Bioinformatics

Lab2

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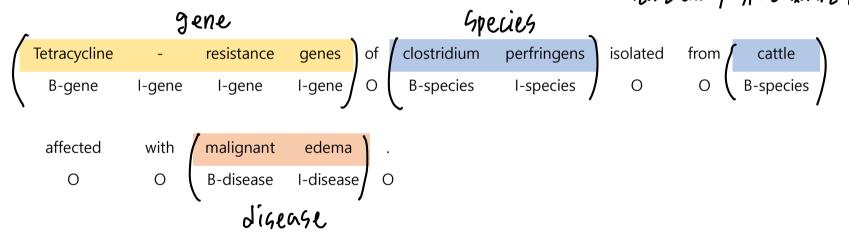
- 1. 개체 명 인식
- 2. 데이터 세트
- 3. Environment
- 4. Transformers
- 5. How to train NER using transformers

개체 명 인식

NER

Language model 정보 추울의 한 뜨대스

- 개체 명 인식 (named entity recognition): 미리 정의해 둔 사람, 회사, 장소, 시간, 단위 등에 해당하는 단어(개체 명)을 문서에서 인식하여 추출 분류하는 기법
- 일반적으로 IOB tag를 사용; B-Begin, I-Inside, O-Others text에서 원하는 entity type은 첫째는 방법



데이터 세트

• https://huggingface.co/datasets/ncbi_disease

id (string)	tokens (sequence)	ner_tags (sequence)
" ₀ "	["Identification", "of", "APC2", ",", "a", "homologue", "of", "the", "adenomatous",	[0,0,0,0,0,0,0,1,2,2,2,0,0]
"1"	["The", "adenomatous", "polyposis", "coli", "(", "APC", ")", "tumour", "-", "suppressor"	[0, 1, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
"2"	["Complex", "formation", "induces", "the", "rapid", "degradation", "of", "betacatenin",	[0, 0, 0, 0, 0, 0, 0, 0]
"3"	["In", "colon", "carcinoma", "cells", ",", "loss", "of", "APC", "leads", "to", "the",	[0, 1, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
"4"	["Here", ",", "we", "report", "the", "identification", "and", "genomic",	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
"5"	["Mammalian", "APC2", ",", "which", "closely", "resembles", "APC", "in",	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
"6"	["Like", "APC", ",", "APC2", "regulates", "the", "formation", "of", "active",	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

ner_tags (IOB tag)

- 0 O
- 1 B-disease
- 2 I-disease

Environment

- Colab
 - Python 3.7.13
 - CUDA 11.2
 - Numpy 1.21.6
 - Scikit-learn 1.0.2
- Pytorch 1.12.0
- Transformers 4.24.0
- Datasets 2.7.1
- Evaluate 0.3.0 がんばれ もけた
- seqeval

मियुक्त प्रेमि भेटाभिक्त यम्प्रय

Transformers

https://huggingface.co/docs/transformers/index

Transformers

State-of-the-art Machine Learning for PyTorch, TensorFlow, and JAX.

Transformers provides APIs and tools to easily download and train state-of-the-art pretrained models. Using pretrained models can reduce your compute costs, carbon footprint, and save you the time and resources required to train a model from scratch. These models support common tasks in different modalities, such as:

- Natural Language Processing: text classification, named entity recognition, question answering, language modeling, summarization, translation, multiple choice, and text generation.
- Computer Vision: image classification, object detection, and segmentation.
- Audio: automatic speech recognition and audio classification.
- Multimodal: table question answering, optical character recognition, information extraction from scanned documents, video classification, and visual question answering.

Code: https://github.com/yesol-park/Bioinformatics2022

Get dataset from dataset repository on the Hub

```
train_dataset = load_dataset("ncbi_disease", split="train")
test_dataset = load_dataset("ncbi_disease", split="test")
print(train_dataset)
print(test_dataset)
```

```
Dataset({
    features: ['id', 'tokens', 'ner_tags'],
    num_rows: 5433
})
Dataset({
    features: ['id', 'tokens', 'ner_tags'],
    num_rows: 941
})
```

Load tokenizer and pretrained model

Bert's token 2542 45

Preprocessing the dataset

```
256 이외의 깃들은 장라누겠다
def tokenize and align labels(examples):
     tokenized inputs = tokenizer(examples["tokens"], padding="max length", truncation=True
                                                                                max length=256, is split into words=True. )
     labels = []
    for i, label in enumerate(examples["ner tags"]):
                word_ids = tokenized_inputs.word_ids(batch_index=i)
                previous_word_idx = None
                                                                                            [None, O. 1, 2, 2, 2, 3, 4, 5, 5, 6, 7, 8, 8, 8, 8, 9, 9, 9, 10, 11, 11, 12, 12, 13, None, None,
                label ids = []
                for word idx in word ids:
                          # Special tokens have a word id that is None. We set the label to -100
                          # so they are automatically ignored in the loss function.
                          if word idx is None:
                                     label ids.append(-100)
                          # We set the label for the first token of each word.
                          elif word idx != previous word idx:
                                      label ids.append(label to id[label[word idx]])
                          # For the other tokens in a word, we set the label to -100.
                          else:
                                      label ids.append(-100)
                          previous word idx = word idx
                labels.append(label ids)
     tokenized_inputs["labels"] = labels
     return tokenized inputs
train dataset = train dataset.map(tokenize and align labels, batched=True, )
test_dataset = test_dataset.map(tokenize_and_align_labels, batched=True, )
                                                                                                                                                                                                                                                                                                                                                                                        9
```

• Preprocessing the dataset – set tag ids

tokenized 하고 label 변경 해구는 작업

Raw text	the	adenomatous			polyposis		coli	tumour			
label ids	0		-	L			2		2		2
Tokenized	the	aden	##oma	##tou	##s	poly	##po	##sis	coli	tu	##mour
label ids	0	1	-100	-100	-100	2	-100	-100	2	2	-100

go having

doing > ?

Tag ID	Tag
1	В
2	1
-100	<sub_token></sub_token>

Set metric function

間には十

transformeron 7/201473

```
def compute metrics(p):
   metric = evaluate.load("segeval")
   predictions, labels = p
    predictions = np.argmax(predictions, axis=2)
    # Remove ignored index (special tokens)
    true predictions = [
        [label_list[p] for (p, I) in zip(prediction, label) if I !=-100]
        for prediction, label in zip(predictions, labels)
    true_labels = [
        [label_list[I] for (p, I) in zip(prediction, label) if I = -100]
        for prediction, label in zip(predictions, labels)
    results = metric.compute(predictions=true predictions, references=true labels)
    return {
        "precision": results["overall precision"],
        "recall": results["overall_recall"],
        "f1": results["overall f1"].
        "accuracy": results["overall accuracy"].
```

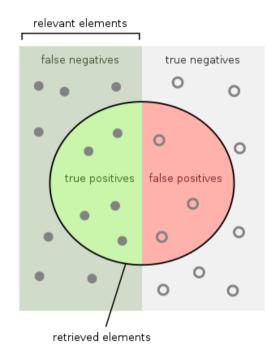
Set metric function

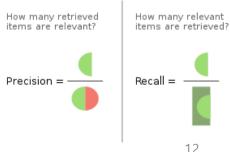
$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

$$F_1 = \frac{2 \times precision \times recall}{precision + recall}$$

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$





of

0

0

Set metric function

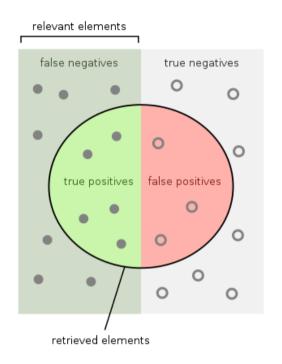
$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

$$F_1 = \frac{2 \times precision \times recall}{precision + recall}$$

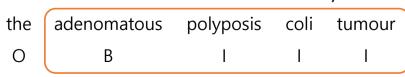
$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

Identification of ACP2 , a homologue





positive



• Train NER model a Dataset of GA WHA APOLES AND \$1684

• Train NER model

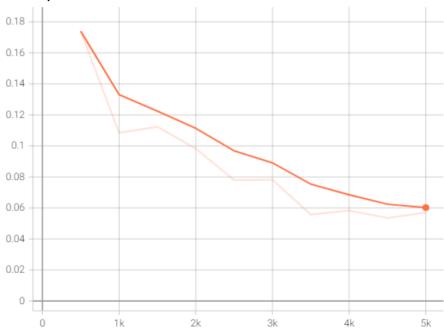
Step	Training Loss
500	0.174000
1000	0.108500
1500	0.112300
2000	0.098300
2500	0.078000
3000	0.078300
3500	0.055800
4000	0.058400
4500	0.053600
5000	0.057000

Training completed. Do not forget to share your model on huggingface.co/models =)

Saving model checkpoint to ./results Configuration saved in ./results/config.json Model weights saved in ./results/pytorch_model.bin

```
%load_ext tensorboard
%tensorboard --logdir="./results"
```

train/loss



Test NER model

```
predictions, labels, metrics = trainer.predict(test_dataset, metric_key_prefix="predict")
print(metrics)
predictions = np.argmax(predictions, axis=2) ላን ሂደ ሚዲ ካገር ይ
true predictions = [
             [label list[p] for (p, I) in zip(prediction, label) if I !=-100]
            for prediction, label in zip(predictions, labels)
for token, prediction in zip(test_dataset["tokens"][0], true_predictions[0]):
    print(f"{token} \text{\text{token}} \text{\text{prediction}} ")
```

Test NER model

```
**** Running Prediction ****
 Num examples = 941
 Batch size = 11
****Metrics****
predict_loss: 0.07623732835054398
predict_precision: 0.8138613861386138
predict recall: 0.85625
predict_f1: 0.8345177664974618
predict_accuracy: 0.9808956198718211
predict_runtime: 21.2564
predict_samples_per_second: 44.269
predict_steps_per_second: 4.046
```

```
****Result****
Clustering
missense
                0
mutations
in
the
ataxia B-Disease
        I-Disease
telangiectasia I-Disease
gene
in
sporadic
        B-Disease
        I-Disease
        I-Disease
cell
leukaemia
                I-Disease
```

Ataxia-telangiectasia is a rare inherited disorder that affects the nervous system, immune system, and other body systems.

T-cell leukemia is an uncommon type of blood cell cancer that affects your white blood cells.