```
In [1]:
         # Import our dependencies
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler,OneHotEncoder, MinMaxScaler
         import pandas as pd
         import tensorflow as tf
         import numpy as np
         # Import our input dataset
         df = pd.read_csv('encoded_binned_df.csv')
         df.head()
```

Out[1]

]:		ERA	Hits	Earned Runs	Strike Outs	Home Runs	Wins	Losses	Outs Pitched	Batters Faced by Pitcher	Games Finished	Weight	Height	Games Started	salBin_low	salBin_ı
	0	4.51	246	106	105	16	10	14	635	925	0	200	75	33	1	
	1	5.97	37	23	25	0	0	5	104	162	0	185	75	7	1	
	2	3.77	13	6	7	0	1	2	43	63	0	195	76	3	1	
	3	4.53	214	95	82	20	7	18	566	797	0	178	71	31	1	
	4	2.76	179	57	127	13	12	8	557	784	1	180	74	24	1	

In [3]:

```
### Drop unnecessary columns
df= df.filter(['Batters Faced by Pitcher','Outs Pitched','ERA','Strike Outs',"salBin_low","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBin_mid","salBi
df.head()
```

Out[3]:		<b>Batters Faced by Pitcher</b>
	0	925
	1	162

Batters Faced by Pitcher	Outs Pitched	ERA	Strike Outs	salBin_low	salBin_mid	salBin_high	salBin_top
925	635	4.51	105	1	0	0	0
162	104	5.97	25	1	0	0	0
63	43	3.77	7	1	0	0	0
797	566	4.53	82	1	0	0	0
784	557	2.76	127	1	0	0	0
	925 162 63 797	925 635 162 104 63 43 797 566	925 635 4.51 162 104 5.97 63 43 3.77 797 566 4.53	925 635 4.51 105 162 104 5.97 25 63 43 3.77 7 797 566 4.53 82	925 635 4.51 105 1 162 104 5.97 25 1 63 43 3.77 7 1 797 566 4.53 82 1	925 635 4.51 105 1 0 162 104 5.97 25 1 0 63 43 3.77 7 1 0 797 566 4.53 82 1 0	162     104     5.97     25     1     0     0       63     43     3.77     7     1     0     0       797     566     4.53     82     1     0     0

## Split Features/Target & Training/Testing Sets

Split into features and target

- y variable: Our target variables, Salary-Bin\_low, Salary-Bin\_mid, Salary-Bin\_high, Salary-Bin\_top
- X variable: Our features

```
In [4]:
         # Split our preprocessed data into our features and target arrays
         y = df[["salBin_low","salBin_mid","salBin_high","salBin_top"]].values
         X = df.drop(["salBin_low", "salBin_mid", "salBin_high", "salBin_top"],1).values
         # Split the preprocessed data into a training and testing dataset
         X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)
```

C:\Users\alyss\anaconda3\envs\mlenv\lib\site-packages\ipykernel\_launcher.py:3: FutureWarning: In a future version of pandas all arguments of DataFrame.drop except for the argument 'labels' will be keyword-only This is separate from the ipykernel package so we can avoid doing imports until

## features

```
In [5]: # Create a StandardScaler instance
scaler = StandardScaler()

# Fit the StandardScaler
X_scaler = scaler.fit(X_train)

# Scale the data
X_train_scaled = X_scaler.transform(X_train)
X_test_scaled = X_scaler.transform(X_test)
```

## **Build Neural Net Framework**

```
In [9]:
         # Define the model - deep neural net
         number_input_features = len(X_train[0])
         hidden_nodes_layer1 = 144
         hidden_nodes_layer2 = 144
         hidden_nodes_layer3 = 32
         hidden_nodes_layer4 = 32
         nn = tf.keras.models.Sequential()
         # First hidden layer
         nn.add(
             tf.keras.layers.Dense(units=hidden_nodes_layer1, input_dim=number_input_features, activation="relu")
         # Second hidden Layer
         nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation="relu"))
         # Third hidden Laver
         nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer3, activation="relu"))
         # Third hidden Layer
         nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer4, activation="relu"))
         # Output Layer
         nn.add(tf.keras.layers.Dense(units=4, activation="softmax"))
         # Check the structure of the model
         nn.summary()
```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #					
dense_5 (Dense)	(None, 144)	720					
dense_6 (Dense)	(None, 144)	20880					
dense_7 (Dense)	(None, 32)	4640					
dense_8 (Dense)	(None, 32)	1056					
dense_9 (Dense)	(None, 4)	132					
Total params: 27,428 Trainable params: 27,428 Non-trainable params: 0							

```
# Compile the model
nn.compile(loss="CategoricalCrossentropy", optimizer="adam", metrics=["accuracy"])
```

## Train the model

```
In [11]: # Train the model
fit_model = nn.fit(X_train,y_train,epochs=200)
```

```
Epoch 1/200
Epoch 2/200
116/116 [================== ] - 0s 722us/step - loss: 1.4584 - accuracy: 0.4103
Fnoch 3/200
Epoch 4/200
116/116 [=========== ] - 0s 748us/step - loss: 1.4084 - accuracy: 0.4238
Epoch 5/200
Epoch 6/200
Epoch 7/200
116/116 [============ ] - 0s 739us/step - loss: 1.2307 - accuracy: 0.4363
Epoch 8/200
Epoch 9/200
Epoch 10/200
Epoch 11/200
116/116 [============ ] - 0s 713us/step - loss: 1.2506 - accuracy: 0.4435
Epoch 12/200
116/116 [================== ] - 0s 765us/step - loss: 1.2255 - accuracy: 0.4600
Epoch 13/200
Epoch 14/200
116/116 [================== ] - 0s 774us/step - loss: 1.1746 - accuracy: 0.4611
Epoch 15/200
Epoch 16/200
116/116 [================== ] - 0s 722us/step - loss: 1.1756 - accuracy: 0.4592
Epoch 17/200
Epoch 18/200
Epoch 19/200
Epoch 20/200
Epoch 21/200
116/116 [================= ] - 0s 730us/step - loss: 1.1830 - accuracy: 0.4608
Epoch 22/200
Epoch 23/200
116/116 [=============== ] - 0s 730us/step - loss: 1.1964 - accuracy: 0.4611
Epoch 24/200
Epoch 25/200
116/116 [================= ] - 0s 833us/step - loss: 1.2864 - accuracy: 0.4211
Epoch 26/200
Epoch 27/200
Epoch 28/200
Epoch 29/200
116/116 [================= ] - 0s 730us/step - loss: 1.1566 - accuracy: 0.4724
Epoch 30/200
Epoch 31/200
Epoch 32/200
```

```
116/116 [============ ] - 0s 730us/step - loss: 1.1580 - accuracy: 0.4611
Epoch 33/200
Epoch 34/200
116/116 [=========== ] - 0s 765us/step - loss: 1.1551 - accuracy: 0.4627
Epoch 35/200
Epoch 36/200
116/116 [=========== ] - 0s 730us/step - loss: 1.1704 - accuracy: 0.4600
Epoch 37/200
Epoch 38/200
Epoch 39/200
Epoch 40/200
Epoch 41/200
Epoch 42/200
116/116 [============ ] - 0s 730us/step - loss: 1.1604 - accuracy: 0.4646
Epoch 43/200
Epoch 44/200
Epoch 45/200
Epoch 46/200
116/116 [============ ] - 0s 730us/step - loss: 1.1633 - accuracy: 0.4543
Epoch 47/200
Epoch 48/200
116/116 [================= ] - 0s 730us/step - loss: 1.1537 - accuracy: 0.4641
Epoch 49/200
Epoch 50/200
Epoch 51/200
Epoch 52/200
Epoch 53/200
116/116 [============ ] - 0s 722us/step - loss: 1.1586 - accuracy: 0.4560
Epoch 54/200
Epoch 55/200
Epoch 56/200
Epoch 57/200
116/116 [============ ] - 0s 774us/step - loss: 1.1582 - accuracy: 0.4670
Epoch 58/200
Epoch 59/200
Epoch 60/200
116/116 [================== ] - 0s 730us/step - loss: 1.1576 - accuracy: 0.4687
Fnoch 61/200
Epoch 62/200
Epoch 63/200
Epoch 64/200
116/116 [================= ] - 0s 730us/step - loss: 1.1497 - accuracy: 0.4727
Epoch 65/200
Epoch 66/200
Epoch 67/200
116/116 [============= ] - 0s 757us/step - loss: 1.1535 - accuracy: 0.4692
Epoch 68/200
Epoch 69/200
116/116 [============== ] - 0s 748us/step - loss: 1.1499 - accuracy: 0.4679
Epoch 70/200
```

```
116/116 [=========== ] - 0s 722us/step - loss: 1.1540 - accuracy: 0.4684
Epoch 71/200
Epoch 72/200
116/116 [=========== ] - 0s 722us/step - loss: 1.1509 - accuracy: 0.4743
Epoch 73/200
Epoch 74/200
116/116 [=========== ] - 0s 757us/step - loss: 1.1498 - accuracy: 0.4754
Epoch 75/200
Epoch 76/200
116/116 [============ ] - 0s 730us/step - loss: 1.1597 - accuracy: 0.4668
Epoch 77/200
Epoch 78/200
Epoch 79/200
116/116 [================== ] - 0s 739us/step - loss: 1.1457 - accuracy: 0.4660
Epoch 80/200
116/116 [============ ] - 0s 739us/step - loss: 1.1471 - accuracy: 0.4681
Epoch 81/200
Epoch 82/200
Epoch 83/200
Epoch 84/200
116/116 [=========== ] - 0s 722us/step - loss: 1.1478 - accuracy: 0.4633
Epoch 85/200
Epoch 86/200
116/116 [================== ] - 0s 739us/step - loss: 1.1446 - accuracy: 0.4727
Epoch 87/200
Epoch 88/200
Epoch 89/200
Epoch 90/200
Epoch 91/200
116/116 [=========== ] - 0s 722us/step - loss: 1.1455 - accuracy: 0.4697
Epoch 92/200
Epoch 93/200
Epoch 94/200
Epoch 95/200
116/116 [============ ] - 0s 739us/step - loss: 1.1460 - accuracy: 0.4743
Epoch 96/200
Epoch 97/200
Epoch 98/200
116/116 [================= ] - 0s 739us/step - loss: 1.1465 - accuracy: 0.4751
Fnoch 99/200
Epoch 100/200
Epoch 101/200
Epoch 102/200
Epoch 103/200
Epoch 104/200
Epoch 105/200
116/116 [================== ] - 0s 722us/step - loss: 1.1440 - accuracy: 0.4765
Epoch 106/200
Epoch 107/200
116/116 [=============== ] - 0s 739us/step - loss: 1.1419 - accuracy: 0.4776
Epoch 108/200
```

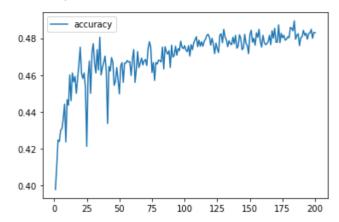
```
116/116 [============ ] - 0s 722us/step - loss: 1.1432 - accuracy: 0.4792
Epoch 109/200
Epoch 110/200
116/116 [============ ] - 0s 739us/step - loss: 1.1423 - accuracy: 0.4754
Epoch 111/200
Epoch 112/200
116/116 [=========== ] - 0s 739us/step - loss: 1.1404 - accuracy: 0.4757
Epoch 113/200
Epoch 114/200
116/116 [============ ] - 0s 739us/step - loss: 1.1441 - accuracy: 0.4757
Epoch 115/200
Epoch 116/200
Epoch 117/200
Epoch 118/200
116/116 [============ ] - 0s 826us/step - loss: 1.1403 - accuracy: 0.4822
Epoch 119/200
Epoch 120/200
Epoch 121/200
Epoch 122/200
116/116 [============ ] - 0s 739us/step - loss: 1.1403 - accuracy: 0.4770
Epoch 123/200
Epoch 124/200
Epoch 125/200
Epoch 126/200
116/116 [=========== ] - 0s 791us/step - loss: 1.1400 - accuracy: 0.4722
Epoch 127/200
Epoch 128/200
Epoch 129/200
116/116 [============ ] - 0s 774us/step - loss: 1.1405 - accuracy: 0.4776
Epoch 130/200
Epoch 131/200
116/116 [=================== - 0s 1ms/step - loss: 1.1407 - accuracy: 0.4808
Epoch 132/200
Epoch 133/200
116/116 [============ ] - 0s 749us/step - loss: 1.1422 - accuracy: 0.4754
Epoch 134/200
Epoch 135/200
Epoch 136/200
Fnoch 137/200
Epoch 138/200
Epoch 139/200
Epoch 140/200
Epoch 141/200
Epoch 142/200
Epoch 143/200
116/116 [============== ] - 0s 765us/step - loss: 1.1378 - accuracy: 0.4800
Epoch 144/200
Epoch 145/200
116/116 [================= ] - 0s 730us/step - loss: 1.1404 - accuracy: 0.4746
Epoch 146/200
```

```
116/116 [=========== ] - 0s 733us/step - loss: 1.1377 - accuracy: 0.4822
Epoch 147/200
Epoch 148/200
116/116 [============ ] - 0s 765us/step - loss: 1.1376 - accuracy: 0.4760
Epoch 149/200
Epoch 150/200
116/116 [============ ] - 0s 843us/step - loss: 1.1381 - accuracy: 0.4822
Epoch 151/200
Epoch 152/200
116/116 [============ - - os 739us/step - loss: 1.1371 - accuracy: 0.4778
Epoch 153/200
Epoch 154/200
Epoch 155/200
Epoch 156/200
116/116 [============ ] - 0s 765us/step - loss: 1.1351 - accuracy: 0.4806
Epoch 157/200
Epoch 158/200
Epoch 159/200
Epoch 160/200
116/116 [=========== ] - 0s 750us/step - loss: 1.1328 - accuracy: 0.4816
Epoch 161/200
Epoch 162/200
116/116 [================= ] - 0s 739us/step - loss: 1.1340 - accuracy: 0.4765
Epoch 163/200
Epoch 164/200
116/116 [=========== ] - 0s 739us/step - loss: 1.1356 - accuracy: 0.4781
Epoch 165/200
Epoch 166/200
Epoch 167/200
116/116 [============ ] - 0s 757us/step - loss: 1.1347 - accuracy: 0.4841
Epoch 168/200
Epoch 169/200
Epoch 170/200
Epoch 171/200
116/116 [============ ] - 0s 731us/step - loss: 1.1327 - accuracy: 0.4778
Epoch 172/200
Epoch 173/200
Epoch 174/200
Epoch 175/200
Epoch 176/200
Epoch 177/200
Epoch 178/200
Epoch 179/200
Epoch 180/200
Epoch 181/200
116/116 [================= ] - 0s 783us/step - loss: 1.1290 - accuracy: 0.4860
Epoch 182/200
Epoch 183/200
116/116 [=============== ] - 0s 748us/step - loss: 1.1281 - accuracy: 0.4841
Epoch 184/200
```

```
116/116 [=========== ] - 0s 776us/step - loss: 1.1285 - accuracy: 0.4895
     Epoch 185/200
     Epoch 186/200
     116/116 [============ ] - 0s 748us/step - loss: 1.1297 - accuracy: 0.4816
     Epoch 187/200
     Epoch 188/200
     116/116 [============ ] - 0s 730us/step - loss: 1.1309 - accuracy: 0.4760
     Fnoch 189/200
     Epoch 190/200
     Epoch 191/200
     116/116 [================= ] - 0s 730us/step - loss: 1.1272 - accuracy: 0.4843
     Epoch 192/200
     Epoch 193/200
     116/116 [============== ] - 0s 799us/step - loss: 1.1268 - accuracy: 0.4827
     Epoch 194/200
     Epoch 195/200
     116/116 [================= ] - 0s 757us/step - loss: 1.1281 - accuracy: 0.4824
     Epoch 196/200
     Epoch 197/200
     Epoch 198/200
     116/116 [============ ] - 0s 791us/step - loss: 1.1273 - accuracy: 0.4800
     Epoch 199/200
     Epoch 200/200
     116/116 [=============== ] - 0s 878us/step - loss: 1.1247 - accuracy: 0.4830
In [12]:
      # Evaluate the model using the test data
      model_loss, model_accuracy = nn.evaluate(X_test_scaled,y_test,verbose=2)
      print(f"Loss: {model_loss*100:.2f}%, Accuracy: {model_accuracy*100:.2f}%")
     39/39 - 0s - loss: 1.2985 - accuracy: 0.3887 - 107ms/epoch - 3ms/step
     Loss: 129.85%, Accuracy: 38.87%
In [13]:
      # Create a DataFrame containing training history
      history_df = pd.DataFrame(fit_model.history, index=range(1,len(fit_model.history["loss"])+1))
      # Plot the loss
      history_df.plot(y="loss")
Out[13]: <AxesSubplot:>
                                 loss
      3 00
      2.75
      2.50
      2.25
      2.00
     1.75
     1.50
      1.25
               50
                      100
                         125
                            150
```

```
# Plot the accuracy
history_df.plot(y="accuracy")
```

Out[14]: <AxesSubplot:>



In [ ]: