Tipping the Scales: A Statistical Analysis of Deflections for Micro-Scouting

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Hockey players are generally type-casted into certain roles. You have your playmakers, your snipers, your grinders; each one comes with certain stat-based qualifiers. Playmakers typically have higher pass volume and passing percentages, snipers score goals with higher shot percentages, grinders are expected to deliver hits and block shots, etc. But some skills are transferable across all roles, and in the modern NHL where versatility is vital to rolling a balanced lineup, certain skills should be coveted across the board. One of those skills is hand-eye coordination, or more specifically, deflections. The value of deflections should be obvious; by forcing a goalie to react twice to a shot that already takes just fractions of a second to reach the net, the chances of a goal, or at the very least a rebound, rise quickly. Deflections don't appear on most box scores, and unless a player has a certain talent for deflections (such as Joe Pavelski or Gabriel Landeskog) they don't usually get the proper recognition for that ability. Part of the reason is that many areas of focus with respect to player analysis tend to take a macro approach, be it expected goals, puck possession, or zone entries. Our goal was to analyze the importance of one particular micro-stat (in this case, deflections), the impact they have on a game, and highlight those who are particularly talented at generating chances using them. Identifying those players could give coaches another way to utilize a player, both at 5v5 and on the powerplay, as well as weaponize otherwise underutilized players. To do this, we broke down and analyzed the Erie Otters dataset, specifically focusing on deflections and those who created deflections as well. However before approaching the analysis, we first had to determine what actually makes a deflection successful or not.

Methodology

When approaching the question of "how do we define what makes a deflection successful", we assume 3 different outcomes from a deflection and assign each a numerical value based on how "successful" the attempt was. A puck that was deflected and missed the net was assigned "0", a puck on net was assigned a "0.5" and a deflection that directly led to a goal was assigned a "1"; an additional 0.25 was assigned to deflections that led to a "second chance" (second chance defined as another shot occurring within 3 second of the original with no other events occurring in between). Factors that were tested but found to be insignificant, harmful, or caused collinearity include shot type, deflections off of one-timers, and deflections that were screened. We believe these factors were heavily correlated with the location of the original shooter or there was not enough data to support their inclusion in the model.

We then analyzed the locations of both the deflection itself, as well as the location of the original shot or pass that resulted in the deflection. The X and Y values were also given a "relative value", measuring distance from the blue line and centre of the net, respectively, where the centre of the net was set to Y=0, with each foot left or right of the net being considered absolute, and the offensive blue line was set to X=0. After a series of testing, we found that a logarithmic function for location, as well as finding that separating the pass and shot deflections, resulted in the most accurate results. We believe the logarithmic test found more success than the test with the actual X and Y values as attempts within 10 feet of the net generally had the most success, so the logarithmic function mitigated the effects of being an additional foot closer to the net compared to being an additional foot closer to the blue line.

The data we had collected was run through an OLS estimator to determine the ideal locations for deflections, as well as the locations of events preceding deflections. The likelihood of a successful deflection off a shot *(D_S)* or a pass *(D_P)* with the location of the deflection *(X_1, Y_1)* and the location of the preceding event *(X_2, Y_2)* in the following formulas:

$$D_S=[log_{10}X_1*0.098]-[log_{10}Y_1*0.049]+[log_{10}X_2*0.147]-[log_{10}Y_2*0.006]$$

$$D_P=[log_{10}X_1*0.581]-[log_{10}Y_1*0.047]-[log_{10}X_2*0.204]-[log_{10}Y_2*0.25]$$

D_S implies that the preferred location of a deflection is closer on both the X and Y axis, while the location of the original shot improves the deflection's chances of success if slightly closer and more centered. Similarly, D_P shares similar effects from the location of the deflection; however, the location of the pass is found to improve the quality of the deflection when the pass comes from further away. We believe a major cause of this is that when a deflection occurs after a shot, the player acts as a screen for the initial shot, giving the goaltender less time to react, and being square to the net allows for more space to hit the net or score a goal. Conversely, a deflection off of a pass is best attempted when the goalie is pulled away from the centre of the net and out of position for the following deflection, sometimes referred to as a "royal road" pass through the crease. After calculating what we believe to be the "best" areas on the ice to generate and receive deflections, we then attempted to find which players on the Otters' team are most effective in those areas.

Findings

After defining success and building the model, we applied the regression to every deflection that had occurred in our data set to give each a likelihood of success rating. The first figure identifies every deflection that occured, if the deflection occurred off a pass or a shot, and its likelihood rating, while the second figure measures the same values but for pass or shot prior to the deflection. Because the model uses the data from both the deflection and the prior event, both the deflection and the preceding event share the same likelihood rating.

Based on Figure A, few deflections occur slightly closer or further away from the slot - unsurprisingly, most occur in the slot area, while the most successful deflections are tight to the crease. Figure B shows that many deflections off of shots occur towards the corners of the blue line;

Figure A

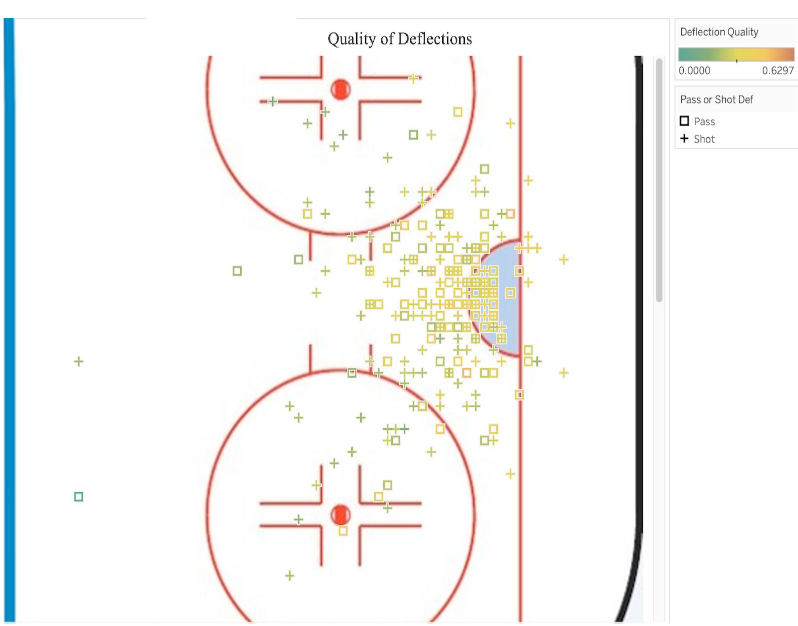
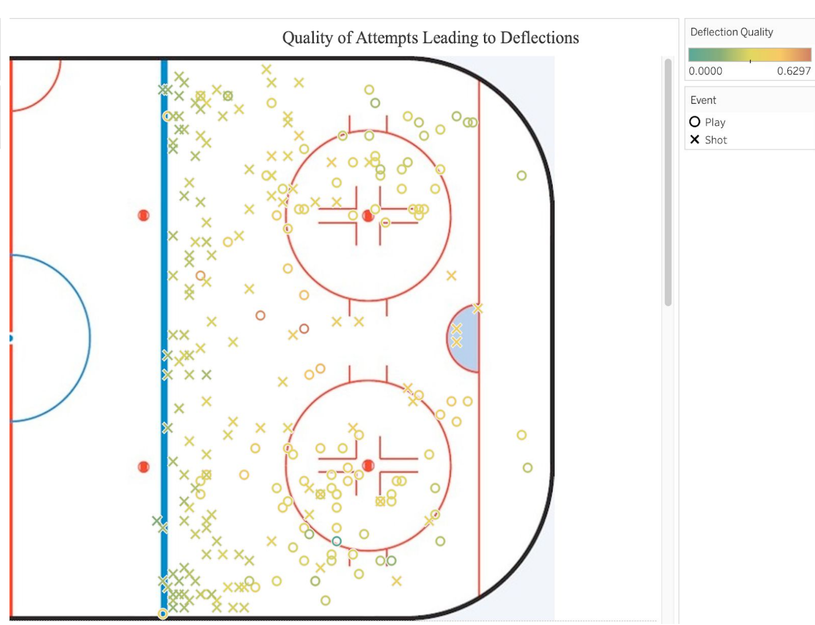
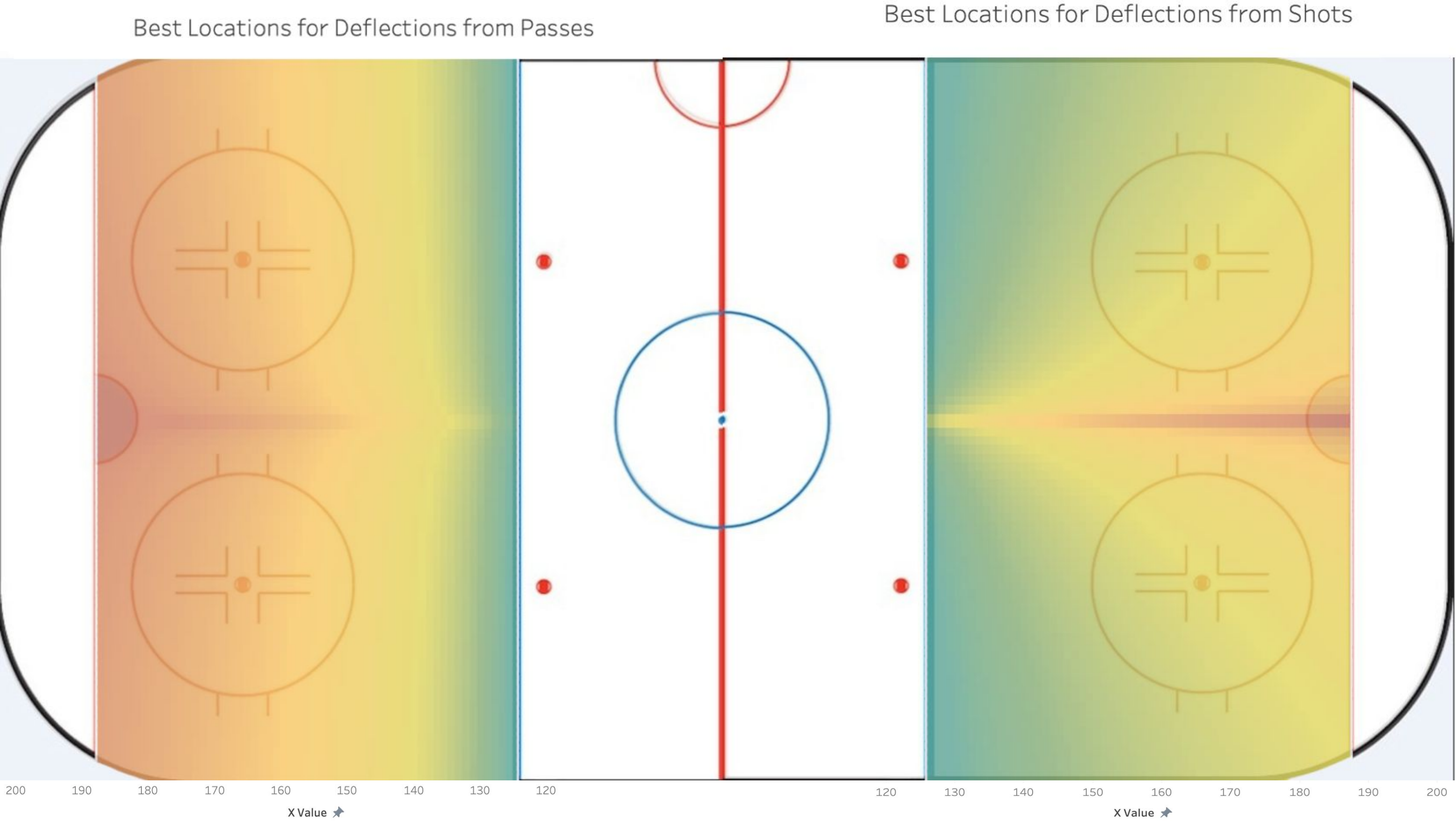


Figure B



however, the model shows that these opportunities are typically low quality. Based on the fact that most successful passes occur close to the offensive faceoff dots and most successful deflections from passes occur to the left or right of the crease, we can assume that these are the result of previously mentioned “royal road” passes. After analyzing the model using the existing deflections, we made a rough heat map to visualize how the model determines which deflection locations would be considered the most likely to be successful. To find this, we isolate the part of the model that accounts for the location of the deflection itself (X_1 and Y_1) and ignore the part that accounts for the prior pass or shot (X_2 and Y_2).

Figure C **Figure D**



While both Figures C and D show that an increase on X_1 correlates to a higher likelihood of success, Figure D shows deflections from shots places a much greater significance on location on Y_1. The formulas used in the model show that deflections occurring off of passes rely much more on Y_2 and X_2 compared to deflections occurring off shots. The heat maps may suggest this as well as Figure C has a much smaller “ideal range” and a much larger “poor range”. Our next step was to find which players our model believes are most proficient at generating deflections with the highest level of success.

Key Action Points:

With the COVID-related interruptions that we've seen across junior hockey at the moment, our data could be key to unearthing talent in a year full of uncertainty. A player showing great success in this field could demonstrate continued progress that they have made over the past year, progress that could have been ultimately missed due to the lack of viewing by scouts this season. Using our findings, we can evaluate a player's individual ability when in position to deflect pucks or create deflection opportunities. Separating these deflections into two categories of shots and passes furthers this assessment by giving a clearer picture of how a player's playmaking and finishing skill can impact deflections.

The table below is divided into four sections (Player Info, Raw Stats, Deflecting, and Deflection Creation), and are highlighted with the strengths and weaknesses of specific players in this field. While the previous section focuses on a general overview from all teams, this section specifically keys in on individuals. We calculated the average quality of deflections/deflections created, and then gave a rating (the total sum of deflection quality) of said shot type to show which players are the most successful at using deflections. Success, as previously mentioned, relates to either scoring a goal, creating a second chance, or landing a deflection on net.

Player Info		Stats					Deflecting					Deflection Creation				
Player	Position	Total Shots	Total Def	Def on Net	Def Goals	2nd Chance %	Shot Def Average	Shot Def Rating	Pass Def Average	Pass Def Rating	Deflecting Rating	Deflection Creation	Shot Def Rating	Pass Def Average	Pass Def Rating	Creation Rating
Chad Yetman	F	156	20	12	1	20%	34%	3.06	34%	4.05	7.11	0%	0.00	41%	1.63	1.63
Brendan Sellan	F	88	23	12	1	22%	28%	3.90	33%	2.95	6.84	30%	0.61	38%	0.76	1.37
Hayden Fowler	F	74	15	8	4	13%	29%	0.88	36%	4.30	5.18	38%	0.38	42%	1.27	1.65
Kyen Sopa	F	40	15	7	1	13%	31%	3.09	33%	1.67	4.76	40%	0.80	35%	1.06	1.86
Daniel D'Amato	F	74	9	3	2	11%	32%	2.84	0%	0.00	2.84	33%	0.33	37%	1.49	1.82
Austen Swankler	F	101	10	3	1	10%	28%	1.99	26%	0.79	2.77	34%	0.67	28%	1.12	1.80
Maxim Golod	F	160	8	6	0	0%	27%	1.09	39%	1.56	2.65	37%	1.84	35%	5.58	7.42
Elias Cohen	F	33	8	4	0	13%	26%	1.06	33%	1.32	2.37	0%	0.00	0%	0.00	0.00
Connor Lockhart	F	56	7	6	1	0%	26%	0.53	37%	1.83	2.36	35%	0.35	24%	0.48	0.83
Danial Singer	F	38	6	2	1	0%	35%	1.38	33%	0.67	2.05	0%	0.00	30%	0.30	0.30
Brendan Hoffmann	F	82	6	2	1	17%	24%	0.95	36%	0.72	1.67	0%	0.00	27%	0.27	0.27
Emmett Sproule	F	68	6	5	1	33%	32%	1.26	25%	0.25	1.51	40%	0.79	32%	0.64	1.43
Jack Duff	D	58	4	1	0	0%	33%	1.00	30%	0.30	1.30	27%	2.17	33%	1.00	3.17
Jamie Drysdale	D	81	3	2	0	33%	40%	0.40	39%	0.77	1.17	30%	5.08	31%	1.55	6.63
Matthew MacDougall	F	21	1	1	0	0%	0%	0.00	30%	0.30	0.30	0%	0.00	0%	0.00	0.00
Jacob Golden	D	39	1	0	0	0%	28%	0.28	0%	0.00	0.28	27%	2.14	36%	1.42	3.56
Brendan Kischnick	D	11	1	0	0	0%	27%	0.27	0%	0.00	0.27	26%	0.77	0%	0.00	0.77
Drew Hunter	D	46	0	0	0	0%	0%	0.00	0%	0.00	0.00	28%	1.66	30%	1.50	3.15
Kurtis Henry	F	47	0	0	0	0%	0%	0.00	0%	0.00	0.00	26%	1.83	35%	0.70	2.54
Cameron Morton	D	32	0	0	0	0%	0%	0.00	0%	0.00	0.00	26%	1.31	37%	0.37	1.68
Luke Beamish	D	11	0	0	0	0%	0%	0.00	0%	0.00	0.00	29%	0.86	33%	0.33	1.19
Alex Gritz	F	5	0	0	0	0%	0%	0.00	0%	0.00	0.00	0%	0.00	0%	0.00	0.00
Daniel Murphy	G	0	0	0	0	0%	0%	0.00	0%	0.00	0.00	0%	0.00	0%	0.00	0.00
Aidan Campbell	G	0	0	0	0	0%	0%	0.00	0%	0.00	0.00	0%	0.00	0%	0.00	0.00
Noah Sedore	F	20	2	2	0	0%	0%	0.00	0%	0.00	0.00	0%	0.00	0%	0.00	0.00
Christian Kyrou	D	3	0	0	0	0%	0%	0.00	0%	0.00	0.00	0%	0.00	0%	0.00	0.00
Brett Bressette	F	2	0	0	0	0%	0%	0.00	0%	0.00	0.00	0%	0.00	0%	0.00	0.00

Due to the small sample size in the given data set, we isolated the Erie Otter data specifically, as any other team didn't appear often enough to generate meaningful results. Our primary example for this analysis will be Chad Yetman, who is excellent at deflecting pucks in part due to his high sample of total shots and deflections on net; he's also excellent at creating a lot of second chances. Additionally, the average quality of both his pass and shot deflections is 34%, which ranks him amongst the top three players on his team. Although he only scored one goal on his 20 on-net deflection attempts, we can see that he is the type of player who can bring consistent success so long as he's consistently deployed in that prime deflection area. When it comes to deflection creation though, he looks like a player that leaves much to be desired. But, upon closer examination, you can see that the reason he does not appear to be such a great creator is because he isn't typically in the position to create those plays. Yetman's average quality when creating pass deflections is 41% (second to only Hayden Fowler), a number that would surely rise if he made more attempts as well. These examples highlight the potential this data has to find unrealized value for teams scouting potential prospects, trade targets, or upcoming opponents.

Summary, Limitations, and Future Considerations

There are plenty of important contextual factors and limitations that should be addressed here. Due to the nature of the dataset, there is obviously a sample size issue, at least regarding our individual players analysis. This issue forced us to re-evaluate what we defined as a "successful deflection"; if we had only used goals, the 17 we tallied would have made it difficult to draw concrete conclusions. The sample size issue didn't just affect that, however. We noted 263 deflections in total across the 40 games' worth of data, but given the fact that only Erie was involved in every game, we believed that isolating the Erie-specific data would give us the best chance to draw conclusions with enough data to support it. While this was the best course of action, it also led to additional limitations. Focusing exclusively on one team means that the data could be skewed to a certain team's playstyle; for example, if Erie favoured a perimeter playstyle, their deflections numbers might be different compared to other junior teams.

On the other hand, it can also lead to promising opportunities when it comes to game-planning, for both a coach's team and their opponent. If a team is generating an above-average amount of deflections against your team, a focus on defending the centre of the ice and tying up sticks could be suggested. If your team is unable to generate second chances on the powerplay, promoting and running the powerplay through your top deflectors could be the solution. Deflections play an important yet understated role in the game, and by utilizing the data we have collected, teams can maximize their chances for success using them. In a game where parity between teams is still growing, finding any way to tip the scales will be crucial, and deflections might just be the missing key to getting there.