Reminder: Multiple Linear Regression

Test-train data split to avoid overfitting

Multiple Linear Regression Model

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + ... \beta_k x_k + \varepsilon$$

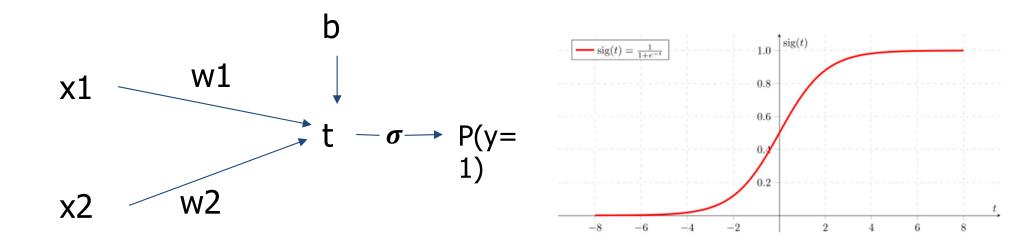
One can also use powers and products of other variables or even non-linear functions like $exp(x_i)$ or $log(x_i)$ instead of x_3, \ldots, x_k .

Example: the general two-variable quadratic regression has 6 constants:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 (x_1)^2 + \beta_4 (x_2)^2 + \beta_5 (x_1 x_2) + \varepsilon$$

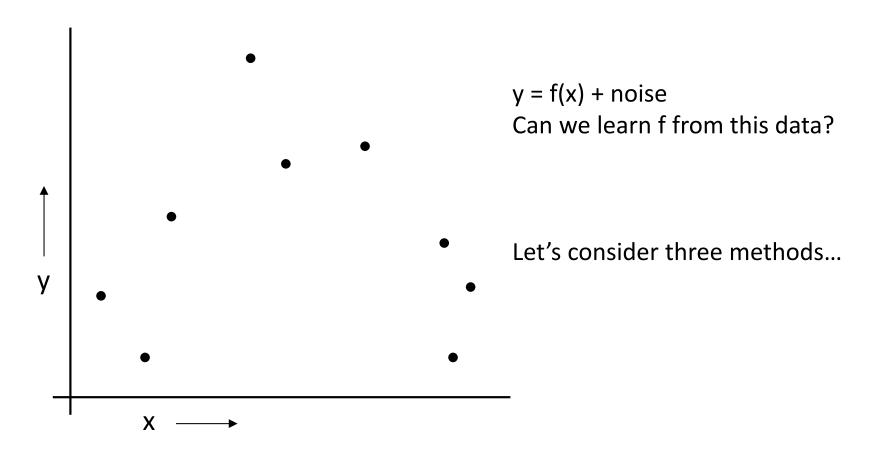
Logistic Regression

$$P(y=1) = \sigma(x1*w1 + x2*w2 + b)$$

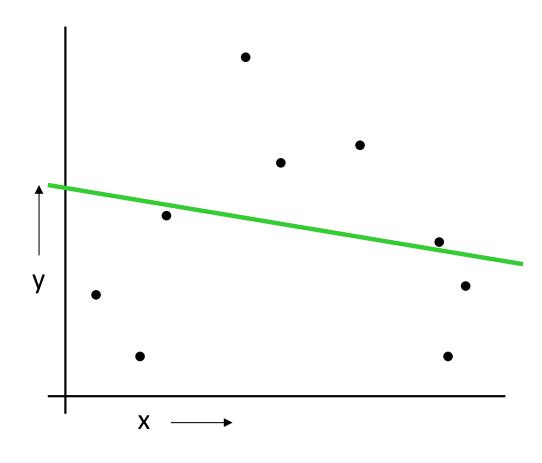


How to know when to stop adding new variables or model parameters in any data fitting algorithm such as multiple linear regression?

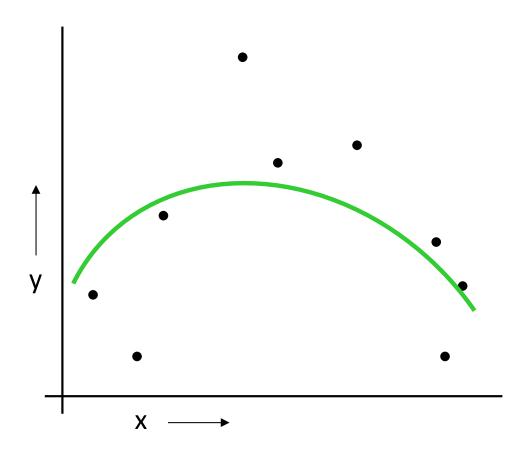
A Regression Problem



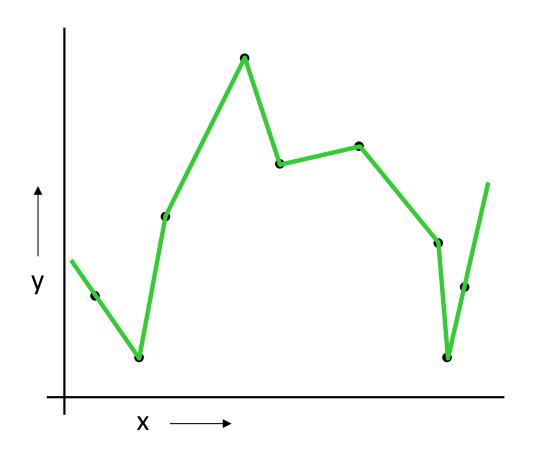
Single Variable Linear Regression



2-variable Linear Regression with x and x²

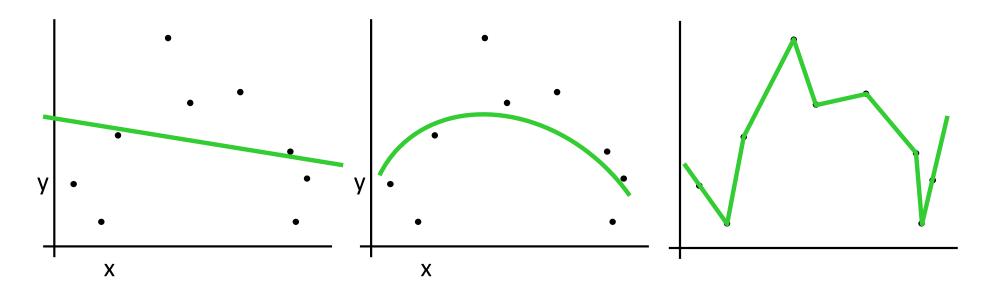


Join-the-dots



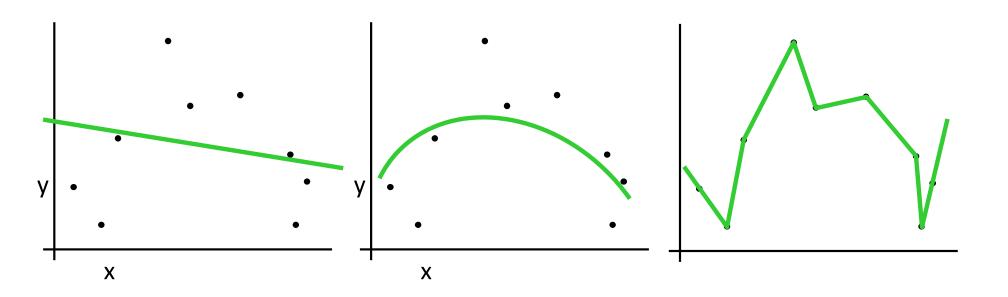
Also known as piecewise linear nonparametric regression if that makes you feel better

Which is best?



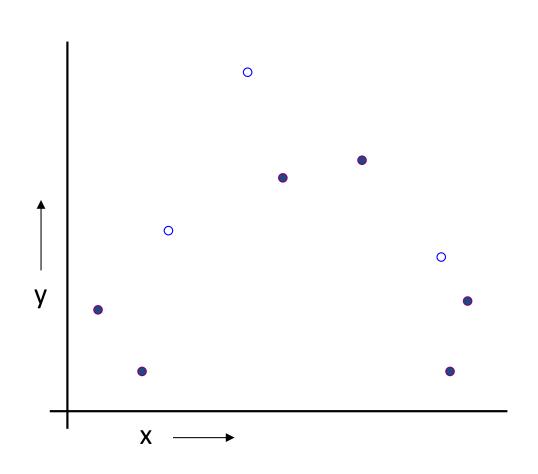
Why not choose the method with the best fit to the data?

What do we really want?

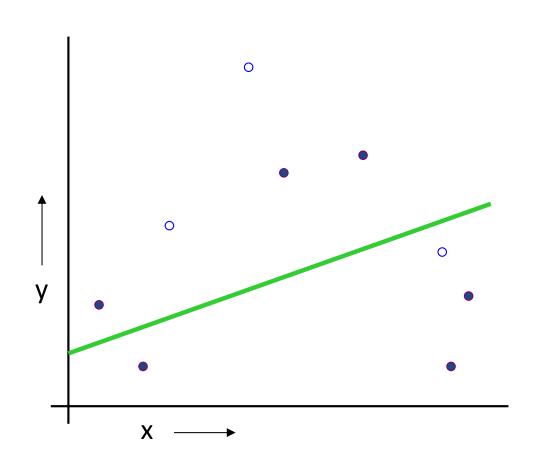


Why not choose the method with the best fit to the data?

"How well are you going to predict future data drawn from the same distribution?"

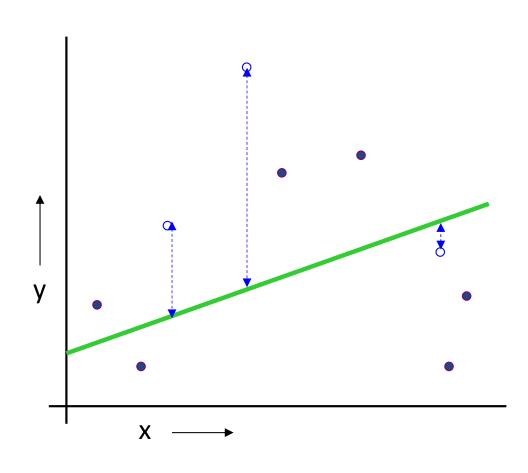


Randomly choose
 of the data to
 in a test set
 The remainder is a training set



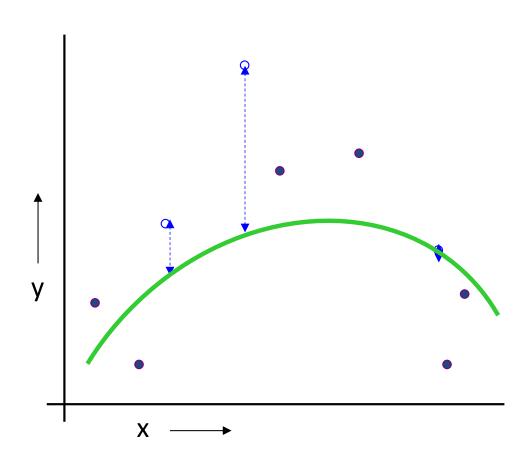
(Linear regression example)

- 1. Randomly choose 30% of the data to be in a test set
- 2. The remainder is a training set
- 3. Perform your regression on the training set



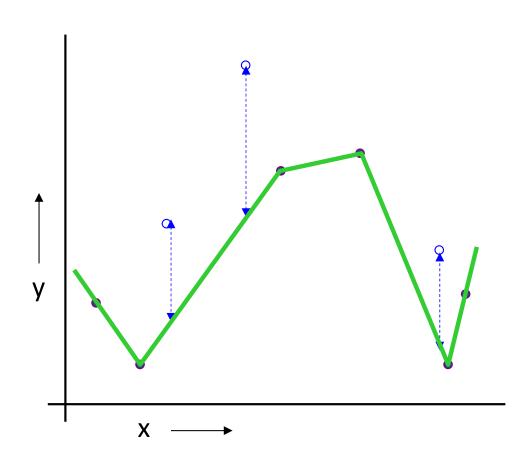
(Linear regression example) Mean Squared Error = 2.4

- 1. Randomly choose 30% of the data to be in a test set
- 2. The remainder is a training set
- 3. Perform your regression on the training set
- 4. Estimate your future performance with the test set



(Quadratic regression example) Mean Squared Error = 0.9

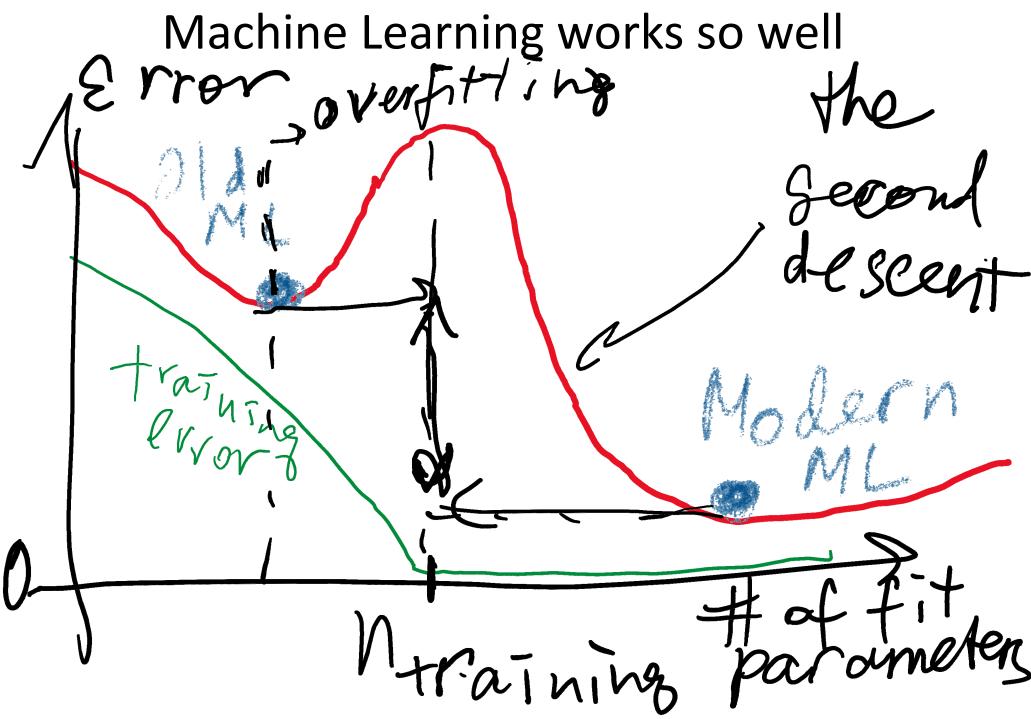
- 1. Randomly choose 30% of the data to be in a test set
- 2. The remainder is a training set
- 3. Perform your regression on the training set
- 4. Estimate your future performance with the test set



(Join the dots example)
Mean Squared Error = 2.2

- 1. Randomly choose 30% of the data to be in a test set
- 2. The remainder is a training set
- 3. Perform your regression on the training set
- 4. Estimate your future performance with the test set

Double descend- the main reason modern



R² and Adjusted R²

The coefficient of multiple determination R²

$$R^2 = \frac{SS_R}{SS_T} = 1 - \frac{SS_E}{SS_T}$$

The adjusted R^2 is

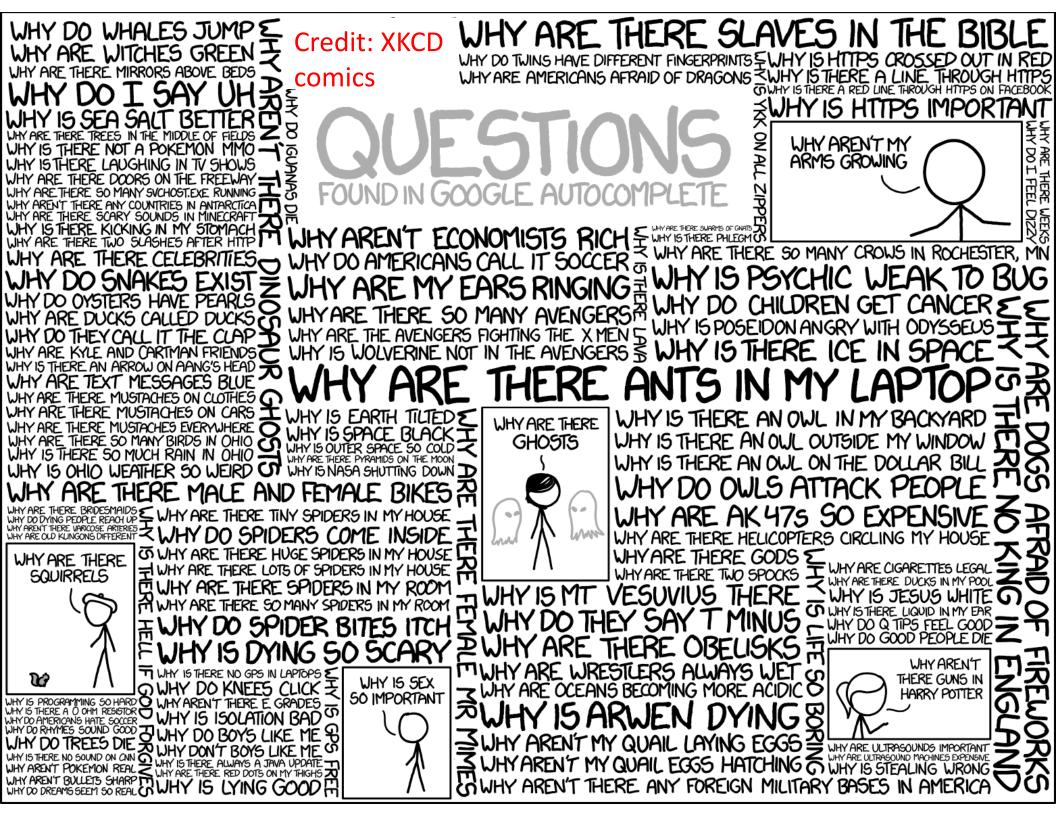
$$R_{\text{adj}}^2 = 1 - \frac{SS_E/(n-p)}{SS_T/(n-1)}$$

- The adjusted R² statistic penalizes adding terms to the MLR model.
- It can help guard against overfitting (including regressors that are not really useful)

How to know where to stop adding variables?

 Adding new variables x_i to MLR watch the adjusted R²

Once the adjusted R²
 no longer increases = stop.
 Now you did the best you can.



Matlab exercise on #2 on MLR

- Every group works with g0=2907; g1=1527; g2=2629; g3=2881; g4=1144; g5=1066;
- Compute Multiple Linear Regression (MLR): where
 y=exp_t (g0); x1= exp_t (g1); x2= exp_t (g2);
- How much better the MLR did compared to the Single Linear Regression (SLR)?
- Continue increasing the number of genes in x until R_adj starts to decrease

How I did it

```
g0=2907; g1=1527; g2=2629; g3=2881;g4=1144; g5=1066;
y=exp t(g0,:)';
• %% first use one x to predict y
* x=exp t(g1,:)';
figure; plot(x,y,'ko')
lm=fitlm(x,y)
y fit=lm.Fitted;
hold on;
plot(x,lm.Fitted,'r-');
• %% now use 2 x's to predict y
 x=[exp t(g1,:)', exp t(g2,:)'];
lm2=fitlm(x,y)
y fit=lm2.Fitted;
 hold on; plot(x(:,1),y fit,'gd');

    % now use m x's to predict y

 corr matrix=corr(exp t');
• g0=2907;
[u v]=sort(corr matrix(q0,:),'descend');
• x=[exp t(v(2:m+1),:)'];
lm3=fitlm(x,y)
y fit=lm3.Fitted;
• plot(x(:,1),y_fit,'s');
```

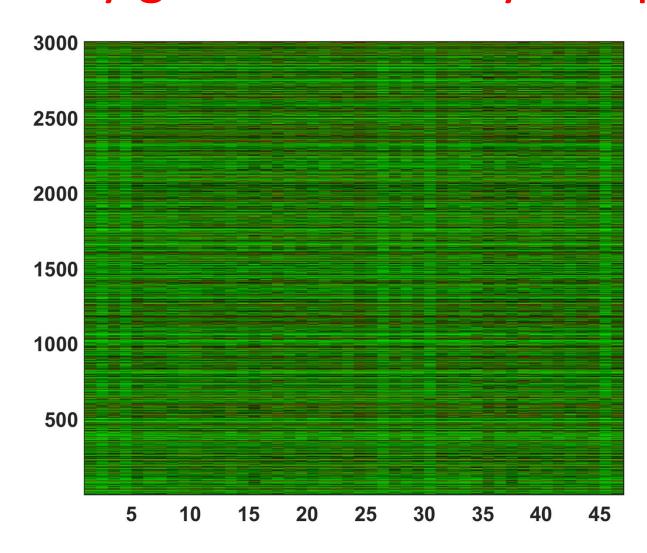
Clustering analysis of gene expression data

Chapter 11 in
Jonathan Pevsner,
Bioinformatics and Functional Genomics,

3rd edition

(Chapter 9 in 2nd edition)

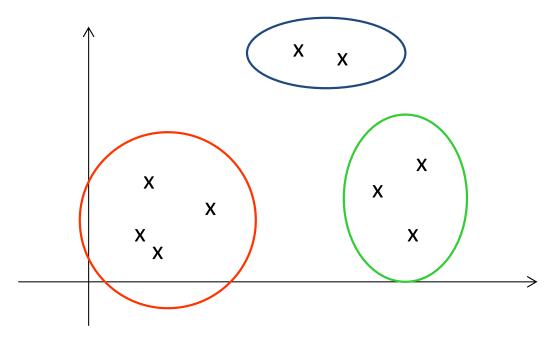
How to find the entire groups of mutually correlated genes if you have many genes and many samples?



Clustering to the rescue!

What is clustering?

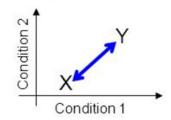
- The goal of clustering is to
 - group data points that are close (or similar) to each other
 - Usually, one needs to identify such groups (or clusters) in an unsupervised manner
 - Sometimes one takes into account prior information (Bayesian methods)
- Need to define some distance d_{ij} between objects i and j
- Clustering is easy in 2 dimensions but hard in 3000 dimensions -> need to somehow reduce dimensionality



How to define the distance?

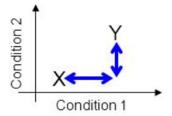
- Euclidean distance:
 - Most commonly used distance
 - Sphere shaped cluster
 - Corresponds to the geometric distance into the multidimensional space

$$d(X,Y) = \sqrt{\sum_{i} (x_i - y_i)^2}$$



- City Block (Manhattan) distance:
 - Sum of differences across dimensions
 - Less sensitive to outliers
 - Diamond shaped clusters

$$d(X,Y) = \sum_{i} |x_i - y_i|$$



The Canberra distance metric is calculated in R by

$$\sum \left(\frac{|x_i - y_i|}{|x_i + y_i|}\right).$$

Correlation coefficient distance

$$d(X,Y) = 1 - \rho(X,Y) = 1 - \frac{Cov(X,Y)}{\sqrt{(Var(X) \cdot Var(Y))}}$$

Common types of clustering algorithms

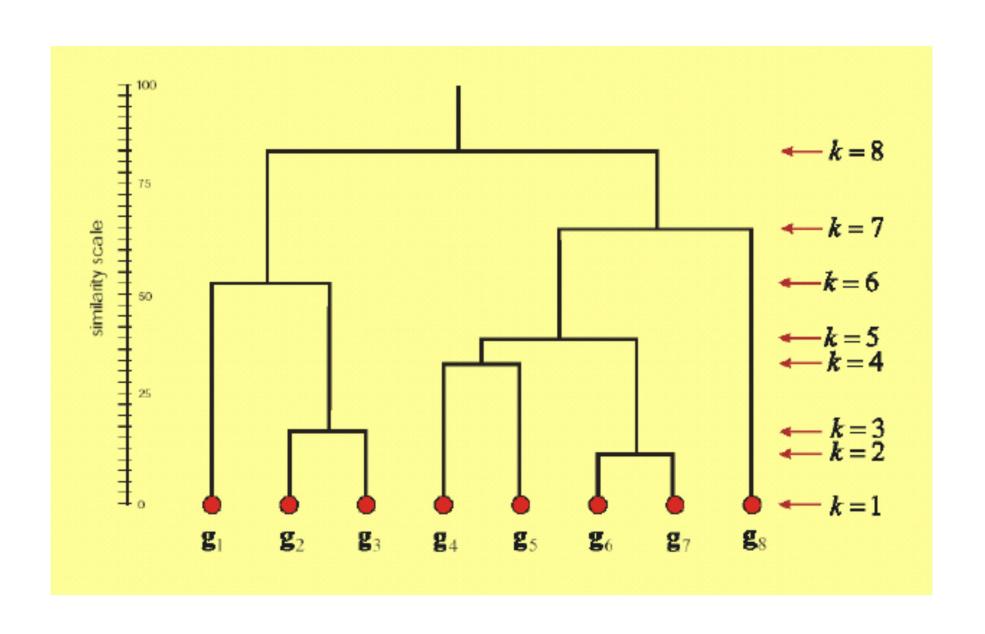
- Hierarchical if one doesn't know in advance the # of clusters
 - Agglomerative: start with N clusters and gradually merge them into 1 cluster
 - Divisive: start with 1 cluster and gradually break it up into N clusters
- Non-hierarchical algorithms
 - K-means clustering:
 - <u>Iteratively</u> apply the following two steps:
 - Calculate the centroid (center of mass) of each cluster
 - Assign each to the cluster to the nearest centroid
 - Principal Component Analysis (PCA)
 - plot pairs of top eigenvectors of the covariance matrix Cov(X_i, X_i) and uses visual information to group

Hierarchical clustering

UPGMA algorithm

- Hierarchical agglomerative clustering algorithm
- UPGMA = Unweighted Pair Group Method with Arithmetic mean
- Iterative algorithm:
- Start with a pair with the smallest d(X,Y)
- Cluster these two together and replace it with their arithmetic mean (X+Y)/2
- Recalculate all distances to this new "cluster node"
- Repeat until all nodes are merged

Output of UPGMA algorithm



Clustering in Matlab

Choices of distance metrics in clustergram(... 'RowPDistValue' ..., 'ColumnPDistValue' ...,)

Metric	Description		
'euclidean'	Euclidean distance (default).		
'seuclidean'	Standardized Euclidean distance. Each coordinate difference between rows in X is scaled by dividing by the corresponding element of the standard deviation S=nanstd(X). To specify another value for S, use D=pdist(X, 'seuclidean', S).		
'cityblock'	City block metric.		
'minkowski'	Minkowski distance. The default exponent is 2. To specify a different exponent, use $D = pdist(X, 'minkowski', P)$, where P is a scalar positive value of the exponent.		
'chebychev'	Chebychev distance (maximum coordinate difference).		
'mahalanobis'	Mahalanobis distance, using the sample covariance of X as computed by nancov. To compute the distance with a different covariance, use D = pdist (X, 'mahalanobis', C), where the matrix C is symmetric and positive definite.		
'cosine'	One minus the cosine of the included angle between points (treated as vectors).		
'correlation'	One minus the sample correlation between points (treated as sequences of values).		
'spearman'	One minus the sample Spearman's rank correlation between observations (treated as sequences of values).		
'hamming'	Hamming distance, which is the percentage of coordinates that differ.		
'jaccard'	One minus the Jaccard coefficient, which is the percentage of nonzero coordinates that differ.		
custom distance function	A distance function specified using @: D = pdist(X,@distfun) A distance function must be of form		
	d2 = distfun(XI,XJ)		
	taking as arguments a 1-by- n vector XI, corresponding to a single row of X, and an $m2$ -by- n matrix XJ, corresponding to multiple rows of X. distfun must accept a matrix XJ with an arbitrary number of rows. distfun must return an $m2$ -by-1 vector of distances d2, whose k th element is the distance between XI and XJ (k ,:).		

Choices of hierarchical clustering algorithm in clustergram(...'linkage',...)

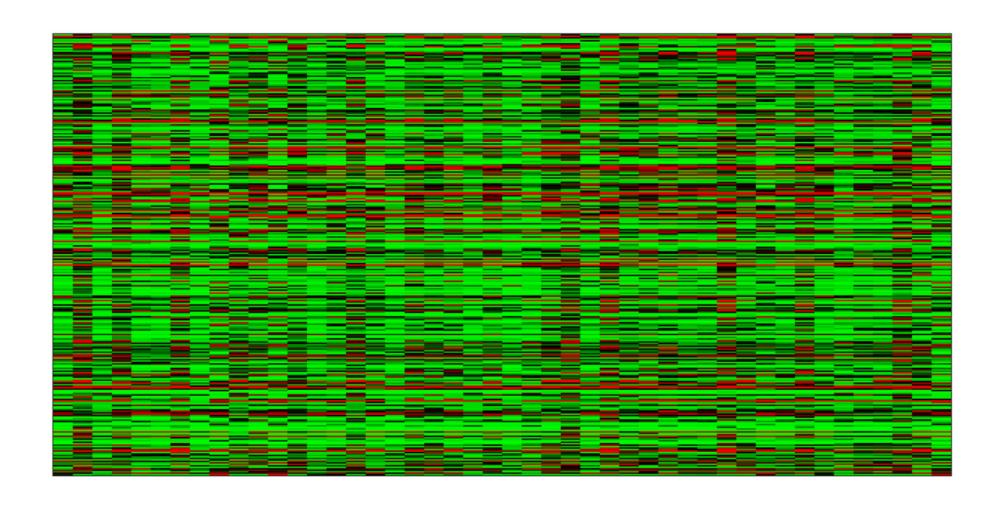
Х		Matrix with two or more rows. The rows represent observations, the columns represent categories or dimensions.		
method	Algorithm for computing distance between clusters.			
	Method	Description		
	'average'	Unweighted average distance (UPGMA)		
	'centroid'	Centroid distance (UPGMC), appropriate for Euclidean distances only		
	'complete'	Furthest distance		
	'median'	Weighted center of mass distance (WPGMC), appropriate for Euclidean distances only		
	'single'	Shortest distance		
	'ward'	Inner squared distance (minimum variance algorithm), appropriate for Euclidean distances only		
	'weighted'	Weighted average distance (WPGMA)		
	Default: 'single'			

Clustering group exercise

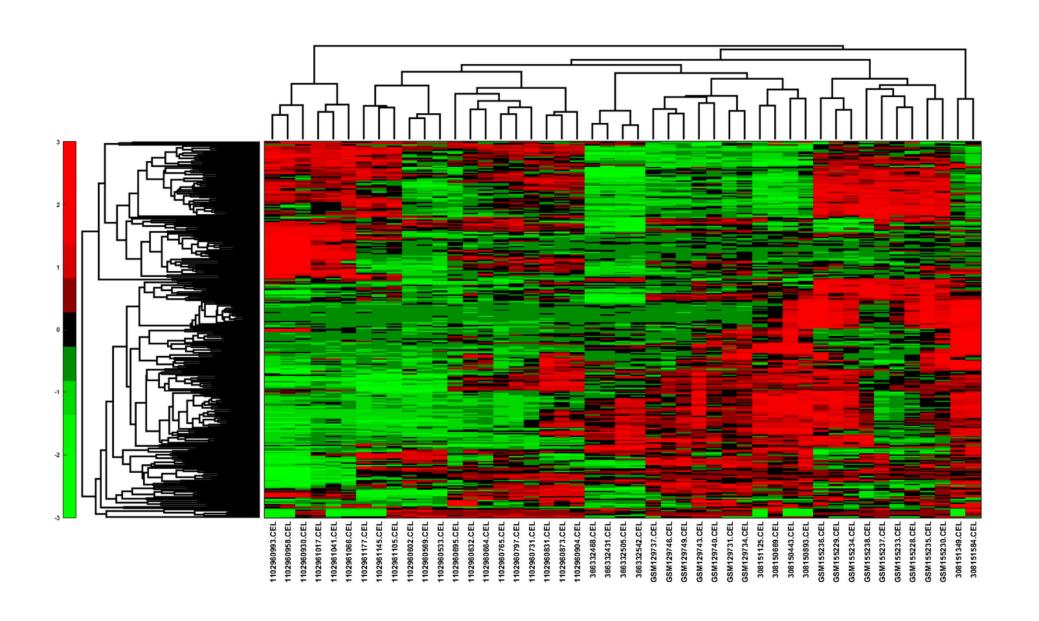
- Each group will analyze a cluster of genes identified in the T cell expression table
- Analyze the table of top 100 genes by variance in 47 samples
- Cluster them using:
 - Group 1: 'linkage', 'average', 'RowPDistValue', 'euclidean',
 - Group 2: 'linkage', 'single', 'RowPDistValue', 'cityblock',
 - Group 3: 'linkage', 'average', 'RowPDistValue', 'correlation',
 - Group 4: 'linkage', 'single', 'RowPDistValue', 'euclidean',
 - Group 5: 'linkage', 'weighted', 'RowPDistValue', 'correlation',
- Use clustergram(..., 'Standardize', 'Row', 'linkage', as specified for your group, 'RowPDistValue' as specified for your group,
 - 'RowLabels', gene names1, 'ColumnLabels', array names)

```
load expression_table.mat
gene_variation=std(exp_t')';
[a,b]=sort(gene variation,'descend');
ngenes=100;
exp_t1=exp_t(b(1:ngenes),:);
gene_names1=gene_names(b(1:ngenes));
%%% for group 1
CGobj1 = clustergram(exp t1,
'Standardize','Row',...
'RowLabels',
gene_names1,'ColumnLabels',array_names)
set(CGobj1,'RowLabels',gene_names1,'ColumnLab
els', array names, 'linkage',
'average','RowPDist','euclidean');
set(CGobj1,'RowLabels',gene_names1,'ColumnLab
els', array names, 'linkage',
'average', 'RowPDist', 'correlation');
```

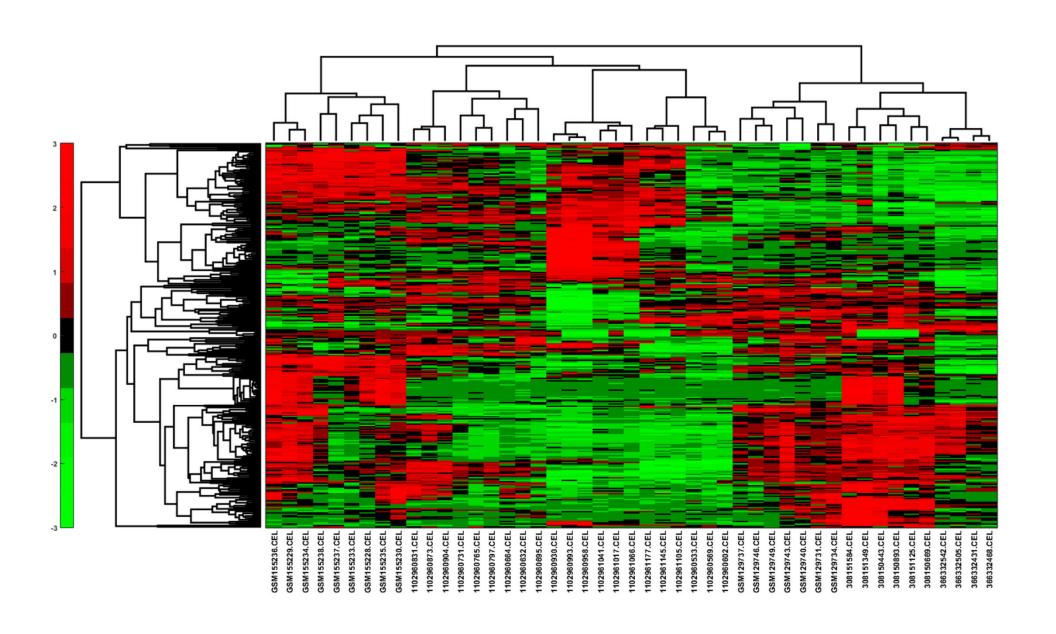
Before clustering



UPGMA hierarchical clustering, Euclidian distance



UPGMA hierarchical clustering, correlation distance



Search for shared biological functions

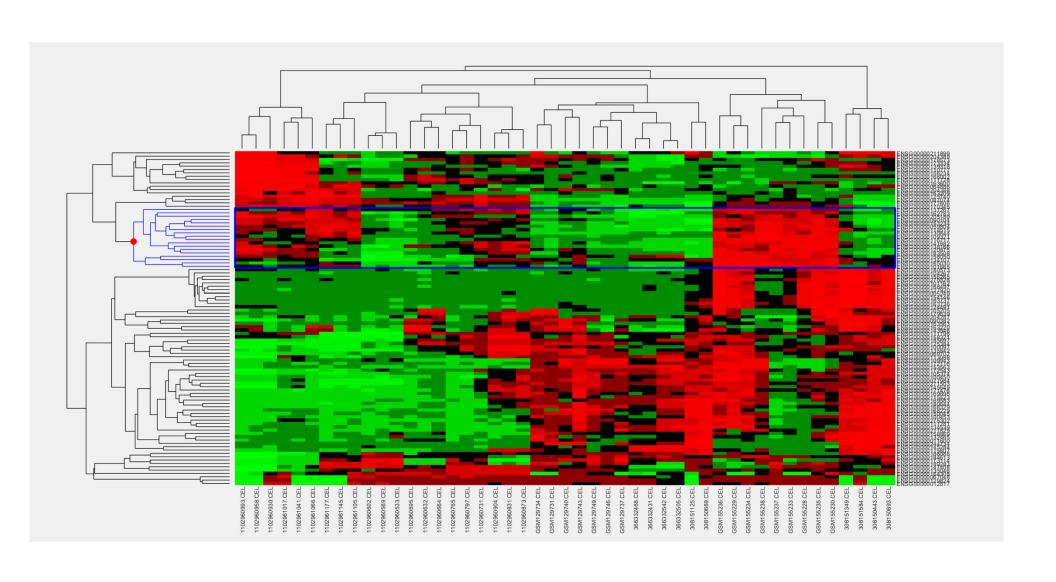
- copy the list of displayed genes
- go to "Start Analysis" on https://david.ncifcrf.gov/tools.jsp
- Paste genes from gene list displayed by Matlab into the box in the left panel of the website
- select ENSEMBL_GENE_ID and "gene list" radio button
- Click "Functional Annotation Clustering"
- Select groups in "Annotation Summary Results" which have many genes from your list. Definitely select "PUBMED_ID" and interaction databases like "Biogrid"
- First look at "Functional Annotation Chart" rectangular button below to display all overrepresented terms. Sort by "Benjamini" correction for multiple hypotheses testing
- Select "Functional Annotation Clustering" rectangular button below to display annotation results for gene list broken into multiple groups (clusters) each with related biological functions
- Write down the # of genes in the cluster and the top functions in two most interesting clusters

```
%%%
%Which biological functions are
overrepresented in different clusters?
%1) Pick a cluster:
%2) Select a node on the tree of rows,
%3) Right click
%4) Choose "export group info" into
the workspace
%5) Name it gene list
%Run the following two Matlab
commands to display genes
g1=gene_list.RowNodeNames;
for m=1:length(g1);
disp(g1{m});
end;
```

- % select ENSEMBL_GENE_ID and "gene list" radio button
- % Click "Functional Annotation Clustering"
- % Select groups in "Annotation Summary Results"
- % which have many genes from your list.
- % Definitely select "PUBMED_ID" and
- % interaction databases like "Biogrid"
- % First look at "Functional Annotation Chart" rectangular button below
- % to display all overrepresented terms.
- % Sort by "Benjamini" correction for multiple hypotheses testing
- % Select "Functional Annotation Clustering" rectangular button below
- % to display annotation results for gene list broken into multiple groups
- % (clusters) each with related biological functions
- % Write down the # of genes in the cluster and the top functions
- % in two most interesting clusters

Using options:

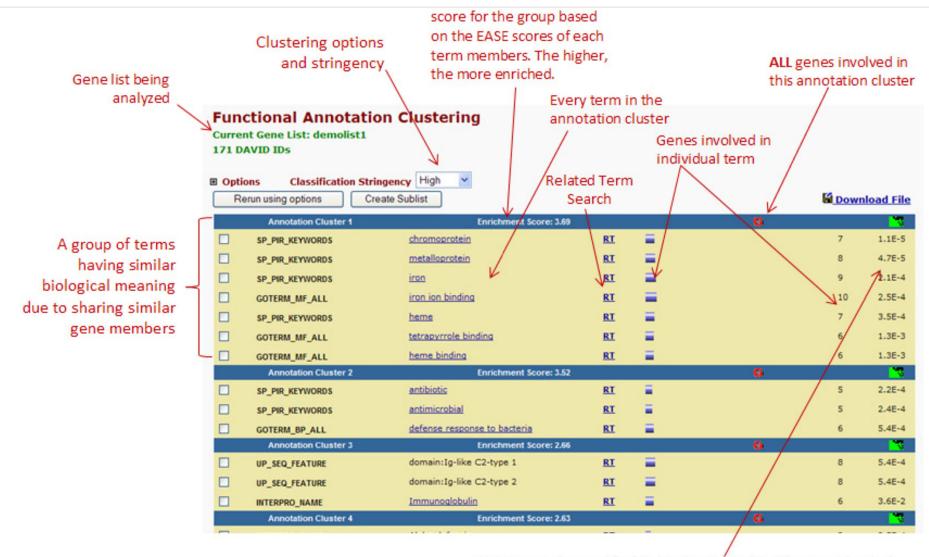
'linkage', 'average', 'RowPDistValue', 'euclidean',



54 chart records

Sublist	<u>Category</u>	<u>Term</u>	‡ RT	Genes	Count	<u>%</u>	<u>Benjamini</u>
	GOTERM_CC_DIRECT	nucleus	<u>RT</u>		16	88.9 8.1E-7	3.7E-5
	PIR_SUPERFAMILY	<u>dual specificity protein phosphatase (MAP kinase phosphatase)</u>	<u>RT</u>	_	3	16.7 4.0E-5	8.0E-5
	GOTERM_MF_DIRECT	protein tyrosine/threonine phosphatase activity	<u>RT</u>		3	16.7 3.4E-5	1.3E-3
	GOTERM_MF_DIRECT	MAP kinase tyrosine phosphatase activity	<u>RT</u>		3	16.7 3.4E-5	1.3E-3
	GOTERM_MF_DIRECT	MAP kinase tyrosine/serine/threonine phosphatase activity	<u>RT</u>		3	16.7 5.9E-5	1.5E-3
	INTERPRO	Mitogen-activated protein (MAP) kinase phosphatase	<u>RT</u>		3	16.7 3.3E-5	1.9E-3
	SMART	RHOD	<u>RT</u>		3	16.7 2.5E-4	4.8E-3
	INTERPRO	Rhodanese-like domain	<u>RT</u>	_	3	16.7 2.2E-4	6.2E-3
	SMART	<u>DSPc</u>	<u>RT</u>		3	16.7 8.4E-4	8.0E-3
	INTERPRO	<u>Dual specificity phosphatase, catalytic domain</u>	<u>RT</u>		3	16.7 6.0E-4	9.2E-3
	INTERPRO	<u>Dual specificity phosphatase, subgroup, catalytic domain</u>	<u>RT</u>		3	16.7 6.6E-4	9.2E-3
	GOTERM_BP_DIRECT	endoderm formation	<u>RT</u>	_	3	16.7 5.6E - 5	1.1E - 2
	UP_KW_CELLULAR_COMPONENT	<u>Nucleus</u>	<u>RT</u>		13	72.2 1.5E-3	1.3E-2
	SMART	PTPc motif	<u>RT</u>	_	3	16.7 2.3E-3	1.5E-2
	GOTERM_MF_DIRECT	phosphoprotein phosphatase activity	<u>RT</u>		3	16.7 8.0E-4	1.5E-2
	INTERPRO	Protein-tyrosine phosphatase, catalytic	<u>RT</u>		3	16.7 1.4E-3	1.6E-2
	UP_KW_PTM	<u>Ubl conjugation</u>	<u>RT</u>		7	38.9 4.5E-3	1.9E-2
	UP_KW_PTM	<u>Isopeptide bond</u>	<u>RT</u>		6	33.3 5.4E-3	1.9E-2
	INTERPRO	Protein-tyrosine phosphatase, active site	<u>RT</u>		3	16.7 2.1E-3	2.0E-2
	INTERPRO	Protein-tyrosine/Dual specificity phosphatase	<u>RT</u>	_	3	16.7 2.8E-3	2.3E-2
	UP_SEQ_FEATURE	DOMAIN:Rhodanese	<u>RT</u>		3	16.7 1.9E-4	2.4E-2
	KEGG_PATHWAY	MAPK signaling pathway	<u>RT</u>	_	5	27.8 5.9E-4	2.8E-2
	GOTERM_MF_DIRECT	myosin phosphatase activity	<u>RT</u>		3	16.7 2.4E-3	3.6E-2
	GOTERM_MF_DIRECT	protein tyrosine phosphatase activity	<u>RT</u>		3	16.7 4.2E-3	5.3E-2
	GOTERM_CC_DIRECT	nucleoplasm	<u>RT</u>		10	55.6 2.3E-3	5.4E-2
	GOTERM_BP_DIRECT	negative regulation of MAPK cascade	<u>RT</u>		3	16.7 7.0E-4	6.8E-2

Mark Download File



EASE Score, the modified Fisher Exact P-Value. They are identical to that in the Chart Report. The smaller, the more enriched.

Help and Manual

Current Gene List: List_3

Current Background: Homo sapiens

18 DAVID IDs

Classification Stringency Medium ~ **■ Options**

Rerun using options

Create Sublist

25 Cluster(s)

	Down	load	File
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Annotatio	on Cluster 1	Enrichment Score: 5.2			Count	P_Value	Benjamini
	DISGENET	Juvenile arthritis	<u>RT</u>		7	1.5E-8	4.7E-7
	DISGENET	Juvenile psoriatic arthritis	<u>RT</u>		7	1.5E-8	4.7E-7
	DISGENET	Polyarthritis, Juvenile, Rheumatoid Factor Negative	<u>RT</u>		7	1.5E-8	4.7E-7
	DISGENET	Polyarthritis, Juvenile, Rheumatoid Factor Positive	<u>RT</u>		7	1.5E-8	4.7E-7
	DISGENET	Juvenile-Onset Still Disease	<u>RT</u>		7	1.8E-8	4.7E-7
	KEGG_PATHWAY	MAPK signaling pathway	RT		5	5.9E-4	2.8E-2
	BIOGRID_INTERACTION	mitogen-activated protein kinase 1(MAPK1)	<u>RT</u>		4	3.8E-3	1.0E0
	WIKIPATHWAYS	MAPK signaling pathway	<u>RT</u>		3	5.8E-2	6.9E-1
	GAD_DISEASE_CLASS	UNKNOWN	<u>RT</u>		5	1.5E-1	9.9E-1
Annotatio	on Cluster 2	Enrichment Score: 2.83		To the second se	Count	P_Value	Benjamini
	INTERPRO	Mitogen-activated protein (MAP) kinase phosphatase	<u>RT</u>		3	3.3E-5	1.9E-3
	GOTERM_MF_DIRECT	protein tyrosine/threonine phosphatase activity	<u>RT</u>	_	3	3.4E-5	1.3E-3
	GOTERM_MF_DIRECT	MAP kinase tyrosine phosphatase activity	<u>RT</u>		3	3.4E-5	1.3E-3
	PIR_SUPERFAMILY	<u>dual specificity protein phosphatase (MAP kinase phosphatase)</u>	<u>RT</u>	=	3	4.0E-5	8.0E-5
	GOTERM_BP_DIRECT	endoderm formation	<u>RT</u>		3	5.6E-5	1.1E-2
	GOTERM_MF_DIRECT	MAP kinase tyrosine/serine/threonine phosphatase activity	<u>RT</u>	=	3	5.9E-5	1.5E-3
	PUBMED_ID	<u>27880917</u>	<u>RT</u>		4	1.7E-4	2.5E-2
	UP_SEQ_FEATURE	DOMAIN: Rhodanese	<u>RT</u>	=	3	1.9E-4	2.4E-2
	INTERPRO	Rhodanese-like domain	<u>RT</u>		3	2.2E-4	6.2E-3
	SMART	RHOD	RT		3	2.5E-4	4.8E-3

					:		
Annotatio	on Cluster 3	Enrichment Score: 2.43	G	<u> </u>	Count	P_Value	Benjamini
	DISGENET	Arsenic Poisoning, Inorganic	<u>RT</u>		3	3.5E-3	4.6E-2
	DISGENET	Nervous System, Organic Arsenic Poisoning	<u>RT</u>	_	3	3.5E-3	4.6E-2
	DISGENET	Arsenic Poisoning	<u>RT</u>	_	3	3.5E-3	4.6E-2
	DISGENET	Arsenic Encephalopathy	<u>RT</u>		3	3.5E-3	4.6E-2
	DISGENET	Arsenic Induced Polyneuropathy	<u>RT</u>	_	3	3.5E-3	4.6E-2
	DISGENET	Dermatologic disorders	<u>RT</u>		3	5.1E-3	5.6E-2
Annotatio	on Cluster 4	Enrichment Score: 2.26	G	in the second se	Count	P_Value	Benjamini
	PUBMED_ID	<u>19322201</u>	<u>RT</u>		7	1.3E-8	5.9E-6
	BIOGRID_INTERACTION	ELAV like RNA binding protein 1(ELAVL1)	<u>RT</u>		7	4.4E-3	1.0E0
	UCSC_TFBS	СЕВРА	<u>RT</u>		7	1.8E-1	1.0E0
	UCSC_TFBS	CDPCR3HD	<u>RT</u>		7	6.5E-1	1.0E0
	UCSC_TFBS	FOXD3	<u>RT</u>		5	7.4E-1	1.0E0
Annotatio	on Cluster 5	Enrichment Score: 2.14	G	The state of the s	Count	P_Value	Benjamini
	GOTERM_BP_DIRECT	negative regulation of transcription from RNA polymerase II promoter	<u>RT</u>		6	1.4E-3	9.1E-2
	BIOGRID_INTERACTION	retinoid X receptor alpha(RXRA)	<u>RT</u>		3	6.1E-3	1.0E0
	GOTERM_MF_DIRECT	protein heterodimerization activity	<u>RT</u>		3	4.5E-2	3.7E-1
Annotatio	on Cluster 6	Enrichment Score: 1.95		in the second se	Count	P_Value	Benjamini
	REACTOME_PATHWAY	Generic Transcription Pathway	<u>RT</u>		7	2.8E-3	1.7E-1
	REACTOME_PATHWAY	RNA Polymerase II Transcription	<u>RT</u>		7	4.6E-3	1.7E-1
	REACTOME_PATHWAY	Gene expression (Transcription)	<u>RT</u>		7	8.2E-3	2.0E-1
	GAD_DISEASE_CLASS	UNKNOWN	<u>RT</u>		5	1.5E-1	9.9E-1
Annotatio	on Cluster 7	Enrichment Score: 1.76			Count	P_Value	Benjamini
	PUBMED_ID	<u>18029348</u>	<u>RT</u>		6	1.8E-5	3.4E-3
	UP_KW_PTM	<u>Isopeptide bond</u>	<u>RT</u>		6	5.4E-3	1.9E-2
	PUBMED_ID	<u>15342556</u>	<u>RT</u>		3	7.9E-3	4.8E-1
	PUBMED_ID	<u>26496610</u>	<u>RT</u>		3	1.0E-1	1.0E0
	GOTERM_MF_DIRECT	metal ion binding	<u>RT</u>		4	4.5E-1	1.0E0
	UCSC_TFBS	TAL1ALPHAE47	RT	_	3	7.9E-1	1.0E0

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Annotatio	on Cluster 3	Enrichment Score: 2.43	G	<u> </u>	Count	P_Value	Benjamini
	DISGENET	Arsenic Poisoning, Inorganic	<u>RT</u>		3	3.5E-3	4.6E-2
	DISGENET	Nervous System, Organic Arsenic Poisoning	<u>RT</u>	_	3	3.5E-3	4.6E-2
	DISGENET	Arsenic Poisoning	<u>RT</u>	_	3	3.5E-3	4.6E-2
	DISGENET	Arsenic Encephalopathy	<u>RT</u>		3	3.5E-3	4.6E-2
	DISGENET	Arsenic Induced Polyneuropathy	<u>RT</u>	_	3	3.5E-3	4.6E-2
	DISGENET	Dermatologic disorders	<u>RT</u>		3	5.1E-3	5.6E-2
Annotatio	on Cluster 4	Enrichment Score: 2.26	G	in the second se	Count	P_Value	Benjamini
	PUBMED_ID	<u>19322201</u>	<u>RT</u>		7	1.3E-8	5.9E-6
	BIOGRID_INTERACTION	ELAV like RNA binding protein 1(ELAVL1)	<u>RT</u>		7	4.4E-3	1.0E0
	UCSC_TFBS	СЕВРА	<u>RT</u>		7	1.8E-1	1.0E0
	UCSC_TFBS	CDPCR3HD	<u>RT</u>		7	6.5E-1	1.0E0
	UCSC_TFBS	FOXD3	<u>RT</u>		5	7.4E-1	1.0E0
Annotatio	on Cluster 5	Enrichment Score: 2.14	G	The state of the s	Count	P_Value	Benjamini
	GOTERM_BP_DIRECT	negative regulation of transcription from RNA polymerase II promoter	<u>RT</u>		6	1.4E-3	9.1E-2
	BIOGRID_INTERACTION	retinoid X receptor alpha(RXRA)	<u>RT</u>		3	6.1E-3	1.0E0
	GOTERM_MF_DIRECT	protein heterodimerization activity	<u>RT</u>		3	4.5E-2	3.7E-1
Annotatio	on Cluster 6	Enrichment Score: 1.95		in the second se	Count	P_Value	Benjamini
	REACTOME_PATHWAY	Generic Transcription Pathway	<u>RT</u>		7	2.8E-3	1.7E-1
	REACTOME_PATHWAY	RNA Polymerase II Transcription	<u>RT</u>		7	4.6E-3	1.7E-1
	REACTOME_PATHWAY	Gene expression (Transcription)	<u>RT</u>		7	8.2E-3	2.0E-1
	GAD_DISEASE_CLASS	UNKNOWN	<u>RT</u>		5	1.5E-1	9.9E-1
Annotatio	on Cluster 7	Enrichment Score: 1.76			Count	P_Value	Benjamini
	PUBMED_ID	<u>18029348</u>	<u>RT</u>		6	1.8E-5	3.4E-3
	UP_KW_PTM	<u>Isopeptide bond</u>	<u>RT</u>		6	5.4E-3	1.9E-2
	PUBMED_ID	<u>15342556</u>	<u>RT</u>		3	7.9E-3	4.8E-1
	PUBMED_ID	<u>26496610</u>	<u>RT</u>		3	1.0E-1	1.0E0
	GOTERM_MF_DIRECT	metal ion binding	<u>RT</u>		4	4.5E-1	1.0E0
	UCSC_TFBS	TAL1ALPHAE47	RT	_	3	7.9E-1	1.0E0

