CS340 Final Project: Depth to Fairness

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Part One. Run the benchmark model and analyze the result (5 points)

1. Train and run the benchmark model to retrieve the prediction result on comment toxicity.

- **Define and train a Convolutional Neural Net for classifying toxic comments**

```
training model
Epoch 1/10
11281/11281 - 1059s - 94ms/step - acc: 0.9326 - loss: 0.1966 - val_acc: 0.9376 - val_loss: 0.1724
Epoch 2/10
11281/11281 - 969s - 86ms/step - acc: 0.9422 - loss: 0.1626 - val_acc: 0.9437 - val_loss: 0.1576
Epoch 3/10
11281/11281 - 921s - 82ms/step - acc: 0.9444 - loss: 0.1548 - val_acc: 0.9450 - val_loss: 0.1536
Epoch 4/10
11281/11281 - 908s - 80ms/step - acc: 0.9456 - loss: 0.1504 - val_acc: 0.9455 - val_loss: 0.1511
Epoch 5/10
11281/11281 - 850s - 75ms/step - acc: 0.9463 - loss: 0.1476 - val_acc: 0.9456 - val_loss: 0.1517
Epoch 6/10
11281/11281 - 1042s - 92ms/step - acc: 0.9470 - loss: 0.1455 - val_acc: 0.9451 - val_loss: 0.1512
Epoch 7/10
11281/11281 - 1028s - 91ms/step - acc: 0.9474 - loss: 0.1439 - val_acc: 0.9460 - val_loss: 0.1497
Epoch 8/10
11281/11281 - 969s - 86ms/step - acc: 0.9477 - loss: 0.1427 - val_acc: 0.9450 - val_loss: 0.1505
Epoch 9/10
11281/11281 - 795s - 71ms/step - acc: 0.9481 - loss: 0.1414 - val_acc: 0.9455 - val_loss: 0.1494
Epoch 10/10
11281/11281 - 837s - 74ms/step - acc: 0.9483 - loss: 0.1406 - val_acc: 0.9459 - val_loss: 0.1490
```

The main content of this program is a function train_model used to train the model. The functions of this function include preparing data, loading pre-trained word vectors, building models, compiling models, and training models.

In the output, we can see that the model was trained for 10 epochs. The training and validation process of each epoch is recorded, including the accuracy (acc) and loss (loss) of the training set and validation set. During the training process, the accuracy of the training set and the validation set gradually increases, and the loss gradually decreases, which indicates that the performance of the model is continuously improving.

In each epoch, the accuracy and loss for training and validation are shown. These metrics can be used to evaluate model performance and monitor model progress during training.

- **Define bias metrics, then evaluate our new model for bias using the validation set predictions**

  Subsequently, several functions were defined to calculate the performance indicators of the model on different subgroups, including subgroup AUC (subgroup_auc), background positive sample subgroup negative sample AUC (bpsn_auc), and background negative sample subgroup positive sample AUC (bnsp_auc). . These metrics are used to assess how biased the model is towards different subgroups.

Metrics	Interpretation
compute_auc	used to calculate AUC (Area Under the Curve), which is the area under the ROC curve.
compute_subgroup_auc	Compute the AUC on a specific subgroup.
compute_bpsn_auc	Calculate the AUC between negative samples within the subpopulation and positive samples in the background.
compute_bnsp_auc	Calculate the AUC between the positive samples within the subpopulation and the background negative samples.
compute_bias_metrics_for_model	Compute the bias metrics of the model on all subgroups.

For the given validation data set and model, the bias index of the model on each subgroup is calculated. The result is as follows:

subgroup	subgroup_size	subgroup_auc	bpsn_auc	bnsp_auc
homosexual_gay_or_lesbian	2171	0.7962	0.7738	0.9533
black	2950	0.7998	0.7677	0.9565
muslim	4246	0.8199	0.8169	0.9458
white	4937	0.8216	0.7690	0.9616
jewish	1469	0.8419	0.8634	0.9280
psychiatric_or_mental_illness	995	0.8724	0.8586	0.9451
male	8875	0.8752	0.8625	0.9436
female	10670	0.8803	0.8784	0.9362
christian	8092	0.8935	0.9135	0.9165

Interpretation of results:

Subpopulation AUC: The AUC of the model on a specific subpopulation. This indicator indicates the accuracy of the model in prediction.

Background positive sample subpopulation negative sample AUC: The AUC of the model between the negative samples within the subpopulation and the positive samples in the background. This indicator indicates the model's prediction accuracy for the positive samples in the background to the negative samples in the subpopulation.

Background negative sample subpopulation positive sample AUC: The AUC of the model between the positive samples within the subpopulation and the negative samples in the background. This indicator indicates the model's prediction accuracy for the negative samples in the background to the positive samples in the subpopulation.

It can be seen from the results that the model performs differently on different subgroups. Some subpopulations have lower AUCs, which may mean that the model is biased on these subpopulations. For example, the relatively low AUC for the homosexual_gay_or_lesbian and black subgroups may indicate that the model has lower prediction accuracy on these subgroups. Further analysis and adjustments may need to be conducted for these subgroups.

- **Summary**

  Finally, a comprehensive metric is implemented to evaluate the performance and bias of the model, and the final evaluation metric is calculated. The function first calculates the p-power average of the bias index, weights the overall AUC score and the average bias index, and finally returns the comprehensive evaluation index. By calling the get_final_metric function and passing in the model's bias indicator DataFrame bias_metrics_df and the overall AUC score, the final evaluation metric is obtained, which is **0.8843**. This value represents the overall performance of the model, taking into account the overall AUC and bias. The higher the value, the better the performance of the model. Since the models and processing methods currently used are very basic and biases are not well eliminated, the overall AUC index needs to be improved.

2. Value Alignment

Here I randomly selected ten reviews and used the model to judge them [See "benchmark.ipynb" for the code]:

Comment	Prediction_score	Predicted_label	My Decision
Dave, I agree the was one of the most entertaining baseball games ever. I often find baseball boring, especially if I don't have a friend or relative playing. Game 2 was a great battle going back and forth. How about an umpire taking a ball to his crotch when a steal at second base was in play!	0.003540	0	0
God save the Queen of Canada	0.016491	0	0
Sounds like a demonic possession or perhaps alien related to me. Whatever, an "odd,squid-pulsing sensation" on the brain should always be a cause of concern..	0.090685	0	0
Hmm ... over 100 "illegal" dispensaries popped-up in Toronto alone last year, and the Liberal plan is to have 40 outlets up and running across the entire province by July next year. \n\nAnd they expect to "choke-off" the black market with this kind of supply-demand equation?	0.033048	0	0
Thank you for the clarification. What makes the situation so dire now is that it is not just government largess that is offered by elected officials but their generosity (at the federal level) uses vast sums of borrowed money. Also, at all levels, elected officials now engage in a sustained effort to choose winners and losers among those who would otherwise be expected to function in a free market economy using innate ability. The classic example of this in Alaska is the Alaska Industrial Development and Export Authority (AIDEA).	0.033048	0	0
In answer to the headline - who cares.	0.033048	0	0

Comment	Prediction_score	Predicted_label	My Decision
And, IRT PostManx, it's still under ACA or Obamacare. If the U.S. Senate drag their feet in presenting a healthcare plan, the current costs are going higher because Hawaii born ex-President Obama kicked the Obamacare can into 2017. Auwe.	0.002903	0	0
I'm sure the transgender kid was a plant by Liberal strategists. Pretty pathetic.	0.973218	1	1
I don't do polls - you are citing the same pollsters who predicted a Hillary win. Obama had no risk associated with sending a seal team to murder Bin Laden. And Obamacare increase the cost for just about everybody, while deadbeats got it for free, and before you say what about the children, every state I have lived in insures children for free.	0.002276	0	0
Well, a few years ago, he was equipped with work boots a hard hat, and air hammer over the community mailbox dustup...so maybe tomorrow he'll be reporting for work somewhere in Quebec.	0.009896	0	0

The model performance is highly consistent with the manual annotation results, indicating that the model prediction results are consistent with human intuition. By further improving the model, the accuracy of judgment in boundary situations and complex contexts can be improved, making it more reliable in practical applications.

3. Model bias assessment using Demographic Parity

[See "benchmark.ipynb" for the code]
Here we use gender, race, and ethnicity as characteristics for bias assessment:

```
Overall Positive Rate: 0.0690
Subgroup 'male' Positive Rate: 0.1263
Subgroup 'female' Positive Rate: 0.1110
Subgroup 'christian' Positive Rate: 0.0704
Subgroup 'muslim' Positive Rate: 0.1662
Subgroup 'jewish' Positive Rate: 0.1175
Subgroup 'white' Positive Rate: 0.2253
Subgroup 'black' Positive Rate: 0.2327
Disparity difference for 'male': 0.0573
Disparity difference for 'female': 0.0420
Disparity difference for 'christian': 0.0014
Disparity difference for 'muslim': 0.0972
Disparity difference for 'jewish': 0.0484
Disparity difference for 'white': 0.1563
Disparity difference for 'black': 0.1637
Disparity ratio for 'male': 0.5466
Disparity ratio for 'female': 0.6217
Disparity ratio for 'christian': 0.9803
Disparity ratio for 'muslim': 0.4154
Disparity ratio for 'jewish': 0.5877
Disparity ratio for 'white': 0.3064
Disparity ratio for 'black': 0.2967
```

Synthesis to a Ratio	Attribute	Value
Smallest Difference	christian	0.0014
Largest Difference	black	0.1637
Smallest ratio	black	0.2967
Maximum ratio	christian	0.9803

- The difference between the **Christian** subgroup and the overall predicted positive proportion is the smallest, only **0.0014**. At the same time, the ratio of the positive predicted proportion to the overall positive predicted proportion is the largest, **0.9803**, indicating that in the Christian subgroup, the model's predictions are almost consistent with the overall prediction, the deviation is minimal.
- The difference between the **black** subgroup and the overall predicted positive class proportion is the largest, **0.1637**. At the same time, the ratio of the positive class prediction proportion to the overall positive class prediction ratio is the smallest, only **0.2967**, indicating that there is a large deviation between the model's prediction and the overall prediction, which requires special attention and improvements.

Part Two. Mitigate bias from a variety of methods. (15 points)

AI predictions and judgments may exhibit errors and biases for a variety of reasons. Sometimes it's social bias that informs the training data and decisions made when developing and deploying these systems. In other cases, it may not be due to social bias, but to characteristics of the data (e.g., too few data points about certain groups of people) or characteristics of the system itself. These causes can be difficult to distinguish, especially since they are not mutually exclusive and often exacerbate each other. Therefore, we define whether an AI system behaves unfairly in terms of its impact on humans (i.e., harm), rather than in terms of specific reasons (e.g., social bias) or intentions (e.g., prejudice).

Identify Groups Who May Be Harmed

In most applications, we consider demographic groups, including historically marginalized groups (e.g., based on gender, race, ethnicity). We should also consider groups relevant to specific use cases or deployment environments. For example, for speech-to-text transcription, this might include groups who speak regional dialects or native or non-native speakers. It's also important to consider group intersections, for example, in addition to considering groups by gender and groups by race, it's also important to consider the intersection of them (e.g., Black women, Latinx non-binary people, etc.)

Based on the information provided by Fairlearn API [https://fairlearn.org/v0.10/user_guide/mitigation/], we have made the following Mitigations, below we discuss the various mitigation techniques implemented in Fairlearn such as Preprocessing, Postprocessing, Reductions, Adversarial Mitigation......

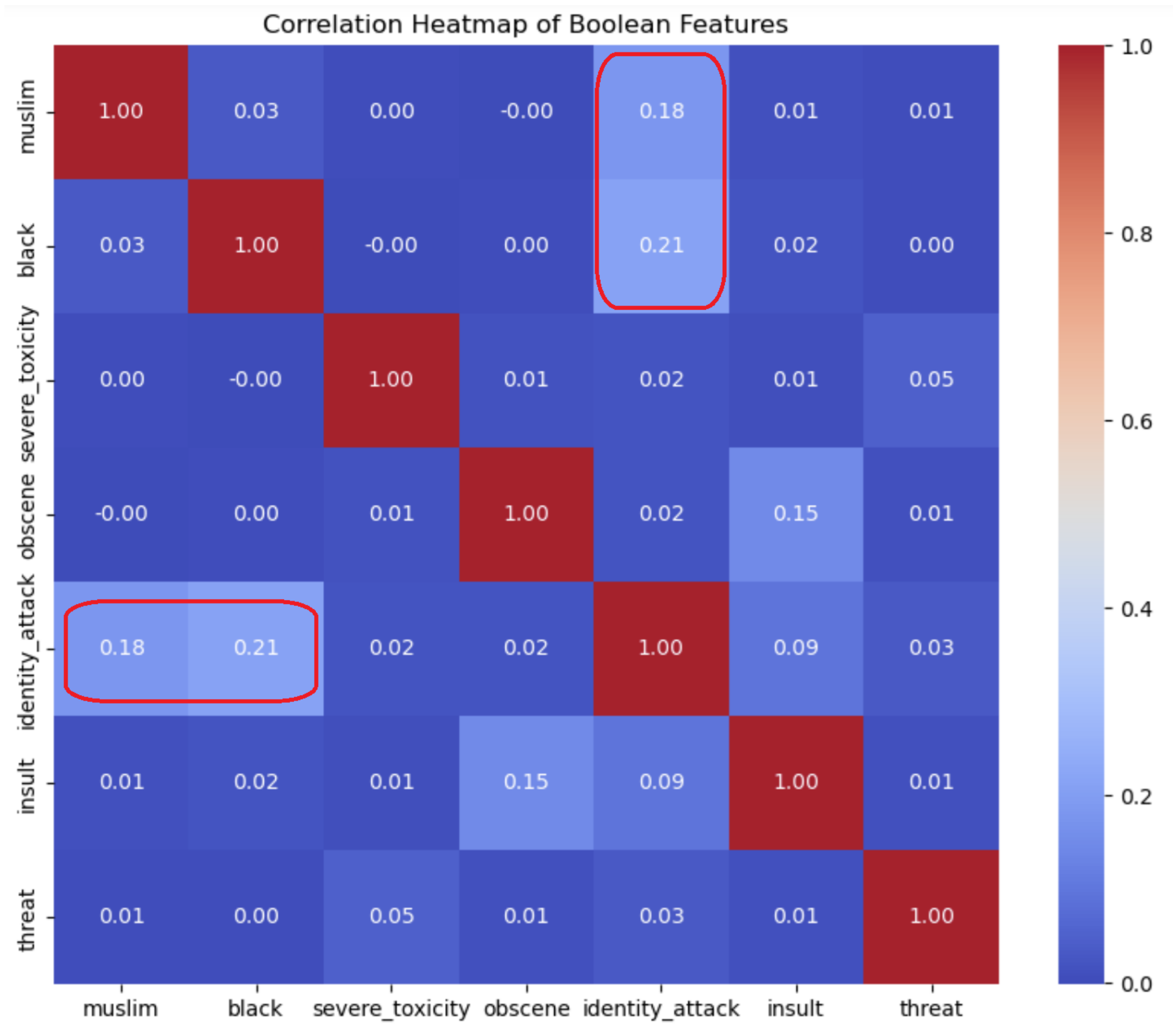
Preprocessing

Preprocessing algorithms transform the data set to mitigate possible inequities in the data. Preprocessing algorithms in Fairlearn follow the class sklearn.base.TransformerMixin, which means they can fit a preprocessing transform on a dataset (or fit_transform to fit and transform in one go). In this project, because the previous bias analysis of the benchmark found that Muslims and black groups are more likely to be related to the toxicity index, so in the preprocessing part, we focused on the relationship between these two features and the toxicity feature, and manually reduced the correlation.

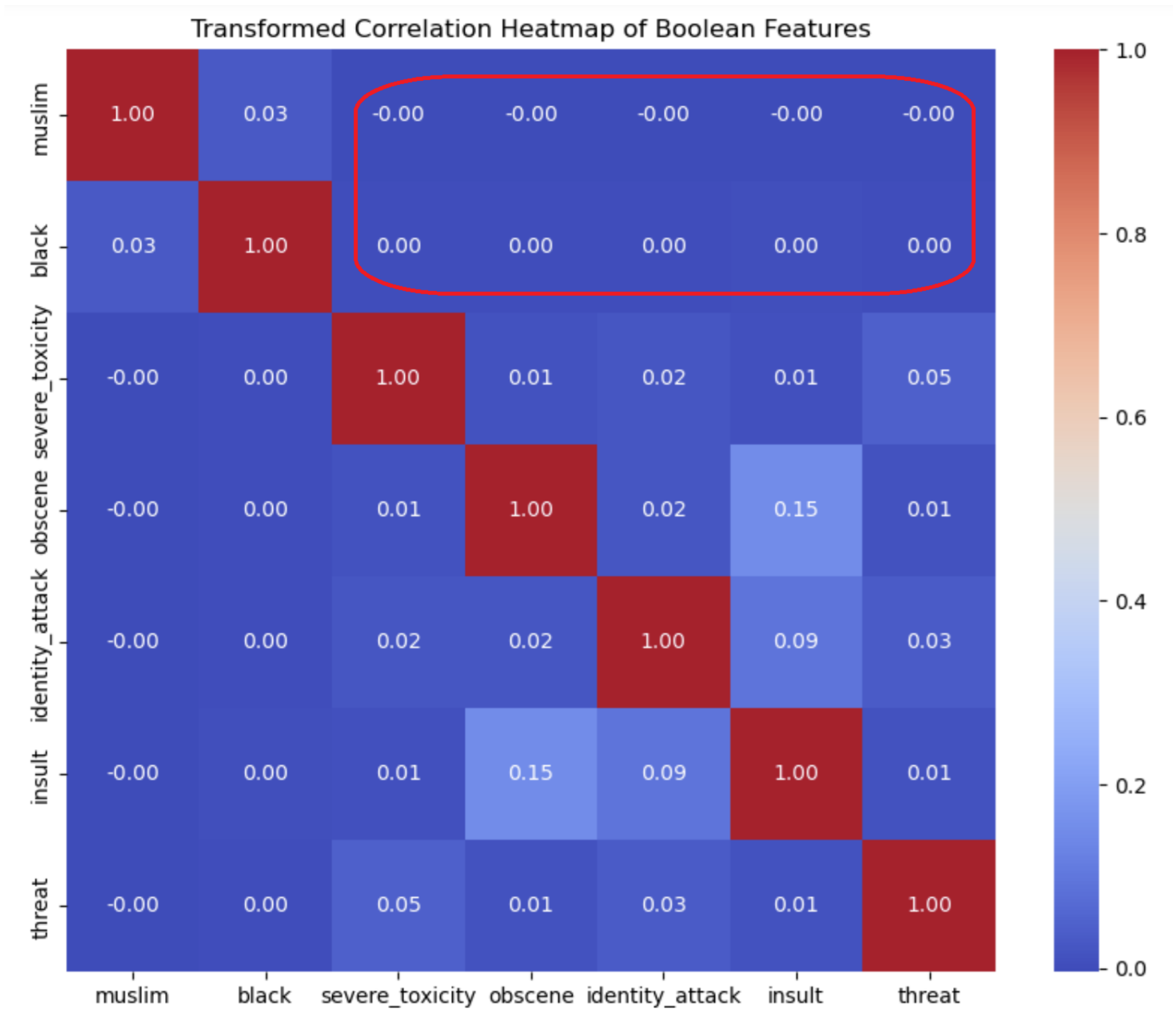
Sensitive features can be associated with non-sensitive features in the dataset. By applying CorrelationRemover, these correlations are projected away while retaining as much detail as possible in the original data (measured by least squares error). In mathematical terms, let's say we have an original data set that contains a set of sensitive attributes and a set of non-sensitive attributes. The elimination of correlation can be described as:

$$\min_{\mathbf{z}_1,\ldots,\mathbf{z}_n} \sum_{i=1}^{n} \|\mathbf{z}_i - \mathbf{x}_i\|^2$$
$$\text{subject to}$$
$$\frac{1}{n}\sum_{i=1}^{n} \mathbf{z}_i(\mathbf{s}_i - \overline{\mathbf{s}})^T = \mathbf{0}$$

In the visualization below we can see the relevant values from the original dataset. We are particularly interested in the correlation between the "muslim", "black" columns and the three non-sensitive attributes 'severe_toxicity', 'obscene', 'identity_attack', 'insult', 'threat'. After generating the correlation matrix, we saw that "identity_attack" has a high and abnormal correlation with "muslim" and "black", so our idea is to eliminate this phenomenon through Fairlearn. The code to generate the correlation matrix can be found in the notebook called [Pre-processing.ipynb].

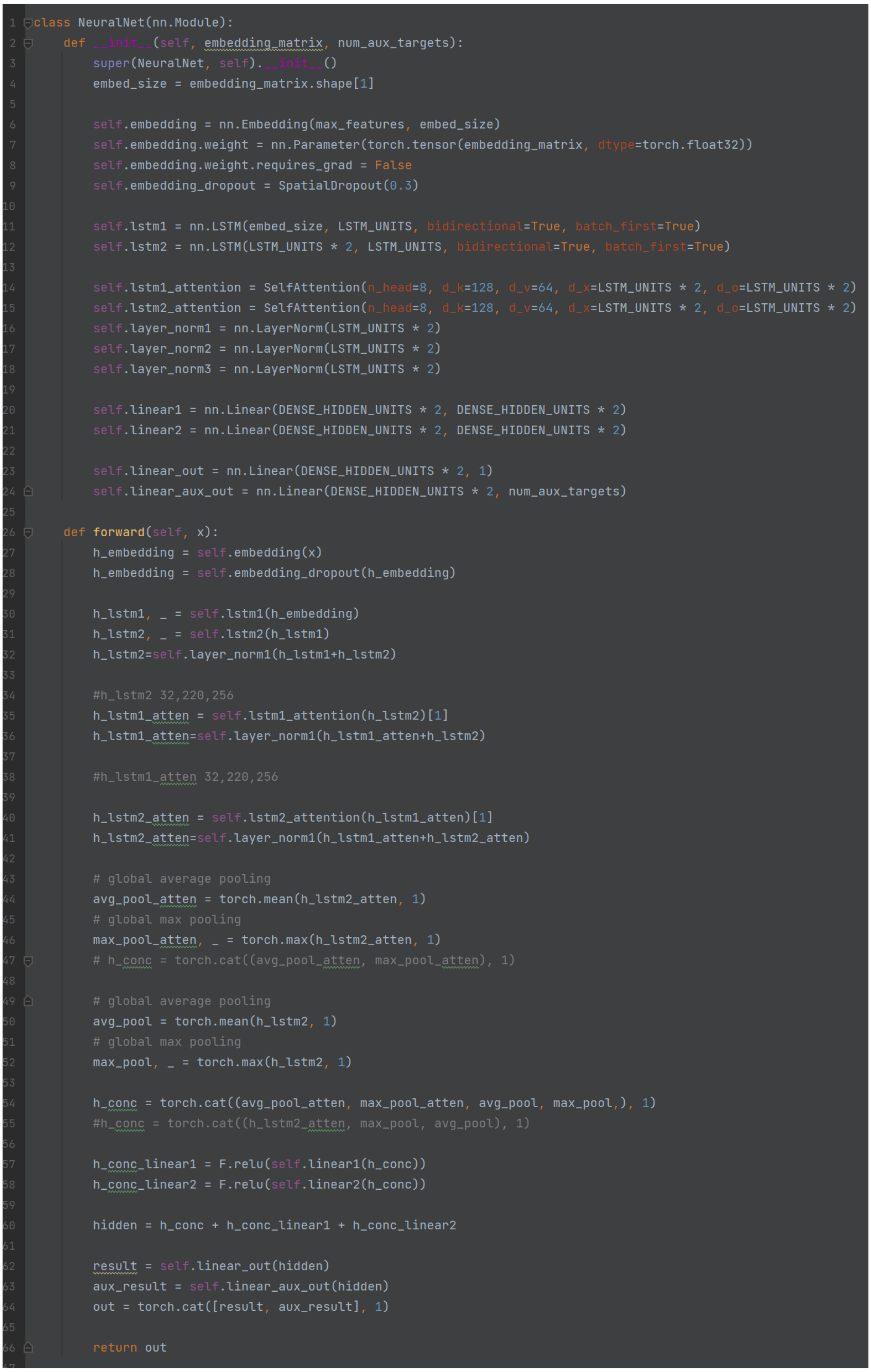


In order to see the effect of CorrelationRemover, we also visualized the changes in the correlation matrix after the data set was transformed. Due to rounding, some 0.0 values appear as -0.0. Either way, CorrelationRemover successfully removes all correlations between "muslim", "black" and other columns, while preserving the correlations between other features.



Model Design

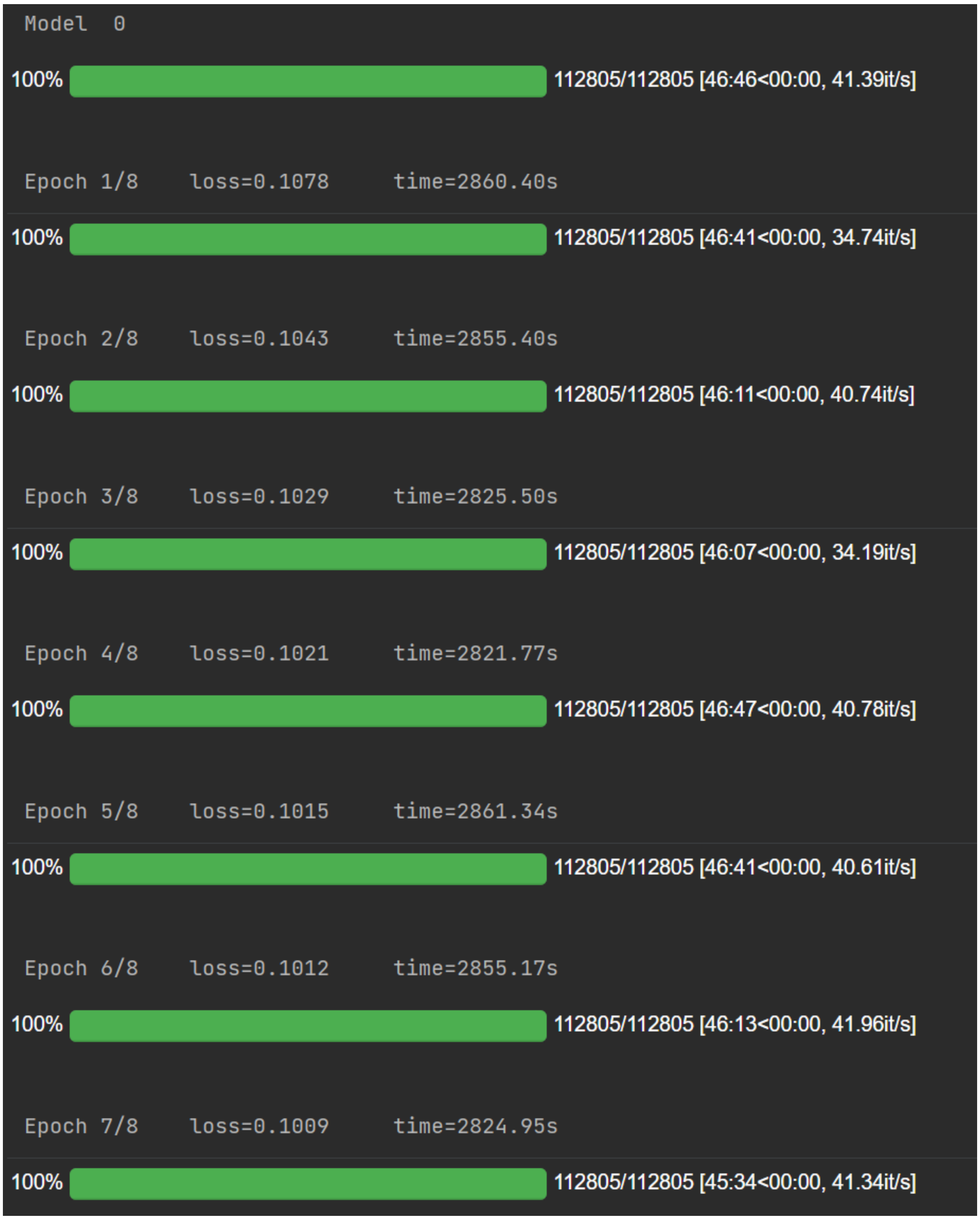
In this section, we have made improvements based on the sample of simple-lstm-example, adding two layers of attention and considering residual connections. We input the output of lstm2 into lstm1_attention, and then the output of lstm1_attention into lstm2_attention. The attention layer is implemented through SelfAttention, and the specific implementation of SelfAttention can be found in the lstm_attention_7.ipynb file. In addition, we have also added residual connections in lstm1 and lstm2, lstm2 and lstm1_attention, lstm1_attention and lstm2_attention, which helps to improve the model accuracy.



```python
class NeuralNet(nn.Module):
    def __init__(self, embedding_matrix, num_aux_targets):
        super(NeuralNet, self).__init__()
        embed_size = embedding_matrix.shape[1]

        self.embedding = nn.Embedding(max_features, embed_size)
        self.embedding.weight = nn.Parameter(torch.tensor(embedding_matrix, dtype=torch.float32))
        self.embedding.weight.requires_grad = False
        self.embedding_dropout = SpatialDropout(0.3)

        self.lstm1 = nn.LSTM(embed_size, LSTM_UNITS, bidirectional=True, batch_first=True)
        self.lstm2 = nn.LSTM(LSTM_UNITS * 2, LSTM_UNITS, bidirectional=True, batch_first=True)

        self.lstm1_attention = SelfAttention(n_head=8, d_k=128, d_v=64, d_x=LSTM_UNITS * 2, d_o=LSTM_UNITS * 2)
        self.lstm2_attention = SelfAttention(n_head=8, d_k=128, d_v=64, d_x=LSTM_UNITS * 2, d_o=LSTM_UNITS * 2)
        self.layer_norm1 = nn.LayerNorm(LSTM_UNITS * 2)
        self.layer_norm2 = nn.LayerNorm(LSTM_UNITS * 2)
        self.layer_norm3 = nn.LayerNorm(LSTM_UNITS * 2)

        self.linear1 = nn.Linear(DENSE_HIDDEN_UNITS * 2, DENSE_HIDDEN_UNITS * 2)
        self.linear2 = nn.Linear(DENSE_HIDDEN_UNITS * 2, DENSE_HIDDEN_UNITS * 2)

        self.linear_out = nn.Linear(DENSE_HIDDEN_UNITS * 2, 1)
        self.linear_aux_out = nn.Linear(DENSE_HIDDEN_UNITS * 2, num_aux_targets)

    def forward(self, x):
        h_embedding = self.embedding(x)
        h_embedding = self.embedding_dropout(h_embedding)

        h_lstm1, _ = self.lstm1(h_embedding)
        h_lstm2, _ = self.lstm2(h_lstm1)
        h_lstm2=self.layer_norm1(h_lstm1+h_lstm2)

        #h_lstm2 32,220,256
        h_lstm1_atten = self.lstm1_attention(h_lstm2)[1]
        h_lstm1_atten=self.layer_norm1(h_lstm1_atten+h_lstm2)

        #h_lstm1_atten 32,220,256

        h_lstm2_atten = self.lstm2_attention(h_lstm1_atten)[1]
        h_lstm2_atten=self.layer_norm1(h_lstm1_atten+h_lstm2_atten)

        # global average pooling
        avg_pool_atten = torch.mean(h_lstm2_atten, 1)
        # global max pooling
        max_pool_atten, _ = torch.max(h_lstm2_atten, 1)
        # h_conc = torch.cat((avg_pool_atten, max_pool_atten), 1)

        # global average pooling
        avg_pool = torch.mean(h_lstm2, 1)
        # global max pooling
        max_pool, _ = torch.max(h_lstm2, 1)

        h_conc = torch.cat((avg_pool_atten, max_pool_atten, avg_pool, max_pool,), 1)
        #h_conc = torch.cat((h_lstm2_atten, max_pool, avg_pool), 1)

        h_conc_linear1 = F.relu(self.linear1(h_conc))
        h_conc_linear2 = F.relu(self.linear2(h_conc))

        hidden = h_conc + h_conc_linear1 + h_conc_linear2

        result = self.linear_out(hidden)
        aux_result = self.linear_aux_out(hidden)
        out = torch.cat([result, aux_result], 1)

        return out
```

Train

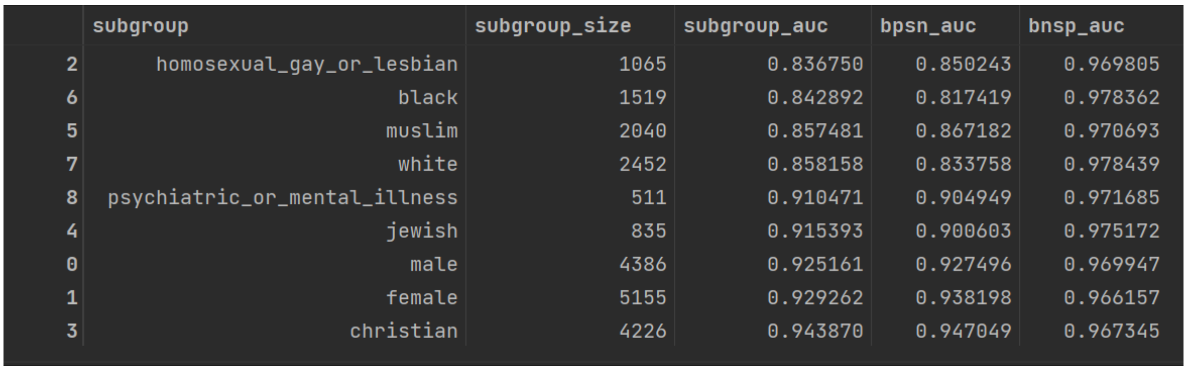
During the training process, we trained for 8 epochs. By printing the results, it was found that the loss reached **0.1078** right from the beginning, thanks to a well-designed model. The loss gradually decreased throughout the training process, indicating an improvement in model performance. The loss corresponding to the model was provided for each iteration cycle. These metrics can be used to evaluate the model's performance and monitor its progress during the training process.



```
Model  0
100% 112805/112805 [46:46<00:00, 41.39it/s]
Epoch 1/8    loss=0.1078      time=2860.40s
100% 112805/112805 [46:41<00:00, 34.74it/s]
Epoch 2/8    loss=0.1043      time=2855.40s
100% 112805/112805 [46:11<00:00, 40.74it/s]
Epoch 3/8    loss=0.1029      time=2825.50s
100% 112805/112805 [46:07<00:00, 34.19it/s]
Epoch 4/8    loss=0.1021      time=2821.77s
100% 112805/112805 [46:47<00:00, 40.78it/s]
Epoch 5/8    loss=0.1015      time=2861.34s
100% 112805/112805 [46:41<00:00, 40.61it/s]
Epoch 6/8    loss=0.1012      time=2855.17s
100% 112805/112805 [46:13<00:00, 41.96it/s]
Epoch 7/8    loss=0.1009      time=2824.95s
100% 112805/112805 [45:34<00:00, 41.34it/s]
```

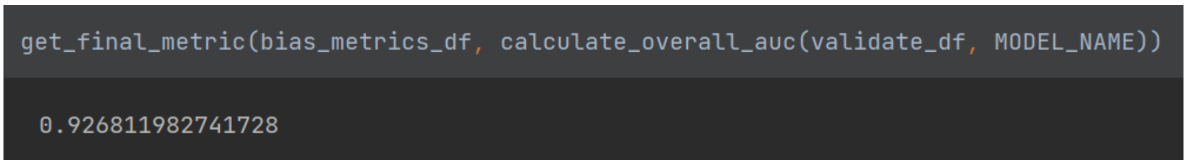
Evaluate our new model for bias using the test set predictions

Using the bias metrics defined above, we can see that the results of the new model have improved in all subgroups and their corresponding three indicators compared to the benchmark results. But homosexual_gay_or_lesbian and black subgroups also have lower AUCs and indicate that the model has lower prediction accuracy on these subgroups.



	subgroup	subgroup_size	subgroup_auc	bpsn_auc	bnsp_auc
2	homosexual_gay_or_lesbian	1065	0.836750	0.850243	0.969805
6	black	1519	0.842892	0.817419	0.978362
5	muslim	2040	0.857481	0.867182	0.970693
7	white	2452	0.858158	0.833758	0.978439
8	psychiatric_or_mental_illness	511	0.910471	0.904949	0.971685
4	jewish	835	0.915393	0.900603	0.975172
0	male	4386	0.925161	0.927496	0.969947
1	female	5155	0.929262	0.938198	0.966157
3	christian	4226	0.943870	0.947049	0.967345

By calling the get_final_metric function and passing in the model's bias indicator DataFrame bias_metrics_df and the overall AUC score, the final evaluation metric is obtained, which is **0.9268**.This value represents the overall performance of the model, taking into account the overall AUC and bias. The higher the value, the better the performance of the model. This score has been greatly improved by proper model design.



```
get_final_metric(bias_metrics_df, calculate_overall_auc(validate_df, MODEL_NAME))
```

```
0.926811982741728
```

Model bias assessment using Demographic Parity

[See "lstm_attention_7.ipynb" for the code]

Here we use gender, race, and ethnicity as characteristics for bias assessment:

```
Overall Positive Rate: 0.0471
Subgroup 'male' Positive Rate: 0.0885
Subgroup 'female' Positive Rate: 0.0795
Subgroup 'christian' Positive Rate: 0.0665
Subgroup 'muslim' Positive Rate: 0.1353
Subgroup 'jewish' Positive Rate: 0.1087
Subgroup 'white' Positive Rate: 0.1617
Subgroup 'black' Positive Rate: 0.1710
Disparity difference for 'male': 0.0413
Disparity difference for 'female': 0.0324
Disparity difference for 'christian': 0.0194
Disparity difference for 'muslim': 0.0882
Disparity difference for 'jewish': 0.0616
Disparity difference for 'white': 0.1146
Disparity difference for 'black': 0.1238
Disparity ratio for 'male': 0.5327
Disparity ratio for 'female': 0.5928
Disparity ratio for 'christian': 0.7083
Disparity ratio for 'muslim': 0.3483
Disparity ratio for 'jewish': 0.4335
Disparity ratio for 'white': 0.2915
Disparity ratio for 'black': 0.2757
```

Synthesis to a Ratio	Attribute	Value
Smallest Difference	christian	0.0194
Largest Difference	black	0.1238
Smallest ratio	black	0.2757
Maximum ratio	christian	0.7083

- The difference between the **Christian** subgroup and the overall predicted positive proportion is the smallest, only **0.0194**. At the same time, the ratio of the positive predicted proportion to the overall positive predicted proportion is the largest, **0.7083**, indicating that in the Christian subgroup, the model's predictions are almost consistent with the overall prediction, the deviation is minimal.

- The difference between the **black** subgroup and the overall predicted positive class proportion is the largest, **0.1238**. At the same time, the ratio of the positive class prediction proportion to the overall positive class prediction ratio is the smallest, only **0.2757**, indicating that there is a large deviation between the model's prediction and the overall prediction, which requires special attention and improvements.
- The new model improves all subgroups with large differences, especially white and black.

  Disparity difference for 'male': 0.0573 ->0.0413

  Disparity difference for 'muslim': 0.0972 -> 0.0882
  Disparity difference for 'white': 0.1563 ->0.1146
  Disparity difference for 'black': 0.1637 ->0.1238
- Although the new model performs well, it takes a long time to train, which takes about 2800s per epoch.