

```
from google.colab import drive
drive.mount('/content/drive')
```

↗ Drive already mounted at /content/drive; to attempt to

✓ Importing the Data

```
import pandas as pd
from sklearn.model_selection import train_test_split, cross
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, mean_absolute
import shap
import numpy as np
from sklearn.decomposition import PCA
import seaborn as sns
import matplotlib.pyplot as plt
```

```
# Load the dataset
ql = pd.read_csv("/content/drive/My Drive/Business Analytic
ql
```

ValueError

ValueError

...



Please explain the error:

TypeError: unsupported operand typ



Hypothesis

The error message "TypeError: unsupported operand type(s) for -: 'NoneType' and 'int'" indicates that you're trying to subtract an integer (10 in this case) from a value that is `None`.

Looking at the traceback and your code, the error occurs in this line:

```
"max_depth": [best_params["max_d
```

[Use code with caution](#)

This line is attempting to create a list of values for the `max_depth` parameter in your Grid Search. The problem is that `best_params["max_depth"]` might be `None` (as indicated by the error).

This happens when the `RandomizedSearchCV` in the previous step determined that the best value for `max_depth` is `None` (which means unlimited depth for the Random Forest).

Suggested Changes

```
param_grid = {
    "n_estimators": [best_params
    "max_depth": [None, best_par
    "min_samples_split": [best_p
    "min_samples_leaf": [best_pa
    "max_features": [best_params
```



	country	Purchasing Power Value	Purchasing Power Category	Safety Value	Safety Category
0	Afghanistan	32.15	'Very Low'	25.33	'Low'
1	Aland Islands	125.01	'Very High'	71.81	'High'
2	Albania	42.82	'Low'	55.52	'Moderate'
3	Alderney	0.00	NaN	83.79	'Very High'
4	Algeria	27.60	'Very Low'	47.54	'Moderate'
...
231	Wallis And Futuna	0.00	NaN	0.00	NaN
232	Western Sahara	0.00	NaN	62.87	'High'
233	Yemen	20.74	'Very Low'	34.07	'Low'
234	Zambia	22.32	'Very Low'	54.39	'Moderate'
235	Zimbabwe	28.76	'Very Low'	39.31	'Low'

236 rows × 19 columns



Next steps:


Generate code with q1

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✓ Data Preprocessing

```
q1.info()
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 236 entries, 0 to 235
Data columns (total 19 columns):
#   Column                                Non-Null Count
---  -
0   country                             236 non-null
1   Purchasing Power Value              236 non-null
2   Purchasing Power Category           190 non-null
3   Safety Value                        236 non-null
4   Safety Category                     234 non-null
```

```
"bootstrap": [best_params["b
}



Use code with caution

Explanation of Changes:

1. Conditional Logic for
max_depth :

    ◦ We use an inline if
      statement to handle the
      case where
      best_params["max_depth"
      is None .
    ◦ If
      best_params["max_depth"
      is None , the list will
      include None ,
      best_params["max_depth"
      None .
    ◦ If it's not None , it'll
      perform the addition ( +
      10 ), ensuring the code
      doesn't try to subtract
      from None .
```

► Sources

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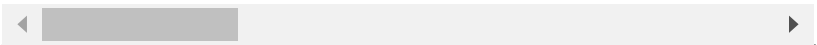
```
5 Health Care Value 236 non-null
6 Health Care Category 221 non-null
7 Climate Value 236 non-null
8 Climate Category 114 non-null
9 Cost of Living Value 236 non-null
10 Cost of Living Category 191 non-null
11 Property Price to Income Value 236 non-null
12 Property Price to Income Category 215 non-null
13 Traffic Commute Time Value 236 non-null
14 Traffic Commute Time Category 207 non-null
15 Pollution Value 236 non-null
16 Pollution Category 226 non-null
17 Quality of Life Value 236 non-null
18 Quality of Life Category 114 non-null
dtypes: float64(7), object(12)
memory usage: 35.2+ KB
```

```
ql['Quality of Life Value'] = ql['Quality of Life Value'].str.strip()
# Removing '' from data in categorical column
categorical_columns = ['Purchasing Power Category', 'Safety Category',
                       'Climate Category', 'Cost of Living Category',
                       'Traffic Commute Time Category', 'Pollution Category']
for col in categorical_columns:
    ql[col] = ql[col].str.replace("", "", regex=True)
ql
```



	country	Purchasing Power Value	Purchasing Power Category	Safety Value	Safe Catego
0	Afghanistan	32.15	Very Low	25.33	L
1	Aland Islands	125.01	Very High	71.81	Hi
2	Albania	42.82	Low	55.52	Moder
3	Alderney	0.00	NaN	83.79	Very Hi
4	Algeria	27.60	Very Low	47.54	Moder
...	
231	Wallis And Futuna	0.00	NaN	0.00	N
232	Western Sahara	0.00	NaN	62.87	Hi
233	Yemen	20.74	Very Low	34.07	L
234	Zambia	22.32	Very Low	54.39	Moder
235	Zimbabwe	28.76	Very Low	39.31	L

236 rows × 19 columns



Next

steps:

Generate code with q1



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```
q1['Property Price to Income Value'] = pd.to_numeric(q1['Pr
q1['Quality of Life Value'] = pd.to_numeric(q1['Quality of
```

```
q1.info()
```



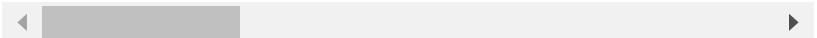
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 236 entries, 0 to 235
Data columns (total 19 columns):
#   Column                                Non-Null Count
---  -----
0   country                             236 non-null
1   Purchasing Power Value               236 non-null
2   Purchasing Power Category           190 non-null
3   Safety Value                         236 non-null
4   Safety Category                     234 non-null
5   Health Care Value                   236 non-null
6   Health Care Category                221 non-null
7   Climate Value                       236 non-null
8   Climate Category                    114 non-null
9   Cost of Living Value                 236 non-null
10  Cost of Living Category              191 non-null
11  Property Price to Income Value       233 non-null
```

```
12 Property Price to Income Category 215 non-null
13 Traffic Commute Time Value         236 non-null
14 Traffic Commute Time Category      207 non-null
15 Pollution Value                    236 non-null
16 Pollution Category                 226 non-null
17 Quality of Life Value               236 non-null
18 Quality of Life Category            114 non-null
dtypes: float64(9), object(10)
memory usage: 35.2+ KB
```

ql.head()



	country	Purchasing Power Value	Purchasing Power Category	Safety Value	Safety Category
0	Afghanistan	32.15	Very Low	25.33	Low
1	Aland Islands	125.01	Very High	71.81	High
2	Albania	42.82	Low	55.52	Moderate
3	Alderney	0.00	NaN	83.79	Very High
4	Algeria	27.60	Very Low	47.54	Moderate



Next steps:

Generate code with ql

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▼ Data Cleaning

ql.isnull().sum()



	0
country	0
Purchasing Power Value	0
Purchasing Power Category	46
Safety Value	0
Safety Category	2
Health Care Value	0
Health Care Category	15
Climate Value	0
Climate Category	122
Cost of Living Value	0
Cost of Living Category	45
Property Price to Income Value	3
Property Price to Income Category	21
Traffic Commute Time Value	0
Traffic Commute Time Category	29
Pollution Value	0
Pollution Category	10
Quality of Life Value	0
Quality of Life Category	122



Using KNN Imputer to handling missing value in numerical and categorical variable

```

from sklearn.impute import KNNImputer
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer

# Select the numerical and categorical columns to be impute
numeric_columns = ['Purchasing Power Value', 'Safety Value'
                   'Climate Value', 'Cost of Living Value',
                   'Traffic Commute Time Value', 'Pollution Value']

# Scaling the numerical data
scaler = StandardScaler()
ql[numeric_columns] = scaler.fit_transform(ql[numeric_columns])

```

```
# Using KNN Imputer to replace missing values in numeric columns
imputer_numeric = KNNImputer(n_neighbors=5) # Menggunakan
ql[numeric_columns] = imputer_numeric.fit_transform(ql[numeric_columns])

# Impute missing values in a categorical column with mode (most frequent)
imputer_categorical = SimpleImputer(strategy='most_frequent')
ql[categorical_columns] = imputer_categorical.fit_transform(ql[categorical_columns])

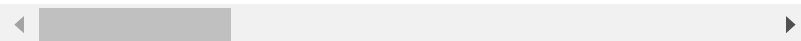
# After imputation, we return the numerical data to their original scale
ql[numeric_columns] = scaler.inverse_transform(ql[numeric_columns])

# Checking the imputation results
ql
```



	country	Purchasing Power Value	Purchasing Power Category	Safety Value	Safety Category
0	Afghanistan	32.15	Very Low	25.33	Low
1	Aland Islands	125.01	Very High	71.81	High
2	Albania	42.82	Low	55.52	Moderate
3	Alderney	0.00	Very Low	83.79	Very High
4	Algeria	27.60	Very Low	47.54	Moderate
...
231	Wallis And Futuna	0.00	Very Low	0.00	Moderate
232	Western Sahara	0.00	Very Low	62.87	High
233	Yemen	20.74	Very Low	34.07	Low
234	Zambia	22.32	Very Low	54.39	Moderate
235	Zimbabwe	28.76	Very Low	39.31	Low

236 rows × 19 columns



Next steps:

[Generate code with ql](#)

[View recommended plots](#)

[Next](#)

Feature Engineering

```
category_mapping = {'Very Low': 1, 'Low': 2, 'Moderate': 3, 'High': 4}
columns_to_map = ['Purchasing Power Category', 'Safety Category']
```

```
'Climate Category', 'Cost of Living Category',  
'Traffic Commute Time Category', 'Pollution Category']
```

```
for col in columns_to_map:  
    ql[col] = ql[col].map(category_mapping)  
ql
```



	country	Purchasing Power Value	Purchasing Power Category	Safety Value	Safe Category
0	Afghanistan	32.15	1	25.33	
1	Aland Islands	125.01	5	71.81	
2	Albania	42.82	2	55.52	
3	Alderney	0.00	1	83.79	
4	Algeria	27.60	1	47.54	
...
231	Wallis And Futuna	0.00	1	0.00	
232	Western Sahara	0.00	1	62.87	
233	Yemen	20.74	1	34.07	
234	Zambia	22.32	1	54.39	
235	Zimbabwe	28.76	1	39.31	

236 rows × 19 columns



Next steps:

Generate code with ql

View recommended plots

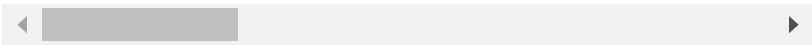
N

```
from sklearn.preprocessing import LabelEncoder  
label_encoder = LabelEncoder()  
  
ql['country'] = label_encoder.fit_transform(ql['country'])  
ql
```




	country	Purchasing Power Value	Purchasing Power Category	Safety Value	Safety Category
0	0	32.15	1	25.33	2
1	1	125.01	5	71.81	4
2	2	42.82	2	55.52	3
3	3	0.00	1	83.79	5
4	4	27.60	1	47.54	3
...
231	231	0.00	1	0.00	3
232	232	0.00	1	62.87	4
233	233	20.74	1	34.07	2
234	234	22.32	1	54.39	3
235	235	28.76	1	39.31	2

236 rows × 19 columns



Next steps:

Generate code with q1

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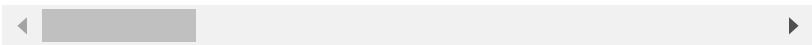
Adding additional features

```
q1['Income_to_Property_Ratio'] = q1['Purchasing Power Value'] / q1['Purchasing Power Category']
q1['Safety_to_Pollution_Ratio'] = q1['Safety Value'] / (q1['Safety Category'] + 1)
q1['Health_Index_Score'] = (q1['Health Care Value'] + q1['Health Care Category']) / 2
q1.head()
```



	country	Purchasing Power Value	Purchasing Power Category	Safety Value	Safety Category	Income_to_Property_Ratio	Safety_to_Pollution_Ratio	Health_Index_Score
0	0	32.15	1	25.33	2	32.15	12.665	33.675
1	1	125.01	5	71.81	4	25.002	17.9525	40.505
2	2	42.82	2	55.52	3	21.41	18.5067	37.9583
3	3	0.00	1	83.79	5	0.00	16.758	33.39
4	4	27.60	1	47.54	3	27.60	15.8467	35.27

5 rows × 22 columns



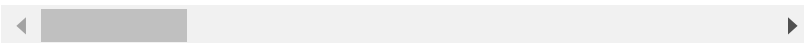
✓ Scaling Numerical Data

```
scaler = StandardScaler()
ql[numeric_columns] = scaler.fit_transform(ql[numeric_columns])
ql
```



	country	Purchasing Power Value	Purchasing Power Category	Safety Value	Safety Category
0	0	-0.451334	1	-1.774126	
1	1	1.337947	5	0.979686	
2	2	-0.245738	2	0.014548	
3	3	-1.070819	1	1.689468	
4	4	-0.539006	1	-0.458245	
...
231	231	-1.070819	1	-3.274858	
232	232	-1.070819	1	0.450015	
233	233	-0.671189	1	-1.256305	
234	234	-0.640744	1	-0.052401	
235	235	-0.516655	1	-0.945849	

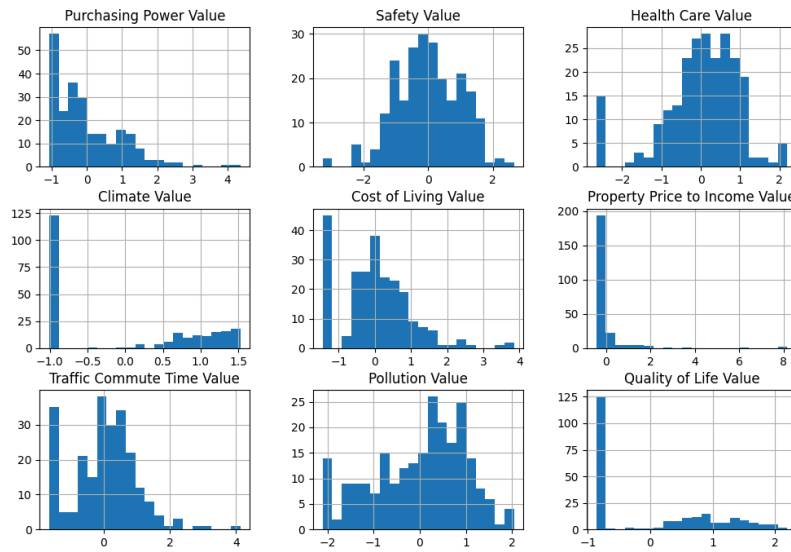
236 rows × 22 columns



✓ EDA (Exploratory Data Analysis)

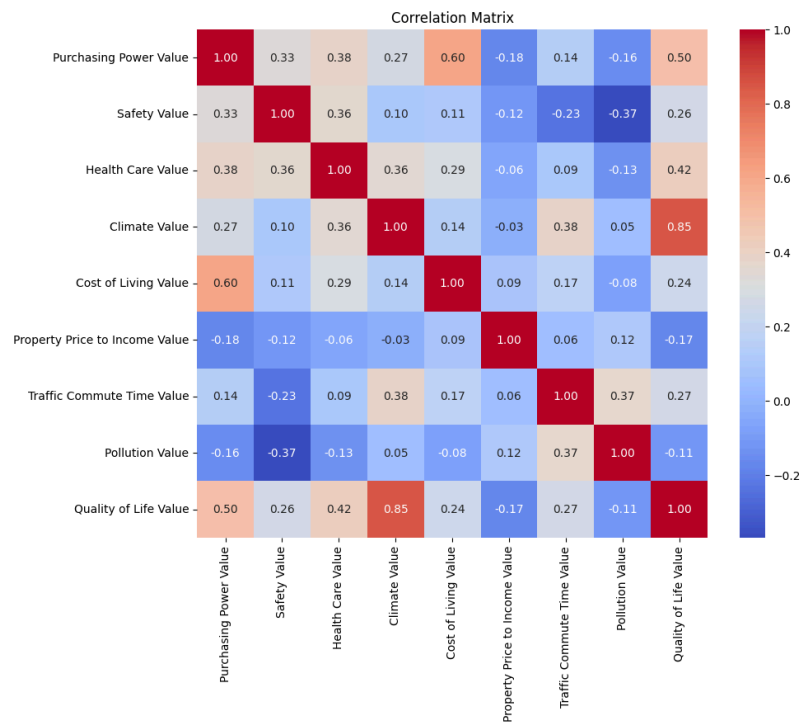
✓ Data Distribution

```
ql[numeric_columns].hist(figsize=(12, 8), bins=20)
plt.show()
```



▼ Correlation

```
plt.figure(figsize=(10, 8))
sns.heatmap(ql[numeric_columns].corr(), annot=True, cmap="c")
plt.title("Correlation Matrix")
plt.show()
```



Model Training and Machine Learning

```
# Using Quality of Life as a target for regression
X = ql.drop(columns=['Quality of Life Value', 'Quality of Li
y = ql['Quality of Life Value']
```

```
# PCA for Dimensionality Reduction
pca = PCA(n_components=5)
X_pca = pca.fit_transform(X)
```

```
# Split the Data
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, te

# Model Evaluation Function
def evaluate_model(model, X_train, X_test, y_train, y_test,
    y_pred = model.predict(X_test)
    rmse = mean_squared_error(y_test, y_pred) ** 0.5
    mae = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    cv_r2 = cross_val_score(model, X_train, y_train, cv=5, s

    print(f"{model_name} Performance:")
    print(f"RMSE: {rmse:.4f}, MAE: {mae:.4f}, R²: {r2:.4f},

    return y_pred

# 1 Linear Regression
lr = LinearRegression()
lr.fit(X_train, y_train)
y_pred_lr = evaluate_model(lr, X_train, X_test, y_train, y_t

# 2 Random Forest Regressor with GridSearchCV
rf_params = {
    'n_estimators': [100, 200],
    'max_depth': [None, 20, 30],
    'min_samples_split': [2, 5]
}
rf = GridSearchCV(RandomForestRegressor(random_state=42), pa
rf.fit(X_train, y_train)
y_pred_rf = evaluate_model(rf.best_estimator_, X_train, X_te

# 3 XGBoost Regressor with SHAP Feature Importance
xgb = XGBRegressor(objective="reg:squarederror", random_stat
xgb.fit(X_train, y_train)
y_pred_xgb = evaluate_model(xgb, X_train, X_test, y_train, y

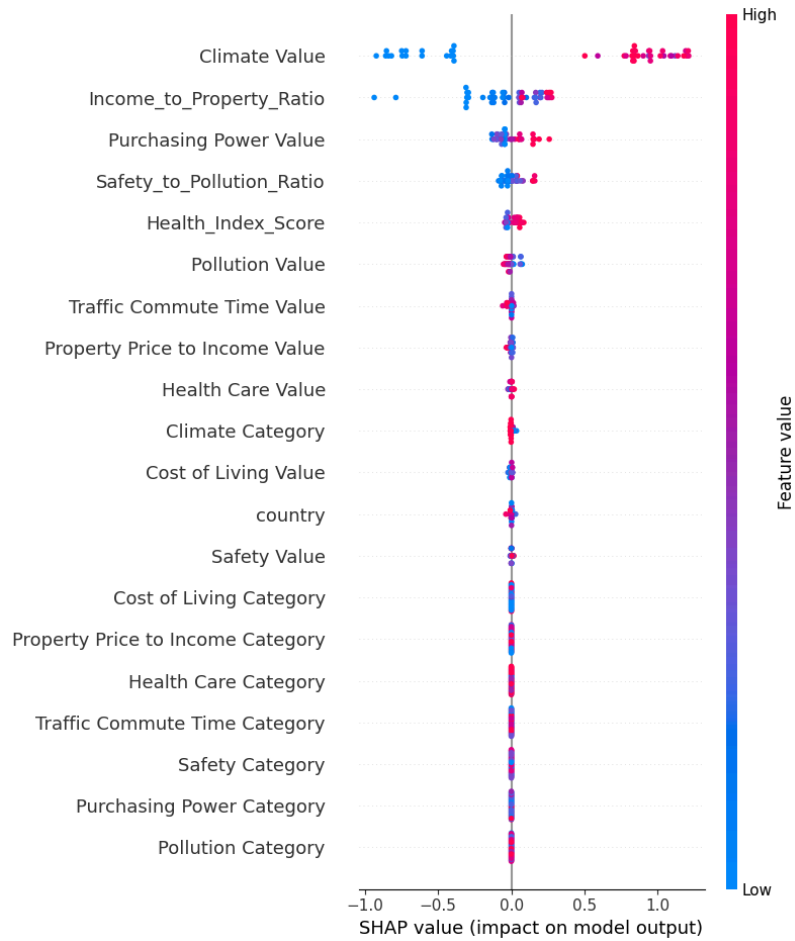
# SHAP Analysis
explainer = shap.Explainer(xgb)
shap_values = explainer(X_test)
shap.summary_plot(shap_values, X_test)
```



Linear Regression Performance:
RMSE: 0.3180, MAE: 0.2272, R^2 : 0.8988, CV R^2 : -11072451

Random Forest Performance:
RMSE: 0.1479, MAE: 0.0927, R^2 : 0.9781, CV R^2 : 0.9483

XGBoost Performance:
RMSE: 0.1523, MAE: 0.0855, R^2 : 0.9768, CV R^2 : 0.9447



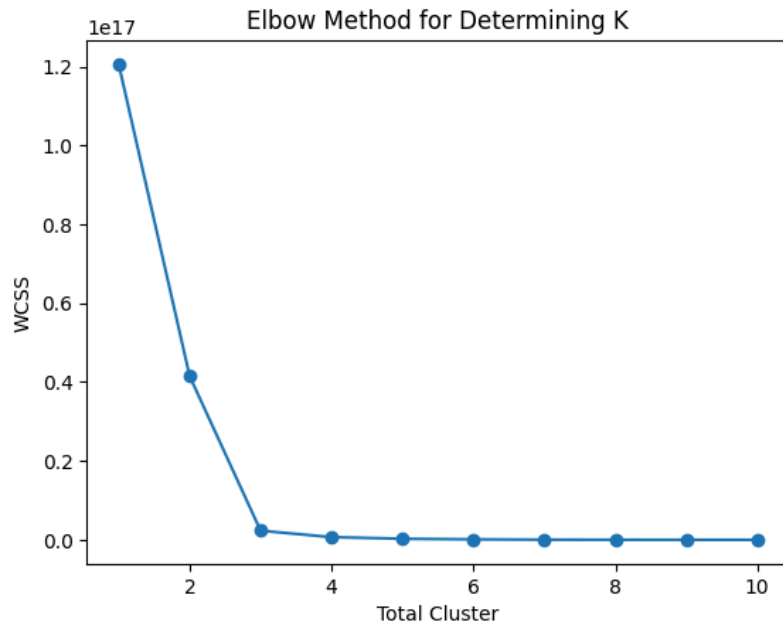
✓ Clustering using K-Means with PCA-Reduced Data

```
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42, n_init=10)
    kmeans.fit(X_pca)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss, marker='o')
plt.xlabel('Total Cluster')
plt.ylabel('WCSS')
plt.title('Elbow Method for Determining K')
plt.show()

kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
ql['Cluster'] = kmeans.fit_predict(X_pca)

sns.scatterplot(x=ql['Purchasing Power Value'], y=ql['Quality of Life'])
plt.title("Clustering K-Means Result")
plt.show()
```



Hyperparameter Tuning

```
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
import shap
```

```
# Hyperparameter Grid for Randomized Search
param_dist = {
    "n_estimators": [50, 100, 200, 300],
    "max_depth": [None, 10, 20, 30, 50],
    "min_samples_split": [2, 5, 10],
    "min_samples_leaf": [1, 2, 5, 10],
    "max_features": ["sqrt", "log2", None],
    "bootstrap": [True, False]
}
```

Enter a prompt here



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