Multi-label Text Classification with BERT and PyTorch Lightning

26.04.2021 — Deep Learning, NLP, Neural Network, PyTorch, Python — 5 min read

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> *TL;DR Learn how to prepare a dataset with toxic comments for multi-label text classification (tagging). We'll fine-tune BERT using PyTorch Lightning and evaluate the model.*

Multi-label text classification (or tagging text) is one of the most common tasks you'll encounter when doing NLP. Modern Transformer-based models (like BERT) make use of pre-training on vast amounts of text data that makes fine-tuning faster, use fewer resources and more accurate on small(er) datasets.

In this tutorial, you'll learn how to:

- Load, balance and split text data into sets
- Tokenize text (with BERT tokenizer) and create PyTorch dataset
- Fine-tune BERT model with PyTorch Lightning
- Find out about warmup steps and use a learning rate scheduler
- Use area under the ROC and binary cross-entropy to evaluate the model during training
- How to make predictions using the fine-tuned BERT model
- Evaluate the performance of the model for each class (possible comment tag)

Will our model be any good for toxic text detection?

- Run the notebook in your browser (Google Colab)
- Read the *Getting Things Done with Pytorch* book

PYTHON

```python
import pandas as pd
import numpy as np

from tqdm.auto import tqdm

import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader

from transformers import BertTokenizerFast as BertTokenizer, BertModel, AdamW, get_linear_schedu

```

```
import pytorch_lightning as pl
from pytorch_lightning.metrics.functional import accuracy, f1, auroc
from pytorch_lightning.callbacks import ModelCheckpoint, EarlyStopping
from pytorch_lightning.loggers import TensorBoardLogger

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, multilabel_confusion_matrix

import seaborn as sns
from pylab import rcParams
import matplotlib.pyplot as plt
from matplotlib import rc

%matplotlib inline
%config InlineBackend.figure_format='retina'

RANDOM_SEED = 42

sns.set(style='whitegrid', palette='muted', font_scale=1.2)
HAPPY_COLORS_PALETTE = ["#01BEFE", "#FFDD00", "#FF7D00", "#FF006D", "#ADFF02", "#8F00FF"]
sns.set_palette(sns.color_palette(HAPPY_COLORS_PALETTE))
rcParams['figure.figsize'] = 12, 8

pl.seed_everything(RANDOM_SEED)
```

Data

Our dataset contains potentially offensive (toxic) comments and comes from the Toxic Comment Classification Challenge. Let's start by download the data (from Google Drive):

```python
!gdown --id 1VuQ-U7TtggShMeuRSA_hzC8qGDl2LRkr
```

Let's load and look at the data:

```python
df = pd.read_csv("toxic_comments.csv")
df.head()
```

	id	comment_text	toxic	severe_toxic	obscene	threat	insult	identity_
0	0000997932d777bf	Explanation\nWhy the edits made under my usern...	0	0	0	0	0	0
1	000103f0d9cfb60f	D'aww! He matches this background colour I'm s...	0	0	0	0	0	0
2	000113f07ec002fd	Hey man, I'm really not trying to edit war. It...	0	0	0	0	0	0
3	0001b41b1c6bb37e	"\nMore\nI can't make any real suggestions on ...	0	0	0	0	0	0

4	0001d958c54c6e35	You, sir, are my hero. Any chance you remember...	0	0	0	0	0	0

We have text (comment) and six different toxic labels. Note that we have clean content, too.

Let's split the data:

PYTHON

```python
train_df, val_df = train_test_split(df, test_size=0.05)
train_df.shape, val_df.shape
```

OUTPUT

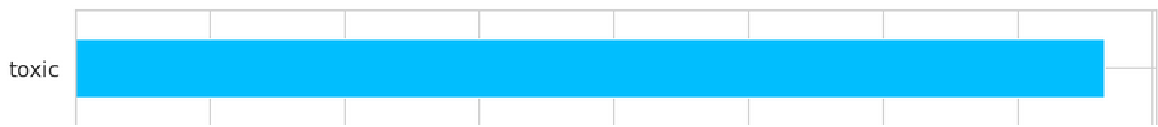
```
((151592, 8), (7979, 8))
```

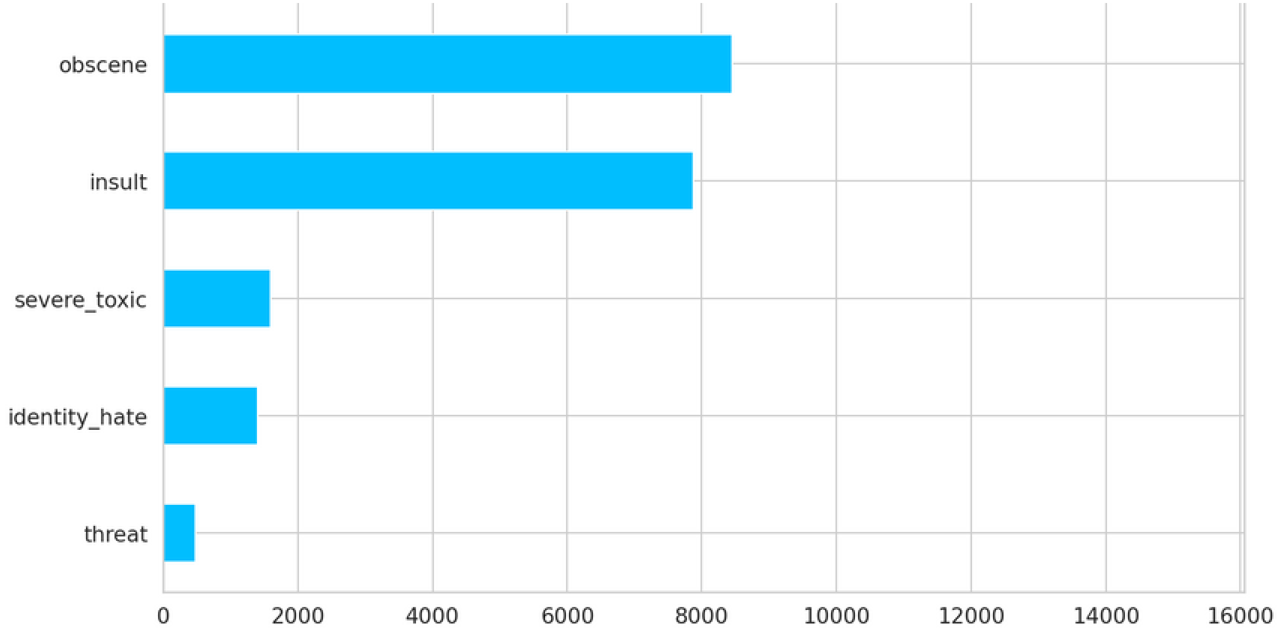
Preprocessing

Let's look at the distribution of the labels:

PYTHON

```python
LABEL_COLUMNS = df.columns.tolist()[2:]
df[LABEL_COLUMNS].sum().sort_values().plot(kind="barh");
```



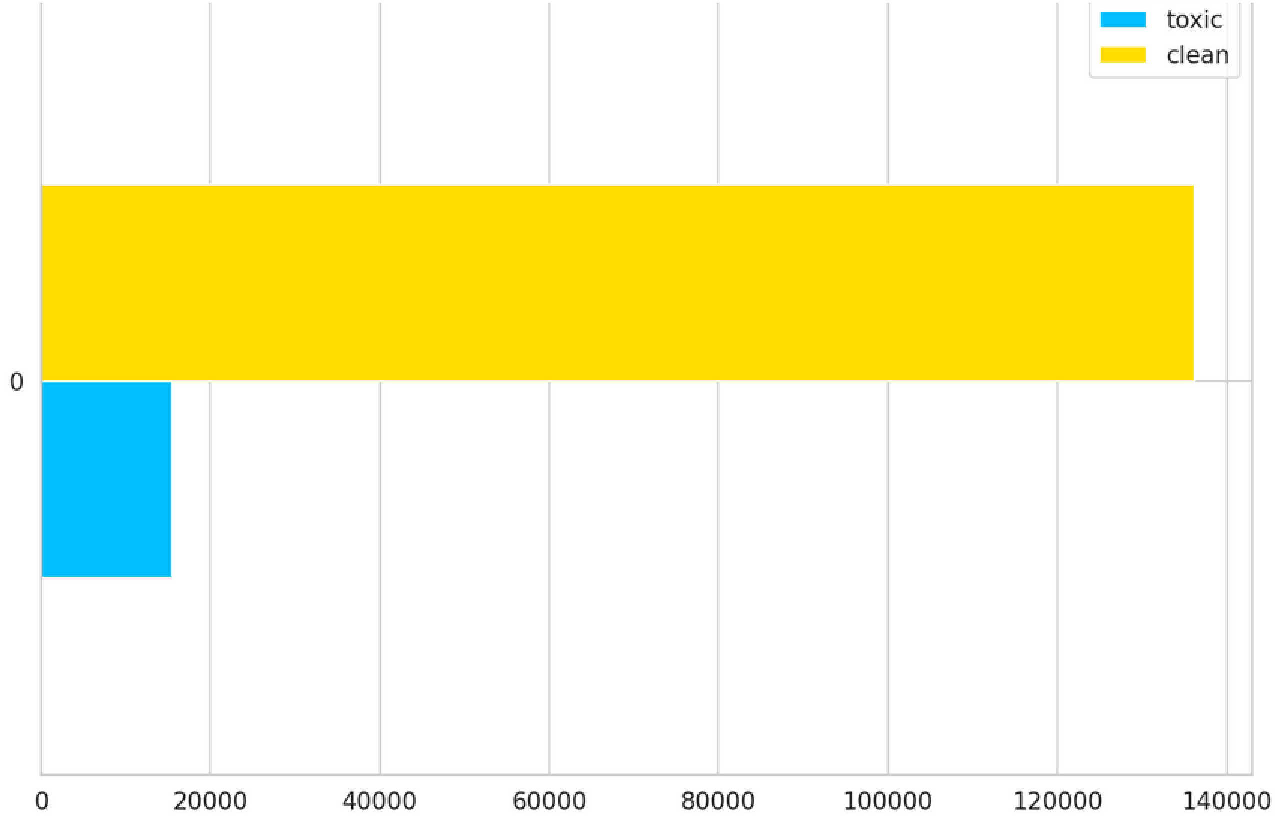


Number of tags in the comments

We have a severe case of imbalance. But that is not the full picture. What about the toxic vs clean comments?

PYTHON

```python
train_toxic = train_df[train_df[LABEL_COLUMNS].sum(axis=1) > 0]
train_clean = train_df[train_df[LABEL_COLUMNS].sum(axis=1) == 0]

pd.DataFrame(dict(
  toxic=[len(train_toxic)],
  clean=[len(train_clean)]
)).plot(kind='barh');
```



Clean vs toxic comment count in the dataset

Again, we have a severe imbalance in favor of the clean comments. To combat this, we'll sample 15,000 examples from the clean comments and create a new training set:

PYTHON

```python
train_df = pd.concat([
  train_toxic,
  train_clean.sample(15_000)
])

```

```
train_df.shape, val_df.shape
```

OUTPUT

```
((30427, 8), (7979, 8))
```

Tokenization

We need to convert the raw text into a list of tokens. For that, we'll use the built-in BertTokenizer:

PYTHON

```python
BERT_MODEL_NAME = 'bert-base-cased'
tokenizer = BertTokenizer.from_pretrained(BERT_MODEL_NAME)
```

Let's try it out on a sample comment:

PYTHON

```python
sample_row = df.iloc[16]
sample_comment = sample_row.comment_text
sample_labels = sample_row[LABEL_COLUMNS]

print(sample_comment)
print()
print(sample_labels.to_dict())
```

OUTPUT

```
Bye!

Don't look, come or think of comming back! Tosser.
```

```
{'toxic': 1, 'severe_toxic': 0, 'obscene': 0, 'threat': 0, 'insult': 0, 'identity_hate': 0}
```

PYTHON

```python
encoding = tokenizer.encode_plus(
  sample_comment,
  add_special_tokens=True,
  max_length=512,
  return_token_type_ids=False,
  padding="max_length",
  return_attention_mask=True,
  return_tensors='pt',
)

encoding.keys()
```

OUTPUT

```
dict_keys(['input_ids', 'attention_mask'])
```

PYTHON

```python
encoding["input_ids"].shape, encoding["attention_mask"].shape
```

OUTPUT

```
(torch.Size([1, 512]), torch.Size([1, 512]))
```

The result of the encoding is a dictionary with token ids `input_ids` and an attention mask `attention_mask` (which tokens should be used by the model 1 - use or 0 - don't use).

Let's look at their contents:

PYTHON

```python
encoding["input_ids"].squeeze()[:20]
```

OUTPUT

```
tensor([  101, 17774,   106,  1790,   112,   189,  1440,   117,  1435,  1137,
         1341,  1104,  3254,  5031,  1171,   106,  1706, 14607,   119,   102])
```

PYTHON

```python
encoding["attention_mask"].squeeze()[:20]
```

OUTPUT

```
tensor([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

You can also inverse the tokenization and get back (kinda) the words from the token ids:

PYTHON

```python
print(tokenizer.convert_ids_to_tokens(encoding["input_ids"].squeeze())[:20])
```

OUTPUT

```
['[CLS]', 'Bye', '!', 'Don', "'", 't', 'look', ',', 'come', 'or', 'think', 'of', 'com', '##ming',
```

We need to specify the maximum number of tokens when encoding (512 is the maximum we can do). Let's check the number of tokens per comment:

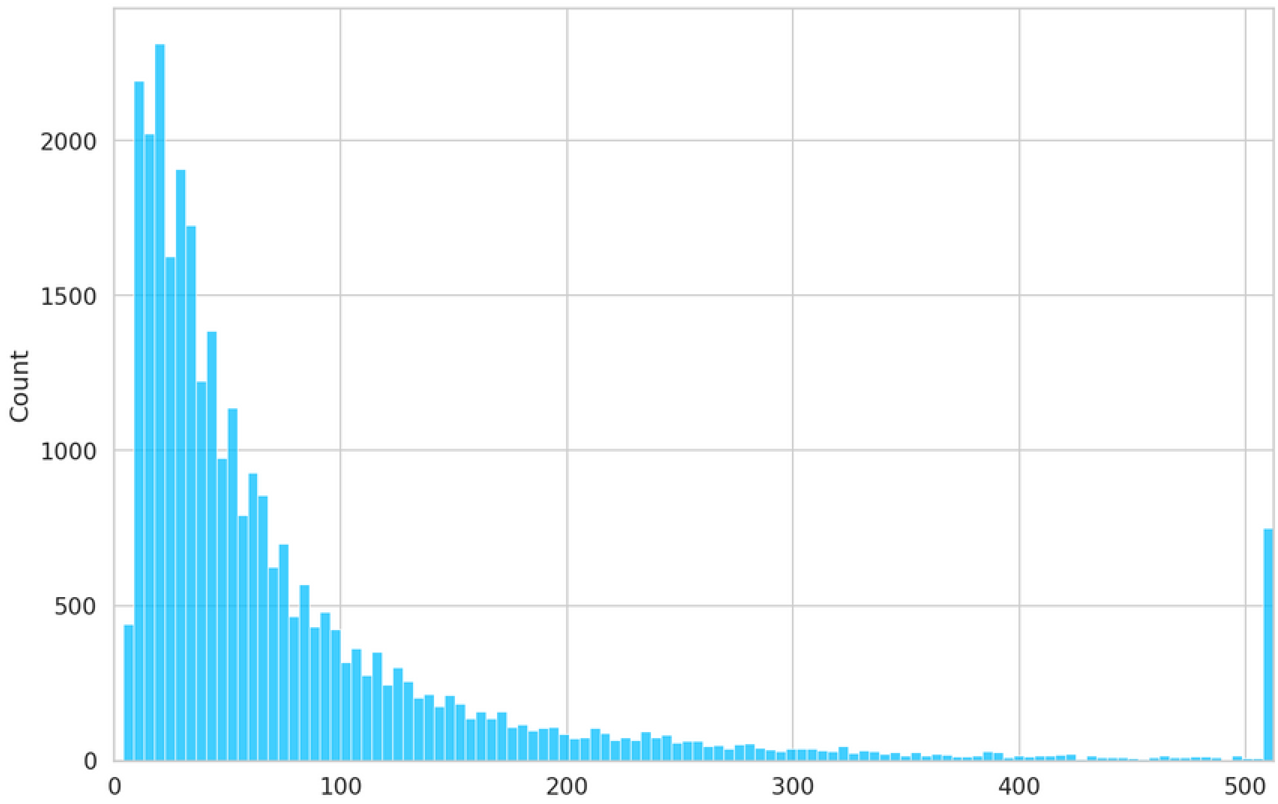
PYTHON

```python
token_counts = []

```

```python
for _, row in train_df.iterrows():
  token_count = len(tokenizer.encode(
    row["comment_text"],
    max_length=512,
    truncation=True
  ))
  token_counts.append(token_count)
```

PYTHON

```python
sns.histplot(token_counts)
plt.xlim([0, 512]);
```



Number of tokens per comment

Most of the comments contain less than 300 tokens or more than 512. So, we'll stick with the limit of 512.

```python
MAX_TOKEN_COUNT = 512
```

Dataset

We'll wrap the tokenization process in a PyTorch Dataset, along with converting the labels to tensors:

```python
class ToxicCommentsDataset(Dataset):

  def __init__(
    self,
    data: pd.DataFrame,
    tokenizer: BertTokenizer,
    max_token_len: int = 128
  ):
    self.tokenizer = tokenizer
    self.data = data
    self.max_token_len = max_token_len

  def __len__(self):
    return len(self.data)
```

```python

    def __getitem__(self, index: int):
      data_row = self.data.iloc[index]

      comment_text = data_row.comment_text
      labels = data_row[LABEL_COLUMNS]

      encoding = self.tokenizer.encode_plus(
        comment_text,
        add_special_tokens=True,
        max_length=self.max_token_len,
        return_token_type_ids=False,
        padding="max_length",
        truncation=True,
        return_attention_mask=True,
        return_tensors='pt',
      )

      return dict(
        comment_text=comment_text,
        input_ids=encoding["input_ids"].flatten(),
        attention_mask=encoding["attention_mask"].flatten(),
        labels=torch.FloatTensor(labels)
      )
```

Let's have a look at a sample item from the dataset:

PYTHON

```python
train_dataset = ToxicCommentsDataset(
  train_df,
  tokenizer,
  max_token_len=MAX_TOKEN_COUNT
)

sample_item = train_dataset[0]
sample_item.keys()
```

OUTPUT

```
dict_keys(['comment_text', 'input_ids', 'attention_mask', 'labels'])
```

PYTHON

```python
sample_item["comment_text"]
```

OUTPUT

```
'Hi, ya fucking idiot. ^_^'
```

PYTHON

```python
sample_item["labels"]
```

OUTPUT

```
tensor([1., 0., 1., 0., 1., 0.])
```

PYTHON

```python
sample_item["input_ids"].shape
```

OUTPUT

```
torch.Size([512])
```

Let's load the BERT model and pass a sample of batch data through:

PYTHON

```python
bert_model = BertModel.from_pretrained(BERT_MODEL_NAME, return_dict=True)

sample_batch = next(iter(DataLoader(train_dataset, batch_size=8, num_workers=2)))
sample_batch["input_ids"].shape, sample_batch["attention_mask"].shape
```

OUTPUT

```
(torch.Size([8, 512]), torch.Size([8, 512]))
```

PYTHON

```python
output = bert_model(sample_batch["input_ids"], sample_batch["attention_mask"])
```

PYTHON

```python
output.last_hidden_state.shape, output.pooler_output.shape
```

OUTPUT

```
(torch.Size([8, 512, 768]), torch.Size([8, 768]))
```

The `768` dimension comes from the BERT hidden size:

PYTHON

```python
bert_model.config.hidden_size
```

OUTPUT

```
768
```

The larger version of BERT has more attention heads and a larger hidden size.

We'll wrap our custom dataset into a LightningDataModule:

PYTHON

```python
class ToxicCommentDataModule(pl.LightningDataModule):

  def __init__(self, train_df, test_df, tokenizer, batch_size=8, max_token_len=128):
    super().__init__()
    self.batch_size = batch_size
    self.train_df = train_df
    self.test_df = test_df
    self.tokenizer = tokenizer
    self.max_token_len = max_token_len

  def setup(self, stage=None):
    self.train_dataset = ToxicCommentsDataset(
      self.train_df,
      self.tokenizer,
      self.max_token_len
    )

    self.test_dataset = ToxicCommentsDataset(
      self.test_df,
      self.tokenizer,
      self.max_token_len
    )

  def train_dataloader(self):
    return DataLoader(
```

```
      self.train_dataset,
      batch_size=self.batch_size,
      shuffle=True,
      num_workers=2
    )

  def val_dataloader(self):
    return DataLoader(
      self.test_dataset,
      batch_size=self.batch_size,
      num_workers=2
    )

  def test_dataloader(self):
    return DataLoader(
      self.test_dataset,
      batch_size=self.batch_size,
      num_workers=2
    )
```

`ToxicCommentDataModule` encapsulates all data loading logic and returns the necessary data loaders. Let’s create an instance of our data module:

PYTHON

```python
N_EPOCHS = 10
BATCH_SIZE = 12

data_module = ToxicCommentDataModule(
```

```
  train_df,
  val_df,
  tokenizer,
  batch_size=BATCH_SIZE,
  max_token_len=MAX_TOKEN_COUNT
)
```

Model

Our model will use a pre-trained BertModel and a linear layer to convert the BERT representation to a classification task. We'll pack everything in a LightningModule:

PYTHON

```python
class ToxicCommentTagger(pl.LightningModule):

  def __init__(self, n_classes: int, n_training_steps=None, n_warmup_steps=None):
    super().__init__()
    self.bert = BertModel.from_pretrained(BERT_MODEL_NAME, return_dict=True)
    self.classifier = nn.Linear(self.bert.config.hidden_size, n_classes)
    self.n_training_steps = n_training_steps
    self.n_warmup_steps = n_warmup_steps
    self.criterion = nn.BCELoss()

  def forward(self, input_ids, attention_mask, labels=None):
    output = self.bert(input_ids, attention_mask=attention_mask)
    output = self.classifier(output.pooler_output)
    output = torch.sigmoid(output)
```

```python
    loss = 0
    if labels is not None:
      loss = self.criterion(output, labels)
    return loss, output

  def training_step(self, batch, batch_idx):
    input_ids = batch["input_ids"]
    attention_mask = batch["attention_mask"]
    labels = batch["labels"]
    loss, outputs = self(input_ids, attention_mask, labels)
    self.log("train_loss", loss, prog_bar=True, logger=True)
    return {"loss": loss, "predictions": outputs, "labels": labels}

  def validation_step(self, batch, batch_idx):
    input_ids = batch["input_ids"]
    attention_mask = batch["attention_mask"]
    labels = batch["labels"]
    loss, outputs = self(input_ids, attention_mask, labels)
    self.log("val_loss", loss, prog_bar=True, logger=True)
    return loss

  def test_step(self, batch, batch_idx):
    input_ids = batch["input_ids"]
    attention_mask = batch["attention_mask"]
    labels = batch["labels"]
    loss, outputs = self(input_ids, attention_mask, labels)
    self.log("test_loss", loss, prog_bar=True, logger=True)
    return loss
```

```python

  def training_epoch_end(self, outputs):

    labels = []
    predictions = []
    for output in outputs:
      for out_labels in output["labels"].detach().cpu():
        labels.append(out_labels)
      for out_predictions in output["predictions"].detach().cpu():
        predictions.append(out_predictions)

    labels = torch.stack(labels).int()
    predictions = torch.stack(predictions)

    for i, name in enumerate(LABEL_COLUMNS):
      class_roc_auc = auroc(predictions[:, i], labels[:, i])
      self.logger.experiment.add_scalar(f"{name}_roc_auc/Train", class_roc_auc, self.current_epoc


  def configure_optimizers(self):

    optimizer = AdamW(self.parameters(), lr=2e-5)

    scheduler = get_linear_schedule_with_warmup(
      optimizer,
      num_warmup_steps=self.n_warmup_steps,
      num_training_steps=self.n_training_steps
    )
```

```

    return dict(
      optimizer=optimizer,
      lr_scheduler=dict(
        scheduler=scheduler,
        interval='step'
      )
    )
```

Most of the implementation is just a boilerplate. Two points of interest are the way we configure the optimizers and calculating the area under ROC. We'll dive a bit deeper into those next.

Optimizer scheduler

The job of a scheduler is to change the learning rate of the optimizer during training. This might lead to better performance of our model. We'll use the get_linear_schedule_with_warmup.

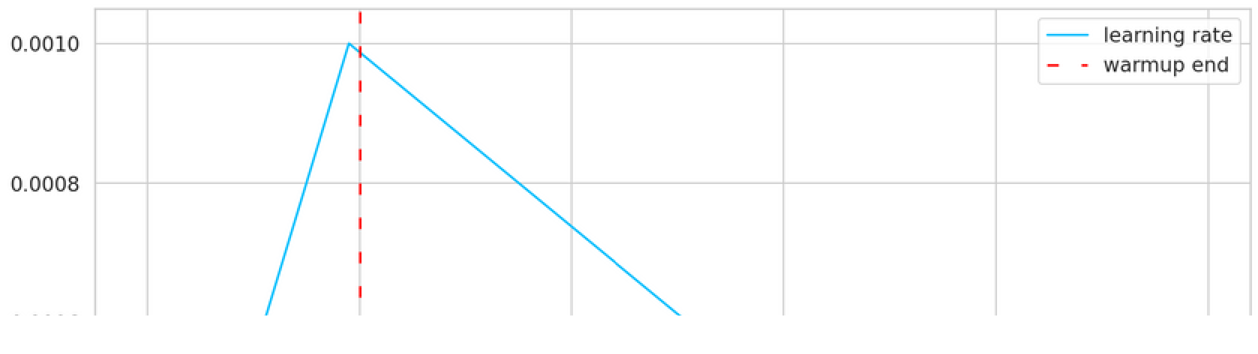
Let's have a look at a simple example to make things clearer:

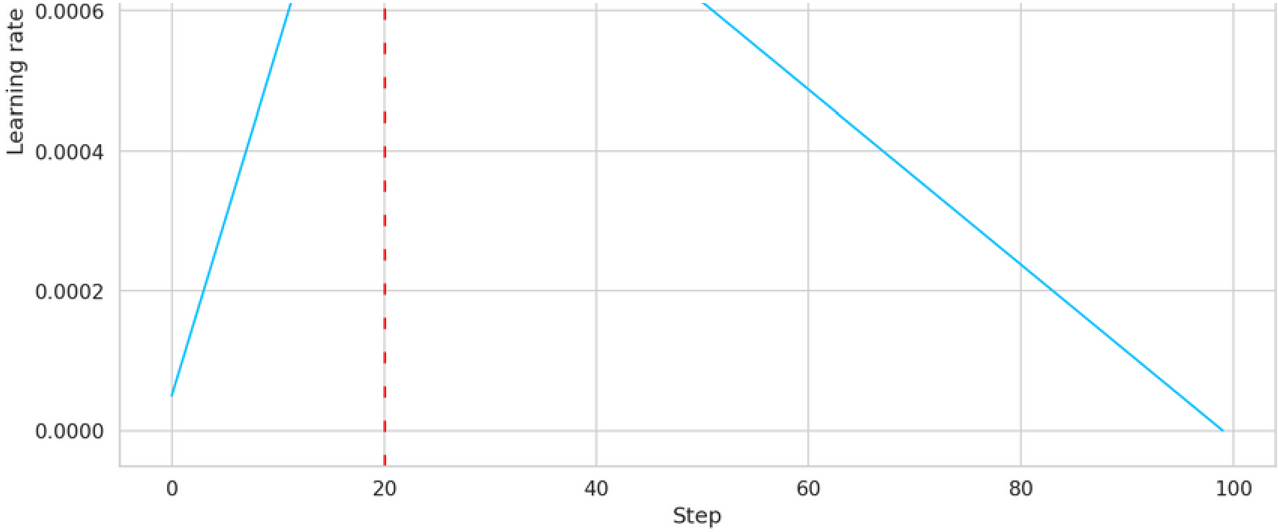
PYTHON

```python
dummy_model = nn.Linear(2, 1)

optimizer = AdamW(params=dummy_model.parameters(), lr=0.001)

warmup_steps = 20
total_training_steps = 100
```

```

scheduler = get_linear_schedule_with_warmup(
  optimizer,
  num_warmup_steps=warmup_steps,
  num_training_steps=total_training_steps
)

learning_rate_history = []

for step in range(total_training_steps):
  optimizer.step()
  scheduler.step()
  learning_rate_history.append(optimizer.param_groups[0]['lr'])
```

```
plt.plot(learning_rate_history, label="learning rate")
plt.axvline(x=warmup_steps, color="red", linestyle=(0, (5, 10)), label="warmup end")
plt.legend()
plt.xlabel("Step")
plt.ylabel("Learning rate")
plt.tight_layout();
```





Linear learning rate scheduling over training steps

We simulate 100 training steps and tell the scheduler to warm up for the first 20. The learning rate grows to the initial fixed value of 0.001 during the warm-up and then goes down (linearly) to 0.

To use the scheduler, we need to calculate the number of training and warm-up steps. The number of training steps per epoch is equal to `number of training examples / batch size`. The number of total training steps is `training steps per epoch * number of epochs`:

PYTHON

```python
steps_per_epoch=len(train_df) // BATCH_SIZE
total_training_steps = steps_per_epoch * N_EPOCHS
```

We'll use a fifth of the training steps for a warm-up:

PYTHON

```python
warmup_steps = total_training_steps // 5
warmup_steps, total_training_steps
```

OUTPUT

```
(5070, 25350)
```

We can now create an instance of our model:

PYTHON

```python
model = ToxicCommentTagger(
  n_classes=len(LABEL_COLUMNS),
  n_warmup_steps=warmup_steps,
  n_training_steps=total_training_steps
)
```

Evaluation

Multi-label classification boils down to doing binary classification for each label/tag.

We'll use Binary Cross Entropy to measure the error for each label. PyTorch has BCELoss, which we're going to combine with a sigmoid function (as we did in the model implementation). Let's look at an example:

PYTHON

```python
criterion = nn.BCELoss()

prediction = torch.FloatTensor(
  [10.95873564, 1.07321467, 1.58524066, 0.03839076, 15.72987556, 1.09513213]
```

```
)
labels = torch.FloatTensor(
  [1., 0., 0., 0., 1., 0.]
)
```

PYTHON

```python
torch.sigmoid(prediction)
```

OUTPUT

```
tensor([1.0000, 0.7452, 0.8299, 0.5096, 1.0000, 0.7493])
```

PYTHON

```python
criterion(torch.sigmoid(prediction), labels)
```

OUTPUT

```
tensor(0.8725)
```

We can use the same approach to calculate the loss of the predictions:

PYTHON

```python
_, predictions = model(sample_batch["input_ids"], sample_batch["attention_mask"])
predictions
```

OUTPUT

```
tensor([[0.3963, 0.6318, 0.6543, 0.5179, 0.4099, 0.4998],
            [0.4008, 0.6165, 0.6733, 0.5460, 0.4378, 0.5083],
            [0.3877, 0.6185, 0.6830, 0.5238, 0.4326, 0.5138],
            [0.3910, 0.6206, 0.6658, 0.5431, 0.4396, 0.5002],
            [0.3792, 0.6241, 0.6508, 0.5347, 0.4374, 0.5110],
            [0.4069, 0.6106, 0.7019, 0.5484, 0.4450, 0.4995],
```

```
        [0.3861, 0.6135, 0.6867, 0.5179, 0.4525, 0.5188],
        [0.3819, 0.6081, 0.6821, 0.5227, 0.4419, 0.5246]],
       grad_fn=<SigmoidBackward>)
```

PYTHON

```python
criterion(predictions, sample_batch["labels"])
```

OUTPUT

```
tensor(0.8056, grad_fn=<BinaryCrossEntropyBackward>)
```

ROC Curve

Another metric we're going to use is the area under the Receiver operating characteristic (ROC) for each tag. ROC is created by plotting the True Positive Rate (TPR) vs False Positive Rate (FPR):

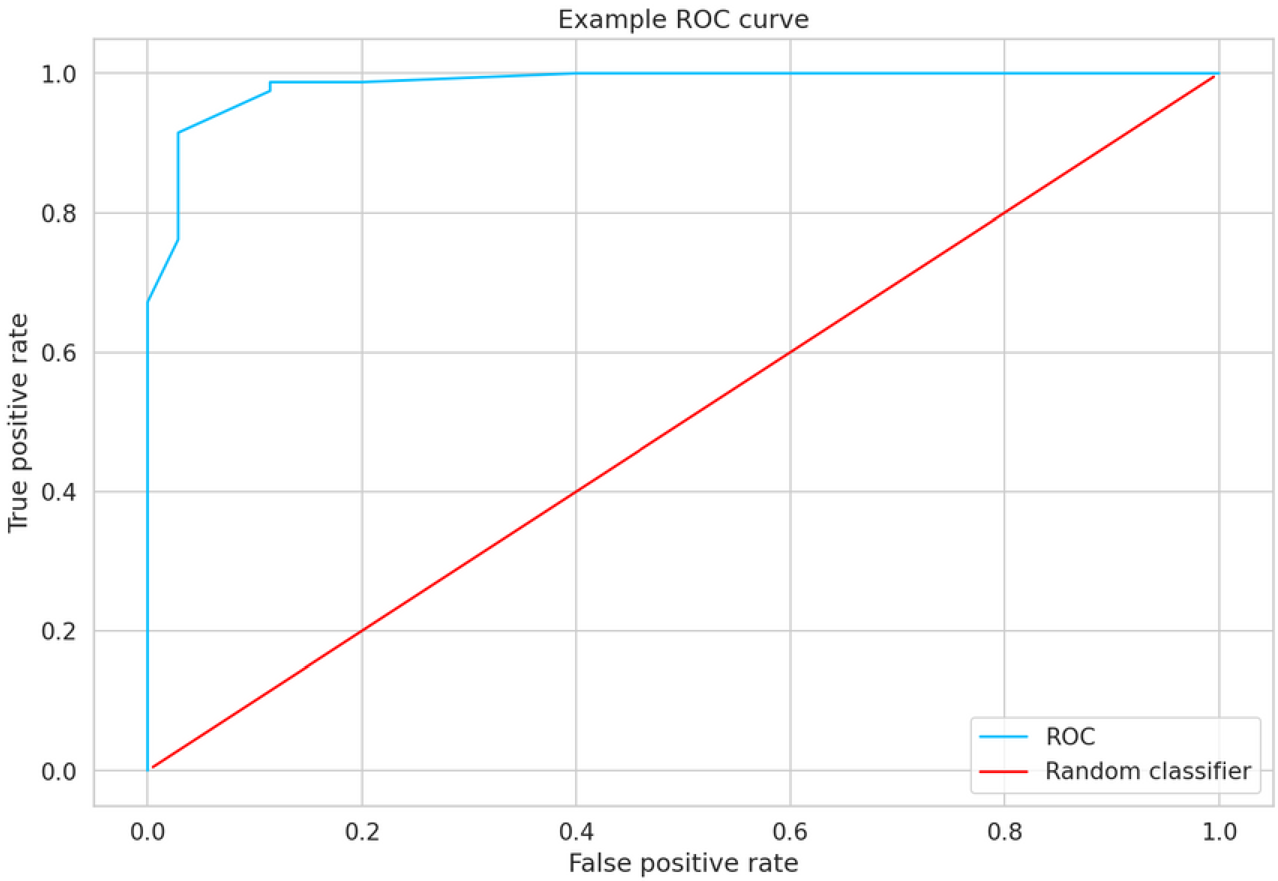
$$\text{TPR} = \frac{\text{TP}}{\text{TP}+\text{FN}}$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP}+\text{TN}}$$

PYTHON

```python
from sklearn import metrics

fpr = [0.        , 0.        , 0.        , 0.02857143, 0.02857143,
       0.11428571, 0.11428571, 0.2       , 0.4       , 1.        ]

tpr = [0.        , 0.01265823, 0.67202532, 0.76202532, 0.91468354,
       0.97468354, 0.98734177, 0.98734177, 1.        , 1.        ]

_, ax = plt.subplots()
```

```
ax.plot(fpr, tpr, label="ROC")
ax.plot([0.05, 0.95], [0.05, 0.95], transform=ax.transAxes, label="Random classifier", color="rec
ax.legend(loc=4)
ax.set_xlabel("False positive rate")
ax.set_ylabel("True positive rate")
ax.set_title("Example ROC curve")
plt.show();
```



Example ROC vaue of a trained classifier vs random classifier

Training

The beauty of PyTorch Lightning is that you can build a standard pipeline that you like and train (almost?) every model you might imagine. I prefer to use at least 3 components.

Checkpointing that saves the best model (based on validation loss):

```python
checkpoint_callback = ModelCheckpoint(
  dirpath="checkpoints",
  filename="best-checkpoint",
  save_top_k=1,
  verbose=True,
  monitor="val_loss",
  mode="min"
)
```

Log the progress in TensorBoard:

```python
logger = TensorBoardLogger("lightning_logs", name="toxic-comments")
```

And early stopping triggers when the loss hasn't improved for the last 2 epochs (you might want to remove/reconsider this when training on real-world projects):

```python
early_stopping_callback = EarlyStopping(monitor='val_loss', patience=2)
```

We can start the training process:

PYTHON

```python
trainer = pl.Trainer(
  logger=logger,
  checkpoint_callback=checkpoint_callback,
  callbacks=[early_stopping_callback],
  max_epochs=N_EPOCHS,
  gpus=1,
  progress_bar_refresh_rate=30
)
```

OUTPUT

```
GPU available: True, used: True
TPU available: False, using: 0 TPU cores
```

PYTHON

```python
trainer.fit(model, data_module)
```

OUTPUT

```
LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]

  | Name       | Type      | Params
-----------------------------------------
0 | bert       | BertModel | 108 M
1 | classifier | Linear    | 4.6 K
2 | criterion  | BCELoss   | 0
-----------------------------------------
108 M     Trainable params
```

```
0          Non-trainable params
108 M      Total params
433.260    Total estimated model params size (MB)


Epoch 0, global step 2535: val_loss reached 0.05723 (best 0.05723), saving model to "/content/che

Epoch 1, global step 5071: val_loss reached 0.04705 (best 0.04705), saving model to "/content/che

Epoch 2, step 7607: val_loss was not in top 1

Epoch 3, step 10143: val_loss was not in top 1
```

The model improved for (only) 2 epochs. We'll have to evaluate it to see whether it is any good. Let's double-check the validation loss:

PYTHON

```python
trainer.test()
```

OUTPUT

```
LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]

--------------------------------------------------------------------------------
DATALOADER:0 TEST RESULTS
{'test_loss': 0.04704693332314491}
--------------------------------------------------------------------------------

[{'test_loss': 0.04704693332314491}]
```

Predictions

I like to look at a small sample of predictions after the training is complete. This builds intuition about the quality of the predictions (qualitative evaluation).

Let's load the best version (according to the validation loss) of our model:

PYTHON

```python
trained_model = ToxicCommentTagger.load_from_checkpoint(
  trainer.checkpoint_callback.best_model_path,
  n_classes=len(LABEL_COLUMNS)
)
trained_model.eval()
trained_model.freeze()
```

We put our model into "eval" mode, and we're ready to make some predictions. Here's the prediction on a sample (totally fictional) comment:

PYTHON

```python
test_comment = "Hi, I'm Meredith and I'm an alch... good at supplier relations"

encoding = tokenizer.encode_plus(
  test_comment,
  add_special_tokens=True,
  max_length=512,
  return_token_type_ids=False,
  padding="max_length",
  return_attention_mask=True,
```

```
  return_tensors='pt',
)

_, test_prediction = trained_model(encoding["input_ids"], encoding["attention_mask"])
test_prediction = test_prediction.flatten().numpy()

for label, prediction in zip(LABEL_COLUMNS, test_prediction):
  print(f"{label}: {prediction}")
```

OUTPUT

```
toxic: 0.02174694836139679
severe_toxic: 0.0013127995189279318
obscene: 0.0035953170154243708
threat: 0.0015959267038851976
insult: 0.003400973277166486
identity_hate: 0.003609051927924156
```

Looks good. This one is pretty clean. We'll reduce the noise of the predictions by thresholding (0.5) them. We'll take only tag predictions above (or equal) to the threshold. Let's try something toxic:

PYTHON

```
THRESHOLD = 0.5

test_comment = "You are such a loser! You'll regret everything you've done to me!"
encoding = tokenizer.encode_plus(
  test_comment,
  add_special_tokens=True,
```

```
  max_length=512,
  return_token_type_ids=False,
  padding="max_length",
  return_attention_mask=True,
  return_tensors='pt',
)

_, test_prediction = trained_model(encoding["input_ids"], encoding["attention_mask"])
test_prediction = test_prediction.flatten().numpy()

for label, prediction in zip(LABEL_COLUMNS, test_prediction):
  if prediction < THRESHOLD:
    continue
  print(f"{label}: {prediction}")
```

OUTPUT

```
toxic: 0.9569520354270935
insult: 0.7289626002311707
```

I definitely agree with those tags. It looks like our model is doing something reasonable, on those two examples.

Evaluation

Let’s get a more complete overview of the performance of our model. We’ll start by taking all predictions and labels from the validation set:

PYTHON

```python
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
trained_model = trained_model.to(device)

val_dataset = ToxicCommentsDataset(
  val_df,
  tokenizer,
  max_token_len=MAX_TOKEN_COUNT
)

predictions = []
labels = []

for item in tqdm(val_dataset):
  _, prediction = trained_model(
    item["input_ids"].unsqueeze(dim=0).to(device),
    item["attention_mask"].unsqueeze(dim=0).to(device)
  )
  predictions.append(prediction.flatten())
  labels.append(item["labels"].int())

predictions = torch.stack(predictions).detach().cpu()
labels = torch.stack(labels).detach().cpu()
```

One simple metric is the accuracy of the model:

PYTHON

```python
accuracy(predictions, labels, threshold=THRESHOLD)
```

OUTPUT

```
tensor(0.9813)
```

That’s great, but you should take this result with a grain of salt. We have a very imbalanced dataset. Let’s check the ROC for each tag:

PYTHON

```python
print("AUROC per tag")
for i, name in enumerate(LABEL_COLUMNS):
  tag_auroc = auroc(predictions[:, i], labels[:, i], pos_label=1)
  print(f"{name}: {tag_auroc}")
```

OUTPUT

```
AUROC per tag
  toxic: 0.985722541809082
  severe_toxic: 0.990084171295166
  obscene: 0.995059609413147
  threat: 0.9909615516662598
  insult: 0.9884428977966309
  identity_hate: 0.9890572428703308
```

Very good results, but just before we go party, let’s check the classification report for each class. To make this work, we must apply thresholding to the predictions:

PYTHON

```python
y_pred = predictions.numpy()
y_true = labels.numpy()

```

```
upper, lower = 1, 0

y_pred = np.where(y_pred > THRESHOLD, upper, lower)

print(classification_report(
  y_true,
  y_pred,
  target_names=LABEL_COLUMNS,
  zero_division=0
))
```

OUTPUT

```
precision    recall  f1-score   support


          toxic       0.68      0.91      0.78       748
   severe_toxic       0.53      0.30      0.38        80
        obscene       0.79      0.87      0.83       421
         threat       0.23      0.38      0.29        13
         insult       0.79      0.70      0.74       410
  identity_hate       0.59      0.62      0.60        71

      micro avg       0.72      0.81      0.76      1743
      macro avg       0.60      0.63      0.60      1743
   weighted avg       0.72      0.81      0.75      1743
    samples avg       0.08      0.08      0.08      1743
```

That gives us a much more realistic picture of the overall performance. The model makes mistakes on the tags will low amounts of examples. What can you do about it?

Summary

Great job, you have a model that can tell (to some extent) if a text is toxic (and what kind) or not! Fine-tuning modern pre-trained Transformer models allow you to get high accuracy on a variety of NLP tasks with little compute power and small datasets.

- Run the notebook in your browser (Google Colab)
- Read the *Getting Things Done with Pytorch* book

In this tutorial, you'll learned how to:

- Load, balance and split text data into sets
- Tokenize text (with BERT tokenizer) and create PyTorch dataset
- Fine-tune BERT model with PyTorch Lightning
- Find out about warmup steps and use a learning rate scheduler
- Use area under the ROC and binary cross-entropy to evaluate the model during training
- How to make predictions using the fine-tuned BERT model
- Evaluate the performance of the model for each class (possible comment tag)

Can you increase the accuracy of the model? How about better parameters or different learning rate scheduling? Let me know in the comments.

References

- Toxic comments EDA
- Receiver operating characteristic on ML crash course

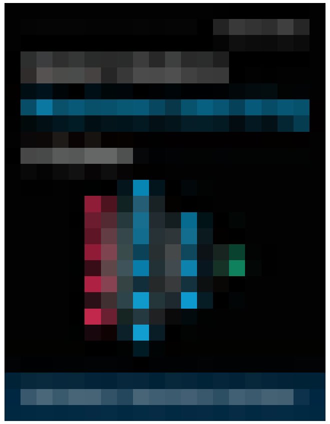
Hacker's Guide to Neural Networks in JavaScript

Build Machine Learning models (especially Deep Neural Networks) that you can easily integrate with existing or new web apps. Think of your

ReactJs, Vue, or Angular app enhanced with the power of Machine Learning models.

Get SH*T Done with PyTorch

Learn how to solve real-world problems with Deep Learning models (NLP, Computer Vision, and Time Series). Go from prototyping to deployment with PyTorch and Python!



Hacker's Guide to Machine Learning with Python

This book brings the fundamentals of Machine Learning to you, using tools and techniques used to solve real-world problems in Computer Vision, Natural Language Processing, and Time Series analysis. The skills taught in this book will lay the foundation for you to advance your journey to Machine Learning Mastery!

Hands-On Machine Learning from Scratch

This book will guide you on your journey to deeper Machine Learning understanding by developing algorithms in Python from scratch! Learn why and when Machine learning is the right tool for the job and how to

why and when Machine learning is the right tool for the job and how to improve low performing models!