0000003	13.815
5	2012-12-01 21:12:12.0000005	10.964
6	2011-10-06 12:10:20.0000001	7.227
7	2011-10-06 12:10:20.0000003	50.993
8	2011-10-06 12:10:20.0000002	11.769
9	2014-02-18 15:22:20.0000002	7.621

[25]:
```
lr.fit(X_train[['haversine', 'abs_lat_diff', 'abs_lon_diff', 'passenger_count']], y_train)

evaluate(lr, ['haversine', 'abs_lat_diff', 'abs_lon_diff', 'passenger_count'],
         X_train, X_valid, y_train, y_valid)
```

```
Training:   rmse = 5.14
Validation: rmse = 6.08
```

[26]:
```
from sklearn.ensemble import RandomForestRegressor

# Create the random forest
random_forest = RandomForestRegressor(n_estimators = 20, max_depth = 20,
                                      max_features = None, oob_score = True,
                                      bootstrap = True, verbose = 1, n_jobs = -1)

# Train on data
random_forest.fit(X_train[['haversine', 'abs_lat_diff', 'abs_lon_diff', 'passenger_count']], y_train)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  20 out of  20 | elapsed:    1.2s finished
/opt/conda/lib/python3.6/site-packages/sklearn/ensemble/forest.py:732: UserWarning: Some inputs do not have OOB scores. This probably means too few trees were used to compute any reliable oob estimates.
  warn("Some inputs do not have OOB scores. "
```

[26]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=20,
           max_features=None, max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=20, n_jobs=-1,
           oob_score=True, random_state=None, verbose=1, warm_start=False)
```

[27]:
```
evaluate(random_forest, ['haversine', 'abs_lat_diff', 'abs_lon_diff', 'passenger_count'],
         X_train, X_valid, y_train, y_valid)
```

```
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  20 out of  20 | elapsed:    0.1s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  20 out of  20 | elapsed:    0.0s finished
Training:   rmse = 2.27
Validation: rmse = 4.67
```

[28]:
```
def model_rf(X_train, X_valid, y_train, y_valid, test, features,
             model = RandomForestRegressor(n_estimators = 20, max_depth = 20,
                                           n_jobs = -1),
             return_model = False):
    """Train and evaluate the random forest using the given set of features."""

    # Train
    model.fit(X_train[features], y_train)

    # Validation
    evaluate(model, features, X_train, X_valid, y_train, y_valid)

    # Make predictions on test and generate submission dataframe
```

```
    preds = model.predict(test[features])
    sub = pd.DataFrame({'key': test_id, 'fare_amount': preds})

    # Extract feature importances
    feature_importances = pd.DataFrame({'feature': features,
                                        'importance': model.feature_importances_}).\
                          sort_values('importance', ascending = False).set_index('feature')

    if return_model:
        return sub, feature_importances, model

    return sub, feature_importances
```

[29]:

```
# Evaluate using 8 features
sub, fi = model_rf(X_train, X_valid, y_train, y_valid, test,
                   features = ['abs_lat_diff', 'abs_lon_diff', 'haversine', 'passenger_count',
                               'pickup_latitude', 'pickup_longitude', 'dropoff_latitude', 'dropoff_longit
```

```
Training:   rmse = 1.85
Validation: rmse = 4.23
```

[30]:

```
import re

def extract_dateinfo(df, date_col, drop=True, time=False,
                     start_ref = pd.datetime(1900, 1, 1),
                     extra_attr = False):
    """
    Extract Date (and time) Information from a DataFrame
    Adapted from: https://github.com/fastai/fastai/blob/master/fastai/structured.py
    """
    df = df.copy()

    # Extract the field
    fld = df[date_col]

    # Check the time
    fld_dtype = fld.dtype
    if isinstance(fld_dtype, pd.core.dtypes.dtypes.DatetimeTZDtype):
        fld_dtype = np.datetime64

    # Convert to datetime if not already
    if not np.issubdtype(fld_dtype, np.datetime64):
        df[date_col] = fld = pd.to_datetime(fld, infer_datetime_format=True)


    # Prefix for new columns
    pre = re.sub('[Dd]ate', '', date_col)
    pre = re.sub('[Tt]ime', '', pre)

    # Basic attributes
    attr = ['Year', 'Month', 'Week', 'Day', 'Dayofweek', 'Dayofyear', 'Days_in_month', 'is_leap_year']

    # Additional attributes
    if extra_attr:
        attr = attr + ['Is_month_end', 'Is_month_start', 'Is_quarter_end',
                       'Is_quarter_start', 'Is_year_end', 'Is_year_start']

    # If time is specified, extract time information
    if time:
        attr = attr + ['Hour', 'Minute', 'Second']

    # Iterate through each attribute
    for n in attr:
        df[pre + n] = getattr(fld.dt, n.lower())

    # Calculate days in year
    df[pre + 'Days_in_year'] = df[pre + 'is_leap_year'] + 365

    if time:
        # Add fractional time of day (0 - 1) units of day
        df[pre + 'frac_day'] = ((df[pre + 'Hour']) + (df[pre + 'Minute'] / 60) + (df[pre + 'Second'] / 60

        # Add fractional time of week (0 - 1) units of week
        df[pre + 'frac_week'] = (df[pre + 'Dayofweek'] + df[pre + 'frac_day']) / 7

        # Add fractional time of month (0 - 1) units of month
        df[pre + 'frac_month'] = (df[pre + 'Day'] + (df[pre + 'frac_day'])) / (df[pre + 'Days_in_month']

        # Add fractional time of year (0 - 1) units of year
        df[pre + 'frac_year'] = (df[pre + 'Dayofyear'] + df[pre + 'frac_day']) / (df[pre + 'Days_in_year'

    # Add seconds since start of reference
    df[pre + 'Elapsed'] = (fld - start_ref).dt.total_seconds()

    if
```

```
    if drop:
        df = df.drop(date_col, axis=1)

    return df
```

[31]:
```
test = extract_dateinfo(test, 'pickup_datetime', drop = False,
                        time = True, start_ref = data['pickup_datetime'].min())
test.head()
```

[31]:

ıp_Hour	pickup_Minute	pickup_Second	pickup_Days_in_year	pickup_frac_day	pickup_frac_week	pickup_frac_month	pickup_frac_year	pickup_Elapsed
13	8	24	365	0.547	0.221	0.861	0.075	191590595.000
13	8	24	365	0.547	0.221	0.861	0.075	191590595.000
11	53	44	365	0.496	0.785	0.265	0.769	87301315.000
21	12	12	366	0.883	0.840	0.059	0.918	123622823.000
21	12	12	366	0.883	0.840	0.059	0.918	123622823.000

[32]:
```
data = extract_dateinfo(data, 'pickup_datetime', drop = False,
                        time = True, start_ref = data['pickup_datetime'].min())
```

[33]:
```
X_train, X_valid, y_train, y_valid = train_test_split(data, np.array(data['fare_amount']),
                                                      stratify = data['fare-bin'],
                                                      random_state = RSEED, test_size = 10000)
```

[34]:
```
time_features = ['pickup_frac_day', 'pickup_frac_week', 'pickup_frac_year', 'pickup_Elapsed']

features = ['abs_lat_diff', 'abs_lon_diff', 'haversine', 'passenger_count',
            'pickup_latitude', 'pickup_longitude',
            'dropoff_latitude', 'dropoff_longitude'] + time_features
```

[35]:
```
# Test using the features
sub, fi = model_rf(X_train, X_valid, y_train, y_valid, test,
                   features = features)
```

```
Training:   rmse = 1.57
Validation: rmse = 3.91
```

[36]:
```
lr = LinearRegression()

# Fit and evaluate
lr.fit(X_train[features], y_train)
evaluate(lr, features, X_train, X_valid, y_train, y_valid)
```

```
Training:   rmse = 4.93
Validation: rmse = 5.79
```

Excluding Time Features

Regression RdmFrst
5.14 2.28 6.08 4.7

Including Time Features

Regression RdmFrst 4.93 1.57 5.79 3.93

Console