DEA/DES in Bioinformatics 2003-2004 Thesis

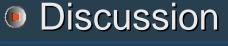
Breast Cancer Diagnosis Using Microarray

Training Master: M. Christos Sotiriou

Training Supervisor: M. Gianluca Bontempi

Benjamin Haibe-Kains

Introduction TransBIG Project Materials Populations Microarray Platform Methods and Results Development Tools Quality Assessment Supervised Classification Gene Ontology



Introduction TransBIG Project Materials Populations Microarray Platform Methods and Results Development Tools Quality Assessment Supervised Classification Gene Ontology Discussion



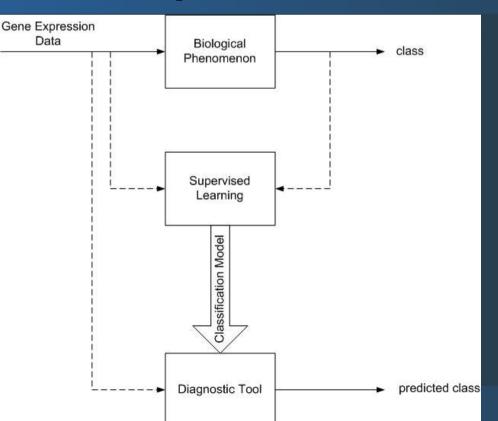
Introduction Breast Cancer Diagnosis

- Several histological criteria characterize breast tumor
 - Invasive/non-invasive tumor
 - Number of involved lymph nodes
 - Size
 - Tumor grade
 - Estrogen receptor status
 - Oncogene over-expression
 - Margins of resection

Introduction Breast Cancer Diagnosis (2)

- Appearance of distant metastases in the first 5 years of follow-up
 - Binary classification (relapse/non-relapse)
- Goals
 - Reduce significantly the patients who receive unnecessary treatments
 - Adverse side effects
 - Treatment costs
 - Isolate involved genes

Introduction Breast Cancer Diagnosis (3) • Histological criteria fail to classify the tumors • Development of new predictors based on gene expression profile



Introduction TransBIG Project Materials Populations Microarray Platform Methods and Results Development Tools Quality Assessment Supervised Classification Gene Ontology Discussion



Introduction TransBIG Project

- TransBIG project
 - Validation of van't Veer signature
 - Agilent microarray technology
 - 70 maker genes (van't Veer et al. 2002)
 - Development of a new signature
 - Affymetrix microarray technology
 - Supervised by Christos Sotiriou at the IJB (Microarray Unity)
 - Collaboration with the SIB

Introduction TransBIG Project (2)

Gene expression profiling predicts clinical outcome of breast cancer

Laura J. van 't Veer*†, Hongyue Dai†‡, Marc J. van de Vijver*†, Yudong D. He‡, Augustinus A. M. Hart*, Mao Mao‡, Hans L. Peterse*, Karin van der Kooy*, Matthew J. Marton‡, Anke T. Witteveen*, George J. Schreiber‡, Ron M. Kerkhoven*, Chris Roberts‡, Peter S. Linsley‡, René Bemards* & Stephen H. Friend‡

* Divisions of Diagnostic Oncology, Radiotherapy and Molecular Carcinogenesis and Center for Biomedical Genetics, The Netherlands Cancer Institute,

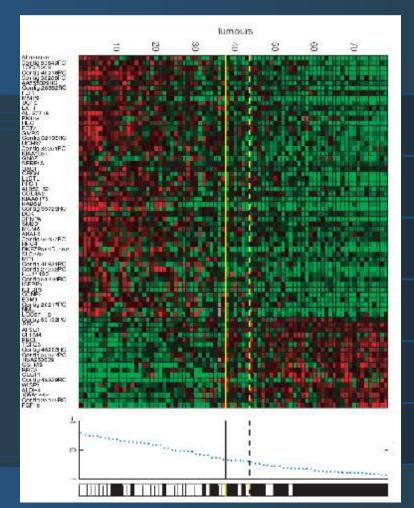
121 Plesmanlaan, 1066 CX Amsterdam, The Netherlands

‡ Rosetta Inpharmatics, 12040 115th Avenue NE, Kirkland, Washington 98034, USA

† These authors contributed equally to this work

Breast cancer patients with the same stage of disease can have markedly different treatment responses and overall outcome. The strongest predictors for metastases (for example, lymph node status and histological grade) fail to classify accurately breast tumours according to their clinical behaviour1-3. Chemotherapy or hormonal therapy reduces the risk of distant metastases by approximately one-third; however, 70-80% of patients receiving this treatment would have survived without it45. None of the signatures of breast cancer gene expression reported to date⁶⁻¹² allow for patient-tailored therapy strategies. Here we used DNA microarray analysis on primary breast tumours of 117 young patients, and applied supervised classification to identify a gene expression signature strongly predictive of a short interval to distant metastases ('poor prognosis' signature) in patients without tumour cells in local lymph nodes at diagnosis (lymph node negative). In addition, we established a signature that identifies tumours of BRCA1 carriers. The poor prognosis signature consists of genes regulating cell cycle, invasion, metastasis and

70 genes of van't Veer Signature



Introduction TransBIG Project Materials Populations Microarray Platform Methods and Results Development Tools Quality Assessment Supervised Classification Gene Ontology Discussion



Materials Populations

John Radcliffe Hospital (JRH, Oxford) • 77 samples hybridized at IJB Gustave Roussy Hospital (IGR, Paris) 65 samples hybridized at IJB
 • Karolinska Institute and Hospital (Karolinska, Stockholm) 19 samples hybridized at IJB 68 samples hybridized at Karolinska

Materials Populations (2)

Highly unbalanced class distribution ¼ of relapses (class 1) ¾ of non-relapses (class 0)

Introduction TransBIG Project Materials Populations Microarray Platform Methods and Results Development Tools Quality Assessment Supervised Classification Gene Ontology Discussion



Materials Microarray Platform

- cRNA microarrays is a recent technique used to determine
 genomewide gene expression levels
- Measurement of the quantity of cRNA, prepared from mRNA, hybridized on the chip

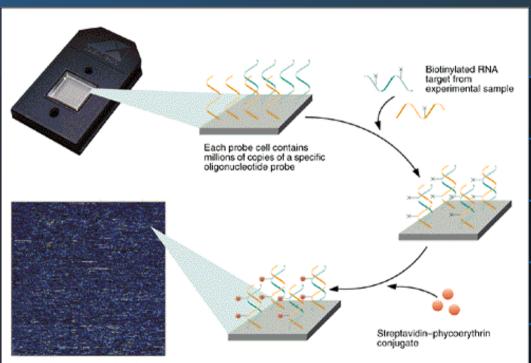
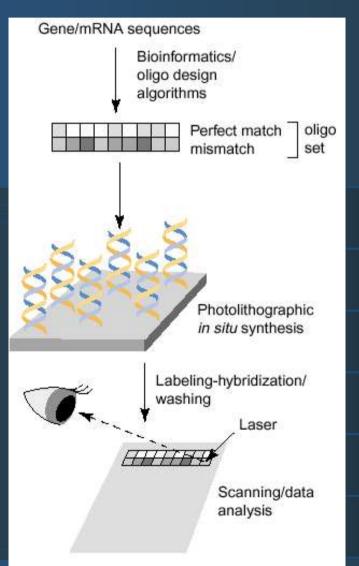


Image of hybridized probe array

Materials Microarray Platform (2)

- Affymetrix: short oligonucleotide technology
- Chip hgu133a
 (22283 probe sets)
- Chip hgu133b (22645 probe sets)
- CEL files



Introduction TransBIG Project Materials Populations Microarray Platform Methods and Results Development Tools Quality Assessment Supervised Classification Gene Ontology Discussion



Methods and Results Development Tools

R and Bioconductor
 Manifold and reliability
 Completeness
 Open-source

Application server installation to carry out large bioinformatics analyzes

Introduction TransBIG Project Materials Populations Microarray Platform Methods and Results Development Tools Quality Assessment Supervised Classification Gene Ontology Discussion



Methods and Results Quality Assessment

 Important step in the analysis design
 During hybridization: tests carried out in laboratory (e.g. tissue purity)

After hybridization: quality controls based on Affymetrix CEL files

- Probe array image
- Average background
- Spike controls and RNA degradation
- Detection calls
- Scaling factor
- Box plots for PM intensities

Methods and Results Quality Assessment (2)

No standard for quality control
 Affymetrix and Bioconductor guidelines

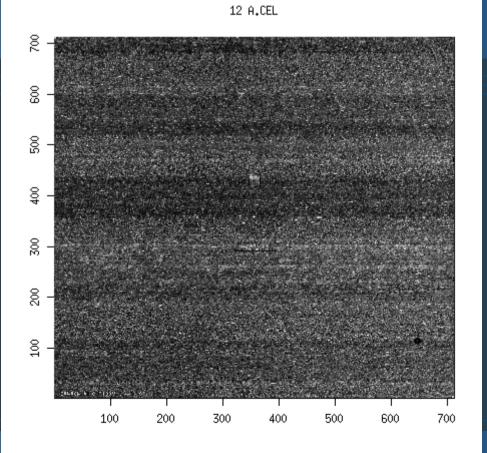
Probe array image
 Gray scale images of the chips
 Gray intensities computed from *CEL* file intensities

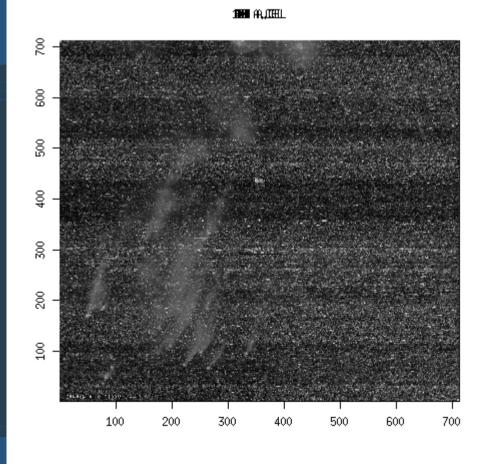
Visual inspection to detect artifacts

Methods and Results Quality Assessment (3)

Good chip

Bad chip



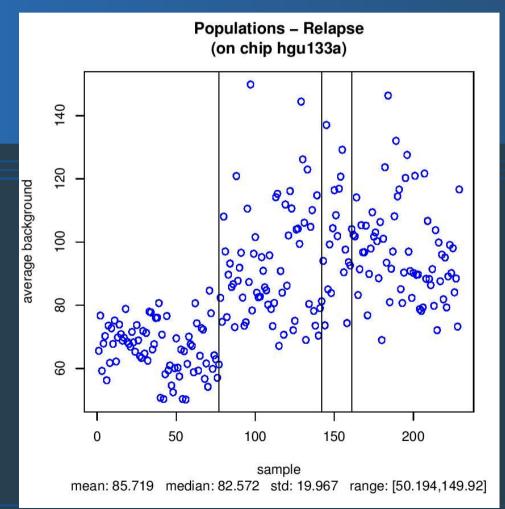


Methods and Results Quality Assessment (4)

Average background

- Assessment of the background intensities in the chip
- Computed by MAS 5.0 algorithm
- Affymetrix guidline: values should be similar and < 100</p>
- Permutation tests to assess difference between populations

Methods and Results Quality Assessment (5)



Chip hgu133a		
Populations	p-value	
JRH < -> IGR	1.903e-9	
JRH <-> Karolinska19	1.08e-10	
IGR < -> Karolinska19	0.06725	

Chip hgu133b	
Populations	p-value
m JRH < -> IGR	2.661e-4
m JRH < -> Karolinska19	0.03496
IGR < -> Karolinska19	0.6224

Methods and Results Quality Assessment (6)

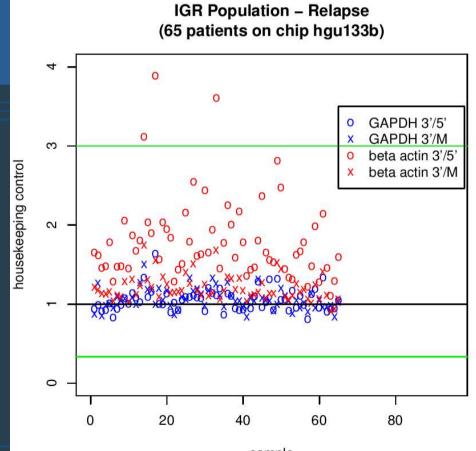
- RNA degradation
 - Typically starts from the 5' end to the 3' end of the molecule (control with GAPDH and beta actin genes)
 - Affymetrix guideline: ratio 3'/5' < 3</p>
 - RNA quality assessment
- Spike controls

Probes spiked during the sample preparation process (BioB, BioC, BioD, CreX should be detected as present)

Hybridization efficiency assessment

Methods and Results Quality Assessment (7)

Good quality for all the populations



sample percent of present calls -> bioB: 100, bioC: 100, bioD: 100, creX: 100

Methods and Results Quality Assessment (8)

Detection calls

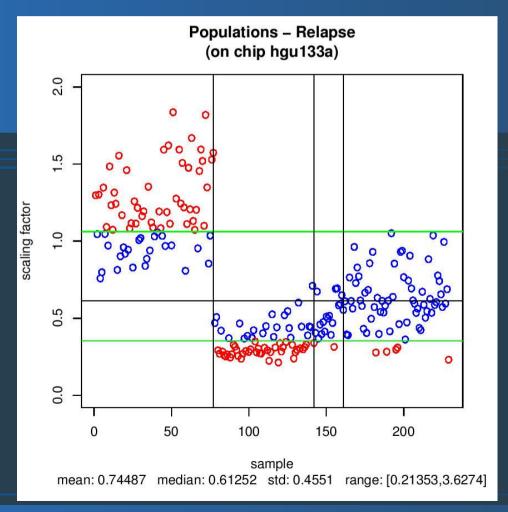
Use of the intensities of the PM and MM probes to test statistically the *presence* or the *absence* of a specific gene

- Computed by MAS 5.0 algorithm
- Affymetrix guideline: extremely low percentage of present calls may indicate poor quality
- Good quality for all the populations

Methods and Results Quality Assessment (9)

- Scaling factor
 - Assessment of the difference in mean intensity between chips
 - Computed by MAS 5.0 algorithm
 - Affymetrix guideline: recommended value of maximum three-fold scaling factor
 - Permutation tests to assess difference between populations

Methods and Results Quality Assessment (10)



Chip hgu133a	
Populations	p-value
JRH < -> IGR	1.166e-6
JRH < -> Karolinska19	0.1066
IGR <-> Karolinska19	5.118e-7

Chip hgu133b	
Populations	p-value
m JRH < -> IGR	3.74e-7
JRH <-> Karolinska19	0.4476
IGR < -> Karolinska19	0.002979

Methods and Results Quality Assessment (11)

Box plots for PM intensities
 Useful to detect outlier and to assess the quality of the normalization

Computation of the median and the interquartile range of PM intensities for each chip

Methods and Results Quality Assessment (12)

Igr Population – Relapse (65 patients on chip hgu133a) 4 10 2 5 10 0 8 5 P216806.A.CEL P246560.A.CEL P256742.A.CEL P307829.A.CEL boxplot of arrays

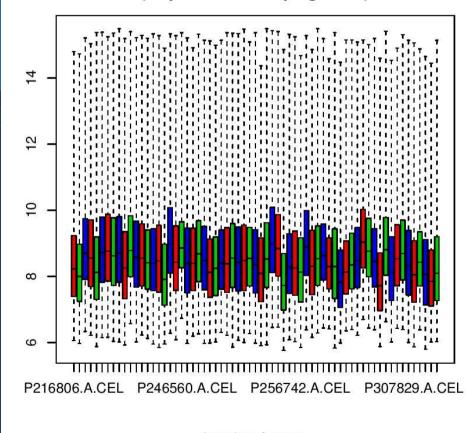
(65 patients on chip hgu133a) P216806.A.CEL P246560.A.CEL P256742.A.CEL P307829.A.CEL

Igr Population – Relapse

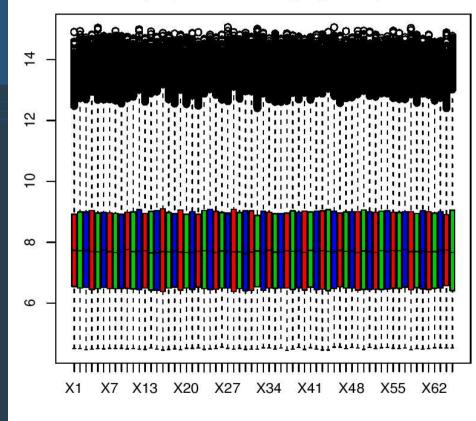
boxplot of MAS arrays

Methods and Results Quality Assessment (13)

Igr Population – Relapse (65 patients on chip hgu133a)



Igr Population – Relapse (65 patients on chip hgu133a)



boxplot of arrays

boxplot of RMA arrays

Methods and Results Quality Assessment (14)

Preliminary conclusion

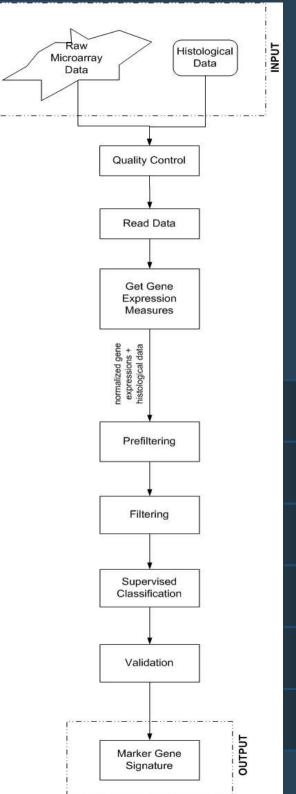
 Statistically significant difference between populations
 Populations are not necessary comparable
 Population preprocessing before analysis (not yet investigated)

Introduction TransBIG Project Materials Populations Microarray Platform Methods and Results Development Tools Quality Assessment Supervised Classification Gene Ontology Discussion



Methods and Results Supervised Classification

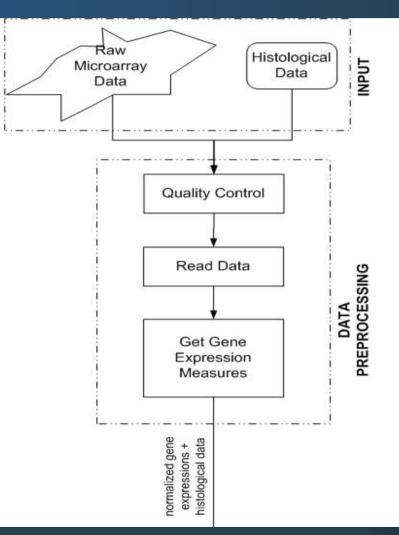
 "Traditional" design of supervised classification in microarray data analysis



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Methods and Results Supervised Classification (2)

 Preprocessing Affymetrix data
 Normalized gene expressions
 Histological data

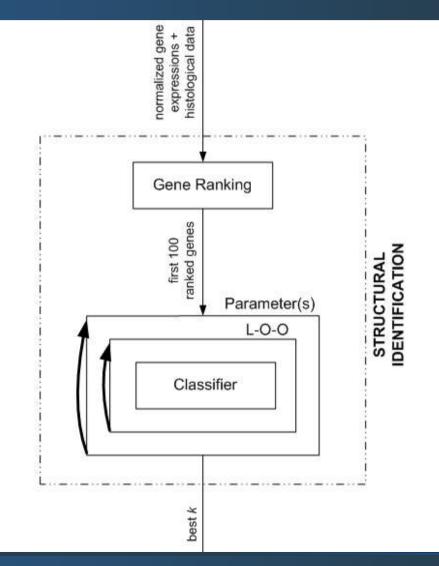


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NB: only 99 patients have been considered in the classification procedure (52 from JRH and 47 from IGR)

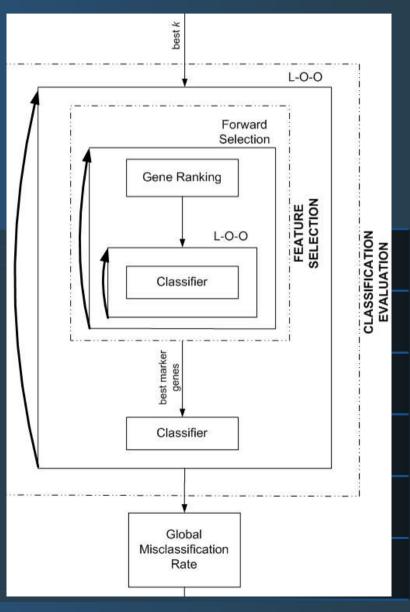
Methods and Results Supervised Classification (3)

Structural identification **Gene ranking** by Pearson correlation coefficient First 100 ranked genes (arbitrary criteria) Olassifier (KNN) Parameter k



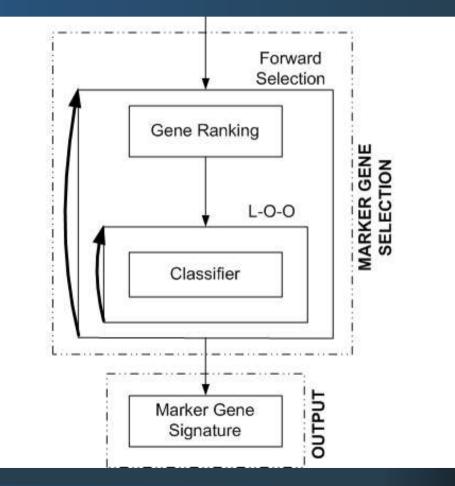
Methods and Results Supervised Classification (4)

 Classification evaluation
 Feature selection by variable ordering
 At each L-O-O, a best set of marker genes is selected



Methods and Results Supervised Classification (5)

- After classification procedure evaluation
- Marker gene selection with all the patients (using the same procedure)
- Assumption: the signature quality increases with the number of patients



Methods and Results Supervised Classification (6) Misclassification type

	Reality	
Prediction	relapse (+)	non-relapse (-)
relapse (+)	TP	FP
non-relapse (-)	FN	TN

Class weights (classifier)

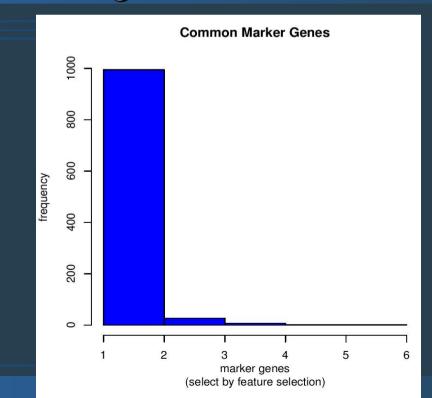
 clw_o = 1 for non-relapse class
 clw₁ = 10 for relapse class

 Quality estimator (feature selection)

 q = clw₀ * FP + clw₁ * FN

Methods and Results Supervised Classification (7)

 Robustness of marker genes selected by the feature selections: frequency of appearance of each marker gene



Methods and Results Supervised Classification (8)

- Signature is very dependent to the training set
- Expected result because of the very small size of signatures (relative to the number of genes)

10 (mean) for the KNN

Indication of poor biological information

Methods and Results Supervised Classification (9) • Global misclassification rate (KNN) • FN: 21/24 • FP: 4/75

Marker gene signature: 2 genes
 224529_s_at (C6ORF69)
 223176_at (NT5C1A)

Methods and Results Supervised Classification (10)

Preliminary conclusion

- Avoid overfitting as much as possible according to computer resources
- Tune the classifier to avoid a high false negative rate

Poor performance:

- Arbitrary number of marker genes in the structural identification
- KNN is sensible to unbalanced data set
- High variance of the procedure (multiple L-O-O and feature selection)

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Introduction TransBIG Project Materials Populations Microarray Platform Methods and Results Development Tools Quality Assessment Supervised Classification Gene Ontology Discussion



Methods and Results Gene Ontology

- GO consortium is setting a dynamic controlled vocabulary that can be applied to all organisms even as knowledge of gene and protein roles in cells is accumulating and changing
- Automatic annotation of marker genes in terms of
 - Molecular function
 - Biological process
 - Cellular component

Methods and Results Gene Ontology (2)

Onto-Express (Ostermeier et al. 2003)

Statistical framework to assess the significance of gene clusters in each GO functional category

Take into account the tested genes (here the whole genome)

Take into account the set of marker genes

Valuable if the number of marker genes in the signature is large (tens or hundreds)

Methods and Results Gene Ontology (3)

Not the case here: 2 marker genes
 Only one gene exists in the GO (224529_s_at)

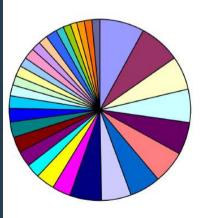
Biological pro	DCess								11-11-11-11-11-11-11-11-11-11-11-11-11-	
GO ID	Function Name		Probe		Gene Symbol		Unigene Cluster		LocusLink ID	
GO:0009116	nucleoside metabolism		224529_s_at		NT5C1A		307006		84618	
Cellular com	ponent	9	52	5.3		2	έλ.	21.57	in and	
GO ID	Function Name	Probe		Gene Symbol		Unigene Cluster		Locus	Link ID	
GO:0005829	cytosol	224529_s_at		NT5C1A		307006		84	618	
Molecular fu			1	1915)	101 - 1021 - 1021	s ou oure	2012-012 OZ		5) - 1975 - 1975 - 1975 - 19	
GO ID	Function Nar	me	Probe		Gene Symbol		Unigene Cluster		LocusLink ID	
GO:0008253	5'-nucleotidase activity		224529_s_at		NT5C1A		307006		84618	

The two genes are not known in breast cancer literature

Methods and Results Gene Ontology (4)

Collaboration: Gene Regulation by Phorbol 12-myristate 13-acetate (PMA) in two Highly Different Breast Cancer Cell Lines. Lacroix M, Haibe-Kains B, Laes JF, Hennuy B, Lallemand F, Gonze I, Cardoso F, Piccart M, Leclerq G, and Sotiriou C (in press, Oncology Report)

Biological Process



Statistical significant p<0.05 FDR

	`	3,
	DNA replication (18)	protein amino acid dephosphorylation (6)
-	regulation of cell cycle (16)	collagen catabolism (5)
	DNA repair (14)	regulation of DNA replication (4)
	oncogenesis (13)	start control point of mitotic cell cycle (4)
-	apoptosis (13)	DNA replication initiation (4)
	immune response (13)	G2/M transition of mitotic cell cycle (4)
	cell cycle (12)	DNA metabolism (4)
	cell-cell signaling (12)	regulation of CDK activity (4)
•	biological_process unknown (12)	cell cycle arrest (4)
	mitosis (8)	blood coagulation (4)
	cell-matrix adhesion (7)	DNA dependent DNA replication (3)
	anti-apoptosis (6)	mitotic chromosome condensation (3)
	cytokinesis (6)	nucleotide biosynthesis (3)
	vision (6)	cell shape and cell size control (3)
	skeletal development (6)	integrin-mediated signaling pathway (3)
		chromosome organization

and biogenesis (sensu Eukarva) (3)

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Discussion

Future Works

Discussion

Microarrays have already provided valuable information about breast cancer

- Promising results in breast cancer diagnosis
- Issues need to be addressed before clinical use
 - Quality standards
 - Multi-populations, multi-platforms and multilaboratories validation

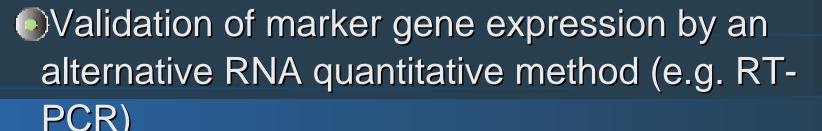


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Discussion

Future Works

Discussion Future Works

- Step by step complexity of analysis design
- Statistical framework for quality assessment
- Parallelism
- Preprocessing data
- Criterion for misclassification rate
- Marker gene stability
- Feature selection
- Independent validation set
- Signature validation and refinement

Applications to Genomic and Proteomic Data

Thanks for your attention

Benjamin Haibe-Kains

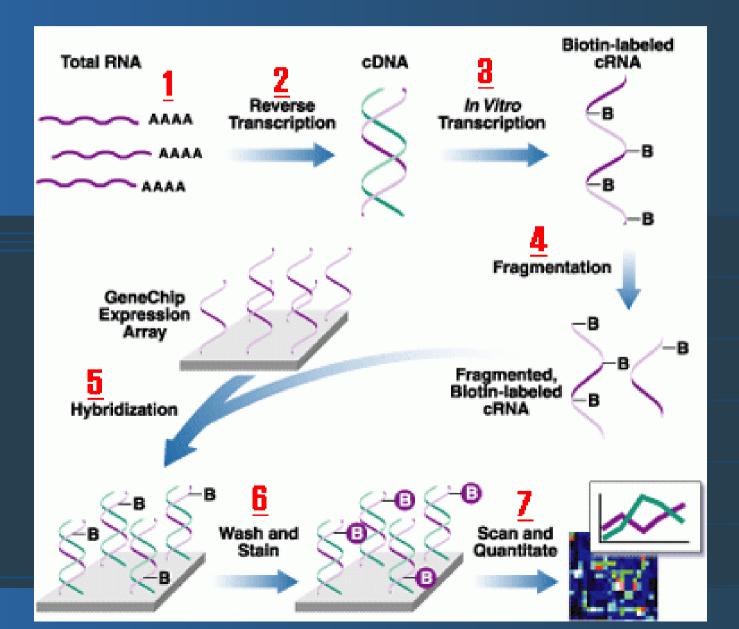
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Appendix

Materials Populations

Lymph node negative
Not treated by adjuvant treatment

Materials Microarray Platform



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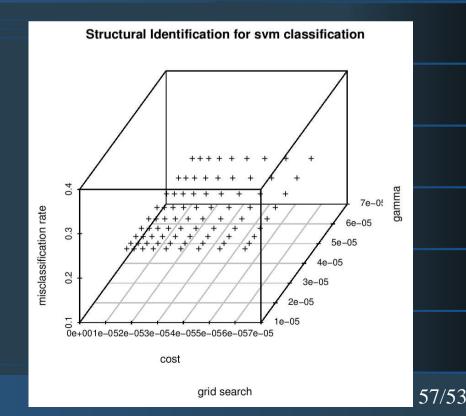
Methods and Results Structural Identification

First 100 ranked genes with all patients

KNN

Structural Identification for knn classification

SVM



Methods and Results Structural Identification

Use of *tune.foo* R function
 Low execution time (relative to the complexity)
 Only global misclassification rate
 No class weights
 Leave-one-out cross-validation
 Approximatively 25% of misclassification

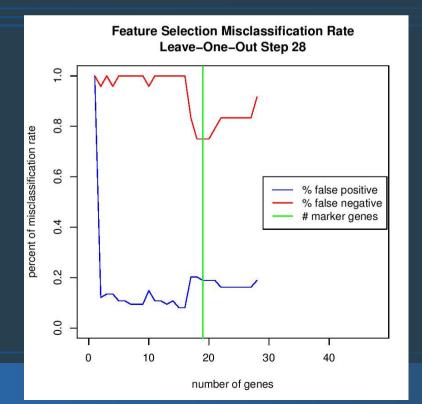
→ No indication about FN and FP

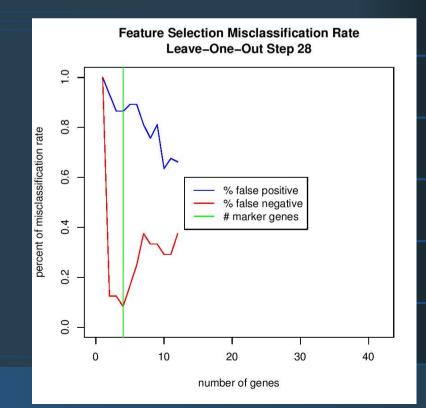
Methods and Results Feature Selection

Misclassification rate: opposite trend between KNN and SVM classifiers

KNN

• SVM





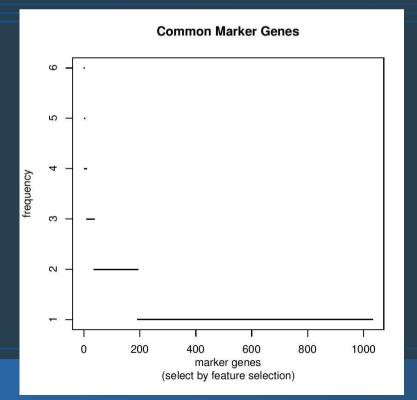
Methods and Results Feature Selection (2)

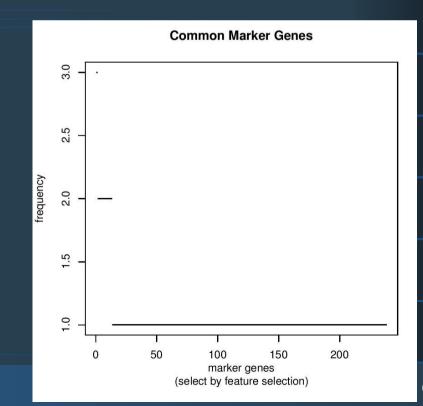
Due to No class weight for the KNN KNN is more sensible to unbalanced data set

Robustness of marker genes selected by the feature selections: frequency of appearance of each marker gene

Methods and Results Feature Selection (3)

Common marker genes during global leaveone-out KNN





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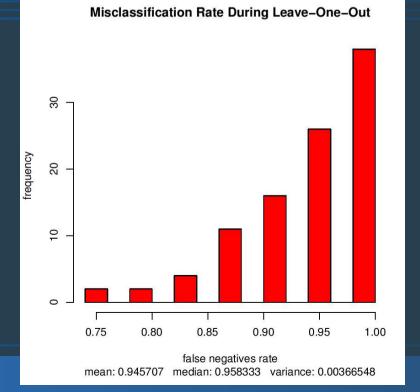
Methods and Results Feature Selection (4)

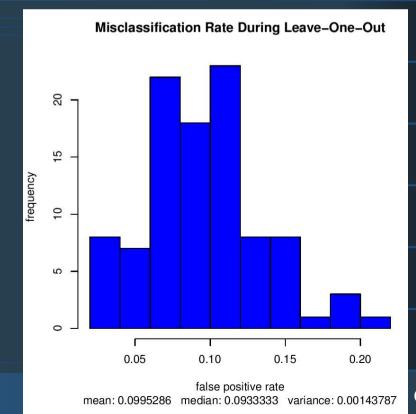
- Similar observations for the KNN and the SVM classifiers
 - Signature is very dependent to the training set
 - Expected result because of the very small size of signatures
 - 10 (mean) for the KNN
 - 2 (mean) in the SVM

Indication of poor biological information

Methods and Results Misclassification Rate

♦ KNN: misclassification during feature selections (global → 21/24 and 4/75) ♦ False negatives



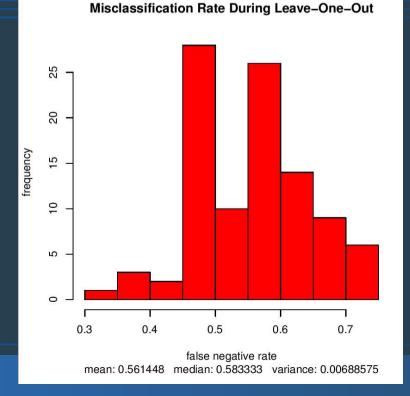


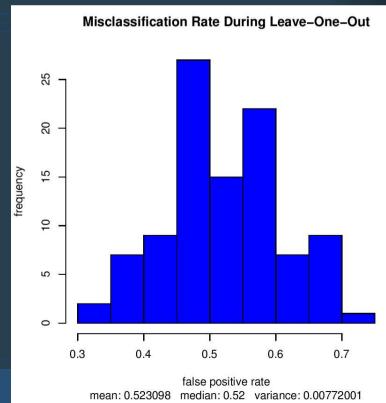
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Methods and Results **Misclassification Rate (2)**

SVM: misclassification during feature selections (global $\rightarrow 2/24$ and 65/75) False negatives







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Methods and Results Gene Ontology

Probe set id: 223176_at

- Accession number: BC003697
- Gene name: chromosome 6 open reading frame 69
- Symbol: C6ORF69
- Unigene: Hs.188757

Methods and Results Gene Ontology

Probe set id: 224529_s_at
Accession number: AY028778
Gene name: 5'-nucleotidase, cytosolic IA
Symbol: NT5C1A
Unigene: Hs.307006

Methods and Results Gene Ontology (3)

Only one gene exists in GO (224529_s_at)

Biological pro	DCess									
GO ID	Function Name		Probe		Gene Symbol		Unigene Cluster		LocusLink II	
GO:0009116	nucleoside metabolism		224529_s_at		NT5C1A		307006		84618	
Cellular component										14
GO ID	Function Name	Probe		Gene Symbol		Unigene Cluster		LocusLink ID		
GO:0005829	cytosol	22452	224529_s_at		NT5C1A		307006		84618	
Molecular fu			5 - 2004-	1914 -		a - 19 - 1999)			97 1000 - 1000 - 1000	
GO ID	Function Nar	Function Name		Probe		Gene Symbol		Unigene Cluster		nk ID
GO:0008253	5'-nucleotidase activity		224529_s_at		NT5C1A		307006		84618	

Nucleoside: combination of a base and a sugar without phosphate

Nucleotide: nucleoside with 1, 2, or 3 phosphate groups

Nucleotidase: enzyme hydrolizing nucleosides to nucleotides; the proportioning of the serum 5'-nucléotidase is used in digestive pathology

