nfl-runvspass

December 3, 2024

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import roc_auc_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix

# shap
import shap

# torch
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader

import pymc as pm
import arviz as az
```

```
WARNING (pytensor.configdefaults): g++ not available, if using conda: `conda
install m2w64-toolchain`
WARNING (pytensor.configdefaults): g++ not detected!  PyTensor will be unable to
compile C-implementations and will default to Python. Performance may be
severely degraded. To remove this warning, set PyTensor flags cxx to an empty
string.
WARNING (pytensor.tensor.blas): Using NumPy C-API based implementation for BLAS
functions.
```

1 Run VS Pass based on pre-snap indicators

The goal of this notebook is to build a model that can predict whether a play is a run or a pass based on pre-snap indicators. the dataset is apart of the NFL Big Data Bowl 2025.

- plays.csv: contains play-by-play data for each game
- player_play.csv: contains player-by-play data for each game

- games.csv: contains game-by-game data for each game
- motion_features.csv: contains motion features for each play
- players.csv: contains player data for each player

The notebook will go through cleaning and preprocessing of the data, feature engineering, and building a "Soft-order" 2D CNN model to make predictions. The model will be trained on a 80/20 split and will use cross-entropy loss.

the only post snap feature will be the isDropback feature. which is 1 if the play is a pass and 0 if it is a run.

[2]:
```python
plays_df = pd.read_csv('./data/plays.csv')
player_play_df = pd.read_csv('./data/player_play.csv')
games_df = pd.read_csv('./data/games.csv')
```

2 check the data

[3]:
```python
plays_df.head()
```

[3]:
```
       gameId  playId                                    playDescription  \
0  2022102302    2655  (1:54) (Shotgun) J.Burrow pass short middle to…
1  2022091809    3698  (2:13) (Shotgun) J.Burrow pass short right to …
2  2022103004    3146  (2:00) (Shotgun) D.Mills pass short right to D…
3  2022110610     348  (9:28) (Shotgun) P.Mahomes pass short left to …
4  2022102700    2799  (2:16) (Shotgun) L.Jackson up the middle to TB…

   quarter  down  yardsToGo possessionTeam defensiveTeam yardlineSide  \
0        3     1         10            CIN           ATL          CIN
1        4     1         10            CIN           DAL          CIN
2        4     3         12            HOU           TEN          HOU
3        1     2         10             KC           TEN          TEN
4        3     2          8            BAL            TB           TB

   yardlineNumber  … yardsGained  homeTeamWinProbabilityAdded  \
0              21  …           9                     0.004634
1               8  …           4                     0.002847
2              20  …           6                     0.000205
3              23  …           4                    -0.001308
4              27  …          -1                     0.027141

   visitorTeamWinProbilityAdded expectedPointsAdded  isDropback  \
0                     -0.004634            0.702717        True
1                     -0.002847           -0.240509        True
2                     -0.000205           -0.218480        True
3                      0.001308           -0.427749        True
4                     -0.027141           -0.638912       False

   pff_runConceptPrimary  pff_runConceptSecondary  pff_runPassOption  \
```

```
0                     NaN                      NaN                     0
1                     NaN                      NaN                     0
2                     NaN                      NaN                     0
3                     NaN                      NaN                     0
4                     MAN              READ OPTION                     0

  pff_passCoverage pff_manZone
0          Cover-3        Zone
1        Quarters         Zone
2        Quarters         Zone
3        Quarters         Zone
4          Cover-1         Man

[5 rows x 50 columns]
```

[4]:
```
print(plays_df['playDescription'][0])
print("drop",len(plays_df[plays_df['qbKneel'] == 1]), "qb kneels")
plays_df = plays_df[plays_df['qbKneel'] == 0]
plays_df.head()
```

```
(1:54) (Shotgun) J.Burrow pass short middle to T.Boyd to CIN 30 for 9 yards
(J.Hawkins).
drop 165 qb kneels
```

[4]:
```
       gameId  playId                                     playDescription  \
0  2022102302    2655  (1:54) (Shotgun) J.Burrow pass short middle to…
1  2022091809    3698  (2:13) (Shotgun) J.Burrow pass short right to …
2  2022103004    3146  (2:00) (Shotgun) D.Mills pass short right to D…
3  2022110610     348  (9:28) (Shotgun) P.Mahomes pass short left to …
4  2022102700    2799  (2:16) (Shotgun) L.Jackson up the middle to TB…

   quarter  down  yardsToGo possessionTeam defensiveTeam yardlineSide  \
0        3     1         10            CIN           ATL          CIN
1        4     1         10            CIN           DAL          CIN
2        4     3         12            HOU           TEN          HOU
3        1     2         10             KC           TEN          TEN
4        3     2          8            BAL            TB           TB

   yardlineNumber  … yardsGained  homeTeamWinProbabilityAdded  \
0              21  …           9                     0.004634
1               8  …           4                     0.002847
2              20  …           6                     0.000205
3              23  …           4                    -0.001308
4              27  …          -1                     0.027141

   visitorTeamWinProbilityAdded expectedPointsAdded  isDropback  \
0                     -0.004634            0.702717        True
1                     -0.002847           -0.240509        True
```

```
2                    -0.000205            -0.218480        True
3                     0.001308            -0.427749        True
4                    -0.027141            -0.638912       False

  pff_runConceptPrimary  pff_runConceptSecondary  pff_runPassOption  \
0                   NaN                      NaN                  0
1                   NaN                      NaN                  0
2                   NaN                      NaN                  0
3                   NaN                      NaN                  0
4                   MAN              READ OPTION                  0

  pff_passCoverage pff_manZone
0          Cover-3        Zone
1        Quarters        Zone
2        Quarters        Zone
3        Quarters        Zone
4          Cover-1         Man

[5 rows x 50 columns]
```

[5]:

```
player_play_df.head()
```

[5]:

```
       gameId  playId  nflId teamAbbr  hadRushAttempt  rushingYards  \
0  2022090800      56  35472      BUF               0             0
1  2022090800      56  42392      BUF               0             0
2  2022090800      56  42489      BUF               0             0
3  2022090800      56  44875      BUF               0             0
4  2022090800      56  44985      BUF               0             0

   hadDropback  passingYards  sackYardsAsOffense  hadPassReception  …  \
0            0             0                   0                 0  …
1            0             0                   0                 0  …
2            0             0                   0                 1  …
3            0             0                   0                 0  …
4            0             0                   0                 0  …

   wasRunningRoute  routeRan  blockedPlayerNFLId1  blockedPlayerNFLId2  \
0              NaN       NaN              47917.0                  NaN
1              NaN       NaN              47917.0                  NaN
2              1.0        IN                  NaN                  NaN
3              NaN       NaN              43335.0                  NaN
4              1.0       OUT                  NaN                  NaN

   blockedPlayerNFLId3  pressureAllowedAsBlocker  \
0                  NaN                       0.0
1                  NaN                       0.0
2                  NaN                       NaN
```

```
3                 NaN                          0.0
4                 NaN                          NaN

   timeToPressureAllowedAsBlocker  pff_defensiveCoverageAssignment  \
0                             NaN                              NaN
1                             NaN                              NaN
2                             NaN                              NaN
3                             NaN                              NaN
4                             NaN                              NaN

   pff_primaryDefensiveCoverageMatchupNflId  \
0                                       NaN
1                                       NaN
2                                       NaN
3                                       NaN
4                                       NaN

   pff_secondaryDefensiveCoverageMatchupNflId
0                                         NaN
1                                         NaN
2                                         NaN
3                                         NaN
4                                         NaN

[5 rows x 50 columns]
```

[6]:
```
games_df.head()
```

[6]:
```
       gameId  season  week   gameDate gameTimeEastern homeTeamAbbr  \
0  2022090800    2022     1   9/8/2022        20:20:00           LA
1  2022091100    2022     1  9/11/2022        13:00:00          ATL
2  2022091101    2022     1  9/11/2022        13:00:00          CAR
3  2022091102    2022     1  9/11/2022        13:00:00          CHI
4  2022091103    2022     1  9/11/2022        13:00:00          CIN

  visitorTeamAbbr  homeFinalScore  visitorFinalScore
0             BUF              10                 31
1              NO              26                 27
2             CLE              24                 26
3              SF              19                 10
4             PIT              20                 23
```

2.1 Merge the datasets

Combine the datasets into one based on the gameId column, and perform data cleaning and feature engineering. This will be the dataset that will be used for modeling.

[7]:
```python
def merge_dataset(plays_df, games_df):
    """
    Combine 2 datasets into one based on the gameId column, and perform
    data cleaning and feature engineering.
    """
    df = plays_df.merge(games_df, on='gameId', how='left')

    df['is_pass'] = df['isDropback'].astype(int)
    df['is_home_team'] = df['possessionTeam'] == df['homeTeamAbbr']

    df['score_differential'] = np.where(
        df['is_home_team'],
        df['preSnapHomeScore'] - df['preSnapVisitorScore'],
        df['preSnapVisitorScore'] - df['preSnapHomeScore']
    )

    print(f"Data set length: {len(df)}")
    print(df.info())

    return df
```

[8]:
```python
df = merge_dataset(plays_df, games_df)
```

```
Data set length: 15959
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15959 entries, 0 to 15958
Data columns (total 61 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   gameId                            15959 non-null  int64
 1   playId                            15959 non-null  int64
 2   playDescription                   15959 non-null  object
 3   quarter                           15959 non-null  int64
 4   down                              15959 non-null  int64
 5   yardsToGo                         15959 non-null  int64
 6   possessionTeam                    15959 non-null  object
 7   defensiveTeam                     15959 non-null  object
 8   yardlineSide                      15740 non-null  object
 9   yardlineNumber                    15959 non-null  int64
 10  gameClock                         15959 non-null  object
 11  preSnapHomeScore                  15959 non-null  int64
 12  preSnapVisitorScore               15959 non-null  int64
 13  playNullifiedByPenalty            15959 non-null  object
 14  absoluteYardlineNumber            15959 non-null  int64
 15  preSnapHomeTeamWinProbability     15959 non-null  float64
 16  preSnapVisitorTeamWinProbability  15959 non-null  float64
 17  expectedPoints                    15959 non-null  float64
 18  offenseFormation                  15936 non-null  object
```

```
 19  receiverAlignment                 15936 non-null  object
 20  playClockAtSnap                   15958 non-null  float64
 21  passResult                        9736 non-null   object
 22  passLength                        8726 non-null   float64
 23  targetX                           8376 non-null   float64
 24  targetY                           8376 non-null   float64
 25  playAction                        15959 non-null  bool
 26  dropbackType                      10249 non-null  object
 27  dropbackDistance                  10158 non-null  float64
 28  passLocationType                  9312 non-null   object
 29  timeToThrow                       8705 non-null   float64
 30  timeInTackleBox                   8917 non-null   float64
 31  timeToSack                        608 non-null    float64
 32  passTippedAtLine                  9336 non-null   object
 33  unblockedPressure                 9755 non-null   object
 34  qbSpike                           9336 non-null   object
 35  qbKneel                           15959 non-null  int64
 36  qbSneak                           6623 non-null   object
 37  rushLocationType                  6623 non-null   object
 38  penaltyYards                      383 non-null    float64
 39  prePenaltyYardsGained             15959 non-null  int64
 40  yardsGained                       15959 non-null  int64
 41  homeTeamWinProbabilityAdded       15959 non-null  float64
 42  visitorTeamWinProbilityAdded      15959 non-null  float64
 43  expectedPointsAdded               15959 non-null  float64
 44  isDropback                        15959 non-null  bool
 45  pff_runConceptPrimary             8906 non-null   object
 46  pff_runConceptSecondary           2820 non-null   object
 47  pff_runPassOption                 15959 non-null  int64
 48  pff_passCoverage                  15931 non-null  object
 49  pff_manZone                       15931 non-null  object
 50  season                            15959 non-null  int64
 51  week                              15959 non-null  int64
 52  gameDate                          15959 non-null  object
 53  gameTimeEastern                   15959 non-null  object
 54  homeTeamAbbr                      15959 non-null  object
 55  visitorTeamAbbr                   15959 non-null  object
 56  homeFinalScore                    15959 non-null  int64
 57  visitorFinalScore                 15959 non-null  int64
 58  is_pass                           15959 non-null  int32
 59  is_home_team                      15959 non-null  bool
 60  score_differential                15959 non-null  int64
dtypes: bool(3), float64(15), int32(1), int64(18), object(24)
memory usage: 7.0+ MB
None
```

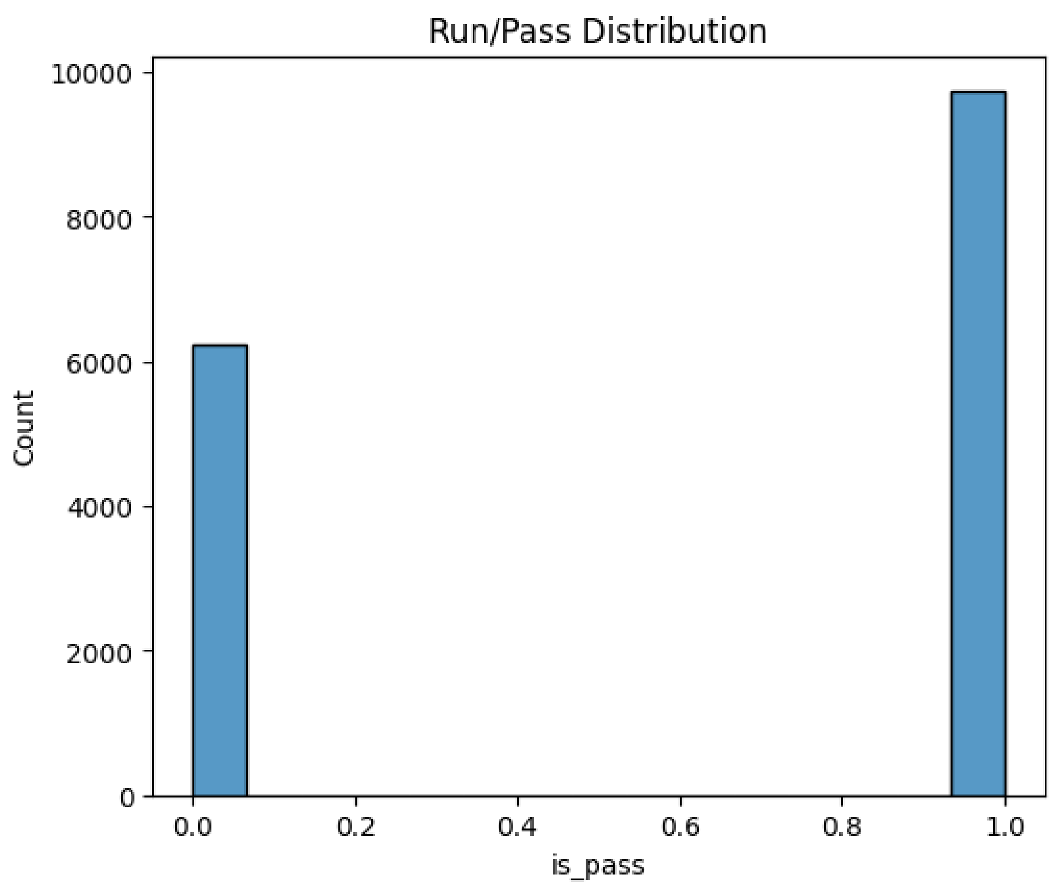
2.2 Check the run/pass distribution

The distribution is skewed towards run plays. This is expected as the NFL has made more of a transition to pass heavy offenses in the recent years.

with 61% of the plays being pass plays and 39% being run plays. The classses are imbalanced, but not severely.

[9]:
```
print("\nRun/Pass Distribution:")
print(df['is_pass'].value_counts(normalize=True))
plt.figure(figsize=(6, 5))
sns.histplot(df, x='is_pass', multiple='stack')
plt.title('Run/Pass Distribution')
plt.show()
```

```
Run/Pass Distribution:
is_pass
1    0.610063
0    0.389937
Name: proportion, dtype: float64
```



2.3 Create motion features

Create more granular motion features based on the motion_features.csv file. This will be used to train the CNN.

2.3.1 Motion features

A few notable features related to motion in the motion_features.csv file create from the tracking data the competition provided.

- The **s** value represents the count of frames where a player had significant movement (speed > 0.62) in the last 10 frames before the snap. Since there are 10 frames total, s would range from 0-10.
- The **x** value represents the total distance moved by all players in the play. i.e the sum of the absolute difference in the x and y coordinates of each player. A motion level of 0 would be no motion, and a motion level of 3 would be the most motion.
- The **motion_intensity** is the **x** value divided by the **s** value. This is a measure of how much motion there is per frame. A motion intensity of 0 would be no motion, and a motion intensity of 3 would be the most motion.

[10]:
```
# get combined tracking weeks csv
motion_features = pd.read_csv('./data/motion_features.csv')
valid_plays = plays_df[['gameId', 'playId']].copy()
all_motion = []

# motion features
motion_features['motion_frames'] = motion_features['s']  # Raw count of motion␣
↪frames
motion_features['total_movement'] = motion_features['x']  # Raw movement␣
↪distance

# numerical motion levels (0-3)
motion_features['motion_level'] = pd.cut(motion_features['s'],
                                        bins=[-float('inf'), 0, 3, 6,␣
↪float('inf')],
                                        labels=[0, 1, 2, 3]).astype(float)

# motion intensity (movement per frame with motion)
motion_features['motion_intensity'] = motion_features['x'] /␣
↪motion_features['s'].clip(lower=1)

# binary flags with thresholds
motion_features['has_motion'] = (motion_features['s'] >= 2).astype(float)
motion_features['significant_movement'] = (motion_features['x'] > 1.5).
↪astype(float)
motion_features['high_intensity'] = (motion_features['motion_intensity'] > 0.3).
↪astype(float)
```

```
# Merge with valid plays
final_motion = motion_features.merge(valid_plays, on=['gameId', 'playId'],␣
 ↪how='right')

print(f"Total plays processed: {len(final_motion)}")
print(f"Plays with motion: {final_motion['has_motion'].sum()}")
print(f"Plays with significant movement: {final_motion['significant_movement'].
 ↪sum()}")
print(f"Plays with high intensity motion: {final_motion['high_intensity'].
 ↪sum()}")
print(final_motion['motion_level'].value_counts(normalize=True))
```

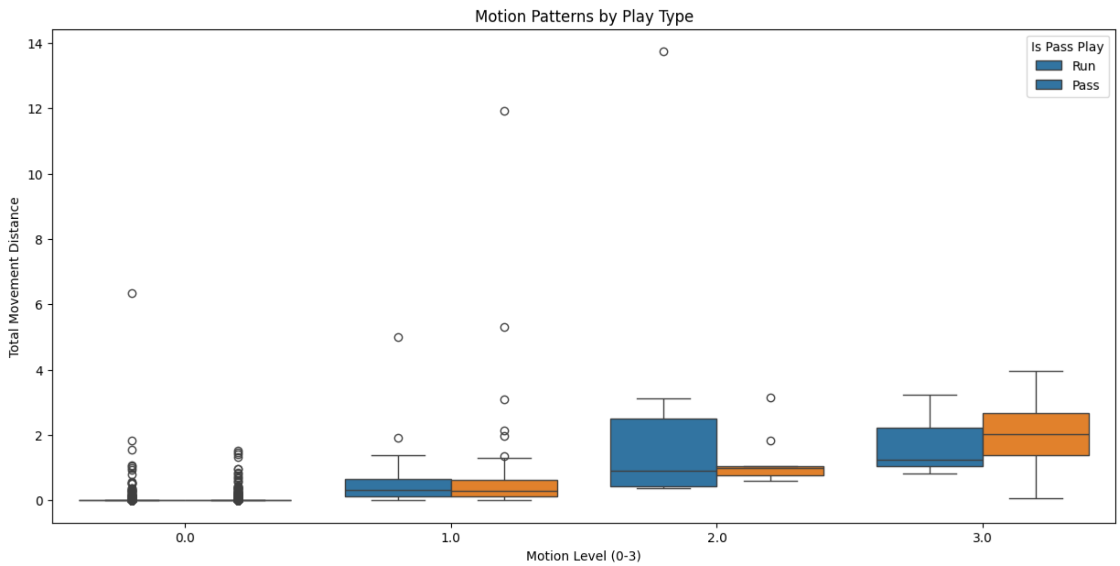
```
Total plays processed: 15959
Plays with motion: 143.0
Plays with significant movement: 20.0
Plays with high intensity motion: 173.0
motion_level
0.0    0.770696
1.0    0.212878
2.0    0.011827
3.0    0.004599
Name: proportion, dtype: float64
```

[11]:
```
# merge with original features
final_motion = final_motion.fillna(0)
print(final_motion.columns)
df = df.merge(final_motion[['gameId', 'playId', 'has_motion',␣
 ↪'significant_movement', 'motion_level', 'motion_frames', 'total_movement',␣
 ↪'motion_intensity', 'playDirection']],
                                    on=['gameId', 'playId'])
```

```
Index(['Unnamed: 0', 'gameId', 'playId', 's', 'x', 'playDirection',
       'motion_frames', 'total_movement', 'motion_level', 'motion_intensity',
       'has_motion', 'significant_movement', 'high_intensity'],
      dtype='object')
```

[12]:
```
plt.figure(figsize=(15, 7))
sns.boxplot(data=df, x='motion_level', y='total_movement', hue='is_pass')
plt.title('Motion Patterns by Play Type')
plt.xlabel('Motion Level (0-3)')
plt.ylabel('Total Movement Distance')
plt.legend(title='Is Pass Play', labels=['Run', 'Pass'])

# Print some summary statistics
print("\nMotion Statistics by Play Type:")
print(df.groupby('is_pass')[['has_motion', 'significant_movement',␣
 ↪'motion_intensity']].mean())
```

```
Motion Statistics by Play Type:
          has_motion  significant_movement  motion_intensity
is_pass
0           0.007231              0.001446          0.010285
1           0.010066              0.001130          0.010150
```



2.4 Create situational features

Create situational features related to down, distance, field position and time.

2.4.1 situational features

Most features are binary indicators based on the situation of the play. except for the **yards_to_goal** feature which is the absolute yardline number of the ball.

[13]:
```
def create_situational_features(df):
    """
    Create situational features related to down, distance, field position and␣
 ↪time
    """
    feature_df = df.copy()
    feature_df = pd.get_dummies(feature_df, columns=['down'], prefix='down')

    # Distance situations
    feature_df['distance_short'] = feature_df['yardsToGo'] <= 3
    feature_df['distance_long'] = feature_df['yardsToGo'] >= 7
    feature_df['is_third_and_long'] = (feature_df['down_3'] == 1) &␣
 ↪feature_df['distance_long']
```

```
    # Clean playDirection first
    feature_df['playDirection'] = feature_df['playDirection'].fillna('right')
    feature_df.loc[feature_df['playDirection'] == 0, 'playDirection'] = 'right'

    # Normalize yard line (0 = own goal line, 100 = opponent goal line)
    feature_df['yards_to_goal'] = np.where(
        feature_df['playDirection'] == 'right',
        100 - feature_df['absoluteYardlineNumber'],
        feature_df['absoluteYardlineNumber']
    )

    # Clip yards_to_goal to valid range
    feature_df['yards_to_goal'] = feature_df['yards_to_goal'].clip(0, 100)
    feature_df['in_redzone'] = feature_df['yards_to_goal'] <= 20
    feature_df['backed_up'] = feature_df['absoluteYardlineNumber'] <= 10

    # Convert game clock to seconds remaining in quarter
    feature_df['game_clock_seconds'] = feature_df['gameClock'].apply(
        lambda x: int(x.split(':')[0]) * 60 + int(x.split(':')[1])
    )

    # End of half situations (last 2 minutes)
    feature_df['end_of_half'] = (feature_df['quarter'].isin([2, 4])) & \
                                (feature_df['game_clock_seconds'] <= 120)

    # scoring situation features
    feature_df['score_differential_bucket'] = pd.cut(
        feature_df['score_differential'],
        bins=[-28, -17, -9, -3, 3, 9, 17, 28],
        labels=['big_deficit', 'medium_deficit', 'small_deficit',
                'close', 'small_lead', 'medium_lead', 'big_lead']
    )

    feature_df['time_remaining_half'] = feature_df.apply(lambda x:
        1800 if x['quarter'] <= 2 else 3600 - x['game_clock_seconds'], axis=1)

    # One-hot encoded downs, week, quarter
    feature_df = pd.get_dummies(feature_df, columns=['quarter'],␣
↪prefix='quarter')

    # Win probability features
    feature_df['win_prob_differential'] =␣
↪feature_df['preSnapHomeTeamWinProbability'] -␣
↪feature_df['preSnapVisitorTeamWinProbability']

    return feature_df
```

[14]:
```python
# Apply the features
df_with_features = create_situational_features(df)
situational_features = [col for col in df_with_features.columns if col not in␣
↪df.columns]
```

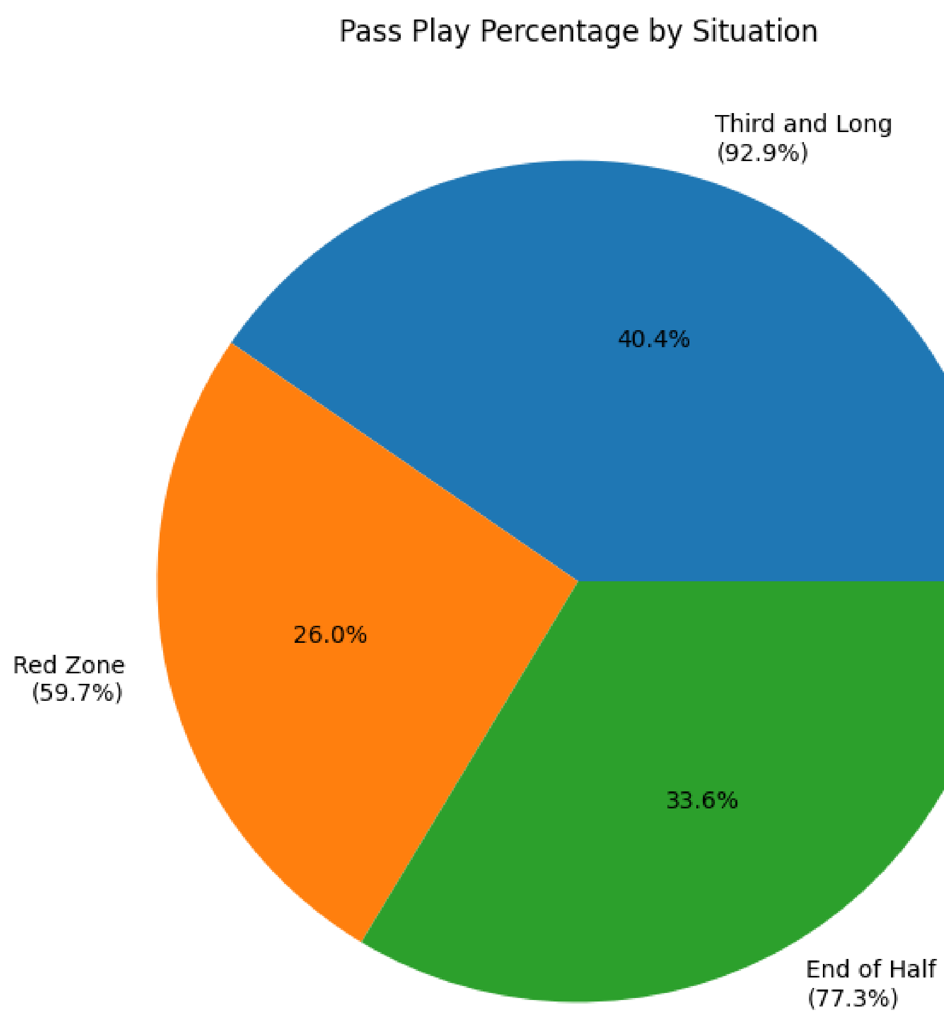
[15]:
```python
# Quick validation
print("\nFeature Statistics:")
for feature in situational_features:
    if df_with_features[feature].dtype in ['int64', 'float64']:
        print(f"\n{feature}:")
        print(df_with_features[feature].describe())
```

```
Feature Statistics:

yards_to_goal:
count    15959.000000
mean        40.884705
std         24.358605
min          0.000000
25%         20.000000
50%         41.000000
75%         61.000000
max        100.000000
Name: yards_to_goal, dtype: float64

game_clock_seconds:
count    15959.000000
mean       434.034275
std        270.506272
min          1.000000
25%        188.000000
50%        425.000000
75%        669.000000
max        900.000000
Name: game_clock_seconds, dtype: float64

time_remaining_half:
count    15959.000000
mean      2483.257723
std        705.780634
min       1800.000000
25%       1800.000000
50%       2700.000000
75%       3175.000000
max       3599.000000
Name: time_remaining_half, dtype: float64
```

```
win_prob_differential:
count    15959.000000
mean         0.104717
std          0.577009
min         -0.997901
25%         -0.346827
50%          0.157877
75%          0.578964
max          0.998393
Name: win_prob_differential, dtype: float64
```

[16]:

```python
# Pass play percentage by situation
plt.figure(figsize=(10, 8))
situations = [
    ('is_third_and_long', 'Third and Long'),
    ('in_redzone', 'Red Zone'),
    ('end_of_half', 'End of Half'),
]
pass_pcts = []
labels = []
for col, label in situations:
    pass_pct = df_with_features[df_with_features[col]][['is_pass']].
  ↪mean()['is_pass']
    pass_pcts.append(pass_pct)
    labels.append(f"{label}\n({pass_pct:.1%})")

plt.pie(pass_pcts, labels=labels, autopct='%1.1f%%')
plt.title('Pass Play Percentage by Situation')
plt.show()
```

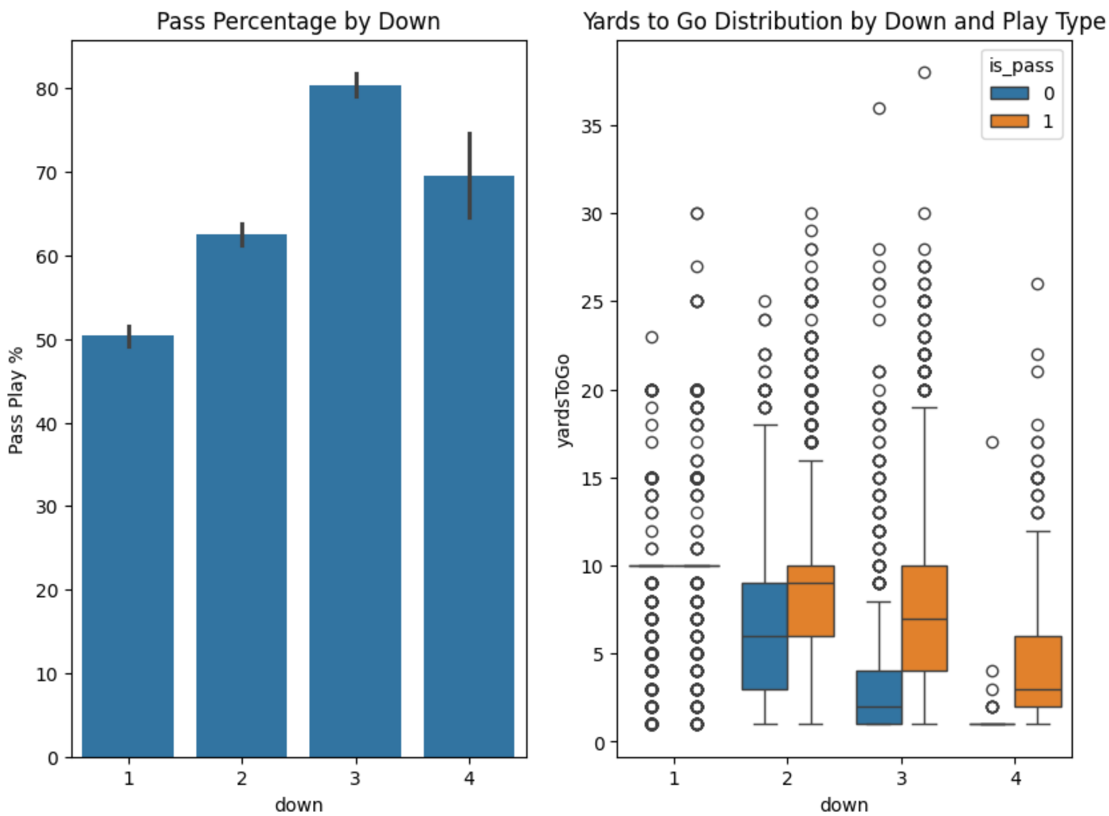


2.5 1.6 Plotting Situational Features

The first subplot on the left shows the pass percentage by down. The second subplot shows the yards to go distribution by down and play type. with the pass plays in blue and the run plays in red.

[17]:
```
plt.figure(figsize=(15, 7))
plt.subplot(131)
sns.barplot(data=df, x='down', y='is_pass',
            errorbar=('ci', 95), estimator=lambda x: sum(x)/len(x)*100)
plt.title('Pass Percentage by Down')
plt.ylabel('Pass Play %')
```

```
plt.subplot(132)
sns.boxplot(data=df, x='down', y='yardsToGo', hue='is_pass')
plt.title('Yards to Go Distribution by Down and Play Type')

plt.show()
```



2.6 Formation Features

Formation features are created by encoding the formation into a binary indicator and then creating additional features based on the receiver alignment.

[18]:
```
def create_formation_features(df):
    """
    Create features based on offensive formation and receiver alignment
    """
    feature_df = df.copy()
    feature_df['offenseFormation'] = feature_df['offenseFormation'].
↪fillna('UNKNOWN')

    # One-hot encode base formation
```

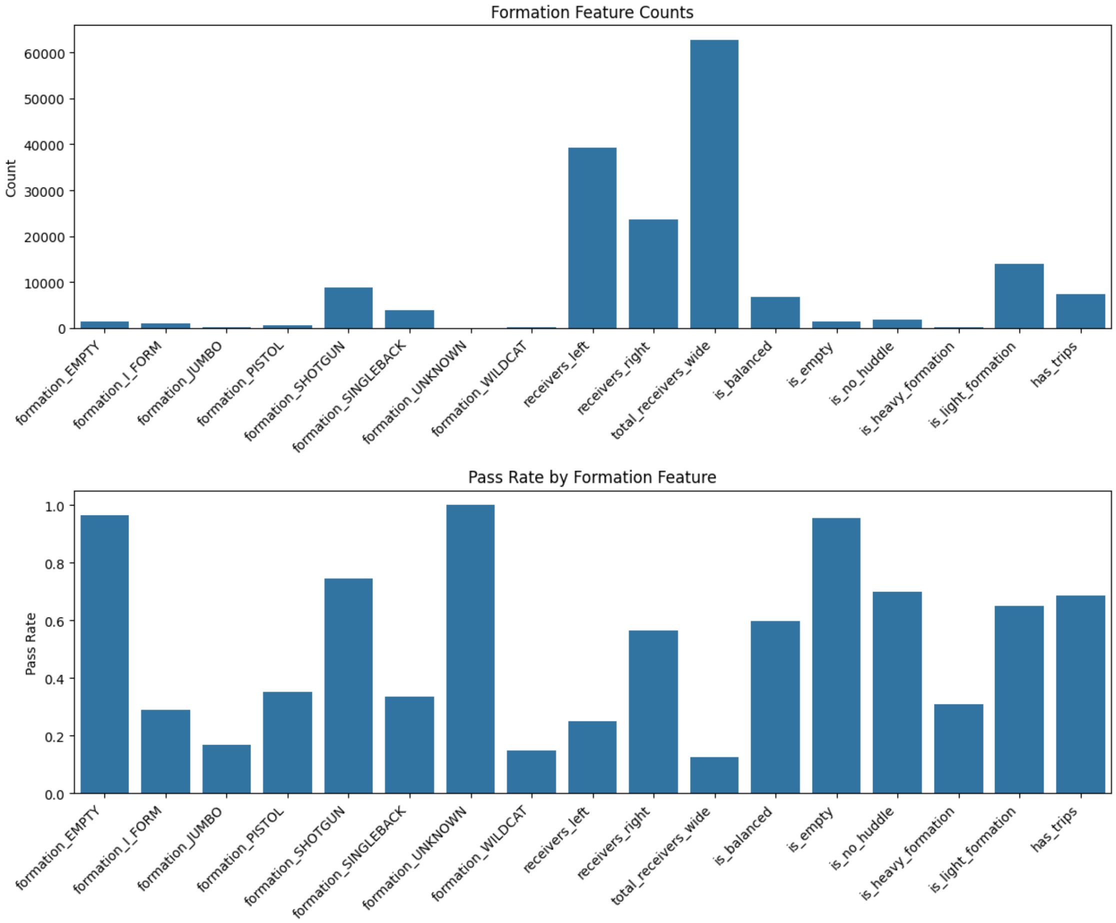
```
    feature_df = pd.get_dummies(feature_df, columns=['offenseFormation'],␣
↪prefix='formation')

    # Clean and process receiver alignment
    feature_df['receiverAlignment'] = feature_df['receiverAlignment'].
↪fillna('0x0')

    # Extract receiver alignment (3x2 is 3 left 2 right)
    alignment_split = feature_df['receiverAlignment'].str.extract(r'(\d)x(\d)')
    feature_df['receivers_left'] = pd.to_numeric(alignment_split[0],␣
↪errors='coerce').fillna(0)
    feature_df['receivers_right'] = pd.to_numeric(alignment_split[1],␣
↪errors='coerce').fillna(0)

    # Total receivers wide
    feature_df['total_receivers_wide'] = feature_df['receivers_left'] +␣
↪feature_df['receivers_right']

    # Balanced/Unbalanced formation
    feature_df['is_balanced'] = feature_df['receivers_left'] ==␣
↪feature_df['receivers_right']

    # Empty backfield (5 or more receivers wide, then backfield is empty)
    feature_df['is_empty'] = feature_df['total_receivers_wide'] >= 5

    # Shotgun vs Under Center (from playDescription)
    feature_df['is_no_huddle'] = feature_df['playDescription'].str.contains('No␣
↪Huddle', case=False, na=False)

    # Heavy personnel (based on receiver count)
    feature_df['is_heavy_formation'] = feature_df['total_receivers_wide'] <= 2
    feature_df['is_light_formation'] = feature_df['total_receivers_wide'] >= 4

    # Trips indicator (3 receivers to one side)
    feature_df['has_trips'] = (feature_df['receivers_left'] == 3) |␣
↪(feature_df['receivers_right'] == 3)

    return feature_df
```

[19]:
```
# Apply the formation features
df_with_formations = create_formation_features(df_with_features)
formation_features = [col for col in df_with_formations.columns if col not in␣
↪df_with_features.columns]
```

[20]:
```
feature_names = []
counts = []
```

```python
pass_rates = []

for col in formation_features:
    if df_with_formations[col].dtype in ['int64', 'float64', 'bool']:
        pass_rate = df_with_formations[df_with_formations[col] == 1]['is_pass'].
 ↪mean()
        count = df_with_formations[col].sum()
        feature_names.append(col)
        counts.append(count)
        pass_rates.append(pass_rate)

fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 10))

# Plot counts
sns.barplot(x=feature_names, y=counts, ax=ax1)
ax1.set_title('Formation Feature Counts')
ax1.set_xticklabels(ax1.get_xticklabels(), rotation=45, ha='right')
ax1.set_ylabel('Count')

# Plot pass rates
sns.barplot(x=feature_names, y=pass_rates, ax=ax2)
ax2.set_title('Pass Rate by Formation Feature')
ax2.set_xticklabels(ax2.get_xticklabels(), rotation=45, ha='right')
ax2.set_ylabel('Pass Rate')

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

```
C:\Users\909ca\AppData\Local\Temp\ipykernel_19988\1800765278.py:19: UserWarning:
set_ticklabels() should only be used with a fixed number of ticks, i.e. after
set_ticks() or using a FixedLocator.
  ax1.set_xticklabels(ax1.get_xticklabels(), rotation=45, ha='right')
C:\Users\909ca\AppData\Local\Temp\ipykernel_19988\1800765278.py:25: UserWarning:
set_ticklabels() should only be used with a fixed number of ticks, i.e. after
set_ticks() or using a FixedLocator.
  ax2.set_xticklabels(ax2.get_xticklabels(), rotation=45, ha='right')
```



2.7 Historical Tendencies

Historical tendencies are created by calculating the average pass rate over the last 20 plays for each team, and the average pass rate for each down and distance combination. using the rolling mean and shift functions.

there is also a recent tendency feature which is the average pass rate over the last 3 plays for each team.

[21]:
```
import numpy as np

def create_historical_tendencies(df):
    """
    Create basic historical tendency features using only prior information
    """
    feature_df = df.copy()
    feature_df = feature_df.sort_values(['gameId', 'playId'])

    # Overall team pass tendency (last 20 plays)
```

```
    feature_df['team_pass_tendency'] = feature_df.
↪groupby('possessionTeam')['is_pass'].transform(
        lambda x: x.rolling(window=20, min_periods=1).mean().shift(1).fillna(x.
↪mean())
    )
    # Last 3 plays
    feature_df['recent_tendency'] = feature_df.
↪groupby('possessionTeam')['is_pass'].transform(
        lambda x: x.rolling(window=3, min_periods=1).mean().shift(1).fillna(x.
↪mean())
    )
    feature_df['team_overall_pass_tendency'] = feature_df.
↪groupby('possessionTeam')['is_pass'].transform('mean')
    feature_df['down_distance_pass_tendency'] = feature_df.groupby(['down_1',␣
↪'down_2', 'down_3', 'down_4', 'distance_short', 'distance_long'])['is_pass'].
↪transform('mean')

    return feature_df
```

[22]:
```
# Apply historical tendency features
df_with_tendencies = create_historical_tendencies(df_with_formations)
```

[23]:
```
tendency_features = ['team_pass_tendency', 'recent_tendency',␣
↪'team_overall_pass_tendency', 'down_distance_pass_tendency']

# Check correlation with actual play calls
print("\nCorrelations with is_pass:")
correlations = df_with_tendencies[tendency_features].
↪corrwith(df_with_tendencies['is_pass'])
print(correlations.sort_values(ascending=False))
```

```
Correlations with is_pass:
down_distance_pass_tendency    0.334682
team_overall_pass_tendency     0.131754
team_pass_tendency             0.120107
recent_tendency                0.093834
dtype: float64
```

[24]:
```
def get_combined_features(df):
    # Formation interactions with down
    for down in [1,2,3,4]:
        df[f'formation_EMPTY_down_{down}'] = (df['formation_EMPTY'] == 1) &␣
↪(df[f'down_{down}'] == 1)
        df[f'formation_SHOTGUN_down_{down}'] = (df['formation_SHOTGUN'] == 1) &␣
↪(df[f'down_{down}'] == 1)
```

```
    # Receiver combinations
    df['receivers_ratio'] = df['total_receivers_wide'] / (df['receivers_left'] +␣
↪df['receivers_right'] + 1)
    df['receiver_balance'] = abs(df['receivers_left'] - df['receivers_right'])

    # Distance and down interactions
    df['critical_distance'] = ((df['down_3'] == 1) | (df['down_4'] == 1)) &␣
↪(df['yardsToGo'] <= 3)
    df['long_distance'] = df['yardsToGo'] > 10

    # Time pressure features
    df['end_quarter_pressure'] = (df['game_clock_seconds'] < 120) &␣
↪((df['quarter_2'] == 1) | (df['quarter_4'] == 1))

    # Formation complexity
    df['complex_formation'] = df['total_receivers_wide'] > 3

    return df
```

2.8 Personnel Features

Personnel features are created by counting the number of players in each position group (RB, TE, WR, FB) and then calculating ratios and packages. They are encoded as binary indicators.

[25]:
```
def get_personnel_features(df, player_plays_df):
    # Create a copy of input dataframe
    personnel_features = df.copy()

    # Merge player positions from players.csv
    players_df = pd.read_csv('data/players.csv')
    player_plays_with_pos = player_plays_df.merge(players_df[['nflId',␣
↪'position']],
                                                    on='nflId', how='left')

    # Position counts per play
    position_counts = player_plays_with_pos.groupby(['gameId', 'playId',␣
↪'position']).size().unstack(fill_value=0)

    # Reset index to merge with main dataframe
    position_counts = position_counts.reset_index()

    # Merge position counts with main features
    personnel_features = personnel_features.merge(position_counts,␣
↪on=['gameId', 'playId'], how='left')

    # Fill NaN values with 0 for position counts
    for pos in ['RB', 'TE', 'WR', 'FB']:
```

```
        if pos in personnel_features.columns:
            personnel_features[f'{pos}_count'] = personnel_features[pos].
↪fillna(0)
        else:
            personnel_features[f'{pos}_count'] = 0

    # Calculate ratios and packages
    personnel_features['heavy_package'] = (personnel_features['TE_count'] +␣
↪personnel_features['FB_count']) >= 2
    personnel_features['spread_formation'] = personnel_features['WR_count'] >= 3
    personnel_features['te_wr_ratio'] = personnel_features['TE_count'] /␣
↪(personnel_features['WR_count'] + 1)

    # Situational features
    personnel_features['goal_line'] =␣
↪personnel_features['absoluteYardlineNumber'] <= 5
    personnel_features['short_yardage'] = personnel_features['yardsToGo'] <= 3

    return personnel_features
```

2.9 1.7 Final Feature Set

The final feature set is created by combining all the relevant features into a single dataframe and then selecting the most important predictive features.

[26]:
```
def prepare_final_features(df):
    """
    Combine all relevant features into final modeling dataset
    Keep only the most important predictive features
    """
    features_df = df.copy()

    # Apply combined features
    features_df = get_combined_features(features_df)

    # Apply personnel features
    features_df = get_personnel_features(features_df, player_play_df)

    # Basic features
    basic_features = [
        'down_1', 'down_2', 'down_3', 'down_4',
        'yardsToGo',
        'quarter_1',
        'quarter_2',
        'quarter_3',
        'quarter_4',
        'quarter_5',
```

```
    ]

    # Motion features
    motion_features = [
        'has_motion', 'significant_movement', 'motion_level',
        'motion_frames', 'total_movement', 'motion_intensity'
    ]

    # Tendency features
    tendency_features = [
        'team_pass_tendency', 'recent_tendency',
        'team_overall_pass_tendency', 'down_distance_pass_tendency'
    ]

    # Situational features
    situational_features = [
        'distance_short', 'distance_long', 'is_third_and_long',
        'yards_to_goal', 'in_redzone', 'backed_up',
        'game_clock_seconds', 'end_of_half',
        'time_remaining_half', 'win_prob_differential',
        'score_differential',
    ]

    # Combined features
    combined_features = [
        'formation_EMPTY_down_1', 'formation_EMPTY_down_2',
        'formation_EMPTY_down_3', 'formation_EMPTY_down_4',
        'formation_SHOTGUN_down_1', 'formation_SHOTGUN_down_2',
        'formation_SHOTGUN_down_3', 'formation_SHOTGUN_down_4',
        'receivers_ratio', 'receiver_balance',
        'critical_distance', 'long_distance',
        'end_quarter_pressure', 'complex_formation'
    ]

    # Personnel features
    personnel_features = [
        'RB_count', 'TE_count', 'WR_count', 'FB_count',
        'heavy_package', 'spread_formation', 'te_wr_ratio',
        'goal_line', 'short_yardage'
    ]

    feature_columns = (basic_features + formation_features
        + tendency_features
        + situational_features + combined_features
        + personnel_features)

    # final feature set
```

```python
    X = features_df[feature_columns]
    y = features_df['is_pass']

    # check feature set
    print("Final feature set:")
    print(X.columns.tolist())
    print("\nFeature set shape:", X.shape)
    print("\nClass distribution:")
    print(y.value_counts(normalize=True))

    return X, y, features_df[feature_columns]
```

[27]:
```python
# Create final feature set
X, y, train_df = prepare_final_features(df_with_tendencies)
```

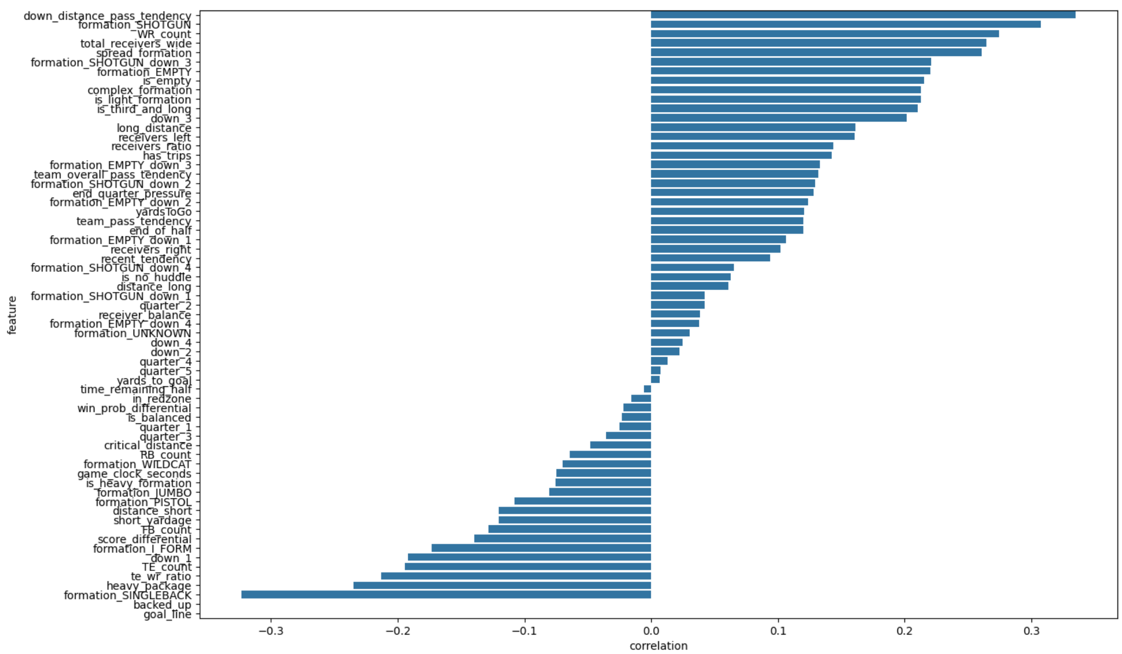
```
Final feature set:
['down_1', 'down_2', 'down_3', 'down_4', 'yardsToGo', 'quarter_1', 'quarter_2',
'quarter_3', 'quarter_4', 'quarter_5', 'formation_EMPTY', 'formation_I_FORM',
'formation_JUMBO', 'formation_PISTOL', 'formation_SHOTGUN',
'formation_SINGLEBACK', 'formation_UNKNOWN', 'formation_WILDCAT',
'receivers_left', 'receivers_right', 'total_receivers_wide', 'is_balanced',
'is_empty', 'is_no_huddle', 'is_heavy_formation', 'is_light_formation',
'has_trips', 'team_pass_tendency', 'recent_tendency',
'team_overall_pass_tendency', 'down_distance_pass_tendency', 'distance_short',
'distance_long', 'is_third_and_long', 'yards_to_goal', 'in_redzone',
'backed_up', 'game_clock_seconds', 'end_of_half', 'time_remaining_half',
'win_prob_differential', 'score_differential', 'formation_EMPTY_down_1',
'formation_EMPTY_down_2', 'formation_EMPTY_down_3', 'formation_EMPTY_down_4',
'formation_SHOTGUN_down_1', 'formation_SHOTGUN_down_2',
'formation_SHOTGUN_down_3', 'formation_SHOTGUN_down_4', 'receivers_ratio',
'receiver_balance', 'critical_distance', 'long_distance',
'end_quarter_pressure', 'complex_formation', 'RB_count', 'TE_count', 'WR_count',
'FB_count', 'heavy_package', 'spread_formation', 'te_wr_ratio', 'goal_line',
'short_yardage']

Feature set shape: (15959, 65)

Class distribution:
is_pass
1    0.610063
0    0.389937
Name: proportion, dtype: float64
```

2.10 Plotting Feature Correlations

This plot shows the correlation between each feature and the target variable (pass or run). Positive correlations indicate that the feature is more likely to be associated with a pass play, while negative correlations suggest the opposite.

```
[28]: # Quick look at feature correlations with target
correlations = pd.DataFrame({
    'feature': X.columns,
    'correlation': X.corrwith(y)
}).sort_values('correlation', ascending=False)
plt.figure(figsize=(15, 10))
sns.barplot(x='correlation', y='feature', data=correlations, orient='h')
plt.show()
```

```
c:\Users\909ca\AppData\Local\Programs\Python\Python312\Lib\site-
packages\numpy\lib\function_base.py:2897: RuntimeWarning: invalid value
encountered in divide
  c /= stddev[:, None]
c:\Users\909ca\AppData\Local\Programs\Python\Python312\Lib\site-
packages\numpy\lib\function_base.py:2898: RuntimeWarning: invalid value
encountered in divide
  c /= stddev[None, :]
```



2.10.1 Feature importance

This visualization shows feature correlations in the engineered features. A few noteable positive features are down_distance_pass_tendency which has the strongest positive correlation (~0.3) WR_count and total_receivers_wide are also highly positively correlated, spread_formation and formation_SHOTGUN_down_3 show significant positive correlations. For the negative correlated features, goal_line shows the strongest negative correlation (~-0.35) backed_up and formation_SINGLEBACK have strong negative correlations, heavy_package follows as another significant negative indicator.

[29]:
```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

[30]:
```
class PlayPredictionDataset(Dataset):
    def __init__(self, features, targets):
        self.features = torch.FloatTensor(features).to(device)
        self.targets = torch.FloatTensor(targets.values).to(device)

    def __len__(self):
        return len(self.features)

    def __getitem__(self, idx):
        return self.features[idx], self.targets[idx]
```

[31]:
```
X_temp, X_test, y_temp, y_test = train_test_split(
    X, y,
    test_size=0.2,
    random_state=42
)

# Then split train+val into train and validation
X_train, X_val, y_train, y_val = train_test_split(
    X_temp, y_temp,
    test_size=0.2,
    random_state=42
)

# Scale features using only training data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)
X_test_scaled = scaler.transform(X_test)

# Create datasets
train_dataset = PlayPredictionDataset(X_train_scaled, y_train)
val_dataset = PlayPredictionDataset(X_val_scaled, y_val)
test_dataset = PlayPredictionDataset(X_test_scaled, y_test)
```

2.11 1.8 Model Architecture

The model architecture is a combination of a convolutional neural network (CNN) and a feature group processing layer. The CNN is used to process the raw numerical features, while the feature group processing layer is used to process the categorical features. The output of the CNN is then combined with the output of the feature group processing layer and passed through a series of fully connected layers to produce the final classification output.

[32]:
```
import torch
import torch.nn as nn
```

```python
class PlayCNN(nn.Module):
    def __init__(self, num_features=X_train.shape[1]):
        super(PlayCNN, self).__init__()
        self.num_features = num_features

        # Feature group processing
        self.feature_groups = nn.Sequential(
            nn.Linear(num_features, 32),
            nn.ReLU(),
            nn.BatchNorm1d(32),
            nn.Dropout(0.4)
        )

        # Convolutional blocks
        self.conv_block1 = nn.Sequential(
            nn.Conv2d(in_channels=1,
                      out_channels=32,
                      kernel_size=(3,1),
                      padding=(1,0)),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.Dropout(0.4)
        )

        # flattened size
        self.flat_features = 32 * num_features * 1

        # Classification head combining conv and feature group outputs
        self.classifier = nn.Sequential(
            nn.Linear(self.flat_features + 32, 64),
            nn.BatchNorm1d(64),
            nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(64, 1),
        )

    def forward(self, x):
        # Process feature groups
        feature_groups = self.feature_groups(x)

        # CNN processing
        x_conv = x.view(-1, 1, self.num_features, 1)
        x_conv = self.conv_block1(x_conv)
        x_conv = x_conv.view(-1, self.flat_features)

        # Combine feature groups with CNN output
        combined = torch.cat((x_conv, feature_groups), dim=1)
```

```python
        # Final classification
        x = self.classifier(combined)
        return x
```

2.11.1 Model Architecture

The model I implemented employs a hybrid architecture that combines neural network components with convolutional processing. It processes input features through two parallel paths:

1. A feature group pathway that uses dense layers with batch normalization and dropout
2. A convolutional pathway that processes the reshaped input through 2D convolutions

The use of parallel processing paths is because some features are more meaningful when processed together. The goal of this hybrid approach is for the CNN pathway to capture formation-based patterns (shown as important in SHAP values later) and the dense feature pathway can process situational features (down, distance, tendencies) This combination allows the model to weigh both structural and situational factors in its predictions

[33]:
```python
# Calculate class weights
n_runs = (y_train == 0).sum()
n_passes = (y_train == 1).sum()

weight_multiplier = 1.45
pos_weight = torch.tensor([n_runs / n_passes * weight_multiplier]).to(device)

print(f"Original weight would be: {n_runs / n_passes:.3f}")
print(f"Adjusted weight: {pos_weight.item():.3f}")
```

```
Original weight would be: 0.643
Adjusted weight: 0.932
```

[34]:
```python
model = PlayCNN(num_features=X_train_scaled.shape[1]).to(device)
criterion = nn.BCEWithLogitsLoss(pos_weight=pos_weight)

train_loader = DataLoader(train_dataset, batch_size=128, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=128, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=128, shuffle=False)

optimizer = torch.optim.AdamW(model.parameters(), lr=0.0001, weight_decay=0.01)

# Learning rate scheduler - reduce LR when validation loss plateaus
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(
    optimizer,
    mode='min',
    factor=0.5,
    patience=3,
    verbose=True,
    min_lr=1e-6
```

```
)
```

```
c:\Users\909ca\AppData\Local\Programs\Python\Python312\Lib\site-
packages\torch\optim\lr_scheduler.py:60: UserWarning: The verbose parameter is
deprecated. Please use get_last_lr() to access the learning rate.
  warnings.warn(
```

[35]:

```
num_epochs = 50
avg_losses = []
val_losses = []
max_grad_norm = 0.4

for epoch in range(num_epochs):
    # Training
    model.train()
    total_train_loss = 0

    for features, targets in train_loader:
        optimizer.zero_grad()
        outputs = model(features)
        loss = criterion(outputs, targets.unsqueeze(1))
        loss.backward()

        # Clip gradients
        torch.nn.utils.clip_grad_norm_(model.parameters(), max_grad_norm)

        optimizer.step()
        total_train_loss += loss.item()

    avg_train_loss = total_train_loss / len(train_loader)

    # Validation
    model.eval()
    total_val_loss = 0
    with torch.no_grad():
        for features, targets in val_loader:
            outputs = model(features)
            val_loss = criterion(outputs, targets.unsqueeze(1))
            total_val_loss += val_loss.item()

    avg_val_loss = total_val_loss / len(val_loader)

    print(f'Epoch [{epoch+1}/{num_epochs}] Train Loss: {avg_train_loss:.4f},␣
↪Val Loss: {avg_val_loss:.4f}')

    # Step scheduler based on val loss
    scheduler.step(avg_val_loss)
```

```
    avg_losses.append(avg_train_loss)
    val_losses.append(avg_val_loss)
```

```
Epoch [1/50] Train Loss: 0.5415, Val Loss: 0.5096
Epoch [2/50] Train Loss: 0.5057, Val Loss: 0.5007
Epoch [3/50] Train Loss: 0.4970, Val Loss: 0.4961
Epoch [4/50] Train Loss: 0.4935, Val Loss: 0.4940
Epoch [5/50] Train Loss: 0.4905, Val Loss: 0.4949
Epoch [6/50] Train Loss: 0.4891, Val Loss: 0.4946
Epoch [7/50] Train Loss: 0.4839, Val Loss: 0.4941
Epoch [8/50] Train Loss: 0.4819, Val Loss: 0.4964
Epoch [9/50] Train Loss: 0.4814, Val Loss: 0.4937
Epoch [10/50] Train Loss: 0.4813, Val Loss: 0.4925
Epoch [11/50] Train Loss: 0.4832, Val Loss: 0.4917
Epoch [12/50] Train Loss: 0.4802, Val Loss: 0.4913
Epoch [13/50] Train Loss: 0.4821, Val Loss: 0.4915
Epoch [14/50] Train Loss: 0.4797, Val Loss: 0.4912
Epoch [15/50] Train Loss: 0.4807, Val Loss: 0.4907
Epoch [16/50] Train Loss: 0.4799, Val Loss: 0.4910
Epoch [17/50] Train Loss: 0.4813, Val Loss: 0.4900
Epoch [18/50] Train Loss: 0.4796, Val Loss: 0.4896
Epoch [19/50] Train Loss: 0.4788, Val Loss: 0.4891
Epoch [20/50] Train Loss: 0.4790, Val Loss: 0.4901
Epoch [21/50] Train Loss: 0.4764, Val Loss: 0.4888
Epoch [22/50] Train Loss: 0.4798, Val Loss: 0.4899
Epoch [23/50] Train Loss: 0.4753, Val Loss: 0.4894
Epoch [24/50] Train Loss: 0.4769, Val Loss: 0.4884
Epoch [25/50] Train Loss: 0.4763, Val Loss: 0.4882
Epoch [26/50] Train Loss: 0.4734, Val Loss: 0.4879
Epoch [27/50] Train Loss: 0.4760, Val Loss: 0.4883
Epoch [28/50] Train Loss: 0.4766, Val Loss: 0.4880
Epoch [29/50] Train Loss: 0.4755, Val Loss: 0.4869
Epoch [30/50] Train Loss: 0.4712, Val Loss: 0.4867
Epoch [31/50] Train Loss: 0.4740, Val Loss: 0.4866
Epoch [32/50] Train Loss: 0.4773, Val Loss: 0.4866
Epoch [33/50] Train Loss: 0.4738, Val Loss: 0.4867
Epoch [34/50] Train Loss: 0.4738, Val Loss: 0.4859
Epoch [35/50] Train Loss: 0.4748, Val Loss: 0.4865
Epoch [36/50] Train Loss: 0.4735, Val Loss: 0.4870
Epoch [37/50] Train Loss: 0.4723, Val Loss: 0.4857
Epoch [38/50] Train Loss: 0.4737, Val Loss: 0.4851
Epoch [39/50] Train Loss: 0.4700, Val Loss: 0.4850
Epoch [40/50] Train Loss: 0.4734, Val Loss: 0.4856
Epoch [41/50] Train Loss: 0.4713, Val Loss: 0.4853
Epoch [42/50] Train Loss: 0.4702, Val Loss: 0.4854
Epoch [43/50] Train Loss: 0.4704, Val Loss: 0.4858
Epoch [44/50] Train Loss: 0.4714, Val Loss: 0.4854
```

```
Epoch [45/50] Train Loss: 0.4696, Val Loss: 0.4854
Epoch [46/50] Train Loss: 0.4702, Val Loss: 0.4847
Epoch [47/50] Train Loss: 0.4701, Val Loss: 0.4853
Epoch [48/50] Train Loss: 0.4710, Val Loss: 0.4851
Epoch [49/50] Train Loss: 0.4719, Val Loss: 0.4844
Epoch [50/50] Train Loss: 0.4691, Val Loss: 0.4845
```

[36]:

```
def predict(model, scaler, features):
    features_scaled = scaler.transform(features)
    features_tensor = torch.FloatTensor(features_scaled).to(device)

    model.eval()
    with torch.no_grad():
        logits = model(features_tensor).to(device)
        probabilities = torch.sigmoid(logits)

    return probabilities.cpu().numpy()

# Example prediction
sample_play = X.iloc[[0]]
print(sample_play)
pred = predict(model, scaler, sample_play)
print(f"Probability of pass: {pred[0][0]:.3f}")
```

```
   down_1  down_2  down_3  down_4  yardsToGo  quarter_1  quarter_2  quarter_3  \
0    True   False   False   False         10       True      False      False

   quarter_4  quarter_5  …  complex_formation  RB_count  TE_count  WR_count  \
0      False      False  …               True         1         1         3

   FB_count  heavy_package  spread_formation  te_wr_ratio  goal_line  \
0         0          False              True         0.25      False

   short_yardage
0          False

[1 rows x 65 columns]
Probability of pass: 0.566
```

[37]:

```
plt.figure(figsize=(15, 5))
plt.plot(avg_losses, label='Train Loss')
plt.plot(val_losses, label='Val Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

3 Keep Track of evaluation metrics

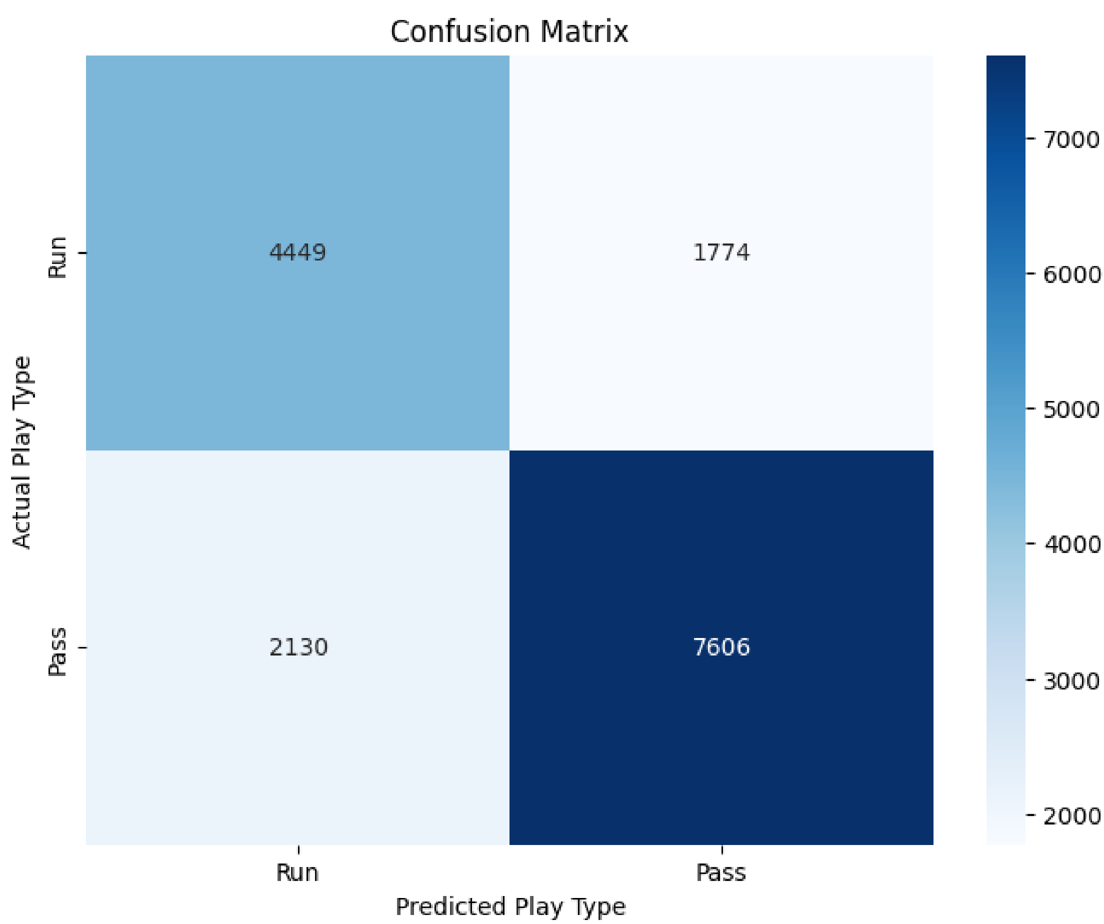
Save eval metrics to a csv.

[38]:
```
# Example prediction
# 10 is a pass play
sample_play = X.iloc[[10]]
pred = predict(model, scaler, sample_play)
print(f"play: {sample_play}")
print(f"Probability of pass: {pred[0][0]:.3f}")
```

```
play:     down_1  down_2  down_3  down_4  yardsToGo  quarter_1  quarter_2  \
10   False   False    True   False          8       True      False

    quarter_3  quarter_4  quarter_5  …  complex_formation  RB_count  \
10      False      False      False  …               True         1

    TE_count  WR_count  FB_count  heavy_package  spread_formation  \
10         1         3         0          False              True

    te_wr_ratio  goal_line  short_yardage
10         0.25      False          False

[1 rows x 65 columns]
Probability of pass: 0.927
```

[39]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns

y_pred_proba = predict(model, scaler, X)[:, 0]
y_true = y.values
```

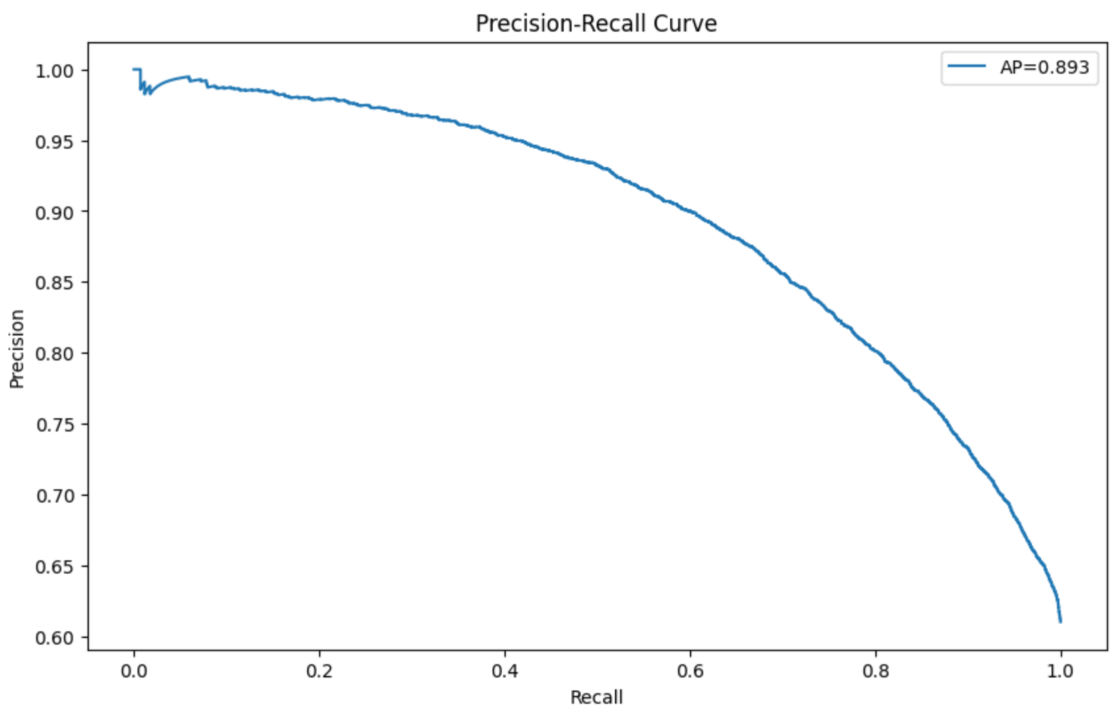
```
y_pred = (y_pred_proba > 0.5).astype(int)
cm = confusion_matrix(y_true, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.ylabel('Actual Play Type')
plt.xlabel('Predicted Play Type')

# Add custom labels
tick_labels = ['Run', 'Pass']
plt.gca().set_xticklabels(tick_labels)
plt.gca().set_yticklabels(tick_labels)

plt.show()
```



[40]:
```
from sklearn.metrics import precision_recall_curve, average_precision_score
```

```python
# Calculate various metrics
precision, recall, thresholds = precision_recall_curve(y_true, y_pred_proba)
ap = average_precision_score(y_true, y_pred_proba)

print(f"Average Precision Score: {ap:.3f}")

# Plot Precision-Recall curve
plt.figure(figsize=(10, 6))
plt.plot(recall, precision, label=f'AP={ap:.3f}')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend()
plt.show()
```

```
Average Precision Score: 0.893
```



[41]:
```python
from sklearn.metrics import classification_report
print(classification_report(y_true, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.68      0.71      0.70      6223
           1       0.81      0.78      0.80      9736
```

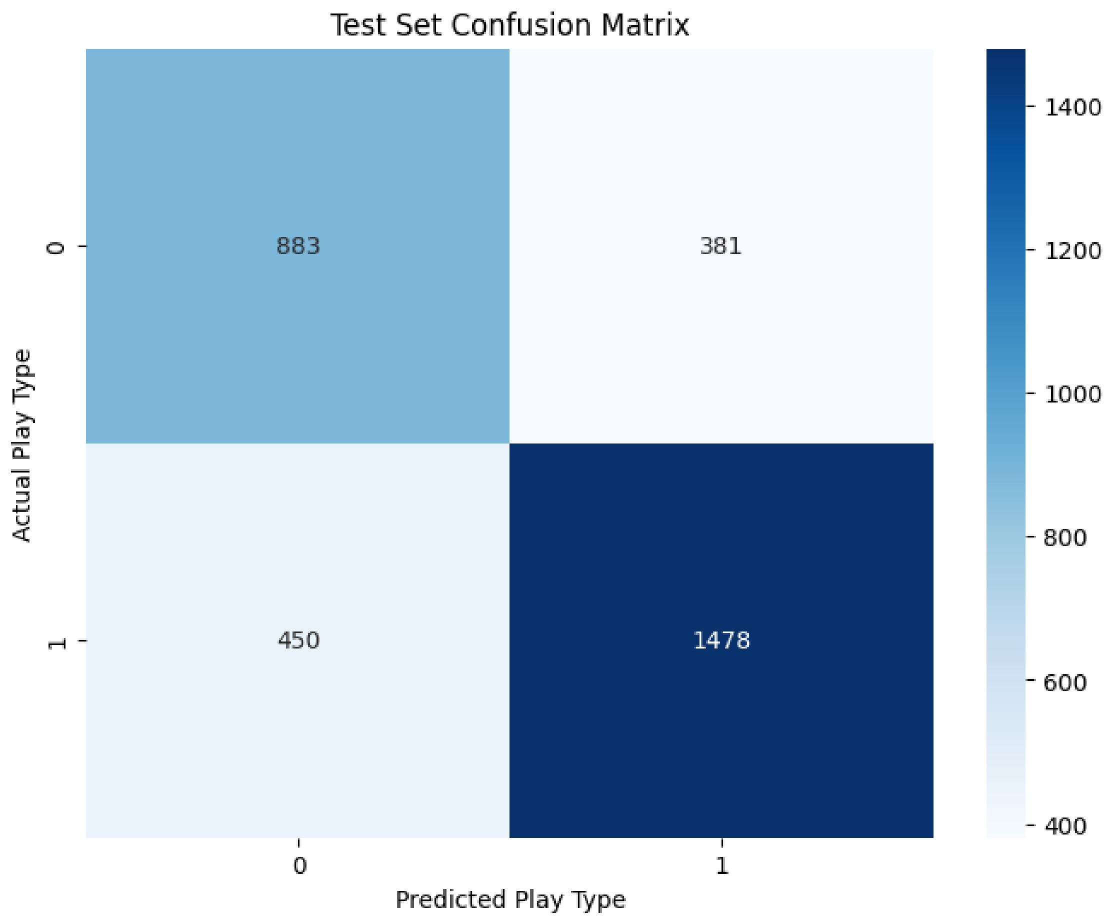
```
    accuracy                           0.76     15959
   macro avg       0.74      0.75      0.75     15959
weighted avg       0.76      0.76      0.76     15959
```

[42]:
```
from sklearn.metrics import classification_report, roc_auc_score
from sklearn.metrics import roc_curve, auc

# Create test loader
test_loader = DataLoader(test_dataset, batch_size=128, shuffle=False)

# Evaluate on test set
model.eval()
test_predictions = []
test_targets = []

with torch.no_grad():
    for features, targets in test_loader:
        features, targets = features.to(device), targets.to(device)
        outputs = model(features)
        probs = torch.sigmoid(outputs)
        test_predictions.extend(probs.cpu().numpy())
        test_targets.extend(targets.cpu().numpy())

test_predictions = np.array(test_predictions)
test_targets = np.array(test_targets)

# Calculate metrics on test set
test_preds_binary = (test_predictions > 0.5).astype(int)

print("\nTest Set Metrics:")
print(classification_report(test_targets, test_preds_binary))
```

```
Test Set Metrics:
              precision    recall  f1-score   support

         0.0       0.66      0.70      0.68      1264
         1.0       0.80      0.77      0.78      1928

    accuracy                           0.74      3192
   macro avg       0.73      0.73      0.73      3192
weighted avg       0.74      0.74      0.74      3192
```

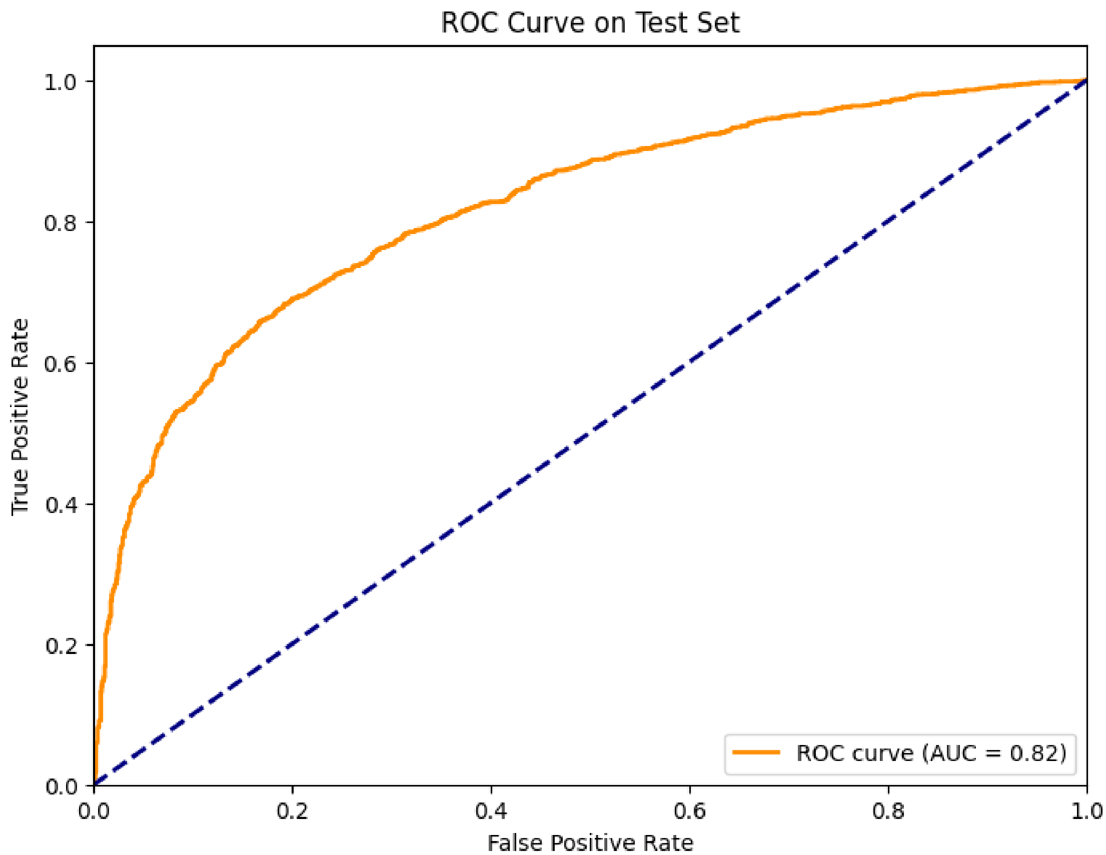
[43]:
```
# Plot confusion matrix for test set
cm_test = confusion_matrix(test_targets, test_preds_binary)
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(cm_test, annot=True, fmt='d', cmap='Blues')
plt.title('Test Set Confusion Matrix')
plt.ylabel('Actual Play Type')
plt.xlabel('Predicted Play Type')
plt.show()
```



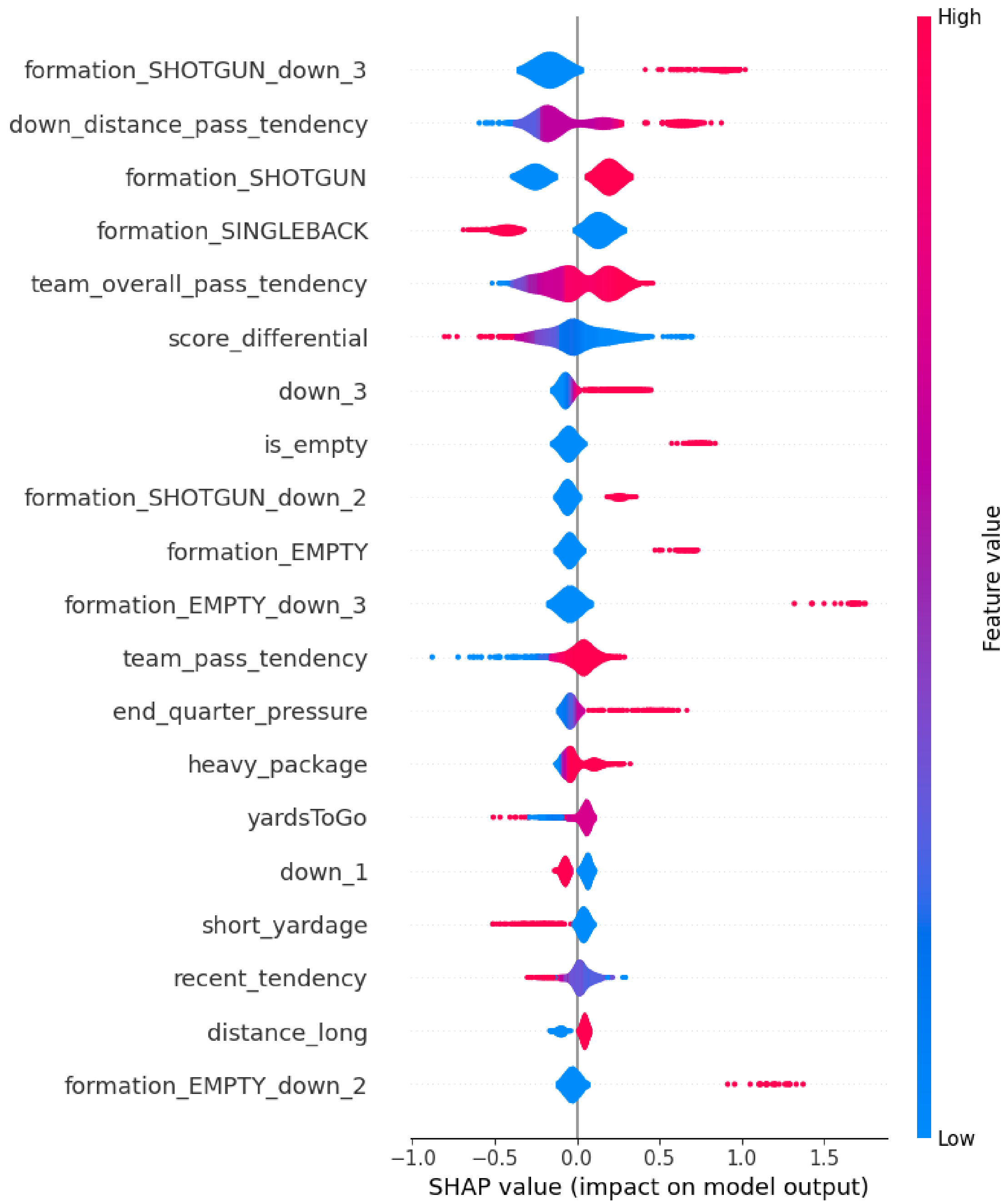
[44]:
```
# Calculate and plot ROC curve for test set
fpr, tpr, _ = roc_curve(test_targets, test_predictions)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
↪2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

```
plt.title('ROC Curve on Test Set')
plt.legend(loc="lower right")
plt.show()
```



[83]:
```
import shap
model.eval()

# Create background dataset from training data
background = torch.FloatTensor(scaler.transform(X[:1000])).to(device)
test_targets = torch.FloatTensor(scaler.transform(X[:1000])).to(device)

# Create explainer using background data
e = shap.DeepExplainer(model, background)
shap_values = e.shap_values(test_targets, check_additivity=False)
```

[84]:
```
# Create plots
plt.figure(figsize=(15, 10))
shap.summary_plot(shap_values.squeeze(), test_targets.cpu().numpy(),
                  feature_names=X.columns.tolist(), plot_type='violin')
```



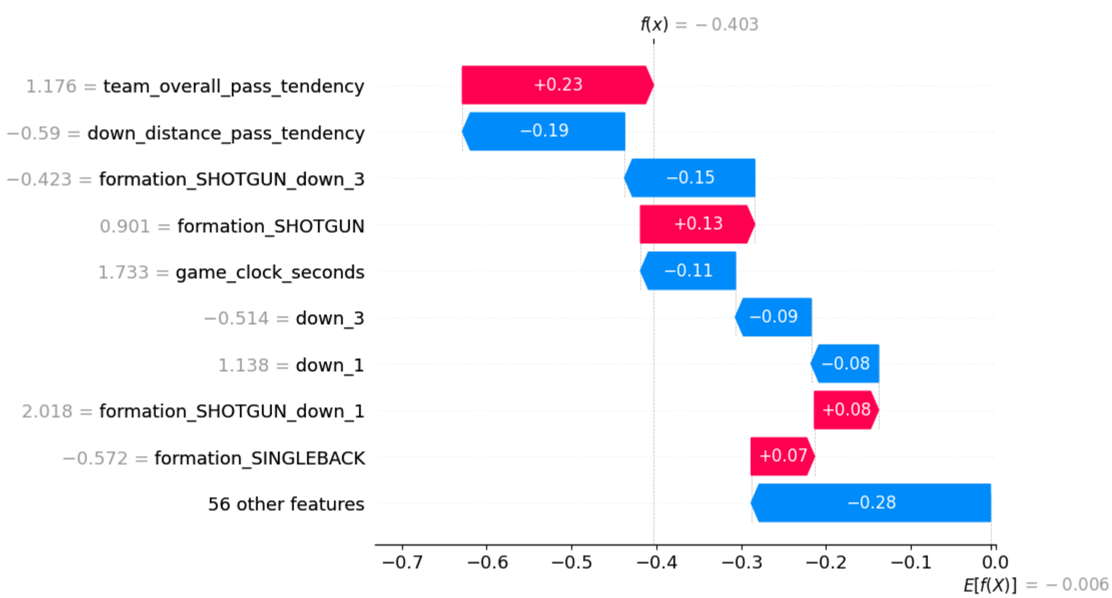
3.0.1 Shapely feature impact

Formations Impact (SHOTGUN, SINGLEBACK, EMPTY) have significant but varying impacts on the model's predictions, SHOTGUN formations in different downs (down_2, down_3) show notable influence. The formation impacts are context-dependent, varying based on the down situation

For Passing Tendencies team_overall_pass_tendency has one of the strongest positive impacts and down_distance_pass_tendency shows a mixed effect, with both positive and negative influences depending on context

With Situational Factors down_3 appears as a significant negative factor, score_differential shows a wide distribution of impacts whereas yardage-related features (yardsToGo, short_yardage, distance_long) have varied effects

[85]:
```
# Calculate base value and get first few predictions
base_value = shap_values[0].mean()
shap_values_few = shap_values[0][:1]

e = shap.Explainer(model, shap_values.squeeze())

shap.waterfall_plot(
    shap.Explanation(
        values=shap_values.squeeze()[0],
        base_values=base_value,
        data=test_targets[0].cpu().numpy(),
        feature_names=X.columns.tolist()
    ),
    show=False
)
plt.show()
```



Final Thoughts An overall accuracy of 75% is decent, Although football is unpredictable, and this task is difficult I feel as though in the future I will be able to improve it, I did a PCA dimensionality reduction and with the current features I would only need 22 to cover 80% of the variance. So, in the future I will be removing some features that may be causing noise. select 22 of the most importatnt features and see how that works. Furthermore maybe attempting a different model architecture although this has been one of the best performing models.