Prediction of Chess Endgame using Decision Tree and SVM Classifiers

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Abstract

Insert Abstract Text Here.

1 Introduction

1.1 Background\Problem Formulation

Discuss what a Chess Endgame is. Discuss how one would go about determining a Chess Endgame?

1.2 Outline of Report

In section(2) we describe the dataset from the UCI repository used for our training and testing environment. We also provide insight into the parameterizations of the original data and why we think those parameterizations will yield improved classification results. In section(3) we discuss the theory and limitations of the two proposed classification methods. In section(4) we will show results heuristically drawn from simulations for the two proposed methods and discuss results related to these findings. Finally, in section(5) we will make final conclusions and possible algorithmic strategies to improve the results.

2 Dataset

2.1 Chess (King-Rook vs. King) Data Set

Discuss the dataset from UCI[1]. Format of the data.

2.1.1 Notation

Chess Board Positions: Let the following notation describe the space of a Chess board,

$$\begin{aligned} \text{File} &\in [a, b, c, d, e, f, g, h] \\ &\in [1, 2, 3, 4, 5, 6, 7, 8] \\ \text{Rank} &\in [1, 2, 3, 4, 5, 6, 7, 8] \end{aligned} \tag{1}$$

Game Pieces: Let the three game pieces be defined as $Piece_i$, where $i = [1, 2, 3]$ represents the piece index,

$$\begin{aligned} Piece &\in [W_k, W_r, B_k] \\ W_k &= \text{White King} \\ W_r &= \text{White Rook} \\ B_k &= \text{Black King} \end{aligned} \tag{2}$$

Examples: Let a example of a game be defined as $Game_j$ where $j = [1, 2, 3, \dots]$ is the game row index,

$$Game_j = [Piece_i \{file_j, rank_j\}] \tag{3}$$

The entire set of examples is labeled as $\mathbf{X}$.

Class Labels: Class labels are defined as the remaining moves till checkmate of B_k. Note, checkmate of B_k is called on the m^{th} move of B_k.

$$\begin{aligned} y_j &\in [draw, 0, 1, 2, 3, 4, \dots, m] \\ &\in [-1, 0, 1, 2, 3, 4, \dots, m] \end{aligned} \tag{4}$$

The entire set of training class labels is labeled as $\mathbf{y}$.

2.2 Parameterization

Discuss how we parameterized the data.

Several parameter functions are used to classify or achieve an objective function, these parameter functions are labeled as $\mathbf{\Phi}(\mathbf{X})$.

3 Theory of Proposed Methods

3.1 Theory: Decision Trees

Theory goes here.

3.2 Theory: Support Vector Machines (SVM)

3.2.1 Binary SVM Classification

A support vector machine (SVM) attempts to draw a decision boundary between two classes, which results in the maximum margin[2]. Margin being defined as the orthogonal distance from the decision boundary to a subset of support points $\mathbf{x}_{support} \subset \mathbf{X}$. Since, we have freedom of normalizing the decision space we set this boundary to 1 and then attempt to solve the following quadratic optimization problem,

$$\begin{aligned} \min_{w,b} \quad & \frac{1}{2} \|\mathbf{w}\|^2 \\ \text{subject to} \quad & y_i \left(\mathbf{w}^T \mathbf{x}_i + b\right) \geq 1 \, , i = 1, \dots, N \end{aligned} \tag{5}$$

The above equation is useful for the linearly separable Hard-Margin case. Since the dataset(2.1) contains overlapping data points for different classes, we require a non-linearly separable SVM, i.e. we need to incorporate a Soft-Margin. This is achievable by relaxing the normalized constraint to allow support points to be within the margin[3]. The common approach, from Linear Programming, shows that adding slack variables $\boldsymbol{\xi}$ along with a trade-off parameter C can achieve this,

$$\begin{aligned} \min_{w,b} \quad & \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^{N} \xi_i \\ \text{subject to} \quad & y_i \left(\mathbf{w}^T \mathbf{x}_i + b\right) \geq 1 - \xi_i \, , \xi_i \geq 0 \, , i = 1, \dots, N \end{aligned} \tag{6}$$

Now, it was observed from the dataset(2.1) that the number of examples for each class was vastly different. In this case, the SVM approximates a majority-class classifier and places the decision boundary extremely close to the minority class.

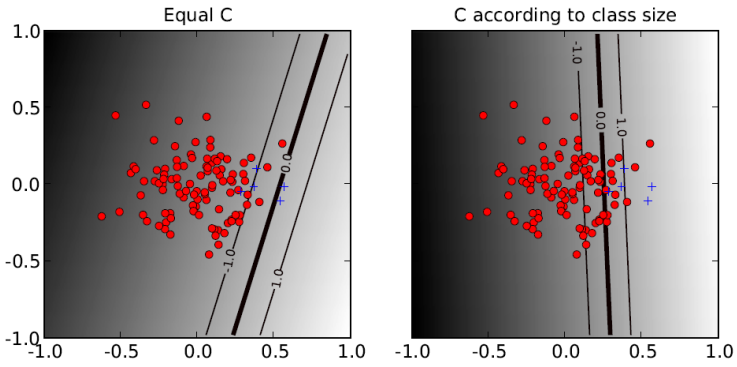

Figure 1: Using different trade-off parameters $\mathbf{C}$ to prevent majority-control (figure from [3])

To avoid majority-control, we can scale the trade-off parameters $\mathbf{C} \in [C_1, C_{-1}]$ so that the minority class caries more weight when misclassified. Such that eq(6) becomes,

$$\begin{aligned} \mathbf{C}\sum_{i=1}^{N}\xi_i &= C_1\sum_{i\in+}^{N}\xi_i + C_{-1}\sum_{i\in-}^{N}\xi_i \\ C_1 &= \frac{n_{-1}}{n_1}C_{-1} \end{aligned} \tag{7}$$

So far eq(6) uses a linear kernel for the inner product of $\mathbf{w}^T\mathbf{x}_i$. We can expand this to use a polynomial kernel $K(x_i, x_j) = (\gamma x_i^T x_j + r)^d$ of various power d or a radial basis function kernel $K(x_i, x_j) = \exp(-\gamma \left\|x_i - x_j\right\|^2)$.

3.2.2 Multi-Class SVM Classification

For this report, we tried two methods for multi-class classification. The first, was *one-versus-the-rest*[4], where K separate SVMs are trained, with the k^{th} class assigned $+1$ and all other classes assigned to -1. Then the classification is provided by $y(\mathbf{x}) = \max_k y_k(\mathbf{x})$.

The second method, was *one-versus-one*[4], where $K(K-1)/2$ separate SVMs are trained against each other. Then the classification is provided by $y(\mathbf{x}) = \max_k \rho_k y_k(\mathbf{x})$. Where, ρ_k is the number of "votes" for a given class y_k.

4 Simulation\Classification Results

4.1 Results: Decision Tree

4.2 Results: Support Vector Machine (SVM)

You can insert images by using the following code. Just place them in the figs folder and make sure they are in *.eps format.[2]

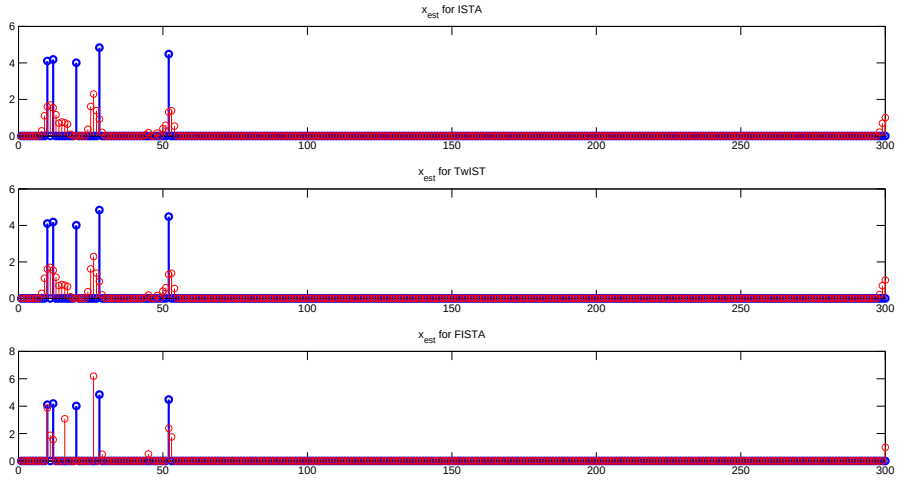

Figure 2: CaptionName: Test Image from figs folder

5 Conclusions

References

[1] Michael Bain, "Chess (king-rook vs. king) data set," 1994.

[2] Christopher M. Bishop, *Pattern Recognition and Machine Learning*, Springer, New York, NY 10013, 2006.

[3] Asa Ben-Hur and Jason Weston, "A users guide to support vector machines," in *Data Mining Techniques for the Life Sciences*, vol. 609 of *Methods in Molecular Biology*, pp. 223–239. Humana Press, 2010.

[4] Vladimir Naumovich Vapnik, *Statistical Learning Theory*, Wiley, New York, NY, 1995.