```
import pandas as pd
import numpy as np
import matplotlib.pyplot  as plt
import matplotlib.image as mpimg
from scipy import stats
import ast
import re

import spacy
from spacy import displacy
from spacy.tokens import DocBin
from tqdm import tqdm
from spacy.util import filter_spans
```

Dataset overview

To start, it is necessary to make or select a dataset with names of mountains for further work with it. After a small search in the Internet was found a dataset on Kaggle, which contains sentences with labeled names of mountains. Therefore, we will take it as a basis. Let's take a look at it

```
df_m = pd.read_csv('mountain_dataset_with_markup.csv')
```

```
df_m.head(15)
```

	text	marker
0	A visit to a science museum for hands-on learn...	[]
1	Voice surface coach set democratic time year. ...	[]
2	Parent according maybe activity activity finis...	[]
3	A visit to a sculpture garden with intriguing ...	[]
4	The Julian Alps in Slovenia offer pristine lak...	[(11, 15)]
5	The referee blows the whistle, signaling the e...	[]
6	Again eat owner drop. Stay recognize none size...	[]
7	Important nearly themselves particular sort cl...	[]
8	Wonder behind everybody dream. Owner much anal...	[]
9	Phone station white leave image.\nSeem Mrs bed...	[]
10	Ten be ten cover use meeting. Season indeed se...	[]
11	Manage trade stand site fund administration. C...	[]
12	Care energy fast almost player source. When vo...	[]
13	The Dolomites in Italy are famous for their un...	[(4, 13)]
14	Civil film yet turn top. Event structure conce...	[]

```
df_m.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1584 entries, 0 to 1583
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   text    1584 non-null   object
 1   marker  1584 non-null   object
dtypes: object(2)
memory usage: 24.9+ KB
```

It is notable that not all sentences among 1584 have a marker for the name of mountains. In the future we will select only the necessary sentences, since the model does not need empty ones for training.

Let's start cleaning the dataset from unnecessary rows (with empty marker) and checking for problematic characters/values

```
# Check the lines for NaN values
df_m.isna().sum()
```

```
text      0
marker    0
dtype: int64
```

```
# Convert the string representation of lists into real lists
df_m['marker'] = df_m['marker'].apply(lambda x: ast.literal_eval(x) if isinstance(x, str) else x)

# Filter rows where 'marker' is not empty (the list contains items)
filtered_df = df_m[df_m['marker'].apply(lambda x: len(x) > 0)]
filtered_df.loc[:, 'marker'] = filtered_df['marker'].apply(lambda x: x[0] if isinstance(x, list) and len(x) > 0 else x)
```

```
filtered_df
```

	text	marker
4	The Julian Alps in Slovenia offer pristine lak...	(11, 15)
13	The Dolomites in Italy are famous for their un...	(4, 13)
21	Feeling the tranquility and serenity of the An...	(44, 49)
22	The Carpathian Mountains are a vital part of E...	(4, 24)
28	I explored the Tatra Mountains, a beautiful ra...	(15, 30)
...	...	...
1547	Discover hidden waterfalls and serene lakes ne...	(63, 80)
1555	I trekked through the Tien Shan mountains in C...	(22, 31)
1565	I marveled at the beauty of the Blue Ridge Mou...	(32, 52)
1577	The Kunlun Mountains stretch across western Ch...	(4, 20)
1580	Witnessing the mesmerizing Northern Lights dan...	(75, 97)

226 rows × 2 columns

After cleaning up the dataset, 226 rows remained

To give an example, let's try to get the name of the mountains from the first sentence based on the marker

```
filtered_df['text'].iloc[0][filtered_df['marker'].iloc[0][0]:filtered_df['marker'].iloc[0][1]]
```

```
'Alps'
```

Let's do a little checking for problematic characters, links, tags and the like.

```
def preprocess_and_find_problems(text_column):
    # Dictionary to store results
    results = {
        'index': [],
        'original_text': [],
        'cleaned_text': [],
        'removed_links': [],
        'removed_telegram_links': [],
        'removed_phone_numbers': [],
        'removed_tags': [],
        'removed_hashtags': [],
        'removed_special_chars': [],
        'removed_extra_spaces': []
    }

    # Regular expressions
    link_pattern = r'http\S+|www.\S+'  # Pattern for detecting regular links
    telegram_pattern = r"(?:https?:\/\/)?(?:www\.)?(?:t\.me\/\S+|telegram\.me\/\S+|telegram\.dog\/\S+)"  # Telegram links
    phone_pattern = r'\(?\+?\d{0,3}\)?[-.\s]?\(?\d{3}\)?[-.\s]?\d{3}[-.\s]?\d{2}[-.\s]?\d{2}'  # Phone numbers
    tag_pattern = r'@\w+'  # Tags (e.g., @username)
    hashtag_pattern = r'#\w+' # Hashtags (e.g., #home)
    special_chars_pattern = r'[\n\t\r]'  # Special characters (newline, tab, carriage return)
    extra_spaces_pattern = r' +'  # Extra spaces (two or more consecutive spaces)

    for idx, text in enumerate(text_column):
        original_text = text

        # Remove links
        removed_links = re.findall(link_pattern, text)
        text = re.sub(link_pattern, '', text)

        # Remove telegram links
        removed_telegram_links = re.findall(telegram_pattern, text)
        text = re.sub(telegram_pattern, '', text)

        # Remove phone numbers
        removed_phone_numbers = re.findall(phone_pattern, text)
        text = re.sub(phone_pattern, '', text)

        # Remove tags (@username)
        removed_tags = re.findall(tag_pattern, text)
        text = re.sub(tag_pattern, '', text)

        # Remove emojis
        removed_hashtags = re.findall(hashtag_pattern, text)
        text = re.sub(hashtag_pattern, '', text)

        # Remove special characters (newlines, tabs, etc.)
        removed_special_chars = re.findall(special_chars_pattern, text)
        text = re.sub(special_chars_pattern, ' ', text)

        # Check for extra spaces
        removed_extra_spaces = bool(re.search(extra_spaces_pattern, text))

        # Remove extra spaces
        text = re.sub(extra_spaces_pattern, ' ', text).strip()

        # Store results in the dictionary
        results['index'].append(idx)
        results['original_text'].append(original_text)
        results['cleaned_text'].append(text)
        results['removed_links'].append(removed_links if removed_links else None)
        results['removed_telegram_links'].append(removed_telegram_links if removed_telegram_links else None)
        results['removed_phone_numbers'].append(removed_phone_numbers if removed_phone_numbers else None)
        results['removed_tags'].append(removed_tags if removed_tags else None)
        results['removed_hashtags'].append(removed_hashtags if removed_hashtags else None)
        results['removed_special_chars'].append(removed_special_chars if removed_special_chars else None)
        results['removed_extra_spaces'].append(removed_extra_spaces)

    # Convert to DataFrame for easier analysis
    return pd.DataFrame(results)

preprocess_and_find_problems(filtered_df['text'])
```

	index	original_text	cleaned_text	removed_links	removed_telegram_links	removed_phone_numbers	removed_tags	removed_hashtag
0	0	The Julian Alps in Slovenia offer pristine lak...	The Julian Alps in Slovenia offer pristine lak...	None	None	None	None	Non
1	1	The Dolomites in Italy are famous for their un...	The Dolomites in Italy are famous for their un...	None	None	None	None	Non
2	2	Feeling the tranquility and serenity of the An...	Feeling the tranquility and serenity of the An...	None	None	None	None	[#naturelove #mountainscap
3	3	The Carpathian Mountains are a vital part of E...	The Carpathian Mountains are a vital part of E...	None	None	None	None	Non
		I explored the Tatra	I explored the Tatra					

Overall you can see that there are no particular problems with the text, except for the hashtags found and extra spaces. According to information from forums, hashtags and spaces should not affect model training, even with the parser parameter. So we leave it as it is

Creating the NER model

Preparing data

To create the NER model it was decided to use spaCy library, based on which you can create your own model with different architecture.

Our model will be trained to find the new class “MOUNTAIN_NAME”. First we need to bring the dataset to the view that spaCy wants for training. It looks like a dataframe, where the first column contains the text to be trained, followed by the entities with their indices that occur in the text. And since the names of mountains occur only once in the original dataset, the process is quite simple.

It is also important to note that mountain names cannot be separated. If the names are two or more words, they should be preserved, because splitting can degrade the model recognition.

```
training_data = {'class' : ["MOUNTAIN_NAME"], 'annotations' : []}

for _, row in filtered_df.iterrows():
    temp_dict = {'text': row['text'], 'entities': []}

    start = row['marker'][0]
    end = row['marker'][1]
    temp_dict['entities'].append((start, end, "MOUNTAIN_NAME"))

    training_data['annotations'].append(temp_dict)

print(training_data['annotations'][0])
```

```
{'text': 'The Julian Alps in Slovenia offer pristine lakes and picturesque landscapes.', 'entities': [(11, 15, 'MOUNTAIN_NAME')]}
```

We can see that the new representation works. We can move on to creating the model itself.

To do this, we create an empty English spaCy model (since the dataset is in English) and create a DocBin class for the example training itself, since spaCy uses the DocBin class for annotated data. (Example)

```
# load a new spacy model
nlp = spacy.blank("en")
# create a DocBin object
doc_bin = DocBin()
```

```
D:\Programming\Python\DataSpell_Projects\Default Environment 311\Lib\site-packages\transformers\utils\generic.py:441: FutureWarning
  _torch_pytree._register_pytree_node(
D:\Programming\Python\DataSpell_Projects\Default Environment 311\Lib\site-packages\transformers\utils\generic.py:309: FutureWarning
  _torch_pytree._register_pytree_node(
```

It is also recommended to use the filter_spans function, which filters a sequence of Span objects and removes duplicates or overlaps. Useful for creating named entities (when one token can be part of only one entity). But in the current case it may not be productive, since we only have one name per sentence. In general, the function is not very demanding, especially with so much information, so we can leave it.

```
for training_example  in tqdm(training_data['annotations']):
    text = training_example['text']
    labels = training_example['entities']
    doc = nlp.make_doc(text)
    ents = []
    for start, end, label in labels:
        span = doc.char_span(start, end, label=label, alignment_mode="contract")
        if span is None:
            print("Skipping entity")
        else:
            ents.append(span)
    filtered_ents = filter_spans(ents)
    doc.ents = filtered_ents
    doc_bin.add(doc)

# save docbin
doc_bin.to_disk("training_data.spacy")
```

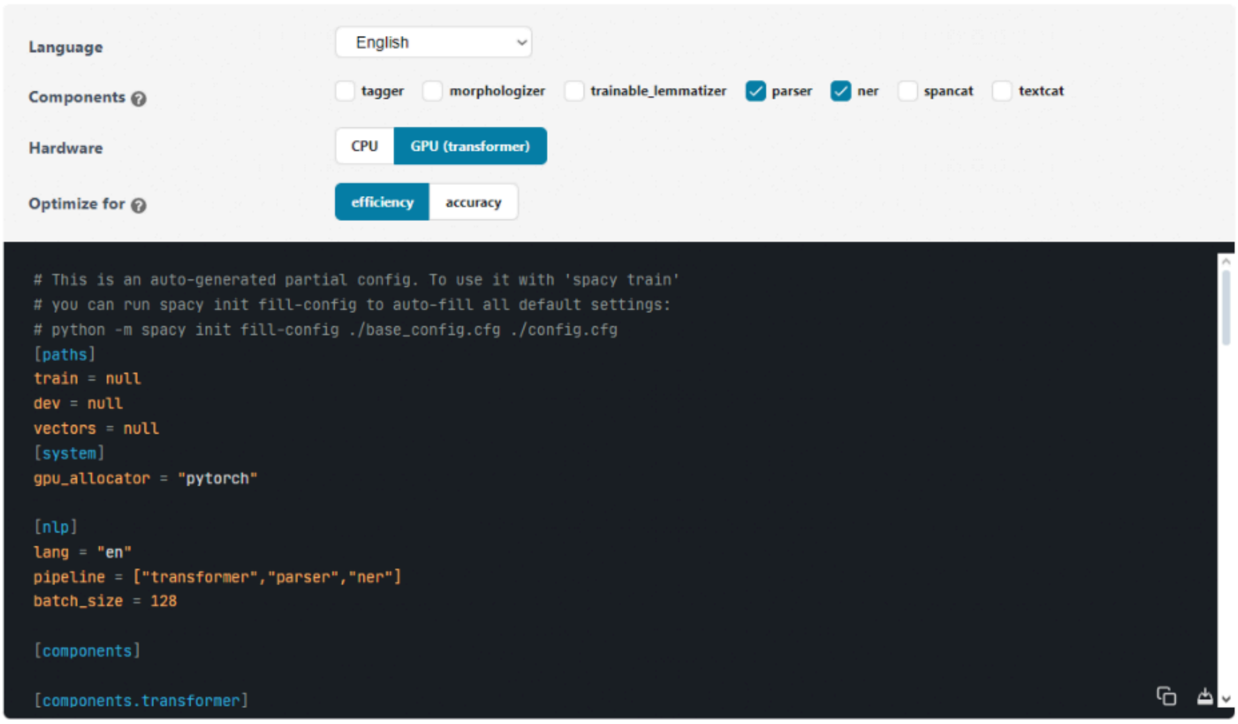
```
100%|██████████| 226/226 [00:00<00:00, 3104.43it/s]
```

Now we need to create a configuration file to run the model. To do this, the library [website](#) has an option to create a file with user preferences, and the library will create the rest automatically. It is also possible to create the file completely manually, but we will use the first option.

```
img = mpimg.imread('Screenshot 2024-10-15 131712.png')

plt.figure(figsize=(12, 14))

plt.imshow(img)
plt.axis('off')
plt.show()
```



In the current task, it is necessary to use the NER parameter, and we can also specify a parser, as mentioned in the beginning. Next, we choose to use transformers, which will allow the model to focus on different parts of the input sequence, thus providing a more efficient understanding of the context and meanings of words in sentences. This requires a lot of computational resources, so it will be trained on the GPU.

The assignment also states, “Select an appropriate model architecture to solve the NER problem” and “Check BERT-based pre-trained models for NER problem”. There are many architectures to choose from in the spaCy library, but the base model has the following parameters:

```
@architectures = "spacy-transformers.TransformerModel.v3"
name = "roberta-base"
tokenizer_config = {"use_fast": true}
```

From the information I found, the current library model is based on just the roberta-base architecture, but slightly improved by the library developers. Therefore, the current parameters can be left and the model can be started

Config model

```
!python -m spacy init fill-config base_config.cfg config.cfg
```

```
[+] Auto-filled config with all values
[+] Saved config
config.cfg
You can now add your data and train your pipeline:
python -m spacy train config.cfg --paths.train ./train.spacy --paths.dev ./dev.spacy
D:\Programming\Python\DataSpell_Projects\Default Environment 311\Lib\site-packages\transformers\utils\generic.py:441: FutureWarning
  _torch_pytree._register_pytree_node(
D:\Programming\Python\DataSpell_Projects\Default Environment 311\Lib\site-packages\transformers\utils\generic.py:309: FutureWarning
  _torch_pytree._register_pytree_node(
```

Train

```
!python -m spacy train config.cfg --output ./ --paths.train ./training_data.spacy --paths.dev ./training_data.spacy --gpu-id 0
```

```
[i] Saving to output directory: .D:\Programming\Python\DataSpell_Projects\Default Environment 311\Lib\site-packages\transformers\ut:
  _torch_pytree._register_pytree_node(
D:\Programming\Python\DataSpell_Projects\Default Environment 311\Lib\site-packages\transformers\utils\generic.py:309: FutureWarning
  _torch_pytree._register_pytree_node(
D:\Programming\Python\DataSpell_Projects\Default Environment 311\Lib\site-packages\huggingface_hub\file_download.py:1142: FutureWarr
  warnings.warn(
D:\Programming\Python\DataSpell_Projects\Default Environment 311\Lib\site-packages\transformers\utils\generic.py:309: FutureWarning
  _torch_pytree._register_pytree_node(
Some weights of RobertaModel were not initialized from the model checkpoint at roberta-base and are newly initialized: ['roberta.poc
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.

[i] Using GPU: 0

=========================== Initializing pipeline ===========================
[+] Initialized pipeline

============================= Training pipeline =============================
[i] Pipeline: ['transformer', 'ner', 'parser']
[i] Initial learn rate: 0.0
E    #       LOSS TRANS...  LOSS NER  LOSS PARSER  ENTS_F  ENTS_P  ENTS_R  DEP_UAS  DEP_LAS  SENTS_F  SCORE
---  ------  -------------  --------  -----------  ------  ------  ------  -------  -------  -------  ------
  0       0        2347.67    340.47         0.00    0.00    0.00    0.00     0.00     0.00     0.00    0.00
100     200      432235.88 129261.11         0.00   18.24   12.29   35.40     0.00     0.00     0.00    0.09
200     400       70628.79  76141.04         0.00    0.00    0.00    0.00     0.00     0.00     0.00    0.00
300     600       50761.94  20791.63         0.00   69.75   90.78   56.64     0.00     0.00     0.00    0.35
400     800       54726.28  10070.48         0.00   84.21   87.20   81.42     0.00     0.00     0.00    0.42
500    1000       57560.41   6165.29         0.00   92.27   92.07   92.48     0.00     0.00     0.00    0.46
600    1200       51808.35   3723.55         0.00   93.89   92.67   95.13     0.00     0.00     0.00    0.47
700    1400       46603.79   2319.63         0.00   95.22   93.59   96.90     0.00     0.00     0.00    0.48
800    1600       47628.50   1691.38         0.00   95.65   94.02   97.35     0.00     0.00     0.00    0.48
900    1800       45338.09   1228.01         0.00   97.40   95.34   99.56     0.00     0.00     0.00    0.49
1000   2000       45436.41    971.38         0.00   98.26   96.58  100.00     0.00     0.00     0.00    0.49
1100   2200       45092.97    776.88         0.00   98.47   97.00  100.00     0.00     0.00     0.00    0.49
1200   2400       49307.40    704.71         0.00   98.47   97.00  100.00     0.00     0.00     0.00    0.49
1300   2600       47846.57    622.29         0.00   98.47   97.00  100.00     0.00     0.00     0.00    0.49
1400   2800       47302.17    549.08         0.00   98.47   97.00  100.00     0.00     0.00     0.00    0.49
1500   3000       50488.36    511.97         0.00   98.47   97.00  100.00     0.00     0.00     0.00    0.49
1600   3200       50326.06    481.54         0.00   98.69   97.41  100.00     0.00     0.00     0.00    0.49
1700   3400       49383.58    442.12         0.00   98.69   97.41  100.00     0.00     0.00     0.00    0.49
1800   3600       48988.44    413.26         0.00   98.69   97.41  100.00     0.00     0.00     0.00    0.49
1900   3800       47618.38    377.53         0.00   98.69   97.41  100.00     0.00     0.00     0.00    0.49
2000   4000       45781.95    351.50         0.00   98.69   97.41  100.00     0.00     0.00     0.00    0.49
2100   4200       44497.04    330.61         0.00   98.69   97.41  100.00     0.00     0.00     0.00    0.49
2200   4400       46827.97    307.82         0.00   98.69   97.41  100.00     0.00     0.00     0.00    0.49
2300   4600       40950.94    266.22         0.00   98.69   97.41  100.00     0.00     0.00     0.00    0.49
2400   4800       42258.23    265.77         0.00   98.69   97.41  100.00     0.00     0.00     0.00    0.49
[+] Saved pipeline to output directory
model-last
```

Best model and tests

Load the best model and test on randomly generated ChatGPT text.

```
nlp_ner = spacy.load("model-best")
```

```
D:\Programming\Python\DataSpell_Projects\Default Environment 311\Lib\site-packages\transformers\utils\generic.py:309: FutureWarning
  _torch_pytree._register_pytree_node(
D:\Programming\Python\DataSpell_Projects\Default Environment 311\Lib\site-packages\spacy_transformers\layers\hf_shim.py:124: FutureW
  self._model.load_state_dict(torch.load(filelike, map_location=device))
```

```
doc = nlp_ner("The hikers planned an adventurous journey through the Alps, scaling Mont Blanc, passing by the Matterhorn, and ending the

colors = {"MOUNTAIN_NAME": "#668eab"}
options = {"colors": colors}

spacy.displacy.render(doc, options= options, style="ent", jupyter=True)
```

The hikers planned an adventurous journey through the Alps **MOUNTAIN_NAME** , scaling Mont Blanc **MOUNTAIN_NAME** , passing by the Matterhorn,

Obtained a result that successfully extracts the names of mountains from the text.

Let's try an example with a large number of names:

```
doc = nlp_ner("Mount Everest, known as the tallest mountain in the world, and K2, the second highest peak, are both part of the majestic

colors = {"MOUNTAIN_NAME": "#668eab"}
options = {"colors": colors}

spacy.displacy.render(doc, options= options, style="ent", jupyter=True)
```

Mount Everest **MOUNTAIN_NAME** , known as the tallest mountain in the world, and K2 **MOUNTAIN_NAME** , the second highest peak, are both part of the majestic Himalayas **MOUNTAIN_NAME** . The Rocky Mountains **MOUNTAIN_NAME** in North America are home to stunning peaks like Mount Elbert **MOUNTAIN_NAME** and Mount Rainier **MOUNTAIN_NAME** , attracting hikers and adventurers alike. In the Andes **MOUNTAIN_NAME** mountain range, Ojos