**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 accounting for 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 will answer.

We borrowed a soccer analytics concept called Expected Threat (xT), developed by Karun Singh to grade offensive production. In addition to adapting xT to hockey, we expanded it by adding time-remaining-in-period and the probability of a turnover in addition to field position, which is the only variable in xT. We are naming the resulting metric: Net Expected Threat (nxT).

The original xT model recognizes that at any point, a soccer 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 depends on field location. If a player chooses to move, there are multiple probable destinations, each with a different probability of success, depending on field location. xT generated (xTg) considers all probabilities and assesses how much a player helps the team place the ball in a position to score, regardless of the actual outcome. 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 xT generated with each move action over the total xT generated in the possession. The result would be credit percentages to calculate which action or player had the highest impact.

In this submission, we will how nxT expands xT to analyze a broader range of outcomes and the methodology behind nxT. Finally, we will utilize nxT to grade offensive players for scouting purposes. *(add something about how this can help NHL and NWHL)*

**Add cool heatmap of xT distribution and how to read it**

**Problem statement / Question asked**

For a long time, hockey analysts have utilized 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 for this problem, but there are some limitations. xT only considers field position when assessing probabilities of shooting, scoring, attempting to move, and successful move. According to our xG model, time remaining in the period is crucial when estimating score probabilities: it significantly alters score probability regardless of field position. xT does not account for the probability of losing the puck; therefore, we cannot use it to measure unsuccessful move actions. xT can only quantify completed passes and successful zone-entries.

There is a glaring opportunity to generate a metric that quantifies successful and unsuccessful move actions and incorporates significant variables such as time-remaining-in-period. By successfully addressing these limitations, we would quantify every offensive action's impact and facilitate the scouting process by

identifying high-threat-generating players regardless of position. A new metric would potentially impact and improve the scouting process by quantifying large amounts of data quickly and effectively.

**Solution**

We decided to add time-remaining-in-period to our xG model to address one of xT's limitations. We used the xG model to generate score-probability matrices and implemented them in our xT model. To address the limitation of not quantifying turnovers required a dynamic programming approach. We estimated the probability of losing the puck at each field position, the probable turnover location, and the expected opposing threat (oxT) metric. By using oxT, we can measure the impact of a turnover by doing:

$$\text{xTg in turnover} = (\text{oxT in next play}) - \text{xT}$$

xT is the Expected Threat that team i had before the turnover (as the possession team). oxT is the Expected Threat that team i had after the turnover (now as the defensive team). This formula is different from the xTg formula in successful actions:

$$\text{xTg} = \text{xT in next play} - \text{xT}$$

As equations a) and b) show, oxT is needed to estimate the effect of turnovers. The previous methodology of xT was limited to equation b) and ignored unsuccessful actions - whenever the possession team lost the puck.

*Add transition matrix GIF**

*Add turnover matrix GIF**

**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 nxT 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 terms of offensive production regardless of their position since every move action generates xT independent of field position and possession outcome. 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. To facilitate the implementation of our metric, we are dreating an open source python module that will be available at: [link].

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