



Contribution of microarrays in Acute Myeloid Leukemia diagnostics

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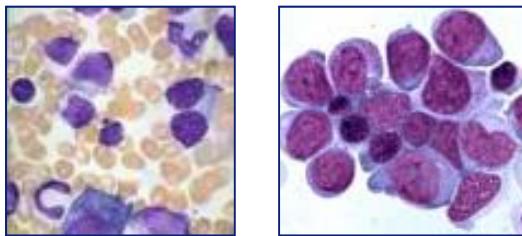
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Societat Catalana
d'Hematologia i Hemoteràpia
Barcelona, June 18th 2010**

Contribution of microarrays in Acute Myeloid Leukemia diagnostics

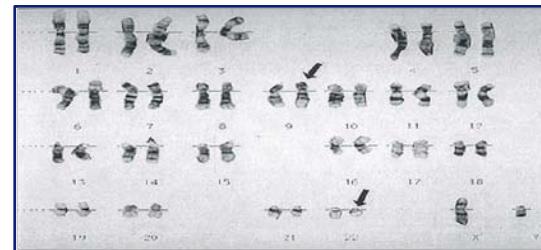
1. Current molecular diagnostics of acute myeloid leukemia (AML)
 - Cytogenetics
 - Mutations
 - Expression markers
2. Genome-wide molecular approaches and molecular diagnostics of AML

AML diagnostics

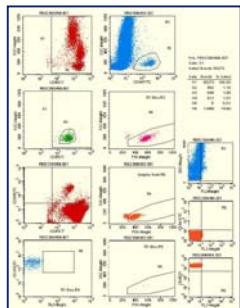
Morphology



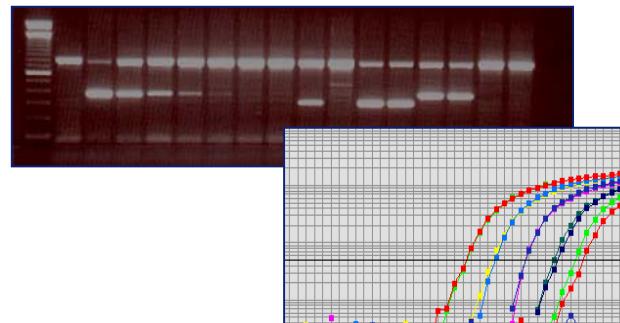
Cytogenetics



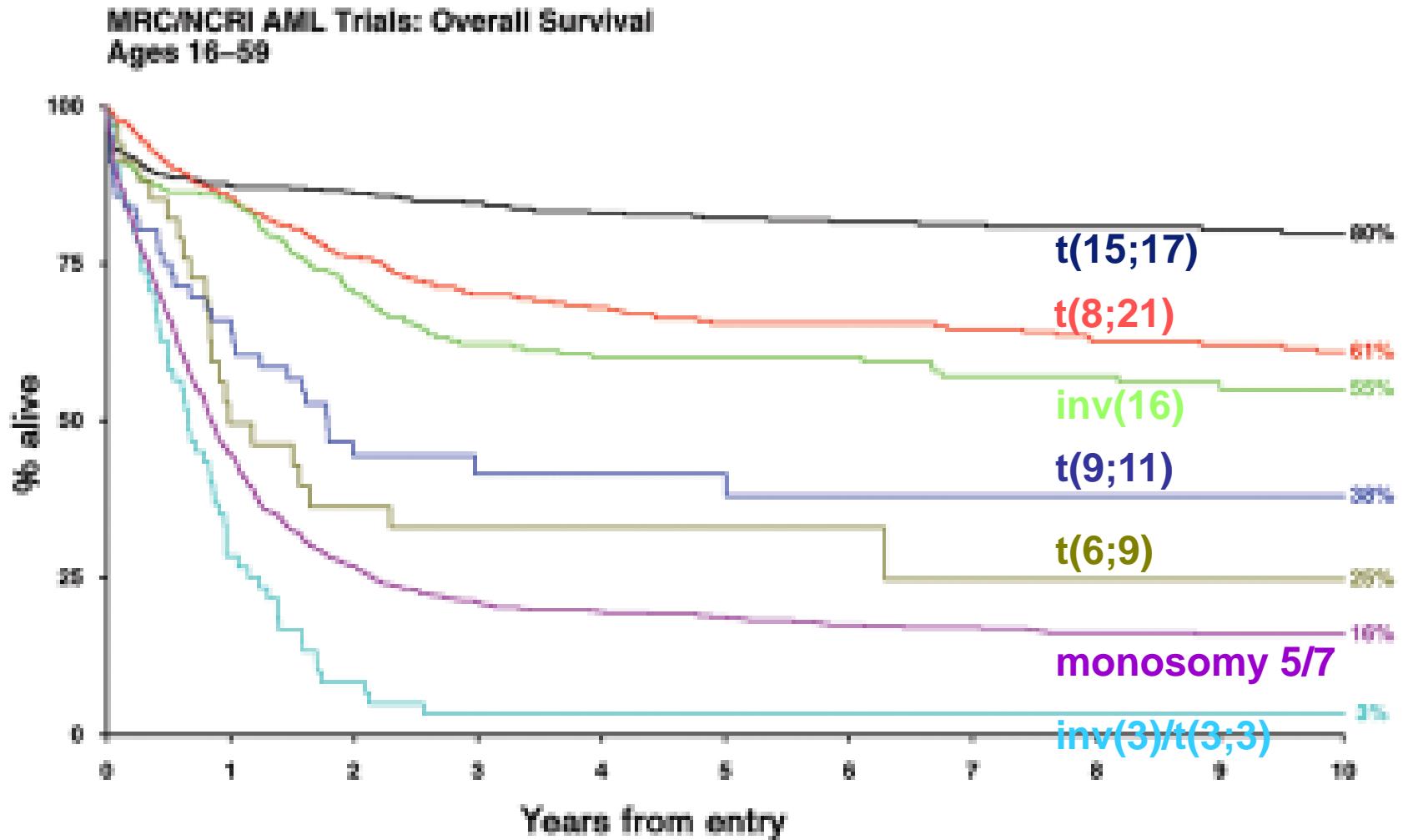
Immunophenotyping



Molecular diagnostics



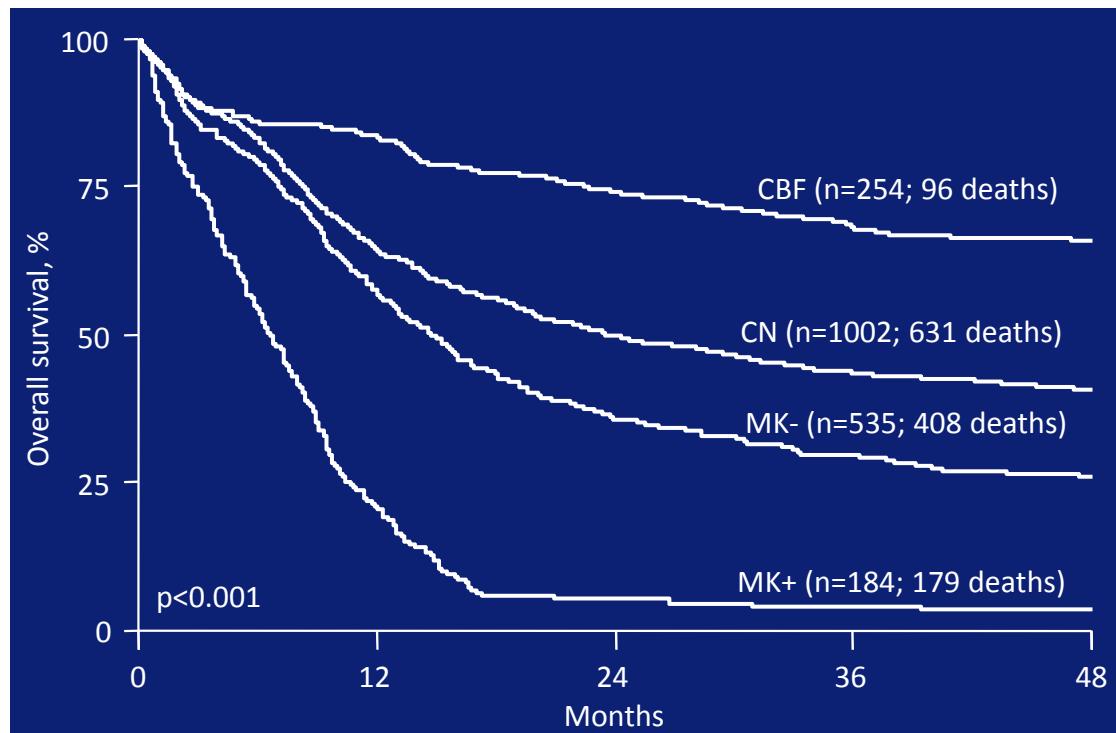
AML survival and cytogenetics



Grimwade en Hills, 2009

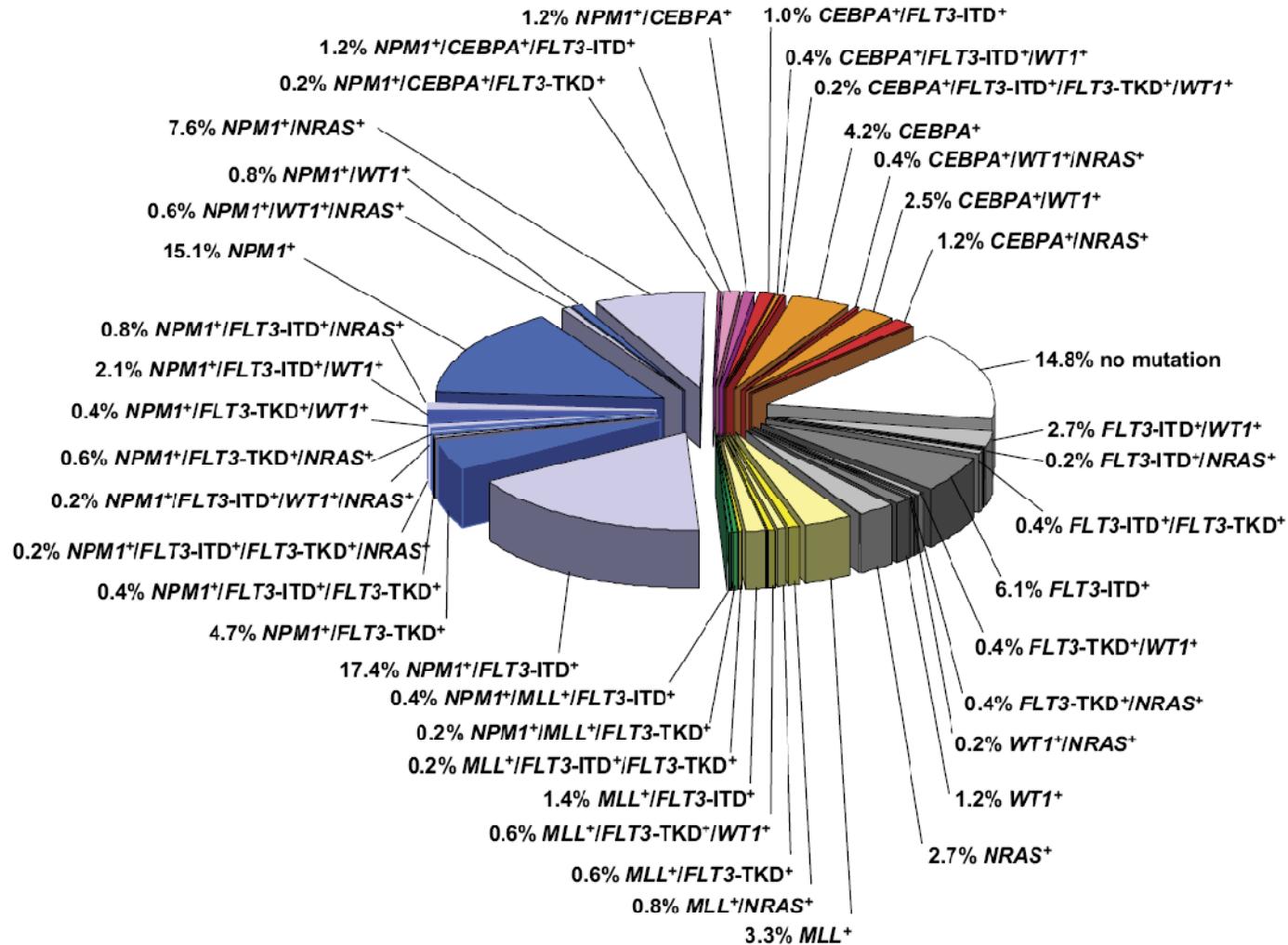
AML with monosomal karyotype

HOVON



Breems et al., 2008

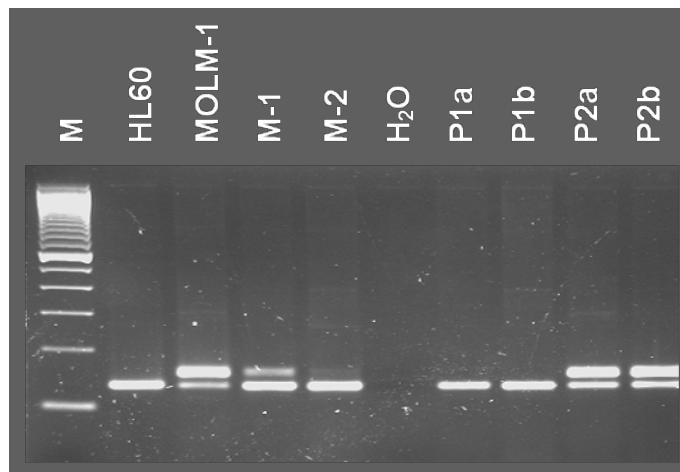
Heterogeneity AML – molecular aberrations



Dohner et al., 2010

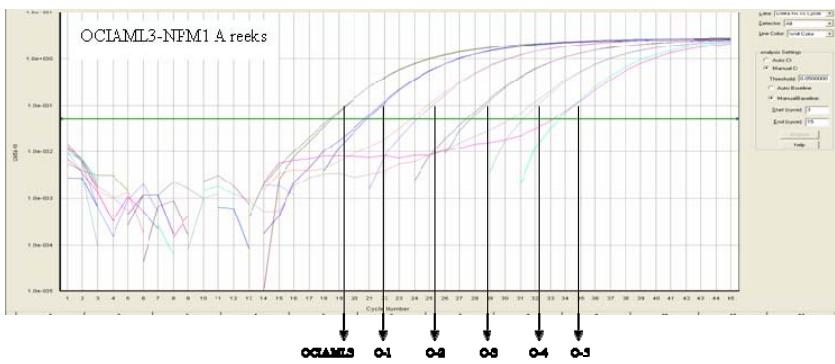
Molecular diagnostics *FLT3* ITD and *NPM1* mutation

RT-PCR *FLT3* ITD

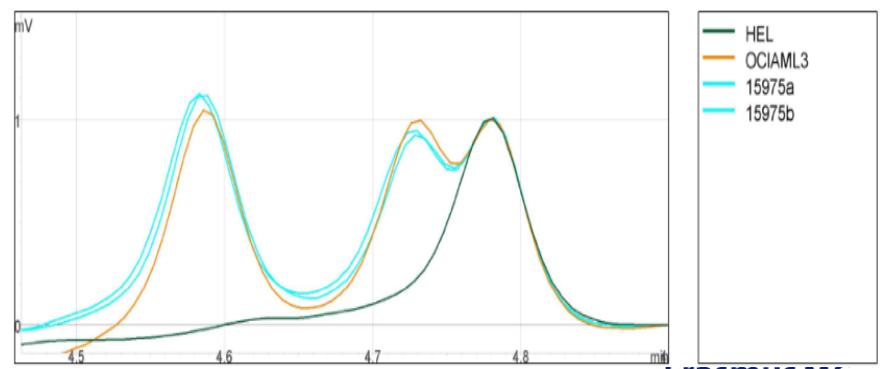


FLT3 ITD
normal allele

RQ-PCR *NPM1* mutation ABD

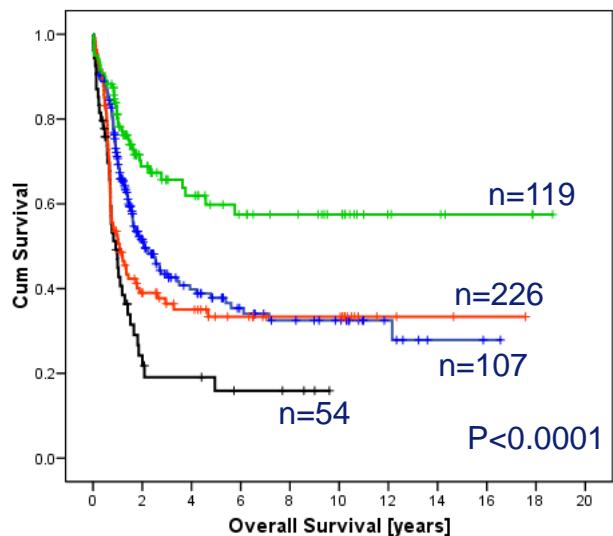


dHPLC WAVE– *NPM1* mutation

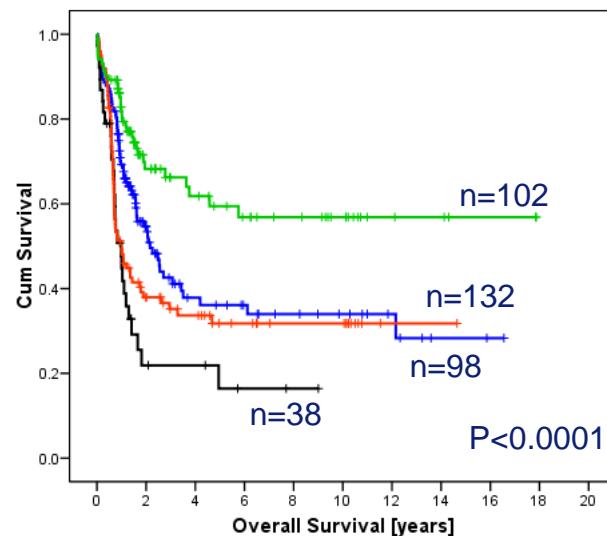


AML survival in *FLT3* ITD en *NPM1* mutation subgroups HOVON4(A), -29, 42(A)

Intermediate karyotype

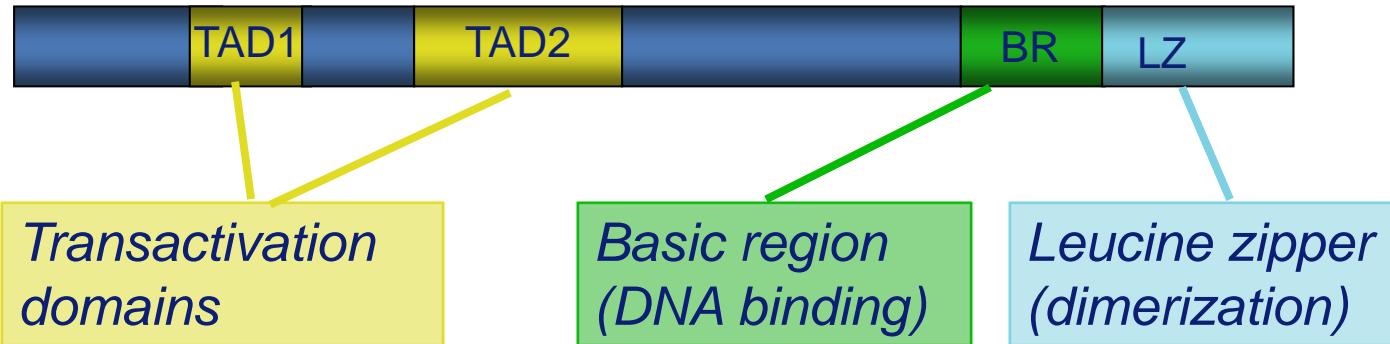


Normal karyotype



— <i>FLT3</i> wt, <i>NPM1</i> wt	— <i>FLT3</i> wt, <i>NPM1</i> mut
— <i>FLT3</i> -ITD, <i>NPM1</i> mut	— <i>FLT3</i> -ITD, <i>NPM1</i> wt

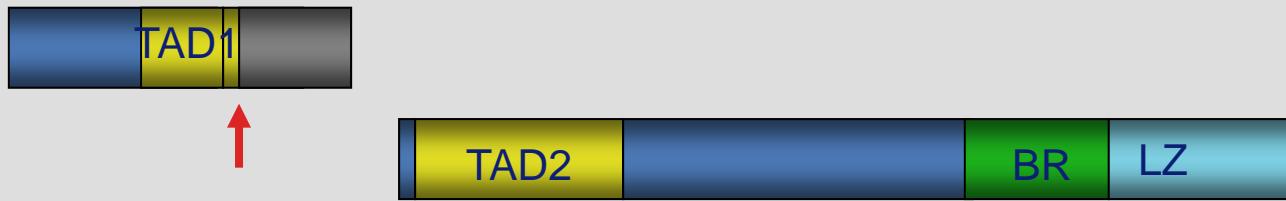
Most common types of *CEBPA* mutations in AML



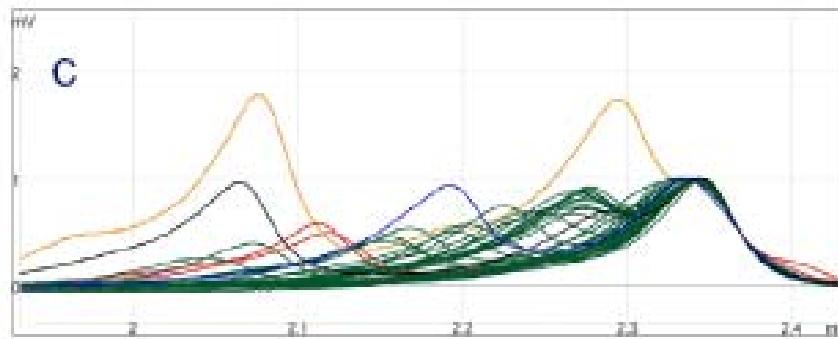
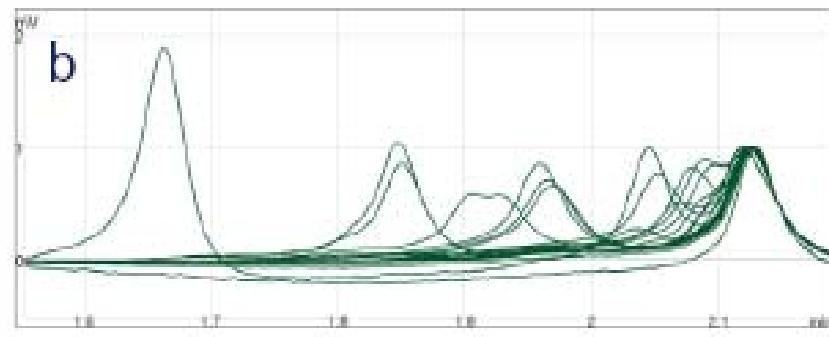
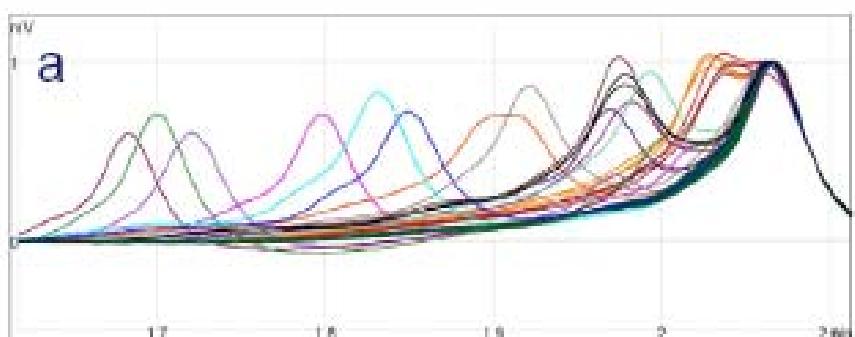
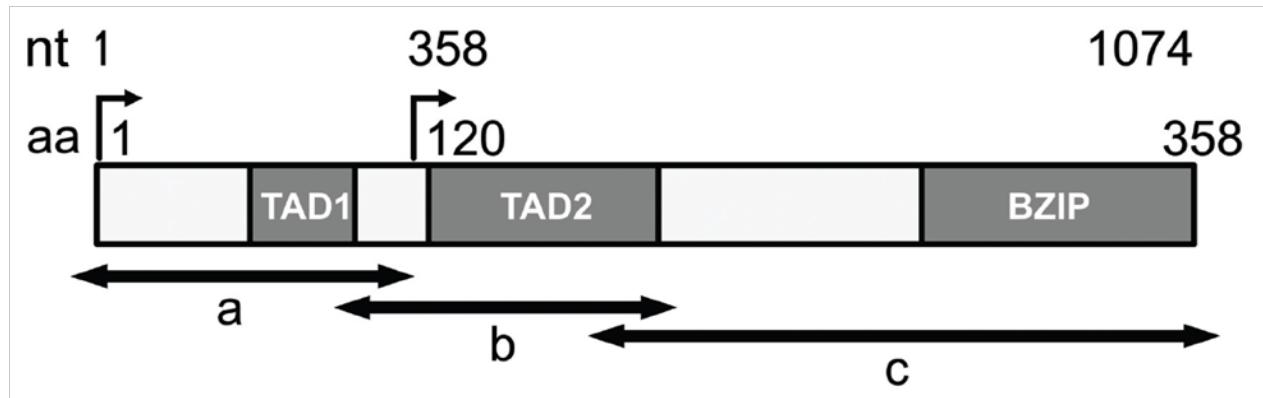
In-frame insertion or deletion in bZIP



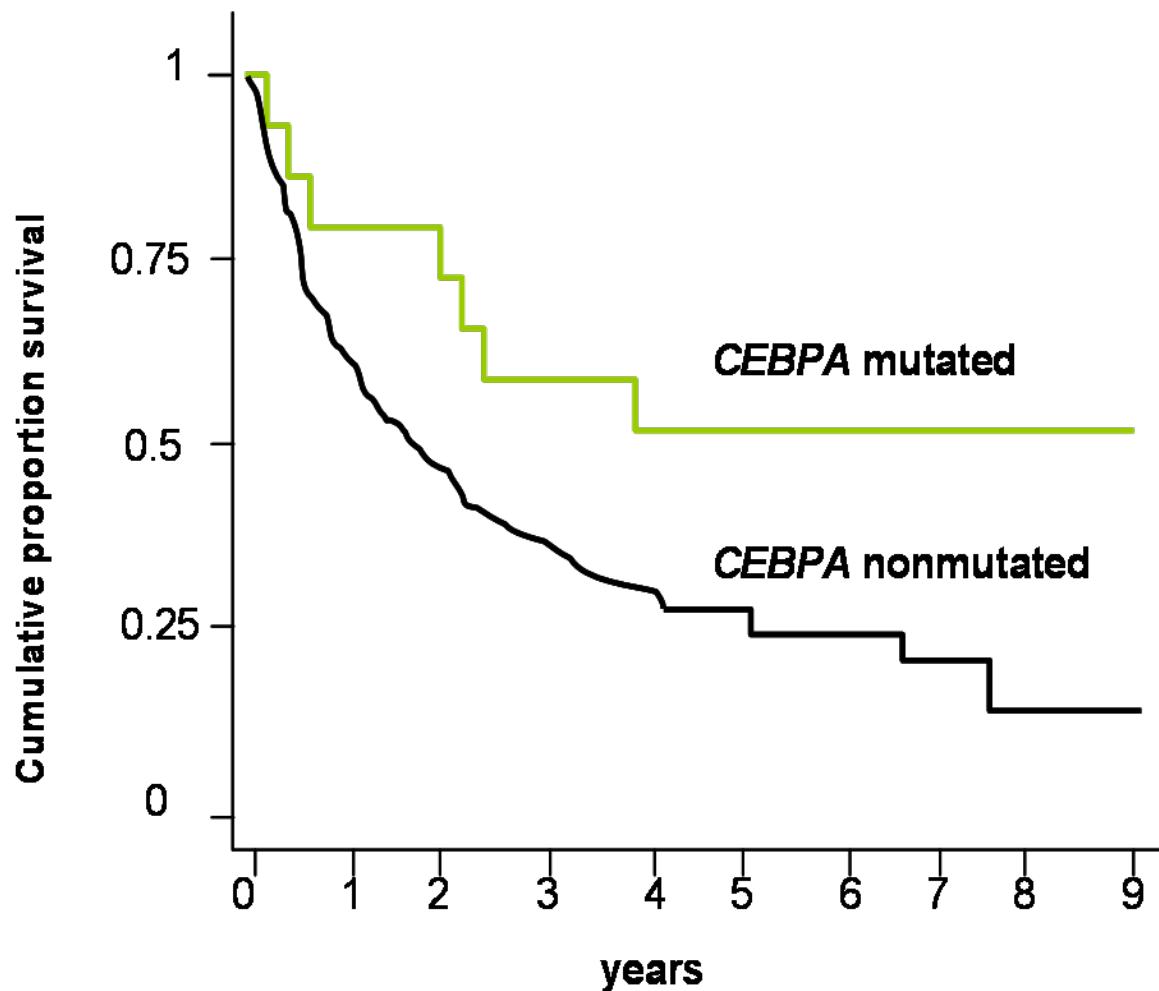
N-terminal truncation mutation



dHPLC assay to detect *CEBPA* mutations



Clinical outcome of AML patients with *CEBPA* mutations



Preudhomme C. et al. (Blood 2002)

Risk-stratification HOVON102

Risk		Definition	% pts (n=424)
Good	G1	t(8;21) , WBC<=20	5.4 %
	G2	inv16	7.3 %
	G3	MI-, CEBPA+	5.2 %
	G4	MI-, FLT3ITD-/NPM1+, CRe	10.1 %
Intermediate	I1	t(8;21) , WBC>20	2.8 %
	I2	CN –X –Y, CRe	15.8 %
Bad	B1	CN –X –Y, not CRe	22.9 %
	B2	CA, non CBF, MI-, no abn3q, EVI1-	13.0 %
Very Bad	VB1	Non CBF, MI+ or abn3q26	6.4 %
	VB2	Non CBF, abn3q26	1.7 %
	VB3	EVI1+	9.4 %

AML: (cyto)genetic aberrations and prognosis

Good

Poor

Cytogenetics

t(8;21)	normal	-7, -5
inv(16)	-Y	t(3;3), inv(3)
t(15;17)	t(9;11)	t(6;9), t(v;11) complex

Mutations

<i>NPM1</i> (FLT3 wild type)	TET2	FLT3 ITD
<i>CEBPA</i>	ASXL1	c-KIT (t(8;21)/inv(16))

IDH1

MLL PTD

Overexpression

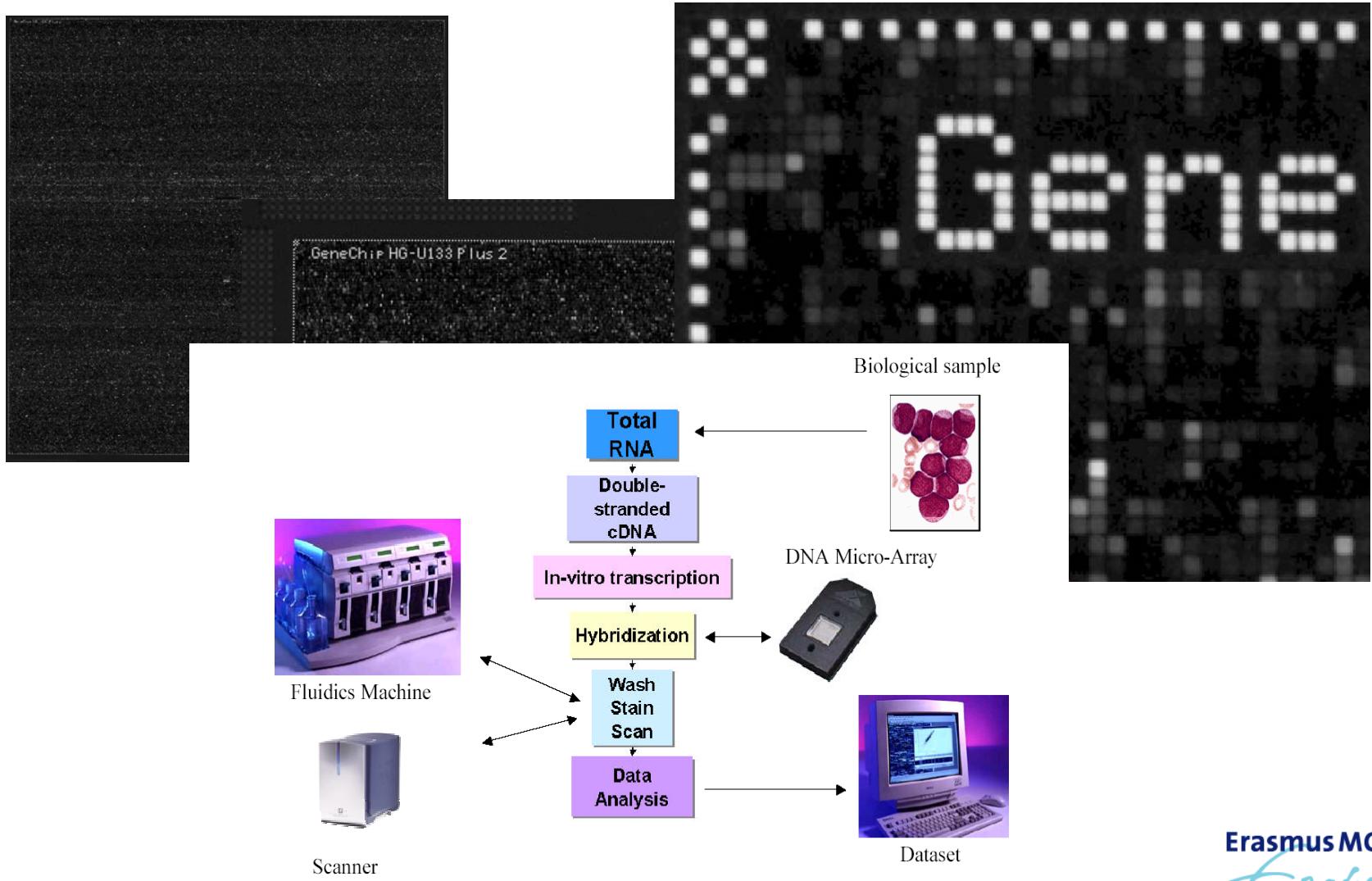
EVI1
BAALC

Microarrays and molecular diagnostics of AML

Can we use microarrays and possibly other types of genome-wide analyses to simplify AML diagnostics?

Can we use microarrays and possibly other types of genome-wide analyses to improve AML diagnostics?

Affymetrix gene expression profiling



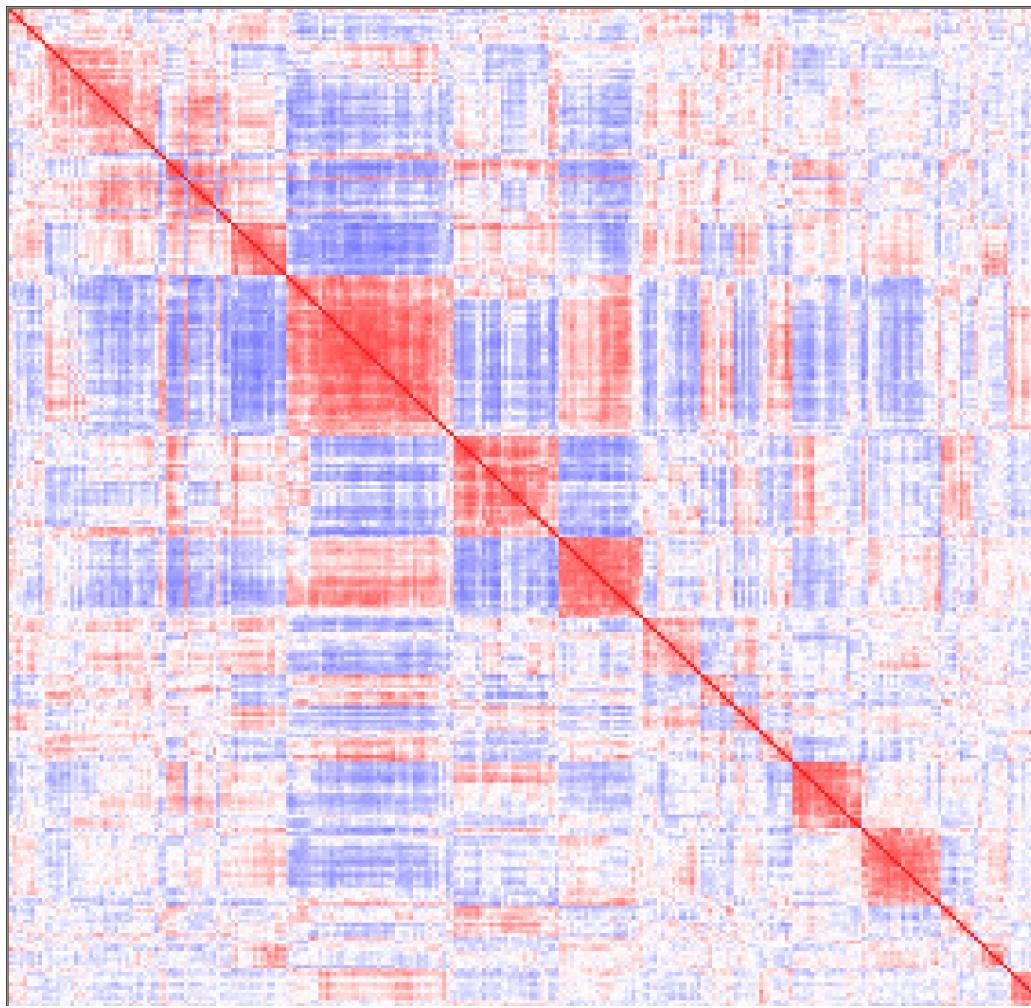
Class discovery in AML

Omniviz correlation view

Clustered order

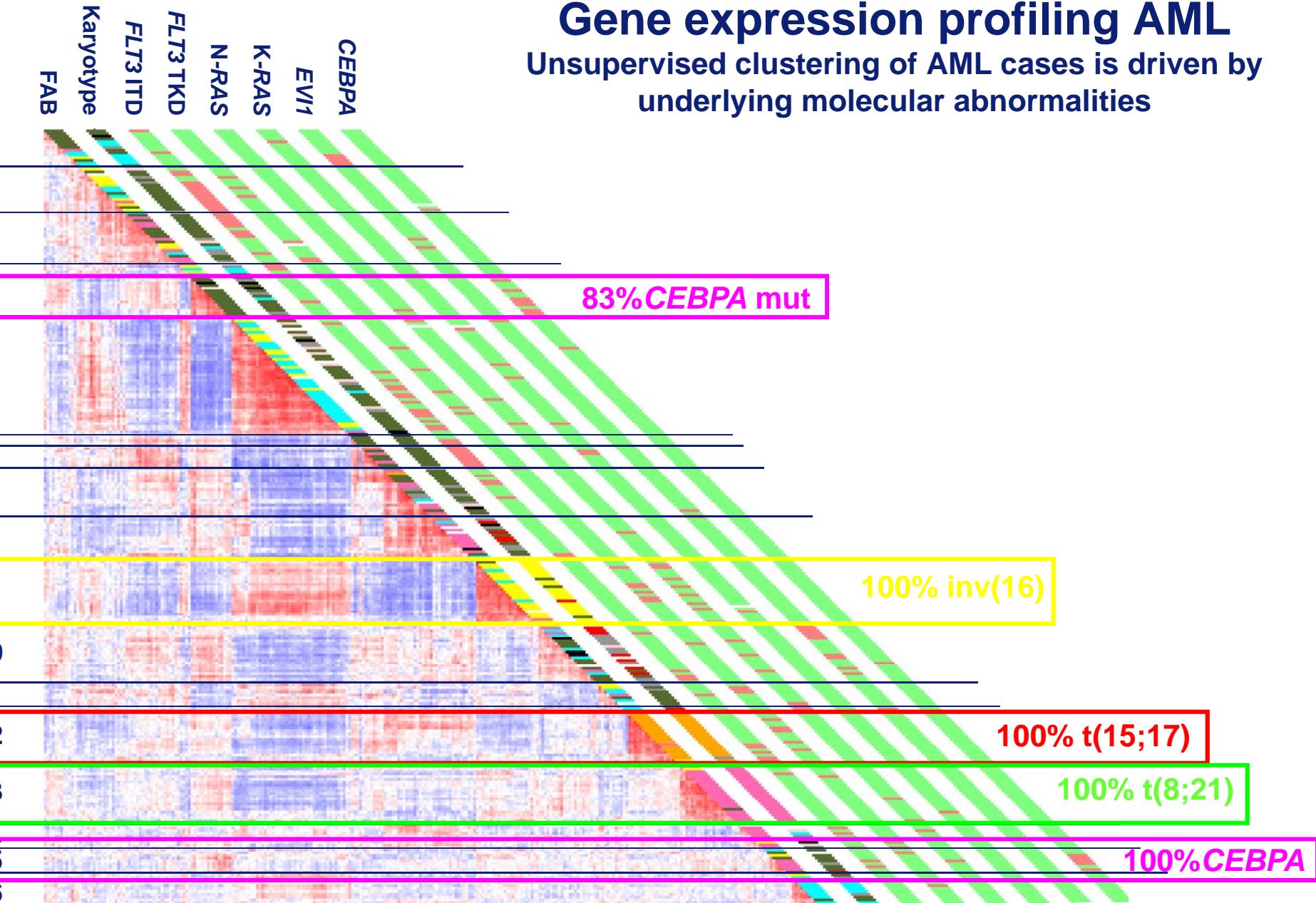
285 AML patients

↓
285 AML patients



Gene expression profiling AML

Unsupervised clustering of AML cases is driven by underlying molecular abnormalities



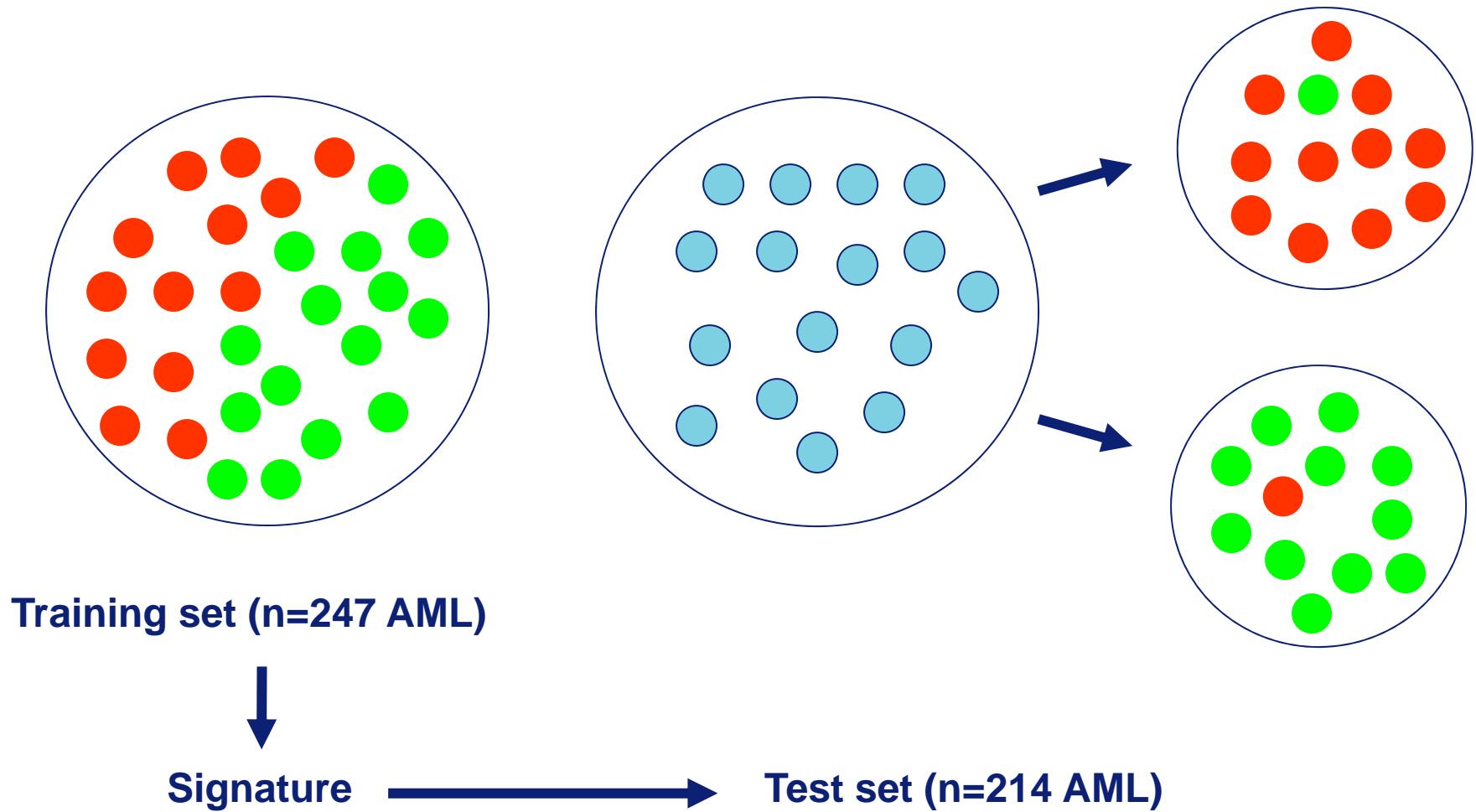
Class prediction in AML (<60 years)

Cytogenetic and molecular abnormalities

Are we able to predict outcome or the prognostically relevant (cyto)genetic abnormalities using representative AML cohorts?

Affymetrix U133 Plus2.0 GeneChip

Prediction by gene expression profiling in AML



Conclusion gene expression profiling AML

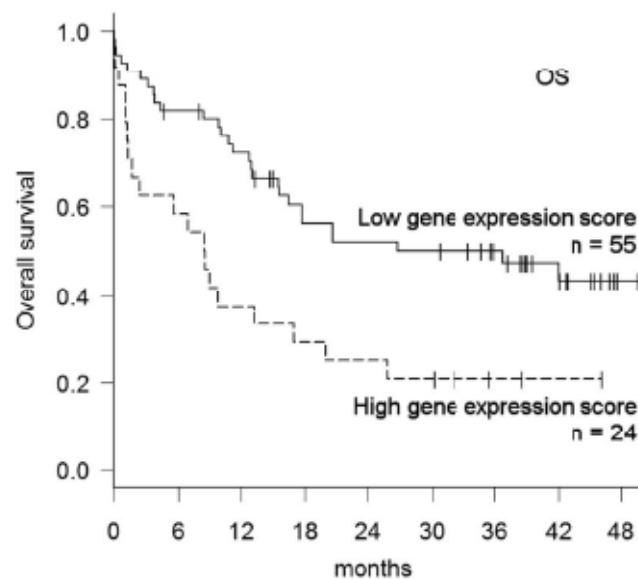
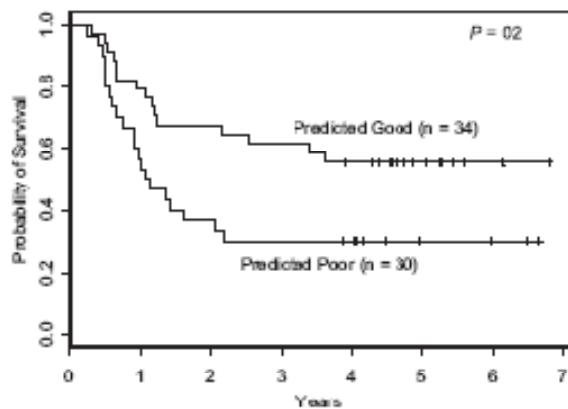
Class prediction

- Complete classification into good and poor treatment outcome possible based on gene expression profiling as single assay?

Classification error of 40% and higher

Gene expression signatures associated with OS in CN-AML

A



C

Predicted Overall Survival Outcome Group			
	Good	Poor	
Actual Overall Survival Outcome			
Alive	19	9	28
Dead	15	21	36
	34	30	64

Prediction Accuracy = 62.5%

86 probe set signature

Metzeler et al 2008

101 probe set signature

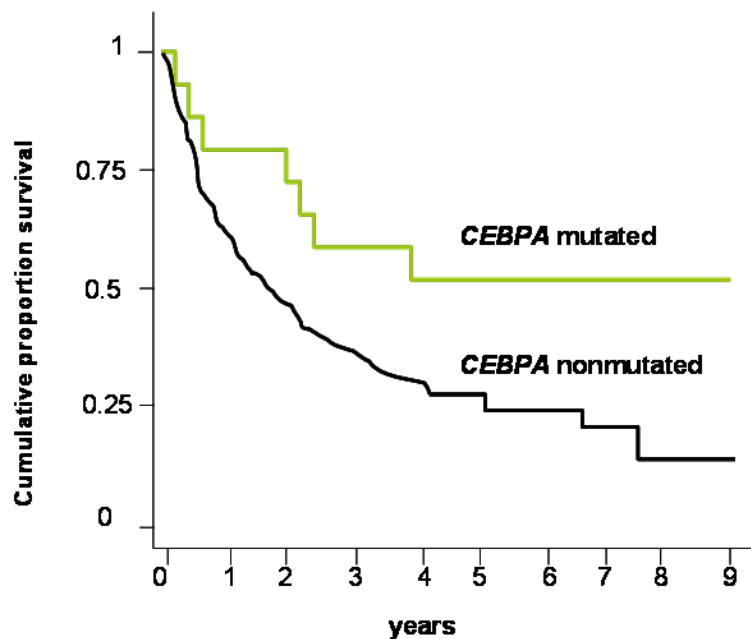
Radmacher et al 2006

Conclusion gene expression profiling AML

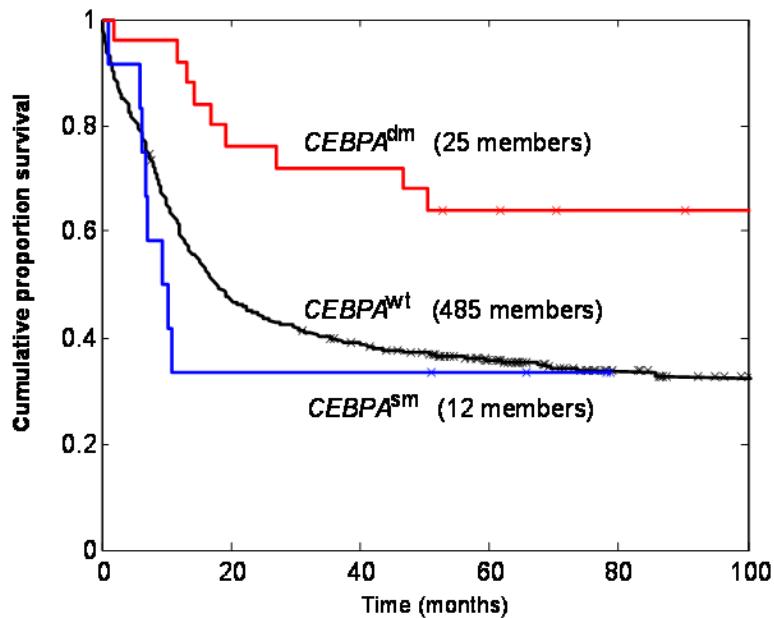
Class prediction

- Particular genetically defined subgroups, i.e., t(8;21), inv(16) and t(15;17) are predicted with high accuracy (positive and negative predictive value: 100%).
- *NPM1* and *CEBPA* mutations are predicted less accurate (positive predictive value: 94% and 70% and negative predictive value: 98 and 99%, respectively).
- Other recurrent molecular abnormalities are not accurately predictable using gene expression signatures.

Treatment outcome of AML single and bi-allelic *CEBPA* mutations



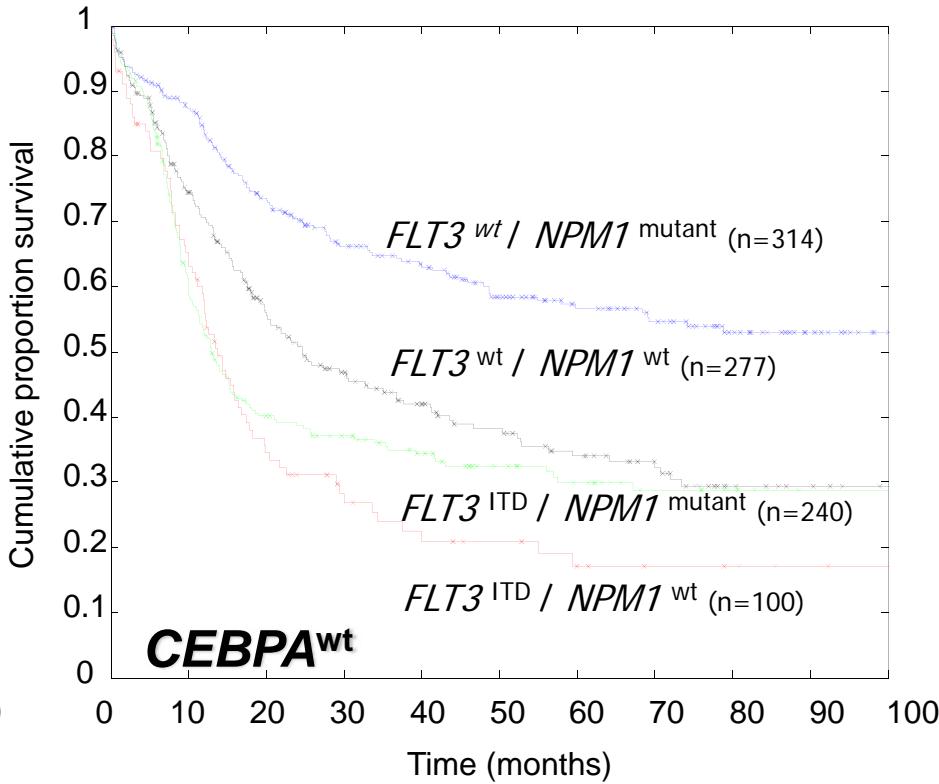
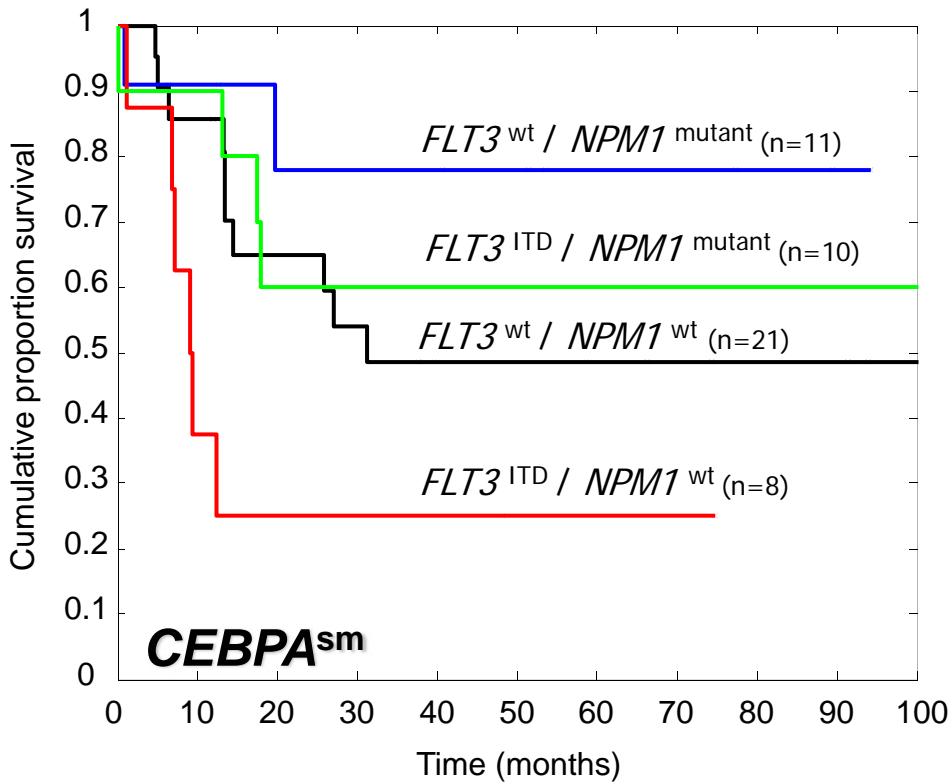
Preudhomme C. et al. (Blood 2002)
Waalwijk van Doorn B. et al. (Hematology 2003)
Fröhling et al. (JCO 2003)
Schlenk, R.F et al. (NEJM 2008)



Wouters B. et al, (Blood 2009)
Dufour, A., et al. (J. Clin. Oncol. 2009)
Hou, H.A., et al. (Br. J. Cancer 2009)
Pabst, T., et al. (Br. J. Cancer, 2009)
Green, C.L., et al. (J. Clin. Oncol. 2010)

Clinical outcome of *smCEBPA* depends on concurrent mutations

Four composite subgroups: $FLT3^{(wt/ITD)}$ / $NPM1^{(wt/mutant)}$



Survival of $CEBPA^{sm}$ follows the same trend as in $CEBPA^{wt}$

Clinical outcome in *CEBPA* subgroups

Multivariate analysis for overall survival (OS) in CN-AML

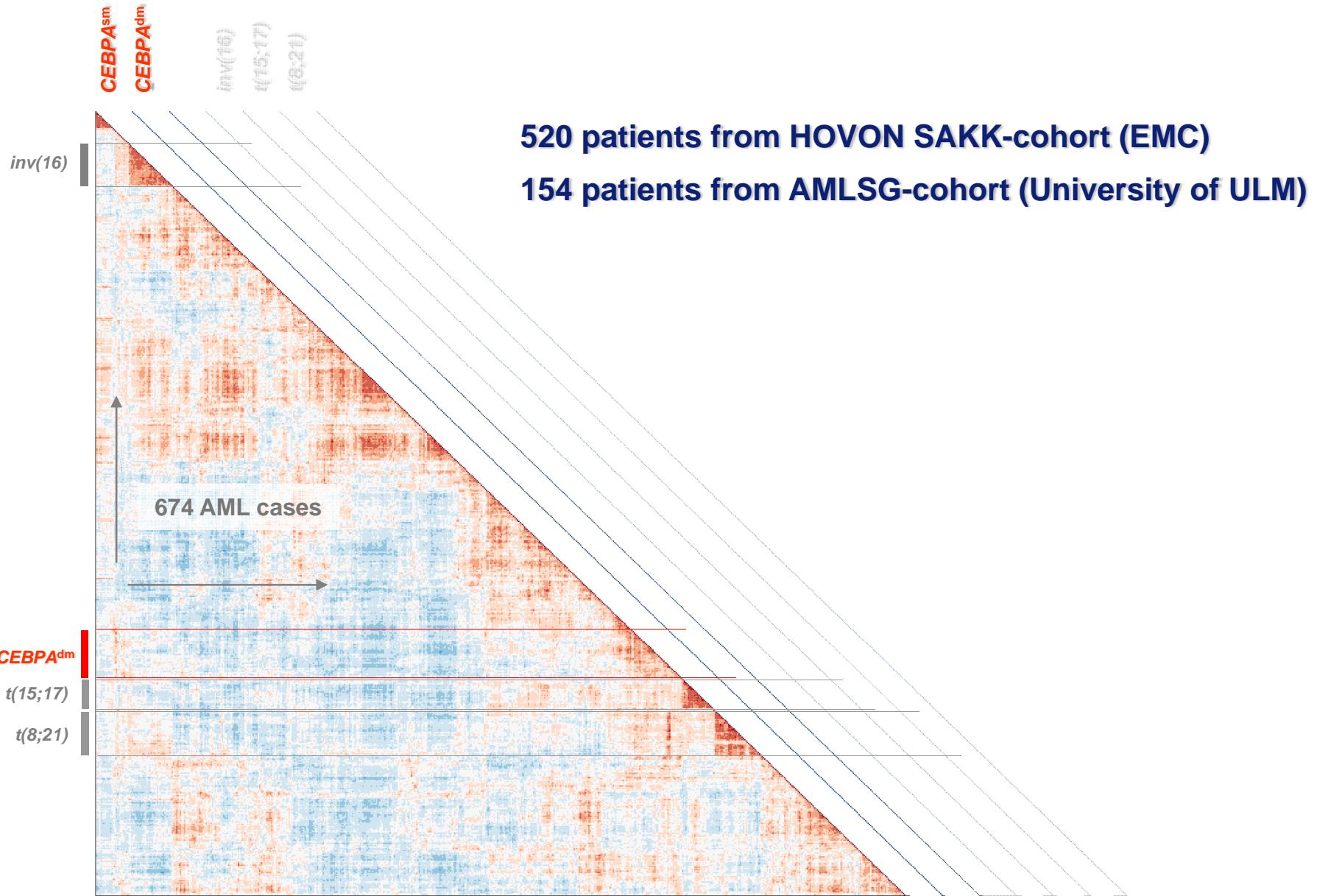
Variables	HR	95% CI	P* value
Overall survival			
<i>CEBPA</i> sm	0.73	0.48 - 1.11	.14
<i>CEBPA</i> ^{dm}	0.36	0.24 - 0.56	< .0001*
<i>FLT3</i> ^{ITD}	1.75	1.44 - 2.13	< .0001*
<i>FLT3</i> ^{TKD}	0.87	0.62 - 1.20	.41
<i>NPM1</i>	0.57	0.47 - 0.69	< .0001*
<i>NRAS</i>	1.07	0.81 - 1.42	.63
WBC count (x10 ⁹ /L)	1.27	1.05 - 1.53	.014*
Age	1.03	1.02 - 1.03	< .0001*

The presence of a double *CEBPA* mutation is an independent prognostic factor whereas a single *CEBPA* mutation is not

AML with CEBPA^{dm} versus CEBPAsm mutations

Is AML with CEBPA^{dm} different to AML with CEBPAsm?

Unsupervised gene expression analyses

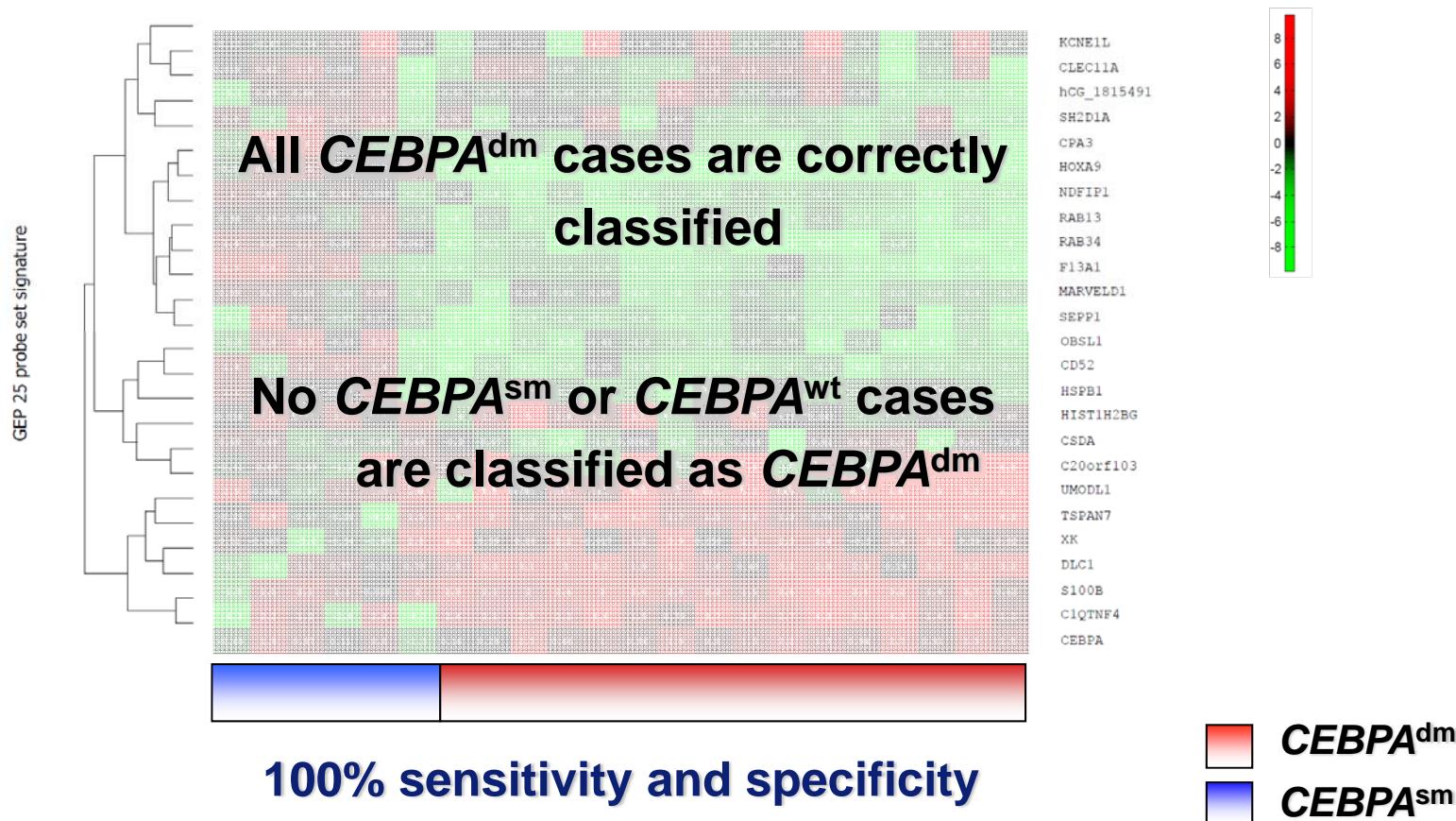


Supervised analyses: prediction of *CEBPA*^{dm}

Independent datasets (train: HOVON SAKK-, test: AMLSG-cohort)

Logistic regression model with lasso regularization

25 probe set predictive signature



Conclusions

CEBPA^{dm}

- › Is a unique subtype within AML
- › Is a prognostic factor which is associated with favorable clinical outcome
- › Significant lower incidence of concurrent mutations than wild-type *CEBPA*
- › Strong homogeneity in gene expression profile between patients
- › Classified with maximum specificity and sensitivity using GEP

AML: (cyto)genetic aberrations and prognosis

Good

Poor

Cytogenetics

t(8;21)	normal	-7, -5
inv(16)	-Y	t(3;3), inv(3)
t(15;17)	t(9;11)	t(6;9), t(v;11)
		complex

Mutations

NPM1 (*FLT3* wild type)
CEBPA

FLT3 ITD
c-KIT (t(8;21)/inv(16))
MLL PTD

Overexpression

EVI1
BAALC

Gene expression markers in AML

EVI1

BAALC

ERG

CD34

INDO1

FLT3

BCL2

MN1

WT1

ABCB1

Affymetrix U133Plus2.0



Prognostic gene expression markers in AML

Mutation and expression markers in intermediate risk AML

- 442 patients under age 60 newly diagnosed with AML
- AML-specific mutations considered for the analysis
 - ~~ ITD at fms-like tyrosine kinase-3 gene : **FLT3ITD**
 - ~~ TKD at fms-like tyrosine kinase-3 gene : **FLT3TKD**
 - ~~ Abberations of CCAAT/enhancer binding protein alpha:
CEBP double mutation
 - ~~ Insertion in the nucleophosmin : **NPM1**
 - ~~ Mutation at GTP-ase **NRAS**
- Selected expression markers considered for the analysis
 - ~~ **BAALC, CD34, MN1, ERG, ABCB1, BCL2, WT1, EVI1, FLT3, INDO1**

Prognostic gene expression markers in AML

Mutation and expression markers in intermediate risk AML

Mutation	Cytogenetical subgroup						P-value
	t(8;21)	inv(16)	t(15;17)	CN	CA	MK	
FLT3 ITD							< 0.0001
No	32	37	17	110	101	27	
Yes	3	0	8	82	25	0	
FLT3 TKD							0.048*
Neg	34	30	19	172	114	26	
Pos	1	7	6	20	12	1	
N-RAS							< 0.0001*
Neg	32	25	25	174	119	24	
Pos	3	12	0	18	7	3	
NPM1							< 0.0001
Neg	35	37	25	79	110	26	
Pos	0	0	0	113	16	1	
CEBP DM							0.034*
Neg	35	37	25	174	121	27	
Pos	0	0	0	18	5	0	
FLT3 ITD×NPM1							*
Neg Neg	32	37	17	58	91	26	
Neg Pos	0	0	0	52	10	1	
Pos Neg	3	0	8	21	19	0	
Pos Pos	0	0	0	61	6	0	

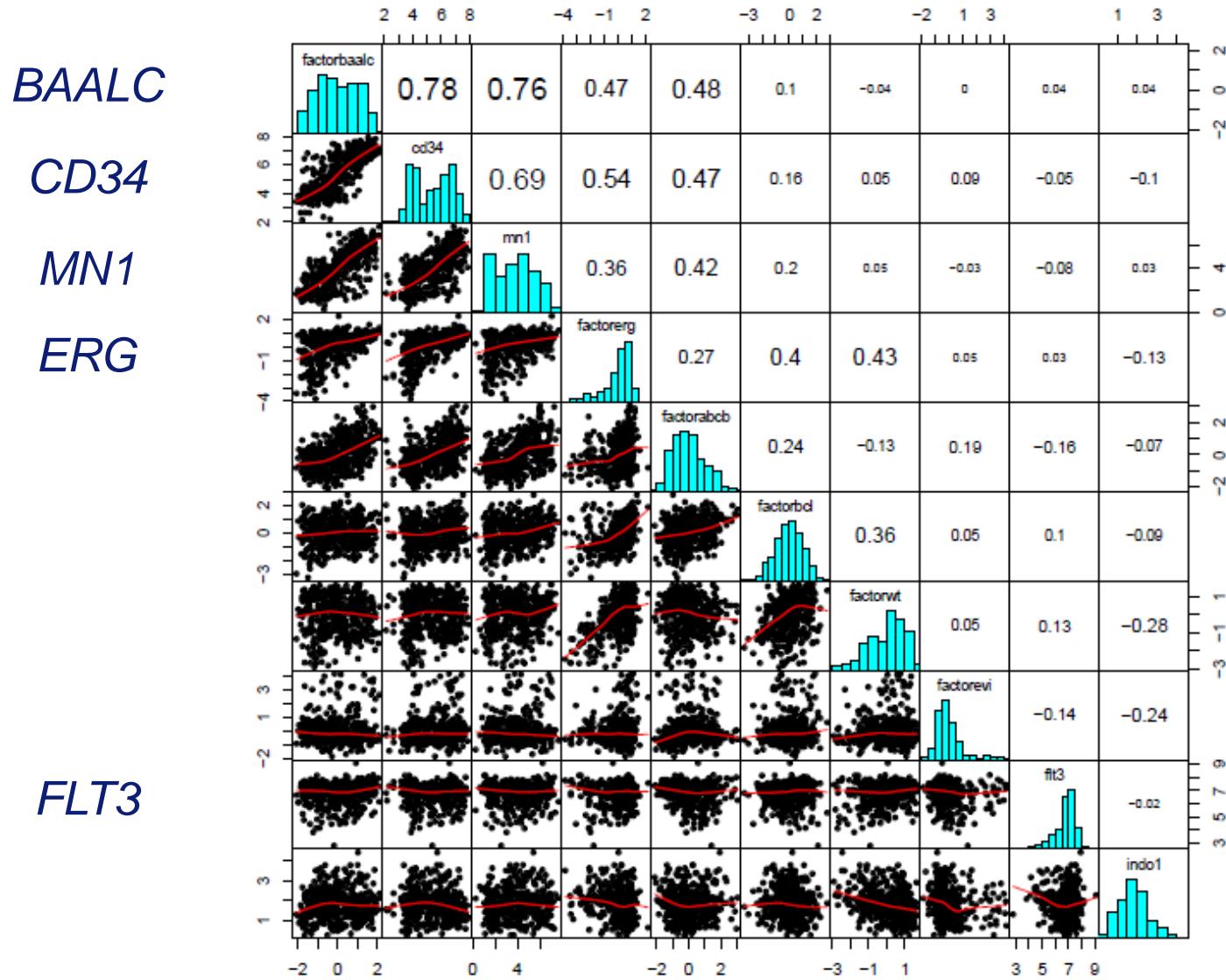
Prognostic gene expression markers in AML

Association between mutation and expression markers in intermediate risk AML

		BAALC	CD34	MN1	ERG	ABCB	BCL	WT	EVI	FLT3	INDO1
CEBP DM	p-value	0.062	0.003	0.006	0.001	<0.001	0.258	0.008	0.518	0.002	0.963
	Median difference	0.39	1.11	0.98	0.36	1.7	0.21	-0.52	-0.08	-0.62	0.05
FLT3ITD	p-value	<0.001	0.005	<0.001	0.832	<0.001	0.205	<0.001	0.039	<0.001	0.572
	Median difference	-0.51	-0.68	-0.92	0.01	-0.63	-0.03	0.44	-0.13	0.22	-0.06
FLT3TKD	p-value	0.002	0.005	0.058	0.188	0.001	0.126	0.352	0.525	0.152	0.021
	Median difference	-0.75	-1.10	-0.80	-0.06	-0.41	-0.24	0.19	-0.06	0.03	-0.40
NRAS	p-value	0.118	0.176	0.001	0.034	0.492	0.312	0.154	0.823	0.047	0.952
	Median difference	0.47	0.40	-1.06	-0.25	-0.10	-0.24	-0.12	0.07	-0.14	0.03
NPM1	p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.137	0.004	0.101
	Median difference	-1.22	-2.07	-2.07	-0.46	-0.83	-0.33	0.42	-0.04	0.17	-0.15

Prognostic gene expression markers in AML

Association between expression markers in intermediate risk AML



Prognostic gene expression markers in AML

Univariate survival analysis

Variable	Overall Survival						Event Free Survival					
	Hazard Ratio	Lower	Upper	p-value	Survival	Hazard Ratio	Lower	Upper	p-value	Survival		
CEBP DM	-	0.38	0.19	0.74	0.004	0.328	0.45	0.25	0.81	0.007	0.244	
	+					0.652					0.522	
FLT3ITD	-	1.41	1.06	1.86	0.017	0.384	1.3	0.99	1.7	0.059	0.275	
	+					0.287					0.242	
NPM1	-	0.73	0.55	0.97	0.03	0.296	0.69	0.53	0.9	0.006	0.207	
	+					0.432					0.347	
FLT3TKD	-	0.82	0.51	1.32	0.418	0.341	0.74	0.47	1.16	0.192	0.255	
	+					0.438					0.344	
NRAS	-	0.94	0.57	1.54	0.798	0.349	1.23	0.77	1.94	0.386	0.268	
	+					0.378					0.215	
FLT3ITD× NPM1	++	1.03	0.72	1.47	0.875	0.355	0.9	0.64	1.27	0.549	0.312	
	- +	0.63	0.42	0.94	0.022	0.515	0.64	0.45	0.93	0.018	0.386	
	+ -	1.67	1.13	2.46	0.01	0.171	1.76	1.21	2.58	0.003	0.125	
	--					0.329					0.229	
BAALC		1.32	1.14	1.52	<0.001	0.358	1.29	1.13	1.48	<0.001	0.267	
CD34		1.28	1.15	1.41	<0.001	0.373	1.26	1.14	1.39	<0.001	0.278	
MN1		1.13	1.05	1.23	0.002	0.358	1.14	1.05	1.23	<0.001	0.269	
ERG		1.24	1.09	1.42	0.001	0.324	1.23	1.08	1.4	0.001	0.238	
ABCB		1	0.88	1.14	0.983	0.352	0.98	0.87	1.11	0.793	0.264	
BCL		1.01	0.89	1.15	0.861	0.352	1.03	0.91	1.16	0.644	0.265	
WT		1.12	0.98	1.28	0.092	0.344	1.11	0.98	1.26	0.106	0.258	
EVI		1.1	0.96	1.26	0.168	0.361	1.16	1.02	1.33	0.028	0.276	
FLT3		0.97	0.83	1.14	0.746	0.354	0.93	0.8	1.08	0.348	0.27	
INDO		0.9	0.76	1.08	0.254	0.353	0.92	0.78	1.08	0.3	0.265	

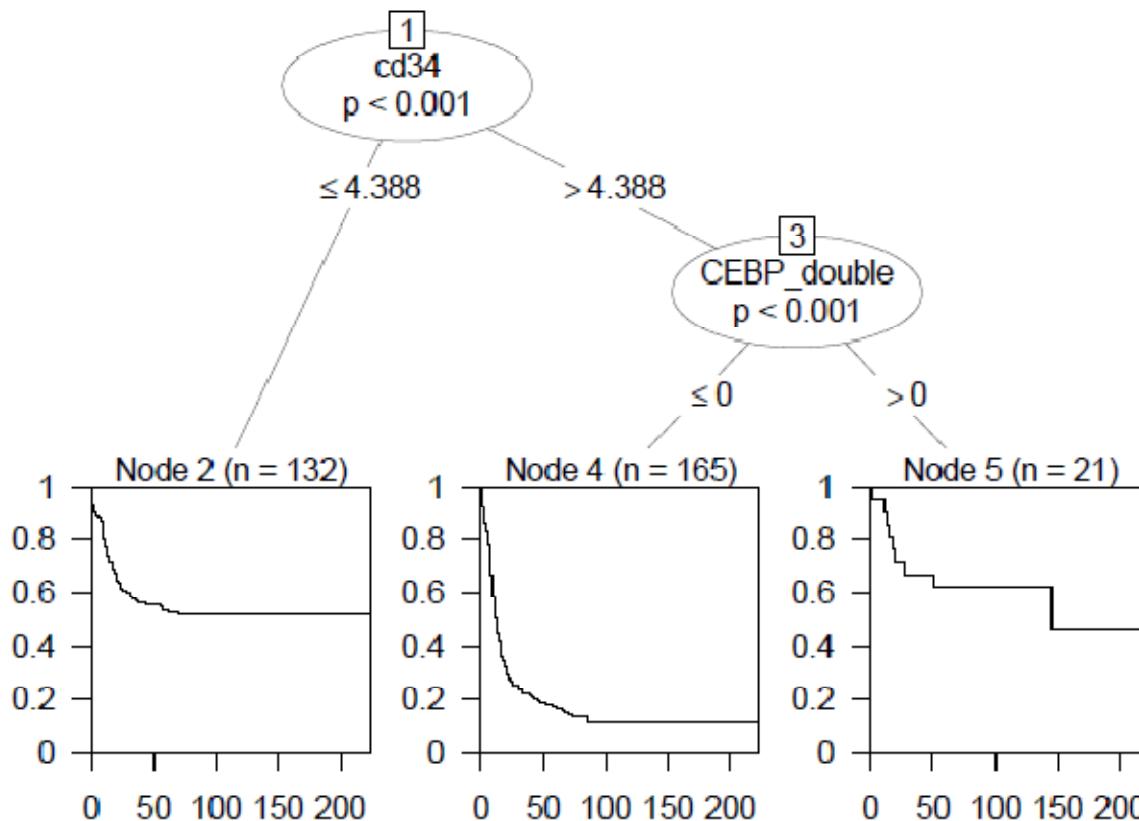
Prognostic gene expression markers in AML

Multivariate survival analysis

Variable	Overall survival					Event free survival				
	Hazard Ratio	Lower	Upper	p-value	Hazard Ratio	Lower	Upper	p-value		
BAALC	1.099	0.826	1.462	0.518	1.052	0.804	1.376	0.711		
CD34	1.333	1.099	1.618	0.004	1.292	1.077	1.548	0.006		
MN1	0.942	0.812	1.091	0.424	0.960	0.828	1.112	0.586		
ERG	1.236	0.981	1.558	0.073	1.228	0.990	1.523	0.061		
ABCB	0.925	0.768	1.113	0.409	0.890	0.748	1.060	0.192		
BCL	0.828	0.699	0.982	0.030	0.862	0.732	1.014	0.072		
WT	0.941	0.777	1.140	0.536	0.930	0.774	1.116	0.434		
EVI	1.011	0.876	1.168	0.879	1.057	0.916	1.220	0.449		
FLT3	0.919	0.766	1.102	0.363	0.914	0.766	1.092	0.322		
INDO1	0.921	0.750	1.131	0.434	0.928	0.766	1.125	0.449		
CEBP	0.299	0.161	0.557	0.0001	0.330	0.187	0.582	0.0001		
FLT3ITD	1.265	0.813	1.970	0.298	1.536	1.001	2.357	0.050		
FLT3TKD	1.200	0.714	2.017	0.491	1.007	0.616	1.645	0.979		
NRAS	1.039	0.619	1.742	0.886	1.328	0.820	2.149	0.249		
NPM1	0.737	0.434	1.251	0.259	0.741	0.450	1.221	0.239		
FLT3ITD:NPM1	1.214	0.646	2.281	0.546	0.855	0.470	1.557	0.609		

Prognostic gene expression markers in AML

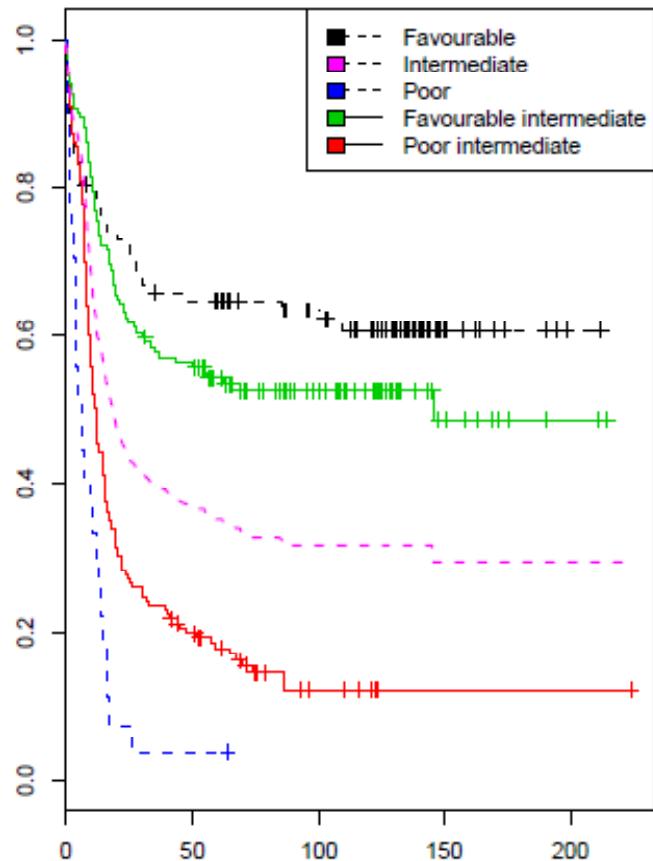
Risk-stratification modeling



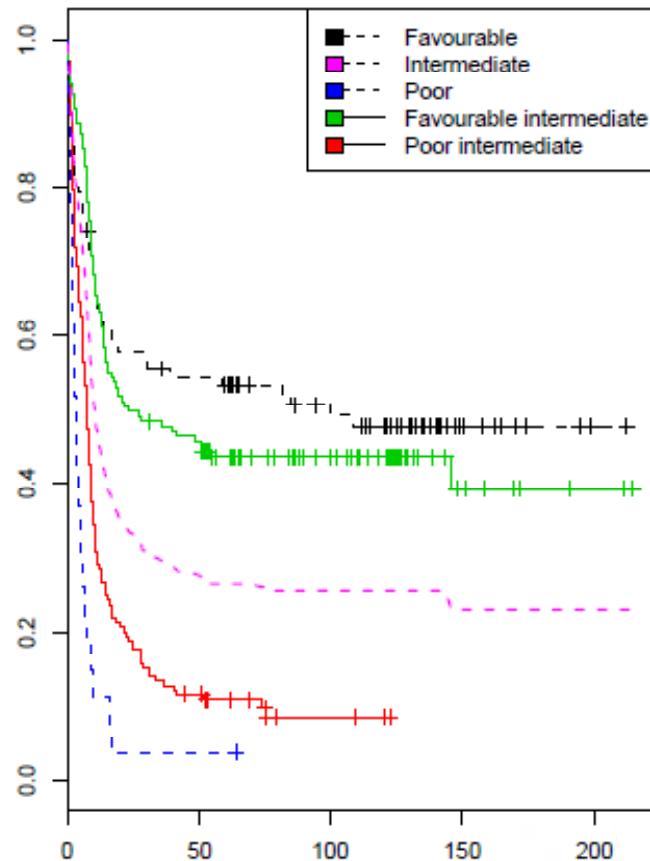
Prognostic gene expression markers in AML

Risk-stratification in intermediate-risk AML

Overall survival: risk stratification



Event free survival: risk stratification



Conclusions

- We have confirmed prognostic ability of some established markers in AML
- We have demonstrated that **CD34 has dominant predictive effect**
- In the hierarchy of importance, **CEBPDM** is the second most **important marker**
- The combination of CD34 and CEBPDM can contribute in risk stratification of the intermediate group

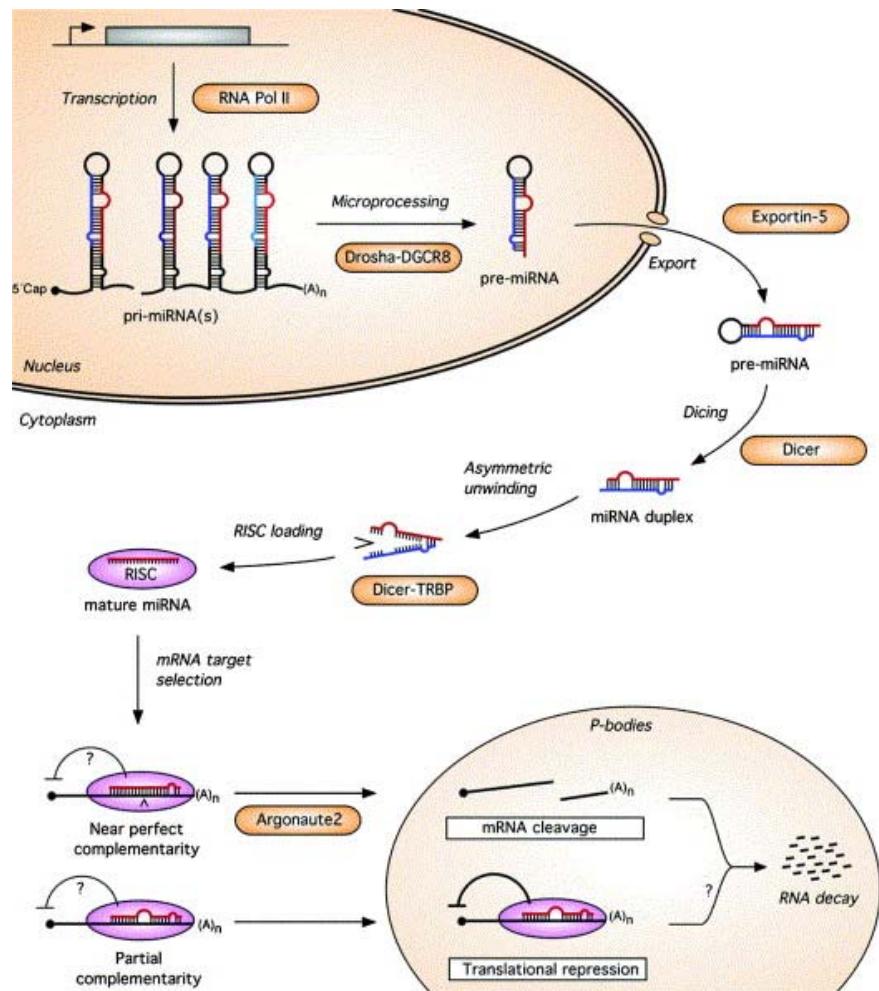
microRNAs in AML

Small conserved RNAs (20-23 nt)

Non-protein coding

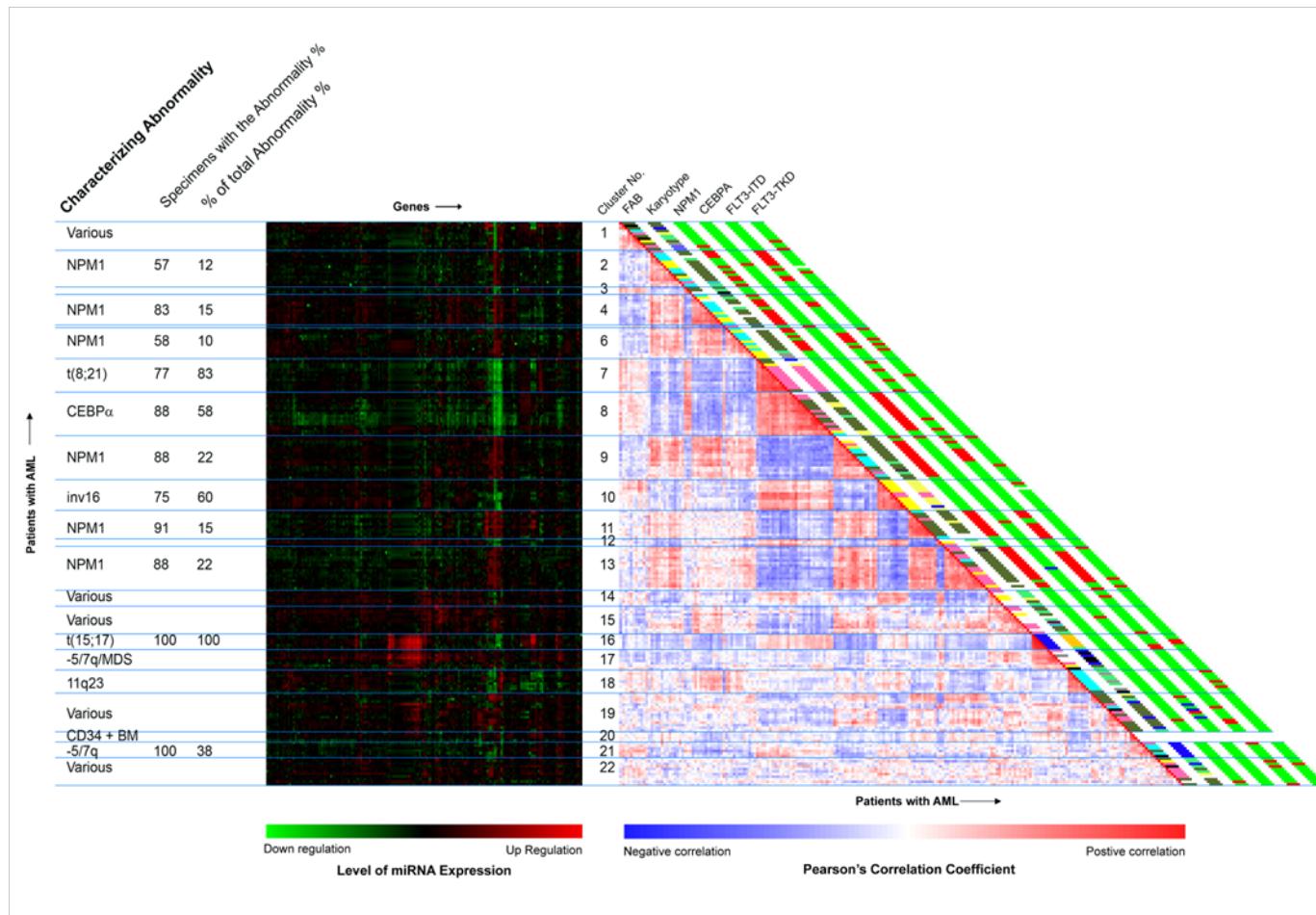
Regulate translation

Bind 3' UTR mRNA



MicroRNA Expression Profiling (GEP) in AML

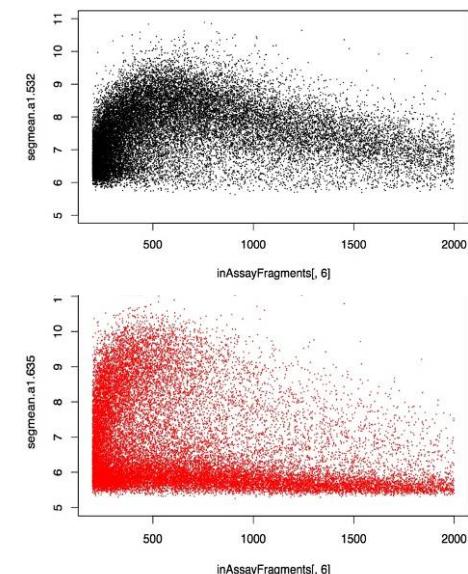
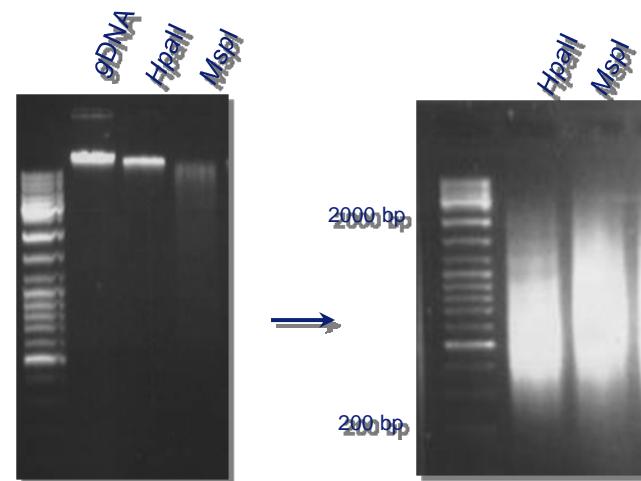
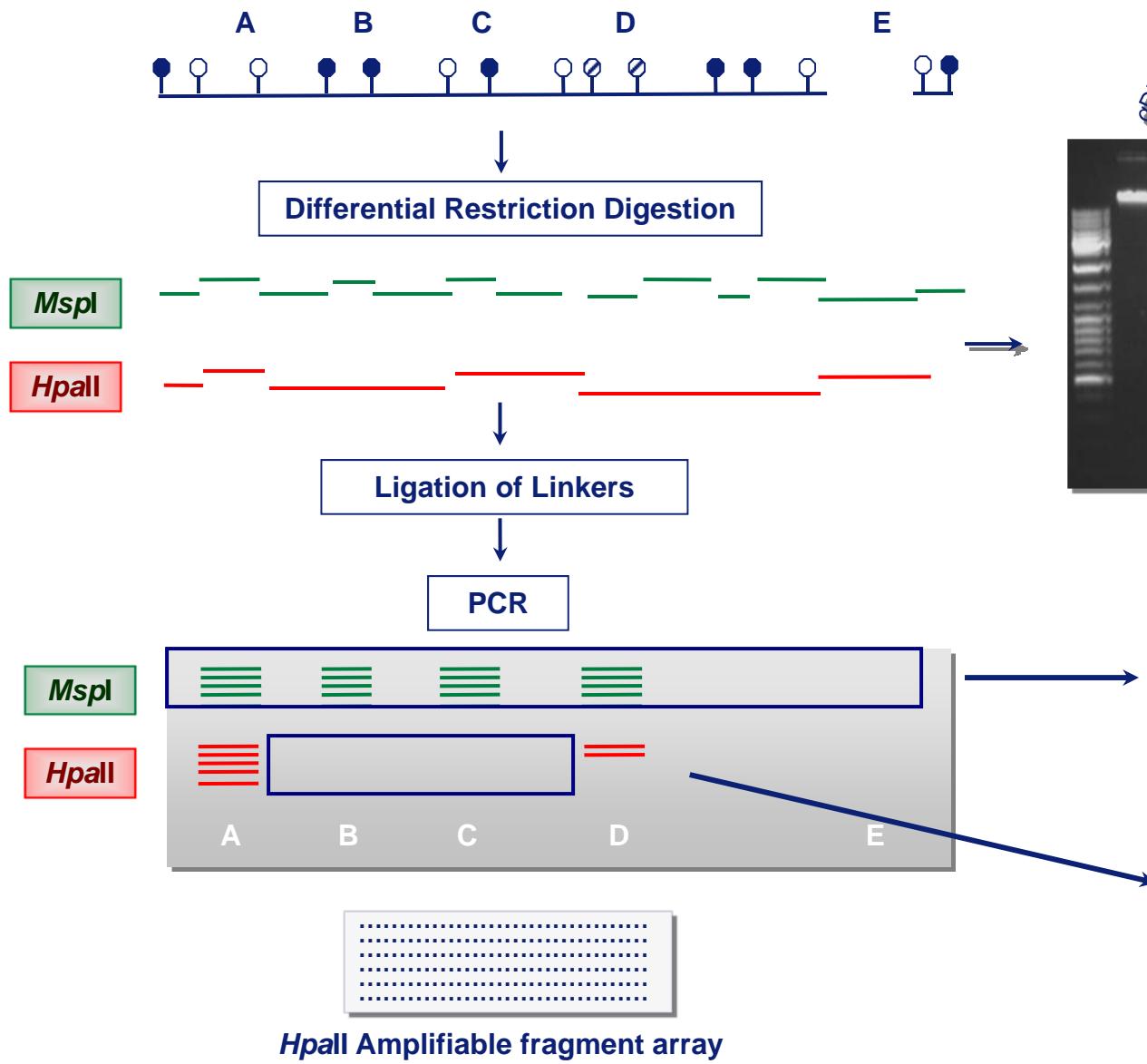
Unsupervised clustering and class comparison



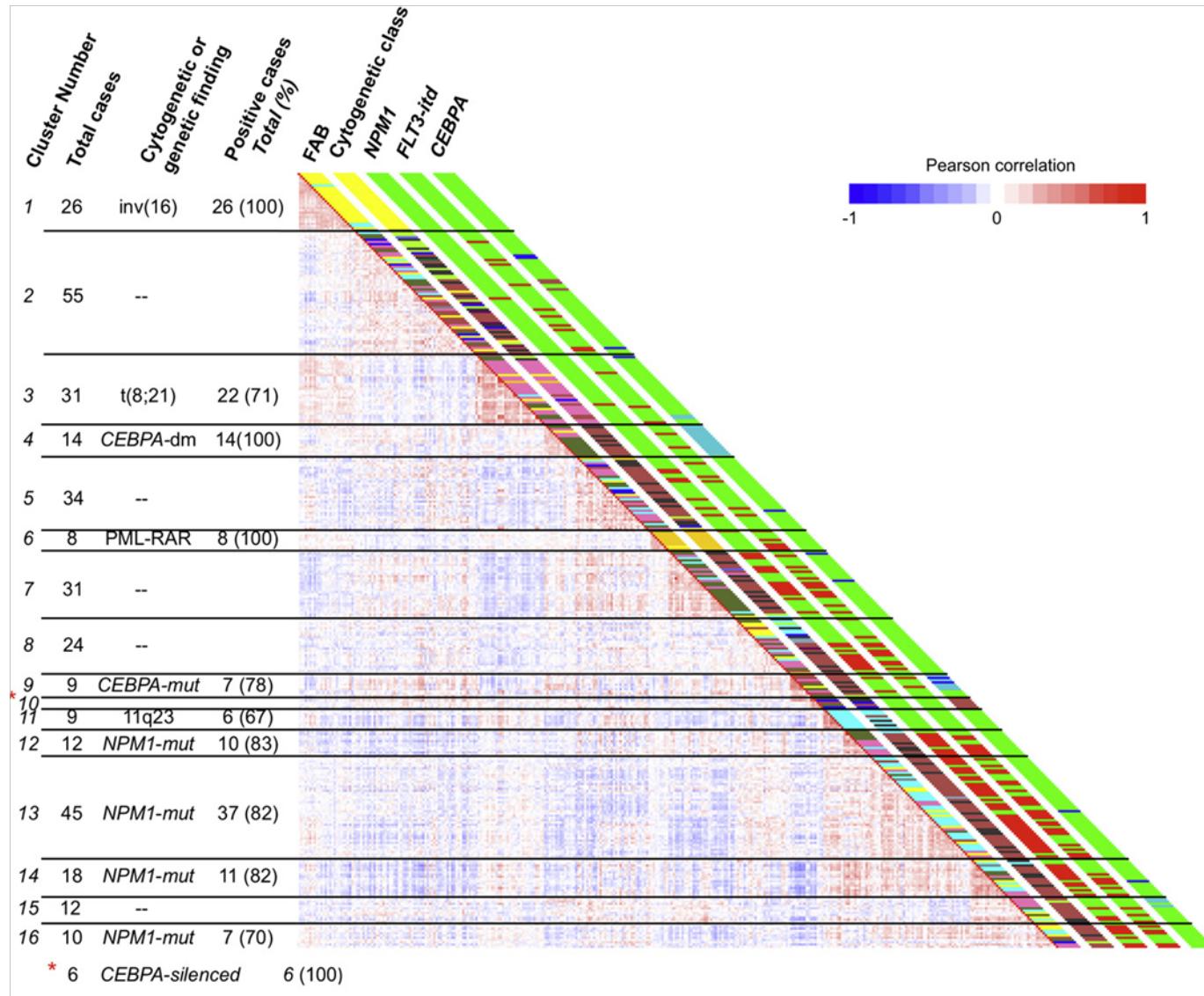
Jongen et al., 2008

Methylation profiling of AML

HELP Assay voor genoom-brede 5me-Cy detectie



Methylation profiling AML



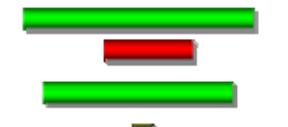
Genome wide genotyping of AML

Identification of novel (recurrent) abnormalities

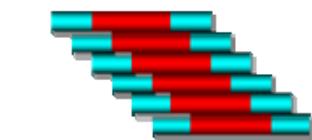
Affymetrix 500K Mapping SNP GeneChips



RE Digestion



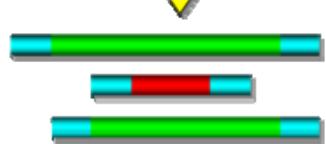
N_{sp}I (250K)



PCR : One Primer
Amplification

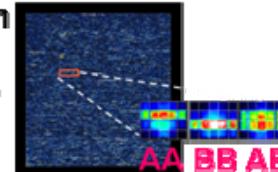
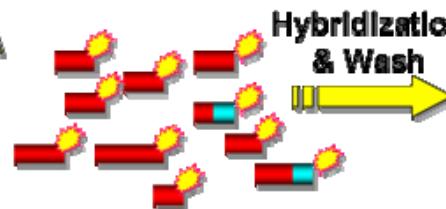


Complexity
Reduction



S₁ I (250K)

Fragmentation
and End Labeling

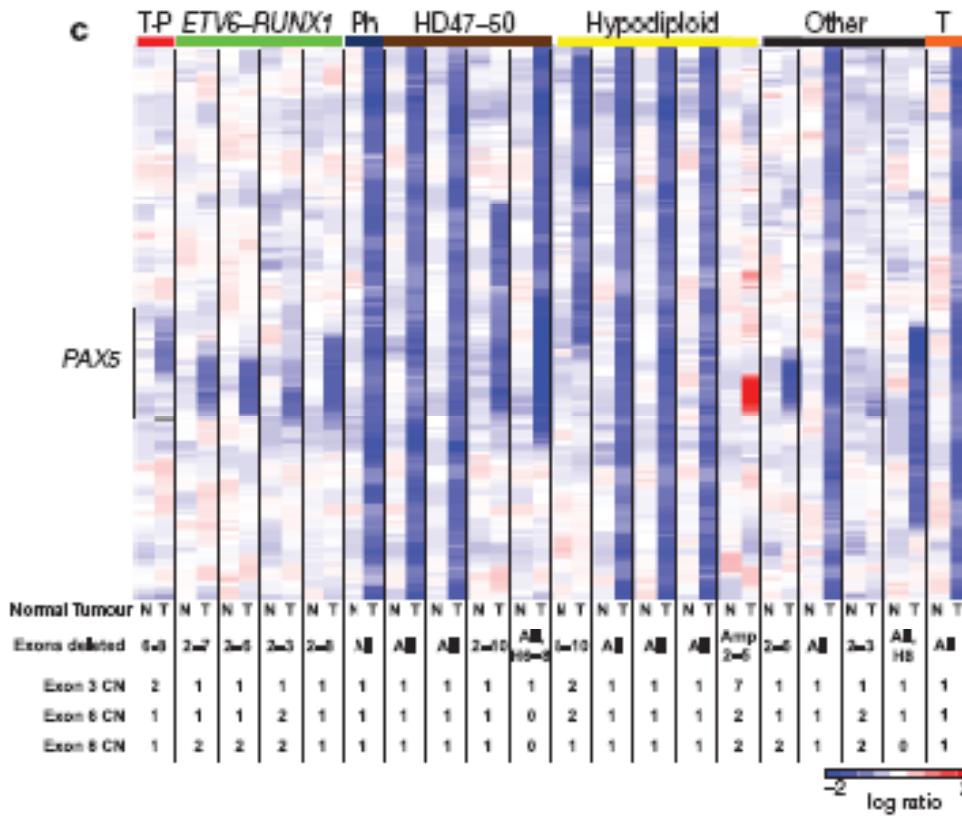


Genotype

Copy number (normal diploid genome as reference) Erasmus MC

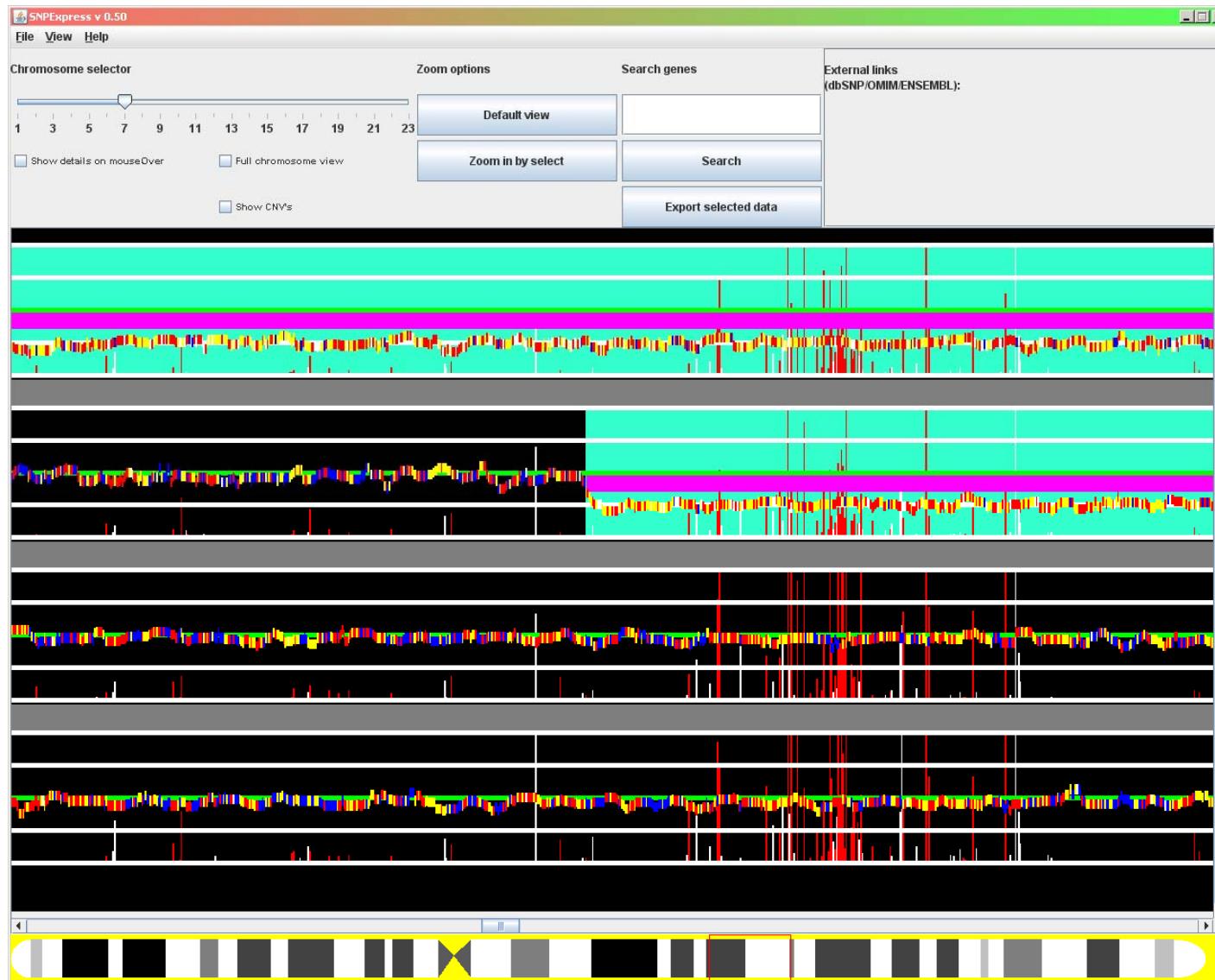
Erasmus

Genome-wide genotyping of ALL



Mullighan et al., 2007

Genome-wide genotyping and gene expression SNPExpress



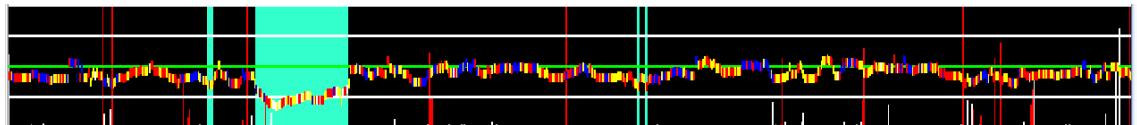
Sanders et al., BMC Genomics 2008

Erasmus MC
Ezafus

Genome-wide genotyping and gene expression of AML

SNPExpress

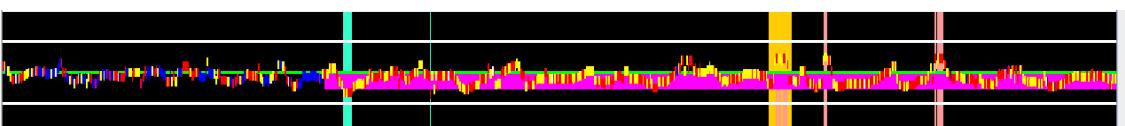
Deletion : tumor suppressor gene



Amplification : oncogene



Uni parental dysomy : recessive mutations



'Cryptic' translocations?

Genome-wide genotyping **AML versus ALL**

ALL many recurrent aberrations present
(PAX5 and IKAROS)

AML few (recurrent) aberrations present
(Downing/Young/others)

→ RAG-mediated rearrangements in ALL

Whole genome sequencing AML

nature

Vol 456 | 6 November 2008 | doi:10.1038/nature07485

ARTICLES

DNA sequencing of a cytogenetically normal acute myeloid leukaemia genome

Timothy J. Ley^{1,2,3,4*}, Elaine R. Mardis^{2,3*}, Li Ding^{2,3}, Bob Fulton³, Michael D. McLellan³, Ken Chen³, David Dooling³, Brian H. Dunford-Shore³, Sean McGrath³, Matthew Hickenbotham³, Lisa Cook³, Rachel Abbott³, David E. Larson³, Dan C. Koboldt³, Craig Pohl³, Scott Smith³, Amy Hawkins³, Scott Abbott³, Devin Locke³, LaDeana W. Hillier^{3,8}, Tracie Miner³, Lucinda Fulton³, Vincent Magrini^{2,3}, Todd Wylie³, Jarret Glasscock³, Joshua Conyers³, Nathan Sander³, Xiaoqi Shi³, John R. Osborne³, Patrick Minx³, David Gordon⁵, Asif Chinwalla³, Yu Zhao¹, Rhonda E. Ries¹, Jacqueline E. Payton⁵, Peter Westervelt^{1,4}, Michael H. Tomasson^{1,4}, Mark Watson^{3,4,5}, Jack Baty⁶, Jennifer Ivanovich^{4,7}, Sharon Heath^{1,4}, William D. Shannon^{1,4}, Rakesh Nagarajan^{4,5}, Matthew J. Walter^{1,4}, Daniel C. Link^{1,4}, Timothy A. Graubert^{1,4}, John F. DiPersio^{1,4} & Richard K. Wilson^{2,3,4}

THE NEW ENGLAND JOURNAL OF MEDICINE

ORIGINAL ARTICLE

Recurring Mutations Found by Sequencing an Acute Myeloid Leukemia Genome

Elaine R. Mardis, Ph.D., Li Ding, Ph.D., David J. Dooling, Ph.D.,
David E. Larson, Ph.D., Michael D. McLellan, B.S., Ken Chen, Ph.D.,
Daniel C. Koboldt, M.S., Robert S. Fulton, M.S., Kim D. Delehaunty, B.A.,
Sean D. McGrath, M.S., Lucinda A. Fulton, M.S., Devin P. Locke, Ph.D.,

1000 mutations per
AML

'driver' versus
'passenger'
mutations

IDH1 mutations

General conclusions

All genome-wide approaches are strongly associated with the known (cyto)genetic subgroups (genetics and epi-genetics)

A number of novel subtypes of AML have been identified using the novel technologies

Validation of these novel subtypes in independent studies is essential, but difficult

Integrated analyses of the various genome-wide data sets

AML is not a single disease, one should study AML within relatively homogeneous subsets, such as t(8;21) inv(16) or mutant CEBPA

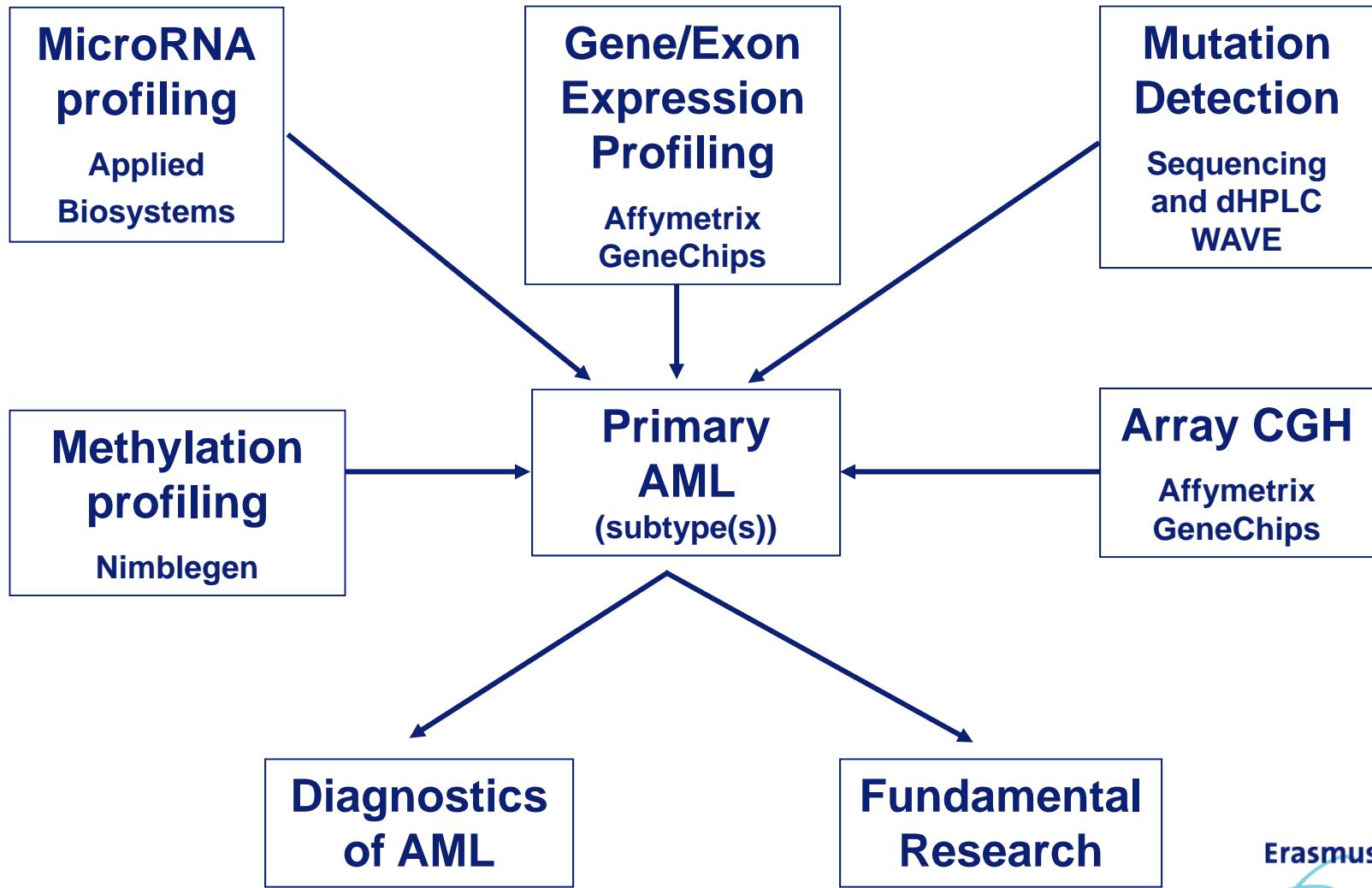
Next generation sequencing may replace microarray analyses

Gene/microRNA expression

Methylation profiling

Novel markers

Genome-wide Approaches to Identify New Subtypes of AML



Contribution of microarrays in Acute Myeloid Leukemia diagnostics

ErasmusMC Hematology

Peter Valk
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Chantal Goudswaard
Bas Wouters
Antoinette Beijen
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Ruud Delwel
Bob Löwenberg

ErasmusMC Clinical Genetics

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ErasmusMC Trial and Statistics

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