Split personalities of NHL players: Using clustering, projection and regression to measure individual point shares

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Abstract

Recent literature in hockey analytics has considered the use of clustering to determine specific categories or types of NHL players. Regression analysis has then been used to measure the contribution of each of these player types to team performance. This paper uses a combination of clustering, projection and regression methods to individualize the classification of NHL players. Instead of assigning each player to only one type, the overall "personality" of the player is split into fractional components representing different player types. The result is a unique make-up for each player, which is used to quantify his individual contributions to his team's performance, a metric known as "point shares". Top ranked players in terms of point shares tend to be winners of major NHL awards, are leaders in scoring, and have the highest salaries. High point shares in a contract year may also factor into salary increases. Overall, a better understanding of individual NHL player characteristics may provide a foundation for deeper, data-driven player analysis.

1 Introduction

Determining the "value" of a professional athlete plays a major role in the determination of salaries, trades, and playing time. One way to measure this quantity is to quantify a player's individual contribution to the overall performance of his or her team. In the NHL, the contribution of a player to his team's performance can be quantified as the number of points his team earns over the course of a season that can be attributed to the player. For example, a player that contributes 10 points to his team's point total on the season is responsible for five wins. This idea is analogous to the concept of "win shares", developed by Bill James for baseball [1], where a player is measured according to the number of wins for which the player is directly responsible. Win shares have also been calculated for basketball [2]. In hockey, the win shares concept has been adapted to "point shares" [3], which is illustrated by the example above.

Recently, one study attempted to quantify the contribution of NHL players to their teams' performance in terms of point shares by using clustering and regression [4]. First, *k*-means clustering was used to identify four types of forwards (Top Line, Second Line, Defensive, Physical), four types of defensemen (Offensive, Defensive, Average, Physical), and three types of goalies (Elite, Average, Bottom). Using post-lockout (2005-2010) data, each player was classified as one of these types. Then, a multiple linear regression was conducted where the numbers of players of each type on a team were the independent variables (adjusted by time-on-ice), while the number of team points earned during the season was the dependent variable. A value was calculated for each player type that represented the contribution of a player of that type to his team's points, if he played every minute of every game in the season. We refer to this metric as "full point shares" or FPS. By multiplying a player's FPS value with his time-on-ice as a fraction of the total ice time in a season, a point shares (PS) value was calculated. While this study generated new player types and FPS values that could be compared across types, there were two limitations of the approach. First, comparisons between players of the same type were limited because players of the same type had the same FPS value. Second, some types were not statistically significant in the regression, and therefore were not associated with an FPS value (i.e., the FPS value of those player types was 0).

In this paper, we develop a new method to determine individualized FPS values for NHL players. We build on the previous study [4] and address the two limitations described above. Instead of classifying each player as one specific player type, we generate a proportional representation of the player among all of the possible player types for his position. In other words, a player previously clustered as a Top Line F may now be represented as a 40/25/20/15 split between the Top Line F/Second Line F/Defensive F/Physical F types. This composite representation also ensures that each player will get a nonzero FPS value, as his FPS value will be a weighted combination of the FPS values of the player types. Our method adds a projection component to the aforementioned clustering and regression approach, so we refer to our method as the Clustering-Projection-Regression (CPR) method for determining NHL player point shares.

2 Clustering background and motivation

We provide a brief background on clustering that will be useful in the development of our CPR method. Suppose each forward is plotted as a point in n-dimensional space according to an n-dimensional vector of his statistics. For example, Sidney Crosby from 2009-2010 can be represented as the six-dimensional vector [51 goals, 58 assists, 15 +/–, 63 Hits, 43 Blocks, 71 PIM], or equivalently, as a vector using the same statistics but first normalizing based on time-on-ice, and then standardized by subtracting the mean and dividing by the standard deviation of the normalized statistics over all forwards (this was the method used in [4]). The k-means clustering method [5] then attempts to group these points into k disjoint sets based on measures of similarity between points within a set and differences between points across sets. Loosely speaking, points that are nearby (i.e., players with similar statistics) will be clustered together. Each cluster is defined by a centroid and points are classified based on their distance to the closest centroid. In principle, a point that is almost equidistant from all k centroids, but slightly closer to centroid 1, would be clustered as type 1. However, in hockey terms, forcing this player to be a 100% type 1 player may be misrepresenting his true, individual personality. Consider Ryan Kesler, who is currently the second line center of the Vancouver Canucks, and who plays on the first power play unit as well as the first penalty kill unit. By virtue of his ability to play in very different game situations, classifying him as one specific player type may not adequately represent his versatility.

3 Clustering-Projection-Regression method

In the CPR method, instead of classifying a player according to only one type, we imagine each player as being a weighted combination of the player types associated with that player's position. Each player will be represented as a k-dimensional vector (k = 4 for forwards and defensemen, k = 3 for goalies; see Table 3 in the Appendix for the player types for each position), whose fractional components sum up to 1 and which represent the composition of the player according to the k player types for his position. This method is a generalization of the previous clustering method of [4], where each player was represented as a k-dimensional unit vector.

First, we present a high level overview of the method and then detail the specific steps afterwards. We assume the clustering of players and subsequent regression is carried out as described in [4]. As output from that step, we have the player types and FPS values shown in Table 3 of the Appendix, as well as the coordinates of all cluster centroids. For a given player, to generate his proportional representation across all the player types, we conduct a series of pairwise comparisons between two types, using their centroid coordinates. The player is projected on to the line that joins the two cluster centroids, and the distance of this projected point to both centroids is measured. Based on the distances, the player is assigned a percentage split between the two types (e.g., 60% Top Line and 40% Second Line if the forward is closer to the Top Line cluster centroid). With k clusters, $k(k-1)/2$ comparisons are made. Once all comparisons are completed, the percentages across all comparisons involving a particular type (e.g., Top Line F) are averaged. The percentages are normalized so that the fractional components of the player sum to one. Lastly, an FPS value is calculated by taking a weighted average (based on the fractional representation) of the FPS values of the player types.

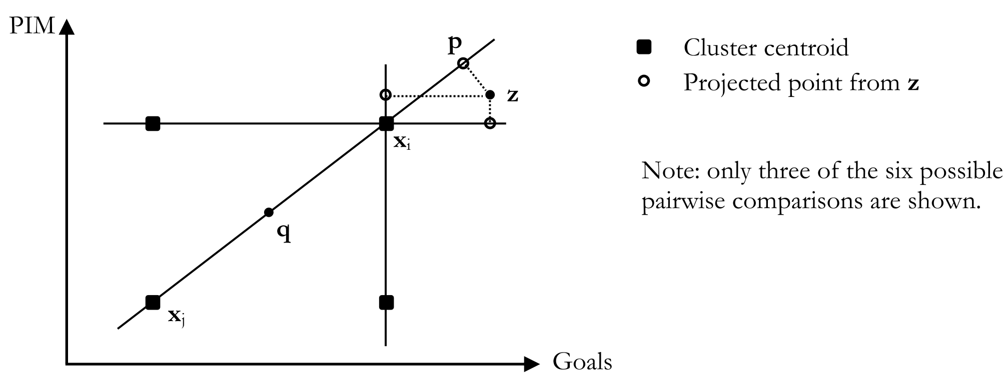

Figure 1. Illustration of the projection aspect of the CPR method.

The specific steps are described next. Bold letters denote vectors. To make things concrete, imagine the steps below as being applied to a forward player, who is initially represented as a vector of six statistics and who will ultimately be transformed into vector of four player types. For defensemen and goalies, the steps are identical, except the number of defining statistics and player types will differ. Figure 1 illustrates the projection aspect of the CPR method.

Step 1: Let $\mathbf{z}$ be a player in the n-dimensional space of clustering statistics. Consider the comparison between cluster i and j, whose centroid coordinates are denoted $\mathbf{x}_i$ and $\mathbf{x}_j$, respectively. Let $\mathbf{d} = \mathbf{x}_i - \mathbf{x}_j$.

Step 2: Project $\mathbf{z}$ on to the line joining $\mathbf{x}_i$ and $\mathbf{x}_j$ (the point $\mathbf{p}$ in Figure 1), using the equations:

$$\mathbf{p} = \mathbf{x}_j + \lambda\mathbf{d}, \qquad \text{where} \qquad \lambda = (\mathbf{d}^T\mathbf{z} - \mathbf{d}^T\,\mathbf{x}_j)/\mathbf{d}^T\mathbf{d}.$$

Step 3: Let $\mathbf{q}$ be the midpoint of $\mathbf{x}_i$ and $\mathbf{x}_j$. Compute

$$\gamma = \frac{1}{1+e^{-\alpha\|\mathbf{p}-\mathbf{q}\|_2}} = \frac{1}{1+e^{-\alpha\sqrt{\sum_{l=1}^{n}(p_l - q_l)^2}}}.$$

Let s_{ij} denote the proportion of the player that is of type i, when conducting the i-j comparison. If $\mathbf{x}_i$ is closer to $\mathbf{p}$ than $\mathbf{x}_j$, then $s_{ij} = \max\{\gamma,1-\gamma\}$ and $s_{ji} = \min\{\gamma,1-\gamma\}$. The assignments are reversed if $\mathbf{x}_j$ is closer to $\mathbf{p}$ than $\mathbf{x}_i$. If both $\mathbf{x}_i$ and $\mathbf{x}_j$ are equidistant from $\mathbf{p}$, then $s_{ij} = s_{ji} = 0.5$.

Step 4: Repeat Steps 1, 2, and 3 for all remaining pairwise comparisons. Then, for each cluster i, compute

$$r_i = \frac{1}{k-1}\sum_{j=1,\, j\neq i}^{k} s_{ij}\,.$$

Step 5: Normalize the vector $\mathbf{r}$ so its components sum to 1. Denote the new vector $\mathbf{R}$, with components

$$R_i = \frac{r_i}{\sum_{i=1}^{k} r_i}.$$

Step 6: Let β_i be the FPS value associated with player type i. Then, the FPS value of the player is

$$\text{FPS} = \sum_{i=1}^{k}\beta_i R_i\,.$$

Notes: The equations in Step 2 are derived from the projection equations of a point on to a line [6]. The parameter α is a tunable parameter. One way to choose α would be to achieve a desired value of $\max\{\gamma,1-\gamma\}$ when $\mathbf{p}$ coincides with one of the cluster centroids in any given pairwise comparison. For example, if it is desired that a player should be 75% cluster i and 25% cluster j when $\mathbf{p} = \mathbf{x}_i$, then set $\gamma = 0.75$ and $\mathbf{p} - \mathbf{q} = (\mathbf{x}_i - \mathbf{x}_j)/2$ in the equation defining γ in Step 3, and solve for α. For a given γ value, a different α may be needed for each i-j comparison. In the results below, we set α for each i-j comparison as described above using the target value $\gamma = 0.75$.

4 Results

We gathered statistics for each forward, defenseman and goalie who played in any NHL regular season from 2005-2006 to 2009-2010. In each season, only the top 75% of players in terms of time-on-ice were kept. The k-means clustering and regression were conducted exactly as described in [4], which resulted in the 11 player types and FPS values shown in Table 3 in the Appendix. Using the CPR method, we generated a proportional representation for each player in each season (Steps 1-5), and then computed his specific FPS value (Step 6). We then computed PS values by multiplying his FPS value with his total playing time that season, divided by the total number of minutes in the season.

Tables 1 and 2 show the top 10 forwards in 2009-2010 ranked by FPS and by PS achieved during the season, respectively. Recall that the FPS value indicates how many points a player would generate for their team if they played every minute of every game, whereas the PS value is based on actual playing time. In other words, FPS values can be thought of as contributions that are normalized for playing time, whereas PS values depend on total playing time. The top three players in FPS (note the five-way tie for second place) Alex Ovechkin, Sidney Crosby, and Henrik Sedin were all nominated for or won major individual awards that season. Ovechkin won the Ted Lindsay Award (most outstanding player, determined by the NHL Players' Association), Crosby co-won the Rocket Richard Trophy (most goals), and H. Sedin won the Hart Memorial Trophy (MVP, determined by the Professional Hockey Writers' Association) and Art Ross Trophy (most points). Note that Ovechkin does not appear on the top 10 PS list because he missed 10 games that season. Interestingly, that may have been a contributor to his winning the Lindsay Award, since he was not far behind H. Sedin in the points race despite missing those 10 games. These results suggest that the CPR method objectively ranks players similarly to those who vote on the major awards, which is often a subjective activity. It is interesting (though perhaps not surprising) to note that twins Henrik and Daniel Sedin have almost identical compositions. Co-winner of the Richard Trophy, Steven Stamkos, appears in the top 10 PS list, along with players who were either the leading or second leading scorers on their respective teams.

Table 1. Top 10 forwards from 2009-2010 ranked by full point shares.

Rank	Name	Salary ($M)	GP	TOI (min.)	Top %	Sec. %	Def. %	Phys. %	FPS	PS
1	Alex Ovechkin	9.5	72	1568	50.0	28.2	13.0	8.8	22.5	7.1
2	Sidney Crosby	8.7	81	1778	49.8	26.2	15.1	8.9	22.4	8.0
3	Henrik Sedin	6.1	82	1614	50.0	28.0	12.8	9.2	22.4	7.3
4	Alexander Semin	4.6	73	1396	50.0	27.6	13.4	9.0	22.4	6.3
5	Nicklas Backstrom	2.4	82	1676	49.7	25.6	15.8	8.9	22.4	7.5
6	Daniel Sedin	6.1	63	1205	50.0	28.2	12.6	9.2	22.4	5.4
7	Patrick Kane	3.7	82	1573	49.5	27.1	14.4	9.0	22.3	7.1
8	Ales Hemsky	4.1	22	395	49.5	25.9	15.6	9.0	22.3	1.8
9	Marian Hossa	5.2	57	1067	49.2	26.7	15.0	9.1	22.3	4.8
10	Marian Gaborik	7.5	76	1614	48.6	26.3	16.0	9.1	22.2	7.2

Table 2. Top 10 forwards from 2009-2010 ranked by point shares.

Rank	Name	Salary ($M)	GP	TOI (min.)	Top %	Sec. %	Def. %	Phys. %	FPS	PS
1	Sidney Crosby	8.7	81	1778	49.8	26.2	15.1	8.9	22.4	8.0
2	Martin St. Louis	5.3	82	1788	41.2	29.1	20.1	9.6	21.4	7.7
3	Patrick Marleau	6.3	82	1738	46.3	26.7	17.3	9.7	21.9	7.7
4	Nicklas Backstrom	2.4	82	1676	49.7	25.6	15.8	8.9	22.4	7.5
5	Steven Stamkos	3.7	82	1685	47.3	26.2	17.2	9.3	22.1	7.5
6	Ilya Kovalchuk	6.4	76	1675	47.5	27.3	15.9	9.3	22.1	7.4
7	Henrik Sedin	6.1	82	1614	50.0	28.0	12.8	9.2	22.4	7.3
8	Anze Kopitar	6.8	82	1786	34.7	29.8	22.9	12.6	20.2	7.3
9	Brad Richards	7.8	80	1668	42.7	29.9	18.0	9.4	21.6	7.3
10	Marian Gaborik	7.5	76	1614	48.6	26.3	16.0	9.1	22.2	7.2

Tables 4 – 7 in the Appendix list the top 10 defensemen and goalies by FPS and PS for 2009-2010 and are accompanied by additional discussion on player performance. Table 8 lists the top 10 players by PS for seasons prior to 2009-2010.

Figure 2 shows a scatter plot of the defensemen from 2009-2010 comparing their "Offensive" (x-axis) and "Defensive" (y-axis) proportions. Duncan Keith beat Mike Green for the Norris Trophy (top defenseman) in 2009-2010, and was part of the Stanley Cup winning Chicago Blackhawks that year. Also, Keith was arguably the best defenseman for Canada in the 2010 Olympics en route to a gold medal, while Green was not selected for the team. At the time, Green's defensive ability was questioned by many. Figure 3 confirms that Green was less defensively oriented compared to Keith. Another interesting observation is that Erik Johnson, Jason Demers and Drew Doughty, who were all young and upcoming defensemen, demonstrated a relatively high offensive orientation, which supports a conventional belief that strong defensive skills take more time to develop than offensive skills. A defender like Shane O'Brien, while clearly not on the efficient frontier of the Offensive/Defensive trade-off curve, contributes primarily through physical play. Mike Komisarek is a prime example of the physical, defensive defenseman (Physical = 33%, Defensive = 42%).

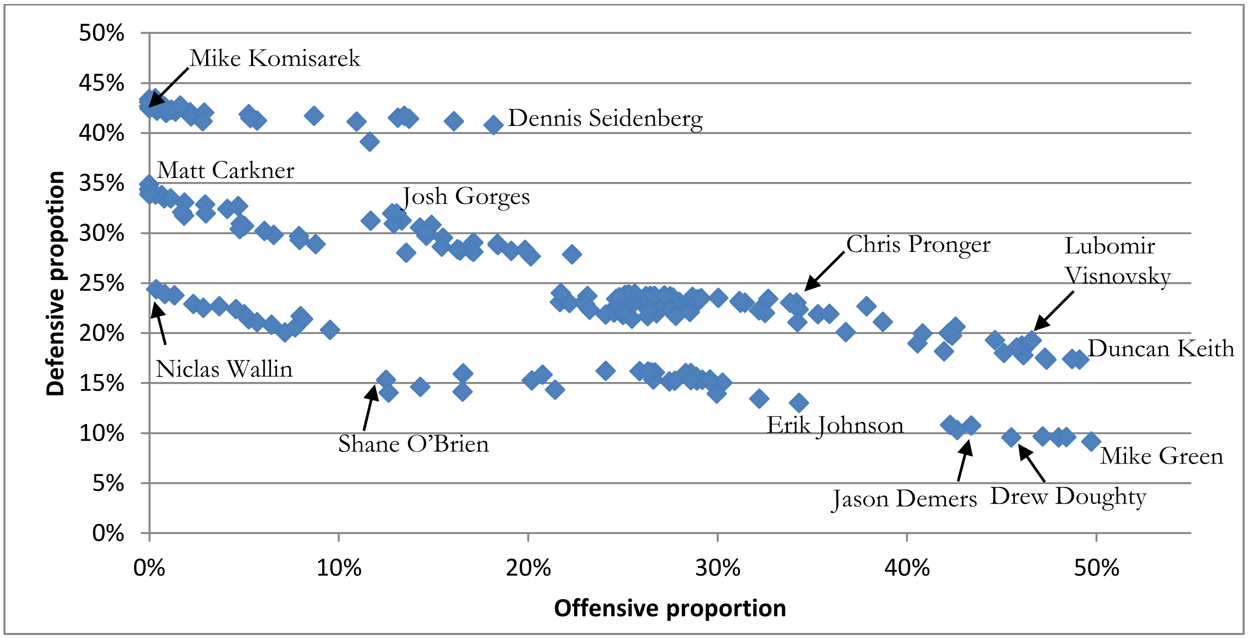

Figure 2. Offensive and defensive orientations of defensemen from 2009-2010

Figure 3 shows a scatter plot of forwards from the 2009-2010 season. On the x-axis, each forward's expected point shares (EPS) is plotted. We define EPS as point shares divided by games played, multiplied by 82 games. This quantity is similar to FPS, except that instead of a player playing every minute of every game, the player is playing every game at their average time-on-ice. EPS can be used to account for games missed due to injury. On the y-axis, each forward's salary cap hit (total salary over life of contract divided by number of years of contract) is shown. Figure 3 shows a positive relationship between EPS and cap hit. In fact, there seems to be a nonlinear growth in salaries as expectations of performance increase. This may be due to the relatively inelastic demand for "superstar" players, whose services require a premium in pay. Vincent and Eastman [7] use cluster analysis to show that players who are more offensively oriented earn more, an observation that is supported here.

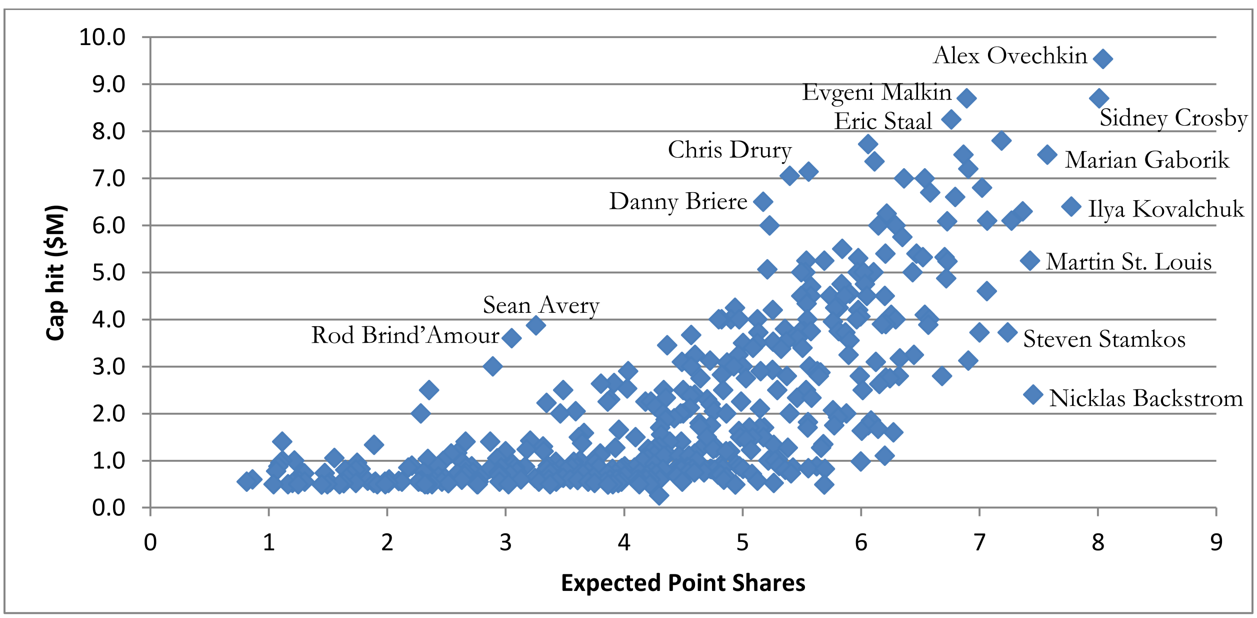

Figure 3. Salary cap hit and expected performance of forwards in 2009-2010.

Does strong performance in a contract year (the last year in the player's current contract) impact the next contract's salary? Figure 4 explores this question. Point share values for forwards from the 2009-2010 season are shown on the x-axis, while changes in relative cap hit are shown on the y-axis. The change in relative cap hit for each player is calculated as (2010-2011 cap hit)/(2010-2011 salary cap) – (2009-2010 cap hit)/(2009-2010 salary cap). Cap hits are normalized to account for annual changes in the salary cap ($56.8M for 2009-2010 and $59.4M for 2010-2011). Only restricted or unrestricted free agents after the 2009-2010 season who received a new contract in 2010-2011 are shown. There appears to be a positive correlation between performance and pay. Higher PS values suggest an increase in salary, though the increase does depend on the starting salary. For example, the fit equation suggests that a player whose PS value was 6.0 and whose base salary was $6M, would earn a $1M raise, while a player with the same base salary and a PS value of 5.0 would earn a $785K raise. Notice the significant raise Nicklas Backstrom received, which could have been predicted from Figure 3. Of course, performance is one of many factors that influence salary. Age is another important factor. The fact that Backstrom and Bobby Ryan were both emerging superstars at the age of 22 and were both finishing their entry-level contracts played a large role in their raise. On the flip side, both Fredrik Modin and Mike Modano took a discount to play for one more year before retiring at the end of the 2010-2011 season. Ilya Kovalchuk landed a contract worth over $100M, but because of its enormous length (17 years), the relative cap hit per year was virtually unchanged.

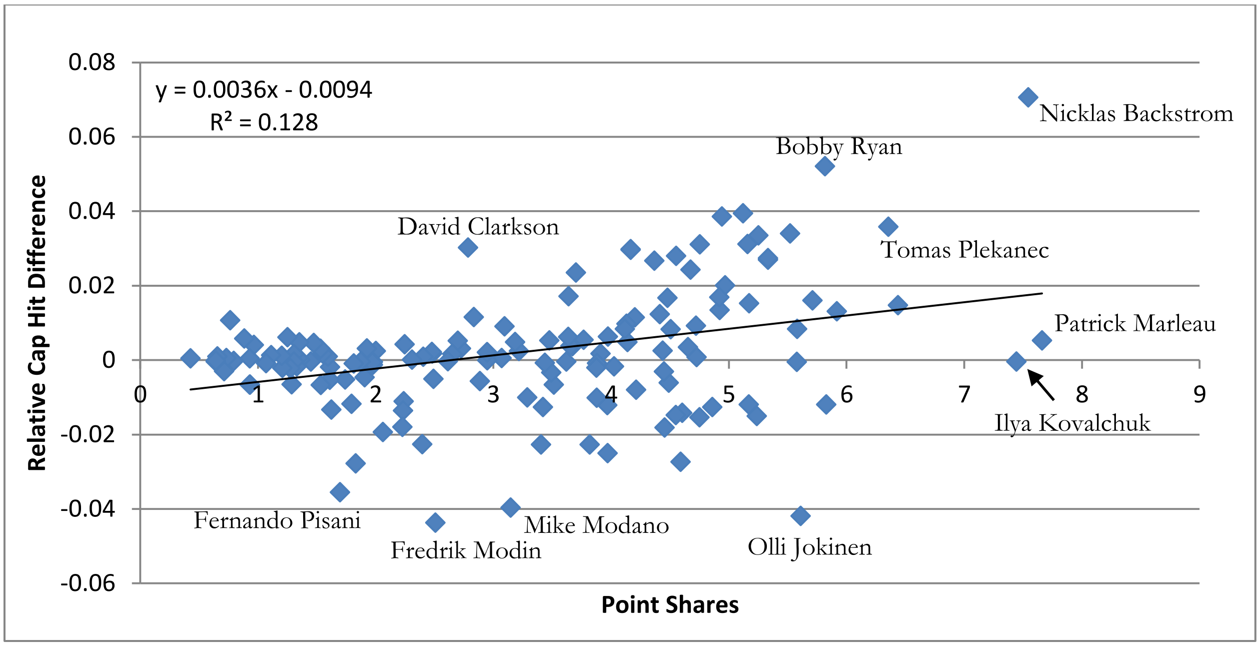

Figure 4. Relative change in cap hit from 2009-2010 to 2010-2011 as a function of 2009-2010 forward point shares.

5 Conclusions

In this paper, we develop a new method, the Clustering-Projection-Regression method, to characterize NHL players and measure their individual contributions to overall team performance. We extend previous approaches that attempt to classify NHL players by generating a proportional representation of each player across multiple player types. Using this representation, a metric that we call "full point shares" is computed, which quantifies the contribution of a player to the total number of points his team receives over the course of the season, if he plays every minute of every game. Given the total playing time of a player in a season, a "point shares" value can be computed, which represents the actual contributions a player made during the season. Forwards with high point share values typically are the top scorers on their team, while those with the highest full point shares tend to win the major NHL player awards. This method allows players to be compared quantitatively across multiple dimensions (e.g., offensive vs. defensive orientation), and provides some insight into the impact of a player's performance on their salary. The results presented in this paper form a brief survey that only scratch the surface of what can be analyzed using a concept like point shares. Generating individualized measures of value for NHL players may be a starting point for future studies on salary determination, optimization of line combinations, career trajectory projections, and trades.

6 References

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7 Appendix

Table 3. The player types and full point share values of each player type as determined in [4]. An FPS value of 0 indicates that the player type was not statistically significantly in the regression.

Position	Cluster	Full point shares	Statistics used in clustering*
Forward	Top Line	28.8	G/TOI, A/TOI, +/–/TOI, Hits/TOI, Blocks/TOI, PIM/TOI
	Second Line	19.9	
	Defensive	18.7	
	Physical	0.0	
Defenseman	Offensive	9.3	Pts/TOI, +/–/TOI, Hits/TOI, Blocks/TOI, PIM/TOI
	Defensive	3.7	
	Average	0.0	
	Physical	0.0	
Goalie	Elite	32.1	Save%, GAA, Wins/GS, SO/GS
	Average	21.2	
	Bottom	0.0	

* G = goals, A = assists, +/– = plus/minus, PIM = penalties in minutes, TOI = time-on-ice, Pts = G + A, GAA = goals against average, GS = games started.

Table 4 shows that Mike Green is the only defenseman in the top 10 as measured by FPS to have a defensive orientation that is less than 10% (roughly half of all the other defensemen on the list). Green's perceived lack of defensive ability was a debated point that may have also cost him the Norris Trophy that year.

Table 4. Top 10 defensemen from 2009-2010 ranked by full point shares.

Rank	Name	Salary ($M)	GP	TOI (min.)	Off. %	Def. %	Avg. %	Phys. %	FPS	PS
1	Duncan Keith	1.5	82	2180	49.1	17.3	23.8	9.8	5.2	2.3
2	M.-A. Bergeron	0.8	60	903	48.7	17.4	23.9	10.0	5.2	0.9
3	Nicklas Lidstrom	7.5	82	2084	47.4	17.3	25.0	10.3	5.0	2.1
4	Jamie McBain	0.9	14	361	46.6	19.3	24.3	9.8	5.0	0.4
5	Brian Campbell	7.1	68	1578	47.3	17.5	25.0	10.2	5.0	1.6
6	Sergei Gonchar	5.0	62	1512	46.1	18.7	24.3	10.9	5.0	1.5
7	Tobias Enstrom	3.8	82	1826	46.2	18.4	25.3	10.1	5.0	1.8
8	Mike Green	5.3	75	1910	49.7	9.2	23.7	17.4	5.0	1.9
9	Keith Yandle	1.2	82	1658	46.1	17.8	25.2	10.9	4.9	1.7
10	Kurtis Foster	0.6	71	1220	45.8	18.6	24.2	11.4	4.0	1.2

Ranked by PS, Duncan Keith remains the most valuable defenseman in Table 5. Both Mike Green and Drew Doughty (the other two Norris Trophy nominees) also appear. Nicklas Lidstrom, considered one of the best defenseman to ever play in the NHL, ranks second, but ranks first in all years prior to 2009-2010 as shown in Table 8. Mark Streit stands out because he had a noticeably lower offensive orientation, but because he was the most capable defenseman on the NY Islanders, he played a significant number of minutes (5th among defensemen that year) and earned a high PS value.

Table 5. Top 10 defensemen from 2009-2010 ranked by point shares.

Rank	Name	Salary ($M)	GP	TOI (min.)	Off. %	Def. %	Avg. %	Phys. %	FPS	PS
1	Duncan Keith	1.5	82	2180	49.1	17.3	23.8	9.8	5.2	2.3
2	Nicklas Lidstrom	7.5	82	2084	47.4	17.3	25.0	10.3	5.0	2.1
3	Dan Boyle	6.7	76	1991	44.7	19.3	24.9	11.1	4.9	2.0
4	Scott Niedermayer	6.8	80	2120	40.6	19.0	28.8	11.6	4.5	1.9
5	Mike Green	5.3	75	1910	49.7	9.2	23.7	17.4	5.0	1.9
6	Drew Doughty	3.5	82	2047	45.5	9.6	24.1	20.8	4.6	1.9
7	Brian Rafalski	6.0	78	1889	45.1	18.0	26.3	10.6	4.9	1.8
8	Tobias Enstrom	3.8	82	1826	46.2	18.4	25.3	10.1	5.0	1.8
9	Christian Ehrhoff	3.1	80	1823	48.0	9.6	24.1	18.3	4.8	1.8
10	Mark Streit	4.1	82	2107	35.3	21.9	29.5	13.3	4.1	1.7

Table 6 shows that Tuukka Rask and Ryan Miller stand out as top goalies. Rask had the highest save percentage in the league while Miller won the Vezina Trophy awarded to the league's best goaltender. Jason LaBarbera played a limited number of games, but when he played, he performed at an elite level.

Table 6. Top 10 goalies from 2009-2010 ranked by full point shares.

Rank	Name	Salary ($M)	GP	TOI (min.)	Elite %	Avg. %	Bot. %	FPS	PS
1	Tuukka Rask	3.2	45	2562	52.2	38.4	9.4	29.3	15.1
2	Jason LaBarbera	1.0	17	928	46.4	45.1	8.5	28.9	5.4
3	Ryan Miller	6.3	69	4047	45.7	44.0	10.3	28.3	23.1
4	Antti Niemi	0.8	39	2190	49.3	37.5	13.2	28.0	12.3
5	Tim Thomas	5.0	43	2442	53.9	29.5	16.6	27.6	13.6
6	Jimmy Howard	0.7	63	3740	45.8	40.9	13.3	27.6	20.8
7	Ilya Bryzgalov	4.3	69	4084	47.7	35.6	16.7	26.9	22.1
8	Martin Brodeur	5.2	77	4499	52.2	28.7	19.1	26.7	24.2
9	Jaroslav Halak	0.8	45	2630	44.3	39.8	15.9	26.7	14.2
10	Evgeni Nabokov	5.4	71	4194	43.5	40.8	15.7	26.7	22.6

Table 7 shows that the three finalists for the Vezina Trophy, Martin Brodeur, Ryan Miller, and Ilya Bryzgalov, were among the top 5 goalies in PS that year. Jonathan Quick stands out for his relatively low proportion of the "Elite" goalie type, but because he played so many games that year, his PS value was still in the top 10.

Table 7. Top 10 goalies from 2009-2010 ranked by point shares.

Rank	Name	Salary ($M)	GP	TOI (min.)	Elite %	Avg. %	Bot. %	FPS	PS
1	Martin Brodeur	5.2	77	4499	52.2	28.7	19.1	26.7	24.2
2	Ryan Miller	6.3	69	4047	45.7	44.0	10.3	28.3	23.1
3	Evgeni Nabokov	5.4	71	4194	43.5	40.8	15.7	26.7	22.6
4	Miikka Kiprusoff	5.8	73	4235	51.8	26.7	21.5	26.0	22.2
5	Ilya Bryzgalov	4.3	69	4084	47.7	35.6	16.7	26.9	22.1
6	Henrik Lundqvist	6.9	73	4204	49.2	29.3	21.5	25.8	21.8
7	Craig Anderson	1.8	71	4235	43.4	35.7	20.9	25.3	21.6
8	Jimmy Howard	0.7	63	3740	45.8	40.9	13.3	27.6	20.8
9	Jonathan Quick	0.8	72	4258	26.8	52.3	20.9	23.6	20.2
10	Roberto Luongo	6.8	68	3899	44.3	34.4	21.3	25.3	19.9

Table 8. Top 10 forwards, defensemen and goalies from 2005-2006 to 2008-2009 ranked by point shares.

Forwards								
	2005-2006		2006-2007		2007-2008		2008-2009	
Rank	**Name**	**PS**	**Name**	**PS**	**Name**	**PS**	**Name**	**PS**
1	Rod Brind'Amour	7.9	Brad Richards	8.2	Alex Ovechkin	8.6	Evgeni Malkin	8.3
2	Brad Richards	7.5	Martin St. Louis	8.2	Jarome Iginla	7.9	Alex Ovechkin	7.7
3	Jarome Iginla	7.5	Jaromir Jagr	7.9	Pavel Datsyuk	7.9	Sidney Crosby	7.4
4	Alex Ovechkin	7.4	Dany Heatley	7.7	Joe Thornton	7.9	Jeff Carter	7.4
5	Jaromir Jagr	7.4	Rod Brind'Amour	7.7	Evgeni Malkin	7.9	Jarome Iginla	7.2
6	Marian Hossa	7.3	Vincent Lecavalier	7.7	Martin St. Louis	7.5	Marc Savard	7.2
7	Ilya Kovalchuk	7.3	Marian Hossa	7.6	Henrik Zetterberg	7.5	Ilya Kovalchuk	7.1
8	Dany Heatley	7.2	Alex Ovechkin	7.5	Ilya Kovalchuk	7.4	Henrik Sedin	7.1
9	Joe Thornton	7.1	Ilya Kovalchuk	7.5	Jason Pominville	7.3	Nicklas Backstrom	7.1
10	Justin Williams	7.0	Joe Thornton	7.5	Derek Roy	7.2	Martin St. Louis	7.1

Defensemen								
	2005-2006		2006-2007		2007-2008		2008-2009	
Rank	**Name**	**PS**	**Name**	**PS**	**Name**	**PS**	**Name**	**PS**
1	Nicklas Lidstrom	2.3	Nicklas Lidstrom	2.3	Nicklas Lidstrom	2.3	Nicklas Lidstrom	2.1
2	Sergei Zubov	2.1	Scott Niedermayer	2.2	Brian Campbell	2.2	Zdeno Chara	2.1
3	Tomas Kaberle	2.1	Sergei Gonchar	2.0	Sergei Gonchar	2.2	Scott Niedermayer	2.0
4	Scott Niedermayer	2.0	Sergei Zubov	2.0	Andrei Markov	2.0	Duncan Keith	1.9
5	Mathieu Schneider	1.8	Dan Boyle	2.0	Tomas Kaberle	2.0	Andrei Markov	1.9
6	Michal Rozsival	1.8	Ryan Whitney	2.0	Dion Phaneuf	1.9	Mike Green	1.9
7	Lubomir Visnovsky	1.8	Tomas Kaberle	2.0	Brian Rafalski	1.9	Brian Rafalski	1.9
8	Chris Pronger	1.8	Brian Rafalski	1.9	Mike Green	1.9	Dennis Wideman	1.9
9	Bryan McCabe	1.8	Bryan McCabe	1.9	Duncan Keith	1.8	Brian Campbell	1.8
10	Brian Rafalski	1.8	Jay Bouwmeester	1.9	Zdeno Chara	1.7	Sheldon Souray	1.8

Goalies								
	2005-2006		2006-2007		2007-2008		2008-2009	
Rank	**Name**	**PS**	**Name**	**PS**	**Name**	**PS**	**Name**	**PS**
1	Roberto Luongo	25.2	Martin Brodeur	30.0	Ryan Miller	25.9	Niklas Backstrom	24.0
2	Curtis Joseph	19.8	Roberto Luongo	25.9	Martin Brodeur	25.4	Steve Mason	22.8
3	Alex Auld	18.1	Miikka Kiprusoff	24.5	Miikka Kiprusoff	25.3	Tim Thomas	21.2
4	John Grahame	17.8	Henrik Lundqvist	22.5	Evgeni Nabakov	25.2	Cam Ward	21.1
5	Mathieu Garon	17.5	Marty Turco	21.3	Tomas Vokoun	22.7	Evgeni Nabokov	21.1
6	Olaf Kolzig	17.4	Dominik Hasek	21.2	Rick DiPietro	22.5	Roberto Luongo	20.5
7	Rick DiPietro	16.7	Rick DiPietro	19.4	Cam Ward	22.0	Miikka Kiprusoff	20.5
8	David Aebischer	16.2	Andrew Raycroft	19.3	Vesa Toskala	21.9	Henrik Lundqvist	19.8
9	Martin Brodeur	15.2	J.-S. Giguere	19.1	Henrik Lundqvist	21.5	Ryan Miller	18.4
10	Nikolai Khabibulin	14.7	M.-A. Fleury	18.9	J.-S. Giguere	20.7	Tomas Vokoun	18.4