

```
In [ ]: # 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()
```

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

Reduce down to top features

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

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 [ ]: # 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)
```

Build and Instantiate StandardScaler object, then standardize numerical features

```
In [ ]: # 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 [39]: # 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 = 15

nn = tf.keras.models.Sequential()

# First hidden layer
nn.add(
    tf.keras.layers.Dense(units=hidden_nodes_layer1, input_dim=number_input_features, activation="selu")
)

# Second hidden layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation="selu"))

# Third hidden layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer3, activation="selu"))

# Fourth hidden layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer4, activation="selu"))

# Output layer
nn.add(tf.keras.layers.Dense(units=10, activation="selu"))

# Check the structure of the model
nn.summary()
```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
=====	=====	=====
dense_30 (Dense)	(None, 50)	400
dense_31 (Dense)	(None, 30)	1530
dense_32 (Dense)	(None, 20)	620
dense_33 (Dense)	(None, 15)	315
dense_34 (Dense)	(None, 10)	160
=====	=====	=====
Total params: 3,025		
Trainable params: 3,025		
Non-trainable params: 0		

Compile the Model

```
In [47]: # Compile the model
nn.compile(loss="mean_squared_logarithmic_error", optimizer="RMSprop", metrics=["accuracy"])
```

Train the model

```
In [48]: # Train the model
```

```
fit_model = nn.fit(X_train,y_train,epochs=200)
```

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Epoch 1/200
116/116 [=====] - 1s 2ms/step - loss: 0.0069 - accuracy: 0.0014
Epoch 2/200
116/116 [=====] - 0s 1ms/step - loss: 0.0068 - accuracy: 0.0014
Epoch 3/200
116/116 [=====] - 0s 1ms/step - loss: 0.0069 - accuracy: 0.0014
Epoch 4/200
116/116 [=====] - 0s 2ms/step - loss: 0.0069 - accuracy: 8.1037e-04
Epoch 5/200
116/116 [=====] - 0s 1ms/step - loss: 0.0069 - accuracy: 8.1037e-04
Epoch 6/200
116/116 [=====] - 0s 1ms/step - loss: 0.0069 - accuracy: 5.4025e-04
Epoch 7/200
116/116 [=====] - 0s 2ms/step - loss: 0.0069 - accuracy: 8.1037e-04
Epoch 8/200
116/116 [=====] - 0s 2ms/step - loss: 0.0069 - accuracy: 0.0014
Epoch 9/200
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Epoch 10/200
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Epoch 14/200
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Epoch 15/200
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Epoch 16/200
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Epoch 17/200
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Epoch 18/200
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Epoch 20/200
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Epoch 24/200
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Epoch 25/200
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Epoch 26/200
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Epoch 28/200
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Epoch 34/200
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Epoch 35/200
116/116 [=====] - 0s 2ms/step - loss: 0.0068 - accuracy: 0.0016
Epoch 36/200
116/116 [=====] - 0s 1ms/step - loss: 0.0068 - accuracy: 0.0024
Epoch 37/200
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Epoch 38/200
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Epoch 190/200
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116/116 [=====] - 0s 2ms/step - loss: 0.0066 - accuracy: 5.4025e-04
Epoch 196/200
116/116 [=====] - 0s 1ms/step - loss: 0.0066 - accuracy: 2.7012e-04
Epoch 197/200
116/116 [=====] - 0s 2ms/step - loss: 0.0066 - accuracy: 5.4025e-04
Epoch 198/200
116/116 [=====] - 0s 2ms/step - loss: 0.0067 - accuracy: 0.0016
Epoch 199/200
116/116 [=====] - 0s 2ms/step - loss: 0.0067 - accuracy: 0.0019
Epoch 200/200
116/116 [=====] - 0s 1ms/step - loss: 0.0066 - accuracy: 2.7012e-04

```

In [49]:

```

# 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: 1.0681 - accuracy: 0.0000e+00 - 162ms/epoch - 4ms/step
Loss: 1.068142533023071, Accuracy: 0.0

```

In [50]:

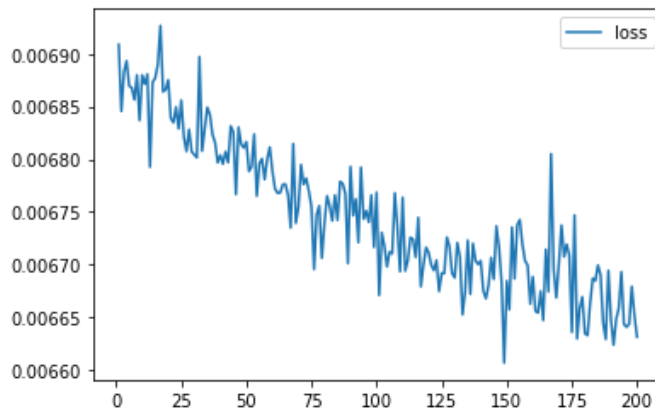
```

# 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[50]: <AxesSubplot:>



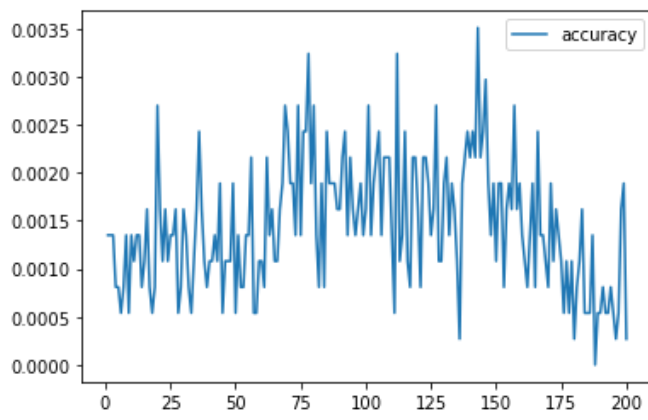
In [51]:

```

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

```

Out[51]: <AxesSubplot:>



In []: