]: _	v white 7.0 0.27 0.36 20.7 0.045 45.0 170.0 1.0010 3.00 0.45 8.8 6 v white 6.3 0.30 0.34 1.6 0.049 14.0 132.0 0.9940 3.30 0.49 9.5 6 white 8.1 0.28 0.40 6.9 0.050 30.0 97.0 0.9951 3.26 0.44 10.1 6 white 7.2 0.23 0.32 8.5 0.058 47.0 186.0 0.9956 3.19 0.40 9.9 6 df . shape (6497, 13) If ixed acidity volatile acidity volatile acidity volatile acidity citric acid residual sugar chlorides free sulfur dioxide total sulfur dioxide total sulfur dioxide density by total sulfur dioxide total sulfur dioxide density ph pH sulphates alcohol quality
r	count 6487.000000 6499.000000 6495.000000 6495.000000 6497.000000 6497.000000 6497.000000 6493.000000 6497.000000 6497.000000 mean 7.216579 0.339691 0.318722 5.444326 0.056042 30.525319 115.744574 0.994697 3.218395 0.531215 10.491801 5.818378 std 1.296750 0.164649 0.145265 4.758125 0.035036 17.749400 56.521855 0.002999 0.160748 0.148814 1.192712 0.873255 min 3.800000 0.080000 0.000000 0.009000 1.000000 6.000000 0.987110 2.720000 0.220000 8.000000 3.000000 25% 6.400000 0.230000 0.250000 1.800000 0.038000 17.000000 77.000000 0.992340 3.110000 0.430000 9.500000 5.000000 50% 7.000000 0.290000 1.800000 18.00000 19.09900 3.320000 0.600000 11.300000 6.000000 max 15.9
- -	<class 'pandas.core.frame.dataframe'=""> RangeIndex: 6497 entries, 0 to 6496 Data columns (total 13 columns): # Column Non-Null Count Dtype 0 type 6497 non-null float64 1 fixed acidity 6489 non-null float64 2 volatile acidity 6489 non-null float64 3 citric acid 6494 non-null float64 4 residual sugar 6495 non-null float64 5 chlorides 6495 non-null float64 6 free sulfur dioxide 6497 non-null float64 7 total sulfur dioxide 6497 non-null float64 8 density 6497 non-null float64</class>
d m	9 pH 6488 non-null float64 10 sulphates 6493 non-null float64 11 alcohol 6497 non-null float64 12 quality 6497 non-null int64 dtypes: float64(11), int64(1), object(1) memory usage: 634.5+ KB #checking null values df.isnull().any() type False fixed acidity True volatile acidity True
r c c f t d d p s a q d	citric acid True residual sugar True chlorides True free sulfur dioxide False total sulfur dioxide False density False pH True sulphates True alcohol False quality False dtype: bool #fill null values with their mean df.fillna(df.mean(), inplace=True)
C a	C:\Users\navon\AppData\Local\Temp/ipykernel_11412/2471838208.py:2: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecat a future version this will raise TypeError. Select only valid columns before calling the reduction. df.fillna(df.mean(), inplace=True) df.isnull().any() type
ft do pp s a a q d	cnlorades False free sulfur dioxide False total sulfur dioxide False density False pH False sulphates False alcohol False quality False dtype: bool #to show types of winery df['type'].unique() array(['white', 'red'], dtype=object)
: : : :	<pre>df['type'].value_counts() white</pre>
9 N	1 1079 4 216 8 193 3 30 9 5 Name: quality, dtype: int64 sns.pairplot(df, hue='quality', corner=True) <seaborn.axisgrid.pairgrid 0xb19f9b8="" at=""></seaborn.axisgrid.pairgrid>
volatile acidity	150 125 100 100 025
citric	115
epixol	905 900 900 900 900 900 900 900 900 900
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ates	099 40 38 36 4 32 30 28 20 175 150 150 20 075
:	0.50
C	C:\Users\navon\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid posit rgument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation. warnings.warn(2500 -
ţ inco	1500 - 1000 - 500 - 3 4 5 66 7 8 9
- N - N	sns.countplot(x="type", hue="quality", data=df) NameError
	plt.figure(figsize = (12,6)) sns.heatmap(corr, cmap = 'coolwarm') plt.show() fixed acidity volatile acidity citric acid residual sugar dhorides free sulfur dioxide free sulfur dioxide free sulfur dioxide
	free sulfur dioxide - total sulfur dioxide - density - pH - sulphates - alcohol - quality - wine_type - wine_type - ### ### ### ### ### ### ### ### ###
:	#converting categorical to numerical df = pd. get_dummies(df, drop_first=True) df.head() fixed acidity volatile acidity citric acid residual sugar chlorides free sulfur dioxide total sulfur dioxide density of the polysor of the po
3 4	1 6.3 0.30 0.34 1.6 0.049 14.0 132.0 0.9940 3.30 0.49 9.5 6 1 2 8.1 0.28 0.40 6.9 0.050 30.0 97.0 0.9951 3.26 0.44 10.1 6 1 3 7.2 0.23 0.32 8.5 0.058 47.0 186.0 0.9956 3.19 0.40 9.9 6 1 df = df.rename(columns={"type_white": "wine_type"}) fixed acidity volatile volatile acidity volatile volatile acidity vol
1 2 3 4	0 7.0 0.27 0.36 20.7 0.045 45.0 170.0 1.0010 3.00 0.45 8.8 6 1 1 6.3 0.30 0.34 1.6 0.049 14.0 132.0 0.9940 3.30 0.49 9.5 6 1 2 8.1 0.28 0.40 6.9 0.050 30.0 97.0 0.9951 3.26 0.44 10.1 6 1 3 7.2 0.23 0.32 8.5 0.058 47.0 186.0 0.9956 3.19 0.40 9.9 6 1 4 7.2 0.23 0.32 8.5 0.058 47.0 186.0 0.9956 3.19 0.40 9.9 6 1 We had an unbalanced dataset with respect to wine quality, we divide the qualities into two groups - 1 (for wine quality 7, 8, 9) and 0 (for 6 and below)
]: 0 1 2	Fixed acidity
]: 0 1 N	y=df["wine_quality"] y.value_counts() 0 5220 1 1277 Name: wine_quality, dtype: int64 y 0 0
2 3 4 6 6 6 6 6 8	1 0 2 0 3 0 4 0 6492 0 6493 0 6494 0 6495 0 6496 0 Name: wine_quality, Length: 6497, dtype: int64 x = df.drop(["quality", "wine_quality"], axis=1)
	fixed acidity volatile acidity citric acid residual sugar chlorides free sulfur dioxide total sulfur dioxide density pH sulphates alcoho wine_type 0 7.0 0.270 0.36 20.7 0.045 45.0 170.0 1.00100 3.00 0.450000 8.8 1 1 6.3 0.300 0.34 1.6 0.049 14.0 132.0 0.99400 3.0 0.490000 9.5 1 2 8.1 0.280 0.40 6.9 0.050 30.0 9.9940 3.0 0.490000 9.5 1 3 7.2 0.230 0.32 8.5 0.058 47.0 186.0 0.9950 3.19 0.400000 9.9 1 4 7.2 0.230 0.32 8.5 0.058 47.0 186.0 0.9950 3.19 0.400000 9.9 1 4 7.2 0.230 0.32 8.5 0.058 47.0 <td< th=""></td<>
666666	6492 6.2 0.600 0.08 2.0 0.090 32.0 44.0 0.9949 3.45 0.58000 10.5 0 6493 5.9 0.550 0.10 2.2 0.062 39.0 51.0 0.99512 3.52 0.531215 11.2 0 6494 6.3 0.510 0.13 2.3 0.076 29.0 40.0 0.99574 3.42 0.750000 11.0 0 6495 5.9 0.645 0.12 2.0 0.075 32.0 44.0 0.99547 3.57 0.710000 10.2 0 6496 6.0 0.310 0.47 3.6 0.067 18.0 42.0 0.99549 3.39 0.660000 11.0 0 6497 rows × 12 columns Model Training
3 9	<pre>from sklearn.model_selection import train_test_split from sklearn.metrics import accuracy_score, confusion_matrix log = pd.DataFrame(columns=["model", "accuracy"]) X_train, X_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state = 42) Logistic Regression</pre>
L	<pre>from sklearn.linear_model import LogisticRegression lr = LogisticRegression(solver='liblinear') lr.fit(X_train, y_train) y_pred = lr.predict(X_test) lr.score(X_train, y_train) score = accuracy_score(y_test, y_pred)</pre>
a a	confusion_matrix(y_test, y_pred) array([[1013, 34], [195, 58]], dtype=int64) log = log.append({"model": "logistic regression", "accuracy": score}, ignore_index=True) Support Vector Classification - SVC from sklearn.svm import SVC
	<pre>Wq = SVC(kernel="rbf", C=1) Wq.fit(X_train, y_train) y_pred = Wq.predict(X_test) score = accuracy_score(y_test, y_pred) confusion_matrix(y_test, y_pred) array([[1047,</pre>
3 1 a	<pre>log = log.append({"model": "SVC", "accuracy": score}, ignore_index=True) log model accuracy 0 logistic regression 0.823846</pre>
3 a	svc 0.805385 K Nearest Neighbour
3 a 4 a 5 6 7 8 7 8 1.	1 SVC 0.805385
3	<pre>Svc 0.805385 K Nearest Neighbour from sklearn.neighbors import KNeighborsClassifier clf = KNeighborsClassifier(n_neighbors=3) clf.fit(X_train, y_train) clf.predict(X_test) y_pred = clf.predict(X_test) score = accuracy_score(y_test, y_pred)</pre>
3	***X Nearest Neighbors* import KNeighborsclassifier **Colf = KNeighbors* lassifier(n_neighbors=3)
	**X Nearest Neighbour **From sklearn.neighbors lamport KNeighborsClassifier **CIT = KNeighborsClassifier(n_neighbors=3)
	Kearest Neighbour From sklaam.neighbors import Keighborsclassifier Clf = Keighborsclassifier(n_eighborsclassifier) Clf = Mening Clf
33 a 34 a 35 a 35 a 36 a 37 a 37 a 38 a 38.	K Nearest Neighbour from scleam, neighbors Saport (AstighborsClassifier) of r = KoorghborsClassifier(r, reighborsClassifier) of r = Log apperd(["model": "K Nearost NeighborsClassifier) of paper(regional RACASS) of paper(regional RACASS)
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