



LRpath analysis reveals common pathways dysregulated via DNA methylation across cancer types

Maureen A. Sartor Computational Medicine and Bioinformatics University of Michigan

Motivation

- The relative contribution of epigenetic mechanisms to carcinogenesis is not well understood - *Do epigenetic mechanisms target similar genes and pathways as somatic mutations or different pathways?*
- Illumina HumanMethylation27 BeadChip platform assesses the percent methylation of over 27,000 CpG sites across the genome
- Several studies have been published testing for genes with aberrant methylation in their promoter regions. Interestingly, a majority of these publicly available datasets are studying cancer

Overview

- The time is ripe for an integrative analysis used data from The Cancer Genome Atlas (TCGA) and NCBI's Gene Expression Omnibus (GEO).
- <u>Hypothesis</u>: During the pathogenesis of cancer, certain pathways or biological gene groups are commonly dysregulated via DNA methylation across cancer types.
- <u>Approach</u>: Employed *LRpath* and clustering analysis to unravel the commonly altered pathways and other biological concepts across 10 different cancer studies of DNA methylation data profiled using the Illumina Infinium HumanMethylation27 BeadChip.

LRpath method



- Sartor MA, et al. Bioinformatics. 2009; 25(2): 211-7.

http://l	path.ncibi.org	
Path	Analysis using Logistic Regression	
	Basic Analysis Options	
	Species Human	~
	Database • Functional Annota	tione
		ta Pathway
		metabolic pathways
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Workbook Views	Show Zoom Window 16.2447876050624 Image: Comparison of Compa	GO Biological Process
A	B C D E F G H I ConceptType #Genes Coeff OddsRatio P-Value FDR Direction SigGenes I	GO Cellular Component
	24368, 24399, 24401, 25179, 25721, 79250, 815	GO Molecular Function
te cycle (TCA cycle)	KEGG Pathway 32 0.449 16.2 1.23E-08 1.67E-06 up <u>307858, 361602</u>	
acid metabolism	KEGG Pathway 28 0.403 12.2 1.10E-06 7.48E-05 up 171155, 291075	Pathway
ine and aspartate metabol	KEGG Pathway 18 0.477 19.3 1.93E-06 8.75E-05 up 171155, 298942 O Panthe	er Pathway
ictive carboxylate cycle (Ci	KEGG Pathway 11 0.558 32.1 6.68E-06 2.27E-04 up 24368, 24399, 24401, 25721, 79250, 81670, 81829 O	
8 C O T T O T T O C C C C C C C C C C C C	KEGG Pathway 44 0.278 5.6 3.64E-05 9.89E-04 up <u>116550, 291103, 295923, 301011, 316632</u>	i
17648 222867 22867 22867 220990 220990 221304 221304 221304 221304 221304 221304	KEGG Pathway 25 0.323 7.4 2.00E-04 0.0044 up 81670 O MeSH	
1 1 2 2 7 7 1 2 3 3 3 3 1 2 1 2 1 2 1 2 1 2 1 2 1 2	KEGG Pathway 32 0.286 5.9 2.33E-04 0.0044 up 24158, 24450, 25045, 25757, 29171, 140638, 49998	
1481 Chronic myeloid leukemia 1482 Carbon fixation	KEGG Dathway 11 0.443 15.7 3.59E.04 0.0054 up 24401 25721 81670 81829 114508 361602	
1483 Arginine and proline metabolis	KEGG Pathway 20 0.334 8.0 5.14E-04 0.0070 µp 24368, 24379, 24401, 24600, 25721 • Targets	
1484 Butanoate metabolism	KEGG Pathway 30 0.263 5.1 0.0010 0.0125 up 140547 O Drug B	<u>Bank</u>
1485 TGF-beta signaling pathway 1486 Andronen and estronen metab 14 (4 → 14) LRpath-results-60-KEGG		ase
		cription Factors
	Interaction	
		a lateractica (LULI)



Pathway Analysis using Logistic Regression

http://lrpath.ncibi.org

Advantages of LRpath

- Strong performance for datasets with both large *and small* sample sizes
- Ability to test both 'directional' and 'non-directional' tests
- Random sets interpretation without the need for significance values to be "approximately normally distributed"
- Identical significance values for repeated runs (no dependence on permutations)
- Flat p-value distribution under the null (i.e. no significant sets)



>21,000 concepts/gene sets total

Basic Analysis Optio	ns		
Species	Human 💌		LR Path
Database			
	 Functional Annotations 		Pathway Analysis using Logistic Regression
	 Biocarta Pathway 		http://lrpath.ncibi.org
	 EHMN metabolic pathway 	<u>/S</u>	
	o 🔲 <u>GO</u>		
	GO Biological Pro	cess	
	GO Cellular Comp	onent	
	GO Molecular Fun	<u>ction</u>	Clustering Options
	 EGG Pathway 		
	o 🔲 <u>Panther Pathway</u>		
	○ □ <u>pFAM</u>	Select	value to cluster by: -log10(p-values) -
	Literature Derived	Select	method for distance matrix: euclidean
	○ <u>MeSH</u>	Select	link for clustering: ward -
	○ □ <u>OMIM</u>		
	Targets		concepts with P-value < 0.05 in at least 1 LRpath comparisons.
	 Drug Bank 	cannot c	
	○ □ <u>miRBase</u>		
	 Transcription Factors 	URL	Comparison Name
	Interaction	URL	Comparison Name
	 Protein Interaction (MiMI) 	UKL	Companson Name
	• Other	Add F	File
	• Metabolite	Enter two	o or more URLs for LRpath text results to cluster, and a name for each comparison/LRpath result (must
	o 🔲 <u>Cytoband</u>	order). E	Example URL: external link: http://Irpath.ncibi.org/result/download999999999.txt
	Selecting multiple, or a large, concept of	latabase	
Directional test?	O Yes No		

Illumina Infinium HumanMethylation27 BeadChip

- Assesses percent methylation of >27,000 sites for >14,000 genes
- Most genes are represented by 1 or 2 sites on the array
- a small percent, (imprinted and cancerrelated genes) are represented by up to a dozen sites.
- In addition, 110 miRNA promoters are covered by 254 sites.



10 tumor vs. normal studies from TCGA and GEO

Source	GEO 17648	GEO 21304	GEO 22867	GEO 26126	GEO 26990	TCGA	TCGA	TCGA	TCGA	TCGA
Tumor Type	Colon	Multiple Myeloma	Glioblas toma	Prostate	Breast	Kidney	Lung AC	Lung SCC	Ovarian	Stomach
Normal Sample #	22	3	4	98	8	199	24	27	8	57
Cancer Sample #	22	161	77	95	47	199	24	27	39	57
P-value < 0.01	7922	4489	1403	9151	3699	10664	6419	6738	4376	8436
P-value < 0.01 and at least 10% change in average methylation		4343	1179	3263	3039	2022	3847	3641	1900	3000

Genes harboring aberrant promoter methylation between normal and cancer samples were determined using an empirical Bayes method. GSE# IDs are provided for data from GEO.

Colon, Kidney, lung, and stomach cancers contained tumor/normal samples matched by patient.



Significance of Overlap Between Pairs of Studies - hypomethylation

GO: Immune response

	Breast	Colon	Glioblastoma	KIRC	LungAC	LungSCC	Myeloma	Ovarian	Prostate	Stomach
Breast										
Colon	3.64E-16									
Glioblastoma	1.39E-09	7.84E-09								
KIRC	7.26E-15	2.90E-29	1.43E-17							
LungAC	2.40E-22	4.90E-22	1.72E-12	4.03E-21						
LungSCC	1.38E-20	1.97E-21	3.53E-10	3.94E-30	5.56E-49					
Myeloma	2.55E-14	7.28E-16	2.45E-08	1.01E-16	1.16E-24	7.26E-25				
Ovarian	1.15E-16	2.37898E-14	3.13E-03	8.41E-11	1.17E-16	5.76E-26	5.75E-11			
Prostate	2.48E-03	0.25	0.19	0.50	0.04	0.09	0.18	0.14		
Stomach	9.40E-09	4.20E-22	9.07E-04	9.31E-14	8.69E-14	1.36E-12	6.32E-08	1.77E-14	0.15	

GO: Epidermis development

	Breast	Colon	Glioblastoma	KIRC	LungAC	LungSCC	Myeloma	Ovarian	Prostate	Stomach
Breast										
Colon	3.38E-06									
Glioblastoma	4.46E-08	6.44E-04								
KIRC	2.46E-08	1.37E-07	1.96E-09							
LungAC	1.14E-08	2.46E-11	3.81E-06	7.39E-09						
LungSCC	1.46E-04	1.03E-03	3.99E-03	9.32E-08	8.61E-10					
Myeloma	4.73E-08	5.23E-04	3.31E-07	2.93E-12	1.63E-08	2.69E-08				
Ovarian	4.42E-06	3.01E-04	3.02E-06	6.76E-06	8.89E-08	2.84E-10	1.13E-05			
Prostate	0.09	0.16	0.51	0.45	0.14	4.72E-02	0.27	0.44		
Stomach	6.30E-08	3.31E-07	2.43E-02	5.28E-05	9.12E-06	1.75E-02	3.33E-03	8.84E-04	4.64E-02	

* Red indicates p-value less than 0.05

Significance of Overlap Between Pairs of Studies - hypermethylation

GO: Neurogenesis

	Breast	Colorectal	Glioblastoma	KIRC	LungAC	LungSCC	Myeloma	Ovarian	Prostate	Stomach
Bre ast										
Colore ctal	6.59E-13									
Glioblastoma	1.27E-09	2.03E-03								
KIRC	1.66E-16	1.22E-08	2.66E-04							
LungAC	7.77E-22	2.08E-25	1.51E-03	1.82E-27						
LungSCC	1.78E-22	4.05E-17	1.16E-07	3.90E-24	4.96E-40					
Myeloma	0.21	0.21	2.35E-02	0.40	0.75	0.10				
Ovarian	0.45	3.15E-03	0.39	0.44	0.35	0.22	0.81			
Prostate	9.31E-17	8.50E-16	1.89E-03	5.25E-13	2.20E-29	2.59E-21	0.47	0.48		
Stomach	1.03E-13	1.95E-33	2.05E-04	2.14E-13	7.76E-30	1.49E-18	0.48	1.40E-02	1.25E-05	

* Red indicates p-value less than 0.05

Conclusions

Pathways affected by differential methylation were surprisingly concordant across cancer types

- Promoters of genes involved in voltage-gated potassium channels, which play a role in cell proliferation processes, tend to be hypermethylated.
- Genes in developmental concepts such as homeobox, embryonic and nerve development tend to be hypermethylated (many PRC2 target genes)
- Genes in epidermis development and keratinization are hypomethylated.
- □ Immune response concepts identified by GO, KEGG pathways, and MeSH terms are hypomethylated (elevated immune response is a commonly affected mechanism across multiple cancer types.)
- □ For most tumor types, similar genes are affected by a change in CpG methylation in a pathway.
 - □ The same significant pathways could be affected by different sets of methylated genes across various cancer types. However, for tested biological concepts, they appear to be mostly the same genes, with a few exceptions.

Conclusions

- DNA repair, one of the most commonly affected pathways in cancer development, is *depleted* in differentially methylated genes.
 - We hypothesize that genes involved in DNA damage and cell cycle tend to be dysregulated by alternative mechanisms such as genomic aberrations.
- Performing an integrative analysis of biological concepts dysregulated via methylation across ten cancer types, we identified concepts affected in multiple cancer types that support biologically important findings.
- A subset of the known cancer pathways appears to be commonly dysregulated via DNA methylation across cancers

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