Bioinformatical Considerations for High Dimensional Data Derived from High Throughput Assays

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The problem

- The major challenge in high throughput experiments, e.g., microarray data, MALDI-TOF data, or SELDI-TOF data, is that the data is often high dimensional.
- When the number of dimensions reaches thousands or more, the computational time for the pattern recognition algorithms can become unreasonable. This can be a problem, especially when some of the features are not discriminatory.

The problem

- The irrelevant features may cause a reduction in the accuracy of some algorithms. For example (Witten 1999), experiments with a decision tree classifier have shown that adding a random binary feature to standard datasets can deteriorate the classification performance by 5 10%.
- Furthermore, in many pattern recognition tasks, the number of features represents the dimension of a search space - the larger the number of features, the greater the dimension of the search space, and the harder the problem.

Issues in the Analysis of High-Throughput Experiment

- Experiment Design
- Measurement
- Preprocessing
 - Filtering, Baseline Correction, Normalization
 - Profile Alignment, Transformation, Variance correction
- Feature Selection
- Classification

Steps in the Analysis of High-Throughput Experiment

Computational Validation

- Estimate the classification error rate
- bootstrapping, k-fold validation, leave-one-out validation

Significance Testing of the Achieved Classification Error

Validation – blind test cohort

Reporting the result - graphic & table

Experiment Design

Study Objectives:

Class Discovery (unsupervised)

Class Comparison (supervised)

Class Prediction (supervised)

Outcome Measurement



Pre-processing (MALDI-TOF)



Pre-processing Wavelet denoise + baseline correction



Pre-processing Wavelet denoise + baseline correction + normalization



MALDI-TOF MS Data Preprocessing Tool



Intra Class Correlation: Training



Intra Class Correlation: Training and Testing Combined



Intra Class Correlation: Training, Testing, and Combined



Dimension Reduction

Possible approaches:

- Principal Component Analysis (PCA)
- Multidimensional scaling (MDS)
- Self-Organizing Map (SOM)

Feature Selection - Class Comparison

- t-test, permutation t-test, permutation F test.
- Weighted Gene Analysis
- Threshold Number of Misclassification Score (TNoM)
- Mutual-information Scoring (Info Score)
- Significance Analysis of Microarray (SAM)
- REML based Mixed effect model
- The P-values for Identifying Differentially Expressed genes (PIDEX)

Feature Selection - Class Comparison

- Tree Algorithms: CART, Quest, Slip, CHAID
- Projection Pursuit Regression (PPR)
- Partially Lease Square Method (PSS)
- Smoothing Spline
- Knowledge Extraction Engines (KXEN)
- Multivariate Adaptive Regression Splines (MARS)
- TreeNet: Stochastic Gradient Boosting (MART)

Classification - Compound Covariate Method

The compound covariate method was proposed by Tukey (1993). Hedenfalk et al. (2001) successfully applied this method to class prediction analysis for BRCA1+ vs. BRCA1-.

This predictor is built in two steps.

First, a statistical test is performed to identify genes with significant differences (at level α , Hedenfalk et al. picked α = 0.0001) between the two tissue classes.

Second, the ratios of differentially expressed genes are combined into a single compound covariate for each tissue sample; the compound covariate is used as the basis for class prediction.

 $C_i = \Sigma_j M_j X_{ij}$



Classification

Weighted Flexible Compound Covariate method

We have proposed a more flexible compound covariate method (Weighted Flexible Compound Covariate method) based on the mutualinformation scoring (*Info Score*), significance analysis of microarrays (SAM), Weighted gene analysis, Fisher's exact test, Mixed effect model and permutation *t*-test. WFCCM: WFCCM is an extension of the compound covariate method which allows considering more than one statistical analysis methods into the compound covariate.

The WFCCM for tumor sample *i* is defined as

$WFCCM(i) = \sum_{j} [\Sigma_{k} (ST_{jk})] [W_{j}]X_{ij},$

where j represents statistically significant gene j. ST_{jk} is the standardized statistic, e.g., t-statistic, for statistical analysis method k.

Validation

Classification (sample size)	No. of diff. Expressed	No. of Misclassified	% of random permutations with
	genes	sample	misclassification
Normal (3) vs. Tumor (26)	54	0 (Normal, 0) (Tumor, 0)	0.7% With \leq 0 misclassification
Lung (24) vs. Non-lung (5)	62	0 (Lung, 0) (N-Lung,0)	0.5% With \leq 0 misclassification

Testing Cohort Lung SPORE Serum Proteomic Study

52 vs 58 tes



WFCCM – Class Prediction Model



Non-Tumor





Multidimensional scaling (MDS)







Things DON'T DO

- Fold-change for feature selection
- Cluster analysis for class comparison
- Cluster analysis for class prediction
- Extremely small sample size for the Independent test cohort
- Only report the good news





