Evaluating Fantasy Football Transactions

Introduction

I made a rookie mistake in one of my fantasy football leagues this year—I (unintentionally) auto drafted. My first four picks were Micheal Thomas, Miles Sanders, DeAndre Hopkins, and Kenny Golladay, respectively. Golladay started the season on IR, and Thomas swould soon join him after an injury in Week 1. This year, more than any other, I needed to improve my roster through trades and waiver pickups to remain competitive. Take a look at my post-draft roster:

Starters		Bench	
Position	Player	Position	Player
QB	Aaron Rodgers	RB	David Johnson
RB	Miles Sanders	RB	D'Andre Swift
RB	Kareem Hunt	RB	Cam Akers
WR	Micheal Thomas	WR	Kenny Golladay
WR	DeAndre Hopkins	WR	Courtland Sutton
TE	Tyler Higbee	WR	Christian Kirk
FLEX	David Montgomery	WR	Deebo Samuel
DEF	Chargers		

Starters		Bench	
K	Jake Elliott		

That is not a very impressive lineup! This is a standard league, and I did not have an elite back—the platform's auto-draft algorithm selected Thomas with the 7th overall pick and left Derrick Henry on the board to be selected 8th. This workbook will describe and evaluate the transactions I've made throughout this season to upgrade my roster. Here is a preview of my current roster:

Starters		Bench	
Position	Player	Position	Player
QB	Patrick Mahomes	QB	Tua Tagovailoa
RB	Alvin Kamara	RB	Tony Pollard
RB	Aaron Jones	WR	Allen Robinson
WR	Kenny Golladay	WR	Robert Woods
WR	Justin Jefferson	WR	Tyler Boyd
TE	Taysom Hill	WR	Ceedee Lamb
FLEX	Kareem Hunt	TE	Jonnu Smith
DEF	Saints	IR	Joe Mixon
K	Younghoe Koo		

As you may have noted, Golladay and Hunt are the only drafted players that I have kept on my roster. While I've included the Defense and Kicker positions on the rosters above, those positions will not be referenced again in this notebook. I typically stream Defenses and Kickers, but I've held on to Younghoe Koo since he returned from injury in Week 7 (because he's a beast).

I understand that there are a number of metrics that help forecast a player's future performance (such as snap counts, air distance yards, red zone targets, etc.). However, not all of those metrics are covered in this workbook. The analysis in this workbook centers on player usage and fantasy points earned.

If you would like to skip over the technical information about data retrieval and formatting, you can start at section three. Section one describes how I retrieve player statistics from online databases as well as how I prepare that data for use in my player evaluations. Section two demonstrates how I apply the scoring system from my fantasy league to calculate each player's current fantasy points. Section three explains why I believe a players usage metrics are a significant indicator of a player's fantasy football performance. Section four illustrates how I compute the value of a baseline player for each position to more effectively compare players across positions. Section five chronicles my transactions throughout the season and evaluates the how those transactions effected the net value of my roster.

Section 1: Importing and Cleaning Data

A. Importing Libraries

I will be using the following libraries in this project:

- Matplotlib
- Numpy
- Pandas
- Seaborn

In [1]:

```
%matplotlib inline

import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
import nflfastpy as nfl
from IPython.display import display
import webarchive

pd.set_option('display.max_columns', None,
              'display.max_rows', None,
              'display.float_format', "{:,.2f}".format)
```

B. Retrieving Data

I'll scrape official NFL statistics for the 2020 season from Pro Football Reference (https://www.pro-football-reference.com/years/2020/fantasy.htm). (Pro Football Reference has been an invaluable resource both for NFL fantasy football coding and for winning bar arguments about who is the greatest player in NBA history). The dataset comprises the aggregated season-total player statistics and is updated after each weekly matchup.

In [2]:

```
link = 'https://tinyurl.com/pfrstats'
df = pd.read_html(link, match='Rk')

df = df[0]
df.head()
```

Out[2]:

	Unnamed: 0_level_0	Unnamed: 1_level_0	Unnamed: 2_level_0	Unnamed: 3_level_0	Unnamed: 4_level_0	Games		Passing				
	Rk	Player	Tm	FantPos	Age	G	GS	Cmp	Att	Yds	TD	Int
0	1	Derrick Henry *+	TEN	RB	26	16	16	0	0	0	0	0
1	2	Alvin Kamara *	NOR	RB	25	15	10	0	0	0	0	0
2	3	Dalvin Cook*	MIN	RB	25	14	14	0	0	0	0	0
3	4	Travis Kelce*+	KAN	TE	31	15	15	1	2	4	0	0
4	5	Davante Adams*+	GNB	WR	28	14	14	0	0	0	0	0

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 646 entries, 0 to 645
Data columns (total 33 columns):
 #   Column                        Non-Null Count  Dtype 
---  ------                        --------------  ----- 
 0   (Unnamed: 0_level_0, Rk)      646 non-null    object
 1   (Unnamed: 1_level_0, Player)  646 non-null    object
 2   (Unnamed: 2_level_0, Tm)      646 non-null    object
 3   (Unnamed: 3_level_0, FantPos) 598 non-null    object
 4   (Unnamed: 4_level_0, Age)     646 non-null    object
 5   (Games, G)                    646 non-null    object
 6   (Games, GS)                   646 non-null    object
 7   (Passing, Cmp)                646 non-null    object
 8   (Passing, Att)                646 non-null    object
 9   (Passing, Yds)                646 non-null    object
 10  (Passing, TD)                 646 non-null    object
 11  (Passing, Int)                646 non-null    object
 12  (Rushing, Att)                646 non-null    object
 13  (Rushing, Yds)                646 non-null    object
 14  (Rushing, Y/A)                375 non-null    object
 15  (Rushing, TD)                 646 non-null    object
 16  (Receiving, Tgt)              646 non-null    object
 17  (Receiving, Rec)              646 non-null    object
 18  (Receiving, Yds)              646 non-null    object
 19  (Receiving, Y/R)              513 non-null    object
 20  (Receiving, TD)               646 non-null    object
 21  (Fumbles, Fmb)                646 non-null    object
 22  (Fumbles, FL)                 646 non-null    object
 23  (Scoring, TD)                 646 non-null    object
 24  (Scoring, 2PM)                74 non-null     object
 25  (Scoring, 2PP)                49 non-null     object
 26  (Fantasy, FantPt)             590 non-null    object
 27  (Fantasy, PPR)                597 non-null    object
 28  (Fantasy, DKPt)               597 non-null    object
 29  (Fantasy, FDPt)               598 non-null    object
 30  (Fantasy, VBD)                94 non-null     object
 31  (Fantasy, PosRank)            646 non-null    object
 32  (Fantasy, OvRank)             98 non-null     object
dtypes: object(33)
memory usage: 166.7+ KB
```

C. Cleaning Data

The dataset has a number of values that I will not be using and needs to be properly formatted. I'll drop the `Fantasy` columns, as I'll be calculating fantasy points based on the scoring system for my league. I will rename the remaining columns and the convert the data type for the numerical columns from `object` to `float`. During this process I will also categorize the columns by they type of statistic—biographical, passing, rushing, receiving, and miscellaneous—and assign each category to a separate variable for use in subsequent sections workbook.

In [4]:

```
df.drop('Fantasy', axis=1, level=0, inplace=True)
df.columns = [''.join(col).strip() for col in df.columns.values]
df.columns
```

Out[4]:

```
Index(['Unnamed: 0_level_0Rk', 'Unnamed: 1_level_0Player',
       'Unnamed: 2_level_0Tm', 'Unnamed: 3_level_0FantPos',
       'Unnamed: 4_level_0Age', 'GamesG', 'GamesGS', 'PassingCmp',
       'PassingAtt', 'PassingYds', 'PassingTD', 'PassingInt', 'RushingAtt',
       'RushingYds', 'RushingY/A', 'RushingTD', 'ReceivingTgt', 'ReceivingRe
       'ReceivingYds', 'ReceivingY/R', 'ReceivingTD', 'FumblesFmb',
       'FumblesFL', 'ScoringTD', 'Scoring2PM', 'Scoring2PP'],
      dtype='object')
```

In [5]:

```
df.drop(
    ['Unnamed: 0_level_0Rk', 'Unnamed: 4_level_0Age', 'GamesGS', 'ScoringTD'
    axis=1, inplace=True)

df.rename(
    {'Unnamed: 1_level_0Player': 'Player',
    'Unnamed: 2_level_0Tm': 'Tm',
    'Unnamed: 3_level_0FantPos': 'Pos',
    'GamesG': 'G'},
    axis=1, inplace=True)
```

In [6]:

```
# removes repeated header rows
df = df.loc[df['G'] != 'G'].copy()

columns_bio = ['Player', 'Tm', 'Pos', 'G']

columns_pass = ['PassingCmp', 'PassingAtt', 'PassingYds', 'PassingTD', 'Pass
columns_rush = ['RushingAtt', 'RushingYds', 'RushingY/A', 'RushingTD']
columns_rec = ['ReceivingTgt', 'ReceivingRec', 'ReceivingYds', 'ReceivingY/R
columns_misc = ['FumblesFmb', 'FumblesFL', 'Scoring2PM', 'Scoring2PP']

columns_stats = columns_pass + columns_rush + columns_rec + columns_misc

for column in columns_stats:
    df[column] = df[column].astype(float)
    df[column] = df[column].fillna(0)

df['G'] = df['G'].astype(int)
df['G'] = df['G'].fillna(0)

df['Pos'] = df['Pos'].fillna('NA')
df = df.loc[df['Pos'] != 'NA'].copy()
```

In [7]:

```
df['Player'] = df['Player'].str.rstrip('+* ')
df['Name'] = df['Player'].str[0] + '.' +  df['Player'].str.split(' ', n=1).s
```

In [8]:

```
df.head()
```

Out[8]:

	Player	Tm	Pos	G	PassingCmp	PassingAtt	PassingYds	PassingTD	PassingInt	Rus
0	Derrick Henry	TEN	RB	16	0.00	0.00	0.00	0.00	0.00	
1	Alvin Kamara	NOR	RB	15	0.00	0.00	0.00	0.00	0.00	
2	Dalvin Cook	MIN	RB	14	0.00	0.00	0.00	0.00	0.00	
3	Travis Kelce	KAN	TE	15	1.00	2.00	4.00	0.00	0.00	
4	Davante Adams	GNB	WR	14	0.00	0.00	0.00	0.00	0.00	

Add 100 Yard Games

The scoring system for this league includes bonus points when a player reaches certain statistical thresholds: 100 yards rushing, 100 yards receiving, 300 yards passing, or 400 yards passing. I'll import data for the games in which players have reached these thresholds from The Football Database (https://www.footballdb.com/stats/index.html). I'll then `merge` the bonus points column with our other statistics.

In [9]:

```
# link_rush100 = 'https://tinyurl.com/fdbrush100'
# link_rec100 = 'https://tinyurl.com/fdbrec100'
# link_pass300 = 'https://tinyurl.com/fdbpass300'

link_rush100 = 'Rushing-100.webarchive'
link_rec100 = 'Receiving-100.webarchive'
link_pass300 = 'Passing-300.webarchive'
```

In [10]:

```
def bonus_yds(link, pts=5):
    save_as = link.strip('.webarchive') + '.html'

    archive = webarchive.open(link)
    archive.extract(save_as)

    bonus_weeks = pd.read_html(save_as)
    df_bonus = pd.DataFrame()
    for week in bonus_weeks:
        df_bonus = pd.concat([df_bonus, week])
        df_bonus = df_bonus.reset_index(drop=True)

    df_bonus['Player'] = df_bonus['Player'].str.rsplit('.', n=1).str.get(0)
    df_bonus['Player'] = df_bonus['Player'].str[:-1]
    df_bonus['Bonus'] = pts

    return df_bonus
```

In [11]:

```
df_rush100 = bonus_yds(link_rush100, 5)
df_rec100 = bonus_yds(link_rec100, 5)
df_pass300 = bonus_yds(link_pass300, 3)

df_pass400 = df_pass300.loc[df_pass300['Yds'] >= 400].copy()
df_pass300 = df_pass300.loc[df_pass300['Yds'] <= 400].copy()
df_pass400['Bonus'] = 2
```

In [12]:

```
bonus_list = [df_rush100, df_rec100, df_pass300, df_pass400]
columns = ['Player', 'Bonus']

df_bonus = pd.DataFrame()
for item in bonus_list:
    df_bonus = pd.concat([df_bonus, item])

df_bonus = df_bonus.reset_index()
df_bonus = df_bonus[columns]
df_bonus = df_bonus.groupby('Player', as_index=False).sum()
```

In [13]:

```
df = df.merge(df_bonus, how='left', on='Player')
df['Bonus'] = df['Bonus'].fillna(0)
```

Section 2: Calculating Fantasy Points

I will first create the dictionary `scoring` and assigned each value from my leagues scoring system to the appropriate key. I will then apply a function that calculates the fantasy points earned by each player. I prefer to look at per game rather than season total statistics when comparing players, so I will next convert each players season total statistics to average per game statistics. Finally, I will append a TD column that contains the sum of each player's passing, rushing, and receiving touchdowns.

In [14]:

```
scoring = {
    'PassingYds': 0.04,
    'PassingTD': 4,
    'PassingInt': -2,
    'RushingYds': 0.1,
    'RushingTD': 6,
    'ReceivingRec': 0.0,
    'ReceivingYds': 0.1,
    'ReceivingTD': 6,
    'Scoring2PM': 2,
    'Scoring2PP': 2,
    'FumblesFL': -2
}
```

In [15]:
```
def inst_col(df=df, name=None, loc=None):
    if name not in df.columns:
        df.insert(loc, name, None)

    return df
```

In [16]:
```
def calc_pts(row, weights=scoring):

    games = row['G']

    points = sum([row[column] * weight for column, weight in weights.items()

    return points
```

In [17]:
```
def calc_bonus(row):

    bonus = row['Bonus']
    points = row['Pts']
    games = row['G']

    bonus = bonus / games
    bonus = bonus + points

    return bonus
```

In [18]:
```
df = inst_col(df, 'Pts', 4)
df = inst_col(df, 'Pts+', 5)
df['Pts'] = df.apply(calc_pts, axis=1)
df['Pts+'] = df.apply(calc_bonus, axis=1)
df = df.sort_values(by='Pts', ascending=False)
```

In [19]:
```
def calc_avg(df, column):
    games = df['G']
    stat = df[column]

    stat = stat / games

    return stat
```

In [20]:
```
columns_avg = columns_stats
columns_avg.remove('RushingY/A')
columns_avg.remove('ReceivingY/R')

for c in columns_avg:
    df[c] = df.apply(calc_avg, column=c, axis=1)

df = inst_col(df, 'PPG', 4)
df['PPG'] = df['Pts'] / df['G']
```

In [21]:
```
df['TD'] = df['PassingTD'] + df['RushingTD'] + df['ReceivingTD']
```

In [22]:

```
df.head(20).sort_values(by='Pts', ascending=False)
```

Out[22]:

	Player	Tm	Pos	G	PPG	Pts	Pts+	PassingCmp	PassingAtt	PassingYds
6	Josh Allen	BUF	QB	16	24.69	395.06	396.62	24.75	35.75	284.0
7	Aaron Rodgers	GNB	QB	16	23.89	382.26	383.38	23.25	32.88	268.6
8	Kyler Murray	ARI	QB	16	23.67	378.74	379.55	23.44	34.88	248.1
9	Patrick Mahomes	KAN	QB	15	24.96	374.40	376.27	26.00	39.20	316.0
10	Deshaun Watson	HOU	QB	16	23.08	369.32	371.20	23.88	34.00	301.4
15	Russell Wilson	SEA	QB	16	22.49	359.78	360.72	24.00	34.88	263.2
22	Ryan Tannehill	TEN	QB	16	21.46	343.36	343.92	19.69	30.06	238.6
24	Tom Brady	TAM	QB	16	21.12	337.92	339.42	25.06	38.12	289.5
28	Justin Herbert	LAC	QB	15	22.19	332.84	334.44	26.40	39.67	289.0
29	Lamar Jackson	BAL	QB	15	22.19	332.78	333.78	16.13	25.07	183.8
0	Derrick Henry	TEN	RB	16	19.63	314.10	317.23	0.00	0.00	0.0
44	Kirk Cousins	MIN	QB	16	19.14	306.20	307.08	21.81	32.25	266.5
1	Alvin Kamara	NOR	RB	15	19.65	294.80	295.47	0.00	0.00	0.0
2	Dalvin Cook	MIN	RB	14	20.99	293.80	296.66	0.00	0.00	0.0
75	Matt Ryan	ATL	QB	16	17.65	282.44	283.31	25.44	39.12	286.3
76	Derek Carr	LVR	QB	16	17.01	272.12	273.25	21.75	32.31	256.4
77	Ben Roethlisberger	PIT	QB	15	17.81	267.22	268.35	26.60	40.53	253.5
78	Matthew Stafford	DET	QB	16	16.29	260.56	261.06	21.19	33.00	255.2
79	Cam Newton	NWE	QB	15	17.27	258.98	259.38	16.13	24.53	177.1
80	Baker Mayfield	CLE	QB	16	15.48	247.62	248.00	19.06	30.38	222.6

Section 3: Player Usage as an Evaluation Metric

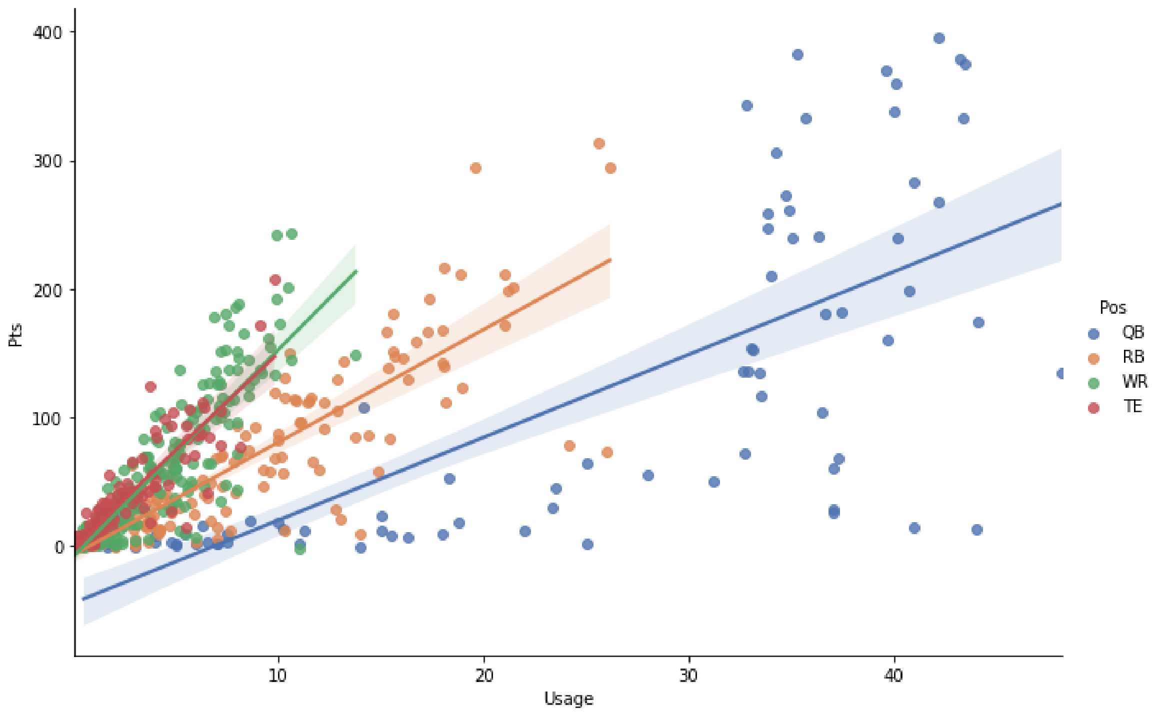
One metric that I like to use for assessing a player's fantasy value is usage—a player's aggregate number of pass attempts, rushing attempts, and receiving targets. While touchdowns are the most valuable statistic in fantasy, touchdowns can be a bit less predictable than how involved a player will be in a game. Generally, players who see more game action are more likely to score touchdowns. I tend to shy away from trading for players with high points but low volume.

In [23]:
```
df = inst_col(df, 'Usage', 6)
df['Usage'] = (df['PassingAtt'] + df['RushingAtt'] + df['ReceivingTgt'])
```

I'll use the Seaborn `lmplot` function to demonstrate the correlation between usage and fantasy points. As you'll see, the two generally have a positive correlation. I go further in depth was to which metrics are the most predictive of future performance in a separate project. For this workbook, we'll stick with usage.

In [24]:
```
sns.lmplot(x='Usage', y='Pts', data=df, hue='Pos', palette='deep', height=6,
```

Out[24]: <seaborn.axisgrid.FacetGrid at 0x7fc8e467ba50>



Section 4: Comparing Players Across Positions - Value Over A Bench Player

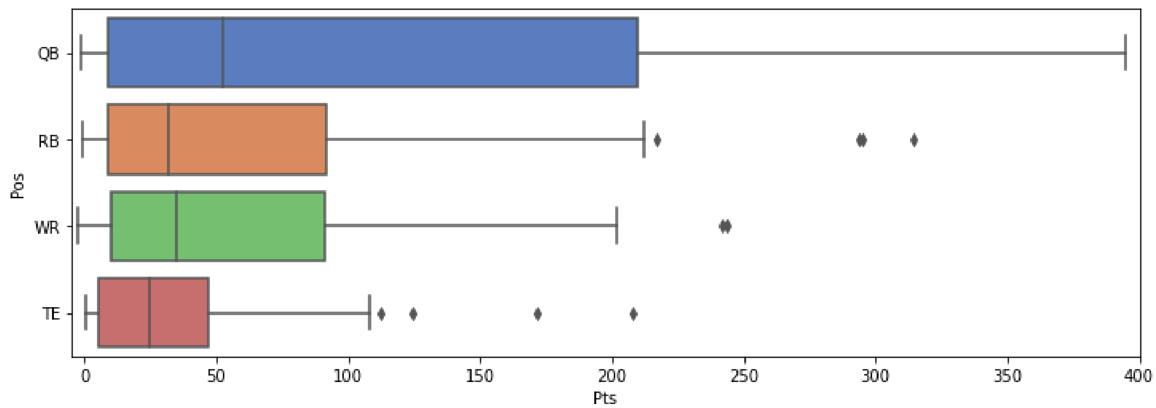
A. Distribution of the Total Player Pool

We can use the Seaborn `boxplot` function to generate a visualization of how fantasy points are distributed amongst each position.

In [25]:

```
fig = plt.figure(figsize=(12, 4))
fig.add_subplot(xlim=(-5, 400))
sns.boxplot(x='Pts', y='Pos', data=df, palette='muted');

# fig = plt.figure(figsize=(12, 4))
# fig.add_subplot(xlim=(-5, 400))
# sns.boxplot(x='Pts+', y='Pos', data=df, palette='muted');
```



In [26]:

```
df.groupby('Pos')['Pts'].describe()
# df.groupby('Pos')['Pts+'].describe()
```

Out[26]:

Pos	count	mean	std	min	25%	50%	75%	max
QB	81.00	114.98	128.31	-1.52	9.02	52.28	209.48	395.06
RB	163.00	58.98	65.64	-1.00	9.05	31.90	91.80	314.10
TE	113.00	35.26	38.31	0.20	5.30	24.90	46.90	207.76
WR	221.00	55.27	54.82	-2.78	10.20	35.22	91.10	243.40

We can see that the distribution of fantasy points, across positions, is positively skewed—indicating that the leading scorer at each position earns substantially more points than a median scorer of the same position. With RBs, for instance, the majority of players at this position average fewer than four points per week, while the upper quartile averages more than 8 points per week. The distribution of points earned by players at the QB, WR, and TE positions follow similar patterns. These higher scoring players are the players we will focus on for our analysis.

B. Position Ranks

We can compare players of the same positions to one another by simply looking at each player's average points. For instance, I know that Alvin Kamara (19.93 ppg through Week 10) has been producing better than has Josh Jacobs (14.34 ppg) so far this season. Let's start by adding position ranks and looking at the top ten RBs.

In [27]:

```
def pos_ranks(df):
    df = inst_col(df, 'Rk', 3)

    ranked = df.loc[df['Pos'] == 'NA'].copy()
    qb = df.loc[df['Pos'] == 'QB'].copy()
    rb = df.loc[df['Pos'] == 'RB'].copy()
    wr = df.loc[df['Pos'] == 'WR'].copy()
    te = df.loc[df['Pos'] == 'TE'].copy()

    positions = [qb, rb, wr, te]
    for p in positions:

        p = p.sort_values(by='Pts', ascending=False)
        p = p.reset_index(drop=True)
        p = p.reset_index()
        p['Rk'] = p['index'] + 1
        p['Rk'] = p['Pos'] + p['Rk'].astype(str)
        p = p.drop(['index'], axis=1)

        ranked = ranked.append(p)

    ranked.sort_values(by='Pts', ascending=False, inplace=True)
    ranked.reset_index(drop=True, inplace=True)

    return ranked
```

In [28]:

```
df = pos_ranks(df)
```

In [29]:

```
df.loc[df['Pos'] == 'QB'].head(10)
```

Out[29]:

	Player	Tm	Pos	Rk	G	PPG	Pts	Usage	Pts+	PassingCmp	PassingAtt	P
0	Josh Allen	BUF	QB	QB1	16	24.69	395.06	42.19	396.62	24.75	35.75	
1	Aaron Rodgers	GNB	QB	QB2	16	23.89	382.26	35.31	383.38	23.25	32.88	
2	Kyler Murray	ARI	QB	QB3	16	23.67	378.74	43.19	379.55	23.44	34.88	
3	Patrick Mahomes	KAN	QB	QB4	15	24.96	374.40	43.47	376.27	26.00	39.20	
4	Deshaun Watson	HOU	QB	QB5	16	23.08	369.32	39.62	371.20	23.88	34.00	
5	Russell Wilson	SEA	QB	QB6	16	22.49	359.78	40.06	360.72	24.00	34.88	
6	Ryan Tannehill	TEN	QB	QB7	16	21.46	343.36	32.81	343.92	19.69	30.06	
7	Tom Brady	TAM	QB	QB8	16	21.12	337.92	40.00	339.42	25.06	38.12	
8	Justin Herbert	LAC	QB	QB9	15	22.19	332.84	43.33	334.44	26.40	39.67	
9	Lamar Jackson	BAL	QB	QB10	15	22.19	332.78	35.67	333.78	16.13	25.07	

In [30]:
```
df.loc[df['Pos'] == 'RB'].head(10)
```

Out[30]:

	Player	Tm	Pos	Rk	G	PPG	Pts	Usage	Pts+	PassingCmp	PassingAtt
10	Derrick Henry	TEN	RB	RB1	16	19.63	314.10	25.56	317.23	0.00	0.00
12	Alvin Kamara	NOR	RB	RB2	15	19.65	294.80	19.60	295.47	0.00	0.00
13	Dalvin Cook	MIN	RB	RB3	14	20.99	293.80	26.14	296.66	0.00	0.00
25	Jonathan Taylor	IND	RB	RB4	15	14.45	216.80	18.07	217.80	0.00	0.00
26	Aaron Jones	GNB	RB	RB5	14	15.14	211.90	18.86	212.97	0.00	0.00
27	David Montgomery	CHI	RB	RB6	15	14.05	210.80	21.00	211.80	0.00	0.00
31	James Robinson	JAX	RB	RB7	14	14.39	201.40	21.43	202.83	0.00	0.00
33	Josh Jacobs	LVR	RB	RB8	15	13.22	198.30	21.20	198.97	0.00	0.00
34	Nick Chubb	CLE	RB	RB9	12	15.97	191.70	17.33	194.20	0.00	0.00
39	Kareem Hunt	CLE	RB	RB10	16	11.28	180.50	15.56	180.81	0.00	0.00

In [31]:
```
df.loc[df['Pos'] == 'WR'].head(10)
```

Out[31]:

	Player	Tm	Pos	Rk	G	PPG	Pts	Usage	Pts+	PassingCmp	PassingAtt
20	Davante Adams	GNB	WR	WR1	14	17.39	243.40	10.64	245.90	0.00	0.00
21	Tyreek Hill	KAN	WR	WR2	15	16.13	241.90	9.87	243.57	0.00	0.00
30	Stefon Diggs	BUF	WR	WR3	16	12.60	201.60	10.44	204.41	0.00	0.00
35	Calvin Ridley	ATL	WR	WR4	15	12.77	191.50	9.87	194.17	0.00	0.00
36	D.K. Metcalf	SEA	WR	WR5	16	11.77	188.30	8.06	189.86	0.00	0.00
37	Justin Jefferson	MIN	WR	WR6	16	11.64	186.20	7.88	188.39	0.00	0.00
41	Adam Thielen	MIN	WR	WR7	15	12.00	180.00	7.40	181.00	0.00	0.00
42	Mike Evans	TAM	WR	WR8	16	11.16	178.60	6.81	180.16	0.00	0.00
44	DeAndre Hopkins	ARI	WR	WR9	16	10.80	172.80	10.06	174.99	0.00	0.00
47	A.J. Brown	TEN	WR	WR10	14	12.25	171.50	7.57	172.93	0.00	0.00

In [32]:

```
df.loc[df['Pos'] == 'TE'].head(10)
```

Out[32]:

	Player	Tm	Pos	Rk	G	PPG	Pts	Usage	Pts+	PassingCmp	PassingAt
29	Travis Kelce	KAN	TE	TE1	15	13.85	207.76	9.80	210.76	0.07	0.13
46	Darren Waller	LVR	TE	TE2	16	10.73	171.60	9.06	173.16	0.00	0.00
93	Robert Tonyan	GNB	TE	TE3	16	7.79	124.60	3.69	124.60	0.00	0.00
108	Mark Andrews	BAL	TE	TE4	14	8.01	112.10	6.29	112.10	0.00	0.00
114	T.J. Hockenson	DET	TE	TE5	16	6.77	108.30	6.38	108.30	0.00	0.00
117	Mike Gesicki	MIA	TE	TE6	15	7.09	106.30	5.67	106.63	0.00	0.00
121	Logan Thomas	WAS	TE	TE7	16	6.54	104.62	7.12	104.93	0.06	0.06
122	Rob Gronkowski	TAM	TE	TE8	16	6.52	104.30	4.81	104.61	0.00	0.00
129	Jonnu Smith	TEN	TE	TE9	15	6.61	99.20	4.47	99.20	0.00	0.00
137	Jimmy Graham	CHI	TE	TE10	16	5.85	93.60	4.75	93.60	0.00	0.00

In [33]:

```
# columns = ['Player', 'G', 'Rk', 'Pts', 'Pts+', 'RushingYds', 'ReceivingYds

# wow = df.loc[df['Pos'] == 'RB', columns] or
# wow = inst_col(wow, 'ScrimmageYds', 6)
# wow['ScrimmageYds'] = wow['RushingYds'] + wow['ReceivingYds']
# wow = wow.sort_values(by='Pts+', ascending=False)
# wow = wow.loc[wow['Pts+'] > 6]
# # wow = wow.loc[wow['ScrimmageYds'] > 70]
# wow = wow.reset_index(drop=True)

# wow
```

In [34]:

```
# columns = ['Player', 'G', 'Rk', 'Pts', 'Pts+', 'Usage', 'TD']

# wow = df.loc[df['Pos'] != 'QB', columns]
# wow = wow.sort_values(by='Pts+', ascending=False)
# wow = wow.loc[wow['Pts+'] > 10]
# wow = wow.reset_index(drop=True)

# wow
```

C. Value Over a Bench Player

3. Value Over a Bench Player

So we can see that we probably shouldn't trade Alvin Kamara for Josh Jacobs, but should we trade Kamara for Patrick Mahomes? We would need a metric other than points per game to determine if Mahomes has preformed better amongst QBs than Kamara has amongst RBs. We can calculate each players production relative to the best bench player of the same position.

There are many more players available in the NFL than are viable starting options for fantasy football. My league is a 10-team league; our starting skill positions are QB, RB, RB, WR, WR, TE, and FLEX. Seeing that each team has seven starting skill positions, we know that only 70 skill position players will be started across the league in any given week. We will need to narrow our pool of total players to the 70 best players. We will also need to include the best bench player at each position.

While QBs are the highest scoring players in fantasy football, we, unfortunately, aren't able to play a QB in every roster slot. There will only be 10 starting QBs across the league each week, and the same is true for TEs (since you should never have a TE in your flex spot unless you have both Travis Kelce and George Kittle, healthy, on your roster). We can included the top 11 QBs in our cutoff pool, 10 starters and the best bench player. We will do the same for TEs. We'll leave the RB and WR positions together, since either can be in the flex position, and keep the best 51 WRRB players in our cutoff pool.

In [35]:

```
def calc_cutoff(df):
    columns = ['Player', 'Pos', 'Rk', 'Pts', 'Usage']

    qb = df.loc[df['Pos'] == 'QB'].copy()
    qb = qb[:11]

    wrrb = df.loc[df['Pos'].isin(['RB', 'WR'])].copy()
    wrrb = wrrb[:51]

    te = df.loc[df['Pos'] == 'TE'].copy()
    te = te[:11]

    cutoff = qb
    cutoff = cutoff.append(wrrb)
    cutoff = cutoff.append(te)
    cutoff = cutoff.sort_values(by='Pts', ascending=False)
    cutoff = cutoff.reset_index(drop=True)
    cutoff = cutoff[columns]

    return cutoff
```

In [36]:
```
df_cutoffs = calc_cutoff(df)
df_cutoffs.tail(15)
```

Out[36]:

	Player	Pos	Rk	Pts	Usage
58	JuJu Smith-Schuster	WR	WR23	137.10	8.00
59	Terry McLaurin	WR	WR24	136.80	9.07
60	Will Fuller	WR	WR25	135.90	6.91
61	Curtis Samuel	WR	WR26	135.10	9.20
62	Diontae Johnson	WR	WR27	133.80	9.80
63	Nyheim Hines	RB	RB24	130.20	10.31
64	Robert Tonyan	TE	TE3	124.60	3.69
65	Mark Andrews	TE	TE4	112.10	6.29
66	T.J. Hockenson	TE	TE5	108.30	6.38
67	Mike Gesicki	TE	TE6	106.30	5.67
68	Logan Thomas	TE	TE7	104.62	7.12
69	Rob Gronkowski	TE	TE8	104.30	4.81
70	Jonnu Smith	TE	TE9	99.20	4.47
71	Jimmy Graham	TE	TE10	93.60	4.75
72	Hayden Hurst	TE	TE11	93.10	5.50

If nothing else, the cutoff pool of players demonstrates that TEs as a collective score the fewest points of all starters. We can compare the distribution of fantasy points scored by players and the total pool to that of those in the cutoff pool.

In [37]:

```
df.groupby('Pos')['Pts'].describe()
df_cutoffs.groupby('Pos')['Pts'].describe()
```

Out[37]:

Pos	count	mean	std	min	25%	50%	75%	max
QB	81.00	114.98	128.31	-1.52	9.02	52.28	209.48	395.06
RB	163.00	58.98	65.64	-1.00	9.05	31.90	91.80	314.10
TE	113.00	35.26	38.31	0.20	5.30	24.90	46.90	207.76
WR	221.00	55.27	54.82	-2.78	10.20	35.22	91.10	243.40

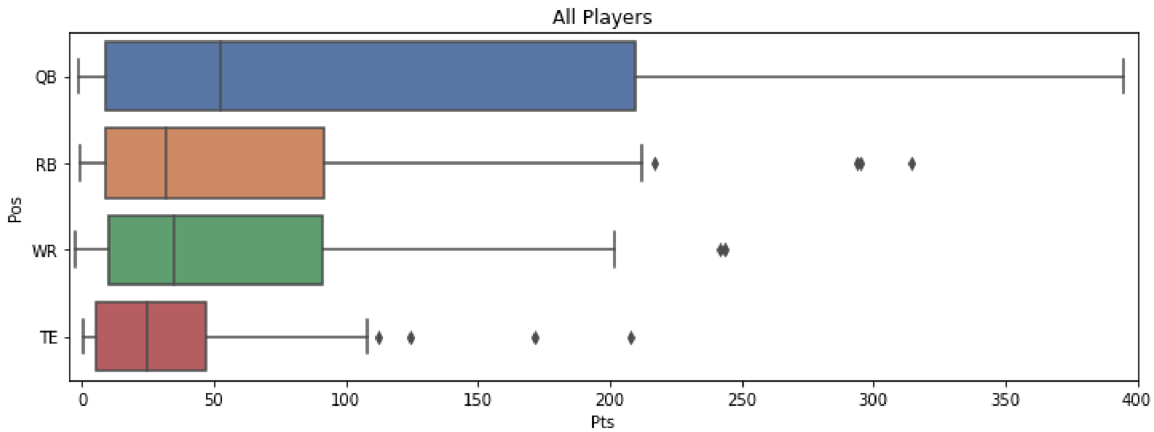
Out[37]:

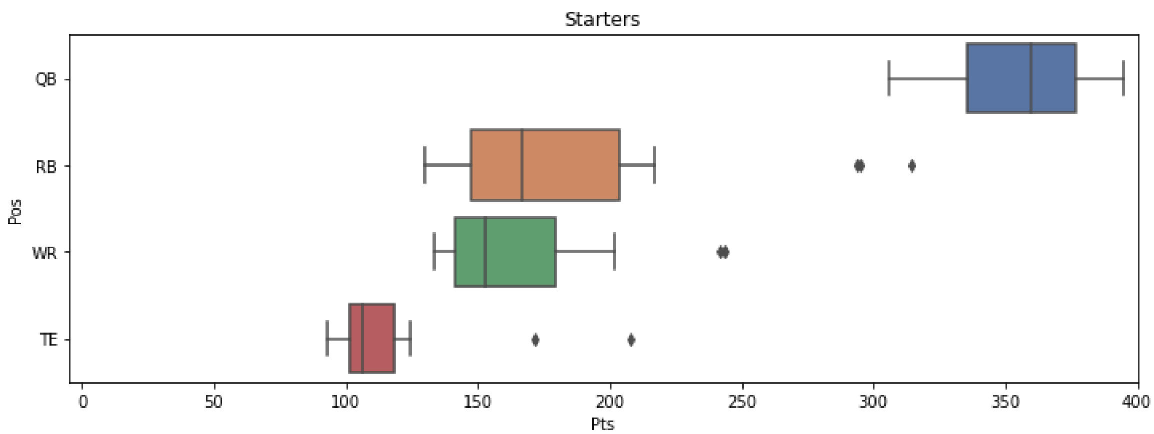
Pos	count	mean	std	min	25%	50%	75%	max
QB	11.00	355.70	27.03	306.20	335.38	359.78	376.57	395.06
RB	24.00	184.74	51.65	130.20	147.25	166.80	203.75	314.10
TE	11.00	120.50	36.20	93.10	101.75	106.30	118.35	207.76
WR	27.00	164.11	30.03	133.80	141.25	152.90	179.30	243.40

In [38]:

```
fig = plt.figure(figsize=(12, 4))
fig.add_subplot(xlim=(-5, 400))
sns.boxplot(x='Pts', y='Pos', data=df, palette='deep').set_title('All Player

fig = plt.figure(figsize=(12, 4))
fig.add_subplot(xlim=(-5, 400))
sns.boxplot(x='Pts', y='Pos', data=df_cutoffs, palette='deep').set_title('St
```





We can see that, across positions, the players in our cutoff pool outscore 75% of players at the same position in the general pool. The QBs in our cutoff pool all earn over 18 ppg, which is more than all but two players outside of the QB position. All but two TEs, on the other hand, score less than all players at any other position.

We can run a few lines of code to pull the highest scoring bench player at each position—or the lowest scoring player at each position in our cutoff pool.

In [39]:

```
positions = ['QB', 'RB', 'WR', 'TE']
replacement_players = {}
replacement_values = {}
replacement_usage = {}
replacement ={}

for _, row in df_cutoffs.iterrows():

    pos = row['Pos']
    player = row['Player']
    pts = row['Pts']
    usage = row['Usage']


    if pos in positions:
        replacement_players[pos] = player
        replacement_values[pos] = pts
        replacement_usage[pos] = usage

        replacement[pos] = [player, pts, usage]

replacement
```

Out[39]:

```
{'QB': ['Kirk Cousins', 306.20000000000005, 34.25],
 'RB': ['Nyheim Hines', 130.2, 10.3125],
 'WR': ['Diontae Johnson', 133.8, 9.799999999999999],
 'TE': ['Hayden Hurst', 93.1, 5.5]}
```

In [40]:

```
df = inst_col(df, 'POB', 7)
df['POB'] = df.apply(
    lambda row: row['Pts'] - replacement_values.get(row['Pos']), axis=1
)

# df.head(10).sort_values(by='POB', ascending=False)
```

In [41]:

```
df = inst_col(df, 'POB/G', 5)
df['POB/G'] = df['POB'] / df['G']
```

In [42]:

```
df = inst_col(df, 'VOB', 8)
df = inst_col(df, 'VOB/G', 6)

df['VOB'] = df['POB'].apply(lambda x: (x - df['POB'].min()) / (df['POB'].max
df['VOB/G'] = df['POB/G'].apply(lambda x: (x - df['POB/G'].min()) / (df['POB

# df.head(10).sort_values(by='VOB', ascending=False)
```

In [43]:

```
# df = inst_col(df, 'UOB', 9)
# df['UOB'] = df.apply(
#     lambda row: row['Usage'] - replacement_usage.get(row['Pos']), axis=1
# )

# df.head(10)
```

In [44]:

```
columns_vob = ['Player', 'G', 'Rk', 'PPG', 'POB/G', 'VOB/G', 'Pts', 'Pts+', 
df_ranks = df[columns_vob].sort_values(by='VOB', ascending=False).reset_inde
df_ranks.head(50)
```

Out[44]:

	Player	G	Rk	PPG	POB/G	VOB/G	Pts	Pts+	POB	VOB	TD
0	Derrick Henry	16	RB1	19.63	11.49	1.00	314.10	317.23	183.90	1.00	1.06
1	Alvin Kamara	15	RB2	19.65	10.97	1.00	294.80	295.47	164.60	0.96	1.40
2	Dalvin Cook	14	RB3	20.99	11.69	1.00	293.80	296.66	163.60	0.96	1.21
3	Travis Kelce	15	TE1	13.85	7.64	0.99	207.76	210.76	114.66	0.86	0.73
4	Davante Adams	14	WR1	17.39	7.83	0.99	243.40	245.90	109.60	0.85	1.29
5	Tyreek Hill	15	WR2	16.13	7.21	0.99	241.90	243.57	108.10	0.85	1.13
6	Josh Allen	16	QB1	24.69	5.55	0.98	395.06	396.62	88.86	0.81	2.88
7	Jonathan Taylor	15	RB4	14.45	5.77	0.98	216.80	217.80	86.60	0.80	0.80
8	Aaron Jones	14	RB5	15.14	5.84	0.98	211.90	212.97	81.70	0.79	0.79
9	David Montgomery	15	RB6	14.05	5.37	0.98	210.80	211.80	80.60	0.79	0.67
10	Darren Waller	16	TE2	10.73	4.91	0.98	171.60	173.16	78.50	0.79	0.56
11	Aaron Rodgers	16	QB2	23.89	4.75	0.98	382.26	383.38	76.06	0.78	3.19
12	Kyler Murray	16	QB3	23.67	4.53	0.98	378.74	379.55	72.54	0.77	2.31
13	James Robinson	14	RB7	14.39	5.09	0.98	201.40	202.83	71.20	0.77	0.71
14	Patrick Mahomes	15	QB4	24.96	4.55	0.98	374.40	376.27	68.20	0.76	2.67
15	Josh Jacobs	15	RB8	13.22	4.54	0.98	198.30	198.97	68.10	0.76	0.80
16	Stefon Diggs	16	WR3	12.60	4.24	0.98	201.60	204.41	67.80	0.76	0.50
17	Deshaun Watson	16	QB5	23.08	3.95	0.98	369.32	371.20	63.12	0.75	2.25
18	Nick Chubb	12	RB9	15.97	5.12	0.98	191.70	194.20	61.50	0.75	1.00
19	Calvin Ridley	15	WR4	12.77	3.85	0.98	191.50	194.17	57.70	0.74	0.60
20	D.K. Metcalf	16	WR5	11.77	3.41	0.97	188.30	189.86	54.50	0.74	0.62
21	Russell Wilson	16	QB6	22.49	3.35	0.97	359.78	360.72	53.58	0.73	2.62
22	Justin Jefferson	16	WR6	11.64	3.27	0.97	186.20	188.39	52.40	0.73	0.44
23	Kareem Hunt	16	RB10	11.28	3.14	0.97	180.50	180.81	50.30	0.73	0.69
24	Adam Thielen	15	WR7	12.00	3.08	0.97	180.00	181.00	46.20	0.72	0.93
25	Mike Evans	16	WR8	11.16	2.80	0.97	178.60	180.16	44.80	0.72	0.81
26	Ezekiel Elliott	15	RB11	11.45	2.77	0.97	171.70	172.37	41.50	0.71	0.53
27	DeAndre Hopkins	16	WR9	10.80	2.44	0.97	172.80	174.99	39.00	0.71	0.38
28	A.J. Brown	14	WR10	12.25	2.69	0.97	171.50	172.93	37.70	0.70	0.79

	Player	G	Rk	PPG	POB/G	VOB/G	Pts	Pts+	POB	VOB	TD
29	Ryan Tannehill	16	QB7	21.46	2.32	0.97	343.36	343.92	37.16	0.70	2.50
30	Kenyan Drake	15	RB12	11.15	2.47	0.97	167.20	167.87	37.00	0.70	0.67
31	Melvin Gordon	15	RB13	11.09	2.41	0.97	166.40	167.07	36.20	0.70	0.67
32	Antonio Gibson	14	RB14	11.87	2.57	0.97	166.20	166.91	36.00	0.70	0.79
33	Tom Brady	16	QB8	21.12	1.98	0.97	337.92	339.42	31.72	0.69	2.69
34	Tyler Lockett	16	WR11	10.34	1.97	0.97	165.40	166.03	31.60	0.69	0.62
35	Robert Tonyan	16	TE3	7.79	1.97	0.97	124.60	124.60	31.50	0.69	0.69
36	Ronald Jones II	14	RB15	11.31	2.01	0.97	158.30	159.73	28.10	0.68	0.57
37	Allen Robinson	16	WR12	10.06	1.69	0.97	160.90	162.15	27.10	0.68	0.38
38	Justin Herbert	15	QB9	22.19	1.78	0.97	332.84	334.44	26.64	0.68	2.40
39	Lamar Jackson	15	QB10	22.19	1.77	0.97	332.78	333.78	26.58	0.68	2.20
40	Robert Woods	16	WR13	9.69	1.33	0.97	155.10	155.73	21.30	0.67	0.50
41	Chris Carson	12	RB16	12.57	1.72	0.97	150.80	150.80	20.60	0.67	0.75
42	J.K. Dobbins	15	RB17	10.03	1.35	0.97	150.50	151.17	20.30	0.67	0.60
43	Chase Claypool	16	WR14	9.56	1.19	0.97	152.90	153.53	19.10	0.66	0.69
44	Mark Andrews	14	TE4	8.01	1.36	0.97	112.10	112.10	19.00	0.66	0.50
45	Marvin Jones	16	WR15	9.49	1.12	0.97	151.80	152.74	18.00	0.66	0.56
46	Mike Davis	15	RB18	9.83	1.15	0.97	147.50	147.50	17.30	0.66	0.53
47	Brandin Cooks	15	WR16	10.07	1.15	0.97	151.00	152.00	17.20	0.66	0.40
48	David Johnson	12	RB19	12.21	1.36	0.97	146.50	147.33	16.30	0.66	0.67
49	T.J. Hockenson	16	TE5	6.77	0.95	0.97	108.30	108.30	15.20	0.66	0.38

Section 5: Evaluating My Transactions

Week	Transaction
Week 3	Traded Aaron Rodgers, Michael Thomas, and Miles Sanders for </br>Patrick Mahomes, Aaron Jones and Robert Woods
Week 4	Acquired Justin Jefferson from waivers
Week 6	Acquired Chase Claypool from waivers
Week 7	Traded DeAndre Hopkins, Chase Claypool, David Johnson, and </br>David Montgomery for Alvin Kamara
Week 8	Acquired Tyler Boyd from waivers
Week 9	Acquired Allan Lazard free agency
Week 10	Acquired Todd Gurley and Allen Robinson from waivers

I'll first write a function to calculate the tradeoff value of players.

In [62]:

```
def calc_tradeoff(trade_dict, df=df, sort_by='Pts'):
    columns = ['Player', 'G', 'Rk', 'PPG', 'Usage', 'TD', 'VOB/G', 'POB/G']

    for key in trade_dict:
        players = trade_dict[key]

        print(key)
        print('-' * 40)

        stats = pd.DataFrame()
        for p in players:
            p = df.loc[df['Player'] == p]
            stats = pd.concat([stats, p])

        stats = stats.sort_values(by=sort_by, ascending=False)
        stats = stats.reset_index(drop=True)
        stats.loc['Total'] = stats.sum(numeric_only=True)
        stats['G'] =  stats['G'].astype(int)
        stats.loc['Total', 'Player'] = '--'
        stats.loc['Total', 'G'] = '--'
        stats.loc['Total', 'Rk'] = '--'
        stats.loc['Total', 'VOB'] = '--'
        display(stats[columns])
```

Week 1

Now let's look at the value of my Week 1 roster. In additional to the players that [auto]drafted, I also moved Deebo Samuel to IR and added Tim Patrick before Week 1 matchups.

In [46]:

```
#     'QB': [],
#     'RB': ['Miles Sanders', 'Kareem Hunt', 'David Montgomery', 'David Johr
#            "D'Andre Swift", 'Cam Akers'],
#     'WR': ['Micheal Thomas', 'DeAndre Hopkins', 'Kenny Golladay', 'Courtlc
#            'Christian Kirk', 'Deebo Samuel'],
#     'TE': ['Tyler Higbee']
```

In [63]:

```
#using the optimal lineup rather than actual starter; to display true vaalue
roster_wk1 = {
    'Starters' : ['Aaron Rodgers',  'Kareem Hunt', "D'Andre Swift", 'Miles S
                    'DeAndre Hopkins', 'Tyler Higbee', 'Christian Kirk'],
     'Bench' : [ 'Courtland Sutton', 'David Montgomery','David Johnson', 'Ke
               'Deebo Samuel',  'Cam Akers', 'Michael Thomas', 'Tim Patrick'
}

calc_tradeoff(roster_wk1, sort_by='VOB')
```

```
Starters
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Aaron Rodgers	16	QB2	23.89	35.31	3.19	0.98	4.75
1	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
2	DeAndre Hopkins	16	WR9	10.80	10.06	0.38	0.97	2.44
3	D'Andre Swift	13	RB20	11.06	13.15	0.77	0.97	1.05
4	Miles Sanders	12	RB21	11.87	18.00	0.50	0.97	1.02
5	Tyler Higbee	15	TE16	5.61	4.07	0.33	0.96	-0.59
6	Christian Kirk	14	WR51	7.03	5.79	0.43	0.96	-2.53
Total	--	--	--	81.54	101.94	6.28	6.77	9.28

```
Bench
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	David Montgomery	15	RB6	14.05	21.00	0.67	0.98	5.37
1	David Johnson	12	RB19	12.21	16.08	0.67	0.97	1.36
2	Tim Patrick	15	WR40	7.35	5.27	0.40	0.96	-1.57
3	Cam Akers	13	RB42	6.98	12.23	0.23	0.95	-3.03
4	Deebo Samuel	7	WR97	6.81	7.43	0.14	0.92	-12.30
5	Kenny Golladay	5	WR100	9.16	6.40	0.40	0.91	-17.60
6	Michael Thomas	7	WR103	6.27	8.00	0.00	0.92	-12.84
7	Courtland Sutton	1	WR175	6.60	6.00	0.00	0.57	-127.20
Total	--	--	--	69.44	82.41	2.51	7.18	-167.82

Week 2

In [64]:

```
roster_wk2 = {
    'Starters' : ['Aaron Rodgers',  'Kareem Hunt', 'Miles Sanders', 'DeAndre
                  'Tyler Higbee', 'Kenny Golladay', "D'Andre Swift"],
    'Bench' : [ 'Courtland Sutton', 'David Montgomery', 'Deebo Samuel', 'Mal
               'Michael Thomas', 'Marquez Valdes-Scantling', 'Nyheim Hines',
}

calc_tradeoff(roster_wk2)
```

```
Starters
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Aaron Rodgers	16	QB2	23.89	35.31	3.19	0.98	4.75
1	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
2	DeAndre Hopkins	16	WR9	10.80	10.06	0.38	0.97	2.44
3	D'Andre Swift	13	RB20	11.06	13.15	0.77	0.97	1.05
4	Miles Sanders	12	RB21	11.87	18.00	0.50	0.97	1.02
5	Tyler Higbee	15	TE16	5.61	4.07	0.33	0.96	-0.59
6	Kenny Golladay	5	WR100	9.16	6.40	0.40	0.91	-17.60
Total	--	--	--	83.67	102.56	6.25	6.73	-5.80

```
Bench
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	David Montgomery	15	RB6	14.05	21.00	0.67	0.98	5.37
1	David Johnson	12	RB19	12.21	16.08	0.67	0.97	1.36
2	Nyheim Hines	16	RB24	8.14	10.31	0.44	0.96	0.00
3	Marquez Valdes-Scantling	16	WR45	6.52	4.19	0.38	0.96	-1.84
4	Malcolm Brown	16	RB45	5.38	8.38	0.31	0.95	-2.76
5	Deebo Samuel	7	WR97	6.81	7.43	0.14	0.92	-12.30
6	Michael Thomas	7	WR103	6.27	8.00	0.00	0.92	-12.84
7	Courtland Sutton	1	WR175	6.60	6.00	0.00	0.57	-127.20
Total	--	--	--	65.98	81.39	2.60	7.24	-150.21

Week 3

In [65]:

```
roster_wk3 = {
    'Starters': ['Patrick Mahomes', 'Aaron Jones', 'Kareem Hunt', 'David Joh
                 'DeAndre Hopkins', 'Robert Woods', 'Tyler Higbee'],
    'Bench': ['David Montgomery', 'Jerick McKinnon', 'Keelan Cole', 'Kenny G
              'Devonta Freeman', 'Jonnu Smith', 'Joe Burrow', 'Deebo Samuel'
}

calc_tradeoff(roster_wk3)
```

```
Starters
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Patrick Mahomes	15	QB4	24.96	43.47	2.67	0.98	4.55
1	Aaron Jones	14	RB5	15.14	18.86	0.79	0.98	5.84
2	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
3	DeAndre Hopkins	16	WR9	10.80	10.06	0.38	0.97	2.44
4	Robert Woods	16	WR13	9.69	9.56	0.50	0.97	1.33
5	David Johnson	12	RB19	12.21	16.08	0.67	0.97	1.36
6	Tyler Higbee	15	TE16	5.61	4.07	0.33	0.96	-0.59
Total	--	--	--	89.69	117.66	6.01	6.80	18.06

```
Bench
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	David Montgomery	15	RB6	14.05	21.00	0.67	0.98	5.37
1	Joe Burrow	10	QB25	17.37	44.10	1.60	0.92	-13.25
2	Jonnu Smith	15	TE9	6.61	4.47	0.60	0.96	0.41
3	Keelan Cole	16	WR54	5.90	5.56	0.31	0.96	-2.46
4	Jerick McKinnon	16	RB40	5.83	7.94	0.38	0.96	-2.31
5	Deebo Samuel	7	WR97	6.81	7.43	0.14	0.92	-12.30
6	Kenny Golladay	5	WR100	9.16	6.40	0.40	0.91	-17.60
7	Devonta Freeman	5	RB85	5.80	12.80	0.20	0.90	-20.24
Total	--	--	--	71.54	109.70	4.30	7.51	-62.38

In [66]:

```
trade1 = {
    'Traded': ['Miles Sanders', 'Michael Thomas'],
    'Aquired': ['Patrick Mahomes', 'Adam Thielen']
}

calc_tradeoff(trade1)
```

```
Traded
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Miles Sanders	12	RB21	11.87	18.00	0.50	0.97	1.02
1	Michael Thomas	7	WR103	6.27	8.00	0.00	0.92	-12.84
Total	--	--	--	18.14	26.00	0.50	1.89	-11.83

```
Aquired
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Patrick Mahomes	15	QB4	24.96	43.47	2.67	0.98	4.55
1	Adam Thielen	15	WR7	12.00	7.40	0.93	0.97	3.08
Total	--	--	--	36.96	50.87	3.60	1.95	7.63

In [67]:

```
trade2 = {
    'Traded': ['Aaron Rodgers', 'Adam Thielen'],
    'Aquired': ['Aaron Jones', 'Robert Woods'],
}

calc_tradeoff(trade2)
```

```
Traded
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Aaron Rodgers	16	QB2	23.89	35.31	3.19	0.98	4.75
1	Adam Thielen	15	WR7	12.00	7.40	0.93	0.97	3.08
Total	--	--	--	35.89	42.71	4.12	1.95	7.83

```
Aquired
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Aaron Jones	14	RB5	15.14	18.86	0.79	0.98	5.84
1	Robert Woods	16	WR13	9.69	9.56	0.50	0.97	1.33
Total	--	--	--	24.83	28.42	1.29	1.95	7.17

In [68]:

```
trade_one_two = {
    'Traded': ['Miles Sanders', 'Michael Thomas', 'Aaron Rodgers'],
    'Aquired': ['Patrick Mahomes', 'Aaron Jones', 'Robert Woods'],
}

calc_tradeoff(trade_one_two)
```

```
Traded
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Aaron Rodgers	16	QB2	23.89	35.31	3.19	0.98	4.75
1	Miles Sanders	12	RB21	11.87	18.00	0.50	0.97	1.02
2	Michael Thomas	7	WR103	6.27	8.00	0.00	0.92	-12.84
Total	--	--	--	42.03	61.31	3.69	2.87	-7.07

```
Aquired
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Patrick Mahomes	15	QB4	24.96	43.47	2.67	0.98	4.55
1	Aaron Jones	14	RB5	15.14	18.86	0.79	0.98	5.84
2	Robert Woods	16	WR13	9.69	9.56	0.50	0.97	1.33
Total	--	--	--	49.79	71.89	3.95	2.93	11.71

In [69]:

```
roster = {
    'Before Trade' : ['Aaron Rodgers',  'Kareem Hunt', 'Miles Sanders', 'DeA
                    'Tyler Higbee', 'David Johnson', 'Kenny Golladay'],
    'After Trade': ['Patrick Mahomes', 'Aaron Jones', 'Kareem Hunt', 'David
                   'DeAndre Hopkins', 'Robert Woods', 'Tyler Higbee']
}
calc_tradeoff(roster)
```

```
Before Trade
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Aaron Rodgers	16	QB2	23.89	35.31	3.19	0.98	4.75
1	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
2	DeAndre Hopkins	16	WR9	10.80	10.06	0.38	0.97	2.44
3	David Johnson	12	RB19	12.21	16.08	0.67	0.97	1.36
4	Miles Sanders	12	RB21	11.87	18.00	0.50	0.97	1.02
5	Tyler Higbee	15	TE16	5.61	4.07	0.33	0.96	-0.59
6	Kenny Golladay	5	WR100	9.16	6.40	0.40	0.91	-17.60
Total	--	--	--	84.82	105.49	6.15	6.73	-5.48

```
After Trade
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Patrick Mahomes	15	QB4	24.96	43.47	2.67	0.98	4.55
1	Aaron Jones	14	RB5	15.14	18.86	0.79	0.98	5.84
2	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
3	DeAndre Hopkins	16	WR9	10.80	10.06	0.38	0.97	2.44
4	Robert Woods	16	WR13	9.69	9.56	0.50	0.97	1.33
5	David Johnson	12	RB19	12.21	16.08	0.67	0.97	1.36
6	Tyler Higbee	15	TE16	5.61	4.07	0.33	0.96	-0.59
Total	--	--	--	89.69	117.66	6.01	6.80	18.06

Week 3

Week 4

In [70]:
```
roster_wk4 = {
    'Starters': ['Patrick Mahomes', 'Aaron Jones', 'Kareem Hunt', 'David Joh
                 'DeAndre Hopkins',  'Justin Jefferson', 'Jonnu Smith'],
    'Bench': ['David Montgomery', 'Jerick McKinnon', 'Kenny Golladay', 'Tyle
              'Devonta Freeman', 'Joe Burrow', 'Deebo Samuel', 'Robert Woods
}

calc_tradeoff(roster_wk4)
```

```
Starters
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Patrick Mahomes	15	QB4	24.96	43.47	2.67	0.98	4.55
1	Aaron Jones	14	RB5	15.14	18.86	0.79	0.98	5.84
2	Justin Jefferson	16	WR6	11.64	7.88	0.44	0.97	3.27
3	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
4	DeAndre Hopkins	16	WR9	10.80	10.06	0.38	0.97	2.44
5	David Johnson	12	RB19	12.21	16.08	0.67	0.97	1.36
6	Jonnu Smith	15	TE9	6.61	4.47	0.60	0.96	0.41
Total	--	--	--	92.64	116.37	6.22	6.81	21.00

```
Bench
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	David Montgomery	15	RB6	14.05	21.00	0.67	0.98	5.37
1	Joe Burrow	10	QB25	17.37	44.10	1.60	0.92	-13.25
2	Robert Woods	16	WR13	9.69	9.56	0.50	0.97	1.33
3	Jerick McKinnon	16	RB40	5.83	7.94	0.38	0.96	-2.31
4	Tyler Higbee	15	TE16	5.61	4.07	0.33	0.96	-0.59
5	Deebo Samuel	7	WR97	6.81	7.43	0.14	0.92	-12.30
6	Kenny Golladay	5	WR100	9.16	6.40	0.40	0.91	-17.60
7	Devonta Freeman	5	RB85	5.80	12.80	0.20	0.90	-20.24
Total	--	--	--	74.33	113.30	4.22	7.52	-59.59

Week 5

Week 6

In [71]:
```
roster_wk6 = {
    'Starters': ['Patrick Mahomes', 'Aaron Jones', 'Kareem Hunt', 'David Joh
                 'DeAndre Hopkins', 'Chase Claypool', 'Jonnu Smith'],
    'Bench': ['David Montgomery', 'Jerick McKinnon', 'Kenny Golladay', 'Robe
              'Henry Ruggs III', 'Justin Jefferson', 'Robert Woods']
}

calc_tradeoff(roster_wk6)
```

```
Starters
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Patrick Mahomes	15	QB4	24.96	43.47	2.67	0.98	4.55
1	Aaron Jones	14	RB5	15.14	18.86	0.79	0.98	5.84
2	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
3	DeAndre Hopkins	16	WR9	10.80	10.06	0.38	0.97	2.44
4	Chase Claypool	16	WR14	9.56	7.44	0.69	0.97	1.19
5	David Johnson	12	RB19	12.21	16.08	0.67	0.97	1.36
6	Jonnu Smith	15	TE9	6.61	4.47	0.60	0.96	0.41
Total	--	--	--	90.55	115.94	6.47	6.80	18.92

```
Bench
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	David Montgomery	15	RB6	14.05	21.00	0.67	0.98	5.37
1	Justin Jefferson	16	WR6	11.64	7.88	0.44	0.97	3.27
2	Robert Woods	16	WR13	9.69	9.56	0.50	0.97	1.33
3	Robert Tonyan	16	TE3	7.79	3.69	0.69	0.97	1.97
4	Jerick McKinnon	16	RB40	5.83	7.94	0.38	0.96	-2.31
5	Henry Ruggs III	13	WR88	4.47	4.00	0.15	0.95	-5.82
6	Kenny Golladay	5	WR100	9.16	6.40	0.40	0.91	-17.60
Total	--	--	--	62.63	60.46	3.22	6.70	-13.79

Week 7

In [72]:

```
trade3 = {
    'Traded': ['DeAndre Hopkins', 'David Montgomery', 'David Johnson', 'Chas
    'Aquired': ['Alvin Kamara'],
}

calc_tradeoff(trade3)
```

```
Traded
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	David Montgomery	15	RB6	14.05	21.00	0.67	0.98	5.37
1	DeAndre Hopkins	16	WR9	10.80	10.06	0.38	0.97	2.44
2	Chase Claypool	16	WR14	9.56	7.44	0.69	0.97	1.19
3	David Johnson	12	RB19	12.21	16.08	0.67	0.97	1.36
Total	--	--	--	46.62	54.58	2.40	3.89	10.36

```
Aquired
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Alvin Kamara	15	RB2	19.65	19.60	1.40	1.00	10.97
Total	--	--	--	19.65	19.60	1.40	1.00	10.97

In [74]:

```
roster_wk7 = {
    'Starters': ['Patrick Mahomes', 'Aaron Jones', 'Kareem Hunt', 'Alvin Kam
                 'Robert Woods', 'Justin Jefferson', 'Jonnu Smith'],
    'Bench': ['Jerick McKinnon', 'Kenny Golladay', 'Robert Tonyan',
             'Henry Ruggs III', 'Phillip Lindsay', 'Jamaal Williams', 'AJ D
}

calc_tradeoff(roster_wk7)
```

```
Starters
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Patrick Mahomes	15	QB4	24.96	43.47	2.67	0.98	4.55
1	Alvin Kamara	15	RB2	19.65	19.60	1.40	1.00	10.97
2	Aaron Jones	14	RB5	15.14	18.86	0.79	0.98	5.84
3	Justin Jefferson	16	WR6	11.64	7.88	0.44	0.97	3.27
4	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
5	Robert Woods	16	WR13	9.69	9.56	0.50	0.97	1.33
6	Jonnu Smith	15	TE9	6.61	4.47	0.60	0.96	0.41
Total	--	--	--	98.97	119.39	7.08	6.84	29.51

```
Bench
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Robert Tonyan	16	TE3	7.79	3.69	0.69	0.97	1.97
1	Jamaal Williams	14	RB38	6.86	11.00	0.21	0.96	-2.44
2	Jerick McKinnon	16	RB40	5.83	7.94	0.38	0.96	-2.31
3	Phillip Lindsay	11	RB61	5.36	12.00	0.09	0.94	-6.47
4	Henry Ruggs III	13	WR88	4.47	4.00	0.15	0.95	-5.82
5	Kenny Golladay	5	WR100	9.16	6.40	0.40	0.91	-17.60
6	AJ Dillon	11	RB76	3.48	4.36	0.18	0.94	-8.35
Total	--	--	--	42.95	49.39	2.10	6.62	-41.03

In [75]:

```
roster = {
    'Before Trade' : ['Patrick Mahomes', 'Aaron Jones', 'Kareem Hunt', 'Davi
                      'DeAndre Hopkins', 'Chase Claypool', 'Jonnu Smith'],
    'After Trade': ['Patrick Mahomes', 'Aaron Jones', 'Kareem Hunt', 'Alvin
                    'Robert Woods', 'Justin Jefferson', 'Jonnu Smith']
}
calc_tradeoff(roster)
```

```
Before Trade
---------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Patrick Mahomes	15	QB4	24.96	43.47	2.67	0.98	4.55
1	Aaron Jones	14	RB5	15.14	18.86	0.79	0.98	5.84
2	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
3	DeAndre Hopkins	16	WR9	10.80	10.06	0.38	0.97	2.44
4	Chase Claypool	16	WR14	9.56	7.44	0.69	0.97	1.19
5	David Johnson	12	RB19	12.21	16.08	0.67	0.97	1.36
6	Jonnu Smith	15	TE9	6.61	4.47	0.60	0.96	0.41
Total	--	--	--	90.55	115.94	6.47	6.80	18.92

```
After Trade
---------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Patrick Mahomes	15	QB4	24.96	43.47	2.67	0.98	4.55
1	Alvin Kamara	15	RB2	19.65	19.60	1.40	1.00	10.97
2	Aaron Jones	14	RB5	15.14	18.86	0.79	0.98	5.84
3	Justin Jefferson	16	WR6	11.64	7.88	0.44	0.97	3.27
4	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
5	Robert Woods	16	WR13	9.69	9.56	0.50	0.97	1.33
6	Jonnu Smith	15	TE9	6.61	4.47	0.60	0.96	0.41
Total	--	--	--	98.97	119.39	7.08	6.84	29.51

Week 11

In [76]:

```
trade4 = {
    'Traded': ['Salvon Ahmed', 'Allen Lazard'],
    'Aquired': ['Joe Mixon', 'Ceedee Lamb'],
}

calc_tradeoff(trade4)
```

```
Traded
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Allen Lazard	10	WR74	6.48	4.80	0.30	0.94	-6.90
1	Salvon Ahmed	6	RB64	9.67	14.83	0.50	0.93	-12.03
Total	--	--	--	16.15	19.63	0.80	1.87	-18.93

```
Aquired
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Joe Mixon	6	RB49	13.10	24.17	0.67	0.94	-8.60
Total	--	--	--	13.10	24.17	0.67	0.94	-8.60

In [77]:

```
roster_wk11 = {
    'Starters': ['Patrick Mahomes', 'Aaron Jones', 'Kareem Hunt', 'Alvin Kam
                 'Robert Woods', 'Justin Jefferson', 'TE Taysom Hill'],
    'Bench': ['Kenny Golladay', 'Jonnu Smith', 'Tyler Boyd', 'Tony Pollard',
              'Allen Robinson', 'Tua Tagovailoa', 'Joe Mixon']
}
calc_tradeoff(roster_wk11, sort_by='POB')
```

```
Starters
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Alvin Kamara	15	RB2	19.65	19.60	1.40	1.00	10.97
1	Aaron Jones	14	RB5	15.14	18.86	0.79	0.98	5.84
2	Patrick Mahomes	15	QB4	24.96	43.47	2.67	0.98	4.55
3	Justin Jefferson	16	WR6	11.64	7.88	0.44	0.97	3.27
4	Kareem Hunt	16	RB10	11.28	15.56	0.69	0.97	3.14
5	Robert Woods	16	WR13	9.69	9.56	0.50	0.97	1.33
Total	--	--	--	92.36	114.92	6.48	5.87	29.11

```
Bench
----------------------------------------
```

	Player	G	Rk	PPG	Usage	TD	VOB/G	POB/G
0	Allen Robinson	16	WR12	10.06	9.50	0.38	0.97	1.69
1	Jonnu Smith	15	TE9	6.61	4.47	0.60	0.96	0.41
2	Tyler Boyd	15	WR38	7.58	7.80	0.27	0.96	-1.34
3	Tony Pollard	16	RB41	5.80	8.81	0.31	0.96	-2.34
4	Joe Mixon	6	RB49	13.10	24.17	0.67	0.94	-8.60
5	Kenny Golladay	5	WR100	9.16	6.40	0.40	0.91	-17.60
6	Tua Tagovailoa	10	QB30	13.55	32.60	1.40	0.91	-17.07
Total	--	--	--	65.85	93.75	4.02	6.60	-44.86

In [61]:

```
# df2 = nfl.load_pbp_data(2020)
# df2.head()
```

In [ ]:

```
```