Predicting Game Play Direction in Football Videos

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Abstract

The aim of this project is to make a machine learning system which will detect the direction in which the offensive team is playing in football videos. This information is necessary when we have to make automated computer vision systems which will provide us with analysis of the footabll games for coaching purposes. To develop such a system, we have used the KLT Tracking system to track seemingly interesting points in the videos, and then use machine learning algorithms of Decision Tree and Decision Stump with Boosting to identify which player tracks are important in making the decision for the direction of the offensive play.

1 Introduction

To come up with good and effective solutions for football coaching software, we require to track players, look for prominently used strategies by different teams, etc. In general we need to find all those properties of a football video that the coach can use to better train his own team, given a set of videos of the opposition team. To do so, in the absence of such a coaching software, the coach or his team of assistants have to look at numerous plays of the team and decipher the playing strategy of the teams. Even after the coach is done doing this, he now has to send out a great deal of documentation to the players so that they know their roles in the game. This leads to a lot of time spent in auxiliary work which could have been automated.

The aim of this project is to help develop a part of such a coaching software. This project will aim at recognizing the direction of the offensive play given a video. This analysis can then be used to make comments about the team that is on offense, the orientation of the players on the offensive team and the player movements in both the teams. It will serve as a major step in developing the coaching software as many other elements of the coaching software are dependent on it.

2 Methodology

In order to recognize the direction of offense we need to know some domain knowledge about football. We will provide with a brief overview of the domain knowledge that we require for this project. Usually when the two teams line up for a play in the game of football, we have two players known as “Wide Receivers” standing at the ends of the field along the line of scrimmage. The line of scrimmage is the line that separates the two teams at the moment of snap. The moment of snap is the time at which the players start to play the game for each play.

These two wide receivers are instrumental in the detection of the direction of the play as they run fast down the field in the direction of offense from the moment of snap and can be used to determine the direction of the play. If we are able to get good, long tracks on these players, and if we are able to tell that these tracks belong to the wide receivers, we can find the direction of those tracks and ultimately determine the offensive direction of play. Figure 1 shows an example of video footage

Figure 1: Example of one particular football play video footage. Note the wide receiver (bottom most player in white) dashes off to the left. The goal is to classify this video as "left" by tracking the wide receiver.

where the wide receiver runs fast down the field in the direction of offense, which is to the left of the video frame.

We decided to use KLT tracks [1,2,3] to do the video tracking on different points in the video. The KLT tracking method selects points that have a high gradient with respect to its neighbors. This makes it select "interesting" points such as corners in the video frame. We want to use these interesting points and specify which of these points correspond to the wide player on the pitch. Using KLT tracks, we can get the length of the track easily by simple geometric computation on the track features. Also, we can get the distance of the track from the bottom edge of the frame.

We use KLT tracks to generate a dataset for the videos with the following features:

1. Track Number
2. Starting Point Co-ordinates of the track
3. Ending Point Co-ordinates of the track
4. Normalized length of the track.
5. Normalized distance of the track from the bottom edge of the figure.
6. Direction of the track.

After getting such a dataset from the KLT tracks, we have to find out a way to determine which of these tracks belong to the wide receiver. We can now use the domain knowledge to determine where to look for the receivers. They will be at the near end and the far end of the field. Also, since they run fast, they will have longer tracks as compared to anyone else on the field. Hence, we have to look for long tracks on both the ends of the field.

We can plot a sample dataset as shown in the following image.

IMAGE!

Here the y-direction represents the length of the track while the x direction represents the closeness to the bottom edge of the field. If $x = 1$, then the track is nearest to the bottom. If $x = 0$ then it is farthest from the bottom.

Now, we have to find a region in this plot where the receiver tracks will be. Using the domain knowledge and the inspection of various videos, we come to know that the receiver tracks will more often than not be in the highlighted part in the figure. But, this region will change from video to video as the orientation of the videos, the resolution quality and even plays will be different in different situations. Here is where we use the machine learning algorithms to determine the rectangle to be considered for determining the direction of play.

We then use a machine learning algorithm to identify the best rectangle which will denote the direction of play. We predict the direction of play by considering a majority vote of all the tracks that fall within the rectangle. If the majority are moving in left direction we say that the direction of the play is left.

3 Features

The features that we have considered here are as follows:

a. Length of the track.

We know from the domain knowledge that the wide player will be the one who will make a big rush down field so that we will get good, continuous and long tracks on him. Also, the other players, like free safety, quarter back or the guard players will not move much in the first one and a half second and will have relatively smaller tracks. So, we wish to select those tracks that have a high length as feature.

b. Distance from the edge of the field.

As mentioned before we know that the wide players will be on the near side of the field. The orientation of the play recording is always such that the wide player that we want to track will always be on the bottom most part of the frame. So, we have selected the distance from the edge of the field as our next feature.

c. Track direction with respect to the field.

This information is vital, since one player will have multiple tracks in one and a half second which will all be close by and going along the same direction. So, if we include the information of the direction of the track (left or right) we will be able to make the differentiation between the noisy tracks and actual wide player tracks better. Thus, the reason for selecting this as a feature.

In short, we want to track those points that have a high length and are closer to the edge of the field, moving in one direction so that we can say that the tracked point is a wide receiver.

In the end, we use 60 different features for each video to submit to our learning algorithms. These 60 features are the predictions of 60 different rectangles.

4 Learning

We decided to use machine learning algorithms that produce nonlinear decision boundaries. Since our features are 60 different rectangles, it is not clear that a linear decision boundary would capture an effective hypothesis space. It is also not clear what type of kernel to use for kernel-based methods.

Therefore we considered tree-based approaches to learning a nonlinear hypothesis. We used two different approaches: AdaBoost [4] with decision stumps and decision trees [5]. We think a hypothesis generated from AdaBoost with decision stumps makes the most sense since the prediction would be a linear combination of the 60 rectangle features. Each feature would be given a weight for prediction. The hypothesis generated from the decision tree makes sense for capturing decisions on a subset of the 60 features, but it is not immediately clear when to stop growing the tree. We investigate this as a parameter in our experiments.

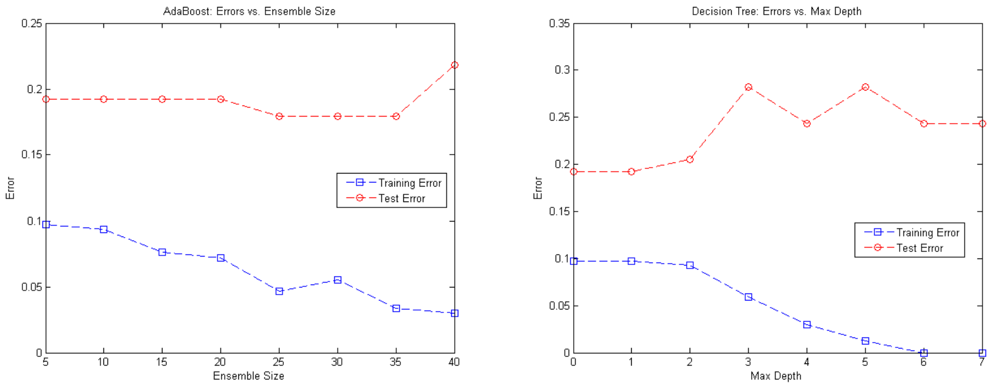
For the decision tree, we used the C4.5 algorithm for generating the decision tree based on information gain. Since our features are continuous, we also threshold each feature and select the threshold that maximizes the information gain, before selecting the maximum information gain from all the features. The decision stump is simply a one-level version of the decision tree used in the AdaBoost meta-learning algorithm.

5 Experiments

Our football dataset consists of three games, which we will call game1, game2 and game3. Game1 consists of 95 videos, game2 consists of 95 videos, and game3 consists of 124 videos. Each video represents a play that contains the moment of snap.

To form our training and test sets for evaluation, we concatenated all three game datasets into one dataset of 314 instances. Each instance corresponds to a video with the 60 features described earlier and its true label (i.e. left or right direction of offensive gameplay). We randomly selected 75% of the instances for our training set and the remaining 25% as our test set.

For empirical evaluation, we compared the performance of using AdaBoost and decision tree on varying parameters. For AdaBoost, we vary the ensemble size as the parameter. For the decision



(a) AdaBoost

(b) Decision Tree

Figure 2: Training and test errors for AdaBoost and decision tree. (a) AdaBoost training and test errors are a function of ensemble size. (b) Decision tree training and test errors are a function of maximum depth size.

tree, we vary the maximum depth size as the parameter; the tree is only allowed to grow up to the maximum depth.

Figure 2a presents the plot of training and test errors as a function of ensemble size. We see that the training error decreases reasonably. We also observe that the test error decreases until ensemble size 35. The test error at that point is a little under 20%, which is reasonable.

Figure 2b presents the plot of training and test errors as a function of the maximum decision tree depth. We also see that the training error decreases reasonably. In fact it goes to zero at around a maximum depth of 6. At that point the test error is not good compared to smaller maximum depth sizes, which indicates that the decision tree is over-fitting the data. We also observe that the test error begins to increase early on. The best maximum depth is probably around 2. The test error is a little under 20%, which is reasonable and comparable to the error from AdaBoost.

6 Conclusion

In this paper, we have motivated the problem of predicting the direction of the offensive play in a video. We have presented a framework for extracting useful features from a video and using them with machine learning to make predictions. Our results using decision trees and boosting are good enough to make accurate predictions.

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