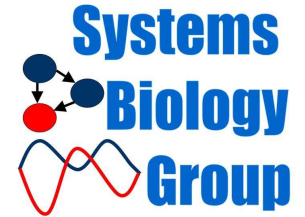
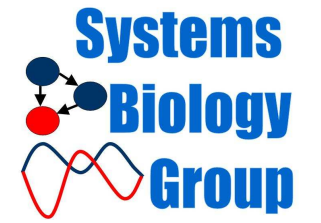


15-780: Graduate Artificial Intelligence



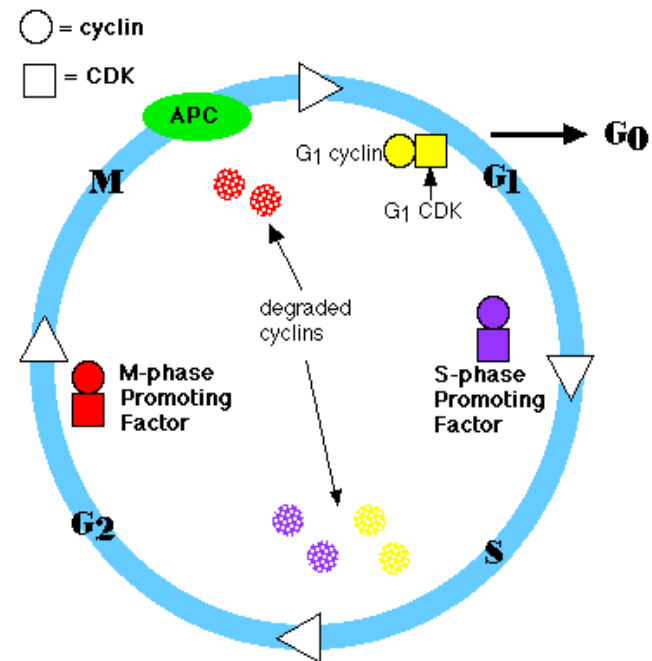
Computational biology: Systems biology and
the cell cycle

Movie1.gvp



The Cell Cycle

- The process in which cells divide.
- Plays key role in development and cancer.

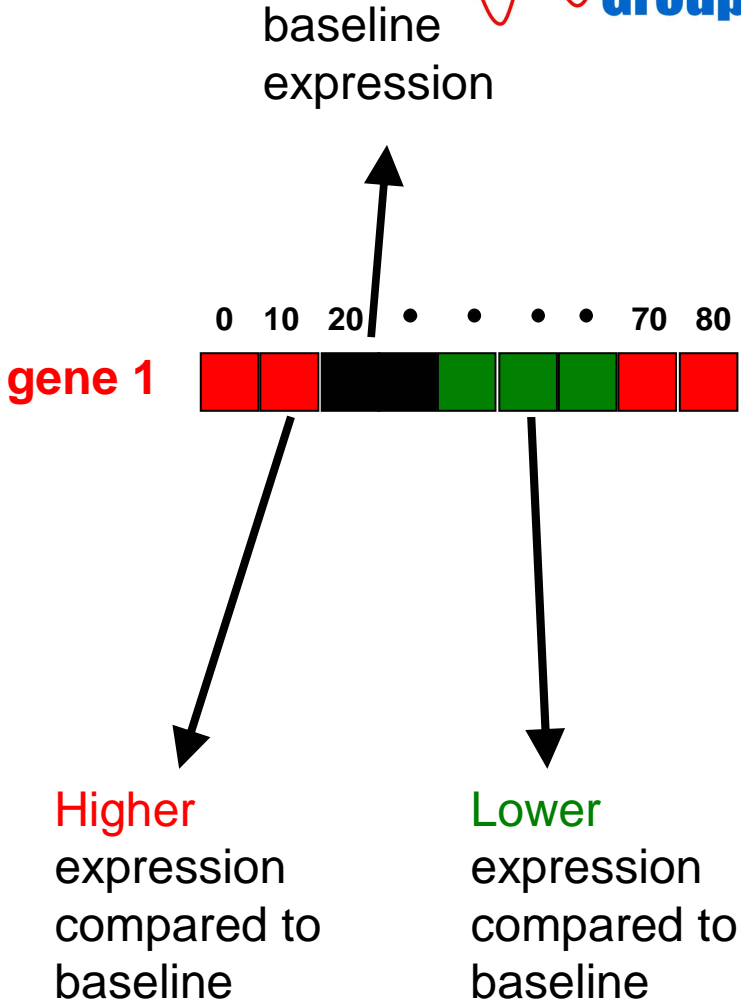
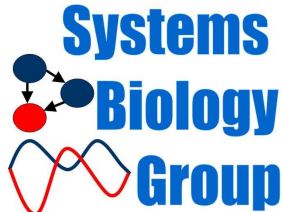
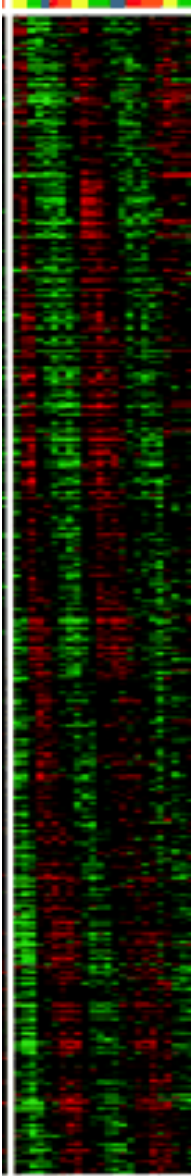


Time series expression data

Expression = level of gene (protein) in this experiment

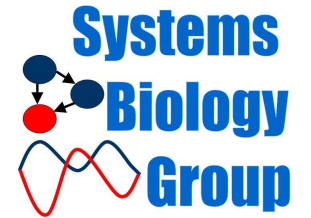
genes

Experiments (over time)

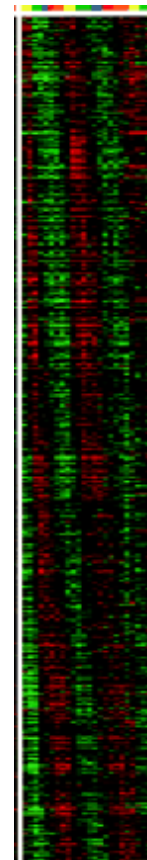


Spellman *et al Mol. Biol. Cell* 1998

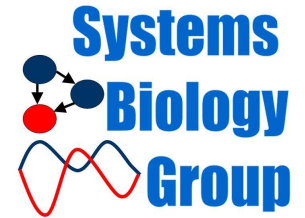
Time line



- 1997, 1998 – budding yeast cell cycle expression
- 2000 – plants
- 1999, 2000 - human
- 2001 – mouse

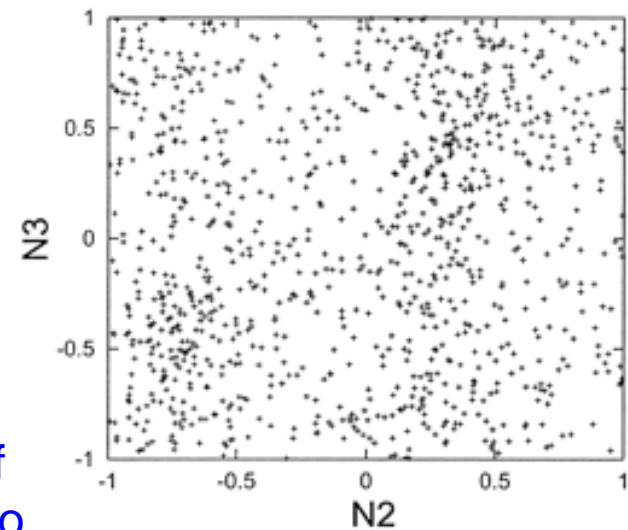


Time line



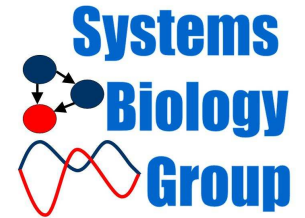
- 1997, 1998 – budding yeast cell cycle expression
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-
- 2002 – Human data is noise !



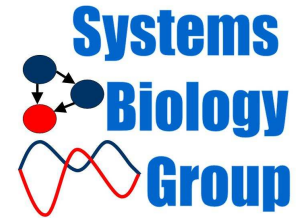
Reproducibility of
peak between two
repeats

Time line



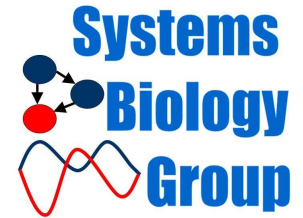
- 1997, 1998 – budding yeast cell cycle expression
 - 2000 – plants
 - 1999, 2000 - human
 - 2001 – mouse
-
- 2002 – Human data is noise !
 - 2002 – Cancer cell cycle expression (approximation)

Time line



- 1997, 1998 – budding yeast cell cycle expression
 - 2000 – plants
 - 1999, 2000 - human
 - 2001 – mouse
-
- **2002 – human data is noise !**
 - 2002 – cancer cell cycle expression (approximation)
 - 2004, 2005 – deconvolution and Checksum
 - 2006 (upcoming) – human cell cycle data

Time line



- 1997, 1998 – budding yeast cell cycle expression
- 2000 – plants
- 1999, 2000 - human
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-
- 2002 – human data is noise !
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 - 2006 (upcoming) – human cell cycle data

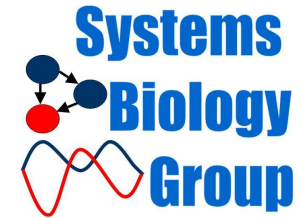
-
- 2004 – fission yeast cell cycle data

Periodic gene expression program of the fission yeast cell cycle

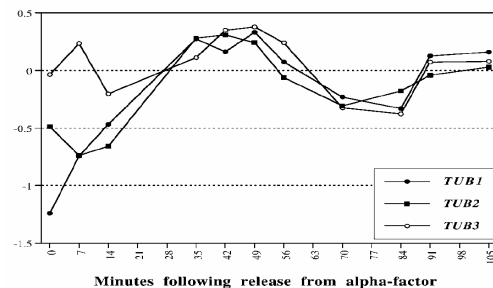
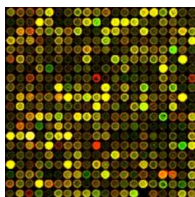
Gabriella Rustici¹, Juan Mata¹, Katja Kivinen², Pietro Lió², Christopher J Penkett¹, Gavin Burns¹, Jacqueline Hayles³, Alvis Brazma², Paul Nurse^{3,4} & Jürg Bähler¹

“Our comparisons with budding yeast data revealed a surprisingly small core set of genes that are periodically expressed in both yeasts.”

From expression values to score

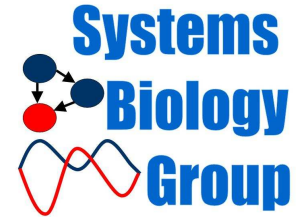


- Cells are *synchronized* to the same phase
- Microarray experiments at *multiple time points* after release from synchronization
- Scores derived from multiple expression time series
- Rank genes based on their scores, and use a *cutoff score* to identify cycling genes

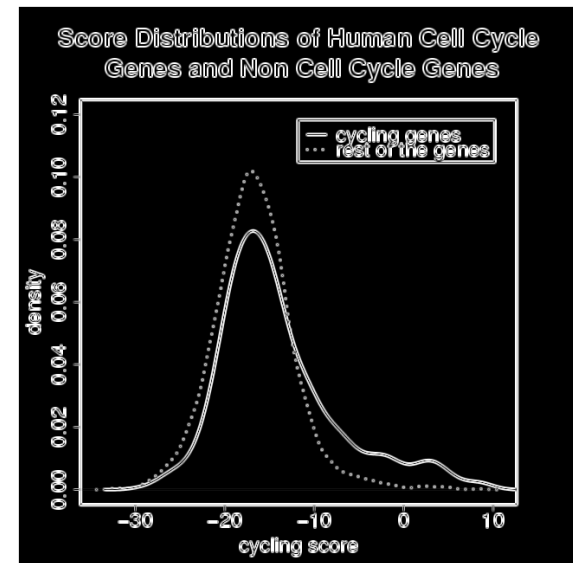


Spellman et al. (1998)

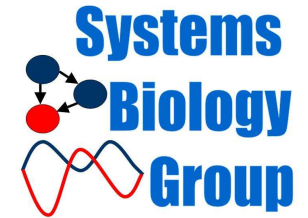
Problems



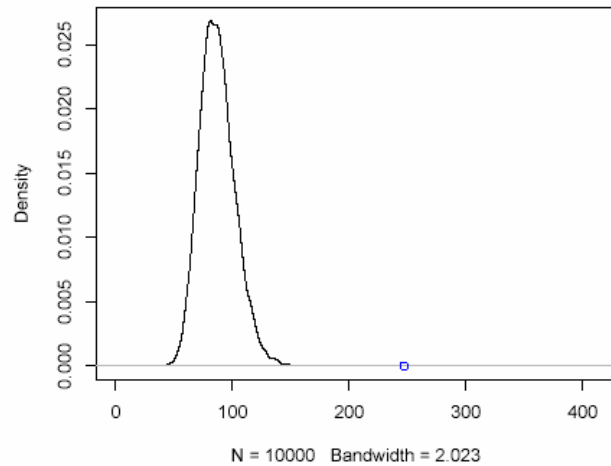
- Different scoring methods result in different lists
- Microarray data are noisy
- Hard to separate scores for cycling and non-cycling genes
 - Score distribution of cell cycle genes (derived from GO) versus the rest
 - solid curve: cycling genes
 - dotted curve: the rest



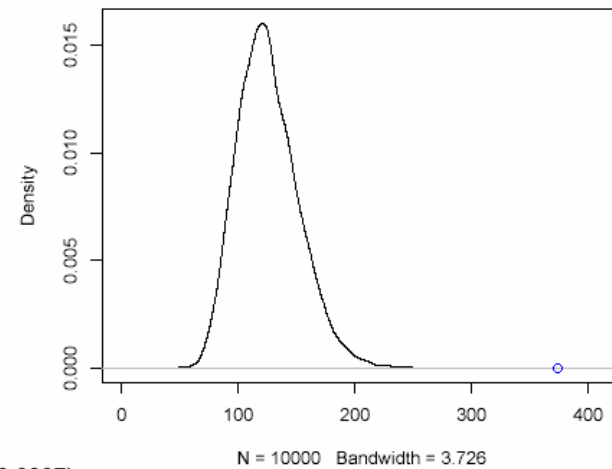
Significance of homolog overlap



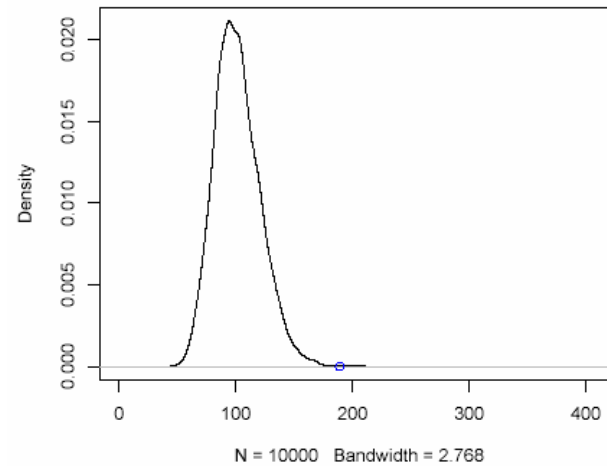
(Budding_Yeast (C), Fission_Yeast (C)) (pval<=1e-05)



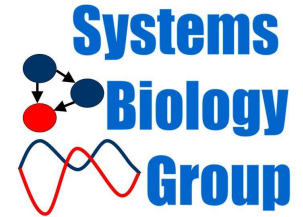
(Budding_Yeast (C), Human (C)) (pval<=1e-05)



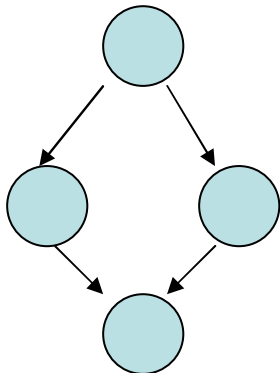
(Arabidopsis (C), Budding_Yeast (C)) (pval<=0.0007)



Graphical models

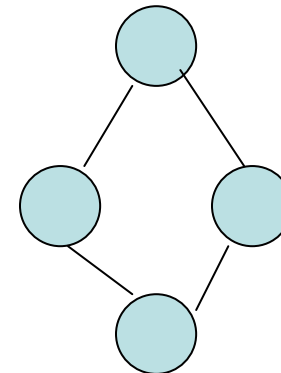


- Efficient way to represent and reason about *joint distributions*
- Graphs in which nodes represent random variables and edges correspond to dependency assumptions
- Two major types: Directed and undirected



$$\prod_i p[x_i | Pa(x_i)]$$

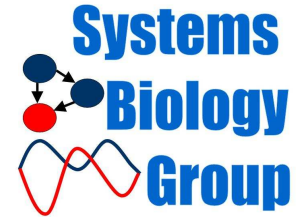
- Bayesian networks
- Hidden Markov models



$$\prod_{i,j} \psi_{i,j}(x_i, x_j)$$

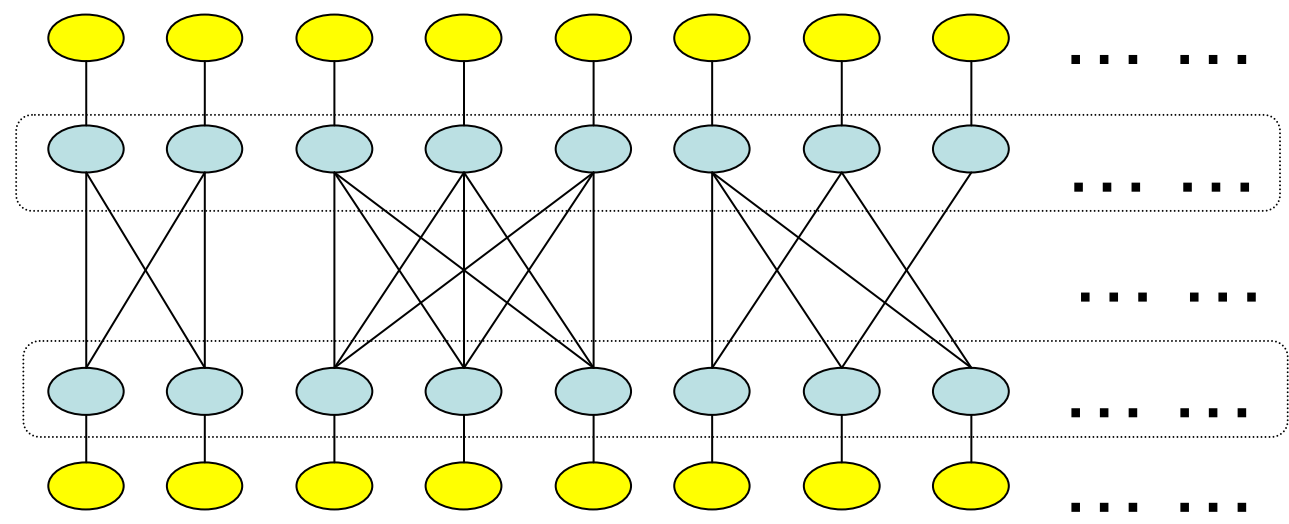
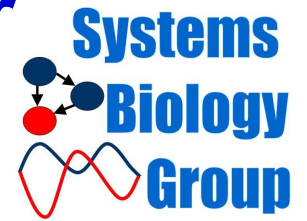
- Markov random fields

Graphical models (cont)


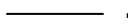


- Parameters are used to specify the conditional probability distribution (directed graphs) or the potential functions (undirected graphs)
- Computational questions:
 - Determining the structure of the model (sometimes)
 - Estimating the parameters of the model
 - Inference

Probabilistic graphical model for combining expression and sequence homology

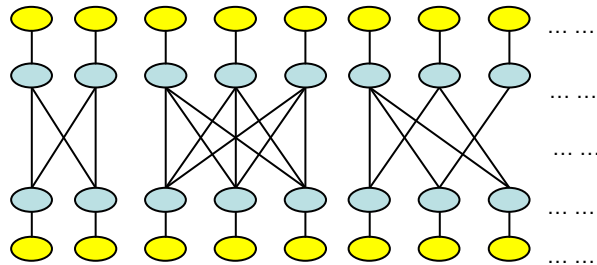


 : C_i : Cycling Status Nodes (unobserved)

 : S_i : **Score** Nodes (observed)  : Encodes Dependency Relations

Numeric summary of expression time series

Likelihood of the model



need to be learned from data

- Node Potential:
- Edge Potential:

$$\psi_i(C_i) = Pr(C_i|S_i)$$

$$\psi_{ij}(C_i, C_j) = 2^{-\lambda w_{ij}(C_i - C_j)^2}$$

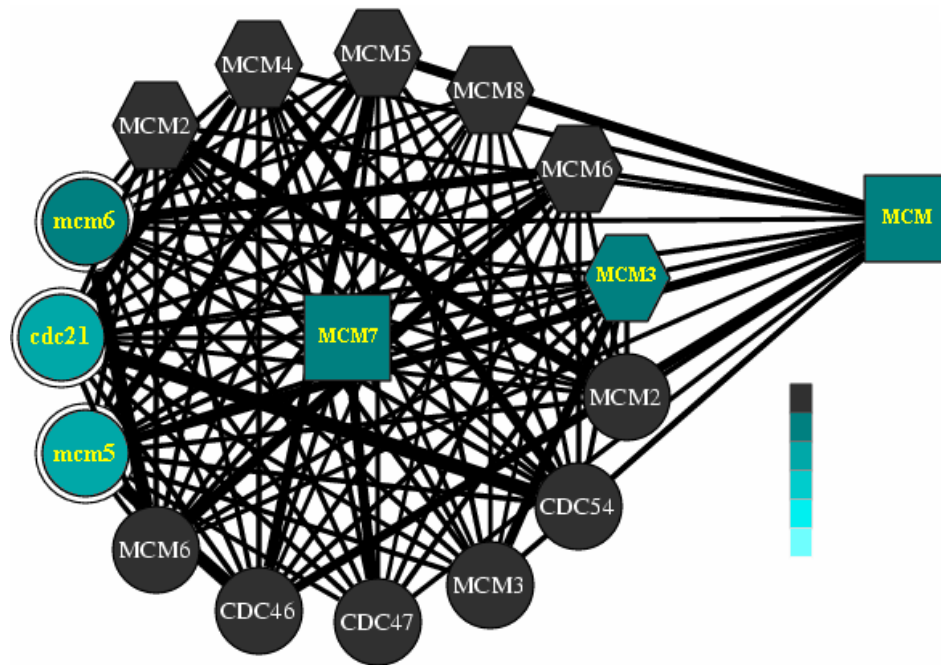
- Joint probability distribution





controls
contribution from
each source

weight (from
homology)

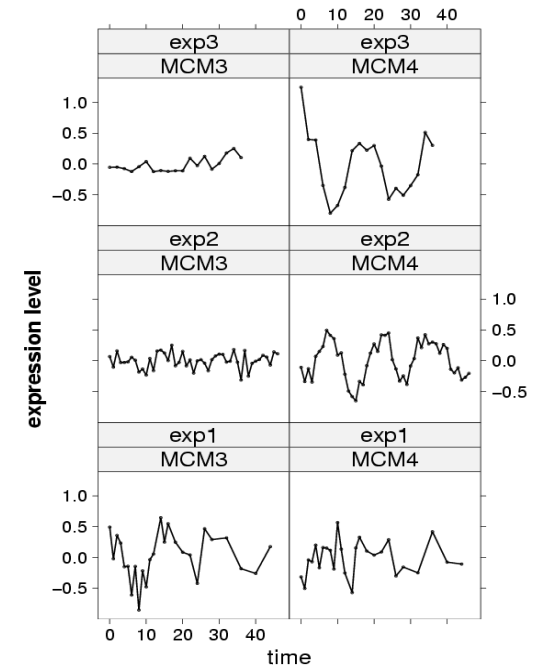
$$L = \frac{1}{Z} \prod_i \psi_i(C_i) \prod_{i,j} \psi_{ij}(C_i, C_j)$$

In what cases can we improve?

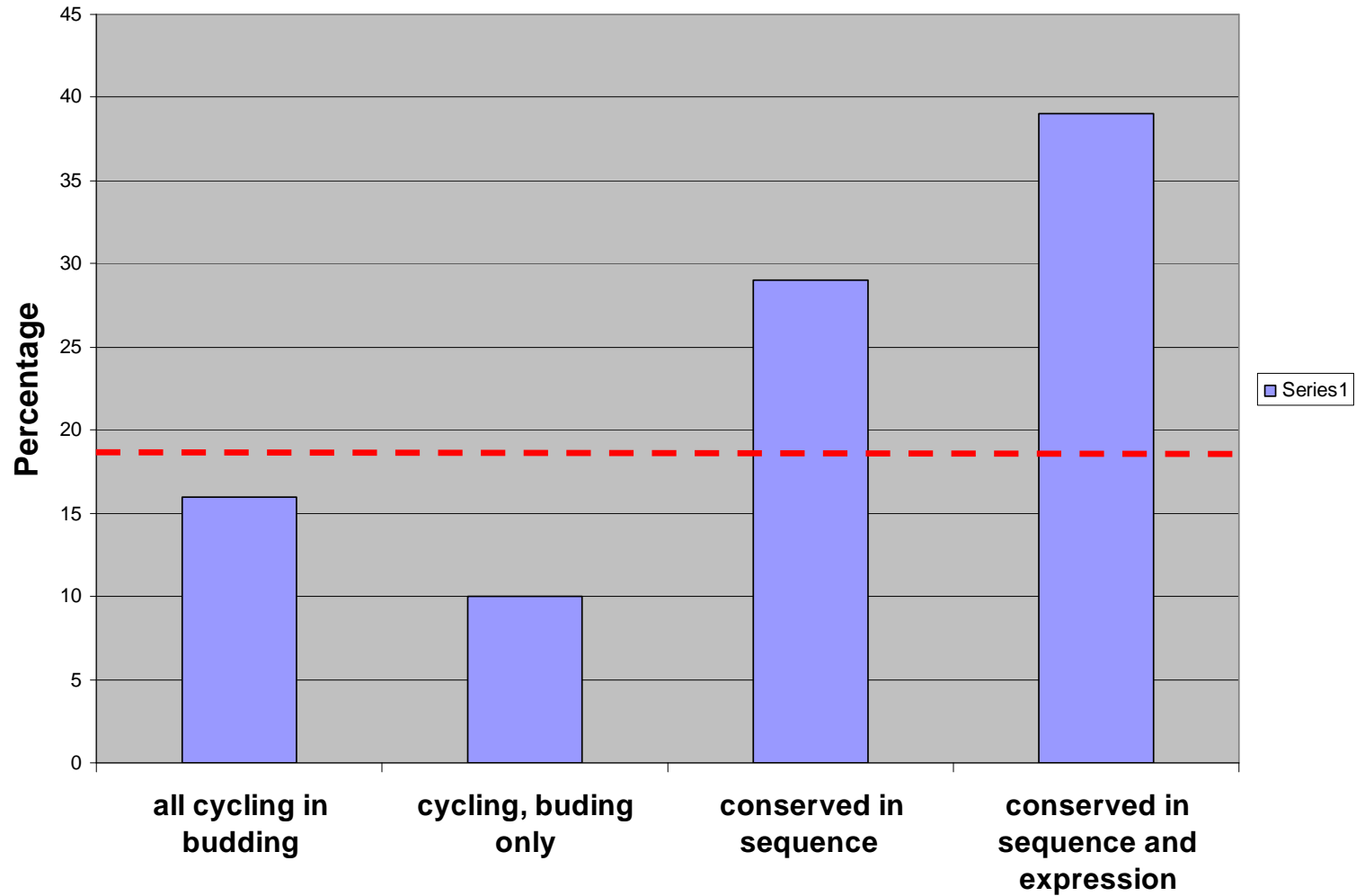
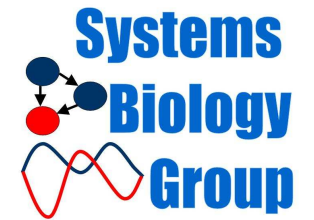


-  human
-  budding yeast
-  fission yeast
-  Arabidopsis

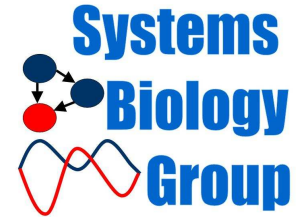
Expression Levels of Human MCM3 and MCM4



Essential yeast genes



10-810: Graduate Computational Genomics



- Spring 2007
- Bar-Joseph, Benos, Xing
- TR 10:30-11:50, Scaife Hall, 208

- Intro to computational biology emphasizing machine learning, sequence analysis and systems biology.