Label

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
# Load the new dataset
df = pd.read_csv("/content/sample_data/Quality_Concrete.csv")
df.head()
⋽₹
                                                 Solids
                                                            Sulfate
                                                                                             Ħ
           Chloride Label Organic Carbon
                                                                       Turbidity
      0 1119.324168
                                 178.253002
                                             526.051381 305.391066 1956.909586 2.019602
                                                                                             ıl.
      1 1036.079757
                                 121.985937
                                             751.978355 202.951022 1816.186138 5.979678
      2 1533.371242
                                 100.844370 1940.216276 158.901826 1850.391669 3.647249
         530.060453
                                 169.685077 1667.346846 312.075730
                                                                      677.841225 5.598852
      4 1633 186960
                                 148 456935 1401 681101 204 934673
                                                                      416 156446 4 234521
 Next steps: ( Generate code with df
                                    View recommended plots
                                                                 New interactive sheet
print(df.shape)
→ (10000, 7)
print(df.columns)
Index(['Chloride', 'Label', 'Organic_Carbon', 'Solids', 'Sulfate', 'Turbidity',
           dtype='object')
df.describe()
→
                                                                           Sulfate
                                                                                                                 \blacksquare
                Chloride
                                 Label Organic Carbon
                                                              Solids
                                                                                       Turbidity
                                                                                                            ph
            10000.000000 10000.000000
                                                        10000.000000 10000.000000
                                                                                   10000.000000 10000.000000
                                          10000.000000
      count
                                                                                                                 ıl.
      mean
             3209.816032
                              0.349000
                                            289.310908
                                                         4706.413051
                                                                        446.180194
                                                                                     2805.481180
                                                                                                      6.992082
             1963.715379
                              0.476678
                                            164.697936
                                                         3620.078892
                                                                        222.009852
                                                                                     1757.869279
                                                                                                      2.868269
       std
      min
              500.007896
                              0.000000
                                             50.002808
                                                          502.309068
                                                                         20.260550
                                                                                       11.057664
                                                                                                      2.000041
                                                                                     1238.594183
      25%
             1454.537607
                              0.000000
                                            142.031853
                                                         1434.354000
                                                                        264.214909
                                                                                                      4.525121
      50%
             2849.755448
                              0.000000
                                            265.943550
                                                                        467.254435
                                                                                                      6.962148
                                                         3600.772034
                                                                                     2686.578239
      75%
             4935.833784
                              1.000000
                                            435.807178
                                                         7905.844100
                                                                        636.283529
                                                                                     4344.418741
                                                                                                      9.458439
             6999.595374
                              1.000000
                                            599.906575 11999.407530
                                                                        799.961446
                                                                                     5999.019634
                                                                                                     11.999440
      max
df.info()
<class 'pandas.core.frame.DataFrame'>
     RangeIndex: 10000 entries, 0 to 9999
     Data columns (total 7 columns):
     #
         Column
                          Non-Null Count Dtype
     0
         Chloride
                          10000 non-null float64
      1
         Label
                          10000 non-null
                                          int64
          Organic_Carbon 10000 non-null
                                          float64
      3
          Solids
                          10000 non-null
                                          float64
                          10000 non-null
          Sulfate
          Turbidity
                          10000 non-null
                                           float64
                          10000 non-null float64
     dtypes: float64(6), int64(1)
     memory usage: 547.0 KB
print(df.nunique())
    Chloride
\rightarrow
                       8000
```

```
Organic_Carbon
                       8000
     Solids
                       8000
     Sulfate
                       8000
     Turbidity
                       8000
                       8000
     dtype: int64
# Drop unnecessary columns
df = df.drop(columns=['Unnamed: 0'])
# Rename columns for consistency
df = df.rename(columns={'Sulphate': 'Sulfate'})
# Check for missing values
print(df.isnull().sum())
→ Chloride
                       a
     Label
     Organic_Carbon
     Solids
                       0
     Sulfate
                       0
     Turbidity
                       0
     nh
                       0
     dtype: int64
# Define features and target
X = df.drop(columns=['Label'])
y = df['Label']
# Standardize features
scaler = StandardScaler()
X scaled = scaler.fit transform(X)
# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.33, random_state=42)
# Logistic Regression
model_lg = LogisticRegression(max_iter=120, random_state=0, n_jobs=20)
model_lg.fit(X_train, y_train)
pred_lg = model_lg.predict(X_test)
print("Logistic Regression Accuracy:", accuracy_score(y_test, pred_lg))
print(classification_report(y_test, pred_lg))
→ Logistic Regression Accuracy: 0.85666666666666667
                                recall f1-score
                   precision
                                                   support
                0
                        0.92
                                  0.85
                                            0.88
                                                      2137
                1
                        0.76
                                  0.87
                                            0.81
                                                      1163
                                            0.86
                                                      3300
        accuracy
                                  0.86
                                                      3300
        macro avg
                        0.84
                                            0.85
     weighted avg
                                  0.86
                                            0.86
                                                      3300
                        0.87
# Decision Tree
model_dt = DecisionTreeClassifier(max_depth=4, random_state=42)
model_dt.fit(X_train, y_train)
pred_dt = model_dt.predict(X_test)
print("Decision Tree Accuracy:", accuracy_score(y_test, pred_dt))
print(classification_report(y_test, pred_dt))
Decision Tree Accuracy: 0.8548484848484849
                   precision
                               recall f1-score
                                                   support
                0
                        0.92
                                  0.85
                                            0.88
                                                      2137
                        0.76
                                  0.87
                                            0.81
                                                      1163
                                            0.85
                                                      3300
        accuracy
                        0.84
                                  0.86
                                            0.85
                                                      3300
        macro avg
                        0.86
                                  0.85
                                            0.86
                                                      3300
     weighted avg
# Random Forest
model_rf = RandomForestClassifier(n_estimators=300, min_samples_leaf=0.16, random_state=42)
model_rf.fit(X_train, y_train)
pred_rf = model_rf.predict(X_test)
print("Random Forest Accuracy:", accuracy_score(y_test, pred_rf))
print(classification_report(y_test, pred_rf))
```

<del></del>	Random	Forest	Accuracy: precision	0.85666666 recall	66666667 f1-score	support
		0 1	0.92 0.76	0.85 0.87	0.88 0.81	2137 1163
	macr	uracy o avg	0.84	0.86	0.86 0.85	3300 3300
	weighte	d avg	0.87	0.86	0.86	3300

# Confusion matrix for visualization sns.heatmap(confusion\_matrix(y\_test, pred\_rf)), annot=True, fmt='0.2%', cmap='Reds') plt.show()

