Football Match Outcome Prediction

MVA 2023/2024: Challenge Data QRT

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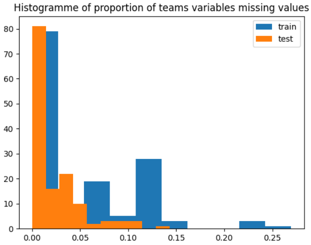
Introduction

- Aim: Predict football match outcomes.
- Target: 3 classes classification problem: win (1), draw (0), loss (-1)
- Utilized datasets: Team and player statistics.

Description and Remarks on the Dataset

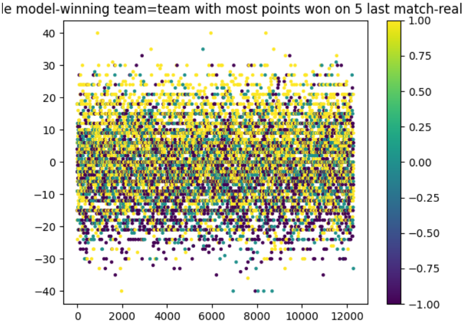
- Important: Match samples consist of home and away team statistics.
- Missing data observed.



Stats	%
Shots Inside Box	11.26
Shots Outside Box	11.27
Passes	11.49
Successful Passes	11.25
Injuries	15.93

Baseline Method

- Baseline: Simple heuristic based on recent team performance.
- **Number of points** (N_p): $N_p = 3 \times N_w + 1 \times N_d + 0 \times N_l$.
- Achieved accuracy: 42%.



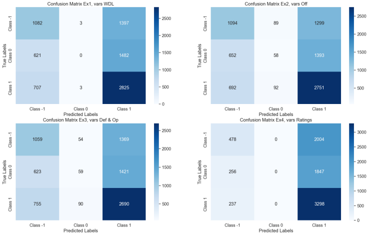
Advanced Methods

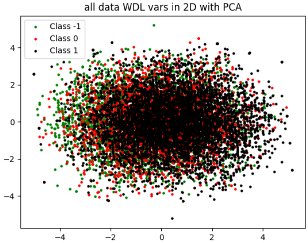
- Logistic regression on WDL features.
- Logistic regression on offensive features.
- Logistic regression on defensive and open play features.
- Search for more discriminative features : players rating

Features	Accuracy(%)
WDL features	48.02
Offensives features	48.42
Defensives & Open play features	47.25
Ratings features	46.70
MoE	49.05

Error Analysis: Summary

- Models face difficulty in detecting draw matches due to imbalanced data, favoring majority classes.
- Projection on 2D PCA(80% of explained variance) shows that features lack of discrimination





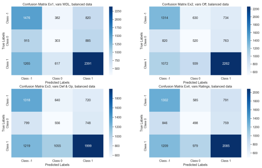
Attempt to fix the issue by balancing the training split

- Train the model on the balanced data allows it to detect more draw matches at the cost of a drop in accuracy
- Classes are unbalanced in test split

Table: Summary of Test Performance Drops

Feature Set	Train(%)	Val(%)
WDL	44.69	45.24
Offensive	42.90	46.05
Defensive + Open Play	45.98	42.78

Attempt to fix the issue by balancing the training split



Data Transformation to Enhance Feature Discrimination

- Kernel Method: Support Vector Classification (SVC).
- Grid search was performed on the training data, with WDL features reduced to three dimensions by PCA, retaining **90%** of the variance.
- Same conclusion: features are sufficiently discriminative as the best model obtained underperforms logistic regression:**47.9310%**

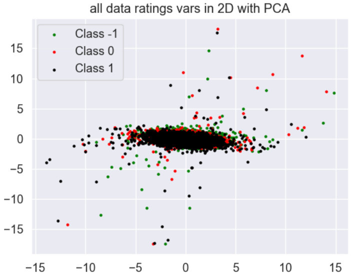
Params name (as in sklearn)	Values
C	[0.1, 1, 10, 100]
gamma	[0.1, 0.01, 0.001]
kernel	[rbf, linear, poly, sigmoid]
best model	C: 10, gamma: 0.1, kernel: rbf
validation score	**47.7586%**

Search for More Discriminative Features in the Players Dataset

- Most player variables have equivalents for teams.
- Team's success isn't solely determined by individual player performance.
- Ratings are potentially decisive variables for predicting match winners.
- **Ratings Variables**: Player Rating season average, Player Rating season std, Player Rating 5 last match average, Player Rating 5 last match std
- **Players Aggregation**: average ratings of top 11 players
- **Logistic regression performance**
  - Training: 46.3064%
  - Validation: 46.6995%

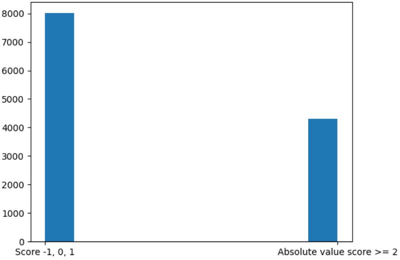
Search for More Discriminative Features in the Players Dataset

- Projection rating features in 2D PCA: 83% of explained variance
- Finally even the ratings features are not enough discriminative



Goal Difference Target For Understanding Models Limitation

- Majority of matches are won by 1 goal difference making more difficult the distinction between a draw(0) and a win(1)/lost(-1)
- The difficulty is enhanced by the dominance of the classes 1 and -1 in the dataset



Final Model: Expert Aggregation

- Mixture of experts (MoE) from four models.
- Majority voting.
- Achieved accuracy: 49.05%, +0.5% than best expert.

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Future Works

- More handcrafted Feature engineering
- Combine balanced and unbalanced models in a MoE algorithm.
- Use deep learning models

Thank you for you attention
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