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1 Setup

[1]:
```
# Imports
from datasets import load_dataset
from transformers import (
    AutoModelForSequenceClassification,
    BertTokenizer,
    DataCollatorWithPadding,
    EarlyStoppingCallback,
    TrainingArguments,
    Trainer,
)
import evaluate
import numpy as np
import torch
```

[2]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

if device.type == "cuda":
    print("CUDA device name:", torch.cuda.get_device_name(0))
```

```
Using device: cuda
CUDA device name: NVIDIA GeForce RTX 4060
```

1.1 Load Dataset

[3]:
```
dataset = load_dataset("stanfordnlp/imdb")

train_validation_dataset = dataset["train"].train_test_split(test_size=0.1,␣
 ↪seed=42)
train_dataset = train_validation_dataset["train"]
validation_dataset = train_validation_dataset["test"]
test_dataset = dataset["test"]

print("Train size:", len(train_dataset))
print("Validation size:", len(validation_dataset))
```

```
print("Test size:", len(test_dataset))
```

```
Train size: 22500
Validation size: 2500
Test size: 25000
```

1.2 Preprocessing of the dataset

[4]:
```
def encode_datasets(tokenizer):
    def preprocess_datasets(examples):
        return tokenizer(
            examples["text"],
            truncation=True,
            max_length=512,
            padding="longest"
        )
    encoded_train = train_dataset.map(preprocess_datasets, batched=True)
    encoded_validation = validation_dataset.map(preprocess_datasets,␣
 ↪batched=True)
    encoded_test = test_dataset.map(preprocess_datasets, batched=True)

    encoded_train = encoded_train.remove_columns(["text"])
    encoded_validation = encoded_validation.remove_columns(["text"])
    encoded_test = encoded_test.remove_columns(["text"])

    encoded_train = encoded_train.with_format("torch")
    encoded_validation = encoded_validation.with_format("torch")
    encoded_test = encoded_test.with_format("torch")

    data_collator = DataCollatorWithPadding(tokenizer=tokenizer)
    return encoded_train, encoded_validation, encoded_test, data_collator
```

1.3 Evaluation metrics

[5]:
```
# Metrics
accuracy = evaluate.load("accuracy")
f1 = evaluate.load("f1")
precision = evaluate.load("precision")
recall = evaluate.load("recall")
id2label = {0: "NEGATIVE", 1: "POSITIVE"}
label2id = {"NEGATIVE": 0, "POSITIVE": 1}
```

[6]:
```
def compute_metrics(eval_pred):
    logits, labels = eval_pred
    preds = np.argmax(logits, axis=-1)
    return {
```

```
        "accuracy": accuracy.compute(predictions=preds,␣
↪references=labels)["accuracy"],
        "f1": f1.compute(predictions=preds, references=labels,␣
↪average="weighted")["f1"],
        "precision": precision.compute(predictions=preds,␣
↪references=labels)["precision"],
        "recall": recall.compute(predictions=preds, references=labels)["recall"]
    }
```

2 Train and test

2.1 Train

[7]:
```
def train_and_test_model(model_name):
    tokenizer = BertTokenizer.from_pretrained(
        model_name
    )
    encoded_train, encoded_validation, encoded_test, data_collator =␣
↪encode_datasets(tokenizer)
    training_args = TrainingArguments(
        output_dir=f"./{model_name}_output",
        eval_strategy="epoch",
        save_strategy="epoch",
        learning_rate=2e-5,
        per_device_train_batch_size=8,
        per_device_eval_batch_size=16,
        num_train_epochs=10,
        weight_decay=0.01,
        logging_steps=100,
        logging_first_step=True,
        load_best_model_at_end=True,
        report_to="none"
    )

    model = AutoModelForSequenceClassification.from_pretrained(
        model_name,
        num_labels=2,
        id2label=id2label,
        label2id=label2id,
    )
    trainer = Trainer(
        model=model,
        args=training_args,
        train_dataset=encoded_train,
        eval_dataset=encoded_validation,
        processing_class=tokenizer,
```

```
        data_collator=data_collator,
        compute_metrics=compute_metrics,
        callbacks=[EarlyStoppingCallback(early_stopping_patience=2)]
    )
    trainer.train()
    trainer.save_model(f"{model_name}_model")
    test_results = trainer.evaluate(encoded_test)

    print("\n====================")
    print(f"Test Results for {model_name}")
    print("====================")
    for k, v in test_results.items():
        print(f"{k}: {v}")

    return trainer, encoded_train, encoded_validation, encoded_test,␣
↪data_collator
```

[8]:
```
# Model names
model_name_uncased = "bert-base-uncased"
model_name_cased = "bert-base-cased"
```

[38]:
```
train_and_test_model(model_name_cased)
```

```
Some weights of BertForSequenceClassification were not initialized from the
model checkpoint at bert-base-cased 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.
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```

```
====================
Test Results for bert-base-cased
====================
eval_loss: 0.2434881031513214
eval_accuracy: 0.92196
eval_f1: 0.9219559990274637
eval_precision: 0.9280902524145768
eval_recall: 0.9148
eval_runtime: 411.1125
eval_samples_per_second: 60.811
eval_steps_per_second: 3.802
epoch: 3.0
```

[38]: <transformers.trainer.Trainer at 0x295e8308350>

[9]:
```
(trainer_uncased,
 encoded_train_uncased,
 encoded_validation_uncased,
 encoded_test_uncased,
 data_collator_uncased
 ) = train_and_test_model(model_name_uncased)
```

```
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.
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```

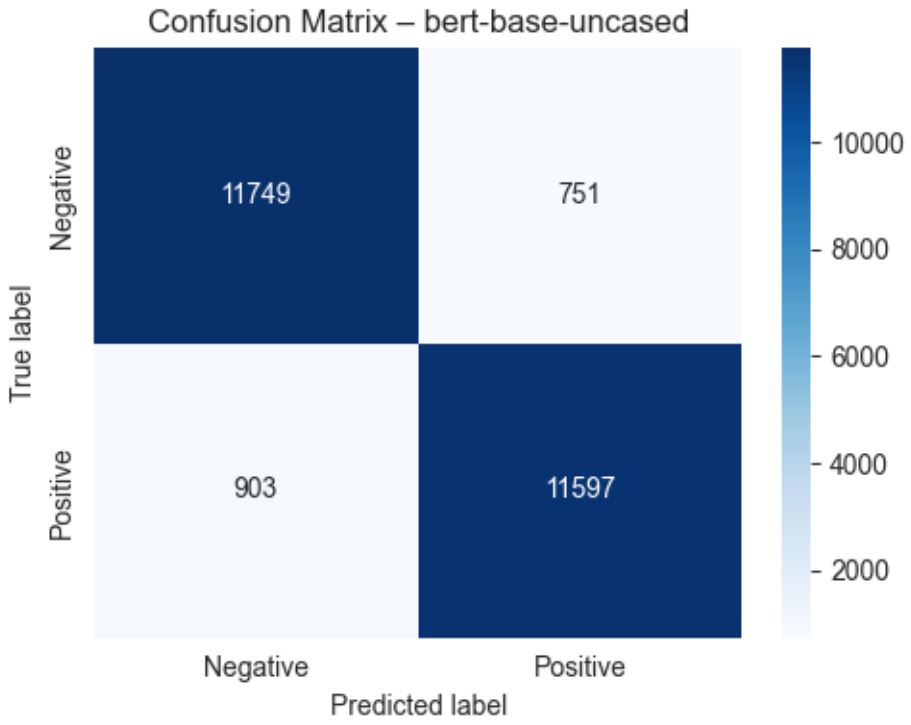
```
====================
Test Results for bert-base-uncased
====================
eval_loss: 0.22767554223537445
eval_accuracy: 0.93384
eval_f1: 0.9338375542125641
eval_precision: 0.9391804340783932
eval_recall: 0.92776
eval_runtime: 411.9745
eval_samples_per_second: 60.683
eval_steps_per_second: 3.794
epoch: 3.0
```

2.2 Visualize Testing

[18]:
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report

label_names = ["Negative", "Positive"]

pred_output = trainer_uncased.predict(encoded_test_uncased)
y_true = pred_output.label_ids
y_pred = np.argmax(pred_output.predictions, axis=1)

cm = confusion_matrix(y_true, y_pred)

plt.figure(figsize=(5, 4))
sns.heatmap(
    cm,
    annot=True,
```

```
    fmt="d",
    cmap="Blues",
    xticklabels=label_names,
    yticklabels=label_names
)
plt.xlabel("Predicted label")
plt.ylabel("True label")
plt.title(f"Confusion Matrix - {model_name_uncased}")
plt.tight_layout()
plt.show()

print("Classification report:")
print(classification_report(y_true, y_pred, target_names=label_names))
```

```
<IPython.core.display.HTML object>
```




```
Classification report:
              precision    recall  f1-score   support

    Negative       0.93      0.94      0.93     12500
    Positive       0.94      0.93      0.93     12500

    accuracy                           0.93     25000
   macro avg       0.93      0.93      0.93     25000
```

```
weighted avg       0.93      0.93      0.93     25000
```

2.2.1 Visualisation of worst performing datapoints

[12]:
```
import torch
import torch.nn.functional as F

val_outputs = trainer_uncased.predict(encoded_validation_uncased)
val_logits = torch.tensor(val_outputs.predictions)
val_labels = torch.tensor(val_outputs.label_ids)

val_loss_per_example = F.cross_entropy(val_logits, val_labels, reduction="none")

val_loss_per_example = val_loss_per_example.detach().cpu().numpy()
```

```
<IPython.core.display.HTML object>
```

[19]:
```
worst_idx = np.argsort(-val_loss_per_example)[:50]

for i in worst_idx[:5]:
    original_example = validation_dataset[int(i)]
    print("INDEX:", i)
    print("Label:", original_example["label"])
    print("Text:", original_example["text"][:],)
    print("Loss:", val_loss_per_example[i])
    print("-" * 80)
```

```
INDEX: 287
Label: 1
Text: I was really excited about seeing this film. I thought finally Australia
had made a good film.. but I was wrong.<br /><br />This was the most pathetic
attempt at a slasher film ever. I feel sorry for Molly Ringwald having to come
all the way to Australia to make an awful movie.<br /><br />The acting was
terrible (especially that Australian guy who was trying to speak in an American
accent), and the plot was also pretty bad.<br /><br />When I first heard about
this film coming out, I thought that the title was pathetic (because it sounds
like the cheesy film "Stab" in Scream 2), but I was willing to let it slide if
it was a good movie.<br /><br />WARNING!!! MAJOR SPOILERS!!!<br /><br />Probably
the worst thing about the film was the ending. I was expecting a big surprise
about who the killer was.. but the killer wasn't even human.. which turned this
realistic slasher film into an awful horror movie.<br /><br />Don't see this
film.. you'll probably be disappointed!
Loss: 6.3604727
--------------------------------------------------------------------------------
INDEX: 482
Label: 1
Text: Its time to pay tribute to the great Charton Heston after his recent
```

passing but this film is not the one. His other films of a past generation were BEN HUR, THE TEN COMMANDENTS, OMEGA MAN and PLANET OF THE APES were his better works.

This film made in 1973 attempts to prophesies a future earth , in 2022, that is so overpopulated that the human race has been manipulated by authorities to eat a universally produced food product called "Soylent Green" which is manufactured with Human flesh. This bizarre and implausible film was as ridiculous at the time of its release as it is now and assumes India's population which would be about 2 billion by that stage would be then meat eaters without knowing it.

Charlton Heston's character this supers secret international conspiracy that world powers have concocted to meet the nutritional demands of overpopulation by using cannibalism.

Unfortunately for the producers of this film the Green message they deliver is not the Greens Party of today's ethos thank god. Cannibalism was practiced by the indigenous populations in New Zealand , Fiji and Borneo up until only 40 years before this film was made but has been long abandoned by human civilization.

Another silly prediction in the film is that women become quasi sex slaves turning back the tide of radical feminism which was on the rise in 1972 when this film was made.

The film was stupid then and is as silly now but does contain a very unmemorable last film performance by the late and great Edward G. Robinson but still no a valid reason to revisit the film other than for academic reasons.

This is a dud of a film and I wouldn't even recommend it to baby boomers or Charlton Heston fans. All the other reviews of this film I have read all sound the same referring to a dystopian society in the future of which the centralised theme only seems to involve the USA in which an ecological disaster has occurred.

The only merit in the film is that earth does face overpopulation.
Loss: 6.263078

INDEX: 2029
Label: 1
Text: …after 16 years Tim Burton finally disappoints me!!!! Whatever happened to the old Burton who read "The Dark Knight Returns" by Frank Miller as research for his preparation to direct Batman back in 1988-89? By the looks of it Burton didn't research the book nor the movie cause he got everything WRONG! This movie sucks! It's not as good as the original and it doesn't deal with the same subject as the original. If you want a good ape movie watch the original.

out of**stars
Loss: 6.215921

INDEX: 963
Label: 1
Text: This film Evil Breed: The legend of samhain contains very little thought or effort. It is ridiculed with specs of ultra fast "slasher" style death and plain disgusting acts of death. The acting was rated a D as the actors show very little ability, and the stupidity of them in the film is too questionable. The way they portrayed what people their ages act like was incredibly different. The odd split of porn is fit in thought it really doesn't offer much, and any area that is respectable but is quite quickly run down with absolute gut wrenching

```
death. Example is the poor fellow whom is disemboweled from his anus, and the
scene lasts for about 5 minutes. It is terribly obvious of how little of a fight
the kids put up. This film is a good choice for someone who likes to watch some
awful deaths and practically torture.
Loss: 6.0665536
--------------------------------------------------------------------------------
INDEX: 2310
Label: 1
Text: The legendary Boris Karloff ended his illustrious career by making four
cheapie fright flick clunkers in Mexico. This is the token moody period Gothic
horror entry from the bunch. Karloff gives a typically spry and dignified
performance as Matthias Morteval, an elderly eccentric patriarch who invites
several of his petty, greedy and backbiting no-count relatives to his creepy
rundown castle for the reading of a will. Pretty soon the hateful guests are
getting bumped off by lethal life-sized toy people who populate the place.
Onetime Mexican sex symbol Andres Garcia of "Tintorera" infamy portrays the
dashing police officer hero and Julissa looks absolutely ravishing as the sole
likable female character. The clunky, plodding (non)direction, trite by-the-
numbers script, ugly, washed-out cinematography, ridiculous murder set pieces (a
gross fat slob gets blasted right in the face by a miniature cannon!),
overwrought string score, morbid gloom-doom atmosphere, largely lousy acting
(Karloff notably excepted), cheesy mild gore, poor dubbing and rousing fiery
conclusion all lend this enjoyably awful lemon a certain endearingly cruddy and
hence oddly amusing ratty charm. A real campy hoot.
Loss: 6.0422764
--------------------------------------------------------------------------------
```

[ ]: