I. INTRODUCTION

Cricket is the most popular sports in India. Different for-mat of this game has gained popularity in different times, and in recent times Twenty-twenty (T20) format of the game has gained popularity. In last eleven years, Indian Premier League (IPL) has created a position of its own in the world cricket community. In this tournament, there are eight teams named after eight cities of India. Each team is owned by one or more franchises. A pool of players is created for an auction. Each player is allotted a base price, and the maximum amount each franchise can spend for its entire team is fixed. The auction determines the team for each franchise.

Naturally, the aim of every franchise is to buy the best players from the auction who can help them win the tournament. Each franchise, therefore, maintains a think-tank whose primary job is to determine the players whom they want to buy from the auction. This is not a trivial task be-cause (i) it is not possible to always pick the best players since the budget for a team is fixed, and (ii) often it so hap-pens that some other franchise buys a player who was in the target list of a franchise. In such situations, the think-tank must determine the best alternate player for the team. The history of IPL has repeatedly seen teams failing to perform in the tournament due to poor player selection. In this paper, we have developed a recommendation sys-tem for player selection based on heuristic ranking of players, and a greedy algorithm for the team selection. The algorithm can help the think-tank to determine the best potential team, and an alternate player if their target player is not available. Previous studies [1, 2, 3, 4] concentrate either on the current form of the players [5, 6], or their long term performance history [7]. However, these two factors individually are not suf-ficient to decide whether a player is to be bought. Other factors such as, whether a batsman is an opener, or middle-order player or finisher, and consideration of features pertinent to those ordering is of utmost necessity. For example, middle-order batsman can afford a lower strike rate if he has a good average, but not a finisher. Furthermore, it is necessary to determine a balance between the recent form of a player, and the past history of a good player whose recent form may not be up to the mark.

In this paper, we have considered a set of traditional and derived features and have quantified them. Not all of these features are equally important for every player in every position. Therefore, we have broadly classified a potential team into multiple positions, and for each position we have heuristically determined the appropriate weight for these features. For each player in the pool, we have obtained a score based on these weighted features, and have ranked them accordingly. The ranking obtained by this technique is in accordance with the well known ranking of players in IPL. Finally, a relative score on the scale of 1-10 is allotted for each player. Moreover, a fixed basis score is allocated for a team of 15 players, which emulates the fixed budget assigned to each team. We then use greedy algorithm to select the best team within this budget using the aforementioned ranking scheme. The rest of the paper is organized as follows - In Section 2, we define the traditional and derived features which have been considered for batsmen, and quantify them. Three clusters - openers, middle-order and finishers, have been defined in Section 3, each having a heuristic scoring formula which is a weighted sum of those features. The batsmen have been ranked into these clusters according to their points by these heuristics. The features for the bowlers are quantified in Sec-tion 4 and the bowlers are ranked accordingly. In
Section 5, we further assign credit points to the players according to their ranks. We present two greedy algorithms for selecting the best IPL team from the previous ranking when the total credit point of the team is fixed. We conclude in Section 6.

II. ANALYZING FEATURES FOR BATSMAEN

We have created a database of all the players and their performance in the last eleven seasons of IPL. Some players, who have already retired, are removed from the database. The performance values for those players who have not played some of the early seasons are assigned 0 for those seasons. This comes handy later on while determining the experience factor. For analysis of current form, we have considered the values from the 2018 season of IPL only. In Table 1 we note the traditional features which are considered for the analysis of players. These are very standard features used to report the performance of players in every cricket matches [8], and hence we do not discuss about these. Apart from these features, some derived features are also quantified, which we shall discuss later in this section.

Table 1. Standard features for batsmen and bowlers

<table>
<thead>
<tr>
<th>Batsmen</th>
<th>Bowlers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innings</td>
<td>Innings</td>
</tr>
<tr>
<td>Runs Scored</td>
<td>Wickets Taken</td>
</tr>
<tr>
<td># Balls Faced</td>
<td># Balls Bowled</td>
</tr>
<tr>
<td>Average Strike Rate</td>
<td>Average Strike Rate</td>
</tr>
<tr>
<td># 100s</td>
<td># Runs Conceded</td>
</tr>
<tr>
<td># 50s</td>
<td>Economy Rate</td>
</tr>
<tr>
<td># 4s Hit</td>
<td># 4 Wickets</td>
</tr>
<tr>
<td># 6s Hit</td>
<td># 5 Wickets</td>
</tr>
</tbody>
</table>

We have grouped the batsmen into three position clusters - openers, middle order batsmen and finisher, since these three types of players have three very different role in the match. In the remaining part of this section, we have quantified the features considered in Table 1 for grouping. How-ever, these features conform to all batsmen, and hence are not sufficient for the clustering. Therefore, we also consider some derived features which take into account the specific roles of batsmen in different position clusters.

- **Batting Average**: This feature denotes the average run scored by a batsman per match before getting out.
  
  \[
  \text{Avg} \text{ - Runs}/(# \text{Innings} - \# \text{Not Out})
  \]

- **Strike Rate**: Strike rate is defined as the average runs scored by a batsman per 100 balls. The higher the strike rate, the more effective a batsman is at scoring runs quickly.
  
  \[
  \text{SR} \text{- } (100\times \text{Runs})/(# \text{Balls})
  \]

- **Running Between the Wicket**: Though this is a very frequently used term in cricket, there is no proper quantification of this feature. We have quantified it as the number of runs scored per ball in which fours or sixes were not hit.
  
  \[
  \text{RunWicket} \text{- } (\text{Runs} - \# \text{Fours}\times 4 - \# \text{Sixes}\times 6)/(# \text{Balls} - \# \text{Fours} - \# \text{Sixes})
  \]

- **Hard Hitting**: T20 is a game of runs, and to win it is necessary to score runs quickly. Therefore, apart from quick running, it is necessary to hit many fours and sixes. “Hard Hitter” is a common term in T20 cricket, but it is not quantified. We have quantified this feature as the number of runs scored per ball by hitting four or six.
  
  \[
  \text{HardHitting} = (\# \text{Fours}\times 4 - \# \text{Sixes}\times 6)/\# \text{Balls}
  \]

In addition to these, we have defined a COST feature for each of the features. The set of COST features is used to obtain a relative score of an individual with respect to all the IPL players. Let f(i) denote the value of a feature f for the i-th player. If the total number of IPL players is n, then the cost feature for f is defined as f(i)/max{f(j)}. Using this formula, we have calculated the cost feature for each of the features discussed above.

Experience of a player is an important criteria which should be considered in addition to the above features. Therefore we have defined experience factor (xfact) as

\[
\text{xfact(i)} = \text{innings(i)}/\# \text{innings in IPL so far}
\]

where innings(i) implies the number of innings the i-th player has played. Define range, fact as follows

\[
\text{range,} \text{fact} = \max \{\text{xfact(j)}\} - \min \{\text{xfact(k)}\}
\]

Then the relative experience of a player (cost, fact) is defined as

\[
\text{cost,} \text{fact(i)} = \text{xfact(i)}/\text{range,} \text{fact}
\]

The calculation of cost feature and cost, fact is similar for bowlers also.

III. CLUSTERING AND RANKING OF BATSMAEN

We have clustered the batsmen into three major categories -(i) opener, (ii) middle order and (iii) finisher. These three types of batsmen are required to play different roles in the match, and hence are expected to have different skills. A total weight of 100 is divided into the features for each bats-man. The division of the total weight into features is heuristic so that it models the skill requirements for batsman in different clusters. Furthermore, the ranking of players obtained by such weight distribution conforms with our known player ranking. In the following subsections we discuss the motivation for weight division in each position cluster, and show the top five players according to our ranking scheme.

3.1 Opening batsman

The responsibility of setting up a good foundation for the team’s score lies on the openers. The openers get to face the maximum number of balls, and therefore is expected to have a high average. Furthermore, they need to score quickly in the first power play. So a handy strike rate is also a good indicator of the effectiveness of an opening batsman. Both...
these features are equally important and are, therefore, assigned the highest weight of 30 each. Furthermore, an opener is ex-pected to stay on the crease for a long time and score big runs. Therefore, we have assigned a weight of 20 to the number of half-centuries (hc) scored by an opener per innings. Often an opener requires some time to set in, and then start hard hitting. During the time, when an opener is still not hitting hard, he should rotate the strikes quickly to keep the score-board moving. However, the necessity of hard hitting cannot be totally ignored during the powerplay. This motivates us to assign a weight of 10 for both running between the wickets and hard hitting. Based on the choice of feature and weight division, the relative score of the i-th opener (opener(i)) is determined as

\[
\text{opener(i)} = \text{cost SR(i)} \times 30 + \text{cost Avg(i)} \times 30 + (hc(i)\text{innings(i)}) \times 20 + \text{cost RunWicket(i)} \times 10 + \text{cost HardHitting(i)} \times 10
\]

We have used the notation f (i) to denote the value of the feature f for the i-th player considering all the seasons of IPL. Another notation f[i] is used to denote the value of the same feature considering only the last season of IPL. The relative current score of the i-th opener (curr opener[i]) is de-termined as

\[
\text{curr opener[i]} = \text{cost SR[i]} \times 30 + \text{cost Avg[i]} \times 30 + (hc[i]\text{innings[i]}) \times 20 + \text{cost RunWicket[i]} \times 10 + \text{cost HardHitting[i]} \times 10
\]

Considering the experience factor for each player, the fi-nal rank of the i-th opener is calculated as

\[
\text{opener rank(i)} = \text{opener(i)} \times \text{cost, fact \times (curr opener[i]/mean opener) + curr opener[i]}
\]

where mean opener is the average score of all the openers. The top five opening batsmen from IPL pool of players - - - - - and their corresponding point derived according to our ranking scheme is shown in Table 2.

Table 2. Top five opening batsmen according to our ranking scheme

<table>
<thead>
<tr>
<th>Batsman</th>
<th>Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>AB de Villiers</td>
<td>173.5798</td>
</tr>
<tr>
<td>MS Dhoni</td>
<td>159.0942</td>
</tr>
<tr>
<td>DA Warner</td>
<td>150.113</td>
</tr>
<tr>
<td>V Kohli</td>
<td>133.8061</td>
</tr>
<tr>
<td>CH Gayle</td>
<td>132.4749</td>
</tr>
</tbody>
</table>

Four out of the five names are indeed the top openers or first down batsmen in IPL. The striking inclusion in this table is MS Dhoni who is almost always a finisher. However, we shall see in the subsequent subsections that the points obtained by Dhoni as a finisher is significantly higher than his points as an opener. That his name appeared in this table simply shows the effectiveness of Dhoni in a T20 match.

3.2 Middle order batsman

The batsmen in these genre need to provide the stability and also must possess the ability to accelerate the scoreboard when chasing a big total. A middle order batsman must be a good runner between the wickets since it becomes difficult to hit big shots during this phase of the match with the fielders spread out. Furthermore, often when one or both the openers get out quickly, the middle order batsmen must take up to re sponsibility to score big runs. Therefore a decent average is necessary.

The weights for middle order batsmen have been dis tributed among the features taking the above requirements into consideration. The relative score of the i-th middle order batsman (middle(i)) is determined as

\[
\text{middle(i)} = \text{cost SR(i)} \times 20 + \text{cost Avg(i)} \times 30 + (hc(i)\text{innings(i)}) \times 10 + \text{cost RunWicket(i)} \times 25 + \text{cost HardHitting(i)} \times 15
\]

In accordance with the calculation for openers, the relative current score of the i-th middle order batsman (curr middle[i]) is determined as

\[
\text{curr middle[i]} = \text{cost SR[i]} \times 20 + \text{cost Avg[i]} \times 30 + (hc[i]\text{innings[i]}) \times 10 + \text{cost RunWicket[i]} \times 25 + \text{cost HardHitting[i]} \times 15
\]

Considering the experience factor for each player, the final rank of the i-th middle order batsman is calculated as

\[
\text{middle rank(i)} = \text{middle(i)} \times \text{cost, fact \times (curr middle[i]/mean middle) + curr middle[i]}
\]

where mean middle is the average score of all the middle order batsmen. Based on the middle rank, we have sorted all the bats-men in descending order of their score. The top five middle order batsmen, according to our scoring scheme is shown in Table 3.

Table 3. Top five middle order batsmen according to our ranking scheme

<table>
<thead>
<tr>
<th>Batsman</th>
<th>Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>AB de Villiers</td>
<td>183.9566</td>
</tr>
<tr>
<td>MS Dhoni</td>
<td>169.7258</td>
</tr>
<tr>
<td>DA Warner</td>
<td>163.6285</td>
</tr>
<tr>
<td>V Kohli</td>
<td>150.5608</td>
</tr>
<tr>
<td>KD Karthik</td>
<td>137.0331</td>
</tr>
</tbody>
</table>

Once again, the names in this ranking do not require any justification. It is worthwhile to note that Dhoni is present in this list also, and his score is slightly higher than his score as an opener. This shows that Dhoni is more effective as a middle order batsman.

3.3 Finisher

Finishers usually have the task of scoring quick runs in the end of the match. Naturally, strike rate and hard hitting are the most important factors for any finisher. It is difficult for a finisher to score big runs regularly since they usually get to play very few overs. Therefore, average score is not consid ered for these players. Running between the wicket is also an important factor for these batsmen. These players are also expected to remain not out and win the match for the team.

In accordance to the above requirements, we have cal culated the relative score of the i-th finisher (finisher(i)) as follows

\[
\text{finisher(i)} = \text{cost SR(i)} \times 40 + \text{cost HardHitting(i)} \times 40 + \text{not out(i) \times 5 + cost RunWicket(i) \times 15}
\]
The current form of the i-th finisher (curr finisher) is calculated considering only the feature scores for last year.

\[
\text{curr finisher}(i) = \text{cost SR}(i) \times 40 + \text{cost HardHitting}(i) \times 40 + \text{not} - \text{out}(i) \times 5 + \text{cost RunWicket}(i) \times 15
\]

Mean finisher is the average score of all the middle or lower batsmen. Eventually the total score of the i-th finisher, considering the experience factor is calculated as follows.

\[
\text{finisher rank}(i) = \text{finisher}(i) \times \text{cost, fact} \times (\text{curr,finisher}(i) / \text{mean,finisher}) + \text{curr,finisher}(i)
\]

Based on the score of finisher rank, the top five finishers in IPL are showed in Table 4 which clearly shows that Dhoni should be used as a finisher rather than an opener or middle-order batsman.

Having obtained the score for each player in these three categories, we assign one or more labels (O (Opener), M (Middle Order), F (Finisher)) to the players. The category

<table>
<thead>
<tr>
<th>Batsman</th>
<th>Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS Dhoni</td>
<td>364.3758</td>
</tr>
<tr>
<td>DJ Bravo</td>
<td>248.9014</td>
</tr>
<tr>
<td>AB de Villiers</td>
<td>223.4076</td>
</tr>
<tr>
<td>YK Pathan</td>
<td>215.7580</td>
</tr>
<tr>
<td>KD Karthik</td>
<td>214.2518</td>
</tr>
</tbody>
</table>

in which the player has the maximum score is naturally assigned as a label for that player. However, if a player has a higher (or equal) rank in some other category, then that category is also assigned to that player. Such players can be used interchangeably among those categories. For example, Dhoni is assigned only as a finisher since both his rank and his score is higher as a finisher than the other two categories. However, de Villiers has a higher score as a finisher, but a better rank as a middle order or opening batsman. So he can be used interchangeably among these three categories. Simil- larly, Karthik can be used both as a middle order batsman or as a finisher.

### IV. ANALYZING THE FEATURES FOR BOWLERS

Similar to batsmen, we have considered a set of parameters for bowlers and have quantified them. The features which have been considered are as follows -

- **Wicket Per Ball:** It is defined as the number of wickets taken per ball.

\[
\text{wicket per ball} = \left( \# \text{ wickets taken} \right) / \left( \# \text{ balls} \right)
\]

- **Average:** It denotes the number of runs conceded per wicket taken.

\[
\text{Ave} = \left( \# \text{ runs conceded} \right) / \left( \# \text{ wickets taken} \right)
\]

- **Economy rate:** Economy rate for a bowler is defined as the number of runs conceded per over bowled.

\[
\text{Eco} = \left( \# \text{ runs conceded} \right) / \left( \# \text{ overs bowled} \right) - \left( \# \text{ runs conceded * 6} \right) / \left( \# \text{ balls} \right)
\]

We have not clustered the bowlers into groups. Instead we have considered two parameters for a good bowler into the same heuristic. A bowler who can take 4 or 5 wickets should be included in the team. However, it is better to take a bowler who can take 1 or 2 wickets per match rather than a bowler who takes 4 or 5 wickets once in a while. Strike rate and consistency has been together quantified for the i-th bowler as

\[
\text{bowler(i)} = \left( 4 \times \text{four}(i) + 5 \times \text{five}(i) + \text{wicket(i)} \right) / \text{ball(i)}
\]

where four(i) and five(i) denote the number of matches where the bowler took 4 and 5 wickets respectively, whereas wicket(i) denote the total number of wickets taken in matches where the bowler did not take 4 or 5 wickets. Taking the other features into consideration, we divide a total weight of 100 as follows -

\[
\text{bowler val(i)} = \text{wicket per ball(i)} \times 35 + \text{bowler(i)} \times 35 + (1 / \text{Ave(i)}) \times 40 + (1 / \text{Eco(i)}) \times 40
\]

The current form of a bowler (curr bowler val) is calculated similarly considering only the last season’s values. The total point of a bowler, considering both current and overall form, is denoted as

\[
\text{final_bowler(i)} = \text{bowler val(i)} \times \left( \text{curr,bowler val(i)} / \text{mean,bowler} \right) \times \text{cost, fact} + \text{curr,bowler val(i)}
\]

Based on this ranking scheme, we show the top 5 bowlers in Table 5.

<table>
<thead>
<tr>
<th>Bowler</th>
<th>Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Tye</td>
<td>335.3772</td>
</tr>
<tr>
<td>A. Mishra</td>
<td>296.390</td>
</tr>
<tr>
<td>S. Narine</td>
<td>254.321</td>
</tr>
<tr>
<td>P. Chawala</td>
<td>223.7809</td>
</tr>
<tr>
<td>R. Jadeja</td>
<td>223.283</td>
</tr>
</tbody>
</table>

In the next section we provide the algorithms for selecting a team of 15 players, where the budget is fixed.

### V. GREEDY ALGORITHM FOR TEAM SELECTION

In this section, we propose two greedy algorithms for team selection. Each team, containing n players, is partitioned into the following buckets: B = {Opener, Middle-order, Finisher, Bowler}, where each bucket B[i] is a set of k_i players such that

\[
k_i = n
\]

\[
i \in B
\]

Each team is allotted a value, which emulates the total budget for a team. The number of players k_i in each bucket B[i] is decided by the user, and the unit for each bucket is unit(B_i) = (value * k_i) / 4.

#### 5.1 Assigning credit points to players

Players in each cluster are further assigned credit points based on their ranking. This helps us to emulate the base price of a player. If a cluster contains c_a players, and it is partitioned into c_p credit point groups, then each group contains c_a / c_p players. The first c_p players are assigned a to the highest credit point group.
In our first algorithm, we consider wicket-keepers as a separate bucket. Therefore, for our first algorithm, Equation 1 is modified as $\sum_{i=1}^{k_i} + w = n$, where $w$ is the number of wicketkeepers. In Algorithm 1, we show our first algorithm for team selection.

**Algorithm 1 Greedy Algorithm 1 for team selection**

**Input:** The pool of players clustered into one or more of the buckets opener, middle-order, finisheder, Bowler) do
1: unit $\leftarrow$ value/5
2: for all $b \in \{\text{Wicketkeeper, Opener, Middle-order, Finisher, Bowler}\}$ do
3: $c_p \leftarrow$ unit $\times k_b$
4: $m_{b} \leftarrow$ minimum credit point of a player in bucket $b$
5: $r$ $\leftarrow$ $c_p$
6: for pos in 1 to $k_b$ do
7: if rem < $m_{b}$ then
8: while True do
9: $j \leftarrow$ pos
10: while rem < $m_{b}$ do
11: $j \leftarrow j - 1$
12: if (credit at $j$) - 1 $\geq m_{b}$ then
13: credit at $j$ $\leftarrow$ (credit at $j$) - 1
14: rem $\leftarrow$ rem - 1
15: end if
16: if rem $\geq m_{b}$ then
17: break
18: end if
19: while rem $\geq m_{b}$ then
20: break
21: end if
22: end while
23: end if
24: end if
25: Assign the highest credit $\leq$ rem in pos
26: rem $\leftarrow$ rem - assigned credit
27: end for
28: end for

**Output:** An optimal team of $n$ players.

5.2 First greedy algorithm
In our first algorithm, we consider wicket-keepers as a separate bucket. Therefore, for our first algorithm, Equation 1 is modified as $\sum_{i=1}^{k_i} + w = n$, where $w$ is the number of wicketkeepers. In Algorithm 1, we show our first algorithm for team selection.

**Table 6. A team of 15 players, with a total credit point of 135, selected using Algorithm 1**

<table>
<thead>
<tr>
<th>Position</th>
<th>Player</th>
<th>Credit Point</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wicketkeeper</td>
<td>M.S. Dhoni</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>S. Samson</td>
<td>8</td>
</tr>
<tr>
<td>Opener</td>
<td>D. Warner</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>K.L. Rahul</td>
<td>8</td>
</tr>
<tr>
<td>Middle-order</td>
<td>V. Kohli</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>A.B. de Villiers</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>F. du Plessis</td>
<td>7</td>
</tr>
<tr>
<td>Finisher</td>
<td>D. Bravo</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>R. Pant</td>
<td>8</td>
</tr>
<tr>
<td>Bowlers</td>
<td>A. Tye</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>A. Mishra</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>T. Boul</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>S. Al Hassan</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>K. Jadav</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>M. Johnson</td>
<td>7</td>
</tr>
</tbody>
</table>

The next $c_p$ players to the second highest credit point group and so on. Finally each group is assigned a credit point that decreases as we go down the groups. This step is necessary because the fixed budget of each team has been emulated as a fixed value for each team. The total credit of the team should not exceed the fixed value.

In the example of the following subsection, we have con-sidered four credit groups with valuation 10, 9, 8 and 7. However, the number of groups, as well as the valuation can be varied according to the team selection criteria.

**5.2 First greedy algorithm**
In our first algorithm, we consider wicket-keepers as a separate bucket. Therefore, for our first algorithm, Equation 1 is modified as $\sum_{i=1}^{k_i} + w = n$, where $w$ is the number of wicketkeepers. In Algorithm 1, we show our first algorithm for team selection.

**5.3 Second Greedy Algorithm**
In the team selected (Table 6) using Algorithm 1, both the wicketkeepers are finishers. Therefore, the selected team ends up with four finishers. To avoid this scenario, the sec-ond greedy algorithm, which is similar to Algorithm 1, keeps an extra restriction that the two wicketkeepers should not be-long to the same bucket. By keeping this restriction, the team is exactly similar to that in Table 6, except that instead of S. Samson, we select...
**Innovative Ranking Strategy For IPL Team Formation**

P. Patel as the second wicketkeeper, who is an opener.

This second algorithm can be easily further modified to ensure the cluster of the wicketkeeper. For example, one can impose a restriction such as one of the wicketkeepers must be an opener. Our proposed algorithm is flexible to handle such restrictions. Moreover, using this algorithm along with the the aforementioned ranking, a franchise can easily determine the best alternate player for a position if one of their target player is not available. For example, both Warner and Gayle have credit point 10, but the rank (and point) of Warner is higher than that of Gayle. Therefore, if Warner is already selected by some other team, then he can be replaced with Gayle. If no player of credit 10 is available, then that position can be filled with players of credit 9, and so on.

**VI. CONCLUSION**

In this paper, we have shown a heuristic method for IPL team selection. For each player, we have considered some traditional and derived features, and have quantified them. We have clustered the players into one or more of the clusters - Opener, Middle-order, Finisher and Bowler according to the score achieved from those features. We have also taken into consideration both the current from and the experience of a player for such ranking. The ranking obtained by our heuristic scheme is in acceptance with the known player rankings in IPL. Finally we have proposed two greedy algorithms to select the best possible team from this ranking when the total credit point and the number of players in each bucket is fixed.

The future scope of this paper is to incorporate two higher level clusters of batting and bowling allrounders. The selection of the team can also include some more flexible buckets where allrounders are given higher preference than batsman and bowlers. A trade-off between inclusion of an allrounder in the team or a batsman or bowler with higher credit point can be studied. Furthermore, the greedy algorithm for team selection has a shortcoming that it may select some high ranking players with some very low ranking ones. A dynamic programming approach may be studied to ensure more or less equal quality players in the team.

**REFERENCES**
