```
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('../neural-network/pitcher_salaries_cleaned.csv')
    df.head()
```

Out[1]:

	Year	Full Name	Age	Salary	ERA	Hits	Earned Runs	Strike Outs	Home Runs	Wins	Losses	Outs Pitched	Faced by Pitcher	Games Finished	Weight	ı
0	1990	AbbottJim	23	185000	4.51	246	106	105	16	10	14	635	925	0	200	
1	1990	AbbottPaul	23	100000	5.97	37	23	25	0	0	5	104	162	0	185	
2	1990	AldredScott	22	100000	3.77	13	6	7	0	1	2	43	63	0	195	
3	1990	AndersonAllan	26	300000	4.53	214	95	82	20	7	18	566	797	0	178	
4	1990	AppierKevin	23	100000	2.76	179	57	127	13	12	8	557	784	1	180	

Dattore

In [2]:

# create log transformed column for salary
df['sal-log']=np.log10(df['Salary'])
df

Out[2]:

0	Year	Full Name	Age	Salary	ERA	Hits	Earned Runs	Strike Outs	Home Runs	Wins	Losses	Outs Pitched	Faced by Pitcher	Games Finished
0	1990	AbbottJim	23	185000	4.51	246	106	105	16	10	14	635	925	0
1	1990	AbbottPaul	23	100000	5.97	37	23	25	0	0	5	104	162	0
2	1990	AldredScott	22	100000	3.77	13	6	7	0	1	2	43	63	0
3	1990	AndersonAllan	26	300000	4.53	214	95	82	20	7	18	566	797	0
4	1990	AppierKevin	23	100000	2.76	179	57	127	13	12	8	557	784	1
•••														
4932	2016	WorleyVance	29	2600000	3.53	84	34	56	11	2	2	260	365	13
4933	2016	WrightMike	26	510500	5.79	81	48	50	12	3	4	224	328	5
4934	2016	WrightSteven	32	514500	3.33	138	58	127	12	13	6	470	656	0
4935	2016	YoungChris	37	4250000	6.19	104	61	94	28	3	9	266	406	7
4936	2016	ZimmermannJordan	30	18000000	4.87	118	57	66	14	9	7	316	450	1

4937 rows × 20 columns

# Reduce down to top features

In [3]: df= df.drop(["Full Name","Team","League","Age","Earned Runs","Home Runs","Wins","Losses","Weight","Height
df.head()

version of pandas all arguments of DataFrame.drop except for the argument 'labels' will be keyword-only """Entry point for launching an IPython kernel.

Out[3]:		ERA	Hits	Strike Outs	Outs Pitched	<b>Batters Faced by Pitcher</b>	<b>Games Finished</b>	<b>Games Started</b>	sal-log
	0	4.51	246	105	635	925	0	33	5.267172
	1	5.97	37	25	104	162	0	7	5.000000
	2	3.77	13	7	43	63	0	3	5.000000
	3	4.53	214	82	566	797	0	31	5.477121
	4	2.76	179	127	557	784	1	24	5.000000

## Split Features/Target & Training/Testing Sets

Split into features and target

- y variable: Our target variable, Salary
- X variable: Our features; just drop Salary and Full Name

```
In [5]: # Split our preprocessed data into our features and target arrays
y = df["sal-log"].values
X = df.drop(["sal-log"],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

# Build and Instantiate StandardScaler object, then standardize numerical features

```
In [6]:
         # Create a StandardScaler instance
         scaler = MinMaxScaler()
         # 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)
In [ ]:
         # see if data scaled properly
         scaled_data=pd.DataFrame(X_train_scaled)
         scaled data.head()
In [ ]:
         # see if data scaled properly
         scaled_y=pd.DataFrame(y_train_scaled)
         scaled_y.head()
```

#### **Build Neural Net Framework**

```
In [19]: # Define the model - deep neural net
number_input_features = len(X_train[0])
```

```
hidden_nodes_layer1 = 50
hidden_nodes_layer2 = 30
hidden_nodes_layer3 = 20
hidden_nodes_layer4 = 10
nn = tf.keras.models.Sequential()
# First hidden Layer
nn.add(
    tf.keras.layers.Dense(units=hidden_nodes_layer1, input_dim=number_input_features, activation="tanh")
# 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"))
# Fourth hidden Layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer4, activation="elu"))
# Output Layer
nn.add(tf.keras.layers.Dense(units=5, activation="elu"))
# Check the structure of the model
nn.summary()
```

Model: "sequential\_3"

Layer (type)	Output Shape	Param #						
dense_15 (Dense)	(None, 50)	400						
dense_16 (Dense)	(None, 30)	1530						
dense_17 (Dense)	(None, 20)	620						
dense_18 (Dense)	(None, 10)	210						
dense_19 (Dense)	(None, 5)	55						
Total params: 2,815 Trainable params: 2,815 Non-trainable params: 0								

## Compile the Model

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

#### Train the model

```
Fnoch 4/200
116/116 [============ ] - 0s 809us/step - loss: 0.4208 - accuracy: 0.0000e+00
Epoch 5/200
Epoch 6/200
116/116 [============ ] - 0s 774us/step - loss: 0.4062 - accuracy: 0.0000e+00
Epoch 7/200
Epoch 8/200
116/116 [============ ] - 0s 748us/step - loss: 0.3888 - accuracy: 0.0000e+00
Epoch 9/200
116/116 [=============] - 0s 843us/step - loss: 0.3802 - accuracy: 0.0000e+00
Epoch 10/200
Epoch 11/200
116/116 [============ ] - 0s 887us/step - loss: 0.3766 - accuracy: 0.0000e+00
Epoch 12/200
Epoch 13/200
Epoch 14/200
Epoch 15/200
116/116 [============ ] - 0s 739us/step - loss: 0.3732 - accuracy: 0.0000e+00
Epoch 16/200
116/116 [============ ] - 0s 774us/step - loss: 0.3896 - accuracy: 0.0000e+00
Epoch 17/200
Epoch 18/200
116/116 [============ ] - 0s 783us/step - loss: 0.3882 - accuracy: 0.0000e+00
Epoch 19/200
Epoch 20/200
116/116 [============ ] - 0s 809us/step - loss: 0.3784 - accuracy: 0.0000e+00
Epoch 21/200
Epoch 22/200
116/116 [============ ] - 0s 1ms/step - loss: 0.3835 - accuracy: 0.0000e+00
Epoch 23/200
116/116 [=============== ] - 0s 2ms/step - loss: 0.3783 - accuracy: 0.0000e+00
Epoch 24/200
116/116 [============ ] - 0s 1ms/step - loss: 0.3803 - accuracy: 0.0000e+00
Epoch 25/200
116/116 [=========== ] - 0s 809us/step - loss: 0.3731 - accuracy: 0.0000e+00
Epoch 26/200
Epoch 27/200
116/116 [============== ] - 0s 774us/step - loss: 0.3750 - accuracy: 0.0000e+00
Epoch 28/200
Epoch 29/200
Epoch 30/200
116/116 [============ ] - 0s 913us/step - loss: 0.3777 - accuracy: 0.0000e+00
Epoch 31/200
Fnoch 32/200
116/116 [============ ] - 0s 817us/step - loss: 0.3735 - accuracy: 0.0000e+00
Epoch 33/200
Epoch 34/200
116/116 [============ ] - 0s 739us/step - loss: 0.3737 - accuracy: 0.0000e+00
Epoch 35/200
Epoch 36/200
Epoch 37/200
116/116 [=========== ] - 0s 835us/step - loss: 0.3941 - accuracy: 0.0000e+00
Epoch 38/200
Epoch 39/200
116/116 [============= ] - 0s 826us/step - loss: 0.3963 - accuracy: 0.0000e+00
Epoch 40/200
Epoch 41/200
```

```
Epoch 42/200
Epoch 43/200
Epoch 44/200
116/116 [============ ] - 0s 774us/step - loss: 0.3632 - accuracy: 0.0000e+00
Epoch 45/200
116/116 [============ ] - 0s 1ms/step - loss: 0.3695 - accuracy: 0.0000e+00
Epoch 46/200
116/116 [=========== - 0s 1ms/step - loss: 0.3709 - accuracy: 0.0000e+00
Epoch 47/200
116/116 [============ ] - 0s 1ms/step - loss: 0.3666 - accuracy: 0.0000e+00
Epoch 48/200
116/116 [=============== ] - 0s 1ms/step - loss: 0.3715 - accuracy: 0.0000e+00
Epoch 49/200
116/116 [============ ] - 0s 765us/step - loss: 0.3770 - accuracy: 0.0000e+00
Epoch 50/200
Epoch 51/200
Epoch 52/200
Epoch 53/200
116/116 [============ ] - 0s 748us/step - loss: 0.3550 - accuracy: 0.0000e+00
Epoch 54/200
116/116 [============ ] - 0s 765us/step - loss: 0.3564 - accuracy: 0.0000e+00
Epoch 55/200
Epoch 56/200
116/116 [============ ] - 0s 774us/step - loss: 0.3576 - accuracy: 0.0000e+00
Epoch 57/200
Epoch 58/200
Epoch 59/200
Epoch 60/200
116/116 [============ ] - 0s 791us/step - loss: 0.3744 - accuracy: 0.0000e+00
Epoch 61/200
Epoch 62/200
Epoch 63/200
116/116 [=========== ] - 0s 817us/step - loss: 0.3721 - accuracy: 0.0000e+00
Epoch 64/200
Epoch 65/200
116/116 [============= ] - 0s 861us/step - loss: 0.3659 - accuracy: 0.0000e+00
Epoch 66/200
Epoch 67/200
Epoch 68/200
116/116 [============ ] - 0s 809us/step - loss: 0.3682 - accuracy: 0.0000e+00
Epoch 69/200
Epoch 70/200
116/116 [=========== ] - 0s 2ms/step - loss: 0.3707 - accuracy: 0.0000e+00
Epoch 71/200
116/116 [============== ] - 0s 1ms/step - loss: 0.3694 - accuracy: 0.0000e+00
Epoch 72/200
116/116 [=========== ] - 0s 1ms/step - loss: 0.3691 - accuracy: 0.0000e+00
Epoch 73/200
Epoch 74/200
Epoch 75/200
116/116 [=========== ] - 0s 731us/step - loss: 0.3790 - accuracy: 0.0000e+00
Epoch 76/200
Epoch 77/200
116/116 [============ ] - 0s 809us/step - loss: 0.3677 - accuracy: 0.0000e+00
Epoch 78/200
Epoch 79/200
```

```
Epoch 80/200
116/116 [============ ] - 0s 800us/step - loss: 0.3676 - accuracy: 0.0000e+00
Epoch 81/200
Epoch 82/200
116/116 [============ ] - 0s 748us/step - loss: 0.3665 - accuracy: 0.0000e+00
Epoch 83/200
Epoch 84/200
116/116 [============ ] - 0s 757us/step - loss: 0.3665 - accuracy: 0.0000e+00
Epoch 85/200
Epoch 86/200
Epoch 87/200
116/116 [============ ] - 0s 722us/step - loss: 0.3742 - accuracy: 0.0000e+00
Epoch 88/200
Epoch 89/200
Epoch 90/200
Epoch 91/200
116/116 [============ ] - 0s 922us/step - loss: 0.3674 - accuracy: 0.0000e+00
Epoch 92/200
116/116 [============ ] - 0s 800us/step - loss: 0.3623 - accuracy: 0.0000e+00
Epoch 93/200
Epoch 94/200
Epoch 95/200
116/116 [=============== ] - 0s 1ms/step - loss: 0.3667 - accuracy: 0.0000e+00
Epoch 96/200
Epoch 97/200
Epoch 98/200
116/116 [============ ] - 0s 774us/step - loss: 0.3692 - accuracy: 0.0000e+00
Epoch 99/200
Epoch 100/200
Epoch 101/200
116/116 [============ ] - 0s 748us/step - loss: 0.3730 - accuracy: 0.0000e+00
Epoch 102/200
Epoch 103/200
116/116 [============= ] - 0s 835us/step - loss: 0.3626 - accuracy: 0.0000e+00
Epoch 104/200
Epoch 105/200
Epoch 106/200
116/116 [================ ] - 0s 1ms/step - loss: 0.3611 - accuracy: 0.0000e+00
Epoch 107/200
116/116 [=============== ] - 0s 1ms/step - loss: 0.3667 - accuracy: 0.0000e+00
Fnoch 108/200
116/116 [============ ] - 0s 904us/step - loss: 0.3661 - accuracy: 0.0000e+00
Epoch 109/200
Epoch 110/200
116/116 [============ ] - 0s 904us/step - loss: 0.3596 - accuracy: 0.0000e+00
Epoch 111/200
116/116 [============== ] - 0s 1ms/step - loss: 0.3669 - accuracy: 0.0000e+00
Epoch 112/200
Epoch 113/200
116/116 [============ ] - 0s 835us/step - loss: 0.3676 - accuracy: 0.0000e+00
Epoch 114/200
116/116 [============== ] - 0s 2ms/step - loss: 0.3691 - accuracy: 0.0000e+00
Epoch 115/200
116/116 [=========== ] - 0s 2ms/step - loss: 0.3614 - accuracy: 0.0000e+00
Epoch 116/200
116/116 [=============== ] - 0s 2ms/step - loss: 0.3575 - accuracy: 0.0000e+00
Epoch 117/200
```

```
116/116 [============ ] - 0s 1ms/step - loss: 0.3597 - accuracy: 0.0000e+00
Epoch 118/200
116/116 [=========== ] - 0s 965us/step - loss: 0.3586 - accuracy: 0.0000e+00
Epoch 119/200
Epoch 120/200
116/116 [============ ] - 0s 826us/step - loss: 0.3585 - accuracy: 0.0000e+00
Epoch 121/200
116/116 [============ ] - 0s 1ms/step - loss: 0.3572 - accuracy: 0.0000e+00
Epoch 122/200
116/116 [============ ] - 0s 826us/step - loss: 0.3645 - accuracy: 0.0000e+00
Epoch 123/200
Epoch 124/200
Epoch 125/200
116/116 [============ ] - 0s 913us/step - loss: 0.3685 - accuracy: 0.0000e+00
Epoch 126/200
Epoch 127/200
116/116 [============ ] - 0s 913us/step - loss: 0.3623 - accuracy: 0.0000e+00
Epoch 128/200
116/116 [============== ] - 0s 1ms/step - loss: 0.3644 - accuracy: 0.0000e+00
Epoch 129/200
Epoch 130/200
Epoch 131/200
Epoch 132/200
116/116 [============ ] - 0s 826us/step - loss: 0.3621 - accuracy: 0.0000e+00
Epoch 133/200
Epoch 134/200
116/116 [============ - 0s 1ms/step - loss: 0.3636 - accuracy: 0.0000e+00
Epoch 135/200
Epoch 136/200
116/116 [=========== ] - 0s 2ms/step - loss: 0.3603 - accuracy: 0.0000e+00
Epoch 137/200
Epoch 138/200
Epoch 139/200
116/116 [=========== ] - 0s 930us/step - loss: 0.3604 - accuracy: 0.0000e+00
Epoch 140/200
Epoch 141/200
116/116 [============= ] - 0s 809us/step - loss: 0.3612 - accuracy: 0.0000e+00
Epoch 142/200
Epoch 143/200
Epoch 144/200
116/116 [================= ] - 0s 2ms/step - loss: 0.3572 - accuracy: 0.0000e+00
Epoch 145/200
116/116 [=============== ] - 0s 1ms/step - loss: 0.3597 - accuracy: 0.0000e+00
Fnoch 146/200
116/116 [============ ] - 0s 896us/step - loss: 0.3555 - accuracy: 0.0000e+00
Epoch 147/200
Epoch 148/200
116/116 [============ ] - 0s 930us/step - loss: 0.3709 - accuracy: 0.0000e+00
Epoch 149/200
Epoch 150/200
Epoch 151/200
116/116 [============ ] - 0s 904us/step - loss: 0.3656 - accuracy: 0.0000e+00
Epoch 152/200
Epoch 153/200
116/116 [============ ] - 0s 1ms/step - loss: 0.3659 - accuracy: 0.0000e+00
Epoch 154/200
116/116 [=============== ] - 0s 1ms/step - loss: 0.3650 - accuracy: 0.0000e+00
Epoch 155/200
```

```
116/116 [============ ] - 0s 1ms/step - loss: 0.3714 - accuracy: 0.0000e+00
Epoch 156/200
Epoch 157/200
116/116 [============ ] - 0s 1ms/step - loss: 0.3645 - accuracy: 0.0000e+00
Epoch 158/200
116/116 [============ ] - 0s 939us/step - loss: 0.3768 - accuracy: 0.0000e+00
Epoch 159/200
Epoch 160/200
116/116 [=========== - 0s 1ms/step - loss: 0.3638 - accuracy: 0.0000e+00
Epoch 161/200
Epoch 162/200
Epoch 163/200
116/116 [============ ] - 0s 843us/step - loss: 0.3637 - accuracy: 0.0000e+00
Epoch 164/200
Epoch 165/200
Epoch 166/200
Epoch 167/200
116/116 [============ ] - 0s 896us/step - loss: 0.3592 - accuracy: 0.0000e+00
Epoch 168/200
116/116 [=========== ] - 0s 913us/step - loss: 0.3546 - accuracy: 0.0000e+00
Epoch 169/200
Epoch 170/200
116/116 [============ ] - 0s 1ms/step - loss: 0.3569 - accuracy: 0.0000e+00
Epoch 171/200
116/116 [============== ] - 0s 1ms/step - loss: 0.3623 - accuracy: 0.0000e+00
Epoch 172/200
116/116 [============ ] - 0s 991us/step - loss: 0.3609 - accuracy: 0.0000e+00
Epoch 173/200
Epoch 174/200
Epoch 175/200
116/116 [=============== ] - 0s 1ms/step - loss: 0.3555 - accuracy: 0.0000e+00
Epoch 176/200
116/116 [============ ] - 0s 1ms/step - loss: 0.3576 - accuracy: 0.0000e+00
Epoch 177/200
116/116 [=========== - 0s 2ms/step - loss: 0.3528 - accuracy: 0.0000e+00
Epoch 178/200
Epoch 179/200
Epoch 180/200
Epoch 181/200
116/116 [=============== ] - 0s 1ms/step - loss: 0.3541 - accuracy: 0.0000e+00
Epoch 182/200
116/116 [============ ] - 0s 852us/step - loss: 0.3535 - accuracy: 0.0000e+00
Epoch 183/200
Fnoch 184/200
Epoch 185/200
Epoch 186/200
Epoch 187/200
Epoch 188/200
116/116 [================ ] - 0s 1ms/step - loss: 0.3624 - accuracy: 0.0000e+00
Epoch 189/200
116/116 [=========== - 0s 1ms/step - loss: 0.3547 - accuracy: 0.0000e+00
Epoch 190/200
116/116 [============== ] - 0s 2ms/step - loss: 0.3603 - accuracy: 0.0000e+00
Epoch 191/200
116/116 [=========== ] - 0s 2ms/step - loss: 0.3593 - accuracy: 0.0000e+00
Epoch 192/200
116/116 [=============== ] - 0s 2ms/step - loss: 0.3573 - accuracy: 0.0000e+00
Epoch 193/200
```

```
116/116 [============ ] - 0s 2ms/step - loss: 0.3644 - accuracy: 0.0000e+00
        Epoch 194/200
        116/116 [============ ] - 0s 2ms/step - loss: 0.3604 - accuracy: 0.0000e+00
        Epoch 195/200
        Epoch 196/200
        116/116 [=========== - 0s 2ms/step - loss: 0.3600 - accuracy: 0.0000e+00
        Epoch 197/200
        116/116 [============ ] - 0s 2ms/step - loss: 0.3532 - accuracy: 0.0000e+00
        Epoch 198/200
        116/116 [============ ] - 0s 2ms/step - loss: 0.3568 - accuracy: 0.0000e+00
        Epoch 199/200
        116/116 [============= ] - 0s 2ms/step - loss: 0.3569 - accuracy: 0.0000e+00
        Epoch 200/200
        In [22]:
        # 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}, Accuracy: {model accuracy}")
        39/39 - 0s - loss: 10.6428 - accuracy: 0.0000e+00 - 121ms/epoch - 3ms/step
        Loss: 10.642814636230469, Accuracy: 0.0
In [23]:
        # 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[23]: <AxesSubplot:>
                                            loss
        8
        6
        4
        2
        0
               25
                   50
                        75
                            100
                                125
                                    150
                                         175
                                             200
In [24]:
        # Plot the accuracy
        history df.plot(y="accuracy")
Out[24]: <AxesSubplot:>

    accuracy

         0.04
         0.02
         0.00
        -0.02
        -0.04
```

100

75

125

150

175

In [ ]:		