Predicting NHL Goal Scoring

Capstone Sprint 1

Taylor Gallivan 20 Oct. 2023

"When I started [in the NHL in 2015], it was, 'Oh, if they have one person in analytics, they're so innovative.' Now if you don't have more than one person, you're behind."

- Alexandra Mandrycky, Assistant GM, Seattle Kraken, 2022

Chase Wilson Pull Sook and Obs Engineer Lead Engineer Lead

'Analytical' hires in NHL front offices

Statistical Analyst

As of Oct. 2022:

Source: The Athletic, Oct. 2022

Vice-President of Hockey Operations

- → 23 teams w/ 3 or more analytical hires (72% of league)
- → 9 teams w/ 5 of more analytical hires (28% of league)
- → Most? Maple Leafs with 8 ... but still no Cup

Project Overview

- The sports analytics industry has been growing consistently since the early 2000's → first widely adopted in the MLB, but now a prominent feature in every major North American league (MLB, NBA, NFL, NHL, MLS)
- With the bevy of NHL data available, merging my hockey fandom with data science was a perfect fit

Problem Statement:

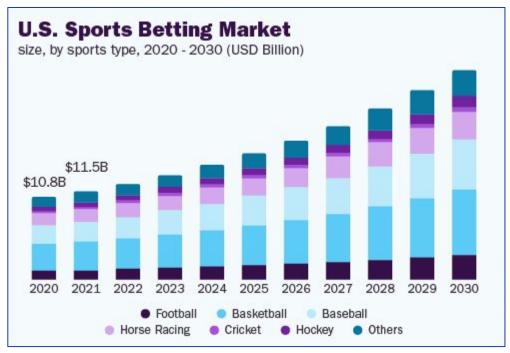
Using season-by-season player statistics, fit an ML model that can effectively predict next season's goal total for a given player

Project Vision

Though not well documented, the NHL makes large portions of their API (Application Programming Interface) open to public access:

- 1. Retrieve statistical data directly from the NHL API, for all seasons between 1990-1991 and 2022-2023
- 2. Perform EDA on the cleaned dataset to identify preliminary trends within predictive variables (dataset currently has 47 columns)
- 3. Fit and test models for accuracy current candidates include:
 - a. Generalized Linear Model (GLM)
 - b. Gaussian Process Regression (GPR)
 - c. Support Vector Machine (SVM) Regression

Potential Impact



Sports betting is big business:

- → USD 83.6 billion market value in 2022 (global)
- → ~10% CAGR expected growth

Pipedream: sell my model to a Vegas sportsbook & retire at 35

Realistic Outcome: use it for my fantasy hockey draft and still finish third place

Source: GrandView Research

The Data...

30,000 player ID's:

- Returns a DataFrame with season-by-season statistics (goals, shots, shooting percentage, etc.)
- Irrelevant positions excluded (goalies) as well as fringe players (less than 3 seasons or 200 total games played)
- Concerns: ability to account for external/untracked factors like contract status, injury history, player conditioning

```
# Call 1: 8477246 - 8482246
main df test = pd.DataFrame()
base_url = 'https://statsapi.web.nhl.com/api/vl/people/
range1 = range(8477246, 8482246)
for num in rangel:
    people_url = f'{base_url}{num}'
    response = requests.get(people url)
    if response.status code != 404:
        suggestions = json.loads(response.content)['people']
        player = (pd.json normalize(suggestions))
        if player['primaryPosition.code'][0] != 'G':
            stats url = f'{base url}{num}/stats/?stats=yearByYear'
            response = requests.get(stats url)
            content = json.loads(response.content)['stats']
            splits = content[0]['splits']
            df_splits = (pd.json_normalize(splits, sep = "_" )
                         .query('league name == "National Hockey League"')
            if df splits.shape[0] >= 3:
                df_splits['player_id'] = player['id'][0]
                df_splits['first_name'] = player['firstName'][0]
                df_splits['last_name'] = player['lastName'][0]
               df_splits['position_code'] = player['primaryPosition.code'][0]
               df_splits['stat_games'] = df_splits['stat_games'].astype(int)
                total games = df splits.groupby(['player id', 'first name', 'last name', 'position code'])['stat games'].sum().reset index()
                filtered_total_games = total_games[total_games['stat_games'] > 200]
                if not filtered total games.empty:
                    df_splits['season_start_yr'] = [x[0:4] for x in df_splits['season']]
                    df_splits['season_start_dt'] = [datetime.strptime(x + '0930', "%V%m%d") for x in df_splits['season_start_yr']]
                    df splits['season end'] = [x[4:8] for x in df splits['season']]
                    df_splits['weight'] = player['weight'][0]
                    df_splits['height'] = player['height'][0]
                    df splits['shot dir'] = player['shootsCatches'][0]
                    df_splits['birth_date'] = pd.to_datetime(player['birthDate'][0])
                    df_splits['age'] = (np.floor((df_splits['season_start_dt'] - df_splits['birth_date'])/ np.timedelta64(1,'Y') ))
                    df_splits['age'] = df_splits['age'].astype(int)
                    df_splits['position_name'] = player['primaryPosition.name'][0]
                    df_splits['position_type'] = player['primaryPosition.type'][0]
                    df_splits['birth_country'] = player['birthCountry'][0]
                    df_splits['nationality'] = player['nationality'][0]
                    main df test = pd.concat([main df test, df splits], sort=False).reset index(drop=True)
                else:
            else:
        else:
    else:
        pass
```

Next Steps

1. Finish compiling data set

- a. Remove unnecessary columns, check for duplicates
- b. Convert 'time on ice' values from string to datetime data types
- c. Make franchise names consistent
- d. Adjust scoring totals for era
- e. Adjust scoring for shortened seasons
- f. Evaluate applicability of aggregated values (for instance, 3-yr weighted averages vs. most recent season's stats)
- g. Evaluate the difficulty/practicality of including additional external variables