EVALUATING DEFENSIVE PERFORMANCE IN THE NHL

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ABSTRACT

- With the NHL planning to release player and puck tracking data in the near future, my goal is to **develop a model to evaluate individual player contributions - specifically defensive contributions - without relying on play outcomes, in order to realize a player's true defensive impact on a game.**
- Building on the efforts by Chris Baker and Stephen Shea in their book "Hockey Analytics: A Game-Changing Perspective" (2017)[1], I propose a model to understand defensive efficiency on a per-possession basis for individual players and defensive pairs.

	Player	Team	Position	GP	TOI	CF	CA	CF%	FF	FA	FF%	SF	SA	SF%	GF	GA	GF%	xGF	xGA
1	Caleb Jones	EDM	D	2	21:52	34	10	77.27	24	6	80.00	21	3	87.50	1	0	100.00	2.37	0.25
2	Olli Juolevi	VAN	D	1	5:10	5	2	71.43	3	2	60.00	1	0	100.00	0	0	-	0.12	0.12
3	Kevin Connauton	COL	D	4	35:36	46	20	69.70	29	16	64.44	21	13	61.76	1	2	33.33	1.34	1.05
4	Jon Merrill	VGK	D	1	13:58	13	7	65.00	8	4	66.67	5	4	55.56	1	0	100.00	0.3	0.28
5	Ryan Ellis	NSH	D	4	78:54	116	63	64.80	89	41	68.46	67	32	67.68	4	4	50.00	4.58	1.53

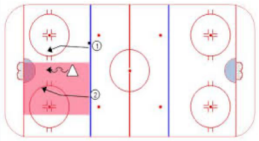
INTRODUCTION & BACKGROUND INFORMATION

Traditional Defenseman Evaluation Techniques

- Existing metrics that the hockey analytics community uses to evaluate defensive performance in the NHL are ineffective.
- Without access to player and puck tracking data, evaluation metrics are based entirely on play outcomes, such as shots, scoring chances, or goals, and they don't consider the many small events that occur leading up to a scoring chance. Metrics like Expected Goals against (xGA%)[2] are an improvement, but still don't tell the whole story.

TCP Model & Defensive Mistakes

- Chris Baker and Stephen Shea presented a novel method to evaluate defensive performance in their book 'Hockey Analytics: A Game-Changing Perspective' (2017)
- Their model, the TCP model, is predicated on the understanding that *73.4%* of all 5v5 goals are scored as a result of *three types of defensive mistakes*:
  1. **Transitions** – Situations where the offensive team out-numbers the defensive team upon entering the offensive zone.
  2. **'Clear-Path' Mistakes** – Situations where the defensive team leaves an offensive player open in in front of the net.
  3. **Penalties**- Leading to a power-play opportunity for the opposition.



- The TCP model suggests that defensive play should be evaluated at the team level by efficiency of defensive mistakes *on a per-possession basis*.
- This framework encourages us to evolve the way we analyze and evaluate defensive performance, shifting from a general 'prevent scoring chances' to a deeper situation-dependent understanding of player efficiency.
  - Does Player X's team give up significantly more transition chances when Player X is on the ice? How effective is he at defending transition chances?
  - Does Player X defend well in the defensive zone? On a per-possession rate, how often does this player's line get trapped in the defensive zone for more than 30 seconds?
  - Answering these questions is very important when trying to comprehend the full value of a defenseman. Existing metrics don't take these factors into account, and therefore do not paint the full picture of defensive value.

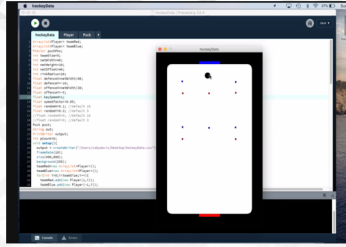
Spatial Tracking & Defensive Possession Database

- Spatial tracking data allows analysts to analyze defensive possessions and positional mistakes like never before.
- Evaluating player efficiency on a per-possession or per-play basis is relatively uncommon in hockey analytics, but is fundamental in the analysis of other sports. Furthermore, other sports (soccer, basketball, and football) have extended upon the concept to identify player movement trends and associated efficiency trends.
  - For example, Akhil Nistala and John Guttag presented the idea of an NBA possessions database, using spatial tracking data, back in their 2017 paper (Using Deep Learning to Understand Patterns of Player Movement in the NBA – 2017)[3]
  - In football, the 2019 Big Data Bowl Winning Paper 'Identifying Routes to Success' (Dani Chu, Lucas Wu, Matthew Reyers, James Thomson)[4] used a clustering technique to identify the routes of receivers using tracking data.
- Both of these papers introduced the concepts of creating **player profiles** based on typical routes ran and movements made by individual players.

OBJECTIVES

- Develop a comprehensive, easy-to-understand framework to evaluate defensive performance in the NHL using spatial tracking data.
- The purpose of this framework is to revolutionize the way defenders are evaluated, moving away from outcome-based summary metrics (such as xGA%) and towards a possession-by-possession breakdown of dangerous chance prevention.

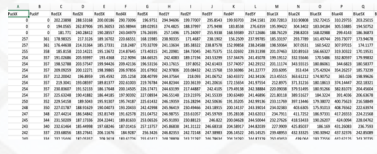
METHODOLOGY



- Without access to NHL player and puck tracking data, I created a video game-like hockey simulation using the program Processing[1].
- By re-creating a hockey rink and using my mouse cursor to control the puck, I created random trajectory patterns for players to follow.
- I created a collection of 200 possessions, with all ten players following randomly assigned patterns while the puck moves towards one team's zone.
- Using the trajectory data in place of NHL player data, I created **Flag Variables** that identify key features of possessions, such as whether or not there was a transition chance (3-on-2, 2-on-1, etc.), the type of transition chance, if a clear-math mistake was committed, if a penalty was taken, or if an open shot was allowed from the slot.

Simulated Possessions Database

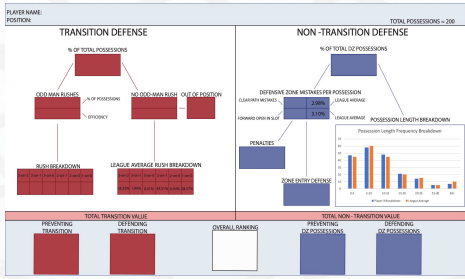
Possession ID	Possession Length (seconds)	Possession Type	Zone Entry	Odd-Man Rush	Type of Odd-Man Rush	Clear-Path Mistake	Uncovered Slot Opportunity	PlayerC60	PlayerC61	PlayerC62
1	1.7707726	Transition	No	0		0	0	0 RedC6	RedC6	RedC6
2	3.7429854	Transition	No	0		0	0	0 RedC6	RedC6	RedC6
3	14.6682286	Defensive Zone	Yes	0		0	0	0 RedC6	RedC6	RedC6
4	2.9852879	Transition	No	0		0	0	0 RedC6	RedC6	RedC6
5	15.873761	Defensive Zone	Yes	0		0	1	0 RedC6	RedC6	RedC6
6	6.7782729	Transition	Yes	0	1 3-on-2	0	0	0 RedC6	RedC6	RedC6
7	3.2952256	Transition	No	0		0	0	0 RedC6	RedC6	RedC6
8	1.176687	Transition	No	0		0	0	0 RedC6	RedC6	RedC6
9	4.0181825	Transition	No	0		0	0	0 RedC6	RedC6	RedC6
10	4.0819267	Transition	No	0		0	0	0 RedC6	RedC6	RedC6
11	11.6568869	Defensive Zone	Yes	0		0	0	0 RedC6	RedC6	RedC6
12	3.8355287	Transition	No	0		0	0	0 RedC6	RedC6	RedC6
13	6.2296473	Transition	Yes	0	1 2-on-1	0	0	0 RedC6	RedC6	RedC6



Output Trajectory Data

MODEL TO EVALUATE DEFENSIVE PERFORMANCE

- Similar to the TCP model from Hockey Analytics (2017), adding spatial tracking data analysis to identify defensive positional mistakes or situations that present dangerous chances against.
- Defensive possessions will be divided into transition defense and non-transition defense.
  1. For **Transition Defense,** players will be evaluated based on (1) their efficiency defending transition chances and (2) their efficiency preventing transition chances altogether.
  - For **Non-Transition Defense,** players will be evaluated based on (1) their efficiency preventing positional mistakes in the defensive zone and (2) their efficiency preventing defensive zone possessions altogether.
- These efficiency metrics can then be compared to teammates or other defensemen around the league, thereby creating a template to evaluate off-puck defensive performance.



RESULTS & DISCUSSION

- This evaluation framework re-defines how to evaluate defensive play in the NHL.
- It provides measures of process to compliment existing outcome-based metrics (like xGA% and CF%) to provide a possession-by-possession breakdown of defensive efficiency.
- This framework and the necessary functions are ready to sort and analyze real NHL Tracking Data.

ACKNOWLEDGEMENTS AND REFERENCES

- Coby Davis, Financial Engineer at Deliotte, for helping with the NHL tracking data simulation.

- [1]Chris Baker and Stephen Shea for their inspiration in 'Hockey Analytics: A Game-Changing Perspective (2017)
- "Hockey Analytics: A Game-Changing Perspective (Baker and Shea, 2017)
- [4]Route Identification in the NFL (Chu, etc.) https://www.degruyter.com/view/journals/jqas/16/2/article-p121.xml
- [3]NBA Possession Mapping: http://www.lukebornn.com/papers/miller_ssac_2017.pdf
- Using Deep Learning to Understand Patterns of Player Movement in the NBA http://www.sloansportsconference.com/wp-content/uploads/2019/02/Using-Deep-Learning-to-Understand-Patterns-of-Player-Movement-in-the-NBA.pdf
- Wide Open Spaces - Zones of Control Soccer http://www.sloansportsconference.com/wp-content/uploads/2018/03/1003.pdf
- https://processing.org/reference/libraries/
- https://cran.r-project.org/web/packages/trajr/trajr.pdf
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