final_report

May 29, 2024

1 Effect of NBA Injuries on Team Performance

Video: https://youtu.be/ZNLW5JyyGuA

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##**Overview**

- Before conducting data analysis, we expect that there exists a negative correlation between the number of injured players on an NBA team and the team's performance.
- After doing the data analysis, we found out that based on the datasets of NBA teams performances and injuries from 2010-2015, the winning percentage decreases as total number of injuries (Relinquished) increases and also increases as the number of previously injured players coming back (Acquired) increases when we predict the winning percentage.
- The linear regression model we generated from the datasets provide enough evidence to support our expectation that there is a negative relationship between injuries and winning percentage and vice versa. However, due to lack of data points, our model is not the best at predicting future winning percentages given the number of injuries on a team.

1.1 Names

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1.2 Research Question

Is there an association between an NBA team's number and type of injuries to their record from the 2010 season through the 2015 season? Also, can we accurately predict a team's change in record based on injuries that occur in future seasons?

1.3 Background and Prior Work

The NBA is revered as the best basketball league in the world due to its highly competitive and captivating environment, features of the best professional athletes, and the ability for players to sign contracts, thus generating millions of dollars in revenue. Athletes in the NBA are considered some of the best competitors due to their agility, endurance, speed, size, skills, and talent. In the NBA, a single game consists of four twelve-minute quarters and the game clock is intermittently stopped for timeouts, fouls, quarter breaks, and a halftime. This makes it difficult to judge the exact duration that athletes are on the court, but it is estimated that the average NBA game lasts around two and a half hours and some games can last around three hours.(1) This means that these highly skilled players are on the court competing for a considerably long duration, sometimes with little rest at all. Due to these competitive conditions, it is common for NBA players to get injured, and consequently, have to sit on the bench until they recover. Additionally, a typical NBA season for a team includes eighty-two regular season games with the possibility of additional games if their team advances to the playoffs. Overall, this combined with the physicality of every minute of each game creates an environment with a high rate of injury.

Statistics have been taken on the distribution of injury types across the NBA and show that 57.8% of injuries involve the lower extremities, 19.3% for the upper extremities, 10% for the torso, and 1.8% are related to cervical trauma.(2) Some of the typical lower extremity injuries include the ankles, knees, foot fractures, and muscle tears. Some other common injuries are sprained fingers, concussions, broken noses, facial injuries, and sometimes even leg open fractures.(3) Among other findings, players who weigh more, are taller, and are between the ages of 26 and 34 are considered the most likely to become injured. Interestingly, a study was administered on NBA games from 1988 to 2005 and showed that there were upwards of 12,500 injuries that took place and around 6,200 of them were related to athletes' ankles. All together, these statistics are concerning, but the NBA released information last year that stated that the injury rates of players was down about six percent.(4)

We want to analyze the impact of how the number of injured players on a team affects the overall team's efficiency and performance.

1. Lw. "NBA Game Length: How Long Is an NBA Game in Minutes?" MARCA, Marca, 10 Mar. 2022, https://www.marca.com/en/basketball/nba/2022/03/10/622a267de2704ef25e8b4585.html.

2. aes5559, and aes5559. "SIOWFA15: Science in Our World: Certainty and Controversy." SiOWfa15 Science in Our World Certainty and Controversy, 11 Dec. 2015, https://sites.psu.edu/siowfa15/2015/12/11/whos-most-likely-to-get-injured-in-the-nba-and-how/.

3. Thompson, Darrelle. "What Are the Most Common Injuries in the NBA?" Sportscasting, 13 Sept. 2019, https://www.sportscasting.com/what-are-the-most-common-injuries-in-the-nba/.

4. Tim Reynolds | The Associated Press. "NBA Says Injury Rate down Slightly from Normal." NBA.com, NBA.com, 15 Apr. 2021, https://www.nba.com/news/nba-says-injury-rate-down-slightly-from-normal.

1.4 Hypothesis

Alternative Hypothesis: We propose that there is an association between the number of injured players on a team and their winning record (winning percentage) through the 2010-2015 seasons. Due to the NBA's highly competitive environment, we predict that there will be a negative relationship between a teams number of injured players and their winning percentage. In other words, the more injured players there are on a team, the lower the team's winning percentage will be. Our reasoning is that the teams with more injured players will consequently have more players sitting out and possess less depth in their rosters, thus limiting the team's performance. Also, we believe that we will be able to effectively predict a teams record in the 2016-17 season based on the number of injuries. Additionally, we propose that lower extremity injuries will have a more negative impact on the teams' winning record. This is because the lower extremities of players serves a crucial role in their performance and allow them to get up and down the court.

Null Hypothesis: NBA player injuries and injury types will have no effect on a team's record as a result of random chance. The test significance is 5%.

1.5 Setup

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import datetime

import patsy
import statsmodels.api as sm
import scipy.stats as stats
from scipy.stats import ttest_ind, chisquare, normaltest
from scipy.stats import ks_2samp
from scipy.stats import pearsonr

import patsy
import statsmodels.api as sm
import statsmodels.formula.api as smf

from sklearn.metrics import accuracy_score
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.model_selection import train_test_split


from IPython.display import display_html
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the
public API at pandas.testing instead.
  import pandas.util.testing as tm
```

```
[ ]: #deal with excel datasets
import pip
pip.main(["install", "openpyxl"])
```

```
WARNING: pip is being invoked by an old script wrapper. This will fail in a
future version of pip.
Please see https://github.com/pypa/pip/issues/5599 for advice on fixing the
underlying issue.
To avoid this problem you can invoke Python with '-m pip' instead of running pip
directly.

Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: openpyxl in /usr/local/lib/python3.7/dist-
packages (3.0.10)
Requirement already satisfied: et-xmlfile in /usr/local/lib/python3.7/dist-
packages (from openpyxl) (1.1.0)
```

```
[ ]: 0
```

1.6 Data Cleaning

The following section presents information on the data cleaning steps for the two datasets used in this report.

1.7 First Dataset - Injury Stats

1.7.1 Link to Dataset: https://www.kaggle.com/datasets/ghopkins/nba-injuries-2010-2018

1.7.2 No. Observations: 17,408

This dataset describes the occurrence, injury type, player team, and time of injury for NBA players in the 2010 - 2020 years.

The information present here will be combined with the Historical NBA Performance dataset to match players with their teams for a given year. This will allow us to show how the number of injuries across different players for the same team impacts the team's historical performance. The data starts as two different types. A relinquished injury has a date, name, and notes about the injury that occured. An acquired injury has a date, name, and notes about the return of the injured player. At the end, we will have counts of the number of acquired/relinquished injuries and counts of injuries that had certain body counts in the 'Notes' column for each season of each team.

```
[ ]: #first dataset - Injury stats
injury = pd.read_csv('injuries_2010-2020.csv')
injury
```

```
[ ]:            Date     Team     Acquired   Relinquished  \
     0    2010-10-03    Bulls          NaN  Carlos Boozer
     1    2010-10-06  Pistons          NaN  Jonas Jerebko
```

```
2      2010-10-06  Pistons           NaN  Terrico White
3      2010-10-08  Blazers           NaN     Jeff Ayres
4      2010-10-08     Nets           NaN    Troy Murphy
…           …       …          …            …
27100  2020-09-30   Lakers  Dion Waiters            NaN
27101  2020-10-02     Heat           NaN    Bam Adebayo
27102  2020-10-02     Heat           NaN   Goran Dragic
27103  2020-10-02     Heat   Chris Silva            NaN
27104  2020-10-06     Heat   Bam Adebayo            NaN

                                                   Notes
0      fractured bone in right pinky finger (out inde…
1          torn right Achilles tendon (out indefinitely)
2      broken fifth metatarsal in right foot (out ind…
3              torn ACL in right knee (out indefinitely)
4                 strained lower back (out indefinitely)
…                                                      …
27100                                 activated from IL
27101                               strained neck (DTD)
27102  placed on IL with torn plantar fascia in left …
27103                                 activated from IL
27104                                returned to lineup

[27105 rows x 5 columns]
```

The NBA season roughly goes from October until June. So we are interpreting the column 'Season' as the year the season started, i.e. any injury happening in the 2015-2016 season will be read as the Season: 2015.

[ ]:
```
injury_original = injury.assign(
    Season = injury.get('Date').apply(lambda s: int(s.split('-')[0])- np.
 ↪where(int(s.split('-')[1]) < 9, 1, 0)))
#2015-16 season ended June 19, 2016
#index 15819 -> end of 2015 season
injury = injury_original[injury_original['Season']<2017]
```

grouped_by_team_year is a data frame that has the counts of Acquired and Relinquished from the injury dataset. Relinquished means that a player was injured and placed on the Injury List (IL) and not playing anymore. Acquired means they were taken off the IL and are playing again. Since each entry in injury corresponds to a relinquishment or acquisition to the IL, we can count how many players were put on the IL (Relinquished) and taken off the IL (Acquired).

[ ]:
```
grouped_by_team_year = injury.groupby(['Season','Team']).count().
 ↪drop(columns=['Date', 'Notes'])
grouped_by_team_year
```

[ ]:
```
                    Acquired  Relinquished
Season Team
```

```
2010   76ers                 26          33
       Blazers               10          48
       Bobcats               52          97
       Bucks                 25          98
       Bulls                 17          33
…                          …          …
2016   Suns                  37          58
       Thunder               23          36
       Timberwolves          18          31
       Warriors              66          88
       Wizards               43          50

[211 rows x 2 columns]
```

Here, we are taking all entries in the injury dataset that are an acquisition from the IR, meaning they are returning to play.

[ ]:
```
acquired_injury = injury.dropna(subset=['Acquired'])
acquired_injury
```

[ ]:
```
             Date       Team          Acquired Relinquished  \
53     2010-10-27       Heat  Jerry Stackhouse          NaN
81     2010-10-27    Rockets   Jermaine Taylor          NaN
101    2010-10-29  Cavaliers   Samardo Samuels          NaN
103    2010-10-29    Celtics    Luke Harangody          NaN
105    2010-10-29  Grizzlies        Marc Gasol          NaN
…             …          …                 …          …
18934  2017-05-19    Celtics     Jordan Mickey          NaN
18937  2017-05-20   Warriors    Andre Iguodala          NaN
18939  2017-05-21    Celtics       James Young          NaN
18942  2017-05-22      Spurs     Kawhi Leonard          NaN
18947  2017-06-01   Warriors     Zaza Pachulia          NaN

                   Notes  Season
53     activated from IL    2010
81     activated from IL    2010
101    activated from IL    2010
103    activated from IL    2010
105    activated from IL    2010
…                    …       …
18934  activated from IL    2016
18937  activated from IL    2016
18939  activated from IL    2016
18942  activated from IL    2016
18947  activated from IL    2016

[6074 rows x 6 columns]
```

[ ]:
```
acquired_injury.groupby(['Season','Team']).count().
    ↪drop(columns=['Date','Notes','Relinquished'])
```

[ ]:
```
                    Acquired
Season Team
2010   76ers              26
       Blazers            10
       Bobcats            52
       Bucks              25
       Bulls              17
…                        …
2016   Suns               37
       Thunder            23
       Timberwolves       18
       Warriors           66
       Wizards            43

[210 rows x 1 columns]
```

Similarly: Here we are taking all entries in the injury dataset that are a relinquishment from the IR, meaning they are now injured and not playing.

[ ]:
```
relinquished_injury = injury.dropna(subset=['Relinquished'])
relinquished_injury
```

[ ]:
```
             Date       Team Acquired       Relinquished  \
0      2010-10-03      Bulls      NaN      Carlos Boozer
1      2010-10-06    Pistons      NaN      Jonas Jerebko
2      2010-10-06    Pistons      NaN      Terrico White
3      2010-10-08    Blazers      NaN          Jeff Ayres
4      2010-10-08       Nets      NaN        Troy Murphy
…             …          …        …                  …
18950  2017-07-25       Suns      NaN     Brandon Knight
18951  2017-07-30   Clippers      NaN   Danilo Gallinari
18952  2017-08-08  Grizzlies      NaN        Ben McLemore
18953  2017-08-10    Thunder      NaN  Patrick Patterson
18954  2017-08-28   Pelicans      NaN        Solomon Hill

                                                  Notes  Season
0      fractured bone in right pinky finger (out inde…    2010
1          torn right Achilles tendon (out indefinitely)    2010
2      broken fifth metatarsal in right foot (out ind…    2010
3              torn ACL in right knee (out indefinitely)    2010
4                 strained lower back (out indefinitely)    2010
…                                                     …      …
18950             torn ACL in left knee (out for season)    2016
18951    fractured bone in right hand (out indefinitely)    2016
18952  surgery on right foot to repair fracture (out …    2016
```

```
18953  arthroscopic surgery on his left knee (out ind…    2016
18954  surgery to repair torn left hamstring (out ind…    2016

[12881 rows x 6 columns]
```

[ ]:
```
relinquished_injury.groupby(['Season','Team']).count().
↪drop(columns=['Date','Notes','Acquired'])
```

[ ]:
```
                     Relinquished
Season Team
2010   76ers                   33
       Blazers                 48
       Bobcats                 97
       Bucks                   98
       Bulls                   33
…                           …
2016   Suns                    58
       Thunder                 36
       Timberwolves            31
       Warriors                88
       Wizards                 50

[211 rows x 1 columns]
```

We also want to observe the type of injury and see if certain injuries hurt a team's record more than others. So we are looking through each entry 'Notes' and counting for each season and team how many knee, ankle, foot, hand, finger, and back injuries there were.

[ ]:
```
knee = injury[injury['Notes'].str.contains("knee")]\
                .groupby(['Season','Team']).count().
↪drop(columns=['Date','Notes', 'Acquired'])
knee = knee.rename(columns={"Relinquished": "Knee injuries"})
ankle = injury[injury['Notes'].str.contains("ankle")]\
                .groupby(['Season','Team']).count().
↪drop(columns=['Date','Notes', 'Acquired'])
ankle = ankle.rename(columns={"Relinquished": "Ankle injuries"})
foot = injury[injury['Notes'].str.contains("foot")]\
                .groupby(['Season','Team']).count().
↪drop(columns=['Date','Notes', 'Acquired'])
foot = foot.rename(columns={"Relinquished": "Foot injuries"})
hand = injury[injury['Notes'].str.contains("hand")]\
                .groupby(['Season','Team']).count().
↪drop(columns=['Date','Notes', 'Acquired'])
hand = hand.rename(columns={"Relinquished": "Hand injuries"})
finger = injury[injury['Notes'].str.contains("finger")]\
                .groupby(['Season','Team']).count().
↪drop(columns=['Date','Notes', 'Acquired'])
```

```
finger = finger.rename(columns={"Relinquished": "Finger injuries"})
back = injury[injury['Notes'].str.contains("back")]\
                .groupby(['Season','Team']).count().
 ↪drop(columns=['Date','Notes', 'Acquired'])
back = back.rename(columns={"Relinquished": "Back injuries"})

knee_styler = knee.head().style.set_table_attributes("style='display:inline'").
 ↪set_caption('injuries related to knee')
ankle_styler = ankle.head().style.set_table_attributes("style='display:
 ↪inline'").set_caption('injuries related to ankle')
foot_styler = foot.head().style.set_table_attributes("style='display:inline'").
 ↪set_caption('injuries related to foot')
finger_styler = finger.head().style.set_table_attributes("style='display:
 ↪inline'").set_caption('injuries related to finger')
back_styler = back.head().style.set_table_attributes("style='display:inline'").
 ↪set_caption('injuries related to back')
hand_styler = hand.head().style.set_table_attributes("style='display:inline'").
 ↪set_caption('injuries related to hand')

display_html(knee_styler._repr_html_()+\
             ankle_styler._repr_html_()+\
             foot_styler._repr_html_()+\
             finger_styler._repr_html_()+\
             back_styler._repr_html_()+\
             hand_styler._repr_html_(), raw=True)
```

1.8 Second Dataset - Historical NBA Performance

1.8.1 Link to Dataset: https://data.world/gmoney/nba-team-records-by-year

1.8.2 No. Observations: 208

This dataset describes the number of wins, number of losses, and winning percentage of an NBA team in a given year.

The information present here will be combined with the injury dataset to match players with their teams present in this dataset for a given year. This will allow us to show how the number of injuries across different players for the same team impacts the team's historical performance. The data starts with a year, team name, record, and winning percentage. We will be creating the 'Season' variable again and adding a 'Win' and 'Loss' column based on the record.

[ ]:
```
#second dataset - Team Performance
performance = pd.read_excel('Historical_NBA_Performance.xlsx')
performance
```

[ ]:
```
        Year     Team Record  Winning Percentage  Unnamed: 4  Unnamed: 5  \
0    2016-17  Celtics  25-15               0.625         NaN         NaN
1    2015-16  Celtics  48-34               0.585         NaN         NaN
```

```
2     2014-15  Celtics  40-42                0.488        NaN         NaN
3     2013-14  Celtics  25-57                0.305        NaN         NaN
4     2012-13  Celtics  41-40                0.506        NaN         NaN
…       …        …       …            …        …          …
1412  1965-66  Bullets  38-42                0.475        NaN         NaN
1413  1964-65  Bullets  37-43                0.463        NaN         NaN
1414  1963-64  Bullets  31-49                0.388        NaN         NaN
1415  1962-63  Zephyrs  25-55                0.313        NaN         NaN
1416  1961-62  Packers  18-62                0.225        NaN         NaN

      Unnamed: 6  Unnamed: 7  Unnamed: 8 Unnamed: 9
0            NaN         NaN         NaN        NaT
1            NaN         NaN         NaN        NaT
2            NaN         NaN         NaN        NaT
3            NaN         NaN         NaN        NaT
4            NaN         NaN         NaN        NaT
…          …          …          …        …
1412         NaN         NaN         NaN        NaT
1413         NaN         NaN         NaN        NaT
1414         NaN         NaN         NaN        NaT
1415         NaN         NaN         NaN        NaT
1416         NaN         NaN         NaN        NaT

[1417 rows x 10 columns]
```

Let performance_clean be the clean dataset with the columns we want.

```
[ ]: performance_clean = performance[['Year', 'Team', 'Record', 'Winning␣
      ↪Percentage']]
```

```
[ ]: performance_clean.get('Team').unique()
```

```
[ ]: array(['Celtics', 'Hawks', 'Blackhawks', 'Nets', 'Hornets', 'Bobcats',
            'Bulls', 'Cavaliers', 'Mavericks', 'Nuggets', 'Pistons',
            'Warriors', 'Rockets', 'Pacers', 'Clippers', 'Braves', 'Lakers',
            'Grizzlies', 'Heat', 'Bucks', 'Timberwolves', 'Pelicans', 'Knicks',
            'Thunder', 'Supersonics', 'Magic', '76ers', 'Nationals', 'Suns',
            'Trail Blazers', 'Kings', 'Royals', 'Spurs', 'Raptors', 'Jazz',
            'Wizards', 'Bullets', 'Zephyrs', 'Packers'], dtype=object)
```

```
[ ]: performance_clean.head()
```

```
[ ]:       Year     Team Record  Winning Percentage
     0  2016-17  Celtics  25-15               0.625
     1  2015-16  Celtics  48-34               0.585
     2  2014-15  Celtics  40-42               0.488
     3  2013-14  Celtics  25-57               0.305
     4  2012-13  Celtics  41-40               0.506
```

```
[ ]: #drops 2016-17 seasons
performance_clean = performance_clean[performance_clean.Year != "2016-17"]
```

To be able to merge this dataset with the injuries dataset we're going to group both by team name and season. The year will reflect this too, and for simplicity we are going to have the same interpretation where 2015-2016 season corresponds to 'Season' 2015. We also will split the record column into two more additional columns that have 'Win' and 'Loss' based on the team's record that season.

```
[ ]: #changes Year column to Season column
performance_clean.rename(columns = {'Year': 'Season'}, inplace = True)
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/frame.py:5047:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  errors=errors,
```

```
[ ]: #adds columnn Year using indexing on Season column
def season_to_year(s):
  return s.split('-')[0]
performance_clean['Year'] = performance_clean['Season'].astype(str).
 ↪apply(season_to_year)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
```

```
[ ]: #filters Year column to grab Seasons 2010-2016
performance_clean['Year'] = performance_clean['Year'].astype(int)

performance_clean = performance_clean[2010 <= performance_clean.get('Year')]\
                     [(performance_clean[2010 <= performance_clean.
 ↪get('Year')]).get('Year')<=2016]
performance_clean
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

[ ]:
```
                    Season     Team Record  Winning Percentage  Year
0                  2016-17  Celtics  25-15               0.625  2016
1                  2015-16  Celtics  48-34               0.585  2015
2                  2014-15  Celtics  40-42               0.488  2014
3                  2013-14  Celtics  25-57               0.305  2013
4                  2012-13  Celtics  41-40               0.506  2012
…                      …       …      …                   …     …
1363               2014-15  Wizards  46-36               0.561  2014
1364               2013-14  Wizards  44-38               0.537  2013
1365               2012-13  Wizards  29-53               0.354  2012
1366             2011-12 *  Wizards  20-46               0.303  2011
1367   2010-11-01 00:00:00  Wizards  23-59               0.280  2010

[208 rows x 5 columns]
```

[ ]:
```python
#cleans irregular values of Season column for the years 2010-11 and 2011-12
def fix_season(s):
  if (s == '2011-12 *'):
    return '2011-12'
  elif (s == datetime.datetime(2010, 11, 1, 0, 0)):
    return '2010-11'
  else:
    return s

performance_clean['Season'] = performance_clean['Season'].apply(fix_season)
#change season to starting year
# performance_clean['Season'] = performance_clean['Season'].split('-')[0]
performance_clean['Season'] = performance_clean['Season'].apply(lambda x: int(x.
 ↪split('-')[0]))
```

Here, we are adding two more columns: ‘Win’ and ‘Loss’ from extraction of the record column.

[ ]:
```python
def win(s):
  return s.split('-')[0]
def loss(s):
  return s.split('-')[1]
performance_clean['Win'] = performance_clean['Record'].apply(win)
performance_clean['Loss'] = performance_clean['Record'].apply(loss)
performance_clean.drop(['Record'], axis=1)
```

[ ]:
```
      Season     Team  Winning Percentage  Year Win Loss
0       2016  Celtics               0.625  2016  25   15
1       2015  Celtics               0.585  2015  48   34
2       2014  Celtics               0.488  2014  40   42
3       2013  Celtics               0.305  2013  25   57
```

```
4       2012  Celtics            0.506  2012  41   40
…      …      …              …    …  ..  …
1363    2014  Wizards            0.561  2014  46   36
1364    2013  Wizards            0.537  2013  44   38
1365    2012  Wizards            0.354  2012  29   53
1366    2011  Wizards            0.303  2011  20   46
1367    2010  Wizards            0.280  2010  23   59

[208 rows x 6 columns]
```

[ ]:
```
unique_team_d1=['Celtics', 'Hawks', 'Blackhawks', 'Nets', 'Hornets', 'Bobcats',
       'Bulls', 'Cavaliers', 'Mavericks', 'Nuggets', 'Pistons',
       'Warriors', 'Rockets', 'Pacers', 'Clippers', 'Braves', 'Lakers',
       'Grizzlies', 'Heat', 'Bucks', 'Timberwolves', 'Pelicans', 'Knicks',
       'Thunder', 'Supersonics', 'Magic', '76ers', 'Nationals', 'Suns',
       'Trail Blazers', 'Kings', 'Royals', 'Spurs', 'Raptors', 'Jazz',
       'Wizards', 'Bullets', 'Zephyrs', 'Packers']

unique_team_d2=['Bulls', 'Pistons', 'Blazers', 'Nets', 'Nuggets', 'Bucks',␣
 ↪'Kings',
 'Bobcats', 'Warriors', 'Suns', 'Heat', 'Thunder', 'Timberwolves',
 'Celtics', 'Lakers', 'Rockets', '76ers', 'Cavaliers', 'Clippers',
 'Grizzlies', 'Hawks', 'Hornets', 'Jazz', 'Knicks', 'Mavericks',
 'Pacers', 'Raptors', 'Spurs', 'Magic', 'Wizards', 'Pelicans',
 'Bullets']

d1_as_set = set(unique_team_d1)
intersection = d1_as_set.intersection(unique_team_d2)

unique_teams = list(intersection)
#unique_teams
```

To combine our two datasets: we will be linking the season columns together. For the injury dataset, this will be the start year of the season (i.e. 2010), and for the performance dataset, this will be the range (2010-11).

1.9 Data Analysis & Results

We need to combine all of our data frames together so we'll be merging them on 'Season' and 'Team'. Our merged data frame will contain the number of relinquished, acquired, and all types of injuries with the record and other data from our performance dataframe.

[ ]:
```
injuries2 = pd.merge(grouped_by_team_year, knee, how='left', on=['Season',␣
 ↪'Team'])
injuries3= pd.merge(injuries2, ankle, how='left', on=['Season', 'Team'])
injuries4 = pd.merge(injuries3, foot, how='left', on=['Season', 'Team'])
injuries5 = pd.merge(injuries4, finger, how='left', on=['Season', 'Team'])
injuries6 = pd.merge(injuries5, back, how='left', on=['Season', 'Team'])
```

```
injuries7 = pd.merge(injuries6, hand, how='left', on=['Season', 'Team'])
merged_data = pd.merge(injuries7, performance_clean, how='right', on=['Season',␣
 ↪'Team'])
```

[ ]:
```
merged_data['Knee injuries'] = merged_data['Knee injuries'].fillna(0)
merged_data['Ankle injuries'] = merged_data['Ankle injuries'].fillna(0)
merged_data['Foot injuries'] = merged_data['Foot injuries'].fillna(0)
merged_data['Finger injuries'] = merged_data['Finger injuries'].fillna(0)
merged_data['Back injuries'] = merged_data['Back injuries'].fillna(0)
merged_data['Hand injuries'] = merged_data['Hand injuries'].fillna(0)
```

[ ]:
```
merged_data
```

[ ]:
```
     Season     Team  Acquired  Relinquished  Knee injuries  Ankle injuries  \
0      2016  Celtics      50.0          65.0            2.0             8.0
1      2015  Celtics      42.0          52.0            2.0             4.0
2      2014  Celtics      28.0          36.0            1.0             6.0
3      2013  Celtics       6.0          99.0           54.0            26.0
4      2012  Celtics       7.0          46.0            8.0            15.0
..      …        …       …            …             …              …
203    2014  Wizards      33.0          43.0            3.0             3.0
204    2013  Wizards      13.0          53.0           18.0             2.0
205    2012  Wizards      13.0          99.0           20.0            16.0
206    2011  Wizards       5.0          68.0           18.0             2.0
207    2010  Wizards      42.0          90.0           41.0             5.0

     Foot injuries  Finger injuries  Back injuries  Hand injuries Record  \
0              0.0              0.0            1.0            0.0  25-15
1              1.0              0.0            2.0            0.0  48-34
2              1.0              1.0            1.0            2.0  40-42
3              0.0              0.0            0.0            0.0  25-57
4              0.0              0.0            2.0            0.0  41-40
..             …              …            …            …     …
203            2.0              0.0            3.0            1.0  46-36
204            7.0              3.0            4.0            0.0  44-38
205            5.0              0.0            2.0           12.0  29-53
206           24.0              1.0            1.0            2.0  20-46
207            9.0              2.0            0.0            0.0  23-59

     Winning Percentage  Year Win Loss
0                 0.625  2016  25   15
1                 0.585  2015  48   34
2                 0.488  2014  40   42
3                 0.305  2013  25   57
4                 0.506  2012  41   40
..                  …     …  ..   …
203               0.561  2014  46   36
```

```
204                0.537  2013  44   38
205                0.354  2012  29   53
206                0.303  2011  20   46
207                0.280  2010  23   59

[208 rows x 15 columns]
```

[ ]:
```
merged_data.sum()
```

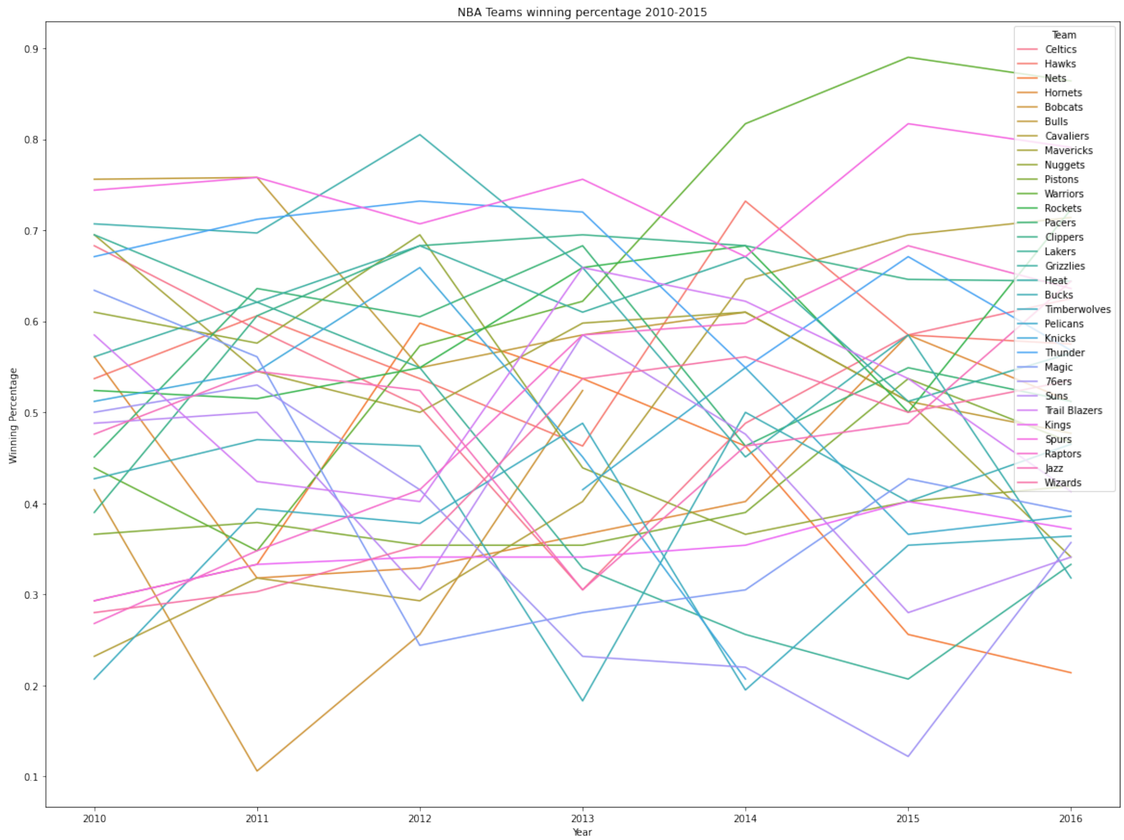
[ ]:
```
Season                                                            418699
Team                      CelticsCelticsCelticsCelticsCelticsCelticsCelt…
Acquired                                                          5810.0
Relinquished                                                     12442.0
Knee injuries                                                     1981.0
Ankle injuries                                                    1521.0
Foot injuries                                                      614.0
Finger injuries                                                    127.0
Back injuries                                                      692.0
Hand injuries                                                      184.0
Record                    25-1548-3440-4225-5741-4039-2756-2623-1748-346…
Winning Percentage                                               104.175
Year                                                              418699
Win                       254840254139562348603844404492138444922242483…
Loss                      1534425740272617342244382638336144383344582134…
dtype: object
```

Above is merged_data or one of our main data frames we used for our analysis, which includes key variables:

- Season
- Acquired (how many injured players returned to the roster in that season)
- Relinquished (total number of the specified injuries per season)
- Injury types:
  - knee/ankle/foot/finger/back/hand
- Record
- Winning Percentage

[ ]:
```
#Plot Winning Percentage (winning vs losing record) over 2010-2015 seasons for␣
 ↪all teams
#x-axis: Year
#y-axis: Winning Percentage
plt.figure(figsize=(20,15))
sns.lineplot(data=merged_data.drop(columns=['Relinquished']), x = "Year", y =␣
 ↪"Winning Percentage", hue = "Team").set_title('NBA Teams winning percentage␣
 ↪2010-2015')
```

[ ]:
```
Text(0.5, 1.0, 'NBA Teams winning percentage 2010-2015')
```



The graph above shows how the Winning Percentage (record) for each team changed over the six seasons we analyzed. It is typical for some teams' records to stay consistent over a duration because they have star players under contract or have consistent talent. Other teams may fluctuate due to losing players during free agency, injury, or trades. This graph is extremely hard to interpret so it only served as our initial data plot to get us started on our analysis.

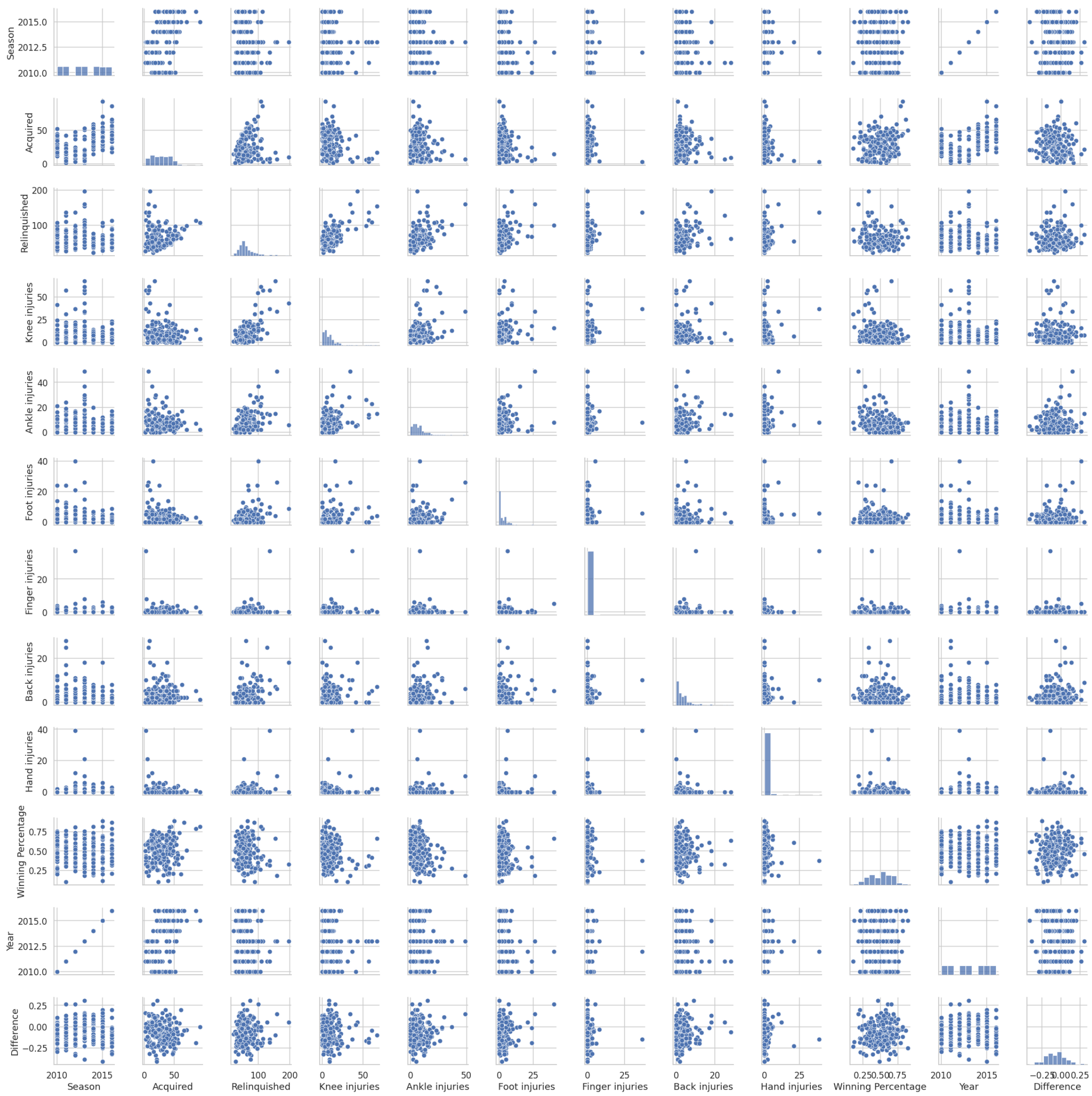
[ ]:
```
#Create Difference variable
#Difference = the current season Winning Percentage of a team minus that team's␣
↪average Winning Percentage
avg = merged_data.groupby(['Team','Season']).sum().get('Winning Percentage')/
↪merged_data.groupby(['Team','Season']).count().get('Winning Percentage')
avg1 = avg.groupby(['Team']).sum()/6
difference = merged_data.drop_duplicates().groupby(['Team','Season']).sum().
↪get('Winning Percentage') - avg1
difference = pd.DataFrame(difference).reset_index().get('Winning Percentage')
merged_data = merged_data.assign(Difference = difference)
merged_data
```

[ ]:
```
   Season     Team  Acquired  Relinquished  Knee injuries  Ankle injuries  \
0    2016  Celtics      50.0          65.0            2.0             8.0
1    2015  Celtics      42.0          52.0            2.0             4.0
```

```
2      2014  Celtics      28.0          36.0            1.0             6.0
3      2013  Celtics       6.0          99.0           54.0            26.0
4      2012  Celtics       7.0          46.0            8.0            15.0
..      …     …       …            …            …             …
203    2014  Wizards      33.0          43.0            3.0             3.0
204    2013  Wizards      13.0          53.0           18.0             2.0
205    2012  Wizards      13.0          99.0           20.0            16.0
206    2011  Wizards       5.0          68.0           18.0             2.0
207    2010  Wizards      42.0          90.0           41.0             5.0

     Foot injuries  Finger injuries  Back injuries  Hand injuries Record  \
0              0.0              0.0            1.0            0.0  25-15
1              1.0              0.0            2.0            0.0  48-34
2              1.0              1.0            1.0            2.0  40-42
3              0.0              0.0            0.0            0.0  25-57
4              0.0              0.0            2.0            0.0  41-40
..              …              …             …             …     …
203            2.0              0.0            3.0            1.0  46-36
204            7.0              3.0            4.0            0.0  44-38
205            5.0              0.0            2.0           12.0  29-53
206           24.0              1.0            1.0            2.0  20-46
207            9.0              2.0            0.0            0.0  23-59

     Winning Percentage  Year Win Loss  Difference
0                 0.625  2016  25   15    0.104000
1                 0.585  2015  48   34    0.134000
2                 0.488  2014  40   42    0.019000
3                 0.305  2013  25   57   -0.164000
4                 0.506  2012  41   40   -0.176000
..                  …     …  ..  …          …
203               0.561  2014  46   36   -0.157667
204               0.537  2013  44   38    0.025333
205               0.354  2012  29   53    0.049333
206               0.303  2011  20   46   -0.011667
207               0.280  2010  23   59    0.023333

[208 rows x 16 columns]
```

[ ]:

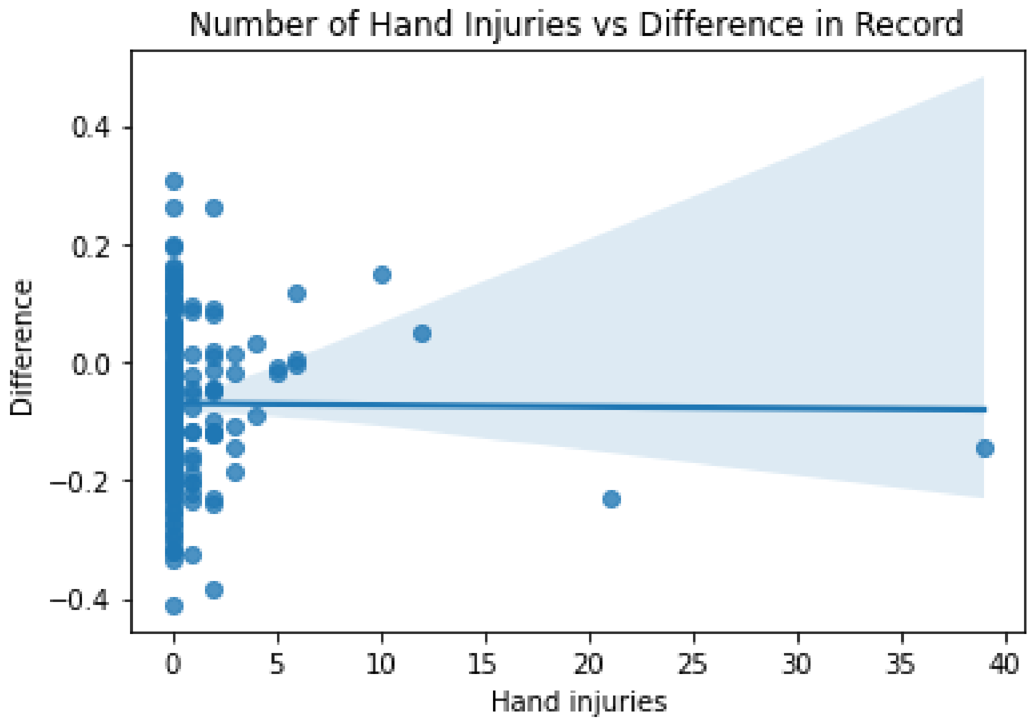
```
#Pairplot of merged_data containing all variables
sns.pairplot(merged_data)
plt.show()
```



The pair plot above shows a combination of the variables from the merged_data dataframe. This served the purpose of giving us a general idea of what the variables mapped on each other would look like.

[ ]:
```
#Exploratory plot: Difference vs. Hand Injury (One such example with Difference)
sns.regplot(data=merged_data, x="Hand injuries", y="Difference").
↪set_title('Number of Hand Injuries vs Difference in Record')
```

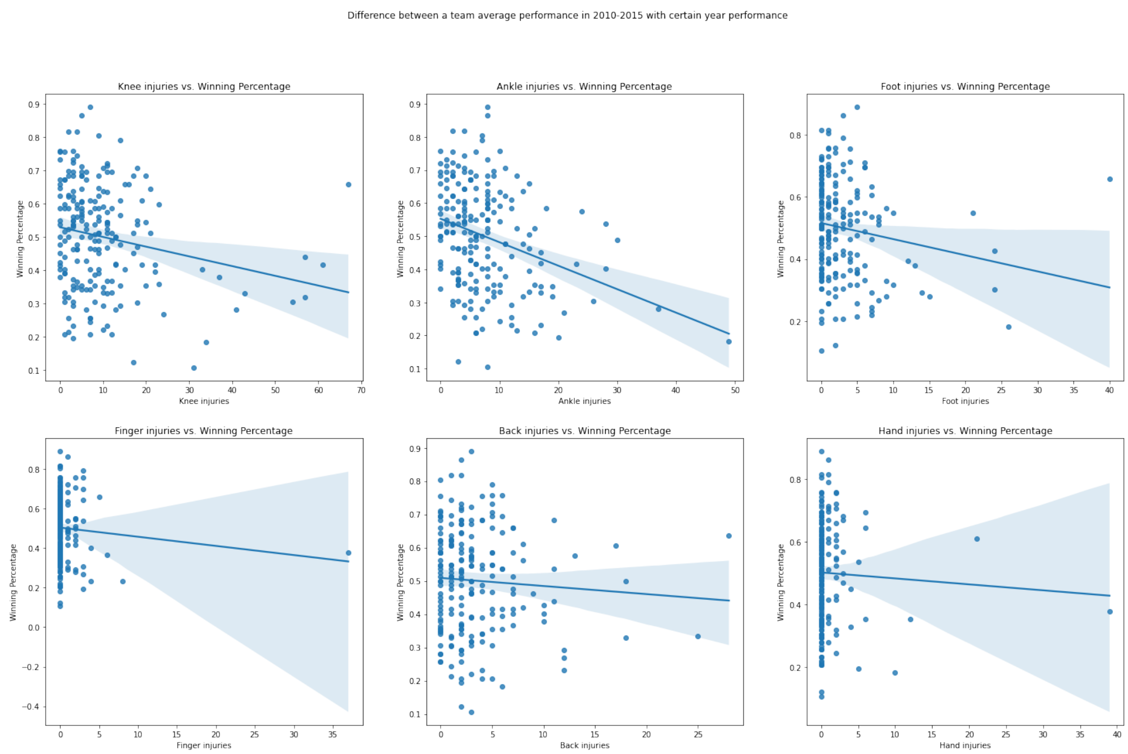
[ ]:
```
Text(0.5, 1.0, 'Number of Hand Injuries vs Difference in Record')
```



After creating the Difference variable, we plotted and tested what it would look like on a scatter plot. Originally, we did this to all injury types on separate scatter plots, but we didn't like what we observed. Many of these data points were clustered near the y-axis (at x = 0) and for the sake of our analysis, going forward we decided that it wasn't the best idea to use Difference as our y variable. We believed that the Difference variable was tragically flawed in that it didn't contain enough data points to be accurately compared. If we were to have conducted our analysis over many more seasons, we believe this would have been a more useful measurement.

[ ]:
```
#x-axis: Injury Type
#y-axis: Winning Percentage

fig, axes = plt.subplots(2, 3, figsize=(25, 15))
fig.suptitle('Difference between a team average performance in 2010-2015 with␣
↪certain year performance')
ax=sns.regplot(ax=axes[0, 0],data=merged_data, x="Knee injuries", y="Winning␣
↪Percentage")
ax.set_title("Knee injuries vs. Winning Percentage")
ax=sns.regplot(ax=axes[0, 1],data=merged_data, x="Ankle injuries", y="Winning␣
↪Percentage")
ax.set_title("Ankle injuries vs. Winning Percentage")
ax=sns.regplot(ax=axes[0, 2],data=merged_data, x="Foot injuries", y="Winning␣
↪Percentage")
ax.set_title("Foot injuries vs. Winning Percentage")
```

```
ax=sns.regplot(ax=axes[1, 0],data=merged_data, x="Finger injuries", y="Winning Percentage")
ax.set_title("Finger injuries vs. Winning Percentage")
ax=sns.regplot(ax=axes[1, 1],data=merged_data, x="Back injuries", y="Winning Percentage")
ax.set_title("Back injuries vs. Winning Percentage")
ax=sns.regplot(ax=axes[1, 2],data=merged_data, x="Hand injuries", y="Winning Percentage")
ax.set_title("Hand injuries vs. Winning Percentage")

f1 = plt.gcf()
```

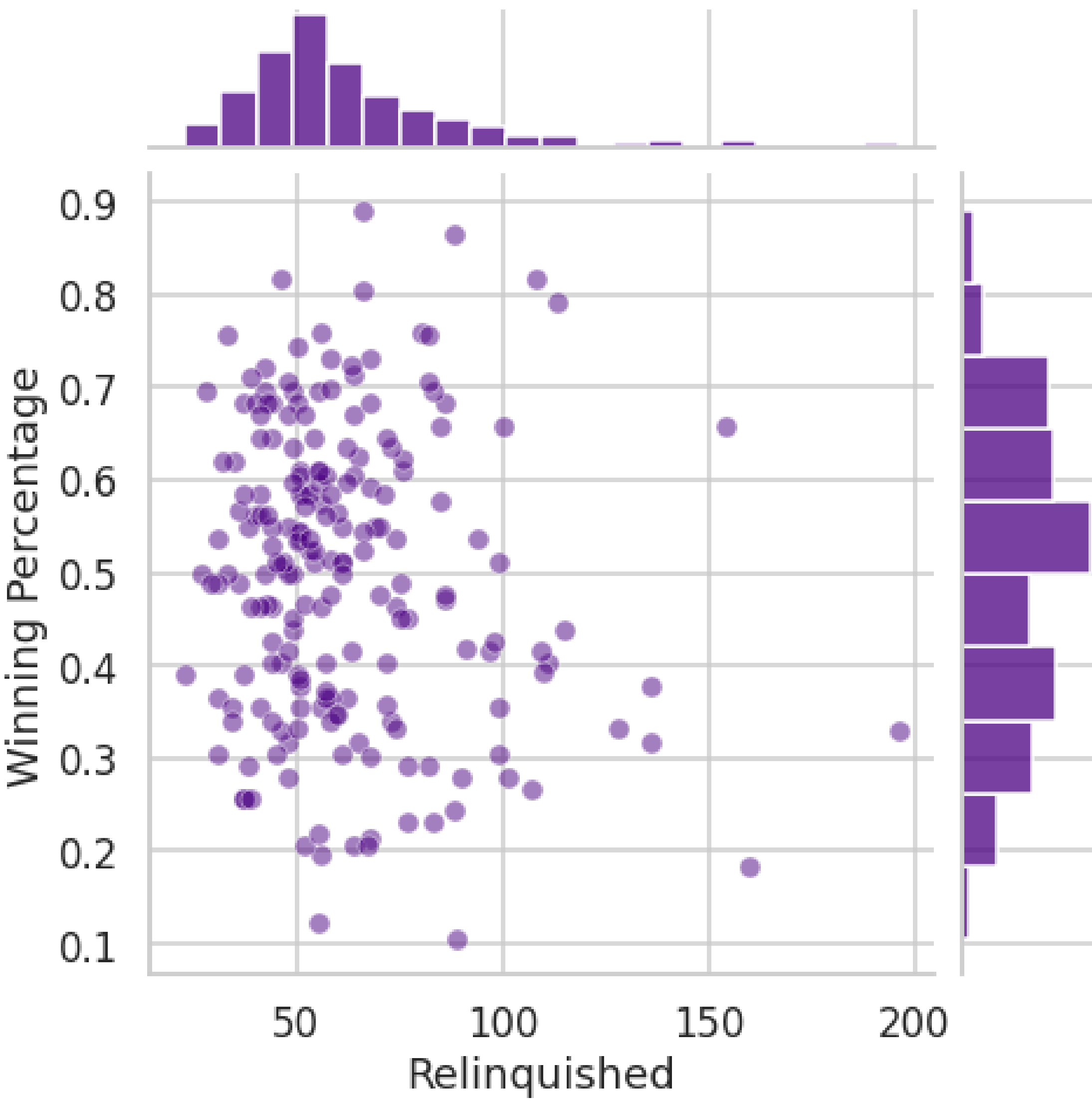


These graphs are a continuation of what we attempted to do above. So, we plotted each type of injury versus the Winning Percentages. From an initial glance, we thought this was much better than plotting Difference vs. Injury types, however, it wasn't exactly what we were looking for. Across the different types of injuries, we observed regression lines that were weak negatives. As a result, we were happy to at least witness that there were somewhat negative relationships between the number of injuries and winning percentages. Additionally, here we witnessed a stronger negative correlation with lower extremity injuries (knee/ankle/foot) than upper extremity injuries (finger/back/hand).

But we were far from done. Many of these data points were still clustered around the y-axis and the regression lines did not fit the data well, so as a result, we believed that the outliers could have skewed the data. Another reason we thought these visualizations weren't the best was because we felt that we did not have enough data, thus potentially leading to confounds or spurious correlations.

[ ]:
```python
#Exploratory plot: relationship between Winning Percentage and Relinquished␣
↪(the overall number of injuries)
#x-axis: Relinquished
#y-axis: Winning Percentage

sns.set()
sns.set_context('talk')
sns.set_style('whitegrid')

sns.jointplot(x = merged_data['Relinquished'], y = merged_data['Winning␣
↪Percentage'], height = 7, color = 'indigo', alpha = 0.5)
#plt.fig.suptitle("Number of Relinquished Injuries vs Winning Percentage")
```

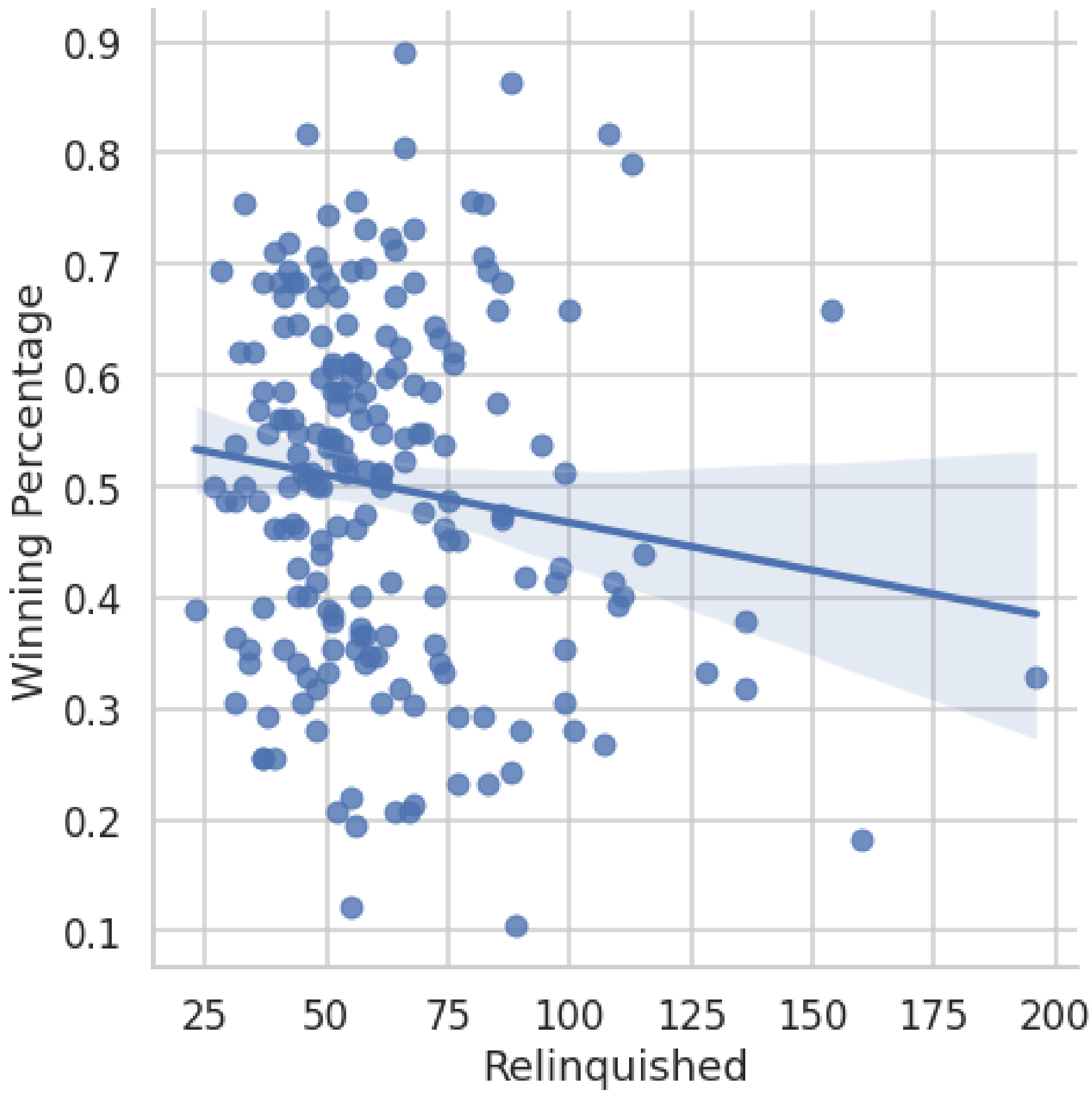
[ ]: <seaborn.axisgrid.JointGrid at 0x7f6a98700f50>



According to this graph, we observed that the distribution of Winning Percentage was relatively normally distributed and the Relinquished variable distribution was rightly skewed. Also, this scatter plot possessed some outliers in the Relinquished direction of the graph.

In order to better understand if there is a linear relationship that exists, we drew a linear regression on the scatter plot.

[ ]:
```
sns.lmplot(x ='Relinquished', y ='Winning Percentage', data = merged_data,␣
 ↪height = 7)
plt.show()
```

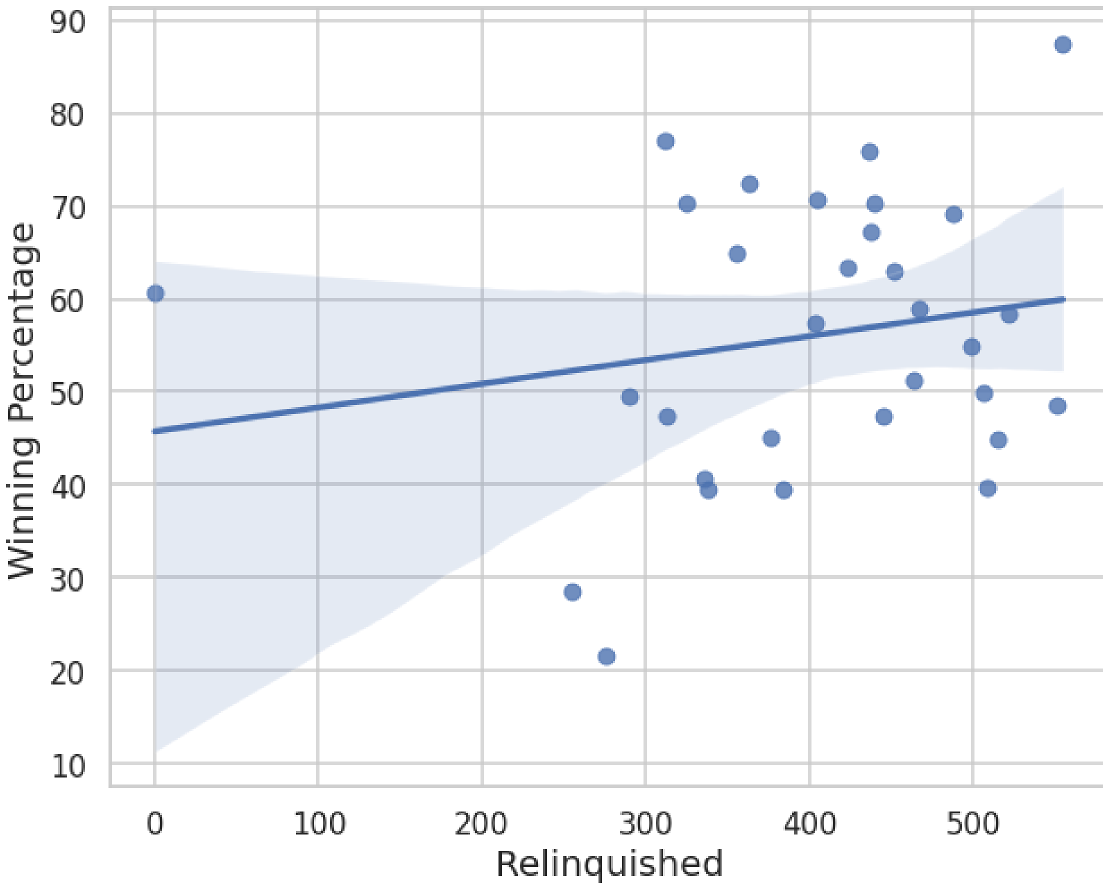


The graph shows the linear relationship between the total number of injuries (Relinquished) against the Winning Percentage. This plot gave us a better perspective of the weak negative linear relationship between these two variables.

```
[ ]: #create group_merged_data, deleting all injuries and adding net injuries column

grouped_merged_data = merged_data.groupby('Team').sum()
grouped_merged_data['Net_Injuries'] = grouped_merged_data['Relinquished'] -␣
 ↪grouped_merged_data['Acquired']
grouped_merged_data['Winning Percentage'] = grouped_merged_data['Winning␣
 ↪Percentage'].apply(lambda x: x/6)

#convert Winning Percentagefrom ratio to actual percentage ~ (0-100)
winningPercentage = [x * 100 for x in grouped_merged_data['Winning Percentage']]
grouped_merged_data = grouped_merged_data.
 ↪assign(winningPercentage=winningPercentage)
Acquired = grouped_merged_data['Acquired']
Relinquished = grouped_merged_data['Relinquished']
Net_Injuries = grouped_merged_data['Net_Injuries']
```

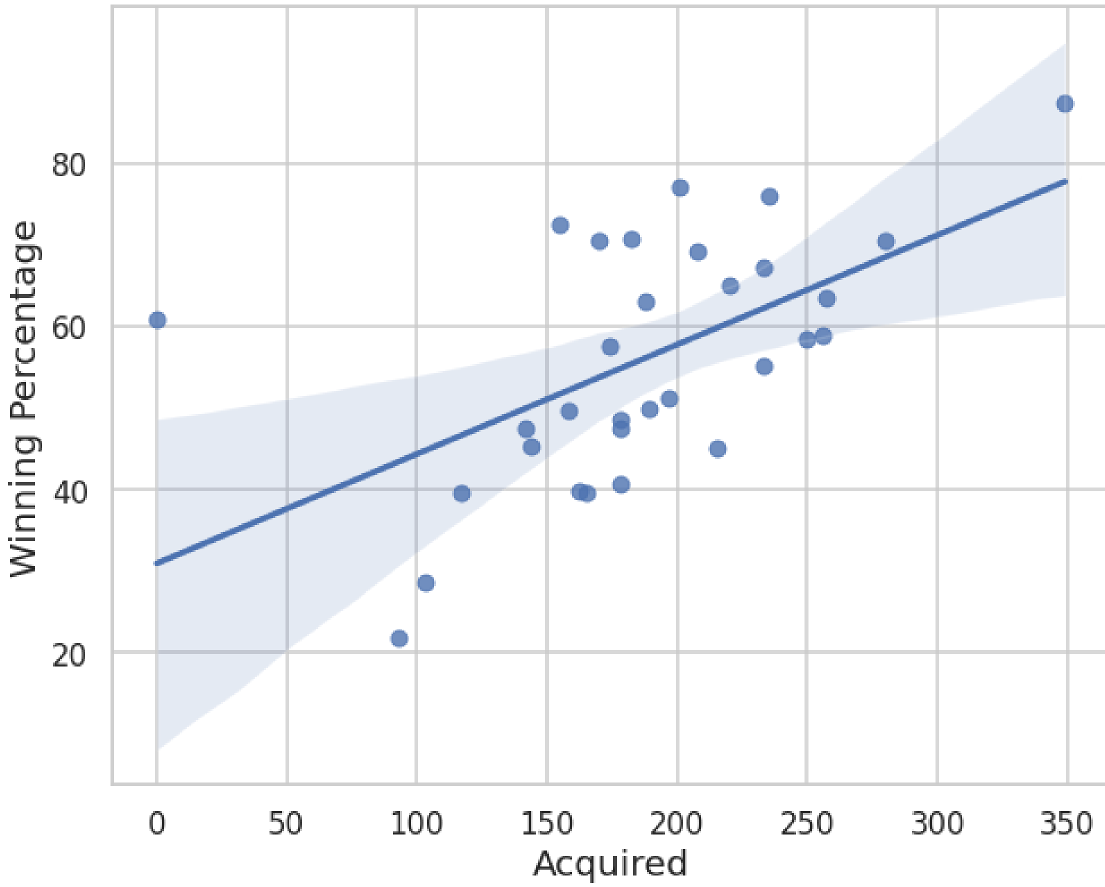
Here we create an additional data frame called grouped_merged_data in which we: - Sum the variables by each team - Create Net_Injuries variable (total number of injured players that didn't return to roster) - Alter Winning Percentage to the average and change to a % from 0-100 - Also created some variables that will be used below

```
[ ]: #x-axis: Relinquished ~ (number of players that got injured per team)
#y-axis: Winning Percentage

plt.figure(figsize=(10,8))
plot = sns.regplot(x=Relinquished, y=winningPercentage)
temp = plot.set_ylabel("Winning Percentage", fontsize = 20)
temp = plot.set_xlabel("Relinquished", fontsize = 20)
```



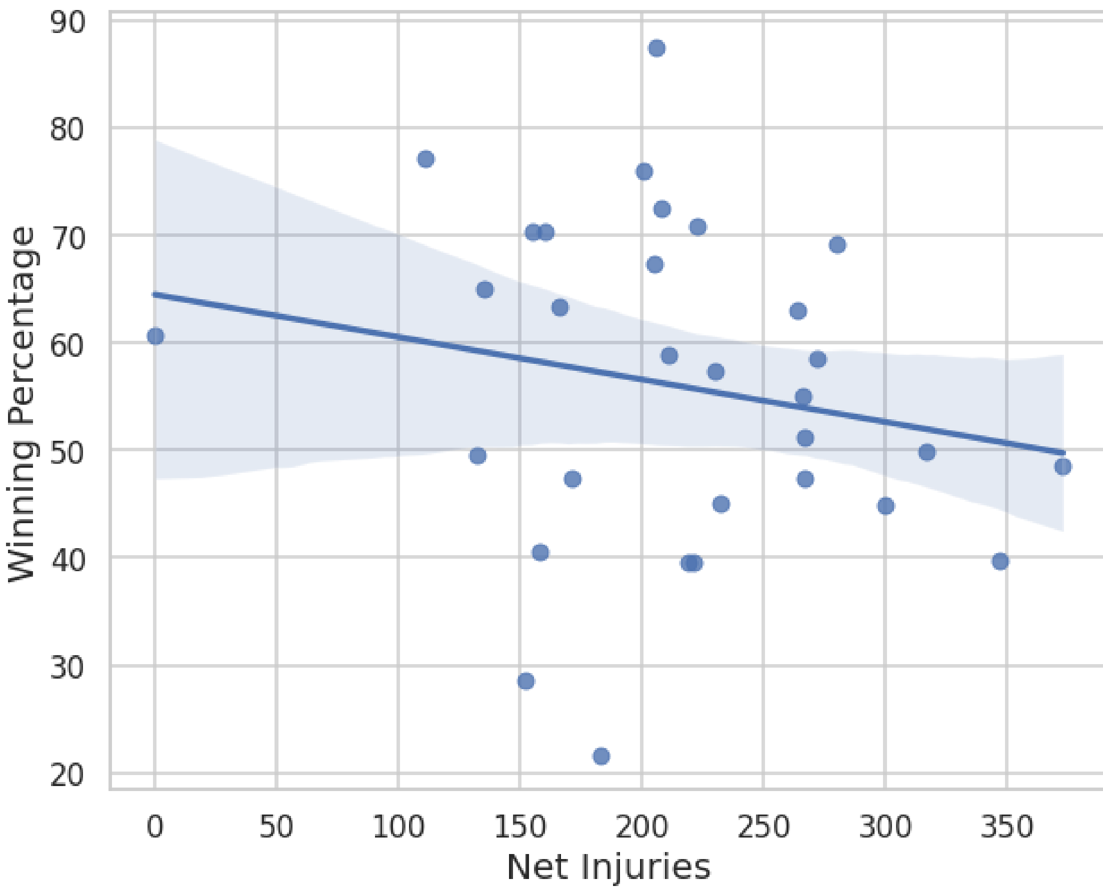
The graph above shows the relationship between the total number of injuries (Relinquished) against their win percentage. There was a good balance between those who had a good season vs bad season with the same number of injuries. We can see this goes against what we thought: we have a positive slope here.

```
[ ]: #x-axis: Acquired ~ (number of players who got injured and returned to roster)
     #y-axis: Winning Percentage

     plt.figure(figsize=(10,8))
     plot = sns.regplot(x=Acquired, y=winningPercentage)
     temp = plot.set_ylabel("Winning Percentage", fontsize = 20)
     temp = plot.set_xlabel("Acquired", fontsize = 20)
```



The graph above shows the relationship between the total number of players returning from injuries (Acquired) against their win percentage. Teams that got more players back from injury ended up having better records.

[ ]:
```
#x-axis: Net_Injuries ~ (number of players that got injured and didn't return␣
  ↪to roster that season)
#y-axis: Winning Percentage

plt.figure(figsize=(10,8))
plot = sns.regplot(x=Net_Injuries, y=winningPercentage)
temp = plot.set_ylabel("Winning Percentage", fontsize = 20)
temp = plot.set_xlabel("Net Injuries", fontsize = 20)
#plt.grid()
```



The graph above shows the relationship between the difference between Relinquished and Acquired against their win percentage. Teams that got less players back from injury (large x axis values) ended up having a worse record, but the best fit line is not very strong; there are many outliers and the error would be pretty high.

We then run OLS regression models individually on Relinquished and Acquired to see if there exists a significant relationship with the Winning Percentage.

[ ]:
```
# Are the amount of injuries in a team correlated to the winning percentage␣
↪over all years?
# The summary shows that it is not at all.
outcome, predictors = patsy.dmatrices('winningPercentage ~ Relinquished')
mod = sm.OLS(outcome, predictors)
res = mod.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      winningPercentage   R-squared:                       0.036
Model:                            OLS   Adj. R-squared:                  0.003
```

```
Method:                 Least Squares   F-statistic:                     1.090
Date:                Sun, 05 Jun 2022   Prob (F-statistic):              0.305
Time:                        20:42:45   Log-Likelihood:                -126.91
No. Observations:                  31   AIC:                             257.8
Df Residuals:                      29   BIC:                             260.7
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept       45.7465     10.190      4.489      0.000      24.906      66.587
Relinquished     0.0256      0.024      1.044      0.305      -0.025       0.076
==============================================================================
Omnibus:                        1.379   Durbin-Watson:                   1.691
Prob(Omnibus):                  0.502   Jarque-Bera (JB):                0.962
Skew:                          -0.053   Prob(JB):                        0.618
Kurtosis:                       2.143   Cond. No.                     1.57e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.57e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In the above linear regression model, we only use one variable 'Relinquished' to predict the winning percentage. From the result, the coefficient is 0.0256, which is close to 0. The p-value is 0.305, which is bigger than the significant level of 0.05. Hence, we fail to reject the null hypothesis and can conclude that there is no significant relationship, and that Relinquished alone might not be a good model to predict the winning percentage.

[ ]:
```python
# Is the amount of players a team acquired correlated to the winning percentage␣
↪over all years?
# The summary shows that this is slightly more probably, but there is no␣
↪significant correlation.
outcome, predictors = patsy.dmatrices('winningPercentage ~ Acquired')
mod = sm.OLS(outcome, predictors)
res = mod.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      winningPercentage   R-squared:                       0.322
Model:                            OLS   Adj. R-squared:                  0.299
Method:                 Least Squares   F-statistic:                     13.79
Date:                Sun, 05 Jun 2022   Prob (F-statistic):           0.000867
Time:                        20:42:46   Log-Likelihood:                -121.45
No. Observations:                  31   AIC:                             246.9
```

```
Df Residuals:                      29   BIC:                             249.8
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     30.8418      7.145      4.317      0.000      16.229      45.454
Acquired       0.1343      0.036      3.713      0.001       0.060       0.208
==============================================================================
Omnibus:                        1.771   Durbin-Watson:                   1.687
Prob(Omnibus):                  0.413   Jarque-Bera (JB):                1.589
Skew:                           0.516   Prob(JB):                        0.452
Kurtosis:                       2.593   Cond. No.                         625.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

In the above linear regression model, we only use one variable 'Acquired', which means the number of injured players returning to the game, to predict the winning percentage. From the result, the coefficient is 0.1343, which means for every returning player that recovered from their injuries, the winning percentage increased by 0.1343. The p-value is 0.001, which is smaller than the significant level of 0.05. Hence, we reject the null hypothesis and conclude that there is a significant relationship by convention; thus, we should consider the variable Acquired in our model.

[ ]:
```python
knee = grouped_merged_data['Knee injuries']
ankle = grouped_merged_data['Ankle injuries']
foot = grouped_merged_data['Foot injuries']
finger = grouped_merged_data['Finger injuries']
back = grouped_merged_data['Back injuries']
hand = grouped_merged_data['Hand injuries']

outcome_1, predictors_1 = patsy.dmatrices('winningPercentage ~ Acquired + knee␣
 ↪+ ankle + foot + finger + back + hand')
mod_1 = sm.OLS(outcome_1, predictors_1)
res_1 = mod_1.fit()
print(res_1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      winningPercentage   R-squared:                       0.630
Model:                            OLS   Adj. R-squared:                  0.517
Method:                 Least Squares   F-statistic:                     5.594
Date:                Sun, 05 Jun 2022   Prob (F-statistic):           0.000736
Time:                        20:42:46   Log-Likelihood:                -112.07
No. Observations:                  31   AIC:                             240.1
Df Residuals:                      23   BIC:                             251.6
```

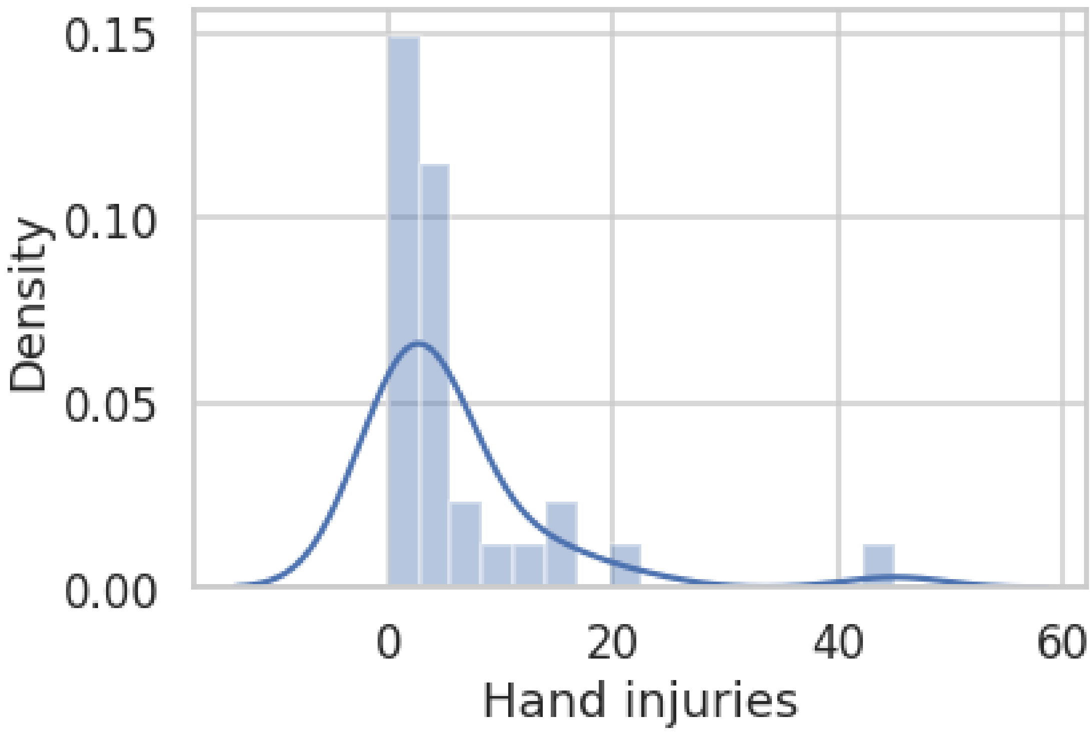
```
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     44.1045      7.139      6.178      0.000      29.336      58.873
Acquired       0.1625      0.035      4.592      0.000       0.089       0.236
knee          -0.1050      0.083     -1.263      0.219      -0.277       0.067
ankle         -0.1377      0.120     -1.148      0.263      -0.386       0.110
foot          -0.2343      0.169     -1.387      0.179      -0.584       0.115
finger        -0.9764      0.423     -2.306      0.030      -1.852      -0.101
back          -0.0658      0.212     -0.310      0.759      -0.505       0.373
hand           0.8465      0.353      2.399      0.025       0.117       1.577
==============================================================================
Omnibus:                        1.390   Durbin-Watson:                   1.900
Prob(Omnibus):                  0.499   Jarque-Bera (JB):                0.552
Skew:                          -0.283   Prob(JB):                        0.759
Kurtosis:                       3.327   Cond. No.                         820.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

In the above model, we explore if the variables of different types of injuries and the Acquired together can form a linear model to predict the winning percentage. Here, we see that we have very small p-values for the acquired. This supports the claim that people that have more people returning from injuries have a better winning percentage. This does not support our hypothesis that the more injured players a team has, the lower the team's winning percentage will be since the coefficient for the hand injuries variable is positive.

[ ]:
```python
#take a look at the distribution of hand injuries to see why the coefficient in
 ↪the model is positive
sns.distplot(grouped_merged_data['Hand injuries'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5680e3a690>
```




```
[ ]: #ignore Season and Year
     grouped_merged_data
```

[ ]:

	Season	Acquired	Relinquished	Knee injuries	Ankle injuries	\
Team						
76ers	14091	165.0	384.0	79.0	40.0	
Bobcats	8046	93.0	276.0	59.0	42.0	
Bucks	14091	178.0	551.0	100.0	85.0	
Bulls	14091	182.0	405.0	48.0	43.0	
Cavaliers	14091	233.0	499.0	83.0	77.0	
Celtics	14091	188.0	452.0	97.0	82.0	
Clippers	14091	155.0	363.0	44.0	23.0	
Grizzlies	14091	170.0	325.0	55.0	39.0	
Hawks	14091	233.0	438.0	47.0	49.0	
Heat	14091	280.0	440.0	59.0	38.0	
Hornets	12078	144.0	376.0	100.0	52.0	
Jazz	14091	174.0	404.0	72.0	46.0	
Kings	14091	178.0	336.0	28.0	37.0	
Knicks	10060	117.0	338.0	74.0	39.0	
Lakers	14091	189.0	506.0	96.0	34.0	
Magic	14091	178.0	445.0	46.0	76.0	
Mavericks	14091	257.0	423.0	65.0	25.0	
Nets	14091	215.0	515.0	43.0	75.0	

Nuggets	14091	250.0	522.0	118.0	80.0
Pacers	14091	220.0	355.0	39.0	43.0
Pelicans	8058	103.0	255.0	84.0	36.0
Pistons	14091	142.0	313.0	39.0	43.0
Raptors	14091	256.0	467.0	77.0	78.0
Rockets	14091	208.0	488.0	87.0	54.0
Spurs	14091	349.0	555.0	41.0	31.0
Suns	14091	158.0	290.0	36.0	47.0
Thunder	14091	201.0	312.0	36.0	16.0
Timberwolves	14091	162.0	509.0	84.0	98.0
Trail Blazers	14091	0.0	0.0	0.0	0.0
Warriors	14091	235.0	436.0	35.0	56.0
Wizards	14091	197.0	464.0	110.0	37.0

Team	Foot injuries	Finger injuries	Back injuries	Hand injuries \
76ers	26.0	9.0	13.0	1.0
Bobcats	10.0	0.0	10.0	2.0
Bucks	59.0	2.0	30.0	13.0
Bulls	24.0	2.0	25.0	1.0
Cavaliers	12.0	6.0	35.0	3.0
Celtics	4.0	2.0	9.0	2.0
Clippers	13.0	0.0	19.0	15.0
Grizzlies	24.0	1.0	18.0	22.0
Hawks	9.0	1.0	43.0	0.0
Heat	20.0	4.0	13.0	7.0
Hornets	17.0	3.0	15.0	4.0
Jazz	17.0	6.0	22.0	0.0
Kings	13.0	5.0	25.0	1.0
Knicks	41.0	5.0	12.0	2.0
Lakers	17.0	0.0	28.0	0.0
Magic	42.0	0.0	20.0	4.0
Mavericks	14.0	4.0	18.0	4.0
Nets	35.0	0.0	55.0	5.0
Nuggets	8.0	0.0	32.0	0.0
Pacers	12.0	0.0	40.0	0.0
Pelicans	4.0	9.0	8.0	2.0
Pistons	23.0	0.0	25.0	6.0
Raptors	14.0	6.0	28.0	5.0
Rockets	23.0	1.0	39.0	4.0
Spurs	12.0	8.0	24.0	9.0
Suns	8.0	2.0	6.0	3.0
Thunder	15.0	2.0	16.0	5.0
Timberwolves	32.0	40.0	27.0	45.0
Trail Blazers	0.0	0.0	0.0	0.0
Warriors	18.0	3.0	22.0	4.0
Wizards	48.0	6.0	15.0	15.0

Team	Winning Percentage	Year	Difference	Net_Injuries	\
76ers	0.396000	14091	-0.692167	219.0	
Bobcats	0.216833	8046	-1.037833	183.0	
Bucks	0.485000	14091	-0.506500	373.0	
Bulls	0.707833	14091	0.145500	223.0	
Cavaliers	0.550000	14091	-1.013500	266.0	
Celtics	0.630500	14091	-0.396000	264.0	
Clippers	0.724500	14091	0.494333	208.0	
Grizzlies	0.703833	14091	-0.556333	155.0	
Hawks	0.672500	14091	0.338667	205.0	
Heat	0.703667	14091	-0.423667	160.0	
Hornets	0.451167	12078	-0.671000	232.0	
Jazz	0.574167	14091	-0.758833	230.0	
Kings	0.406000	14091	-0.770500	158.0	
Knicks	0.395667	10060	0.434167	221.0	
Lakers	0.498333	14091	-0.521667	317.0	
Magic	0.473667	14091	-0.588833	267.0	
Mavericks	0.633500	14091	-0.476500	166.0	
Nets	0.449000	14091	-0.450500	300.0	
Nuggets	0.584500	14091	-0.794833	272.0	
Pacers	0.649833	14091	-0.443500	135.0	
Pelicans	0.286000	8058	-0.423000	152.0	
Pistons	0.474500	14091	-0.237000	171.0	
Raptors	0.588833	14091	-0.607000	211.0	
Rockets	0.692167	14091	-0.301167	280.0	
Spurs	0.874000	14091	-0.396667	206.0	
Suns	0.495833	14091	-0.874000	132.0	
Thunder	0.770500	14091	-0.474500	111.0	
Timberwolves	0.396667	14091	-0.654000	347.0	
Trail Blazers	0.607000	14091	-0.495833	0.0	
Warriors	0.758833	14091	-0.947167	201.0	
Wizards	0.511667	14091	-0.511667	267.0	

Team	winningPercentage
76ers	39.600000
Bobcats	21.683333
Bucks	48.500000
Bulls	70.783333
Cavaliers	55.000000
Celtics	63.050000
Clippers	72.450000
Grizzlies	70.383333
Hawks	67.250000
Heat	70.366667

```
Hornets                  45.116667
Jazz                     57.416667
Kings                    40.600000
Knicks                   39.566667
Lakers                   49.833333
Magic                    47.366667
Mavericks                63.350000
Nets                     44.900000
Nuggets                  58.450000
Pacers                   64.983333
Pelicans                 28.600000
Pistons                  47.450000
Raptors                  58.883333
Rockets                  69.216667
Spurs                    87.400000
Suns                     49.583333
Thunder                  77.050000
Timberwolves             39.666667
Trail Blazers            60.700000
Warriors                 75.883333
Wizards                  51.166667
```

[ ]:
```
grouped_merged_data[grouped_merged_data['Hand injuries'] > 40]
```

[ ]:
```
              Season  Acquired  Relinquished  Knee injuries  Ankle injuries  \
Team
Timberwolves   14091     162.0         509.0           84.0            98.0

              Foot injuries  Finger injuries  Back injuries  Hand injuries  \
Team
Timberwolves           32.0             40.0           27.0           45.0

              Winning Percentage   Year  Difference  Net_Injuries  \
Team
Timberwolves            0.396667  14091      -0.654         347.0

              winningPercentage
Team
Timberwolves          39.666667
```

One of the possible reasons this phenomenon occurs is that we do not have enough data points. In fact, out of the 12,442 injury data points that we had, only 5,119 were categorized into the 6 groups we see above. Therefore, the remaining half of the injuries could potentially play a significantly greater impact than the ones listed above. Head trauma, back fractures, and other serious but less frequently occurring injuries will probably be more predictive simply due to their severe nature.

When it comes to the categories we do have, we can see that the distribution of Hand Injuries above is not normally distributed and contains outliers. On this graph one team had 44 hand injuries while most of the teams had less than 10. Hence, it is possible that the team with large amounts of hand injuries are a strong team by coincidence and therefore have a greater winning percentage, which might influence the result of the model.

Since Acquired means how many players come back from injuries and Relinquished means the total amount of injuries of all types, we want to consider both of them simultaneously. Due to the nature of the variables, we try to combine Acquired and Relinquished in our model.

Here we construct a multivariate linear regression model.

[ ]:
```
outcome_2, predictors_2 = patsy.dmatrices('winningPercentage ~␣
 ↪Acquired+Relinquished')
mod_2 = sm.OLS(outcome_2, predictors_2)
res_2 = mod_2.fit()
print(res_2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      winningPercentage   R-squared:                       0.471
Model:                            OLS   Adj. R-squared:                  0.433
Method:                 Least Squares   F-statistic:                     12.46
Date:                Sun, 05 Jun 2022   Prob (F-statistic):           0.000135
Time:                        20:42:46   Log-Likelihood:                -117.61
No. Observations:                  31   AIC:                             241.2
Df Residuals:                      28   BIC:                             245.5
Df Model:                           2
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept       42.7885      7.709      5.551      0.000      26.997      58.580
Acquired         0.2441      0.051      4.795      0.000       0.140       0.348
Relinquished    -0.0810      0.029     -2.804      0.009      -0.140      -0.022
==============================================================================
Omnibus:                        0.309   Durbin-Watson:                   1.475
Prob(Omnibus):                  0.857   Jarque-Bera (JB):                0.486
Skew:                           0.060   Prob(JB):                        0.784
Kurtosis:                       2.399   Cond. No.                     1.74e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.74e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The above linear regression model is consistent with what we assumed. As we assumed, more acquired (players returning from injuries) would increase the winning percentage; while more relinquished (total number of players who got injured) would decrease the winning percentage. Both variables have a p-value smaller than the significance level 0.05, hence we can reject the null hypothesis and conclude that there exists a significant relationship between acquired + relinquished with winning percentage by convention.

Now we have two linear regression models that we want to consider: - mod_1: that takes 'Acquired + knee + ankle + foot + finger + back + hand' as variables to predict the winning percentage and - mod_2: that only takes 'Acquired + Relinquished'

We will evaluate the model by using Train/Test split to calculate the root of mean squared error. The model with a smaller root of mean squared error will be considered as a better prediction for winning percentage.

[ ]:
```
#calculate the RMSE from mod_1
X = grouped_merged_data[['Acquired','Finger injuries','Hand injuries',
                        'Knee injuries', 'Ankle injuries', 'Foot␣
 ↪injuries','Back injuries']]
y = grouped_merged_data['winningPercentage']

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=3)

# Instantiate model
lm2 = LinearRegression()

# Fit Model
lm2.fit(X_train, y_train)

# Predict
y_pred = lm2.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
20.806928184333792
```

[ ]:
```
#calculate the RMSE from mod_2
X = grouped_merged_data[['Acquired', 'Relinquished']]
y = grouped_merged_data['winningPercentage']

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=3)

# Instantiate model
lm2 = LinearRegression()

# Fit Model
lm2.fit(X_train, y_train)

# Predict
```

```
y_pred = lm2.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
10.861318226985368
```

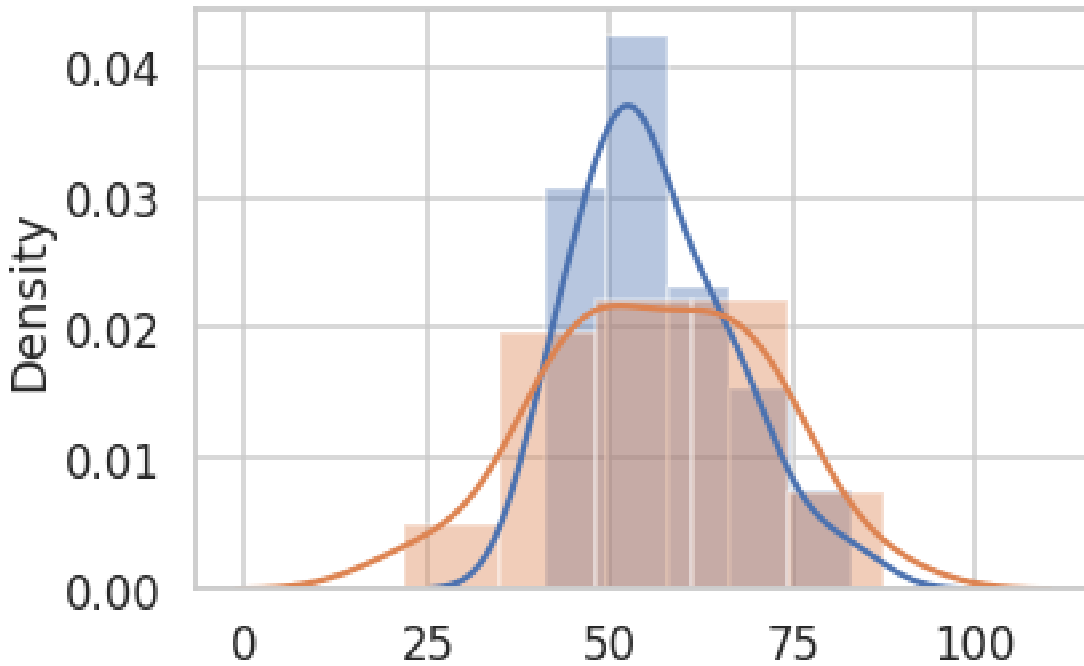
From the above results, we find out that mod_2 has a smaller root mean squared error. This result supports our interpretation of the models because mod_2 shows more relinquish(injuries) decreases winning percentage and more acquired(players coming back) will increase the winning percentage. Also, both two parameters in mod_2 have a p-value that is smaller than the significant level, which means there exists a significant relationship, while mod_1 does not. Therefore, we can conclude that mod_2 is more appropriate than mod_1.

[ ]:
```
def predict_model_2(acquired, relinquished):
    predict_y = []
    for idx in range(len(acquired)):
        a = acquired[idx]
        r = relinquished[idx]
        predict_winning_percent = 42.7885 + 0.2441*a - 0.0810*r
        predict_y.append(predict_winning_percent)
    return predict_y

a = list(grouped_merged_data['Acquired'])
r = list(grouped_merged_data['Relinquished'])
y_true = list(grouped_merged_data['winningPercentage'])
y_pred_2 = predict_model_2(a,r)
```

[ ]:
```
sns.distplot(y_pred_2)
sns.distplot(y_true)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6a940a70d0>
```



The above distribution graph shows the distribution for the value of predicted winning percentage (blue) and the true value of winning percentage from 2010-2015 (orange).

Both distribution graphs show roughly normal with similar mean located at the center. However, the True winning percentage curve is more spread out than the predicted winning percentage curve.

[ ]:
```
injury2016 = injury_original[injury_original['Season']==2016]
injury2016 = injury2016.groupby(['Team']).count().drop(columns=['Date',␣
↪'Notes', 'Season'])
injury2016['pred_win_percent'] = 42.7885 + (6*0.2441*injury2016['Acquired']) -␣
↪(6*0.0810*injury2016['Relinquished'])
injury2016['2016_win_percent'] = [34.1, 50.0, 51.2, 50.0, 62.2, 64.6, 62.2, 52.
↪4, 52.4, 50.0, 43.9, 62.2, 39.0, 37.8, 31.7, 35.4, 40.2, 24.4, 48.8, 51.2,␣
↪41.5, 45.1, 62.2, 67.1, 74.4, 29.3, 57.3, 37.8, 81.7, 59.8]
injury2016['difference'] =␣
↪abs(injury2016['2016_win_percent']-injury2016['pred_win_percent'])
injury2016
```

[ ]:
```
            Acquired  Relinquished  pred_win_percent  2016_win_percent  \
Team
76ers             40            72           66.3805              34.1
Blazers           27            47           59.4907              50.0
Bucks             37            52           71.7067              51.2
Bulls             55            70           89.3215              50.0
Cavaliers         47            64           80.5207              62.2
```

Celtics	50	65	84.4285	64.6
Clippers	25	41	59.4775	62.2
Grizzlies	48	60	83.9293	52.4
Hawks	35	56	66.8335	52.4
Heat	33	48	67.7923	50.0
Hornets	40	54	75.1285	43.9
Jazz	47	72	76.6327	62.2
Kings	40	57	73.6705	39.0
Knicks	60	80	91.7845	37.8
Lakers	57	74	90.3067	31.7
Magic	33	37	73.1383	35.4
Mavericks	50	73	80.5405	40.2
Nets	48	68	80.0413	24.4
Nuggets	63	91	90.8323	48.8
Pacers	43	61	76.1203	51.2
Pelicans	34	51	67.7989	41.5
Pistons	34	43	71.6869	45.1
Raptors	37	49	73.1647	62.2
Rockets	47	63	81.0067	67.1
Spurs	86	113	113.8261	74.4
Suns	37	58	68.7907	29.3
Thunder	23	36	58.9783	57.3
Timberwolves	18	31	54.0853	37.8
Warriors	66	88	96.6841	81.7
Wizards	43	50	81.4663	59.8

	difference
Team	
76ers	32.2805
Blazers	9.4907
Bucks	20.5067
Bulls	39.3215
Cavaliers	18.3207
Celtics	19.8285
Clippers	2.7225
Grizzlies	31.5293
Hawks	14.4335
Heat	17.7923
Hornets	31.2285
Jazz	14.4327
Kings	34.6705
Knicks	53.9845
Lakers	58.6067
Magic	37.7383
Mavericks	40.3405
Nets	55.6413
Nuggets	42.0323

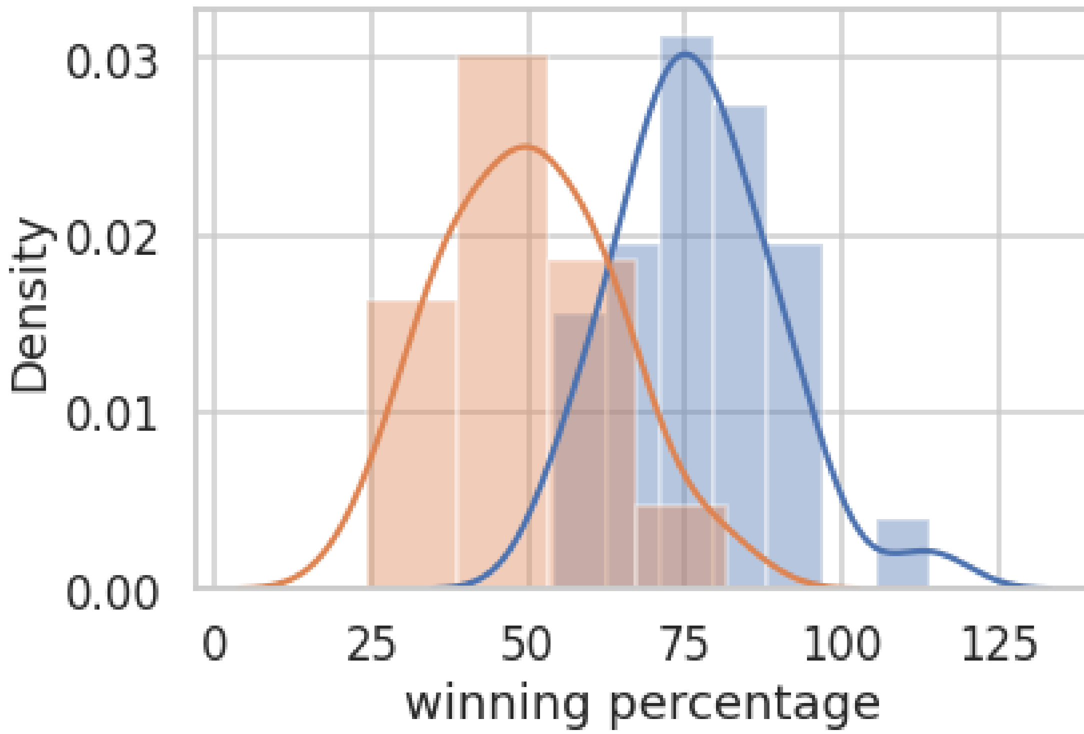
```
Pacers          24.9203
Pelicans        26.2989
Pistons         26.5869
Raptors         10.9647
Rockets         13.9067
Spurs           39.4261
Suns            39.4907
Thunder          1.6783
Timberwolves    16.2853
Warriors        14.9841
Wizards         21.6663
```

We will try to use our equation from 2010-2015 data to predict the winning percentages from 2016. The above data frame shows the number of Acquired and Relinquished players for each team for the 2016 season. It then predicts the win percentages based on these numbers. It also shows the True win percentages from the 2016 season as well as the differences between them to see how close our predictions were.

[ ]:
```
sns.distplot(injury2016['pred_win_percent']) #blue
sns.distplot(injury2016['2016_win_percent']) #orange
plt.xlabel('winning percentage')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

[ ]:
```
Text(0.5, 0, 'winning percentage')
```



The above distribution graph shows the distribution for the value of predicted winning percentage (blue) and the true value of winning percentage from 2016 (orange).

[ ]:
```
x = injury2016['pred_win_percent']
y = injury2016['2016_win_percent']
```

In order to see if our model works, we use the selected model to predict the winning percentage. - x: the predicted winning percentage for 2016 by using our linear regression model. - y: the true winning percentage of teams in 2016

If we want to see if our model works, we need to compare the distribution of the predicted winning percentage for 2016 with the true winning percentage in 2016. Therefore, we use a two-sample Kolmogorov-Smirnov test, which is included in the scipy.stats in order to compare the two distributions.

Under the null hypothesis, the two distributions are identical, which means our model can efficiently predict the winning percentage in 2016. If the K-S statistic is small or the p-value is higher than the significance level 0.05, then we fail to reject the hypothesis and we conclude that the distributions of the predicted winning percentage and the true winning percentage are the same. Conversely, if p-value is smaller than 0.05, then we can reject the null hypothesis and that implies that our model does not correctly predict the winning percentage.

[ ]:
```
ks_2samp(x, y)
```

[ ]:
```
Ks_2sampResult(statistic=0.7666666666666667, pvalue=6.531235554884833e-09)
```

From the result above, we have a p-value smaller than the significance level 0.05. Therefore, we reject the null hypothesis and conclude that the predicted winning percentage for 2016 by using our linear regression model is not the same distribution as the true winning percentage in 2016.

1.10 Ethics & Privacy

We got our data from Kaggle and information made public by the NBA. With the topic we chose, there is not really much of a privacy concern to worry about since all of the data participants/subjects are professional basketball players and teams whose information is knowingly and voluntarily public. Therefore, there is no reason or need to use some sort of ID number to hide the players' privacy. We will do our best to make sure we explain all the analysis we conduct and how we conduct it in order to be as transparent as possible.

1.11 Conclusion & Discussion

In closing, we can confidently conclude that there does exist a relationship between an NBA team's number and injuries in general. The higher the number of acquired players from injuries, the better a team's winning percentage will be. This is clearly depicted in the small mean squared error above between the acquired, relinquished, and injured categories and the miniscule p-value between the acquired and winning percentage categories in the OLS regression. We did notice that of our 6 labeled injury types, the 3 lower extremity injury categories had a stronger negative correlation with winning percentage than the upper extremity injuries. However, due to a lack of data, our analysis was not able to thoroughly conclude if the type of the injury is actually relevant to a team's winning record.

Despite these findings, there were several limitations with our approach. The first and foremost one is the categorization of the injury data. This task required some natural language processing and splitting the injuries into the broadest groups possible (i.e. hand, foot, ankle, etc.). Unfortunately, roughly half of the data remained uncategorized and simply part of the relinquished category. While more categories could have been added, our team decided not to move forth with this idea since the proposed categories contained less than a hundred injuries; such few data points would not be useful in any meaningful analysis. In fact, this leads into our second limitation: the small amount of data in the existing categories. As described in our analysis, the category "Hand Injuries" had 184 injuries in total for example, but 44 of them came from the Timberwolves team alone! The main reason for such large variation is the limited number of data from the datasets available to us. Our analysis relied on historical team performance and player injuries; therefore, we had to have both available for a given season in order to include that season. This led to us using only seasons 2010-2020, and with 82 games a year per team, this equated to 820 games for every team over that decade. While this seems like a reasonable amount of data, only the games that produced injuries would be included, and only the identifiable injuries would be included and further filtered down further into their respective categories. This is what ultimately led to a shortage of data for some of the injury categories.

Due to the difficulty of categorization and the overall shortage of data, our results cannot completely dismiss the impact of certain types of injuries on a team's number (their winning percentage). Therefore, while acquired injuries certainly play a role, only an analysis without these limitations could say for certain how the type of injury contributes to a team's number.

1.12 Team Contributions

Connor McManigal: summarized results, background info, hypothesis, data cleaning of original datasets, and helped with plotting

Matthew Cohen: ethics and privacy, summarized plot results, modeled and tested how accurate our data is at predicting future seasons

Egor Pustovalov: conclusion & discussion, constructed original OLS models, helped with data cleaning and data visualization

Xuwen Yan(Ella): constructed and ran the linear regression models, overview, compared models with different parameters, helped with interpreting the results.

Ryan Swartz: cleaned the datasets, summarized data cleaning, constructed plots, organized setup and group collaboration