College Swimming Lineup Game Theory

Import Packages

```
In [ ]:
         import numpy as np
         import pandas as pd
         import os
         #import grahpics packages
         import seaborn as sns
         import matplotlib as mpl
         import matplotlib.pvplot as plt
         import re
         from collections import Counter
         plt.style.use('ggplot')
         # LIST THE INPUT FILES USED!
In [ ]:
         os.getcwd()
         c:\\Users\\mdb025\\Documents\\GitHub\\collegeswimming.com-Data-Analysis'
Out[ ]
In [ ]:
         # Get the swimmer names to numbers
         Swimmer Names df = pd.read csv("SwimmerNames.csv",index col='swimmer id')
         #print(Swimmer Names df)
         #Swimmer Names dict = dict(zip(Swimmer Names df.swimmer id, Swimmer Names df.name))
         #Swimmer Names dict
```

Read in and convert Swimmer Performance Predictions

These are formatted so that the performance in a relay leg or leadoff is the same for each swimmer (whether in team A, B, C, etc.). For example, it's just the swimmer's best leadoff leg for a relay (FLF50A, FLF50B,...)

TO DO: Read in raw data and do a sanity/viz check and then add the 3X times after we review the input data

F = Female

L = Lead, 1=Freestyle, 2=Backstroke, 3=Breaststroke, 4=Butterfly

Unless relay than L,2,3,4 are sequence in relay for medley or L,1 for lead off (1) and leg (2-4) swimmers.

FLFM50A = Female, lead swimmer in 200Y medley realay on A team

```
# Fvent Labels Conversion - Don't Currently Use
EventLabelConvertDict = { 'F1200Y': '200Y Free', 'F150Y': '50Y Free', 'F1100Y': '100Y Free', 'F4100Y': '100Y Free'
                  'F2100Y':'100Y Back'. 'F2200Y':'200Y Back'. 'F1500Y':'500Y Free'. 'F5200Y':'200Y IM'. 'F3100Y':'100Y Breast'. \
                 'F4200Y':'200Y Fly','F3200Y':'200Y Breast','F11650Y':'1650Y Free', \
                 'FLM50A': '200Y Medley Relay Back A', 'F2M50A': '200Y Medley Relay Breast A', 'F3M50A': '200Y Medley Relay Fly A', 'F4M50A': '200Y Medley Relay Fre
                 'FLM50B': '200Y Medlev Relay Back B', 'F2M50B': '200Y Medlev Relay Breast B', 'F3M50B': '200Y Medlev Relay Fly B', 'F4M50B': '200Y Medlev Relay Fre
                 'FLM50C': '200Y Medley Relay Back C'. 'F2M50C': '200Y Medley Relay Breast C'. 'F3M50C': '200Y Medley Relay Fly C'. 'F4M50C': '200Y Medley Relay Fre
                 'FLM50D': '200Y Medlev Relay Back D'. 'F2M50D': '200Y Medley Relay Breast D'. 'F3M50D': '200Y Medley Relay Fly D'. 'F4M50D': '200Y Medley Relay Fre
                 'FLF50A':'200Y Free Relay Lead A', 'F1F50A':'200Y Free Relay Leg A', \
                 'FLF50B':'200Y Free Relay Lead B'.'F1F50B':'200Y Free Relay Leg B'. \
                 'FLF50C':'200Y Free Relay Lead C'.'F1F50C':'200Y Free Relay Leg C'. \
                 'FLF50D':'200Y Free Relay Lead D', 'F1F50D':'200Y Free Relay Leg D'}
print(EventLabelConvertDict)
EventOrder = ['FLM50A', 'F2M50A', 'F3M50A', 'F4M50A',
                 'FLM50B', 'F2M50B', 'F3M50B', 'F4M50B', \
                 'FLM50C', 'F2M50C', 'F3M50C', 'F4M50C', \
                 'FLM50D', 'F2M50D', 'F3M50D', 'F4M50D', \
                 'F11650Y', 'F1200Y', 'F2100Y', 'F3100Y', \
                 'F4200Y', 'F150Y', 'F1100Y', 'F2200Y', \
                 'F3200Y', 'F1500Y', 'F4100Y', 'F5200Y', \
                 'FLF50A', 'F1F50A', 'FLF50B', 'F1F50B', \
                 'FLF50C', 'F1F50C', 'FLF50D', 'F1F50D']
print(EventOrder)### Order and names for meet scored events
```

{'F1200Y': '200Y Free', 'F150Y': '50Y Free', 'F1100Y': '100Y Free', 'F4100Y': '100Y Fly', 'F2100Y': '100Y Back', 'F2200Y': '200Y Back', 'F1500Y': '500Y Free', 'F5200Y': '200Y Medley Relay Breast', 'F4200Y': '200Y Fly', 'F3200Y': '200Y Breast', 'F11650Y': '1650Y Free', 'FLM50A': '200Y Medley Relay Back A', 'F2M50A': '200Y Medley Relay Fly A', 'F4M50A': '200Y Medley Relay Free A', 'FLM50B': '200Y Medley Relay Back B', 'F3M50B': '200Y Medley Relay Fly B', 'F4M50B': '200Y Medley Relay Free B', 'FLM50C': '200Y Medley Relay Back C', 'F2M50C': '200Y Medley Relay Fly C', 'F4M50C': '200Y Medley Relay Free C', 'FLM50D': '200Y Medley Relay Back D', 'F2M50D': '200Y Medley Relay Fly D', 'F4M50D': '200Y Medley Relay Free D', 'FLF50A': '200Y Free Relay Lead A', 'F1F50A': '200Y Free Relay Leg A', 'FLF50B': '200Y Free Relay Lead B', 'F1F50B': '200Y Free Relay Leg B', 'FLF50C': '200Y Free Relay Lead C', 'F1F50C': '200Y Free Relay Leg C', 'FLF50D': '200Y Free Relay Leg D'}

['FLM50A', 'F2M50A', 'F3M50A', 'F4M50A', 'F1M50B', 'F2M50B', 'F3M50B', 'F4M50B', 'F1M50C', 'F1M50C', 'F1M50C', 'F1M50C', 'F1M50D', 'F1F50A', 'F1F50B', 'F1F50B', 'F1F50C', 'F1F5

Order and names for meet scored events

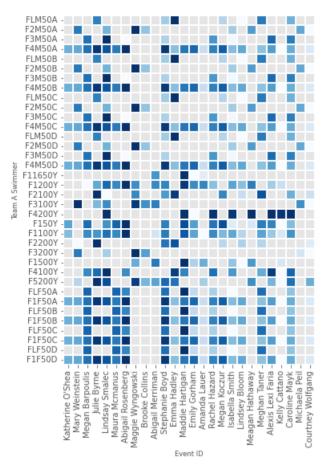
```
TeamA Perf df = pd.read csv("BucknellPerfwNAs.csv")
          TeamB Perf df = pd.read csv("LehighPerfwNAs.csv")
          TeamA Perf df.head()
Out[ ]:
            Swimmer F1200Y F150Y F1100Y F4100Y F2100Y F2200Y F1500Y F5200Y F3100Y ... F3M50D
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        5 rows × 37 columns
In [ ]:
          # Change the index to the unique Swimmer numbers
          TeamA Perf df.set index('Swimmer', inplace=True)
          TeamB Perf df.set index('Swimmer', inplace=True)
          # Reorder the columns based on the order of events in a meet
          TeamA Perf df = TeamA Perf df[EventOrder]
          TeamB Perf df = TeamB Perf df[EventOrder]
In [ ]:
          # Look at mins/max for outliers, errors, and omissions.
          TeamA Perf df.describe()
Out[]:
                 FLM50A
                           F2M50A
                                     F3M50A
                                               F4M50A
                                                          FLM50B
                                                                    F2M50B
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        8 rows × 36 columns
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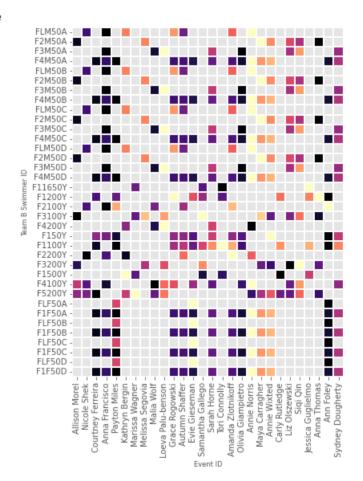
```
# Look at mins/max for outliers, errors, and omissions.
          TeamB Perf df.describe()
                                                          FLM50B
Out[ ]:
                 FLM50A
                           F2M50A
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        8 rows × 36 columns
```

Visualize the predicted time in each event for each swimmer. Heat map.

```
# Displaying performance data frame as a heatmap
# with diverging colourman as RdYLGn
fig. axs = plt.subplots(1, 2, figsize=(18, 8), constrained layout=True)
# Make swimmer names the index
TeamA_Perf_Clean_df = pd.merge(left= TeamA_Perf_df, right= Swimmer_Names_df[['name']], how= 'left', left_index= True, right_index=True).set_index('name')
TeamB Perf Clean df = pd.merge(left= TeamB Perf df, right= Swimmer Names df[['name']], how= 'left', left index= True, right index=True).set index('name')
# Scale the columns to min/max
TeamA Perf Clean df = (TeamA Perf Clean df - TeamA Perf Clean df.min())/(TeamA Perf Clean df.max()-TeamA Perf Clean df.min())
TeamB Perf Clean df = (TeamB Perf Clean df - TeamB Perf Clean df.min())/(TeamB Perf Clean df.max()-TeamB Perf Clean df.min())
sns.heatmap(TeamA Perf Clean df.T, linewidths = 0.30, annot = False, cbar= False, square= True, ax= axs[0], cmap= 'Blues r')
sns.heatmap(TeamB Perf Clean df.T, linewidths = 0.30, annot = False, cbar= False, square= True, ax= axs[1], cmap= 'magma' )
#clean up the charts
fig.suptitle('Swimmer Performance')
axs[0].set ylabel('Team A Swimmer',fontsize='small')
axs[1].set_ylabel('Team B Swimmer ID',fontsize='small')
axs[0].set xlabel('Event ID', fontsize='small')
axs[1].set xlabel('Event ID', fontsize='small')
plt.show()
```

Swimmer Performance





```
from matplotlib.colors import ListedColormap
    # Just Bucknell for Dan:
    # Displaying performance data frame as a heatmap
    fig, axs = plt.subplots(1, 1, figsize=(26, 10), constrained_layout=False)

# Make swimmer names the index
TeamA_Perf_Clean_df = pd.merge(left= TeamA_Perf_df, right= Swimmer_Names_df[['name']], how= 'left', left_index= True,right_index=True).set_index('name')
TeamA_Lineup_Clean_events_df = TeamA_Perf_Clean_df.rename(columns=EventLabelConvertDict)

sns.heatmap(TeamA_Lineup_Clean_events_df, linewidths = 0.10, annot = True, fmt= '.2f', cbar= False, square= False, ax= axs, cmap = ListedColormap(['white'])
#clean up the charts
fig.suptitle('Swimmer Predicted Performance')
axs.set_ylabel('Team A Swimmer',fontsize='small')
axs.set_xlabel('Event ID', fontsize='small')
plt.show()
```

Katherine O'Shea -				24.92				24.92				24.92				24.92						25.06	54.88							24.92		24.92		24.92		24.92
Mary Weinstein		30.62		24.92		30.62		24.92		30.62		24.82		30.62		24.82				65.77		25.00	34.00	131.82	143.20			136.12		24.82		24.82		24.82		24.82
Megan Barpoulis -		50.02	25.41			30.02	25 41	24.02		30.02	25.41			30.02	25.41			125.89		33.77		24.31	53 15	131.02	215.20		58.79	130.12	24 43		24 43	24.05	24 43		24 43	24.05
Julie Byrne -	26.68		25.71	23.25	26.68		23.41	23.25	26.68		23.71	23.25	26.68		23.41	23.25			54.76	69.67		24.51	53.45	117 11				122.27	24.45	23.25	24.43	23.25	24.43	23.25		23.25
Lindsay Smalec -	20.00	31 72	24.37		20.00	31.72	24.37	23.66	20.00	31.72	24 37	23.66	20.00	31 72	24.37			112.56	_	_	124 42	24.81			150.69			124.53		23.66		23.66		23.66		23.66
Maura Mcmanus -		51.72	2.4.37	24.15		31.72	24.57	24.15		31.72	24.57	24.15		32.72	24.57	24.15		114.53	05.05	00.52	22.7.72				150.05		33.00	12.4.55	24.43		24.43	24.15	24.43			24.15
Abigail Rosenberg -			28 47	23.17			28 47	23.17			28.47				28.47			108.83				23.52					58.94		_			23.17	_		_	
Maggie Wyngowski -		29.33	20.47	25.11		29.33	20.47	23.17		29.33	20.47	23.17		29.33	20.47	23.17		115.00	57.60	66.03		25.52	30.41		137.35	301.82	30.34	123.35	24.75	25.17	24.75	25.17	24.75	25.17	24.73	23.17
Brooke Collins -		32.08				32.08				32.08				32.08				115.00		68.42					146.29	301.02		132.69								
Abigail Merriman -		52.00				52.00				52.00				52.00			1018.38	114 71		67.92			56.88			296.33		131.16								
Stephanie Boyd -	28 10		27 14	23.28	28 10		27 14	23.28	28 10		27 14	23.28	28 10		27.14			114.32	_	07.52		24 53	52.69	120 98		250.55			24 53	23.28	24 53	23.28	24 53	23 28	24 53	23.28
a Emma Hadley -			27.24	25.16			27.24	25.16	_		27.27	25.16			27.24	25.16			55.10			24.55		119.17			55 75	127.38	24.33	25.16	24.55	25.16	24.33	25.16		25.16
Maddie Hartigan -				24.11				24.11				24.11	20100				1004.99		33.20		125.72	23.90				289.16			23.90		23.90	24.11	23.90			
్ల్ K Emily Gorham -				23.91				23.91				23.91				23.91	1039.34	114.87			397.26	24.98	53.95			306.46						23.91				23.91
Amanda Lauer -				25.84				25.84				25.84				25.84	1035.66	114.37					58.26			302.03		135.10		25.84		25.84		25.84		25.84
Rachel Hazard -			26.00	24.23			26.00	24.23			26.00	24.23			26.00	24.23		118.68			130.20	24.41	53.06				57.76		25.63	24.23	25.63	24.23	25.63	24.23	25.63	24.23
Megan Koczur -	28.35			23.78	28.35			23.78	28.35			23.78	28.35			23.78			57.46			23.92	54.72	127.67						23.78		23.78		23.78		23.78
Isabella Smith -		32.26	28.33	25.13		32.26	28.33	25.13		32.26	28.33	25.13		32.26	28.33	25.13		116.62			132.42	26.49	54.09			304.51	59.40		26.49	25.13	26.49	25.13	26.49	25.13	26.49	25.13
Lindsey Bloom -	29.63			24.79	29.63			24.79	29.63			24.79	29.63			24.79		118.59	61.12				55.93	127.09		314.71				24.79		24.79		24.79		24.79
Meagan Hathaway -		31.25				31.25				31.25				31.25				113.85			123.89	26.36				299.44		129.32								
Meghan Taner -	26.58			25.20	26.58			25.20	26.58			25.20	26.58			25.20			55.83			24.51	53.91	127.40			60.36		24.51	25.20	24.51	25.20	24.51	25.20	24.51	25.20
Alexis Lexi Faria -	-		25.28	24.64			25.28	24.64			25.28	24.64			25.28	24.64		119.80			124.40	24.60	55.24				55.65	132.75		24.64		24.64		24.64		24.64
Kelly Cattano -	-			26.64				26.64				26.64				26.64		122.06			130.63	26.90	57.05			310.44	65.88	141.87		26.64		26.64		26.64		26.64
Caroline Mayk -	27.55		25.58	24.88	27.55		25.58	24.88	27.55		25.58	24.88	27.55		25.58	24.88			58.94		124.37	25.43	53.39				57.31	127.14	25.43	24.88	25.43	24.88	25.43	24.88	25.43	24.88
Michaela Peil -	-	31.50				31.50				31.50				31.50						68.42					154.34											
Courtney Wolfgang -	-	33.91		26.14		33.91		26.14		33.91		26.14		33.91		26.14			61.23	72.94				130.03	157.78			132.06		26.14		26.14		26.14		26.14
	200Y Medley Relay Back A -	200Y Medley Relay Breast A -	200Y Medley Relay Fly A -	200Y Medley Relay Free A -	200Y Medley Relay Back B –	200Y Medley Relay Breast B -	200Y Medley Relay Fly B -	200Y Medley Relay Free B -	200Y Medley Relay Back C -	200Y Medley Relay Breast C -	200Y Medley Relay Fly C -	200Y Medley Relay Free C -	200Y Medley Relay Back D -	200Y Medley Relay Breast D -	200Y Medley Relay Fly D –	200Y Medley Relay Free D –	1650Y Free -	200Y Free –	100Y Back –	100Y Breast -	200Y Fly -	50Y Free –	100Y Free -	200Y Back -	200Y Breast -	500Y Free -	100Y Fly -	200Y IM -	200Y Free Relay Lead A -	200Y Free Relay Leg A -	200Y Free Relay Lead B -	200Y Free Relay Leg B -	200Y Free Relay Lead C -	200Y Free Relay Leg C -	200Y Free Relay Lead D -	200Y Free Relay Leg D -

```
# Write performance to Excel for Dan
TeamA_Lineup_Clean_events_df.to_excel('Bucknell_Predicted_Performance.xlsx')
```

Now compute the BigM values and add to the performance dataFrame

```
In []:
# define the BigM value for each event and replace the NaNs with the BigM value
BigM = dict()
TeamA_Perf_wM_df = TeamA_Perf_df.copy()
TeamB_Perf_wM_df = TeamB_Perf_df.copy()

for ev in EventOrder:

#Big M is defined at 1.5x the largest observed value in the event
temp = 4*max(TeamA_Perf_df[ev].max(),TeamB_Perf_df[ev].max())
BigM[ev] = temp

TeamA_Perf_wM_df[ev] = TeamA_Perf_df[ev].fillna(temp)
TeamB_Perf_wM_df[ev] = TeamB_Perf_df[ev].fillna(temp)
```

```
# Create the BigM for the relay events from the four legs
BigM['M50'] = BigM['FLF50A'] + 3*BigM['F1F50A']
BigM['F50'] = BigM['FLM50A'] + BigM['F2M50A'] + BigM['F3M50A'] + BigM['F4M50A']

# Display the BigM values as a dataframe
pd.DataFrame.from_dict(BigM, orient='index',columns= ['BigM'])
```

Out[]: BigM FLM50A 118.52 **F2M50A** 135.64 **F3M50A** 114.72 F4M50A 112.44 FLM50B 118.52 F2M50B 135.64 F3M50B 114.72 F4M50B 112.44 FLM50C 118.52 **F2M50C** 135.64 **F3M50C** 114.72 **F4M50C** 112.44 FLM50D 118.52 F2M50D 135.64 F3M50D 114.72 F4M50D 112.44 **F11650Y** 4396.20 **F1200Y** 503.56 **F2100Y** 252.20 **F3100Y** 291.76 **F4200Y** 1589.04 **F150Y** 107.60 F1100Y 233.04 F2200Y 527.28 F3200Y 631.12 **F1500Y** 1259.96 **F4100Y** 263.52

```
F5200Y
                   567.48
          FLF50A
                   105 96
          F1F50A
                   112.44
          FLF50B
                   105.96
          F1F50B
                   112.44
          FLF50C
                   105.96
          F1F50C
                  112 44
          FLF50D
                   105.96
          F1F50D
                   112 44
            M50
                   443.28
             F50 481.32
          TeamA Perf wM df.describe()
                                                                                                                   F2M50C ...
Out[ ]:
                  FLM50A
                            F2M50A
                                       F3M50A
                                                  F4M50A
                                                             FLM50B
                                                                       F2M50B
                                                                                  F3M50B
                                                                                             F4M50B
                                                                                                        FLM50C
                                                                                                                                 F4100Y
                                                                                                                                            F5200Y
                                                                                                                                                       FLF50A
                                                                                                                                                                  F1F50A
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                           26.000000
                                      26.000000
                                                 26.000000
                                                           26.000000
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         count
         mean
                94.005769
                          103.622692
                                      87.520769
                                                 41.459615
                                                           94.005769
                                                                     103.622692
                                                                                 87.520769
                                                                                            41.459615
                                                                                                       94.005769
                                                                                                                103.622692 ... 168.859615 332.003846
                                                                                                                                                     74.817308
                                                                                                                                                                41.459615
                41.192889
                           48.982069
                                      41.614367
                                                 35.330854
                                                           41.192889
                                                                                            35.330854
                                                                                                      41.192889
                                                                                                                 48.982069 ... 104.286845 222.360636
           std
                                                                      48.982069
                                                                                 41.614367
                                                                                                                                                     40.175779
                                                                                                                                                                35.330854
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                25.380000
                           29.330000
                                      24.370000
                                                 23.170000
                                                           25.380000
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                                                                                                                                                     23.900000
                                                                                                                                                                23.170000
                                                                                                                                                                          23.9
          min
                                                                      29.330000
                                                                                 24.370000
                                                                                                                               55.080000
                                                                                                                                         122.270000
                           32.672500
          25%
                51.852500
                                      28.365000
                                                 24.065000
                                                           51.852500
                                                                      32.672500
                                                                                 28.365000
                                                                                            24.065000
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                                                                                                                  32.672500 ...
                                                                                                                               58.625000
                                                                                                                                         129.780000
                                                                                                                                                     25.480000
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                                     114.720000
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                                                                                                                135.640000 ... 263.520000 567.480000
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                                                                                                                                                                         105.9
          8 rows × 36 columns
          TeamB Perf wM df.describe()
Out[ ]:
                 FLM50A
                           F2M50A
                                      F3M50A
                                                 F4M50A
                                                           FLM50B
                                                                      F2M50B
                                                                                F3M50B
                                                                                           F4M50B
                                                                                                     FLM50C
                                                                                                                F2M50C ...
                                                                                                                               F4100Y
                                                                                                                                         F5200Y
                                                                                                                                                    FLF50A
                                                                                                                                                               F1F50A
                                                                                                                                                                          FLF!
         count
                28.00000
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                                     28.000000
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                                                           28.00000
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                95.84750
                         109.513571
                                     89.501786
                                                68.449643
                                                           95.84750
                                                                   109.513571
                                                                               89.501786
                                                                                          68.449643
                                                                                                     95.84750
                                                                                                              109.513571 ...
                                                                                                                           168.372500
                                                                                                                                       349.088214
                                                                                                                                                  97.146429
                                                                                                                                                             68.449643
                                                                                                                                                                        97.146
         mean
                39.99489
                          46.084782
                                     40.611306
                                                44.813983
                                                          39.99489
                                                                    46.084782
                                                                               40.611306
                                                                                          44.813983
                                                                                                     39.99489
                                                                                                              46.084782 ...
                                                                                                                           104.089356 222.417407
                                                                                                                                                  25.909695
                                                                                                                                                             44.813983
                                                                                                                                                                        25.909
           std
```

BigM

	FLI	M50A	F2M50A	F3M50A	F4M50A	FLM50B	F2M50B	F3M50B	F4M50B	FLM50C	F2M50C	•••	F4100Y	F5200Y	FLF50A	F1F50A	FLF!
n	nin 25.9	96000	29.840000	24.890000	22.660000	25.96000	29.840000	24.890000	22.660000	25.96000	29.840000		55.470000	123.850000	23.280000	22.660000	23.280
2	5% 96.2	25750	109.815000	28.480000	23.877500	96.25750	109.815000	28.480000	23.877500	96.25750	109.815000		58.545000	129.972500	105.960000	23.877500	105.960
50)% 118.5	52000	135.640000	114.720000	70.275000	118.52000	135.640000	114.720000	70.275000	118.52000	135.640000		263.520000	353.540000	105.960000	70.275000	105.960
7	5% 118.5	52000	135.640000	114.720000	112.440000	118.52000	135.640000	114.720000	112.440000	118.52000	135.640000		263.520000	567.480000	105.960000	112.440000	105.960
m	ax 118.5	52000	135.640000	114.720000	112.440000	118.52000	135.640000	114.720000	112.440000	118.52000	135.640000		263.520000	567.480000	105.960000	112.440000	105.960
8 ro	8 rows × 36 columns																

Read in initial lineups for both teams and put in a list. We'll create improvedd lineups later.

```
In [ ]:
         # GLobal
         TOTAL LINEUPS = 4
         # Initialize lists of lineups for teams A and B
         TeamA Lineup df = [None] * TOTAL LINEUPS
         TeamB Lineup df = [None] * TOTAL LINEUPS
         # Read the initial lineups into a list as the first (base) lineup
         TeamA_Lineup_df[0] = pd.read_csv("Bucknell_1_Lineup.csv",index_col='Swimmer')
         TeamB Lineup df[0] = pd.read csv("Lehigh 1 Lineup.csv".index col='Swimmer')
         #TeamA Lineup df = [1]
         #TeamA Lineup df.append(pd.read csv("Bucknell 1 Lineup.csv",index col='Swimmer'))
         #TeamB Lineup df = [1]
         #TeamB Lineup df.append(pd.read csv("Lehigh 1 Lineup.csv",index col='Swimmer'))
         # What are the line up events we'll need to assign later?
         # We won't really need the D relay team, but keep for consistency
         Lineup Events = tuple(TeamA Lineup df[0].columns.tolist())
         # Order the columnns to the meet event order
         TeamA Lineup df[0] = TeamA Lineup df[0][EventOrder]
         TeamB Lineup df[0] = TeamB Lineup df[0][EventOrder]
         print(Lineup Events)
```

('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F4200Y', 'F3200Y', 'F11650Y', 'F11650Y',

The base meet did NOT swim a 1650Y Free (F11650Y) or 200Y Free Relay, they swam a 1000Y Free (F11000Y) and 400Y Free Relay instead, make some adjustments to the lineups

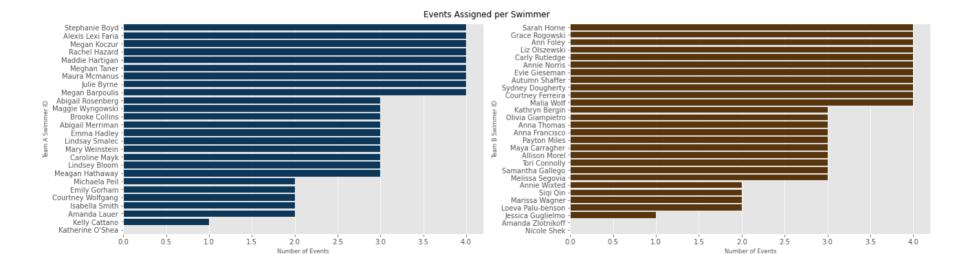
```
# Swimmers were accidentally put in 100Y that actually swam the 1000Y Free from Data Scrape
TeamA_Lineup_df[0].at[260001,'F1100Y'] = 0
```

```
TeamA Lineup df[0].at[402879, 'F1100Y'] = 0
         TeamB Lineup df[0].at[330114.'F1100Y'] = 0
         TeamB Lineup df[0].at[696579.'F1100Y'] = 0
In [ ]:
         # # Add the 1650 Swimmers from the meet that swam the 1000Y Free instead
         TeamA Lineup df[0].at[330237.'F11650Y'] = 1
         TeamA Lineup df[0].at[260001.'F11650Y'] = 1
         TeamA Lineup df[0].at[356813, 'F11650Y'] = 1
         TeamA Lineup df[0].at[330324, 'F11650Y'] = 1
         TeamB Lineup df[0].at[404163, 'F11650Y'] = 1
         TeamB Lineup df[0].at[342505.'F11650Y'] = 1
         TeamB Lineup df[0].at[271442.'F11650Y'] = 1
         TeamB Lineup df[0].at[422229.'F11650Y'] = 1
In [ ]:
         # Add the 200 Free Relay from the 400 Free Relay for TEAM A
         TeamA Lineup df[0].at[329465, 'FLF50A'] = 1
         TeamA Lineup df[0].at[265562, 'F1F50A'] = 1
         TeamA Lineup df[0].at[233650, 'F1F50A'] = 1
         TeamA Lineup df[0].at[342607, 'F1F50A'] = 1
         TeamA Lineup df[0].at[221480, 'FLF50B'] = 1
         TeamA Lineup df[0].at[342611, 'F1F50B'] = 1
         TeamA Lineup df[0].at[382148,'F1F50B'] = 1
         TeamA Lineup df[0].at[395502.'F1F50B'] = 1
         TeamA Lineup df[0].at[260001,'FLF50C'] = 1
         TeamA Lineup df[0].at[356813, 'F1F50C'] = 1
         TeamA Lineup df[0].at[347298, 'F1F50C'] = 1
         TeamA Lineup df[0].at[344005, 'F1F50C'] = 1
In [ ]:
         # Add the 200 Free Relay from the 400 Free Relay Roster for TEAM B
         TeamB Lineup df[0].at[494957, 'FLF50A'] = 1
         TeamB Lineup df[0].at[233836, 'F1F50A'] = 1
         TeamB Lineup df[0].at[342918, 'F1F50A'] = 1
         TeamB Lineup df[0].at[213253, 'F1F50A'] = 1
         TeamB Lineup df[0].at[330114,'FLF50B'] = 1
         TeamB Lineup df[0].at[282290, 'F1F50B'] = 1
         TeamB Lineup df[0].at[323285, 'F1F50B'] = 1
         TeamB Lineup df[0].at[330349, 'F1F50B'] = 1
         TeamB Lineup df[0].at[696579, 'FLF50C'] = 1
         TeamB_Lineup_df[0].at[273646,'F1F50C'] = 1
         TeamB Lineup df[0].at[291023, 'F1F50C'] = 1
         TeamB Lineup df[0].at[404163,'F1F50C'] = 1
```

```
TeamA_Lineup_df[0] = TeamA_Lineup_df[0][TeamA_Lineup_df[0].columns].astype('int8')
TeamB_Lineup_df[0] = TeamB_Lineup_df[0][TeamB_Lineup_df[0].columns].astype('int8')
```

EDA on the Base Team Lineups

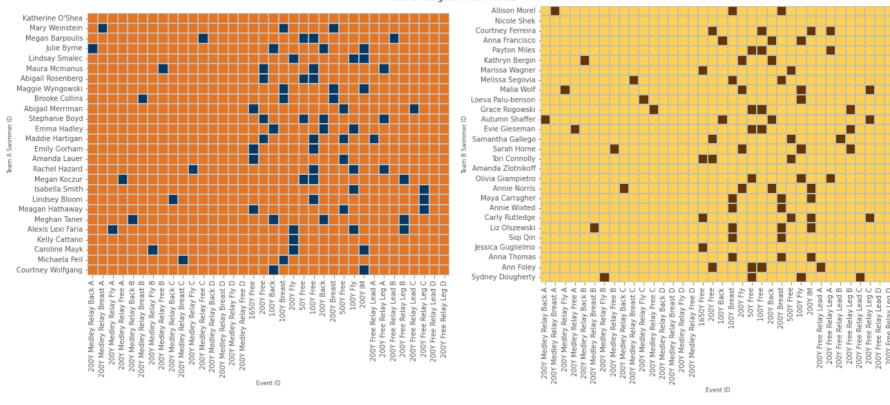
```
# Some colors for consistency
TeamA blue = (0..22..4)
TeamA orange = (0.9, 0.46, 0.13)
TeamB vellow = (1.0.82, 0.309)
TeamB brown = (0.396, 0.211, 0)
TeamA colors = [TeamA orange, TeamA blue]
TeamB colors = [TeamB vellow, TeamB brown]
# How many Events for each swimmer?
fig, axs = plt.subplots(1, 2, figsize=(18, 5), constrained layout=True)
# Team A
TeamA TotEventsPerAth = TeamA Lineup df[0].sum(axis=1).sort values(ascending=False).to frame().rename(columns={0: "tot events"})
TeamA TotEventsPerAth = pd.merge(left= TeamA TotEventsPerAth, right= Swimmer Names df[['name']], how= 'left', left index= True, right index=True)
sns.barplot(y=TeamA TotEventsPerAth.name, x=TeamA TotEventsPerAth.tot events, color= TeamA blue,ax=axs[0])
TeamB TotEventsPerAth = TeamB Lineup df[0].sum(axis=1).sort values(ascending=False).to frame().rename(columns={0: "tot events"})
TeamB TotEventsPerAth = pd.merge(left= TeamB TotEventsPerAth, right= Swimmer Names df[['name']], how= 'left', left index= True, right index=True)
sns.barplot(y=TeamB TotEventsPerAth.name, x=TeamB TotEventsPerAth.tot events, color= TeamB brown,ax=axs[1])
#clean up the charts
fig.suptitle('Events Assigned per Swimmer')
axs[0].set ylabel('Team A Swimmer ID',fontsize='small')
axs[1].set ylabel('Team B Swimmer ID',fontsize='small')
#for ax in axs:
# ax.set ylim([0, 4.2])
axs[0].set xlabel('Number of Events', fontsize='small')
axs[1].set xlabel('Number of Events', fontsize='small')
plt.show()
```



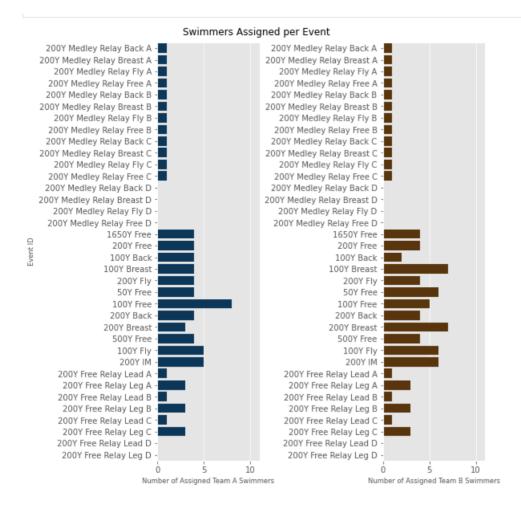
We can see that some swimmers were put in an as many as four swimming events at this meet. The focus of on our analysis is on assignments that will likely score in the meet. The coach can make adjustments to add athletes they want in events, but likely won't score.

```
In [ ]:
         # Displaying dataframe as an heatmap
         # with diverging colourmap as RdYLGn
         fig, axs = plt.subplots(1, 2, figsize=(18, 8), constrained layout=True)
         # Make swimmer names the index
         TeamA Lineup Clean df = pd.merge(left= TeamA Lineup df[0], right= Swimmer Names df[['name']], how= 'left', left index= True, right index=True).set index('name')
         TeamB Lineup Clean df = pd.merge(left= TeamB Lineup df[0], right= Swimmer Names df[['name']], how= 'left', left index= True, right index=True).set index('name')
         TeamA Lineup Clean df = TeamA Lineup Clean df.rename(columns=EventLabelConvertDict)
         TeamB Lineup Clean df = TeamB Lineup Clean df.rename(columns=EventLabelConvertDict)
         sns.heatmap(TeamA_Lineup_Clean_df, linewidths = 0.1, annot = False, cbar= False, square= True, ax= axs[0], cmap= TeamA_colors, linecolor='0.75')
         sns.heatmap(TeamB Lineup Clean df, linewidths = 0.1, annot = False, cbar= False, square= True, ax= axs[1], cmap= TeamB colors. linecolor='0.75')
         #clean up the charts
         fig.suptitle('Events Assigned to Swimmers')
         axs[0].set ylabel('Team A Swimmer ID',fontsize='small')
         axs[1].set ylabel('Team B Swimmer ID',fontsize='small')
         axs[0].set_xlabel('Event ID', fontsize='small')
         axs[1].set xlabel('Event ID', fontsize='small')
         # colorbar = axs[0].collections[0].colorbar
         # colorbar.set_ticks([.25,.75])
         # colorbar.set ticklabels(['Not Assigned','Assigned'])
         # colorbar2 = axs[1].collections[0].colorbar
         # colorbar2.set ticks([.25,.75])
         # colorbar2.set ticklabels(['Not Assigned', 'Assigned'])
```

Events Assigned to Swimmers



```
# How many athletes for each event?
fig, axs = plt.subplots(1, 2, figsize=(8, 8), sharey=False, constrained_layout=True)
# Team A
TeamA = TeamA_Lineup_df[0].rename(columns=EventLabelConvertDict).sum(axis=0)
sns.barplot(y=TeamA.index, x=TeamA.values, color= TeamA blue,ax=axs[0], ci=None)
#Team B
TeamB = TeamB Lineup df[0].rename(columns=EventLabelConvertDict).sum(axis=0)
sns.barplot(y=TeamB.index, x=TeamB.values, color= TeamB_brown, ax=axs[1], ci=None)
#clean up the charts
fig.suptitle('Swimmers Assigned per Event')
axs[0].set_ylabel('Event ID',fontsize='small')
for ax in axs:
   ax.set_xlim([0, 11])
axs[0].set_xlabel('Number of Assigned Team A Swimmers', fontsize='small')
axs[1].set_xlabel('Number of Assigned Team B Swimmers', fontsize='small')
plt.show()
```



Set the scoring rules for the meet

```
# Point Values for each place in an event category. Format: {# of Lanes: [1st place, 2nd place,... nth place]}
INDIVIDUAL_POINTS = {"Six Lane": [9, 4, 3, 2, 1, 0], "Five Lane": [5, 3, 1, 0]}
RELAY_POINTS = {"Six Lane": [11, 4, 2], "Five Lane": [7, 0]}
# Limit for number of people who can score per team in each event type. Format: {# of Lanes: [Individual, Relay]}
SCORER_LIMIT = {"Six Lane": [3,2], "Five Lane": [2,1]}
```

Determine the Expected Score for Team A and Team B when using a given set of performances AND lineups

```
def calculate_pred_score(perf_team_a, line_team_a, perf_team_b, line_team_b, scoring_method="Six Lane"):
    """
    returns the predicted score of team A for a swimming meet
    :param perf_team_a: Pandas dataframe of predicted performances for a given team A's swimmers
    :param line_team_a: Pandas Dataframe of a given lineup for a team A
    :param perf_team_b: Pandas dataframe of predicted performances for a given team B's swimmers
```

```
:param line team b: Pandas Dataframe of a given lineup for a team B
:param scoring method: used to determine how points are allocated
:return: pred score: Integer value of team A's predicted
# create predicted performance matrices that only contain values for swimmers in the lineup
lineup scores a = perf team a[line team a == 1]
lineup scores b = perf team b[line team b == 1]
# Team scores are integer values, initialize them at 0
score a = score b = 0
# Find times for all relay events and put them together in one dictionary
event list = lineup scores a.columns.tolist()
# Look for relay events, the Lookup is performed by finding the Leadoff
r = re.compile(".L[MF].+")
relav list = list(filter(r.match, event list))
#print(relay list)
relay event results = dict()
for value in relav list:
    #find out what type of relay value is and make list of leas in relay
    if value[2] == "F":
        # relay is a freestyle relay, so there are two types of leas
        legs = [value, value[:1]+"1"+value[2:]]
    elif value[2] == "M":
        # relav is medlev relav. so there are four different leas
        legs = [value, value[:1] + "2" + value[2:], value[:1] + "3" + value[2:], value[:1] + "4" + value[2:]]
    # aet sum of leas in relay for full relay time.
    time a = lineup scores a[legs].sum().sum()
    time b = lineup scores b[legs].sum().sum()
    # if event is in dictionary, update data, if not then append it
    if value[2:-1] in relay event results:
        if time a != 0:
            relay event results[value[2:-1]][0].append(time a)
        if time b != 0:
            relay event results[value[2:-1]][1].append(time b)
    else:
        relay event results[value[2:-1]] = [[time a],[time b]]
        if time a == 0:
            relay event results[value[2:-1]][0].pop()
        if time b == 0:
            relay event results[value[2:-1]][1].pop()
# dataframe to keep event scores
eventScore df = pd.DataFrame(columns = ['event', 'team', 'score'])
# score the relays
for event in relay event results:
    # get results for each team by event
    results a = relay event results[event][0]
    #print("results for relay event ", event, " are ", results a)
    results b = relay event results[event][1]
    temp a, temp b = score event(results a, results b, RELAY POINTS[scoring method], SCORER LIMIT[scoring method][1])
    score a += temp a
    score b += temp b
    eventScore_df = eventScore_df.append({'event' : event, 'team': 'Team A', 'score' : temp_a},ignore_index= True)
```

```
eventScore df = eventScore df.append({'event' : event, 'team': 'Team B', 'score' : temp b},ignore index= True)
    #print("Event ". event. ":")
    #print("\tBucknell: ".temp a.". Lehiah: ".temp b)
# score individual events, which we identify in the line below
individual events = list(filter(lambda x: x[2] not in "MF", event list))
for column name in individual events:
    results a = lineup scores a[column name][lineup scores a[column name].notna()].tolist()
    #print("results for event ". column name. " are ". results a)
    results b = lineup scores b[column name][lineup scores b[column name].notna()].tolist()
    temp a, temp b = score event(results a, results b, INDIVIDUAL POINTS[scoring method],
                                 SCORER LIMIT[scoring method][0])
    # cannot add to two values at same time. so we have to assign points to temp values and then add those to score
    score a += temp a
    score b += temp b
    #print("Event ". column name. ":")
    #print("\tBucknell: ",temp a,", Lehigh: ",temp b)
    eventScore df = eventScore df.append({'event' : column name, 'team': 'Team A', 'score' : temp a}.ignore index= True)
    eventScore df = eventScore df.append({'event' : column name, 'team': 'Team B', 'score' : temp b},ignore index= True)
return score a, score b, eventScore df
```

```
In [ ]:
         def score event(results a, results b, places, scoring limit):
             assigns points to groups based on who has the smallest score/time.
             :param results a: list of recorded times for team a
             :param results b: list of recorded times for team b
             :param places: list of point values awarded for first, second, etc place
             :param scoring limit: the maximum number of swimmers per team that can score in the event
             :return: scores of team a and b
             score a = score b = place counter = 0
             all times = results a + results b # make a list of all times scored in the event
             all times.sort() # sort the list in ascending order
             a scorers = b scorers = 0
             results dict = dict(Counter(all times)) # convert list to dictionary. key is time, value is frequency of time
             for i in results dict:
                 if place counter >= len(places): # When there are no more points to award for the event break the Loop
                     break
                 if results dict[i] == 1: # only one instance of the given time in either list (i.e. not a tie)
                     if i in results a:
                         if a scorers <= scoring limit:</pre>
                             score_a = score_a + places[place_counter]
                     else:
                         if b scorers <= scoring limit:</pre>
                             score_b = score_b + places[place_counter]
                 else: # this signifies a tie, results dict[i] > 1
                     # split points awarded among all tied players
                     points per player = sum(places[place counter: place counter + results dict[i]]) / results dict[i]
                     if a scorers <= scoring limit:</pre>
                         score a += results a.count(i) * points per player
                     if b scorers <= scoring limit:</pre>
                         score_b += results_b.count(i) * points_per_player
```

```
a_scorers += results_a.count(i)
b_scorers += results_b.count(i)
place_counter = place_counter + results_dict[i]

return score_a, score_b
```

Return Data to project who should win which events based on lineups and predicted performances and show on chart

19 total points for indiv and 17 for relay

12 indiv and 2 relay = 262 total points

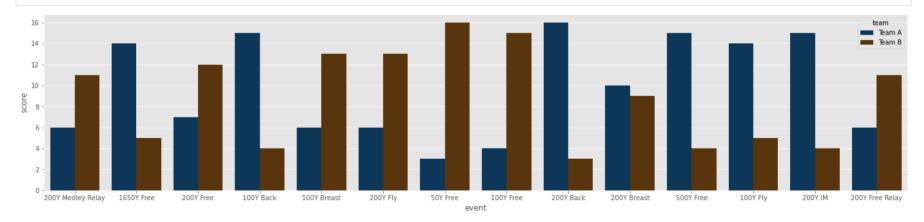
In the actual 1/26/2019 Team A (Bucknell) won 161-137 (including diving events).

In just swimming events the actual score was 137-125 as we just predicted.

Function to Display bar chart of team scores in events:

```
def ChartScore(EventScores, TeamAcolor, TeamBcolor, FigSize h, FigSize l):
    :param Scores: A dataframe of the two two scores for each event
    :param TeamLineup: Dataframe of team lineup. Index is swimmer id and columns are events
    :param TeamAColor: Matplotlib color for Team A columns, e.g. (0,.22,.4)
    :param TeamBColor: Matplotlib color for Team B columns, e.g. (0,.22,.4)
    :param FigSize h, FigSize l: figur height and width in inches.
   #returns plot of given lineup
   # Initialize the matplotlib figure
   f, ax = plt.subplots(figsize=(FigSize h, FigSize l))
   # Set event field as category, reorder to meet order, and rename to user-friendly names
   Scores = EventScores.copy()
    Scores.event = Scores.event.astype('category')
    Scores.event = Scores.event.cat.reorder_categories(EventScoreOrder)
   Scores.event = Scores.event.cat.rename categories(EventScoreLabelConvertDict)
    sns.barplot(x="event", y="score", hue='team', data=Scores, palette=[TeamAcolor,TeamBcolor], ci=None);
    return
```





For a given opponent lineup, generate the top three sorted scores in each event. Then add ghost max scores for places 4, 5

What should max time and Big_M be for each event?

```
def create opptime dict(perf team a, line team a, Big M):
   MDB function Addition
   returns the predicted opposition times for a given line up (scenario)
   :param perf team a: Pandas dataframe of predicted performances for a given team A's swimmers
    :param line team a: Pandas Dataframe of a given lineup for a team A
    :param Big M: A dictionary of the Big M values for each scoring event AND the relay legs
   :return: opptime team a: dictionary of team A's top three times in each event
   # We're going to reduce all the opptimes by 0.001 to avoid ties by MeetOpt the precision for the input data is only to
   # t0 0.01, so this should affect points, but will avoid ties with how MeetOpt works. For more precise input data,
   # this may not be necessary, but it should be at least one place of precision more than the input data.
    tiebreak = 0.001
   # create predicted performance matrices that only contain values for swimmers in the lineup
   lineup scores a = perf team a[line team a == 1]
    # Find times for all relay events and put them together in one dictionary
    event list = lineup scores a.columns.tolist()
    # look for relay events. the lookup is performed by finding the leadoff
   r = re.compile(".L[MF].+")
    relay_list = list(filter(r.match, event_list))
    relay event results = dict()
```

```
#print(relay list)
for value in relay list:
    #find out what type of relay value is and make list of legs in relay
    if value[2] == "F":
        # relay is a freestyle relay, so there are two types of Leas
        legs = [value, value[:1]+"1"+value[2:1]
    elif value[2] == "M":
        # relav is medlev relav. so there are four different leas
        legs = [value, value[:1] + "2" + value[2:], value[:1] + "3" + value[2:], value[:1] + "4" + value[2:]]
    # aet sum of Leas in relay for full relay time.
    time a = lineup scores a[legs].sum().sum()
    # if event is in dictionary, update data, if not then append it
    if value[2:-1] in relay event results:
        if time a != 0:
            relay event results[value[2:-1]][0].append(time a)
    else:
        relay event results[value[2:-1]] = [[time a]]
        if time a == 0:
            relay event results[value[2:-1]][0].pop()
# create opptime team a sorted dictionary of predicted opponent times by event
# number of places to score the events (likely three for a dual meet) ... SHOULD NOT HARD CODE THIS!
places = [1, 2, 3, 4, 5]
opptime team a = {}
for p in places:
    opptime team a[p] = \{\}
relav events = list()
for event in relay event results:
    # get results for each team by event
    results a = relay event results[event][0]
    results a.sort()
    # set the opptime dictionary to sorted time of opp pred times
    for p in places:
        if p <= len(results a):</pre>
            opptime team a[p][event] = results a[p-1] - tiebreak
            # Make the filler event time a little smaller for the opposing team (tie goes to home)
            opptime team a[p][event] = Big M[event] - tiebreak
    # add the event to the list of events
    relay events.append(event)
# score individual events, which we identify in the line below
individual events = list(filter(lambda x: x[2] not in "MF", event list))
for column name in individual events:
    event = column name
    results_a = lineup_scores_a[event][lineup_scores_a[event].notna()].tolist()
    results a.sort()
    for p in places:
        if p <= len(results_a):</pre>
            opptime_team_a[p][event] = results_a[p-1] - tiebreak
```

```
else:
    # Make the filler event time a little larger for the opposing team (tie goes to home)
    opptime_team_a[p][event] = Big_M[event] - tiebreak

return opptime_team_a
```

Get opptime for Team B's lineup(s)

OK, now we have performance data for Team A (Bucknell) and opptime prediction for Team B (Lehigh) with the given lineups.

Compute a (possibly) better lineup for Team A (Bucknell) vs. this lineup

Get the Pred Performance dictionary with the right column names to match what MeetOpt (MO) wants

```
# Do this for Team A and then make a new function after getting it to work
         # Drop all the peformance columns for B, C, and D relays. They are all identical to the A values
         TeamA Perf df MO = TeamA Perf wM df.loc[:,~TeamA Perf wM df.columns.str.endswith(('B','C','D'))]
         # List the columns of the predicted performance list
         pred perf events = TeamA Perf df MO.columns.tolist()
         print(pred perf events)
        ['FLM50A', 'F2M50A', 'F3M50A', 'F4M50A', 'F11650Y', 'F1200Y', 'F2100Y', 'F3100Y', 'F4200Y', 'F150Y', 'F1100Y', 'F2200Y', 'F3200Y', 'F1500Y', 'F4100Y', 'F52
        00Y', 'FLF50A', 'F1F50A']
In [ ]:
         # Get list of swimmers from Team A
         TeamA swimmers = TeamA Perf df MO.index.values.tolist()
         print(TeamA_swimmers)
         [167013, 214963, 221480, 228451, 233487, 233650, 235482, 255871, 256775, 260001, 265562, 270043, 329465, 330237, 330324, 342607, 342611, 344005, 347298, 35
        6813, 382148, 395502, 402879, 403012, 409578, 586800]
In [ ]:
         # Create the TeamA dictionary in the right structure
         # Convert pandas to dict and use Swimmer as row index and Event as columns
         TeamA Perf dict = TeamA Perf df MO.to dict(orient='index')
         # Show the values
         TeamA Perf dict[167013]['FLF50A']
```

```
Out[ ]: 105.96
                     # Get the number of opponent lineups (scenarios) and their associated probabilities
                     # These will be generated from game theory later
                     # Need to use this structre for MeetOpt and to allow for more than one scenario later
                     # for 3 lineuns
                     # opp lineup nums = [1,2,3]
                     # opp lineup num = (.1, .5, .4)
                     oppB lineup nums = [1]
                     oppB lineup select prob = (1,)
                     # connect the lineup nums with their associate probs in a dictionary for MeetOpt
                     oppB scenario prob = dict(zip(oppB lineup nums,oppB lineup select prob))
                     print(oppB scenario prob)
                   {1: 1}
                     # Necessary Lists and dicts for MeetOpt
                     individual scored events = ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F3200Y', 'F3200Y',
                     relay scored events = ('M50', 'F50')
                     relay noMR = ('F50',)
                     indiv pastperf events = individual scored events
                     relay pastperf events = ('FLM50A', 'F2M50A', 'F3M50A', 'F4M50A', 'F1F50A', 'F1F50A')
                     MR legs = ('FLM50A', 'F2M50A', 'F3M50A', 'F4M50A')
                     # the events in opptime for ranking
                     total scored events = individual scored events + relay scored events
                     # the events in pred perf for performance prediction
                     total pastperf events = indiv pastperf events + relay pastperf events
                     # Lineup Events are the events for assignment from the x,y,z variables (1st, 2nd, 3rd) from within MeetOpt
                     print(total scored events)
                     print(total pastperf events)
                     print(Lineup Events)
                    ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F4200Y', 'F3200Y', 'F11650Y', 'M50', 'F50')
```

```
('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F4200Y', 'F3200Y', 'F11650Y', 'F11650Y', 'F11650Y', 'F11650Y', 'F3100Y', 'F4400Y', 'F3100Y', 'F4400Y', 'F3100Y', 'F310Y', 'F310Y
```

Input the MeetOpt function to create an improved lineup vs. an opponent or distribution of opponents.

```
In [ ]: #Import PuLP modeller functions
from math import *
```

```
import pulp as pl
import time
import os
Created on Sat Jan 12 09:14:40 2019
@author: mdb025
def MeetOpt(athleteFull.scenario.scenprob.indiv events.relay scored events.relaynoMR.stroke.relay pastperf events.lineup events. playperf.opptime. Big M):
   :param athletFull: list of athlete IDs
   :param scenario: integer list of the opponent lineups, e.g. [1, 2]
   :param scenprob: dictionary of scenarios to probability (or weight) of selection. This will be the
   the likelihood that the lineup is chosen from a game theory distribution.
   :param indiv scored events: a list of the names of the events that are scored in a meet for the individuals
   :param relaynoMR: the list of names of scored freestyle relay events (no medleys)
   :param stroke: the list of names of the legs of the medley relay
   :param relay scored events: names of relay events scored and in opptime
   :param lineup events: the events list that need to be returned for Team A includes relays A.B.C data from xvar, vvar, zvar.
   :param playperf: the dictionary of predicted performances for Team A athletes in each event. indexed by (indiv scored events and relay past perf events
   :param opptime: the dictionary of opposing team ranked performances. Indexed by scenario (lineup), rank (1,2,3,4,5), events (indiv scored events and re
   :param Bib M: dictionary of the BigM values for missing times for the scoring events and legs.
   #returns optimal response line up to the given opponent lineup(s) (called scenarios)
   print("NOW WE'RE IN MEETOPT: \n")
   ## Beain INPUT SETTINGS
   # 1 if want to write output to file at the following path
   # WriteOutput = 0
   # path of the output file adjust for user
   # if WriteOutput == 1:
   # path = "G:\My Drive\SwimMeetOpt" + "\SwimMeetOptTrialResults.csv"
   # Used for comparison
   tot scored events = indiv events + relay scored events
   tot pastperf events = indiv events + relay pastperf events
   tot assgn events = lineup events
   relay = relay scored events
   #tuples for dictionaries
   event noMR = indiv events + relaynoMR
   print("event noMR: ", event noMR)
   print(scenprob)
   print("total SCORED events: ", tot scored events)
   print("total PERF events: ", tot_pastperf_events)
   print("total ASSIGNED events:", lineup_events)
   homerank = (1,2,3)
   place = (1,2,3,4,5,6)
   ind_points = (9, 4, 3, 2, 1, 0)
```

```
relav points = (11,4,2,0,0,0)
indivplcscore = dict(zip(place,ind points))
relayplcscore = dict(zip(place,relay points))
indiv = indiv events
#Do these exist in college?
Maxevent = 4
Maxrelavevent = 1
Maxindevent = 3
TopopprankIndiv = 5
TopopprankRelav = 3
#Set solve time limit in seconds and optimality gap
MaxSolveTime = 10
SolverTimeLimit = MaxSolveTime*60
OptGap = 0.01
#Which Solver?
SolverUsed = "Gurobi"
#SolverUsed = "Gurobi"
if SolverUsed == "CBC":
    #Choose solver, and set it to problem, and build the model
    #Solve with CBC with Logaina and time limit. Parameter option: keepFiles=1 breaks it!
    #solver = pl.COIN CMD(msg=1, keepFiles=1, presolve=0, threads=1, maxSeconds=SolverTimeLimit,fracGap = OptGap)
    #solver = pulp.COIN CMD(msq=1, keepFiles=1, presolve=1, maxSeconds=SolverTimeLimit,fracGap=OptGap)
    pl.PULP CBC CMD()
else:
    #Solve with Gurobi
    #solver = pulp.GUROBI CMD(keepFiles=1,options=[("MIPFocus",1),("TimeLimit",SolverTimeLimit)])
    #solver = pl.GUROBI CMD(keepFiles=1,options=[("MIPFocus",1),("MIPGap",OptGap),("TimeLimit",SolverTimeLimit)])
    solver = pl.GUROBI()
    #Solve with Cplex. Throws error for write sol file
    #solver = pulp.CPLEX scCMD(msq=1,options = ['set mip tolerances mipgap 0.2'])
    #solver = pulp.CPLEX CMD(msq=1,timelimit=30)
#highest relative rank for home
Tophomerank = 3:
# small constant
EPS = 0.0001:
#number of people on a relay team
relaySize = 4;
#subset of the actual athletes with some
#ahosts because of hard relay requirements
#realathlete are only the actual athletes
# ActAthNum = len(athleteFull)
# athlete = athleteFull[:int(ActAthNum)+4]
# realathlete = athleteFull[:int(ActAthNum)]
athlete = athleteFull
# for i in realathlete:
     print("current realathlete index ", realathlete[realathlete.index(i)])
```

```
print("previous athlete ". realathlete[realathlete.index(i)-1])
#OUTPUT Arrays and Variables
#Start the clock for first setup
setupStart = time.time()
print("Check Done")
#Instantiate our problem class
SwimMeetOpt = pl.LpProblem("MeetMax", pl.LpMaximize)
#Initialize the decision variables
#Scenario scores vs. opps
scenscorevars = {}
# if assigned athlete has 1st time in event
xvars = {}
# if assigned athlete has 2nd best time in event
vvars = {}
# if assigned athlete has 3rd best time in event
zvars = \{\}
# if assigned athlete has 1st time in start time in event 200MR
xvarleads = {}
# if assigned athlete has 2nd best time in start time in event 200MR
vvarleads = {}
# if assigned athlete has 3rd best time in start time in event 200MR
zvarleads = {}
# if assigned athlete has 1st time in medlev
xMRvars = {}
# if assigned athlete has 2nd best time in medley
vMRvars = {}
# if assigned athlete has 3rd best time in medley
zMRvars = {}
# rank of our athletes assigned to events
rvars = {}
#indicator variables of for outcome of event j versus opp 1
wvars = \{\}
#assignments
asgnvars = {}
#OPTIMIZATION DECISION VARIABLES defined in the MeetOpt paper using PuLP:
#scenscorevar is a placeholder which will hold the expected score of our optimal
#lineup against the lineup given in scenario i
scenscorevar = pl.LpVariable.dicts('scenscorevar',(scenario),0,None,pl.LpContinuous)
#these are placement variables for our athletes to events
#xvar will hold the best assigned athlete from our team in an event
#yvar will hold the second best assigned athlete from our team in an event
#zvar will hold the third best assigned athlete from our team in an event
#We assume that exactly three athletes are assigned to each event
#the optimization creates the assignment and the ordering
xvar = pl.LpVariable.dicts('xvar',(athlete,indiv),0,1,pl.LpBinary)
yvar = pl.LpVariable.dicts('yvar',(athlete,indiv),0,1,pl.LpBinary)
zvar = pl.LpVariable.dicts('zvar',(athlete,indiv),0,1,pl.LpBinary)
```

```
#Same as above, but the starting leg for the "non-Medley freestyle Relay" relays
xFRvarlead = pl.LpVariable.dicts('xFRvarlead',(athlete.relavnoMR).0.1.pl.LpBinarv)
vFRvarlead = pl.InVariable.dicts('vFRvarlead', (athlete.relaynoMR), 0.1.pl.InBinary)
zFRvarlead = pl.LpVariable.dicts('zFRvarlead',(athlete,relaynoMR),0,1,pl.LpBinary)
#Same ordering as above, but for the athletes assigned to the
#best, second best, and third best LEGS of Freestyle relay
xFRvar = pl.LpVariable.dicts('xFRvar',(athlete, relaynoMR),0,1,pl.LpBinary)
vFRvar = pl.LpVariable.dicts('vFRvar'.(athlete. relaynoMR).0.1.pl.LpBinary)
zFRvar = pl.LpVariable.dicts('zFRvar',(athlete, relaynoMR),0,1,pl.LpBinary)
#Same ordering as above, but for the athletes assigned to the
#best, second best, and third best medley relay
xMRvar = pl.LpVariable.dicts('xMRvar',(athlete, stroke),0,1,pl.LpBinary)
vMRvar = pl.LpVariable.dicts('vMRvar',(athlete, stroke),0,1,pl.LpBinary)
zMRvar = pl.LpVariable.dicts('zMRvar',(athlete, stroke),0,1,pl.LpBinary)
#rvar will hold the TTME of our first, second, and third fastest entrants in each event
rvar = pl.LpVariable.dicts('rvar',(homerank.tot scored events),None,None,pl.LpContinuous)
#wvar will be 1 if our athlete with homerank h, in event j, finishes in overall place k, against
#opponent scenario L
#with this we can answer in which place our assigned athletes actually finish and score the meet!
wvar = pl.LpVariable.dicts('wvar',(tot scored events.homerank, place, scenario),0.1.pl.LpBinary)
#asanvar is a generic variable which will be 1 if athlete i is assigned to event i (ignoring rank, etc.)
#iust answers the question "Is this athlete doing in this event?"
#asanvar = pl.LpVariable.dicts('asanvar'.(athlete.tot assan events).0.1.pl.LpBinarv)
#Objective Function - Maximize the weighted scenario (or expected) score against
#over eact scenario (or against each team)
SwimMeetOpt += pl.lpSum(scenprob[s]*scenscorevar[s] for s in scenario), "Total Expected Score"
print("obi done")
# Multiple relay teams and they cannot sweep so only the top two relay teams are included in the home team score
# defines the variable scenscorevar (scenario score variable) for each scenario
for s in scenario:
    SwimMeetOpt += scenscorevar[s] == pl.lpSum(indivplcscore[p]*wvar[j][k][p][s] for j in indiv for k in homerank for p in place if k<=p) + \
        pl.lpSum(relayplcscore[p]*wvar[j][k][p][s] for j in relay_scored_events for k in homerank for p in place if k<=p) + \
        pl.lpSum(2*wvar[j][1][4][s] - 2*wvar[j][3][3][s] for j in relay scored events), "Scenario %s Score"%s
#CREATING THE CONSTRAINTS FOR THE OPTIMIZATION PROBLEM:
# Exactly one 1st. 2nd. 3rd best time athlete in each indiv event
# WARNING 5/27/21 Make this strict, but assumes you have enough athletes to field 3 in every indiv event, and 12 in each relay under the max event rule
for j in indiv:
    SwimMeetOpt += pl.lpSum(xvar[i][j] for i in athlete) == 1, "Exactly one 1st for indiv event %s"%j
    SwimMeetOpt += pl.lpSum(yvar[i][i] for i in athlete) == 1, "Exactly one 2nd for indiv event %s"%j
    SwimMeetOpt += pl.lpSum(zvar[i][j] for i in athlete) == 1, "Exactly one 3rd for indiv event %s"%j
# Exactly 4 athletes in a relay for our first, second, and third relays
# accounting for the opening leg not being a flying start in the non-MR relays
for j in relaynoMR:
```

```
SwimMeetOpt += pl.lpSum(xFRvar[i][i] for i in athlete) == relavSize-1, "Exactly 3 legs in 1st relay %s"%i
            SwimMeetOpt += pl.lpSum(vFRvar[i][i] for i in athlete) == relaySize-1, "Exactly 3 legs in 2nd relay %s"%j
            SwimMeetOnt += pl.lpSum(zFRvar[i][i] for i in athlete) == relavSize-1. "Exactly 3 legs in 3rd relay %s"%i
            SwimMeetOpt += pl.lpSum(xFRvarlead[i][i] for i in athlete) == 1, "Exactly 1 to start 1st relay %s"%i
            SwimMeetOpt += pl.lpSum(vFRvarlead[i][i] for i in athlete) == 1, "Exactly 1 to start 2nd relay %s"%i
            SwimMeetOpt += pl.lpSum(zFRvarlead[i][i] for i in athlete) == 1, "Exactly 1 to start 3rd relay %s"%j
# Exactly 4 athletes in the first, second, and third best medley relay
SwimMeetOpt += pl.lpSum(xMRvar[i][i] for i in athlete for i in stroke) == relavSize, "Exactly 4 in 1st MR"
SwimMeetOpt += pl.lpSum(yMRvar[i][j] for i in athlete for j in stroke) == relaySize, "Exactly 4 in 2nd MR"
SwimMeetOpt += pl.lpSum(zMRvar[i][i] for i in athlete for i in stroke) == relavSize. "Exactly 4 in 3rd MR"
# Athletes in at most Maxevent
for i in athlete:
            SwimMeetOpt += pl.lpSum(xvar[i][i] + yvar[i][i] + zvar[i][i] + zvar[i][i] for i in indiv) + pl.lpSum(xFRvar[i][i] + yFRvar[i][i] + zFRvar[i][i] + xFRvarlead[i]
# Athletes in at most Maxrelavevent
for i in athlete:
            SwimMeetOpt += pl.lpSum(xFRvar[i][i] + yFRvar[i][i] + zFRvar[i][i] + xFRvarlead[i][i] + yFRvarlead[i][i] + zFRvarlead[i][i] + z
            # Athletes in at most Maxindivevent
            SwimMeetOpt += pl.lpSum(xvar[i][i] + vvar[i][i] + zvar[i][i] for i in indiv) <= Maxindevent. "Max Indiv events for athlete %s"%i
            # Back to back event constraints
            #HARD CODED WITH EVENT NAMES AND NEEDS TO BE CHECKED
            SwimMeetOpt += xvar[i]["100F"] + yvar[i]["100F"] + zvar[i]["100F"] + xvar[i]["500F"] + yvar[i]["500F"] + zvar[i]["500F"] + zvar[i]["500F"]
            SwimMeetOpt += xvar[i]["200F"] + yvar[i]["200F"] + zvar[i]["200F"] + zvar[i]["200IM"] + yvar[i]["200IM"] + zvar[i]["200IM"] + z
            SwimMeetOpt += xvar[i]["100BS"] + yvar[i]["100BS"] + zvar[i]["100BS"] + xvar[i]["100BR"] + yvar[i]["100BR"] + zvar[i]["100BR"] 
            # Athletes can only be one of the 1st, 2nd, or 3rd ranked athletes assigned to an event j
            for i in indiv:
                        SwimMeetOpt += xvar[i][j] + yvar[i][j] + zvar[i][j] <= 1, "athlete %s can only be one of the 1st, 2nd, or 3rd ranked athletes assigned to an eve
#Athletes can only be 1st, 2nd, or 3rd ranked relay team for each relay j
for i in athlete:
            for j in relaynoMR:
                        SwimMeetOpt += xFRvar[i][j] + yFRvar[i][j] + zFRvar[i][j] + xFRvarlead[i][j] + yFRvarlead[i][j] + zFRvarlead[i][j] <= 1, "athlete %s can only be
            # Each athlete can only perform one stroke in medley relay
            SwimMeetOpt += pl.lpSum(xMRvar[i][j]+yMRvar[i][j]+zMRvar[i][j] for j in stroke) <= 1, "Athlete %s can only perform one stroke in medley relay"%i
#Each stroke on each relay team can only have one athlete assigned
for j in stroke:
            SwimMeetOpt += pl.lpSum(xMRvar[i][j]for i in athlete) <= 1, "Stroke %s on 1st MR can only have one athlete"%j</pre>
            SwimMeetOpt += pl.lpSum(yMRvar[i][j]for i in athlete) <= 1, "Stroke %s on 2nd MR can only have one athlete"%j</pre>
            SwimMeetOpt += pl.lpSum(zMRvar[i][j]for i in athlete) <= 1, "Stroke %s on 3rd MR can only have one athlete"%j
#realized rank of athletes from assignments
#IF NO RUNNER NEED TO ASSIGN A time larger than the third runner, smaller than the BigM for rank
for j in indiv:
            SwimMeetOpt += rvar[1][j] == pl.lpSum(playperf[i][j]*xvar[i][j] for i in athlete) + 0.5*Big M[j] + 1.0 - pl.lpSum(xvar[i][j]*(0.5*Big M[j] + 1) for
            SwimMeetOpt += rvar[2][j] == pl.lpSum(playperf[i][j]*yvar[i][j] for i in athlete) + 0.5*Big M[j] + 2.0 - pl.lpSum(yvar[i][j]*(0.5*Big M[j] + 2) for
            SwimMeetOpt += rvar[3][j] == pl.lpSum(playperf[i][j]*zvar[i][j] for i in athlete) + 0.5*Big M[j] + 3.0 - pl.lpSum(zvar[i][j]*(<math>0.5*Big M[j] + 3) for
```

```
# The problem data is written to an .lp file
#SwimMeetOpt.writeLP("SwimMeetOpt.Lp")
#WARNING: Sloppy hard code fix for legacy data structure
nlavnerfleg = dict()
playperfLead = dict()
for i in athlete:
    # declare dicts
    playperfLeg[i] = dict()
    playperfLead[i] = dict()
    for i in relaynoMR:
        playperfLeg[i][i] = playperf[i]['F1F50A']
        playperfLead[i][i] = playperf[i]['FLF50A']
for i in relaynoMR:
    SwimMeetOpt += rvar[1][i] == pl.lpSum(playperfLeg[i][i]*xFRvar[i][i] + playperfLead[i][i]*xFRvarlead[i][i] for i in athlete) + relavSize*0.5*Big M[
    SwimMeetOpt += rvar[2][i] == pl.lpSum(playperfLeg[i][i]*vFRvar[i][i] + playperfLead[i][i]*vFRvarlead[i][i] for i in athlete) + relavSize*0.5*Big M[
    SwimMeetOpt += rvar[3][i] == pl.lpSum(playperfLeg[i][i]*zFRvar[i][i] + playperfLead[i][i]*zFRvarlead[i][i] for i in athlete) + relaySize*0.5*Big M[
SwimMeetOpt += rvar[1]["M50"] == pl.lpSum(playperf[i][i]*xMRvar[i][i] for i in athlete for i in stroke) + relavSize*0.5*Big M["M50"] + relavSize*1.0 -
SwimMeetOpt += rvar[2]["M50"] == pl.lpSum(playperf[i][i]*vMRvar[i][i] for i in athlete for i in stroke) + relavSize*0.5*Big M["M50"] + relavSize*2.0 -
SwimMeetOpt += rvar[3]["M50"] == pl.lpSum(playperf[i][i]*zMRvar[i][i] for i in athlete for i in stroke) + relaySize*0.5*Big M["M50"] + relaySize*3.0 -
#force consistency in rank order
for k in homerank:
    for i in tot scored events:
        if k < Tophomerank:</pre>
            SwimMeetOpt += rvar[k][i] <= rvar[k+1][i]</pre>
#runner/team of rank k can be place in at most one place (1st. 2nd. or 3rd) vs opp 1
for i in indiv:
    for k in homerank:
        for s in scenario:
            SwimMeetOpt += pl.lpSum(wvar[i][k][1][s] for 1 in place if 1 >= k) <= 1
for j in relay:
    for k in homerank:
        for s in scenario:
            SwimMeetOpt += pl.lpSum(wvar[j][k][l][s] for l in place if l >= k) <= 1
#Did your first runner 1st runner 1st, 2nd in 2nd or 3rd in third vs opp
for i in indiv:
    for k in homerank:
        for 1 in place:
            for s in scenario:
                if k==1:
                    #print("ath: ",j,"homerank: ",k,"place: ",l, "scen: ",s)
                    SwimMeetOpt += rvar[k][i] <= opptime[s][1][j]*wvar[j][k][1][s] + Big_M[j] - Big_M[j]*wvar[j][k][1][s]
                if l>k and l<(TopopprankIndiv + k):</pre>
                    #print("ath: ",j,"homerank: ",k,"place: ",l, "scen: ",s, "l-k+1: ", l-k+1)
                    SwimMeetOpt += rvar[k][j] <= opptime[s][l-k+1][j]*wvar[j][k][l][s] + Big\_M[j] - Big\_M[j]*wvar[j][k][l][s]
                if l>k and l<=(TopopprankIndiv + k):</pre>
                    #print("ath: ",j,"homerank: ",k,"place: ",l, "scen: ",s, "l-k: ", l-k)
                    SwimMeetOpt += rvar[k][j] >= opptime[s][l-k][j]*wvar[j][k][l][s]
#Did your first relay 1st runner 1st, 2nd in 2nd or 3rd in third vs opp
for j in relay:
```

```
for k in homerank:
        for 1 in place:
            for s in scenario:
                if k==1:
                    SwimMeetOpt += rvar[k][j] <= opptime[s][1][j]*wvar[j][k][1][s] + 5*Big M[j] - 5*Big M[j]*wvar[j][k][1][s]
                if l>k and l< (TopopprankRelay + k):</pre>
                    SwimMeetOpt += rvar[k][i] <= opptime[s][l-k+1][j]*wvar[j][k][l][s] + 5*Big M[j]- 5*Big M[j]*wvar[j][k][l][s]
                if l>k and l<=(TopopprankRelav + k):</pre>
                    SwimMeetOpt += rvar[k][j] >= opptime[s][1-k][j]*wvar[j][k][1][s]
#Report the total setup time
setupStop = time.time()
print("Total Setup Time = ", int(setupStop - setupStart), " secs")
# The problem data is written to an .lp file
SwimMeetOpt.writeLP("SwimMeetOpt.lp")
SwimMeetOpt.setSolver(solver)
#Solve the WHOLE problem with selected Solver
print("Solve the baseline problem:")
solveStart = time.time()
SwimMeetOpt.solve()
solveStop = time.time()
print(" Total Solve Time = ", int((solveStop - solveStart)/60.0), " mins")
#The status of the solution is printed to the screen
print(" Status:", pl.LpStatus[SwimMeetOpt.status])
print(" Objective: ", pl.value(SwimMeetOpt.objective), " points")
#Return the objective function value for the best feasible soln found
BestObjective = pl.lpSum(scenprob[s]*scenscorevar[s].varValue for s in scenario)
print(" Best Found Solution Objective= ", BestObjective)
OptObj = pl.value(SwimMeetOpt.objective)
scenscore = dict()
for s in scenario:
    scenscore[s] = scenscorevar[s].varValue
    print(" Score under Scenario ",s, "is ", int(scenscorevar[s].varValue))
# Each of the variables is printed with it's resolved optimum value
optLineup = {}
for i in athlete:
    optLineup[i] = {}
    for j in indiv:
        optLineup[i][j] = xvar[i][j].varValue + yvar[i][j].varValue + zvar[i][j].varValue
    # TO DO!! Add code for other relays
    optLineup[i]['FLF50A'] = xFRvarlead[i]['F50'].varValue
    optLineup[i]['F1F50A'] = xFRvar[i]['F50'].varValue
    optLineup[i]['FLF50B'] = yFRvarlead[i]['F50'].varValue
    optLineup[i]['F1F50B'] = yFRvar[i]['F50'].varValue
    optLineup[i]['FLF50C'] = zFRvarlead[i]['F50'].varValue
    optLineup[i]['F1F50C'] = zFRvar[i]['F50'].varValue
```

```
# No need for D teams
                 ontlineun[i]['FLF50D'] = 0
                 optLineup[i]['F1F50D'] = 0
                 for i in stroke:
                     leg = i[:-1]
                     optLineup[i][[leg+'A'] = xMRvar[i][i].varValue
                     optLineup[i][leg+'B'] = yMRvar[i][j].varValue
                     optLineup[i][leg+'C'] = zMRvar[i][j].varValue
                     # No need for D teams
                     optLineup[i][[leg+'D'] = 0
             HomeAthPredTime = {}
             HomeAthFinPlace = {}
             for i in tot scored events:
                 HomeAthPredTime[i] = {}
                 HomeAthFinPlace[i] = {}
                 for k in homerank:
                     # mins = int(rvar[k][i].varValue/60)
                     # secs = rvar[k][j].varValue - mins*60
                     # HomeAthPredTime[i][k] = str(mins)+":"+str(secs)
                     HomeAthPredTime[j][k] = rvar[k][j].varValue
                     for p in place:
                         if wvar[i][k][p][1].varValue == 1:
                            HomeAthFinPlace[i][k] = p
             # END: Save the finish place and time
             #Return the lineup found in form of a 2-D dictionary of assignment for each athlete
             #NEED this to match the events and A/B/C team of relays.
             optlineup df = pd.DataFrame.from dict(optLineup)
             optLUtime df = pd.DataFrame.from dict(HomeAthPredTime)
             optLUplace df = pd.DataFrame.from dict(HomeAthFinPlace)
             # Return the transpose to get swimmers as index
             return optlineup df.T, optLUtime df, optLUplace df
         #pl.pulpTestAll()
         pl.listSolvers(onlyAvailable=True)
        No parameters matching '_test' found
Out[]: ['GLPK_CMD', 'GUROBI', 'GUROBI_CMD']
```

Create the new lineup for Team A in response to Team B's lineup

```
# def MeetOpt(athleteFull,scenario,scenprob,indiv_events,relay_scored_events,relaynoMR,stroke,relay_pastperf_events,lineup_events, playperf,opptime):
# Test MeetOpt inputs and outputs
```

```
TeamA Lineup df[1]. . = MeetOpt(TeamA swimmers, oppB lineup nums, oppB scenario prob, individual scored events, \
                       relay scored events, relay noMR, MR legs, relay pastperf events, Lineup Events, TeamA Perf dict, opptime TeamB dict, BigM)
     # Reorder the columns to the meet event order
     TeamA Lineup df[1] = TeamA Lineup df[1][EventOrder]
NOW WE'RE IN MEETOPT:
event noMR: ('F1200Y', 'F150Y', 'F1100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F3200Y', 'F3100Y', 'F3200Y', 'F320Y', 'F32
total SCORED events: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3200Y', 'F320Y', 'F320Y
0')
total PERF events: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F3200Y', 'F3200Y', 'F11650Y', 'F11650Y', 'F2100Y', 'F2100Y', 'F3100Y', 'F310
50A', 'F3M50A', 'F4M50A', 'FLF50A', 'F1F50A')
total ASSIGNED events: ('F1200Y', 'F150Y', 'F1100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F3100Y', 'F3100Y', 'F3200Y', 'F3100Y', 'F3100Y', 'F3200Y', 'F3300Y', 'F3
  'F2M50A'. 'F3M50A'. 'F4M50A'. 'FLM50B'. 'F2M50B'. 'F3M50B'. 'F4M50B'. 'FLM50C'. 'F3M50C'. 'F4M50C'. 'FLM50D'. 'F2M50D'. 'F3M50D'. 'F4M50D'. 'F4M50
0A', 'F1F50A', 'FLF50B', 'F1F50B', 'FLF50C', 'F1F50C', 'F1F50D')
Check Done
obi done
Total Setup Time = 0 secs
Solve the baseline problem:
Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
Thread count: 4 physical cores, 8 logical processors, using up to 8 threads
Optimize a model with 960 rows, 1657 columns and 8493 nonzeros
Model fingerprint: 0x64a65c1a
Variable types: 43 continuous, 1614 integer (0 binary)
 Coefficient statistics:
         Matrix range
                                                                                          [1e-03, 4e+03]
         Objective range [1e+00, 1e+00]
         Bounds range
                                                                                         [1e+00, 1e+00]
         RHS range
                                                                                          [1e+00, 4e+03]
Presolve removed 327 rows and 85 columns
Presolve time: 0.03s
Presolved: 633 rows, 1572 columns, 7224 nonzeros
Variable types: 0 continuous, 1572 integer (1530 binary)
Root relaxation: objective 1.778217e+02, 376 iterations, 0.01 seconds (0.00 work units)
                   Nodes
                                                                                    Current Node
                                                                                                                                                                                           Objective Bounds
                                                                                                                                                                                                                                                                                                                               Work
     Expl Unexpl | Obj Depth IntInf | Incumbent
                                                                                                                                                                                                                                      BestBd
                                                                                                                                                                                                                                                                             Gap | It/Node Time
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                       0
                                                   0 146.00000
                                                                                                                              0 10 143.00000 146.00000 2.10%
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```

0s

0

0

0 146.00000

146.0000000 146.00000 0.00%

0 10 146.00000 146.00000 0.00%

```
Cutting planes:
          Gomory: 3
          Cover: 30
          Clique: 24
          MTR: 26
          StrongCG: 5
          GUB cover: 41
          RIT: 5
          Relax-and-lift: 15
        Explored 1 nodes (1275 simplex iterations) in 0.35 seconds (0.09 work units)
        Thread count was 8 (of 8 available processors)
        Solution count 3: 146 143 141
        Optimal solution found (tolerance 1.00e-04)
        Best objective 1.460000000000e+02, best bound 1.46000000000e+02, gap 0.0000%
        Gurobi status= 2
         Total Solve Time = 0 mins
         Status: Ontimal
         Objective: 146.0 points
         Best Found Solution Objective= 146.0
         Score under Scenario 1 is 146
In [ ]:
         # Clean up the output (-0.0) by making all integers
         TeamA Lineup df[1] = TeamA Lineup df[1][TeamA Lineup df[1].columns].astype('int8')
```

EDA on the new Lineup compared to the old

```
def ChartLineup(TeamName, TeamColors, TeamLineup, FigSize h, FigSize l):
    :param TeamName: String name of the Team for the lineup, e.g. 'Team A'
    :param TeamLineup: Dataframe of team lineup. Index is swimmer id and columns are events
    :param TeamColors: list of matplotlib colors (2), e.g. [(0,.22,.4), (0.9,0.46,0.13)]
    :param FigSize h, FigSize 1: figur height and width in inches.
   #returns plot of given lineup
   # Check out the "new" Lineup
   # Displaying dataframe as an heatmap with two categories
    fig, axs = plt.subplots(1, 1, figsize=(FigSize_h, FigSize_l), constrained_layout=True)
   # Make swimmer names the index
   Team_Lineup_Clean_df = pd.merge(left= TeamLineup, right= Swimmer_Names_df[['name']], how= 'left', left_index= True, right_index=True).set_index('name')
   Team Lineup Clean df = Team Lineup Clean df.rename(columns=EventLabelConvertDict)
    sns.heatmap(Team_Lineup_Clean_df, linewidth= 0.1, annot= False, cbar= False, square= True, ax= axs, cmap= TeamColors, linecolor= '.75')
    #clean up the charts
    fig.suptitle('Events Assigned to Swimmers')
    axs.set ylabel('{} Swimmer ID'.format(TeamName),fontsize='small')
```

```
axs.set_xlabel('Event ID', fontsize='small')

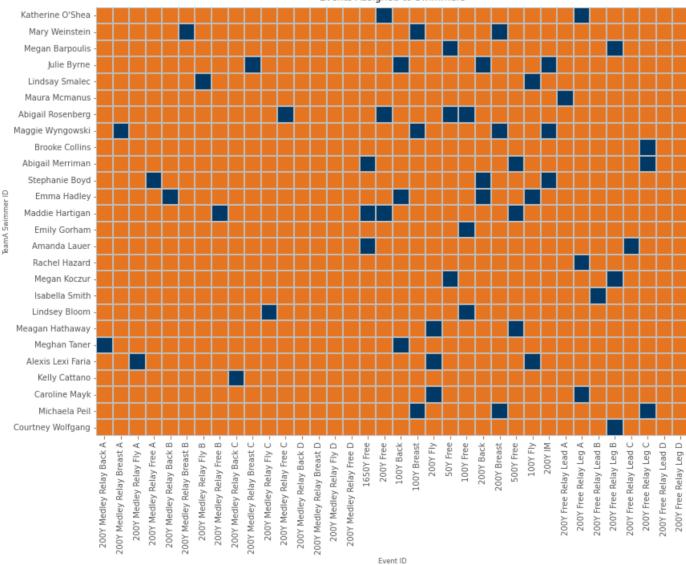
# colorbar = axs.collections[0].colorbar
# colorbar.set_ticks([.25,.75])
# colorbar.set_ticklabels(['Not Assigned','Assigned'])
# #colorbar.ax.invert_yaxis()

plt.show()

return

In []:
# Check out the "new" Lineup
Chartlineup('TeamA', TeamA colors, TeamA Lineup df[1], 18, 10)
```

Events Assigned to Swimmers



How have the total events per athlete changed?

```
# How many Events for each swimmer?

fig, axs = plt.subplots(1, 2, figsize=(18, 5), constrained_layout=True)

# Team A Lineup 0

TeamA0_TotEventsPerAth = TeamA_Lineup_df[0].sum(axis=1).sort_values(ascending=False).to_frame().rename(columns={0: "tot_events"})
TeamA0_TotEventsPerAth = pd.merge(left= TeamA0_TotEventsPerAth, right= Swimmer_Names_df[['name']], how= 'left', left_index= True, right_index=True)
```

```
sns.barplot(y=TeamA0_TotEventsPerAth.name, x=TeamA0_TotEventsPerAth.tot_events, order=TeamA0_TotEventsPerAth.name,color= TeamA_blue,ax=axs[0])
# Team A Lineup 1
TeamA1_TotEventsPerAth = TeamA_Lineup_df[1].sum(axis=1).to_frame().rename(columns={0: "tot_events"})
TeamA1_TotEventsPerAth = pd.merge(left= TeamA1_TotEventsPerAth, right= Swimmer_Names_df[['name']], how= 'left', left_index= True,right_index=True)
sns.barplot(y=TeamA1_TotEventsPerAth.name, x=TeamA1_TotEventsPerAth.tot_events, order=TeamA0_TotEventsPerAth.name, color = TeamA_orange,ax=axs[1])
#clean up the charts
fig.suptitle('Events Assigned per Swimmer')
axs[0].set_ylabel('Team A0 Swimmer ID',fontsize='small')
axs[0].set_ylabel('Team A1 Swimmer ID',fontsize='small')
#for ax in axs:
# ax.set_ylim[[0, 4.2])
axs[0].set_xlabel('Number of Events', fontsize='small')
axs[1].set_xlabel('Number of Events', fontsize='small')
plt.show()
```

Events Assigned per Swimmer Stephanie Boyd Stephanie Boyd -Alexis Lexi Faria Alexis Lexi Faria Megan Koczur Megan Koczur Rachel Hazard Rachel Hazard Maddie Hartigan Maddie Hartigan Meghan Taner Meghan Taner Maura Mcmanus Maura Mcmanus Iulie Byrne Iulie Byrne Megan Barpoulis Megan Barpoulis Abigail Rosenberg Abigail Rosenberg Maggie Wyngowski Maggie Wyngowski Brooke Collins Brooke Collins Abigail Merriman Abigail Merriman Emma Hadley Emma Hadley Lindsay Smalec Lindsay Smaled Mary Weinstein Mary Weinstein Caroline Mavk Caroline Mayk Lindsey Bloom Lindsey Bloom Meagan Hathaway Meagan Hathaway Michaela Peil Michaela Peil Emily Gorham Emily Gorham Courtney Wolfgang Courtney Wolfgang Isabella Smith Isabella Smith Amanda Lauer Amanda Lauer Kelly Cattano Kelly Cattano Katherine O'Shea Katherine O'Shea 0.5 10 1.5 20 2.5 3.0 3.5 4.0 0.5 10 1.5 2.0 2.5 3.0 3.5 Number of Events Number of Events

```
In []: # How many athletes for each event?

fig, axs = plt.subplots(1, 2, figsize=(8, 8), sharey=False, constrained_layout=True)

# Team A old
TeamM = TeamM_Lineup_df[0].rename(columns=EventLabelConvertDict).sum(axis=0)
sns.barplot(y=TeamA.index, x=TeamA.values, color= TeamA_blue,ax=axs[0], ci=None)

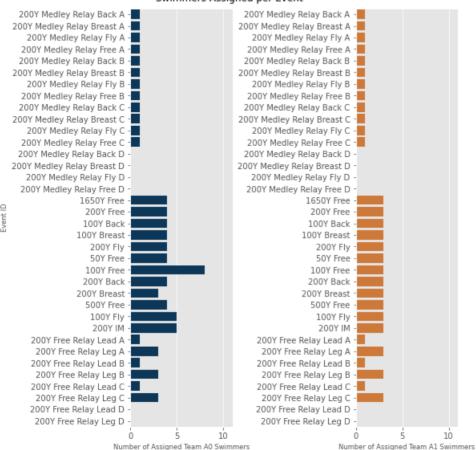
#Team A new
TeamM1 = TeamM_Lineup_df[1].rename(columns=EventLabelConvertDict).sum(axis=0)
sns.barplot(y=TeamA1.index, x=TeamA1.values, color= TeamA_orange, ax=axs[1], ci=None)

#clean up the charts
fig.suptitle('Swimmers Assigned per Event')
axs[0].set_ylabel('Event ID',fontsize='small')

for ax in axs:
```

```
ax.set xlim([0, 11])
axs[0].set xlabel('Number of Assigned Team A0 Swimmers', fontsize='small')
axs[1].set xlabel('Number of Assigned Team A1 Swimmers', fontsize='small')
nlt.show()
```





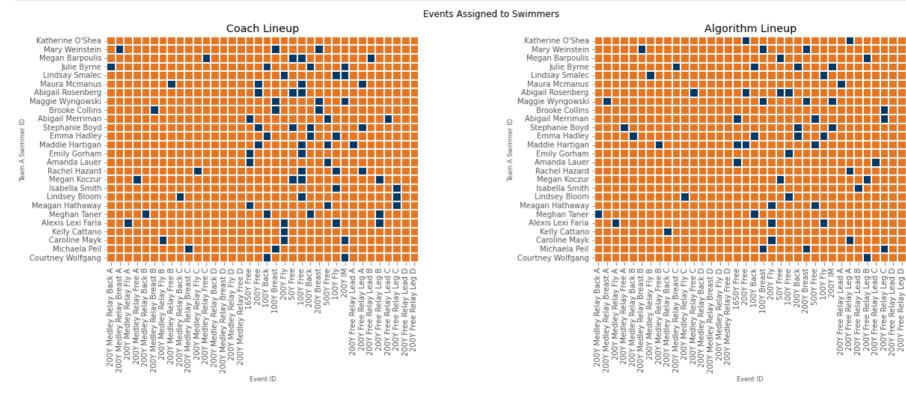
```
# Displaying dataframe as a heatmap
fig, axs = plt.subplots(1, 2, figsize=(18, 7), constrained_layout=True)
# Make swimmer names the index
TeamA0 Lineup Clean df = pd.merge(left= TeamA Lineup df[0], right= Swimmer Names df[['name']], how= 'left', left index= True, right index=True).set index('n
TeamA1_Lineup_Clean_df = pd.merge(left= TeamA_Lineup_df[1], right= Swimmer_Names_df[['name']], how= 'left', left_index= True,right_index=True).set_index('n
TeamA0 Lineup Clean df = TeamA0 Lineup Clean df.rename(columns=EventLabelConvertDict)
TeamA1 Lineup Clean df = TeamA1 Lineup Clean df.rename(columns=EventLabelConvertDict)
sns.heatmap(TeamA0 Lineup Clean df, linewidths = 0.30, annot = False, cbar= False, square= True, ax= axs[0], cmap= TeamA colors)
sns.heatmap(TeamA1 Lineup Clean df, linewidths = 0.30, annot = False, cbar= False, square= True, ax= axs[1], cmap= TeamA colors )
#clean up the charts
```

```
fig.suptitle('Events Assigned to Swimmers')
axs[0].set_ylabel('Team A Swimmer ID',fontsize='small')
axs[1].set_ylabel('Team A Swimmer ID',fontsize='small')

axs[0].set_xlabel('Event ID', fontsize='small')
axs[1].set_xlabel('Event ID', fontsize='small')

axs[0].set_title("Coach Lineup")
axs[1].set_title("Algorithm Lineup")

plt.show()
```



Highlight the differences between the two lineups

MAKE THIS A FUNCTION TO ACCEPT TWO LINEUPS AND RETURN THE DIFF LU_old and LU_new

```
#returns plot of given lineup
"""

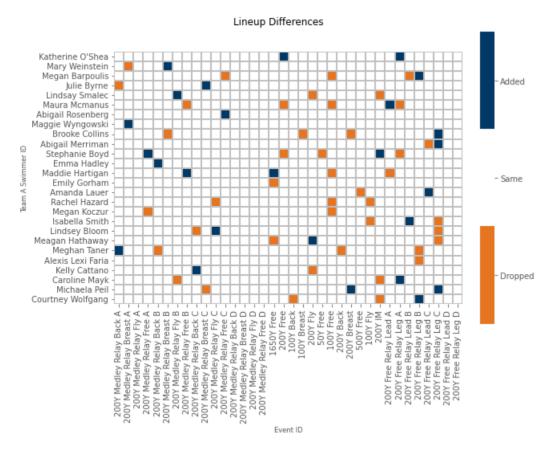
# Displaying dataframe of differences as a heatmap
fig, ax = plt.subplots(1, 1, figsize=(FigSize_h, FigSize_l), constrained_layout=True)

# values are 1/0, so + diff is an add in the new LU, 0 is no change, and -1 is dropped.
sns.heatmap((LU_new - LU_old), linewidths = 0.10, annot = False, ax=ax, cbar= True, square= True, cmap= Team3color, linecolor='.75')

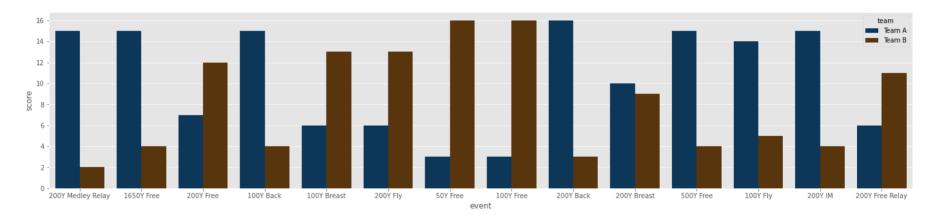
#clean up the charts
fig.suptitle('Lineup Differences')
ax.set_ylabel('{} Swimmer ID'.format(TeamName),fontsize='small')
ax.set_xlabel('Event ID', fontsize='small')

colorbar = ax.collections[0].colorbar
colorbar.set_ticks([-2/3,0, 2/3])
colorbar.set_tickslabels(['Dropped', 'Same', 'Added'])
#colorbar.ax.invert_yaxis()
return
```

```
TeamA_3colors = [TeamA_orange, (1,1,1), TeamA_blue ]
ChartLUdiff('Team A', TeamA_3colors, TeamA0_Lineup_Clean_df, TeamA1_Lineup_Clean_df, 9, 7)
```



Score the meet with the new lineup (137 vs 125 predicted for Team A under old lineup).



So our improved lineup results in a forecasted win by 30 points from the previous lineup's forecasted win by 12 points. What doe's the algorithm say that Team B should do to lineups 0 (base) and optimized (1)? Assume that the opponents lineup is known

Team B recommended response to the base lineup (Team A LU 0):

1. Get opptime for Team A's Base Lineup

```
# opponents times needs to be in lineup (or scenario), opponent rank (1,2,3,4), then the name of the scored event
 TeamA lineupNums = 1
 opptime TeamA dict = dict()
 for i in range(TeamA lineupNums):
     opptime TeamA dict[i+1] = create opptime dict(TeamA Perf wM df, TeamA Lineup df[i], BigM)
 print(opptime TeamA dict[1][3])
{'M50': 111.1789999999999, 'F50': 268.319, 'F11650Y': 1039.339, 'F1200Y': 114.318999999999, 'F2100Y': 55.829, 'F3100Y': 68.419, 'F4200Y': 124.419, 'F150
Y': 24.3089999999997, 'F1100Y': 53.059000000000005, 'F2200Y': 120.979, 'F3200Y': 146.289, 'F1500Y': 299.439, 'F4100Y': 55.749, 'F5200Y': 124.529}
```

2. Find the MeetOpt lineup for the base Team A lineup

```
# Do this for Team A and then make a new function after getting it to work
# Drop all the peformance columns for B, C, and D relays. They are all identical to the A values
TeamB Perf df MO = TeamB Perf wM df.loc[:,~TeamB Perf wM df.columns.str.endswith(('B','C','D'))]
# List the columns of the predicted performance list
# TeamB_pred_perf_events = TeamB_Perf_df_MO.columns.tolist()
# print(TeamB_pred_perf_events)
# Get list of swimmer IDs from Team B
TeamB swimmers = TeamB Perf df MO.index.values.tolist()
print(TeamB swimmers)
```

[195456, 197178, 213253, 233796, 233836, 256012, 271442, 271492, 273646, 273907, 282290, 291023, 323285, 330114, 330349, 342505, 342630, 342918, 345696, 37

```
In [ ]:
                               # Create the Team B dictionary in the right structure
                                # Convert nandas to dict and use Swimmer as row index and Event as columns
                                TeamB Perf dict = TeamB Perf df MO.to dict(orient='index')
                                # Show the values
                                TeamB Perf dict[197178]['FLF50A']
                            105.96
Out[ ]:
In [ ]:
                                # For CONSTSTENCY:
                                # Get the number of opponent lineups (scenarios) and their associated probabilities
                                # These will be generated from game theory later
                                # Need to use this structre for MeetOpt and to allow for more than one scenario later
                                # for 3 lineups
                               # opp lineup_nums = [1,2,3]
                                # opp Lineup num = (.1..5..4)
                                oppA lineup nums = [1]
                                oppA lineup select prob = (1,)
                                # connect the lineup nums with their associate probs in a dictionary for MeetOpt
                                oppA scenario prob = dict(zip(oppA lineup nums,oppA lineup select prob))
                                print(oppA scenario prob)
                             {1: 1}
In [ ]:
                               # Find MeetOpt response for Team B to the base for Team A (LU 0)
                                TeamB Lineup df[1], , = MeetOpt(TeamB swimmers, oppA lineup nums, oppA scenario prob, individual scored events, \
                                            relay scored events, relay noMR, MR legs, relay pastperf events, Lineup Events, TeamB Perf dict, opptime TeamA dict, BigM)
                                # Reorder the columns to the meet event order
                                TeamB Lineup df[1] = TeamB Lineup df[1][EventOrder]
                            NOW WE'RE IN MEETOPT:
                            event noMR: ('F1200Y', 'F150Y', 'F1100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F3200Y', 'F320Y', 'F3200Y', 'F320
                            {1: 1}
                            total SCORED events: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F4200Y', 'F3200Y', 'F11650Y', 'M50', 'F5
                            0')
                            total PERF events: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F4200Y', 'F3200Y', 'F11650Y', 'FLM50A', 'F2M
                            50A', 'F3M50A', 'F4M50A', 'FLF50A', 'F1F50A')
                            total ASSIGNED events: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F4200Y', 'F3100Y', 'F3
                              'F2M50A', 'F3M50A', 'F4M50A', 'FLM50B', 'F2M50B', 'F3M50B', 'F4M50B', 'FLM50C', 'F2M50C', 'F3M50C', 'F4M50C', 'FLM50D', 'F2M50D', 'F3M50D', 'F4M50D', 'F4M50
                            0A', 'F1F50A', 'FLF50B', 'F1F50B', 'F1F50C', 'F1F50C', 'F1F50D', 'F1F50D')
                            Check Done
                            obi done
                            Total Setup Time = 0 secs
                            Solve the baseline problem:
                            Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
                            Thread count: 4 physical cores, 8 logical processors, using up to 8 threads
                            Optimize a model with 994 rows, 1765 columns and 9057 nonzeros
```

7792, 403859, 404163, 405026, 411706, 422229, 432465, 494957, 6965791

```
Model fingerprint: 0xfafe8554
Variable types: 43 continuous, 1722 integer (0 binary)
Coefficient statistics:
  Matrix range
                  [1e-03, 4e+03]
  Objective range [1e+00, 1e+00]
  Bounds range
                  [1e+00, 1e+00]
  RHS range
                  [1e+00, 4e+03]
Presolve removed 331 rows and 95 columns
Presolve time: 0.04s
Presolved: 663 rows, 1670 columns, 7661 nonzeros
Variable types: 0 continuous, 1670 integer (1628 binary)
Root relaxation: objective 1.579464e+02, 330 iterations, 0.01 seconds (0.00 work units)
    Nodes
                 Current Node
                                      Objective Bounds
                                                                 Work
 Expl Unexpl |
               Obi Depth IntInf | Incumbent
                                               BestBd
                                                       Gap | It/Node Time
    0
          0 157,93524
                          0 73
                                         - 157.93524
    a
          0 141.87825
                          0 111
                                         - 141.87825
                                                                     95
          0 138.89824
                             92
                                         - 138.89824
                                         - 138.89824
    0
          0 138.89824
                         0 93
                                                                     05
    0
          0 132,95296
                         0 78
                                         - 132.95296
                                                                     0s
                               117.0000000 132.91050 13.6%
                                                                     95
    0
          0 132.91050
                          0 67 117.00000 132.91050 13.6%
                                                                     05
    0
                               123.0000000 132.91050 8.06%
                                                                     05
          0 132.85034
                         0 56 123.00000 132.85034 8.01%
    0
                                                                     0s
    0
          0 132,00000
                         0 34 123.00000 132.00000 7.32%
                                                                     0s
Н
    0
                               132.0000000 132.00000 0.00%
                                                                     05
          0 132.00000 0 34 132.00000 132.00000 0.00%
Cutting planes:
  Gomorv: 4
  Cover: 27
  Clique: 14
  MIR: 10
  StrongCG: 2
  GUB cover: 40
  RLT: 8
  Relax-and-lift: 12
Explored 1 nodes (1298 simplex iterations) in 0.34 seconds (0.08 work units)
Thread count was 8 (of 8 available processors)
Solution count 3: 132 123 117
Optimal solution found (tolerance 1.00e-04)
Best objective 1.320000000000e+02, best bound 1.32000000000e+02, gap 0.0000%
Gurobi status= 2
 Total Solve Time = 0 mins
 Status: Optimal
 Objective: 132.0 points
 Best Found Solution Objective= 132.0
 Score under Scenario 1 is 132
```

```
# Clean up the output (-0.0) by making all integers
TeamB_Lineup_df[1] = TeamB_Lineup_df[1][TeamB_Lineup_df[1].columns].astype('int8')
```

MeetOpt creates a lineup with an expected score of 132 points for Team B vs. the base lineup from Team A. Recall that with Team B's base lineup (vs. Team A's base lineup) we projected (and in reality it matched) a score of 137-125. To account for the tie rules, what is the better prediction from these two lineups?

What if each team used the MeetOpt lineups vs each other?

GAME THEORY: What if these were the only two lineups they could use? What would be the best response?

First create a function to solve a game theory matrix

```
In []:
    from gurobipy import *

def FindOptStrategy(team, payoffmatrix):
    try:
        # Create variables
        numrows = len(payoffmatrix)  # payoff matrix number of rows
        numcols = len(payoffmatrix[0]) # payoff matrix number of columns

if team == "B":
        # Create a new model
        optModelB = Model("TeamBStrategy")
        optModelB.reset()

        # optModelB.setParam('Presolve',0)

        g = optModelB.addVars(numcols, lb= 0.0, ub=GRB.INFINITY, vtype=GRB.CONTINUOUS, name="g")
        u = optModelB.addVar(lb=-GRB.INFINITY, ub=GRB.INFINITY, vtype=GRB.CONTINUOUS, name="u")

# Set objective
```

```
optModelB.setObjective(u, GRB.MINIMIZE)
           # Add constraint: sumproduct down rows <= hound u.
           optModelB.addConstrs((quicksum(pavoffmatrix[i][i]*g[i] for i in range(numcols)) <= u for i in range(numrows))."bounds")
           # Add constraint: sum of f = 1, well defined distribution
           optModelB.addConstr(quicksum(g[i] for i in range(numcols)) == 1, "c1")
           optModelB.optimize()
           print (optModelB.display())
           policy, value = printSolution(optModelB)
       elif team == "\Delta":
           # Create a new model
           optModelA = Model("TeamAStrategy")
           optModelA.reset()
           #optModelA.setParam('Presolve',0)
           f = optModelA.addVars(numrows, lb=0.0, ub=GRB.INFINITY, vtvpe=GRB.CONTINUOUS, name="f")
           v = optModelA.addVar(lb=-GRB.INFINITY, ub=GRB.INFINITY, vtype=GRB.CONTINUOUS, name="v")
           # Set objective
           optModelA.setObjective(v, GRB.MAXIMIZE)
           # Add constraint: sumproduct down rows <= bound u.
           optModelA.addConstrs((quicksum(payoffmatrix[i][j]*f[i] for i in range(numrows)) >= v for j in range(numcols)), "bounds")
           # Add constraint: sum of f = 1, well-defined distribution
           optModelA.addConstr(quicksum(f[i] for i in range(numrows)) == 1, "c2")
           optModelA.optimize()
           print (optModelA.display())
           policy, value = printSolution(optModelA)
       return policy, value
   except GurobiError as e:
       print('Error code ' + str(e.errno) + ": " + str(e))
   except AttributeError:
       print('Encountered an attribute error')
def printSolution(m):
   answer_dic = {}
   for var in m.getVars():
       print('%s %g' % (var.varName, var.x))
       answer_dic.update({var.varName : var.x})
   print('Obj: %g' % m.objVal)
   #return the variables and their optimal values
   return answer_dic, m.objVal
```

Use model to find the optimal strategy for each team

Optimize a model with 3 rows, 3 columns and 8 nonzeros

```
# Create the score matrix with Team
 LineupA0vB0 = 12
 LineupA0vB1 = -2
 LineupA1vB0 = 30
 LineupA1vB1 = 30
 score matrix = [[LineupA0vB0 .LineupA0vB1]. [LineupA1vB0.LineupA1vB1]]
 #Return the Nash equilibrium mixed strategy and expected points for team A and team B.
 f,optB = FindOptStrategy('A', score matrix)
 g,optA = FindOptStrategy('B', score matrix)
 print('\n Printing f: ',f)
 print('\n Printing optA: ', optA)
 print('\n Printing g: ', g)
 print('\n Printing optB: ',optB)
Discarded solution information
Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
Thread count: 4 physical cores, 8 logical processors, using up to 8 threads
Optimize a model with 3 rows, 3 columns and 8 nonzeros
Model fingerprint: 0x093028a7
Coefficient statistics:
  Matrix range
                   [1e+00, 3e+01]
  Objective range [1e+00, 1e+00]
  Bounds range
                   [0e+00, 0e+00]
  RHS range
                   [1e+00, 1e+00]
Presolve removed 3 rows and 3 columns
Presolve time: 0.01s
Presolve: All rows and columns removed
Iteration Objective
                             Primal Inf.
                                            Dual Inf.
                                                            Time
           3.0000000e+01 0.000000e+00 0.000000e+00
Solved in 0 iterations and 0.01 seconds (0.00 work units)
Optimal objective 3.000000000e+01
Maximize
  <gurobi.LinExpr: v>
Subject To
  bounds[0]: \{gurobi.LinExpr: 12.0 f[0] + 30.0 f[1] + -1.0 v\} >= 0
  bounds[1]: \langle gurobi.LinExpr: -2.0 f[0] + 30.0 f[1] + -1.0 v \rangle = 0
  c2: \langle gurobi.LinExpr: f[0] + f[1] \rangle = 1
Bounds
  v free
None
f[0] 0
f[1] 1
v 30
Obi: 30
Discarded solution information
Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
Thread count: 4 physical cores, 8 logical processors, using up to 8 threads
```

```
Model fingerprint: 0xe002b602
Coefficient statistics:
  Matrix range
                    [1e+00, 3e+01]
  Objective range [1e+00, 1e+00]
  Bounds range
                    [0e+00, 0e+00]
  RHS range
                    [1e+00, 1e+00]
Presolve removed 3 rows and 3 columns
Presolve time: 0.01s
Presolve: All rows and columns removed
Iteration Objective
                              Primal Inf.
                                              Dual Inf
                                                              Time
           3.0000000e+01 0.000000e+00
       0
                                             0.0000000+00
Solved in 0 iterations and 0.01 seconds (0.00 work units)
Optimal objective 3.000000000e+01
Minimize
  <gurobi.LinExpr: u>
Subject To
  bounds[0]: \langle gurobi.LinExpr: 12.0 g[0] + -2.0 g[1] + -1.0 u \rangle \langle = 0
  bounds[1]: \langle gurobi.LinExpr: 30.0 g[0] + 30.0 g[1] + -1.0 u \rangle \langle = 0
  c1: \langle gurobi.LinExpr: g[0] + g[1] \rangle = 1
Bounds
  u free
None
g[0] 1
g[1] 0
u 30
Obj: 30
 Printing f: {'f[0]': 0.0, 'f[1]': 1.0, 'v': 30.0}
 Printing optA: 30.0
 Printing g: {'g[0]': 1.0, 'g[1]': 0.0, 'u': 30.0}
 Printing optB: 30.0
```

Display the Payoff Matrix for all four lineup pairs

```
In [ ]: #from tabulate import tabulate
from IPython.display import display, HTML

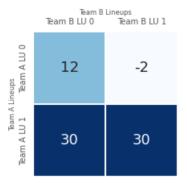
payoff_df = pd.DataFrame({"Team B LU 0": [LineupA0vB0, LineupA1vB0], "Team B LU 1": [LineupA0vB1, LineupA1vB1]}, index=['Team A LU 1'])
display(HTML(payoff_df.to_html()))
#df.to_latex()
```

```
        Team B LU 0
        Team B LU 1

        Team A LU 0
        12
        -2

        Team A LU 1
        30
        30
```

```
In [ ]:
# Displaying dataframe as an heatmap
fig, axs = plt.subplots(1, 1, figsize=(3, 3), constrained_layout=True)
```



FIX WORDING: The Nash Equilibrium is for both teams to use their respective lineups 1. Where Lehigh will lose by 25 points. These lineups (created by MeetOpt) are in response to the other team using LU 0, so a better lineup in response to LU 1 may also exist leading to a 3x3 strategy. Alternatively, you could create a lineup in response to the other team being equally likely to choose one of the other lineups.

Let's extend this one more step by adding optimal responses to opponents LU 1s.

Team A's response to Team B's LU 1:

1. Get opptime for Team B's LU 1:

```
# opponents times needs to be in lineup (or scenario), opponent rank (1,2,3,4), then the name of the scored event

TeamB_lineupNums = 1
opptime_TeamB_dict = dict()
for i in range(TeamB_lineupNums):
    # Doing this for LU 1 for Team B
    opptime_TeamB_dict[i+1] = create_opptime_dict(TeamB_Perf_wM_df, TeamB_Lineup_df[1], BigM)

print(opptime_TeamB_dict[1][3])

{'M50': 481.319, 'F50': 443.279, 'F11650Y': 1099.049, 'F1200Y': 112.639, 'F2100Y': 252.1989999999998, 'F3100Y': 66.919, 'F4200Y': 1589.039, 'F150Y': 23.81
9, 'F1100Y': 51.499, 'F2200Y': 130.599, 'F3200Y': 143.049, 'F1500Y': 307.529, 'F4100Y': 61.169000000000004, 'F5200Y': 139.599}
```

2. Find the MeetOpt response to Team B LU 1

```
# def MeetOnt(athleteFull.scenario.scennroh.indiv events.relav scored events.relavnoMR.stroke,relav pastperf events,lineup events, playperf,opptime):
     # Find MeetOpt response lineup to the base
     TeamA Lineup df[2],r,w = MeetOpt(TeamA swimmers, oppB lineup nums, oppB scenario prob, individual scored events, \
                    relay scored events, relay noMR, MR legs, relay pastperf events, Lineup Events, TeamA Perf dict, opptime TeamB dict, BigM)
     # Reorder the columns to the meet event order
     TeamA Lineup df[2] = TeamA Lineup df[2][EventOrder]
NOW WE'RE IN MEETOPT:
event noMR: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F3200Y', 'F3200Y', 'F3200Y', 'F3100Y', 'F3200Y', 'F320Y', 'F32
  {1: 1}
 total SCORED events: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F4200Y', 'F3200Y', 'F11650Y', 'M50', 'F5
0')
total PERF events: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F1500Y', 'F1500Y', 'F3100Y', 'F3100Y', 'F3200Y', 'F3100Y', 'F3100Y
50A', 'F3M50A', 'F4M50A', 'FLF50A', 'F1F50A')
 total ASSIGNED events: ('F1200Y', 'F150Y', 'F1100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F3100Y', 'F3200Y', 'F3200Y', 'F150Y', 'F1650Y', 'F1650Y', 'F160Y', 'F160Y', 'F3200Y', 'F320Y', 'F3200Y', 'F320Y', 'F320Y'
  'F2M50A', 'F3M50A', 'F4M50A', 'FLM50B', 'F2M50B', 'F3M50B', 'F4M50B', 'FLM50C', 'F3M50C', 'F4M50C', 'F4M50D', 'F2M50D', 'F3M50D', 'F3M50
 0A', 'F1F50A', 'FLF50B', 'F1F50B', 'F1F50C', 'F1F50C', 'F1F50D', 'F1F50D')
Check Done
 obi done
Total Setup Time = 0 secs
 Solve the baseline problem:
Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
Thread count: 4 physical cores, 8 logical processors, using up to 8 threads
Optimize a model with 960 rows, 1657 columns and 8493 nonzeros
Model fingerprint: 0x227c8b80
Variable types: 43 continuous, 1614 integer (0 binary)
 Coefficient statistics:
        Matrix range
                                                                         [1e-03, 4e+03]
        Objective range [1e+00, 1e+00]
        Bounds range
                                                                          [1e+00, 1e+00]
        RHS range
                                                                          [1e+00, 4e+03]
 Presolve removed 319 rows and 95 columns
Presolve time: 0.02s
Presolved: 641 rows, 1562 columns, 7202 nonzeros
Variable types: 0 continuous, 1562 integer (1520 binary)
Root relaxation: objective 1.779294e+02, 394 iterations, 0.01 seconds (0.00 work units)
                Nodes
                                                                      Current Node
                                                                                                                                                          Objective Bounds
                                                                                                                                                                                                                                                                      Work
     Expl Unexpl
                                                             Obj Depth IntInf | Incumbent
                                                                                                                                                                                             BestBd
                                                                                                                                                                                                                              Gap | It/Node Time
                    0
                                           0 176.91340
                                                                                                        0 105
                                                                                                                                                                     - 176.91340
                                                                                                                                                                                                                                                                                     0s
                    0
                                          0
                                                                                                                                122.0000000 164.12523 34.5%
Н
                   0
                                          0
                                                                                                                               129.0000000 164.12523 27.2%
                                                                                                                                                                                                                                                                                     0s
                                          0 164.12523
                                                                                                        0 119 129.00000 164.12523 27.2%
                                                                                                                                                                                                                                                                                     0s
                    0
Н
                   0
                                                                                                                               140.0000000 164.12523 17.2%
                                                                                                                                                                                                                                                                                     0s
                                                                                                                               144.0000000 164.12212 14.0%
                                                                                                                                                                                                                                                                                     0s
                    0
                                                                                                        0 118 144.00000 164.12212 14.0%
                                          0 164.12212
                                                                                                                                                                                                                                                                                     0s
                                                                                                                               151.0000000 159.42658 5.58%
                                                                                                                                                                                                                                                                                     0s
                                          0 159.42658 0 84 151.00000 159.42658 5.58%
                                                                                                                                                                                                                                                                                     0s
```

```
0
                  0 159.42357 0 91 151.00000 159.42357 5.58%
                                                                            05
            a
                                       152.0000000 159.42357 4.88%
                                                                            0s
            0
                  0 158.98552
                                 0 58 152,00000 158,98552 4,60%
                                                                            05
                                       154.0000000 158.98552 3.24%
                                                                            05
                  0 158.00000 0 34 154.00000 158.00000 2.60%
                                                                            05
                  0 158,00000
                                0 24 154.00000
                                                   158.00000 2.60%
                                                                            0s
                  0 158.00000
                                     29 154.00000 158.00000 2.60%
                  0 158.00000
                                                   158.00000 2.60%
                                     26 154.00000
                                                                            05
            0
                  0 158.00000
                                 0
                                     28 154.00000 158.00000 2.60%
                                                                            05
                  0 158.00000
                                 0 29 154.00000 158.00000 2.60%
                                                                            95
            0
                  0 158.00000
                                      8 154.00000
                                                   158.00000 2.60%
                                                                            05
                                       156.0000000 158.00000 1.28%
                                                                            05
                                 0 20 156.00000 158.00000 1.28%
                                                                            05
            0
                  0 158.00000
            a
                  a
                                       158.0000000 158.00000 0.00%
                                                                            ۵s
            0
                  0 158,00000
                                 0 17 158.00000 158.00000 0.00%
                                                                            0s
       Cutting planes:
          Gomory: 7
          Cover: 45
         Clique: 20
         MIR: 20
         StrongCG: 4
         GUB cover: 47
         Inf proof: 1
          RLT: 10
          Relax-and-lift: 13
        Explored 1 nodes (3198 simplex iterations) in 0.61 seconds (0.16 work units)
       Thread count was 8 (of 8 available processors)
       Solution count 9: 158 156 154 ... 122
       Optimal solution found (tolerance 1.00e-04)
        Best objective 1.580000000000e+02, best bound 1.58000000000e+02, gap 0.0000%
        Gurobi status= 2
        Total Solve Time = 0 mins
         Status: Optimal
         Objective: 158.0 points
         Best Found Solution Objective= 158.0
        Score under Scenario 1 is 158
         # Clean up the output (-0.0) by making all integers
         TeamA_Lineup_df[2] = TeamA_Lineup_df[2][TeamA_Lineup_df[2].columns].astype('int8')
In [ ]:
        #########
         # JUST FOR DEBUGGING
         indiv_score_dict = {1:9,2:4,3:3,4:2,5:1,6:0}
         relay_score_dict = {1:11,2:4,3:2}
         #########
         # JUST FOR DEBUGGING
         for ev in ['F11650Y','F1200Y','F2100Y','F3100Y','F4200Y','F150Y','F1100Y','F2200Y','F3200Y','F1500Y','F4100Y','F5200Y']:
```

In []:

In []:

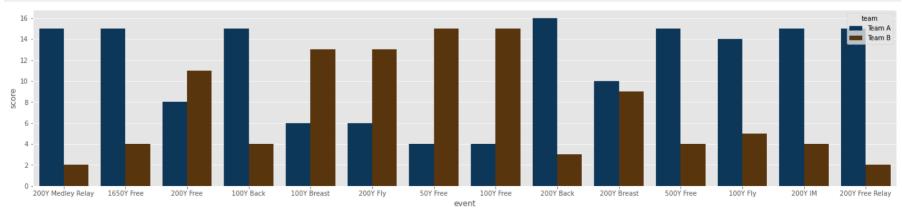
```
tot=0
    for p in [1,2,3]:
       if isnan(w.loc[p.ev]):
            point = 0
       else:
            point = indiv score dict[w.loc[p,ev]]
            #point = w.loc[p.ev]
       tot = point + tot
   print(ev, " ", tot)
for ev in ['M50','F50']:
   tot=0
   for p in [1,2,3]:
       if isnan(w.loc[p,ev]):
            point = 0
       else:
            point = relay score dict[w.loc[p,ev]]
            #point = w.loc[p.ev]
       tot = point + tot
   print(ev, " ", tot)
##########
```

F11650Y 15
F1200Y 8
F2100Y 15
F3100Y 6
F4200Y 6
F150Y 4
F1100Y 4
F2200Y 16
F3200Y 10
F1500Y 15
F4100Y 14
F5200Y 15
F4500Y 15
F500 15

3. Verify the score would be if these two LUs competed

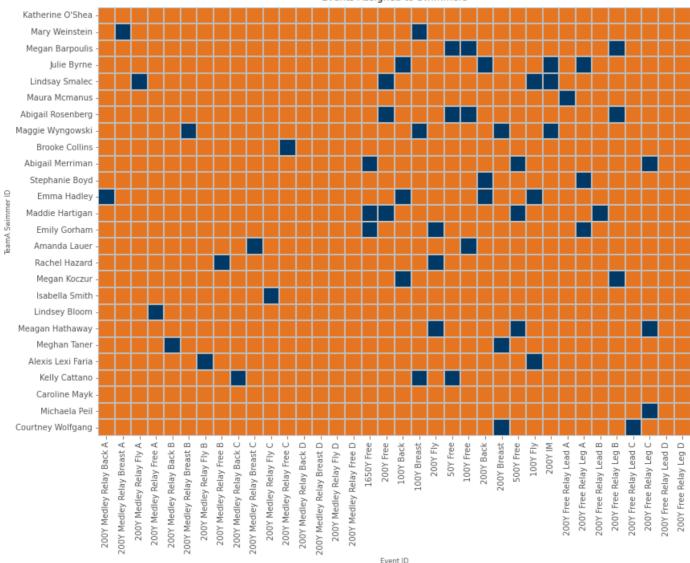
CHECK: It's not assigning swimmers to events when it can do leave it empty and still get points. Need to make sure that it assigns a person if it can.

```
In [ ]:
         # Viz of team scores for Team A LU 2 vs Team B LU 1
         ChartScore(eventScore df 5, TeamA blue, TeamB brown, 24,5)
```



```
In [ ]:
         #####
         # Debugging Code
          print((TeamA_Lineup_df[2]*TeamA_Perf_wM_df)[['FLM50A', 'F2M50A', 'F3M50A', 'F3M50A', 'F3M50A']].max().sum(), " ",\
              (TeamA_Lineup_df[2]*TeamA_Perf_wM_df)[['FLM50B', 'F2M50B', 'F3M50B', 'F4M50B']].max().sum(), " ", \
             (TeamA Lineup df[2]*TeamA Perf wM df)[['FLM50C', 'F2M50C', 'F3M50C', 'F4M50C']].max().sum())
        105.16
                  105.42
                            394.9299999999999
In [ ]:
         #####
         # Debugging Code
          print((TeamB_Lineup_df[1]*TeamB_Perf_wM_df)[['FLM50A', 'F2M50A', 'F3M50A', 'F3M50A', 'F3M50A']].max().sum(), " ",\
              (TeamB_Lineup_df[1]*TeamB_Perf_wM_df)[['FLM50B', 'F2M50B', 'F3M50B', 'F4M50B']].max().sum(), " ", \
              (TeamB_Lineup_df[1]*TeamB_Perf_wM_df)[['FLM50C', 'F2M50C', 'F3M50C', 'F4M50C']].max().sum())
        105.47999999999999
                               106.11
                                         481.32
In [ ]:
         # Viz of Team LU 2
         ChartLineup('TeamA', TeamA_colors, TeamA_Lineup_df[2], 18, 10)
```

Events Assigned to Swimmers



Team A LU 2 vs Team B LU 1 and Team A wins by 54.

Team B's Response to Team A's LU 1:

1. Get opptime for Team A's LU 1:

```
opptime_TeamA_dict = dict()
for i in range(TeamA_lineupNums):
    # Doing this for LU 1 for Team A
    opptime_TeamA_dict[i+1] = create_opptime_dict(TeamA_Perf_wM_df, TeamA_Lineup_df[1], BigM)
print(opptime_TeamA_dict[1][3])
```

{'M50': 392.0490000000004, 'F50': 443.279, 'F11650Y': 1035.659, 'F1200Y': 503.559, 'F2100Y': 55.829, 'F3100Y': 68.419, 'F4200Y': 124.399, 'F150Y': 24.3089 9999999997, 'F1100Y': 55.929, 'F2200Y': 120.979, 'F3200Y': 154.339, 'F1500Y': 299.439, 'F4100Y': 55.749, 'F5200Y': 126.598999999999}

2. Find the MeetOpt Team B response LU to Team A LU 1

```
# def MeetOpt(athleteFull.scenario.scenprob.indiv events.relay scored events.relaynoMR.stroke.relay pastperf events.lineup events. playperf.opptime):
     # Find MeetOpt response lineup to the base
     TeamB Lineup df[2], = MeetOpt(TeamB swimmers, oppA lineup nums, oppA scenario prob, individual scored events, \
                     relay scored events, relay noMR, MR legs, relay pastperf events, Lineup Events, TeamB Perf dict, opptime TeamA dict, BigM)
     # Reorder the columns to the meet event order
     TeamB Lineup df[2] = TeamB Lineup df[2][EventOrder]
NOW WE'RE IN MEETOPT:
event noMR: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F3200Y', 'F3200Y', 'F3200Y', 'F3100Y', 'F3200Y', 'F320Y', 'F3200Y', 'F320
 {1: 1}
total SCORED events: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F4200Y', 'F3200Y', 'F11650Y', 'M50', 'F5
total PERF events: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F1500Y', 'F5200Y', 'F5200Y', 'F3100Y', 'F3100Y', 'F3200Y', 'F3100Y', 'F3100Y
50A', 'F3M50A', 'F4M50A', 'FLF50A', 'F1F50A')
total ASSIGNED events: ('F1200Y', 'F150Y', 'F1100Y', 'F4100Y', 'F2100Y', 'F2200Y', 'F1500Y', 'F5200Y', 'F3100Y', 'F4200Y', 'F3100Y', 'F3
  'F2M50A', 'F3M50A', 'F4M50A', 'FLM50B', 'F2M50B', 'F3M50B', 'F4M50B', 'FLM50C', 'F3M50C', 'F4M50C', 'F4M50D', 'F2M50D', 'F3M50D', 'F3M50
0A', 'F1F50A', 'FLF50B', 'F1F50B', 'FLF50C', 'F1F50C', 'F1F50D', 'F1F50D')
Check Done
obi done
Total Setup Time = 0 secs
Solve the baseline problem:
Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
Thread count: 4 physical cores, 8 logical processors, using up to 8 threads
Optimize a model with 994 rows, 1765 columns and 9057 nonzeros
Model fingerprint: 0x9ca1c4b7
Variable types: 43 continuous, 1722 integer (0 binary)
Coefficient statistics:
        Matrix range
                                                                                 [1e-03, 4e+03]
         Objective range [1e+00, 1e+00]
        Bounds range
                                                                                   [1e+00, 1e+00]
         RHS range
                                                                                  [1e+00, 4e+03]
Presolve removed 327 rows and 108 columns
Presolve time: 0.04s
Presolved: 667 rows, 1657 columns, 7626 nonzeros
Variable types: 0 continuous, 1657 integer (1615 binary)
Root relaxation: objective 1.549638e+02, 356 iterations, 0.01 seconds (0.00 work units)
                  Nodes
                                                                             Current Node
                                                                                                                                                                             Objective Bounds
                                                                                                                                                                                                                                                                                                     Work
                                                                                                                                                                                                          BestBd Gap | It/Node Time
     Expl Unexpl | Obj Depth IntInf | Incumbent
```

```
a
          0 150.96018
                            71
                                         - 150.96018
          0 137.95756
                          0 102
                                         - 137.95756
                                                                     05
          0 137.95756
                             97
                                         - 137.95756
          0 132.44650
                             94
                                         - 132.44650
                                                                     05
          0 132,44098
                             85
                                            132,44098
                             37
                                            131.00000
          0 131.00000
    0
          0 131.00000
                             30
                                            131.00000
                                                                     05
    0
          0
                               107.0000000
                                           131.00000 22.4%
                                                                     05
          0 131 00000
                             20 107.00000 131.00000
                                                      22.4%
    0
                               128.0000000
                                           131.00000
                                                      2.34%
                                                                     05
          0 131.00000
                         0 18 128.00000
                                           131.00000 2.34%
                              3 128.00000
          0 131.00000
                                           131.00000 2.34%
                                                                     05
    0
    a
                               129.0000000
                                           131.00000 1.55%
                                                                     ۵s
    0
          0 131.00000
                         0 16 129.00000
                                           131.00000 1.55%
                                                                     0s
    0
                               130.0000000
                                            131.00000
                                                      0.77%
                                                                     0s
    0
          0 131.00000
                              6 130,00000
                                           131.00000
                                                      0.77%
                                                                     05
                               131.0000000 131.00000 0.00%
                                                                     0s
    a
          0 131.00000
                              6 131.00000 131.00000 0.00%
                                                                     95
Cutting planes:
  Gomory: 3
  Cover: 32
  Clique: 16
  MIR: 12
  StrongCG: 1
  GUB cover: 42
  Inf proof: 1
  Zero half: 2
  RLT: 3
  Relax-and-lift: 9
Explored 1 nodes (1925 simplex iterations) in 0.46 seconds (0.11 work units)
Thread count was 8 (of 8 available processors)
Solution count 5: 131 130 129 ... 107
Optimal solution found (tolerance 1.00e-04)
Best objective 1.310000000000e+02, best bound 1.31000000000e+02, gap 0.0000%
Gurobi status= 2
 Total Solve Time = 0 mins
 Status: Optimal
 Objective: 131.0 points
 Best Found Solution Objective= 131.0
 Score under Scenario 1 is 131
```

3. Verify the score if these two LUs compete.

NEED TO FIX eventScore_df to be a list of dfs!

```
# Which Lineups to score in a competition?
TeamA_LU = 1
TeamB_LU = 2
```

```
score_A,score_B,eventScore_df_6 = calculate_pred_score(TeamA_Perf_wM_df, TeamA_Lineup_df[TeamA_LU], \
    TeamB_Perf_wM_df, TeamB_Lineup_df[TeamB_LU], scoring_method="Six Lane")

print("Projected scores: \nTeam A: ",score_A,"\nTeam B: ",score_B, "\nDiff: ", score_A-score_B)

Projected scores:
Team A: 131
Team B: 131
Diff: 0
```

Team A LU 1 vs. Team B LU 2 and Team A wins by 8.

Game Theory 3x3

```
# Create the score matrix with Team
LineupA0vB0 = 12
LineupA0vB1 = -2
LineupA0vB2 = 16
LineupA1vB0 = 30
LineupA1vB1 = 26
LineupA1vB2 = 0
LineupA2vB0 = 22
LineupA2vB1 = 54
LineupA2vB2 = 24
score_matrix = [[LineupA0vB0, LineupA0vB1, LineupA0vB2], [LineupA1vB0, LineupA1vB1, LineupA1vB2], [LineupA2vB0, LineupA2vB1, LineupA2vB2]]
#Return the Nash equilibrium mixed strategy and expected points for team A and team B.
f,optB = FindOptStrategy('A', score matrix)
g,optA = FindOptStrategy('B', score_matrix)
print('\n Printing f: ',f)
print('\n Printing optA: ', optA)
print('\n Printing g: ', g)
print('\n Printing optB: ',optB)
```

```
Discarded solution information
Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
Thread count: 4 physical cores, 8 logical processors, using up to 8 threads
Optimize a model with 4 rows, 4 columns and 14 nonzeros
Model fingerprint: 0xdcca856d
Coefficient statistics:
  Matrix range
                   [1e+00, 5e+01]
  Objective range [1e+00, 1e+00]
  Bounds range
                   [0e+00, 0e+00]
  RHS range
                   [1e+00, 1e+00]
Presolve removed 1 rows and 0 columns
Presolve time: 0.01s
Presolved: 3 rows, 4 columns, 11 nonzeros
Iteration
             Objective 0
                             Primal Inf.
                                             Dual Inf.
                                                            Time
       0
            2.4000000e+01 2.500000e-01
                                           0.000000e+00
                                                              05
       1
            2.2500000e+01 0.000000e+00
                                           0.0000000+00
                                                              05
Solved in 1 iterations and 0.01 seconds (0.00 work units)
Optimal objective 2.250000000e+01
Maximize
  <gurobi.LinExpr: v>
Subject To
  bounds[0]: \{gurobi.LinExpr: 12.0 f[0] + 30.0 f[1] + 22.0 f[2] + -1.0 v\} = 0
  bounds[1]: \langle gurobi.LinExpr: -2.0 f[0] + 26.0 f[1] + 54.0 f[2] + -1.0 v \rangle = 0
  bounds[2]: \langle gurobi.LinExpr: 16.0 f[0] + 24.0 f[2] + -1.0 v \rangle >= 0
  c2: \langle gurobi.LinExpr: f[0] + f[1] + f[2] \rangle = 1
Bounds
  v free
None
f[0] 0
f[1] 0.0625
f[2] 0.9375
v 22.5
Obj: 22.5
Discarded solution information
Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
Thread count: 4 physical cores, 8 logical processors, using up to 8 threads
Optimize a model with 4 rows, 4 columns and 14 nonzeros
Model fingerprint: 0xbeadd041
Coefficient statistics:
  Matrix range
                   [1e+00, 5e+01]
  Objective range [1e+00, 1e+00]
                    [0e+00, 0e+00]
  Bounds range
  RHS range
                   [1e+00, 1e+00]
Presolve removed 1 rows and 0 columns
Presolve time: 0.01s
Presolved: 3 rows, 4 columns, 11 nonzeros
Iteration
                                             Dual Inf.
                                                            Time
             Objective 0
                             Primal Inf.
            0.0000000e+00
                            5.000000e+00
                                           0.000000e+00
                                                              0s
       1
            2.2500000e+01 0.000000e+00
                                           0.000000e+00
Solved in 1 iterations and 0.01 seconds (0.00 work units)
Optimal objective 2.250000000e+01
Minimize
```

```
<gurobi.LinExpr: u>
Subject To
  bounds[0]: \langle gurobi.LinExpr: 12.0 g[0] + -2.0 g[1] + 16.0 g[2] + -1.0 u \rangle <= 0
  bounds[1]: <gurobi.LinExpr: 30.0 g[0] + 26.0 g[1] + -1.0 u> <= 0
  bounds[2]: \langle gurobi.LinExpr: 22.0 g[0] + 54.0 g[1] + 24.0 g[2] + -1.0 u \rangle <= 0
  c1: \langle gurobi.LinExpr: g[0] + g[1] + g[2] \rangle = 1
Bounds
  u free
None
g[0] 0.75
g[1] 0
g[2] 0.25
u 22.5
Obj: 22.5
 Printing f: {'f[0]': 0.0, 'f[1]': 0.0625, 'f[2]': 0.9375, 'v': 22.5}
 Printing optA: 22.5
 Printing g: {'g[0]': 0.75, 'g[1]': 0.0, 'g[2]': 0.25, 'u': 22.5}
 Printing optB: 22.5
```

Optimal mixed strategy is for Team A (0,1/16,15/16) for Team B (3/4,0,1/4) with expected score of Team A winning by 24.5 points on average.

```
payoff3x3_df = pd.DataFrame({"Team B LU 0": [LineupA0vB0, LineupA1vB0, LineupA2vB0], "Team B LU 1": [LineupA0vB1, LineupA1vB1, LineupA2vB1], "Team B LU 2": display(HTML(payoff3x3_df.to_html()))
#df.to_Latex()
```

	Team B LU 0	Team B LU 1	Team B LU 2
Team A LU 0	12	-2	16
Team A LU 1	30	26	0
Team A LU 2	22	54	24

plt.show()

	Team B LU 0	Team B Lineups Team B LU 1	Team B LU 2
Team A LU 0	12	-2	16
Feam A Lineups Team A LU 1	30	26	0
Team A LU 2	22	54	24

Determining the Swimmer Meet Impact (SMI) for a given opponent and lineup (later: distribution of opponent lineups). The SMI for a swimmer can never be more than the total expected points the swimmer is projected to receive versus an opponent, but it can be as low as zero if an adjusted lineup exists where swimmers can be shuffled to still acheive all the points lost by the removed swimmer. Therefore, this is the "impact" of that swimmer with respect to the current opponent and projected performance times.

Create a MeetOpt version where a swimmer (and events can be restricted from the optimization)

```
:param scenprob: dictionary of scenarios to probability (or weight) of selection. This will be the
the likelihood that the lineup is chosen from a game theory distribution.
:naram indiv scored events: a list of the names of the events that are scored in a meet for the individuals
:param relaynoMR: the list of names of scored freestyle relay events (no medleys)
:naram stroke: the list of names of the legs of the medley relay
:param relay scored events: names of relay events scored and in opptime
:naram lineum events: the events list that need to be returned for Team A includes relays A.B.C data from xvar. yvar.
:param playperf: the dictionary of predicted performances for Team A athletes in each event, indexed by (indiv scored events and relay past perf events
:param opptime: the dictionary of opposing team ranked performances. Indexed by scenario (lineup), rank (1,2,3,4.5), events (indiv scored events and re
:param: SMI athlete: the string code of the athlete to restrict from an event (or all events)
:param: SMI event: A list of events for which the athlete is restricted from participating (use specific code or 'M50' 'F50' for relays)
        or 'All' if restricted from all events to get the event independent SMI, e.g ['M50', 'All', 'F150Y']
#returns optimal response line up to the given opponent lineup(s) (called scenarios)
# Assumes there are enough athletes to field a full team
print("NOW WE'RE IN MEETOPT with SMI: \n")
## Beain INPUT SETTINGS
# 1 if want to write output to file at the following path
# WriteOutput = 0
# path of the output file adjust for user
# if WriteOutput == 1:
# path = "G:\Mv Drive\SwimMeetOpt" + "\SwimMeetOptTrialResults.csv"
# Used for comparison
tot scored events = indiv events + relay scored events
tot pastperf events = indiv events + relay pastperf events
tot assgn events = lineup events
relay = relay scored events
#tuples for dictionaries
event noMR = indiv events + relaynoMR
print("event noMR: ", event noMR)
print(scenprob)
print("total SCORED events: ", tot scored events)
print("total PERF events: ", tot_pastperf_events)
print("total ASSIGNED events:", lineup events)
homerank = (1,2,3)
place = (1,2,3,4,5,6)
ind points = (9, 4, 3, 2, 1, 0)
relay points = (11,4,2,0,0,0)
indivplcscore = dict(zip(place,ind points))
relayplcscore = dict(zip(place,relay points))
indiv = indiv events
#Do these exist in college?
Maxevent = 4
Maxrelayevent = 1
```

```
Maxindevent = 3
TopopprankIndiv = 5
TopopprankRelav = 3
#Set solve time limit in seconds and optimality aap
MaxSolveTime = 10
SolverTimeLimit = MaxSolveTime*60
OptGap = 0.01
#Which Solver?
SolverUsed = "Gurobi"
#SolverUsed = "Gurohi"
if Solverlised == "CBC":
    #Choose solver, and set it to problem, and build the model
    #Solve with CBC with Logaina and time limit. Parameter option: keepFiles=1 breaks it!
    #solver = pl.COIN CMD(msa=1, keepFiles=1, presolve=0, threads=1, maxSeconds=SolverTimeLimit,fracGap = OptGap)
    #solver = pulp.COIN CMD(msq=1, keepFiles=1, presolve=1, maxSeconds=SolverTimeLimit,fracGap=OptGap)
    pl.PULP CBC CMD()
else:
    #Solve with Gurobi
    #solver = pulp.GUROBI CMD(keepFiles=1,options=[("MIPFocus",1),("TimeLimit",SolverTimeLimit)])
    #solver = pl.GUROBI CMD(keepFiles=1,options=[("MIPFocus",1),("MIPGap",OptGap),("TimeLimit",SolverTimeLimit)])
    solver = pl.GUROBI()
    #Solve with Cplex. Throws error for write sol file
    #solver = pulp.CPLEX_scCMD(msg=1,options = ['set mip tolerances mipgap 0.2'])
    #solver = pulp.CPLEX CMD(msq=1,timelimit=30)
#highest relative rank for home
Tophomerank = 3:
# small constant
EPS = 0.0001:
#number of people on a relay team
relaySize = 4;
#subset of the actual athletes with some
#qhosts because of hard relay requirements
#realathlete are only the actual athletes
# ActAthNum = len(athleteFull)
# athlete = athleteFull[:int(ActAthNum)+4]
#realathlete = athleteFull[:int(ActAthNum)]
athlete = athleteFull
# for i in realathlete:
      print("current realathlete index ", realathlete[realathlete.index(i)])
       print("previous athlete ", realathlete[realathlete.index(i)-1])
#OUTPUT Arrays and Variables
#Start the clock for first setup
setupStart = time.time()
print("Check Done")
#Instantiate our problem class
```

```
SwimMeetOpt = pl.LpProblem("MeetMax", pl.LpMaximize)
#Initialize the decision variables
#Scenario scores vs. onns
scenscorevars = {}
# if assigned athlete has 1st time in event
# if assigned athlete has 2nd best time in event
vvars = {}
# if assigned athlete has 3rd best time in event
zvars = {}
# if assigned athlete has 1st time in start time in event 200MR
xvarleads = {}
# if assigned athlete has 2nd best time in start time in event 200MR
vvarleads = {}
# if assigned athlete has 3rd best time in start time in event 200MR
zvarleads = {}
# if assigned athlete has 1st time in medley
xMRvars = {}
# if assigned athlete has 2nd best time in medlev
vMRvars = {}
# if assigned athlete has 3rd best time in medley
zMRvars = {}
# rank of our athletes assigned to events
rvars = {}
#indicator variables of for outcome of event i versus opp 1
wvars = {}
#assianments
asgnvars = {}
#OPTIMIZATION DECISION VARIABLES defined in the MeetOpt paper using PulP:
#scenscorevar is a placeholder which will hold the expected score of our optimal
#lineup against the lineup given in scenario i
scenscorevar = pl.LpVariable.dicts('scenscorevar',(scenario),0,None,pl.LpContinuous)
#these are placement variables for our athletes to events
#xvar will hold the best assigned athlete from our team in an event
#vvar will hold the second best assigned athlete from our team in an event
#zvar will hold the third best assigned athlete from our team in an event
#We assume that exactly three athletes are assigned to each event
#the optimization creates the assignment and the ordering
xvar = pl.LpVariable.dicts('xvar',(athlete,indiv),0,1,pl.LpBinary)
yvar = pl.LpVariable.dicts('yvar',(athlete,indiv),0,1,pl.LpBinary)
zvar = pl.LpVariable.dicts('zvar',(athlete,indiv),0,1,pl.LpBinary)
#Same as above, but the starting leg for the "non-Medley freestyle Relay" relays
xFRvarlead = pl.LpVariable.dicts('xFRvarlead',(athlete,relaynoMR),0,1,pl.LpBinary)
yFRvarlead = pl.LpVariable.dicts('yFRvarlead',(athlete,relaynoMR),0,1,pl.LpBinary)
zFRvarlead = pl.LpVariable.dicts('zFRvarlead',(athlete,relaynoMR),0,1,pl.LpBinary)
#Same ordering as above, but for the athletes assigned to the
#best, second best, and third best LEGS of Freestyle relay
xFRvar = pl.LpVariable.dicts('xFRvar',(athlete, relaynoMR),0,1,pl.LpBinary)
yFRvar = pl.LpVariable.dicts('yFRvar',(athlete, relaynoMR),0,1,pl.LpBinary)
```

```
zFRvar = pl.LpVariable.dicts('zFRvar',(athlete, relaynoMR),0,1,pl.LpBinary)
#Same ordering as above, but for the athletes assigned to the
#hest, second hest, and third hest medley relay
xMRvar = nl.Invariable.dicts('xMRvar', (athlete, stroke), 0.1.nl.InBinary)
yMRvar = pl.LpVariable.dicts('yMRvar',(athlete, stroke),0,1,pl.LpBinary)
zMRvar = nl.lnVariable.dicts('zMRvar', (athlete, stroke), 0.1.nl.lnBinary)
#rvar will hold the TIME of our first, second, and third fastest entrants in each event
rvar = pl.LpVariable.dicts('rvar',(homerank,tot scored events),None,None,pl.LpContinuous)
#wvar will be 1 if our athlete with homerank h. in event i. finishes in overall place k. against
#onnonent scenario |
#with this we can answer in which place our assigned athletes actually finish and score the meet!
wvar = pl.LpVariable.dicts('wvar',(tot scored events,homerank, place, scenario),0,1,pl.LpBinary)
#asanvar is a generic variable which will be 1 if athlete i is assigned to event j (ignoring rank, etc.)
#iust answers the auestion "Is this athlete doing in this event?"
#asanvar = pl.LpVariable.dicts('asanvar'.(athlete.tot assan events).0.1.pl.LpBinarv)
#Ohiective Function - Maximize the weighted scenario (or expected) score against
#over eact scenario (or against each team)
SwimMeetOpt += pl.lpSum(scenprob[s]*scenscorevar[s] for s in scenario), "Total Expected Score"
print("obj done")
# Multiple relay teams and they cannot sweep so only the top two relay teams are included in the home team score
# defines the variable scenscorevar (scenario score variable) for each scenario
for s in scenario:
    SwimMeetOpt += scenscorevar[s] == pl.lpSum(indivplcscore[p]*wvar[i][k][p][s] for i in indiv for k in homerank for p in place if k<=p) + \
        pl.lpSum(relayplcscore[p]*wyar[i][k][p][s] for i in relay scored events for k in homerank for p in place if k<=p) + \
        pl.lpSum(2*wvar[i][1][4][s] - 2*wvar[i][3][3][s] for i in relay scored events), "Scenario %s Score"%s
#CREATING THE CONSTRAINTS FOR THE OPTIMIZATION PROBLEM:
# Exactly one 1st, 2nd, 3rd best time athlete in each indiv event
# WARNING: ASSUMES you have sufficent swimmers to meet all the events and relays with max requirements
for i in indiv:
    SwimMeetOpt += pl.lpSum(xvar[i][j] for i in athlete) == 1, "Exactly one 1st for indiv event %s"%j
    SwimMeetOpt += pl.lpSum(vvar[i][i] for i in athlete) == 1. "Exactly one 2nd for indiv event %s"%i
    SwimMeetOpt += pl.lpSum(zvar[i][j] for i in athlete) == 1, "Exactly one 3rd for indiv event %s"%j
# Exactly 4 athletes in a relay for our first, second, and third relays
# accounting for the opening leg not being a flying start in the non-MR relays
for i in relaynoMR:
    SwimMeetOpt += pl.lpSum(xFRvar[i][j] for i in athlete) == relaySize-1, "Exactly 3 legs in 1st relay %s"%j
    SwimMeetOpt += pl.lpSum(yFRvar[i][j] for i in athlete) == relaySize-1, "Exactly 3 legs in 2nd relay %s"%j
    SwimMeetOpt += pl.lpSum(zFRvar[i][i] for i in athlete) == relaySize-1, "Exactly 3 legs in 3rd relay %s"%j
    SwimMeetOpt += pl.lpSum(xFRvarlead[i][i] for i in athlete) == 1, "Exactly 1 to start 1st relay %s"%j
    SwimMeetOpt += pl.lpSum(yFRvarlead[i][j] for i in athlete) == 1, "Exactly 1 to start 2nd relay %s"%j
    SwimMeetOpt += pl.lpSum(zFRvarlead[i][j] for i in athlete) == 1, "Exactly 1 to start 3rd relay %s"%j
# Exactly 4 athletes in the first, second, and third best medley relay
SwimMeetOpt += pl.lpSum(xMRvar[i][j] for i in athlete for j in stroke) == relaySize, "Exactly 4 in 1st MR"
SwimMeetOpt += pl.lpSum(yMRvar[i][j] for i in athlete for j in stroke) == relaySize, "Exactly 4 in 2nd MR"
SwimMeetOpt += pl.lpSum(zMRvar[i][j] for i in athlete for j in stroke) == relaySize, "Exactly 4 in 3rd MR"
```

```
# Athletes in at most Mayevent
for i in athlete:
                    SwimMeetOpt += pl.lpSum(xvar[i][i] + vvar[i][i] + zvar[i][i] + zvar[i]
# START: Added for SMI Changes
# For the SMI athlete restrict from assigning them the restricted events and build a lineup
print("Computing SMI for athlete ", SMI athlete, " and event ", SMI event)
# If user is blocking individual event for swimmer
for i in indiv:
                   if ('All' in SMI event) or (i in SMI event):
                                      SwimMeetOpt += xvar[SMI athlete][i]==0
                                      SwimMeetOpt += yvar[SMI athlete][j]==0
                                      SwimMeetOpt += zvar[SMI athlete][j]==0
# If user is blocking 200 Free Relay (F50) relay for swimmer
if ('All' in SMI event) or ('F50' in SMI event):
                   for j in relaynoMR:
                                      SwimMeetOpt += xFRvar[SMI athlete][i]==0
                                      SwimMeetOpt += vFRvar[SMI athlete][i]==0
                                      SwimMeetOpt += zFRvar[SMI athlete][i]==0
                                      SwimMeetOpt += xFRvarlead[SMI athlete][i]==0
                                      SwimMeetOpt += vFRvarlead[SMI athlete][i]==0
                                      SwimMeetOpt += zFRvarlead[SMI athlete][i]==0
# if user is blocking 200 Med Relay (M50) for swimmer
if ('All' in SMI event) or ('M50' in SMI event):
                   for i in stroke:
                                      SwimMeetOpt += xMRvar[SMI athlete][i]==0
                                      SwimMeetOpt += yMRvar[SMI athlete][j]==0
                                      SwimMeetOpt += zMRvar[SMI athlete][j]==0
# END: Added for SMI Changes
# Athletes in at most Maxrelavevent
for i in athlete:
                    SwimMeetOpt += pl.lpSum(xFRvar[i][i] + yFRvar[i][i] + zFRvar[i][i] + xFRvarlead[i][i] + yFRvarlead[i][i] + zFRvarlead[i][i] + z
                    # Athletes in at most Maxindivevent
                   SwimMeetOpt += pl.lpSum(xvar[i][j] + yvar[i][j] + zvar[i][j] for j in indiv) <= Maxindevent, "Max Indiv events for athlete %s"%i
                    # Back to back event constraints
                    #HARD CODED WITH EVENT NAMES AND NEEDS TO BE CHECKED
                    SwimMeetOpt += xvar[i]["100F"] + yvar[i]["100F"] + zvar[i]["100F"] + xvar[i]["500F"] + yvar[i]["500F"] + zvar[i]["500F"] + zvar[i]["500F"]
                    SwimMeetOpt += xvar[i]["200F"] + yvar[i]["200F"] + zvar[i]["200F"] + xvar[i]["200IM"] + yvar[i]["200IM"] + zvar[i]["200IM"] + z
                    SwimMeetOpt += xvar[i]["100BS"] + yvar[i]["100BS"] + zvar[i]["100BS"] + xvar[i]["100BR"] + yvar[i]["100BR"] + zvar[i]["100BR"] 
                    # Athletes can only be one of the 1st, 2nd, or 3rd ranked atheletes assigned to an event j
```

```
for i in indiv:
        SwimMeetOpt += xvar[i][i] + yvar[i][i] + zvar[i][i] <= 1, "athlete %s can only be one of the 1st, 2nd, or 3rd ranked athletes assigned to an eve
#Athletes can only be 1st. 2nd. or 3rd ranked relay team for each relay i
for i in athlete:
    for i in relaynoMR:
        SwimMeetOpt += xFRvar[i][i] + yFRvar[i][i] + zFRvar[i][i] + xFRvarlead[i][i] + yFRvarlead[i][i] + zFRvarlead[i][i] <= 1. "athlete %s can only be
    # Each athlete can only perform one stroke in medley relay
    SwimMeetOpt += pl.lpSum(xMRvar[i][i]+yMRvar[i][j]+zMRvar[i][j] for j in stroke) <= 1, "Athlete %s can only perform one stroke in medley relay"%i
#Each stroke on each relay team can only have one athlete assigned
for j in stroke:
    SwimMeetOpt += pl.lpSum(xMRvar[i][i]for i in athlete) <= 1. "Stroke %s on 1st MR can only have one athlete"%i
    SwimMeetOpt += pl.lpSum(vMRvar[i][i]for i in athlete) <= 1. "Stroke %s on 2nd MR can only have one athlete"%i
    SwimMeetOpt += pl.lpSum(zMRvar[i][i]for i in athlete) <= 1, "Stroke %s on 3rd MR can only have one athlete"%i</pre>
#realized rank of athletes from assignments
#IF NO RUNNER, NEED TO ASSIGN A time larger than the third runner, smaller than the BiaM for rank
for i in indiv:
    SwimMeetOpt += rvar[1][j] == pl.lpSum(playperf[i][j]*xvar[i][j] \ for \ i \ in \ athlete) + 0.5*Big \ M[j] + 1.0 - pl.lpSum(xvar[i][j]*(0.5*Big \ M[j] + 1.0) \ for \ i \ in \ athlete) + 0.5*Big \ M[j] + 1.0 - pl.lpSum(xvar[i][j]*(0.5*Big \ M[j] + 1.0) \ for \ i \ in \ athlete) + 0.5*Big \ M[j] + 1.0 - pl.lpSum(xvar[i][j]*(0.5*Big \ M[j] + 1.0) \ for \ i \ in \ athlete)
    SwimMeetOpt += rvar[2][i] == pl.lpSum(playperf[i][i]*yvar[i][i] for i in athlete) + 0.5*Big M[i] + 2.0 - pl.lpSum(yvar[i][i]*(0.5*Big M[i] + 2.0) f
    SwimMeetOpt += rvar[3][j] == pl.lpSum(playperf[i][j]*zvar[i][j] for i in athlete) + 0.5*Big M[j] + 3.0 - pl.lpSum(zvar[i][j]*(0.5*Big M[j] + 3.0) f
 # The problem data is written to an .lp file
#SwimMeetOpt.writeLP("SwimMeetOpt.Lp")
#WARNING: Sloppy hard code fix for legacy data structure
playperfLeg = dict()
playperfLead = dict()
for i in athlete:
    # declare dicts
    playperfLeg[i] = dict()
    playperfLead[i] = dict()
    for j in relaynoMR:
        playperfLeg[i][j] = playperf[i]['F1F50A']
        playperfLead[i][j] = playperf[i]['FLF50A']
for j in relaynoMR:
    SwimMeetOpt += rvar[1][j] == pl.lpSum(playperfLeg[i][j]*xFRvar[i][j] + playperfLead[i][j]*xFRvarlead[i][j] for i in athlete) + relaySize*0.5*Big M[
    SwimMeetOpt += rvar[2][j] == pl.lpSum(playperfLeg[i][j]*yFRvar[i][j] + playperfLead[i][j]*yFRvarlead[i][j] for i in athlete) + relaySize*0.5*Big_M[
    SwimMeetOpt += rvar[3][j] == pl.lpSum(playperfLeg[i][j]*zFRvar[i][j] + playperfLead[i][j]*zFRvarlead[i][j] for i in athlete) + relaySize*0.5*Big M[
SwimMeetOpt += rvar[1]["M50"] == pl.lpSum(playperf[i][j] *xMRvar[i][j] for i in athlete for j in stroke) + relaySize*0.5*Big_M["M50"] + relaySize*1.0 -
SwimMeetOpt += rvar[2]["M50"] == pl.lpSum(playperf[i][j]*yMRvar[i][j] for i in athlete for j in stroke) + relaySize*0.5*Big_M["M50"] + relaySize*2.0 -
SwimMeetOpt += rvar[3]["M50"] == pl.lpSum(playperf[i][i]*zMRvar[i][i] for i in athlete for j in stroke) + relaySize*0.5*Big M["M50"] + relaySize*3.0 -
#force consistency in rank order
for k in homerank:
    for j in tot scored events:
        if k < Tophomerank:</pre>
            SwimMeetOpt += rvar[k][j] <= rvar[k+1][j]</pre>
#runner/team of rank k can be place in at most one place (1st, 2nd, or 3rd) vs opp 1
for j in indiv:
```

```
for k in homerank:
        for s in scenario:
            SwinMeetOnt += pl.lpSum(wvar[i][k][l][s] for l in place if l >= k) <= 1
for i in relay:
    for k in homerank:
        for s in scenario:
            SwimMeetOpt += pl.lpSum(wvar[i][k][1][s] for l in place if l >= k) <= 1</pre>
#Did vour first runner 1st runner 1st. 2nd in 2nd or 3rd in third vs opp
for i in indiv:
    for k in homerank:
        for 1 in place:
            for s in scenario:
                if k==1.
                    #print("ath: ",j,"homerank: ",k,"place: ",l, "scen: ",s)
                    SwimMeetOpt += rvar[k][j] <= opptime[s][1][j]*wvar[j][k][1][s] + Big M[j] - Big M[j]*wvar[j][k][1][s]
                if l>k and l<(TopopprankIndiv + k):</pre>
                    #print("ath: ",j,"homerank: ",k,"place: ",l, "scen: ",s, "l-k+1: ", l-k+1)
                    SwimMeetOpt += rvar[k][j] <= opptime[s][l-k+1][j]*wvar[j][k][l][s] + Big M[j] - Big M[j]*wvar[j][k][l][s]
                if l>k and l<=(TopopprankIndiv + k):</pre>
                    #print("ath: ".i."homerank: ".k."place: ".l. "scen: ".s. "l-k: ". l-k)
                    SwimMeetOpt += rvar[k][i] >= opptime[s][1-k][i]*wvar[i][k][1][s]
#Did vour first relay 1st runner 1st. 2nd in 2nd or 3rd in third vs opp
for i in relav:
    for k in homerank:
        for 1 in place:
            for s in scenario:
                if k==1:
                    SwimMeetOpt += rvar[k][i] <= opptime[s][1][j]*wvar[j][k][1][s] + 5*Big\_M[j] - 5*Big\_M[j]*wvar[j][k][1][s]
                if l>k and l< (TopopprankRelay + k):</pre>
                    SwimMeetOpt += rvar[k][j] <= opptime[s][l-k+1][j]*wvar[j][k][l][s] + 5*Big M[j] - 5*Big M[j]*wvar[j][k][l][s]
                if l>k and l<=(TopopprankRelay + k):</pre>
                    SwimMeetOpt += rvar[k][j] >= opptime[s][1-k][j]*wvar[j][k][1][s]
#Report the total setup time
setupStop = time.time()
print("Total Setup Time = ", int(setupStop - setupStart), " secs")
# The problem data is written to an .lp file
SwimMeetOpt.writeLP("SwimMeetOpt.lp")
SwimMeetOpt.setSolver(solver)
#Solve the WHOLE problem with selected Solver and report it to Excel
print("Solve the baseline problem:")
solveStart = time.time()
SwimMeetOpt.solve()
solveStop = time.time()
print(" Total Solve Time = ", int((solveStop - solveStart)/60.0), " mins")
#The status of the solution is printed to the screen
print(" Status:", pl.LpStatus[SwimMeetOpt.status])
print(" Objective:", pl.value(SwimMeetOpt.objective), " points")
#Return the objective function value for the best feasible soln found
```

```
BestObjective = pl.lpSum(scenprob[s]*scenscorevar[s].varValue for s in scenario)
print(" Best Found Solution Objective= ". BestObjective)
OptObi = pl.value(SwimMeetOpt.objective)
scenscore = dict()
for s in scenario:
   scenscore[s] = scenscorevar[s].varValue
   print(" Score under Scenario ".s. "is ". int(scenscorevar[s].varValue))
# Each of the variables is printed with it's resolved optimum value
optLineup = {}
for i in athlete:
   optLineup[i] = {}
   for i in indiv:
       optLineup[i][i] = xvar[i][i].varValue + vvar[i][i].varValue + zvar[i][i].varValue
    # TO DO!! Add code for other relays
   optLineup[i]['FLF50A'] = xFRvarlead[i]['F50'].varValue
    optLineup[i]['F1F50A'] = xFRvar[i]['F50'].varValue
    optLineup[i]['FLF50B'] = vFRvarlead[i]['F50'].varValue
    optLineup[i]['F1F50B'] = yFRvar[i]['F50'].varValue
   optLineup[i]['FLF50C'] = zFRvarlead[i]['F50'].varValue
   optLineup[i]['F1F50C'] = zFRvar[i]['F50'].varValue
   # No need for D teams
   optLineup[i]['FLF50D'] = 0
   optLineup[i]['F1F50D'] = 0
   for i in stroke:
       leg = i[:-1]
       optLineup[i][leg+'A'] = xMRvar[i][j].varValue
       optLineup[i][leg+'B'] = yMRvar[i][j].varValue
       optLineup[i][leg+'C'] = zMRvar[i][j].varValue
       #print("ath ", i, " stroke ", leq+'C', " is ", zMRvar[i][i].varValue)
       # No need for D teams
       optLineup[i][leg+'D'] = 0
# START: Save the finish place and time
HomeAthPredTime = {}
HomeAthFinPlace = {}
for j in tot scored events:
   HomeAthPredTime[j] = {}
   HomeAthFinPlace[j] = {}
   for k in homerank:
       # mins = int(rvar[k][j].varValue/60)
       # secs = rvar[k][j].varValue - mins*60
       # HomeAthPredTime[j][k] = str(mins)+":"+str(secs)
       HomeAthPredTime[i][k] = rvar[k][i].varValue
       for p in place:
           if wvar[j][k][p][1].varValue == 1:
               HomeAthFinPlace[j][k] = p
# END: Save the finish place and time
```

```
#Return the lineup found in form of a 2-D dictionary of assignment for each athlete
#NFFD this to match the events and A/B/C team of relays.
optlineup df = pd.DataFrame.from dict(optLineup)
optLUtime df = pd.DataFrame.from dict(HomeAthPredTime)
ont!Unlace df = nd.DataFrame.from dict(HomeAthFinPlace)
# Return the transpose to get swimmers as index
return optlineup df.T. optLUtime df. optLUplace df
```

Check for Team A LU 1 vs. Team B LU 0 (expected score of Team A 146) and for athlete 233487

I167013, 214963, 221480, 228451, 233487, 233650, 235482, 255871, 256775, 260001, 265562, 270043, 329465, 330237, 330324, 342607, 342611, 344005, 347298, 356813, 382148, 395502, 402879, 403012, 409578, 5868001

```
# opponents times needs to be in lineup (or scenario), opponent rank (1.2.3.4), then the name of the scored event
         TeamB lineupNums = 1
         opptime TeamB dict = dict()
         for i in range(TeamB lineupNums):
             # Doing this for LU 1 for Team B
             opptime TeamB dict[i+1] = create opptime dict(TeamB Perf wM df, TeamB Lineup df[0], BigM)
         print(opptime TeamB dict[1][2])
        {'M50': 110.6589999999999, 'F50': 177.439, 'F11650Y': 1046.029, 'F1200Y': 109.719, 'F2100Y': 57.549, 'F3100Y': 65.818999999999, 'F4200Y': 122.839, 'F150'
        Y': 23.1989999999998, 'F1100Y': 50.149, 'F2200Y': 124.169, 'F3200Y': 142.4789999999998, 'F1500Y': 300.35900000000004, 'F4100Y': 56.159, 'F5200Y': 126.69
         # Find MeetOpt response lineup to the base
         TeamA Lineup SMI, , = MeetOptwSMI(TeamA swimmers, oppB lineup nums, oppB scenario prob, individual scored events, \
             relay scored events, relay noMR, MR legs, relay pastperf events, Lineup Events, TeamA Perf dict, opptime TeamB dict, 228451, 'All', BigM)
         # Reorder the columns to the meet event order
         TeamA Lineup SMI = TeamA Lineup SMI[EventOrder]
In [ ]:
         # Which Lineups to score in a competition?
         TeamB LU = 0
         TeamA Lineup SMI = TeamA Lineup SMI[TeamA Lineup SMI.columns].round().astype('int8')
         score A,score B,eventScore df 6 = calculate pred score(TeamA Perf wM df, TeamA Lineup SMI, \
             TeamB Perf wM df, TeamB Lineup df[TeamB LU], scoring method="Six Lane")
         print("Projected scores: \nTeam A: ",score_A,"\nTeam B: ",score_B, "\nDifference: ", score_A-score_B)
        Projected scores:
        Team A: 142.0
        Team B: 120.0
        Difference: 22.0
```

So, swimmer '228451' has a SMI of 4 points since 146 was the score for Team A using LU 1 vs Team B LU 0 when the swimmer was included.

Let's check the rest of the team Team A LU 1 vs Team B LU 0. All Team A swimmers are replaceable.

```
In [ ]:
         # Create a dataframe for the swimmer SMI scores for just Team A ('184')
         TeamA Swimmer SMI = Swimmer Names df[Swimmer Names df['team id'] == 184].copy()
         TeamA Swimmer SMI['All'] = np.nan
In [ ]:
         Base Score = 146
         for swimmer id in TeamA swimmers:
             TeamA Lineup SMI, , = MeetOptwSMI(TeamA swimmers, oppB lineup nums, oppB scenario prob, individual scored events, \
             relay scored events, relay noMR, MR legs, relay pastperf events, Lineup Events, TeamA Perf dict, opptime TeamB dict, swimmer id, 'All', BigM)
             TeamA Lineup SMI = TeamA Lineup SMI[TeamA Lineup SMI.columns].round().astype('int8')
             score A,score B,eventScore df = calculate pred score(TeamA Perf wM df, TeamA Lineup SMI, \
             TeamB Perf wM df, TeamB Lineup df[0], scoring method="Six Lane")
             TeamA Swimmer SMI.at[swimmer id, 'All'] = Base Score - score A
         # Check the scores
         TeamA Swimmer SMI = TeamA Swimmer SMI.dropna().sort values(by='All', ascending=False).set index('name').drop(columns=['gender', 'team id'])
         # Displaying dataframe as an heatmap
         fig, axs = plt.subplots(1, 1, figsize=(3, 10), constrained layout=True)
         g = sns.heatmap(TeamA Swimmer SMI, linewidths = 0.3, annot = True,
                     annot kws={"size": 12},cbar= False, square= False, xticklabels= False, cmap= 'Blues')
         g.set(ylabel=None)
         g.set xlabel('SMI')
         axs.xaxis.set label position('top')
         axs.xaxis.tick top()
         g.tick params(left=False, top=False) ## other options are right and top
         plt.show()
```

	SMI
Maggie Wyngowski	11
Lindsay Smalec	7
Maddie Hartigan	6
Abigail Rosenberg	6
Emma Hadley	5
Julie Byrne	4
Mary Weinstein	4
Abigail Merriman	4
Meagan Hathaway	2
Alexis Lexi Faria	2
Stephanie Boyd	2
Meghan Taner	0
Katherine O'Shea	0
Lindsey Bloom	0
Caroline Mayk	0
Michaela Peil	0
Kelly Cattano	0
Emily Gorham	0
Isabella Smith	0
Megan Koczur	0
Rachel Hazard	0
Amanda Lauer	0
Brooke Collins	0
Maura Mcmanus	0
Megan Barpoulis	0
Courtney Wolfgang	0

Can also do for all swimmer and event pairs and store in a dataframe

```
In []: # Create a dataframe for the swimmer SMI scores for just Team A ('184')
    TeamA_SMI = Swimmer_Names_df[Swimmer_Names_df['team_id'] == 184].copy()

    TeamA_SMI = TeamA_SMI.drop(columns=['gender', 'team_id'])

    TeamA_SMI.head()
```

```
Out[ ]:
                                                         name
                  swimmer id
                         167013 Katherine O'Shea
                         214963
                                           Mary Weinstein
                         221480
                                        Megan Barpoulis
                         228451
                                                 Julie Byrne
                         233487
                                           Lindsay Smalec
                   # Create an empty column for swimmer SMI score
                   TeamA SMI['All'] = np.nan
                   # Create columns for each event for swimmer-event SMI
                   tot scored events = individual scored events + relay scored events
                   for ev in tot scored events:
                           TeamA SMI[ev] = np.nan
                   TeamA SMI = TeamA SMI[['name', 'All'] + EventScoreOrder]
                   TeamA SMI.head()
Out[ ]:
                                                                        All M50 F11650Y F1200Y F2100Y F3100Y F4200Y F150Y F1100Y F2200Y F3200Y F1500Y F4100Y F5200Y F50
                                                         name
                  swimmer id
                         167013 Katherine O'Shea NaN
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                                           Mary Weinstein NaN
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                                        Megan Barpoulis NaN
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                                                  Julie Byrne NaN
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                   # List of events to eliminate (including 'All'). It has memory issues if you try to do the full list of events, but can do a few at a time
                   # Write to file
                   # Event codes: = ['ALL', 'M50', 'F11650Y', 'F1200Y', 'F2100Y', 'F3100Y', 'F4200Y', 'F150Y', 'F1100Y', 'F2200Y', 'F3200Y', 'F3200Y', 'F1500Y', 'F5200Y', 'F5200Y', 'F5200Y', 'F3100Y', 'F310Y', 'F310Y',
                   ev = ['F4100Y','F5200Y','F50']
                   # This is for Team A LU 1 vs. Team B LU 0
                   # Check the SMI for the swimmer and event (ev) pair
                   for event in ev:
                           for swimmer id in TeamA swimmers:
                                   TeamA_Lineup_SMI,_,_ = MeetOptwSMI(TeamA_swimmers, oppB_lineup_nums, oppB_scenario_prob, individual_scored_events, \
                                           relay_scored_events, relay_noMR, MR_legs,relay_pastperf_events,Lineup_Events,TeamA_Perf_dict,opptime_TeamB_dict, swimmer_id, [event], BigM)
                                   TeamA Lineup SMI = TeamA Lineup SMI[TeamA Lineup SMI.columns].round().astype('int8')
                                   score A, , = calculate pred score(TeamA Perf wM df, TeamA Lineup SMI, \
                                           TeamB_Perf_wM_df, TeamB_Lineup_df[0], scoring_method="Six Lane")
```

```
TeamA SMI
         # Write table to CSV
         TeamA SMI.to csv('Bucknell SMI.csv')
In [ ]:
         # Order swimmers by their 'All' SMI and set the index to the names
         TeamA SMI = TeamA SMI.dropna().sort values(by='All', ascending=False).set index('name')
In [ ]: | # Order the columns by
         TeamA_SMI = TeamA_SMI[['All'] + EventScoreOrder]
         # Rename the events
         TeamA SMI = TeamA SMI.rename(columns=EventScoreLabelConvertDict)
         TeamA SMI
In [ ]:
         # Make a pretty SMI Table by displaying dataframe as an heatmap
         fig, axs = plt.subplots(1, 1, figsize=(13, 10), constrained layout=True)
         g = sns.heatmap(TeamA SMI, linewidths = 0.3, annot = True,
                     annot kws={"size": 12},cbar= False, square= False, xticklabels= True, cmap= 'Blues', linecolor= '.75')
         #clean up the charts
         fig.suptitle('Swimmer\'s Meet Impact (SMI) Score')
         g.set(ylabel=None)
         axs.xaxis.set label position('top')
         axs.xaxis.tick top()
         g.tick_params(left=False, top=False) ## other options are right and top
         plt.xticks(rotation=90)
         plt.show()
```

TeamA SMI.at[swimmer id,event] = Base Score - score A

Swimmer's Meet Impact (SMI) Score

	All	200Y Medley Relay	1650Y Free	200Y Free	100Y Back	100Y Breast	200Y Fly	50Y Free	100Y Free	200Y Back	200Y Breast	500Y Free	100Y Fly	200Y IM	200Y Free Relay
Maggie Wyngowski	11	0	0	0	0	2	0	0	0	0	8	0	0	1	0
Lindsay Smalec	7	0	0	0	0	0	0	0	0	0	0	0	7	0	0
Maddie Hartigan	6	0	0	1	0	0	0	0	0	0	0	2	0	0	0
Abigail Rosenberg	6	0	0	2	0	0	0	2	2	0	0	0	0	0	0
Emma Hadley	5	0	0	0	1	0	0	0	0	2	0	0	2	0	0
Julie Byrne	4	0	0	0	1	0	0	0	0	2	0	0	0	1	0
Mary Weinstein	4	0	0	0	0	3	0	0	0	0	1	0	0	0	0
Abigail Merriman	4	0	1	0	0	0	0	0	0	0	0	3	0	0	0
Meagan Hathaway	2	0	0	0	0	0	0	0	0	0	0	2	0	0	0
Alexis Lexi Faria	2	0	0	0	0	0	0	0	0	0	0	0	2	0	0
Stephanie Boyd	2	0	0	0	0	0	0	0	0	2	0	0	0	0	0
Meghan Taner	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Katherine O'Shea	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Lindsey Bloom	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Caroline Mayk	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Michaela Peil	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kelly Cattano	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Emily Gorham	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Isabella Smith	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Megan Koczur	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Rachel Hazard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Amanda Lauer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Brooke Collins	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Maura Mcmanus	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Megan Barpoulis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Courtney Wolfgang	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Because of ties in the relays. We can subtract 0.001 (due to the precision of the input data, this won't have a real affect except to avoid ties) from the opptime values to force MeetOpt to look for a "non-tie" lineup. This shouldn't be an issue as long an equal point solution exists. In this meet with these teams, that is true.

```
In []:
    #####
# Debugging Code
# Check LU 1 vs the LU missing this swimmer
TeamA_3colors = [TeamA_orange, (1,1,1), TeamA_blue ]
ChartLUdiff('TeamA', TeamA_3colors, TeamA_Lineup_df[1], TeamA_Lineup_SMI, 9, 7)
```

```
In [ ]:
         # Debugaina Code
         print((TeamB Lineup df[0]*TeamB Perf wM df)[['FLF50A', 'F1F50A']].sum().sum(), " ".\
             (TeamB_Lineup_df[0]*TeamB_Perf_wM_df)[['FLF50B', 'F1F50B']].sum().sum(), " ", \
             (TeamB Lineup df[0]*TeamB Perf wM df)[['FLF50C', 'F1F50C']].sum().sum())
        92.0
               177,44
                         354.75
In [ ]:
         #####
         # Debugging Code
         print((TeamA Lineup df[1]*TeamA Perf wM df)[['FLF50A', 'F1F50A']].sum().sum(), " ",\
             (TeamA Lineup df[1]*TeamA Perf wM df)[['FLF50B', 'F1F50B']].sum().sum(), " ", \
             (TeamA Lineup df[1]*TeamA Perf wM df)[['FLF50C', 'F1F50C']].sum().sum())
        95.31
                 96.300000000000001
                                      443.28
In [ ]:
         #####
         # Debugging Code
         print((TeamA Lineup SMI*TeamA_Perf_wM_df)[['FLF50A', 'F1F50A']].sum().sum(), " ",\
             (TeamA_Lineup_SMI*TeamA_Perf_wM_df)[['FLF50B', 'F1F50B']].sum().sum()." ". \
             (TeamA Lineup SMI*TeamA Perf wM df)[['FLF50C', 'F1F50C']].sum().sum())
        177.31
                 177.44 443.28
In [ ]:
         #####
         # Debugging Code
         (TeamA Lineup SMI*TeamA Perf wM df)[['FLF50B', 'F1F50B']].sum()
                  105.96
        FLF50B
Out[ ]:
        F1F50B
                   71.48
        dtype: float64
In [ ]:
         #####
         # Debugging Code
         (TeamB_Lineup_df[0]*TeamB_Perf_wM_df)[['FLF50B', 'F1F50B']].sum()
        FLF50B
                  105.96
Out[ ]:
        F1F50B
                   71.48
        dtype: float64
```

"Ghost" Swimmers should be added if the team cannot create a feasible lineup with 3 in each indiv event and 12 in relay events.