Brenden Picioane

Professor Neale

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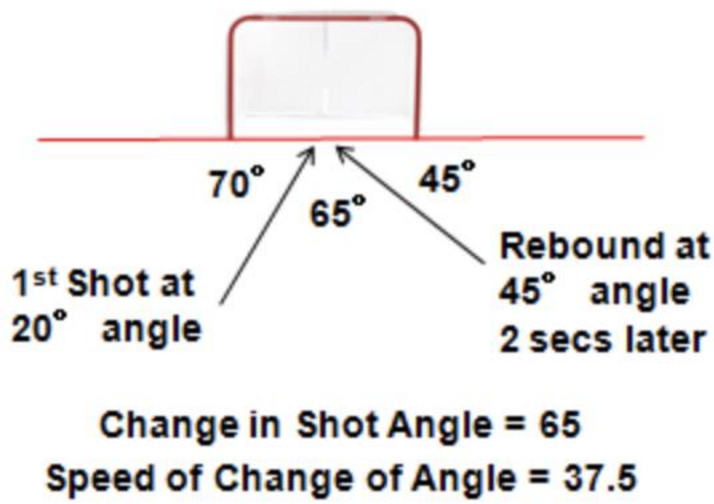
WAR on Ice: Development of Expected Goals Models in the NHL

More than in other sports, the adoption of analytics in hockey has been marred by executives refusing to jump on the bandwagon. The “eye test” is still the primary metric of evaluating talent in junior and professional leagues, which has set the scene for some disastrous draft selections and free agency signings over the past few seasons; players are valued more for their ‘grit’ and ‘intangibles’ rather than their skill and contributions to the main goal of the sport: scoring goals. However, since the Pittsburgh Penguins won the cup in 2016 on the back of War-on-Ice founder and analytics consultant Sam Ventura, teams are looking deeper into players that might be producing more than what meets the eye (Goldman). Today, savvy NHL GMs look for bargain deals at trade deadlines, draft days, and free agency openings to maximize value in a hard-cap league. With the addition of player tracking data in the 2021 season partnered with public-facing shot data dating back to 2007 (MoneyPuck), both teams and fans can engage in analytic evaluation of players beyond the inherently flawed box score stats.

One of the advanced metrics that is touted as the most important for evaluating player performance is expected goals (xGoals), a value between 0 and 1 that represents the probability of a shot being a goal if performed by an average skater on an average goalie. This statistic takes heavy inspiration from its soccer equivalent, but takes different variables into account given the nature of the sport. Almost every major xGoals model revolves around three key factors: shot type, shot location, and game state (power play, shorthanded, even strength) (Goldman). In hockey, xGoals are almost exclusively applied to the individual player to evaluate their individual skill and contribution. This gives way for single-player analytics such as goals scored/saved above expected (GSAx) and wins/goals above replacement (WAR/GAR), which are the main advanced metrics for evaluating a player's goal-scoring ability. If a player is scoring many goals above expected, then they may be on a hot streak or have shooting talent that is above average; a negative GSAx may indicate the opposite. Several public-facing xGoals models have been cited in NHL media, and while they all rely on the key factors indicated previously, they vary in other variables included, the sample of shots used in training, and the type of statistical or neural model implemented, amongst other attributes. This report will include a discussion of what makes some of the most popular xGoals models unique as well as a statistical deep dive on how these models can be recreated with shot data from 2007-2021.

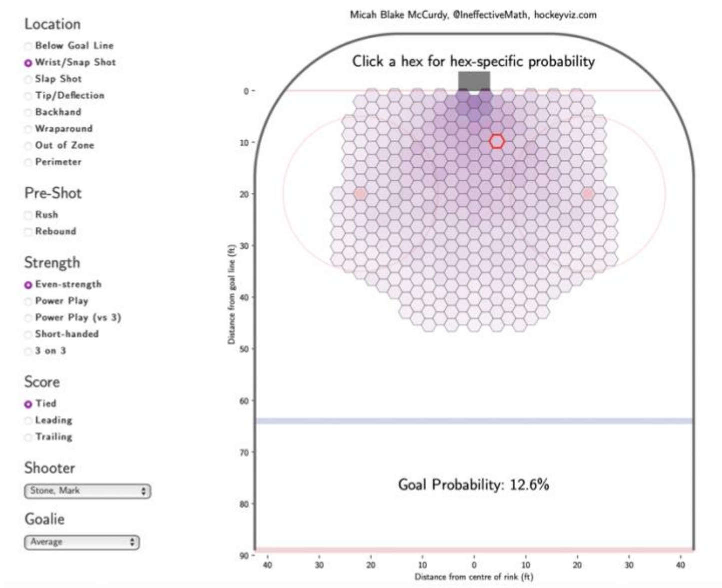
MoneyPuck Expected Goals

The creators of MoneyPuck have been cited as creating the first NHL xGoals model to implement gradient boosting (Goldman), which is a machine learning algorithm that uses an ensemble of weighted decision trees to repeatedly tune the importance of each variable in a regression model. One important property of gradient boosting algorithms is that they work especially well with variables that interact with each other; this is particularly useful with xGoals models since sports events are commonly dependent on many factors at once. For example, different types of shots are more effective at various distances from the net, so it is more realistic for a model to take into account shot type (backhand, wrist, slap, etc.) in relation to the distance from the goal to boost the effect of these factors on the regression prediction. Due to MoneyPuck's work on gradient boosting dating back to 2016, almost all public xGoals models have some implementation of the algorithm. Another unique factor of MoneyPuck's model is their focus on shot angle and its accompanying attributes in their calculations. Not only is the angle of each shot accounted for, but the change in angle from the previous event as well as the speed in which this angle has changed is calculated and factored in so that rebounds with a huge swing in shot angle, for example, have a higher expected goals value than simply a shot from that location on the ice. See the diagram below for a visual representation of this calculation.



HockeyViz Expected Goals

HockeyViz takes a soccer-like approach to location-based xGoals by introducing zones to the offensive zone of the shooter. Rather than recording the exact coordinates of a shot, this model is based on "a 'fabric' of hexagons which cover the offensive zone, one fabric for every shot type (slapshot, wrist shot, tip/deflection, and backhand)" (Goldman). This reduces the states of a shot down to a finite set; distance is ultimately a continuous variable that may add unnecessary noise to a model, so by creating a set of states that depend on discrete variables a more digestible and potentially accurate model can be made. Since there is no official xGoals model that the NHL uses, it is hard to measure if it's any more accurate to reduce the problem to a finite space, but from a human standpoint it definitely becomes more understandable for visual analysis. On the HockeyViz website, users can view the following interactive diagram that is split into zones for a better idea of shooting probabilities with various variables to toggle.



Another unconventional aspect of the HockeyViz model is that the xGoals value accounts for shooting talent (which can be taken out if a user wants). It is commonly accepted that adding in a factor for shooting talent takes away from the essence of the metric, which is really meant to evaluate the quality of shooting chances, not shooting talent (Goldman). The reason why GSAx has so much value in the analytics community is that it allows for the evaluation of players and their specific shooting performances, and by counting this ability into the xGoals model, one may be taking away from the usefulness of GSAx. However, the HockeyViz team believes that by incorporating shooting talent, users of the model can get a better idea of a player's individual scoring chances as it relates to their gameplay and style. It could add more context to a player's goal scoring: if they're better shooting from a specific zone or with a specific shot type they may shoot like that more often despite the shooter-agnostic models telling them that the chances of scoring in that way are low.

Common Limitations of Public Models

Outside of the eccentricities that make each xGoals model unique, it is hard to directly criticize their approaches since there is no official baseline set by the NHL to compare it to. One could use the fact that these models output a percentage of a goal happening to compare it to all shot data from previous seasons (which will be done later in this report), but even that is flawed since there isn't a consensus on the cutoff point for an xGoal value to predict a goal. For example, my exploratory data analysis of MoneyPuck's shot data, I found that setting the cutoff probability at the league average shooting percentage of 9.6% generated the best accuracy for MoneyPuck's xGoals model. This will not be the same for every model, so it is hard to compare across algorithms.

Something that analytics consumers can evaluate is the quality of the data that the NHL provides, which is a source for many of the limitations of these models. For one, there are some variables that model builders think would be extremely useful in increasing the accuracy of their models. One of these is the location of blocked shots, which is not currently available from the league; this could help the model by understanding how the distance and angle between a blocked shot and the shot after it interact to benefit the shooter, similar to the evaluation of rebounds. Another lapse in NHL data is that shot location data is subject to error and misrepresentation. Shots from behind the net are not recorded as shots on goal, and since arenas are shaped slightly differently, coordinate data for shots may not translate accurately from stadium to stadium (Goldman).

Finally, since true player tracking data has been collected for a little over one season, model builders could unlock a whole new world of possibilities when it comes to goalie positioning, net battles, and flurries between skaters and goalies upon non-frozen rebounds. No one can say how exactly this will affect model performance or if these variables will even be significant enough to include, but since the data is so limited and novel, it will be a few seasons before hockey analytics will include them across the board.

BPxG: A Proprietary Expected Goals Model

One of the core difficulties with machine learning models such as the xGoals models discussed in this report is that they can become a black box that cannot be understood and replicated by its consumers. To combat this problem, I propose the BPxG (https://github.com/bpicioane/BPxG), an xGoals model that I have created using shot data from 2007-2021 found on MoneyPuck's website. The BPxG model is a logistic regression written in R that uses 77 variables (including dummy variables for non-ranked discrete quantities) across a sample of 561,523 shots on goal. The reason why logistic regression was used as opposed to gradient boosting is twofold: it is much less computationally intensive (which allows me to use more observations/variables and allows for replication on other people's machines without the need for extra compute power) and it is easier for one to understand each variable's importance in the model (as log odds from training can be translated to marginal effects). The data was segmented into an 80/20 train/test split, and the objective of the model was to predict the 'goal' column from the remaining 76 variables. Most of the variables used are consistent with other models as explained throughout this report, but some unique ones include the time since the last event, the type of event that occurred before the shot, and if the player was on their off-wing (shooting from the left of the goal if right-handed and vice versa). All evaluations of accuracy will be made in comparison to MoneyPuck's xGoals model.

When evaluating my model, I first wanted to treat it as a binary classifier to see how good it is at predicting if a shot will be a goal. The cutoff point for the value to predict a goal was 0.096 (league average shooting percentage). The results are summarized in the table below. As the table shows, the BPxG model represents a loss of less than 2% of accuracy, but shows a much worse recall at only 42.27%. This means that of all the actual goals scored, my model predicted less than half correctly. Targeting a higher recall in future iterations of this model would be a key objective.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Measure**
MoneyPuck	81.31%	19.48%	58.42%	29.22%
BPxG	79.91%	14.83%	42.27%	21.95%

I also evaluated this model's strength as a continuous statistic that could accumulate throughout a player's career and give some insight on their shooting performance. To do so, I aggregated each player's shot and BPxG data into career-long numbers and ranked all players (career shots > 500) by total BPxG and BPxG/shot. I then did the same for their MoneyPuck xGoals, calculating the two ranks the same way. To test the BPxG model for accuracy, I performed a two Spearman rank correlations on the BPxG against the MoneyPuck rankings (one for total xGoals and one for xGoals/shot). This method found a 99.51% correlation for total xGoals and a 93.76% correlation for xGoals/shot; this indicates that while my model may not hold up as a classifier just yet, it is very strong as a counting stat on its own. An example of my rankings for both aggregate metrics can be found below.

player	cBPxG	rank
Alex Ovechkin	178.93203	1
Joe Pavelski	138.91077	2
Auston Matthews	136.42915	3
Patrick Kane	135.34619	4
Sidney Crosby	129.90620	5
Jeff Carter	129.55404	6
Nathan MacKinnon	127.89588	7
Leon Draisaitl	127.43488	8
Connor McDavid	126.30727	9
Zach Parise	126.29328	10

player	cBPxG	rank
Leon Draisaitl	0.09742728	1
Paul Stastny	0.09735381	2
Alex Chiasson	0.09734097	3
Chris Kreider	0.09692764	4
Tyler Bertuzzi	0.09424835	5
Zach Hyman	0.09393320	6
Connor McDavid	0.09383898	7
Zach Parise	0.09320537	8
Patric Hornqvist	0.09298034	9
Anders Lee	0.09258025	10

Going back to the GSAx metric discussed previously, I wanted to see what my model could reveal in terms of certain players showcasing career-wide shooting talent above or below average. The top and bottom 10 in GSAx from 2007-2021 according to BPxG are shown below.

player	cBPxG	goals	GSAx	rank
Alex Ovechkin	178.93203	247	68.067973	1
Auston Matthews	136.42915	191	54.570855	2
Leon Draisaitl	127.43488	182	54.565123	3
Steven Stamkos	93.95543	148	54.044573	4
Brayden Point	91.39492	141	49.605083	5
David Pastrnak	116.62519	165	48.374811	6
Elias Lindholm	78.96496	119	40.035037	7
Andre Burakovsky	45.36147	84	38.638532	8
Brad Marchand	97.42271	134	36.577286	9
David Perron	84.55791	121	36.442089	10

player	cBPxG	goals	GSAx	rank
Brady Tkachuk	116.829789	86	-30.829789	2173
Patric Hornqvist	90.841792	67	-23.841792	2172
Jason Blake	40.195336	19	-21.195336	2171
Jordan Martinook	44.680162	25	-19.680162	2170
Vincent Trocheck	82.333718	63	-19.333718	2169
Jaccob Slavin	41.897277	23	-18.897277	2168
Mikael Backlund	77.747081	59	-18.747081	2167
Sam Gagner	57.622935	39	-18.622935	2166
Ryan Carpenter	32.339127	14	-18.339127	2165
Carl Hagelin	37.174631	19	-18.174631	2164

Final Thoughts: Insights and Limitations of BPxG

Looking at the results of my model (and of xGoals models generally), it is clear that a certain type of hockey player is valued more heavily. Players that are on the power play who mostly hover as close to the goalie as possible (Brady Tkachuk, Chris Kreider) or players that have a very strong one-timer slap shot (Alex Ovechkin, Leon Draisaitl) are more likely to soar up the xGoals leaderboard. Future work on this model could factor in the new NHL tracking data as it becomes available or implement other machine learning algorithms (k-nearest neighbors, support vector machine) that require more time and processing power. As a work in progress, this model mimics the work already done quite closely while optimizing for useability for the common fan; due to this, I would consider the BPxG model a success.

Works Cited

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