Identifying significantly impacted pathways: a comprehensive review and assessment (Supplementary Materials)

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1 Benchmark Data Sets

Table [S1](#page-1-0) provides detailed information regarding the 75 human data sets used for benchmarking methods' ability to identify target pathways. This information includes: GEO ID, disease, number of normal samples and phenotype samples, Pubmed ID, tissue from which the samples were taken, and the platform used for the experiment.

Table [S2](#page-3-0) provides detailed information regarding the 11 benchmark KO data sets used. This information includes: the GEO ID, symbol of KO gene, number of truly impacted pathways, number of normal samples, number of phenotype samples, Pubmed ID, tissue from which the samples were taken, and the platform used for the experiment.

All data sets were downloaded from Gene Expression Omnibus database. We normalized them using RMA background adjustment, quantile normalization, and median polish summarization. We used the threestep function from affyPLM package to perform those steps. Subsequently, standard genome wide annotation packages corresponding to the platform, e.g. hgu133a.db for HG-U133A, were used to map probes to genes. In case there are multiple probes mapped to the same gene, the median value is chosen.

GEO ID	Disease	#Normal	#Condition	Pubmed ID	Tissue	Platform
GSE781	Renal cell carcinoma	5	12	14641932	Kidney	$HG-U133A$
GSE14762	Renal cell carcinoma	$12\,$	$\boldsymbol{9}$	19252501	Kidney	HG-U133 Plus 2.0
GSE6357	Renal cell carcinoma	12	$\,6$	27063186	$CD8+$ T Cell	HG-U133A
GSE6344	Renal cell carcinoma	10	10	17699851	Clear cell RCC	HG-U133A
GSE48352	Renal cell carcinoma	$8\,$	24	NA	Kidney	HG-U133 Plus 2.0
GSE1297	Alzheimer's disease	$\boldsymbol{9}$	$\overline{7}$	14769913	Hippocampal CA1	HG -U133A
GSE5281EC	Alzheimer's disease	13	10	17077275	Brain, Entorhinal Cortex	HG-U133 Plus 2.0
GSE5281HIP	Alzheimer's disease	13	$10\,$	17077275	Brain, hippocampus	HG-U133 Plus 2.0
GSE5281VCX	Alzheimer's disease	12	$19\,$	17077275	Brain, primary visual cortex	HG-U133 Plus 2.0
GSE16759	Alzheimer's disease	$8\,$	$\,4\,$	20126538	Parietal lobe	HG-U133 Plus 2.0
GSE3467	Thyroid cancer	$\boldsymbol{9}$	$\boldsymbol{9}$	16365291	Thyroid	HG-U133 Plus 2.0
GSE3678	Thyroid cancer	$\overline{7}$	$\overline{7}$	NA	Thyroid	HG-U133 Plus 2.0
GSE58545	Thyroid cancer	18	27	26625260	Thyroid	HG-U133A
GSE85457	Thyroid cancer	$\sqrt{3}$	$\overline{4}$	NA	Thyroid	HG-U133 Plus 2.0
GSE58689	Thyroid cancer	18	27	26625260	Thyroid	$HG-U133A$
GSE3585	Dilated cardiomyopathy	$\bf 5$	$\overline{7}$	17045896	Heart, subendocardial left ventricular	HG-U133A
GSE33970	Dilated cardiomyopathy	18	$\overline{5}$	NA	Whole blood and heart	HG-U133 Plus 2.0
GSE29819	Dilated cardiomyopathy	$12\,$	14	22085907	Heart, left and right ventricular	HG-U133 Plus 2.0
GSE79962	Dilated cardiomyopathy	11	9	NA	Heart	HuGene-10st
GSE21610	Dilated cardiomyopathy	$8\,$	42	20460602	Heart	HG-U133 Plus 2.0
GSE4107	Colorectal cancer	10	12	17317818	Colonic mucosa	HG-U133 Plus 2.0
GSE8671	Colorectal cancer	32	$32\,$	18171984	Colon	HG-U133 Plus 2.0
GSE9348	Colorectal cancer	12	70	20143136	Colon	HG-U133 Plus 2.0
GSE23878	Colorectal cancer	19	$19\,$	21281787	Colon	HG-U133 Plus 2.0
GSE4183	Colorectal cancer	$8\,$	15	18776587	Colon	HG-U133 Plus 2.0
GSE6956C	Prostate cancer	11	$36\,$	18245496	Prostate	HG-U133A 2
GSE6956AA	Prostate cancer	$\overline{\mathbf{7}}$	33	18245496	Prostate	HG-U133A 2
GSE55945	Prostate cancer	$\overline{7}$	12	19737960	Prostate	HG-U133 Plus 2.0
GSE26910	Prostate cancer	6	$\,6$	21611158	Prostate	HG-U133 Plus 2.0
GSE104749	Prostate cancer	$\overline{4}$	$\overline{4}$	NA	Prostate	HG-U133 Plus 2.0
GSE8762	Huntington's disease	10	$12\,$	17724341	Lymphocyte	HG-U133 Plus 2.0
GSE24250	Huntington's disease	$\,6$	$8\,$	21969577	Venous cellular whole blood	$HG-U133A$
GSE73655	Huntington's disease	$\overline{7}$	13	26756592	Subcutaneous adipose	HuGene-10st
GSE45516	Huntington's disease	3	$\,6$	24296361	Fibroblasts	HG-U133 Plus 2.0
GSE37517	Huntington's disease	$\bf 5$	$8\,$	22748968	Neural stem cell	HuGene-10st
GSE9476	Acute Myeloid Leukemia	37	26	17910043	Peripheral blood, bone marrow	$HG-U133A$
GSE14924_CD4	Acute Myeloid Leukemia	10	10	19710498	CD4 T Cell	HG-U133 Plus 2.0
GSE14924_CD8	Acute Myeloid Leukemia	11	10	19710498	CD8 T Cell	HG-U133 Plus 2.0
GSE92778	Acute Myeloid Leukemia	6	6	29035359	Bone marrow stroma cells	HuGene-10st

Table S1: 75 benchmark data sets of 15 diseases used to compare 11 methods in this paper.

*Leukemic stem cells (LSC), hematopoietic stem cells (HSCs), and AML bulk cells (CD34+CD38+, CD34-CD38+ and CD34-CD38)

GEO ID	KO gene	$\#\text{Impacted}$ Pathways	$\#\text{Normal}$	$\#\text{Condition}$	Pubmed ID	Tissue	Platform
GSE22873	Myd88	19	11	8	22075646	Liver	$Mouse430_2$
GSE6030	Neurod ₁		5.	3	17630985	Pineal gland	$Mouse430_2$
GSE29048	Pdx1	3	4	4	22135308	Intestinal epithelium	$Mouse430_2$
GSE70302	IL1a	20	4	4	26224856	Spinal cord	$MoGene-1_0-st$
GSE70302	IL1b	34	4	4	26224856	Spinal cord	$MoGene-1_0-st$
GSE58120	IL2	3	6	6	25652593	Myeloid dendritic cells	$MoGene-1_0-st$
GSE46211	TGFBR2	20	12	6	24496627	Anterior palatal tissue & posterior palatal tissue	Mouse430 ₋₂
GSE49166	BHLHE40			3	24699451	$CD4T$ cells	$MoGene-1$ $0-st$
GSE50933	ID3	$\overline{2}$		5	24244015	Natural killer T cells	$Mouse430-2$
GSE62999	DUSP ₅		10	10	25398911	Bone marrow	$Mouse430_2$
GSE57917	ONECUR1	$\overline{2}$	3	3	25313862	Retinas	$Mouse430_2$

Table S2: 11 knock-out benchmark data sets used to compare 8 methods in this paper.

2 Problems with Classical Selection of DE Genes

Setting thresholds based on their p-values and unsigned log-fold changes is a widely used method to obtain a list of DE genes. However, the numbers of DE genes obtained from different studies of the same condition often differ significantly due to the heterogeneity present in the individual experiments. For example, with the thresholds of 1.5 for unsigned log-fold changes and and 5% for the corrected p-values, 21 out of 75 human gene expression data sets studied do not have any DE gene, whereas one data set has more than one thousand DE genes (Fig. [S1\)](#page-4-0). A similar problem occurs with the 11 KO data sets, 5 of which do not have any DE gene according to these criteria (Fig. [S2\)](#page-5-0).

Fig. S1: Distribution of number of DE genes of 75 human gene expression data sets using corrected p-value threshold of 0.05 and unsigned log-fold change threshold of 1.5. The number of DE genes varies considerably across all the data sets. In fact, 21 data sets do not have any DE genes whereas there is one data set that has more than 1000 DE genes.

Here, to eliminate the effect of the thresholds, we select the same number of DE genes for each experiment. This is consistent with the findings of the MAQC consortium which reported that the best reproducibility across labs and platforms is obtained when genes are selected based on their fold changes [\[1,](#page-12-0) [2\]](#page-12-1). The procedure to select the DE genes was as follows. First, we calculated the gene level p-values using the two sample t-test. Subsequently, we selected genes with p-values less than 5%. Finally, the top 400 (around 10% number of genes present in KEGG) genes with the highest unsigned log-fold changes were considered as DE genes.

3 Accuracy, sensitivity, and specificity

KO data sets are used to calculate the statistical measures of 10 methods (CePaGSA, CePaORA, and PathNet are not included in this comparison because they do not support mouse pathways). After defining the true positives, true negatives, false positives, and false negatives, the accuracy, sensitivity, specificity, and the AUC are measured using formula in sub-section "Statistical measures". In this supplementary we plotted only the former three measures into Fig. [S3.](#page-6-0) ROntoTools and PADOG have the highest median value of accuracy (0.91). ROntoTools also has the highest median value of specificity (0.94). All of the methods show rather low sensitivity. Among them, KS is the best one with the median value of sensitivity of 0.2.

Fig. S2: Distribution of number of DE genes of 11 mouse gene expression data sets using corrected p-value threshold of 0.05 and unsigned log-fold change threshold of 1.5 Five of them do not have any DE genes.

4 Empirical null distributions

Pathway analysis methods work under an assumption that empirical null distributions of p-values of all pathways are uniformly distributed under the true null hypothesis. However, this does not hold true in most of the cases. Fig. [S4](#page-7-0) and Fig. [S5](#page-8-0) show some examples of pathways that have empirical null distribution of p-values as reported by various methods, biased toward 0 and 1, respectively.

GSEA is the only method in this study that is unbiased for all the pathways. Fig. [S6](#page-9-0) shows that the aggregate p-values of all pathways generated by GSEA are uniformly distributed.

5 Number of methods biased for each pathway

While benchmarking pathway analysis methods, it is important to choose appropriate data sets. In a fair comparison, the target pathways related to the disease or condition of these data sets should have unbiased null distributions of p-value produced by all methods studied. If the null-distribution of p-values of a target pathway is not available, knowing the probability of that pathway being biased toward 0 or 1 is also helpful. In an attempt to provide this information, for each pathway we report the number of methods (out of the 11 methods investigated) biased toward 0 or 1 (Table [S3\)](#page-10-0).

Fig. S3: Comparison of 8 methods using 11 KO data sets in term of accuracy (a), sensitivity (b), and specificity (c). In term of accuracy, ROntoTools and PADOG have the highest median value (0.91). ROntoTools also has the highest median value of specificity (0.94). The best method in term of sensitivity is KS which has the median value of sensitivity of 0.2. However, KS also has the lowest median specificity.

Fig. S4: Examples of pathways that have empirical null distributions of pvalue biased toward 0. The procedure for generating null distributions is described in Fig. [5.](#page-0-0) The x-axes display the p-values whereas the y-axes display the frequencies. These pathways are likely to be falsely identified as significantly impacted by the corresponding method (false positive).

Fig. S5: Examples of pathways that have empirical null distributions of pvalue biased toward 1. In these sub-figures, x-axes represent the p-value, while y-axes represent their frequencies. These pathways are often incorrectly excluded in the list of significant pathways by the corresponding method even when they are indeed impacted (false negative).

Fig. S6: Aggregate p-values of all the pathways generated by GSEA are uniformly distributed under the null. The uniform distribution proves that GSEA is extremely unbiased.

References

- [1] MAQC Consortium: The MicroArray Quality Control (MAQC) project shows inter- and intraplatform reproducibility of gene expression measurements. Nature Biotechnology 24(9), 1151–1161 (2006)
- [2] Chen, J.J., Hsueh, H.-M., Delongchamp, R.R., Lin, C.-J., Tsai, C.-A.: Reproducibility of microarray data: a further analysis of microarray quality control (MAQC) data. BMC Bioinformatics 8(1), 412 (2007)