Gene expression analysis: Some lessons for statistical hypothesis testing

WONG Limsoon



Plan, 20/1/2025

Statistical hypothesis testing

Onus of proof

Anna Karenina Principle

Null hypothesis & null distribution

Getting them right

Gene expression profiling

Differentially expressed genes (DEG) selection

Poor DEG selection replicability

Addressing the replicability crisis

Statistical hypothesis testing

Formulate null hypothesis H0 and alternate hypothesis H1

Devise a test statistic, $t(\cdot)$

Evaluate t(S) on a sample S

Compare t(S) to the null distribution

This does not mean we accept H0!

If significant, reject H0; otherwise, reject H1

Null distribution is the distribution of t(S0) where S0 ranges over the set of null samples for which H0 holds

Onus of proof: Rejecting H1 ≠ accepting H0

"... a p-value is large doesn't mean that the null hypothesis is true. All a hypothesis test does is measure the strength of evidence against the null hypothesis. That is, we assume the null hypothesis is true until we have enough evidence to reject. Crucially, we never actually claim that the null hypothesis is true - it is just an assumption!"

A pharmaceutical research team constructs a significant test:

HO – Side effects of new drug X are same as standard drug Y

H1 - Side effects of new drug X are different from standard drug Y

Would you be happy to use the new drug based on a large statistically insignificant p-value?

Anna Karenina Principle

There are many ways to violate the null hypothesis but only one way that is truly pertinent to the outcome of interest

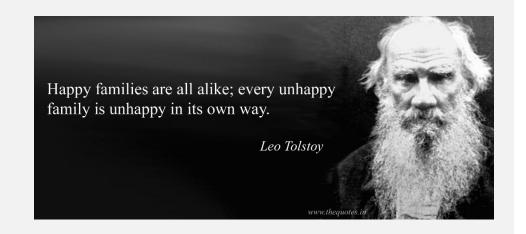
Sample is biased

Null distribution used is inappropriate

Null hypothesis incorrectly stated

Inappropriate expt design

And so on



Exercise

SNP rs123 is good biomarker for a disease:

If rs123 is AA or GG, low risk for disease

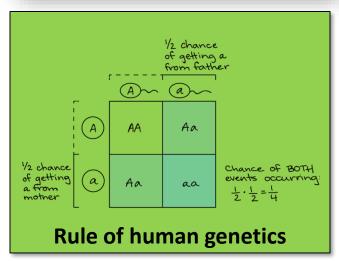
If rs123 is AG, high risk for disease

Straightforward χ 2 test. Anything wrong?

Group								
SNP	Genotypes	Cont	rols [n(%)]	Cases	s [n(%)]	χ²	P value	
rs123	AA	1	0.9%	0	0.0%		4.78E-21 ^b	
	AG	38	35.2%	79	97.5%			
	GG	69	63.9%	2	2.5%			
Abbreviation:	Abbreviation: SNP, single nucleotide polymorphism.							

Calculations

Group								
SNP		Genotypes	Cont	rols [n(%)]	Cases	s [n(%)]	χ²	P value
rs1		AA	1	0.9%	0	0.0%		4.78E-21 ^b
23		AG	38	35.2%	79	97.5%		
		GG	69	63.9%	2	2.5%		



$$AG = 38 + 79 = 117,$$

Controls + cases = 189

 \Rightarrow Population is 117 / 189 = 62% AG

$$P(AA) = ...$$

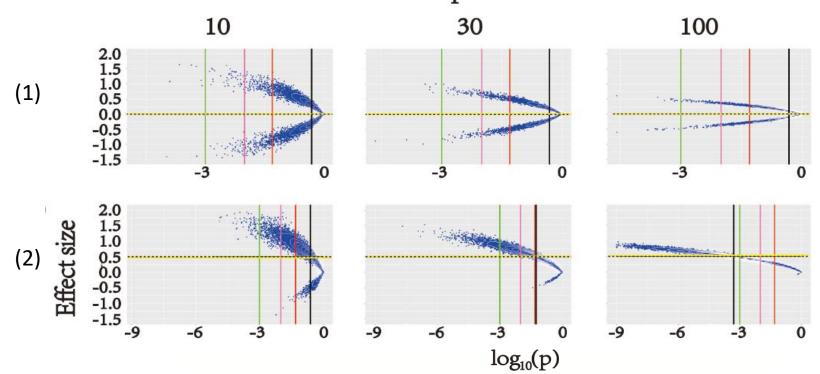
Sample may be biased

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Sampling bias happens often

	Distribution		Mean		Standard deviation				
Scenario	A	В	A	В	A	В	Sample size		
(1)	Normal	Normal	0	0	1	1	10	30	100
(2)	Normal	Normal	0	0.5	1	1	10	30	100

Sample size



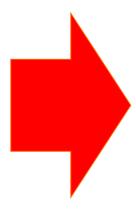
Careless null hypothesis

H₀

rs123 alleles are identically distributed in the two samples

Assumption

Distributions of rs123 alleles in the two samples are resp. identical to the two populations



Apparent H1

rs123 alleles are differently distributed in the two populations

"Actual" H1

rs123 alleles are differently distributed in the two populations OR

Distribution of rs123 alleles in the two samples are not identical to the two populations

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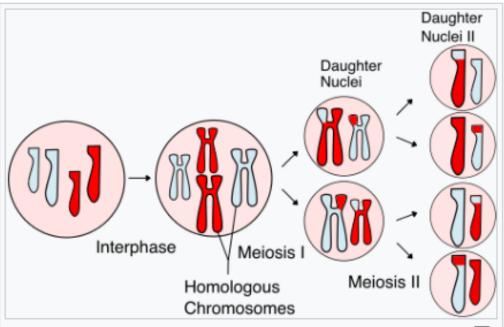
Exercise

Suppose distributions of rs123 alleles in the two samples are identical to the corresponding populations and the test is significant

Can we say rs123 mutation causes the disease?

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Meiosis

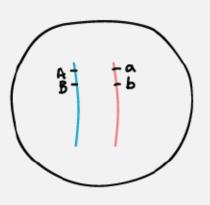


In meiosis, the chromosomes duplicate (during interphase) and homologous chromosomes exchange genetic information (chromosomal crossover) during the first division, called meiosis I. The daughter cells divide again in meiosis II, splitting up sister chromatids to form haploid gametes. Two gametes fuse during fertilization, forming a diploid cell (zygote) with a complete set of paired chromosomes.

Image credit: Wikipedia

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When two genes are close together, this is what happens during meiosis



Gametes made:

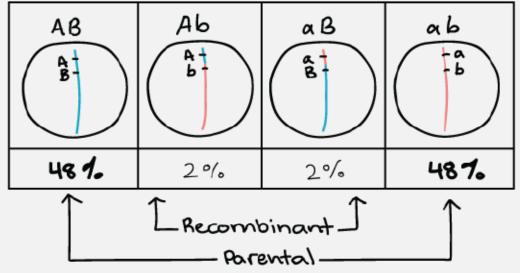
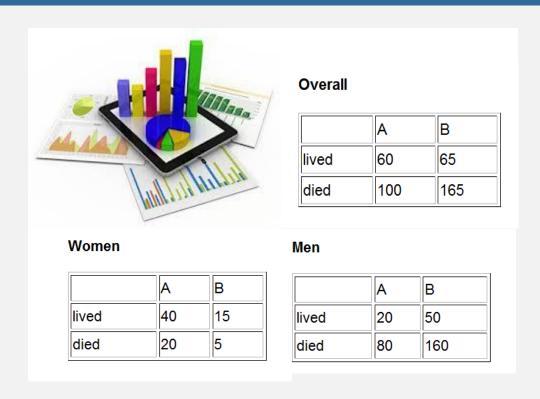


Image credit: Khan Academy

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Exercise



Treatment A is better

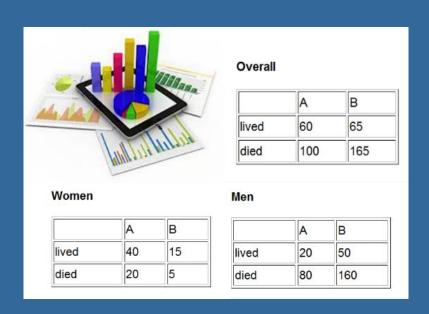


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Treatment B is better

What is happening here?

A/B sample not equalized in other attributes, ...



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Careless null hypothesis

H0

Treatment effects are identically distributed in the two samples

Assumption

All other factors are equalized in the two samples



Apparent H1

Treatment effects are differently distributed in the two populations

"Actual" H1

Treatment effects are differently distributed in the two populations OR

Some other factors aren't equalized in the two samples

Exercise

I asked ChatGPT how to test whether my income is atypically low

What do you think of ChatGPT's response?



ChatGPT

To test whether your income is atypically low given the mean income (X) and standard deviation (Y), you can use z-scores to determine how many standard deviations your income is away from the mean. This helps identify whether your income is significantly lower or higher than the average.

The z-score formula is:

$$z = \frac{\text{Your Income-Mean Income}}{\text{Standard Deviation}} = \frac{\text{Your Income-}X}{Y}$$

Once you calculate the z-score for your income using this formula, you can interpret its value:

- If the z-score is significantly less than -2 (approximately), your income might be considered atypically low.
- A z-score less than -2 indicates that your income is more than two standard deviations below the mean income, which is relatively rare in a normal distribution.

A nation of unusually poor people, really?

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Homework, due 24/1/2025

Read this paper

Inferring synthetic lethal interactions from mutual exclusivity of genetic events in cancer

<u>Sriganesh Srihari, Jitin Singla, Limsoon Wong</u> № <u>& Mark A. Ragan</u>

Biology Direct 10, Article number: 57 (2015) Cite this article

Write a 1-page review report focusing how it tests for synthetic-lethal gene pairs. Discuss whether their test is a good one

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Microarray

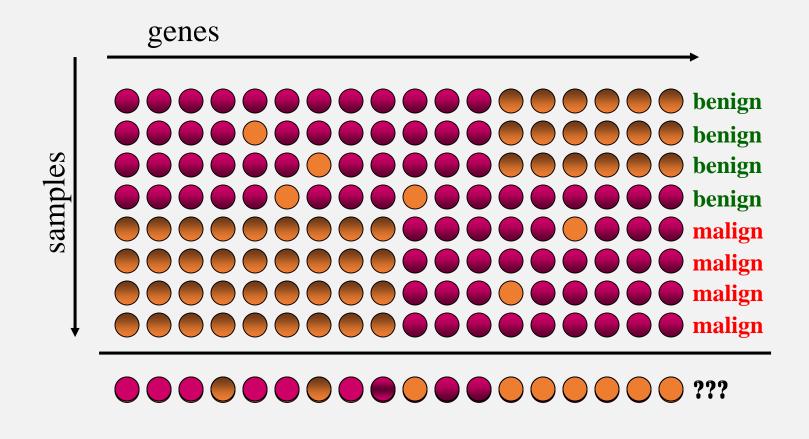
Contain large numbers of DNA molecules spotted on glass slides, nylon membranes, or silicon wafers

Detect what genes are being expressed or found in a cell of a tissue sample

Measure expression of thousands of genes simultaneously

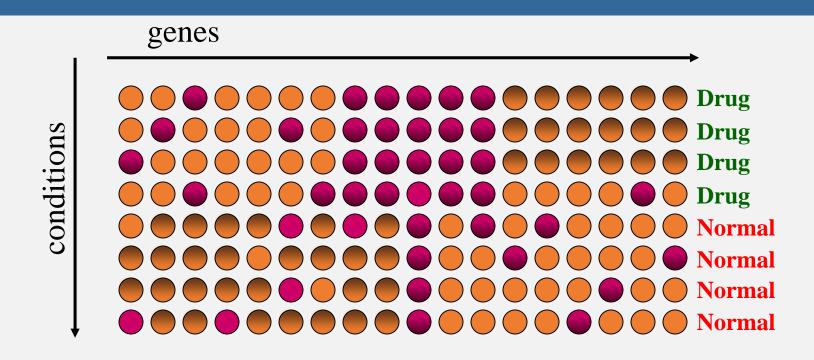
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Application: Disease subtype diagnosis



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Application: Drug-action inference



Which group of genes does the drug affect? Why?

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Diagnosis using microarrays & machine learning

Gene expression data collection

Gene selection using e.g., χ 2

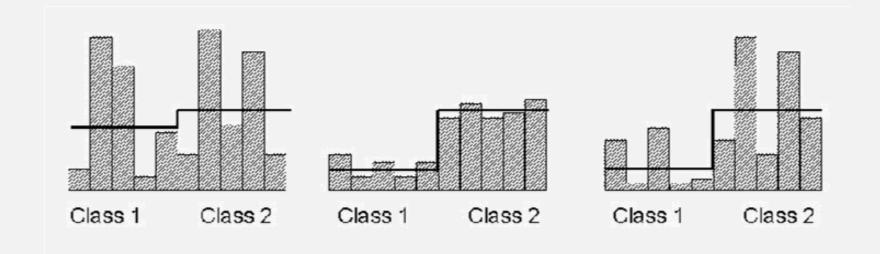
Classifier training

Classifier tuning (optional for some machine learning methods)

Apply classifier for diagnosis of future cases

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Gene selection basic idea



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Gene selection by $\chi 2$

The \mathcal{X}^2 value of a signal is defined as:

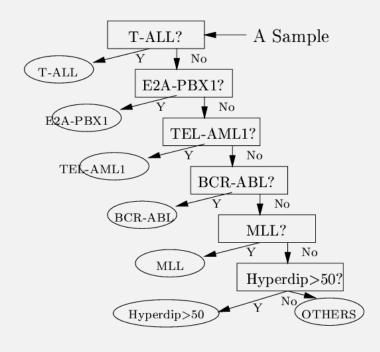
$$\mathcal{X}^{2} = \sum_{i=1}^{m} \sum_{j=1}^{k} \frac{(A_{ij} - E_{ij})^{2}}{E_{ij}},$$

where m is the number of intervals, k the number of classes, A_{ij} the number of samples in the ith interval, jth class, R_i the number of samples in the ith interval, C_j the number of samples in the jth class, N the total number of samples, and E_{ij} the expected frequency of A_{ij} ($E_{ij} = R_i * C_i/N$).

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Performance of various classifiers

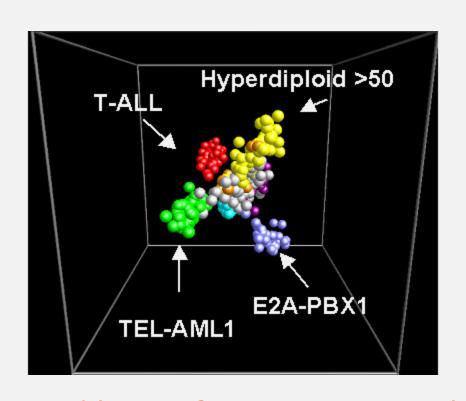
Testing Data	Error rate of different models				
	C4.5	SVM	NB	PCL	
T-ALL vs OTHERS1	0:1	0:0	0:0	0:0	
E2A-PBX1 vs OTHERS2	0:0	0:0	0:0	0:0	
TEL-AML1 vs OTHERS3	1:1	0:1	0:1	1:0	
BCR-ABL vs OTHERS4	2:0	3:0	1:4	2:0	
MLL vs OTHERS5	0:1	0:0	0:0	0:0	
Hyperdiploid $>$ 50 vs OTHERS	2:6	0:2	0:2	0:1	
Total Errors	14	6	8	4	

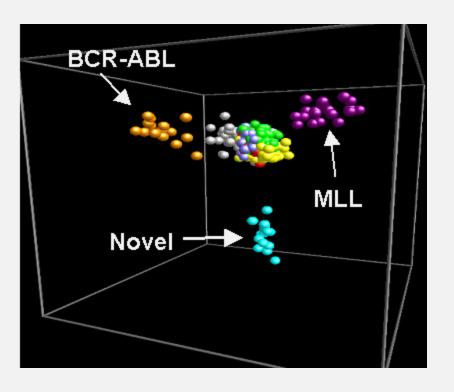


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Classifiers based 20 genes selected by $\chi 2$ at each level of the tree

Multidimensional scaling plot for subtype diagnosis





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Obtained by performing PCA on the 20 genes chosen for each level

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Poor replicability of gene selection

Low % of overlapping genes from diff expt

Prostate cancer

Lapointe et al, 2004 vs Singh et al, 2002

Lung cancer

• Garber et al, 2001 vs Bhattacharjee et al, 2001

DMD

Haslett et al, 2002 vs Pescatori et al, 2007

Datasets	DEG	POG
Prostate	Top 10	0.30
Cancer	Top 50	0.14
	Top100	0.15
Lung	Top 10	0.00
Cancer	Top 50	0.20
	Top100	0.31
DMD	Top 10	0.20
DMD	Top 50	0.42
	Top100	0.54

Individual genes

Suppose:

Each gene has 50% chance to be high You have 3 disease and 3 normal samples

How many genes on a microarray are expected to perfectly correlate to these samples?

Prob(gene is correlated) = $1/2^6$

of genes on array = 25,000

E(# of correlated genes) = 390

⇒ Many false positives; these cannot be eliminated based on pure statistics!

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Group of genes

Suppose:

Each gene has 50% chance to be high You have 3 disease & 3 normal samples

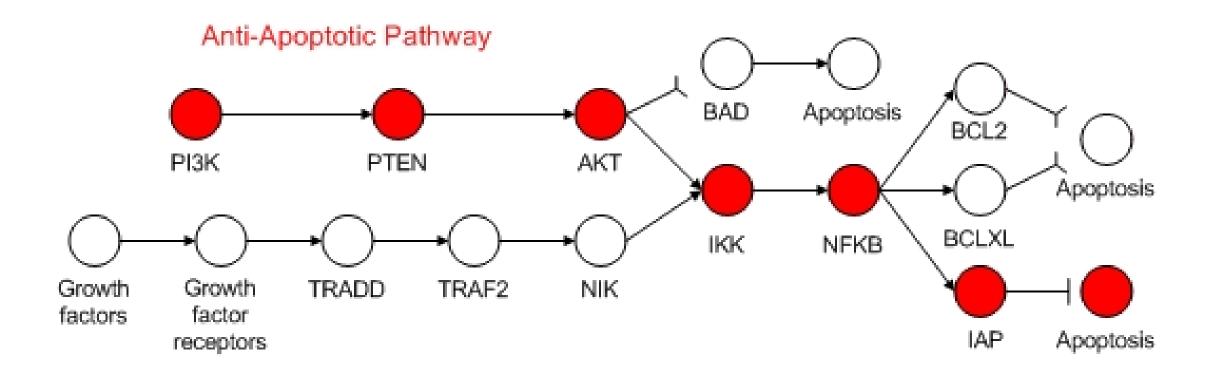
What's the chance for a group of 5 genes to perfectly correlate to these samples?

When only 1 group is considered, $<<1/2^6$ # of groups = 25000 C₅ E(# of correlated groups) = 25000 C₅* $(1/2^6)^5$ = 7.58 * 10 ¹⁰

⇒ Even more false positives?

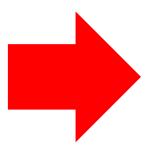
Perhaps no need to consider every group

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Each disease phenotype has some underlying cause

There is some unifying biological theme for genes that are truly associated with a disease subtype



Uncertainty in selected genes reduced using biological processes

The unifying biological theme is basis for inferring underlying cause of disease subtype

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Group of Genes

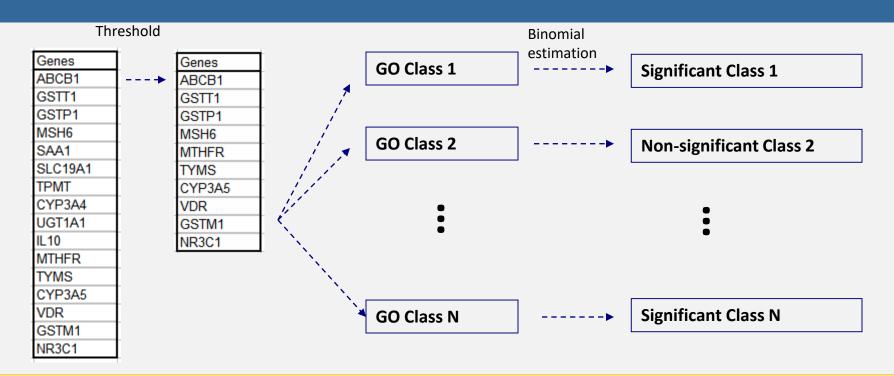
- Suppose
 - Each gene has 50% chance to be high
 - You have 3 disease and 3 normal samples
- What is the chance of a group of 5 genes being perfectly correlated to these samples?

- Prob(group of genes correlated) = $(1/2^6)^5$
 - Good, << 1/26
- # of groups = 25000 C₅
- ⇒ E(# of groups of genessis) correlated) = $\frac{25000}{5}$ (1/26)5 = 7.58*10¹⁰
- ⇒ Even more false positives?
- Perhaps no need to consider every group

of pathways = 1000

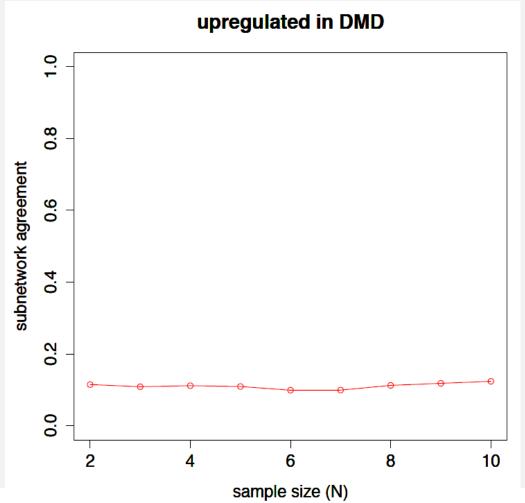
E(# of pathways correlated) = 1000 * $(1/2^6)^5 = 9.3*10^{-7}$

Pathway overlap analysis via Onto-Express (aka ORA)



ORA tests whether a pathway is significant by intersecting the genes in the pathway with a predetermined list of DE genes (e.g., genes whose t-statistic meets the 5% significance threshold of t-test), and checking the significance of the size of the intersection using the hypergeometric test

The bewilderment persists... a crisis?



DMD gene expression data

- Pescatori et al., 2007
- Haslett et al., 2002

Pathway data

PathwayAPI, Soh et al., 2010

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Exercise

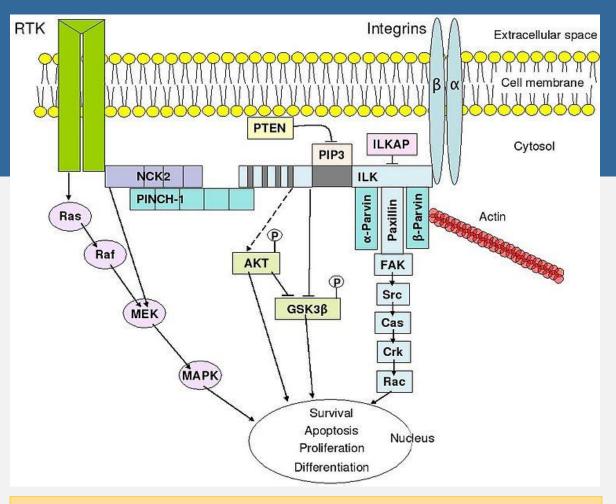
Why does ORA perform so poorly in selecting differentially expressed genes?

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Issue #1 with ORA

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A biological pathway is a chain of actions of molecules in cell leading to a change in cell

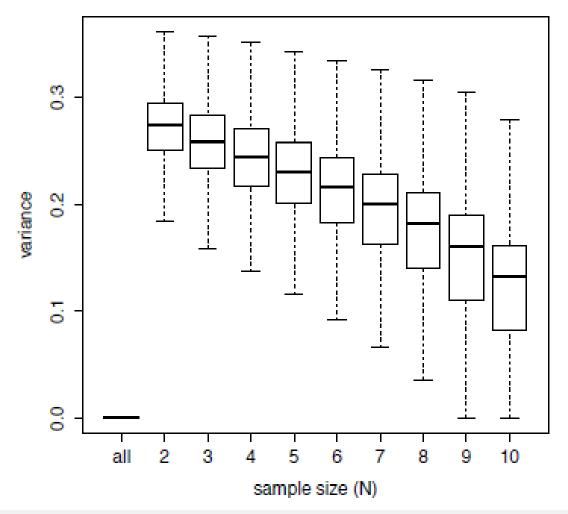
⇒ Behavour of genes in a pathway is more coordinated than random ones

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Issue #2 with ORA

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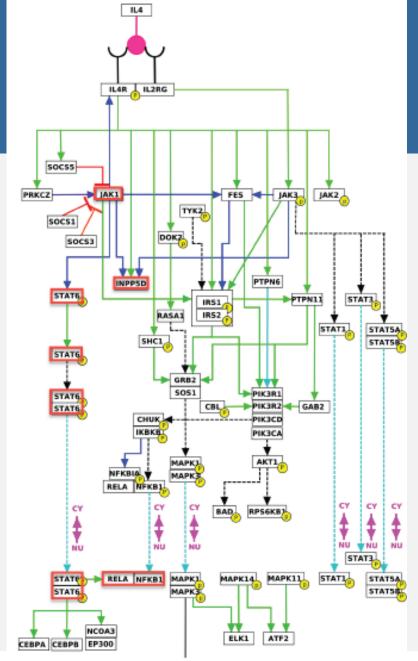
t-test p.value(s)



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Issue #3 with ORA

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Exercise

How to solve the issues identified in ORA?

ORA-Paired: Paired test and new null hypothesis

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Issue #1 is solved

Null hypothesis is "Pathway P is irrelevant to the difference between patients and normals, and the genes in P behave similarly in patients and normals"

Issue #2 is solved

No need pre-determined list of DE genes

Issue #3 is unsolved

Assume absence of batch effects

Exercise

Let g_i be a gene in a pathway P Let p_j be a patient Let q_k be a normal

Let $\Delta_{i,j,k} = \text{Expr}(g_i,p_j) - \text{Expr}(g_i,q_k)$

Test whether $\Delta_{i,j,k}$ is a distribution with mean 0

How many $\Delta_{i,j,k}$ are there?

|patients| * |normals| * |genes in P|

Does this mean sample size now larger?

Does this mean more degrees of freedom?

Testing the null hypothesis "Pathway P is irrelevant to the diff betw patients and normals and so, the genes in P behave similarly in patients and normals"

Method #1

T-test w/ the right degrees of freedom?

normals + # patients - 1

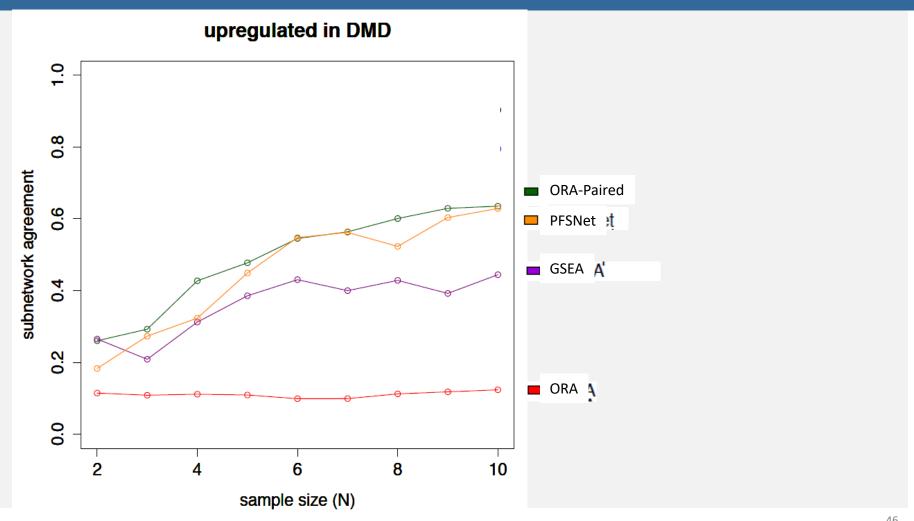
Method #2

By the null hypothesis, a dataset & its class-label permutations are exchangeable

Get null distribution by class-label permutations

Only for large-size sample

Better, but not super-duper good



NEA-Paired: Paired test on subnetworks

Given a pathway P

Let each node and its immediate neighbourhood in P be a subnetwork

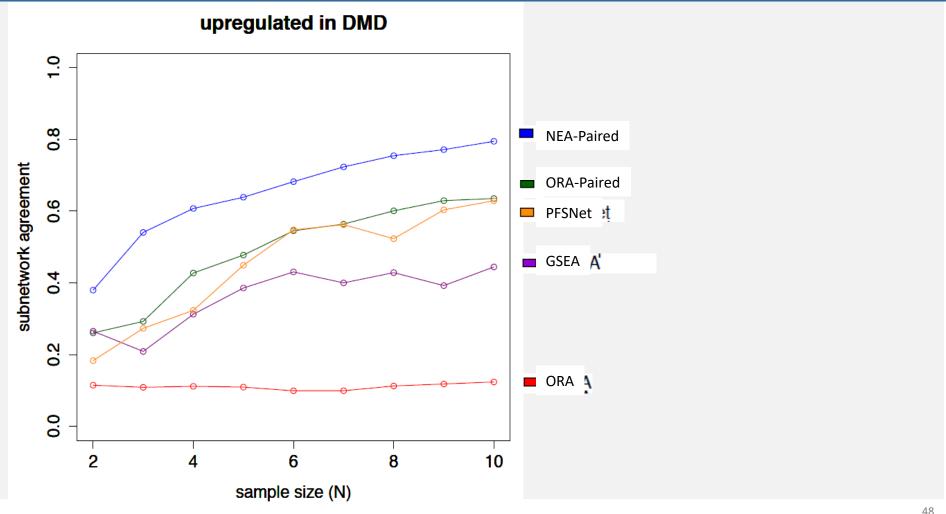
Apply ORA-Paired on each subnetwork individually

Issues #1 & #2 are solved as per ORA-Paired

Issue #3 is partly solved

Testing subnetworks instead of whole pathways

Much better performance



Take-home messages

Statistical hypothesis testing needs careful thought

Right null hypothesis

Right null distribution

Many nuances wrt confounding factors

Make effort to understand the domain

A little domain insight goes a really long way

References

Draghici et al., "Global functional profiling of gene expression", *Genomics*, 81(2):98-104, 2003

Lim et al., "A quantum leap in the reproducibility, precision, and sensitivity of gene expression profile analysis even when sample size is extremely small", *Journal of Bioinformatics and Computational Biology*, 13(4):1550018, 2015

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Presentations and discussion on ...

Research Open access Published: 01 October 2015

Inferring synthetic lethal interactions from mutual exclusivity of genetic events in cancer

<u>Sriganesh Srihari</u>, <u>Jitin Singla</u>, <u>Limsoon Wong</u> [™] & <u>Mark A. Ragan</u> [™]

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