

Sentiment analysis using a transformer

Model evaluation

Table of Contents

Sentiment analysis using a transformer

Model evaluation

Load data

Tokenise

Evaluate

Test data

Examples

Probabilities

Single sample

Conclusion

Quick disclaimer, I was unable to run the training data after changing it as the training was taking o...

Restart

```
1 begin
2
      import Pkg
3
      Pkg.activate(mktempdir())
4
      Pkg.develop(url="https://github.com/rgreilly/Transformers")
      5
6
          "DataStructures", "ProgressMeter", "RemoteFiles"])
 7
8
      using Revise
9
10
      using TransformersLite
      using PlutoUI
11
12
      using Flux
13
      using Flux: DataLoader
14
      using Plots
15
      using DataFrames
      using Printf
16
17
      using BSON, JSON
18
      using Arrow
19
      using StatsBase
20
      using Unicode
21
      using Random
      using DataStructures
22
23
      using ProgressMeter
24
      using RemoteFiles
25 end;
```

```
Activating new project at `C:\Users\alexm\AppData\Local\Temp\jl_xnjEWG
     Cloning git-repo 'https://github.com/rgreilly/Transformers'
Path 'C:\Users\alexm\.julia\dev\TransformersLite' exists and looks like the
correct repo. Using existing path.
   Resolving package versions...
   Updating `C:\Users\alexm\AppData\Local\Temp\jl_xnjEWG\Project.toml`
  [6579f8b0] + TransformersLite v0.1.0 'C:\Users\alexm\.julia\dev\Transforme
rsLite'
    Updating `C:\Users\alexm\AppData\Local\Temp\jl_xnjEWG\Manifest.toml`
  621f4979] + AbstractFFTs v1.5.0
  79e6a3ab] + Adapt v3.7.2
   dce04be8] + ArgCheck v2.3.0
   69666777] + Arrow v2.7.0
   31f734f8] + ArrowTypes v2.3.0
   a9b6321e] + Atomix v0.1.0
   ab4f0b2a] + BFloat16s v0.4.2
   fbb218c0] + BSON v0.3.7
   198e06fe] + BangBang v0.3.39
   9718e550] + Baselet v0.1.1
  c3b6d118] + BitIntegers v0.3.1
  fa961155] + CEnum v0.4.2
  [052768ef] + CUDA v4.4.1
   1af6417a] + CUDA_Runtime_Discovery v0.2.2
   082447d4] + ChainRules v1.58.1
   d360d2e6] + ChainRulesCore v1.19.0
   5ba52731] + CodecLz4 v0.4.1
   6b39b394] + CodecZstd v0.8.1
   bbf7d656] + CommonSubexpressions v0.3.0
   34da2185] + Compat v4.10.1
  [a33af91c] + CompositionsBase v0.1.2
   f0e56b4a] + ConcurrentUtilities v2.3.0
  [187b0558] + ConstructionBase v1.5.4
```

```
1 begin
      @RemoteFileSet FILES "Transformer utilities" begin
3
          reporting = @RemoteFile
      "https://github.com/rgreilly/Transformers/blob/main/examples/reporting.jl"
      dir="utilities" file="reporting.jl.json"
          utilities = @RemoteFile
4
      "https://github.com/rgreilly/Transformers/blob/main/examples/utilities.jl"
      dir="utilities" file="utilities.jl.json"
          training = @RemoteFile
5
          "https://github.com/rgreilly/Transformers/blob/main/examples/training.jl"
          dir="utilities" file="training.jl.json"
6
      end
      download(FILES) # Files downloaded in JSON format
9 end
```

convertJSON (generic function with 1 method)

```
function convertJSON(inFile, outFile)
body = JSON.parsefile(inFile)["payload"]["blob"]["rawLines"]
open(outFile, "w") do f
for i in body
println(f, i)
end
end
end
```

```
begin

convertJSON("utilities/reporting.jl.json", "utilities/reporting.jl")

convertJSON("utilities/utilities.jl.json", "utilities/utilities.jl")

convertJSON("utilities/training.jl.json", "utilities/training.jl")

include("utilities/reporting.jl")

include("utilities/utilities.jl")

include("utilities/training.jl")

end;
```

Multi-class classification: stars from 1 to 5

Load data

The original CSV data format has been converted to arrow format for faster loading.

```
begin
path = "datasets/amazon_reviews_multi/en/1.0.0/"
file_train = "train.arrow"
file_test = "test.arrow"
nlabels = 5
end;
```

Load training and test data into dataframes and about the size of both.

(205000, 5000)

1 begin
2 filepath = joinpath(path, file_train)
3 df = DataFrame(Arrow.Table(filepath))

4
5 filepath = joinpath(path, file_test)
6 df_test = DataFrame(Arrow.Table(filepath))

7
8 (nrow(df), nrow(df_test))
9 end

Extract just the review text and the star rating

```
begin
documents = df[:, "review_body"]
labels = df[:, "stars"]

println("training samples: ", size(documents), " ", size(labels))
end

training samples: (205000,) (205000,)
```

Do the same for the test data

```
begin
documents_test = df_test[:, "review_body"]
labels_test = df_test[:, "stars"];
println("test samples: ", size(documents_test), " ", size(labels_test))
end

test samples: (5000,) (5000,)
```

Load the already trained and saved model. Note that models and associated details are stored in the outputs directory under a sub-directory name generated from the time it was saved in the format: yyyymmdd_hhmm.

```
1 begin
           directory = "../outputs/20231219_1608/" #CHANGE HERE
       saved_objects = BSON.load(joinpath(directory, "model.bson"))
3
       tokenizer = saved_objects[:tokenizer]
4
5
       @show tokenizer
6
       indexer = saved_objects[:indexer]
7
       @show indexer
       model = saved_objects[:model]
8
       display(model)
10 end;
```

```
tokenizer = identity
                                                                                                 ?
indexer = IndexTokenizer{String}(length(vocabulary)=6654, unksym=[UNK])
TransformerClassifier(
  Embed((32, 6654)),
                                                  # 212_928 parameters
  PositionEncoding(32),
  Dropout(0.1),
  TransformerEncoderBlock(
    MultiheadAttention(num_heads=4, head_size=8, 32=>32)(
       denseQ = Dense(32 \Rightarrow 32), # 1_056 parameters
denseK = Dense(32 \Rightarrow 32), # 1_056 parameters
denseV = Dense(32 \Rightarrow 32), # 1_056 parameters
denseO = Dense(32 \Rightarrow 32), # 1_056 parameters
       dense0 = Dense(32 \Rightarrow 32),
                                                # 1_056 parameters
    Dropout(0.1),
    LayerNorm(32),
                                                 # 64 parameters
     Dense(32 => 128, relu),
                                                # 4_224 parameters
     Dense(128 \Rightarrow 32),
                                                # 4_128 parameters
     Dropout(0.1),
     LayerNorm(32),
                                                 # 64 parameters
  Dense(32 \implies 1),
                                                  # 33 parameters
  FlattenLayer(),
  Dense(50 \Rightarrow 5),
                                                  # 255 parameters
           # Total: 21 trainable arrays, 225_920 parameters,
            # plus 1 non-trainable, 32_000 parameters, summarysize 1009.188 KiB.
```

Tokenise

Tokenise the training and test data

```
1 begin
       max_length = size(model.classifier.weight, 2)
 3
       @time tokens = map(d->preprocess(d, tokenizer, max_length=max_length),
       documents) #takes about 30 seconds for all documents
       @time indices = indexer(tokens) #takes about 12 seconds for all documents
 4
 5
 6
       y_train = copy(labels)
 7
       idxs = Base.OneTo(length(labels))
       X_train, y_train = indices[:, idxs], y_train[idxs];
8
       y_train = Flux.onehotbatch(y_train, 1:5) # multi-class
       train_data, val_data = split_validation(X_train, y_train;
10
11
           rng=MersenneTwister(2718))
12
                                    ", size(train_data[1]), " ", size(train_data[2]))
13
       println("train samples:
       println("validation samples: ", size(val_data[1]), " ", size(val_data[2]))
14
15 end
```

```
4.125783 seconds (28.48 M allocations: 1.786 GiB, 16.44% gc time)
12.979427 seconds (4 allocations: 79.765 MiB)
train samples: (50, 184500) (5, 184500)
validation samples: (50, 20500) (5, 20500)
```

```
1 begin
 2
       y_test = copy(labels_test)
 3
       y_test = Flux.onehotbatch(y_test, 1:5);
 4
       @time tokens_test = map(d->preprocess(d, tokenizer, max_length=max_length),
 5
       documents_test)
 6
       @time indices_test = indexer(tokens_test)
 7
8
       X_test = indices_test
       println("test indices: ", size(indices_test))
10
       println("test samples: ", size(X_test), " ", size(y_test))
11
12 end
```

```
0.100063 seconds (718.85 k allocations: 46.182 MiB, 26.17% compilation ti (2) me)
0.307723 seconds (19 allocations: 1.946 MiB, 1.12% compilation time) test indices: (50, 5000) test samples: (50, 5000) (5, 5000)
```

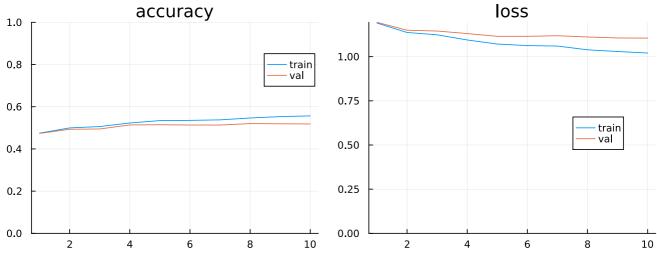
Create the training and validation data loaders

```
321-element DataLoader(::Tuple{Matrix{Int64}, OneHotArrays.OneHotMatrix{UInt32, Vector{UI
with first element:
  (50×64 Matrix{Int64}, 5×64 OneHotMatrix(::Vector{UInt32}) with eltype Bool,)
```

```
begin
train_data_loader = DataLoader(train_data; batchsize=64, shuffle=false);
val_data_loader = DataLoader(val_data; batchsize=64, shuffle=false);
end
```

Evaluate

```
accuracy (generic function with 1 method)
    1 begin
                             loss(x, y) = Flux.logitcrossentropy(model(x), y)
     2
                             loss(x::Tuple) = loss(x[1], x[2])
                             accuracy(\hat{y}, y) = mean(Flux.onecold(\hat{y}) .== Flux.onecold(y))
     5 end
0.5520271002710027
     1 @time batched_metric(model, accuracy, train_data_loader)
                     39.119026 seconds (6.73 M allocations: 56.692 GiB, 8.86% gc time, 10.61% c ?)
                 ompilation time)
0.5595121951219513
     1 @time batched_metric(model, accuracy, val_data_loader)
                         3.695079 seconds (100.34 k allocations: 6.257 GiB, 9.76% gc time)
                                                                                                                                                                                                                                                                                                                      ②
history =
      Dict("train_loss" \Rightarrow [1.19026, 1.13687, 1.12365, 1.0945, 1.07144, 1.06278, 1.06003, 1.036003, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945, 1.0945
     1 history = open(joinpath(directory, "history.json"), "r") do f
                              JSON.parse(read(f, String))
     3 end
```



```
begin
       epochs = 1:length(history["train_acc"])
 2
       p1 = plot(epochs, history["train_acc"], label="train")
 3
       plot!(p1, epochs, history["val_acc"], label="val")
4
5
       plot!(p1, ylims=[0, 1], title="accuracy", legend=(0.9, 0.8))
6
       p2 = plot(epochs, history["train_loss"], label="train")
8
       plot!(p2, epochs, history["val_loss"], label="val")
       plot!(p2, title="loss", ylims=[0, Inf], legend=(0.8, 0.5))
9
10
       p3 = plot(p1, p2, layout=grid(1, 2), size=(800, 300))
11
       savefig(p3, joinpath(directory, "history.png"))
12
13
       рЗ
14 end
```

Test data

```
0.5242

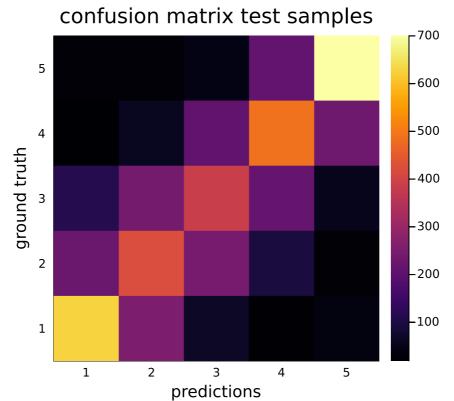
1 begin
2   logits = model(X_test)
3   accuracy(logits, y_test)
4 end
```

```
[1, 1, 1, 2, 2, 1, 4, 1, 2, 1, 3, 1, 1, 2, 1, 1, 2, 1, 2, 2, more ,3, 5, 1, 5, 2, 3, 5, 5
```

```
begin
probs = softmax(logits, dims=1)
y_pred = Flux.onecold(probs);
end
```

```
cm = 5×5 Matrix{Int64}:
                              36
      627
            252
                   64
                         21
       221
                  242
                         92
                              24
            421
                        215
      110
            239
                  385
                              51
       19
             57
                  206
                       488
                             230
       25
             26
                       208
                   41
                             700
```

```
1 cm = confusion_matrix(vec(y_pred), Flux.onecold(y_test), 1:nlabels)
```



1 classification_report(cm, 1:nlabels)

```
precision
                          recall
                                  f1-score
                                             support
                                                                                 ②
                    0.63
                            0.63
                                       0.63
                                                 1000
           2
                    0.42
                            0.42
                                       0.42
                                                 1000
                            0.39
           3
                    0.41
                                       0.40
                                                 1000
           4
                            0.49
                    0.48
                                       0.48
                                                 1000
                    0.67
                            0.70
                                       0.69
                                                 1000
weighted avg
                            0.52
                                                 5000
                    0.52
                                       0.52
```

Examples

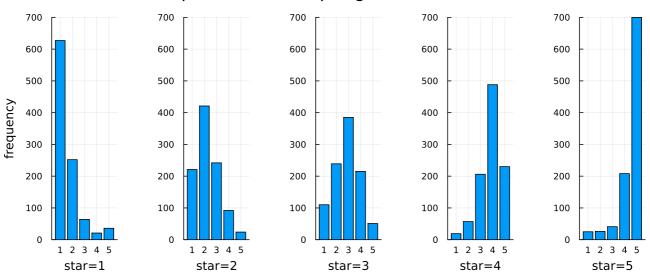
```
begin
println("star y ŷ prob")
for star in nlabels:-1:1
pos_max = argmax(probs[star, :])
@printf(" %1d %d %d %.4f\n %s\n\n",
star, labels_test[pos_max], y_pred[pos_max], probs[star, pos_max],
documents_test[pos_max]

end
end
end
```

```
?
star y ŷ
           prob
  5 5 5 0.9818
Best USB cable I ever owned. Fit and finish are top notch. Highly recommende
  4 4 4 0.9047
I like the case, it works well. I wish it came in purple. The only complaint
I have is that it doesn't charge well on the cordless charger.
  3 3 0.6972
Works ok kinda cheap
  2 4 2 0.6562
The cover and shams look as pictured, Very soft and comfortable. Its very del
icate, I tore a hole by the zipper very easily. I did not return cover because
it was super cheap.
  1 1 1 0.9905
I didn't even want to give this 1 star! This is a piece of JUNK! Terrible mad
e! I am having. Such a HARD TIME RETURNING THIS PRODUCT! Don't WASTE YOUR MONE
Y. It looks like these toys were made for a doll house. Wrongly advertised!
```

Probabilities

predicted class per ground truth class



```
1
   begin
 2
       canvases1 = []
 3
       label_names = 1:5
 4
       for gt_star in 1:5
 5
           idxs = labels_test .== gt_star
           value_counts = [sum((y_pred[idxs]) .== l) for l in 1:nlabels]
 6
           p = bar(value_counts, xlabel="star=$gt_star",legend=:none, xticks=
 7
       (1:nlabels, 1:5))#["neg", "mix", "pos"]))
 8
           push!(canvases1, p)
 9
       plot!(canvases1[1], ylabel="frequency")
10
       p5 =plot(canvases1..., layout=(1, 5), link=:y, size=(900, 400),
11
       plot_title="predicted class per ground truth class",
           margin=5Plots.mm)
12
13
       savefig(p5, joinpath(directory, "prediction_star.png"))
14
15 end
```

Single sample

```
1 begin
 2
       idx = 4600
 3
       d = documents_test[idx]
 4
 5
       println(labels_test[idx])
 6
       println(d)
 7
       println("")
 8
9
        tokens2 = preprocess(d, tokenizer, max_length=50)
       println(join(tokens2, "|"))
10
11
       println("")
12
       x = indexer(tokens2)
13
        x = \overline{vcat(x, ones(Int, 50 - length(x)))}
14
       println(join(x, "|"))
15
16 end
```

```
5×1 Matrix{Float32}:
    0.0014079323
    0.00606461
    0.028641572
    0.2757954
    0.6880905

1 softmax(model(x))
```

Conclusion

Quick disclaimer, I was unable to run the training data after changing it as the training was taking over double the time it took to run it initially. Later on it wouldn't even get past the model creation stage without any changes that couls possibly break it. The Train_multi.jl/pdf is the same as the file that was used to generate the output for this evaluation

The reason why I was able to slightly improve the model's performance was because I added some transformerEncoderBlocks, one of which made use of Attention heads to improve the models capacity to capture complex patterns and to focus on different elements of the input. I also added some dense layers. I added dropout layers to prevent overfitting.

Apart from this I experimented with different values for the Dropout Rate to prevent overfitting aswell as the size of the embedding to find a sweet spot.

```
1 md"""
2 # Conclusion
4 ## Quick disclaimer, I was unable to run the training data after changing it as the
   training was taking over double the time it took to run it initially. Later on it
   wouldn't even get past the model creation stage without any changes that couls
   possibly break it. The Train_multi.jl/pdf is the same as the file that was used to
   generate the output for this evaluation
6 ###
7 The reason why I was able to slightly improve the model's performance was because I
   added some transformerEncoderBlocks, one of which made use of Attention heads to
   improve the models capacity to capture complex patterns and to focus on different
   elements of the input.
8 I also added some dense layers.
9 I added dropout layers to prevent overfitting.
11 Apart from this I experimented with different values for the Dropout Rate to
   prevent overfitting aswell as the size of the embedding to find a sweet spot.
```