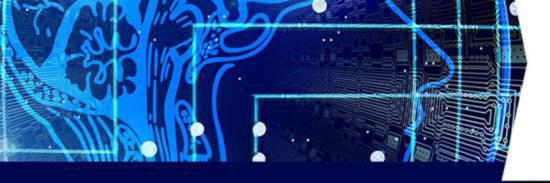




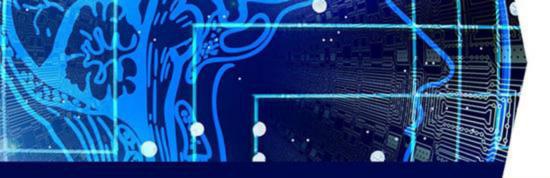
## Reason for subject selection

- Fake or misleading news can be dangerous
- It is also used for making money via advertising (clickbait)
- Prevalence has increased with the rise of social media
- Social media algorithms have been implicated in the spread of fake news
- Since coronavirus appeared fake news have been on the rise
- Anti-vaccination movement is growing vastly via fake news, meanwhile WHO declared it one of the top ten global threats
- Therefore, vastly reducing fake news is crucial for the society's own good



#### The data

- Dataset retrieved from kaggle
- Used data from 20800 article news labeled 'Real' or 'Fake'



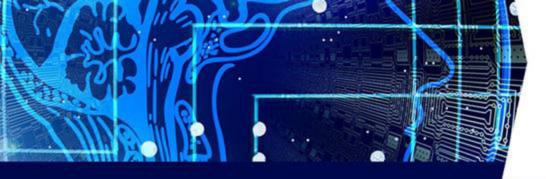
#### Bag-of-words model

- Text is changed into vectors of numbers to be processed by machine learning algorithms (feature encoding)
- Describes the occurrence of words within a document
- Transform each document from a corpus of documents into a vector and use it as an input to a machine learning algorithm



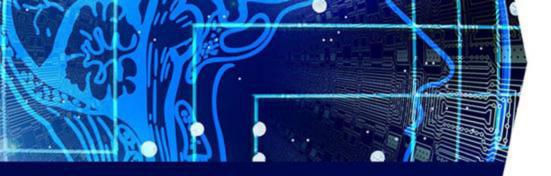
### Feature extraction with TF-IDF

- Statistical measure that shows how important a word is to a document in an entire corpus of documents
- Term frequency shows the frequency of a word in a document
- TF = Word occurrence / vocabulary of document
- Inverse document frequency shows the frequency of a word within the corpus of documents.
- IDF = log(Entire corpus of documents / number of documents containing specific word)
- TF-IDF score = TF \* IDF
- The higher the score, the more relevant that word is in that particular document
- Sklearn TfidfVectorizer used for different case scenarios



## Train test split and cross-validation

- Sklearn train\_test\_split was used for splitting the dataset. Different case scenarios were tested to see which one provided best results.
- But what if the training dataset includes only articles from a specific author. Then our data is biased.
- This is why cross-validation is crucial.
- Cross-validation was implemented with sklearn Kfold to check the accuracy on the training data (while splitting) compared to the predicted data.
- This way we can check if our data is biased or not.
- Cross-validations is also used for tuning the hyperparameters of a classifier.



### Logistic regression metrics

- Cross-validation mean accuracy: 93.2%
- Accuracy: 93.55%
- Confusion matrix:

Actual class

Predicted

[[1982 118]

class

[ 150 1910]]

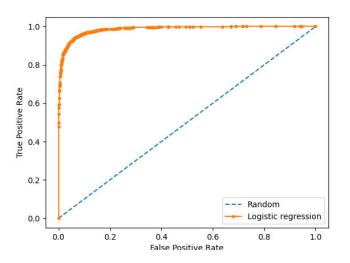
- Precision: 0.9418
- Recall: 0.9271
- Specificity: 0.9438
- False positive rate: 0.056
- F1-score: 0.9344

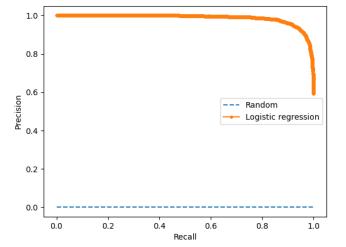


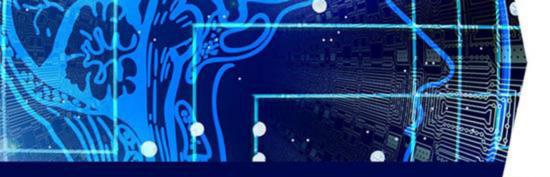
# Logistic regression ROC/Precision recall curves

• ROC AUC: 0.9853

ROC AUC: 0.9857







### Naïve Bayes metrics

Cross-validation mean accuracy: 87.76%

Accuracy: 87.21%

Confusion matrix:

Actual class

Predicted

[[1752 348]

class

[ 184 1876]]

• Precision: 0.8435

Recall: 0.9106

Specificity: 0.8342

False positive rate: 0.1657

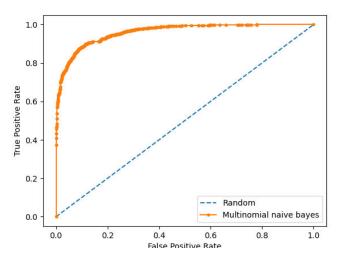
• F1-score: 0.8758

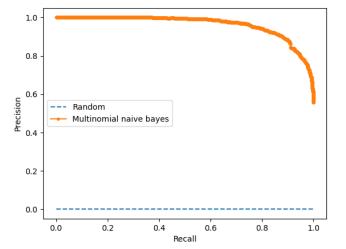


# Naïve Bayes ROC/Precision recall curves

• ROC AUC: 0.9601

• ROC AUC: 0.9626







### K-nearest neighbor metrics

- Cross-validation mean accuracy: 72.51%
- Accuracy: 73.72%
- Confusion matrix:

Actual class

Predicted

[[1994 106]

class

[ 987 1073]]

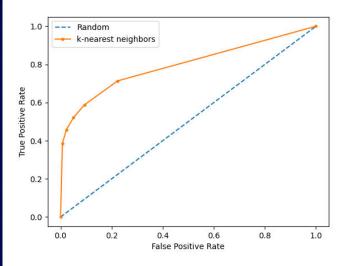
- Precision: 0.91
- Recall: 0.5208
- Specificity: 0.9495
- False positive rate: 0.05
- F1-score: 0.6625

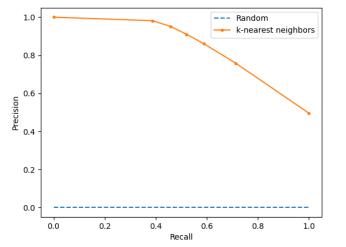


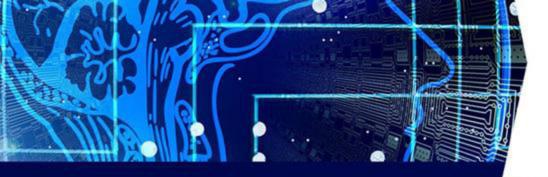
# K-nearest neighbor ROC/Precision recall curves

• ROC AUC: 0.7953

• ROC AUC: 0.8511







#### Decision tree metrics

- Cross-validation mean accuracy: 87.6%
- Accuracy: 87.3%
- Confusion matrix:

Predicted

class

**Actual class** 

[[1822 278]

[ 250 1810]]

- Precision: 0.8668
- Recall: 0.8786
- Specificity: 0.8676
- False positive rate: 0.1323
- F1-score: 0.8727



# Decision tree ROC/Precision recall curves

• ROC AUC: 0.8714

• ROC AUC: 0.9012

