

FinalVersion

April 22, 2018

1 Take Your Shot

1.1 Final Submission

1.1.1 Jacob Brown, Avery Smith, and Kyle Salisbury

Members	email	uid
Jacob Brown	u0729080@utah.edu	u0729080
Avery Smith	averyjs@gmail.com	u0838931
Kyle Salisbury	Kcsals@gmail.com	u0711328

Video Presentation Link: <https://www.youtube.com/watch?v=HDrmcKn1qhI>

1.1.2 Primary Questions:

What are the natural groupings/clusters of shots on a basketball court?

Which combinations of player and shooting location have the highest expected value (shooting pct * points)?

Are the differences in shooting percentage statistically significant?

How does shooting pct vary at Home vs. Away?

Given only the location and shooters for a game not in our dataset, can we predict the final score of the Jazz, the amount of points each player scored, and whether or not they won?

1.2 Accomplished:

- Web scraped all data from sources and created "final" csv
- Obtained key data points using Regex
- Cleaned data and created various dataframes
- Unsupervised clustering (k-means) to divide court into 6 clusters (further divided by 2 pointer and 3 pointer)
- Calculated expected value for each player in each court position and reported them on shot charts
- Calculated significance for shooting percentages by player and location

- Explored expected value difference for Home VS Away games
- Predicted the score of Jazz game, along with individual player totals.

1.2.1 Methods Used:

- Web scraping
- Regex
- Dataframes (including masking)
- Unsupervised clustering (k-means)
- Loops and logic
- Hypothesis Testing
- Visualizations (Scatter plots, heat maps)
- Predictions via pseduo-model

1.3 Programming and Methods:

In [3]: *# Import All Library Packages*

```

from bs4 import BeautifulSoup
import requests
import urllib.request
import re
import time
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn import metrics
from sklearn.metrics import silhouette_samples, silhouette_score
import math
import scipy as sc
from scipy.stats import norm

# Develop some color maps
seven_colors = ListedColormap(["#e41a1c", "#984ea3", "#a65628", "#377eb8", "#f1a340", "#4daf4a", "#f781bf"])
cmap_bold = ListedColormap(['#FF0000', '#00FF00'])

# Load in the court picture
img = plt.imread('JazzCortHalf.png')

```

1.3.1 Data Aquisition Process

(This may take quite a while to run. It also saves local htmls so it is suggested, if running the code, to start later at Exploratory Analysis section) We scraped shot charts for the Utah Jazz from <http://www.espn.com> . We used the hyperlinks on the Jazz schedule page to find all the Jazz games for the entire season. We saved each page as a .html file so we could interact with them without having to scrape them over and over again.

```
In [ ]: # Function to get soups for a given URL
def getWebsiteAsSoup(url):
    """
    Retrieve a website and return it as a BeautifulSoup object.
    """

    req = urllib.request.Request(url)
    with urllib.request.urlopen(req) as response:
        classlist_html = response.read()

    class_soup = BeautifulSoup(classlist_html, 'html.parser')
    with open('class_list.html', 'w') as new_file:
        new_file.write(str(class_soup))

    return class_soup

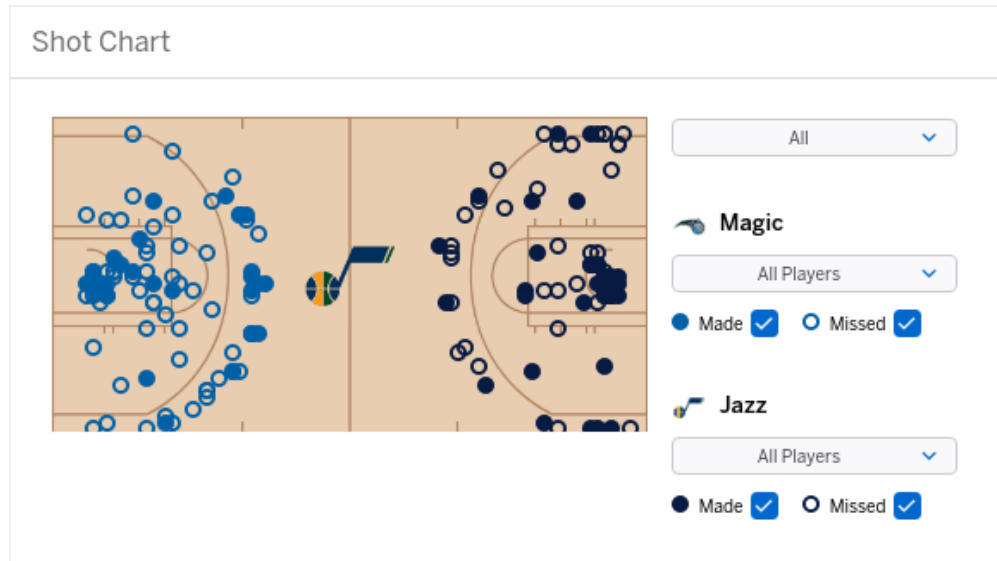
In [ ]: # url for the jazz schedule
schedule_url = "http://www.espn.com/nba/team/schedule/_/name/utah/utah-jazz"
schedule_soup = getWebsiteAsSoup(schedule_url)
base_url = "http://www.espn.com/nba/game?gameId=" # append url_endings to
url_endings = []
regex = 'http://www.espn.com/nba/recap/_/id/(\d+)'
for a_element in schedule_soup.find_all('a'): # find all elements of type
    ending = re.findall(regex, str(a_element))
    if ending != []: # many of these elements won't contain the regular ex
        url_endings.append(ending[0])

print('Number of Jazz Games:')
print(len(url_endings)) # shows how many games the Jazz have played so far

In [ ]: # Function to save html for a given URL
def saveWebsiteToLocal(url, number):
    """
    Retrieve a website and save it locally as an html.
    """

    req = urllib.request.Request(url)
    with urllib.request.urlopen(req) as response:
        classlist_html = response.read()

    # print(classlist_html)
```



ESPN Shot Chart

```
class_soup = BeautifulSoup(classlist_html, 'html.parser')
with open('html/game_' + str(number) + '.html', 'w') as new_file:
    new_file.write(str(class_soup))

return
```

```
In [ ]: # download all the games to a local copy
i = 1
for game in url_endings:
    saveWebsiteToLocal(base_url+url_endings[i-1], i)
    i+=1
    time.sleep(10)
```

1.3.2 Data Processing

The following image was screenshots from the url <http://www.espn.com/nba/game?gameId=400975701>. Each of the dots is an element of type 'li' which can be scraped.

We used beautiful soup to identify the html element for each shot, and used regular expressions to extract the interesting data from each shot. This is what the HTML looks like. We were mostly interested in data-text, data-homeaway, data-shooter, and left and top positions.

```
In [4]: # regular expressions to obtain key data
utah_regex = 'utah.png'
made_missed_regex = r'class="(\w+)"'
period_regex = r'data-period="(\d)"'
shooter_regex = r'data-shooter="(\d+)"'
blocks_regex = r'blocks'
blocks_shooter_name_regex = r'blocks (\w+ \w+)'
shooter_name_regex = r'data-text="(\w+ \w+)"'
```

```

▶<li id="shot34" class="made" data-text="Derrick Favors makes 7-foot two point
shot (Joe Ingles assists)" data-homeaway="home" data-period="2" data-shooter="4257"
style="border-color:#06143F;background-color:#06143F;left:86.88888888888889%;top:
42.0%;">...</li>
▶<li id="shot35" class="missed" data-text="Dante Exum misses driving layup" data-
homeaway="home" data-period="2" data-shooter="3102528" style="border-color:#06143F;
left:92.44444444444444%;top:54.0%;">...</li>
▶<li id="shot36" class="made" data-text="Jonas Jerebko makes 25-foot three point
jumper (Joe Ingles assists)" data-homeaway="home" data-period="2" data-shooter=
"3998" style="border-color:#06143F;background-color:#06143F;left:
84.66666666666667%;top:2.0%;">...</li>
▶<li id="shot37" class="made" data-text="Royce O'Neale makes two point shot (Joe
Ingles assists)" data-homeaway="home" data-period="2" data-shooter="2583632" style=
"border-color:#06143F;background-color:#06143F;left:91.33333333333333%;top:54.0%;">
...</li>
▶<li id="shot38" class="made" data-text="Royce O'Neale makes 27-foot three point
jumper (Dante Exum assists)" data-homeaway="home" data-period="2" data-shooter=
"2583632" style="border-color:#06143F;background-color:#06143F;left:
65.77777777777777%;top:30.0%;">...</li> == $0
▶<li id="shot39" class="made" data-text="Royce O'Neale makes two point shot" data-
homeaway="home" data-period="2" data-shooter="2583632" style="border-color:#06143F;
background-color:#06143F;left:91.33333333333333%;top:54.0%;">...</li>
▶<li id="shot40" class="missed" data-text="Ricky Rubio misses 25-foot three point
jumper" data-homeaway="home" data-period="2" data-shooter="4011" style="border-
color:#06143F;left:65.77777777777777%;top:44.0%;">...</li>
▶<li id="shot41" class="made" data-text="Derrick Favors makes layup" data-
homeaway="home" data-period="2" data-shooter="4257" style="border-color:#06143F;
background-color:#06143F;left:91.33333333333333%;top:46.0%;">...</li>
▶<li id="shot42" class="made" data-text="Ricky Rubio makes 26-foot three point
shot" data-homeaway="home" data-period="2" data-shooter="4011" style="border-color:
#06143F;background-color:#06143F;left:71.33333333333333%;top:18.0%;">...</li>
▶<li id="shot43" class="missed" data-text="Rudy Gobert misses 10-foot hook shot"
data-homeaway="home" data-period="2" data-shooter="3032976" style="border-color:
#06143F;left:82.44444444444444%;top:44.0%;">...</li>
▶<li id="shot44" class="missed" data-text="Dante Exum misses 24-foot three point

```

HTML for Shot Chart

```

distance_regex = r' (\d+-foot)'
type_regex = r'foot ([\w ]+)[ "'
alt_type_regex = r'e*s ([\w ]+)[ "\('
assist_regex = r'\((\w+ \w+) assists\)'
left_regex = r'left:(\d+.\d+)%'
top_regex = r'top:(\d+.\d+)%'
three_regex = r'three'

```

In [5]: # Obtaining key words from scraping

```

start = time.clock()
array = []
tot_games = 80
for i in range(1, tot_games+1):
    GameWebsite = BeautifulSoup(open("html/game_" + str(i) + ".html"), "html")
    court_symbol = GameWebsite.select('.shot-chart > .team-logo')
    home_team = re.findall(utah_regex, str(court_symbol))
    if home_team:
        AllJazzShots = GameWebsite.find_all(class_="shots home-team")[0]
        homeaway = 1
    else:
        AllJazzShots = GameWebsite.find_all(class_="shots away-team")[0]
        homeaway = 0
    for j in range(0, 300):
        Shot = AllJazzShots.find(id="shot" + str(j))
        if Shot == None:
            continue
        game = i
        shot = j
        made_missed = re.findall(made_missed_regex, str(Shot))[0]
        if made_missed == "made":
            made_missed = 1
        else:
            made_missed = 0
        period = re.findall(period_regex, str(Shot))[0]
        shooter = re.findall(shooter_regex, str(Shot))[0]
        block = re.findall(blocks_regex, str(Shot))
        shooter_name = re.findall(shooter_name_regex, str(Shot))
        if block:
            shooter_name = re.findall(blocks_shooter_name_regex, str(Shot))
        elif shooter_name == []:
            shooter_name = None
        else:
            shooter_name = shooter_name[0]
        distance = re.findall(distance_regex, str(Shot))
        if distance == []:
            distance = None
        else:
            distance = distance[0]

```

```

shot_type = re.findall(type_regex, str(Shot))
if shot_type == []:
    shot_type = re.findall(alt_type_regex, str(Shot))
    #if shot_type == []:
    #    shot_type = "deviant"
shot_type = shot_type[0]
# clears out some problems associated with greedy regex
start = shot_type.find("makes ") + len("makes ")
if start >= len("makes "):
    shot_type = shot_type[start:]
start = shot_type.find("misses ") + len("misses ")
if start >= len("misses "):
    shot_type = shot_type[start:]
assist = re.findall(assist_regex, str(Shot))
if assist == []:
    assist = None
else:
    assist = assist[0]
left = float(re.findall(left_regex, str(Shot))[0])
# one axis needs to be flipped depending on if it is home or away
if (homeaway == 0):
    left = 100-left
    #print('away')
top = float(re.findall(top_regex, str(Shot))[0])
if homeaway:
    top = 100-top
three = re.findall(three_regex, shot_type)
if three == []:
    three = 0
else:
    three = 1
game_array = [game, shot, homeaway, made_missed, period, shooter, s
               assist, left, top, three]
array.append(game_array)
end = time.clock()
print("This took " + str(end-start) + " seconds to run")

```

This took 41.315738 seconds to run

```

In [6]: columns = ["game", "shot", "home/away", "made/missed", "period", "shooter",
                  "distance", "shot_type", "assist", "left", "top", "ThreePt"]
print('Total Number of Shots: ' + str(len(array))) # total number of shots
print('Average Shots Per Game: ' + str(len(array)/tot_games)) # avg shots

```

Total Number of Shots: 6630

Average Shots Per Game: 82.875

```
In [7]: panda_dataframe = pd.DataFrame(array, columns=columns)
panda_dataframe.head()
```

```
Out [7]:
```

	game	shot	home/away	made/missed	period	shooter	shooter_name	\
0	1	0	0	0	1	4011	Ricky Rubio	
1	1	1	0	1	1	2968436	Joe Ingles	
2	1	2	0	1	1	3908809	Donovan Mitchell	
3	1	3	0	1	1	3032976	Rudy Gobert	
4	1	4	0	0	1	4011	Ricky Rubio	

	distance	shot_type	assist	left	top	ThreePt
0	17-foot	pullup jump shot	None	76.666667	58.0	0
1	24-foot	three point shot	Donovan Mitchell	90.000000	2.0	1
2	None	dunk	Ricky Rubio	94.444444	50.0	0
3	None	dunk	Derrick Favors	95.555556	50.0	0
4	None	two point shot	None	95.555556	52.0	0

```
In [8]: panda_dataframe.to_csv("shots_dataframe_final.csv")
```

2 Exploratory Analysis

Data can be read from here without having to run the top half of the notebook - (which could take a while)

```
In [9]: # data can be read from here without having to run the top half of the notebook
# (which could take a while)
ShotsPD = pd.read_csv("shots_dataframe.csv")
```

```
In [10]: # Describe Data Set
ShotsPD.describe()
```

```
Out [10]:
```

	Unnamed: 0	game	shot	home/away	made/missed	\
count	6793.000000	6793.000000	6793.000000	6793.000000	6793.000000	
mean	3396.000000	41.636096	49.889445	0.496688	0.462093	
std	1961.114522	23.667811	30.681017	0.500026	0.498598	
min	0.000000	1.000000	0.000000	0.000000	0.000000	
25%	1698.000000	21.000000	23.000000	0.000000	0.000000	
50%	3396.000000	42.000000	49.000000	0.000000	0.000000	
75%	5094.000000	62.000000	75.000000	1.000000	1.000000	
max	6792.000000	82.000000	133.000000	1.000000	1.000000	

	period	shooter	left	top	ThreePt
count	6793.000000	6.793000e+03	6793.000000	6793.000000	6793.000000
mean	2.474901	1.736174e+06	83.788835	50.669071	0.342264
std	1.129431	1.664691e+06	10.165391	21.980889	0.474502
min	1.000000	1.007000e+03	48.000000	2.000000	0.000000
25%	1.000000	4.257000e+03	74.666667	44.000000	0.000000
50%	2.000000	2.581177e+06	87.777778	50.000000	0.000000
75%	3.000000	3.032976e+06	92.444444	60.000000	1.000000
max	5.000000	4.065673e+06	98.888889	98.000000	1.000000


```
In [11]: print('Number of Shots Taken by Each Player:')
         print('-----')
         ShotsPD = ShotsPD.replace("Royce O", "Royce O'Neale")
         print(ShotsPD['shooter_name'].value_counts(), '\n')
```

Number of Shots Taken by Each Player:

```
-----
Donovan Mitchell      1361
Ricky Rubio           827
Joe Ingles             718
Derrick Favors        702
Rodney Hood           552
Rudy Gobert           442
Alec Burks            413
Jonas Jerebko         341
Jae Crowder           295
Royce O'Neale         285
Thabo Sefolosha       240
Joe Johnson           226
Raul Neto             151
Ekpe Udoh             119
Dante Exum            87
Tony Bradley          11
Georges Niang          11
Nate Wolters           6
David Stockton         3
Erik McCree           2
Naz Mitrou            1
```

Name: shooter_name, dtype: int64

```
In [12]: # filter out any shooter with less than 100 shots for the season
         ShotsPD = ShotsPD[ShotsPD["shooter_name"]!="Dante Exum"]
         ShotsPD = ShotsPD[ShotsPD["shooter_name"]!="Tony Bradley"]
         ShotsPD = ShotsPD[ShotsPD["shooter_name"]!="Nate Wolters"]
         ShotsPD = ShotsPD[ShotsPD["shooter_name"]!="David Stockton"]
         ShotsPD = ShotsPD[ShotsPD["shooter_name"]!="Georges Niang"]
         ShotsPD = ShotsPD[ShotsPD["shooter_name"]!="Erik McCree"]
         ShotsPD = ShotsPD[ShotsPD["shooter_name"]!="Naz Mitrou"]
```

```
In [13]: print('Types of Shots Taken:')
         print('-----')
         print(ShotsPD['shot_type'].value_counts(), '\n')
```

Types of Shots Taken:

```
-----
three point jumper      2004
two point shot          901
```

driving layup	590
jumper	533
pullup jump shot	490
layup	371
dunk	235
step back jumpshot	190
layup	185
driving floating jump shot	141
three point pullup jump shot	135
dunk	131
tip shot	118
driving layup	103
two point shot	90
three pointer	84
hook shot	70
three point jumper	55
jump bank shot	36
driving dunk	34
alley oop dunk shot	28
alley oop layup	26
alley oop dunk shot	26
jumper	21
three point shot	20
alley oop layup	10
finger roll layup	10
running pullup jump shot	9
driving dunk	9
finger roll layup	4
pullup jump shot	4
hook shot	3
shot	3
jump bank shot	1
driving floating jump shot	1
step back jumpshot	1

Name: shot_type, dtype: int64

2.0.1 Unsupervised clustering via kmeans to find natural clusters of the shots

We ultimately wanted to group the shots into different clusters for further analysis as groups. We wanted to try an unsupervised clustering algorithm to give us some insight into how the computer might see the court. We used kmeans because it was easy to implement, and because we were interested only in x and y location as our variables, so kmeans seemed like it would naturally lend itself to our analysis.

We used kmeans to cluster the basketball shots based on their X and Y locations on the court. We chose to use 6 different clusters, because that lead to results that were the most easily identifiable by humans. We were quite happy with our results. One group was right by the rim in

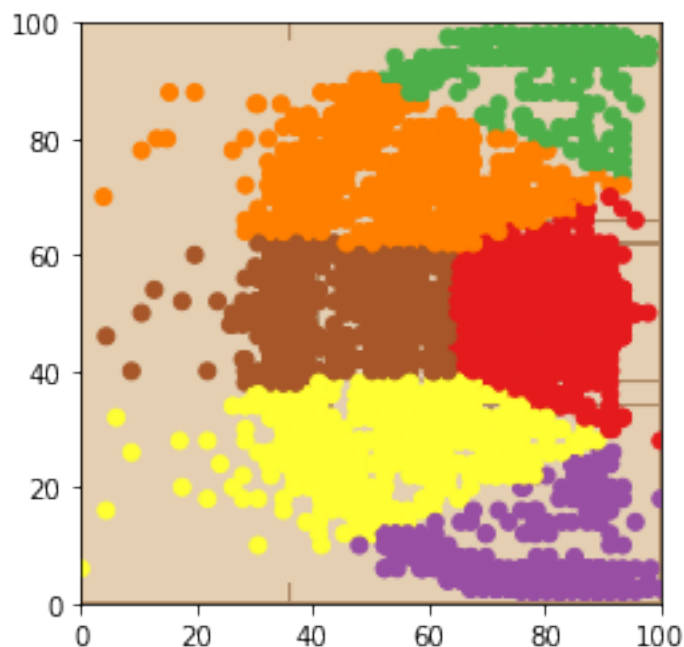
the area called the key/paint/post. There were 5 other regions spanning the court that included both 2 pointers and 3 pointers. These zones correlated quite nicely with what we would naturally identify as the left and right corners, wings, and the middle of the court. Further dividing the groups into two-pointers and three-pointers gives us 11 separate clusters for further analysis.

```
In [14]: # Show the Natural Clusterings on the court with colors
X = np.zeros( (len(ShotsPD), 2) )
X[:, 0] = ShotsPD['left']
X[:, 1] = ShotsPD['top']
y_pred = KMeans(n_clusters=6, n_init=10, init='random', max_iter=300).fit_

# Saves these locations to the dataframe
ShotsPD['LocationCluster'] = y_pred
ShotsPD.to_csv("location_dataframe_final.csv")

# Redistribute the left data to be on scale of 0-100 (to plot on court pic)
xNorm = 100*(ShotsPD['left'] - min(ShotsPD['left'])) / (max(ShotsPD['left']

plt.scatter(xNorm[:, 0], X[:, 1], c=ShotsPD['LocationCluster'], marker="o",
plt.imshow(img, zorder=0, extent=[0, 100, 0, 100.0])
plt.grid(False)
plt.show()
```



These clusters are interesting. They naturally appear to match what we would identify as the key, the left and right corners, the wings, and the middle of the court. We added these groupings to our dataset

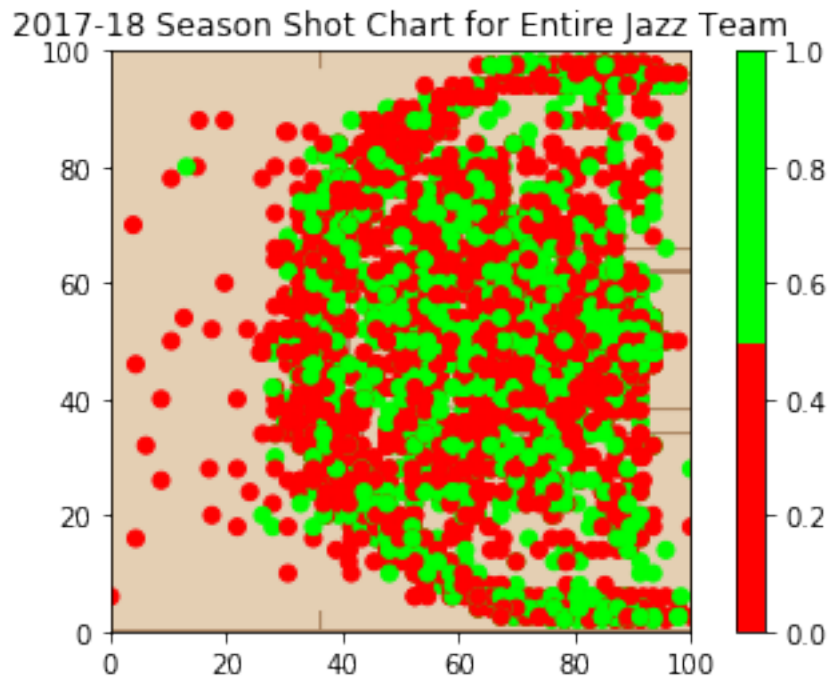
2.0.2 We created shot charts for the team as a whole, and for each individual player

```
In [15]: # unsupervised clustering can give different labels
# so read in already clustered data for consistency

ShotsPD = pd.read_csv("location_dataframe_final.csv")
ShotsPD = ShotsPD.replace("Royce O", "Royce O'Neale")

# Redistribute the left data to be on scale of 0-100
xNorm = 100*(ShotsPD['left'] - min(ShotsPD['left'])) / (max(ShotsPD['left'] - min(ShotsPD['left'])))
ShotsPD['left'] = xNorm

In [16]: # Entire shots by Jazz by location, makes and misses
# greens are makes, reds are misses
cmap_bold = ListedColormap(['#FF0000', '#00FF00'])
plt.scatter(ShotsPD['left'], ShotsPD['top'], c=ShotsPD['made/missed'], cmap=cmap_bold)
plt.colorbar()
plt.imshow(img, zorder=0, extent=[0, 100, 0, 100.0])
plt.title('2017-18 Season Shot Chart for Entire Jazz Team')
plt.grid(False)
plt.show()
```



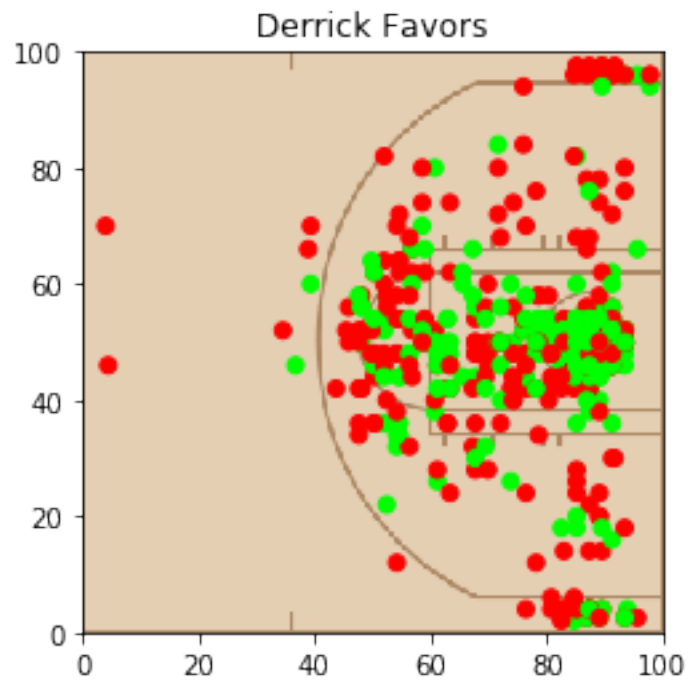
Individual players

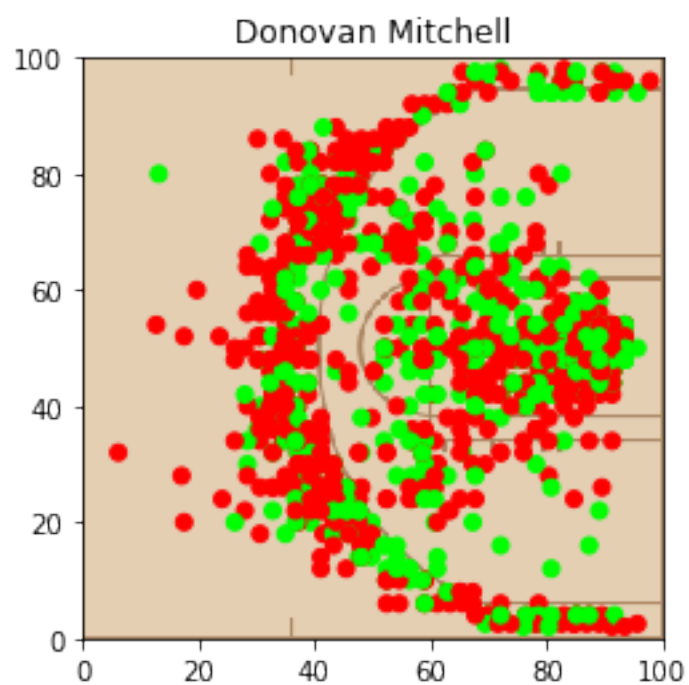
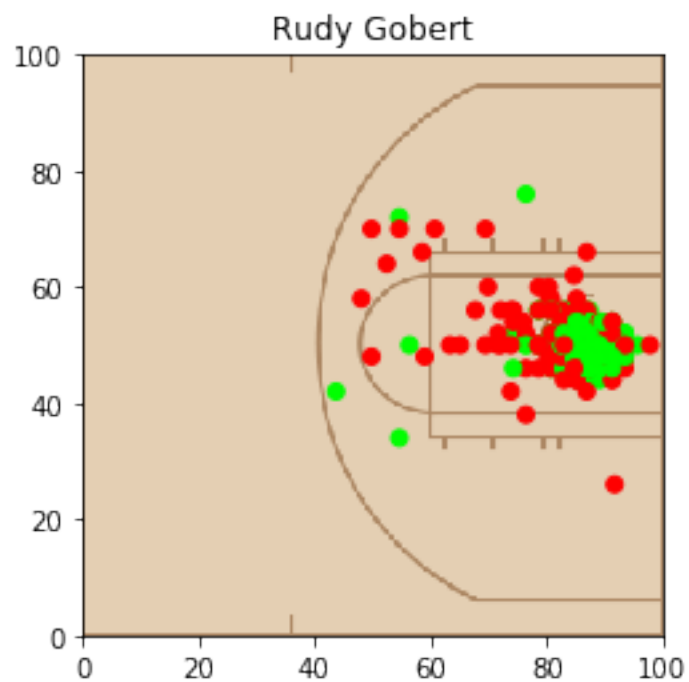
```
In [17]: # shot chart for every player on the Jazz
# greens are makes, reds are misses
```

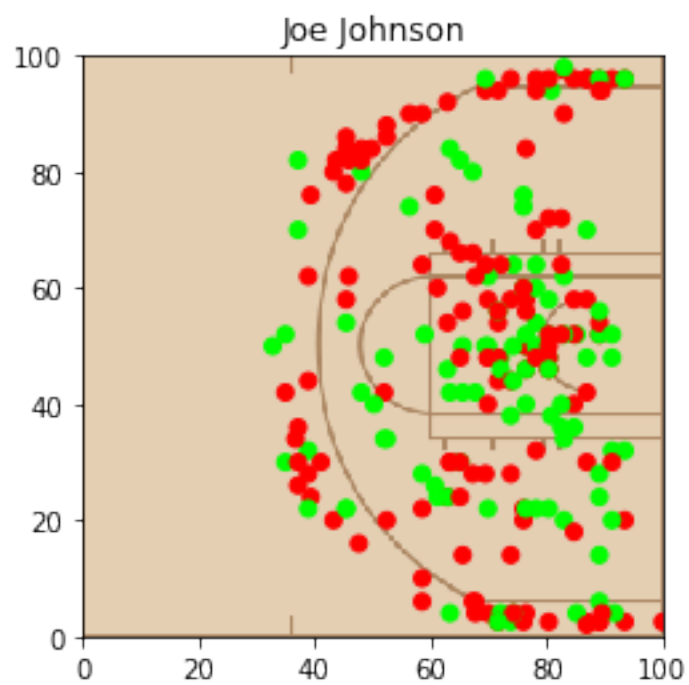
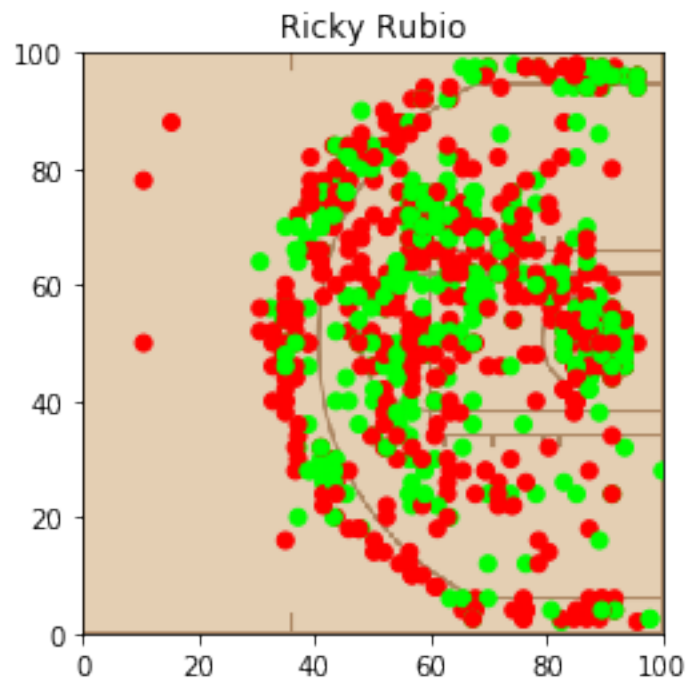
```

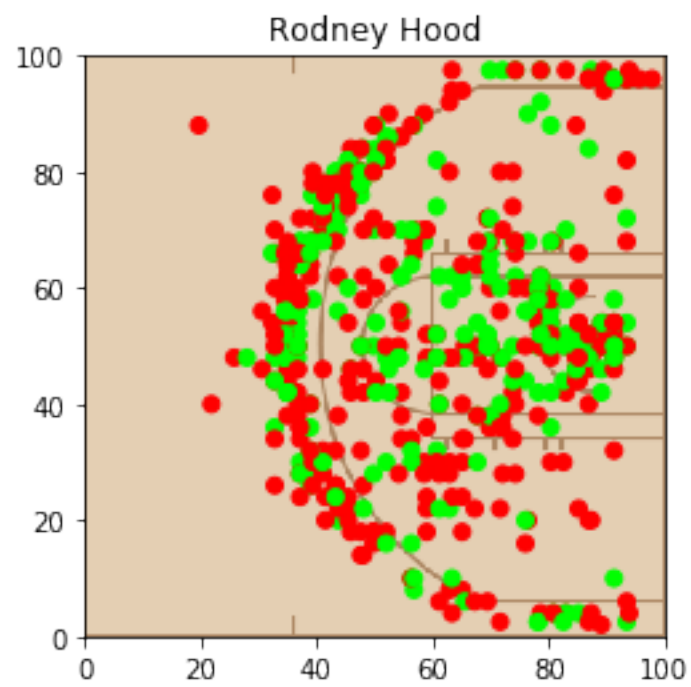
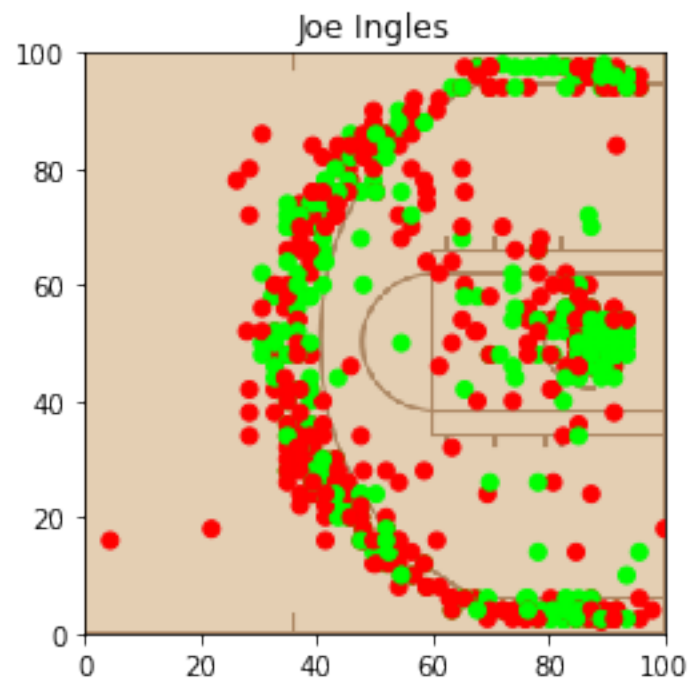
for shooter_name in ShotsPD['shooter_name'].unique():
    shooter_shots = ShotsPD[ShotsPD['shooter_name'] == shooter_name]
    plt.scatter(shooter_shots['left'], shooter_shots['top'], c=shooter_shots['shooter_name'])
    plt.title(str(shooter_name))
    plt.imshow(img, zorder=0, extent=[0, 100, 0, 100.0])
    plt.grid(False)
    plt.show()

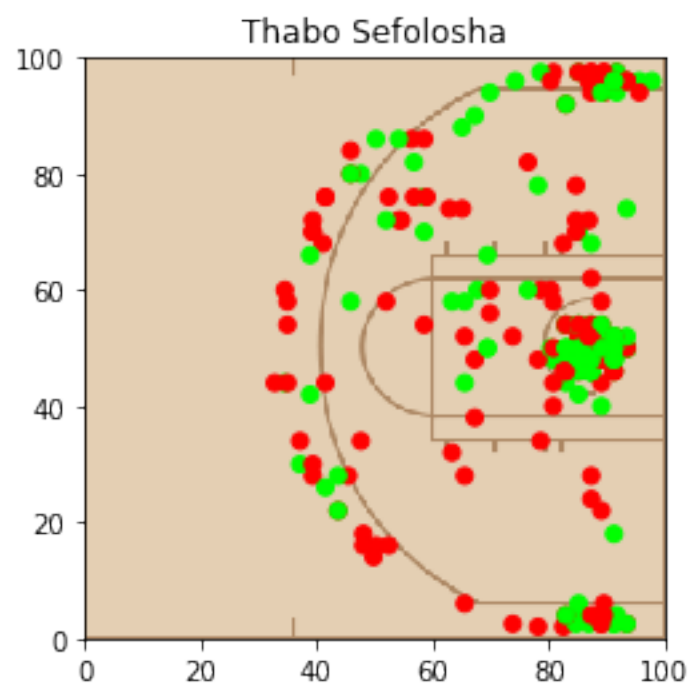
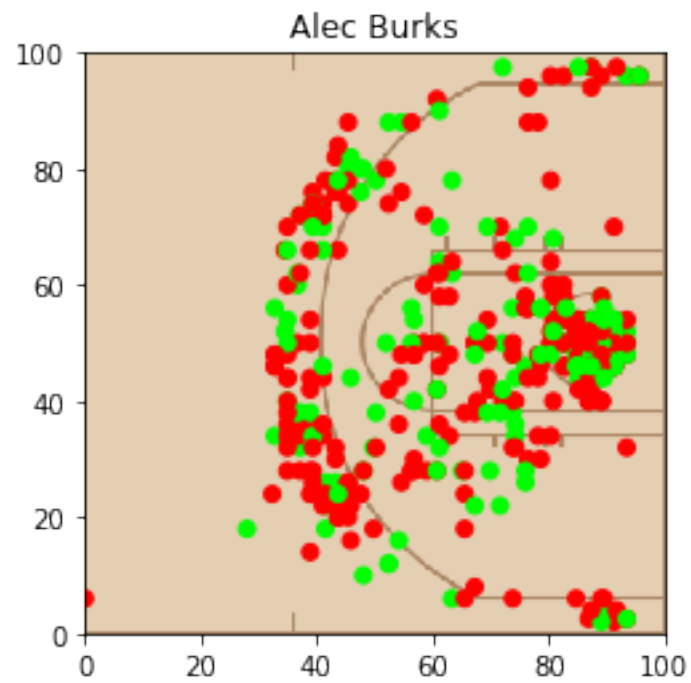
```

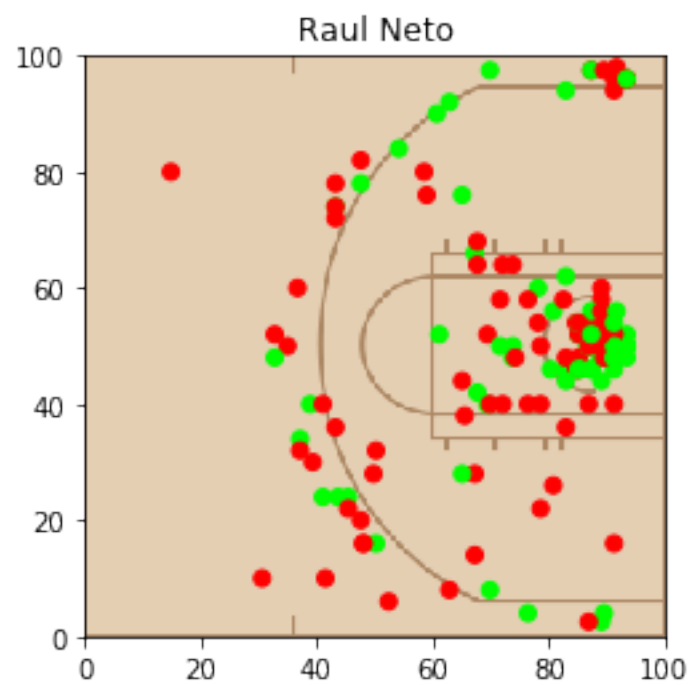
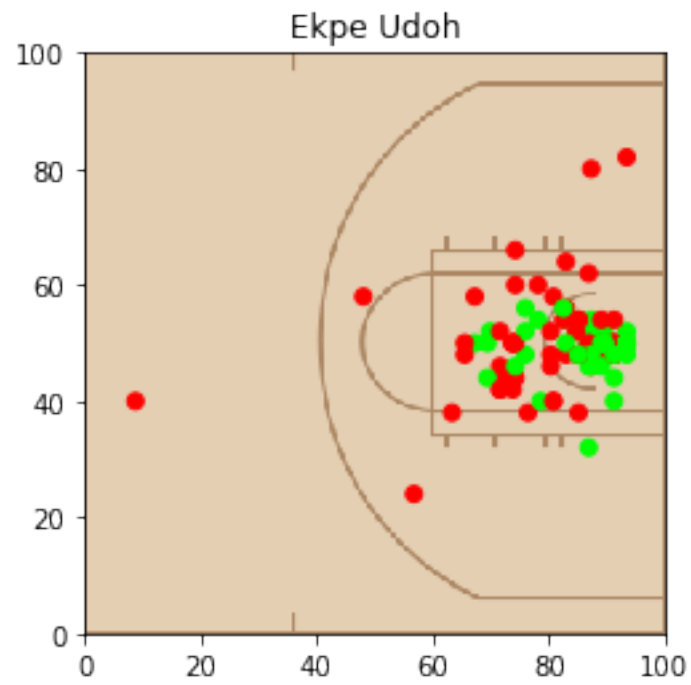


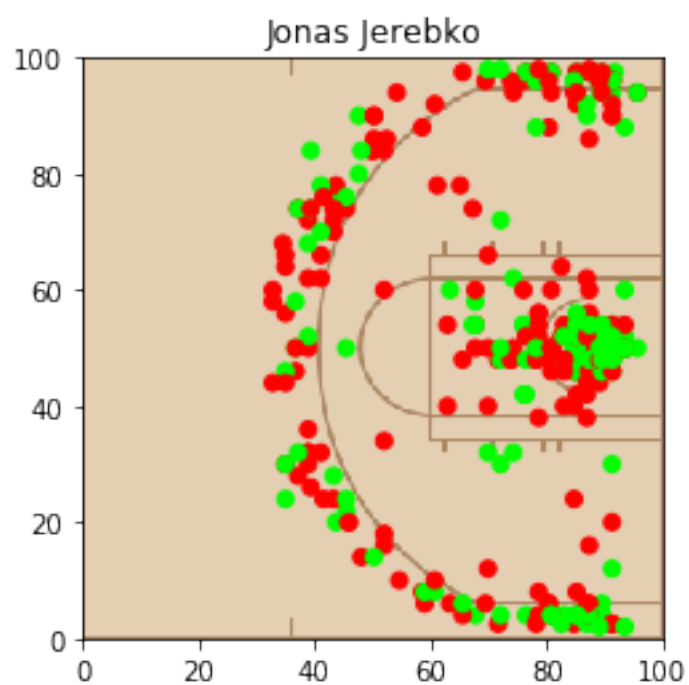
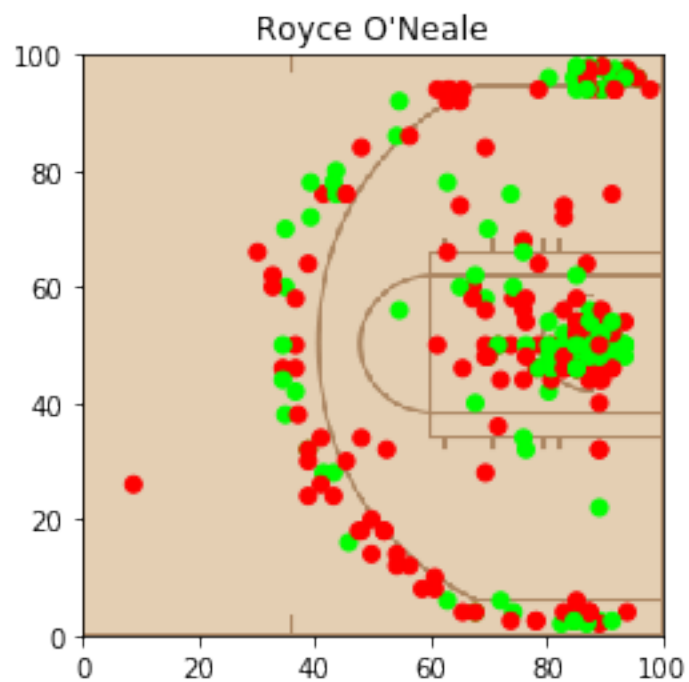


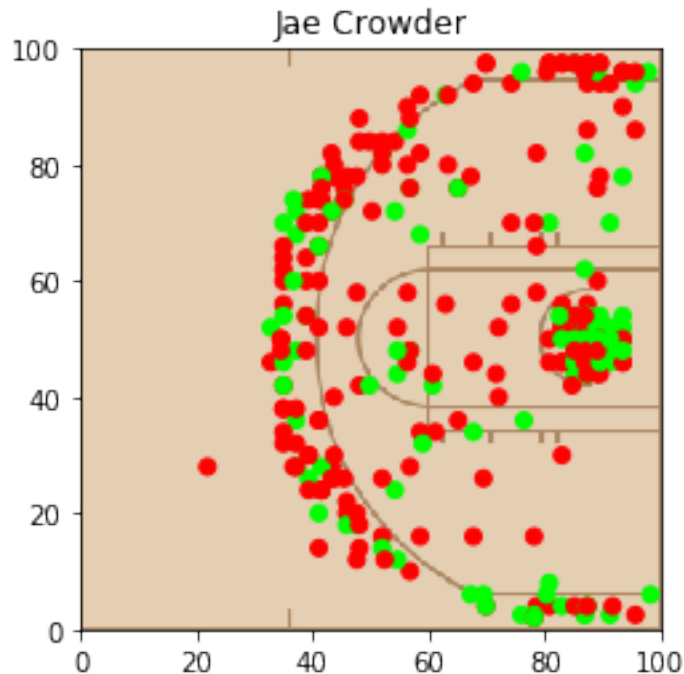












We can use simple data frame masking and math to compute some simple statistics for individual players

```
In [18]: mitchell_shots = ShotsPD[ShotsPD["shooter_name"]=="Donovan Mitchell"]
print('Number of Shots Mitchell has shot: ' + str(len(mitchell_shots)))
mitchell_makes = mitchell_shots[mitchell_shots["made/missed"]==1]
mitchell_misses = mitchell_shots[mitchell_shots["made/missed"]==0]
print('Number of Shots Mitchell has made: ' + str(len(mitchell_makes)))
print('Number of Shots Mitchell has missed: ' + str(len(mitchell_misses)))
print('Mitchell Field Goal Percentage: ' + str(len(mitchell_makes)/len(mitchell_shots)))
```

Number of Shots Mitchell has shot: 1361

Number of Shots Mitchell has made: 595

Number of Shots Mitchell has missed: 766

Mitchell Field Goal Percentage: 0.4371785451873622

```
In [19]: mitchell_threes = mitchell_shots[mitchell_shots["ThreePt"]==1]
mitchell_twos = mitchell_shots[mitchell_shots["ThreePt"]==0]
two_pt_pct = len(mitchell_twos[mitchell_twos["made/missed"]==1])/len(mitchell_twos)
three_pt_pct = len(mitchell_threes[mitchell_threes["made/missed"]==1])/len(mitchell_threes)
print("Mitchell's two point percentage is: " + str(round(two_pt_pct*100, 2)))
print("Mitchell's three point percentage is: " + str(round(three_pt_pct*100, 2)))
```

Mitchell's two point percentage is: 49.71 %

Mitchell's three point percentage is: 33.79 %

We try to get an idea of which regions have the highest expected value (for the team as a whole). We'll plot them later as well. This shows the expected values for 3 pointers and then two pointers

```
In [20]: ## Team Stats -- 3 Pointers
# 3 pointers
PercMadeDif3 = []
NumShots = []
NumMade = []
ExpectedValue3 = []
AvLeft3 = []
AvTop3 = []
PtVal = 3
for i in range(0,6):
    Location = ShotsPD[(ShotsPD['LocationCluster']==i) & (ShotsPD['ThreePt']==1)]
    NumShots.append(len(Location['made/missed']))
    NumMade.append(len(Location[Location['made/missed']==1]))
    if NumShots[i] > 1:
        PercMade = NumMade[i] / NumShots[i]
        PercMadeDif3.append(PercMade)
    else:
        PercMadeDif3.append(0)

    ExpectedValue3.append(PercMadeDif3[i]*PtVal)

    AvLeft3.append(np.mean(Location['left']))
    AvTop3.append(np.mean(Location['top']))

print('---- 3 Pointers ----')
print('Percentages')
print(PercMadeDif3)
print('-----')
print('Expected Values')
print(ExpectedValue3)
```

```
---- 3 Pointers ----
Percentages
[0, 0.4004474272930649, 0.35537190082644626, 0.3146551724137931, 0.3982102908277405, 0.35537190082644626]
-----
Expected Values
[0, 1.2013422818791946, 1.0661157024793388, 0.9439655172413792, 1.1946308724832215, 1.0661157024793388]
```

```
In [21]: ## Team Stats -- 2 Pointers
# 2 pointers
PercMadeDif2 = []
NumShots = []
NumMade = []
ExpectedValue2 = []
```

```

PtVal = 2
AvLeft2 = []
AvTop2 =[]

for i in range(0,6):
    Location = ShotsPD[(ShotsPD['LocationCluster']==i) & (ShotsPD['ThreePt']
    NumShots.append(len(Location['made/missed']))
    NumMade.append(len(Location[Location['made/missed']==1]))
    PercMade = NumMade[i] / NumShots[i]
    PercMadeDif2.append(PercMade)
    ExpectedValue2.append(PercMadeDif2[i]*PtVal)

    AvLeft2.append(np.mean(Location['left']))
    AvTop2.append(np.mean(Location['top']))

print('---- 2 Pointers ----')
print('Percentages')
print(PercMadeDif2)
print('-----')
print('Expected Values')
print(ExpectedValue2)

```

```

---- 2 Pointers ----
Percentages
[0.564875491480996, 0.4235294117647059, 0.44141689373297005, 0.34770114942528735, 0.
-----
Expected Values
[1.129750982961992, 0.8470588235294118, 0.8828337874659401, 0.6954022988505747, 0.7

```

```

In [22]: ## Delete some parts mostly because the paint (key) cluster won't have a J
xx = np.isnan(AvLeft3)
DeleteVar = []
for i in range(0, len(AvLeft3)):
    if xx[i] == True:
        DeleteVar = i
DeleteVar
del AvLeft3[DeleteVar]
del AvTop3[DeleteVar]

```

```

In [23]: # Show where each cluster is located on the court (the means!)
import seaborn as sns

df = pd.DataFrame({
    'x': AvLeft3 + AvLeft2,
    'y': AvTop3 + AvTop2,
    'group': ['0', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10']
})

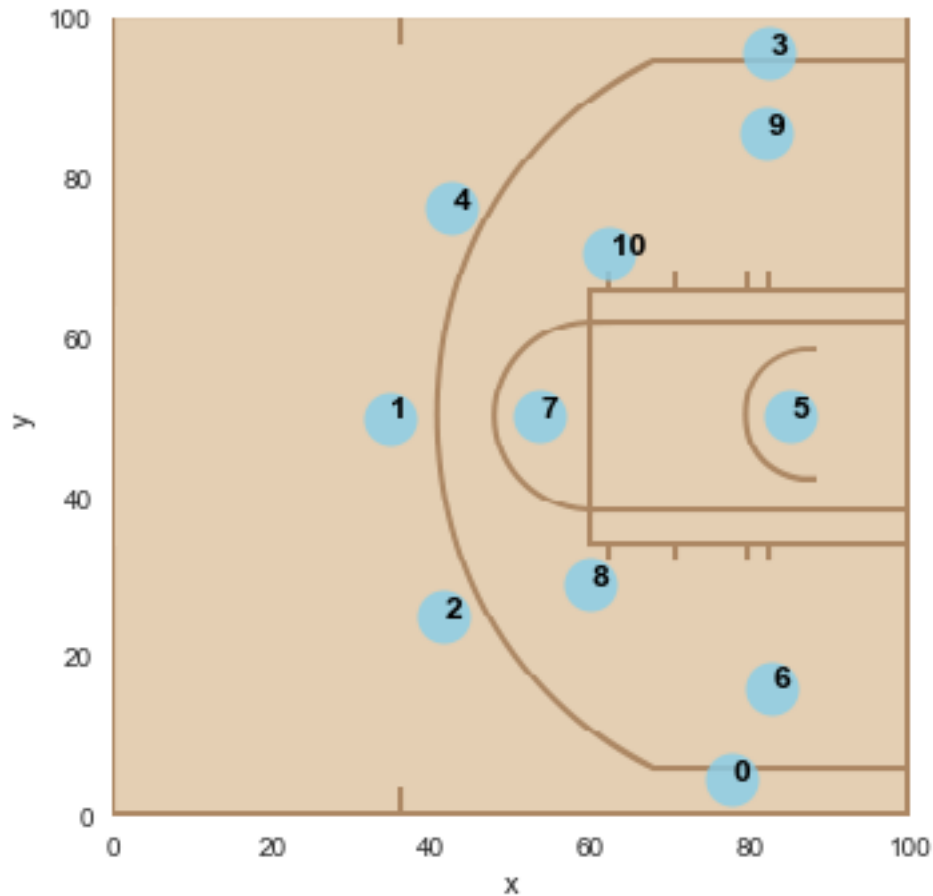
```

```

pl=sns.regplot(data=df, x="x", y="y", fit_reg=False, marker="o", color="sk
for line in range(0,df.shape[0]):
    pl.text(df.x[line]+0.2, df.y[line], df.group[line], horizontalalignmen
            color='black', weight='semibold')

plt.imshow(img, zorder=0, extent=[0, 100, 0, 100.0])
plt.grid(False)
plt.show()

```



```

In [24]: ## Delete the 3's for the parents of cluster 5
for i in range(0,len(ExpectedValue3)):
    if ExpectedValue3[i] == 0:
        Extra = i
del ExpectedValue3[Extra]

# Create expected values and round it for simplicity
ExpectedValue = ExpectedValue3 + ExpectedValue2
ExpectedValueRound = np.round_(ExpectedValue, decimals=2)

```

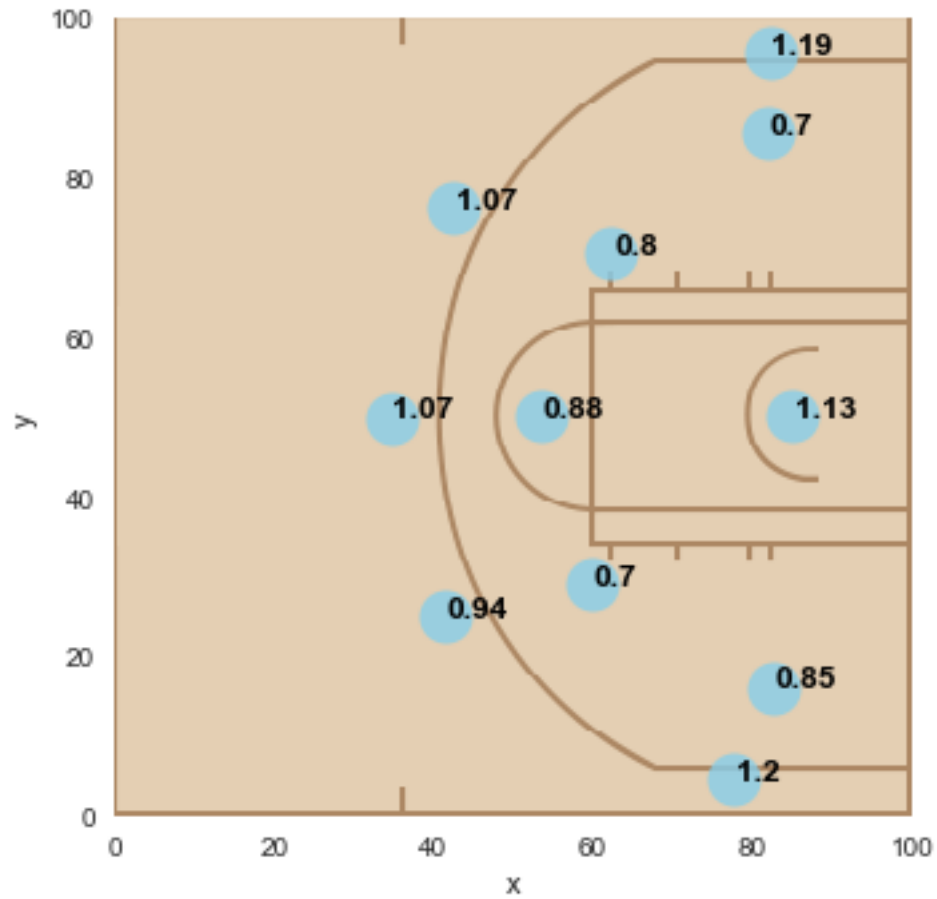
2.1 Analysis

Plot the expected values for the team

```
In [25]: ## Team chart with expected values
ExpectedValue = ExpectedValue3 + ExpectedValue2
df = pd.DataFrame({
    'x': AvLeft3 + AvLeft2,
    'y': AvTop3 + AvTop2,
    'group': [str(ExpectedValueRound[0]), str(ExpectedValueRound[1]), str(ExpectedValueRound[2]),
              str(ExpectedValueRound[3]), str(ExpectedValueRound[4]), str(ExpectedValueRound[5]),
              str(ExpectedValueRound[6]), str(ExpectedValueRound[7]), str(ExpectedValueRound[8]),
              str(ExpectedValueRound[9]), str(ExpectedValueRound[10])]
})

p1=sns.regplot(data=df, x="x", y="y", fit_reg=False, marker="o", color="sk
for line in range(0,df.shape[0]):
    p1.text(df.x[line]+0.2, df.y[line], df.group[line], horizontalalignmen
            size='medium', color='black', weight='semibold')

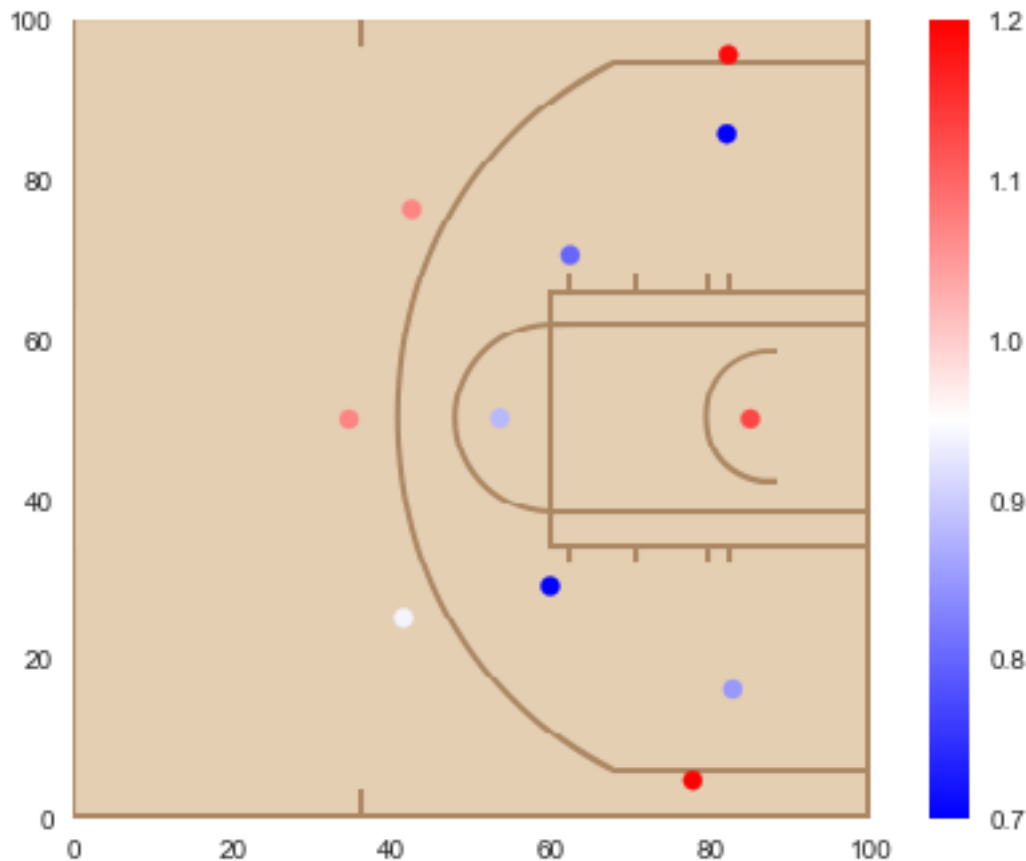
plt.imshow(img, zorder=0, extent=[0, 100, 0, 100.0])
plt.grid(False)
sns.plt.show()
```

Heat map for the team with color scale

```
In [26]: x = AvLeft3 + AvLeft2
         y = AvTop3 + AvTop2
         B = ExpectedValueRound
         low = np.min(B)
         high = np.max(B)
         cs = plt.scatter(x,y,c=B,cmap=plt.cm.bwr,vmin=low,vmax=high)

         plt.colorbar(cs)
         plt.imshow(img, zorder=0, extent=[0, 100, 0, 100.0])
         plt.grid(False)
         plt.show()
         # red is hot--high expected value. blue is cool--low expected value
```



As we can see, corner threes and twos in the key are the most efficient shots for the Jazz team overall. The longer jumper two's are the worst shot the Jazz can shoot as a team. Hence, from this plot we can take it that shooting a two pointer isn't really worth it, unless it is inside the paint. Using masking and loops with added logic, we are able to look at all the expected values on the court for each player. We will also print out the values and player name

```
In [27]: # 3 pointers
PlayerIDs = np.unique(ShotsPD['shooter'])
PlayerNames = np.unique(ShotsPD['shooter_name'])
NumOPlayers = len(PlayerNames)
for Name in range(0,NumOPlayers):
    PercMadeDif3 = []
    NumShots = []
    NumMade = []
    ExpectedValue3 =[]
    AvLeft3 = []
    AvTop3 =[]
    PtVal3 = 3
    PtVal2 = 2
```

```

PercMadeDif2 = []
NumShots3 = []
NumShots2 = []
NumMade3 = []
NumMade2 = []
ExpectedValue2 = []
ExpectedValueRound = []

AvLeft2 = []
AvTop2 = []

for i in range(0,6):
    Location = ShotsPD[(ShotsPD['LocationCluster']==i) & (ShotsPD['Th
                        & ( ShotsPD['shooter_name'] == PlayerNames[Name
    NumShots3.append(len(Location['made/missed']))
    NumMade3.append(len(Location[Location['made/missed']==1]))
    PercMade3 = 0
    if NumShots3[i] > 1:
        PercMade3 = NumMade3[i] / NumShots3[i]
        PercMadeDif3.append(PercMade3)
    else:
        PercMadeDif3.append(0)

    ExpectedValue3.append(PercMadeDif3[i]*PtVal3)

    AvLeft3.append(np.mean(Location['left']))
    AvTop3.append(np.mean(Location['top']))


    Location = ShotsPD[(ShotsPD['LocationCluster']==i) & (ShotsPD['Th
                        & ( ShotsPD['shooter_name'] == PlayerNames[Name
    NumShots2.append(len(Location['made/missed']))
    NumMade2.append(len(Location[Location['made/missed']==1]))
    PercMade2 = 0
    if NumShots2[i] > 1:
        PercMade2 = NumMade2[i] / NumShots2[i]
        PercMadeDif2.append(PercMade2)
    else:
        PercMadeDif2.append(0)
    ExpectedValue2.append(PercMadeDif2[i]*PtVal2)

    AvLeft2.append(np.mean(Location['left']))
    AvTop2.append(np.mean(Location['top']))

print('-----')

```

```

print(PlayerNames[Name])
print('-----')
print('---- 3 Pointers ----')
print('Percentages')
print(PercMadeDif3)
print('-----')
print('Expected Values')
print(ExpectedValue3)

print('---- 2 Pointers ----')
print('Percentages')
print(PercMadeDif2)
print('-----')
print('Expected Values')
print(ExpectedValue2)

for mm in range(0, len(ExpectedValue3)):
    if ExpectedValue3[mm] == 0:
        Extra = mm
del ExpectedValue3[Extra]

xx = np.isnan(AvLeft3)
for mm in range(0, len(AvLeft3)):
    if xx[mm] == True:
        DeleteVar = mm

del AvLeft3[DeleteVar]
del AvTop3[DeleteVar]

ExpectedValue = ExpectedValue3 + ExpectedValue2
ExpectedValueRound = np.round_(ExpectedValue, decimals=2)

AvLefts = AvLeft3 + AvLeft2
AvTops = AvTop3 + AvTop2

for u in range(0, len(AvLefts)):
    if math.isnan(AvLefts[u]):
        AvLefts[u]=90
    if math.isnan(AvTops[u]):
        AvTops[u]= 0

x = np.round(AvLefts, decimals=0)
y = np.round(AvTops, decimals=0)
valz = [str(ExpectedValueRound[0]), str(ExpectedValueRound[1]), str(ExpectedValueRound[2]),
        str(ExpectedValueRound[3]), str(ExpectedValueRound[4]), str(ExpectedValueRound[5]), str(ExpectedValueRound[6]), str(ExpectedValueRound[7]), str(ExpectedValueRound[8]), str(ExpectedValueRound[9])]

```

```

        str(ExpectedValueRound[6]),str(ExpectedValueRound[7]),str(ExpectedValueRound[8]),
        str(ExpectedValueRound[9]),str(ExpectedValueRound[10]))]
df = pd.DataFrame({
    'x': x,
    'y': y,
    'group': valz
})

p1=sns.regplot(data=df, x="x", y="y", fit_reg=False, marker="o", color="r",
               for line in range(0,df.shape[0]):
    p1.text(df.x[line]+0.2, df.y[line], df.group[line], horizontalalign="left",
            size='medium', color='black', weight='semibold')

plt.title(PlayerNames[Name])
plt.imshow(img, zorder=0, extent=[0, 100, 0, 100.0])
plt.grid(False)
plt.show()

```

Alec Burks

---- 3 Pointers ----

Percentages

[0, 0.3888888888888889, 0.34615384615384615, 0.225, 0.375, 0.38235294117647056]

Expected Values

[0, 1.1666666666666667, 1.0384615384615383, 0.675, 1.125, 1.1470588235294117]

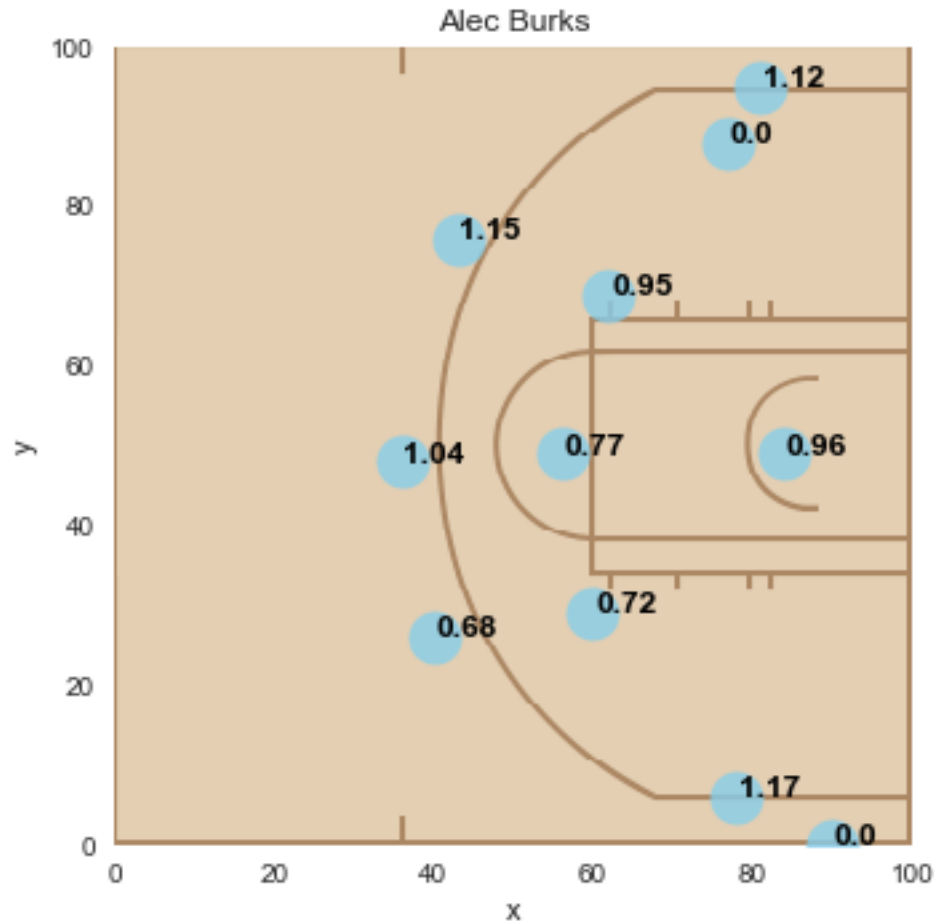
---- 2 Pointers ----

Percentages

[0.4816753926701571, 0, 0.38461538461538464, 0.358974358974359, 0.0, 0.47619047619047619]

Expected Values

[0.9633507853403142, 0, 0.7692307692307693, 0.717948717948718, 0.0, 0.9523809523809523]



Derrick Favors

---- 3 Pointers ----

Percentages

[0, 0.26666666666666666, 0.3333333333333333, 0, 0.19230769230769232, 0.0]

Expected Values

[0, 0.8, 1.0, 0, 0.576923076923077, 0.0]

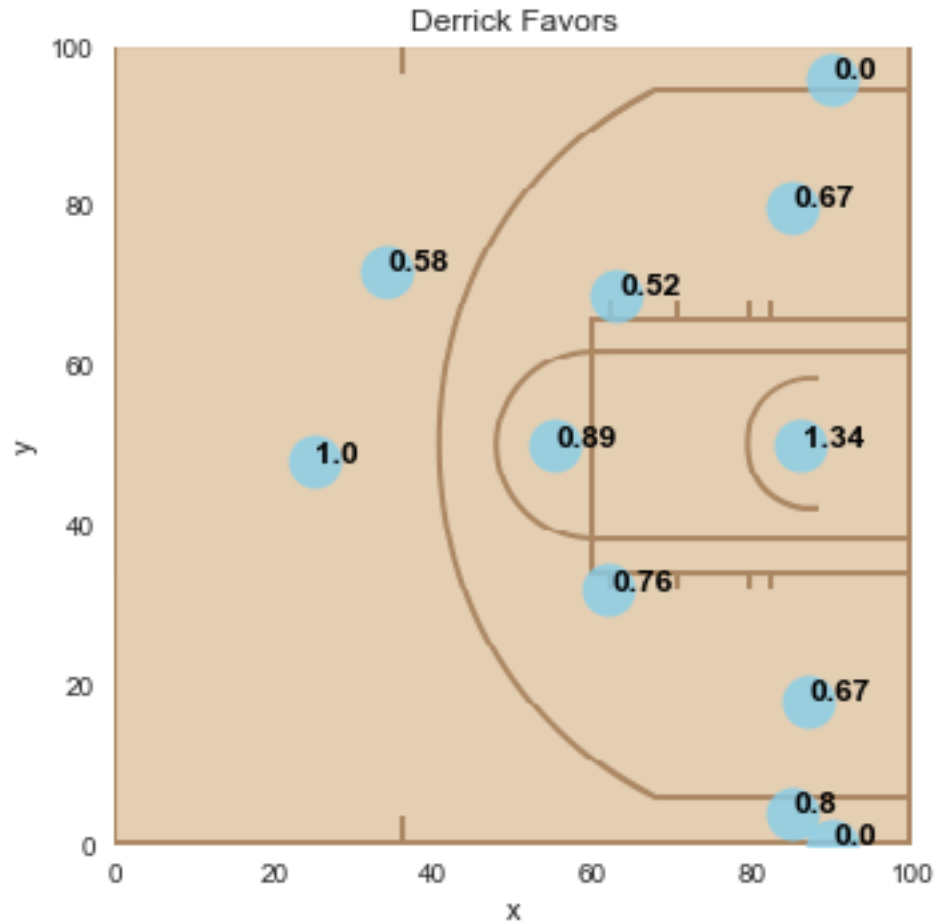
---- 2 Pointers ----

Percentages

[0.6680584551148225, 0.3333333333333333, 0.4473684210526316, 0.3793103448275862, 0.0]

Expected Values

[1.336116910229645, 0.6666666666666666, 0.8947368421052632, 0.7586206896551724, 0.0]



Donovan Mitchell

---- 3 Pointers ----

Percentages

[0, 0.36764705882352944, 0.35454545454545455, 0.3115942028985507, 0.5434782608695652]

Expected Values

[0, 1.1029411764705883, 1.0636363636363637, 0.9347826086956521, 1.6304347826086956]

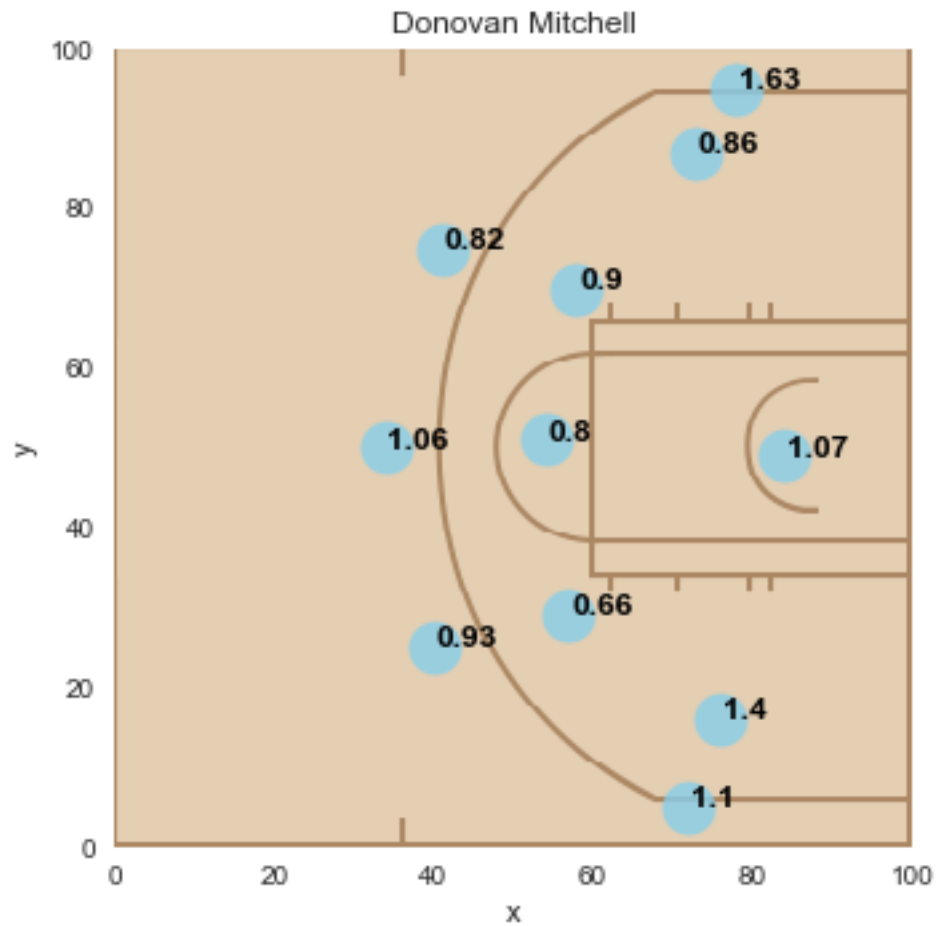
---- 2 Pointers ----

Percentages

[0.5358931552587646, 0.7, 0.4, 0.32941176470588235, 0.42857142857142855, 0.4487179487179487]

Expected Values

[1.0717863105175292, 1.4, 0.8, 0.6588235294117647, 0.8571428571428571, 0.8974358974358974]



Ekpe Udoh

---- 3 Pointers ----

Percentages

[0, 0, 0, 0, 0, 0, 0]

Expected Values

[0, 0, 0, 0, 0, 0, 0]

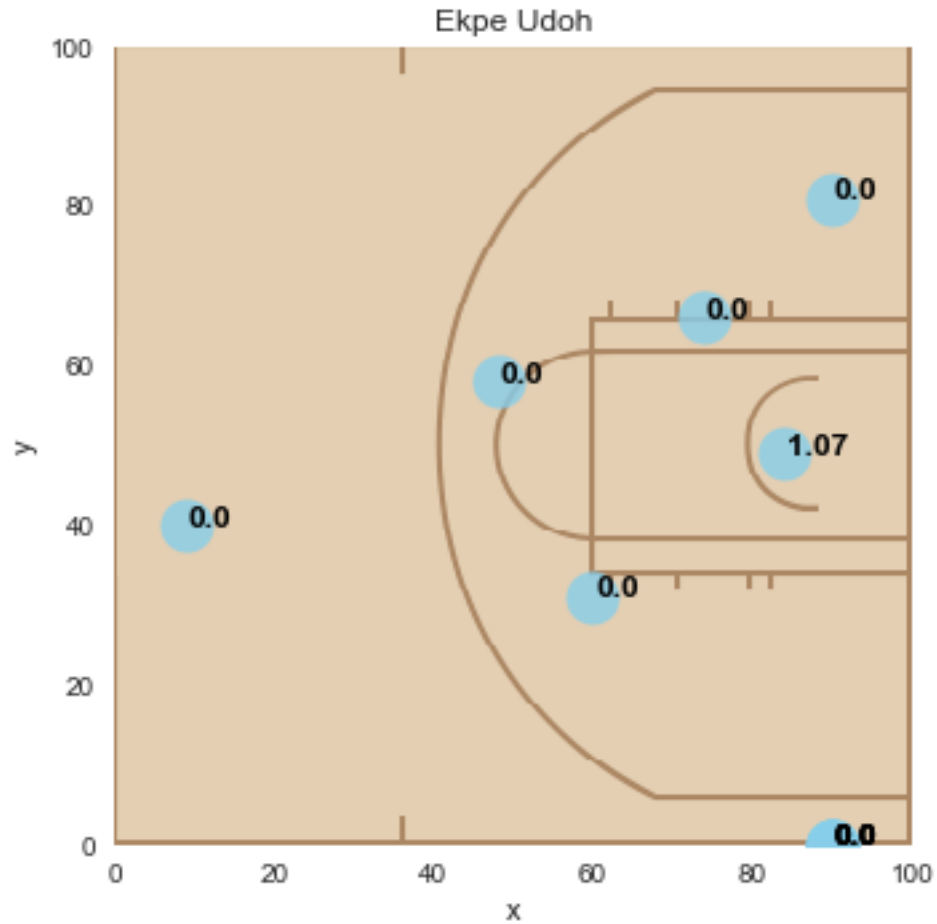
---- 2 Pointers ----

Percentages

[0.5357142857142857, 0, 0, 0.0, 0.0, 0]

Expected Values

[1.0714285714285714, 0, 0, 0.0, 0.0, 0]



Jae Crowder

---- 3 Pointers ----

Percentages

[0, 0.5833333333333334, 0.3, 0.2727272727272727, 0.21875, 0.2777777777777778]

Expected Values

[0, 1.75, 0.8999999999999999, 0.8181818181818181, 0.65625, 0.8333333333333334]

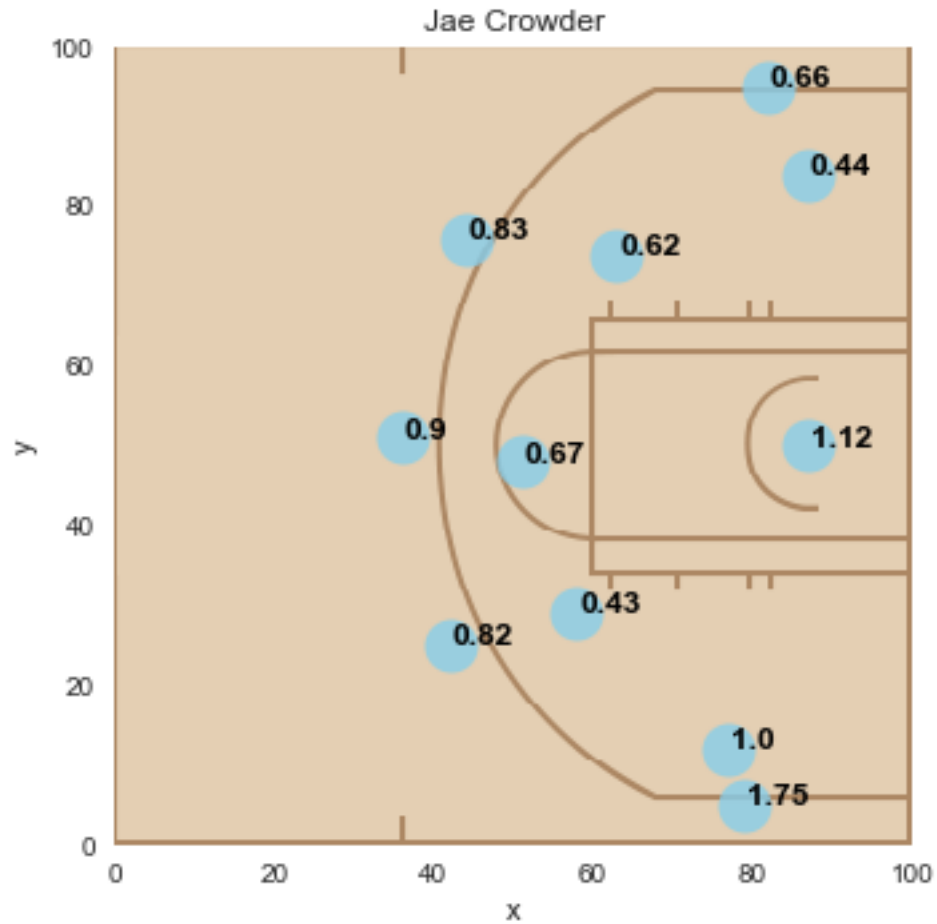
---- 2 Pointers ----

Percentages

[0.5617977528089888, 0.5, 0.3333333333333333, 0.21428571428571427, 0.2222222222222222]

Expected Values

[1.1235955056179776, 1.0, 0.6666666666666666, 0.42857142857142855, 0.4444444444444444]



Joe Ingles

---- 3 Pointers ----

Percentages

[0, 0.46296296296296297, 0.45614035087719296, 0.3655913978494624, 0.493975903614457]

Expected Values

[0, 1.3888888888888888, 1.3684210526315788, 1.096774193548387, 1.4819277108433735,

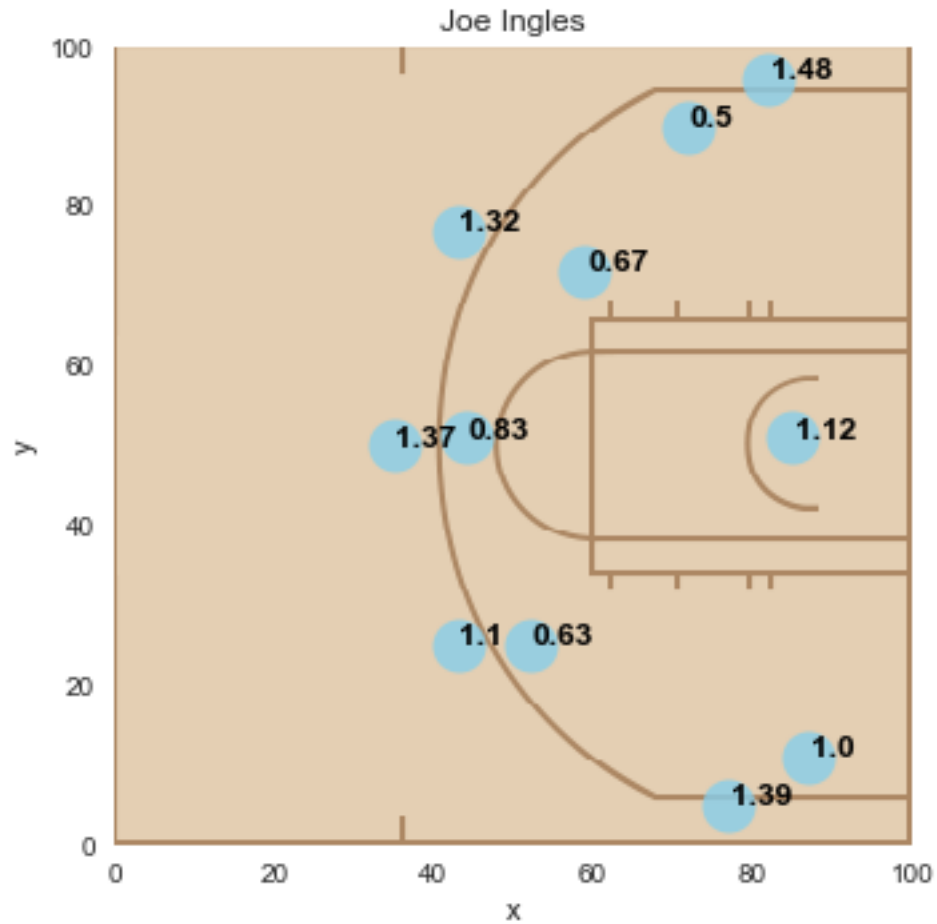
---- 2 Pointers ----

Percentages

[0.5621890547263682, 0.5, 0.41666666666666667, 0.3157894736842105, 0.25, 0.3333333333333333]

Expected Values

[1.1243781094527363, 1.0, 0.8333333333333334, 0.631578947368421, 0.5, 0.6666666666666666]



Joe Johnson

---- 3 Pointers ----

Percentages

[0, 0.3076923076923077, 0.4, 0.35714285714285715, 0.21739130434782608, 0.14285714285714285]

Expected Values

[0, 0.9230769230769231, 1.2000000000000002, 1.0714285714285714, 0.6521739130434783, 0.42857142857142855]

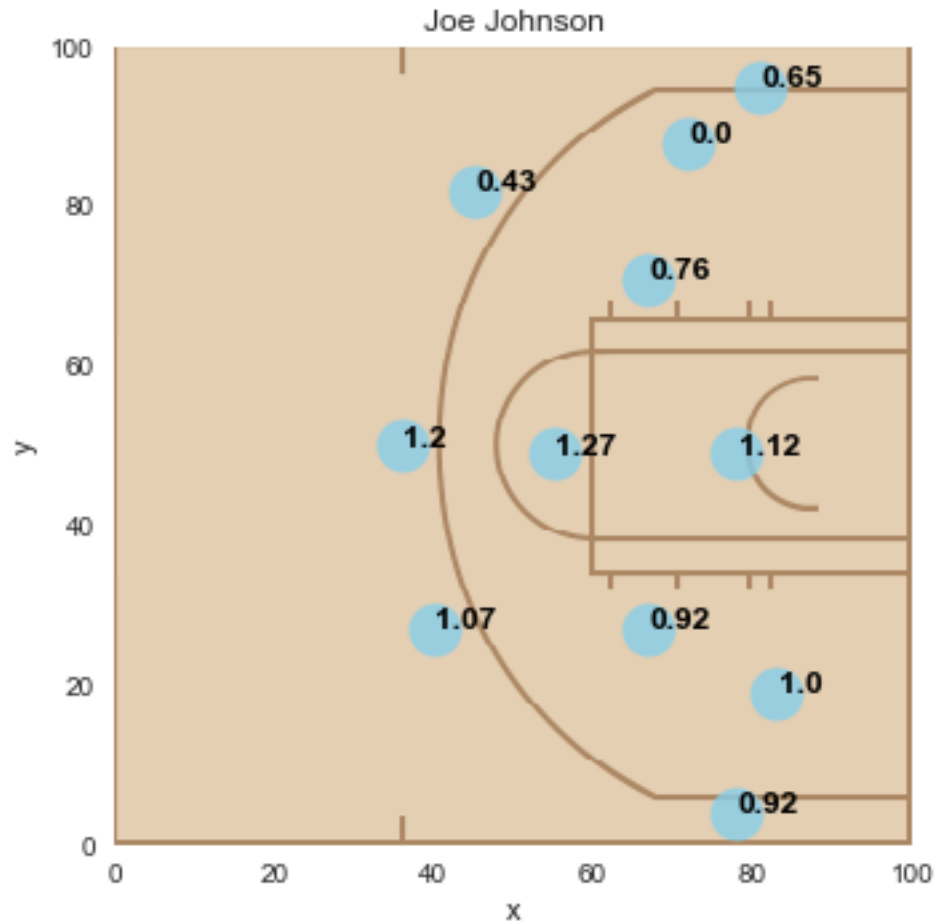
---- 2 Pointers ----

Percentages

[0.56, 0.5, 0.6363636363636364, 0.4583333333333333, 0.0, 0.38095238095238093]

Expected Values

[1.12, 1.0, 1.2727272727272727, 0.9166666666666666, 0.0, 0.7619047619047619]



Jonas Jerebko

---- 3 Pointers ----

Percentages

[0, 0.4883720930232558, 0.2857142857142857, 0.3333333333333333, 0.4772727272727273,

Expected Values

[0, 1.4651162790697674, 0.8571428571428571, 1.0, 1.4318181818181819, 1.064516129032,

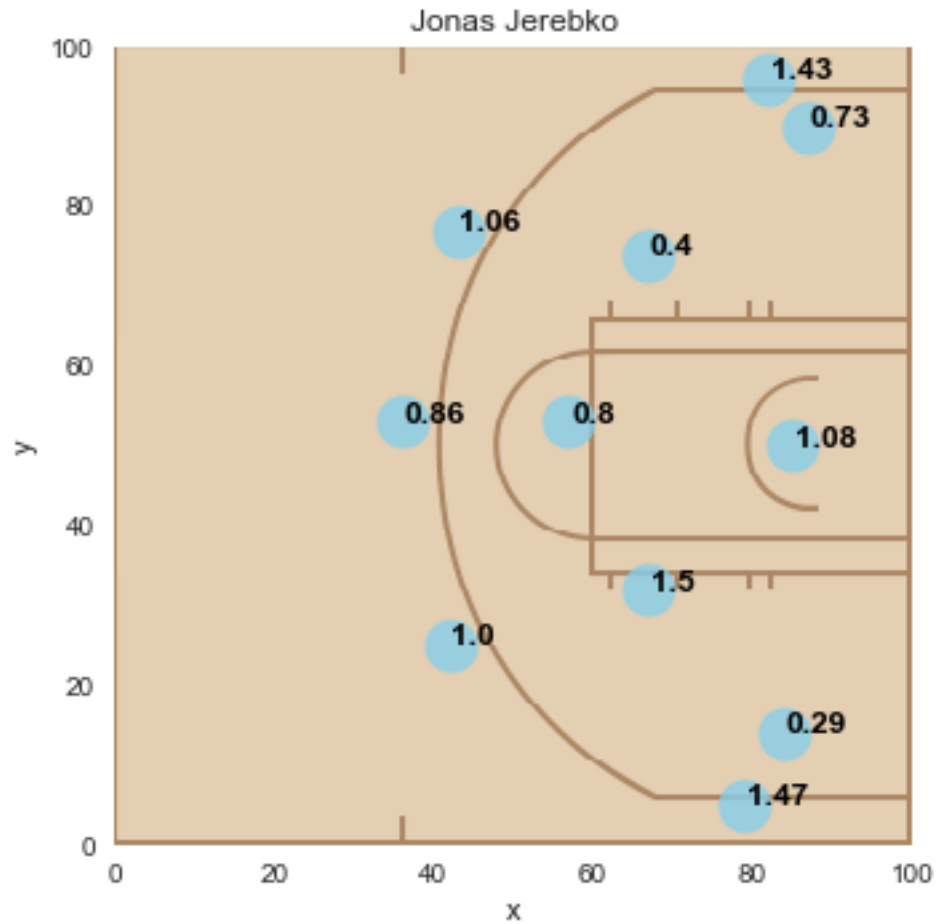
---- 2 Pointers ----

Percentages

[0.5424836601307189, 0.14285714285714285, 0.4, 0.75, 0.36363636363636365, 0.2]

Expected Values

[1.0849673202614378, 0.2857142857142857, 0.8, 1.5, 0.7272727272727273, 0.4]



Raul Neto

---- 3 Pointers ----

Percentages

[0, 0.5, 0.2, 0.38461538461538464, 0.46153846153846156, 0.375]

Expected Values

[0, 1.5, 0.6000000000000001, 1.153846153846154, 1.3846153846153846, 1.125]

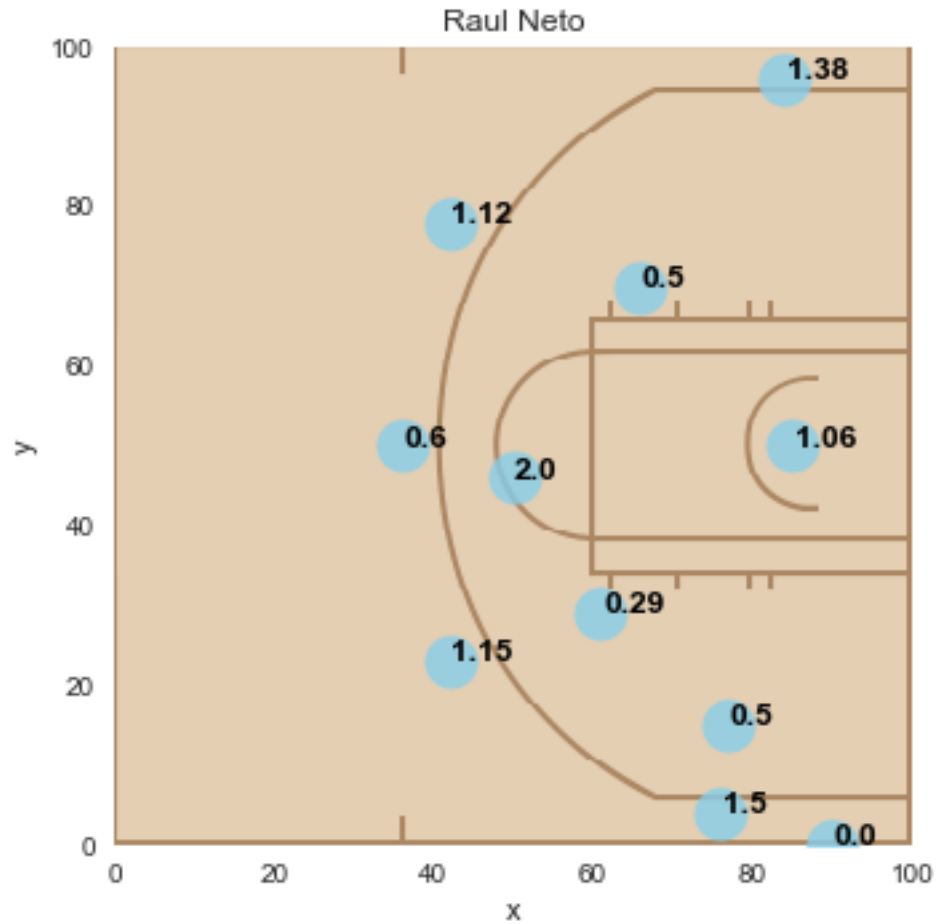
---- 2 Pointers ----

Percentages

[0.5294117647058824, 0.25, 1.0, 0.14285714285714285, 0, 0.25]

Expected Values

[1.0588235294117647, 0.5, 2.0, 0.2857142857142857, 0, 0.5]



 Ricky Rubio

 ---- 3 Pointers ----

Percentages

[0, 0.2619047619047619, 0.22727272727272727, 0.42857142857142855, 0.4090909090909091]

 Expected Values

[0, 0.7857142857142858, 0.6818181818181818, 1.2857142857142856, 1.2272727272727273]

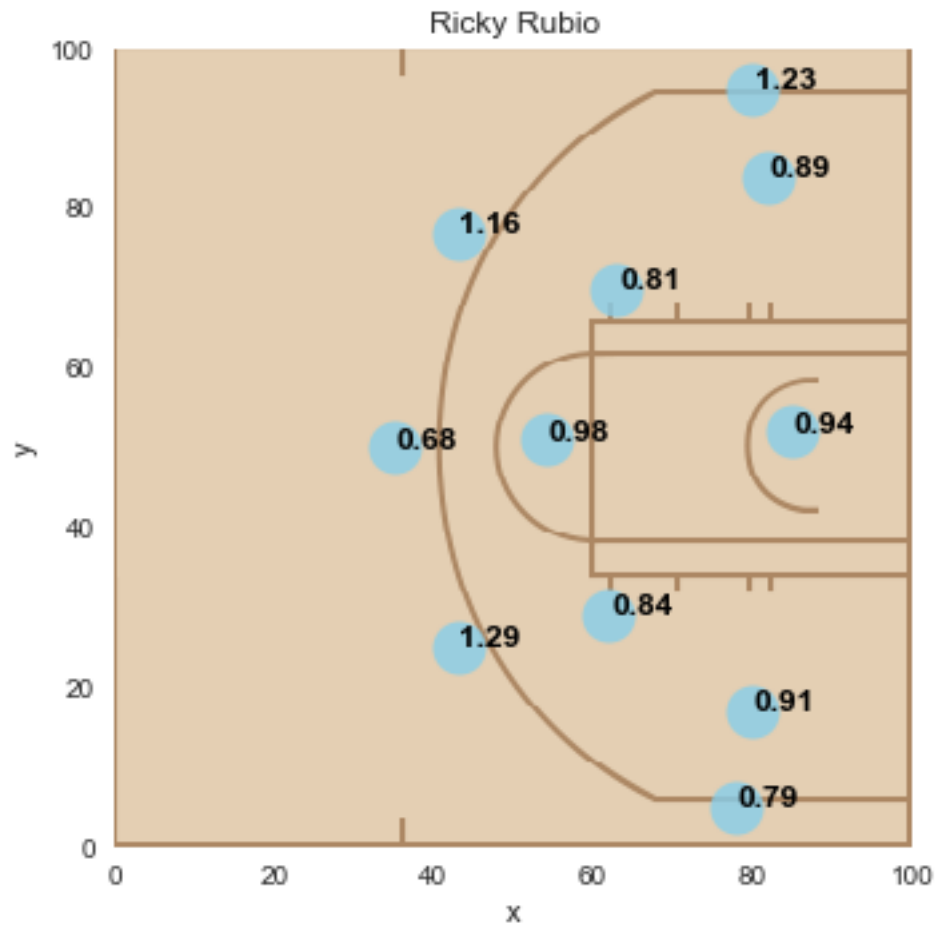
 ---- 2 Pointers ----

Percentages

[0.47107438016528924, 0.45454545454545453, 0.4883720930232558, 0.41935483870967744]

 Expected Values

[0.9421487603305785, 0.9090909090909091, 0.9767441860465116, 0.8387096774193549, 0.8387096774193549]



Rodney Hood

---- 3 Pointers ----

Percentages

[0, 0.4074074074074074, 0.4098360655737705, 0.27906976744186046, 0.28125, 0.4395604]

Expected Values

[0, 1.2222222222222222, 1.2295081967213115, 0.8372093023255813, 0.84375, 1.318681318]

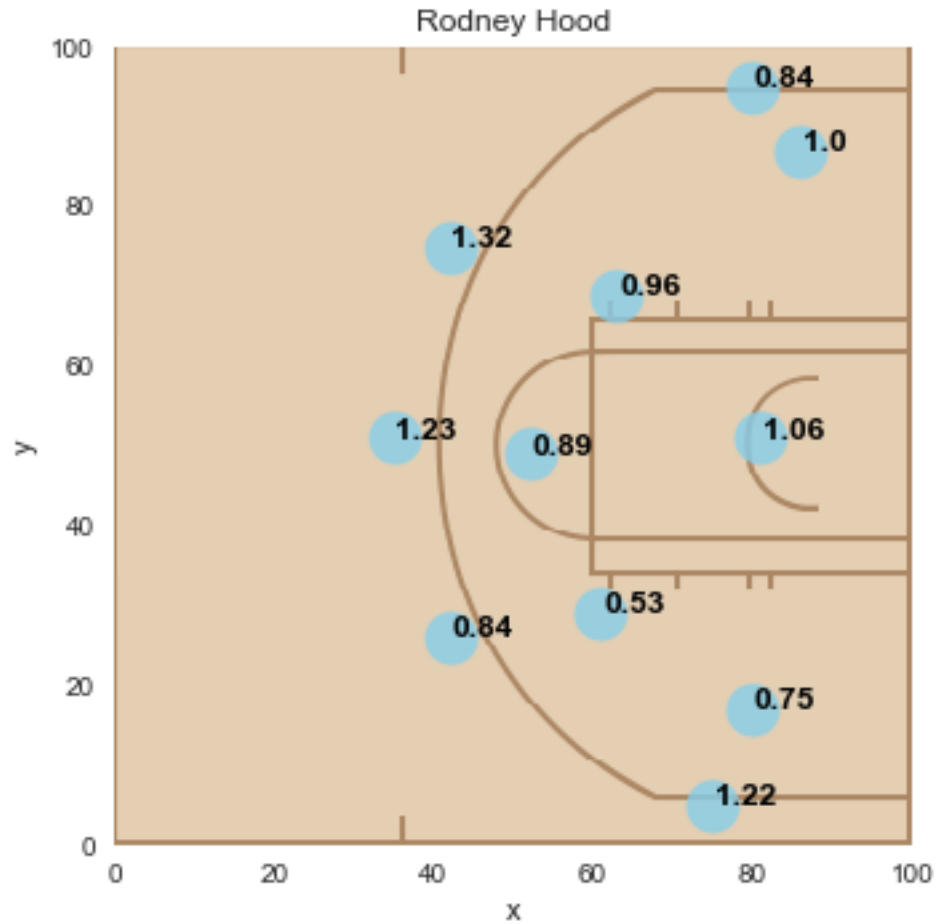
---- 2 Pointers ----

Percentages

[0.5289855072463768, 0.375, 0.4444444444444444, 0.2653061224489796, 0.5, 0.48]

Expected Values

[1.0579710144927537, 0.75, 0.8888888888888888, 0.5306122448979592, 1.0, 0.96]



 Royce O'Neale

 ---- 3 Pointers ----

Percentages

[0, 0.34285714285714286, 0.36363636363636365, 0.16666666666666666, 0.36842105263157894]

 Expected Values

[0, 1.0285714285714285, 1.0909090909090908, 0.5, 1.1052631578947367, 1.25]

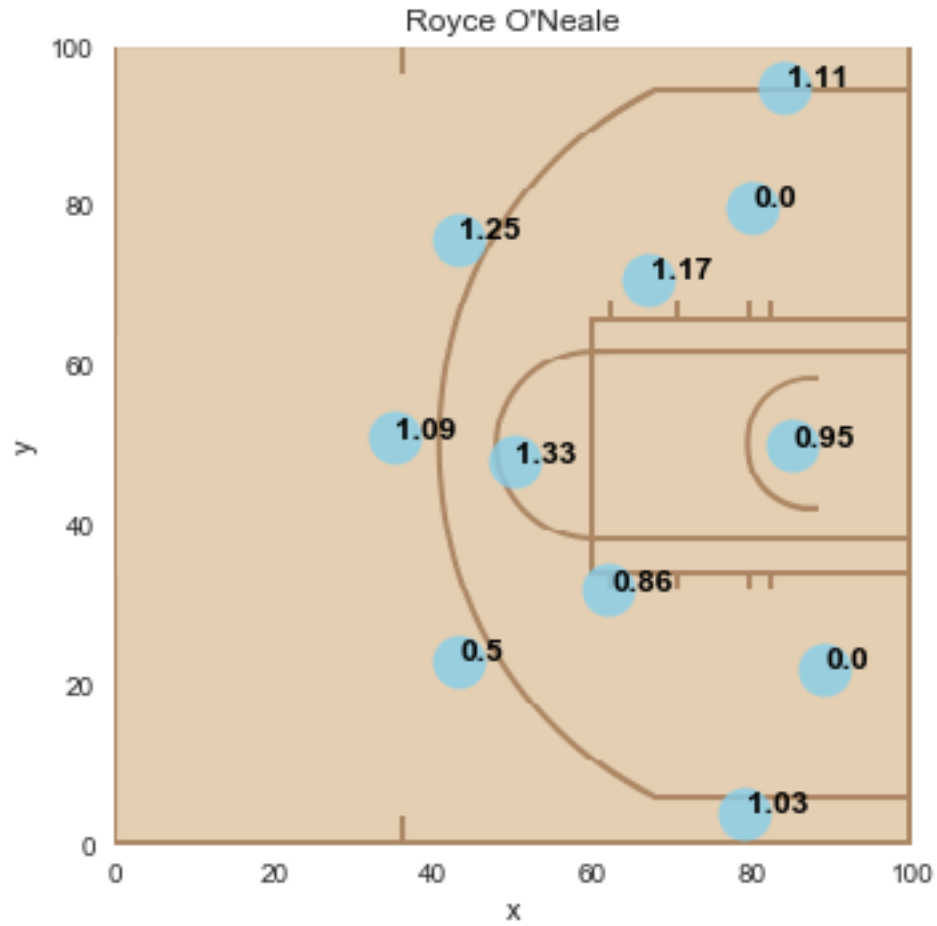
 ---- 2 Pointers ----

Percentages

[0.4726027397260274, 0, 0.6666666666666666, 0.42857142857142855, 0.0, 0.5833333333333333]

 Expected Values

[0.9452054794520548, 0, 1.3333333333333333, 0.8571428571428571, 0.0, 1.1666666666666666]



 Rudy Gobert

 ---- 3 Pointers ----

Percentages

[0, 0, 0, 0, 0, 0, 0]

 Expected Values

[0, 0, 0, 0, 0, 0, 0]

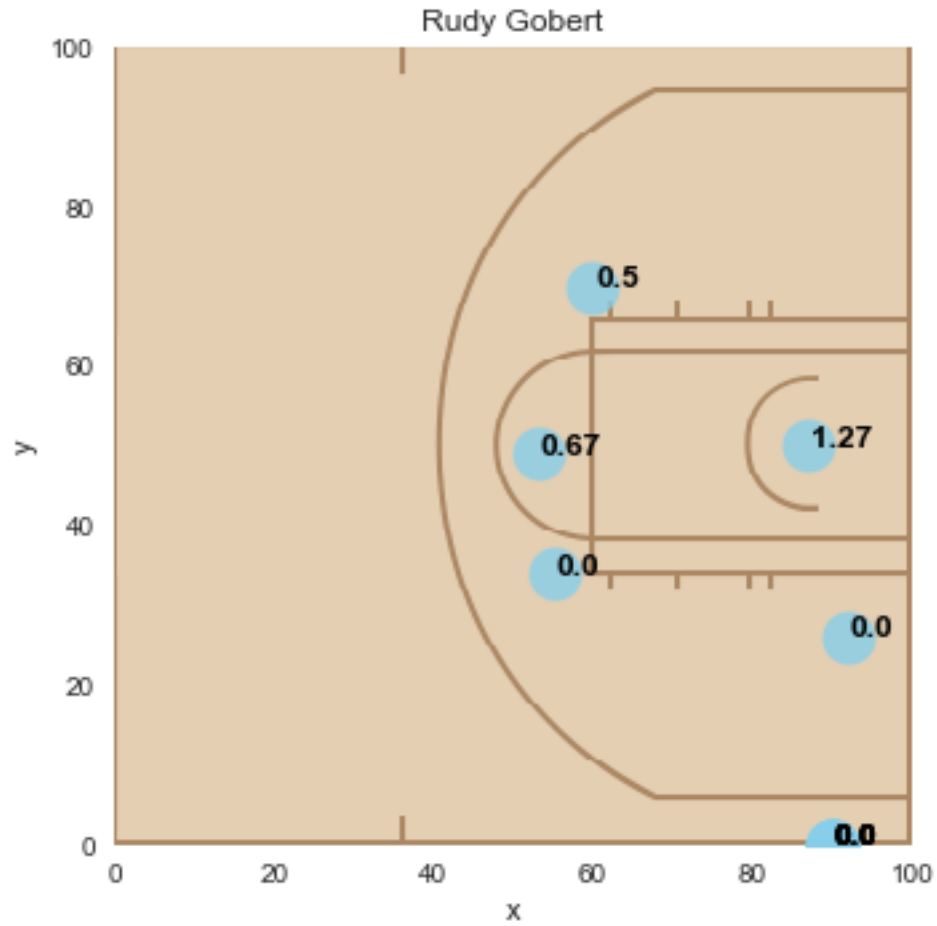
---- 2 Pointers ----

Percentages

[0.636150234741784, 0, 0.3333333333333333, 0, 0, 0.25]

 Expected Values

[1.272300469483568, 0, 0.6666666666666666, 0, 0, 0.5]



 Thabo Sefolosha

 ---- 3 Pointers ----

Percentages

[0, 0.45, 0.3333333333333333, 0.23076923076923078, 0.42857142857142855, 0.35714285714285715]

 Expected Values

[0, 1.35, 1.0, 0.6923076923076923, 1.2857142857142856, 1.0714285714285714]

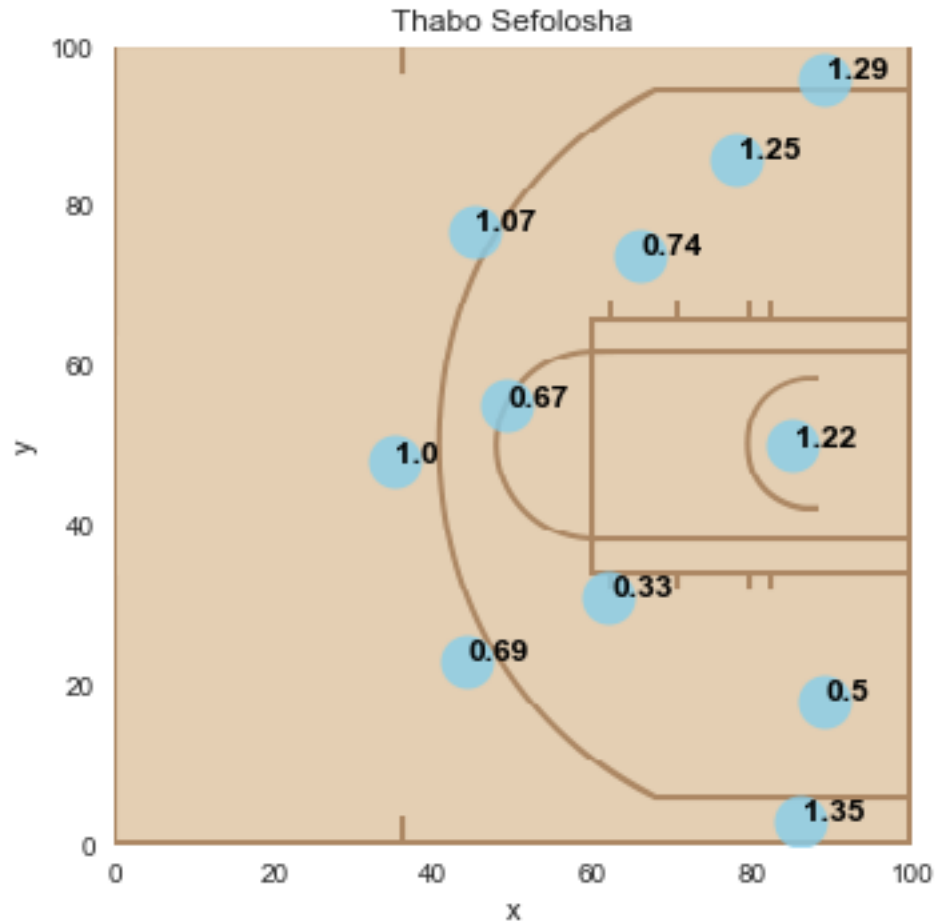
 ---- 2 Pointers ----

Percentages

[0.6120689655172413, 0.25, 0.3333333333333333, 0.16666666666666666, 0.625, 0.3684210526315789]

 Expected Values

[1.2241379310344827, 0.5, 0.6666666666666666, 0.3333333333333333, 1.25, 0.7368421052631579]



2.2 Statistical Significance

At low sampling rates, a given shot could have a high expected value purely by chance. For example, 25% of the time, a 50% shooter will make two shots in a row. If those two shots are the only sample we have, we might conclude that the shooter is a 100% shooter. For this reason, it is important to determine if results are statistically significant, or if they most likely occurred by chance. Hypothesis testing is a good way to measure statistical significance. It involves formulating a null hypothesis that you would like to disprove, calculating the probability of a given result occurring if you were to assume that the null hypothesis is true, and rejecting the null hypothesis if that probability is sufficiently low.

2.2.1 Hypothesis Testing:

Player p-test: - Take as the null hypothesis that the shooting percentage for a given shot is less than or equal to the average percentage for that player for threes or twos.

Team p-test: - Take as the null hypothesis that the shooting percentage for a given shot is less than or equal to the average percentage for the whole team for threes or twos.

Location p-test: - Take as the null hypothesis that the shooting percentage for a given shot is less than or equal to the average percentage for the whole team from that location.

```
In [28]: shots_array = np.array([["shooter", "three", "cluster", 'num_shots', "num_
                                "Player_p", "Team_p", "Location_p"]])

threemask = ShotsPD["ThreePt"] == 1
twomask = ShotsPD["ThreePt"] == 0
threePD = ShotsPD[threemask]
twoPD = ShotsPD[twomask]

for shooter in threePD["shooter_name"].unique():
    mask = threePD["shooter_name"] == shooter
    ShooterShots = threePD[mask]
    for cluster in ShooterShots["LocationCluster"].unique():
        mask2 = ShooterShots["LocationCluster"] == cluster
        ClusterShots = ShooterShots[mask2]
        num_shots = len(ClusterShots)
        mask_made = ClusterShots["made/missed"] == 1
        num_makes = len(ClusterShots[mask_made])
        pct = num_makes/num_shots
        expectedval = pct*3
        # player p-value
        avg_pct = len(ShooterShots[ShooterShots["made/missed"]==1])/len(ShooterShots)
        # total 3 pt avg for this player
        mu = num_shots*avg_pct # mean number of makes for this cluster as
        sigma = sc.sqrt(mu*(1-avg_pct)) # standard deviation?
        player_p = 1-norm.cdf(num_makes, loc=mu, scale=sigma)
        # team p-value
        avg_pct = len(threePD[threePD["made/missed"]==1])/len(threePD)
        mu = num_shots*avg_pct
        sigma = sc.sqrt(mu*(1-avg_pct))
        team_p = 1-norm.cdf(num_makes, loc=mu, scale=sigma)
        # location p-value
        teamClusterPD = threePD[threePD["LocationCluster"] == cluster]
        avg_pct = len(teamClusterPD[teamClusterPD["made/missed"]==1])/len(teamClusterPD)
        # team 3 pt avg from this cluster
        mu = num_shots*avg_pct
        sigma = sc.sqrt(mu*(1-avg_pct))
        location_p = 1-norm.cdf(num_makes, loc=mu, scale=sigma)

    shots_array = np.append(shots_array, [[shooter, 1, cluster, num_shots,
                                            num_makes, pct, expectedval,
                                            team_p, location_p]], axis=0)

for shooter in twoPD["shooter_name"].unique():
    mask = twoPD["shooter_name"] == shooter
    ShooterShots = twoPD[mask]
    for cluster in ShooterShots["LocationCluster"].unique():
        mask2 = ShooterShots["LocationCluster"] == cluster
        ClusterShots = ShooterShots[mask2]
        num_shots = len(ClusterShots)
        mask_made = ClusterShots["made/missed"] == 1
        num_makes = len(ClusterShots[mask_made])
        pct = num_makes/num_shots
        expectedval = pct*2
        # player p-value
        avg_pct = len(ShooterShots[ShooterShots["made/missed"]==1])/len(ShooterShots)
        # total 2 pt avg for this player
        mu = num_shots*avg_pct # mean number of makes for this cluster as
        sigma = sc.sqrt(mu*(1-avg_pct)) # standard deviation?
        player_p = 1-norm.cdf(num_makes, loc=mu, scale=sigma)
        # team p-value
        avg_pct = len(twoPD[twoPD["made/missed"]==1])/len(twoPD)
        mu = num_shots*avg_pct
        sigma = sc.sqrt(mu*(1-avg_pct))
        team_p = 1-norm.cdf(num_makes, loc=mu, scale=sigma)
        # location p-value
        teamClusterPD = twoPD[twoPD["LocationCluster"] == cluster]
        avg_pct = len(teamClusterPD[teamClusterPD["made/missed"]==1])/len(teamClusterPD)
        # team 2 pt avg from this cluster
        mu = num_shots*avg_pct
        sigma = sc.sqrt(mu*(1-avg_pct))
        location_p = 1-norm.cdf(num_makes, loc=mu, scale=sigma)

    shots_array = np.append(shots_array, [[shooter, 0, cluster, num_shots,
                                            num_makes, pct, expectedval,
                                            team_p, location_p]], axis=0)
```

```

mask2 = ShooterShots["LocationCluster"] == cluster
ClusterShots = ShooterShots[mask2]
num_shots = len(ClusterShots)
mask_made = ClusterShots["made/missed"] == 1
num_makes = len(ClusterShots[mask_made])
pct = num_makes/num_shots
expectedval = pct*2

avg_pct = len(ShooterShots[ShooterShots["made/missed"]==1])/len(ShooterShots)
#total 3 pt avg for this player
mu = num_shots*avg_pct # mean number of makes for this cluster
sigma = sc.sqrt(mu*(1-avg_pct)) # standard deviation?
player_p = 1-norm.cdf(num_makes, loc=mu, scale=sigma)
# team p-value
avg_pct = len(twoPD[twoPD["made/missed"]==1])/len(twoPD) # total
mu = num_shots*avg_pct
sigma = sc.sqrt(mu*(1-avg_pct))
team_p = 1-norm.cdf(num_makes, loc=mu, scale=sigma)
# location p-value
teamClusterPD = twoPD[twoPD["LocationCluster"] == cluster]
avg_pct = len(teamClusterPD[teamClusterPD["made/missed"]==1])/len(teamClusterPD)
# team 3 pt avg from this cluster
mu = num_shots*avg_pct
sigma = sc.sqrt(mu*(1-avg_pct))
location_p = 1-norm.cdf(num_makes, loc=mu, scale=sigma)

shots_array = np.append(shots_array, [[shooter, 0, cluster, num_shots,
                                         num_makes, pct, expectedval,
                                         team_p, location_p]], axis=0)

/Users/averysmith/anaconda/lib/python3.6/site-packages/scipy/stats/_distn_infrastructure.py:101: RuntimeWarning: divide by zero encountered in true_divide
  x = np.asarray((x - loc)/scale, dtype=dtyp)

In [29]: NewLocationPD = pd.DataFrame(data=shots_array[1:],
                                     columns=shots_array[0])

In [30]: NewLocationPD["three"] = NewLocationPD["three"].map(int)
NewLocationPD["cluster"] = NewLocationPD["cluster"].map(int)
NewLocationPD["num_shots"] = NewLocationPD["num_shots"].map(int)
NewLocationPD["num_makes"] = NewLocationPD["num_makes"].map(int)
NewLocationPD["pct"] = NewLocationPD["pct"].map(float)
NewLocationPD["expectedval"] = NewLocationPD["expectedval"].map(float)
NewLocationPD["Player_p"] = NewLocationPD["Player_p"].map(float)
NewLocationPD["Team_p"] = NewLocationPD["Team_p"].map(float)
NewLocationPD["Location_p"] = NewLocationPD["Location_p"].map(float)
print(NewLocationPD.dtypes, '\n')

shooter      object
three        int64

```

```

cluster          int64
num_shots        int64
num_makes        int64
pct             float64
expectedval      float64
Player_p        float64
Team_p          float64
Location_p      float64
dtype: object

```

```

In [31]: # print the 40 best expected value shots()
NewLocationPD.sort_values(by=["expectedval"], ascending=False).head(40)

```

```

Out[31]:

```

	shooter	three	cluster	num_shots	num_makes	pct	\
120	Raul Neto	0	2	2	2	1.000000	
68	Rudy Gobert	0	3	1	1	1.000000	
127	Royce O'Neale	0	1	1	1	1.000000	
56	Jae Crowder	1	1	24	14	0.583333	
15	Donovan Mitchell	1	4	46	25	0.543478	
43	Raul Neto	1	1	6	3	0.500000	
133	Jonas Jerebko	0	3	4	3	0.750000	
2	Joe Ingles	1	4	83	41	0.493976	
53	Jonas Jerebko	1	1	43	21	0.488372	
51	Jonas Jerebko	1	4	44	21	0.477273	
76	Donovan Mitchell	0	1	10	7	0.700000	
1	Joe Ingles	1	1	108	50	0.462963	
41	Raul Neto	1	4	13	6	0.461538	
4	Joe Ingles	1	2	57	26	0.456140	
31	Thabo Sefolosha	1	1	20	9	0.450000	
60	Derrick Favors	0	0	479	320	0.668058	
125	Royce O'Neale	0	2	3	2	0.666667	
10	Rodney Hood	1	5	91	40	0.439560	
3	Joe Ingles	1	5	98	43	0.438776	
27	Ricky Rubio	1	3	35	15	0.428571	
30	Thabo Sefolosha	1	4	28	12	0.428571	
85	Joe Johnson	0	2	11	7	0.636364	
66	Rudy Gobert	0	0	426	271	0.636150	
48	Royce O'Neale	1	5	12	5	0.416667	
104	Thabo Sefolosha	0	4	8	5	0.625000	
13	Rodney Hood	1	2	61	25	0.409836	
24	Ricky Rubio	1	4	66	27	0.409091	
100	Thabo Sefolosha	0	0	116	71	0.612069	
12	Rodney Hood	1	1	27	11	0.407407	
6	Joe Johnson	1	2	5	2	0.400000	
126	Royce O'Neale	0	5	12	7	0.583333	
37	Alec Burks	1	1	18	7	0.388889	

26	Ricky Rubio	1	5	85	33	0.388235
42	Raul Neto	1	3	13	5	0.384615
35	Alec Burks	1	5	34	13	0.382353
38	Alec Burks	1	4	16	6	0.375000
40	Raul Neto	1	5	8	3	0.375000
106	Joe Ingles	0	0	201	113	0.562189
135	Jae Crowder	0	0	89	50	0.561798
83	Joe Johnson	0	0	75	42	0.560000

	expectedval	Player_p	Team_p	Location_p
120	2.000000	0.070967	8.451872e-02	0.055820
68	2.000000	0.219013	1.654043e-01	0.085393
127	2.000000	0.148750	1.654043e-01	0.121673
56	1.750000	0.002547	1.302116e-02	0.033736
15	1.630435	0.001599	5.874529e-03	0.022075
43	1.500000	0.308538	2.455023e-01	0.309358
133	1.500000	0.166598	1.724358e-01	0.045564
2	1.481928	0.169766	7.192182e-03	0.037354
53	1.465116	0.170106	4.596406e-02	0.119662
51	1.431818	0.207412	6.035049e-02	0.142014
76	1.400000	0.099649	1.195645e-01	0.038416
1	1.388889	0.329792	1.690596e-02	0.092435
41	1.384615	0.325306	2.340261e-01	0.320453
4	1.368421	0.414382	7.567107e-02	0.055972
31	1.350000	0.267932	2.139309e-01	0.325538
60	1.336117	0.000679	7.471357e-12	0.000003
125	1.333333	0.258235	2.983175e-01	0.216022
10	1.318681	0.128747	6.886178e-02	0.050148
3	1.316327	0.524938	6.372811e-02	0.045587
27	1.285714	0.174564	2.160885e-01	0.073353
30	1.285714	0.308814	2.411689e-01	0.371386
85	1.272727	0.195294	2.082976e-01	0.096441
66	1.272300	0.308772	2.249937e-07	0.001502
48	1.250000	0.270146	3.541097e-01	0.333140
104	1.250000	0.329155	2.648511e-01	0.052477
13	1.229508	0.326626	2.317928e-01	0.187069
24	1.227273	0.169904	2.266797e-01	0.428352
100	1.224138	0.080125	1.723821e-02	0.152624
12	1.222222	0.392461	3.222499e-01	0.470582
6	1.200000	0.253123	4.348063e-01	0.417421
126	1.166667	0.235837	3.152880e-01	0.096841
37	1.166667	0.292241	4.154618e-01	0.539860
26	1.164706	0.247965	3.258260e-01	0.274026
42	1.153846	0.545075	4.406020e-01	0.293500
35	1.147059	0.251295	4.151666e-01	0.378921
38	1.125000	0.345582	4.657783e-01	0.575210
40	1.125000	0.557383	4.757867e-01	0.457732
106	1.124378	0.053589	8.558441e-02	0.530618

```

135      1.123596  0.019917  1.832057e-01    0.523351
83      1.120000  0.179038  2.124386e-01    0.533935

```

```

In [32]: # identify the mean location for each of the six clusters identified through
# (ignoring two and three point differences)
left_coordinates = np.array([])
top_coordinates = np.array([])
clusters = np.arange(0, 6)
for cluster in clusters:
    cluster_mask = ShotsPD['LocationCluster'] == cluster
    cluster_df = ShotsPD[cluster_mask]
    left_coord = cluster_df["left"].mean()
    top_coord = cluster_df["top"].mean()
    left_coordinates = np.append(left_coordinates, left_coord)
    top_coordinates = np.append(top_coordinates, top_coord)

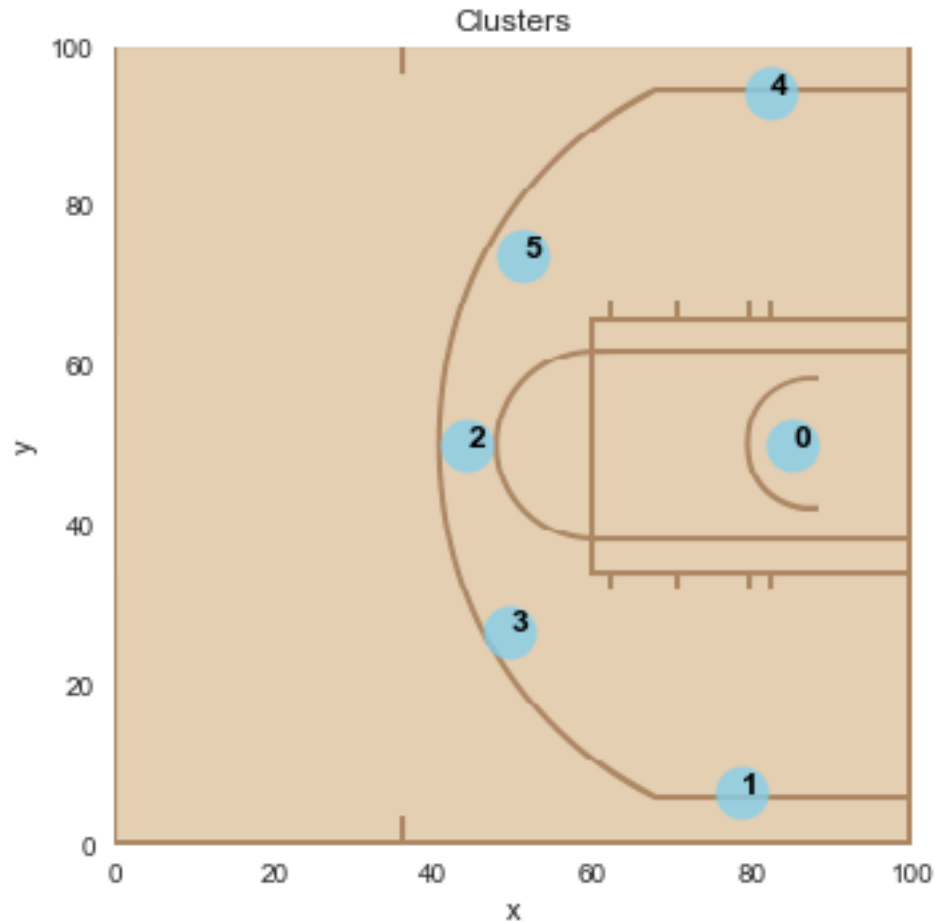
In [33]: # plot the mean location of each cluster on the court for reference purposes
import seaborn as sns

df = pd.DataFrame({
    'x': left_coordinates,
    'y': top_coordinates,
    'group': clusters
})

p1=sns.regplot(data=df, x="x", y="y", fit_reg=False, marker="o", color="skate",
               for line in range(0,df.shape[0]):
                    p1.text(df.x[line]+0.2, df.y[line], df.group[line], horizontalalignment='right',
                           size='medium', color='black', weight='semibold')

plt.title('Clusters')
plt.imshow(img, zorder=0, extent=[0, 100, 0, 100.0])
plt.grid(False)
plt.show()

```

We choose a threshold for significance of $p < .05$ in order to reject the null hypothesis.

For each p-test we used, we filter the results for only the statistically significant shots.

The way to interpret these p-values is: if that location was not better than average (for the player or team as a whole), then the p-value represents the probability that the player would still, by coincidence, shoot as well from that location as they did.

Player p-test

```
In [34]: statistically_significant_mask = NewLocationPD["Player_p"] < .05
         SignificantPD = NewLocationPD[statistically_significant_mask]
         SignificantPD.sort_values(by=["expectedval"], ascending=False)
```

```
Out [34]:
```

	shooter	three	cluster	num_shots	num_makes	pct	\
56	Jae Crowder	1	1	24	14	0.583333	
15	Donovan Mitchell	1	4	46	25	0.543478	
60	Derrick Favors	0	0	479	320	0.668058	
135	Jae Crowder	0	0	89	50	0.561798	
71	Donovan Mitchell	0	0	599	321	0.535893	

	expectedval	Player_p	Team_p	Location_p
56	1.750000	0.002547	1.302116e-02	0.033736
15	1.630435	0.001599	5.874529e-03	0.022075
60	1.336117	0.000679	7.471357e-12	0.000003
135	1.123596	0.019917	1.832057e-01	0.523351
71	1.071786	0.028644	1.412531e-01	0.923749

This indicates that Jae Crowder shoots significantly better from the right corner than he does from any other three point location, and Donovan Mitchell shoots significantly better from the left corner than he does from any other three point location. This information could help coaches modify the offense so that Crowder and Mitchell spend more time on the right and left side respectively.

Unsurprisingly, we found that Derrick Favors, Jae Crowder, and Donovan Mitchell all shoot better from the post than they do from any other two-point position. That is unsurprising because the post is much closer to the basket than other locations, and is expected to have a better shooting percentage.

```
In [35]: statistically_significant_mask = NewLocationPD["Team_p"] < .05
TeamSignificantPD = NewLocationPD[statistically_significant_mask]
TeamSignificantPD.sort_values(by=["expectedval"], ascending=False)
```

```
Out [35]:
```

	shooter	three	cluster	num_shots	num_makes	pct	\
56	Jae Crowder	1	1	24	14	0.583333	
15	Donovan Mitchell	1	4	46	25	0.543478	
2	Joe Ingles	1	4	83	41	0.493976	
53	Jonas Jerebko	1	1	43	21	0.488372	
1	Joe Ingles	1	1	108	50	0.462963	
60	Derrick Favors	0	0	479	320	0.668058	
66	Rudy Gobert	0	0	426	271	0.636150	
100	Thabo Sefolosha	0	0	116	71	0.612069	

	expectedval	Player_p	Team_p	Location_p
56	1.750000	0.002547	1.302116e-02	0.033736
15	1.630435	0.001599	5.874529e-03	0.022075
2	1.481928	0.169766	7.192182e-03	0.037354
53	1.465116	0.170106	4.596406e-02	0.119662
1	1.388889	0.329792	1.690596e-02	0.092435
60	1.336117	0.000679	7.471357e-12	0.000003
66	1.272300	0.308772	2.249937e-07	0.001502
100	1.224138	0.080125	1.723821e-02	0.152624

This indicates that the three point shots noted above for Jae Crowder and Donovan Mitchell are also significantly better than the team average for three point shots. Joe Ingles (an excellent three point shooter) also shoots significantly better from both corners than the team three point average (although he does not shoot significantly better from the corners than he does from the other three point spots because his overall three point shooting percentage is so high). Jonas Jerebko also shoots significantly better from the right corner than the team average for three pointers.

For two pointers, we now find that Derrick Favors, Rudy Gobert, and Thabo Sefolosha all shoot significantly better from the post than the team average for two pointers. The p-values for Derrick

Favors and Rudy Gobert are extremely small, partially due to the large number of shots taken by both players from that location (>400). Rudy Gobert likely didn't show up on the previous list because such a high percentage of his shots are taken from the post that his two point percentage is effectively the same as his shooting percentage from the post.

```
In [36]: statistically_significant_mask = NewLocationPD["Location_p"] < .05
LocationSignificantPD = NewLocationPD[statistically_significant_mask]
LocationSignificantPD.sort_values(by=["expectedval"], ascending=False)
```

```
Out [36]:
```

	shooter	three	cluster	num_shots	num_makes	pct	\
56	Jae Crowder	1	1	24	14	0.583333	
15	Donovan Mitchell	1	4	46	25	0.543478	
133	Jonas Jerebko	0	3	4	3	0.750000	
2	Joe Ingles	1	4	83	41	0.493976	
76	Donovan Mitchell	0	1	10	7	0.700000	
60	Derrick Favors	0	0	479	320	0.668058	
3	Joe Ingles	1	5	98	43	0.438776	
66	Rudy Gobert	0	0	426	271	0.636150	

	expectedval	Player_p	Team_p	Location_p
56	1.750000	0.002547	1.302116e-02	0.033736
15	1.630435	0.001599	5.874529e-03	0.022075
133	1.500000	0.166598	1.724358e-01	0.045564
2	1.481928	0.169766	7.192182e-03	0.037354
76	1.400000	0.099649	1.195645e-01	0.038416
60	1.336117	0.000679	7.471357e-12	0.000003
3	1.316327	0.524938	6.372811e-02	0.045587
66	1.272300	0.308772	2.249937e-07	0.001502

The last hypothesis tested was whether certain players shot much better than the team average for that specific location. Apart from identifying some of the same shots as above, this test would be expected to find some players who shoot exceptionally well from more difficult spots.

Jonas Jerebko shooting two pointers from the right wing, Donovan Mitchell shooting two pointers from the right corner, Joe Ingles shooting from the top of the three-point arc, and Rodney Hood shooting three pointers from the left wing would all appear to fit in this category, although each falls just at the limits of statistical significance ($.4 < p < .5$).

Conclusions This information can help coaches and decision-makers design offensive sets and plays, and can help players with shot-selection.

For example, for the first p-test, we would advise Donovan Mitchell to take more three point shots from the left corner, and Jae Crowder to take more from the right corner. Coaches could design their offense so both players spend more time on those sides. We would also advise Donovan Mitchell to drive all the way to the basket when taking a two-point shot.

For the second p-test, we would advise the coaches to develop their offense to maximize corner threes by Crowder, Mitchell, Ingles, and Jerebko, and post shots by Favors and Gobert.

2.3 Some additional Analysis

2.3.1 Home and Away Differences

- We wanted to explore how the expected values for each player differ in home games vs away games. Once again, we used simple masking to compare how players shoot at home and away.

```
In [38]: ## HOME
```

```
# 3 pointers
PlayerIDs = np.unique(ShotsPD['shooter'])
PlayerNames = np.unique(ShotsPD['shooter_name'])
NumOPlayers = len(PlayerNames)
for Name in range(0, NumOPlayers):
    PercMadeDif3 = []
    NumShots = []
    NumMade = []
    ExpectedValue3 = []
    AvLeft3 = []
    AvTop3 = []
    PtVal3 = 3
    PtVal2 = 2
    PercMadeDif2 = []
    NumShots3 = []
    NumShots2 = []
    NumMade3 = []
    NumMade2 = []
    ExpectedValue2 = []
    ExpectedValueRound = []

    AvLeft2 = []
    AvTop2 = []

    for i in range(0, 6):
        Location = ShotsPD[(ShotsPD['LocationCluster']==i) & (ShotsPD['Th
                                & ( ShotsPD['shooter_name'] == PlayerNames[Name
        NumShots3.append(len(Location['made/missed']))
        NumMade3.append(len(Location[Location['made/missed']==1]))
        PercMade3 = 0
        if NumShots3[i] > 1:
            PercMade3 = NumMade3[i] / NumShots3[i]
            PercMadeDif3.append(PercMade3)
        else:
            PercMadeDif3.append(0)

    ExpectedValue3.append(PercMadeDif3[i]*PtVal3)

    AvLeft3.append(np.mean(Location['left']))
```

```

AvTop3.append(np.mean(Location['top']))

Location = ShotsPD[(ShotsPD['LocationCluster']==i) & (ShotsPD['Th
                    & ( ShotsPD['shooter_name'] == PlayerNames[Name
NumShots2.append(len(Location['made/missed']))
NumMade2.append(len(Location[Location['made/missed']==1]))
PercMade2 = 0
if NumShots2[i] > 1:
    PercMade2 = NumMade2[i] / NumShots2[i]
    PercMadeDif2.append(PercMade2)
else:
    PercMadeDif2.append(0)
ExpectedValue2.append(PercMadeDif2[i]*PtVal2)

AvLeft2.append(np.mean(Location['left']))
AvTop2.append(np.mean(Location['top']))

print('-----')
print(PlayerNames[Name])
print('-----')
print('---- 3 Pointers ----')
print('Percentages')
print(PercMadeDif3)
print('-----')
print('Expected Values')
print(ExpectedValue3)

print('---- 2 Pointers ----')
print('Percentages')
print(PercMadeDif2)
print('-----')
print('Expected Values')
print(ExpectedValue2)

for mm in range(0,len(ExpectedValue3)):
    if ExpectedValue3[mm] == 0:
        Extra = mm
    del ExpectedValue3[Extra]

xx = np.isnan(AvLeft3)
for mm in range(0, len(AvLeft3)):
    if xx[mm] == True:

```

```

DeleteVar = mm

del AvLeft3[DeleteVar]
del AvTop3[DeleteVar]

ExpectedValue = ExpectedValue3 + ExpectedValue2
ExpectedValueRound = np.round_(ExpectedValue, decimals=2)

AvLefts = AvLeft3 + AvLeft2
AvTops = AvTop3 + AvTop2

for u in range(0, len(AvLefts)):
    if math.isnan(AvLefts[u]):
        AvLefts[u]=90
    if math.isnan(AvTops[u]):
        AvTops[u]= 0

x = np.round(AvLefts, decimals=0)
y = np.round(AvTops, decimals=0)
valz = [str(ExpectedValueRound[0]), str(ExpectedValueRound[1]), str(ExpectedValueRound[2]),
        str(ExpectedValueRound[3]), str(ExpectedValueRound[4]), str(ExpectedValueRound[5]),
        str(ExpectedValueRound[6]), str(ExpectedValueRound[7]), str(ExpectedValueRound[8]),
        str(ExpectedValueRound[9]), str(ExpectedValueRound[10])]
df = pd.DataFrame({
    'x': x,
    'y': y,
    'group': valz
})

p1=sns.regplot(data=df, x="x", y="y", fit_reg=False, marker="o", color="r")
for line in range(0, df.shape[0]):
    p1.text(df.x[line]+0.2, df.y[line], df.group[line], horizontalalign="left",
            size='medium', color='black', weight='semibold')
plt.imshow(img, zorder=0, extent=[0, 100, 0, 100.0])
plt.grid(False)

plt.show()

```

Alec Burks

---- 3 Pointers ----

Percentages

[0, 0.2222222222222222, 0.4, 0.125, 0.25, 0.2777777777777778]

Expected Values

[0, 0.6666666666666666, 1.2000000000000002, 0.375, 0.75, 0.8333333333333334]

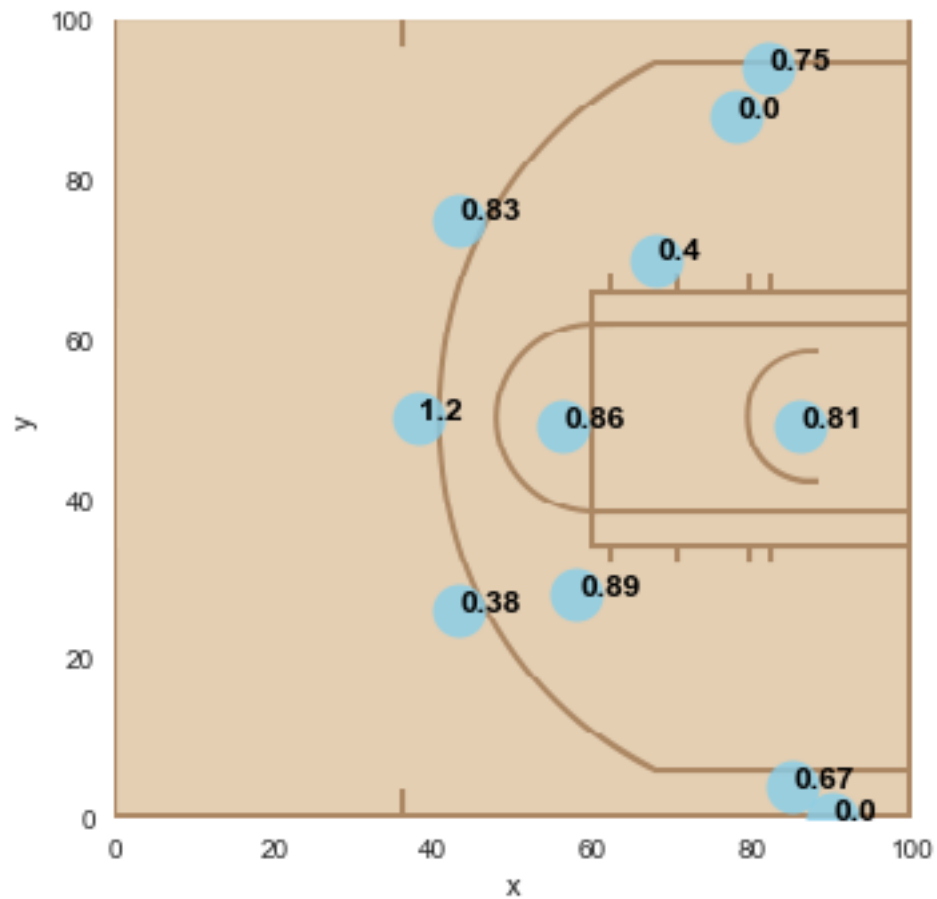
---- 2 Pointers ----

Percentages

[0.40540540540540543, 0, 0.42857142857142855, 0.4444444444444444, 0, 0.2]

Expected Values

[0.8108108108108109, 0, 0.8571428571428571, 0.8888888888888888, 0, 0.4]



Derrick Favors

---- 3 Pointers ----

Percentages

[0, 0.38461538461538464, 0.5, 0, 0.2, 0.0]

Expected Values

[0, 1.153846153846154, 1.5, 0, 0.6000000000000001, 0.0]

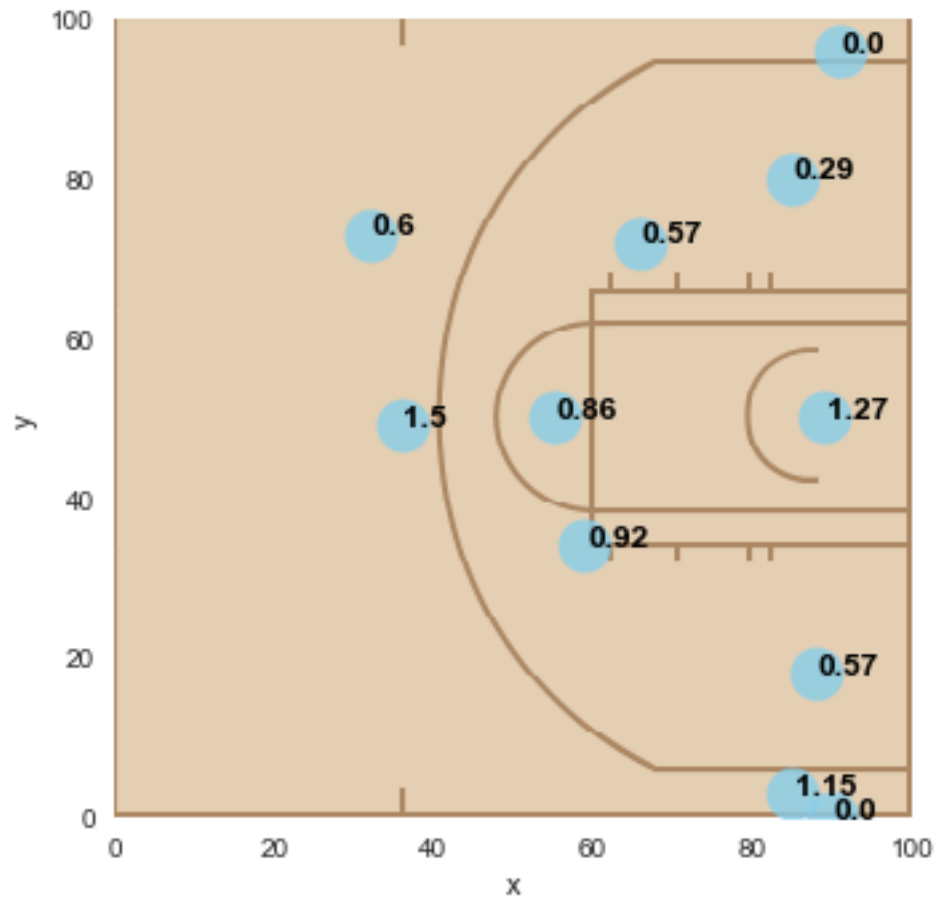
---- 2 Pointers ----

Percentages

[0.6329113924050633, 0.2857142857142857, 0.42857142857142855, 0.46153846153846156,

Expected Values

[1.2658227848101267, 0.5714285714285714, 0.8571428571428571, 0.9230769230769231, 0.



Donovan Mitchell

---- 3 Pointers ----

Percentages

[0, 0.3793103448275862, 0.38181818181818183, 0.35526315789473684, 0.45, 0.287878787

Expected Values

[0, 1.1379310344827585, 1.1454545454545455, 1.0657894736842106, 1.35, 0.86363636363

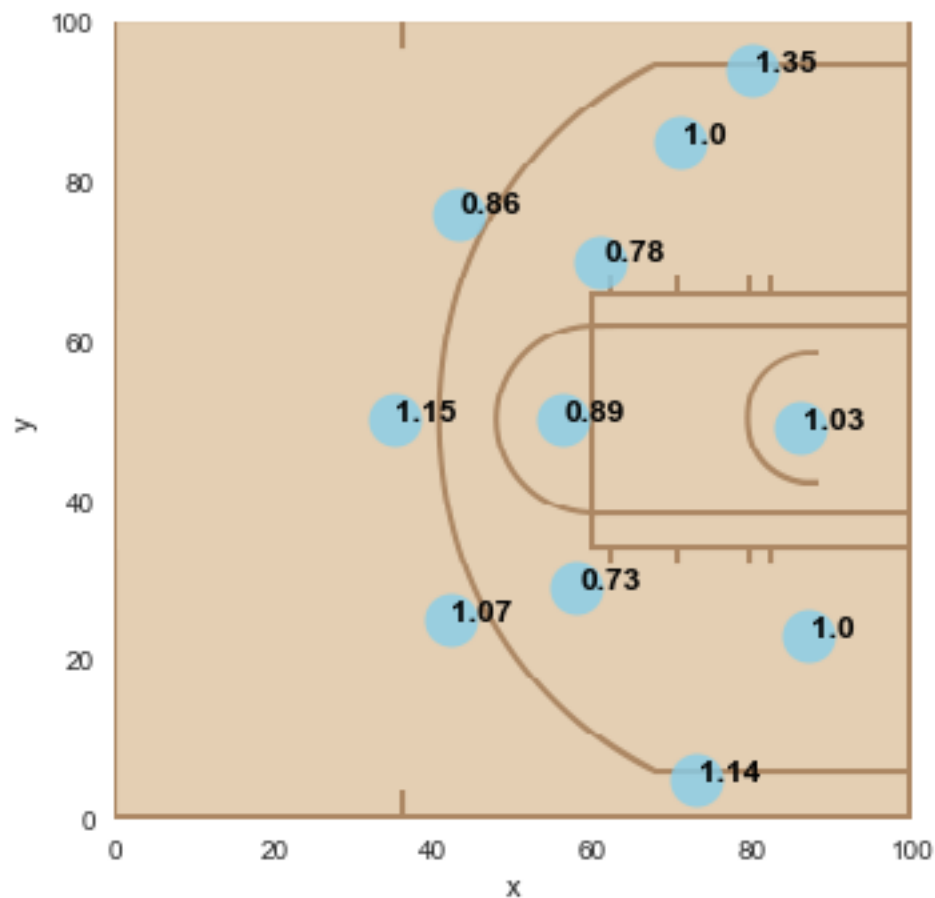
---- 2 Pointers ----

Percentages

[0.5144694533762058, 0.5, 0.44444444444444444, 0.36585365853658536, 0.5, 0.388888888

Expected Values

[1.0289389067524115, 1.0, 0.8888888888888888, 0.7317073170731707, 1.0, 0.7777777777777777]



Ekpe Udoh

---- 3 Pointers ----

Percentages

[0, 0, 0, 0, 0, 0]

Expected Values

[0, 0, 0, 0, 0, 0]

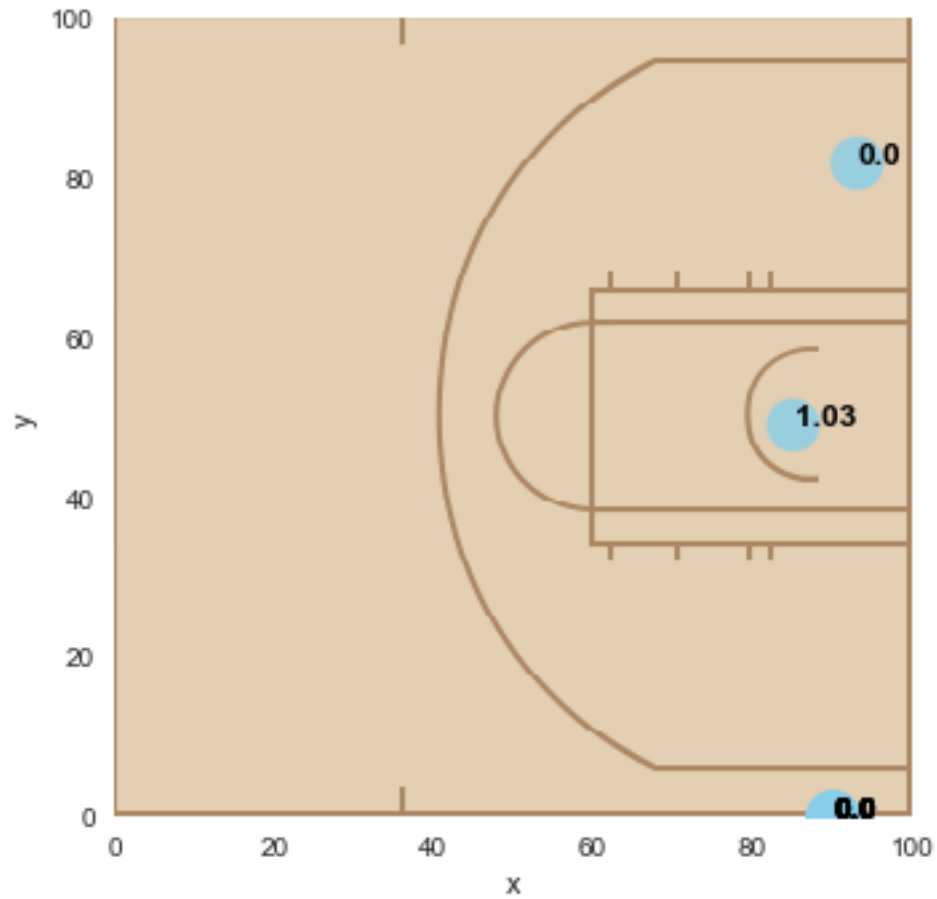
---- 2 Pointers ----

Percentages

[0.515625, 0, 0, 0, 0, 0]

Expected Values

[1.03125, 0, 0, 0, 0, 0]



Jae Crowder

---- 3 Pointers ----

Percentages

[0, 0.8, 0.2222222222222222, 0.23076923076923078, 0.42857142857142855, 0.3]

Expected Values

[0, 2.4000000000000004, 0.6666666666666666, 0.6923076923076923, 1.2857142857142856,

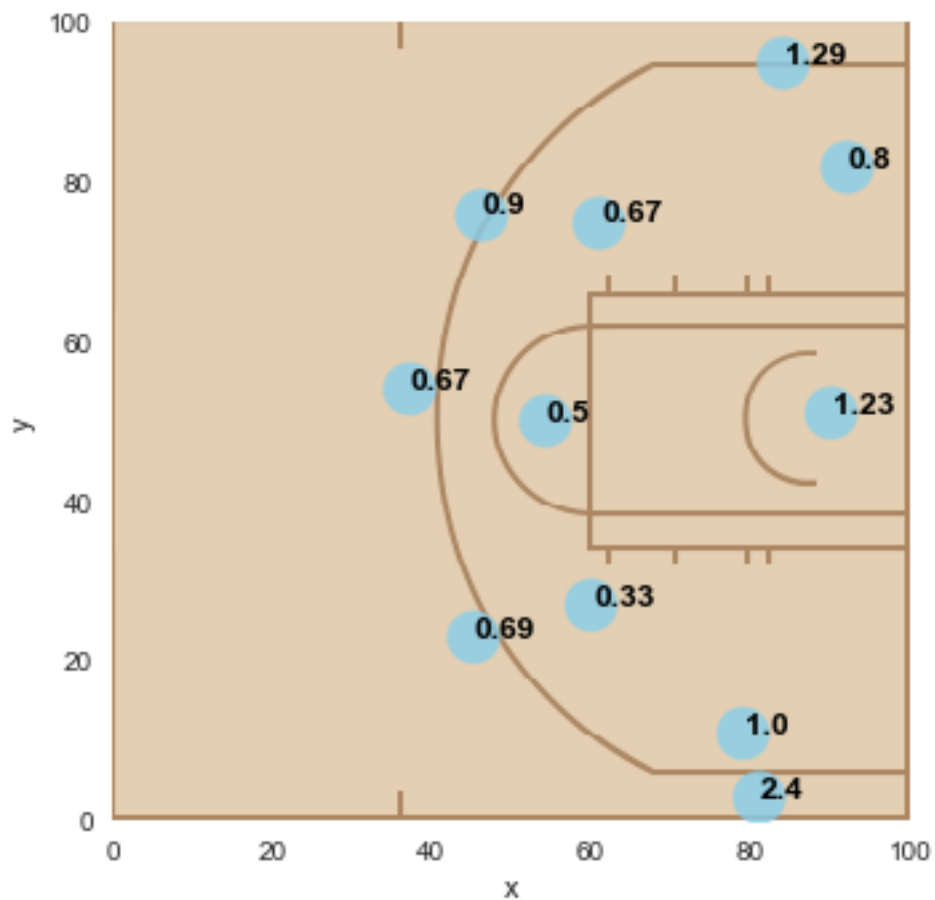
---- 2 Pointers ----

Percentages

[0.6129032258064516, 0.5, 0.25, 0.16666666666666666, 0.4, 0.3333333333333333]

Expected Values

[1.2258064516129032, 1.0, 0.5, 0.3333333333333333, 0.8, 0.6666666666666666]



Joe Ingles

---- 3 Pointers ----

Percentages

[0, 0.43478260869565216, 0.5333333333333333, 0.38095238095238093, 0.5135135135135135]

Expected Values

[0, 1.3043478260869565, 1.6, 1.1428571428571428, 1.5405405405405403, 1.529411764705882]

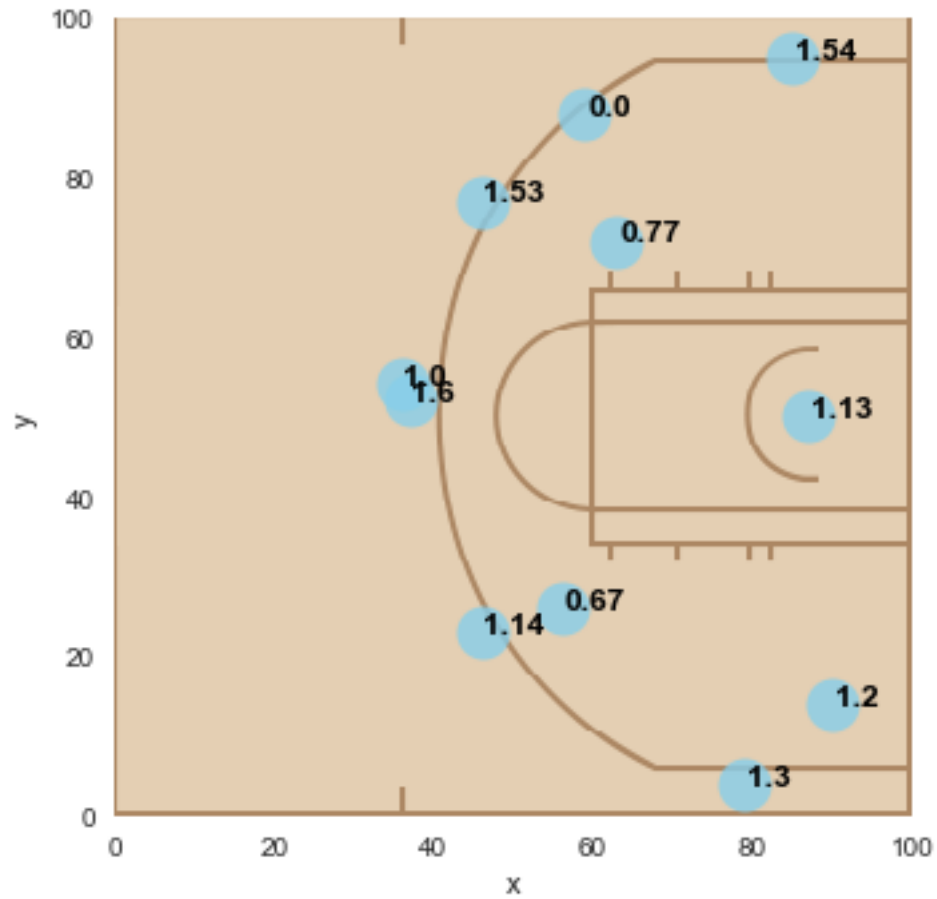
---- 2 Pointers ----

Percentages

[0.5670103092783505, 0.6, 0.5, 0.3333333333333333, 0, 0.38461538461538464]

Expected Values

[1.134020618556701, 1.2, 1.0, 0.6666666666666666, 0, 0.7692307692307693]



Joe Johnson

---- 3 Pointers ----

Percentages

[0, 0.2, 0.0, 0.4444444444444444, 0.15789473684210525, 0.0]

Expected Values

[0, 0.6000000000000001, 0.0, 1.3333333333333333, 0.47368421052631576, 0.0]

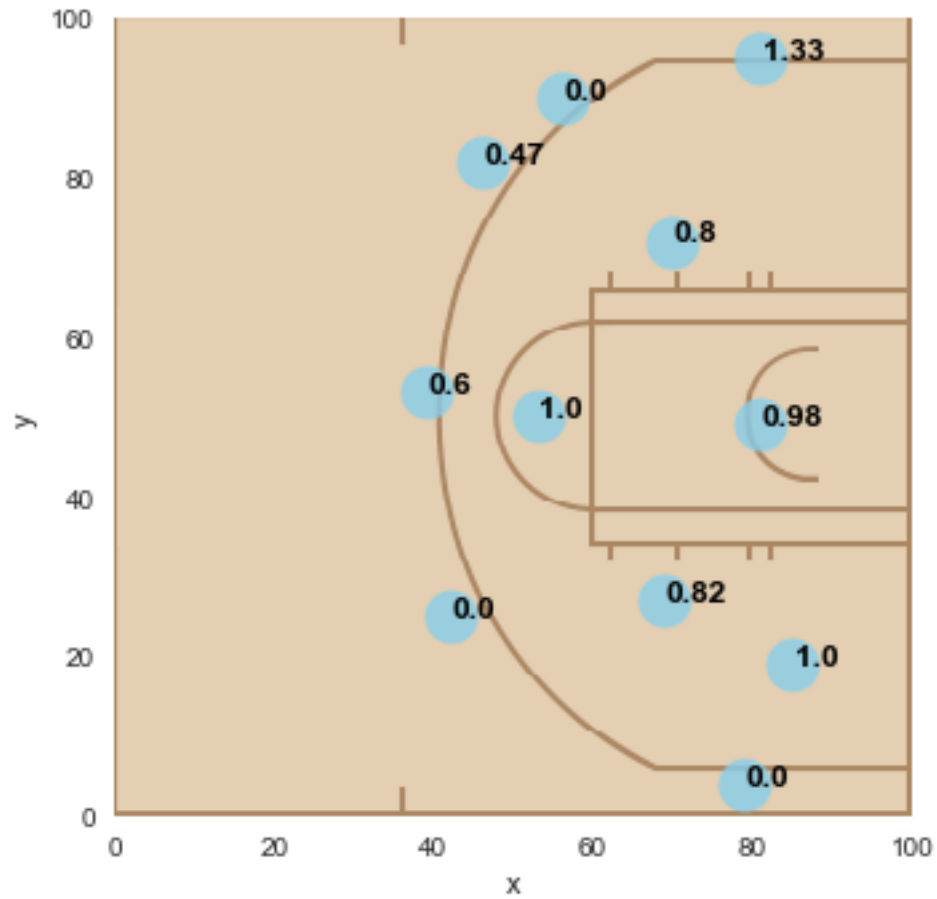
---- 2 Pointers ----

Percentages

[0.48936170212765956, 0.5, 0.5, 0.4117647058823529, 0, 0.4]

Expected Values

[0.9787234042553191, 1.0, 1.0, 0.8235294117647058, 0, 0.8]



Jonas Jerebko

---- 3 Pointers ----

Percentages

[0, 0.35294117647058826, 0.375, 0.25, 0.42857142857142855, 0.4]

Expected Values

[0, 1.0588235294117647, 1.125, 0.75, 1.2857142857142856, 1.2000000000000002]

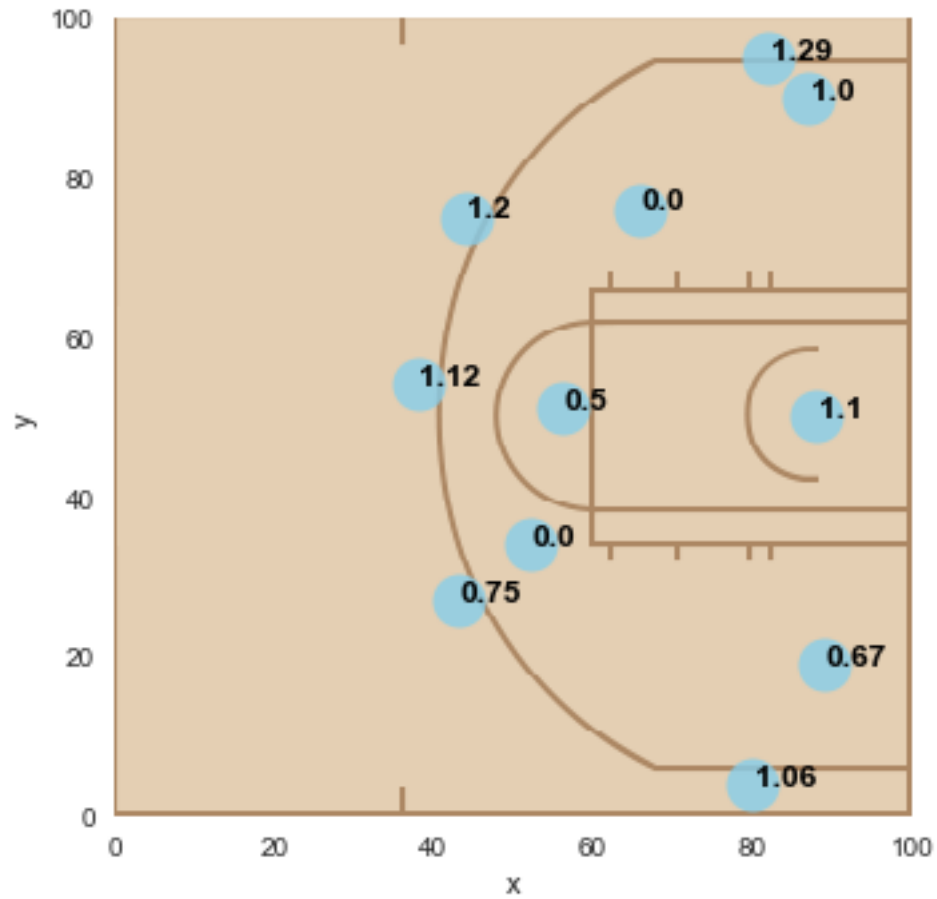
---- 2 Pointers ----

Percentages

[0.5487804878048781, 0.3333333333333333, 0.25, 0, 0.5, 0.0]

Expected Values

[1.0975609756097562, 0.6666666666666666, 0.5, 0, 1.0, 0.0]



Raul Neto

---- 3 Pointers ----

Percentages

[0, 0.3333333333333333, 0.0, 0.5, 0.42857142857142855, 0.375]

Expected Values

[0, 1.0, 0.0, 1.5, 1.2857142857142856, 1.125]

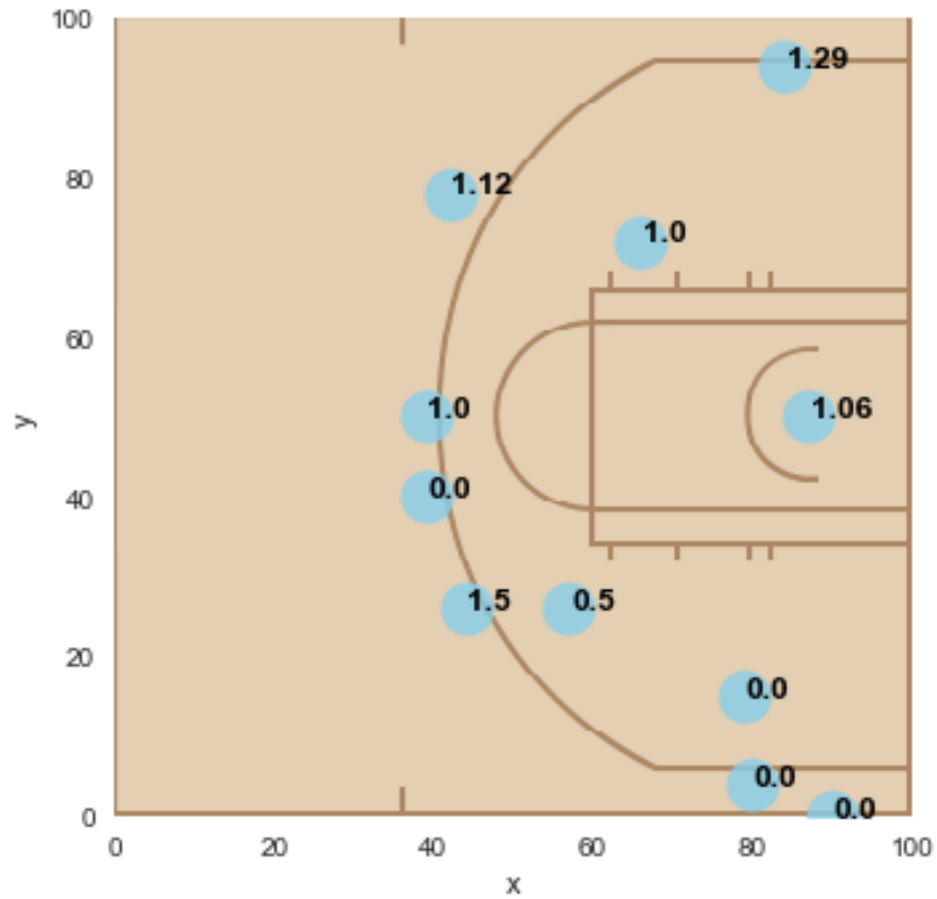
---- 2 Pointers ----

Percentages

[0.5294117647058824, 0.0, 0, 0.25, 0, 0.5]

Expected Values

[1.0588235294117647, 0.0, 0, 0.5, 0, 1.0]



 Ricky Rubio

 ---- 3 Pointers ----

Percentages

[0, 0.25, 0.25, 0.5555555555555556, 0.45714285714285713, 0.45]

 Expected Values

[0, 0.75, 0.75, 1.6666666666666667, 1.3714285714285714, 1.35]

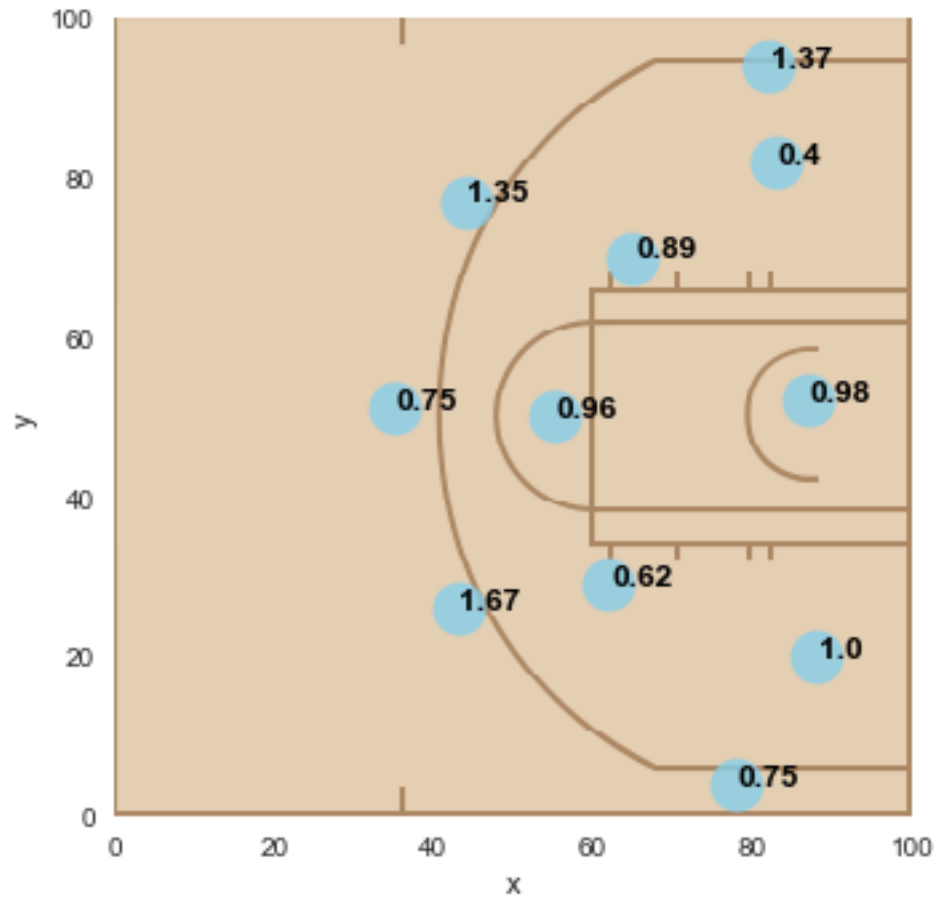
 ---- 2 Pointers ----

Percentages

[0.4892086330935252, 0.5, 0.4782608695652174, 0.3125, 0.2, 0.4457831325301205]

 Expected Values

[0.9784172661870504, 1.0, 0.9565217391304348, 0.625, 0.4, 0.891566265060241]



Rodney Hood

---- 3 Pointers ----

Percentages

[0, 0.35714285714285715, 0.5, 0.3333333333333333, 0.17647058823529413, 0.4727272727272727]

Expected Values

[0, 1.0714285714285714, 1.5, 1.0, 0.5294117647058824, 1.4181818181818182]

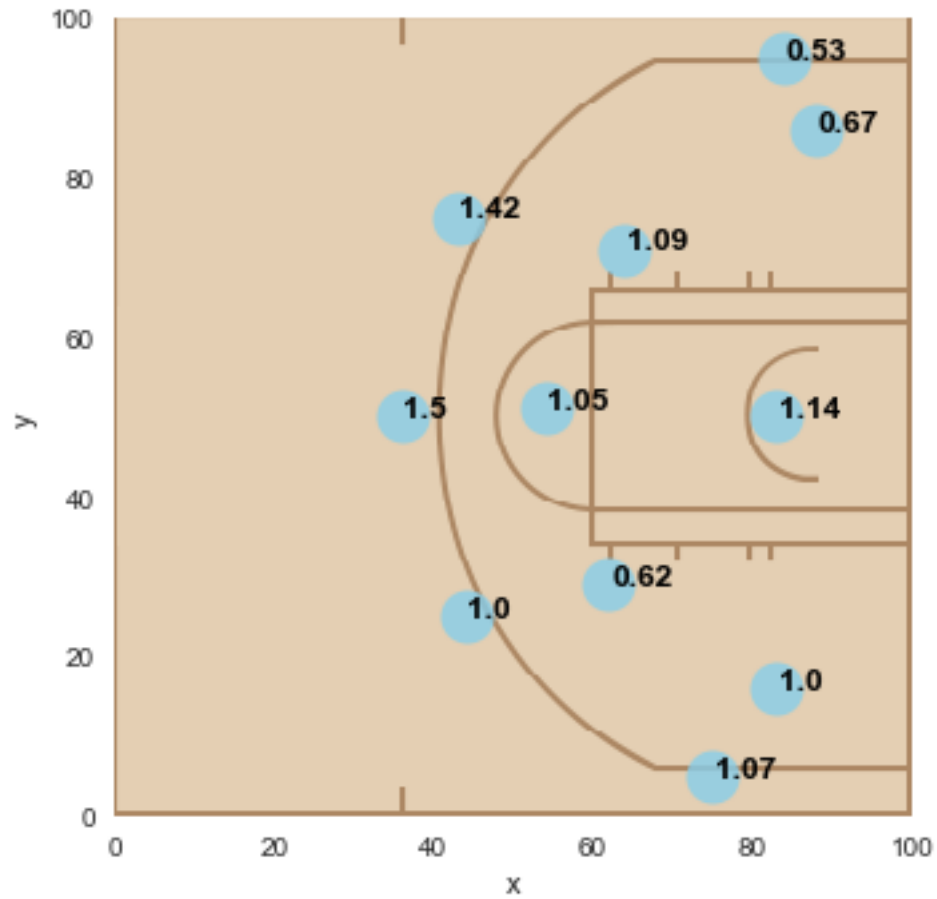
---- 2 Pointers ----

Percentages

[0.5681818181818182, 0.5, 0.5263157894736842, 0.3076923076923077, 0.3333333333333333]

Expected Values

[1.1363636363636365, 1.0, 1.0526315789473684, 0.6153846153846154, 0.6666666666666666]



Royce O'Neale

---- 3 Pointers ----

Percentages

[0, 0.45, 0.42857142857142855, 0.13333333333333333, 0.375, 0.16666666666666666]

Expected Values

[0, 1.35, 1.2857142857142856, 0.4, 1.125, 0.5]

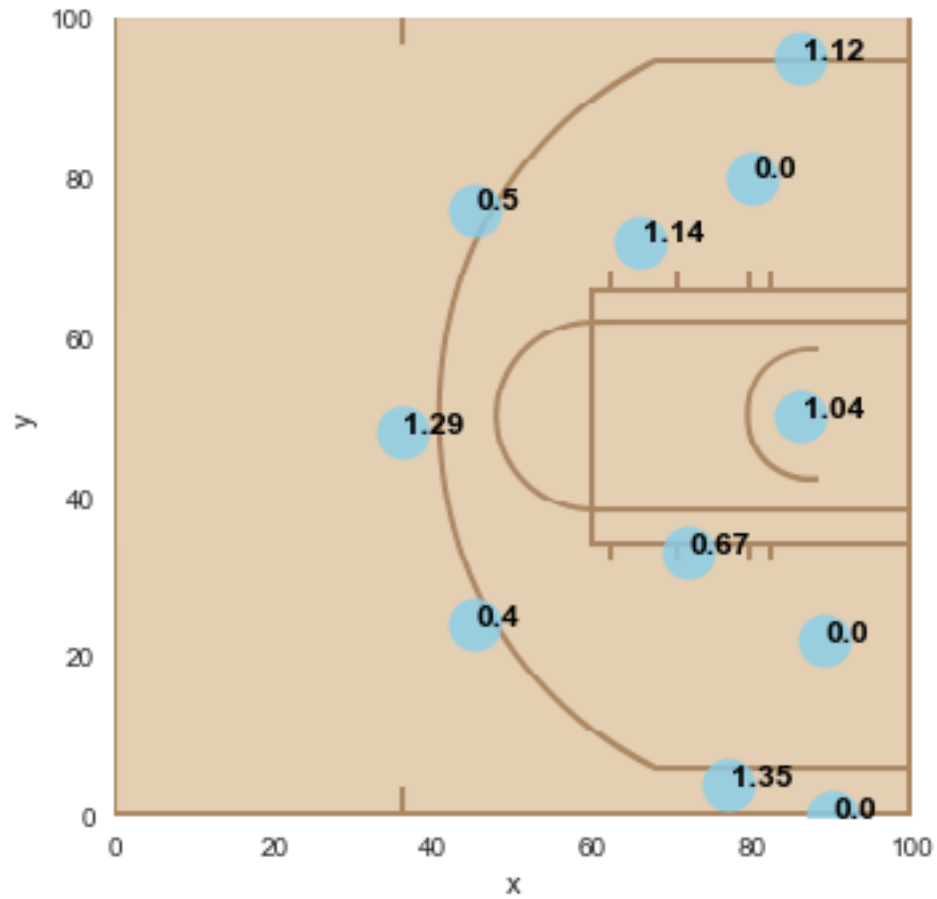
---- 2 Pointers ----

Percentages

[0.5194805194805194, 0, 0, 0.3333333333333333, 0.0, 0.5714285714285714]

Expected Values

[1.0389610389610389, 0, 0, 0.6666666666666666, 0.0, 1.1428571428571428]



Rudy Gobert

---- 3 Pointers ----

Percentages

[0, 0, 0, 0, 0, 0]

Expected Values

[0, 0, 0, 0, 0, 0]

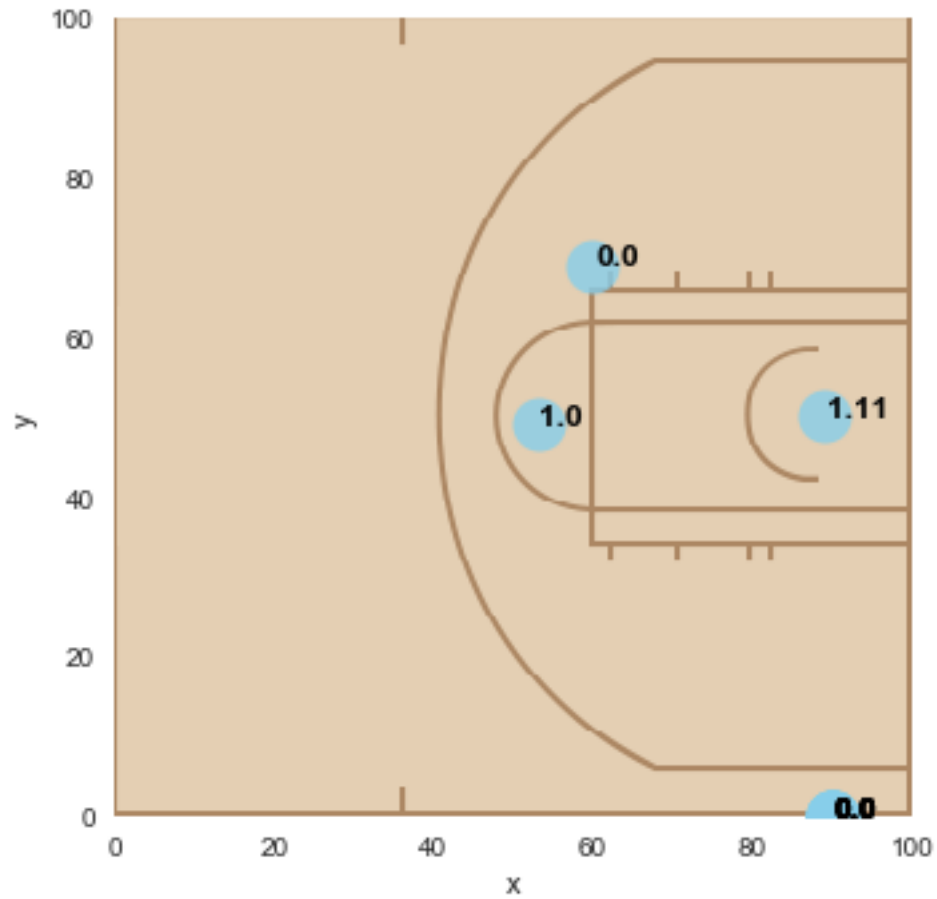
---- 2 Pointers ----

Percentages

[0.5555555555555556, 0, 0.5, 0, 0, 0.0]

Expected Values

[1.1111111111111112, 0, 1.0, 0, 0, 0.0]



 Thabo Sefolosha

---- 3 Pointers ----

Percentages

[0, 0.45454545454545453, 1.0, 0.0, 0.5, 0.6]

Expected Values

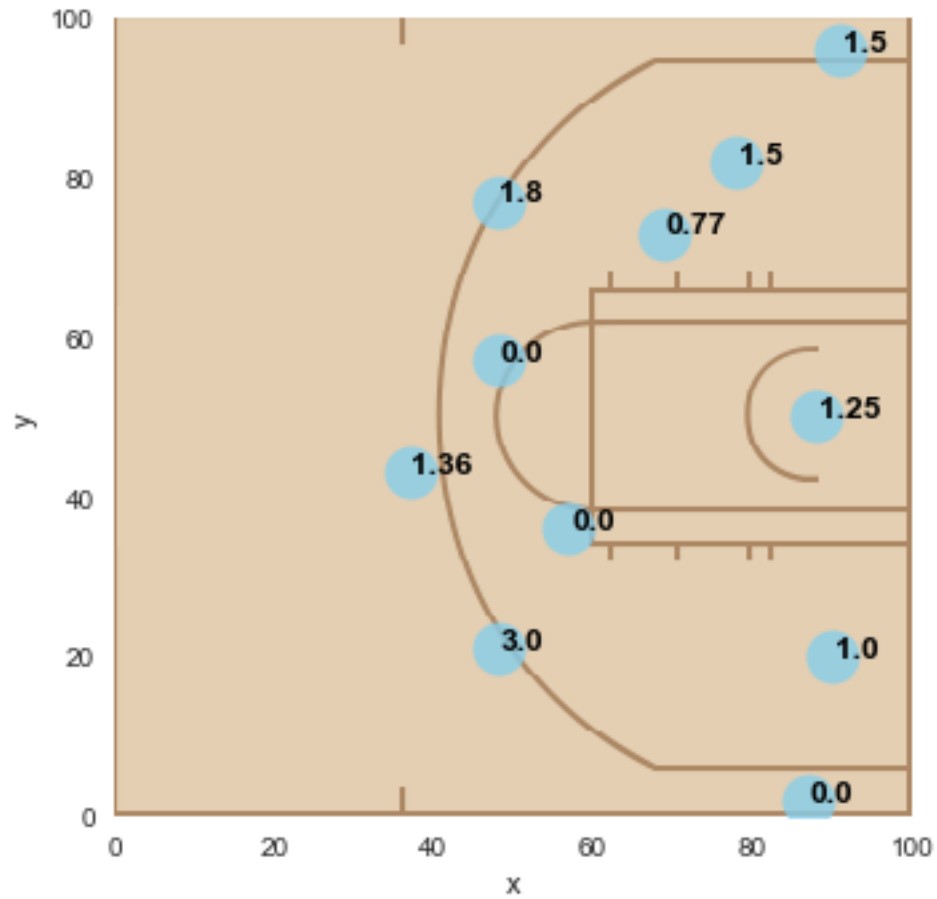
[0, 1.3636363636363635, 3.0, 0.0, 1.5, 1.7999999999999998]
 ---- 2 Pointers ----

Percentages

[0.6226415094339622, 0.5, 0.0, 0.0, 0.75, 0.38461538461538464]

Expected Values

[1.2452830188679245, 1.0, 0.0, 0.0, 1.5, 0.7692307692307693]



```
In [39]: ## Away

# 3 pointers
PlayerIDs = np.unique(ShotsPD['shooter'])
PlayerNames = np.unique(ShotsPD['shooter_name'])
NumOPlayers = len(PlayerNames)
for Name in range(0,NumOPlayers):
    PercMadeDif3 = []
    NumShots = []
    NumMade = []
    ExpectedValue3 =[]
    AvLeft3 = []
    AvTop3 =[]
    PtVal3 = 3
    PtVal2 = 2
    PercMadeDif2 = []
    NumShots3 = []
    NumShots2 = []
    NumMade3 = []
```

```

NumMade2 = []
ExpectedValue2 = []
ExpectedValueRound = []

AvLeft2 = []
AvTop2 = []

for i in range(0,6):
    Location = ShotsPD[(ShotsPD['LocationCluster']==i) & (ShotsPD['Thru']
        & ( ShotsPD['shooter_name'] == PlayerNames[Name]))
    NumShots3.append(len(Location['made/missed']))
    NumMade3.append(len(Location[Location['made/missed']==1]))
    PercMade3 = 0
    if NumShots3[i] > 1:
        PercMade3 = NumMade3[i] / NumShots3[i]
        PercMadeDif3.append(PercMade3)
    else:
        PercMadeDif3.append(0)

    ExpectedValue3.append(PercMadeDif3[i]*PtVal3)

    AvLeft3.append(np.mean(Location['left']))
    AvTop3.append(np.mean(Location['top']))


    Location = ShotsPD[(ShotsPD['LocationCluster']==i) & (ShotsPD['Thru']
        & ( ShotsPD['shooter_name'] == PlayerNames[Name]))
    NumShots2.append(len(Location['made/missed']))
    NumMade2.append(len(Location[Location['made/missed']==1]))
    PercMade2 = 0
    if NumShots2[i] > 1:
        PercMade2 = NumMade2[i] / NumShots2[i]
        PercMadeDif2.append(PercMade2)
    else:
        PercMadeDif2.append(0)

    ExpectedValue2.append(PercMadeDif2[i]*PtVal2)

    AvLeft2.append(np.mean(Location['left']))
    AvTop2.append(np.mean(Location['top']))

print('-----')
print(PlayerNames[Name])
print('-----')
print('---- 3 Pointers ----')
print('Percentages')

```

```

print(PercMadeDif3)
print('-----')
print('Expected Values')
print(ExpectedValue3)

print('---- 2 Pointers ----')
print('Percentages')
print(PercMadeDif2)
print('-----')
print('Expected Values')
print(ExpectedValue2)

for mm in range(0, len(ExpectedValue3)):
    if ExpectedValue3[mm] == 0:
        Extra = mm
del ExpectedValue3[Extra]

xx = np.isnan(AvLeft3)
for mm in range(0, len(AvLeft3)):
    if xx[mm] == True:
        DeleteVar = mm

del AvLeft3[DeleteVar]
del AvTop3[DeleteVar]

ExpectedValue = ExpectedValue3 + ExpectedValue2
ExpectedValueRound = np.round_(ExpectedValue, decimals=2)

AvLefts = AvLeft3 + AvLeft2
AvTops = AvTop3 + AvTop2

for u in range(0, len(AvLefts)):
    if math.isnan(AvLefts[u]):
        AvLefts[u]=90
    if math.isnan(AvTops[u]):
        AvTops[u]= 0

x = np.round(AvLefts, decimals=0)
y = np.round(AvTops, decimals=0)
valz = [str(ExpectedValueRound[0]), str(ExpectedValueRound[1]), str(ExpectedValueRound[2]), str(ExpectedValueRound[3]), str(ExpectedValueRound[4]), str(ExpectedValueRound[5]), str(ExpectedValueRound[6]), str(ExpectedValueRound[7]), str(ExpectedValueRound[8]), str(ExpectedValueRound[9]), str(ExpectedValueRound[10])]
df = pd.DataFrame({
    'x': x,

```

```

'y': y,
'group': valz
})

p1=sns.regplot(data=df, x="x", y="y", fit_reg=False, marker="o", color
for line in range(0,df.shape[0]):
    p1.text(df.x[line]+0.2, df.y[line], df.group[line], horizontalalign
            size='medium', color='black', weight='semibold')

plt.imshow(img, zorder=0, extent=[0, 100, 0, 100.0])
plt.grid(False)

plt.show()

```

Alec Burks

---- 3 Pointers ----

Percentages

[0, 0.5555555555555556, 0.3125, 0.2916666666666667, 0.5, 0.5]

Expected Values

[0, 1.6666666666666667, 0.9375, 0.875, 1.5, 1.5]

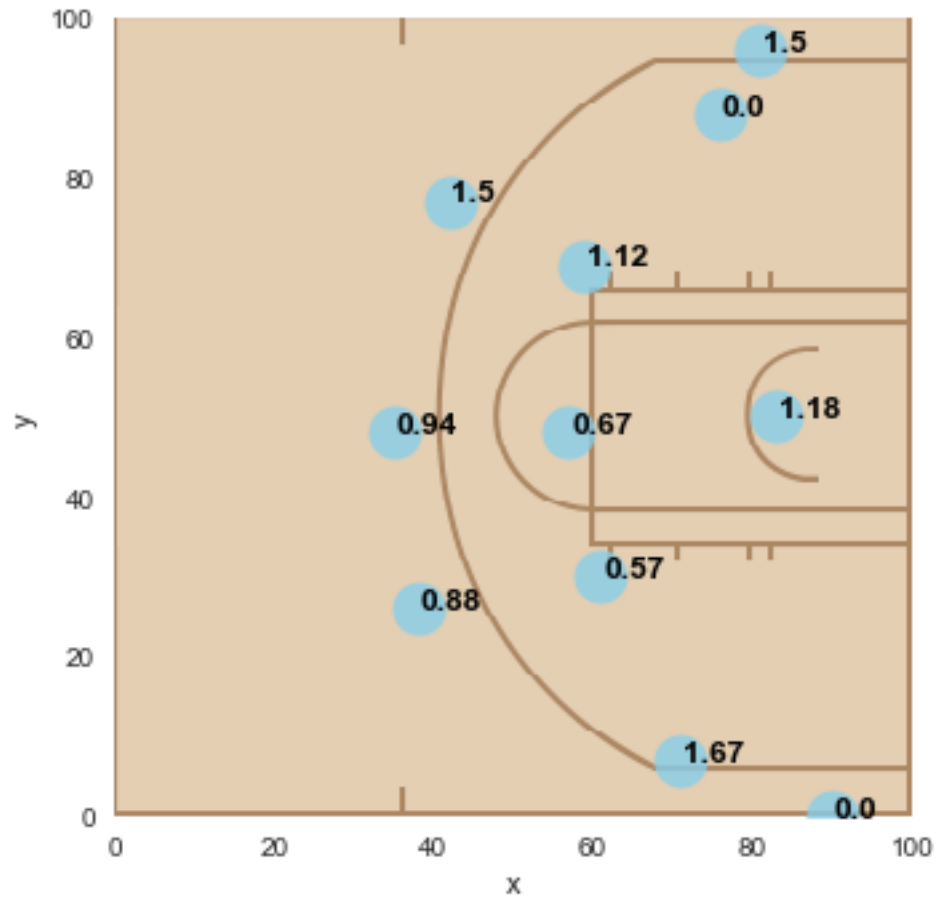
---- 2 Pointers ----

Percentages

[0.5875, 0, 0.3333333333333333, 0.2857142857142857, 0, 0.5625]

Expected Values

[1.175, 0, 0.6666666666666666, 0.5714285714285714, 0, 1.125]



Derrick Favors

---- 3 Pointers ----

Percentages

[0, 0.17647058823529413, 0, 0, 0.18181818181818182, 0]

Expected Values

[0, 0.5294117647058824, 0, 0, 0.5454545454545454, 0]

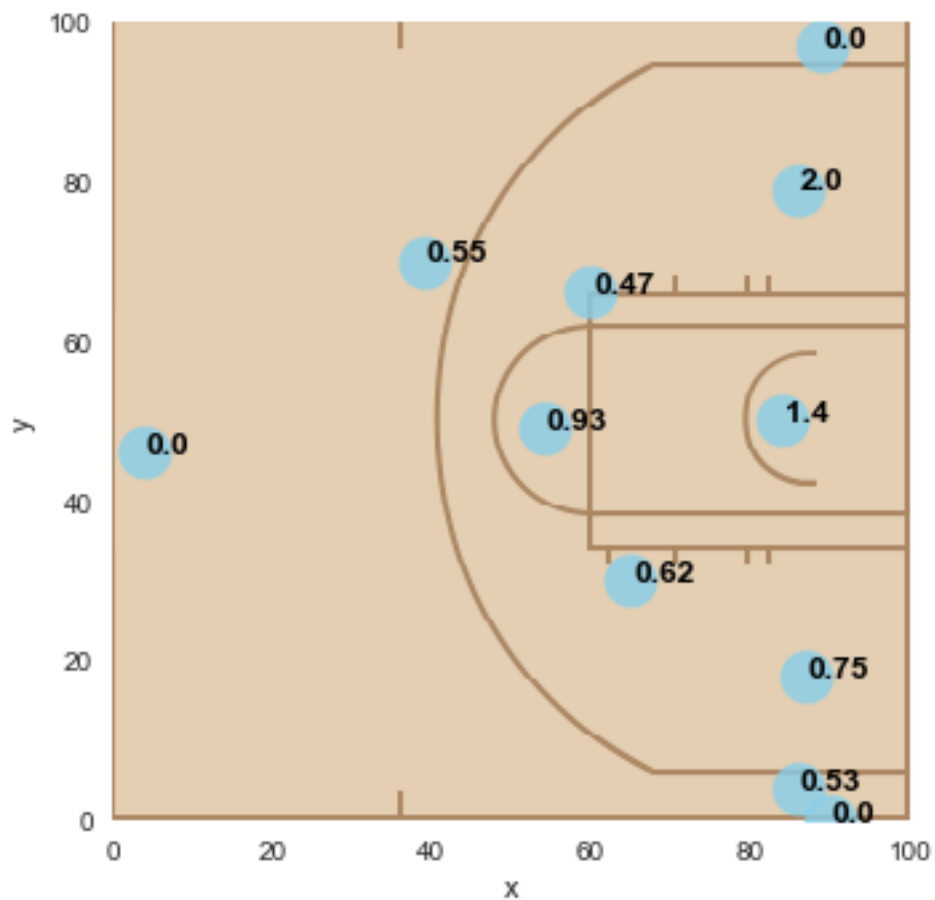
---- 2 Pointers ----

Percentages

[0.7024793388429752, 0.375, 0.4634146341463415, 0.3125, 1.0, 0.23529411764705882]

Expected Values

[1.4049586776859504, 0.75, 0.926829268292683, 0.625, 2.0, 0.47058823529411764]



Donovan Mitchell

---- 3 Pointers ----

Percentages

[0, 0.358974358974359, 0.327272727272727, 0.25806451612903225, 0.6153846153846154,

Expected Values

[0, 1.0769230769230769, 0.9818181818181818, 0.7741935483870968, 1.8461538461538463,

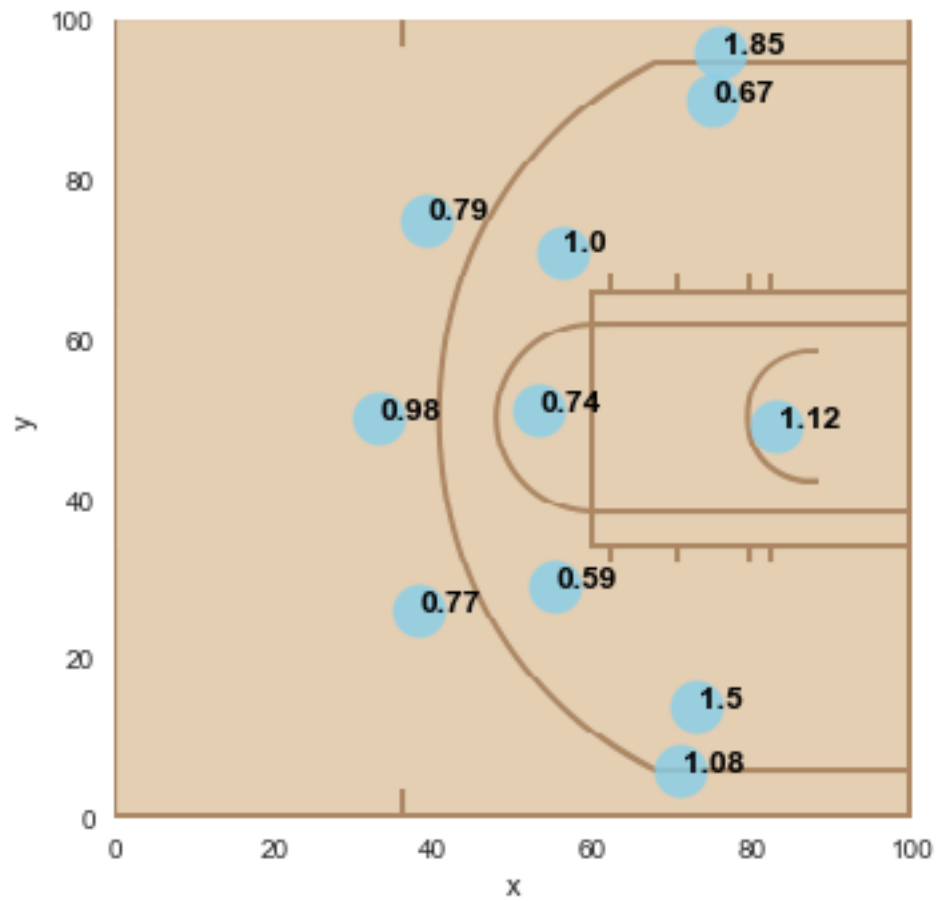
---- 2 Pointers ----

Percentages

[0.5590277777777778, 0.75, 0.37209302325581395, 0.29545454545454547, 0.3333333333333333,

Expected Values

[1.1180555555555556, 1.5, 0.7441860465116279, 0.5909090909090909, 0.6666666666666666,



Ekpe Udoh

---- 3 Pointers ----

Percentages

[0, 0, 0, 0, 0, 0]

Expected Values

[0, 0, 0, 0, 0, 0]

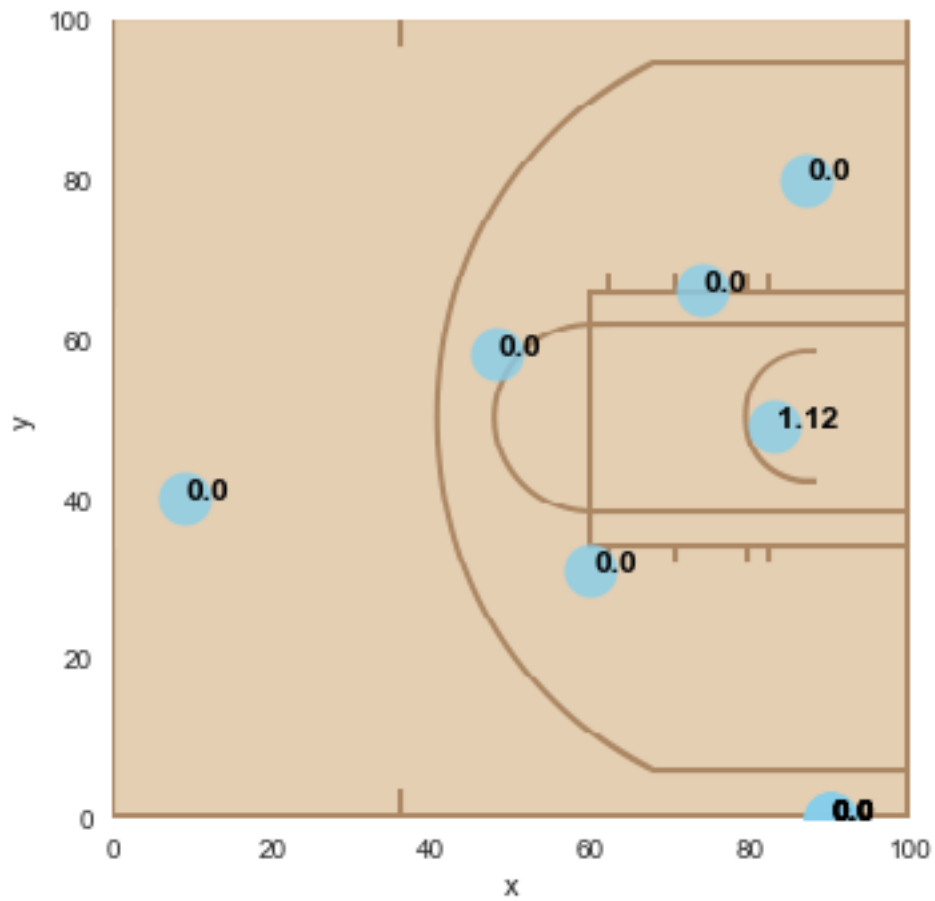
---- 2 Pointers ----

Percentages

[0.5625, 0, 0, 0.0, 0, 0]

Expected Values

[1.125, 0, 0, 0.0, 0, 0]



Jae Crowder

---- 3 Pointers ----

Percentages

[0, 0.42857142857142855, 0.36363636363636365, 0.3, 0.05555555555555555, 0.25]

Expected Values

[0, 1.2857142857142856, 1.0909090909090908, 0.8999999999999999, 0.16666666666666666]

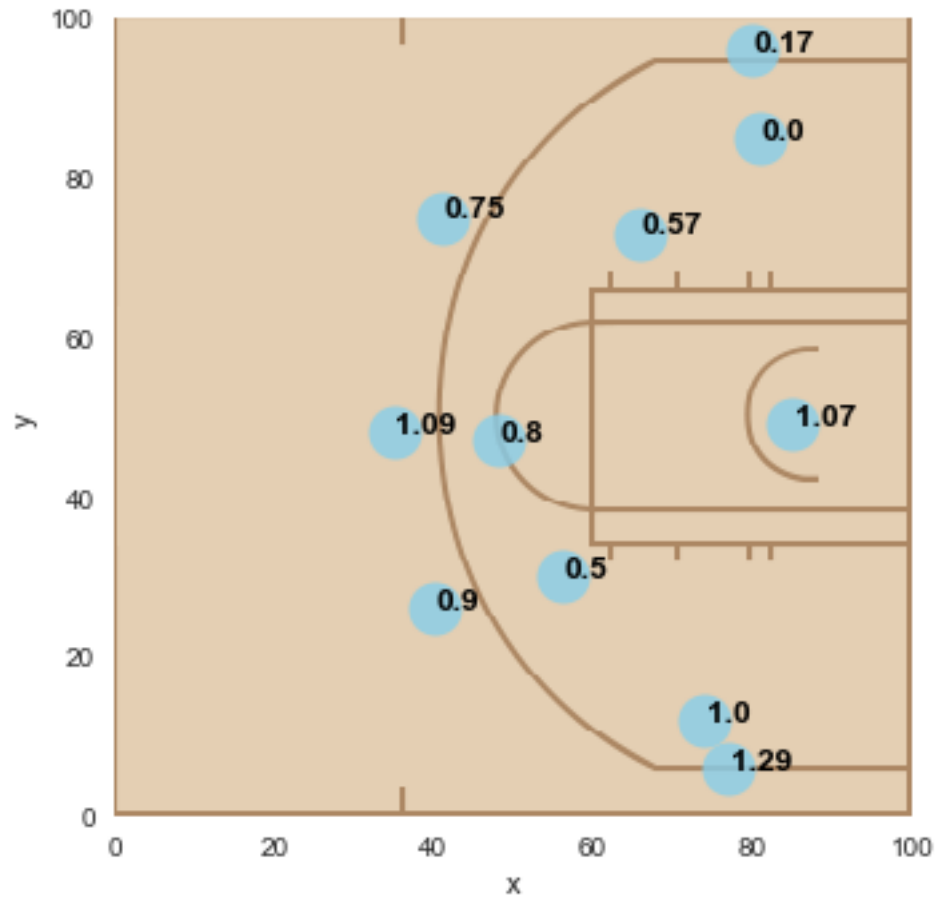
---- 2 Pointers ----

Percentages

[0.5344827586206896, 0.5, 0.4, 0.25, 0.0, 0.2857142857142857]

Expected Values

[1.0689655172413792, 1.0, 0.8, 0.5, 0.0, 0.5714285714285714]



Joe Ingles

---- 3 Pointers ----

Percentages

[0, 0.4838709677419355, 0.37037037037037035, 0.35294117647058826, 0.4782608695652174]

Expected Values

[0, 1.4516129032258065, 1.1111111111111112, 1.0588235294117647, 1.4347826086956523, 1.0588235294117647]

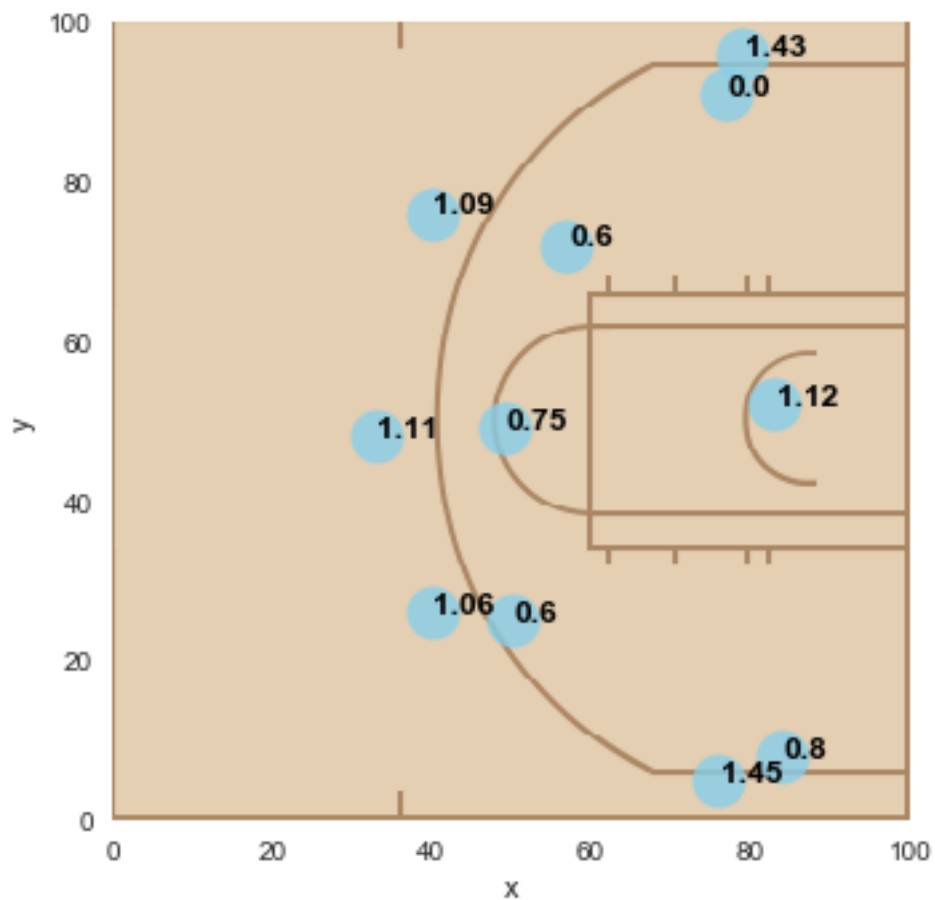
---- 2 Pointers ----

Percentages

[0.5576923076923077, 0.4, 0.375, 0.3, 0.0, 0.3]

Expected Values

[1.1153846153846154, 0.8, 0.75, 0.6, 0.0, 0.6]



Joe Johnson

---- 3 Pointers ----

Percentages

[0, 0.45454545454545453, 0.6666666666666666, 0.2, 0.5, 0.2222222222222222]

Expected Values

[0, 1.3636363636363635, 2.0, 0.6000000000000001, 1.5, 0.6666666666666666]

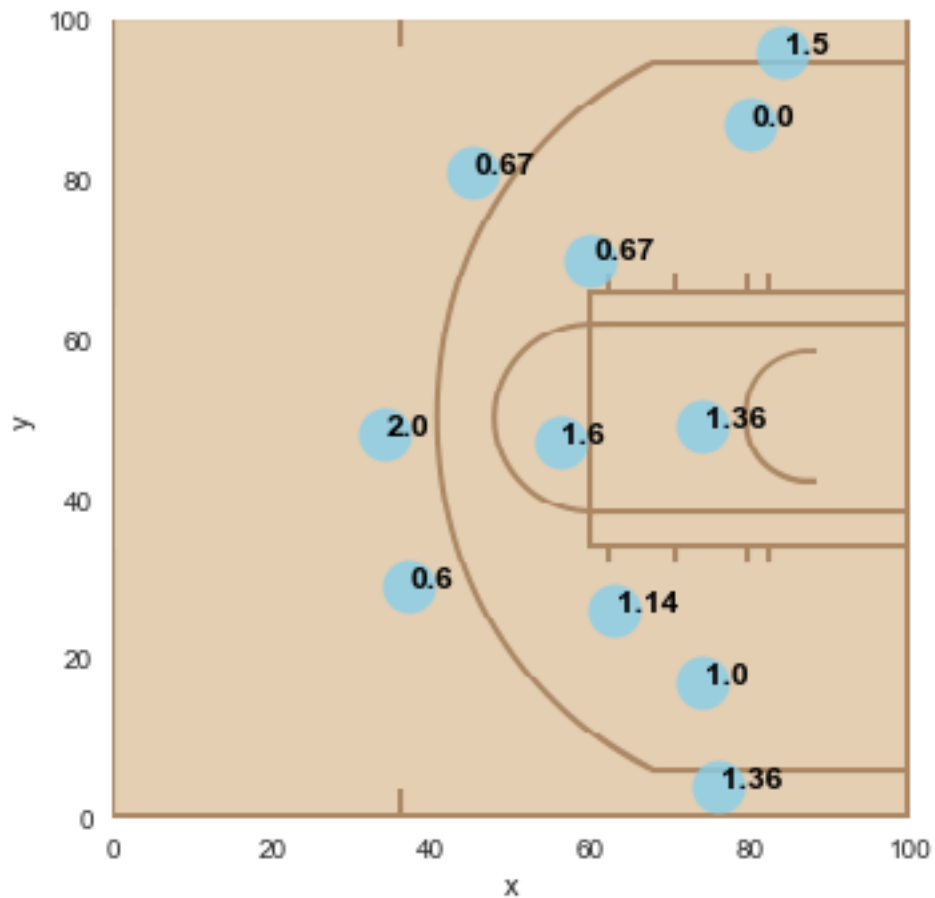
---- 2 Pointers ----

Percentages

[0.6785714285714286, 0.5, 0.8, 0.5714285714285714, 0.0, 0.3333333333333333]

Expected Values

[1.3571428571428572, 1.0, 1.6, 1.1428571428571428, 0.0, 0.6666666666666666]



Jonas Jerebko

---- 3 Pointers ----

Percentages

[0, 0.5769230769230769, 0.16666666666666666, 0.41666666666666667, 0.5217391304347826]

Expected Values

[0, 1.7307692307692306, 0.5, 1.25, 1.5652173913043477, 0.9375]

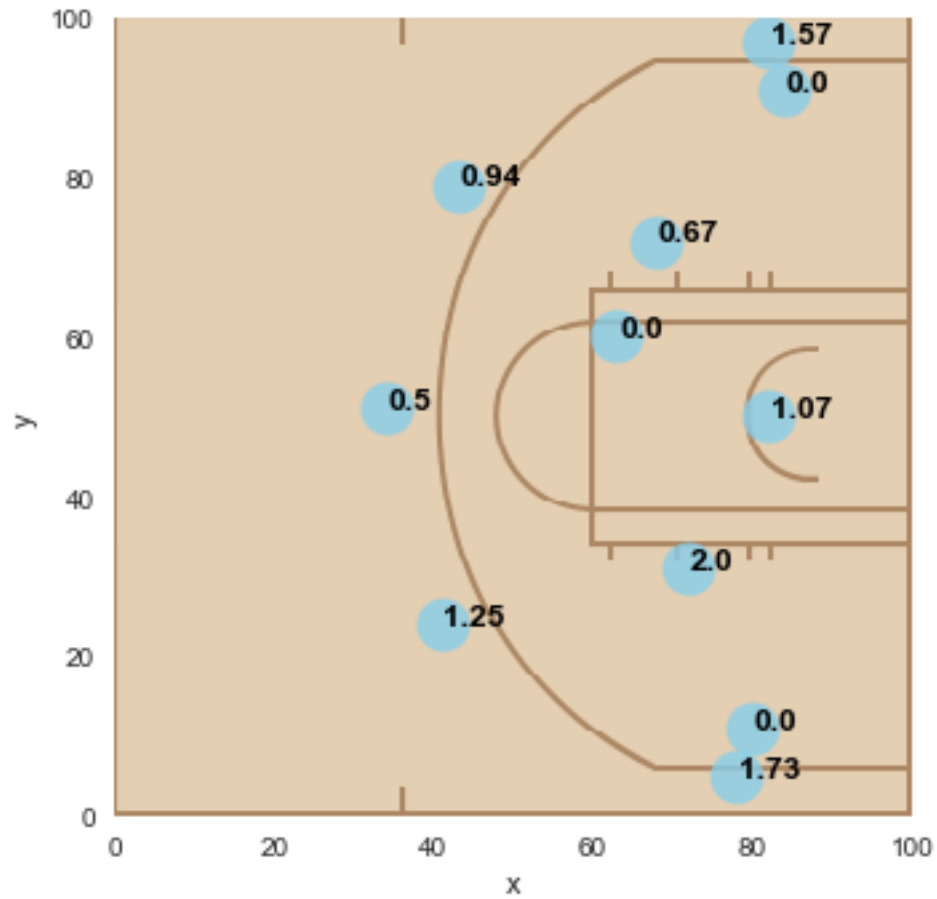
---- 2 Pointers ----

Percentages

[0.5352112676056338, 0.0, 0, 1.0, 0.0, 0.3333333333333333]

Expected Values

[1.0704225352112675, 0.0, 0, 2.0, 0.0, 0.6666666666666666]



Raul Neto

---- 3 Pointers ----

Percentages

[0, 0.6666666666666666, 0.3333333333333333, 0.3333333333333333, 0.5, 0]

Expected Values

[0, 2.0, 1.0, 1.0, 1.5, 0]

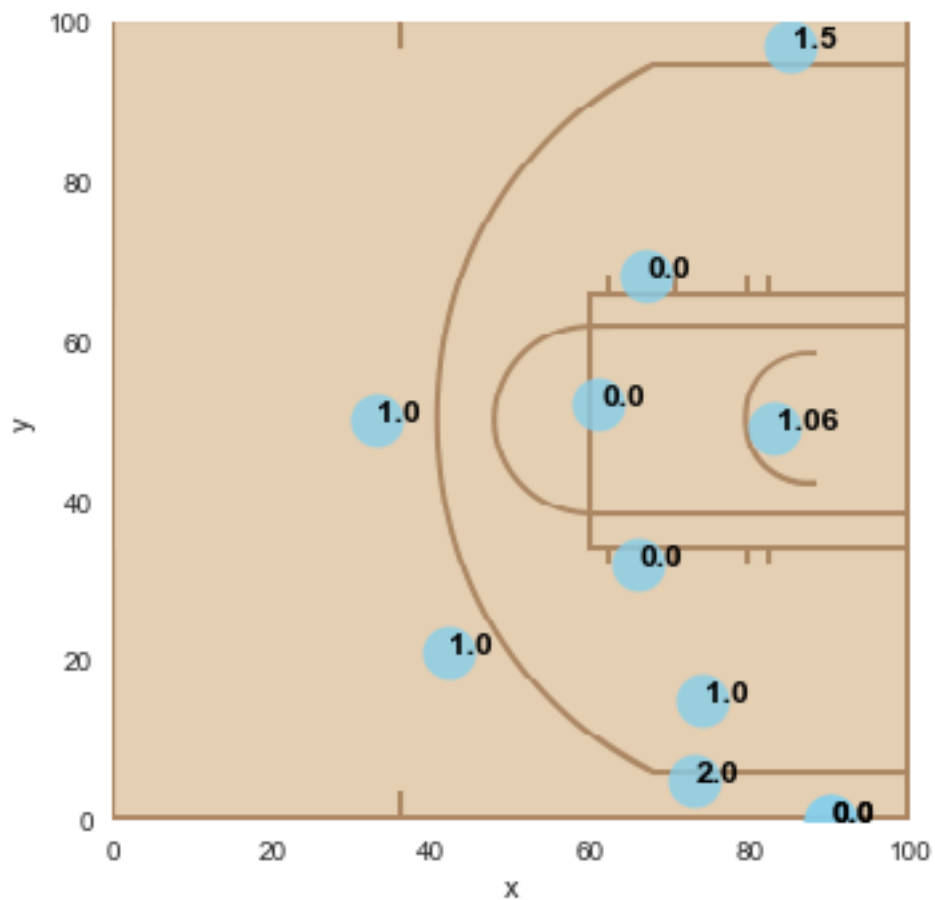
---- 2 Pointers ----

Percentages

[0.5294117647058824, 0.5, 0, 0.0, 0, 0.0]

Expected Values

[1.0588235294117647, 1.0, 0, 0.0, 0, 0.0]



 Ricky Rubio

 ---- 3 Pointers ----

Percentages

[0, 0.2692307692307692, 0.20833333333333334, 0.29411764705882354, 0.35483870967741935]

 Expected Values

[0, 0.8076923076923077, 0.625, 0.8823529411764706, 1.064516129032258, 1.0]

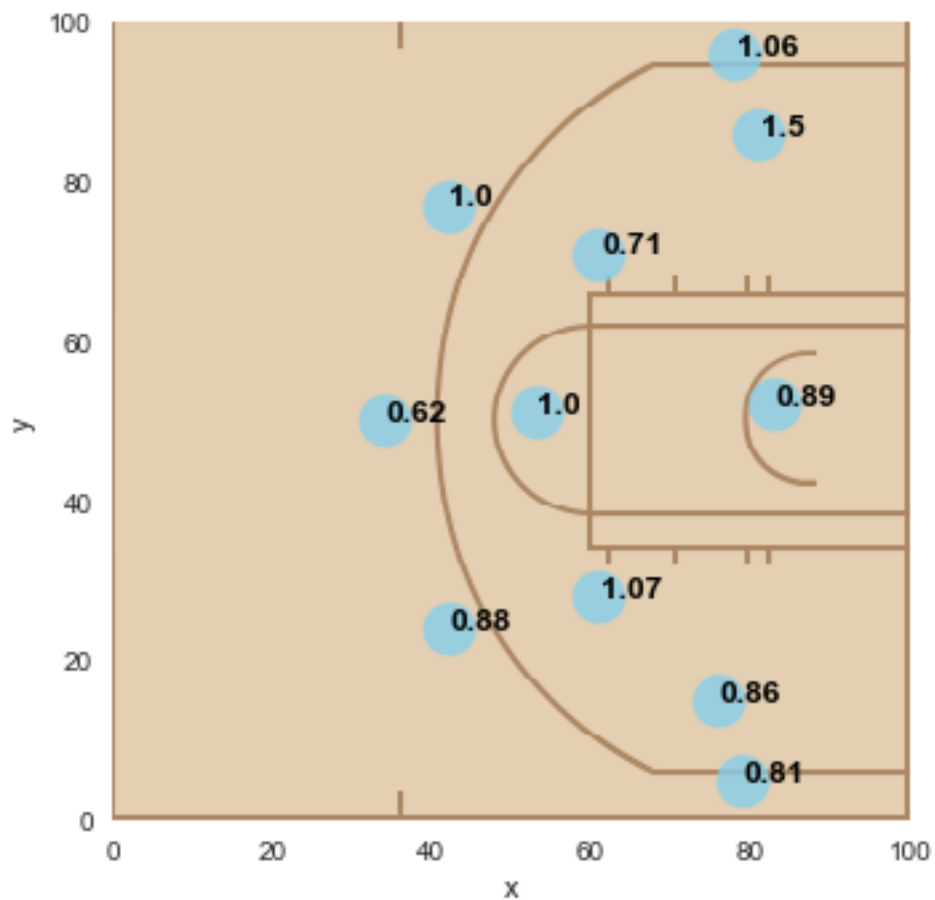
---- 2 Pointers ----

Percentages

[0.44660194174757284, 0.42857142857142855, 0.5, 0.5333333333333333, 0.75, 0.35483870967741935]

 Expected Values

[0.8932038834951457, 0.8571428571428571, 1.0, 1.0666666666666667, 1.5, 0.7096774193548387]



Rodney Hood

---- 3 Pointers ----

Percentages

[0, 0.46153846153846156, 0.3103448275862069, 0.21052631578947367, 0.4, 0.3888888888888889]

Expected Values

[0, 1.3846153846153846, 0.9310344827586208, 0.631578947368421, 1.2000000000000002,

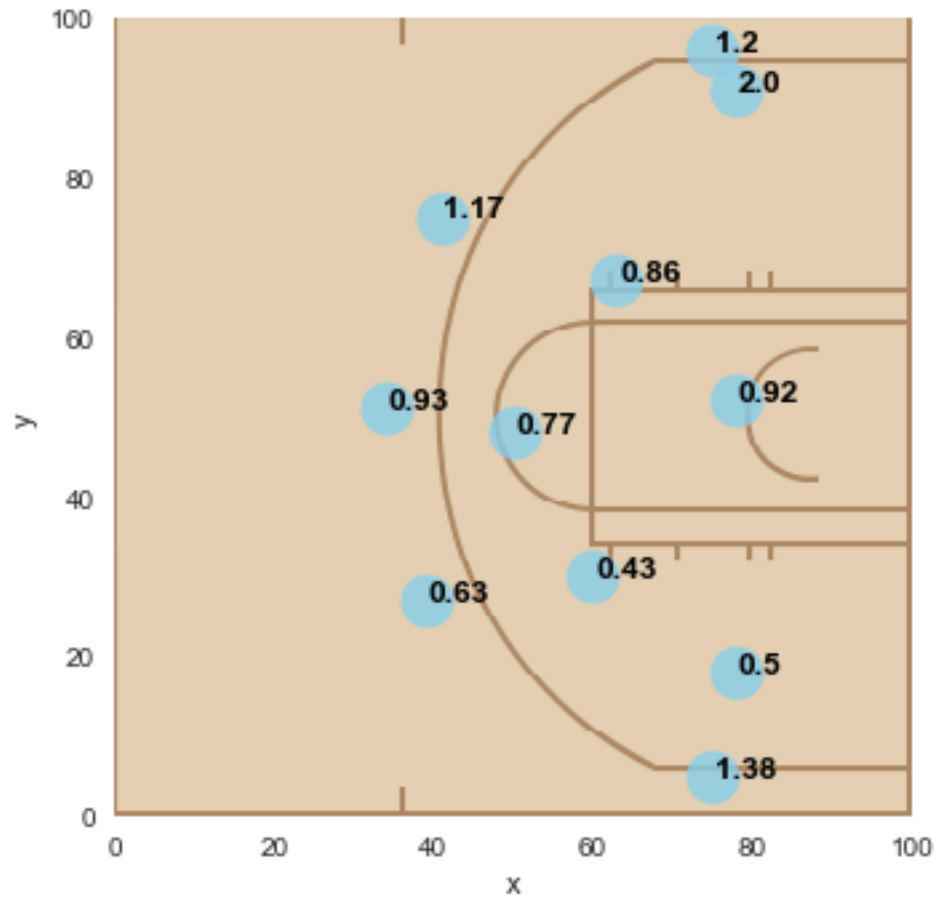
---- 2 Pointers ----

Percentages

[0.46, 0.25, 0.38461538461538464, 0.21739130434782608, 1.0, 0.42857142857142855]

Expected Values

[0.92, 0.5, 0.7692307692307693, 0.43478260869565216, 2.0, 0.8571428571428571]



Royce O'Neale

---- 3 Pointers ----

Percentages

[0, 0.2, 0.25, 0.3333333333333333, 0.36363636363636365, 0.6666666666666666]

Expected Values

[0, 0.6000000000000001, 0.75, 1.0, 1.0909090909090908, 2.0]

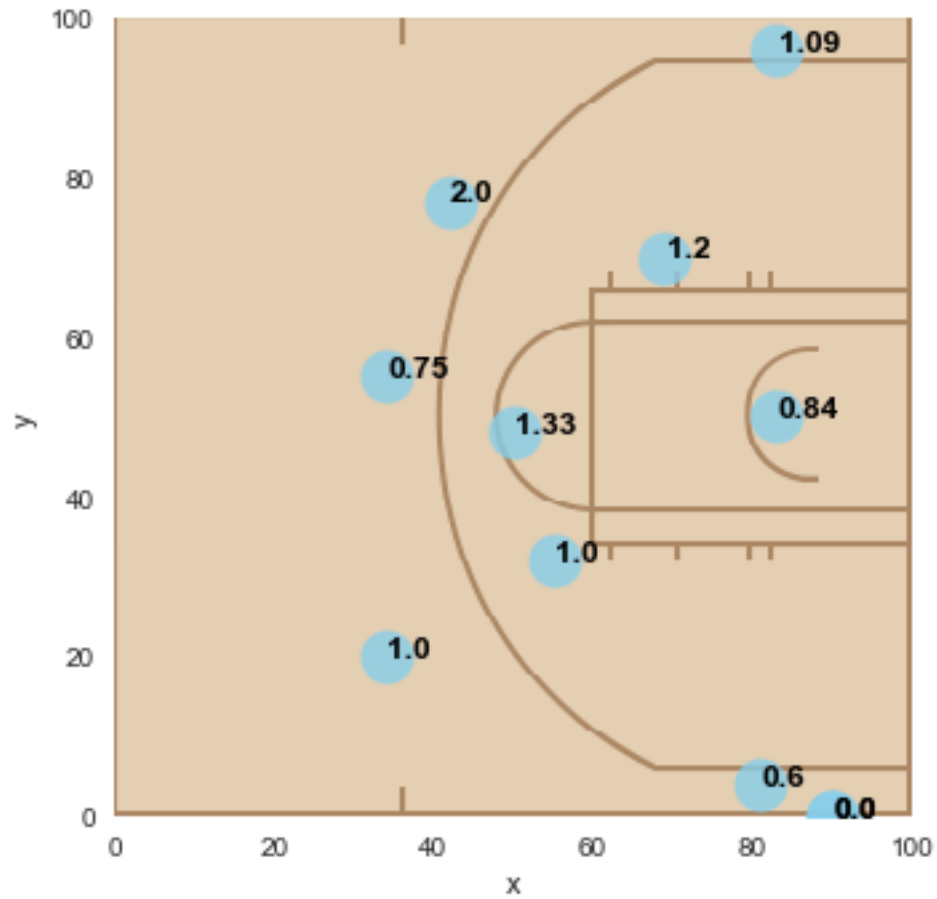
---- 2 Pointers ----

Percentages

[0.42028985507246375, 0, 0.6666666666666666, 0.5, 0, 0.6]

Expected Values

[0.8405797101449275, 0, 1.3333333333333333, 1.0, 0, 1.2]



Rudy Gobert

---- 3 Pointers ----

Percentages

[0, 0, 0, 0, 0, 0]

Expected Values

[0, 0, 0, 0, 0, 0]

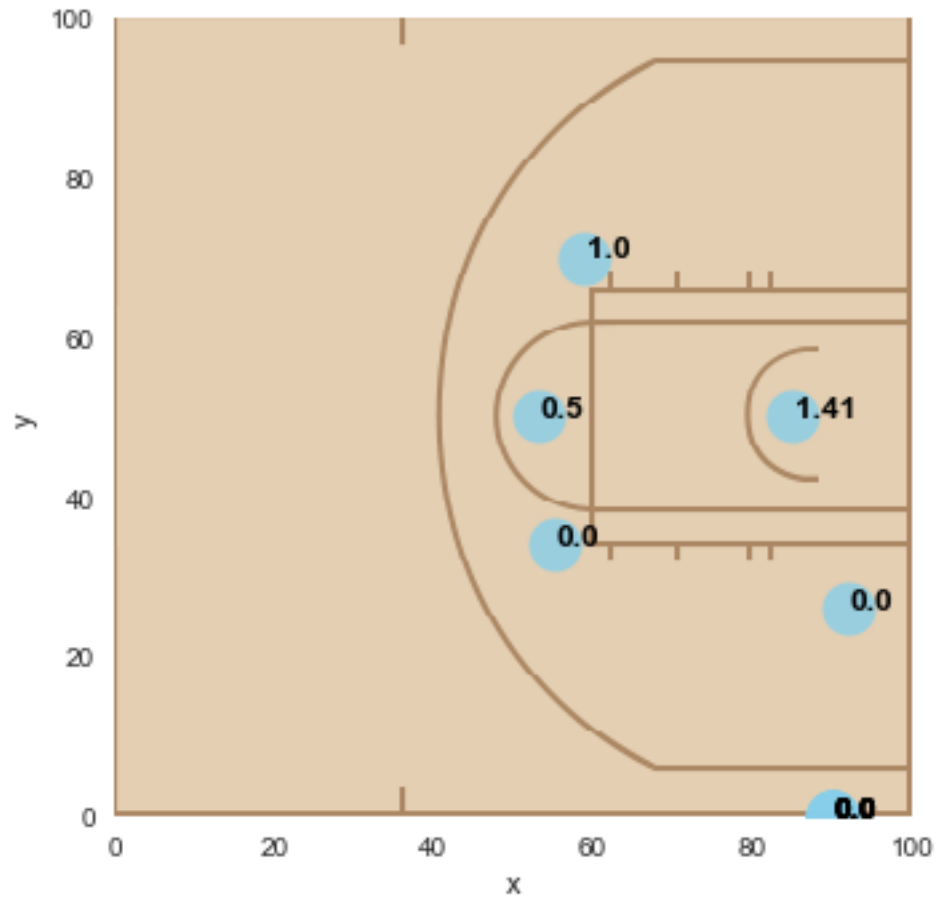
---- 2 Pointers ----

Percentages

[0.706140350877193, 0, 0.25, 0, 0, 0.5]

Expected Values

[1.412280701754386, 0, 0.5, 0, 0, 1.0]



 Thabo Sefolosha

---- 3 Pointers ----

Percentages

[0, 0.4444444444444444, 0.0, 0.2727272727272727, 0.35714285714285715, 0.2222222222222222]

 Expected Values

[0, 1.3333333333333333, 0.0, 0.8181818181818181, 1.0714285714285714, 0.6666666666666666]

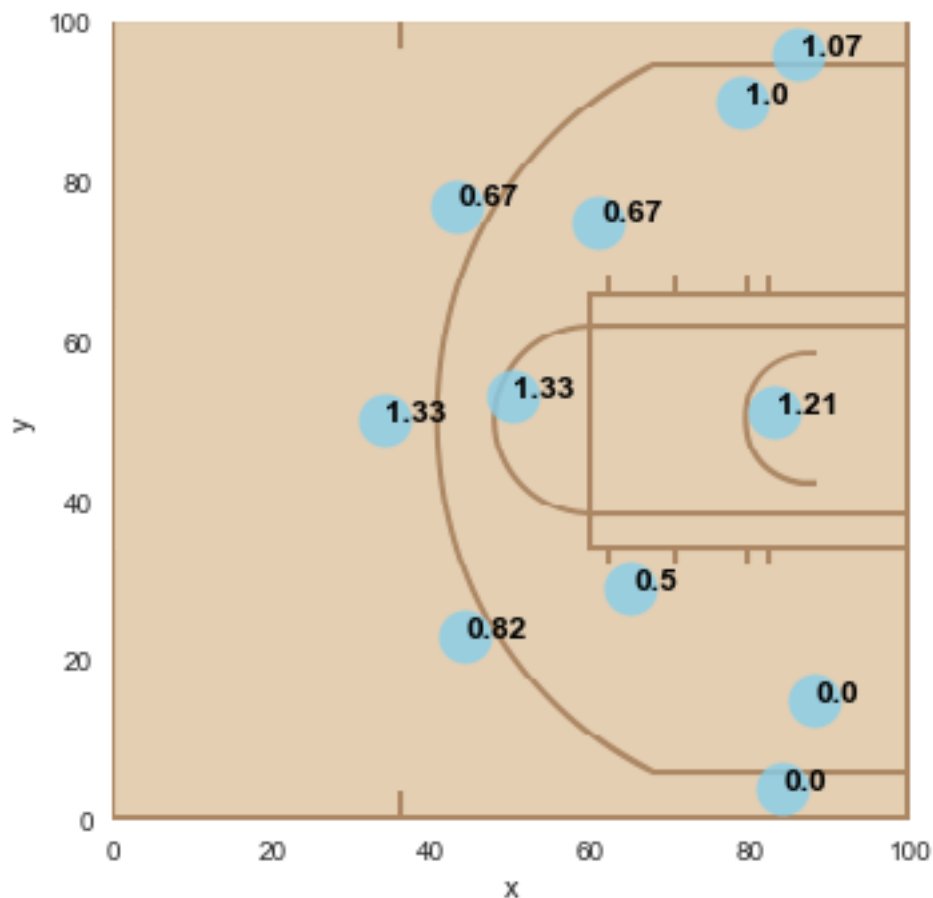
---- 2 Pointers ----

Percentages

[0.6031746031746031, 0.0, 0.6666666666666666, 0.25, 0.5, 0.3333333333333333]

 Expected Values

[1.2063492063492063, 0.0, 1.3333333333333333, 0.5, 1.0, 0.6666666666666666]



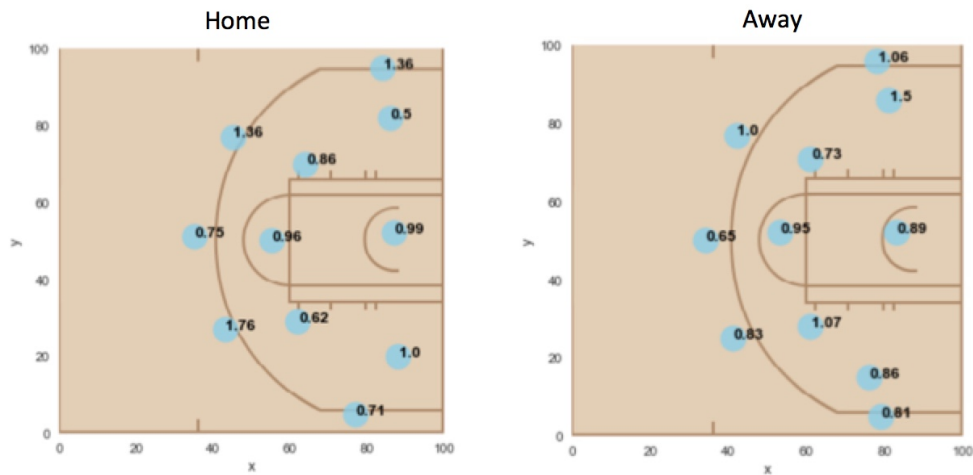
**** Conclusions****

From this, we can see that some players shoot different shots at much different expected values based on whether they are home or away. This could come from players having more nerves at away games and shooting worse altogether, or from being more comfortable with certain courts and stadiums. In the comparison below, we can see that Ricky Rubio is a much better 3-point shooter at home; but interestingly enough, he shoots the baseline jumper 3x better away than at home. It is interesting to think players can shoot better or worse just depending on whether it is a home or an away game.

2.3.2 Score Prediction

Finally, we were able to look at predicting a game based on the knowledge of the shot attempts to guess the team score and individual scores. We actually did quite well by looking at the boxscore listed below. This was the first game of the season. We over predicted Donovan Mitchell's score, probably as this was his first game in the NBA, and he may have shot worse due to nerves and getting used to the flow. Alec Burks was playing better at the time, so he actually did better than we predicted. We were able to decently predict a score based upon the expected values we found. However, our methods don't take into account free throws, so our final scores will be a little off depending on free throws.

Ricky Rubio



Ricky Rubio

We were able to be within 7 points for each player. The model predicted Joe Johnson's score perfectly while we were 7 off of Alec Burks actual total. We were 8 short of the team total.

```
In [40]: GameOfInterest = 1
         GameX = ShotsPD[ShotsPD['game'] == GameOfInterest]

In [41]: # Predicting a game
         # 3 pointers
         PlayerIDs = np.unique(GameX['shooter'])
         PlayerNames = np.unique(GameX['shooter_name'])
         NumOPlayers = len(PlayerNames)
         TotalPts = []
         PlayerToalPts = []
         PlayerToalPtsActual = []
         TotalPtsActual = []
         TotalTotalPts = []
         for Name in range(0, NumOPlayers):
             PercMadeDif3 = []
             NumShots = []
             NumMade = []
             ExpectedValue3 = []
             PtVal3 = 3
             PtVal2 = 2
             PercMadeDif2 = []
             NumShots3 = []
             NumShots2 = []
             NumMade3 = []
             NumMade2 = []
             ExpectedValue2 = []
             ExpectedValueRound = []
```

```

NumShotsRecreate3 = []
NumShotsRecreate2 = []
LocationRecreate2 = []
LocationRecreate3 = []
ExpectedPoints3Recreate = []
ExpectedPoints2Recreate= []
PlayerToalPts = []

NumShotsRecreate3Actual = []
NumShotsRecreate2Actual = []
LocationRecreate2Actual = []
LocationRecreate3Actual = []
ExpectedPoints3RecreateActual = []
ExpectedPoints2RecreateActual= []
PlayerToalPts = []

for i in range(0,6):
    Location = ShotsPD[(ShotsPD['LocationCluster']==i) & (ShotsPD['Th
                        & ( ShotsPD['shooter_name'] == PlayerNames[Name
    NumShots3.append(len(Location['made/missed']))
    NumMade3.append(len(Location[Location['made/missed']==1]))
    PercMade3 = 0
    if NumShots3[i] > 1:
        PercMade3 = NumMade3[i] / NumShots3[i]
        PercMadeDif3.append(PercMade3)
    else:
        PercMadeDif3.append(0)

    ExpectedValue3.append(PercMadeDif3[i]*PtVal3)

    AvLeft3.append(np.mean(Location['left']))
    AvTop3.append(np.mean(Location['top']))

    Location = ShotsPD[(ShotsPD['LocationCluster']==i) & (ShotsPD['Th
                        & ( ShotsPD['shooter_name'] == PlayerNames[Name
    NumShots2.append(len(Location['made/missed']))
    NumMade2.append(len(Location[Location['made/missed']==1]))
    PercMade2 = 0
    if NumShots2[i] > 1:

```

```

        PercMade2 = NumMade2[i] / NumShots2[i]
        PercMadeDif2.append(PercMade2)
    else:
        PercMadeDif2.append(0)
    ExpectedValue2.append(PercMadeDif2[i]*PtVal2)

    AvLeft2.append(np.mean(Location['left']))
    AvTop2.append(np.mean(Location['top']))

for i in range(0,6):
    LocationRecreate3 = GameX[(GameX['LocationCluster']==i) & (GameX['T
                                & (GameX['shooter_name'] == PlayerNames
    NumShotsRecreate3.append(len(LocationRecreate3['made/missed']))
    ExpectedPoints3Recreate.append(NumShotsRecreate3[i]*ExpectedValue3

for i in range(0,6):
    LocationRecreate2 = GameX[(GameX['LocationCluster']==i) & (GameX['T
                                & (GameX['shooter_name'] == PlayerNames
    NumShotsRecreate2.append(len(LocationRecreate2['made/missed']))
    ExpectedPoints2Recreate.append(NumShotsRecreate2[i]*ExpectedValue2

Player3pts = np.sum(ExpectedPoints3Recreate)
Player2pts = np.sum(ExpectedPoints2Recreate)

PlayerToalPts = Player3pts + Player2pts

TotalPts.append(int(PlayerToalPts))

## Actual Results of the Game

for i in range(0,6):

```



```

LocationRecreate3Actual = GameX[(GameX['LocationCluster']==i)& (GameX['shooter_name'] == PlayerNames[Name])
                               & (GameX['made/missed'] == 1)]
NumShotsRecreate3Actual.append(len(LocationRecreate3Actual['made/missed']))
ExpectedPoints3RecreateActual.append(NumShotsRecreate3Actual[i]*3)

for i in range(0,6):
    LocationRecreate2Actual = GameX[(GameX['LocationCluster']==i)& (GameX['shooter_name'] == PlayerNames[Name])
                                   & (GameX['made/missed'] == 1)]
    NumShotsRecreate2Actual.append(len(LocationRecreate2Actual['made/missed']))
    ExpectedPoints2RecreateActual.append(NumShotsRecreate2Actual[i]*2)

Player3ptsActual = np.sum(ExpectedPoints3RecreateActual)
Player2ptsActual = np.sum(ExpectedPoints2RecreateActual)

PlayerToalPtsActual = Player3ptsActual + Player2ptsActual

TotalPtsActual.append(int(PlayerToalPtsActual))

print('-----')
print(PlayerNames[Name])
print('Predicted: ' + str(int(PlayerToalPts)))
print('Actual: ' + str(PlayerToalPtsActual))

TotalTotalPts = np.sum(TotalPts)
TotalTotalPtsActual = np.sum(TotalPtsActual)
print('-----')
print('-----')
print('Final Jazz Score:')
print('Predicted: ' + str(TotalTotalPts))
print('Actual: ' + str(TotalTotalPtsActual))

```

```

-----
Alec Burks
Predicted: 9
Actual: 16
-----

```

```

-----
Derrick Favors
Predicted: 13
Actual: 14
-----

```

Donovan Mitchell

Predicted: 12

Actual: 6

Ekpe Udoh

Predicted: 0

Actual: 0

Joe Ingles

Predicted: 7

Actual: 11

Joe Johnson

Predicted: 10

Actual: 10

Ricky Rubio

Predicted: 8

Actual: 7

Rodney Hood

Predicted: 4

Actual: 6

Rudy Gobert

Predicted: 11

Actual: 14

Thabo Sefolosha

Predicted: 7

Actual: 6

Final Jazz Score:

Predicted: 81

Actual: 90

2.4 Conclusion:

We successfully were able to: - Acquire the data needed from ESPN - Clean the data to extract the needed values for analysis - Cluster the shots into natural groupings - Look at expected values for both the team and individuals - Perform significance testing on the data - Compare expected values between home and away games - Predict a Jazz game outcome using a model

Jazz															
STARTERS	MIN	FG	3PT	FT	OREB	DREB	REB	AST	STL	BLK	TO	PF	+/-	PTS	
D. Favors ^{PF}	28	7-14	0-1	0-0	0	4	4	4	1	0	1	4	+4	14	
J. Ingles ^{SF}	33	4-6	3-5	0-0	0	5	5	6	2	0	0	3	-6	11	
R. Gobert ^C	35	7-9	0-0	4-4	3	7	10	1	0	1	6	4	-14	18	
R. Rubio ^{PG}	32	3-9	1-5	2-3	0	5	5	10	2	0	3	1	-14	9	
D. Mitchell ^{SG}	26	3-11	0-2	4-4	0	1	1	4	0	1	3	1	+22	10	
BENCH	MIN	FG	3PT	FT	OREB	DREB	REB	AST	STL	BLK	TO	PF	+/-	PTS	
T. Sefolosha ^{SF}	21	3-7	0-2	1-1	0	2	2	2	2	0	0	0	+25	7	
E. Udoh ^C	13	0-1	0-0	2-2	1	1	2	0	0	3	1	0	+24	2	
J. Johnson ^{SG}	20	5-10	1-4	2-2	2	2	4	1	1	0	1	3	+6	13	
A. Burks ^{SG}	15	7-10	2-2	0-0	0	1	1	0	1	0	0	1	+16	16	
R. Hood ^{SG}	18	2-4	2-3	0-0	0	2	2	0	0	0	0	1	-13	6	
J. Jerebko ^{PF}	DNP-COACH'S DECISION														
R. O'Neale ^{SF}	DNP-COACH'S DECISION														
N. Wolters ^{PG}	DNP-COACH'S DECISION														
TEAM		41-81	9-24	15-16	6	30	36	28	9	5	15	18		106	
		50.6%	37.5%	93.8%											

JazzFirstGame

2.4.1 Ideas for future study:

- Effects of fatigue and overshooting in locations
- Correlation between shot selection and winning
- Compare Jazz's losing streak with winning streak
- Predict fouls and foul shots
- Evolution of Donovan Mitchell over the season