GOVERNMENT ENGINEERING COLLEGE THRISSUR

2019

CS451 - B.TECH SEMINAR REPORT

ON

Team Composition in PES2018 Using Submodular Function Optimization

Presented by

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DEPARTMENT OF CSE

ABSTRACT

With the development of computer game technologies,we know that gameplay becomes very realistic in many sports games, therefore providing appealing play experience to game players. To get the victory in a football pitch, team composition is one of the most important thing needed. There is little research on the automatic team composition in sports games particularly in a popular game of Pro Evolution Soccer (PES). So we consider the team composition as one team player recommendation problem.We also know that a paticular team is composed of several players in a game. Subsequently, we aim to recommend a list of sufficiently good football players to game players.

We will convert the team player recommendation into one optimization problem and produce greedy algorithm-based solutions. We deal with a coverage function that quantifies the degree of soccer skills to be covered by each selected players.Also we improve the greedy algorithm to solve the function optimization problem.

ACKNOWLEDGEMENT

It gives me great pleasure to present my seminar report on "Team Composition in PES2018 Using Submodular Function Optimization".No work, however big or small,has ever been done without the contribution of others.So these words of acknowledgement come as a small gesture of gratitude towards all those people, without whom the successful completion of this report would not have been possible.
I would like to express my gratitude towards seminar coordinators Prof. Helen K J,Associate Professor and Prof. George Mathew, Assistant Professor, Department of Computer Science and Engineering who gave me their valuable suggestions, reviews, motivation and direction.
I would also like to thank all lab staff for providing with the necessary facilities for the presentation, it would have been impossible to complete seminar without their prompt cooperation. Last but not the least I would like to thank all my friends, who supported me with their valuable criticism, advice and support.

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PES Pro Evolution Soccer
PS4 Play Station 4
CEFG Cost Effective Forward selection Greedy
MAB Man Blue
MSB Mercyside Blue
HER HampshirE Red

1 Introduction

1.1 Pro Evolution Soccer

In this modern world, many sport games have appeared and attracted more and more players in game markets. Pro Evo- lution Soccer 2018 (PES2018) is one of the popular football game produced and released by Konami.It can be played on a personal computer, PS4 or XBOX and in Mobiles. This game can be controlled by human or computer players, and can fully simulate a football match. It gives the human player an opportunity to compose a team of avatars each of which sim- ulates a real-world football player, e.g. Lionel Messi, Cristiano Ronaldo,Eden Hazard etc., in a competitive game. So as usual the selection of team members becomes more interesting and important in PES..

We all see football and it is the worlds game,it gets reflected in a game like PES.The team composition depends on preferences and knowledge of a human-player who, however, still expects inputs from the gaming system.We,the human players,will be satisfied if we get a team that we are dreaming of ad gets the favorite players to our team. This is well aligned with entertainment spirit in the content recommendation in computer games.Hence a team recommender becomes an important feature in a sport game not just limited in PES

In PES, every football player is specified by a set of attributes

- Attacking Prowess
- Ball Control
- Speed
- Jump etc...

Each attribute is associated with a specific value all of which decide the player performance in a match. The strength of a team is mainly influenced by the performance of individual players. The team is more likely to win a match if more skillful players are selected into the team. However, as each player has a specific position and a limited number of positions (a football match needs 11 players) exist in a pitch, the team composition is not straightforward given the known ratings of the players that indicate their performance. Things become more complicated since a human-player is often given a limited budget for purchasing a team of players each of which costs a certain value corresponding to his skills. It is very much difficult ,if we even compare with the various fantasy leagues for various sports.A fixed cost will be given earlier and we need to get our ideal an optimized team within that cost limit.It have to be done all manually and need to observe all the games to select a team for the next gameweek and its all based on humans knowledge about various players,their playing styles and positions.As an example,we can take the fantasy leagues to know more about the team composition.

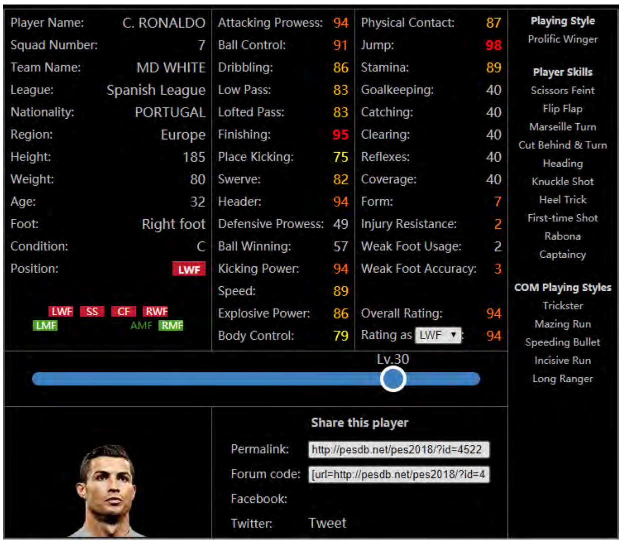

Figure 1: Player attributes in PES2018

1.2 Submodular Function

A function is submodular if it complies the following property: when you add a set to a solution "A" the improvement is worst than adding the same set to a subset of "A". Submodularity is a discrete version of concavity.

An example is the set cover problem. You have a set of sets and you have to find the minimum combination of those sets to cover some universe of elements.

For example let the universe be: U=1,2,3,4,5,6,7,8 and our sets: S1 = 1,2,3 S2= 1,4,5,6 S3= 4,5,7 S4 = 2,4,6,8 S5 =6,8 S6 =1,3,5,7

The solution is of course S4 S6.

So in more mathematical way,For a set of objects V = v 1 , . . . , v n and a function f : 2 V R, if for each A B V and e V B, it holds that M (e p A) greater than equal to M (e p B), then the function f is submodular, where

(e1 A)=f(A U e)-f(A)

One important property of submodularity is diminishing marginal returns, i.e., adding an element to a small set is more influential than adding it to a large set.

2 Related Work

Research of team composition is most important and relevant to team recommendation where a list of teams are recommended. More often,team recommendation comes from organizational andbehavioral sciences and research on social web application thathas appeared for a team recommendation since 2012.

	ID	1	2	3	4	...
	player_name	C.RONALDO	L.MESSI	L.SUAREZ	M.NEUER	...
	position	LWF	RWF	CF	GK	...
	rating	94	94	92	91	...
ability	attacking_prowess	94	95	95	42	...
	ball_control	91	96	86	68	...
	dribbling	86	96	84	60	...
	low_pass	83	88	82	65	...
	lofted_pass	83	86	77	69	...
	finishing	95	95	95	43	...
	header	94	68	77	70	...
	defensive_prowess	49	43	58	60	...
	speed	89	86	78	71	...
	goalkeeping	40	40	40	98	...

Figure 2: Player attributes and possible values for the attributes

3 Player Recommendation As A Submodular Function Optimization

Here,we formulate the player recommendation into one optimization problem and prove the submodularity property of this function as well.

3.1 Function for skill coverage

Given the PES platform, we choose ten players attributes as the most important skills for the team composition,i.e. attacking prowess, ball control, dribbling, low pass,lofted pass, finishing, header, defensive prowess, speed, and goalkeeping. In addition, we consider the players number, name, position, salary and overall rating. Hence each player has 15 attributes.
For each player pi,we use s to represent the players ability such as attacking prowess, ball control, and speed.

$$cov_{s_j}(p_i) = a_{s_j}(p_i)/(\sum_{p_k \in U} a_{s_j}(p_k))$$

Subsequently, we can define the skill coverage function for a set of team players, T , that is a subset of all potential players. We measures the degree to which the ability sj is covered by at least one player in T .

$$cov_{s_j}(T) = 1 - \prod_{p_i \in T} (1 - cov_{s_j}(p_i))$$

$$F(T) = \sum_{s_j \in S} \beta cov_{s_j}(T)$$

Figure 3: Function of T covering S defined as F(T

3.2 Recommender model

We aim to find an optimal team that maximizes the coverage value,also we need to consider the cost of composing the team of players for optimization. So this can also be seen as solving the below optimization problem.

maxF(T) subject to mod T = 11 and c(T) less that or equal to C

where c(T) is the sum of the salary of the total eleven players in T and C is the salary constraint for the entire team.

Proposition 1: The monotone function $F(T)$ (in Eq. 4) is submodular.

proof: We calculate the marginal gain of the skill coverage when one player is added into a potential team $\hat{T} \subseteq U$.

$$cov(\hat{T} \cup p_j) - cov(\hat{T})(1 - \prod_{p_i \in \hat{T}} (1 - cov(p_i)) * (1 - cov(p_j)))$$
$$-(1 - \prod_{p_i \in \hat{T}} (1 - cov(p_i)))$$
$$= cov(p_j) * \prod_{p_i \in \hat{T}} (1 - cov(p_i))$$

Similarly, for a small team $\check{T}$, we have

$$cov(\check{T} \cup p_j) - cov(\check{T}) = cov(p_j) * \prod_{p_i \in \check{T}} (1 - cov(p_i)),$$

where $\check{T} \subseteq \hat{T} \subseteq U$. Moreover, since $1 - cov(p_i) < 1, cov(\hat{T} \cup p_j) - cov(\hat{T}) \leq cov(\check{T} \cup p_j) - cov(\check{T})$, we have $cov(T)$ is submodular.

Figure 4: Proof for submodular

4 Algorithms For Optimization

Here we will be making use of Greedy Algorithms to solve the recommendation problem that is formulated as one submodular function optimization problem

and improve the algorithm to solve the problem.

4.1 Generalized greedy algorithm

The algorithm iteratively selects a player p such that the ratio of the marginal gain for objective function F and con- straint c is maximized by adding p. The best subset T found is eventually returned.

Input: an objective function F, a cost constraint C, and player database U

Output: a solution $T \subseteq U$ with $c(T) \leq C$

$T \longleftarrow \emptyset$;
repeat
  $p \longleftarrow argmax_{p \in U} \frac{F(T \cup p) - F(T)}{c(T \cup p) - c(T)}$
  if $c(T \cup p) \leq C$ **then** $T = T \cup p$
  end if
  $U = U \setminus p$
until $U = 0$
return T

Figure 5: Generalized Greedy Algorithm

4.2 Limit greedy algorithm

Input: a submodular objective function F, a cost constraint C, and player database U

Output: a solution $T \subseteq U$ with $c(T) \leq C$ and $|T| = 11$

$T \longleftarrow \emptyset$;
repeat
  $p \longleftarrow argmax_{p \in U} \frac{F(T \cup p) - F(T)}{c(p)}$
  if $c(T \cup p) \leq C$ **then** $T = T \cup p$
  end if
  $U = U \setminus p$
until $|T| = 11$
return T

Figure 6: Limit Greedy Algorithm

As in our recommendation problem there are eleven play- ers in a football team, the length of T needs to be limited. In addition, c(T U p) c(T) = c(p)

as the constraint is linear and discrete. Hence we adapt the generalized greedy algorithm into Limit Greedy Algorithm.

In each iteration, we will select the player p from a set of players U with the largest ratio of the increase of the objective function to the wage cost under the cost constraint C, until the team length is equal to eleven.

4.3 Cost effective forward selection algorithm

Here,we are given by the submodular coverage function F, a set of players U and a salary cost constraint C.We first use the unit cost greedy algorithm to select the player p with the maximum increment of the objective function, which means the best player is added to the team T . Hence, we can make the most of the cost space and choose the player who is outstanding enough in the initial selection stage. We will not select a player twice in each iteration. Then we enter the second selection stage and use the greedy algorithm for the consideration of the remaining cost. By doing this, we have a team of players that meets the cost constraint and contains sufficiently good play- ers, which generates better results than the generalized greedy algorithm

Input: a submodular objective function F, a cost constraint C, and player database U
Output: a solution $T \subseteq U$ with $c(T) \leq C$ and $|T| = 11$

$T \longleftarrow \emptyset$;
repeat
  $p \longleftarrow argmax_{p \in U} F(T \cup p) - F(T)$
  if $c(T \cup p) \leq C$ **then** $T = T \cup p$
  end if
  $U = U \setminus p$
  if $C - c(T \cup p) < \varepsilon$ **then**
    repeat
      $p \longleftarrow argmax_{p \in U} \frac{F(T \cup p) - F(T)}{c(p)}$
      if $c(T \cup p) \leq C$ **then** $T = T \cup p$
      end if
      $U = U \setminus p$
    until $|T| = 11$
  end if
until $|T| = 11$
return T

Figure 7: CEFG Algorithm

5 Experiments And Real Game Results

The algorithms are implemented in Matlab2018 and conduct all the numerical computations on a Windows PC.All the games are simulated in a quick game of PES2018 that is downloaded from a platform Steam on Windows10 computer system.

5.1 Analysis of data

For the position of each player on the football pitch, we consider equivalence of positions and normalize the posi- tion as shown in figure given below.

Position	Specific position	Number
Goalkeeper	GK	1
	CB	2
Guard	LB	3
	RB	4
	DMF	5
	CMF	5
Midfielder	RMF	5
	LMF	5
	AMF	5
	LWF	6
Forward	RWF	7
	CF	8
	SS	8

Figure 8: Positions of players and their equivalent numbers

Based on the PES game experience, we choose the team of 4-3-3 formations which means there are one Goalkeeper, four Guard, three Midfielder and three Forward in the team.
For the cost constraint, there is no players salary data in the official website. Considering that the players salary is often positively correlated with his rating, we fit the wages with scores of some players based on the existing data. We find that the data is exponentially distributed and therefore use the least squares method for regression. The fitting curve formulated below is shown in Fig. 9

$$y(i) = \eta \cdot e^{\theta x(i)}$$

where n = 6.375 10 4 , and theta = 0.1029. Then through the curve, we can find the y-axis of the corresponding point based on the x-axis, which means we can get a players salary based on his ratings.

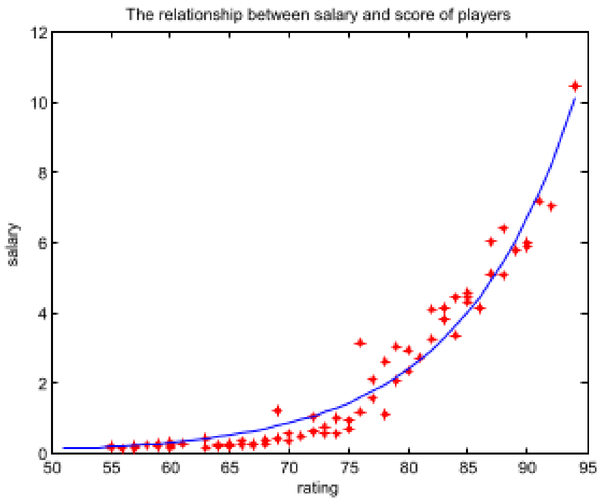

Figure 9: Cost of players as a function of their ratings

5.2 Experimental Results

We select a total of 8,762 players,for ensuring the credibility of results ,with the ratings larger than or equal to 60 in the database, and recommend a team including 11 players. We use the CEFG Algorithm to solve the optimization prob- lem and set a sufficiently large cost as retrieved from the curve in Fig. 9 Based on the recommended players, we compose a Dream Team. To conduct comparison of the algorithm per- formance, we randomly generate a team in the PES without any cost constraint and then simulate the battle between the two teams (including the players) as shown in Fig. 10. AMIENS represents the Dream Team and DIJON represents the random team. The final result from all the five matches is 4:1 and the dream team dominates most of the competitions.

For verifying the accuracy and strength of the CEFG algorithm, we select

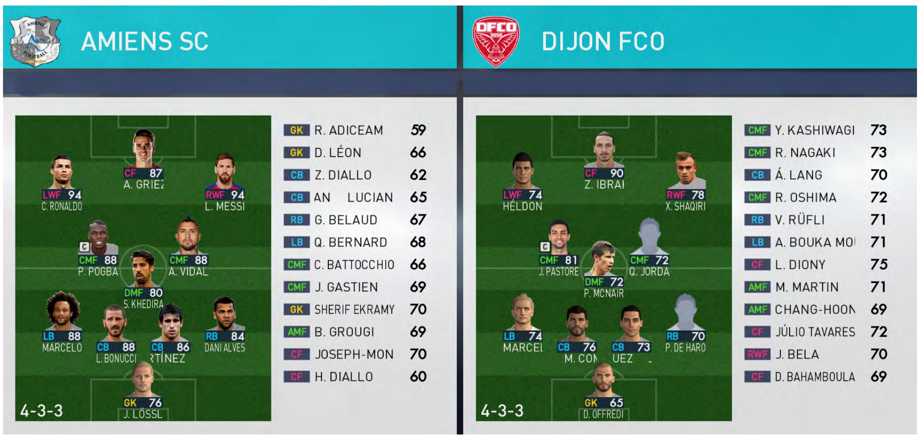

Figure 10: Dream team vs Random team

MAB, MSB and HER teams in the game all of which exist in the real game-play. We calculate the costs of the three teams, and use them as constraint to

recommend a team of players based on the CEFG algorithm. We then match the recommended team with the existing three teams and gives the results in the fig.11 and fig.12.

Battle	Score										Win Number	Goal Difference	Cost Constraint	Actual Cost Comparison
AMIENS4 VS MAB	3:1 0:0 0:2	1:4 1:0 1:0	0:0 2:0 4:1	2:2 1:1 2:0	1:3 2:4 0:0	3:0 0:0 1:1	3:1 4:2 0:2	1:0 2:2 2:0	2:1 2:0 2:2	0:0 0:1 3:1	19	0.47	36.95	35.21 : 36.95
AMIENS5 VS MSB	0:0 2:0 1:0	2:2 2:2 2:0	0:1 0:1 0:0	3:1 0:1 3:1	0:0 1:1 0:0	4:0 1:0 0:1	2:2 0:0 0:2	1:3 4:2 2:2	2:2 2:0 1:0	1:0 0:0 1:1	17.5	0.4	26.38	23.00 : 26.38
AMIENS6 VS HER	2:4 0:1 0:3	1:0 2:0 1:0	1:4 4:2 0:0	3:1 0:2 1:1	0:0 1:1 1:0	1:0 4:0 2:0	3:0 0:2 0:0	2:3 3:0 3:0	0:0 0:0 1:3	0:0 1:1 1:1	17	0.3	15.70	13.18 : 15.70

Figure 11: Match results of CEFG vs actual teams

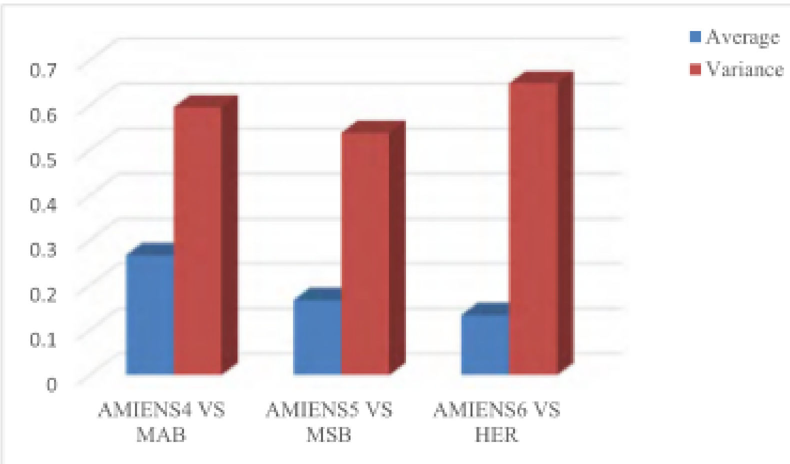

Figure 12: Normalized results of the CEFG v.s. the actual teams

We can find that under the same cost constraint (or in a sense of rating), the teams recommended by CEFG algorithm are stronger than actual teams. The teams generated by the CEFG algorithm dominate the play in the football pitch.

6 Conclusion

We make an in-depth analysis of team composition in PES that can be converted into a player recommenda- tion problem. As there is no clear approach for football player recommendation in a game, we propose a skill coverage function to quantify the complementary capability of a proper team. We then improve the greedy algorithm to solve the recommendation problem. We conduct empirical study of the proposed recommendation techniques in a game platform of PES2018. The results demonstrate the strength of the team as well as the effectiveness of our approach. Although we investigate our techniques in the context of PES, the proposed recommendation model based on the submodular function is rather general and can be adapted to solve other team compo- sition problems. We notice that the player recommendation technique can also be used to improve a game engine by suggesting a good team to computer-controlled characters in a sport game. Improving the CEFG algorithm is a great challenge. We will seek for a better bound so as to improve the player recommendation quality.

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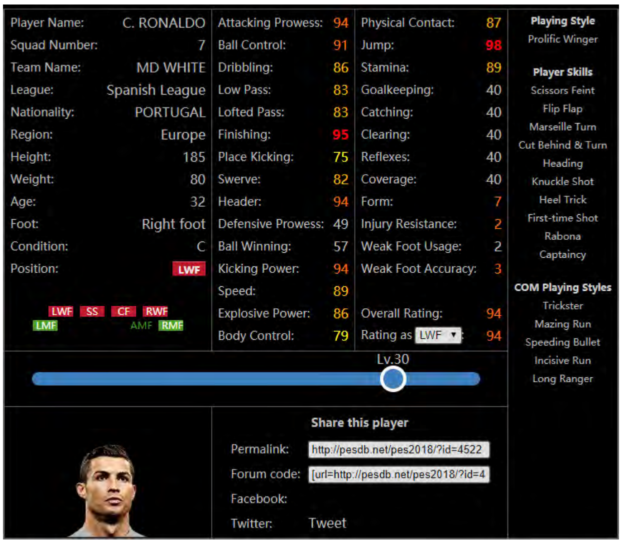

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Similarly, for a small team $\check{T}$, we have

$$cov(\check{T} \cup p_j) - cov(\check{T}) = cov(p_j) * \prod_{p_i \in \check{T}} (1 - cov(p_i)),$$

where $\check{T} \subseteq \hat{T} \subseteq U$. Moreover, since $1 - cov(p_i) < 1$, $cov(\hat{T} \cup p_j) - cov(\hat{T}) \leq cov(\check{T} \cup p_j) - cov(\check{T})$, we have $cov(T)$ is submodular.

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Figure 5: Generalized Greedy Algorithm

4.2 Limit greedy algorithm

Input: a submodular objective function F, a cost constraint C, and player database U
Output: a solution $T \subseteq U$ with $c(T) \leq C$ and $|T| = 11$

$T \longleftarrow \emptyset$;
repeat
  $p \longleftarrow argmax_{p \in U} \frac{F(T \cup p) - F(T)}{c(p)}$
  if $c(T \cup p) \leq C$ **then** $T = T \cup p$
  end if
  $U = U \setminus p$
until $|T| = 11$
return T

Figure 6: Limit Greedy Algorithm

As in our recommendation problem there are eleven play- ers in a football team, the length of T needs to be limited. In addition, c(T U p) c(T) = c(p)

as the constraint is linear and discrete. Hence we adapt the generalized greedy algorithm into Limit Greedy Algorithm.

In each iteration, we will select the player p from a set of players U with the largest ratio of the increase of the objective function to the wage cost under the cost constraint C, until the team length is equal to eleven.

4.3 Cost effective forward selection algorithm

Here,we are given by the submodular coverage function F, a set of players U and a salary cost constraint C.We first use the unit cost greedy algorithm to select the player p with the maximum increment of the objective function, which means the best player is added to the team T . Hence, we can make the most of the cost space and choose the player who is outstanding enough in the initial selection stage. We will not select a player twice in each iteration. Then we enter the second selection stage and use the greedy algorithm for the consideration of the remaining cost. By doing this, we have a team of players that meets the cost constraint and contains sufficiently good play- ers, which generates better results than the generalized greedy algorithm

Input: a submodular objective function F, a cost constraint C, and player database U

Output: a solution $T \subseteq U$ with $c(T) \leq C$ and $|T| = 11$

$T \longleftarrow \emptyset$;
repeat
    $p \longleftarrow argmax_{p \in U} F(T \cup p) - F(T)$
    if $c(T \cup p) \leq C$ **then** $T = T \cup p$
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    if $C - c(T \cup p) < \varepsilon$ **then**
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Figure 7: CEFG Algorithm

5 Experiments And Real Game Results

The algorithms are implemented in Matlab2018 and conduct all the numerical computations on a Windows PC.All the games are simulated in a quick game of PES2018 that is downloaded from a platform Steam on Windows10 computer system.

5.1 Analysis of data

For the position of each player on the football pitch, we consider equivalence of positions and normalize the posi- tion as shown in figure given below.

Position	Specific position	Number
Goalkeeper	GK	1
	CB	2
Guard	LB	3
	RB	4
	DMF	5
	CMF	5
Midfielder	RMF	5
	LMF	5
	AMF	5
	LWF	6
Forward	RWF	7
	CF	8
	SS	8

Figure 8: Positions of players and their equivalent numbers

Based on the PES game experience, we choose the team of 4-3-3 formations which means there are one Goalkeeper, four Guard, three Midfielder and three Forward in the team.
For the cost constraint, there is no players salary data in the official website. Considering that the players salary is often positively correlated with his rating, we fit the wages with scores of some players based on the existing data. We find that the data is exponentially distributed and therefore use the least squares method for regression. The fitting curve formulated below is shown in Fig. 9

$$y(i) = \eta \cdot e^{\theta x(i)}$$

where n = 6.375 10 4 , and theta = 0.1029. Then through the curve, we can find the y-axis of the corresponding point based on the x-axis, which means we can get a players salary based on his ratings.

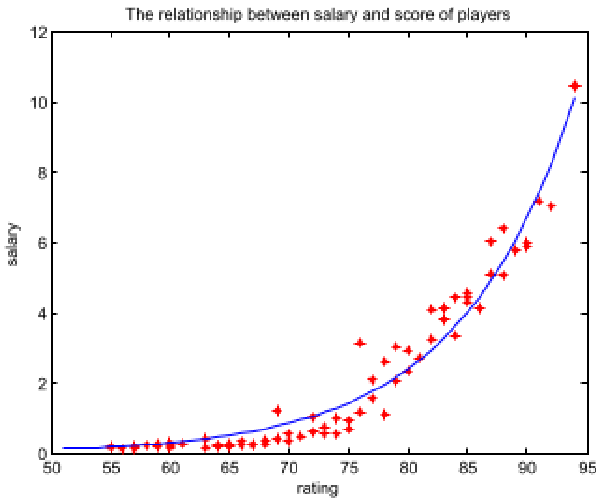

Figure 9: Cost of players as a function of their ratings

5.2 Experimental Results

We select a total of 8,762 players,for ensuring the credibility of results ,with the ratings larger than or equal to 60 in the database, and recommend a team including 11 players. We use the CEFG Algorithm to solve the optimization prob- lem and set a sufficiently large cost as retrieved from the curve in Fig. 9 Based on the recommended players, we compose a Dream Team. To conduct comparison of the algorithm per- formance, we randomly generate a team in the PES without any cost constraint and then simulate the battle between the two teams (including the players) as shown in Fig. 10. AMIENS represents the Dream Team and DIJON represents the random team. The final result from all the five matches is 4:1 and the dream team dominates most of the competitions.

For verifying the accuracy and strength of the CEFG algorithm, we select

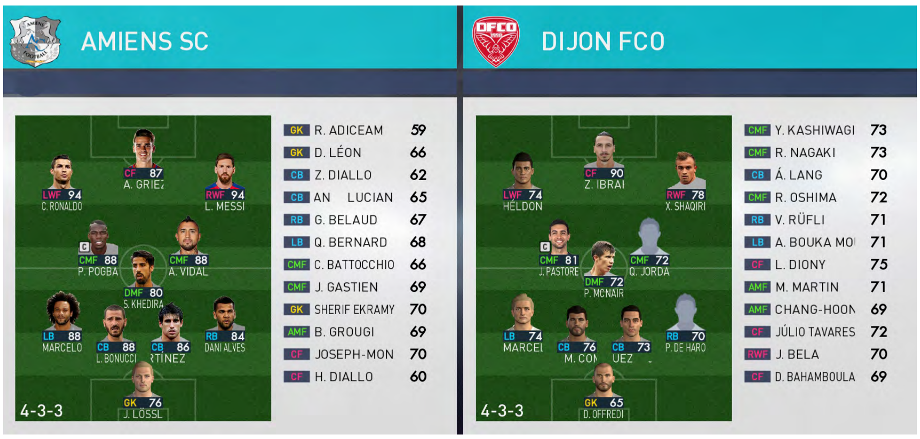

Figure 10: Dream team vs Random team

MAB, MSB and HER teams in the game all of which exist in the real game-play. We calculate the costs of the three teams, and use them as constraint to

recommend a team of players based on the CEFG algorithm. We then match the recommended team with the existing three teams and gives the results in the fig.11 and fig.12.

Battle	Score										Win Number	Goal Difference	Cost Constraint	Actual Cost Comparison
AMIENS4 VS MAB	3:1 0:0 0:2	1:4 1:0 1:0	0:0 2:0 4:1	2:2 1:1 2:0	1:3 2:4 0:0	3:0 0:0 1:1	3:1 4:2 0:2	1:0 2:2 2:0	2:1 2:0 2:2	0:0 0:1 3:1	19	0.47	36.95	35.21 : 36.95
AMIENS5 VS MSB	0:0 2:0 1:0	2:2 2:2 2:0	0:1 0:1 0:0	3:1 0:1 3:1	0:0 1:1 0:0	4:0 1:0 0:1	2:2 0:0 0:2	1:3 4:2 2:2	2:2 2:0 1:0	1:0 0:0 1:1	17.5	0.4	26.38	23.00 : 26.38
AMIENS6 VS HER	2:4 0:1 0:3	1:0 2:0 1:0	1:4 4:2 0:0	3:1 0:2 1:1	0:0 1:1 1:0	1:0 4:0 2:0	3:0 0:2 0:0	2:3 3:0 3:0	0:0 0:0 1:3	0:0 1:1 1:1	17	0.3	15.70	13.18 : 15.70

Figure 11: Match results of CEFG vs actual teams

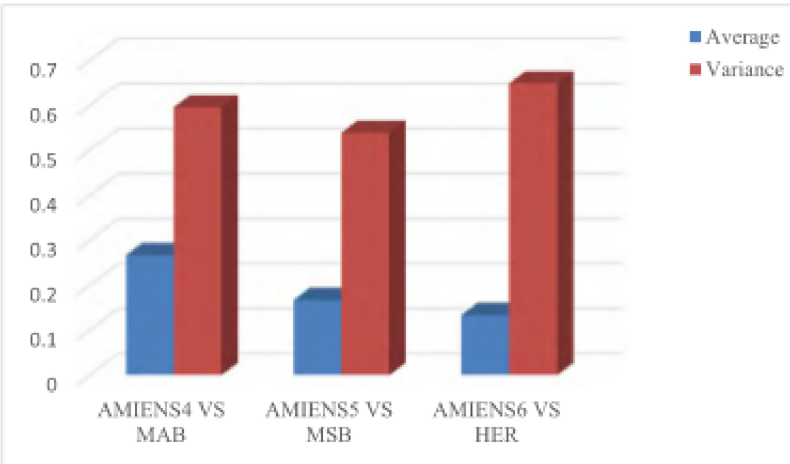

Figure 12: Normalized results of the CEFG v.s. the actual teams

We can find that under the same cost constraint (or in a sense of rating), the teams recommended by CEFG algorithm are stronger than actual teams. The teams generated by the CEFG algorithm dominate the play in the football pitch.

6 Conclusion

We make an in-depth analysis of team composition in PES that can be converted into a player recommenda- tion problem. As there is no clear approach for football player recommendation in a game, we propose a skill coverage function to quantify the complementary capability of a proper team. We then improve the greedy algorithm to solve the recommendation problem. We conduct empirical study of the proposed recommendation techniques in a game platform of PES2018. The results demonstrate the strength of the team as well as the effectiveness of our approach. Although we investigate our techniques in the context of PES, the proposed recommendation model based on the submodular function is rather general and can be adapted to solve other team compo- sition problems. We notice that the player recommendation technique can also be used to improve a game engine by suggesting a good team to computer-controlled characters in a sport game. Improving the CEFG algorithm is a great challenge. We will seek for a better bound so as to improve the player recommendation quality.

GOVERNMENT ENGINEERING COLLEGE THRISSUR

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CS451 - B.TECH SEMINAR REPORT

ON

Team Composition in PES2018 Using Submodular Function Optimization

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ABSTRACT

With the development of computer game technologies,we know that gameplay becomes very realistic in many sports games, therefore providing appealing play experience to game players. To get the victory in a football pitch, team composition is one of the most important thing needed. There is little research on the automatic team composition in sports games particularly in a popular game of Pro Evolution Soccer (PES). So we consider the team composition as one team player recommendation problem.We also know that a paticular team is composed of several players in a game. Subsequently, we aim to recommend a list of sufficiently good football players to game players.

We will convert the team player recommendation into one optimization problem and produce greedy algorithm-based solutions. We deal with a coverage function that quantifies the degree of soccer skills to be covered by each selected players.Also we improve the greedy algorithm to solve the function optimization problem.

ACKNOWLEDGEMENT

It gives me great pleasure to present my seminar report on ”Team Composition in PES2018 Using Submodular Function Optimization”.No work, however big or small,has ever been done without the contribution of others.So these words of acknowledgement come as a small gesture of gratitude towards all those people, without whom the successful completion of this report would not have been possible.

I would like to express my gratitude towards seminar coordinators Prof. Helen K J,Associate Professor and Prof. George Mathew, Assistant Professor, Department of Computer Science and Engineering who gave me their valuable suggestions, reviews, motivation and direction.

I would also like to thank all lab staff for providing with the necessary facilities for the presentation, it would have been impossible to complete seminar without their prompt cooperation. Last but not the least I would like to thank all my friends, who supported me with their valuable criticism, advice and support.

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List of Abbreviations

PES Pro Evolution Soccer
PS4 Play Station 4
CEFG Cost Effective Forward selection Greedy
MAB Man Blue
MSB Mercyside Blue
HER HampshirE Red

1 Introduction

1.1 Pro Evolution Soccer

In this modern world, many sport games have appeared and attracted more and more players in game markets. Pro Evo- lution Soccer 2018 (PES2018) is one of the popular football game produced and released by Konami.It can be played on a personal computer, PS4 or XBOX and in Mobiles. This game can be controlled by human or computer players, and can fully simulate a football match. It gives the human player an opportunity to compose a team of avatars each of which sim- ulates a real-world football player, e.g. Lionel Messi, Cristiano Ronaldo,Eden Hazard etc., in a competitive game. So as usual the selection of team members becomes more interesting and important in PES..

We all see football and it is the worlds game,it gets reflected in a game like PES.The team composition depends on preferences and knowledge of a human-player who, however, still expects inputs from the gaming system.We,the human players,will be satisfied if we get a team that we are dreaming of ad gets the favorite players to our team. This is well aligned with entertainment spirit in the content recommendation in computer games.Hence a team recommender becomes an important feature in a sport game not just limited in PES

In PES, every football player is specified by a set of attributes

- Attacking Prowess
- Ball Control
- Speed
- Jump etc...

Each attribute is associated with a specific value all of which decide the player performance in a match. The strength of a team is mainly influenced by the performance of individual players. The team is more likely to win a match if more skillful players are selected into the team. However, as each player has a specific position and a limited number of positions (a football match needs 11 players) exist in a pitch, the team composition is not straightforward given the known ratings of the players that indicate their performance. Things become more complicated since a human-player is often given a limited budget for purchasing a team of players each of which costs a certain value corresponding to his skills. It is very much difficult ,if we even compare with the various fantasy leagues for various sports.A fixed cost will be given earlier and we need to get our ideal an optimized team within that cost limit.It have to be done all manually and need to observe all the games to select a team for the next gameweek and its all based on humans knowledge about various players,their playing styles and positions.As an example,we can take the fantasy leagues to know more about the team composition.

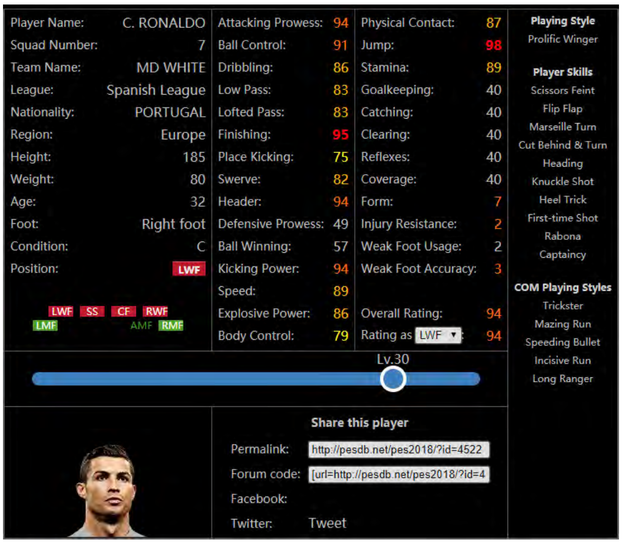

Figure 1: Player attributes in PES2018

1.2 Submodular Function

A function is submodular if it complies the following property: when you add a set to a solution "A" the improvement is worst than adding the same set to a subset of "A". Submodularity is a discrete version of concavity.

An example is the set cover problem. You have a set of sets and you have to find the minimum combination of those sets to cover some universe of elements.

For example let the universe be: U=1,2,3,4,5,6,7,8 and our sets: S1 = 1,2,3 S2= 1,4,5,6 S3= 4,5,7 S4 = 2,4,6,8 S5 =6,8 S6 =1,3,5,7

The solution is of course S4 S6.

So in more mathematical way,For a set of objects V = v 1 , . . . , v n and a function f : 2 V R, if for each A B V and e V B, it holds that M (e p A) greater than equal to M (e p B), then the function f is submodular, where

(e1 A)=f(A U e)-f(A)

One important property of submodularity is diminishing marginal returns, i.e., adding an element to a small set is more influential than adding it to a large set.

2 Related Work

Research of team composition is most important and relevant to team recommendation where a list of teams are recommended. More often,team recommendation comes from organizational andbehavioral sciences and research on social web application thathas appeared for a team recommendation since 2012.

	ID	1	2	3	4	...
	player_name	C.RONALDO	L.MESSI	L.SUAREZ	M.NEUER	...
	position	LWF	RWF	CF	GK	...
	rating	94	94	92	91	...
ability	attacking_prowess	94	95	95	42	...
	ball_control	91	96	86	68	...
	dribbling	86	96	84	60	...
	low_pass	83	88	82	65	...
	lofted_pass	83	86	77	69	...
	finishing	95	95	95	43	...
	header	94	68	77	70	...
	defensive_prowess	49	43	58	60	...
	speed	89	86	78	71	...
	goalkeeping	40	40	40	98	...

Figure 2: Player attributes and possible values for the attributes

3 Player Recommendation As A Submodular Function Optimization

Here,we formulate the player recommendation into one optimization problem and prove the submodularity property of this function as well.

3.1 Function for skill coverage

Given the PES platform, we choose ten players attributes as the most important skills for the team composition,i.e. attacking prowess, ball control, dribbling, low pass,lofted pass, finishing, header, defensive prowess, speed, and goalkeeping. In addition, we consider the players number, name, position, salary and overall rating. Hence each player has 15 attributes.
For each player pi,we use s to represent the players ability such as attacking prowess, ball control, and speed.

$$cov_{s_j}(p_i) = a_{s_j}(p_i)/(\sum_{p_k \in U} a_{s_j}(p_k))$$

Subsequently, we can define the skill coverage function for a set of team players, T , that is a subset of all potential players. We measures the degree to which the ability sj is covered by at least one player in T .

$$cov_{s_j}(T) = 1 - \prod_{p_i \in T} (1 - cov_{s_j}(p_i))$$

$$F(T) = \sum_{s_j \in S} \beta cov_{s_j}(T)$$

Figure 3: Function of T covering S defined as F(T

3.2 Recommender model

We aim to find an optimal team that maximizes the coverage value,also we need to consider the cost of composing the team of players for optimization. So this can also be seen as solving the below optimization problem.

maxF(T) subject to mod T = 11 and c(T) less that or equal to C

where c(T) is the sum of the salary of the total eleven players in T and C is the salary constraint for the entire team.

Proposition 1: The monotone function $F(T)$ (in Eq. 4) is submodular.

proof: We calculate the marginal gain of the skill coverage when one player is added into a potential team $\hat{T} \subseteq U$.

$$cov(\hat{T} \cup p_j) - cov(\hat{T})(1 - \prod_{p_i \in \hat{T}} (1 - cov(p_i)) * (1 - cov(p_j)))$$
$$-(1 - \prod_{p_i \in \hat{T}} (1 - cov(p_i)))$$
$$= cov(p_j) * \prod_{p_i \in \hat{T}} (1 - cov(p_i))$$

Similarly, for a small team $\check{T}$, we have

$$cov(\check{T} \cup p_j) - cov(\check{T}) = cov(p_j) * \prod_{p_i \in \check{T}} (1 - cov(p_i)),$$

where $\check{T} \subseteq \hat{T} \subseteq U$. Moreover, since $1 - cov(p_i) < 1, cov(\hat{T} \cup p_j) - cov(\hat{T}) \leq cov(\check{T} \cup p_j) - cov(\check{T})$, we have $cov(T)$ is submodular.

Figure 4: Proof for submodular

4 Algorithms For Optimization

Here we will be making use of Greedy Algorithms to solve the recommendation problem that is formulated as one submodular function optimization problem

and improve the algorithm to solve the problem.

4.1 Generalized greedy algorithm

The algorithm iteratively selects a player p such that the ratio of the marginal gain for objective function F and con- straint c is maximized by adding p. The best subset T found is eventually returned.

Input: an objective function F, a cost constraint C, and player database U

Output: a solution $T \subseteq U$ with $c(T) \leq C$

```
T ⟵ Ø;
repeat
    p ⟵ argmax_{p∈U} (F(T∪p) − F(T)) / (c(T∪p) − c(T))
    if c(T ∪ p) ≤ C then T = T ∪ p
    end if
    U = U \ p
until U = 0
return T
```

Figure 5: Generalized Greedy Algorithm

4.2 Limit greedy algorithm

Input: a submodular objective function F, a cost constraint C, and player database U

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As in our recommendation problem there are eleven play- ers in a football team, the length of T needs to be limited. In addition, c(T U p) c(T) = c(p)

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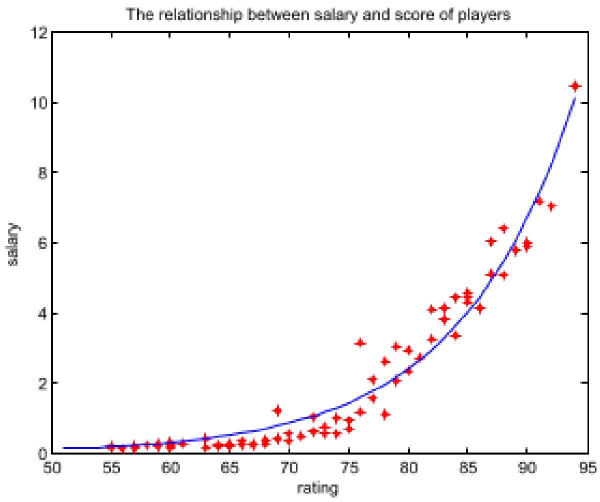

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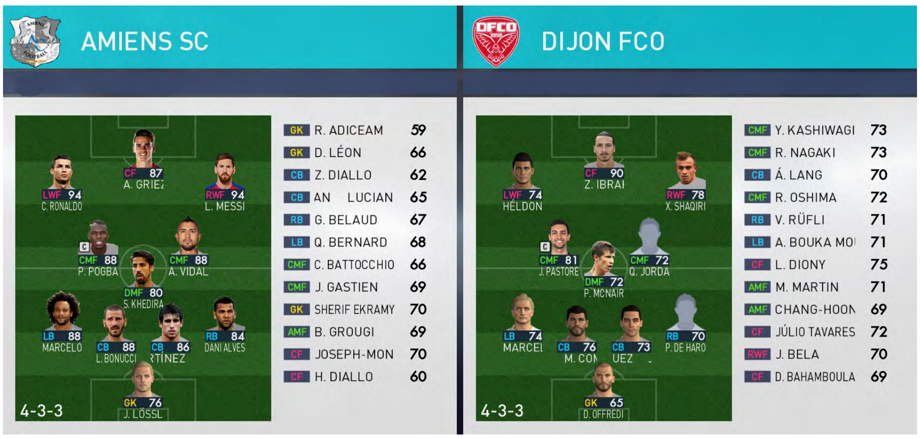

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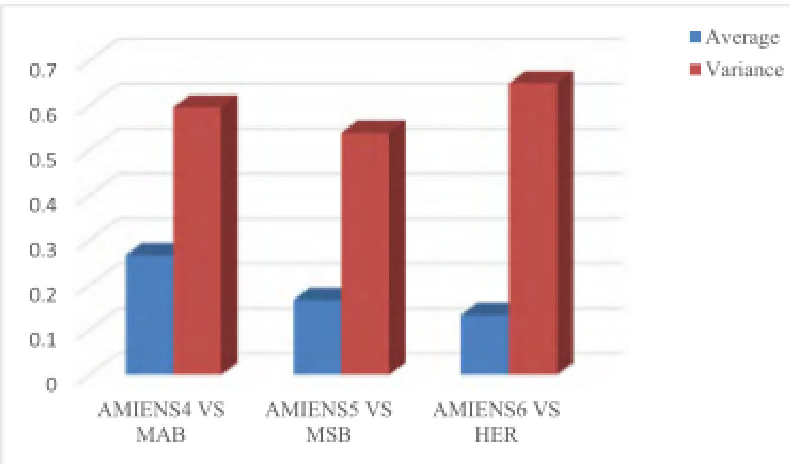

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It gives me great pleasure to present my seminar report on "Team Composition in PES2018 Using Submodular Function Optimization".No work, however big or small,has ever been done without the contribution of others.So these words of acknowledgement come as a small gesture of gratitude towards all those people, without whom the successful completion of this report would not have been possible.
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I would also like to thank all lab staff for providing with the necessary facilities for the presentation, it would have been impossible to complete seminar without their prompt cooperation. Last but not the least I would like to thank all my friends, who supported me with their valuable criticism, advice and support.

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List of Abbreviations

PES Pro Evolution Soccer
PS4 Play Station 4
CEFG Cost Effective Forward selection Greedy
MAB Man Blue
MSB Mercyside Blue
HER HampshirE Red

1 Introduction

1.1 Pro Evolution Soccer

In this modern world, many sport games have appeared and attracted more and more players in game markets. Pro Evo- lution Soccer 2018 (PES2018) is one of the popular football game produced and released by Konami.It can be played on a personal computer, PS4 or XBOX and in Mobiles. This game can be controlled by human or computer players, and can fully simulate a football match. It gives the human player an opportunity to compose a team of avatars each of which sim- ulates a real-world football player, e.g. Lionel Messi, Cristiano Ronaldo,Eden Hazard etc., in a competitive game. So as usual the selection of team members becomes more interesting and important in PES..

We all see football and it is the worlds game,it gets reflected in a game like PES.The team composition depends on preferences and knowledge of a human-player who, however, still expects inputs from the gaming system.We,the human players,will be satisfied if we get a team that we are dreaming of ad gets the favorite players to our team. This is well aligned with entertainment spirit in the content recommendation in computer games.Hence a team recommender becomes an important feature in a sport game not just limited in PES

In PES, every football player is specified by a set of attributes

- Attacking Prowess
- Ball Control
- Speed
- Jump etc...

Each attribute is associated with a specific value all of which decide the player performance in a match. The strength of a team is mainly influenced by the performance of individual players. The team is more likely to win a match if more skillful players are selected into the team. However, as each player has a specific position and a limited number of positions (a football match needs 11 players) exist in a pitch, the team composition is not straightforward given the known ratings of the players that indicate their performance. Things become more complicated since a human-player is often given a limited budget for purchasing a team of players each of which costs a certain value corresponding to his skills. It is very much difficult ,if we even compare with the various fantasy leagues for various sports.A fixed cost will be given earlier and we need to get our ideal an optimized team within that cost limit.It have to be done all manually and need to observe all the games to select a team for the next gameweek and its all based on humans knowledge about various players,their playing styles and positions.As an example,we can take the fantasy leagues to know more about the team composition.

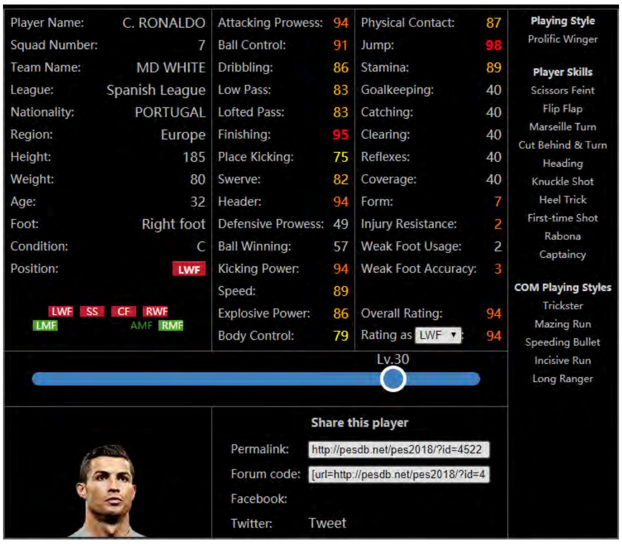

Figure 1: Player attributes in PES2018

1.2 Submodular Function

A function is submodular if it complies the following property: when you add a set to a solution "A" the improvement is worst than adding the same set to a subset of "A". Submodularity is a discrete version of concavity.

An example is the set cover problem. You have a set of sets and you have to find the minimum combination of those sets to cover some universe of elements.

For example let the universe be: U=1,2,3,4,5,6,7,8 and our sets: S1 = 1,2,3 S2= 1,4,5,6 S3= 4,5,7 S4 = 2,4,6,8 S5 =6,8 S6 =1,3,5,7

The solution is of course S4 S6.

So in more mathematical way,For a set of objects V = v 1 , . . . , v n and a function f : 2 V R, if for each A B V and e V B, it holds that M (e p A) greater than equal to M (e p B), then the function f is submodular, where

(e1 A)=f(A U e)-f(A)

One important property of submodularity is diminishing marginal returns, i.e., adding an element to a small set is more influential than adding it to a large set.

2 Related Work

Research of team composition is most important and relevant to team recommendation where a list of teams are recommended. More often,team recommendation comes from organizational andbehavioral sciences and research on social web application thathas appeared for a team recommendation since 2012.

	ID	1	2	3	4	...
	player_name	C.RONALDO	L.MESSI	L.SUAREZ	M.NEUER	...
	position	LWF	RWF	CF	GK	...
	rating	94	94	92	91	...
ability	attacking_prowess	94	95	95	42	...
	ball_control	91	96	86	68	...
	dribbling	86	96	84	60	...
	low_pass	83	88	82	65	...
	lofted_pass	83	86	77	69	...
	finishing	95	95	95	43	...
	header	94	68	77	70	...
	defensive_prowess	49	43	58	60	...
	speed	89	86	78	71	...
	goalkeeping	40	40	40	98	...

Figure 2: Player attributes and possible values for the attributes

3 Player Recommendation As A Submodular Function Optimization

Here,we formulate the player recommendation into one optimization problem and prove the submodularity property of this function as well.

3.1 Function for skill coverage

Given the PES platform, we choose ten players attributes as the most important skills for the team composition,i.e. attacking prowess, ball control, dribbling, low pass,lofted pass, finishing, header, defensive prowess, speed, and goalkeeping. In addition, we consider the players number, name, position, salary and overall rating. Hence each player has 15 attributes.
For each player pi,we use s to represent the players ability such as attacking prowess, ball control, and speed.

$$cov_{s_j}(p_i) = a_{s_j}(p_i)/(\sum_{p_k \in U} a_{s_j}(p_k))$$

Subsequently, we can define the skill coverage function for a set of team players, T , that is a subset of all potential players. We measures the degree to which the ability sj is covered by at least one player in T .

$$cov_{s_j}(T) = 1 - \prod_{p_i \in T} (1 - cov_{s_j}(p_i))$$

$$F(T) = \sum_{s_j \in S} \beta cov_{s_j}(T)$$

Figure 3: Function of T covering S defined as F(T

3.2 Recommender model

We aim to find an optimal team that maximizes the coverage value,also we need to consider the cost of composing the team of players for optimization. So this can also be seen as solving the below optimization problem.

maxF(T) subject to mod T = 11 and c(T) less that or equal to C

where c(T) is the sum of the salary of the total eleven players in T and C is the salary constraint for the entire team.

Proposition 1: The monotone function $F(T)$ (in Eq. 4) is submodular.

proof: We calculate the marginal gain of the skill coverage when one player is added into a potential team $\hat{T} \subseteq U$.

$$cov(\hat{T} \cup p_j) - cov(\hat{T})(1 - \prod_{p_i \in \hat{T}} (1 - cov(p_i)) * (1 - cov(p_j)))$$
$$-(1 - \prod_{p_i \in \hat{T}} (1 - cov(p_i)))$$
$$= cov(p_j) * \prod_{p_i \in \hat{T}} (1 - cov(p_i))$$

Similarly, for a small team $\check{T}$, we have

$$cov(\check{T} \cup p_j) - cov(\check{T}) = cov(p_j) * \prod_{p_i \in \check{T}} (1 - cov(p_i)),$$

where $\check{T} \subseteq \hat{T} \subseteq U$. Moreover, since $1 - cov(p_i) < 1, cov(\hat{T} \cup p_j) - cov(\hat{T}) \leq cov(\check{T} \cup p_j) - cov(\check{T})$, we have $cov(T)$ is submodular.

Figure 4: Proof for submodular

4 Algorithms For Optimization

Here we will be making use of Greedy Algorithms to solve the recommendation problem that is formulated as one submodular function optimization problem

and improve the algorithm to solve the problem.

4.1 Generalized greedy algorithm

The algorithm iteratively selects a player p such that the ratio of the marginal gain for objective function F and con- straint c is maximized by adding p. The best subset T found is eventually returned.

Input: an objective function F, a cost constraint C, and player database U
Output: a solution $T \subseteq U$ with $c(T) \leq C$

$T \longleftarrow \emptyset$;
repeat
  $p \longleftarrow argmax_{p \in U} \frac{F(T \cup p) - F(T)}{c(T \cup p) - c(T)}$
  if $c(T \cup p) \leq C$ **then** $T = T \cup p$
  end if
  $U = U \setminus p$
until $U = 0$
return T

Figure 5: Generalized Greedy Algorithm

4.2 Limit greedy algorithm

Input: a submodular objective function F, a cost constraint C, and player database U
Output: a solution $T \subseteq U$ with $c(T) \leq C$ and $|T| = 11$

$T \longleftarrow \emptyset$;
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  $p \longleftarrow argmax_{p \in U} \frac{F(T \cup p) - F(T)}{c(p)}$
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  end if
  $U = U \setminus p$
until $|T| = 11$
return T

Figure 6: Limit Greedy Algorithm

As in our recommendation problem there are eleven play- ers in a football team, the length of T needs to be limited. In addition, c(T U p) c(T) = c(p)

as the constraint is linear and discrete. Hence we adapt the generalized greedy algorithm into Limit Greedy Algorithm.

In each iteration, we will select the player p from a set of players U with the largest ratio of the increase of the objective function to the wage cost under the cost constraint C, until the team length is equal to eleven.

4.3 Cost effective forward selection algorithm

Here,we are given by the submodular coverage function F, a set of players U and a salary cost constraint C.We first use the unit cost greedy algorithm to select the player p with the maximum increment of the objective function, which means the best player is added to the team T . Hence, we can make the most of the cost space and choose the player who is outstanding enough in the initial selection stage. We will not select a player twice in each iteration. Then we enter the second selection stage and use the greedy algorithm for the consideration of the remaining cost. By doing this, we have a team of players that meets the cost constraint and contains sufficiently good play- ers, which generates better results than the generalized greedy algorithm

Input: a submodular objective function F, a cost constraint C, and player database U

Output: a solution $T \subseteq U$ with $c(T) \leq C$ and $|T| = 11$

$T \longleftarrow \emptyset$;
repeat
  $p \longleftarrow argmax_{p \in U} F(T \cup p) - F(T)$
  if $c(T \cup p) \leq C$ **then** $T = T \cup p$
  end if
  $U = U \setminus p$
  if $C - c(T \cup p) < \varepsilon$ **then**
    repeat
      $p \longleftarrow argmax_{p \in U} \frac{F(T \cup p) - F(T)}{c(p)}$
      if $c(T \cup p) \leq C$ **then** $T = T \cup p$
      end if
      $U = U \setminus p$
    until $|T| = 11$
  end if
until $|T| = 11$
return T

Figure 7: CEFG Algorithm

5 Experiments And Real Game Results

The algorithms are implemented in Matlab2018 and conduct all the numerical computations on a Windows PC.All the games are simulated in a quick game of PES2018 that is downloaded from a platform Steam on Windows10 computer system.

5.1 Analysis of data

For the position of each player on the football pitch, we consider equivalence of positions and normalize the posi- tion as shown in figure given below.

Position	Specific position	Number
Goalkeeper	GK	1
Guard	CB	2
	LB	3
	RB	4
Midfielder	DMF	5
	CMF	5
	RMF	5
	LMF	5
	AMF	5
Forward	LWF	6
	RWF	7
	CF	8
	SS	8

Figure 8: Positions of players and their equivalent numbers

Based on the PES game experience, we choose the team of 4-3-3 formations which means there are one Goalkeeper, four Guard, three Midfielder and three Forward in the team.
For the cost constraint, there is no players salary data in the official website. Considering that the players salary is often positively correlated with his rating, we fit the wages with scores of some players based on the existing data. We find that the data is exponentially distributed and therefore use the least squares method for regression. The fitting curve formulated below is shown in Fig. 9

$$y(i) = \eta \cdot e^{\theta x(i)}$$

where n = 6.375 10 4 , and theta = 0.1029. Then through the curve, we can find the y-axis of the corresponding point based on the x-axis, which means we can get a players salary based on his ratings.

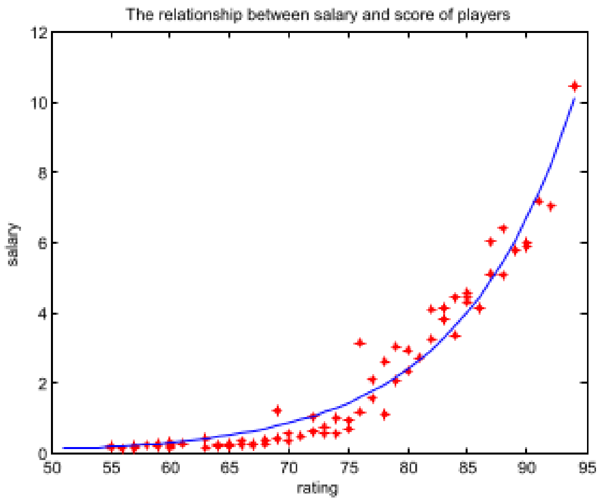

Figure 9: Cost of players as a function of their ratings

5.2 Experimental Results

We select a total of 8,762 players,for ensuring the credibility of results ,with the ratings larger than or equal to 60 in the database, and recommend a team including 11 players. We use the CEFG Algorithm to solve the optimization prob- lem and set a sufficiently large cost as retrieved from the curve in Fig. 9 Based on the recommended players, we compose a Dream Team. To conduct comparison of the algorithm per- formance, we randomly generate a team in the PES without any cost constraint and then simulate the battle between the two teams (including the players) as shown in Fig. 10. AMIENS represents the Dream Team and DIJON represents the random team. The final result from all the five matches is 4:1 and the dream team dominates most of the competitions.

For verifying the accuracy and strength of the CEFG algorithm, we select

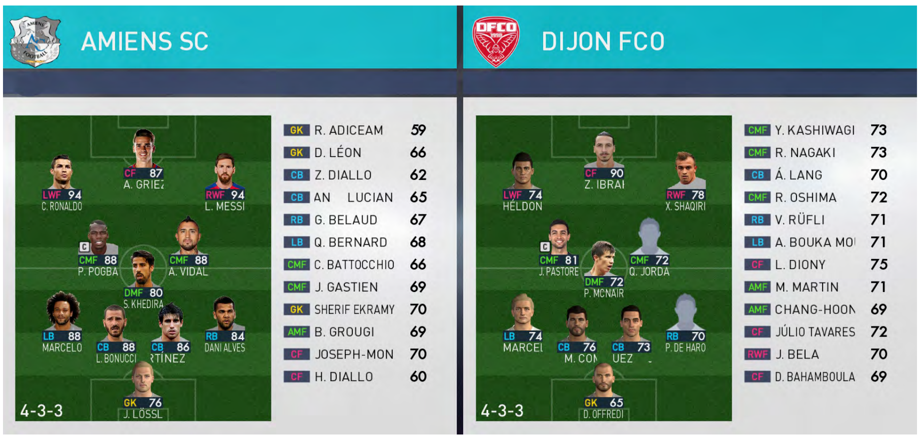

Figure 10: Dream team vs Random team

MAB, MSB and HER teams in the game all of which exist in the real game-play. We calculate the costs of the three teams, and use them as constraint to

recommend a team of players based on the CEFG algorithm. We then match the recommended team with the existing three teams and gives the results in the fig.11 and fig.12.

Battle	Score										Win Number	Goal Difference	Cost Constraint	Actual Cost Comparison
AMIENS4 VS MAB	3:1 0:0 0:2	1:4 1:0 1:0	0:0 2:0 4:1	2:2 1:1 2:0	1:3 2:4 0:0	3:0 0:0 1:1	3:1 4:2 0:2	1:0 2:2 2:0	2:1 2:0 2:2	0:0 0:1 3:1	19	0.47	36.95	35.21 : 36.95
AMIENS5 VS MSB	0:0 2:0 1:0	2:2 2:2 2:0	0:1 0:1 0:0	3:1 0:1 3:1	0:0 1:1 0:0	4:0 1:0 0:1	2:2 0:0 0:2	1:3 4:2 2:2	2:2 2:0 1:0	1:0 0:0 1:1	17.5	0.4	26.38	23.00 : 26.38
AMIENS6 VS HER	2:4 0:1 0:3	1:0 2:0 1:0	1:4 4:2 0:0	3:1 0:2 1:1	0:0 1:1 1:0	1:0 4:0 2:0	3:0 0:2 0:0	2:3 3:0 3:0	0:0 0:0 1:3	0:0 1:1 1:1	17	0.3	15.70	13.18 : 15.70

Figure 11: Match results of CEFG vs actual teams

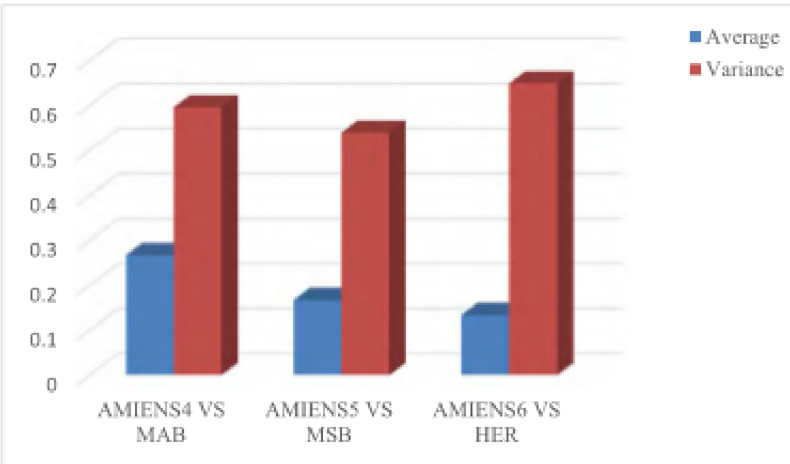

Figure 12: Normalized results of the CEFG v.s. the actual teams

We can find that under the same cost constraint (or in a sense of rating), the teams recommended by CEFG algorithm are stronger than actual teams. The teams generated by the CEFG algorithm dominate the play in the football pitch.

6 Conclusion

We make an in-depth analysis of team composition in PES that can be converted into a player recommenda- tion problem. As there is no clear approach for football player recommendation in a game, we propose a skill coverage function to quantify the complementary capability of a proper team. We then improve the greedy algorithm to solve the recommendation problem. We conduct empirical study of the proposed recommendation techniques in a game platform of PES2018. The results demonstrate the strength of the team as well as the effectiveness of our approach. Although we investigate our techniques in the context of PES, the proposed recommendation model based on the submodular function is rather general and can be adapted to solve other team compo- sition problems. We notice that the player recommendation technique can also be used to improve a game engine by suggesting a good team to computer-controlled characters in a sport game. Improving the CEFG algorithm is a great challenge. We will seek for a better bound so as to improve the player recommendation quality.

GOVERNMENT ENGINEERING COLLEGE THRISSUR

2019

CS451 - B.TECH SEMINAR REPORT

ON

Team Composition in PES2018 Using Submodular Function Optimization

Presented by

V ROHITH

TCR16CS059

DEPARTMENT OF CSE

ABSTRACT

With the development of computer game technologies,we know that gameplay becomes very realistic in many sports games, therefore providing appealing play experience to game players. To get the victory in a football pitch, team composition is one of the most important thing needed. There is little research on the automatic team composition in sports games particularly in a popular game of Pro Evolution Soccer (PES). So we consider the team composition as one team player recommendation problem.We also know that a paticular team is composed of several players in a game. Subsequently, we aim to recommend a list of sufficiently good football players to game players.

We will convert the team player recommendation into one optimization problem and produce greedy algorithm-based solutions. We deal with a coverage function that quantifies the degree of soccer skills to be covered by each selected players.Also we improve the greedy algorithm to solve the function optimization problem.

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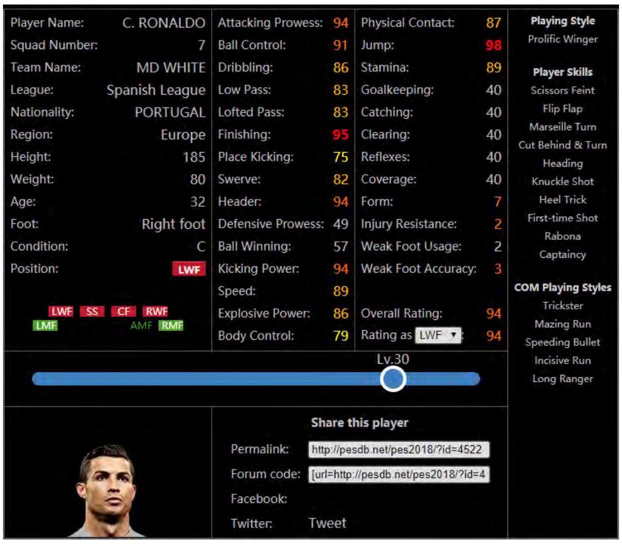

Figure 1: Player attributes in PES2018

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where $\check{T} \subseteq \hat{T} \subseteq U$. Moreover, since $1 - cov(p_i) < 1$, $cov(\hat{T} \cup p_j) - cov(\hat{T}) \leq cov(\check{T} \cup p_j) - cov(\check{T})$, we have $cov(T)$ is submodular.

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In each iteration, we will select the player p from a set of players U with the largest ratio of the increase of the objective function to the wage cost under the cost constraint C, until the team length is equal to eleven.

4.3 Cost effective forward selection algorithm

Here,we are given by the submodular coverage function F, a set of players U and a salary cost constraint C.We first use the unit cost greedy algorithm to select the player p with the maximum increment of the objective function, which means the best player is added to the team T . Hence, we can make the most of the cost space and choose the player who is outstanding enough in the initial selection stage. We will not select a player twice in each iteration. Then we enter the second selection stage and use the greedy algorithm for the consideration of the remaining cost. By doing this, we have a team of players that meets the cost constraint and contains sufficiently good play- ers, which generates better results than the generalized greedy algorithm

Input: a submodular objective function F, a cost constraint C, and player database U
Output: a solution $T \subseteq U$ with $c(T) \leq C$ and $|T| = 11$

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    $p \longleftarrow argmax_{p \in U} F(T \cup p) - F(T)$
    if $c(T \cup p) \leq C$ **then** $T = T \cup p$
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Figure 7: CEFG Algorithm

5 Experiments And Real Game Results

The algorithms are implemented in Matlab2018 and conduct all the numerical computations on a Windows PC.All the games are simulated in a quick game of PES2018 that is downloaded from a platform Steam on Windows10 computer system.

5.1 Analysis of data

For the position of each player on the football pitch, we consider equivalence of positions and normalize the posi- tion as shown in figure given below.

Position	Specific position	Number
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	CB	2
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	RB	4
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	AMF	5
	LWF	6
Forward	RWF	7
	CF	8
	SS	8

Figure 8: Positions of players and their equivalent numbers

Based on the PES game experience, we choose the team of 4-3-3 formations which means there are one Goalkeeper, four Guard, three Midfielder and three Forward in the team.

For the cost constraint, there is no players salary data in the official website. Considering that the players salary is often positively correlated with his rating, we fit the wages with scores of some players based on the existing data. We find that the data is exponentially distributed and therefore use the least squares method for regression. The fitting curve formulated below is shown in Fig. 9

$$y(i) = \eta \cdot e^{\theta x(i)}$$

where n = 6.375 10 4 , and theta = 0.1029. Then through the curve, we can find the y-axis of the corresponding point based on the x-axis, which means we can get a players salary based on his ratings.

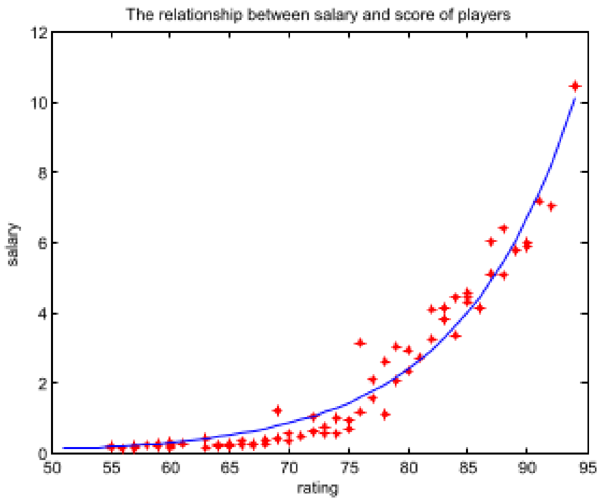

Figure 9: Cost of players as a function of their ratings

5.2 Experimental Results

We select a total of 8,762 players,for ensuring the credibility of results ,with the ratings larger than or equal to 60 in the database, and recommend a team including 11 players. We use the CEFG Algorithm to solve the optimization prob- lem and set a sufficiently large cost as retrieved from the curve in Fig. 9 Based on the recommended players, we compose a Dream Team. To conduct comparison of the algorithm per- formance, we randomly generate a team in the PES without any cost constraint and then simulate the battle between the two teams (including the players) as shown in Fig. 10. AMIENS represents the Dream Team and DIJON represents the random team. The final result from all the five matches is 4:1 and the dream team dominates most of the competitions.

For verifying the accuracy and strength of the CEFG algorithm, we select

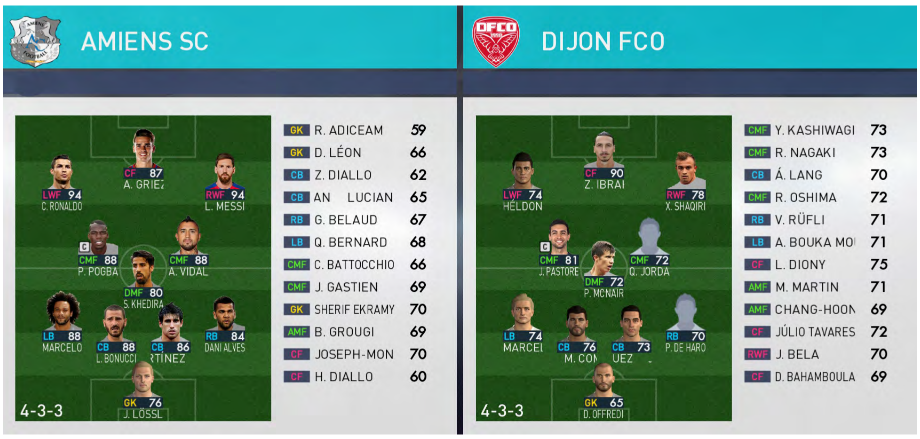

Figure 10: Dream team vs Random team

MAB, MSB and HER teams in the game all of which exist in the real game-play. We calculate the costs of the three teams, and use them as constraint to

recommend a team of players based on the CEFG algorithm. We then match the recommended team with the existing three teams and gives the results in the fig.11 and fig.12.

Battle	Score										Win Number	Goal Difference	Cost Constraint	Actual Cost Comparison
AMIENS4 VS MAB	3:1 0:0 0:2	1:4 1:0 1:0	0:0 2:0 4:1	2:2 1:1 2:0	1:3 2:4 0:0	3:0 0:0 1:1	3:1 4:2 0:2	1:0 2:2 2:0	2:1 2:0 2:2	0:0 0:1 3:1	19	0.47	36.95	35.21 : 36.95
AMIENS5 VS MSB	0:0 2:0 1:0	2:2 2:2 2:0	0:1 0:1 0:0	3:1 0:1 3:1	0:0 1:1 0:0	4:0 1:0 0:1	2:2 0:0 0:2	1:3 4:2 2:2	2:2 2:0 1:0	1:0 0:0 1:1	17.5	0.4	26.38	23.00 : 26.38
AMIENS6 VS HER	2:4 0:1 0:3	1:0 2:0 1:0	1:4 4:2 0:0	3:1 0:2 1:1	0:0 1:1 1:0	1:0 4:0 2:0	3:0 0:2 0:0	2:3 3:0 3:0	0:0 0:0 1:3	0:0 1:1 1:1	17	0.3	15.70	13.18 : 15.70

Figure 11: Match results of CEFG vs actual teams

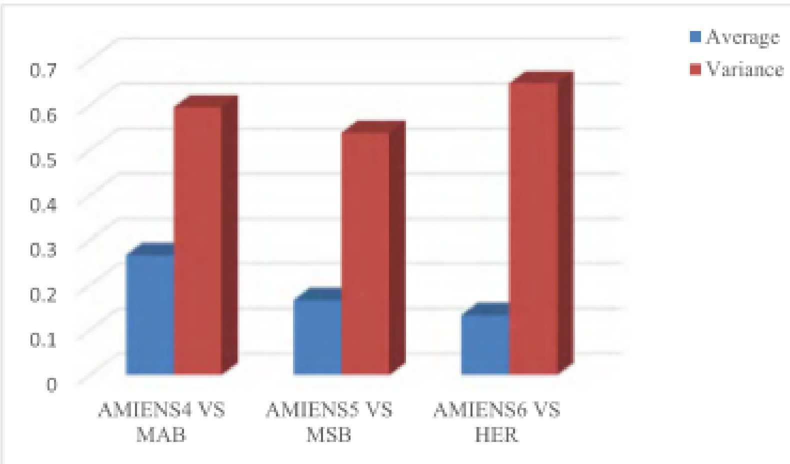

Figure 12: Normalized results of the CEFG v.s. the actual teams

We can find that under the same cost constraint (or in a sense of rating), the teams recommended by CEFG algorithm are stronger than actual teams. The teams generated by the CEFG algorithm dominate the play in the football pitch.

6 Conclusion

We make an in-depth analysis of team composition in PES that can be converted into a player recommenda- tion problem. As there is no clear approach for football player recommendation in a game, we propose a skill coverage function to quantify the complementary capability of a proper team. We then improve the greedy algorithm to solve the recommendation problem. We conduct empirical study of the proposed recommendation techniques in a game platform of PES2018. The results demonstrate the strength of the team as well as the effectiveness of our approach. Although we investigate our techniques in the context of PES, the proposed recommendation model based on the submodular function is rather general and can be adapted to solve other team compo- sition problems. We notice that the player recommendation technique can also be used to improve a game engine by suggesting a good team to computer-controlled characters in a sport game. Improving the CEFG algorithm is a great challenge. We will seek for a better bound so as to improve the player recommendation quality.

GOVERNMENT ENGINEERING COLLEGE THRISSUR

2019

CS451 - B.TECH SEMINAR REPORT

ON

Team Composition in PES2018 Using Submodular Function Optimization

Presented by

V ROHITH

TCR16CS059

DEPARTMENT OF CSE

ABSTRACT

With the development of computer game technologies,we know that gameplay becomes very realistic in many sports games, therefore providing appealing play experience to game players. To get the victory in a football pitch, team composition is one of the most important thing needed. There is little research on the automatic team composition in sports games particularly in a popular game of Pro Evolution Soccer (PES). So we consider the team composition as one team player recommendation problem.We also know that a paticular team is composed of several players in a game. Subsequently, we aim to recommend a list of sufficiently good football players to game players.

We will convert the team player recommendation into one optimization problem and produce greedy algorithm-based solutions. We deal with a coverage function that quantifies the degree of soccer skills to be covered by each selected players.Also we improve the greedy algorithm to solve the function optimization problem.

ACKNOWLEDGEMENT

It gives me great pleasure to present my seminar report on ”Team Composition in PES2018 Using Submodular Function Optimization”.No work, however big or small,has ever been done without the contribution of others.So these words of acknowledgement come as a small gesture of gratitude towards all those people, without whom the successful completion of this report would not have been possible.
I would like to express my gratitude towards seminar coordinators Prof. Helen K J,Associate Professor and Prof. George Mathew, Assistant Professor, Department of Computer Science and Engineering who gave me their valuable suggestions, reviews, motivation and direction.
I would also like to thank all lab staff for providing with the necessary facilities for the presentation, it would have been impossible to complete seminar without their prompt cooperation. Last but not the least I would like to thank all my friends, who supported me with their valuable criticism, advice and support.

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List of Abbreviations

PES Pro Evolution Soccer
PS4 Play Station 4
CEFG Cost Effective Forward selection Greedy
MAB Man Blue
MSB Mercyside Blue
HER HampshirE Red

1 Introduction

1.1 Pro Evolution Soccer

In this modern world, many sport games have appeared and attracted more and more players in game markets. Pro Evo- lution Soccer 2018 (PES2018) is one of the popular football game produced and released by Konami.It can be played on a personal computer, PS4 or XBOX and in Mobiles. This game can be controlled by human or computer players, and can fully simulate a football match. It gives the human player an opportunity to compose a team of avatars each of which sim- ulates a real-world football player, e.g. Lionel Messi, Cristiano Ronaldo,Eden Hazard etc., in a competitive game. So as usual the selection of team members becomes more interesting and important in PES..

We all see football and it is the worlds game,it gets reflected in a game like PES.The team composition depends on preferences and knowledge of a human-player who, however, still expects inputs from the gaming system.We,the human players,will be satisfied if we get a team that we are dreaming of ad gets the favorite players to our team. This is well aligned with entertainment spirit in the content recommendation in computer games.Hence a team recommender becomes an important feature in a sport game not just limited in PES

In PES, every football player is specified by a set of attributes

- Attacking Prowess
- Ball Control
- Speed
- Jump etc...

Each attribute is associated with a specific value all of which decide the player performance in a match. The strength of a team is mainly influenced by the performance of individual players. The team is more likely to win a match if more skillful players are selected into the team. However, as each player has a specific position and a limited number of positions (a football match needs 11 players) exist in a pitch, the team composition is not straightforward given the known ratings of the players that indicate their performance. Things become more complicated since a human-player is often given a limited budget for purchasing a team of players each of which costs a certain value corresponding to his skills. It is very much difficult ,if we even compare with the various fantasy leagues for various sports.A fixed cost will be given earlier and we need to get our ideal an optimized team within that cost limit.It have to be done all manually and need to observe all the games to select a team for the next gameweek and its all based on humans knowledge about various players,their playing styles and positions.As an example,we can take the fantasy leagues to know more about the team composition.

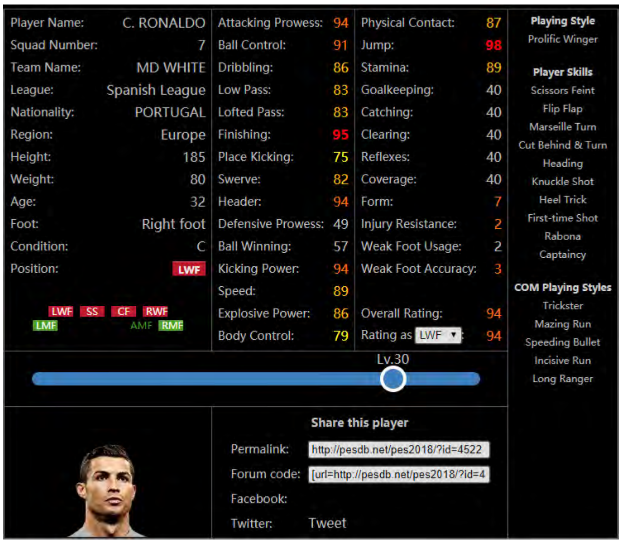

Figure 1: Player attributes in PES2018

1.2 Submodular Function

A function is submodular if it complies the following property: when you add a set to a solution "A" the improvement is worst than adding the same set to a subset of "A". Submodularity is a discrete version of concavity.

An example is the set cover problem. You have a set of sets and you have to find the minimum combination of those sets to cover some universe of elements.

For example let the universe be: U=1,2,3,4,5,6,7,8 and our sets: S1 = 1,2,3 S2= 1,4,5,6 S3= 4,5,7 S4 = 2,4,6,8 S5 =6,8 S6 =1,3,5,7

The solution is of course S4 S6.

So in more mathematical way,For a set of objects V = v 1 , . . . , v n and a function f : 2 V R, if for each A B V and e V B, it holds that M (e p A) greater than equal to M (e p B), then the function f is submodular, where

(e1 A)=f(A U e)-f(A)

One important property of submodularity is diminishing marginal returns, i.e., adding an element to a small set is more influential than adding it to a large set.

2 Related Work

Research of team composition is most important and relevant to team recommendation where a list of teams are recommended. More often,team recommendation comes from organizational andbehavioral sciences and research on social web application thathas appeared for a team recommendation since 2012.

	ID	1	2	3	4	...
	player_name	C.RONALDO	L.MESSI	L.SUAREZ	M.NEUER	...
	position	LWF	RWF	CF	GK	...
	rating	94	94	92	91	...
ability	attacking_prowess	94	95	95	42	...
	ball_control	91	96	86	68	...
	dribbling	86	96	84	60	...
	low_pass	83	88	82	65	...
	lofted_pass	83	86	77	69	...
	finishing	95	95	95	43	...
	header	94	68	77	70	...
	defensive_prowess	49	43	58	60	...
	speed	89	86	78	71	...
	goalkeeping	40	40	40	98	...

Figure 2: Player attributes and possible values for the attributes

3 Player Recommendation As A Submodular Function Optimization

Here,we formulate the player recommendation into one optimization problem and prove the submodularity property of this function as well.

3.1 Function for skill coverage

Given the PES platform, we choose ten players attributes as the most important skills for the team composition,i.e. attacking prowess, ball control, dribbling, low pass,lofted pass, finishing, header, defensive prowess, speed, and goalkeeping. In addition, we consider the players number, name, position, salary and overall rating. Hence each player has 15 attributes.
For each player pi,we use s to represent the players ability such as attacking prowess, ball control, and speed.

$$cov_{s_j}(p_i) = a_{s_j}(p_i)/(\sum_{p_k \in U} a_{s_j}(p_k))$$

Subsequently, we can define the skill coverage function for a set of team players, T , that is a subset of all potential players. We measures the degree to which the ability sj is covered by at least one player in T .

$$cov_{s_j}(T) = 1 - \prod_{p_i \in T} (1 - cov_{s_j}(p_i))$$

$$F(T) = \sum_{s_j \in S} \beta cov_{s_j}(T)$$

Figure 3: Function of T covering S defined as F(T

3.2 Recommender model

We aim to find an optimal team that maximizes the coverage value,also we need to consider the cost of composing the team of players for optimization. So this can also be seen as solving the below optimization problem.

maxF(T) subject to mod T = 11 and c(T) less that or equal to C

where c(T) is the sum of the salary of the total eleven players in T and C is the salary constraint for the entire team.

Proposition 1: The monotone function $F(T)$ (in Eq. 4) is submodular.

proof: We calculate the marginal gain of the skill coverage when one player is added into a potential team $\hat{T} \subseteq U$.

$$cov(\hat{T} \cup p_j) - cov(\hat{T})(1 - \prod_{p_i \in \hat{T}} (1 - cov(p_i)) * (1 - cov(p_j)))$$

$$-(1 - \prod_{p_i \in \hat{T}} (1 - cov(p_i)))$$

$$= cov(p_j) * \prod_{p_i \in \hat{T}} (1 - cov(p_i))$$

Similarly, for a small team $\check{T}$, we have

$$cov(\check{T} \cup p_j) - cov(\check{T}) = cov(p_j) * \prod_{p_i \in \check{T}} (1 - cov(p_i)),$$

where $\check{T} \subseteq \hat{T} \subseteq U$. Moreover, since $1 - cov(p_i) < 1, cov(\hat{T} \cup p_j) - cov(\hat{T}) \leq cov(\check{T} \cup p_j) - cov(\check{T})$, we have $cov(T)$ is submodular.

Figure 4: Proof for submodular

4 Algorithms For Optimization

Here we will be making use of Greedy Algorithms to solve the recommendation problem that is formulated as one submodular function optimization problem

and improve the algorithm to solve the problem.

4.1 Generalized greedy algorithm

The algorithm iteratively selects a player p such that the ratio of the marginal gain for objective function F and con- straint c is maximized by adding p. The best subset T found is eventually returned.

Input: an objective function F, a cost constraint C, and player database U
Output: a solution $T \subseteq U$ with $c(T) \leq C$

$T \longleftarrow \emptyset$;
repeat
  $p \longleftarrow argmax_{p \in U} \frac{F(T \cup p) - F(T)}{c(T \cup p) - c(T)}$
  if $c(T \cup p) \leq C$ **then** $T = T \cup p$
  end if
  $U = U \setminus p$
until $U = 0$
return T

Figure 5: Generalized Greedy Algorithm

4.2 Limit greedy algorithm

Input: a submodular objective function F, a cost constraint C, and player database U
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return T

Figure 6: Limit Greedy Algorithm

As in our recommendation problem there are eleven play- ers in a football team, the length of T needs to be limited. In addition, c(T U p) c(T) = c(p)

as the constraint is linear and discrete. Hence we adapt the generalized greedy algorithm into Limit Greedy Algorithm.

In each iteration, we will select the player p from a set of players U with the largest ratio of the increase of the objective function to the wage cost under the cost constraint C, until the team length is equal to eleven.

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Here,we are given by the submodular coverage function F, a set of players U and a salary cost constraint C.We first use the unit cost greedy algorithm to select the player p with the maximum increment of the objective function, which means the best player is added to the team T . Hence, we can make the most of the cost space and choose the player who is outstanding enough in the initial selection stage. We will not select a player twice in each iteration. Then we enter the second selection stage and use the greedy algorithm for the consideration of the remaining cost. By doing this, we have a team of players that meets the cost constraint and contains sufficiently good play- ers, which generates better results than the generalized greedy algorithm

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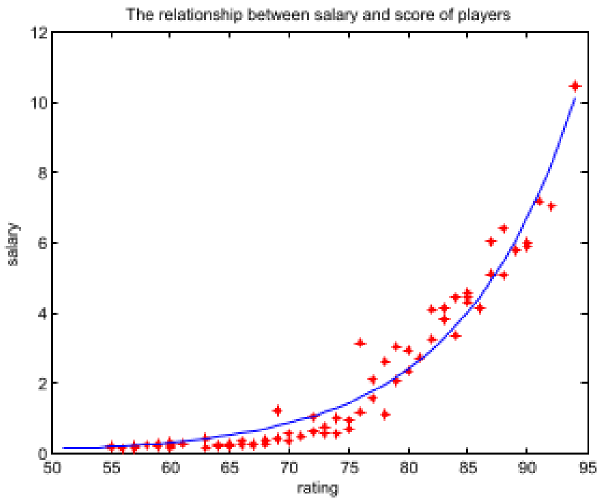

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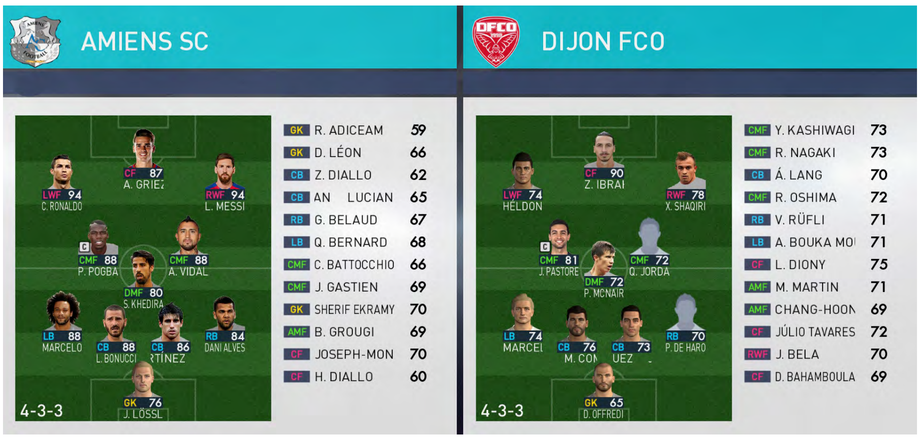

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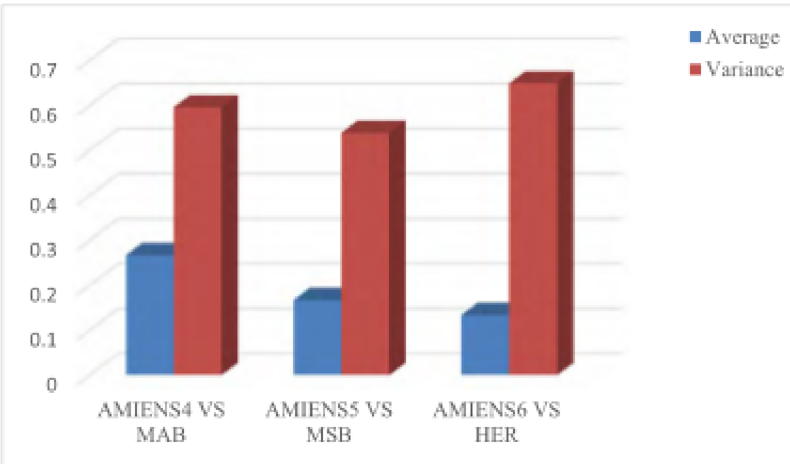

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