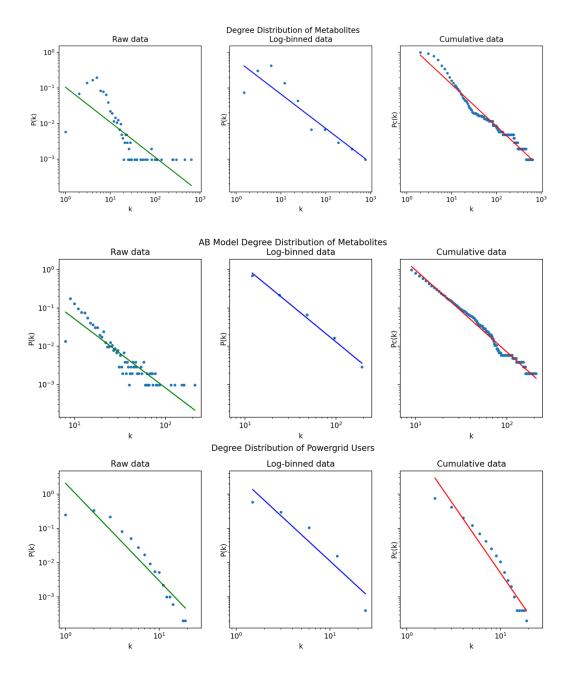
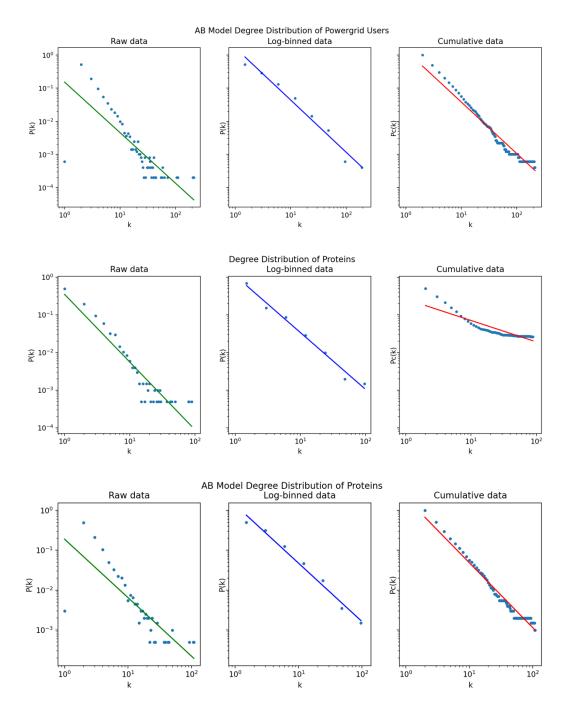
COMP 596 Assignment 1

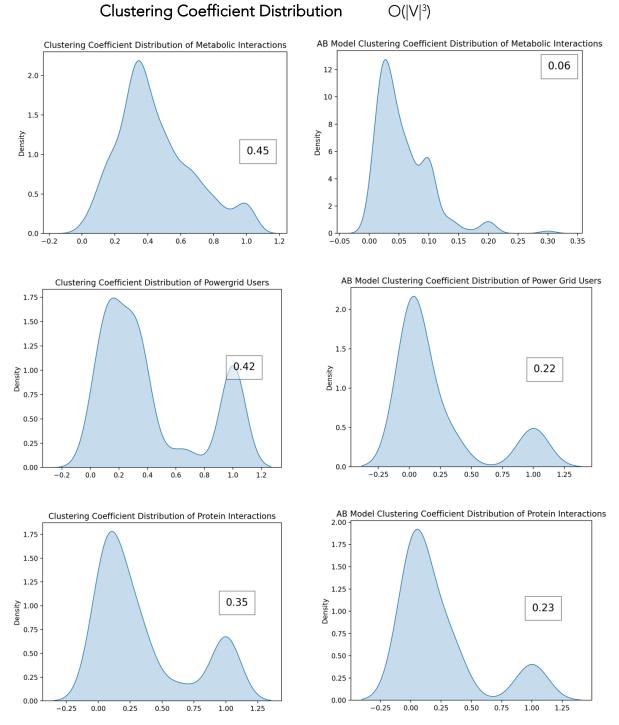
Jessica Chan Sep. 20, 2020 260734339

jessica.chan5@mail.mcgill.ca



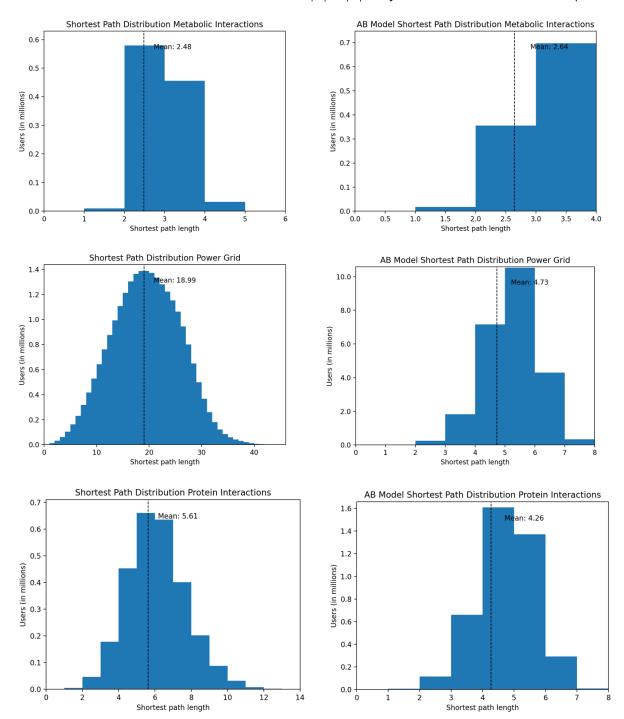


Clustering Coefficient Distribution

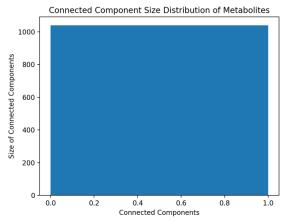


Shortest Paths Distribution

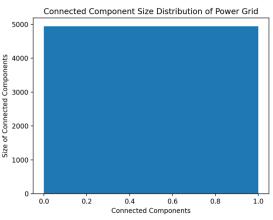
O(|V| + |E|) (Dijkstra's with Fibonacci heaps)



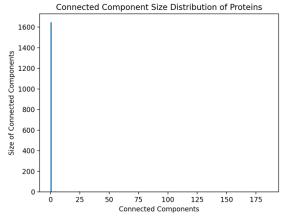
$\begin{tabular}{ll} \textbf{Connected Components} & O(|V|+|E|) \ (DFS \ from \ unvisited \ nodes) \\ Used \ connected_components \ from \ scipy.sparse.csgraphs \\ \end{tabular}$



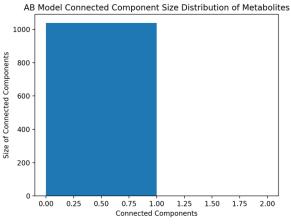
Nodes in GCC: 1039/1039



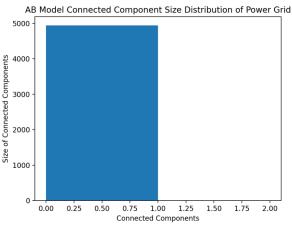
Nodes in GCC: 4941/4941



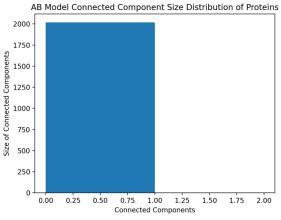
Nodes in GCC: 1647/2018



1038/1039

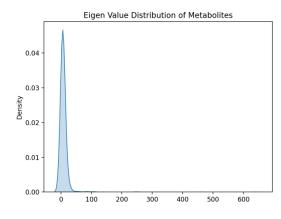


4940/4941

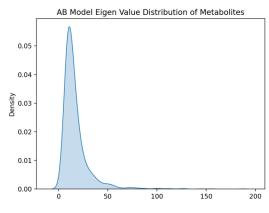


2017/2018

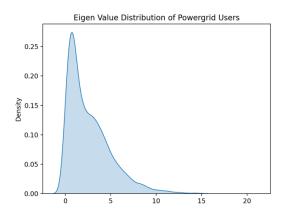
Eigen Value Distribution $O(|N|^3)$ Used np.linalg.eigh to get all eigen values



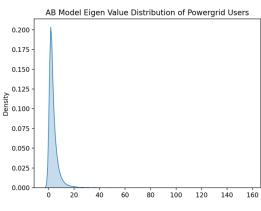




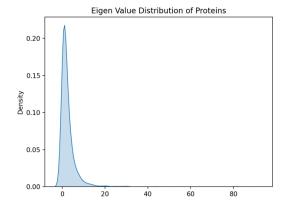
3.6053812001996244



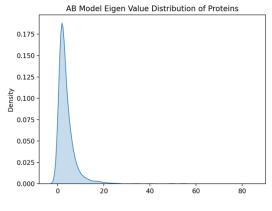
Spectral gaps: 0.0007592122113561372



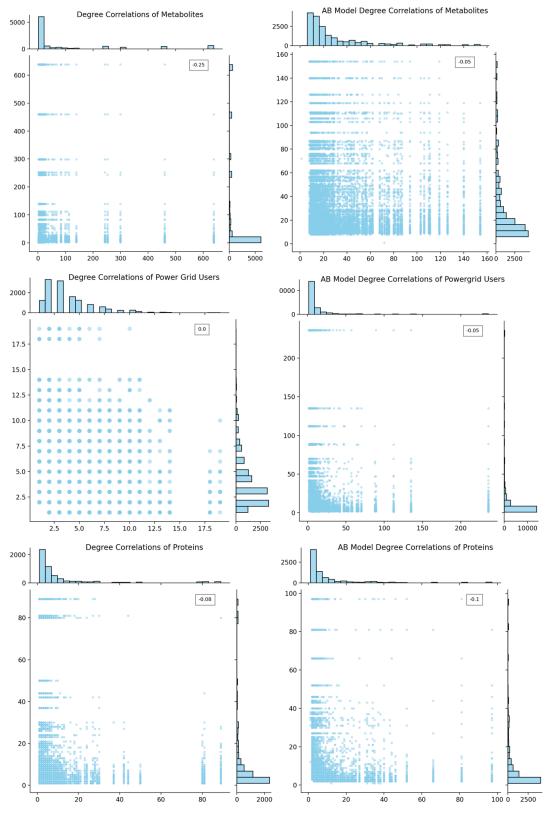
0.5157255200674538



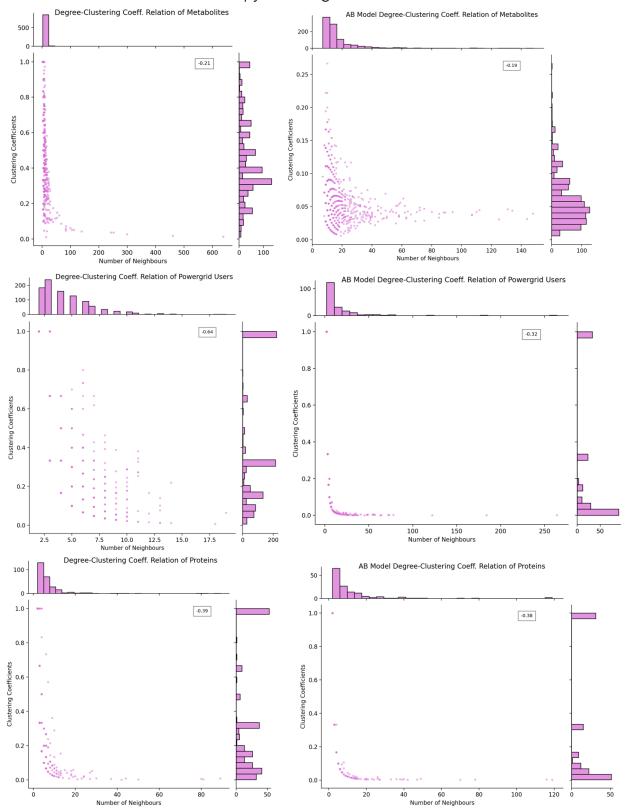
Spectral gaps: 0.041823143729712



0.5095942692760469



Degree-Clustering Coefficient Distribution $O(|V|^3)$ (O(V) degrees + $O(V^3)$ cc) Used Pearsonr correlation from scipy.stats to get overall correlation



AB Model

The AB model implementation used is a hybrid of the LCD (Linearized Chord Diagram) model of AB outlined in Barabasi's text and the original AB calculation. Probabilities are calculated as below:

$$p(i) = \begin{cases} \frac{1}{\sum_{j} d_{j} + 1}, & if \ d_{i} = 0\\ \frac{d_{i}}{\sum_{j} d_{j} + 1}, & otherwise \end{cases}$$

In this model, self-loops are considered with a small probability when node i is being added to allow for the possibility of disconnected components. The model used borrows the first time step of LCD, creating a self loop for the first node added to the graph. All self-loops are removed at the end to maintain simple graph properties. np.random was used to randomly select the vertex to link to.

In the above plots, AB_LCD_hybrid_model(m, n, A) takes 3 inputs:

m = average degree of nodes in A

n = number of nodes in A

A = original network adjacency matrix

The values for each network are as follows:

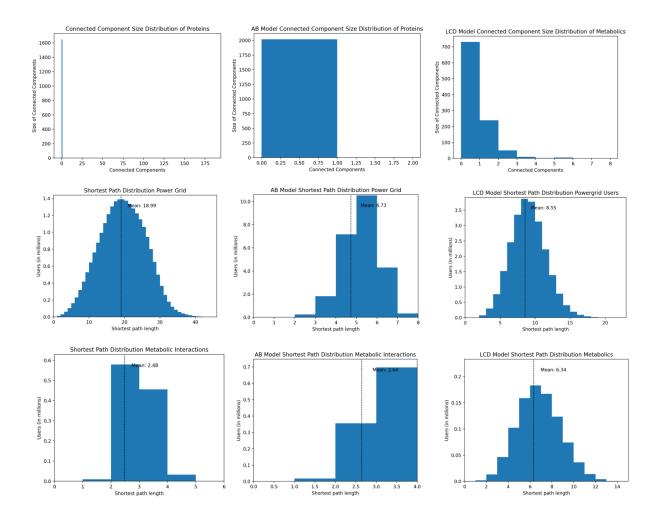
In the code, m edges are added per node where possible, where m is the average degree from the original network. I've found that lower values of m result in more similarly behaving networks. Higher values of m increase the average degree of the resulting AB model network, and causes the AB network to behave differently from the original. Specifically, AB model networks with high average degree seem to have far more edges than the original network.

In the code, one can also find the LCD model that adds one node and edge at a time, calculated with the use of the time step t:

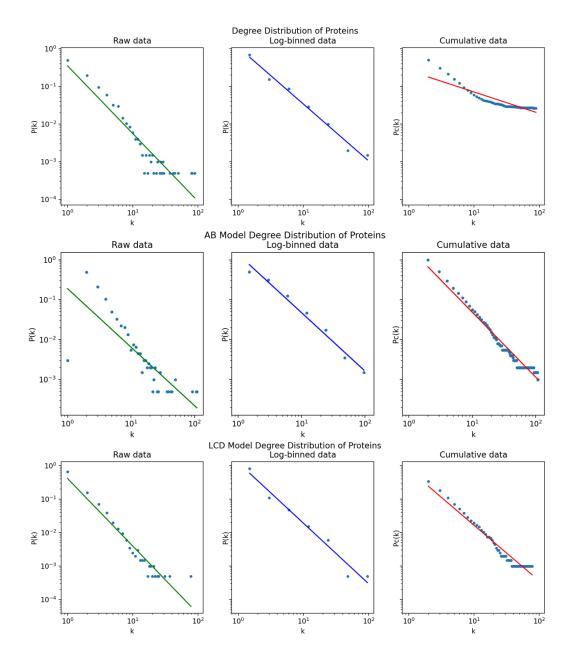
$$p(i) = \begin{cases} \frac{d_i}{2t-1}, & if \ 1 \le i \le t-1\\ \frac{1}{2t-1}, & if \ i = t. \end{cases}$$

The issue with using the LCD probability for adding multiple edges per node is that the time step does not increase as the degrees increase. LCD expects that one node per edge is added at each time step. Violating this results in a probability sum greater than 1.

I've included some LCD network distributions that are of note below.



Here we can see that the LCD algorithm achieves a more accurate representation of connected components in proteins, a network with a low average degree (m=2) and high number of nodes (n=2018). The LCD model also seems to achieve a more accurate representation of shortest paths distributions in networks with higher average degree (eg. Power grid m=9). The AB hybrid model performs better for networks with lower average degree (eg. metabolic m=2).



In future I would like to try the LCD algorithm with a probability function and time step that changes with the number of edges added, rather than the number of nodes added. This way it could be possible to limit the amount of edges created in the graph, though some problems could arise with high values of m in sparsely connected networks. I also experimented with randomizing the selection of vertices to add, though this seems to have little to no effect on the data.