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Link to Github Repo: https://github.com/A-Goretsky/CMSC858_Bioinformatics_Assignment1

Task 1: bit-vector rank

Implementation

For the implementation of this data structure, I followed the strategy and technique learned in class and discussed over Piazza. The RankSupport structure consists of a bit_vector, an appropriately sized int_vector of superblocks, as based on the size of the input bit_vector, and an appropriately sized int_vector of blocks, as based on the size of the bit_vector and superblock. rank1() is implemented as a constant time operation, accessing the appropriate elements from the superblocks and blocks, and using popcount instead of a lookup table for r_p.

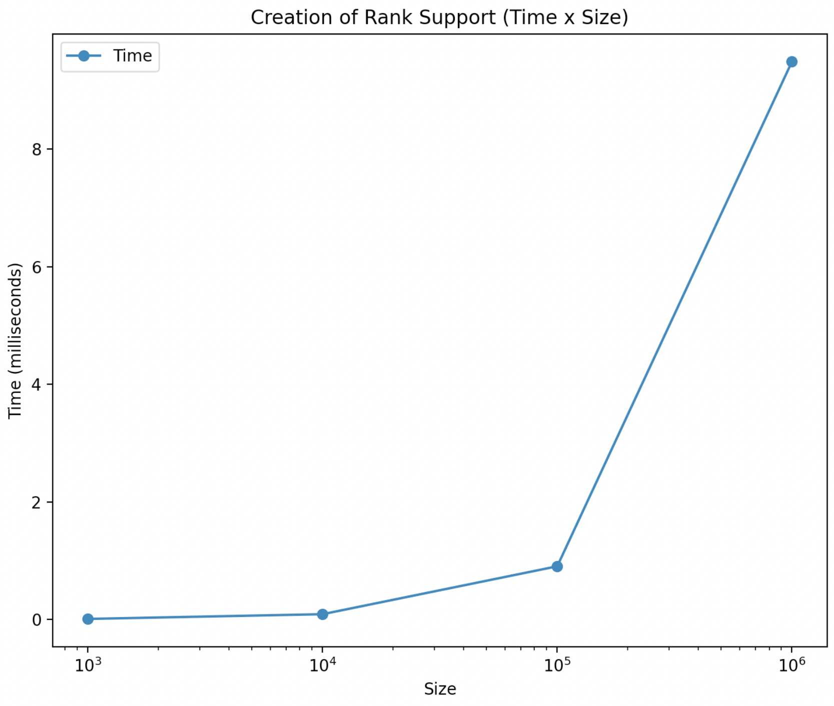
Challenges

Handling the edge cases of sizing and confirming my understanding from class was the hardest part. I understood the general theory, but realized I had many little questions about sizing specificities or how things should align. MG's questions on Piazza significantly helped in covering exactly what I was unsure about.

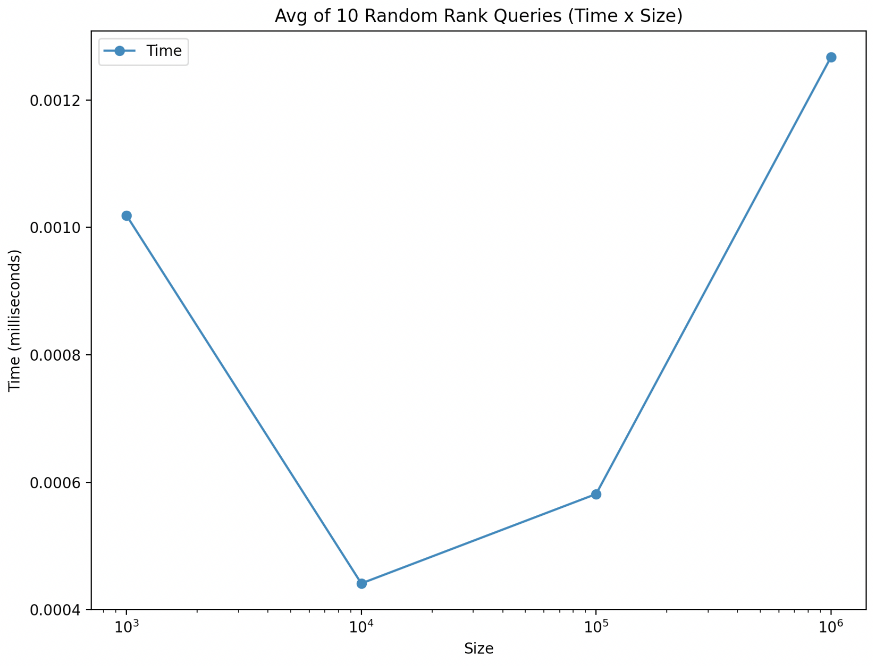
Experiments / Plots

Provided are plots and descriptions on RankSupport structures built around input bit_vectors of the following sizes: 1000, 10,000, 100,000, 1,000,000 bits. Provided are charts that timed the average initialization of the RankSupport structure, average lookup speed of 10 random rank1() queries, and the average overhead for each Structure. Each test was repeated 10 times and timings were averaged together.

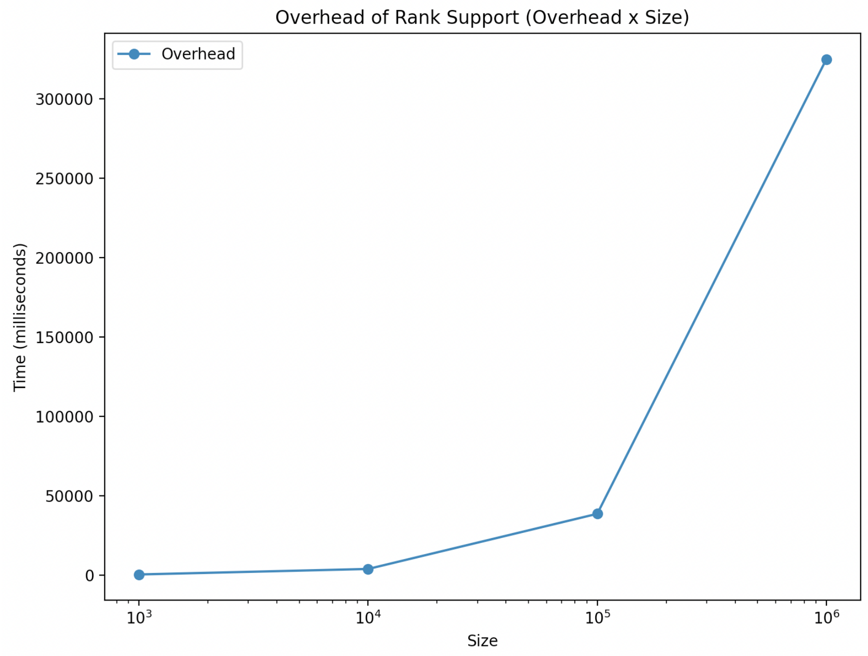
All graphs shown have a linear y-scale and log(n) x-scale.



There appears to be a linear relationship between the size of the given bit vector and the time of creation (y scale is linear, x scale is log(n)). This is consistent with expectations. We only require one pass over the bit vector in order to populate the rest of the RankSupport structures.



There does seem to be a constant time relationship between performing random rank1() queries on bit_vectors of varying sizes. The drop and rise between size 1000 and 1000000 is a bit strange, however, I am not sure why the two sizes tested in between fall in such a manner.



There appears to be a linear relationship between the overhead of the RankSupport structure and the given bit vector. This is consistent with our expectations. ***(Once again noting the y-scale for ALL of this presentation is linear, while the x-scale is logarithmic).***

Task 2: bit-vector select

Implementation

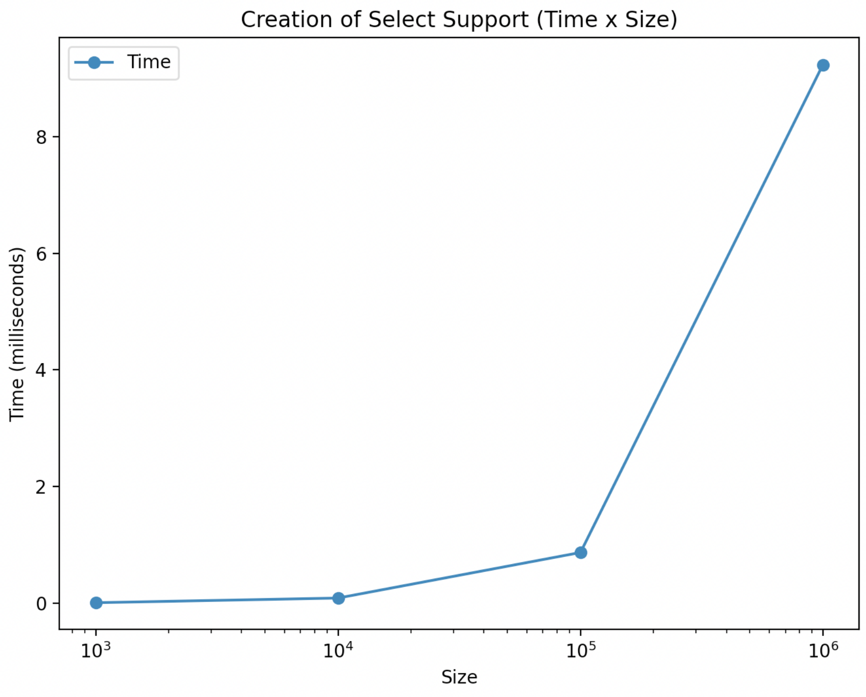
The SelectSupport structure simply contains a reference to a RankSupport structure within. select1() functionality was simply built on top of the existing RankSupport class.

Challenges

No particular challenges with this one, although I did mess up my index changes in the binary search the first time.

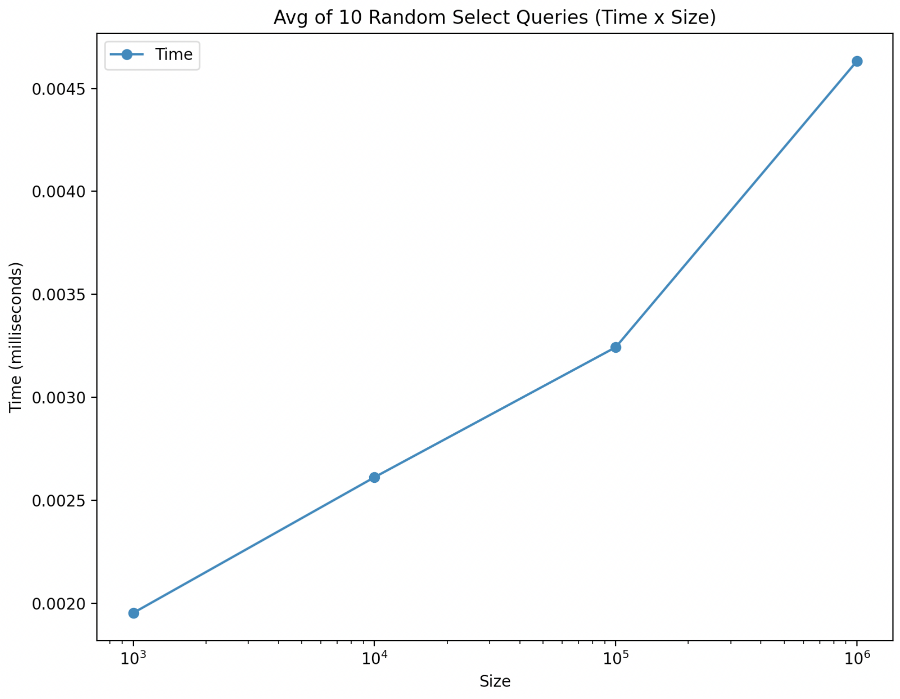
Experiments / Plots

Just as with RankSupport, provided are plots and descriptions on SelectSupport structures built around input bit_vectors of the following sizes: 1000, 10,000, 100,000, 1,000,000 bits. Provided are charts that timed the average initialization of the SelectSupport structure, average lookup speed of 10 random select1() queries, and the average overhead for each Structure. Each test was repeated 10 times and timings were averaged together.

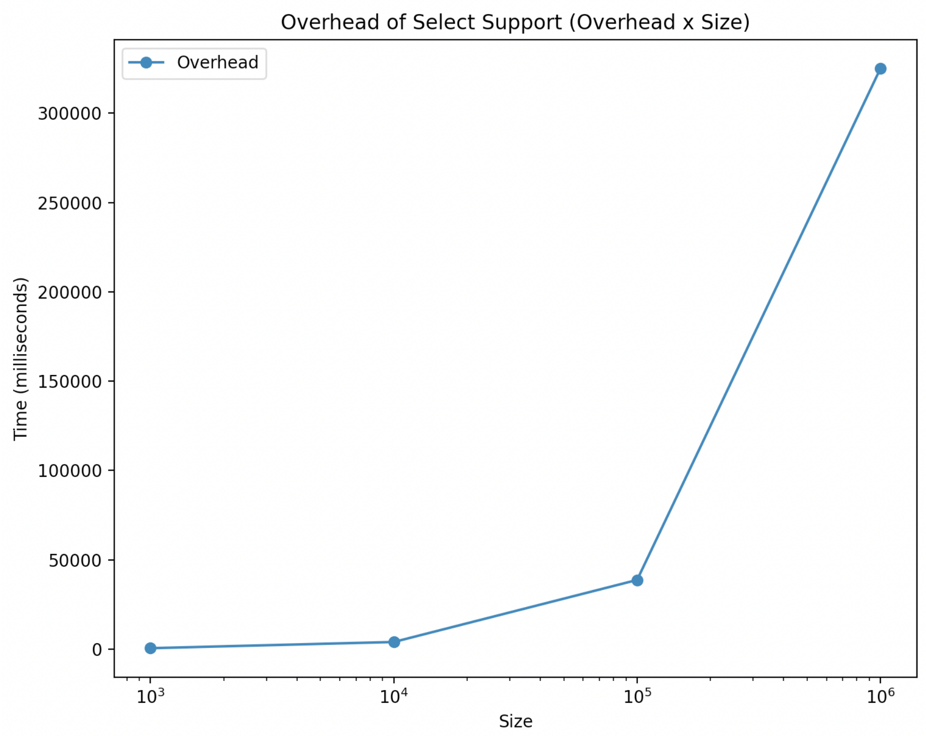


This chart is inevitably almost exactly the same as the one given for RankSupport, as there are no additional vector like structures on top of RankSupport, just some different methods and variables.

This chart is consistent with our expectations of a linear relationship. (**y-scale is linear, x-scale is logarithmic)**



Averaging over random select1() queries we begin to see a logarithmic relationship between the time and size of the bit vector. This is to be expected, as select1() as implemented is simply a binary search, running in O(log2n) time.



This chart is inevitably almost exactly the same as the one given for RankSupport, as there are no additional vector like structures on top of RankSupport, just some different methods and variables.

This chart is consistent with our expectations of a linear relationship.

Task 3: Sparse Array

Implementation

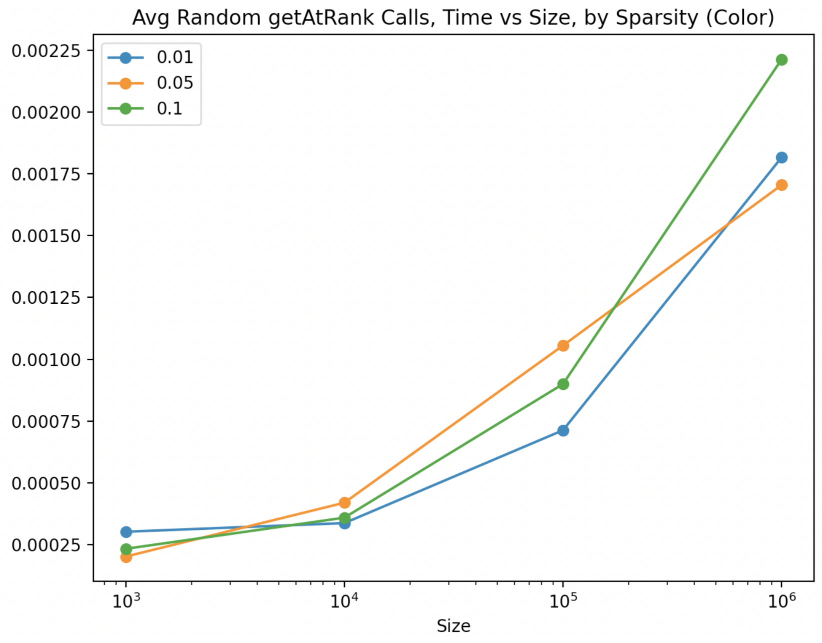
The SparseArray class contains a reference to a RankSupport structure within. Given the choice of storage of elements themselves (std::vector), it was all that was necessary for efficient querying. One can initialize the SparseArray with a size.

Challenges

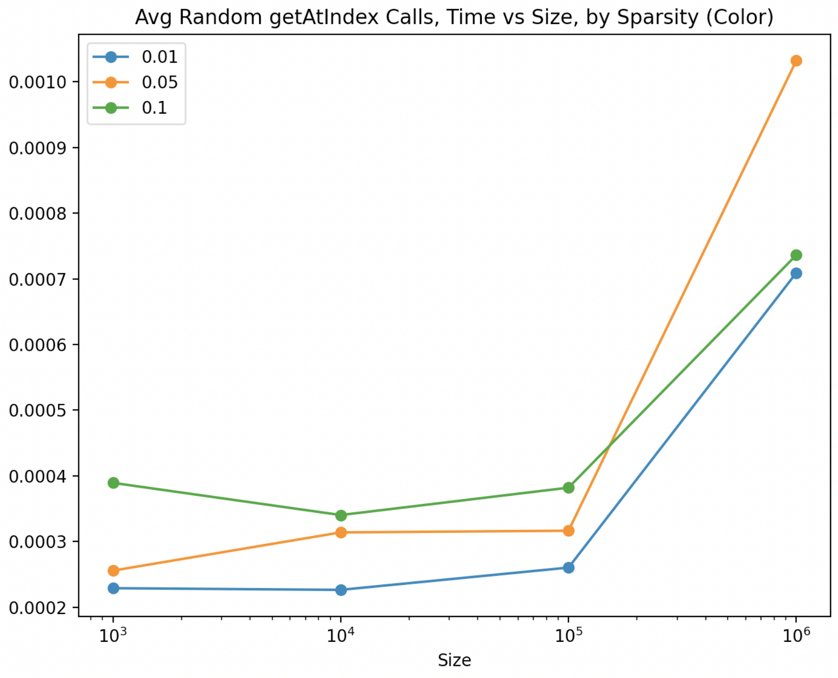
There weren't any particular challenges here, I decided to add a variable that determines when to dynamically update the RankSupport object (only prior to a function call that requires it), and also added a method that allows for it to be done anytime.

Experiments / Plots

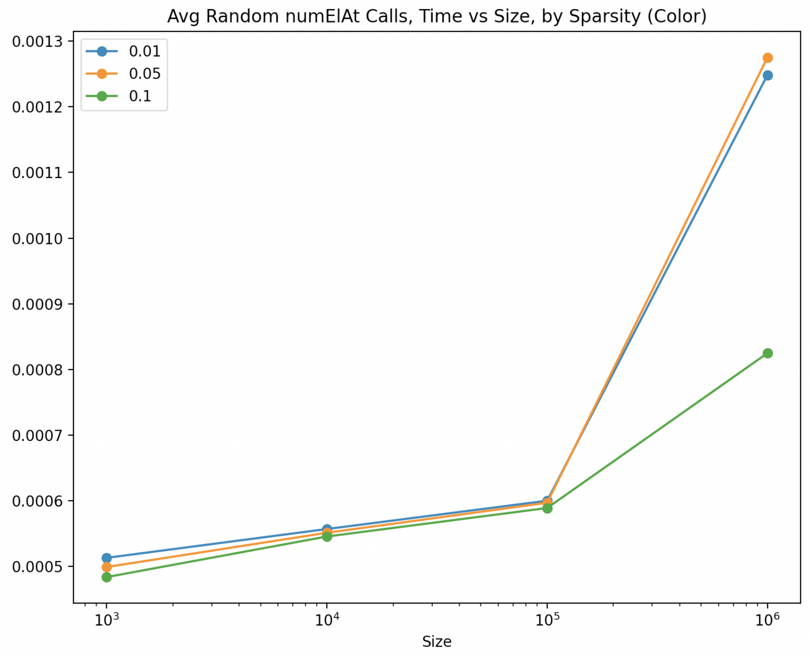
Supplied are plots comparing time (in milliseconds) to size of sparse array by sparsity level, for three different function calls, namely getAtRank, getAtIndex, and numElAt.



getAtRank was called for 20 random inputs, a process which was repeated 10 times and averaged. We can see a linear trend in the time as the amount of bits increases. All sparsity levels seem to operate with a similar time, but with the densest array being slower at the highest bit counts.



getAtIndex was called for 20 random inputs, a process which was repeated 10 times and averaged. We see a sudden spike in time necessary for all sparsities, but especially for 5%.



numElAt was called for 20 random inputs, a process which was repeated 10 times and averaged. We see a sudden spike in time necessary for all sparsities, but especially for the lowest densities, 1% and 5%. Otherwise all densities followed each other very closely .

Sparse array storage versus “empty” elements, like empty strings

A sparse array is built directly on top of a RankSupport object. The size of such an object consists of the bit vector, superblock vector and block vector. The total size of that would be:

Superblock structure bit size: log2(log2(n)^2) * n / log2(n)^2

Block data structure bit size: log2(log2(n)) * n / log2(n)

I will make the assumption that an empty element requires 1 byte (or 8 bits) of storage. If that is the case. This would equate to a storage of 8n(1 - sparsity_proportion), aka the storage of the empty elements minus those that are used.

Thus the dense array will be more beneficial when 8n(1 - sparsity_propotion) is less than the total RankSupport object size, aka the sum of the two structures above + n.