# Named Entity Recognition. DistilBERT

#### Борисочкин М. И. ИУ5-21М

```
In [1]: from datasets import load_dataset
    from transformers import DataCollatorForTokenClassification
    from transformers import AutoTokenizer, AutoModelForTokenClassification
    from transformers import TrainingArguments, Trainer

import numpy as np
import evaluate
```

## Загрузка набора данных

Для обучения будем использовать "русскую" часть WikiNEuRal

#### Предобработка данных

```
In [4]: # Загрузка токенизатора
tokenizer = AutoTokenizer.from_pretrained(
        "distilbert/distilbert-base-multilingual-cased"
)

In [5]: # Пример работы токенизатора
example = dataset["train_ru"][0]
tokenized_input = tokenizer(example["tokens"], is_split_into_words=True)
tokens = tokenizer.convert_ids_to_tokens(tokenized_input["input_ids"])
tokens
```

```
Out[5]: ['[CLS]',
         'Де',
          '##тство',
          'провёл',
          'в',
          'Над',
          '##ь',
          '##com',
          '##бат',
          '##e',
          'c',
          '1860',
          'Γ',
          ٠٠',
          '[SEP]']
In [6]: def tokenize_and_align_labels(examples):
            """Корректировка токенизации
            Parameters
            -----
            examples
                Входное предложение
            Returns
            _____
                tokenized_inputs
                    Токенизированный вход
            tokenized_inputs = tokenizer(
                examples["tokens"], truncation=True, is_split_into_words=True
            )
            labels = []
            for i, label in enumerate(examples[f"ner_tags"]):
                word_ids = tokenized_inputs.word_ids(batch_index=i) # Токенизация
                previous_word_idx = None
                label_ids = []
                for word_idx in word_ids: # Установка значения спец. токенов -100
                    if word_idx is None:
                         label_ids.append(-100)
                    elif (
                        word_idx != previous_word_idx
                    ): #Применяем метку только к первому слову в предложении при нескольк
                        label_ids.append(label[word_idx])
                         label_ids.append(-100)
                    previous_word_idx = word_idx
                labels.append(label_ids)
            tokenized_inputs["labels"] = labels
            return tokenized_inputs
```

```
In [7]: # Применение токенизатора к ∂атасету tokenized_dataset = dataset.map(tokenize_and_align_labels, batched=True)
```

```
Map: 0%| | 0/11069 [00:00<?, ? examples/s]

In [8]: # 3αεργ3κα DataCollator
data_collator = DataCollatorForTokenClassification(tokenizer=tokenizer)</pre>
```

### Обучение модели

#### Метрики качества

```
In [9]: seqeval = evaluate.load("seqeval")
In [12]: def compute_metrics(p):
             """Функция для расчёта метрик
             Parameters
                 Предсказание
             Returns
             _____
             metrics
                 Метрики качества
             predictions, labels = p
             predictions = np.argmax(predictions, axis=2)
             label_list = [
                 "0",
                 "B-PER",
                 "I-PER",
                 "B-ORG",
                  "I-ORG",
                 "B-LOC",
                 "I-LOC",
                 "B-MISC",
                  "I-MISC",
             ]
             true_predictions = [
                  [label_list[p] for (p, 1) in zip(prediction, label) if l != -100]
                 for prediction, label in zip(predictions, labels)
             true_labels = [
                  [label_list[l] for (p, l) in zip(prediction, label) if l != -100]
                 for prediction, label in zip(predictions, labels)
             1
             results = seqeval.compute(predictions=true_predictions, references=true_labels)
             return {
                  "precision": results["overall_precision"],
                  "recall": results["overall_recall"],
                  "f1": results["overall_f1"],
                  "accuracy": results["overall_accuracy"],
             }
```

### Загрузка и обучение модели

Для обучения будем использовать мультиязычную версию distilBERT

```
In [10]: id2label = {
             0: "0",
             1: "B-PER",
             2: "I-PER",
             3: "B-ORG",
             4: "I-ORG",
             5: "B-LOC",
             6: "I-LOC",
             7: "B-MISC",
             8: "I-MISC",
         label2id = {
             "0": 0,
             "B-PER": 1,
             "I-PER": 2,
             "B-ORG": 3,
             "I-ORG": 4,
             "B-LOC": 5,
             "I-LOC": 6,
             "B-MISC": 7,
             "I-MISC": 8,
In [11]: # Загрузка модели
         model = AutoModelForTokenClassification.from_pretrained(
             "distilbert/distilbert-base-multilingual-cased",
             num_labels=9,
             id2label=id2label,
             label2id=label2id,
```

Some weights of DistilBertForTokenClassification were not initialized from the model checkpoint at distilbert/distilbert-base-multilingual-cased and are newly initialize d: ['classifier.bias', 'classifier.weight'] You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.

```
In [13]: # Аргументы для обучения
         training_args = TrainingArguments(
             output_dir="distilBERT",
             learning rate=2e-5,
             per_device_train_batch_size=16,
             per_device_eval_batch_size=16,
             num_train_epochs=3,
             weight_decay=0.01,
             eval_strategy="epoch",
             save_strategy="epoch",
             load_best_model_at_end=True,
             push_to_hub=False,
In [14]: # Описание тренера
         trainer = Trainer(
             model=model,
             args=training_args,
             train_dataset=tokenized_dataset["train_ru"],
             eval_dataset=tokenized_dataset["val_ru"],
             tokenizer=tokenizer,
             data_collator=data_collator,
             compute_metrics=compute_metrics,
        # Обучение модели
In [15]:
         trainer.train()
                                                [17310/17310 34:58, Epoch 3/3]
        Epoch Training Loss Validation Loss Precision
                                                     Recall
                                                                 F1 Accuracy
                  0.047400
                                 0.042902
                                          0.882115  0.899506  0.890726
            1
                                                                     0.985407
                  0.029300
                                 0.041630
                                          0.893203 0.912136 0.902570
                                                                     0.986338
            3
                  0.018500
                                 Out[15]: TrainOutput(global_step=17310, training_loss=0.03671303313292223, metrics={'train_
         runtime': 2098.6184, 'train_samples_per_second': 131.973, 'train_steps_per_secon
         d': 8.248, 'total_flos': 5941936302049440.0, 'train_loss': 0.03671303313292223, 'e
         poch': 3.0})
In [16]: # Качество лучшей модели
         trainer.evaluate()
```

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