distilation-bert

March 23, 2025

1 DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter

In this lecture, we will explore the architecture of DistilBERT, its key components, and how it can be utilized for various natural language processing tasks. Additionally, we'll discuss its advantages, limitations, and provide hands-on examples to showcase its effectiveness.

Reference: The Theory | Code

```
import copy
# Set GPU device
# os.environ["CUDA_VISIBLE_DEVICES"] = "2"

# os.environ['http_proxy'] = 'http://192.41.170.23:3128'
# os.environ['https_proxy'] = 'http://192.41.170.23:3128'

!pip install datasets transformers evaluate import datasets

import torch import torch.nn as nn import torch.optim as optim from torch.nn import Module import torch.nn.functional as F from torch.utils.data import DataLoader
```

```
from tqdm.auto import tqdm
import random, math, time
import numpy as np
!pip install opencv-python opencv-python-headless
import transformers
from transformers import TrainingArguments, Trainer, default_data_collator
from transformers import AutoModelForSequenceClassification, AutoTokenizer, __
  →DataCollatorWithPadding
from transformers.models.bert.modeling_bert import BertPreTrainedModel, u
 →BertConfig
from transformers.models.bert.modeling bert import BertEncoder, BertModel
from transformers import get_scheduler
print(datasets.__version__, transformers.__version__, torch.__version__)
import evaluate
from sklearn.metrics import accuracy_score, precision_score, recall_score,
 →f1_score, ConfusionMatrixDisplay
from sklearn.metrics import classification_report
import matplotlib.pyplot as plt
!pip install peft
from peft import LoraConfig, TaskType, get_peft_model
Requirement already satisfied: datasets in /usr/local/lib/python3.10/dist-
packages (3.3.1)
Requirement already satisfied: transformers in /usr/local/lib/python3.10/dist-
packages (4.47.0)
Collecting evaluate
 Downloading evaluate-0.4.3-py3-none-any.whl.metadata (9.2 kB)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-
packages (from datasets) (3.17.0)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-
packages (from datasets) (1.26.4)
Requirement already satisfied: pyarrow>=15.0.0 in
/usr/local/lib/python3.10/dist-packages (from datasets) (19.0.1)
Requirement already satisfied: dill<0.3.9,>=0.3.0 in
/usr/local/lib/python3.10/dist-packages (from datasets) (0.3.8)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages
(from datasets) (2.2.3)
Requirement already satisfied: requests>=2.32.2 in
/usr/local/lib/python3.10/dist-packages (from datasets) (2.32.3)
Requirement already satisfied: tqdm>=4.66.3 in /usr/local/lib/python3.10/dist-
packages (from datasets) (4.67.1)
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Requirement already satisfied: xxhash in /usr/local/lib/python3.10/dist-packages
(from datasets) (3.5.0)
Requirement already satisfied: multiprocess<0.70.17 in
/usr/local/lib/python3.10/dist-packages (from datasets) (0.70.16)
Requirement already satisfied: fsspec<=2024.12.0,>=2023.1.0 in
/usr/local/lib/python3.10/dist-packages (from
fsspec[http]<=2024.12.0,>=2023.1.0->datasets) (2024.12.0)
Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-
packages (from datasets) (3.11.12)
Requirement already satisfied: huggingface-hub>=0.24.0 in
/usr/local/lib/python3.10/dist-packages (from datasets) (0.29.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from datasets) (24.2)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-
packages (from datasets) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.10/dist-packages (from transformers) (2024.11.6)
Requirement already satisfied: tokenizers<0.22,>=0.21 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.21.0)
Requirement already satisfied: safetensors>=0.4.1 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.4.5)
Requirement already satisfied: aiohappyeyeballs>=2.3.0 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (2.4.6)
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/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (1.3.2)
Requirement already satisfied: async-timeout<6.0,>=4.0 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (5.0.1)
Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.10/dist-
packages (from aiohttp->datasets) (25.1.0)
Requirement already satisfied: frozenlist>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (1.5.0)
Requirement already satisfied: multidict<7.0,>=4.5 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (6.1.0)
Requirement already satisfied: propcache>=0.2.0 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (0.2.1)
Requirement already satisfied: yarl<2.0,>=1.17.0 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (1.18.3)
Requirement already satisfied: typing-extensions>=3.7.4.3 in
/usr/local/lib/python3.10/dist-packages (from huggingface-hub>=0.24.0->datasets)
(4.12.2)
Requirement already satisfied: mkl_fft in /usr/local/lib/python3.10/dist-
packages (from numpy>=1.17->datasets) (1.3.8)
Requirement already satisfied: mkl_random in /usr/local/lib/python3.10/dist-
packages (from numpy>=1.17->datasets) (1.2.4)
Requirement already satisfied: mkl_umath in /usr/local/lib/python3.10/dist-
packages (from numpy>=1.17->datasets) (0.1.1)
Requirement already satisfied: mkl in /usr/local/lib/python3.10/dist-packages
(from numpy>=1.17->datasets) (2025.0.1)
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Requirement already satisfied: tbb4py in /usr/local/lib/python3.10/dist-packages
(from numpy>=1.17->datasets) (2022.0.0)
Requirement already satisfied: mkl-service in /usr/local/lib/python3.10/dist-
packages (from numpy>=1.17->datasets) (2.4.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests>=2.32.2->datasets)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests>=2.32.2->datasets) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests>=2.32.2->datasets)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests>=2.32.2->datasets)
(2025.1.31)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas->datasets) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas->datasets) (2025.1)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-
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Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.8.2->pandas->datasets) (1.17.0)
Requirement already satisfied: intel-openmp>=2024 in
/usr/local/lib/python3.10/dist-packages (from mkl->numpy>=1.17->datasets)
(2024.2.0)
Requirement already satisfied: tbb==2022.* in /usr/local/lib/python3.10/dist-
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Requirement already satisfied: tcmlib==1.* in /usr/local/lib/python3.10/dist-
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Requirement already satisfied: intel-cmplr-lib-rt in
/usr/local/lib/python3.10/dist-packages (from mkl_umath->numpy>=1.17->datasets)
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openmp>=2024->mkl->numpy>=1.17->datasets) (2024.2.0)
Downloading evaluate-0.4.3-py3-none-any.whl (84 kB)
                         84.0/84.0 kB
2.7 MB/s eta 0:00:00
Installing collected packages: evaluate
Successfully installed evaluate-0.4.3
Requirement already satisfied: opency-python in /usr/local/lib/python3.10/dist-
packages (4.10.0.84)
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/usr/local/lib/python3.10/dist-packages (4.10.0.84)
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packages (from numpy>=1.21.2->opencv-python) (1.3.8)
Requirement already satisfied: mkl_random in /usr/local/lib/python3.10/dist-
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Requirement already satisfied: peft in /usr/local/lib/python3.10/dist-packages
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Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-
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Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from peft) (24.2)
Requirement already satisfied: psutil in /usr/local/lib/python3.10/dist-packages
(from peft) (5.9.5)
Requirement already satisfied: pyyaml in /usr/local/lib/python3.10/dist-packages
(from peft) (6.0.2)
Requirement already satisfied: torch>=1.13.0 in /usr/local/lib/python3.10/dist-
packages (from peft) (2.5.1+cu121)
Requirement already satisfied: transformers in /usr/local/lib/python3.10/dist-
packages (from peft) (4.47.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(from peft) (4.67.1)
Requirement already satisfied: accelerate>=0.21.0 in
/usr/local/lib/python3.10/dist-packages (from peft) (1.2.1)
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/usr/local/lib/python3.10/dist-packages (from peft) (0.29.0)
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Requirement already satisfied: fsspec>=2023.5.0 in
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(2024.12.0)
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Requirement already satisfied: mkl random in /usr/local/lib/python3.10/dist-
packages (from numpy>=1.17->peft) (1.2.4)
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packages (from numpy>=1.17->peft) (0.1.1)
Requirement already satisfied: mkl in /usr/local/lib/python3.10/dist-packages
(from numpy>=1.17->peft) (2025.0.1)
Requirement already satisfied: tbb4py in /usr/local/lib/python3.10/dist-packages
(from numpy>=1.17->peft) (2022.0.0)
Requirement already satisfied: mkl-service in /usr/local/lib/python3.10/dist-
packages (from numpy>=1.17->peft) (2.4.1)
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-
packages (from torch>=1.13.0->peft) (3.4.2)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages
(from torch >= 1.13.0 -> peft) (3.1.4)
Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.10/dist-
packages (from torch>=1.13.0->peft) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
/usr/local/lib/python3.10/dist-packages (from
sympy==1.13.1->torch>=1.13.0->peft) (1.3.0)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.10/dist-packages (from transformers->peft) (2024.11.6)
Requirement already satisfied: tokenizers<0.22,>=0.21 in
/usr/local/lib/python3.10/dist-packages (from transformers->peft) (0.21.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2->torch>=1.13.0->peft)
Requirement already satisfied: intel-openmp>=2024 in
/usr/local/lib/python3.10/dist-packages (from mkl->numpy>=1.17->peft) (2024.2.0)
Requirement already satisfied: tbb==2022.* in /usr/local/lib/python3.10/dist-
packages (from mkl->numpy>=1.17->peft) (2022.0.0)
Requirement already satisfied: tcmlib==1.* in /usr/local/lib/python3.10/dist-
packages (from tbb==2022.*->mkl->numpy>=1.17->peft) (1.2.0)
Requirement already satisfied: intel-cmplr-lib-rt in
/usr/local/lib/python3.10/dist-packages (from mkl_umath->numpy>=1.17->peft)
(2024.2.0)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->huggingface-
```

```
hub >= 0.25.0 - peft) (3.4.1)
    Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
    packages (from requests->huggingface-hub>=0.25.0->peft) (3.10)
    Requirement already satisfied: urllib3<3,>=1.21.1 in
    /usr/local/lib/python3.10/dist-packages (from requests->huggingface-
    hub >= 0.25.0 - peft) (2.3.0)
    Requirement already satisfied: certifi>=2017.4.17 in
    /usr/local/lib/python3.10/dist-packages (from requests->huggingface-
    hub>=0.25.0->peft) (2025.1.31)
    Requirement already satisfied: intel-cmplr-lib-ur==2024.2.0 in
    /usr/local/lib/python3.10/dist-packages (from intel-
    openmp>=2024->mkl->numpy>=1.17->peft) (2024.2.0)
[]: device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
     print(device)
     #make our work comparable if restarted the kernel
     SEED = 1234
     torch.manual_seed(SEED)
     torch.backends.cudnn.deterministic = True
    cuda
[]: # from huggingface_hub import login
     # login()
```

1.1 1. Loading our MNLI part of the GLUE dataset

```
[ ]: ###1. Load Dataset
     task_to_keys = {
         "cola": ("sentence", None),
         "mnli": ("premise", "hypothesis"),
         "mrpc": ("sentence1", "sentence2"),
         "qnli": ("question", "sentence"),
         "qqp": ("question1", "question2"),
         "rte": ("sentence1", "sentence2"),
         "sst2": ("comment_text", None),
         "stsb": ("sentence1", "sentence2"),
         "wnli": ("sentence1", "sentence2"),
         "cstm": ("comment_text", None),
     }
     task_name = "cstm"
     # dataset: https://huggingface.co/datasets/OxAISH-AL-LLM/wiki_toxic
     # https://huggingface.co/datasets/mteb/toxic_conversations_50k
     # raw_datasets = datasets.load_dataset("glue", task_name)
     raw_datasets = datasets.load_dataset("OxAISH-AL-LLM/wiki_toxic")
     raw datasets
```

```
| 0.00/4.30k [00:00<?, ?B/s]
    README.md:
                 0%1
                     0%|
                                   | 0.00/4.55k [00:00<?, ?B/s]
    wiki_toxic.py:
    0000.parquet:
                    0%|
                                 | 0.00/35.2M [00:00<?, ?B/s]
    0000.parquet:
                    0%1
                                 | 0.00/8.85M [00:00<?, ?B/s]
    0000.parquet:
                    0%|
                                 | 0.00/17.3M [00:00<?, ?B/s]
    0000.parquet:
                                 | 0.00/6.18M [00:00<?, ?B/s]
                    0%|
    Generating train split:
                              0%|
                                            | 0/127656 [00:00<?, ? examples/s]
                                   0%1
                                                 | 0/31915 [00:00<?, ? examples/s]
    Generating validation split:
    Generating test split: 0%|
                                           | 0/63978 [00:00<?, ? examples/s]
    Generating balanced_train split:
                                       0%|
                                                     | 0/25868 [00:00<?, ? examples/s]
[ ]: DatasetDict({
         train: Dataset({
             features: ['id', 'comment_text', 'label'],
             num_rows: 127656
         })
         validation: Dataset({
             features: ['id', 'comment_text', 'label'],
             num_rows: 31915
         })
         test: Dataset({
             features: ['id', 'comment_text', 'label'],
             num_rows: 63978
         })
         balanced_train: Dataset({
             features: ['id', 'comment_text', 'label'],
             num_rows: 25868
         })
    })
[]: label_list = raw_datasets['balanced_train'].features['label'].names
     label2id = {v: i for i, v in enumerate(label_list)}
     label2id
[]: {'non': 0, 'tox': 1}
[]: id2label = {i: v for v, i in label2id.items()}
     id2label
[]: {0: 'non', 1: 'tox'}
```

1.2 2. Model & Tokenization

```
[]: num_labels = np.unique(raw_datasets['balanced_train']['label']).size
     num_labels
[]: 2
[]: teacher_id = "bert-base-uncased"
     tokenizer = AutoTokenizer.from_pretrained(teacher_id)
     teacher_model = AutoModelForSequenceClassification.from_pretrained(
         teacher_id,
         num_labels = num_labels,
         id2label = id2label,
         label2id = label2id,
     teacher_model
                             0%1
                                           | 0.00/48.0 [00:00<?, ?B/s]
    tokenizer_config.json:
                                 | 0.00/570 [00:00<?, ?B/s]
    config.json:
                   0%1
                 0%1
                              | 0.00/232k [00:00<?, ?B/s]
    vocab.txt:
    tokenizer.json:
                      0%1
                                    | 0.00/466k [00:00<?, ?B/s]
    model.safetensors:
                         0%1
                                       | 0.00/440M [00:00<?, ?B/s]
    Some weights of BertForSequenceClassification were not initialized from the
    model checkpoint at bert-base-uncased and are newly initialized:
    ['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.
[ ]: BertForSequenceClassification(
       (bert): BertModel(
         (embeddings): BertEmbeddings(
           (word_embeddings): Embedding(30522, 768, padding_idx=0)
           (position_embeddings): Embedding(512, 768)
           (token_type_embeddings): Embedding(2, 768)
           (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
           (dropout): Dropout(p=0.1, inplace=False)
         (encoder): BertEncoder(
           (layer): ModuleList(
             (0-11): 12 x BertLayer(
               (attention): BertAttention(
                 (self): BertSdpaSelfAttention(
                   (query): Linear(in_features=768, out_features=768, bias=True)
                   (key): Linear(in_features=768, out_features=768, bias=True)
```

```
(value): Linear(in_features=768, out_features=768, bias=True)
               (dropout): Dropout(p=0.1, inplace=False)
             (output): BertSelfOutput(
               (dense): Linear(in_features=768, out_features=768, bias=True)
               (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
               (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (intermediate): BertIntermediate(
             (dense): Linear(in_features=768, out_features=3072, bias=True)
             (intermediate_act_fn): GELUActivation()
          )
          (output): BertOutput(
             (dense): Linear(in_features=3072, out_features=768, bias=True)
             (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
             (dropout): Dropout(p=0.1, inplace=False)
        )
      )
    )
    (pooler): BertPooler(
      (dense): Linear(in_features=768, out_features=768, bias=True)
      (activation): Tanh()
    )
  (dropout): Dropout(p=0.1, inplace=False)
  (classifier): Linear(in_features=768, out_features=2, bias=True)
)
1.3 3. Preprocessing
    sentence1_key, sentence2_key = task_to_keys[task_name]
```

```
[]: def tokenize_function(examples):
         args = (
             (examples[sentence1_key],) if sentence2_key is None else_

  (examples[sentence1_key], examples[sentence2_key])
         result = tokenizer(*args, max_length=128, truncation=True)
         return result
```

```
[]: tokenized_datasets = raw_datasets.map(tokenize_function, batched=True)
    tokenized_datasets
```

```
0%|
                    | 0/127656 [00:00<?, ? examples/s]
Map:
                    | 0/31915 [00:00<?, ? examples/s]
Map:
       0%|
                    | 0/63978 [00:00<?, ? examples/s]
       0%1
Map:
```

```
Map:
         0%1
                        | 0/25868 [00:00<?, ? examples/s]
[ ]: DatasetDict({
         train: Dataset({
             features: ['id', 'comment_text', 'label', 'input_ids', 'token_type_ids',
     'attention_mask'],
             num rows: 127656
         })
         validation: Dataset({
             features: ['id', 'comment_text', 'label', 'input_ids', 'token_type_ids',
     'attention_mask'],
             num_rows: 31915
         })
         test: Dataset({
             features: ['id', 'comment_text', 'label', 'input_ids', 'token_type_ids',
     'attention_mask'],
             num_rows: 63978
         })
         balanced_train: Dataset({
             features: ['id', 'comment_text', 'label', 'input_ids', 'token_type_ids',
     'attention_mask'],
             num rows: 25868
         })
     })
[]: # list(task_to_keys[task_name])
     column_dataset = [item for item in task_to_keys[task_name] if item is not None]
     column_dataset
[]: ['comment_text']
[]: #remove column : 'premise', 'hypothesis', 'idx'
     tokenized_datasets = tokenized_datasets.remove_columns(column_dataset + ["id"])
     #rename column : 'labels'
     tokenized_datasets = tokenized_datasets.rename_column("label", "labels")
     tokenized_datasets.set_format("torch")
     tokenized_datasets
[ ]: DatasetDict({
         train: Dataset({
             features: ['labels', 'input_ids', 'token_type_ids', 'attention_mask'],
             num rows: 127656
         })
         validation: Dataset({
             features: ['labels', 'input_ids', 'token_type_ids', 'attention_mask'],
             num rows: 31915
         })
         test: Dataset({
```

```
features: ['labels', 'input ids', 'token_type ids', 'attention_mask'],
            num_rows: 63978
        })
        balanced_train: Dataset({
            features: ['labels', 'input_ids', 'token_type_ids', 'attention_mask'],
            num_rows: 25868
        })
    })
[]: tokenized_datasets['balanced_train'][0]['input_ids']
[]: tensor([ 101, 1000, 2025, 2065, 1045, 2064, 2393,
                                                              2009, 1012,
                                                                            8494.
            14540, 5178, 2003, 2062, 2066, 2009, 1012,
                                                              1012,
                                                                     1012,
                                                                            1012,
            13029, 1000,
                            102])
[]: tokenizer.decode(tokenized_datasets['balanced_train'][0]['input_ids'])
[]: '[CLS] " not if i can help it. mudslide is more like it... 127 " [SEP]'
    1.4 4. Preparing the dataloader
[]: data_collator = DataCollatorWithPadding(tokenizer=tokenizer)
     #Data collator that will dynamically pad the inputs received.
[]: small_train_dataset = tokenized_datasets["balanced_train"].shuffle(seed=1150).
     ⇒select(range(25868))
    small eval dataset = tokenized datasets["validation"].shuffle(seed=1150).
     ⇒select(range(1000))
    small_test_dataset = tokenized_datasets["test"].shuffle(seed=1150).
      ⇒select(range(1000))
[]: train_dataloader = DataLoader(
         small_train_dataset, shuffle=True, batch_size=32, collate_fn=data_collator)
    test dataloader = DataLoader(
         small_test_dataset, batch_size=32, collate_fn=data_collator)
    eval dataloader = DataLoader(
         small_eval_dataset, batch_size=32, collate_fn=data_collator)
[]: for batch in train_dataloader:
        break
    batch['labels'].shape, batch['input_ids'].shape, batch['attention_mask'].shape
[]: (torch.Size([32]), torch.Size([32, 128]), torch.Size([32, 128]))
```

1.5 5. Design the model and losses

1.5.1 5.1 Teacher Model & Student Model

Architecture In the present work, the student - DistilBERT - has the same general architecture as BERT. - The token-type embeddings and the pooler are removed while the number of layers is reduced by a factor of 2. - Most of the operations used in the Transformer architecture linear layer and layer normalisation are highly optimized in modern linear algebra frameworks. - our investigations showed that variations on the last dimension of the tensor (hidden size dimension) have a smaller impact on computation efficiency (for a fixed parameters budget) than variations on other factors like the number of layers. - Thus we focus on reducing the number of layers.

Initialize Student Model

- To initialize a new model from an existing one, we need to access the weights of the old model (the teacher).
- In order to get the weights, we first have to know how to access them. We'll use BERT as our teacher model.

```
[]: teacher_model.config
```

```
[]: BertConfig {
       "_attn_implementation_autoset": true,
       " name or path": "bert-base-uncased",
       "architectures": [
         "BertForMaskedLM"
       ],
       "attention_probs_dropout_prob": 0.1,
       "classifier_dropout": null,
       "gradient_checkpointing": false,
       "hidden_act": "gelu",
       "hidden_dropout_prob": 0.1,
       "hidden size": 768,
       "id2label": {
         "0": "non",
         "1": "tox"
       },
       "initializer_range": 0.02,
       "intermediate size": 3072,
       "label2id": {
         "non": 0,
         "tox": 1
       },
       "layer_norm_eps": 1e-12,
       "max_position_embeddings": 512,
       "model_type": "bert",
       "num_attention_heads": 12,
       "num hidden layers": 12,
```

```
"pad_token_id": 0,
   "position_embedding_type": "absolute",
   "transformers_version": "4.47.0",
   "type_vocab_size": 2,
   "use_cache": true,
   "vocab_size": 30522
}
```

- \bullet The student model has the same configuration, except the number of layers is reduced by a factor of 2
- The student layers are initilized by copying one out of two layers of the teacher, starting with layer 0.
- The head of the teacher is also copied.

```
[]: # Get teacher configuration as a dictionnary configuration = teacher_model.config.to_dict() # configuration
```

```
[]: # Half the number of hidden layer
configuration['num_hidden_layers'] //= 2
# Convert the dictionnary to the student configuration
conf_odd = BertConfig.from_dict(configuration)
conf_even = copy.deepcopy(BertConfig.from_dict(configuration))
```

```
[]: # Create uninitialized student model
model_odd = type(teacher_model)(conf_odd)
model_odd

# Create uninitialized student model
model_even = type(teacher_model)(conf_even)
model_even
```

```
(query): Linear(in_features=768, out_features=768, bias=True)
              (key): Linear(in_features=768, out_features=768, bias=True)
              (value): Linear(in_features=768, out_features=768, bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            (output): BertSelfOutput(
              (dense): Linear(in_features=768, out_features=768, bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (intermediate): BertIntermediate(
            (dense): Linear(in features=768, out features=3072, bias=True)
            (intermediate_act_fn): GELUActivation()
          )
          (output): BertOutput(
            (dense): Linear(in_features=3072, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
        )
      )
    )
    (pooler): BertPooler(
      (dense): Linear(in_features=768, out_features=768, bias=True)
      (activation): Tanh()
    )
 )
  (dropout): Dropout(p=0.1, inplace=False)
  (classifier): Linear(in_features=768, out_features=2, bias=True)
)
```

- Recursively copies the weights of the (teacher) to the (student).
- This function is meant to be first called on a BertFor... model, but is then called on every children of that model recursively.
- The only part that's not fully copied is the encoder, of which only half is copied.

```
[]: def distill_bert_weights(
    teacher : Module,
    student : Module,
    iseven: bool,
) → None:
    """

Recursively copies the weights of the (teacher) to the (student).
    This function is meant to be first called on a BertFor... model, but is 
    → then called on every children of that model recursively.
```

```
The only part that's not fully copied is the encoder, of which only half is \sqcup
      \hookrightarrow copied.
         11 11 11
         # If the part is an entire BERT model or a BERTFor..., unpack and iterate
         if isinstance(teacher, BertModel) or type(teacher).__name__.
      ⇔startswith('BertFor'):
             for teacher_part, student_part in zip(teacher.children(), student.
      ⇔children()):
                 distill_bert_weights(teacher_part, student_part, iseven)
         # Else if the part is an encoder, copy one out of every layer
         elif isinstance(teacher, BertEncoder):
             teacher_encoding_layers = [layer for layer in next(teacher.children())]
      ⇔#12 layers
             student_encoding_layers = [layer for layer in next(student.children())]_
      →#6 layers
             # for i in range(len(student_encoding_layers)):
             # student_encoding_layers[i].
      → load_state_dict(teacher_encoding_layers[2*i].state_dict())
             for i in range(len(teacher_encoding_layers)):
                 # ODD
                 if not iseven and i % 2:
                     student_encoding_layers[j].
      aload_state_dict(teacher_encoding_layers[i].state_dict())
                     j += 1
                 elif iseven and i % 2 == 0:
                     student_encoding_layers[j].
      →load_state_dict(teacher_encoding_layers[i].state_dict())
                     i += 1
         # Else the part is a head or something else, copy the state_dict
         else:
             student.load_state_dict(teacher.state_dict())
         return student
[]: model_odd = distill_bert_weights(teacher=teacher_model, student=model_odd,_u
      ⇔iseven=False)
     model_even = distill_bert_weights(teacher=teacher_model, student=model_even,_
      ⇒iseven=True)
[ ]: def count_parameters(model):
         return sum(p.numel() for p in model.parameters() if p.requires_grad)
     print('Teacher parameters :', count_parameters(teacher_model))
     print('Student parameters even layers:', count_parameters(model_even))
```

print('Student parameters odd layers:', count_parameters(model_odd))

Teacher parameters: 109483778

Student parameters even layers: 66956546 Student parameters odd layers: 66956546

- []: print(count_parameters(model_even)/count_parameters(teacher_model) * 100) print(count_parameters(model_odd)/count_parameters(teacher_model) * 100)
 - 61.156590705154514
 - 61.156590705154514
- []: #It has 61% less parameters than bert-base-uncased

1.5.2 5.2 Loss function

Softmax

$$P_i(\mathbf{z}_i, T) = \frac{\exp(\mathbf{z}_i/T)}{\sum_{q=0}^k \exp(\mathbf{z}_q/T)}$$

Knowledge Distillation

CE Loss

$$\mathcal{L}_{\text{CE}} = -\sum_{j=0}^{N} \sum_{i=0}^{k} y_i^{(j)} \log(P_i(v_i^{(j)}, 1))$$

KL Loss

$$\mathcal{L}_{\text{KD}} = -\sum_{j=0}^{N} \sum_{i=0}^{k} P_{i}(z_{i}^{(j)}, T) \log(P_{i}(v_{i}^{(j)}, T))$$

Cosine Embedding Loss

$$\mathcal{L}_{\text{cosine}}(x_1, x_2, y) = \frac{1}{N} \sum_{i=1}^{N} \left(1 - y_i \cdot \cos(\theta_i)\right)$$

Total Loss

$$\mathcal{L} = \mathcal{L}_{\mathrm{KD}} + \mathcal{L}_{\mathrm{CE}} + \mathcal{L}_{\mathrm{cosine}}$$

[]: class DistillKL(nn.Module):

11 11 11

Distilling the Knowledge in a Neural Network

Compute the knowledge-distillation (KD) loss given outputs, labels.

"Hyperparameters": temperature and alpha

NOTE: the KL Divergence for PyTorch comparing the softmaxs of teacher and student expects the input tensor to be log probabilities!

```
def __init__(self):
    super(DistillKL, self).__init__()

def forward(self, output_student, output_teacher, temperature=1):
    '''
    Note: the output_student and output_teacher are logits
    '''
    T = temperature #.cuda()

KD_loss = nn.KLDivLoss(reduction='batchmean')(
        F.log_softmax(output_student/T, dim=-1),
        F.softmax(output_teacher/T, dim=-1)
    ) * T * T

    return KD_loss
```

```
[]: criterion_div = DistillKL()
criterion_cos = nn.CosineEmbeddingLoss()
```

1.6 6. Optimizer

```
#training hyperparameters
optimizer_even = optim.Adam(params=model_even.parameters(), lr=lr)
optimizer_odd = optim.Adam(params=model_odd.parameters(), lr=lr)
```

```
[]: model_even = model_even.to(device)
model_odd = model_odd.to(device)
teacher_model = teacher_model.to(device)
```

1.7 7. Learning rate scheduler

```
[]: num_epochs = 5
   num_update_steps_per_epoch = len(train_dataloader)
   num_training_steps = num_epochs * num_update_steps_per_epoch

lr_scheduler_even = get_scheduler(
        name="linear",
        optimizer=optimizer_even,
        num_warmup_steps=0,
        num_training_steps=num_training_steps
)

lr_scheduler_odd = get_scheduler(
        name="linear",
        optimizer=optimizer_odd,
```

```
num_warmup_steps=0,
num_training_steps=num_training_steps
)
```

1.8 8. Metric

```
[]: # !pip3 install evaluate

[]: # Get the metric function
    # if task_name is not None:
    # metric = evaluate.load("glue", "sst2")
    # else:
    metric = evaluate.load("accuracy")
```

Downloading builder script: 0%| | 0.00/4.20k [00:00<?, ?B/s]

1.9 9. Train

```
[]: progress_bar = tqdm(range(num_training_steps))
     eval_metrics = 0
     # Lists to store losses for each epoch
     train_losses_odd = []
     train_losses_cls_odd = []
     train losses div odd = []
     train_losses_cos_odd = []
     eval_losses_odd = []
     for epoch in range(num_epochs):
         model_odd.train()
         teacher_model.eval()
         train_loss = 0
         train_loss_cls = 0
         train_loss_div = 0
         train_loss_cos = 0
         for batch in train_dataloader:
             batch = {k: v.to(device) for k, v in batch.items()}
             # compute student output
             outputs = model_odd(**batch)
             # compute teacher output
             with torch.no_grad():
                 output_teacher = teacher_model(**batch)
             # assert size
             assert outputs.logits.size() == output_teacher.logits.size()
             # cls loss
```

```
loss_cls = outputs.loss
      train loss cls += loss cls.item()
       # distillation loss
      loss_div = criterion_div(outputs.logits, output_teacher.logits)
      train_loss_div += loss_div.item()
       # cosine loss
      loss_cos = criterion_cos(output_teacher.logits, outputs.logits, torch.
⇔ones(output_teacher.logits.size()[0]).to(device))
      train_loss_cos += loss_cos.item()
      # Average the loss and return it
      loss = (loss_cls + loss_div + loss_cos) / 3
      train_loss += loss.item()
      loss.backward()
      # accelerator.backward(loss)
      # Step with optimizer
      optimizer_odd.step()
      lr scheduler odd.step()
      optimizer_odd.zero_grad()
      progress_bar.update(1)
  train_losses_odd.append(train_loss / len(train_dataloader))
  train_losses_cls_odd.append(train_loss_cls / len(train_dataloader))
  train_losses_div_odd.append(train_loss_div / len(train_dataloader))
  train_losses_cos_odd.append(train_loss_cos / len(train_dataloader))
  print(f'Epoch at {epoch+1}: Train loss {train_loss/len(train_dataloader):.

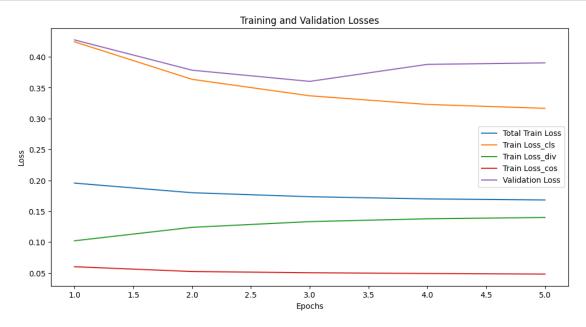
4f}:')

  print(f' - Loss_cls: {train_loss_cls/len(train_dataloader):.4f}')
  print(f' - Loss_div: {train_loss_div/len(train_dataloader):.4f}')
  print(f' - Loss_cos: {train_loss_cos/len(train_dataloader):.4f}')
  model odd.eval()
  eval_loss = 0
  for batch in eval_dataloader:
      batch = {k: v.to(device) for k, v in batch.items()}
      with torch.no_grad():
          outputs = model_odd(**batch)
      loss_cls = outputs.loss
      predictions = outputs.logits.argmax(dim=-1)
      eval_loss += loss_cls.item()
      # predictions, references = accelerator.gather((predictions, ____
⇒batch["labels"]))
      metric.add_batch(
```

```
predictions=predictions,
                references=batch["labels"])
         eval_metric = metric.compute()
        eval_metrics += eval_metric['accuracy']
        eval_losses_odd.append(eval_loss / len(eval_dataloader)) # Save the_
      ⇔evaluation loss for plotting
        print(f"Epoch at {epoch+1}: Test Acc {eval_metric['accuracy']:.4f}")
    print('Avg Metric', eval_metrics/num_epochs)
      0%|
                   | 0/4045 [00:00<?, ?it/s]
    Epoch at 1: Train loss 0.1955:
      - Loss_cls: 0.4242
      - Loss_div: 0.1021
      - Loss_cos: 0.0601
    Epoch at 1: Test Acc 0.8940
    Epoch at 2: Train loss 0.1799:
      - Loss_cls: 0.3635
      - Loss_div: 0.1239
      - Loss_cos: 0.0524
    Epoch at 2: Test Acc 0.9390
    Epoch at 3: Train loss 0.1735:
      - Loss_cls: 0.3368
      - Loss_div: 0.1332
      - Loss_cos: 0.0504
    Epoch at 3: Test Acc 0.9390
    Epoch at 4: Train loss 0.1699:
      - Loss_cls: 0.3228
      - Loss_div: 0.1378
      - Loss_cos: 0.0492
    Epoch at 4: Test Acc 0.9210
    Epoch at 5: Train loss 0.1682:
      - Loss_cls: 0.3166
      - Loss_div: 0.1399
      - Loss_cos: 0.0482
    Epoch at 5: Test Acc 0.9280
    []: # Plotting
    epochs_list = range(1, num_epochs + 1)
    plt.figure(figsize=(12, 6))
    plt.plot(epochs_list, train_losses_odd, label='Total Train Loss')
    plt.plot(epochs_list, train_losses_cls_odd, label='Train Loss_cls')
    plt.plot(epochs_list, train_losses_div_odd, label='Train Loss_div')
```

```
plt.plot(epochs_list, train_losses_cos_odd, label='Train Loss_cos')
plt.plot(epochs_list, eval_losses_odd, label='Validation Loss')

plt.title('Training and Validation Losses')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
[]: y_true_odd = []
y_pred_odd = []

for batch in test_dataloader:
    input_ids, attention_mask, labels = batch['input_ids'],
    obatch['attention_mask'], batch['labels']
    input_ids, attention_mask, labels = input_ids.to(device), attention_mask.
    oto(device), labels.to(device)
    with torch.no_grad():
        outputs = model_odd(input_ids, attention_mask=attention_mask)
        logits = outputs.logits
        batch_predictions = torch.argmax(logits, dim=1)

        y_true_odd.extend(labels.cpu().numpy())
        y_pred_odd.extend(batch_predictions.cpu().numpy())

accuracy_odd = accuracy_score(y_true_odd, y_pred_odd)
precision_odd = precision_score(y_true_odd, y_pred_odd, average='weighted')
```

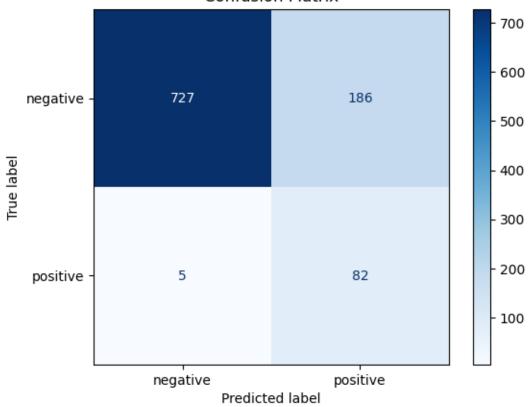
```
recall_odd = recall_score(y_true_odd, y_pred_odd, average='weighted')
f1_odd = f1_score(y_true_odd, y_pred_odd, average='weighted')
labels = ["negative", "positive"]

ConfusionMatrixDisplay.from_predictions(
    y_true_odd,
    y_pred_odd,
    display_labels=labels,
    cmap=plt.cm.Blues,
    xticks_rotation='horizontal'
)

plt.title('Confusion Matrix')
plt.show()

print(classification_report(y_true_odd, y_pred_odd, target_names=labels))
```

Confusion Matrix



precision recall f1-score support

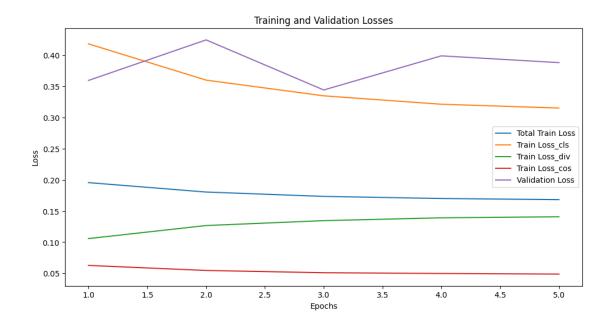
```
negative
                   0.99
                             0.80
                                        0.88
                                                   913
                   0.31
                              0.94
                                        0.46
                                                     87
    positive
                                        0.81
                                                   1000
    accuracy
                   0.65
                                        0.67
                                                   1000
  macro avg
                             0.87
weighted avg
                   0.93
                              0.81
                                        0.85
                                                   1000
```

```
[]: progress_bar = tqdm(range(num_training_steps))
     eval_metrics = 0
     # Lists to store losses for each epoch
     train losses even = []
     train_losses_cls_even = []
     train_losses_div_even = []
     train_losses_cos_even = []
     eval_losses_even = []
     for epoch in range(num_epochs):
         model_even.train()
         teacher_model.eval()
         train_loss = 0
         train_loss_cls = 0
         train loss div = 0
         train_loss_cos = 0
         for batch in train_dataloader:
             batch = {k: v.to(device) for k, v in batch.items()}
             # compute student output
             outputs = model_even(**batch)
             # compute teacher output
             with torch.no_grad():
                 output_teacher = teacher_model(**batch)
             # assert size
             assert outputs.logits.size() == output_teacher.logits.size()
             # cls loss
             loss_cls = outputs.loss
             train_loss_cls += loss_cls.item()
             # distillation loss
             loss_div = criterion_div(outputs.logits, output_teacher.logits)
             train_loss_div += loss_div.item()
             # cosine loss
             loss_cos = criterion_cos(output_teacher.logits, outputs.logits, torch.
      →ones(output_teacher.logits.size()[0]).to(device))
             train_loss_cos += loss_cos.item()
```

```
# Average the loss and return it
      loss = (loss_cls + loss_div + loss_cos) / 3
      train_loss += loss.item()
      loss.backward()
      # accelerator.backward(loss)
      # Step with optimizer
      optimizer even.step()
      lr_scheduler_even.step()
      optimizer even.zero grad()
      progress_bar.update(1)
  train_losses_even.append(train_loss / len(train_dataloader))
  train_losses_cls_even.append(train_loss_cls / len(train_dataloader))
  train_losses_div_even.append(train_loss_div / len(train_dataloader))
  train_losses_cos_even.append(train_loss_cos / len(train_dataloader))
  print(f'Epoch at {epoch+1}: Train loss {train_loss/len(train_dataloader):.

4f}:')
  print(f' - Loss cls: {train loss cls/len(train dataloader):.4f}')
  print(f' - Loss_div: {train_loss_div/len(train_dataloader):.4f}')
  print(f' - Loss_cos: {train_loss_cos/len(train_dataloader):.4f}')
  model_even.eval()
  eval_loss = 0
  for batch in eval_dataloader:
      batch = {k: v.to(device) for k, v in batch.items()}
      with torch.no_grad():
          outputs = model_even(**batch)
      loss cls = outputs.loss
      predictions = outputs.logits.argmax(dim=-1)
      eval_loss += loss_cls.item()
      # predictions, references = accelerator.gather((predictions, ____
⇒batch["labels"]))
      metric.add_batch(
          predictions=predictions,
          references=batch["labels"])
  eval_metric = metric.compute()
  eval_metrics += eval_metric['accuracy']
  eval_losses_even.append(eval_loss / len(eval_dataloader)) # Save the_
→evaluation loss for plotting
  print(f"Epoch at {epoch+1}: Test Acc {eval_metric['accuracy']:.4f}")
```

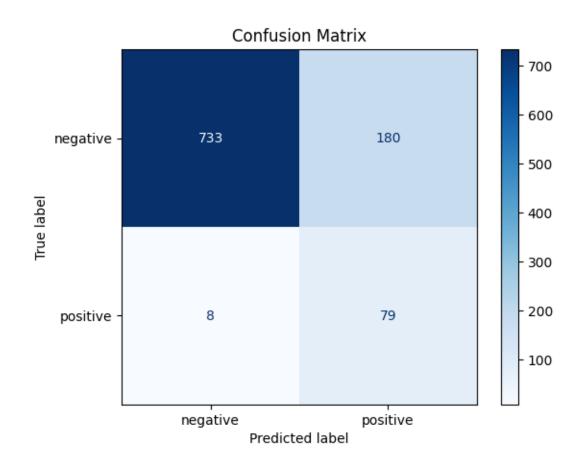
```
print('Avg Metric', eval_metrics/num_epochs)
      0%1
                   | 0/4045 [00:00<?, ?it/s]
    Epoch at 1: Train loss 0.1955:
      - Loss_cls: 0.4183
      - Loss div: 0.1057
      - Loss_cos: 0.0626
    Epoch at 1: Test Acc 0.9270
    Epoch at 2: Train loss 0.1804:
      - Loss_cls: 0.3601
      - Loss_div: 0.1266
      - Loss_cos: 0.0545
    Epoch at 2: Test Acc 0.9100
    Epoch at 3: Train loss 0.1734:
      - Loss_cls: 0.3349
      - Loss_div: 0.1345
      - Loss cos: 0.0509
    Epoch at 3: Test Acc 0.9390
    Epoch at 4: Train loss 0.1700:
      - Loss_cls: 0.3214
      - Loss div: 0.1390
      - Loss_cos: 0.0497
    Epoch at 4: Test Acc 0.9190
    Epoch at 5: Train loss 0.1682:
      - Loss_cls: 0.3153
      - Loss_div: 0.1407
      - Loss_cos: 0.0487
    Epoch at 5: Test Acc 0.9230
    Avg Metric 0.923600000000001
[]: # Plotting
     epochs_list = range(1, num_epochs + 1)
     plt.figure(figsize=(12, 6))
     plt.plot(epochs_list, train_losses_even, label='Total Train Loss')
     plt.plot(epochs_list, train_losses_cls_even, label='Train Loss_cls')
     plt.plot(epochs_list, train_losses_div_even, label='Train Loss_div')
     plt.plot(epochs_list, train_losses_cos_even, label='Train Loss_cos')
     plt.plot(epochs_list, eval_losses_even, label='Validation Loss')
     plt.title('Training and Validation Losses')
     plt.xlabel('Epochs')
     plt.ylabel('Loss')
     plt.legend()
     plt.show()
```



```
[]: y true even = []
     y_pred_even = []
     for batch in test_dataloader:
         input_ids, attention_mask, labels = batch['input_ids'],__
      ⇔batch['attention_mask'], batch['labels']
         input ids, attention mask, labels = input ids.to(device), attention mask.
      ⇔to(device), labels.to(device)
         with torch.no_grad():
             outputs = model_even(input_ids, attention_mask=attention_mask)
             logits = outputs.logits
             batch_predictions = torch.argmax(logits, dim=1)
             y_true_even.extend(labels.cpu().numpy())
             y_pred_even.extend(batch_predictions.cpu().numpy())
     accuracy_even = accuracy_score(y_true_even, y_pred_even)
     precision_even = precision_score(y_true_even, y_pred_even, average='weighted')
     recall_even = recall_score(y_true_even, y_pred_even, average='weighted')
     f1_even = f1_score(y_true_even, y_pred_even, average='weighted')
     labels = ["negative", "positive"]
     ConfusionMatrixDisplay.from_predictions(
         y_true_even,
         y_pred_even,
         display_labels=labels,
```

```
cmap=plt.cm.Blues,
    xticks_rotation='horizontal'
)
plt.title('Confusion Matrix')
plt.show
print(classification_report(y_true_even, y_pred_even, target_names=labels))
```

	precision	recall	f1-score	support
negative positive	0.99 0.31	0.80 0.91	0.89 0.46	913 87
accuracy macro avg weighted avg	0.65 0.93	0.86 0.81	0.81 0.67 0.85	1000 1000 1000



1.9.1 Appendix (Teacher Model)

```
[]: lr = 5e-5
     #training hyperparameters
     optimizer = optim.Adam(params=teacher_model.parameters(), lr=lr)
     progress_bar = tqdm(range(num_training_steps))
     eval_metrics = 0
     for epoch in range(num_epochs):
         teacher_model.train()
         train_loss = 0
         for step, batch in enumerate(train_dataloader):
             batch = {k: v.to(device) for k, v in batch.items()}
             output_teacher = teacher_model(**batch)
             # cls loss
             loss = output_teacher.loss
             train_loss += loss.item()
             loss.backward()
             # accelerator.backward(loss)
             # Step with optimizer
             optimizer.step()
             lr_scheduler_even.step()
             optimizer.zero_grad()
             progress_bar.update(1)
         print(f'Epoch at {epoch+1}: Train loss {train_loss/len(train_dataloader):.

4f}:')

         teacher_model.eval()
         for step, batch in enumerate(eval_dataloader):
             batch = {k: v.to(device) for k, v in batch.items()}
             with torch.no_grad():
                 outputs = teacher_model(**batch)
             predictions = outputs.logits.argmax(dim=-1)
             # predictions, references = accelerator.gather((predictions, ___
      ⇔batch["labels"]))
             metric.add_batch(
                 predictions=predictions,
                 references=batch["labels"])
         eval_metric = metric.compute()
         eval_metrics += eval_metric['accuracy']
         print(f"Epoch at {epoch+1}: Test Acc {eval_metric['accuracy']:.4f}")
     print('Avg Metric', eval_metrics/num_epochs)
```

```
0%1
                   | 0/4045 [00:00<?, ?it/s]
    Epoch at 1: Train loss 0.2022:
    Epoch at 1: Test Acc 0.8980
    Epoch at 2: Train loss 0.1137:
    Epoch at 2: Test Acc 0.9250
    Epoch at 3: Train loss 0.0588:
    Epoch at 3: Test Acc 0.8930
    Epoch at 4: Train loss 0.0365:
    Epoch at 4: Test Acc 0.8900
    Epoch at 5: Train loss 0.0243:
    Epoch at 5: Test Acc 0.9390
    Avg Metric 0.909
[]: save_directory = "./models/bert_odd_st"
     model_odd.save_pretrained(save_directory)
     tokenizer.save_pretrained(save_directory)
     save_directory = "./models/bert_even_st"
     model_even.save_pretrained(save_directory)
     tokenizer.save_pretrained(save_directory)
[]: ('./models/bert_even_st/tokenizer_config.json',
      './models/bert_even_st/special_tokens_map.json',
      './models/bert_even_st/vocab.txt',
      './models/bert_even_st/added_tokens.json',
      './models/bert_even_st/tokenizer.json')
    1.9.2 LoRA
[]: |lora model = AutoModelForSequenceClassification.from pretrained(
         teacher_id,
         num_labels = num_labels,
         id2label = id2label,
         label2id = label2id,
     print(lora_model)
     cfgs = LoraConfig(
         task_type=TaskType.SEQ_CLS,
         inference_mode=False,
         r=8.
         lora_alpha=32,
         lora_dropout=0.1,
         bias="none",
         target_modules=["query", "key", "value"]
```

```
lora_model = get_peft_model(lora_model, cfgs)
def compute_metrics(eval_preds):
    Compute accuracy and other metrics for evaluation.
    Args:
    eval_preds: A tuple (predictions, labels) where:
        - predictions: model's predictions (logits or class probabilities)
        - labels: ground truth labels
    Returns:
    A dictionary with the evaluation metric(s).
    logits, labels = eval_preds
    predictions = np.argmax(logits, axis=-1)
    accuracy = accuracy_score(labels, predictions)
    return {"accuracy": accuracy}
training_args = TrainingArguments(
    output dir="./models/bert-lora",
    logging_dir="./logs",
    logging_steps=50,
    evaluation_strategy="steps",
    eval_steps=100,
    save_steps=100,
    report_to=["tensorboard"]
)
trainer = Trainer(
    model=lora_model,
    args=training_args,
    train_dataset=small_train_dataset,
    eval_dataset=small_eval_dataset,
    tokenizer=tokenizer,
)
```

```
Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-uncased and are newly initialized:
['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.
/usr/local/lib/python3.10/dist-packages/transformers/training_args.py:1575:
FutureWarning: `evaluation_strategy` is deprecated and will be removed in version 4.46 of Transformers. Use `eval_strategy` instead
```

```
warnings.warn(
<ipython-input-44-c7ec1e3816f7>:50: FutureWarning: `tokenizer` is deprecated and
will be removed in version 5.0.0 for `Trainer.__init__`. Use `processing_class`
instead.
  trainer = Trainer(
BertForSequenceClassification(
  (bert): BertModel(
    (embeddings): BertEmbeddings(
      (word embeddings): Embedding(30522, 768, padding idx=0)
      (position_embeddings): Embedding(512, 768)
      (token_type_embeddings): Embedding(2, 768)
      (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    (encoder): BertEncoder(
      (layer): ModuleList(
        (0-11): 12 x BertLayer(
          (attention): BertAttention(
            (self): BertSdpaSelfAttention(
              (query): Linear(in_features=768, out_features=768, bias=True)
              (key): Linear(in_features=768, out_features=768, bias=True)
              (value): Linear(in_features=768, out_features=768, bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            (output): BertSelfOutput(
              (dense): Linear(in_features=768, out_features=768, bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (intermediate): BertIntermediate(
            (dense): Linear(in_features=768, out_features=3072, bias=True)
            (intermediate_act_fn): GELUActivation()
          (output): BertOutput(
            (dense): Linear(in_features=3072, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
        )
      )
    (pooler): BertPooler(
      (dense): Linear(in_features=768, out_features=768, bias=True)
      (activation): Tanh()
    )
  )
```

```
(dropout): Dropout(p=0.1, inplace=False)
      (classifier): Linear(in_features=768, out_features=2, bias=True)
[]: trainer.train()
     trainer.save_model()
     lora_model.save_pretrained("./models/bert-lora")
    <IPython.core.display.HTML object>
    /usr/local/lib/python3.10/dist-packages/peft/utils/other.py:716: UserWarning:
    Unable to fetch remote file due to the following error
    (ReadTimeoutError("HTTPSConnectionPool(host='huggingface.co', port=443): Read
    timed out. (read timeout=10)"), '(Request ID:
    6baa4e07-0ff7-41ae-a9d8-6ca2609b8772)') - silently ignoring the lookup for the
    file config.json in bert-base-uncased.
      warnings.warn(
    /usr/local/lib/python3.10/dist-packages/peft/utils/save_and_load.py:246:
    UserWarning: Could not find a config file in bert-base-uncased - will assume
    that the vocabulary was not modified.
      warnings.warn(
[]: import matplotlib.pyplot as plt
     loss values = [entry["loss"] for entry in trainer.state.log history if "loss" |
      →in entry]
     eval_values = [entry["eval_loss"] for entry in trainer.state.log history if

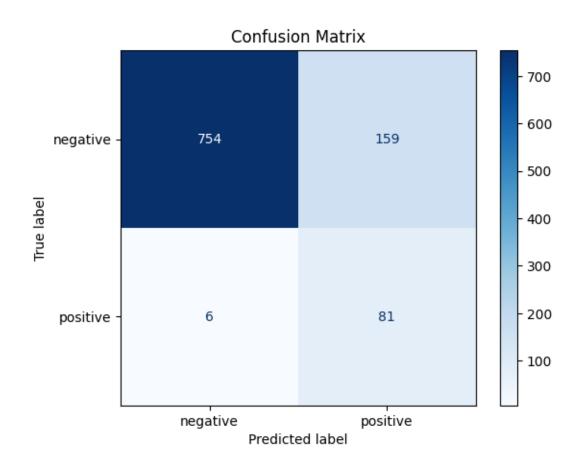
¬"eval_loss" in entry]
     plt.figure(figsize=(8, 4))
     plt.plot(loss values, label="Training Loss")
     plt.plot(eval_values, label="Validation Loss")
     plt.xlabel("Logging Steps")
     plt.ylabel("Loss")
     plt.title("Training Loss over Steps")
     plt.legend()
     plt.show()
```



```
[]: y_true_lora = []
     y_pred_lora = []
     for batch in test_dataloader:
         input_ids, attention_mask, labels = batch['input_ids'],__
      ⇔batch['attention_mask'], batch['labels']
         input_ids, attention_mask, labels = input_ids.to(device), attention_mask.
      ⇔to(device), labels.to(device)
         with torch.no_grad():
             outputs = lora_model(input_ids, attention_mask=attention_mask)
             logits = outputs.logits
             batch_predictions = torch.argmax(logits, dim=1)
             y_true_lora.extend(labels.cpu().numpy())
             y_pred_lora.extend(batch_predictions.cpu().numpy())
     accuracy_lora = accuracy_score(y_true_lora, y_pred_lora)
     precision_lora = precision_score(y_true_lora, y_pred_lora, average='weighted')
     recall_lora = recall_score(y_true_lora, y_pred_lora, average='weighted')
     f1_lora = f1_score(y_true_lora, y_pred_lora, average='weighted')
     labels = ["negative", "positive"]
     ConfusionMatrixDisplay.from_predictions(
         y_true_lora,
         y_pred_lora,
         display_labels=labels,
```

```
cmap=plt.cm.Blues,
    xticks_rotation='horizontal'
)
plt.title('Confusion Matrix')
plt.show
print(classification_report(y_true_lora, y_pred_lora, target_names=labels))
```

	precision	recall	f1-score	support
negative	0.99	0.83	0.90	913
positive	0.34	0.93	0.50	87
accuracy			0.83	1000
macro avg	0.66	0.88	0.70	1000
weighted avg	0.94	0.83	0.87	1000



```
[]: !zip -r models.zip ./models
     # !zip -r models.zip ./logs
      adding: models/ (stored 0%)
      adding: models/bert_even_st/ (stored 0%)
      adding: models/bert even st/tokenizer.json (deflated 71%)
      adding: models/bert_even_st/vocab.txt (deflated 53%)
      adding: models/bert_even_st/config.json (deflated 49%)
      adding: models/bert_even_st/model.safetensors (deflated 8%)
      adding: models/bert_even_st/special_tokens_map.json (deflated 42%)
      adding: models/bert_even_st/tokenizer_config.json (deflated 75%)
      adding: models/bert_odd_st/ (stored 0%)
      adding: models/bert_odd_st/tokenizer.json (deflated 71%)
      adding: models/bert_odd_st/vocab.txt (deflated 53%)
      adding: models/bert_odd_st/config.json (deflated 49%)
      adding: models/bert_odd_st/model.safetensors (deflated 8%)
      adding: models/bert_odd_st/special_tokens_map.json (deflated 42%)
      adding: models/bert_odd_st/tokenizer_config.json (deflated 75%)
[]: from IPython.display import FileLink
     FileLink(r'models.zip')
```

[]: /kaggle/working/models.zip