Characterizing Playing Styles for Ice Hockey Players

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Abstract. Although analytics is being used in, e.g., the evaluation of players and scouting, it is still challenging to quantify skills and playing styles of players. Such information is important for roster creation and scouting, where teams want to find players that have a playing style that fits within the team, as well as for game preparation to understand the playing style of opponents. In this paper we use player vectors to characterize a player's playing style. The player vectors contain representations of skills that are computed from game event data. Further, we use fuzzy clustering on the vectors to generate five types of defender playing styles and five types of forward playing styles. For these types, we show the typical skill levels and players with similar styles.[1]

1 Introduction

In ice hockey, the general manager and scouts are responsible for identifying the most skilled players to build a high-performing team within their budget limits. Historically, the teams relied on the manual analysis conducted by scouts and general managers. The introduction of data analytics transformed the process for scouting hockey players [18]. By leveraging data-based metrics, teams were able to adopt a more objective approach to decision-making, particularly in evaluating player performance. However, despite the growing influence of analytics in areas such as scouting and player performance evaluation, quantifying the nuanced skills and playing styles of individual players remains a challenge. Such information is important for roster creation, where teams want to find players that have a playing style that fits within the team.

In the complex and dynamic game of hockey, characterizing playing styles is challenging due to multiple aspects. One such aspect is that certain features are difficult to quantify, making it a challenge to identify appropriate variables for model building. Moreover, skills are typically not explicitly encoded and stored in the available event data, but rather must be derived from player actions or performance across various event types. For instance, a certain kind of defensive skill may depend on how well the defender performs in different aspects such as blocked shots, hits, and dump outs.

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In this paper, we characterize the playing style of a player in a data-driven manner. We use event data from hockey games of three leagues and 2.5 seasons (Sect. 3) to define different kinds of skills for defenders and forwards (Sect. 4). A player's playing style is then represented by how the player performs for these different skills. Formally, the player's playing style is represented by a skill vector. Further, we use fuzzy clustering to define five distinct playing styles for both defenders and forwards (Sect. 5). We show the typical skill levels for prototypical players in the clusters and give examples. Information about the clusters can be used for scouting, e.g., for finding players with similar playing style, as well as for game preparation, as understanding the playing style of the opponent can offer certain tactical advantages.

2 Related Work

There has been research on different topics that relate to trying to characterize and compare players in ice hockey.

One approach has been to define performance metrics. Many performance metrics assign values based on particular types of actions in the game. For instance, goals, assists, and Corsi attribute a value to goal-scoring actions, to passes that lead to goals and to different types of shots, respectively. Variants of traditional metrics have been proposed such as regression models replacing the +/- measure (e.g., [16,17,7]). In [8] principal component analysis was performed based on 18 traditional metrics and a performance metric based on the four most important components was proposed. More recent work takes the context in which actions are performed into account. For instance, [20] attributes value to goals, but the value of the goal depends on the situation in which it is scored. Event impacts for different kinds of actions in [26] are based on the probability that the event leads to a goal (for or against) in the next 20 seconds. Several works model the dynamics of an ice hockey game using Markov games (e.g., [29,9]). In [21,27,28,13,24,15] action-value Q-functions are learned with respect to different targets. Different goal-based performance metrics taking the importance of goals into account are defined in [10,22]. Player rankings are presented in [25,14,11].

Another approach uses a probabilistic method for quantifying player roles in ice hockey. Earlier work allowed for a player to only belong to one role [30,2], while more recent work allows for a player to belong to different roles with some probability [23]. In the latter case, players can be compared based on their membership in different roles.

In other sports player vectors have been used to try to characterize a player's playing style. In [6], a basketball player's defensive play is characterized by shot taker, shot location, and expected outcome of the shot. In [3], a football player's playing style vector represents the areas on the field where the player tends to be and which actions in terms of passes, dribbles, crosses, and shots, the player performs in these areas. Movement patterns in shot situations in football were predicted in [12].

3 Data

The data we used is a proprietary dataset produced by Sportlogiq [2]. The dataset consists of event data from the following leagues: Swedish Hockey League (SHL), Hockeyallsvenskan (HA) and the American Hockey League (AHL). The choice of these three leagues originates from the fact that many transfers happen between these leagues. For instance, traditionally, many imports to the SHL come from the AHL, and many drafted SHL players start out in the AHL. As HA is the league one step down from SHL, SHL is a natural next step for many HA players. The data includes complete seasons for the three leagues for 2021/2022 and 2022/2023, as well as data from the 2023/2024 season up until January 28th, 2024. In total the dataset contains 7,532 games, 4,014 unique players, 68 unique teams and 28.5 million events. An event is described by more than 50 different parameters. The dataset comprises 2,553 forwards, 1,393 defenders, and 452 goaltenders, totaling 4,398 players. This figure exceeds the number of unique players, capturing that some individuals have played both forward and defender.

4 Player Vectors

4.1 Feature selection

Based on domain expert knowledge, we decided to use the skill sets as shown in Tables 1 and 2, for defenders and forwards respectively. For each skill, we utilized dataset features that influence it. Examples are given in the tables.Features can belong to different skills. For defenders there are 13 different skills that are described by five to seven features/actions and for forwards there are 18 different skills that are described by two to seven features/actions.

Table 1: Skills and example actions for defenders.

Skills	**Actions**
Passing	e.g., different types of passes
Skating	e.g., exits, entries, dumps
Shooting	e.g., different types of shots
Defensive Stickwork	e.g., blocked passes, loose puck recoveries
Puck Moving	e.g, some types of passes, dump-in recoveries
Point Producing	e.g., different offensive zone events
Powerplay Playmaking	e.g., powerplay playmaking events
Powerplay Scoring	e.g., powerplay shots and goals
Physical Play	e.g., body checks and defensive plays
Slot Defense	e.g., blocked shots and dump outs
Stay at Home	e.g., different defensive zone events
Penalty Killing	e.g., different penalty killing events related to puck recovery
Penalty Killing Slot Defense	e.g., different penalty killing defensive plays

[2] https://www.sportlogiq.com/hockey/

Table 2: Skills and example actions for forwards.

Skills	Actions
Passing	e.g., different types of passes
Skating	e.g., different types of controlled entries
Powerplay Playmaking	e.g., different types of controlled entries and passes in powerplay
Powerplay Slot Engagement	e.g., powerplay actions close to net
Powerplay Scoring	e.g., powerplay shots and goals
Defensive Puck Control	e.g., dump outs and loose puck recoveries
Defensive Zone Play	e.g., different defensive zone actions
Defensive Positioning	e.g., blocked shots and passes
Slot Defense	e.g., rebounds and dump outs
Penalty Killing	e.g., shorthanded defensive plays
Slot Engagement	e.g., offensive actions close to net
Heavy Game	e.g., body checks and defensive plays
Forechecking	e.g., offensive zone loose puck recoveries
Cycling the Puck	e.g., puck protections and receptions
Neutral Zone	e.g., different neutral zone actions
Puck Moving	e.g, some types of passes, entries
Offensive Zone Play	e.g., different offensive zone events
Shooting	e.g., different types of shots

4.2 Player vector construction

The player vectors are constructed based on the skills in Tables 1 and 2. First, all players who played less than 200 minutes were filtered out. Next, 13 feature vectors were created for each defender and 18 feature vectors for each forward. Each of these feature vectors quantifies a skill and contains the frequency of each action that describes that skill. For instance, for a particular defender, a defender skill with seven actions is represented by a vector of length seven where each element in the vector represents an action and its frequency for the defender in the dataset.

After constructing all feature vectors, we normalize them based on the player's ice time, i.e., the values are divided by the time on ice (TOI) of the player and multiplied by 60 (where 60 minutes is the length of a game in regulation time). This ice-time normalization was done to address potential differences in event frequency attributed to playing time disparities. Further, the values are standardized using MinMaxScaler in the scikit-learn library for Python [19]. This method transforms each feature by scaling it to a value between 0 and 1. This was done to take into account that some events are more frequent than others in a game and would otherwise have an undesired larger weight. For example, a pass happens much more often than a body check. In Fig. 1 we show the distribution of some events in the dataset. We note that passes, pass receptions, and loose puck recoveries account for the majority of events in the data with a total of 65.1% of all events.

Further, we apply non-negative matrix factorization (NMF) to each feature vector using the NMF in the scikit-learn library for python [19] to reduce its dimensionality to a single component. Thus, after this operation, every skill is

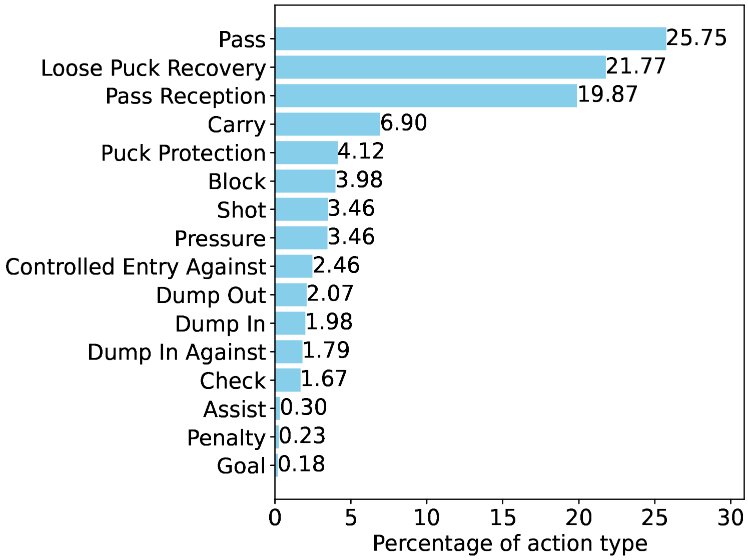


Fig. 1: Distribution on event frequency.

represented by one feature. Note that this operation leads to the fact that some values are higher than 1. Figs. 3a and 4a show the distributions of the values for the skills for defenders and forwards, respectively, using boxplots[3].

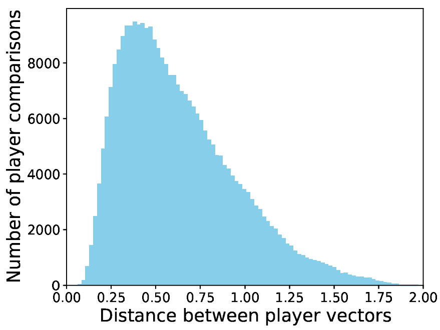
Finally, all features are concatenated together for each player, resulting in player vectors with 13 skill features for defenders and 18 skill features for forwards.

Figs. 2a and 2b display the distribution of the Euclidean distances between player vectors. As discussed before, defender vectors have length 13, while vectors for forwards have length 18. Each defender is compared to each other defender, and similarly for forwards. The distances between these vectors range from approximately 0.1 to 1.75 for both forwards and defenders. Most defenders fall within the range of 0.4 to 0.75, whereas forwards are typically found between 0.4 and 1.0.

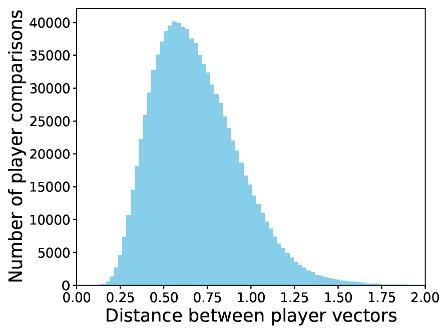
5 Playing Style Classification

Given the skill vectors for players, our aim is to generate different categories of playing styles. As we wanted to model that players can take on different

[3] The lower edge of the box represents the lower quartile value (25%) value, the (yellow) line in the box the median (50%) value, and the upper edge of the box the higher quartile (75%) value. The lower whisker shows the minimum value and the upper whisker the maximum value. Points below the lower whisker or above the upper whisker are outliers.

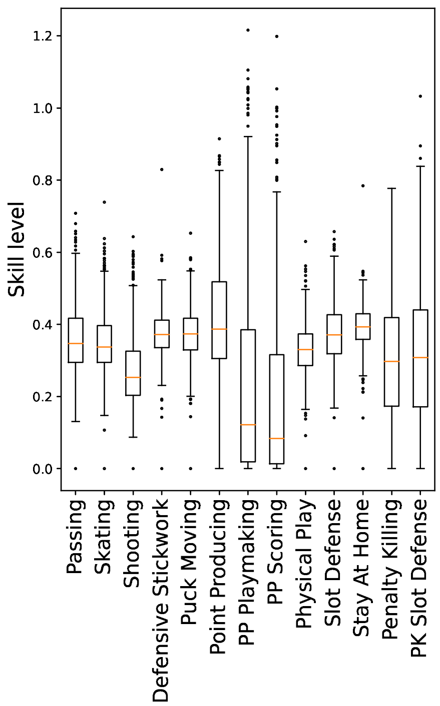


(a) Skill vectors for defenders.

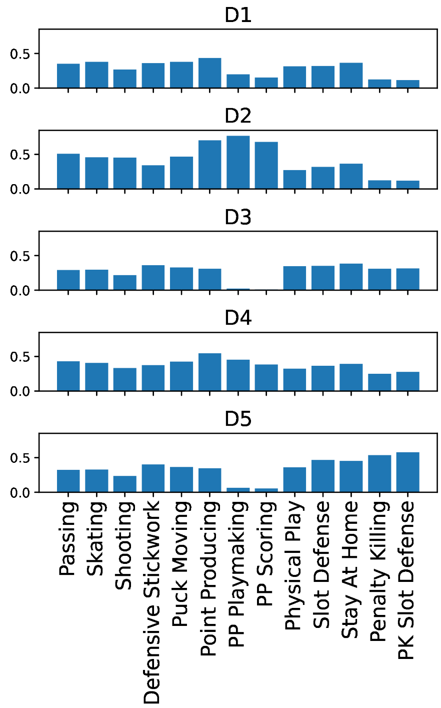


(b) Skill vectors for forwards.

Fig. 2: Distribution of Euclidean distances between player vectors.

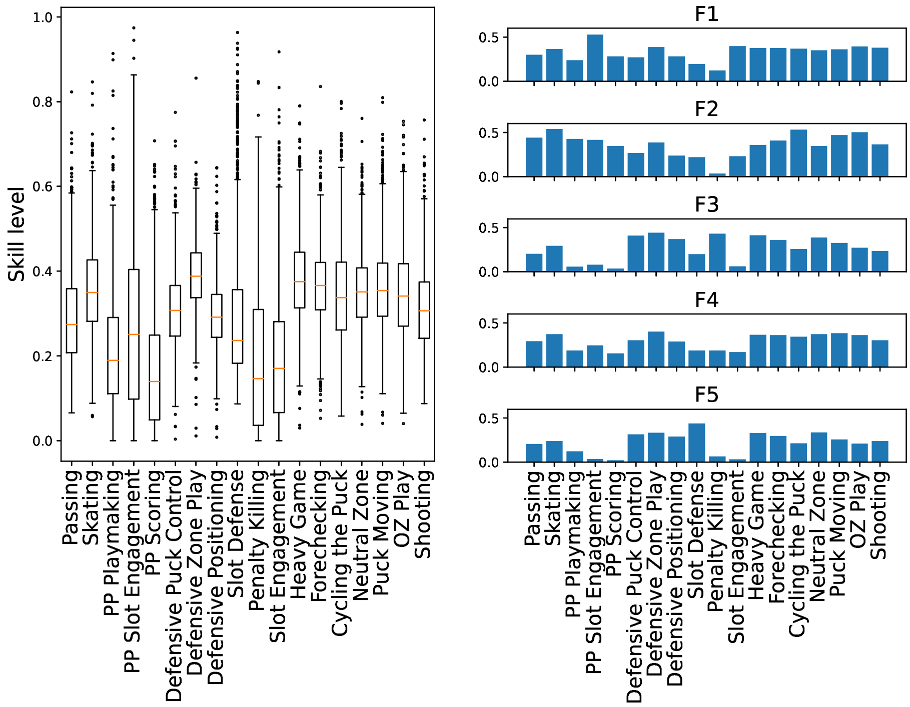


(a) Skill distribution (D).



(b) Cluster centroids (D).

Fig. 3: Skill distribution and centroid values (D).



(a) Skill distribution (F).

(b) Cluster centroids (F).

Fig. 4: Skill distribution and centroid values (F).

playing styles to certain degrees and that styles may have overlapping elements, we opted to use a fuzzy clustering approach. In this paper, we used the fuzzy c-means algorithm [5,1]. The objective in fuzzy c-means is to create k fuzzy partitions among a set of n objects from a data vector $\mathbf{x}$ by solving (1) until convergence.

$$\min_{\mathbf{U},\mathbf{C}} J_m = \sum_{i=1}^{n}\sum_{j=1}^{k} u_{ij}^m d^2(\mathbf{x}_i, \mathbf{c}_j) \quad s.t. \quad u_{ij} \in [0,1], \sum_{j=1}^{k} u_{ij} = 1 \tag{1}$$

In (1), d denotes the distance between object i and the j:th cluster centroid c_j. Further, u_{ij} is the degree of membership for object i to cluster j. The hyperparameter m controls the degree of fuzziness, where a higher m leads to a fuzzier solution. The fuzzy solution converges to the crisp solution when $m \to 1$. When $m \to \infty$ then $u_{ij} \to \frac{1}{k}$.

For the implementation of fuzzy c-means clustering the open source fuzzy-c-means package for Python was used [4]. We used the maximum possible number (1,000) of iterations. The hyperparameter m was set to 1.5, which was determined by calculating the Fuzzy Partition Coefficient (FPC) that indicates how well the model can divide the data points into clean clusters across different m-values. We investigated which value for k to use with different methods and decided to use 5.

The clustering resulted in five clusters for defenders and five clusters for forwards, where players have certain degrees of membership for each of the clusters of their role. In Tables 3 and 4 we show for each cluster the ten defenders and forwards, respectively, that have the highest degree of membership for that cluster. All of these degrees of membership for the top ten players are over 0.8.

Table 3: Clusters for defenders.

Cluster D1 (91 players)	Cluster D2 (229 players)	Cluster D3 (188 players)	Cluster D4 (128 players)	Cluster D5 (142 players)
S Forsmark (SHL)	R Murphy (AHL)	J Nyberg (SHL)	D Brickley (SHL/HA)	B Pachal (AHL)
H Skinner (AHL)	L Cormier (AHL)	A Söderberg (HA)	F Kral (AHL)	A Strand (AHL)
W Wallinder (SHL/AHL)	T Smith (AHL)	Y Kuznetsov (AHL)	E Sjöström (SHL/HA)	D Samorukov (AHL)
J Andersson (SHL)	L Mailloux (AHL)	K Lowe (SHL)	M Setkov (HA)	I Solovyov (AHL)
H Gabrielsson (HA)	C Carrick (AHL)	P Tischke (AHL)	S Åkerström (HA)	G Brisebois (AHL)
A Brandhammar (HA)	T Niemelä (AHL)	V Pulli (AHL)	M Björk (AHL/SHL)	M Kokkonen (AHL)
H Styf (HA)	A Lindelöf (HA)	J Lundegård (SHL)	K Johansson (HA)	W Aamodt (AHL)
C.J Lerby (SHL/HA)	J Laleggia (SHL)	L Jardeskog (HA)	J Jansson (HA)	M Karow (AHL)
Q Schmiemann (AHL)	A Kniazev (AHL)	H Falk (HA)	J McIsaac (AHL)	D Helleson (AHL)
J Brook (AHL)	J Pudas (SHL)	I Heens (SHL/HA)	O Nilsson (SHL)	S Santini (AHL)

To investigate which skills are important in the different clusters, we used the ten players with highest membership degree from each cluster to compute centroids for the clusters.

In Fig. 3b we show the values for the skills of the centroids in the defender clusters. As these values are based on the skill values of the players with top

Table 4: Clusters for forwards.

Cluster F1 (302 players)	Cluster F2 (359 players)	Cluster F3 (255 players)	Cluster F4 (243 players)	Cluster F5 (250 players)
T Barron (AHL)	L Larsson (SHL)	J Grönhagen (HA)	R Damiani (AHL)	M Strömwall (AHL/SHL)
M Westfält (SHL)	O Sillinger (AHL)	F Nilsson (SHL)	S Walker (AHL)	O Palve (SHL)
N Caamano (AHL)	R Elie (SHL)	F Barklund (HA)	N Todd (AHL)	M Ruohomaa (SHL)
N Jones (AHL)	A Räty (AHL)	J Devane (AHL)	R Marenis (HA)	D Holloway (AHL)
K MacLean (AHL)	J Kellman (SHL)	R Clune (AHL)	A Beckman (AHL)	D Tomasek (SHL)
M Marushev (AHL)	J Lauko (AHL)	R Muzik (SHL)	C Conacher (AHL)	J Looke (SHL/HA)
M O'Leary (AHL)	A Poganski (AHL)	O Pettersson (SHL)	A Andreoff (AHL)	A Petersson (SHL)
B Maxwell (SHL)	G Meireles(AHL)	J Joshua (AHL)	J Doan (AHL)	A Louis (AHL)
T Kaspick(AHL)	P Carlsson (SHL)	K Gabriel (AHL)	B McCartney (AHL)	M Modigs (HA)
J Labate (AHL)	E Desnoyers (AHL)	I McKinnon (AHL)	S Wright (AHL)	L Bristedt (SHL)

membership degrees, they can be seen as the skill levels representing the playing style for a prototypical player for that cluster.[4] Defenders in D1 do not excel in any particular skill, but they also do not rank the worst in any category. The skills with the highest values are those that facilitate point production and puck movement, which suggests a somewhat more offensive than defensive role in the team. D2 defenders are the most offensively skilled defenders that significantly outperform other defenders in point producing and powerplay skills. These defenders show lower values in the defensive skills such as physical play and penalty killing skills. D3 is comparable to D5 in terms of overall defensive capabilities, although D3 defenders demonstrate lower values in all skills than D5 defenders. This suggests that D3 players are more defensive-minded, but not necessarily the top defensive performers. Further, D4 shows high values overall in all skills but excel the most in passing, point producing and powerplay playmaking. This indicates that these defenders can play both in powerplay and boxplay as they excel both in the defense and offense. The strengths for D5 are penalty killing where they have the highest skill level of all playing styles. D1 also has high values in defensive skills such as defensive stickwork, physical play, slot defense and stay at home. D5 shows lower values in more offensive skills such as passing, skating, shooting, puck moving, and point producing. The powerplay skills are almost non-existent indicating that most of these players do not play in powerplay.

In Fig. 4b we show the values for the skills of the centroids in the forwards clusters. The F1 forwards show high values across all skills, with the highest skill level observed in powerplay slot engagement. This indicates that F1 forwards excel in both defensive and offensive skills. F2 forwards are the offensively skilled players with high values in skating, cycling the puck, and offensive zone play, as well as powerplay skills. F3 forwards demonstrate higher values in defensive skills and lower in the offensive skills. F3 also obtains the highest skill level in boxplay out of all playing styles. F4 shows similar skill values as F1 except a bit

[4] The histogram visualization for the values for the centroids for the clusters would show a similar shape if we would have taken the average values of all players in the clusters instead of the average values for the top 10 players in the clusters, although the peaks would be lower. This is also the case for the forward clusters.

lower powerplay skills exchanged for a bit higher boxplay skills. F4 shows decent skill levels in both the offense and the defense. F5 forwards demonstrate lower offensive values together with decent defensive skill levels. F5 has the highest value of all forwards in slot defense indicating a lot of ice time in the defensive zone.

6 Conclusion

In this paper we represented the playing styles for ice hockey defenders and forwards based on skill sets. The skills were computed based on event data. Further, we used fuzzy clustering to define five types of playing styles each for defenders and forwards and showed typical skill levels and example players for these playing styles. This information can be used for scouting and game preparation.

As future work, we will define a new similarity between players based on their membership values to the playing style clusters. This will not only allow for finding players with the same main playing style, but also where the secondary styles are similar. Further, we will investigate in other clustering methods such as Gaussian Mixture Models.

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