Evaluating Passing Talent in the OHL

March 2021

1 Introduction

In recent years, sports have experienced what could be described as a data *renaissance*. Ice hockey is no exception. Numbers are involved in the decision-making process at nearly every level of the organization, ranging from in-game strategy to player valuation and much more. Amateur scouting is included as an area that has been affected by this transformation. As analytics have become more commonplace in the hockey world, process-focused metrics such as zone exits/entries and shot impacts have entered the conversation alongside the traditional results-focused metrics such as goals and assists. There are, however, important evaluation metrics that have remained largely unexplored through an analytics lens, primarily due to the lack of available data. Passing ability is one of these metrics.

The ability to consistently complete passes and limit turnovers is a skillset in high demand. Just like all other skills, some players are more adept at passing than others. Unlike most skills though, there is not a clear way to quantify a player's passing ability. Players with a dangerous shot may be near the top of the league in shooting percentage. Players who play a hard-nosed physical game may be among the league leaders in hits. The closest way to approximate a player's passing ability through traditional metrics is by the number of assists they accrue, which occur seldomly compared to how many passes a player makes throughout a game. A statistic that accurately summarizes a player's passing ability would be invaluable to the scouting and player evaluation process.

This paper will aim to lend insight to passing ability by introducing two metrics:

1) Expected Pass Percentage (XPP); the probability of a pass being completed. XPP is calculated for every pass attempt.
2) Pass Percentage Over Expected (PPOE); which is calculated for each player by subtracting the difference between their actual pass completion percentage and their average XPP. (*actual pass percentage - expected pass percentage*) [1]

2 Data

The dataset consists of 40 games played by the Erie Otters of the Ontario Hockey League during the 2019-2020 season and was published by Stathletes to be used in the 2021 Big Data Cup [2]. This paper will only consist of passes that take place at full, even strength (5v5). The main reason for this decision is that teams modify their tactics during alternative strength states (5v4, 4v5, etc.), which in turn affect passing decisions. Further, there are not enough non-5v5 events in a 40 game sample to produce reliable estimates.

2.1 Variables and Feature Engineering

Variables included in the data are the (x,y) coordinates of the passer and intended pass receiver, whether the pass was direct or indirect, and contextual information about the game (score, period, time remaining, etc.). There are plenty of additional factors we can specify to aid in the modeling process. Using the (x,y) coordinates we can compute which zone the pass originated and ended, how far the pass traveled, how close each player was to the attacking net, and more. In total, fifteen variables were used to create the XPP model.

Variable	Description
period	Current period (1, 2, 3, or 4)
time_remaining	Seconds remaining in the period
score_state	Score differential from the perspective of the passing team
x_passer	X coordinate of the passing player
y_passer	Y coordinate of the passing player
x_receiver	X coordinate of the intended pass receiver
y_receiver	Y coordinate of the intended pass receiver
pass_dist	Distance the pass traveled between the passer and receiver
passer_dist_from_goal	Distance between the passer and the offensive goal
receiver_dist_from_goal	Distance between the receiver and the offensive goal
angle_formed_with_goal	The angle formed between the passer, receiver, and offensive goal
pass_type	Denotes whether the pass was Direct or Indirect
zone	Zone the pass originated and where it ended, i.e. - DZ-NZ, OZ-OZ, etc.
lane	Lane the pass originated and where it ended, i.e - Up the Wall, Outside-In, etc.
cluster	Result of a K-means clustering algorithm on the pass locations

Figure 1: Extensive list of features used for calculating completed pass probabilities.

Notably, not included in the list of variables is the name of the player attempting or receiving the pass, making the model player-agnostic. This causes XPP to assume an average talent level of the players sending and receiving each pass. Also, due to data limitations, the position of each player (defense, wing, etc.) is not included.

2.2 Viewing the Features

Let's look at a sample pass to see how the features describe it [3].

Label	Variable	Value
	period	2
	time_remaining	383
	score_state	-1
A	x_passer	143
A	y_passer	77
B	x_receiver	160
B	y_receiver	24
ab	pass_dist	55.7
ac	passer_dist_from_goal	57.5
bc	receiver_dist_from_goal	34.4
c	angle_formed_with_goal	69
	pass_type	Direct
	zone	Off-Off
	lane	Cross Ice
	cluster	OZ Perimeter Far

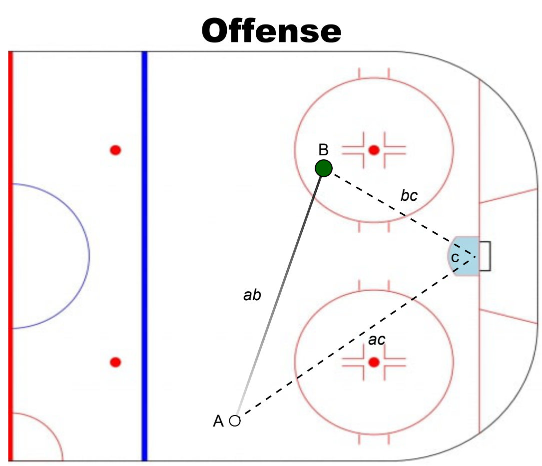


Figure 2: Pass features in action. White dot is the passer, green dot is the receiver.

This pass originated near the right point in the offensive zone (A) as the receiver was positioned near the top of the left circle (B). The fifteen variables describing this pass are shown in the table. Along with the contextual factors (period, time remaining, and score) there are a dozen physical features that describe the pass. Positional coordinates, distances, and angles complement a handful of categorical variables. The categorical variables for this pass describe how it originated and ended in the offensive zone, traversed cross ice from the right lane to the left lane (imagine dividing the ice into thirds length-wise), and was noted to be in a cluster of similar passes that originated towards the perimeter and went a relatively far distance.

3 The Model

XPP was created using an XGBoost model. The final dataset was divided into a training and testing set. Both the training and testing datasets were stratified by the outcome variable (whether the pass was completed) to avoid a class imbalance caused by the fact that 69.5% of passes are completed. This resulted in 2/3 of the data being used for training while the remaining was 1/3 used for testing.

Using the training data, a 10-fold cross validation set was constructed to tune the hyperparameters with Area Under the Curve (AUC) being the primary metric used to measure model performance. The final model used 1000 trees, a depth of 6, a learning rate of .01, and all 15 predictors were randomly sampled at each split [4].

3.1 Results

The model performed with an AUC of .732 on the testing data and an accuracy of .736. It excelled at correctly categorizing the successful passes (sensitivity = .940) but was weaker at categorizing the incomplete passes (specificity = .271). Given the fact that the positioning of three additional teammates and all on-ice five defenders are not considered in the model framework, the results are encouraging.

	AUC	Accuracy	Sensitivity	Specificity	Precision
training	0.843	0.774	0.959	0.352	0.771
testing	0.732	0.736	0.940	0.271	0.746

While a slight decline in performance metrics between the training and testing may hint at some degree of overfitting, the takeaways will be valid due to its demonstrated predictive capabilities.

3.2 Variable Importance

Another useful part of the finished model is the ability to uncover which features are most important to its predictions. Below we show an importance plot of the top variables.

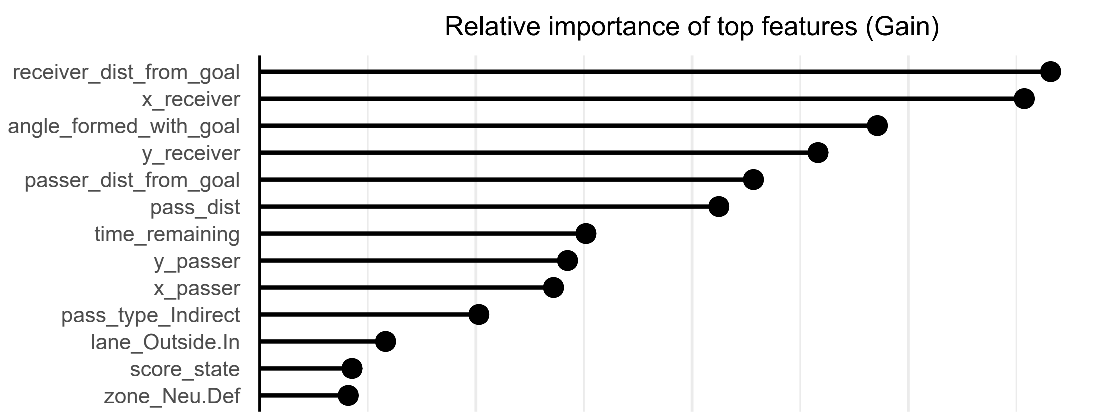


Figure 3: Variable importance plot.

Variables that contributed most to the model's predictions are denoted by a longer bar. The lengths of each bar can be interpreted as relative importance. For example the receiver's distance from the offensive goal is the most important variable to the model. The X and Y coordinate of the passer are of similar importance, but both are less important than the receiver's distance from goal.

We see that information about the receiver is more important than information about the passer. Also, two of the game-context variables, time_remaining and score_state are non-trivial. This hints at players altering their decision making by attempting more or less difficult passes depending on whether their team is winning or losing, or if the period is expiring.

3.3 Modeling Outcomes

Let's look at direct passes with the lowest and highest XPP in the dataset, excluding passes that traveled less than one foot. Completed passes are denoted by a green circle, incomplete passes are gray.

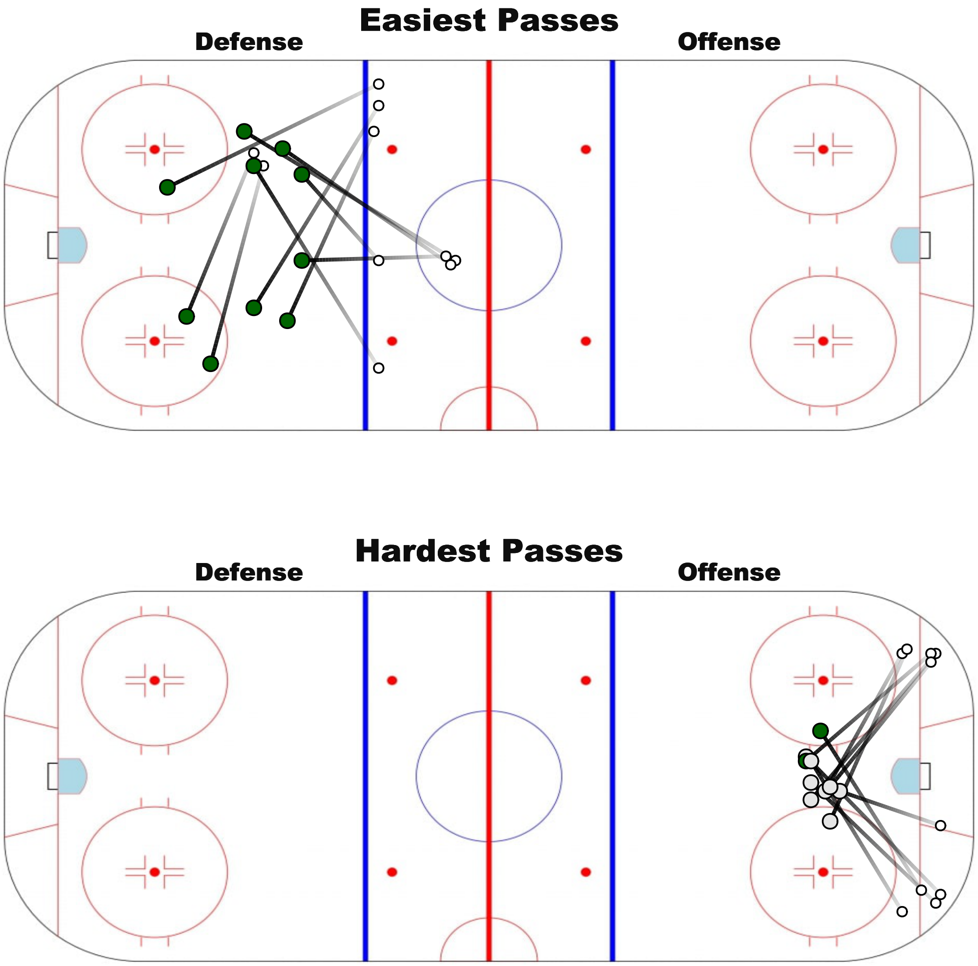
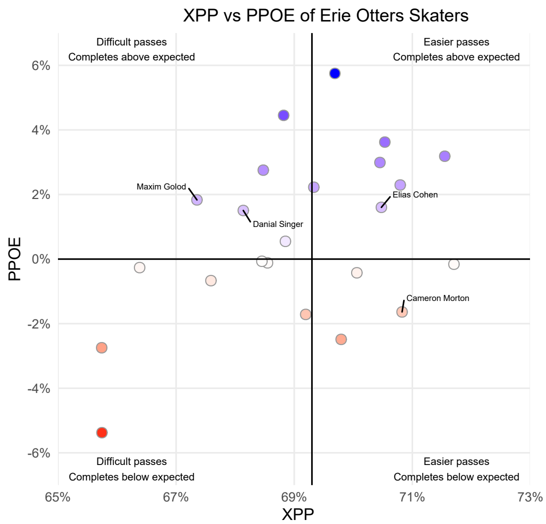


Figure 4: Passes with the highest and lowest XPP.

The ten passes with the highest probability of being completed all happened on the defending half of the ice and were directed either backwards or sideways. These are known as 'regroup' passes; a low-risk pass to/between defensemen before starting an offensive attack. The ten least probable direct passes by XPP look nearly identical. They all began near the attacking goal line and were intended for a receiver in the slot. Notably, the ten 'easiest' passes had an average XPP of 98% and all ten were completed. Conversely, the ten 'hardest' passes had an average XPP of 16% and two out of ten were completed. It appears the model has grasped what makes a pass easier or harder.

4 Player Evaluation

With the XPP calculated for all pass attempts we can now examine each player's Pass Percentage Over Expected (PPOE). PPOE allows us to look at which players consistently complete passes while also adjusting for the difficulty of their pass attempts. The scatterplot below shows the XPP and PPOE of the Erie Otters skaters [5].



Passer	Attempts	PP	XPP	PPOE
Luke Beamish	228	75.4%	69.7%	5.7%
Kyen Sopa	217	73.3%	68.8%	4.5%
Matthew MacDougall	178	74.2%	70.5%	3.6%
Jamie Drysdale	847	74.7%	71.5%	3.2%
Chad Yetman	674	73.4%	70.5%	3%
Drew Hunter	577	71.2%	68.5%	2.8%
Kurtis Henry	955	73.1%	70.8%	2.3%
Jacob Golden	668	71.6%	69.3%	2.2%
Maxim Golod	860	69.2%	67.4%	1.8%
Elias Cohen	462	72.1%	70.5%	1.6%
Danial Singer	168	69.6%	68.1%	1.5%
Brendan Sellan	634	69.4%	68.9%	0.5%
Noah Sedore	291	68.4%	68.5%	-0.1%
Brendan Hoffmann	491	68.4%	68.5%	-0.1%
Jack Duff	977	71.5%	71.7%	-0.2%
Emmett Sproule	670	66.1%	66.4%	-0.3%
Brendan Kischnick	247	69.6%	70.1%	-0.4%
Daniel D'Amato	650	66.9%	67.6%	-0.7%
Cameron Morton	555	69.2%	70.8%	-1.6%
Connor Lockhart	532	67.5%	69.2%	-1.7%
Christian Kyrou	104	67.3%	69.8%	-2.5%
Austen Swankler	708	63%	65.7%	-2.7%
Hayden Fowler	651	60.4%	65.7%	-5.4%

Figure 5: XPP describes the difficulty of passes while PPOE is determined by the outcome of the passes.

There are a couple of things to point out. First, the average XPP for all players is slightly more than 69%, which mirrors the average pass completion percentage of all players in the dataset. Second, the average PPOE for all players is ~0%, hinting at well-calibrated estimates. The table on the right side shows each players' PPOE along with their actual pass percentage (PP) and XPP. A positive PPOE means a player exceeded expecations while a negative PPOE means a player was below expectations. Therefore Luke Beamish completed passes at the highest rate above expectations and Hayden Fowler completed passes at the lowest rate below expectations.

The most powerful feature of PPOE is that it gives context to each individual player's passes. If one were to compare Maxim Golod's and Cameron Morton's passing percentage (each were 69.2%), they may come to the conclusion that the two players were similar in terms of passing skill. However, PPOE shows that Golod's passing percentage exceed expectations by 1.8% while Morton's passing percentage was 1.6% lower than expected, providing evidence that Golod has been the stronger passer.

5 Scouting

Using XPP and PPOE in the scouting process would give decision-makers more information about both the passing abilities and habits of players. PPOE can be used to answer the *what* question - as in "All things considered, what is this player's ability to complete the passes he attempts?" Then, XPP can be used to answer the *why* and provide context. Does the player defer to the easier, safer passes or do they frequently attempt the low-probability, difficult passes? Further, knowing both of these metrics would help decision-makers evaluate potential player acquisition moves. For example, a team may be considering adding a player who has a low XPP and a low PPOE. This would suggest this player is attempting low-probability passes and is struggling to complete them. This player may see more passing success by reducing their risk-taking and opting for safer, higher-probability passes. If the decision-maker's team's philosophy emphasized high-probability passes, acquiring this player may be a smart move. However, if the player would continue to be asked to complete low-probability passes, the low PPOE may persist on the new team.

Another way these metrics could be used in the context of scouting is by using them to gain insight into individual tendencies, or style of play. A common sentiment is that teams and more specifically, line combinations, should be constructed with players whose skillsets complement one another. PPOE could be used to help identify how a player's play style may mesh with potential linemates. A simple example would be pairing a high-PPOE player with an adept goal scorer to maximize both players' skillsets.

Discussion

Although the XPP calculation does not consider which player is on the receiving end of each pass, receving a pass is most likely a talent just like delivering a pass. We saw in section 3.2 that variables pertaining to the receiver were most important in the XPP calculation [6]. One may surmise that a player can consistently raise or lower the expected outcome of a pass intended for him by strategically choosing his positioning. In this sense, the methodology used in this paper to calculate PPOE can be applied to describe receiving talent with minimal effort. By simply subtracting a player's pass *receiving* percentage from the average XPP of passes intended for him, one could obtain a congruent stat of PPOE; Receiving Percentage Over Expected (RPOE). This stat could also be used in the scouting process alongside PPOE.

Coaches or analysts looking to use PPOE in a game setting could do so in real-time; nearly as fast as the tracking data is updated. The 15 factors are all that's needed to calculate XPP and the XGBoost algorithm is efficient enough to quickly provide the output. With this ability, PPOE can be used to inform decisions in the short-term such as tactical adjustments between periods of a game.

The metrics presented in this paper provide a framework for how an organization may utilize advanced passing statistics to gain more information about a player's skillset. As the hockey analytics landscape continues to evolve, metrics such as these will continue to be refined and deepen our understanding of the game's most important details. Enhanced tracking data would be able to improve upon XPP and PPOE by accounting for key factors such as defensive pressure and the current speed/direction of other players, but also teasing out minor nuances such as the effects of handedness, chemistry, coaching systems, and more. Although those factors were beyond the scope of this analysis, the concept of using advanced passing metrics such as XPP and PPOE as part of the player evaluation process can provide a competitive advantage to perceptive teams.

References

[1] This concept is an adaptation of an advanced NFL metric; completion percentage over expected.

Sebastian Carl and Ben Baldwin (2020). nflfastR:
Functions to Efficiently Access NFL Play by Play Data.
R package version 3.0.0.
https://CRAN.R-project.org/package=nflfastR

[2] https://www.stathletes.com/big-data-cup/

[3] The ice rink used in this figure and succeeding figures was created by War On Ice.

War-on-ice.com. "Make your own NHL rink plot in R,"
http://blog.war-on-ice.com/make-your-own-nhl-rink-plot-in-r/index.html.

[4] XGBoost is a frequent choice for analysts in data competitions due to its robust results and its relative ease of use. Inspiration was gathered from the winning submission of the 2020 Big Data Bowl collegiate division:

Ploenzke, Matt. "NFL Big Data Bowl Sub-Contest,"
https://operations.nfl.com/media/4204/bdb_ploenzke.pdf, 2020.

[5] Just for fun: among all players in the dataset with at least 25 passes, the top three in terms of PPOE are Jack Quinn, Brandt Clarke, and Marco Rossi.

[6] With sufficiently large samples, PPOE will do a good job capturing passing talent despite not accounting for varying levels of receiver talent. The effect of receiving talent will be diminished as the player diversifies their pass targets.