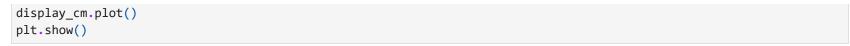
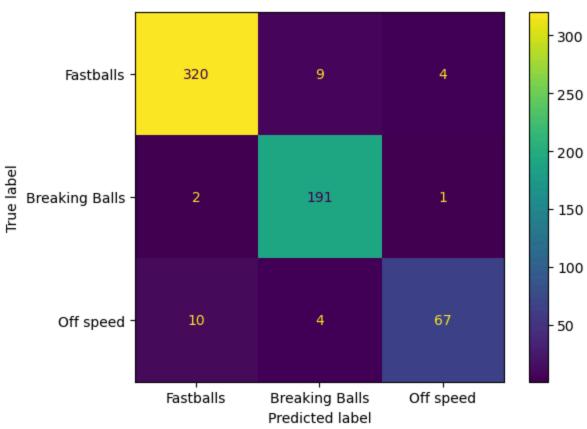
```
In [1]: import matplotlib.pyplot as plt
         import numpy as np
         import pandas as pd
         from sklearn.metrics import ConfusionMatrixDisplay, confusion matrix
         from sklearn.model selection import train test split
         from sklearn.preprocessing import StandardScaler
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.linear model import LogisticRegression
         from sklearn.preprocessing import StandardScaler
         import altair as alt
         import warnings
         warnings.filterwarnings("ignore")
In [26]: # Load Data (Courtesy of Baseball Savant)
         raw_data = pd.read_csv('data/MLB_pitches_13SEP24.csv')
         # Restrict to right handed pitchers as lefties will have opposite axis
         clean_data = raw_data[raw_data.p_throws == 'R']
         # Carry forward the metrics that we would know the instant the ball leaves the pitchers hand
         clean_data = clean_data[['pitch_type', 'release_speed', 'release_pos_x', 'release_pos_z', 'release_extension','release_speed'
         # Drop rows with eephus and screwballs because of small samples and atypical characteristics
         drop_list = ['EP','SC']
         clean_data = clean_data[clean_data.pitch_type.isin(drop_list) == False]
         # Turn pitch_type numeric, grouping into fastballs (1), breaking balls (2), and off speed (3)
         clean_data['pitch_type'] = clean_data['pitch_type'].map({
             'FF':1.
             'FC':1.
             'SI':1.
             'CU':2.
             'KC':2.
             'SL':2.
             'ST':2.
             'SV':2,
             'CH':3,
             'FS':3
         })
```

```
clean_data.head()
Out[26]:
             pitch type release speed release pos x release pos z release extension release spin rate spin axis
          0
                     1
                               102.9
                                             -2.90
                                                            6.35
                                                                              6.3
                                                                                             2230
                                                                                                        220
          1
                               102.4
                                             -2.90
                                                            6.29
                                                                              6.2
                                                                                             2396
                     1
                                                                                                        226
          2
                     1
                               102.3
                                                                              6.9
                                             -1.75
                                                            6.17
                                                                                             2613
                                                                                                        219
          3
                     1
                               102.0
                                             -2.57
                                                            6.40
                                                                              6.2
                                                                                             2247
                                                                                                        222
          4
                     1
                               102.0
                                             -2.78
                                                            6.42
                                                                              6.1
                                                                                                        221
                                                                                             2359
 In [3]: # Confirm sample size
          len(clean_data)
 Out[3]: 3040
 In [4]: # Split data into train and test samples
         X_train, X_test, y_train, y_test = train_test_split(clean_data.drop('pitch_type',axis=1), clean_data['pitch_type'],
          # Scale inputs to assure larger values aren't over valued
          scaler = StandardScaler()
          X_train = scaler.fit_transform(X_train)
          X_test = scaler.fit_transform(X_test)
 In [5]: # Use a Random Forest Model to train and test a model
         model = RandomForestClassifier(n_estimators = 500, max_depth = 10, random_state = 42).fit(X_train, y_train)
         mean_accuracy = model.score(X_test, y_test)
          print(mean accuracy)
        0.9802631578947368
 In [6]: # Use Linear Regression to validate results
          lr = LogisticRegression(random state=42, max iter=1000).fit(X train, y train)
         y_pred = lr.predict(X_test)
          conf matrix = confusion matrix(y test, y pred)
         display_cm = ConfusionMatrixDisplay(confusion_matrix=conf_matrix, display_labels=['Fastballs', 'Breaking Balls', 'Off
```



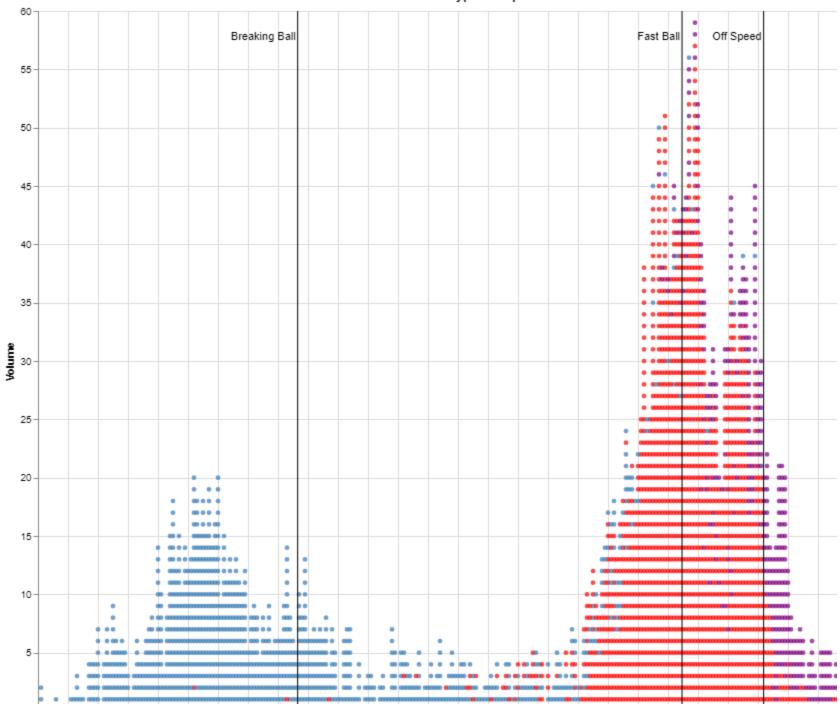


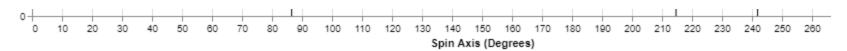
```
In [7]: # Investigate what features of a pitch make it most identifiable?
    feat_names = clean_data.columns[1:7]
    feat_scores = model.feature_importances_
    top_feats = list(zip(feat_names, feat_scores))
    top_feats = sorted(top_feats, key=lambda tup: tup[1], reverse = True)
    top_feats
```

```
Out[7]: [('spin axis', 0.44084825259185295),
          ('release speed', 0.3084926472259159),
           ('release_spin_rate', 0.1630722726830902),
           ('release_pos_x', 0.03290931384236659),
           ('release pos z', 0.032834191275292676),
           ('release extension', 0.021843322381481574)]
 In [8]: # Prepare data for plotting by renaming pitch type from numeric to group name
         clean_data['pitch_type'] = clean_data['pitch_type'].map({
             1: 'Fastball',
             2: 'Breaking Ball',
             3: 'Off Speed',
         })
 In [9]: # Create plot for all pitches
         pitch plot = alt.Chart(clean data).transform bin(
             field="spin axis",
             as ="bin",
             bin=alt.BinParams(step=0.5)
         ).transform window(
             pitch count="rank()",
             groupby=["bin"]
         ).transform joinaggregate(
             spin_axis_dg="median(spin_axis)",
             groupby=["bin"]
         ).mark circle(size=20, clip=True).encode(
             x= alt.X("spin axis dg:Q").scale(domain=[0,285]),
             y="pitch count:Q",
             color=alt.Color('pitch type', type='nominal').title('Pitch Type').scale(range = ['#377eb8', 'red', 'purple'])#domar
         ).properties(width=900, height=700)
In [10]: # Create small data frame showing mean spin axis by pitch type
         spin_axis_mean = list(clean_data.groupby('pitch_type').spin_axis.mean())
         column_names = ['Breaking Ball', 'Fast Ball', 'Off Speed']
         vert lines = pd.DataFrame(list(zip(column_names,spin_axis_mean)),columns=['Pitch_Type','Mean_Spin_Axis'])
In [11]: # Plot vertical lines of mean spin axis by pitch type
         pitch means = alt.Chart(vert lines).mark rule(color="black").encode(x='Mean Spin Axis')
         labels = alt.Chart(vert lines).mark text(align = 'right', baseline = 'top', dx = -2, dy = -330).encode(
             alt.X('Mean Spin Axis'),
```



Pitch Type vs. Spin Axis





In []: