Project: Using a linear classifier to train the LEDGAR set

Last updated: February 27, 2023

February 27, 2023

1/19



- A basic understanding of how linear text classification works
- Get familiar with the LibMultiLabel linear API

• □ ▶ • 4□ ▶ • Ξ ▶ •









э

▶ < ∃ >

Image: A mathematical states of the state

Outline



Project Contents

February 27, 2023 4 / 19

э

< □ > < 同 > < 回 > < 回 > < 回 >

Text Classification I

- Text classification is the task of assigning a class to a given document. It has been applied in many fields for automatically categorizing news, legal documents, and electronic medical records, etc.
- You might be curious about how it works. Let's start with an example

Example I

- **Text**: During the Term of Executive's Agreement, the Executive shall be entitled to be paid vacation in accordance with the most favorable plans ...
- Class: 93 (Vacations)
- The text snippet is the regulation of the paid holidays, so it belongs to class Vacations

Vectorizers (BOW and TF-IDF) I

- To perform text classification, we will start by vectorizing text to the feature vector
- One effective way is **Bag of Words (BOW)** which converts text to a column vector of word counts
- So going back to the example, the vocabulary of the given text is: accordance, agreement, be, during, entitled, executive, favorable, in, most, of, paid, plans, shall, term, the, to, vacation, with

< □ > < □ > < □ > < □ > < □ > < □ >

Vectorizers (BOW and TF-IDF) II

- The corresponding BOW representation: $\mathbf{x} = [1, 1, 2, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 3, 1, 1, 1]$ where 3 is the number of word "the"
- Another way to vectorize text is TF-IDF (Term Frequency-Inverse Document Frequency)
 We're not going deep in this class. You can find more information here

Multi-class Classification I

- After transforming a text to a feature vector, we can predict a class (say Vacations) by the linear techniques taught in the first lesson
- But we only covered binary classification in class
- There are several methods for multi-class classification, including one-vs-rest, one-vs-one, etc.

Multi-class Classification II

- The following describes how one-vs-rest works:
 - Assume ℓ is the number of classes. For class
 i = 1...ℓ, we train a binary classifier *w_i* using
 instances belonging to class *i* as positive
 instances, and the others as negative instances
 - After obtaining classifiers *w*₁,..., *w*_ℓ, given an instance *x*, we predict the class ŷ with the largest decision value, i.e.,

$$\hat{y} \in \underset{1 \leq i \leq \ell}{\operatorname{arg\,max}} \boldsymbol{w}_i^T \boldsymbol{x}.$$

Multi-class Classification III

- An example: assume $\ell = 3$ and we have x_1, x_2 : class 1, x_3 : class 2 and x_4 : class 3.
 - Train w_1 using { $(x_1, +1), (x_2, +1), (x_3, -1), (x_4, -1)$ }
 - Train w_2 using $\{(x_1, -1), (x_2, -1), (x_3, +1), (x_4, -1)\}$
 - Train w_3 using $\{(x_1, -1), (x_2, -1), (x_3, -1), (x_4, +1)\}.$
 - Given unknown instance x, predict the class with the largest decision value

< ロ > < 同 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ >

Outline





э

イロト イポト イヨト イヨト

Project Setup I

- Your codes and experiments are required to run on /tmp2 of 217 workstations (linux[1-15]) so that we can check your codes if needed.
- Please set up an virtual environment as the following:

virtualenv -p /usr/bin/python3 \
/tmp2/\$USER/venv

• The downloaded pip cache is stored in the home directory, which takes up large space. You can create symbolic links to /tmp2.

Project Setup II

- Download the LEDGAR (LexGLUE) set (ledgar_lexglue_raw_texts_*.txt.bz2) to data
- Install LibMultiLabel in the virtual environment

 venv/bin/activate
 pip3 install libmultilabel

< □ ▶ < □ ▶ < □ ▶ < □ ▶ < □ ▶ < □ ▶</p>
February 27, 2023

14/19

Project Description I

- Let's run linear classification with LibMultiLabel API
- The tutorial shows you how to train a linear classifier with customized TF-IDF features

```
vectorizer = TfidfVectorizer(
    max_features=20000,
    min_df=3)
```

• You are going to try feature generation methods to demonstrate what vectorizer/parameters are suitable for the LEDGAR set (see Text feature extraction)

Project Description II

- After obtaining the corresponding numerical features for each text, we would like to compare the performance between logistic regression and SVM.
 - In the class, we mentioned that their performance is similar. Please check whether it's the case for this dataset.
- Besides, you're also going to check whether proper regularization indeed improves the classification results by selecting different C's.

< □ > < 同 > < 三 > <

February 27, 2023

16/19

Project Description III

- To test different classification methods and parameters, you need to pass different options strings to liblinear. Details can be found in this README page.
- LibMultiLabel supports easy hyperparameter selection; see this tutorial about GridSearchCV for reference.

Submission I

- Write a 2-page report about the experimental results and findings on the following questions:
 - For the LEDGAR set, does changing the parameters of vectorizer improve the performance? For example, what are the pros and cons of reducing the feature size?
 - Are the test performances for logistic regression and SVM similar? If not, could you provide some explanations?

< □ > < □ > < □ > < □ >

Submission II

- Does the optimal regularization parameter C vary based on the choice of max_features in TfidfVectorizer?
- Please specify on which /tmp2 you store your code and keep it private before the deadline to avoid plagiarism.
- Upload your report in PDF format to NTU COOL before 2023/03/14 23:59