CS3315 Project: MLP with Keras, Dropout

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

In [2]:
```python
# 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	proto
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]:
```python
# 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]:
```python
# 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]:
```python
# 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, test_s

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, 'Validat

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

```
Training set:  X:  (592690, 15) y:  (592690,) Validation set:  X:  (148173,
15) printy:  (148173,)
[-0.05565213 -0.24851657 -0.4012423  -0.13191521 -0.1413975  -1.3449873
 -0.27015576 -0.2850236  -0.40847424 -0.50115682  0.54239382  0.33245924
  0.33237538 -0.20292837 -0.33436206]
0
```

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

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

import os
```

```
2022-12-01 21:00:35.449590: I tensorflow/core/platform/cpu_feature_guard.c
c:193] This TensorFlow binary is optimized with oneAPI Deep Neural Network
Library (oneDNN) to use the following CPU instructions in performance-criti
cal operations:  AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
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.Dropout(.5),
    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

 dropout (Dropout)           (None, 300)               0

 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")
```

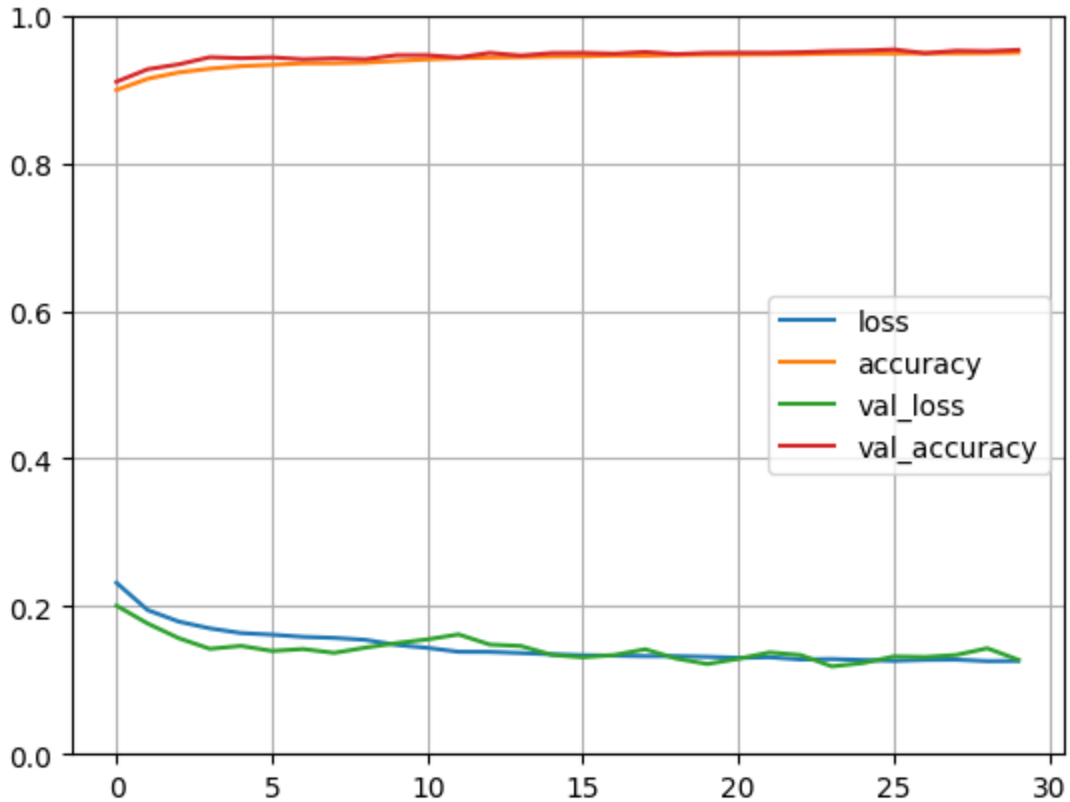
In [12]:
```
# train the model
num_epochs=30
print(X_train.shape)
history = model.fit(X_train, y_train,
                    epochs=num_epochs,
                    validation_data=(X_val, y_val))

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

```
(592690, 15)
Epoch 1/30
18522/18522 [==============================] - 38s 2ms/step - loss: 0.2318
- accuracy: 0.8989 - val_loss: 0.2009 - val_accuracy: 0.9102
Epoch 2/30
18522/18522 [==============================] - 38s 2ms/step - loss: 0.1950
- accuracy: 0.9141 - val_loss: 0.1768 - val_accuracy: 0.9270
Epoch 3/30
18522/18522 [==============================] - 36s 2ms/step - loss: 0.1793
- accuracy: 0.9227 - val_loss: 0.1569 - val_accuracy: 0.9337
Epoch 4/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.1702
- accuracy: 0.9277 - val_loss: 0.1425 - val_accuracy: 0.9433
Epoch 5/30
18522/18522 [==============================] - 37s 2ms/step - loss: 0.1638
- accuracy: 0.9312 - val_loss: 0.1464 - val_accuracy: 0.9420
Epoch 6/30
18522/18522 [==============================] - 37s 2ms/step - loss: 0.1617
- accuracy: 0.9330 - val_loss: 0.1396 - val_accuracy: 0.9431
Epoch 7/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.1587
- accuracy: 0.9350 - val_loss: 0.1422 - val_accuracy: 0.9405
Epoch 8/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1573
- accuracy: 0.9351 - val_loss: 0.1370 - val_accuracy: 0.9418
Epoch 9/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1546
- accuracy: 0.9360 - val_loss: 0.1441 - val_accuracy: 0.9406
Epoch 10/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1478
- accuracy: 0.9383 - val_loss: 0.1502 - val_accuracy: 0.9461
Epoch 11/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.1438
- accuracy: 0.9404 - val_loss: 0.1553 - val_accuracy: 0.9460
Epoch 12/30
18522/18522 [==============================] - 37s 2ms/step - loss: 0.1385
- accuracy: 0.9420 - val_loss: 0.1620 - val_accuracy: 0.9430
Epoch 13/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.1383
- accuracy: 0.9429 - val_loss: 0.1483 - val_accuracy: 0.9492
Epoch 14/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1368
- accuracy: 0.9435 - val_loss: 0.1463 - val_accuracy: 0.9455
Epoch 15/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.1351
- accuracy: 0.9443 - val_loss: 0.1343 - val_accuracy: 0.9489
Epoch 16/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.1338
- accuracy: 0.9446 - val_loss: 0.1311 - val_accuracy: 0.9491
Epoch 17/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1333
- accuracy: 0.9455 - val_loss: 0.1340 - val_accuracy: 0.9480
Epoch 18/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.1326
- accuracy: 0.9453 - val_loss: 0.1419 - val_accuracy: 0.9504
Epoch 19/30
```

```
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1326
- accuracy: 0.9463 - val_loss: 0.1293 - val_accuracy: 0.9474
Epoch 20/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.1316
- accuracy: 0.9467 - val_loss: 0.1220 - val_accuracy: 0.9491
Epoch 21/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.1303
- accuracy: 0.9469 - val_loss: 0.1290 - val_accuracy: 0.9493
Epoch 22/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1310
- accuracy: 0.9472 - val_loss: 0.1376 - val_accuracy: 0.9493
Epoch 23/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1281
- accuracy: 0.9474 - val_loss: 0.1340 - val_accuracy: 0.9501
Epoch 24/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1286
- accuracy: 0.9482 - val_loss: 0.1187 - val_accuracy: 0.9515
Epoch 25/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1274
- accuracy: 0.9484 - val_loss: 0.1232 - val_accuracy: 0.9522
Epoch 26/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1262
- accuracy: 0.9484 - val_loss: 0.1321 - val_accuracy: 0.9538
Epoch 27/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1276
- accuracy: 0.9487 - val_loss: 0.1314 - val_accuracy: 0.9487
Epoch 28/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1278
- accuracy: 0.9486 - val_loss: 0.1341 - val_accuracy: 0.9521
Epoch 29/30
18522/18522 [==============================] - 34s 2ms/step - loss: 0.1258
- accuracy: 0.9488 - val_loss: 0.1432 - val_accuracy: 0.9514
Epoch 30/30
18522/18522 [==============================] - 35s 2ms/step - loss: 0.1260
- accuracy: 0.9496 - val_loss: 0.1276 - val_accuracy: 0.9532
```

In [13]:

```
# 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]:
```
# save model
#model.save("project_mlp_2_layers")
```

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

```
4631/4631 [==============================] - 4s 783us/step
```

In [16]:
```
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 ... 1 2 2]
Actual labels:           [0 1 0 ... 2 2 1]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     75511
           1       0.87      0.85      0.86     24572
           2       0.92      0.93      0.93     48090

    accuracy                           0.95    148173
   macro avg       0.93      0.93      0.93    148173
weighted avg       0.95      0.95      0.95    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]:
```python
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]:
```python
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 790us/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       0.99      0.99      0.99    366310
           1       0.16      0.10      0.13     69389
           2       0.82      0.88      0.85    335154

    accuracy                           0.86    770853
   macro avg       0.66      0.66      0.66    770853
weighted avg       0.84      0.86      0.85    770853
```

In [ ]:

In [ ]:

In [ ]: