

Model Based Target Identification from Gene Expression with Gaussian Processes

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work with Magnus Rattray (co-PI)

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Outline

Motivation

Cascade Differential Equations

Discussion and Future Work

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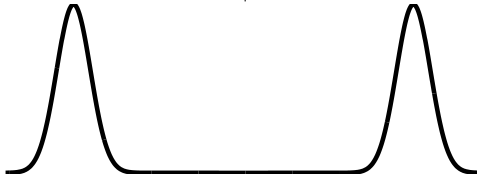
Discussion and Future Work

Computational Biology vs Computational Systems Biology

Broadly Speaking: Two approaches to modeling

data-modeling

mechanistic-modeling



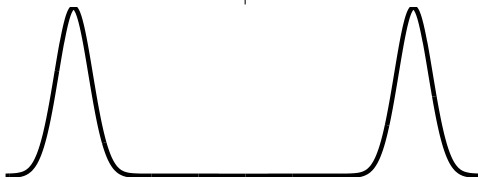
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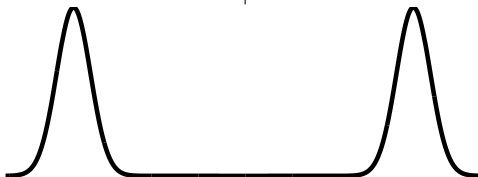
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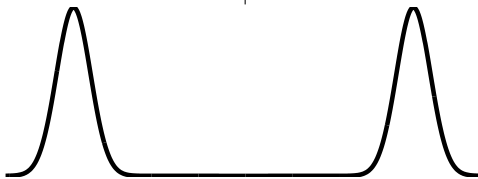
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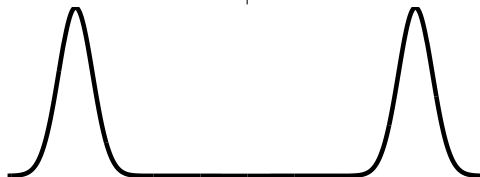
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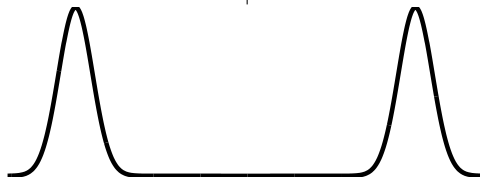
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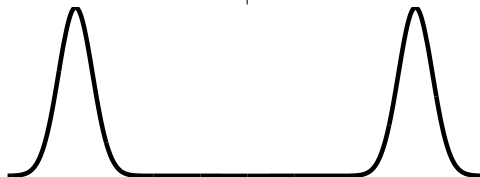
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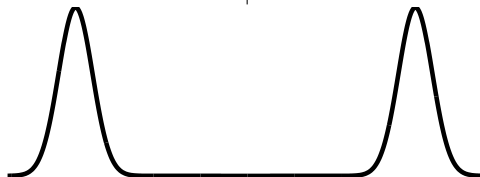
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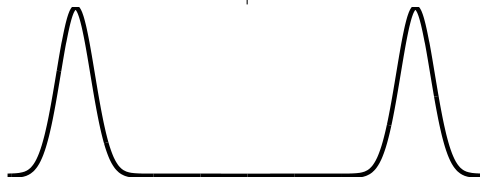
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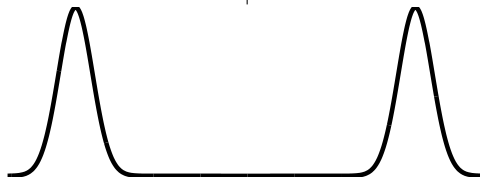
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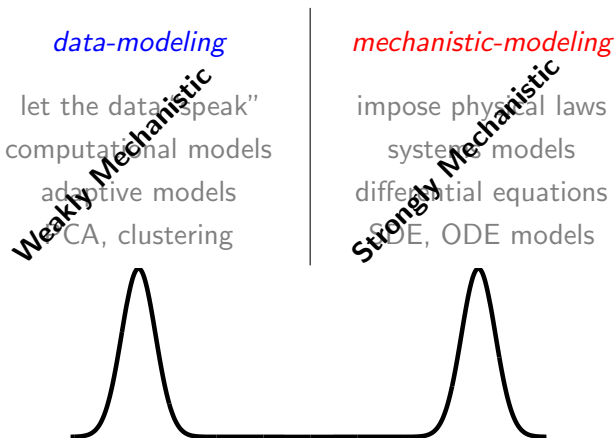
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Computational Biology vs Computational Systems Biology

Broadly Speaking: Two approaches to modeling



A Hybrid Approach

Introduce aspects of systems biology to computational models

- ▶ We advocate an approach *between* systems and computational biology.
- ▶ Introduce aspects of systems biology to the computational approach.
 - ▶ There is a computational penalty, but it may be worth paying.
 - ▶ Ideally there should be a smooth transition from pure computational (PCA, clustering, SVM classification) to systems (non-linear (stochastic) differential equations).

Standard Approach

Clustering of Gene Expression Profiles

- ▶ Assume that coregulated genes will cluster in the same groups.
- ▶ Perform clustering, and look for clusters containing target genes.
- ▶ These are candidates, look for confirmation in the literature etc.

Mathematical Model

- Differential equation model of system.

$$\frac{dm_j(t)}{dt} = b_j + s_j p(t) - d_j m_j(t)$$

rate of mRNA transcription, baseline transcription rate,
transcription factor activity, mRNA decay

- We have observations of $m_j(t)$ from gene expression.

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- Differential equation model of system.

$$\frac{dm_j(t)}{dt} = b_j + s_j p(t) - d_j m_j(t)$$
$$d_j m_j(t) + \frac{dm_j(t)}{dt} = b_j + s_j p(t)$$

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Mathematical Model

- ▶ Clustering model is equivalent to assuming d_j , b_j , and s_j are v. large.

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- ▶ We have observations of $m_j(t)$ from gene expression.
- ▶ Reorder differential equation and ignore gradient term.

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- ▶ We have observations of $m_j(t)$ from gene expression.
- ▶ Reorder differential equation and ignore gradient term.
- ▶ This suggests genes are scaled and offset versions of the TF.
- ▶ By normalizing data and clustering we hope to find those TFs.

Method

Open Access

Ranked prediction of p53 targets using hidden variable dynamic modeling

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Example: Transcriptional Regulation

- ▶ First Order Differential Equation

$$\frac{dm_j(t)}{dt} = b_j + s_j p(t) - d_j m_j(t)$$

- ▶ We can use a probabilistic process model for $p(t)$.
- ▶ This implies a probabilistic process over $p(t)$ and all its targets: $m_1(t), m_2(t), \dots$ etc.
- ▶ This incorporates the assumptions in the differential equation.
- ▶ This gives us a *probabilistic* model for transcriptional regulation.

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Joint Sampling of $f(t)$ and $x(t)$

► `simSample`

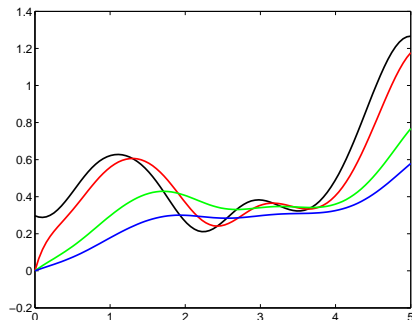


Figure: Joint samples from the ODE covariance, *black*: $p(t)$, *red*: $m_1(t)$ (high decay/sensitivity), *green*: $m_2(t)$ (medium decay/sensitivity) and *blue*: $m_3(t)$ (low decay/sensitivity).

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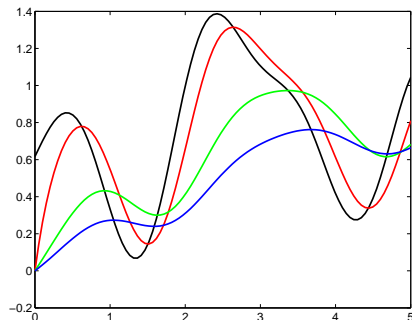


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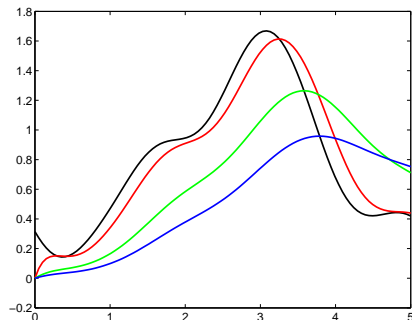


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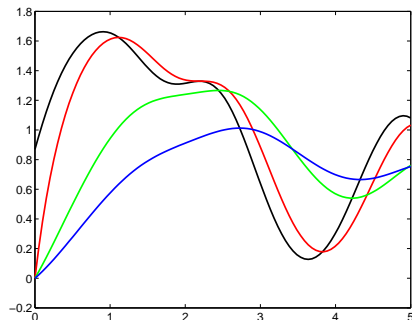
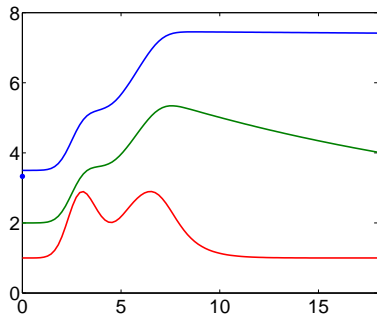


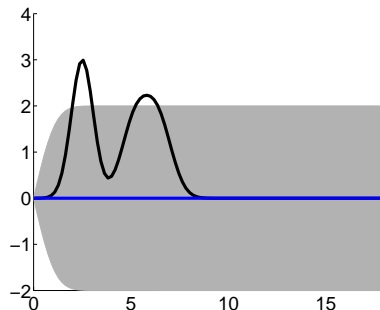
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Inferring TF activity from artificially sampled genes.



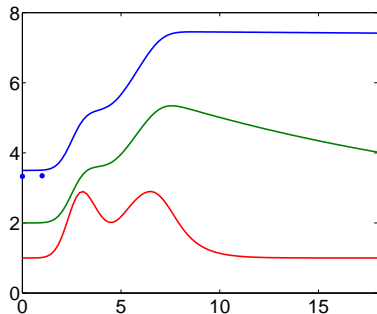
True “gene profiles” and noisy observations.



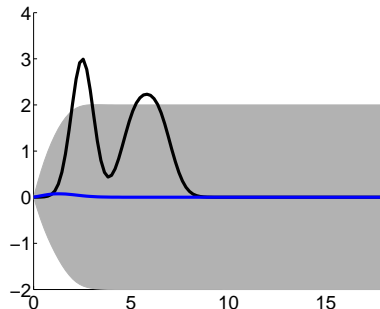
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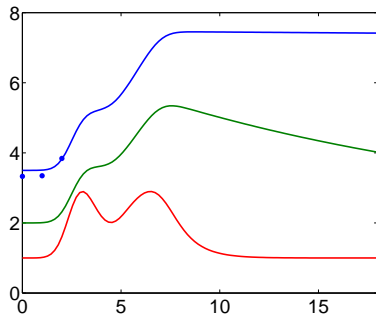
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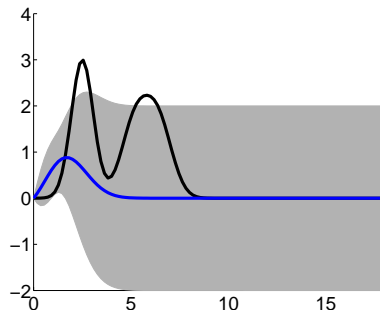
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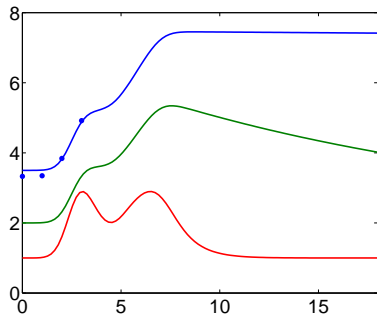
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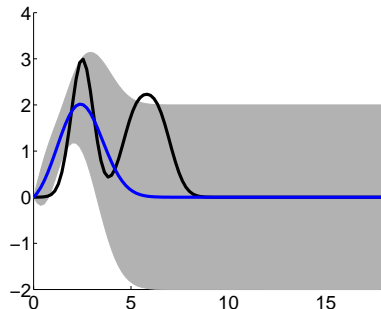
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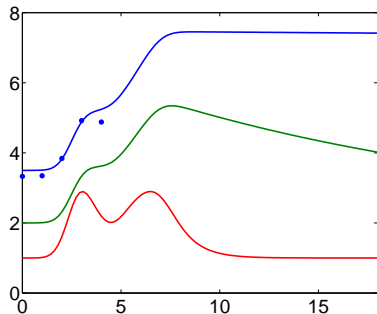
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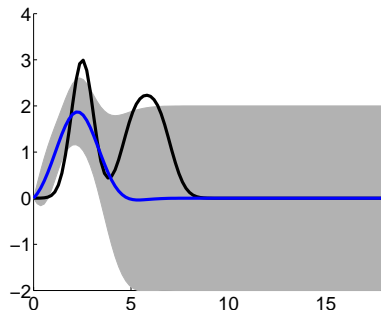
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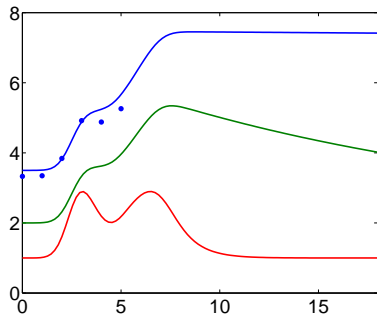
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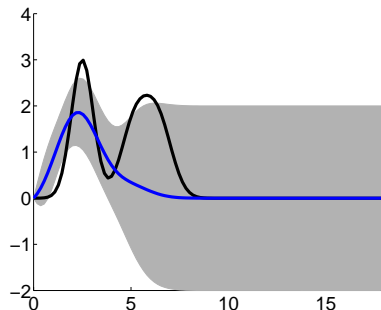
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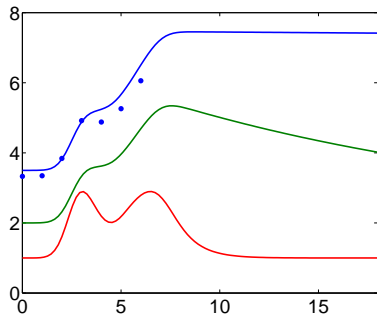
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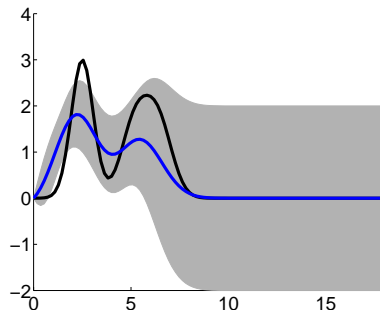
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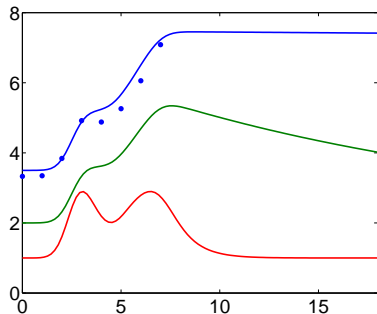
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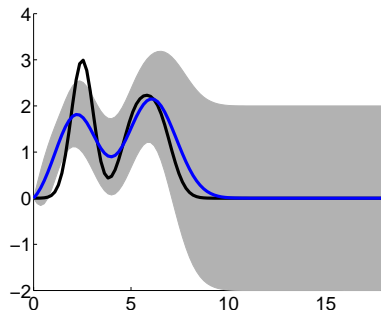
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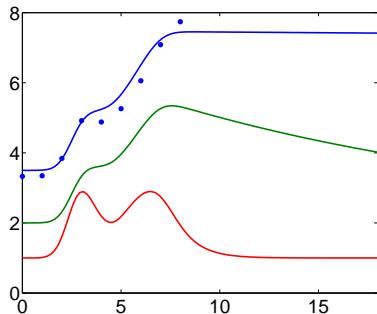
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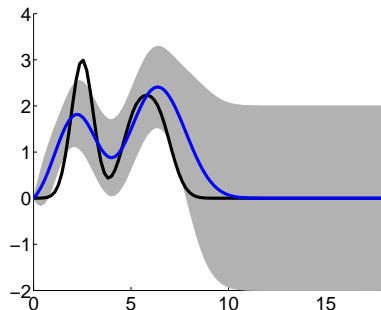
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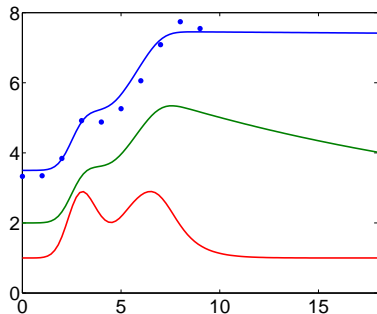
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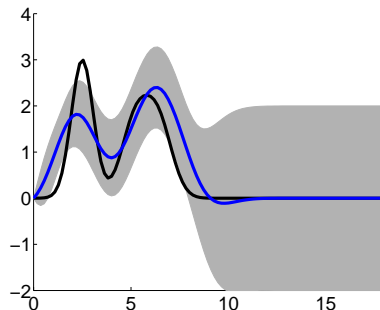
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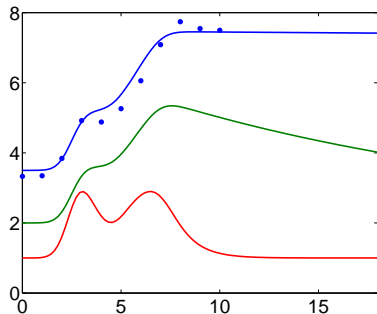
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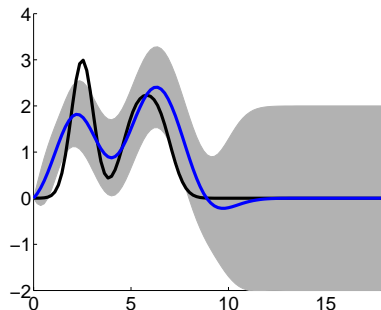
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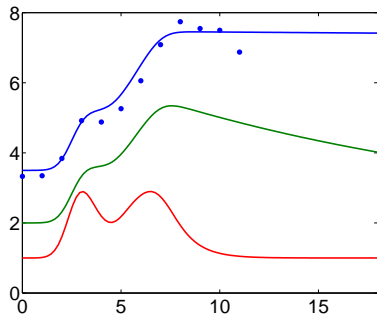
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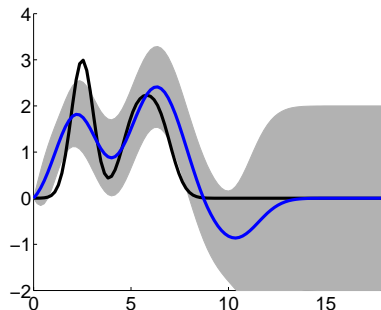
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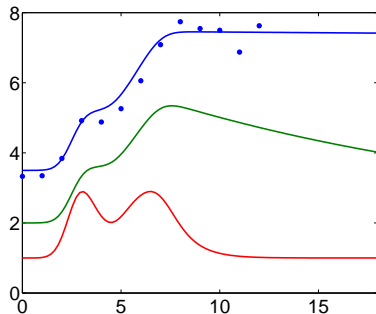
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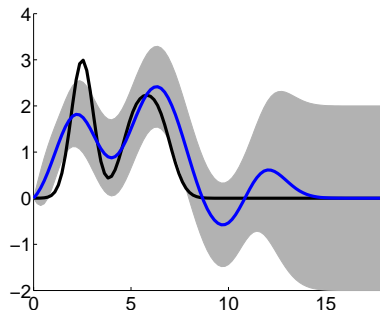
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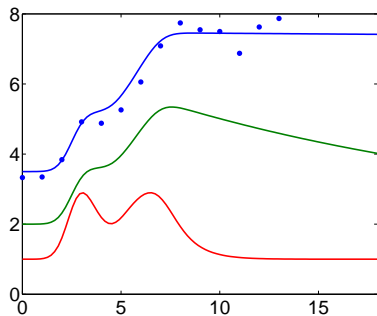
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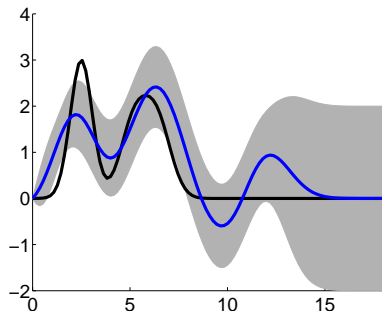
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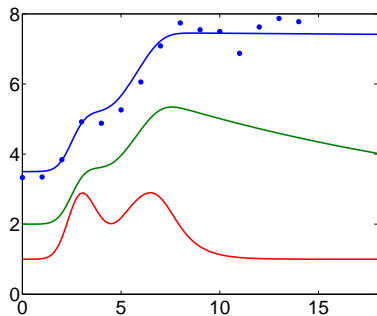
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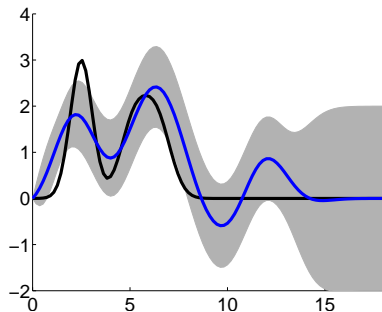
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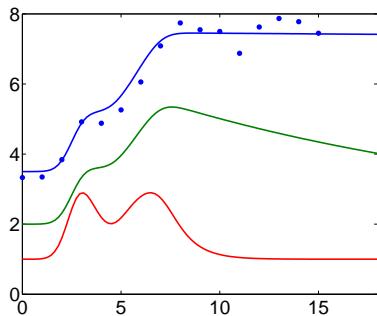
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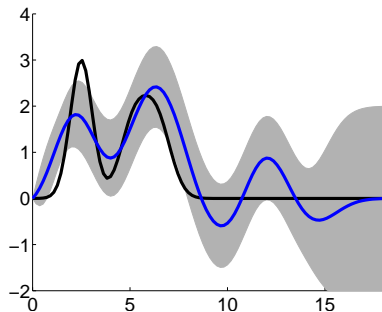
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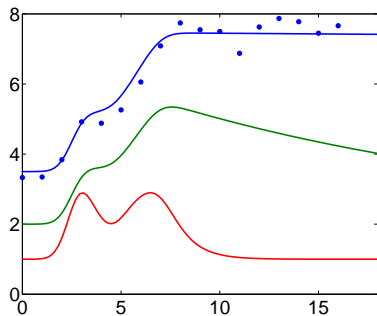
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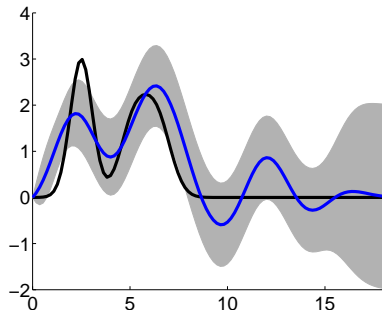
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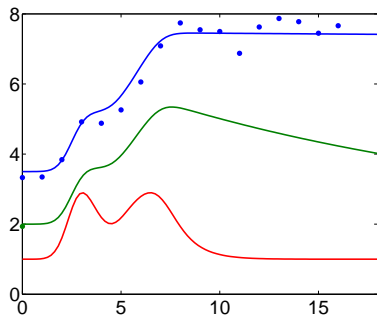
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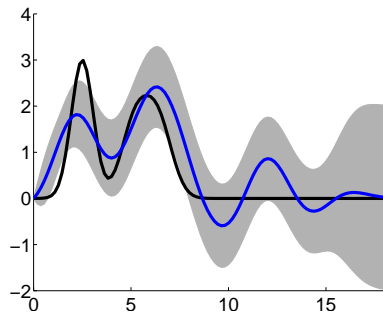
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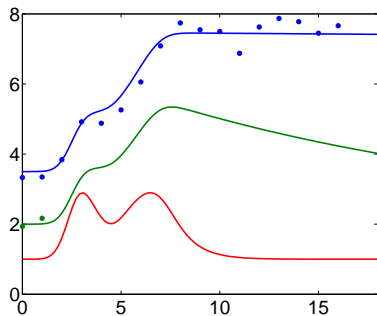
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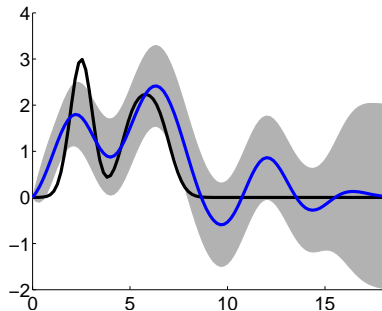
Inferred transcription factor activity.

Artificial Example: Inferring $p(t)$

Inferring TF activity from artificially sampled genes.



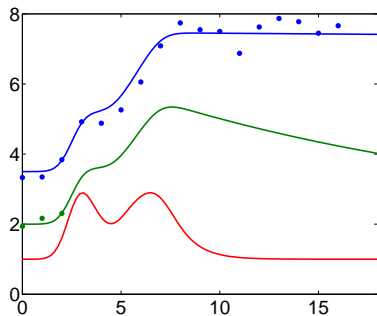
True “gene profiles” and noisy observations.



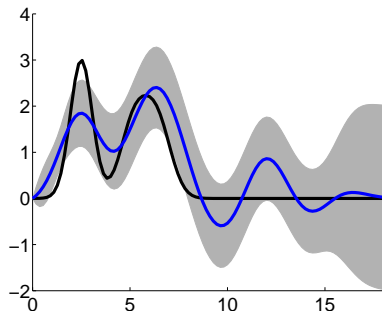
Inferred transcription factor activity.

Artificial Example: Inferring $p(t)$

Inferring TF activity from artificially sampled genes.



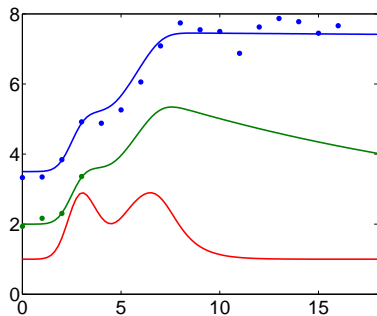
True “gene profiles” and noisy observations.



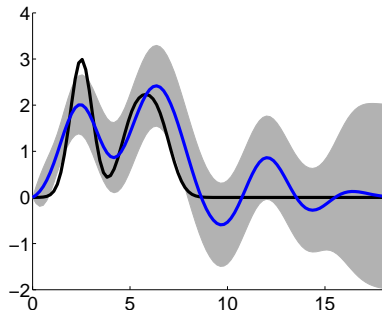
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



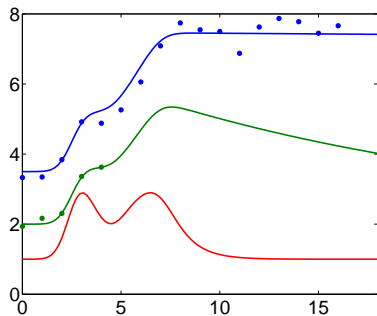
True “gene profiles” and noisy observations.



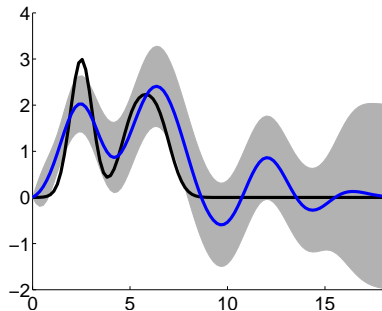
Inferred transcription factor activity.

Artificial Example: Inferring $p(t)$

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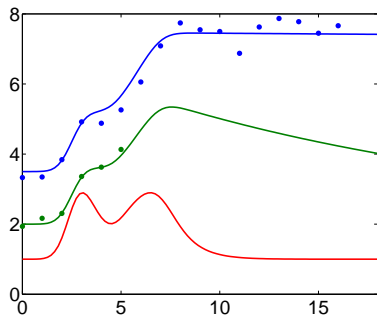
True “gene profiles” and noisy observations.



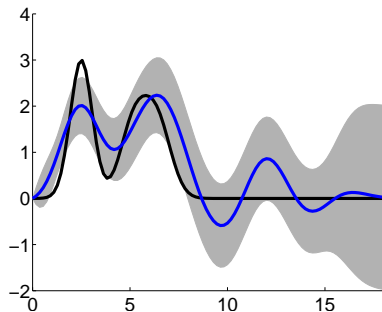
Inferred transcription factor activity.

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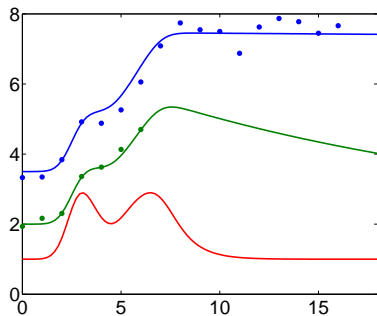
True “gene profiles” and noisy observations.



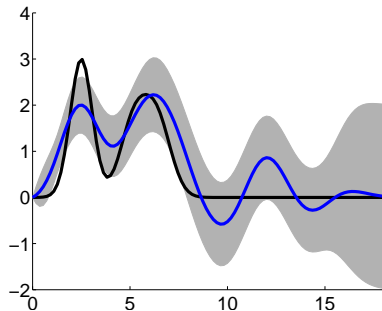
Inferred transcription factor activity.

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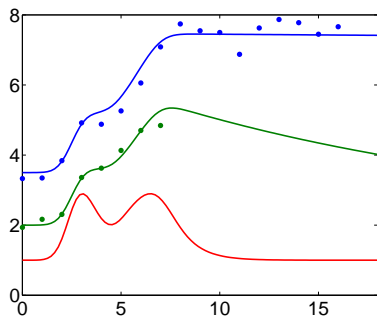
True “gene profiles” and noisy observations.



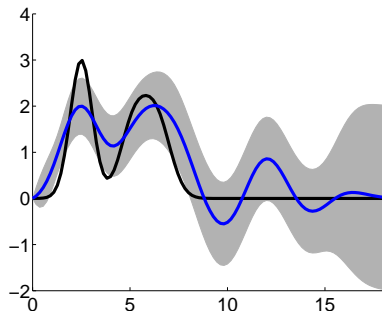
Inferred transcription factor activity.

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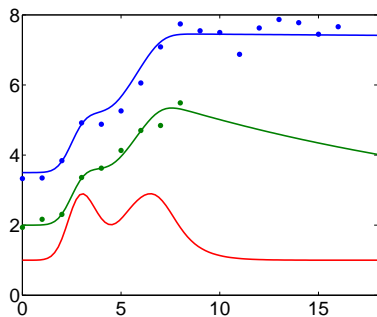
True “gene profiles” and noisy observations.



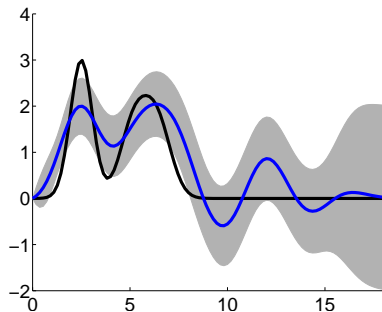
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



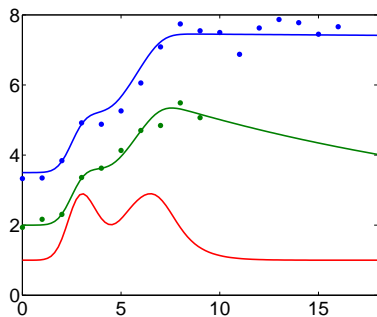
True “gene profiles” and noisy observations.



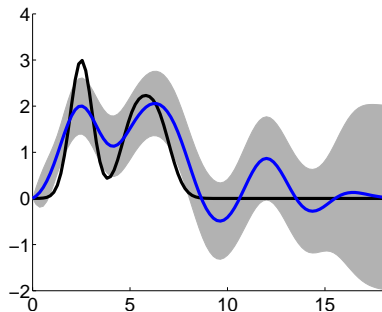
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



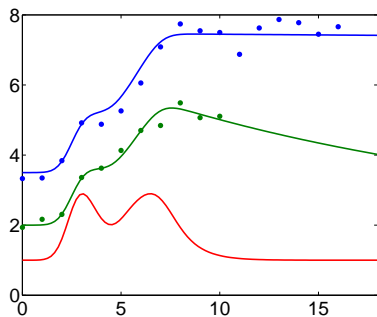
True “gene profiles” and noisy observations.



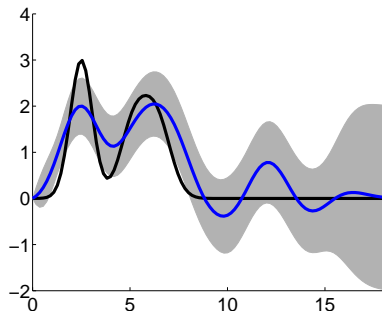
Inferred transcription factor activity.

Artificial Example: Inferring $p(t)$

Inferring TF activity from artificially sampled genes.



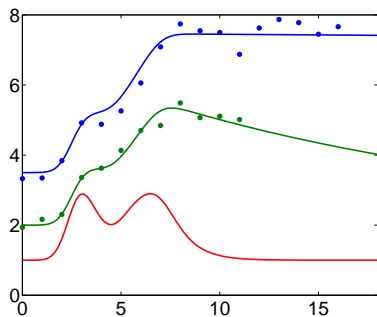
True “gene profiles” and noisy observations.



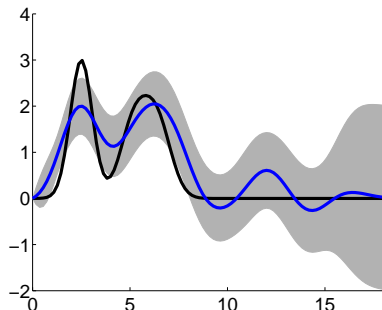
Inferred transcription factor activity.

Artificial Example: Inferring $p(t)$

Inferring TF activity from artificially sampled genes.



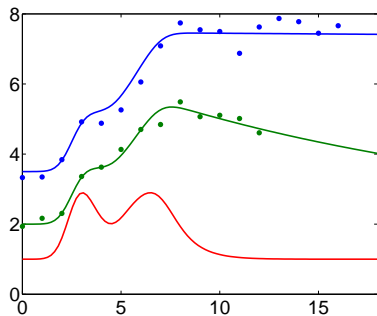
True “gene profiles” and noisy observations.



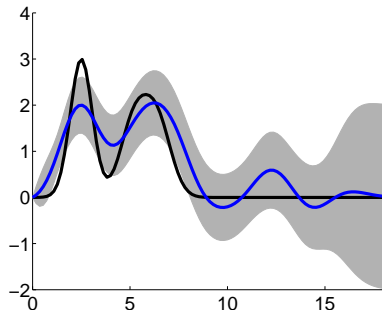
Inferred transcription factor activity.

Artificial Example: Inferring $p(t)$

Inferring TF activity from artificially sampled genes.



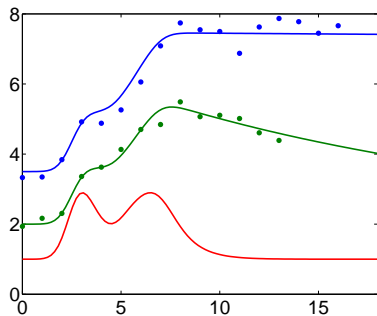
True “gene profiles” and noisy observations.



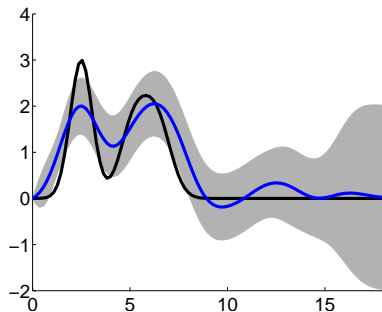
Inferred transcription factor activity.

Artificial Example: Inferring $p(t)$

Inferring TF activity from artificially sampled genes.



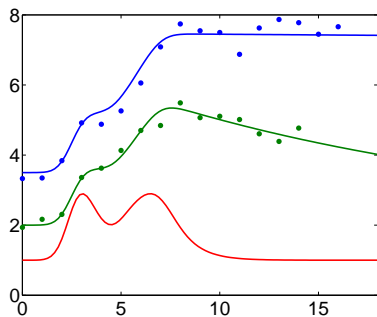
True “gene profiles” and noisy observations.



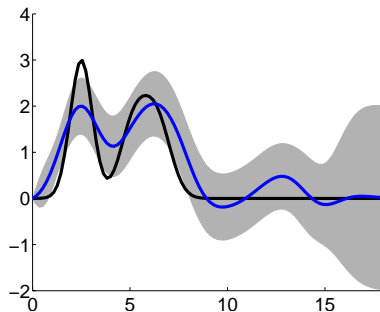
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



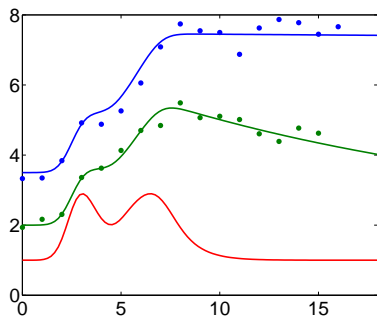
True “gene profiles” and noisy observations.



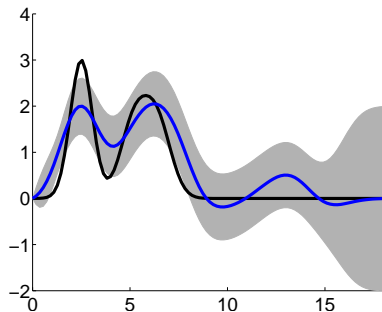
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



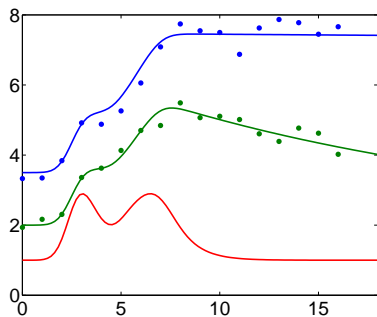
True “gene profiles” and noisy observations.



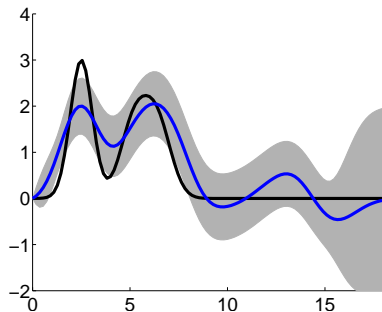
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



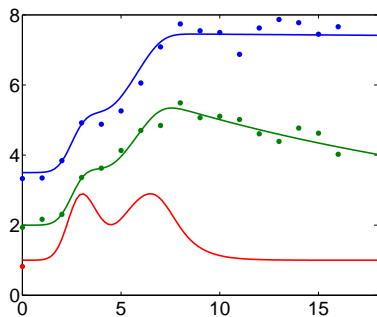
True “gene profiles” and noisy observations.



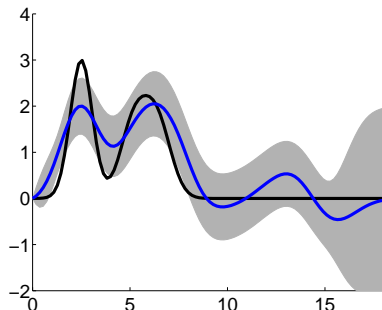
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



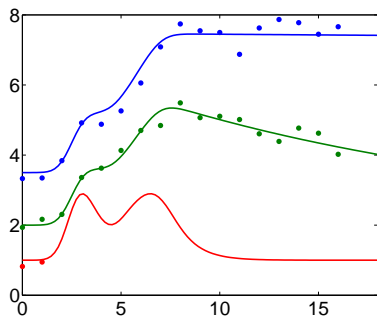
True “gene profiles” and noisy observations.



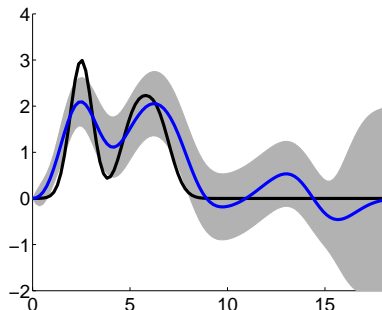
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



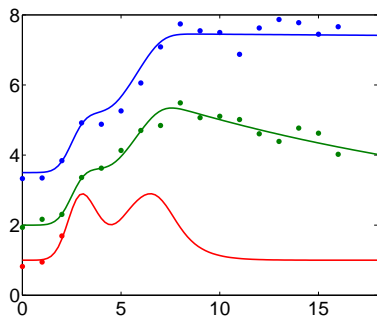
True “gene profiles” and noisy observations.



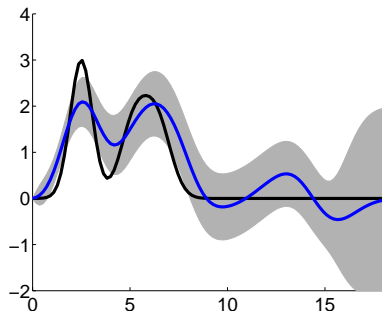
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



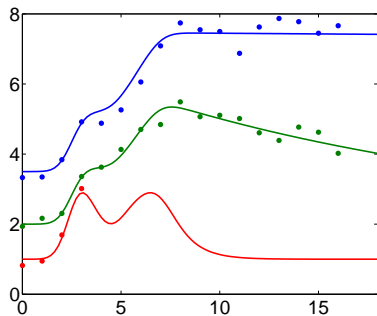
True “gene profiles” and noisy observations.



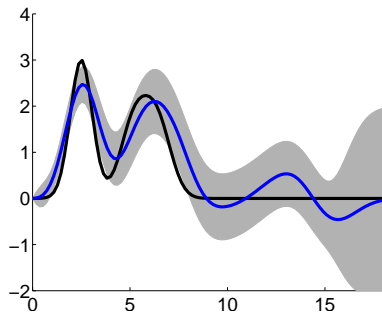
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



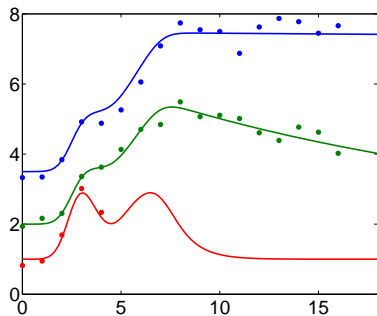
True “gene profiles” and noisy observations.



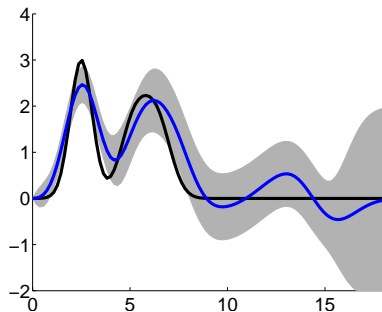
Inferred transcription factor activity.

Artificial Example: Inferring $p(t)$

Inferring TF activity from artificially sampled genes.



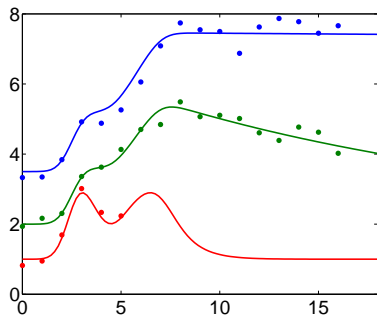
True “gene profiles” and noisy observations.



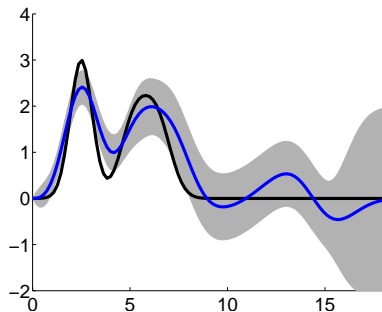
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



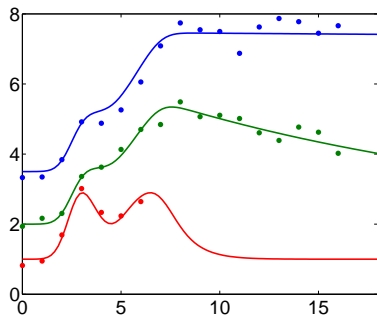
True “gene profiles” and noisy observations.



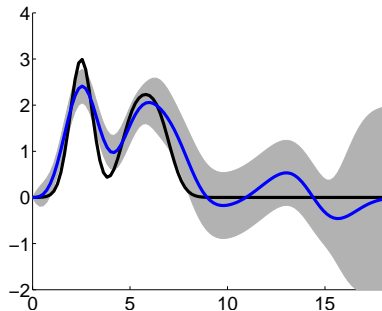
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



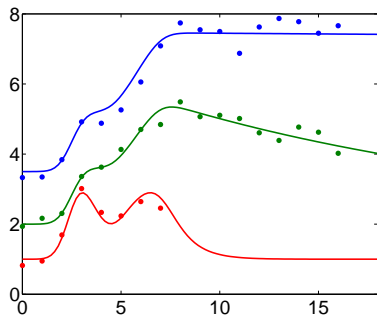
True “gene profiles” and noisy observations.



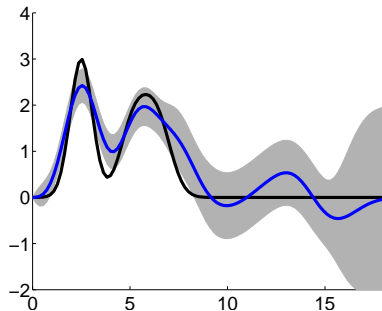
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



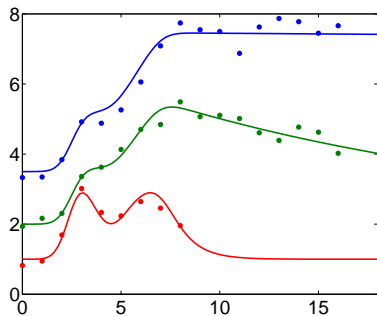
True “gene profiles” and noisy observations.



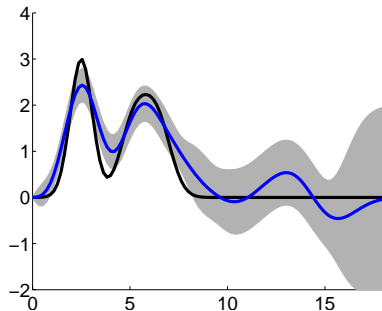
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



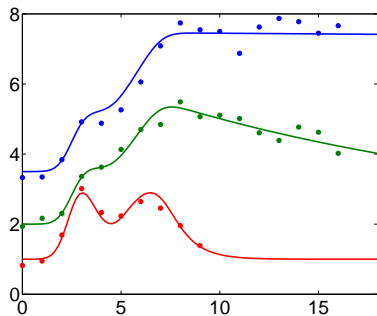
True “gene profiles” and noisy observations.



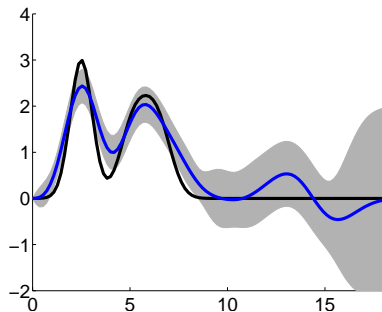
Inferred transcription factor activity.

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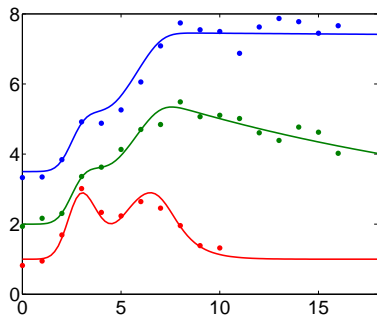
True “gene profiles” and noisy observations.



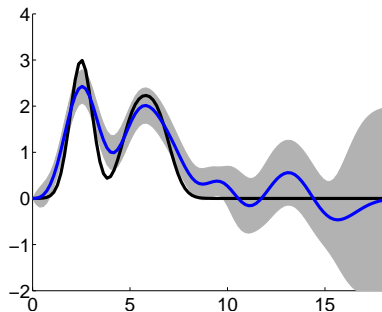
Inferred transcription factor activity.

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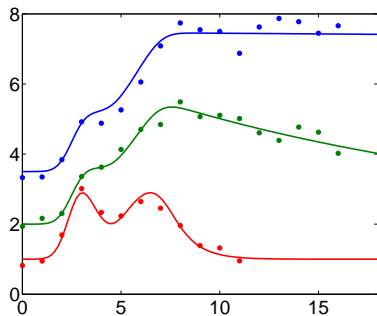
True “gene profiles” and noisy observations.



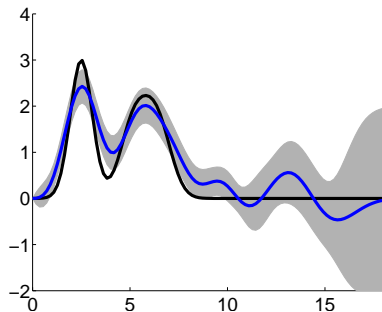
Inferred transcription factor activity.

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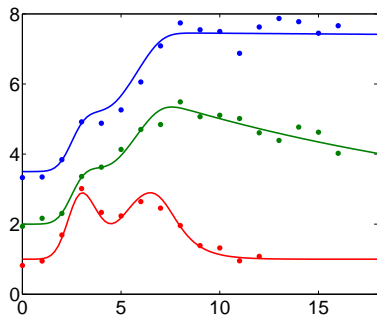
True “gene profiles” and noisy observations.



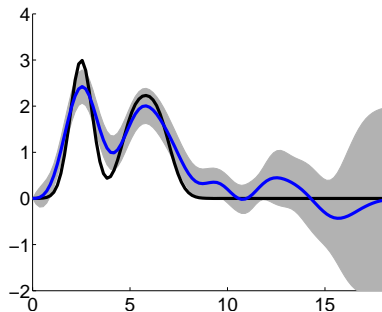
Inferred transcription factor activity.

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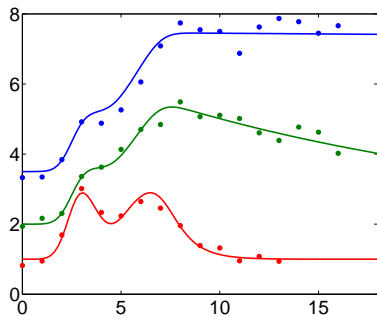
True “gene profiles” and noisy observations.



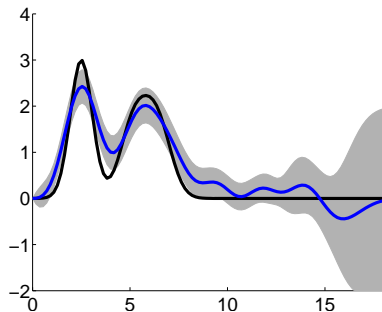
Inferred transcription factor activity.

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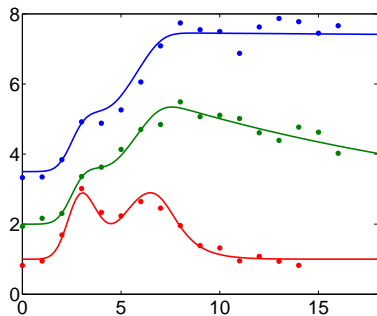
True “gene profiles” and noisy observations.



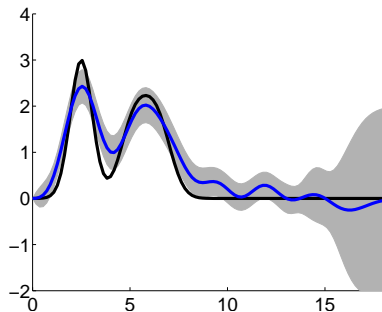
Inferred transcription factor activity.

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Inferring TF activity from artificially sampled genes.



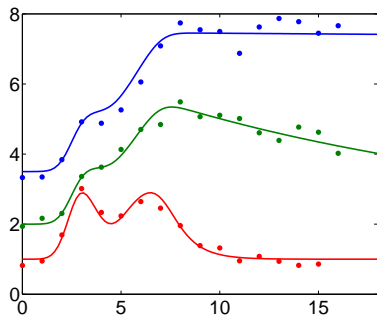
True “gene profiles” and noisy observations.



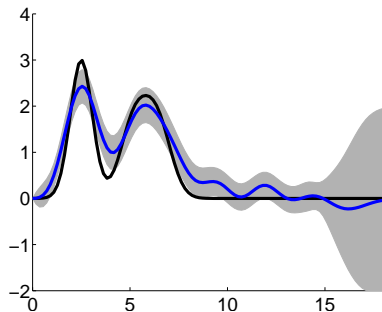
Inferred transcription factor activity.

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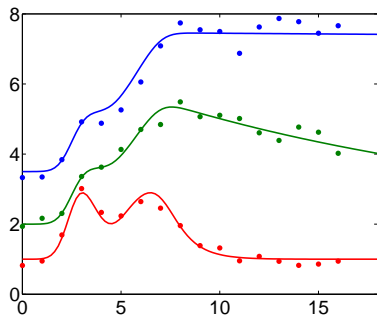
True “gene profiles” and noisy observations.



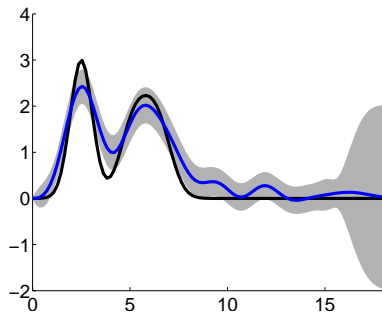
Inferred transcription factor activity.

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True “gene profiles” and noisy observations.



Inferred transcription factor activity.

Outline

Motivation

Cascade Differential Equations

Discussion and Future Work

Model-based method for transcription factor target identification with limited data

Antti Honkela^{a,1}, Charles Girardot^b, E. Hilary Gustafson^b, Ya-Hsin Liu^b, Eileen E. M. Furlong^b, Neil D. Lawrence^{c,1}, and Magnus Rattray^{c,1}

^aDepartment of Information and Computer Science, Aalto University School of Science and Technology, Helsinki, Finland; ^bGenome Biology U European Molecular Biology Laboratory, Heidelberg, Germany; and ^cSchool of Computer Science, University of Manchester, Manchester, United Kingdom

Edited by David Baker, University of Washington, Seattle, WA, and approved March 3, 2010 (received for review December 10, 2009)

We present a computational method for identifying potential targets of a transcription factor (TF) using wild-type gene expression time series data. For each putative target gene we fit a simple differential equation model of transcriptional regulation, and the

used for genome-wide scoring of putative target genes. The only data required to apply our method is wild-type time series data collected over a period where TF activity is changing. Our method allows for complementary evidence from expression

(Honkela et al., 2010)

- ▶ Transcription factor protein also has governing mRNA.
- ▶ This mRNA can be measured.
- ▶ In signalling systems this measurement can be misleading because it is activated (phosphorylated) transcription factor that counts.
- ▶ In development phosphorylation plays less of a role.

Twist Results

- ▶ Use mRNA of Twist as driving input.
- ▶ For each gene build a cascade model that forces Twist to be the only TF.
- ▶ Compare fit of this model to a baseline (e.g. similar model but sensitivity zero).
- ▶ Rank according to the likelihood above the baseline.
- ▶ Compare with correlation, knockouts and time series network identification (TSNI) (Della Gatta et al., 2008).

Results for Twi using the Cascade model

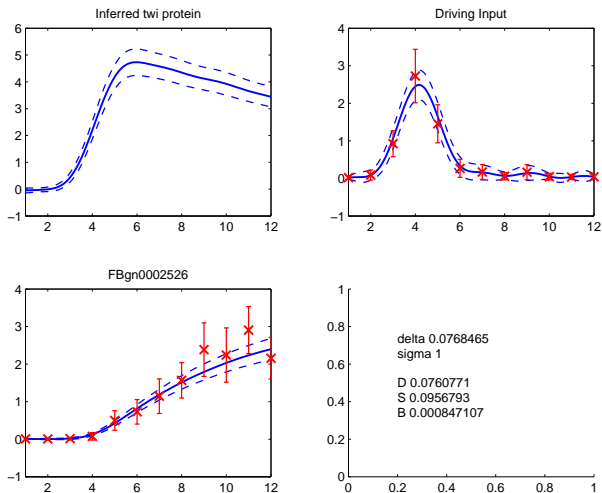


Figure: Model for flybase gene identity FBgn0002526.

Results for Twi using the Cascade model

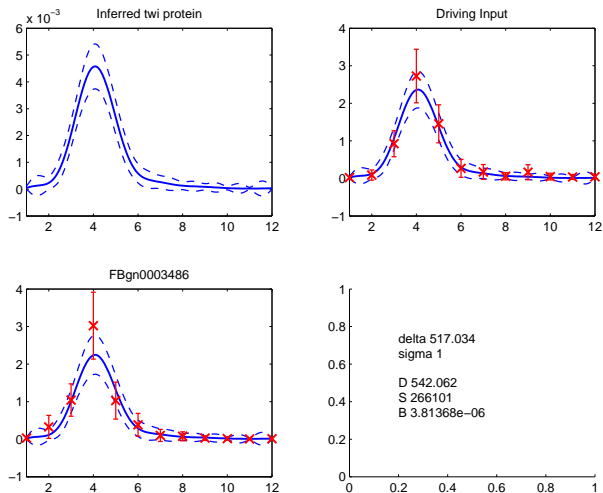


Figure: Model for flybase gene identity FBgn0003486.

Results for Twi using the Cascade model

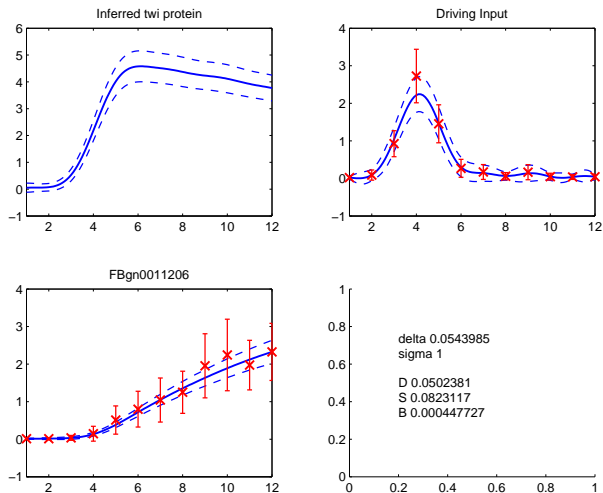


Figure: Model for flybase gene identity FBgn0011206.

Results for Twi using the Cascade model

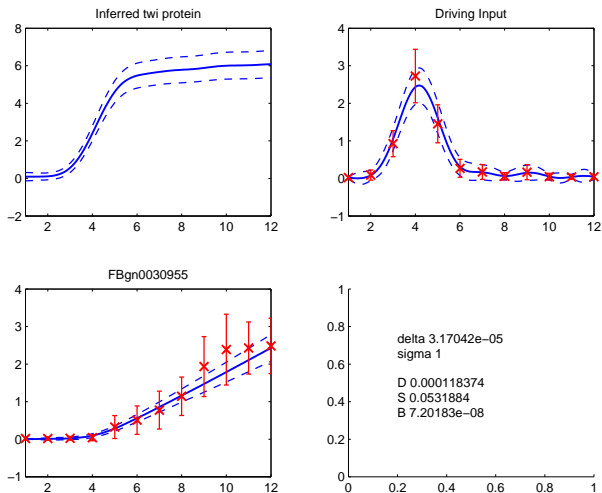


Figure: Model for flybase gene identity FBgn00309055.

Results for Twi using the Cascade model

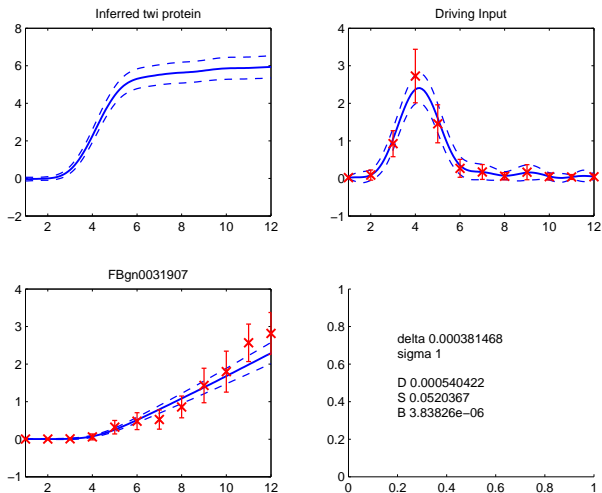


Figure: Model for flybase gene identity FBgn0031907.

Results for Twi using the Cascade model

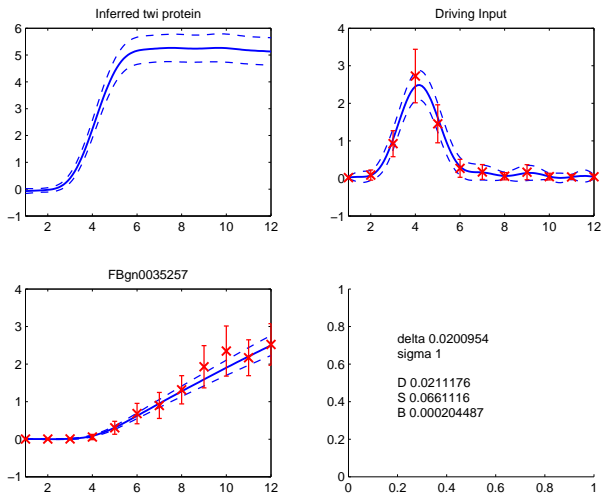


Figure: Model for flybase gene identity FBgn0035257.

Results for Twi using the Cascade model

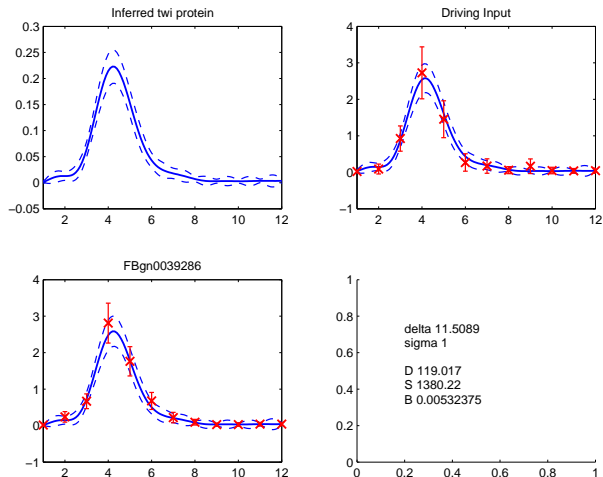
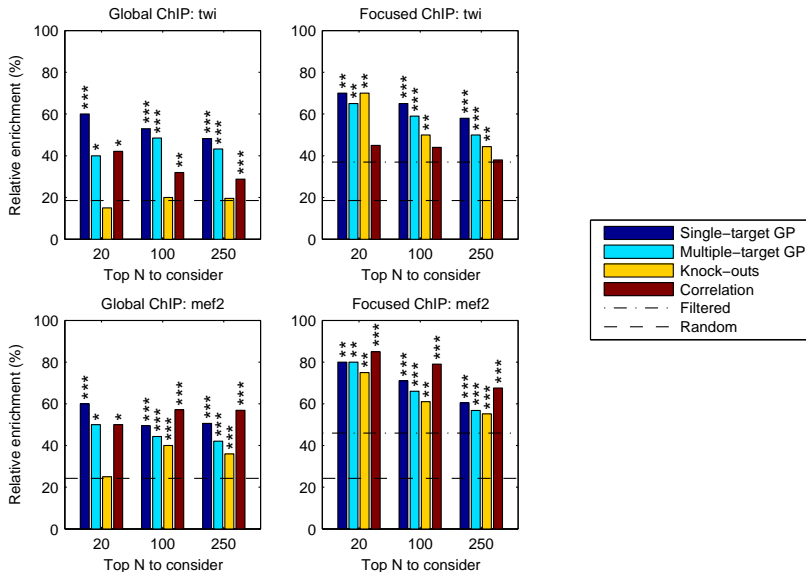


Figure: Model for flybase gene identity FBgn0039286.

Evaluation methods

- ▶ Evaluate the ranking methods by taking a number of top-ranked targets and record the number of “positives” (Zinzen et al., 2009):
 - ▶ targets with ChIP-chip binding sites within 2 kb of gene
 - ▶ (targets differentially expressed in TF knock-outs)
- ▶ Compare against
 - ▶ Ranking by correlation of expression profiles
 - ▶ Ranking by q -value of differential expression in knock-outs
- ▶ Optionally focus on genes with annotated expression in tissues of interest

Results



****: $p < 0.001$, ***: $p < 0.01$, **: $p < 0.05$

Summary

- ▶ Cascade models allow genomewide analysis of potential targets given only expression data.
- ▶ Once a set of potential candidate targets have been identified, they can be modelled in a more complex manner.
- ▶ We don't have ground truth, but evidence indicates that the approach *can* perform as well as knockouts.

Outline

Motivation

Cascade Differential Equations

Discussion and Future Work

Discussion and Future Work

- ▶ Integration of probabilistic inference with mechanistic models.
- ▶ Software available through bioconductor (TIGRE Package)
<http://bioconductor.org/packages/2.6/bioc/html/tigre.html>.
- ▶ Applications in modeling gene expression.
- ▶ Ongoing/other work:
 - ▶ Non linear response and non linear differential equations.
 - ▶ Improving computational complexity.
 - ▶ Stochastic differential equations.
 - ▶ Cascade model introduces model of translation.

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