

Overview

Purpose:

To build a computational protein-protein interaction prediction system for *Arabidopsis* thaliana

Approaches:

- Integrated direct experimental methods with indirect biological datasets.
- Generated a list of known interactions and a list of non-interacting proteins.
- Designed feature sets used for prediction
- Utilized various classifiers (machine learning methods) to process the data

<u>Results:</u>

Results are based on the score values assigned to the feature sets by machine learning methods. The feature set values were further converted into to graphs and charts using the Weka machine learning software.¹ It was observed that the different computational methods were able to predict protein-protein interactions with a 75% accuracy.

Introduction

A protein's function and its activity are usually modulated by the proteins with which it interacts. Therefore, it is important to understand the mechanism by which proteins communicate and collaborate. However, predicting protein-protein interactions is one of the most challenging problem of the post-genomic era. Highthroughput experimental approaches provide some data about protein interactions, but the data is fairly noisy and the results are incomplete and often yield high false-positive and false-negative rates². Therefore, computational methods are often employed in addition to experimental methods in order to improve the success of protein interaction prediction. Here we use computational techniques to predict protein interactions in the model plant Arabidopsis Thaliana. Several genes in A. Thaliana are similar to those found in crop and medicinal plants therefore a complete proteome of Arabidopsis will be of great industrial use.

Designing a computational system to predict protein-protein interactions in Arabidopsis thaliana

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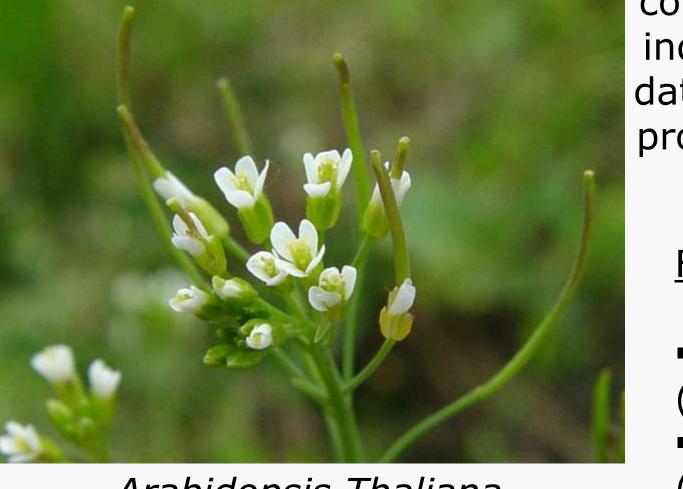
Method

There are a multitude of methods that can predict protein-protein interactions but each technique has its strengths and weaknesses. Experimental methods include the Two-Hybrid (Y2H)² screens and mass spectrometry techniques such as tandem affinity purification (TAP)², and high-throughput mass-spectrometric protein complex identification (HMS-PCI)². These methods have limited screening and specificity capabilities allowing many protein interactions to go undetected. Hence,

it was suggested that experimental data with datasets (e.g. sequence the task of predicting interactions.³

Dataset Used:

The Arabidopsis Information Resource (TAIR) to generate: Positive set – pairs of interacting proteins Negative set – noninteracting proteins



Arabidopsis Thaliana

Protein1	Protein2	Label	Ortholog	MicroArray
AT1G12220	AT5G13160	1	0	88.518
AT2G01570	AT4G24210	1	0	379.701
AT4G35000	AT4G35450	1	1	101.24
AT3G20780	AT2G26990	1	1	573.883
AT1G26830	AT5G02820	1	0	141.174

Table 1: Features Used

The positive and negative sets were assigned values of 1 and 0, respectively. A pair from either set if present in the ortholog data received a value of 1, and 0 otherwise. For the microarray data the pairs were assigned unique values based on the absolute difference in average intensity.

Results Weka, a machine learning software Ortholog Figure 3 contains the absolute was used to difference of intensity values analyze and between each pair. The x-axis visualize the contains the average intensity feature set data. values and from the y-axis it The figure below can be seen that the values is of a histogram for the positive set is which contains a approximately half the values total of 3000 Figure2: Ortholog feature set of the negative set. protein pars of In figure above it can be which seen that of the 800 positive approximately pairs 58 of them are also 800 are identified present in the ortholog as positive. feature set. However, note that none of the pairs from negative set are the identified in the ortholog data.

Figure1: Positive vs. Negative interactions

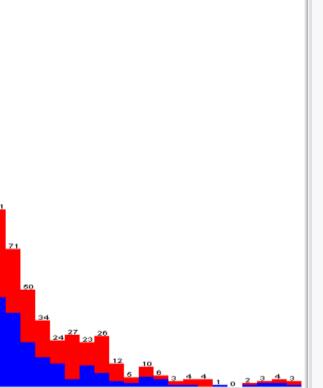
Figure3: MicroArray feature set



combining direct indirect biological data) can optimize protein - protein

Features Used:

 Ortholog data (InParanoid program) Gene expression data (Microarray)



Conc

the vario All generated the resu correctly predicted that even with just

the classifiers have some ability to predict the protein interaction pairs in A. thaliana.

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Aus classifiers utilized but value, 75 percent pairs, which indicates two features www.example.com/line but for the state of the state
BBSI program om) is a joint initiative of SF-EEC, and the BBSI @ by the National Science of EEC-0234002. man, Department of the University of Pittsurgh Technologies Institute of er Science at Carnegie
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 rank (2005) "Data Mining: Practical d techniques", 2nd Edition, Morgan 2005. ein-Seetharaman J. Evaluation of and computational classification ein interaction prediction. Proteins Snel B, Cornell M, Oliver S, Fields S, essment of large-scale data sets of s. Nature 2002;417:399-403.

However, predicting two feature sets d evaluate the differen used for the predict order to differentiat classifiers additiona required.

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- 3. Von Mering C, Krause r, SS Bork P. Comparative asses protein-protein interactions.