

Homework 3:

Classification with Scikit-Learn

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In this homework you will learn something about the Python library 'scikit-learn' or 'sklearn', a well known and very useful toolbox for research areas like data analysis and machine learning.

Exercise 1: CountVectorizer [4 points]

In the script `hw03_sklearn_paraphrases/small_functions` complete the function `trigram_quadragram_vectorizer(texts)` that takes a list of text strings, and returns a `CountVectorizer` that considers all trigrams and quadragrams that occur in at least 3 of the given texts. Use the `CountVectorizer` defaults for preprocessing of text (tokenization, lower-casing etc.). You can test your function with:

```
python3 -m unittest -v hw03_sklearn_paraphrases/test_small_functions.py
```

Exercise 2: DictVectorizer

In this exercise we will do some small experiments with sklearn's `DictVectorizer`. To complete this exercise you will need the documentation: http://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.DictVectorizer.html

Exercise 2.1: DictVectorizer - Part 1 [4 points]

In Machine Learning in the context of NLP a common task is to efficiently transform dictionaries of word counts to feature matrices, where each row stands for a dictionary (e.g. a sentence) and each column for a word. Each position in the matrix denotes the number of occurrences of a word in a sentence. So given a large number of dictionaries, one must:

- Derive the set of all words that occur in any sentence.
- Iterate over all dictionaries, count the word occurrences and fill them into the matrix.

This can easily be done with sklearn's `DictVectorizer`! In the file `sklearn_experiments.py` write a function `make_matrix1` that performs these two things on a given list. The function should return a `scipy.sparse` matrix.

Call the function on `list_of_dicts_1` and examine the result.

Note: Usually the sklearn `DictVectorizer` works with *sparse matrices* which is indispensable when working with large data. But to examine these toy matrices you might want to convert the returned sparse matrix. You can also use our `print_sparse_matrix` function to print it.

Exercise 2.2: DictVectorizer - Part 2 [4 points]

In applications, usually the training data is transformed to such a matrix. But it is important to understand that if new sentences come in to be classified, they must be transformed to a matrix with the same number of columns as the training matrix! The bag of words features are defined by the training data only!

Write a function `make_matrix2(list_of_dicts_A, list_of_dicts_B)` that uses sklearn's `DictVectorizer` to do the following:

- Consider `list_of_dicts_A` to be your 'training data' that defines the known words.
- Transform `list_of_dicts_B` to a feature matrix with respect to the words seen in `list_of_dicts_A`. (Count only words that have been seen in `list_of_dicts_A`).

The function should return a `scipy.sparse` matrix. Call the function on `list_of_dicts_1` and `list_of_dicts_2` and examine the result. The matrix should have the same shape as the one from Ex 2.1.

To check if your code for exercise 2 works correctly, call the unittest:
`python3 -m unittest -v hw03_sklearn_paraphrases/test_sklearn_experiments.py`

Exercise 3: Paraphrase Detection

In this exercise we will use the tools provided by sklearn (including the `DictVectorizer`) to again approach the paraphrase detection task that you already know from last homework.

Exercise 3.1: From files to feature matrices [4 points]

In the file `paraphrases_scikit.py` complete the function `paraphrases_to_dataset`. This function is analogical to the function from last exercise and should do the following things:

- Given a filename, all lines in the file should be read and converted to a `features-dictionary` just like in the last homework. (Code is already there).

- If no DictVectorizer is given, the function should create a new one and fit it with the feature Dictionaries created before.
- The DictVectorizer should now be used to create a sparse feature matrix from the feature dictionaries created before.
- The function returns the feature matrix, the extracted labels, and the vectorizer.

Exercise 3.2: Obtaining our matrices [4 points]

Complete the function `readData`. This function should use the function `paraphrases_to_dataset` to create the following things:

- Training matrix `train_X`, training labels `train_Y` and a `vectorizer` based on the training data.
- Development matrix `dev_X` and development labels `dev_Y` based on the previously constructed `vectorizer`.
- Same for testing: `test_X` and `test_Y`

Exercise 3.3: Classifying [4 points]

With sklearn one can create a classifier by a single line of code. In this example, we'll try different parameter settings for two types of classifiers: logistic regression (=MaxEnt) and Support Vector Machines.

The classifiers work on the paraphrase detection task. The only thing missing is to pass the training matrix and labels to the classifier. Search http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html for a way to do that!

To check if your code for exercise 3 works correctly, call the unittest:

```
python3 -m unittest -v hw03_sklearn_paraphrases/test_paraphrases_scikit.py
```

To see if everything works right and to get some actual results, move into the `src` folder and call:

```
python3 -m hw03_sklearn_paraphrases.paraphrases_scikit -t
data/paraphrases/train.txt -d data/paraphrases/dev.txt -e
data/paraphrases/test.txt
```

You should receive something like this:

```
Classifier: LinearSVC(C=0.1) - Development Accuracy: 0.7190
Classifier: LinearSVC(C=1.0) - Development Accuracy: 0.7190
Classifier: LogisticRegression(C=0.01, penalty="l2") - Development Accuracy: 0.7378
Classifier: LogisticRegression(C=0.1, penalty="l2") - Development Accuracy: 0.7255
Classifier: LogisticRegression(C=1.0, penalty="l2") - Development Accuracy: 0.7173
Classifier: LogisticRegression(C=0.01, penalty="l1") - Development Accuracy: 0.7405
Classifier: LogisticRegression(C=0.1, penalty="l1") - Development Accuracy: 0.7431
Classifier: LogisticRegression(C=1.0, penalty="l1") - Development Accuracy: 0.7088
Best classifier: LogisticRegression(C=0.1, penalty="l1") - Test Accuracy: 0.8687
```