Not all goals are equally important - a study for the NHL

Jon Vik, Min-Chun Shih, Rabnawaz Jansher,
Niklas Carlsson, Patrick Lambrix

Linköping University, Sweden*†

Abstract

The evaluation of player performance is an important topic in sport analytics and is used by coaches for team management, in scouting and in sports broadcasts. When evaluating the performance of ice hockey players many metrics are used, including traditional metrics such as goals, assists, points and modern metrics such as Corsi. One weakness of such metrics is that they do not take into consideration the context in which the value for the metric was assigned. For instance, when a player scores a goal, then the value of the goals metric for that player is raised by one, regardless of the importance of the goal. In this paper, we introduce new variants of classical metrics based on the importance of the goals regarding their contribution to team wins and ties. Further, we investigate using play-by-play data from the 2013-2014 NHL season how these new metrics relate to the classical metrics and which players stand out with respect to important goals.

1 Introduction

When evaluating the performance of ice hockey players, it is most common to use metrics that attribute a value to the actions the player performs (e.g., scoring a goal for the goals metric or giving a pass that leads to a goal for the assists metric) and then compute a sum over all those actions. Some extensions to these traditional metrics have been proposed, e.g., for the +/- metric [7, 1]. There is also work on combining metrics such as in [2]. Some of the approaches for player performance metrics take game context into account such as event impacts [11]. Other works model the dynamics of an ice hockey game using Markov games where two opposing sides (e.g., the home team and the away team) try to reach states in which they are rewarded (e.g., scoring a goal) [14, 3, 9, 12, 13, 5, 10, 6]. An approach to predict the tier (e.g., top 10%, 25% or 50%) to which a player belongs is presented in [4].

Although some metrics take context into account for goals, e.g., the location of the shot, few take into account the importance of goals. For instance, a goal scored when

*Contact: niklas.carlsson@liu.se, patrick.lambrix@liu.se

†Presented at 8th MathSport International 2021.

the team is in the lead with 9–2 at the end of the game is most likely not crucial for winning. In contrast, scoring a goal when the score is tied at 2–2 with fifteen seconds left of the game is of more importance for winning.

Furthermore, some players have a reputation to often make important goals, while others may have the reputation to mainly score when the team is playing 'easier' games. For instance, during the 2013-2014 season the Washington Capitals' Alexander Ovechkin ranked the highest regarding game-tying and lead-taking goals while he only ranked 29th regarding goals scored when the team is already in the lead.

The importance of goals was taking into account in the added goal value metric in [8] and in this paper we introduce variants of the classical goals, points[1], assists and +/- metrics that take into account the importance of the goals.

2 Game points importance value

As a basis for our new metrics we need to formally define the importance of a goal. Our intuition is that the importance of the goal represents the change in probability of the team taking points for the game before and after the goal has been scored.[2] As we only look at regulation time, in the NHL the team can earn 2 points for a win, 1 for a tie and 0 for a loss.[3]

First, we define the probability of an outcome given a context, where outcome is one of win, tie, or loss, as the ratio of the number of occurrences of the context given the outcome and the number of occurrences of the context in our data set.

$$P(outcome \mid context) = \frac{Occ(context \mid outcome)}{Occ(context)} \tag{1}$$

In our experiments the context is defined by time (t) in one second intervals, goal differential (GD) and manpower differential (MD).

We attribute a game points importance value (GPIV) to a context. Intuitively, the GPIV represents how much a goal in a particular context increases or decreases the expected game points taking into account that a win gives 2 points, while a tie gives 1 point. When a goal is scored the context after the goal (context AG) has the same time as the context before the goal (context BG), but the GD is changed by one and the MD may (minor penalty power-play goal) or may not change (even strength, short-handed, or major penalty power-play goal).

$$\begin{aligned} GPIV(context) = {} & 2 * [P(win \mid contextAG) - P(win \mid contextBG)] \\ & +1 * [P(tie \mid contextAG) - P(tie \mid contextBG)] \end{aligned} \tag{2}$$

[1]Defined as the number of goals plus the number of assists for the player and often denoted by P. In this paper we also use the points a team receives for a win or a tie, which are used to produce a ranking of the teams, often denoted by PTS. To avoid confusion, we call this latter kind of points 'game points'.

[2]In [8] only the change in win probability is considered.

[3]When taking overtime into account, an extra point will be distributed to the winner in overtime for a game that was tied in regulation time. Therefore, in the NHL a team is awarded 2 points for a win (in regulation time or overtime), 1 point for a loss in overtime, and 0 points for a loss in regulation time. The distribution of points can be different in other leagues, e.g., in the SHL (Sweden) 3 points are always awarded for each game.

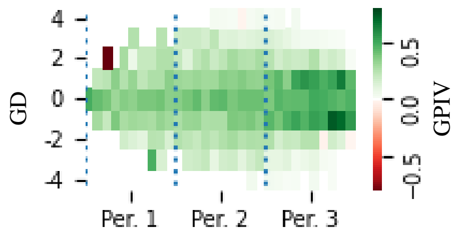


Figure 1: GPIV versus GD. Each bin is two minutes. Less than three observations for each bin are left out.

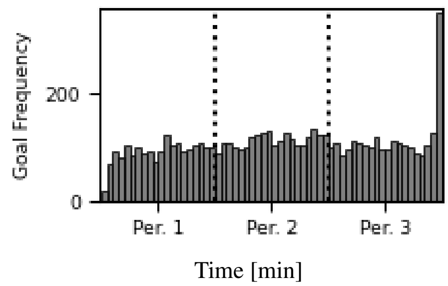


Figure 2: Goal frequency for each minute of the first three periods in the NHL during the 2013-2014 season.

From Fig. 1 we note that the value of GPIV is high when the GD is between -1 and 1 at the end of the third period, as scoring then will tie the game (going from 0 to 1 game point) or result in a 1 or 2 goals lead (going from 1 to 2 points for GD = 0, or strengthening the probability of the win for GD = 1). However, as the scoring frequency in the last minute is three times higher than at any other arbitrary minute in the game (see Fig. 2), this increase in GPIV may not be as high as expected.

Scoring goals is not always positive for the probability of taking game points. We noted that taking a 2 or 3 goal lead early in the game may have negative consequences. This could be explained by the possibility of the leading team becoming too complacent with a comfortable lead. In general, negative consequences were limited to the first period or special MD cases in the beginning of the second period.

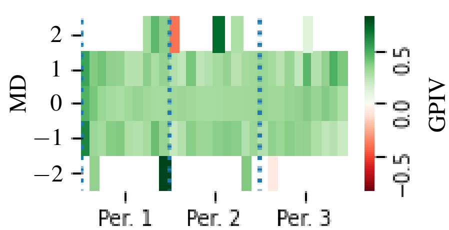


Figure 3: GPIV versus MD. Each bin is two minutes. Less than three observations for each bin are left out.

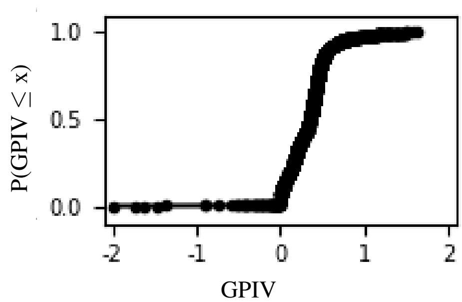
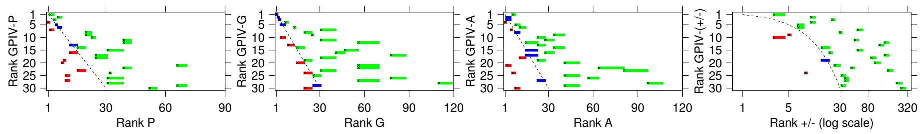


Figure 4: Cumulative distribution function of GPIV.

In contrast to GD, MD does not seem to have as much influence on the GPIV, except for some goal scoring with MD = 2 or -2 (See Fig. 3).

In Fig. 4 we see that the probability of a negative GPIV is 0.02. Nearly 82% of all GPIV range between 0 and 0.5. Further, 18% of the GPIVs range from 0.5 to 1.64. What is interesting with this last group is that they have the same or greater GPIV (0.5) as typical game deciding goals scored in overtime (which results in the team directly



(a) Points (P) (b) Goals (G) (c) Assist (A) (d) Plus-minus (+/-)

Figure 5: Rank comparisons. Here, colors are used to show players that see improved (green), similar (blue), and reduced (red) ranking when using the weighted metrics.

being awarded an extra point instead of - on average - getting the extra point with probability 0.5).

3 GPIV-weighted performance metrics

We define new variants of the classical metrics goals (G), assists (A), points (P) and +/- which we call GPIV-G, GPIV-A, GPIV-P and GPIV-+/-, respectively. In the classical metrics the value is raised by 1 when a goal is scored (for G and P), an assist is giving to a goal (for A and P) or the player is on the ice when a goal is scored (for +/-). For the latter when a goal is scored by the opposing team the value is decreased by 1. For the variants of the metrics, instead of raising or decreasing by 1, we raise or decrease the value by the GPIV of the goal. The new metrics value the amount of goals as well as the importance of goals. Some of the highest ranked players are involved in many goals, while others may be involved in fewer goals, but with higher importance.

One way to compare the classical metrics and their new variants is to compute their correlations. For P and GPIV-P the maximal information coefficient is 0.765, the Pearson correlation coefficient is 0.944 and Spearman's rank correlation coefficient is 0.949. For the correlations between +/- and GPIV-+/- the values were 0.384, 0.769, and 0.750, respectively. The much weaker correlation for the +/- metrics is also illustrated in Fig. 5. Here, we use colors to show the top 30 players according to the GPIV-based metrics that see increased, same, or reduced rank with the GPIV-based metrics compared to the classical metrics.

Another way to check whether metrics are reasonable is to perform the eye test. Looking closer at the results[4], several players stand out. First, Alex Ovechkin went from a rank of tied for 6-7 (P) to being ranked 2^{nd} (GPIV-P) when using the weighted points. This is a considerable difference in rank, but can be explained by the many important goals he scored that season. For example, as mentioned already in the introduction, Alexander Ovechkin had the most game-tying and lead-taking goals while he only ranked 29$^{\text{th}}$ regarding goals scored when the team is already in the lead.

Other players on the top-10 list that saw significant increases in their relative point-based rankings where Blake Wheeler (Winnipeg Jets), Anze Kopitar (LA Kings), and Eric Staal (Caroline Hurricanes). Similar to Alexander Ovechkin, the last two of these are players that have proven they can take their game to the next level during the playoffs (when goals are tougher to get by and each goal is typically considered of greater

[4] Tab. 1 shows the top 10 players with respect to GPIV-P. The complete results for the 2013-2014 season for GPIV-G, GPIV-A, GPIV-P and GPIV-+/- are available at `https://www.ida.liu.se/research/sportsanalytics/projects/conferences/MathSport-21/`.

Table 1: Top-10 players according to GPIV-P with rank according to traditional points (P-rank), rank according to GPIV-weighted points (GPIV-P-Rank), the difference between these ranks (Rank-diff), the player name (Player) and position (Position), the points (P) and the GPIV-weighted points (GPIV-P).

P-Rank	GPIV-P-Rank	Rank-diff	Player	Position	P	GPIV-P
2-3	1	1	Sidney Crosby	C	69	25.734
6-7	2	4	Alex Ovechkin	R	64	25.085
4	3	1	Joe Pavelski	C	67	23.467
1	4	-3	Tyler Seguin	C	70	22.259
5	5	0	Phil Kessel	R	66	22.006
6-7	6	0	Ryan Getzlaf	C	64	21.366
2-3	7	-5	Corey Perry	R	69	20.803
20-22	8	12	Blake Wheeler	R	51	20.295
20-22	9	11	Anze Kopitar	C	51	19.812
23-24	10	13	Eric Staal	C	50	19.791

value). For example, these three players have all won the Stanley Cup (Ovechkin 2018, Kopitar 2012 and 2014, and Staal 2006) and all had the most points or goals during the playoffs of all players in the league during the years they won the Stanley Cup. Furthermore, all four these players are or have been captains of their respective teams (including Wheeler).

In general, we see many Stanley Cup winners on the top-10 list (8 out of 10), as only Pavelski (rank 3) and Wheeler (rank 8) have not won the Stanley Cup. However, both these players have been known for their high compete level and are both considered game changing players.

A closer look at the top-30 lists for the GPIV-based points, goals, assist, and +/- metrics reveals many other names that saw substantial increases in their relative rankings. In most cases, these players can typically be labeled as players known to have seen great success in the playoffs, for being strong two-way players, or that are remembered for having been game changers for at least part of their career.

4 Conclusions

In this paper we introduced new variants of the classical metrics goals, assists, points and +/- by taking into account the context in which goals are scored. The new metrics weigh goals regarding the change in probability of obtaining game points. The new metrics pass the eye test.

For future work we will compute the newly introduced metrics for other NHL seasons. It will be interesting to see whether the observations of the 2013-2014 season regarding the new metrics will also be observed in the other seasons. We also want to see whether trends for players in the classic metrics will be followed by the new metrics.

References

[1] R Gramacy, S Jensen, and M Taddy. Estimating player contribution in hockey with regularized logistic regression. *JQAS*, 9:97–111, 2013.

[2] W Gu, K Foster, J Shang, and L Wei. A game-predicting expert system using big data and machine learning. *Expert Sys with Appl*, 130:293–305, 2019.

[3] E Kaplan, K Mongeon, and J Ryan. A Markov Model for Hockey: Manpower Differential and Win Probability Added. *INFOR*, 52(2):39–50, 2014.

[4] T Lehmus Persson, H Kozlica, N Carlsson, and P Lambrix. Prediction of tiers in the ranking of ice hockey players. In *MLSA 2020*, pages 89–100, 2020.

[5] G Liu and O Schulte. Deep reinforcement learning in ice hockey for context-aware player evaluation. In *IJCAI*, pages 3442–3448, 2018.

[6] D Ljung, N Carlsson, and P Lambrix. Player pairs valuation in ice hockey. In *MLSA 2018*, pages 82–92, 2019.

[7] B Macdonald. A Regression-Based Adjusted Plus-Minus Statistic for NHL Players. *JQAS*, 7(3):Article 4, 2011.

[8] S Pettigrew. Assessing the offensive productivity of NHL players using in-game win probabilities. In *MIT Sloan Sports Analytics Conference*, 2015.

[9] K Routley and O Schulte. A Markov Game Model for Valuing Player Actions in Ice Hockey. In *UAI*, pages 782–791, 2015.

[10] C Sans Fuentes, N Carlsson, and P Lambrix. Player impact measures for scoring in ice hockey. In *MathSport*, pages 307–317, 2019.

[11] M Schuckers and J Curro. Total Hockey Rating (THoR): A comprehensive statistical rating of National Hockey League forwards and defensemen based upon all on-ice events. In *MIT Sloan Sports Analytics Conference*, 2013.

[12] O Schulte, M Khademi, S Gholami, Z Zhao, M Javan, and P Desaulniers. A Markov Game model for valuing actions, locations, and team performance in ice hockey. *Data Min Knowl Disc*, 31(6):1735–1757, 2017.

[13] O Schulte, Z Zhao, M Javan, and P Desaulniers. Apples-to-apples: Clustering and Ranking NHL Players Using Location Information and Scoring Impact. In *MIT Sloan Sports Analytics Conference*, 2017.

[14] A Thomas, S Ventura, S Jensen, and S Ma. Competing Process Hazard Function Models for Player Ratings in Ice Hockey. *Ann Appl Stat*, 7(3):1497–1524, 2013.