Wild BlueBerry Yield Predictions

Submissions will be evaluated using Mean Absolute Error (MAE)

In [1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/playground-series-s3e14/sample_submission.csv
/kaggle/input/playground-series-s3e14/train.csv
/kaggle/input/playground-series-s3e14/test.csv
```

In [2]:
```
import warnings
warnings.filterwarnings('ignore')

import matplotlib.pyplot as plt
import seaborn as sns
```

Reading the dataset

In [3]:
```
df = pd.read_csv('/kaggle/input/playground-series-s3e14/train.csv')
test = pd.read_csv('/kaggle/input/playground-series-s3e14/test.csv')
df.head(10)
```

Out[3]:

	id	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange	MinOfUpperT
0	0	25.0	0.50	0.25	0.75	0.50	69.7	
1	1	25.0	0.50	0.25	0.50	0.50	69.7	
2	2	12.5	0.25	0.25	0.63	0.63	86.0	
3	3	12.5	0.25	0.25	0.63	0.50	77.4	
4	4	25.0	0.50	0.25	0.63	0.63	77.4	
5	5	25.0	0.50	0.25	0.63	0.75	94.6	
6	6	12.5	0.25	0.38	0.50	0.63	86.0	
7	7	12.5	0.25	0.25	0.75	0.75	86.0	
8	8	25.0	0.50	0.38	0.38	0.75	94.6	
9	9	25.0	0.50	0.25	0.63	0.63	94.6	

Exploratory Data Analysis

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In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15289 entries, 0 to 15288
Data columns (total 18 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   id                    15289 non-null  int64  
 1   clonesize             15289 non-null  float64
 2   honeybee              15289 non-null  float64
 3   bumbles               15289 non-null  float64
 4   andrena               15289 non-null  float64
 5   osmia                 15289 non-null  float64
 6   MaxOfUpperTRange      15289 non-null  float64
 7   MinOfUpperTRange      15289 non-null  float64
 8   AverageOfUpperTRange  15289 non-null  float64
 9   MaxOfLowerTRange      15289 non-null  float64
 10  MinOfLowerTRange      15289 non-null  float64
 11  AverageOfLowerTRange  15289 non-null  float64
 12  RainingDays           15289 non-null  float64
 13  AverageRainingDays    15289 non-null  float64
 14  fruitset              15289 non-null  float64
 15  fruitmass             15289 non-null  float64
 16  seeds                 15289 non-null  float64
 17  yield                 15289 non-null  float64
dtypes: float64(17), int64(1)
memory usage: 2.1 MB
```

In [5]:
```
df.describe().T
```

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Out[5]:

	count	mean	std	min	25%	
id	15289.0	7644.000000	4413.698468	0.000000	3822.000000	76
clonesize	15289.0	19.704690	6.595211	10.000000	12.500000	
honeybee	15289.0	0.389314	0.361643	0.000000	0.250000	
bumbles	15289.0	0.286768	0.059917	0.000000	0.250000	
andrena	15289.0	0.492675	0.148115	0.000000	0.380000	
osmia	15289.0	0.592355	0.139489	0.000000	0.500000	
MaxOfUpperTRange	15289.0	82.169887	9.146703	69.700000	77.400000	
MinOfUpperTRange	15289.0	49.673281	5.546405	39.000000	46.800000	
AverageOfUpperTRange	15289.0	68.656256	7.641807	58.200000	64.700000	
MaxOfLowerTRange	15289.0	59.229538	6.610640	50.200000	55.800000	
MinOfLowerTRange	15289.0	28.660553	3.195367	24.300000	27.000000	
AverageOfLowerTRange	15289.0	48.568500	5.390545	41.200000	45.800000	
RainingDays	15289.0	18.660865	11.657582	1.000000	16.000000	
AverageRainingDays	15289.0	0.324176	0.163905	0.060000	0.260000	
fruitset	15289.0	0.502741	0.074390	0.192732	0.458246	
fruitmass	15289.0	0.446553	0.037035	0.311921	0.419216	
seeds	15289.0	36.164950	4.031087	22.079199	33.232449	
yield	15289.0	6025.193999	1337.056850	1945.530610	5128.163510	61

In [6]:

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

Out[6]:

```
id                      0
clonesize               0
honeybee                0
bumbles                 0
andrena                 0
osmia                   0
MaxOfUpperTRange        0
MinOfUpperTRange        0
AverageOfUpperTRange    0
MaxOfLowerTRange        0
MinOfLowerTRange        0
AverageOfLowerTRange    0
RainingDays             0
AverageRainingDays      0
fruitset                0
fruitmass               0
seeds                   0
yield                   0
dtype: int64
```

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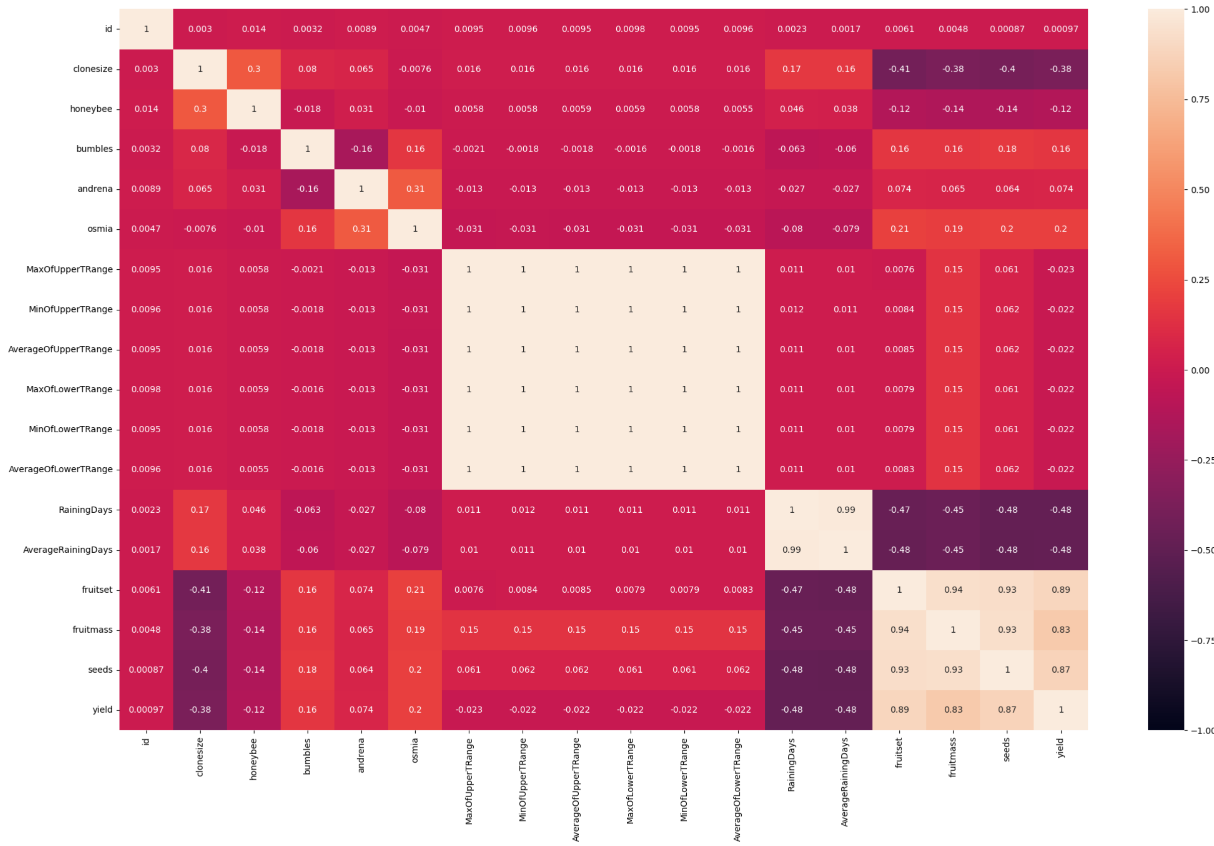
Out[7]: (15289, 18)

Learn some more exploratory vizualization for numerical variables

Feature selection using Correlation matrix

In [8]:
```python
f,ax = plt.subplots(figsize=(25,15))
sns.heatmap(df.corr(),annot=True,vmin=-1,vmax=1)
```

Out[8]: <AxesSubplot: >



There are few columns which has perfect co-linearity, Delete these columns

In [9]:
```python
corr_matrix = df.corr().abs()
upper_tri = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astyp
to_drop = [column for column in upper_tri.columns if any(upper_tri[column] >
df_new = df.drop(df[to_drop], axis=1)
test_new = test.drop(test[to_drop], axis=1)

df_new.head()
```

Out[9]:

	id	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange	RainingDays
0	0	25.0	0.50	0.25	0.75	0.50	69.7	24.0
1	1	25.0	0.50	0.25	0.50	0.50	69.7	24.0
2	2	12.5	0.25	0.25	0.63	0.63	86.0	24.0
3	3	12.5	0.25	0.25	0.63	0.50	77.4	24.0
4	4	25.0	0.50	0.25	0.63	0.63	77.4	24.0

Train Test Split

In [10]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(df_new.drop(['yield'],axis=
X_train.head()
```

Out[10]:

	id	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange	Raini
7794	7794	25.0	0.50	0.25	0.38	0.63	77.4	
2444	2444	25.0	0.50	0.25	0.63	0.50	86.0	
3931	3931	12.5	0.25	0.25	0.38	0.75	69.7	
15264	15264	12.5	0.25	0.25	0.63	0.50	86.0	
4323	4323	25.0	0.50	0.25	0.38	0.50	94.6	

1. Linear Regression

In [11]:

```
from sklearn.linear_model import LinearRegression

linreg = LinearRegression()

linreg.fit(X_train,y_train)

y_pred = linreg.predict(X_test)
```

In [12]:

```
from sklearn.metrics import mean_absolute_percentage_error
import math
from sklearn import metrics

mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

results = pd.DataFrame([['Linear Regression', mae, mape, mse, r2, rmse]], co
results
```

Out[12]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.06654	348539.25045	0.809118	590.372129

In [13]:

```
## 2. RidgeCV Regression

# from sklearn.linear_model import Ridge

# ridreg = Ridge(random_state=3)
# ridreg.fit(X_train,y_train)
# y_pred = ridreg.predict(X_test)

# mae = metrics.mean_absolute_error(y_test, y_pred)
# mape = mean_absolute_percentage_error(y_test, y_pred)
# mse = metrics.mean_squared_error(y_test, y_pred)
# r2 = metrics.r2_score(y_test, y_pred)
# rmse = math.sqrt(mse)

# temp_results = pd.DataFrame([['Ridge Regression', mae, mape, mse, r2, rmse
# results = pd.concat([results,temp_results], ignore_index=True)
# results
```

2. RidgeCV regession

In [14]:

```
from sklearn.linear_model import RidgeCV
alphas = [0.1,0.3,0.5,0.7,0.9,1.0]
ridregcv = RidgeCV(alphas = alphas)
ridregcv.fit(X_train,y_train)
y_pred = ridregcv.predict(X_test)
```

In [15]:

```
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['Ridge CV Regression', mae, mape, mse, r2, rms
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[15]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	348539.250450	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	348576.327256	0.809098	590.403529

3. Lasso Regression

In [16]:

```
from sklearn.linear_model import LassoCV

alphas = [0.1,0.3,0.5,0.7,0.9,1.0]
```

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```
lassocv = LassoCV(alphas=alphas,cv=10,random_state=3,)
lassocv.fit(X_train,y_train)
y_pred = lassocv.predict(X_test)
```

In [17]:
```
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['Lasso Regression', mae, mape, mse, r2, rmse]]
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[17]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	348539.250450	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	348576.327256	0.809098	590.403529
2	Lasso Regression	369.814016	0.066591	348717.957516	0.809020	590.523461

4.Elastic Net Regression

In [18]:
```
from sklearn.linear_model import ElasticNetCV
ela_reg = ElasticNetCV(cv =10,random_state =3)
ela_reg.fit(X_train,y_train)
y_pred = ela_reg.predict(X_test)
```

In [19]:
```
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['ElasticNetCV Regression', mae, mape, mse, r2,
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[19]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	348539.250450	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	348576.327256	0.809098	590.403529
2	Lasso Regression	369.814016	0.066591	348717.957516	0.809020	590.523461
3	ElasticNetCV Regression	724.442793	0.140578	876815.066589	0.519801	936.384038

5. Support Vector Regression

In [20]:
```
from sklearn.svm import SVR

svr_reg = SVR()
svr_reg.fit(X_train,y_train)
y_pred = svr_reg.predict(X_test)
```

In [21]:
```
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['Support Vector Regression', mae, mape, mse, r
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[21]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	3.485393e+05	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	3.485763e+05	0.809098	590.403529
2	Lasso Regression	369.814016	0.066591	3.487180e+05	0.809020	590.523461
3	ElasticNetCV Regression	724.442793	0.140578	8.768151e+05	0.519801	936.384038
4	Support Vector Regression	1101.513076	0.216331	1.844379e+06	-0.010097	1358.079187

6. Decision Tree Regression

In [22]:
```
from sklearn.tree import DecisionTreeRegressor
dt_reg = DecisionTreeRegressor(random_state=3)
dt_reg.fit(X_train,y_train)
y_pred = dt_reg.predict(X_test)
```

In [23]:
```
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['Decision Tree Regression', mae, mape, mse, r2
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[23]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	3.485393e+05	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	3.485763e+05	0.809098	590.403529
2	Lasso Regression	369.814016	0.066591	3.487180e+05	0.809020	590.523461
3	ElasticNetCV Regression	724.442793	0.140578	8.768151e+05	0.519801	936.384038
4	Support Vector Regression	1101.513076	0.216331	1.844379e+06	-0.010097	1358.079187
5	Decision Tree Regression	531.537727	0.093867	7.005332e+05	0.616344	836.978594

7. Random Forest Regression

In [24]:

```
from sklearn.ensemble import RandomForestRegressor
ranfor_reg = RandomForestRegressor(max_depth=2, random_state=3)
ranfor_reg.fit(X_train,y_train)
y_pred = ranfor_reg.predict(X_test)
```

In [25]:

```
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['Random Forest Regression', mae, mape, mse, r2
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[25]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	3.485393e+05	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	3.485763e+05	0.809098	590.403529
2	Lasso Regression	369.814016	0.066591	3.487180e+05	0.809020	590.523461
3	ElasticNetCV Regression	724.442793	0.140578	8.768151e+05	0.519801	936.384038
4	Support Vector Regression	1101.513076	0.216331	1.844379e+06	-0.010097	1358.079187
5	Decision Tree Regression	531.537727	0.093867	7.005332e+05	0.616344	836.978594
6	Random Forest Regression	476.724418	0.088170	4.650179e+05	0.745327	681.922238

8. Xgboost Regressor

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In [26]:
```
import xgboost as xgb
xbg_reg = xgb.XGBRegressor()
xbg_reg.fit(X_train,y_train)
y_pred = xbg_reg.predict(X_test)
```

In [27]:
```
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['XGB Regression', mae, mape, mse, r2, rmse]],
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[27]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	3.485393e+05	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	3.485763e+05	0.809098	590.403529
2	Lasso Regression	369.814016	0.066591	3.487180e+05	0.809020	590.523461
3	ElasticNetCV Regression	724.442793	0.140578	8.768151e+05	0.519801	936.384038
4	Support Vector Regression	1101.513076	0.216331	1.844379e+06	-0.010097	1358.079187
5	Decision Tree Regression	531.537727	0.093867	7.005332e+05	0.616344	836.978594
6	Random Forest Regression	476.724418	0.088170	4.650179e+05	0.745327	681.922238
7	XGB Regression	366.258016	0.065761	3.400084e+05	0.813790	583.102404

9. LightGBM Regression

In [28]:
```
from lightgbm import LGBMRegressor
lgb_reg = LGBMRegressor()
lgb_reg.fit(X_train,y_train)
y_pred = lgb_reg.predict(X_test)
```

In [29]:
```
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['LGBM Regressor', mae, mape, mse, r2, rmse]],
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[29]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	3.485393e+05	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	3.485763e+05	0.809098	590.403529
2	Lasso Regression	369.814016	0.066591	3.487180e+05	0.809020	590.523461
3	ElasticNetCV Regression	724.442793	0.140578	8.768151e+05	0.519801	936.384038
4	Support Vector Regression	1101.513076	0.216331	1.844379e+06	-0.010097	1358.079187
5	Decision Tree Regression	531.537727	0.093867	7.005332e+05	0.616344	836.978594
6	Random Forest Regression	476.724418	0.088170	4.650179e+05	0.745327	681.922238
7	XGB Regression	366.258016	0.065761	3.400084e+05	0.813790	583.102404
8	LGBM Regressor	352.459321	0.063037	3.237303e+05	0.822705	568.973006

10. CatBoost Regression

In [30]:

```
import catboost as cb
cb_reg = cb.CatBoostRegressor()
cb_reg.fit(X_train,y_train,verbose=False)
y_pred = cb_reg.predict(X_test)
```

In [31]:

```
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['CatBoost Regressor', mae, mape, mse, r2, rmse
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[31]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	3.485393e+05	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	3.485763e+05	0.809098	590.403529
2	Lasso Regression	369.814016	0.066591	3.487180e+05	0.809020	590.523461
3	ElasticNetCV Regression	724.442793	0.140578	8.768151e+05	0.519801	936.384038
4	Support Vector Regression	1101.513076	0.216331	1.844379e+06	-0.010097	1358.079187
5	Decision Tree Regression	531.537727	0.093867	7.005332e+05	0.616344	836.978594
6	Random Forest Regression	476.724418	0.088170	4.650179e+05	0.745327	681.922238
7	XGB Regression	366.258016	0.065761	3.400084e+05	0.813790	583.102404
8	LGBM Regressor	352.459321	0.063037	3.237303e+05	0.822705	568.973006
9	CatBoost Regressor	352.250722	0.063093	3.229476e+05	0.823134	568.284748

11. Decision Tree Regressor with GridSearchCV

In [32]:

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV

dtree = DecisionTreeRegressor()

param_grid = {
    'max_depth': [2, 4, 6, 8],
    'min_samples_split': [2, 4, 6, 8],
    'min_samples_leaf': [1, 2, 3, 4],
    'max_features': ['auto', 'sqrt', 'log2'],
    'random_state': [0, 42]
}

grid_search = GridSearchCV(dtree, param_grid, cv=5, scoring='neg_mean_square

grid_search.fit(X_train, y_train)
```

Out[32]:

```
▸ GridSearchCV
▸ estimator: DecisionTreeRegressor
    ▸ DecisionTreeRegressor
```

In [33]:

```
y_pred = grid_search.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
                 r2_score(y_test, y_pred)
```

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```
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['Decision Tree Regressor CV', mae, mape, mse,
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[33]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	3.485393e+05	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	3.485763e+05	0.809098	590.403529
2	Lasso Regression	369.814016	0.066591	3.487180e+05	0.809020	590.523461
3	ElasticNetCV Regression	724.442793	0.140578	8.768151e+05	0.519801	936.384038
4	Support Vector Regression	1101.513076	0.216331	1.844379e+06	-0.010097	1358.079187
5	Decision Tree Regression	531.537727	0.093867	7.005332e+05	0.616344	836.978594
6	Random Forest Regression	476.724418	0.088170	4.650179e+05	0.745327	681.922238
7	XGB Regression	366.258016	0.065761	3.400084e+05	0.813790	583.102404
8	LGBM Regressor	352.459321	0.063037	3.237303e+05	0.822705	568.973006
9	CatBoost Regressor	352.250722	0.063093	3.229476e+05	0.823134	568.284748
10	Decision Tree Regressor CV	366.877558	0.065821	3.457081e+05	0.810669	587.969481

SO,, after applying 10 Regression base models on our dataset, we can see that **LGBM Regressor** has performed the best, followed closely by **CatBoost Regressor**, and Linear Regression, Ridge Regression, Lasso Regression & XGB Regression also have fairly low score. So let's Tune Hyperparameters for all these regressions and find the best model

Hyper Parameter Tuning

CatBoost Regressor

In [ ]:

```
from catboost import CatBoostRegressor
from sklearn.model_selection import GridSearchCV

params = {
    'learning_rate': [0.01, 0.05, 0.1],
    'depth': [3, 5, 7],
    'l2_leaf_reg': [1, 3, 5],
    'iterations': [100, 200]
}
```

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```
model = CatBoostRegressor()
grid = GridSearchCV(estimator=model,param_grid=params,scoring='neg_mean_squa

# Set up the cross-validation scheme
cv = 5

# Train and evaluate the model with each combination of hyperparameters
grid.fit(X_train, y_train)

# Get the best hyperparameters from grid search and use them to train a fina
best_params = grid.best_params_
best_catboost = CatBoostRegressor(**best_params)
best_catboost.fit(X_train, y_train)
```

In [35]:

```
y_pred = best_catboost.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

temp_results = pd.DataFrame([['Best CatBoost Regression', mae, mape, mse, r2
results = pd.concat([results,temp_results], ignore_index=True)
results
```

Out[35]:

	Model	MAE	MAPE	MSE	R2	RMSE
0	Linear Regression	369.661843	0.066540	3.485393e+05	0.809118	590.372129
1	Ridge CV Regression	369.785828	0.066591	3.485763e+05	0.809098	590.403529
2	Lasso Regression	369.814016	0.066591	3.487180e+05	0.809020	590.523461
3	ElasticNetCV Regression	724.442793	0.140578	8.768151e+05	0.519801	936.384038
4	Support Vector Regression	1101.513076	0.216331	1.844379e+06	-0.010097	1358.079187
5	Decision Tree Regression	531.537727	0.093867	7.005332e+05	0.616344	836.978594
6	Random Forest Regression	476.724418	0.088170	4.650179e+05	0.745327	681.922238
7	XGB Regression	366.258016	0.065761	3.400084e+05	0.813790	583.102404
8	LGBM Regressor	352.459321	0.063037	3.237303e+05	0.822705	568.973006
9	CatBoost Regressor	352.250722	0.063093	3.229476e+05	0.823134	568.284748
10	Decision Tree Regressor CV	366.877558	0.065821	3.457081e+05	0.810669	587.969481
11	Best CatBoost Regression	351.511129	0.062874	3.229349e+05	0.823141	568.273597

Final Model

Catboost Regression

In [36]:
```
predictions = best_catboost.predict(test_new)

output = pd.DataFrame({'id': test.id, 'yield': predictions})
output.to_csv('submission.csv', index=False)
print("Your submission was successfully saved!")
```

```
Your submission was successfully saved!
```