Basics in ML with Python

Exercise 1 : Visualizing Word2Vec Word Embeddings using t-SNE

Word embeddding is a type of word representation, by means of a high-dimensional numerical vector (around hundred of components). Popular word embeddings as `Word2Vec`, `BERT` are based on neural networks.

To understand how we can visualize word clusters, we shall combine `Word2Vec` representation and `t-SNE`.
To do so we shall use `gensim` Python library and begin to import the embeddings

```
import numpy
import gensim
model_gn = gensim.models.KeyedVectors.
load_word2vec_format('/home/marianne/GoogleNews-vectors-negative300.bin.gz',
binary=True)
```

The embeddings can be downloaded with the link

`https://drive.google.com/file/d/1Jqn0svMINDhi2zSPkAT6T21H1XQFf-WB/view?usp=sharing`

1. We now create synthetic data, naturally associated to clusters
   ```
   keys = ['Paris', 'Python', 'Sunday', 'Tolstoy', 'Twitter', 'bachelor',
   'delivery', 'election', 'expensive', 'experience', 'financial', 'food',
   'iOS', 'peace', 'release', 'war']

   embedding_clusters = []
   word_clusters = []
   for word in keys:
        embeddings = []
        words = []
        for similar_word, _ in model_gn.most_similar(word, topn=30):
             words.append(similar_word)
             embeddings.append(model_gn[similar_word])
        embedding_clusters.append(embeddings)
        word_clusters.append(words)

   embedding_clusters = np.array(embedding_clusters)
   n, m, k = embedding_clusters.shape
   ```

2. Perform PCA on this synthetic dataset and visualize the different clusters related to each `key`

3. Perform t-SNE and and visualize the different clusters related to each `key` in the t-SNE space

4. Compare both

For the two next exercises, one may rely on the notebook `Introduction to Classical ML models`

Exercise 2 : Classification on the Breast Cancer dataset

The Breast Cancer Wisconsin (Diagnostic) Data Set is a classical dataset widely used in classification. The task consists in predicting if a tumor is malignant (M) or benign (B) depending on certain features, that can be downloaded from the UCI Machine Learning repository. More details here
`https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Diagnostic)`
We want to compare the performance of Logistic Regression, SVM and Random Forest on this classification task. The confusion matrix is the matrix

$$M = \begin{pmatrix} TN & FP \\ FN & TP \end{pmatrix}$$

where TP : True Positive, TN : True Negative, FP : False Positive, FN : False Negative. We recall the notion of precision and recall

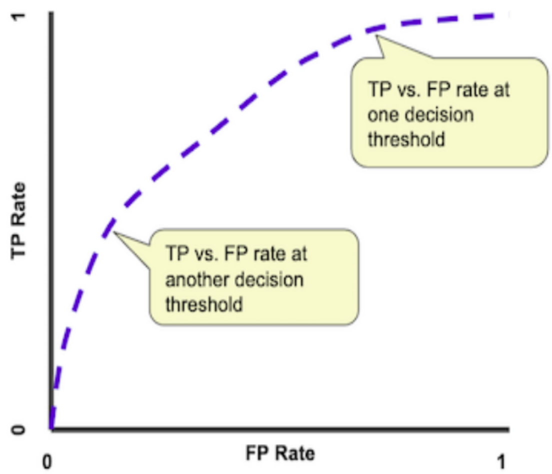
$$\text{Precision} = \frac{TP}{TP + FP}, \text{ Recall} = \frac{TP}{TP + FN}$$

The accuracy is then defined as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Accuracy is a very useful metric when all the classes are equally important. But this might not be the case if we are predicting if a patient has cancer. In this example, we can probably tolerate FPs but not FNs. This metric could also be not so relevant when considering imbalanced data.

ROC curve : A ROC curve (receiver operating characteristic curve) graph shows the performance of a classification model at all classification thresholds.



AUC : AUC stands for Area under the ROC Curve. It provides an aggregate measure of performance across all possible classification thresholds.

The higher the area under the ROC curve (AUC), the better the classifier. A perfect classifier would have an AUC of 1. Usually, if your model behaves well, you obtain a good classifier by selecting the value of the threshold that gives TPR close to 1 while keeping FPR near 0.

1. Import the dataset `breast_cancer.csv`. Drop the `unnamed` and `id columns`.

2. In each case, for each classification method (Logistic Regression, SVM and Random Forest)

   (a) Give the confusion matrix

   (b) Evaluate the accuracy of the model

   (c) Plot the ROC curve

Exercise 3 : Deal with imbalanced dataset

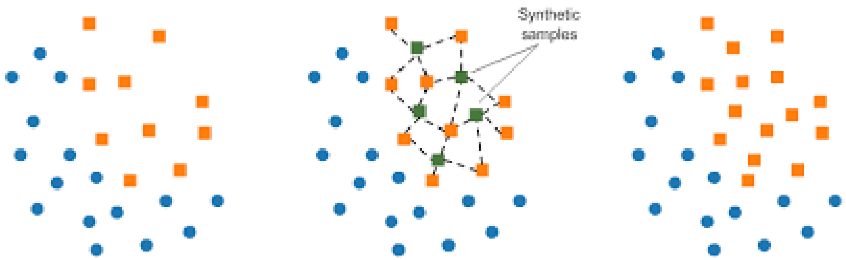
We now consider a dataset aout fraudulent credit card transaction
`https://www.kaggle.com/mlg-ulb/creditcardfraud`

1. Import the dataset `creditcardfraud.csv` from the website. What is the distribution of the target variable? Explain the specificity of this dataset

2. A strategy consists in oversampling the minority class using the so-called SMOTE method which is implemented in Python in the library `imblearn`
   `https://imbalanced-learn.org/stable/generated/imblearn.over_sampling.SMOTE.html`
   The idea is to synthesize new examples from the minority class. SMOTE first selects a minority class instance a at random and finds its k nearest minority class neighbors.

   The synthetic instance is then created by choosing one of the k nearest neighbors b at random and connecting a and b to form a line segment in the feature space.

   The synthetic instances are generated as a convex combination of the two chosen instances a and b.

   Apply SMOTE to oversample the minority class.

3. For Logistic Regression

   (a) Give the confusion matrix

   (b) Evaluate the accuracy of the model. Do you think this metric is relevant for imbalanced classification?

   (c) An alternative consists in defining Sensitivity-Specificity Metrics. One defines

$$Sensitivity = \frac{TP}{TP + FN}$$

   Specificity is the complement to sensitivity, or the true negative rate, and summarises how well the negative class was predicted.

$$Specificity = \frac{TN}{FP + TN}$$

   For imbalanced classification, the sensitivity might be more interesting than the specificity. One then defines the G–mean as

$$G - Mean = \sqrt{(Sensitivity \times Specificity)}$$

   Use these alternative metrics that can be found at
   `https://imbalanced-learn.org/stable/api.html#module-imblearn.metrics`

   (d) We now define the following metrics

$$F_\beta = \frac{(1 + \beta^2) \cdot Precision \cdot Recall}{(\beta^2 \cdot Precision + Recall)}$$

   When will be the F_1 (resp $F_{0.5}$, F_2 mesure relevant)? What happens in our case?
   Hint : use the functions `f1_score` and `fbeta_score` of the library `metrics` of `sklearn`

Exercise 4 : Feature importance and Random Forests

In this exercise we aim at exploring the different concepts of feature importance for Random Forests. To illustrate this question, we consider the following data file `rent.csv` describing New York City apartment rent prices with several additional criteria

1. Download the data `rent.csv`, store it in a dataframe and add the names of the columns to the dataframe. We add also a column of random feature.
2. We explore a first importance measure for Random Forest that is implemented in scikit-learn. Recall that the features for internal nodes are selected with some criterion, Gini impurity for classification tasks, variance reduction for regression. We can measure how each feature decrease the impurity of the split (the feature with highest decrease is selected for internal node). For each feature we can collect how on average it decreases the impurity. The average over all trees in the forest is **the measure of the feature importance** implemented in scikit-learn. See `https://scikit-learn.org/stable/auto_examples/ensemble/plot_forest_importances.html` for more details.
   (a) Train a regressor to predict New York City apartment rent prices using four apartment features. Thereafter calculate the Random Forest Built-in Feature Importance for the data `rent.csv` of each feature using the function `feature_importances_`. Comment
   (b) Train a classifier predicting apartment interest level (low, medium, high) using 5 features + the random column. Thereafter calculate the Random Forest Built-in Feature Importance for the data `rent.csv` of each feature using the function `feature_importances_`. Comment
3. Breiman defined also another importance measure called `permutation measure` defined in the following way. Record a baseline accuracy (classifier) or R2 score (regressor). Permute the column values of a single predictor feature and then pass all test samples back through the Random Forest and recompute the accuracy or R2. The importance of that feature is the difference between the baseline and the drop in overall accuracy or R2 caused by permuting the column.
   (a) Define a Python function which calculate this permutation importance
   (b) Calculate it in the two previous cases. Comment

Exercise 5 : Quantile regression with ensemble methods

In this exercise, we consider the results of a survey given to visitors of hostels listed on Booking.com and TripAdvisor.com. Our features here are the average ratings for different categories

- "f1": "Staff"

- "f2": "Hostel booking"
- "f3": "Check-in and check-out"
- "f4": "Room condition"
- "f5": "Shared kitchen condition"
- "f6": "Shared space condition"
- "f7": "Extra services"
- "f8": "General conditions conveniences"
- "f9": "Value for money"
- "f10": "Customer Co-creation"

Our target variable is the hostel's overall `rating` on the website. The dataset is `hostel_factors.csv` and can be downloaded on the github repository

1. Fit a Quantile Gradient Boosting Tree using the option `loss='quantile'` in the usual Gradient Boosting Regressor
2. Store the quantiles corresponding to the 97.5th and 2.5th percentile
3. Plot the confidence intervals for the regression