CS410 Course Project Documentation

Team Name: SearchExperts (Fall 2021)

1. **Course Project:**
   Expert Search
2. **Team Git Repository:**
   https://github.com/genggeng88/CourseProject
3. **Tutorial Presentation Link:**
   xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx
4. **Team members:**

   a. Qin Geng (qingeng2@illinois.edu) (Capitain)
   b. Aditya Vyas (vyas7@illinois.edu)
   c. Junwei Chen (junweic4@illinois.edu)
   d. Peter Zhang (aijun2@illinois.edu)

Abstract:

Searching is a significant part of Text Information Retrieval and building a search engine is more meaningful than text searching. In our project, we aimed at improving the existing expertise searching engine (ExpertSearch) from two aspects. First, we will help in automatically scraping faculty links from a random website (Task 2 ~ 4). Second, we will extract more information, including the professor's telephone number and research areas (Task 5 ~ 6). Our work on improving this project is meaningful for both project developers and users. With our efforts on automatically scraping, the project developers can spend less time on manually scraping and get more data meanwhile. As we extract more information, the users of the search engine can get more information about the professors when they are searching.

1. Introduction

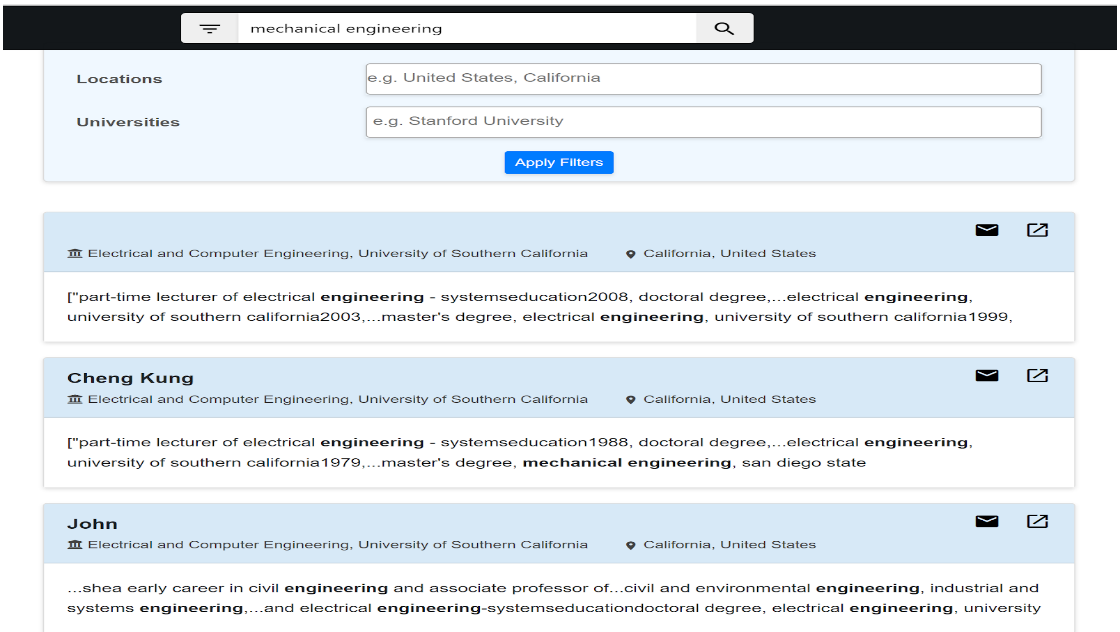


Figure 1.1

The Expert Search was developed by some previous students as part of their course project, based on the dataset of faculty links and bios. The links and bios are scraped from a given department link by each student manually in MP2.2. After we set up the environment for Expert Search, we can do expertise searching in it, as shown in Figure 1.1. This search engine can also apply filters, like locations and universities to narrow down the searching results.

2. Related Work

Our team's related work contains two parts: automatically scraping links and extracting more information. As we discussed in the Introduction part, the dataset Expert Search uses is scraped from a given department link by each student manually. Our team will help with automatically scraping the urls and bios from a given university website. After doing the searching, we can tell from Figure 1.1 that the shown information is kind of limited. Our team extracted more information, including telephone number and research areas, and showed the extra information on the search page. Table 2.1 shows the content of each specific task. Our team has completed all the tasks listed in our proposal and reached a workload hour of 180. The next part will give more detailed descriptions for each task.

Table 2.1

Task No.	Task Description	Workload	Completion
Task 1	Setting up the environment	35hr	Completed
Task 2	Writing a function of automatically crawling random web pages, and collecting them for the next step use.	10hr	Completed
Task 3	Building a regex-based model to identify faculty directory webpages. Improving this model to achieve an accuracy of 70%.	20hr	Completed
Task 4	Building a binary classifier model to identify bio_url. Improving this model to achieve an accuracy of 70%.	30hr	Completed
Task 5	Writing an extracting function based on Natural Language Processing techniques to recognize and extract names/profiles in web links.	15hr	Completed
Task 6	Writing a topic mining function in extracting common search areas, and displaying it in the web page.	25hr	Completed
Task 7	Integrate all functions and models to the original project (ExpertSearch) and test the whole project.	35hr	Completed
Task 8	Weekly meeting and discussion	10hr	Completed
Total		**180hr**	

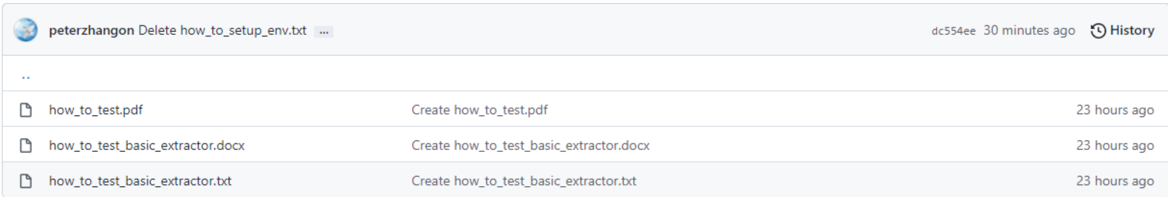
3. Description and Significance

3.1 Setting Up Environment

As the readme in the original project is very simple, and Python 2.7 is outdated, we spent a lot of time to find a solution to set up an environment. We tried Oracle Linux box, Docker, AWS Cloud 9, AWS EC2. At last,

1. we decided to use Windows 10 + Ubuntu 18.04 to set up ENV
2. We changed the server code a little bit to ensure we can really query via Web page;

To share the experience, we created the following readme files.

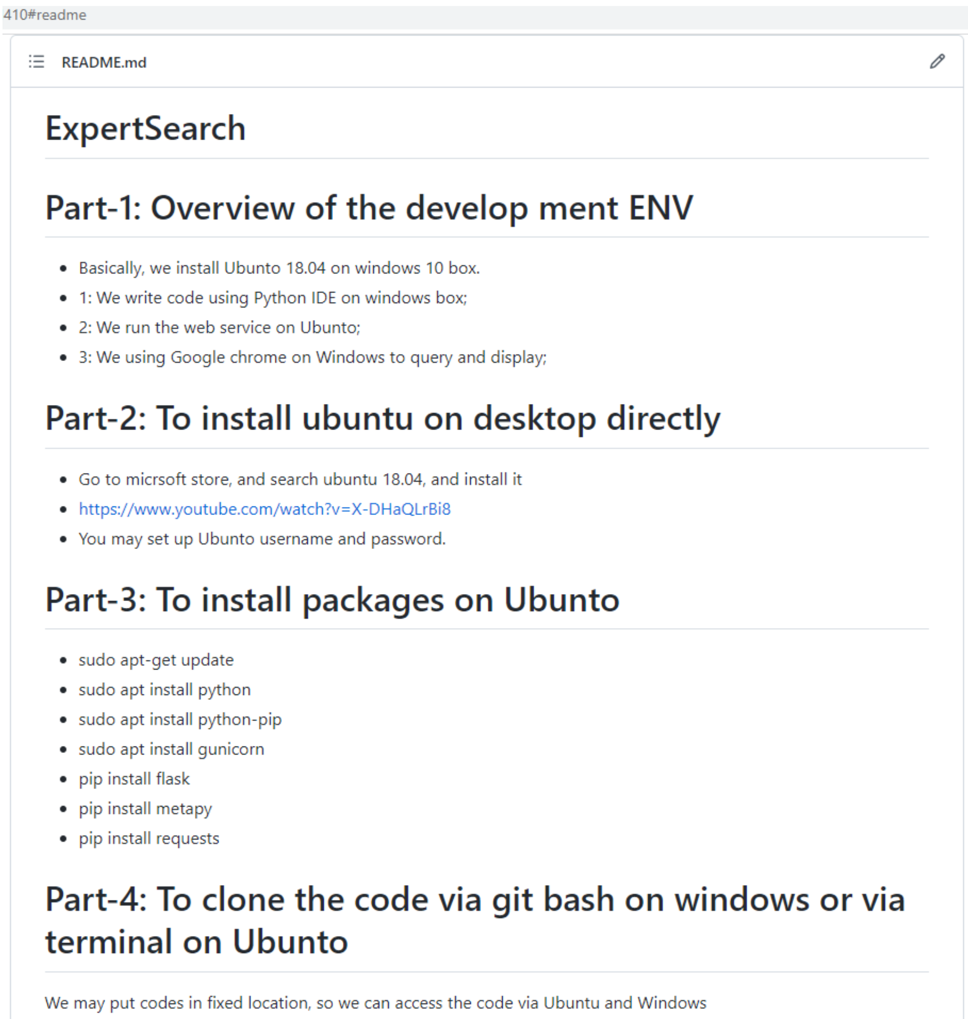


peterzhangon Delete how_to_setup_env.txt ... dc554ee 30 minutes ago History

..

how_to_test.pdf	Create how_to_test.pdf	23 hours ago
how_to_test_basic_extractor.docx	Create how_to_test_basic_extractor.docx	23 hours ago
how_to_test_basic_extractor.txt	Create how_to_test_basic_extractor.txt	23 hours ago

And also,



410#readme

README.md

ExpertSearch

Part-1: Overview of the develop ment ENV

- Basically, we install Ubunto 18.04 on windows 10 box.
- 1: We write code using Python IDE on windows box;
- 2: We run the web service on Ubunto;
- 3: We using Google chrome on Windows to query and display;

Part-2: To install ubuntu on desktop directly

- Go to micrsoft store, and search ubuntu 18.04, and install it
- https://www.youtube.com/watch?v=X-DHaQLrBi8
- You may set up Ubunto username and password.

Part-3: To install packages on Ubunto

- sudo apt-get update
- sudo apt install python
- sudo apt install python-pip
- sudo apt install gunicorn
- pip install flask
- pip install metapy
- pip install requests

Part-4: To clone the code via git bash on windows or via terminal on Ubunto

We may put codes in fixed location, so we can access the code via Ubuntu and Windows

This head readme file contains 10 detailed parts. For more details, you may go to the following site: https://github.com/genggeng88/CourseProject/blob/main/README.md

3.2 Scraping the web-pages

Task 2 primarily focuses on scraping web pages from the internet. To implement it, we created a scraper in the Python programming language using Requests and BeautifulSoup4.

Through this task we were able to fetch details and content of the page for future use. (You can find the code in scraper.py file as a function names as *get_links*)

This task was tricky as we needed to fetch the links having bios specifically, so we used regex methods to identify the links with popular faculty terms. The overall accuracy we were able to achieve was more than 70%.

3.3 Extracting Bios

Task 3 focuses on extracting the bios from the links we received from Task 2 using HTML parser by BeautifulSoup4. We extracted <p> tags to get the text data and finally saved it to the directory for web search application. The separate text files can be seen in figure 3.3.1.

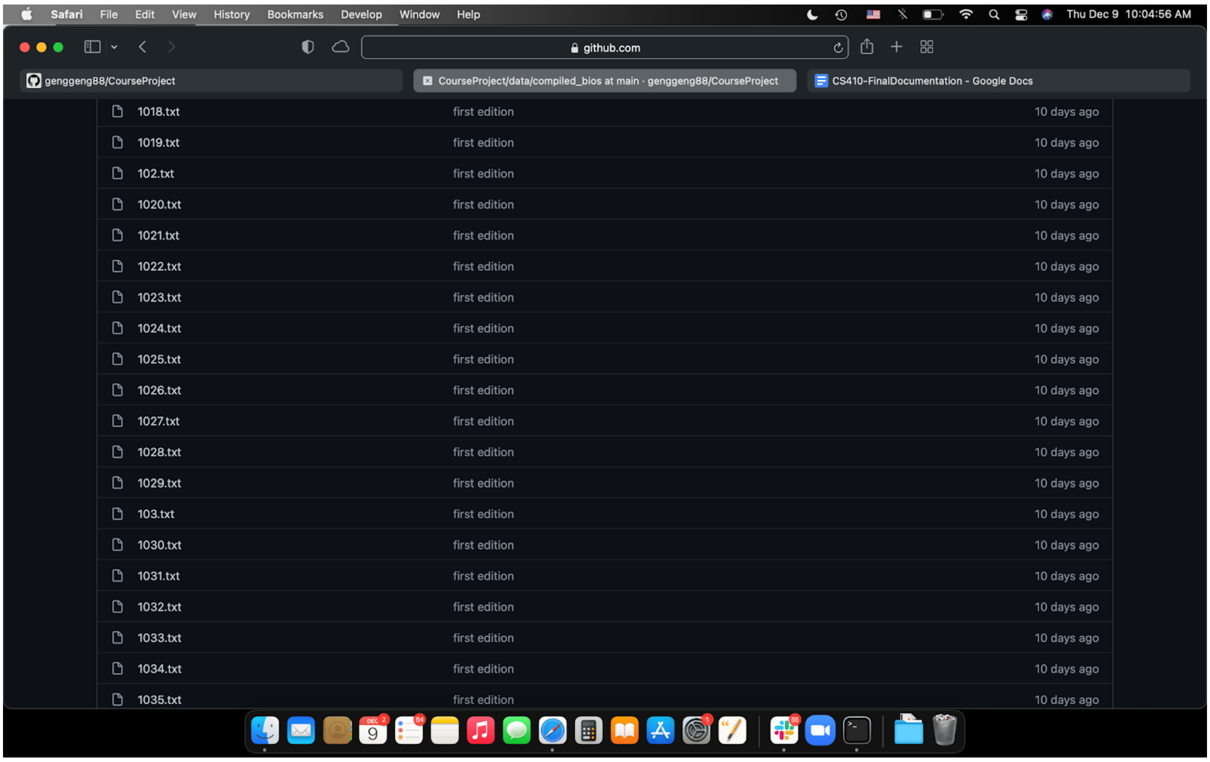


Figure 3.3.1

3.4 Binary Classifier

Task 4 mainly focuses on building and training a binary classifier to predict whether a given link is a faculty link or not. This task contains two smaller parts: data pre-processing and classifier training. (You can get the complete code from “preProcess.py” and “BinaryClassifier.ipynb”)

3.4.1 Data Pre-Processing

From MP2.1, we already got abundant faculty links, contributed by current and previous students from this course. This part of data, including 16,492 links, can be the positive dataset for the classifier. We also need some negative dataset, namely the links that are identified as non-faculty links. In order to get the negative dataset, we wrote a code snippet to automatically scrape random links from a given list of non-educational websites, as shown in Figure 3.4.1. All the non-faculty links are automatically scraped and saved in the "urls_negative.txt" file.

```
base_urls = ['https://www.coursera.org', 'https://www.apple.com', 'https://www.linkedin.com',
             'https://github.com', 'https://stackoverflow.com', 'https://aclibrary.org',
             'https://www.youtube.com','https://twitter.com/', 'https://store.google.com',
             'http://www.google.com', 'https://www.udemy.com/', 'https://harness.io/',
             'https://blockchain.berkeley.edu/', 'https://openclassrooms.com/',
             'https://campuswire.com/', 'https://docs.oracle.com/',
             'https://algs4.cs.princeton.edu/', 'https://www.outreachy.org/',
             'https://world.taobao.com/']

f = open('urls_negative.txt', 'w')
for url in base_urls:
    reqs = requests.get(url)
    soup = BeautifulSoup(reqs.text, 'html.parser')
    s = 'http'
    for link in soup.find_all('a'):
        url2 = str(link.get('href'))
        if s in url2:
            f.write(url2)
            f.write('\n')
        else:
            url_new = url + url2
            f.write(url_new)
            f.write('\n')
f.close()
```

Figure 3.4.1

```
# collection of all the attributes
keywords_ = ['faculty','staff','people','professor','bio','index','id','profile','outcome']

# Write attribute into the data file
my_data = open('bio_Binary.csv', 'w')
s = ','
keyword_str = s.join(keywords_)
my_data.write(keyword_str)
my_data.write('\n')

m = len(contents_p)
n = len(contents_n)
k = len(keywords_)

my_data_arr = ['']*(m+n)
for i in range(m):
    for j in range(k-1):
        if keywords_[j] in contents_p[i]:
            my_data_arr[i] += ('1,')
        else:
            my_data_arr[i] += ('0,')
    my_data_arr[i] += ('1')
    my_data.write(my_data_arr[i])
    my_data.write('\n')
```

Figure 3.4.2

Next processing is to add attributes to all the data as input to our classifier. As we can see from Figure 3.4.2, there is a collection of keywords. We set these keywords as attributes, and the value of a specific attribute will be marked “1” if the link contains the corresponding keyword and marked “0” inversely. The last label “outcome” denotes the link is a faculty link with marking it “1” and marking it “0” inversely. All the data after processing will be saved in the “bio_Binary.csv” file as input of the classifier.

3.4.2 Classifier Training

After we collected and pre-processed all the data, we can start building and training our classifier. We first randomly shuffled the dataset and divided it into two parts: training dataset and evaluation dataset, and separated each part of data into features and outcomes. We used the scikit learn package in this part and chose the Gaussian Naive-Bayes model as our classifier. After training the Gaussian Naive-Bayes classifier with our training features and training outcome, we predicted if a given link is a faculty link or not.

4 Train Classifier

We first train the the classifier gnb with the built-in Gaussian Naive-Bayes model with our train_features and train labels. Then we did the prediction for both the train features and evaluation features. Finally we got the accuracy of over 70% for both training dataset and evaluation dataset.

```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB().fit(train_features, train_labels)
train_pred_sk = gnb.predict(train_features)
eval_pred_sk = gnb.predict(eval_features)
print(f'The training data accuracy of your trained model is {(train_pred_sk == train_labels).mean()}')
print(f'The evaluation data accuracy of your trained model is {(eval_pred_sk == eval_labels).mean()}')
```

```
The training data accuracy of your trained model is 0.7343033256880734
The evaluation data accuracy of your trained model is 0.7294353683003726
```

Figure 3.4.3

Finally, as shown in Figure 3.4.3, we got the prediction accuracy of over 70% for both the training dataset and the evaluation dataset which achieved our goal in our project proposal.

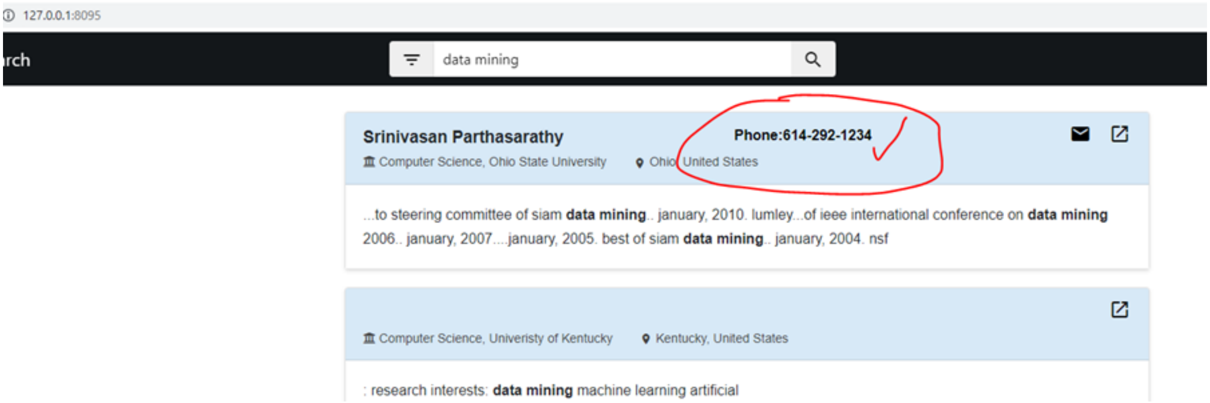
3.4.3 Significance

With building the classifier with a prediction accuracy of over 70%, we can help to realize automatic scraping faculty links from a random department link. We can also use this classifier in identifying whether a link is a wanted link or not only by changing the attributes.

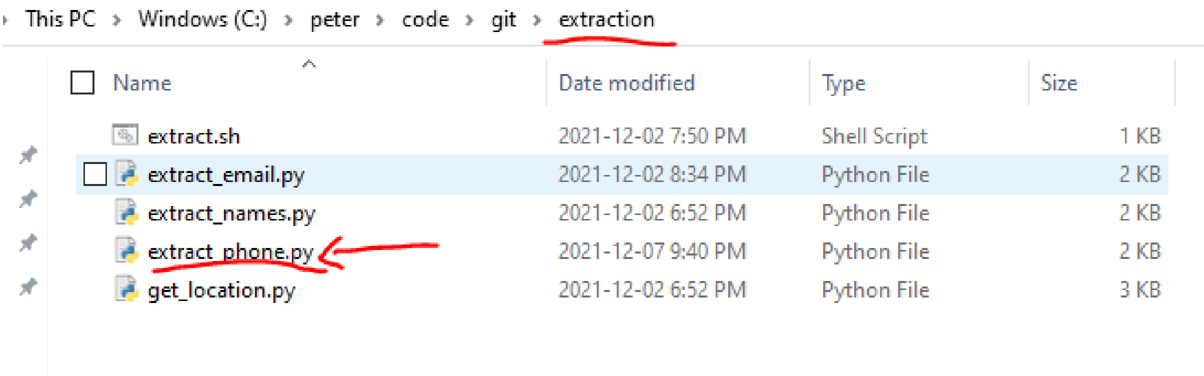
3.5 Extract A Common Field

After discussing with the team, we decided to add the phone number into the web page as follows. To make this change, we researched the Flask web page solution, tested the end to end web solution, and made changes in a lot of places.

The new common field is displayed this way.

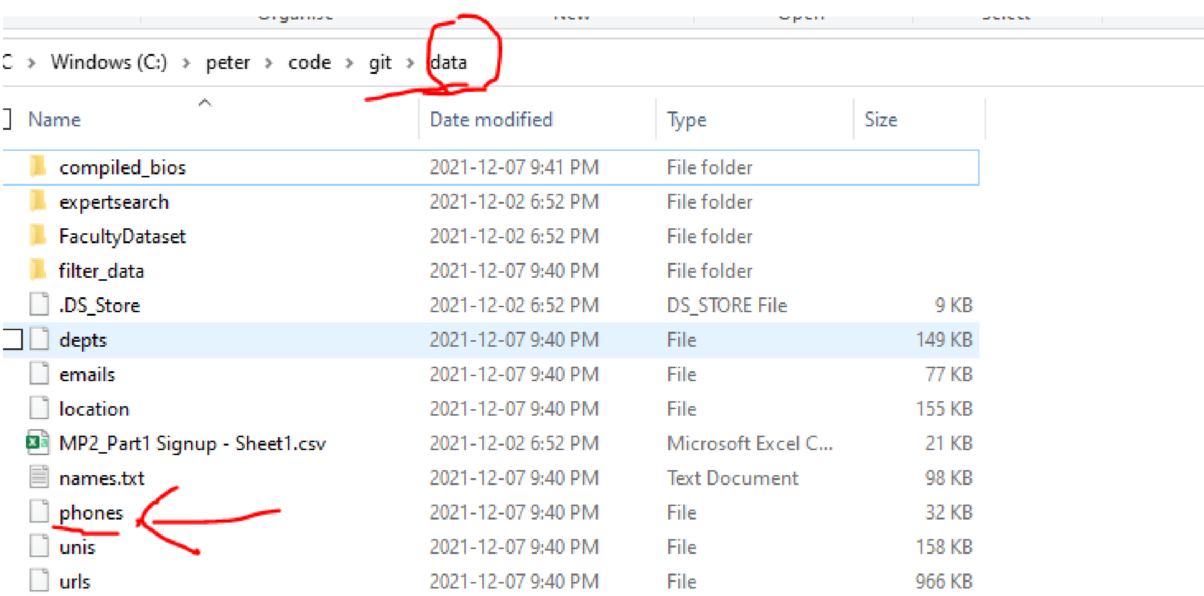


We added code to extract phone numbers.



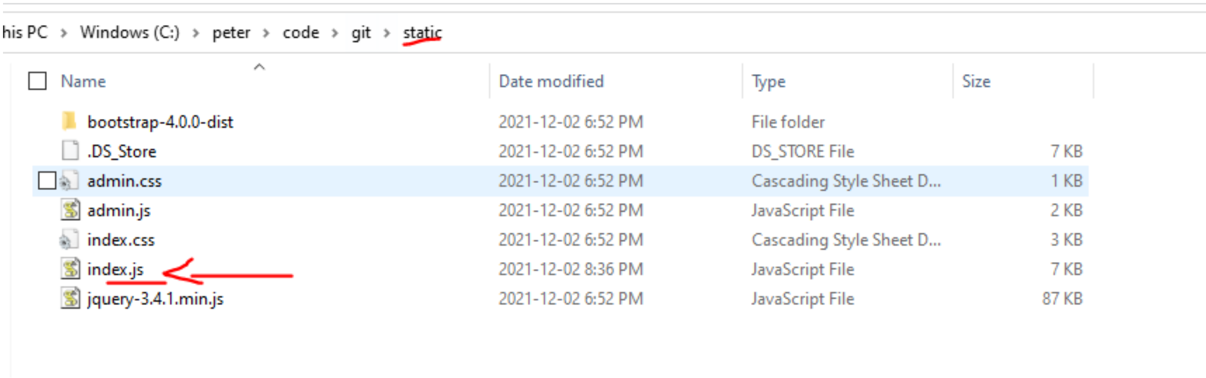
https://github.com/peterzhangon/Final410/blob/master/extraction/extract_phone.py

The new phone number data file is as follows.



https://github.com/peterzhangon/Final410/blob/master/data/phones

Also, we added phone number into the web page.



https://github.com/peterzhangon/Final410/blob/master/static/index.css

3.6 Topic Modeling

PLSA and LDA have been shown excellence in performance especially in the field of NLP. However, they can be cumbersome to train and tweak. Here I leveraged BERT embedding, which stands for Bidirectional Encoder Representation from Transformers. It's designed to pre-train deep bidirectional representation from unlabeled text by jointly conditioning on both left and right context. As a result, the BERT model can be fine tuned for NLP tasks.

3.6.1 Embeddings

First step to convert data to numerical data; Subsequently I used sentence-transformers for embedding documents, you can choose whatever package you want. Then I chose to use distilbert for compromising speed and performance.

```
from sentence_transformers import SentenceTransformer
model = SentenceTransformer('distilbert-base-nli-mean-tokens')
embeddings = model.encode(data, show_progress_bar=True)
```

3.6.2 Clustering

I wanted to make sure similar topics are clustered together. UMAP is used for high dimensional reduction while local structure in lower dimensionality.

```
umap_embeddings = umap.UMAP(n_neighbors=15,
                            n_components=5,
                            metric='cosine').fit_transform(embeddings)
```

Data are reduced to dimension of 5 and local neighborhood at 15. UMAP did not cluster anything but reducing dimensions. This package called HDBSAN was used for clustering.

```
import hdbscan
cluster = hdbscan.HDBSCAN(min_cluster_size=15,
                          metric='euclidean',
                          cluster_selection_method='eom').fit(umap_embeddings)
```

3.6.3 Data Preparation & create TF-IDF score

```
[ ]: import matplotlib.pyplot as plt

     # Prepare data
     umap_data = umap.UMAP(n_neighbors=15, n_components=2, min_dist=0.0, metric='cosine').fit_transform(embeddings)
     result = pd.DataFrame(umap_data, columns=['x', 'y'])
     result['labels'] = cluster.labels_
```

```
[ ]: docs_df = pd.DataFrame(data, columns=["Doc"])
     docs_df['Topic'] = cluster.labels_
     docs_df['Doc_ID'] = range(len(docs_df))
     docs_per_topic = docs_df.groupby(['Topic'], as_index = False).agg({'Doc': ' '.join})
```

$$c - TF - IDF_i = \frac{t_i}{w_i} \times \log \frac{m}{\sum_j^n t_j}$$

Where the frequency of each word t is extracted for each class i and divided by the total number of words w. This action can be seen as a form of regularization of frequent words in the class. Next, the total, unjoined, number of documents m is divided by the total frequency of word t across all classes n.

3.6.4 Topic representation

After we have an important value for each word in the cluster which can create the topic. If I take the top 10 most important words in each cluster, then we get a topic.

[ ]:

	Topic	Size
0	-1	9816
35	34	843
58	57	808
19	18	767
72	71	613
20	19	580
77	76	378
75	74	365
49	48	324
68	67	258

Topic size means how frequently certain topics appear. Topic name -1 refers to all documents that didn't have a topic assigned. This is a big thanks to HDBSCAN package which doesn't force every word towards a certain cluster. Our output data size from web scraping is relatively small compared to mainstream big data size. Hence the realistic Topic and Size looked like below.

[78]:

	Topic	Size
0	-1	12

[79]:
```
top_n_words[-1][:10]
```

[79]:
```
[('data', 0.22105663849357624),
 ('project', 0.17193515657377895),
 ('level', 0.14652345295965485),
 ('understanding', 0.14652345295965485),
 ('cell', 0.14652345295965485),
 ('systems', 0.14652345295965485),
 ('modelling', 0.14652345295965485),
 ('pathways', 0.12039518302700086),
 ('complex', 0.12039518302700086),
 ('signalling', 0.12039518302700086)]
```

Above we have top 10 significant words for a given topic. Yes, topic -1 meaning these words did not have a “topic assigned”. But because they are in the same group and they do have significant scores. We can still rely on the data. Top_n_words[-1][:10] means that for topic -1, the top 10 significant words within topic -1 are as such. The topic “data” has the highest score. Hence the topic is about Data.

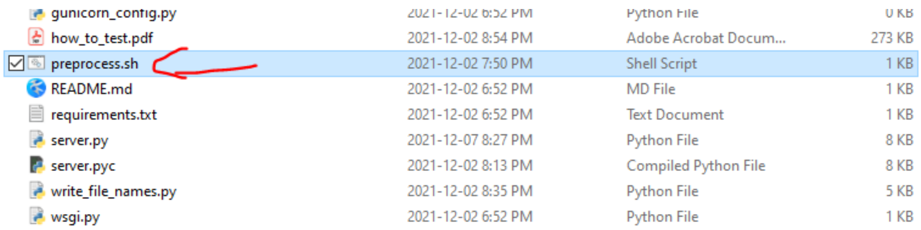
3.7 Integration

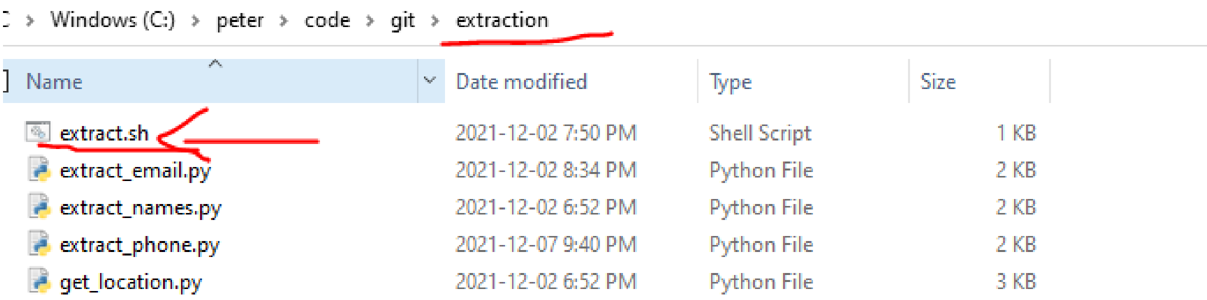
To support future expansion, we created new scripts to preprocess the data files.

```
   85  history
peter@LAPTOP-MSKOE3G5:/mnt/c/peter/code/git_local$ pwd
/mnt/c/peter/code/git_local
peter@LAPTOP-MSKOE3G5:/mnt/c/peter/code/git_local$ ./preprocess.sh 6524
Max txt file id: 6524
***** Begin to preprocess data.************************
/mnt/c/peter/code/git_local
+++++ Begin to extract information.+++++++++++++++++++++++++
Max txt file id: 6524
/mnt/c/peter/code/git_local

Begin to process emails, the source is at: /mnt/c/peter/code/git_local/data/compiled_bios
The destination is at : /mnt/c/peter/code/git_local/data/emails
File: /mnt/c/peter/code/git_local/data/compiled_bios/0.txt
```

In the preprocess file, we extract common fields like email, and phone numbers, and the existing functions are called also to update all the related data files like names, locs and so on.





To help the team to test the basic functions, we also created a doc named "how to test", via which the team member can **know all the processes.**

4. Summary

With all the work described above, our team has done a remarkable job on the course project. We finished all the tasks we proposed, and contributed to the original project from both automatically scraping and extra information extraction.