Aalto University
School of Science

Mixture Models from Multiresolution data

Prem Raj Adhikari[1,2]

Parsimonious Modeling Research Group in
[1]Department of Information and Computer Science
Aalto University School of Science, Finland
[2]Helsinki Institute for Information Technology (HIIT)
prem.adhikari@aalto.fi

Management Summary

- Motivation for the Work
- Multiresolution Data
- Algorithms and Experiments
- Summary and Conclusions

Modelling : the general perspectives

> *Modeling is like vintage wine; it matures with time.*
>
> — DECISIONCRAFT INC.
>
> *www.decisioncraft.com*

Modelling : the general perspectives

> *Modeling is like vintage wine; it matures with time.*
>
> — DECISIONCRAFT INC.
>
> *www.decisioncraft.com*

> *People may mature with time but models mature only with increasing data.*
>
> — PREM RAJ ADHIKARI
>
> *PhD Student*

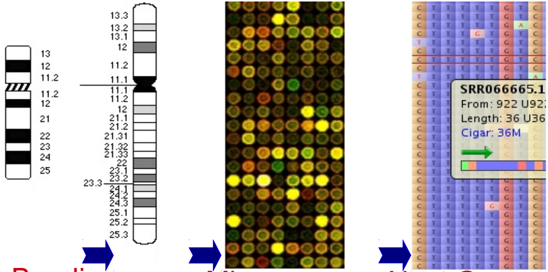
Importance of Using More Samples

The Square Root Law

$$\text{Accuracy of Information} = \sqrt{\text{Volume of Information}}$$

The Multiresolution data

Dimension In hundreds | Dimension In thousands | Dimension In millions



Banding | Microarrays | Next Generation Sequencing

- Multiresolution data is everywhere: biology, computer vision, telecoms ...
- Older Generation Technology $\Rightarrow$ Data in Coarse Resolution
- Newer Generation Technology $\Rightarrow$ Data in Fine Resolution

Mixture Modeling of Multiresolution 0–1 Data

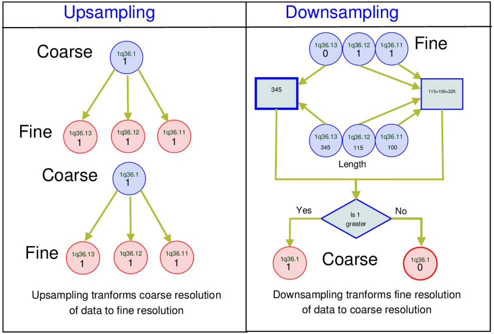
- Why Mixture Models?
- Cancer is a heterogeneous collection of several diseases and mixture models are well known for their ability to model heterogeneity
- Mixture models generally cannot model multiresolution data

$$P(x) = \sum_{j=1}^{J} \pi_j P(x|\theta_j) = \sum_{j=1}^{J} \pi_j \boxed{\prod_{i=1}^{d} \theta_{ji}^{x_i}(1-\theta_{ji})^{1-x_i}}$$

i is different for each resolution and requires different models for each resolution

- Only mixture modeling solution to multiresolution data is to model each resolution separately

Data transformation for multiresolution modelling



We upsample and downsample the data and integrate the data in same resolution before mixture modelling

P. R. Adhikari, J. Hollmén, UP'2010
Patterns from Multiresolution 0-1 data

Results of Mixture Models

Data Resolution	J	Likelihood
Original in Coarse	8	-3.39
Original in Fine	8	-4.75
Downsampled to Coarse	6	-3.41
Upsampled to Fine	6	-5.23
Combined in Coarse	7	-3.36
Combined in Fine	7	-5.11

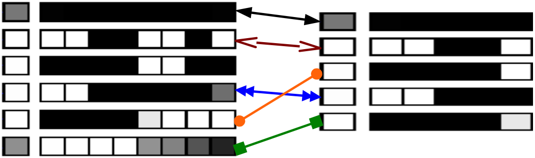
Table : Results of experiments on chromosome-17. J denotes the selected number of component distributions.

P. R. Adhikari, J. Hollmén, UP'2010
Patterns from Multiresolution 0-1 data

Multiresolution Mixture Modelling by Merging of Mixture Components

- What is done?

Iteratively merge Mixture Components from two mixture models



Until the change in KL divergence is very small

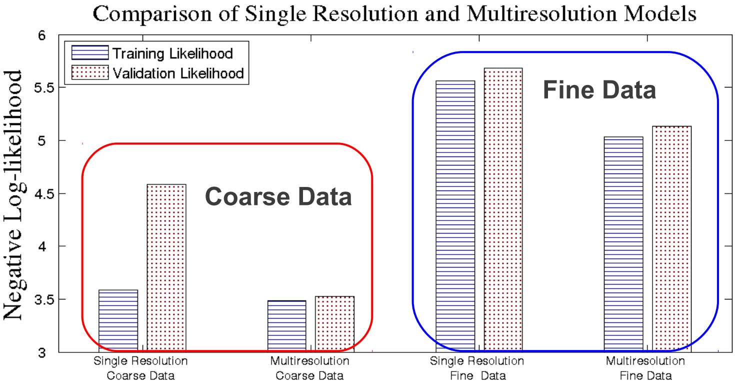
- How is it done?
- Fast approximation of KL divergence (P. R. Adhikari, J. Hollmén, DS 2012)

$$KL = \sum_{i \in X^*} \pi_\alpha \prod_{m=1}^{d} \left(\alpha_m^{X^*_{im}} (1 - \alpha_m)^{(1 - X^*_{im})} \right) - \sum_{i\prime \in Y^*} \pi_\beta \prod_{n=1}^{d'} \left(\beta_n^{Y^*_{i\prime n}} (1 - \beta_n)^{(1 - Y^*_{i\prime n})} \right)$$

- Retrain the mixture models in different resolutions

  P. R. Adhikari, J. Hollmén, ACML'2012
  Multiresolution Mixture Modeling using Merging of Mixture Components

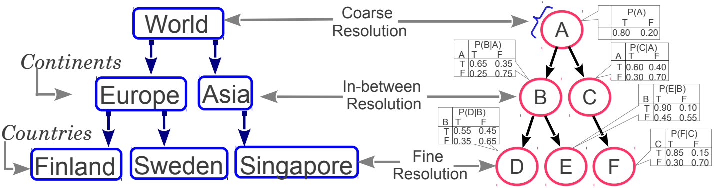
Performance of Multiresolution Mixture Model



Better generalization through merging of mixture components

P. R. Adhikari, J. Hollmén, ACML'2012
Multiresolution Mixture Modeling using Merging of Mixture Components

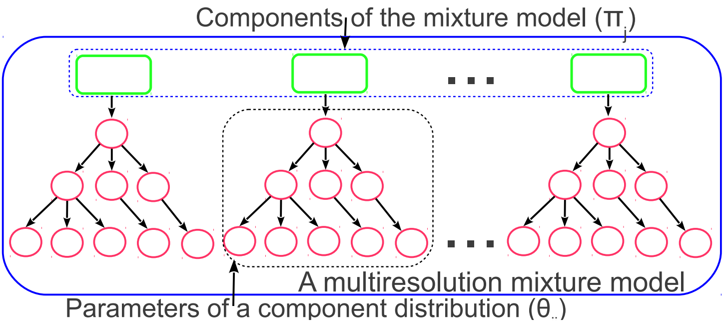
Multiresolution Mixture Components



- Domain ontology provides information about relationships between features in different resolutions
- We can create a tree structure where features in the coarse resolution form the root and features in the fine resolution leaves of the tree

  P. R. Adhikari, J. Hollmén, DS'2013
  Mixture Models from Multiresolution 0-1 Data.

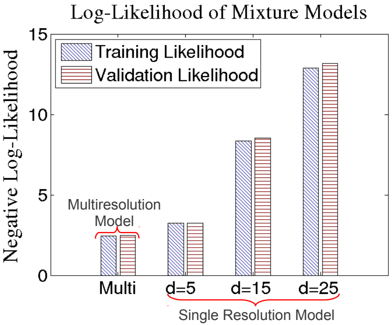
Structure of Mixture Model



- The components of the mixture model are Bayesian networks themselves
- Now, the problem is to learn the parameters $\mathbf{\Theta} = \{J, \{\pi_j, \theta_j\}_{j=1}^{J}\}$

P. R. Adhikari, J. Hollmén, DS'2013
Mixture Models from Multiresolution 0-1 Data.

Multiresolution Mixture Model Results



- The Y-axis shows the negative log likelihood, therefore, the shorter the bar, better the result
- The multiresolution model outperforms single resolution models

P. R. Adhikari, J. Hollmén, DS'2013
Mixture Models from Multiresolution 0-1 Data.

Summary and Conclusions

- Mixture Modeling of Multiresolution 0–1 Data in three ways:
  - Data Transformation
  - Merging of mixture components
  - Bayesian network as component distributions
- Experiments on multiresolution chromosomal datasets
- Experiments show that multiresolution models outperform single resolution models

Questions, Comments, Feedback and Acknowledgment

? ! ”

The work is funded by Helsinki Doctoral Programme in Computer Science–Advanced Computing and Intelligent Systems (Hecse)