## BSC 4934: Q'BIC Capstone Workshop

# Giri Narasimhan

ECS 254A; Phone: x3748 giri@cs.fiu.edu http://www.cs.fiu.edu/~giri/teach/BSC4934\_Su11.html July 2011

### Microarray Data

|       | Expression Levels   |                       |  |
|-------|---------------------|-----------------------|--|
| Gene  | Sample A<br>CONTROL | Sample B<br>TREATMENT |  |
| Gene1 |                     |                       |  |
| Gene2 |                     |                       |  |
| Gene3 |                     |                       |  |
| •••   |                     |                       |  |

#### **Microarray Analysis**

Is Gene X upregulated? Downregulated? Had no change in expression levels?

Genes are represented by probes

Experiments may have repeats

#### **NULL HYPOTHESIS**

There is no change in gene expression levels for Gene X between <u>Control</u> and <u>Treatment</u>

## Accept/Reject H<sub>0</sub> (Null Hypothesis)?

#### P-value thresholds

- P-value is probability of data assuming  $H_0$  holds
- P-value threshold of 0.05 means probability of error when H<sub>0</sub> is <u>rejected</u> is 5%
- Fold change
  - If no repeats are done
- □t-Test
  - Parametric
  - Non-parametric
    - >Wilcoxon rank sum

## Hypothesis Testing Logic

|          |    | Hypothesis Choice      |                         |  |
|----------|----|------------------------|-------------------------|--|
|          |    | НО                     | H1                      |  |
| Decision | НО | Correctly Accept (TN)  | Type II Error (FN)<br>β |  |
|          | H1 | Type I Error (FP)<br>a | Correctly Reject (TP)   |  |

#### Typical Values:

- Type I error of 0.05
- Type II error of 0.2

### **Problem with Hypothesis Testing**

Not testing just one gene

- If multiple genes are tested, then t-Test assumes each test is independent
- Are the tests independent?
  - No!
- Need Correction
  - P-values need to be adjusted
  - Bonferroni or other correction methods needed
  - Achieved by controlling Type I error

## Multiple Testing & Type I Errors

Type I Error of 0.05 means that there is a 5% error in prediction of FN by t-Test. IMPLICATIONS?

- If N=1000 genes & d=40 are differentially expressed (DE), then ...
  - ≻960 X 0.05 = 48 FPs
  - > There are more FPs than TPs
  - Type I error and correcting for multiple hypothesis testing are connected

#### **Multiple Test Corrections**

Bonferroni correction

- Use type I error = a / g = FWER = 0.05/1000
  - Family-wise Error (FWER)

>Too Conservative! Also reduce true positives!

Other less conservative corrections possible

Sidak correction, Westfall-Young correction, ...

Using False Discovery Rate (FDR) [Benjamini & Hochberg '95, Storey '02 & '03]

Earlier: 5% of all tests will result in FPs

With FDR adjusted p-value (or q-value): 5% of significant tests will result in false positives.

| Rank | Anova (p) | q Value | <ul> <li>Power</li> </ul> | Cluster |   |
|------|-----------|---------|---------------------------|---------|---|
| 30   | 0.00436   | 0.0119  | 0.993                     |         |   |
| 77   | 0.00536   | 0.0119  | 0.987                     |         |   |
| 97   | 0.00631   | 0.0119  | 0.98                      |         |   |
| 29   | 0.00655   | 0.0119  | 0.979                     |         |   |
| 43   | 0.00605   | 0.0119  | 0.982                     |         |   |
| 23   | 0.0067    | 0.0119  | 0.977                     |         |   |
| 36   | 0.00632   | 0.0119  | 0.98                      |         |   |
| 28   | 0.00698   | 0.0119  | 0.975                     |         |   |
| 76   | 0.00685   | 0.0119  | 0.976                     |         |   |
| 60   | 0.0067    | 0.0119  | 0.977                     | 0       |   |
| 10   | 0.00479   | 0.0119  | 0.991                     |         |   |
| 13   | 0.00467   | 0.0119  | 0.991                     |         |   |
| 51   | 0.00432   | 0.0119  | 0.993                     |         |   |
| 91   | 0.0062    | 0.0119  | 0.981                     |         |   |
| 21   | 0.00611   | 0.0119  | 0.982                     |         |   |
| 46   | 0.00414   | 0.0119  | 0.994                     |         |   |
| 45   | 0.00739   | 0.0127  | 0.972                     |         | L |
| 25   | 0.00822   | 0.0137  | 0.964                     |         |   |
| 53   | 0.00903   | 0.0137  | 0.956                     |         |   |
| 6    | 0.00919   | 0.0138  | 0.955                     | 0       |   |
| 52   | 0.01      | 0.0141  | 0.946                     |         |   |
| 2    | 0.00976   | 0.0141  | 0.949                     |         |   |
| 87   | 0.0101    | 0.0141  | 0.946                     |         |   |
| 19   | 0.0109    | 0.0141  | 0.938                     | 0       |   |
| 96   | 0.0102    | 0.0141  | 0.944                     |         |   |
| 55   | 0.011     | 0.0141  | 0.937                     |         |   |
| 50   | 0.00949   | 0.0141  | 0.952                     |         |   |
| 49   | 0.0115    | 0.0144  | 0.931                     |         |   |
| 32   | 0.0127    | 0.0144  | 0.918                     |         |   |

#### P-value vs Q-value

Consider example shown. Let N = 839. Marked item has p-value 0.01 and qvalue 0.0141. P-value threshold of 0.01 implies a 1% chance of false positives. Thus, we expect 839\*0.01 = 8.39 FPs. Since item has rank 52, we expect to have 8 or 9 of these to be FPs.

Q-value threshold of 0.0141 implies a 1.41% of all spots with q-value less than this to be FPs. Thus, we expect 52\*0.0141 = 0.7332 FPs, i.e., less than one FP.

## Annotation

Annotation: association of raw sequence data and useful biological information.

□Integrates:

computational analyses,

- auxiliary biological data and
- biological expertise.

## Gene Ontology

Ontology: entities and their relationships

Ontology: representation of knowledge as a set of concepts within a domain

Provides a shared vocabulary

Gene Ontology (GO): project to

Standardize representation of gene & gene product attributes across species and DBs

Provide controlled vocabulary for data and features

- Provide tools to access and process knowledgebase
- Recent: Renal and Cardiovascular GO

## GO Hierarchy is a Graph



3 Hierarchies: Cellular Component, Biological Process, Molecular Function

#### **GO** Terms

Every term has a name

- E.g., ribosome, glucose transport, amino acid binding
- Every term has a unique accession number or ID
   E.g., GO:0005125, GO:0060092
- Terms may be related by relationships:
  - is-a: E.g., GO:0015758 glucose transport is a GO: 0015749 monosaccharide transport
  - **part-of**: E.g., GO:0031966 mitochondrial membrane is part of GO:0005740 mitochondrial envelope
  - regulates: E.g., GO:0006916 anti-apoptosis regulates GO: 0012501 programmed cell death

## Sample GO Term

```
id: GO:0016049
   name: cell growth
   namespace: biological_process
   def: "The process in which a cell irreversibly increases in size over time by accretion and
   biosynthetic production of matter similar to that already present." [GOC:ai]
   subset: goslim_generic
   subset: goslim_plant
   subset: gosubset_prok
  synonym: "cell expansion" RELATED []
  synonym: "cellular growth" EXACT []
  synonym: "growth of cell" EXACT []
   is_a: GO:0009987 ! cellular process
   is_a: GO:0040007 ! growth
   relationship: part_of GO:0008361 ! regulation of cell size
```

#### The 3 hierarchies

- Cellular Component: A component of the cell, i.e., location
  - E.g., rough endoplasmic reticulum, nucleus, ribosome, proteasome
- Biological Process: A biological process is series of events accomplished by one or more ordered assemblies of molecular functions.
  - E.g., cellular physiological process, signal transduction, pyrimidine metabolic process, alpha-glucoside transport
- Molecular Function: Activities, such as catalytic or binding activities, that occur at the molecular level
  - E.g., catalytic activity, transporter activity, binding; adenylate cyclase activity, Toll receptor binding

#### **Biological Process & Molecular Function**



#### **Cellular Component**



3/24/2011

#### Go Hierarchy is a Graph: Yeast



#### Utility of GO Annotations

- Assign annotations to new genes based on their similarities or proximities to annotated genes
- Enrichment Analysis: Overrepresentation or underrepresentation in sets of genes
  - 'Developmental Process' was most significantly overrepresented GO term (P = 0.0006), involving 26% of all regulated genes.

• P-value = 
$$\sum_{i=q}^{m} \frac{\binom{m}{i}\binom{t-1}{k-1}}{\binom{t}{k}}$$

#### Example [Zheng et al., BMC Gen 2010]

**Results**: Zebrafish were treated with zinc-depleted and zinc-adequate conditions for 2 weeks. Gill samples were collected at 5 time points and transcriptome changes analysed in quintuplicate using a microarray. A total of 333 genes showed differential regulation by zinc depletion (fold-change > 1.8; adjusted P-value < 0.1; 10% FDR). Down-regulation was dominant at most time points and distinct sets of genes were regulated at different stages. GO enrichment analysis showed 'Developmental Process' as the most significantly overrepresented GO term (P =0.0006), involving 26% of all regulated genes. Other significant terms related to development, cell cycle, cell differentiation, gene regulation, butanoate metabolism, lysine degradation, protein tyrosin phosphatases, nucleobase, nucleoside and nucleotide metabolism, and cellular metabolic processes. Network analysis of the temporal expression profile indicated that transcription factors fox11, wt1, nr5a1, nr6a1, and especially, *hnf4a* may be key coordinators of the homeostatic response to zinc depletion.

## Networks

Genes & Proteins form complex network of dependencies

Regulatory Networks

Edge from TFs to genes they regulate

Protein-protein interaction (PPI) Networks

Other Networks: KEGG

- Metabolic Pathways
- Genetic Info Processing
- Environmental Info Processing
- Cellular Processes
- Organismal Systems
- Human Disease, ...

http://www.genome.jp/kegg/

### **KEGG Metabolic Pathways**

- Carbohydrate Metabolism
  - Glycolysis, citrate, pyruvate, starch, sucrose, ascorbate, ...
- Energy Metabolism
  - Photosynthesis, carbon & nitrogen fixation, sulfur & methane metabolism, ...
- 🗅 Lipid Metabolism
  - Biosynthesis of fatty acid, steroid, ketone, bile acid, ...
- Nucleotide Metabolism
- Amino Acid Metabolism
- Metabolism of other amino acids
- Glycan Biosynthesis & Metabolism
- Metabolism of Cofactors and Vitamins
- Metabolism of Terpenoids & Polyketides
- Biosynthesis of Other Secondary Metabolites
- Xenobiotics Biodegradation and Metabolism

#### **KEGG: Info Processing**

#### **Genetic Info Processing**

- Transcription
- Translation
- Folding, Sorting & Degradation
- Replication & Repair

Environmental Info Processing
Membrane Transport
Signal Transduction
Signaling Molecules & Interaction

#### **KEGG: Misc Networks**

#### Organismal Systems

- □Immune Systems
- Endocrine, Circulatory
- Digestive, Excretory
- Nervous, Sensory
- Development
- Environmental Adaptation

Cellular Processes
Transport & Catabolism
Cell Motility
Cell Growth & Death
Cell Communication

#### KEGG: More Networks ...

#### Disease

- Cancers
- Immune System Diseases
- Neurodegenerative
  Cardiovascular
  Metabolic
- Infectious

DrugsAntibiotics

- Chronology: Antineoplastics, nervous system agents, misc., ...
- Target-based: GPCRs, Nuclear, Ion Channels, Enzymes
- □ Structure-based
- Skeleton-based

#### Pathway Example from KEGG



3/24/2011



## Omics

Genomics
Proteomics
Transcriptomics
Metabolomics
Glycomics
Cytomics
Lipidomics

## Genomics

Study of all genes in a genome, or comparison of whole genomes.

- Whole genome sequencing
- Whole genome annotation & Functional genomics

Whole genome comparison

PipMaker: uses BLASTZ to compare very long sequences (> 2Mb); http://www.cse.psu.edu/ pipmaker/

Mummer: used for comparing long microbial sequences (uses Suffix trees!)

#### Genomics

Study of all genes in a genome
 All aspects of total gene content
 Gene Expression
 Microarray experiments & analysis
 RNA-Seq

#### **Comparative Genomics**

#### Comparison of whole genomes.

- Sequence comparison
- Content comparison
- Functional annotation comparison
- ...

#### **Databases for Comparative Genomics**

#### GreenGenes

- PEDANT useful resource for standard questions in comparative genomics. For e.g., how many known proteins in XXX have known 3-d structures, how many proteins from family YYY are in ZZZ, etc.
- **COGs** Clusters of orthologous groups of proteins.
- MBGD Microbial genome database searches for homologs in all microbial genomes

#### **Proteomics**

Study of all proteins in a genome, or comparison of whole genomes.

- Whole genome annotation & Functional proteomics
- Whole genome comparison
- Protein Expression: 2D Gel Electrophoresis

#### **2D-Gels**



CAP5510 / CGS5166

3/24/2011

#### **2D Gel Electrophoresis**



3/24/2011

## 2D-gels


## Mass Spectrometry



### Mass measurements By Time-of-Flight

- Laser ionizes protein
- Electric field accelerates molecules in sample toward detector
- Time to detector is inversely proportional to mass of molecule
- □ Infer molecular weights of proteins and peptides

## Mass Spectrometry (MS)

### Using Peptide Masses to Identify Proteins

- Peptide mass fingerprint is a compilation of molecular weights of peptides
- Use molecular weight of native protein and MS signature to search database for similarly-sized proteins with similar MS maps
- Fairly easy to sequence proteins using MS



3/24/2011

CAP5510 / CGS5166

39

# **Other Proteomics Tools**

### From ExPASy/SWISS-PROT:

- AACompIdent identify proteins from aa composition
- [Input: aa composition, isoelectric point, mol wt., etc. Output: proteins from DB]
- AACompSim compares proteins aa composition with other proteins
- MultIdent uses mol wt., mass fingerprints, etc. to identify proteins
- PeptIdent compares experimentally determined mass fingerprints with theoretically determined ones for all proteins
- FindMod predicts post-translational modifications based on mass difference between experimental and theoretical mass fingerprints.
- PeptideMass theoretical mass fingerprint for a given protein.
- GlycoMod predicts oligosaccharide modifications from mass difference
- **TGREASE** calculates hydrophobicity of protein along its length

## STSs and ESTs

Sequence-Tagged Site: short, unique sequence

- Expressed Sequence Tag: short, unique sequence from a coding region
  - 1991: 609 ESTs [Adams et al.]
  - June 2000: 4.6 million in dbEST
  - Genome sequencing center at St. Louis produce 20,000 ESTs per week.

### What Are ESTs and How Are They Made?

- Small pieces of DNA sequence (usually 200 500 nucleotides) of low quality.
- Extract mRNA from cells, tissues, or organs and sequence either end. Reverse transcribe to get cDNA (5' EST and 3'EST) and deposit in EST library.
- Used as "**tags**" or markers for that gene.
- Can be used to identify similar genes from other organisms (Complications: variations among organisms, variations in genome size, presence or absence of introns).
- 5' ESTs tend to be more useful (cross-species conservation), 3' EST often in UTR.

## **DNA Markers**

Uniquely identifiable DNA segments.
Short, <500 nucleotides.</li>

Layout of these markers give a map of genome.
Markers may be polymorphic (variations among individuals). Polymorphism gives rise to alleles.
Found by PCR assays.

# Polymorphisms

- Length polymorphisms
  - Variable # of tandem repeats (VNTR)
  - Microsatellites or short tandem repeats
  - Restriction fragment length polymorphism (RFLP) caused by changes in restriction sites.
- Single nucleotide polymorphism (SNP)
  - Average once every ~100 bases in humans
  - Usually biallelic
  - dbSNP database of SNPs (over 100,000 SNPs)
  - ESTs are a good source of SNPs

## **SNPs**

- SNPs often act as "disease markers", and provide "genetic predisposition".
- SNPs may explain differences in drug response of individuals.
- Association study: study SNP patterns in diseased individuals and compare against SNP patterns in normal individuals.
- □ Many diseases associated with SNP profile.

## **Comparative Interactomics**



**Shotgun Sequencing** 

Hierarchical shotgun sequencing



Assembly ... ACCGTAAATGGGCTGATCATGCTTAAACCCTGTGCATCCTACTG...

From http://www.tulane.edu/~biochem/lecture/723/humgen.html

2/22/11

CAP5510 / CGS 5166

### Sequencing



FIGURE 13.1 Shotgun cloning. Genomic DNA sequencing begins with isolated genomic DNA in green at the top of the figure. In the hierarchical clone-based shotgun approach on the left, DNA is sheared and the size is selected for large fragments on the order of 200 Kb, then ligated to a suitable vector, such as a BAC vector shown in blue. Individually isolated clones in turn are sheared independently, generating fragments of approximately 4 Kb, which are then ligated to a small-scale vector, typically a plasmid (red bar) suitable for sequencing reactions. The whole genome shotgun approach bypasses the intermediate large-insert clone and generates large numbers of small fragments, typically 4 Kb and 10 Kb.

CAP5510 / CGS 5166

# Shotgun Sequencing



From http://www.tulane.edu/~biochem/lecture/723/humgen.html

## **Paired Reads**

Scaffold (supercontig): formed when two contigs with no sequence overlap can be linked

Data from paired end reads help create scaffolds with known gaps
> If two reads end up in two different contigs, then we can link contigs to form

scaffold.

## Assembly: Simple Example

□ ACCGT, CGTGC, TTAC, TACCGT

Total length = ~10

- --ACCGT--
- ----CGTGC
- **TTAC**-----
- -TACCGT-
- TTACCGTGC

# **Assembly: Complications**

- Errors in input sequence fragments (~3%)
  - Indels or substitutions
- Contamination by host DNA
- Chimeric fragments (joining of non-contiguous fragments)
- Unknown orientation
- Repeats (long repeats)
  - Fragment contained in a repeat
  - Repeat copies not exact copies
  - Inherently ambiguous assemblies possible
  - Inverted repeats
- Inadequate Coverage

### **Assembly: Complications**

- w = AGTATTGGCAATC
- z = AATCGATG
- u = ATGCAAACCT
- x = CCTTTTGG
- y = TTGGCAATCACT

| AGTATTGGCAATCAATCGATG                            |
|--|
| ATGCAAACCT                                       |
| TTGGCAATCACTCCTTTTGG                             |
| λοπλητικού λατολοπολοτος Αλαροπατικά Αλαροπατικά |

#### **FIGURE 4.20**

A bad solution for an assembly problem, with a multiple alignment whose consensus is a shortest common superstring. This solution has length 36 and is generated by the Greedy algorithm. However, its weakest link is zero.

| AGTATTGGCAATCCCTTTTGG                 |
|---------------------------------------|
| TTGGCAATCGATGTTGGCAATCACT             |
| ATGCAAACCT                            |
| AGTATTGGCAATCGATGCAAACCTTTTGGCAATCACT |

#### **FIGURE 4.21**

Solution according to the unique Hamiltonian path. This solution has length 37, but exhibits better linkage. Its weakest link is 3.

2/22/11

### **Assembly: Complications**



#### FIGURE 4.8

Target sequence leading to ambiguous assembly because of repeats of the form XXX.



Target sequence leading to ambiguous assembly because of repeats of the form XYXY.



Target sequence leading to ambiguous assembly because of repeats of the form XYXY.



#### **FIGURE 4.10**



## Assemblers

TIGR Assembler (TIGR)
Phrap (U Washington)
Celera Assembler (Celera Genomics)
Arachne (Broad Institute of MIT & Harvard)
Phusion (Sanger Center)
Atlas (Baylor College of Medicine)

## Sources of Assembly Errors

Errors in reads - caused by technology

- Error in base calls, color calls (SOLID Technology), or repeated base calls (454 Technology)
- Missing reads sequencing bias
- Read orientation error
  - One or both orientations may occur
  - Not told which ones are present
- Sequence Variations mixed sample study
  - SNP, cancer, metagenomics studies

### **REPEATS**

Combinations of the above

## How to deal with REPEAT Regions

- If no errors or repeat regions, then the graph has a unique path through all the edges.
- Problem: REPEAT regions cause branching in graph. If no errors in reads, then the graph has a unique path through all edges, but with some edges traversed more than once.
- □ How to identify REPEAT regions:
  - Higher coverage of repeat regions
  - Branching of nodes

## **Protein Structures**

- Sequences of amino acid residues
- 20 different amino acids



## Proteins

Primary structure is the sequence of amino acid residues of the protein, e.g., Flavodoxin: AKIGLFYGTQTGVTQTIAESIQQEFGGESIVDLNDIANADA...

Different regions of the sequence form local regular secondary structures, such as

Alpha helix, beta strands, etc.

AKIGLFYGTQTGVTQTIAESIQQEFGGESIVDLNDIANADA...





## More on Secondary Structures

### $\Box \alpha$ -helix

- Main chain with peptide bonds
- Side chains project outward from helix
- Stability provided by H-bonds between CO and NH groups of residues 4 locations away.

## $\Box\beta$ -strand

 Stability provided by H-bonds with one or more β-strands, forming β-sheets. Needs a β-turn.

## Proteins

Tertiary structures are formed by packing secondary structural elements into a globular structure.



Myoglobin

Lambda Cro

### **Quaternary Structures in Proteins**

 The final structure may contain more than one "chain" arranged in a quaternary structure.





**Insulin Hexamer** 

### More quaternary structures



Muscle creatine kinase (Homodimer)

# Bovine deoxyhemoglobin (Heterotetramer)









wire-frame



ball and stick



space-filling



surface



 $C_{\alpha}$  representation

 $\alpha/\beta$  schematic

## **Amino Acid Types**



## Structure of a single amino acid



Chains of amino acids



**Amino acids vs Amino acid residues** 

### Angles $\phi$ and $\psi$ in the polypeptide chain



### Ramachandran Plot





Amino Acid Structures from Klug & Cummings



3. Polar: positively charged (basic)




## Amino Acid Structures from Klug & Cummings

## Alpha Helix



7/21/10





3.6residues  $C'7 C_{\alpha}7$  C'6  $C'7 C_{\alpha}7$  C'7  $C_{\alpha}5$  C'5 C'4 C'

(6)

Cat



(a)

## **Beta Strands and Sheets**



7/21/10



7/21/10

**Modular Nature of Proteins** 

## Proteins are collections of "modular" domains. For example,



