imports and setup

```
In [ ]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import matplotlib.ticker as tck
        import seaborn as sns
        from sklearn.preprocessing import LabelEncoder
        from sklearn.model_selection import train_test_split
```

preliminary data cleaning

```
In [ ]: # Read in the dataframe.
        df_10_11 = pd.read_csv('data/dylan_data/play_by_play_2010_11.csv', encoding=
        df_10_11.head()
```

Out[ ]:

	xg	event_id	event_type	event	secondary_type	event_team	ev
0	NaN	2.010020e+13	GAME_SCHEDULED	Game Scheduled	NaN	NaN	
1	NaN	2.010020e+13	CHANGE	Change	NaN	Montréal Canadiens	
2	NaN	2.010020e+13	CHANGE	Change	Line change	Toronto Maple Leafs	
3	NaN	2.010020e+13	FACEOFF	Faceoff	NaN	Montréal Canadiens	
4	NaN	2.010020e+13	HIT	Hit	NaN	Toronto Maple Leafs	

5 rows × 107 columns

We see that this data is messy and contains a lot of unnecessary information. We will clean the data and remove the unnecessary information using the `get_data()` function (see `Appendix: Helper Functions`).

In [ ]:
```
# Copy the dataframe (so we don't have to reload it)
df_copy = df_10_11.copy()

# Drop NaN's from event_team_type (drops events that are not helpful)
    # This includes things like game stats, end of periods, etc.
df_copy = df_copy.dropna(subset=['event_team'])

# Get all of the unique game ids, thus getting all of the games
unique_game_ids = df_10_11.game_id.unique()

# Get the label encoder for the teams
team_names = np.sort(df_copy.event_team.dropna().unique())  # Sort first to
label_encoder = get_label_encoder(team_names)               # Get the label

# Label encode the teams
df_copy['team_encoded'] = label_encoder.transform(df_copy.event_team)

# Iterate through the games
final_df = pd.DataFrame()
for game_id in unique_game_ids:
    home_df, away_df = get_data(df_copy, game_id)
    final_df = final_df.append(home_df)
    final_df = final_df.append(away_df)
```

The `get_data()` function creates a state-vector for each team in each game (home and away). The data points we have determined to be important are faceoff, hit, giveaway, blocked_shot, shot, missed_shot, goal, takeaway, penalty, time_remaining, team. Each of these features is essentially a count of the number of times that event occurred in the current game (exluding team, which is unchanging). We can view what this dictionary now looks like (see `2. Data Examination`).

Data Cleaning Descriptive Statistics Tasks

1. Train-Test

Before doing any exploration, consider when and how you plan on holding out data for model evaluation. The gold standard is to have totally independent data you have never seen before tucked away so you can evaluate model performance at the end, but there can be many reasons this may not work. Explain your choice. If you do want to hold out the same data every time, consider fixing a random seed when you make the test-train split.

In [ ]:
```
'''
The way we decided to train_test split our data is to use the last half of c
Our plan is to use all historical data in our model. The main reason for thi
in a previous year is a good indicator of how well they will do in the next
years to help predict the outcome of current games. By excluding the second
simulate how our model would perform in a real world scenario. As an example
the example dataframe (from the 2010-2011 season) as an example of how this
```

```
'''
train_df, test_df = final_df.iloc[:328227], final_df.iloc[328227:]

# We can now split the data into features and labels
X_train, y_train = train_df.drop(['WIN'], axis=1), train_df['WIN']
X_test, y_test = test_df.drop('WIN', axis=1), test_df['WIN']
```

2. Data Examination

Print out a few dozen rows of the data. Is there anything you didn't expect to see? What opportunities for data cleaning and feature engineering may be important? Take care of these things.

Our helper function `get_data()` has already cleaned the data for us. However, there is still room for feature engineering. Some potential features are

- Power play percentage (how good a team is at scoring when they have a powerplay)
- Penalty kill percentage (how good a team is at preventing goals when they are on the penalty kill)
- Momentum (what is the change of data in the last 5 minutes of the game)
- Time of possession (how long a team has the puck) <-- This one will require a different dataset.

```
In [ ]: display(X_train.head())
        display(y_train.head())
```

	index	FACEOFF	HIT	GIVEAWAY	BLOCKED_SHOT	SHOT	MISSED_SHOT	GOAL	TA
0	0	0	1	0	0	0	0	0	
1	1	0	1	1	0	0	0	0	
2	2	0	1	1	1	0	0	0	
3	3	0	1	2	1	0	0	0	
4	4	1	1	2	1	0	0	0	

```
0    1
1    1
2    1
3    1
4    1
Name: WIN, dtype: object
```

3. Time Series Examination

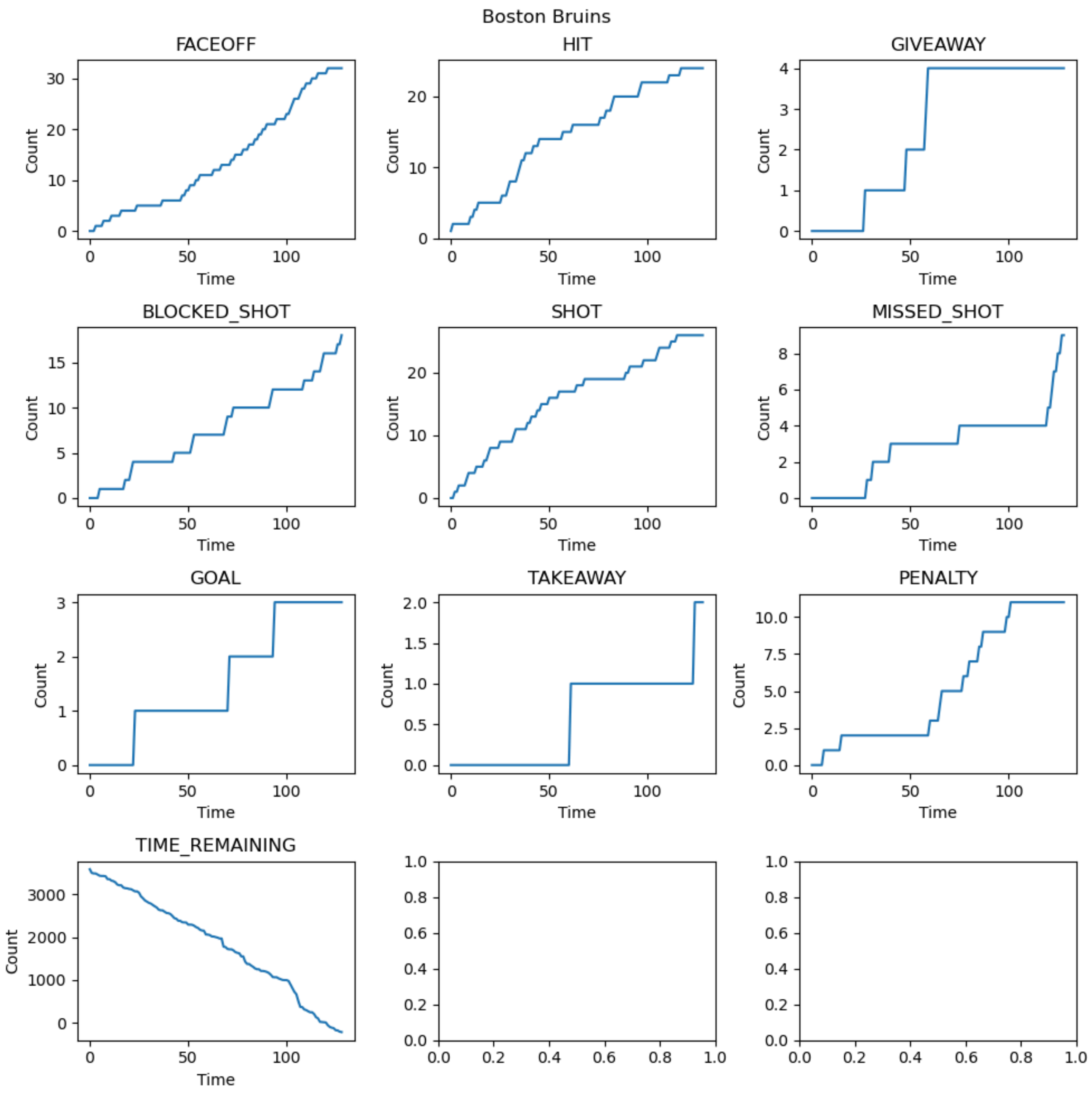
Plot a few individual time series and do a similar check. Is there anything unbelievable you see?

The easiest way to see if things make sense is to plot the change in the state vector over the course of a game. We can do this by plotting the state vector for each team in a randomly selected game.

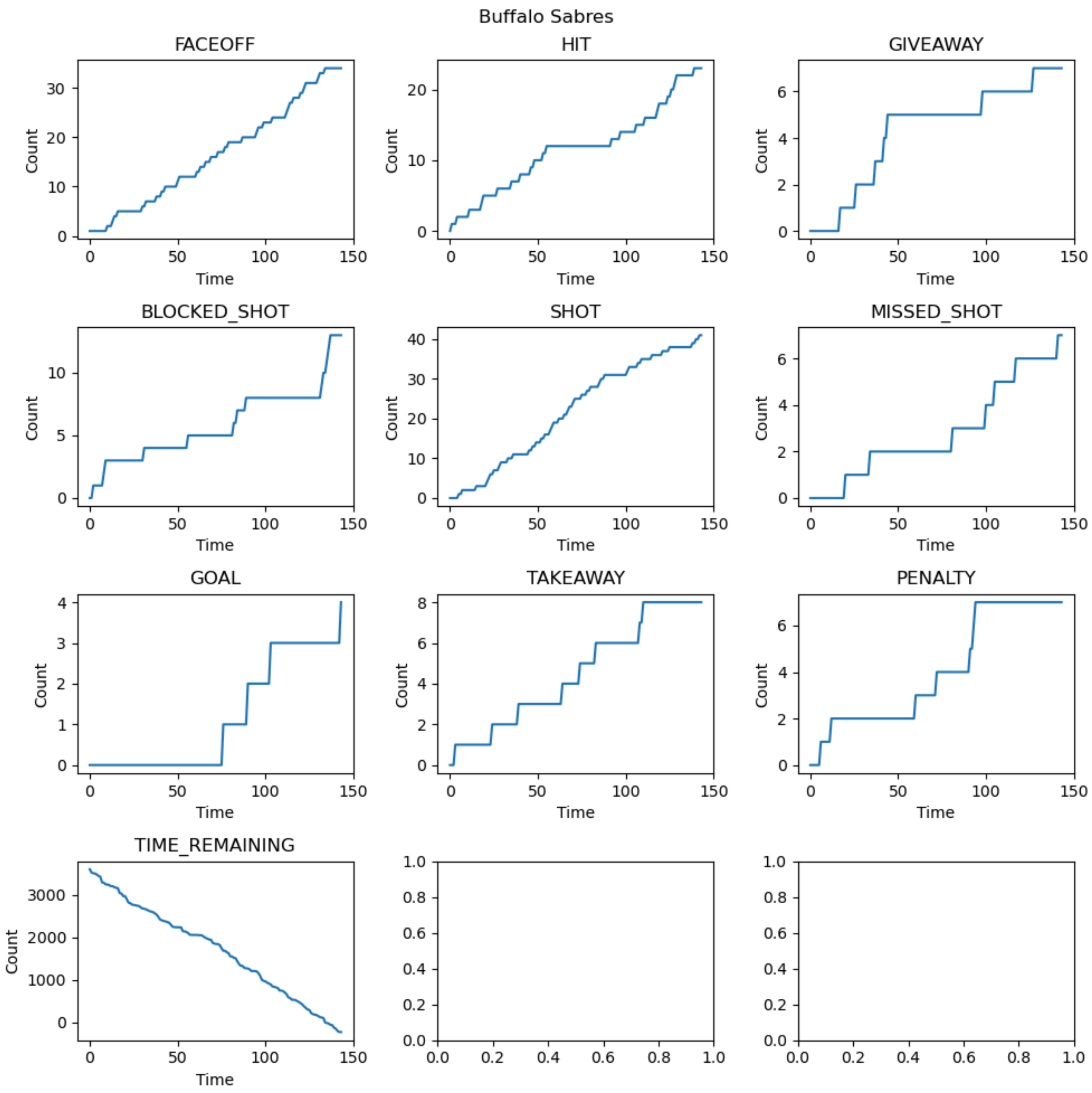
We do this using the `plot_game()` function (see `Appendix: Helper Functions`). This function plots each element of the state vector for each team over the course of the game. As we expect, the only feature that decreases overtime is time_remaining. The other features should either increase or stay stagnant for each time set. We can see that this is the case for the game we have selected. Since this game was randomly selected, we can assume that this is the case for all games.

```
In [ ]: # Select a random game to visualize
        selected_game = X_train.GAME_ID.sample(1).values

        # Get the selected game
        selected_game_df = X_train[X_train.GAME_ID == selected_game[0]]

        # Break the selected game into home and away teams
        home_team_selected = selected_game_df[selected_game_df.HOME == 1]
        away_team_selected = selected_game_df[selected_game_df.HOME == 0]
```

```
In [ ]: # Plot for the home team
        # Get rid of extra columns
        team_id = home_team_selected.TEAM.unique()[0]
        home_team_plot = home_team_selected.drop(columns=['index', 'HOME', 'GAME_ID'

        # Plot the game (helper function)
        plot_game(home_team_plot, team_id)
```



In [ ]:
```
# Plot for the away team
# Get rid of extra columns
team_id = away_team_selected.TEAM.unique()[0]
away_team_plot = away_team_selected.drop(columns=['index', 'HOME', 'GAME_ID'

# Plot the game (helper function)
plot_game(away_team_plot, team_id)
```



4. Missing data

How much data is missing? Is the distribution of missing data likely different from the distribution of non-missing data? How might you do a meaningful imputation (if needed)? Are there variables that should be dropped? Implement some initial solutions.

So far in our data exploration we have not found any missing data. In our `get_data()` function, we have a line that drops all rows with NaN values in the `event_team_type` column. This is done to remove any rows that do not contain important data. For example, when a game starts, a period ends, or a game ends, the `event_team_type` column is NaN. We can see that this is the case for all games. Thus, since none of those events are important features for our analysis, we can drop them without much thought.

5. Data vs. Application

Is there any hint that the data you have collected is differently distributed from the actual application of interest? If so, is there a strategy, such as reweighing samples, that might help?

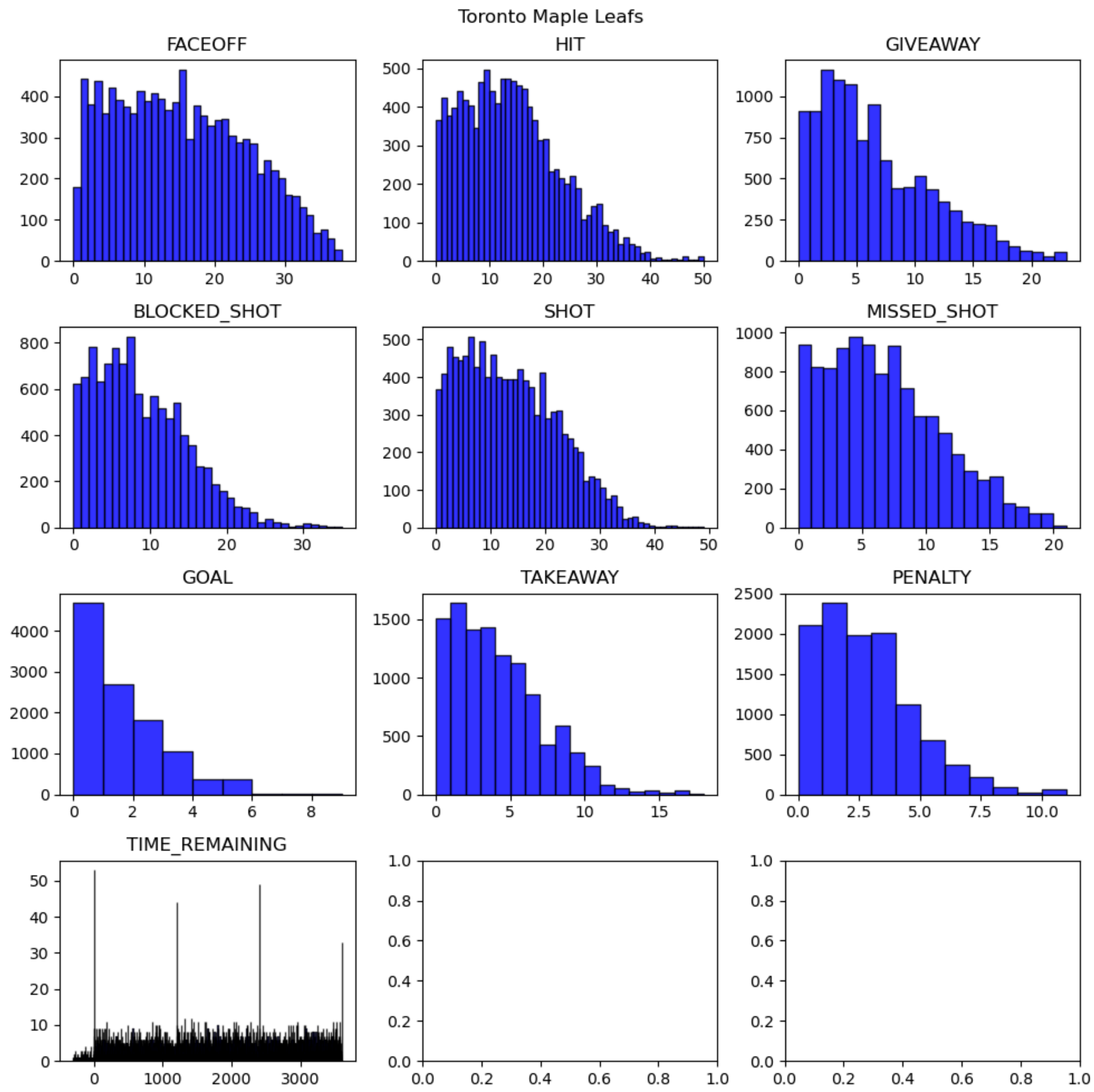
No. As this is live game data, and we are interested in predicting events for live games, this data has the exact distribution that we need. And based on the graphs shown here, the data is believeable and we see no reason to believe that it is not actually game data.

6. Histogram/KDE and outliers

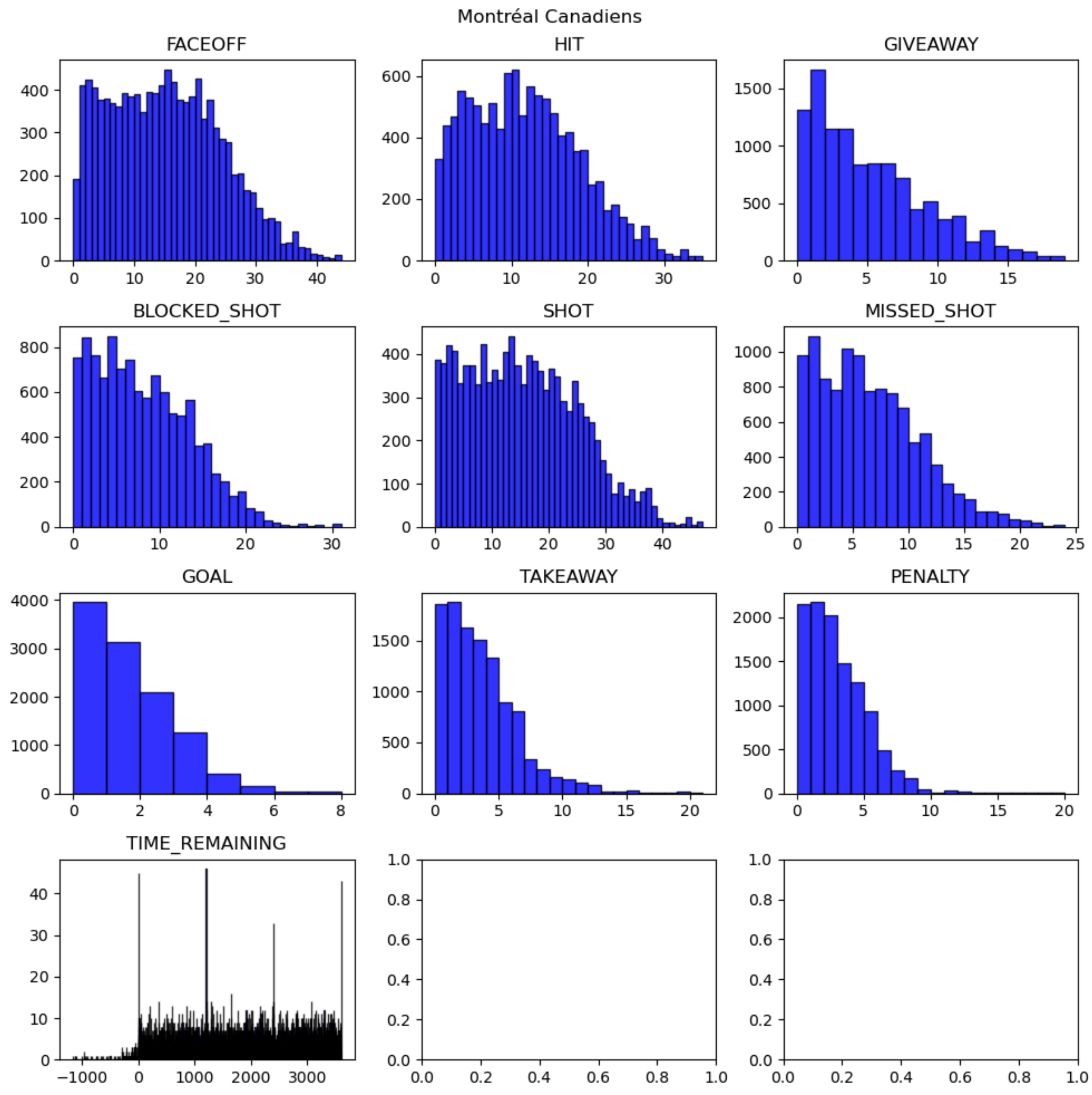
Use a histogram or KDE to visualize the distribution of key variables. Consider log-scaling or other scaling of the axes. How should you think about outliers? Is there a natural scaling for certain variables?

To do this, we can randomly select a few teams and plot the histogram for each feature throughout the whole season. We expect to see a pretty heavy right skew for most of the features. This is because most of the features are counts of events that occur in a game, initially starting at 0.

```
In [ ]:
# Randomly select two teams to plot
team_1 = X_train.TEAM.unique()[0]
team_2 = X_train.TEAM.unique()[1]

# Get the games for the two teams
team_1_games = X_train[X_train.TEAM == team_1]
team_2_games = X_train[X_train.TEAM == team_2]

# Drop the extra columns
team_1_games = team_1_games.drop(columns=['index', 'HOME', 'GAME_ID', 'TEAM'
team_2_games = team_2_games.drop(columns=['index', 'HOME', 'GAME_ID', 'TEAM'

# Plot the hist for the first team.
plot_hist(team_1_games, team_1)
```



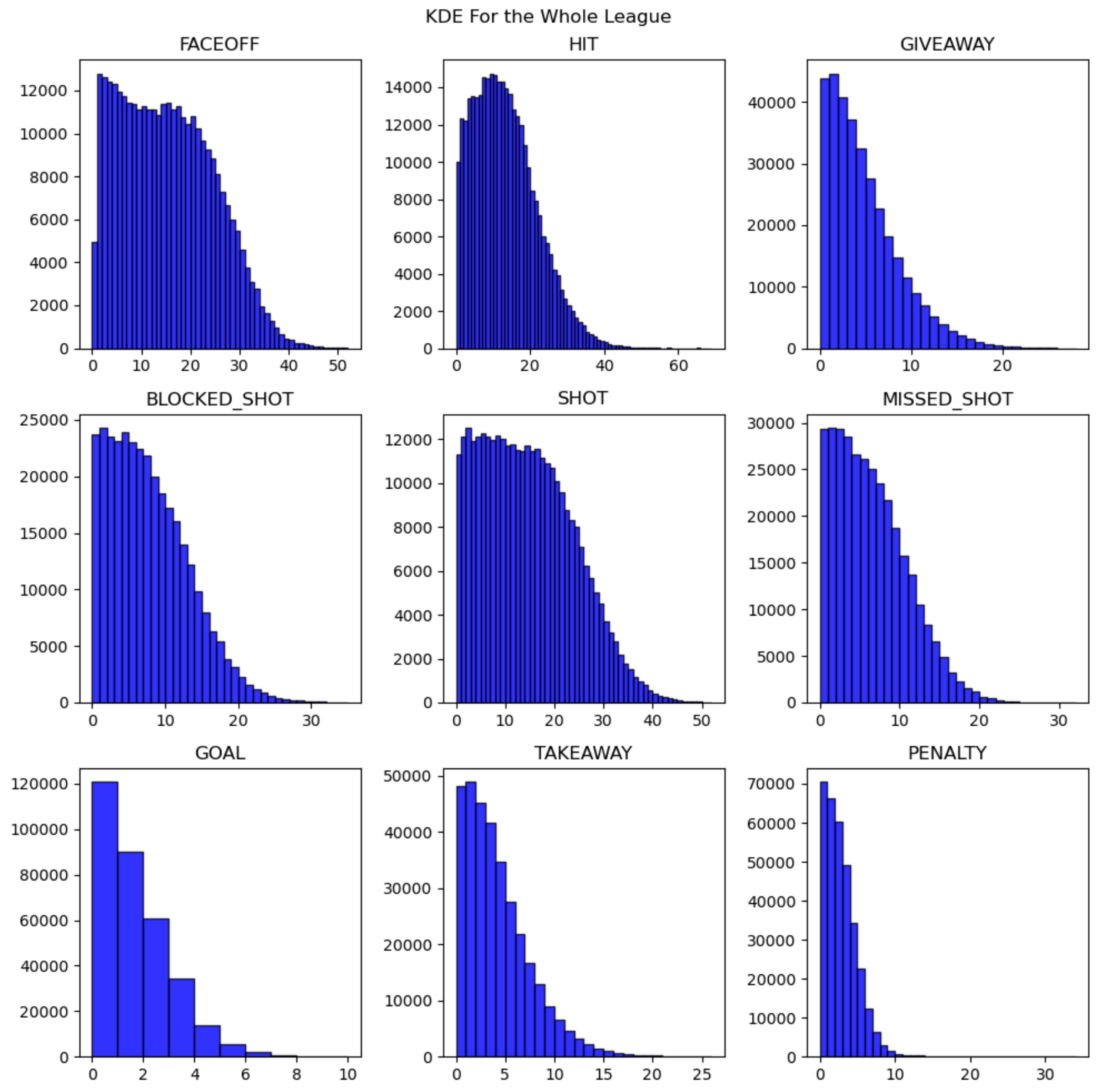
```
In [ ]: # Plot the hist for the second team.
        plot_hist(team_2_games, team_2)
```



For time remaining, negative time corresponds to overtime.

We now look at the distribution of the same features above (excluding time remaining) for all of our data to get a better understanding of the distribution for the whole league.

```
In [ ]: # Plot the whole league.
        league_dists = X_train.drop(columns=['index', 'HOME', 'GAME_ID', 'TEAM', 'TI
        plot_hist(league_dists, 'KDE For the Whole League')
```



7. Relationships

Use 2D and/or 3D plot scatter plots, histograms, or heat maps to look for important relationships between variables. Consider using significance tests, linear model fits, or correlation matrices to clarify relationships.

One of the first things we will do is do a correlation matrix for all of the features. To do this, we will get a subset of data that only includes the ending state vector for each game. We will then do a correlation matrix on this subset of data.

In [ ]:
```
# Get a dataframe that just has the ending state vector for each game in our
# We drop the index, time remaining, and game id columns.
ending_state_per_game = X_train.groupby(['HOME', 'GAME_ID']).tail(1).drop(co

# Convert each of these values to integers
ending_state_per_game = ending_state_per_game.astype(int)
```

```
# Create a correlation matrix for these ending vectors
corr_matrix = ending_state_per_game.drop(columns=['HOME', 'TEAM']).corr()
corr_matrix
```

Out[ ]:

	FACEOFF	HIT	GIVEAWAY	BLOCKED_SHOT	SHOT	MISSE
FACEOFF	1.000000	0.051900	0.063562	0.149849	0.237220	
HIT	0.051900	1.000000	0.000588	0.074176	0.017125	
GIVEAWAY	0.063562	0.000588	1.000000	0.144243	0.058906	
BLOCKED_SHOT	0.149849	0.074176	0.144243	1.000000	0.257282	
SHOT	0.237220	0.017125	0.058906	0.257282	1.000000	
MISSED_SHOT	0.167457	0.074115	0.131860	0.270056	0.257440	
GOAL	0.177765	-0.053945	-0.037907	-0.183110	-0.098345	-
TAKEAWAY	0.068832	0.007997	0.268601	0.113115	0.072667	
PENALTY	0.083485	0.012464	-0.054195	-0.051015	-0.099398	-

Interpreting these results is interesting. None of the variables appear to be highly correlated, with the maximum correlation being 0.270056 being between missed_shot and blocked_shot. But even then, this is not a very high correlation. If we instead create a correlation matrix for every entry (not just the ending state vector), we get:

In [ ]:

```
# Drop unnecessary columns for our problem.
subset_df = X_train.drop(columns=['index', 'GAME_ID', 'HOME', 'TEAM'])

# Convert the dataframe to integers
subset_df = subset_df.astype(int)

# Create a correlation matrix for the subset dataframe
corr_matrix = subset_df.corr()
corr_matrix
```

Out[ ]:

	FACEOFF	HIT	GIVEAWAY	BLOCKED_SHOT	SHOT	MISS
FACEOFF	1.000000	0.734616	0.580440	0.756351	0.843311	
HIT	0.734616	1.000000	0.491475	0.642769	0.692392	
GIVEAWAY	0.580440	0.491475	1.000000	0.539919	0.554279	
BLOCKED_SHOT	0.756351	0.642769	0.539919	1.000000	0.752895	
SHOT	0.843311	0.692392	0.554279	0.752895	1.000000	
MISSED_SHOT	0.742229	0.637414	0.527803	0.696661	0.739660	
GOAL	0.565016	0.421600	0.333994	0.390598	0.482090	
TAKEAWAY	0.588805	0.495005	0.536402	0.542280	0.577913	
PENALTY	0.633922	0.522302	0.379895	0.494675	0.547059	
TIME_REMAINING	-0.911818	-0.801822	-0.627231	-0.799651	-0.881090	

This produces more interesting results. For example, we see that there is a higher correlation between faceoff and shot. This makes sense because if a team wins a faceoff (especially if they are in the opposing teams end) they are much more likely to shoot the puck. In fact, we see a decently high correlation between faceoff and the other types of shots (blocked and missed).

Another interesting correlation is actually the inverse correlation between time remaining and the other features. Before looking at the data, let's talk about what happens when a game is about to end. Typically in the last few minutes of a game, the team that is losing will pull their goalie. This means that they will have an extra attacker on the ice, meaning they are more likely to control the puck. Because of their desperation to score, there is much more action than the rest of the game. So, we expect the team to shoot the puck more (this leads to more blocked shots, shots, and missed shots). This will increase the chance the goalie freezes the puck (stops the play), which results in more faceoffs (everytime the puck is frozen, a faceoff occurs). Now, turning our attention back to the TIME_REMAINING column of our correlation matrix, we see that there is a negative correlation between time remaining and all of the other features. This is exactly what we expect to see.

Another correlation we expect to see is between faceoffs, shots, and goals; takeaways and goals; shots, goals, and wins; and wins and if the team is the home team or not. We will look at these correlations by a few plots.

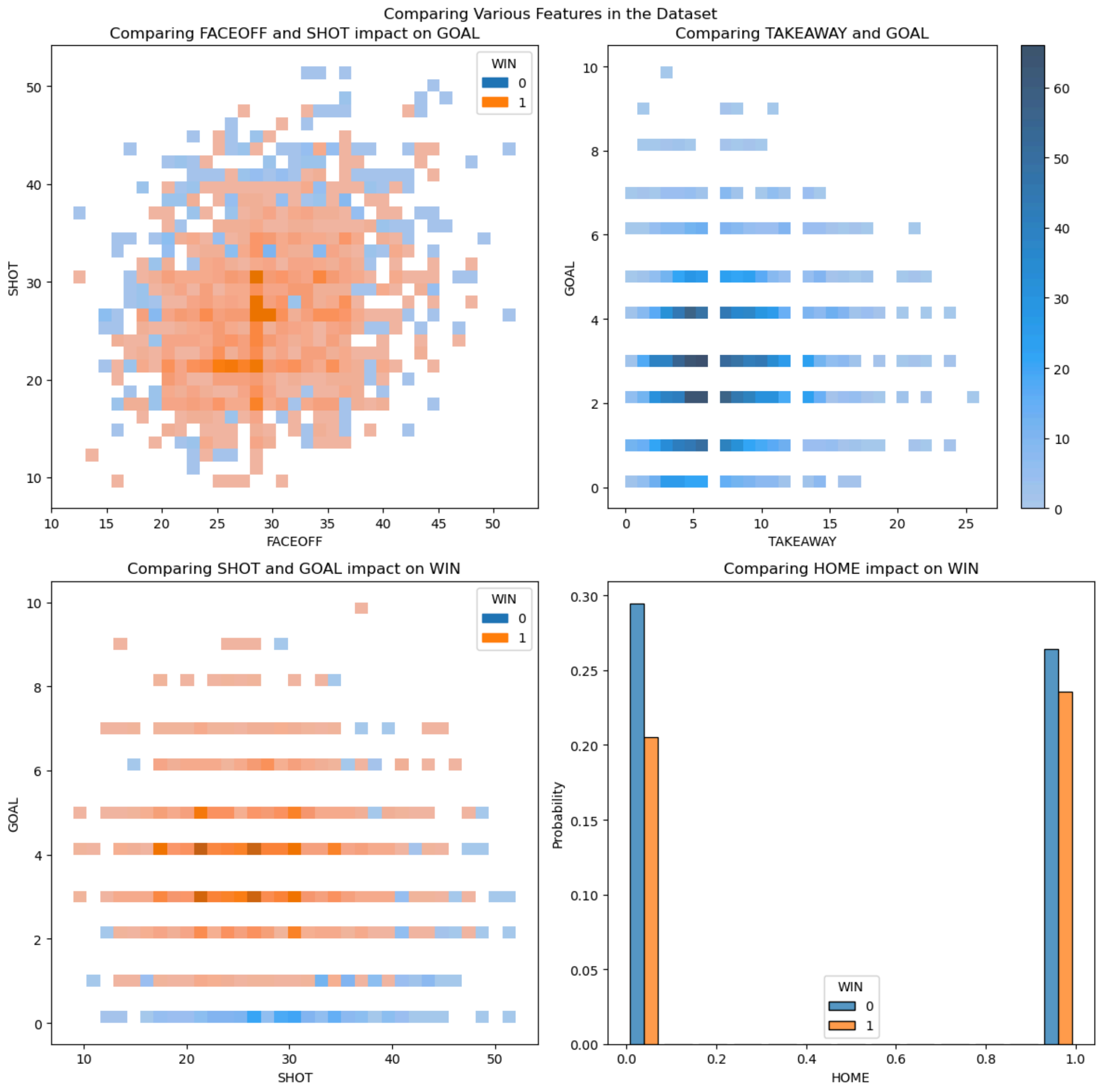
In [ ]:

```python
# Get our working subset.
subset_df = X_train.drop(columns=['index']).copy()

# Merge with our labels (because we are looking at wins).
subset_df['WIN'] = y_train
```

```
# Get the last row for each game.
subset_df = subset_df.groupby(['HOME', 'GAME_ID']).tail(1)

# Create a list of the columns we want to look at.
columns_to_look_at = [['FACEOFF', 'SHOT', 'GOAL'], ['TAKEAWAY', 'GOAL'], ['S
```

In [ ]:

```
# Create 2-d scatter plots for each set of columns.
fig, ax = plt.subplots(2, 2, figsize=(12, 12))
num_cols = 2
for i, columns in enumerate(columns_to_look_at):
    # Get the current row and column
    row = i // num_cols
    col = i % num_cols

    # If we have categorical data, use a histogram
    if i == len(columns_to_look_at) - 1:
        sns.histplot(data=subset_df, x=columns[0], hue=columns[1], multiple=
        ax[row, col].set_title(f'Comparing {columns[0]} impact on WIN')
        continue


    if len(columns) == 3:
        sns.histplot(data=subset_df, x=columns[0], y=columns[1], hue='WIN',
        ax[row, col].set_title(f'Comparing {columns[0]} and {columns[1]} imp
    elif len(columns) == 2:
        sns.histplot(data=subset_df, x=columns[0], y=columns[1], ax=ax[row,
        ax[row, col].set_title(f'Comparing {columns[0]} and {columns[1]}')

plt.suptitle('Comparing Various Features in the Dataset')
plt.tight_layout()
plt.show()
```



The bottom right plot would seem to suggest that you are more likely to lose both home and away, which doesn't make sense, however, this is a sum of the final outcome based on every recorded event, and there are more away events than home, so more overall loss events than win events overall. In summary, the bottom right histogram is a bad way of displaying the data, but doesn't show any apparent error in the data.

8. Model selection

Does what you see change any of your ideas for what models might be appropriate? Among other things, if your models rely on specific assumptions, is there a way you can check if these assumptions actually hold by looking at the data? If you are using linear models, do the relevant plots look linear? Is there some other scaling where the model assumptions might more nearly hold?

Looking at and analyzing our data, the question we want to analyze becomes clearer to us. As we see above, we have clear time series for games that are updated whenever an event is recorded. So the question that we want to answer on the data, is given a current 'state', what is the probability that the home team wins? This is can be formulated as $P(\mathrm{win}|x_t)$ where x_t corresponds to the current state vector of all the events shown above. We can use several different predictive methods for this question, such as random forests or logistic regression. We are also interested in sampling from this 'posterior' distribution using MCMC methods, or forecasting treating the 'probability' as a hidden state and the state vector as the observed state

Appendix: Helper Functions

In [ ]:
```
def get_data(df, game_id):
    """
    Extracts and organizes event data for a specific game.

    Args:
    df (DataFrame): The DataFrame containing the game data.
    game_id (int): The ID of the game to retrieve data for.

    Returns:
    tuple: A tuple containing two DataFrames, one for home team events and o
    """

    # Filter the DataFrame to get data for the specified game and drop rows
    game1 = df[df.game_id == game_id]
    game1 = game1.dropna(subset=['event_team_type'])

    # Get unique event types (excluding CHANGE)
    event_types = game1.event_type.unique()
    event_types = np.delete(event_types, np.where(event_types == 'CHANGE'))
    event_types = np.append(event_types, ['TIME_REMAINING', 'HOME', 'WIN', '

    # Create dictionaries to store event counts for home and away teams
    home_dict = {event: 0 for event in event_types}
    away_dict = {event: 0 for event in event_types}

    # Create DataFrames to store event data for home and away teams
    home_df = pd.DataFrame(columns=home_dict.keys())
    away_df = pd.DataFrame(columns=away_dict.keys())

    # Iterate through the events in the game and count them
    for _, row in game1.iterrows():
        # Skip events with NaN event_team_type or events of type CHANGE
        if pd.isnull(row['event_team_type']) or row['event_type'] == 'CHANGE
            continue

        # Determine if the event belongs to the home or away team and update
        if row['event_team_type'] == 'home':
            home_dict[row['event_type']] += 1
            home_dict['TIME_REMAINING'] = row['game_seconds_remaining']
            home_dict['HOME'] = 1
            home_dict['WIN'] = 1 if row['home_final'] > row['away_final'] el
            home_dict['TEAM'] = row['team_encoded']
            home_dict['GAME_ID'] = game_id
            home_df = home_df.append(home_dict, ignore_index=True)
        else:
            away_dict[row['event_type']] += 1
            away_dict['TIME_REMAINING'] = row['game_seconds_remaining']
            away_dict['HOME'] = 0
            away_dict['WIN'] = 1 if row['home_final'] < row['away_final'] el
            away_dict['TEAM'] = row['team_encoded']
            away_dict['GAME_ID'] = game_id
            away_df = away_df.append(away_dict, ignore_index=True)

    return home_df, away_df


def get_label_encoder(teams):
    le = LabelEncoder()
    le.fit(teams)
    return le


def plot_game(team, team_id):
    """
    Plot the data for a given team.

    Parameters:
        team (DataFrame): The data for the team to be plotted.
        team_id (int): The ID of the team.

    Returns:
        None: This function displays the plot but does not return any value.
    """

    # Get the columns we need to plot.
    plot_names = team.columns

    # Get the number of rows and columns necessary for the plot
    num_cols = 3
    num_rows = len(plot_names) // num_cols + 1 if len(plot_names) % num_cols

    # Create the plot
    fig, ax = plt.subplots(num_rows, num_cols, figsize=(10, 10))

    # Get x-axis values
    x = range(len(team))

    # Iterate through the columns and plot them
    for i, column in enumerate(plot_names):
        row = i // num_cols
        col = i % num_cols
        ax[row, col].plot(x, team[column])
        ax[row, col].set_title(column)
        ax[row, col].set_xlabel('Time')
        ax[row, col].set_ylabel('Count')

    # Set the title
    fig.suptitle(label_encoder.inverse_transform([team_id])[0])  # Assuming
    plt.tight_layout()
    plt.show()


def plot_hist(team, team_id, normalize=False):
    """
    Plot Histogram Density plots for each column of the team data.

    Parameters:
        team (DataFrame): The data for the team to be plotted.
        team_id (int): The ID of the team.

    Returns:
        None: This function displays the plot but does not return any value.
    """

    # Get the columns we need to plot.
    plot_names = team.columns

    # Get the number of rows and columns necessary for the plot
    num_cols = 3
    num_rows = len(plot_names) // num_cols + 1 if len(plot_names) % num_cols

    # Create the plot
    fig, ax = plt.subplots(num_rows, num_cols, figsize=(10, 10))

    # Iterate through the columns and plot the KDE for each
    for i, column in enumerate(plot_names):
        row = i // num_cols
        col = i % num_cols

        # Plot the histogram
        ax[row, col].hist(team[column], bins=len(team[column].unique())-1, a
        ax[row, col].set_title(column)

    # Set the main title of the plot
    if type(team_id) == str:
        fig.suptitle(team_id)
    else:
        plt.suptitle(label_encoder.inverse_transform([team_id])[0])  # Assum

    # Adjust layout and display the plot
    plt.tight_layout()
    plt.show()
```