MODEL DESIGN DEEP LEARNING AND ITS APPLICATIONS IN THE NBA

John Zhang (jz5jx)
School of Data Science
University of Virginia
Charlottesville, VA 22903
jz5jx@virginia.edu

Youssef Abubaker(yaa2vb)
School of Data Science
University of Virginia
Charlottesville, VA 22903
yaa2vb@virginia.edu

Joseph Cho (jc4jx)
School of Data Science
University of Virginia
Charlottesville, VA 22903
jc4jx@virginia.edu

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1 Code Repository

https://github.com/jz5jx/deep_learning_NBA_MSDS

2 Experiments

We developed two different models based on different perspectives of the movement of the ball. For our log-it model we utilized the coordinate positions from the last frame of each individual shot to predict shot outcome. The second model we evaluated was a custom neural net model. For the neural net model we started with a standard Keras Sequential Model. Then we added a Dense layer with 12 nodes and passed each input through "Relu" Activation Functions. From this first layer we then added a second layer with 8 nodes and another "Relu" Activation function. From the subsequent layer we then passed all the inputs through the output layer which mapped our matrix manipulations through a sigmoid activation function which predicted our inputs to either a "1" (Success) or "0" (Failure).

3 Results

We implemented our logit model in python using the LogisticRegression() function with cross validation from the sklearn library. For cross validation we used a .67/.33 train-test split and observed 64.9% accuracy. For our Deep Learning model, we used the Keras framework to build a Neural Network of 3 dense layers. This model was trained on the "binary_crossentrophy" loss function and optimized using the Adam algorithm. Training consisted of 10 epochs with a batch side of 10 which yielded a accuracy of 64.1%.

4 Design Choices and Architecture

4.1 Logistic Regression

Our baseline Model is the Logistic Regression, it predicts class membership based upon the final frames of the basketball's position. We chose this model to be our baseline because the latter movements and positions of a basketball are more indicative of membership than the initial release frames. Most of the Logistic Regression Architecture is implemented using matrices. Such matrices calculate the parameters of the model using MLE (Maximum Likelihood Estimators).

4.2 Neural Net Architecture

Our comparative Model is a custom built neural network. For the neural net model we started with a standard Keras Sequential Model. Then we added a Dense layer with 12 nodes and passed each input through "Relu" Activation

Functions. From this first layer we then added a second layer with 8 nodes and another "Relu" Activation function. From the subsequent layer we then passed all the inputs through the output layer which mapped our matrix manipulations through a sigmoid activation function which predicted our inputs to either a "1" (Success) or "0" (Failure).

4.3 Motivation

The motivations to use a logistic regression are as follows. Logistic Regression is easy to train, implement and is more efficient to train. Additionally, Logisitic Regression is less prone to over-fitting and assumes no assumptions of the distributions of the classes in feature space. For these following reasons this is why we believe logistic regression is useful as our baseline model.

The motivation to use a Artificial Neural Net using initial release data is as follows. Initial release data should be less indicative of class membership of a made shot, however, there are several advantages that an ANN has to overcome this particular problem. ANN's requires less statistical knowledge, models any complex relationship between input and output variables (This can be non linear), good generalization, and can detect implicit relationships within the data.

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