Machine Learning Engineer Nanodegree

Capstone Project

Shubham suya Jan 20,2020

Appliance Energy Prediction

In [2]:
```
# Import necessary libs

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

%matplotlib inline

# Common seed value to be used whenever required
seed = 79
np.random.seed(seed)
```

Read the data

In [3]:
```
energy = pd.read_csv(".\\training.csv")
```

In [4]:
```
# Display first 5 rows
energy.head()
```

Out[4]:

	T1	RH_1	T2	RH_2	T3	RH_3	T4	RH_4	T5	
0	20.20	37.500000	17.823333	39.300000	20.29	36.560000	18.200000	37.290000	17.926667	47.

	T1	RH_1	T2	RH_2	T3	RH_3	T4	RH_4	T5	
1	20.00	42.700000	19.100000	42.466667	20.79	44.500000	17.790000	43.790000	17.594444	54.
2	20.60	36.833333	17.500000	40.223333	21.60	34.863333	20.390000	35.363333	19.290000	47.
3	22.39	39.090000	19.890000	41.000000	24.89	37.045000	22.290000	35.652857	20.815000	53.
4	20.20	40.526667	18.390000	41.363333	21.00	39.700000	20.823333	39.500000	17.878889	49.

5 rows × 25 columns

Exploratory Analysis

In [5]:

```
# Dataset characteristics
print("Number of instances in dataset = {}".format(energy.shape[0]))
print("Total number of columns = {}".format(energy.columns.shape[0]))
print("Column wise count of null values:-")
print(energy.isnull().sum())
```

```
Number of instances in dataset = 14801
Total number of columns = 25
Column wise count of null values:-
T1             0
RH_1           0
T2             0
RH_2           0
T3             0
RH_3           0
T4             0
RH_4           0
T5             0
RH_5           0
T6             0
RH_6           0
T7             0
RH_7           0
T8             0
```

```
RH_8            0
T9              0
RH_9            0
T_out           0
Press_mm_hg     0
RH_out          0
Windspeed       0
Visibility      0
Tdewpoint       0
Appliances      0
dtype: int64
```

Therefore, we can conclude that the dataset has no missing values in any columns.

Column wise statistics

In [6]:
```
# Columns for temperature sensors
temp_cols = ["T1", "T2", "T3", "T4", "T5", "T6", "T7", "T8", "T9"]

# Columns for humidity sensors
rho_cols = ["RH_1", "RH_2", "RH_3", "RH_4", "RH_5", "RH_6", "RH_7", "RH
_8", "RH_9"]

# Columns for weather data
weather_cols = ["T_out", "Tdewpoint", "RH_out", "Press_mm_hg", "Windspe
ed", "Visibility"]

# Target variable column
target = ["Appliances"]
```

In [6]:
```
energy[temp_cols].describe()
```

Out[6]:

	T1	T2	T3	T4	T5	T6	
count	14801.000000	14801.000000	14801.000000	14801.000000	14801.000000	14801.000000	1480

	T1	T2	T3	T4	T5	T6
mean	21.691343	20.344518	22.278802	20.860393	19.604773	7.923216
std	1.615790	2.202481	2.012934	2.048076	1.849641	6.117495
min	16.790000	16.100000	17.200000	15.100000	15.340000	-6.065000
25%	20.760000	18.790000	20.790000	19.533333	18.290000	3.626667
50%	21.600000	20.000000	22.100000	20.666667	19.390000	7.300000
75%	22.633333	21.500000	23.340000	22.100000	20.653889	11.226667
max	26.260000	29.856667	29.236000	26.200000	25.795000	28.290000

In [7]:
```
energy[rho_cols].describe()
```

Out[7]:

	RH_1	RH_2	RH_3	RH_4	RH_5	RH_6
count	14801.000000	14801.000000	14801.000000	14801.000000	14801.000000	14801.000000
mean	40.267556	40.434363	39.243995	39.043799	51.014065	54.615000
std	3.974692	4.052420	3.245701	4.333479	9.107390	31.160835
min	27.023333	20.596667	28.766667	27.660000	29.815000	1.000000
25%	37.363333	37.900000	36.900000	35.560000	45.433333	29.996667
50%	39.693333	40.500000	38.560000	38.433333	49.096000	55.267500
75%	43.066667	43.273453	41.730000	42.200000	53.773333	83.226667
max	63.360000	54.766667	50.163333	51.090000	96.321667	99.900000

In [8]:
```
energy[weather_cols].describe()
```

Out[8]:

	T_out	Tdewpoint	RH_out	Press_mm_hg	Windspeed	Visibility
count	14801.000000	14801.000000	14801.000000	14801.000000	14801.000000	14801.000000

	T_out	Tdewpoint	RH_out	Press_mm_hg	Windspeed	Visibility
mean	7.421836	3.782509	79.824197	755.480135	4.029001	38.290284
std	5.343737	4.194994	14.901776	7.389218	2.448171	11.789650
min	-5.000000	-6.600000	24.000000	729.300000	0.000000	1.000000
25%	3.666667	0.933333	70.500000	750.900000	2.000000	29.000000
50%	6.933333	3.483333	83.833333	756.000000	3.666667	40.000000
75%	10.433333	6.600000	91.666667	760.833333	5.500000	40.000000
max	26.100000	15.316667	100.000000	772.300000	14.000000	66.000000

In [10]:
```
energy[target].describe()
```

Out[10]:

	Appliances
count	14801.000000
mean	97.875144
std	102.314986
min	10.000000
25%	50.000000
50%	60.000000
75%	100.000000
max	1080.000000

Observations

- Temperature ranges for all home sensors is between 14.89°C to 29.86°C except for T6 for which it is -6.06°C to 28.29°C. The reason for such low readings is that the sensor is kept outside.

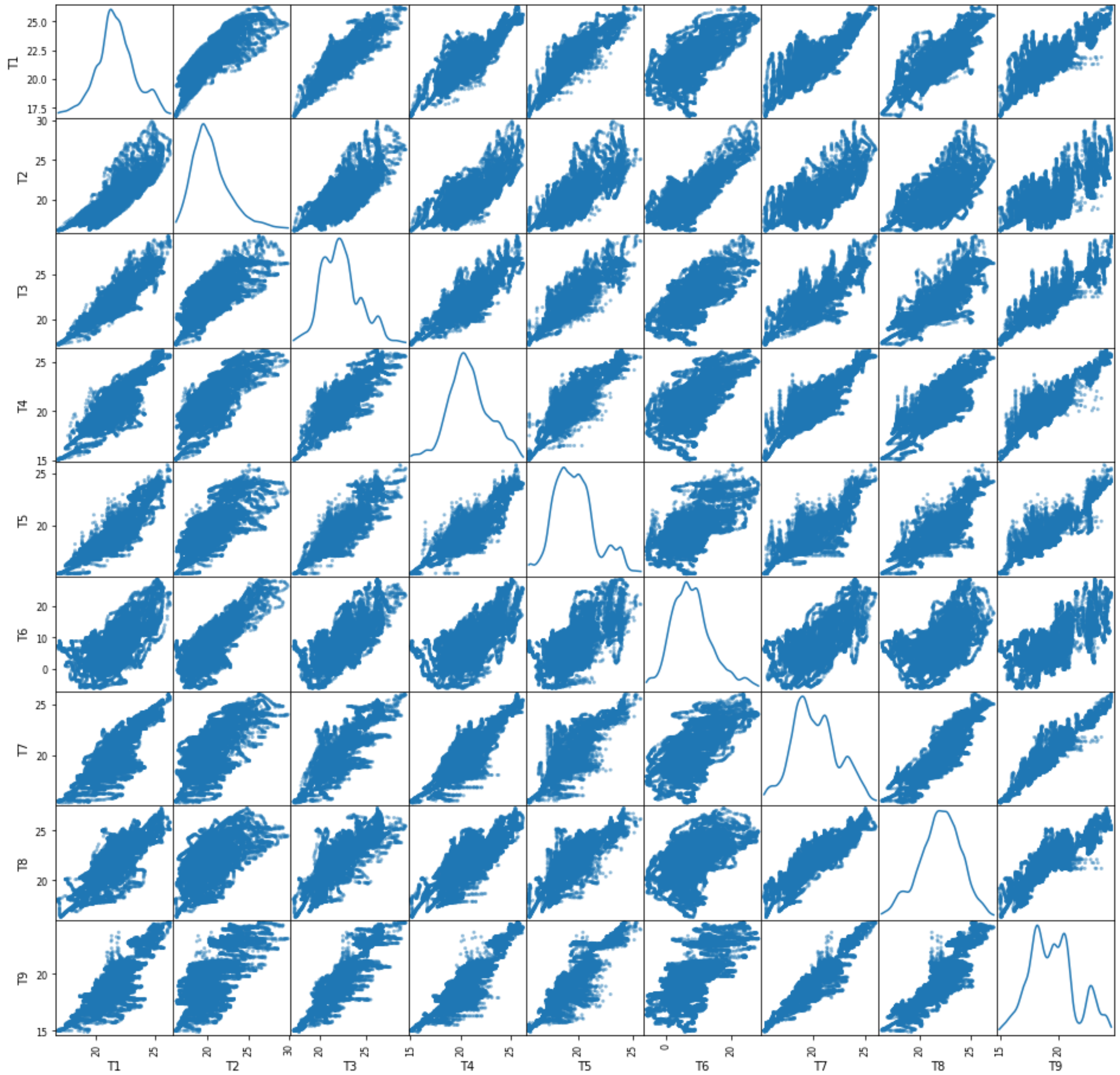
- Similarly, humudity ranges for all home sensors is between 20.60 `%` to 63.36%. Except for RH_5 and RH_6, whose ranges are 29.82 `%` to 96.32 `%` and 1 `%` to 99.9 `%` respectively.
    - The reason behind this is that RH_5 is inside the bathroom,
    - And RH_6 is outside the building, explaining the high humidity values.
- One interesting observation can be seen in `Appliances` column that although the max consumption is 1080 `Wh`, 75 `%` of values are less than 100 `Wh`. This shows that there are fewer cases when Appliance energy consumption is very high.

Exploratory Visualization

Correlation plots

Temperature sensors

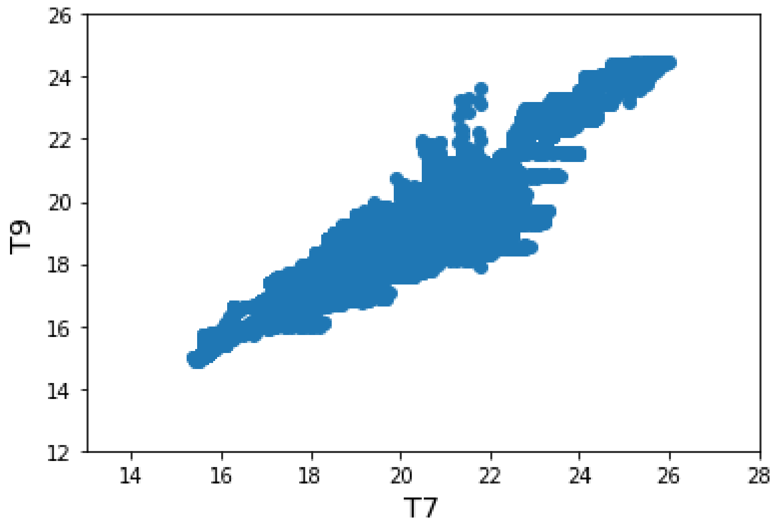
In [9]:
```
temp_scatter = pd.plotting.scatter_matrix(energy[temp_cols], diagonal=
"kde", figsize=(16, 16))
```



We can see that there is a significant correlation between the columns `T7` and `T9`. We will check this correlation statistically in later section. Let's check the plot between these two columns once more.

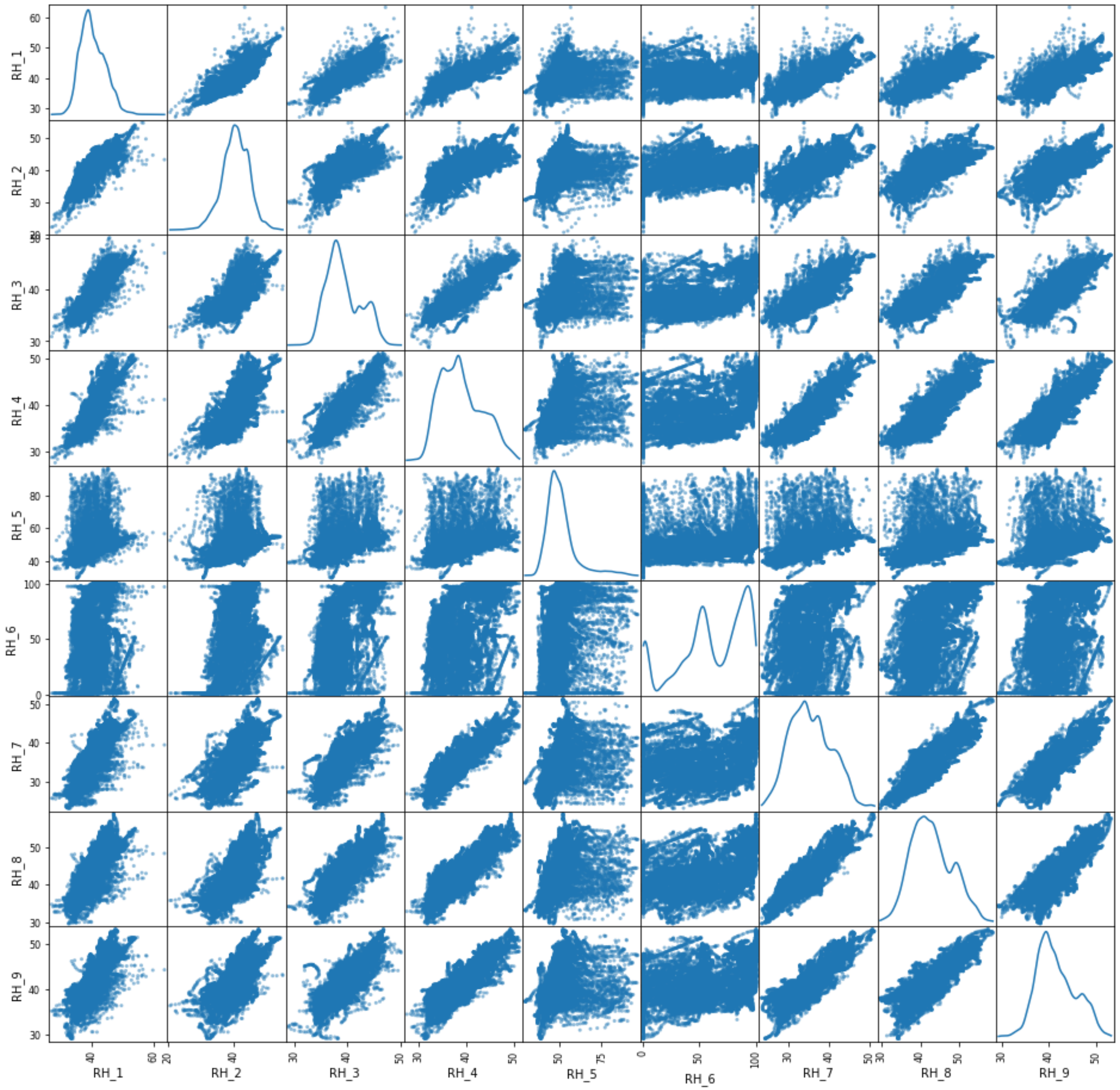
In [11]:
```
plt.xlabel("T7", fontsize='x-large')
plt.ylabel("T9", fontsize='x-large')

plt.xlim(int(energy.T7.min()) - 2, int(energy.T7.max()) + 2)
plt.ylim(int(energy.T9.min()) - 2, int(energy.T9.max()) + 2)

plt.scatter(energy["T7"], energy["T9"])
```

Out[11]: <matplotlib.collections.PathCollection at 0x20fafa38b70>



Humidity sensors

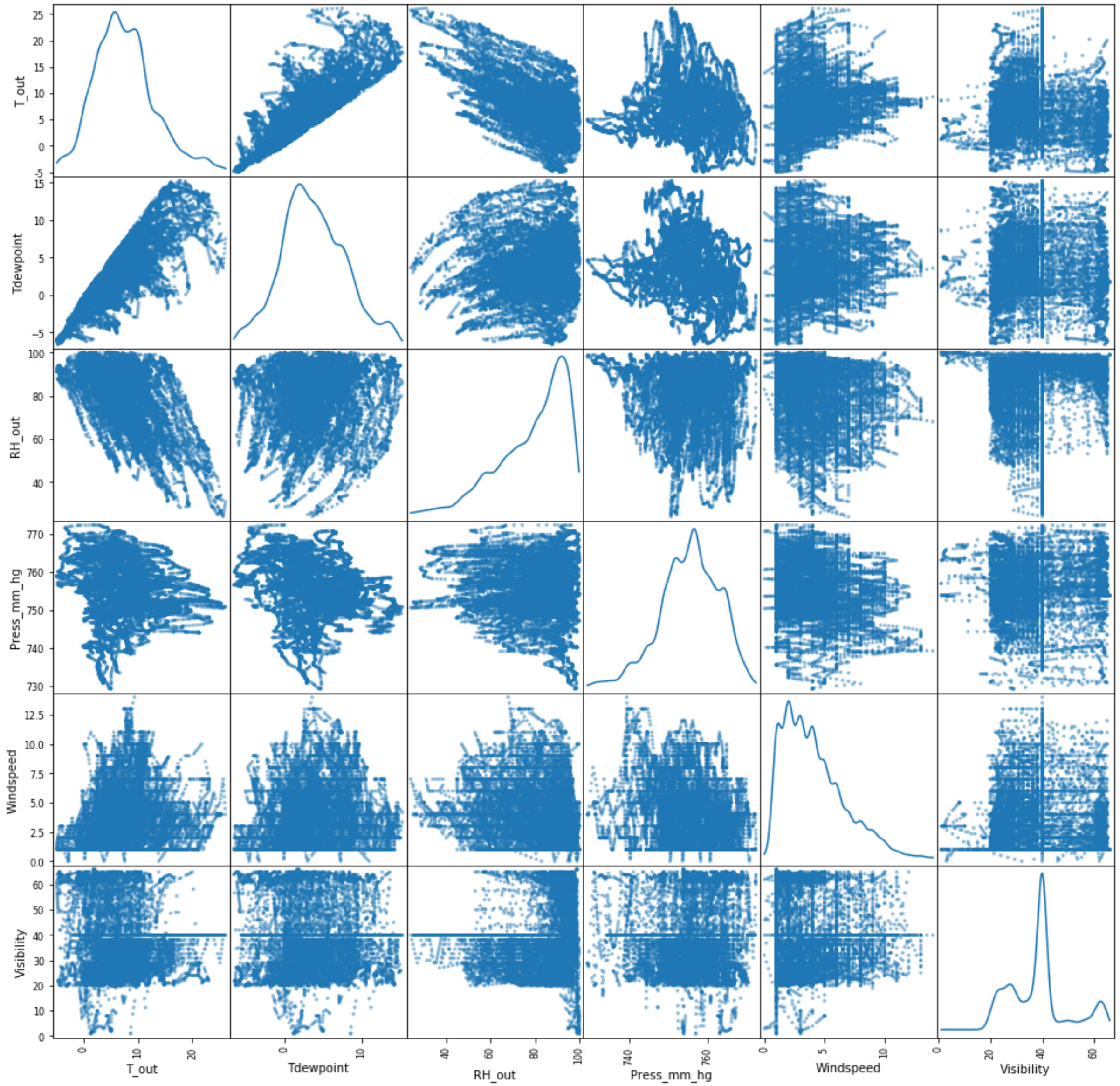
In [12]:
```
rho_scatter = pd.plotting.scatter_matrix(energy[rho_cols], diagonal="kd
e", figsize=(16, 16))
```



No significant correlation among for humidity sensors.

Weather data

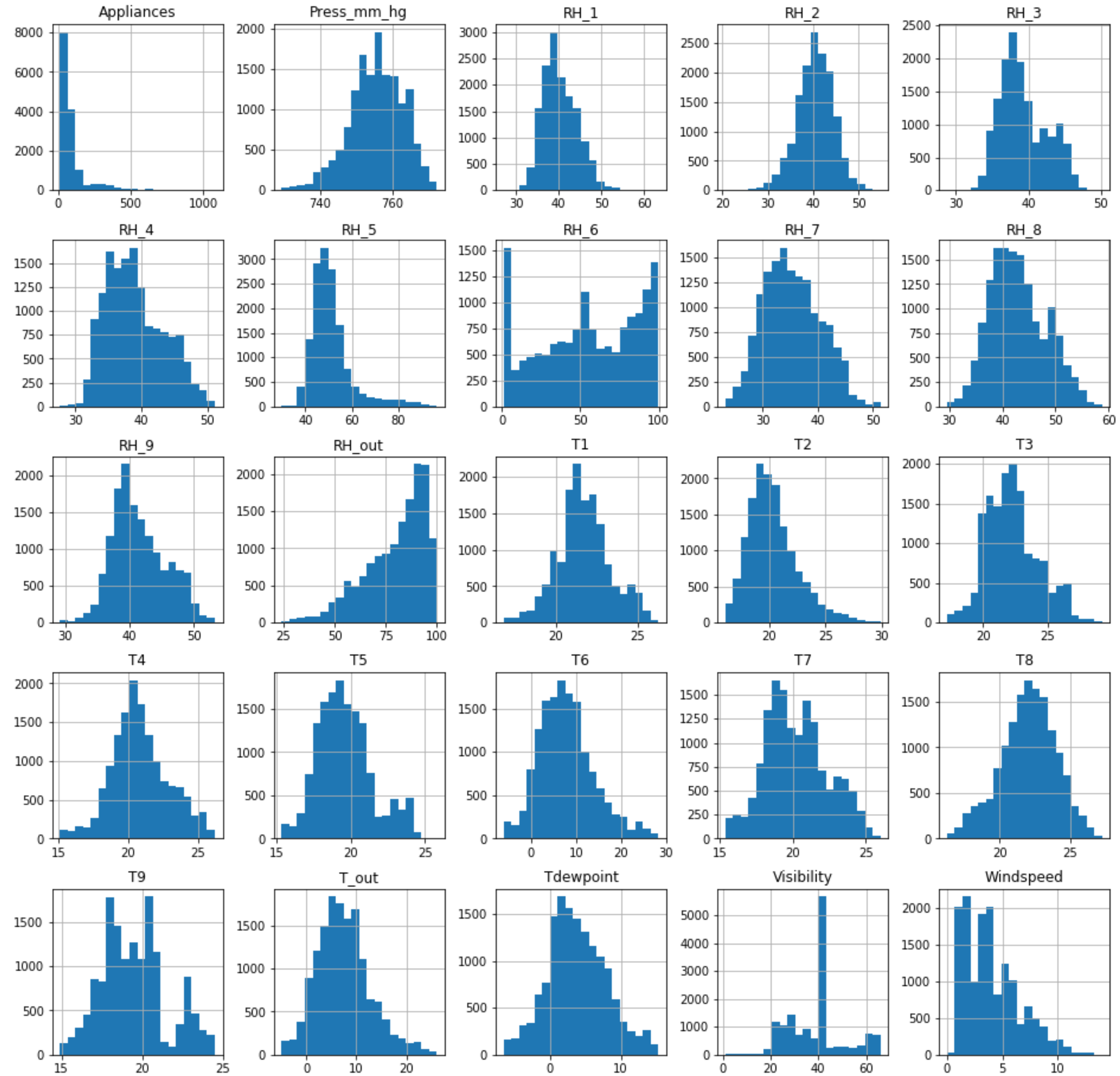
In [13]:
```
weather_scatter = pd.plotting.scatter_matrix(energy[weather_cols], diagonal="kde", figsize=(16, 16))
```



We can see here that the features of weather data are uncorrelated to one another.

Histogram for each column

In [14]:
```
histograms = energy.hist(figsize=(16, 16), bins=20)
```



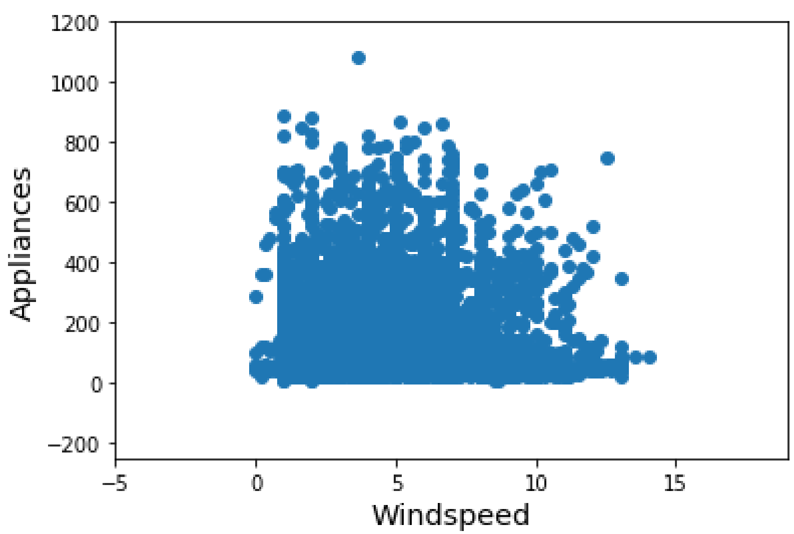
It can be observed from Histograms that:-

- All humidity values except `RH_6` and `RH_out` follow a Normal distribution. That is, all the readings from sensors inside the home are from a Normal distribution.
- Similarly, all temperature readings follow a Normal distribution except for `T9`.
- Out of the remaining columns, we can see that `Visibility`, `Windspeed` and **`Appliances`** are skewed.
- Also, there is no similarity between our target variable, **`Appliances`** and the remaining 24 columns. `Windspeed` looks similar but the number of observations are different as seen from the y-axes of both plots.

Let's confirm this by plotting **`Appliances`** against `Windspeed`. Also, let's plot **`Appliances`** histogram separately to get better idea about it's distribution.

In [15]:
```
plt.xlabel("Windspeed", fontsize='x-large')
plt.ylabel("Appliances", fontsize='x-large')

plt.xlim(-5, energy.Windspeed.max() + 5)
plt.ylim(-250, 1200)

plt.scatter(energy["Windspeed"], energy["Appliances"])
```

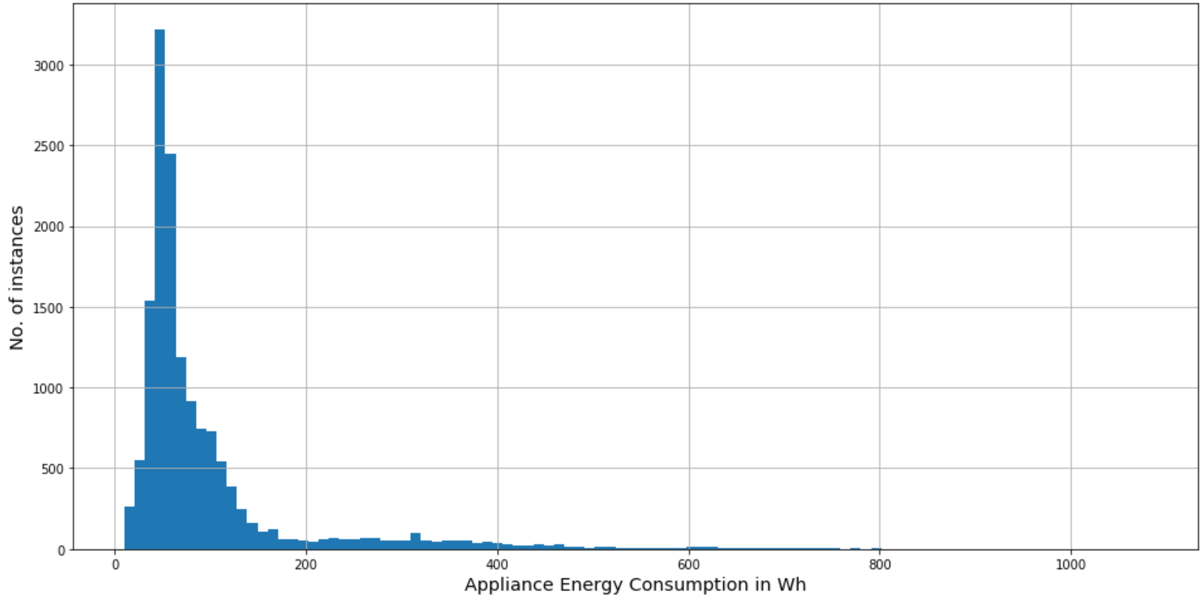
Out[15]: <matplotlib.collections.PathCollection at 0x20fb5290908>



Hence, it is confirmed that `Windspeed` does not share a linear relationship with **`Appliances`** column.

In [16]:
```
# Histogram for appliances

plt.xlabel("Appliance Energy Consumption in Wh", fontsize="x-large")
plt.ylabel("No. of instances", fontsize="x-large")

energy["Appliances"].hist(figsize=(16, 8), bins=100)
```

Out[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20fb5443b00>
```



We can see that most values are in the range of 0-200 `Wh`, strengthening our assumption that there are few cases of high energy consumption. The percentage of values within this range is calculated below.

In [17]:
```
print("Percentage of dataset in range of 0-200 Wh")
print("{:.3f}%".format(
```

```
    (energy[energy.Appliances <= 200]["Appliances"].count()*100.0) / en
ergy.shape[0]
))
```

```
Percentage of dataset in range of 0-200 Wh
90.183%
```

Now let's check the correlation between `T7` and `T9`.

In [18]:
```python
# Import pearson relation method from SciPy
from scipy.stats import pearsonr

# Calculate the coefficient and p-value
corr_coef, p_val = pearsonr(energy["T7"], energy["T9"])
print("Correlation coefficient : {}".format(corr_coef))
print("p-value : {}".format(p_val))
```

```
Correlation coefficient : 0.9460586115166221
p-value : 0.0
```

We can see that there is a very high degree of positive correlation between this two columns. Also, p-value is less than 0.01. Thereofore, we can reject the `null hypothesis` that this two columns don't affect each other.

Let's manually calculate which column pairs have a high degree of correlation (> 0.9).

In [19]:
```python
# To generate all pairs for given columns
from itertools import combinations

for pair in combinations(energy.columns, 2):
    col_1, col_2 = pair
    # Calculate the coefficient and p-value
    corr_coef, p_val = pearsonr(energy[col_1], energy[col_2])
    # Check for high correlation
    if corr_coef > 0.9 or corr_coef < -0.9:
        # Print details for pairs with high correlation
        print("Column pair : {}, {}".format(*pair))
```

```
        print("Correlation coefficient : {}".format(corr_coef))
        print("p-value : {}".format(p_val))
```

```
Column pair : T3, T9
Correlation coefficient : 0.9009710955349393
p-value : 0.0
Column pair : T5, T9
Correlation coefficient : 0.9101631787384007
p-value : 0.0
Column pair : T6, T_out
Correlation coefficient : 0.9747835663815296
p-value : 0.0
Column pair : T7, T9
Correlation coefficient : 0.9460586115166221
p-value : 0.0
```

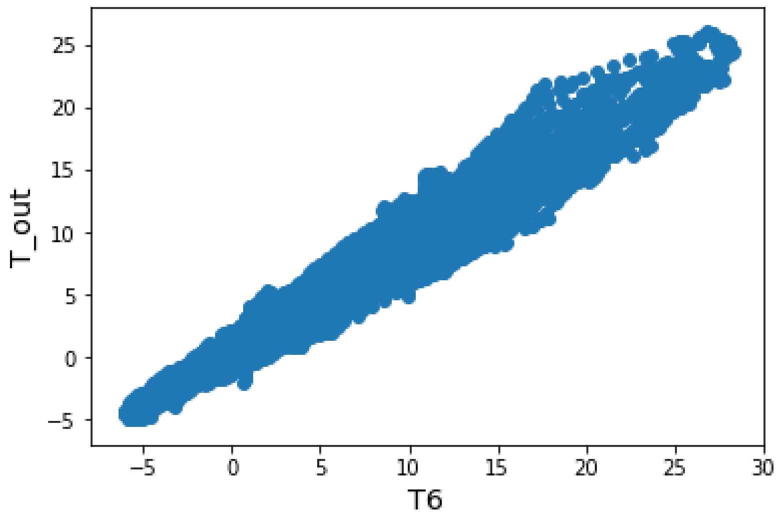
Interestingly, 3 columns have a high degree of correlation with `T9`, all of which have a p-value < 0.01. Therefore, `T9` can be considered as redundant.

Also, a very high correlation exists between features `T6` and `T_out`. This shouldn't be surprising as `T6` is reading from a temperature sensor kept outside the building and `T_out` is temperature obtained from Weather station.

Let's plot `T6` and `T_out` to get a detailed visualization.

In [20]:
```
plt.xlabel("T6", fontsize='x-large')
plt.ylabel("T_out", fontsize='x-large')

plt.xlim(int(energy.T6.min()) - 2, int(energy.T6.max()) + 2)
plt.ylim(int(energy.T_out.min()) - 2, int(energy.T_out.max()) + 2)

plt.scatter(energy["T6"], energy["T_out"])
```

Out[20]:
```
<matplotlib.collections.PathCollection at 0x20fb582ab38>
```



It is evident from the plot as well that these two features are highly correlated.

Benchmark Model

For benchmark, I will use Linear regression, using all the features as input data and without scaling the dataset. This will give an idea about the improvements gained from:

- Performing feature scaling.
- Performing feature selection.
- Performing cross validation.
- Using more complex Regression algorithms.
- Hyper-parameter tuning of the regressor.

In [22]:
```
from sklearn.linear_model import LinearRegression
from time import time

# Prepare the data
X_train = energy.drop("Appliances", axis=1)
```

```
y_train = energy["Appliances"]

# Initialize and fit the model
benchmark_model = LinearRegression()
start = time()
benchmark_model.fit(X_train, y_train)
end = time()

print("Classifier fitted in {:.3f} seconds".format(end-start))

# Load the test dataset
test = pd.read_csv(".//testing.csv")

# Separate the features and the target variable
X_test = test.drop("Appliances", axis=1)
y_test = test["Appliances"]

# Print scores on both
print("Score on training data : {:.3f}%".format(benchmark_model.score(X
_train, y_train) * 100))
print("Score on testing data : {:.3f}%".format(benchmark_model.score(X_
test, y_test) * 100))
```

```
Classifier fitted in 0.020 seconds
Score on training data : 14.687%
Score on testing data : 14.258%
```

Data Preprocessing

In [23]:

```
# Remove correlated features T6 and T9
train = energy.drop(["T6", "T9"], axis=1)
test.drop(["T6", "T9"], axis=1, inplace=True)
```

In [24]:

```
# Import scaler
from sklearn.preprocessing import StandardScaler
```

```
# Scales the data to zero mean and unit variance
standard_scaler = StandardScaler()
```

In [25]:
```
# Create dummy dataframes to hold the scaled train and test data
train_scaled = pd.DataFrame(columns=train.columns, index=train.index)
test_scaled = pd.DataFrame(columns=test.columns, index=test.index)
```

In [26]:
```
# Store the scaled data in new dataframes
train_scaled[train_scaled.columns] = standard_scaler.fit_transform(trai
n)
test_scaled[test_scaled.columns] = standard_scaler.fit_transform(test)
```

```
C:\Users\shsurya\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\preprocessing\data.py:645: DataConversionWarning: Data with input
dtype int64, float64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\shsurya\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\base.py:464: DataConversionWarning: Data with input dtype int64,
float64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
C:\Users\shsurya\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\preprocessing\data.py:645: DataConversionWarning: Data with input
dtype int64, float64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
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learn\base.py:464: DataConversionWarning: Data with input dtype int64,
float64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

In [27]:
```
# Prepare training and testing data
X_train = train_scaled.drop("Appliances", axis=1)
y_train = train_scaled["Appliances"]

X_test = test_scaled.drop("Appliances", axis=1)
y_test = test_scaled["Appliances"]
```

Algorithms to be used

Regularized Linear models as an improvement over Linear Regression.

- Ridge Regression
- Lasso Regression

Ensemble based Tree Regression models to deal robustly with outlier data and large number of features.

- Random Forests
- Gradient Boosting
- Extra Trees

Neural networks for exploring non linear relationships between features and target.

- Multi-Layer Preceptron

Model Implementation

In [28]:

```
# To calculate Root mean squared error
from sklearn.metrics import mean_squared_error

# Function to fit the regressor and record its metrics
def pipeline(reg, X_train, y_train, X_test, y_test, **kwargs):
    # Dictionary to hold the properties
    reg_props = {}

    # Initialize and fit the regressor while recording the time taken f
or fitting
    regressor = reg(**kwargs)
    start = time()
    regressor.fit(X_train, y_train)
    end = time()

    # Store the metrics for the regressor
    reg_props["name"] = reg.__name__
    reg_props["train_time"] = end - start
```

```
    reg_props["train_score"] = regressor.score(X_train, y_train)
    reg_props["test_score"] = regressor.score(X_test, y_test)
    reg_props["rmse"] = np.sqrt(mean_squared_error(y_test, regressor.pr
edict(X_test)))

    return reg_props
```

In [31]:

```
# Import the required Regression algorithms
from sklearn.linear_model import Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor, GradientBoostingReg
ressor, ExtraTreesRegressor
from sklearn.neural_network import MLPRegressor

# Function to execute each algorithm through the pipeline
def execute_pipeline():
    # Create the list of algorithms
    regressors = [
        Ridge,
        Lasso,
        RandomForestRegressor,
        GradientBoostingRegressor,
        ExtraTreesRegressor,
        MLPRegressor
    ]

    # To store the properties for each regressor
    props = []

    """
    Iterate thorugh the list of regressors,
    passing each thorugh the pipeline and
    storing its properites
    """
    for reg in regressors:
        properites = pipeline(reg, X_train, y_train, X_test, y_test, ra
ndom_state=seed)
        props.append(properites)

    return props
```

In [32]:
```
# Consolidate the properties into a DataFrame
def get_properties():
    # Obtain the properties after executing the pipeline
    properties = execute_pipeline()

    # Extract each individual property of the Regressors
    names = [prop["name"] for prop in properties]
    train_times = [prop["train_time"] for prop in properties]
    train_scores = [prop["train_score"] for prop in properties]
    test_scores = [prop["test_score"] for prop in properties]
    rmse_vals = [prop["rmse"] for prop in properties]

    # Create a DataFrame from these properties
    df = pd.DataFrame(index=names,
                      data = {
                          "Training times": train_times,
                          "Training scores": train_scores,
                          "Testing scores": test_scores,
                          "RMSE": rmse_vals
                      }
                     )

    return df
```

In [33]:
```
# Obain the properties in a structured DataFrame after executing the pi
peline
properties = get_properties()
```

```
C:\Users\shsurya\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\ensemble\forest.py:246: FutureWarning: The default value of n_est
imators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
C:\Users\shsurya\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\ensemble\forest.py:246: FutureWarning: The default value of n_est
imators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Visualizing Performance

In [35]:
```
# Calculate RMSE for the Benchmark model

test_data = pd.read_csv(".//testing.csv")

# For calculating RMSE of Linear Regression (Benchmark Model),
# we will scale the dataset so that all RMSE values are in the same sca
le
# We can inverse scale the data for other Regressor, but that will be m
ore cumbersome to do

data = standard_scaler.fit_transform(energy)
test_data = standard_scaler.fit_transform(test_data)

X = data[:, :-1]
y = data[:, -1]
X_t = test_data[:, :-1]
y_t = test_data[:, -1]

# Fit the model
start = time()
benchmark_model.fit(X, y)
end = time()

# Append the peoperties of Benchmark model to the DataFrame
# storing the properties of selected models

properties = pd.concat(
    [properties,
    pd.Series(
    {
        "RMSE": np.sqrt(mean_squared_error(y_t, benchmark_model.predict
(X_t))),
        "Training scores": benchmark_model.score(X, y),
        "Testing scores" :benchmark_model.score(X_t, y_t),
        "Training times": end - start,
        "Name": "Linear Regression (Benchmark)"
    }
```

```
    ).to_frame().T.set_index(["Name"])]
)

properties
```

```
C:\Users\shsurya\AppData\Local\Continuum\anaconda3\lib\site-packages
\sklearn\preprocessing\data.py:645: DataConversionWarning: Data with
input dtype int64, float64 were all converted to float64 by StandardS
caler.
  return self.partial_fit(X, y)
C:\Users\shsurya\AppData\Local\Continuum\anaconda3\lib\site-packages
\sklearn\base.py:464: DataConversionWarning: Data with input dtype in
t64, float64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
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\sklearn\preprocessing\data.py:645: DataConversionWarning: Data with
input dtype int64, float64 were all converted to float64 by StandardS
caler.
  return self.partial_fit(X, y)
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\sklearn\base.py:464: DataConversionWarning: Data with input dtype in
t64, float64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
C:\Users\shsurya\AppData\Local\Continuum\anaconda3\lib\site-packages
\ipykernel_launcher.py:35: FutureWarning: Sorting because non-concate
nation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=Tr
ue'.
```

Out[35]:

	RMSE	Testing scores	Training scores	Training times
Ridge	0.936121	0.123677	0.137409	0.0255983
Lasso	1	0	0	0.0107265
RandomForestRegressor	0.728899	0.468707	0.913055	5.33615

GradientBoostingRegressor	0.86821	0.246212	0.331539	2.98591

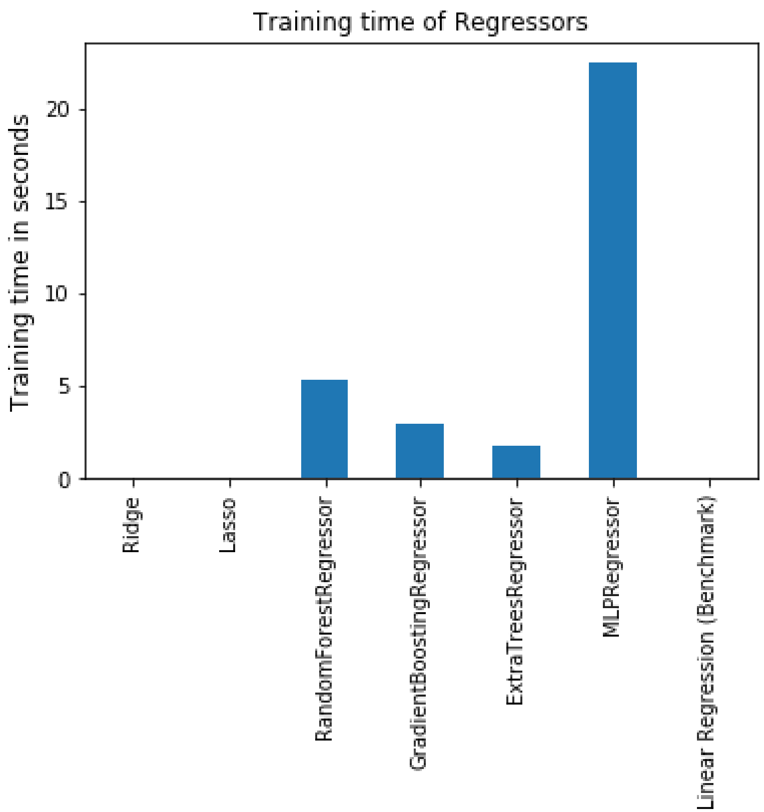
	RMSE	Testing scores	Training scores	Training times
ExtraTreesRegressor	0.664811	0.558027	1	1.75868
MLPRegressor	0.813745	0.337819	0.448612	22.3978
Linear Regression (Benchmark)	0.926026	0.142476	0.146873	0

In [36]:

```
# Plot to compare the training time of algorithms
plt.ylabel("Training time in seconds", fontsize="large")
properties["Training times"].plot(kind="bar", title="Training time of R
egressors")
```

Out[36]:

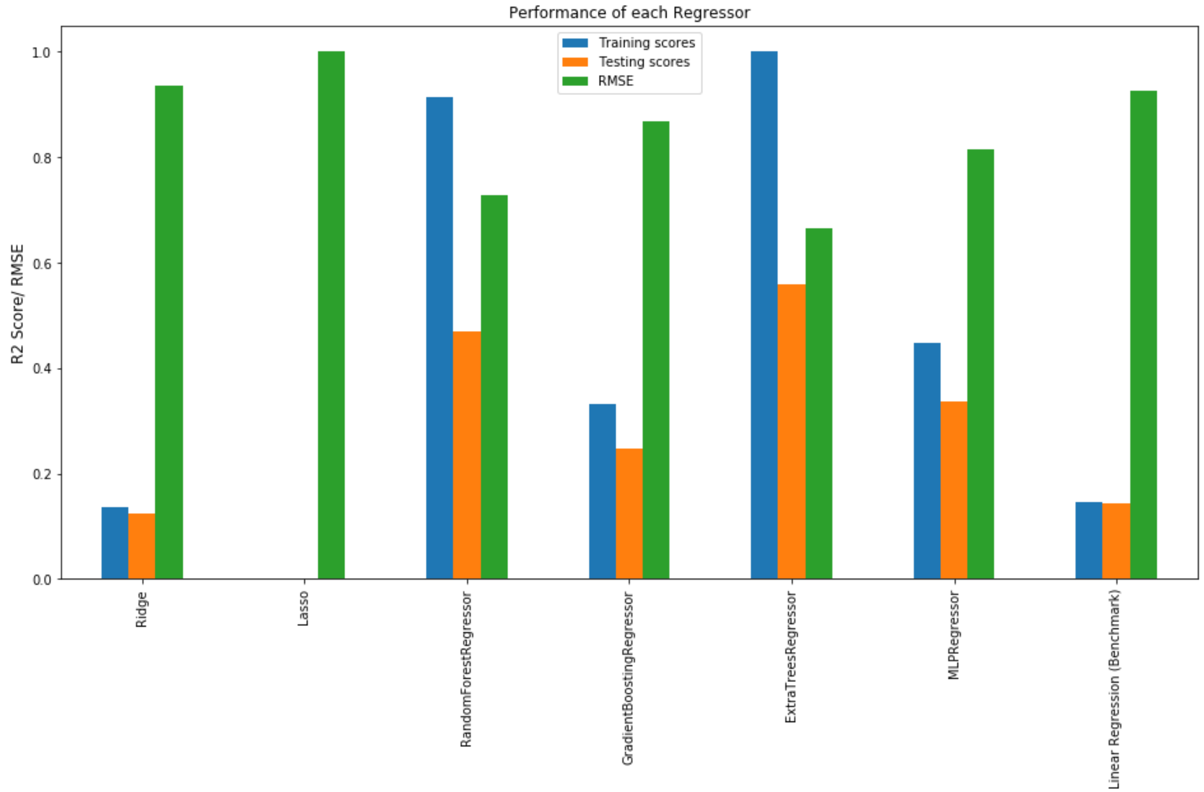
```
<matplotlib.axes._subplots.AxesSubplot at 0x20fb7f04a20>
```



- Fastest Regressor to train - Linear, Ridge and Lasso Regressors
- Slowest Regressor to train - Multi Layer Perceptron

In [37]:
```
# Plot to compare the performance of the algorithms on both datasets
ax= properties[["Training scores", "Testing scores", "RMSE"]].plot(kind
="bar", title="Performance of each Regressor", figsize=(16, 8))
ax.set_ylabel("R2 Score/ RMSE", fontsize="large")
```

Out[37]:
```
Text(0, 0.5, 'R2 Score/ RMSE')
```



- Least performing Regressor - Lasso Regressor
- Best performing Regressor - Extra Trees Regressor

Even though Extra Trees Regressor has a R2 score of 1.0 on traininig set, which might suggest overfitting but, it has the highest score on test set and also, it's RMSE value is also the lowest. Clearly, ExtraTreesRegressor is the best model out of given models.

Hyperparameter Tuning

In [39]:
```
from sklearn.model_selection import RandomizedSearchCV

# Initialize the best performing regressor
```

```
clf = ExtraTreesRegressor(random_state=seed)

# Define the parameter subset
param_grid = {
    "n_estimators": [10, 50, 100, 200, 250],
    "max_features": ["auto", "sqrt", "log2"],
    "max_depth": [None, 10, 50, 100, 200, 500]
}

# Use Randomized search to try 20 subsets from parameter space with 5-f
old cross validation
grid_search = RandomizedSearchCV(clf, param_grid, n_iter=20, scoring="r
2", cv=5, n_jobs=-1, verbose=2, random_state=seed)
grid_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent work
ers.
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:   39.5s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  3.7min finished
```

Out[39]:
```
RandomizedSearchCV(cv=5, error_score='raise-deprecating',
          estimator=ExtraTreesRegressor(bootstrap=False, criterion='ms
e', max_depth=None,
          max_features='auto', 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='warn', n_jobs=Non
e,
          oob_score=False, random_state=79, verbose=0, warm_start=Fals
e),
          fit_params=None, iid='warn', n_iter=20, n_jobs=-1,
          param_distributions={'n_estimators': [10, 50, 100, 200, 250],
'max_features': ['auto', 'sqrt', 'log2'], 'max_depth': [None, 10, 50, 1
00, 200, 500]},
          pre_dispatch='2*n_jobs', random_state=79, refit=True,
          return_train_score='warn', scoring='r2', verbose=2)
```

Review

In [40]:
```
# Display best params
print("Parameters of best Regressor : {}".format(grid_search.best_param
s_))
```

```
Parameters of best Regressor : {'n_estimators': 250, 'max_features': 'l
og2', 'max_depth': None}
```

In [41]:
```
best_model = grid_search.best_estimator_

# Display metrics on training and test set
print("R2 score on Training set = {:.3f}".format(best_model.score(X_tra
in, y_train)))
print("RMSE on Training set = {:.3f}".format(np.sqrt(mean_squared_error
(y_train, best_model.predict(X_train)))))
print("R2 score on Testing set = {:.3f}".format(best_model.score(X_test
, y_test)))
print("RMSE on Testing set = {:.3f}".format(np.sqrt(mean_squared_error(
y_test, best_model.predict(X_test)))))
```

```
R2 score on Training set = 1.000
RMSE on Training set = 0.000
R2 score on Testing set = 0.610
RMSE on Testing set = 0.624
```

R2 score improvement from Benchmark model = 0.467.

RMSE improvement from Benchmark model = 0.302.

R2 score improvement from Untuned model = 0.058.

RMSE improvement from Untuned model = 0.041.

Feature Analysis

In [42]:
```
# Find the index of most and least important feature and display that c
olumn
print("Most important feature = {}".format(X_train.columns[np.argmax(be
```

```
st_model.feature_importances_)]))
print("Least important feature = {}".format(X_train.columns[np.argmin(b
est_model.feature_importances_)]))

# Get the indices based on feature importance in ascending order
feature_indices = np.argsort(best_model.feature_importances_)

print("\nTop 5 most important features:-")
# Reverse the array to get important features at the beginning
for index in feature_indices[::-1][:5]:
    print(X_train.columns[index])

print("\nTop 5 least important features:-")
for index in feature_indices[:5]:
    print(X_train.columns[index])
```

```
Most important feature = RH_1
Least important feature = Visibility

Top 5 most important features:-
RH_1
T3
RH_out
RH_8
Press_mm_hg

Top 5 least important features:-
Visibility
T4
T1
Windspeed
RH_9
```

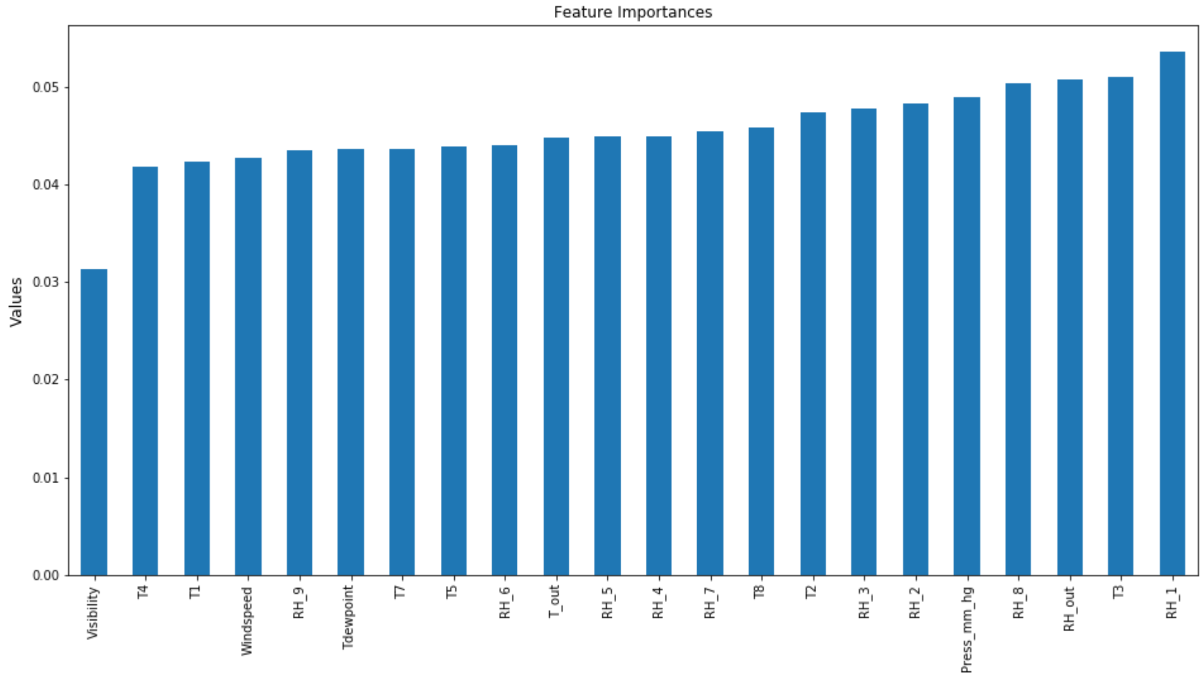
In [43]:

```
# Plot feature importance

fi = pd.DataFrame(index=X_train.columns[feature_indices], data=np.sort(
best_model.feature_importances_))

ax = fi.plot(kind="bar", title="Feature Importances", figsize=(16, 8))
```

```python
ax.set_ylabel("Values", fontsize="large")
ax.legend_.remove()
```



In [44]:
```python
# Constructing data set from reduced feature space
X_train_reduced = X_train[X_train.columns[feature_indices[::-1][:5]]]
X_test_reduced = X_test[X_test.columns[feature_indices[::-1][:5]]]
```

In [45]:
```python
from sklearn.base import clone

# Clone the best model
reg_best = clone(best_model)
# Fit the model on reduced data set
reg_best.fit(X_train_reduced, y_train)
print("R2 Score on testing dataset = {:.3f}".format(reg_best.score(X_te
st_reduced, y_test)))
print("RMSE Score on testing dataset = {:.3f}".format(np.sqrt(mean_squa
red_error(y_test, reg_best.predict(X_test_reduced)))))
```

```
R2 Score on testing dataset = 0.499
RMSE Score on testing dataset = 0.708
```

Difference in R2 score = 0.111 or 11.1% loss of explained variance.
Increase in RMSE = 0.084

This is a very high difference and hence we cannot reduce the feature space for final model.

Conclusion

- Best Algorithm = Extra Trees Regressor
- Variance explained on test set = 61 `%`.
- Improvement from benchmark model in terms of percentage of variance explained:-
  - Training data = 85.3 `%`
  - Test data = 46.7 `%`
- No. of features used in final model = 22.

In [ ]: