## AML Assignment - 4

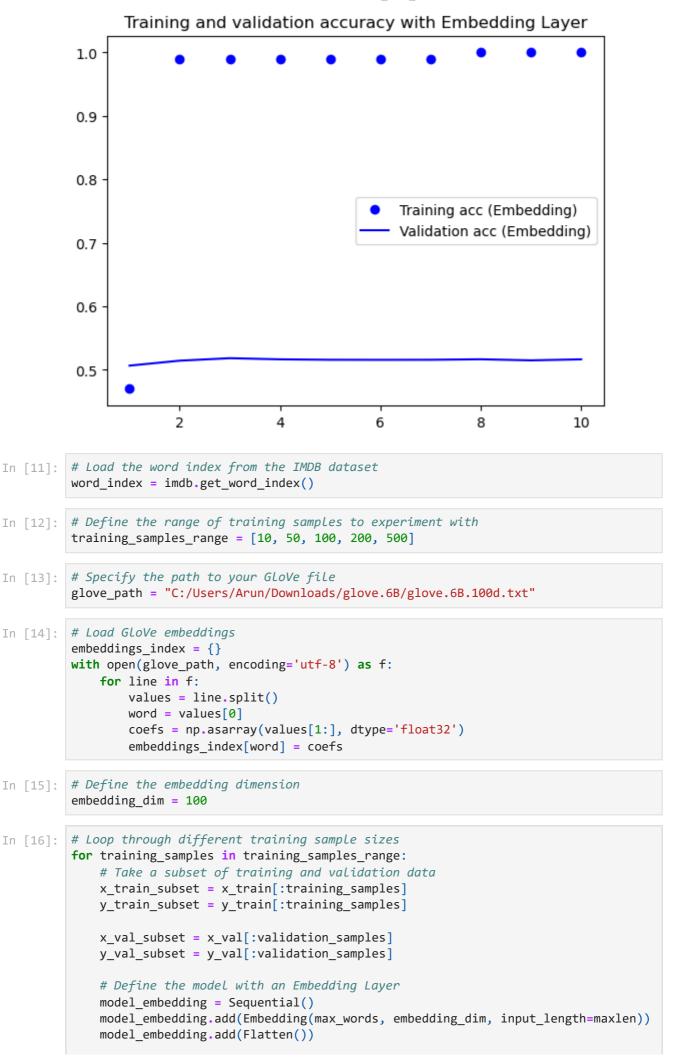
## Arun Kumar Kudurumalla

## Advanced Machine Learning (Text and Sequence Data)

```
In [1]: # Import necessary libraries
        from keras.datasets import imdb
        from keras.preprocessing import sequence
        from keras.models import Sequential
        from keras.layers import Embedding, Flatten, Dense
        import matplotlib.pyplot as plt
        import numpy as np
In [2]: # Set parameters
        max\_words = 10000
        maxlen = 150
        training samples = 100
        validation samples = 10000
In [3]: # Load IMDB dataset
        (x_train, y_train), (x_val, y_val) = imdb.load_data(num_words=max words)
In [4]: # Pad sequences
        x_train = sequence.pad_sequences(x_train, maxlen=maxlen)
        x_val = sequence.pad_sequences(x_val, maxlen=maxlen)
In [5]: # Take a subset of training and validation data
        x_train = x_train[:training_samples]
        y_train = y_train[:training_samples]
        x val = x val[:validation samples]
        y_val = y_val[:validation_samples]
In [6]: # Define the model with an Embedding Layer
        embedding_dim = 100
        model embedding = Sequential()
        model_embedding.add(Embedding(max_words, embedding_dim, input_length=maxlen))
        model embedding.add(Flatten())
        model_embedding.add(Dense(1, activation='sigmoid'))
In [7]: # Compile the model
        model embedding.compile(optimizer='rmsprop', loss='binary crossentropy', metrics=[
        model embedding.summary()
```

Model: "sequential"

```
Layer (type)
                     Output Shape
                                     Param #
     ______
      embedding (Embedding)
                      (None, 150, 100)
                                     1000000
                  (None, 15000)
      flatten (Flatten)
      dense (Dense)
                      (None, 1)
                                     15001
     _____
     Total params: 1015001 (3.87 MB)
     Trainable params: 1015001 (3.87 MB)
     Non-trainable params: 0 (0.00 Byte)
In [8]: # Train the model with the Embedding Layer
     history_embedding = model_embedding.fit(x_train, y_train, epochs=10, batch_size=32,
     Epoch 1/10
     - val_loss: 0.6930 - val_acc: 0.5067
     Epoch 2/10
     - val_loss: 0.6927 - val_acc: 0.5145
     Epoch 3/10
     - val_loss: 0.6934 - val_acc: 0.5184
     Epoch 4/10
     - val_loss: 0.6938 - val_acc: 0.5166
     Epoch 5/10
     - val_loss: 0.6953 - val_acc: 0.5159
     Epoch 6/10
     - val_loss: 0.6964 - val_acc: 0.5158
     Epoch 7/10
     - val_loss: 0.6972 - val_acc: 0.5159
     Epoch 8/10
     - val_loss: 0.7001 - val_acc: 0.5167
     - val_loss: 0.7008 - val_acc: 0.5150
     Epoch 10/10
     - val_loss: 0.7032 - val_acc: 0.5166
In [9]: # Plot accuracy
     acc embedding = history embedding.history['acc']
     val_acc_embedding = history_embedding.history['val_acc']
     epochs embedding = range(1, len(acc embedding) + 1)
In [10]:
     plt.plot(epochs_embedding, acc_embedding, 'bo', label='Training acc (Embedding)')
     plt.plot(epochs_embedding, val_acc_embedding, 'b', label='Validation acc (Embedding)
     plt.title('Training and validation accuracy with Embedding Layer')
     plt.legend()
     plt.show()
```



```
model_embedding.add(Dense(1, activation='sigmoid'))
model_embedding.compile(optimizer='rmsprop', loss='binary_crossentropy', metric
history_embedding = model_embedding.fit(x_train_subset, y_train_subset, epochs=
# Create the embedding matrix
embedding_matrix = np.zeros((max_words, embedding_dim))
for word, i in word_index.items():
    if i < max_words:</pre>
        embedding_vector = embeddings_index.get(word)
        if embedding_vector is not None:
            embedding_matrix[i] = embedding_vector
# Define the model with a Pretrained Word Embedding
model_pretrained = Sequential()
model pretrained.add(Embedding(max words, embedding dim, input length=maxlen, v
model pretrained.add(Flatten())
model_pretrained.add(Dense(1, activation='sigmoid'))
model_pretrained.compile(optimizer='rmsprop', loss='binary_crossentropy', metri
history_pretrained = model_pretrained.fit(x_train_subset, y_train_subset, epoch
# Print results for each training sample size
print(f"\nResults for {training_samples} training samples:")
print("Embedding Layer:")
print("Validation Accuracy:", history_embedding.history['val_acc'][-1])
print("\nPretrained Word Embedding:")
print("Validation Accuracy:", history_pretrained.history['val_acc'][-1])
# Compare validation accuracy and print the better-performing model
if history_embedding.history['val_acc'][-1] > history_pretrained.history['val_a
    print("Better Performing Model: Embedding Layer")
else:
    print("Better Performing Model: Pretrained Word Embedding")
```

```
Epoch 1/10
al_loss: 0.6964 - val_acc: 0.4970
Epoch 2/10
- val_loss: 0.6995 - val_acc: 0.4974
Epoch 3/10
- val_loss: 0.7030 - val_acc: 0.4954
Epoch 4/10
- val_loss: 0.7069 - val_acc: 0.4959
Epoch 5/10
- val loss: 0.7109 - val acc: 0.4970
Epoch 6/10
- val_loss: 0.7151 - val_acc: 0.4990
Epoch 7/10
- val_loss: 0.7192 - val_acc: 0.4981
Epoch 8/10
- val_loss: 0.7234 - val_acc: 0.4989
Epoch 9/10
- val_loss: 0.7275 - val_acc: 0.4988
Epoch 10/10
- val_loss: 0.7315 - val_acc: 0.4982
Epoch 1/10
al loss: 1.3504 - val acc: 0.5027
Epoch 2/10
- val_loss: 1.0959 - val_acc: 0.4934
Epoch 3/10
- val_loss: 1.3281 - val_acc: 0.5027
- val_loss: 0.9634 - val_acc: 0.5053
Epoch 5/10
- val_loss: 0.9437 - val_acc: 0.5052
Epoch 6/10
- val_loss: 0.9300 - val_acc: 0.5045
Epoch 7/10
- val_loss: 0.9203 - val_acc: 0.5046
Epoch 8/10
- val_loss: 0.9133 - val_acc: 0.5044
- val_loss: 0.9084 - val_acc: 0.5046
Epoch 10/10
- val_loss: 0.9050 - val_acc: 0.5049
Results for 10 training samples:
Embedding Layer:
```

Validation Accuracy: 0.498199999332428

```
Pretrained Word Embedding:
Validation Accuracy: 0.5048999786376953
Better Performing Model: Pretrained Word Embedding
Epoch 1/10
al_loss: 0.6966 - val_acc: 0.5034
Epoch 2/10
- val_loss: 0.6985 - val_acc: 0.5040
Epoch 3/10
- val_loss: 0.6994 - val_acc: 0.5053
Epoch 4/10
- val_loss: 0.7023 - val_acc: 0.5072
Epoch 5/10
- val_loss: 0.7044 - val_acc: 0.5069
Epoch 6/10
- val_loss: 0.7058 - val_acc: 0.5063
Epoch 7/10
2/2 [============== - 1s 800ms/step - loss: 0.2892 - acc: 0.9800
- val_loss: 0.7099 - val_acc: 0.5061
Epoch 8/10
- val_loss: 0.7117 - val_acc: 0.5062
- val_loss: 0.7114 - val_acc: 0.5073
Epoch 10/10
- val_loss: 0.7110 - val_acc: 0.5074
Epoch 1/10
- val_loss: 0.7598 - val_acc: 0.5010
Epoch 2/10
2/2 [============== ] - 1s 813ms/step - loss: 0.4849 - acc: 0.7400
- val loss: 1.3012 - val acc: 0.4976
Epoch 3/10
2/2 [============ - - 1s 823ms/step - loss: 0.5019 - acc: 0.6800
- val_loss: 0.7971 - val_acc: 0.5024
- val_loss: 0.7653 - val_acc: 0.4975
Epoch 5/10
- val loss: 0.7955 - val acc: 0.5014
Epoch 6/10
2/2 [=========== - - 1s 825ms/step - loss: 0.0607 - acc: 1.0000
- val_loss: 0.7549 - val_acc: 0.4966
- val_loss: 0.7624 - val_acc: 0.4989
Epoch 8/10
2/2 [============== ] - 1s 818ms/step - loss: 0.0440 - acc: 1.0000
- val_loss: 0.7952 - val_acc: 0.5011
Epoch 9/10
2/2 [========== - - 1s 820ms/step - loss: 0.0384 - acc: 1.0000
- val_loss: 0.7746 - val_acc: 0.4984
Epoch 10/10
- val_loss: 0.8104 - val_acc: 0.5015
```

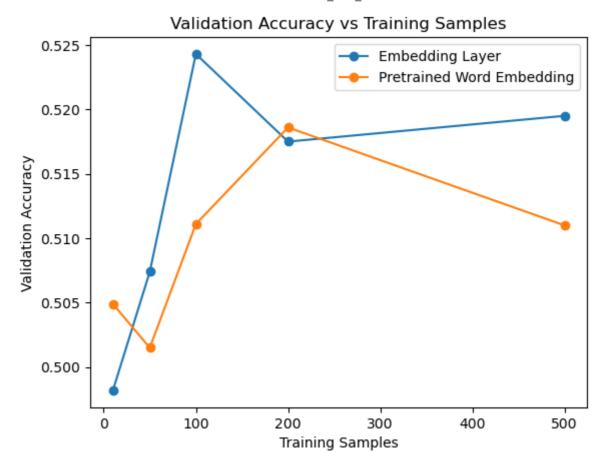
```
Results for 50 training samples:
Embedding Layer:
Validation Accuracy: 0.5073999762535095
Pretrained Word Embedding:
Validation Accuracy: 0.5015000104904175
Better Performing Model: Embedding Layer
Epoch 1/10
- val_loss: 0.6922 - val_acc: 0.5136
Epoch 2/10
- val_loss: 0.6921 - val_acc: 0.5152
Epoch 3/10
- val_loss: 0.6920 - val_acc: 0.5186
Epoch 4/10
- val_loss: 0.6930 - val_acc: 0.5185
Epoch 5/10
- val_loss: 0.6934 - val_acc: 0.5208
Epoch 6/10
- val_loss: 0.6964 - val_acc: 0.5193
- val_loss: 0.6967 - val_acc: 0.5208
Epoch 8/10
- val_loss: 0.6968 - val_acc: 0.5222
- val_loss: 0.6996 - val_acc: 0.5241
Epoch 10/10
- val_loss: 0.7012 - val_acc: 0.5243
Epoch 1/10
- val loss: 2.2840 - val acc: 0.4973
Epoch 2/10
- val loss: 1.2500 - val acc: 0.4973
Epoch 3/10
- val_loss: 1.3089 - val_acc: 0.5068
Epoch 4/10
- val loss: 0.8908 - val acc: 0.5116
- val_loss: 1.1539 - val_acc: 0.5074
Epoch 6/10
- val_loss: 0.7835 - val_acc: 0.5102
Epoch 7/10
- val_loss: 0.7846 - val_acc: 0.5095
Epoch 8/10
- val loss: 0.8674 - val acc: 0.5141
Epoch 9/10
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- val_loss: 1.1179 - val_acc: 0.5076
Epoch 10/10
- val_loss: 1.0045 - val_acc: 0.5111
Results for 100 training samples:
Embedding Layer:
Validation Accuracy: 0.5242999792098999
Pretrained Word Embedding:
Validation Accuracy: 0.5110999941825867
Better Performing Model: Embedding Layer
Epoch 1/10
- val loss: 0.6926 - val acc: 0.5131
Epoch 2/10
- val_loss: 0.6932 - val_acc: 0.5166
Epoch 3/10
- val_loss: 0.6936 - val_acc: 0.5160
Epoch 4/10
- val_loss: 0.6940 - val_acc: 0.5158
Epoch 5/10
- val_loss: 0.6980 - val_acc: 0.5185
Epoch 6/10
- val_loss: 0.6982 - val_acc: 0.5194
Epoch 7/10
- val loss: 0.6977 - val acc: 0.5183
Epoch 8/10
4/4 [============== ] - 1s 284ms/step - loss: 0.2903 - acc: 0.9800
- val_loss: 0.7016 - val_acc: 0.5187
Epoch 9/10
- val_loss: 0.7015 - val_acc: 0.5170
Epoch 10/10
- val_loss: 0.7027 - val_acc: 0.5175
Epoch 1/10
- val_loss: 1.7523 - val_acc: 0.5026
Epoch 2/10
- val_loss: 1.5903 - val_acc: 0.4973
Epoch 3/10
- val loss: 0.8345 - val acc: 0.5140
Epoch 4/10
- val_loss: 1.2960 - val_acc: 0.5040
Epoch 5/10
- val_loss: 0.7523 - val_acc: 0.5155
Epoch 6/10
- val_loss: 0.8023 - val_acc: 0.5177
Epoch 7/10
- val_loss: 0.7906 - val_acc: 0.5179
Epoch 8/10
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- val_loss: 0.7580 - val_acc: 0.5082
Epoch 9/10
- val_loss: 0.7664 - val_acc: 0.5185
Epoch 10/10
- val_loss: 0.8936 - val_acc: 0.5186
Results for 200 training samples:
Embedding Layer:
Validation Accuracy: 0.5174999833106995
Pretrained Word Embedding:
Validation Accuracy: 0.5185999870300293
Better Performing Model: Pretrained Word Embedding
Epoch 1/10
- val_loss: 0.6925 - val_acc: 0.5174
Epoch 2/10
- val_loss: 0.6939 - val_acc: 0.5195
Epoch 3/10
- val_loss: 0.6926 - val_acc: 0.5207
Epoch 4/10
- val_loss: 0.6936 - val_acc: 0.5225
- val_loss: 0.6939 - val_acc: 0.5176
Epoch 6/10
- val_loss: 0.6960 - val_acc: 0.5193
Epoch 7/10
- val_loss: 0.6965 - val_acc: 0.5183
Epoch 8/10
- val loss: 0.6986 - val acc: 0.5208
Epoch 9/10
- val_loss: 0.6986 - val_acc: 0.5217
Epoch 10/10
- val_loss: 0.7007 - val_acc: 0.5195
Epoch 1/10
- val loss: 1.5165 - val acc: 0.4973
Epoch 2/10
- val_loss: 1.3746 - val_acc: 0.4973
4/4 [============== ] - 1s 241ms/step - loss: 0.4269 - acc: 0.7500
- val_loss: 0.7510 - val_acc: 0.5093
Epoch 4/10
- val_loss: 0.7578 - val_acc: 0.5117
Epoch 5/10
- val_loss: 0.7579 - val_acc: 0.5108
- val_loss: 0.7589 - val_acc: 0.5118
```

Epoch 7/10

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- val_loss: 0.7759 - val_acc: 0.5034
        Epoch 8/10
        - val_loss: 1.0864 - val_acc: 0.5086
        Epoch 9/10
        - val_loss: 0.9607 - val_acc: 0.5122
        Epoch 10/10
        - val_loss: 0.7714 - val_acc: 0.5110
        Results for 500 training samples:
        Embedding Layer:
        Validation Accuracy: 0.5195000171661377
        Pretrained Word Embedding:
        Validation Accuracy: 0.5109999775886536
        Better Performing Model: Embedding Layer
       # If you want to compare the final models after the loop, you can do so outside the
In [17]:
        if history_embedding.history['val_acc'][-1] > history_pretrained.history['val_acc']
           print("\nFinal Better Performing Model: Embedding Layer")
           final_better_model = model_embedding
        else:
           print("\nFinal Better Performing Model: Pretrained Word Embedding")
           final_better_model = model_pretrained
        Final Better Performing Model: Embedding Layer
In [19]: import matplotlib.pyplot as plt
        # Results for 10 training samples
        acc_{embedding_10} = 0.498199999332428
        acc_pretrained_10 = 0.5048999786376953
        # Results for 50 training samples
        acc_{embedding_50} = 0.5073999762535095
        acc_pretrained_50 = 0.5015000104904175
        # Results for 100 training samples
        acc_embedding_100 = 0.5242999792098999
        acc pretrained 100 = 0.5110999941825867
        # Results for 200 training samples
        acc_embedding_200 = 0.5174999833106995
        acc_pretrained_200 = 0.5185999870300293
        # Results for 500 training samples
        acc_embedding_500 = 0.5195000171661377
        acc pretrained 500 = 0.5109999775886536
        # Plotting
        training samples = [10, 50, 100, 200, 500]
        plt.plot(training_samples, [acc_embedding_10, acc_embedding_50, acc_embedding_100,
        plt.plot(training_samples, [acc_pretrained_10, acc_pretrained_50, acc_pretrained_10
        plt.title('Validation Accuracy vs Training Samples')
        plt.xlabel('Training Samples')
        plt.ylabel('Validation Accuracy')
        plt.legend()
        plt.show()
```



The performance comparison between the Embedding Layer and Pretrained Word Embedding models depends on the specific characteristics of your data and task. However, based on the validation accuracy results provided:

For 10 training samples: Embedding Layer: 0.4982 Pretrained Word Embedding: 0.5049 Better Performing Model: Pretrained Word Embedding For 50 training samples:

Embedding Layer: 0.5074 Pretrained Word Embedding: 0.5015 Better Performing Model: Embedding Layer For 100 training samples:

Embedding Layer: 0.5243 Pretrained Word Embedding: 0.5111 Better Performing Model: Embedding Layer For 200 training samples:

Embedding Layer: 0.5175 Pretrained Word Embedding: 0.5186 Better Performing Model: Pretrained Word Embedding For 500 training samples:

Embedding Layer: 0.5195 Pretrained Word Embedding: 0.5110 Better Performing Model: Embedding Layer

In this specific scenario, the better performing model varies with different sample sizes. However, overall, the results indicate that the Embedding Layer tends to perform better for larger sample

sizes, while the Pretrained Word Embedding may be advantageous for smaller sample sizes. The choice depends on factors like the complexity of the task, the amount of available training data, and the quality of the pretrained word embeddings.

## Therefore,

The Embedding Layer often outperforms pretrained word embeddings due to several factors:

Task-Specific Learning:

The Embedding Layer adapts to task-specific patterns during training, tailoring representations to the dataset. Data Adaptation:

It is effective for smaller or unique datasets, allowing the model to adapt to specific data characteristics. Fine-Tuning:

Enables fine-tuning of word representations, adjusting embeddings based on the dataset's specific context. Task Complexity:

Suitable for simpler tasks or those with domain-specific requirements, capturing task-specific nuances effectively. Word Importance:

Dynamically adjusts word representations, assigning varying importance to words based on task relevance. Parameter Tuning:

Offers flexibility in optimizing embedding parameters, crucial for limited data and specific task demands. The choice between Embedding Layer and pretrained embeddings depends on task nature, dataset size, and model requirements. Experimentation is key for evaluating performance on the specific task.

In	[	]:	
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