Introduction

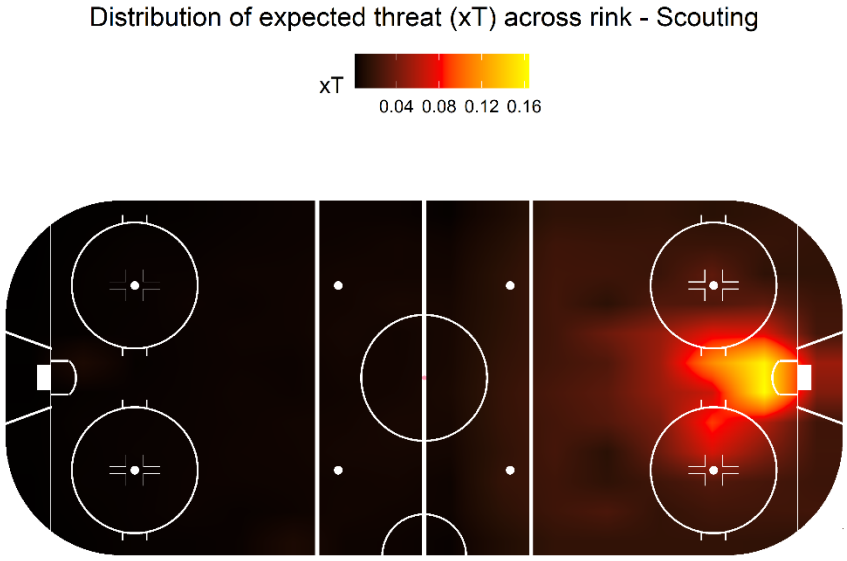
How can we measure offensive production beyond assists, goals, and expected goals in hockey?

Imagine a five-play possession that ended in a goal; the credited players would be the scoring player and up to two assisting players (last two touches). However, how are we crediting the other players who helped develop the possession? Which offensive action was the most impactful and significant to put the team in a position to score? These are the questions that our analysis answers.

We borrowed a soccer analytics concept called Expected Threat (xT), developed by Karun Singh to grade offensive production based on the field location at the start vs. the end of the play. In addition to adapting xT to hockey, we expanded it by adding time-remaining-in-period and turnover probability. We name the new metric: Net Expected Threat (nxT).

In soccer, the original xT model recognizes that at any point, a player possessing the ball has two options: to shoot (attempt to score) or to move the ball (dribble or pass). If a player chooses to shoot, the score-probability will depend on field location. If a player decides to move, there are multiple probable destinations, each with a different probability of success, depending on field location. xT generated (xTg) considers all possibilities and assesses by how much a player helped the team place the ball in a position to score, regardless of the actual outcome of the possession. To understand xT from a hockey perspective, interchange "ball" with "puck" and "dribble" with "zone-entry." One of the many benefits of this metric is the ability to divide credit. Take our five-play scoring-possession example. In that scenario, we can divide the xTg of each move action over the possession's total xTg. The result would be credit percentages to calculate which action or player had the highest impact.

In this submission, we explain how nxT expands xT to analyze a broader range of outcomes. Then, we describe the methodology behind nxT. Finally, we utilize nxT generated (nxTg) to grade offensive players for scouting purposes.



Problem statement

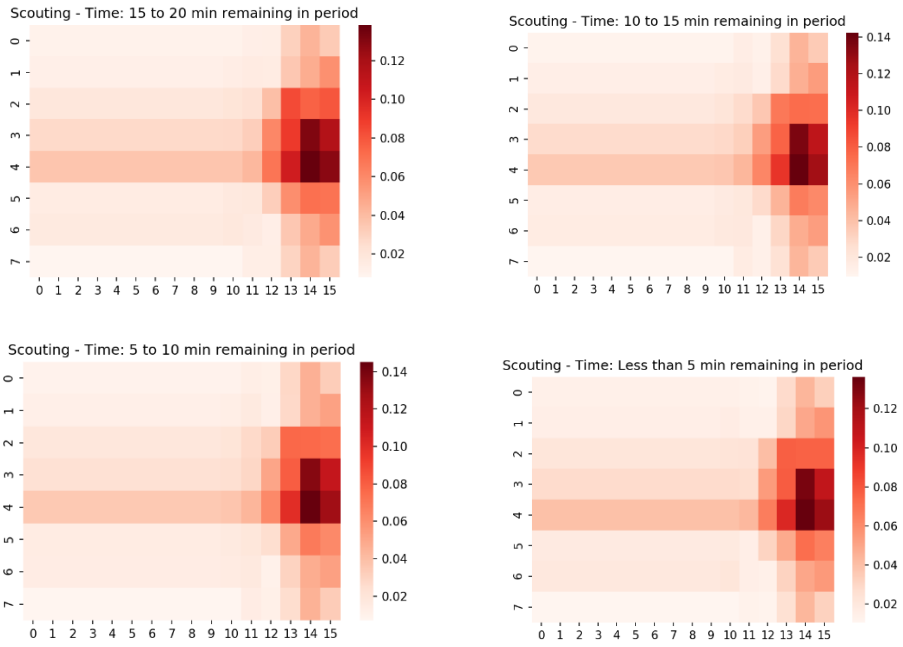
Hockey analysts utilize standard metrics such as assists and goals to grade offensive hockey players. The analytics revolution brought metrics like expected goals xG, which have become a staple in the hockey analytics community. However, there is still a need to quantify each move action's impact to create a scoring threat. Expected Threat (xT) is a partial solution, but there are some limitations. xT only considers field position when assessing probabilities of shooting, scoring, attempting to move, and successfully moving the puck. According to our xG model, time-remaining-in-period is crucial when estimating score probabilities and significantly alters score probability regardless of field position. Also, xT does not account for the probability of losing the puck; therefore, we cannot measure the impact of unsuccessful move actions. As a result, xT can only quantify the effect of completed passes and successful zone-entries.

There is a glaring opportunity to generate a metric that quantifies successful and unsuccessful move actions and incorporates time-remaining-in-period. By successfully addressing these limitations, we would quantify the impact of every offensive move action. The new metric would facilitate the scouting process by quickly analyzing large amounts of data and identifying threat-generating players regardless of position.

Solution

We decided to add time-remaining-in-period to an xG model, along with field location, to address one of xT's limitations. Then, we used the xG model to generate score-probability matrices and implemented them in our xT model.

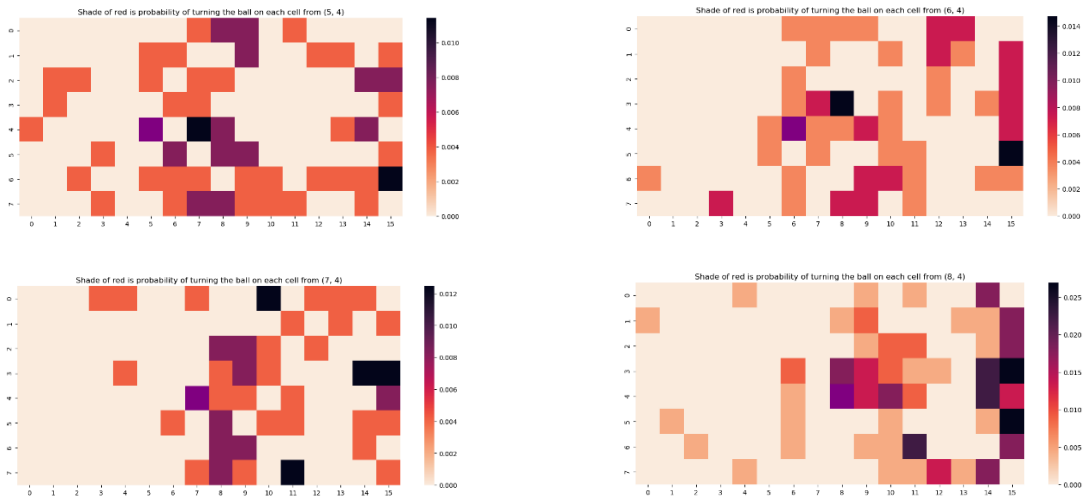
Formula, mentioning the difference in score probability



At this stage, our xT model is very similar to Singh's, except for adding an extra variable to generate the score-probability matrix.

Accounting for the probability of a turnover required a dynamic programming approach, similar to Singh's process when creating the move transition matrix for his xT model. We split the field into 128 cells: 8 width cells and 16 length cells. Then, we estimated the probability of losing the puck at each cell, each probable turnover cell location, and the hypothetical opposing xT for each turnover cell location. By multiplying each cell's probability of turnover by their corresponding hypothetical xT and summing the results, we obtain Opposing Expected Threat (oxT).

Formula



We can account for the probability of turnover by obtaining the difference between the possession team's Expected Threat (xT) and the opposing team's Expected Threat (oxT). The resulting metric is called Net Expected Threat (nxT), which is our proposed solution.

$$nxT = oxT - xT$$

nxT tells us the level of threat that each team represents at every point based on field location (cell) and time-remaining-in-half. To quantify each move action's impact, we calculate the difference in nxT before and after each play.

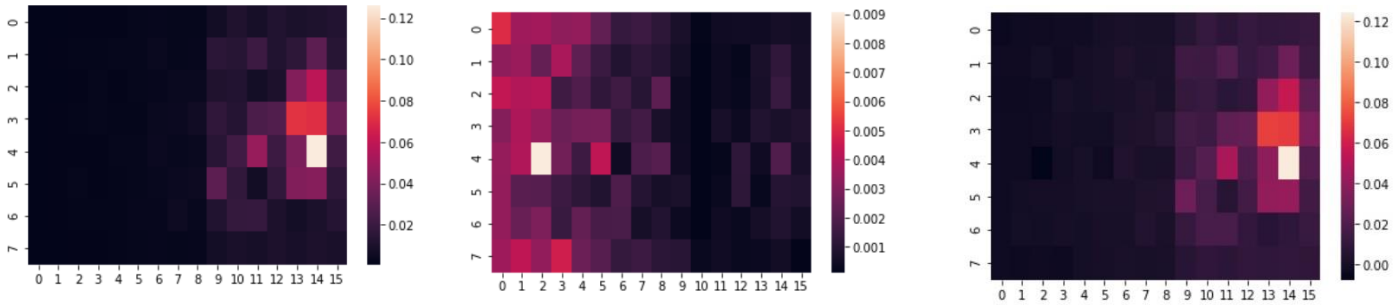
$$nxTg = nxT \text{ after the play} - nxT \text{ before the play}$$

By using oxT, we can measure the impact of a turnover by doing:

$$nxTg \text{ in turnover} = (oxT \text{ at the end of the play}) - nxT$$

nxT is the Expected Threat that team *i* had before the turnover (as the possession team). oxT is the Expected Threat that team *i* has after the turnover (now as the defensive team). This formula is different from equation b), which is the formula for nxTg when the play is successful.

As equation c) shows, oxT is needed to estimate the effect of turnovers. The previous methodology of xT was limited to equation b) and ignored unsuccessful actions: when the possession team loses the puck.



Methodology

Here we will use a lot of fancy math equations. We want to describe the whole dynamic programming and probability estimates using fancy words and algorithms. Here we can add the charts Pablo made with the arrows.

Findings/Results

Here we present our findings: best players, create tables, charts, how nxTg relates to goals scored or win probability.

** I am sure Evan can add something cool here**

Action points

Using this metric, we were able to grade thousands of players in the scouting league in offensive production regardless of their position. Every move action generates xT irrespective of how close the play happened to the opposing net and whether the possession ended in a goal or not. nxT can quantify the effect of both successful and failed move attempts; therefore, players making mistakes are penalized accordingly.

We invite teams and scouting departments to implement a version of this metric to boost their scouting efforts and provide an extra layer of information to their evaluation and decision-making process. We create an open-source python module available **here** to facilitate our metric's implementation.

We are presenting examples of visualizations to analyze players and teams using nxTg.

** I am sure Evan can add something cool here**