

EECE6086 - HW 1

Max Thrun

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1 Objective

The objective of this assignment was to implement the Kernighan—Lin graph partitioning algorithm and attempt to achieve the smallest cutsize in the shortest amount of time.

2 Implementation Details

My implementation of the KL algorithm is fairly standard with the exception of how nodes are selected to be swapped. Traditionally, nodes of each group are exhaustively combined in order to see which pair results in the greatest cutsize reduction. After testing the original algorithm and seeing how incredibly slow this method is I have decided that instead of testing every combination it is sufficient to just select the two most costly nodes from each group. While there are definitely some cases where this method is unable to reach to exact optimal cutsize the speed boost gained by avoiding the exhaustive search is enormous.

My first implementation attempt was written in Python (see `parprog.py`) in order to prove I understood the algorithm and that it was working correctly. This also helped serve as a baseline to check my C++ implementation against. Unsurprisingly, the Python implementation was incredibly slow which made it virtually unusable. I then reimplemented it in C++ using all the same data structures (maps, sets, etc...). While this implementation was significantly faster I found after profiling it that it spent the majority of its execution time in the standard library dealing with these complex data structures. I then iteratively went through the process of converting my structures into something simpler (basically flat arrays) and re-profiling my code. As it stands now all my data structures are just flat integer arrays with the exception of my sparse connection matrix which is a flat array of type `std::unordered_set`. I decided to use a set to hold the connections for each cell for two main reasons. Firstly, I needed a dynamically sized array and secondly I needed to be able to quickly see if a value is contained within the array. These requirements leave `std::unordered_set` as the only logical datatype. The choice of `std::unordered_set` over `std::set` was that the unordered version provides a faster lookup time as it is implemented with a hashtable.

I also implemented an optional ‘cheat’ mode which only continues searching for a longer swap subset so long as the current swap cost is positive. As we’ll see later this leads to a significant decrease in execution time at the cost of slightly higher cutsizes in some cases.

A very high level psuedo code overview is shown below.

```

1  read in connection pairs
2  split nodes into two even groups
3  while 1
4      loop through all connections and compute cost
5      for k in (num_cells / 2)
6          loop through all cells
7              if cell is marked skip it
8              if cell is in group A
9                  check if it is new maximum of group A
10             if cell is in group B
11                 check if it is new maximum of group B
12             if maximum of group A is connected to maximum of group B
13                 cost = cost_a + cost_b - 2
14             else
15                 cost = cost_a + cost_b
16             cost_sum += cost
17             if cost_sum > cost_max
18                 store current cost_sum as cost_max
19                 save this k value (k_max)
20             record what nodes we swapped
21             mark them as swapped
22             update the costs of effected nodes
23         if cost_max <= 0
24             exit and print results
25         else
26             exchange up to k_max cells

```

Listing 1: Implementation Psuedo Code

3 Usage

Building is accomplished via a Makefile which generates an executable named `parprog`. Additional build options are shown below

```

1 $ make           # regular build
2 $ make cheat     # builds with the swap subset cheat
3 $ make benchmarks # runs all the benchmarks in the BM directory

```

The program accepts input via `stdin` and will write the final output to `stdout`. These can be redirected from and to a file respectively. Debugging/Status messages are written to `stderr`. The first line of the output file is the achieved cutsize. The next two lines are the A and B groups respectively. The final line is the CPU execution time in seconds.

```

1 $ ./parprog < BM/B1 > R1
2 Num verts: 50
3 Num edges: 150
4 ===== Iteration 1 =====
5 k_max: 13 cost_max: 41
6 Elapsed time: 0.000000 seconds
7 ===== Iteration 2 =====
8 k_max: 1 cost_max: 8
9 Elapsed time: 0.000000 seconds
10 ===== Iteration 3 =====
11 k_max: 0 cost_max: 0
12 Done
13 $ cat R1
14 15
15 2 3 6 8 9 11 13 14 16 21 22 23 25 26 28 29 33 34 36 37 38 41 42 45 50
16 1 4 5 7 10 12 15 17 18 19 20 24 27 30 31 32 35 39 40 43 44 46 47 48 49
17 0.000000

```

4 Results

All benchmarks were compiled and run with the following compiler and CPU

```
g++-4.8.2 -Ofast -std=c++0x -march=native -Wall -flto -funroll-loops
Intel i7 920 @ 2.67Ghz
```

The table below summarizes the results for the given benchmark files.

Name	# Cells	# Nets	Given Cutsizes	Achieved Cutsizes	Execution Time	Memory Usage
B1	50	150	15	15	0.00s	1.068 MB
B2	500	3500	-	346	0.00s	1.328 MB
B3	4500	27000	401	405	0.16s	3.708 MB
B4	10000	150000	-	916	0.96s	14.532 MB
B5	25000	500000	4346	4346	5.62s	45.680 MB
B6	45000	450000	-	2624	15.57s	42.248 MB
B7	50000	500000	-	4274	19.16s	46.740 MB
B8	100000	5000000	-	28486	87.62s	437.000 MB

Table 1: Final Benchmark Results

The table below shows the original benchmarks versus the benchmarks achieved using the cheaty method described earlier. We can see that exiting the swap subset search as soon as we see a negative cost allows us to achieve at least a 3x increase in speed. Interestingly, for all the given benchmarks we achieved the same cutsizes with the exception of B3.

Name	Achieved Cutsizes	Execution Time	Achieved Cutsizes	Execution Time	Speedup
B1	15	0.00s	15	0.00s	-
B2	346	0.00s	346	0.00s	-
B3	405	0.16s	406	0.05s	3.20x
B4	916	0.96s	916	0.32s	3.00x
B5	4346	5.62s	4346	1.64s	3.42x
B6	2624	15.57s	2624	3.32s	4.68x
B7	4274	19.16s	4274	3.80s	5.04x
B8	28486	87.62s	28486	22.40s	3.91x

Table 2: Cheaty Benchmark Results

Just checking against the 8 given benchmarks was not enough to determine if the cheaty method was good enough to become the default. To test it I generated 1000 random netlists with up to 25,000 cells and 1,250,000 nets. I then calculated the percent increase in cutsizes of the cheaty method over the original method. I found that on average the cheaty method increased the cutsizes by around 20%. I felt that this was too high for the cheaty method to become the default so I left it as a build option.

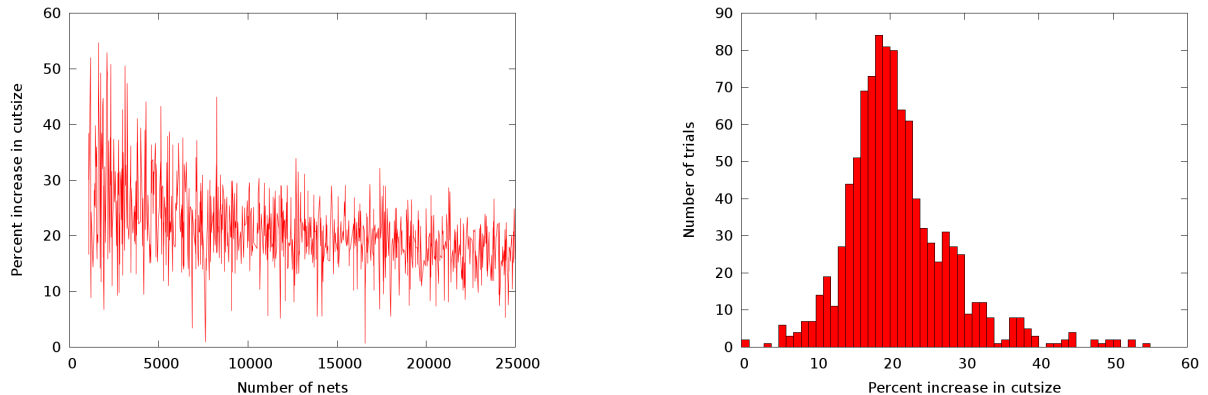


Figure 1: Percent increase in cutsizes using subset search cheat

5 Performance Trends

In order to get an overall idea about the performance of my implementation I measured the execution time of the 1000 randomly generated netlists. Specifically, I wanted to see how the number of cells and nets each effected the execution time. The two line graphs below show the execution time vs the number of cells and nets. Without figuring out the actual complexity of our algorithm we can only guess the type of curve that best fits our data. After fitting both linear and exponential curves I found the linear curve to be the best fit. This conclusion may be deceiving given that I am only going up to 25,000 cells. Plugging in 100,000 cells, which is the number of cells in B8, we find that our trendline predicts an execution time of 90 seconds. This is very close to the actual time of 87 seconds which gives us confidence that this trendline is true at least up to 100,000 cells. In reality the total execution time is really dependant on both the number of cells **and** the number of nets which is easy to visualize in the heatmap shown below. To truly form an accurate equation we would need to fit a 3D curve which I did not attempt.

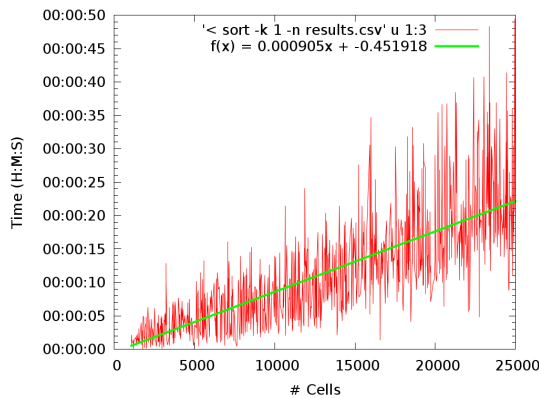


Figure 2: Time vs #Cells

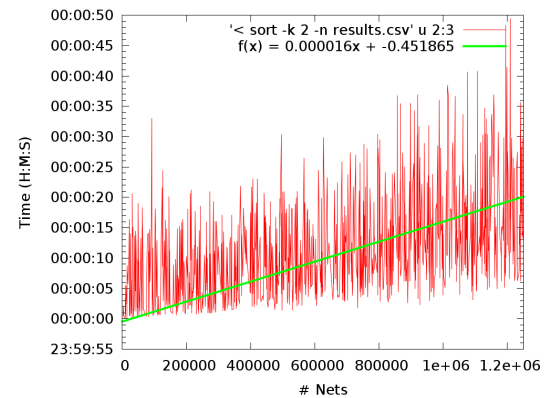


Figure 3: Time vs #Nets

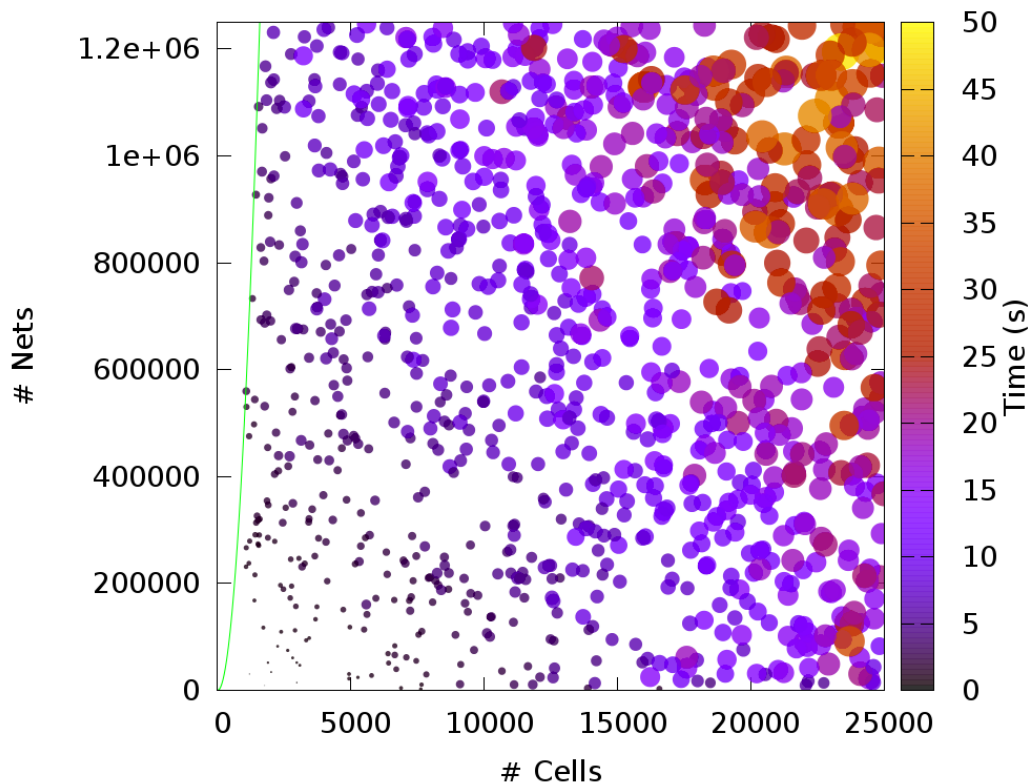


Figure 4: Time vs #Cells & #Nets (size of circle proportional to square root of time)