```
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 [2]:

### Drop unnecessary columns
df= df.filter(['Batters Faced by Pitcher','Outs Pitched','ERA','Games Finished','Strike Outs',"salBin\_low
df.head()

Out[2]:

•		Batters Faced by Pitcher	Outs Pitched	ERA	Games Finished	Strike Outs	salBin_low	salBin_mid	salBin_high	salBin_top	
(	0	925	635	4.51	0	105	1	0	0	0	
	1	162	104	5.97	0	25	1	0	0	0	
2	2	63	43	3.77	0	7	1	0	0	0	
3	3	797	566	4.53	0	82	1	0	0	0	
4	4	784	557	2.76	1	127	1	0	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

```
# 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 [4]: # 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 [11]:
          # Define the model - deep neural net
          number_input_features = len(X_train[0])
          hidden_nodes_layer1 = 144
          hidden_nodes_layer2 = 64
          hidden_nodes_layer3 = 16
          nn = tf.keras.models.Sequential()
          # First hidden Layer
          nn.add(
              tf.keras.layers.Dense(units=hidden nodes layer1, input dim=number input features, activation="elu")
          # Second hidden Layer
          nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation="elu"))
          # Third hidden Layer
          nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer3, activation="elu"))
          # Output Layer
          nn.add(tf.keras.layers.Dense(units=4, activation="elu"))
          # Check the structure of the model
          nn.summary()
```

### Model: "sequential\_1"

Layer (type)	Output Shape	Param #					
dense_4 (Dense)	(None, 144)	864					
dense_5 (Dense)	(None, 64)	9280					
dense_6 (Dense)	(None, 16)	1040					
dense_7 (Dense)	(None, 4)	68					
Total params: 11,252 Trainable params: 11,252 Non-trainable params: 0							

## Compile the Model

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

```
In [13]:
```

```
# Train the model
fit_model = nn.fit(X_train,y_train,epochs=200)
```

```
Epoch 1/200
Epoch 2/200
Epoch 3/200
Epoch 4/200
Epoch 5/200
Epoch 6/200
Epoch 7/200
Epoch 8/200
116/116 [=========== ] - 0s 704us/step - loss: 1.1964 - accuracy: 0.4489
Epoch 9/200
Epoch 10/200
Epoch 11/200
Epoch 12/200
116/116 [============ ] - 0s 722us/step - loss: 1.1982 - accuracy: 0.4225
Epoch 13/200
116/116 [================== ] - 0s 739us/step - loss: 1.1906 - accuracy: 0.4165
Epoch 14/200
Epoch 15/200
116/116 [================== ] - 0s 739us/step - loss: 1.2001 - accuracy: 0.4152
Epoch 16/200
Epoch 17/200
116/116 [================= ] - 0s 722us/step - loss: 1.1700 - accuracy: 0.4384
Epoch 18/200
Epoch 19/200
116/116 [=========== ] - 0s 704us/step - loss: 1.1652 - accuracy: 0.4554
Epoch 20/200
116/116 [================= ] - 0s 713us/step - loss: 1.1573 - accuracy: 0.4706
Epoch 21/200
Epoch 22/200
Epoch 23/200
Epoch 24/200
116/116 [================= ] - 0s 722us/step - loss: 1.1445 - accuracy: 0.4841
Epoch 25/200
Epoch 26/200
116/116 [================== ] - 0s 713us/step - loss: 1.1912 - accuracy: 0.4773
Epoch 27/200
Epoch 28/200
116/116 [================== ] - 0s 722us/step - loss: 1.1386 - accuracy: 0.4876
Epoch 29/200
Epoch 30/200
Epoch 31/200
Epoch 32/200
Epoch 33/200
Epoch 34/200
116/116 [================ ] - 0s 704us/step - loss: 1.1361 - accuracy: 0.4884
Epoch 35/200
```

```
116/116 [=========== ] - 0s 722us/step - loss: 1.1332 - accuracy: 0.4827
Epoch 36/200
Epoch 37/200
116/116 [=========== ] - 0s 722us/step - loss: 1.1343 - accuracy: 0.4900
Epoch 38/200
Epoch 39/200
116/116 [============ ] - 0s 713us/step - loss: 1.1479 - accuracy: 0.4841
Epoch 40/200
Epoch 41/200
116/116 [============ ] - 0s 722us/step - loss: 1.1424 - accuracy: 0.4835
Epoch 42/200
116/116 [================= ] - 0s 722us/step - loss: 1.1264 - accuracy: 0.4841
Epoch 43/200
Epoch 44/200
116/116 [================= ] - 0s 713us/step - loss: 1.1505 - accuracy: 0.4762
Epoch 45/200
116/116 [=========== ] - 0s 704us/step - loss: 1.1439 - accuracy: 0.4849
Epoch 46/200
Epoch 47/200
Epoch 48/200
Epoch 49/200
116/116 [=========== ] - 0s 730us/step - loss: 1.1341 - accuracy: 0.4870
Epoch 50/200
Epoch 51/200
Epoch 52/200
Epoch 53/200
Epoch 54/200
Epoch 55/200
Epoch 56/200
116/116 [============ ] - 0s 713us/step - loss: 1.1704 - accuracy: 0.4760
Epoch 57/200
Epoch 58/200
Epoch 59/200
Epoch 60/200
116/116 [============ ] - 0s 713us/step - loss: 1.1309 - accuracy: 0.4870
Epoch 61/200
116/116 [================== ] - 0s 730us/step - loss: 1.1624 - accuracy: 0.4789
Epoch 62/200
Epoch 63/200
116/116 [================= ] - 0s 704us/step - loss: 1.1307 - accuracy: 0.4854
Fnoch 64/200
Epoch 65/200
Epoch 66/200
Epoch 67/200
Epoch 68/200
Epoch 69/200
Epoch 70/200
Epoch 71/200
Epoch 72/200
116/116 [================= ] - 0s 730us/step - loss: 1.1330 - accuracy: 0.4860
Epoch 73/200
```

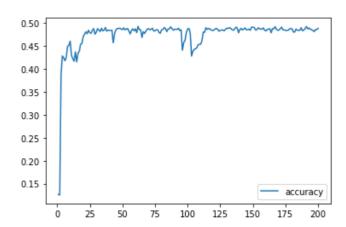
```
116/116 [=========== ] - 0s 730us/step - loss: 1.1304 - accuracy: 0.4884
Epoch 74/200
Epoch 75/200
116/116 [=========== ] - 0s 722us/step - loss: 1.1305 - accuracy: 0.4827
Epoch 76/200
Epoch 77/200
116/116 [============ ] - 0s 730us/step - loss: 1.1311 - accuracy: 0.4849
Epoch 78/200
Epoch 79/200
116/116 [============ ] - 0s 713us/step - loss: 1.1292 - accuracy: 0.4773
Epoch 80/200
116/116 [================= ] - 0s 713us/step - loss: 1.1257 - accuracy: 0.4849
Epoch 81/200
Epoch 82/200
Epoch 83/200
116/116 [============ ] - 0s 722us/step - loss: 1.1305 - accuracy: 0.4881
Epoch 84/200
Epoch 85/200
Epoch 86/200
Epoch 87/200
116/116 [============ ] - 0s 730us/step - loss: 1.1239 - accuracy: 0.4914
Epoch 88/200
Epoch 89/200
116/116 [================= ] - 0s 730us/step - loss: 1.1226 - accuracy: 0.4841
Epoch 90/200
Epoch 91/200
Epoch 92/200
Epoch 93/200
Epoch 94/200
116/116 [============ ] - 0s 722us/step - loss: 1.1246 - accuracy: 0.4833
Epoch 95/200
Epoch 96/200
Epoch 97/200
Epoch 98/200
116/116 [=========== ] - 0s 722us/step - loss: 1.2031 - accuracy: 0.4619
Epoch 99/200
Epoch 100/200
Epoch 101/200
Fnoch 102/200
Epoch 103/200
Epoch 104/200
Epoch 105/200
Epoch 106/200
Epoch 107/200
Epoch 108/200
Epoch 109/200
Epoch 110/200
Epoch 111/200
```

```
116/116 [============ ] - 0s 713us/step - loss: 1.1757 - accuracy: 0.4616
Epoch 112/200
Epoch 113/200
116/116 [=========== ] - 0s 722us/step - loss: 1.1553 - accuracy: 0.4795
Epoch 114/200
Epoch 115/200
116/116 [============ ] - 0s 713us/step - loss: 1.1382 - accuracy: 0.4860
Epoch 116/200
Epoch 117/200
116/116 [============ ] - 0s 720us/step - loss: 1.1326 - accuracy: 0.4870
Epoch 118/200
Epoch 119/200
Epoch 120/200
116/116 [================= ] - 0s 730us/step - loss: 1.1300 - accuracy: 0.4841
Epoch 121/200
116/116 [============ ] - 0s 722us/step - loss: 1.1354 - accuracy: 0.4868
Epoch 122/200
Epoch 123/200
Epoch 124/200
Epoch 125/200
116/116 [========== ] - 0s 730us/step - loss: 1.1425 - accuracy: 0.4835
Epoch 126/200
Epoch 127/200
Epoch 128/200
Epoch 129/200
116/116 [=========== ] - 0s 800us/step - loss: 1.1259 - accuracy: 0.4862
Epoch 130/200
Epoch 131/200
Epoch 132/200
116/116 [=========== ] - 0s 730us/step - loss: 1.1237 - accuracy: 0.4895
Epoch 133/200
Epoch 134/200
Epoch 135/200
Epoch 136/200
116/116 [============ ] - 0s 722us/step - loss: 1.1286 - accuracy: 0.4868
Epoch 137/200
Epoch 138/200
Epoch 139/200
Fnoch 140/200
Epoch 141/200
Epoch 142/200
Epoch 143/200
Epoch 144/200
Epoch 145/200
Epoch 146/200
Epoch 147/200
Epoch 148/200
116/116 [================== ] - 0s 707us/step - loss: 1.1358 - accuracy: 0.4838
Epoch 149/200
```

```
116/116 [=========== ] - 0s 730us/step - loss: 1.1228 - accuracy: 0.4908
Epoch 150/200
Epoch 151/200
116/116 [=========== ] - 0s 791us/step - loss: 1.1211 - accuracy: 0.4900
Epoch 152/200
Epoch 153/200
116/116 [============ ] - 0s 739us/step - loss: 1.1224 - accuracy: 0.4849
Epoch 154/200
Epoch 155/200
116/116 [============ ] - 0s 739us/step - loss: 1.1279 - accuracy: 0.4878
Epoch 156/200
Epoch 157/200
Epoch 158/200
116/116 [================= ] - 0s 739us/step - loss: 1.1213 - accuracy: 0.4889
Epoch 159/200
116/116 [============ ] - 0s 713us/step - loss: 1.1206 - accuracy: 0.4841
Epoch 160/200
Epoch 161/200
Epoch 162/200
Epoch 163/200
116/116 [=========== ] - 0s 751us/step - loss: 1.1297 - accuracy: 0.4873
Epoch 164/200
Epoch 165/200
Epoch 166/200
Epoch 167/200
116/116 [=========== ] - 0s 739us/step - loss: 1.1195 - accuracy: 0.4919
Epoch 168/200
Epoch 169/200
Epoch 170/200
116/116 [============ ] - 0s 722us/step - loss: 1.1236 - accuracy: 0.4846
Epoch 171/200
Epoch 172/200
Epoch 173/200
Epoch 174/200
116/116 [=========== ] - 0s 722us/step - loss: 1.1180 - accuracy: 0.4849
Epoch 175/200
116/116 [================= ] - 0s 713us/step - loss: 1.1218 - accuracy: 0.4835
Epoch 176/200
Epoch 177/200
Fnoch 178/200
Epoch 179/200
Epoch 180/200
Epoch 181/200
Epoch 182/200
Epoch 183/200
Epoch 184/200
116/116 [================= ] - 0s 739us/step - loss: 1.1226 - accuracy: 0.4843
Epoch 185/200
Epoch 186/200
116/116 [=============== ] - 0s 783us/step - loss: 1.1219 - accuracy: 0.4841
Epoch 187/200
```

```
116/116 [=========== ] - 0s 774us/step - loss: 1.1202 - accuracy: 0.4895
      Epoch 188/200
      Epoch 189/200
      116/116 [============ ] - 0s 704us/step - loss: 1.1233 - accuracy: 0.4843
      Epoch 190/200
      Epoch 191/200
      116/116 [=========== ] - 0s 748us/step - loss: 1.1293 - accuracy: 0.4922
      Epoch 192/200
      Epoch 193/200
      116/116 [============ ] - 0s 765us/step - loss: 1.1212 - accuracy: 0.4889
      Epoch 194/200
      116/116 [================= ] - 0s 713us/step - loss: 1.1194 - accuracy: 0.4860
      Epoch 195/200
      Epoch 196/200
      Epoch 197/200
      116/116 [============ ] - 0s 713us/step - loss: 1.1334 - accuracy: 0.4811
      Epoch 198/200
      116/116 [============== ] - 0s 713us/step - loss: 1.1251 - accuracy: 0.4857
      Epoch 199/200
      Epoch 200/200
      In [14]:
      # 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: 7.1363 - accuracy: 0.1830 - 85ms/epoch - 2ms/step
      Loss: 713.63%, Accuracy: 18.30%
In [15]:
      # 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[15]: <AxesSubplot:>
                                   loss
      12
      10
       8
       6
       4
       2
                      100
                         125
                             150
                                175
                                    200
         0
            25
               50
                   75
In [16]:
      # Plot the accuracy
      history_df.plot(y="accuracy")
```

Out[16]: <AxesSubplot:>



In [ ]: