A 3-LAYER NEURAL NETWORK MODEL FOR INCREASING A GOALKEEPER'S ACCURACY

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Abstract

The rapid progress in artificial intelligence (AI) and machine learning has opened unprecedented analytics possibilities in various team and individual sports, including baseball, basketball, and tennis. More recently, AI techniques have been applied to football, due to a huge increase in data collection by professional teams, increased computational power, and advances in machine learning, with the goal of better addressing new scientific challenges involved in the analysis of both individual players' and coordinated teams' behaviors. The research challenges associated with predictive and prescriptive football analytics require new developments and progress at the intersection of statistical learning, game theory, and computer vision. In this paper, we developed a model that helps to improve the performance of the team and increase the probability of winning a game competition. We built an algorithm that recommends the positions where the goalkeeper should kick the ball so that his team players can hit the ball with their heads. We trained our dataset on 3 different models and observed how each model reduced overfitting on the dataset. We concluded by highlighting that the Dropout model technique fitted the dataset better with increased accuracy on the test set.

1. Introduction

Recent years have seen tremendous growing interest in sports analytics, not only from an economic and commercial perspective, but also from a purely scientific one, viz. the growing number of publications (Baumer & Zimbalist, 2014; Beal, Norman, & Ramchurn, 2019; Shih, 2017) and scientific events organized on the topic (e.g., MIT Sloan Sports Analytics Conference (2020), CVSports International Workshop on Computer Vision in Sports at CVPR (2020), and Machine Learning and Data Mining for Sports Analytics (2020)). As evident in many different downstream domains that have benefited from applications of artificial intelligence (AI) and machine learning (ML), this is due to important technological advances in data collection and processing capabilities, progress in statistical and in particular deep learning, increased compute resources, and ever-growing economic activities associated with sports and culture (e.g., emergent consultancy ventures revolving around sports data collection and statistics (Beal et al., 2019; ChyronHego, 2020; InStat, 2020; Kuper & Szymanski, 2018; Opta, 2020; StatsBomb, 2020)).
Predictive analytics has been investigated and applied in the context of several sports in the past decades, including basketball (Skinner, 2010), tennis (Gauriot, Page, & Wooders, 2016; Walker & Wooders, 2001), and baseball (Albert, 2010; Albert, Bennett, & Mead, 2002; Baumer & Zimbalist, 2 2014; Costa, Huber, & Saccoman, 2009; Michael, 2004; Puerzer, 2002; Song, Severini, & Allada, 2017), with data for the latter having been systematically collected since the 19th century. Although statistical analysis of data has led to impressive outcomes in various sports (e.g., Moneyball in baseball (Baumer & Zimbalist, 2014; Michael, 2004)), football started participating rather late in this data collection and number-crunching game, with the data science transformation that informs stakeholders (e.g., decisions related to player transfers, scouting, pre- and post-match analysis, etc.) still in its infancy (Kuper & Szymanski, 2018). Several factors influenced this late arrival. Football takes place under far less controllable settings than other sports due to its outdoor and highly dynamic nature, a larger pitch, a large number of players involved, a low number of player changes, and longer non-interrupted game sequences than sports such as basketball. As a result, football analytics companies have only relatively recently started collecting so-called big

data (e.g., high-resolution videos, annotated event streams, player tracking, and pose information). Concurrently, only recently have major breakthroughs been made in deep learning, yielding techniques that can handle such new high-dimensional data sets (Arel, Rose, & Karnowski, 2010; Bengio, 2009; Goodfellow, Bengio, & Courville, 2016; LeCun, Bengio, & Hinton, 2015; Schmidhuber, 2015). Finally, for a long time, credibility in decision-making primarily depended on human specialists such as managers, retired players, and scouts, all of them with track records and experience in professional football, in part due to cultural reasons (Decroos & Davis, 2019; Kuper & Szymanski, 2018). As a result of these various factors, the potential influence and gains of predictive analytics on the football game have also been less obvious, with sports analytics as a game-changing phenomenon not realized until recent years. In more philosophical terms, Kuper and Szymanski (2018) highlight a cultural hesitation regarding the integration of data science into football and an overdependence on gut instincts, noting that "until very recently, soccer had escaped the Enlightenment".

Despite football's late adoption of sports analytics, there are a number of early-bird approaches from different areas of AI such as statistical learning (SL), computer vision (CV), and game theory (GT) that are making initial contributions to support the decision-making of managers, coaches, and players. For example, basic statistical learning tools such as principal component analysis (PCA) already enable automated means of identifying player types (Decroos & Davis, 2019), training models predicting trajectories of individual teams or imitating league-average behaviors (H. Le, Carr, Yue, & Lucey, 2017), and valuing individual player decisions (such as passes or tackles) in a series of actions leading up to a goal (Decroos, Bransen, Haaren, & Davis, 2019). The study of interactive decision-making as formalized by game theory plays a critical role in AI for systems involving more than one actor (human or artificial)

While these separate areas within AI research have independently been demonstrated to be effective for football analytics, we believe that the most pertinent research problems lie in the underexplored intersection of statistical learning, computer vision, and game theory. In this research, we have used the statistical data of the Franch football team to develop a model with higher accuracy capable of recommending the position team players to the goalkeeper before hitting the ball as shown in figure 1. We trained our dataset on three different models and observed the model with the best reduction of overfitting and higher accuracy.

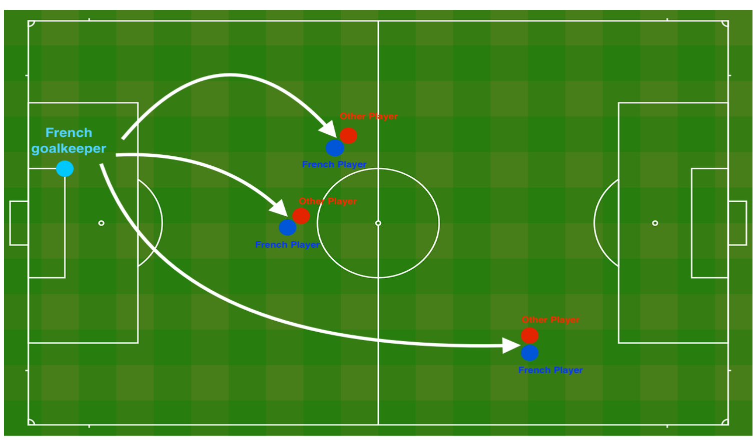

Figure 1: Illustration of the model's recommendation to goalkeeper

2. Details of the approach

2.1 Data Acquisition

The data used in this project consists of the french team's 2D dataset for the past 10 games gotten from the Kaggle resource site. It contains the train and test cases After loading the dataset, a scatterplot as shown in the diagram below was plotted. Each dot corresponds to a position on the football field where a football player has hit the ball with his/her head after the French goalkeeper has shot the ball from the left side of the football field. If the dot is blue, it means the French player managed to hit the ball with his/her head but If the dot is red, it means the other team's player hit the ball with their head.

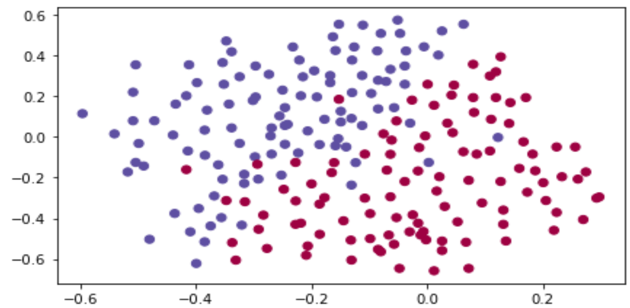

Figure 2: Scatterplot of the French football team and its opponent

2.2 Analysis of the dataset.

The scatterplot showed a noisy dataset, however, the distribution of the points showed that a diagonal line separating the upper left half (blue) from the lower right half (red) would work well.

2.3 Machine Learning Model

Three different machine learning models were used in this research paper to reduce overfitting on the dataset. The models include the non-regularization model, L2-regularization, and the drop-0ut technique. Following the result of our models, the behavior of the boundary line differs. Moreso, the training and test accuracy of the dataset improved between models.

2.3.1 Non-Regularization model

The model was first learned without any regularization. The hyperparameter (λ) was set to zero with the larning_rate (α) = 0.3 and keep_prob = 1. The non-regularized model overfitted the training set and fitted the noisy points. Two other models were used on the dataset to avoid overfitting and improve the accuracy of the train and test sets. The logistic regression cost function was used in the non-regularized model. The cost function is given as

$$J = -\frac{1}{m}\sum_{i=1}^{m}\{y^{(i)}\log(a^{(L)(i)}) + (1 - y^{(i)})\log(1 - a^{(L)(i)})\}$$

2.3.2 Regularization model

L2-regularization relies on the assumption that a model with small weights is simpler than a model with large weights. Thus, by penalizing the square values of the weights in the cost function we drive all the weights to smaller values. It becomes too costly for the cost to have large weights. This leads to a smoother model in which the output changes more slowly as the input changes. Although regularization hurts training set performance by limiting the ability of the network to overfit the training set, it ultimately gives better test accuracy. The L2 regularization model was used on the dataset to avoid overfitting by modifying the cost function used in the non-regularized model. The cost function was modified to

$$\text{Jregularized} = -\frac{1}{m}\sum_{i=1}^{m}\{y^{(i)}\log(a^{(L)(i)}) + (1 - y^{(i)})\log(1 - a^{(L)(i)})\} + \frac{1}{m}\frac{\lambda}{2}\sum_{i}\sum_{k}\sum_{j} W^{[l](i)}$$

Backpropagation was computed on the dataset using the hyperparameter (λ) set to 0.7 and learning_rate increased to 0.7. The regularization model fitted the dataset more accurately with an improvement in the train and test accuracy.

2.3.3 The Dropout Model

Dropout is a widely used regularization technique that is specific to deep learning. It randomly shuts down some neurons in each iteration. At each iteration, each neuron of a layer was shut down (= set to zero) with probability 1−keep_prob or keep it with probability keep_prob(50%). The dropped neurons do not contribute to the training in both the forward and backward propagations of the iteration. The idea behind drop-out is that at each iteration, a different model that uses only a subset of the neurons was trained. With dropout, the neurons become less sensitive to the activation of one other specific neuron, because that other neuron might be shut down at any time. The dropout model was able to remove overfitting with increased train and test accuracy.

3.0 Results

We observed that the three models learned the dataset differently as seen in the graphs and table. The non-regularized model overfitted the dataset It has a training accuracy of 95% and a test accuracy of 91.5%. The high difference between the train and test accuracy is a result of fitting the noisy points in the dataset. The model has a high bias.
The L2 regularization model produced a higher accuracy of 93% in the test set compared to the case of the non-regularized model. The difference between its train and test accuracy is 1% which shows a lower bias and better fitting of the dataset with a smoother slope of its boundary line.
Finally, the dropout technique gave the highest test accuracy of 95% compared to the two other techniques. It introduced a little variance into the model, however, the overfitting in the dataset was removed.

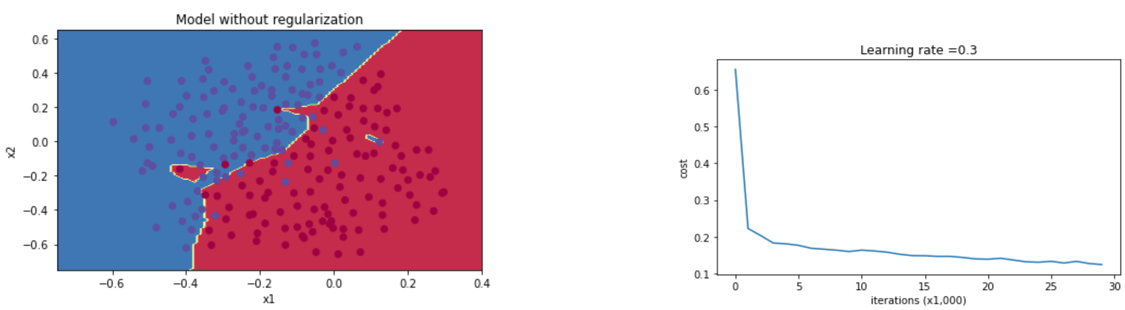

Figure 3: Performance of the Non-regularized model. It is obviously overfitting the training set and fitting the noisy points

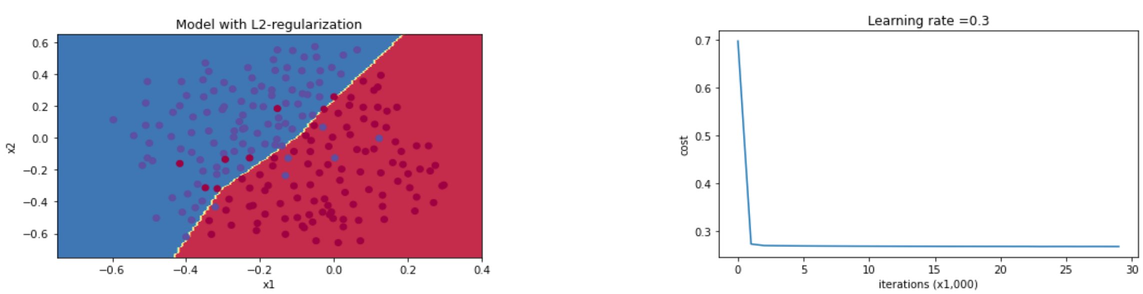

Figure 4: Performance of the L2 Regularization model. It reduced overfitting, makes the decision boundary smoother, and drives weights to lower values.

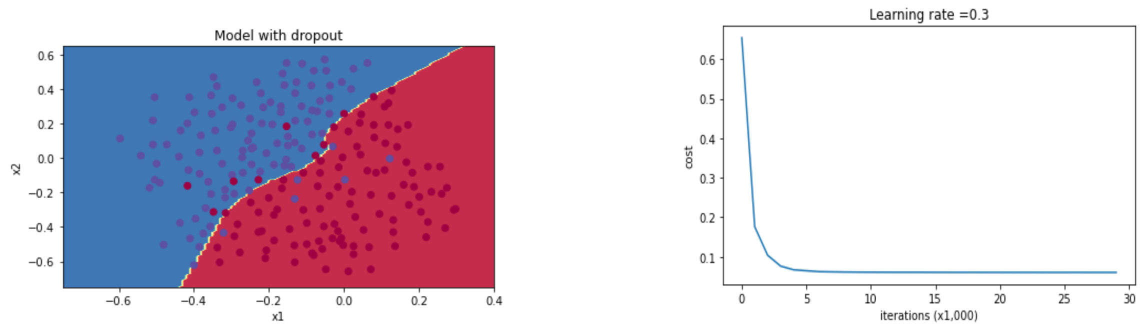

Figure 5: Performance of the Dropout Regularization. The model is not overfitting the training set and does a great job on the test set.

Model	Train Accuracy	Test Accuracy
3-layer NN without regularization	95%	91.5%
3-layer NN with regularization	94%	93%
3-layer NN with dropout	93%	95%

Table 1: Table showing the performance of non-regularized, L2-regularized and Dropout regularization techniques of a machine learning model

4.0 Discussion and Conclusion

In this work, we learned our dataset on three different models to improve the performance of the goalkeeper. Two of the models are regularization techniques commonly used in machine learning projects. We also observed the behavior of the model when there is no regularization. We concluded that the Dropout regularization technique has a higher test accuracy and a better to improve the accuracy of the goalkeeper. Note that regularization hurts training set performance because it limits the ability of the network to overfit the training set. However since it ultimately gives better test accuracy, it helps our system. The value of λ is a hyperparameter that can be tuned using a development set. If it is too large, it is possible to "over smooth", resulting in a model with high bias. Moreso, a common mistake when using dropout is to use it both in training and testing. Dropout (randomly eliminating nodes) should be used only in training.

5.0 References

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