Prediction of NHL Rookie Salary with ML Models

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*Abstract*— NHL player salaries are capped by a set amount per team. It is then imperative that recruiting managers and talent scouts determine the appropriate salary to offer new recruits. This can be difficult given the subjective nature of ‘scoring’ candidate recruits. One way to do so is to look at how the NHL at large is allocating their salary budget. In this paper, several machine learning models designed to predict the salary of NHL players given some common stats among the players are presented and discussed.

# Introduction

The NHL has a salary cap on each team, meaning every team has the same total salary to be split among the active players on each team. Better players earn a larger portion of their teams cap, so a player’s salary is normally reflective of their importance to the team.

There is also a lot of information available on the players like shot percentage, goals scored, and shots blocked that may indicate this importance and in turn their salary. Our goal is to use a regression model to predict player salaries from a set of the statistics about each player.

# Data Discussion

The data acquired for this report was collected from a popular dataset sharing resource, Kaggle.com. The data consists of 874 samples of rookie NHL player salaries and their corresponding statistics. Each sample contains 153 features. These features contain a mixture of categorical and numeric data.

Initially the dataset was broken into multiple files, one purpose-split for training and another for testing. The two files were conglomerated into a single file such that it could be split again using a standard ratio of 80% training data and 20% testing data.

The author of the data set conveyed that the data set was incomplete, and some features were missing for some of the represented samples. To remedy this, mean imputation was applied to the data set such that all missing features were replaced with the mean.

After doing this the data was then visualized to gain some intuition behind the features. A histogram of the salary values was produced and is presented. It demonstrates a non-normal distribution of salaries heavily weighted towards smaller values.

Chart, histogram

Description automatically generated

Figure - Histogram of Salaries

Plots were also produced to determine the correlation between select features and salary. The features selected were ones believed to be correlated with athletic performance, such as points scored and overall draft pick.

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| Figure Salary vs. Points Scored |
| Chart, scatter chart  Description automatically generated  Figure - Salary vs Overall Draft Pick |

Of these two features, only points scored showed a marginal correlation to salary, but one is present. It was then decided that some features must be highly correlated. With this in mind, and considering the relatively high dimensionality of the data, the decision was made to perform some measure of feature selection.

Firstly, all non-numeric features were stripped from the data. This reduced the dimensionally from 153 features to 144. Highly correlated features (>90% correlated) were compared and trimmed stochastically. This further reduced the number of features to 74. From there, the number of features was reduced even further by only selecting the 30 features most closely correlated with salary.

# Model Discussion

# Results