# Time Series to observe DAILY temperature variations

# **Daily temperature prediction using Random Forest**

Going one step deeper than a tree, we use in the notebook below

Random Forests: We begin by loading all necessary libraries and paths to read the "pickles" as well as store image for the graph towards the end of our code. The pickles are read and the data is fed into an RF model

Finally, we have two graphs showing the RF results vs. the fitted model as well as predicted results vs. actuals and test data

```
In [224]: import warnings
    warnings.filterwarnings('ignore')

%run helper_functions.py
%matplotlib inline
```

Create a folder for every run of the Random forest to store images

```
In [225]: city='Miami' # New_York Atlanta Boston Dallas Houston Miami
analysis_type = 'Enhanced_Signals' # Basic, Inc_Signals, Enhanced_Signals
In [226]: EXPERIMENT DIR EXPERIMENT ID = specific perpuration provides perpuration.
```

```
In [226]: EXPERIMENT_DIR, EXPERIMENT_ID = create_results_perrun()
    print(f"Experiment ID: {EXPERIMENT_ID}")
    print(f"Path of the results directory:{EXPERIMENT_DIR}")
```

Experiment ID: 36
Path of the results directory:../experiment results/RUN-36

Here we are importing the train and test Data from pickle files created through the EDA file

```
In [227]: X_train = pd.read_pickle(f'{PICKLE_PATH}/X_train_{city}_{analysis_type}.pkl')
Y_train = pd.read_pickle(f'{PICKLE_PATH}/Y_train_{city}_{analysis_type}.pkl')

X_test = pd.read_pickle(f'{PICKLE_PATH}/X_test_{city}_{analysis_type}.pkl')
Y_test = pd.read_pickle(f'{PICKLE_PATH}/Y_test_{city}_{analysis_type}.pkl')

print("Shape of Training Dataset " , X_train.shape)
print("Shape of Testing Dataset " , X_test.shape)
```

Shape of Training Dataset (1399, 17) Shape of Testing Dataset (90, 17)

```
In [228]: # Fitting a decision tree regressor with max denth and n estimators
          max depth = 8
          n = 50
          fitted model = RandomForestRegressor(max depth=max depth, random state=0, n estimators=n estimators)
          fitted model.fit(X train, Y train)
          # Dataframe to show features and their importances
          top features = 10
          features importances df= show feature importances(X train.columns.values.tolist().
                                                           fitted model.feature importances ,top features)
          # Top 10 features
          features importances df.head(10)
          # Store results
          features importances df.to csv(f'{EXPERIMENT DIR}/feature importances.csv')
In [229]: # Run the model on the training dataset
          Y train pred = fitted model.predict(X train)
          # Calculate mean sauared error for the predicted values
          mse train = mean squared error(Y train, Y train pred)
          print('Mean Squared Error for the training dataset: %.3f' % mse train)
```

Mean Squared Error for the training dataset: 0.757

```
In [230]: # Run the model on the testing dataset
    Y_test_pred = fitted_model.predict(X_test)
    # Calculate mean squared error for the test vs predicted values
    mse_test = mean_squared_error(Y_test, Y_test_pred)
    print('Mean Squared Error for the testing dataset: %.3f' % mse_test)
```

Mean Squared Error for the testing dataset: 1.169

```
In [231]: # Creating a dataframe for predicted/fitted values
    future_forecast = pd.DataFrame(Y_test_pred,index = Y_test.index,columns=['Fitted'])

# Concatenate the predicted/fitted values with actual values to display graphs
    predictions = pd.concat([Y_test,future_forecast],axis=1)
    predictions.columns = ["Actual","Fitted"]

# Displaying few of the predicted values
    predictions.head(10)
```

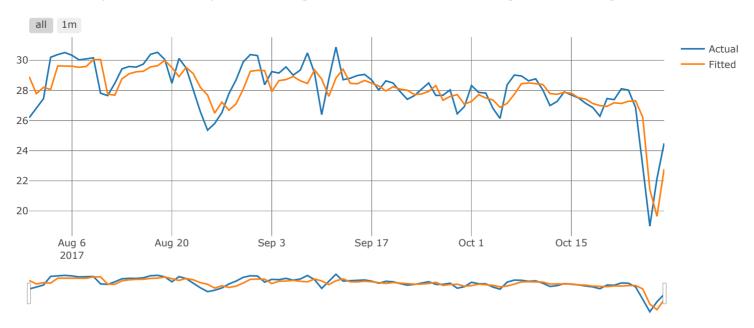
#### Out[231]:

	Actual	Fitted
datetime		
2017-07-31	26.192917	28.903332
2017-08-01	26.835000	27.783733
2017-08-02	27.449583	28.204148
2017-08-03	30.198333	28.059736
2017-08-04	30.380000	29.627431
2017-08-05	30.513333	29.596322
2017-08-06	30.326667	29.604831
2017-08-07	30.024583	29.532938
2017-08-08	30.094583	29.588812
2017-08-09	30.160833	30.038199

```
In [232]: city = city.replace('_',' ')
# Plotting the daily predicted temperature vs Actual Temperature - Decision Tree
fig = charter_helper_fitted(f"Daily Predicted Temperature using Decision Tree for {city} using {analysis_type}", predictions)
iplot(fig)

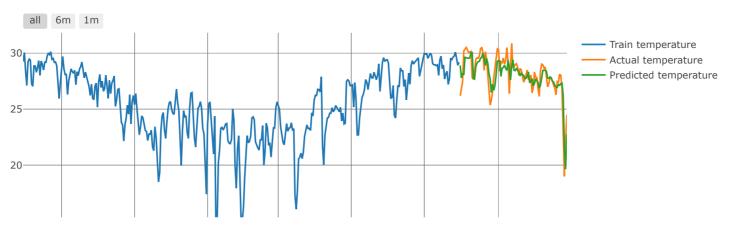
py.image.save_as(fig, f'{EXPERIMENT_DIR}/Daily_actual_vs_predict.png')
```

## Daily Predicted Temperature using Decision Tree for Miami using Enhanced\_Signals



Export to plot.ly »

## Daily Predicted Temperature using Decision Tree for Miami using Enhanced\_Signals



In [235]: results.tail(1)

Out[235]:

_	RU	N_ID	DATETIME	MODEL_NAME	CITY	FEATURE_TYPE	HOST_MACHINE	MODEL_PARAMETERS	MODEL_RESULTS	MEAN_SQUARED_ERROR
	35	36	2018-08-14 19:56:51.638468	RANDOM FOREST	Miami	Enhanced_Signals	DESKTOP- KN40C32	{'max_depth': 8, 'n_estimators': 50, 'Info': {	{'features': ['temperature_lag1', 'temperature	1.16879

In [236]: results = pd.read\_pickle('../pickles/results.pkl') results

Out[236]:

0 1 2018-08-14 DECISION New Basic DESKTOP- {'max_depth': 8, 'Info': ['tempe	Very design of the strength of	
0 1 19:41:45 275297 TREE York Basic KN40C32 //feature_set_type! ['tempe	perature_lag1', 5.799872 'temperature	
	(If a share	
	('features': iperature_lag1', 8.436149 itemperature	
	{'features': perature_lag1', 16.504857 'temperature	
	{'features': perature_lag1', 12.523335 'temperature	
19.42.41.506483 IREE KNAUCSZ ZTEATURE SET TYDE'' - '	{'features': perature_lag1', 7.705077 'temperature	
2018_08_14 DECISION DESKTOP. J'may denth' & 'Info'	{'features':	•

In [ ]:[