In [ ]:
```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, AdaB
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
import xgboost as xgb
from catboost import CatBoostRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import warnings
```

In [ ]:
```
df=pd.read_csv('data/crop_production.csv')
```

In [ ]:
```
df.head(5)
```

Out[ ]:

	index	LOCATION	INDICATOR	SUBJECT	MEASURE	FREQUENCY	TIME	Value	Fl Cod
0	0	AUS	CROPYIELD	RICE	TONNE_HA	A	1990	8.314607	Na
1	1	AUS	CROPYIELD	RICE	TONNE_HA	A	1991	8.394737	Na
2	2	AUS	CROPYIELD	RICE	TONNE_HA	A	1992	8.094340	Na
3	3	AUS	CROPYIELD	RICE	TONNE_HA	A	1993	8.336000	Na
4	4	AUS	CROPYIELD	RICE	TONNE_HA	A	1994	8.537815	Na

In [ ]:
```
new_data=df.drop(['index', 'INDICATOR', 'FREQUENCY','Flag Codes'], axis=1)
```

In [ ]:
```
new_data
```

Out[ ]:

	LOCATION	SUBJECT	MEASURE	TIME	Value
0	AUS	RICE	TONNE_HA	1990	8.314607
1	AUS	RICE	TONNE_HA	1991	8.394737
2	AUS	RICE	TONNE_HA	1992	8.094340
3	AUS	RICE	TONNE_HA	1993	8.336000
4	AUS	RICE	TONNE_HA	1994	8.537815
...	...	...	...	...	...
20561	OECD	SOYBEAN	THND_HA	2021	37010.208830
20562	OECD	SOYBEAN	THND_HA	2022	37069.214850
20563	OECD	SOYBEAN	THND_HA	2023	37143.459750
20564	OECD	SOYBEAN	THND_HA	2024	37013.651900
20565	OECD	SOYBEAN	THND_HA	2025	37041.401580

20566 rows × 5 columns

In [ ]:

```
new_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20566 entries, 0 to 20565
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   LOCATION  20566 non-null  object 
 1   SUBJECT   20566 non-null  object 
 2   MEASURE   20566 non-null  object 
 3   TIME      20566 non-null  int64  
 4   Value     20566 non-null  float64
dtypes: float64(1), int64(1), object(3)
memory usage: 803.5+ KB
```

In [ ]:

```
new_data.isnull().sum()
```

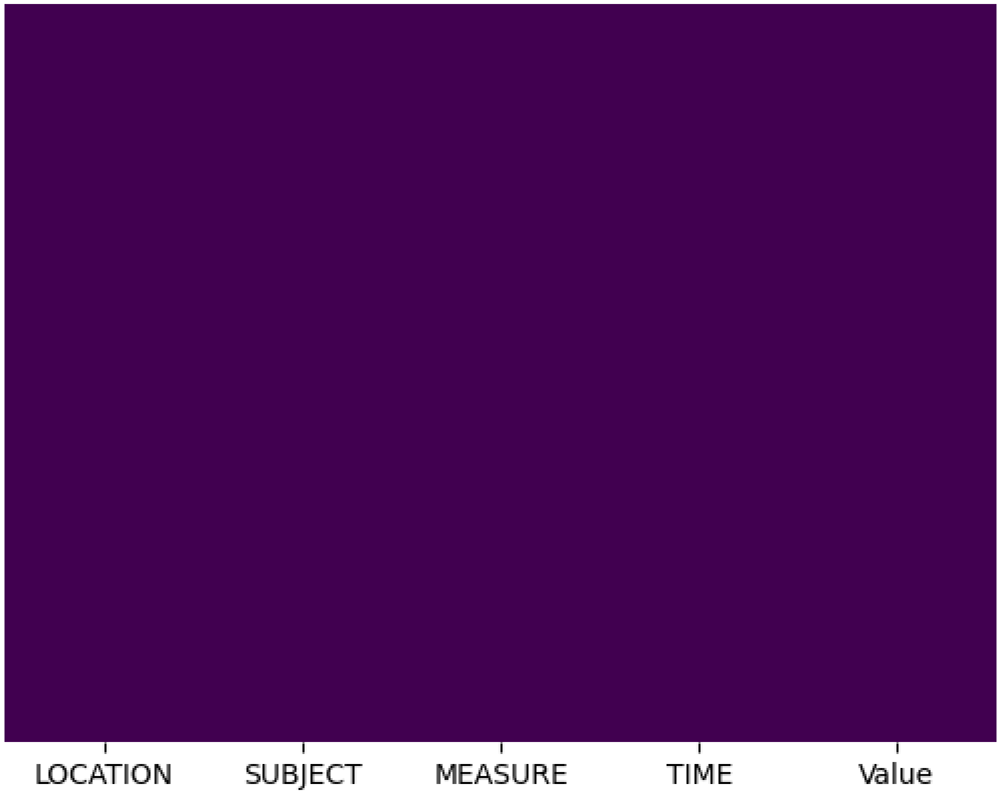
Out[ ]:

```
LOCATION    0
SUBJECT     0
MEASURE     0
TIME        0
Value       0
dtype: int64
```

In [ ]:

```
sns.heatmap(data=new_data.isnull(), cbar=False, yticklabels=False, cmap='viridis')
```

Out[ ]: <Axes: >



This shows no missing data

Perparing X and y

In [ ]:
```
X=new_data.drop(columns='Value', axis=1)
```

In [ ]:
```
X
```

Out[ ]:

	LOCATION	SUBJECT	MEASURE	TIME
0	AUS	RICE	TONNE_HA	1990
1	AUS	RICE	TONNE_HA	1991
2	AUS	RICE	TONNE_HA	1992
3	AUS	RICE	TONNE_HA	1993
4	AUS	RICE	TONNE_HA	1994
...	...	...	...	...
20561	OECD	SOYBEAN	THND_HA	2021
20562	OECD	SOYBEAN	THND_HA	2022
20563	OECD	SOYBEAN	THND_HA	2023
20564	OECD	SOYBEAN	THND_HA	2024
20565	OECD	SOYBEAN	THND_HA	2025

20566 rows × 4 columns

In [ ]:
```
y=new_data['Value']
```

In [ ]:
```
y
```

Out[ ]:
```
0            8.314607
1            8.394737
2            8.094340
3            8.336000
4            8.537815
               ...
20561    37010.208830
20562    37069.214850
20563    37143.459750
20564    37013.651900
20565    37041.401580
Name: Value, Length: 20566, dtype: float64
```

In [ ]:
```
# representing y in a dataframe
y=pd.DataFrame(y)
```

In [ ]:
```
y
```

Out[ ]:

	Value
0	8.314607
1	8.394737
2	8.094340
3	8.336000
4	8.537815
...	...
20561	37010.208830
20562	37069.214850
20563	37143.459750
20564	37013.651900
20565	37041.401580

20566 rows × 1 columns

Identifying categorical and numeric features

In [ ]:
```
categorical_cols = X.select_dtypes(include=['object', 'category']).columns.tolist()
numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns.tolist()  #
```

In [ ]:
```
categorical_cols
```

Out[ ]:
```
['LOCATION', 'SUBJECT', 'MEASURE']
```

In [ ]:
```
numerical_cols
```

Out[ ]:
```
['TIME']
```

Creating the transformer pipeline

In [ ]:
```
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols),  # One-h
        ('num', MinMaxScaler(), numerical_cols)  # Scale numerical features
    ]
)
```

Creating models and parameter tuning

In [ ]:
```
model_params = {
    'Linear Regression': {
        'model': LinearRegression(),
        'params': {}
    },
    'Ridge Regression': {
        'model': Ridge(),
        'params': {'model__alpha': [0.1, 1.0, 10.0, 100.0]}
    },
    'Lasso Regression': {
        'model': Lasso(),
        'params': {'model__alpha': [0.01, 0.1, 1.0, 10.0]}
    },
    'ElasticNet Regression': {
        'model': ElasticNet(),
        'params': {'model__alpha': [0.1, 1.0, 10.0], 'model__l1_ratio': [0.1, 0.5,
    },
    'Decision Tree': {
        'model': DecisionTreeRegressor(),
        'params': {'model__max_depth': [3, 5, 10, None], 'model__min_samples_split'
    },
    'Random Forest': {
        'model': RandomForestRegressor(),
        'params': {'model__n_estimators': [50, 100, 200], 'model__max_depth': [3, 5
    },
    'AdaBoost': {
        'model': AdaBoostRegressor(),
        'params': {'model__n_estimators': [50, 100, 200], 'model__learning_rate': [
    },
    'SVR': {
        'model': SVR(),
        'params': {'model__C': [0.1, 1, 10], 'model__kernel': ['linear', 'rbf']}
    },
    'KNN': {
        'model': KNeighborsRegressor(),
        'params': {'model__n_neighbors': [3, 5, 7, 9], 'model__weights': ['uniform'
    },
    'Gradient Boosting': {
        'model': GradientBoostingRegressor(),
        'params': {'model__n_estimators': [50, 100, 200], 'model__learning_rate': [
    },
    'XGBoost': {
        'model': xgb.XGBRegressor(),
        'params': {'model__n_estimators': [50, 100, 200], 'model__learning_rate': [
    },
    'CatBoost': {
        'model': CatBoostRegressor(verbose=0),  # Disable verbose output for CatBoo
        'params': {'model__iterations': [50, 100, 200], 'model__learning_rate': [0.
    }
}
```

Setting up pipe line for hyper parameter tunning using gridsearch cv

In [ ]:
```
# Set up Pipelines and Perform Hyperparameter Tuning using GridSearchCV
best_models = {}
for model_name, mp in model_params.items():
    pipeline = Pipeline(steps=[
        ('preprocessor', preprocessor),  # Apply preprocessing
        ('model', mp['model'])  # Model-specific step
    ])

    grid_search = GridSearchCV(pipeline, mp['params'], cv=5, scoring='neg_mean_squa
    grid_search.fit(X, y)

    best_models[model_name] = grid_search.best_estimator_
    print(f"{model_name} Best Params: {grid_search.best_params_}")
```

```
Linear Regression Best Params: {}
Ridge Regression Best Params: {'model__alpha': 10.0}
Lasso Regression Best Params: {'model__alpha': 10.0}
ElasticNet Regression Best Params: {'model__alpha': 0.1, 'model__l1_ratio': 0.9}
Decision Tree Best Params: {'model__max_depth': None, 'model__min_samples_split': 1
0}
Random Forest Best Params: {'model__max_depth': None, 'model__n_estimators': 100}
AdaBoost Best Params: {'model__learning_rate': 0.01, 'model__n_estimators': 200}
SVR Best Params: {'model__C': 10, 'model__kernel': 'linear'}
KNN Best Params: {'model__n_neighbors': 5, 'model__weights': 'distance'}
Gradient Boosting Best Params: {'model__learning_rate': 0.1, 'model__max_depth': 3,
'model__n_estimators': 100}
XGBoost Best Params: {'model__learning_rate': 0.5, 'model__max_depth': 5, 'model__n_
estimators': 100}
CatBoost Best Params: {'model__depth': 3, 'model__iterations': 200, 'model__learning
_rate': 0.5}
```

In [ ]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [ ]:
```
# Make Predictions with the Best Tuned Models
predictions = {name: model.predict(X_test) for name, model in best_models.items()}
```

In [ ]:
```
#Evaluate Accuracy using MAE, MSE, RMSE, R²
results = {}
```

In [ ]:
```
for name, pred in predictions.items():
    mae = mean_absolute_error(y_test, pred)
    mse = mean_squared_error(y_test, pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, pred)
    accuracy_percentage = r2 * 100  # Convert R² to percentage
    results[name] = {'MAE': mae, 'MSE': mse, 'RMSE': rmse, 'R²': r2,'Accuracy (%)':
```

In [ ]:
```
# Display results and select the best model
print("\nModel Performance after Hyperparameter Tuning:")
for model_name, metrics in results.items():
    print(f"{model_name}: MAE: {metrics['MAE']:.4f}, MSE: {metrics['MSE']:.4f}, RMS
```

```
Model Performance after Hyperparameter Tuning:
Linear Regression: MAE: 18859.1114, MSE: 2067952989.8716, RMSE: 45474.7511, R²: 0.38
96, Accuracy: 38.96%

Ridge Regression: MAE: 18723.0167, MSE: 2066125204.2962, RMSE: 45454.6500, R²: 0.390
1, Accuracy: 39.01%

Lasso Regression: MAE: 18800.1005, MSE: 2068570162.9068, RMSE: 45481.5365, R²: 0.389
4, Accuracy: 38.94%

ElasticNet Regression: MAE: 17507.6508, MSE: 2179778008.0420, RMSE: 46688.0928, R²:
0.3566, Accuracy: 35.66%

Decision Tree: MAE: 370.2604, MSE: 3990724.6579, RMSE: 1997.6798, R²: 0.9988, Accura
cy: 99.88%

Random Forest: MAE: 162.6405, MSE: 984527.5446, RMSE: 992.2336, R²: 0.9997, Accurac
y: 99.97%

AdaBoost: MAE: 13070.0162, MSE: 1011475681.1946, RMSE: 31803.7055, R²: 0.7014, Accur
acy: 70.14%

SVR: MAE: 12289.3711, MSE: 3491862384.4853, RMSE: 59091.9824, R²: -0.0307, Accuracy:
-3.07%

KNN: MAE: 0.0000, MSE: 0.0000, RMSE: 0.0000, R²: 1.0000, Accuracy: 100.00%

Gradient Boosting: MAE: 6431.3492, MSE: 277686396.1003, RMSE: 16663.9250, R²: 0.918
0, Accuracy: 91.80%

XGBoost: MAE: 860.3780, MSE: 5061240.1444, RMSE: 2249.7200, R²: 0.9985, Accuracy: 9
9.85%

CatBoost: MAE: 5851.8358, MSE: 197088812.5506, RMSE: 14038.8323, R²: 0.9418, Accurac
y: 94.18%
```

We will choose XGBoost cause it does not overfit

Creating a pipeline for xgboost

In [ ]:
```
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),  # Preprocessing steps
    ('model', xgb.XGBRegressor(objective='reg:squarederror'))  # XGBoost model
])
```

In [ ]:
```
param_grid = {
    'model__n_estimators': [50, 100, 200],
    'model__learning_rate': [0.01, 0.1, 0.5],
```

```
    'model__max_depth': [3, 5, 10],
    'model__subsample': [0.7, 0.8, 1.0],
    'model__colsample_bytree': [0.7, 0.8, 1.0]
}
```

In [ ]:
```
grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='neg_mean_squared_er
```

In [ ]:
```
grid_search.fit(X_train, y_train)
```

Out[ ]:

```
GridSearchCV
estimator: Pipeline
preprocessor: ColumnTransformer
cat                num
OneHotEncoder      MinMaxScaler
XGBRegressor
```

In [ ]:
```
best_xgb_model = grid_search.best_estimator_
best_params = grid_search.best_params_

print(f"Best XGBoost Parameters: {best_params}")
```

```
Best XGBoost Parameters: {'model__colsample_bytree': 1.0, 'model__learning_rate': 0.
1, 'model__max_depth': 10, 'model__n_estimators': 200, 'model__subsample': 0.7}
```

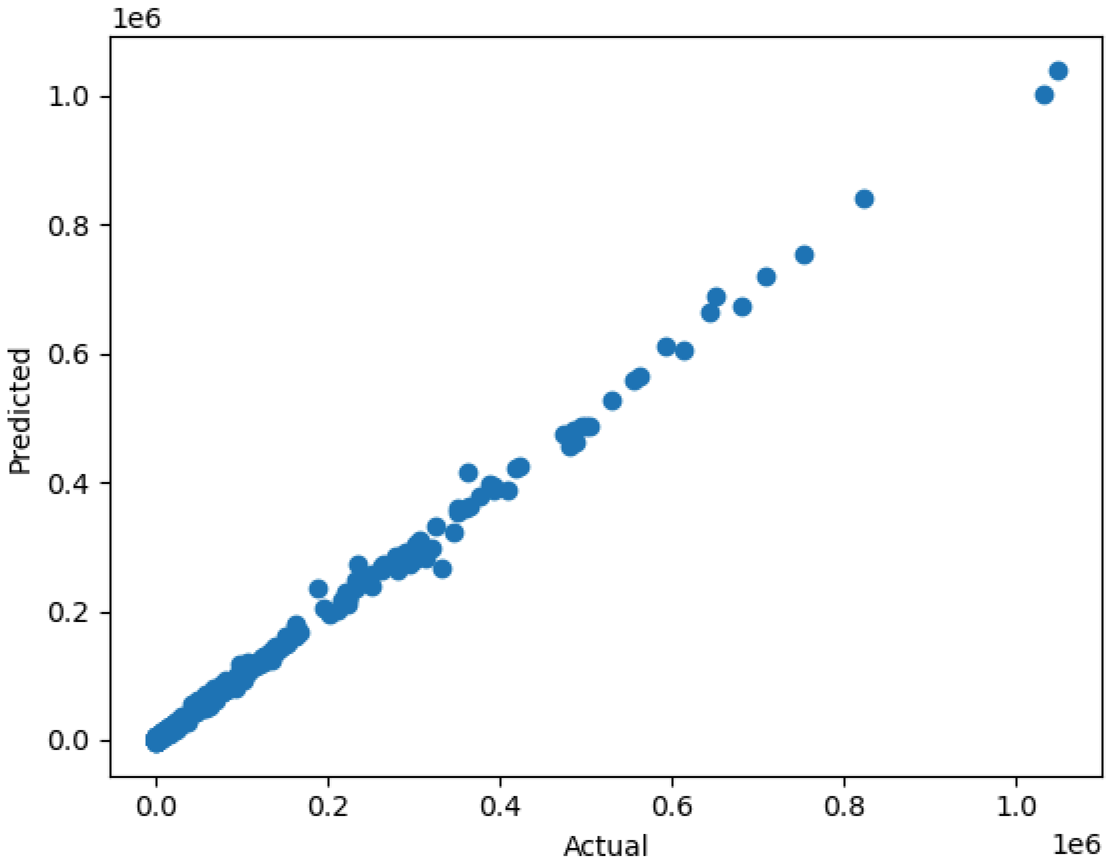
In [ ]:
```
y_pred = best_xgb_model.predict(X_test)
```

In [ ]:
```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
```

In [ ]:
```
print(f"Mean Absolute Error: {mae:.4f}")
print(f"Mean Squared Error: {mse:.4f}")
print(f"Root Mean Squared Error: {rmse:.4f}")
print(f"R² Score: {r2:.4f}")
```

```
Mean Absolute Error: 621.8347
Mean Squared Error: 6917015.9369
Root Mean Squared Error: 2630.0220
R² Score: 0.9980
```

In [ ]:
```
plt.scatter(y_test,y_pred);
plt.xlabel('Actual');
plt.ylabel('Predicted');
```


1e6
1.0
0.8
0.6
0.4
0.2
0.0
Predicted
0.0
0.2
0.4
0.6
0.8
1.0
Actual
1e6