

# **Progression and Gene Expression in Cervical Cancer** N. Fillmore<sup>1</sup>, P.F. Lambert<sup>2</sup>, P. Ahlquist<sup>3</sup>, and M.A. Newton<sup>4</sup> <sup>1</sup>Computer Sciences, <sup>2</sup>McArdle Lab. for Cancer Research, <sup>3</sup>Inst. for Molecular Virology and Howard Hughes Medical Inst., <sup>4</sup>Statistics and BMI

# Goal

Develop a statistical model of changes in gene expression through four stages in the development of cervical cancer, and use this model to understand aspects of cervical cancer progression.

## Model - Overview

Tissue at each stage of the progression leading to cervical cancer is composed of cells of several different types, mixed together; different stages are associated with different relative proportions of each type:<sup>*a*</sup>



# Model - Details

#### Fixed quantities:

- $\triangleright$  n = 128 tissue samples, indexed by i.
- $\sigma_i$  the stage of each tissue sample.
- $G \approx 54,000$  genes, indexed by g.
- T types, indexed by t.
- ► J patterns of differential expression, indexed by j; J is a function of T.

#### Parameters of interest:

- $\mathbf{r}_1, \ldots, \pi_J$  coefficients of mixture over patterns of differential expression.
- >  $p_{\sigma,t}$  proportion of cells of type t in tissue at stage  $\sigma$ .



► Each type of cell in a tissue sample has a separate "pure" gene-expression profile:



Since the cells in each tissue sample are all mixed together, the observed gene-expression profile is a weighted average of the pure type-specific profiles; the weights are the proportions of cells of each type at each stage of the progression:



- ► *a* shape parameter for distribution around each subgroup's mean.
- $\triangleright$   $a_0$  shape parameter for distribution of subgroup means around the grand mean.
- $\blacktriangleright$   $\nu$  scale parameter for distribution of subgroup means around the grand mean.

#### Random variables:

- ▶  $Z_g$  gene g's expression pattern; follows Categorical( $\boldsymbol{\pi}$ ).
- $\land \Lambda_{j,\mathcal{T}} a/\Lambda_{j,\mathcal{T}}$  is the mean expression level within subgroup  $\mathcal{T}$  of expression pattern j;  $\Lambda_{i,\mathcal{T}}$  follows Gamma $(a_0,\nu)$ .
- ▶  $X_{i,g,t}$  expression level of gene g within cells of type t in tissue sample i; follows Gamma $(a, \lambda_{z_a, \mathcal{T}})$ , where  $\mathcal{T}$  is the subgroup of expression pattern  $z_g$  that contains type t.
- ▶  $S_{i,g}$  overall expression level of gene g in tissue sample i;  $S_{i,g} = \sum_{t=1}^{T} p_{\sigma_i,t} X_{i,g,t}$ .

 $S_{i,q}$  is observed; all other variables are latent.

• Each gene follows a particular pattern of differential expression across the cell types:



Each subgroup of types within each differential expression pattern is associated with a common mean expression level shared across patients, genes following the pattern, and types contained in the subgroup; each specific expression measurement is assumed to follow a gamma distribution around the mean, with a shape parameter shared by all genes, patients, and types.

#### Data

- Each of 128 cervical tissue samples (24) normal, 36 CIN 1/2, 40 CIN 3, 28 cancerous) was measured by an Affymetrix whole genome microarray, which contains about 54,000 probe sets.
- Data is from the Study to Understand Cervical Cancer Early Endpoints and Determinants.
- ► A previous analysis (M.A. Newton) identified genes showing various patterns of differential expression among the four stages.

### **Estimation - In Progress**

- Markov chain Monte Carlo simulation of the parameters and the latent variables, given the observed expression levels.
- Posterior mean estimate of each parameter.



#### Same across two types, different in the third





The mean expression levels are also assumed to follow a gamma distribution, with a single grand mean and shape.<sup>b</sup>

<sup>a</sup> Figure from http://staffwww.dcs.shef.ac.uk/people/D.Walker/research/probe\_cin.jpg. <sup>b</sup> Gamma-gamma model from Kendziorski et al. (2003).

### **Other Work**

With Colin Dewey and Bo Li, I am working on principled evaluation of de novo transcriptome assemblies from RNA-seq data.

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#### Large Data Sets in Medical Informatics

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