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Project: ***Measure Energy Consumption***

Introduction:

- **Certainly, using time series analysis and machine learning models to predict future energy consumption patterns is a promising approach.**
- **Here's how you can explore these techniques for energy consumption prediction.**

Objective

- **Explore innovative techniques such as time series analysis and machine learning models to predict future energy consumption patterns**
- **In PHASE 1 we discussed about the problem definition and their application used in artificial intelligence.**

Phase 2:

- **Consider Certainly, using time series analysis and machine learning models to predict future energy consumption patterns is a promising approach.**
- **Here's how you can explore these techniques for energy consumption prediction..Here is the following contents.**
- **Here are some key components and methods commonly used in such solutions:**

1.Data Collection:

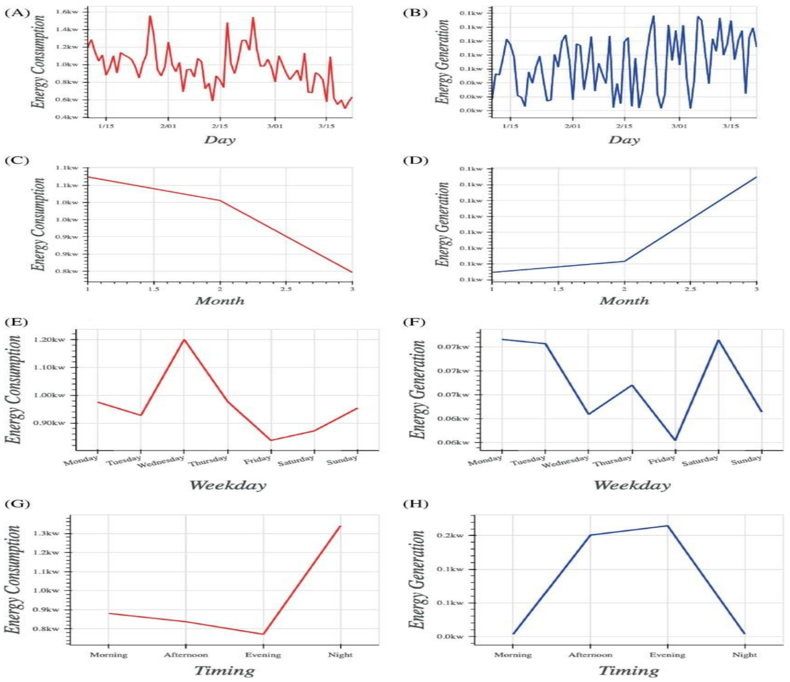
- **Gather historical energy consumption data.**
- **This data should include information about the time and date of measurements, energy usage, and potentially other relevant factors like temperature, holidays, or special events.**
- **Dataset link is below here:** https://www.kaggle.com/datasets/robikscube/hourly-energy-consumption

2. Data Preprocessing:

- **Data preprocessing is an important step before applying machine learning methods for energy or load prediction.**
- **It improves accuracy and reliability.**
- **There are four types of data processing**
    1. **Data cleaning**
    2. **Data integration**
    3. **Data transformation**
    4. **Data reduction**

3.Exploratory Data Analysis (EDA):

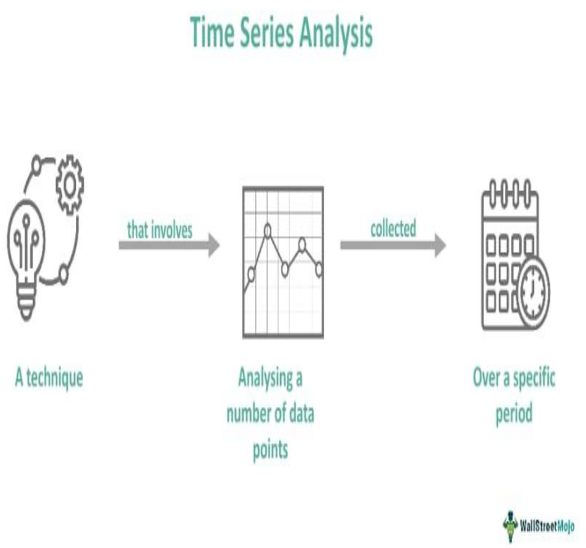
- **Perform EDA to gain insights into the data.**
- **Learn everything you need to know about exploratory data analysis, a method used to analyze and summarize data sets.**
- **Exploratory data analysis (EDA) is used by data scientists to analyze and investigate data sets and summarize their main characteristics, often employing data visualization methods.**
- **Visualize trends, seasonality, and correlations between energy consumption and other variables.**



4.Time Series Analysis:

- **It comprises of ordered sequence of data at equally spaced interval**.
- **In particular, a time series allows one to see what factors influence certain variables from period to period.**

1. **Decomposition:**
   Decompose the time series data into its trend, seasonal, and residual components to understand underlying patterns.
2. **Smoothing:**
   Apply smoothing techniques like moving averages or exponential smoothing to reduce noise in the data.



5.Feature Engineering:

- **Create additional features that could impact energy consumption, such as holidays, weather data, day of the week, and time of day.**
- **This includes the use of electricity, gas, diesel, oil, and biomass. The concept of energy consumption is directly related to energy efficiency since higher consumption results in lower energy efficiency.**
- **TEE includes three core components**

1.Resting metabolic rate, or resting energy expenditure (REE)

2.The thermic effect of food (TEF)

3. Diet-induced thermogenesis DIT)

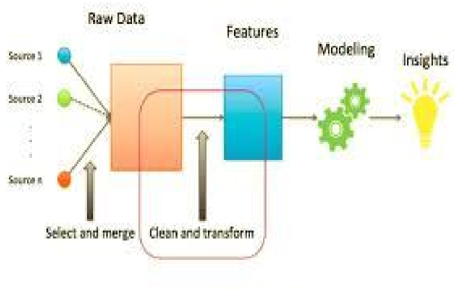


Figure 1-2. The place of feature engineering in the machine learning workflow.

6.Machine Learning Models:

A) Regression Models:

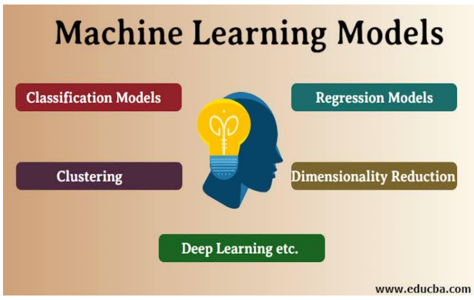
- **Utilize linear regression, decision trees, or random forests to build models that predict energy consumption based on relevant features.**

B) Time Series Forecasting:

- **Implement specialized time series forecasting models like ARIMA, Prophet, or LSTM (Long Short-Term Memory) neural networks.**

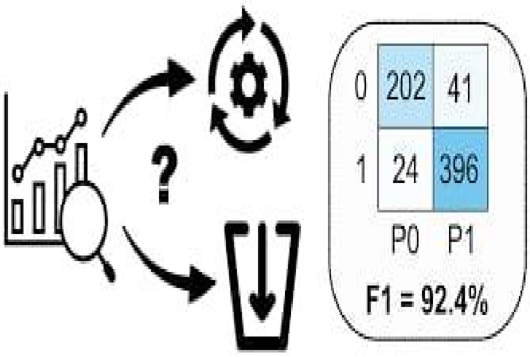
C)Ensemble Methods:

- **Combine multiple models to improve prediction accuracy.**



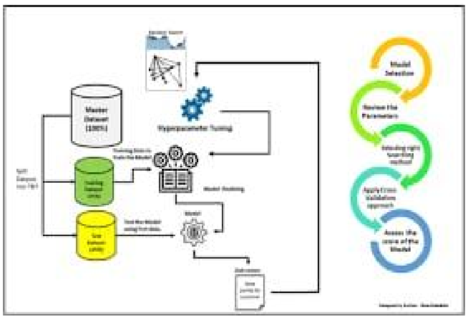
7.Model Evaluation:

- **Energy consumption modeling seeks to determine energy requirements as a function of input parameters.**
- **Models may be used for determining the requirements of energy supply and the consumer consumption variations while an upgrade or addition of technology exist.**
- **Use appropriate metrics such as**
  - **I. Mean Absolute Error (MAE)**
  - **II. Mean Squared Error (MSE)**
  - **III. Root Mean Squared Error (RMSE)**



8.Hyperparameter Tuning:

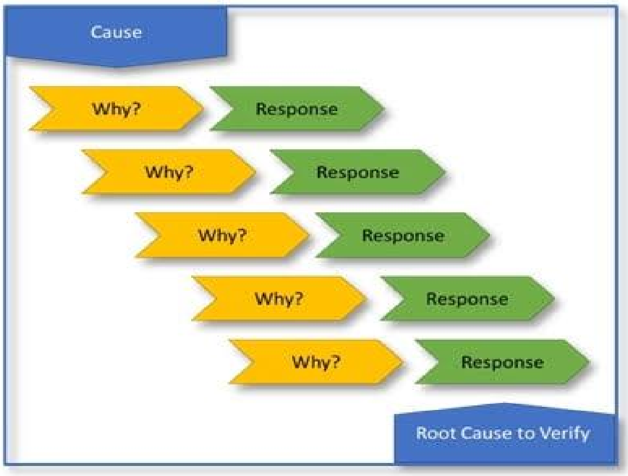
- **Optimize model hyperparameters to enhance predictive accuracy.**
- **Hyperparameter tuning allows data scientists to tweak model performance for optimal results.**



9.Cross-Validation:

- **Employ cross-validation techniques to assess the model’s generalization performance.**
- **Cross-validation is a statistical method used to estimate the performance (or accuracy) of machine learning models.**

- It is used to protect against overfitting in a predictive model, particularly in a case where the amount of data may be limited.



10.Monitoring and Updating:

- **Continuously monitor the model's performance and update it as needed with new data.**

11.Deployment:

- **Once you have a reliable model, deploy it in a real-world environment to make real-time predictions.**

12.Interpretability:

- **Understand the factors driving energy consumption by examining feature importance and model explanations.**

13.Integration:

- **Integrate the energy consumption prediction model into your energy management system to optimize resource allocation and reduce costs.**

Source code:

Int[1]:

```
Import numpy as np
Import pandas as pd
Import matplotlib.pyplot as plt
Import matplotlib.dates as mdates
%matplotlib inline
Import seaborn as sns
Import warnings
Warnings.filterwarnings("ignore")
From pandas.plotting import lag_plot
From pylab import rcParams
From statsmodels.tsa.seasonal import seasonal_decompose
From pandas import DataFrame
From pandas import concat
```

Int[2]:

```
Df=pd.read_csv("../input/hourly-energy-consumption/AEP_hourly.csv",index_col='Datetime',parse_dates=True)
Df.head()
```

Out[2]:

	AEP_MW
Datetime	
2004-12-31 01:00:00	13478.0
2004-12-31 02:00:00	12865.0
2004-12-31 03:00:00	12577.0
2004-12-31 04:00:00	12517.0
2004-12-31 05:00:00	12670.0

Int[3]:

```
df.sort_values(by='Datetime', inplace=True)
print(df)
```

Int[4]:

```
df.shape
```

Out[4]:

(121273, 1)

Int[5]:

df.info()

Out[5]:

<class 'pandas.core.frame.DataFrame'>

DatetimeIndex: 121273 entries, 2004-10-01 01:00:00 to 2018-08-03 00:00:00

Data columns (total 1 columns):

 #   Column Non-Null Count   Dtype

--- ------ --------------   -----

 0   AEP_MW 121273 non-null float64

dtypes: float64(1)

memory usage: 1.9 MB

Int[6]:

df.describe()

Out[6]:

	AEP_MW

count	121273.000000
mean	15499.513717
std	2591.399065
min	9581.000000
25%	13630.000000
50%	15310.000000
75%	17200.000000
100%	25695.000000

Int[7]:

```
df.index = pd.to_datetime(df.index)
```

Int[8]:

```
# Extract all Data Like Year MOnth Day Time etc
df["Month"] = df.index.month
df["Year"] = df.index.year
df["Date"] = df.index.date
df["Hour"] = df.index.hour
df["Week"] = df.index.week
df["Day"] = df.index.day_name()
```

df.head()

Out[8]:

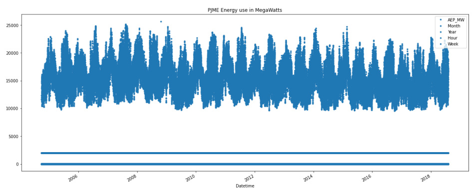
	AEP_MW	Month	Year	Date	Hour	Week	Day
Datetime							
2004-10-01 01:00:00	12379.0	10	2004	2004-10-01	1	4	Friday
2004-10-01 02:00:00	11935.0	10	2004	2004-10-01	2	4	Friday
2004-10-01 03:00:00	11692.0	10	2004	2004-10-01	3	4	Friday

2004-10-01 04:00:00	11597.0	10	2004	2004-10-01 1	4	4	Friday
2004-10-01 05:00:00	05:00:00	10	2004	2004-10-01 1	5	4	Friday

Int[9]:

```
df.plot(title="PJME Energy use in MegaWatts",
        figsize=(20, 8),
        style=".",
        color=sns.color_palette()[0])

plt.show()
```

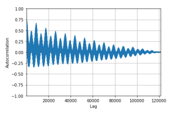
Out[9]:



Int[10]:

```
from pandas.plotting import autocorrelation_plot
autocorrelation_plot(df['AEP_MW'])
plt.show()
```

Out[10]:



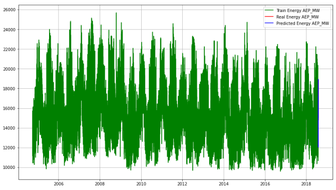
Int[11]:

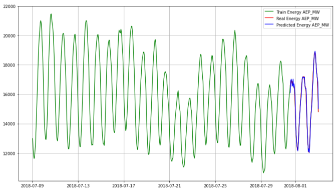
```
#Train Arima Model
train_arima = train_data['AEP_MW']
test_arima = test_data['AEP_MW']

history = [x for x in train_arima]
y = test_arima
# make first prediction
predictions = list()
model = sm.tsa.arima.ARIMA(history, order=(5,1,0))
model_fit = model.fit()
yhat = model_fit.forecast()[0]
```

```
predictions.append(yhat)
history.append(y[0])
# rolling forecasts
for i in range(1, len(y)):
    # predict
    model = sm.tsa.arima.ARIMA(history,
order=(5,1,0))
    model_fit = model.fit()
    yhat = model_fit.forecast()[0]
    # invert transformed prediction
    predictions.append(yhat)
    # observation
    obs = y[i]
    history.append(obs)

plt.figure(figsize=(14,8))
plt.plot(df.index, df['AEP_MW'], color='green',
label = 'Train Energy AEP_MW')
plt.plot(test_data.index, y, color = 'red', label = 'Real
Energy AEP_MW')
plt.plot(test_data.index, predictions, color = 'blue',
label = 'Predicted Energy AEP_MW')
```

```
plt.legend()
plt.grid(True)
plt.show()

plt.figure(figsize=(14,8))
plt.plot(df.index[-600:], df['AEP_MW'].tail(600), color='green', label = 'Train Energy AEP_MW')
plt.plot(test_data.index, y, color = 'red', label = 'Real Energy AEP_MW')
plt.plot(test_data.index, predictions, color = 'blue', label = 'Predicted Energy AEP_MW')
plt.legend()
plt.grid(True)
plt.show()

print('MSE: '+str(mean_squared_error(y, predictions)))
print('MAE: '+str(mean_absolute_error(y, predictions)))
print('RMSE: '+str(sqrt(mean_squared_error(y, predictions))))
```

Out[11]:





Conclusion:

- Remember that the accuracy of your predictions will depend on the quality and quantity of data, as well as the choice of the most appropriate modeling techniques.
- Regularly updating the model with new data is crucial to ensure it remains accurate as consumption patterns evolve.