2EL1730: MACHINE LEARNING
CENTRALESUPÉLEC
Lab 5: SVMs and Text Categorization

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1 Goal of the Lab

The goal of this lab is to experiment with Support Vector Machines (SVMs).

2 Support Vector Machines (SVMs)

In the first part this lab, we will apply support vector machines (SVMs) on two different 2D artificial datasets. Applying SVM[1] in these datasets will help us gain an intuition of how SVMs work. Additionally, you will try using different values of the C parameter with SVMs. Actually, the C parameter is a positive value that controls the penalty for misclassified training examples. A large C parameter tells the SVM to try to classify all the examples correctly. C plays a role similar to $\frac{1}{\lambda}$, where λ is the regularization parameter that we were using previously for logistic regression. Additionally, we will implement and examine two different types of kernel function, the linear kernel and the Gaussian kernel.

2.1 SVM with linear kernels

We will begin with a simple dataset which is linear separable. The script `main1.py` will plot the training data (see Fig.1). In this dataset, the positions of the positive examples (indicated with o) and the negative examples (indicated with +) suggest a natural separation indicated by the gap. However, notice that there is an outlier positive example o on the far left at about $(0.1, 4.1)$. As part of this exercise, you will also see how this outlier affects the SVM decision boundary.

In this point, we need to implement a linear kernel. The linear kernel between a pair of instances, $(\boldsymbol{x}^{(i)}, \boldsymbol{x}^{(j)})$ is given as:

$$K(\boldsymbol{x}^{(i)}, \boldsymbol{x}^{(j)}) = \sum_{k=0}^{m} x_k^{(i)} x_k^{(j)}, \tag{1}$$

where m is the number of features.

2.1.1 Tasks to be performed

1. Fill in the code in `linearKernel.py` function to compute the linear kernel between two examples, $(\boldsymbol{x}^{(i)}, \boldsymbol{x}^{(j)})$.

[1] In our code, we will use the SVM classifier implemented at `scikit-learn`.

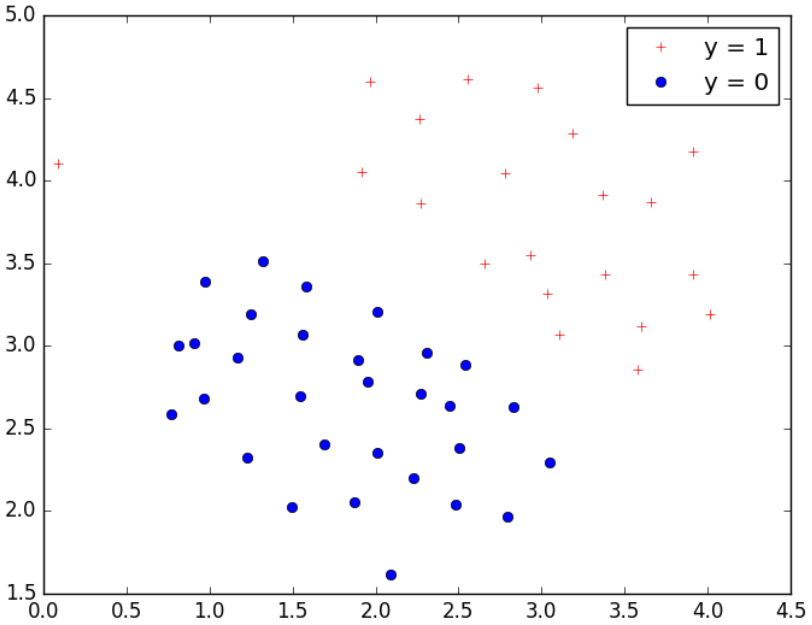


Figure 1: Dataset 1

2. Try different values of C on this dataset. Specifically, you should select the value of C in the script `main1.py` to $C = \{1, 100\}$ and run the SVM training. When $C = 100$, you should observe that the SVM now classifies every single example correctly, but has a decision boundary that does not appear to be a natural fit for the data. When $C = 1$, you should find that the SVM puts the decision boundary in the gap between the two datasets and misclassifies the data point on the far left.

2.2 SVM with Gaussian kernels

Now, we are going to use SVMs for non-linear classification. More specifically, you will be using SVMs along with Gaussian kernels on datasets where classes are not linearly separable. From the illustration of the dataset in Fig. 2, it is apparent that there is no linear decision boundary that separates the positive and negative examples for this dataset. However, by using the Gaussian kernel with the SVM, you will be able to learn a non-linear decision boundary that can perform reasonably well for the dataset.

2.2.1 Gaussian kernel

To find non-linear decision boundaries with the SVM, we need to implement a Gaussian kernel. The Gaussian kernel can be seen as a similarity function that measures the distance between a pair of instances, $(\boldsymbol{x}^{(i)}, \boldsymbol{x}^{(j)})$. The Gaussian kernel is also parameterized by a bandwidth parameter, σ, which determines how fast the similarity metric decreases (toward 0) as the examples are further apart. The Gaussian kernel is defined as follows:

$$K(\boldsymbol{x}^{(i)}, \boldsymbol{x}^{(j)}) = \exp\left(-\frac{\|\boldsymbol{x}^{(i)} - \boldsymbol{x}^{(j)}\|^2}{2\sigma^2}\right) \tag{2}$$

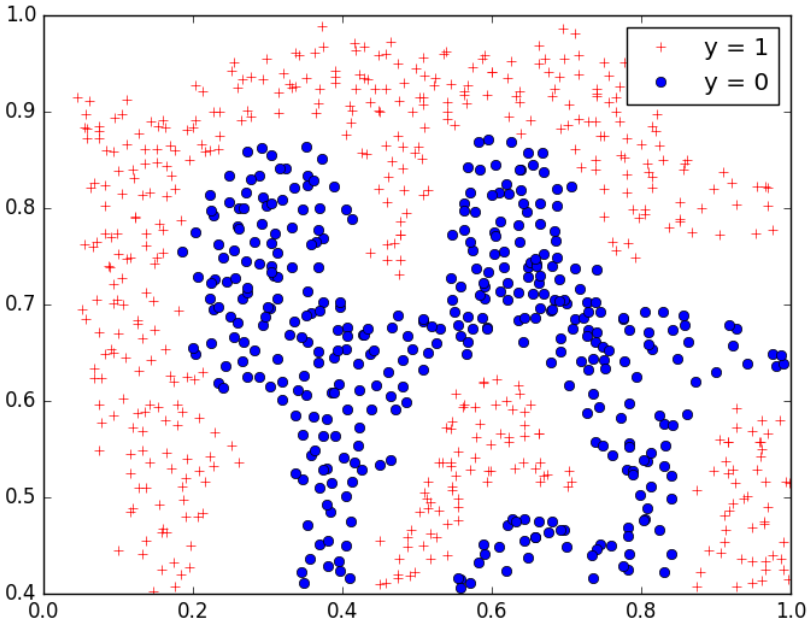


Figure 2: Dataset 2

2.2.2 Tasks to be performed

1. Fill in the code in `gaussianKernel.py` function in order to compute the Gaussian kernel between two examples, $(\boldsymbol{x}^{(i)}, \boldsymbol{x}^{(j)})$.

2. Examine different values for C and σ and try to interpret the effects on the performance of SVM.

3 (Optional) Text Categorization with SVMs

The goal of the second part of the lab is to work with textual data, applying machine learning techniques. The basic objective of *text mining* concerns the discovery and extraction of relevant and valuable information from large volumes of text data. More precisely, we will focus on the *opinion mining* problem (also known as sentiment analysis), which refers to the use of natural language processing, text analysis and machine learning tools in order to identify and extract subjective information from text corpora.

Our goal is to identify *positive* and *negative* opinions in reviews expressed by natural language (i.e., text) about a specific product. Opinion mining can be useful in several ways. It can help a company to evaluate the success of an ad campaign for new product, determine which versions of a product or service are popular and identify which demographics like or dislike particular product features.

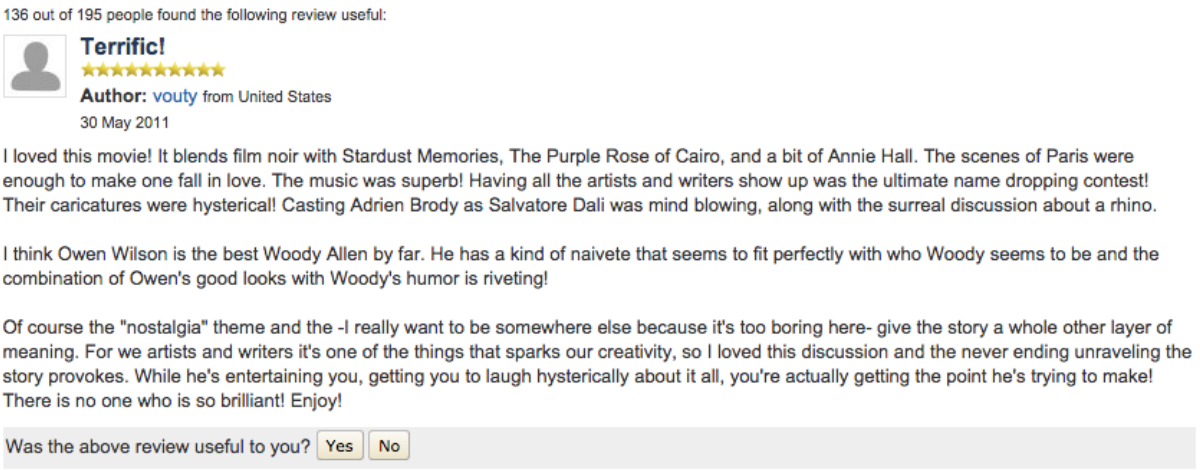
There are several challenges in the problem of opinion mining. The first one concerns the fact that a specific word used to describe a product can be considered either as positive or as negative depending on the context or the product. Let's take as example a review about a laptop that contains the word "long". If a customer said that the battery life of the laptop was long, that would be a positive opinion. However, if the customer said that the laptop's start-up time was long, that would correspond to a negative opinion. This example indicates that an opinion system, trained to gather opinions about a

type of product or product's feature, may not perform very well on another. A second challenge is that people do not always express their opinions in the same way. Most traditional text processing relies on the fact that small differences between two pieces of text do not change the meaning that much. However, in opinion mining, "the laptop was great" is very different from "the laptop was not great". Lastly, people can combine contradictory statements in their reviews, where both positive and negative comments are written in the same sentence. Although this is easy for a human to understand, it is very challenging for a computer to parse.

In the context of this lab, we will analyze reviews about movies (e.g., obtained from *IMDb*[2], an online database of information related to films and television programs). We will follow a text categorization (or classification) approach to infer if a review is positive or negative (i.e., classify a review text as positive or negative). Next, we briefly describe the reviews dataset that will be used and then we present the steps of the pipeline that need to be performed for the sentiment analysis task.

3.1 Dataset Description

The dataset that will be used in the lab concerns movie reviews. As you may have observed, in movie review websites like IMDb, any user can write its own review for a particular movie or television show. For example, Fig. 3 shows the review of the movie *Midnight in Paris* given by a user. As we can observe, the opinion of this user for the movie is positive.


136 out of 195 people found the following review useful:

Terrific!

Author: vouty from United States

30 May 2011

I loved this movie! It blends film noir with Stardust Memories, The Purple Rose of Cairo, and a bit of Annie Hall. The scenes of Paris were enough to make one fall in love. The music was superb! Having all the artists and writers show up was the ultimate name dropping contest! Their caricatures were hysterical! Casting Adrien Brody as Salvatore Dali was mind blowing, along with the surreal discussion about a rhino.

I think Owen Wilson is the best Woody Allen by far. He has a kind of naivete that seems to fit perfectly with who Woody seems to be and the combination of Owen's good looks with Woody's humor is riveting!

Of course the "nostalgia" theme and the -I really want to be somewhere else because it's too boring here- give the story a whole other layer of meaning. For we artists and writers it's one of the things that sparks our creativity, so I loved this discussion and the never ending unraveling the story provokes. While he's entertaining you, getting you to laugh hysterically about it all, you're actually getting the point he's trying to make! There is no one who is so brilliant! Enjoy!

Was the above review useful to you? Yes No

Figure 3: Example review of the movie *Midnight in Paris* in IMDb.

Here, we will consider such a dataset, where each review has been characterized as *positive* or *negative*. The data is given in the `movie_reviews.csv` file. The file is composed by $1,959$ reviews (one per line) and each one has been characterized as positive or negative. For example, Fig. 4 shows the first entry of the file. As you can observe, this review has been categorized as positive.

```
"This movie is really not all that bad. But then again, this movie genre is right down my alley.
Sure, the sets are cheap, but they really did decent with what they had. If you like cheap,
futuristic, post-apocalyptic B movies, then you'll love this one!! I sure did!",positive
```

Figure 4: Example review from the dataset.

[2] `http://www.imdb.com/`

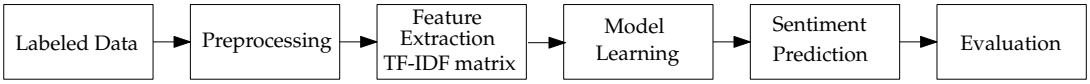


Figure 5: Pipeline of the sentiment analysis task.

3.2 Description of the Task and the Pipeline

Our goal is to build a system that, given the review text of a movie, it will be able to predict if the opinion of the user is positive or negative. We will treat the problem as a classification one, where the goal is predict the class label, i.e., positive or negative, for a given review. In the description that follows, we use the word "document" to refer to text reviews. The outline of the task is given in Fig. 5.

The pipeline that typically is followed to deal with the problem is similar to the one applied in any classification problem; the goal is to learn the parameters of a classifier from a collection of training documents (i.e., those reviews that we know if they are positive or negative) and then to predict the class of unlabeled documents. The first step in text categorization is to transform documents, which typically are strings of characters, into a representation suitable for the learning algorithm and the classification task. Here, we will employ the *Vector Space Model*, a spatial representation of text documents. In this model, each document is represented by a vector in a n-dimensional space, where each dimension corresponds to a term (i.e., word) from the overall vocabulary of the given document collection. More formally, let $\mathcal{D} = \{d_1, d_2, \ldots, d_m\}$ denote a collection of m documents, and $\mathcal{T} = \{t_1, t_2, \ldots, t_n\}$ be the dictionary, i.e., the set of words in the corpus $\mathcal{D}$. As we will describe later, $\mathcal{T}$ is obtained by applying some standard natural language processing techniques, such as stop words removal and stemming. Each document $d_i \in \mathcal{D}$ is represented as a vector of term weights $d_i = \{w_{i,1}, w_{i,2}, \ldots, w_{i,n}\}$, where $w_{i,k}$ is the weight of term k in document d_i. That way, data can be represented by the *Document-Term matrix* $\mathbf{DT}$ of size $m \times n$, where the rows correspond to documents and the columns to the different terms (i.e., features) of set $\mathcal{T}$. Additionally, each document d_i is associated with a class label $y_i = \{+, -\}$ (i.e., positive/negative opinion) forming the class vector $\mathbf{Y}$, and the goal is to predict the class labels for a set of test documents. Based on this formulation, traditional classification algorithms that we have seen in the class (e.g., SVMs, Logistic Regression, AdaBoost, etc.) can be applied to predict the category label of test documents.

Next, we describe the tasks that need to be performed for each each part, providing also the related parts of Python code.

3.2.1 Load the data

Initially, we should load the data contained in the `movie_reviews.csv` file. Later on, we will describe how part of this dataset will be used to train (i.e., build) our model and then, to test it. To import the data, we have to parse the .csv file line by line; recall that each line contains the text review and the opinion (positive/negative). To do that, we will use Python's built-in function `csv.reader(csv_file, delimiter=',',quotechar='"')`. The main point here is to split each line of the file into two parts, the one that corresponds to the text review (list `data`) and the other to the opinion (list `labels`). Next, we give the code for this part.

```
with open('movie_reviews.csv') as csv_file:
        reader = csv.reader(csv_file, delimiter=',',quotechar='"')
        # Initialize lists for data and class labels
        data =[]
        labels = []
        # For each row of the csv file
        for row in reader:
```

```
    # skip missing data
            if row[0] and row[1]:
                    data.append(row[0])
                    y_label = -1 if row[1]=='negative' else 1
                    labels.append(y_label)
```

3.2.2 Data preprocessing

Before applying any learning algorithm to the data, it is necessary to apply some preprocessing tasks as shown below:

- Remove punctuation marks (e.g., . , ? : ( ) [ ])[3] and transform all characters to lowercase. This can be done using Python's *NLTK* library (`http://www.nltk.org/`) as follows:

```
# Remove punctuation and lowercase characters
punctuation = set(string.punctuation)
doc = ''.join([w for w in text.lower() if w not in punctuation])
```

- Remove stop words. These are words that are filtered out before processing any natural language data. This set of words does not offer information about the content of the document and typically corresponds to a set of commonly used words in any language. For example, in the context of a search engine, suppose that your search query is "how to categorize documents". If the search engine tries to find web pages that contain the terms "how", "to", "categorize", "documents", it will find many more pages that contain the terms "how" and "to" than pages that contain information about document categorization. This is happening because the terms "how" and "to" are commonly used in the English language.

  Tasks to be done. In the code, we provide a list of stop words that should be removed (list `stopwords`). Fill in the Python code to remove these stop words from all documents.

- The third preprocessing step is the one of stemming[4], i.e., the process of reducing the words to their word stem or root. For example, a stemming algorithm reduces the words "fishing", "fished", and "fisher" to the root word, "fish".

  Task to be done. In the lab, we will use *Porter's* stemmer, contained in the NLTK library. Use the following code to perform stemming:

```
# Stemming
stemmer = PorterStemmer()
doc = [stemmer.stem(w) for w in doc]
```

3.2.3 Feature extraction and the TF-IDF matrix

After applying the preprocessing step, the text data (i.e., all the possible documents-reviews) should be transformed to a format that will be used in the learning (i.e., classification) task. As we describe above, the data will be represented by the Document-Term matrix, where the rows correspond to the different documents of the collection (i.e., reviews) and the columns to the features, which in our case are the different terms (i.e., words). Here, we are interested to find relevant weighting criteria for the Document-Term matrix, i.e., assign a relevance score w_{ij} to each term t_j for each document d_i as shown in Fig. 6.

[3] Wikipedia's lemma for *Punctuation*: `http://en.wikipedia.org/wiki/Punctuation`.
[4] Wikipedia's lemma for *Stemming*: `http://en.wikipedia.org/wiki/Stemming`.

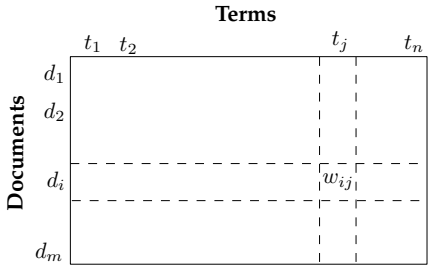


Figure 6: Schematic representation of the Document-Term matrix.

We will consider the *Bag-of-Words* representation of the documents. In this case, the importance of a term $t \in \mathcal{T}$ within a document $d \in \mathcal{D}$ is based on the frequency $tf(t, d)$ of the term in the document (TF). Furthermore, terms that occur frequently in one document but rarely in the rest of the documents, are more likely to be relevant to the topic of the document. This is known as the inverse document frequency (IDF) factor, and is computed at the collection level. It is obtained by dividing the total number of documents by the number of documents containing the term, and then taking the logarithm of that quotient, as follows:

$$idf(t, \mathcal{D}) = \log \frac{m}{|\{d \in \mathcal{D} : t \in d|\}},$$

where m is the total number of documents in collection $\mathcal{D}$, and the denominator captures the number of documents that term t appears. Having computed the TF and IDF metrics, we can combine them to get the TF-IDF score:

$$tf\text{-}idf(t, d, \mathcal{D}) = tf(t, d) \times idf(t, \mathcal{D}).$$

This function captures the intuitions that (i) the more often a term occurs in a document, the more it is representative of its content, and (ii) the more documents a term occurs in, the less discriminating it is[5]. Using the TF-IDF score of each term for each document, we can fill in the weights w_{ij} of the Document-Term matrix (see Fig. 6).

Task to be done. In the lab, we will use the *scikit-learn* Python library to automatically construct the TF-IDF matrix, and more specifically the `TfidfVectorizer` class. Let `data` be the list with the pre-processed documents created in the previous step. Then, the following code will return the TF-IDF matrix (sparse matrix stored in `tfidf_matrix`). Also examine the size and the sparsity of this matrix (i.e., fraction of non-zero elements). What do you observe?

```
# Create the Document–Term TF–IDF matrix
m = TfidfVectorizer()
tfidf_matrix = m.fit_transform(data)
tfidf_matrix = tfidf_matrix.toarray() # convert to numpy array
print "Size of TF–IDF matrix: ", tfidf_matrix.shape
```

3.2.4 Model learning and prediction

After having form the TF-IDF matrix, the problem has been transformed to a typical classification task: the rows of the matrix correspond to the instances (i.e., reviews) and the columns to the features (i.e., terms). Recall that, for each document we also have class information, i.e., positive or negative review,

[5]Several variants of the *tf-idf* score have been proposed. See also the description given in Ref. [**?**], pages 12-14.

contained in the `labels` list (this list was created during the data load step). In order to train a classification model, we will split the dataset (`tfidf_matrix`) into two sets: training and test. The training set will be used to learn the parameters of the classification model, that later will be applied to the test part in order to examine the accuracy of the model. We will use the following code to split the TF-IDF matrix:

```
# Split the data into random train and test subsets. Here we use 40% # of the data for testing
data_train, data_test, labels_train, labels_test = cross_validation.train_test_split(
                                        tfidf_matrix, labels, test_size=0.4, random_state=42)
```

Now, the `data_train` is the matrix for the training step, while the `data_test` will be used in the evaluation phase.

Tasks to be done.

- The next step of the pipeline involves the examination of different classification algorithms () for the specific problem. Here, you can test the performance of them and choose the best one. We will use built-in implementations of the classification algorithms provided by *scikit-learn*. Typically, in *scikit-learn*, we follow three steps in order to apply a classification algorithm:

  1. create an object of the classifier,
  2. fit the parameters of the classifier to the training data,
  3. do predictions on the test data.

  Run the following code, to predict the class labels using the Linear SVM classification model[6]:

  ```
  # Initialize the model
  clf = svm.LinearSVC()
  # Fit the model to the training data
  y_score = clf.fit(data_train, labels_train).predict_proba(data_test)
  # Perform classification of test data
  labels_predicted = clf.predict(data_test)
  ```

  Now, the list `labels_predicted` will contain the predicted labels (positive/negative review) of the test data. In the following section, we present how to evaluate the results.

  Parameter tuning. We should note here that the proper choice of parameters is critical for the SVMs performance. For instance, training an SVM with the Radial Basis Function (RBF) kernel, two parameters must be considered: `C` and `gamma`. The parameter `C`, common to all SVM kernels, trades off misclassification of training examples against simplicity of the decision surface. A low `C` makes the decision surface smooth, while a high `C` aims at classifying all training examples correctly. On the other hand, `gamma` defines how much influence a single training example has. The larger `gamma` is, the closer other examples must be to be affected. For this task, experiment with different types of kernels (linear, polynomial, and RBF) for the SVM learning algorithm and tune their parameters.

[6]scikit-learn: `http://scikit-learn.org/stable/modules/classes.html#module-sklearn.svm`

3.2.5 Evaluation of the classification results

For the evaluation of the classification results, we will use the precision, recall[7] and F_1-score (combination of precision and recall)[8]:

$$\text{precision} = \frac{TP}{TP + FP}, \qquad \text{recall} = \frac{TP}{TP + FN}, \qquad F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}.$$

The precision for a class is the number of true positives TP (i.e., the number of items correctly labeled as belonging to the positive class) divided by the total number of elements labeled as belonging to the positive class (i.e., the sum of true positives TP and false positives FN, which are items incorrectly labeled as belonging to the class). Recall in this context is defined as the number of true positives TP divided by the total number of elements that actually belong to the positive class (i.e., the sum of true positives TP and false negatives FN, which are items which were not labeled as belonging to the positive class but should have been).

Task to be done. We will use build-in tools of *scikit-learn* to do the evaluation. Run the following code that computes the precision, recall, F_1 score.

```
# Evaluation of the prediction
print classification_report(labels_test, labels_predicted)
print "The accuracy score is {:.2%}".format(accuracy_score(labels_test, labels_predicted))
```

References

[7] Wikipedia's lemma for *Precision and Recall*: http://en.wikipedia.org/wiki/Precision_and_recall.
[8] Wikipedia's lemma for *F1-score*: http://en.wikipedia.org/wiki/F1_score.