NHL_Clutch_Goalscoring_Model

November 17, 2024

1 Predicting Clutch Goalscorers in the NHL using Machine Learning Techniques

In this project, I explored various machine learning techniques to determine the best performing NHL forwards in close and tied games (often referred to as "clutch" moments). The process involved several key steps:

1.0.1 1. Identifying Correct Sources of Data

I needed to scrape data from the NHL API and Natural Stat Trick. The NHL API offers a good foundation for player bios and common goal statistics. However, Natural Stat Trick provided many advanced metrics as well as goals scored by players in close and tied games.

1.0.2 2. Data Cleaning

I merged data from the NHL API and Natural Stat Trick, then ensured the data was accurate and filtered appropriately.

1.0.3 3. Establishing a Definition of Clutch

I computed a "clutch score" for players by weighing the number of goals they scored in close and tied situations as well as in overtime.

1.0.4 4. Building a Classification Model

I attempted to classify players as "clutch" and "non-clutch" by setting thresholds for the clutch score. I used metrics such as expected goals, scoring chances, and other advanced statistics as features. The model was trained on data from the 2020-2021 to 2022-2023 NHL seasons. While the model was successful in identifying elite players and those below average, it struggled with players who fell near the classification boundaries, where small differences in their stats made it difficult to confidently label them as clutch or non-clutch.

1.0.5 5. Switching to a Regression Model

I realized that linear regression was a more feasible approach since many of the features were strongly correlated with a clutch score. It would, therefore, be easier to predict a player's clutch score rather than assigning the player an ambiguous label.
I refined the model by using Ridge regression and performed cross-validation to ensure there was no overfitting.

1.0.6 6. Dealing with Outliers

I used Cook's Distance to identify influential points. I discovered that the model underpredicted the clutch score of elite players because their feature stats set a "ceiling" for their clutch ability. The model also overestimated some elite players who had strong underlying metrics but did not perform well in clutch games. In addition, the model struggled with below-average players who scored clutch goals at a rate that did not match their advanced stats.
This prompted me to use a log transformation, which enabled the model to generate better predictions for elite players and significantly reduced the number of influential points. However, this transformation caused some inaccuracies for below-average players, as it amplified the difference between predicted and actual clutch scores for players with low stats.

1.0.7 7. Using the Model on a Final Test Set

After I was satisfied with the model, I used it to predict the clutch score of players based on their statistics from the start of the 2023-2024 season to the current point of the 2024-2025 season.
In the coming weeks, I plan to deploy the model and connect it to a Power BI dashboard, which will provide real-time updates of a player's current clutch score and their predicted clutch score.

1.0.8 Imports

These are the necessary imports for the project.

[4]:
```python
# Warnings
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

# General imports
import time
import math
import json
import requests
import functools as ft
import scipy.stats as stats

# Data manipulation and visualization
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm

# XGBoost and machine learning
import xgboost as xgb
from xgboost import XGBClassifier, plot_importance

# Sklearn
from sklearn.model_selection import train_test_split, StratifiedKFold,
 ↪cross_validate, learning_curve
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, mean_squared_error, mean_absolute_error, r2_score,␣
↪median_absolute_error, PrecisionRecallDisplay, make_scorer
from sklearn.linear_model import RidgeCV, LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.utils.class_weight import compute_sample_weight
from sklearn.decomposition import PCA

# Hyperparameter tuning with Skopt
from skopt import BayesSearchCV
from skopt.space import Integer, Real, Categorical

# Statsmodels
from statsmodels.stats.outliers_influence import variance_inflation_factor

#Saving Model
import joblib
```

1.0.9 NHL API

The following snippet of code scrapes data from the NHL API for the 2020-2021 to 2022-2023 NHL seasons, while accounting for any issues that may occur when connecting to the API. It also combines a player's stats across these seasons.

[6]:
```
all_seasons = []

for season in range(2020, 2023):
    summary_url = f"https://api.nhle.com/stats/rest/en/skater/summary?
↪limit=-1&cayenneExp=seasonId={season}{season+1}%20and%20gameTypeId=2"

    try:
        summary_resp = requests.get(summary_url)
        summary_resp.raise_for_status()
        summary_json =  summary_resp.json()

        if summary_json['data']:
            df_summary = pd.DataFrame(summary_json['data'])
            all_seasons.append(df_summary)
            df_summary['season'] = f"{season}-{season + 1}"
            print(f"Successfully fetched data for season {season}-{season+1}")
        else:
            print(f"No data returned for season {season}-{season + 1}")

    except requests.exceptions.RequestException as e:
        print(f"Error fetching data for season {season}-{season + 1}: {e}")

if all_seasons:
```

```
    nhl_api_df = pd.concat(all_seasons, ignore_index=True)
    nhl_api_df = nhl_api_df.groupby('playerId').agg({
            'playerId': 'first',
            'skaterFullName': 'first',
            'positionCode': 'first',
            'gamesPlayed': 'sum',
            'assists': 'sum',
            'otGoals': 'sum',
            'timeOnIcePerGame': 'mean'
        }).reset_index(drop = True)
```

```
Successfully fetched data for season 2020-2021
Successfully fetched data for season 2021-2022
Successfully fetched data for season 2022-2023
```

1.0.10 Cleaning the Scraped NHL API Data

The next step is to clean the data properly: - Only forwards are included since defensemen score at different rates. - I kept players who appeared in at least 60 games across the three seasons (approximately 20 games each season). This ensured that there was a sufficient sample size for each player. - Finally, some columns are renamed to maintain a consistent naming format.

[8]:
```
nhl_api_df = nhl_api_df.loc[(nhl_api_df['positionCode'] != 'D') &␣
 ↪(nhl_api_df['gamesPlayed'] >= 60)]
nhl_api_df = nhl_api_df.reset_index(drop = True)
nhl_api_df = nhl_api_df.fillna(0)

nhl_api_df.rename(columns = {'gameWinningGoals': 'game_winning_goals'}, inplace␣
 ↪= True)
nhl_api_df.rename(columns = {'otGoals': 'ot_goals'}, inplace = True)
nhl_api_df.rename(columns = {'skaterFullName': 'Player'}, inplace = True)
nhl_api_df.rename(columns={'timeOnIcePerGame': 'time_on_ice_per_game'},␣
 ↪inplace=True)
```

1.0.11 Scraping Data from Natural Stat Trick

The code below establishes URL links for the pages needed from Natural Stat Trick.

[10]:
```
start_season = "20202021"
end_season = "20222023"
goals_up_one_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={start_season}&thruseason={end_season}&stype=2&sit=all&score=u1&stdoi=std&rate=n
goals_down_one_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={start_season}&thruseason={end_season}&stype=2&sit=all&score=d1&stdoi=std&rate=n
tied_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={start_season}&thruseason={end_season}&stype=2&sit=all&score=tied&stdoi=std&rate
total_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={start_season}&thruseason={end_season}&stype=2&sit=all&score=all&stdoi=std&rate=
```

1.0.12 Scraping Data from Natural Stat Trick

The code below scrapes data from Natural Stat Trick and stores the data for each page in a dataframe.

[12]:
```
urls = {
    "goals_up_one": (goals_up_one_url, 'goals_up_by_one'),
    "goals_down_one": (goals_down_one_url, 'goals_down_by_one'),
    "tied": (tied_url, 'goals_when_tied'),
    "total": (total_url, 'total_goals'),
}

dataframes = {}

for name, (url, new_column_name) in urls.items():
    df = pd.read_html(url, header=0, index_col=0, na_values=["-"])[0]
    df.rename(columns={'Goals': new_column_name}, inplace=True)
    dataframes[name] = df

goals_up_one_df = dataframes["goals_up_one"]
goals_down_one_df = dataframes["goals_down_one"]
goals_tied_df = dataframes["tied"]
total_df = dataframes["total"]
```

1.0.13 Cleaning Data from Natural Stat Trick

After scraping the data from Natural Stat Trick, only relevant columns are included for each dataframe. These dataframes are then merged into one dataframe containing all statistics from Natural Stat Trick.

Similar to the NHL API data, only players who have played at least 60 games are included.

The dataframes do not need to be filtered for forwards because it was easier to do this through the URLs.

[14]:
```
goals_up_one_df = goals_up_one_df[['Player', 'GP', 'goals_up_by_one']]
goals_down_one_df = goals_down_one_df[['Player', 'goals_down_by_one']]
goals_tied_df = goals_tied_df[['Player', 'goals_when_tied']]
total_df = total_df[['Player', 'total_goals', 'Shots', 'ixG', 'iFF', 'iSCF',␣
  ↪'iHDCF', 'Rebounds Created', 'iCF']]

dfs_natural_stat = [goals_up_one_df, goals_down_one_df, goals_tied_df, total_df]

merged_natural_stat = ft.reduce(lambda left, right: pd.merge(left, right,␣
  ↪on='Player'), dfs_natural_stat)
merged_natural_stat = merged_natural_stat.loc[merged_natural_stat['GP'] >= 60]
merged_natural_stat.rename(columns={'Shots': 'shots'}, inplace=True)
merged_natural_stat.rename(columns={'Rebounds Created': 'rebounds_created'},␣
  ↪inplace=True)
```

1.0.14 Standardize Player Names

Some players from Natural Stat Trick have different names compared to the NHL API. It is important to use standard names in both dataframes before merging them.

[16]:
```
natural_stat_names = ["Pat Maroon", "Alex Kerfoot", "Nicholas Paul", "Zach␣
↪Sanford", "Alex Wennberg", "Mitchell Marner", "Zach Aston-Reese",  "Max␣
↪Comtois", "Alexei Toropchenko", "Cameron Atkinson", "Thomas Novak"]
nhl_names = ["Patrick Maroon", "Alexander Kerfoot", "Nick Paul", "Zachary␣
↪Sanford", "Alexander Wennberg", "Mitch Marner", "Zachary Aston-Reese", ␣
↪"Maxime Comtois", "Alexey Toropchenko", "Cam Atkinson", "Tommy Novak"]
merged_natural_stat = merged_natural_stat.replace(natural_stat_names, nhl_names)
```

[17]:
```
merged_natural_stat
```

[17]:
```
              Player   GP  goals_up_by_one  goals_down_by_one  \
0       Joe Thornton   78                1                  3
2       Jason Spezza  125                3                  4
6         Eric Staal  125                3                  2
7        Jeff Carter  209               10                 11
8       Dustin Brown  113                5                  5
..               …    …              …                  …
750    Matty Beniers   90                6                  4
755   Cole Sillinger  143                3                  5
758   Wyatt Johnston   82                4                  4
759   Mason McTavish   89                2                  6
769  Andrei Kuzmenko   81                5                  8

     goals_when_tied  total_goals  shots    ixG  iFF  iSCF  iHDCF  \
0                  1           10     68   7.27   91    72     36
2                  7           22    178  17.16  243   155     66
6                  8           19    188  21.77  253   206    106
7                 11           49    493  51.65  618   450    236
8                  6           26    275  30.32  364   241    122
..               …          …    …    …  …   …    …
750                8           27    166  22.91  244   174     85
755                6           19    241  27.17  338   276    115
758                8           24    160  18.92  207   192     94
759                5           19    173  22.67  231   174     92
769               12           39    143  21.92  210   209    119

     rebounds_created  iCF
0                  10  110
2                  24  313
6                  28  328
7                  89  781
8                  22  445
..                …  …
```

```
750                14  306
755                36  433
758                35  281
759                35  285
769                21  276

[490 rows x 13 columns]
```

[18]:
```
nhl_api_df
```

[18]:
```
     playerId           Player positionCode  gamesPlayed  assists  ot_goals  \
0     8466138     Joe Thornton            C           78       20         0
1     8469455     Jason Spezza            C          125       33         0
2     8470595       Eric Staal            C          125       23         1
3     8470604      Jeff Carter            C          209       55         2
4     8470606     Dustin Brown            R          113       33         0
..        …              …          …           …        …        …
486   8482665    Matty Beniers            C           90       39         1
487   8482705   Cole Sillinger            C          143       23         0
488   8482740   Wyatt Johnston            C           82       17         0
489   8482745   Mason McTavish            C           89       27         0
490   8483808  Andrei Kuzmenko            L           81       35         2

     time_on_ice_per_game
0               744.77870
1               653.25985
2               868.72430
3               958.84570
4               970.80450
..                    …
486            1020.96250
487             810.29235
488             928.90240
489             853.62010
490             974.50610

[491 rows x 7 columns]
```

1.0.15 Merging the Data

The dataframes containing the information from the NHL API and Natural Stat Trick are merged.

[20]:
```
merged_clutch_goals = nhl_api_df.merge(merged_natural_stat, on = 'Player', how␣
 ↪= 'inner')
```

[21]:
```
merged_clutch_goals
```

```
[21]:      playerId            Player positionCode  gamesPlayed  assists  ot_goals  \
     0     8466138      Joe Thornton            C           78       20         0
     1     8469455      Jason Spezza            C          125       33         0
     2     8470595        Eric Staal            C          125       23         1
     3     8470604       Jeff Carter            C          209       55         2
     4     8470606      Dustin Brown            R          113       33         0
     ..        …               …          …          …        …        …
     485   8482665    Matty Beniers            C           90       39         1
     486   8482705    Cole Sillinger           C          143       23         0
     487   8482740    Wyatt Johnston           C           82       17         0
     488   8482745    Mason McTavish           C           89       27         0
     489   8483808  Andrei Kuzmenko            L           81       35         2

          time_on_ice_per_game   GP  goals_up_by_one  goals_down_by_one  \
     0               744.77870   78                1                  3
     1               653.25985  125                3                  4
     2               868.72430  125                3                  2
     3               958.84570  209               10                 11
     4               970.80450  113                5                  5
     ..                    …   …               …                  …
     485            1020.96250   90                6                  4
     486             810.29235  143                3                  5
     487             928.90240   82                4                  4
     488             853.62010   89                2                  6
     489             974.50610   81                5                  8

          goals_when_tied  total_goals  shots    ixG  iFF  iSCF  iHDCF  \
     0                  1           10     68   7.27   91    72     36
     1                  7           22    178  17.16  243   155     66
     2                  8           19    188  21.77  253   206    106
     3                 11           49    493  51.65  618   450    236
     4                  6           26    275  30.32  364   241    122
     ..               …          …     …     …   …    …     …
     485                8           27    166  22.91  244   174     85
     486                6           19    241  27.17  338   276    115
     487                8           24    160  18.92  207   192     94
     488                5           19    173  22.67  231   174     92
     489               12           39    143  21.92  210   209    119

          rebounds_created  iCF
     0                  10  110
     1                  24  313
     2                  28  328
     3                  89  781
     4                  22  445
     ..                …   …
     485                14  306
```

```
486                   36  433
487                   35  281
488                   35  285
489                   21  276

[490 rows x 19 columns]
```

1.0.16 Null values

Check that there are no Null values after merging.

[23]:
```
merged_clutch_goals = merged_clutch_goals.fillna(0)
null_rows = merged_clutch_goals[merged_clutch_goals.isnull().any(axis=1)]
print("Rows with null values:")
print(null_rows)
```

```
Rows with null values:
Empty DataFrame
Columns: [playerId, Player, positionCode, gamesPlayed, assists, ot_goals,
time_on_ice_per_game, GP, goals_up_by_one, goals_down_by_one, goals_when_tied,
total_goals, shots, ixG, iFF, iSCF, iHDCF, rebounds_created, iCF]
Index: []
```

1.0.17 Changing Columns

Drop the "GP" column since it existed in both previously merged dataframes.

Compute per game stats to accurately compare players.

[25]:
```
merged_clutch_goals.drop(columns = 'GP', axis = 1, inplace = True)
columns = ['ot_goals', 'assists', 'goals_up_by_one', 'goals_down_by_one',␣
 ↪'goals_when_tied', 'shots', 'ixG', 'iFF', 'iSCF', 'iHDCF', 'iCF',␣
 ↪'rebounds_created']
for column in columns:
    per_game_string = f"{column}_per_game"
    merged_clutch_goals[per_game_string] = merged_clutch_goals[column] /␣
 ↪merged_clutch_goals['gamesPlayed']
```

1.0.18 Clutch Score

After cleaning the data, we can now compute a weighted clutch score for each player. - Goals scored when tied and down by one are given the most weighting since these are the most representative of high-pressure situations. - Goals scored when up by one are still close situations but may not be as "clutch" compared to goals scored when tied and down by one. - OT goals are also given a smaller weight, since they occur infrequently compared to other goals. They are also only scored during 3v3 play, which differs from the traditio5nal v5.

[27]:

```
merged_clutch_goals['clutch_score'] = 0.3 *␣
↪merged_clutch_goals['goals_when_tied_per_game'] + 0.3 *␣
↪merged_clutch_goals['goals_down_by_one_per_game'] + 0.2 *␣
↪merged_clutch_goals['goals_up_by_one_per_game'] + 0.2 *␣
↪merged_clutch_goals['ot_goals_per_game']
```

1.0.19 Rankings Players Based on their Clutch Score

All scores are multiplied by 100 to make them more interpretable. The scores are then ranked and the top 20 players are shown below.

[29]:
```
merged_clutch_goals['clutch_score'] *= 100
merged_clutch_goals['clutch_score_rank']  = merged_clutch_goals['clutch_score'].
↪rank(ascending = False, method = 'min')
merged_clutch_goals['clutch_score'] = merged_clutch_goals['clutch_score'].
↪apply(lambda x: round(x, 2))
merged_clutch_goals.sort_values('clutch_score_rank', inplace = True)
merged_clutch_goals[['Player','clutch_score', 'clutch_score_rank']].head(20)
```

[29]:

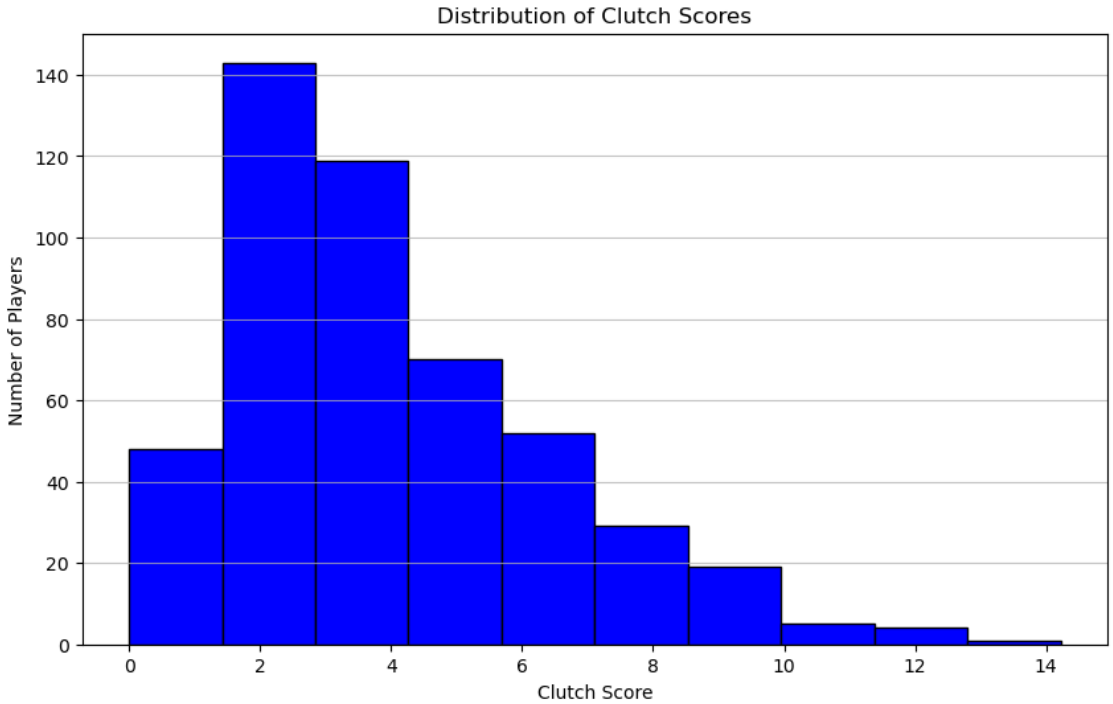
	Player	clutch_score	clutch_score_rank
334	Auston Matthews	14.22	1.0
283	Connor McDavid	12.75	2.0
253	David Pastrnak	12.52	3.0
239	Leon Draisaitl	12.13	4.0
320	Kirill Kaprizov	11.87	5.0
54	Max Pacioretty	10.76	6.0
339	Alex DeBrincat	10.32	7.0
399	Jason Robertson	10.24	8.0
14	Alex Ovechkin	10.21	9.0
290	Sebastian Aho	10.00	10.0
287	Mikko Rantanen	9.95	11.0
218	Nathan MacKinnon	9.95	12.0
219	Aleksander Barkov	9.78	13.0
361	Tage Thompson	9.69	14.0
245	Jakub Vrana	9.60	15.0
241	William Nylander	9.58	16.0
171	Filip Forsberg	9.49	17.0
86	Chris Kreider	9.33	18.0
60	Steven Stamkos	9.30	19.0
280	Kyle Connor	9.22	20.0

1.0.20 Distribution of Clutch Scores

As shown by the histogram below, the data for clutch scores is right skewed. Most players have a below average clutch score and there are a small number of elite players

[31]:
```
plt.figure(figsize=(10, 6))
plt.hist(merged_clutch_goals['clutch_score'], color='blue', edgecolor='black')
```

```
plt.grid(axis='y', alpha=0.75)
plt.xlabel("Clutch Score")
plt.ylabel("Number of Players")
plt.title("Distribution of Clutch Scores")
plt.show()
```



1.0.21 Threshold for Clutch Scores

It makes sense to label "clutch" goalscorers as a higher percentile of data. Thus, all players who had a clutch score in the 85th percentile were in the positive class. This approach already highlights the potential shortcomings of classification for this project. Is a player in the 80 to 84th percentile suddenly not "clutch"? Even if we used a multiclass classification approach, how can we distinguish between players who fall near the boundaries?

[33]:
```
threshold_elite = merged_clutch_goals['clutch_score'].quantile(0.85)
threshold_high = merged_clutch_goals['clutch_score'].quantile(0.7)
threshold_average = merged_clutch_goals['clutch_score'].quantile(0.5)


def label_clutchness(row):
    clutch_score = row['clutch_score']
    if clutch_score >= threshold_elite:
        return 1
    else:
```

```
        return 0

merged_clutch_goals['clutch_label'] = merged_clutch_goals.
 ↪apply(label_clutchness, axis=1)
```

1.0.22 Class Imbalance

Due to the right skew distribution of the data, there are very few goalscorers classified as "clutch".

[35]:
```
merged_clutch_goals['clutch_label'].value_counts()
```

[35]:
```
clutch_label
0    416
1     74
Name: count, dtype: int64
```

1.0.23 Setting up a Classification Model

My initial approach was to select various classification models (e.g. XGBoost, random forest, KNN) and compare them with the Friedman statistical test. I started working on an XGBoost model, but then realized that a classification approach was not idea.

1.0.24 Starting with XGBoost

XGBoost builds an ensemble of decision trees by correcting the prediction errors of previous trees.

Many statistics relevant to a player's goalscoring (e.g. shooting, assists, ice time) are used as features. The model is then trained on an 80-20 split of the data. The **stratify = y** parameter ensures that the training and testing sets have the same class distribution as the original dataset (i.e. same representation of the number of clutch and non-clutch goalscorers). Therefore, the minority class (clutch goalscorers) will not be underrepresented.

The model uses the log loss evaluation metric, which measures the difference between the true class labels (0 or 1) and the predicted probabilities fir the positive class. A greater difference between the predicted probabilities and the actual labels results in a higher log loss.

A full glossary of the features can be found on the **Natural Stat Trick website.**

[38]:
```
x_var = ['shots_per_game', 'ixG_per_game', 'iFF_per_game', 'iSCF_per_game',␣
 ↪'iHDCF_per_game', 'assists_per_game', 'iCF_per_game',␣
 ↪'rebounds_created_per_game','time_on_ice_per_game']
y_var = 'clutch_label'

X = merged_clutch_goals[x_var]
y = merged_clutch_goals[y_var]

train_x, test_x, train_y, test_y = train_test_split(X, y, test_size = 0.2,␣
 ↪stratify = y)
xgb_model = xgb.XGBClassifier(n_estimators=100, eval_metric='logloss')
xgb_model.fit(train_x, train_y)
```

```
[38]: XGBClassifier(base_score=None, booster=None, callbacks=None,
                    colsample_bylevel=None, colsample_bynode=None,
                    colsample_bytree=None, device=None, early_stopping_rounds=None,
                    enable_categorical=False, eval_metric='logloss',
                    feature_types=None, gamma=None, grow_policy=None,
                    importance_type=None, interaction_constraints=None,
                    learning_rate=None, max_bin=None, max_cat_threshold=None,
                    max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
                    max_leaves=None, min_child_weight=None, missing=nan,
                    monotone_constraints=None, multi_strategy=None, n_estimators=100,
                    n_jobs=None, num_parallel_tree=None, random_state=None, …)
```

1.0.25 Initial Evaluation of the Model

The XGBoost model is evaluated using StratifiedKFold cross-validation with 10 splits. Four metrics are used to assess the model's performance: accuracy, precision, recall, and F1 score.

With 10-fold cross-validation, the dataset is divided into 10 groups. We train the model on 10 - 1 = 9 groups and test the model (evaluate its metrics) on the remaining group. This process is repeated 10 times to ensure every group serves as a test set. The metrics are then average across the 10 folds.

As with stratify = y, each fold has the same class distribution as the original dataset (i.e. same representation of the number of clutch and non-clutch goalscorers).

1.0.26 Definitions of Metrics

Accuracy: The proportion of correct predictions among the total number of predictions.

Precision: The proportion of true positives among all instances predicted as positive. It answers the question: "When we predicted positive (a player classified as clutch), how many times were we correct?"

Recall: The proportion of true positives among all actual positives. It answers the question: "Of all the actual positives (clutch goalscorers), how many did the model correctly identify?"

F1 Score: The harmonic mean of precision and recall. Taking the harmonic mean ensures the F1 Score is not skewed by extreme values of precision and recall.

1.0.27 Inflated Accuracy

The model's accuracy appears to be quite high (approximately 90%), but this is most likely due to the high class imbalance. The model can predict the majority class most of the time, without effectively learning to identify the minority class.

The model seems to have a high precision and low recall. It is very cautious about predicting the minority class (clutch goalscorers), which results in fewer false positives. So when the model predicits positive, it is mostly correct. However, this means that the model misses many clutch goalscorers and has a low recall.

The F1 score is pulled down by the low recall to highlight the model's issues with rarely predicting the positive class and missing clutch goalscorers.

[42]:
```
skf = StratifiedKFold(n_splits=10)

scoring = {
    'accuracy': 'accuracy',
    'precision': make_scorer(precision_score, zero_division=0),
    'recall': make_scorer(recall_score, zero_division=0),
    'f1': make_scorer(f1_score, zero_division=0)
}

scores = cross_validate(xgb_model, X, y, cv = skf, scoring = scoring)

df_scores = pd.DataFrame.from_dict(scores)

df_scores.mean()
```

[42]:
```
fit_time          0.166162
score_time        0.020895
test_accuracy     0.897959
test_precision    0.876048
test_recall       0.623214
test_f1           0.637532
dtype: float64
```

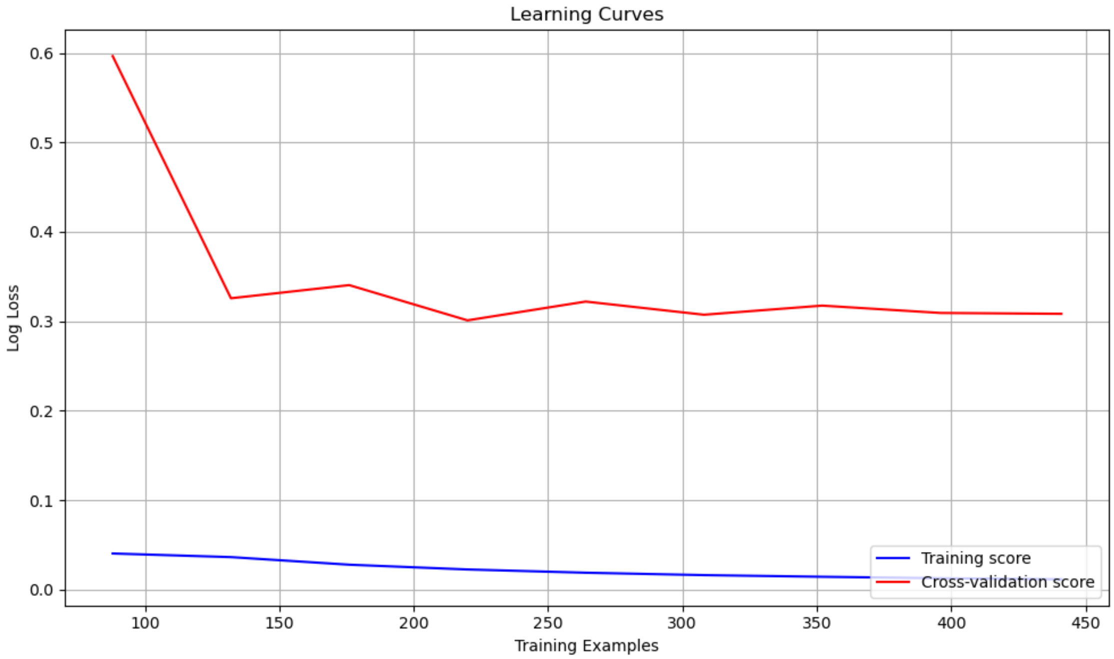
1.0.28 Learning Curves

The learning curves plot the log loss of the training against the log loss for cross-validation. The very low log loss for training indicates that the model has nearly 100% accuracy in predicting clutch players from the training data. However, the log loss increases to 0.4 on the cross-validation data. Due to the high negative class imbalance, the model can just predict non-clutch most of the time. When it predicts the positive class, it may not be confident enough which shows the model has memorized the patterns in the training data and cannot generalize to new data during cros-validation

[44]:
```
cv = StratifiedKFold(n_splits=10)

train_sizes = np.linspace(0.1, 1.0, 10)

train_sizes, train_scores, valid_scores = learning_curve(
    xgb_model, X, y,
    cv=cv,
    n_jobs=-1,
    train_sizes=train_sizes,
    scoring='neg_log_loss',
)

train_mean = -np.mean(train_scores, axis=1)
train_std = -np.std(train_scores, axis=1)
valid_mean = -np.mean(valid_scores, axis=1)
```

```
valid_std = -np.std(valid_scores, axis=1)

plt.figure(figsize=(10, 6))
plt.plot(train_sizes, train_mean, label='Training score', color='blue')
plt.plot(train_sizes, valid_mean, label='Cross-validation score', color='red')

plt.title(f'Learning Curves')
plt.xlabel('Training Examples')
plt.ylabel('Log Loss')
plt.grid(True)
plt.legend(loc='lower right')
plt.tight_layout()
plt.show()
```

```
C:\Users\Work\anaconda3\Lib\site-
packages\sklearn\model_selection\_validation.py:547: FitFailedWarning:
10 fits failed out of a total of 100.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
10 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\Work\anaconda3\Lib\site-
packages\sklearn\model_selection\_validation.py", line 895, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\Work\anaconda3\Lib\site-packages\xgboost\core.py", line 726, in
inner_f
    return func(**kwargs)
           ^^^^^^^^^^^^^^
  File "C:\Users\Work\anaconda3\Lib\site-packages\xgboost\sklearn.py", line
1491, in fit
    raise ValueError(
ValueError: Invalid classes inferred from unique values of `y`.  Expected: [0],
got [1]

  warnings.warn(some_fits_failed_message, FitFailedWarning)
```

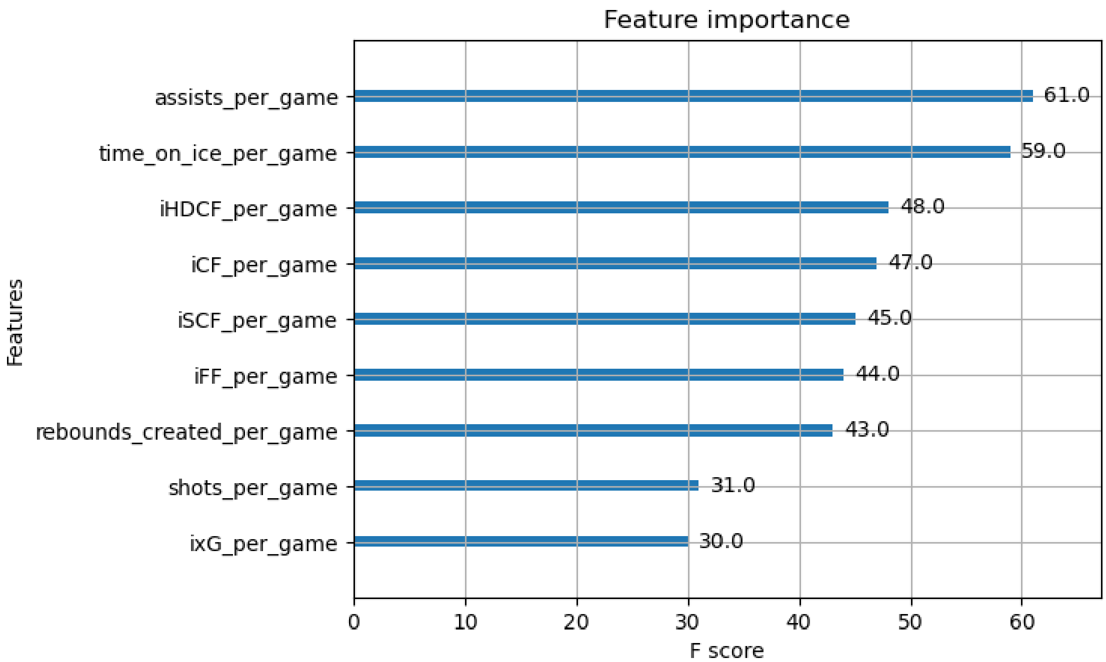


1.0.29 Feature importance

Feature importance helps us to determine which features the model relies on during training and remove less influential features. This enables the model to focus on the most relevant information when training and improve its ability to generalize to unseen data.

The F score (Feature Importance score) reflects how frequently a feature contributes to the decision-making process in the model. For gradient boosting models, importance is based on the improvement in the loss function when a feature is used to split the data within the trees.

[46]:
```
plot_importance(xgb_model)
plt.show()
```



1.0.30 Obtaining the Most Important Features

The following lines of code obtain all features with an F score greater than 40.

[48]:
```
importance = xgb_model.get_booster().get_score(importance_type='weight')
important_features = {}

for feature, score in importance.items():
    if score >= 40:
        important_features[feature] = score

important_feature_names = list(important_features.keys())

X_adjusted = merged_clutch_goals[important_feature_names]
```

1.0.31 Hyperparameter tuning

Hyperparameter tuning involves adjusting parameters to improve the model's metrics and reduce overfitting. These parameters are set before training since the model cannot learn them from the data. Below are hyperparameters that are tuned for the XGBoost model:

- **max_depth:** This controls the maximum depths of the trees. Although a greater depth allows the model to capture more intricate patterns in the data, it can start memorizing patterns in the data and overfit.
- **min_child_weight:** As each node is split based on a condition, data is passed down to nodes. min_child_weight is the minimum number of samples that a node must hold before

it is split further. If there are less than min_child_weight samples at that node, the node will not be split further. This means that the node becomes a leaf.

A higher min_child_weight means that a split will only occur if there is enough data and the model will not overfit to small non-representative samples of the data.

- **n_estimators:** n_estimators represents the number of trees that the model will use during training. As with depth, a higher number of trees can help the model identify more complex patterns in the data. However, the model can become too complex and may start memorizing the data. This will lead to overfitting.
- **learning_rate:** learning_rate controls how much each tree's contribution is scaled during training.

  A lower learning rate means that each tree's contribution is smaller, and the model will make smaller adjustments after adding a new tree. This can help the model generalize the data, but may also require more trees, thus leading to overfitting.

  A higher learning rate means each tree's contribution is larger and the model will make larger adjustments after adding a new tree. This can lead to a faster solution but cause the model to miss important details in the data and overfit.
- **reg_alpha:** This parameter helps to reduce the number of features considered in splits. If a feature has no or little contribution in splits, reg_alpha pushes its weight to 0. This enables the model to focus on important features and leads to better generalization.
- **reg_lamda:** reg_lamda adds a penalty to the squared values of the feature weights that are have no or little contribution in splits. This discourages large weights but does not force weights to zero, unlike reg_alpha. This leads to better generalization without necessarily eliminating features.
- **subsample:** subsample controls the fraction of data that is randomly sampled for training in each tree. By limiting the amount of training data, subsample prevents the model from memorizing details in the data and leads to less overfitting.
- **colsample_bytree :** This parameter controls the fraction of features that are randomly sampled for each tree. Since colsample_bytree limits the number of features used in each tree, it prevent the model from becoming overly dependent on any single feature and leads to better generalization.

[50]:
```
from scipy.stats import randint, uniform

param_grid = {
    'max_depth': randint(2, 6),
    'min_child_weight': randint(2, 4),
    'n_estimators': randint(200, 301),
    'learning_rate': uniform(0.03, 0.01),
    'reg_alpha': uniform(0.75, 0.6),
    'reg_lambda': uniform(0.75, 0.6),
    'subsample': uniform(0.7, 0.3),
    'colsample_bytree': uniform(0.7, 0.3)
}
```

1.0.32 Random Search

Random search is a hyperparameter tuning technique that randomly samples hyperparameter combinations from the parameter grid. The model is then trained and evaluated using k-Fold cross-validation on k - 1 subsets of the training data. The cross-validation score (in this case, F1 score) is calculated for the test fold, and the average score across all k iterations is used to evaluate the performance of that particular set of hyperparameters. This method helps to find a good set of hyperparameters without exhaustively testing every possible combination, unlike grid search.

I have repeated random search multiple times on different train and test splits to obtain a good representation of the model's performance. After each train and test split, the model's class weights are adjusted.

1.0.33 Results of Hyperparameter Tuning

From the learning curves, it seems that hyperparameter tuning has helped to reduce overfitting.

With regards to the model's performance metrics, it is simply not enough to look at the recall and precision score. We must understand where the model is misclassifying clutch players.

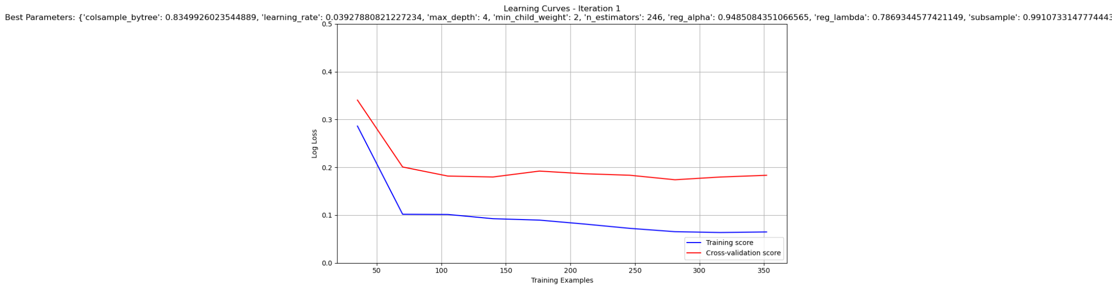
After each randomly selected train test split, I printed out the model's classification results. It appears that the model can correctly classify higher ranked players but struggles with players close to the boundary points (ranks between 45 and 74). The model also incorrectly classifies players with varying performance over the three seasons.

This makes sense because we are essentially assigning an ambiguous label to a clutch player. Is a player 0n the 84th to 83rd percentile suddenly not clutch? Classification may also have difficulties detecting trends in player performance.

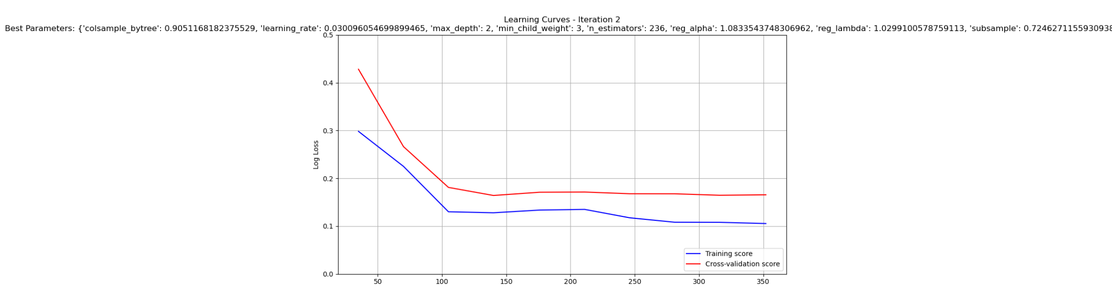
[53]:
```
from sklearn.model_selection import RandomizedSearchCV

cv = StratifiedKFold(n_splits=10)

precision_list = []
recall_list = []
f1_list = []

def plot_learning_curves(estimator, X, y, cv, iteration, title):

    train_sizes = np.linspace(0.1, 1.0, 10)

    train_sizes, train_scores, valid_scores = learning_curve(
        estimator, X, y,
        cv=cv,
        n_jobs=-1,
        train_sizes=train_sizes,
        scoring='neg_log_loss'
    )

    train_mean = -np.mean(train_scores, axis=1)
```

```
    train_std = -np.std(train_scores, axis=1)
    valid_mean = -np.mean(valid_scores, axis=1)
    valid_std = -np.std(valid_scores, axis=1)

    plt.figure(figsize=(10, 6))
    plt.plot(train_sizes, train_mean, label='Training score', color='blue')

    plt.plot(train_sizes, valid_mean, label='Cross-validation score',␣
 ↪color='red')

    plt.title(f'Learning Curves - Iteration {iteration}\n{title}')
    plt.xlabel('Training Examples')
    plt.ylabel('Log Loss')
    plt.ylim(0, 0.5)
    plt.grid(True)
    plt.legend(loc='lower right')
    plt.tight_layout()
    plt.show()


for _ in range(5):
    rs = np.random.randint(1, 1000)

    train_x, test_x, train_y, test_y = train_test_split(
    X_adjusted,
    y,
    test_size=0.2,
    stratify=y,
    random_state = rs
    )

    class_weights = compute_sample_weight(class_weight='balanced', y=train_y)

    xgb_model_adjusted = xgb.XGBClassifier(n_estimators = 100, eval_metric =␣
 ↪'logloss')
    xgb_model_adjusted.fit(train_x, train_y, sample_weight = class_weights)

    random_search = RandomizedSearchCV(xgb_model_adjusted, param_grid, cv=cv,␣
 ↪n_iter=20, n_jobs = -1, scoring = 'f1')

    new = random_search.fit(train_x,train_y)

    xgb_best_model = new.best_estimator_

    title = f'Best Parameters: {random_search.best_params_}'
    plot_learning_curves(xgb_best_model, train_x, train_y, cv, _+1, title)
```

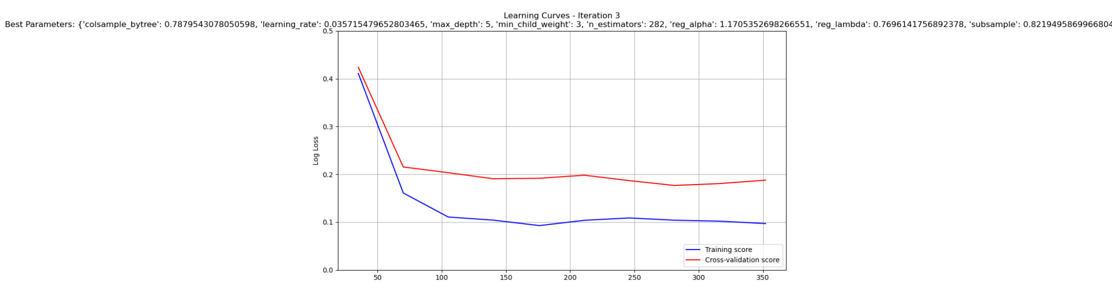
```
    y_pred = xgb_best_model.predict(test_x)
    y_pred_prob = xgb_best_model.predict_proba(test_x)

    precision = precision_score(test_y, y_pred, zero_division=0)
    recall = recall_score(test_y, y_pred)
    f1 = f1_score(test_y, y_pred)

    print("")
    print("Precision Score: ", precision)
    print("Recall Score: ", recall)
    print("")


    results = pd.DataFrame({
    'Player': merged_clutch_goals.loc[test_y.index, 'Player'],
    'clutch_score_rank': merged_clutch_goals.loc[test_y.index,␣
 ↪'clutch_score_rank'],
    'Actual': test_y,
    'Predicted': y_pred,
    })

    print("Correct Classfications")
    print(results.loc[(results['Actual'] == 1) & (results['Predicted'] == 1)])

    print("")

    print("Missed Cltuch Players")
    print(results.loc[(results['Actual'] == 1) & (results['Predicted'] == 0)])

    print("")

    precision_list.append(precision)
    recall_list.append(recall)
    f1_list.append(f1)

print("Average Precision:", np.mean(precision_list))
print("Average Recall:", np.mean(recall_list))
print("Average F1 Score:", np.mean(f1_list))
```




```
Precision Score:  0.6470588235294118
Recall Score:  0.7333333333333333

Correct Classfications
               Player  clutch_score_rank  Actual  Predicted
14       Alex Ovechkin                9.0       1          1
306       Mitch Marner               37.0       1          1
341     Clayton Keller               51.0       1          1
299        Roope Hintz               23.0       1          1
340       Patrik Laine               47.0       1          1
286         Timo Meier               44.0       1          1
150     Mark Scheifele               29.0       1          1
386       Nico Hischier              49.0       1          1
10    Patrice Bergeron               54.0       1          1
283      Connor McDavid               2.0       1          1
332    Matthew Tkachuk               56.0       1          1

Missed Cltuch Players
                Player  clutch_score_rank  Actual  Predicted
86       Chris Kreider                 18.0       1          0
357  Pierre-Luc Dubois                 69.0       1          0
323         Troy Terry                 48.0       1          0
252       Jared McCann                 61.0       1          0
```



```
Precision Score:  0.6666666666666666
Recall Score:  0.6666666666666666

Correct Classfications
                Player  clutch_score_rank  Actual  Predicted
15       Evgeni Malkin               53.0       1          1
284        Jack Eichel               67.0       1          1
286         Timo Meier               44.0       1          1
10    Patrice Bergeron               54.0       1          1
314     Artemi Panarin               64.0       1          1
399    Jason Robertson                8.0       1          1
60      Steven Stamkos               19.0       1          1
146  Gabriel Landeskog               30.0       1          1
306       Mitch Marner               37.0       1          1
238       Sam Reinhart               43.0       1          1

Missed Cltuch Players
                Player  clutch_score_rank  Actual  Predicted
22         T.J. Oshie               74.0       1          0
357  Pierre-Luc Dubois               69.0       1          0
252       Jared McCann               61.0       1          0
203   Carter Verhaeghe               58.0       1          0
105       Brock Nelson               36.0       1          0
```

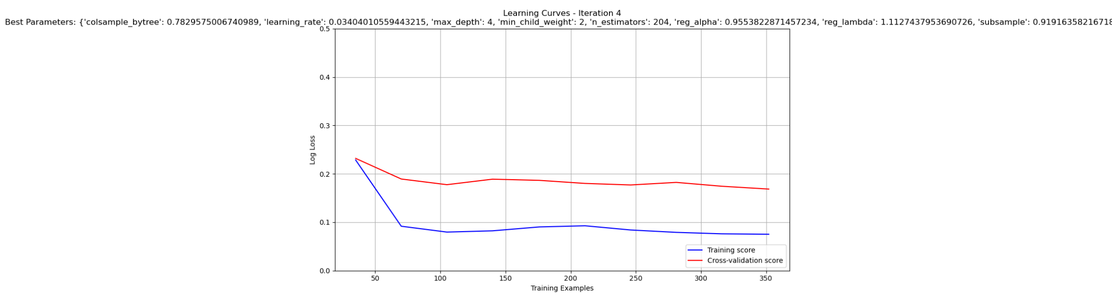



```
Precision Score:  1.0
Recall Score:  0.8

Correct Classfications
                    Player  clutch_score_rank  Actual  Predicted
27           Brad Marchand               38.0       1          1
158  Jonathan Marchessault               72.0       1          1
10        Patrice Bergeron               54.0       1          1
244            Kevin Fiala               68.0       1          1
280            Kyle Connor               20.0       1          1
```

392	Elias Pettersson	39.0	1	1
218	Nathan MacKinnon	12.0	1	1
15	Evgeni Malkin	53.0	1	1
200	Jake Guentzel	27.0	1	1
144	Nikita Kucherov	65.0	1	1
286	Timo Meier	44.0	1	1
113	Zach Hyman	41.0	1	1

Missed Cltuch Players

	Player	clutch_score_rank	Actual	Predicted
403	Martin Necas	71.0	1	0
489	Andrei Kuzmenko	22.0	1	0
245	Jakub Vrana	15.0	1	0



Precision Score: 0.6
Recall Score: 0.6

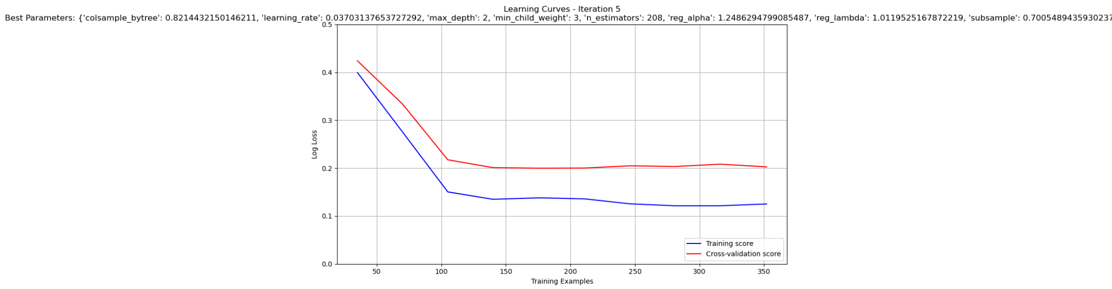
Correct Classfications

	Player	clutch_score_rank	Actual	Predicted
332	Matthew Tkachuk	56.0	1	1
10	Patrice Bergeron	54.0	1	1
262	Brayden Point	26.0	1	1
283	Connor McDavid	2.0	1	1
290	Sebastian Aho	10.0	1	1
399	Jason Robertson	8.0	1	1
108	Vladimir Tarasenko	66.0	1	1
455	Cole Caufield	33.0	1	1
280	Kyle Connor	20.0	1	1

Missed Cltuch Players

	Player	clutch_score_rank	Actual	Predicted
150	Mark Scheifele	29.0	1	0
252	Jared McCann	61.0	1	0
15	Evgeni Malkin	53.0	1	0
245	Jakub Vrana	15.0	1	0

```
323         Troy Terry                  48.0       1          0
203  Carter Verhaeghe                   58.0       1          0
```




```
Precision Score:  0.8125
Recall Score:  0.8666666666666667

Correct Classfications
                   Player  clutch_score_rank  Actual  Predicted
320        Kirill Kaprizov                5.0       1          1
238           Sam Reinhart               43.0       1          1
54          Max Pacioretty                6.0       1          1
284            Jack Eichel               67.0       1          1
280            Kyle Connor               20.0       1          1
339         Alex DeBrincat                7.0       1          1
14           Alex Ovechkin                9.0       1          1
221         Elias Lindholm               50.0       1          1
399        Jason Robertson                8.0       1          1
306           Mitch Marner               37.0       1          1
287         Mikko Rantanen               11.0       1          1
113             Zach Hyman               41.0       1          1
158  Jonathan Marchessault               72.0       1          1

Missed Cltuch Players
               Player  clutch_score_rank  Actual  Predicted
50       David Perron               73.0       1          0
357  Pierre-Luc Dubois               69.0       1          0

Average Precision: 0.7452450980392157
Average Recall: 0.7333333333333334
Average F1 Score: 0.7363530465949821
```

1.0.34 Switching to Regression

Although the classification model does show advantages in correctly classifying some player, I believe that regression is more suitable:

1. Unlike Classification, regression can be used to predict the player's clutch score (a continuous label), rather than assigning them to classes that may not clearly define a "clutch player". This makes the model easier to interpret and leads to more accurate predictions.
2. Regression can account for the trends in player performance and provide better predictions.

1.0.35 Features

The same features from classification are used. These features show a strong positive correlation with clutch score, which indicates that a linear regression model is suitable

[56]:
```
x_var = ['shots_per_game', 'ixG_per_game', 'iFF_per_game', 'iSCF_per_game',␣
 ↪'iHDCF_per_game', 'assists_per_game', 'iCF_per_game',␣
 ↪'rebounds_created_per_game', 'time_on_ice_per_game']
X= merged_clutch_goals[x_var]
y_var = 'clutch_score'
y = merged_clutch_goals[y_var]

correlation = X.corrwith(y)
print(correlation)
```

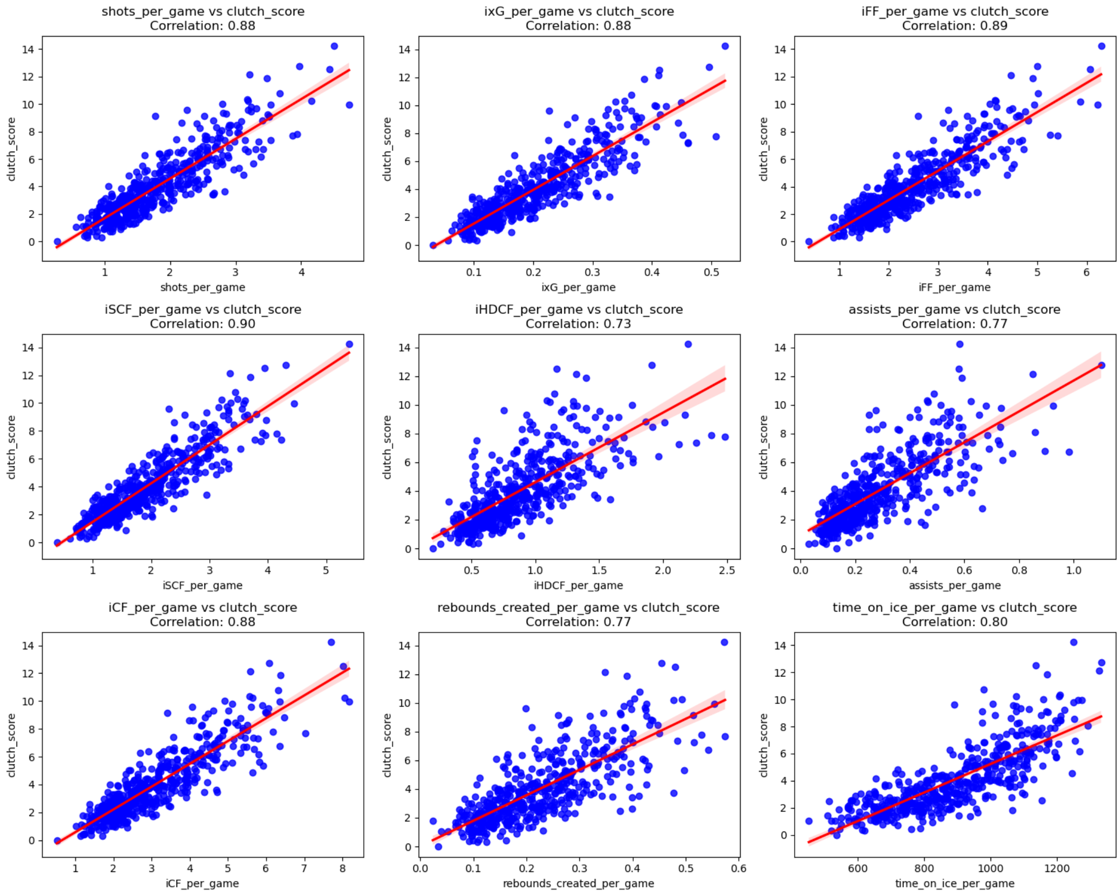
```
shots_per_game               0.882954
ixG_per_game                 0.884833
iFF_per_game                 0.886259
iSCF_per_game                0.897483
iHDCF_per_game               0.727755
assists_per_game             0.769966
iCF_per_game                 0.880728
rebounds_created_per_game    0.768760
time_on_ice_per_game         0.796485
dtype: float64
```

1.0.36 Scatter Plots

The scatter plots further show the strong positive correlation of the features with clutch score.

[58]:
```
plt.figure(figsize=(15, 12))

for i, var in enumerate(x_var):
    plt.subplot(3, 3, i+1)

    sns.regplot(data=merged_clutch_goals, x=var, y=y, scatter_kws={'color':␣
 ↪'blue'}, line_kws={'color': 'red'})

    plt.title(f'{var} vs {y_var}\nCorrelation: {correlation[var]:.2f}',␣
 ↪fontsize=12)
    plt.xlabel(var)
    plt.ylabel(y_var)

plt.tight_layout()
```

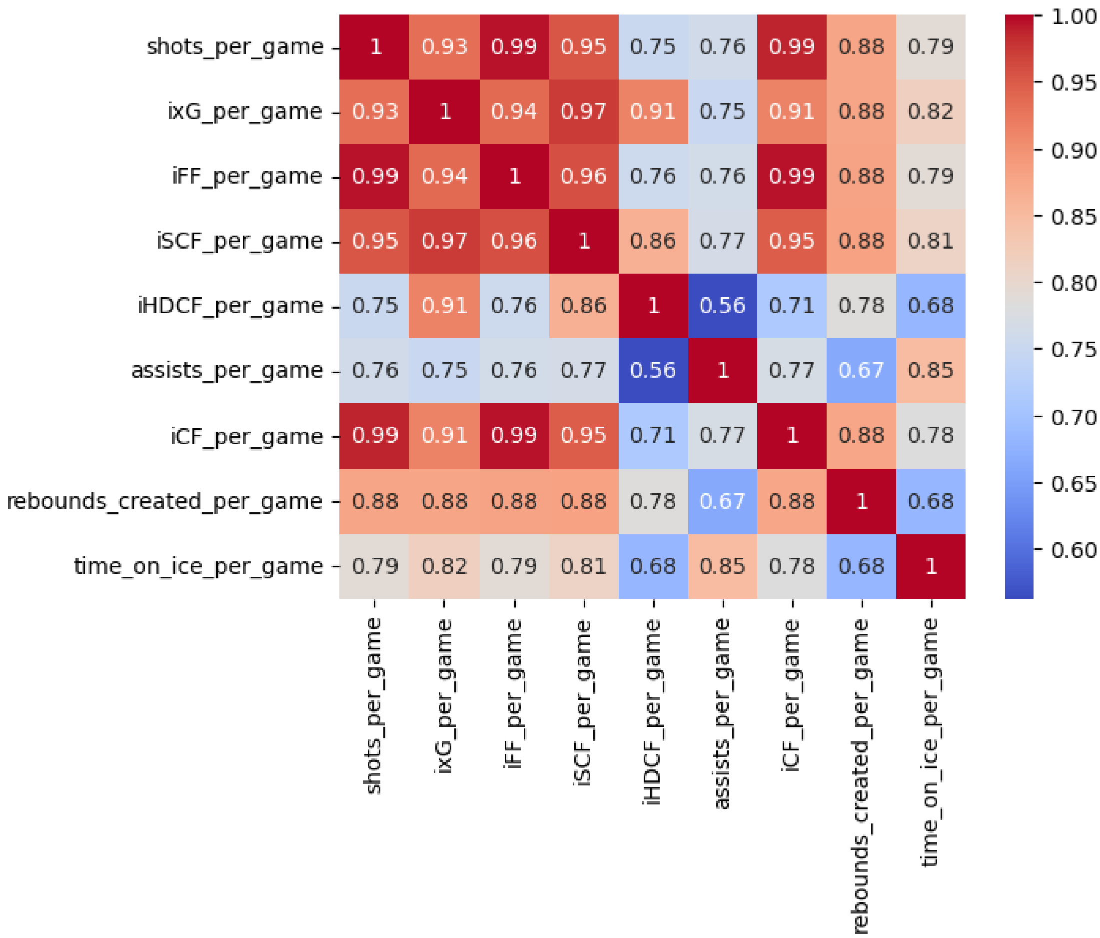
```
plt.show()
```



1.0.37 Multicollinearity

Even though the features are highly correlated with each other, we should not expect any change in predictive performance because the correlations will exist in the test and training set. The model can still use the correlated features to make accurate predictions because the feature patterns learned during training will apply similarly in the test set.

[60]:
```
sns.heatmap(X.corr(), annot=True, cmap='coolwarm')
plt.show()
```



1.0.38 Ridge Regression

Ridge Regression is a variant of linear regression that applies a penalty to the squared values of the coefficients in the regression equation. The penalty is controlled by the alpha parameter, which determines the strength of regularization. A higher value of alpha applies a stronger penalty which decreases the coefficients more. Unlike Lasso Regression, Ridge Regression does not set coefficients to zero and eliminate features. It instead keeps all features in the model but reduces the influence of less important features by shrinking their coefficients

Decreasing coefficients reduces the complexity of the model since the model will not become heavily reliant on certain features. It can instead focus on relevant features and generalize to unseen data.

We also must scale the data by setting the mean of each feature to 0 and standard deviation to 0, so that not one single feature dominates the model. .

1.0.39 Metrics

- MSE (Mean Squared Error): MSE measures the average squared difference between the predicted values and the actual values. Lower values indicate better model performance. It penalizes large errors more because the differences are squared.

- RMSE (Root Mean Squared Error): RMSE is the square root of MSE. It provides errors in the same units as the original data, making it easier to interpret. Like MSE, lower values are better, and it emphasizes larger errors due to squaring.
- MAE (Median Absolute Error): MAE is the median of the absolute differences between predicted and actual values and is not skewed by large errors, unlike MSE and RMSE.
- R^2: R^2 represents the proportion of the variance in the dependent variable (y) that is explained by the independent variable(s) (x) in the model. In other words, it shows how well the changes in x can explain or predict the changes in y. Values closer to 1 indicate that the model explains most of the variability in y, meaning a better fit, while values closer to 0 suggest that the model explains little of the variability in y, meaning a poorer fit. However, R^2 can be inflated by overfitting. As more predictors are features to the data, R^2 increases because the model can explain more variance in y, even if the features are not important.
- Adjusted R^2: Adjusted R^2 adjusts R^2 for the number of predictors in the model. It accounts for overfitting by penalizing excessive use of unhelpful features. Like R^2, higher values are better.

[63]:
```
x_var = ['shots_per_game', 'ixG_per_game', 'iFF_per_game', 'iSCF_per_game',␣
 ↪'iHDCF_per_game',
         'assists_per_game', 'iCF_per_game', 'rebounds_created_per_game',␣
 ↪'time_on_ice_per_game']
X_adjusted = merged_clutch_goals[x_var]
y_var = 'clutch_score'
y = merged_clutch_goals[y_var]

X_scaled = StandardScaler().fit_transform(X_adjusted)

train_x, test_x, train_y, test_y = train_test_split(X_scaled, y, test_size=0.2,␣
 ↪random_state=42)

alphas_random = np.random.uniform(0.0001, 1000, 50)

ridge_cv = RidgeCV(alphas=alphas_random, store_cv_values=True)
ridge_cv.fit(train_x, train_y)

y_pred = ridge_cv.predict(test_x)

mse = mean_squared_error(test_y, y_pred)
rmse = np.sqrt(mse)
mae = median_absolute_error(test_y, y_pred)
r2 = r2_score(test_y, y_pred)

print("MSE: ", mse)
print("RMSE: ", rmse)
print("MAE: ", mae)
```

```
print("R²: ", r2)
print("Adjusted R²: ", 1 - (1 - r2) * (len(train_y) - 1) / (len(train_y) -␣
↪train_x.shape[1] - 1))
```

```
MSE:  0.9712995403425273
RMSE:  0.9855453010098152
MAE:  0.5920400036150384
R²:  0.8613554126349052
Adjusted R²:  0.8580889171210679
```

1.0.40 Learning Curves

It is important to evaluate the learning curves for ridge regression to determine if there is overfitting in the model.

Although many of scikit-learn's metrics are regarded as better when they return higher values, MSE is a loss function. Therefore, we take the negative value of MSE for the learning curve since higher positive values of MSE will yield more negative values.

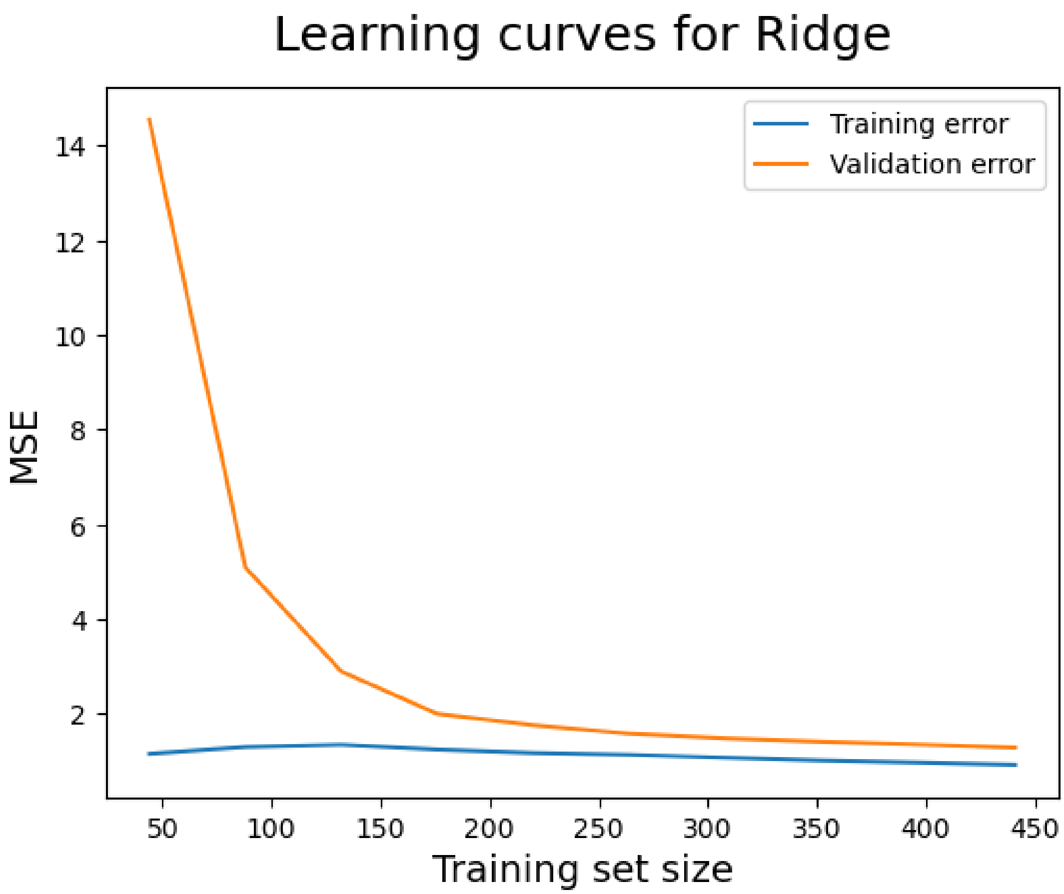
1.0.41 Interpreting the Graph

The MSE is multiplied by one, so the learning curve graph shows positive MSE and is easier to interpret (as smaller values of MSE are better).

The learning curves do not show significant overfitting. After approximately 250 samples, both training and validation curves converge to an MSE of less than 2. Thus, Ridge Regression is the correct choice for generalizing the training data.

[66]:
```
train_sizes = np.linspace(0.1, 1.0, 10)

train_sizes, train_scores, validation_scores = learning_curve(
ridge_cv,
X_scaled,
y, train_sizes = train_sizes, cv = 10,
scoring = 'neg_mean_squared_error')

train_scores_mean = -train_scores.mean(axis = 1)
validation_scores_mean = -validation_scores.mean(axis = 1)

plt.plot(train_sizes, train_scores_mean, label = 'Training error')
plt.plot(train_sizes, validation_scores_mean, label = 'Validation error')
plt.ylabel('MSE', fontsize = 14)
plt.xlabel('Training set size', fontsize = 14)
plt.title('Learning curves for Ridge', fontsize = 18, y = 1.03)
plt.legend()
```

[66]: <matplotlib.legend.Legend at 0x1f3724ff980>



1.0.42 Analyzing the Residuals

It is important to not just look at MSE and MAE, but also where the model is having issues with predicting the clutch scores of players.

From the dataframe below, it appears the model is underpredicting many elite players who excel in close and tied situations.

[68]:
```
results = pd.DataFrame({'Player': merged_clutch_goals.loc[test_y.index,␣
↪'Player'], 'Actual': test_y, 'Predicted': y_pred})

results['Error'] = abs(results['Actual'] - results['Predicted'])
results.sort_values(by=['Error'], inplace = True, ascending = False)

print("All predictions and actual values:")
print(results.head(60))
```

```
All predictions and actual values:
                  Player  Actual  Predicted     Error
432    Andrei Svechnikov    5.33   7.865614  2.535614
```

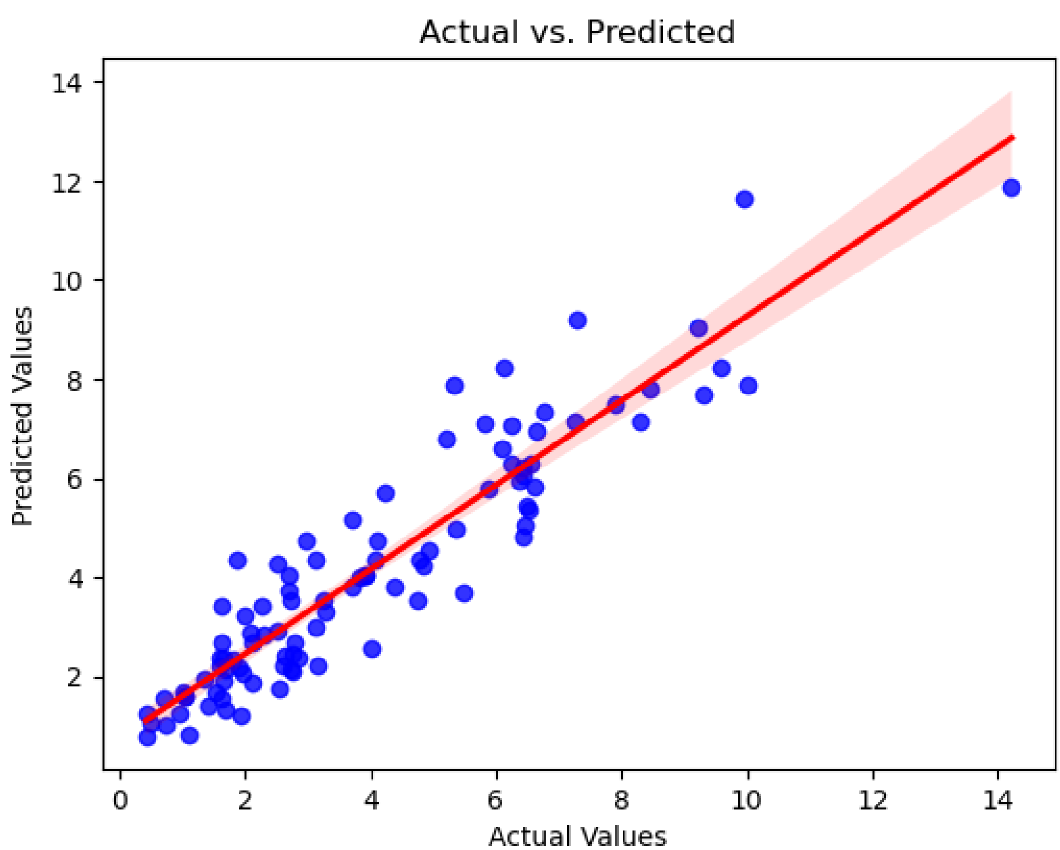
479	Cole Perfetti	1.88	4.366978	2.486978
334	Auston Matthews	14.22	11.887834	2.332166
290	Sebastian Aho	10.00	7.896408	2.103592
51	Patrick Kane	6.14	8.232624	2.092624
332	Matthew Tkachuk	7.28	9.203428	1.923428
98	Calle Jarnkrok	5.48	3.678842	1.801158
220	Jonathan Drouin	1.62	3.409344	1.789344
342	Jesse Puljujarvi	2.97	4.757768	1.787768
117	Mikael Granlund	2.52	4.271494	1.751494
218	Nathan MacKinnon	9.95	11.639604	1.689604
60	Steven Stamkos	9.30	7.672605	1.627395
208	Andre Burakovsky	6.43	4.826562	1.603438
240	Sam Bennett	5.22	6.810860	1.590860
102	Evgeny Kuznetsov	4.23	5.711369	1.481369
143	William Karlsson	3.71	5.160201	1.450201
129	Travis Boyd	4.00	2.553799	1.446201
118	Nino Niederreiter	6.46	5.067330	1.392670
241	William Nylander	9.58	8.222285	1.357715
71	Tyler Johnson	2.70	4.037948	1.337948
248	Alex Tuch	5.81	7.088850	1.278850
88	Tomas Tatar	3.12	4.364554	1.244554
285	Jordan Greenway	2.00	3.217243	1.217243
294	Tommy Novak	4.74	3.546247	1.193753
179	Jordan Martinook	2.27	3.434966	1.164966
22	T.J. Oshie	6.52	5.361857	1.158143
223	Bo Horvat	8.29	7.138105	1.151895
181	Teddy Blueger	1.64	2.697972	1.057972
309	Jake DeBrusk	6.48	5.429753	1.050247
79	Jakob Silfverberg	2.71	3.741728	1.031728
125	Colin Blackwell	3.16	2.213455	0.946545
321	Dominik Simon	0.72	1.539078	0.819078
457	Matt Boldy	6.25	7.067454	0.817454
486	Cole Sillinger	2.73	3.545154	0.815154
483	Nils Aman	0.44	1.252581	0.812581
166	Mark Jankowski	2.54	1.753675	0.786325
403	Martin Necas	6.62	5.834563	0.785437
91	Casey Cizikas	1.61	2.387206	0.777206
162	Alex Galchenyuk	2.10	2.874134	0.774134
160	Luke Glendening	1.65	2.357685	0.707685
289	Jansen Harkins	1.92	1.215974	0.704026
92	Nicolas Deslauriers	1.00	1.656126	0.656126
407	Filip Chytil	4.10	4.753704	0.653704
365	Brandon Duhaime	2.75	2.115345	0.634655
149	Mika Zibanejad	8.45	7.816221	0.633779
39	Mathieu Perreault	1.60	2.206884	0.606884
303	Daniel Sprong	4.85	4.249564	0.600436
23	Andrew Cogliano	1.35	1.948585	0.598585
243	Nick Ritchie	4.39	3.794205	0.595795

59	Jay Beagle	0.48	1.068285	0.588285
329	Ryan Lomberg	2.11	2.685188	0.575188
438	Jack McBain	2.72	2.146654	0.573346
439	Karson Kuhlman	1.80	2.353237	0.553237
420	Parker Kelly	1.03	1.580878	0.550878
77	Kyle Clifford	1.04	1.587397	0.547397
314	Artemi Panarin	6.78	7.321429	0.541429
349	Max Jones	2.31	2.839530	0.529530
477	Tim Stützle	6.10	6.591797	0.491797
142	Matt Nieto	2.85	2.377458	0.472542
47	Logan Couture	6.37	5.929780	0.440220

1.0.43 Scatter Plot and Line of Best Fit

Since most points fall near the line of best fit, the model is generally accurate in predicting values. However, there are a few outliers which need to be corrected.

[70]:
```python
sns.regplot(data=merged_clutch_goals, x=test_y, y=y_pred, scatter_kws={'color':
 ↪'blue'}, line_kws={'color': 'red'})
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted')
plt.show()
```

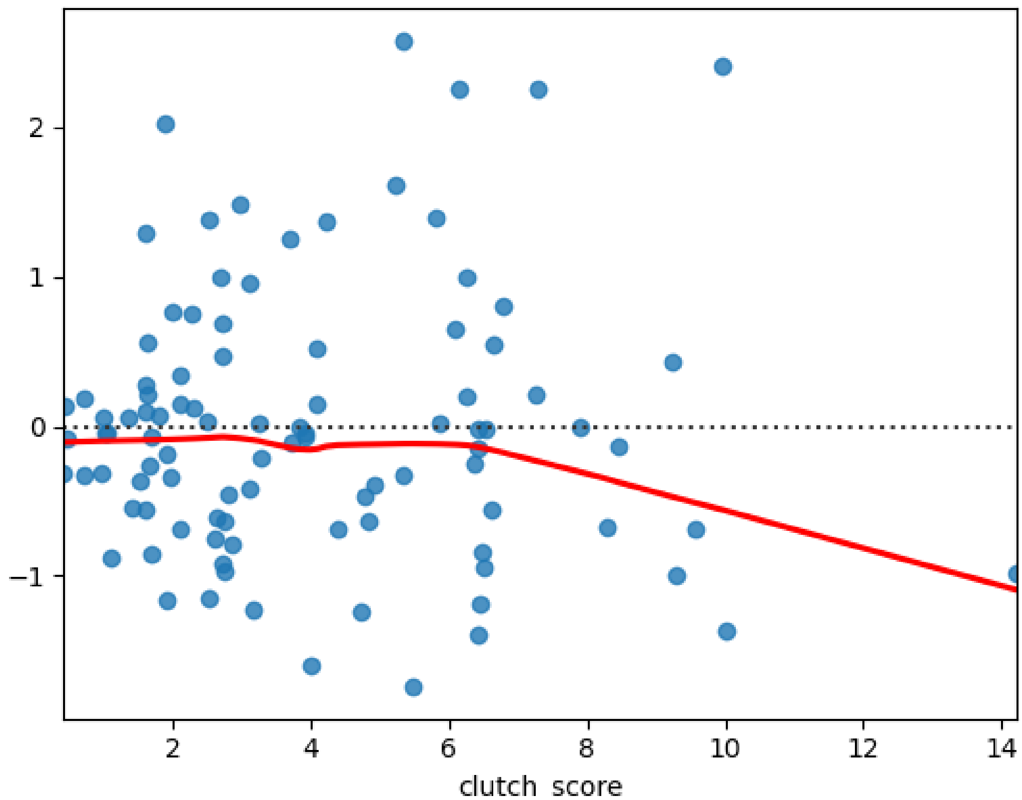


1.0.44 Residual Plot

The residual plot shows more errors in predicting the clutch score are between 1 and -1. However, there are a few points outside of this range, which may be considered as outliers.

[72]:
```
sns.residplot(data=merged_clutch_goals, x=test_y, y=y_pred, lowess=True,␣
    ↪line_kws=dict(color="r"))
```

[72]:
```
<Axes: xlabel='clutch_score'>
```



1.0.45 Cook's Distance

Cook's distance enables us to evaluate influential points in the model. Influential points are data points that significantly change the fit of the model if removed.

Cook's distance combines residuals (difference between the observed and predicted values) and leverage (how far away a data point is from the average of the predictor values) to determine the effect of the fit and predictions of a model when a data point is removed. A Cook's distance larger than the threshold (4 / n, with n being the number of observations) suggests that removing a particular data point would significantly change the model.

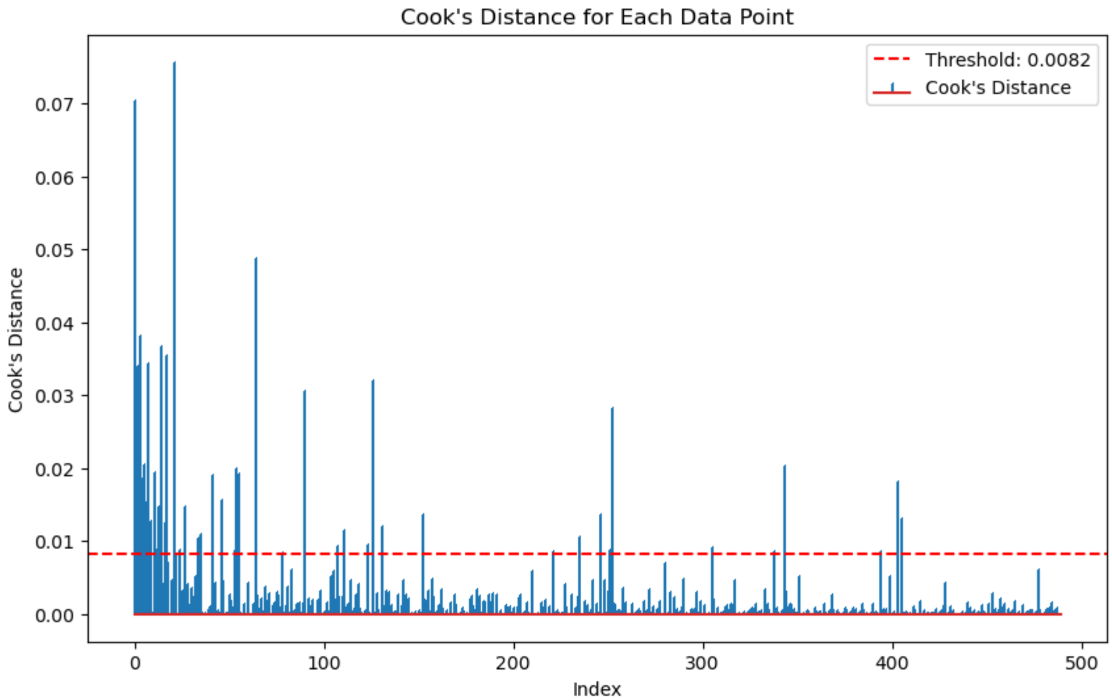
As shown below, the model tends to underestimate the performance of several elite players (e.g., McDavid and Matthews) in clutch situations. These players' statistics may have created an artificial "ceiling" that limits the model's ability to accurately predict their scoring ability in close and tied situations.

Conversely, the model overestimates the performance of other elite players (e.g., Kucherov and both Tkachuks), who do not perform as well in clutch scoring situations as their general statistics suggest.

[74]:
```
X_with_intercept = sm.add_constant(X_scaled)

ols_model = sm.OLS(y, X_with_intercept).fit()

influence = ols_model.get_influence()
cooks_d, _ = influence.cooks_distance

threshold = 4 / len(X_adjusted)
outliers = np.where(cooks_d > threshold)[0]

results = pd.DataFrame({
    'Player': merged_clutch_goals.loc[y.index, 'Player'],
    'Actual': y,
    'Predicted': ols_model.fittedvalues,
    'Cook\'s Distance': cooks_d
})

outliers_df = results.iloc[outliers]

print("There are", outliers_df.shape[0], "influential points.")
print("Outliers based on Cook's Distance:")
print(outliers_df)

plt.figure(figsize=(10, 6))
plt.stem(cooks_d, markerfmt=",", label="Cook's Distance")
plt.axhline(y=threshold, color='r', linestyle='--', label=f"Threshold:␣
↪{threshold:.4f}")
plt.xlabel('Index')
plt.ylabel("Cook's Distance")
plt.title("Cook's Distance for Each Data Point")
plt.legend()
plt.show()
```

```
There are 45 influential points.
Outliers based on Cook's Distance:
                  Player  Actual  Predicted  Cook's Distance
334      Auston Matthews   14.22  12.062853         0.070461
283        Connor McDavid   12.75  11.602638         0.023405
253        David Pastrnak   12.52  10.384466         0.034058
```

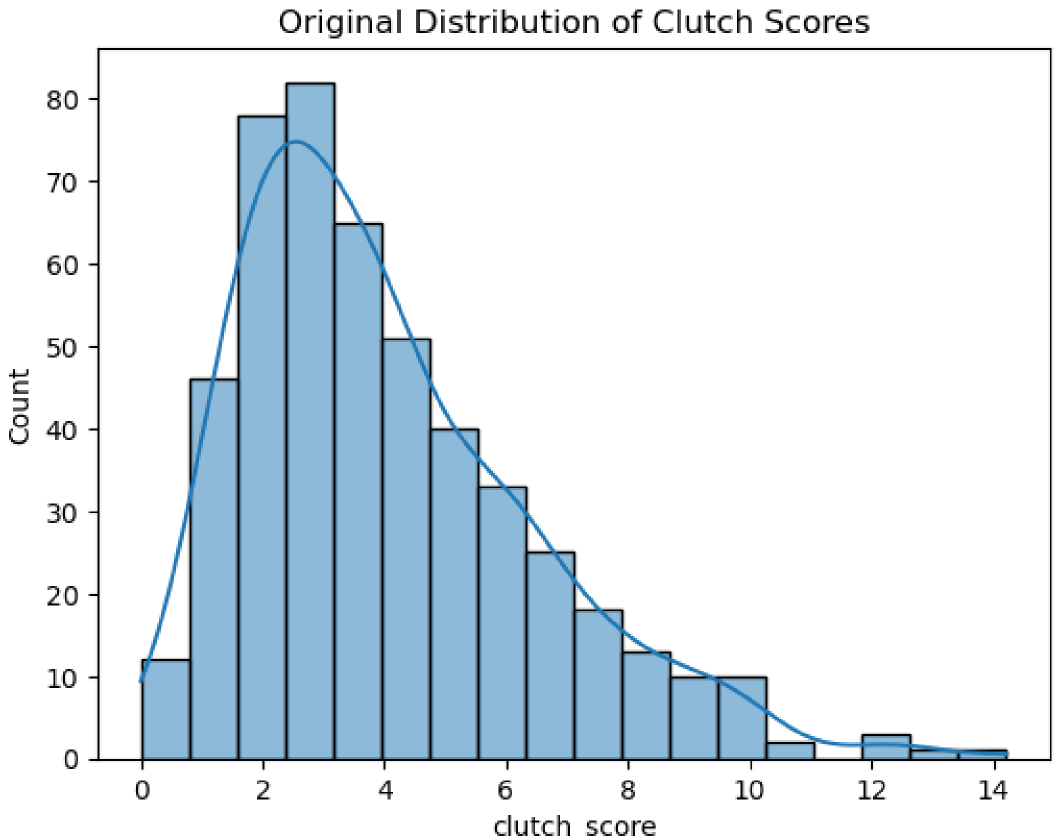
239	Leon Draisaitl	12.13	9.763624	0.038212
320	Kirill Kaprizov	11.87	9.201083	0.018471
54	Max Pacioretty	10.76	8.583603	0.020553
339	Alex DeBrincat	10.32	8.947553	0.015284
399	Jason Robertson	10.24	7.575257	0.034294
290	Sebastian Aho	10.00	8.030088	0.012663
218	Nathan MacKinnon	9.95	11.389116	0.019361
219	Aleksander Barkov	9.78	8.237749	0.009001
361	Tage Thompson	9.69	7.298691	0.014655
245	Jakub Vrana	9.60	5.390432	0.036714
171	Filip Forsberg	9.49	7.826739	0.012543
86	Chris Kreider	9.33	7.014317	0.035376
489	Andrei Kuzmenko	9.14	5.137839	0.075704
242	Nikolaj Ehlers	8.83	7.581498	0.008720
404	Josh Norris	8.62	5.607570	0.014727
254	Adrian Kempe	8.29	6.685850	0.010354
105	Brock Nelson	8.24	6.384332	0.010933
426	Brady Tkachuk	7.79	9.203920	0.019140
340	Patrik Laine	7.52	5.859637	0.015554
10	Patrice Bergeron	7.37	8.723491	0.008819
80	John Tavares	7.35	9.041044	0.019921
332	Matthew Tkachuk	7.28	8.975105	0.019211
144	Nikita Kucherov	6.74	8.823220	0.048766
208	Andre Burakovsky	6.43	4.711810	0.008391
51	Patrick Kane	6.14	7.956596	0.030550
145	Ryan Nugent-Hopkins	5.74	7.411197	0.009237
84	Nazem Kadri	5.65	8.138356	0.011418
487	Wyatt Johnston	5.37	4.113243	0.009488
432	Andrei Svechnikov	5.33	7.854711	0.032083
240	Sam Bennett	5.22	6.997656	0.012101
264	Viktor Arvidsson	4.87	7.275135	0.013610
4	Dustin Brown	3.81	5.362690	0.008572
53	Mikael Backlund	3.62	6.183608	0.010653
26	Patric Hornqvist	3.51	4.953123	0.013692
313	Evan Rodrigues	3.44	5.417291	0.008763
122	Brendan Gallagher	3.44	6.004279	0.028240
55	Jakub Voracek	2.80	4.071743	0.009197
117	Mikael Granlund	2.52	4.265668	0.008557
473	Jack Quinn	2.47	4.284984	0.020264
17	Alexander Radulov	1.95	3.629519	0.008582
479	Cole Perfetti	1.88	4.455844	0.018178
6	Ryan Getzlaf	1.83	3.985061	0.013074

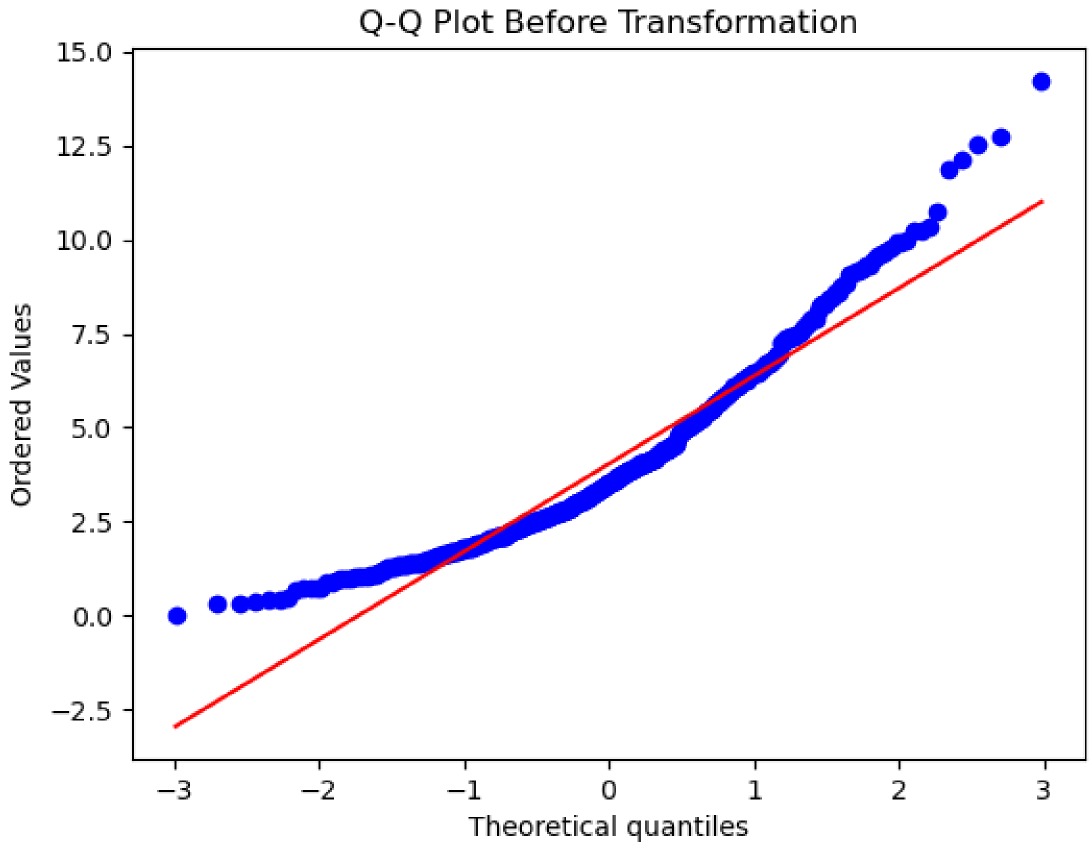


1.0.46 Evaluating the Distribution of the Data

The histogram and QQ plot show that the data has a right skew distribution, which may explain why the model has difficulties in predicting the clutch score of elite players on the right side of the tail.

[76]:
```
sns.histplot(y, kde=True)
plt.title("Original Distribution of Clutch Scores")
plt.show()
stats.probplot(y, dist="norm", plot=plt)
plt.title("Q-Q Plot Before Transformation")
plt.show()
```

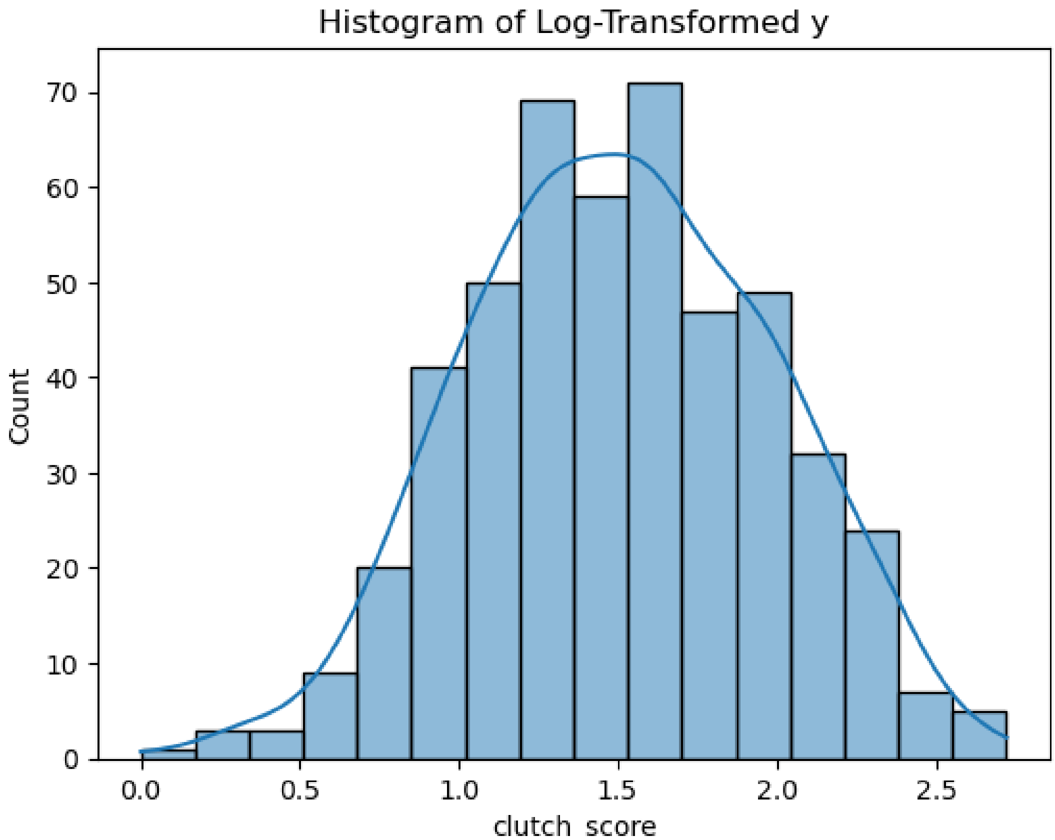

Original Distribution of Clutch Scores
Count
clutch_score
0
2
4
6
8
10
12
14
0
10
20
30
40
50
60
70
80

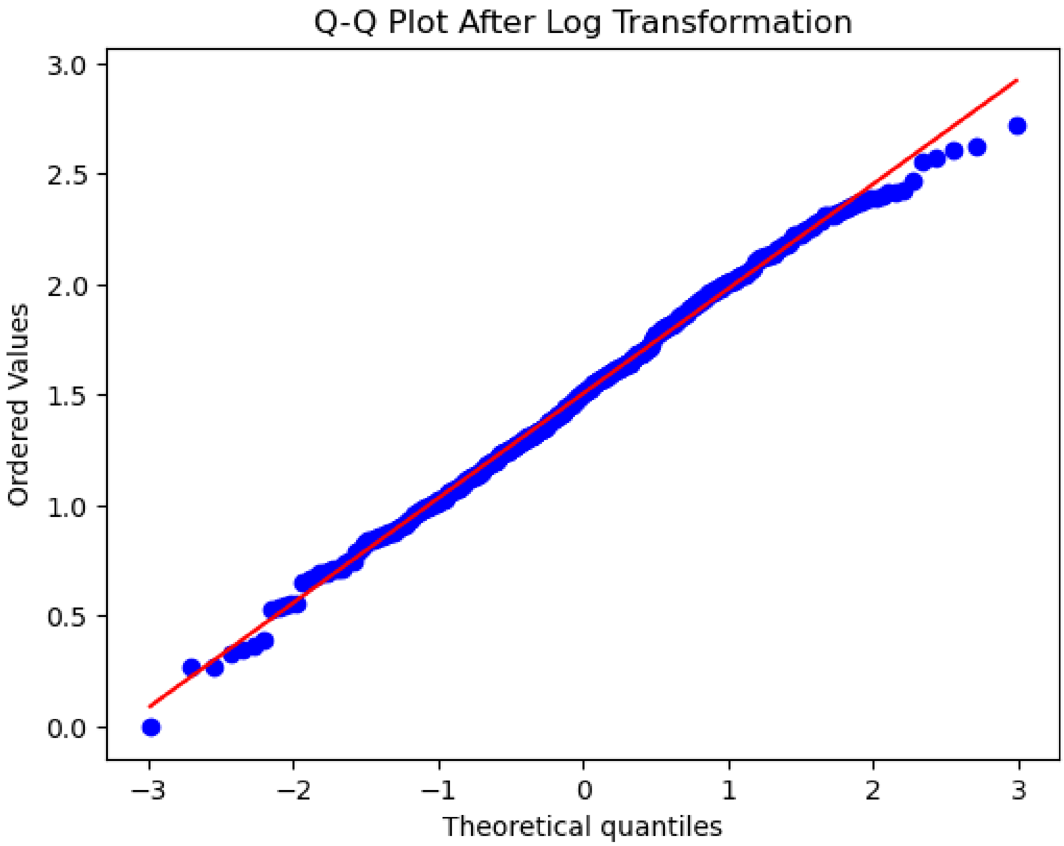


1.0.47 Transforming the Data to a Normal Distribution with Log

As shown below, a log transformation is used to reduce the skew of the data and create a normal distribution. This ensures the predictions are not affected by the influential points we identified in Cook's distance.

[78]:
```
y_log = np.log(y + 1)

sns.histplot(y_log, kde=True)
plt.title("Histogram of Log-Transformed y")
plt.show()

stats.probplot(y_log, dist="norm", plot=plt)
plt.title("Q-Q Plot After Log Transformation")
plt.show()
```


Histogram of Log-Transformed y
Count
clutch_score
0
10
20
30
40
50
60
70
0.0
0.5
1.0
1.5
2.0
2.5



1.0.48 Evaluating Metrics after the Log Transformation

After using a log transformation, it appears that the residuals have significantly decreased. However, it is important to remember the scale of the data has changed and we must look at the model's predictions of certain data points.

[80]:
```
epsilon = np.abs(X_scaled.min()) + 1

X_shifted = X_scaled + epsilon

y_log = np.log(y + 1)

X_log = np.log(X_shifted)

train_x, test_x, train_y, test_y = train_test_split(
    X_log,
    y_log,
    test_size=0.2,
    random_state=200
)
```

```
alphas_random = np.random.uniform(0.0001, 1000, 50)
ridge_cv_log = RidgeCV(alphas=alphas_random, store_cv_values=True)
ridge_cv_log.fit(train_x, train_y)
y_pred = ridge_cv_log.predict(test_x)

mse = mean_squared_error(test_y, y_pred)
rmse = np.sqrt(mse)
mae = median_absolute_error(test_y, y_pred)
r2 = r2_score(test_y, y_pred)

print("MSE: ", mse)
print("RMSE: ", rmse)
print("MAE: ", mae)
print("R²: ", r2)
print("Adjusted R²: ", 1 - (1 - r2) * (len(train_y) - 1) / (len(train_y) -␣
↪train_x.shape[1] - 1))
```

```
MSE:  0.036194917800475374
RMSE:  0.19024961971177595
MAE:  0.1351159301419933
R²:  0.8486176900133973
Adjusted R²:  0.8450510910870114
```

[81]:
```
results = pd.DataFrame({'Player': merged_clutch_goals.loc[test_y.index,␣
↪'Player'], 'Actual': test_y, 'Predicted': y_pred})

results['Error'] = abs(results['Actual'] - results['Predicted'])
results.sort_values(by=['Error'], inplace = True, ascending = False)

print("All predictions and actual values:")
print(results.head(55))
```

```
All predictions and actual values:
                  Player    Actual  Predicted     Error
479         Cole Perfetti  1.057790   1.564966  0.507176
56           Carl Hagelin  0.824175   1.266003  0.441827
53        Mikael Backlund  1.530395   1.955653  0.425258
120        Joonas Donskoi  1.064711   1.458884  0.394174
409           David Kampf  0.896088   1.253788  0.357700
444          John Leonard  0.810930   1.146314  0.335384
222          Sean Monahan  1.350667   1.670336  0.319669
92   Nicolas Deslauriers  0.693147   1.000502  0.307355
482       Yegor Chinakhov  1.007958   1.308333  0.300375
263        Michael Amadio  1.460938   1.160819  0.300119
342      Jesse Puljujarvi  1.378766   1.674431  0.295665
232        Ryan Carpenter  0.698135   0.993689  0.295554
388   Kristian Vesalainen  0.270027   0.558735  0.288708
```

115	Ryan Johansen	1.800058	1.515972	0.284087
105	Brock Nelson	2.223542	1.954938	0.268604
291	Evgeny Svechnikov	1.324419	1.060113	0.264305
361	Tage Thompson	2.369309	2.116117	0.253192
299	Roope Hintz	2.314514	2.061986	0.252527
23	Andrew Cogliano	0.854415	1.101128	0.246712
93	Cody Eakin	0.672944	0.917601	0.244656
89	Marcus Foligno	1.585145	1.343329	0.241816
455	Cole Caufield	2.228939	1.990731	0.238208
49	Colton Sceviour	1.131402	0.893546	0.237856
425	Philipp Kurashev	1.078410	1.313944	0.235534
230	Nathan Walker	1.238374	1.002856	0.235518
400	Morgan Frost	1.283708	1.511768	0.228060
150	Mark Scheifele	2.259678	2.033122	0.226555
79	Jakob Silfverberg	1.311032	1.537031	0.225999
224	Valeri Nichushkin	1.720979	1.945199	0.224220
427	Ryan McLeod	0.982078	1.205636	0.223558
335	Wade Allison	1.553925	1.332064	0.221861
397	Robert Thomas	1.754404	1.549018	0.205386
42	Nick Bonino	1.581038	1.377106	0.203932
1	Jason Spezza	1.415853	1.213578	0.202275
323	Troy Terry	2.135349	1.933636	0.201713
341	Clayton Keller	2.129421	1.932722	0.196699
476	Anton Lundell	1.483875	1.673963	0.190089
270	Anders Bjork	1.169381	0.989217	0.180165
218	Nathan MacKinnon	2.393339	2.558826	0.165487
171	Filip Forsberg	2.350422	2.185237	0.165186
190	Liam O'Brien	0.559616	0.723680	0.164064
362	Drake Caggiula	0.916291	1.075767	0.159476
39	Mathieu Perreault	0.955511	1.114562	0.159050
485	Matty Beniers	1.880991	1.722730	0.158261
133	Adam Lowry	1.340250	1.491925	0.151675
35	Derick Brassard	1.442202	1.294529	0.147673
155	Phillip Danault	1.859418	1.720691	0.138727
237	Tomas Nosek	1.064711	1.203101	0.138390
423	Oliver Wahlstrom	1.699279	1.564064	0.135215
310	Yakov Trenin	1.313724	1.448741	0.135017
329	Ryan Lomberg	1.134623	1.269585	0.134963
387	Jesper Boqvist	1.280934	1.146202	0.134732
281	Colin White	1.160021	1.289559	0.129538
202	Anthony Duclair	1.922788	1.797959	0.124829
50	David Perron	2.020222	1.896330	0.123893

1.0.49 Calculating Cook's Distance

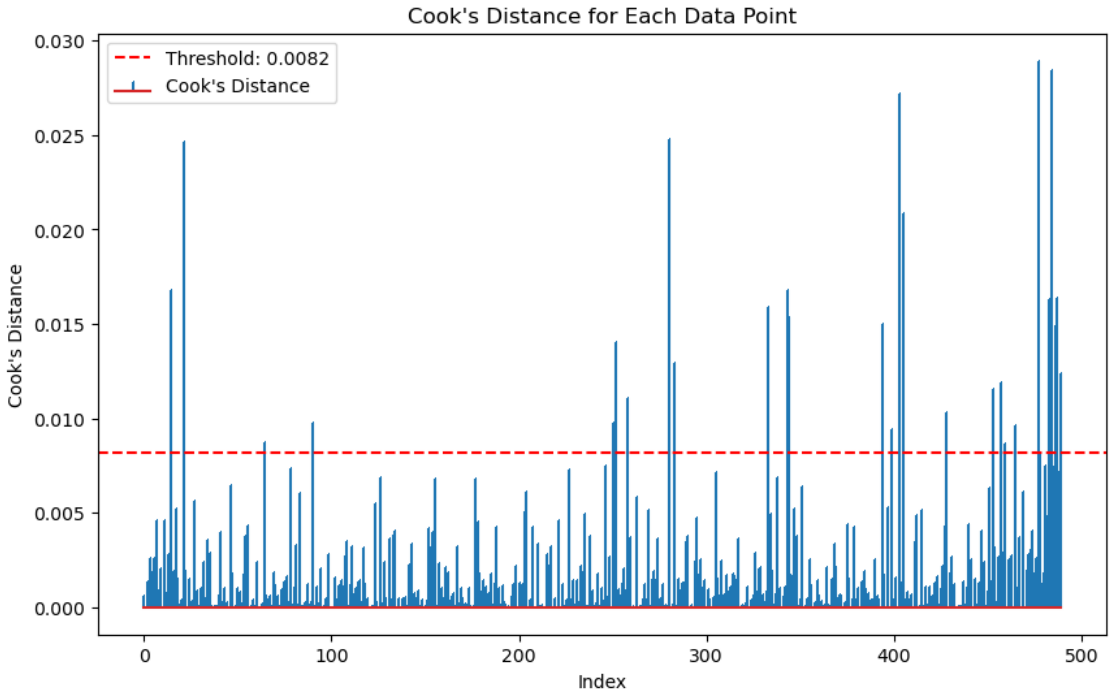
After we apply the log transformation and calculate Cook's distance, we can see that the elite players are no longer influential points. However, there are some players which the model still struggles with. The model undervalues some players (e.g. Vrana, Kuzmenko) who may perform better in close and tied situations than their metrics suggest. On the other hand, some players are overvalued and may have better metrics that may not fully reflect their clutch performance (e.g. Kucherov, Kane). While influential points are often viewed negatively, they can provide valuable insights. These points could help NHL coaching staff and management identify players who perform well in high-pressure situations, even if they aren't considered elite based on traditional metrics.

Finally, some below-average players become influential because the log transformation tends to amplify the difference between smaller actual and predicted values.

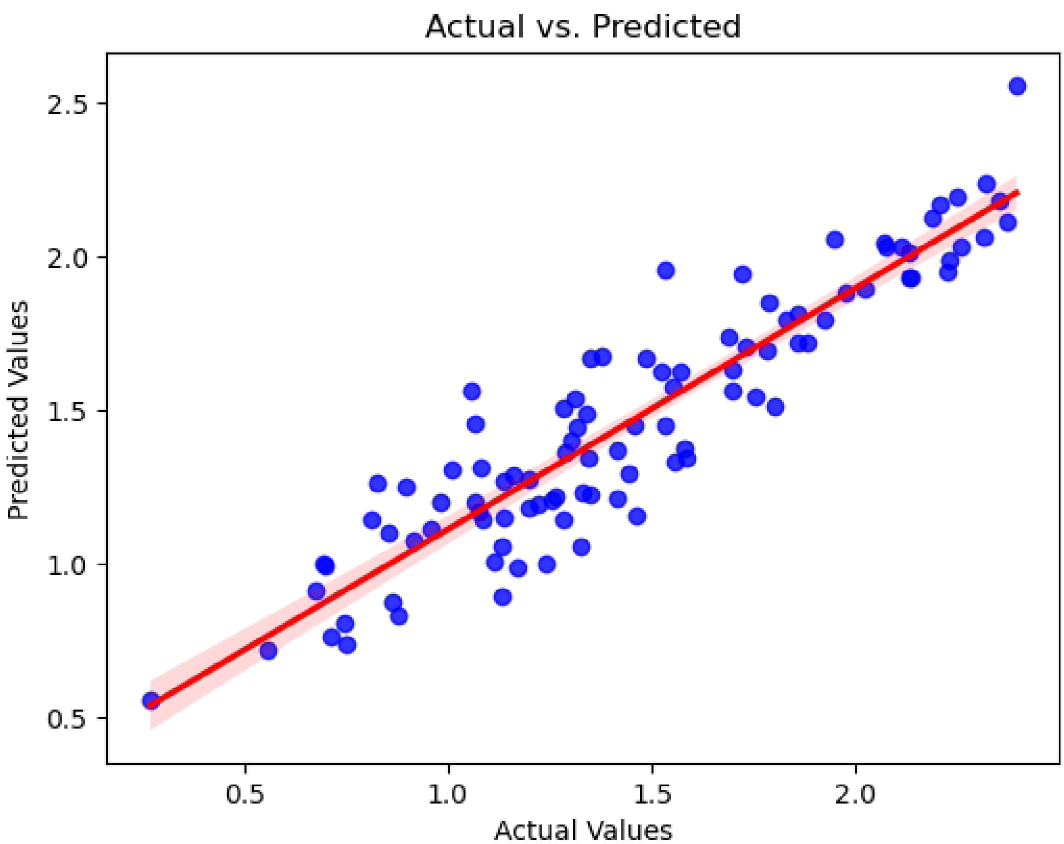
[83]:
```
X_with_intercept = sm.add_constant(X_log)

ols_model = sm.OLS(y_log, X_with_intercept).fit()

influence = ols_model.get_influence()
cooks_d, _ = influence.cooks_distance


# Determine n (number of observations) and p (number of predictors)
n = X_with_intercept.shape[0]  # Number of rows in the data (observations)
p = X_with_intercept.shape[1]  # Number of columns in X_with_intercept␣
 ↪(predictors + intercept)

# Calculate the threshold for Cook's Distance
threshold = 4 / len(X_with_intercept)

outliers = np.where(cooks_d > threshold)[0]

results = pd.DataFrame({
    'Player': merged_clutch_goals.loc[y.index, 'Player'],
    'Actual': y_log,
    'Predicted': ols_model.fittedvalues,
    'Cook\'s Distance': cooks_d
})

outliers_df = results.iloc[outliers]

print("There are", outliers_df.shape[0], "influential points.")
print("Outliers based on Cook's Distance:")
print(outliers_df)

plt.figure(figsize=(10, 6))
plt.stem(cooks_d, markerfmt=",", label="Cook's Distance")
plt.axhline(y=threshold, color='r', linestyle='--', label=f"Threshold:␣
 ↪{threshold:.4f}")
plt.xlabel('Index')
plt.ylabel("Cook's Distance")
plt.title("Cook's Distance for Each Data Point")
plt.legend()
```

```python
plt.show()
```

```
There are 28 influential points.
Outliers based on Cook's Distance:
                  Player    Actual  Predicted  Cook's Distance
245          Jakub Vrana  2.360854   1.795426         0.016769
489      Andrei Kuzmenko  2.316488   1.788527         0.024615
144      Nikita Kucherov  2.046402   2.309242         0.008741
51          Patrick Kane  1.965713   2.241410         0.009754
383  Jaret Anderson-Dolan  1.492904   0.992345         0.009743
122    Brendan Gallagher  1.490654   1.923002         0.014019
126         Ryan Dzingel  1.465568   1.128650         0.011106
376           Mason Shaw  1.401183   1.049030         0.024798
317       Kevin Stenlund  1.393766   1.025212         0.012931
268        Dakota Joshua  1.269761   0.924761         0.015897
473           Jack Quinn  1.244155   1.611213         0.016799
369     Michael Pezzetta  1.241269   0.840451         0.015330
17     Alexander Radulov  1.081805   1.499851         0.014983
120       Joonas Donskoi  1.064711   1.528124         0.009399
479        Cole Perfetti  1.057790   1.644382         0.027161
6           Ryan Getzlaf  1.040277   1.549430         0.020843
220      Jonathan Drouin  0.963174   1.369027         0.010282
24           Darren Helm  0.854415   1.211153         0.011535
56          Carl Hagelin  0.824175   1.200115         0.011875
444         John Leonard  0.810930   1.080587         0.008669
467      Aliaksei Protas  0.741937   1.159611         0.009660
478      Quinton Byfield  0.647103   1.262697         0.028934
9          Loui Eriksson  0.559616   0.910781         0.008208
59            Jay Beagle  0.392042   0.832538         0.016322
483            Nils Aman  0.364643   0.868756         0.028410
381      Jake Leschyshyn  0.329304   0.851089         0.014918
196      Saku Maenalanen  0.270027   0.825166         0.016405
229        Ross Johnston  0.000000   0.309714         0.012387
```



[84]:
```
sns.regplot(data=merged_clutch_goals, x=test_y, y=y_pred, scatter_kws={'color':
 ↪'blue'}, line_kws={'color': 'red'})
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted')
plt.show()
```



1.0.50 Making Predicitons on Current Season Data

We save “ridge_cv_log” for reproductible results. We can then use it to make predictions on the current statistics of players (from 2023-2024 season to the current 2024-2025 season).

[86]:
```
joblib.dump(ridge_cv_log, 'ridge_cv_model.pkl')
ridge_cv_log_loaded = joblib.load('ridge_cv_model.pkl')
```

[87]:
```
all_seasons = []

for season in range(2023, 2025):
    summary_url = f"https://api.nhle.com/stats/rest/en/skater/summary?
 ↪limit=-1&cayenneExp=seasonId={season}{season+1}%20and%20gameTypeId=2"

    try:
        summary_resp = requests.get(summary_url)
        summary_resp.raise_for_status()
        summary_json =  summary_resp.json()

        if summary_json['data']:
```

```python
            df_summary = pd.DataFrame(summary_json['data'])
            all_seasons.append(df_summary)
            df_summary['season'] = f"{season}-{season + 1}"
            print(f"Successfully fetched data for season {season}-{season+1}")
        else:
            print(f"No data returned for season {season}-{season + 1}")

    except requests.exceptions.RequestException as e:
        print(f"Error fetching data for season {season}-{season + 1}: {e}")

if all_seasons:
    nhl_api_df = pd.concat(all_seasons, ignore_index=True)
    nhl_api_df = nhl_api_df.groupby('playerId').agg({
            'playerId': 'first',
            'skaterFullName': 'first',
            'positionCode': 'first',
            'gamesPlayed': 'sum',
            'assists': 'sum',
            'otGoals': 'sum',
            'gameWinningGoals': 'sum',
            'timeOnIcePerGame': 'mean'
        }).reset_index(drop = True)

print(nhl_api_df)
```

```
Successfully fetched data for season 2023-2024
Successfully fetched data for season 2024-2025
     playerId      skaterFullName positionCode  gamesPlayed  assists  otGoals  \
0     8470600         Ryan Suter            D          100       18        0
1     8470604         Jeff Carter            C           72        4        0
2     8470610         Zach Parise            L           30        5        0
3     8470613         Brent Burns            D           98       38        0
4     8470621         Corey Perry            R           72       11        0
..        …                 …          …          …       …       …
959   8484779        Jett Luchanko            C            4        0        0
960   8484801    Macklin Celebrini            C            7        1        0
961   8484911          Collin Graf            R            7        2        0
962   8484958       Maxim Tsyplakov            R           18        8        0
963   8485105   Nikita Prishchepov            C            6        0        0

     gameWinningGoals  timeOnIcePerGame
0                   1        1239.66730
1                   4         754.23610
2                   1         778.03330
3                   0        1286.30560
4                   3         738.21295
..                …               …
959                 0         843.25000
```

```
960                    0        1163.85710
961                    0         995.71420
962                    0        1000.66660
963                    0         437.50000

[964 rows x 8 columns]
```

[88]:
```
nhl_api_df = nhl_api_df.loc[(nhl_api_df['positionCode'] != 'D') &␣
 ↪(nhl_api_df['gamesPlayed'] >= 35)]
nhl_api_df = nhl_api_df.reset_index(drop = True)
nhl_api_df = nhl_api_df.fillna(0)

nhl_api_df.rename(columns = {'gameWinningGoals': 'game_winning_goals'}, inplace␣
 ↪= True)
nhl_api_df.rename(columns = {'otGoals': 'ot_goals'}, inplace = True)
nhl_api_df.rename(columns = {'skaterFullName': 'Player'}, inplace = True)
nhl_api_df.rename(columns={'timeOnIcePerGame': 'time_on_ice_per_game'},␣
 ↪inplace=True)
nhl_api_df['regulation_game_winning'] = nhl_api_df['game_winning_goals'] -␣
 ↪nhl_api_df['ot_goals']
```

[89]:
```
start_season = "20232024"
end_season = "20242025"
goals_up_one_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={start_season}&thruseason={end_season}&stype=2&sit=all&score=u1&stdoi=std&rate=n
goals_down_one_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={start_season}&thruseason={end_season}&stype=2&sit=all&score=d1&stdoi=std&rate=n
tied_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={start_season}&thruseason={end_season}&stype=2&sit=all&score=tied&stdoi=std&rate
total_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={start_season}&thruseason={end_season}&stype=2&sit=all&score=all&stdoi=std&rate=
```

[90]:
```
urls = {
    "goals_up_one": (goals_up_one_url, 'goals_up_by_one'),
    "goals_down_one": (goals_down_one_url, 'goals_down_by_one'),
    "tied": (tied_url, 'goals_when_tied'),
    "total": (total_url, 'total_goals'),
}

dataframes = {}

for name, (url, new_column_name) in urls.items():
    df = pd.read_html(url, header=0, index_col=0, na_values=["-"])[0]
    df.rename(columns={'Goals': new_column_name}, inplace=True)
    dataframes[name] = df

goals_up_one_df = dataframes["goals_up_one"]
```

```
goals_down_one_df = dataframes["goals_down_one"]
goals_tied_df = dataframes["tied"]
total_df = dataframes["total"]
```

[91]:
```
goals_up_one_df = goals_up_one_df[['Player', 'GP', 'goals_up_by_one']]
goals_down_one_df = goals_down_one_df[['Player', 'goals_down_by_one']]
goals_tied_df = goals_tied_df[['Player', 'goals_when_tied']]
total_df = total_df[['Player', 'total_goals', 'Shots', 'ixG', 'iFF', 'iSCF',␣
↪'iHDCF', 'Rebounds Created', 'iCF']]

dfs_natural_stat = [goals_up_one_df, goals_down_one_df, goals_tied_df, total_df]

merged_natural_stat = ft.reduce(lambda left, right: pd.merge(left, right,␣
↪on='Player'), dfs_natural_stat)
merged_natural_stat = merged_natural_stat.loc[merged_natural_stat['GP'] >= 35]
merged_natural_stat.rename(columns={'Shots': 'shots'}, inplace=True)
merged_natural_stat.rename(columns={'Rebounds Created': 'rebounds_created'},␣
↪inplace=True)
```

[92]:
```
natural_stat_names = ["Pat Maroon", "Alex Kerfoot", "Nicholas Paul", "Zach␣
↪Sanford", "Alex Wennberg", "Mitchell Marner", "Zach Aston-Reese",  "Max␣
↪Comtois", "Alexei Toropchenko", "Cameron Atkinson", "Alexander Nylander",␣
↪"Jacob Lucchini", ]
nhl_names = ["Patrick Maroon", "Alexander Kerfoot", "Nick Paul", "Zachary␣
↪Sanford", "Alexander Wennberg", "Mitch Marner", "Zachary Aston-Reese", ␣
↪"Maxime Comtois", "Alexey Toropchenko", "Cam Atkinson", "Alex Nylander",␣
↪"Jake Lucchini"]
merged_natural_stat = merged_natural_stat.replace(natural_stat_names, nhl_names)
```

[93]:
```
merged_clutch_goals_prediction = nhl_api_df.merge(merged_natural_stat, on =␣
↪'Player', how = 'left')
```

[94]:
```
merged_clutch_goals_prediction.drop(columns = 'GP', axis = 1, inplace = True)
```

[95]:
```
columns = ['ot_goals', 'regulation_game_winning', 'assists', 'goals_up_by_one',␣
↪'goals_down_by_one', 'goals_when_tied', 'shots', 'ixG', 'iFF', 'iSCF',␣
↪'iHDCF', 'iCF', 'rebounds_created']
for column in columns:
    per_game_string = f"{column}_per_game"
    merged_clutch_goals_prediction[per_game_string] =␣
↪merged_clutch_goals_prediction[column] /␣
↪merged_clutch_goals_prediction['gamesPlayed']
```

[96]:

```
merged_clutch_goals_prediction['clutch_score'] = 0.3 *␣
↪merged_clutch_goals_prediction['goals_when_tied_per_game'] + 0.3 *␣
↪merged_clutch_goals_prediction['goals_down_by_one_per_game'] + 0.2 *␣
↪merged_clutch_goals_prediction['goals_up_by_one_per_game'] + 0.1 *␣
↪merged_clutch_goals_prediction['regulation_game_winning_per_game'] + 0.1 *␣
↪merged_clutch_goals_prediction['ot_goals_per_game']
```

[97]:
```
merged_clutch_goals_prediction['clutch_score'] *= 100
merged_clutch_goals_prediction['clutch_score_rank']  =␣
↪merged_clutch_goals_prediction['clutch_score'].rank(ascending = False,␣
↪method = 'min')
merged_clutch_goals_prediction['clutch_score'] =␣
↪merged_clutch_goals_prediction['clutch_score'].apply(lambda x: round(x, 2))
merged_clutch_goals_prediction.sort_values('clutch_score_rank', inplace = True)
merged_clutch_goals_prediction[['Player','clutch_score', 'clutch_score_rank']].
↪head(20)
```

[97]:

	Player	clutch_score	clutch_score_rank
253	Auston Matthews	16.49	1.0
172	Sam Reinhart	15.60	2.0
185	David Pastrnak	12.97	3.0
173	Leon Draisaitl	12.73	4.0
242	Kirill Kaprizov	12.50	5.0
237	Artemi Panarin	12.06	6.0
207	Kyle Connor	11.81	7.0
192	Brayden Point	11.61	8.0
91	Nikita Kucherov	11.24	9.0
213	Mikko Rantanen	11.12	10.0
116	Filip Forsberg	11.00	11.0
178	Dylan Larkin	10.94	12.0
159	Valeri Nichushkin	10.91	13.0
153	Nathan MacKinnon	10.50	14.0
216	Sebastian Aho	10.43	15.0
98	J.T. Miller	10.21	16.0
46	Chris Kreider	10.10	17.0
301	Gabriel Vilardi	10.00	18.0
6	Sidney Crosby	10.00	18.0
175	William Nylander	9.90	20.0

[98]:
```
merged_clutch_goals_prediction.fillna(0, inplace = True)
null_rows = merged_clutch_goals_prediction[merged_clutch_goals_prediction.
↪isnull().any(axis=1)]
print("Rows with null values:")
print(null_rows)
```

```
Rows with null values:
Empty DataFrame
Columns: [playerId, Player, positionCode, gamesPlayed, assists, ot_goals,
```

```
game_winning_goals, time_on_ice_per_game, regulation_game_winning,
goals_up_by_one, goals_down_by_one, goals_when_tied, total_goals, shots, ixG,
iFF, iSCF, iHDCF, rebounds_created, iCF, ot_goals_per_game,
regulation_game_winning_per_game, assists_per_game, goals_up_by_one_per_game,
goals_down_by_one_per_game, goals_when_tied_per_game, shots_per_game,
ixG_per_game, iFF_per_game, iSCF_per_game, iHDCF_per_game, iCF_per_game,
rebounds_created_per_game, clutch_score, clutch_score_rank]
Index: []

[0 rows x 35 columns]
```

[99]:
```
x_var = ['shots_per_game', 'ixG_per_game', 'iFF_per_game', 'iSCF_per_game',␣
↪'iHDCF_per_game',
         'assists_per_game', 'iCF_per_game', 'rebounds_created_per_game',␣
↪'time_on_ice_per_game']
X_adjusted = merged_clutch_goals_prediction[x_var]
y_var = 'clutch_score'
y = merged_clutch_goals_prediction[y_var]
```

[100]:
```
X_scaled = StandardScaler().fit_transform(X_adjusted)
X_scaled = np.nan_to_num(X_scaled, nan=0)

epsilon = np.abs(X_scaled.min()) + 1

X_shifted = X_scaled + epsilon

y_log = np.log(y + 1)

X_log = np.log(X_shifted)

y_pred = ridge_cv_log_loaded.predict(X_log)
```

[101]:
```
merged_clutch_goals_prediction
```

[101]:
```
     playerId               Player positionCode  gamesPlayed  assists  \
253   8479318      Auston Matthews            C           94       44
172   8477933         Sam Reinhart            C          100       52
185   8477956       David Pastrnak            R          101       72
173   8477934       Leon Draisaitl            C           99       76
242   8478864       Kirill Kaprizov            L           92       70
..        …                  …          …          …        …
215   8478424       Jansen Harkins            C           48        5
341   8480870            Bo Groulx            C           45        2
265   8479379         Givani Smith            R           40        3
52    8475235  Nicolas Deslauriers            L           67        4
349   8481058          Jesse Ylonen            R           59        4
```

	ot_goals	game_winning_goals	time_on_ice_per_game	\
253	3	8	1253.60915	
172	3	11	1211.57720	
185	1	7	1193.91650	
173	5	11	1257.78080	
242	2	10	1313.24780	
..	…	…	…	
215	0	0	539.74440	
341	0	0	731.31110	
265	0	0	407.90275	
52	0	0	426.91185	
349	0	1	614.23720	

	regulation_game_winning	goals_up_by_one	…	goals_when_tied_per_game	\
253	5	15.0	…	0.223404	
172	8	17.0	…	0.270000	
185	6	14.0	…	0.227723	
173	6	5.0	…	0.212121	
242	8	9.0	…	0.206522	
..	…	…	…	…	
215	0	0.0	…	0.000000	
341	0	0.0	…	0.000000	
265	0	0.0	…	0.000000	
52	0	0.0	…	0.000000	
349	1	0.0	…	0.000000	

	shots_per_game	ixG_per_game	iFF_per_game	iSCF_per_game	\
253	4.521277	0.563723	6.638298	5.457447	
172	2.800000	0.452100	4.290000	3.480000	
185	4.594059	0.450099	6.376238	4.049505	
173	2.666667	0.348990	4.000000	2.868687	
242	3.597826	0.494022	5.358696	4.097826	
..	…	…	…	…	
215	0.791667	0.062083	1.041667	0.562500	
341	0.711111	0.081333	1.200000	0.911111	
265	0.825000	0.094500	1.075000	0.675000	
52	0.791045	0.093284	1.283582	0.761194	
349	0.000000	0.000000	0.000000	0.000000	

	iHDCF_per_game	iCF_per_game	rebounds_created_per_game	clutch_score	\
253	2.393617	8.574468	0.851064	16.49	
172	1.820000	5.340000	0.580000	15.60	
185	1.326733	8.603960	0.712871	12.97	
173	1.060606	5.191919	0.434343	12.73	
242	1.706522	7.630435	0.750000	12.50	
..	…	…	…	…	
215	0.270833	1.479167	0.125000	0.00	

```
341         0.422222     1.822222                   0.133333         0.00
265         0.475000     1.425000                   0.225000         0.00
52          0.432836     1.641791                   0.089552         0.00
349         0.000000     0.000000                   0.000000         0.00

     clutch_score_rank
253                1.0
172                2.0
185                3.0
173                4.0
242                5.0
..                 …
215              429.0
341              429.0
265              429.0
52               429.0
349                0.0

[435 rows x 35 columns]
```

[102]:
```python
merged_clutch_goals_prediction['predicted_clutch_score'] = y_pred
merged_clutch_goals_prediction['log'] = np.
 ↪log(merged_clutch_goals_prediction['clutch_score'] + 1)
```

[103]:
```python
merged_clutch_goals_prediction['log_adjusted'] = np.
 ↪log(merged_clutch_goals_prediction['clutch_score'] + 1) * 10
merged_clutch_goals_prediction['predicted_clutch_score_adjusted'] = y_pred * 10
merged_clutch_goals_prediction = merged_clutch_goals_prediction.
 ↪sort_values(by='predicted_clutch_score_adjusted', ascending = False)
merged_clutch_goals_prediction['log_adjusted'] =␣
 ↪merged_clutch_goals_prediction['log_adjusted'].apply(lambda x: round(x, 2))
merged_clutch_goals_prediction['predicted_clutch_score_adjusted'] =␣
 ↪merged_clutch_goals_prediction['predicted_clutch_score_adjusted'].
 ↪apply(lambda x: round(x, 2))
```

1.0.51 Making the Results Interpretable

To make the results more interpretable, I have made the following changes: - Player's predicted and clutch score multiplied by 10 - A tier for the player based on how far they are from the mean for clutch score - A percentage difference between their actual and predicted values - A classification for the percentage diff

The results will be saved in an Excel file: "Player Clutch Statisticserence

[105]:
```python
def create_clutch_rankings(df):

    rankings = df.copy()
```

```
    mean_score = rankings['predicted_clutch_score_adjusted'].mean()
    std_score = rankings['predicted_clutch_score_adjusted'].std()

    rankings['standard_deviations'] = (rankings['predicted_clutch_score_adjusted'] - mean_score) / std_score

    def assign_tier(z_score):
        if z_score >= 2:
            return 'Franchise'
        elif z_score >= 1.5:
            return 'Elite'
        elif z_score >= 1:
            return 'Above Average'
        elif z_score > -1:
            return 'Below Average'
        else:
            return 'Limited Clutch Impact'

    rankings['tier'] = rankings['standard_deviations'].apply(assign_tier)

    rankings['vs_predicted'] = ((rankings['log_adjusted' ] - rankings['predicted_clutch_score_adjusted']) / rankings['predicted_clutch_score_adjusted'] * 100).round(2)
    rankings['vs_predicted'] = rankings['vs_predicted'].apply(lambda x: f"+{x}%" if x > 0 else f"{x}%")

    def assign_tier(percentage):
        if z_score >= 2:
            return 'Franchise'
        elif z_score >= 1.5:
            return 'Elite'
        elif z_score >= 1:
            return 'Above Average'
        elif z_score > -1:
            return 'Below Average'
        else:
            return 'Limited Clutch Impact'

    def get_prediction_reliability(diff):
        diff_num = float(diff.rstrip('%'))
        if diff_num >= 0:
            if  diff_num <= 10:
                return 'Slightly Overperforming'
            elif diff_num <= 20:
                return 'Overperforming'
            else:
                return 'Heavily Overperforming'
```

```
        elif diff_num <= 0:
            if  diff_num >= -10:
                return 'Slightly Underperforming'
            elif diff_num >= -20:
                return 'Underperforming'
            else:
                return 'Heavily Underperforming'


    rankings['Prediction Reliability'] = rankings['vs_predicted'].
↪apply(get_prediction_reliability)

    output = rankings[[
        'Player',
        'predicted_clutch_score_adjusted',
        'log_adjusted',
        'tier',
        'vs_predicted',
        'Prediction Reliability'
    ]].sort_values('predicted_clutch_score_adjusted', ascending=False)

    output = output.reset_index(drop=True)
    output.index = output.index + 1

    output.columns = ['Player', 'Predicted Clutch Score', 'Actual Clutch␣
↪Score', 'Tier', 'Predicted VS Actual', 'Reliability']

    output.to_excel("Player Clutch Statistics.xlsx")

    return output
```

[106]:
```
create_clutch_rankings(merged_clutch_goals_prediction)
```

[106]:
```
                Player  Predicted Clutch Score  Actual Clutch Score  \
1       Auston Matthews                   26.36                28.62
2      Nathan MacKinnon                   26.00                24.42
3        David Pastrnak                   25.38                26.37
4       Kirill Kaprizov                   25.14                26.03
5         Brady Tkachuk                   24.93                23.20
..                  …                      …                    …
431         Ryan Reaves                    9.73                 5.71
432       Chris Tierney                    9.62                10.04
433       Austin Watson                    8.75                 9.97
434    Kurtis MacDermid                    6.81                 8.20
435        Jesse Ylonen                    6.30                 0.00

                      Tier Predicted VS Actual               Reliability
```

```
1                  Franchise              +8.57%   Slightly Overperforming
2                  Franchise              -6.08%  Slightly Underperforming
3                  Franchise               +3.9%   Slightly Overperforming
4                  Franchise              +3.54%   Slightly Overperforming
5                  Franchise              -6.94%  Slightly Underperforming
..                       …                     …                         …
431  Limited Clutch Impact               -41.32%   Heavily Underperforming
432  Limited Clutch Impact                +4.37%   Slightly Overperforming
433  Limited Clutch Impact               +13.94%            Overperforming
434  Limited Clutch Impact               +20.41%    Heavily Overperforming
435  Limited Clutch Impact               -100.0%   Heavily Underperforming

[435 rows x 6 columns]
```

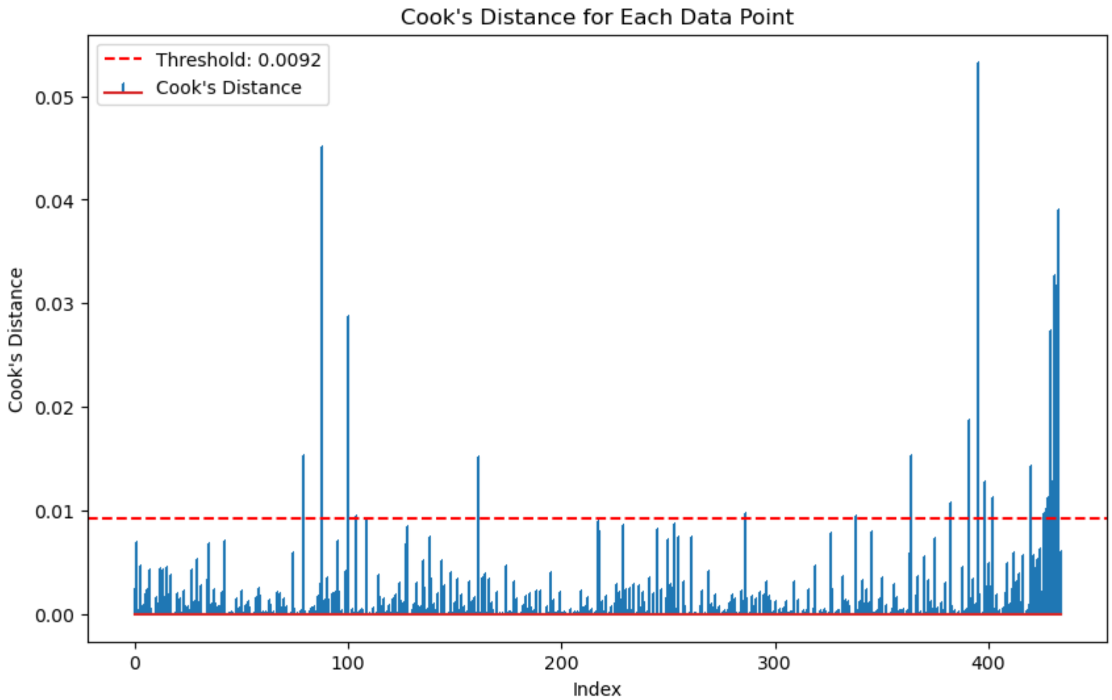
1.0.52 Cook's Distance Observations

The model shows the same patterns as before - it undervalues and overvalues some players. A few differences are also amplified by the log transformation.

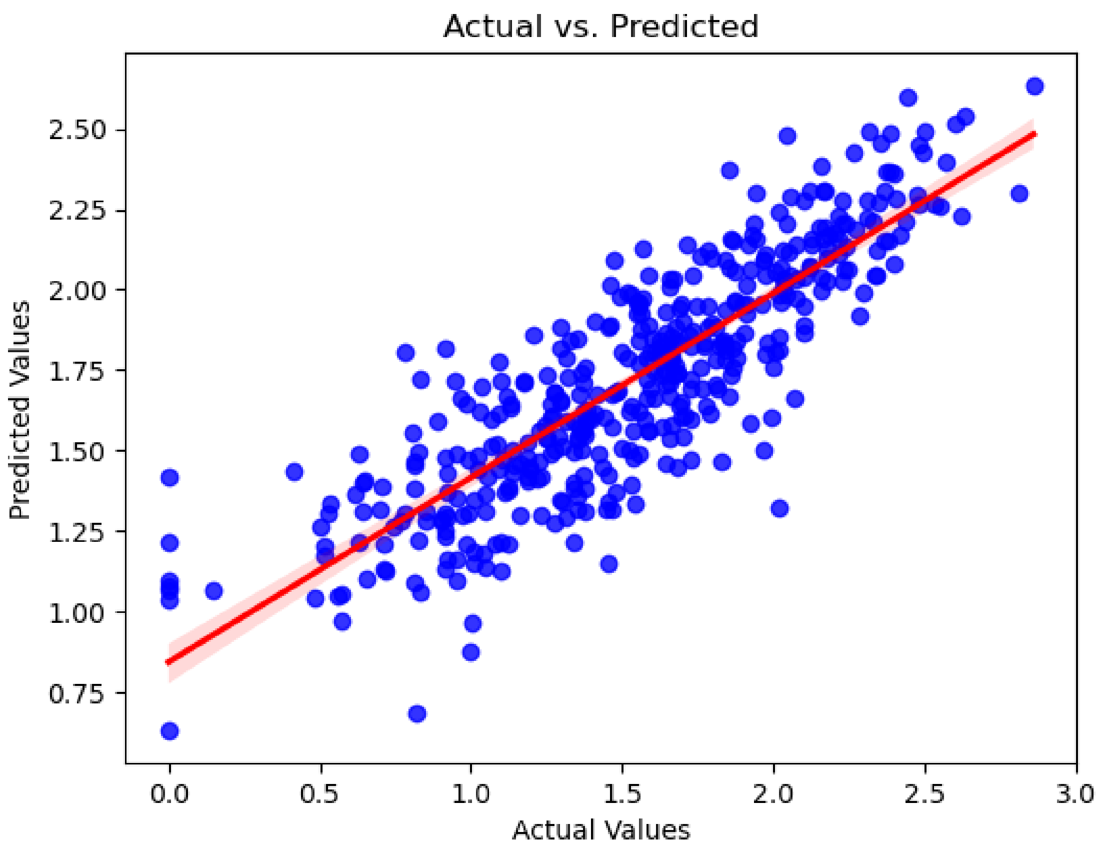
[108]:
```python
X_with_intercept = sm.add_constant(X_log)

ols_model = sm.OLS(y_log, X_with_intercept).fit()

influence = ols_model.get_influence()
cooks_d, _ = influence.cooks_distance

threshold = 4 / len(X_adjusted)

outliers = np.where(cooks_d > threshold)[0]

results = pd.DataFrame({
    'Player': merged_clutch_goals_prediction.loc[y.index, 'Player'],
    'Actual': y_log,
    'Predicted': ols_model.fittedvalues,
    'Cook\'s Distance': cooks_d
})

outliers_df = results.iloc[outliers]

print("There are", outliers_df.shape[0], "influential points.")
print("Outliers based on Cook's Distance:")
print(outliers_df)

plt.figure(figsize=(10, 6))
plt.stem(cooks_d, markerfmt=",", label="Cook's Distance")
plt.axhline(y=threshold, color='r', linestyle='--', label=f"Threshold:␣
 ↪{threshold:.4f}")
```

```
plt.xlabel('Index')
plt.ylabel("Cook's Distance")
plt.title("Cook's Distance for Each Data Point")
plt.legend()
plt.show()
```

```
There are 23 influential points.
Outliers based on Cook's Distance:
                  Player    Actual  Predicted  Cook's Distance
136         Jake Guentzel  2.047693   2.528530         0.015258
179          Sonny Milano  2.020222   1.067941         0.045172
280       Michael Carcone  1.969906   1.121896         0.028704
83       Vincent Trocheck  1.943049   2.337721         0.009490
281        Justin Brazeau  1.921325   1.431978         0.009230
374       Simon Holmstrom  1.726332   1.169874         0.015227
288        Vinni Lettieri  1.342865   0.899939         0.009793
60       Evgeny Kuznetsov  1.118415   1.564307         0.009454
66          Austin Watson  0.996949   0.483627         0.015375
27         Max Pacioretty  0.916291   1.563345         0.010701
411   Alexander Barabanov  0.832909   1.484753         0.018710
130      Kurtis MacDermid  0.819780   0.200693         0.053284
190      Christian Dvorak  0.810930   1.300390         0.012746
141            Miles Wood  0.779325   1.604173         0.011198
352         Reese Johnson  0.536493   1.130105         0.014363
200          Kevin Labanc  0.412110   1.082357         0.009783
278      Michael Pezzetta  0.148420   0.595992         0.010222
201           Sammy Blais  0.000000   0.698489         0.011223
376      Vasily Podkolzin  0.000000   1.144429         0.027410
215        Jansen Harkins  0.000000   0.634292         0.012861
341             Bo Groulx  0.000000   0.813136         0.032744
265          Givani Smith  0.000000   0.581975         0.031870
52    Nicolas Deslauriers  0.000000   0.670159         0.039052
```



[170]:
```
sns.regplot(data=merged_clutch_goals_prediction,␣
 ↪x=merged_clutch_goals_prediction['log'],␣
 ↪y=merged_clutch_goals_prediction['predicted_clutch_score'],␣
 ↪scatter_kws={'color': 'blue'}, line_kws={'color': 'red'})
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted')
plt.show()
```



1.0.53 Concluding Thoughts

Through this project, I hope that I have built a well-tuned regression model that is able to perform well in predicting the clutch score of NHL players. Although Cook's distance did identify some influential points in the final model, these points may be useful in determining overvalued and undervalued players.

I hope to deploy this model with Flask or Django and connect it to a PowerBI dashboard to provide real-time updates on the clutch performance of players.

[5]:
```
!jupyter nbconvert --to pdf NHL_Clutch_Goalscoring_Model.ipynb
```

```
[NbConvertApp] Converting notebook NHL_Clutch_Goalscoring_Model.ipynb to html
[NbConvertApp] WARNING | Alternative text is missing on 22 image(s).
[NbConvertApp] Writing 2247468 bytes to NHL_Clutch_Goalscoring_Model.html
```

[ ]:
```

```