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

import shap

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

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'] >= 100)]
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']]
```

```python
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']]
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'] >= 100]

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]:
```python
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]:
```python
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]:

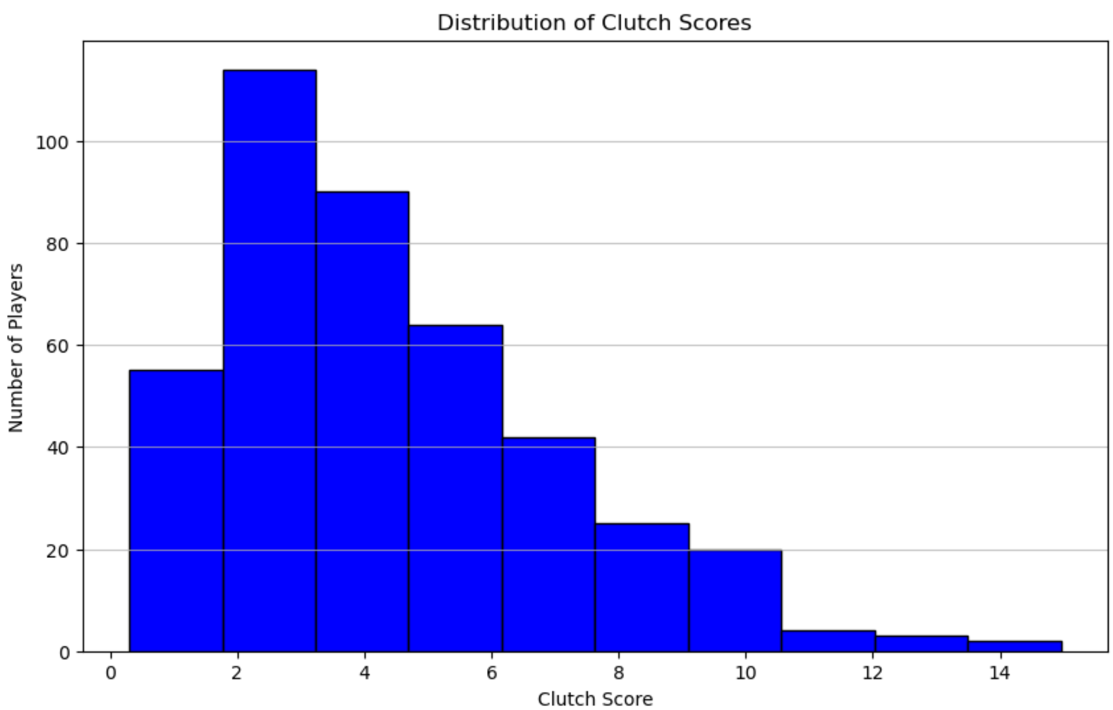
	Player	clutch_score	clutch_score_rank
277	Auston Matthews	14.96	1.0
205	David Pastrnak	13.50	2.0
267	Kirill Kaprizov	13.25	3.0
192	Leon Draisaitl	12.26	4.0
232	Connor McDavid	12.16	5.0
131	Filip Forsberg	11.44	6.0
388	Jack Hughes	11.01	7.0
213	Brayden Point	10.81	8.0
301	Tage Thompson	10.64	9.0
37	Steven Stamkos	10.52	10.0

```
194  William Nylander         10.08               11.0
235        Timo Meier         10.00               12.0
337       Josh Norris         10.00               13.0
198      Dylan Larkin          9.93               14.0
229       Kyle Connor          9.89               15.0
248       Roope Hintz          9.83               16.0
236    Mikko Rantanen          9.79               17.0
171  Nathan MacKinnon          9.75               18.0
191      Sam Reinhart          9.69               19.0
333   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]:
```python
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    356
1     63
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 = ['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',
         'off_zone_starts_per_game', 'on_the_fly_starts_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)
```

[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.

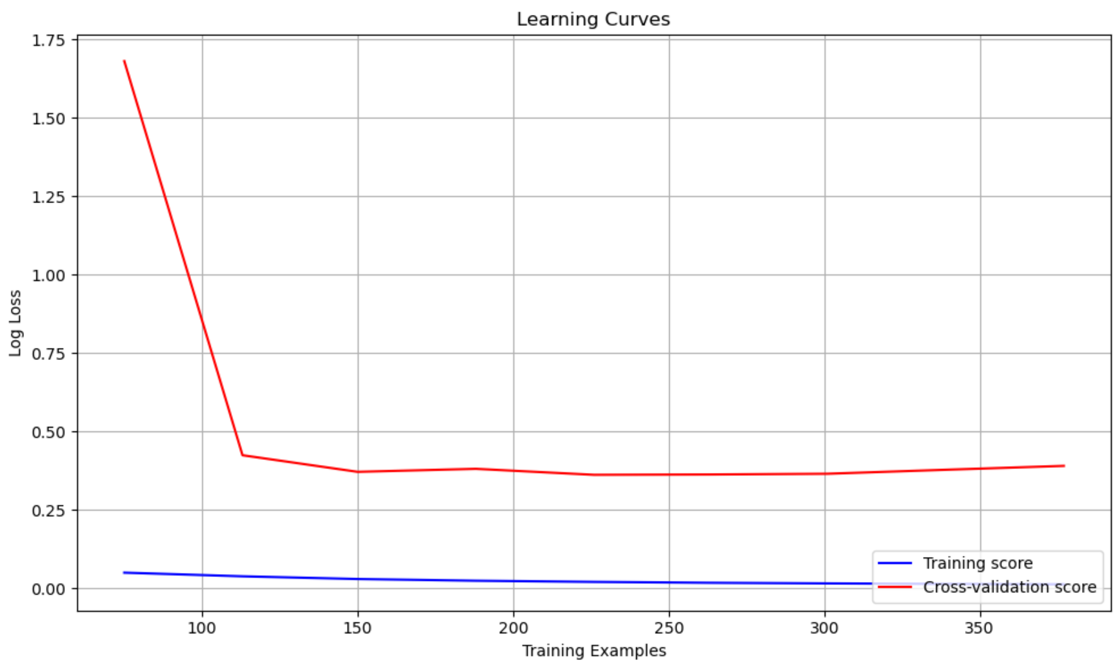
[33]:
```
skf = StratifiedKFold(n_splits=10)

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          0.050484
score_time        0.010597
test_accuracy     0.878339
test_precision    0.730435
test_recall       0.578571
test_f1           0.588824
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 cros-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.

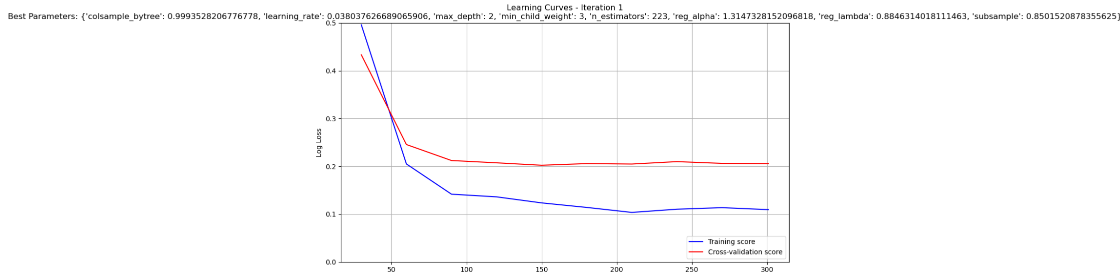
After each randomly selected train test split, I printed out the model's classification results. It appears that the model can correctly classify higher ranked players but struggles with players close to the boundary points (ranks between 45 and 74). The model also incorrectly classifies players with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

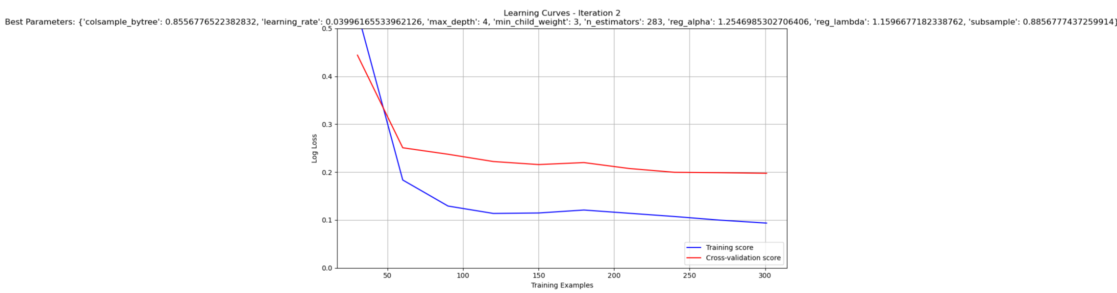



```
Precision Score:  0.8333333333333334
Recall Score:  0.7692307692307693

Correct Classfications
               Player  clutch_score_rank  Actual  Predicted
229       Kyle Connor               15.0       1          1
213     Brayden Point                8.0       1          1
```

	Player	clutch_score_rank	Actual	Predicted
388	Jack Hughes	7.0	1	1
255	Mitch Marner	35.0	1	1
233	Jack Eichel	27.0	1	1
153	Jake Guentzel	47.0	1	1
275	Matthew Tkachuk	58.0	1	1
194	William Nylander	11.0	1	1
176	Bo Horvat	21.0	1	1
281	Alex DeBrincat	36.0	1	1

Missed Cltuch Players

	Player	clutch_score_rank	Actual	Predicted
425	Andrei Kuzmenko	41.0	1	0
75	Brock Nelson	26.0	1	0
81	Jeff Skinner	48.0	1	0



Precision Score: 0.5714285714285714
Recall Score: 0.6153846153846154

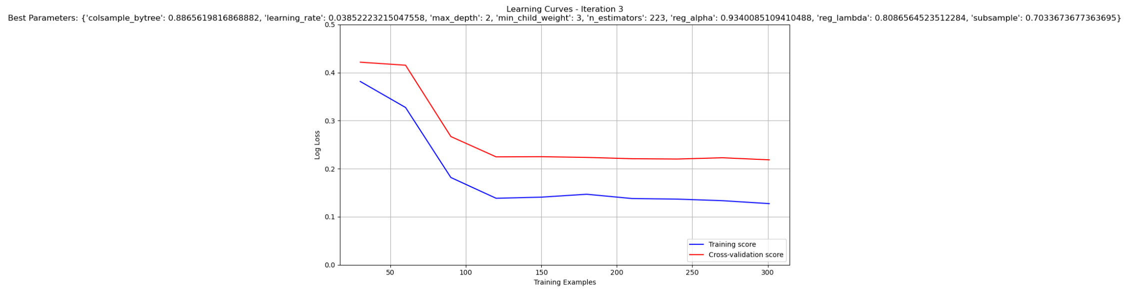
Correct Classfications

	Player	clutch_score_rank	Actual	Predicted
385	Cole Caufield	31.0	1	1
333	Jason Robertson	20.0	1	1
206	Adrian Kempe	33.0	1	1
153	Jake Guentzel	47.0	1	1
327	Elias Pettersson	49.0	1	1
111	Mika Zibanejad	29.0	1	1
301	Tage Thompson	9.0	1	1
33	Patrick Kane	44.0	1	1

Missed Cltuch Players

	Player	clutch_score_rank	Actual	Predicted
235	Timo Meier	12.0	1	0
112	Mark Scheifele	23.0	1	0
54	Evander Kane	46.0	1	0
75	Brock Nelson	26.0	1	0

58	Chris Kreider	32.0	1	0



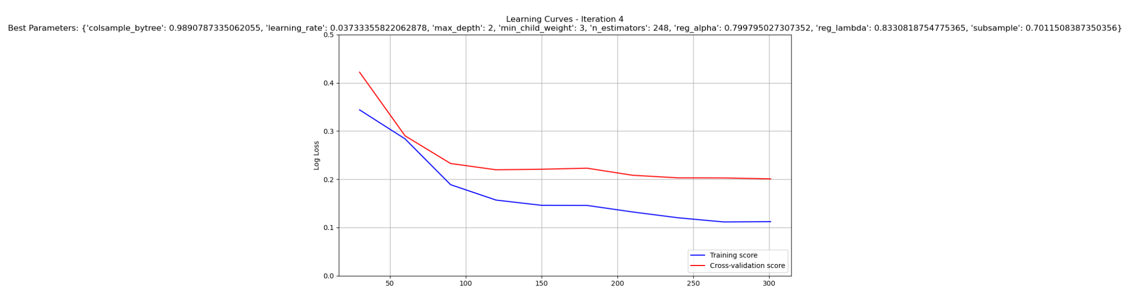

```
Precision Score:  1.0
Recall Score:  0.7692307692307693
```

Correct Classfications

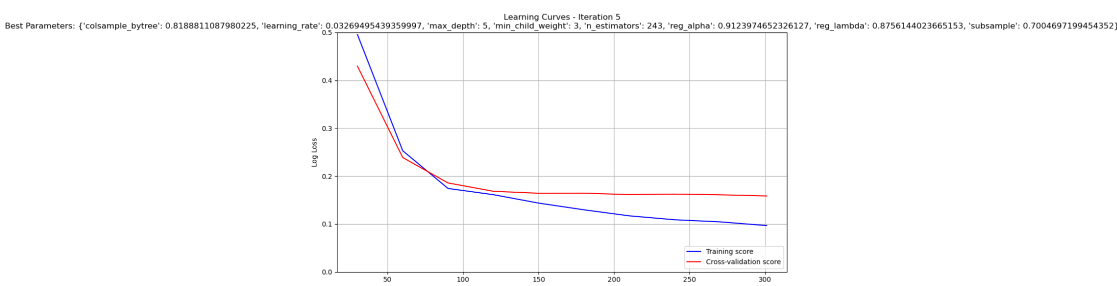
	Player	clutch_score_rank	Actual	Predicted
14	Brad Marchand	55.0	1	1
172	Aleksander Barkov	40.0	1	1
103	Boone Jenner	37.0	1	1
33	Patrick Kane	44.0	1	1
333	Jason Robertson	20.0	1	1
267	Kirill Kaprizov	3.0	1	1
82	Zach Hyman	51.0	1	1
131	Filip Forsberg	6.0	1	1
388	Jack Hughes	7.0	1	1
205	David Pastrnak	2.0	1	1

Missed Cltuch Players

	Player	clutch_score_rank	Actual	Predicted
268	Troy Terry	34.0	1	0
81	Jeff Skinner	48.0	1	0
337	Josh Norris	13.0	1	0



```
Precision Score:  0.7692307692307693
Recall Score:  0.7692307692307693

Correct Classfications
             Player  clutch_score_rank  Actual  Predicted
333  Jason Robertson               20.0       1          1
192   Leon Draisaitl                4.0       1          1
52      John Tavares               45.0       1          1
9      Sidney Crosby               28.0       1          1
197      Kevin Fiala               59.0       1          1
283   Clayton Keller               25.0       1          1
5      Alex Ovechkin               63.0       1          1
54      Evander Kane               46.0       1          1
235       Timo Meier               12.0       1          1
277  Auston Matthews                1.0       1          1

Missed Cltuch Players
             Player  clutch_score_rank  Actual  Predicted
268       Troy Terry               34.0       1          0
81      Jeff Skinner               48.0       1          0
328  Gabriel Vilardi               43.0       1          0
```




```
Precision Score:  0.5333333333333333
Recall Score:  0.6153846153846154

Correct Classfications
             Player  clutch_score_rank  Actual  Predicted
213     Brayden Point                8.0       1          1
191      Sam Reinhart               19.0       1          1
267   Kirill Kaprizov                3.0       1          1
236    Mikko Rantanen               17.0       1          1
322     Nico Hischier               41.0       1          1
```

```
6      Evgeni Malkin               54.0       1           1
176         Bo Horvat              21.0       1           1
197      Kevin Fiala               59.0       1           1

Missed Cltuch Players
               Player  clutch_score_rank  Actual  Predicted
425   Andrei Kuzmenko               41.0       1          0
370  Kirill Marchenko               53.0       1          0
283    Clayton Keller               25.0       1          0
204      Jared McCann               57.0       1          0
81       Jeff Skinner               48.0       1          0

Average Precision: 0.7414652014652015
Average Recall: 0.7076923076923076
Average F1 Score: 0.7205634301286474
```

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 = ['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',
         'off_zone_starts_per_game']
X= merged_clutch_goals[x_var]
y_var = 'clutch_score'
y = merged_clutch_goals[y_var]

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

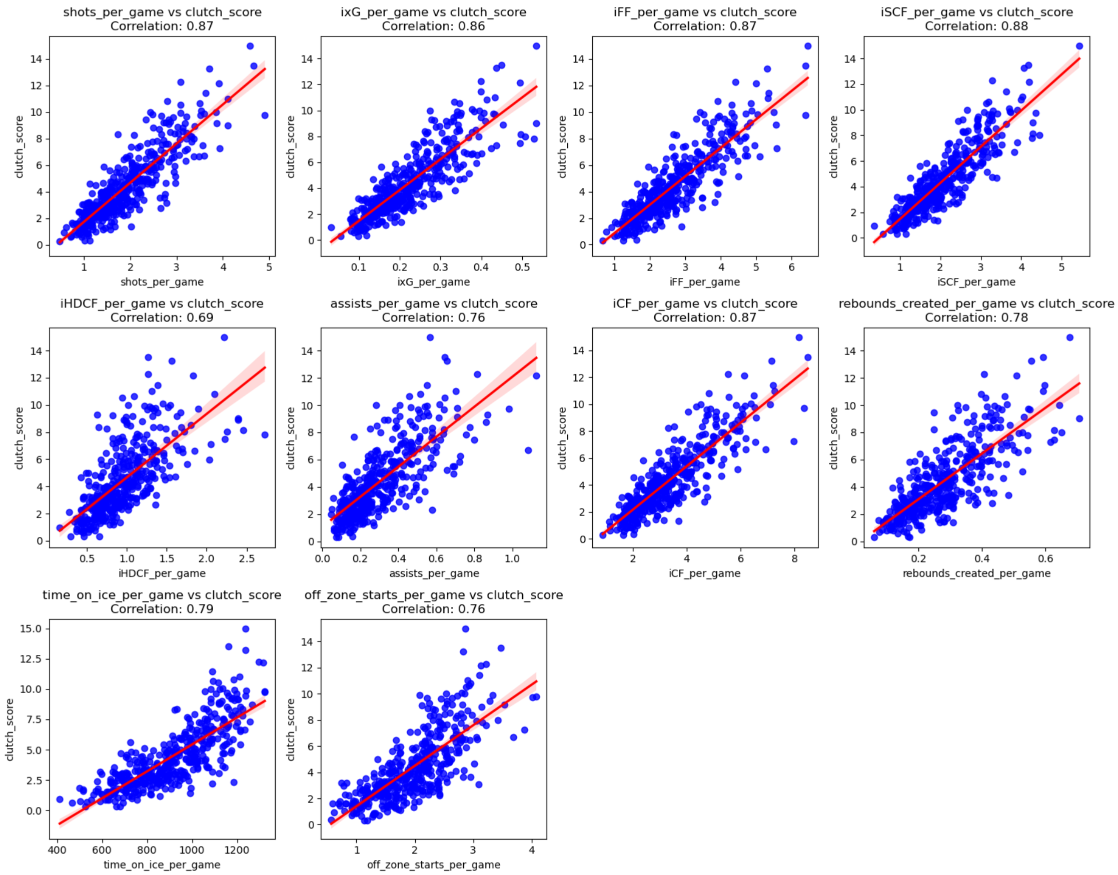
```
shots_per_game              0.870929
ixG_per_game                0.858424
iFF_per_game                0.874788
iSCF_per_game               0.883971
iHDCF_per_game              0.689704
assists_per_game            0.758345
```

```
iCF_per_game                 0.868702
rebounds_created_per_game    0.781486
time_on_ice_per_game         0.791332
off_zone_starts_per_game     0.756099
dtype: float64
```

1.0.22 Scatter Plots

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

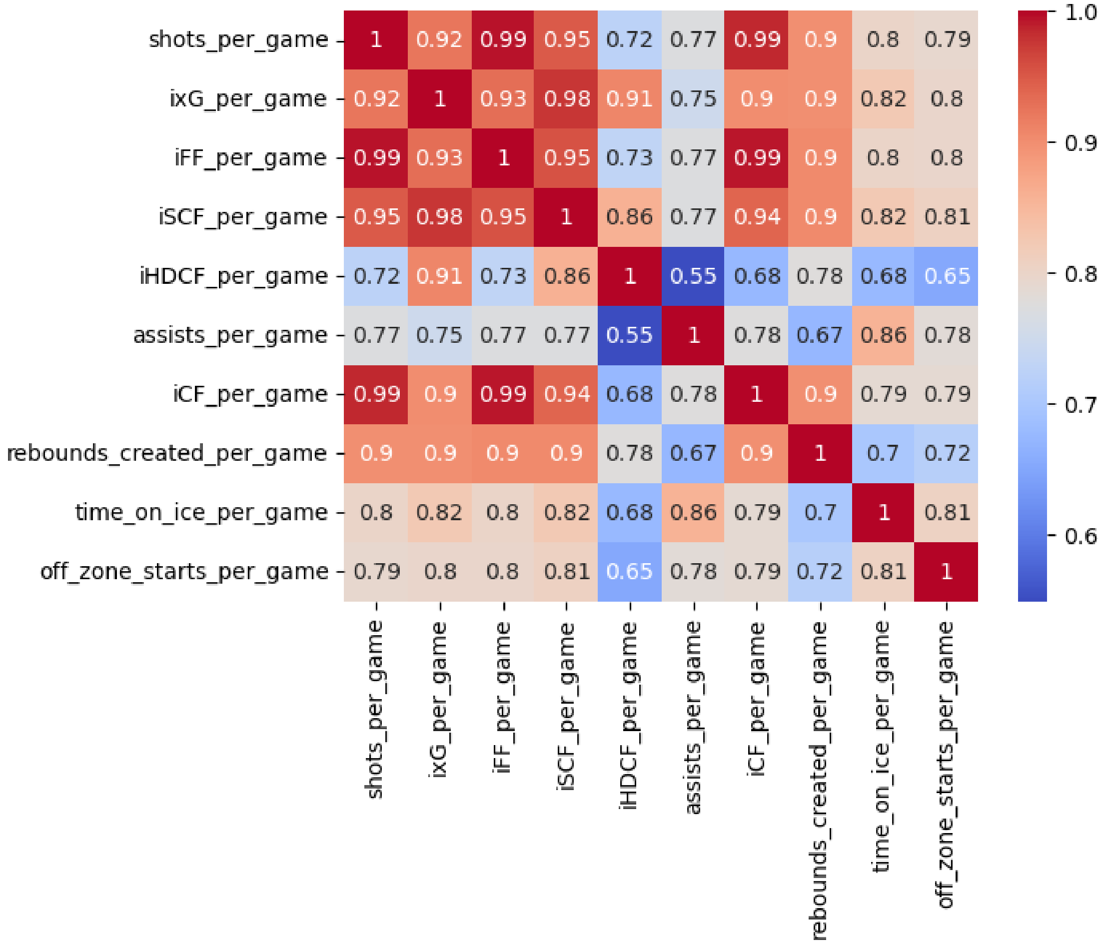
[45]:
```
plt.figure(figsize=(15, 12))

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 Multicollinearity

As the heatmap shows, there is high multicollinearity among features, which would lead to instability in coefficients and make it difficult to interpret the impact of features on the clutch score. Therefore, a small subset of features were kept (scoring chances, assists, time on ice, rebounds created, offensive zone starts).

[47]:
```
sns.heatmap(X.corr(), annot=True, cmap='coolwarm')
plt.show()
```



1.0.24 Ridge Regression

Ridge regression is used to ensure there is less overfitting. 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.

[49]:
```
x_var = ['iSCF_per_game', 'assists_per_game', 'rebounds_created_per_game',␣
↪'time_on_ice_per_game', 'off_zone_starts_per_game']

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)

alphas = np.logspace(-3, 3, 20)

ridge_cv = RidgeCV(alphas=alphas, cv=5)
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:  1.739532865672575
RMSE:  1.3189135171316484
Median Error:  0.8171137231089316
R²:  0.7936333979708128
Adjusted R²:  0.7904971274232567
```

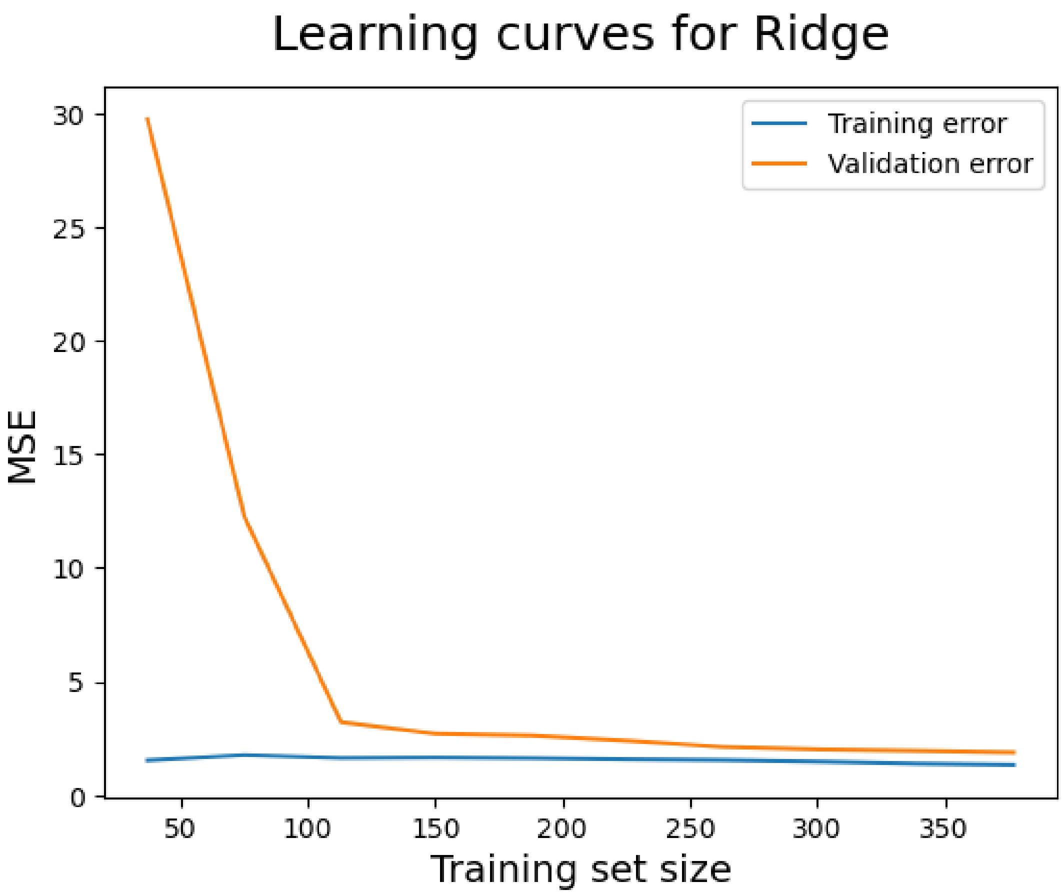
1.0.25 Learning Curves

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 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()
```

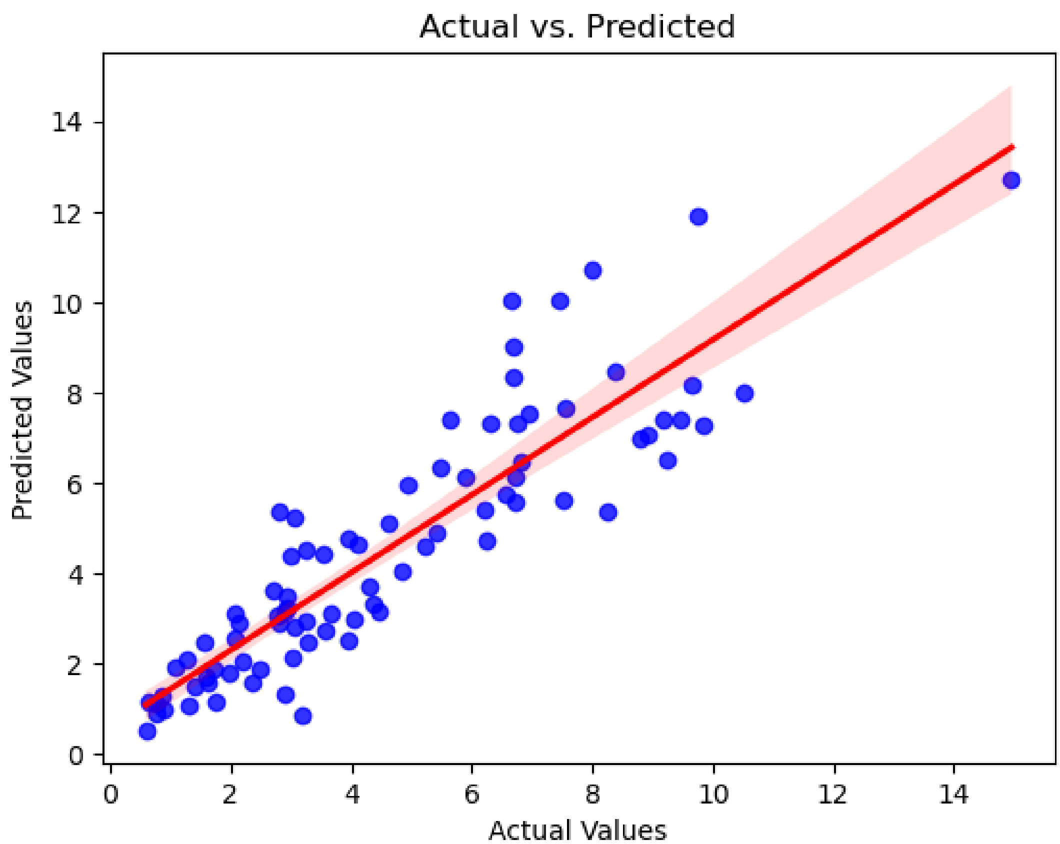
[51]: <matplotlib.legend.Legend at 0x2b94e8fef00>



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()
```

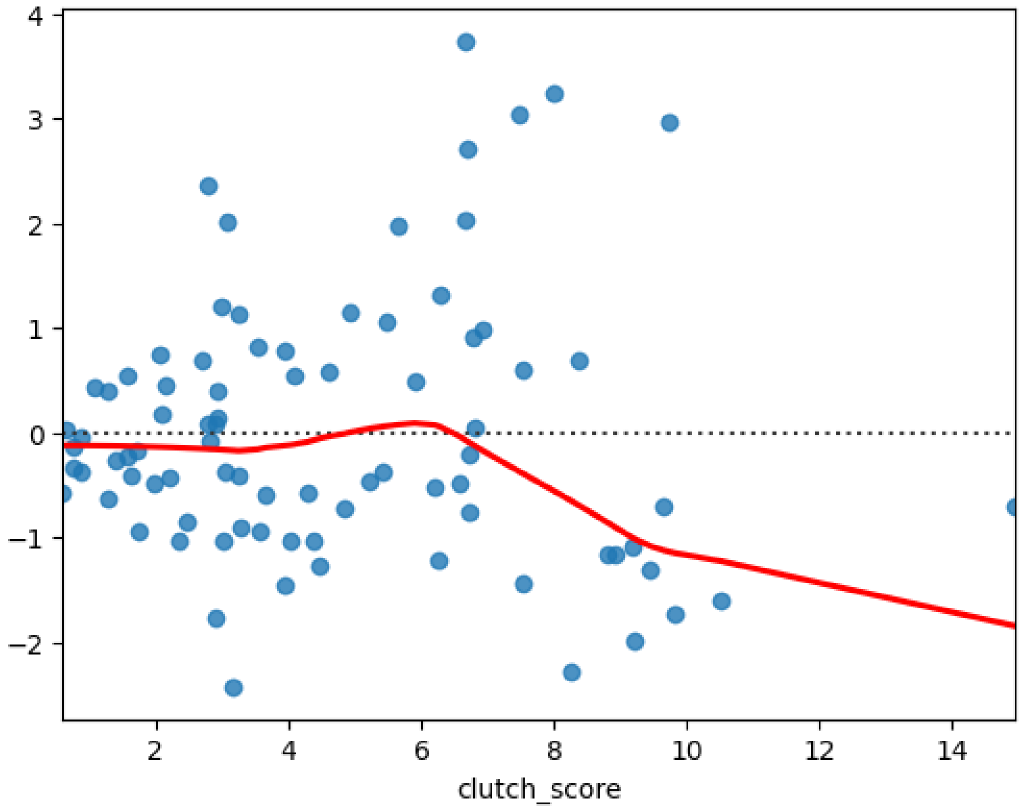


1.0.27 Residual Plot

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., 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.

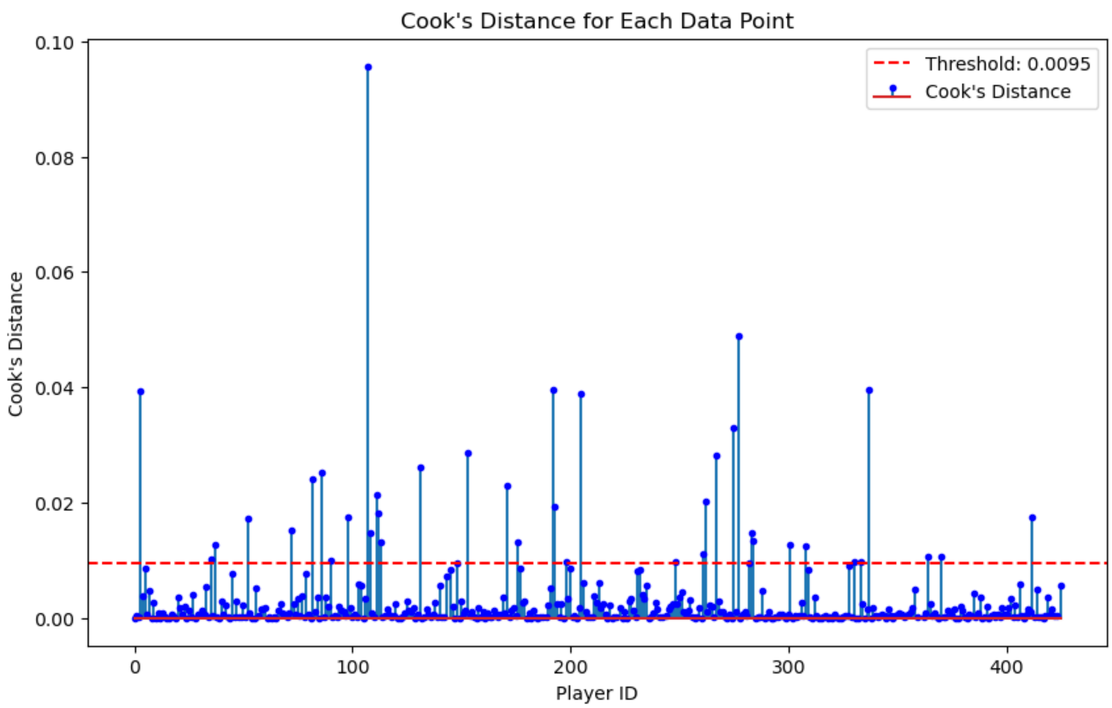
Conversely, the model overestimates the performance of other elite players (e.g., Matthew Tkachuk), who do not perform as well in clutch scoring situations as their general statistics suggest.

[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 39 influential points.
Outliers based on Cook's Distance:
                  Player  Actual  Predicted  Cook's Distance
277      Auston Matthews   14.96  12.963729         0.048987
205       David Pastrnak   13.50  10.160584         0.038814
267      Kirill Kaprizov   13.25  10.028615         0.028231
192       Leon Draisaitl   12.26   8.752896         0.039674
131       Filip Forsberg   11.44   8.562596         0.026046
301        Tage Thompson   10.64   7.516535         0.012699
37        Steven Stamkos   10.52   7.825069         0.012684
337          Josh Norris   10.00   6.079354         0.039513
198         Dylan Larkin    9.93   8.005587         0.009832
248         Roope Hintz    9.83   7.324113         0.009728
171      Nathan MacKinnon    9.75  11.539954         0.023042
333      Jason Robertson    9.66   7.907912         0.009744
176            Bo Horvat    9.61   7.620011         0.013059
112       Mark Scheifele    9.46   7.489897         0.018050
262       Artemi Panarin    9.27   7.671073         0.020307
283       Clayton Keller    9.23   6.383099         0.014636
111       Mika Zibanejad    9.10   6.268174         0.021240
282         Patrik Laine    8.37   6.344561         0.009573
52          John Tavares    8.14  10.009996         0.017304
153        Jake Guentzel    8.01  10.703404         0.028732
82            Zach Hyman    7.79  10.048862         0.024116
```

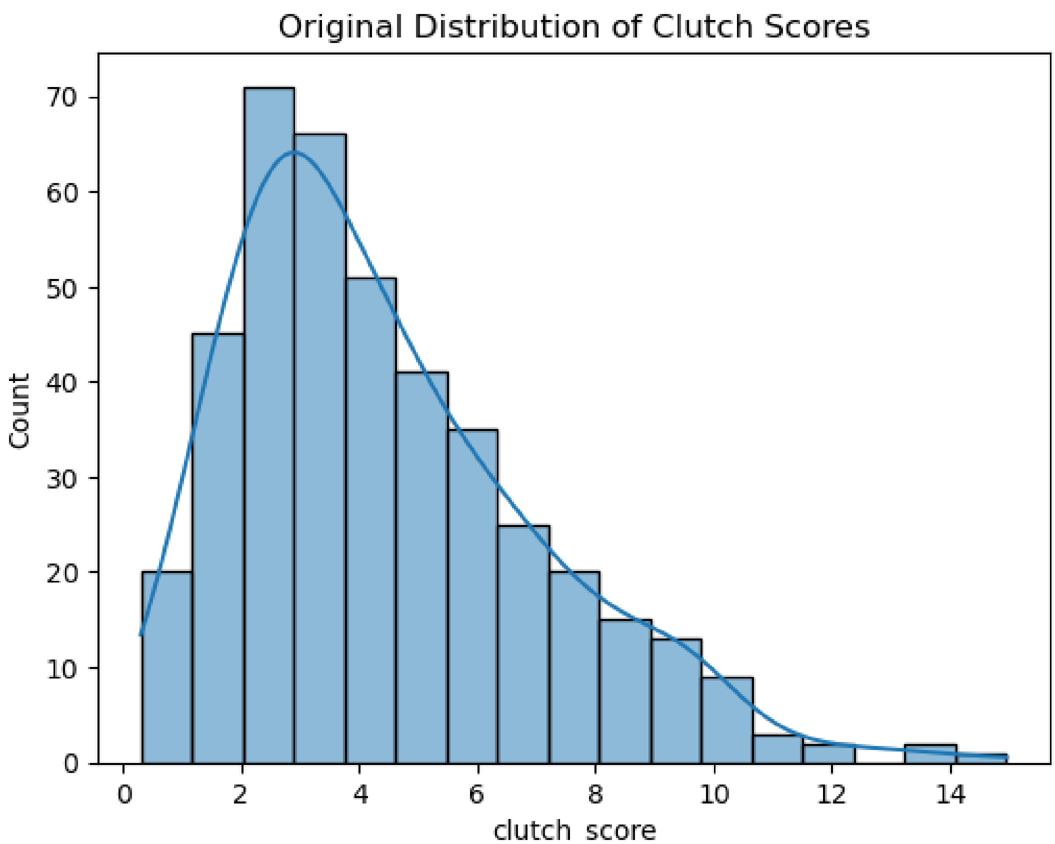
370	Kirill Marchenko	7.66	5.757824	0.010701
275	Matthew Tkachuk	7.47	9.682897	0.032967
330	Nick Suzuki	7.34	5.618391	0.009639
3	Patrice Bergeron	6.69	9.134738	0.039395
107	Nikita Kucherov	6.67	9.351439	0.095672
364	Andrei Svechnikov	5.15	7.365668	0.010713
108	Ryan Nugent-Hopkins	4.96	7.260685	0.014844
98	Vincent Trocheck	4.73	7.936354	0.017470
412	Alexander Holtz	4.68	1.954984	0.017415
193	Sam Bennett	4.66	7.632800	0.019245
113	Sean Couturier	3.54	5.283957	0.013061
90	Brendan Gallagher	3.38	5.116352	0.009898
35	Mikael Backlund	3.17	5.808941	0.010255
72	Evgeny Kuznetsov	3.07	5.104774	0.015144
261	Evan Rodrigues	2.79	5.328727	0.011034
86	Mikael Granlund	2.30	4.956959	0.025229
284	Jesse Puljujarvi	2.28	4.257273	0.013305
308	Michael Eyssimont	1.36	3.432229	0.012483

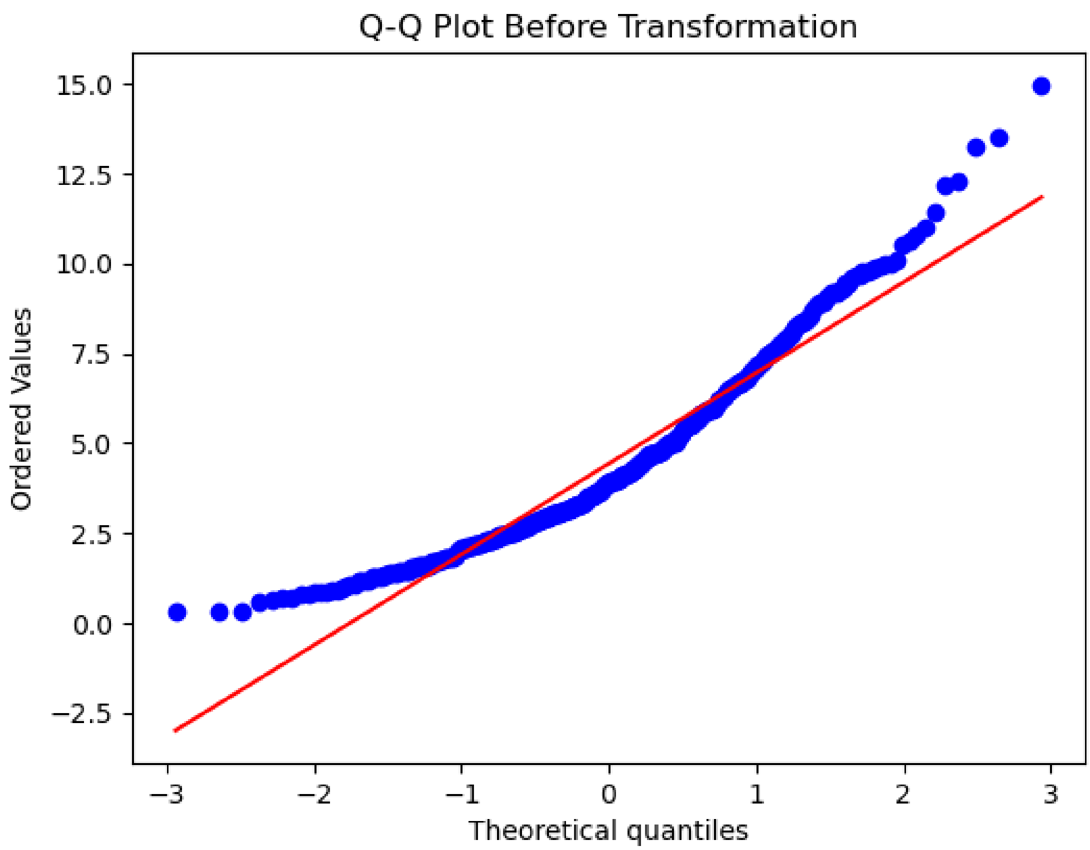


1.0.29 Evaluating the Distribution of the Data

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()
```

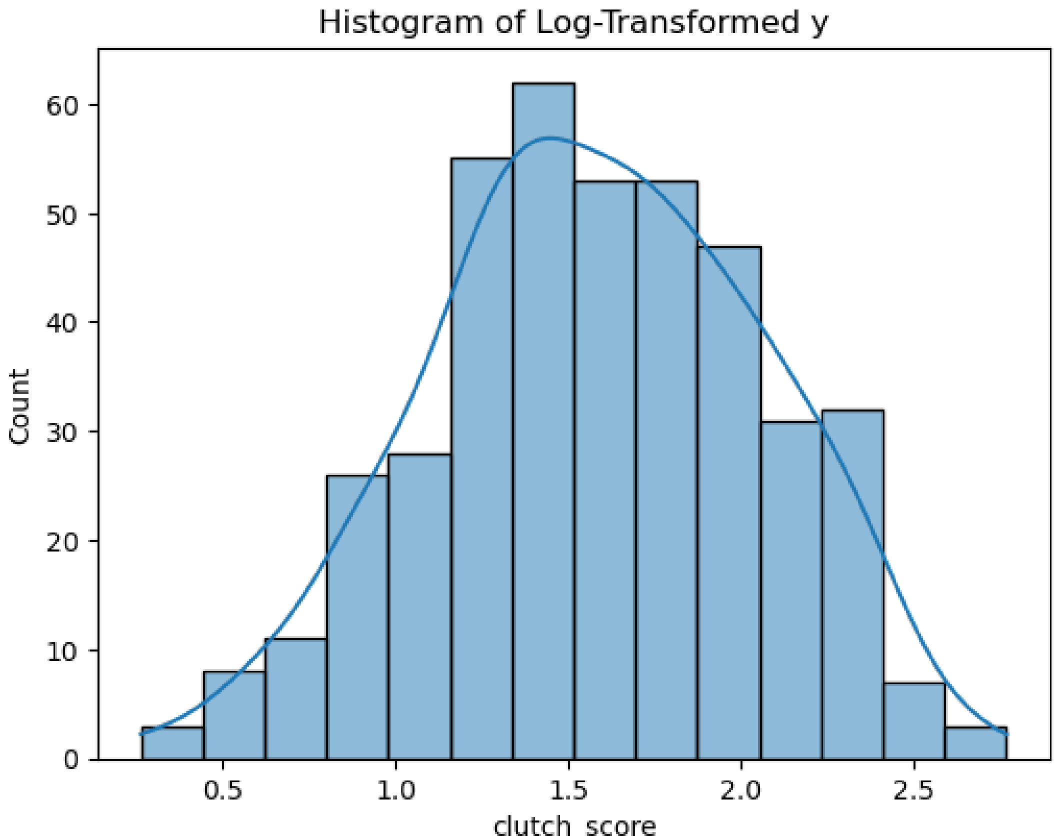




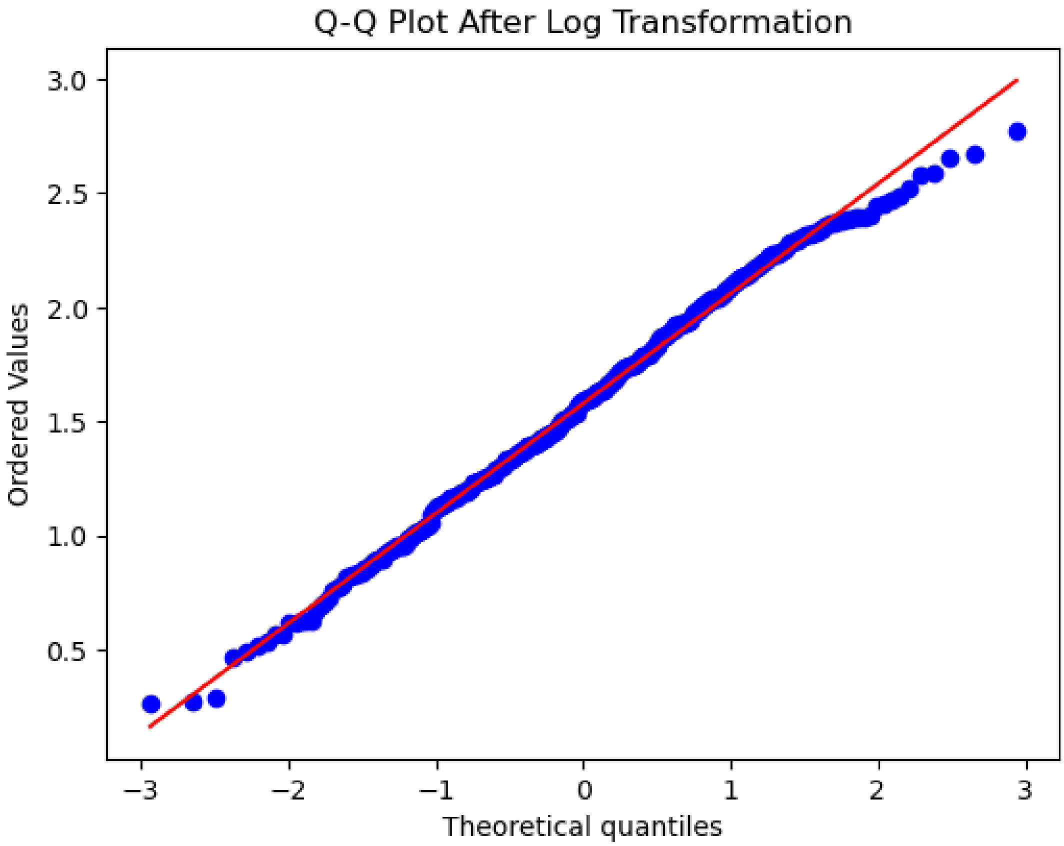
1.0.30 Transforming the Data to a Normal Distribution with Log

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
0.5
1.0
1.5
2.0
2.5



1.0.31 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.

[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)

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:  0.060926944197601814
RMSE:  0.24683383924738078
MAE:  0.16244763748540536
R²:  0.726397088336697
Adjusted R²:  0.7222389893752486
```

1.0.32 Calculating Cook's Distance

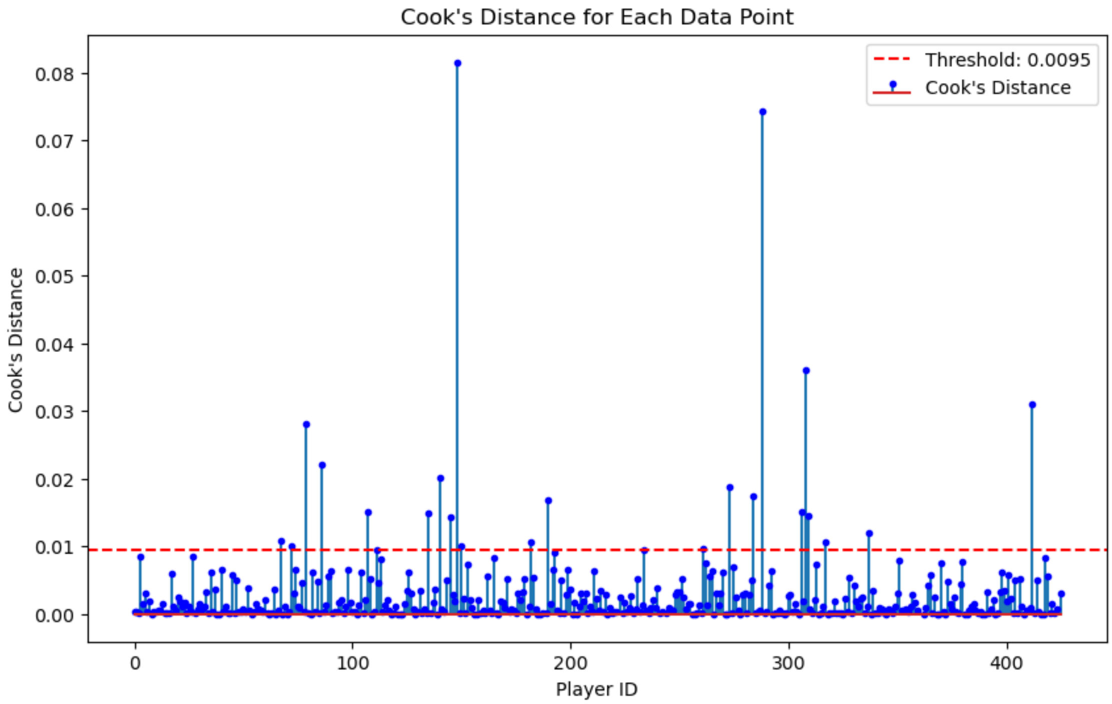
After we apply the log transformation and calculate Cook's distance, we can see that the elite players are no longer influential points. However, there are some players which the model still struggles with. The model undervalues some players (e.g. Vrana, Laine) who may perform better in close and tied 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.

[65]:
```
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({
```

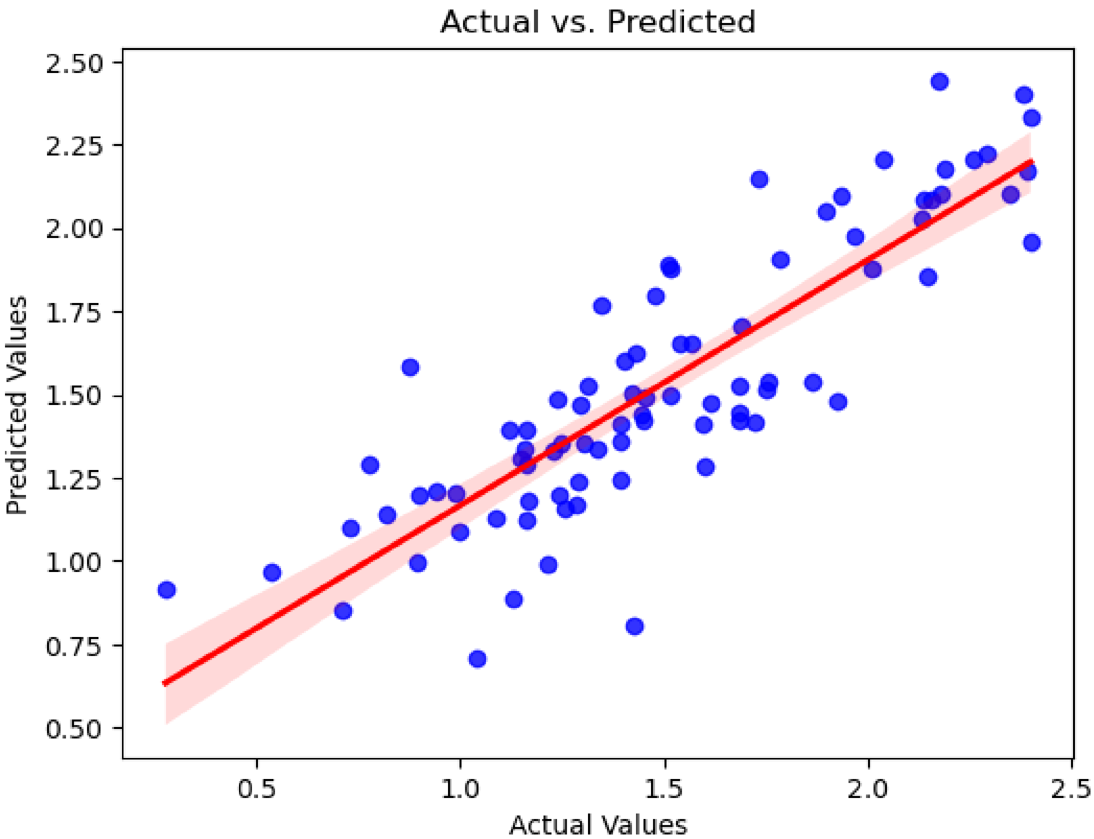
```
    'Player': merged_clutch_goals.loc[y.index, 'Player'],
    'Actual': y_log,
    'Predicted': ols_model.fittedvalues,
    'Cook\'s Distance': cooks_d
})

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 22 influential points.
Outliers based on Cook's Distance:
                 Player    Actual  Predicted  Cook's Distance
337         Josh Norris  2.397895   1.945223         0.012030
107      Nikita Kucherov  2.037317   2.323783         0.015041
309      Michael Carcone  1.890095   1.259313         0.014450
412     Alexander Holtz  1.736951   1.144675         0.030971
67             Nic Dowd  1.437463   1.127307         0.010745
79        Austin Watson  1.427916   0.792459         0.028046
72     Evgeny Kuznetsov  1.403643   1.760049         0.010078
261      Evan Rodrigues  1.332366   1.827961         0.009698
86      Mikael Granlund  1.193922   1.703392         0.022121
284    Jesse Puljujarvi  1.187843   1.589896         0.017418
306    Michael Pezzetta  1.040277   0.732644         0.015157
150         Tyler Motte  0.900161   1.300086         0.010025
145        Connor Brown  0.875469   1.553427         0.014381
308   Michael Eyssimont  0.858662   1.409689         0.035956
140       Teddy Blueger  0.774727   1.269674         0.020195
148    Kurtis MacDermid  0.667829   0.201521         0.081510
190         Tomas Nosek  0.615186   1.042041         0.016808
317     Jonah Gadjovich  0.570980   0.844170         0.010602
135         Devin Shore  0.518794   0.819861         0.014850
288      Beck Malenstyn  0.292670   0.959196         0.074310
273        Kevin Rooney  0.277632   0.881802         0.018819
182      Ross Johnston   0.262364   0.566005         0.010631
```



1.0.33 Final Scatter Plot from Training

[67]:
```
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()
```



1.0.34 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).

[69]:
```
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')
```

[69]: ['epsilon.pkl']

[70]:
```
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          103     59       47
4      8471215    Evgeni Malkin           C           94     24       55
…          …              …            …            …    …     …
1004   8485483  Karsen Dorwart            L            5      0        0
1005   8485493   David Tomasek            R           22      3        2
1006   8485511     Quinn Hutson           R            5      1        0
1007   8485512       Tim Washe            C            2      0        0
1008   8485702    Max Shabanov            R           25      3        7

      otGoals  timeOnIcePerGame teamAbbrevs
0           0        1168.28040         STL
```

```
1           0       1213.52205        COL
2           0        764.64335        LAK
3           1       1064.67810        WSH
4           1       1058.75845        PIT
…       …               …         …
1004        0        658.80000        PHI
1005        0        645.50000        EDM
1006        0        629.75000        EDM
1007        0        464.00000        ANA
1008        0        839.16000        NYI

[1009 rows x 9 columns]
```

[71]:
```
nhl_api_df = nhl_api_df.loc[(nhl_api_df['positionCode'] != 'D') &␣
  ↪(nhl_api_df['gamesPlayed'] >= 100)]
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)
```

[72]:
```
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
```

[73]:
```
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', ' ')
```

[74]:
```
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']]
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)
```

[75]:
```
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)
```

[76]:
```
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()
```

[77]:
```
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']
```

[78]:
```
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']
)
```

[79]:
```
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)
```

[79]:

	Player	clutch_score	clutch_score_rank
91	Leon Draisaitl	15.18	1.0
144	Alex DeBrincat	11.74	2.0
240	Dylan Guenther	11.70	3.0
159	Morgan Geekie	11.34	4.0
201	Cole Caufield	11.18	5.0
152	Tage Thompson	10.88	6.0
18	John Tavares	10.80	7.0
85	Bo Horvat	10.79	8.0
2	Sidney Crosby	10.39	9.0
62	Tom Wilson	10.34	10.0
90	Sam Reinhart	10.22	11.0
50	Mark Scheifele	10.17	12.0
93	William Nylander	9.96	13.0
169	Jason Robertson	9.88	14.0
100	Adrian Kempe	9.87	15.0
45	Nikita Kucherov	9.73	16.0

```
219        Seth Jarvis          9.63               17.0
83    Nathan MacKinnon          9.53               18.0
96         Dylan Larkin          9.34               19.0
99      David Pastrnak          9.14               20.0
```

[80]:
```
x_var = ['iSCF_per_game', 'assists_per_game', 'rebounds_created_per_game',␣
 ↪'time_on_ice_per_game', 'off_zone_starts_per_game']
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)
```

1.0.35 Evaluating the Model after Testing

The R^2 indicates the model explains approximately 70% of variance in clutch performance, which is strong given the inherent randomness in clutch situations.

[82]:
```
r2 = r2_score(y_log, y_pred)
rmse = np.sqrt(mean_squared_error(y, y_pred))
mae = mean_absolute_error(y, 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: 0.6951
RMSE: 4.0731
MAE: 3.3352
```

[83]:
```
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))
```

1.0.36 Prediction Intervals

95% 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. The intervals are generated using a bootstrap procedure with resampled residual noise, which ensures that the intervals reflect randomness in clutch performance.

[85]:
```
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'
)
```

1.0.37 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.

[87]:
```
explainer = shap.LinearExplainer(ridge_cv_log_loaded, X_log)
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]
```

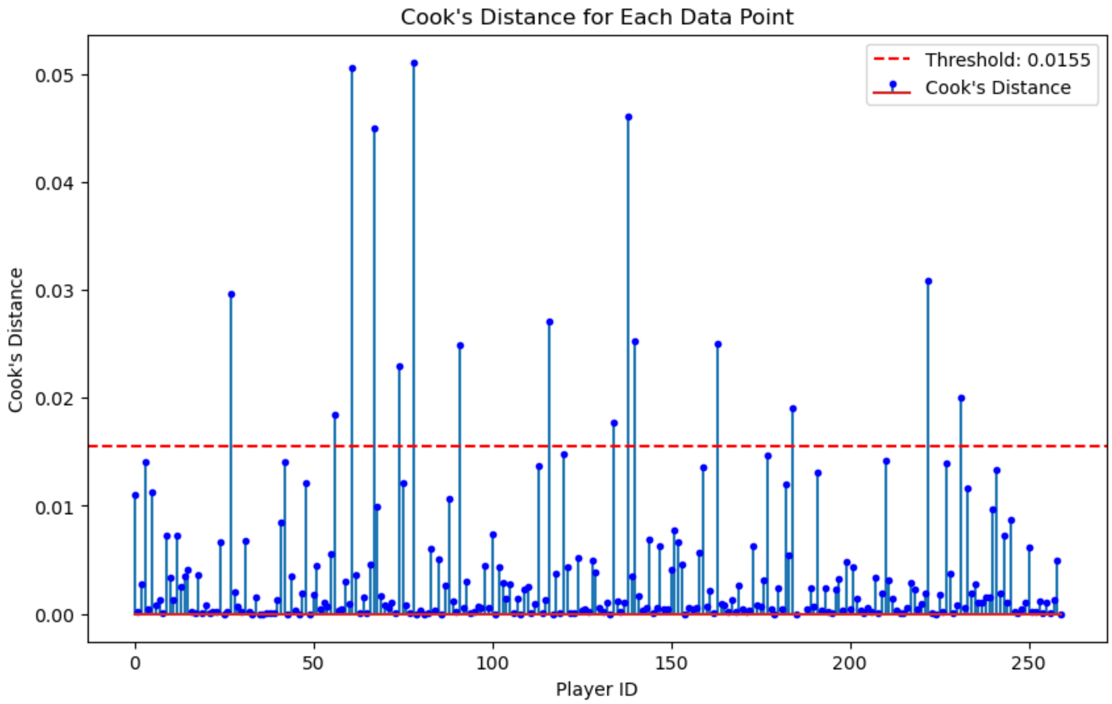
1.0.38 Cook's Distance Observations

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.

[89]:
```
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.iloc[:
↪len(y_log)].copy().reset_index(drop=True)

results = pd.DataFrame({
    'Player': merged_clutch_goals_prediction['Player'].values,
    'Actual': y_log,
    'Predicted': ols_model.fittedvalues,
    "Cook's Distance": cooks_d
```

```python
})

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()
```

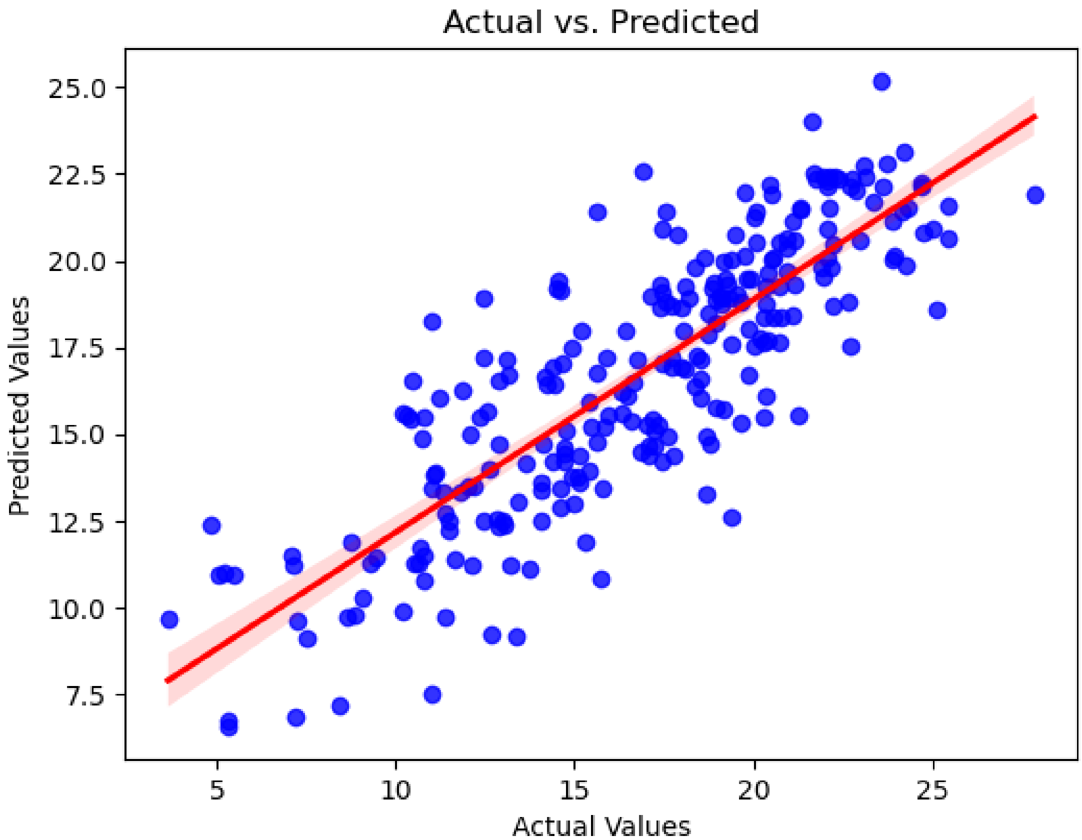
```
There are 15 influential points.
Outliers based on Cook's Distance:
                 Player    Actual  Predicted  Cook's Distance
91       Nathan MacKinnon  2.783776   2.218980         0.024895
231       Leon Draisaitl  2.270062   1.714501         0.020003
138        Robert Thomas  1.935860   1.216957         0.046092
67         Dawson Mercer  1.870263   1.417876         0.044969
116          Ridly Greig  1.690096   2.328874         0.027104
163      Luke Evangelista  1.574846   1.092325         0.024990
27       Jordan Martinook  1.530395   1.205385         0.029605
222             Nic Dowd  1.098612   1.806045         0.030844
140         Yakov Trenin  1.098612   0.741612         0.025233
184       Colton Sissons  1.047319   1.610444         0.019085
56         Casey Cizikas  1.043804   1.498506         0.018482
134      Garnet Hathaway  0.708036   1.127417         0.017733
78    Marat Khusnutdinov  0.548121   1.057412         0.051079
61       Luke Glendening  0.482426   1.223288         0.050608
74          Ryan Lomberg  0.364643   0.988031         0.022953
```



1.0.39 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.

[91]:
```
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()
```



1.0.40 Conclusion

Through this project, I hope that NHL fans 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".

While there were still some influential points in the final model, these points may be useful in determining overvalued and undervalued players. One potential limitation in the cltuch score is that it includes goals from all periods. It would be useful to have only third period goals given these are the most clutch goals, but I was not able to filter by period on Natural Stat Trick.