Network inference and modeling

BIOINF 525 Module 3, Lecture 3 4/4/2017

Whole cell models allow prediction of phenotype from genotype



Whole cell models allow prediction of phenotype from genotype



(Karr et al., Cell, 2012)

Spatially resolved cell-scale models



(Earnest et al., Biophys. J. 2015)

Spatially resolved cell-scale models



Building systems-level models

- Motif and GO term analysis
- Kinetic modeling of simple networks
- Constraint-based modeling of cellular metabolism

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So what do you do once you have peaks/expression calls/etc.?

- Direct inspection of known biological targets
- Literature-driven inference and hypothesis generation
- Gene set enrichment analysis
- Motif analysis
- Network inference

Identification of gene categories (e.g., GO terms) that are correlated with another data set

Common Tools: GSEA, DAVID, iPAGE

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- N = total number of elements
- m = number of marked elements
- k = number of sampled elements
- x = number of marked sampled elements

Identification of gene categories (e.g., GO terms) that are correlated with another data set

Example: Gene expression



Normalized expression change

ribosome biogenesis and assembly, GO:0042254 ER to Golgi vesicle-mediated transport, GO:0006888 tRNA aminoacylation, GO:0043039 DNA replication, GO:0006260 RNA splicing, GO:0008380 mitotic cell cycle, GO:0000278 ubiquitin-dependent protein catabolic process, GO:0006511 microtubule biogenesis, GO:0000226 oxidative phosphorylation, GO:0006119 positive regulation of apoptosis, GO:0043065 cAMP-mediated signaling, GO:0019933 humoral immune response, GO:0006959 potassium ion transport, GO:0006813 homophilic cell adhesion, GO:0007156 sodium ion transport, GO:0006814 lymphocyte activation, GO:0046649

(From Goodarzi et al., Mol. Cell, 2009)

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Example: Integration of data sets



Motif analysis

Identify motifs (typically nucleic acid sequences) correlated with a data set of interest

Used in a variety of applications (RNA-seq, ChIPseq, ribosome profiling, etc.)

Example tools: MEME suite, FIRE/TEISER, kmersvm

Motif analysis



(Image from Elemento et al., Mol. Cell 2007)

Motif analysis

Inferred from knockdown:



(Bottom adapted from Hafner, Cell 2010)

Interpretation of GO term/motif analysis

- Where possible find consensus from multiple programs
- Use as a starting point for more experiments (hypothesis generating tool)
- Keep in mind often high false discovery rates
- Look in detail at constituents giving rise to observations

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Building motifs into networks

ARMADA: Inference from time courses

Motif name	Z-value 🗸	Associated genes	Profile	Logo
IRF1.2.7.p3	10.966	IRF1 (MAR, IRF-1) IRF2 (IRF-2, DKFZp686F0244) IRF7 (IRF7A, IRF-7H)		2 IRF1.2.7.p3 g1- Charles Charles 0 - Other Charles 0 - Other Charles
NFKB1_REL_RELA.p2	6.611	RELA.(p65) REL.(I-Rel) NFKB1.(KBF1, p105)		2-NFKBL REL RELA.p2 2-SECOND CONTRACTOR
XBP1.p3	3.173	XBP1_	Leven respectively	
E2F15.p2	2.979	E2F4 (E2F-4) E2F5 E2F2 (E2F-2) E2F1 (RBP3) E2F3		2 g1 g2 g2 g2 g2 g2 g2 g2 g2 g2 g2 g2 g2 g2
PRDM1.p3	2.973	PRDM1 (PRDI-BF1)		PRDMLp3

(Pemberton-Ross et al., Methods, 2015)

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Lazebnik, Y. Cancer Cell 2002

We know how to model electronic circuits



We know how to model electronic circuits



$$i=rac{V}{R}\Big(1-e^{-(R/L)t}\Big)$$

(Images from intmath.com)

We know how to model electronic circuits



Differential equations are the language of change

dx/dt = ... x' = ... x = ...

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dx/dt = ... x' = ... x = ... All mean:

The rate of change in x per unit time is ...





Our constant goal: What is x(t)?





- Start at some position we'll call it C
- Every second, add to the current position the distance that the car travels in one second
- Keep doing that until we reach the time that we are interested in

}

 $\frac{dx}{dt} = 10$

```
carloc <- function(t,v,C)
{
    x.curr <- C
    t.curr <- 0
    while (t.curr < t) {
        t.curr <- t.curr+1
        x.curr <- x.curr + v
    }
    return(x.curr)</pre>
```

}



```
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```

```
carloc <- function(t,v,C)</pre>
                          ł
    dx
                            x.curr < - C
    \frac{du}{dt} = 10
                            t.curr <-0
                            while (t.curr < t) {
                              t.curr <- t.curr+1
                              x.curr < - x.curr + v
x(t) = 10t + C
                            }
                            return(x.curr)
                          }
                                    Numerical
        Analytical
```

Differential equations are the language of biology



(Images from wikipedia)

Two common motifs



x' = kx






Synthesis

Degredation



Synthesis

Degredation

How can we model the level of the transcript at any given time?



Synthesis

Degredation









Stationary point analysis



Stationary point analysis



Stationary point: dx/dt = 0 (for all variables)

Finding these gives steady state values



$$\frac{dY}{dt} = F(X, T_y) - \alpha Y$$

(Shen-Orr et al., Nat. Gen. 2002)







 $\frac{dt}{dt} = F(X, T_y) - \alpha T$ $\frac{dZ}{dt} = F(X, T_y)F(Y, T_z) - \alpha Z$

(Shen-Orr et al., Nat. Gen. 2002)

Can we test our answers from Lab 1?

Working with an assigned group of peers, design a BioBrick-based construct that would yield a transient burst of GFP expression when E. coli cells bearing the plasmid undergo cold shock (20 C) while growing in glucose minimal media. Indicate the part numbers to be assembled (in order), draw a schematic of the resulting mini-network, and explain why your construct will implement the desired function.



















Bifurcation analysis



Bifurcation: Change in qualitative behavior of system as parameters change

Building models: SBML

$$E + S \xrightarrow[k_{\text{off}}]{k_{\text{off}}} ES \xrightarrow[k_{\text{cat}}]{k_{\text{cat}}} E + P$$



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The Systems Biology Markup Language

Building models for humans: SBGN





sbgn.github.io

Tools for building and simulating DE-based models

- COPASI
- CellDesigner
- BioSpice
- (and a bunch more)



Finding pre-built models



http://www.ebi.ac.uk/biomodels-main

How do we build models?

Networks/wiring from:

- Next gen sequencing
- Protein-protein interactions
- Enzyme characterization

Parameters from:

- Direct measurement of key constants
- Fitting parameters to experimental results

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Constraint-based modeling allows simplified metabolic simulation



(Image from Thomas Forth)

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⁽Orth et al., Nat. Biotechnol. 2010)

Usage cases for constraint-based modeling

Strengths:

- Fast model evaluation
- Simple interpretation
- Can work from somewhat incomplete data
 Weaknesses:
- No concentrations, only fluxes
- No dynamics
- Optimality assumption
Usage cases for constraint-based modeling

- Designing metabolic networks to make specific products
- Identifying/understanding effects of mutations
- Finding holes in current state of knowledge on metabolic networks
- Optimizing media for growth or production

Example: Identifying key metabolic parameters in E. coli



(Edwards et al., Nat. Biotech., 2001)

Example: Engineering strains to produce L-valine



Gave 45% improvement over rationally designed strain

(Park et al., PNAS, 2007)

Tools for constraint-based modeling

- COBRA toolbox (matlab)
- MASS toolbox (mathematica)
- Sybil (R)
- cobrapy, PyFBA (python)

Most allow SBML import

- Flux Variability Analysis (FVA): Give boundaries on solutions
- Minimization of Metabolic Adjustment (MOMA): Find smallest possible perturbation
- Regulatory on-off minimization (ROOM): Minimize number of regulatory changes



(Image by Thomas Forth)

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(Segre et al., PNAS, 2002)

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Prediction of knockout lethality:

	FBA	MOMA	ROOM
True-positive	449	399	449
False-positive	64	60	62
True-negative	23	27	25
False-negative	19	69	19
Positively predicted genes	96%	85%	96%
Negatively predicted genes	26%	31%	29%
Overall prediction	85.0%	76.7%	85.4%

(Shlomi et al., PNAS, 2005)