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Network analysis of metabolic subsystems

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Abstract. Subsystems are parts of a metabolism that perform different important tasks in a cell. In this article, we explore these subsystems from a network science point of view. We attempt to find ways of detecting subsystems in a metabolic network using community detection algorithms. We use the algorithms on a metabolic network of the Chinese hamster ovary cell, a mammalian cell that is commonly used in biomedical research and in biotechnology.

1 Introduction

Since the turn of the century, life sciences have been evolving rapidly. Advances in data acquisition, storage and analysis technology have allowed scientist to gather immense amounts of data and build complex models from it [5]. These complicated models have brought people of various backgrounds, such as physics, mathematics and computer science into the field of biology.

One such field is network science, which is often used to analyze different kinds of networks that appear in the various subfields of modern biology, including ecology [9], systems biology [1] and neuroscience [10].

Metabolic networks [6] are used to model the metabolisms of various organisms. They are usually represented with a bipartite graph composed of two types of vertices: reactions and chemicals produced and consumed by the reactions. The edges in such a network connect chemicals to reactions. Furthermore, the edges are directed indicating whether the chemical was produced or consumed. A third kind of vertex can be added to represent enzymes that catalyze the reaction, but do not directly partake in it. Other commonly used representations are simplified representations, where one of the types of vertices is omitted [8].

In this article, we analyze the subsystems in a metabolic network of the Chinese hamster ovary cell. We explore different methods of detecting the subsystems and compare their structures.

2 Related works

3 Methods

We apply a few different community detection methods and compare how well they detect the subsystems of a metabolic network.

We haven't decided on the algorithms yet, but we try some of the following:

- Some of the algorithms from the lectures.
- Community detection based on motifs [2].
- Removing nodes with the highest betweenness centrality (or some other measure) and observing how the network falls apart [4].

4 Results

In this article, we analyse a metabolic network of the Chinese hamster ovary (CHO) cell. The CHO cell is frequently used in biological and medical research and in the production of biopharmaceuticals [3].

We used a whole-cell metabolic network of the Chinese hamster ovary (CHO) cell that was taken from the BiGG database [7,3]. The original network contains 4,456 metabolites that take part in 6,663 reactions. The reactions and metabolites are annotated with additional metadata, such as name, subsystem, BiGG ID etc.

We simplify the network to a simple directed graph, where reactions are represented with nodes. If one reaction produces a metabolite that is used by another reaction, they are connected by an arc. This network has 6,663 nodes and 656,609 arcs. If we treat as an undirected network, it has 546208 edges.

The network has a very large connected component of 6,036 nodes, while the other components are very small, as they are composed of at most 4 nodes. The largest connected component contains a strongly connected component of 5,307 nodes, while the other nodes are isolated. These probably represent sources and sinks of the metabolism.

The network appears to have a scale-free structure. Its in-degree, out-degree and degree distributions are plotted in figure 1. It has a very low clustering coefficient, around 0.069.

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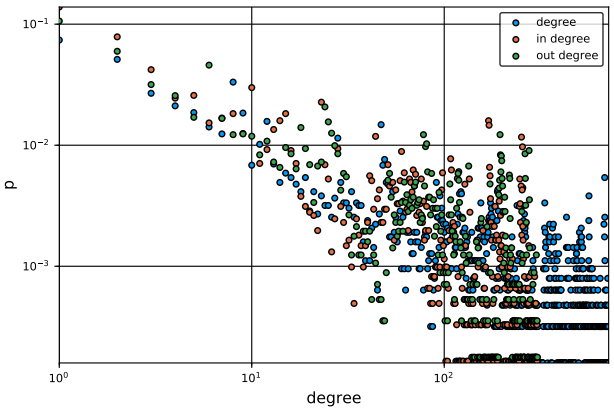

Fig. 1. The in-degree, out-degree and degree distributions of the network.

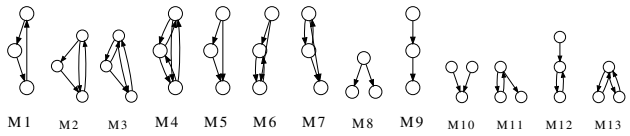

Fig. 2. All 13 directed three-node motifs.

5 Authors contributions

All the authors were involved in the preparation of the manuscript. All the authors have read and approved the final manuscript.

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