

## Statistical Microarry Data Analysis

### Review of Microarray

Elements of Gene Expression Data Analysis

- Comparative study
- Clustering

Introduction to Pathway and Gene Ontology Enrichment Analysis

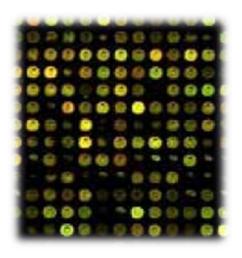
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## Representation

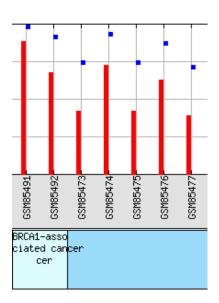


10	500	30	100	
20	28	7	42	
53	11	10	40	
1	1000	200	51	

Gene 1	10
Gene 2	500
Gene 3	30
Gene 4	100
Gene 5	20
Gene 6	28
Gene 7	7
	•••

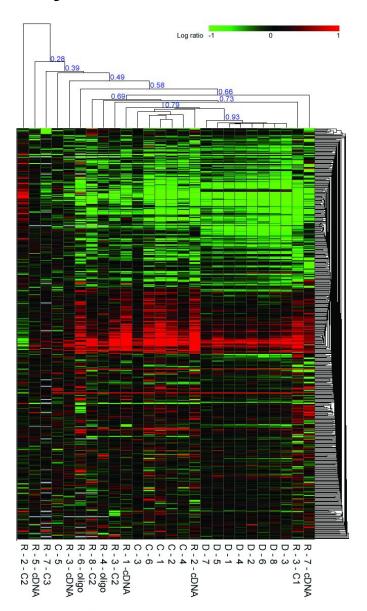


Gene 1	10	50	60	
Gene 2	500	400	800	
Gene 3	30	38	35	
Gene 4	100	107	120	
Gene 5	20	50	70	
Gene 6	28	42	33	
Gene 7	7	15	8	



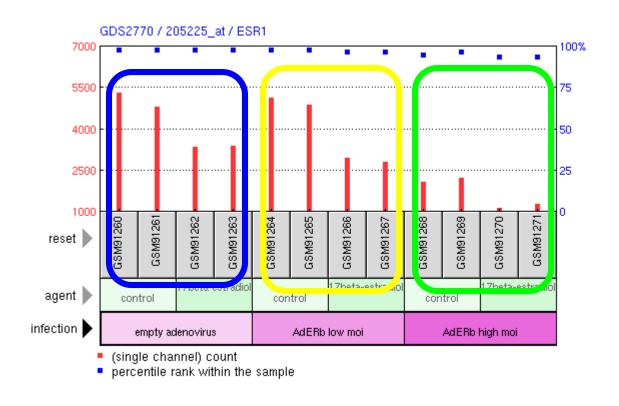
#### How do we use microarray?

- Profiling
- Comparative study
- Clustering
- Inference



### Hypothesis Testing

 Two set of samples sampled from two distributions (N=2)



## Hypothesis Testing

- Two set of samples sampled from two distributions (N=2)
- Hypothesis

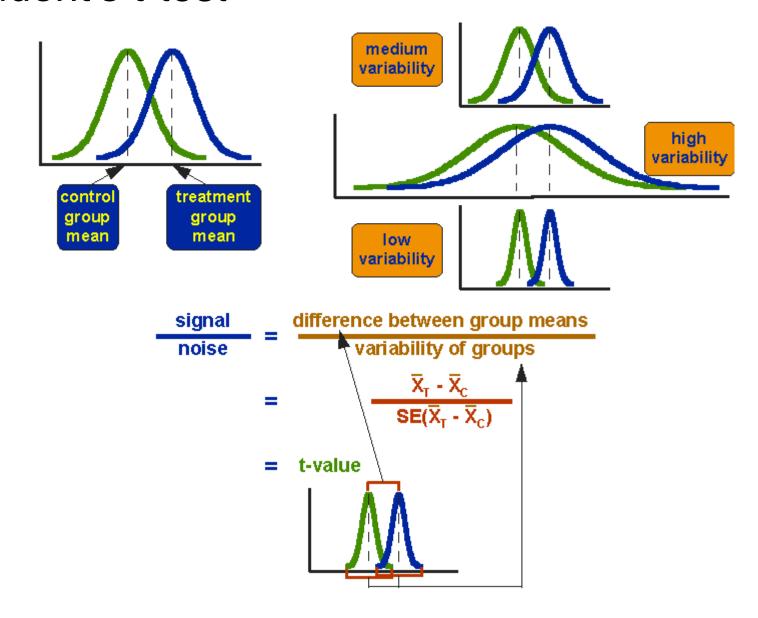
$$H_0$$
:  $\mu_1 - \mu_2 = 0$  Null hypothesis

$$H_1: \mu_1 - \mu_2 \neq 0$$
 Alternative hypothesis

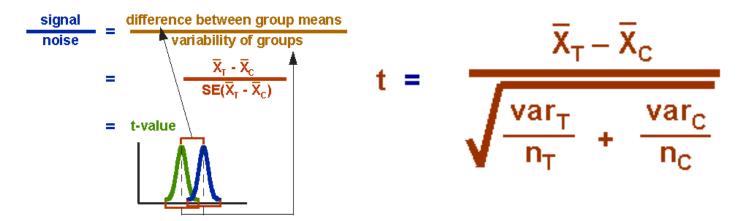
 $\mu_1$  and  $\mu_2$  are the means of the two distributions.

	True State of the Null Hypothesis			
Statistical Decision	H <sub>0</sub> True	${ m H_0^{}}$ False		
Reject H <sub>0</sub>	Type I error	Correct		
Do not Reject H <sub>0</sub>	Correct	Туре ІІ еггог		

#### Student's t-test



#### Student's t-test



p-value can be computed from t-value and number of freedom (related to number of samples) to give a bound on the probability for type-I error (claiming insignificant difference to be significant) assuming normal distributions.

#### Student's t-test

Dependent (paired) t-test

### Permutation (t-)test

T-test relies on the parametric distribution assumption (normal distribution). Permutation tests do not depend on such an assumption. Examples include the permutation t-test and Wilcoxon rank-sum test.

Perform regular t-test to obtain t-value  $t_0$ . The randomly permute the  $N_1+N_2$  samples and designate the first  $N_1$  as group 1 with the rest being group 2. Perform t-test again and record the t-value t. For all possible  $K = \binom{N_1+N_2}{N_1}$  permutations, count how many t-values are larger than  $t_0$  and write down the number  $K_0$ .

$$p = \frac{1 + K_0}{1 + K}$$

## Multiple Classes (N>2) F-test

- The null hypothesis is that the distribution of gene expression is the same for all classes.
- The alternative hypothesis is that at least one of the classes has a distribution that is different from the other classes.
- Which class is different cannot be determined in F-test (ANOVA). It can only be identified post hoc.

## Example

GEO Dataset Subgroup Effect

- p-value cutoff = 0.05 (probability for false positive - type-I error)
- 22,000 probesets
- False discovery 22,000X0.05=1,100
- Focus on the 1,100 genes in the second speciman. False discovery 1,100X0.05 = 55

- State the set of genes explicitly before the experiments
  - Problem: not always feasible, defeat the purpose of large scale screening, could miss important discovery
- Statistical tests to control the false positives

- Statistical tests to control the false positives
  - Controlling for no false positives (very stringent, e.g. Bonferroni methods)
  - Controlling the number of false positives (
  - Controlling the proportion of false positives
  - Note that in the screening stage, false positive is better than false negative as the later means missing of possibly important discovery.

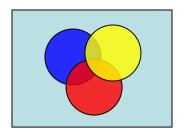
### Gene Discovery and Multiple T-tests

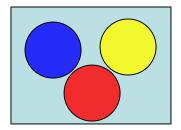
#### Controlling False Positives

- Statistical tests to control the false positives
  - Controlling for no false positives (very stringent)
  - Bonferroni methods and multivariate permutation methods

#### Bonferroni inequality

$$Prob(E_1 \cup E_2 \cup \cdots \cup E_K) \leq \sum_{i=1}^K Prob(E_i)$$





Area of union < Sum of areas

$$Prob(E_i) = 0.05, K = 20$$
  
 $Prob(E_1 \cup E_2 \cup \dots \cup E_K) \le \sum_{i=1}^K Prob(E_i) = 1$ 

#### Gene Discovery and Multiple T-tests

#### Bonferroni methods

Bonferroni adjustment

$$Prob(E_i) = 0.05, K = 20$$
  
 $Prob(E_1 \cup E_2 \cup \dots \cup E_K) \le \sum_{i=1}^K Prob(E_i) = 1$ 

- If E<sub>i</sub> is the event for false positive discovery of gene I, conservative speaking, it is almost guaranteed to have false positive for K > 19.
- So change the p-value cutoff line from p<sub>0</sub> to p<sub>0</sub>/K. This is called Bonferroni adjustment.
- If K=20, p<sub>0</sub>=0.05, we call a gene i is significantly differentially expressed if pi<0.0025.

#### Gene Discovery and Multiple T-tests

#### Bonferroni methods

- Bonferroni adjustment
- Too conservative. Excessive stringency leads to increased false negative (type II error).
- Has problem with metaanalysis.
- Variations: sequential Bonferroni test (Holm-Bonferroni test)
  - Sort the K p-values from small to large to get p<sub>1</sub>≤p<sub>2</sub>≤...≤p<sub>K</sub>.
  - So change the p-value cutoff line for the *i*th p-value to be  $\mathbf{p_0/(K-i+1)}$  (ie,  $p_1 \le p_0/K$ ,  $p_2 \le p_0/(K-1)$ , ...,  $p_K \le p_0$ .
  - If  $p_j \le p_0/(K-j+1)$  for all  $j \le i$  but  $p_{i+1} > p_0/(K-i+1+1)$ , reject all the alternative hypothesis from i+1 to K, but keep the hypothesis from 1 to i.

- Statistical tests to control the false positives
  - Controlling the number of false positives
    - Simple approach choose a cutoff for pvalues that are lower than the usual 0.05 but higher than that from Bonferroni adjustment
    - More sophisticated way: a version of multivariate permutation.

- Statistical tests to control the false positives
  - Controlling the proportion of false positives

Let  $\gamma$  be the portion (percentage) of false positive in the total discovered genes.

$$p_1 \leq p_2 \leq \cdots \leq p_D \leq \cdots \leq p_K$$

$$D = \underset{\text{positive}}{\operatorname{arg}} \max(p_i \cdot K/i < \gamma)$$
False Total positive

 $p_D$  is the choice. There are other ways for estimating false positives. Details can be found in Tusher et. al. PNAS 98:5116-5121.

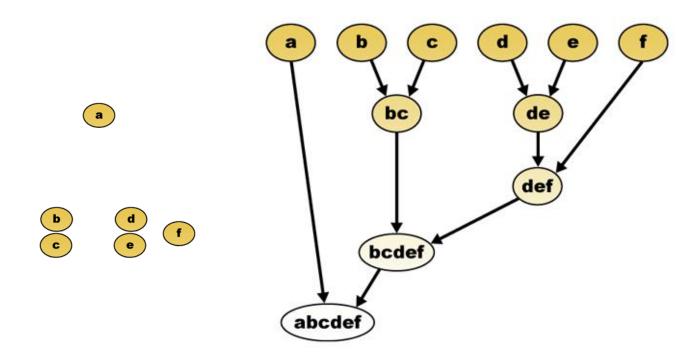
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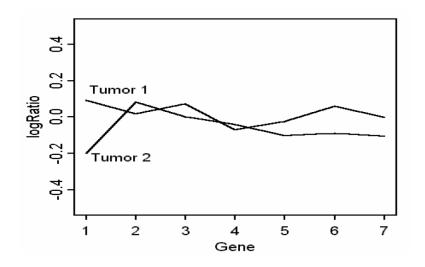
Introduction to Pathway and Gene Ontology Enrichment Analysis

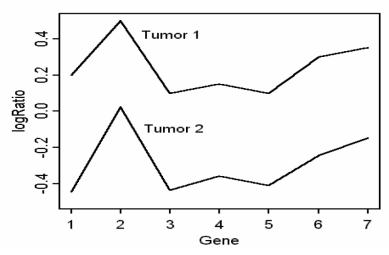
-Unsupervised Learning - Hierarchical Clustering



### Distance Measure (Metric?)

- What do you mean by "similar"?
- Euclidean
- Uncentered correlation
- Pearson correlation





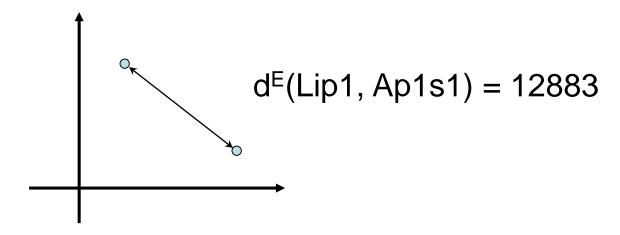
#### Distance Metric

#### - Euclidean

$$\mathbf{x} = (x_1, x_2, \cdots, x_n)^T$$
  
 $\mathbf{y} = (y_1, y_2, \cdots, y_n)^T$ 

$$d^{E}(\mathbf{x}, \mathbf{y}) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2}$$

102123_at	Lip1	1596.000	2040.900	1277.000	4090.500	1357.600	1039.200	1387.300
	3189.000	1321.300	2164.400	868.600	185.300	266.400	2527.800	
160552_at	Ap1s1	4144.400	3986.900	3083.100	6105.900	3245.800	4468.400	7295.000
	5410.900	3162.100	4100.900	4603.200	6066.200	5505.800	5702.700	



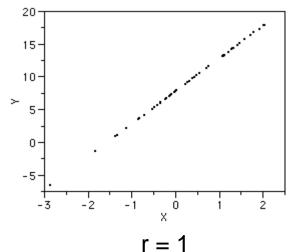
#### Distance Metric

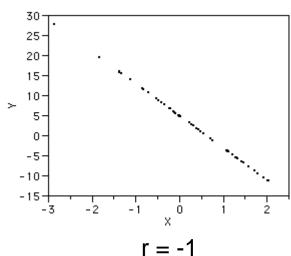
#### - Pearson Correlation

$$\mathbf{x} = (x_1, x_2, \cdots, x_n)^T$$
  
 $\mathbf{y} = (y_1, y_2, \cdots, y_n)^T$ 

$$r_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

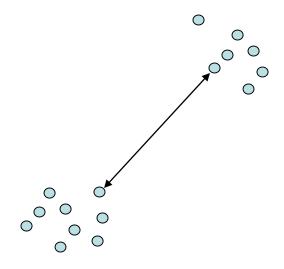
Ranges from 1 to -1.





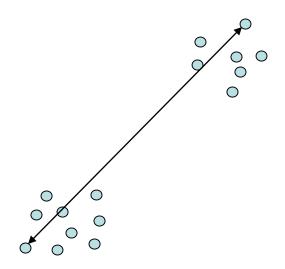
## -Unsupervised Learning - Hierarchical Clustering

Single linkage: The linking distance is the minimum distance between two clusters.



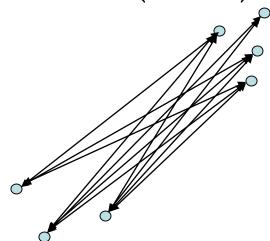
## -Unsupervised Learning - Hierarchical Clustering

Complete linkage: The linking distance is the maximum distance between two clusters.



## -Unsupervised Learning - Hierarchical Clustering

Average linkage/UPGMA: The linking distance is the average of all pair-wise distances between members of the two clusters. Since all genes and samples carry equal weight, the linkage is an Unweighted Pair Group Method with Arithmetic Means (UPGMA).



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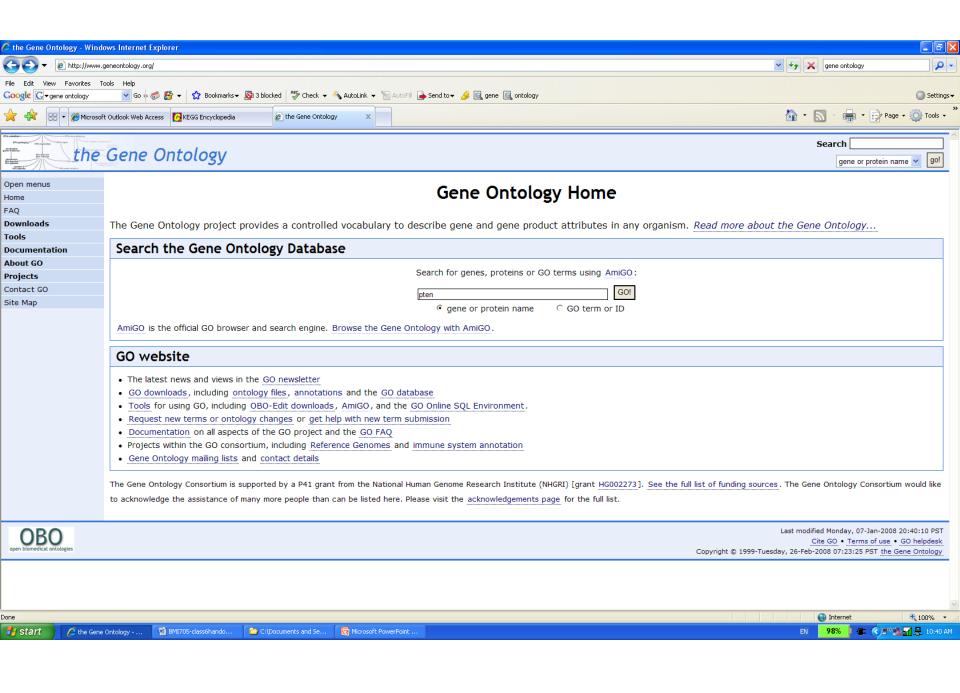
#### Where do I get the gene list?

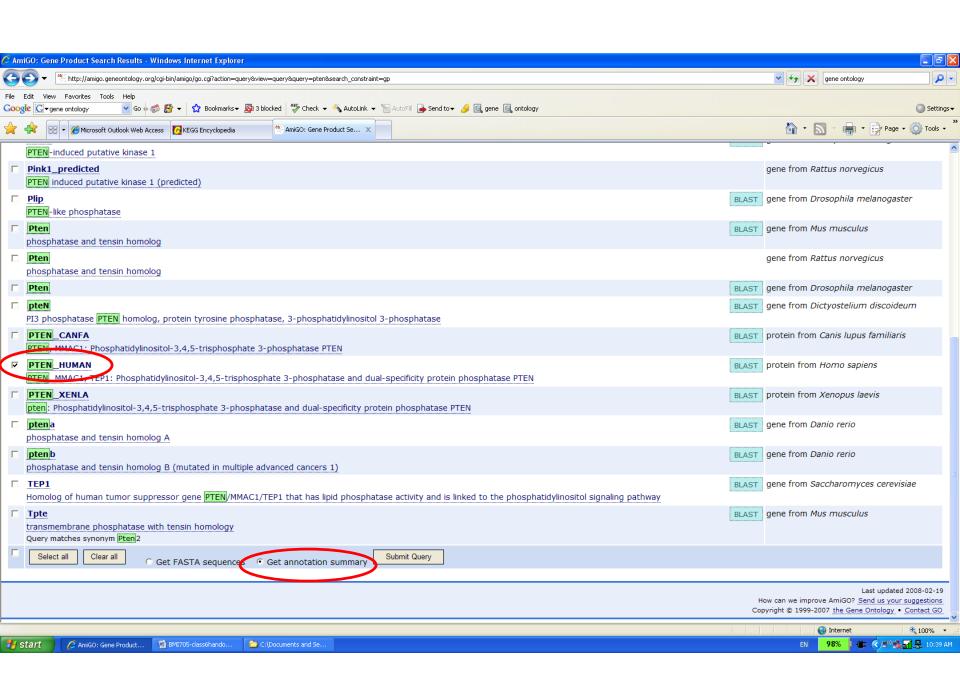
- Comparative study
  - ➤ e.g., microarray experiments between two types of samples or two disease states (can also be from RT-PCA, proteomics, ...)
- Clustering / classification of genes
  - ≽e.g., co-expressed genes
- Homologue analysis
  - >e.g., genes from BLAST
- Other sources

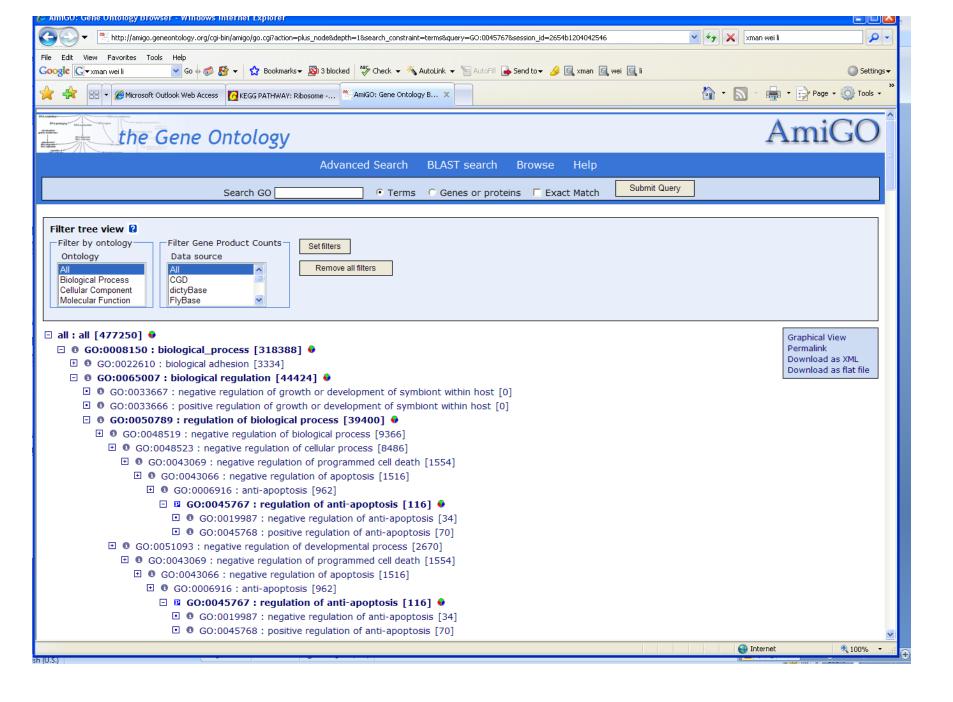
# What do I do with the gene list – enrichment analysis?

- Find commonality among the gene
  - ➤ Common molecular functions (GO)
  - ➤ Common biological processes (GO)
  - ➤ Common cellular components (GO)
  - ➤ Common pathways
  - ➤Interact with common genes
  - ➤ Common sequences / molecular structures
  - ➤ Regulated by common Transcription Factors
  - ➤ Targeted by common microRNAs
  - >Involved in the same disease
  - >...
- Generate new hypothesis based on the commonality

GO enrichment analysis

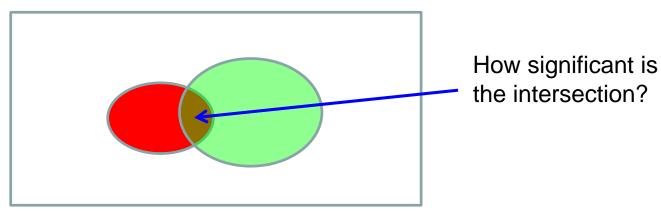






## How do I find commonality from my gene list?

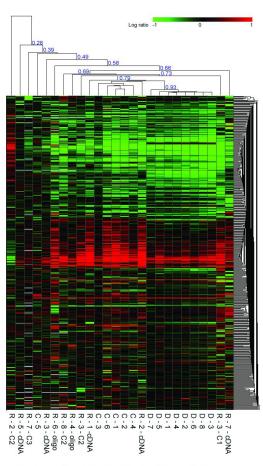
- Using a priori knowledge (e.g., gene ontology, pathway, annotation, etc.)
- Fisher's exact test, hypergeometric test, Bayesian-based methods, etc.



 Good news – most of the time you can use software to do it

#### What softwares are available?

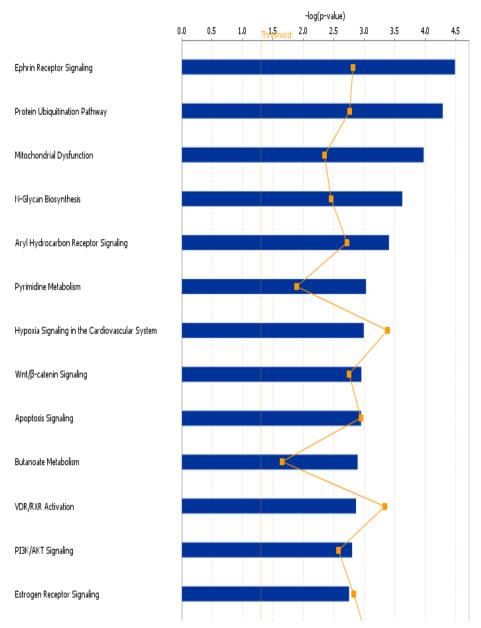
- DAVID (<a href="http://david.abcc.ncifcrf.gov/">http://david.abcc.ncifcrf.gov/</a>)
- TOPPGene
- Cytoscape
  - GOTerm
  - BiNGO
- GSEA
- GenMapp (Free)
- Pathway Architect (Commercial)
- Pathway Studio (Commercial)
- Ingenuity Pathway Analysis (Commercial)
  - Manually curated
  - On-demand computation



Supplementary Figure 1: Clustering of laboratory/platform combinations using log ratio values of commone genes

Analysis: Tsai-array II MaxDiff New - 2008-01-28 10:14 PM

Tsai-array II MaxDiff New - 2008-01-28 10:14 PM

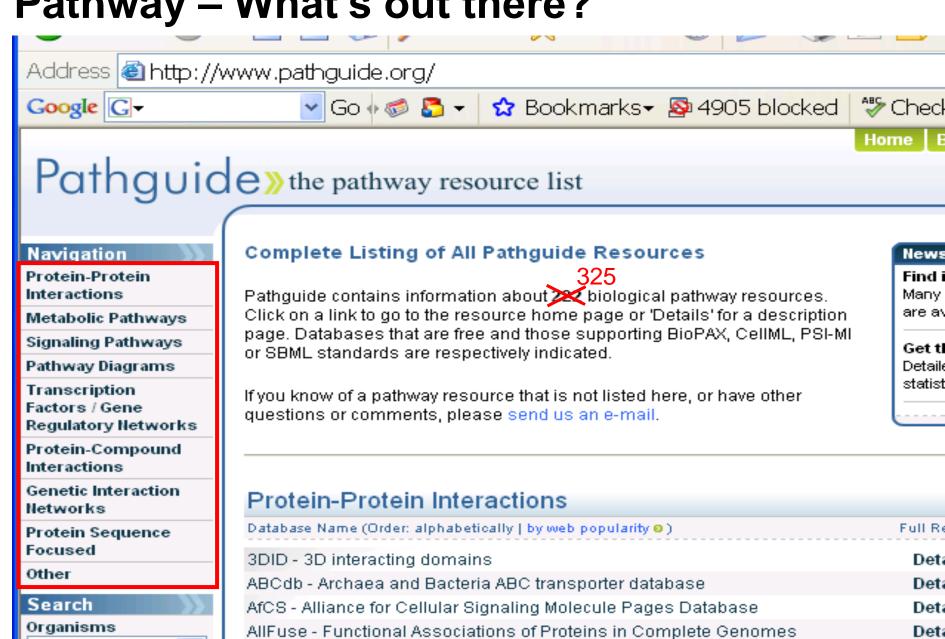


**Genes** 



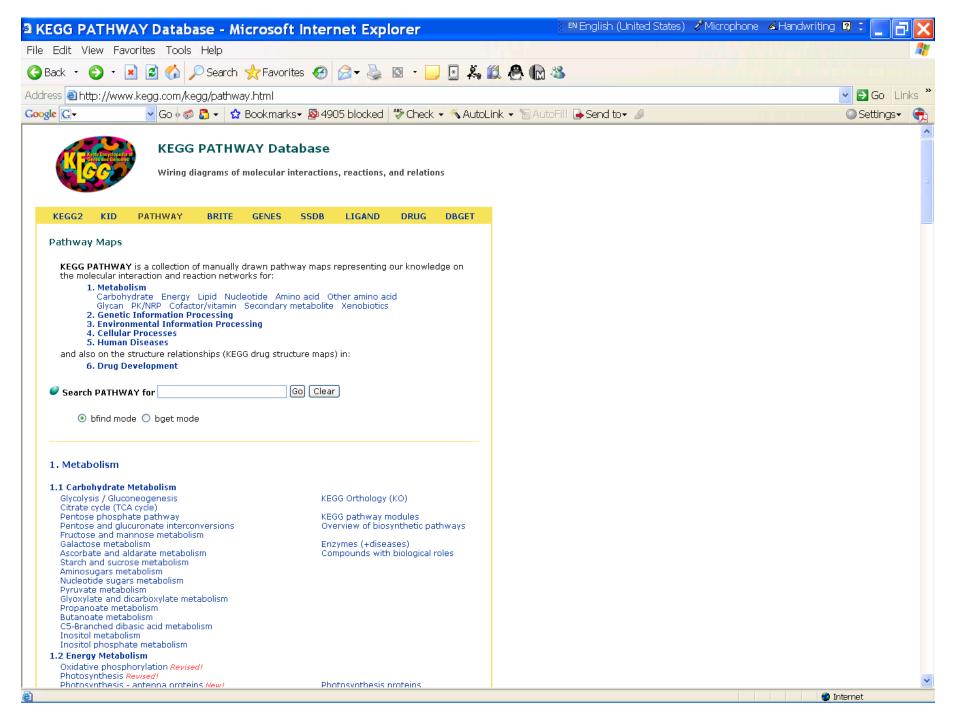
#### Pathway – What's out there?

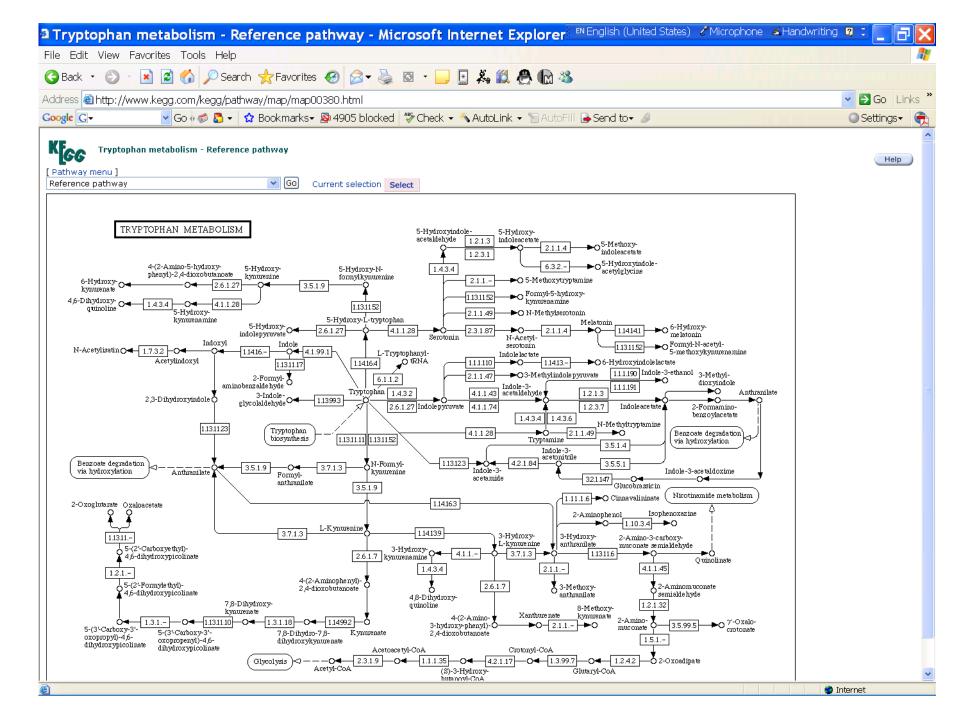
ΑII



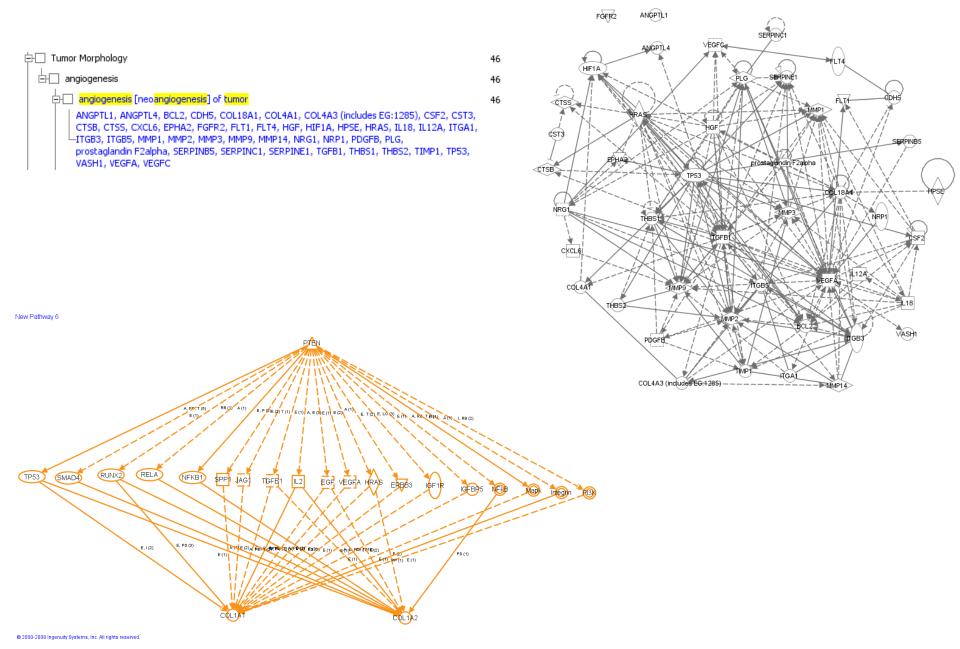
ASEdb - Alanine Scanning Energetics Database

Deta





#### **Ingenuity Pathway Analysis (IPA)**



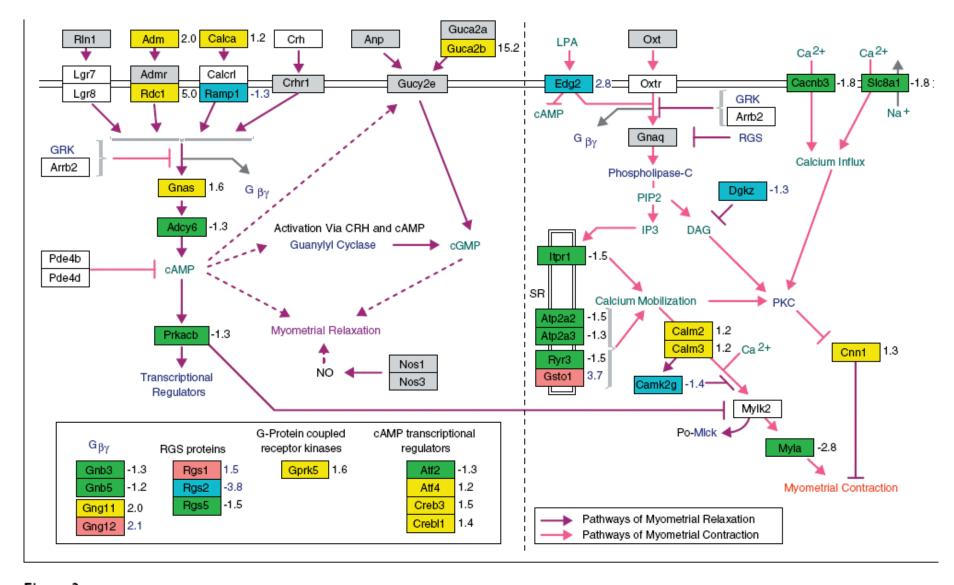


Figure 3
Analysis of pathways of uterine smooth muscle contraction. (a) Prostaglandin synthesis and (b) G-protein signaling pathways in the myometrium are overlaid with gene-expression color criterion and fold-changes from the program GenMAPP. Interactions suggested by results of this microarray analysis are included in these figures. Detailed gene-expression data, statistics and full gene annotations are available on the GenMAPP interactive version of these pathways online [40].

#### Demo

- DAVID (<a href="http://david.abcc.ncifcrf.gov/">http://david.abcc.ncifcrf.gov/</a>)
- TOPPGene

Gene List1: AURKA BIRC5ASPM

Ingenuity Pathway Analysis

```
ACOT7 CDC20 CDC45LCDCA8 CENPE CENPF
                                            CEP55
                                                  CKS2
            DKFZp762E1312 DLG7
                               DNA2L E2F8
                                            EPR1
      CHEK1
            HMMR KIF4A
      FANCI
                         LMNB1
                               MAD2L1 MELK
                                            NCAPG
      RANBP1RRM2 SPAG5 STIL
                               TACC3 TPX2
                                            TRIP13 TTK
      UBE2C UBE2S
Gene List2: Al445650
                  CD2
                         CCR5
                               CD247 CD27
                                            CD38
                                                  CD3D
            CD3G
                  CD79A CD8A
                               CRTAM CST7
                                            CTSW
      CD3E
      CXCR6 DENND2D
                         FAIM3 FMNL1 GZMA
                                            GZMB
                                                  GZMH
      GZMK
            HLA-DOB
                        IL21R
                               IL2RB
                                     IL2RG
                                                  KLRK1
                                            IL7R
      LAG3
            LAT
                  LAX1
                        MIRN650
                                     NKG7
                                            NM 014792
                         RUNX3 SELPLGSEPT6
      PTPN7 RASGRP1
                                            SERPINB9
      SH2D1A SIRPG SLAMF7 SOCS1 TBX21 TRBC1 WAS
                                                  XCL1
            XCL2
                  ZAP70
      CCL4
```

BUB1

CCNA2 CCNB2 CDC2