X-Factors: External Influences of a Hockey Goaltender's Performance*

Higher Team Score Differential, Shot Activity, and Momentum Boost Goals Saved Above Expected

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This paper investigates how external factors influence hockey goaltenders' performance during games, using Goals Saved Above Expected (GSAx) over 10-minute time intervals as the measure of success. Variables relating to pre-game context, in-game performance, and recent form are analyzed to understand their impact on performance. Our findings reveal that goaltenders perform better when their team is leading and when they are actively engaged, but sustained workloads negatively affect outcomes. These results provide a clearer understanding of how game context shapes performance, offering practical implications for evaluating and optimizing goaltender usage.

1 Introduction

Few team sport athletes have as much influence on team performance as the hockey goaltender. Legendary performances, like Dominik Hasek single-handedly dragging Czechia past heavy favourites Canada and Russia to win the 1998 Olympic gold medal, are etched in the history books forever. Yet up until recently, it was hard to quantify goaltender performances; standard metrics such as wins, percentage of shots saved, and goals allowed per game did not tell the full story about goaltender's performance. The explosion in popularity of sports analytics has led to new metrics that better measure what fans see with the eye test. The most popular advanced metric, Goals Saved Above Expected (GSAx), is an all-encompassing statistic that captures a goaltender's performance relative to their peers. This is calculated by finding the difference between the goals a goaltender allows and the number a goaltender is 'expected' to allow; the expectation is quantified using an advanced model with many factors, such as MoneyPuck's model (Tanner 2024b).

*Code and data are available at: https://github.com/danield424/HockeyShotAnalysis.

Although GSAx is an established metric that outlines which goaltenders consistently overperform, it still isn't clear *why* they, beyond obvious factors like skill level and experience. Questions about the impact of external factors like workload, game state, or recent engagement remain largely unanswered, with discussions often reduced to subjective terms like "mentality" or "being on a roll." This paper aims to address these gaps by analyzing the impact of external factors on a goaltender's GSAx during a game. Specifically, it investigates how variables relating to game state, in-game performance, and recent form influence a goaltender's performance within a 10-minute game interval; the estimand is the magnitude of the effects of these factors. Using a regression model, we quantify the relationship between these external variables and performance outcomes, providing a clearer understanding of what drives overperformance or underperformance.

Our findings show that external factors significantly shape goaltender performance. Increased shot activity in the preceding three minutes and positive prior performance as a proxy for momentum are associated with improved performance, while sustained workloads lead to declines. These patterns suggest that in-game context is most important in determining goaltender performance.

The remainder of this paper is structured as follows: Section 2 introduces the data and methodology used; Section 3 describes the model used to answer our research question; Section 4 presents the key findings; Section 5 discusses the real-world implications of these results.

2 Data

2.1 Overview

To analyze the effect of external factors on goaltender performance, we use a log of 394,250 shots taken during the 2021-22 to 2024-25 NHL regular and post-seasons, provided by Money-Puck (Tanner 2024a). These shot datasets are split by season and labelled "2021-2022 Season (121,471 Shots)", "2022-2023 Season (122,026 Shots)", "2023-2024 Season (122,472 Shots)", and "2024-2025 Season (33,648 shots)". Moneypuck is a publicly available source of hockey analytics that tracks advanced statistics, playoff odds, and event data. The shot data is updated daily from official NHL game reports. For the current 2024-25 season, data is included up to November 26, 2024.

The dataset includes well-documented variables essential for analyzing goaltender performance, and was selected for its reliability, comprehensive coverage, and accessibility. While other sources, such as the NHL's API or third-party aggregators like Natural Stat Trick, offer similar information, Moneypuck's integration of official NHL reporting, consistent data updates, and easy access make it the preferred choice. Shot data available for all years since 2008-09; we choose the 2021-22 season as the dataset starting point as this was the first full season following the COVID-19 pandemic.

The data spans 137 variables that provide metadata and contextual information about each shot. This analysis focuses on external factors hypothesized to influence goaltender performance, grouped into categories related to game state, in-game performance, and recent performance (see Section 2.3). Data cleaning steps ensured consistency and accuracy, with a detailed explanation provided in Section B.

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2.2 Measurement and Limitations

Shots, defined as any player's attempt to score by directing the puck at the net, are classified as an event type by the NHL. Events, along with their associated attributes and metadata, are officially recorded by Sportradar, the NHL's data partner, using AI-powered data tools ("Sportradar" 2024). Events are also counted and verified by official scorekeepers.

Both AI and human collection methods are subject to potential errors, including misclassification or missed events; the exact processes used to address data discrepancies are not disclosed, introducing a level of uncertainty. However, the likelihood of significant errors is low given the importance of accurate statistics to the NHL - statistics are critical for tracking individual and team performance, determining award winners, and informing league decisions, such as rule enforcement or changes. Therefore, Moneypuck's integration of this information provides a reliable resource for analytics.

2.3 Variables

From the cleaned dataset, we calculate response variable `GSAx_segment`, which represents the average goals saved above expected by a goaltender over a 10-minute segment. Our goal is to identify external factors that influence a goaltender's performance; below we outline the reasons for measuring performance with `GSAx_segment`. We select predictor variables representing external factors hypothesized to affect goaltender performance during the time interval. These predictors are categorized into three groups:

1. Game state:

- `isHomeTeam`: Indicates whether the goaltender is playing at home or away.
- `isPlayoffGame`: Indicates whether the game is a regular-season or playoff game.

2. In-game performance and workload: sll of these metrics are measured by first finding the value for each shot in a `GSAx_segment` based on prior shot data, then getting the final value by averaging the shot-level values across the segment.

- `period`: the game period (e.g. 1st, 2nd).
- `goalieTeamScoreDifferential`: the score differential for the goaltender's team (positive when winning, negative when losing).
- `shots_faced`: a measure of the total shots the goaltender has faced in the game.
- `shotslast3min`: the shots the goaltender has faced in the last 3 minutes.
- `GSAx_so_far`: the goaltender's GSAx so far in the game.

3. Recent games performance:

- `last_game_GSAx`: GSAx from the previous game, representing goaltender performance in the previous game.

- `last_5_avg_GSAx`: average GSAx from the 5 previous games, representing performance in the previous 5 games.

Some pairs of predictors are closely related, such as `shots_faced` and `shotslast3min`, and `last_game_GSAx` and `last_5_avg_GSAx`. Potential multicollinearity arising from these relationships is addressed in Section 3, where we also explore interactions between predictors.

Our research focuses on how external circumstances influence goaltender performance, not the difficulty of the shots themselves. Therefore, we exclude variables directly used in the calculation of `GSAx`, such as shot danger and location. These variables measure the intrinsic difficulty of the shots faced and are already incorporated into `GSAx`. Including them as predictors would conflate shot quality with the external factors we want to analyze, such as game state, workload, and recent form.

By excluding these variables, we ensure the model evaluates the situational factors that drive over or underperformance relative to the expectations set by the shots faced, as captured by `GSAx_segment`.

2.3.1 Outcome variable

`GSAx_segment` quantifies goaltender performance over 10-minute time intervals during a game. It is calculated by averaging the Goals Saved Above Expected (GSAx) of all shots faced by a goaltender within 10-minute chunks of game time. This approach aggregates performance across several shots to provide a more stable measure of goaltender ability, minimizing the influence of variability inherent within single shots. Using time-segmented data, rather than shot-specific values, allows us to evaluate patterns of performance more reliably across a game.

Using 10-minute time segments to measure GSAx has limitations, as the intervals do not align perfectly with the key game events such as periods of player imbalance or of high shot volume. Furthermore, segments in games with overtime are cut short due to sudden-death scoring, potentially biasing its comparability with other segments. However, `GSAx_segment` is still valuable as it balances granularity and interpretability, providing snapshots of short-term performance without the noise introduced analyzing shot by shot. It also allows for uniform comparison across games and goaltenders, facilitating broader analysis of performance trends.

The following is a statistical summary of `GSAx_segment` and its distribution:

Table 1: Summary statistics for response variable GSAx_segment

Summary Statistic	GSAx_segment
Min	-0.99
1st Quantile.25%	-0.05
Median	0.03
Mean	-0.01
3rd Quantile.75%	0.06
Max	0.50
Standard Deviation	0.13

From Table 1, the mean GSAx_segment is -0.01, close to the expected value of 0. This aligns with the idea that GSAx should average out to 0 when aggregated across many segments and goaltenders, as GSAx represents the difference between actual and expected goals. The median is slightly positive at 0.03, indicating that a slight majority of time segments may reflect slightly above-average performance. The standard deviation of 0.13 `GSAx_segment` indicates moderate variability in performance across time segments.

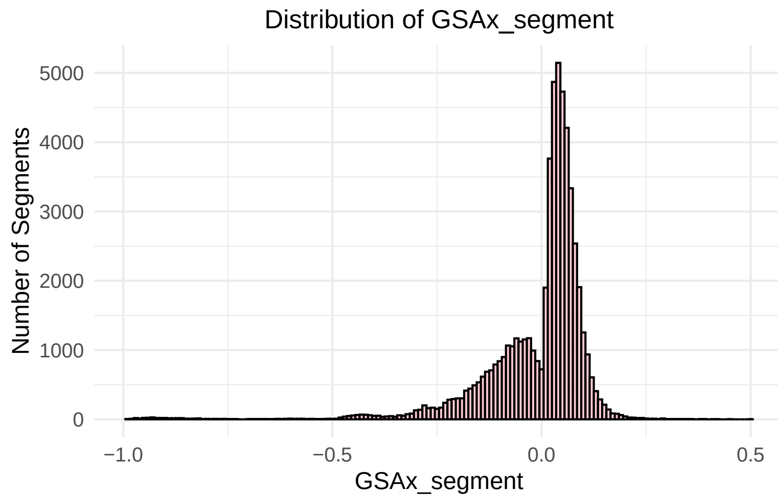


Figure 1: Distribution of GSAx_segment

From Figure 1, the distribution sharply peaks near 0, with a long tail extending toward both positive and negative extremes; this indicates most time segments exhibit performance close to expected levels, with occasional outliers where goaltenders significantly underperform or overperform. The distribution's longer negative tail reflects the occasional high-impact errors (e.g., letting in unexpected goals) that skews `GSAx_segment` in short time frames.

2.3.2 Predictor variables

2.3.2.1 Game state predictors: Home vs Away, Regular Season vs Playoffs

`isHomeTeam` is a binary variable equal to 1 if the goaltender is playing at home, and 0 if playing away. This variable examines the impact of home-ice advantage on performance, given that teams historically perform better at home Bischof (2021).

`isPlayoffGame` is a binary variable equal to 1 for playoff games and 0 for regular-season games. Playoff games are higher-stakes, lower-scoring environments that may influence a goaltender's mindset, workload, or performance Donchess (2022). By including this variable, we assess whether this affects performance.

These game state variables are static for each segment, as segments occur entirely within single games. Table 2 summarizes the dataset's segments, categorized by the two predictors.

Table 2: Count of segments by game state

Is Home Team	Is Playoff Game	Count
0	0	26436
1	0	26517
0	1	1681
1	1	1686

As expected, the dataset primarily contains regular-season games. Additionally, the `GSAx_segments` for home and away games are similar, as each game involves one goalie playing at home and another playing away; discrepancies are attributable to infrequent goaltender substitutions.

2.3.2.2 In-game performance and workload predictors: period, score, shots faced, shots in last 3 minutes, performance so far

`period` is a categorical variable representing the period the segment takes place in, created by splitting the game into 20-minute intervals. Note that since segments are 10 minutes and almost all periods are 20 minutes, every segment will take place within one period. The only exception is regular season 5 minute overtime periods, but these are guaranteed to be the game's final period, so it still holds true that no segment overlaps periods.

We analyze if the period has any effect on goaltender performance, choosing to represent periods categorically to capture unique performance differences in each period without assuming a linear progression. In Table 3 and Table 4 we see segments that fall in each period for regular season and playoff games.

Table 3: Segment breakdown for regular season periods

Period	Number of Segments
1st Period	17100
2nd Period	17194
3rd Period	17050
Overtime	1609

Predictably, segments are similar across the first 3 periods. We can infer that roughly 10% of games require the extra 5-minute overtime period.

Table 4: Segment breakdown for playoff periods

Period	Number of Segments
1st Period	1064
2nd Period	1076
3rd Period	1056
Overtime	138
2nd OT or later	33

Periods are similar for playoff games, with the difference being that overtime periods are the same length as regular periods, and additional overtime periods are required if there is no scoring. Roughly 13% of games require overtime.

- `goalieTeamScoreDifferential` represents the average differential of the game score over the course of the 10 minute segment. It is positive if the goaltender's team is leading, 0 if the game is tied, and negative if the goaltender's team is trailing; this allows us to analyze whether goaltenders perform better when their team is winning or losing, or depending on how close the game is. Decimal values reflect score changes within the segment.

Table 5: Summary of segments by goaltender team score differential

Summary Statistic	Goalie Team Score Diff.
Min	-9.5
1st Quantile.25%	-0.9
Median	0.0
Mean	0.0
3rd Quantile.75%	1.0
Max	9.5
Standard Deviation	1.6

Table 5 shows this stat is symmetrical, as every non-tied segment has a winning and losing goalie. Both the median and mean are 0, representing tied segments. The median and mean is 0, representing segments where the game is tied. Due to its symmetry, we can better visualize the `goalieTeamScoreDifferential` distribution by taking the absolute value in Figure 2.

Most segments occur when the game is tied, and the number of segments decreases exponentially with an increase in score differential. Segments with a larger differential are rarer, as games tend to remain close in score.

To analyze for winning and losing game states without the symmetry effect, we can look at the distribution for an individual goaltender such as Vancouver's Thatcher Demko. From Figure 3,

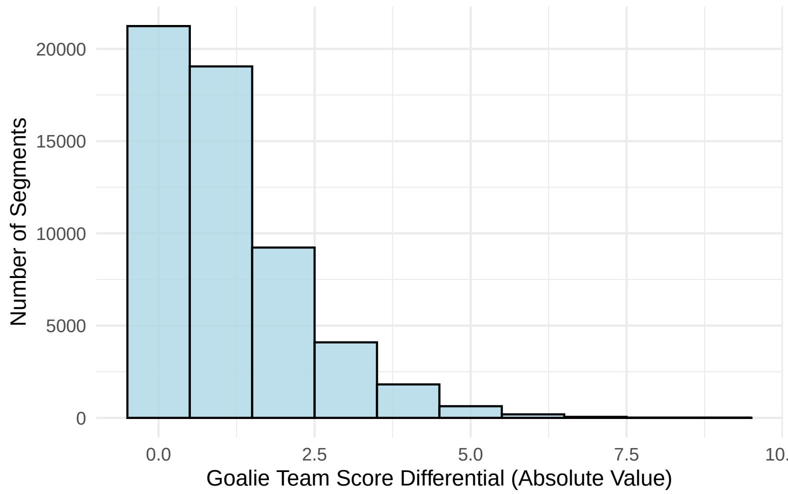


Figure 2: Distribution of the absolute value of the score differential in segments.

many segments were tied throughout, and he spent slightly more time with his team winning. Most segments have unchanging score differentials, categorized by the integer average.

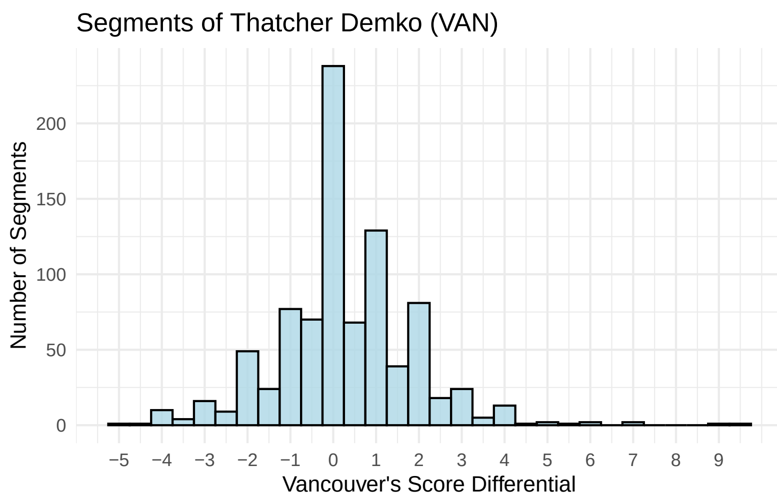


Figure 3: Distribution of the score differential for segments of goaltender Thatcher Demko.

- `shots_faced` represents the cumulative number of shots a goaltender has faced in the game prior to each shot in the segment, averaged over each shot. This gives a measure of the goaltender's prior workload; we analyze how it influences the goaltender's ability to stop subsequent shots.

Table 6: Summary of segments by shots faced

Summary Statistic	Shots Faced
Min	0
1st Quantile.25%	6
Median	14
Mean	15
3rd Quantile.75%	22
Max	78
Standard Deviation	10

From Table 6, the mean of 15 indicates that a goaltender has faced 15 prior shots across the average segment. The maximum prior workload for a segment was 78 shots.

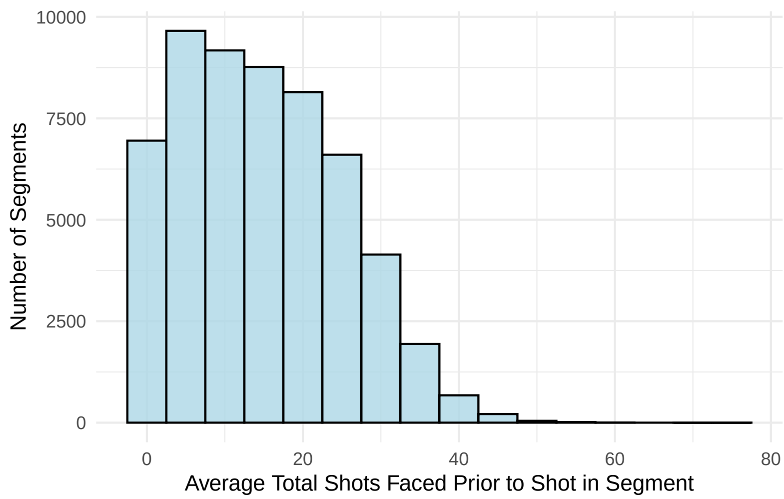


Figure 4: Distribution of shots faced so far, averaged across shots in segment.

We see in Figure 4 that the distribution of `shots_faced` is close to uniform for values between 0-25. Beyond 20 shots, the number of segments decreases exponentially, reflecting that fewer games reach very high shot counts.

- `shotslast3min` finds the shots the goaltender has faced in the 3 minutes prior to each shot in the segment, then takes the average across all shots in the segment. Note this is not equivalent to the shots faced in the 3 minutes prior to the segment; it is a dynamic value that can vary for each shot in the segment. By measuring this value, we evaluate whether facing many shots in quick succession can improve performance by keeping the goaltender "in rhythm" or more alert, or decrease performance by increasing pressure on the goaltender.

Table 7: Summary of segments by the average shots faced in the last 3 minutes, across segment shots.

Summary Statistic	ShotsLast3min
Min	0.0
1st Quantile.25%	0.7
Median	1.2
Mean	1.3
3rd Quantile.75%	1.8
Max	9.0
Standard Deviation	0.8

From Table 7 and Figure 5, segments are roughly normally distributed with a mean of 1.3, meaning a goaltender saw ~1.3 shots in the 3 minutes prior to every shot in an average segment. Segments ranged from those with no shots in the preceding 3 minutes to segments where the goaltender saw an average of 9 shots in the last 3 minutes.

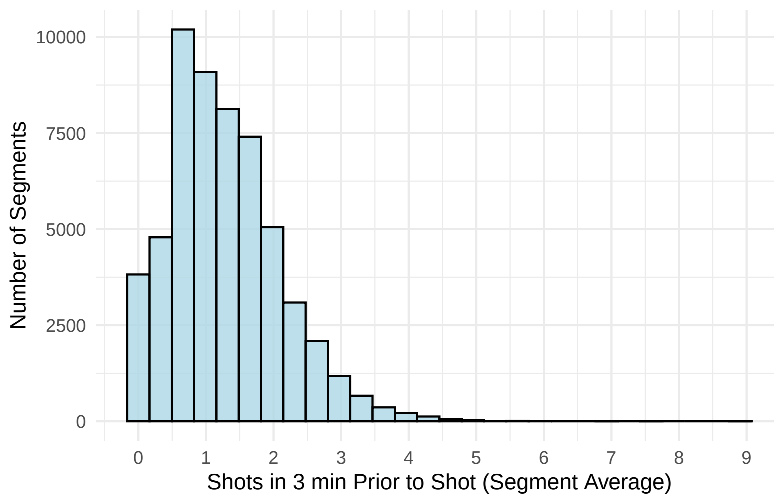


Figure 5: Distribution of segments depending on average shots seen in the last 3 minutes averaged across the segment.

- `GSAx_so_far` is the cumulative GSAx of a goaltender up to the current point in the game, prior to the shots in the segment. This variable captures how well a goaltender has performed relative to expectation throughout the game up to the current moment, enabling exploration of whether strong performance early in a game carries over into later segments, and vice versa.

Table 8: Summary of segments by accumulated GSAx prior to segment.

Summary Statistic	GSAx so far
Min	-5.98
1st Quantile.25%	-0.44
Median	0.12
Mean	0.10
3rd Quantile.75%	0.64
Max	6.06
Standard Deviation	1.01

In Table 8, the median 0.12 and mean 0.1 suggest that goaltender performance prior to segments is generally close to expectations, with slight overperformance common. In Figure 6 the distribution is approximately normal and centered near 0; the range (-5.98 to 6.06) and standard deviation 1.01 indicate considerable variability in in-game performance.

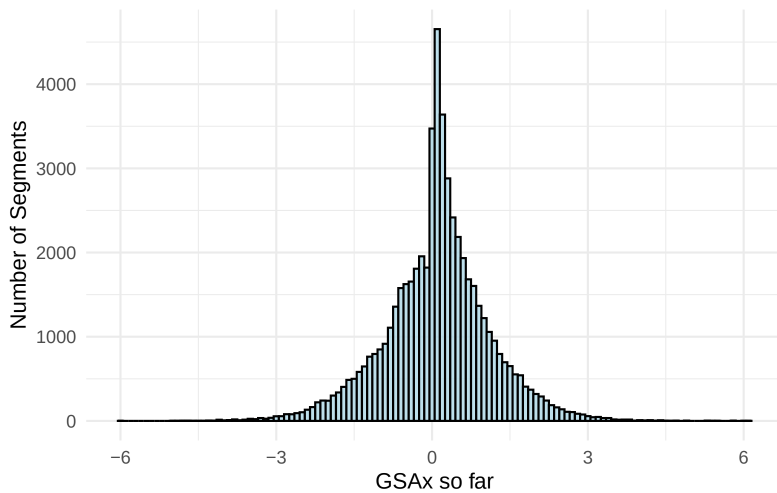


Figure 6: Distribution of segments based on the goaltender's accumulated GSAx prior to segment.

2.3.2.3 Recent performance predictors: Last game and last 5 games

- `last_game_GSAx` represents the goaltender's performance in the previous game, measured with the cumulative GSAx.
- `last_5_avg_GSAx` representing the goaltender's performance in the previous 5 games, measured with average cumulative GSAx.

With these, we can see if the previous performance or stretch of performances carries over to the next goaltender performance.

Table 9: Summary of segments by goaltender GSAx in the previous game.

Summary Statistic	Last game GSAx
Min	-5.99
1st Quantile.25%	-0.99
Median	0.12
Mean	0.06
3rd Quantile.75%	1.13
Max	6.99
Standard Deviation	1.59

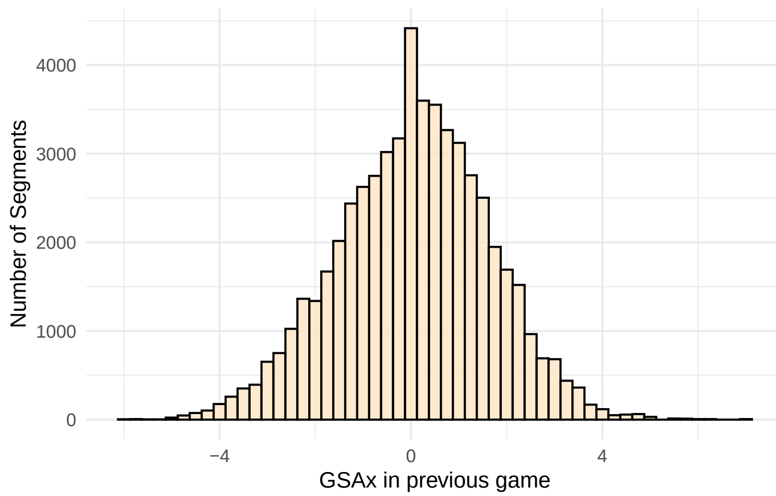


Figure 7: Distribution of segments based on the goaltender's previous game GSAx.

From Figure 7, we observe a roughly normal distribution centered near 0, which aligns with expectations. The mean of 0.06 in Table 9 may reflect a selection effect, as goaltenders with particularly poor performances in their previous games may not play in the following game, skewing the distribution slightly toward positive values.

From Figure 8, when we increase the prior performance sample to 5 games, the tails are shorter, with average GSAx falling mostly between -2 and 2. The lower standard deviation in Table 10 confirms this. Other variable features are similar to `last_game_GSAx`.

Table 10: Summary of segments by average goaltender GSAx in the previous 5 games.

Summary Statistic	Last 5 Average GSAx
Min	-5.99
1st Quantile.25%	-0.43
Median	0.06
Mean	0.06
3rd Quantile.75%	0.55
Max	3.60
Standard Deviation	0.76

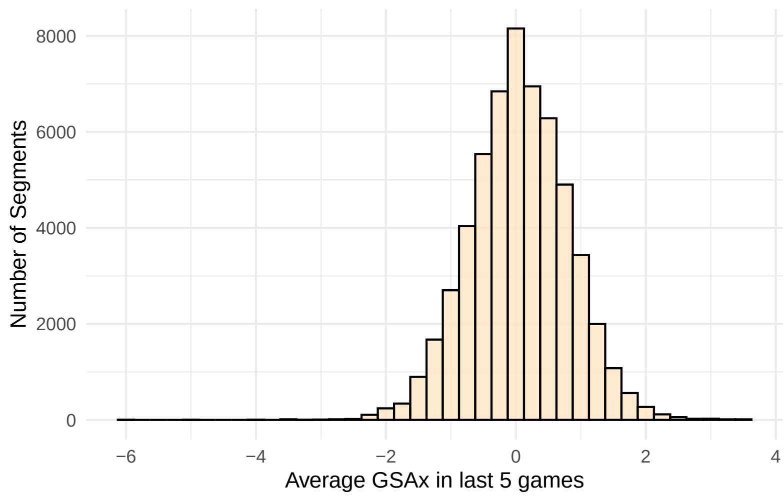


Figure 8: Distribution of segments based on the average GSAx of the goaltender's previous 5 games.

3 Model

Using the statistical programming software R (R Core Team 2023) as well as packages tidyverse (Wickham et al. 2019), modelsummary (Arel-Bundock 2022) and caret (Kuhn and Max 2008), we develop a linear regression model with `GSAx_segment` as the response variable and our outlined factors as predictor variables. The objective of this model is to identify which predictors significantly influence goaltender performance, using p-values to assess significance and coefficients to evaluate the magnitude of their effects.

Alternative modeling approaches were considered, such as using shot-level or game-cumulative GSAx as the response variable. These approaches analyze different levels of granularity; we chose the segment-based model as it is detailed and interpretable. It focuses on how external factors shape performance without introducing excessive uncertainty or overly broadening the scope of analysis. This aligns with the goal of understanding the predictors' effect on the response rather than creating a highly predictive model.

Background details and diagnostics are included in Appendix D

3.1 Model

$$
\begin{aligned}
\text{GSAx\_segment}_i = \beta_0 &+ \beta_1 \times \text{isHomeTeam}_i && (1)\\
&+ \beta_2 \times \text{isPlayoffGame}_i && (2)\\
&+ \beta_3 \times \text{period2nd Period}_i && (3)\\
&+ \beta_4 \times \text{period3rd Period}_i && (4)\\
&+ \beta_5 \times \text{periodOvertime}_i && (5)\\
&+ \beta_6 \times \text{period2nd OT or later}_i && (6)\\
&+ \beta_7 \times \text{goalieTeamScoreDifferential}_i && (7)\\
&+ \beta_8 \times \text{shots\_faced}_i && (8)\\
&+ \beta_9 \times \text{shotslast3min}_i && (9)\\
&+ \beta_{10} \times \text{GSAx\_so\_far}_i && (10)\\
&+ \beta_{11} \times \text{last\_game\_GSAx}_i && (11)\\
&+ \beta_{12} \times \text{last\_5\_avg\_GSAx}_i && (12)\\
&+ \beta_{13} \times (\text{isHomeTeam}_i \times \text{isPlayoffGame}_i) && (13)\\
&+ \beta_{14} \times (\text{goalieTeamScoreDifferential}_i \times \text{shotslast3min}_i) && (14)\\
&+ \beta_{15} \times (\text{goalieTeamScoreDifferential}_i \times \text{shots\_faced}_i) && (15)\\
&+ \beta_{16} \times (\text{GSAx\_so\_far}_i \times \text{shotslast3min}_i) && (16)
\end{aligned}
$$

- β_0: The intercept of the model, representing the expected value of `GSAx_segment` when all predictors are set to zero (i.e., when the game is neither a home game nor a playoff game, the score differential is zero, and no shots have been faced in the last three minutes, etc.).

- β_1: The coefficient representing the change in `GSAx_segment` when the game is a home game (as indicated by `isHomeTeam = 1`), compared to when the game is an away game, holding all other variables constant.
- β_2: The coefficient representing the change in `GSAx_segment` when the game is a playoff game (`isPlayoffGame = 1`), compared to when it is a regular season game, holding all other variables constant.
- $\beta_3, \beta_4, \beta_5, \beta_6$: The coefficients representing the change in `GSAx_segment` compared to the baseline 1st period, depending on if the game is in the 2nd, 3rd, OT, or extra OT periods respectively, holding all other variables constant. As discussed in Section 2.3.2.2, `period` is categorical to avoid assuming a linear progression.
- β_7: The coefficient representing the change in `GSAx_segment` for a one-unit increase in the `goalieTeamScoreDifferential`, holding all other variables constant. This variable measures the score difference between the goaltender's team and the opponent, reflecting the impact of game context on goaltender performance.
- β_8: The coefficient representing the change in `GSAx_segment` for a one-unit increase in `shots_faced` by the goaltender during the game, holding all other predictors constant. This represents how goaltender performance changes with an increased workload.
- β_9: The coefficient representing the change in `GSAx_segment` for a one-unit increase in the number of `shotslast3min`, the average count of shots faced in the last 3 minutes, holding all other predictors constant. This quantifies how recent shot activity affects the goaltender's performance.
- β_{10}: The coefficient representing the change in `GSAx_segment` for a one-unit increase in `GSAx_so_far`, the prior cumulative performance of the goaltender, holding all other predictors constant. This accounts for how a goaltender's in-game performance thus far influences current performance.
- β_{11}: The coefficient representing the change in `GSAx_segment` when the goaltender's performance in the previous game (`last_game_GSAx`) increases by one GSAx, holding all other predictors constant. This captures the effect of previous game performance trend on current performance.
- β_{12}: The coefficient representing the change in `GSAx_segment` when the average performance over the last five games (`last_5_avg_GSAx`) increases by one GSAx, holding all other predictors constant. This captures the effect of the goaltender's longer-term performance trend on current performance.

- β_{13}: The coefficient representing the change in `GSAx_segment` due to the interaction between being a home game (`isHomeTeam`) and a playoff game (`isPlayoffGame`). This accounts for how home-ice advantage may differ in high-stakes playoff games and how this combination influences goaltender performance.
- β_{14}: The coefficient representing the change in `GSAx_segment` due to the interaction between `goalieTeamScoreDifferential` and `shotslast3min`, recognizing that the goaltenders may be affected differently by recent shot activity depending on the game score.
- β_{15}: The coefficient representing the change in `GSAx_segment` due to the interaction between `goalieTeamScoreDifferential` and `shots_faced`. recognizing that the goaltenders may be affected differently by a high workload depending on the game score.
- β_{16}: The coefficient representing the change in `GSAx_segment` due to the interaction between `GSAx_so_far` and `shotslast3min`, accounting for how a goaltender's prior performance and recent shot activity jointly impact their current performance.

3.2 Assumptions and validation

The model assumes no systematic relationship between the residuals and the fitted values of the response variable, or between residuals and any predictor. This ensures that the unexplained variance is random and does not display patterns that might indicate unaddressed non-linear relationships. We assess these assumptions using residuals vs. fitted values plots.

The model also assumes a linear relationship between the predictors and the response variable GSAx_segment. This means the effect of each predictor on GSAx_segment is additive and constant. Residual plots are used to evaluate whether the linearity assumption holds.

Additionally, the model assumes that the residuals are normally distributed, independent, and have constant variance (homoscedasticity). If these assumptions are violated, the model's estimates may be biased or invalid. We check these with a normal QQ plot.

We mentioned earlier in Section 2.3 that we need to check for multicollinearity. Predictors should not be highly correlated, as this can lead to unstable estimates and inflate standard errors. We used Generalized Variance Inflation Factor (GVIF) analysis to identify potential multicollinearity issues.

To validate the model, we perform a train-test split (80/20). The model is fit using the training set, and performance is evaluated on the test set using the Mean Squared Error (MSE) and R-squared values. Since the R-squared of the model on the training and testing set is similar, we conclude that the model generalizes well and is not overfit.

Further details and graphs are included in Appendix D.

3.3 Limitations

There are a few limitations to our model:

Due to lack of data, the model does not include all possible external factors influencing goaltender performance. Some other possible factors include such as team overall performance, team tactics, current health, days of rest since last game, contract situation, or game-specific psychological factors. These omissions could lead to lack of model precision or biased estimates for included predictors.

We assume linearity for all predictor variables. While this simplifies the model, it may not fully capture the complexities of goaltender performance.

The model's response variable has flaws, as discussed in Section 2.3.1.

The R-squared value indicates that only a small portion of variance in `GSAx_segment` is explained by the model, so the model cannot be used to draw extremely strong conclusions about the relationships between our predictors and `GSAx_segment`.

3.4 Appropriate use

There are some contexts where the model is not appropriate for use:

The model may not be suitable when interactions or dynamics beyond those included (e.g., omitted variables discussed above) significantly influence performance.

The model is designed to estimate the effects of external factors on goaltender over- or underperformance rather than to maximize predictive accuracy. As such, it does not perform well when asked to precisely predict the response `GSAx_segment`.

4 Results

Our model regression coefficients and their associated standard errors are summarized in Table 11.

4.1 Coefficient Interpretation

From the provided table of regression coefficients, we can draw the conclusions about the model's results. Each coefficient represents the magnitude of the effect of the corresponding variable or interaction term on GSAx_segment, holding other variables constant. The standard error (in parentheses) allows us to determine if terms are significant; if the coefficients are a standard error from 0, and have p-values above a 0.05 significance level, they are likely insignificant.

Table 11: Coefficient values and their errors

	(1)
(Intercept)	−0.010
	(0.001)
isHomeTeam	−0.003
	(0.001)
isPlayoffGame	0.005
	(0.003)
goalieTeamScoreDifferential	0.011
	(0.001)
shotslast3min	0.009
	(0.001)
shots_faced	−0.001
	(0.000)
period2nd OT or later	−0.013
	(0.025)
period2nd Period	0.000
	(0.002)
period3rd Period	0.013
	(0.003)
periodOvertime	−0.092
	(0.004)
GSAx_so_far	0.022
	(0.001)
last_game_GSAx	0.000
	(0.000)
last_5_avg_GSAx	0.001
	(0.001)
isHomeTeam × isPlayoffGame	−0.001
	(0.005)
goalieTeamScoreDifferential × shotslast3min	0.001
	(0.000)
goalieTeamScoreDifferential × shots_faced	−0.001
	(0.000)
shotslast3min × GSAx_so_far	0.002
	(0.001)

4.1.1 Significant terms

Binary/Categorical:

- `isHomeTeam`
  Coefficient: `-0.003`
  Implication: Playing at home is associated with a slight decrease in `GSAx_segment`, suggesting that goaltenders may slightly underperform at home.

- `period3rd Period`
  Coefficient: `0.013`
  Implication: Performance improves slightly in the 3rd period compared to the baseline 1st period.

- `periodOvertime`
  Coefficient: `-0.091`
  Implication: Goaltenders perform significantly worse during overtime compared to the baseline 1st period.

Continuous:

- `goalieTeamScoreDifferential`
  Coefficient: `0.011`
  Implication: An increase in the score differential (goalie's team scores a goal) is associated with an increase in `GSAx_segment`, indicating improved goaltender performance when leading.

- `shotslast3min`
  Coefficient: `0.009`
  Implication: Facing more shots in the last three minutes is associated with a better `GSAx_segment`, suggesting that recent activity may keep the goaltender in a rhythm or alert.

- `shots_faced`
  Coefficient: `-0.001`
  Implication: Each additional shot faced is associated with a small decrease in `GSAx_segment`, suggesting that increased workload slightly reduces performance.

- `GSAx_so_far`
  Coefficient: `0.022`
  Implication: Better cumulative performance earlier in the game is associated with improved performance during the segment, indicating momentum or consistency.

- `shotslast3min * GSAx_so_far`
  Coefficient: `0.002`
  Implication: The interaction between recent activity (shots in the last three minutes)

and cumulative performance (GSAx_so_far) suggests that recent activity amplifies the positive effects of prior performance.

Effect of continuous predictors on GSAx_segment: for a one-unit increase in each of the 5 continuous variables/interaction terms above, GSAx_segment changes by the magnitude of the coefficient. For example, if the goalie's team were to score an extra goal, GSAx_segment would increase by 0.011.

Although the coefficients are small, they still have some significance. For example, the 0.013 coefficient for period3rd Period can be interpreted as a 1.3% increase in goaltender performance in the 3rd period compared to the 1st.

4.1.2 Insignificant terms

The coefficients for these variables are likely to be 0, meaning the effects of these variables on GSAx_segment are not strong enough to make conclusions:

- Intercept: The baseline value itself is not particularly meaningful since most predictors will not realistically be zero.
- isPlayoffGame
- period2nd OT or later
- period2nd Period
- last_game_GSAx
- last_5_avg_GSAx
- isHomeTeam * isPlayoffGame interaction
- goalieTeamScoreDifferential * shotslast3min interactoin

4.2 Effects of Significant Terms

To better visualize the effects of significant terms, here are how the values of GSAx_segment differ for each of our significant terms.

4.2.1 Home vs Away

Table 12 compares goaltender performance GSAx_segment between home and away games. The average GSAx_segment for away games is -0.0076, while for home games, it is -0.0087. This small difference (-0.0012) is consistent with the model findings, indicating that goaltenders perform slightly worse at home, with a 0.12% decrease in performance. This could be due to increased pressure at home, although 0.12% is a very small difference.

Table 12: GSAx_segment values for home and away

Goaltender Team	Count	Avg GSAx_Segment
Away	28117	-0.0075587
Home	28203	-0.0087676

4.2.2 Goalie Team Score Differential

Table 13: GSAx_segment values by score differential

Score Differential	Segments	Avg GSAx of Segment
4+	1461	0.0159524
3	2054	0.0177675
2	5214	0.0112033
1	9567	0.0117394
0	21234	-0.0091289
-1	8840	-0.0255358
-2	4660	-0.0336153
-3	1886	-0.0323749
-4+	1404	-0.0377781

Table 13 summarizes `GSAx_segment` values based on the game score, represented as the score differential of the goalie's team. As the goaltender's team gains an additional goal, the average `GSAx_segment` improves, from being negative when the goaltending team is trailing to positive when the team is ahead. The data reveals a trend where goaltenders perform better as their team increases their lead, likely due to reduced pressure or easier defensive situations. Conversely, performance decreases when the team is trailing, potentially reflecting higher-pressure situations or increased shot difficulty.

4.2.3 Shots faced in last 3 minutes

Table 14: GSAx_segment values versus shots faced in last 3 minutes

Avg. Shots in last 3 min	Segments	Avg GSAx of Segment
0	11710	-0.0286755
1	24307	-0.0062646

Table 14: GSAx_segment values versus shots faced in last 3 minutes

Avg. Shots in last 3 min	Segments	Avg GSAx of Segment
2	15969	-0.0008660
3	3525	0.0094621
4	703	0.0088892
5+	106	0.0234829

Table 14 examines how recent shot activity influences goaltender performance. Segments with zero shot activity have the lowest average `GSAx_segment` at -0.029; this steadily increases until we reach segments with five or more shots, which have the highest average of 0.024. This trend suggests that goaltenders perform better when actively engaged, possibly due to improved focus or rhythm. Conversely, performance decreases when goaltenders are inactive for extended periods.

Shots Faced So Far	Segments	Avg GSAx of Segment
0-5	12260	-0.0038470
5-10	9116	-0.0048480
10-15	8887	-0.0073134
15-20	8564	-0.0074205
20-25	7527	-0.0091401
25-30	5317	-0.0132248
30-35	2965	-0.0197011
35+	1684	-0.0251613

Figure 9: GSAx_segment values versus cumulative shots faced

Figure 9 examines the relationship between the total number of shots faced by a goaltender so far in a game and the corresponding `GSAx_segment`. The data show a clear downward trend in performance as the cumulative number of shots faced increases. Segments where the goaltender has faced 0–5 shots have the highest average `GSAx_segment` of -0.003, and this decreases until we reach segments with 35 or more shots, with average `GSAx_segment` -0.025.

This trend suggests that as goaltenders face more shots over the course of a game, their performance tends to decline. This may be due to physical fatigue or mental strain as the game prorgresses. Notably, the decline in performance accelerates beyond 25 shots, indicating that heavy workloads can have a pronounced negative impact on `GSAx_segment`.

Figure 10 shows the relationship between a goaltender's cumulative performance up to a given segment, measured by `GSAx_so_far`, and their performance during that segment `GSAx_segment`. The positive slope of the trend line indicates that better cumulative performance is associated with better segment performance. This suggests a momentum effect,

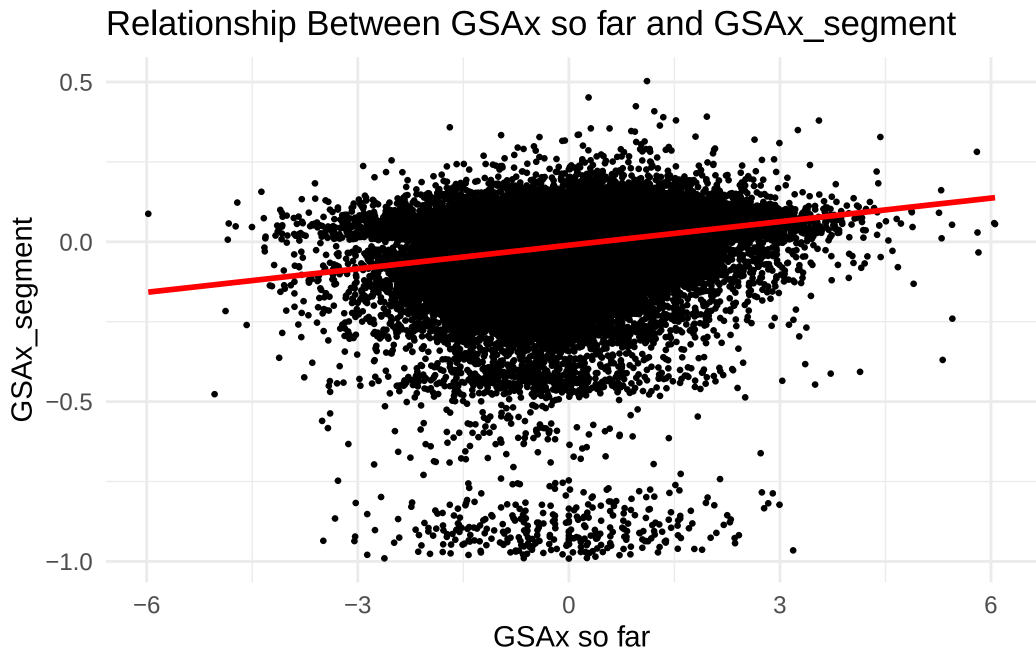


Figure 10: Scatterplot of GSAx_segment values versus GSAx_so_far

where goaltenders who perform well earlier in the game are more likely to continue performing well.

However, the spread of residuals shows significant variability in segment performance, showing that `GSAx_so_far` is still far from fully explaining segment performance, and the relationship between the two is relatively weak. This aligns with the model finding that `GSAx_so_far` has a significant but modest effect size.

5 Discussion

5.1 Significant Predictors of Goaltender Overperformance

The analysis identifies several significant predictors that shape goaltender performance, as measured by goals saved above expected over 10 minute segments. Among these, score differential shows that performance improves as the goaltender's team takes a lead, reflecting reduced pressure or fewer high-quality scoring chances when leading. This result highlights the importance of game context in shaping outcomes, as trailing teams may expose their goaltenders to more challenging scenarios, and winning teams may put extra effort into defending their goaltender.

Recent shot activity also plays a meaningful role, with increased engagement in the minutes preceding a segment positively affecting performance. This suggests that consistent involvement helps goaltenders maintain focus and rhythm. Conversely, the cumulative number of shots faced in a game negatively impacts performance, illustrating the toll of sustained workloads and fatigue.

The sum of in-game GSAx prior to segments, a measure of cumulative performance within the game, has a positive relationship with segment performance, suggesting momentum or consistency. Goaltenders who perform well earlier in the game are more likely to sustain that level of performance later. The interaction between this variable and recent shot activity underscores this trend, indicating that recent activity enhances the positive effects of prior performance.

5.2 Insignificant Predictors and their Implications

Not all factors examined in the model significantly influenced goaltender overperformance. Neither recent performance metrics, such as goaltender overperformance in the previous or past 5 games, nor broader game state variables like home/away or playoff status showed a meaningful relationship with segment performance. These results suggest that external situational factors within the game have a stronger impact on goaltender outcomes than historical trends or the context surrounding the game.

The lack of influence from recent performance metrics challenges the popular notion of "hot streaks" among goaltenders. Similarly, the negative effect of playing at home implies that home-ice advantage has little bearing on individual goaltending performance, even if it is a factor in overall team success. These findings reveal that in-game dynamics are more likely to explain performance variability.

5.3 Weaknesses and next steps

As discussed, the analysis model has several limitations. First, the relatively low predictive power indicates that many unmeasured variables influence overperformance. Incorporating elements measuring factors such as team overall performance, team tactics, current health, days of rest since last game, contract situation, or game-specific psychological factors in future models could enhance the explanatory power of the analysis. New datasets could also help; for example, puck and player tracking data would greatly supplement traditional event data, providing in-game context that is currently unaccounted for.

The assumption of linear relationships between predictors and the performance simplifies complex dynamics. For instance, the relationship between workload and performance may follow a non-linear pattern, with sharp declines after a certain threshold. Non-linear models or machine learning approaches could address these complexities more effectively. We could also create complex models combining segment-level data with shot-level or game-level analysis, particularly during critical moments in games.

Future work could also validate these findings across different leagues, and levels of play. The NHL represents the best of the best and all of its goaltenders are of elite skill level; it would be informative to see what trends develop when analyzing data of lesser professionals or even amateurs. Expanding the scope to include more holistic groups would contribute to a more detailed understanding of what drives goaltender performance under varying conditions.

6 Extras

A datasheet for the dataset is found in Section A.

Appendix

A Datasheet

The following datasheet is provided that provides essential, structured information about the MoneyPuck hockey shot dataset (Tanner 2024a). It extracts questions from *Datasheets for Datasets* (Gebru et al. 2021) as a resource on information included.

Motivation

1. *For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.*
   - The dataset was created to centralize and compile existing NHL data into an easily accessible resource. It is the largest publicly available collection of NHL shot data.
2. *Who created the dataset (for example, which team, research group) and on behalf of which entity (for example, company, institution, organization)?*
   - It was created by hockey analyst Peter Tanner for his website Moneypuck, where he runs various statistical analyses using the data.
3. *Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.*
   - The NHL funds the collection of the its own league's shot data, which is collected in the dataset.
4. *Any other comments?*
   - More information on Moneypuck and how data is collected is available at https://moneypuck.com/about.htm (Tanner 2024b).

Composition

1. *What do the instances that comprise the dataset represent (for example, documents, photos, people, countries)? Are there multiple types of instances (for example, movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.*
   - They represent hockey players on NHL teams; each instance has a shooter and a goaltender, and the result of that particular shot. A shot is the only type of instance.
2. *How many instances are there in total (of each type, if appropriate)?*

- There are this many instances in each section of the dataset, sorted by season: 2021-2022 Season (121,471 instances) 2022-2023 Season (122,026 instances) 2023-2024 Season (122,472 instances) 2024-2025 Season (40,156 instances) (Includes data as of 2024-12-14)

3. *Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (for example, geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (for example, to cover a more diverse range of instances, because instances were withheld or unavailable).*

   - It contains all possible instances of shots that take place during the corresponding time frame; it is not a sample of a larger set.

4. *What data does each instance consist of? "Raw" data (for example, unprocessed text or images) or features? In either case, please provide a description.*

   - Each instance consists of raw data columns that hold information about the shot and the event the instance takes place in.

5. *Is there a label or target associated with each instance? If so, please provide a description.*

   - There are shot IDs associated with each instance, and game IDs, which are different for each shot and game in the season. When combining between seasons, we alter gameID to contain the season as well.

6. *Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (for example, because it was unavailable). This does not include intentionally removed information, but might include, for example, redacted text.*

   - There is no information missing from individual instances.

7. *Are relationships between individual instances made explicit (for example, users' movie ratings, social network links)? If so, please describe how these relationships are made explicit.*

   - Shots that take place within the same game are labelled by the game_id. Shots are each labelled with the shooter and goaltender name, allowing us to group by the player.

8. *Are there recommended data splits (for example, training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.*

   - When creating the model, we use a 80/20 train/test split to ensure our model does not overfit. The split allows a large portion of shots to be used, while still keeping a significant portion for the testing; this is necessary as most shots do not result in goals, so there needs to be a signiifcant number of goals in the test data.

9. *Is the dataset self-contained, or does it link to or otherwise rely on external resources (for example, websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (that is, including the external resources as they existed at the time the dataset was created); c) are there any restrictions (for example, licenses, fees) associated with any of the external resources that might apply to a dataset consumer? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.*

    - It is self-contained; the only other information potentially needed is a codebook explaining variables, which is updated when new variables are added, so there is no reliance on other resources.

10. *Does the dataset contain data that might be considered confidential (for example, data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)? If so, please provide a description.*

    - No, NHL shots are publicly available events.

11. *Does the dataset contain data that might be considered sensitive in any way (for example, data that reveals race or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.*

    - No, all NHL players are identifiable public figures, and NHL games are not private events. The shot data itself is not related to any personal information of players, aside from their hockey affiliations.

Collection process

1. *How was the data associated with each instance acquired? Was the data directly observable (for example, raw text, movie ratings), reported by subjects (for example, survey responses), or indirectly inferred/derived from other data (for example, part-of-speech tags, model-based guesses for age or language)? If the data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.*

    - Data related to the shot is directly observable and can be collected both manually and by using the assistance of artificial intelligence. Shot metadata is also inferred from the NHL data of the game itself, which is validated by the NHL and easily verifiable.

2. *What mechanisms or procedures were used to collect the data (for example, hardware apparatuses or sensors, manual human curation, software programs, software APIs)? How were these mechanisms or procedures validated?*

- The initial shot data is provided by the NHL's data partner Sportradar; it is unclear how they collect the data, aside from the fact that it is AI-assisted.
  - The data is then gathered by Moneypuck with Python and AWS. It is unclear how this is validated.

3. *Who was involved in the data collection process (for example, students, crowdworkers, contractors) and how were they compensated (for example, how much were crowdworkers paid)?*
   - Sportradar scorekeepers are involved in the data collection process; their compensation is not public.

4. *Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (for example, recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.*
   - The data was collected over the 2021-2025 NHL seasons; it is collected as events occur and is up-to-date.

Uses

1. *Has the dataset been used for any tasks already? If so, please provide a description.*
   - Yes, Moneypuck data is used frequently by hockey analysts, both professional and amateur.

2. *Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point.*
   - No.

3. *Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a dataset consumer might need to know to avoid uses that could result in unfair treatment of individuals or groups (for example, stereotyping, quality of service issues) or other risks or harms (for example, legal risks, financial harms)? If so, please provide a description. Is there anything a dataset consumer could do to mitigate these risks or harms?*
   - No.

Maintenance

1. *Who will be supporting/hosting/maintaining the dataset?*
    - Peter Tanner, who runs the Moneypuck website, supports the dataset maintenance.
2. *How can the owner/curator/manager of the dataset be contacted (for example, email address)?*
    - He can be contacted at moneypuck.com@gmail.com, (**pr__tanner?**) on Twitter, or at peter-tanner.com which has more research and analytics.
3. *Will the dataset be updated (for example, to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to dataset consumers (for example, mailing list, GitHub)?*
    - It is updated daily to add new instances/delete erroneous instances. Since updates are very frequent and individual changes are unlikely to affect analyses, updates are not communicated.
4. *If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (for example, were the individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced.*
    - No, there are no limits, as all NHL game data is and will continue to remain publicly available.
5. *Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to dataset consumers.*
    - Historical hockey shot data is available since 2008; since it does not need to be maintained, it is likely to be kept available.
6. *If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to dataset consumers? If so, please provide a description.*
    - No, currently not. If there are any new variables that become relevant, it is possible that someone can contact Peter Tanner, who manages the dataset; however, this process is not made clear and it is unlikely that anyone will need to do so. This is because the dataset gathers all current relevant and available data, as provided by the NHL; if new data is available to be gathered by the NHL, it is likely that they will be the first to provide it rather than any other party.

B Data cleaning and preparation

To clean the data, we first drop erroneous entries - shots with NA values for goaltender name `goalieNameForShot`, boolean variable `goal`, or identifier `game_id`. We remove shots taken on an empty net from when the goaltender was substituted for an extra skater. In addition, we transform team variables categorized by `home` or `away` team to the goalie's team or shooting team, depending on which team is taking the shot.

We calculate variables required for our analysis model: Goals Saved Above Expected (`GSAx`) for each shot is obtained by subtracting the expected goal value of the shot `xGoal` from boolean value `goal`. `xGoal` is modelled by Moneypuck based on many other shot variables ((Tanner 2024b)).

`period`, which is categorical, is obtained based on the `time` in seconds elapsed. Goaltender-specific variables such as `shots_faced`, `shotslast3min` and `GSAx_so_far` are obtained by counting shots and their associated GSAx.

Recent performance variables `last_game_GSAx` and `last_5_avg_GSAx` are calculated by first finding the current game's total `GSAx` and average of the last 5 games, respectively, and then shifting this data to the next game. We imputate the NA values for `last_game_GSAx` and `last_5_avg_GSAx` (occurs for the goaltender's first game) by assigning them to the median of the goalie's `last_game_GSAx` and `last_5_avg_GSAx` for the season.

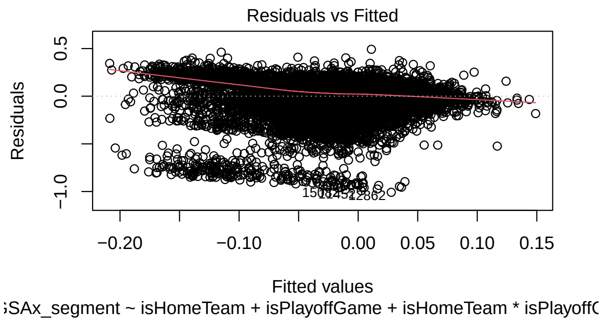
Prior to modelling, we create 10-minute time segments based on `time`, group all shots by segments, and average all of their variables (both predictors and response) across the segment.

C Data manipulation details

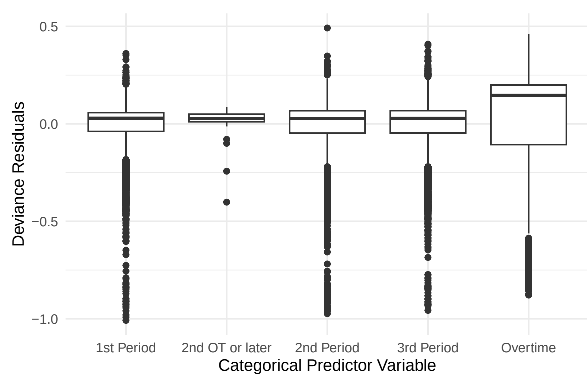
Data was cleaned using R (R Core Team 2023) and packages arrow (Richardson et al. 2024), tidyverse (Wickham et al. 2019), zoo (Zeileis and Grothendieck 2005). Data was tested and analyzed with testthat (Wickham 2011), caret (Kuhn and Max 2008), and knitr (Xie 2014). Data visualizations were created with kableExtra (Zhu 2021).

D Model details

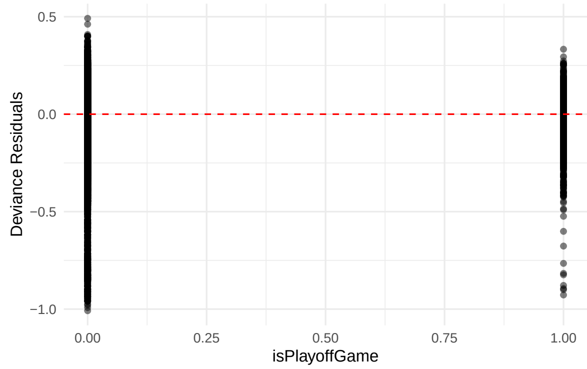
D.0.1 Checking Residual vs Fitted Values

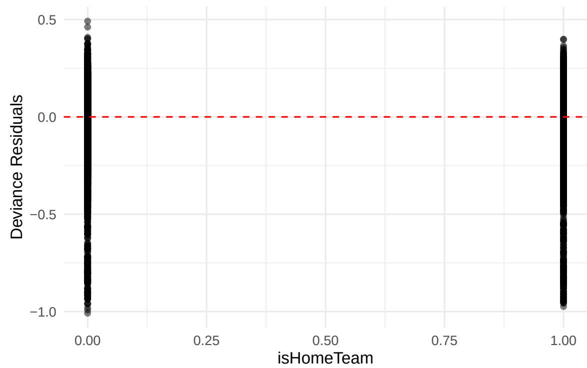


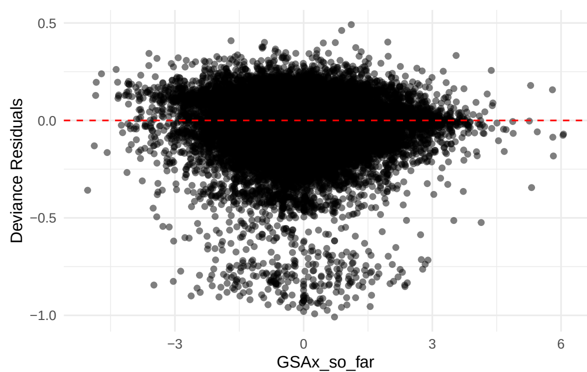
D.0.2 Checking relationship between predictors and residuals

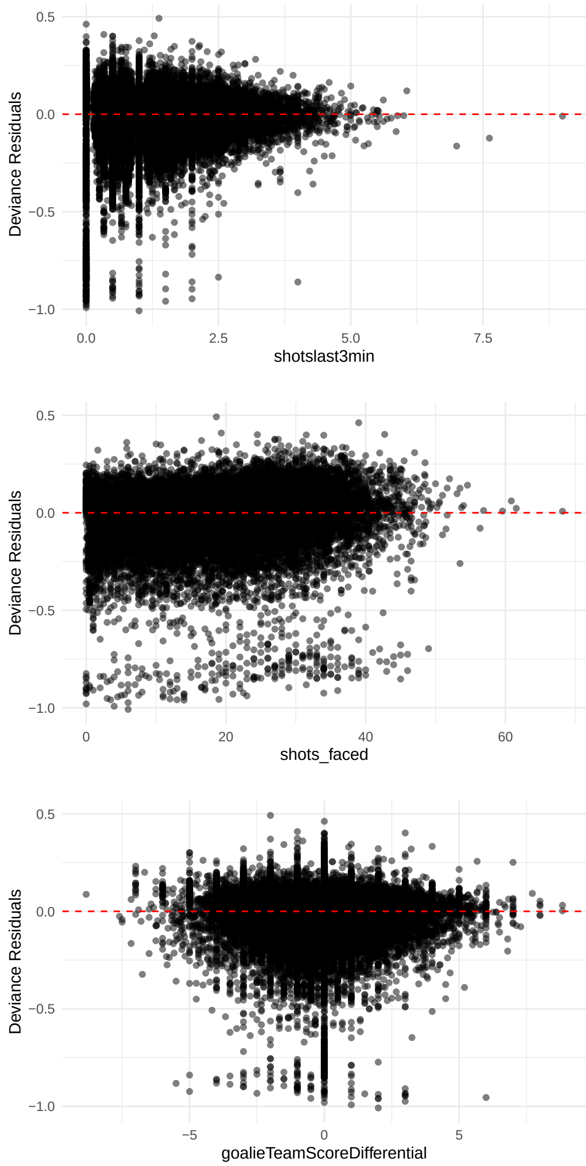


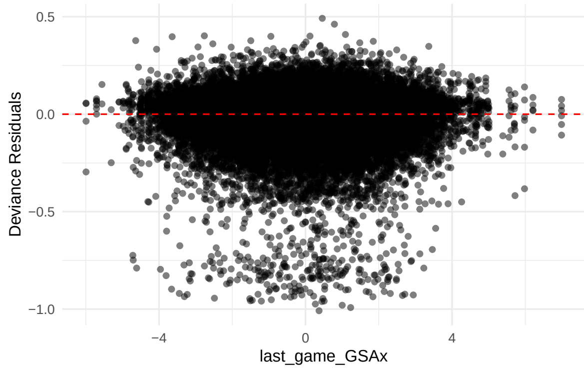

```
Warning: `aes_string()` was deprecated in ggplot2 3.0.0.
i Please use tidy evaluation idioms with `aes()`.
i See also `vignette("ggplot2-in-packages")` for more information.
```

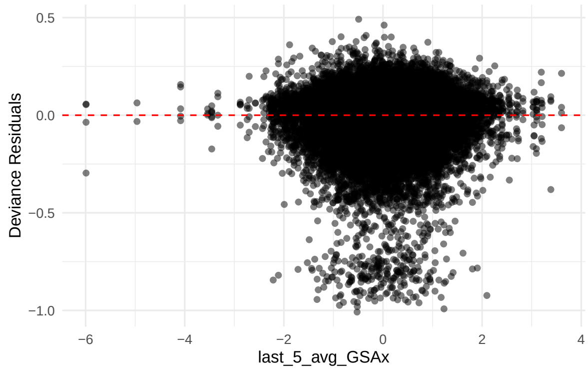

Deviance Residuals
0.5
0.0
−0.5
−1.0
0.00
0.25
0.50
0.75
1.00
isPlayoffGame


Deviance Residuals
0.5
0.0
−0.5
−1.0
0.00
0.25
0.50
0.75
1.00
isHomeTeam

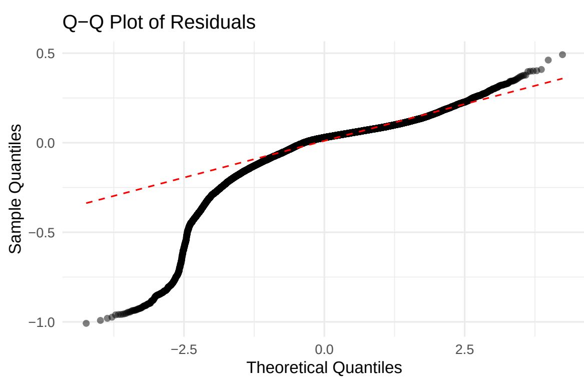

Deviance Residuals
0.5
0.0
−0.5
−1.0
−3
0
3
6
GSAx_so_far


Deviance Residuals
shotslast3min
Deviance Residuals
shots_faced
Deviance Residuals
goalieTeamScoreDifferential





D.0.3 Normal Q-Q plot to check normality



References

Arel-Bundock, Vincent. 2022. "modelsummary: Data and Model Summaries in R." *Journal of Statistical Software* 103 (1): 1–23. https://doi.org/10.18637/jss.v103.i01.

Bischof, Zachary. 2021. "How Significant Is Home Advantage in the NHL?" https://www.zbischof.com/hockey/2021-03-01-home-adv/.

Donchess, Jeff. 2022. "NHL Scoring Trends: Regular Season Vs. Playoffs." *DRatings*. https://www.dratings.com/nhl-scoring-trends-regular-season-vs-playoffs/.

Gebru, Timnit, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé III, and Kate Crawford. 2021. "Datasheets for Datasets." https://www.microsoft.com/en-us/research/uploads/prod/2019/01/1803.09010.pdf.

Kuhn, and Max. 2008. "Building Predictive Models in r Using the Caret Package." *Journal of Statistical Software* 28 (5): 1–26. https://doi.org/10.18637/jss.v028.i05.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Richardson, Neal, Ian Cook, Nic Crane, Dewey Dunnington, Romain François, Jonathan Keane, Dragoș Moldovan-Grünfeld, Jeroen Ooms, Jacob Wujciak-Jens, and Apache Arrow. 2024. *Arrow: Integration to 'Apache' 'Arrow'*. https://github.com/apache/arrow/.

"Sportradar." 2024. *Sportradar*. https://developer.sportradar.com/ice-hockey/reference/nhl-overview.

Tanner, Peter. 2024a. *Moneypuck NHL Shot Data*. https://moneypuck.com/data.htm.

———. 2024b. "Moneypuck Shot Model." *MoneyPuck*. https://moneypuck.com/data.htm.

Wickham, Hadley. 2011. "Testthat: Get Started with Testing." *The R Journal* 3: 5–10. https://journal.r-project.org/archive/2011-1/RJournal_2011-1_Wickham.pdf.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Xie, Yihui. 2014. "knitr: A Comprehensive Tool for Reproducible Research in R." In *Implementing Reproducible Computational Research*, edited by Victoria Stodden, Friedrich Leisch, and Roger D. Peng. Chapman; Hall/CRC.

Zeileis, Achim, and Gabor Grothendieck. 2005. "Zoo: S3 Infrastructure for Regular and Irregular Time Series." *Journal of Statistical Software* 14 (6): 1–27. https://doi.org/10.18637/jss.v014.i06.

Zhu, Hao. 2021. *kableExtra: Construct Complex Table with 'Kable' and Pipe Syntax*. https://CRAN.R-project.org/package=kableExtra.