

Data Collection

data.shape

(569, 33)

Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.

M = malignant, B = benign

Exploring Data Analysis

data.info()

- 0 id
- 1 diagnosis
- 2 radius_mean
- 3 texture_mean
- 4 perimeter_mean
- 5 area_mean
- 6 smoothness_mean
- 7 compactness_mean
- 8 concavity_mean
- 9 concave points_
- 10 symmetry_mean
- 11 fractal_dimension_mean
- 12 radius_se
- 13 texture_se
- 14 perimeter_se
- 15 area_se

- 16 smoothness_se
- 17 compactness_se
- 18 concavity_se
- 19 concave points_se
- 20 symmetry_se
- 21 fractal_dimension_se
- 22 radius_worst
- 23 texture_worst
- 24 perimeter_worst
- 25 area_worst
- 26 smoothness_worst
- 27 compactness_worst
- 28 concavity_worst
- 29 concave
- 30 symmetry_worst
- 31 fractal_dimension_worst
- 32 Unnamed: 32



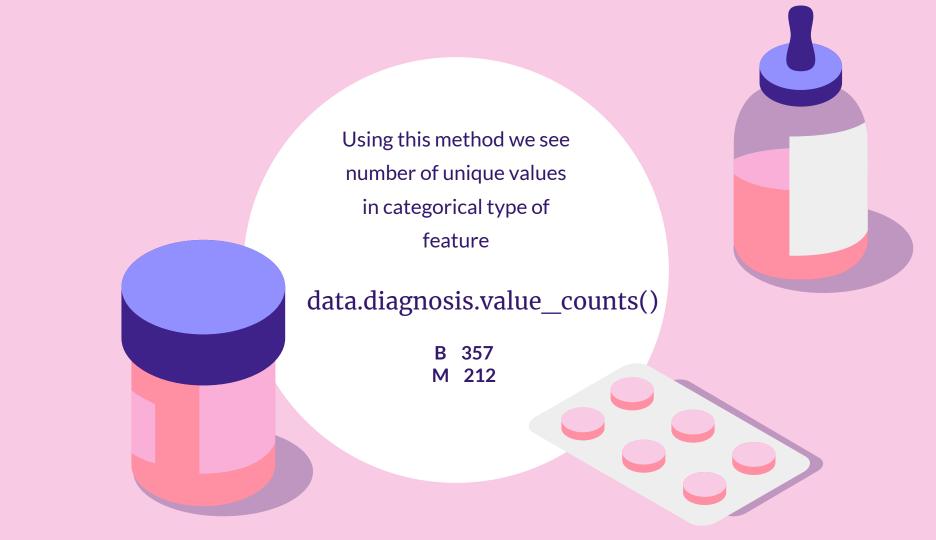
Only one single feature is categorical and it's values are B and M:

diagnosis

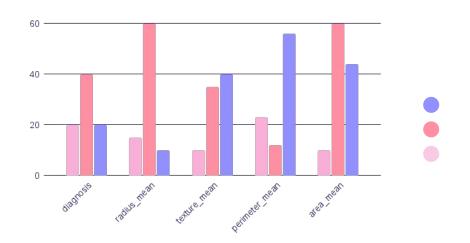
data.d	lescribe	e(inclu	de="0")

			-	_	_	-	_
		•					•
d	u	_		•	-	-	•
		_					

count	569
unique	2
top	В
freq	357



Data Visualization



```
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph objects as go
```

Data Filtering

We have one categorical feature, so we need to convert it into numeric values using LabelEncoder:



ML models are supposed to deal only with numerical values



- M
- B

- 1
- 0

0 357

Find the correlation between other features

How features correspond with the output

data[cols].corr()

			_		_		•	•			
	Correlation Graph										
diagnosis	100.0%		41.5%	74.3%	70.9%	35.9%	59.7%	69.6%	77.7%	33.0%	-1.3%
radius_mean	73.0%	100.0%	32.4%	99.8%	98.7%	17.1%	50.6%	67.7%	82.3%	14.8%	-31.2%
texture_mean	41.5%	32.4%	100.0%	33.0%	32.1%	-2.3%	23.7%	30.2%	29.3%	7.1%	-7.6%
perimeter_mean	74.3%	99.8%	33.0%	100.0%	98.7%	20.7%	55.7%	71.6%	85.1%	18.3%	-26.1%
area_mean	70.9%	98.7%	32.1%	98.7%	100.0%	17.7%	49.9%	68.6%	82.3%	15.1%	-28.3%
smoothness_mean	35.9%	17.1%	-2.3%	20.7%	17.7%	100.0%	65.9%	52.2%	55.4%	55.8%	58.5%
compactness_mean	59.7%	50.6%	23.7%	55.7%	49.9%	65.9%	100.0%	88.3%	83.1%	60.3%	56.5%
concavity_mean	69.6%	67.7%	30.2%	71.6%	68.6%	52.2%	88.3%	100.0%	92.1%	50.1%	33.7%
concave points_mean	77.7%	82.3%	29.3%	85.1%	82.3%	55.4%	83.1%	92.1%	100.0%	46.2%	16.7%
symmetry_mean	33.0%	14.8%	7.1%	18.3%	15.1%	55.8%	60.3%	50.1%	46.2%	100.0%	48.0%
fractal_dimension_mean	-1.3%	-31.2%	-7.6%	-26.1%	-28.3%	58.5%	56.5%	33.7%	16.7%	48.0%	100.0%
	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	noothness_mean	npactness_mean	concavity_mean	ave points_mean	symmetry_mean	dimension_mean

- 0.4



Model Implementation

Preprocessing and model selection

from sklearn.model_selection import
train_test_split

from sklearn.preprocessing import
StandardScaler



Compare the relative value of different statistical models and determine which one is the best fit for the observed data.

Machine Learning Models

01

LogisticRegression

03

DecisionTreeClassifier

05

GaussianNB

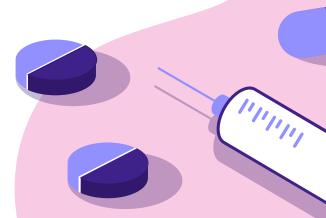
02

RandomForestClassifier

04

SVC

06KNeighborsClassifier



To check the Model Accuracy, Errors and it's Validations i've used:

```
from sklearn.metrics import accuracy_score, confusion_matrix, f1_score
from sklearn.metrics import classification_report

from sklearn.model_selection import KFold

from sklearn.model_selection import cross_validate, cross_val_score

from sklearn.svm import SVC

from sklearn import metrics
```

Feature Selection

```
prediction_feature = [ 'radius_mean',
   'perimeter_mean', 'area_mean',
   'symmetry_mean', 'compactness_mean',
   'concave points_mean']

targeted feature = 'diagnosis'
```

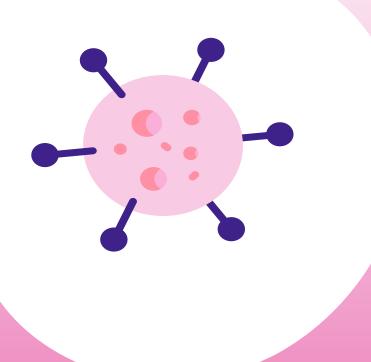
Split the dataset into Training Set $\cuperbox{$rac{1}{2}$}$ and Testing Set $\cupe{$rac{1}{2}$}$ by 33% and set the 15 fixed records

X train, X test, y train, y test = train test split(X, y, test size=0.33, random state=15)

Perform Feature Standard Scaling

Standardize features by removing the mean and scaling to unit variance

Scale the data to keep all the values in the same magnitude



Model Building

```
def model_building(model, X_train, X_test,
y_train, y_test):

   model.fit(X_train, y_train)
   score = model.score(X_train, y_train)
   predictions = model.predict(X_test)
   accuracy = accuracy_score(predictions,
y_test)

return (score, accuracy, predictions)
```

A dictionary for multiple models for bulk predictions

"LogisticRegression"

"RandomForestClassifier"

"DecisionTreeClassifier"

"SVC"



While Predict we can store model's score & prediction values to new generated dataframe

	model_name	score	accuracy_score	accuracy_percentage
0	LogisticRegression	0.916010	0.909574	90.96%
1	RandomForestClassifier	0.992126	0.925532	92.55%
2	DecisionTreeClassifier	1.000000	0.909574	90.96%
3	SVC	0.923885	0.914894	91.49%

Cross-validation is primarily used in applied machine learning to estimate the skill of a machine learning model on unseen data. That is, to use a limited sample in order to estimate how the model is expected to perform in general when used to make predictions on data not used during the training of the model.



Call the function to know the cross validation function by mean for our select model prediction



Full-Data Accuracy: 1.0

Cross Validation Score of RandomForestClassifier '

Score: 0.99 Score: 0.99 Score: 0.99 Score: 1.0 Score: 1.0

Full-Data Accuracy: 1.0

Cross Validation Score of DecisionTreeClassifier '

Score: 1.0 Score: 1.0 Score: 1.0 Score: 1.0 Score: 1.0 Some of the model are giving prefect scoring. It means sometimes overfitting occurs.

HyperTuning the ML Model

For HyperTunning I used **GridSearchCV** to know the best performing parameters.

Hyperparameters can have a big impact on model training as it relates to **training time**, **infrastructure resource requirements**, **model convergence** and **model accuracy**.

```
DecisionTreeClassifier : Max_features / min_samples_split /
min_samples_leaf
KNeighborsClassifier : N_neighbors / leaf_size / weights
SVC : C / kernel / gamma
RandomForestClassifier : bootstrap / max_depth / max_features /
min_samples_leaf / min_samples_split / n_estimators
```

Deploy Model

Finally, we are done so far.

The last step is to deploy our model in production map.

So we need to export our model and bind with web application API.

Pickle is the standard way of serializing objects in Python

I've used streamlit to build the Web App



Presented By Wiem BELHADJ Thanks



Demo