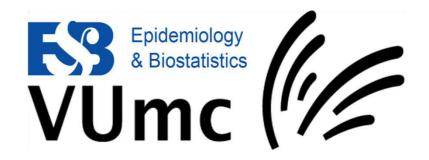


Longitudinal modeling of omics data from HPV-induced carcinogenesis

Viktorian Miok





Contributors

Biostatistics department

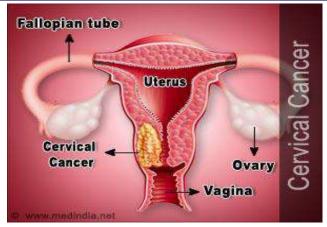
- Viktorian Miok
- Wessel van Wieringen
- Mark van de Wiel

Pathology department

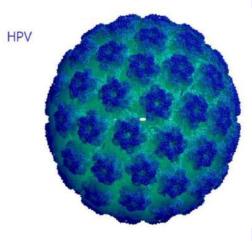
- Saskia Wilting
- Annelieke Jaspers
- Renske Steenbergen
- Peter Snijders

Cervical cancer study

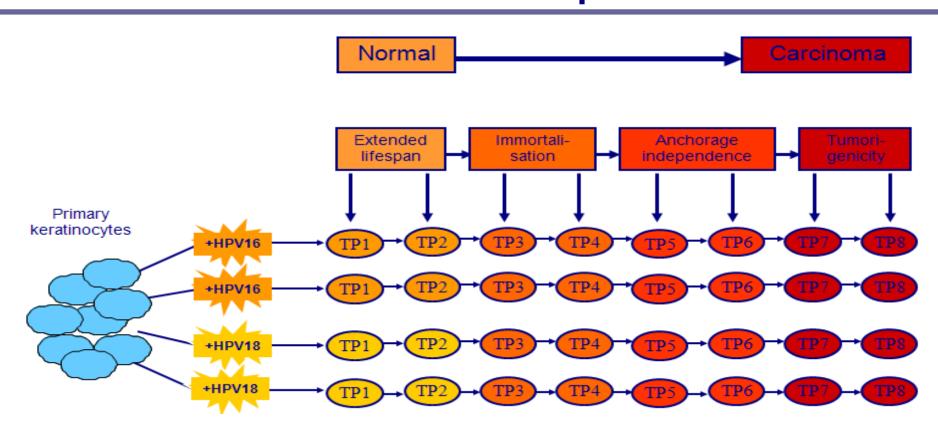
Third most common cancer in women worldwide.



- Caused by HPV virus (70% cases HPV16 and HPV18) and followed by additional (epi)genetic abnormalities.
- Cell line model in vitro model system of HPV-induced transformation.
- Integration high-throughput multi level molecular data sets.
- Understand molecular mechanism driving cervical carcinogenesis

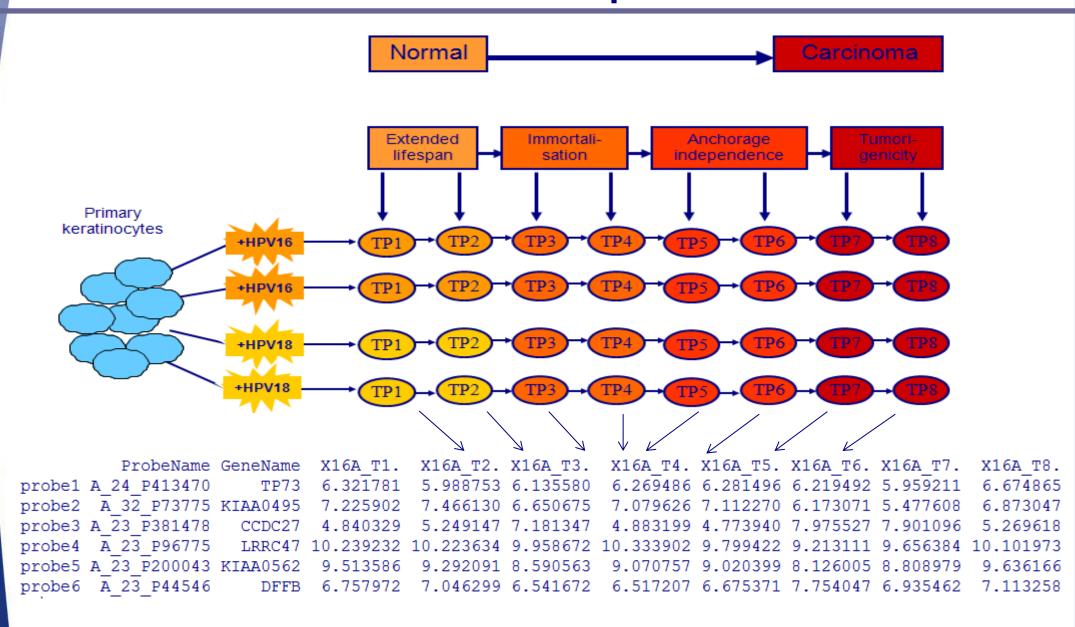


Time-course experiment



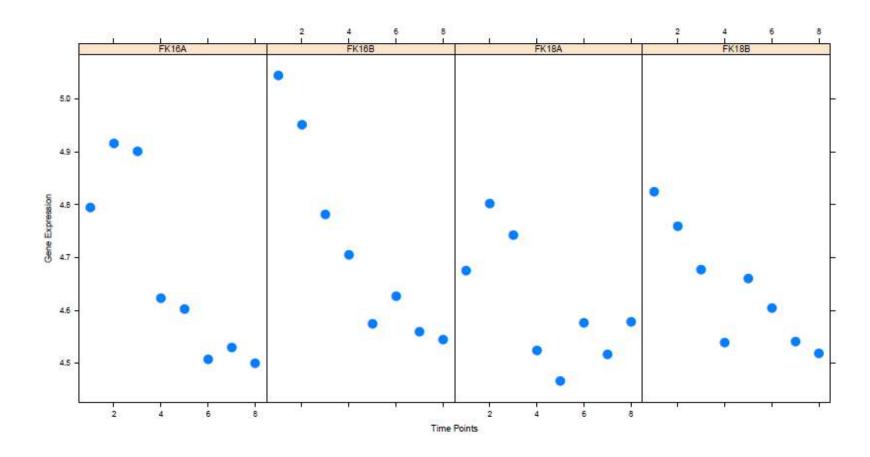


Time-course experiment



Why time-course experiments?

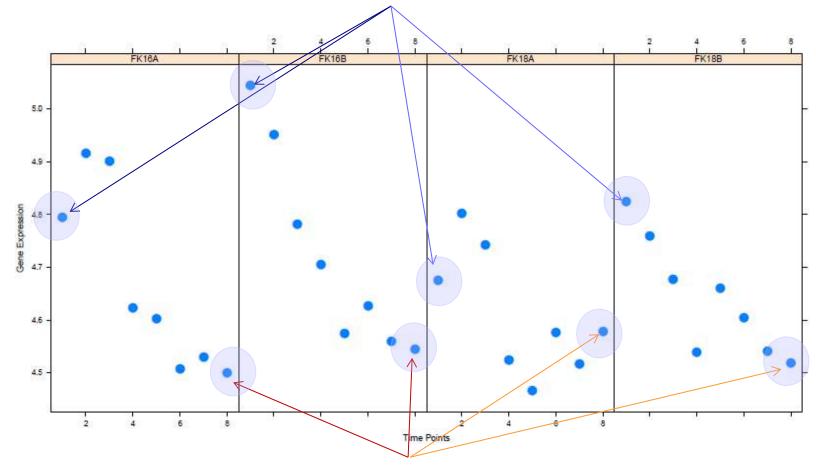
miR-218:



Pick one moment in time

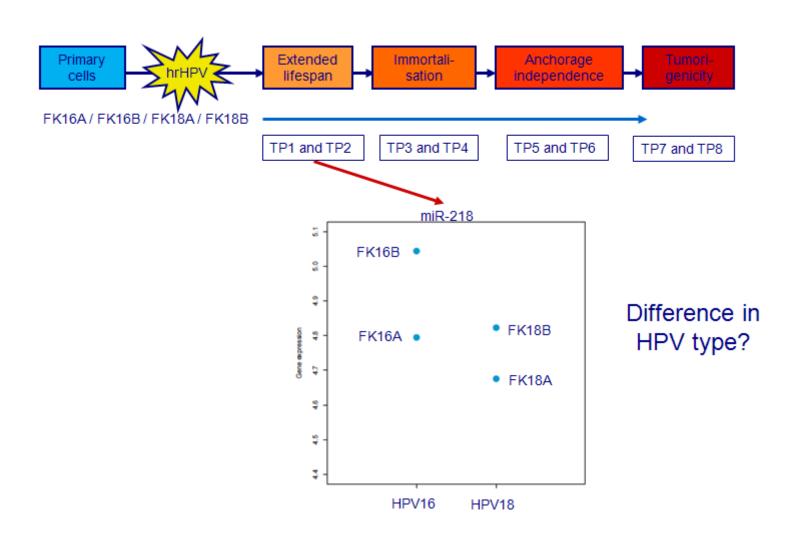
miR-218:

one moment in time: TP1

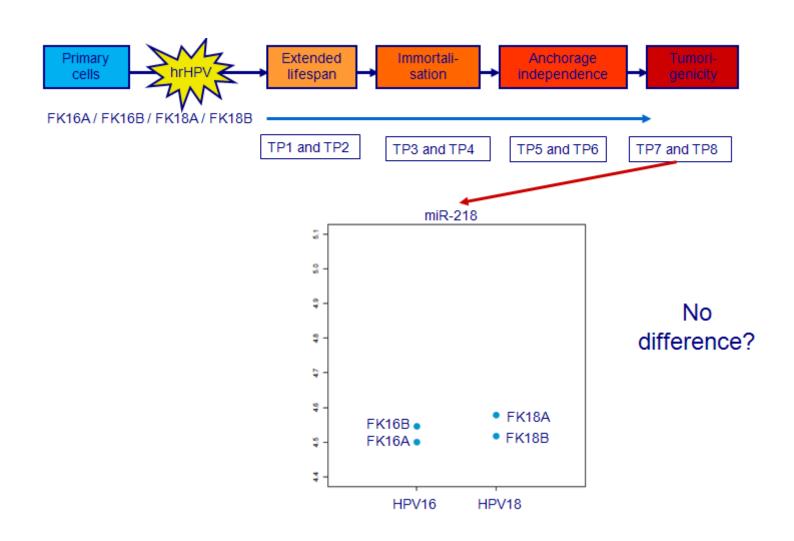


one moment in time: TP8

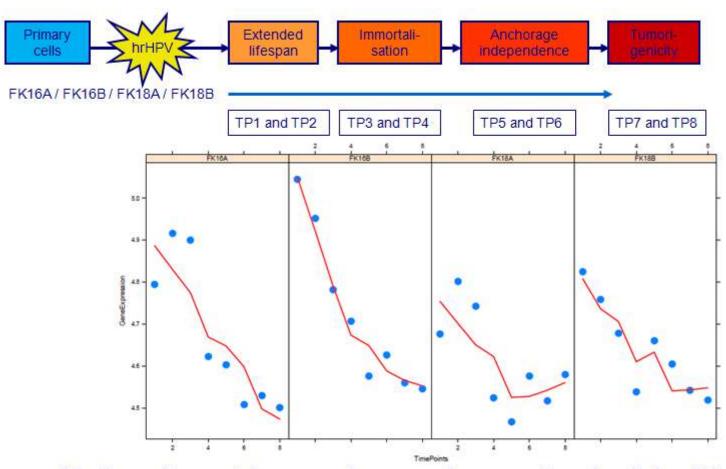
Inference based on TP1



Inference based on TP8



Strength of time-course



Similar pattern of decreased expression over time in all 4 cell lines

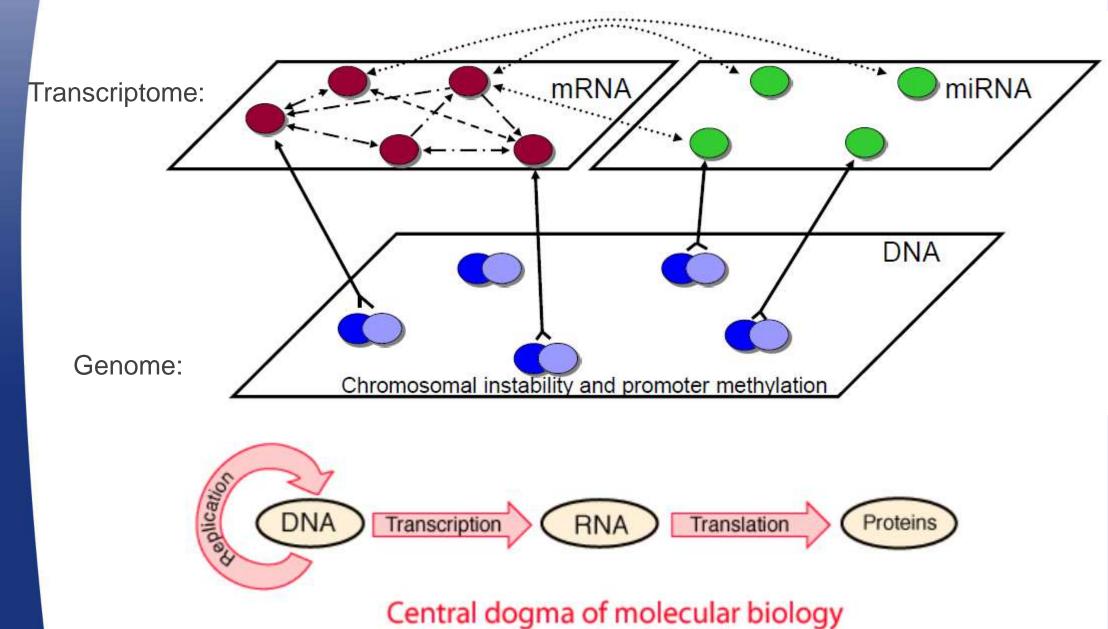


Why integration?



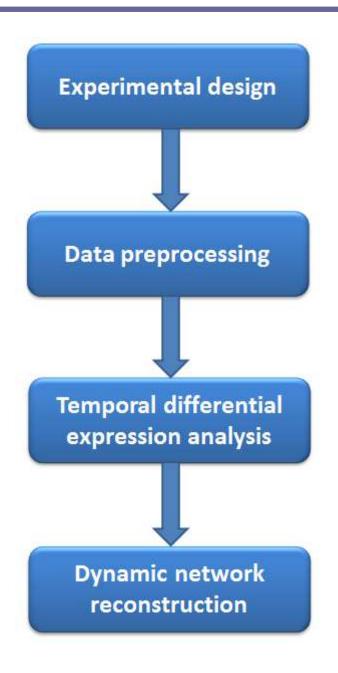
"Blind monks examining an elephant" by Itcho Hanabusa 1888

Multi-omics data integration





What we did?



mRNA: 45K probes arrays

miRNA: 60K probes arrays

CN: 180K probes arrays

mRNA: 27637 genes

miRNA: 1187 genes

CN: 27637 genes

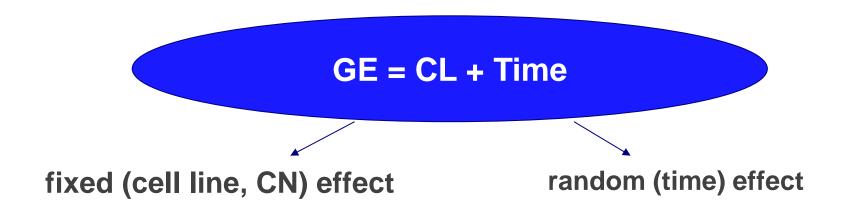
mRNA: 3642 genes

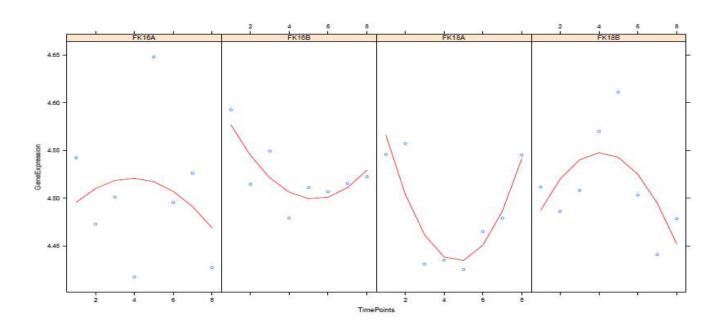
miRNA: 106 genes

mRNA: 64 genes linked to p53 signaling pathway

miRNA: 106 genes which target mRNA

Temporal differential expression

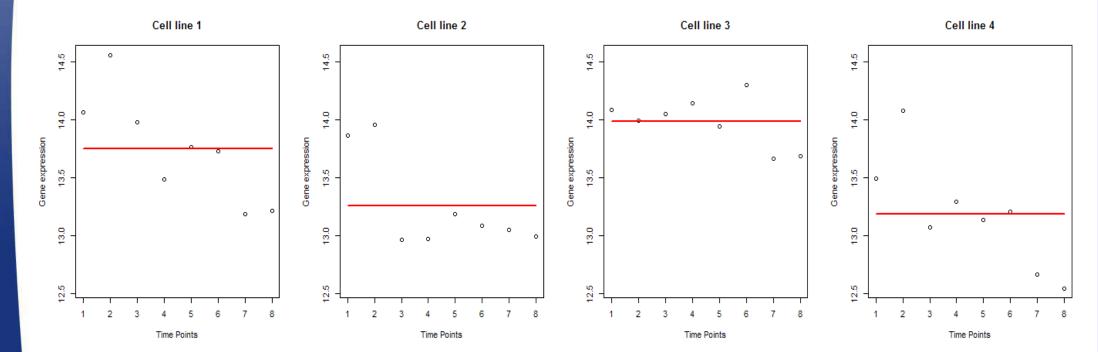






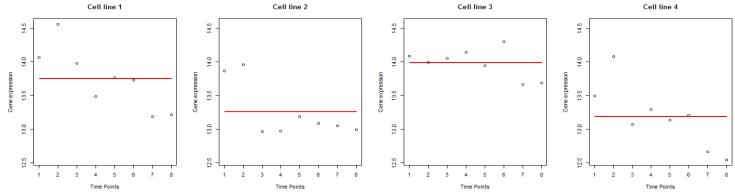
Cell line effect

SP1



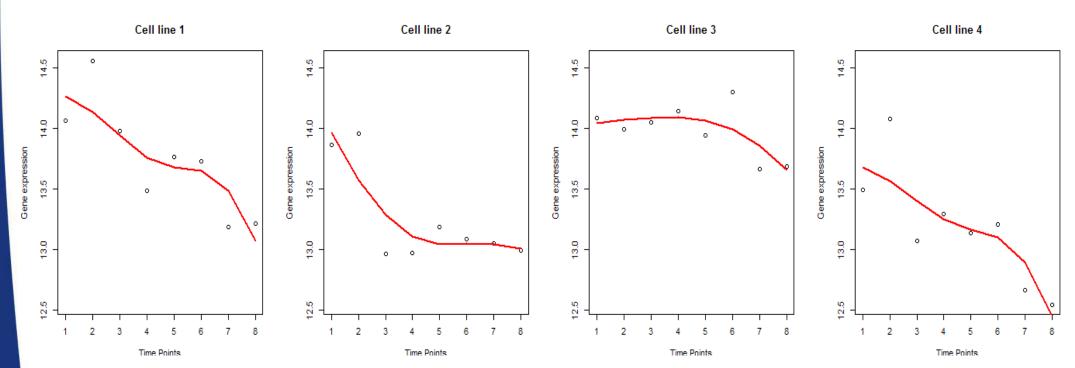
Cell line effect





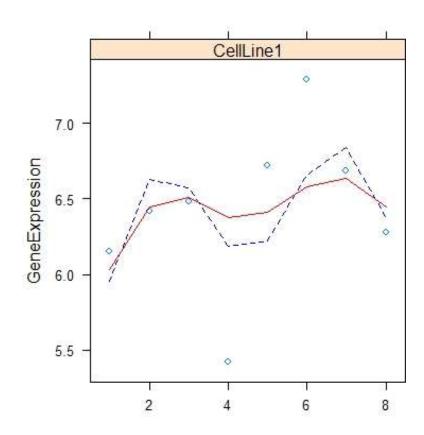
Cell line and Time effect

SP1



Shrinkage

- borrowing information across the genes
- better control of false positives
- improvement of reproducibility
- leads to more stable estimates



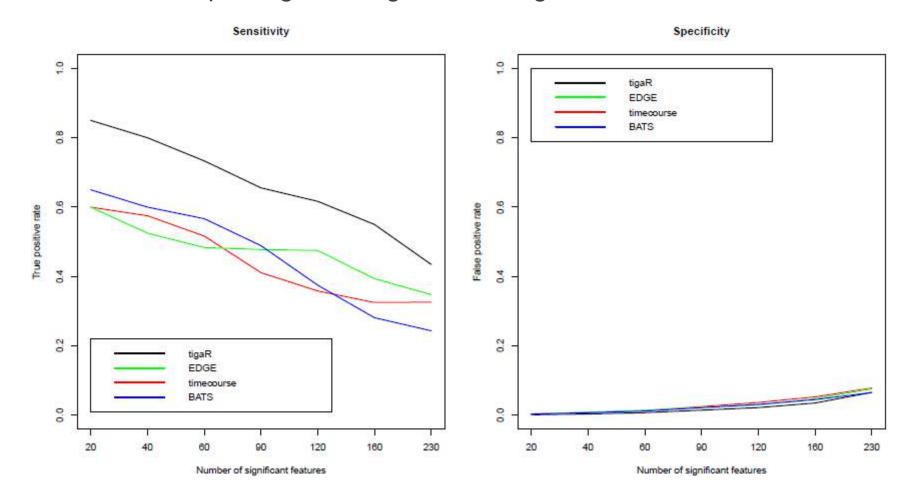
Comparison

- Comparison of following methods:
 - ➤ timecourse Tai and Speed, Annals of Statistics, 2006.
 - ➤ **EDGE** Storey et al., PNAS, 2005.
 - ➤ BATS Angelini et al., BMC Bioinformatics, 2008.
 - ➤ tigaR Miok et al., BMC Bioinformatics, 2014.

- Method is applied on two data sets
 - > Data from our experiment (only mRNA data)
 - ➤ Data from Storey et al., PNAS, 2005.

Sensitivity and specificity

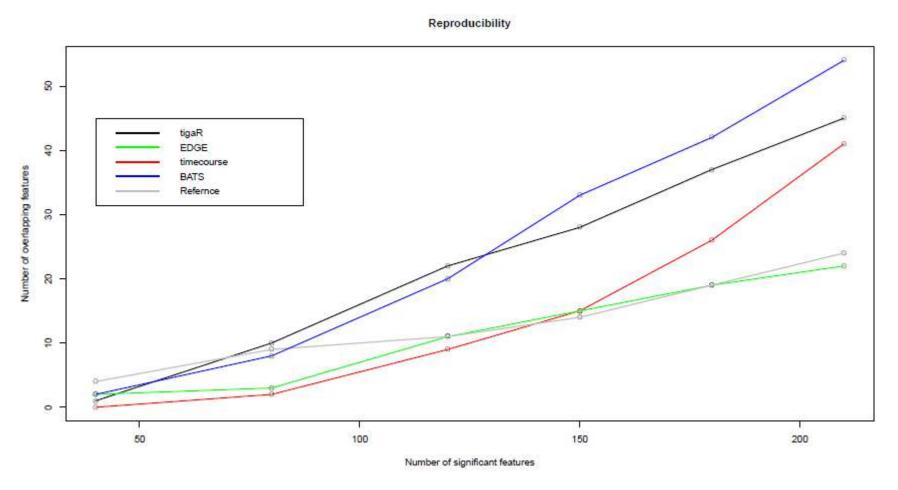
• Truth – overlap of significant genes among methods.





Reproducibility

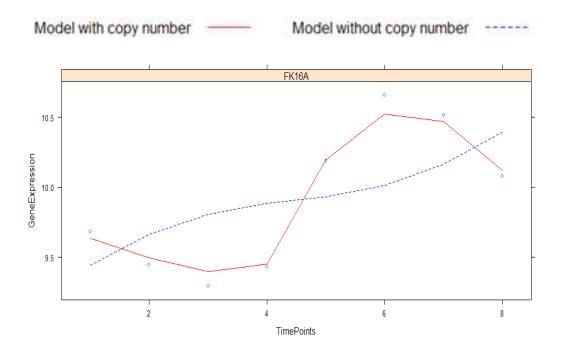
Equally divided data set in two groups.



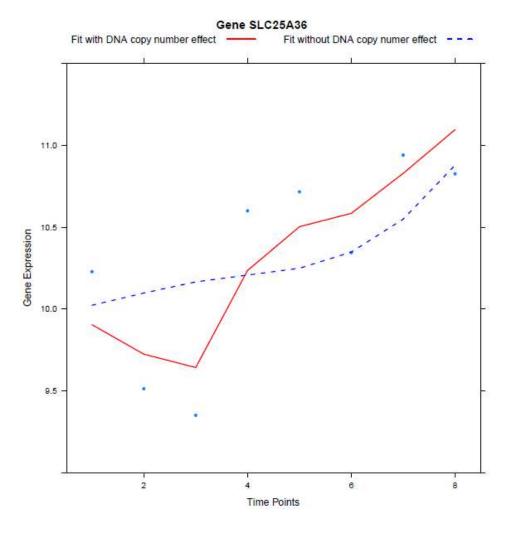
DNA copy number (CN)

GE = CL + CN + Time

Gene GSTM3:



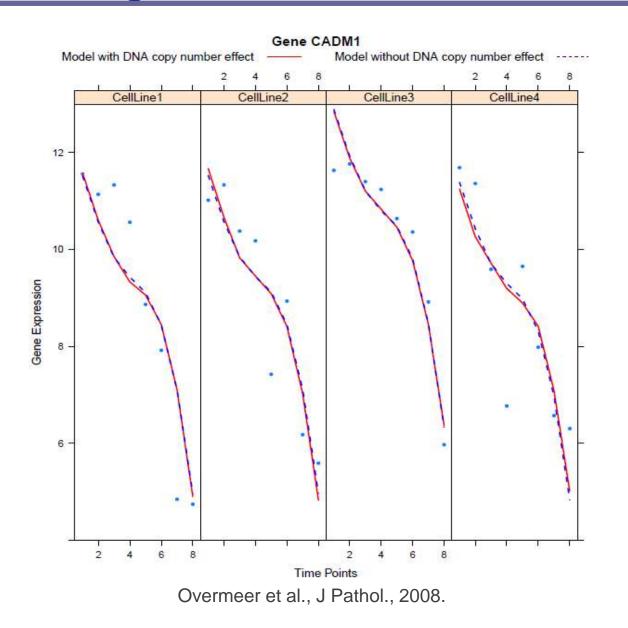
SLC25A36 – gene with CN effect



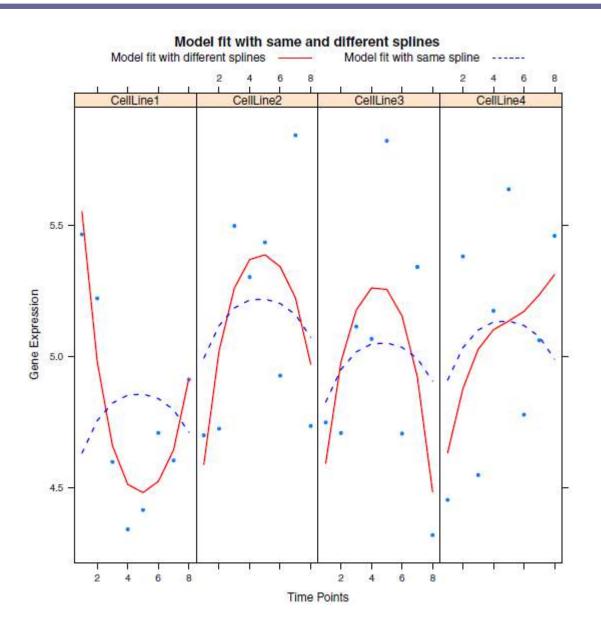
Wilting et al., Genes, Chromosomes and Cancer, 2008.



CADM1- gene without CN effect

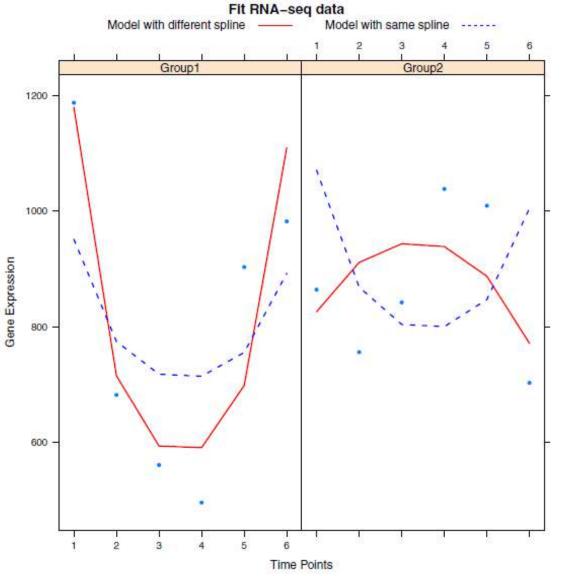


Fit flexibility

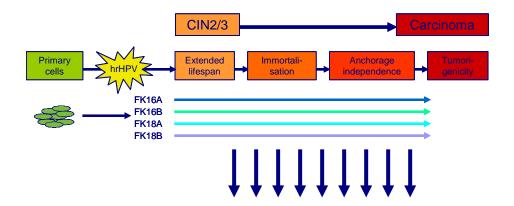


RNA-seq data

- Changing link function method can deal with count data.
- Two group time-course RNA-seq data.

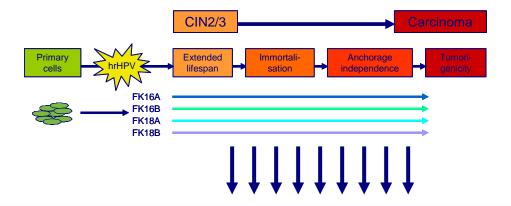


tigaR analysis



Measured expression of 1187 miRNAs and 27637 mRNAs

tigaR analysis



Measured expression of 1187 miRNAs and 27637 mRNAs

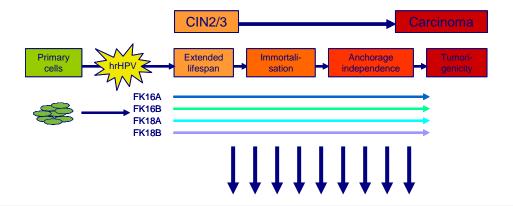




(concordant change in expression in at least 3 cell lines)



tigaR analysis



Measured expression of 1187 miRNAs and 27637 mRNAs





(concordant change in expression in at least 3 cell lines)



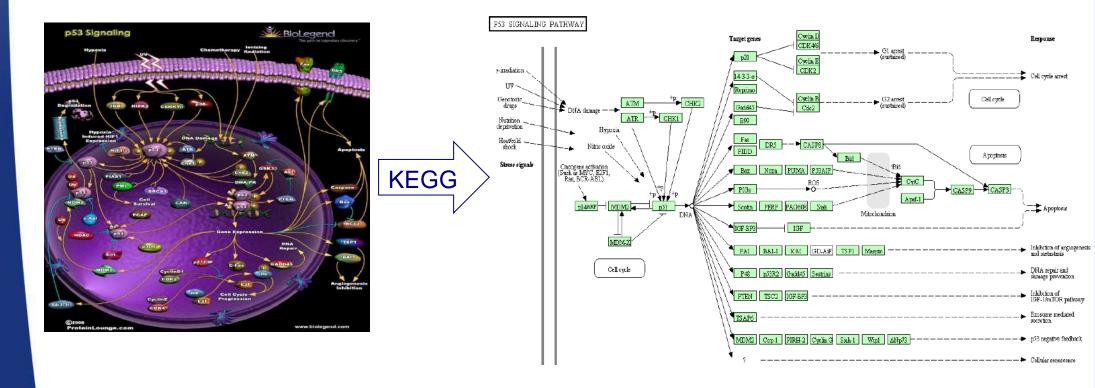


(~34% of altered expression in both cases)



Pathways

- Pathway are defined using repositories: **KEGG**, **GO**, **Reactome**...
- Problems with repositories:
 - > Incomplete
 - Mostly well-known pathways
 - Loosely defined
- Reconstruction of the p53 signaling pathway in cervical cancer



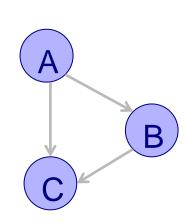
Network

Pathway can be represented by network or graph

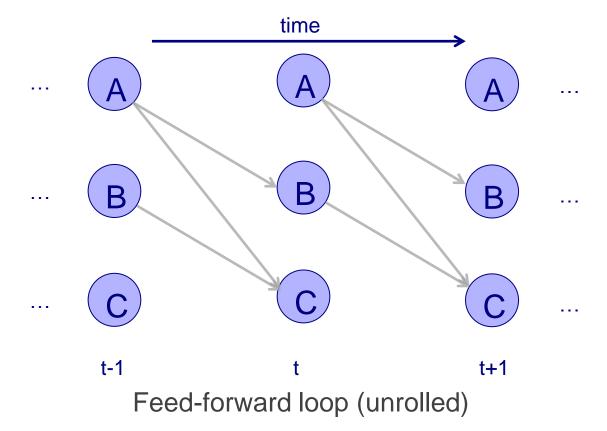


node or vertex, indicate a gene

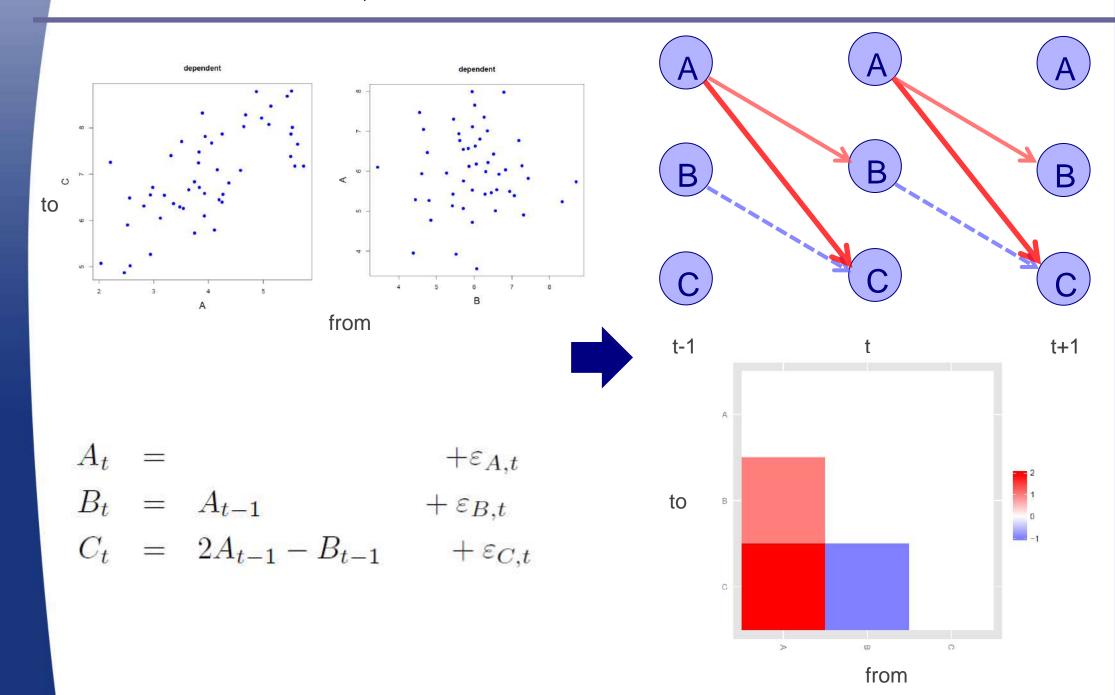
Edge or arrow, indicating an interaction between two genes



Feed-forward loop

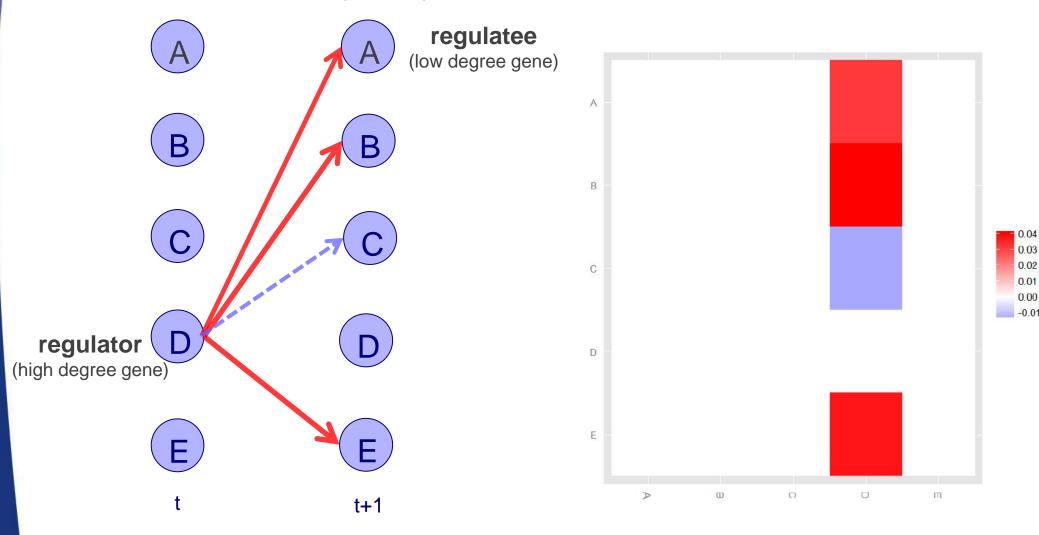


Data, model and network

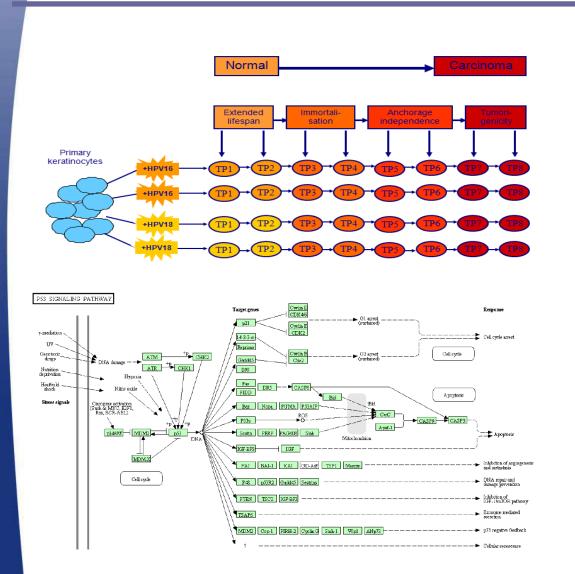


Hub genes

- Hub gene with many connections disease genes
- Important roles for diagnosing and therapy



Real data and network



64 mRNAs mapped to p53 signalling pathway

(28% of genes with significant time effect)

CDK6 THB\$1 CCNE2 TP53 PMAIP1 IGFBP3 **GF1** CDKN1A **RPRM** BBC3 GADD45G TP73 SÉSM PERP TP53AIP1 PTEN **CCNB3** BID **É**124 CCNG1 ATM TNFRSF10B RFWD2 SHISA5 GADD45B

CDK6 THB\$1 CCNE2 TP53 IGFBP3 OADD45G **TP73** SESN1 TP53AIP1 SFN CCNB3 **E124** CCNG1 TNFRSF10B RFWD2 SHISA5 GADD45B

Model

$\overline{GE(t)} = A * \overline{GE(t-1)}$

TP53 gene:
$$\mathbf{TP53}_t = \mathbf{a_1}\mathbf{TP53}_{t-1} + \mathbf{a_2}\mathbf{IGF1}_{2,t-1} + \mathbf{a_3}\mathbf{SFN}_{t-1} + \boldsymbol{\varepsilon}_{1,t}$$

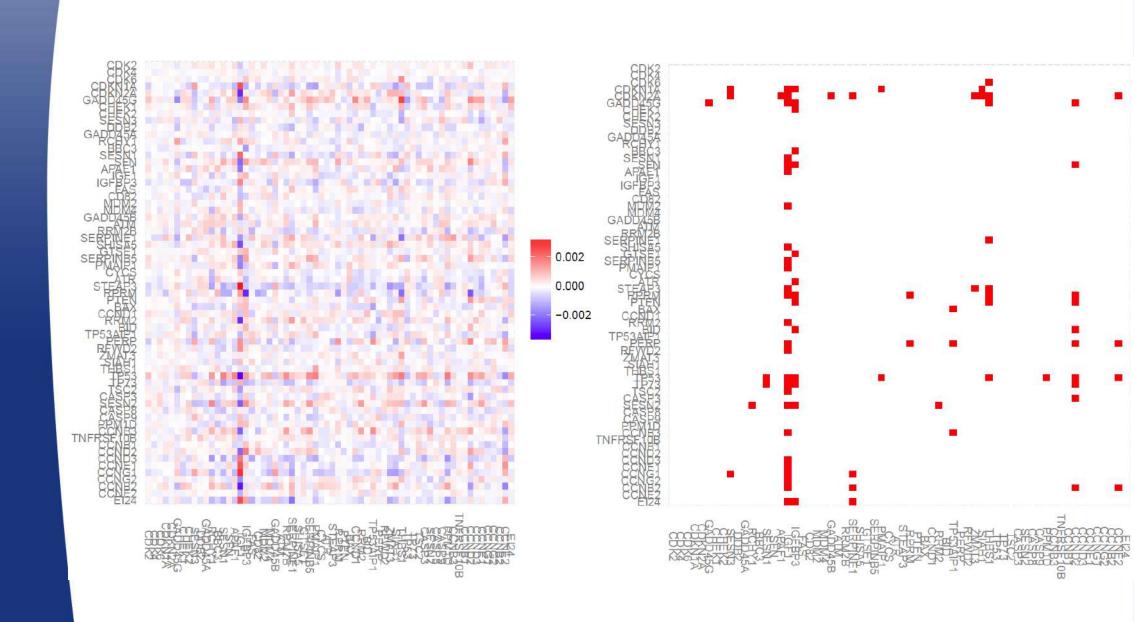
TP53

IGF1

SFN

$$t-1$$
 t

Estimation and sparsification



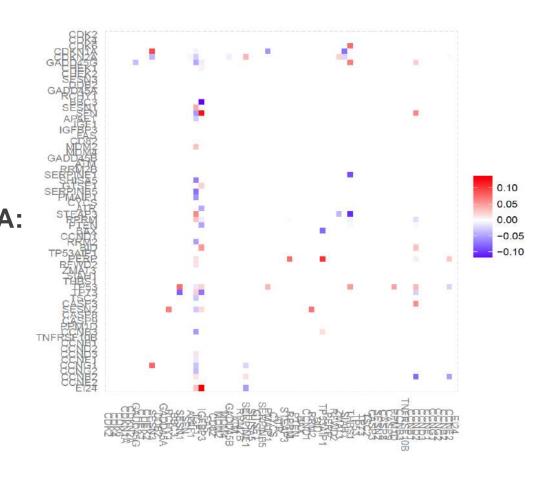
Prior knowledge and re-estimation

- User-specified prior knowledge on the parameters
- Estimated from pilot study publicly available data

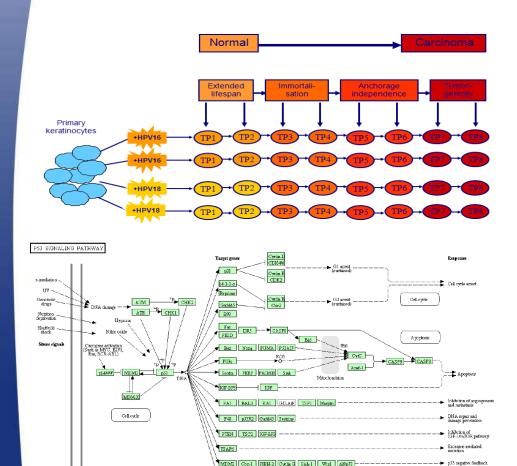


Analytic solution, efficiently evaluable

Less biased estimates of A





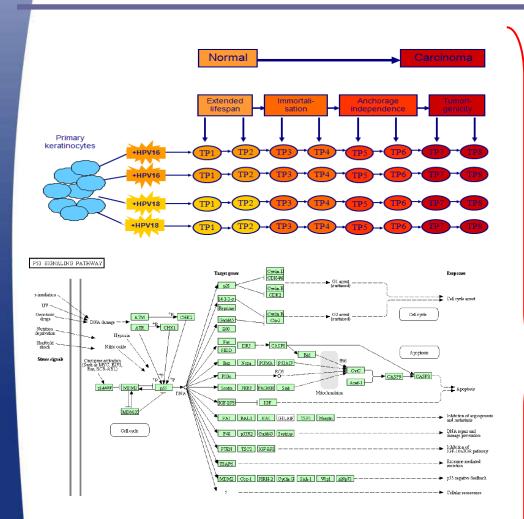


R-package

rags2ridges

(available from CRAN)

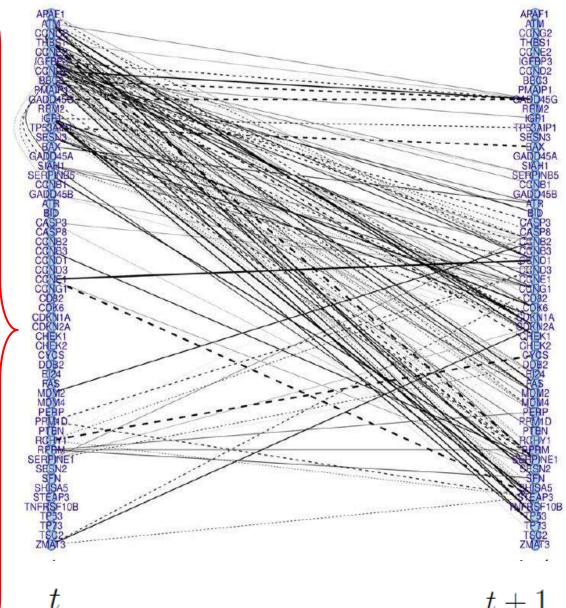




R-package

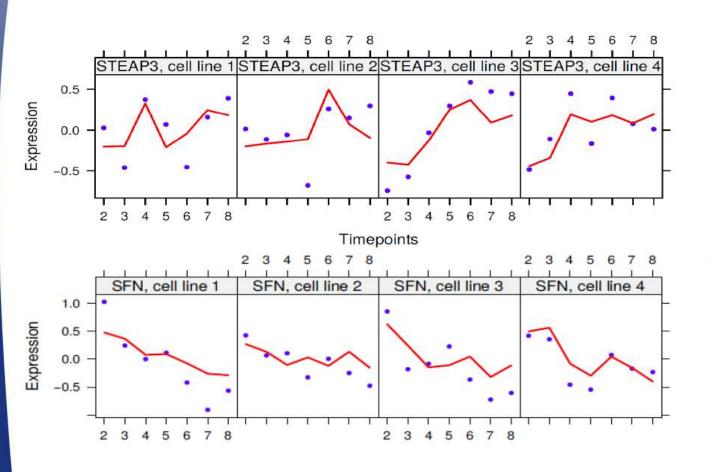
rags2ridges

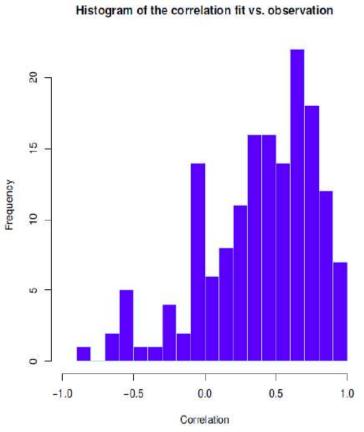
(available from CRAN)





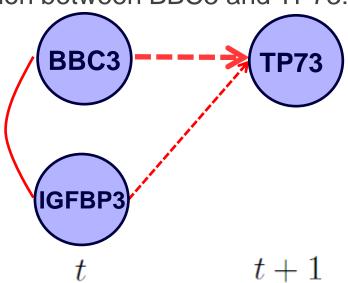
Diagnostics





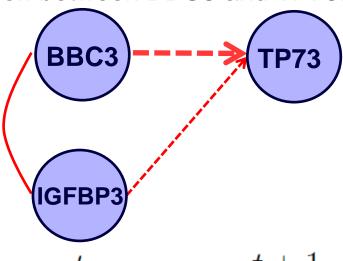
Path decomposition

Contribution between BBC3 and TP73: -0.003168001



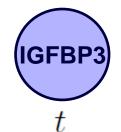
Path decomposition

Contribution between BBC3 and TP73: -0.003168001



Contribution path 1: -0.002483485

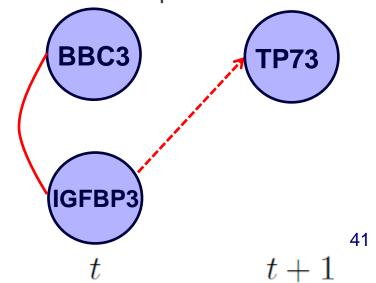




t+1

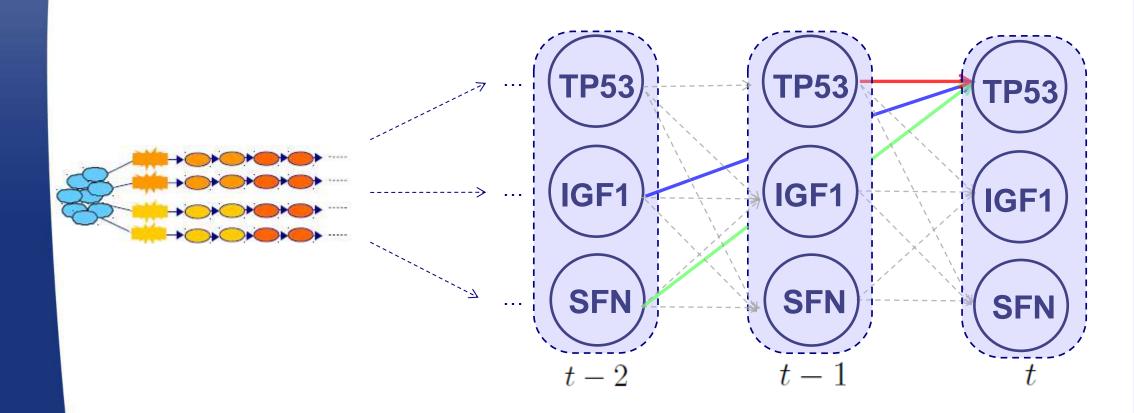
t+1

Contribution paths 2: -0.0006845158

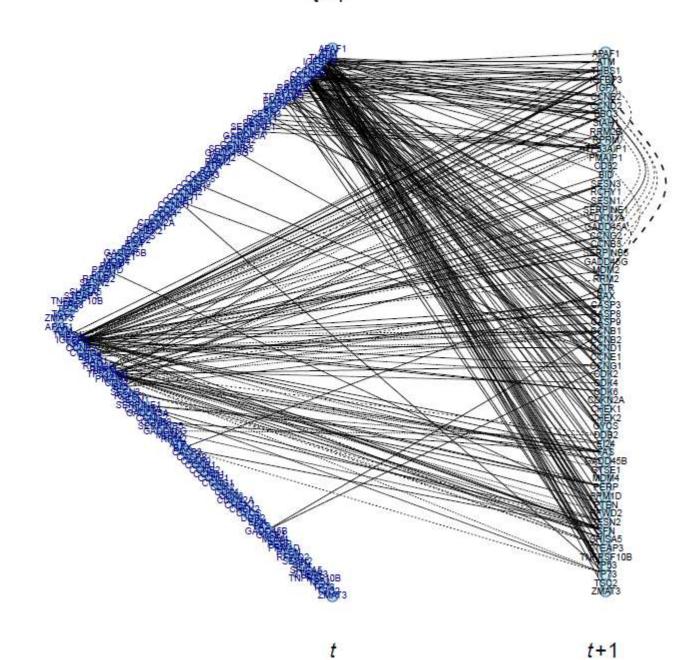


More explanatory time points?

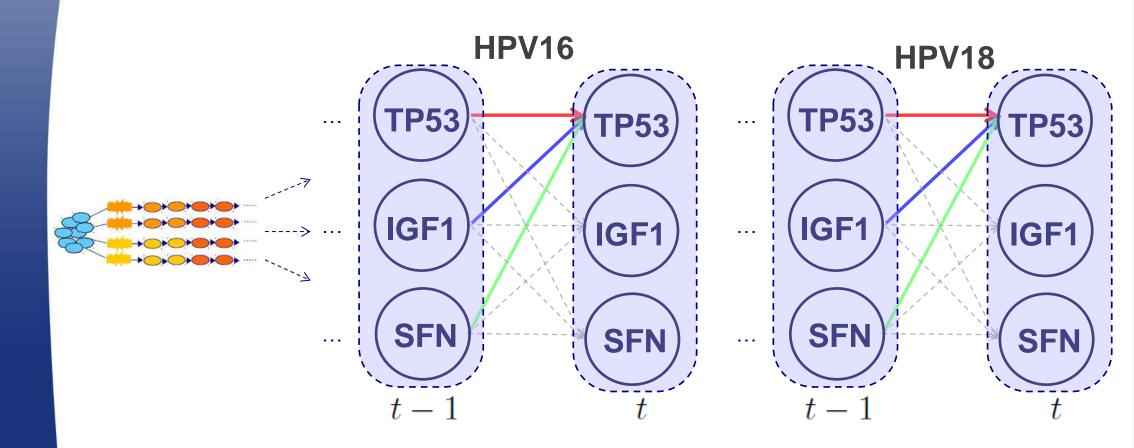
GE(t) = A1 * GE(t-1) + A2 * GE(t-2)

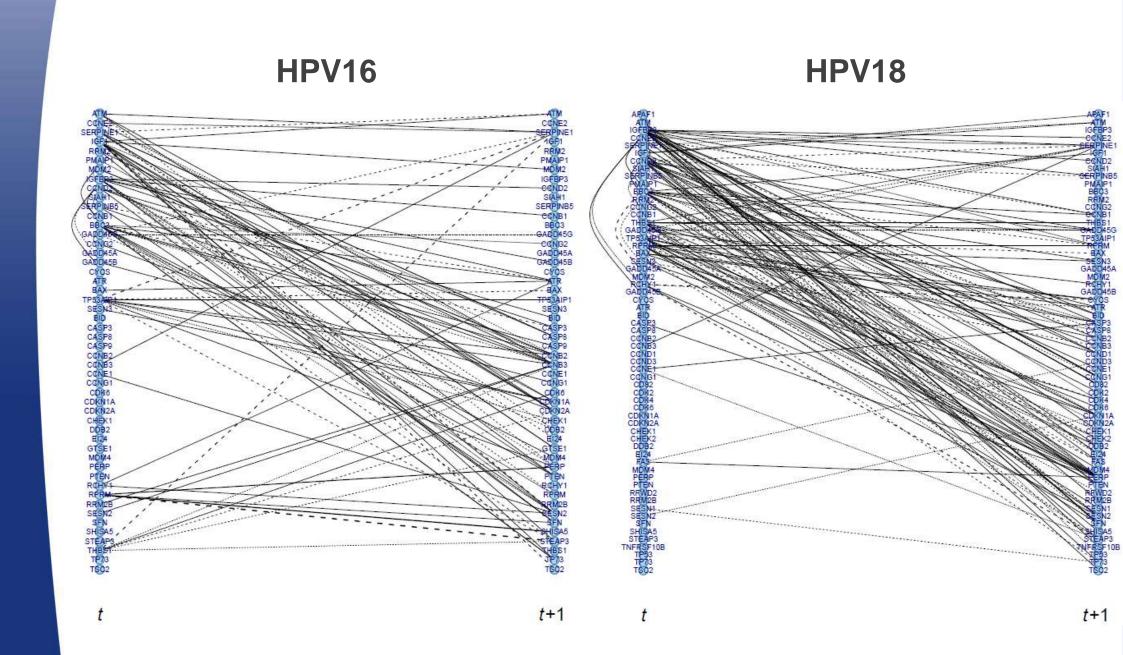


t-1

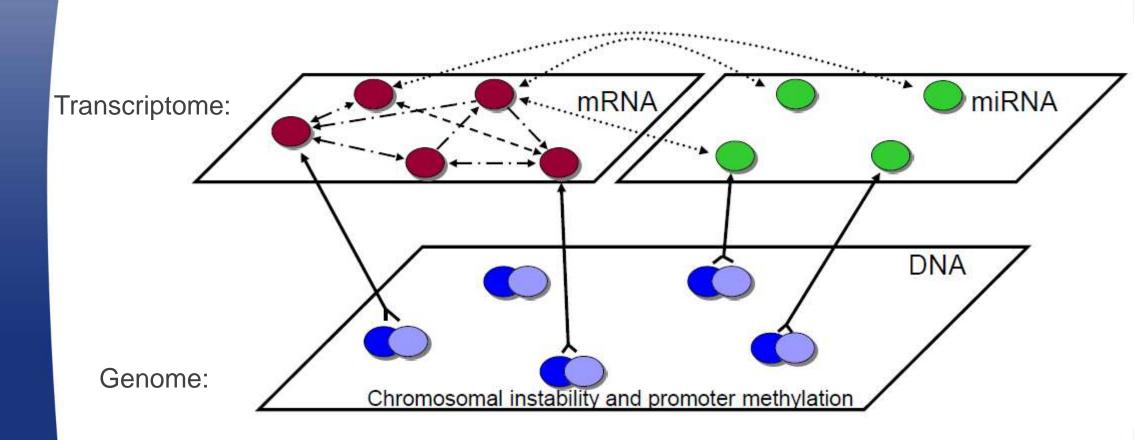


Identify the difference between groups





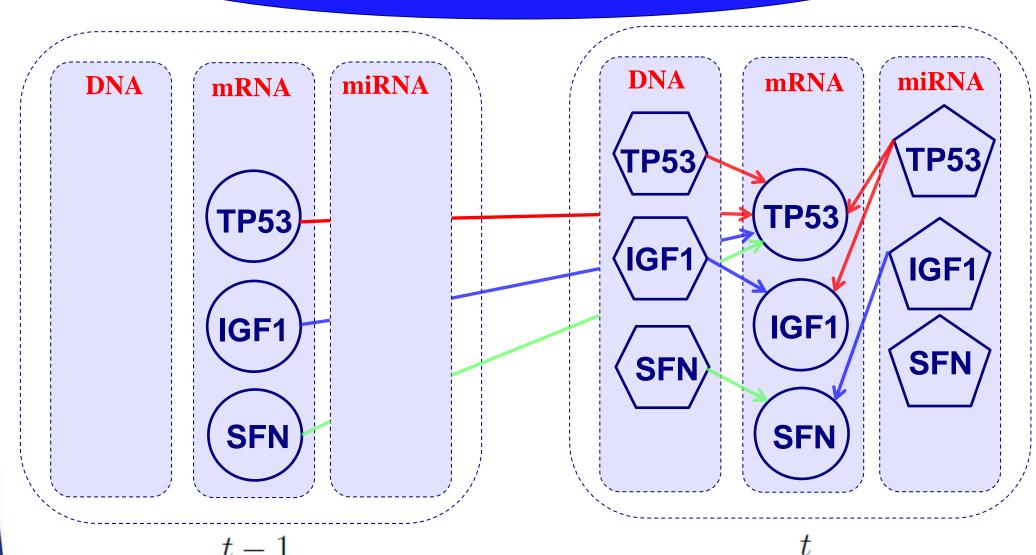
Multi-omics data integration





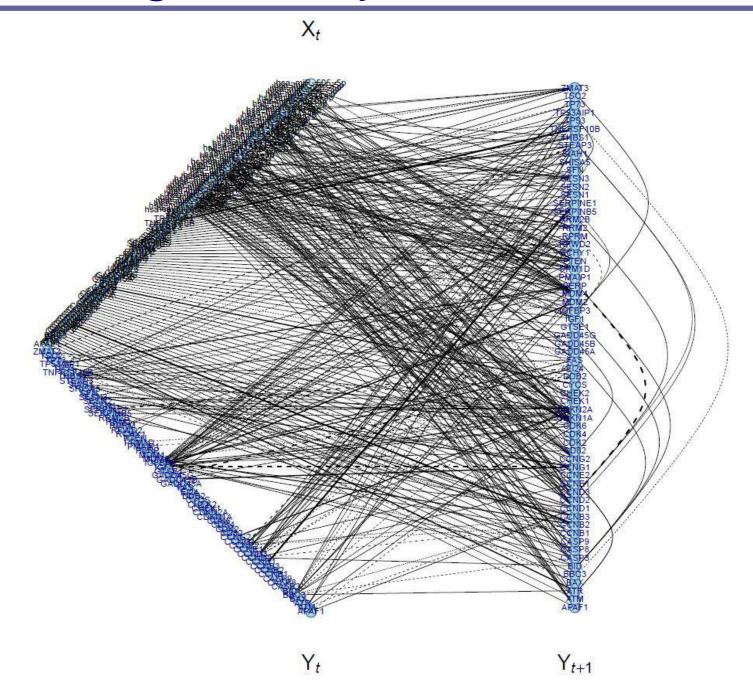
Integration of multi-level dynamic network







Integrated dynamic network





Thank you for your attention!