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#### Introduction

Listeria monocytogenes is a serious foodborne pathogen that has the ability to form filaments under certain environmental stress such as the presence antimicrobials. Filament formation is the phenotypical sign of antimicrobial stress of L. monocytogenes.

Microarrays are useful tools for measuring gene expression of *L. monocytogenes*, and can be used to determine if a cell population undergoes antimicrobial stress.

Machine learning (ML) algorithms can use a dataset derived from microarrays to learn a classifier that can later identify if a novel cell population is involved in a proposed biological process. While these algorithms [including Bayesian Net, J48 Decision Tree, Random Forest and Support Vector Machine (SVM)] are often used to classify eukaryote microarray experiments, this study focuses on a prokaryotic application using two strains of L. monocytogenes as examples.

#### Objectives

To explore if a machine learning algorithm can learn a classifier that can predict if a population of . monocytogenes is under stress from an antimicrobial:

- to distinguish between cefuroxime treated and untreated *L. monocytogenes* EGE-e, based on expression level (represented as the fluorescence intensity) for each gene from 32 samples [GEO accession GPL14687 (4)];
- to distinguish between L. monocytogenes 08-5923 treated with carnocyclin A (cclA) and untreated L. monocytogenes 08-5923, based on expression level of 15 selected genes that were  $\geq$  2-fold up or down-regulated in the presence of ccIA. Features were selected using in-fold feature selection (2).

# **Using Machine Learning Algorithms to Detect Cellular Stress** of Listeria monocytogenes from cDNA Microarray Data

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### Results

#### Expression levels of genes relevant to cell morphology and death

Table 1: Genes  $\geq$  2-fold up or downregulated in *L. monocytogenes* 08-5923 when exposed to ccIA. The genes from this table, as well as other relevant genes involved in cell division and PTS system (1, 5) such as *Imo2002*, *Imo1973*, *Imo0633*, Imo1438 and Imo1892, were included in the dataset for the subsequent classifying task.

| Gene                            | Function of gene product | Fold<br>change       | Differential expression |  |  |  |
|---------------------------------|--------------------------|----------------------|-------------------------|--|--|--|
| Cell division protein           |                          |                      |                         |  |  |  |
| lmo2687                         | FtsW                     | 2.39                 | Up                      |  |  |  |
| lmo2033                         | FtsA                     | 2.17                 | Up                      |  |  |  |
| Phosphotransferase (PTS) system |                          |                      |                         |  |  |  |
| lmo0096                         | Mannose-specific         | 3.60                 | Up                      |  |  |  |
| lmo1035                         | Beta-glucoside-specific  | 2.45                 | Up                      |  |  |  |
| lmo1971                         | Pentitol-specific        | 2.29                 | Down                    |  |  |  |
| lmo2782                         | Cellobiose-specific      | obiose-specific 2.23 |                         |  |  |  |
| lmo0023                         | Fructose-specific        | 2.14 Down            |                         |  |  |  |
| lmo2097                         | Galactitol-specific      | 2.03 Down            |                         |  |  |  |
| lmo0503                         | Fructose-specific        | 2.01                 | Down                    |  |  |  |

#### Performance of ML algorithms

Table 2: the accuracy of various algorithms in predicting if a population of *L. monocytogenes* was under stress.

| Task                 | Algorithm        | Test mode                       | Accuracy | Accuracy (in<br>fold cross<br>validation) |
|----------------------|------------------|---------------------------------|----------|---|
| clA-stress           | J48              | 5-fold cross-<br>validation     | 90%      | 90%                                       |
|                      | Bayes<br>Network |                                 | 90%      | 90%                                       |
|                      | Random<br>Forest |                                 | 50%      | 90%                                       |
|                      | SMO              |                                 | 70%      | 60%                                       |
|                      | Naiive<br>Bayes  |                                 | 20%      | 90%                                       |
| efuroxime-<br>stress | J48              | 10-fold<br>cross-<br>validation | 90.63%   | N/A                                       |
|                      | J48              | 32-fold<br>cross-<br>validation | 96.88%   | N/A                                       |

#### Conclusions

#### **Future Work**

### References

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J48 Decision Tree was the most accurate algorithm for predicting cefuroxime stress (96.9%) accuracy with leave-one-out cross validation)

Both the J48 Decision Tree and Bayesian Network were equally effective for predicting whether L. monocytogenes was under stress from carnocyclin A (90.0% accuracy with 5-fold cross validation)

Bayesian Nets and J48 Decision Tree could be applied to detect the presence of cellular stress in prokaryotes using data from DNA microarrays

Use J48 and Bayes Networks with in fold cross validation to analyze microarray data from the cefuroxime-stress study

Examine the consistency of the performance of these algorithms in all the biological replicates of the microarray experiments

Test the performance of the algorithms with various datasets containing expression values of genes from different signalling pathways

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