CS3315 Project: MLP with Keras

In [1]:
```
import numpy as np
import pandas as pd
from sklearn.linear_model import Perceptron
```

In [2]:
```
# import data
filename = 'data/2020.06.19.csv'
df = pd.read_csv(filename)

# sample small subset
# df = df.sample(500000, random_state=78)
df.info()
df.head(2)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 765360 entries, 0 to 765359
Data columns (total 16 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   avg_ipt        765360 non-null  float64
 1   bytes_in       765360 non-null  int64  
 2   bytes_out      765360 non-null  int64  
 3   dest_ip        765360 non-null  int64  
 4   dest_port      740863 non-null  float64
 5   entropy        765360 non-null  float64
 6   num_pkts_out   765360 non-null  int64  
 7   num_pkts_in    765360 non-null  int64  
 8   proto          765360 non-null  int64  
 9   src_ip         765360 non-null  int64  
 10  src_port       740863 non-null  float64
 11  time_end       765360 non-null  int64  
 12  time_start     765360 non-null  int64  
 13  total_entropy  765360 non-null  float64
 14  label          765360 non-null  object 
 15  duration       765360 non-null  float64
dtypes: float64(6), int64(9), object(1)
memory usage: 93.4+ MB
```

Out[2]:

	avg_ipt	bytes_in	bytes_out	dest_ip	dest_port	entropy	num_pkts_out	num_pkts_in	protc
0	7.5	342	3679	786	9200.0	5.436687	2	2	6
1	0.0	0	0	786	55972.0	0.000000	1	1	6

In [3]:
```
# clean data
df.dropna(inplace=True)
df.isna().sum()

# need to clean for features that are 0 and don't make sense (bytes = 0
```

Out[3]:
```
avg_ipt          0
bytes_in         0
bytes_out        0
dest_ip          0
dest_port        0
entropy          0
num_pkts_out     0
num_pkts_in      0
proto            0
src_ip           0
src_port         0
time_end         0
time_start       0
total_entropy    0
label            0
duration         0
dtype: int64
```

In [4]:
```
print('label values:', df['label'].unique())

def ordinal_encoder(category):
    dict = {'benign':0, 'outlier':1, 'malicious':2}
    return dict[category]

print('benign', ordinal_encoder('benign'))
print('outlier', ordinal_encoder('outlier'))
print('malicious', ordinal_encoder('malicious'))
df['label'] = df['label'].apply(ordinal_encoder)
```

```
label values: ['benign' 'outlier' 'malicious']
benign 0
outlier 1
malicious 2
```

In [5]:
```
features = ['avg_ipt',
            'bytes_in',
            'bytes_out',
            'dest_ip',
            'dest_port',
            'entropy',
            'num_pkts_in',
            'num_pkts_out',
            'proto',
            'src_ip',
            'src_port',
            'time_end',
            'time_start',
            'total_entropy',
            'duration']

X = df.loc[:, features]
y = df.loc[:,'label']
```

In [6]:
```
# Scale features
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
# try PolyScaler?

scaler = StandardScaler()
scaler.fit(X)
X = scaler.transform(X)
```

In [7]:
```
# test/train split

from sklearn.model_selection import train_test_split

# 80/20 training/validation split
X_train, X_val, y_train, y_val = train_test_split(X,y, train_size=.8, t

y_train = y_train.to_numpy()
y_val = y_val.to_numpy()

# should print number of shape: (num features, num entries)
print('Training set: ', 'X: ', X_train.shape, 'y: ', y_train.shape, 'Va

print(X_train[1])
print(y_train[1])
```

```
Training set:  X:  (592690, 15) y:  (592690,) Validation set:  X:  (14
8173, 15) printy:  (148173,)
[-0.05565213 -0.24851657 -0.4012423  -0.13191521 -0.1413975  -1.344987
3
 -0.27015576 -0.2850236  -0.40847424 -0.50115682  0.54239382  0.332459
24
  0.33237538 -0.20292837 -0.33436206]
0
```

In [8]:
```
# import tensorflow and keras

import tensorflow as tf
from tensorflow import keras
print(tf.__version__)
print(keras.__version__)

import os
```

```
2022-12-01 20:11:34.181032: I tensorflow/core/platform/cpu_feature_gua
rd.cc:193] This TensorFlow binary is optimized with oneAPI Deep Neural
Network Library (oneDNN) to use the following CPU instructions in perf
ormance-critical operations:  AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the approp
riate compiler flags.
```

```
2.12.0-dev20221112
2.12.0
```

In [9]:
```
# keras sequential API model (pg 299)

model = keras.models.Sequential([
    keras.layers.InputLayer(input_shape=(X_train.shape[1])),
    keras.layers.Dense(300, activation="relu"),
    keras.layers.Dense(200, activation="relu"),
    keras.layers.Dense(3, activation="softmax")
])
print(X_train.shape[1])

model.summary()
```

```
15
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 300)               4800

 dense_1 (Dense)             (None, 200)               60200

 dense_2 (Dense)             (None, 3)                 603

=================================================================
Total params: 65,603
Trainable params: 65,603
Non-trainable params: 0
_________________________________________________________________
```

In [10]:
```
# TODO: adjust kernel initializer or bias initializer?
# https://keras.io/initializers/
```

In [11]:

```
# compile the model
model.compile(loss="sparse_categorical_crossentropy",
              optimizer = "adam",
              metrics="accuracy")
```

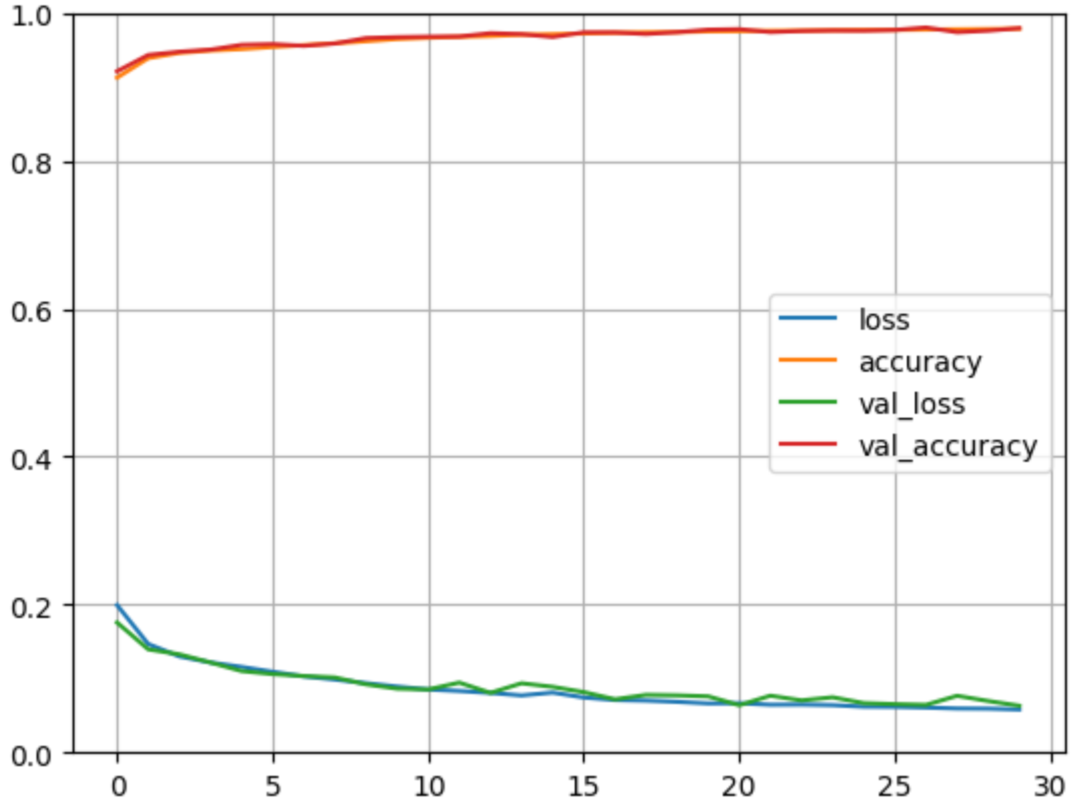
In [12]:
```
# train the model
num_epochs=30
print(X_train.shape)
history = model.fit(X_train, y_train,
                    epochs=num_epochs,
                    validation_data=(X_val, y_val))

# loss is nan -> probably indicative of exploding gradients -- try agai
```

```
(592690, 15)
Epoch 1/30
18522/18522 [==============================] - 36s 2ms/step - loss: 0.
1993 - accuracy: 0.9124 - val_loss: 0.1757 - val_accuracy: 0.9210
Epoch 2/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
1467 - accuracy: 0.9387 - val_loss: 0.1395 - val_accuracy: 0.9430
Epoch 3/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
1299 - accuracy: 0.9459 - val_loss: 0.1327 - val_accuracy: 0.9474
Epoch 4/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
1217 - accuracy: 0.9491 - val_loss: 0.1217 - val_accuracy: 0.9503
Epoch 5/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
1157 - accuracy: 0.9510 - val_loss: 0.1102 - val_accuracy: 0.9567
Epoch 6/30
18522/18522 [==============================] - 33s 2ms/step - loss: 0.
1092 - accuracy: 0.9538 - val_loss: 0.1061 - val_accuracy: 0.9577
Epoch 7/30
18522/18522 [==============================] - 33s 2ms/step - loss: 0.
1029 - accuracy: 0.9564 - val_loss: 0.1034 - val_accuracy: 0.9555
Epoch 8/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.
0987 - accuracy: 0.9589 - val_loss: 0.1014 - val_accuracy: 0.9586
Epoch 9/30
18522/18522 [==============================] - 37s 2ms/step - loss: 0.
0937 - accuracy: 0.9616 - val_loss: 0.0922 - val_accuracy: 0.9659
Epoch 10/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.
0891 - accuracy: 0.9646 - val_loss: 0.0863 - val_accuracy: 0.9671
Epoch 11/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0852 - accuracy: 0.9663 - val_loss: 0.0853 - val_accuracy: 0.9678
Epoch 12/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0832 - accuracy: 0.9676 - val_loss: 0.0945 - val_accuracy: 0.9680
Epoch 13/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0806 - accuracy: 0.9687 - val_loss: 0.0806 - val_accuracy: 0.9725
Epoch 14/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0772 - accuracy: 0.9704 - val_loss: 0.0936 - val_accuracy: 0.9713
Epoch 15/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0810 - accuracy: 0.9712 - val_loss: 0.0888 - val_accuracy: 0.9674
Epoch 16/30
```

```
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0744 - accuracy: 0.9721 - val_loss: 0.0817 - val_accuracy: 0.9737
Epoch 17/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0710 - accuracy: 0.9731 - val_loss: 0.0719 - val_accuracy: 0.9735
Epoch 18/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0702 - accuracy: 0.9739 - val_loss: 0.0779 - val_accuracy: 0.9714
Epoch 19/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0685 - accuracy: 0.9740 - val_loss: 0.0773 - val_accuracy: 0.9739
Epoch 20/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0664 - accuracy: 0.9750 - val_loss: 0.0759 - val_accuracy: 0.9772
Epoch 21/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0666 - accuracy: 0.9752 - val_loss: 0.0639 - val_accuracy: 0.9780
Epoch 22/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0646 - accuracy: 0.9757 - val_loss: 0.0768 - val_accuracy: 0.9740
Epoch 23/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0648 - accuracy: 0.9760 - val_loss: 0.0705 - val_accuracy: 0.9755
Epoch 24/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0641 - accuracy: 0.9765 - val_loss: 0.0747 - val_accuracy: 0.9762
Epoch 25/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0619 - accuracy: 0.9770 - val_loss: 0.0667 - val_accuracy: 0.9759
Epoch 26/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0616 - accuracy: 0.9771 - val_loss: 0.0653 - val_accuracy: 0.9769
Epoch 27/30
18522/18522 [==============================] - 33s 2ms/step - loss: 0.
0607 - accuracy: 0.9774 - val_loss: 0.0644 - val_accuracy: 0.9802
Epoch 28/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0595 - accuracy: 0.9778 - val_loss: 0.0767 - val_accuracy: 0.9738
Epoch 29/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0593 - accuracy: 0.9781 - val_loss: 0.0696 - val_accuracy: 0.9759
Epoch 30/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.
0581 - accuracy: 0.9786 - val_loss: 0.0632 - val_accuracy: 0.9793
```

In [13]:
```python
# plot loss vs. accuracy (HOML p. 305)
import matplotlib.pyplot as plt
pd.DataFrame(history.history).plot()
plt.grid(True)
plt.gca().set_ylim(0,1)
plt.show()
```



In [14]:
```python
# save model
#model.save("project_mlp_2_layers")
```

In [15]:
```python
# test predictions
X_new = X_val
test_pred = np.argmax(model.predict(X_new), axis=-1)
```

```
4631/4631 [==============================] - 4s 775us/step
```

In [16]:
```python
from sklearn.metrics import *
print("Predicted labels:\t", test_pred)
print("Actual labels:\t\t", y_val)
print(classification_report(y_val, test_pred))
```

```
Predicted labels:        [0 1 0 ... 2 2 1]
Actual labels:           [0 1 0 ... 2 2 1]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     75511
           1       0.96      0.92      0.94     24572
           2       0.96      0.98      0.97     48090

    accuracy                           0.98    148173
   macro avg       0.97      0.97      0.97    148173
weighted avg       0.98      0.98      0.98    148173
```

Validate Model with Data from June 2022

In [17]:
```
# import data
filename = 'data/2020.06.20.csv'
df2 = pd.read_csv(filename)

# sample small subset
#df2 = df2.sample(n=100000, random_state=78)
df2.info()
df2.head(2)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 770853 entries, 0 to 770852
Data columns (total 16 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   avg_ipt        770853 non-null  float64
 1   bytes_in       770853 non-null  int64  
 2   bytes_out      770853 non-null  int64  
 3   dest_ip        770853 non-null  int64  
 4   dest_port      770853 non-null  int64  
 5   entropy        770853 non-null  float64
 6   num_pkts_out   770853 non-null  int64  
 7   num_pkts_in    770853 non-null  int64  
 8   proto          770853 non-null  int64  
 9   src_ip         770853 non-null  int64  
 10  src_port       770853 non-null  int64  
 11  time_end       770853 non-null  int64  
 12  time_start     770853 non-null  int64  
 13  total_entropy  770853 non-null  float64
 14  label          770853 non-null  object 
 15  duration       770853 non-null  float64
dtypes: float64(4), int64(11), object(1)
memory usage: 94.1+ MB
```

Out[17]:

	avg_ipt	bytes_in	bytes_out	dest_ip	dest_port	entropy	num_pkts_out	num_pkts_in	pro
0	34.57143	34	29	786	5900	5.040459	7	10	
1	37.00000	34	29	786	5900	5.127916	7	10	

In [18]:
```
# clean data
df2.dropna(inplace=True)
df2.isna().sum()
```

Out[18]:
```
avg_ipt          0
bytes_in         0
bytes_out        0
dest_ip          0
dest_port        0
entropy          0
num_pkts_out     0
num_pkts_in      0
proto            0
src_ip           0
src_port         0
time_end         0
time_start       0
total_entropy    0
label            0
duration         0
dtype: int64
```

In [19]:
```
print('label values:', df2['label'].unique())

def ordinal_encoder(category):
    dict = {'benign':0, 'outlier':1, 'malicious':2}
    return dict[category]

print('benign', ordinal_encoder('benign'))
print('outlier', ordinal_encoder('outlier'))
print('malicious', ordinal_encoder('malicious'))
df2['label'] = df2['label'].apply(ordinal_encoder)
```

```
label values: ['malicious' 'benign' 'outlier']
benign 0
outlier 1
malicious 2
```

In [20]:
```
features = ['avg_ipt',
            'bytes_in',
            'bytes_out',
            'dest_ip',
            'dest_port',
            'entropy',
            'num_pkts_in',
            'num_pkts_out',
            'proto',
            'src_ip',
            'src_port',
            'time_end',
            'time_start',
            'total_entropy',
            'duration']

X_22 = df2.loc[:, features]
y_22 = df2.loc[:,'label']
```

In [21]:
```
# Scale features
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
# try PolyScaler?

scaler = StandardScaler()
scaler.fit(X_22)
X_22 = scaler.transform(X_22)

# change labels to numpy
y_22 = y_22.to_numpy()
```

In [22]:
```
# test predictions
X_test_new = X_22
test_pred_22 = np.argmax(model.predict(X_test_new), axis=-1)
```

```
24090/24090 [==============================] - 19s 778us/step
```

In [23]:
```
print("Predicted labels:\t", test_pred_22)
print("Actual labels:\t\t", y_22)
print(classification_report(y_22, test_pred_22))
```

```
Predicted labels:        [2 2 2 ... 2 2 2]
Actual labels:           [2 2 2 ... 1 1 2]
              precision    recall  f1-score   support

           0       1.00      0.87      0.93    366310
           1       0.26      0.23      0.24     69389
           2       0.76      0.88      0.82    335154

    accuracy                           0.82    770853
   macro avg       0.67      0.66      0.66    770853
weighted avg       0.83      0.82      0.82    770853
```

In [ ]:
```

```