Classifying Olympic Athletes By Sport and Event

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Abstract

1 Introduction

1.1 Motivation

To what extent do biological traits determine sporting success? At the highest level of amateur sports–the Olympic games–we see differences in the physical characteristics of participants across sports. Can these differences be exploited to classify individuals by sport or event given their physical attributes?

This project was inspired by a claim made by David Epstein, author of *The Sports Gene* [**?**]. This claim is expressed in an interview with Russ Roberts:

> **Roberts**: [You argue that] if you simply had the height and weight of an Olympic roster, you could do a pretty good job of guessing what their events are. Is that correct?
> **Epstein**: That's definitely correct. I don't think you would get every person accurately, but... *I think you would get the vast majority of them correctly.* And frankly, you could definitely do it easily if you had them charted on a height-and-weight graph, and I think you could do it for most positions in something like football as well.[1]

Epstein's work is in large part a counter-argument to the "10,000 hour rule," popularized by Malcolm Gladwell, which claims that that amount of practice is necessary to attain mastery of a skill [**?**]. The results in this paper show whether an athlete's sport or event can be accurately predicted by their physical features. If true, that suggests that athletes choose the event that best leverages their natural predisposition. If not, that would suggest that athletic ability can be understood as a latent trait that can be applied to the sport of one's choice. The remainder of this paper describes related work, outlines the machine learning methods used, and presents the results.

1.2 Related Work

2 Model and Methods

2.1 Problem Definition and Data Sources

The goal of this project is to predict an athlete's Olympic event given their height, weight, age, and sex. Given data $\mathcal{D}$ on these $p = 4$ features our goal is to predict athletes' sports or events $\mathbf{y}$ (which are nested in sports).[2] The quantity we are interested in, then, is $p(\mathbf{y}|\mathcal{D})$.

Data was obtained for 10,383 participants in the 2012 London Olympics from *The Guardian*. The processed data consists of 8,856 complete cases. Of these, 6,956 participants were split into training (n=3,520) and test (n=3,436) sets for classification by sports. In 2012 there were 27 sports in the Summer Olympic Games, excluding participants in the "Athletics" sports category. Because Athletics is such a large category (with 1,900 participants and 48 events) with participants' exhibiting a wide range of body types, it tended to dominate the classification models when it was included. Omitting Athletics participants from the sport classification task substantially improved accuracy. The remaining 1,900 Athletics participants were split into training (n=907) and test (n=993) sets for classification by event.

2.2 Features of the Data

For both classification tasks participants' height, weight, age, and sex were used as features. Some sports and events exhibit relatively well-clustered features, whereas others are less clearly defined. In the sport classification task, participants in archery, handball, swimming, and triathlon exhibited similar features–and were thus difficult to classify accurately–while basketball players, rowers, weightlifters, and wrestlers had more distinct features (Figure 1. For event classification it was difficult to classify athletes in the 100m race, 400m hurdles,

[1] An audio recording of the interview, as well as a partial transcript, is available at `http://www.econtalk.org/archives/2013/09/david_epstein_o.html`.

[2] In the Olympic games, "sports" are somewhat broad categories, such as athletics and weightlifting, whereas "events" refers to specific competitions such as the men's 100-meter race.

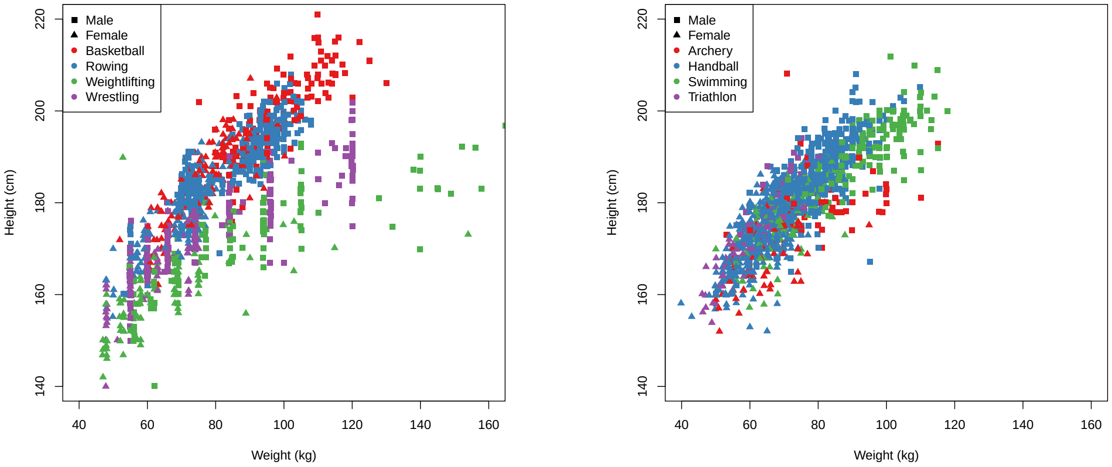


Figure 1: Comparing well-differentiated and poorly-differentiated feature clusters for sports classification.

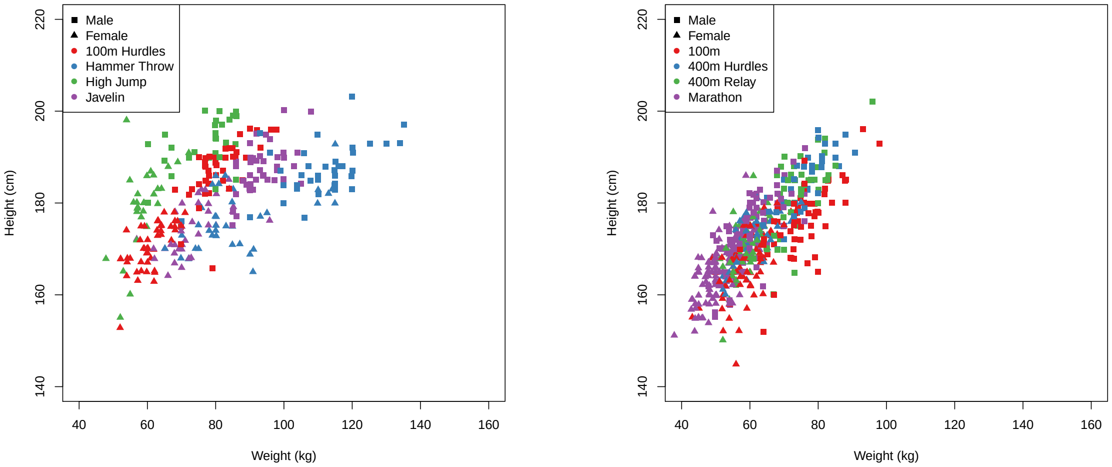


Figure 2: Comparing well-differentiated and poorly-differentiated feature clusters for event classification.

400m relay, and marathon, but easier to classify participants in the 100m hurdles, hammer throw, high jump, and javelin events (Figure 2.

2.3 Model

In order to classify an athlete from the test set, we can use the posterior predictive distribution

$$p(\mathbf{y}|\mathcal{D}) \quad = \quad \sum_{k \in N} w_k p(\mathbf{y}|\mathcal{D}_k),$$

where w_k is the weight on cluster k, $\mathcal{D}_k$ is the feature data for observations in cluster k, N is the set of nodes in the tree, and N_k represents the nodes lying on the path from the root to node k's parent.

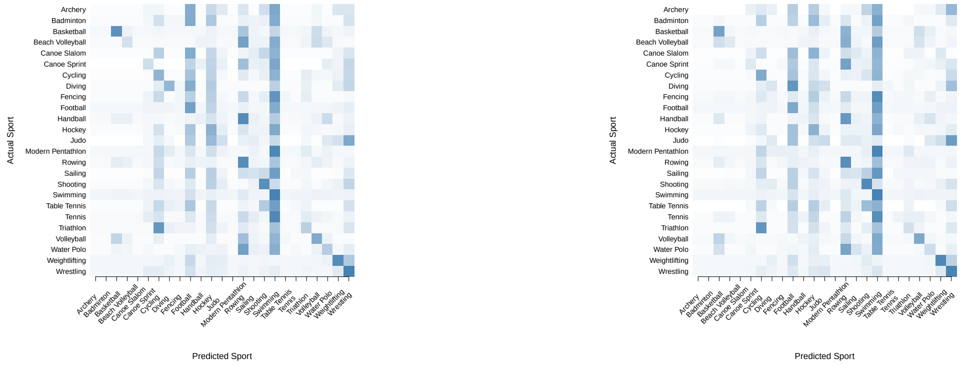
2.4 Machine Learning Methods

Several machine learning methods were applied to this classification problem. Conditional inference trees were formed by recursive binary partitioning. Evolutionary trees were constructed to be globally optimal by minimizing the misclassification rate. Breiman's Random Forest algorithm was used with 500 trees. Single-hidden-layer neural networks were constructed with 30 units in the hidden layer for sport classification and 50 for event classification.

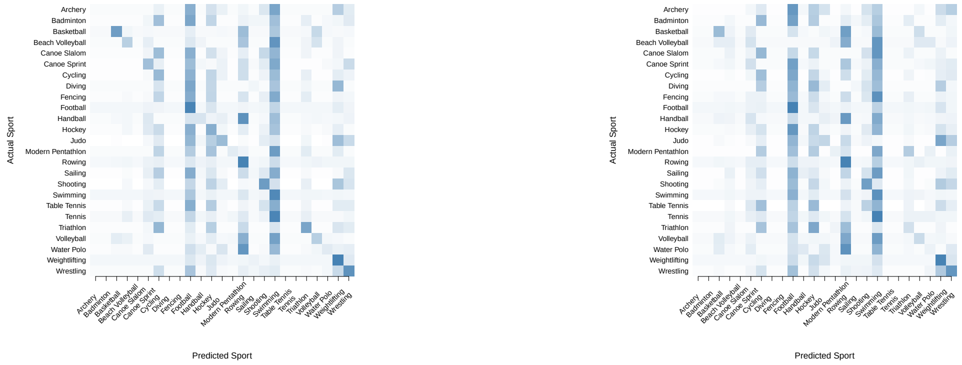
3 Results

3.1 Classification by Sport

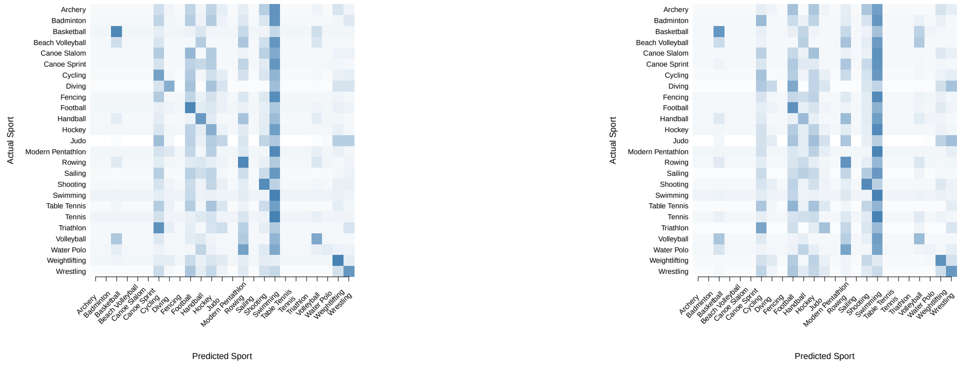
Hierarchical Clustering



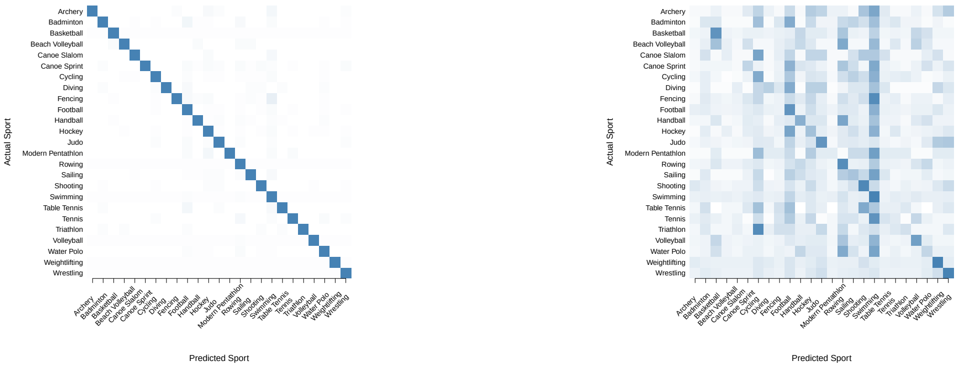
Conditional Inference Tree



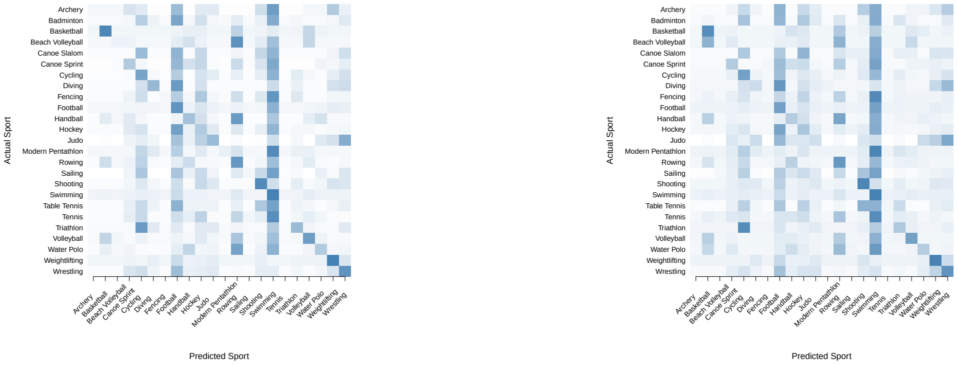
Evolutionary Tree



Random Forest



Neural Network



3.2 Classification by Event

3.3 Interpretation

3.4 Model Diagnostics

Table 1 presents the accuracy of each model for the sport and event classification tasks. Hierarchical clustering could not be used for event classification due to the small sizes of the clusters (for example, there was complete data for only one participant in the women's triathlon). The ratio columns indicate how well the model performs on the test data relative to the training data. Values near one mean that the model does about as well out-of-sample as it does on the training data, while values near zero suggests a model that is overfit to the trianing data.

Evolutionary trees and neural networks both exhibit higher accuracy for events than sports, and maintain acceptable out-of-sample accuracy. Conditional inference trees do slightly less well for both training and test sets. Random forests tend to overfit the training data but still do well on the test set. Overall, this appears to be a difficult classification problem.

Table 1: Accuracy for training and test sets.

		Sports			Events	
	Train	Test	Ratio	Train	Test	Ratio
Hierarchical Clustering	.272	.271	.998			
Conditional Inference Tree	.279	.219	.784	.277	.218	.787
Evolutionary Tree	.292	.236	.807	.303	.230	.757
Random Forest	.923	.244	.265	.976	.228	.233
Neural Network	.280	.265	.949	.397	.249	.623

4 Conclusion

- Classifying athletes by sport can be achieved with moderate accuracy using only a few features
- Additional features such as arm length and torso length could improve predictive accuracy
- Traits of athletes in some sports and events exhibit noticeable clustering, while other categories are less distinct (multi-modal)
- Above a minimum threshold of physicality, success in many sports is dependent on training
- Athletes in some sports and events have a well-defined body type, but Olympians exhibit a wide range of physical features

Acknowledgments

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References