CAMP: A Context-Aware Cricket Players Performance Metric

Muhammad Sohaib Ayub[a], Naimat Ullah[a], Sarwan Ali[b], Imdad Ullah Khan[a*], Mian Muhammad Awais[a], Muhammad Asad Khan[c] and Safiullah Faizullah[d]

[a]Department of Computer Science, LUMS, Pakistan; [b]Department of Computer Science, Georgia State University, USA; [c]Department of Telecommunication, Hazara University, Pakistan; [d]Department of Computer Science, Islamic University, KSA

ARTICLE HISTORY
Compiled August 19, 2022

ABSTRACT
Cricket is the second most popular sport after soccer in terms of viewership. However, the assessment of individual player performance, a fundamental task in team sports, is currently primarily based on aggregate performance statistics, including average runs and wickets taken. We propose **C**ontext-**A**ware **M**etric of player **P**erformance, CAMP, to quantify individual players' contributions toward a cricket match outcome. CAMP employs data mining methods and enables efficient, unbiased, and data-driven decision-making for selection and drafting, coaching and training, team line-ups, and strategy development. CAMP incorporates the exact context of performance, such as opponents' strengths and specific circumstances of games, such as pressure situations. We empirically evaluate CAMP on data of limited-over cricket matches between 2001 and 2019. In every match, a committee of experts declares one player as the best player, called ***M**an **o**f the **M**atch* (MoM). The top two rated players by CAMP match with MoM in 83% of the 961 games. Thus, the CAMP rating of the best player closely matches that of the domain experts. By this measure, CAMP significantly outperforms the current best-known players' contribution measure based on the Duckworth-Lewis-Stern (DLS) method.

KEYWORDS
Sports analytics, Cricket players ratings, Cricket data analysis, Players' contribution

1. Introduction

Analysis of fine-grained sports data plays a pivotal role in data-driven decision-making in all aspects of sports management Fried and Mumcu (2016). Many machine learning models have been proposed for game modeling and match outcome prediction for soccer Bai, Gedik, and Egilmez (2022); Davis, Bransen, Decroos, Robberechts, and Haaren (2019); Decroos, Bransen, Haaren, and Davis (2019), basketball Deshpande and Jensen (2016), and hockey Liu and Schulte (2018); Lord, Pyne, Welvaert, and

* Corresponding author
E-mail addresses: 15030039@lums.edu.pk (MS. Ayub), 18030048@lums.edu.pk (N. Ullah), sali85@student.gsu.edu (S. Ali), imdad.khan@lums.edu.pk (IU. Khan), awais@lums.edu.pk (MM. Awais), asadkhan@hu.edu.pk (MA. Khan), safi@iu.edu.sa (S. Faizullah)

Mara (2022). However, data-driven decision-making has not received much attention in cricket, which has the second-highest viewership Sankaranarayanan, Sattar, and Lakshmanan (2014) after soccer and is a multi-billion dollar industry.

In addition to tournaments organized by the International Cricket Council (ICC)[1], numerous cricket leagues and regional and inter-departmental games are played across the globe. A fundamental task at every level and game aspect is to measure players' quality and worth. All the key stakeholders of the game (e.g., selectors, coaches, franchise owners, and even brand managers) are often interested in the following question: *How much does the performance of an individual player impact the outcome of a given match Decroos et al. (2019)?* Players' performance assessment helps franchise owners and selectors in drafting contracts, sports bodies in talent hunt, coaches to determine optimal bowler versus batter matchups, and brand managers to organize media promotions.

Currently, performance assessment in cricket is primarily made by experts based on qualitative judgments by scrutinizing the entire match situation. These judgments rely on aggregate statistics of standard performance measures. However, these measures of batting and bowling performance (e.g., batting average, batting strike rate Barr and Kantor (2004), bowling economy[2]) have three significant limitations. Firstly, these measures assign a fixed value to each achievement Davis, Perera, and Swartz (2015); Stern (2009), regardless of the specific opponent against whom the achievement was made. For instance, for bowlers, wickets are considered equivalent irrespective of the batters' quality, and for batters, runs scored carry equal weight regardless of the bowlers' strength. Secondly, these measures do not account for the stage of the innings, such as pressure index Shah and Shah (2014). Lastly, they only consider immediate effects and do not incorporate the downstream impact. For example, the early wicket loss of an opening batter also reduces the team's overall capability to score runs.

Data analysis on the fine-grained cricket data can highlight slim differences in skills and performance imperceptible to a human. Actionable analytics drawn from data will aid 'managers' in optimal decision-making, reduce players' contract costs, increase efficiency, and minimize bias. Some data analytics work has been done to quantify players' performance Lewis (2005, 2008) and a pair of batters Bhattacharjee, Lemmer, Saikia, and Mukherjee (2018). However, these approaches only consider the remaining resources (remaining overs and wickets) as game context, whereas qualitative aspects of remaining players and resources also contribute to important contextual information.

In this paper, we propose a novel tool, **C**ontext **A**ware **M**etric of player **P**erformance (CAMP), to rate the players by measuring their contributions considering the context of the game. Unlike the current state of the art work, referred to as **L**ewis **N**et **C**ontribution (LNC) Lewis (2005), we also consider additional features like the quality of the remaining resources and performance made so far by a team as the game context. CAMP calculates each player's contribution score incorporating the game venue, the stage of the match, the opposing players, and the overall strength of the opposition team.

We estimate the expected runs to be scored by the batting team at every stage of the

[1]We provide a brief overview of the cricket game with the terminology and rules of the game in Appendix A. Detailed information regarding cricket is also available online https://www.icc-cricket.com/about/cricket/rules-and-regulations/playing-conditions

[2]The batting strike rate is the percentage of runs scored from the balls faced by the batter ($\frac{runs}{balls} * 100$). The bowling economy is the number of runs conceded by the bowler per over ($\frac{runs}{overs}$).

game, using a combination of supervised and unsupervised machine learning techniques. We use current match information and historical game data to capture context about *similar* performing teams and players. Based on the expected and actual runs scored in an over, we measure over-by-over players' contribution, which is aggregated for players' ratings at the match level.

We compare CAMP players' ratings with the ICC announced **M**an **o**f the **M**atch (referred as MoM) and LNC Lewis (2005). We show that the experts' opinion-based top-rated player (MoM) is the top-rated player and one of the top two rated players by CAMP in 66% and 83% of the games, respectively. This indicates that at least at one end of the spectrum, CAMP successfully emulates domain experts. While our approach can be used for any format of the game, in this paper, we focus on one of the limited-over formats known as *One Day International* (ODI).

The main features of this work are the following:

- We propose CAMP that quantify the contributions of all 22 players in a cricket match. It computes rating considering the context of the match (opposition strength, stage of the innings). Various stakeholders (selectors, coaches, franchise owners, brand managers) can use CAMP for efficient decision-making.
- As a subroutine, we develop a model that predicts projected runs at any stage of the game (i.e., runs the batting team can score in the remaining part of the game). This model is helpful for strategy adjustments during a live game and may be of independent research interest.
- The results show that the performance score by CAMP agrees with that of experts' decision of MoM to a greater extent as MoM is the top-rated or one of the top two rated players by CAMP in 66% and 83% of the games, respectively. CAMP also outperforms the state of the art approach LNC based on the Duckworth-Lewis-Stern (DLS) method.
- CAMP ratings at match level can be extended to series level (a set of consecutive matches) and career level to estimate the *net worth* of a player. These estimates are of particular interest to international cricket bodies and franchise owners.
- We perform experiments on a comprehensive dataset of 961 ODI matches played between 2001 and 2019. We make the preprocessed dataset publicly available, opening up a broad avenue of further research in cricket data analytics.

The rest of the paper is organized as follows. In Section 2, we briefly review the literature on sports data analytics. Section 3 presents our proposed approach CAMP. We give the detailed experimental setup in Section 4. We present the empirical results in Section 5 and conclude the paper in Section 6.

2. Related Work

Quantifying the impact of players' performance is a well-studied problem in sports data analysis, particularly for basketball Deshpande and Jensen (2016), soccer Bai et al. (2022); Decroos et al. (2019), and hockey Liu and Schulte (2018).

Several machine learning models have been proposed for game modeling and outcome prediction, ranging from simple supervised and unsupervised learning to graphical models Bunker and Thabtah (2019); Joseph, Fenton, and Neil (2006). Dolores adopts a neural network-based approach using dynamic ratings and Bayesian networks for predicting the outcome of football matches Constantinou (2019). Outcome prediction in sports is generally treated as a classification problem with two or three classes (win, lose or draw) Prasetio and Harlili (2016); Shi, Moorthy, and Zimmermann (2013). However, few studies have used regression-based approaches to predict game outcome Delen, Cogdell, and Kasap (2012); Goddard (2005). These studies also predict victory margins (e.g., the difference between the number of goals scored by each team in a soccer game).

Although many popular sports are well studied in the literature, cricket remains unexplored mainly due to the game's dynamic and unpredictable nature. The Duckworth-Lewis (DL) method Duckworth and Lewis (1998) is a technique to reset the batting targets for interrupted limited-overs matches. Adopted in 1999 by ICC as the official target resetting method, DL method is based on a resource table where each entry represents the percentage of resources available to the batting team. The main limitation of the DL method is using the same resource table for both innings, whereas scoring patterns in the second innings differ significantly from the first. Factors such as the pressure of chasing contribute to the fact that the first innings cannot be directly compared to the second innings. To overcome this problem, Stern (2009) extended the DL method, known as the Duckworth-Lewis-Stern (DLS) method and proposed a separate resource table for second innings.

Clarke (1988) used dynamic programming to model cricket game progression. For any stage of the first innings, he proposes a dynamic programming-based optimal scoring rate along with an estimated total number of runs that would be scored. For each stage of the second innings, he models the probability of winning considering wickets in hand, number of overs remaining, and runs yet to be scored. Beaudoin and Swartz (2003) developed a new technique for analyzing team performance and finding the most valuable players using the DL resource table. Lemmer (2008) proposes an approach that assigns weights to traditional performance measures (such as batting averages, count of scores while remaining not-out, and bowling averages) to analyze the players' performance. Jhanwar and Pudi (2016) uses various features of batters and bowlers to predict the match outcome using the nearest neighbor classifier. Lewis (2005) proposed LNC to measure player performance using the DL resource table. Based on the percentage of the resources remaining at any stage of an innings, LNC estimates the expected runs to be scored. Players' contribution is then estimated from expected runs and actual runs scored. This approach relies on the DL resource table, which is too general and does not consider the match-specific details.

Various works incorporate historical information to predict match outcome and suggest suitable team combination. A combination of linear regression and nearest neighbor algorithm predicts the winning team by estimating the runs to be scored in the innings' remaining part. The estimated runs are updated based on historical and current match data after an interval of 5 overs Sankaranarayanan et al. (2014). An approach suggests a suitable team combination by applying association rule mining on historical players' performance Bhattacherjee, Sahoo, and Goswami (2015); Norman and Clarke (2010); Swartz, Gill, Beaudoin, and DeSilva (2006). Similarly, teams strength is analyzed based on the players' historical performance, and match outcome is predicted based on current match data in T20 format Viswanadha, Sivalenka, Jhawar, and Pudi (2017), TEST Scarf and Akhtar (2011) and ODI Hasanika, Dilhara, Liyanage, Bandaranayake, and Deegalla (2021) cricket.

3. Proposed Approach: The CAMP Algorithm

In this section, we formulate the problem of quantifying players' contributions from ball-by-ball ODI matches data. For each over, we estimate the expected runs using the current game's status, teams' strength, players' quality, and match venue. CAMP computes the contributions of the players (batters and bowlers) based on the difference between expected runs and actual runs scored. For simplicity, we divide our problem into the following two sub-problems:

(1) Estimation of expected runs to be scored in any over at a given stage of the innings. The challenging part of this problem is to capture the context of the game, including the players' quality determined from players' past game history, teams' strength, match venue and remaining resources. Moreover, It also requires avoiding the cold-start problem to capture players' quality.

Due to the cold-start problem, data sparsity hinders learning the players' features. A significant challenge in the accurate computation of expected score is limited (*'data sparsity'*) or no available data (*'cold start'* problem). Given the amount and timeline of data, a given batter b may have no or very sparse playing history against a bowler l Sankaranarayanan et al. (2014). Thus, a machine learning model may not be able to learn any valuable insight for prediction. Therefore, we cluster the batters and bowlers to tackle the cold-start and data sparsity problem as similar batters or bowlers can be considered in place of a specific query batter or bowler. We empirically validate the players' clustering in Section 5.1 and Section 5.2.

(2) Computation of players' ratings based on the expected runs and actual runs scored in an over. The challenging part of this problem is finding players' ratings confirming the experts' decision-based top-rated player (MoM).

A list of frequently used symbols with their description is given in Table 1. We provide an overview of CAMP in Figure 1 and each step is explained in the following sections.

3.1. Projected Score Computation

This section describes our methodology to compute projected remaining runs using historical data and current match information for both teams, including their participating players and venue. We define S_i as the stage of an innings at the start of over i, $1 \leq i \leq 50$. The projected remaining runs at S_i are represented by $R(S_i)$. To capture the qualitative aspect of resources (overs, wickets) in S_i, we represent teams and players as feature vectors and cluster them into performance-based groups. These teams' and players' clusters, along with current match data, are used to generate match stage feature vector $\Omega(S_i)$, which are used to predict $R(S_i)$.

3.1.1. Teams' Clustering

We group ten regular and ICC-ranked teams into different clusters. This categorization of teams helps avoid the data sparsity problem (a new player having no historical information against specific players of other teams) in players' clustering. For this purpose, we design a 72-d vector/embedding (based on the batting performance of teams) that contains the average runs scored and the team's winning probability against each of the 9 opponent teams while playing both innings for both types of venues

Symbol	Description
S_i	Innings stage at start of over i
$P(S_i)$	Projected total runs estimated at S_i
$T(S_i)$	Total runs scored till S_i
$R(S_i)$	Projected remaining runs at S_i. Runs to be scored after S_i
$A(S_i)$	Actual runs scored after S_i
r_i	Total runs scored in over i
r_i^p	Runs scored by player p in over i
e_i	Expected runs in over i
c_i^p	Contribution by player p in over i
$C_{bat}(p)$	Aggregated batting contribution for player p in a match
$C_{bowl}(p)$	Aggregated bowling contribution for player p in a match
CAMP$_{score}$	Net contribution vector for all participating players
ϕ_p	Batters feature vector for player p
ψ_p	Bowlers feature vector for player p
$\Omega(S_i)$	Feature vector to predict $R(S_i)$ at S_i

Table 1.: Notations used in our proposed model CAMP.

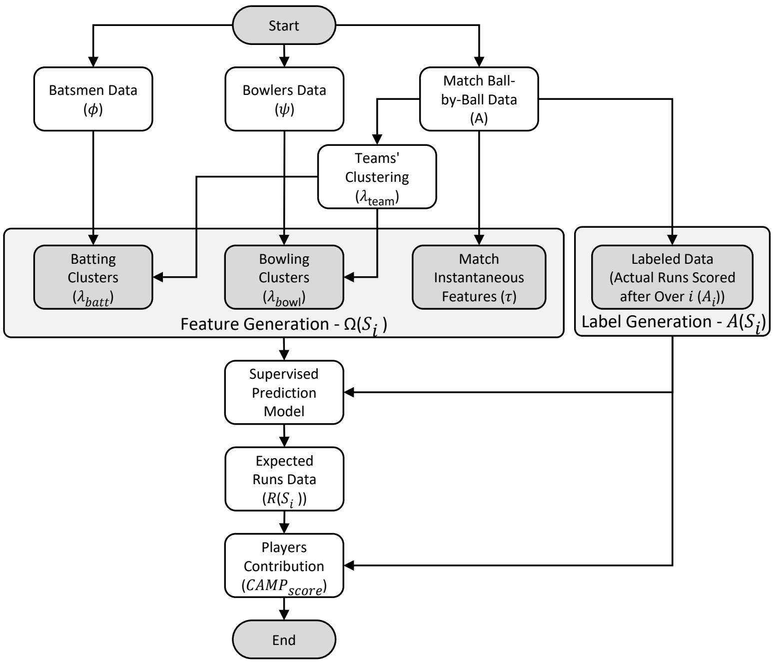


Figure 1.: Flow diagram of our proposed model CAMP.

"home/away". The feature vector is shown in Figure 2. The feature embeddings are then used as input to the standard k-means clustering algorithm to cluster the teams (where $k = 3$, decided using the standard validation set approach Devijver and Kittler (1982)). The teams in different clusters are shown in Table 2.

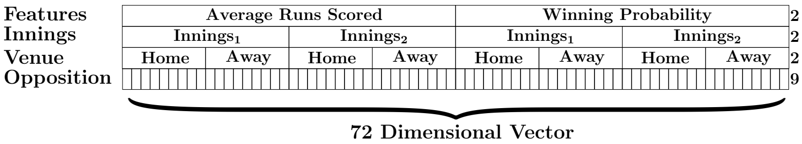


Figure 2.: Teams feature vector generated using historical batting data. Historical data of a team is collected against each of the 9 ICC top-ranked teams for different features such as venue, innings, average runs scored and winning probability.

Remark 1. *We also clustered teams' by their bowling records (Average Runs Scored, Winning Probability and Wickets Taken), but the clusters remain the same.*

Cluster ID	Teams			
Cluster 1	Australia (AUS)	England (ENG)	South Africa (SA)	Sri Lanka (SL)
Cluster 2	India (IND)	Pakistan (PAK)	Bangladesh (BAN)	-
Cluster 3	West Indies (WI)	New Zealand (NZ)	Zimbabwe (ZIM)	-

Table 2.: Top 10 ICC ranked teams grouped into 3 clusters to avoid the cold-start problem by considering the similar teams' cluster in place of a specific query team.

These teams' clusters are used in the players' feature vectors to avoid data sparsity problem by considering the similar team's cluster in place of a specific query team.

3.1.2. Batters Clusters

To cluster the players based on their batting quality, we represent each player by a feature vector comprised of past batting performances at different venues, against different oppositions (teams clusters) in the first or second innings (Figure 3). More formally, we form a feature embedding, ϕ_p for player p based on the 11 performance parameters. ϕ_p discretizes the runs scored and the strike rate into 6 and 3 bins, respectively, such that each bin contains the count of the corresponding value. We also record the total number of boundaries scored and the count of matches in which p remains not-out.

We keep these 11 performance parameters for granularity level of innings, opposition's strength and venue class. For the first granularity level, the match venue is categorized into two classes, Asia and non-Asia (Level 2 in Figure 3). This classification is significant since the pitch (i.e., the area where the ball is bowled and pitched) conditions vary across the regions, and teams perform differently at different venues Sankaranarayanan et al. (2014). In Section 5.4, we empirically demonstrate the significance of the difference in scoring patterns at these two classes of venues. For each venue class, the second granularity level contains opposition teams (Level 3 in Figure 3), divided into 3 teams' clusters (Section 3.1.1). There are two innings for each match with the opposition, i.e., first and second innings (Level 4 in Figure 3). From these 3 granularity levels, we get 12 different scenarios for 11 batting performance parameters resulting in a 132-d feature vector shown in Figure 3.

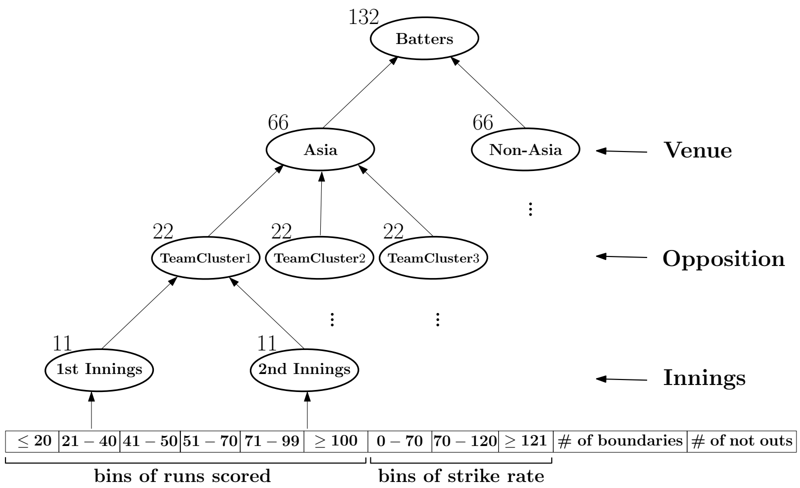


Figure 3.: A feature vector for a batter consists of 5 bins for runs scored, 3 bins for strike rate, count of boundaries, and count of not-outs. These 11 performance parameters are recorded across different venues, oppositions and innings to form a 132-d feature vector.

The batters clusters are formed with the standard k-means clustering on the batters feature vectors (where $k = 4$, decided using the standard validation set approach Devijver and Kittler (1982)). The players who never batted are placed into a “fifth” cluster. In addition to avoiding the cold-start problem, these batters’ clusters are used in match stage feature vector $\Omega(S_i)$ (in Section 3.1.4) to capture the batters’ quality.

3.1.3. Bowlers Clusters

For the representation of bowlers, similar to the batters feature vectors, the bowlers feature vectors contain bowling performance data such as bowling average, strike rate, and bowling economy. The bowling feature vectors, ψ_q for a bowler q contains 13 bowling performance features, i.e., bowling average, strike rate and bowling economy discretized into 4, 5, and 4 bins, respectively. Similar to batters feature vector, we keep these 13 performance parameters for granularity level of innings, opposition’s strength and venue class. From these 3 granularity levels, we get 12 scenarios for 13 bowlers’ performance parameters, resulting in a 156-d feature vector (Figure 4).

The bowlers feature vectors are input to the standard k-means clustering algorithm ($k = 4$) to obtain the bowlers’ clusters. Players having no previous bowling record are placed in a separate “fifth” cluster. In addition to avoiding players’ cold-start problem, like batters clusters, the bowlers clusters are used in match stage feature vector $\Omega(S_i)$ (in Section 3.1.4) to capture the bowlers quality.

3.1.4. Over-by-Over Projections

Given the batters and bowlers clusters, we represent the stage of the game by feature vectors, $\Omega(S_i)$ that capture the game context to predict $R(S_i)$ as shown in Figure 5.

First, we aggregate ball-by-ball match data to an over-by-over level without loss of necessary information. In $\Omega(S_i)$, cluster ID of batting and bowling teams are used to avoid team sparsity problem. Similarly, to capture the quantitative and qualitative

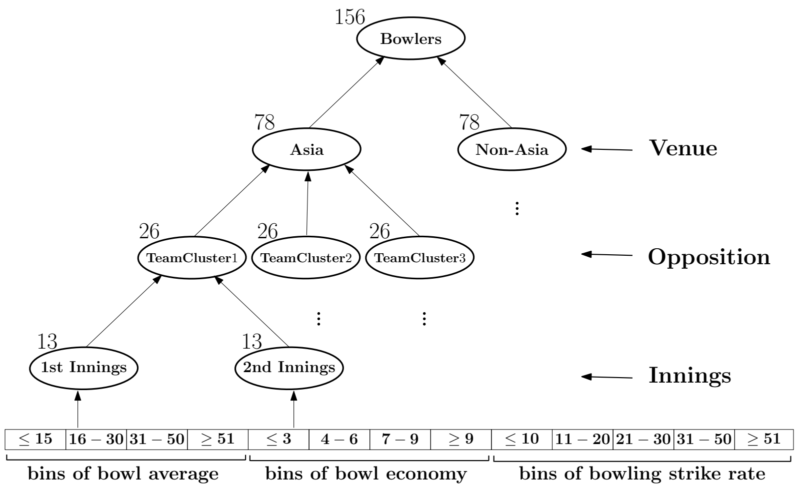


Figure 4.: A feature vector for a bowler consists of 4 bins for bowling average, 4 bins for economy and 5 bins for strike rate. The 13 performance parameters are aggregated across the different venue, opposition and innings levels to form a 156-d feature vector.

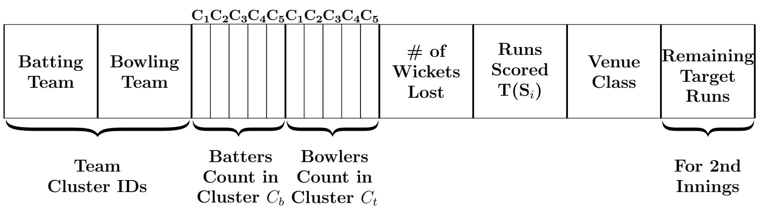


Figure 5.: Match stage feature vector $\Omega(S_i)$ for Stage S_i to capture game context, teams and players' strength. It contains the batting and bowling teams' cluster IDs, cluster-wise counts of remaining batters and bowlers, number of wickets lost, current batting team's score, match venue (Asia and Non-Asia) and remaining target runs.

aspect of remaining resources at stage S_i, we keep the count of batters $C_b,\ b \in \{1, \cdots, 5\}$ belonging to batters cluster b and the count of bowlers $C_t, t \in \{1, \cdots, 5\}$ belonging to bowler cluster t. The counts of players in respective clusters capture the context in terms of the quality of the players remaining at stage S_i, e.g., a stage S_j with 5 top-order batters of cluster C_1 is qualitatively better than the stage S_k with 5 lower-order batters of cluster C_4 and no top-order batters of cluster C_1. Further, to quantify bowling resources, we multiply the count of bowlers in C_t with 10, considering ODI rules in which a bowler can bowl a maximum of 10 overs in an innings. This quantification helps maintain the count of remaining overs and the bowlers' quality. The count of the players who never bowl remains the same across all innings, not affecting the prediction.

In $\Omega(S_i)$, we also incorporate the match instantaneous features, such as the number of wickets lost, total runs scored, venue class and remaining target runs. This match stage feature vector $\Omega(S_i)$ containing the overall game context is used to predict the expected remaining runs $R(S_i)$ and calculate the players' ratings (CAMP$_{score}$).

3.1.5. Projected Score Computation

For a given S_i, we compute the projected total runs in the innings, $P(S_i)$. The $P(S_i)$ is estimated considering runs scored so far, the number of remaining overs, wickets in hand, the quality of remaining players (batters and bowlers), and the strength of the batting and bowling teams. The teams' strength and players' batting/bowling quality are determined by forming clusters based on their past performance. The difference between the projected total runs $P(S_i)$ and the total score of a team $T(S_i)$ gives the projected remaining runs $R(S_i)$ for a given S_i in the innings. More formally:

$$R(S_i) \;=\; P(S_i) - T(S_i) \tag{1}$$

We also consider the actual runs scored, $A(S_i)$, by a team after S_i. The following section explains the computation of projected remaining runs $R(S_i)$ at any stage of the game.

3.1.6. Algorithms for Projected Score Computation

The main ingredient for CAMP$_{score}$ is the projected remaining score, $R(S_i)$ at any stage S_i of the game. Algorithm 1 describes the computation of $R(S_i)$ with the nearest neighbors approach using a test point $\Omega(S_i)'$ feature vector as input. In Line 1, we use the leave-one-out strategy for the test point $\Omega(S_i)'$ and collect all training examples $\ominus$ corresponding to S_i where wicket lost and overs remaining are equivalent to resources of $\Omega(S_i)'$. In the following line 2, the actual runs $A_\ominus$ for collected training examples $\ominus$ are calculated. We compute the similarity score ($simVec$) using Euclidean distance for the filtered training set (Line 3). In the last line 4, the target variable $R(S_i)$ is calculated using a weighted average of $simVec$ and $A_\ominus$.

Algorithm 1 kNN based projected runs estimation

Input: $\Omega(S_i)'$ ▷ Test Point
Output: $R(S_i)$
1: $\ominus \leftarrow$ set of $\Omega(S_i)$ with same number of resources as $\Omega(S_i)'$ ▷ All innings training examples
2: $A_\ominus \leftarrow A(\textsc{Index}(\ominus))$ ▷ Actual runs vector corresponding to training examples
3: $simVec \leftarrow \textsc{similarity}(\Omega(S_i)', \ominus)$
4: $R(S_i) \leftarrow \textsc{WeightedAvg}(simVec \times A_\ominus)$

We also compute $R(S_i)$ using regression (Ridge Regression and Random Forest Regressor) with k-fold cross-validation, as shown in Algorithm 2. We split the input $\Omega(S_i)$ into training and testing sets according to the k-fold split (Line 1). For each k-fold split, we find the indices of the train set (Line 3) and test set (Line 4). We apply the regression technique to compute our target projected remaining runs vector $R(S_i)$ (Line 5).

3.2. Computing Players Contributions

After computation of projected remaining runs $R(S_i)$, our goal is to compute player contributions by CAMP. $R(S_i)$ and $A(S_i)$ is used to calculate over-by-over contribution

Algorithm 2 Regression-based projected runs estimation

Input: $\Omega(S_i)$ ▷ All matches data for first and second innings
Output: $R(S_i)$
1: $[\Gamma, \gamma] \leftarrow$ KFOLDSPLIT($\Omega(S_i)$) ▷ Γ is train set, γ is test set
2: **for** j $\leftarrow$ 1:k **do**
3: $ind_{tr} \leftarrow$ INDEX(Γ_j) ▷ Indices of train set values
4: $ind_{ts} \leftarrow$ INDEX(γ_j) ▷ Indices of test set values
5: $R_{ind_{ts}} \leftarrow$ REGRESSION($\Omega(ind_{tr}), A(ind_{tr}), \Omega(ind_{ts})$) ▷ using Random Forest and Ridge Regression
6: **end for**

scores using expected runs e_i and actual runs r_i. These contributions are aggregated for the complete match to obtain all players batting and bowling ratings (CAMP$_{score}$).

3.2.1. Estimation of Over-by-over Expected Runs

After computation of projected remaining runs $R(S_i)$ for a given S_i, we compute the expected runs for i^{th} over, e_i. The change between $R(S_i)$ and $R(S_{i+1})$ is equivalent to expected runs, e_i, in the i^{th} over. More formally:

$$e_i = R(S_i) - R(S_{i+1}) \tag{2}$$

There are two possible scenarios in an over i: either the batting team loses wicket(s) or not. The expected runs for that over, e_i change accordingly. In case of the wicket(s) lost in an over, the team's capability to score runs in the remaining part of the innings is affected, and $P(S_{i+1})$ decreases depending on the importance of the wicket lost. As a result, the change in two projections $P(S_i)$ and $P(S_{i+1})$ increases compared to the case when no wicket is lost. This increased difference in $P(S_i)$ and $P(S_{i+1})$ is due to the higher worth of the wicket lost, i.e., if wicket(s) is/are lost in initial overs, the change in two projections will be higher than that if the wicket is lost in final overs.

For each wicket lost, e_i is modified according to wicket weight (w) to penalize the outgoing batter and reduce expectation from the incoming batter. e_i remains the same for no loss of wicket. More formally:

$$e'_i = \begin{cases} (1-w)e_i & \text{wicket lost, } w \in [0.1, 1] \\ e_i & \text{otherwise} \end{cases} \tag{3}$$

These expected runs, e'_i are used to calculate players' contributions in equation (5) and equation (6) of Section 3.2.2.

Remark 2. *Note that* MoM *is an expert opinion based metric and identifies the* "top performing" *player. We use it to validate the players' rating computed by* CAMP.

MoM is the only metric that provides a baseline measure to compare the top contributor of CAMP. Therefore, wicket weights (w) are adjusted empirically by maximizing the agreement of the top contributor by CAMP with the experts' opinion-based top contributor (MoM). We use a varying value of w to get a maximal agreement of our top contributor with the MoM. We use $w \in [0.1, 1]$ with the increase of 0.05 and for $w = 1$, we get maximum matching with MoM. The selection of w is not a subjective decision. w serves as a hyperparameter of our technique, which is not required to be adjusted for each iteration. To bring the expectation level to ball-by-ball, e'_i is uniformly divided among each ball of the over as $e'_i/6$.

3.2.2. Computing Over-by-over Contribution Scores

As the innings proceeds, we compute $R(S_i)$, projected remaining runs in the innings. We also consider the actual runs scored, $A(S_i)$, by a team after S_i. Thus, the actual runs scored in over i are as follows:

$$r_i \; = \; A(S_i) - A(S_{i+1}) \tag{4}$$

Similarly, r_i^p represents the actual runs scored by batter p in over i, where $p \in [1, 22]$ is the unique identifier for each player. For a batter facing the bowler, his contribution is quantified by how well he performs with respect to e'_i. The expected score for a batter p is computed as $e'_i \times b_p/6$, where b_p is the number of balls faced by the batter in the respective over (recall that an over consist of 6 balls). The contribution c_i^p of the batter p in i^{th} over is computed as follow:

$$c_i^p \; = \; r_i^p - \frac{e'_i}{6} \times b_p \quad p \in [1, 22] \tag{5}$$

The net contribution in i^{th} over (c_i^p) can be positive or negative depending on whether the batter scored above or below expectation. A positive batter contribution implies a negative contribution of the bowler and vice versa. Similarly, minimizing the runs conceded in an over or taking wickets contribute positively towards bowler's contribution.

Remark 3. *Note that batters are only credited for the runs they score but for a bowler's extras (e.g., wide ball, no ball) are also counted as runs conceded by the bowler.*

The contribution of a bowler is computed as:

$$\hat{c}_i^p \; = \; e'_i - r_i \quad p \in [1, 22] \tag{6}$$

3.2.3. Computing Players Rating using Over-by-over Contribution Vector

After computing over-by-over contribution scores of players for both innings of a match, we aggregate contributions c_i^p and $\hat{c}_i^p$ over a complete match for each player. Since both teams have 11 players, we associate batting and bowling contributions with each player to get a 44-d resultant vector.

If a batter remains on the crease for overs in a set Q and loses his wicket in j^{th} over, his aggregated batting contribution is computed as:

$$C_{bat}(p) \;=\; \begin{cases} \sum_{i\in Q} c_i^p - (w \times e_j) & \text{wicket lost} \\ \sum_{i\in Q} c_i^p & \text{otherwise} \end{cases} \tag{7}$$

For a bowler, who bowled overs in a set Q, his contribution is defined analogously as:

$$C_{bowl}(p) \;=\; \sum_{i\in Q} \hat{c}_i^p + \sum_{k\,\in\,\text{overs with wickets}} (w \times e_k) \tag{8}$$

Remark 4. *A wicket loss by run-out is debited against the batter but is not credited to the bowler.*

We compute the net contribution, CAMP$_{score}$ (players' rating) as follows:

$$\text{CAMP}_{score} \;=\; w_{bat} \times C_{bat}(p) + w_{bowl} \times C_{bowl}(p) \tag{9}$$

where w_{bat} and w_{bowl} are user-set parameters and weight batting and bowling contributions, respectively. We use varying weights for batting and bowling contributions in Equation (9) to calculate all players' ratings as CAMP$_{score}$ vector. To make a comparison with MoM, we adjust weights (w_{bat} and w_{bowl}) such that the top contributor from CAMP agrees with MoM. For $w_{bat} = 1$ and $w_{bowl} = 0.2$, we get maximum matching with the expert opinion based top contributor MoM. The players' contribution scores can be aggregated to match, series, or tournament level along multiple dimensions (e.g., batting, bowling, or both). This paper shows our work at the match and series level; however, the approach can be extended to any level.

3.2.4. The CAMP *Algorithm*

Algorithm 3 contains the pseudo-code to compute CAMP$_{score}$ vector for all 22 players. It uses Algorithm 1 or Algorithm 2 as a subroutine to project the remaining score at a stage. In Line 1 and Line 2, we respectively form the batters and bowlers clusters λ_{batt} and λ_{bowl}, using batters and bowlers feature vectors $\phi(\cdot)$ and $\psi(\cdot)$. In Line 4, we use the batters and bowlers clusters along with instantaneous match features at match stage S_i to obtain the match stage feature vector, $\Omega(S_i)$. Line 5 computes projected remaining score at stage S_i, $R(S_i)$ using $\Omega(S_i)$ (Algorithm 1). In Line 6, CAMP$_{score}$ is calculated from $R(S_i)$ and the actual runs data $A(S_i)$ by Equation (9).

4. Experimental Setup

This section describes our dataset consisting of one-day international cricket matches and players, along with preprocessing of the dataset. Moreover, we discuss the performance metrics used to evaluate the proposed model against baseline methods.

Algorithm 3 CAMP algorithm for players ratings

Input: Batters Data ϕ, Bowlers Data ψ, Ball-by-Ball Data A
Output: Players Ratings (CAMP$_{score}$)

```
λ_batt ← PerformClustering(φ)                         ▷ k-means with k = 4, Section 3.1.2
λ_bowl ← PerformClustering(ψ)                         ▷ k-means with k = 4, Section 3.1.3
for i = 1 → 50 do
    Ω(S_i) ← GenerateFeatureVector(S_i, λ_batt, λ_bowl)   ▷ Section 3.1.4
    R(S_i) ← EstimateProjection(Ω(S_i))                   ▷ Section 3.2.1
    CAMP_score ← ComputeRatings(R(S_i), A(S_i))           ▷ Section 3.2.2
end for
```

4.1. Dataset Statistics

ESPNcricinfo[3], a leading sports website, records cricket data for every match played under the ICC rules. We extracted ball-by-ball data, match summaries, and player performance statistics at the innings level from ESPNcricinfo. We used the data of 1625 complete ODI matches played between January 2001 to October 2019 among 10 full-time ICC member teams (Table 2) in our analysis.

4.1.1. Players' Data

The individual players' data comprises performance statistics aggregated to the innings level for all matches. The players' performance data is divided into batting and bowling data. Batters data consists of 1002 unique players from the top 10 teams who faced at least one ball, while bowling data contains 802 unique bowlers who have bowled at least one over in their ODI career. We have made this comprehensive preprocessed dataset and our code publicly available online[4] for academic research.

4.1.2. Match Summary Data

The match summary data contains the general and specific information of participating teams, venue, date, toss-winner, total runs scored in both innings, wickets lost, run rates, match winner, and victory margin, respectively. The total runs scored in any innings show the team's batting capability and the bowling strength of the opposition. The most important piece of information in match summary data is the player declared as Man of the Match (MoM), which we use to validate CAMP$_{score}$.

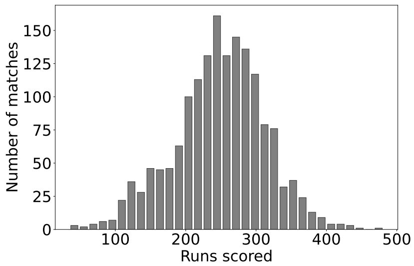
4.2. Data Preprocessing

We preprocess the data to remove inconsistencies and find the most informative set of matches. We only keep those matches in which the runs scored in both innings are within 2 standard deviations of the mean innings scores. We observe that the two teams, BAN and ZIM (with lower ICC rankings during the sampled years), generally scored significantly less than other teams. We removed all matches involving these two teams. Figure 9 shows the distributions of innings scores before and after removing outliers. A summary of match scores before and after preprocessing is given in Table 3.

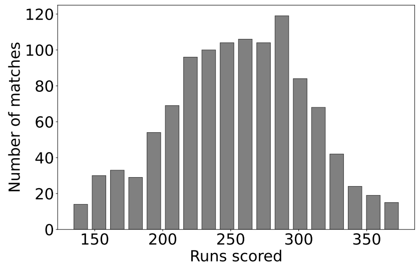
[3] https://www.espncricinfo.com/
[4] Available in the published version

	All 1625 matches		After preprocessing 1110 matches	
	First Innings	Second Innings	First Innings	Second Innings
Min	35	40	133	112
Max	481	438	375	332
Mean	249	216	256	226
Std.	64	58	50	47

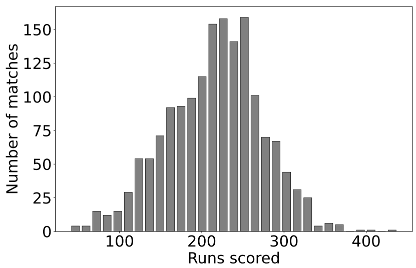
Table 3.: Statistics of runs for both innings before and after removing outlier matches, i.e., the matches with average runs scored beyond two standard deviations from mean runs and matches played by the low-scoring teams (BAN and ZIM).



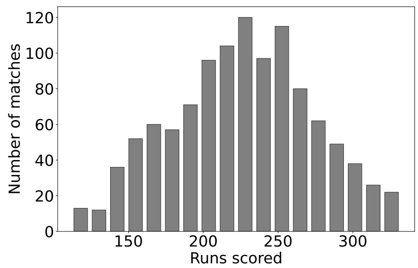
(a) First innings before preprocessing



(b) First innings after preprocessing



(c) Second innings before preprocessing



(d) Second innings after preprocessing

Figure 6.: Total runs distribution of all matches in both innings before and after removing the low runs scorer teams (BAN and ZIM) and matches with runs scored less than two standard deviations from mean runs.

4.3. Evaluation Measures

We evaluate the effectiveness of CAMP in terms of accuracy of the projected scores, quality of players' ratings, and by validating the teams and players clustering. We compare the projected scores $R(S_i)$ by kNN, Random Forest, and Ridge Regression with the actual runs scored $A(S_i)$ and report the mean absolute error (MAE). We also report the MAE of $R(S_i)$ computed by LNC based on the resource table in Lewis (2005). For LNC, we use the publicly available Duckworth-Lewis (DL) resource table (Table A1 in Appendix). LNC proposes $Z(50, 0) = 235$ for the first innings and target runs for the second innings as expected runs with all wickets in hand and 50 overs remaining. The table entries show the percentage of Z runs that can be scored after a specific stage.

We can only evaluate players' performance based on the agreement of the top contributor (top-rated player) of CAMP with the MoM declared by ICC since there is no ground truth for players' true contributions in a given match. We report the fraction of matches in which MoM is the top and one of the top two contributors by CAMP. We also compare the CAMP ratings with LNC both at the match and series level.

We also validate the intermediate steps of teams and players' clustering to demonstrate that our feature vectors are meaningful and that the clusterings are well-formed.

5. Results and Discussion

In this section, we start with validating players' clusters using ICC top 100 players' ratings for bowling and batters clusters. We show that these are well-formed quality clusters using clusters of top ICC-rated players in Section 5.1 and visually using t-SNE diagrams in Section 5.2. In the next Section 5.3, we investigate the important features from the players' feature vector. Section 5.4 explains the validation for venue-wise distribution of teams. We perform the evaluation of CAMP using projected remaining runs and players' rating in Section 5.5 and Section 5.6, respectively.

5.1. Players' Clustering Validation using ICC Ratings

We compare the players' clustering with the ICC top players rankings to evaluate the goodness of batters and bowlers clusters. The historical data for players' clustering from January 1, 2000 to October 20, 2019 along with the ICC top players rankings on October 20, 2019[5] is used for clustering validation. Table 4 shows the batters and bowlers clusters for ICC top 10 players. All ICC top-ranked batters are in the same batters cluster, validating the quality of our batters clusters. Whereas the bowlers clusters of these batters vary as opposed to the batters cluster showing that the top-ranked batters do not necessarily have the same bowling quality. For example, few batters (e.g., B. Azam, Q. Kock and J. Roy) are in the fifth dummy bowlers cluster as they have never bowled. Similarly, ICC's top 10 bowlers belong to the two nearby clusters of bowlers. Moreover, clusters containing top batters are generally mutually exclusive with clusters containing top bowlers except for the case of all-rounders. For example, "C. Woakes", a good all-rounder, is in the same cluster 2 as the top 10 ICC batters in Table 4.

5.2. Players' Clustering Validation using Feature Vectors Visualization

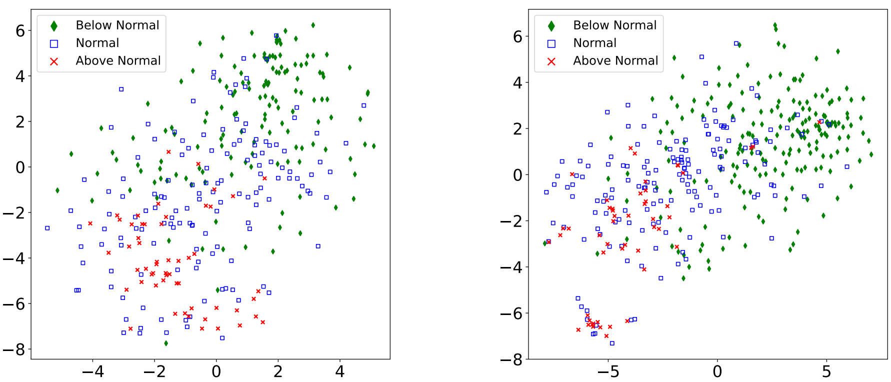
To visualize the batters and bowlers feature vectors, we use t-distributed stochastic neighbor embedding (t-SNE) Van der Maaten and Hinton (2008) to map the data into $\mathbb{R}^2$ (Figure 7). We collected the quarterly ICC player ratings of top 100 batters and bowlers from 2001 to 2019 (total 76 measurements). These ratings are aggregated for each player giving a total of 410 ICC-rated batters and 376 bowlers, i.e., the players rated at least once from 2001 to 2019. These aggregate ratings, grouped into three clusters (using k-means with $k = 3$), are used as labels for players' feature embeddings in the t-SNE diagram. We observe that the players with similar ICC ratings lie in the same proximity in the t-SNE diagram (Figure 7). This demonstrate that the players' feature vectors capture the players' quality (determined by the ICC top players ratings).

[5] ICC Men's ODI Players Rankings on October 20, 2019 - https://www.icc-cricket.com/rankings/mens/player-rankings/odi?at=2019-10-20

ICC Batter Rank	Name	ICC Rating	Batters Cluster	Bowlers Cluster
1	V. Kohli	895	2	1
2	R. Sharma	863	2	1
3	B. Azam	834	2	5
4	F. Plessis	820	2	1
5	L. Taylor	817	2	2
6	K. Williamson	796	2	2
7	D. Warner	794	2	1
8	J. Root	787	2	1
9	Q. Kock	781	2	5
10	J. Roy	774	2	5

ICC Bowler Rank	Name	ICC Rating	Bowlers Cluster	Batters Cluster
1	J. Bumrah	797	3	4
2	T. Boult	740	3	1
3	K. Rabada	694	3	1
4	P. Cummins	693	4	1
6	C. Woakes	676	3	2
7	M. Starc	663	4	4
7	M. Amir	663	3	1
8	M. Henry	656	4	4
9	L. Ferguson	649	4	4
10	K. Yadav	642	3	1

Table 4.: ICC top-ranked batters and bowlers with their cluster IDs. All top-ranked players are grouped into the same or nearby clusters showing that clustering captures the players' quality. Top all-rounders (e.g., C. Woakes) belong to the top-quality batters and top-quality bowlers cluster.

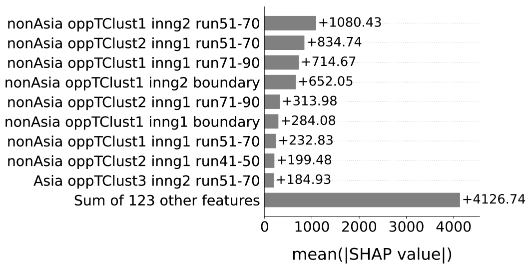


(a) Batters (b) Bowlers

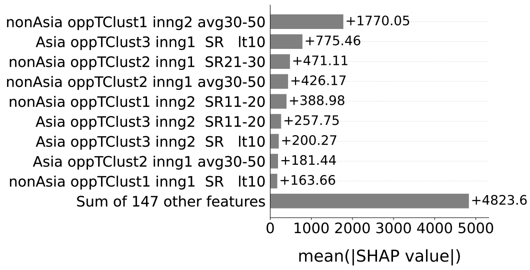
Figure 7.: 156-d and 132-d batters and bowlers feature vectors mapped to $\mathbb{R}^2$ using t-SNE in **(a)** and **(b)**, resp.. The aggregated ICC quarterly players ratings from 2001 to 2019 are used as labels to group similarly rated players. Figures are best seen in color.

5.3. SHAP Analysis for Players' Feature Importance

We apply SHAP (SHapley Additive exPlanations) analysis Lundberg and Lee (2017) to quantify the significance of features in determining the final prediction of the model. SHAP analysis runs a large number of predictions and compares the impacts of each feature. For SHAP analysis, we used bowlers and batters features vectors against the aggregated quarterly ICC ratings over the last 19 years. Figure 8a shows that runs scored by the batters against top batting teams in Non-Asian venues is the most important feature for the batter. The Bowling strike rate in Non-Asian venues is the most important feature for the bowler, as shown in Figure 8b.



(a) Batters

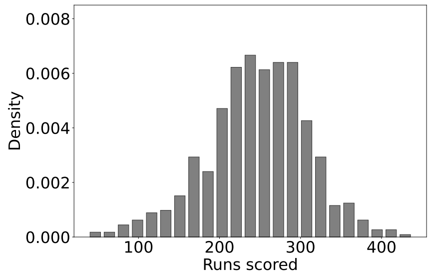


(b) Bowlers

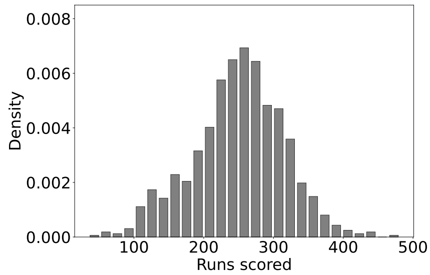
Figure 8.: Mean absolute value of SHAP values for batters features **(a)** shows that runs scored against top batting teams at non-Asian venues is the most important feature. For bowlers **(b)** bowling strike rates in non-Asian venues is most significant.

5.4. Validation of Venue-wise Distribution of Matches

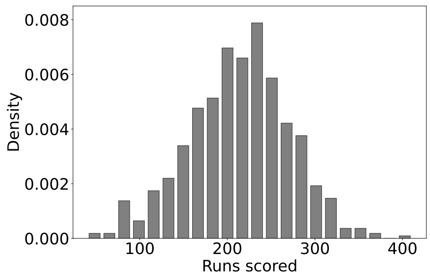
We demonstrate that scoring patterns vary significantly at different pitch conditions to validate the classification of match venues into Asian and non-Asian pitches. Figure 9 shows the innings-wise distribution of scores in all matches on Asian and Non-Asian pitches. Significantly different distribution of total innings scores on Non-Asian and Asian venues justify distinguishing match venues for score projection.



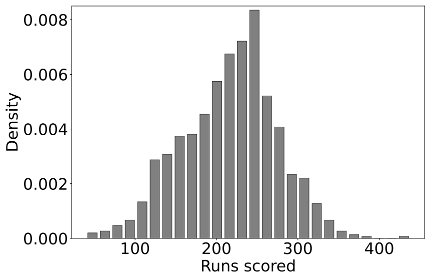
(a) 1st inning scores at Asian venues



(b) 1st inning scores at Non-Asian venues



(c) 2nd inning scores at Asian venues



(d) 2nd inning scores at Non-Asian venues

Figure 9.: Innings score distribution at Asian and Non-Asian venues. Innings scores on Asian pitches (**(a)** and **(c)**) exhibit substantially different patterns than those on Non-Asian pitches (**(b)** and **(d)**).

5.5. *Evaluating Projected Remaining Runs*

This section describes the accuracy of the computation of the projected scores by CAMP. We compute the mean absolute error (MAE) in the projected scores $R(S_i)$ and the actual runs scored $A(S_i)$ by CAMP using kNN, Random Forest and Ridge Regression, and LNC. Figure 10 shows the MAE in projected runs using CAMP (by applying kNN, Random Forest, and Ridge Regression) and using LNC.

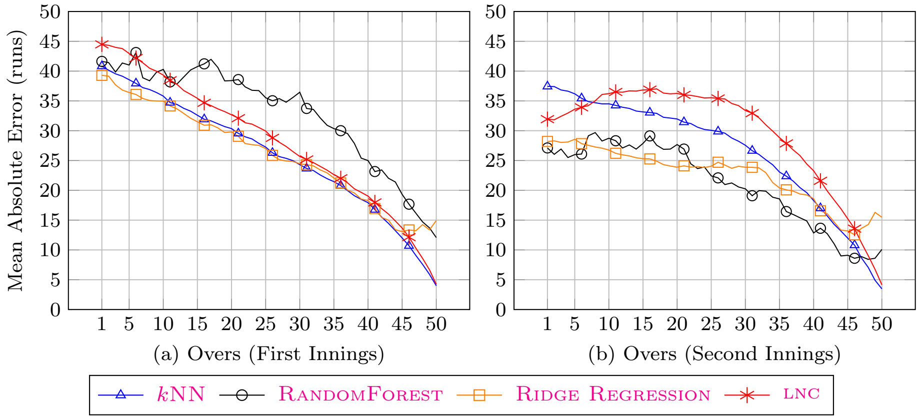


Figure 10.: MAE in projected remaining ($R(S_i)$) and actual $A(S_i)$ scores for both innings. $R(S_i)$ is predicted using kNN, Random Forest, Ridge Regression, and LNC.

Figure 10(a) shows that our kNN and Ridge Regression approaches outperform LNC throughout the first innings. However, the Random Forest is not as good as the inning proceeds. Figure 10(b) shows the performance of our model and its comparison with LNC for second innings. In the second innings, since LNC uses the same resource table (as the first innings), the error for LNC is higher. Since CAMP also considers the target remaining, it remains better at the start of the second innings (for kNN and Random Forest). For kNN, since we have the same resources at the beginning of the second innings, but the target is different, the error is higher as the feature vector does not have enough information. Also, the standard deviation of second innings runs is high, making it difficult for kNN to achieve higher accuracy at the start of the second innings. However, as the overs progress, the richer feature vectors for the kNN improve accuracy.

5.6. *Evaluating Players' Ratings*

Evaluating the performance of CAMP is challenging as no objective ground truth exists for all players' contributions in a match. LNC gives some idea about the players' rankings, which is somewhat similar to ours, and MoM only identifies the *"top-rated"* player. We evaluate CAMP in three aspects.

(1) Firstly, we present a case study of a single match and show how our measure captures the context and quality of the opponent batter or bowler as opposed to the standard performance measure.

(2) We then report the agreement of our top contributor with MoM and compare this agreement with that of LNC.

(3) Finally, we compare the performance of CAMP on the case study of a series reported by LNC.

5.6.1. Comparison with Traditional Batting and Bowling Performance Measures

Traditional performance measures of batting and bowling offer no objective way to incorporate the situation in which runs are scored or conceded. For example, two batters scoring the same number of runs in the same number of deliveries at different stages of games facing different types of bowlers are not valued equally, and nearly always, some verbal qualification is required to place the statistics into context. We show how CAMP caters to this limitation through the case study of a randomly selected match between NZ and PAK on October 25, 2006 at Mohali[6].

In this game, Fleming scored 80 runs (strike rate 76.10) and was declared MoM, which is not obvious from the scorecard (Table 5 for the scorecards). Styris scored the highest runs (86 (strike rate 76.19)) with the highest number of boundaries in his batting. Bond took the highest wickets (3)(economy 4.50). Oram scored 31 runs (strike rate 119.23), which is more than the strike rate of Styris and Fleming. Also, Oram took 2 wickets with the highest economy (3.12). The top performer (Fleming) is not obvious from the scorecard only. However, the context-aware CAMP offers more meaningful insights (Table 6). Fleming (MoM) has the highest CAMP$_{score}$, which agrees with experts' decision of MoM. In this case study, CAMP also outperforms LNC. According to LNC, Oram is the best contributor, and Fleming (MoM) is ranked $2nd$ in the winning team ($3rd$ among all 22 players). Also, note that Styris and Bond are declared the best performing batter and bowler by ESPNcricinfo.

Player	Team	Runs	Balls	$4s$	$6s$	Out by
S. Fleming	NZ	80	105	8	1	S. Malik
P. Fulton	NZ	7	14	1	0	I. Anjum
S. Styris	NZ	86	113	10	0	I. Anjum
J. Oram	NZ	31	26	4	1	U. Gul
B. McCullum	NZ	27	13	3	1	S. Malik
J. Franklin	NZ	9	5	1	0	not out
M. Yousuf	PAK	71	92	9	0	S. Fleming

Player	Team	Overs	Runs	Wickets	Economy
K. Mills	NZ	7.3	38	2	5.06
S. Bond	NZ	10	45	3	4.50
J. Franklin	NZ	9	47	1	5.22
J. Oram	NZ	8	25	2	3.12
D. Vettori	NZ	10	52	1	5.20
N. Astle	NZ	2	11	0	5.50
S. Malik	PAK	5	25	1	5.00

Table 5.: Batting and bowling scorecards of the randomly selected NZ vs. PAK (2006) match due to non-obvious MoM (S. Fleming) from the winning team's (NZ) scorecards.

Player	Team	CAMP$_{score}$	CAMP$_{rank}$	LNC$_{score}$	LNC$_{rank}$
S. Fleming	NZ	+35.4	1	+28.77	3
S. Bond	NZ	+15.4	2	+28.26	4
J. Oram	NZ	+11.2	4	+36.55	1
S. Styris	NZ	+10.5	5	+13.62	7
B. McCullum	NZ	+6.2	7	+11.02	8
K. Mills	NZ	+0.56	10	−7.22	12
M. Yousuf	PAK	+12.7	3	+34.81	2
M. Hafeez	PAK	+10.0	6	+7.515	9
S. Malik	PAK	+5.82	8	+19.83	5
K. Akmal	PAK	+5.0	9	+14.36	6

Table 6.: CAMP ratings of prominent performers from both teams in the randomly selected SA vs. IND (2001) match due to non-obvious MoM (S. Fleming).

[6] Full Scorecard of NZ vs. PAK 14th Match in ICC Champions Trophy (2006/07) - https://www.espncricinfo.com/series/232694/scorecard/249752/

We also show that if the top contributor by CAMP disagrees with MoM, the difference between CAMP ratings among top-rated players is very small. A case study of a randomly selected match between SA and IND on October 26, 2001 at Durban is used to evaluate the contribution difference between top players for non-obvious MoM[7].

In this game, the MoM (S. Pollock from the winning team) is not obvious from the scorecard (Table 7). Kirsten scored 87 runs in 108 balls, Kemp took 3 wickets with economy 3.15 and Pollock took 2 wickets with economy 2.11. The top performer is not obvious from the scorecard. However, the context-aware CAMP offers more meaningful insights (Table 8). Kirsten has the highest CAMP_{score}, followed by Kemp and Pollock with a very slight difference. However, Pollock was awarded MoM. It is important to note that the contribution difference between Pollock and the players above him is very little. If MoM is not the top contributor, this may be due to experts' subjective judgment that considers other factors such as fielding, captaincy, and wicket-keeping.

Player	Team	Runs	Balls	4s	6s	Out by
G. Kirsten	SA	87	108	9	1	H. Singh
J. Kallis	SA	39	63	5	0	S. Tendulkar
S. Pollock	SA	0	4	0	0	Not Out
S. Ganguly	IND	9	17	1	0	S. Pollock
R. Dravid	IND	77	102	6	0	J. Kemp
Y. Singh	IND	2	3	0	0	J. Kemp
A. Kumble	IND	0	2	0	0	J. Kemp

Player	Team	Overs	Runs	Wickets	Economy
S. Pollock	SA	9	19	2	2.11
J. Kemp	SA	6.2	20	3	3.15
N. Hayward	SA	10	38	2	3.80
J. Kallis	SA	8	41	0	5.12
L. Klusener	SA	5	19	1	3.80
H. Singh	IND	10	48	2	4.80
S. Tendulkar	IND	5	27	2	5.40

Table 7.: Batting and bowling scorecards of the randomly selected SA vs. IND (2001) match due to non-obvious MoM (S. Pollock) from the winning team's (SA) scorecards.

Player	Team	C_{bat}	C_{bowl}	CAMP_{score}	CAMP_{rank}	LNC_{score}	LNC_{rank}
G. Kirsten	SA	+12.95	0	+12.95	2	+23.32	1
J. Kemp	SA	0	+64.20	+12.84	3	+19.72	3
S. Pollock	SA	+0.10	+61.10	+12.22	4	+22.83	2
N. Hayward	SA	0	+55.00	+11.00	6	+11.35	5
L. Klusener	SA	0	+20.30	+4.06	12	+5.62	7
J. Kallis	SA	−14.08	−17.00	−17.48	16	−24.33	22
R. Dravid	IND	+17.02	0	+17.02	1	+16.61	4

Table 8.: CAMP ratings of prominent performers from both teams in the randomly selected SA vs. IND (2001) match due to non-obvious MoM (S. Pollock).

5.6.2. *Comparison with Man of the Match (*MoM*)*

The man of the match (MoM) is nominated through a rigorous subjective process by field experts who observe the match closely. The highest net contributor by CAMP closely agrees with the MoM. We report the *agreement accuracy* (fraction of matches where the top contributor by CAMP is the MoM). We implemented LNC technique to select the top contributor[8]. Table 9 shows that CAMP outperforms LNC in agreement accuracy. The agreement accuracy of CAMP is 66% to 90%. To the best of our knowledge, this is the highest MoM agreement accuracy reported for ODI cricket.

[7] Scorecard: SA vs. IND SB Triangular Tournament(01/02)-https://www.espncricinfo.com/series/8660/scorecard/66107/

[8] Available in the published version

	11 players of winning team		22 players of both teams	
	CAMP	LNC	CAMP	LNC
MoM having rank 1 on CAMP scale	638(66.3%)	585(60.8%)	458(47.6%)	461(47.9%)
MoM among top 2 on CAMP scale	799(83.1%)	784(81.5%)	686(71.3%)	650(67.6%)
MoM among top 3 on CAMP scale	867(90.2%)	864(89.9%)	789(82.1%)	773(80.4%)

Table 9.: Comparison with MoM in 961 matches among the 11 winner team and all 22 players.

It is well known that MoM is mostly from the winning team. Therefore, we report results for MoM rank among the winning team players and all 22 players of both teams separately in Table 9. As the accuracy of MoM being the top contributor among 22 players is relatively low, we have observed that out of total 961 matches, there are 228 such matches, where MoM is ranked second among all 22 players. However, out of these 228 matches, MoM is the top contributor of his team in 154 matches, which shows the bias toward selecting MoM from the winning team.

5.6.3. Comparison with LNC on Series Level

Similar to MoM, ICC also announces **P**layer **o**f the **S**eries (PoS) based on the overall performance of participating players through the series (tournament). CAMP evaluates players' contributions in each match of a series. Since there is no other baseline metric to validate the ratings of players at a series level, we utilize the accuracy of the agreement between the (aggregated) top contributor of the series and PoS. Lewis (2005) evaluated LNC on the **V**ictoria **B**itter VB Series (2002-03) played between ENG, AUS and SL. The contribution scores aggregated over the 14 matches by CAMP and by LNC are given in Table 10.

Player	Team	CAMP_{score}	CAMP_{rank}	LNC_{score}	LNC_{rank}
S. Jayasuriya	SL	89.86	1	97.18	4
P. Collingwood	ENG	65.66	2	110.94	2
B. Lee	AUS	65.42	3	33.99	14
A. Bichel	AUS	50.89	4	45.90	10
B. Williams	AUS	49.50	5	29.77	15
D. Lehmann	AUS	48.32	6	75.62	5
A. Gilchrist	AUS	46.63	7	105.25	3
M. Hayden	AUS	35.33	8	152.76	1
A. Caddick	ENG	32.82	9	56.00	6
N. Bracken	AUS	31.00	10	48.29	8

Table 10.: Comparison of scores and ranks by CAMP and LNC for top 10 players in VB series (02-03). LNC_{score} are reported in Lewis (2005). Brett Lee was the PoS.

In this series, PoS nominated by ICC (Brett Lee)[9] is the top 1 for the series-winning team (AUS) and among the top 3 for all matches by CAMP. However, LNC places him at the 14^{th} position. This analysis exhibits that CAMP is more effective than LNC for

[9] Player of the Series announced by ICC

players' contributions at the series level as well. The overall MoM agreement of our proposed model (for the VB-series) are given in Table 11.

	Agreement	Agreement Accuracy
MoM ranked 1^{st} by CAMP	10 times	**71.14 %**
MoM ranked among top 2 by CAMP	12 times	**85.71 %**

Table 11.: CAMP rankings of MoM for the 14 matches in VB series (2002-2003).

6. Conclusion

We proposed the CAMP measure to objectively quantify players' performance and assess players' contribution to a cricket game. CAMP's data-driven players rating achieves close agreement with the man of the match awards. Our approach can be extended to any format of cricket. An individual player's contribution is measured based on the game's context and the opposition's strength. Each stage of the innings demands a different nature of play, and expectations from players and their performances change over time. Our framework keeps track of the current match situation and assigns context-aware ratings to the players. In the future, we aim to extend CAMP to incorporate other factors such as fielding, captaincy, and wicket-keeping by using text analytics of match commentary and crowd opinions voiced through social media.

References

Bai, L., Gedik, R., & Egilmez, G. (2022). What does it take to win or lose a soccer game? A machine learning approach to understand the impact of game and team statistics. *Journal of the Operational Research Society*, *0*(0), 1–22.

Barr, G., & Kantor, B. (2004). A Criterion for Comparing and Selecting Batsmen in Limited Overs Cricket. *Journal of the Operational Research Society*, *55*(12), 1266–1274.

Beaudoin, D., & Swartz, T. B. (2003). The Best Batsmen and Bowlers in One-Day Cricket. *South African Statistical Journal*, *37*(2), 203–222.

Bhattacharjee, D., Lemmer, H. H., Saikia, H., & Mukherjee, D. (2018). Measuring Performance of Batting Partners in Limited Overs Cricket. *South African Journal for Research in Sport, Physical Education and Recreation*, *40*(3), 1–12.

Bhattacherjee, S., Sahoo, J., & Goswami, A. (2015). Association Rule Mining Approach in Strategy Planning for Team India in Icc World Cup 2015. In *International conference on advances in computing and communication engineering* (pp. 616–621).

Bunker, R. P., & Thabtah, F. (2019). A Machine Learning Framework for Sport Result Prediction. *Applied Computing and Informatics*, *15*(1), 27–33.

Clarke, S. R. (1988). Dynamic Programming in One-Day Cricket-Optimal Scoring Rates. *Journal of the Operational Research Society*, *39*(4), 331–337.

Constantinou, A. C. (2019). Dolores: A Model that Predicts Football Match Outcomes from All Over the World. *Machine Learning*, *108*(1), 49–75.

Davis, J., Bransen, L., Decroos, T., Robberechts, P., & Haaren, J. V. (2019). Assessing the Performances of Soccer Players. In *International symposium on computer science in sport* (pp. 3–10).

Davis, J., Perera, H., & Swartz, T. B. (2015). Player Evaluation in Twenty20 Cricket. *Journal of Sports Analytics*, *1*(1), 19–31.

Decroos, T., Bransen, L., Haaren, J. V., & Davis, J. (2019). Actions Speak Louder than Goals: Valuing Player Actions in Soccer. In *International conference on knowledge discovery & data mining* (pp. 1851–1861).

Delen, D., Cogdell, D., & Kasap, N. (2012). A Comparative Analysis of Data Mining Methods in Predicting NCCA Bowl Outcomes. *International Journal of Forecasting*, *28*(2), 543–552.

Deshpande, S. K., & Jensen, S. T. (2016). Estimating an Nba Player's Impact on His Team's Chances of Winning. *Journal of Quantitative Analysis in Sports*, *12*(2), 51–72.

Devijver, P., & Kittler, J. (1982). *Pattern Recognition: A Statistical Approach.* London, GB: Prentice-Hall.

Duckworth, F., & Lewis, A. (1998). A Fair Method for Resetting the Target in Interrupted One-Day Cricket Matches. *Journal of the Operational Research Society*, *49*(3), 220–227.

Duckworth, F., & Lewis, A. (2004). A Successful Operational Research Intervention in One-Day Cricket. *Journal of the Operational Research Society*, *55*(7), 749–759.

Fried, G., & Mumcu, C. (2016). *Sport Analytics: A Data-Driven Approach to Sport Business and Management.* Taylor & Francis.

Goddard, J. (2005). Regression Models for Forecasting Goals and Match Results in Association Football. *International Journal of Forecasting*, *21*(2), 331–340.

Hasanika, D., Dilhara, R., Liyanage, D., Bandaranayake, A., & Deegalla, S. (2021). Data Mining System for Predicting a Winning Cricket Team. In *International conference on industrial and information systems* (pp. 92–97).

Jhanwar, M. G., & Pudi, V. (2016). Predicting the Outcome of ODI Cricket Matches: A Team Composition Based Approach. In *Ecml/pkdd workshop on machine learning and data mining for sports analytics* (pp. 35–44).

Joseph, A., Fenton, N. E., & Neil, M. (2006). Predicting Football Results Using Bayesian Nets and Other Machine Learning Techniques. *Knowledge-Based Systems*, *19*(7), 544–553.

Lemmer, H. H. (2008). An Analysis of Players' Performances in the First Cricket Twenty20 World Cup Series. *South African Journal for Research in Sport, Physical Education and Recreation*, *30*(2), 71–77.

Lewis, A. (2005). Towards Fairer Measures of Player Performance in One-Day Cricket. *Journal of the Operational Research Society*, *56*(7), 804–815.

Lewis, A. (2008). Extending the Range of Player-Performance Measures in One-Day Cricket. *Journal of the Operational Research Society*, *59*(6), 729–742.

Liu, G., & Schulte, O. (2018). Deep Reinforcement Learning in Ice Hockey for Context-Aware Player Evaluation. In *International joint conference on artificial intelligence* (pp. 3442–3448).

Lord, F., Pyne, D. B., Welvaert, M., & Mara, J. K. (2022). Field Hockey from the Performance Analyst's Perspective: A Systematic Review. *International Journal of Sports Science & Coaching*, *17*(1), 220–232.

Lundberg, S. M., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions. In *Advances in neural information processing systems* (pp. 4765–4774).

Norman, J. M., & Clarke, S. R. (2010). Optimal batting orders in cricket. *Journal of the Operational Research Society*, *61*(6), 980–986.

Prasetio, D., & Harlili, D. (2016). Predicting Football Match Results with Logistic Regression. In *International conference on advanced informatics: Concepts, theory and application* (pp. 1–5).

Sankaranarayanan, V. V., Sattar, J., & Lakshmanan, L. V. (2014). Auto-play: A Data Mining Approach to ODI Cricket Simulation and Prediction. In *International conference on data mining* (pp. 1064–1072).

Scarf, P., & Akhtar, S. (2011). An analysis of strategy in the first three innings in test cricket: declaration and the follow-on. *Journal of the Operational Research Society*, *62*(11), 1931–1940.

Shah, P., & Shah, M. (2014). Pressure Index in Cricket. *Journal of Sports and Physical Education*, *1*(5), 9–11.

Shi, Z., Moorthy, S., & Zimmermann, A. (2013). Predicting NCAAB Match Outcomes Using

ML Techniques-Some Results and Lessons Learned. In *Ecml/pkdd workshop on machine learning and data mining for sports analytics* (pp. 69–78).

Stern, S. (2009). An Adjusted Duckworth-Lewis Target in Shortened Limited Overs Cricket Matches. *Journal of the Operational Research Society*, *60*(2), 236–251.

Swartz, T. B., Gill, P. S., Beaudoin, D., & DeSilva, B. M. (2006). Optimal Batting Orders in One-Day Cricket. *Computers & Operations Research*, *33*(7), 1939—1950.

Van der Maaten, L., & Hinton, G. (2008). Visualizing Data using t-SNE. *Journal of Machine Learning Research*, *9*(11), 2579–2605.

Viswanadha, S., Sivalenka, K., Jhawar, M. G., & Pudi, V. (2017). Dynamic Winner Prediction in Twenty20 Cricket: Based on Relative Team Strengths. In *Ecml/pkdd workshop on machine learning and data mining for sports analytics* (pp. 41–50).

Appendix A. Rules and Objectives of One Day International Cricket Game

This section presents an overview of the objective and basic rules of the ODI cricket game, along with a few basic terminologies.

Toss: As in other sports, a cricket match starts with a toss. The toss-winning team has the choice to bat first or ask the opponent to bat first. This important decision is made considering the nature of the field, weather conditions, and the teams' relative strengths.

Objective: A match is played between two teams of 11 players each. Suppose $team_A$ is batting first, at the start of the first innings, $team_A$ has 50 overs and 10 wickets to score the maximum runs before either 50 overs are completed or 10 wickets are lost. An over consists of 6 balls to be bowled by any player of the second team, $team_B$. The other 10 players spread in the field to stop as many runs as possible. A bowler can bowl a maximum of 10 overs in an innings. Runs are scored by hitting the ball and exchanging positions between two batters or hitting the ball outside the boundary for 4 and 6. $Team_B$ starts its innings with the same resources (overs and wickets). However, $team_B$ has to chase the target ($team_A$'s score plus one) to win. The second innings finishes when the resources are consumed or the target is achieved, whichever happens first.

Wicket Loss: A batter can lose his wicket in several pre-defined ways, such as bowled, caught by opponents, run-out, or Leg Before Wicket (LBW).

Target Runs: The number of runs accumulated by $team_A$ after the first innings plus 1 is set as a target for the $team_B$ batting in the second innings.

Match Outcome: The team with the highest score is declared the winner if both innings are completed without interruption (rain or other severe weather conditions).

Resources: A team batting first has 10 wickets and 50 overs collectively called resources. $Team_A$ tries to maximize runs while consuming the resources. The first innings comes to an end when either of the resources finishes.

Duckworth-Lewis Resource Table: The DL resource table (Table A1) represents the mean percentage of further runs scored with w wickets lost and u overs left. For an average ODI, the total score of team 1 is 235. Readers are referred to Duckworth and Lewis (1998, 2004); Lewis (2005) (and the references therein) for details.

Overs left	Wickets lost			
	0	2	4	9
50	100	83.8	62.4	7.6
40	90.3	77.6	59.8	7.6
30	77.1	68.2	54.9	7.6
20	58.9	54.0	46.1	7.6
10	34.1	32.5	29.8	7.6

Table A1.: DL resource table showing the percentage of remaining expected scores with the number of overs left and wickets lost.