

Transcriptome Analysis:

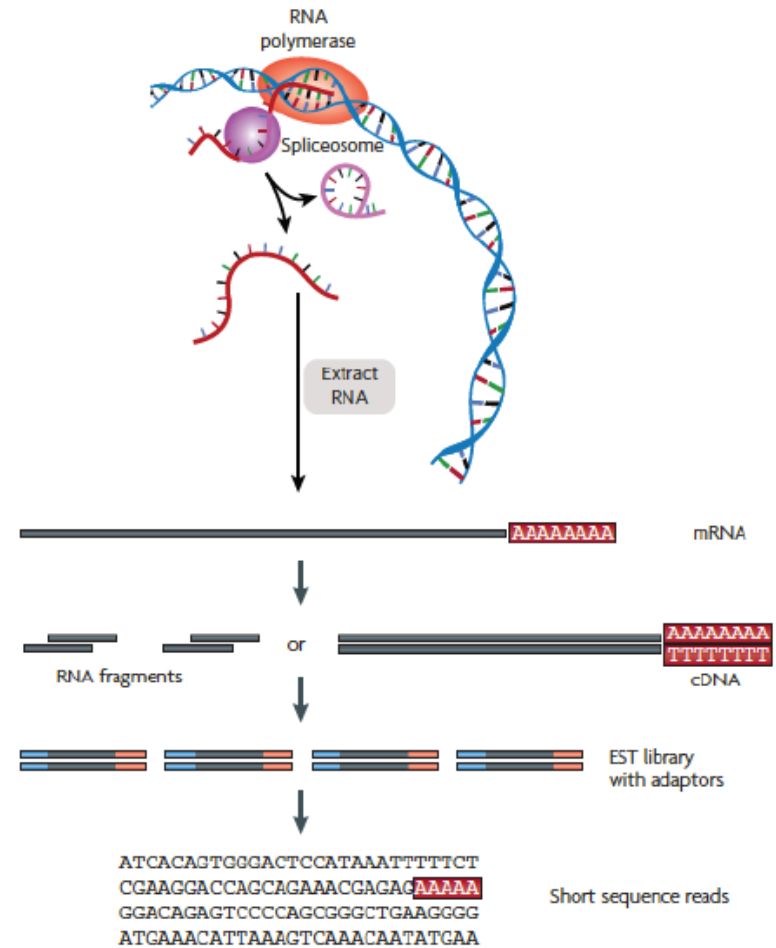
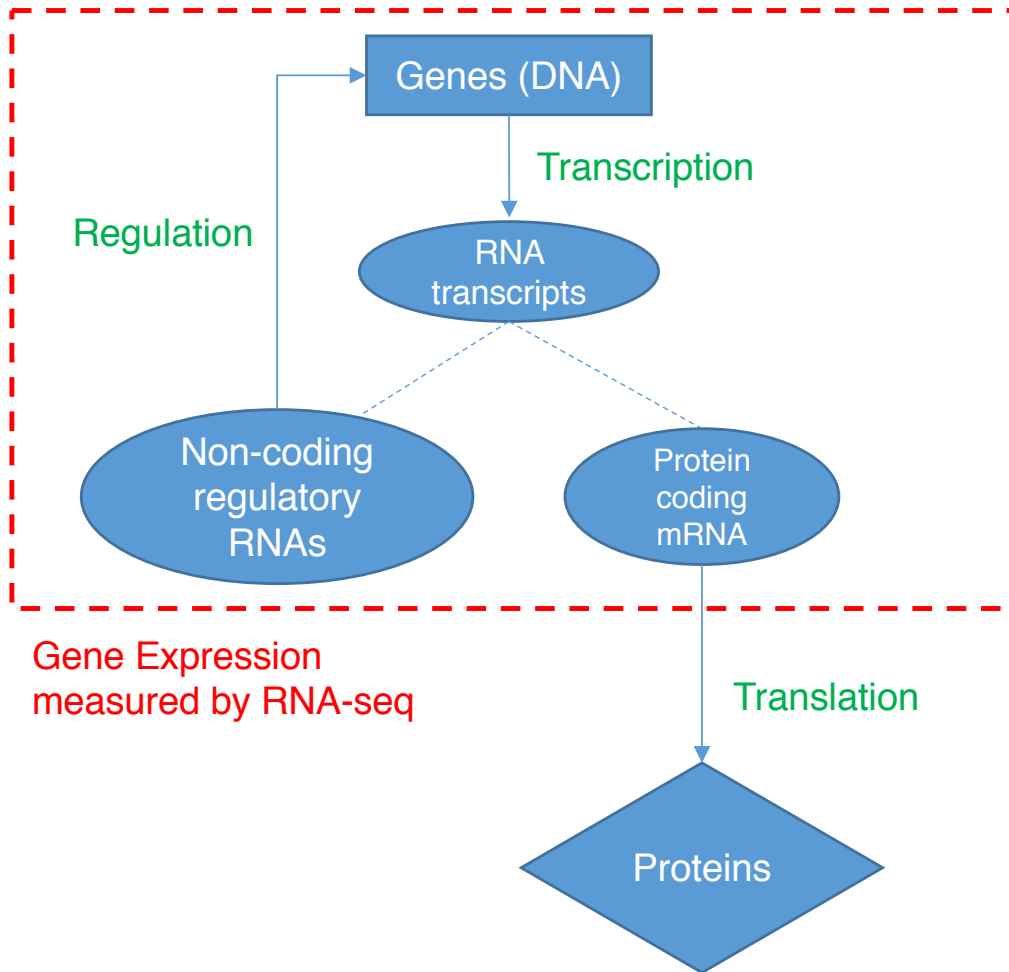
Tackling core issues related to regulation & also mining the “data exhaust” of this activity



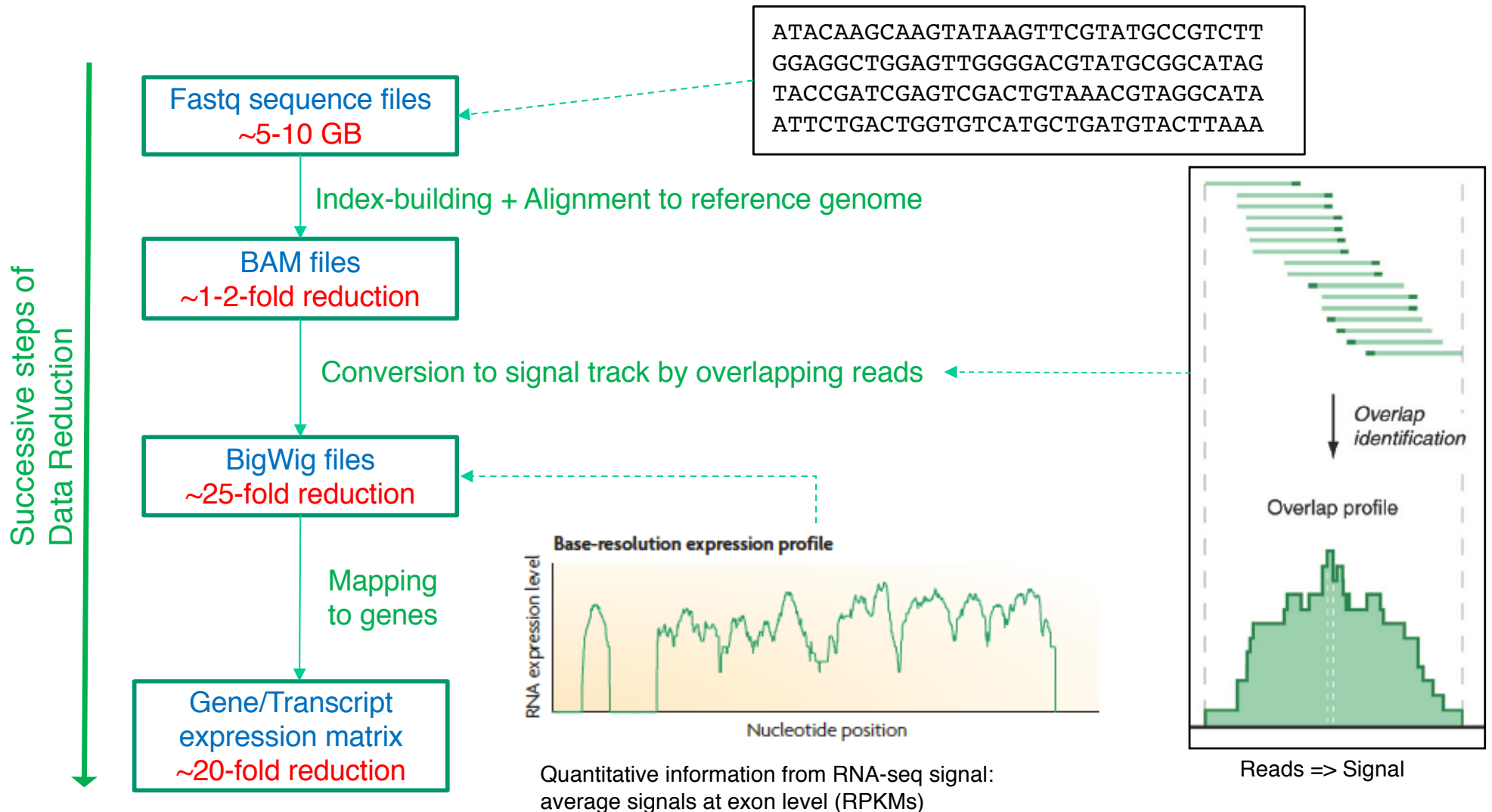
Mark Gerstein, Yale

Slides freely downloadable from
Lectures.GersteinLab.org
& “tweetable” (via @markgerstein)
See last slide for more info.

Expression of genes is quantified by transcription: RNA-Seq measures mRNA transcript amounts



RNA-Seq Overview



[NAT. REV. 10: 57; PLOS CB 4:e1000158; PNAS 4:107: 5254]



Activity Patterns

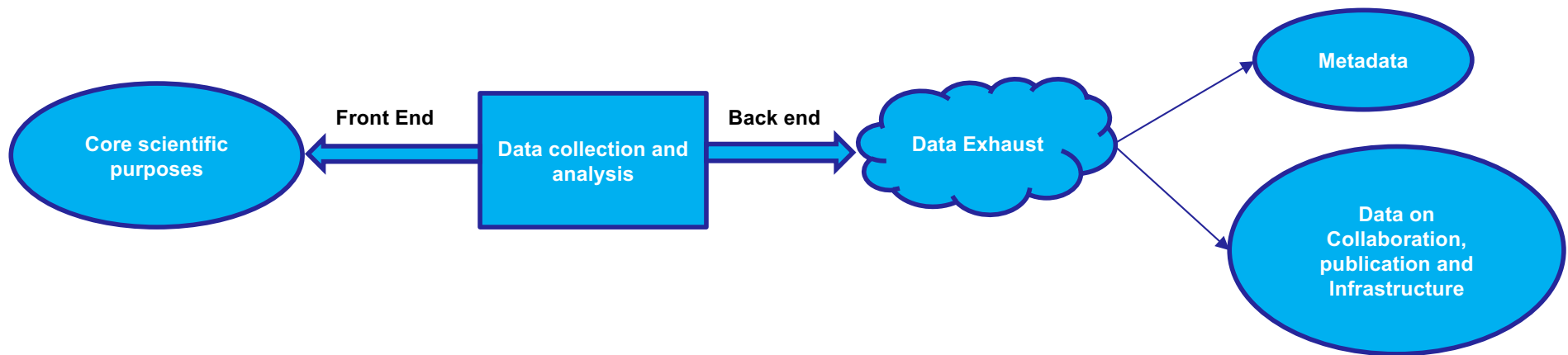
- RNA Seq. gives rise to activity patterns of genes & regions in the genome

Some Core Science Qs Addressed by RNA-seq

- Gene activity as a function of:
 - Developmental stage: basic patterns and clusters of co-active genes across an organisms development
 - Evolutionary relationships: behavior preserved across a wide range of organisms; patterns and clusters in model organisms in relation to those in humans
 - Tissue- and cell-type: relationship of expression and specialized function
 - Disease phenotypes: disruption of patterns in disease
 - Individual variation: person-to-person discrepancies; personalized medicine

Studying large-scale functional genomics data also produces

Data Exhaust



- Data Exhaust = Exploitable byproducts of big data collection and analysis

[PHOTO: RELAXNEWS; from <http://www.lapresse.ca>]

Transcriptome Analysis: Tackling core issues related to regulation & also mining the “data exhaust” of this activity

- **Expression Clustering, Cross-species**
 - Comparative ENCODE – Lots of worm-fly-human matched data & developmental timecourses
 - Optimization gives 16 conserved co-expression modules
- **State Space Models of Gene Expression**
 - Using dimensionality reduction to help determine internal & external drivers
 - Decoupling expression changes into those from conserved vs species-specific genes
 - Also, conserved genes have similar canonical patterns (iPDPs) in contrast to species specific ones (Ex of ribosomal v signaling genes)
- **Using Logic Gates to Model of Transcriptome Activity**
 - Preponderance of OR gates in cancer v. cell-cycle (esp. for MYC)
- **The General Dilemma of Genomic Privacy**
 - Fundamental, inherited info that's very private v need for large-scale mining for med. research
 - Issues w/ current social & tech approaches: inconsistencies & burdensome security
- **RNA-seq: How to Publicly Share it**
 - Presents a tricky privacy issue since much of the sequencing is for general, non-individual specific results yet it's tagged with individual information
 - Geuvadis w/ 1000G genotypes
 - Quantifying & removing variant info from expression levels + eQTLs using ICI & predictability
 - Instantiating a practical linking attack using extreme expression levels
 - Quantifying accuracy of prediction, via gap between best & 2nd best match
- **Value of publication patterns generated by the data producing consortia**
 - Co-authorship network statistics relate to publication rollouts & show gradual adoption by a diverse community
 - Key role of brokers in data dissemination

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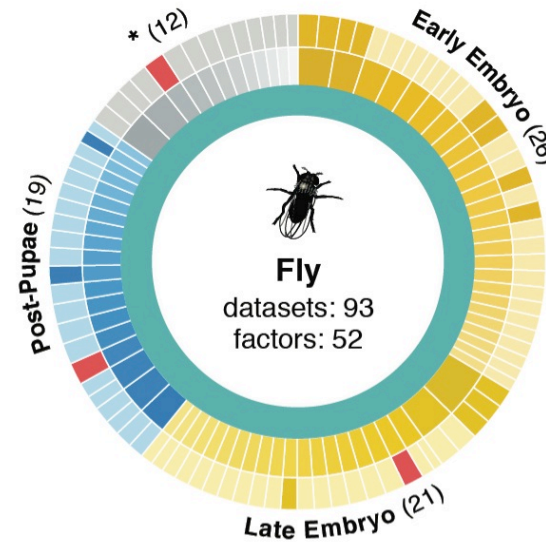
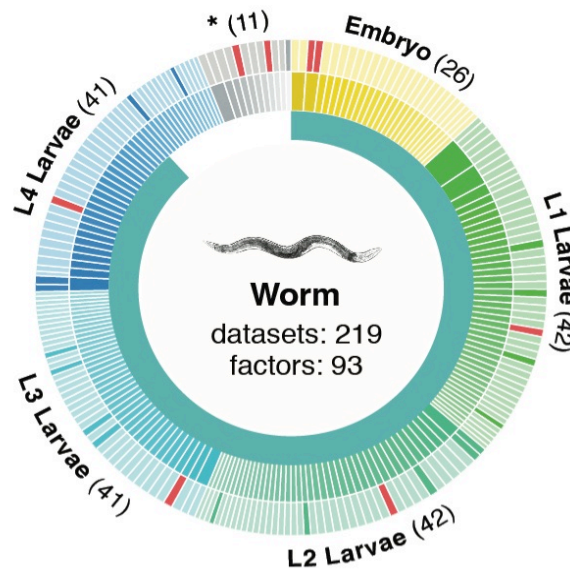
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Time-course gene expression data of worm & fly development

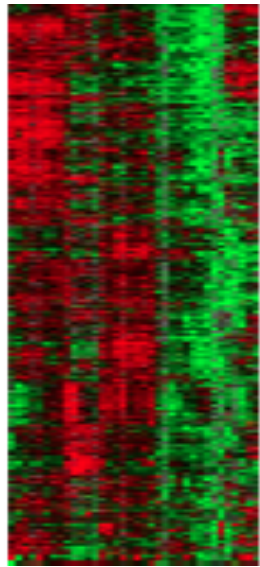


Comparative ENCODE Functional Genomics Resource
(EncodeProject.org/comparative)

Organism	Major developmental stages
worm (<i>C. elegans</i>)	33 stages: 0, 0.5, 1, ..., 12 hours, L1, L2, L3, L4, ..., Young Adults, Adults
fly (<i>D. mel.</i>)	30 stages: 0, 2, 4, 6, 8, ..., 20, 22 hours, L1-L4, Pupae, Adults

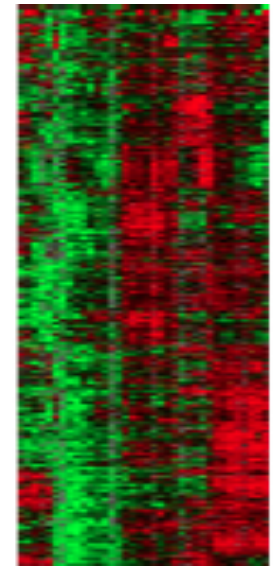
- Broad sampling of conditions across transcriptomes & regulomes for human, worm & fly
 - embryo & ES cells
 - developmental time course (worm-fly)
- In total: ~3000 datasets (~130B reads)

Expression clustering: revisiting an ancient problem



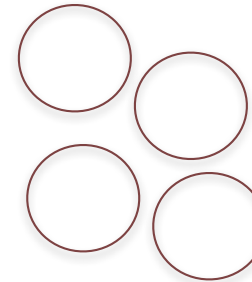
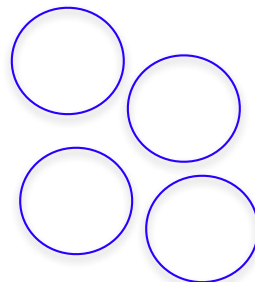
Species A

Species B



Clustering
algorithm

Clustering
algorithm

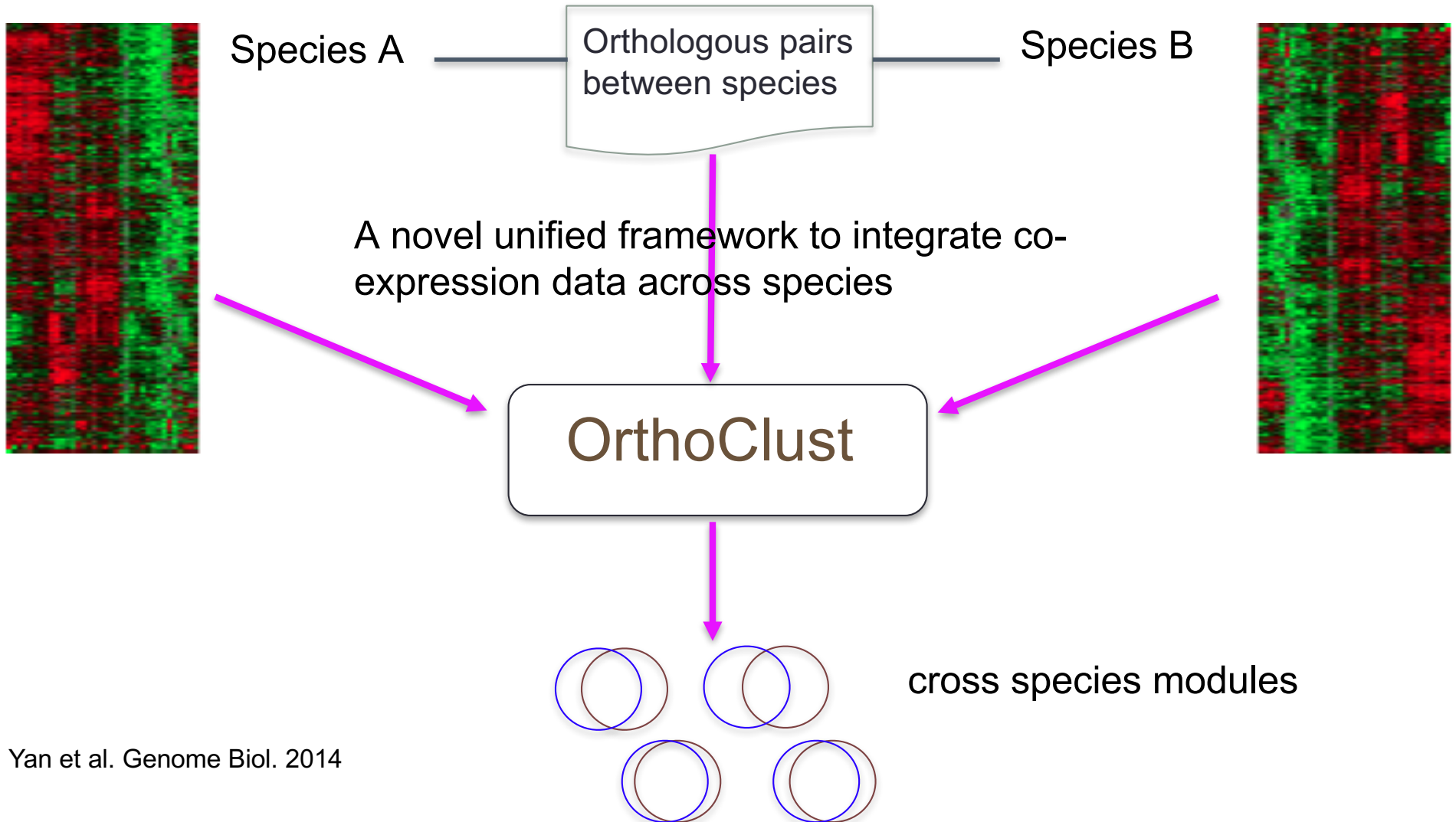


co-expressed genes
responsible for the same
function in a species

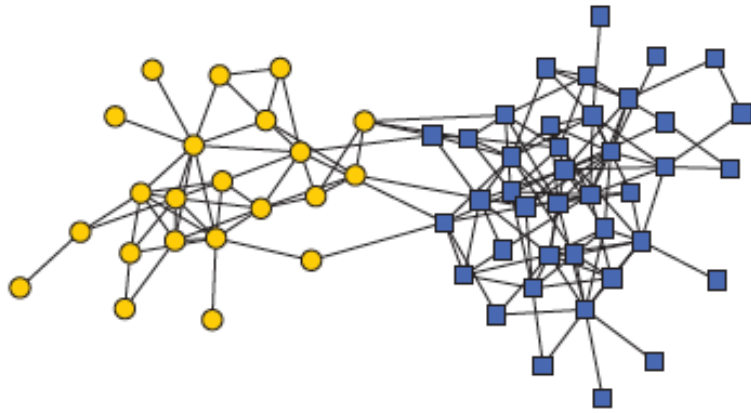
two independent sets
of modules

Eisen MB et al. PNAS 1998
Langfelder P et al. BMC Bioinfo. 2008
Tamayo P et al. PNAS 1999
Kluger Y et al. Genome Res. 2003

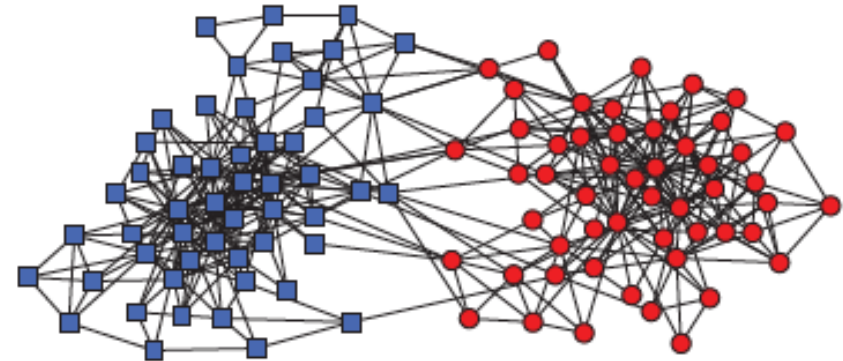
Expression clustering: revisiting an ancient problem



Network modularity



Dolphin social network



Political books

Newman Phys. Rev. E 2013

adjacency matrix

$$Q = \frac{1}{2m} \sum_{i,j} \left(W_{ij} - \frac{k_i k_j}{2m} \right) \delta_{\sigma_i \sigma_j}$$

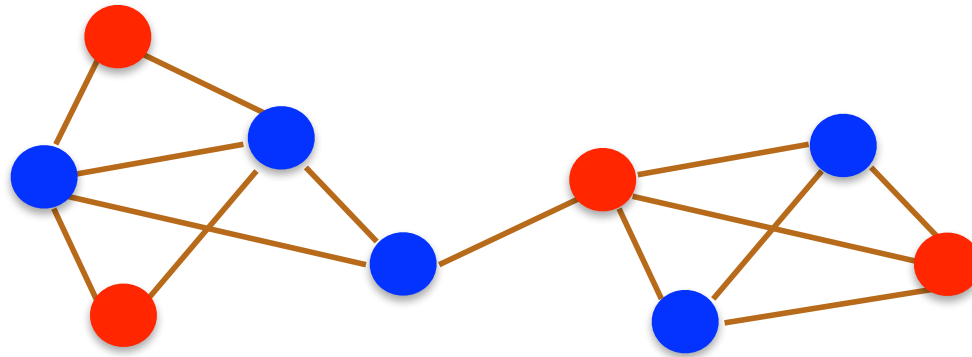
number of edges

degree of node i

expected number of edges between i and j

whether or not i, j are in the same module

Network modularity

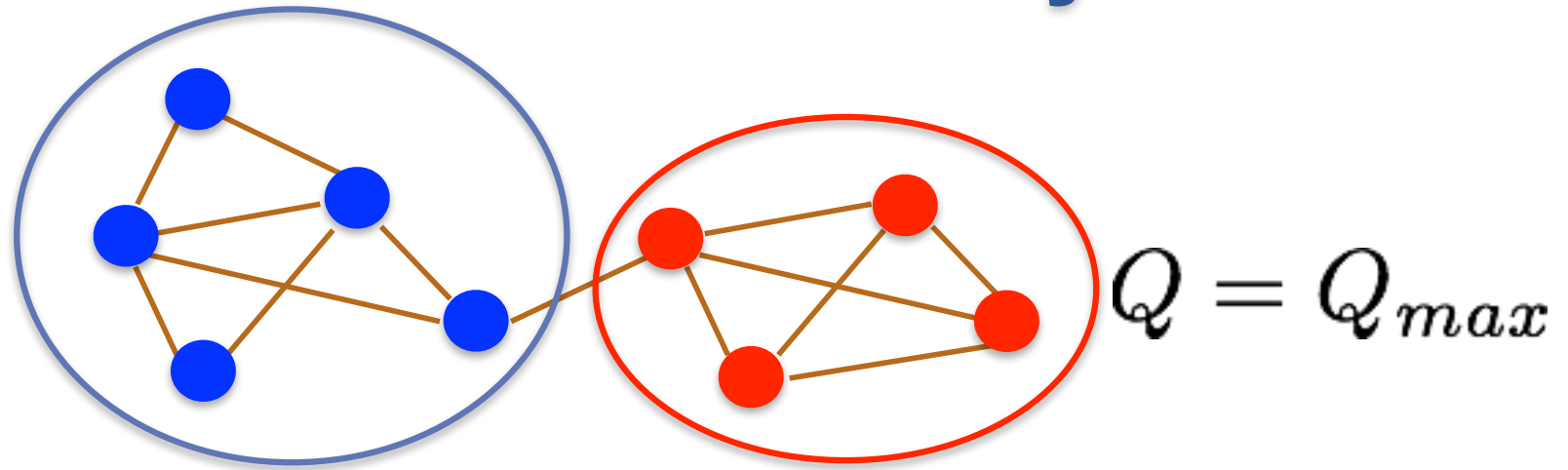


$$Q \approx 0$$

$$Q = \frac{1}{2m} \sum_{i,j} \left(W_{ij} - \frac{k_i k_j}{2m} \right) \delta_{\sigma_i \sigma_j}$$

adjacency matrix W_{ij}
 degree of node i k_i
 number of edges $2m$
 expected number of edges between i and j $\frac{k_i k_j}{2m}$
 whether or not i, j are in the same module $\delta_{\sigma_i \sigma_j}$

Network modularity

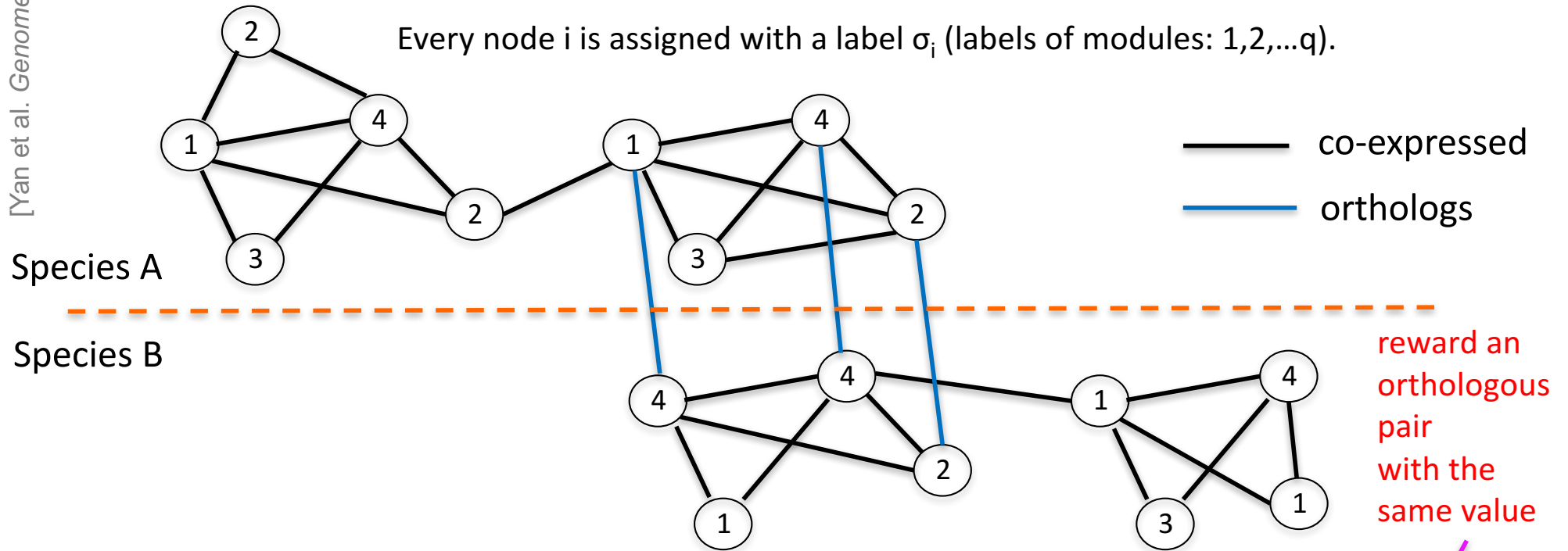


Optimization problem for sim. annealing

$$Q = \frac{1}{2m} \sum_{i,j} \left(W_{ij} - \frac{k_i k_j}{2m} \right) \delta_{\sigma_i \sigma_j}$$

adjacency matrix W_{ij}
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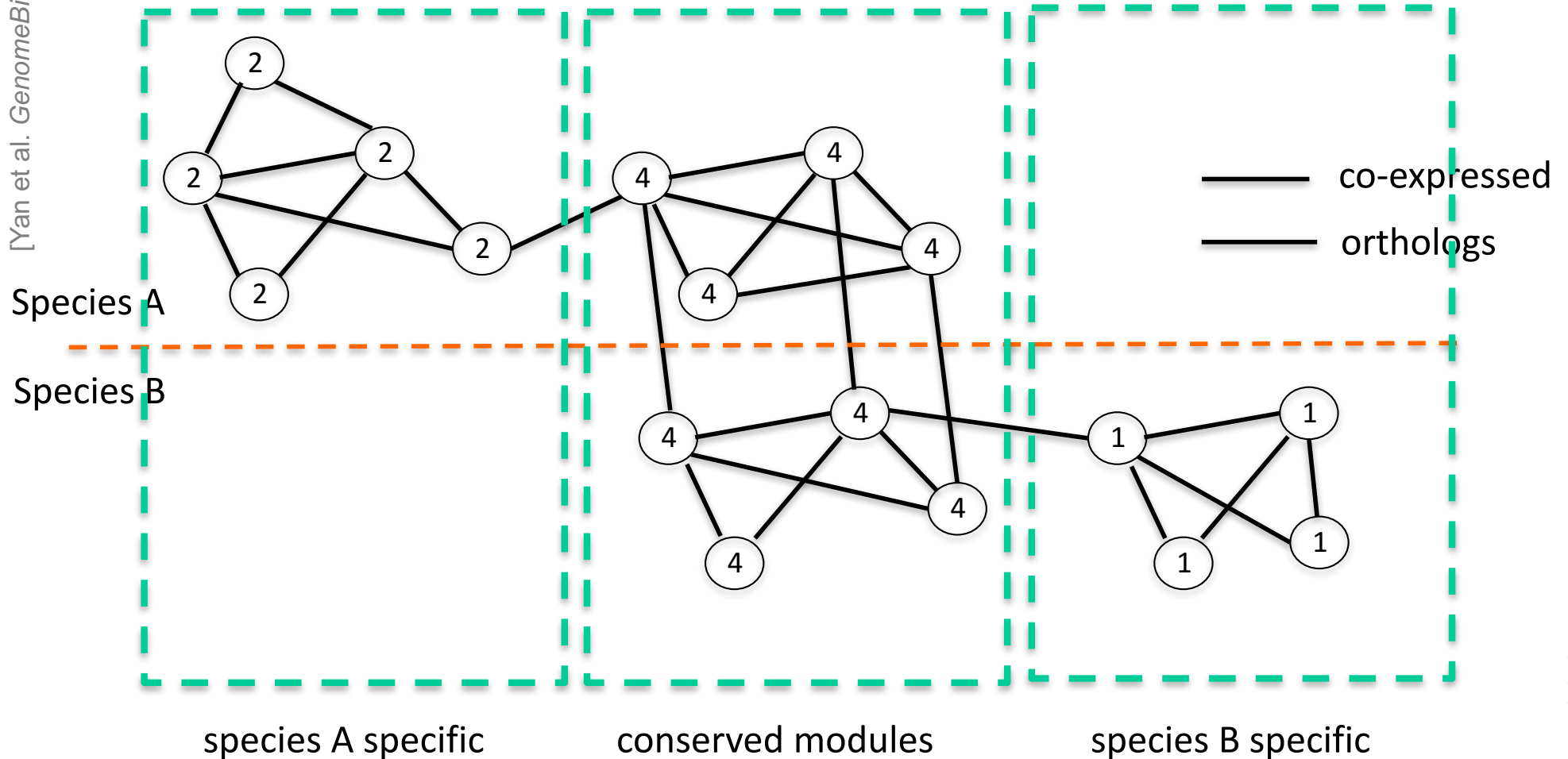
A toy example [orthoclust]



$$H = \boxed{Q(\text{for all } \sigma_i \text{ in A}) + Q(\text{for all } \sigma_i \text{ in B})} + K \sum_{(i,j') \in \text{Ortho}} \delta_{\sigma_i \sigma_{j'}}$$

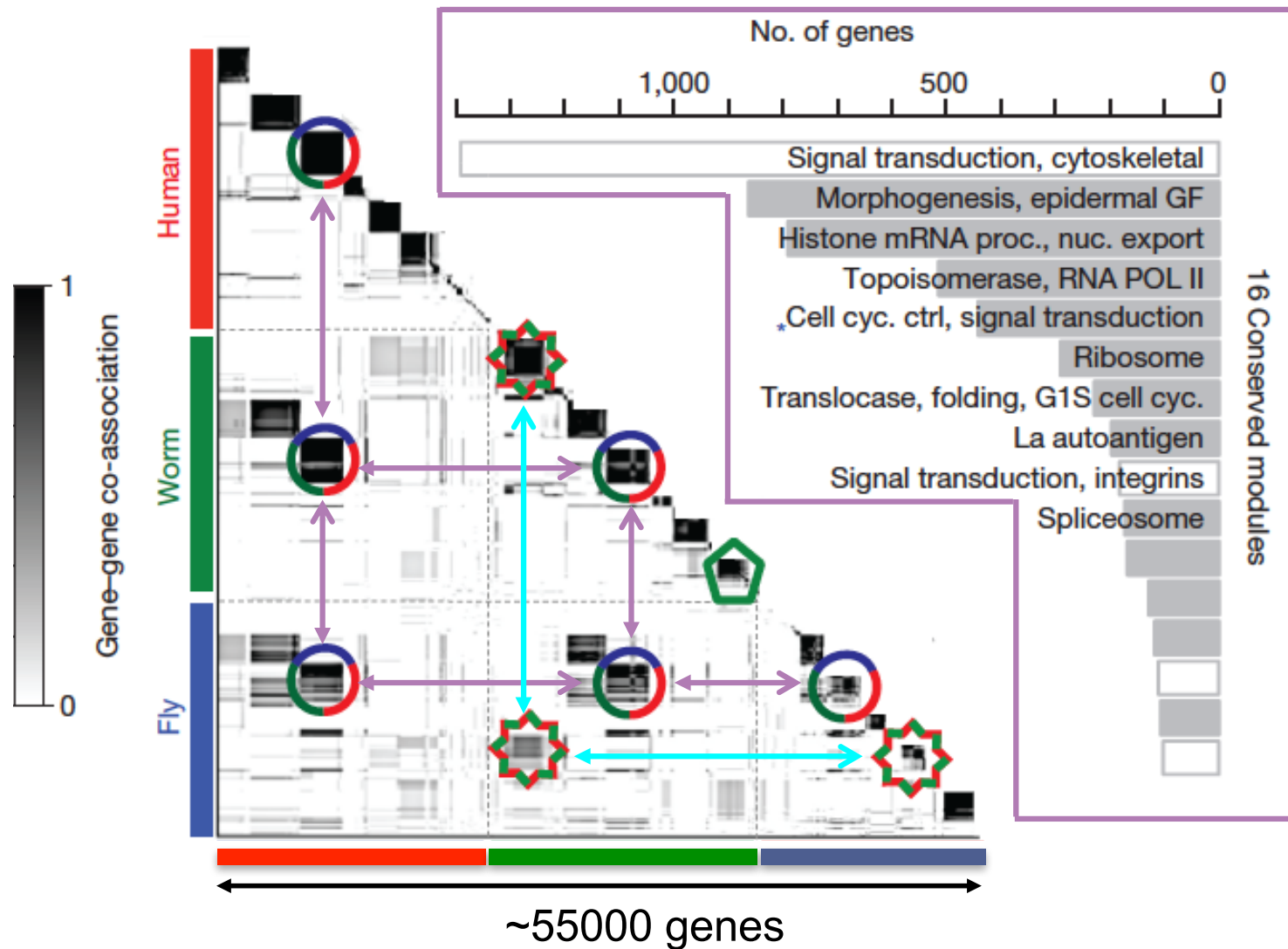
Favorableness = "Modularity" in species A + "Modularity" in species B + consistency betw. A & B

A toy example [orthoclust]



Use Potts model (generalized Ising model) to simultaneously cluster co-expressed genes within an organism as well as orthologs shared between organisms. Here, the ground state configuration correspond to three modules: 1, 2, 4.

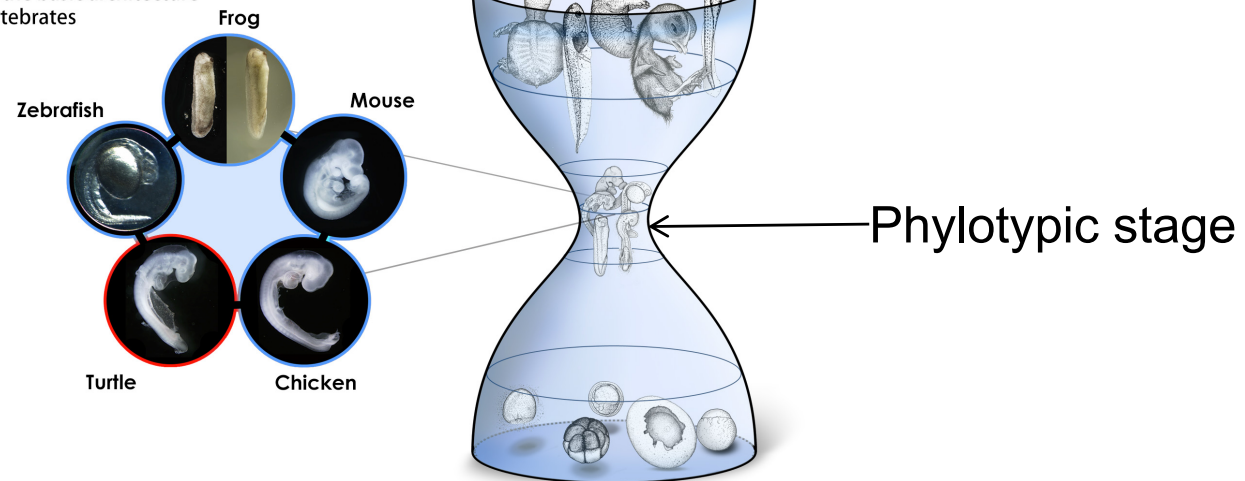
Application for more than 2



[Nature 512:445 ('14); doi: 10.1038/nature13424]

Conserved modules exhibit canonical hourglass behavior

Developmental stages that show the basic architecture of vertebrates



Illustrations courtesy Naoki Irie

Canonical Inter-organism Behavior

- “Hourglass hypothesis”: all organisms go through a particular stage in embryonic development (“phylotypic” stage) where inter-organism expression differences of orthologous genes are smallest.
- **We identify modules (12 out of 16) which have this behavior at the phylotypic stage.**

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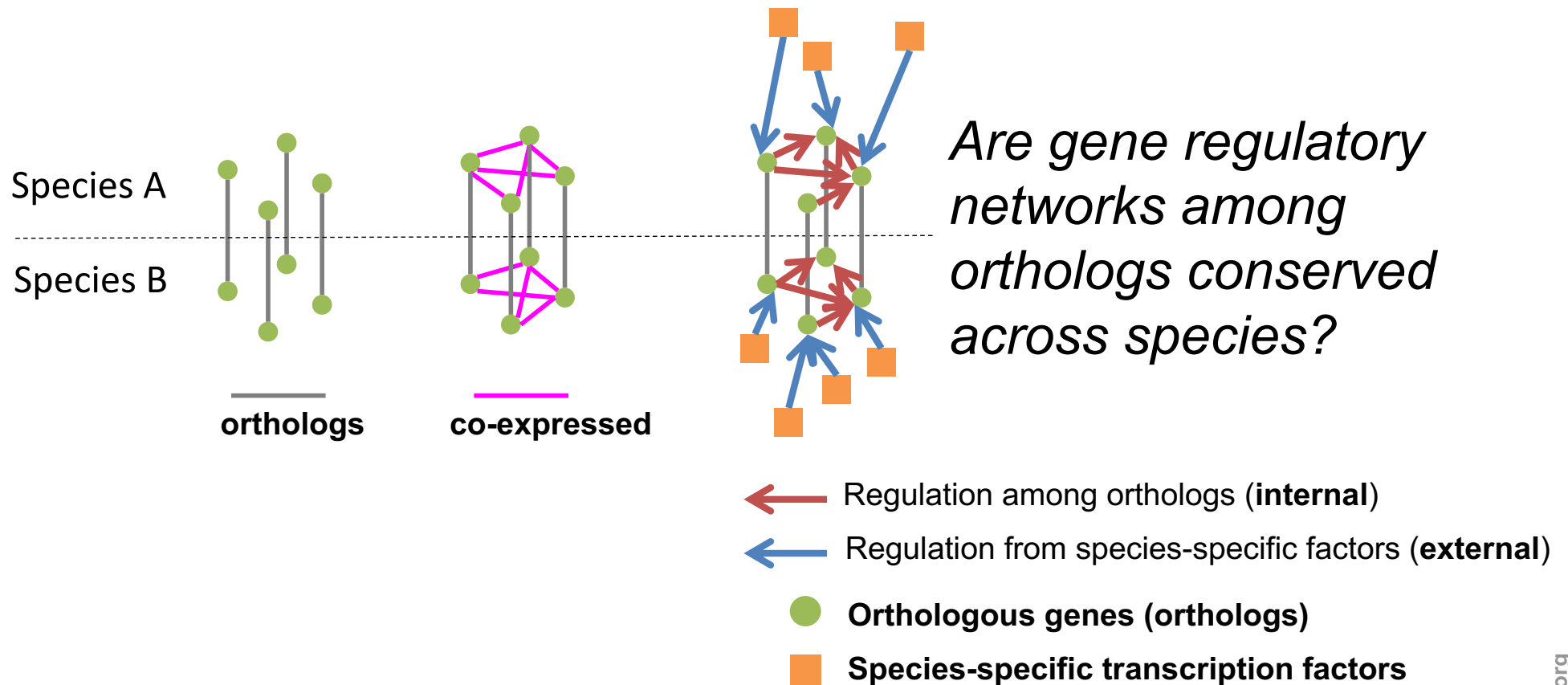
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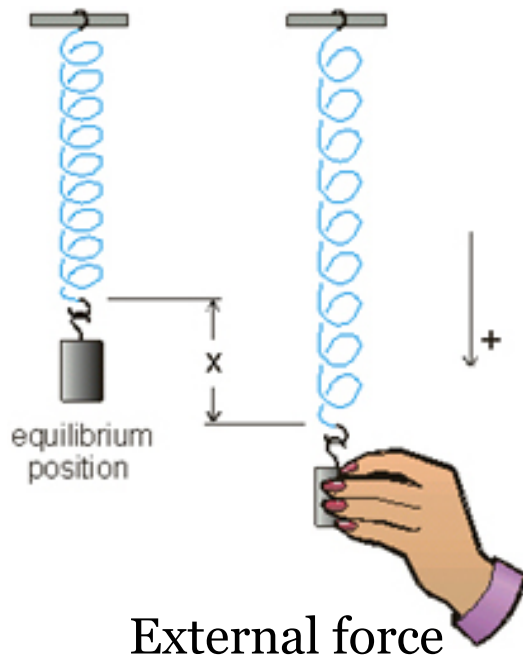
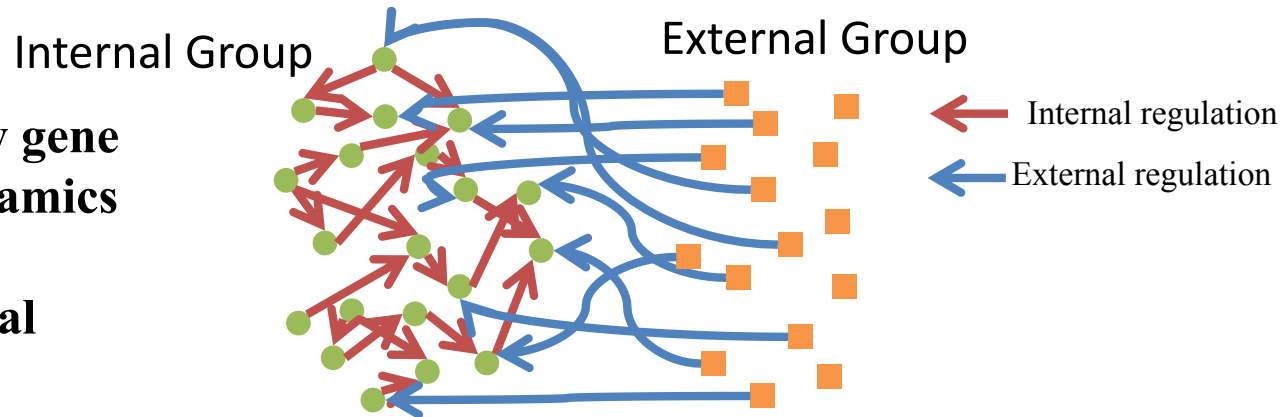
Are gene regulations among orthologs conserved across species?



To what degree can't ortholog expression levels be predicted due to species-specific regulation

Internal & external gene regulatory networks

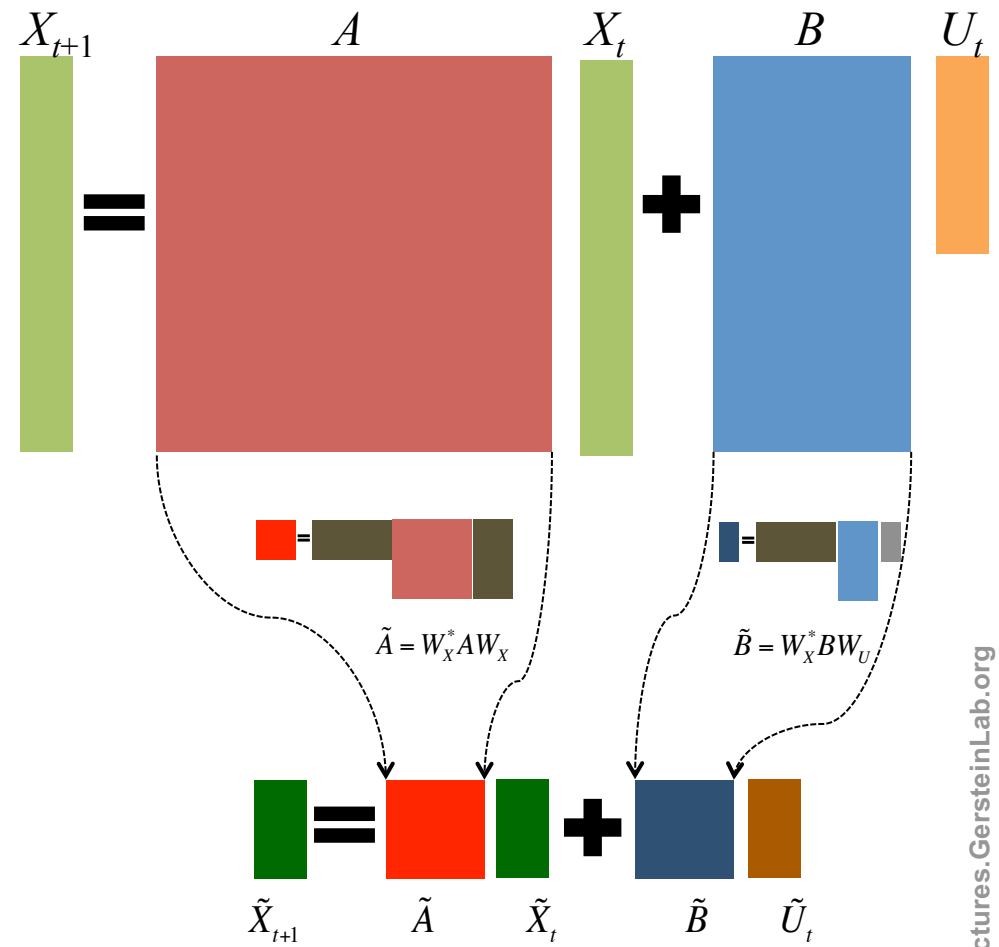
How to identify gene expression dynamics driven by internal/external regulation?



Interested system	Internal regulatory network	External regulatory network
Cross-species conserved genes	Conserved transcriptional factors (TFs)	Non-conserved TFs
Protein-coding genes	TFs	micro-RNAs
Individual's protein coding genes	Wild-type TFs	Somatic mutated TFs
Protein-coding genes in brain	Commonly expressed TFs	Brain-specific expressed TFs
Protein-coding genes in development	House-keeping TFs	Developmental TFs

State-space model for internal and external gene regulatory networks

- **State X_{t+1} :** Gene expression vector of Group X at time $t+1$
- A_{ij} captures temporal casual influence from Gene i to Gene j in internal group
- **State X_t :** Gene expression vector of internal group at time t
- B_{kl} captures temporal casual influence from external factor k to Gene l in internal group
- **Control U_t :** Gene expression vector of external factors at time t



State-space model for internal and external gene regulatory networks

Not enough data to estimate state space model for genes
(e.g., 25 time points per gene to estimate 4 million elements of A or B for 2000 genes)

$$X_{t+1} = AX_t + BU_t$$

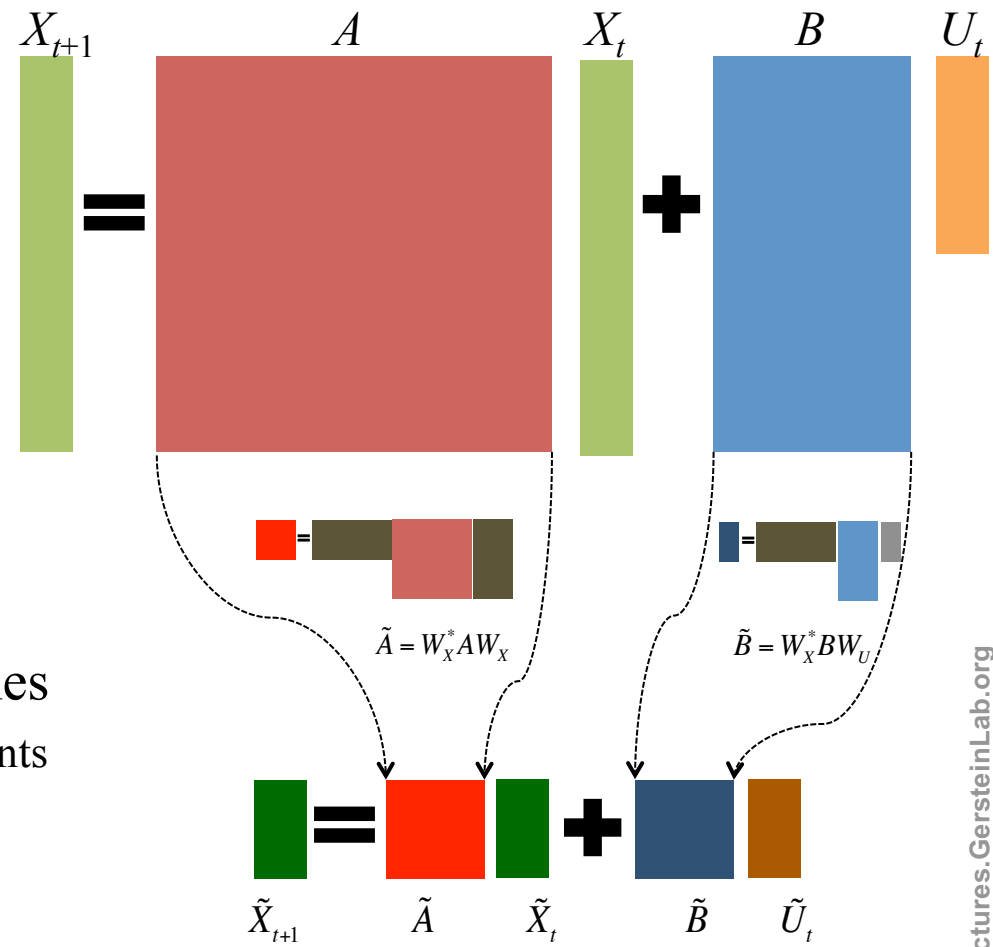


Dimensionality reduction from genes to meta-genes (e.g., SVD)



Effective state space model for meta-genes
(e.g., 250 time points to estimate 50 matrix elements if 5 meta-genes)

$$\tilde{X}_{t+1} = \tilde{A}\tilde{X}_t + \tilde{B}\tilde{U}_t$$



Canonical temporal expression trajectories from effective state space model

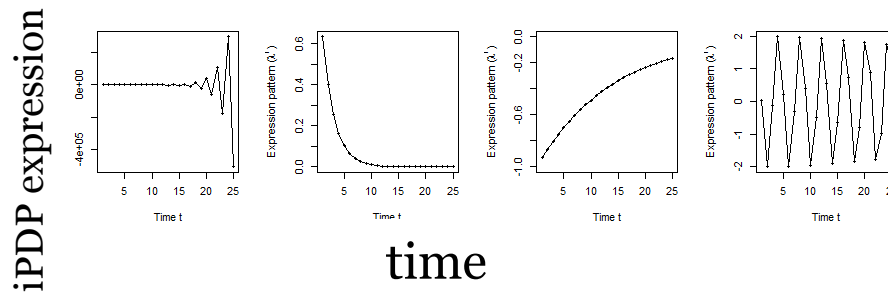
Is a std. 1st order homogeneous matrix difference equation. It can be solved by diagonalizing A giving....

$$\tilde{X}_{t+1} = \tilde{A} \tilde{X}_t + \tilde{B} \tilde{U}_t$$

p^{th} internal principal dynamic pattern (iPDP): $[\lambda_p^1, \lambda_p^2, \dots, \lambda_p^T]$, where λ_p is p^{th} eigenvalue of \tilde{A} .

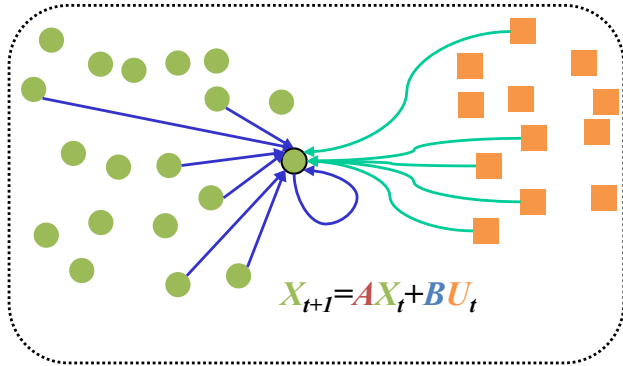


Canonical temporal expression trajectories (e.g., degradation, growth, damped oscillation, etc.)

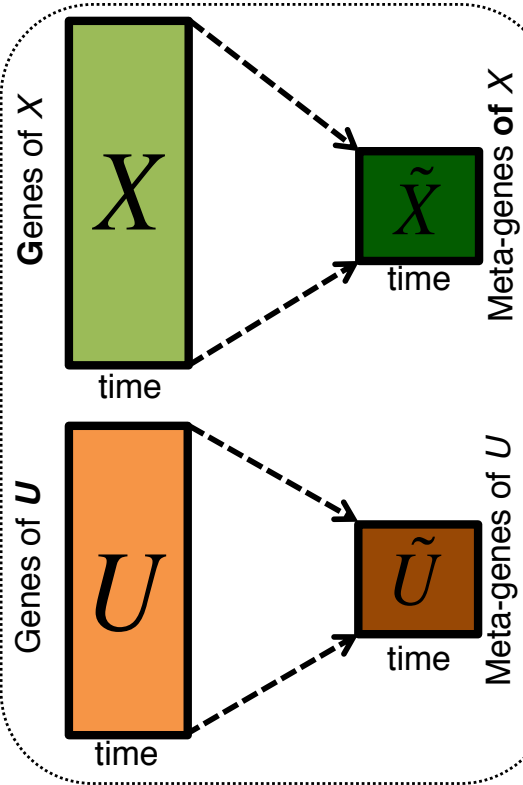


Flowchart

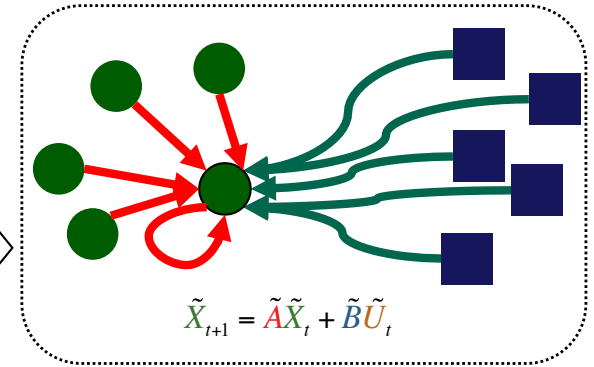
A. Gene state-space model



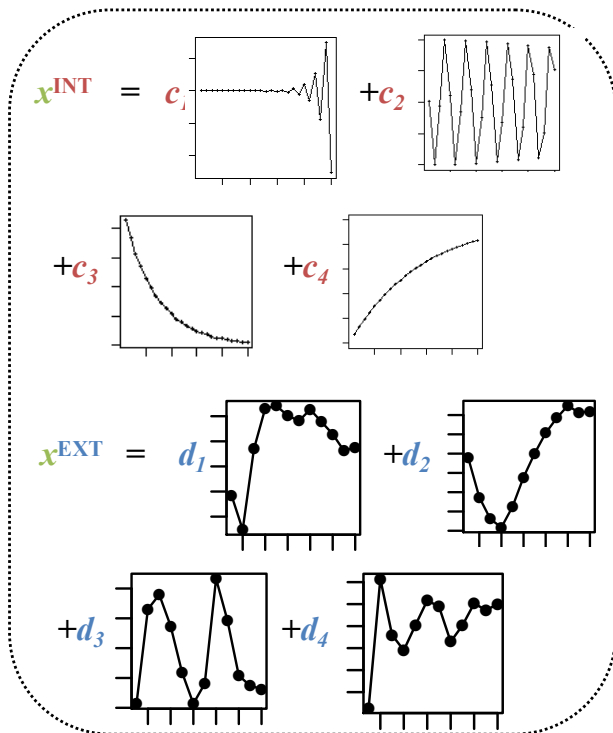
B. Dimensionality Reduction



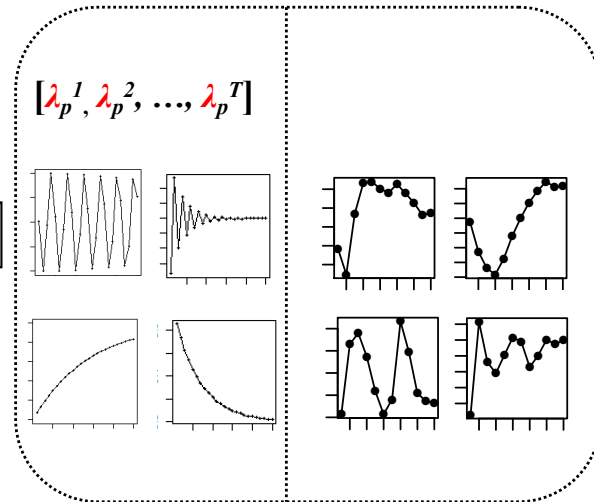
C. Meta-gene state-space model



E. Gene's internal (INT) and external (EXT) driven expression dynamics composed of PDPs



D. Internal/External Principal Dynamic Patterns (PDPs)

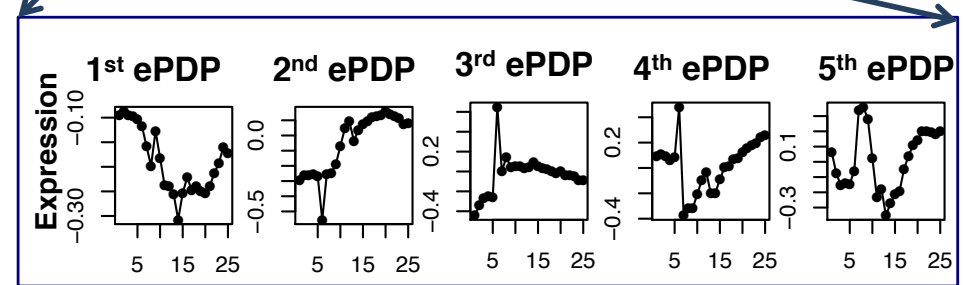
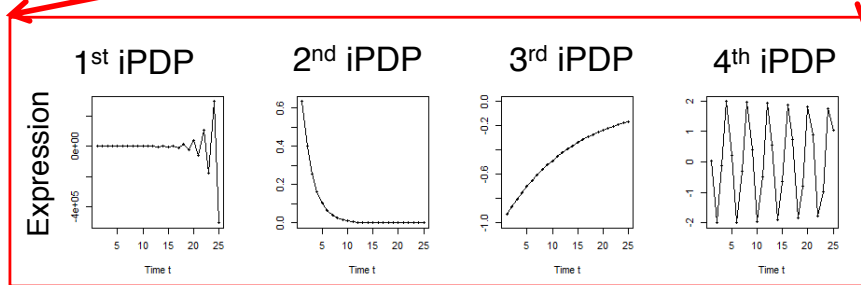


- ← ← Internal regulation among internal genes/meta-genes by A/\tilde{A}
- ← ← External regulation from external genes/meta-genes to internal genes/meta-genes in Group X by B/\tilde{B}
- ● Internal genes/meta-genes
- ■ External genes/meta-genes

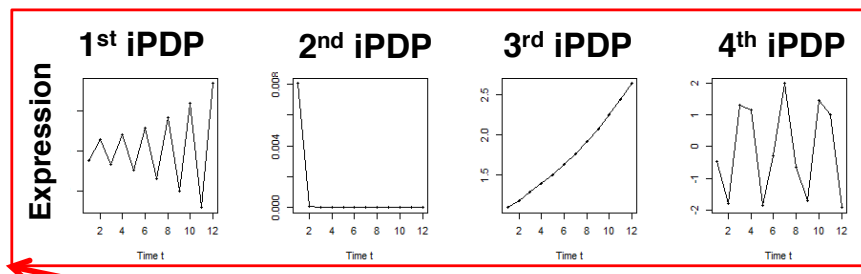
Orthologs have similar internal but different external dynamic patterns during embryonic development

Worm's effective state space model

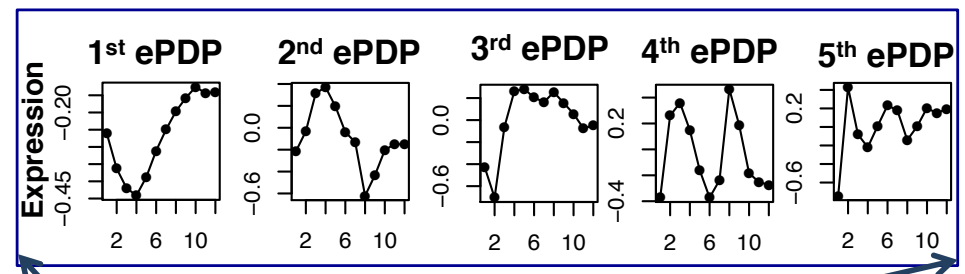
$$\text{Green} = \text{Red} \text{ Green} + \text{Blue} \text{ Orange}$$



Similar



Different

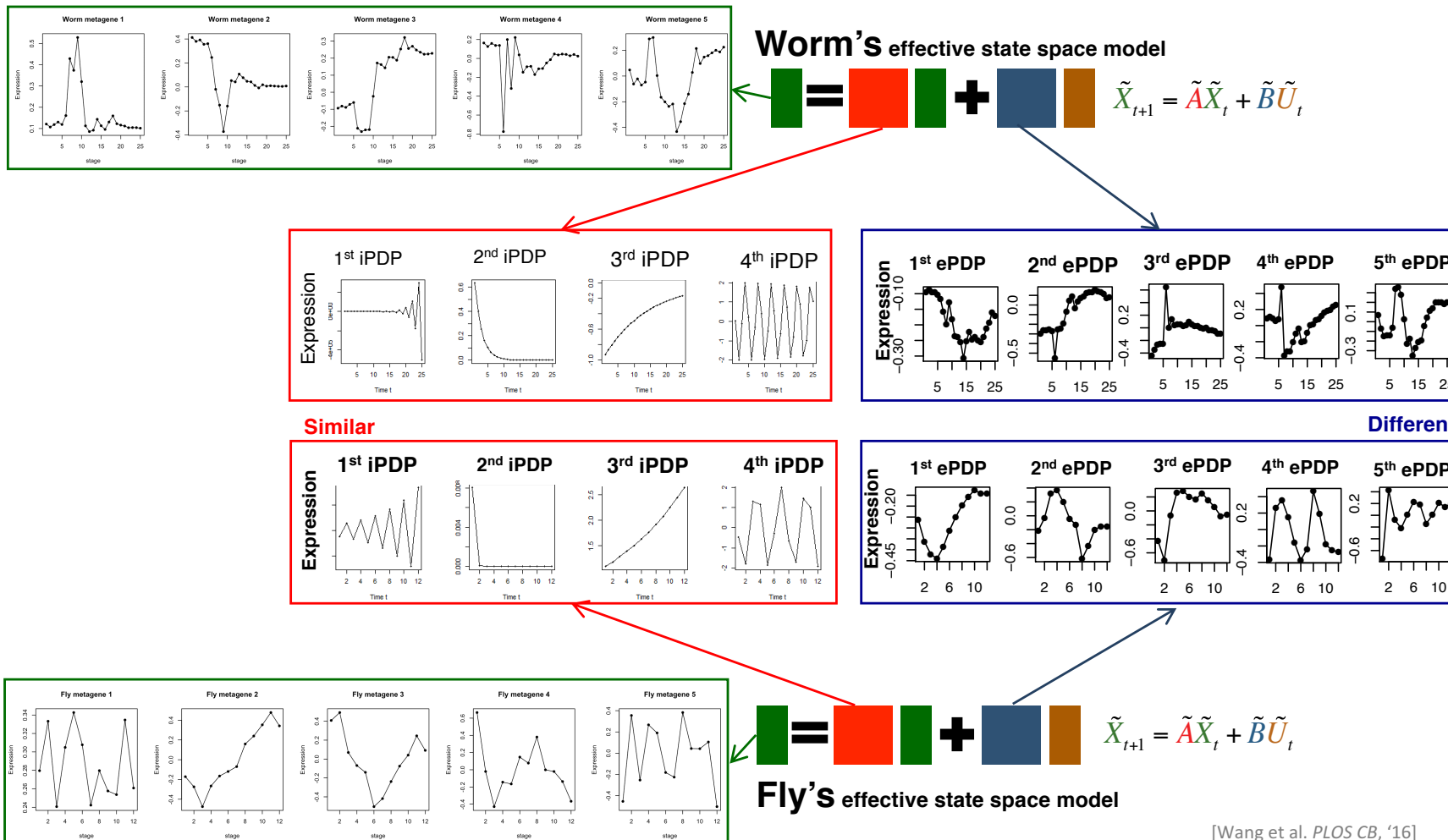


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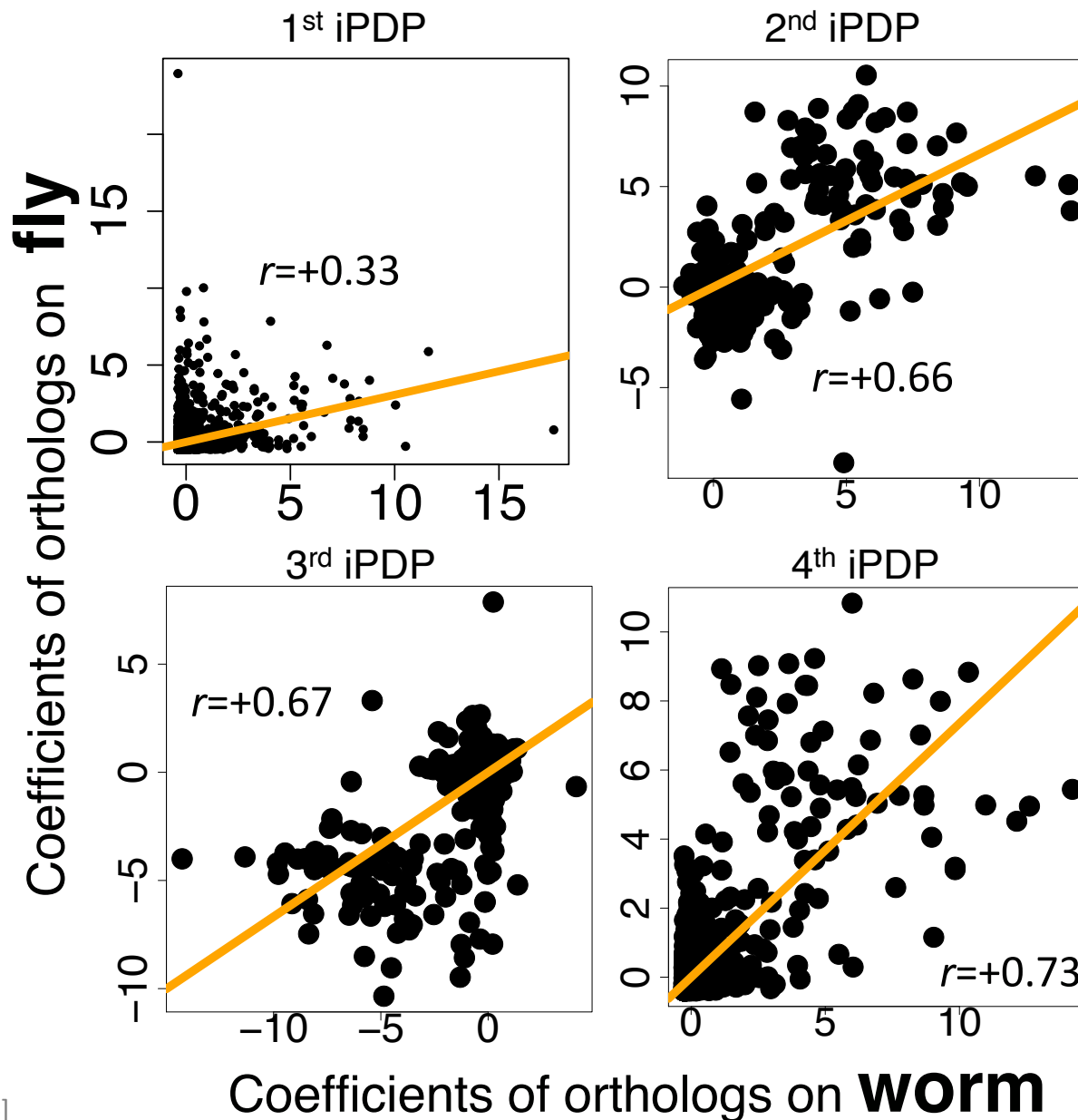
Fly's effective state space model

$$\tilde{X}_{t+1} = \tilde{A}\tilde{X}_t + \tilde{B}\tilde{U}_t$$

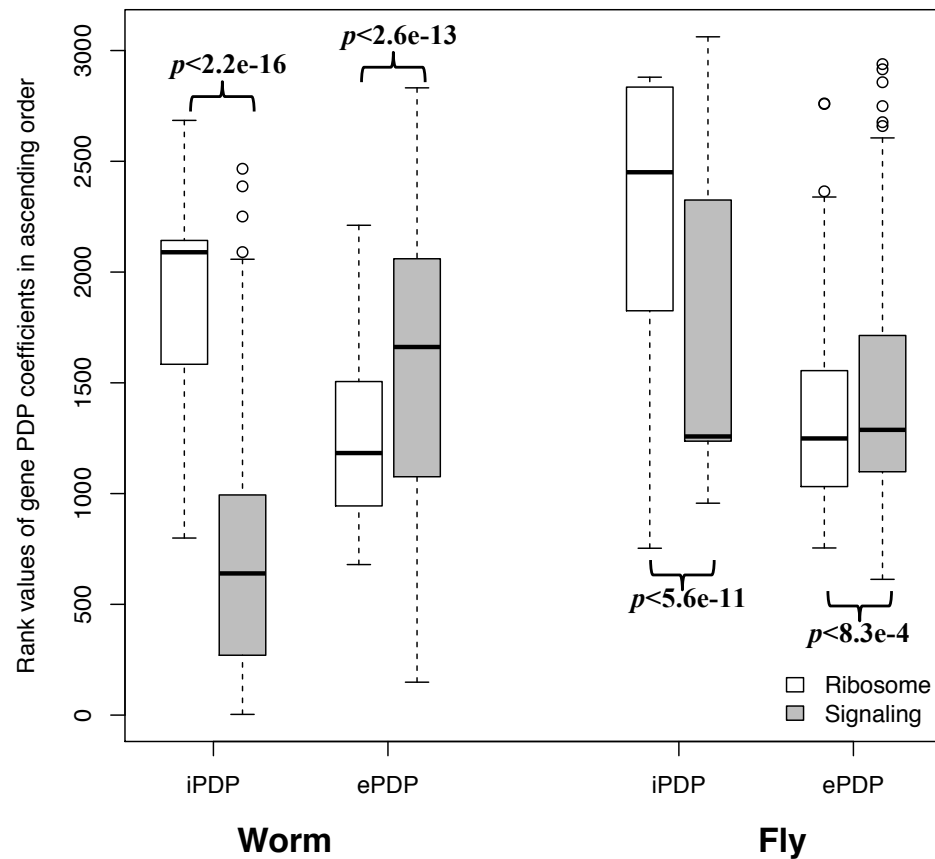
Orthologs have similar internal but different external dynamic patterns during embryonic development



Orthologs have correlated iPDP coefficients



Evolutionarily conserved & younger genes exhibit the opposite internal & external PDP coefficients



Ribosomal genes have significantly larger coefficients for the internal than external PDPs, but signaling genes exhibit the opposite trend

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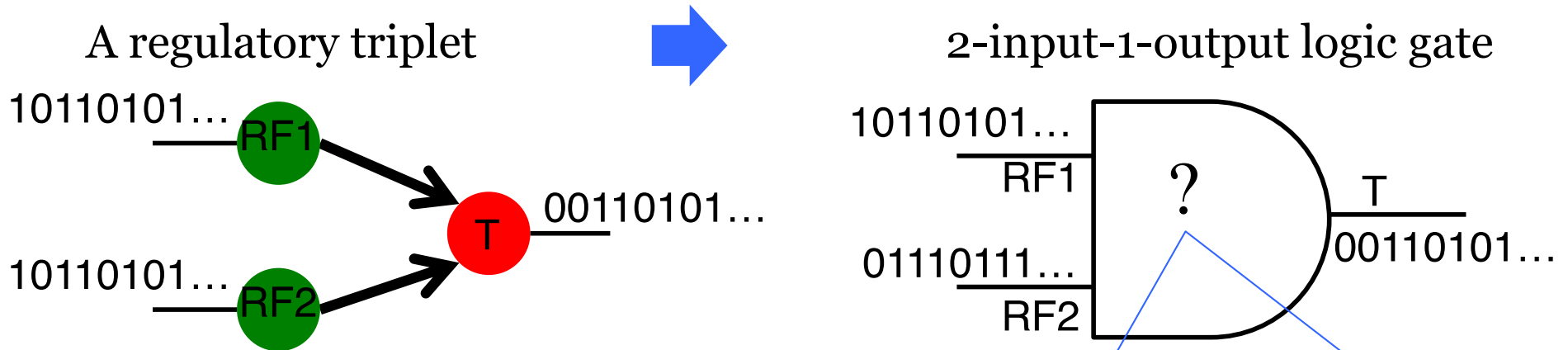
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Modeling cooperativity between TFs to target gene using logic gates



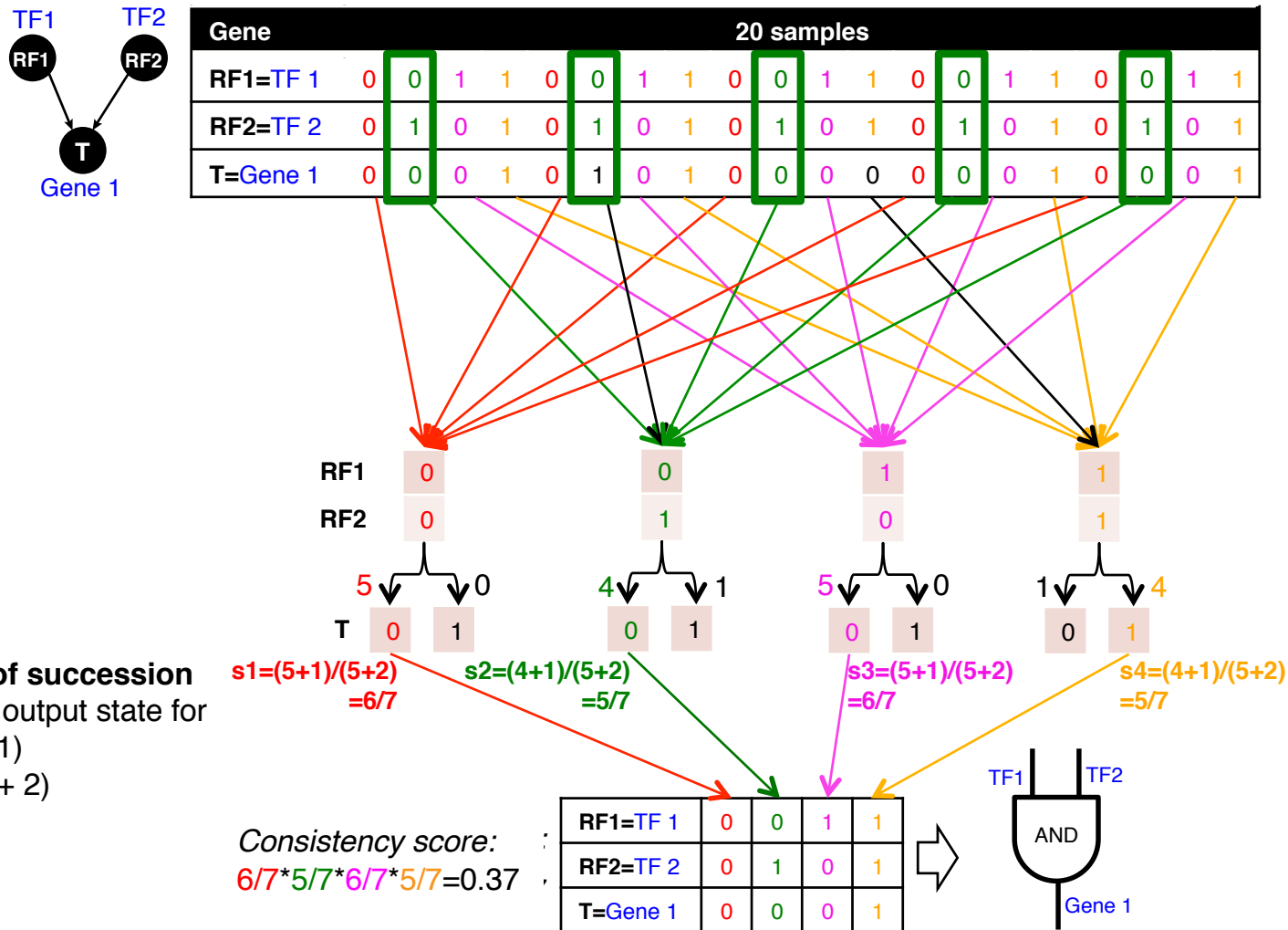
0 – gene off
 1 – gene on
 after binarizing gene
 expression data*

Input type (RF1, RF2)	RF1	0	0	1	1	} Binarized expression
	RF2	0	1	0	1	
Output	T	X	X	X	X	

X can be 0 or 1, so there are $2^4=16$ possible output combinations, each of which corresponds to a unique 2-input-1-output logic gate

*BoolNet, R package

An example: selection of the best-matched logic gate



Laplace's rule of succession
 $s = (\# \text{ of selected output state for the input type} + 1) / (\# \text{ of input type} + 2)$

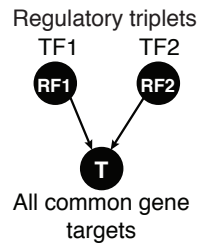
$s_1 = (5+1)/(5+2) = 6/7$

$s_2 = (4+1)/(5+2) = 5/7$

$s_3 = (5+1)/(5+2) = 6/7$

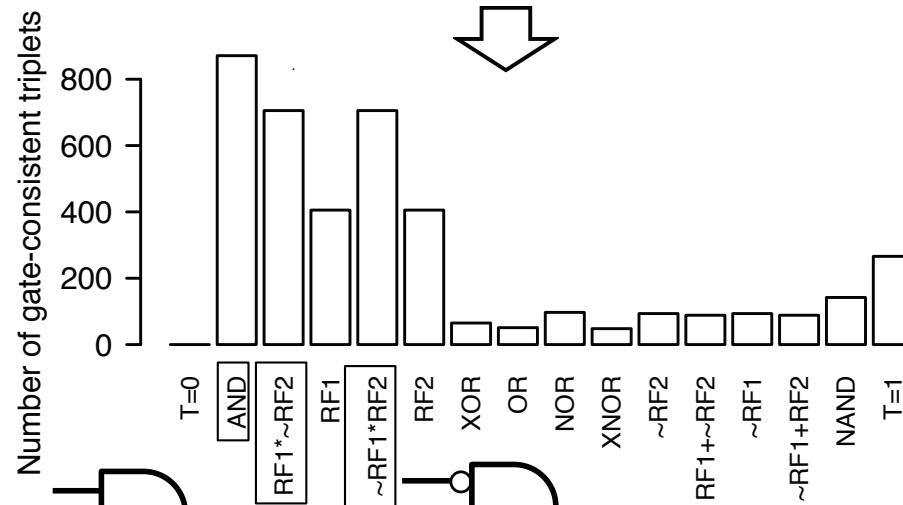
$s_4 = (4+1)/(5+2) = 5/7$

App. 1 – TF cooperativity in the cell cycle

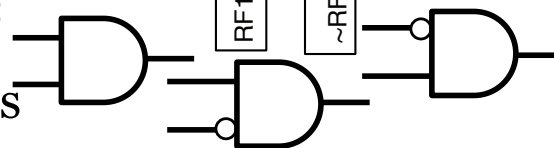


Target gene	2464
TF	176
Triplet	39,011
Time point	59

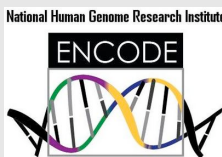

Triplet ID	RF1	RF2	Common Target Gene (T)	Matched logic gate
1	YHR084W	YBR083W	YBR082C	AND
2	YKL112W	YIL131C	YMR198W	OR
...
39011	YOR113W	YBL103C	YDR042C	XOR



AND-like gates

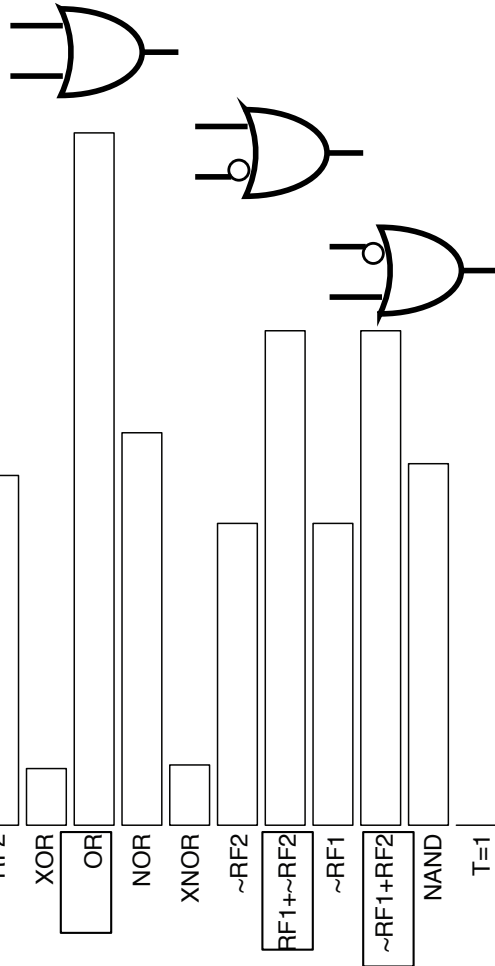


Acute Myeloid Leukemia (AML)

Target gene	1824	ENCODE Data (K562, ChIP-seq)
TF	70	 The logo for the ENCODE project, featuring a stylized DNA double helix in purple and yellow, with the word "ENCODE" in a black box above it. Above the logo is the text "National Human Genome Research Institute".
Regulatory triplet	50,865	TCGA Data (AML, level 3, RNA-seq) https://tcga-data.nci.nih.gov/tcga/tcgaDownload.jsp
Patient sample	197	 The logo for The Cancer Genome Atlas (TCGA), featuring a stylized DNA double helix in purple and yellow, with the text "THE CANCER GENOME ATLAS" and a globe icon below it.

App. 2 – TF cooperativity in AML

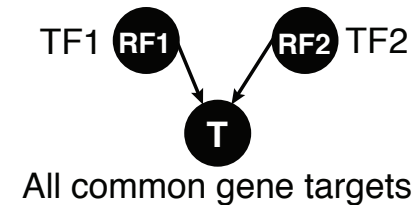
OR-like gates



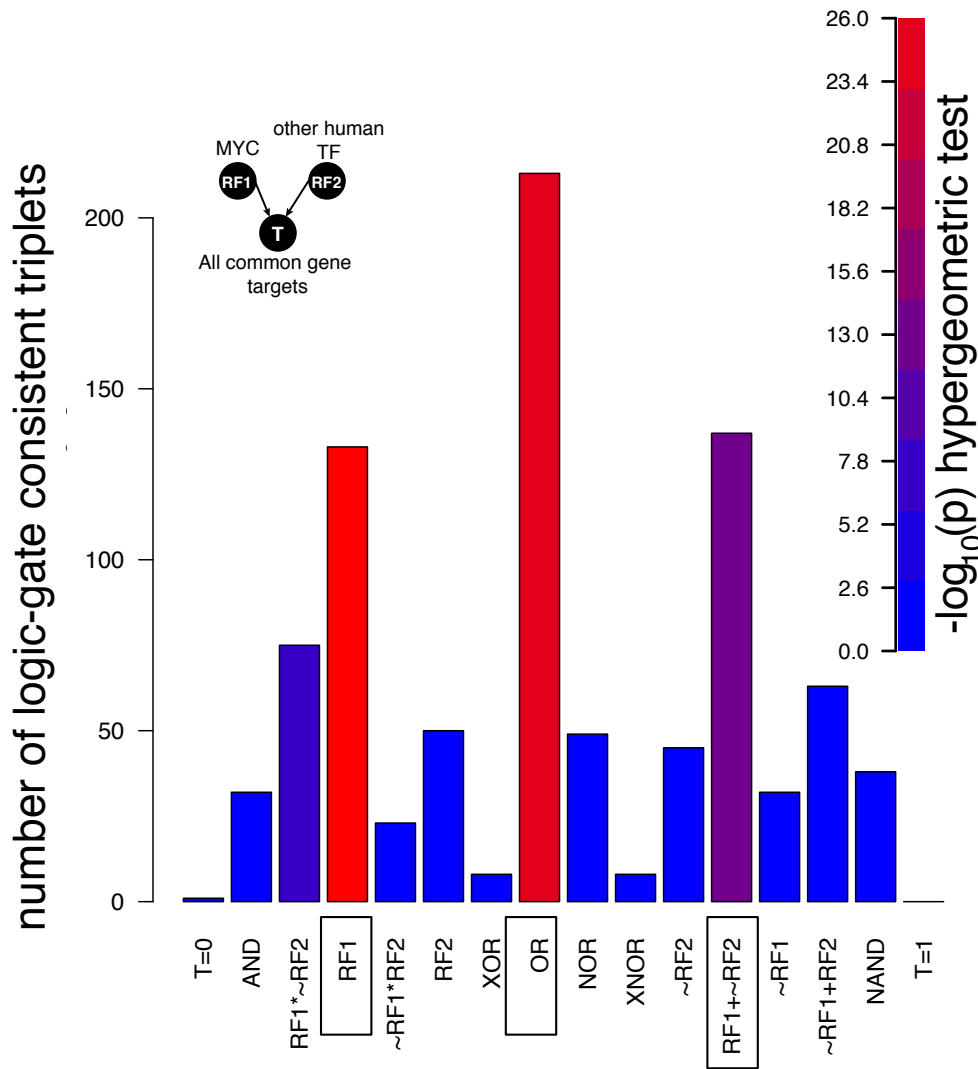
Regulatory triplet from ENCODE	50,865
Patient sample for TCGA AML expression data	197

Human TF-TF-target

RF1	RF2	Common Target Gene (T)	Matched logic gate
ATF3	BDP1	YPEL1	AND
MYC	BCL3	BCR	T=RF1
ATF3	BRF2	AIF1L	AND
...



Cancer-related TF, MYC, universally amplifies target expression



Restrict to RF1=MYC, giving 2,153 triplets

- RF1
- OR(RF1, RF2)
- OR(RF1, NOT RF2)



High expression of MYC is sufficient for high target gene expression

c-Myc Is a Universal Amplifier of Expressed Genes in Lymphocytes and Embryonic Stem Cells

Cell

Zuqin Nie,^{1,6} Gangqing Hu,^{2,6} Gang Wei,² Kairong Cui,² Arito Yamane,³ Wolfgang Resch,³ Ruoning Wang,⁴ Douglas R. Green,⁴ Lino Tessarollo,⁵ Rafael Casellas,³ Keji Zhao,^{2,*} and David Levens^{1,*}

Transcriptome Analysis: Tackling core issues related to regulation & also mining the “data exhaust” of this activity

- **Expression Clustering**,

Cross-species

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- The General

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- Issues w/ current social & tech approaches: inconsistencies & burdensome security

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- Co-authorship network statistics relate to publication rollouts & show gradual adoption by a diverse community
- Key role of brokers in data dissemination

2-sided nature of functional genomics data: Analysis can be very General/Public or Individual/Private



- General quantifications related to overall aspects of a condition & are not tied to an individual's genotype - ie what genes go up in cancer
 - However, data is derived from an individual & tagged with an individual's genotype
- Other calculations aim to use genotype & specific aspects of the quantification to derive general relations related to sequence variation & gene expression
- Some calculations and data derive finding very specific to the variants in a particular individual

Tricky Privacy Considerations in Personal Genomics

- **Genetic Exceptionalism :**
The Genome is very fundamental data, potentially very revealing about one's identity & characteristics
- **Personal Genomic info. essentially meaningless currently but will it be in 20 yrs? 50 yrs?**
 - Genomic sequence very revealing about one's children. Is true consent possible?
 - Once put on the web it can't be taken back
- **Culture Clash:**
Genomics historically has been a proponent of “open data” but not clear personal genomics fits this.
 - Clinical Medicine has a very different culture.
- **Ethically challenged** history of genetics
 - Ownership of the data & what consent means (Hela)
 - Could your genetic data give rise to a product line?



Genomics has similar "Big Data" Dilemma in the Rest of Society

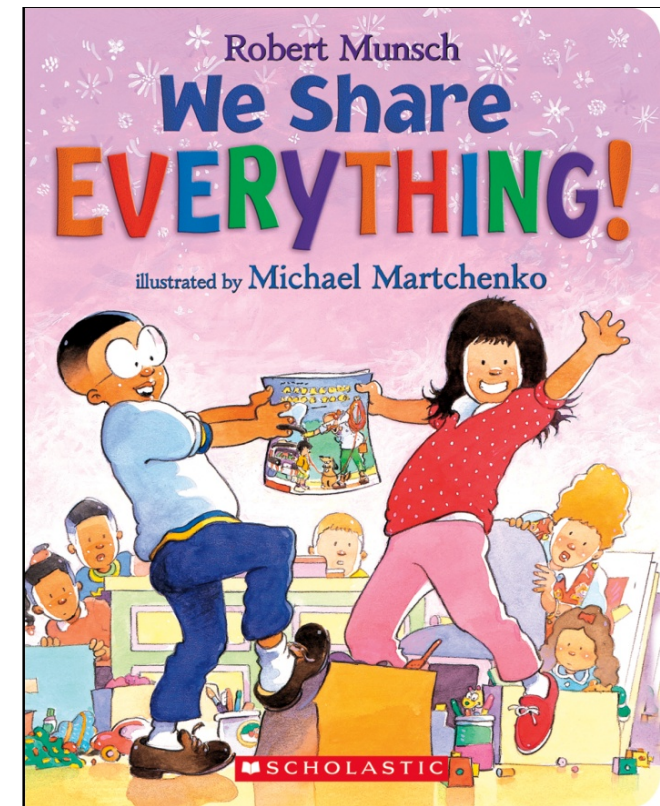
- Sharing & "peer-production" is central to success of many new ventures, with the same risks as in genomics
 - **EG web search**: Large-scale mining essential



- We confront privacy risks every day we access the internet
- (...or is the genome more exceptional & fundamental?)

The Other Side of the Coin: Why we should share

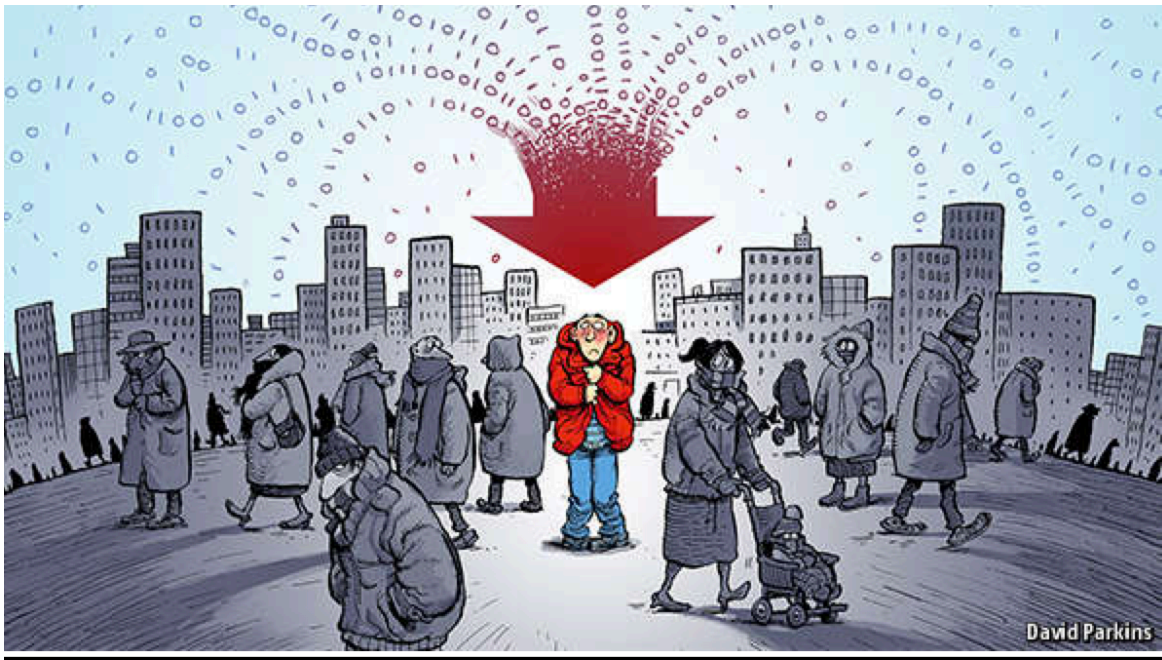
- Sharing helps **speed research**
 - Large-scale mining of this information is important for medical research
 - Privacy is cumbersome, particularly for big data
- Sharing is important for **reproducible research**
- Sharing is useful for **education**
 - More fun to study a known person's genome
 - Eg Zimmer's Game of Genomes in STAT



[Yale Law Roundtable ('10). *Comp. in Sci. & Eng.* 12:8; D Greenbaum & M Gerstein ('09). *Am. J. Bioethics*; D Greenbaum & M Gerstein ('10). *SF Chronicle*, May 2, Page E-4; Greenbaum et al. *PLOS CB* ('11)]

CARL ZIMMER'S
GAME OF GENOMES
SEASON 1





[Economist, 15 Aug '15]

The Dilemma

- The individual (harmed?) v the collective (benefits)
 - But do sick patients care about their privacy?
- How to balance risks v rewards - Quantification
 - What is acceptable risk? What is acceptable data leakage?
Can we quantify leakage?
 - Ex: photos of eye color
 - Cost Benefit Analysis: how helpful is identifiable data in genomic research v. potential harm from a breach?

Current Social & Technical Solutions

- **Closed Data** Approach

- Consents
- “Protected” distribution via dbGAP
- Local computes on secure computer

- Issues with Closed Data

- Non-uniformity of consents & paperwork
 - Different international norms, leading to confusion
- Encryption & computer security creates burdensome requirements on data sharing & large scale analysis
- Many schemes get “hacked”

- **Open Data**

- Genomic “test pilots” (ala PGP)?
 - Sports stars & celebrities?
- Some public data & data donation is helpful but is this a realistic solution for an unbiased sample of ~1M

Strawman Hybrid **Social** & **Tech** Proposed Solution?

- Fundamentally, researchers have to keep genetic secrets.
 - **Need for an (international) legal framework**
 - Genetic Licensure & training for individuals (similar to medical license, drivers license)
- Technology to make things easier
 - Cloud computing & enclaves (eg solution of Genomics England)
- Technological barriers shouldn't create a social incentive for “hacking”
- **Quantifying Leakage & allowing a small amounts of it**
- **Careful separation & coupling of private & public data**
 - **Lightweight, freely accessible secondary datasets coupled to underlying variants**
 - Selection of stub & "test pilot" datasets for benchmarking
 - Develop programs on public stubs on your laptop, then move the program to the cloud for private production run

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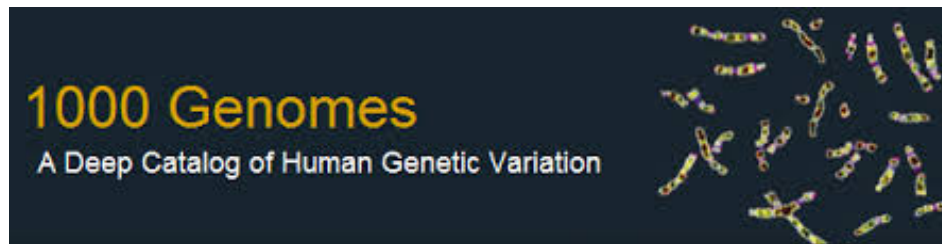
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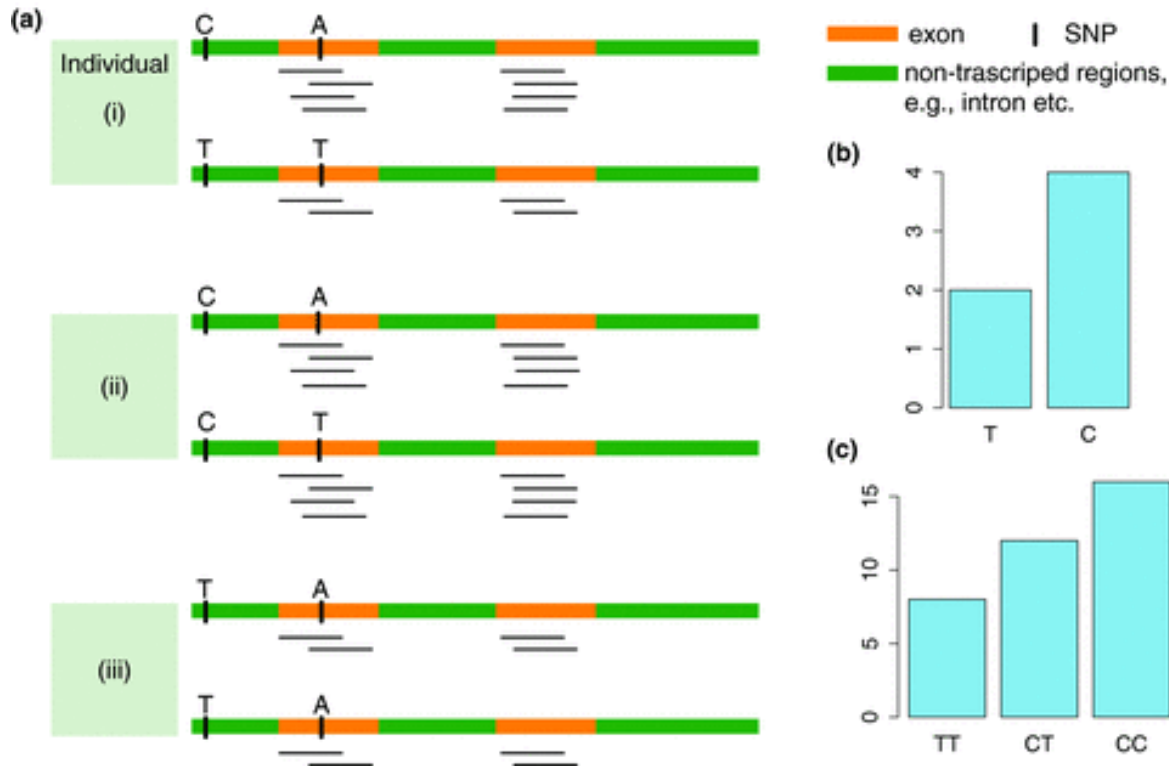
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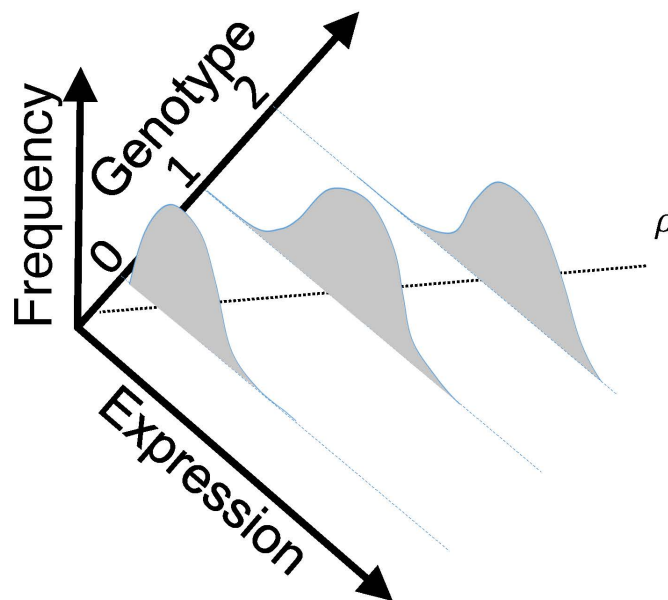
Representative Expression, Genotype, eQTL Datasets

- Genotypes are available from the 1000 Genomes Project
- mRNA sequencing for 462 individuals
 - Publicly available quantification for protein coding genes
- Approximately 3,000 cis-eQTL (FDR<0.05)





[Biometrics 68(1) 1–11]



eQTL Mapping Using RNA-Seq Data

- eQTLs are genomic loci that contribute to variation in mRNA expression levels
- eQTLs provide insights on transcription regulation, and the molecular basis of phenotypic outcomes
- eQTL mapping can be done with RNA-Seq data

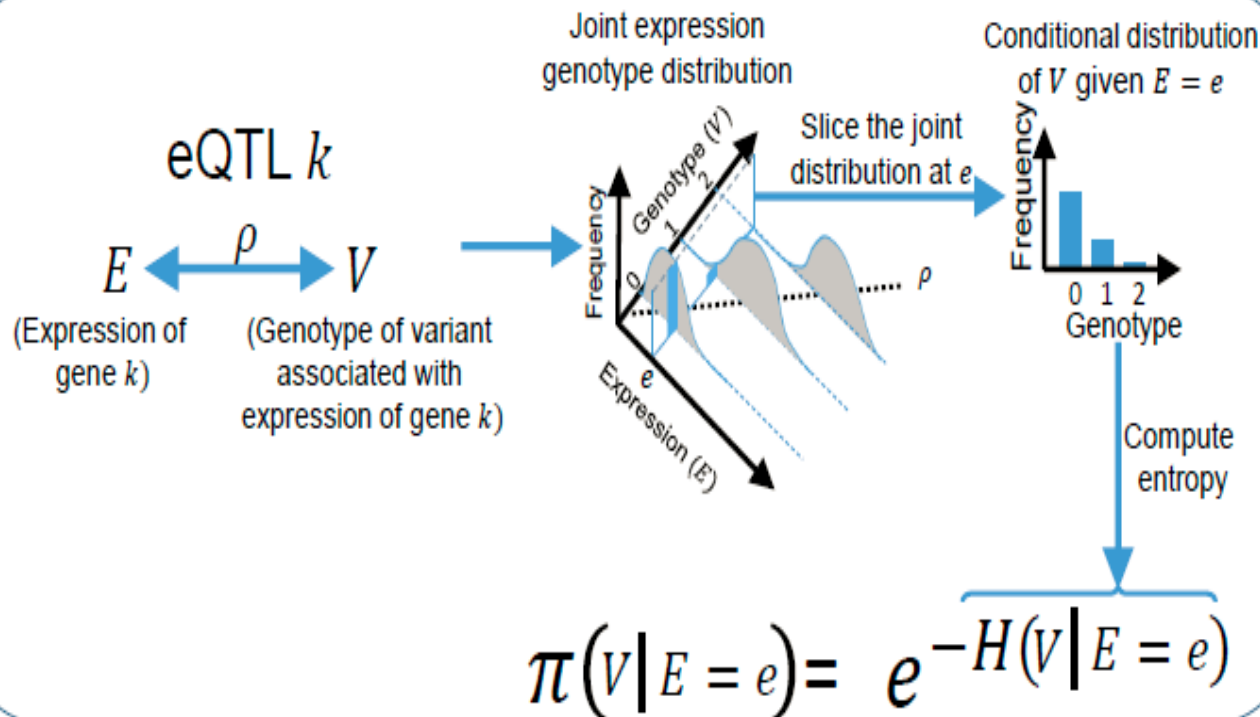
Information Content and Predictability

$$ICI \left(\begin{array}{l} \text{Individual has variant} \\ \text{genotypes } g_1, g_2, \dots, g_n \\ \text{for variants } V_1, V_2, \dots, V_n \end{array} \right) = \log \left(\frac{1}{\text{Frequency of } V_1 \text{ genotype}} \right) + \log \left(\frac{1}{\text{Frequency of } V_2 \text{ genotype}} \right) + \dots + \log \left(\frac{1}{\text{Frequency of } V_n \text{ genotype}} \right)$$

$g_1 = 2$ $g_2 = 1$ $g_n = 2$

V_1 genotype frequencies V_2 genotype frequencies V_n genotype frequencies

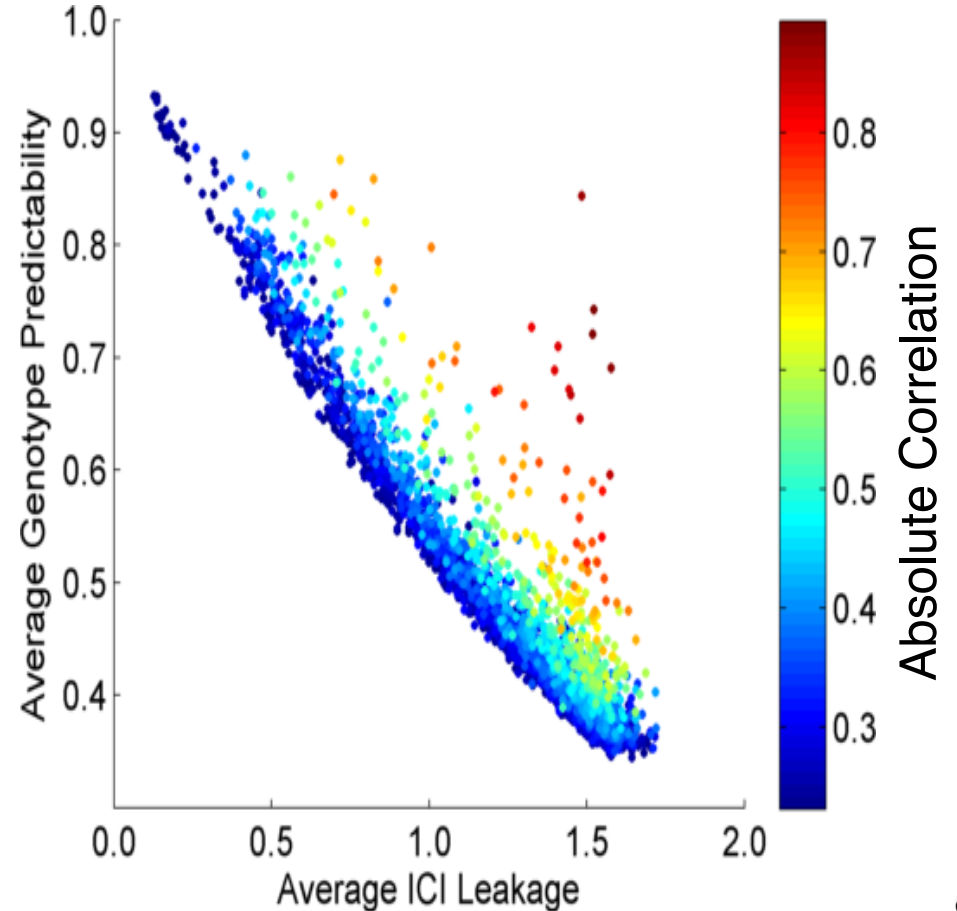
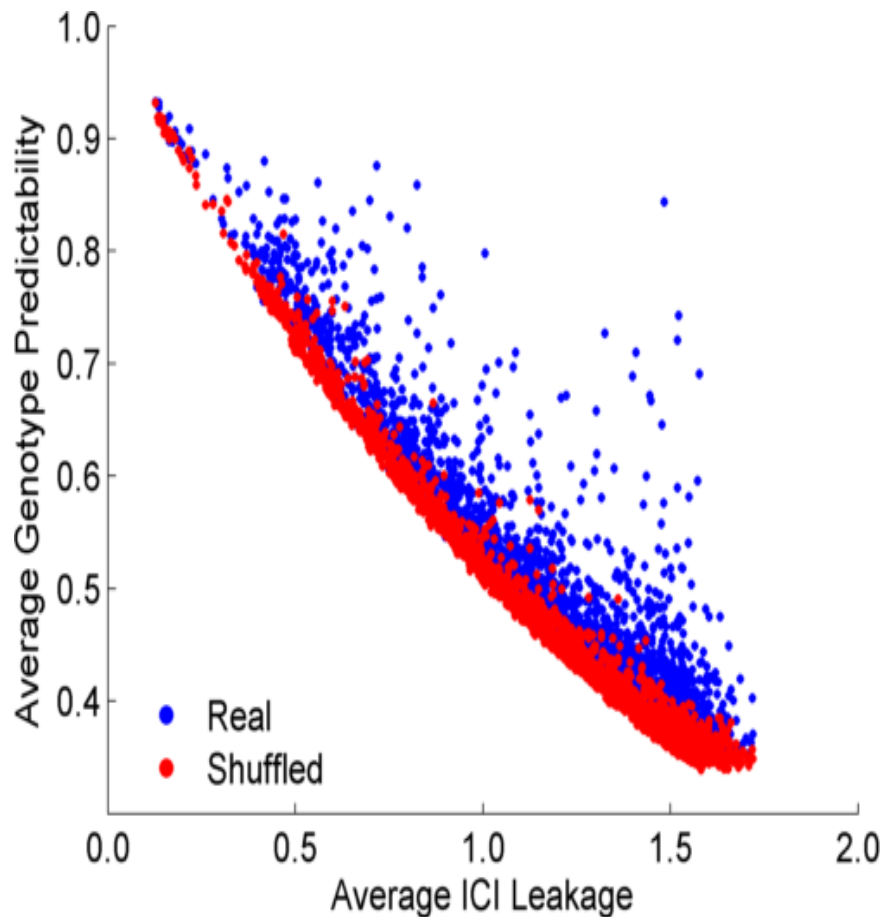
- Higher frequency: Lower ICI
- Lower frequency: Higher ICI
- Additive for multiple variants



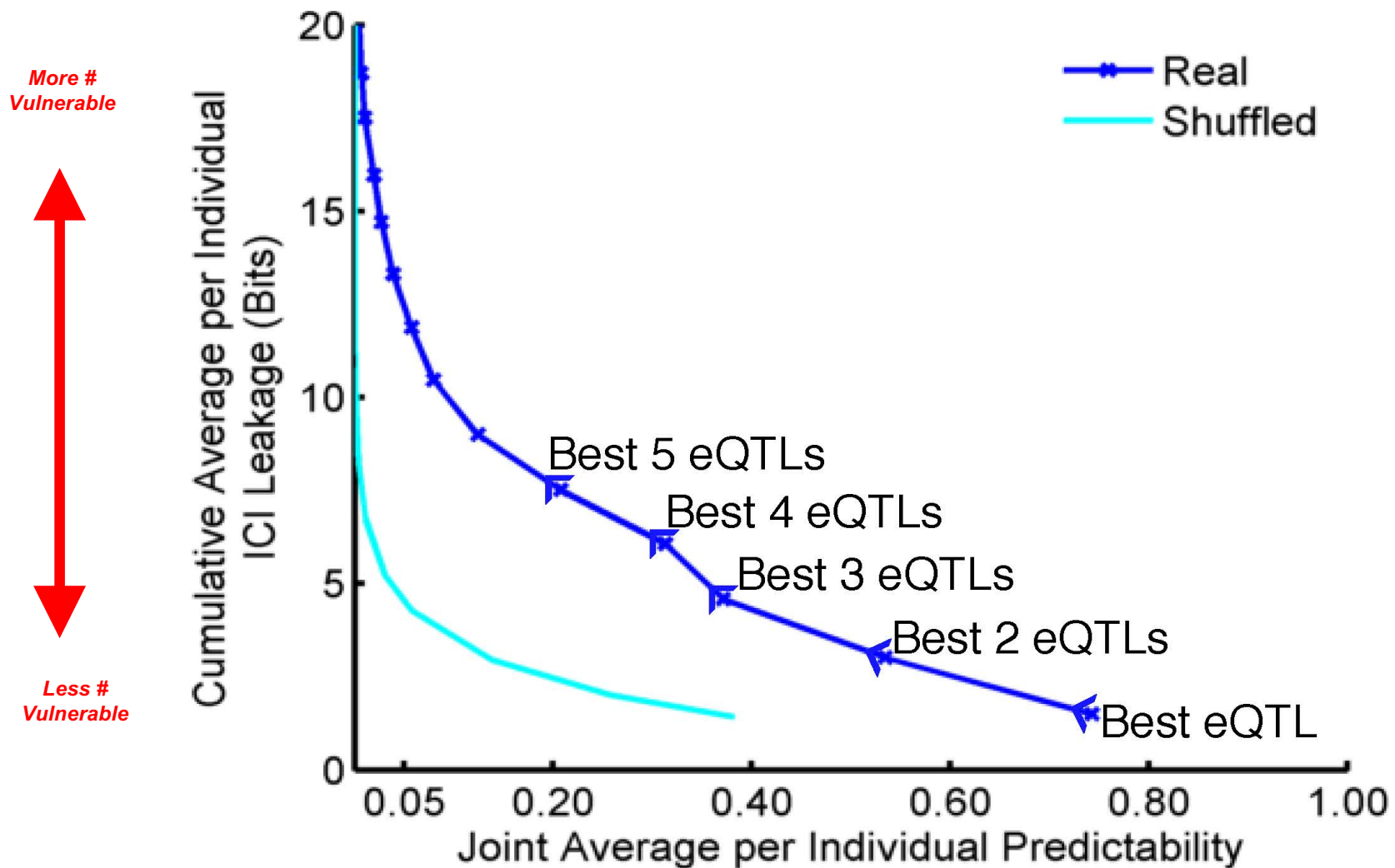
- Condition specific entropy
- Higher cond. entropy: Lower predictability
- Lower cond. entropy: Higher predictability
- Additive for multiple eQTLs

Per eQTL and ICI Cumulative Leakage versus Genotype Predictability

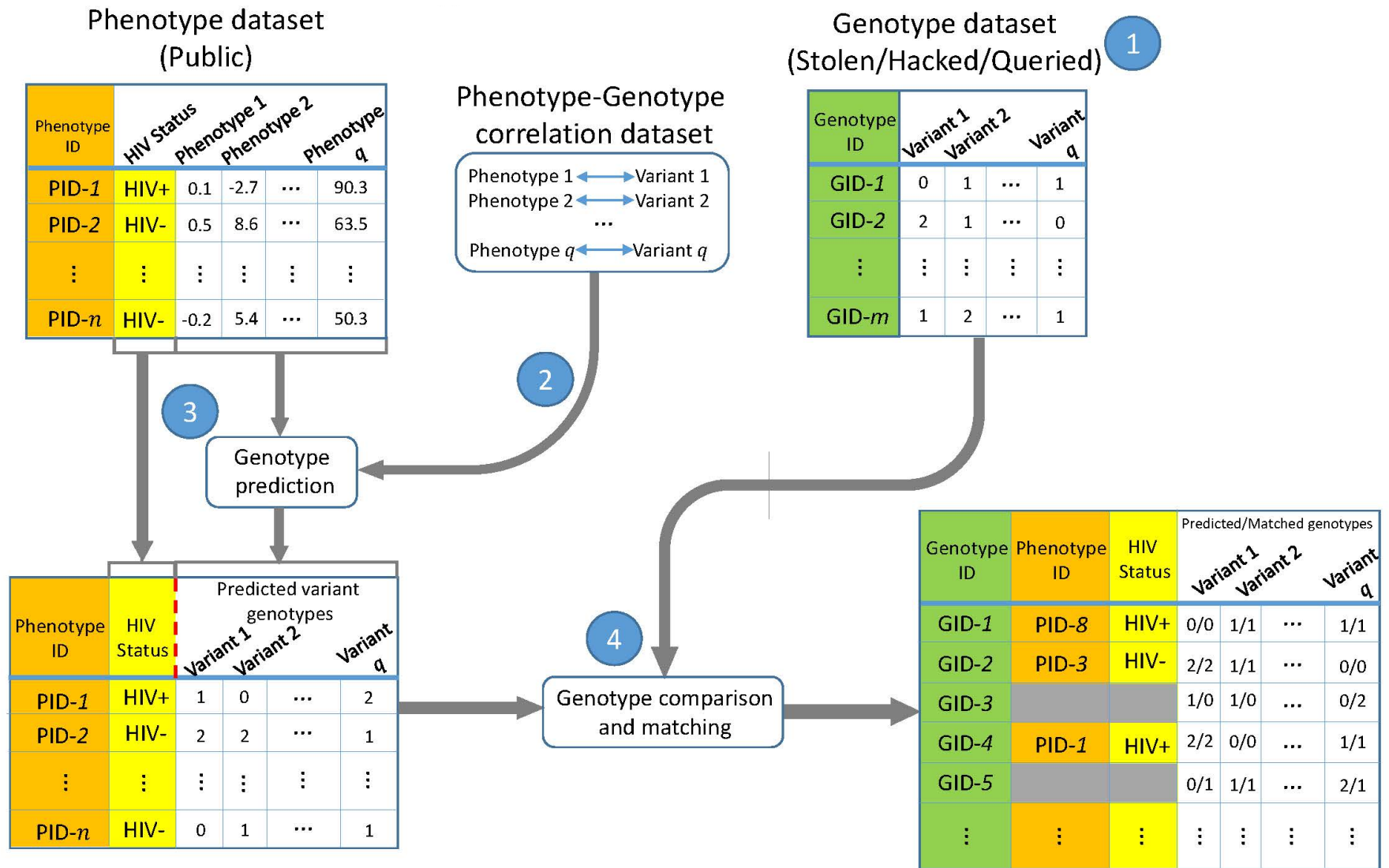
Colors by absolute correlation



Cumulative Leakage versus Joint Predictability



Linking Attack Scenario



Linking Attacks: Case of Netflix Prize



Names available for many users!

User (ID)	Movie (ID)	Date of Grade	Grade [1,2,3,4,5]
NTFLX-0	NTFLX-19	10/12/2008	1
NTFLX-1	NTFLX-116	4/23/2009	3
NTFLX-2	NTFLX-92	5/27/2010	2
NTFLX-1	NTFLX-666	6/6/2016	5
...
...

User (ID)	Movie (ID)	Date of Grade	Grade [0-10]
IMDB-0	IMDB-173	4/20/2009	5
IMDB-1	IMDB-18	10/18/2008	0
IMDB-2	IMDB-341	5/27/2010	-
...
...
...

- Many users are shared
- The grades of same users are correlated
- A user grades one movie around the same date in two databases

Anonymized Netflix Prize Training Dataset
made available to contestants

Linking Attacks: Case of Netflix Prize



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- IMDB users are public
- NetFLIX and IMdB moves are public

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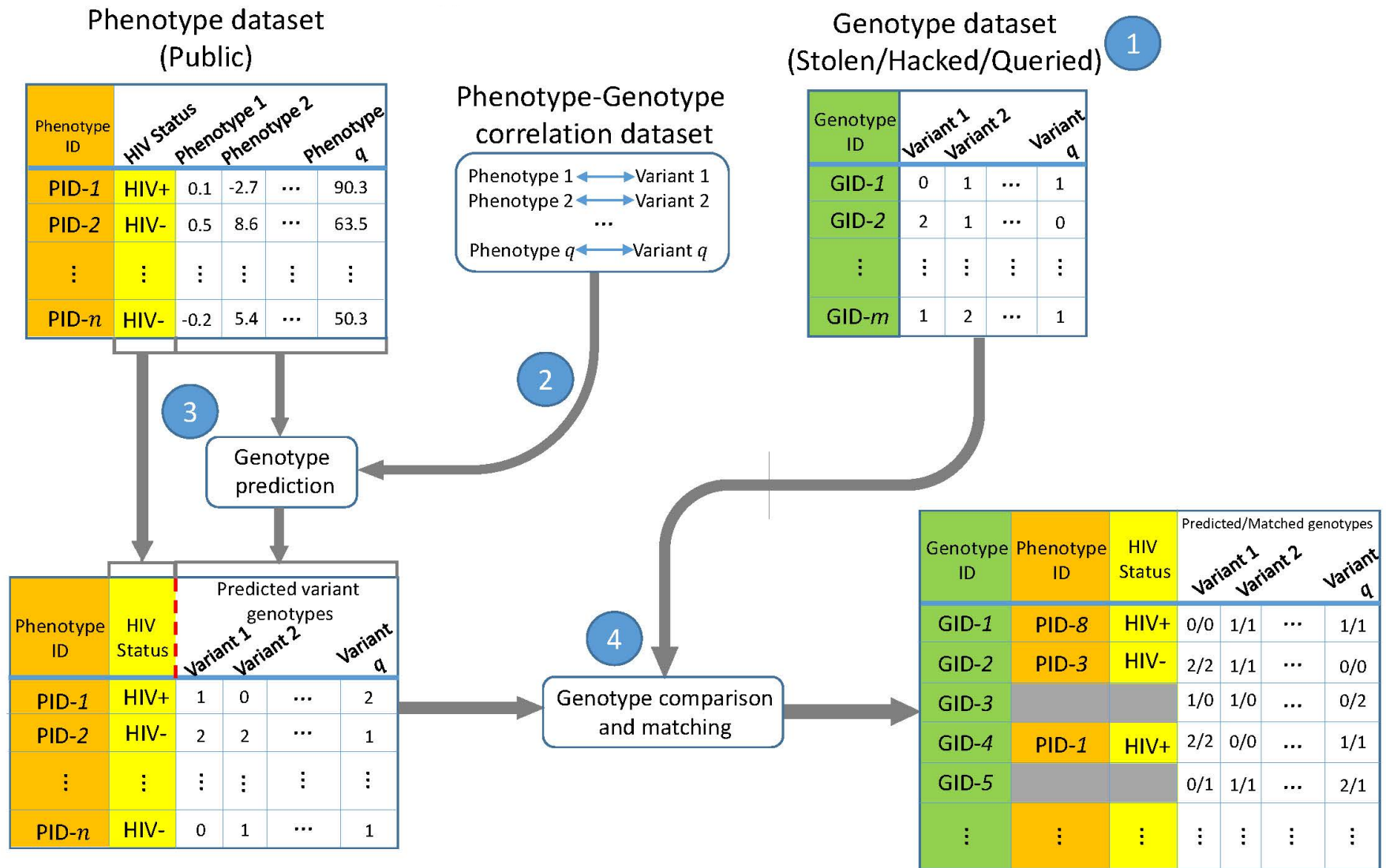


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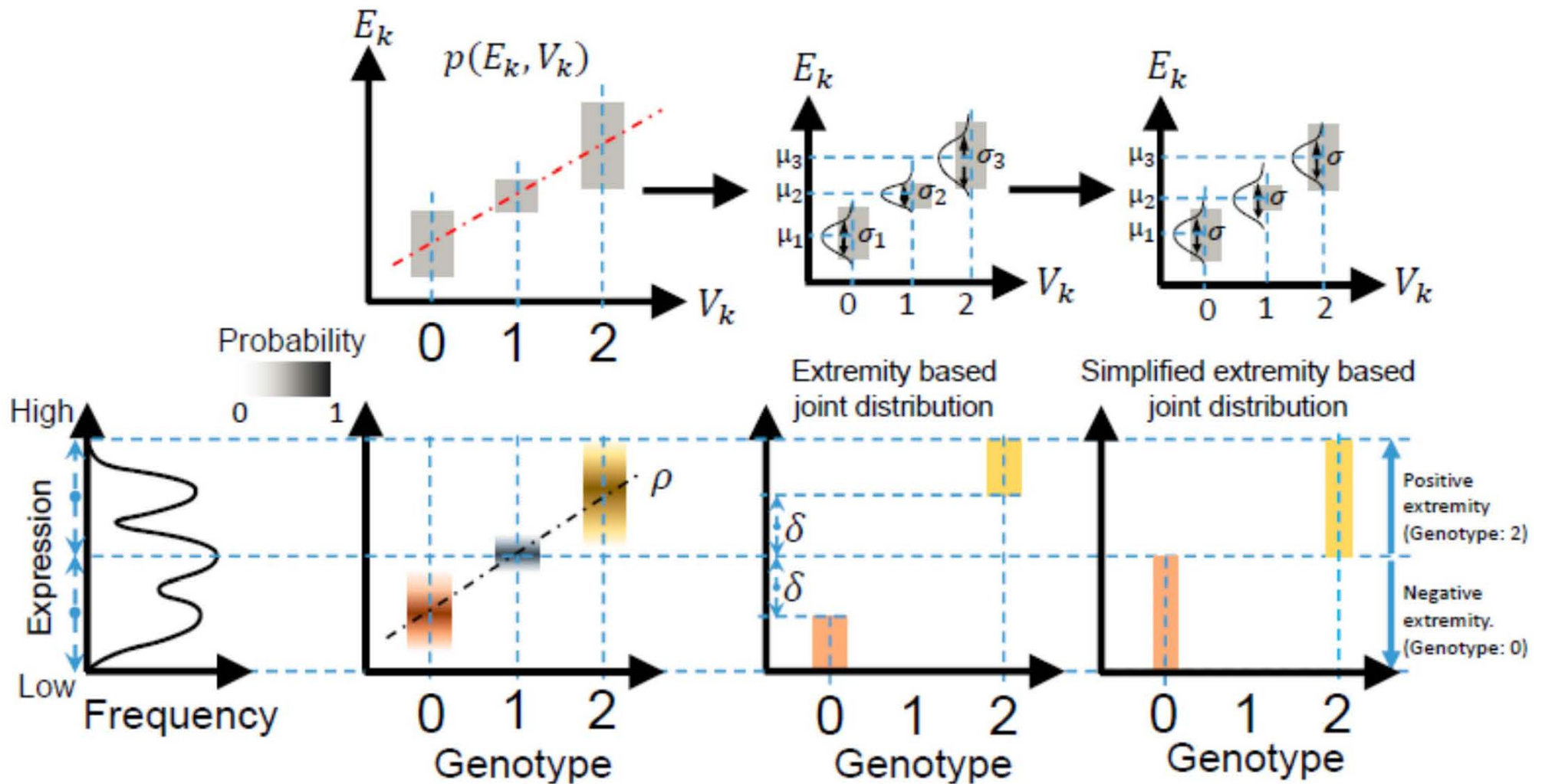
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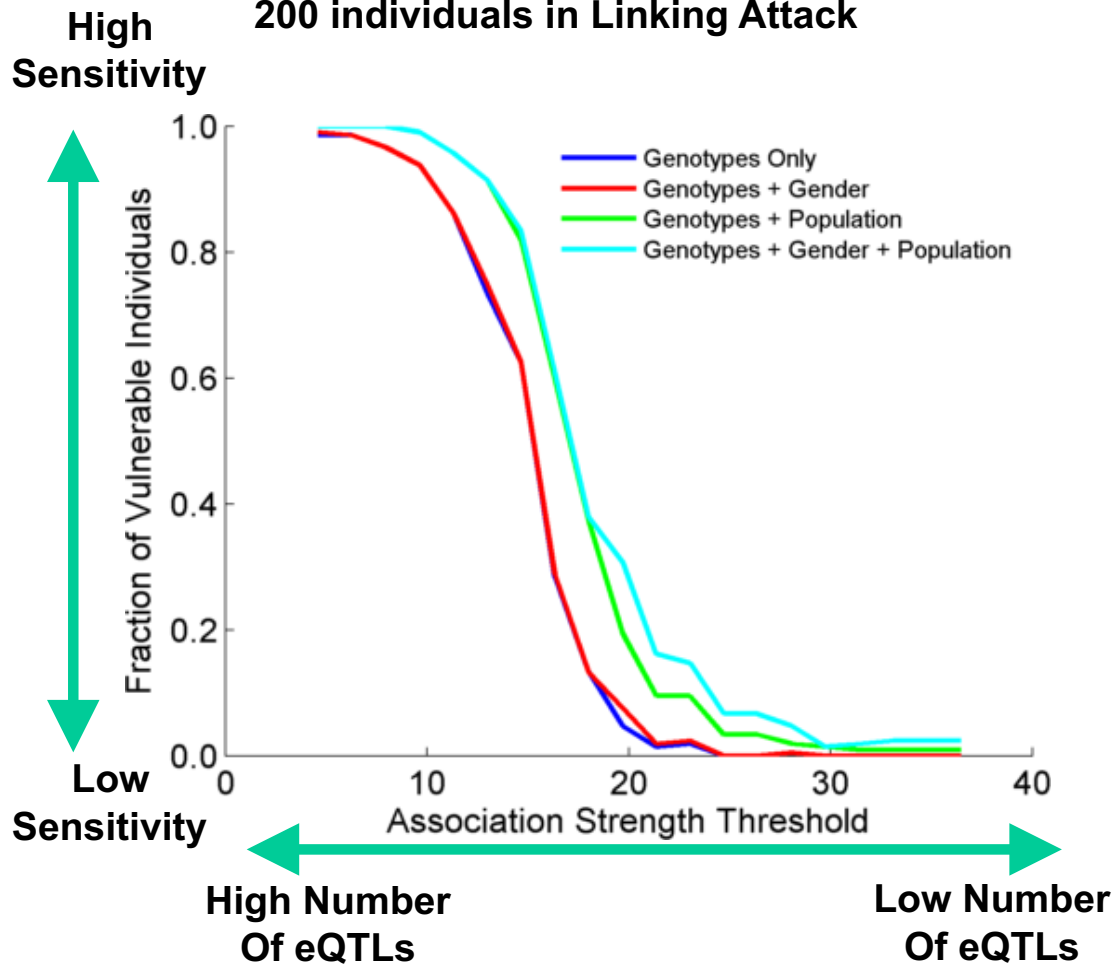


Levels of Expression-Genotype Model Simplifications for Genotype Prediction



Success in Linking Attack with Extremity based Genotype Prediction

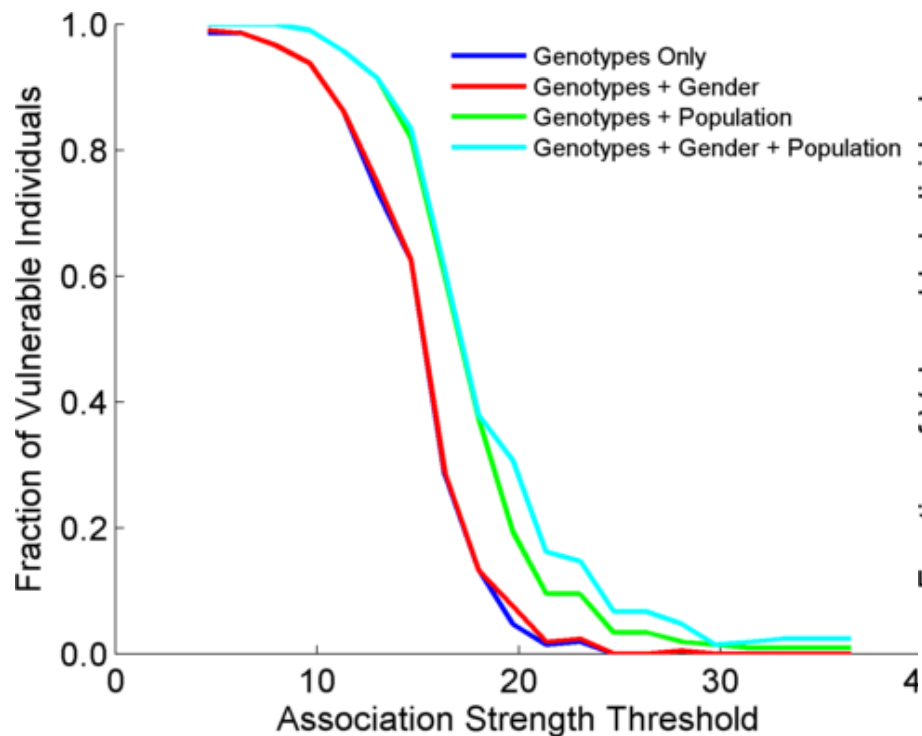
200 individuals eQTL Discovery
200 individuals in Linking Attack



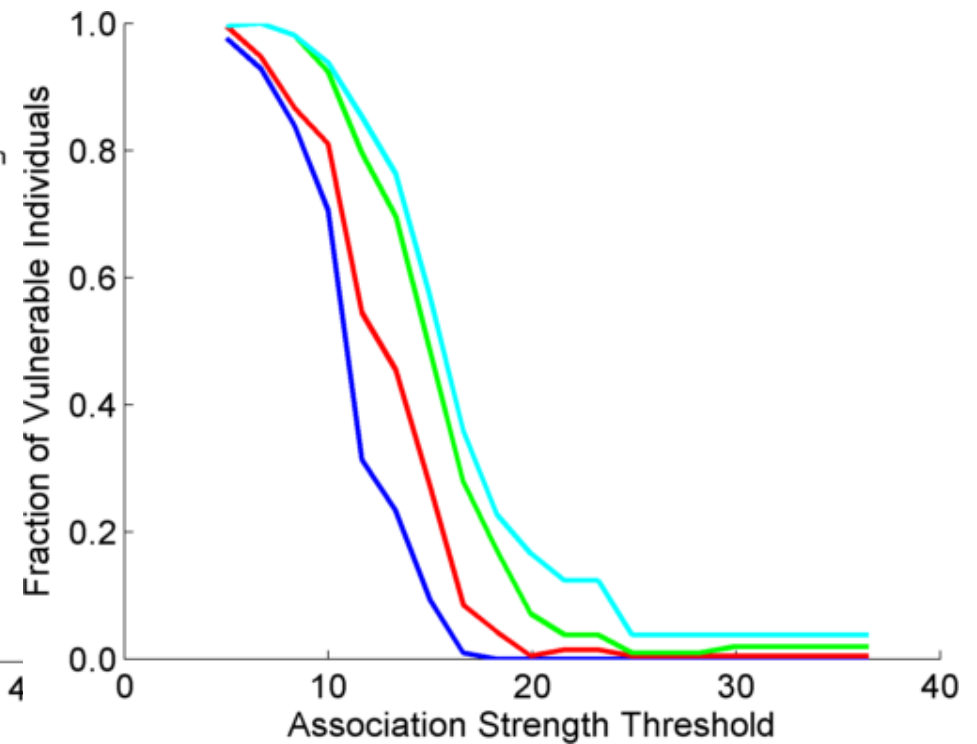
[Harmanci et al. *Nat. Meth.* (16)]

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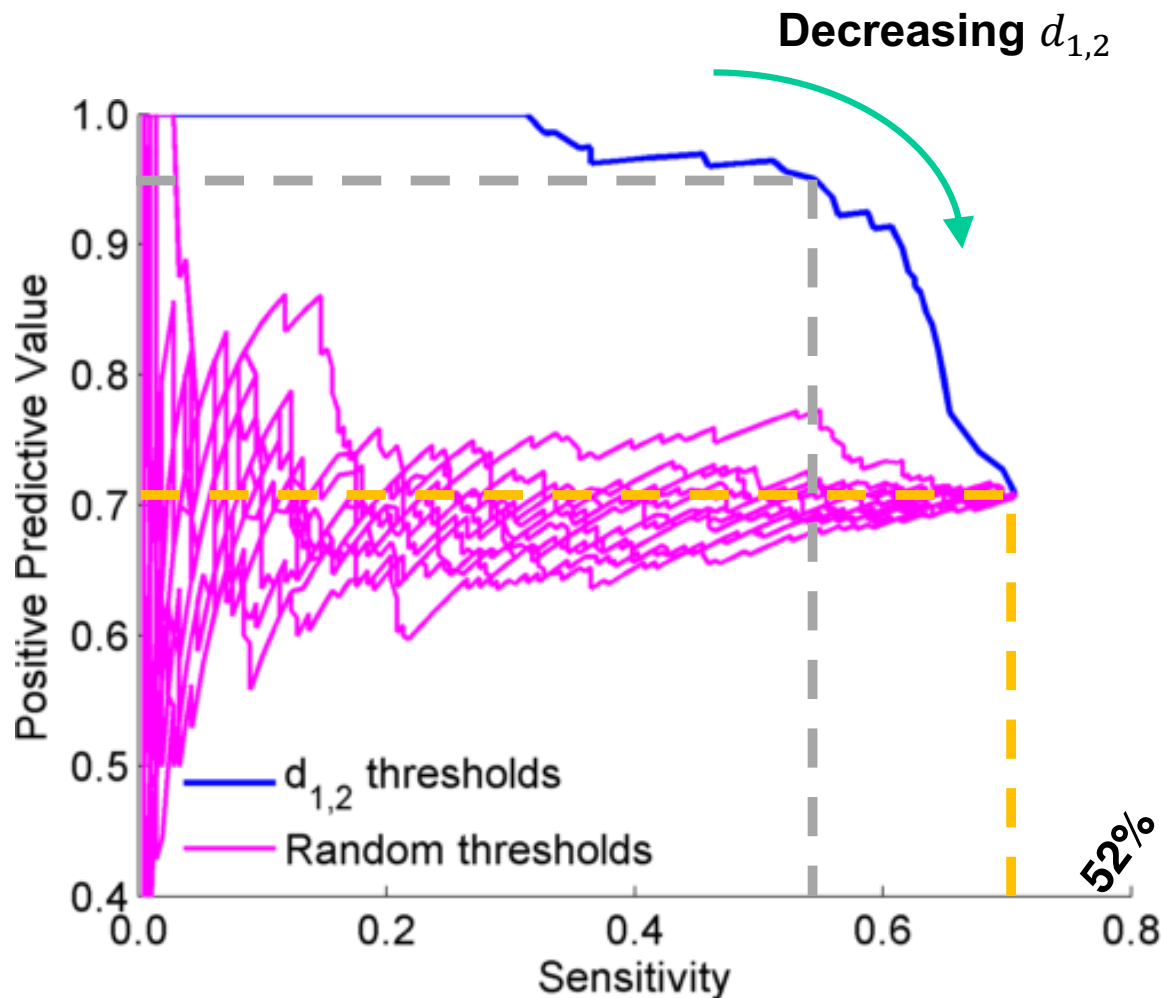
200 individuals eQTL Discovery
200 individuals in Linking Attack



200 individuals eQTL Discovery
100,200 individuals in Linking Attack



Sensitivity vs PPV for Linkings selected per 1st distance gap, $d_{1,2}$



- Say
 - Attacker arbitrarily selects eQTLs with strength >10
 - 70% of the individuals are linked correctly...but which 70%?
- Is there a way ahead of time to differentiate linkings based on their reliability?
- 1st Distance Gap:
 - Difference between the genotype distance of 2nd best & 1st best matching individuals
 - $d_{1,2} = d_{second} - d_{first}$

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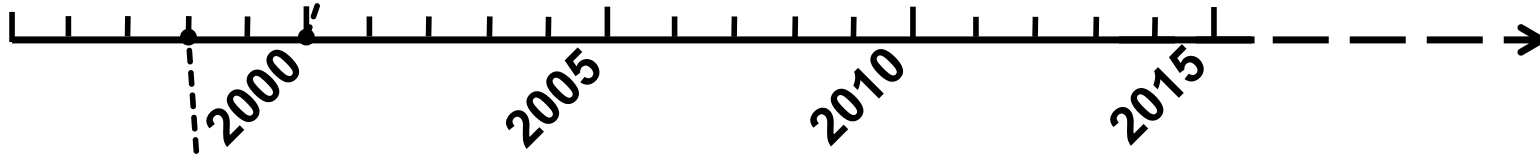
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The Human Genome Project

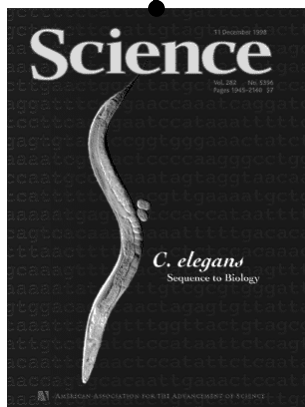


Worm Genome

The Human Genome Project

ENCODE Pilot

ENCODE Production



Worm Genome

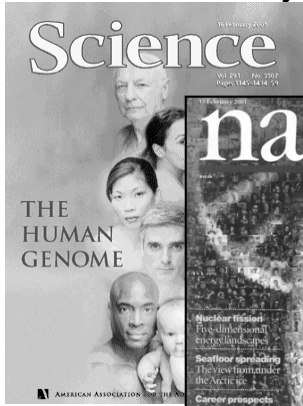
modENCODE

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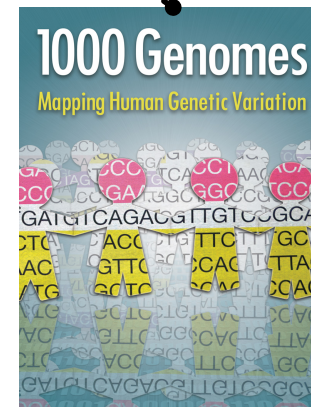
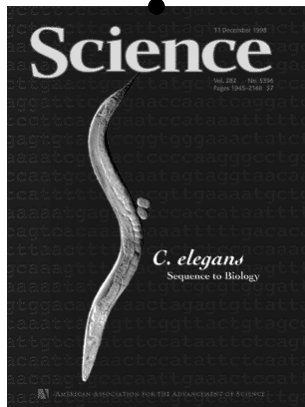


2000

2005

2010

2015



Worm Genome

modENCODE

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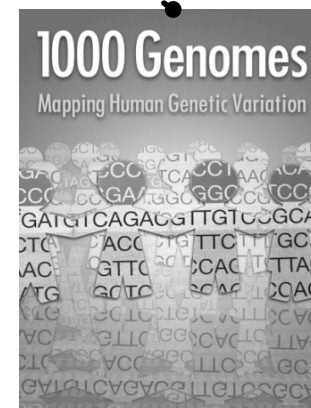
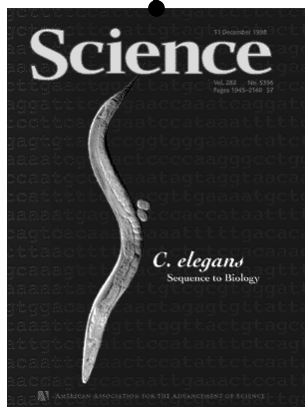
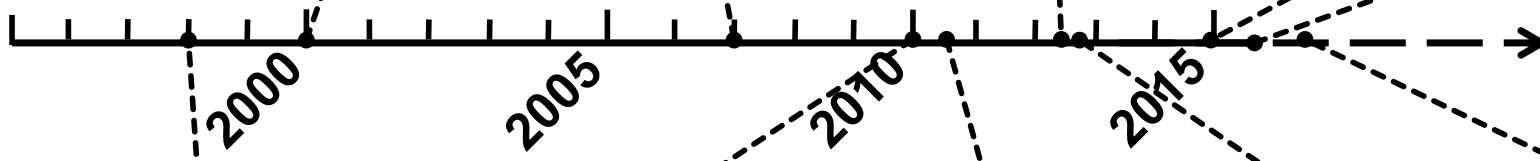
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ENCODE Pilot

ENCODE Production

Comparative ENCODE

Epigenome Roadmap



Worm Genome

modENCODE

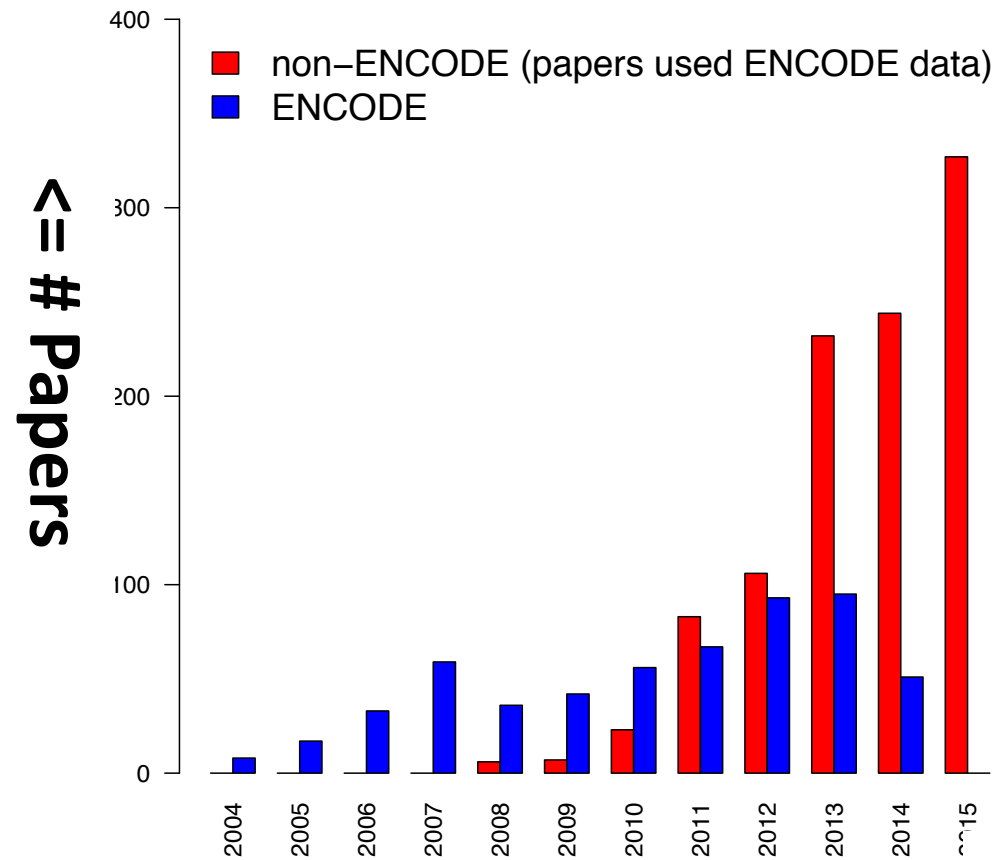
1000 Genomes Pilot

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GTEX

With help of M Pazin at NHGRI, identified: **702 community papers that used ENCODE data but were not supported** by ENCODE funding & **558 consortium papers supported by ENCODE funding** (<https://www.encodeproject.org/search/?type=Publication> for up-to-date query)
Then identified **1,786 ENCODE members** & **8,263 non-members** .

■ non-ENCODE (papers used ENCODE data) ■ ENCODE



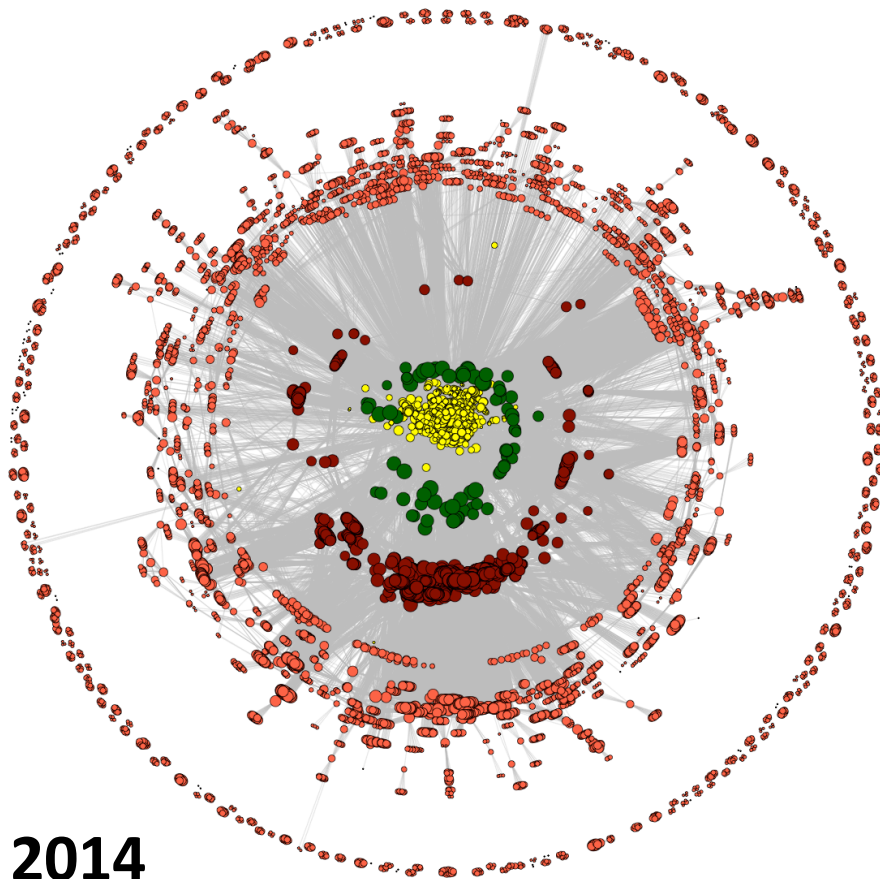
Authors

[Wang et al., TIG ('16)]

Yr. ('04 to '15)

Co-authorship Network of ENCODE members & Data Users

- ENCODE member
- non-member
- ENCODE member broker
- non-member broker
- co-authorship

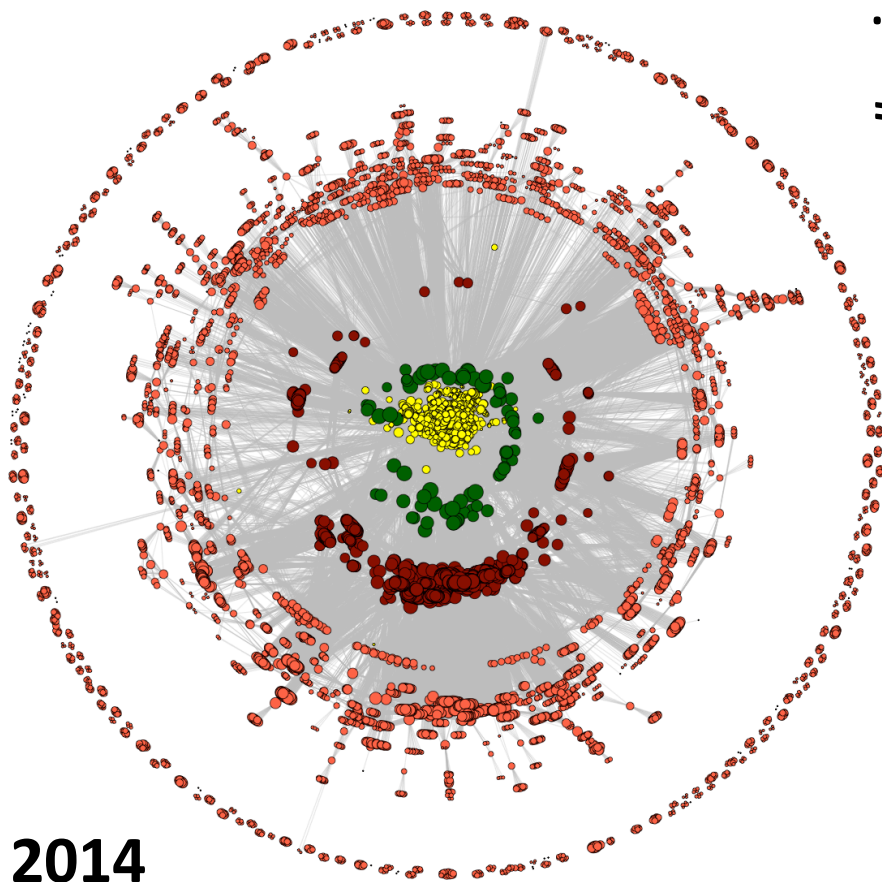


2014

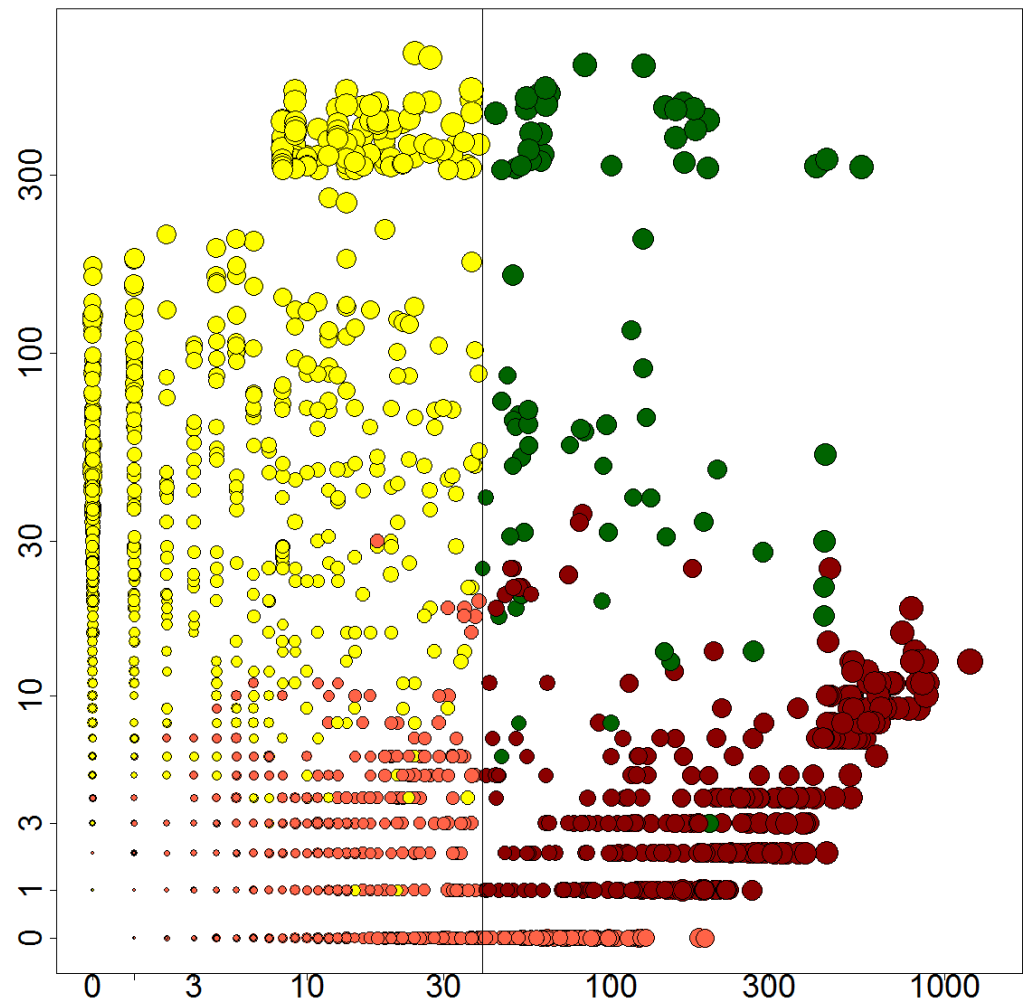
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neighbors: **non-ENCODE** ==>



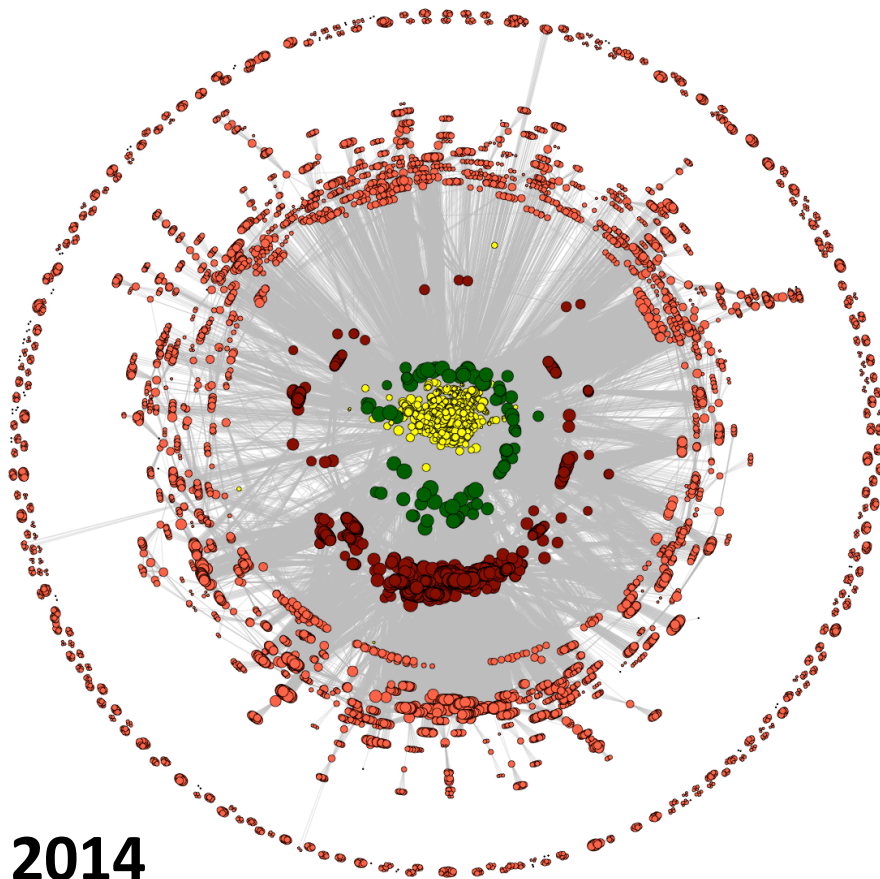
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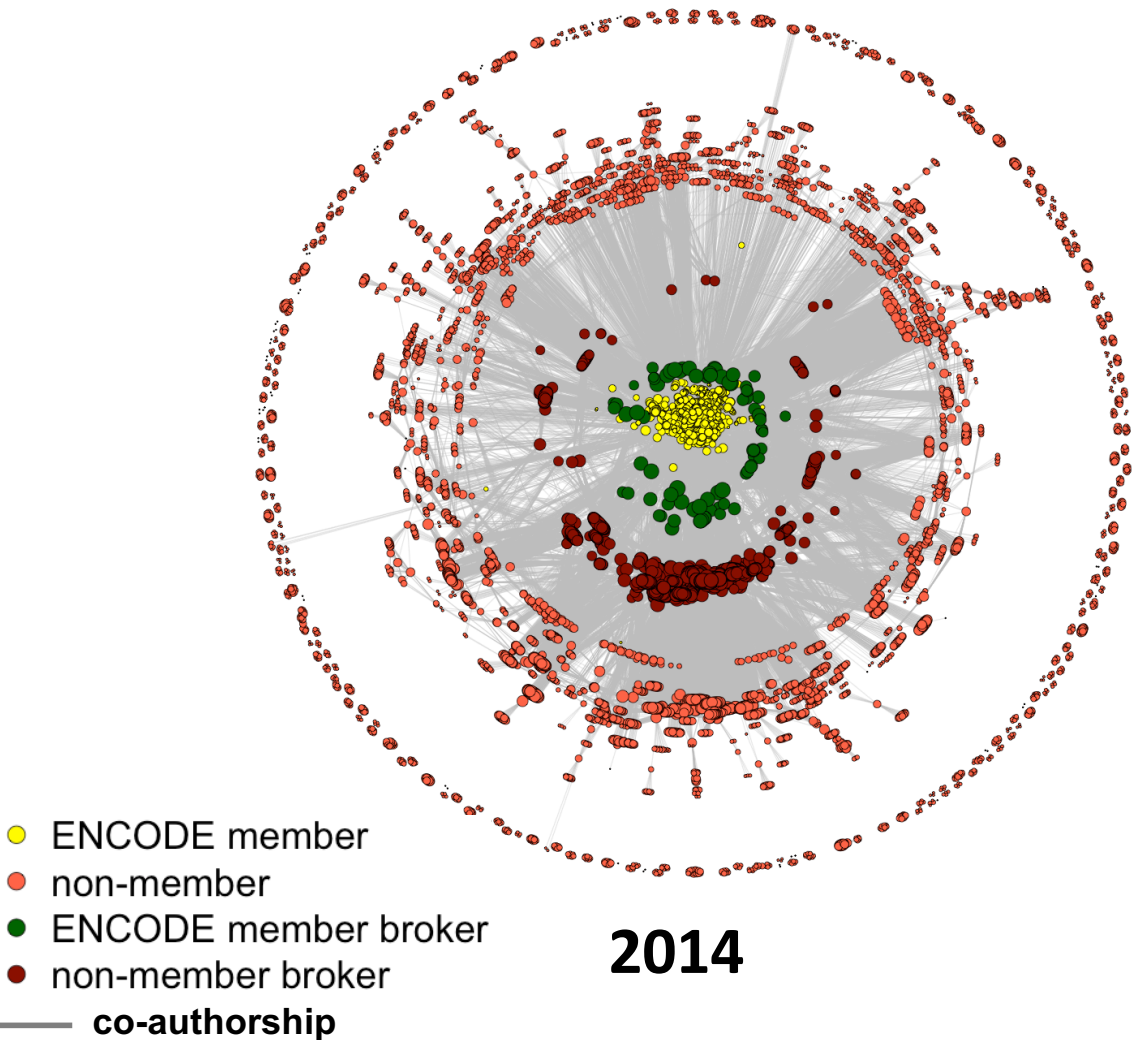
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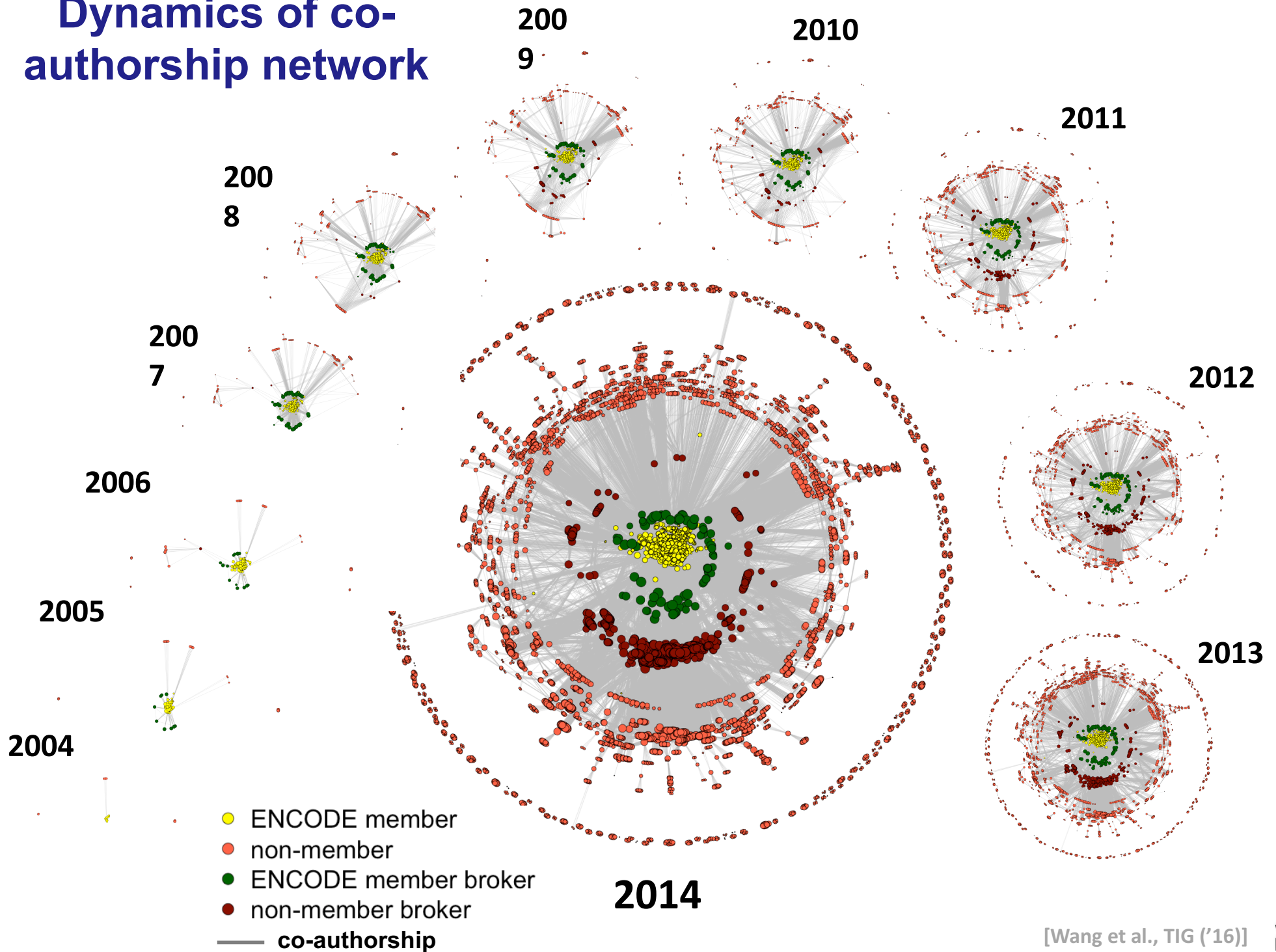
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Dynamics of co-authorship network



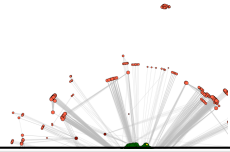
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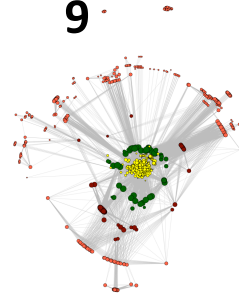


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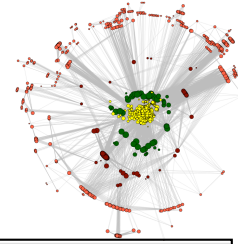
2008



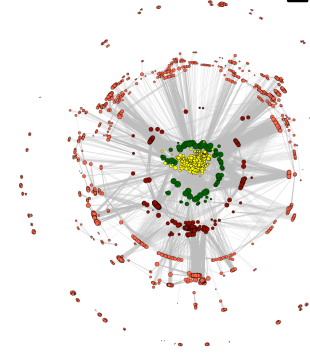
2009



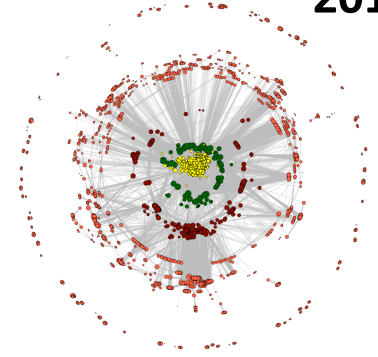
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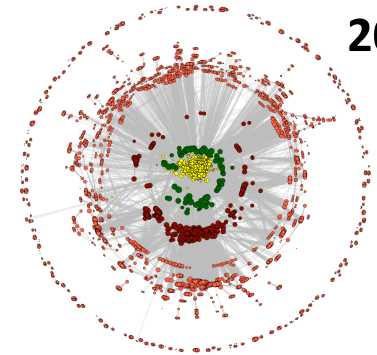
2011



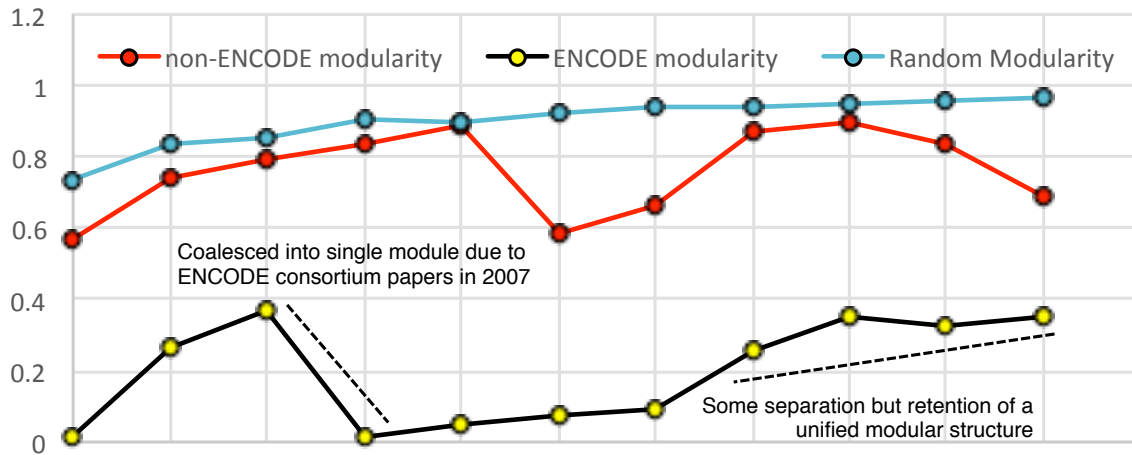
2012



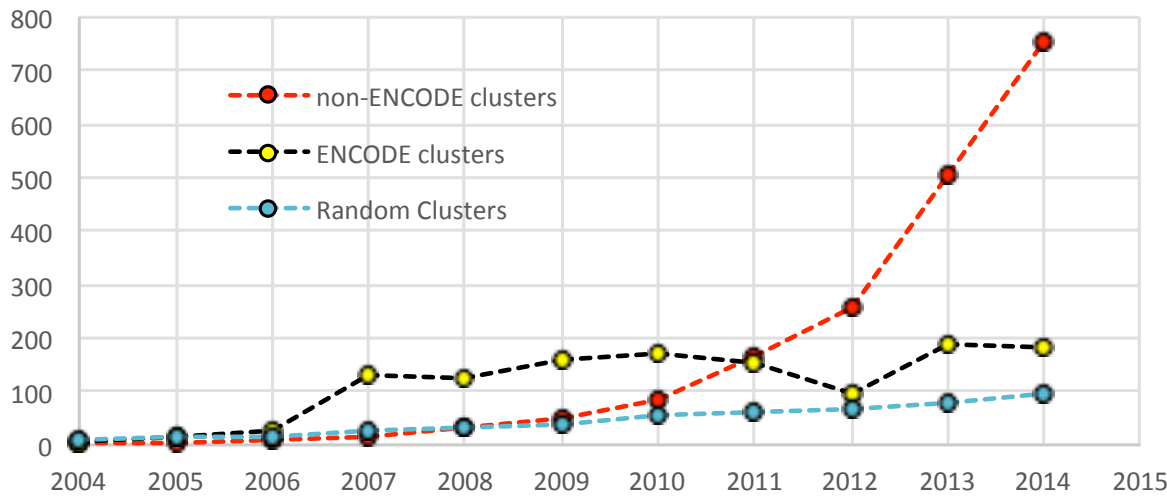
2013



“Modularity”



Number of clusters



[Wang et al., TIG ('16)]

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- Fundamental, inherited info that's very private v need for large-scale mining for med. research
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- Co-authorship network statistics relate to publication rollouts & show gradual adoption by a diverse community
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Transcriptome Analysis: Tackling core issues related to regulation & also mining the “data exhaust” of this activity

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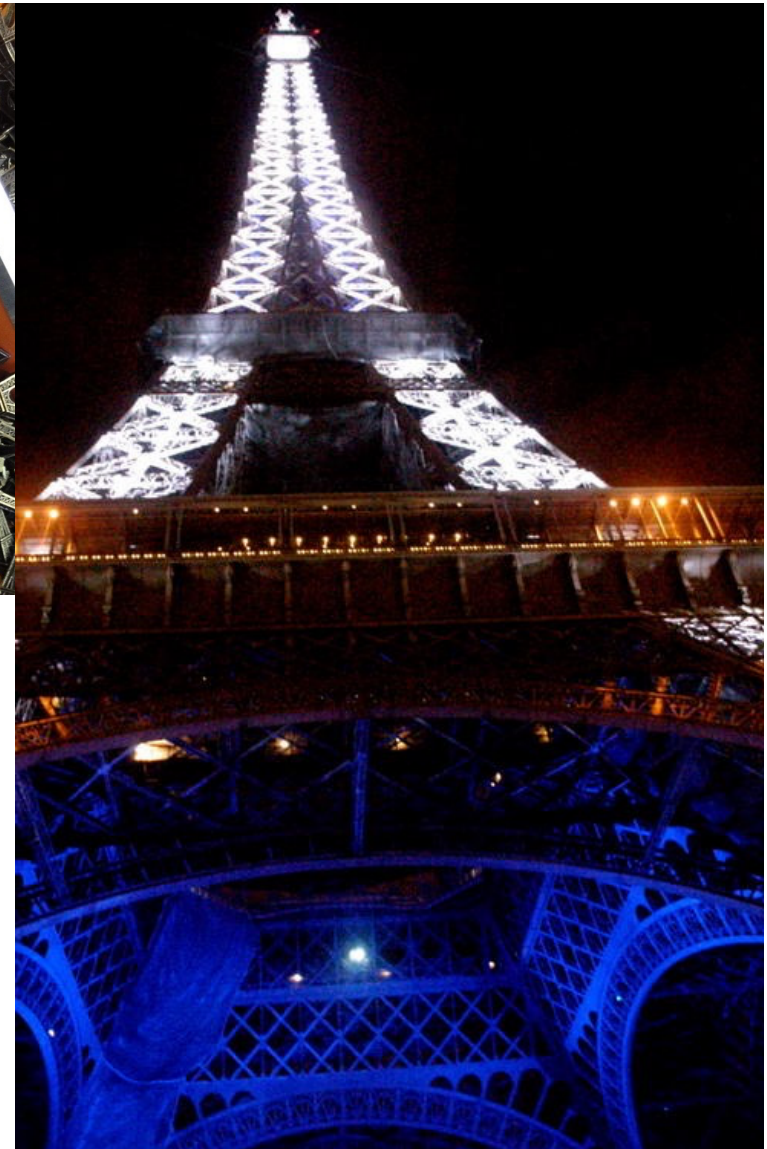
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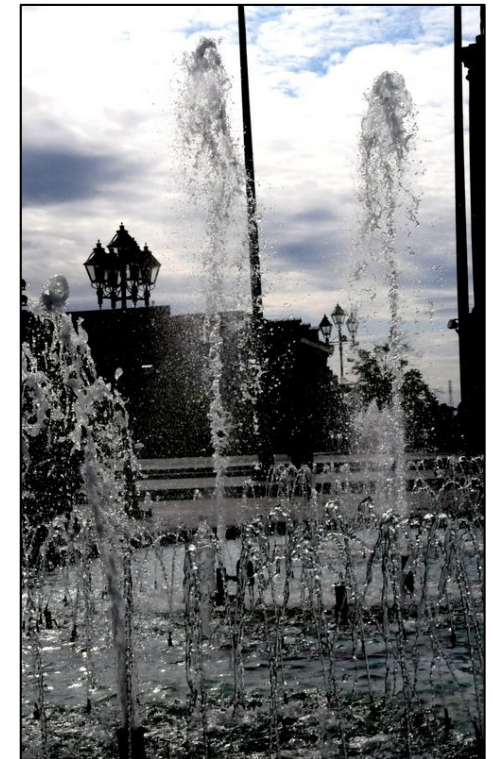
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