Predicting Pitch Outcomes for Major League Pitchers in 2024

Introduction to Data Science | Fall 2024

Sara Clokey

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Quick Survey!

Data Science in Baseball

- Relatively new phenomenon - last 20 years
- Sabermetrics: "the search for objective knowledge about baseball" (Costa, Huber, and Saccoman (2019))
- First wave: developing new statistics (Tango, Lichtman, and Dolphin (2007))
- Second wave: advanced tracking technology (Healey (2017))
- Third (current) wave: using models for predicting player performance

Research Question at Hand

- How can we predict pitch outcomes using sabermetric variables?
- How can we assess relative pitcher performance?

Data

- Pitch level data from Major League Baseball for the first half of the 2024 season ("CSAS 2025: Data Challenge" (2024))
- After processing:
  - Over 343,000 data points
  - 68 variables
- Potential limitation

Baseball Basics

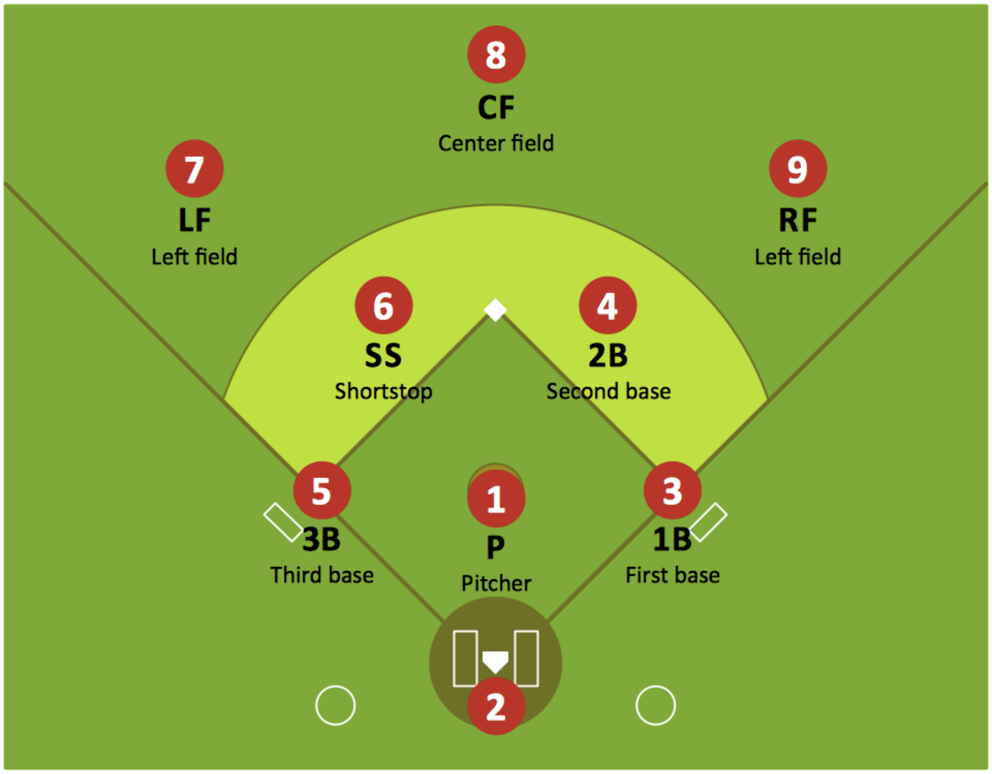


Figure 1: Baseball Field Positioning

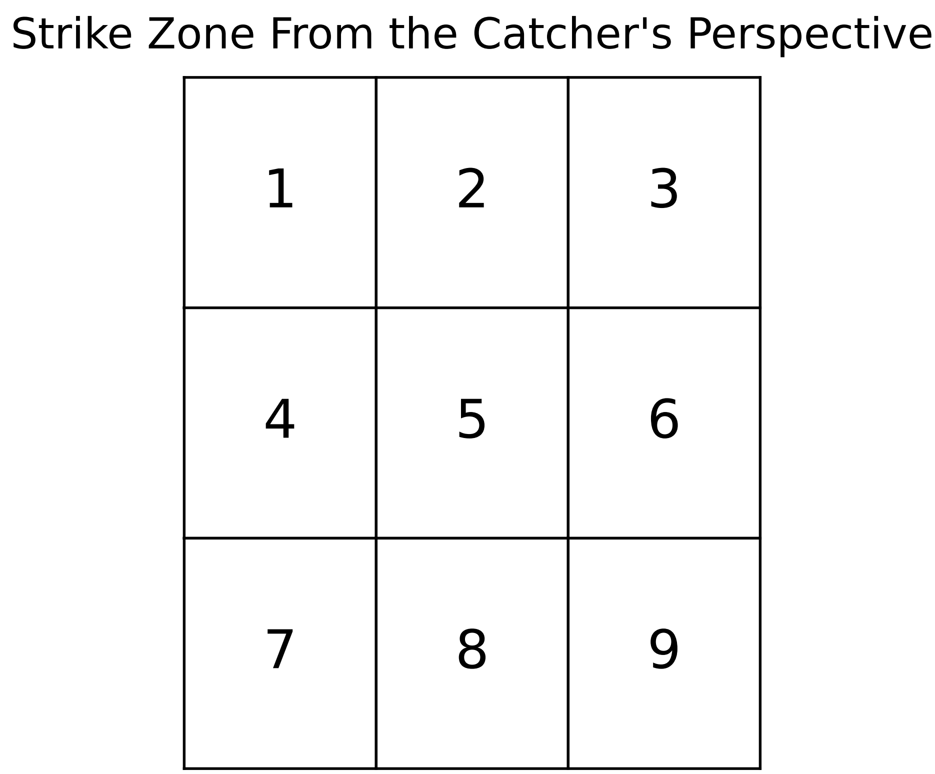
Defining Pitch Outcomes

- The result of every pitch
  - If batter hits the ball:
    * fielded out (ball is caught or thrown to a base)
    * hit
  - If batter does not hit the ball:
    * ball (called by umpire outside of the strike zone)
    * strike (called by umpire inside the strike zone or batter swings and misses)

Pitch Zone Visualization

```
import matplotlib.pyplot as plt

fig, axs = plt.subplots(3, 3, figsize=(3, 4),
```

```
                                gridspec_kw={'wspace': 0, 'hspace': 0})

fig.suptitle("Strike Zone From the Catcher's Perspective", fontsize=16)

axs[0, 0].text(0.5, 0.5, '1', fontsize=20, ha='center', va='center')
axs[0, 1].text(0.5, 0.5, '2', fontsize=20, ha='center', va='center')
axs[0, 2].text(0.5, 0.5, '3', fontsize=20, ha='center', va='center')

axs[1, 0].text(0.5, 0.5, '4', fontsize=20, ha='center', va='center')
axs[1, 1].text(0.5, 0.5, '5', fontsize=20, ha='center', va='center')
axs[1, 2].text(0.5, 0.5, '6', fontsize=20, ha='center', va='center')

axs[2, 0].text(0.5, 0.5, '7', fontsize=20, ha='center', va='center')
axs[2, 1].text(0.5, 0.5, '8', fontsize=20, ha='center', va='center')
axs[2, 2].text(0.5, 0.5, '9', fontsize=20, ha='center', va='center')

for ax in axs.flat:
    ax.set_xticks([])
    ax.set_yticks([])

for ax in axs.flat:
    for _, spine in ax.spines.items():
        spine.set_visible(True)
        spine.set_linewidth(1)
        spine.set_edgecolor('black')

plt.tight_layout(pad=0)
plt.subplots_adjust(top=0.9)
plt.show()
```

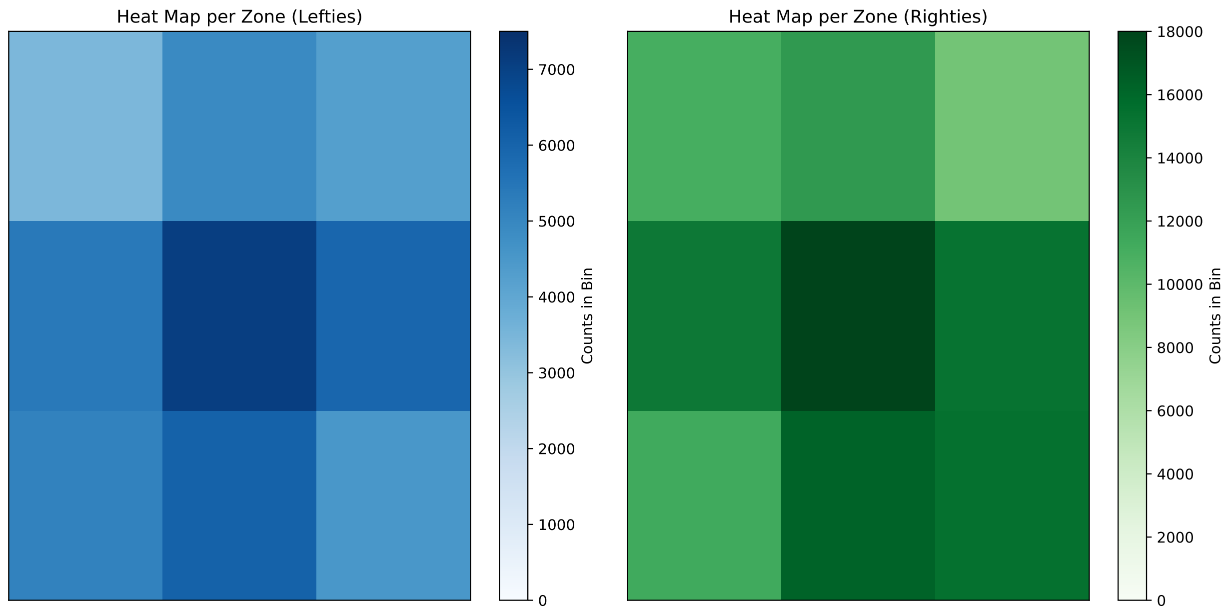


Pitch Zone Usage in MLB Data

```python
import os
import pandas as pd
import pyarrow as pa

file_path = (
    'data/statcast_pitch_swing_data_20240402_20240630.arrow'
)

table = pa.ipc.open_file(file_path).read_all()

df = table.to_pandas()

df.rename(columns={'type': 'category'}, inplace=True)

missing_percentage = df.isnull().mean() * 100

high_missing_columns = missing_percentage[missing_percentage >= 65].index
```

```python
df = df.drop(high_missing_columns, axis=1)

df = df.drop(['bat_speed', 'swing_length'], axis=1)


are_fielder2_equal = (df['fielder_2'] == df['fielder_2_1']).all()

df = df.drop(['game_year', 'fielder_2_1'], axis=1)

out_of_range = df[(df['release_speed'] < 60) | (df['release_speed'] > 105)]
unique_out_of_range = out_of_range['release_speed'].unique()

df.drop(
    df[(df['release_speed'] < 60) | (df['release_speed'] > 105)].index,
    inplace=True
)

unique_home_teams = df['home_team'].unique()

unique_away_teams = df['away_team'].unique()

clean_df = df.dropna()

def assign_x_coord(row):
    if row.zone in [1, 4, 7]:
        return 1
    if row.zone in [2, 5, 8]:
        return 2
    if row.zone in [3, 6, 9]:
        return 3

def assign_y_coord(row):
    if row.zone in [1, 2, 3]:
        return 3
    if row.zone in [4, 5, 6]:
        return 2
    if row.zone in [7, 8, 9]:
        return 1

clean_df_zones = clean_df.copy().loc[df.zone <= 9]

clean_df_zones['zone_x'] = clean_df_zones.apply(assign_x_coord, axis=1)
clean_df_zones['zone_y'] = clean_df_zones.apply(assign_y_coord, axis=1)
```

```python
clean_df_lefties = clean_df_zones[clean_df_zones['p_throws'] == 'L']
clean_df_righties = clean_df_zones[clean_df_zones['p_throws'] == 'R']

plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
plt.hist2d(
    clean_df_lefties.zone_x, clean_df_lefties.zone_y, bins=3, cmap='Blues',
    vmin=0, vmax=7500
)
plt.title('Heat Map per Zone (Lefties)')
plt.gca().get_xaxis().set_visible(False)
plt.gca().get_yaxis().set_visible(False)
cb_left = plt.colorbar()
cb_left.set_label('Counts in Bin')


plt.subplot(1, 2, 2)
plt.hist2d(
    clean_df_righties.zone_x, clean_df_righties.zone_y, bins=3, cmap='Greens',
    vmin=0, vmax=18000
)
plt.title('Heat Map per Zone (Righties)')
plt.gca().get_xaxis().set_visible(False)
plt.gca().get_yaxis().set_visible(False)
cb_right = plt.colorbar()
cb_right.set_label('Counts in Bin')

plt.tight_layout()
plt.show()
```



Pitch Groups

- Create groups based on the goal of a pitch
- Fastballs: focus on velocity
- Breaking balls: focus on horizontal and vertical movement
- Offspeed: focus on disrupting batter's timing
- Knuckleball: focus on a lack of spin

Velocity

- The maximum speed of a given pitch at any point from its release to the time it crosses home plate
- Measured in miles per hour (MPH)
- Focus of fastball group

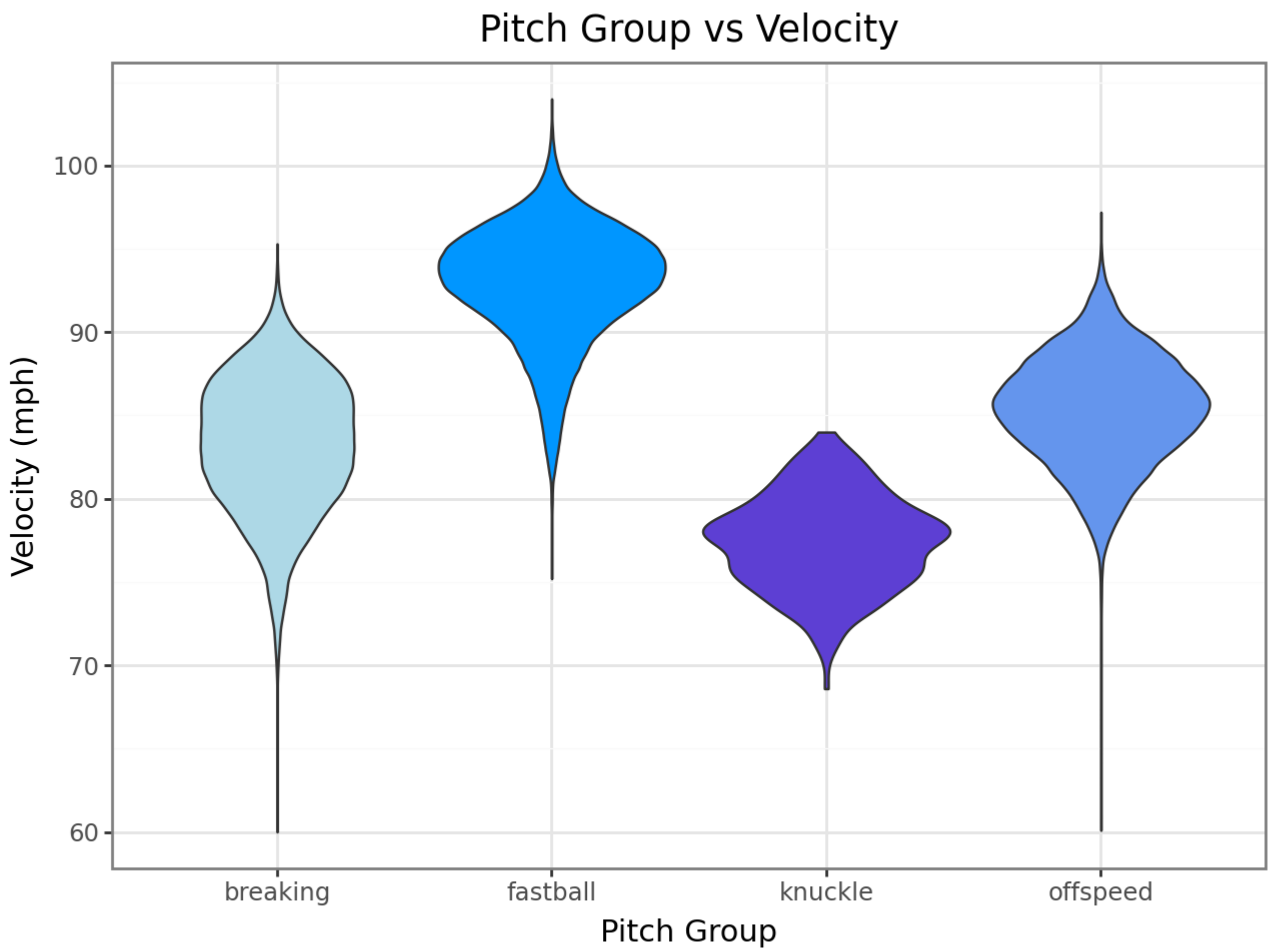
Velocity in MLB Data

```
bad_events = ['single', 'walk', 'home_run', 'double', 'field_error',
              'hit_by_pitch', 'catcher_interf', 'triple', 'sac_fly',
              'sac_bunt', 'stolen_base_2b']
good_events = ['strikeout', 'field_out', 'force_out',
               'grounded_into_double_play', 'double_play', 'fielders_choice',
               'caught_stealing_home', 'fielders_choice_out',
```

```
               'caught_stealing_2b', 'strikeout_double_play',
               'caught_stealing_3b', 'other_out',
               'pickoff_caught_stealing_home', 'pickoff_caught_stealing_3b',
               'pickoff_3b', 'sac_fly_double_play', 'pickoff_1b', 'triple_play']

def classify_pitch_outcome(row):
    if row['events'] in bad_events or row['category'] == 'B':
        return '0'
    elif row['events'] in good_events or row['category'] == 'S':
        return '1'
    else:
        return 'None'

clean_df['pitch_outcome'] = clean_df.apply(classify_pitch_outcome, axis=1)

clean_df = clean_df.drop(
    clean_df[clean_df['pitch_type'].isin(['PO', 'EP', 'FA', 'CS'])].index
)

outcome_counts = clean_df['pitch_outcome'].value_counts()

pitch_group_mapping = {
    'FC': 'fastball', 'FF': 'fastball', 'FS': 'fastball', 'SI': 'fastball',
    'FO': 'fastball', 'SL': 'breaking', 'ST': 'breaking', 'CU': 'breaking',
    'SC': 'breaking', 'KC': 'breaking', 'SV': 'breaking', 'CH': 'offspeed',
    'KN': 'knuckle'
}

clean_df['pitch_group'] = clean_df['pitch_type'].apply(
    lambda x: pitch_group_mapping.get(x, 'unknown')
)

from plotnine import *

clean_filtered_df = clean_df[clean_df['pitch_group'] != 'unknown']

colors = ['#ADD8E6', '#0096FF', '#5D3FD3', '#6495ED']

violin_plot = (
    ggplot(clean_filtered_df,
           aes(x='pitch_group', y='release_speed', fill='pitch_group'))
    + geom_violin(show_legend=False)
    + scale_fill_manual(values=colors)
    + labs(title='Pitch Group vs Velocity', x='Pitch Group', y='Velocity (mph)')
```

```
    + theme_bw()
)

violin_plot.show()
```

```
C:\Users\18607\AppData\Local\Temp\ipykernel_13680\2694131178.py:20: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/ind
```



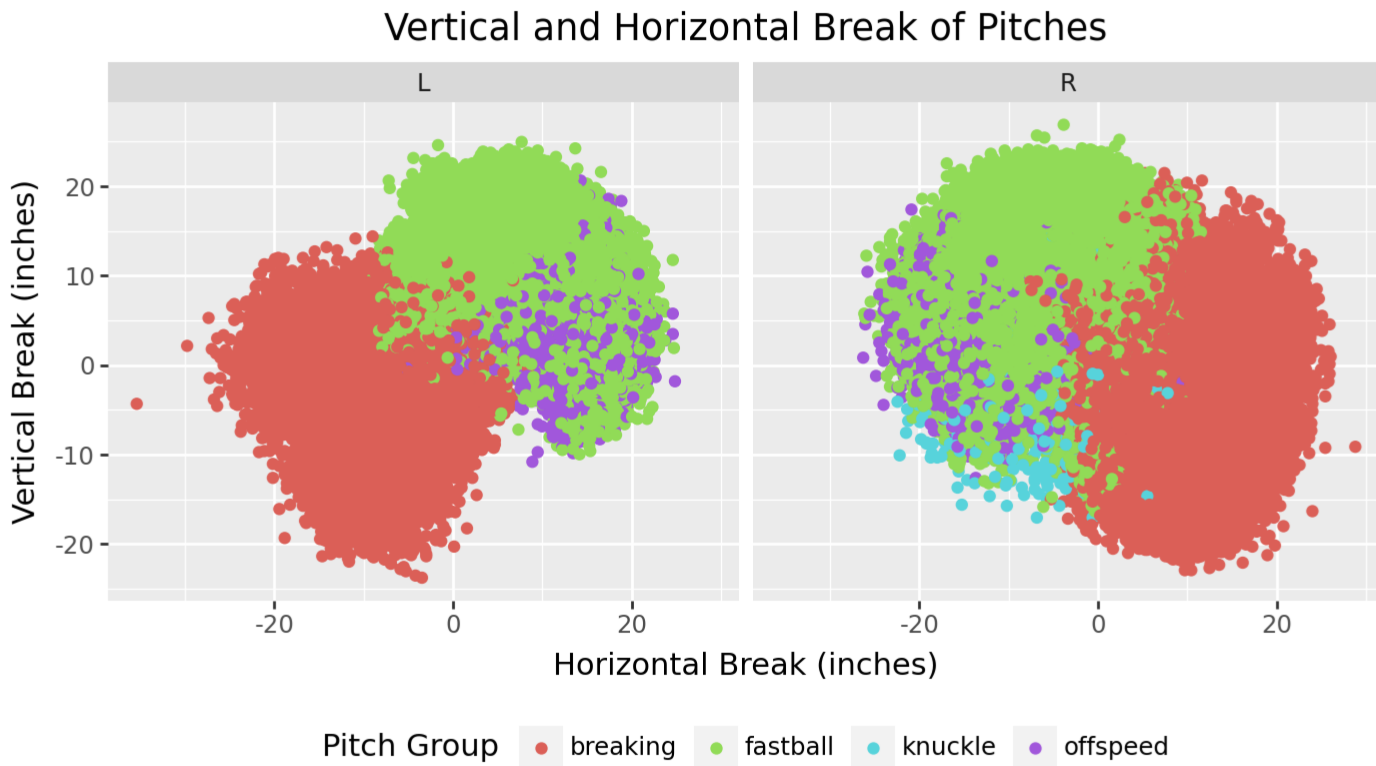
Break

- Horizontal break: distance, in inches, of lateral movement that a pitcher imparts on a ball (Maschino (2023))

- Induced vertical break: distance, in inches, of vertical movement that a pitcher imparts on a ball (Maschino (2023))
    - considered in a vaccuum due to gravity
- Focus of breaking balls pitch group

Break in MLB Data

```
clean_df['pfx_x'] = clean_df['pfx_x'] * 12
clean_df['pfx_z'] = clean_df['pfx_z'] * 12

(ggplot(clean_df, aes(x='pfx_x', y='pfx_z', color='pitch_group')) +
    geom_point() +
    labs(title='Vertical and Horizontal Break of Pitches',
         x='Horizontal Break (inches)',
         y='Vertical Break (inches)',
         color='Pitch Group') +
    coord_fixed(ratio=1) +
    theme(figure_size=(7, 5), legend_position='bottom') +
    facet_wrap('~p_throws')
)
```



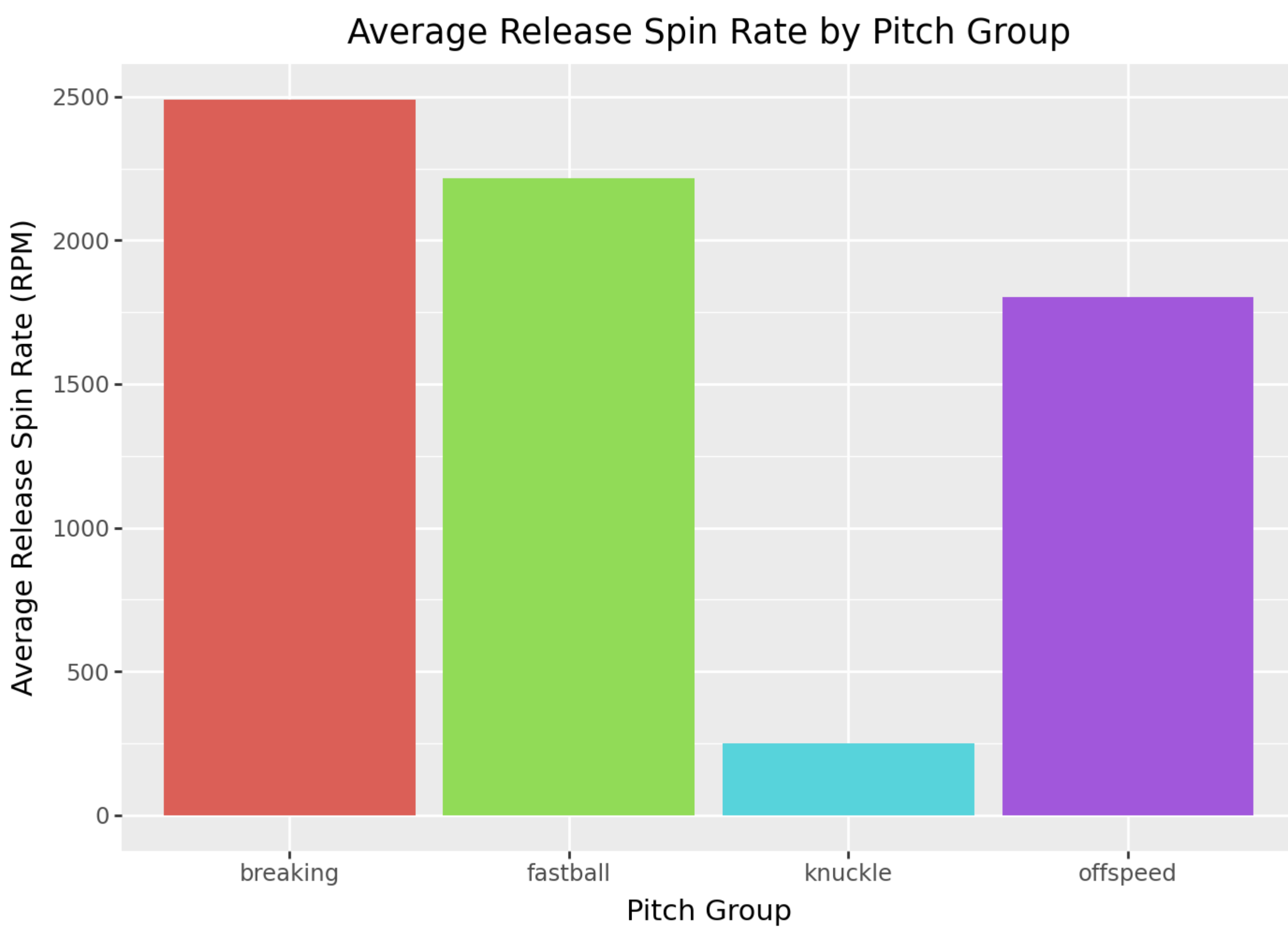
Spin Rate

- Rate of spin on a baseball after it is released in revolutions per minute (RPM)
  - RPM changes pitch trajectory; same pitch with same velocity will end up in a different place depending on how much it spins ("Spin Rate (SR)" (2024))
- Focus of knuckleball pitch group
  - Aim for lowest possible RPM

Spin Rate in MLB Data

```
avg_spin_rate_by_pitch_group = clean_filtered_df.groupby('pitch_group')[
    'release_spin_rate'].mean().reset_index()
```

```
(ggplot(avg_spin_rate_by_pitch_group,
        aes(x='pitch_group', y='release_spin_rate', fill='pitch_group'))
 + geom_bar(stat='identity', show_legend=False)
 + labs(
     title='Average Release Spin Rate by Pitch Group',
     x='Pitch Group',
     y='Average Release Spin Rate (RPM)'
   )
 + theme(figure_size=(7, 5), legend_position='bottom')
)
```



Revisiting Pitch Outcome Definition

- After analyzing some aspects of pitch performance, let's see if they affect pitch outcome
- Considered from pitcher's perspective
  - positive events sorted as 1s
  - negative events sorted as 0s
- Result is a binary variable to be predicted through model building
- Potential limitation

Prediction Model

- Using LASSO logistic regression (Tibshirani (1996))
  - Binary variable
  - Variable reduction, overfitting prevention, interpretable
- Determine if existing variables can predict whether pitch outcome is positive or negative from the pitcher's perspective

Model Results

- LASSO logistic model validation with best parameters:

```
categorical_col = [
    'pitch_type',
    'stand',
    'p_throws',
    'home_team',
    'away_team',
    'bb_type',
    'inning_topbot',
    'if_fielding_alignment',
    'of_fielding_alignment',
    'pitch_group'
]

numerical_col = [
    'release_speed', 'release_pos_x', 'release_pos_z', 'batter', 'pitcher',
    'zone', 'balls', 'strikes', 'pfx_x', 'pfx_z', 'plate_x', 'plate_z',
    'outs_when_up', 'inning', 'sz_top', 'sz_bot', 'release_spin_rate',
    'release_extension', 'game_pk', 'release_pos_y', 'at_bat_number',
    'pitch_number', 'home_score', 'away_score', 'bat_score', 'fld_score',
    'spin_axis'
```

```
]

from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
import numpy as np

numerical_transformer = StandardScaler()

categorical_transformer = OneHotEncoder()

preprocessor = ColumnTransformer(
    transformers=[
        ('cat', categorical_transformer, categorical_col),
        ('num', numerical_transformer, numerical_col)
    ]
)

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline

pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(penalty='l1', solver='saga',
                                      max_iter=1000))
])

X = X = clean_df[numerical_col + categorical_col]
y = clean_df['pitch_outcome']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=1918)

pipeline.fit(X_train, y_train)

model = pipeline.named_steps['classifier']
intercept = model.intercept_
coefficients = model.coef_[0]

from sklearn.metrics import (
    recall_score, precision_score, f1_score, accuracy_score, confusion_matrix
)

y_pred = pipeline.predict(X_test)
```

```python
y_test = y_test.astype(int)
y_pred = y_pred.astype(int)

accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred, average='binary')
precision = precision_score(y_test, y_pred, average='binary')
f1 = f1_score(y_test, y_pred, average='binary')
cm = confusion_matrix(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")
print(f"F1 Score: {f1}")
print("Confusion Matrix:")
print(cm)
```

```
Accuracy: 0.7816103669190448
Recall: 0.731134320134245
Precision: 0.8725490196078431
F1 Score: 0.7956066118855866
Confusion Matrix:
[[24489  4264]
 [10735 29192]]
```

Coefficients associated with pitch groups:

```python
pipeline.fit(X_train, y_train)

categorical_transformer = pipeline.named_steps['preprocessor'].transformers_[0][1]

categorical_feature_names = categorical_transformer.get_feature_names_out(
    categorical_col
)

all_feature_names = numerical_col + list(categorical_feature_names)

feature_importance = pd.DataFrame({
    'Feature': all_feature_names,
    'Coefficient': coefficients
})

feature_importance['Abs_Coefficient'] = feature_importance['Coefficient'].abs()
```

```python
pitch_group_features = [
    feature for feature in categorical_feature_names if 'pitch_group' in feature
]

feature_importance_pitch_group = feature_importance[
    feature_importance['Feature'].isin(pitch_group_features)
]

print(feature_importance_pitch_group[['Feature', 'Coefficient',
                                      'Abs_Coefficient']])
```

```
                 Feature  Coefficient  Abs_Coefficient
117  pitch_group_breaking     0.010833         0.010833
118  pitch_group_fastball     0.002829         0.002829
119   pitch_group_knuckle     0.027161         0.027161
120  pitch_group_offspeed     0.019792         0.019792
```

Results Interpretation

- Overall, this model predicts pitch outcome correctly 78.2% of the time
- The pitch group variable seems to have a meaningful contribution to this prediction capability
- Based on these results, we can use pitch group sabermetrics (velocity and break) to help assess relative pitcher performance

K-Means Clustering Assessment

- Strategy used to help pitchers "maximize their effectiveness" (Andrews et al. (2021))
- Groups players with similar break and velocity tendencies
- Sort those groups into relative rankings to find pitcher priorities

Pitchers Prioritizing Movement

- Pitches in the top 30% for both horizonal and vertical break but in the bottom 20% for velocity
- The 5 pitchers with the most pitches that fit this criteria:

```python
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

features = clean_df[['release_speed', 'pfx_x', 'pfx_z']]
```

```python
features = pd.get_dummies(features, drop_first=True)

scaler = StandardScaler()
scaled_features = scaler.fit_transform(features)

pca = PCA(n_components=2)
pca_components = pca.fit_transform(scaled_features)

kmeans = KMeans(n_clusters=5, random_state=1918)
clean_df['cluster'] = kmeans.fit_predict(pca_components)

clean_df.loc[:, 'velocity_rank'] = clean_df.groupby('cluster')['release_speed']\
    .rank(pct=True)
clean_df.loc[:, 'hbreak_rank'] = clean_df.groupby('cluster')['pfx_x']\
    .rank(pct=True)
clean_df.loc[:, 'vbreak_rank'] = clean_df.groupby('cluster')['pfx_z']\
    .rank(pct=True)

clean_df.loc[:, 'vbreak_decile'] = (clean_df['vbreak_rank'] * 10).astype(int)
clean_df.loc[:, 'velocity_decile'] = (clean_df['velocity_rank'] * 10).astype(int)
clean_df.loc[:, 'hbreak_decile'] = (clean_df['hbreak_rank'] * 10).astype(int)

clean_df['velocity_improvement_candidate'] = (
    (clean_df['vbreak_decile'] >= 3) &
    (clean_df['hbreak_decile'] >= 3) &
    (clean_df['velocity_decile'] <= 2)
)

velocity_improvement_candidates = clean_df[clean_df[
    'velocity_improvement_candidate'] == True].copy()

velocity_improvement_candidates_sorted = (
    velocity_improvement_candidates.sort_values(by='pitcher')
)

top_5_velocity_improvement_pitchers = velocity_improvement_candidates_sorted[
    'pitcher'].value_counts().head(5)

print("Top 5 Pitchers Prioritizing Movement:")
print(top_5_velocity_improvement_pitchers)
```

```
Top 5 Pitchers Prioritizing Movement:
pitcher
542881    1072
```

```
596295     745
676710     686
594902     676
684007     655
Name: count, dtype: int64
```

Pitcher Names - Prioritizing Movement

- 542881: Tyler Anderson
- 596295: Austin Gomber
- 676710: Kutter Crawford
- 594902: Ben Lively
- 684007: Shota Imanaga ("MLBAMIDs for Active MLB Players" (2024))

Pitchers Prioritizing Velocity

- Pitches in the top 20% for velocity but the bottom 30% for both horizonal and vertical break
- The 5 pitchers with the most pitches that fit this criteria:

```
clean_df['break_improvement_candidate'] = (
    (clean_df['vbreak_decile'] <= 3) &
    (clean_df['hbreak_decile'] <= 3) &
    (clean_df['velocity_decile'] >= 8)
)

break_improvement_candidates = clean_df[clean_df[
    'break_improvement_candidate'] == True].copy()

break_improvement_candidates_sorted = break_improvement_candidates.sort_values(
    by='pitcher')

top_5_break_improvement_pitchers = break_improvement_candidates_sorted[
    'pitcher'].value_counts().head(5)

print("\nTop 5 Pitchers Prioritizing Velocity:")
print(top_5_break_improvement_pitchers)
```

```
Top 5 Pitchers Prioritizing Velocity:
pitcher
667755    518
665625    367
666974    364
```

```
694973    358
656557    331
Name: count, dtype: int64
```

Pitcher Names - Prioritizing Velocity

- 667755: Jose Soriano
- 665625: Elvis Peguero
- 666974: Yennier Cano
- 694973: Paul Skenes
- 656557: Tanner Houck ("MLBAMIDs for Active MLB Players" (2024))

Results Interpretation

- Players prioritizing movement average 1.45 home runs per game and an earned run average (ERA) of 3.93 ("Baseball Stats & History" (2024))
  - Need significant zone control
- Players prioritizing velocity average 0.65 home runs per game and an ERA of 2.93 ("Baseball Stats & History" (2024))
  - Generally considered elite pitchers in 2024
  - Average shorter stints in-game: arm fatigue

Conclusions

- Pitch outcome can be predicted with relative success using sabermetric statistics
- Among those meaningful predictors, sabermetrics regarding pitch differentiation (velocity and break) demonstrate clear performance differences between pitchers

References

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