da24c005

November 14, 2024

1 ML Challenge

2 DA24C005

[2]:
```
import tensorflow as tf
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MultiLabelBinarizer
from scipy.sparse import csr_matrix
```

[3]:
```
embedding1 = '/kaggle/input/challenge-dataset/embeddings_1.npy'
label1 = '/kaggle/input/challenge-dataset/icd_codes_1.txt'
embedding2 = '/kaggle/input/challenge-dataset/embeddings_2.npy'
label2 = '/kaggle/input/challenge-dataset/icd_codes_2.txt'
test_data = '/kaggle/input/challenge-dataset/test_data.npy'
```

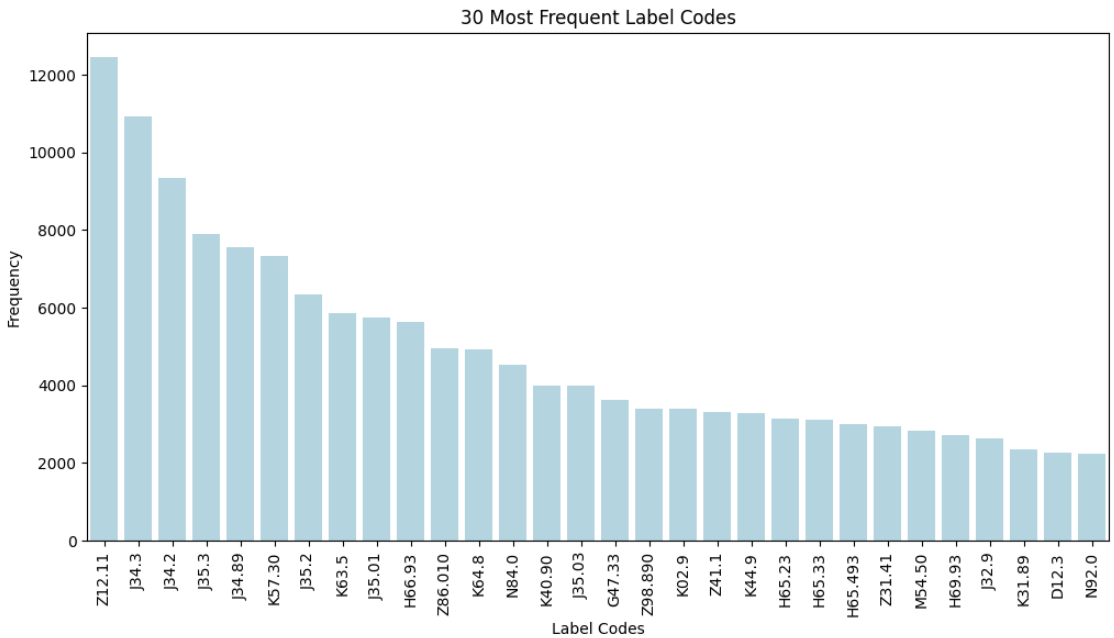
[4]:
```
labels = []
for f in [label1,label2]:
    with open(f, 'r') as file:
        labels += [line.strip().replace("'", "").split(';') for line in file]

embeddings1 = np.load(embedding1)
embeddings2 = np.load(embedding2)
embeddings = np.vstack([embeddings1, embeddings2])
```

2.0.1 Multi hot encoding to transform text labels into binary representation as ML models can only process numerical input

[5]:
```
mlb = MultiLabelBinarizer()
multihot_labels = mlb.fit_transform(labels)
```

2.0.2 Visualising the most frequent label codes

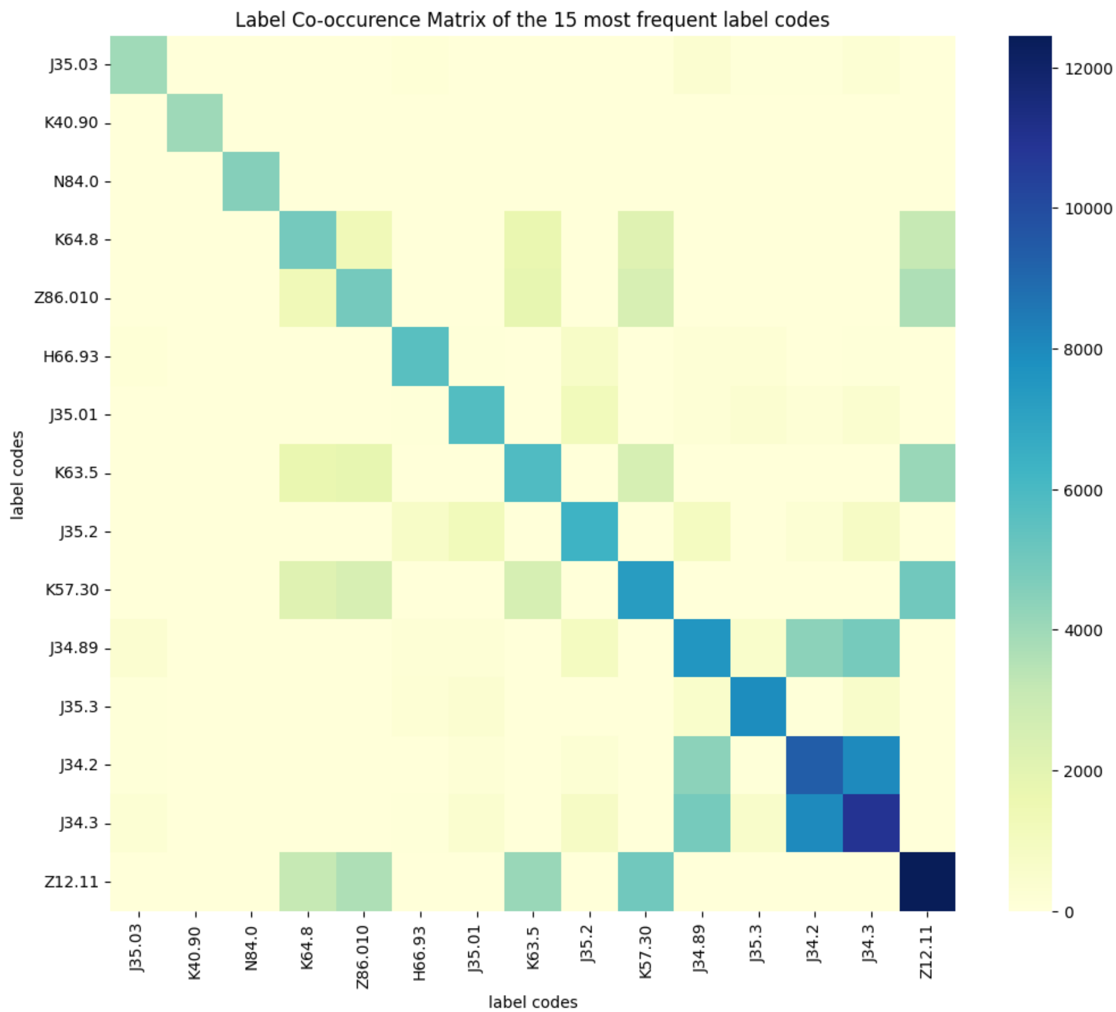
[6]:
```
labels_ = [code for sublist in labels for code in sublist]
label_freq = pd.Series(labels_).value_counts()
plt.figure(figsize=(12, 6))
labels30 = label_freq[:30]
codes = labels30.index
freq = labels30.values
sns.barplot(x=codes, y=freq, color="lightblue")
plt.title('30 Most Frequent Label Codes')
plt.xlabel('Label Codes')
plt.ylabel('Frequency')
plt.xticks(rotation=90)
plt.show()
```



2.0.3 Visualising the co-occurence of the 15 most frequent label codes

[7]:
```
codes = mlb.classes_
labels_ = csr_matrix(multihot_labels)
freqs = labels_.sum(axis=0).A1
indices15 = np.argsort(freqs)[-15:]
labels15 = labels_[:, indices15]
co_occurrence = labels15.T.dot(labels15).toarray()
codes15 = [codes[i] for i in indices15]

plt.figure(figsize=(12, 10))
```

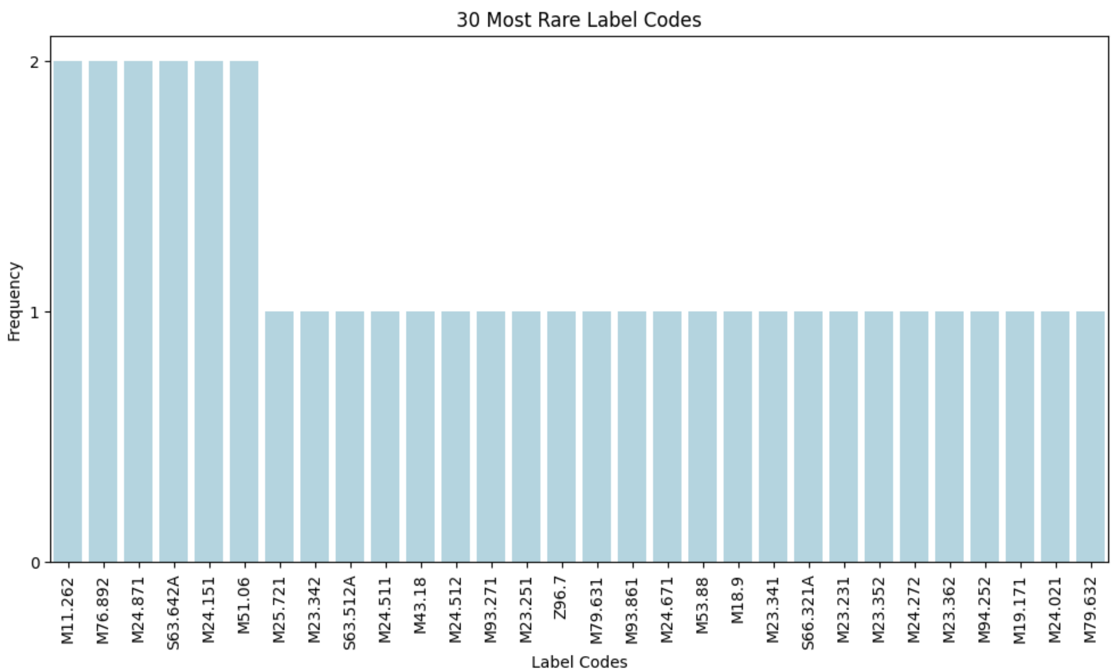
```
sns.heatmap(co_occurrence, annot=False, cmap="YlGnBu", xticklabels=codes15,␣
↪yticklabels=codes15)
plt.title("Label Co-occurence Matrix of the 15 most frequent label codes")
plt.xlabel("label codes")
plt.ylabel("label codes")
plt.show()
```



2.0.4 Visualising the 15 most rarely occuring labels

[12]:
```
plt.figure(figsize=(12, 6))
labels30 = label_freq[-30:]
codes = labels30.index
freq = labels30.values
sns.barplot(x=codes, y=freq, color="lightblue")
plt.title('30 Most Rare Label Codes')
```

```
plt.xlabel('Label Codes')
plt.ylabel('Frequency')
plt.xticks(rotation=90)
plt.yticks(np.arange(0, np.max(freq) + 1, 1))
plt.show()
```



2.0.5 Table to visualise the frequency distribution of the label codes

[13]:

```
labels_ = [code for sublist in labels for code in sublist]
label_freq = pd.Series(labels_).value_counts()
freq = pd.cut(label_freq, bins=[0, 10, 100, 1000, 5000, 10000, float('inf')],
              labels=['<10', '10-100', '100-1000', '1000-5000', '5000-10000',␣
↪'>10000'], right=False)
label_freq_ = freq.value_counts().sort_index()

df = pd.DataFrame({
    'Frequency':label_freq_.index,
    'Label Codes': label_freq_.values
})
df
```

[13]:

	Frequency	Label Codes
0	<10	187
1	10-100	574
2	100-1000	546

```
3    1000-5000          83
4   5000-10000           8
5       >10000           2
```

2.0.6 Oversampling to address class imbalance

[9]:
```python
rare_threshold = 100
label_freq = multihot_labels.sum(axis=0)
rare_idx = np.where(label_freq < rare_threshold)[0]

os_embeds, os_labels = [], []
for i in range(len(embeddings)):
    os_embeds.append(embeddings[i])
    os_labels.append(multihot_labels[i])
    if any(multihot_labels[i][j] == 1 for j in rare_idx):
        os_embeds.append(embeddings[i])
        os_labels.append(multihot_labels[i])

os_embeddings = np.array(os_embeds)
os_labels = np.array(os_labels)

X_train, X_val, y_train, y_val = train_test_split(os_embeddings, os_labels,␣
 ↪test_size=0.001, random_state=1)
```

2.0.7 Custom function to calculate performance of the model using F2 score

[10]:
```python
def f2_score(y_actual, y_pred, threshold=0.5):
    y_actual = tf.cast(y_actual, tf.float32)
    y_pred = tf.cast(y_pred > threshold, tf.float32)

    true_pos = tf.reduce_sum(y_actual * y_pred)
    false_pos = tf.reduce_sum((1 - y_actual) * y_pred)
    false_neg = tf.reduce_sum(y_actual * (1 - y_pred))

    precision = true_pos / (true_pos + false_pos + tf.keras.backend.epsilon())
    recall = true_pos / (true_pos + false_neg + tf.keras.backend.epsilon())

    f2_score = (5 * precision * recall) / (4 * precision + recall + tf.keras.
 ↪backend.epsilon())

    return f2_score
```

2.0.8 Function to predict on test data

[11]:
```
def predict(model, test_data, mlb):
    test_embeddings = np.load(test_data)
    preds = model.predict(test_embeddings)
    pred_labels = (preds > 0.5).astype(int)
    pred_codes = mlb.inverse_transform(pred_labels)
    str_pred = [";".join(codes) for codes in pred_codes]
    submission = pd.DataFrame({'id': np.arange(1, len(str_pred) + 1), 'labels':␣
↪str_pred})
    return submission
```

2.0.9 Using neural network model using different values of dropout and negative_slope

[12]:
```
dropouts = [0.5, 0.6, 0.7, 0.8]
neg_slopes = [0.1, 0.2, 0.3]
results = []

for d in dropouts:
    for ns in neg_slopes:
        model = tf.keras.Sequential([
            tf.keras.layers.Input(shape=(1024,)),
            tf.keras.layers.Dense(2900),
            tf.keras.layers.LeakyReLU(negative_slope=ns),
            tf.keras.layers.BatchNormalization(),
            tf.keras.layers.Dropout(d),
            tf.keras.layers.Dense(2900),
            tf.keras.layers.LeakyReLU(negative_slope=ns),
            tf.keras.layers.BatchNormalization(),
            tf.keras.layers.Dropout(d),
            tf.keras.layers.Dense(1400, activation='sigmoid')
        ])

        model.compile(optimizer='adam',
                      loss='binary_crossentropy',
                      metrics=[f2_score])

        h = model.fit(X_train, y_train, validation_data=(X_val, y_val),␣
↪epochs=65, batch_size=128, verbose=0)

        train_loss = h.history['loss'][-1]
        train_f2 = h.history['f2_score'][-1]
        val_loss = h.history['val_loss'][-1]
        val_f2 = h.history['val_f2_score'][-1]

        results.append({
            'dropout': d,
```

```
            'negative slope': ns,
            'train loss': train_loss,
            'train f2': train_f2,
            'validation loss': val_loss,
            'validation f2': val_f2
        })

        submission = predict(model, test_data, mlb)
        submission.to_csv(f'dropout_{d}_negslope_{ns}.csv', index=False)
```

```
WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1731534386.297263     139 service.cc:145] XLA service 0x78d804004fa0
initialized for platform CUDA (this does not guarantee that XLA will be used).
Devices:
I0000 00:00:1731534386.297315     139 service.cc:153]   StreamExecutor device
(0): Tesla T4, Compute Capability 7.5
I0000 00:00:1731534386.297319     139 service.cc:153]   StreamExecutor device
(1): Tesla T4, Compute Capability 7.5
I0000 00:00:1731534390.275391     139 device_compiler.h:188] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.
```

```
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
3110/3110            4s 1ms/step
```

2.0.10 Visualising the performance of different neural network models on train and validation data

[2]:
```
result_df = pd.DataFrame(results)
result_df
```

[2]:

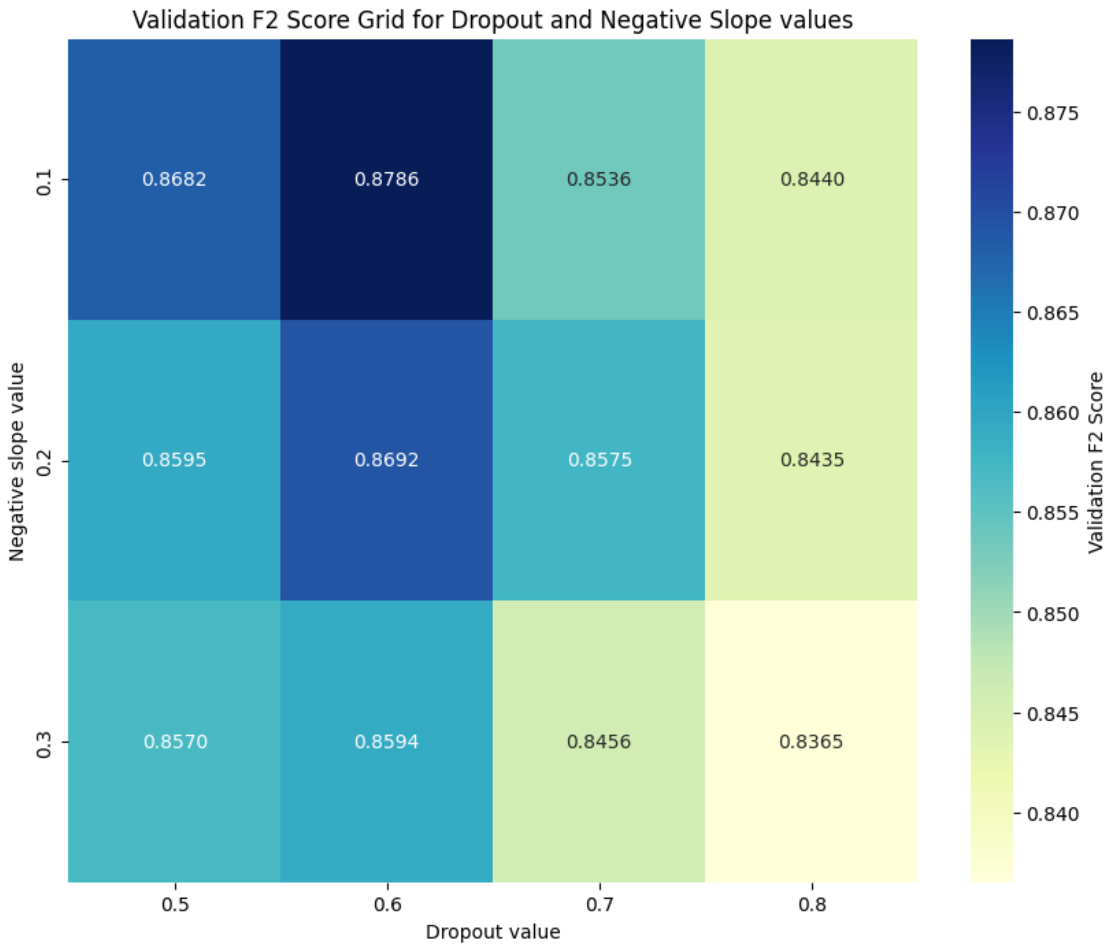
	dropout	negative slope	train loss	train f2	validation loss	\
0	0.5	0.1	0.000626	0.914677	0.001376	
1	0.5	0.2	0.000705	0.903479	0.001323	
2	0.5	0.3	0.000798	0.890446	0.001384	
3	0.6	0.1	0.000841	0.884251	0.001351	
4	0.6	0.2	0.000907	0.874769	0.001306	
5	0.6	0.3	0.000984	0.864075	0.001332	

```
6         0.7              0.1    0.001122  0.845012          0.001443
7         0.7              0.2    0.001160  0.840220          0.001413
8         0.7              0.3    0.001209  0.833573          0.001377
9         0.8              0.1    0.001493  0.794311          0.001646
10        0.8              0.2    0.001512  0.791786          0.001573
11        0.8              0.3    0.001543  0.788541          0.001505

    validation f2
0        0.868200
1        0.859466
2        0.856970
3        0.878619
4        0.869177
5        0.859350
6        0.853594
7        0.857456
8        0.845616
9        0.843956
10       0.843524
11       0.836517
```

2.0.11 Visualising a grid of dropout and negative slope values to help us identity optimal hyperparameter values for our model

[3]:

```python
grid = result_df.pivot(index="negative slope", columns="dropout", values="validation f2")
plt.figure(figsize=(10, 8))
sns.heatmap(grid, annot=True, fmt=".4f", cmap="YlGnBu", cbar_kws={'label': 'Validation F2 Score'})
plt.title("Validation F2 Score Grid for Dropout and Negative Slope values")
plt.xlabel("Dropout value")
plt.ylabel("Negative slope value")
plt.show()
```


Validation F2 Score Grid for Dropout and Negative Slope values
Negative slope value
0.1
0.2
0.3
0.8682
0.8786
0.8536
0.8440
0.8595
0.8692
0.8575
0.8435
0.8570
0.8594
0.8456
0.8365
0.5
0.6
0.7
0.8
Dropout value
Validation F2 Score
0.875
0.870
0.865
0.860
0.855
0.850
0.845
0.840