Predicting NHL Clutch Goalscorers

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1 Predicting NHL Clutch Goalscorers

This project applies machine learning techniques to identify and predict NHL forwards who excel in "clutch" situations (close, tied, and overtime games). The goal is not only to measure clutch performance but also to model expected clutch scoring given a player's underlying metrics and understand the reasoning behind the predictions.

The final model has been deployed to a Streamlit Dashboard that is updated at 9:00 a.m. EST daily.

[3]:
```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

from sklearn.exceptions import FitFailedWarning
warnings.filterwarnings("ignore", category=FitFailedWarning)

import time
import math
import json
import requests
import functools as ft
import scipy.stats as stats

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm

import xgboost as xgb
from xgboost import XGBClassifier, plot_importance

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 Ridge, RidgeCV, LinearRegression
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.utils.class_weight import compute_sample_weight
from sklearn.decomposition import PCA
from sklearn.utils import resample

from skopt import BayesSearchCV
from skopt.space import Integer, Real, Categorical

from statsmodels.stats.outliers_influence import variance_inflation_factor
from scipy.stats import pearsonr

import shap
import joblib
```

1.0.1 NHL API

[5]:
```
all_seasons = []

for season in range(2021, 2024):
    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)
print(nhl_api_df)
```

```
Successfully fetched data for season 2021-2022
Successfully fetched data for season 2022-2023
Successfully fetched data for season 2023-2024
      playerId     skaterFullName positionCode  gamesPlayed  assists  otGoals  \
0      8465009        Zdeno Chara            D           72       12        0
1      8466138       Joe Thornton            C           34        5        0
2      8469455       Jason Spezza            C           71       13        0
3      8470281       Duncan Keith            D           64       20        0
4      8470595         Eric Staal            C           72       15        0
…        …                …          …          …       …      …
1250   8484314       Jiri Smejkal            L           20        1        0
1251   8484321  Nikolas Matinpalo            D            4        0        0
1252   8484325    Waltteri Merela            C           19        0        0
1253   8484326        Patrik Koch            D            1        0        0
1254   8484911        Collin Graf            R            7        2        0

      timeOnIcePerGame
0            1123.9027
1             666.3529
2             644.7605
3            1183.6093
4             854.2222
…                …
1250          568.7000
1251          420.2500
1252          588.9473
1253          560.0000
1254          995.7142

[1255 rows x 7 columns]
```

1.0.2 Cleaning the NHL API Data

- Only forwards are included since defensemen score at different rates.
- Players must have 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.

[7]:
```
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)

rename_columns = {
    'otGoals': 'ot_goals',
    'skaterFullName': 'Player',
```

```
    'timeOnIcePerGame': 'time_on_ice_per_game'
}

nhl_api_df.rename(columns = rename_columns,  inplace = True)
```

1.0.3 Scraping Data from Natural Stat Trick

[9]:
```
start_season = "20212022"
end_season = "20232024"
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=
on_ice_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={start_season}&thruseason={end_season}&stype=2&sit=5v5&score=all&stdoi=oi&rate=n
```

[10]:
```
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'),
    "on_ice": (on_ice_url, '')
}

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"]
on_ice_df = dataframes["on_ice"]
on_ice_df.columns = on_ice_df.columns.str.replace('\xa0', ' ')
```

1.0.4 Cleaning Data from Natural Stat Trick

Similar to the NHL API data, only players who have played at least 60 games are included. The dataframes have already been filtered for forwards through the URLs.

[12]:
```
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', 'SH%']]
on_ice_df = on_ice_df[['Player', 'Off. Zone Starts', 'On The Fly Starts']]

dfs_natural_stat = [goals_up_one_df, goals_down_one_df, goals_tied_df,␣
 ↪total_df, on_ice_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]

rename_columns = {
    'Shots': 'shots',
    'Rebounds Created': 'rebounds_created',
    'Off. Zone Starts': 'off_zone_starts',
    'On The Fly Starts': 'on_the_fly_starts'
}

merged_natural_stat.rename(columns = rename_columns, inplace=True)
```

1.0.5 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.

[14]:
```
natural_stat_names = ["Pat Maroon", "Alex Kerfoot", "Nicholas Paul", "Zach␣
 ↪Sanford", "Alex Wennberg", "Mitchell Marner",  "Max Comtois", "Alexei␣
 ↪Toropchenko", "Cameron Atkinson", "Thomas Novak", "Zack Bolduc", "Frederic␣
 ↪Gaudreau"]
nhl_names = ["Patrick Maroon", "Alexander Kerfoot", "Nick Paul", "Zachary␣
 ↪Sanford", "Alexander Wennberg", "Mitch Marner", "Maxime Comtois", "Alexey␣
 ↪Toropchenko", "Cam Atkinson", "Tommy Novak", "Zachary Bolduc", "Freddy␣
 ↪Gaudreau"]
merged_natural_stat = merged_natural_stat.replace(natural_stat_names, nhl_names)
```

1.0.6 Merging the Data

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

[16]:
```
merged_clutch_goals = nhl_api_df.merge(merged_natural_stat, on = 'Player', how␣
 ↪= 'left')
merged_clutch_goals = merged_clutch_goals.dropna()
```

1.0.7 Changing Columns

Compute per game stats to accurately compare players.

[18]:
```
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', 'off_zone_starts', 'on_the_fly_starts']
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']
```

1.0.8 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 regular 5v5.

[20]:
```
merged_clutch_goals['clutch_score'] = (
    0.45 * merged_clutch_goals['goals_down_by_one_per_game'] +
    0.35 * merged_clutch_goals['goals_when_tied_per_game'] +
    0.2 * merged_clutch_goals['ot_goals_per_game']
)
```

1.0.9 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.

[22]:
```
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)
```

[22]:

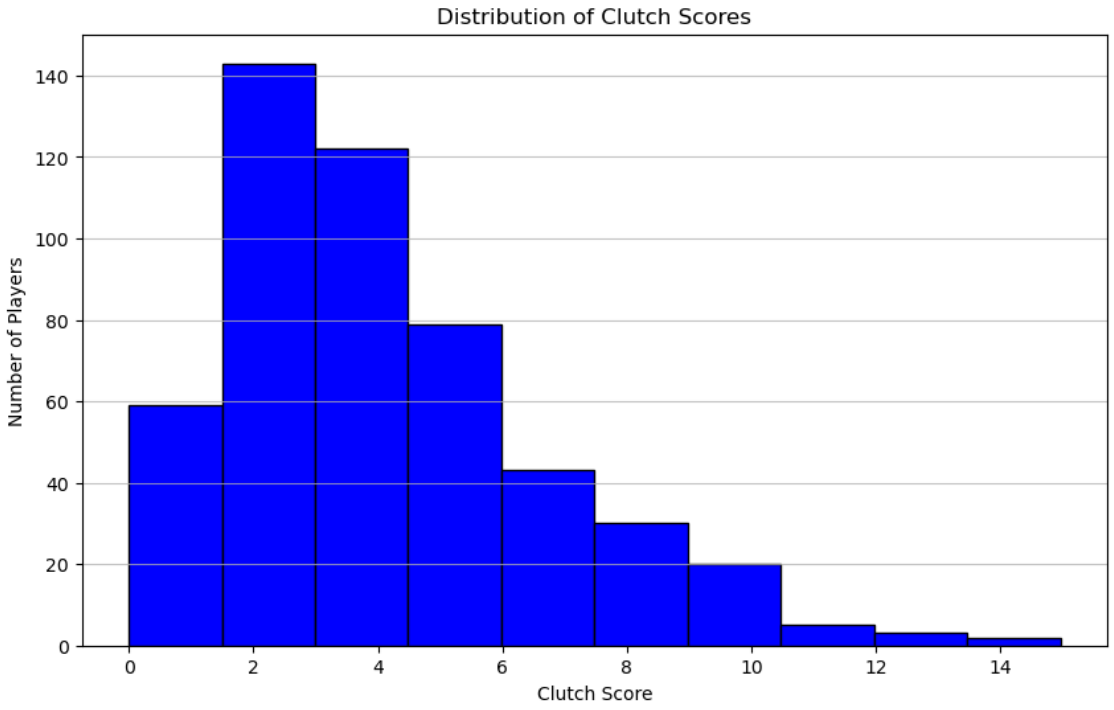
	Player	clutch_score	clutch_score_rank
318	Auston Matthews	14.96	1.0
236	David Pastrnak	13.50	2.0
304	Kirill Kaprizov	13.25	3.0
222	Leon Draisaitl	12.26	4.0
267	Connor McDavid	12.16	5.0
152	Filip Forsberg	11.44	6.0
453	Jack Hughes	11.01	7.0

245	Brayden Point	10.81	8.0
346	Tage Thompson	10.64	9.0
50	Steven Stamkos	10.52	10.0
224	William Nylander	10.08	11.0
270	Timo Meier	10.00	12.0
390	Josh Norris	10.00	13.0
229	Dylan Larkin	9.93	14.0
264	Kyle Connor	9.89	15.0
283	Roope Hintz	9.83	16.0
271	Mikko Rantanen	9.79	17.0
201	Nathan MacKinnon	9.75	18.0
221	Sam Reinhart	9.69	19.0
385	Jason Robertson	9.66	20.0

1.0.10 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

[24]:
```
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()
```



1.0.11 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?

[26]:
```
threshold_elite = merged_clutch_goals['clutch_score'].quantile(0.85)

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)
```

1.0.12 Class Imbalance

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

[28]:
```
merged_clutch_goals['clutch_label'].value_counts()
```

[28]:
```
clutch_label
0    430
1     76
Name: count, dtype: int64
```

1.0.13 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 noidealea.

1.0.14 Starting with XGBoost

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

[31]:
```
x_var = ['iSCF_per_game', 'assists_per_game', 'rebounds_created_per_game',␣
 ↪'off_zone_starts_per_game', 'SH%']
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)
```

[31]:
```
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, …)
```

1.0.15 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.

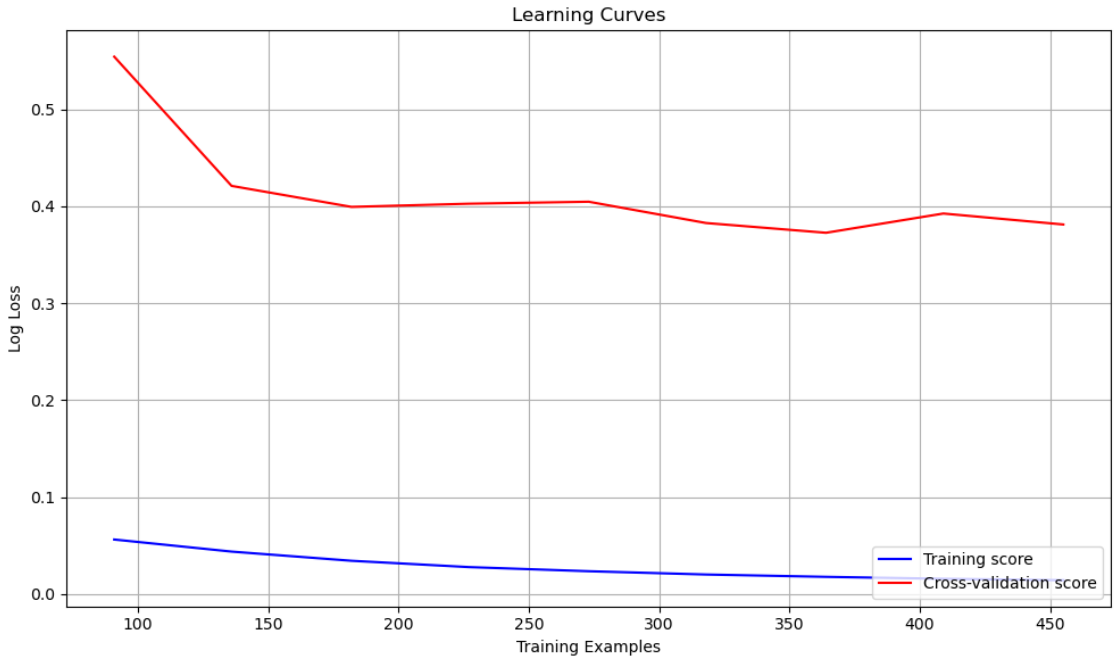
[33]:
```
skf = StratifiedKFold(n_splits=10)

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()
```

[33]:
```
fit_time          0.048868
score_time        0.010495
test_accuracy     0.887725
test_precision    0.848571
test_recall       0.651786
test_f1           0.651368
dtype: float64
```

1.0.16 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 cross-validation Note: The high imbalance in the dataset means that stratified cross-validation may not be able to create balanced splits, leading to the error message.

[35]:
```
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()
```



1.0.17 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 better generalization.

[37]:
```
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)
}
```

1.0.18 Random 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.

1.0.19 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.

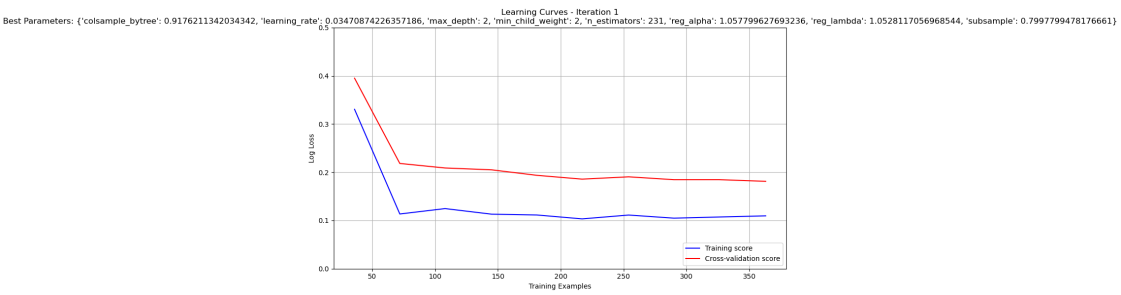
After each randomly selected train test split, I printed out the model's classification results. It appears that the model can correctly classify higher ranked players but struggles with players close to the boundary points (ranks between 45 and 74). The model also incorrectly classifies players with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

[40]:
```
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,
    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))
```

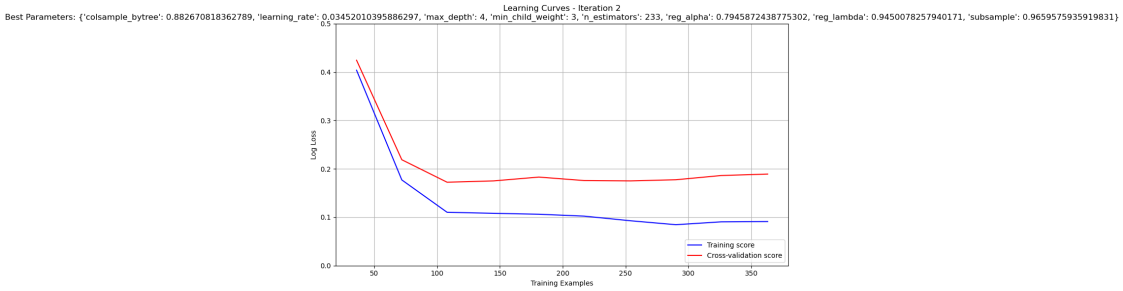



```
Precision Score:  0.6875
Recall Score:  0.7333333333333333

Correct Classfications
              Player  clutch_score_rank  Actual  Predicted
304  Kirill Kaprizov                3.0       1          1
271   Mikko Rantanen               17.0       1          1
```

290	Mitch Marner	37.0	1	1
133	J.T. Miller	53.0	1	1
385	Jason Robertson	20.0	1	1
222	Leon Draisaitl	4.0	1	1
11	Evgeni Malkin	57.0	1	1
245	Brayden Point	8.0	1	1
131	Mark Scheifele	23.0	1	1
283	Roope Hintz	16.0	1	1
152	Filip Forsberg	6.0	1	1

Missed Cltuch Players

	Player	clutch_score_rank	Actual	Predicted
381	Nick Suzuki	65.0	1	0
449	Cole Caufield	31.0	1	0
68	Evander Kane	49.0	1	0
130	Mika Zibanejad	29.0	1	0



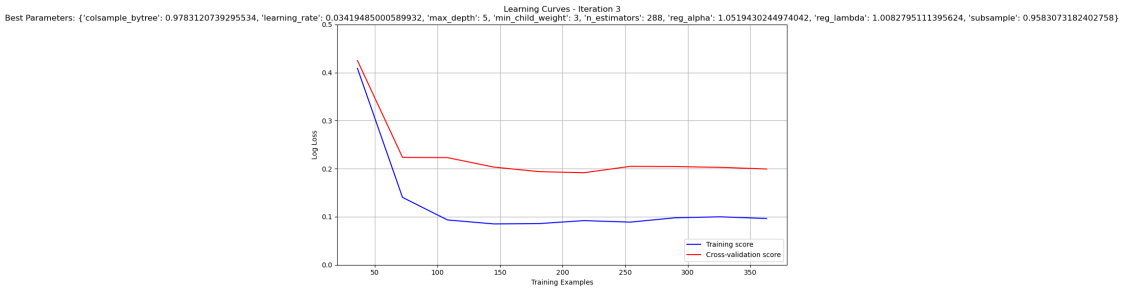
Precision Score: 0.7333333333333333
Recall Score: 0.7333333333333333

Correct Classfications

	Player	clutch_score_rank	Actual	Predicted
221	Sam Reinhart	19.0	1	1
131	Mark Scheifele	23.0	1	1
72	Chris Kreider	32.0	1	1
290	Mitch Marner	37.0	1	1
323	Alex DeBrincat	38.0	1	1
11	Evgeni Malkin	57.0	1	1
182	Jake Guentzel	50.0	1	1
67	Matt Duchene	55.0	1	1
413	Brady Tkachuk	30.0	1	1
150	Tomas Hertl	73.0	1	1
90	Brock Nelson	26.0	1	1

Missed Cltuch Players

	Player	clutch_score_rank	Actual	Predicted
227	Kevin Fiala	62.0	1	0
235	Jared McCann	60.0	1	0
474	Lucas Raymond	64.0	1	0
228	Jakub Vrana	34.0	1	0



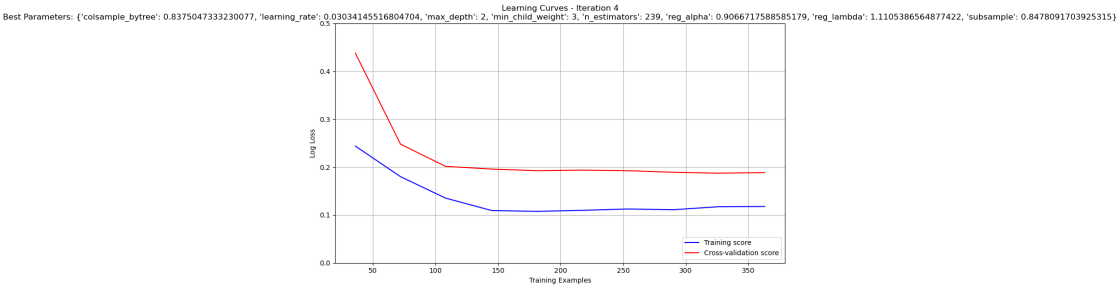
Precision Score: 0.5833333333333334
Recall Score: 0.9333333333333333

Correct Classfications

	Player	clutch_score_rank	Actual	Predicted
224	William Nylander	11.0	1	1
339	Jordan Kyrou	59.0	1	1
50	Steven Stamkos	10.0	1	1
346	Tage Thompson	9.0	1	1
221	Sam Reinhart	19.0	1	1
271	Mikko Rantanen	17.0	1	1
378	Elias Pettersson	52.0	1	1
390	Josh Norris	13.0	1	1
182	Jake Guentzel	50.0	1	1
379	Gabriel Vilardi	46.0	1	1
67	Matt Duchene	55.0	1	1
11	Evgeni Malkin	57.0	1	1
10	Alex Ovechkin	66.0	1	1
245	Brayden Point	8.0	1	1

Missed Cltuch Players

	Player	clutch_score_rank	Actual	Predicted
130	Mika Zibanejad	29.0	1	0



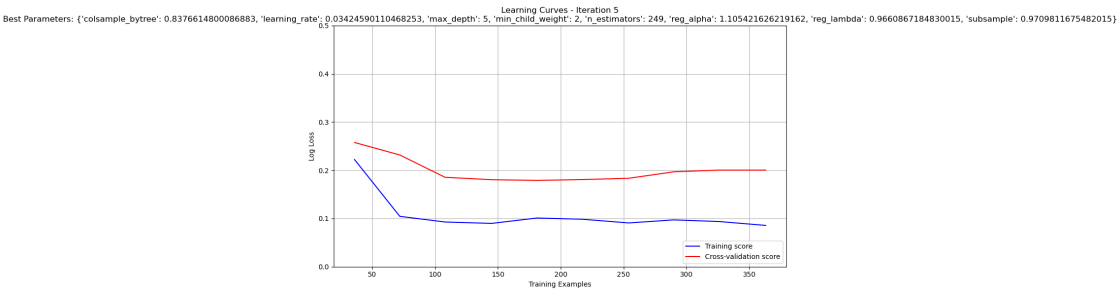

```
Precision Score:  0.8461538461538461
Recall Score:  0.7333333333333333
```

Correct Classfications

	Player	clutch_score_rank	Actual	Predicted
510	Andrei Kuzmenko	44.0	1	1
283	Roope Hintz	16.0	1	1
98	Zach Hyman	54.0	1	1
202	Aleksander Barkov	43.0	1	1
511	Connor Bedard	33.0	1	1
304	Kirill Kaprizov	3.0	1	1
72	Chris Kreider	32.0	1	1
290	Mitch Marner	37.0	1	1
109	Mark Stone	63.0	1	1
343	Jesper Bratt	74.0	1	1
264	Kyle Connor	15.0	1	1

Missed Cltuch Players

	Player	clutch_score_rank	Actual	Predicted
449	Cole Caufield	31.0	1	0
225	Nikolaj Ehlers	68.0	1	0
474	Lucas Raymond	64.0	1	0
381	Nick Suzuki	65.0	1	0



```
Precision Score:  0.6842105263157895
Recall Score:  0.8666666666666667

Correct Classfications
              Player  clutch_score_rank  Actual  Predicted
343     Jesper Bratt               74.0       1          1
346    Tage Thompson                9.0       1          1
245    Brayden Point                8.0       1          1
315  Matthew Tkachuk               61.0       1          1
90      Brock Nelson               26.0       1          1
72     Chris Kreider               32.0       1          1
304  Kirill Kaprizov                3.0       1          1
385  Jason Robertson               20.0       1          1
453      Jack Hughes                7.0       1          1
10     Alex Ovechkin               66.0       1          1
133      J.T. Miller               53.0       1          1
50    Steven Stamkos               10.0       1          1
206        Bo Horvat               21.0       1          1

Missed Cltuch Players
            Player  clutch_score_rank  Actual  Predicted
29   Claude Giroux               75.0       1          0
511  Connor Bedard               33.0       1          0

Average Precision: 0.7069062078272605
Average Recall: 0.8
Average F1 Score: 0.7422759277408233
```

1.0.20 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.

1.0.21 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

[43]:
```
x_var = ['iSCF_per_game', 'assists_per_game', 'rebounds_created_per_game',␣
 ↪'off_zone_starts_per_game', 'SH%']
X= merged_clutch_goals[x_var]
y_var = 'clutch_score'
y = merged_clutch_goals[y_var]
```

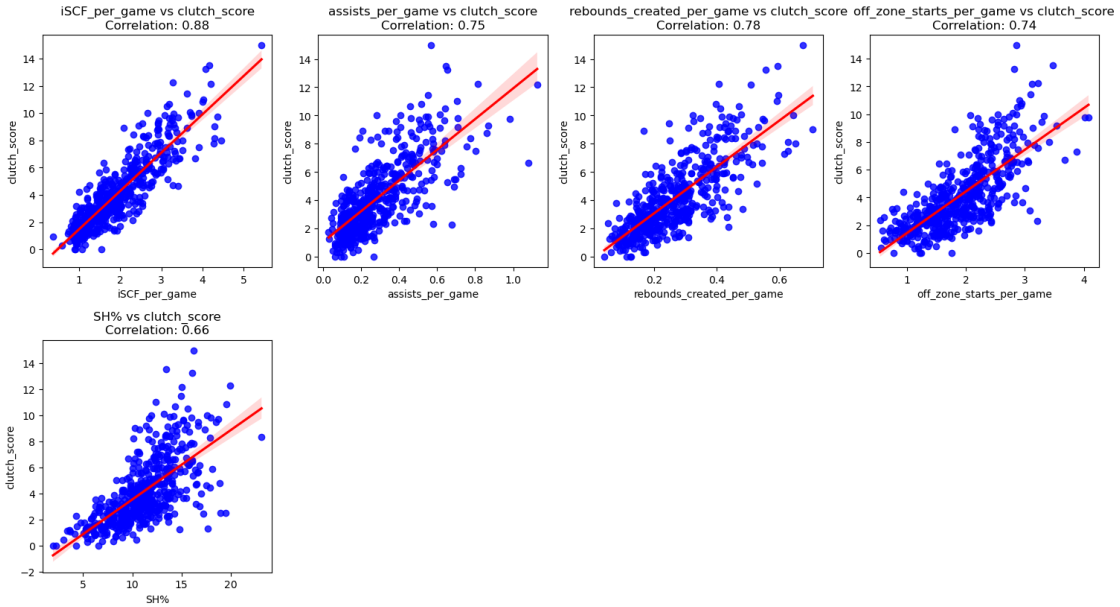
```
correlation = X.corrwith(y)
print(correlation)
```

```
iSCF_per_game                0.876447
assists_per_game             0.745530
rebounds_created_per_game    0.781373
off_zone_starts_per_game     0.744034
SH%                          0.660370
dtype: float64
```

1.0.22 Scatter Plots

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

[45]:
```
plt.figure(figsize=(15, 12))

for i, var in enumerate(x_var):
    plt.subplot(3, 4, 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()
```



1.0.23 Ridge Regression

Ridge regression helps to reduce the effect of multicollinearity on coefficients by reducing correlated coefficients towards 0. This improves their stability compared to standard OLS. Unlike lasso regression, it does not set coefficients to exactly 0. Ridge regression also ensures there is less overfitting. Time Series Cross-Validation is used to avoid leaking future information during traning due to the temporal nature of the data (2021-2024 seasons).

The model shows good performance because it has a low MSE of approximately 1 and R^2 of approximately 80%. In future sections, the outliers are evaluated to determine the model's limitations which are not obvious with the MSE and R^2.

[47]:
```
from sklearn.model_selection import TimeSeriesSplit

x_var = ['iSCF_per_game', 'assists_per_game', 'rebounds_created_per_game',␣
 ↪'off_zone_starts_per_game', 'SH%']

X_adjusted = merged_clutch_goals[x_var]
y_var = 'clutch_score'
y = merged_clutch_goals[y_var]

scaler = StandardScaler()
X_scaled = scaler.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)

tscv = TimeSeriesSplit(n_splits=5)
alphas = np.logspace(-3, 3, 20)
ridge_cv = RidgeCV(alphas=alphas, cv=tscv)
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)
median_error = median_absolute_error(test_y, y_pred)
r2 = r2_score(test_y, y_pred)

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

```
MSE:  1.4040069668995052
```

```
RMSE:  1.1849079993398244
Median Error:  0.6759729307200341
R²:  0.8318865976269685
Adjusted R²:  0.8297746202102219
```

1.0.24 Multicollinearity

The extreme VIF values indicate strong correlation between the features. The multicollinearity is expected because offensive statistics are closely correlated.

[49]:
```
vif_data = pd.DataFrame()
vif_data["feature"] = X_adjusted.columns

vif_data["VIF"] = [variance_inflation_factor(X_adjusted.values, i)
                           for i in range(len(X_adjusted.columns))]
print(vif_data)
```

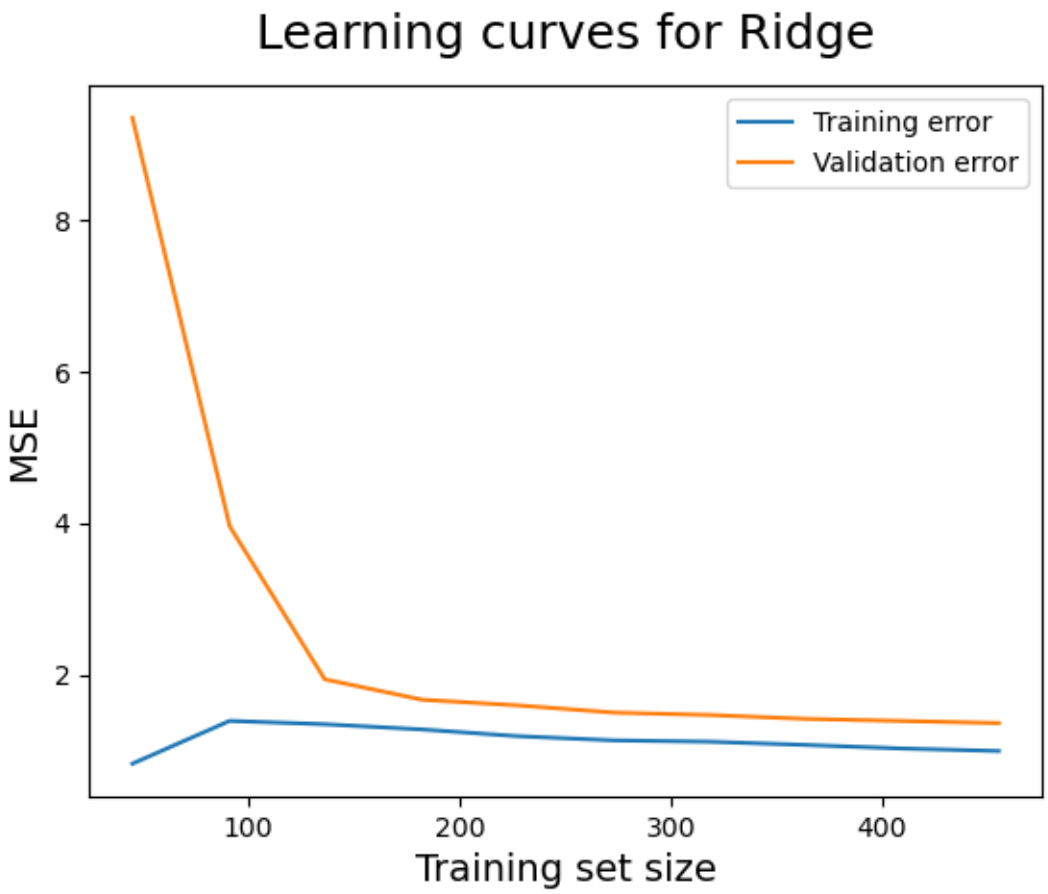
```
                     feature        VIF
0              iSCF_per_game  60.610194
1          assists_per_game   9.857434
2  rebounds_created_per_game  31.722175
3   off_zone_starts_per_game  28.652523
4                        SH%  11.765479
```

1.0.25 Learning Curves

The learning curves do not show significant overfitting. After approximately 150 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 dat.

[51]:
```
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()
```

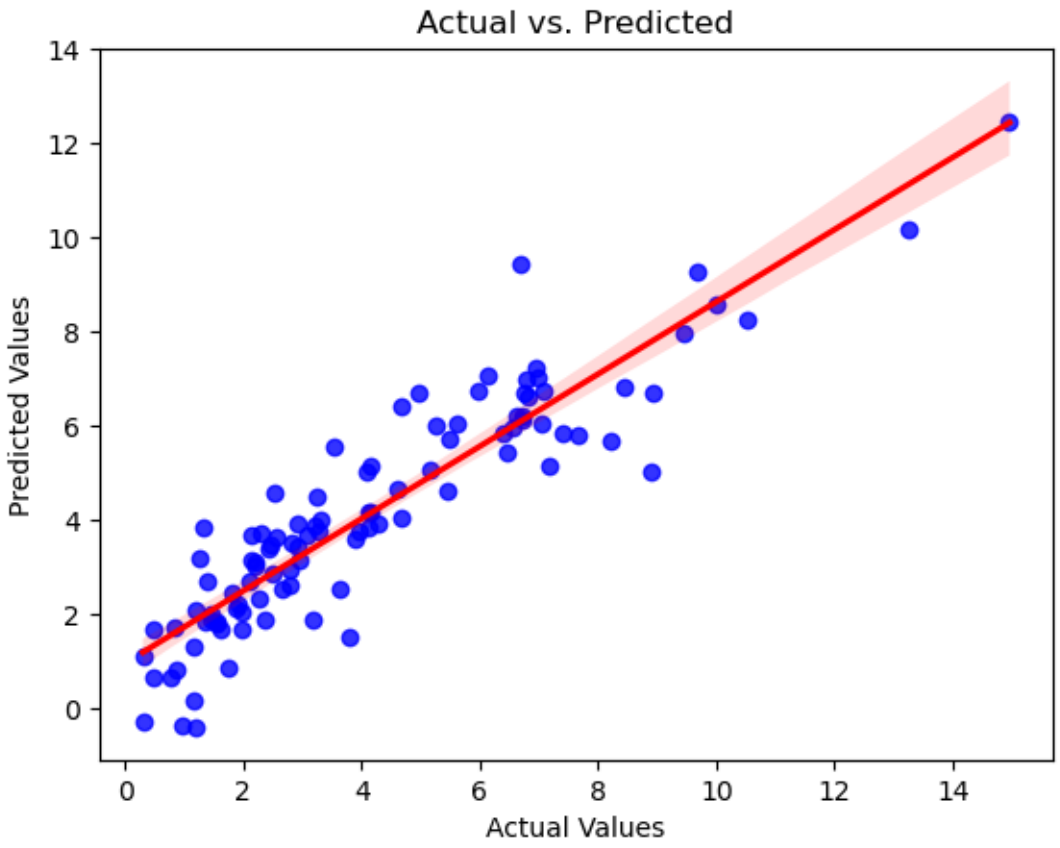
[51]:
```
<matplotlib.legend.Legend at 0x1fa0fe42270>
```



1.0.26 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.

[53]:
```
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()
```

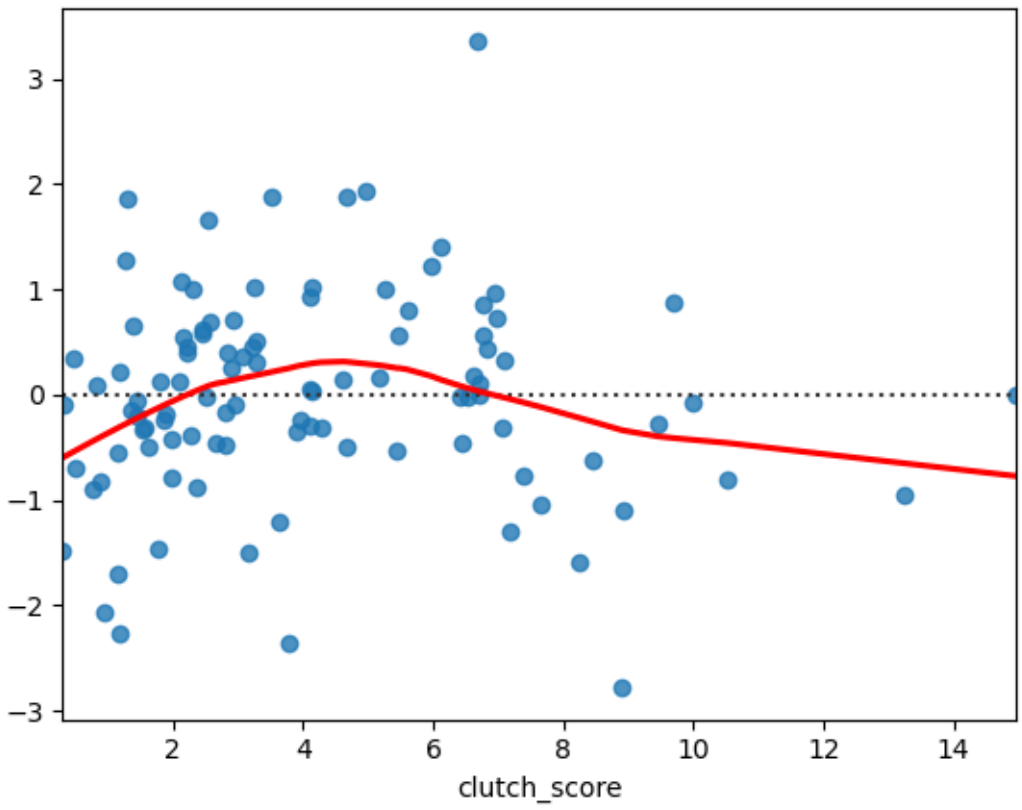


1.0.27 Residual Plot

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.

[55]:
```
sns.residplot(data=merged_clutch_goals, x=test_y, y=y_pred, lowess=True,␣
↪line_kws=dict(color="r"))
```

[55]:
```
<Axes: xlabel='clutch_score'>
```



1.0.28 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.

As shown below, the model tends to underestimate the performance of several elite players (e.g., Connor McDavid) 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. These points also have extreme feature values (e.g. iSCF, SH%, assists) which give them high leverage.

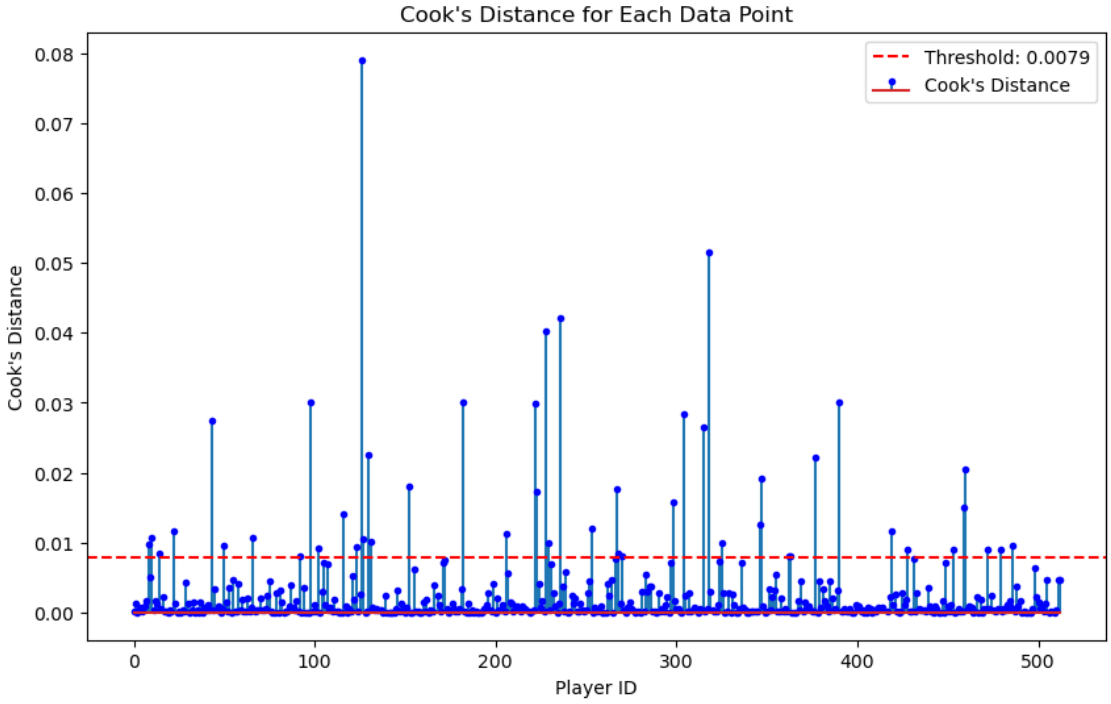
Conversely, the model overestimates the performance of other elite players (e.g., Matthew Tkachuk), who do not perform as well in clutch scoring situations as their general statistics suggest.

[57]:
```
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.loc[results["Cook's Distance"] > threshold]

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(results.index, cooks_d, markerfmt='b.', label="Cook's Distance")
plt.axhline(y=threshold, color='r', linestyle='--', label=f"Threshold:␣
 ↪{threshold:.4f}")
plt.xlabel("Player ID")
plt.ylabel("Cook's Distance")
plt.title("Cook's Distance for Each Data Point")
plt.legend()
plt.show()
```

```
There are 47 influential points.
Outliers based on Cook's Distance:
                  Player  Actual  Predicted  Cook's Distance
318      Auston Matthews   14.96  13.024524         0.051457
236       David Pastrnak   13.50   9.896027         0.042172
304      Kirill Kaprizov   13.25  10.347138         0.028432
222       Leon Draisaitl   12.26   9.813629         0.029952
267       Connor McDavid   12.16  10.980364         0.017686
152       Filip Forsberg   11.44   9.084847         0.017971
453          Jack Hughes   11.01   9.465530         0.008931
346        Tage Thompson   10.64   7.824191         0.012615
50        Steven Stamkos   10.52   8.233797         0.009576
270           Timo Meier   10.00   8.765977         0.007965
390          Josh Norris   10.00   7.108220         0.029991
229         Dylan Larkin    9.93   8.104445         0.009968
206            Bo Horvat    9.61   7.722145         0.011296
131       Mark Scheifele    9.46   8.117292         0.010170
298       Artemi Panarin    9.27   7.953454         0.015854
325       Clayton Keller    9.23   6.910853         0.009983
268          Jack Eichel    9.18   6.598628         0.008489
130       Mika Zibanejad    9.10   6.250837         0.022575
228          Jakub Vrana    8.89   5.187661         0.040210
460      Pavel Dorofeyev    8.43   5.699281         0.020465
```

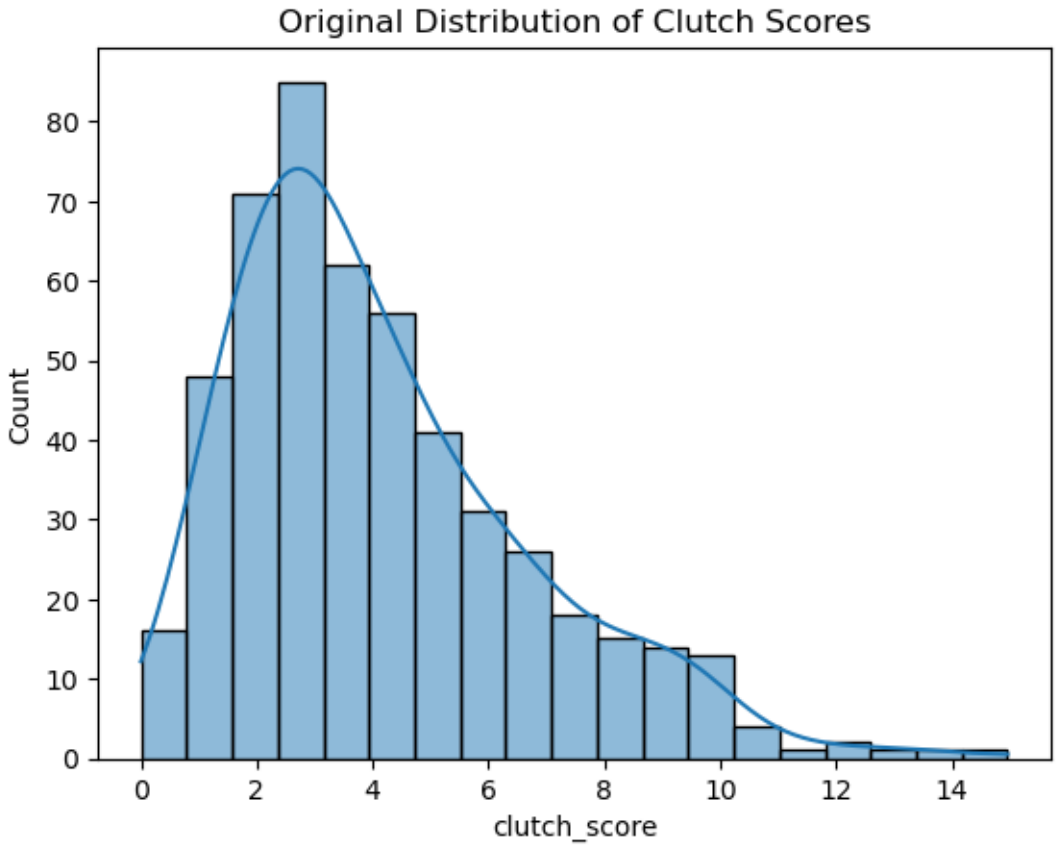
43	Patrick Kane	8.23	5.689504	0.027489
66	John Tavares	8.14	9.584227	0.010611
182	Jake Guentzel	8.01	10.616683	0.030008
98	Zach Hyman	7.79	10.083423	0.030058
428	Kirill Marchenko	7.66	6.033027	0.008919
315	Matthew Tkachuk	7.47	9.499702	0.026559
10	Alex Ovechkin	7.27	8.427472	0.010623
8	Patrice Bergeron	6.69	7.808629	0.009802
126	Nikita Kucherov	6.67	9.127695	0.079088
472	Connor Zary	6.35	4.508752	0.009059
419	Andrei Svechnikov	5.15	7.357494	0.011617
92	Kevin Hayes	5.02	3.289811	0.008069
127	Ryan Nugent-Hopkins	4.96	6.685779	0.010411
116	Vincent Trocheck	4.73	7.199042	0.014009
486	Alexander Holtz	4.68	2.828540	0.009522
223	Sam Bennett	4.66	7.104920	0.017361
362	Vinni Lettieri	4.23	1.772061	0.008056
123	Brett Ritchie	3.79	1.589283	0.009336
14	David Krejci	3.57	5.089770	0.008451
479	Jack Quinn	2.84	5.456560	0.009058
363	Mason Shaw	2.56	0.762972	0.008116
347	Rem Pitlick	2.52	4.462657	0.019128
459	Simon Holmstrom	2.48	4.184196	0.014991
253	Dakota Joshua	2.47	4.326488	0.012050
102	Mikael Granlund	2.30	3.927473	0.009119
22	Patric Hornqvist	2.13	3.677950	0.011581
377	Klim Kostin	1.31	3.760123	0.022213

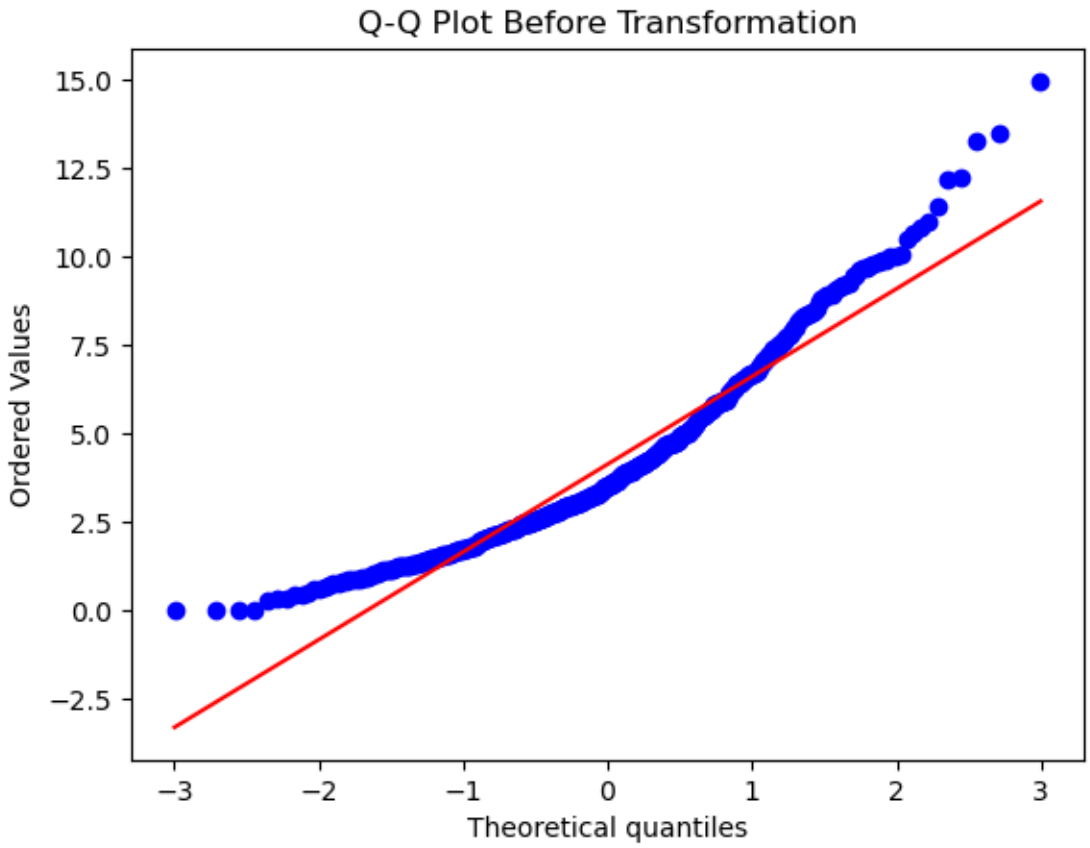


1.0.29 Evaluating the Distribution of the Data

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.

[59]:
```
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()
```

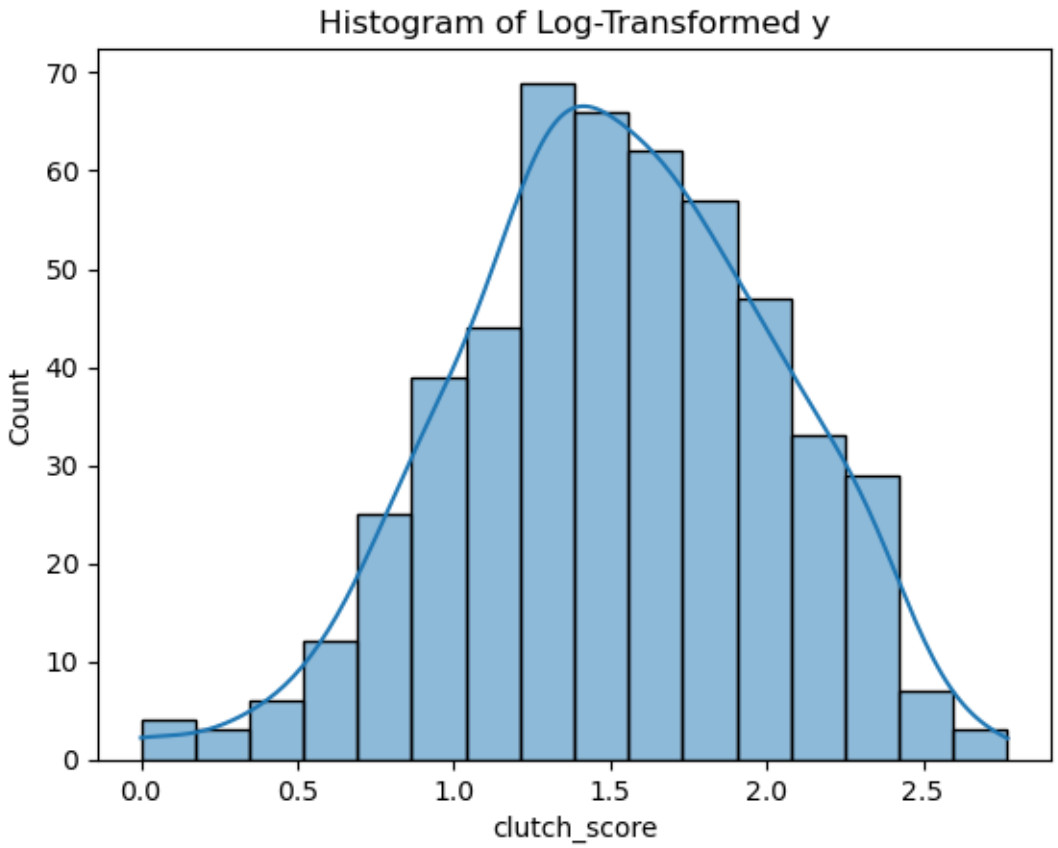


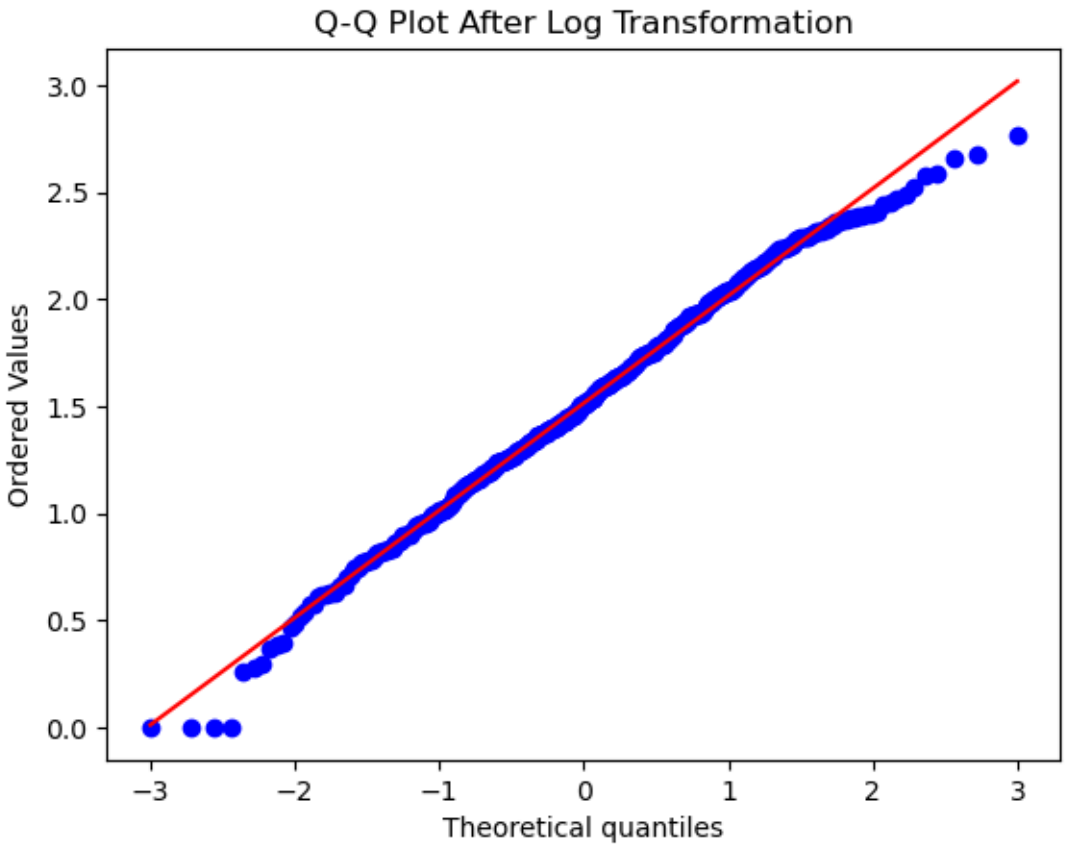


1.0.30 Transforming the Data to a Normal Distribution with Log

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.

[61]:
```
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



1.0.31 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. Jakub Vrana) 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. Matthew Tkachuk, Nikita Kucherov). 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.

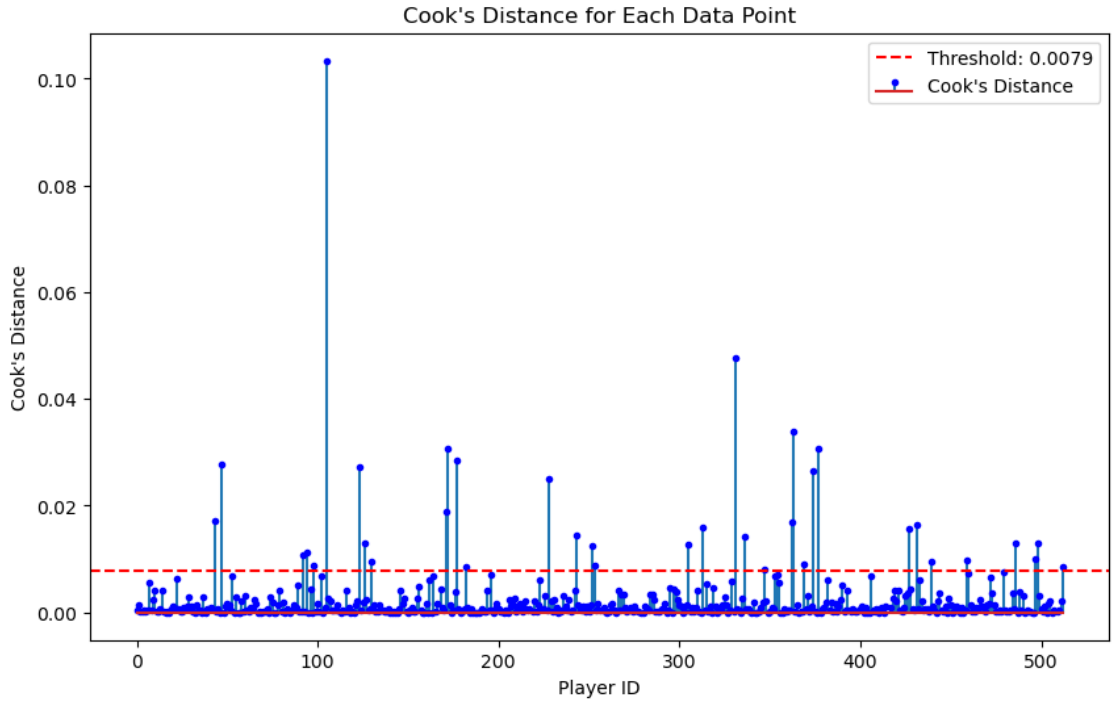
[63]:
```
epsilon = np.abs(X_scaled.min()) + 1
X_shifted = X_scaled + epsilon
y_log = np.log(y + 1)
X_log = np.log(X_shifted)

train_x, test_x, train_y, test_y = train_test_split(
    X_log,
```

```
    y_log,
    test_size=0.2,
    random_state=200
)

alphas = np.logspace(-3, 3, 20)
ridge_cv_log = RidgeCV(alphas=alphas, cv=5)
ridge_cv_log.fit(train_x, train_y)
y_pred = ridge_cv_log.predict(test_x)
```

[64]:
```
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_with_intercept)

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.loc[results["Cook's Distance"] > threshold]

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(results.index, cooks_d, markerfmt='b.', label="Cook's Distance")
plt.axhline(y=threshold, color='r', linestyle='--', label=f"Threshold:␣
 ↪{threshold:.4f}")
plt.xlabel("Player ID")
plt.ylabel("Cook's Distance")
plt.title("Cook's Distance for Each Data Point")
plt.legend()
plt.show()
```

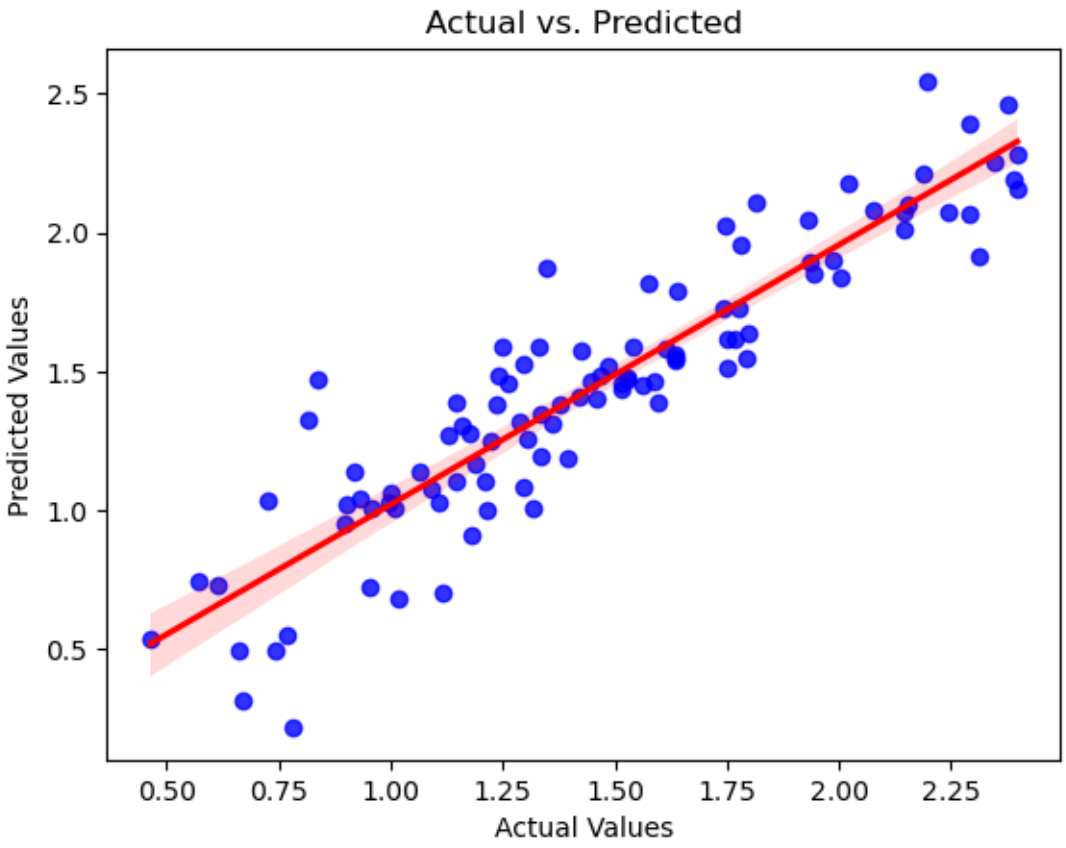
```
There are 35 influential points.
Outliers based on Cook's Distance:
                   Player    Actual  Predicted  Cook's Distance
130        Mika Zibanejad  2.312535   1.921011         0.009599
228           Jakub Vrana  2.291524   1.752050         0.025135
43          Patrick Kane  2.222459   1.785499         0.017112
```

182	Jake Guentzel	2.198335	2.540125	0.008432
98	Zach Hyman	2.173615	2.485331	0.008883
126	Nikita Kucherov	2.037317	2.312351	0.012923
92	Kevin Hayes	1.795087	1.408628	0.010649
486	Alexander Holtz	1.736951	1.362788	0.012986
498	Walker Duehr	1.688249	1.241293	0.012898
362	Vinni Lettieri	1.654411	1.074635	0.016830
123	Brett Ritchie	1.566530	1.003427	0.027178
94	Austin Watson	1.427916	1.046980	0.011184
369	Jaret Anderson-Dolan	1.319086	0.985356	0.009075
252	Max Willman	1.313724	0.840344	0.012393
363	Mason Shaw	1.269761	0.728668	0.033929
347	Rem Pitlick	1.258461	1.538930	0.007967
459	Simon Holmstrom	1.247032	1.536749	0.009698
253	Dakota Joshua	1.244155	1.598076	0.008911
47	Jakub Voracek	1.187843	0.913119	0.027658
336	Jonathan Dahlen	1.000632	1.585076	0.014229
512	Zach Benson	0.963174	1.487000	0.008494
439	Reese Johnson	0.887891	0.548466	0.009598
377	Klim Kostin	0.837248	1.435943	0.030602
431	Pontus Holmberg	0.815365	1.313703	0.016438
172	Jayson Megna	0.779325	0.274330	0.030775
305	Dominik Simon	0.746688	0.462873	0.012750
171	Kurtis MacDermid	0.667829	0.340067	0.018917
427	Jakub Lauko	0.609766	0.971738	0.015796
497	Nils Aman	0.488580	0.925799	0.010146
243	Juho Lammikko	0.385262	1.014998	0.014337
331	Beck Malenstyn	0.292670	0.868257	0.047649
313	Kevin Rooney	0.277632	0.877689	0.015835
105	Joonas Donskoi	0.000000	0.439734	0.103384
374	Jonas Rondbjerg	0.000000	0.564423	0.026513
177	Saku Maenalanen	0.000000	0.697184	0.028458



1.0.32 Final Scatter Plot from Training

[66]:
```
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()
```



1.0.33 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 2024-2025 season to the current 2025-2026 season).

[68]:
```
joblib.dump(ridge_cv_log, 'ridge_cv_model.pkl')
ridge_cv_log_loaded = joblib.load('ridge_cv_model.pkl')

joblib.dump(scaler, 'scaler.pkl')
joblib.dump(epsilon, 'epsilon.pkl')
```

[68]:
```
['epsilon.pkl']
```

[69]:
```
all_seasons = []

for season in range(2024, 2026):
    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',
            'goals': 'sum',
            'assists': 'sum',
            'otGoals': 'sum',
            'timeOnIcePerGame': 'mean',
            'teamAbbrevs': 'last'
        }).reset_index(drop = True)

print(nhl_api_df)
```

```
Successfully fetched data for season 2024-2025
Successfully fetched data for season 2025-2026
      playerId  skaterFullName positionCode  gamesPlayed  goals  assists  \
0      8470600      Ryan Suter            D           82      2       13
1      8470613     Brent Burns            D          119     11       37
2      8470621     Corey Perry            R          112     26       20
3      8471214   Alex Ovechkin            L          104     59       47
4      8471215   Evgeni Malkin            C           94     24       55
…        …              …          …          …    …       …
1005   8485483  Karsen Dorwart            L            5      0        0
1006   8485493   David Tomasek            R           22      3        2
1007   8485511    Quinn Hutson            R            5      1        0
1008   8485512       Tim Washe            C            2      0        0
1009   8485702    Max Shabanov            R           26      4        7

      otGoals  timeOnIcePerGame teamAbbrevs
0           0        1168.28040         STL
```

```
1            0        1213.52205         COL
2            0         764.64335         LAK
3            1        1066.70510         WSH
4            1        1058.75845         PIT
…          …                …          …
1005         0         658.80000         PHI
1006         0         645.50000         EDM
1007         0         629.75000         EDM
1008         0         464.00000         ANA
1009         0         840.23070         NYI

[1010 rows x 9 columns]
```

[70]:
```
nhl_api_df = nhl_api_df.loc[(nhl_api_df['positionCode'] != 'D') &␣
 ↪(nhl_api_df['gamesPlayed'] >= 40)]
nhl_api_df = nhl_api_df.reset_index(drop = True)

rename_columns = {
    'otGoals': 'ot_goals',
    'skaterFullName': 'Player',
    'timeOnIcePerGame': 'time_on_ice_per_game'
}

nhl_api_df.rename(columns = rename_columns,  inplace = True)
```

[71]:
```
start_season = "20242025"
end_season = "20252026"
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=
on_ice_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={start_season}&thruseason={end_season}&stype=2&sit=5v5&score=all&stdoi=oi&rate=n
```

[72]:
```
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'),
    "on_ice": (on_ice_url, '')
}

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"]
on_ice_df = dataframes["on_ice"]
on_ice_df.columns = on_ice_df.columns.str.replace('\xa0', ' ')
```

[73]:
```
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', 'SH%']]
on_ice_df = on_ice_df[['Player', 'Off. Zone Starts', 'On The Fly Starts']]

dfs_natural_stat = [goals_up_one_df, goals_down_one_df, goals_tied_df,␣
 ↪total_df, on_ice_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'] >= 40]

rename_columns = {
    'Shots': 'shots',
    'Rebounds Created': 'rebounds_created',
    'Off. Zone Starts': 'off_zone_starts',
    'On The Fly Starts': 'on_the_fly_starts'
}
merged_natural_stat.rename(columns = rename_columns, inplace=True)
```

[74]:
```
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", "Zack Bolduc", "Frederic Gaudreau"]
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", "Zachary Bolduc", "Freddy Gaudreau" ]
merged_natural_stat = merged_natural_stat.replace(natural_stat_names, nhl_names)
```

[75]:
```
merged_clutch_goals_prediction = nhl_api_df.merge(merged_natural_stat, on =␣
 ↪'Player', how = 'left')
merged_clutch_goals_prediction.drop(columns = 'GP', axis = 1, inplace = True)
merged_clutch_goals_prediction = merged_clutch_goals_prediction.dropna()
```

[76]:
```
columns = ['ot_goals', 'assists', 'goals_up_by_one', 'goals_down_by_one',␣
 ↪'goals_when_tied', 'shots', 'ixG', 'iFF', 'iSCF', 'iHDCF', 'iCF',␣
 ↪'rebounds_created', 'off_zone_starts', 'on_the_fly_starts']
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']
```

[77]:
```
merged_clutch_goals_prediction['clutch_score'] = (
    0.45 * merged_clutch_goals_prediction['goals_down_by_one_per_game'] +
    0.35 * merged_clutch_goals_prediction['goals_when_tied_per_game'] +
    0.2 * merged_clutch_goals_prediction['ot_goals_per_game']
)
```

[78]:
```
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)
```

[78]:

	Player	clutch_score	clutch_score_rank
149	Leon Draisaitl	15.05	1.0
212	Kirill Kaprizov	11.81	2.0
391	Dylan Guenther	11.70	3.0
226	Alex DeBrincat	11.64	4.0
253	Morgan Geekie	11.34	5.0
324	Cole Caufield	11.08	6.0
136	Bo Horvat	11.00	7.0
94	Tom Wilson	10.92	8.0
240	Tage Thompson	10.79	9.0
27	John Tavares	10.71	10.0
289	Brady Tkachuk	10.44	11.0
148	Sam Reinhart	10.43	12.0
3	Sidney Crosby	10.30	13.0
268	Josh Norris	10.29	14.0
78	Mark Scheifele	10.08	15.0
151	William Nylander	9.96	16.0

```
73    Nikita Kucherov          9.96              17.0
265   Jason Robertson          9.88              18.0
161      Adrian Kempe          9.87              19.0
224   Auston Matthews          9.65              20.0
```

[79]:
```
x_var = ['iSCF_per_game', 'assists_per_game', 'rebounds_created_per_game',␣
 ↪'off_zone_starts_per_game', 'SH%']
X_adjusted = merged_clutch_goals_prediction[x_var]
y_var = 'clutch_score'
y = merged_clutch_goals_prediction[y_var]

scaler = joblib.load('scaler.pkl')
epsilon = joblib.load('epsilon.pkl')

X_scaled = scaler.transform(X_adjusted)
X_scaled = np.nan_to_num(X_scaled, nan=0)

X_shifted = X_scaled + epsilon
X_log = np.log(X_shifted)

y_log = np.log(y + 1)
y_pred = ridge_cv_log_loaded.predict(X_log)
```

1.0.34 Evaluating the Model after Testing

The R^2 indicates the model explains approximately 77% of variance in clutch performance, which is strong given the inherent randomness in clutch situations.

[81]:
```
r2 = r2_score(y_log, y_pred)
rmse = np.sqrt(mean_squared_error(y_log, y_pred))
mae = mean_absolute_error(y_log, y_pred)

print(f"Test Set Performance:")
print(f"R²: {r2:.4f}")
print(f"RMSE: {rmse:.4f}")
print(f"MAE: {mae:.4f}")
```

```
Test Set Performance:
R²: 0.7746
RMSE: 0.2624
MAE: 0.1861
```

[82]:
```
y_pred = ridge_cv_log_loaded.predict(X_log)
merged_clutch_goals_prediction['predicted_clutch_score'] = y_pred

merged_clutch_goals_prediction['log'] = np.
 ↪log(merged_clutch_goals_prediction['clutch_score'] + 1)
```

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

1.0.35 Prediction Intervals

95% bootstrapping prediction intervals were generated for each player. If actual clutch scores fall outside the intervals, this indicates that clutch performance is significantly different from expectations.

[84]:
```
n_boot = 1000
alpha = ridge_cv_log_loaded.alpha_

boot_preds = np.zeros((n_boot, len(X_log)))

for i in range(n_boot):
    idx = np.random.choice(len(X_log), size=len(X_log), replace=True)

    X_res = X_log[idx]
    y_res = y_log.iloc[idx]

    ridge = Ridge(alpha=alpha)
    ridge.fit(X_res, y_res)

    preds = ridge.predict(X_log)

    residuals = y_log - ridge_cv_log_loaded.predict(X_log)
    noise = np.random.choice(residuals, size=len(X_log), replace=True)

    boot_preds[i] = preds + noise

lower_log = np.percentile(boot_preds, 2.5, axis=0)
upper_log = np.percentile(boot_preds, 97.5, axis=0)

merged_clutch_goals_prediction['lower_bound_log'] = (lower_log * 10).round(2)
merged_clutch_goals_prediction['upper_bound_log'] = (upper_log * 10).round(2)

merged_clutch_goals_prediction['Significantly_Clutch'] = np.where(
    (merged_clutch_goals_prediction['log_adjusted'] >=␣
 ↪merged_clutch_goals_prediction['lower_bound_log']) &
```

```
    (merged_clutch_goals_prediction['log_adjusted'] <=␣
 ↪merged_clutch_goals_prediction['upper_bound_log']),
    'Inside Range',
    'Outside Range'
)
```

1.0.36 Shap Values

SHAP values were calculated to explain which features most influenced each player's prediction. This is useful for the dashboard since users can understand how clutch scores are predicted.

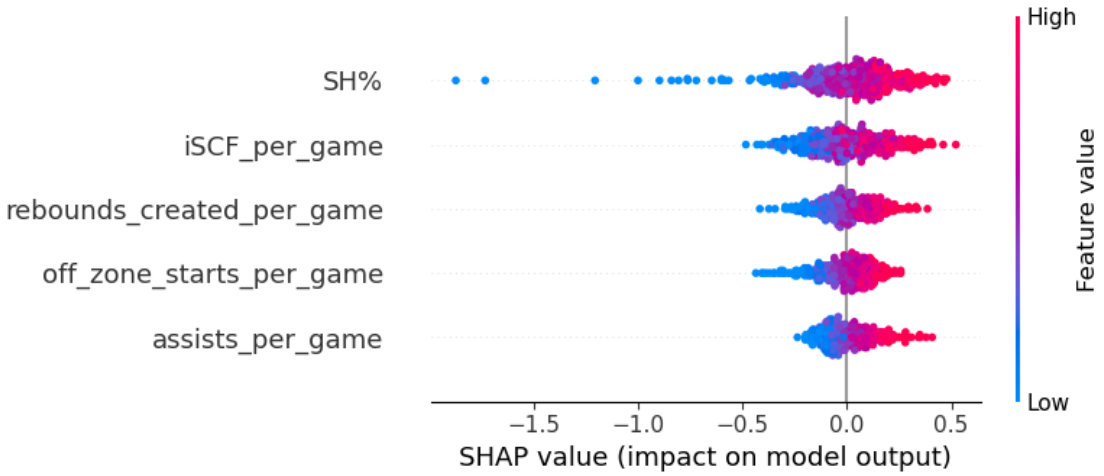
Due to the extremely high VIF values, multicollinearity may still be present even when using ridge regression. Therefore, SHAP is used with **feature_perturbation = "correlation_dependent"**. This accounts for correlations between the features when determining their contributions. Therefore, SHAP values will better reflect the true conditional contribution of each feature, rather than being distorted by multicollinearity.

The SHAP plot indicates that SH% is the dominant feature since a higher shooting percentage naturally leads to increased clutch goalscoring. The remaining features show similar SHAP magnitudes which suggests that the features are stable, improving the reliability of the interpretation.

[86]:
```
explainer = shap.LinearExplainer(
    ridge_cv_log_loaded,
    X_log,
    feature_perturbation="correlation_dependent"
)
shap_values = explainer(X_log)

shap_df = pd.DataFrame(
    shap_values.values,
    columns=X_adjusted.columns,
    index=X_adjusted.index
)

for col in shap_df.columns:
    merged_clutch_goals_prediction[f'shap_{col}'] = shap_df[col]

shap.initjs()

X_log_df = pd.DataFrame(X_log, columns=X_adjusted.columns)

shap.summary_plot(shap_values.values, X_log_df, show=True)
```

```
Estimating transforms:   0%|          | 0/1000 [00:00<?, ?it/s]
```

```
<IPython.core.display.HTML object>
```



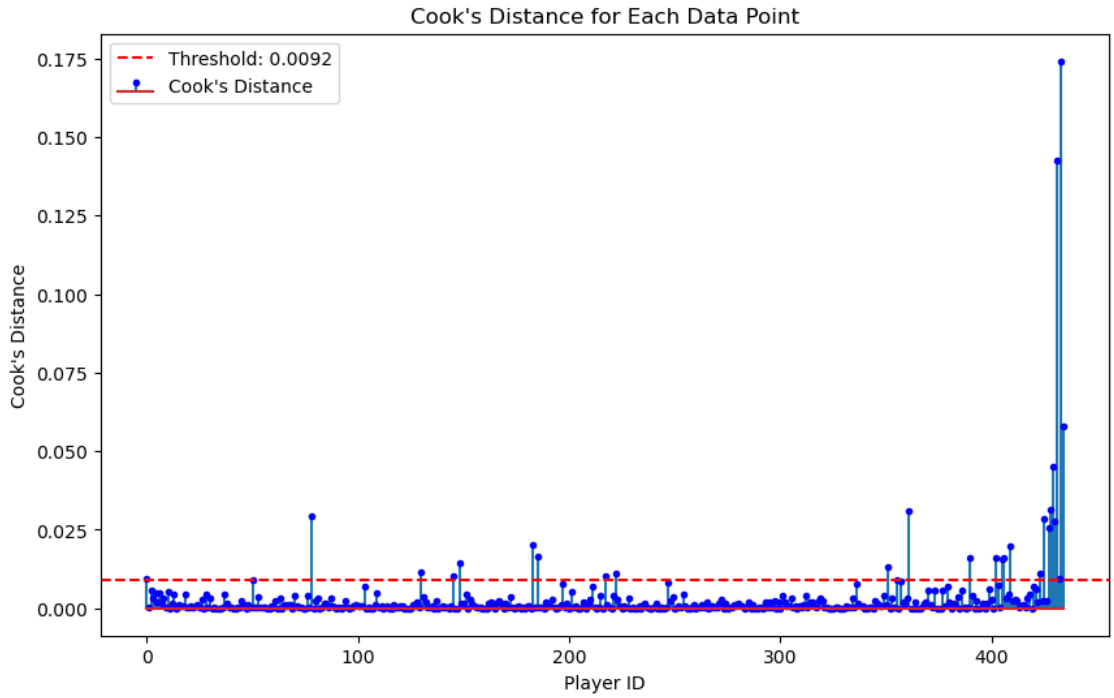
1.0.37 Cook's Distance Observations

The model shows the same patterns as before - it undervalues and overvalues some players. Clutch scores of low performing players are also amplified by the log transformation. These players are excluded in the final dashboard by only including players with 20+ goals.

[88]:
```
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)

merged_clutch_goals_prediction = merged_clutch_goals_prediction.
 ↪reset_index(drop=True)

results = pd.DataFrame({
    'Player': merged_clutch_goals_prediction['Player'].values,
    'Actual': merged_clutch_goals_prediction['log'].values,
    'Predicted': merged_clutch_goals_prediction['predicted_clutch_score'].
 ↪values,
    "Cook's Distance": cooks_d
})

outliers_df = results.loc[results["Cook's Distance"] > threshold]

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(results.index, cooks_d, markerfmt='b.', label="Cook's Distance")
plt.axhline(y=threshold, color='r', linestyle='--', label=f"Threshold:␣
 ↪{threshold:.4f}")
plt.xlabel("Player ID")
plt.ylabel("Cook's Distance")
plt.title("Cook's Distance for Each Data Point")
plt.legend()
plt.show()
```

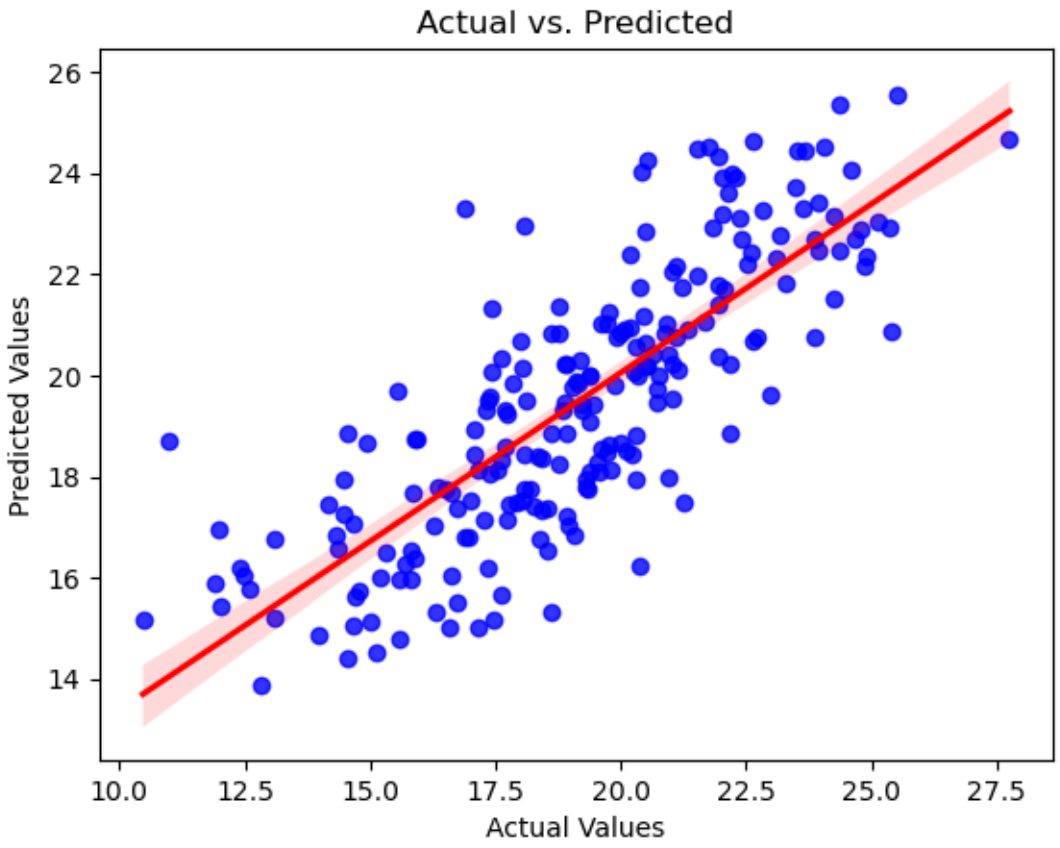
```
There are 26 influential points.
Outliers based on Cook's Distance:
                Player    Actual  Predicted  Cook's Distance
0      Kirill Kaprizov  2.550226   2.553580         0.009431
78     Aliaksei Protas  2.063058   2.041781         0.029213
130    Michael Bunting  1.492904   1.865944         0.011396
145        Corey Perry  1.877937   1.825481         0.010132
148       Shane Wright  1.717395   1.811643         0.014568
183      Emmitt Finnie  1.609438   1.724491         0.020376
185      Eeli Tolvanen  1.726332   1.715744         0.016665
217      Frank Vatrano  1.519513   1.598769         0.010185
222    Mathieu Olivier  1.190888   1.590095         0.010886
351          Sam Steel  1.150572   1.142069         0.013056
361    Brandon Duhaime  1.134623   1.083805         0.031126
390     Patrick Maroon  0.989541   0.912195         0.016062
402      Ross Johnston  0.693147   0.818748         0.015873
405     Beck Malenstyn  0.746688   0.766595         0.015626
406        Radek Faksa  0.722706   0.766121         0.016201
409        Noah Gregor  0.732368   0.760442         0.019880
423       Conor Sheary  0.741937   0.541493         0.011020
425    Mattias Janmark  0.357674   0.499921         0.028517
427      Ty Dellandrea  0.506818   0.442737         0.025453
428     Ryan Winterton  1.007958   0.419777         0.031256
429        Tomas Nosek  0.000000   0.303699         0.045285
430  Christian Fischer  0.683097   0.205636         0.027661
431        Devin Shore  0.000000   0.029362         0.142739
432     Zack Ostapchuk  0.398776   0.011061         0.009246
433   Hendrix Lapierre  0.000000  -0.501359         0.174204
434          Ben Jones  0.000000  -0.755099         0.058094
```



1.0.38 Final Scatter Plot after Testing

The Actual vs. Predicted shows a well-fitted model for clutch performance. There is a strong linear releationship and homoscedasticity. Some points may deviate from the line of best fit, but this is to be expected due to players naturally overperforming/underpeforming their clutch scores.

[90]:
```
merged_clutch_goals_prediction = merged_clutch_goals_prediction.
 ↪loc[merged_clutch_goals_prediction['total_goals'] >= 20]
sns.regplot(data=merged_clutch_goals_prediction,␣
 ↪x=merged_clutch_goals_prediction['log_adjusted'],␣
 ↪y=merged_clutch_goals_prediction['predicted_clutch_score_adjusted'],␣
 ↪scatter_kws={'color': 'blue'}, line_kws={'color': 'red'})
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted')
plt.show()
```



1.0.39 Temporal Stability

It is important to verify if clutch scoring truly exists. The year-over-year correlations (r = 0.57 for 2021-2022 vs 2022-2023, r = 0.54 for 2022-2023 vs 2023-2024, r = 0.52 for 2023-2024 vs 2024-2026) are all greater than 0.5, which shows clutch scoring is a stable, repeatable skill rather than random variance.

[92]:
```
all_seasons = []

for season in range(2021, 2024):
    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', 'season'], as_index = False).
 ↪agg({
            'playerId': 'first',
            'skaterFullName': 'first',
            'positionCode': 'first',
            'gamesPlayed': 'sum',
            'otGoals': 'sum',

        }).reset_index(drop = True)

nhl_api_df = nhl_api_df.loc[(nhl_api_df['positionCode'] != 'D')]
nhl_api_df = nhl_api_df.reset_index(drop = True)

rename_columns = {
    'otGoals': 'ot_goals',
    'skaterFullName': 'Player',
    'timeOnIcePerGame': 'time_on_ice_per_game'
}

nhl_api_df.rename(columns = rename_columns,  inplace = True)
```

```
Successfully fetched data for season 2021-2022
Successfully fetched data for season 2022-2023
Successfully fetched data for season 2023-2024
```

[93]:
```
seasons = ['20212022', '20222023', '20232024']

for item in seasons:

    goals_down_one_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={item}&thruseason={item}&stype=2&sit=all&score=d1&stdoi=std&rate=n&team=ALL&pos=
    tied_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={item}&thruseason={item}&stype=2&sit=all&score=tied&stdoi=std&rate=n&team=ALL&po
    total_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={item}&thruseason={item}&stype=2&sit=all&score=all&stdoi=std&rate=n&team=ALL&pos
```

```
    on_ice_url = f"https://www.naturalstattrick.com/playerteams.php?
 ↪fromseason={item}&thruseason={item}&stype=2&sit=5v5&score=all&stdoi=oi&rate=n&team=ALL&pos=

    urls = {
        "goals_down_one": (goals_down_one_url, 'goals_down_by_one'),
        "tied": (tied_url, 'goals_when_tied')
    }

    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)
        df['season'] = item
        dataframes[name] = df
        time.sleep(2)

    if item == '20212022':
        goals_down_one_df_21_22 = dataframes["goals_down_one"]
        goals_tied_df_21_22 = dataframes["tied"]

    elif item == '20222023':
        goals_down_one_df_22_23 = dataframes["goals_down_one"]
        goals_tied_df_22_23 = dataframes["tied"]

    elif item == '20232024':
        goals_down_one_df_23_24 = dataframes["goals_down_one"]
        goals_tied_df_23_24 = dataframes["tied"]

    time.sleep(2)

dfs_natural_stat = [goals_down_one_df_21_22, goals_tied_df_21_22,␣
 ↪goals_down_one_df_22_23, goals_tied_df_22_23, goals_down_one_df_23_24,␣
 ↪goals_tied_df_23_24]

goals_down_one = pd.concat([goals_down_one_df_21_22, goals_down_one_df_22_23,␣
 ↪goals_down_one_df_23_24])
goals_when_tied = pd.concat([goals_tied_df_21_22, goals_tied_df_22_23,␣
 ↪goals_tied_df_23_24])

goals_down_one = goals_down_one[['Player', 'goals_down_by_one', 'season']]
goals_when_tied = goals_when_tied[['Player', 'goals_when_tied', 'season']]

merged_natural_stat = goals_down_one.merge(goals_when_tied, on = ['Player',␣
 ↪'season'], how = 'left')
merged_natural_stat['season'] = merged_natural_stat['season'].astype(str).
 ↪apply(lambda x: x[:4] + '-' + x[4:])
```

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

merged_clutch_goals_21_24 = nhl_api_df.merge(merged_natural_stat, on =␣
 ↪['Player', 'season'], how = 'left')
merged_clutch_goals_21_24 = merged_clutch_goals_21_24.dropna()

columns = ['ot_goals', 'goals_down_by_one', 'goals_when_tied']
for column in columns:
    per_game_string = f"{column}_per_game"
    merged_clutch_goals_21_24[per_game_string] =␣
 ↪merged_clutch_goals_21_24[column] / merged_clutch_goals_21_24['gamesPlayed']

merged_clutch_goals_21_24['clutch_score'] = (
    0.45 * merged_clutch_goals_21_24['goals_down_by_one_per_game'] +
    0.35 * merged_clutch_goals_21_24['goals_when_tied_per_game'] +
    0.2 * merged_clutch_goals_21_24['ot_goals_per_game']
)

merged_clutch_goals_21_24['clutch_score'] *= 100

merged_clutch_goals_21_24['log'] = np.
 ↪log(merged_clutch_goals_21_24['clutch_score'] + 1)
merged_clutch_goals_21_24['log_adjusted'] = np.
 ↪log(merged_clutch_goals_21_24['clutch_score'] + 1) * 10
merged_clutch_goals_21_24['log_adjusted'] =␣
 ↪merged_clutch_goals_21_24['log_adjusted'].apply(lambda x: round(x, 2))

merged_clutch_goals_21_24 = merged_clutch_goals_21_24.
 ↪loc[merged_clutch_goals_21_24['Player'].
 ↪isin(merged_clutch_goals_prediction['Player'].values)]
```

[97]:
```
merged_clutch_goals_prediction['season'] = '2024-2026'

merged_clutch_goals_21_25_testing = pd.concat([merged_clutch_goals_21_24,␣
 ↪merged_clutch_goals_prediction])
```

```
merged_clutch_goals_21_25_testing = merged_clutch_goals_21_25_testing.
 ↪groupby(['Player', 'season'])['clutch_score'].mean().reset_index()

pivot = merged_clutch_goals_21_25_testing.pivot(index='Player',␣
 ↪columns='season', values='clutch_score')

seasons = pivot.columns
for i in range(len(seasons)-1):
    valid = pivot[[seasons[i], seasons[i+1]]].dropna()
    r, p = pearsonr(valid[seasons[i]], valid[seasons[i+1]])
    print(f"{seasons[i]} vs {seasons[i+1]}: r = {r:.3f}")
```

```
2021-2022 vs 2022-2023: r = 0.570
2022-2023 vs 2023-2024: r = 0.542
2023-2024 vs 2024-2026: r = 0.519
```

[99]:
```
merged_clutch_goals_21_24.to_csv("21_24_clutch.csv")
merged_clutch_goals_prediction.to_csv("clutch.csv")
```

1.0.40 Conclusion

Through this project, I hope that I developed a statistically sound goalscoring model. NHL fans, coaches and management can identify forwards who perform well in close game situations and use the regression model to determine if they are underperforming/overperforming expectations. The SHAP analysis should make the model less of a "black box" and enable users to gain more insight into playing styles that influence the predictions. For those more statistically inclined, the prediction intervals can show players who are truly "clutch". The influential points also identify genuinely clutch performers who exceed statistical expectations.

There are potential extensions for this model (e.g. including playoff data, goalie quality adjustments, venue effects). Third-period filtering would be ideal, as trailing with near the end of the game creates maximum pressure. Future versions could incorporate play-by-play timestamps. While the model has limitations, it provides a data-driven framework for evaluating clutch performance.