Course: CSCE 5215 Machine Learning

Professor: Zeenat Tariq

Activity 9

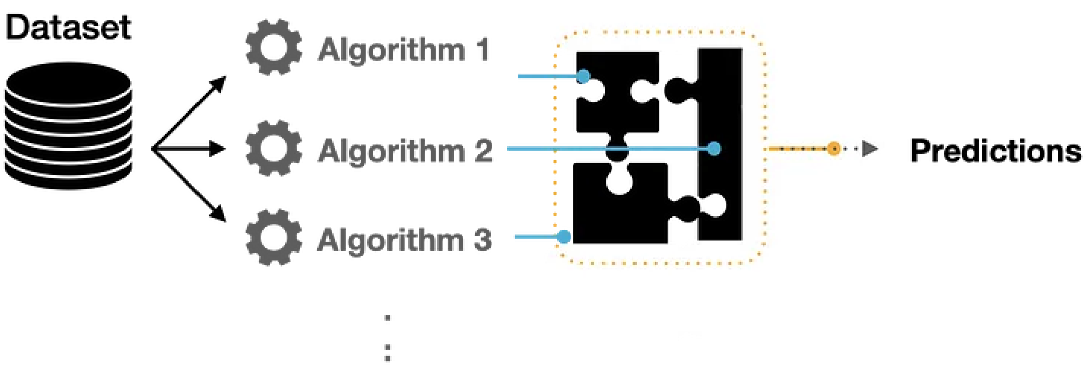
Ensemble Models

Ensemble models is a machine learning approach to combine multiple other models in the prediction process.

In [3]:
```
from IPython.display import Image
from sklearn.model_selection import GridSearchCV
import warnings
warnings.filterwarnings("ignore")
from sklearn.ensemble import BaggingClassifier, GradientBoostingClassifier, AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
```

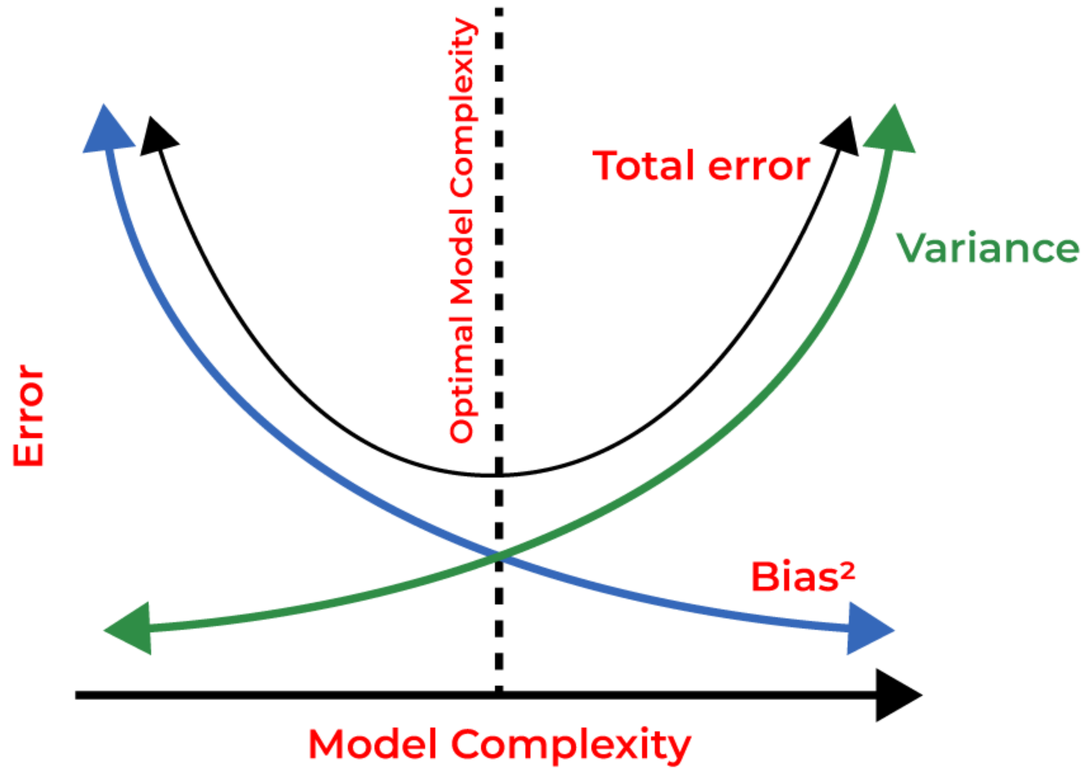
In [4]:
```
Image(url="https://miro.medium.com/v2/resize:fit:720/format:webp/1*22Ukd9hgt1rOV6k0RXwOBA.png")
```

Out[4]:



In [5]:
```
Image(url="https://media.geeksforgeeks.org/wp-content/uploads/20230315100857/ML--Bias-Vs-Variance-(1).png")
```

Out[5]:

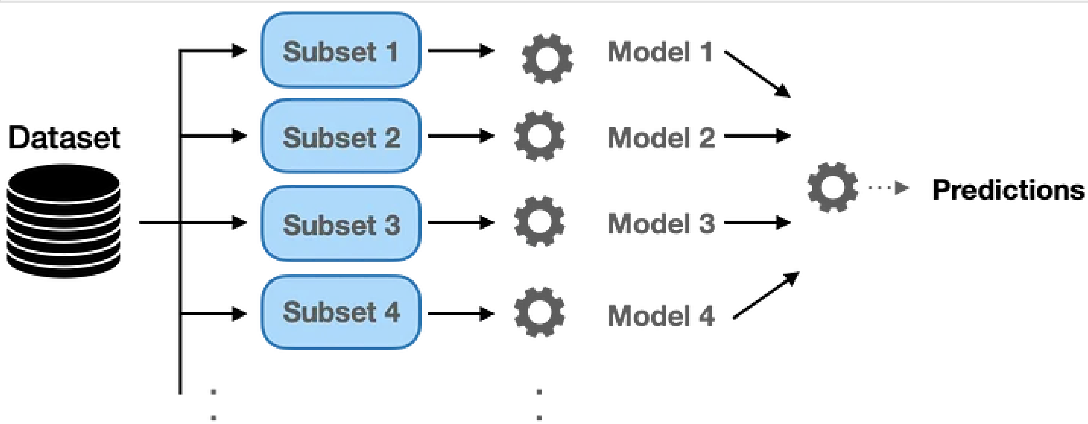


Bagging : Implementation using Scikit library

Bagging, short for Bootstrap Aggregating, is an ensemble learning method in machine learning. It aims to improve the accuracy and robustness of a predictive model by combining multiple individual models trained on different subsets of the training data. Bagging operates by creating several bootstrap samples (random samples with replacement) from the original training dataset and training a separate model on each sample. These models are typically referred to as base estimators or weak learners.

In [6]:
```
Image(url="https://miro.medium.com/v2/resize:fit:720/format:webp/1*-PXzSlXtFEGTxgcmCyMkjQ.png")
```

Out[6]:



Import the necessary libraries:

BaggingClassifier from sklearn.ensemble is used for bagging. DecisionTreeClassifier from sklearn.tree is used as the base estimator. Other libraries are imported for dataset handling, evaluation, and splitting.

Load the dataset:

For this task, we use the breast cancer dataset, which is loaded using breast_cancer().

In [7]:
```
# Load the breast cancer
breast_cance = load_breast_cancer()
X = breast_cance.data
y = breast_cance.target
```

In [8]:
```
breast_cance = pd.DataFrame(breast_cance.data, columns = breast_cance.feature_names)
breast_cance
```

Out[8]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst radius	worst texture
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.2419	0.07871	...	25.380	17.33
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.1812	0.05667	...	24.990	23.41
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.2069	0.05999	...	23.570	25.53
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2597	0.09744	...	14.910	26.50
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.1809	0.05883	...	22.540	16.67
...	...	...	...	...	...	...	...	...	...	...	...	...	...
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726	0.05623	...	25.450	26.40
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752	0.05533	...	23.690	38.25
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590	0.05648	...	18.980	34.12
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.2397	0.07016	...	25.740	39.42
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587	0.05884	...	9.456	30.37

569 rows × 30 columns

Split the dataset:

The dataset is split into training and testing sets using train_test_split() from sklearn.model_selection.

In [9]:
```
X = MinMaxScaler().fit_transform(X)
```

In [10]:
```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Create a BaggingClassifier:

We create an instance of BaggingClassifier and pass DecisionTreeClassifier as the base estimator. The number of estimators (individual classifiers) is set to 10, and a random state is provided for reproducibility.

https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.BaggingClassifier.html

In [11]:
```
# Create a BaggingClassifier with DecisionTreeClassifier as the base estimator
bagging = BaggingClassifier(base_estimator=DecisionTreeClassifier(), n_estimators=10, random_state=42)
```

In [12]:
```
bagging.get_params()
```

Out[12]:
```
{'base_estimator__ccp_alpha': 0.0,
 'base_estimator__class_weight': None,
 'base_estimator__criterion': 'gini',
 'base_estimator__max_depth': None,
 'base_estimator__max_features': None,
 'base_estimator__max_leaf_nodes': None,
 'base_estimator__min_impurity_decrease': 0.0,
 'base_estimator__min_samples_leaf': 1,
 'base_estimator__min_samples_split': 2,
 'base_estimator__min_weight_fraction_leaf': 0.0,
 'base_estimator__random_state': None,
 'base_estimator__splitter': 'best',
 'base_estimator': DecisionTreeClassifier(),
 'bootstrap': True,
 'bootstrap_features': False,
 'estimator': None,
 'max_features': 1.0,
 'max_samples': 1.0,
 'n_estimators': 10,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}
```

Train the BaggingClassifier:

The fit() method is used to train the bagging ensemble on the training set.

In [13]:
```python
# Train the BaggingClassifier
bagging.fit(X_train, y_train)
```

Out[13]:
```
▸ BaggingClassifier
▸ base_estimator: DecisionTreeClassifier
    ▸ DecisionTreeClassifier
```

Make predictions:

The predict() method is used to make predictions on the testing set.

In [14]:
```python
# Make predictions on the testing set
y_pred = bagging.predict(X_test)
```

Evaluate the accuracy:

The accuracy of the predictions is calculated using accuracy_score() from sklearn.metrics.

Print the accuracy:

The accuracy score is printed to the console.

In [15]:
```python
# Calculate accuracy score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.956140350877193
```

Tuning parameters

In [16]:
```python
param_grid = {
    'base_estimator__max_depth' : [1, 2, 3, 4, 5],
    'max_samples' : [0.05, 0.1, 0.2, 0.5]
}

bagging_classifier = GridSearchCV(BaggingClassifier(DecisionTreeClassifier(),
                                     n_estimators = 100, max_features = 0.5),
                   param_grid, scoring = "accuracy")
bagging_classifier.fit(X_train, y_train)
```

Out[16]:

```
▸ GridSearchCV
▸ estimator: BaggingClassifier
  ▸ estimator: DecisionTreeClassifier
    ▸ DecisionTreeClassifier
```

In [17]:

```
bagging_classifier.best_params_
```

Out[17]:

```
{'base_estimator__max_depth': 5, 'max_samples': 0.5}
```

In [18]:

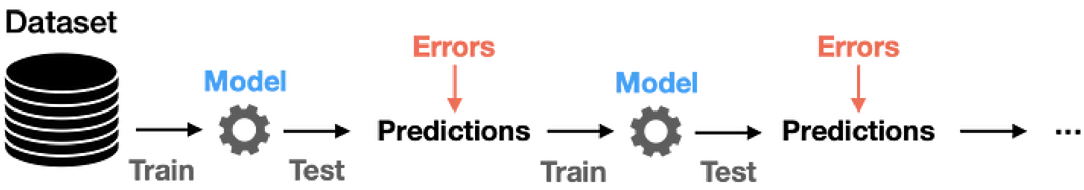
```
y_pred = bagging_classifier.best_estimator_.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.9649122807017544
```

In [19]:

```
Image(url="https://miro.medium.com/v2/resize:fit:720/format:webp/1*trWLNnfyqdRklFmLGcF_Zw.png")
```

Out[19]:



c. Gradient boosting : Implementation using scikit learn library

Gradient Boosting is an ensemble learning method that combines multiple weak predictive models, typically decision trees, to create a strong predictive model. Unlike bagging, which focuses on reducing variance, gradient boosting aims to minimize bias and improve the model's predictive power by iteratively fitting new models to the residuals of the previous models.

Create a GradientBoostingClassifier:

We create an instance of GradientBoostingClassifier and specify the number of estimators (100) and the learning rate (0.1). The random state is set for reproducibility.

In [20]:

```
# Create a GradientBoostingClassifier
gradient_boosting = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, random_state=42)
```

In [21]:

```
gradient_boosting.get_params()
```

Out[21]:

```
{'ccp_alpha': 0.0,
 'criterion': 'friedman_mse',
 'init': None,
 'learning_rate': 0.1,
 'loss': 'log_loss',
 'max_depth': 3,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_iter_no_change': None,
 'random_state': 42,
 'subsample': 1.0,
 'tol': 0.0001,
 'validation_fraction': 0.1,
 'verbose': 0,
 'warm_start': False}
```

Train the GradientBoostingClassifier and Make predictions:

In [22]:

```
# Train the GradientBoostingClassifier
gradient_boosting.fit(X_train, y_train)
```

```
# Make predictions on the testing set
y_pred = gradient_boosting.predict(X_test)
```

Calculate and print the accuracy

In [23]:
```
# Calculate accuracy score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.956140350877193
```

Tuning parameters

In [24]:
```
param_grid = {
    'max_depth' : [5, 10, 20]
}

gradient_boosting = GridSearchCV(GradientBoostingClassifier(
                                     n_estimators = 100, max_features = 0.5),
                   param_grid, scoring = "accuracy")
gradient_boosting.fit(X_train, y_train)
```

Out[24]:
```
▸ GridSearchCV
▸ estimator: GradientBoostingClassifier
    ▸ GradientBoostingClassifier
```

In [25]:
```
y_pred = gradient_boosting.best_estimator_.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.9649122807017544
```

AdaBoost Classifier

Adaptive Boosting, is a Boosting technique used as an Ensemble Method in Machine Learning. It is called Adaptive Boosting as the weights are re-assigned to each instance, with higher weights assigned to incorrectly classified instances.

In [26]:
```
# Create a GradientBoostingClassifier
adaboosting = AdaBoostClassifier(n_estimators=100, learning_rate=0.1, random_state=42)
```

In [27]:
```
adaboosting.get_params()
```

Out[27]:
```
{'algorithm': 'SAMME.R',
 'base_estimator': 'deprecated',
 'estimator': None,
 'learning_rate': 0.1,
 'n_estimators': 100,
 'random_state': 42}
```

In [28]:
```
# Train the GradientBoostingClassifier
adaboosting.fit(X_train, y_train)

# Make predictions on the testing set
y_pred = adaboosting.predict(X_test)
```

In [29]:
```
# Calculate accuracy score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.9649122807017544
```

XGBoost

XGBoost is a refined and customized version of a gradient boosting decision tree system, created with performance and speed in mind. XGBoost actually stands for "eXtreme Gradient Boosting"

Load the classifier

In [30]:
```
from xgboost import XGBClassifier
```

Fit the model

In [31]:
```
xgb_clf = XGBClassifier()
xgb_clf.fit(X_train, y_train)
```

Out[31]:
```
▾ XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

Calculate and print the accuracy

In [32]:
```
y_pred = xgb_clf.predict(X_test)
# Calculate accuracy score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.956140350877193
```

Tuning parameters

In [33]:
```
param_grid = {
    'max_depth' : [5, 10, 20]
}

xgb = GridSearchCV(XGBClassifier(
                                     n_estimators = 100, max_features = 0.5),
                   param_grid, scoring = "accuracy")
xgb.fit(X_train, y_train)
```

Out[33]:
```
▸ GridSearchCV
▸ estimator: XGBClassifier
     ▸ XGBClassifier
```

In [34]:
```
y_pred = xgb.best_estimator_.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.956140350877193
```

Sentiment Analysis

In [35]:
```
pip install lime
```

```
Collecting lime
  Downloading lime-0.2.0.1.tar.gz (275 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 275.7/275.7 kB 4.9 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from lime) (3.7.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from lime) (1.23.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from lime) (1.11.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from lime) (4.66.1)
Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/python3.10/dist-packages (from lime) (1.
2.2)
Requirement already satisfied: scikit-image>=0.12 in /usr/local/lib/python3.10/dist-packages (from lime) (0.
19.3)
Requirement already satisfied: networkx>=2.2 in /usr/local/lib/python3.10/dist-packages (from scikit-image>=
0.12->lime) (3.2.1)
Requirement already satisfied: pillow!=7.1.0,!=7.1.1,!=8.3.0,>=6.1.0 in /usr/local/lib/python3.10/dist-packa
ges (from scikit-image>=0.12->lime) (9.4.0)
Requirement already satisfied: imageio>=2.4.1 in /usr/local/lib/python3.10/dist-packages (from scikit-image>
=0.12->lime) (2.31.6)
Requirement already satisfied: tifffile>=2019.7.26 in /usr/local/lib/python3.10/dist-packages (from scikit-i
mage>=0.12->lime) (2023.9.26)
Requirement already satisfied: PyWavelets>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-ima
ge>=0.12->lime) (1.4.1)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from scikit-image
>=0.12->lime) (23.2)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=
0.18->lime) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-
learn>=0.18->lime) (3.2.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib-
>lime) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->lim
e) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib
->lime) (4.44.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib
->lime) (1.4.5)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib-
>lime) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplot
lib->lime) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.
7->matplotlib->lime) (1.16.0)
Building wheels for collected packages: lime
  Building wheel for lime (setup.py) ... done
  Created wheel for lime: filename=lime-0.2.0.1-py3-none-any.whl size=283834 sha256=bde5dfc9afa6636cd8b4d746
69c631ee3d84a76552b10698f908c9fc0c5d35fd
  Stored in directory: /root/.cache/pip/wheels/fd/a2/af/9ac0a1a85a27f314a06b39e1f492bee1547d52549a4606ed89
Successfully built lime
Installing collected packages: lime
Successfully installed lime-0.2.0.1
```

In [36]:

```python
import nltk
from nltk.corpus import stopwords
nltk.download('punkt')
nltk.download('stopwords')
from sklearn.feature_extraction.text import CountVectorizer
import re
from wordcloud import WordCloud
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from lime import lime_text
from sklearn.metrics import f1_score
stop_words = stopwords.words()
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

In [37]:

```python
imdb  = pd.read_csv('/content/drive/MyDrive/ColabNotebooks/IMDB Dataset.csv').head(100)
```

In [38]:

```python
imdb.head()
```

Out[38]:

	review	sentiment
0	One of the other reviewers has mentioned that ...	positive
1	A wonderful little production. The...	positive
2	I thought this was a wonderful way to spend ti...	positive
3	Basically there's a family where a little boy ...	negative
4	Petter Mattei's "Love in the Time of Money" is...	positive

In [39]:
```
# Clean the data
def cleaning(text):
    text = text.lower() # converting to lowercase
    text = re.sub(r'[^a-z\s]', '', text) # removing number and special characters
    return text

imdb['review'] = imdb['review'].apply(cleaning)
```

In [40]:
```
imdb
```

Out[40]:

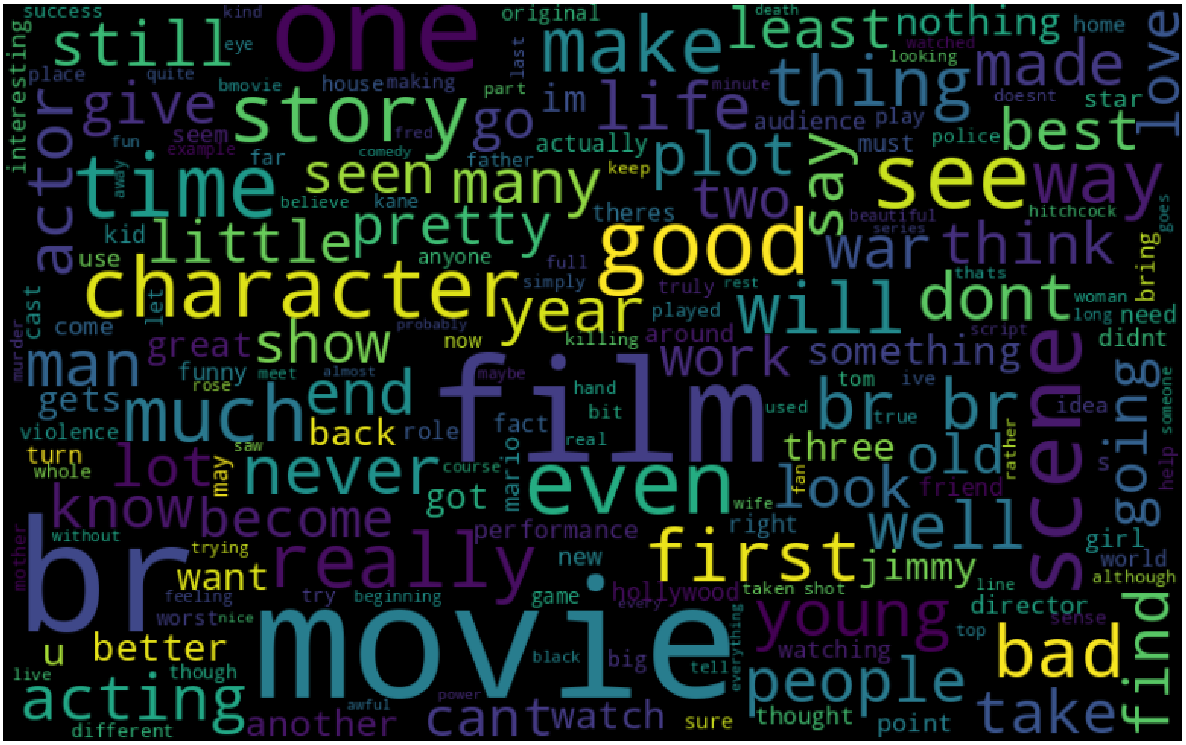
	review	sentiment
0	one of the other reviewers has mentioned that ...	positive
1	a wonderful little production br br the filmin...	positive
2	i thought this was a wonderful way to spend ti...	positive
3	basically theres a family where a little boy j...	negative
4	petter matteis love in the time of money is a ...	positive
...	...	...
95	daniel daylewis is the most versatile actor al...	positive
96	my guess would be this was originally going to...	negative
97	well i like to watch bad horror bmovies cause ...	negative
98	this is the worst movie i have ever seen as we...	negative
99	i have been a mario fan for as long as i can r...	positive

100 rows × 2 columns

In [41]:
```
sum(imdb.isna().sum())
```

Out[41]:
```
0
```

In [42]:
```
all_words = ' '.join([text for text in imdb['review']])
wordcloud = WordCloud(width=800, height=500, random_state=21, max_font_size=110).generate(all_words)
plt.figure(figsize=(10, 7))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis('off')
plt.show()
```



In [43]:
```
label_encoder = LabelEncoder()
imdb["sentiment"] = label_encoder.fit_transform(imdb["sentiment"])
```

In [44]:
```
imdb["sentiment"].value_counts()
```

Out[44]:
```
0    58
1    42
Name: sentiment, dtype: int64
```

In [45]:
```
# Building a model classification matrix
vectorizer = CountVectorizer()
train_data = vectorizer.fit_transform(imdb['review'])
train_data.shape
```

Out[45]:
```
(100, 4953)
```

In [46]:
```
y1=imdb['sentiment']
X1_train, X1_test, y1_train, y1_test = train_test_split(train_data, y1, test_size=0.2, random_state=42, stra
```

In [47]:
```
xgb_model = XGBClassifier(max_depth=6, n_estimators=10).fit(X1_train, y1_train)
prediction = xgb_model.predict(X1_test)
f1_score(y1_test, prediction)
```

Out[47]:
```
0.6
```

In [48]:
```
def predict(new_sentence):
  new_sentence = vectorizer.transform(new_sentence)
  prediction = xgb_model.predict(new_sentence)
  if prediction[0] == 0:
      sentiment = "Positive"
  else:
      sentiment = "Negative"

  print(f"Sentence sentiment: {sentiment}")
  print(f"Probability: {xgb_model.predict_proba(new_sentence)}")
```

In [49]:
```
new_sentence = ["Machine learning is awesome"]
predict(new_sentence)
```

```
Sentence sentiment: Positive
Probability: [[0.52114856 0.47885147]]
```

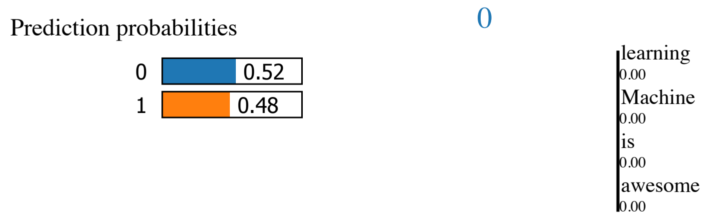
In [50]:
```
new_sentence = ["covid did not killed a lot of peaple"]
predict(new_sentence)
```

```
Sentence sentiment: Positive
Probability: [[0.60366607 0.39633396]]
```

In [51]:
```
# !pip install lime
```

In [52]:
```
def pred_fn(text):
    text_transformed = vectorizer.transform(text)
    return xgb_model.predict_proba(text_transformed)
```

In [53]:
```
from lime.lime_text import LimeTextExplainer
text_explainer = LimeTextExplainer(class_names=[0, 1])
text = "Machine learning is awesome"
explanation = text_explainer.explain_instance(text, classifier_fn=pred_fn)
explanation.show_in_notebook()
```



Text with highlighted words

Machine learning is awesome

In [54]:
```
X_train[0]
```

Out[54]:
```
array([0.09692839, 0.25769361, 0.10365559, 0.04538706, 0.48722578,
       0.37396479, 0.73336457, 0.21744533, 0.53080808, 0.64237574,
       0.07818215, 0.18427334, 0.05314988, 0.02029892, 0.26637658,
       0.62943491, 0.76717172, 0.62928585, 0.47965329, 0.29933115,
       0.08466738, 0.28331557, 0.07515315, 0.03428529, 0.50868388,
       0.39701759, 1.        , 0.60137457, 0.52493594, 0.40968123])
```

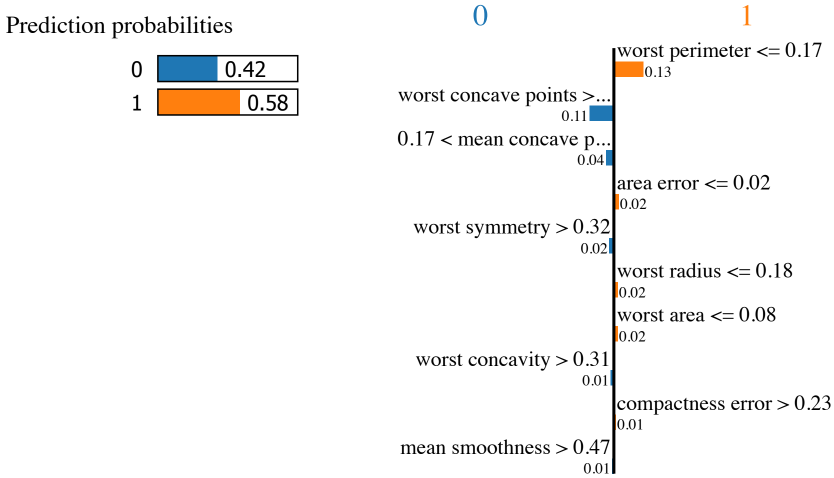
Lime

local interpretable model-agnostic explanations, is a technique that approximates any black box machine learning model with a local, interpretable model to explain each individual prediction.

https://christophm.github.io/interpretable-ml-book/lime.html

In [55]:
```
from lime.lime_tabular import LimeTabularExplainer
tabular_explainer = LimeTabularExplainer(X_train, mode="classification",
                                              class_names=["0","1"],
                                              feature_names=breast_cance.columns,
                                             )
tabular_explanation = tabular_explainer.explain_instance(X_train[0], adaboosting.predict_proba)
print(y[0])
tabular_explanation.show_in_notebook()
```

```
0
```



Feature	Value
worst perimeter	0.08
worst concave points	0.60
mean concave points	0.22
area error	0.02
worst symmetry	0.52
worst radius	0.08
worst area	0.03
worst concavity	1.00
compactness error	0.63

Practice

In [56]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

In [57]:
```
# Import the libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
```

In [58]:
```
# Load a dataset

# dataset = https://www.kaggle.com/gargmanas/pima-indians-diabetes

file_path = '/content/drive/MyDrive/ColabNotebooks/diabetes.csv'
data = pd.read_csv(file_path)
X = data.drop("Outcome",axis="columns")
y = data.Outcome
```

In [59]:
```
data.describe()
```

Out[59]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	76
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	

In [60]:
```
# Check if the dataset has nan value, if yes, impute nan values (KNNImputer)
data.isnull().sum()
```

Out[60]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [61]:
```
# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, stratify=y, random_state=10)
```

In [62]:
```
# select bagging and boosting classifier (2 models) and train them on the same dataset. Make sure you perfor
```

In [63]:
```
# Bagging
bagging_classifier = BaggingClassifier(DecisionTreeClassifier(random_state=123), random_state=10)
```

In [64]:
```
bagging_params = {
    'n_estimators': [5, 50, 100, 500],
    'max_samples': [0.02, 0.2, 0.7, 0.8],
    'max_features': [0.5, 0.7, 5.0 , 10.0],
}
bagging_clf = GridSearchCV(bagging_classifier, bagging_params, cv=5, scoring='accuracy')
bagging_clf.fit(X_train, y_train)
```

Out[64]:
```
▸ GridSearchCV
▸ estimator: BaggingClassifier
▸ estimator: DecisionTreeClassifier
▸ DecisionTreeClassifier
```

In [65]:
```
best_bagging_clf = bagging_clf.best_estimator_
best_bagging_clf.fit(X_train, y_train)
```

Out[65]:
```
▸ BaggingClassifier
▸ estimator: DecisionTreeClassifier
▸ DecisionTreeClassifier
```

In [66]:
```
# Show your result

#Bagging Result

print("Best Parameters for Bagging Classifier:")
print(bagging_clf.best_params_)
```

```
bagging_acc = accuracy_score(y_test, best_bagging_clf.predict(X_test))
print(f"Bagging Classifier Accuracy: {bagging_acc}")
```

```
Best Parameters for Bagging Classifier:
{'max_features': 0.7, 'max_samples': 0.2, 'n_estimators': 100}
Bagging Classifier Accuracy: 0.8051948051948052
```

In [67]:

```
# Boosting

boost_classifier = AdaBoostClassifier(DecisionTreeClassifier(max_depth=1, random_state = 10), random_state=4
```

In [68]:

```
boost_param = {
    'n_estimators': [5, 15, 50, 100, 500],
    'learning_rate': [0.01, 0.02, 0.1, 0.5],
}
boost_clf = GridSearchCV(boost_classifier, boost_param, cv=3, scoring='accuracy')
boost_clf.fit(X_train, y_train)
```

Out[68]:

```
▸ GridSearchCV
▸ estimator: AdaBoostClassifier
▸ estimator: DecisionTreeClassifier
▸ DecisionTreeClassifier
```

In [69]:

```
best_boost_clf = boost_clf.best_estimator_
best_boost_clf.fit(X_train, y_train)
```

Out[69]:

```
▸ AdaBoostClassifier
▸ estimator: DecisionTreeClassifier
▸ DecisionTreeClassifier
```

In [70]:

```
# Show your result

# Boosting Result

print("Best Parameters for AdaBoost Classifier:")
print(boost_clf.best_params_)

boost_accuracy = accuracy_score(y_test, boost_clf.predict(X_test))
print(f"AdaBoost Classifier Accuracy: {boost_accuracy}")
```

```
Best Parameters for AdaBoost Classifier:
{'learning_rate': 0.02, 'n_estimators': 100}
AdaBoost Classifier Accuracy: 0.8008658008658008
```

In [71]:

```
# Show your result

print("Best Parameters for Bagging Classifier:")
print(bagging_clf.best_params_)

bagging_acc = accuracy_score(y_test, best_bagging_clf.predict(X_test))
print(f"Bagging Classifier Accuracy: {bagging_acc}")

print("Best Parameters for AdaBoost Classifier:")
print(boost_clf.best_params_)

boost_accuracy = accuracy_score(y_test, boost_clf.predict(X_test))
print(f"AdaBoost Classifier Accuracy: {boost_accuracy}")
```

```
Best Parameters for Bagging Classifier:
{'max_features': 0.7, 'max_samples': 0.2, 'n_estimators': 100}
Bagging Classifier Accuracy: 0.8051948051948052
Best Parameters for AdaBoost Classifier:
{'learning_rate': 0.02, 'n_estimators': 100}
AdaBoost Classifier Accuracy: 0.8008658008658008
```

Explain your understanding of today's activity in 200 words

The dataset taken is to predict Pima Indians Diabetes. First, we make sure that our data do not have any null values. For the above model, there are no null values. If there were null values we need to handle them. We have used a decision tree classifier to train a stand-alone model. We have used 2 classifiers which is bagging and boosting.

Bagging is an ensemble learning, machine learning technique that combines the predictions of different models to improve accuracy. It involves creating subsets from an original dataset by randomly selecting the samples. Bagging reduces overfitting and increase the model stability.

Boosting is also an ensemble learning technique that combines weak models. It is used to improve efficiency, improve accuracy and Curbs over-fitting. It works with the principle of Boosting algorithm.

For the base classifier, we use the Decision Tree classifier for bagging. To optimize the model further we use different hyperparameters. The models are been trained on different hyper parameter values to get more accurate results.

The hyperparameter which gives the best results are printed for both bagging and boosting.

Next we fit the model with the best hyperparameters to get the accuracy of the model for bagging and boosting. For both bagging the model accuracy is 80.5% and for boosting the best accuracy is 80%