Player Report

February 19, 2020

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.patches as patches
import seaborn as sns
%matplotlib inline

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report,␣
↪precision_recall_curve, auc, matthews_corrcoef, accuracy_score
from sklearn.pipeline import Pipeline

from xgboost import XGBClassifier
```

[2]:
```
train_df = pd.read_csv('../Data/2020-train.csv')
```

[3]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 582205 entries, 0 to 582204
Data columns (total 36 columns):
pitcher_id              582205 non-null object
pitcher_side            582205 non-null object
batter_id               582205 non-null object
batter_side             582205 non-null object
stadium_id              582205 non-null object
umpire_id               582205 non-null object
catcher_id              582205 non-null object
inning                  582205 non-null int64
top_bottom              582205 non-null int64
outs                    582053 non-null float64
balls                   582205 non-null int64
strikes                 582205 non-null int64
release_speed           582093 non-null float64
vert_release_angle      582093 non-null float64
horz_release_angle      582093 non-null float64
spin_rate               573194 non-null float64
spin_axis               582093 non-null float64
```

```
tilt                      580953 non-null object
rel_height                582093 non-null float64
rel_side                  582093 non-null float64
extension                 582093 non-null float64
vert_break                582093 non-null float64
induced_vert_break        582093 non-null float64
horz_break                582093 non-null float64
plate_height              582139 non-null float64
plate_side                582139 non-null float64
zone_speed                582093 non-null float64
vert_approach_angle       582093 non-null float64
horz_approach_angle       582093 non-null float64
zone_time                 582093 non-null float64
x55                       582093 non-null float64
y55                       582205 non-null int64
z55                       582093 non-null float64
pitch_type                581720 non-null object
pitch_call                582205 non-null object
pitch_id                  582205 non-null object
dtypes: float64(20), int64(5), object(11)
memory usage: 159.9+ MB
```

So we're looking at a specific catcher here and his pitch receiving skills, let's pick him out and see how big our data set is.

[4]:
```python
player_df = train_df[train_df['catcher_id'] == 'f06c9fdf']
player_df
```

[4]:
```
       pitcher_id pitcher_side batter_id batter_side stadium_id umpire_id  \
35       f4414aa0         Left  f57085ec       Right   43dd6efb  a86853a2
256      ed8aa16f        Right  fbc0970f       Right   45b7bf7c  c229ef9e
353      0d8afd1d         Left  1813cf1c        Left   d0e0eb76  9c02aab4
397      870b67d9        Right  2d75ea3e       Right   43dd6efb  d057fd71
418      f58fcfef        Right  277ee019       Right   d0e0eb76  5d49d16c
…             …           …         …           …          …         …
581483   309f3c2d        Right  675b0ce5        Left   d0e0eb76  5d49d16c
581503   fe642525        Right  76c0475e       Right   a5ce1bf6  b0106fa5
581550   12b0433b        Right  d59d0d36        Left   d0e0eb76  4e713444
581864   d8352da3        Right  daa1322d       Right   934c75c6  51a1c7ee
582073   309f3c2d        Right  0e9cc95b        Left   0c59f5af  3007964d

       catcher_id  inning  top_bottom  outs  …  zone_speed  \
35       f06c9fdf       9           1   1.0  …   83.303299
256      f06c9fdf       5           2   0.0  …   78.985100
353      f06c9fdf       8           1   0.0  …   73.143700
397      f06c9fdf       6           1   0.0  …   83.313301
418      f06c9fdf       7           1   1.0  …   83.698898
…             …       …           …     …   …  …         …
```

```
581483   f06c9fdf        1           1   1.0  …   90.457703
581503   f06c9fdf        7           2   1.0  …   82.521301
581550   f06c9fdf        2           1   0.0  …   78.001503
581864   f06c9fdf        5           2   0.0  …   86.916801
582073   f06c9fdf        1           2   0.0  …   86.889099

        vert_approach_angle  horz_approach_angle  zone_time       x55  y55  \
35                 -4.02502             0.834138   0.421826  0.759003   55
256                -8.73613            -0.713829   0.451039 -1.810170   55
353                -9.74545             4.512090   0.483157  2.432580   55
397                -4.06607            -1.724440   0.413309 -2.126510   55
418                -5.63199             0.283421   0.406953 -1.736550   55
…                       …                   …         …         …   …
581483             -4.08045            -1.345470   0.382682 -2.063990   55
581503             -6.17842            -0.372579   0.417648 -2.032460   55
581550             -6.18036            -0.723831   0.440129 -2.356510   55
581864             -4.86654             1.099070   0.393080 -1.019420   55
582073             -5.65405            -3.638330   0.397248 -2.655230   55

            z55 pitch_type      pitch_call  pitch_id
35      6.17413         FA      BallCalled  c6607ace
256     6.29071         CH        FoulBall  8ef9aca4
353     6.46889         CU        FoulBall  b93024dc
397     6.00446         FA      BallCalled  2e4cf21e
418     5.69398         FA        FoulBall  b5157dae
…           …        …             …         …
581483  5.83140         FA        FoulBall  622c34e4
581503  5.92519         CH     StrikeCalled  ac39f15d
581550  6.00084         CH  StrikeSwinging  8040e585
581864  6.47430         FA      BallCalled  199f7047
582073  5.98179         FA      BallCalled  7f6b1f3b

[8822 rows x 36 columns]
```

8800 data points, not too bad. We can get some good data out of this. Let's see what happened on each of those pitches.

[5]:
```
player_df['pitch_call'].value_counts()
```

[5]:
```
BallCalled        3451
InPlay            1516
FoulBall          1460
StrikeCalled      1381
StrikeSwinging     980
HitByPitch          34
Name: pitch_call, dtype: int64
```

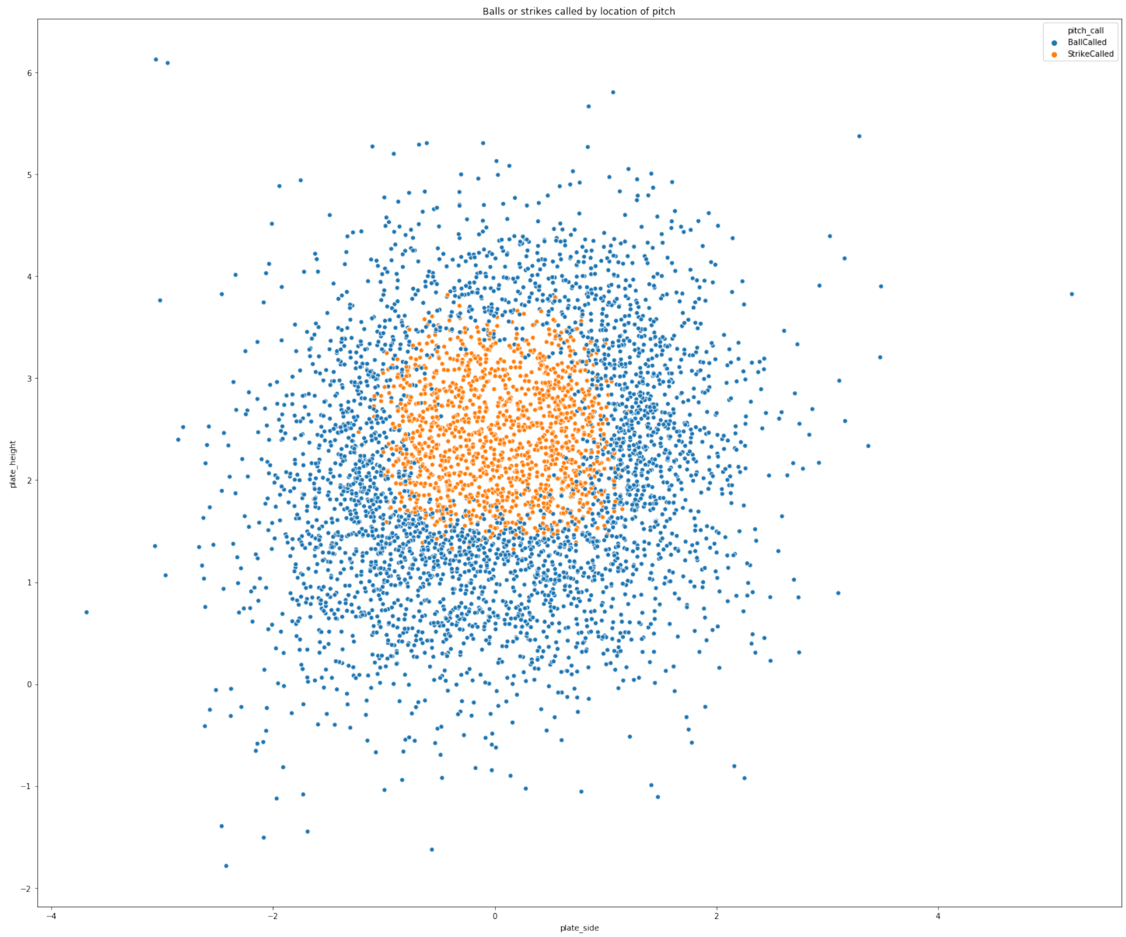
Lots of balls called, not good. Though that could be more on the pitcher that's throwing to him than the catcher himself. Let's put these on a scatter plot to see where all of these pitches crossed the plate.

[6]:
```
plt.figure(figsize=(12,9))
sns.scatterplot('plate_side', 'plate_height', data=player_df, hue='pitch_call')
plt.show()
```

That doesn't give a whole lot of information. Since we're looking at pitch receiving skills, let's take a look and called balls and strikes, perhaps we can see how well he's framing pitches.

[7]:
```
framing_df = player_df[(player_df['pitch_call'] == 'StrikeCalled') |␣
 ↪(player_df['pitch_call'] == 'BallCalled')]
```

[8]:
```
plt.figure(figsize=(25,21))
sns.scatterplot('plate_side', 'plate_height', data=framing_df, hue='pitch_call')
plt.title('Balls or strikes called by location of pitch')
plt.show()
```



Interesting. It seems like this catcher is good at framing pitches, with the orange dots being strikes called extending into areas of majority blue dots. But, it also goes the other way around. Let's clean and wrangle our data set like we did in the "Mariners Challenge" notebook to run some machine learning on it and draw some conclusions about how well this catcher frames pitches.

[9]:
```
def clean_and_wrangle(df):

    df = df.drop(df[df['release_speed'].isnull()].index)
    df = df.drop(df[df['outs'].isnull()].index)
    df['spin_rate'].fillna(df['spin_rate'].mean(), inplace=True)
    df = df.drop(df[df['tilt'].isnull()].index)
    df = df.drop(df[df['pitch_type'].isnull()].index)
    df = df.reset_index().drop('index', axis=1)

    df['tilt'] = df['tilt'].map(lambda x: sum(a*int(t) for a, t in zip([3600,␣
↪60], x.split(':'))) \
                                            if ':' in x else int(x[:-5]))
    return df
```

[10]:
```
framing_df = clean_and_wrangle(framing_df)
```

[11]:
```
is_strike = []
for i in framing_df['pitch_call']:
    if i == 'StrikeCalled':
        is_strike.append(1)
    else:
        is_strike.append(0)

framing_df['is_strike'] = is_strike
```

[12]:
```
framing_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4830 entries, 0 to 4829
Data columns (total 37 columns):
pitcher_id              4830 non-null object
pitcher_side            4830 non-null object
batter_id               4830 non-null object
batter_side             4830 non-null object
stadium_id              4830 non-null object
umpire_id               4830 non-null object
catcher_id              4830 non-null object
inning                  4830 non-null int64
top_bottom              4830 non-null int64
outs                    4830 non-null float64
balls                   4830 non-null int64
strikes                 4830 non-null int64
release_speed           4830 non-null float64
vert_release_angle      4830 non-null float64
horz_release_angle      4830 non-null float64
spin_rate               4830 non-null float64
spin_axis               4830 non-null float64
tilt                    4830 non-null int64
rel_height              4830 non-null float64
rel_side                4830 non-null float64
extension               4830 non-null float64
vert_break              4830 non-null float64
induced_vert_break      4830 non-null float64
horz_break              4830 non-null float64
plate_height            4830 non-null float64
plate_side              4830 non-null float64
zone_speed              4830 non-null float64
vert_approach_angle     4830 non-null float64
horz_approach_angle     4830 non-null float64
zone_time               4830 non-null float64
x55                     4830 non-null float64
```

```
y55                     4830 non-null int64
z55                     4830 non-null float64
pitch_type              4830 non-null object
pitch_call              4830 non-null object
pitch_id                4830 non-null object
is_strike               4830 non-null int64
dtypes: float64(20), int64(7), object(10)
memory usage: 1.4+ MB
```

After cleaning and getting our target variable, let's take a look at it and see if we're dealing with another imbalanced classification problem.

[13]:
```
framing_df['is_strike'].value_counts()
```

[13]:
```
0    3450
1    1380
Name: is_strike, dtype: int64
```

Yes, a similar imbalanced classification problem to the "Mariners Challenge" notebook. We'll tune an XGB Classifier model to model our data and draw some conclusions from its predictions, let's get that model ready to go.

[14]:
```
framing_df['pitch_type'].value_counts()
```

[14]:
```
FA    2576
SL    1029
CH     694
CU     528
XX       3
Name: pitch_type, dtype: int64
```

[15]:
```
framing_df = framing_df.drop(framing_df[framing_df['pitch_type'] == 'XX'].index)
framing_df = pd.get_dummies(framing_df, prefix=['pitcher', 'batter', 'is'],␣
 ↪columns=['pitcher_side', 'batter_side', 'pitch_type'])
```

[16]:
```
X = framing_df.drop(['pitcher_id', 'batter_id', 'stadium_id', 'umpire_id',␣
 ↪'catcher_id', 'pitch_call', 'is_strike', 'pitch_id'], axis=1)
y = framing_df['is_strike']

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
 ↪random_state=34, test_size=0.15)
```

[17]:
```
steps = [('xgb', XGBClassifier(seed=34))]
param_grid = {'xgb__n_estimators': np.arange(10, 210, 10),
              'xgb__max_depth': np.arange(1,6,2)}
pipeline = Pipeline(steps)
cv_1 = GridSearchCV(pipeline, param_grid, cv=3)
cv_1.fit(X_train, y_train)
```

```
print(cv_1.best_params_, cv_1.best_score_)
n_estimators = cv_1.best_params_['xgb__n_estimators']
max_depth = cv_1.best_params_['xgb__max_depth']
```

```
{'xgb__max_depth': 3, 'xgb__n_estimators': 150} 0.9261326933524986
```

[18]:
```
xgb = XGBClassifier(n_estimators=n_estimators, max_depth=max_depth, seed=34)
xgb.fit(X_train, y_train)
xgb_pred = xgb.predict(X_test)
```

[19]:
```
print(f'XGB Classifier Train Accuracy: {round(xgb.score(X_train, y_train) *␣
 ↪100, 2)}%')
print(f'XGB Classifier Test Accuracy: {round(xgb.score(X_test, y_test) * 100,␣
 ↪2)}%')
print('\n')
print('XGB Classifier Classification Report')
print(classification_report(y_test, xgb_pred))
print('\n')
print(f'XGB Classifier MCC Score: {matthews_corrcoef(y_test, xgb_pred)}')
```

```
XGB Classifier Train Accuracy: 95.95%
XGB Classifier Test Accuracy: 92.14%


XGB Classifier Classification Report
              precision    recall  f1-score   support

           0       0.96      0.92      0.94       518
           1       0.83      0.91      0.87       207

    accuracy                           0.92       725
   macro avg       0.90      0.92      0.91       725
weighted avg       0.93      0.92      0.92       725



XGB Classifier MCC Score: 0.8149311048301918
```

Looks like a good model here. No signs of overfitting, it has a good recall and precision on both classes, and has an excellent MCC score. To evaluate this catcher's performance on framing pitches, I'm going to use a method for determining the number of "extra strikes" this catcher either gives up or gets called for him. I sourced it from this recent blog post from DataRobot: https://blog.datarobot.com/catcher-pitch-framing-using-machine-learning-part-1

The number of extra strikes is the number of false negatives - false positives. So the number of strikes the model thought were balls, minus the number of balls the model thought were strikes. This will tell us whether or not the catcher is getting more strikes called for his pitcher by framing the ball well. If the number is positive, that means the catcher is framing up the ball well and getting more strikes called for his pitcher, and vice versa if the number is negative. Let's take a look.

[20]:
```
compare_df = y_test.to_frame()
compare_df['xgb_predict'] = xgb_pred
compare_df
```

[20]:

	is_strike	xgb_predict
1149	0	0
1537	0	0
2543	0	0
2933	0	0
4762	0	0
…	…	…
2731	1	1
3951	0	0
76	0	0
4807	1	0
2766	1	1

[725 rows x 2 columns]

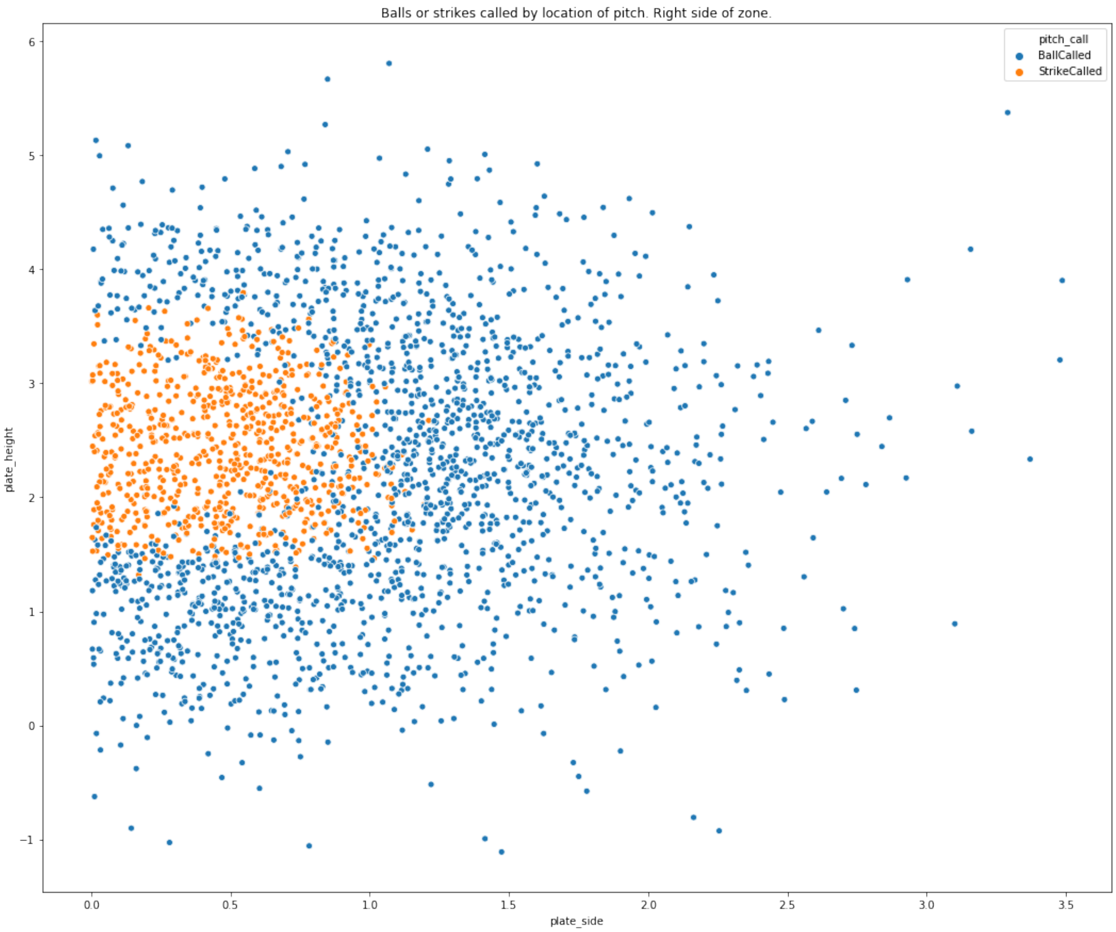
[21]:
```
len(compare_df[(compare_df['is_strike'] == 1) & (compare_df['xgb_predict'] ==␣
↪0)]) - \
len(compare_df[(compare_df['is_strike'] == 0) & (compare_df['xgb_predict'] ==␣
↪1)])
```

[21]: -21

His extra strikes number is negative, which means he's not framing the ball very well and getting balls called that would normally be called for strikes. -21 isn't a huge number, so he's definitely not the worst at this, but he certainly has room for improvement. That was for the entire zone, so let's take a look at each side of the zone, left and right, and see what side he's better on. Starting with the right side.

[22]:
```
right_framing = framing_df[framing_df['plate_side'] > 0]
```

[23]:
```
plt.figure(figsize=(18,15))
sns.scatterplot('plate_side', 'plate_height', data=right_framing,␣
↪hue='pitch_call')
plt.title('Balls or strikes called by location of pitch. Right side of zone.')
plt.show()
```



[24]:
```
X = right_framing.drop(['pitcher_id', 'batter_id', 'stadium_id', 'umpire_id',␣
↪'catcher_id', 'pitch_call', 'is_strike', 'pitch_id'], axis=1)
y = right_framing['is_strike']

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
↪random_state=34, test_size=0.15)
```

[25]:
```
right_pred = xgb.predict(X_test)
```

[26]:
```
right_compare_df = y_test.to_frame()
right_compare_df['right_predict'] = right_pred
right_compare_df
```

[26]:

	is_strike	right_predict
1859	1	1
504	0	0
2136	0	0
3876	0	0

```
1988           1              1
…        …              …
924            0              0
1113           0              0
2585           0              0
2448           0              0
940            1              1

[378 rows x 2 columns]
```

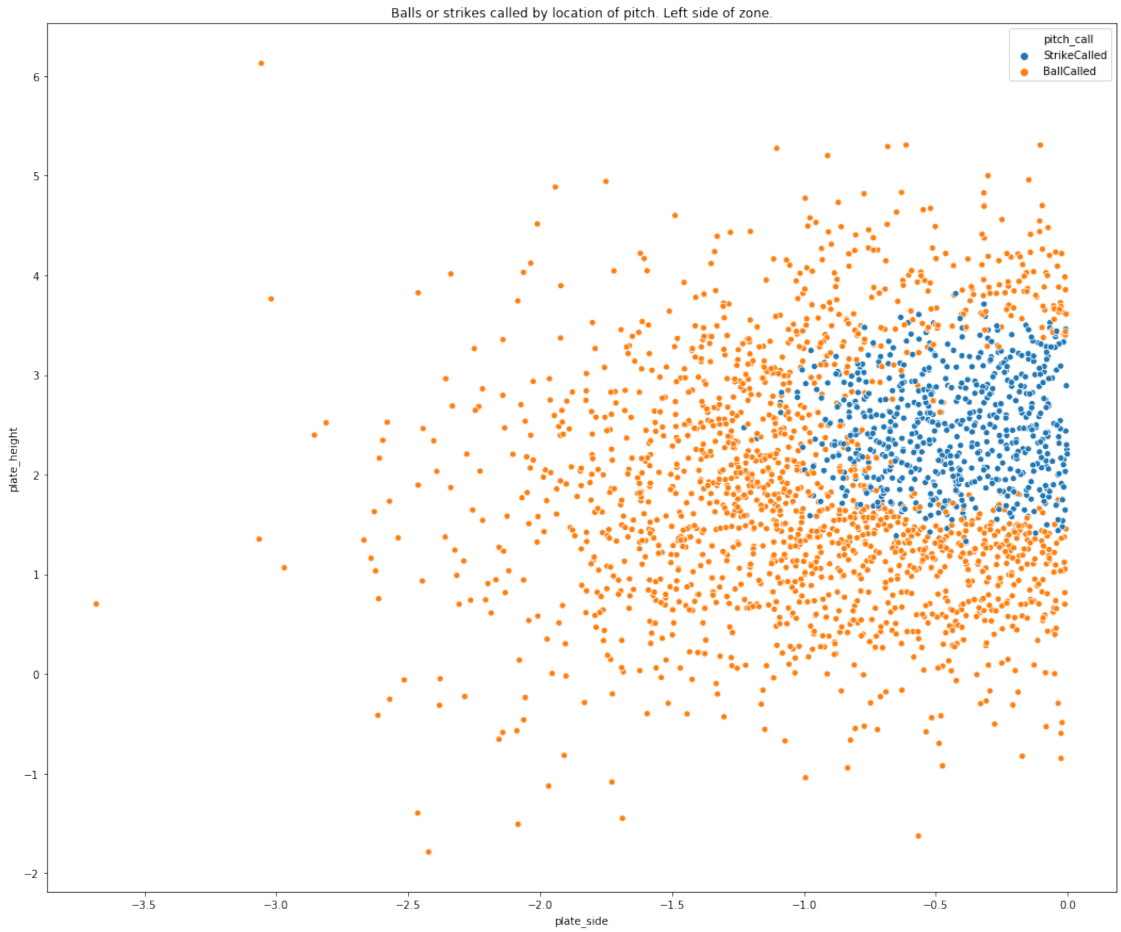
[27]:
```
len(right_compare_df[(right_compare_df['is_strike'] == 1) &
 ↪(right_compare_df['right_predict'] == 0)]) - \
len(right_compare_df[(right_compare_df['is_strike'] == 0) &
 ↪(right_compare_df['right_predict'] == 1)])
```

[27]:
```
-10
```

Still negative, which isn't good. Let's take a look att he left side and see if its the same as the right side.

[28]:
```
left_framing = framing_df[framing_df['plate_side'] < 0]
```

[29]:
```
plt.figure(figsize=(18,15))
sns.scatterplot('plate_side', 'plate_height', data=left_framing,
 ↪hue='pitch_call')
plt.title('Balls or strikes called by location of pitch. Left side of zone.')
plt.show()
```



[30]:
```
X = left_framing.drop(['pitcher_id', 'batter_id', 'stadium_id', 'umpire_id',␣
↪'catcher_id', 'pitch_call', 'is_strike', 'pitch_id'], axis=1)
y = left_framing['is_strike']

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
↪random_state=34, test_size=0.15)
```

[31]:
```
left_pred = xgb.predict(X_test)
```

[32]:
```
left_compare_df = y_test.to_frame()
left_compare_df['left_predict'] = left_pred
left_compare_df
```

[32]:

	is_strike	left_predict
616	1	0
746	1	1
3747	1	1
1019	0	0

```
513              0              0
...            ...            ...
981              1              1
1136             0              0
737              0              0
2587             0              0
886              0              0

[347 rows x 2 columns]
```

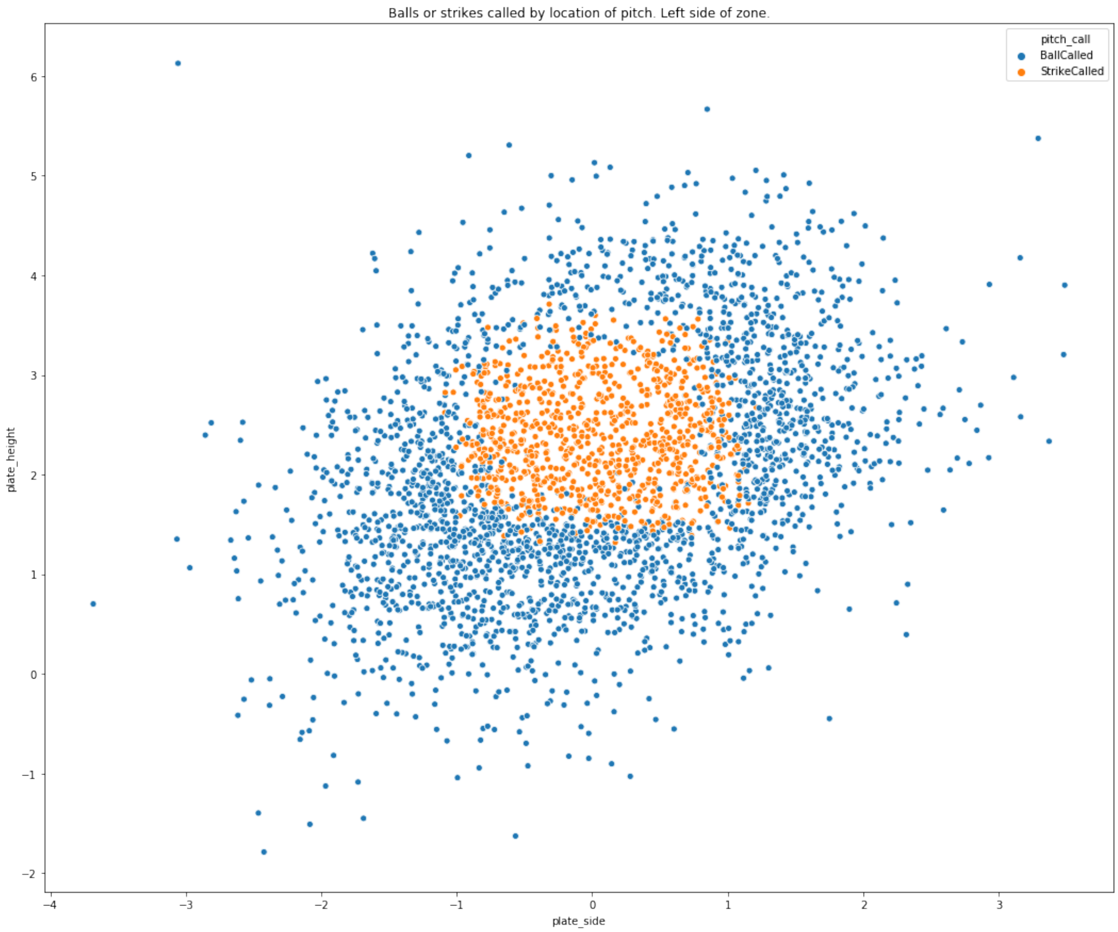
[33]:
```
len(left_compare_df[(left_compare_df['is_strike'] == 1) &
 ↪(left_compare_df['left_predict'] == 0)]) - \
len(left_compare_df[(left_compare_df['is_strike'] == 0) &
 ↪(left_compare_df['left_predict'] == 1)])
```

[33]:
```
-5
```

Less negative, which means this catcher does a slightly better job framing up pitches on the left side of the zone than the right side of the zone. What about from righty or lefty pitchers? Let's take a look at those data points and see who he's better for framing the ball for.

[34]:
```
rp_framing = framing_df[framing_df['pitcher_Right'] == 1]
```

[35]:
```
plt.figure(figsize=(18,15))
sns.scatterplot('plate_side', 'plate_height', data=rp_framing, hue='pitch_call')
plt.title('Balls or strikes called by location of pitch. Left side of zone.')
plt.show()
```



[36]:
```
X = rp_framing.drop(['pitcher_id', 'batter_id', 'stadium_id', 'umpire_id',␣
↪'catcher_id', 'pitch_call', 'is_strike', 'pitch_id'], axis=1)
y = rp_framing['is_strike']

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
↪random_state=34, test_size=0.15)
```

[37]:
```
rp_pred = xgb.predict(X_test)
```

[38]:
```
rp_compare_df = y_test.to_frame()
rp_compare_df['rp_predict'] = rp_pred
rp_compare_df
```

[38]:

	is_strike	rp_predict
312	1	1
4551	0	0
2985	1	1
1986	0	0

```
1426           1           1
…          …          …
1031           0           0
2287           0           0
1250           1           1
2041           1           1
4802           0           0

[477 rows x 2 columns]
```

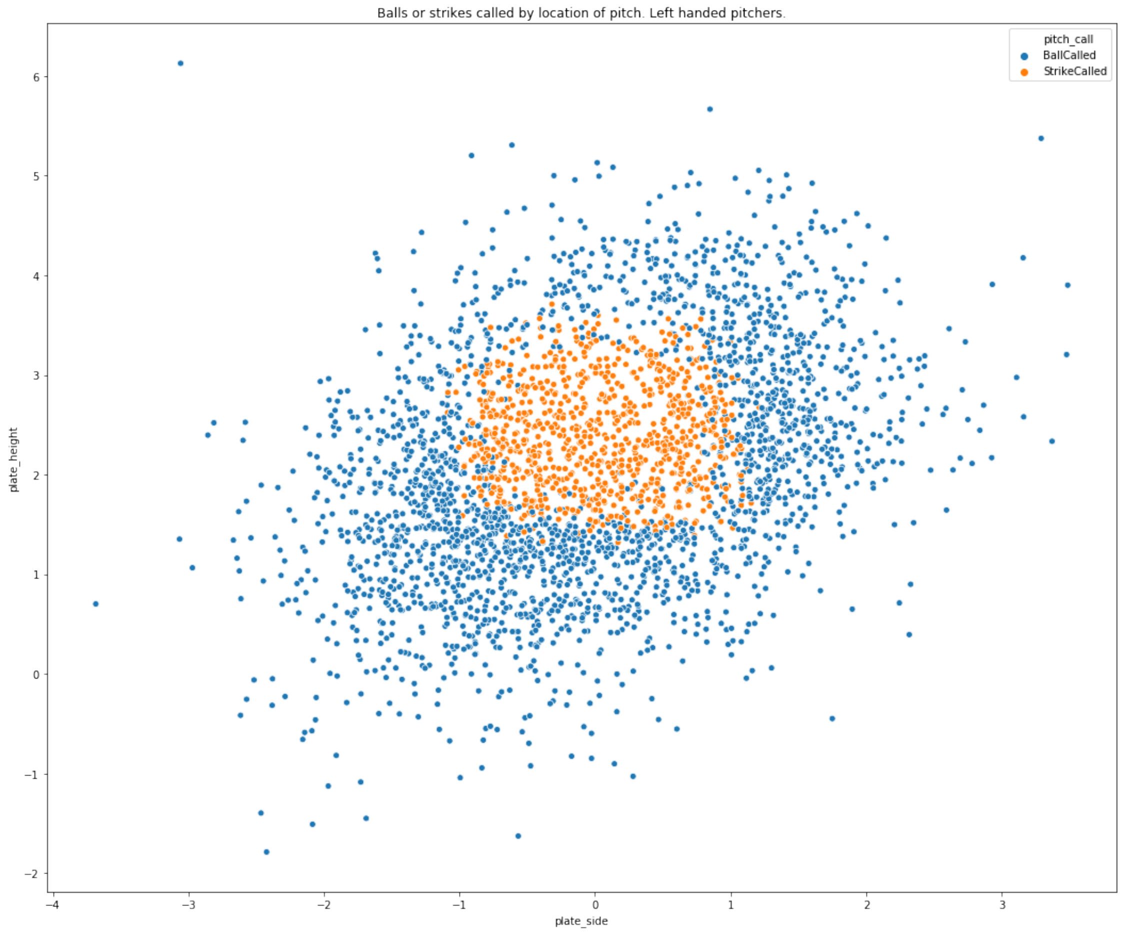
[39]:
```
len(rp_compare_df[(rp_compare_df['is_strike'] == 1) &␣
↪(rp_compare_df['rp_predict'] == 0)]) - \
len(rp_compare_df[(rp_compare_df['is_strike'] == 0) &␣
↪(rp_compare_df['rp_predict'] == 1)])
```

[39]: -9

Similar number to the right side of the zone, let's take a look at the lefties.

[40]:
```
lp_framing = framing_df[framing_df['pitcher_Left'] == 1]
```

[41]:
```
plt.figure(figsize=(18,15))
sns.scatterplot('plate_side', 'plate_height', data=rp_framing, hue='pitch_call')
plt.title('Balls or strikes called by location of pitch. Left handed pitchers.')
plt.show()
```



[42]:
```
X = lp_framing.drop(['pitcher_id', 'batter_id', 'stadium_id', 'umpire_id',␣
 ↪'catcher_id', 'pitch_call', 'is_strike', 'pitch_id'], axis=1)
y = lp_framing['is_strike']

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
 ↪random_state=34, test_size=0.15)
```

[43]:
```
rp_pred = xgb.predict(X_test)
```

[44]:
```
rp_compare_df = y_test.to_frame()
rp_compare_df['rp_predict'] = rp_pred
rp_compare_df
```

[44]:

	is_strike	rp_predict
98	0	0
4522	0	0
1661	0	0
913	0	0

```
2131          0          0
…        …         …
4703          0          0
1038          0          0
1788          0          0
2208          0          0
34            1          1

[248 rows x 2 columns]
```

[45]:
```
len(rp_compare_df[(rp_compare_df['is_strike'] == 1) &
 ↪(rp_compare_df['rp_predict'] == 0)]) - \
len(rp_compare_df[(rp_compare_df['is_strike'] == 0) &
 ↪(rp_compare_df['rp_predict'] == 1)])
```

[45]:
```
-4
```

Smaller number, similar to the left side of the zone. This catcher is better at framing pitches on the left side of the zone from left handed pitchers. He could be good to bring in for lefty specialist type pitchers, for throwing inside to left handed batters or low and away from right handed batters. Overall not a bad catcher, but definitely has room for improvement.