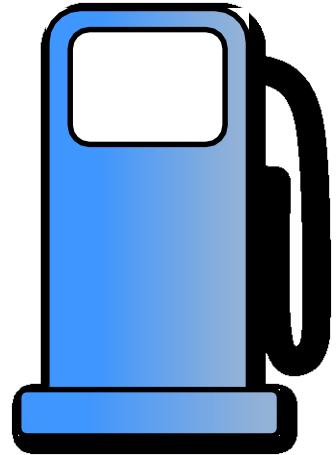


Ministério da Saúde
FIOCRUZ
Fundação Oswaldo Cruz

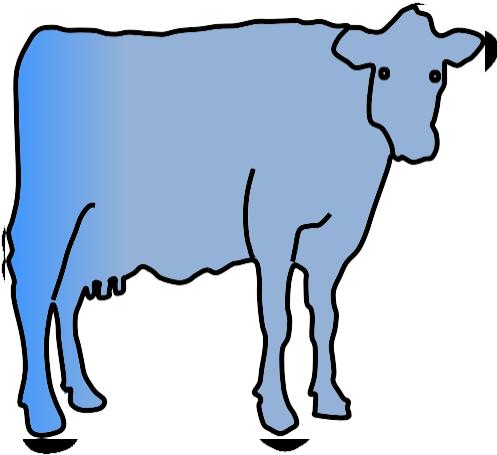
Integração de Modelos Biológicos

Doutorando Fernando Medeiros



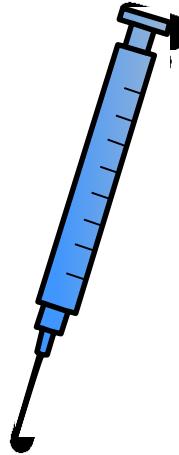
Produtos Químicos e Combustíveis

Otimize o
rendimento
Minimize o
custo



Alimento

Otimizar o
rendimento
Resistir à seca
Evitar a
infecção

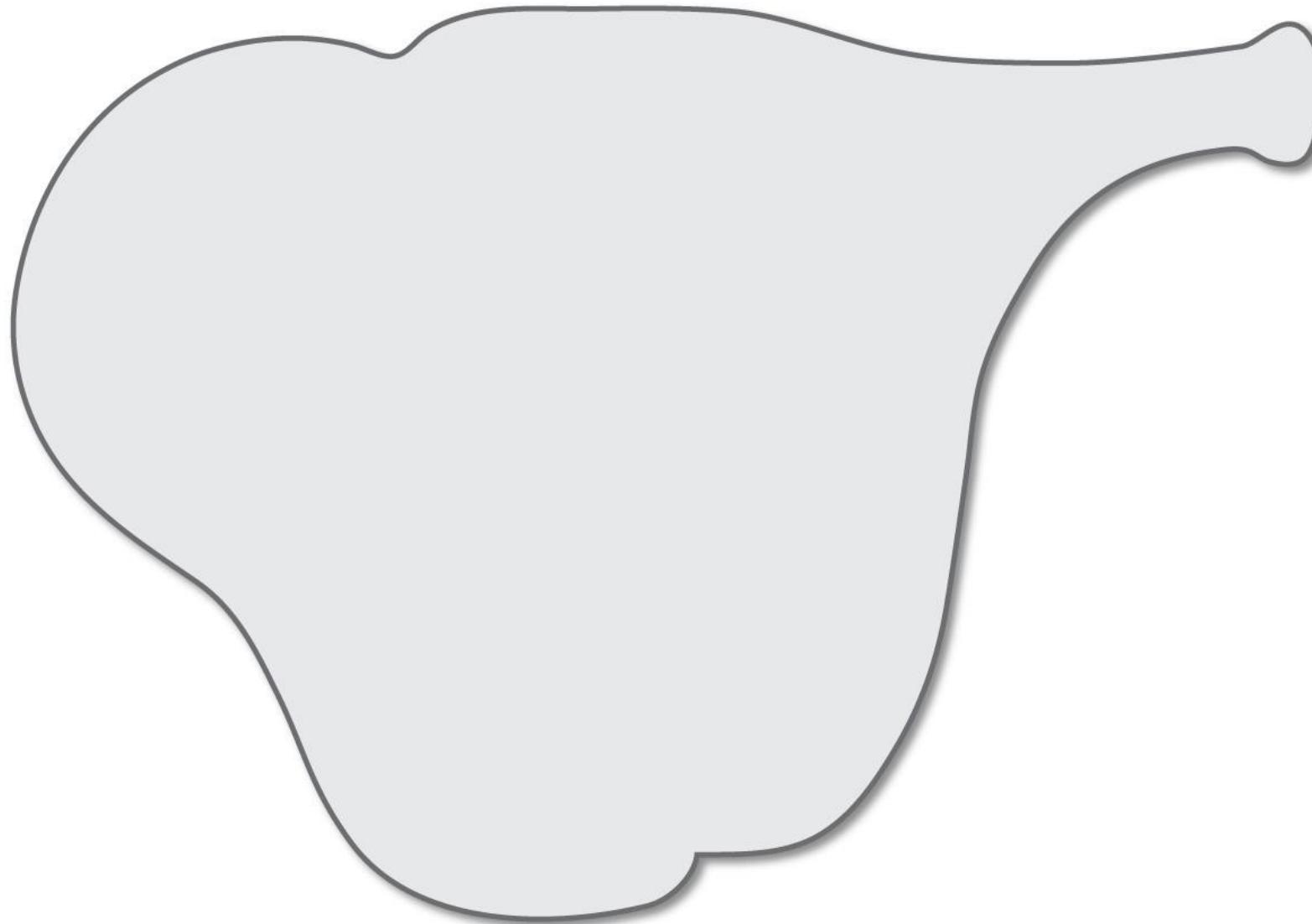


Medicina

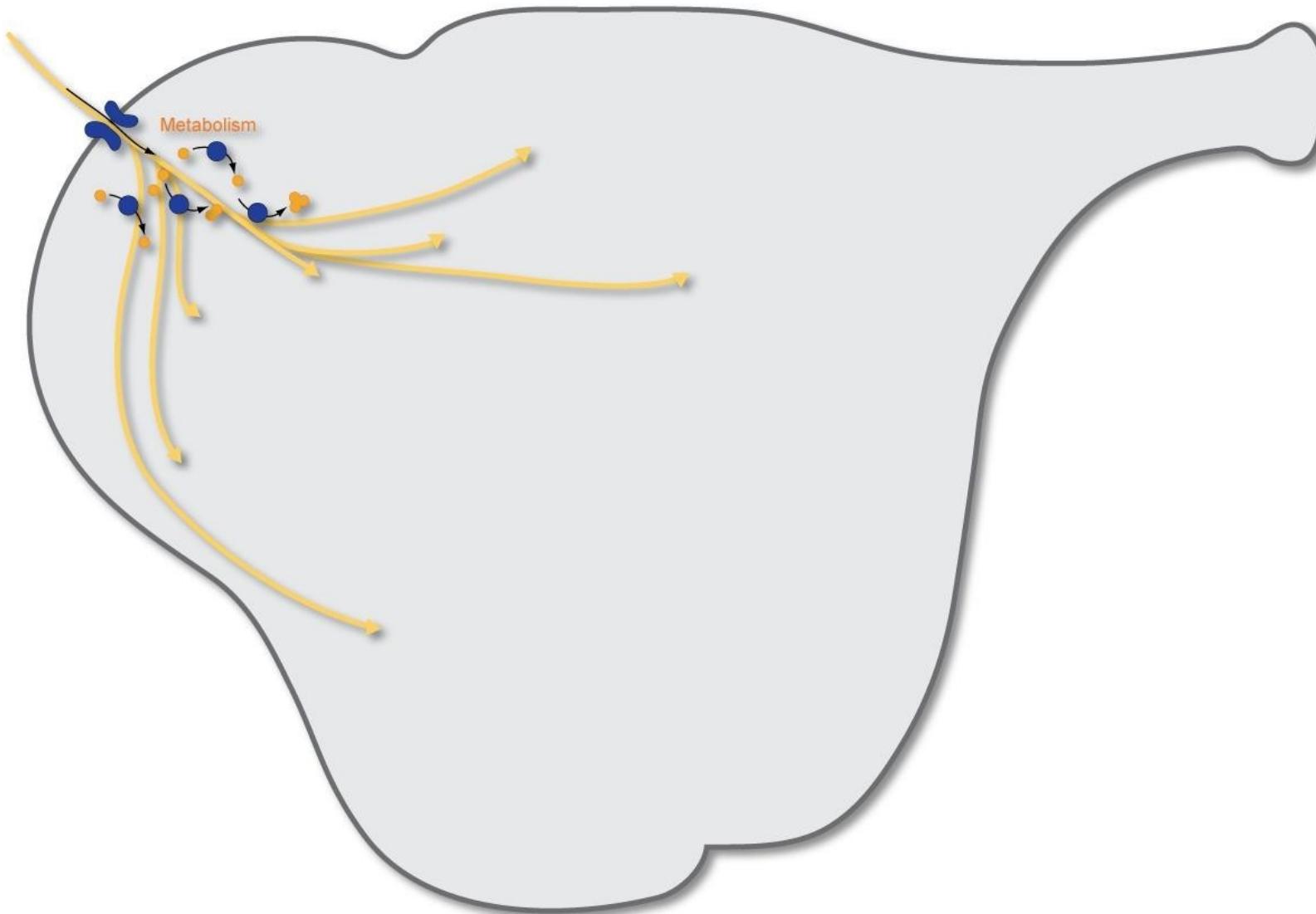
Prever prognósticos
Otimizar a terapia
Maximizar a qualidade
de vida

Desafio central: prever o fenótipo do genótipo

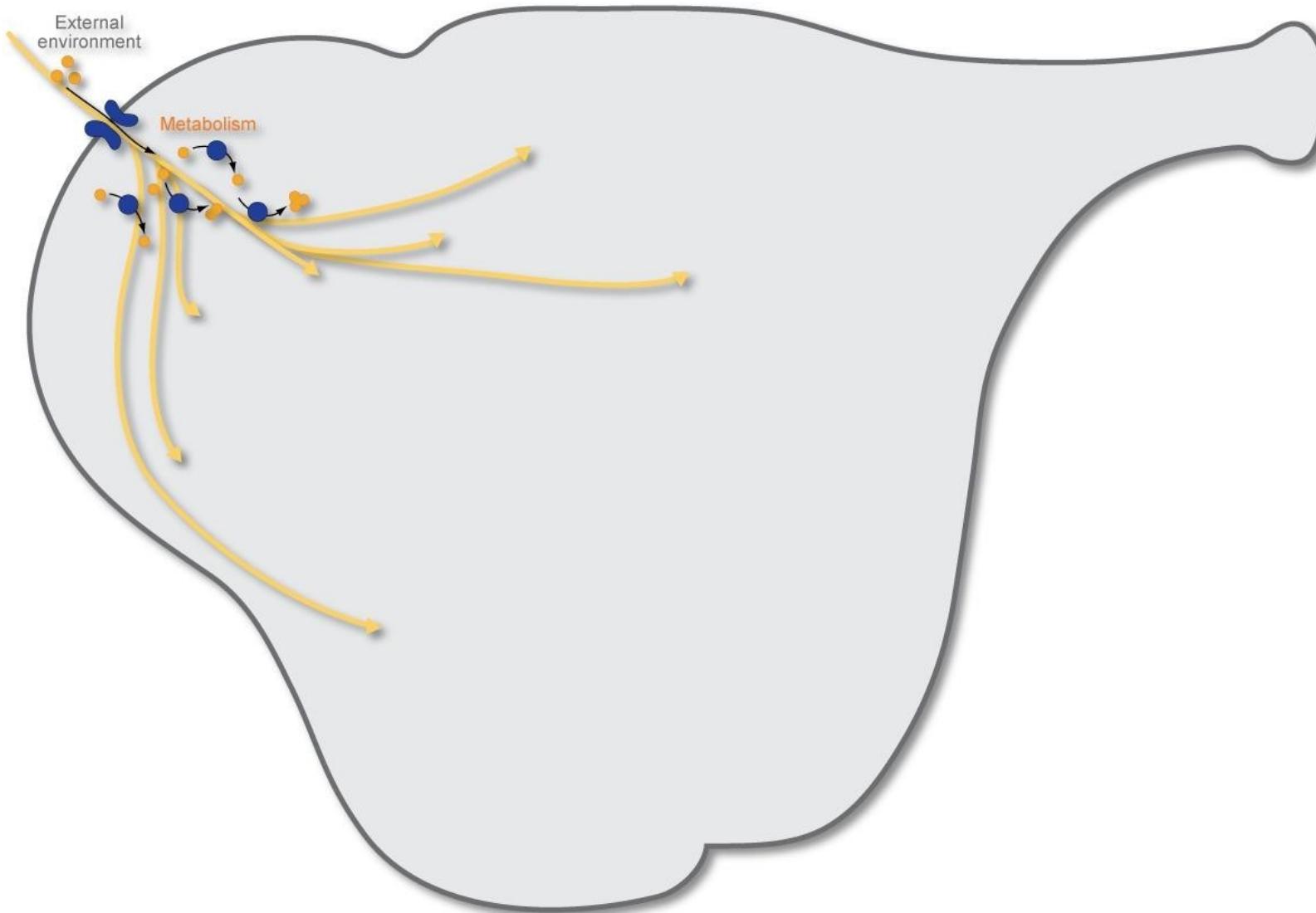
Exemplo: biossíntese de drogas



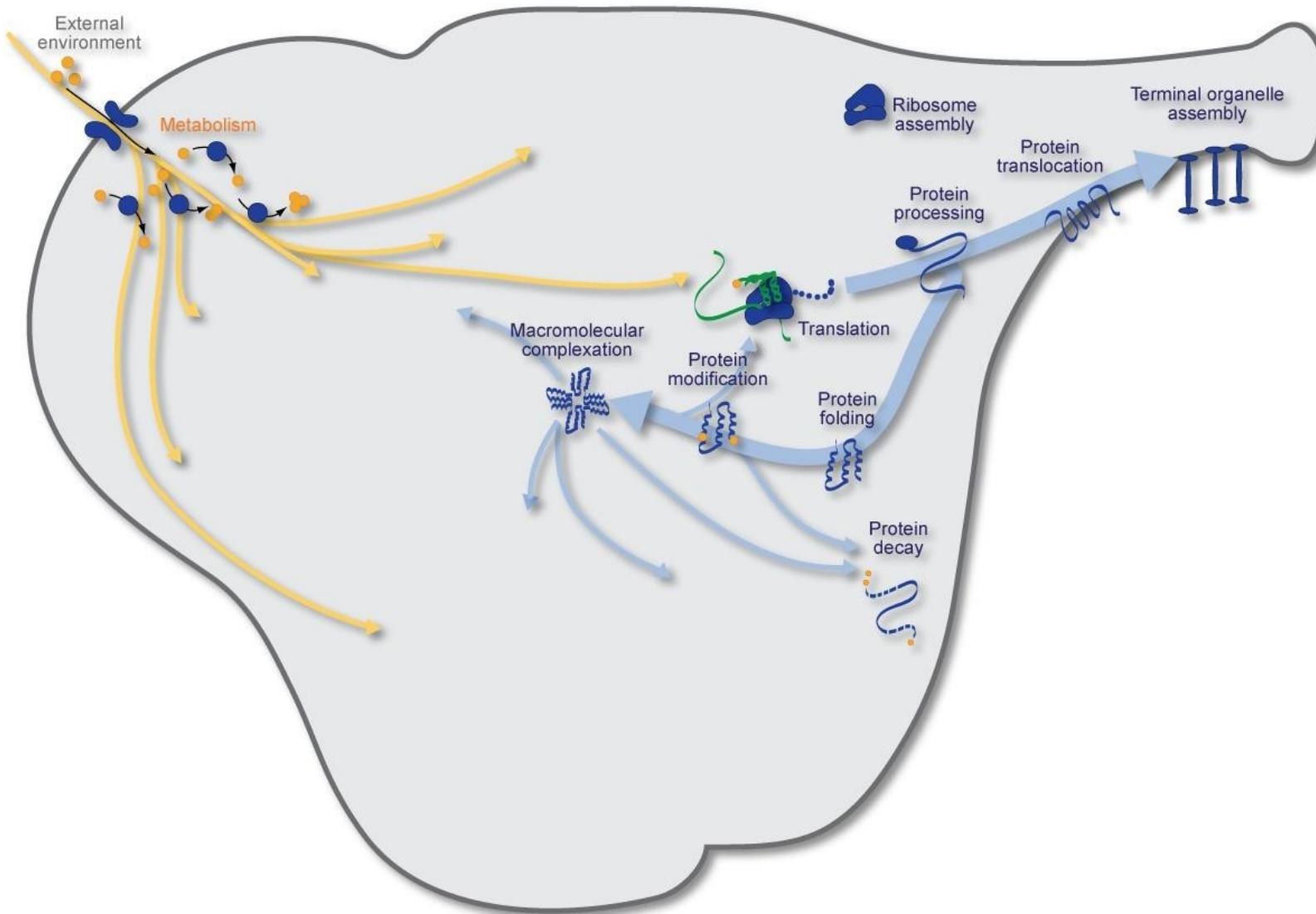
Exemplo: biossíntese de drogas



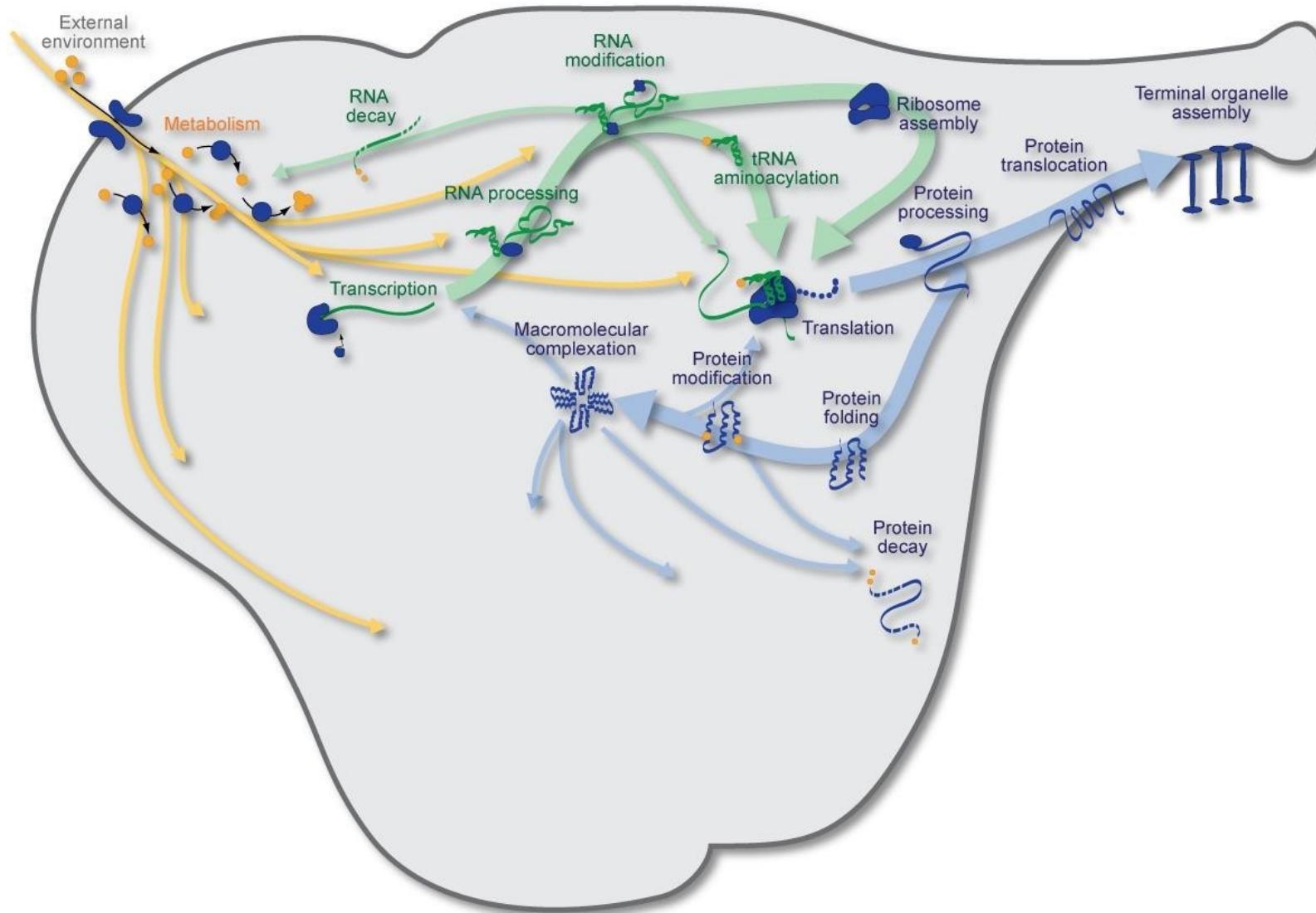
Exemplo: biossíntese de drogas



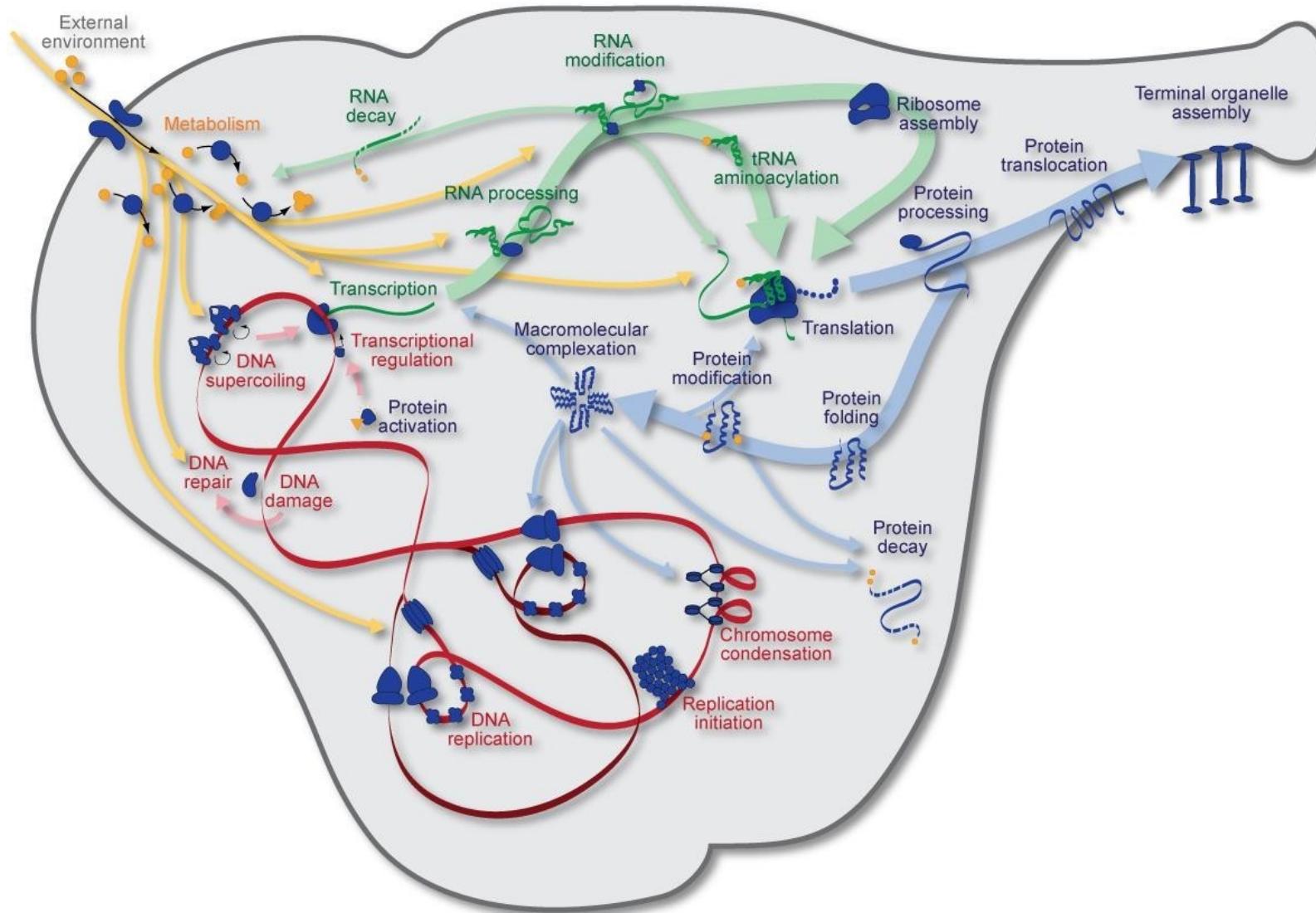
Example: drug biosynthesis



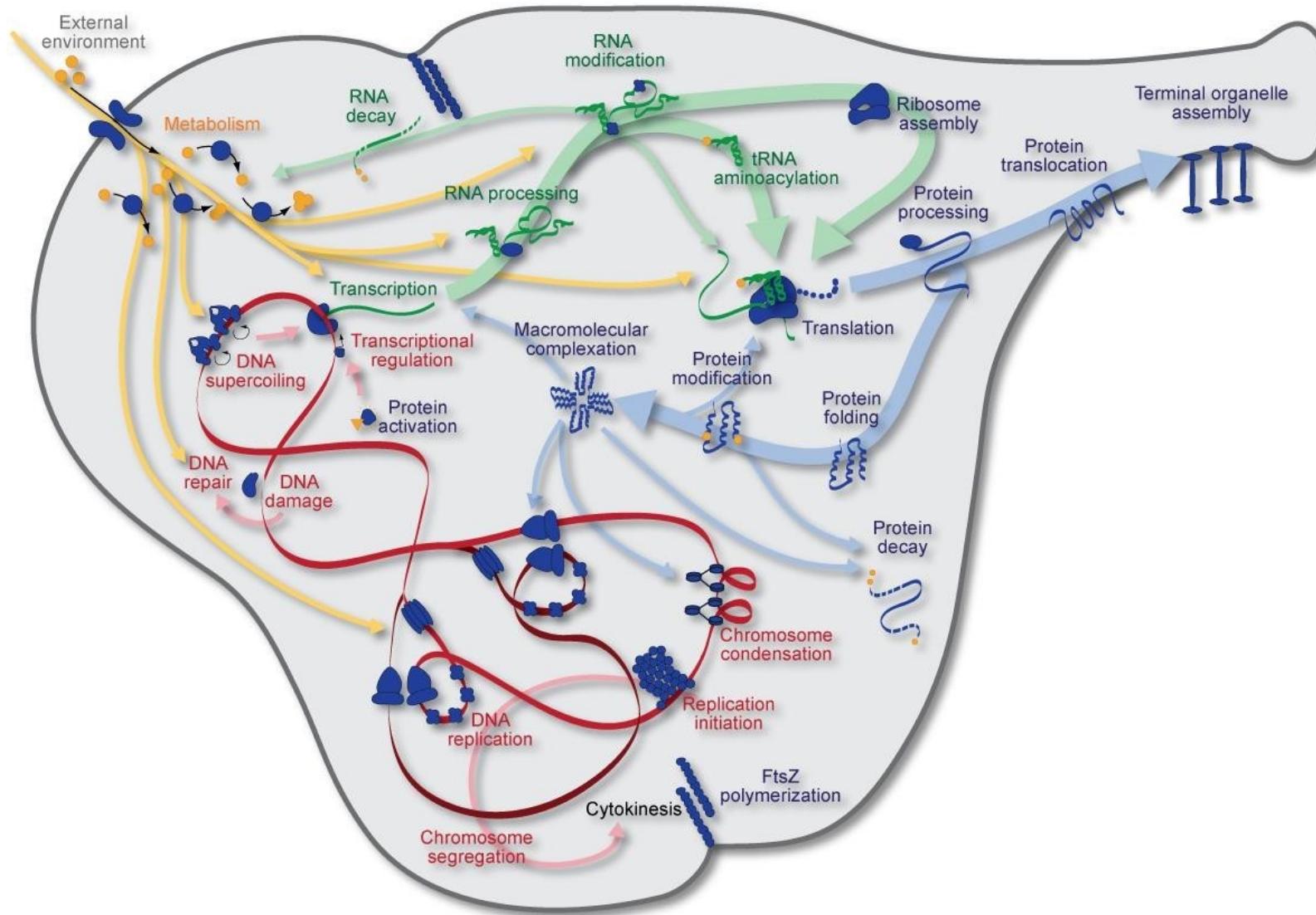
Exemplo: biossíntese de drogas



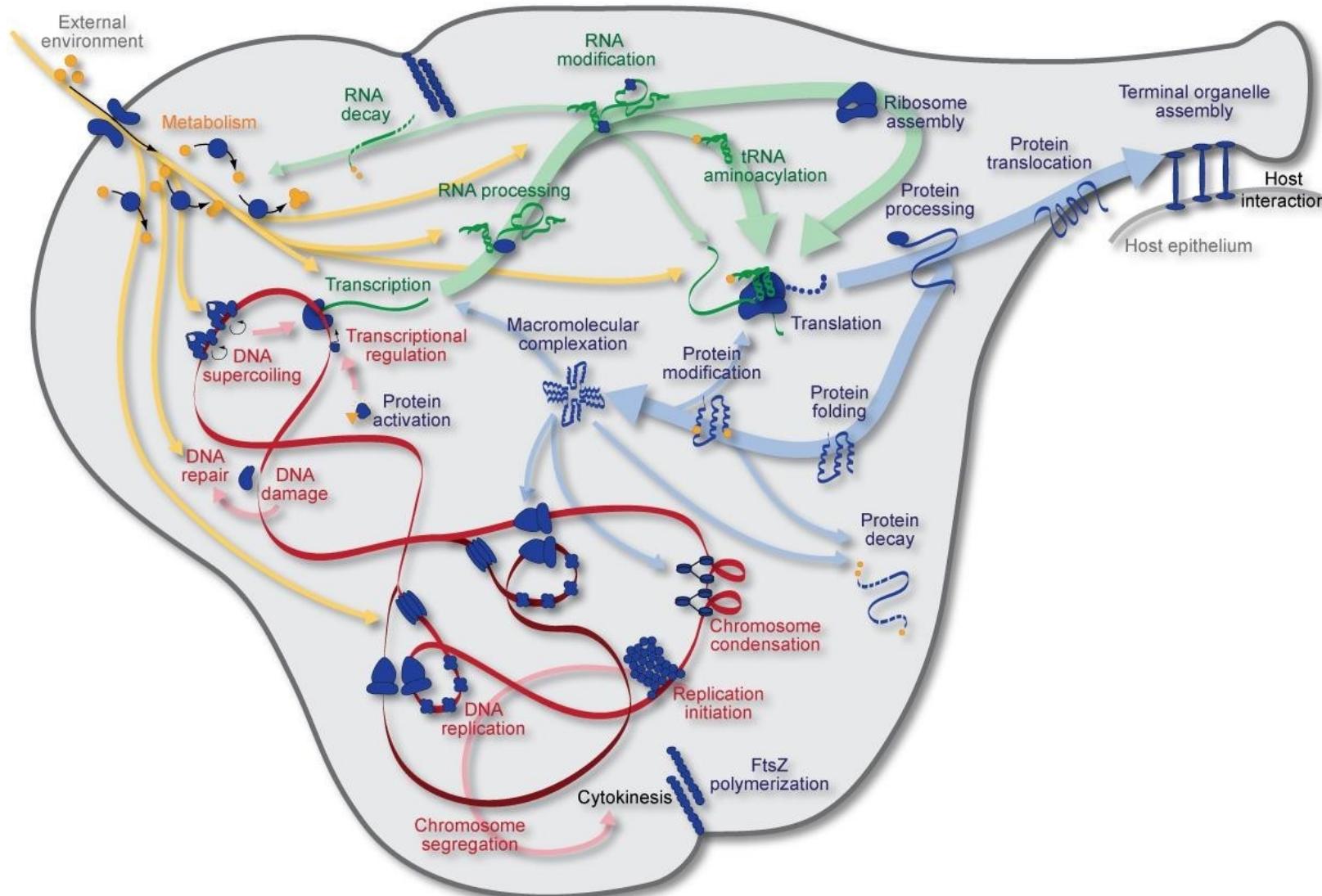
Exemplo: biossíntese de drogas



Exemplo: biossíntese de drogas

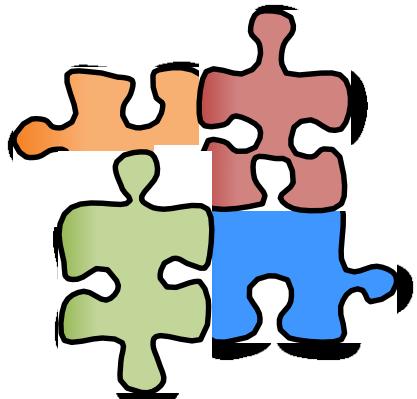


Exemplo: biossíntese de drogas

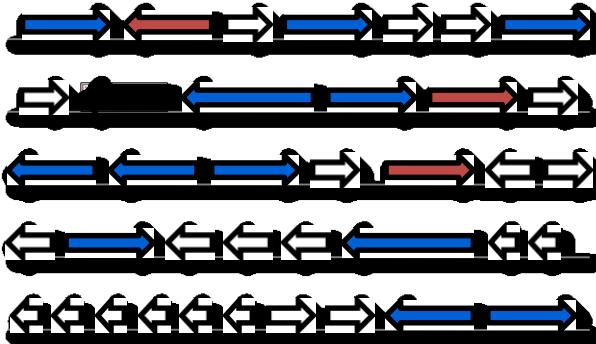


A previsão do fenótipo a partir do genótipo requer modelos “célula inteira”

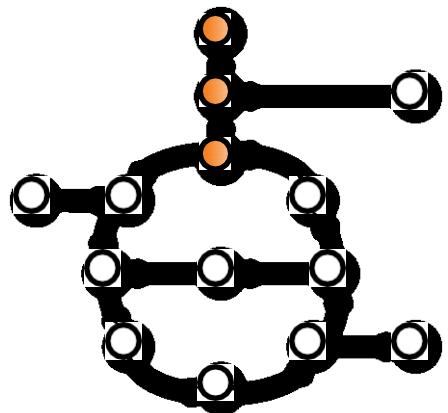
Whole-cell modeling principles



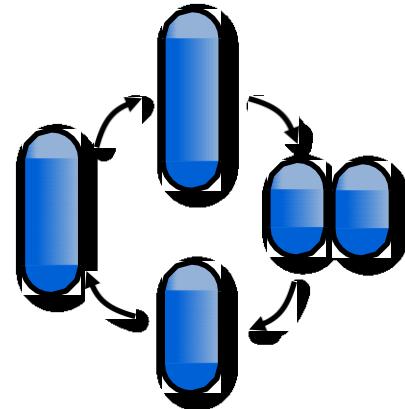
Integrated



Gene-complete



Comprehensive



Dynamic



“A modelagem de células inteiras pode permitir bioengenharia racional e medicina de precisão.”



“Propomos vários princípios-chave da modelagem de células inteiras.”



“Descrevemos como construir um modelo de célula inteira, destacando as ferramentas disponíveis.”

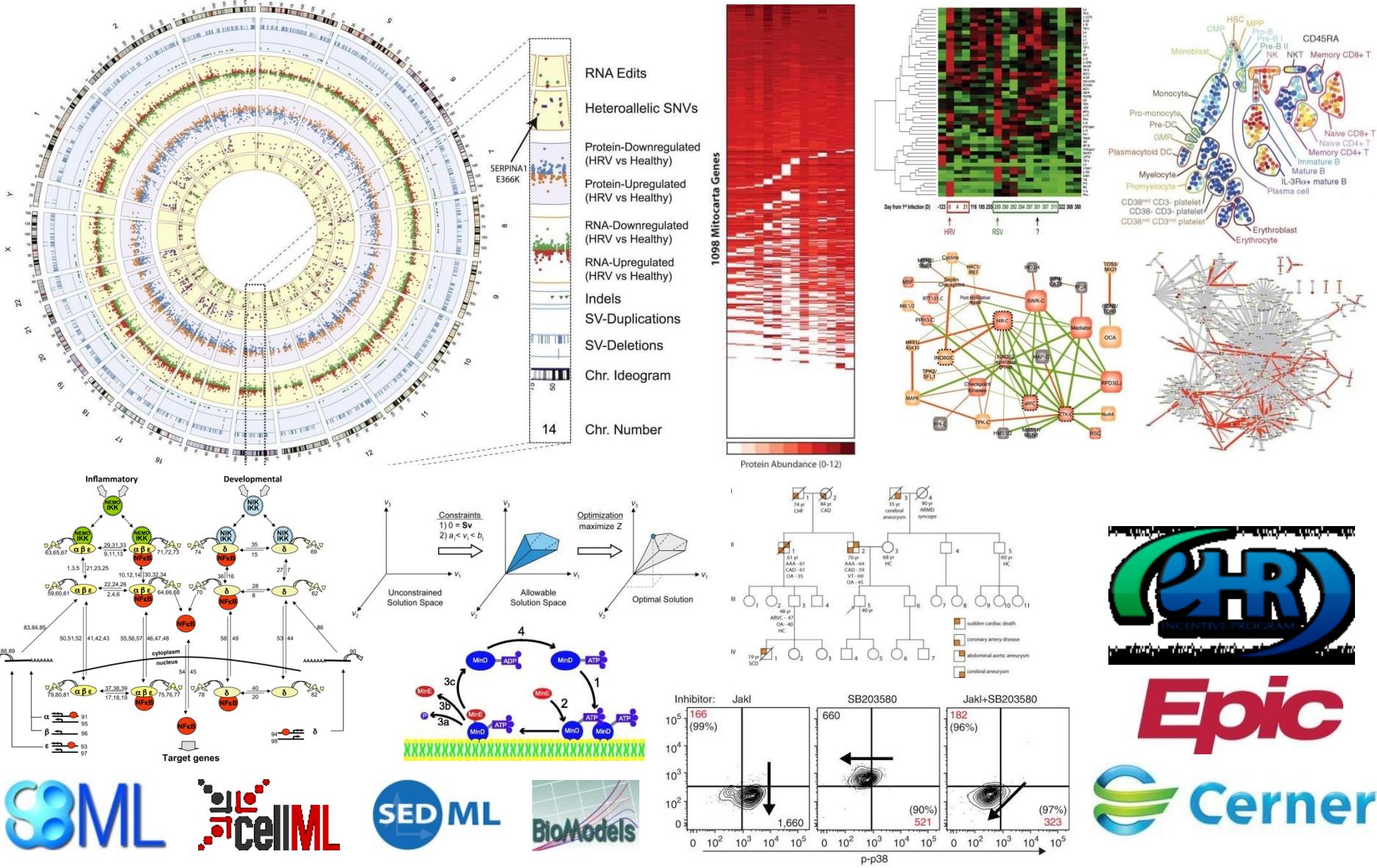


“Descrevemos os principais desafios de modelagem computacional e experimental de células inteiras em código aberto”

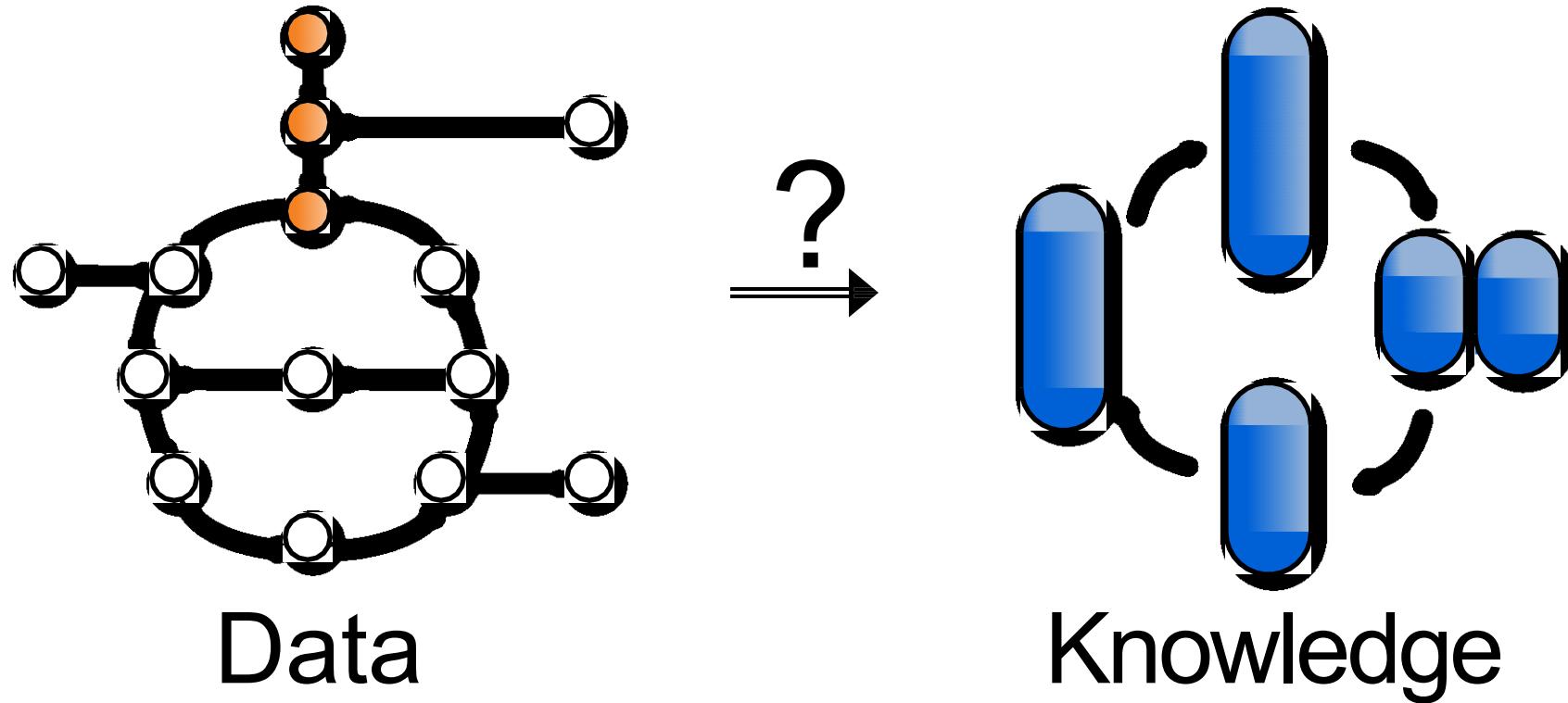


“Alcançar modelos completos de células inteiras requer uma forte comunidade interdisciplinar.”

Disponibilidade dos Dados



Objetivos do Whole-cell model



Whole-cell modeling

A grand challenge of the 21st century

– *Masaru Tomita*

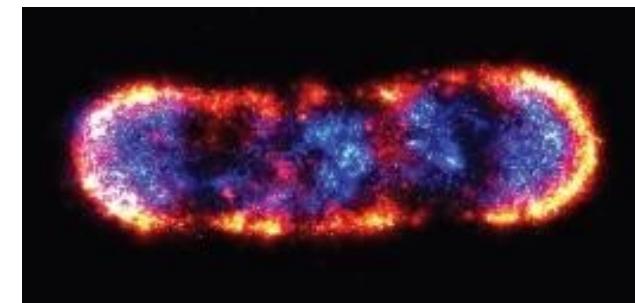
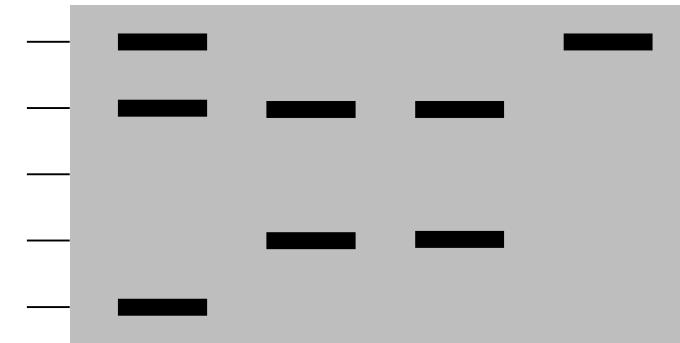
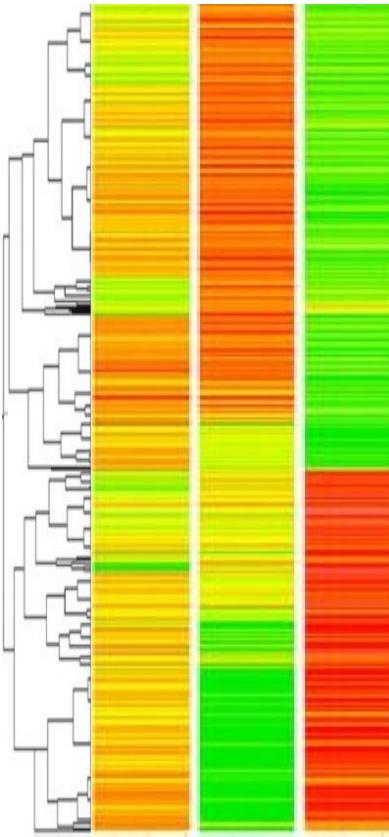
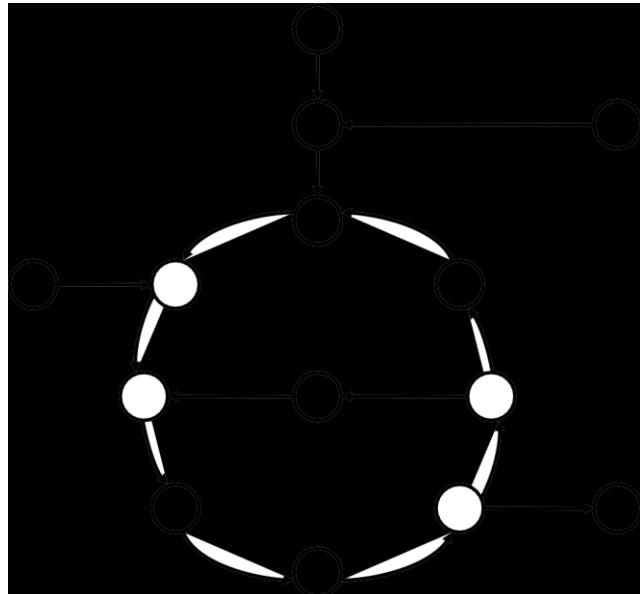
A biologia precisa urgentemente de uma base teórica para unificá-la

– *Sydney Brenner*

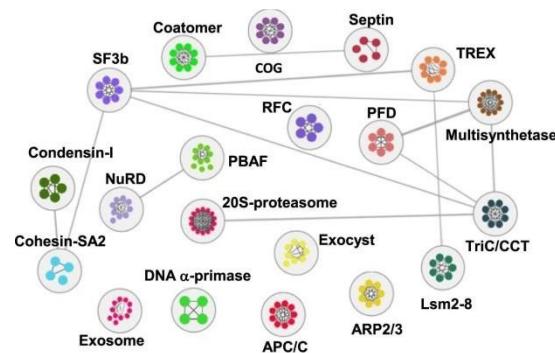
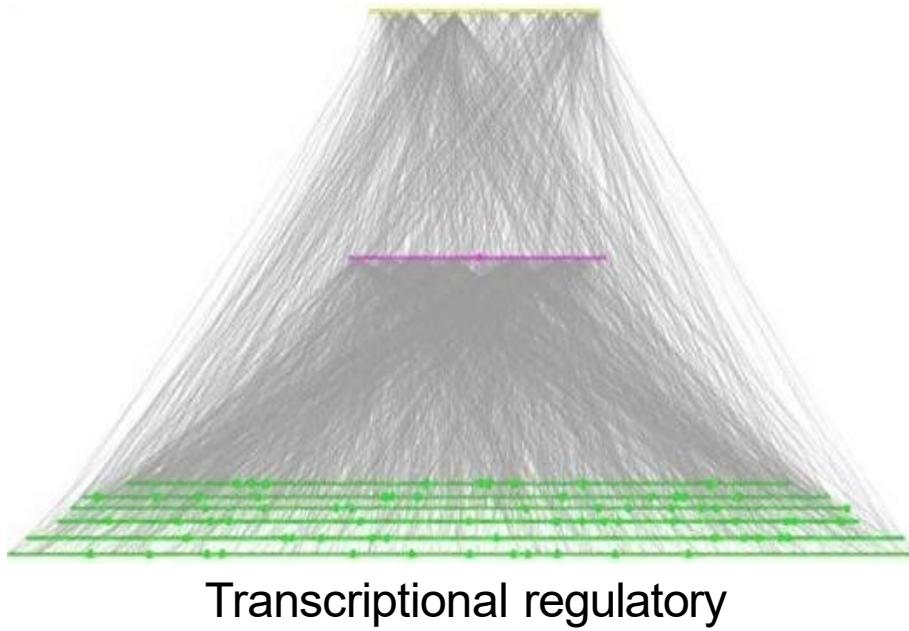
O teste final de entender uma célula simples, mais do que ser capaz de construir uma, seria construir um modelo computacional da célula.

– *Clyde Hutchison*

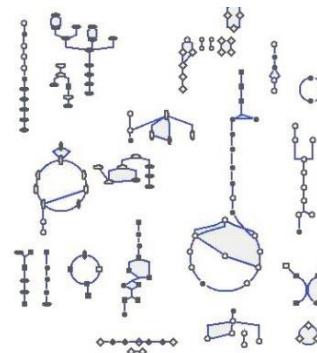
Desafio de modelagem de dados



Modelling challenge

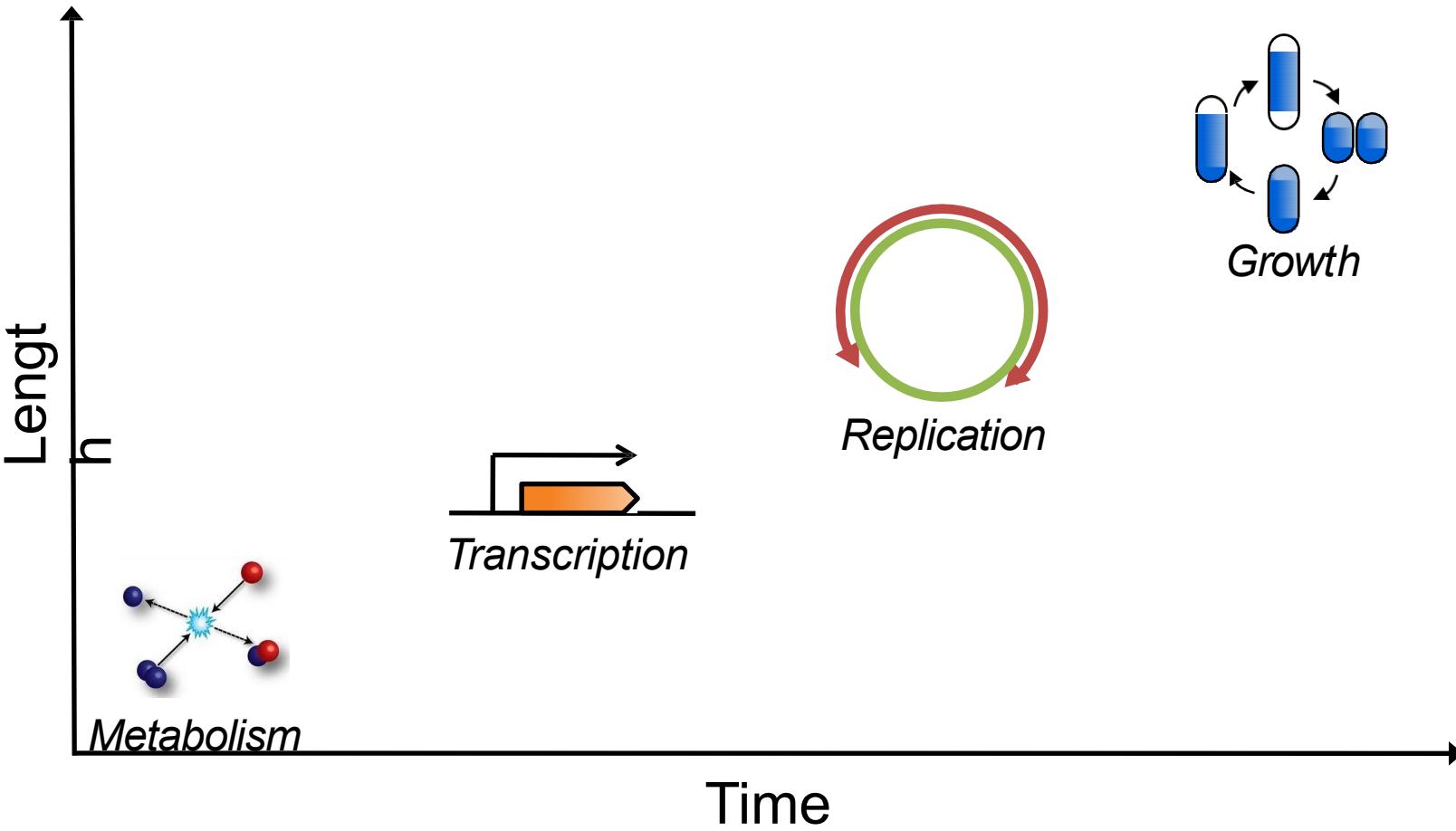


Signaling

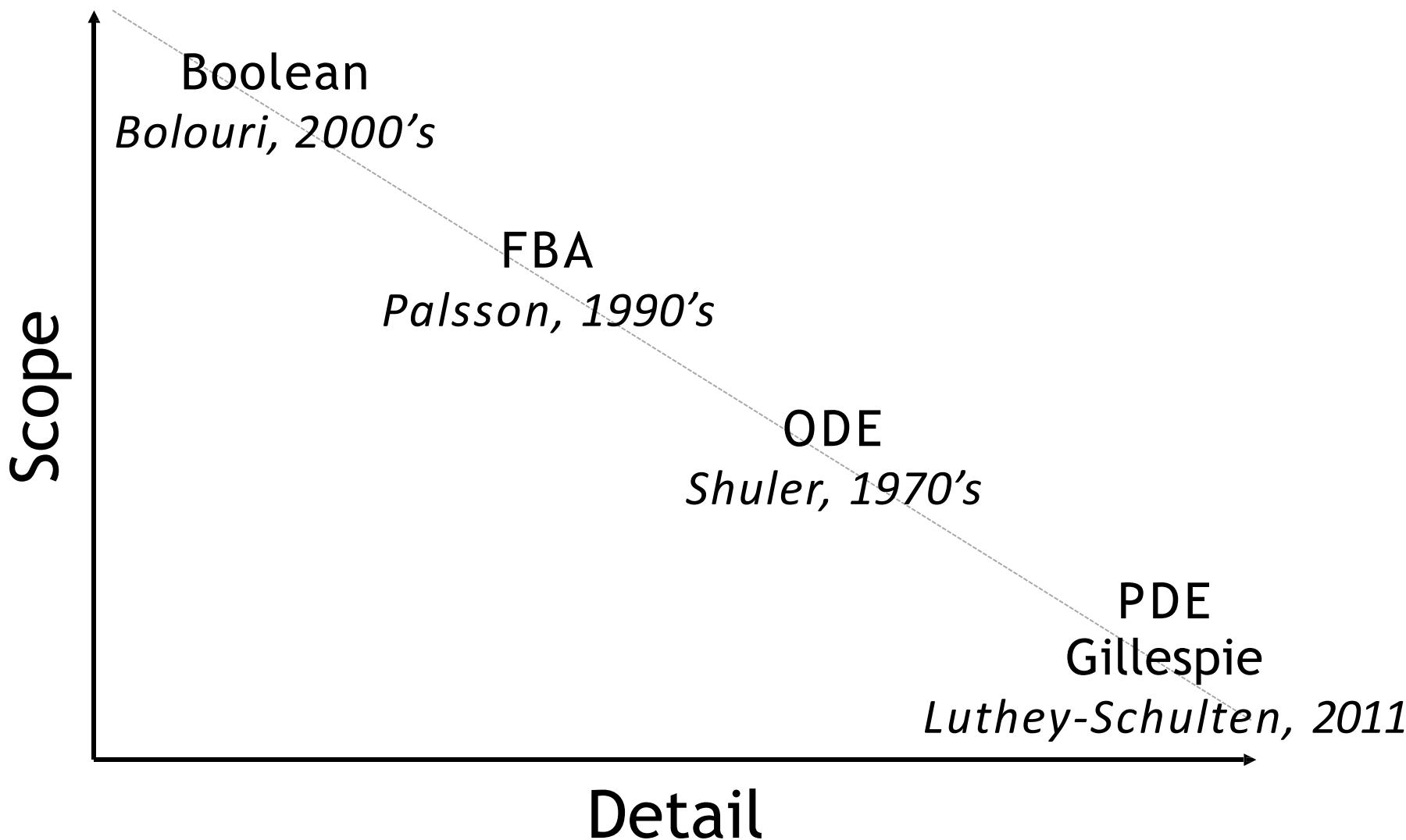


Metabolic

Modeling challenge

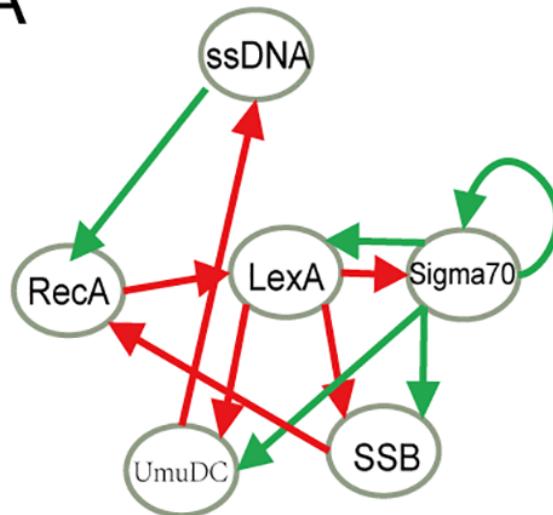


Predictive modeling methodologies



Predictive modeling methodologies

A

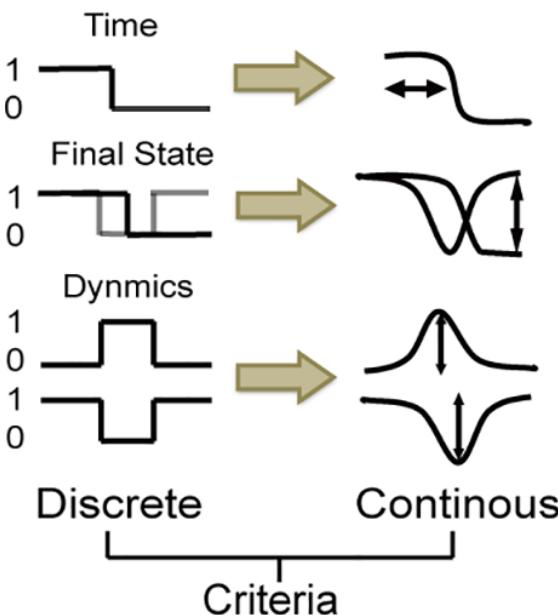


B

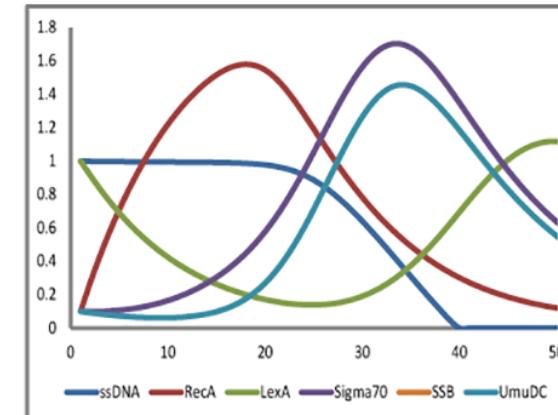
time	ssDNA	RecA	LexA	Sigma70	UmuDC	SSB
1	1	0	1	0	0	0
2	1	1	1	0	0	0
3	1	1	0	0	0	0
4	1	1	0	1	0	0
5	1	1	0	1	1	1
6	0	0	0	1	1	1
7	0	0	1	1	1	1
8	0	0	1	0	0	0

Boolean network model

C

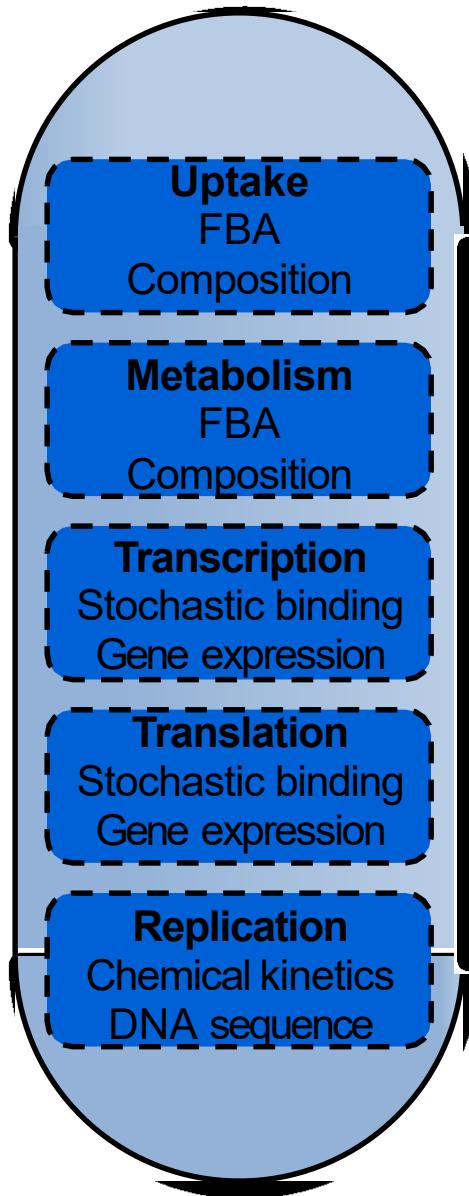


D

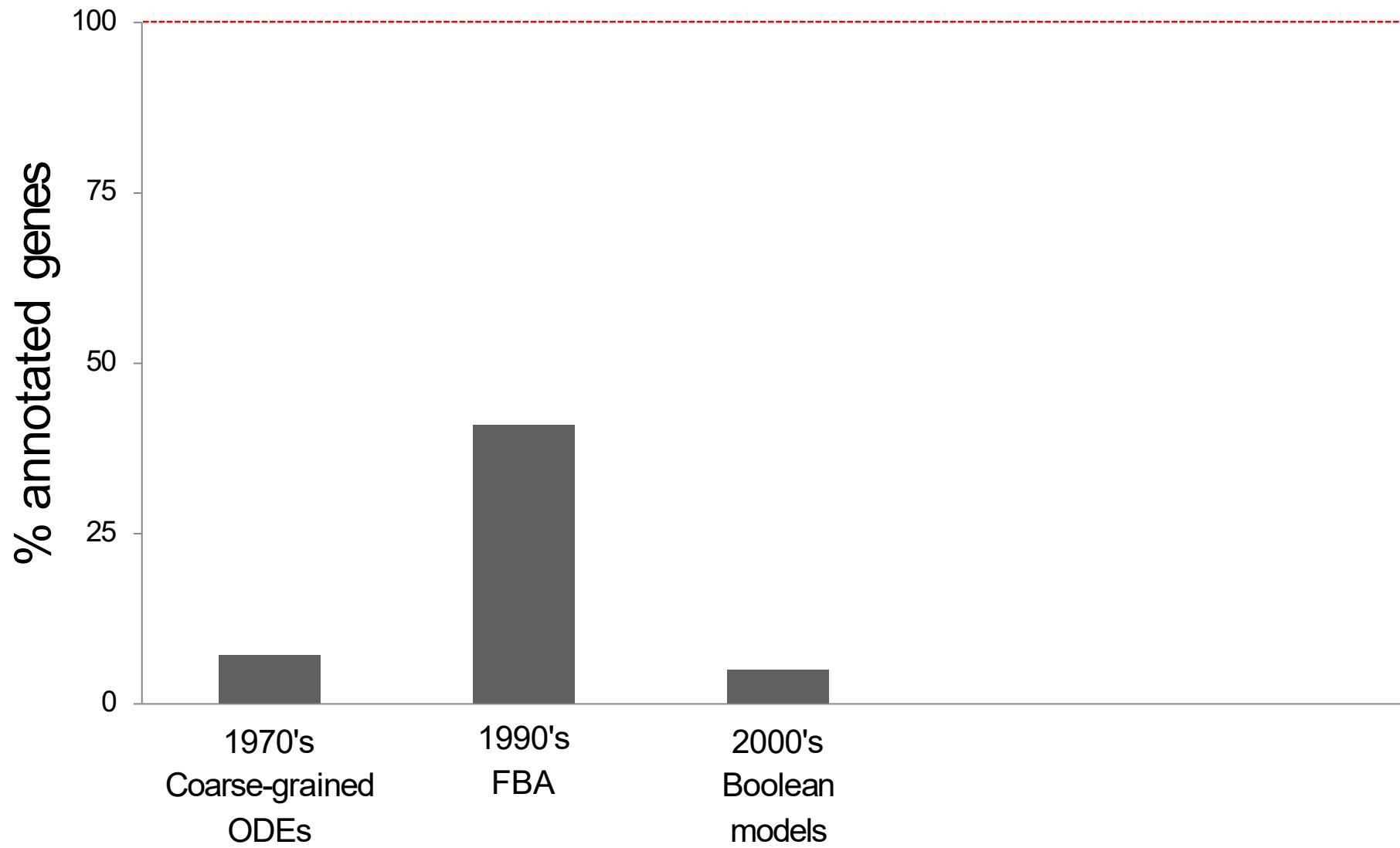


ODE model

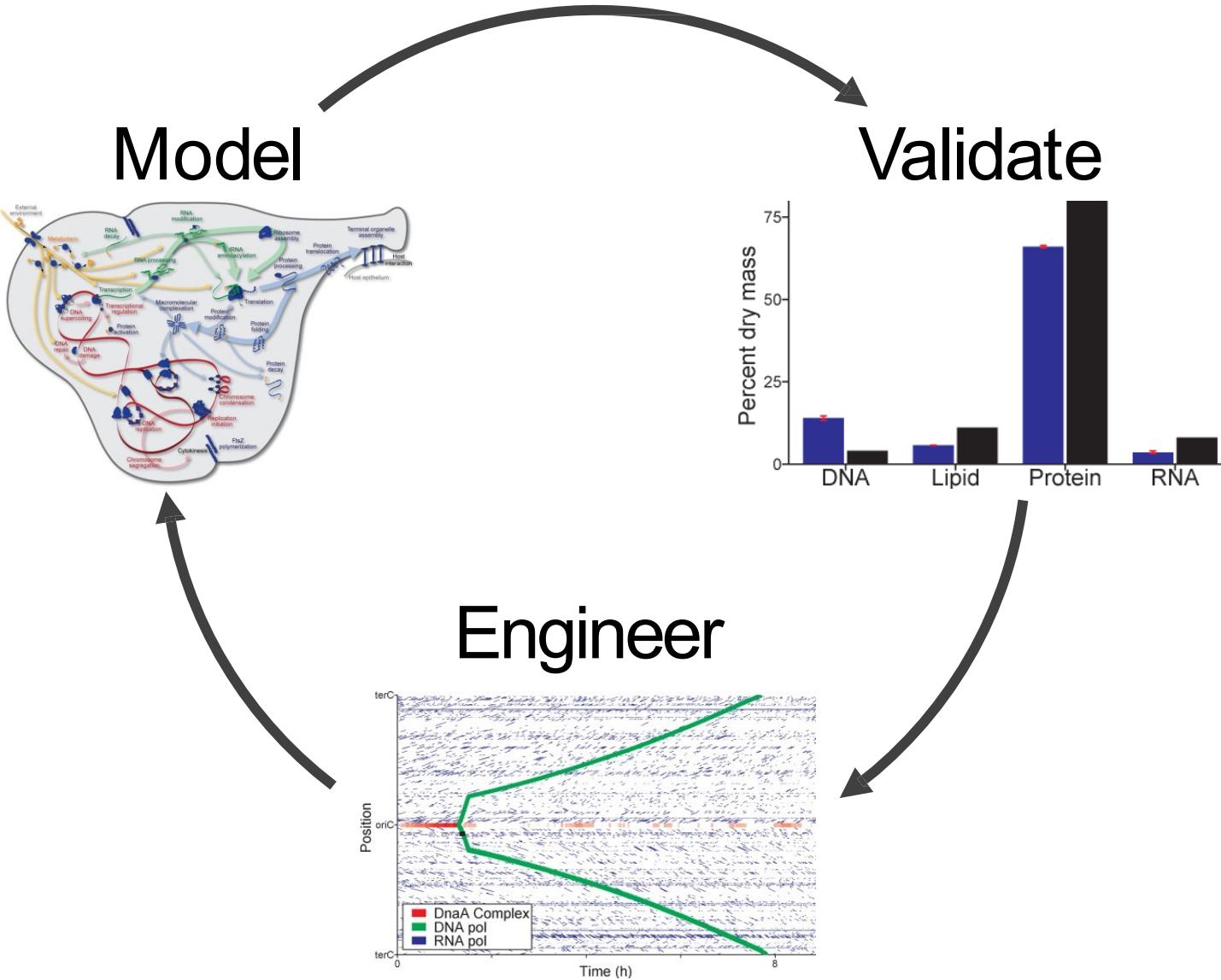
Solution: integrated models



Whole-cell modeling progress

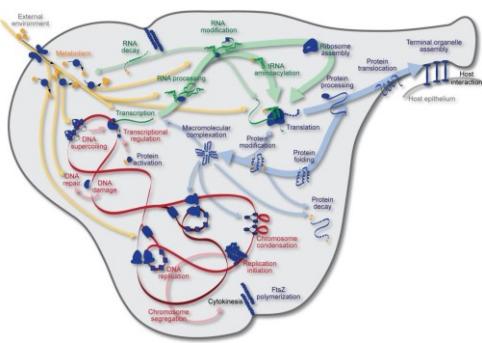


Whole-cell modeling

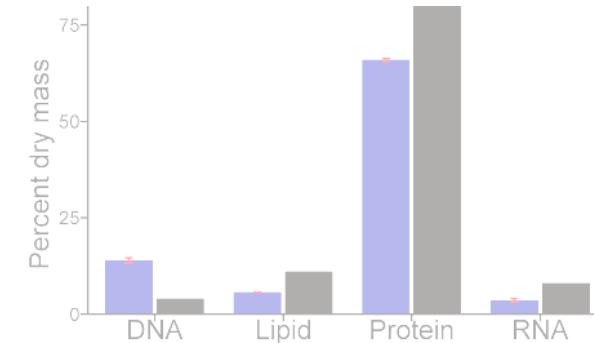


Whole-cell modeling

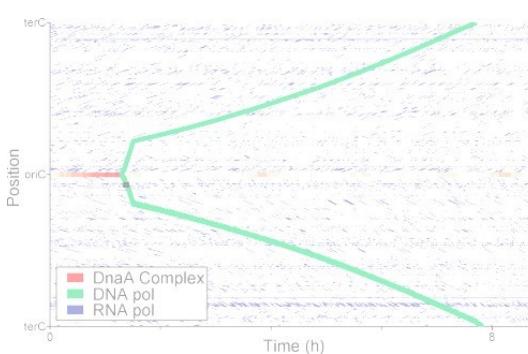
Model



Validate



Engineer



Model construction

1. Definir sistema

2. Definir escopo

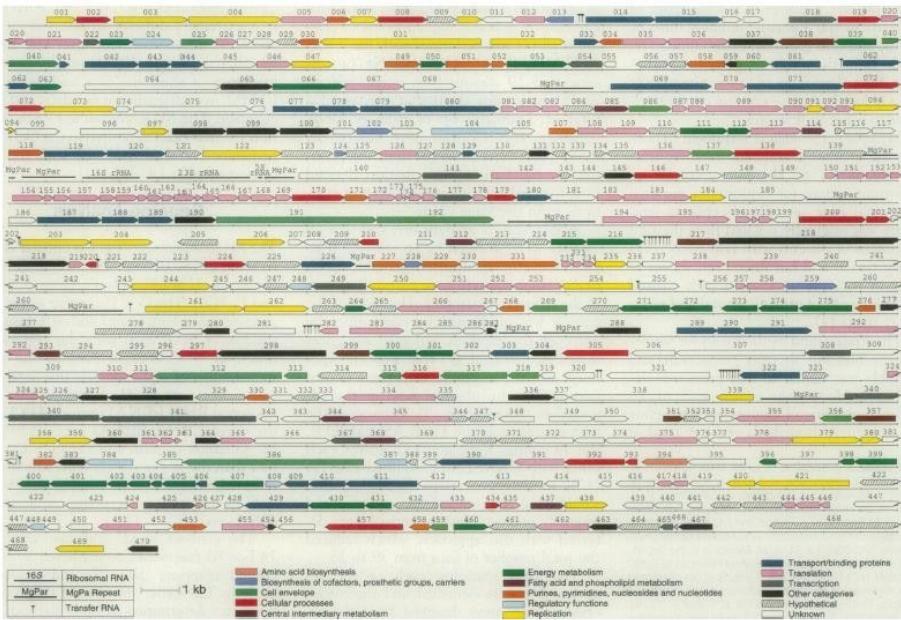
3. Curar dados

4. Escolha a representação

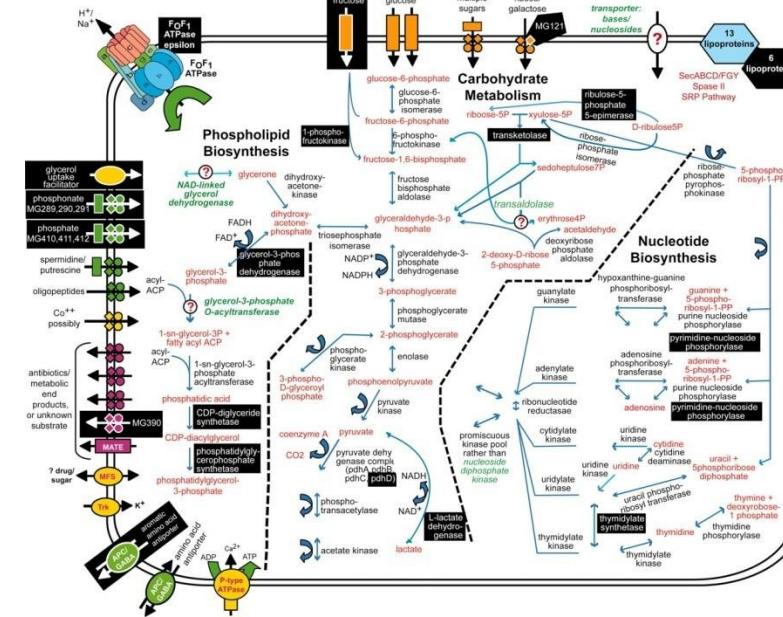
5. Identifique parâmetros

6. Testar previsões

M. genitalium is well-characterized

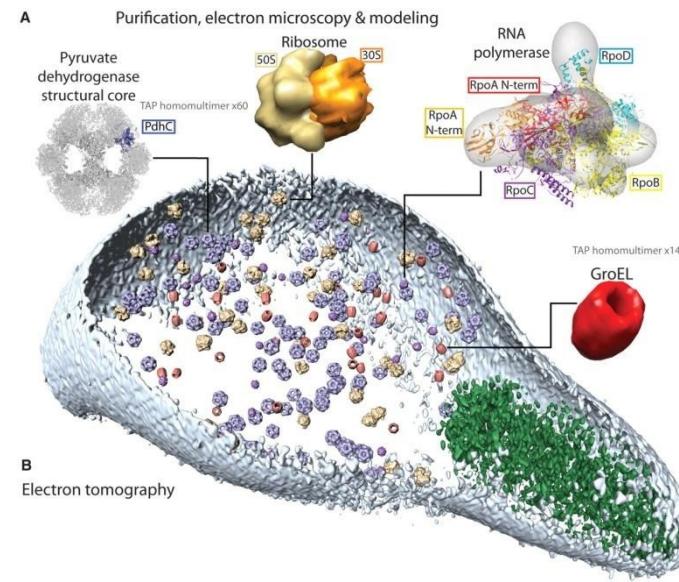


Comparative genomics
Frazier et. al, 1995



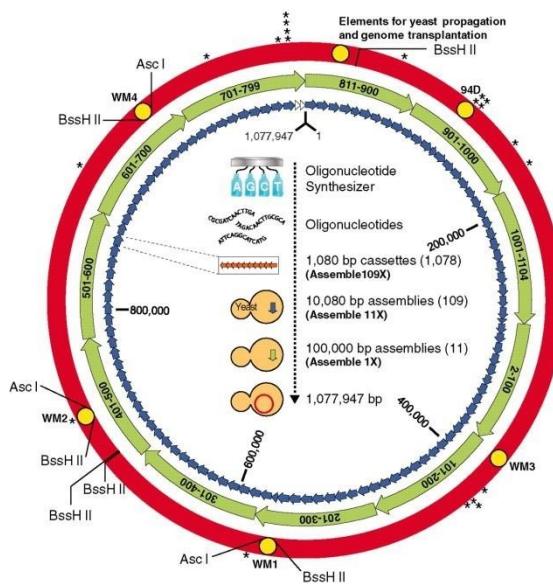
Genome-wide essentiality
Glass et. al, 1999

M. genitalium is well-characterized

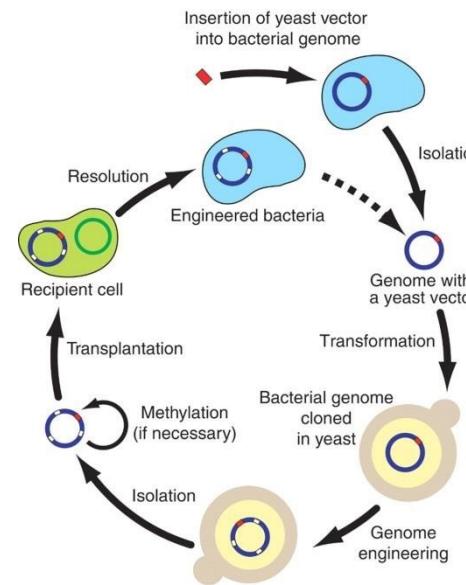


Genomic-scale data
Kühner et. al, 2009

M. genitalium has unique engineering tools

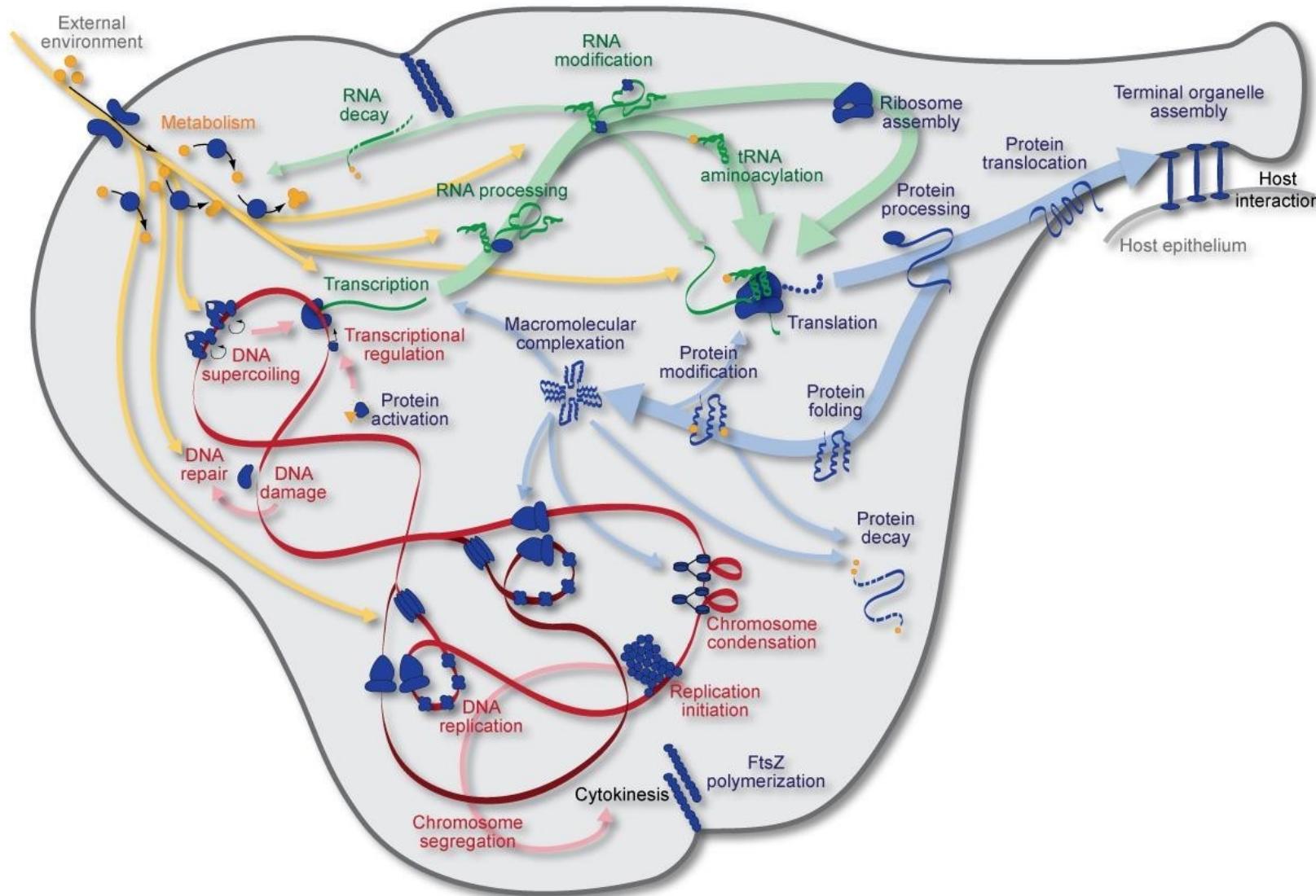


Genomic synthesis
Gibson et. al, 2009



Genomic transplantation
Lartigue et. al, 2009

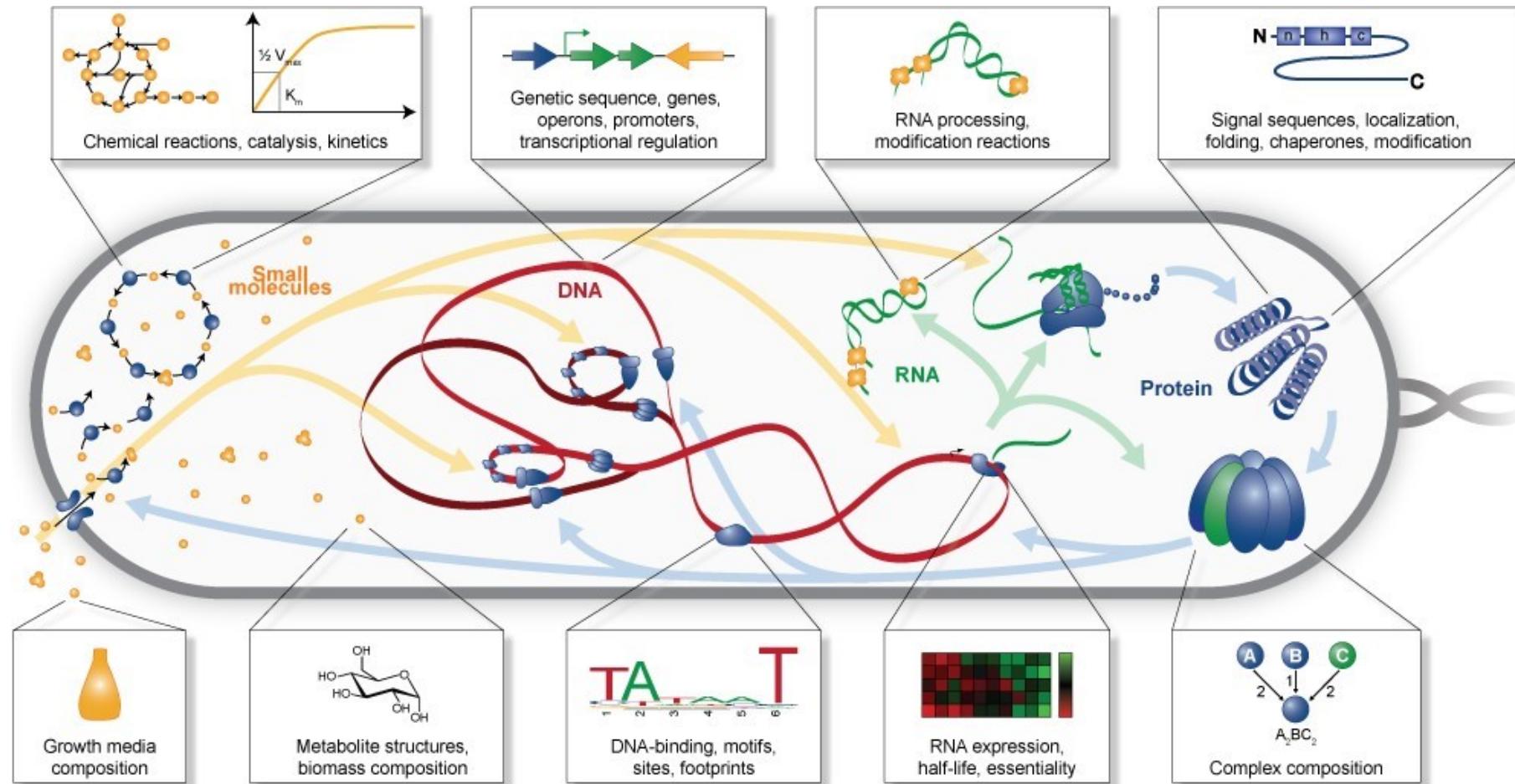
2. Escolher o escopo do modelo



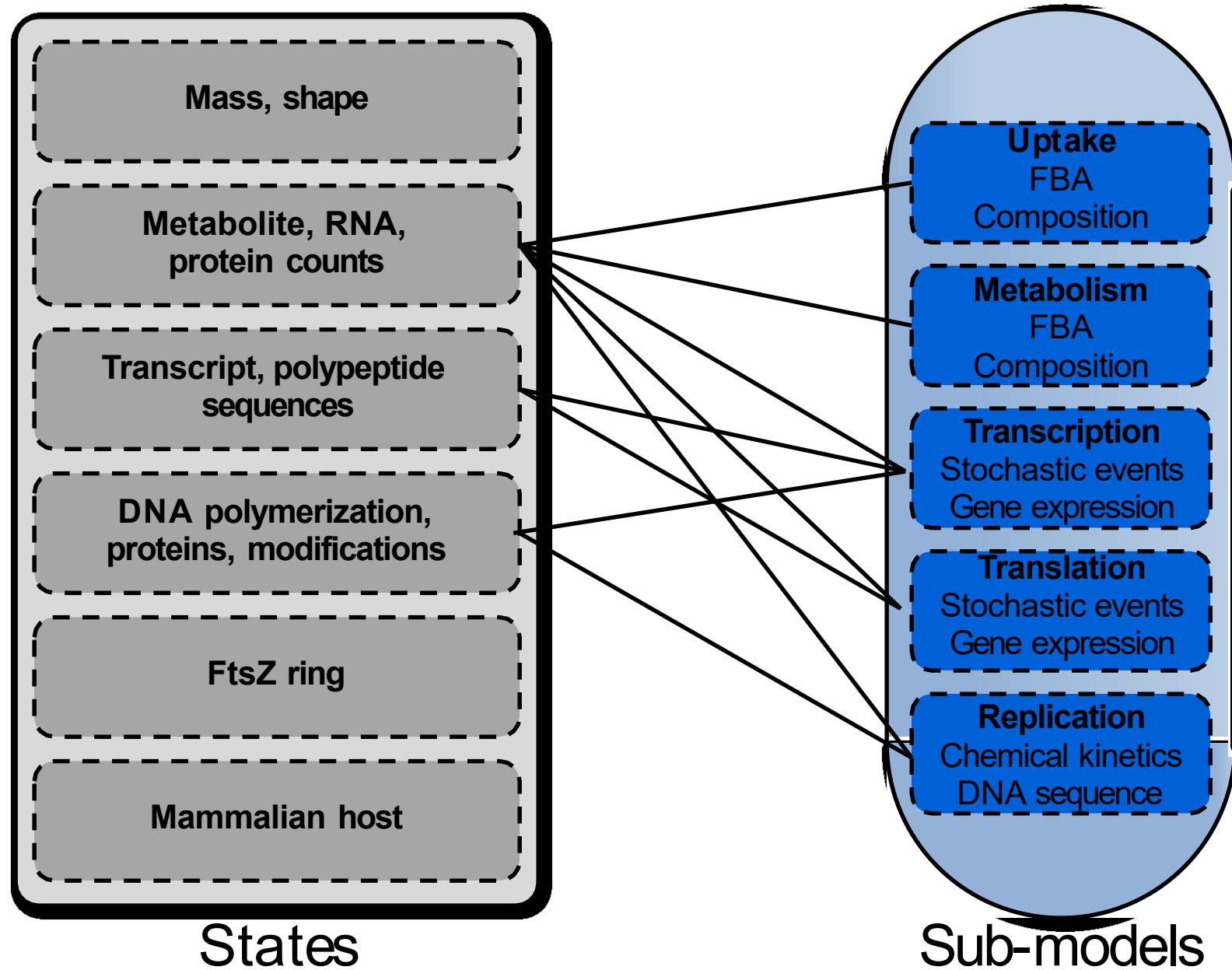
2. Escolher o escopo do modelo

- Representam explicitamente cada metabólito, gene, RNA e proteína;
- Modelam explicitamente a função de cada produto gênico caracterizado;
- Explica o custo metabólico de todos os produtos gênicos não caracterizados
- Representa moléculas importantes e bem caracterizadas individualmente

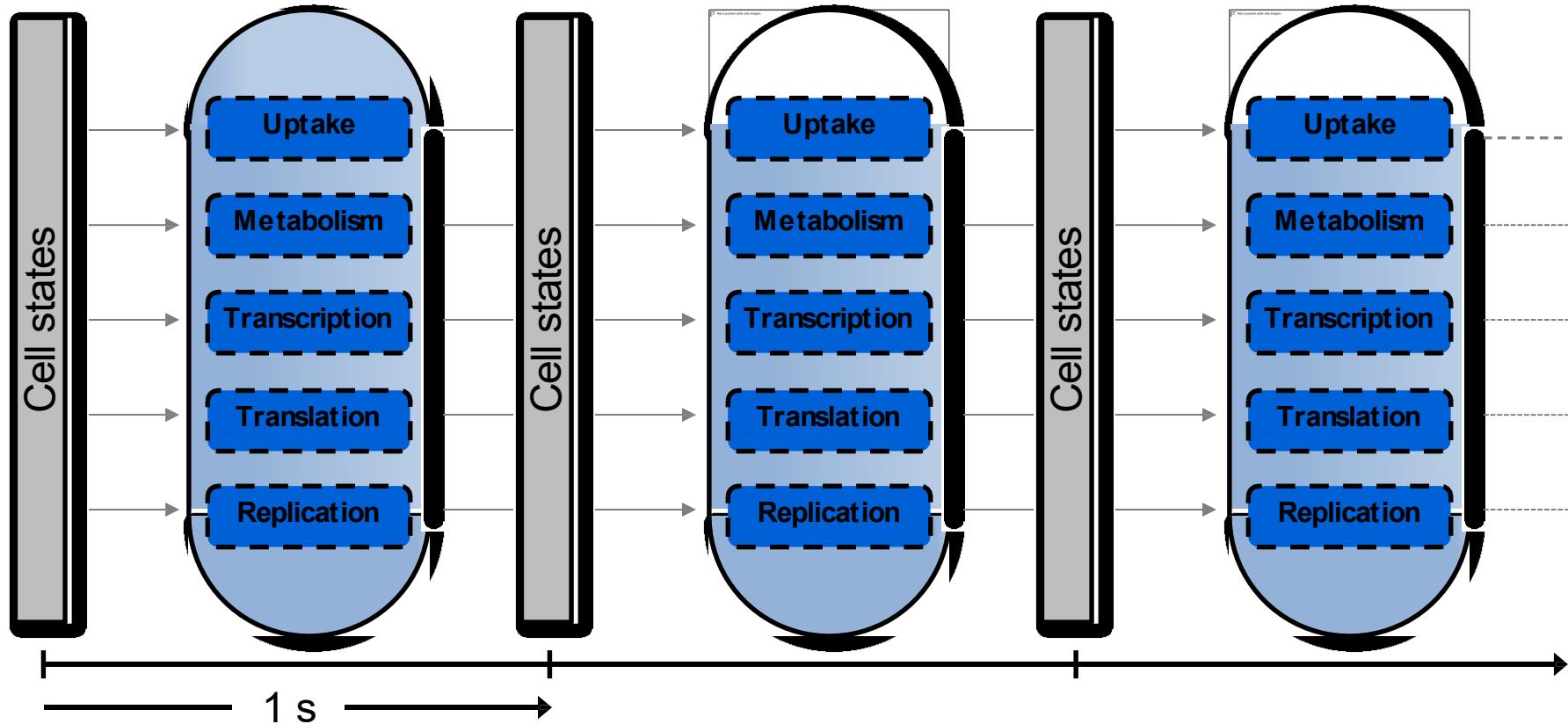
3. Fazer curadoria dos dados



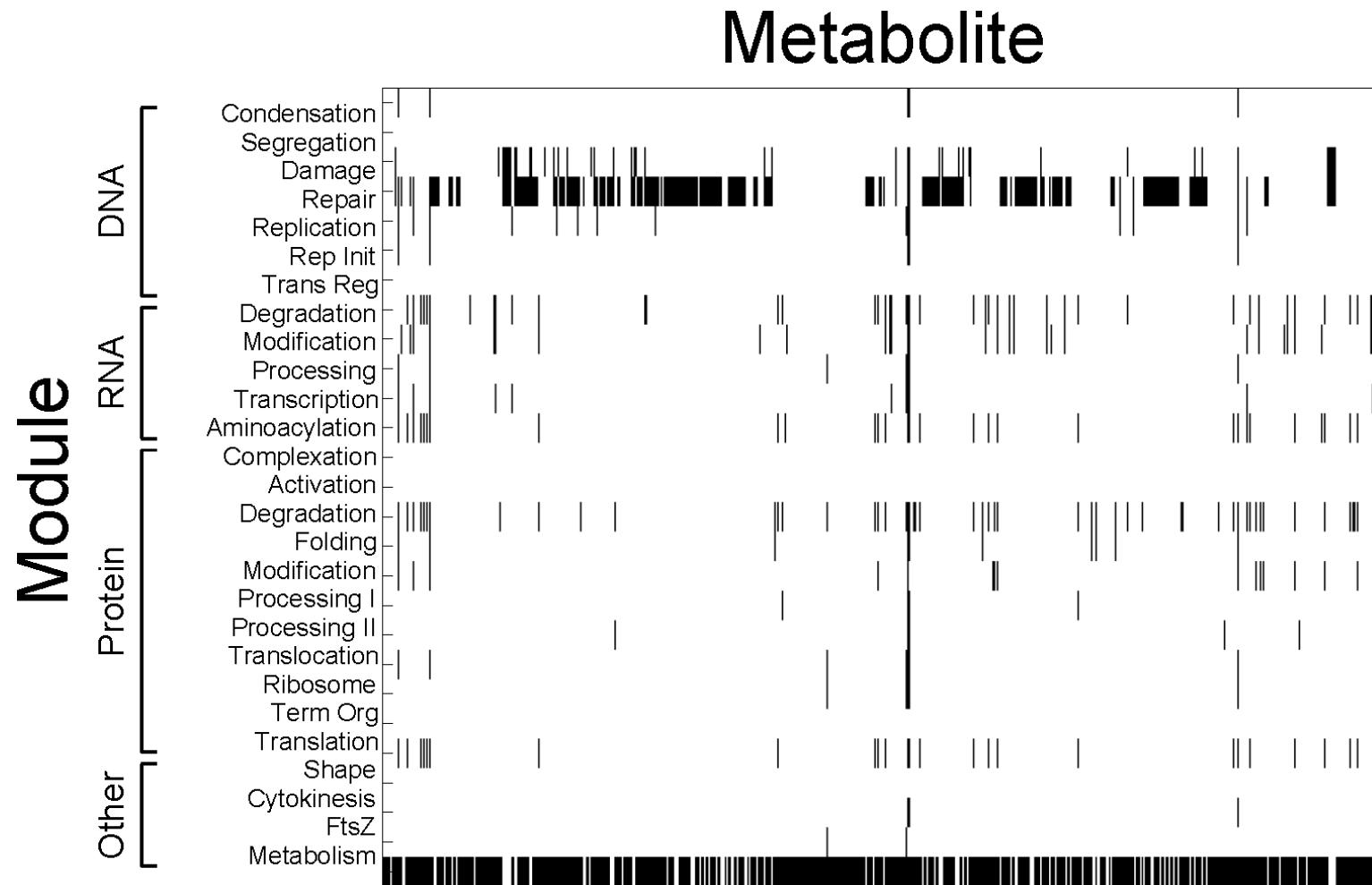
4. Selecionar a representação matemática mais adequada



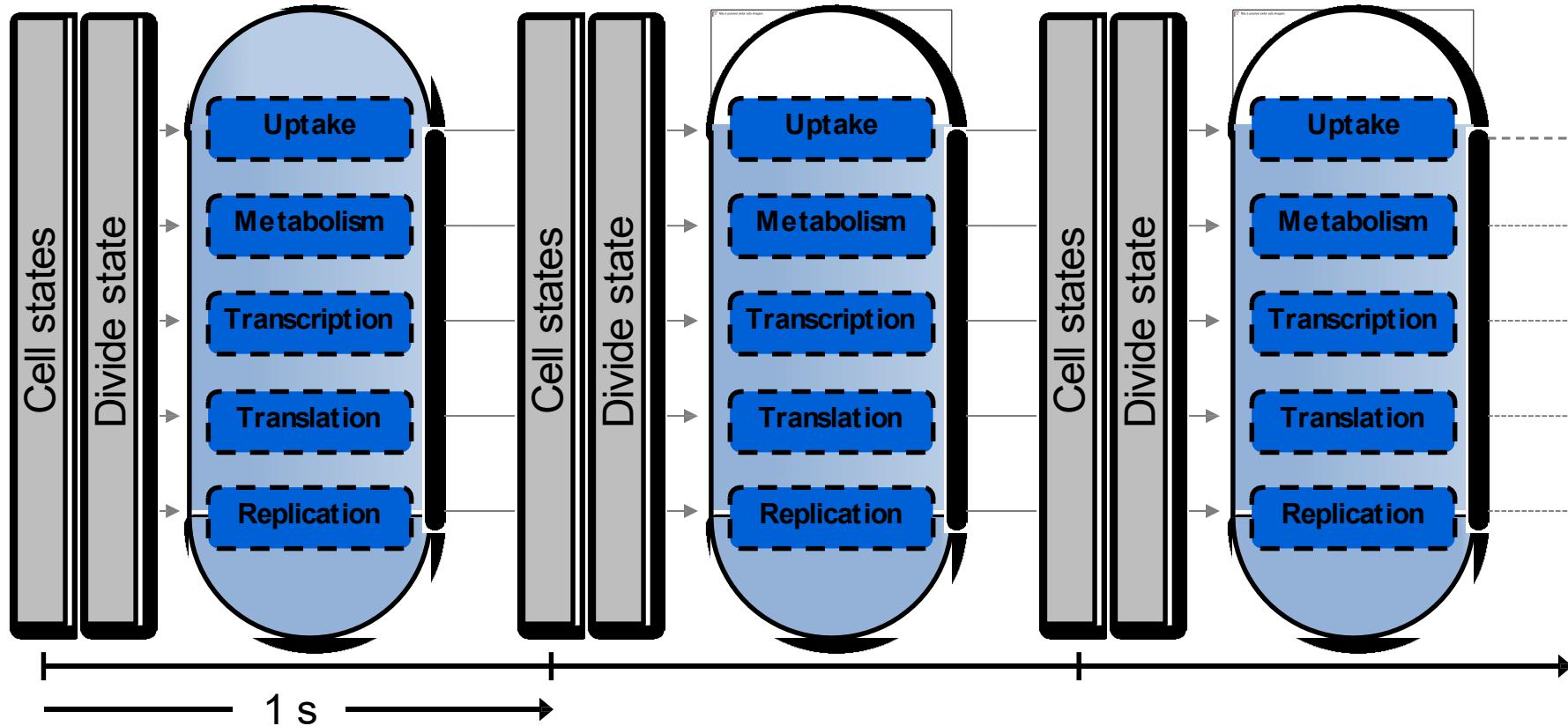
Simular o algoritmo



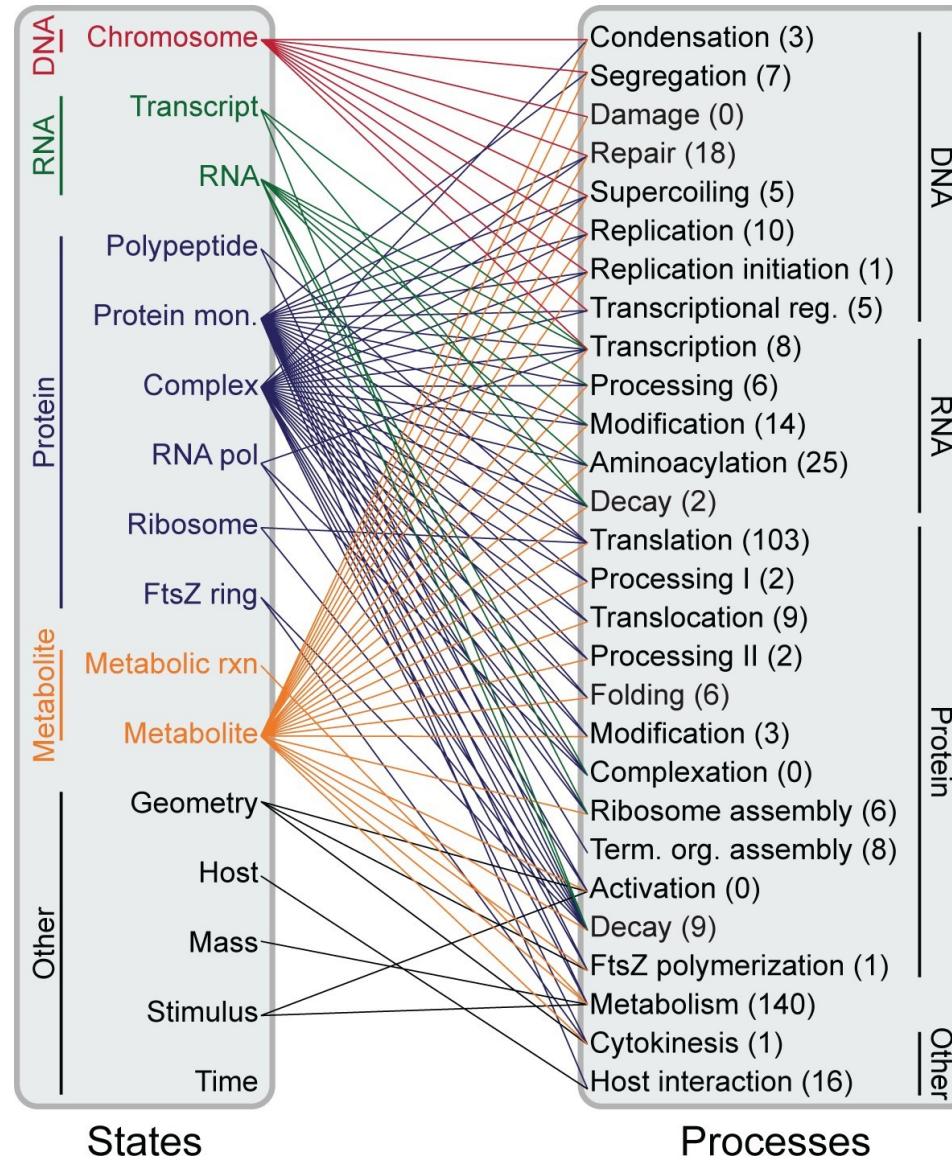
Muitos recursos são compartilhados



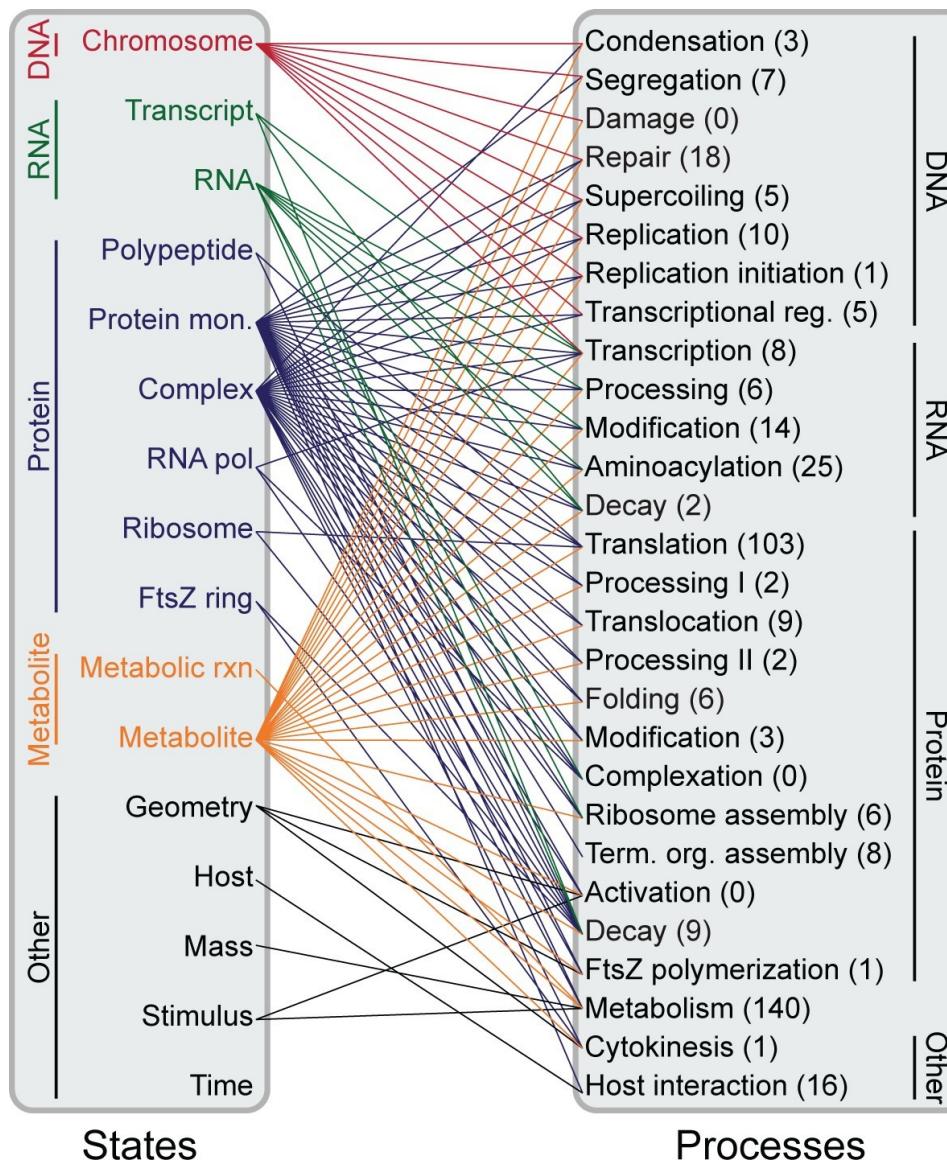
Simular o algoritmo



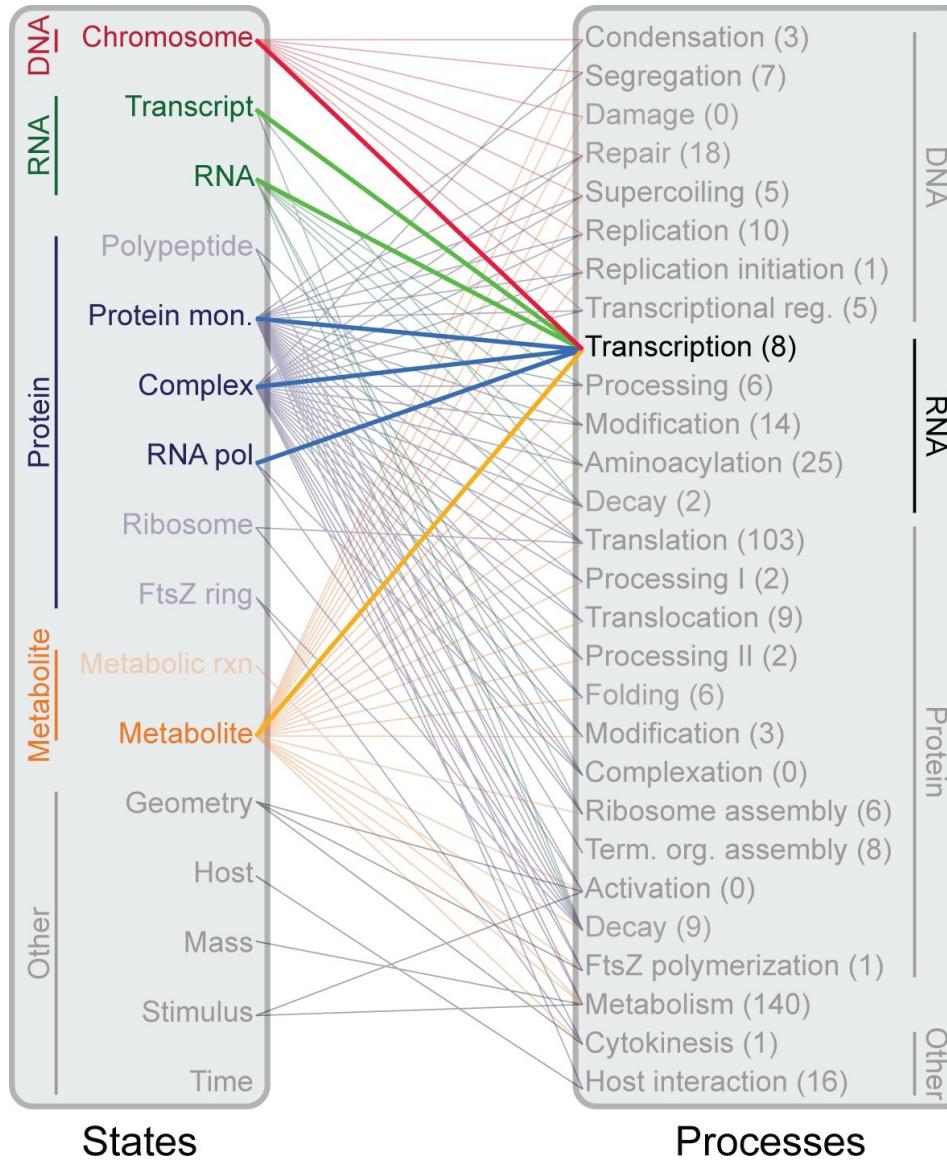
O modelo da Mycoplasma contém 28 sub-models



Example sub-model: Transcription

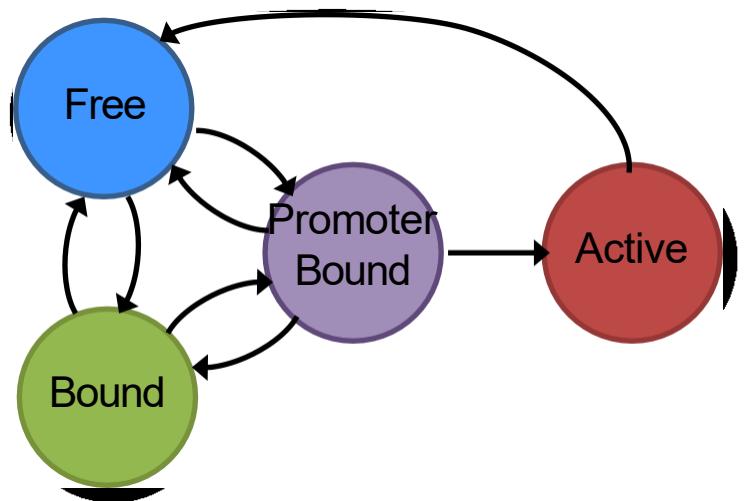


Example sub-model: Transcription

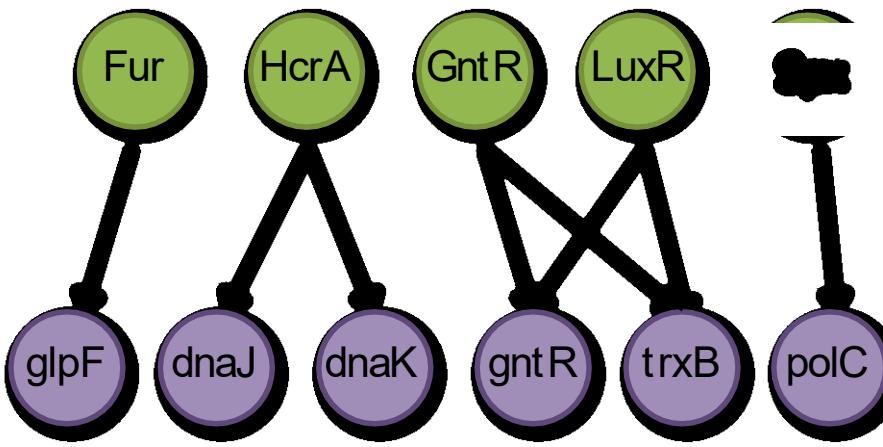


Example sub-model: Transcrição

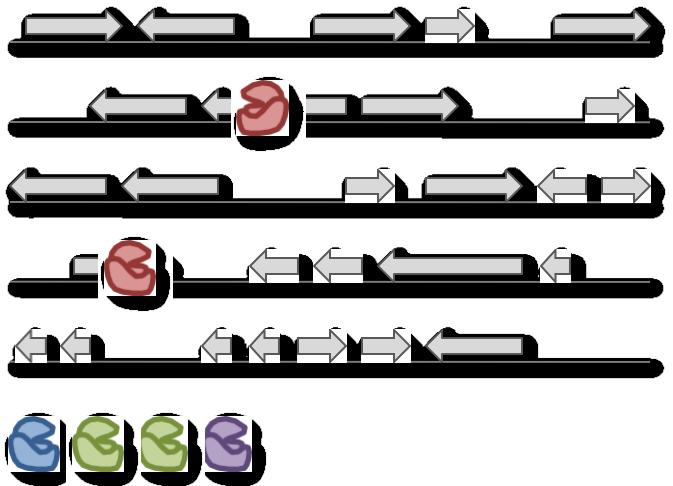
1. Update RNA polymerase states



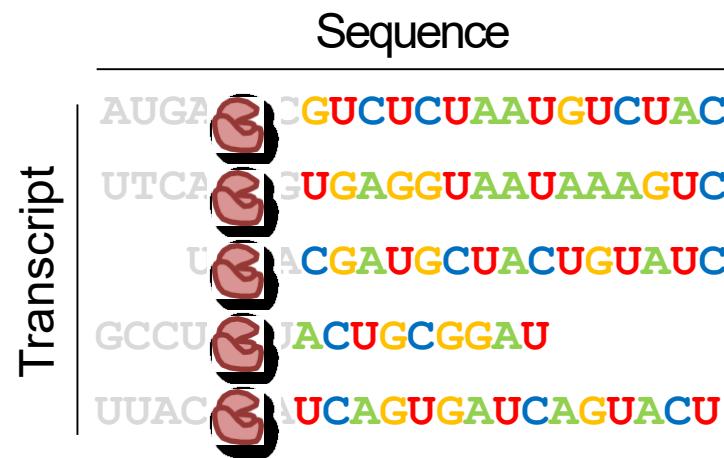
2. Calculate promoter affinities



3. Bind RNA polymerase

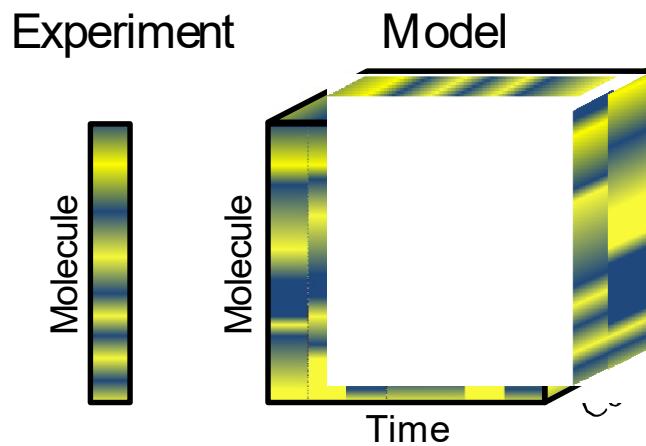


4. Elongate and terminate transcripts



A redução do modelo permite a identificação de parâmetros

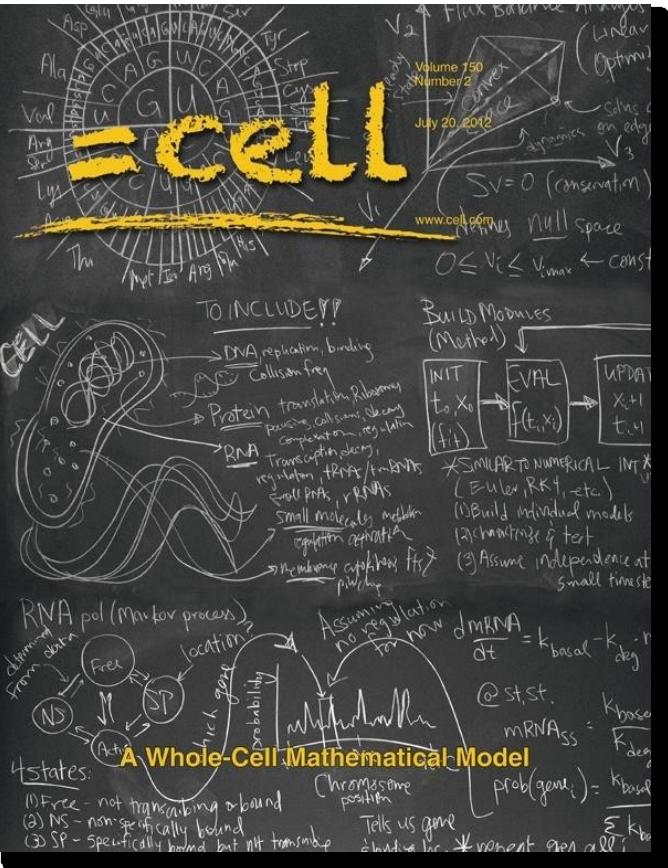
1. Reduce model



2. Identify reduced model parameters using traditional methods

3. Manually tune parameters using full model

Software: wholecell.org



including previously unobserved cellular behaviors, including *in vivo* rates of protein-DNA association using the necessary model parameters. Subsequently, alternative whole-cell computational model

Predicts Phenotype from Genotype

Jonathan R. Karr,^{1,4} Jayodita C. Sanghvi,^{2,4} Derek N. Macklin,² Miriam V. Gutschow,² Jared M. Jacobs,² Benjamin Bolival, Jr.,² Nacyra Assad-Garcia,³ John I. Glass,³ and Markus W. Covert^{2,*}

¹Graduate Program in Biophysics

²Department of Bioengineering

Stanford University, Stanford, CA 94305, USA

³J. Craig Venter Institute, Rockville, MD 20850, USA

*These authors contributed equally to this work

*Correspondence: mcovert@stanford.edu

<http://dx.doi.org/10.1016/j.cell.2012.05.044>

SUMMARY

Understanding how complex phenotypes arise from individual molecules and their interactions is a primary challenge in biology that computational approaches are poised to tackle. We report a whole-cell computational model of the life cycle of the human pathogen *Mycoplasma genitalium* that includes all of its molecular components and their interactions. An integrative approach to modeling that combines diverse mathematics enabled the simultaneous inclusion of fundamentally different cellular processes and experimental measurements. Our whole-cell model accounts for all annotated gene functions and was validated against a broad range of data. The model provides insights into many previously unobserved cellular behaviors, including *in vivo* rates of protein-DNA association using the necessary model parameters. Subsequently, alternative whole-cell computational model

First, until recently, not enough has been known about the individual molecules and their interactions to completely model any one organism. The advent of genomics and other high-throughput measurement techniques has accelerated the characterization of some organisms to the extent that comprehensive modeling is now possible. For example, the mycoplasmas, a genus of bacteria with relatively small genomes that includes several pathogens, have recently been the subject of an exhaustive experimental effort by a European consortium to determine the transcriptome (Güell et al., 2009), proteome (Kühner et al., 2009), and metabolome (Yus et al., 2009) of these organisms.

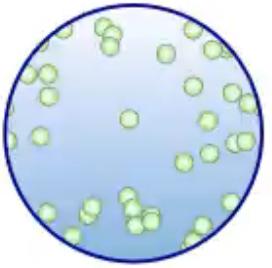
The second limiting factor has been that no single computational method is sufficient to explain complex phenotypes in terms of molecular components and their interactions. The first approaches to modeling cellular physiology, based on ordinary differential equations (ODEs) (Atlas et al., 2008; Browning et al., 2004; Castellanos et al., 2004, 2007; Domach et al., 1984; Tomita et al., 1999), were limited by the difficulty in obtaining the parameters required to describe the system accurately, alternately, alternative

Software

- ODE models
 - COPASI: copasi.org
 - V-Cell: nrcam.uchc.edu
 - Systems biology toolbox
- Boolean models
 - CellNOpt
- Flux-balance analysis
 - openCOBRA: opencobra.sourceforge.net
 - RAVEN
- Integrative models
 - E-Cell: e-cell.org
 - Whole-cell: wholecell.org
- Standards
 - SBML: sbml.org
 - CellML: cellml.org

A Whole-Cell Model Predicts Phenotype from Genotype

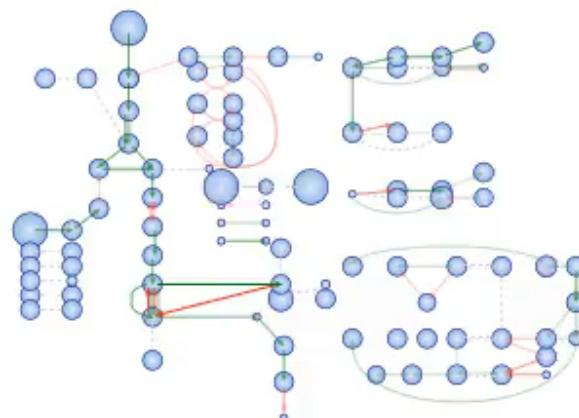
Cell Growth



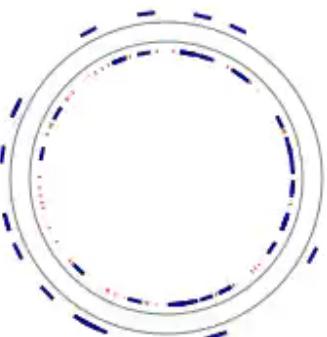
Ribosomes
— Active
— Stalled
— Free 30S
— Free 50S

FtsZ
— Straight
— Bent

Metabolism

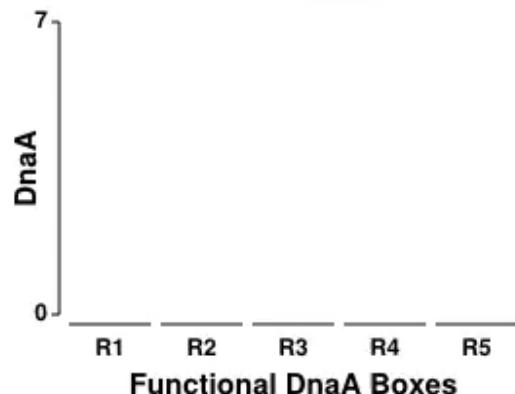


Chromosome



— DNA — Protein — RNA Pol

Replication Initiation



Growth ($\text{f} \cdot \text{g h}^{-1}$)

9051

4459

44079

19479

168

39

12

6

0

Time (h)

Amino Acid
tRNA
NTP

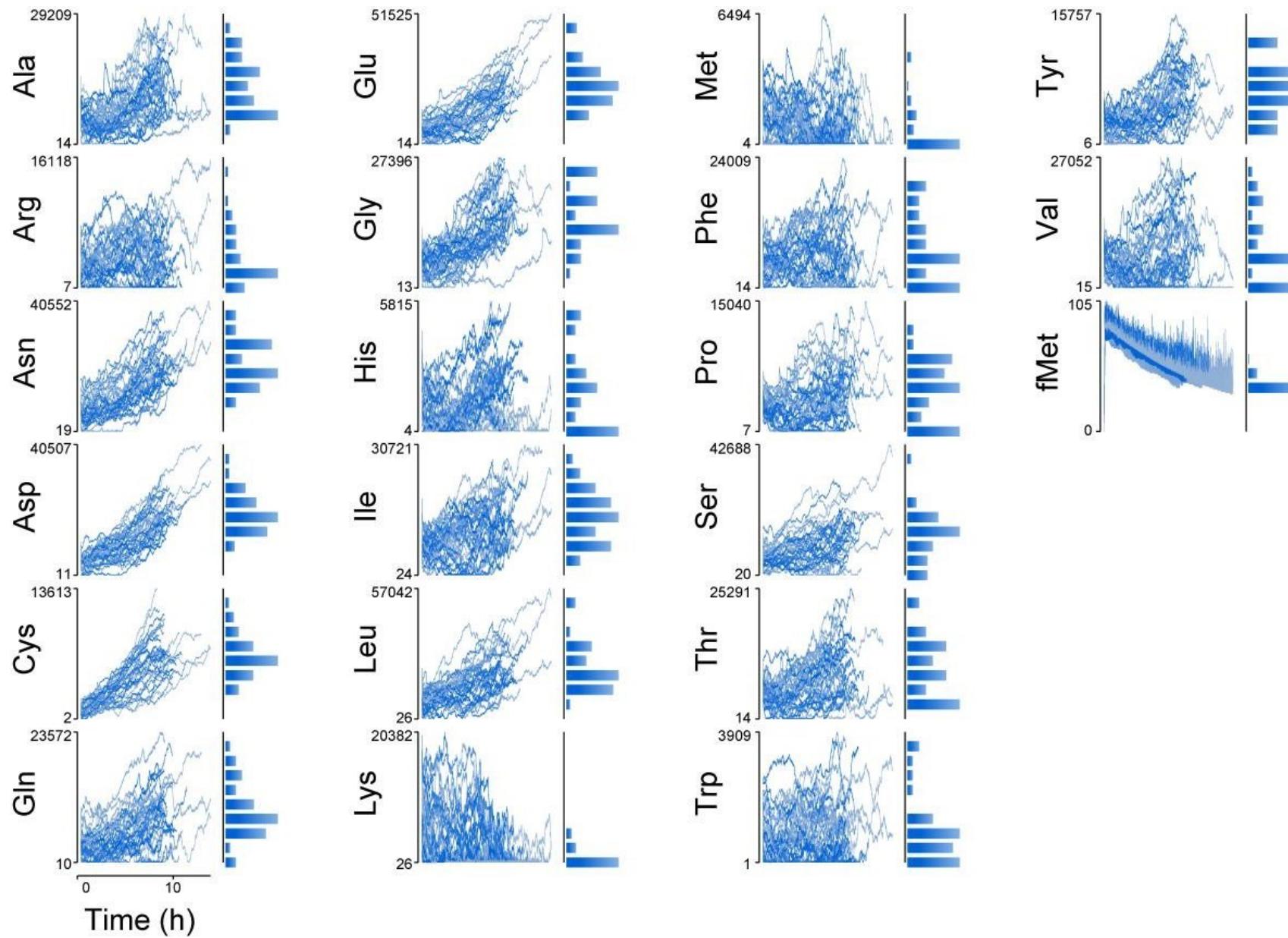
217065

58554

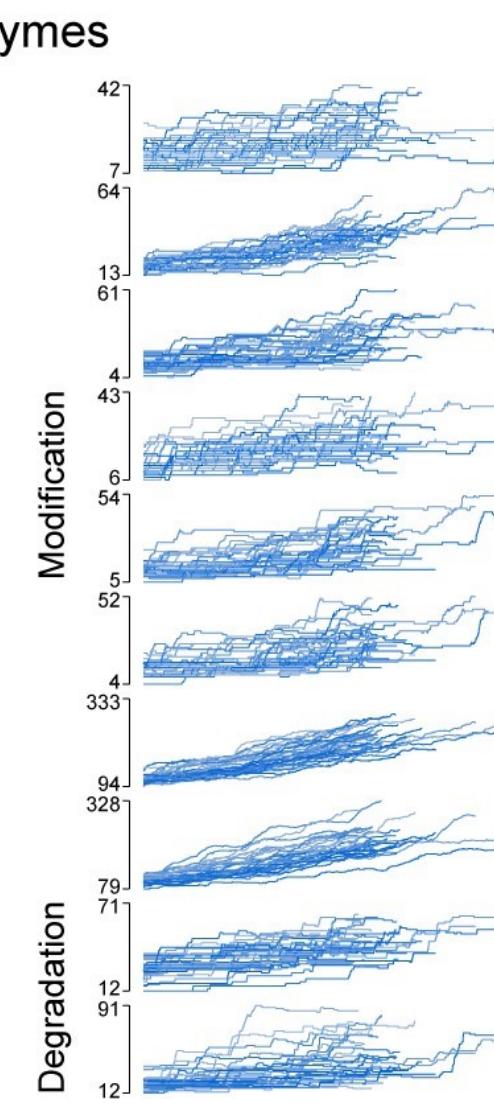
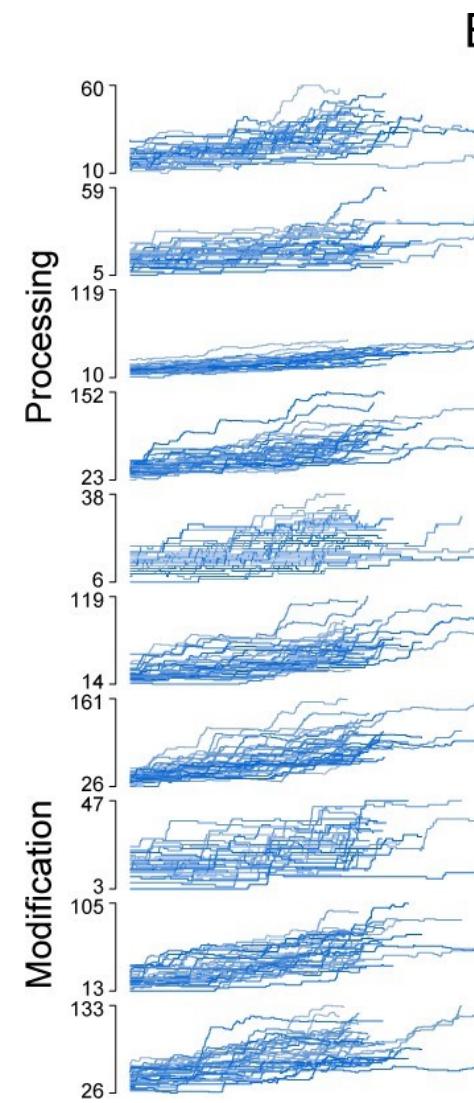
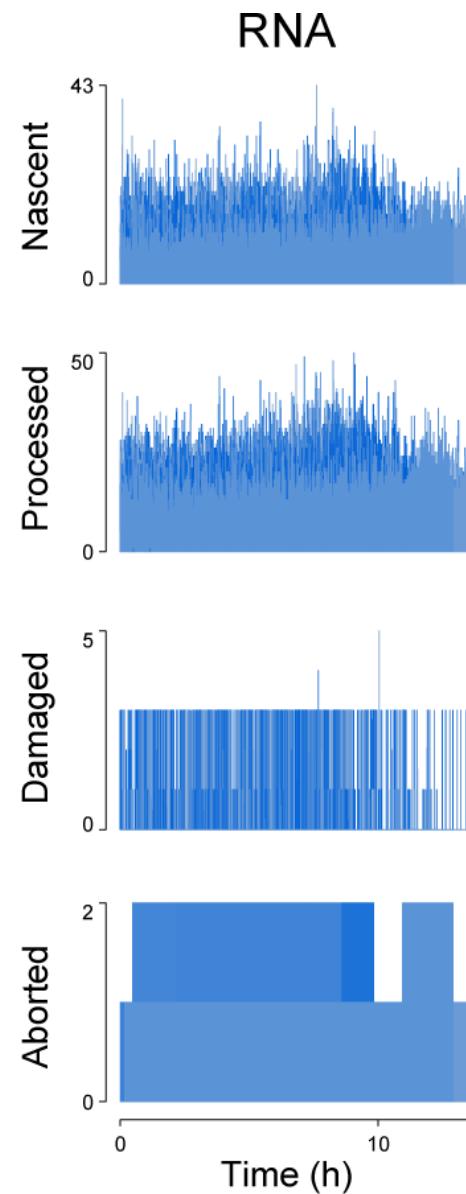
166833

74769

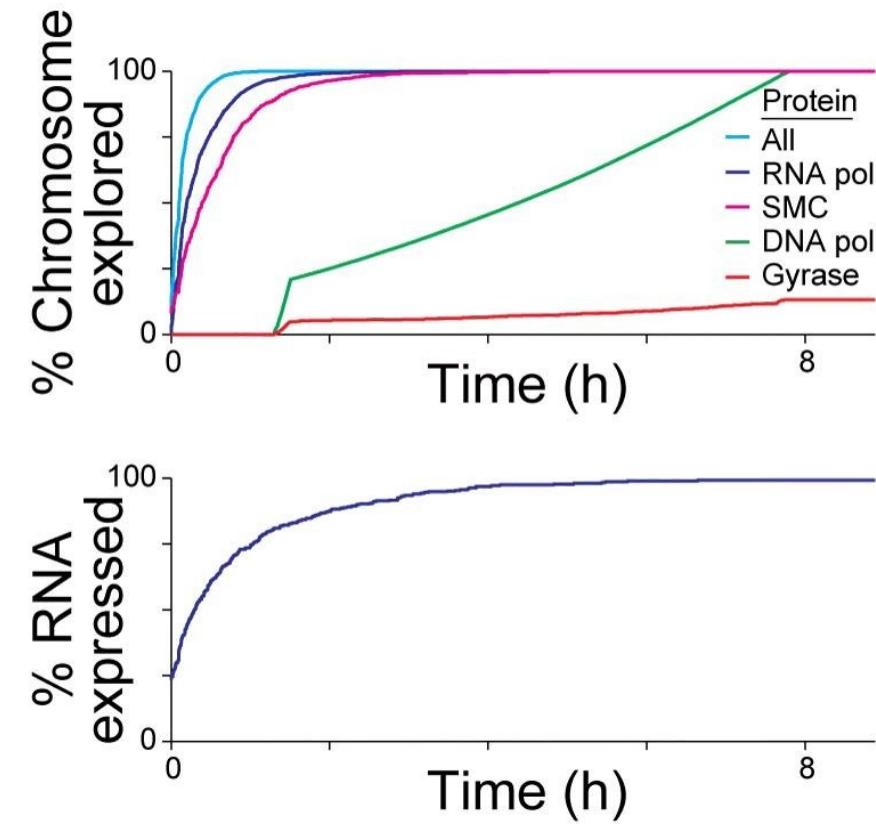
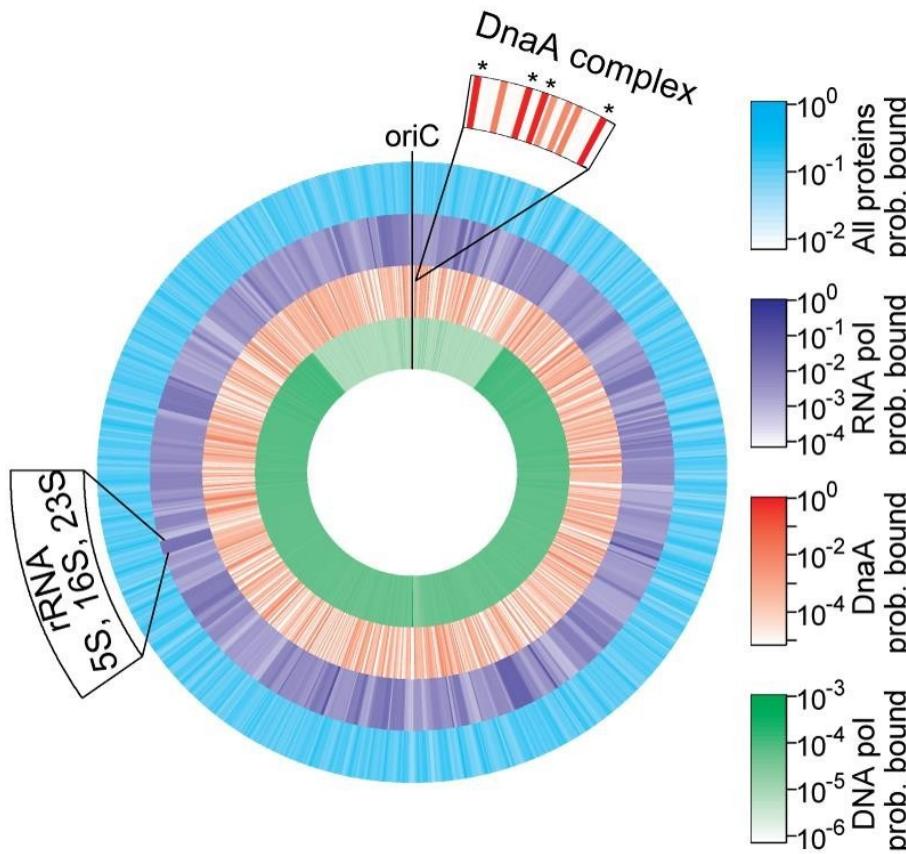
Metabolite concentrations



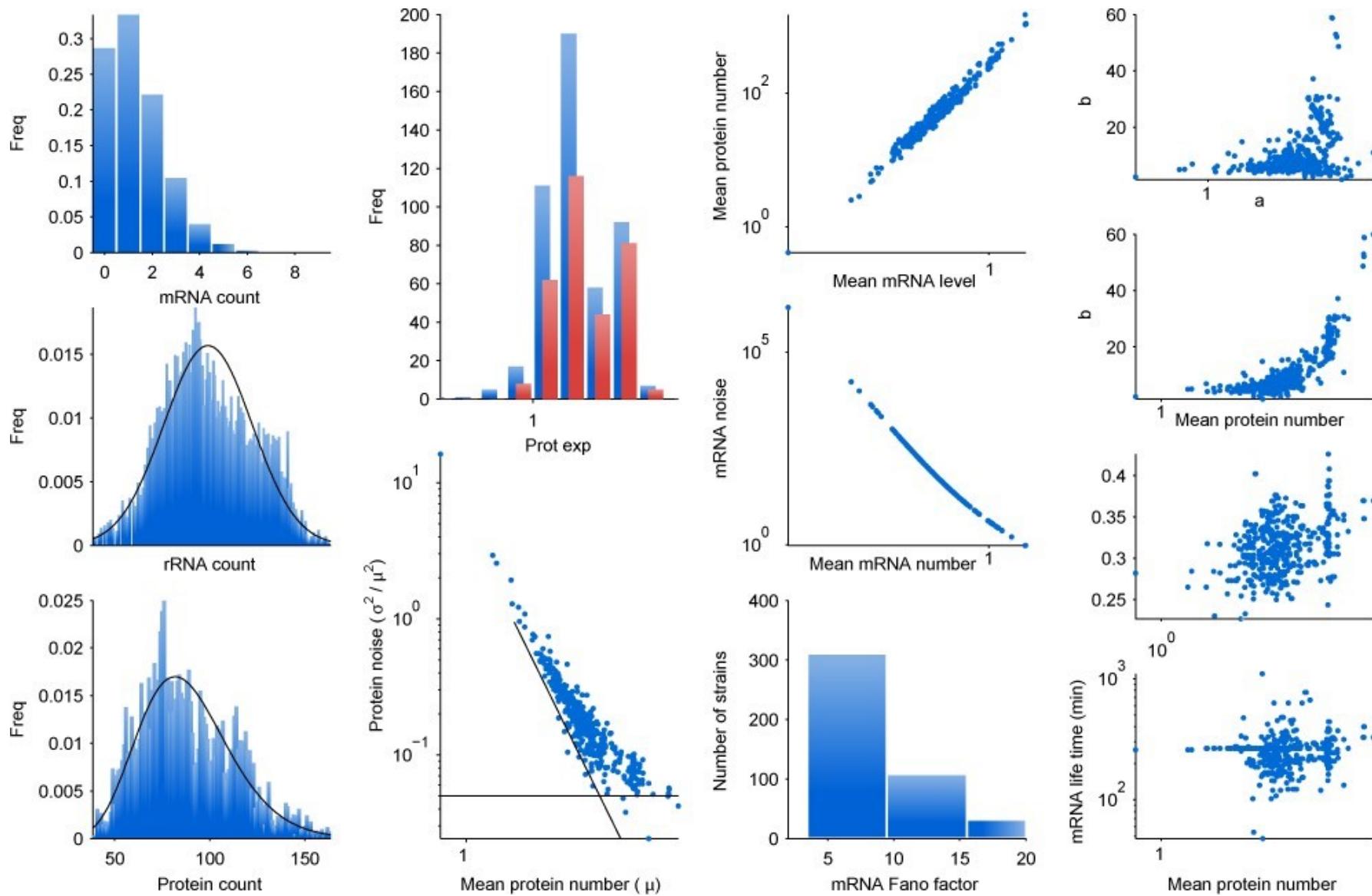
RNA synthesis rates



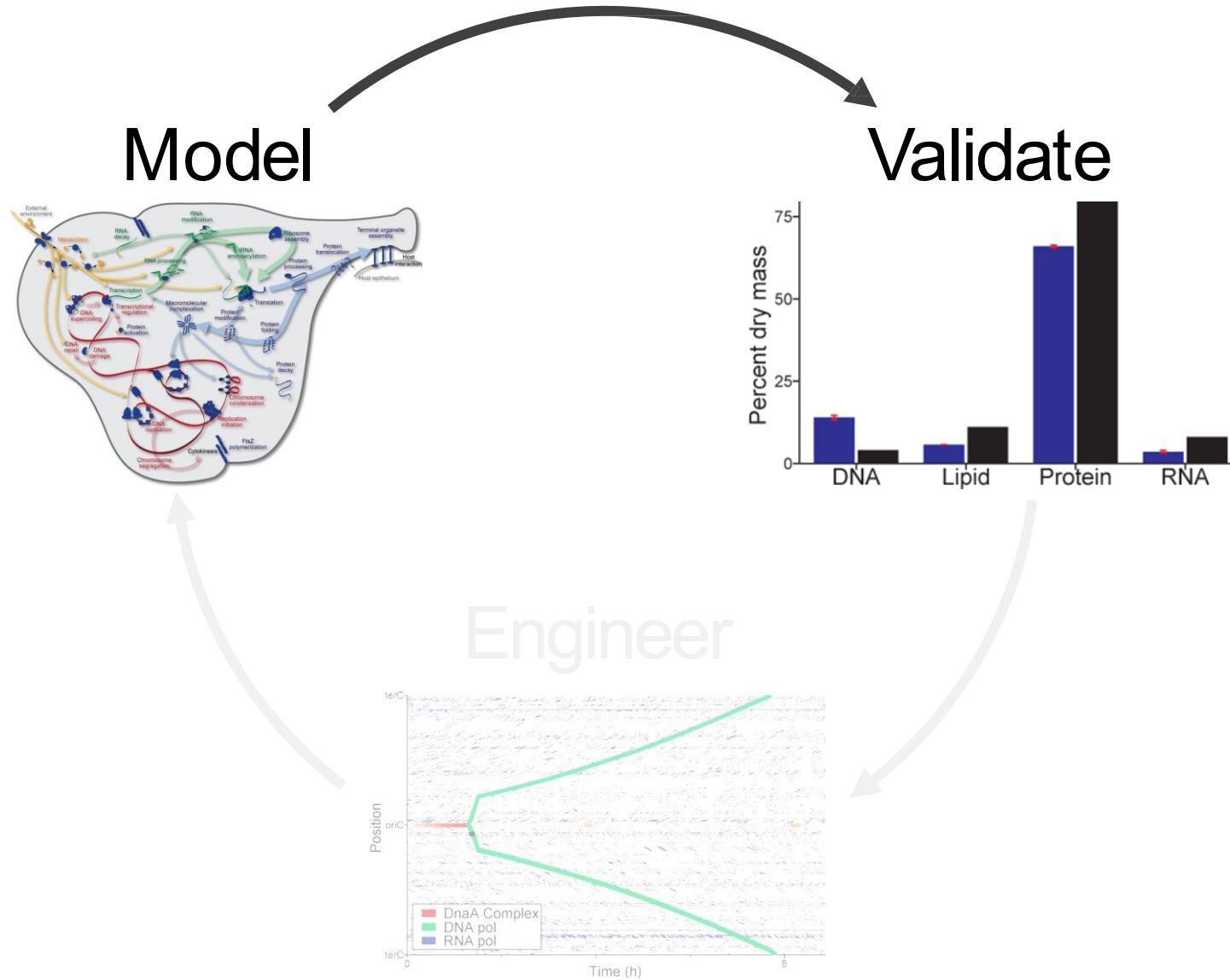
DNA binding



Translation



Whole-cell modeling



Validate model against experiments and theory

Matches training data

- Cell mass, volume
- Biomass composition
- RNA, protein expression, half-lives
- Superhelicity

Matches published data

- Metabolite concentrations
- DNA-bound protein density
- Gene essentiality

Matches new data

- Wild-type growth rate
- Disruption strain growth rates

Matches theory

- Mass conservation
- Central dogma
- Cell theory
- Evolution

No obvious errors

- Plot model predictions
- Manually inspect data
- Compare to known biology

Software stable

- Simulation code is stable
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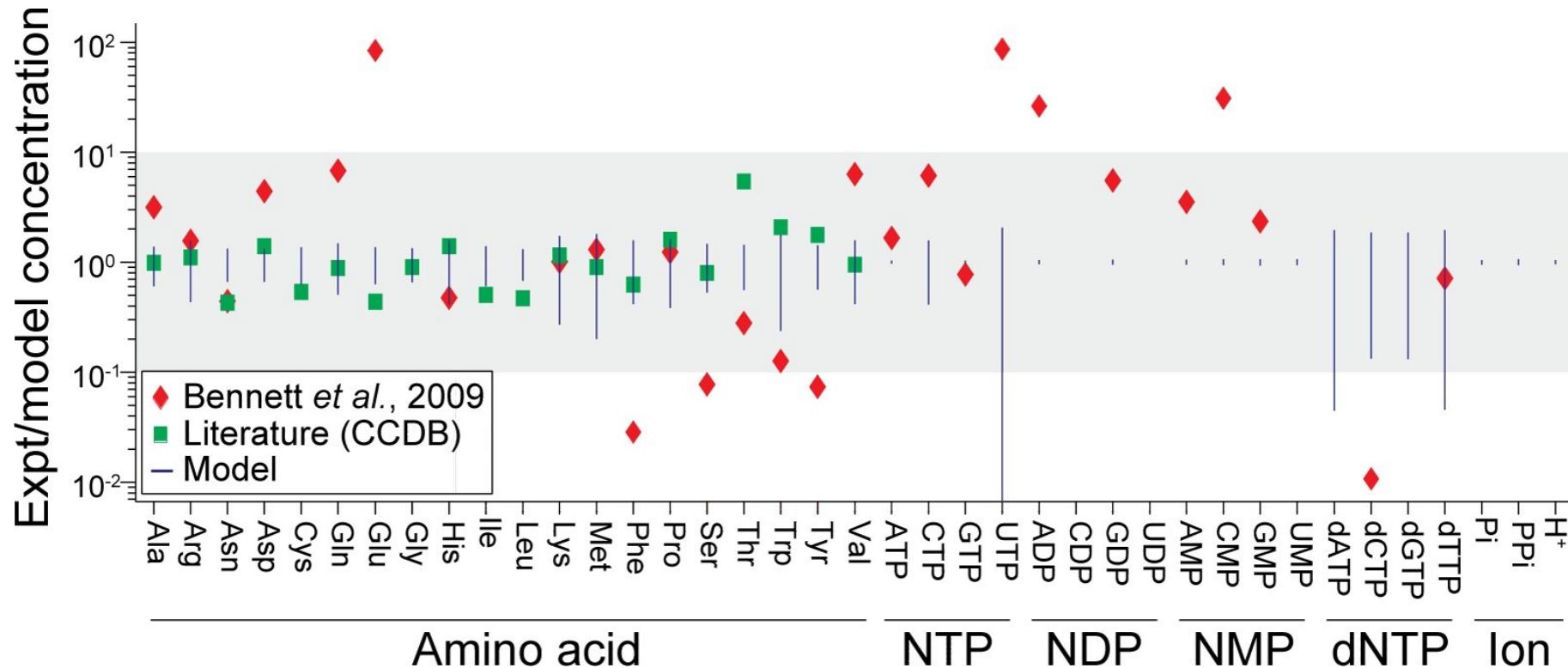
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Model reproduces observed metabolomics



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Desafios

- Como podemos modelar fisiologia mais complexa?
- Como podemos modelar organismos mais complexos?
 - Larger bacteria
 - Eukaryotes
 - Multicellularity
 - Humans
- Como podemos usar modelos para direcionar a engenharia?

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