Metrics to assess passing skill in junior hockey - An Erie Otters study.

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Introduction

Passing is a fundamental aspect of the game of hockey. The ability to make accurate passes and advance play up the ice using skilled and accurate passing is perhaps one of the most important skill sets a player can have. But how do we statistically assess a player's passing skills? Several methods of assessing passing skills are described herein based on Stathletes dataset of the Erie Otters 2019-2020 season.
In each case, only direct passes at 5v5 are considered. There is no real reason different strengths cannot be considered, however, given the fundamental change in play dynamics it was considered that assessing passing only at 5v5 would give more consistent results. Indirect passes are inherently more stochastic and therefore omitted for simplicity.

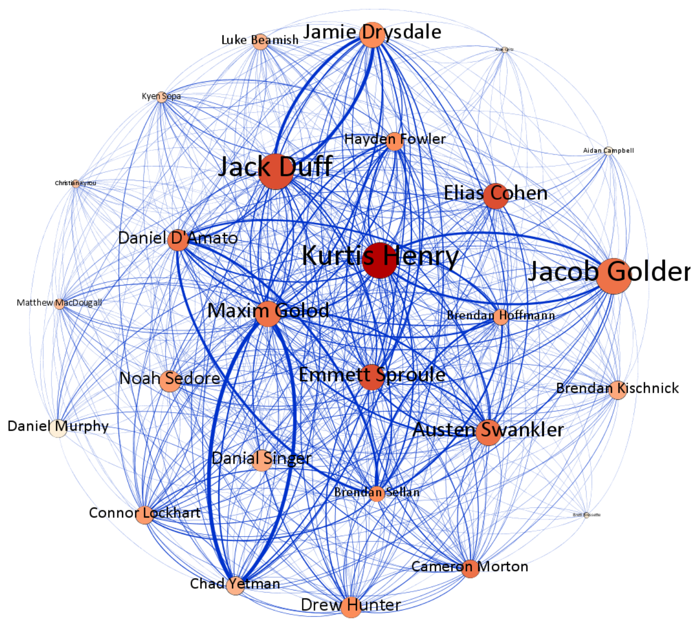

Figure 1: Erie Otters Network Graph

Network Analysis

Network Analysis is a tool that has been used widely in sports including soccer[1] and basketball[2], as well as hockey[3], including a previous look at some Erie Otters Games[4]. Network analysis makes various measurements of nodes (players) and edges (passes) to assess aspects of the network itself. Hockey differs from many other team sports in that players play a fraction of the minutes of a game and that only a minority of players are on the ice at any one time, limiting the total interactions between players. However, the data set here is sufficiently large that it is still

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[1] **Exploring Team Passing Networks and Player Movement Dynamics in Youth Association Football** Gonçalves B, Coutinho D, Santos S, Lago-Penas C, Jiménez S, et al. (2017) Exploring Team Passing Networks and Player Movement Dynamics in Youth Association Football. PLOS ONE 12(1): e0171156. https://doi.org/10.1371/journal.pone.0171156

[2] **Basketball Teams as Strategic Networks** Fewell JH, Armbruster D, Ingraham J, Petersen A, Waters JS (2012) Basketball Teams as Strategic Networks. PLOS ONE 7(11): e47445. https://doi.org/10.1371/journal.pone.0047445

[3] https://hockeygraphsdotcom.files.wordpress.com/2015/10/passing-networks-in-hockey.pptx

[4] https://hockey-graphs.com/2015/11/09/the-2015-ohl-final-part-one-erie-otters-passing-network/

likely possible to derive meaningful metrics from any evaluation.

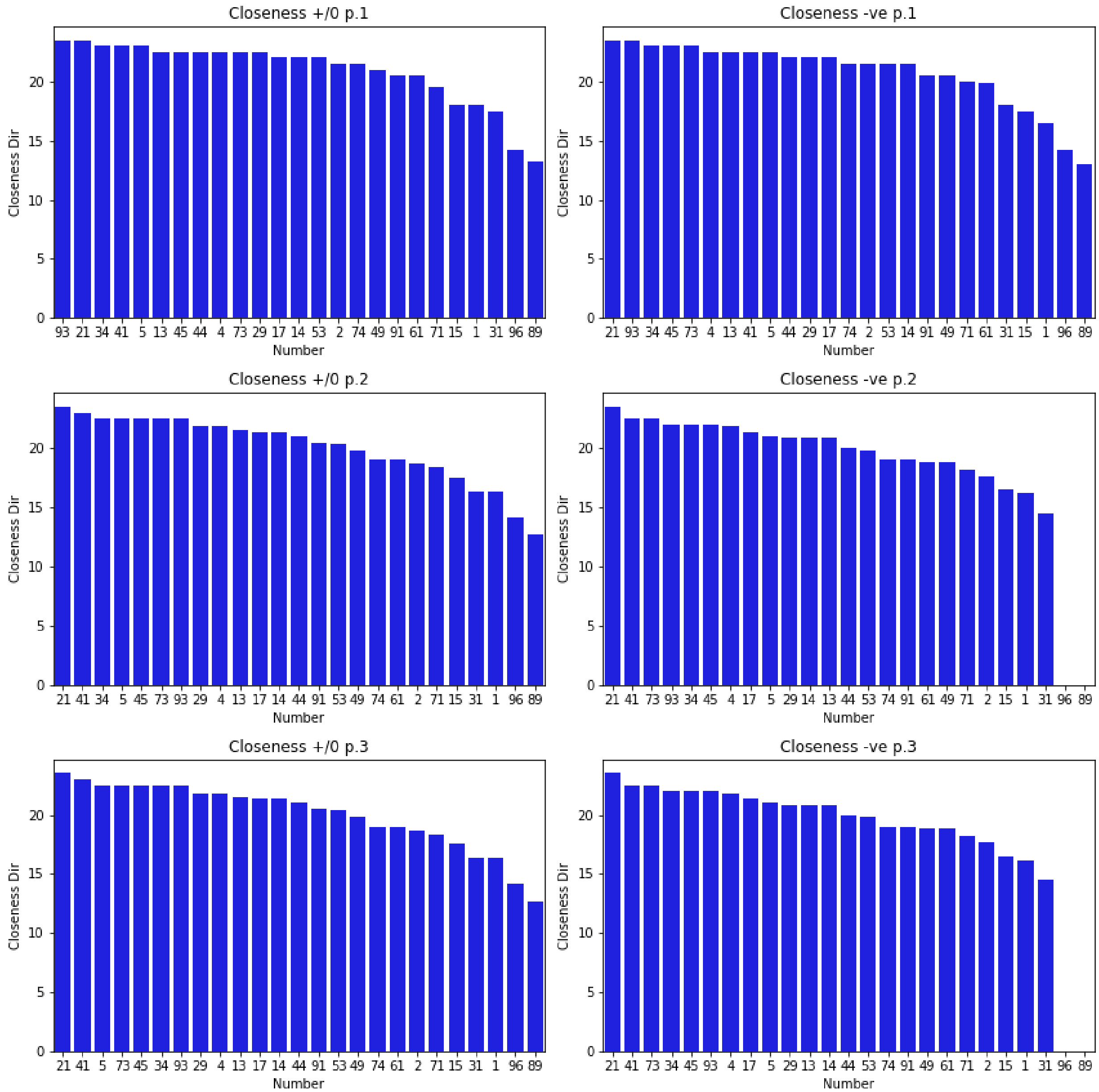
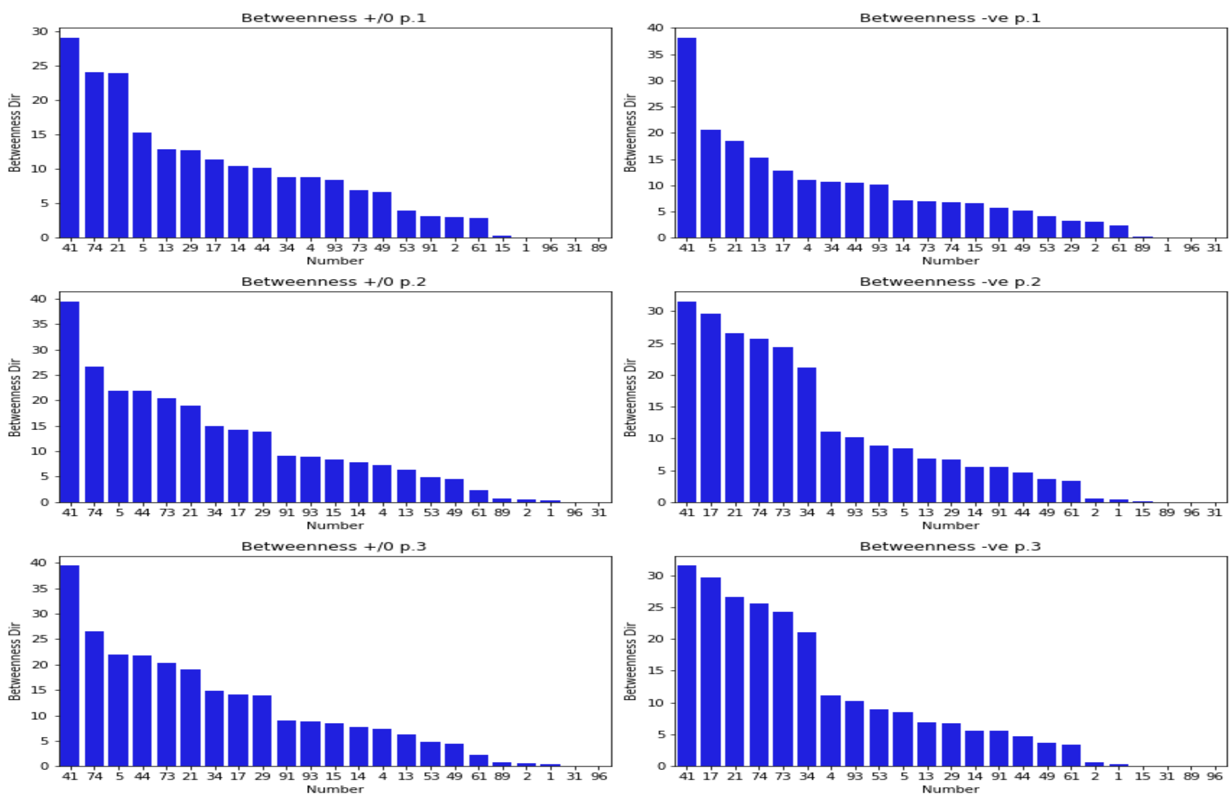


Figure 2: Closeness Centrality distribution

An initial network graph was constructed using Gephi to provide a visual analysis of player passing networks. Figure 1 shows the constructed passing network. The node size is given by the total number of passes made by a player and the edge weight (thickness) by the number of passes between individual players.
Several pairs of players appear to have significant edge weights between them, including Jamie Drysdale and Jack Duff, Maxim Golod and Chad Yetzman, Maxim Golod and Austen Swankler, and Kurtis Henry and multiple players. The players closest to the center of the graph are those that have the largest number of connections with other players. The network graph in Figure 1 clearly represents the players who the team are most reliant on for passing play.

Two important network analysis measures are betweenness centrality, which measures the importance of a node (i.e. player) to a graph, and closeness centrality, which measures how central a node (i.e player) is to a network. Betweenness centrality can, in this context, be thought of as how well a player distributes the puck and their criticality in distributing pucks to teammates (i.e. a possible target for opposition to disrupt play) and closeness centrality can be thought of as how reliant the network (team) is on individual players to make passes. Centiscape, a plugin to the open source graph analysis package Cytoscape was used to compute the betweenness centrality and closeness centrality for each player on the Erie Otters The graph was constructed as a directed graph (as passes to and from each player are not necessarily equivalent), where the edge weights were provided by the number of plays between each player.



<u>Figure 3: Betweenness Centrality distribution</u>

Closeness Centrality

Studies on soccer teams[5] have suggested that teams where a few players have a high closeness centrality are typically less successful than those with more equally distributed centrality. Intuitively this makes sense, teams that are heavily reliant on single players likely having less depth.

[5] Grund, Thomas U. “Network structure and team performance: The case of English Premier League soccer teams.” Social Networks 34.4 (2012): 682–690.

Figure 2 shows the calculated closeness centrality for the Erie Otters. We can see, that as we would hope to see, the team (apart from a small tail) of players has a largely well-distributed closeness centrality, however, 21 (Austen Swankler - C), 41 (Kurtis Henry - D), 73 (Connor Lockhart - C) seem to be players, in particular that have high closeness centrality. 34 (Jack Duff - D) and 5 (Jacob Golden - D) are also notable. 93 (Emmett Sproule - LW) would appear to be the most important winger, with 29 (Chad Yetman - RW) being most important on the right wing.

Betweenness Centrality

It's immediately obvious from Figure 3 that number 41 (Kurtis Henry - D) is a key player for puck distribution when looking at betweenness centrality. Perhaps unsurprisingly - as a rather defensive defenseman this is particularly true when the score is even or the Otters are defending a lead. The other thing that is immediately obvious is that, with the exception of the first period, the Otters are reliant on a wider pool of players to distribute the puck when behind than when ahead or neutral.

Several players, in addition to Henry, also appear critical across all situations including number 21 (Austen Swankler - C) and number 74 (Noah Sedore - LW). Number 5 (Jacob Golden - D) appears to be significantly more crucial when maintaining a lead, whereas number 73 (Connor Lockhart - C), number 17 (Daniel D'Amato - RW), and number 34 (Jack Duff - D) appear to increase in importance when the team is behind.

Pass Locations

Looking at the players highlighted above, can the distribution of where they are taking shots tell us anything about why they seem to drive play most effectively? Figure 4 shows the distribution of passing locations for the above players.

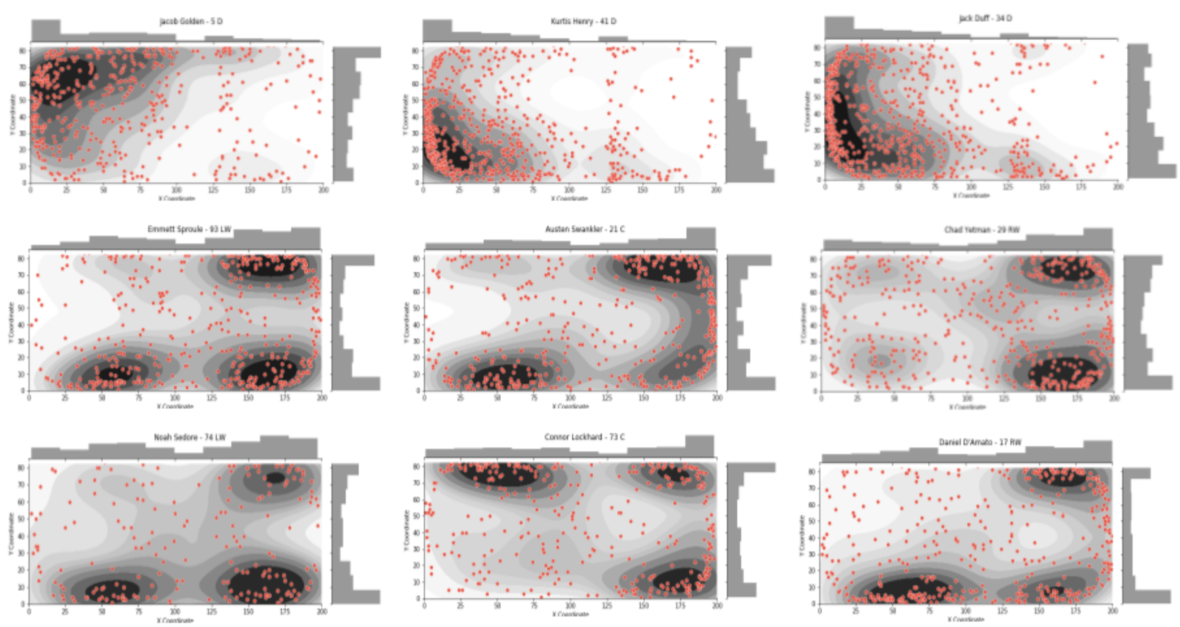
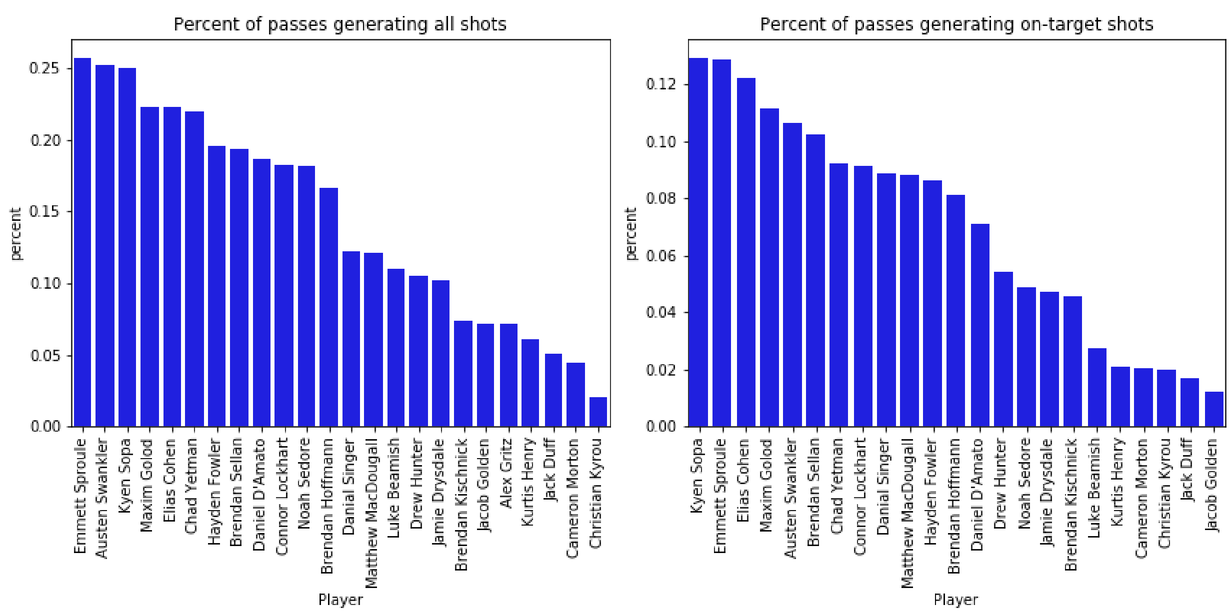


Figure 4: Pass Origination for players highlighted in network analysis

Perhaps surprisingly, given the seeming criticality of his play to puck distribution by the team, 41 (Kurtis Henry - D) drives play primarily behind his own net, as well as passing the puck from the opposing team blue line. He seems to be particularly effective containing and moving the puck on the right-hand side of the net.
In contrast 5 (Jacob Golden - D) is also a left shot, however who is particularly effective generating passes from behind and around the left side of the net.
34 (Jack Duff - D) is also a left shot who seems to operate effectively on both sides of the ice. Notable for all three defensemen who ranked highly in our betweenness centrality is, although focused in their own defensive zone, they appear to distribute the puck well laterally. They also appear to distribute the puck well from the blue line. The clustering along the boards potentially indicates successful forechecking and prevention of defensive zone exits by the other team and passing to team-mates (this could easily be determined by evaluating the preceding play).
All six forwards selected from the network analysis show a rather similar pattern with a wide distribution of pass locations end to end along the rink. However, the pass distribution is heavily weighted to the wings. The pass distribution is rather similar, regardless of whether the player is a center or a wing. One locus is along the boards in the defensive zone, with a horseshoe shaped distribution in and around the opposition net. The exception is 71 (Noah Sedore - LW) who appears to not really pass the puck from behind the opposition net in any significant fashion. The locus in the defensive zone for passes by forwards appears relient on shot handedness. All but 73 (Connor Lockhart - C) and 29 (Chand Yetman - RW) are left shots.

<u>Shot generation</u>



<u>Figure 5 Shot generation from passes - all shots and on-target shots</u>

Ultimately shot generation from passes is key to winning hockey games. Here we compute the percentage of passes by various players that generated shots. The total percentage of 5v5 direct passes that lead directly to a shot as the next event can easily be computed. The left hand graph in Figure 5 shows the percentage of passing plays that lead directly to all shots. The right hand graph shows the passing plays that lead to on-target weighted heavily to fowards with 93 (Emmett Sproule - LW) being the leading passer in shot generation and close to the leading passer in on-target shot generation. 71 (Kyen Sopa - RW) is also highly ranked, as is 21 (Austen Swankler -C), and 77 (Maxim Golod - LW). While it is unsurprising that forwards lead the team in passing plays leading to shots, for defensive players 49 (Luke Beamish) leads the team in passing plays leading to all shots, and 45 (Drew Hunter) in passing plays leading to shots on goal. 4 (Jamie Drysdale) - is the leading defensemen on the team in assists and is second among defensemen in passes leading to on target shots.

Somewhat surprisingly 5 (Jacob Golden), is among the lowest percentage in pass-to shot generation and pass to on target shot generation and is second on the team in overall assists. However, as noted above Golden is one of the leading members of the team in overall network importance. Therefore, one could imagine a scenario in which - as a defensemen, pucks are carried forward and passed into the offensive zone, generating secondary assists.

Of course one weakness of this analysis is that it does not account for teammate xG or shot accuracy, passes can be exceptional, however if passing to a teammate with little shooting ability there will be little payoff. That being said, excellent passes set up for success.

Conclusion

The analysis presented here is a preliminary attempt to use the principles of network analysis to determine the key players driving pass dynamics. The players highlighted by the network analysis were studied in more detail to highlight the morphology of their passing play. Finally passing plays that drive shots were studied. It was found that players that were key in the passing network were not necessarily players that drive shot production, particularly defensive players. This may indicate that network analysis can be a useful tool in identifying players that make major contributions to team play but do not necessarily show up on the score sheet.

Future work

There are some simple ways this work could be extended and/or improved. One obvious way would be to look at different game states (power-play, penalty-kill, etc.). We could also easily look at players receiving passes. It would also be possible to consider indirect passes. There are also other metrics (page-rank etc.) that could be used. Data on player game time could also be used to normalize the data somewhat. However, this data was not readily available. Szczepański and Hale[6] used a general linear mixed model (GLMM) to obtain a metric for pass-difficulty to evaluate passing skill by computing a metric for pass difficulty. While this would seem a fruitful area for future work (initial runs gave a model accuracy of ~75%, there was insufficient time to validate and tune the model for presentation here.

[6] Szczepański, Ł, & McHale, I. (2016). Beyond completion rate: Evaluating the passing ability of footballers. *Journal of the Royal Statistical Society. Series A (Statistics in Society), 179*(2), 513-533. Retrieved March 5, 2021, from http://www.jstor.org/stable/43965554