Welcome To This Notebook 😃

Project Name :- Total Caps Production Predictor

Problem Statement :-

The goal of this project is to train a Machine Learning model that accurately estimates the total production of caps based on Date & Time and Production per hour features. The model aims to contribute to optimizing production planning and resource allocation.

Problems to Solve:-

1) Outlier Detection and outlier treatment of 'Production Per Hour' feature

2) Train a Machine Learning model that accurately estimates the total production of caps based on Date & Time and Production per hour features.

Dataset:

The dataset includes the following features:

Date & Time: The timestamp indicating when the production data was recorded.

Production per Hour: The amount of production recorded per hour.

Target Variable:

Total Production: The total production accumulated during the recorded period.

Importing Libraries

In [309…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score
from sklearn.model_selection import GridSearchCV
```

Importing the Dataset

In [310…

```
df1 = pd.read_csv(r"C:\Users\91770\Downloads\cap-production-data.csv")
```

Setiing Display options to ensure feature name visibility

In [311…
```
pd.set_option('display.max_columns',None)
```

Warning Suppression

In [312…
```
import warnings
warnings.filterwarnings('ignore')
```

Creating copy of original dataset

In [313…
```
df = df1.copy()
```

Eyeballing Dataset

In [314…
```
#Checking first 5 rows of dataset

df.head()
```

Out[314]:

	Date & Time	Production per hour	Total Production
0	27/01/2024 17:11:44	77	77
1	27/01/2024 18:11:44	52	129
2	27/01/2024 19:11:44	62	191
3	27/01/2024 20:11:44	47	238
4	27/01/2024 21:11:44	35	273

In [315…
```
# Checking shape of dataset

df.shape
```

Out[315]:
```
(499, 3)
```

In [316…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 499 entries, 0 to 498
Data columns (total 3 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   Date & Time          499 non-null    object
 1   Production per hour  499 non-null    int64 
 2   Total Production     499 non-null    object
dtypes: int64(1), object(2)
memory usage: 11.8+ KB
```

In [317…
```
# Checing columns

df.columns
```

Out[317]:
```
Index(['Date & Time', 'Production per hour', 'Total Production'], dtype='object')
```

In [318…
```
# Checking datatypes

df.dtypes
```

Out[318]:
```
Date & Time            object
Production per hour     int64
Total Production       object
dtype: object
```

In [319…
```
# Checking Duplicated values

df.duplicated().sum()
```

Out[319]:
```
0
```

Initial Observations About Raw Data

- 1. We have 499 rows and 3 columns

  Independent Feature : 'Date & Time' and 'Production per hour'

  Dependent Feature : 'Total Production'
- 1. Datatypes of 'Date & Time' and 'Production per hour' are 'object' we have to change it to 'datetime' and 'int64' respectively.
- 1. We have to create some useful features using 'Date & Time' feature so we can enrich our dataset.
- 1. In Total production there is comma in some 'Total Production' feature, e.g.;-22,685, we have replace comma.
- 1. There are no duplicate values in the dataset
- 1. Rename feature name 'Production per hour' to 'Production Per Hour'.

Data Cleaning

In [320…
```
# Replacing comma with space in Total Production variable

df['Total Production'] = df['Total Production'].str.replace(',','')
```

In [321…
```
# Changing datatype of 'Total Production Column'

df['Total Production'] = df['Total Production'].astype('int64')
```

In [322…
```
# Changing Datatype of 'Date & Time' feature

df['Date & Time'] = pd.to_datetime(df['Date & Time'], format='%d/%m/%Y %H:%M:%S')
```

In [323…
```
# Checking datatypes

df.dtypes
```

Out[323]:
```
Date & Time            datetime64[ns]
Production per hour             int64
Total Production                int64
dtype: object
```

In [324…
```
# Renaming feature name 'Production per hour' to 'Production Per Hour'.

df.rename(columns={'Production per hour': 'Production Per Hour'}, inplace=True)
```

In [325…
```
df.sample()
```

Out[325]:

	Date & Time	Production Per Hour	Total Production
294	2024-02-08 23:11:44	63	21419

Enriching our dataset using 'Date & Time' Variable

Extracting Year, Month and Days

In [326…
```
df['Year'] = df['Date & Time'].dt.year

df['Month'] = df['Date & Time'].dt.month

df['Day'] = df['Date & Time'].dt.day
```

Extracting Day of Week

In [327…
```
df['Day_of_Week'] = df['Date & Time'].dt.dayofweek
```

Extracting Hour, Minutes and Seconds

In [328…
```
df['Hour'] = df['Date & Time'].dt.hour
df['Minute'] = df['Date & Time'].dt.minute
df['Second'] = df['Date & Time'].dt.second
```

In [329…
```
# Checking first 5 rows just to confirm about all features created
df.head()
```

Out[329]:

	Date & Time	Production Per Hour	Total Production	Year	Month	Day	Day_of_Week	Hour	Minute	Second
0	2024-01-27 17:11:44	77	77	2024	1	27	5	17	11	44
1	2024-01-27 18:11:44	52	129	2024	1	27	5	18	11	44
2	2024-01-27 19:11:44	62	191	2024	1	27	5	19	11	44
3	2024-01-27 20:11:44	47	238	2024	1	27	5	20	11	44
4	2024-01-27 21:11:44	35	273	2024	1	27	5	21	11	44

In [330…
```
# Checking datatypes of newely created features

df.dtypes
```

Out[330]:
```
Date & Time            datetime64[ns]
Production Per Hour             int64
Total Production                int64
Year                            int64
Month                           int64
Day                             int64
Day_of_Week                     int64
Hour                            int64
Minute                          int64
Second                          int64
dtype: object
```

As we have extracted required information from 'Date & Time' feature, we will now drop 'Date & Time' feature from dataset because of below reason

If the date and time features you extracted to capture the information you need for your analysis or modeling, keeping the original datetime column might introduce redundancy and unnecessary dimensionality.

In [331…
```
df = df.drop(['Date & Time'],axis=1)
```

Exploratory Data Analysis (EDA)

In [332…
```
df.describe()
```

Out[332]:

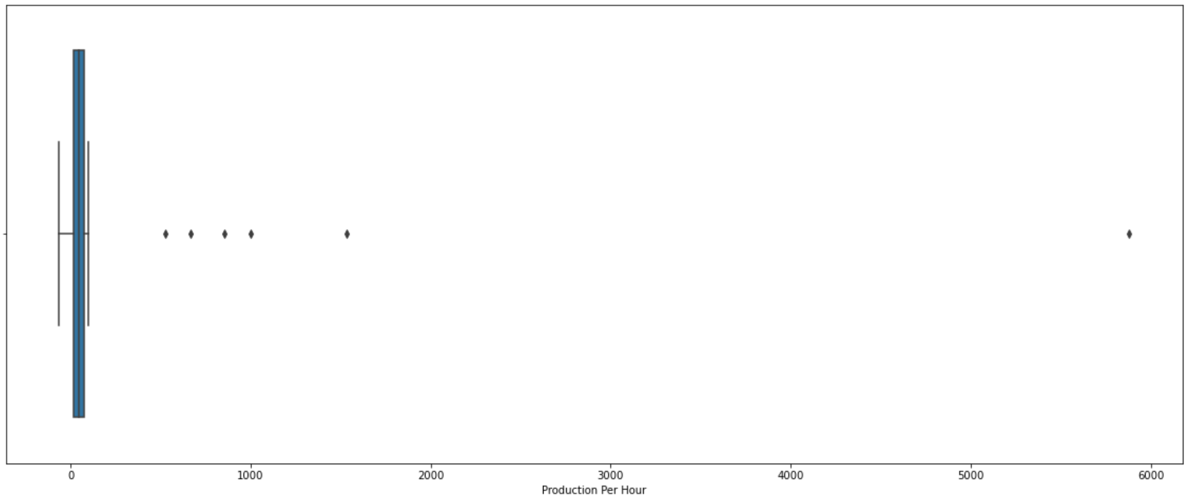
	Production Per Hour	Total Production	Year	Month	Day	Day_of_Week	Hour	Minu
count	499.000000	499.000000	499.0	499.000000	499.000000	499.000000	499.000000	499
mean	65.917836	18268.839679	2024.0	1.793587	13.004008	2.979960	11.474950	11
std	278.952637	8902.021523	0.0	0.405136	9.373550	2.001907	6.957767	(
min	-63.000000	77.000000	2024.0	1.000000	1.000000	0.000000	0.000000	11
25%	16.500000	11916.500000	2024.0	2.000000	6.000000	1.000000	5.000000	11
50%	46.000000	18970.000000	2024.0	2.000000	11.000000	3.000000	11.000000	11
75%	75.000000	25150.000000	2024.0	2.000000	16.000000	5.000000	18.000000	11
max	5879.000000	32893.000000	2024.0	2.000000	31.000000	6.000000	23.000000	11

Observation

There are outliers in 'Production Per Hour' feature.

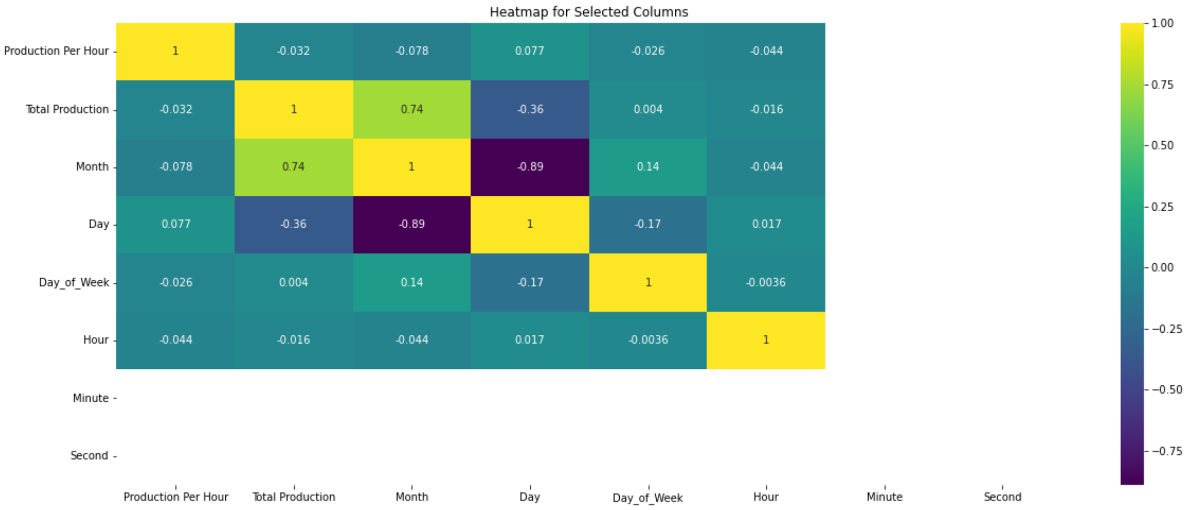
In [333…
```
# Checking outliers for 'Production Per Hour' feature using boxplot

plt.figure(figsize=(20, 8))
```

```
sns.boxplot(x='Production Per Hour', data=df)
plt.show()
```



In [334…

```
# Creating heat map

selected_columns = ['Production Per Hour', 'Total Production', 'Month', 'Day', 'Day

plt.figure(figsize=(20, 8))
sns.heatmap(df[selected_columns].corr(), annot=True, cmap='viridis')
plt.title('Heatmap for Selected Columns')
plt.show()
```



In [335…

```
# Checking Missing Values

df.isna().sum()
```

Out[335]:

```
Production Per Hour    0
Total Production       0
Year                   0
Month                  0
Day                    0
Day_of_Week            0
Hour                   0
Minute                 0
Second                 0
dtype: int64
```

Observation :

- 1. There are no any highly correlated feature which is greater than 0.9.

- 1. There are no any missing values in dataset

Feature Engineering

Train Test Split

In [336…
```
X = df.drop(['Total Production'],axis=1)
y = df['Total Production']
```

In [337…
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.3, random_stat
```

In [338…
```
X_train.shape
```

Out[338]:
```
(349, 8)
```

In [339…
```
X_test.shape
```

Out[339]:
```
(150, 8)
```

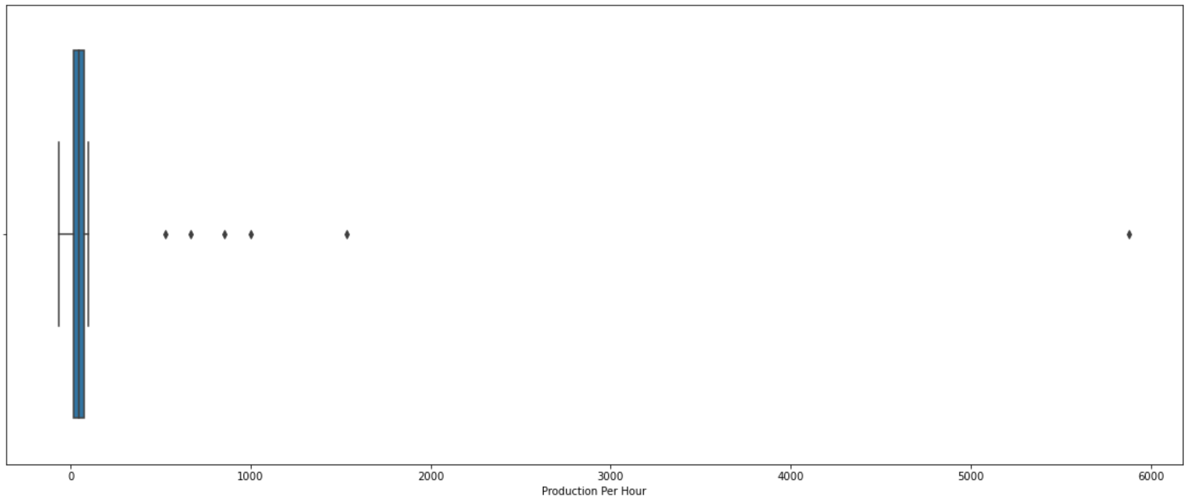
Problem No. 1

To detect anamolies/outliers in 'Production Per Hour' feature and treat them.

Detecting of outlier :- Using Box Plot

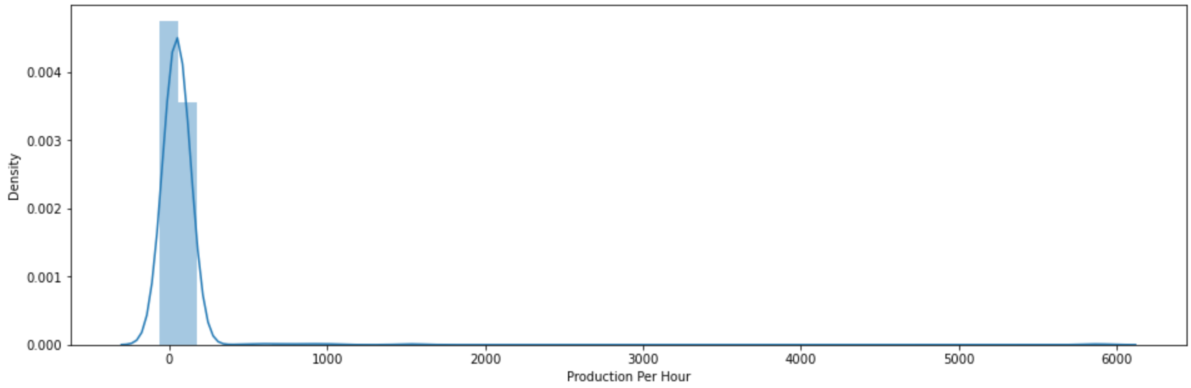
Treatment for outlier :- Capping

In [340…
```
# Checking outliers for 'Production Per Hour' feature using boxplot

plt.figure(figsize=(20,8))
sns.boxplot(x='Production Per Hour', data=df)
plt.show()
```



In [341…
```
plt.figure(figsize=(16,5))
sns.distplot(df['Production Per Hour'])
```

Out[341]:
```
<AxesSubplot:xlabel='Production Per Hour', ylabel='Density'>
```



Observation:-

As we can see 'Production Per Hour' follows skewed distribution, hence we will use upper limit and lower limit using IQR method to cap the outliers.

In [342...

```
# Calculating 25th and 75th percentile

percentile25 = X_train['Production Per Hour'].quantile(0.25)
percentile75 = X_train['Production Per Hour'].quantile(0.75)
```

In [343...

```
# Calculating IQR

IQR = percentile75 - percentile25
```

In [344...

```
IQR
```

Out[344]:

```
61.0
```

In [345...

```
upper_limit = percentile75 + 1.5 * IQR
lower_limit = percentile25 - 1.5 * IQR
```

In [346...

```
print('Upper_limit',upper_limit)
print('Lower_limit',lower_limit)
```

```
Upper_limit 168.5
Lower_limit -75.5
```

Finding Outliers

In [347...

```
X_train[X_train['Production Per Hour'] > upper_limit]
```

Out[347]:

	Production Per Hour	Year	Month	Day	Day_of_Week	Hour	Minute	Second
184	1532	2024	2	4	6	9	11	44
62	5879	2024	1	30	1	7	11	44
21	1002	2024	1	28	6	14	11	44
151	526	2024	2	3	5	0	11	44

In [348...

```
X_train[X_train['Production Per Hour'] < lower_limit]
```

Out[348]:

Production Per Hour	Year	Month	Day	Day_of_Week	Hour	Minute	Second

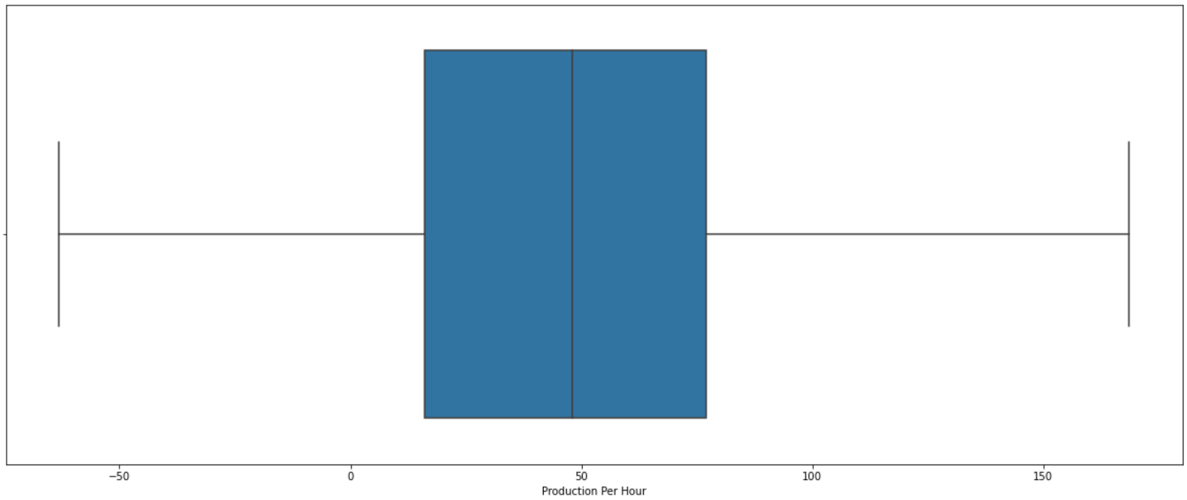
Capping the anamolies/outliers

In [349...

```
X_train['Production Per Hour'] = np.where(
   X_train['Production Per Hour'] > upper_limit,
   upper_limit,

   np.where(
      X_train['Production Per Hour'] < lower_limit,
      lower_limit,
      X_train['Production Per Hour']
   )

)
```

In [350...

```
# Checking outliers for 'Production Per Hour' feature using boxplot after capping

plt.figure(figsize=(20,8))
sns.boxplot(x='Production Per Hour', data=X_train)
plt.show()
```



Problem No. 2 :

Model Training

In [351...

```
def train_test_models(models, X_train, X_test, y_train, y_test):
    r2_scores = {}

    for model_name, model in models.items():

        model.fit(X_train, y_train)

        r2 = r2_score(y_test, model.predict(X_test))

        r2_scores[model_name] = r2

        print(f"{model_name} R2 Score: {r2}")

    return r2_scores
```

In [352...

```
models = {
    'Decision Tree':DecisionTreeRegressor(),
```

```
    'Random Forest':RandomForestRegressor()
}
```

In [353…

```
results = train_test_models(models, X_train, X_test, y_train, y_test)
```

```
Decision Tree R2 Score: 0.9998756544197035
Random Forest R2 Score: 0.99956006932605
```

Observation:-

We are getting 0.99 r2 score for both models

Hyperparametr Tunning

In [354…

```
def hyperparameter_tuning(models, param_grids, X_train, X_test, y_train, y_test):
    best_params = {}
    best_scores = {}

    for model_name, model in models.items():
        param_grid = param_grids[model_name]

        grid_search = GridSearchCV(model, param_grid, scoring='r2', cv=5)
        grid_search.fit(X_train, y_train)

        best_params[model_name] = grid_search.best_params_
        best_scores[model_name] = grid_search.best_score_

        best_estimator = grid_search.best_estimator_
        test_predictions = best_estimator.predict(X_test)
        test_score = r2_score(y_test, test_predictions)

        print(f"{model_name} - Best Parameters: {best_params[model_name]}")
        print(f"{model_name} - Best r2 Score: {best_scores[model_name]}")
        print(f"{model_name} - Test Score: {test_score}\n")

    return best_params, best_scores
```

In [355…

```
param_grids = {
    'Decision Tree': {
        'criterion': ['mse', 'mae'],
        'max_depth': [None, 5, 10, 15],
        'min_samples_split': [2, 5, 10]
    },
    'Random Forest': {
        'n_estimators': [50, 100, 150],
        'criterion': ['mse', 'mae'],
        'max_depth': [None, 5, 10, 15],
        'min_samples_split': [2, 5, 10]
    }
}
```

In [356…

```
best_params, best_scores = hyperparameter_tuning(models, param_grids, X_train, X_te
```

```
Decision Tree - Best Parameters: {'criterion': 'mse', 'max_depth': 10, 'min_sample
s_split': 2}
Decision Tree - Best r2 Score: 0.9986768282159989
Decision Tree - Test Score: 0.9998566041718395

Random Forest - Best Parameters: {'criterion': 'mae', 'max_depth': None, 'min_samp
les_split': 2, 'n_estimators': 150}
Random Forest - Best r2 Score: 0.9987925711595385
Random Forest - Test Score: 0.9995921472740097
```

Observation :

Both models are giving good prediction

Thank You For Going Through This Notebook 🤩