**Electricity Prices Prediction**

**Problem Definition:**

* The problem at hand is to predict electricity prices accurately.
* Accurate electricity price predictions are crucial for various stakeholders, including consumers, energy providers, and policymakers.
* Accurate predictions can help consumers make informed decisions about their energy usage, energy providers optimize their operations, and policymakers implement effective energy policies.
* The challenge lies in developing a reliable model that can forecast electricity prices with a high degree of accuracy.

**Design Thinking:**

1. **Data Source:** 
   * Identify reliable sources for historical electricity price data. These sources might include government agencies, energy market websites, or utility companies.
   * Consider collecting additional relevant data, such as weather information, demand patterns, supply data, and regulatory changes, as these factors can influence electricity prices.
2. **Data Preprocessing:** 
   * Understand the quality and availability of historical electricity price data.

Identify missing values, outliers, and data anomalies.

* + Convert timestamps into a usable format for time-series analysis.
  + Normalize or scale the data if necessary to ensure all features are on the same scale.
  + Split the data into training, validation, and test sets to evaluate your model properly.

1. **Feature Engineering**:
   * Explore creative ways to engineer features, such as creating lag features for past prices or using domain knowledge to construct relevant variables.
   * Use domain knowledge to engineer features that could be relevant, such as holidays, energy market events, or economic indicators.
2. **Model Selection:** 
   * Experiment with various machine learning algorithms suitable for time-series forecasting, such as:
   * ARIMA (AutoRegressive Integrated Moving Average)
   * LSTM (Long Short-Term Memory) networks
   * Gradient Boosting algorithms (e.g., XGBoost, LightGBM)
   * Explore various model architectures and hyperparameters to see which ones align best with your problem.
3. **Model Training**:
   * Create a preliminary version of your model and train them on a portion of your dataset.
   * Implement techniques like cross-validation to fine-tune model parameters and prevent overfitting.

* + Explore rolling-window approaches for time-series data to simulate realtime forecasting.

1. **Evaluation:** 
   * Assess the model’s performance using appropriate evaluation metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), or Root Mean Squared Error (RMSE).
   * Consider using quantile regression to predict price percentiles, which can be crucial for risk management in energy trading.
   * Establish monitoring systems to track the model’s performance over time, and set up alerts for significant deviations or degradation in accuracy.

**Innovation**

Electricity price prediction is the process of using various techniques, such as statistical analysis, machine learning, and data modeling, to forecast the future cost of electricity. This prediction is vital for consumers, businesses, and energy companies to make informed decisions regarding energy consumption, cost management, and resource allocation. It considers factors like historical data, supply and demand dynamics, weather conditions, renewable energy integration, and consumer behavior to provide accurate estimates of future electricity prices. Accurate price predictions support cost savings, efficient energy management, and the integration of renewable energy sources into the grid.

**About Dataset:**

**Dataset link**:https://www.kaggle.com/datasets/chakradharmattapalli/electricity-priceprediction

This is the link about the Electricity price prediction ,this link is got form www.kaggle.com/data.

The price of electricity depends on many factors. Predicting the price of electricity helps many businesses understand how much electricity they have to pay each year. The Electricity Price Prediction task is based on a case study where you need to predict the daily price of electricity based on the daily consumption of heavy machinery used by businesses.

This dataset contains 38015 rows and 18 columns. By which It is useful for electricity price prediction.

**Details about columns:**

 Date & Time: Date and time of the record

 Holiday: contains the name of the holiday if the day is a national holiday  Holiday Flag: contains 1 if it’s a bank holiday otherwise 0

 Day Of Week: contains values between 0-6 where

0 is Monday  Week Of Year: week of the year

 Day: Day of the date

 Month: Month of the date  Year: Year of the date

 Period Of Day: half-hour period of the day

 For cast Wind Production: forecasted wind production  System Load EA

:forecasted national load

 SMPEA: forecasted price

 ORK Temperature: actual temperature measured  ORK Windspeed: actual windspeed measured

 CO2Intensity: actual C02 intensity for the electricity produced

 Actual Wind Production: actual wind energy production  SystemLoadEP2: actual national system load

 SMPEP2: the actual price of the electricity consumed (labels or values to be predicted)

**Details of libraries:**

Reducing electricity costs typically involves optimizing energy consumption, improving energy efficiency, and sometimes integrating renewable energy sources. Python offers a wide range of libraries and tools that can be used in various aspects of electricity price reduction. Here are some key libraries and tools:

Pandas: Pandas is essential for data manipulation and analysis. You can use it to preprocess and analyze electricity consumption data, perform datadriven decisions, and forecast energy usage.

**How to install:**

Step 1: Open your command prompt or terminal.

Step 2: Check if pip is installed:

Step 3: pip install pandas

Step 4: Wait for the installation to flnish.

Step 5: Verify the installation by running a Python script that includes: import pandas as pd print(pd.version)

If you see the version number, pandas is successfully installed.

Num Py : NumPy is crucial for numerical computing. It can be used for mathematical calculations related to electricity usage and cost reduction strategies.

How to install:

Step 1: Open your command prompt or terminal

Step 2: Check if pip iinstalled:

Step 3: pip install NumPy

Step 4: Wait for the installation to flnish.

Step 5: Verify the installation by running a Python script that includes:

import numpy as np

print(np.\_\_version\_\_)

If you see the version number, pandas is successfully installed.

Matplotlib and Seaborn: These libraries are excellent for data visualization. They can help you present insights and trends in a clear and understandable way.

**How to install:**

Step 1: Open your command prompt

Step 2: Check if pip is installed:

Step 3: pip install matplotlib

Step 4: Wait for the installation to flnish.

Step 5: Verify the installation by running a Python script that includes: import matplotlib print(matplotlib.\_\_version\_\_)

If you see the version number, pandas is successfully installed.

interface in Python.machine learning and statistical modeling including classiflcation, regression, clustering and dimensionality reduction via a consistence Sklearn: Scikit -learn (Sklearn) is thin Python. It provides a s most useful and robust llection of efficient tools for brary for

How to install:

Step 1: Open your command prompt or terminal. Step 2: Check if pip is installed:

Step 3: pip install scikit-learn

Step 4: Wait for the installation to flnish.

Step 5: Verify the installation by running a Python script that includes:

import sklearn print(sklearn.\_\_version\_\_)

If you see the version number, pandas is successfully installed.

How to train and test dataset:

The train-test split is used to estimate the performance of machine learning algorithms that are

applicable for prediction-based Algorithms/Applications. This method is a fast and easy procedure to perform such that we can compare our own machine learning model results to machine results.

By default, the Test set is split into 30 % of actual data and the training set is split into 70% of the actual data.

We need to split a dataset into train and test sets to evaluate how well our machine learning model performs. The train set is used to flt the model, and the statistics of the train set are known. The second set is called the test data set, this set is solely used for predictions.

Syntax:

train\_test\_split(\*arrays, test\_size=None, train\_size=None, random\_state=None, shuffle=True, stratify=None)

code:

# import

modules import pandas as pd from sklearn.linear\_model import LinearRegression from sklearn.model\_selection import

train\_test\_split

# read the dataset df = pd.read\_csv(“Electricity price.csv”)

# get the location s X = df.iloc[:, :-1]

y = df.iloc[:, -1]

# split the dataset

X\_train, X\_test, y\_train, y\_test = train\_test\_split( X, y,

test\_size=0.05, random\_state=0)

Metrics used for the accuracy check for electricity price prediction:

Evaluation metrics are tied to machine learning tasks, There are different metrics for the tasks classification and regression. Some metrics, like precision-recall, are useful for multiple tasks. Classification and regression are examples of supervised learning, which constitutes a machine learning applications. Using different metrics for performance evaluation, we should to improve our model’s overall predictive power before we roll it out for production on unseen Without doing a proper evaluation of the Machine Learning model by using different

metrics, and only depending on accuracy, can lead to a problem when the respective model is deployed on unseen data and may end in poor predictions. Classification Metrics in Machine Learning

Classification is about predicting the class labels given input data. In binary classification, there are only two possible output classes(i.e., Dichotomy). In multiclass classification, more than two possible classes can be present. I’ll focus only on binary classification Accuracy

Accuracy simply measures how often the classifier correctly predicts. We

can define accuracy as the ratio of the number of correct predictions and the total number of predictions.

The four commonly used metrics for evaluating classifier performance are:

Accuracy: The proportion of correct predictions out of the total predictions.

Precision: The proportion of true positive predictions out of the total positive predictions (precision = true positives / (true positives + false positives)).

Recall (Sensitivity or True Positive Rate): The proportion of true positive predictions out of the total actual positive instances (recall = true positives / (true positives + false negatives)).

F1 Score: The harmonic mean of precision and recall, providing a balance between the two metrics (F1 score = 2 \* ((precision \* recall) / (precision + recall))).

Libraries for Electricity price prediction import csv from sklearn.model\_selection import train\_test\_split Nmpy

Pandas from sklearn.preprocessing import onehotEncoder from sklearn.preprocessing import LabelEncoder import matplotlib.pyplot from sklearn.datasets import load\_iris from sklearn.linear\_model import linearRegression from sklearn.preprocessing import standard scaler from sklearn.ensemble import randomforestclassifier Importing the Data Set:

import csv file = open('data.csv', 'rU') reader = csv.reader(file) matrix=[] for row in reader: matrix.append(row) print(matrix)

**Handling the Missing Data:**

In this we use the sklearn.preprocessing import imputer it is used to fill the missing data.

The imputer is an estimator used to fill the missing values in datasets. For numerical values, it uses mean, median, and constant. For categorical values, it uses the most frequently used and constant value.

**Encode categorical Data:**

For Encoding the categorical data using the one-hot encoding and it is used to convert a categorical variables into a binary matrix.

This is commonly used in machine learning algorithms that cannot work with categorical data directly.

We can use libraries like scikit-learn or keras to perform one-hot encoding easily.

Splitting the Data Set:

In this we are using the from sklearn.model\_selection import train\_test\_split

library for splitting the data set as the test data and the trained data from the data set.

The train-test split procedure is used to estimate the performance of machine learning algorithms when they are used to make predictions on data not used to train the model.

The dataframe gets divided into X\_train,X\_test , y\_train and y\_test.

X\_train and y\_train sets are used for training and fitting the model. The X\_test and y\_test sets are used for testing the model if it's predicting the right outputs/labels.

Feature Scaling:

Sklearn library offers us with StandardScaler() function to standardize the data values into a standard format.

The library is from sklearn.preprocessing import standard scaler.

Syntax:

object = StandardScaler() object.fit\_transform(data)

Csv File:



data.csv

**Feature engineering**

* Explore creative ways to engineer features, such as creating lag features for past prices or using domain knowledge to construct relevant variables.
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**Model Training:**

* Create a preliminary version of your model and train them on a portion of your dataset.

* Implement techniques like cross-validation to fine-tune model parameters and prevent overfitting.
* Explore rolling-window approaches for time-series data to simulate realtime forecasting.

**code:**

import matplotlib.pyplot as plt import pandas as pd

import seaborn as sns

from sklearn.model\_selection import train\_test\_split from sklearn.metrics import

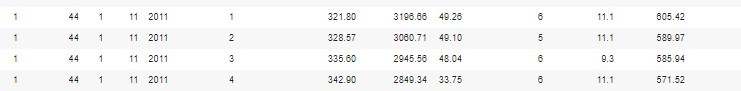
mean\_squared\_error from sklearn.ensemble import RandomForestRegressor from sklearn.tree import DecisionTreeRegressor

from sklearn.linear\_model import LinearRegression

from sklearn.neighbors import KNeighborsRegressor

df=pd.read\_csv("/content/data.csv", low\_memory=False) df.head()

Output:



**All model trining:**

Code:

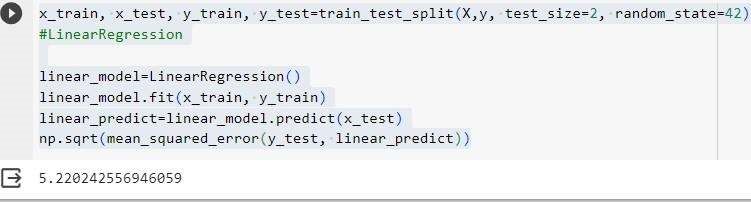
x\_train, x\_test, y\_train, y\_test=train\_test\_split(X,y, test\_size=2, random\_state=42) #LinearRegression

linear\_model=LinearRe gression() linear\_model.fit(x\_train, y\_train)

linear\_predict=linear\_model.predict(x\_test)

np.sqrt(mean\_squared\_error(y\_test, linear\_predict))

**Output:**



**KNeighborsRegressor:**

**Code:**

#KNeighborsRegressor

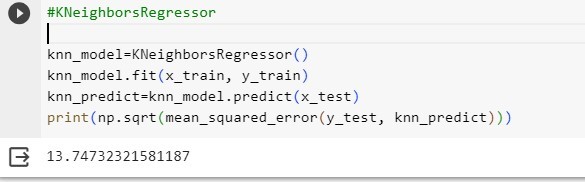
knn\_model=KNeighborsRegressor

() knn\_model.fit(x\_train, y\_train)

knn\_predict=knn\_model.predict(x\_test)

print(np.sqrt(mean\_squared\_error(y\_test, knn\_predict)))

**Output:**



**Evaluation:**

Assess the model’s performance using appropriate evaluation metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), or Root Mean Squared Error (RMSE).Consider using quantile regression to predict price percentiles, which can be crucial for risk management in energy trading.Establish monitoring systems to track the model’s performance over time, and set up alerts for significant deviations or degradation in accuracy.

**Code:**

some\_data=x\_test.iloc[50:60] some\_data\_label=y\_test.iloc[50:60]

some\_predict=forest\_model.predict(some\_data)

pd.DataFrame({'Predict':some\_predict,'Label':some\_data\_label})

**Output**:

