### A three-state model for multidimensional data integration

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# Outline

- GBM Data
- Low-level analyses
- Pipeline and timeline
- Access to TCGA data
- Data integration real challenge
- Strategy for integrative analysis
- Results
- Discussion
- Remarks



### GBM Data





### mRNA level 1 data

- 495 tumor samples and 10 controls
- normalized using quantile normalization
- summarized using medianpolish
- classification based on log fold-change, B-statistic and adjusted p-values



### miRNA level 2 data

- 245 tumor sam- ples and 10 controls
- According to TCGA portal data were background corrected using RMA and quantile normalized.







### Methylation level 2 data

- from 291 tumor samples and 1 control with 6 replicates
- normalized and processed using genome wide Infinium HumanMethylation27 BeadChip Array
- ~ 27,578 CpG sites.
- Beta-values and confidence p-values were further examined
- Missing beta-values were calculated using the signal intensity (M) and the un-methylated signal intensity (U).



### CNVs level 3 data

- Data for 461 samples processed with array CGH technology
- Data reported to be lowess normalized.
- Regions of gain and loss were identified using Circular Binary Segmentation algorithm

Our part:

- Which genes are in each reported segment?
- Algorithm



### NGS level 3 data

- somatic nucleotide alteration data for 143 samples in 3 databases were analyzed.
- The three databases were combined and relevant mutations were selected.
- The final database contained 1032 unique gene-mutation pairs, for 500 different genes and 7 different mutation types:





### Clinical Data

### IDs curated "TA.0001.F.D.44.WT.NPG.RA.CH.B1"

- T : describes sample type (T=Primary Tumor, B=Blood Derived Normal, N=Solid Tumor Tissue)
- A : indicates replicate A=1, B=2
- "0001": corresponds to patient ID
- F : indicates gender (F=Female, M=Male)
- D : corresponden al Vital status (D= Deceased, L=Living)
- "44" : is the patient's age
- Cancer status: WT=with tumor,TF= tumor free
- Prior glioma: PG= Prior glioma,NPG=non-prior glioma
- Therapy: CH= chemotherapy,HO=hormonal therapy,IM= immuno therapy,RA=radiations therapy,TM= targeted molecular therapy

### All Data



- Genome\_Wide\_SNP\_6 --> GWS6
- HG-CGH-244A --> CGH244
- HumanHap550 --> Hh550
- HumanMethylation27 --> HMet27
- IlluminaDNAMethylation --> IllMet
- HT\_HG-U133A --> Exp133A
- HuEx-1\_0-st-v2 --> ExpExon
- AgilentG4502A\_07 --> ExpAgi
- H-miRNA\_8x15K --> ExpmiR
- ABI --> ABI
- HG-CGH-415K\_G4124A --> CGH415



# TCGA data portal

### Notes & Remarks

- Gene expression data from three different platforms was badly combined. So can't always trust level 3 data ...
- Access to SNP 6.0 array data would have given us the opportunity of doing some ancestry analysis
- Access to Level 1 Human Gene 1.0 ST would have given us a chance to do outlier detection using COPA



#### PROJECT: TCGA GLIOBLASTOMA MULTIFORME PLATFORM PARTICIPATION

MARCH 29 START-UP & ASSIGNATION

INTEGRANTE	PLATAFORMA												
	GE	miRNA	Meth	CNV	SNP	Clin	NGS						
Claudia Rangel													
Enrique Hernández													
Alfredo Hidalgo													
Mauricio Rodríguez													
Rodrigo García													
Claudia Hernández													
Iván Imaz													
Iván Salido													
Rodrigo Flores													
Rodrigo Mendoza													
Karol Baca													
María D. Correa													
Aldo Josué Huerta													
Ana Victoria Martínez													
Alejandra Medina													

Nomenclature	
GE	gene transcript expresión (435 cáncer patients versus 11 control)
miRNA	miRNA expression (426 tumour samples versus 10 controls)
Meth	genomic DNA methylation (256 tumour samples versus a control)
CNV	copy number variation (465 tumour samples vs 430 controls [402 matched normals])
SNP	SNPs
Clin	clinical parameters and survival outcomes
NGS	sequencing



INTEGRANTE	PLATAFORMA											
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Aldo Josué Huerta												
Ana Victoria Martínez												
Alejandra Medina												

#### APRIL 5 TO 19: RESEARCH

#### APRIL 26: RESEARCH & EXECUTION

INTEGRANTE							
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Claudia Rangel							
Enrique Hernández							
Alfredo Hidalgo							
Mauricio Rodríguez							
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Karol Baca							
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Aldo Josué Huerta							
Ana Victoria Martínez							
Alejandra Medina							

#### MAY 3: EXECUTION & MONITORING

#### MAY 10: EXECUTION & MONITORING

INTEGRANTE	PLATAFORMA											
	GE	miRNA	Meth	CNV	SNP	Clin	NGS					
Claudia Rangel												
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#### MAY 17: CONCLUSIONS

INTEGRANTE	PLATAFORMA											
	GE	miRNA	Meth	CNV	SNP	Clin	NGS					
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# Computational Genomics



# Strategy for integrative analysis

3-State Model



# Three-State Model

- Combinatorial data driven approach
- We first selected the list for most significant genes based on mRNA levels
- For each gene *i*, let  $S_{i1}$ ,  $S_{i2}$ , ...,  $S_{ik}$  be a sequence of states where  $S_{ik}$  denotes the state of gene *i* in platform *k*
- Each state can take values {-1,0,1} based on whether it reports to be *up*, with *no change* or *down* regulated respectively.
- Platforms are combined following basic set theory

$$P_i \bigcup P_j = (P_i \cap P_j) \bigcup (P_i \setminus P_j) \bigcup (P_j \setminus P_i)$$



### Three-State Model

### Example

- Suppose we choose 3-Platform approach {Mutation, Methylation, mRNA}
- A gene taking values {1,-1,1} indicates that it contains somatic nucleotide alteration, is hypo-methylated and differentially up-regulated



### How many scenarios?

- Under the approach described we have 3<sup>k</sup> possible scenarios for a k-platform analysis assuming a 3-state model
- It allows simple consideration such as 2-state for NGS
- So, when we begin the integration we could have up to

$$\sum_{h=1}^{k} 3^{h} \begin{pmatrix} k \\ h \end{pmatrix}$$

possible combinations (scenarios)

- How many do make sense?
- How many do we have?

# Results & Visualization

3-Platform Integration2 Platforms for validation

### {Mutations, Methylation, mRNA}











### visualization





# Discussion & Remarks

A case of study 3-MDI as tool Noise classification CpG islands and methylation profiles Machine Learning



# A case of study



{Mutations, Methylation, mRNA}

- No mutations present
- Hyper-methylated
- Up-regulated

 $\{0, 1, 1\}$ 



# A case of study

		G	ENE	METHYLATION			MRNA (EXP)			CNV		MIRNAS		5
Symbol	EntrezID	AffyID	Genename	logFC a	ndj.P.Val	в	logFC	adj.P.Val	в	State	log2ratio	ID	в	logFC
C1QB	713	202953_at	complement component 1, q sub- component, B chain	0.5806987	7.89E-05	2.59954224	1.72571387	9.74E-07	5.81806926	1	2.5037			
CHI3L1	1116	209395_at	chitinase 3-like 1 (cartilage glycoprotein- 39)	0.53471899	1.39E-04	1.98691274	3.0113802	7.26E-07	6.11706531	1	4.5605			
CNGA3	1261	207261_at	cyclic nucleotide gated channel alpha 3	0.75515746	5.78E-06	5.44191865	0.94567934	3.16E-05	2.19357849	1	1.3556			
ISG20L2	81875	212766_s_at	interferon stimulated exonuclease gene 20kDa-like 2	0.52188853	1.62E-04	1.82234246	0.53682824	1.96E-07	7.47850377	1	1.0703			
MEST	4232	202016_at	mesoderm specific transcript homolog (mouse)	0.62521946	4.04E-04	0.79919017	1.55695286	1.96E-06	5.09225184	1	1.2402			
RRM2	6241	201890_at	ribonucleotide reductase M2	0.72181342	5.27E-05	3.03224659	2.54968335	7.83E-20	36.7650371	1	2.0995			
S100A4	6275	203186_s_at	S100 calcium binding protein A4	0.6237743	4.70E-04	0.62914316	1.29357192	8.51E-05	1.16566955	1	1.3317			

	GENE				METHYLATION			MRNA (EXP)			CNV		MIRNAS	
Symbol	EntrezID	AffyID	Genename	logFC	adj.P.Val	в	logFC	adj.P.Val	в	State	log2ratio	ID	в	logFC
ARHGDIB	397	201288_at	Rho GDP dissociation inhibitor (GDI) beta	0.64854773	1.73E-04	1.74564726	1.2888788	5.05E-09	11.2671565	-1	-1.1883			
CARD8	22900	204950_at	caspase recruitment domain family, member 8	0.64521368	7.46E-05	2.66048954	0.54313616	1.37E-07	7.84458636	-1	-1.0601			
LAPTM5	7805	201721_s_at	lysosomal protein transmembrane 5	0.6531502	8.17E-06	5.06839223	1.48065566	1.67E-06	5.25798456	-1	-1.0158			
LCP2	3937	205269_at	lymphocyte cytosolic protein 2 (SH2 domain containing leukocyte protein of 76kDa)	0.60803781	2.50E-05	3.85558023	0.60159827	8.42E-05	1.17706784	-1	-1.3352			
MFNG	4242	204153_s_at	MFNG O-fucosylpeptide 3-beta-N- acetylglucosaminyltransferase	0.58575345	2.95E-04	1.15442156	0.61781958	5.73E-08	8.75097006	-1	-1.0267			
XBP1	7494	200670_at	X-box binding protein 1	0.53788523	7.96E-04	0.04070759	0.67093005	4.24E-05	1.88822193	-1	-1.0267			



# A case of study

		G	ENE	M	THYLATIC	N	MRNA (EXP)			CNV		MIRNAS		
Symbol	EntrezID	AffyID	Genename	logFC	adj.P.Val	в	logFC	adj.P.Val	в	State	log2ratio	ID	в	logFC
BCL10	8915	205263_at	B-cell CLL/lymphoma 10	0.69353091	4.62E-05	3.18165475	0.66475439	3.80E-13	21.0297724	0	NA			
C17orf62	79415	218130_at	chromosome 17 open reading frame 62	0.77898896	2.61E-05	3.80954612	0.6251037	3.19E-11	16.4910205	0	NA			
CASP8	841	213373_s_at	caspase 8, apoptosis-related cysteine peptidase	0.57505083	2.76E-04	1.22780207	0.8925942	3.23E-11	16.4779556	0	NA			
CCDC102B	79839	220301_at	coiled-coil domain containing 102B	0.75470659	2.51E-05	3.85412056	0.67428373	1.61E-06	5.29457173	0	NA			
CD74	972	209619_at	CD74 molecule, major histocompatibility complex, class II invariant chain	0.74687132	3.52E-05	3.48308756	1.27063336	8.33E-05	1.18857131	0	NA			
CEBPG	1054	204203_at	CCAAT/enhancer binding protein (C/EBP), gamma	0.70511548	9.12E-06	4.94670063	0.50824842	2.99E-06	4.65021566	0	NA	hsa-miR-26a	4.65021566	-1.1027814
DEGS1	8560	209250_at	degenerative spermatocyte homolog 1, lipid desaturase (Drosophila)	0.71405207	2.87E-05	3.70742286	0.51615931	4.26E-06	4.28256387	0	NA			
HCLS1	3059	202957_at	hematopoietic cell-specific Lyn substrate 1	0.59940536	8.59E-05	2.51158356	1.02641369	5.03E-05	1.71173475	0	NA			
HLA-DMA	3108	217478_s_at	major histocompatibility complex, class II, DM alpha	0.53117564	8.12E-06	5.07587603	1.4830763	2.70E-07	7.14688746	0	NA			
HLA-DRA	3122	210982_s_at	major histocompatibility complex, class II, DR alpha	0.5406111	4.91E-04	0.57657426	1.72628114	9.58E-06	3.440525	0	NA			
ITGA6	3655	201656_at	integrin, alpha 6	0.54015082	1.38E-05	4.4996224	0.56813049	9.14E-05	1.08901991	0	NA	hsa-miR-30c	1.08901991	-0.63956264
LRRFIP1	9208	211452_x_at	leucine rich repeat (in FLII) interacting protein 1	0.80252485	1.53E-05	4.38133604	0.78400513	1.87E-06	5.14074119	0	NA	hsa-miR-132	5.14074119	0.56647552
MGAT1	4245	201126_s_at	mannosyl (alpha-1,3-)-glycoprotein beta- 1,2-N-acetylglucosaminyltransferase	0.89526986	4.39E-06	5.73368044	0.5029207	2.65E-07	7.16562564	0	NA			
RUNX1	861	209360_s_at	runt-related transcription factor 1	0.62554243	2.84E-04	1.19718408	0.68621719	6.69E-05	1.41689062	0	NA	hsa-miR-144	1.41689062	-0.51084961
										0		hsa-miR-27a	1.41689062	-0.6980027
										0		hsa-miR-27b	1.41689062	-0.71691851
										0		hsa-miR-30c	1.41689062	-0.63956264
TCF3	6929	213730_x_at	transcription factor 3 (E2A immunoglobulin enhancer binding factors E12/E47)	0.69550004	9.84E-06	4.86300736	0.71872229	1.25E-18	33.9322673	0	NA	hsa-miR-15a	33.9322673	-0.59481687
TNFAIP8	25816	208296_x_at	tumor necrosis factor, alpha-induced protein 8	0.85572523	5.39E-06	5.51452479	0.66355047	1.13E-04	0.86749401	0	NA			
VAMP8	8673	202546_at	vesicle-associated membrane protein 8 (endobrevin)	0.57635568	3.69E-07	8.28791969	1.25009374	4.78E-05	1.76505389	0	NA	hsa-miR-15a	1.76505389	-0.59481687

### DNA methylation—miRNA network analysis

- Integrated analysis of DNA methylation profiles in CpG islands and miRNA differential expression can be explored with our 3-state model
- It can also be represented in a network-based analysis
- Results suggest that DNA methylation and miRNA transcriptional regulation are closely related for a particular state-vector representing a novel characteristic pattern.

### DNA methylation—miRNA network analysis



### DNA methylation—miRNA network analysis

- For instance, this analysis shows 9 miRNAs related (as putative targets) to genes over-represented with respect to changes in the CpG methylation status.
- That is, genes whose methylation profiles and miRNA targeting status may potentially affect their corresponding mRNA expression levels.
- Pathway enrichment analysis using GO for this set of 9 genes shows only a few pathways significantly enriched in biological processes mainly involved in neuronal functions (eg. Axon guidance, synaptical transmission)



### Remarks

- Data driven approaches for large multiplatform data may fit better than biological ones
- Each additional genomic dimension increases both the amount of information and consequently the biological and computational complexity of the analysis
- Noise behavior should be explored
- Machine learning approaches can be applied regardless of the number of platforms
- Bayesian approach might be improved by the prior information from the counts