

Puck Predictions: Unraveling the NHL Game Forecasting Riddle

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Abstract

The goal of this project is simple: predict the outcomes of NHL games from any given state during the game. To solve this problem we use three primary methods: Bayesian Network to train a DAG, XGBoost on game states, and an MCMC game simulator. We use each of these methods to generate win probabilities for each time step throughout various NHL games, thus emulating a live win probability. Finally, we analyze the accuracy of these three methods and considered ethical implications of our results.

1 Problem Statement and Motivation

In the world of sports analytics, predicting the outcomes of games is a common and challenging problem, with live win predictions adding an extra layer of complexity. For most sports, there are a plethora of widely accepted—yet hidden—predictive models and methods that are used to predict games. In addition to this, most sports have easily accessible statistics and graphics that give current win probabilities for any live game.

Hockey, however, is a different story. While there are some methods used to predict the outcome of National Hockey League (NHL) games, these models typically belong to sport books and their nuances are not publicly disclosed. Additionally, hockey analytics is not as developed as it is in other sports, such as basketball or baseball. This lack of model transparency and public interest in hockey analytics makes predicting the outcomes of NHL games a very underdeveloped and challenging problem. Previous attempts and research into predicting NHL games has relied on methods such as decision trees and artificial neural networks [3] (from 2014), naïve bayes and

support vector machines [4] (from 2013), and Monte Carlo simulations [5] (from 2014).

In addition to model research, some research has also gone into developing new features that can be used to better predict the game outcomes. The two biggest engineered classes of features are the Corsi and Fenwick¹ metrics (both around 2007).

Our project seeks a similar outcome to the research mentioned above: predict the outcomes of NHL games. Not only this, but we seek to provide live, accurate win probabilities for any given game state. Despite the simplicity of the problem statement, as mentioned, the solution is not so straightforward. The NHL provides fast-paced games with many events occurring in quick succession. Our goal is to use this abundance of data and new approaches to build upon previous research.

Our motivation for this project exists strictly as fans of the sport and as data scientists. Our model is not intended to be used for gambling or any other nefarious purposes—any use of this model for such purposes is a misuse of our work.

2 Data

Our data came from the hockeyR Github repository [2]. This repository contains an abundance of data about every NHL game that has occurred since the 2010-11 season. This data includes information about the events that transpire in a game (hits, shots, goals, etc.), which teams are playing, who is on the ice, and the final score of the game. The data is stored in a series of `.csv.gz` files, allowing for easy access and manipulation.

Each game in a season is given a unique identifier (`game_id`), which is constant across all events in a game. Every event that occurs in a game will be stored in the `event_type` column. There are 17 unique event types, including things such as game start, faceoff, shot, hit, and goal. Most of these event types are not relevant to our analysis, so we remove them from the dataset. After removing the unnecessary events, we are left with nine events: blocked shot, faceoff, giveaway, goal, hit, missed shot, penalty, shot, and takeaway. These events are attributed to the team and player that perform the event. We only take into consideration the team that performs

¹These metrics were created by sports bloggers Tim Barnes and Mark Fenwick, respectively. We were unable to locate the original blog posts talking about these metrics, but a good article to learn more about the math can be found here <https://thehockeywriters.com/corsi-fenwick-stats-what-are-they/>.

the event and discard the player information.

The data also contains information about when the event occurred. This appears in a variety of formats, but we only use the `game_time_remaining` column. `game_time_remaining` starts at 3600 (60 minutes) and counts down to 0. If the game goes into extra time, i.e., it is tied after 60 minutes, `game_time_remaining` will be a negative value.

We found that our data did not contain any missing values that was not easily explainable. For example, if a game is starting, there will be no events for penalties, which will result in a NaN value in the penalties column. Additionally, any data that was confusing or not easily explainable (for example the home team having 7 players on the ice and the away team having 5), was manually verified by watching a clip of the game where the event occurred to make sure the event was recorded correctly. We did not find any incorrectly recorded events, so we did not remove any strange events from our dataset.

3 Methods

3.1 Bayesian Network

We first used a Bayesian Network to establish a benchmark for probability using several key features.

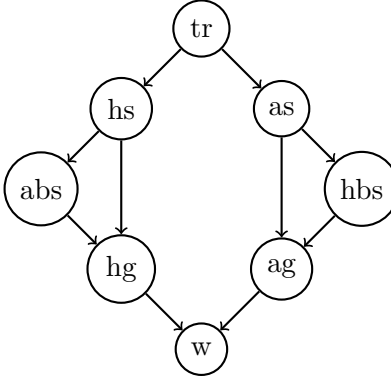
Bayesian networks are probabilistic graphical models that represent probabilistic relationships among a set of variables using a directed acyclic graph (DAG). In a Bayesian network, nodes represent random variables, and directed edges between nodes represent probabilistic dependencies between the variables. Each node in the graph is associated with a conditional probability distribution that quantifies the probability of that variable given its parent variables in the graph.

For our purposes, we predefined the structure of the network, and used the data to calculate the conditional probabilities for each node. We then used the network to calculate the probability of a team winning given the current state of the game.

The computational complexity of Bayesian Network inference is high, with exact inference being an NP-hard problem [1]. Using the python package pgmpy, we originally tried to fit a network with all 26 of our features, but our computational resources failed to fit this network. Then, to get a baseline for our future predictions, we simply fitted the model with the base features of time remaining (tr), home goals (hg), away goals (ag), home shots (hs), away shots (as), home blocked shots (hbs), and away blocked

shots (abs) in order to predict wins (w). These features were chosen as priors because of our opinion that they are the most important to the game, based upon our knowledge of hockey.

The conditional dependencies of the chosen network are shown in the DAG below:



This model was chosen for the task because different stats in hockey are conditionally dependent of each other, so by modeling those conditional dependencies and feeding them into the model, we can hopefully achieve a more accurate prediction of the outcome of the game.

3.2 XGBoost

In our NHL analysis research, we partitioned the dataset into segments corresponding to individual teams' games over multiple seasons. This enabled the creation of time series data in the form of a state vector, capturing the play-by-play dynamics of each team's matches. We then trained separate XGBoost models for each team to learn their unique patterns and strategies. We chose to create an XGBoost model for each team because we felt it would be more accurate than a single model for all teams. This is because some teams do very well and some teams do very poorly, and we felt this difference necessitated a model for each team.

3.3 MCMC Game Simulation

To simulate hockey games, we created a Markov Chain where the states are a tuple of three consecutive events that occurred. For example, if the home team won a faceoff, the home team lost the puck, and then the away team shot the puck and missed, the markov chain would look like Figure 1.

Sample Markov Chain	
<i>Next Event</i>	<i>Transition Probability</i>
Shot Away	0.1853207
Blocked Shot Away	0.1138666
⋮	⋮
Penalty Away	0.0167210
Goal Home	0.0085793

Figure 1: The transition events and probabilities when the previous three events were Faceoff Home, Giveaway Home, and Missed Shot Away, respectively.

The probabilities of transitioning from one triple-state to another triple-state is calculated by:

$$\begin{aligned}
 P(s_{t+1} = (B, C, D) \mid s_t = (A, B, C)) &= P(D \mid (A, B, C)) \\
 &= \frac{\{\# \text{ of times } (A, B, C, D) \text{ happened}\}}{\{\# \text{ of times } (A, B, C) \text{ happened}\}}
 \end{aligned}$$

Where A, B, C, D represent events that can occur in a game, and the tuple (A, B, C, D) represents that “A then B then C then D” happened right after each other in a game.

To simulate a game, we performed this Monte Carlo Algorithm (see Algorithm 1) that acted like a random walk through the Markov Chain (Note that the `KDE_times()` is a KDE model fit on the amount of seconds that transpired between each hockey event for all NHL games over the course of 13 years).

To predict a team’s winning probability, we would simulate 50 hockey games with the initial starting states (s_0, s_1, s_2) set to the most current events in the hockey game. By looking at each games final event counts, we could compute each game’s winner. Then we computed the probability as $P(\text{home winning}) = \{\# \text{ home simulation wins}\}/50$ and $P(\text{away winning}) = 1 - P(\text{home winning})$.

Algorithm 1 Simulation Algorithm

```
1: time_remaining  $\leftarrow$  3600  $\triangleright$  NHL games are 3600 seconds
2:  $s_0 \leftarrow \text{"\#"}$   $\triangleright$  The "\#" symbol represents the start of a game
3:  $s_1 \leftarrow \text{"\#"}$ 
4:  $s_2 \leftarrow \text{"\#"}$ 
5: event_counts  $\leftarrow$  dictionary()
6: while time_remaining  $>$  0 do
7:   next_state  $\leftarrow$  sample from MC(curr_state)
8:   event_counts[next_state]  $+=$  1
9:    $s_0 \leftarrow s_1$ 
10:   $s_1 \leftarrow s_2$ 
11:   $s_2 \leftarrow$  next_state
12:  event_time  $\leftarrow$  sample from KDE_times()
13:  time_remaining  $\leftarrow$  (time_remaining - event_time)
14: end while
```

4 Results and Analysis

4.1 Bayesian Network

Overall, the Bayesian Network performed well, and was able to produce realistic win probabilities. Because it defined a joint distribution using a DAG and then used that distribution to fit the data, it was able to correctly predict accuracies using the few features provided. However, the Bayesian Network struggled to capture the intricate dependencies of factors other than goals that could affect the win probabilities, so the predicted probabilities are little more than an over probability calculation of goals and time remaining given historical data. We see this in the probability graph below, where the changes in probability correspond to the goals scored in the game. A sample win probability graph is seen below in Figure 2.

4.2 XGBoost

As mentioned in the methods section, we trained an XGBoost model for each team in the NHL. One main benefit of this approach is the ability to leverage the `.predict_proba()` method of XGBoost. Using this method, we generated probabilistic predictions at various stages of a game, allowing us to plot the evolving probability of each team winning throughout the match (see Figure 3). This approach provided insights into momentum shifts (when one team has an advantage due to them having more players

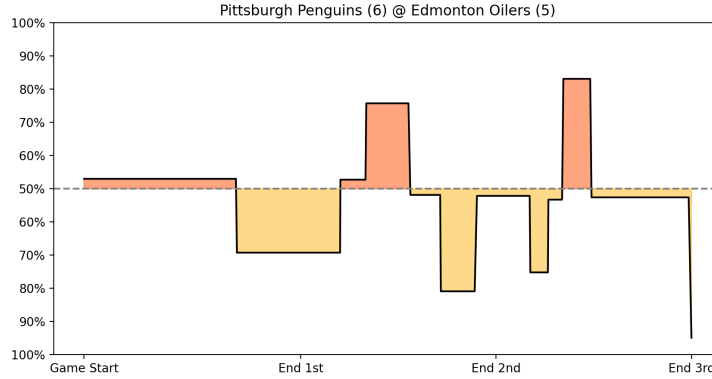
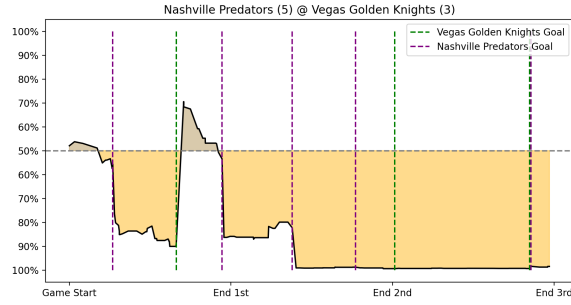


Figure 2: Win probability graph using the Bayesian Network. As seen above, the win probability stayed rather stagnant until a goal was scored, where the probability shifted.

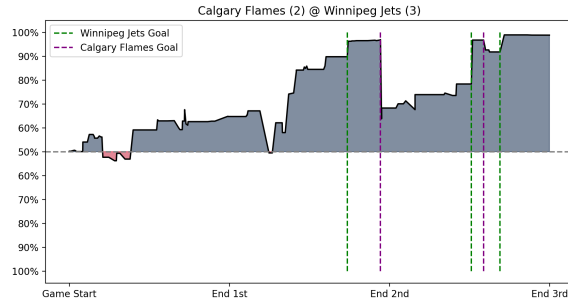
on the ice due to a penalty by the opposing team), key moments (such as goals and penalties, and critical plays influencing game outcomes).

4.3 MCMC Simulator

To evaluate our simulation’s effectiveness at accurately modeling actual hockey games, we combined a dataset with the final event counts for 1500 actual hockey games and for 1500 simulated games. We then performed two experiments. First, We trained a KMeans, Logistic Regression, Random-Forest and XGBoost model on this dataset with default parameters, to see if they could classify games as simulated or real. With a 70-30 train-test split, the accuracies on the test set were 47.9%, 48.5%, 67.5% and 69.3% respectively. Second, we fit and transformed this dataset using PCA, t-SNE and UMAP dimensionality reductions using various perplexity and neighbor hyperparameters to see if these algorithms clustered the synthetic games and actual games in different clusters. As shown below in Figure 4, the simulated games and actual games are all clustered together. From these two experiments, we conclude that our simulator effectively models live NHL games.



(a)



(b)

Figure 3: For both of these plots, the home team is above the the 50% line, with the away team below. The title has the final score of the game.

(a) The live win probabilities for the Nashville Predators at the Vegas Golden Knights. Notice the probability shifts after one team scores a goal.

(b) The live win probabilities for the Calgary Flames at the Winnipeg Jets. Notice the stark changes in probabilities after each goal. Also notice the shift in probabilities even when no goals are scored.

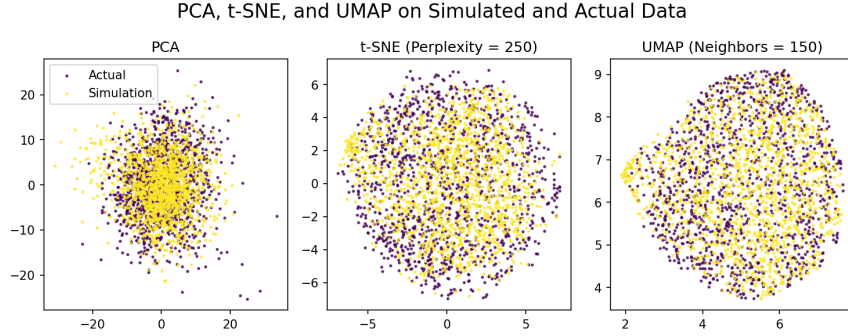


Figure 4: PCA, t-SNE, and UMAP performed on a dataset with final event counts for 1500 simulated and 1500 actual NHL games. The joined grouping demonstrates that our simulation accurately emulates live NHL games. Note that we performed the t-SNE and UMAP on many different values of perplexity and neighbors, but all of the plots looked the same, so we just show this one

4.4 Method Comparison

Each of the methods described above had one general purpose: accurately predict the outcome of a hockey game regardless of the point in the game. To evaluate our models, we randomly selected 100 games outside of the training data, and for various time steps throughout these games we had each model calculate a win probability. We then used the probability threshold of 0.5 to determine whether or not each model predicted if the home team won or lost. We then computed each model’s accuracy across all 50 games for each of the time steps.

In Figure 5 we note that each model increased in accuracy as the game progressed. We also notice that the MCMC simulation method appears to have the highest accuracy regardless of the point in the game while XGBoost appears to be the least accurate. We infer that the XGBoost models were overfit, since they appeared to perform very well on games within the training set. Also, during experimentation with the models, we noticed that the MCMC simulator and the Bayesian Network tended to produce higher probabilities for the away team winning, and the XGBoost model tended to give higher probabilities to the home team winning. The MCMC and Bayesian Network are structured to model the flow of events, so it appears that they picked up on a more predictive flow in how away teams play.

Accuracy Comparison Between Models			
<i>Game Seconds Played</i>	<i>MCMC</i>	<i>XGBoost</i>	<i>Bayesian</i>
0	a	a	a
600	a	a	a
1200	a	a	a
1800	a	a	a
2400	a	a	a
3000	a	a	a
3600	a	a	a

Figure 5: Each of our model’s predictive accuracy over the course of 100 games

5 Ethical Considerations

Predicting win percentages or outcomes in hockey games, like any sport, raises several ethical considerations relating to the fairness and integrity of the sport. We believe that the main ethical issue with our model is the potential for it to be used for gambling purposes. We do not condone the use of our model for gambling, and the purpose of our model is purely for educational and entertainment purposes. However, we recognize that the primary reason the the public uses sports predicting models is for gambling reasons.

The juxtaposition of our reasoning for completing this research and how we believe this research would be used is an interesting ethical dilemma. One could argue that because our model will be used for gambling, we should not have released or published this work in the first place. However, we believe that the technological and mathematical advancements that we have made in this project are valuable and should be shared with the public. We also believe that the potential for our model to be used for gambling is not a reason to withhold our work from the public.

Gambling is harmful because it can lead to addiction, financial ruin, and other negative consequences. Gambling can also affect outcomes of games unfairly if players, coaches, owners, or referees illegally participate in gambling. Corrupt actors could create a destructive feedback loop using our predictions to gamble and then therefore influence the outcome of the game to match our predictions. We wish to make it clear that we are vehemently against sports gambling, and we support laws, policies, and practices that prevent gambling from negatively affecting sports and encourage healthy

and responsible gambling practices.

Additionally, there are no privacy concerns with our data as we only collected publicly available NHL data.

6 Conclusion

In this project, we used three different methods to predict the outcomes of NHL games. We used a Bayesian Network to model the conditional dependencies of key features, XGBoost to model the play-by-play dynamics of each team, and an MCMC simulator to simulate the flow of events in a hockey game. We found that the MCMC simulator was the most accurate, with the Bayesian Network coming in second, and XGBoost coming in last. The win percentages predicted are more for entertainment and educational purposes, and should not be used for gambling or performance purposes, as they do not have an incredibly high degree of accuracy. There are many variables in a hockey game that affect win probability, and given more time and more data we would love to model other factors such as momentum, historical success, coaching, etc. Our project was limited by the data we had access to and computational resources, but nonetheless we were able to produce a model that can predict the outcome of NHL games with a reasonable degree of accuracy.

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