```
In [2]: import requests
        from bs4 import BeautifulSoup
        from datetime import datetime, timedelta
        import time
        import pandas as pd
        import numpy as np
        import random
        from tqdm import tqdm
        import torch
        import torch.nn as nn
        import torch.nn.functional as F
        from torch.utils.data import TensorDataset, DataLoader
        from sklearn.model_selection import train_test_split, KFold
        import matplotlib.pyplot as plt
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.metrics import accuracy_score
        from sklearn.ensemble import RandomForestRegressor
        from sklearn.metrics import mean_squared_error
        from sklearn.preprocessing import OneHotEncoder, StandardScaler
```

Section 1: Data Scraping & Wrangling Data

```
In [67]: def daterange(start_date, end_date):
              for n in range(int((end_date - start_date).days) + 1):
                  yield start_date + timedelta(days=n)
         team name mapping = {
              "Cleveland": "CLE",
              "Charlotte": "CHO",
              "LA Lakers": "LAL",
              "New Orleans": "NOP",
              "Brooklyn": "BRK",
              "Oklahoma City": "OKC",
              "Milwaukee": "MIL",
              "Phoenix": "PHO",
              "New York": "NYK",
              "Atlanta": "ATL",
              "Boston": "BOS",
              "Chicago": "CHI",
              "Dallas": "DAL",
              "Denver": "DEN",
              "Detroit": "DET",
              "Golden State": "GSW",
              "Houston": "HOU",
              "Indiana": "IND",
              "LA Clippers": "LAC",
              "Memphis": "MEM",
              "Miami": "MIA",
              "Minnesota": "MIN",
              "Orlando": "ORL",
              "Philadelphia": "PHI",
              "Portland": "POR",
              "Sacramento": "SAC"
              "San Antonio": "SAS",
              "Toronto": "TOR",
              "Utah": "UTA",
```

```
"Washington": "WAS",
}
def rate_limit(requests, per_minute, last_request_time):
    if len(requests) >= per_minute:
        time_since_oldest_request = datetime.now() - requests[0]
        if time since oldest request < timedelta(minutes=1):</pre>
            sleep_time = (timedelta(minutes=1) - time_since_oldest_request).total_secc
            print(f"Rate limit reached, sleeping for {sleep_time} seconds.")
            time.sleep(sleep_time)
        requests.pop(0)
    requests.append(datetime.now())
request_times = []
def scrape_basic_box_score_stats(url, team_abbr):
    headers = {
        'User-Agent': 'Mozilla/5.0 (Macintosh; Intel Mac OS X 10.15; rv:86.0) Gecko/20
    response = requests.get(url, headers=headers)
    rate_limit(request_times, 9, datetime.now())
    if response.status_code != 200:
        print(f"Failed to retrieve data from {url}")
        return {}
    soup = BeautifulSoup(response.content, 'html.parser')
    table id = f'box-{team abbr}-game-basic'
    table = soup.find('table', id=table_id)
    desired_stats = {
        'FGA': None,
        'FG_pct': None,
        'FTA': None,
        'FT pct': None,
        'TRB': None,
        'fg3a': None,
        'fg3_pct': None,
        'TOV': None,
        'stl': None,
        'blk': None,
        'ast': None
    }
    if table:
        totals row = table.find('tfoot').find('tr')
        if totals_row:
            for stat in desired_stats.keys():
                data cell = totals row.find('td', {'data-stat': stat.lower()})
                if data cell:
                    desired_stats[stat] = data_cell.text.strip()
    return desired_stats
def scrape_general_game_info(date):
    headers = {
        'User-Agent': 'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (K
    url = f"https://www.basketball-reference.com/boxscores/?month={date.month:02d}&day
    rate_limit(request_times, 9, datetime.now())
    response = requests.get(url, headers=headers)
```

```
if response.status_code != 200:
    print(f"Request failed for {url} with status code {response.status code}")
    return []
soup = BeautifulSoup(response.content, 'html.parser')
games info = []
game_summaries = soup.find_all('div', class_='game_summary expanded nohover')
for game_summary in game_summaries:
    teams = game_summary.find_all('tr', class_=['winner', 'loser'])
    box_score_link_tag = game_summary.find('p', class_='links').find('a', text='Bc
    if len(teams) == 2 and box_score_link_tag:
        box_score_link = "https://www.basketball-reference.com" + box_score_link_t
        team1, team1_score = teams[0].find('a').text.strip(), teams[0].find('td',
        team2, team2_score = teams[1].find('a').text.strip(), teams[1].find('td',
        game_info = {
            'date': date.strftime('%Y-%m-%d'),
            'team1': team1,
            'team1_score': team1_score,
            'team2': team2,
            'team2_score': team2_score,
            'box_score_link': box_score_link
        }
        game_info['team1_stats'] = scrape_basic_box_score_stats(box_score_link, te
        game_info['team2_stats'] = scrape_basic_box_score_stats(box_score_link, team2_stats')
        games_info.append(game_info)
return games_info
```

```
In [ ]: #date range
        start_date = datetime(2023, 11, 1)
        end_date = datetime(2024, 4, 5)
        total_days = (end_date - start_date).days + 1
        #collecting all games data
        all_games_data = []
        for single_date in tqdm(daterange(start_date, end_date), total=total_days, desc = "Scr
             games_info = scrape_general_game_info(single_date)
             all games data.extend(games info)
        expanded_games_data = []
        for game in all_games_data:
            #extracting basic game info
             game_info = {
                 'date': game['date'],
                 'team1': game['team1'],
                 'team1_score': game['team1_score'],
                 'team2': game['team2'],
                 'team2_score': game['team2_score'],
            }
            #extracting team1 stats and prefix with 'team1_'
            team1_stats = {f'team1_{k}': v for k, v in game['team1_stats'].items()}
            game info.update(team1 stats)
            #extracting team2 stats and prefix with 'team2_'
            team2_stats = {f'team2_{k}': v for k, v in game['team2_stats'].items()}
            game_info.update(team2_stats)
```

```
#adding the expanded game info to the new list
    expanded_games_data.append(game_info)

#converting to a DataFrame for analysis
    df_games = pd.DataFrame(expanded_games_data)

print("Dataset with General Game Info and Basic Box Score Stats:")
print(df_games)

In []: #converted scraped data to csv to save it... so i don't spend another 5 hours data scr
    df_games.to_csv('br.csv', index = False)

In [68]: br_df = pd.read_csv('br.csv')
print(br_df)
```

```
team1 team1_score
           date
                                                 team2 team2_score \
0
     11/1/2023
                 Washington
                                     121
                                               Atlanta
                                                                130
1
     11/1/2023
                    Indiana
                                     104
                                                Boston
                                                                155
2
     11/1/2023
                    Chicago
                                     105
                                                Dallas
                                                                114
3
     11/1/2023
                  Portland
                                     110
                                               Detroit
                                                                101
     11/1/2023 Sacramento
4
                                     101 Golden State
                                                                102
1098
     4/5/2024
                    Detroit
                                     90
                                               Memphis
                                                                108
1099
                                     117
                                             Milwaukee
      4/5/2024
                    Toronto
                                                                111
1100
     4/5/2024 San Antonio
                                     111
                                           New Orleans
                                                                109
1101
       4/5/2024
                Minnesota
                                     87
                                               Phoenix
                                                                 97
1102
      4/5/2024
                  Portland
                                     108
                                            Washington
                                                                102
      team1_FGA team1_FG_pct team1_FTA team1_FT_pct team1_TRB ...
0
            101
                       0.505
                                     14
                                                0.643
                                                              35
1
            101
                       0.455
                                     12
                                                0.583
                                                              31
                                                                  . . .
2
            89
                                     11
                                                0.909
                                                              43 ...
                       0.472
3
            81
                       0.469
                                     33
                                                0.818
                                                              44 ...
4
            88
                       0.409
                                     23
                                                0.783
                                                              48
                                                                  . . .
                                     . . .
                                                 . . .
            79
                                                0.750
1098
                       0.405
                                     24
                                                              38
                                                                  . . .
            79
1099
                       0.456
                                     36
                                                0.861
                                                              47
            83
                                     13
                                                              34
1100
                       0.506
                                                0.769
                                                                  . . .
1101
            85
                       0.388
                                     14
                                                0.786
                                                              44 ...
1102
            94
                       0.436
                                     24
                                                0.708
                                                              55
      team2_FG_pct team2_FTA team2_FT_pct team2_TRB team2_fg3a \
0
            0.500
                          32
                                     0.906
                                                   57
                                                               32
1
            0.568
                          28
                                     0.964
                                                   57
                                                               35
2
                          28
                                                   45
                                                               48
            0.457
                                     0.714
3
            0.444
                                     0.909
                                                   38
                                                               29
                          11
4
            0.481
                          15
                                     0.867
                                                   36
                                                               31
            0.467
                                     0.875
                                                   49
1098
                          16
                                                               31
                                                               42
1099
            0.436
                          21
                                     0.810
                                                   45
1100
            0.512
                          12
                                     1.000
                                                   41
                                                               29
1101
            0.434
                          29
                                     0.759
                                                   49
                                                               26
1102
            0.432
                          30
                                     0.700
                                                   45
                                                               33
      team2 fg3 pct team2 TOV team2 stl team2 blk team2 ast
0
             0.281
                           20
                                       8
                                                  3
                                                            26
                                                  2
1
             0.571
                           11
                                       5
                                                            27
2
                                      7
                                                  2
                                                            23
                           13
             0.417
                                      12
3
             0.379
                           18
                                                  4
                                                            24
4
             0.355
                           17
                                       5
                                                  6
                                                            32
               . . .
                                                  7
1098
             0.323
                           20
                                      13
                                                            24
1099
             0.286
                           13
                                      8
                                                  6
                                                            21
                           17
                                      11
                                                  2
                                                            28
1100
             0.310
                                                  3
                                                            29
1101
             0.346
                           18
                                      12
                                                  5
                            9
                                       9
             0.152
                                                            24
1102
```

[1103 rows x 27 columns]

```
unique_teams = pd.unique(br_df[['team1', 'team2']].values.ravel('K'))
In [69]:
         #mapped each team to a unique integer
         team_to_id = {team: i for i, team in enumerate(unique_teams)}
         print(team to id)
         br_df['Home_Team_ID'] = br_df['team2'].map(team_to_id) # home team is team 2
         br_df['Away_Team_ID'] = br_df['team1'].map(team_to_id) # away team is team 1
```

```
#added win column
br_df['HomeWin'] = (br_df['team2_score'] > br_df['team1_score']).astype(int) #astype of
br_df['date'] = pd.to_datetime(br_df['date'])
br_df['month'] = (br_df['date'].dt.month - 11) % 12
print(br_df)
```

{'Washington': 0, 'Indiana': 1, 'Chicago': 2, 'Portland': 3, 'Sacramento': 4, 'Charlo

tte': 5, 'LA Clippers': 6, 'Brooklyn': 7, 'Denver': 8, 'Cleveland': 9, 'New Orleans': 10, 'Milwaukee': 11, 'Memphis': 12, 'Detroit': 13, 'Toronto': 14, 'San Antonio': 15, 'Orlando': 16, 'Dallas': 17, 'New York': 18, 'Golden State': 19, 'Boston': 20, 'Uta h': 21, 'Atlanta': 22, 'LA Lakers': 23, 'Phoenix': 24, 'Miami': 25, 'Philadelphia': 2 6, 'Oklahoma City': 27, 'Minnesota': 28, 'Houston': 29} team1 team1 score date team2 team2 score \ 2023-11-01 Washington Atlanta 2023-11-01 Boston Indiana 2023-11-01 Chicago Dallas 2023-11-01 Portland Detroit 2023-11-01 101 Golden State Sacramento 1098 2024-04-05 Memphis Detroit 1099 2024-04-05 Milwaukee Toronto 1100 2024-04-05 San Antonio New Orleans 1101 2024-04-05 Minnesota Phoenix 1102 2024-04-05 Portland Washington team1 FGA team1_FG_pct team1_FTA team1_FT_pct team1_TRB 0.505 0.643 . . . 0.455 0.583 0.472 0.909 . . . 0.469 0.818 . . . 0.409 0.783 0.405 0.750 . . . 0.456 0.861 0.506 0.769 . . . 0.388 0.786 0.436 0.708 . . . team2_fg3a team2_fg3_pct team2_TOV team2_stl team2_blk team2_ast \ 0.281 0.571 0.417 0.379 0.355 0.323 0.286 0.310 0.346 0.152 Home_Team_ID Away_Team_ID HomeWin month

[1103 rows x 31 columns]

```
In [ ]: #I saved the new 31 column version of dataframe
br_df.to_csv('br31.csv', index = False)
```

Section 2: Predicting Wins with BR31 Dataframe

```
In [70]:
         home team = torch.tensor(br df['Home Team ID'], dtype=torch.long)
         away_team = torch.tensor(br_df['Away_Team_ID'], dtype=torch.long)
         num classes = 30
         home_teams_ohe = F.one_hot(home_team, num_classes=num_classes)
         away teams ohe = F.one hot(away team, num classes=num classes)
         date_stuff = torch.tensor(br_df['month'], dtype=torch.long)
         months_ohe = F.one_hot(date_stuff, num_classes = 6)
         x_ohe_tensor = torch.cat((home_teams_ohe, away_teams_ohe), dim=1)
         numeric_data = br_df.drop(['date', 'month', 'Home_Team_ID', 'team1_score', 'team2_score')
         scaler = StandardScaler()
         x_norm = scaler.fit_transform(numeric_data)
         x norm tensor = torch.tensor(x norm, dtype=torch.float32)
         X_almost = torch.cat((x_norm_tensor, x_ohe_tensor), dim=1)
         X = torch.cat((X_almost, months_ohe), dim = 1)
         print(X.shape)
         y = torch.tensor(br_df['HomeWin'], dtype=torch.long)
         torch.Size([1103, 88])
In [71]: class Trainer:
             def __init__(self, model, opt_method, learning_rate, batch_size, epoch, 12):
                 self.model = model
                 if opt_method == "adam":
                      self.optimizer = torch.optim.Adam(model.parameters(), learning_rate, weigh
                 else:
                      raise NotImplementedError("This optimization is not supported")
                 self.epoch = epoch
                 self.batch_size = batch_size
             def train(self, X_train, y_train, X_val, y_val, early_stop=True, draw_curve=True):
                 train_dataset = TensorDataset(X_train, y_train)
                 train_loader = DataLoader(train_dataset, batch_size=self.batch_size, shuffle=1
                 val_dataset = TensorDataset(X_val, y_val)
                 val_loader = DataLoader(val_dataset, batch_size=self.batch_size, shuffle=False
                 train_loss_list, train_acc_list = [], []
                 val_loss_list, val_acc_list = [], []
                 weights = self.model.state_dict()
                 lowest_val_loss = np.inf
                 loss_func = nn.CrossEntropyLoss()
                 for n in tqdm(range(self.epoch), leave=True):
                     # enable train mode
```

```
self.model.train()
        epoch_loss, epoch_acc = 0.0, 0.0
        for X_batch, y_batch in train_loader:
            batch_importance = y_batch.shape[0] / len(train_dataset)
            y_pred = self.model(X_batch)
            batch_loss = loss_func(y_pred, y_batch)
            self.optimizer.zero_grad()
            batch_loss.backward()
            self.optimizer.step()
            epoch_loss += batch_loss.detach().cpu().item() * batch_importance
            batch_acc = torch.sum(torch.argmax(y_pred, axis=1) == y_batch) / y_bat
            epoch_acc += batch_acc.detach().cpu().item() * batch_importance
        train loss list.append(epoch loss)
        train_acc_list.append(epoch_acc)
        val_loss, val_acc = self.evaluate(val_dataset)
        val_loss_list.append(val_loss)
        val_acc_list.append(val_acc)
        if early_stop:
            if val_loss < lowest_val_loss:</pre>
                lowest_val_loss = val_loss
                weights = self.model.state_dict()
    if draw_curve:
        x axis = np.arange(self.epoch)
        fig, axes = plt.subplots(1, 2, figsize=(10, 4))
        axes[0].plot(x_axis, train_loss_list, label="Train")
        axes[0].plot(x_axis, val_loss_list, label="Validation")
        axes[0].set_title("Loss")
        axes[0].legend()
        axes[1].plot(x_axis, train_acc_list, label='Train')
        axes[1].plot(x_axis, val_acc_list, label='Validation')
        axes[1].set_title("Accuracy")
        axes[1].legend()
        print(f"Validation accuracy: {np.mean(val_acc_list)}+/-{np.std(val_acc_list)}
    if early_stop:
        self.model.load_state_dict(weights)
    return {
        "train loss list": train loss list,
        "train_acc_list": train_acc_list,
        "val_loss_list": val_loss_list,
        "val_acc_list": val_acc_list,
    }
def evaluate(self, data, print_acc=False):
    # enable evaluation mode
    self.model.eval()
    loader = DataLoader(data, batch_size=self.batch_size, shuffle=True)
    loss func = nn.CrossEntropyLoss()
    acc, loss = 0.0, 0.0
    for X_batch, y_batch in loader:
        with torch.no_grad():
            batch_importance = y_batch.shape[0] / len(data)
            y_pred = self.model(X_batch)
            batch_loss = loss_func(y_pred, y_batch)
            batch_acc = torch.sum(torch.argmax(y_pred, axis=1) == y_batch) / y_bat
```

```
acc += batch_acc.detach().cpu().item() * batch_importance
    loss += batch_loss.detach().cpu().item() * batch_importance

if print_acc:
    print(f"Accuracy: {acc:.3f}")

return loss, acc
```

```
In [72]: def KFoldCrossValidation(
             model class, k,
             Х, у,
             opt method='adam', learning rate=1e-4, batch size=32, epoch=100, 12=0
         ):
             _, X_test, _, y_test = train_test_split(X, y, test_size=0.2)
             test dataset = TensorDataset(X test, y test)
             kf = KFold(n_splits = k, shuffle = True)
             train_acc_list, test_acc_list = [], []
             for i, (train index, val index) in enumerate(kf.split(X)):
                 print(f"Fold {i}:")
                 X_train, X_val = X[train_index], X[val_index]
                 y_train, y_val = y[train_index], y[val_index]
                 model = model_class()
                 # initialize a Trainer object
                 trainer = Trainer(model, opt_method, learning_rate, batch_size, epoch, 12)
                 # call trainer.train() here
                 res = trainer.train(X_train, y_train, X_val, y_val)
                 train_acc_best = res['train_acc_list'][np.argmin(res['val_loss_list'])]
                 test_loss, test_acc = trainer.evaluate(test_dataset)
                 if i == 1:
                     torch.save(model.state_dict(), f'model_weights_fold_1.pth')
                 train_acc_list.append(train_acc_best)
                 test_acc_list.append(test_acc)
                 print(f"Training accuracy: {train_acc_best}")
                 print(f"Test accuracy: {test acc}")
             print("Final results:")
             print(f"Training accuracy: {np.mean(train_acc_list)}+/-{np.std(train_acc_list)}")
             print(f"Test accuracy: {np.mean(test acc list)}+/-{np.std(test acc list)}")
In [73]: class WinPredictor(nn.Module):
             def __init__(self, ):
                 super(WinPredictor, self).__init__()
                 self.fc1 = nn.Linear(88, 128)
                 self.fc2 = nn.Linear(128, 64)
                 self.output_layer = nn.Linear(64, 2)
             def forward(self, x):
                 x = F.relu(self.fc1(x))
                 x = F.relu(self.fc2(x))
                 # Using softmax activation function
                 win_prob = F.softmax(self.output_layer(x), dim = -1)
                 return win_prob
```

In [75]: KFoldCrossValidation(WinPredictor, 3, X, y)

Fold 0:

100%| 100/100 [00:14<00:00, 6.96it/s]

Validation accuracy: 0.9277445652173916+/-0.07012459269549368

Training accuracy: 1.0

Test accuracy: 0.9864253393665159

Fold 1:

100% | 100/100 [00:10<00:00, 9.62it/s]

Validation accuracy: 0.9235054347826086+/-0.05982628715643639

Training accuracy: 1.0

Test accuracy: 0.9773755631835214

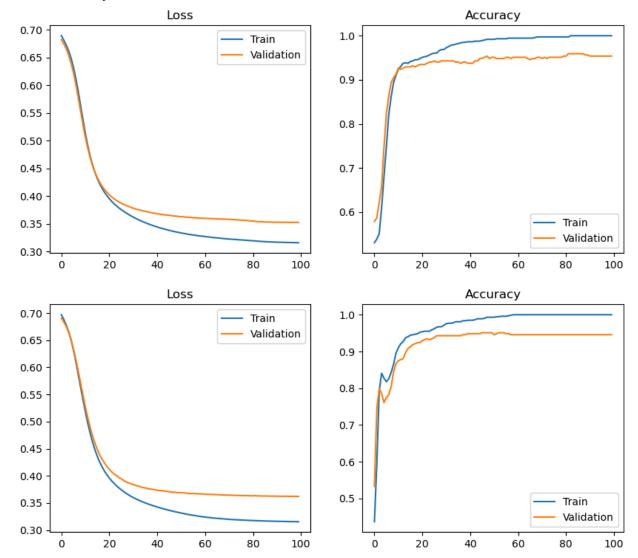
Fold 2:

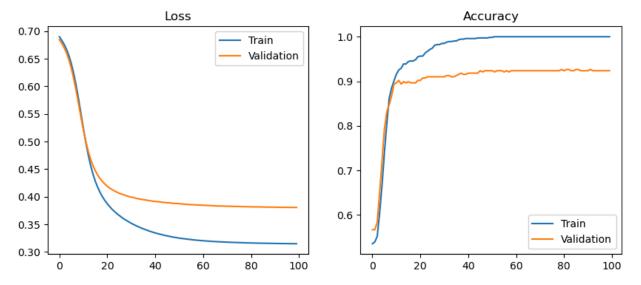
100%| 100%| 100/100 [00:10<00:00, 9.46it/s]

Validation accuracy: 0.8991553135691287+/-0.0688608152054051

Final results:

Training accuracy: 0.999999999999999+/-2.1259152388627147e-16 Test accuracy: 0.9819004508704623+/-0.0036945556557881403





Analysis:

- 1. High variance/overfitting. Model is not learning underlying relationships.
- 2. Given team stats for every game, model predicts wins very well (i.e., much better than random chance).

Section 2: Creating rolling average and over/under prediction

```
In [76]: #prepared stats for team1 and team2
         br df = pd.read csv('br31.csv')
         team1_stats = br_df.filter(regex='team1').rename(columns=lambda x: x.replace('team1_';
         team1 stats['team'] = br df['team1']
         team1_stats['date'] = br_df['date']
         team2 stats = br df.filter(regex='team2').rename(columns=lambda x: x.replace('team2').
         team2_stats['team'] = br_df['team2']
         team2_stats['date'] = br_df['date']
         #concatenate and calculate cumulative stats
         all stats = pd.concat([team1 stats, team2 stats])
         all_stats_grouped = all_stats.groupby(['team', 'date']).sum(numeric_only=True).groupby
         all_stats_grouped['games_played'] = all_stats.groupby(['team', 'date']).size().groupby
         #ensured indices are aligned properly
         current game stats = all stats.groupby(['team', 'date']).sum(numeric only=True)
         current_game_stats = current_game_stats.reindex(all_stats_grouped.index)
         #calculated running averages by excluding current game stats
         all_stats_grouped['games_played'] = all_stats_grouped['games_played'] - 1 # Decrement
         avg_stats_per_game = (all_stats_grouped - current_game_stats)
         avg_stats_per_game = avg_stats_per_game.div(all_stats_grouped['games_played'], axis=0)
```

```
# Handle division by zero for the first game
         avg_stats_per_game = avg_stats_per_game.replace([np.inf, -np.inf], np.nan).fillna(0)
         avg_stats_per_game.reset_index(inplace=True)
         print(avg_stats_per_game)
                    team
                               date
                                           FGA
                                                  FG pct
                                                               FTA
                                                                      FT pct \
                 Atlanta 2023-11-01 0.000000 0.000000
         0
                                                         0.000000 0.000000
         1
                 Atlanta 2023-11-04 92.000000 0.500000 32.000000 0.906000
         2
                 Atlanta 2023-11-06 92.500000 0.492000 28.000000 0.849000
         3
                 Atlanta 2023-11-09 95.666667 0.452333 29.333333 0.847333
                 Atlanta 2023-11-11 93.000000 0.459750 29.500000 0.827250
                                . . .
                     . . .
                                           . . .
                                                   . . .
                                                               . . .
         2201 Washington 2024-03-29 91.457143 0.471600 20.071429 0.762443
         2202 Washington 2024-03-31 91.408451 0.470718 19.901408 0.762268
         2203 Washington 2024-04-02 91.361111 0.470500 19.916667 0.762264
         2204 Washington 2024-04-03 91.383562 0.470973 19.876712 0.763110
              Washington 2024-04-05 91.378378 0.471297 19.783784 0.765270
         2205
                                                                      fg3a \
                    TOV
                               TRB
                                         ast
                                                   blk
                                                        fg3_pct
         0
               0.000000 0.000000
                                   0.000000 0.000000 0.000000
                                                                 0.000000
         1
              20.000000 57.000000 26.000000 3.000000 0.281000 32.000000
         2
              15.500000 54.500000 27.000000 4.500000 0.311000 36.500000
              15.333333 56.000000 27.000000 4.000000 0.318333 38.333333
         3
         4
              15.750000 51.000000 25.750000 4.750000 0.335000 38.500000
         2201 13.571429 40.885714 28.071429 5.100000 0.349043 35.157143
         2202 13.633803 40.971831 27.985915 5.084507 0.347972 35.126761
         2203 13.652778 40.986111 27.972222 5.027778 0.347153 35.166667
         2204 13.602740 41.027397 27.945205 4.986301 0.345644 35.205479
         2205 13.662162 41.000000 27.918919 4.972973 0.346770 35.297297
              games_played
                                score
                                            stl
                       0.0
         0
                             0.000000 0.000000
         1
                       0.0 130.000000 8.000000
         2
                       0.0 126.500000 6.000000
                       0.0 123.333333 6.666667
         3
         4
                       0.0 122.500000 8.250000
                       . . .
                                  . . .
                      0.0 113.742857 7.571429
         2201
         2202
                       0.0 113.366197 7.492958
         2203
                      0.0 113.277778 7.472222
         2204
                      0.0 113.328767 7.493151
         2205
                      0.0 113.418919 7.540541
         [2206 rows x 15 columns]
In [77]: #Loading original data
         br_df = pd.read_csv('br31.csv')
         #making sure date is in datetime format
         br df['date'] = pd.to datetime(br df['date'])
         avg_stats_per_game['date'] = pd.to_datetime(avg_stats_per_game['date'])
         #creating unique indentifiers for merging
         br_df['team_date'] = br_df['team1'].astype(str) + '_' + br_df['date'].dt.strftime('%Y-
         avg_stats_per_game['team_date'] = avg_stats_per_game['team'].astype(str) + '_' + avg_s
         #renaming date to avoid conflict
         avg_stats_per_game = avg_stats_per_game.rename(columns={'date': 'date_avg'})
```

```
# Rename columns in avg_stats_per_game for team1
avg_stats_per_game_team1 = avg_stats_per_game.rename(columns=lambda x: x + '_avg1' if
# Merge the average statistics with the game results for team1
br_df = pd.merge(br_df, avg_stats_per_game_team1, on='team_date', how='left')
# Restore original 'date' column
br_df['date_avg1'] = br_df['date_avg']
br_df.drop(columns=['date_avg'], inplace=True)
# Update the unique identifiers for merging team2 statistics
br_df['team_date'] = br_df['team2'].astype(str) + '_' + br_df['date'].dt.strftime('%Y-
# Rename columns in avg stats per game for team2
avg_stats_per_game_team2 = avg_stats_per_game.rename(columns=lambda x: x + ' avg2' if
# Merge the average statistics with the game results for team2
br_df = pd.merge(br_df, avg_stats_per_game_team2, on='team_date', how='left')
# Restore original 'date' column for team2
br_df['date_avg2'] = br_df['date_avg']
br_df.drop(columns=['date_avg'], inplace=True)
# Clean up unnecessary columns
columns_to_keep = [
    'date', 'team1', 'team1_score', 'team2', 'team2_score', 'Home_Team_ID', 'Away_Team
    'FGA_avg1', 'FG_pct_avg1', 'FTA_avg1', 'FT_pct_avg1', 'TOV_avg1', 'TRB_avg1', 'ast
    'fg3_pct_avg1', 'fg3a_avg1', 'score_avg1', 'stl_avg1', 'FGA_avg2', 'FG_pct_avg2',
    'TOV_avg2', 'TRB_avg2', 'ast_avg2', 'blk_avg2', 'fg3_pct_avg2', 'fg3a_avg2', 'scor
br_df = br_df[columns_to_keep]
#saved the final DataFrame
#br df.to csv('br33.csv', index=False)
print(br df)
```

```
date
                               team1_score
                                                     team2
                                                             team2_score
                   Washington
     2023-11-01
0
                                        121
                                                   Atlanta
                                                                     130
1
     2023-11-01
                      Indiana
                                        104
                                                    Boston
                                                                     155
2
     2023-11-01
                      Chicago
                                        105
                                                    Dallas
                                                                     114
3
     2023-11-01
                     Portland
                                        110
                                                   Detroit
                                                                     101
4
     2023-11-01
                   Sacramento
                                        101
                                             Golden State
                                                                     102
1098 2024-04-05
                      Detroit
                                         90
                                                   Memphis
                                                                     108
1099 2024-04-05
                      Toronto
                                        117
                                                 Milwaukee
                                                                     111
1100 2024-04-05
                                        111
                                               New Orleans
                                                                     109
                  San Antonio
1101 2024-04-05
                                                   Phoenix
                                                                      97
                    Minnesota
                                         87
1102 2024-04-05
                                        108
                                                                     102
                     Portland
                                                Washington
      Home_Team_ID
                     Away_Team_ID
                                    HomeWin
                                              month
                                                      FGA_avg1
                                                                        FTA_avg2
0
                 22
                                                                       0.000000
                                 0
                                          1
                                                      0.000000
1
                 20
                                 1
                                          1
                                                      0.000000
                                                                       0.000000
2
                 17
                                          1
                                                      0.000000
                                                                       0.000000
3
                                 3
                                                      0.000000
                                                                       0.000000
4
                 19
                                 4
                                                      0.000000
                                                                       0.000000
1098
                12
                               13
                                          1
                                                  5
                                                     88.333333
                                                                      21.430556
1099
                11
                                14
                                          0
                                                  5
                                                     89.875000
                                                                      24.150685
                 10
                                15
                                                  5
                                          a
                                                     90.847222
1100
                                                                      23.301370
1101
                                                     84.863014
                                                                      23.763889
                                 3
1102
                                                     89.236111
                                                                      19.783784
                     TOV_avg2
                                TRB_avg2
                                             ast_avg2
                                                                  fg3_pct_avg2
      FT_pct_avg2
                                                       blk_avg2
0
         0.000000
                     0.000000
                                 0.000000
                                             0.000000
                                                       0.000000
                                                                      0.000000
1
         0.000000
                     0.000000
                                 0.000000
                                             0.000000
                                                       0.000000
                                                                      0.000000
2
         0.000000
                                 0.000000
                                             0.000000
                                                       0.000000
                     0.000000
                                                                      0.000000
3
                                 0.000000
                                                                      0.000000
         0.000000
                     0.000000
                                             0.000000
                                                       0.000000
4
         0.000000
                     0.000000
                                 0.000000
                                             0.000000
                                                       0.000000
                                                                      0.000000
         0.757750
1098
                    14.180556
                               42.347222
                                           25.041667
                                                       6.208333
                                                                      0.346667
1099
         0.769904
                    11.986301
                                44.465753
                                           26.890411
                                                       5.095890
                                                                      0.375247
1100
         0.771411
                    12.260274
                                44.191781
                                           27.136986
                                                       4.739726
                                                                      0.377164
1101
         0.802083
                    13.930556
                                44.125000
                                           27.236111
                                                                      0.382958
                                                       6.069444
1102
                               41.000000
                                           27.918919
         0.765270
                    13.662162
                                                       4.972973
                                                                      0.346770
      fg3a_avg2
                 score avg2
                               stl avg2
0
       0.000000
                    0.000000
                              0.000000
1
       0.000000
                    0.000000
                              0.000000
2
       0.000000
                    0.000000
                               0.000000
3
       0.000000
                    0.000000
                              0.000000
4
       0.000000
                    0.000000
                               0.000000
      38.138889
                 106.013889
                              7.930556
1098
1099
      38.383562
                  120.136986
                               6.684932
1100
      32.191781
                 115.589041
                               8.246575
1101
      32.22222
                  117.194444
                               7.222222
      35.297297
1102
                  113.418919
                              7.540541
```

Over/Under Prediction With RandomForestClassifier and BR33 Dataframe That Uses Rolling Averages

[1103 rows x 33 columns]

```
team1 team1_score
            date
                                                    team2_score \
0
      2023-11-02
                      Detroit
                                       116
                                              New Orleans
                                                                   125
1
                      Toronto
                                        99
                                             Philadelphia
                                                                   114
      2023-11-02
2
      2023-11-03
                     Brooklyn
                                       109
                                                  Chicago
                                                                   107
3
      2023-11-03
                       Dallas
                                       114
                                                   Denver
                                                                   125
                                       116
4
      2023-11-03
                    Cleveland
                                                  Indiana
                                                                   121
                                                                    . . .
1083
     2024-04-05
                      Detroit
                                        90
                                                  Memphis
                                                                   108
                                        117
                                                Milwaukee
                                                                   111
1084
      2024-04-05
                      Toronto
                                              New Orleans
1085
      2024-04-05 San Antonio
                                       111
                                                                   109
1086
      2024-04-05
                    Minnesota
                                        87
                                                  Phoenix
                                                                    97
1087
      2024-04-05
                     Portland
                                        108
                                               Washington
                                                                   102
      Home_Team_ID
                    Away_Team_ID HomeWin
                                            month
                                                    FGA_avg1
                                                                   FT_pct_avg2 \
0
                10
                                                0
                                                                       0.586000
                              13
                                         1
                                                   90.000000
1
                26
                              14
                                         1
                                                0
                                                   91.000000
                                                                       0.000000
                                                              . . .
2
                 2
                               7
                                         0
                                                0
                                                   82.000000
                                                                       0.909000
3
                 8
                              17
                                         1
                                                   81.000000
                                                                       0.700000
4
                 1
                               9
                                         1
                                                   74.000000
                                                                       0.583000
                                                              . . .
1083
                12
                              13
                                        1
                                                5
                                                   88.333333
                                                                       0.757750
1084
                11
                              14
                                         0
                                                5
                                                   89.875000
                                                                       0.769904
                10
                              15
                                                5 90.847222
1085
                                         0
                                                                       0.771411
1086
                24
                              28
                                         1
                                                   84.863014
                                                                       0.802083
                                                              . . .
1087
                 0
                               3
                                                5
                                                   89.236111
                                         0
                                                                       0.765270
       TOV_avg2
                 TRB_avg2
                                        blk_avg2
                                                   fg3_pct_avg2 fg3a_avg2
                             ast_avg2
0
      10.000000
                 58.000000
                            23.000000
                                         5.000000
                                                       0.310000 42.000000
1
                  0.000000
       0.000000
                             0.000000
                                         0.000000
                                                       0.000000
                                                                  0.000000
2
      13.000000
                 43.000000
                                         3.000000
                                                       0.333000 33.000000
                            19.000000
3
      15.000000
                                                       0.182000
                 43.000000
                            23.000000 10.000000
                                                                 33.000000
4
       9.000000
                 31.000000
                            26.000000
                                        6.000000
                                                       0.135000
                                                                 37.000000
     14.180556
                 42.347222
1083
                            25.041667
                                         6.208333
                                                       0.346667
                                                                 38.138889
1084
      11.986301
                 44.465753
                            26.890411
                                         5.095890
                                                       0.375247
                                                                 38.383562
1085
      12.260274
                 44.191781
                            27.136986
                                        4.739726
                                                       0.377164
                                                                 32.191781
1086
      13.930556
                 44.125000
                            27.236111
                                         6.069444
                                                       0.382958
                                                                 32.22222
1087
      13.662162 41.000000
                                                       0.346770 35.297297
                            27.918919
                                        4.972973
      score avg2
                   stl avg2
                             OverUnder
0
      110.000000
                   8.000000
                                      1
1
                   0.000000
                                      0
        0.000000
2
                                      0
      105.000000 10.000000
3
      89.000000
                   6.000000
                                      1
4
      104.000000
                   6.000000
                                      1
1083
     106.013889
                   7.930556
                                      0
1084
      120.136986
                   6.684932
                                      1
                                      0
1085
      115.589041
                   8.246575
1086
      117.194444
                   7.222222
                                      0
1087
      113.418919
                   7.540541
                                      0
[1088 rows x 34 columns]
numeric_data = br_df.drop(['date', 'month', 'team1_score', 'team2_score', 'OverUnder',
                            'HomeWin', 'team1', 'team2'], axis = 1).values
```

```
file:///C:/Users/Tyler/Documents/PDFs/Basketball ML Project.html
```

X = numeric_data

In [79]:

```
y = br_df['OverUnder'].values
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
In [80]: rf = RandomForestClassifier(random_state=42, n_jobs=-1)
         params = {
             'max_depth': [2,3,5,10,20],
             'min_samples_leaf': [5,10,20,50,100,200],
              'n_estimators': [10,25,30,50,100,200]
         from sklearn.model selection import GridSearchCV
         # Instantiate the grid search model
         grid search = GridSearchCV(estimator=rf,
                                     param_grid=params,
                                     cv = 4,
                                     n_jobs=-1, verbose=1, scoring="accuracy")
         grid search.fit(X train, y train)
         Fitting 4 folds for each of 180 candidates, totalling 720 fits
         [Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
         [Parallel(n_jobs=-1)]: Done 46 tasks
                                                     elapsed:
                                                                  11.4s
         [Parallel(n jobs=-1)]: Done 196 tasks
                                                      elapsed:
                                                                  34.1s
         [Parallel(n_jobs=-1)]: Done 446 tasks
                                                     | elapsed: 1.3min
         [Parallel(n_jobs=-1)]: Done 720 out of 720 | elapsed: 2.2min finished
         GridSearchCV(cv=4, error_score=nan,
Out[80]:
                      estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                                        class weight=None,
                                                        criterion='gini', max_depth=None,
                                                        max_features='auto',
                                                        max_leaf_nodes=None,
                                                        max samples=None,
                                                        min_impurity_decrease=0.0,
                                                        min_impurity_split=None,
                                                        min_samples_leaf=1,
                                                        min samples split=2,
                                                        min weight fraction leaf=0.0,
                                                        n_estimators=100, n_jobs=-1,
                                                        oob_score=False, random_state=42,
                                                        verbose=0, warm_start=False),
                      iid='deprecated', n jobs=-1,
                      param_grid={'max_depth': [2, 3, 5, 10, 20],
                                   'min_samples_leaf': [5, 10, 20, 50, 100, 200],
                                   'n_estimators': [10, 25, 30, 50, 100, 200]},
                      pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                      scoring='accuracy', verbose=1)
In [81]:
         print(grid_search.best_score_)
         rf_best = grid_search.best_estimator_
         print(rf_best)
```

```
In [82]: # Instantiate the model
         rf = RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                                 criterion='gini', max_depth=5, max_features='auto',
                                 max_leaf_nodes=None, max_samples=None,
                                 min_impurity_decrease=0.0, min_impurity_split=None,
                                 min_samples_leaf=20, min_samples_split=2,
                                 min_weight_fraction_leaf=0.0, n_estimators=200,
                                 n_jobs=-1, oob_score=False, verbose=0,
                                warm_start=False)
         # Train the model
         rf.fit(X_train, y_train)
         # Make predictions
         y_pred = rf.predict(X_test)
         #print(rf.oob_score_)
         # Evaluate the model
         accuracy = accuracy_score(y_test, y_pred)
         print(f'Accuracy: {accuracy}')
```

Accuracy: 0.6697247706422018

With standard scaling and onehot encoding

```
In [83]: cat = br_df[['Home_Team_ID', 'Away_Team_ID']].values
         encoder = OneHotEncoder()
         cat_ohe = encoder.fit_transform(cat).toarray()
         numeric_data = br_df.drop(['date', 'month', 'team1_score', 'team2_score', 'OverUnder',
                                     'Home_Team_ID', 'Away_Team_ID', 'HomeWin', 'team1', 'team2'
         scaler = StandardScaler()
         x_norm = scaler.fit_transform(numeric_data)
         X = np.hstack((x_norm, cat_ohe))
         print(X.shape)
         y = br df['OverUnder'].values
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
         # Instantiate the model
         rf = RandomForestClassifier(bootstrap=True, ccp alpha=0.0, class weight=None,
                                criterion='gini', max_depth=5, max_features='auto',
                                 max_leaf_nodes=None, max_samples=None,
                                 min_impurity_decrease=0.0, min_impurity_split=None,
                                min_samples_leaf=20, min_samples_split=2,
                                 min_weight_fraction_leaf=0.0, n_estimators=200,
                                 n_jobs=-1, oob_score=False, verbose=0,
```

```
# Train the model
rf.fit(X_train, y_train)

# Make predictions
y_pred = rf.predict(X_test)
#print(rf.oob_score_)
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
(1088, 84)
```

(1088, 84) Accuracy: 0.6880733944954128

Invidivual match prediction

```
date
                                 team1_score
                                                       team2
                                                              team2_score
      2023-11-02
                                                New Orleans
0
                       Detroit
                                          116
                                                                       125
1
                                           99
      2023-11-02
                       Toronto
                                               Philadelphia
                                                                       114
2
      2023-11-03
                      Brooklyn
                                          109
                                                     Chicago
                                                                       107
3
      2023-11-03
                        Dallas
                                          114
                                                      Denver
                                                                       125
4
      2023-11-03
                     Cleveland
                                          116
                                                     Indiana
                                                                       121
1083
      2024-04-05
                       Detroit
                                           90
                                                     Memphis
                                                                       108
                                          117
1084
      2024-04-05
                       Toronto
                                                   Milwaukee
                                                                       111
1085
      2024-04-05
                   San Antonio
                                          111
                                                 New Orleans
                                                                       109
      2024-04-05
                     Minnesota
                                           87
                                                     Phoenix
                                                                        97
1086
1087
      2024-04-05
                      Portland
                                          108
                                                 Washington
                                                                       102
      Home_Team_ID
                     Away_Team_ID
                                    HomeWin
                                              month
                                                       FGA_avg1
                                                                         FTA_avg2
0
                                                                       29.000000
                 10
                                13
                                           1
                                                      90.000000
1
                 26
                                           1
                                                   0
                                                      91.000000
                                                                         0.000000
2
                  2
                                 7
                                           0
                                                      82.000000
                                                                       11.000000
3
                  8
                                17
                                           1
                                                      81.000000
                                                                       10.000000
4
                  1
                                 9
                                           1
                                                      74.000000
                                                                       12.000000
1083
                 12
                                13
                                           1
                                                   5
                                                      88.333333
                                                                       21.430556
1084
                 11
                                14
                                           0
                                                   5
                                                      89.875000
                                                                       24.150685
                 10
                                15
                                                   5
                                           a
                                                      90.847222
                                                                       23.301370
1085
1086
                 24
                                28
                                           1
                                                      84.863014
                                                                       23.763889
                  0
                                 3
                                           0
                                                      89.236111
1087
                                                                       19.783784
                                 TRB_avg2
      FT_pct_avg2
                     TOV_avg2
                                             ast_avg2
                                                         blk_avg2
                                                                    fg3_pct_avg2
0
         0.586000
                    10.000000
                                58.000000
                                            23.000000
                                                         5.000000
                                                                         0.310000
1
         0.000000
                     0.000000
                                 0.000000
                                             0.000000
                                                         0.000000
                                                                         0.000000
2
         0.909000
                                43.000000
                    13.000000
                                            19.000000
                                                         3.000000
                                                                        0.333000
3
         0.700000
                    15.000000
                                43.000000
                                            23.000000
                                                        10.000000
                                                                        0.182000
4
         0.583000
                     9.000000
                                31.000000
                                            26.000000
                                                         6.000000
                                                                         0.135000
         0.757750
1083
                    14.180556
                                42.347222
                                            25.041667
                                                         6.208333
                                                                        0.346667
1084
         0.769904
                    11.986301
                                44.465753
                                            26.890411
                                                         5.095890
                                                                         0.375247
1085
         0.771411
                    12.260274
                                44.191781
                                            27.136986
                                                         4.739726
                                                                        0.377164
1086
         0.802083
                    13.930556
                                44.125000
                                            27.236111
                                                         6.069444
                                                                         0.382958
1087
                                41.000000
                                            27.918919
         0.765270
                    13.662162
                                                         4.972973
                                                                        0.346770
      fg3a_avg2
                  score avg2
                                stl avg2
0
      42.000000
                  110.000000
                                8.000000
1
       0.000000
                    0.000000
                                0.000000
2
      33.000000
                  105.000000
                               10.000000
3
      33.000000
                   89.000000
                                6.000000
4
      37.000000
                  104.000000
                                6.000000
      38.138889
                  106.013889
                                7.930556
1083
1084
      38.383562
                  120.136986
                                6.684932
1085
      32.191781
                  115.589041
                                8.246575
1086
      32.22222
                  117.194444
                                7.222222
1087
      35.297297
                  113.418919
                                7.540541
[1088 rows x 33 columns]
```

With OHE and Standard Scaling

```
In [59]: team_names = {
    0: 'Washington',
```

```
1: 'Indiana',
  2: 'Chicago',
 3: 'Portland',
 4: 'Sacramento',
  5: 'Charlotte',
  6: 'LA Clippers',
 7: 'Brooklyn',
  8: 'Denver',
  9: 'Cleveland',
 10: 'New Orleans',
  11: 'Milwaukee',
  12: 'Memphis',
  13: 'Detroit',
  14: 'Toronto',
  15: 'San Antonio',
  16: 'Orlando',
  17: 'Dallas',
  18: 'New York',
  19: 'Golden State',
  20: 'Boston',
  21: 'Utah',
  22: 'Atlanta',
  23: 'LA Lakers',
  24: 'Phoenix',
  25: 'Miami',
  26: 'Philadelphia',
  27: 'Oklahoma City',
 28: 'Minnesota',
 29: 'Houston'
def prepare_features(home_stats, away_stats):
    Prepares the numeric feature vector from home and away team stats.
    Uses suffixes '_1' for home team stats and '_2' for away team stats as per the dat
    #stats list for home and away teams as per suffix conventions
   home_stats_list = [
        'FGA_avg1', 'FG_pct_avg1', 'FTA_avg1', 'FT_pct_avg1', 'TOV_avg1',
        'TRB_avg1', 'ast_avg1', 'blk_avg1', 'fg3_pct_avg1', 'fg3a_avg1',
        'score_avg1', 'stl_avg1'
    away stats list = [
        'FGA_avg2', 'FG_pct_avg2', 'FTA_avg2', 'FT_pct_avg2', 'TOV_avg2',
        'TRB_avg2', 'ast_avg2', 'blk_avg2', 'fg3_pct_avg2', 'fg3a_avg2',
        'score_avg2', 'stl_avg2'
    ]
    #extract the respective stats for home and away teams
    home_features = home_stats[home_stats_list].values.flatten()
    away_features = away_stats[away_stats_list].values.flatten()
    #combine home and away features
    return np.hstack([home_features, away_features])
def get_latest_team_stats(team_stats_df, team_id, home = None):
    Retrieves the latest stats for a given team_id based on the most recent date.
    if home is not None:
```

```
team_data = team_stats_df[team_stats_df['Home_Team_ID'] == team_id]
        latest_entry = team_data.sort_values(by='date', ascending=False).iloc[0]
    else:
        team_data = team_stats_df[team_stats_df['Away_Team_ID'] == team_id]
        latest_entry = team_data.sort_values(by='date', ascending=False).iloc[0]
    return latest entry
def predict_tomorrow_games(matchups, team_stats_df, thresholds):
   predictions = []
    all_team_ids = np.unique(team_stats_df[['Home_Team_ID', 'Away_Team_ID']].values.fl
    encoder = OneHotEncoder(categories=[all_team_ids, all_team_ids])
    scaler = StandardScaler()
    #preparing the numeric data for scaling and categorical data for encoding
    numeric_columns = team_stats_df.drop(['date',
                                           'month',
                                          'team1_score',
                                           'team2_score',
                                          'Home Team ID',
                                           'Away_Team_ID',
                                          'HomeWin',
                                          'team1',
                                          'team2'], axis = 1).values
   x_norm = scaler.fit_transform(numeric_columns)
    cat = team_stats_df[['Home_Team_ID', 'Away_Team_ID']].values
    cat ohe = encoder.fit transform(cat).toarray()
   X = np.hstack((x_norm, cat_ohe)) # Full feature set for training
   for index, (home_id, away_id) in enumerate(matchups):
        threshold = thresholds[index]
        probabilities_list = []
        accuracy list = []
        team_stats_df2 = team_stats_df.copy(deep=True)
        for _ in range(20):
            team_stats_df2['OverUnder'] = (team_stats_df['team2_score'] + team_stats_d
            y = team_stats_df2['OverUnder'].values
            #split data for training and testing
            X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)
            rf = RandomForestClassifier(n_estimators=200)
            rf.fit(X_train, y_train)
            y_pred = rf.predict(X_test)
            accuracy = accuracy_score(y_test, y_pred)
            accuracy_list.append(accuracy)
            # prepare features for prediction for the current game
            home_stats = get_latest_team_stats(team_stats_df2, home_id, home=True)
            away stats = get latest team stats(team stats df2, away id, home=None)
            numeric_features = prepare_features(home_stats, away_stats)
            numeric_features = scaler.fit_transform(numeric_features.reshape(1, -1))
            categorical_features = np.array([[home_id, away_id]])
            encoded_features = encoder.transform(categorical_features).toarray()
            game_features = np.hstack((encoded_features, numeric_features))
```

```
# Predict probabilities and store them
probabilities = rf.predict_proba(game_features)[0, 1]
probabilities_list.append(probabilities)

#average the probabilities and accuracies for current matchup
avg_probability = np.mean(probabilities_list)
avg_accuracy = np.mean(accuracy_list)
final_decision = "Over" if avg_probability > 0.5 else "Under"
confidence = "High Confidence" if avg_probability >= 0.60 or avg_probability 
predictions.append((team_names[home_id], team_names[away_id], round(avg_accuracy_name)

return predictions
```

Without Standard Scaling and One Hot Encoding

('Minnesota', 'Chicago', 0.932, 200, 0.986, 'Over', 'High Confidence')]

```
In [57]: | team_names = {
             0: 'Washington', 1: 'Indiana', 2: 'Chicago', 3: 'Portland', 4: 'Sacramento',
             5: 'Charlotte', 6: 'LA Clippers', 7: 'Brooklyn', 8: 'Denver', 9: 'Cleveland',
             10: 'New Orleans', 11: 'Milwaukee', 12: 'Memphis', 13: 'Detroit', 14: 'Toronto',
             15: 'San Antonio', 16: 'Orlando', 17: 'Dallas', 18: 'New York', 19: 'Golden State'
             20: 'Boston', 21: 'Utah', 22: 'Atlanta', 23: 'LA Lakers', 24: 'Phoenix', 25: 'Mian
             26: 'Philadelphia', 27: 'Oklahoma City', 28: 'Minnesota', 29: 'Houston'
         def prepare_features(home_stats, away_stats):
             Prepares the numeric feature vector from home and away team stats.
             Uses suffixes '_avg1' for home team stats and '_avg2' for away team stats as per t
             home_stats_list = [
                 'FGA_avg1', 'FG_pct_avg1', 'FTA_avg1', 'FT_pct_avg1', 'TOV_avg1',
                  'TRB_avg1', 'ast_avg1', 'blk_avg1', 'fg3_pct_avg1', 'fg3a_avg1',
                  'score_avg1', 'stl_avg1'
             away_stats_list = [
                  'FGA_avg2', 'FG_pct_avg2', 'FTA_avg2', 'FT_pct_avg2', 'TOV_avg2',
                  'TRB_avg2', 'ast_avg2', 'blk_avg2', 'fg3_pct_avg2', 'fg3a_avg2',
                  'score_avg2', 'stl_avg2'
```

```
home_features = home_stats[home_stats_list].values.flatten()
    away_features = away_stats[away_stats_list].values.flatten()
    return np.hstack([home_features, away_features])
def get_latest_team_stats(team_stats_df, team_id, home=None):
   Retrieves the latest stats for a given team_id based on the most recent date.
   if home:
        team_data = team_stats_df[team_stats_df['Home_Team_ID'] == team_id]
   else:
        team_data = team_stats_df[team_stats_df['Away_Team_ID'] == team_id]
    latest_entry = team_data.sort_values(by='date', ascending=False).iloc[0]
    return latest entry
def predict_tomorrow_games(matchups, team_stats_df, thresholds):
    predictions = []
    for index, (home_id, away_id) in enumerate(matchups):
        threshold = thresholds[index]
        probabilities_list = []
        accuracy_list = []
        team_stats_df2 = team_stats_df.copy(deep=True)
        for _ in range(20):
            team_stats_df2['OverUnder'] = (team_stats_df2['team2_score'] + team_stats_
            y = team_stats_df2['OverUnder'].values
            # Prepare numeric features and categorical team IDs for training
            numeric_columns = team_stats_df2.drop(columns=['date', 'month', 'team1_scc')
            X_numeric = numeric_columns.values
            X_team_ids = team_stats_df2[['Home_Team_ID', 'Away_Team_ID']].values
            X = np.hstack((X_numeric, X_team_ids))
            X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
            rf = RandomForestClassifier(n estimators=200, random state=42)
            rf.fit(X_train, y_train)
            y_pred = rf.predict(X_test)
            accuracy = accuracy_score(y_test, y_pred)
            accuracy_list.append(accuracy)
            home_stats = get_latest_team_stats(team_stats_df2, home_id, home=True)
            away_stats = get_latest_team_stats(team_stats_df2, away_id, home=False)
            numeric_features = prepare_features(home_stats, away_stats)
            game_features = np.hstack((numeric_features, [home_id, away_id])).reshape(
            probabilities = rf.predict_proba(game_features)[0, 1]
            probabilities_list.append(probabilities)
        avg_probability = np.mean(probabilities_list)
```

```
avg_accuracy = np.mean(accuracy_list)
final_decision = "Over" if avg_probability > 0.5 else "Under"
confidence = "High Confidence" if avg_probability >= 0.60 or avg_probability <
predictions.append((team_names[home_id], team_names[away_id], round(avg_accurate)
return predictions</pre>
```