heuristic_analysis

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1 Heuristic Analysis

In this analysis report, we analyze results of the three heuristics that were developed for the Isolation Game Agent project. The process that is illustrated below performs the following actions for each heuristic: - Extract the Win ratio results from 10 test runs that was captured in the log file that was generated during the simulation runs - Combine the data into a Dataframe for analysis and visualization

We complete the report by giving a recommendation based on the analysis performed. Below are a few helper functions that are used throughout the analysis process.

In [8]:
```
import re
import pandas as pd
%matplotlib inline

def extract_results(filename):
    with open(filename,'r') as rf:
        lines = rf.readlines()
        id_results = [line for i,line in enumerate(lines) if i % 4 == 1 ]
        student_results = [line for i,line in enumerate(lines) if i % 4 ==
        return id_results,student_results

def get_win_ratios(l):
    tmp = []
    for line in l:
        score = re.compile(r'(ID_Improved|Student):([0-9\.]+).*')
        m = score.match(line)
        if m:
            tmp.append(m.group(2))
    return tmp

def build_dict(filename):
    id_results,student_results = extract_results(filename)
    id_results = get_win_ratios(id_results)
    student_results = get_win_ratios(student_results)
    ids = [i for i in range(1,11)]
    df = {'Test Run': ids, 'ID_Improved':id_results, 'Student':student_resu
    return df
```

1.1 Hueristic 1: Number of Overlapping moves

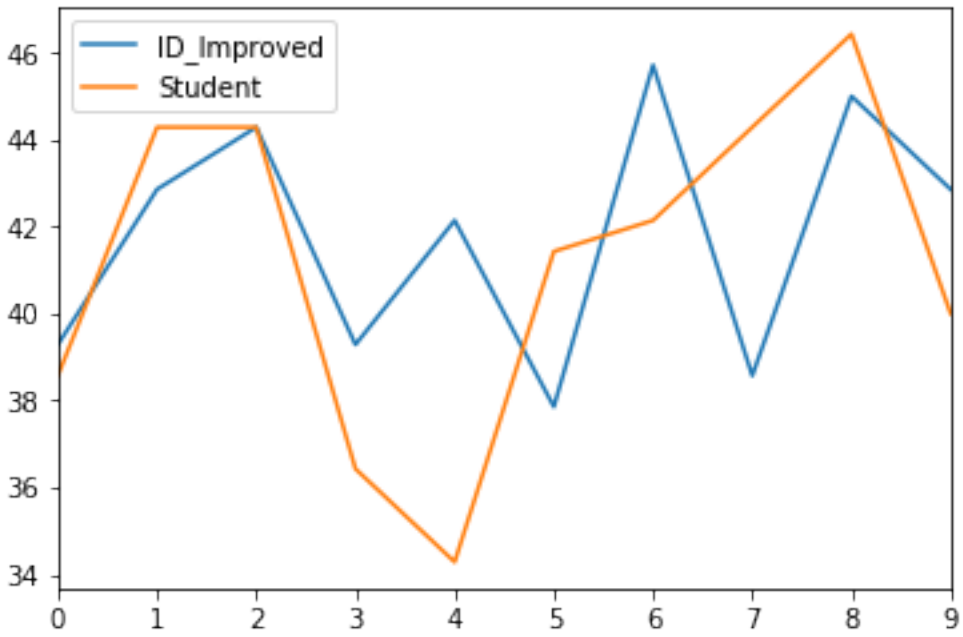
For this heuristic, we calculate the number of overlapping moves that our agent has in common with our opponent. The intuition here was that if there are moves that both the agents can take in the future, we want to try to eliminate those options from our opponent, reducing the number of legal moves they would have in the future.

```
In [17]: d = build_dict('overlapping_results.log')
         df3 = pd.DataFrame(d)
         df3['Heuristic'] = 'overlapping'
         df3['ID_Improved'] = pd.to_numeric(df3['ID_Improved'])
         df3['Student'] = pd.to_numeric(df3['Student'])
         df3[['ID_Improved','Student']].describe()
```

```
Out[17]:        ID_Improved    Student
         count    10.000000  10.000000
         mean     41.785714  41.214286
         std       2.842223   3.883946
         min      37.857143  34.285714
         25%      39.285714  38.928571
         50%      42.500000  41.785714
         75%      43.928571  44.285714
         max      45.714286  46.428571
```

```
In [13]: df3[['ID_Improved','Student']].plot()
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x2e96c7e3940>
```



We can see our overlapping heuristic performed worst on average than the iterative deeping improved heuristic. This doesn't seem to be a good approach and possibly it may be more beneficial looking at the number of non-overlapping moves.

1.2 Heuristic 2: Number of Non Overlapping Moves

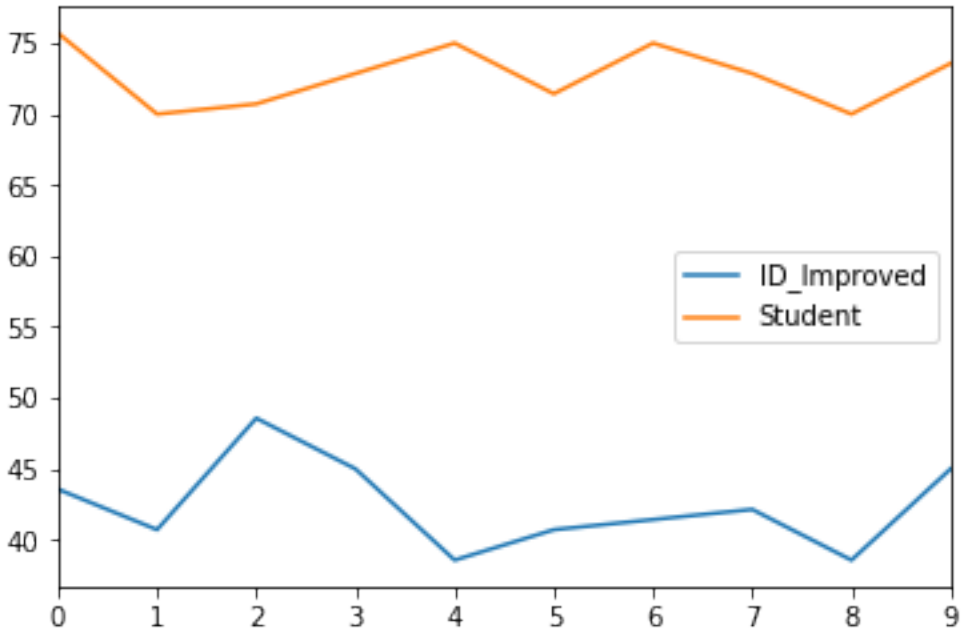
This heuristic calculates the number of non-overlapping moves that it has with its opponent. The intuition here is that if the player has more moves that are not in conflict with its opponent, it has more options to choose from and possibly covering board space that the opponent is not interested in exploring or cannot reach

```
In [20]: d = build_dict('non_overlapping_results.log')
         df2 = pd.DataFrame(d)
         df2['Heuristic'] = 'non_overlapping'
         df2['ID_Improved'] = pd.to_numeric(df2['ID_Improved'])
         df2['Student'] = pd.to_numeric(df2['Student'])
         df2[['ID_Improved','Student']].describe()
```

```
Out[20]:        ID_Improved    Student
         count    10.000000  10.000000
         mean     42.428571  72.714286
         std       3.144300   2.124258
         min      38.571429  70.000000
         25%      40.714286  70.892857
         50%      41.785714  72.857143
         75%      44.642857  74.642857
         max      48.571429  75.714286
```

```
In [11]: df2[['ID_Improved','Student']].plot()
```

```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x2e96c714780>
```



We can see there is an 30% increase in improvement over the iterative deepening agent. It's worth noting that this technique seems to have small standard deviation from the mean value. Based on these trial runs, it would seem that this heuristic performs consisently through multiple simulation runs.

1.3 Heuristic 3: Number of Blank Spaces along Vertical split

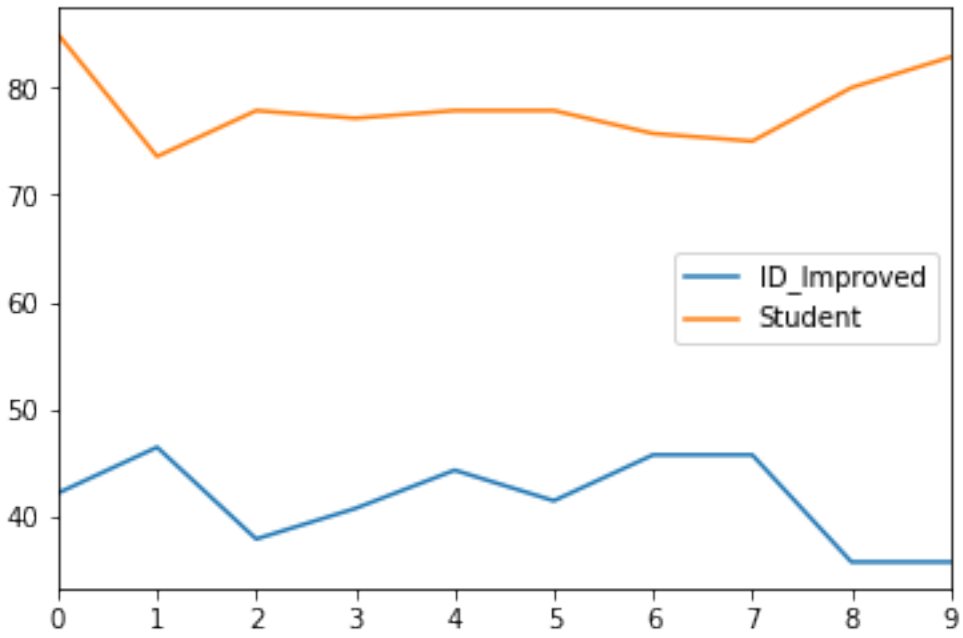
This heuristic calculates the number of blank spaces that are on the same side as the current location relative to a vertical pivot point at the midpoint of the board. The intuition here is that if there are more blank spaces on the same side as the current location, then the player has more spaces in the future to move. Since we are choosing the most optimal move for our opponent, then the number of blank spaces is a good indicator for our game agent.

```
In [23]: d = build_dict('blank_space_results.log')
         df1 = pd.DataFrame(d)
         df1['Heuristic'] = 'blank space'
         df1['ID_Improved'] = pd.to_numeric(df1['ID_Improved'])
         df1['Student'] = pd.to_numeric(df1['Student'])
         df1[['ID_Improved','Student']].describe()
```

```
Out[23]:        ID_Improved    Student
         count    10.000000  10.000000
         mean     41.571429  78.285714
         std       4.065786   3.502510
         min      35.714286  73.571429
         25%      38.571429  76.071429
         50%      41.785714  77.857143
         75%      45.357143  79.464286
         max      46.428571  85.000000
```

```
In [9]: df1[['ID_Improved','Student']].plot()
```

```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x2e96c6e35f8>
```



We can see that this heuristic performs the best with a 37% increase which is almost a 2X improvement over the iterative deepening heuristic. This heuristic at a minimum performs better than the average performance of the non overlapping heuristic. It also worth noting that this heuristic captured a win ratio of 85% which is pretty impressive for a simple heuristic approach.

Below we illustrate a table of the raw values of all the simulation runs captured during this analysis.

```
In [14]: df = pd.concat([df1,df2,df3])
         df
```

Out[14]:

	ID_Improved	Student	Test Run	Heuristic
0	42.142857	85.000000	1	blank space
1	46.428571	73.571429	2	blank space
2	37.857143	77.857143	3	blank space
3	40.714286	77.142857	4	blank space
4	44.285714	77.857143	5	blank space
5	41.428571	77.857143	6	blank space
6	45.714286	75.714286	7	blank space
7	45.714286	75.000000	8	blank space
8	35.714286	80.000000	9	blank space
9	35.714286	82.857143	10	blank space
0	43.571429	75.714286	1	non_overlapping
1	40.714286	70.000000	2	non_overlapping
2	48.571429	70.714286	3	non_overlapping
3	45.000000	72.857143	4	non_overlapping
4	38.571429	75.000000	5	non_overlapping
5	40.714286	71.428571	6	non_overlapping

6	41.428571	75.000000	7	non_overlapping
7	42.142857	72.857143	8	non_overlapping
8	38.571429	70.000000	9	non_overlapping
9	45.000000	73.571429	10	non_overlapping
0	39.285714	38.571429	1	overlapping
1	42.857143	44.285714	2	overlapping
2	44.285714	44.285714	3	overlapping
3	39.285714	36.428571	4	overlapping
4	42.142857	34.285714	5	overlapping
5	37.857143	41.428571	6	overlapping
6	45.714286	42.142857	7	overlapping
7	38.571429	44.285714	8	overlapping
8	45.000000	46.428571	9	overlapping
9	42.857143	40.000000	10	overlapping

1.4 Recommendation

I would recommend the **blank spaces** heuristic as it is shown to be a simple yet powerful heuristic. The simplicity of its implementation allows for it to be computed efficiently so that more time can be used for searching and exploring other branches within the search tree. At a minimum it has shown to give a 73% win ratio and its best performance was shown to be 85% is a 2X improvement over the average itertive deepening heuristic approach. It has also been shown to have a small standard deviation therefore we can expect consistent results across multiple simulation runs.