

# NETWORK-BASED INTEGRATION OF OMICS DATA

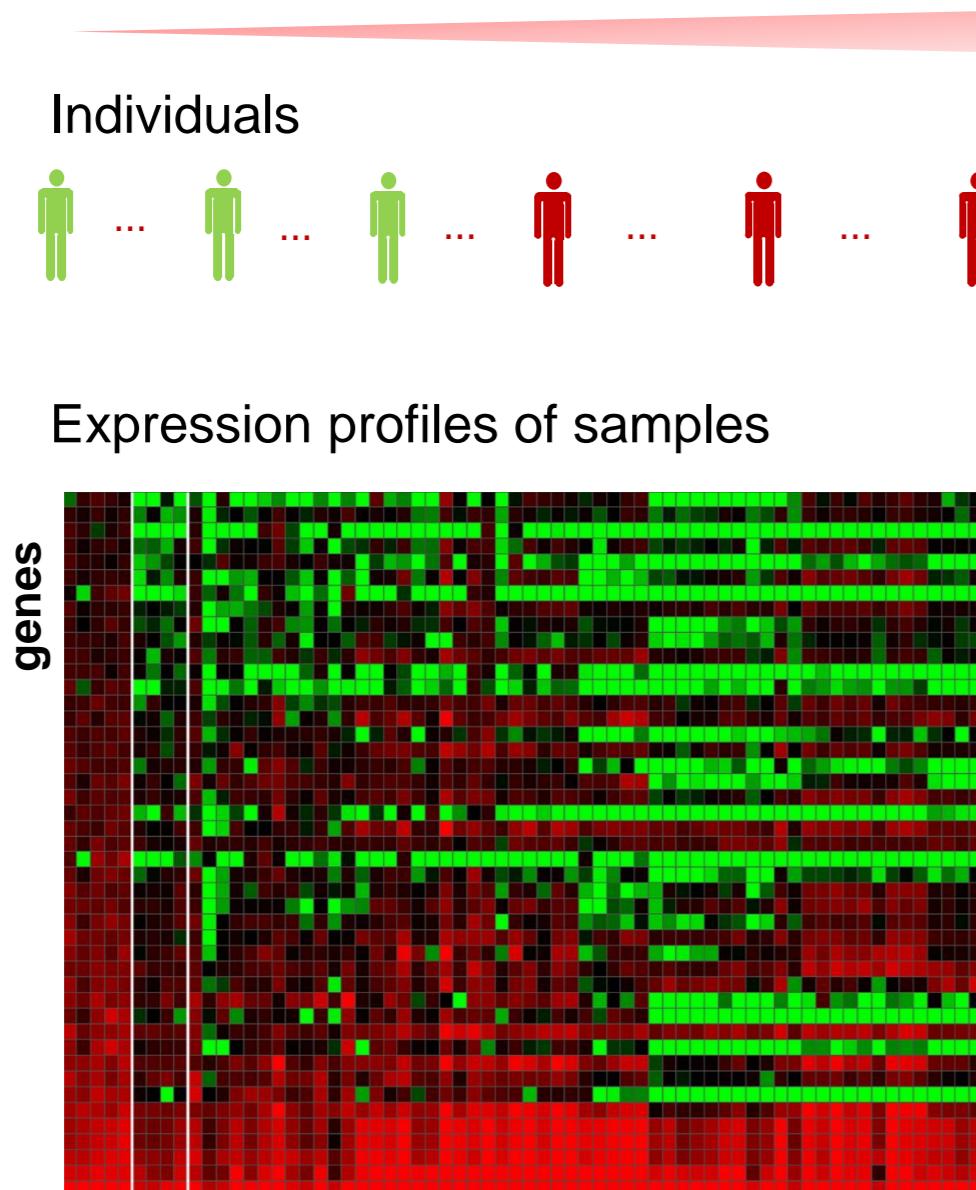
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Dept of Information Technology, IMEC

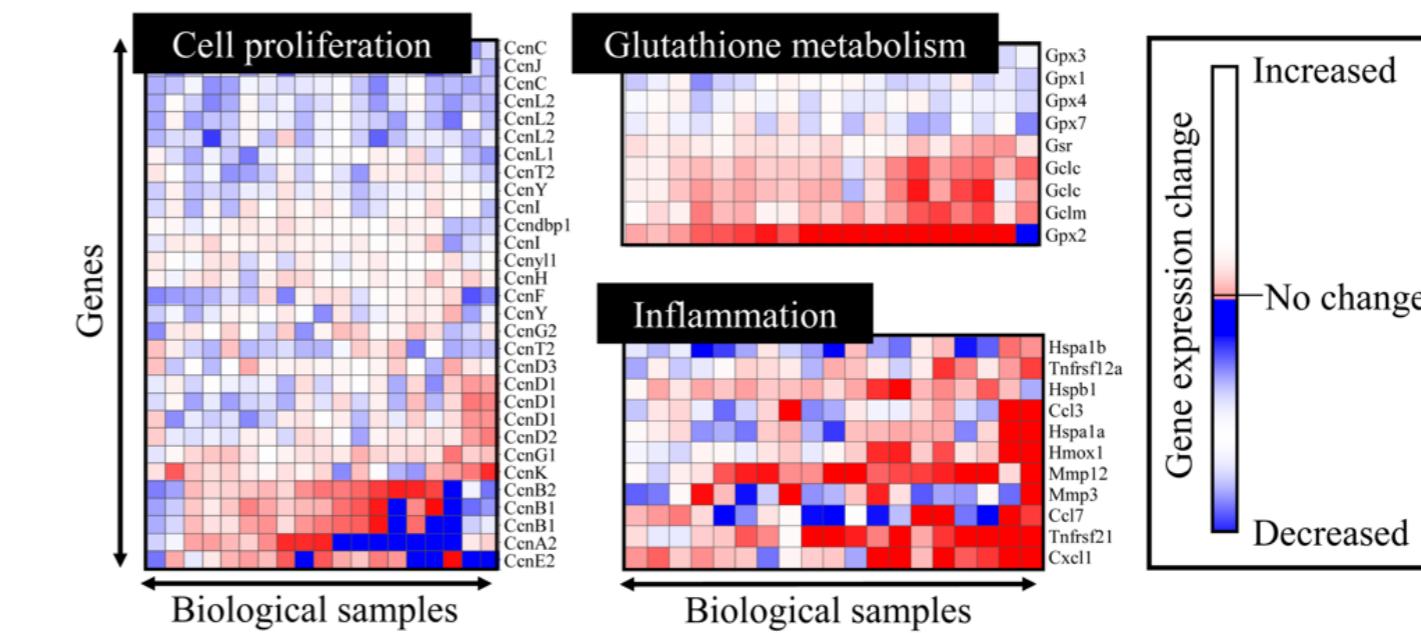
Dept of Plant Biotechnology and Bioinformatics

# Omics data for food safety assessment

## Assessing the molecular signature of a toxic compound

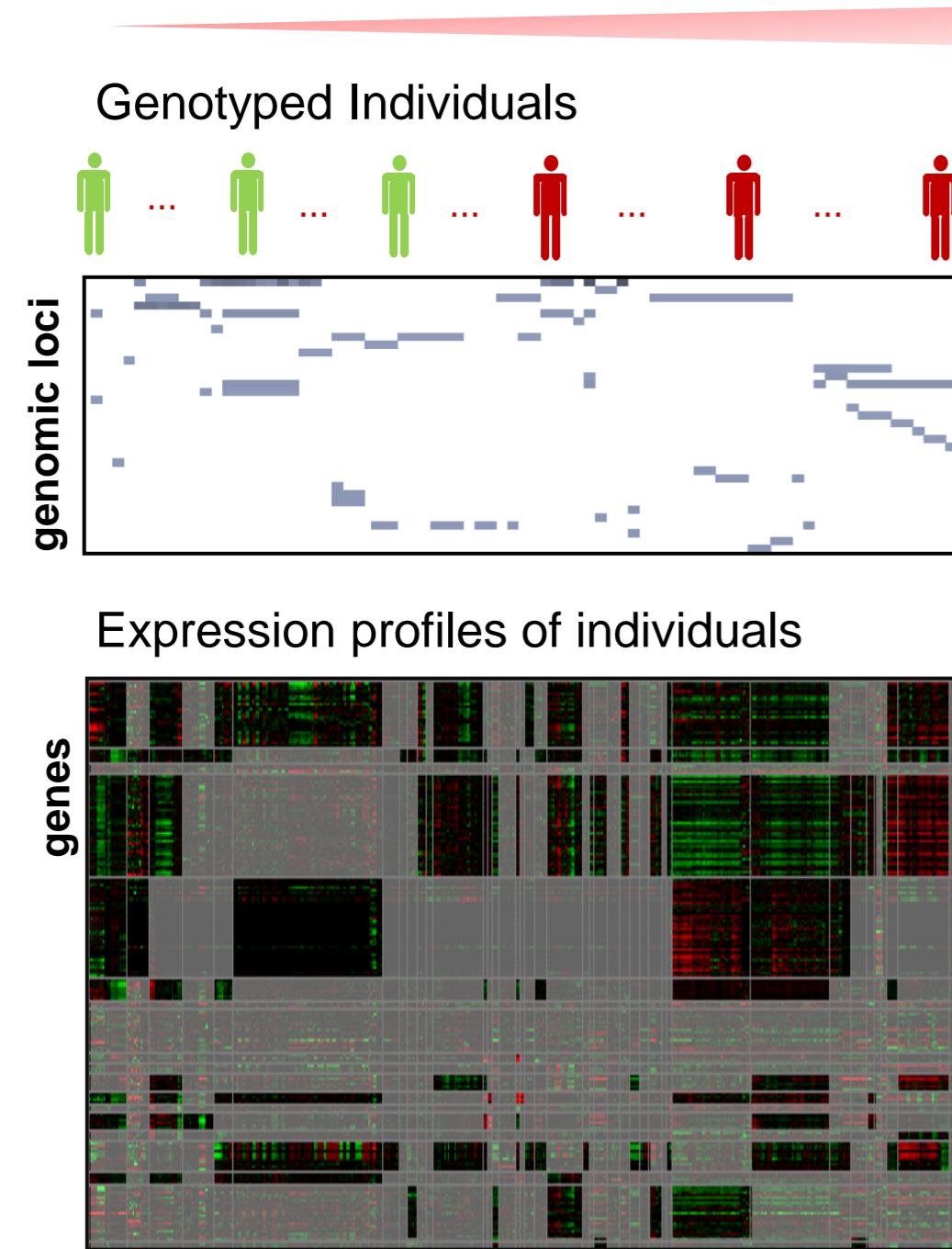


Use expression as a molecular phenotype to identify **molecular signatures** that can be used as biomarkers & ideally **unveil the mode of action** of the toxicity



# Omics data for food safety assessment

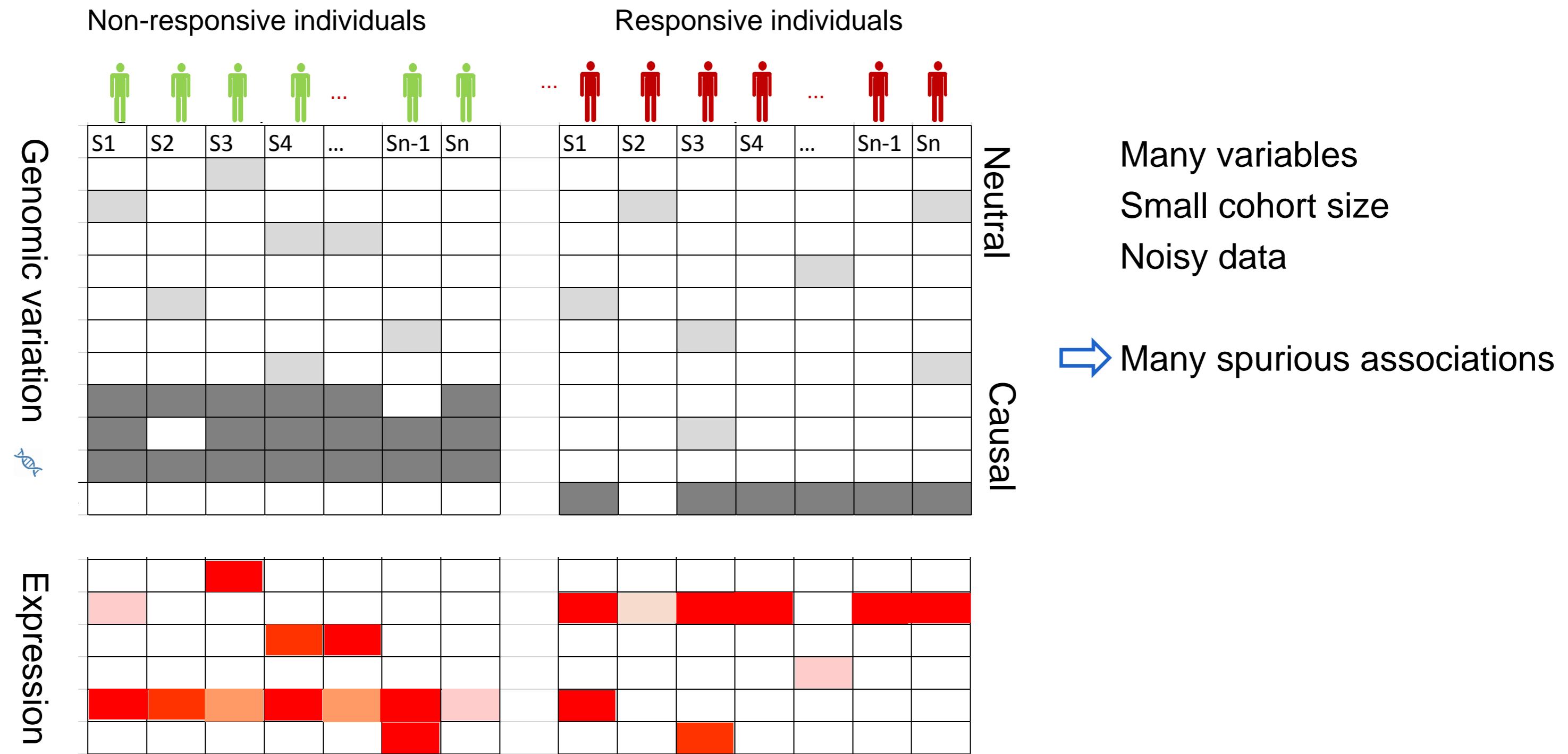
## Personalized nutrigenomics



Identifying genomic biomarkers that determine whether or not an individual will elicit a toxic response boils down to omics-based cohort analysis

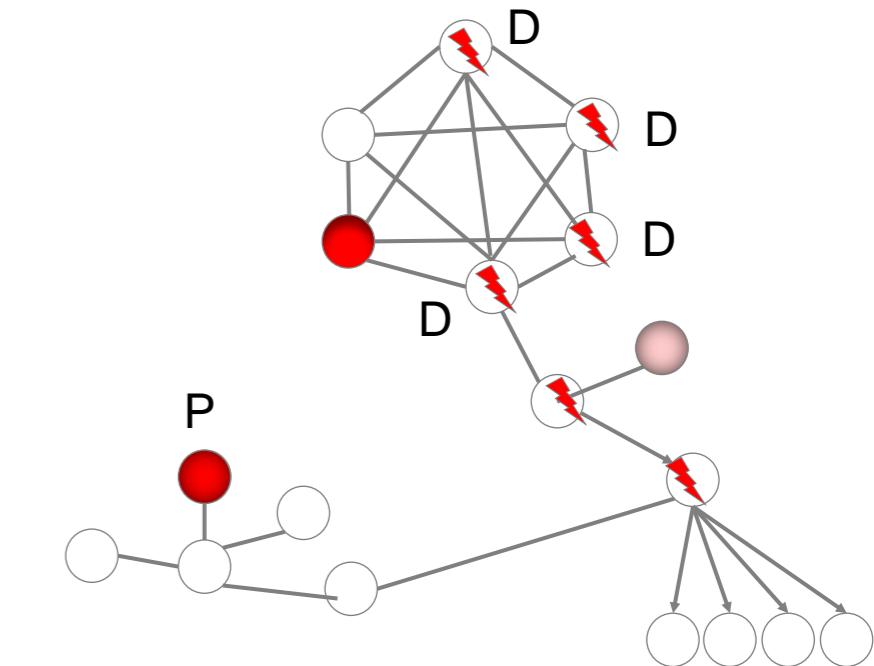
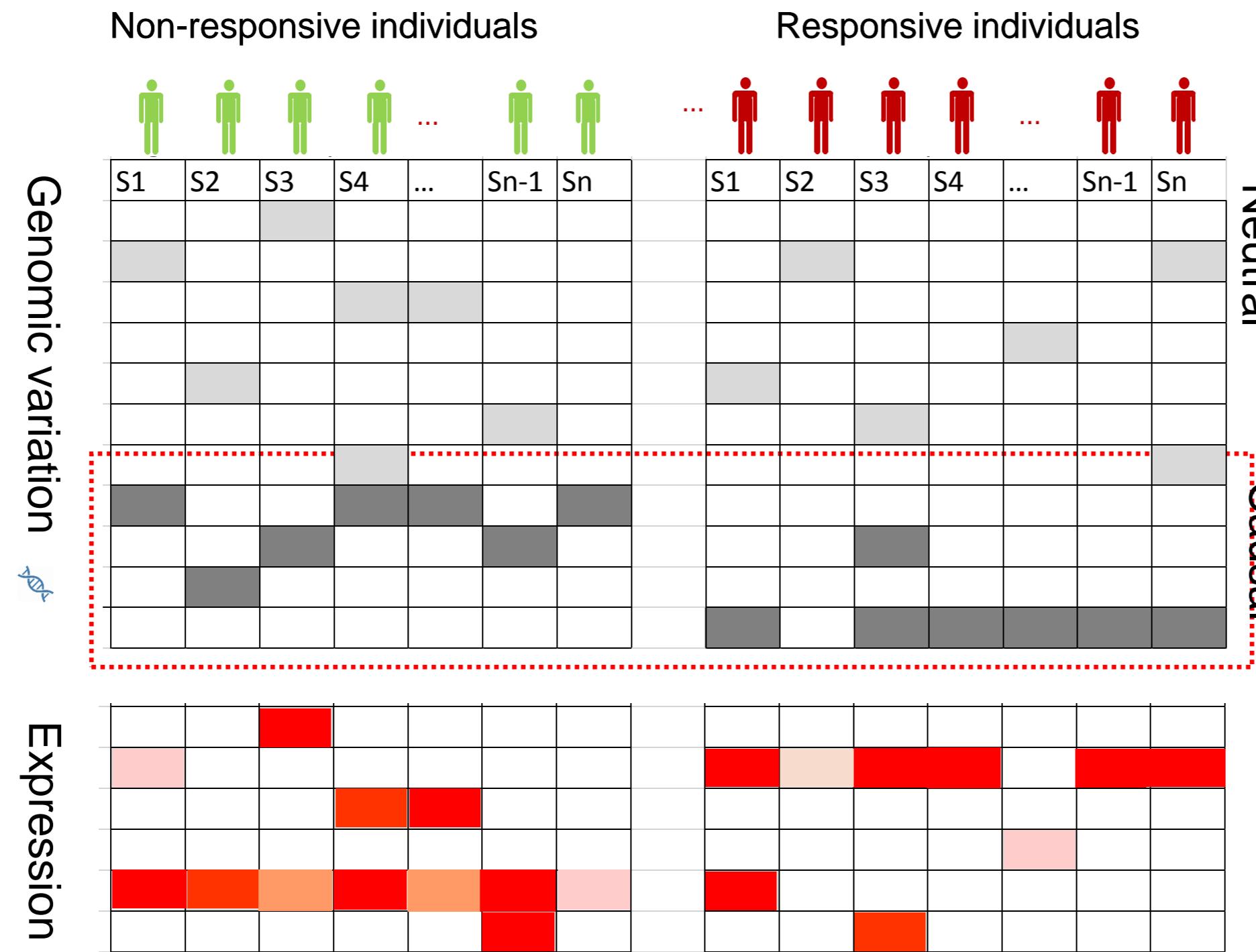
# Omics data integration is statistically ill defined

## Multivariate approaches: ANOVA (QTL, eQTL)



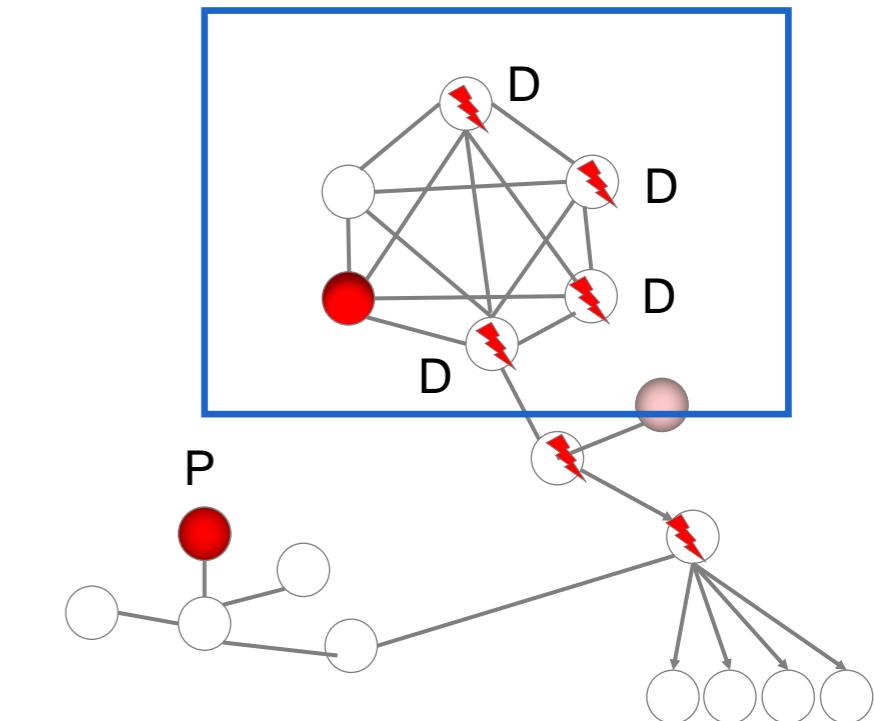
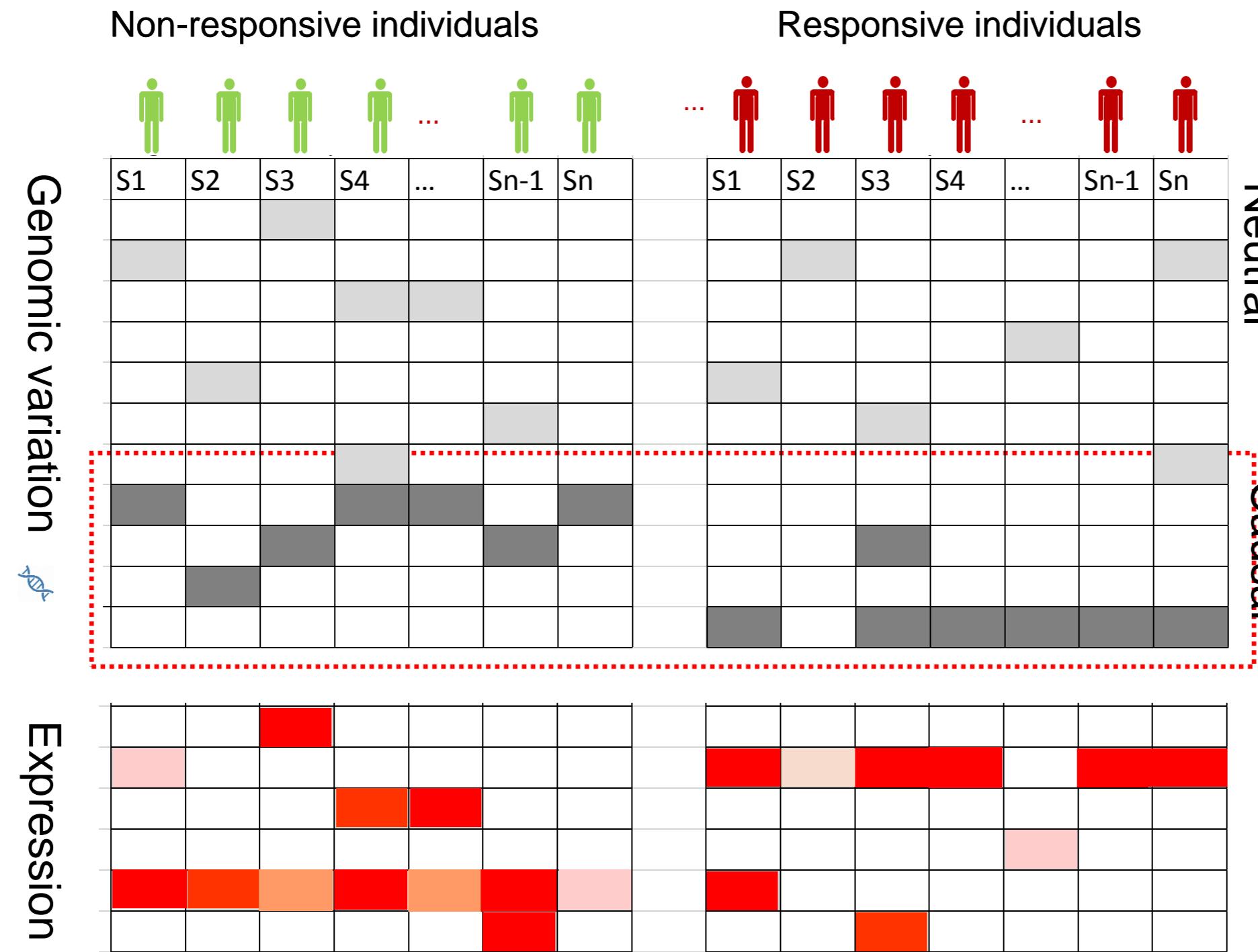
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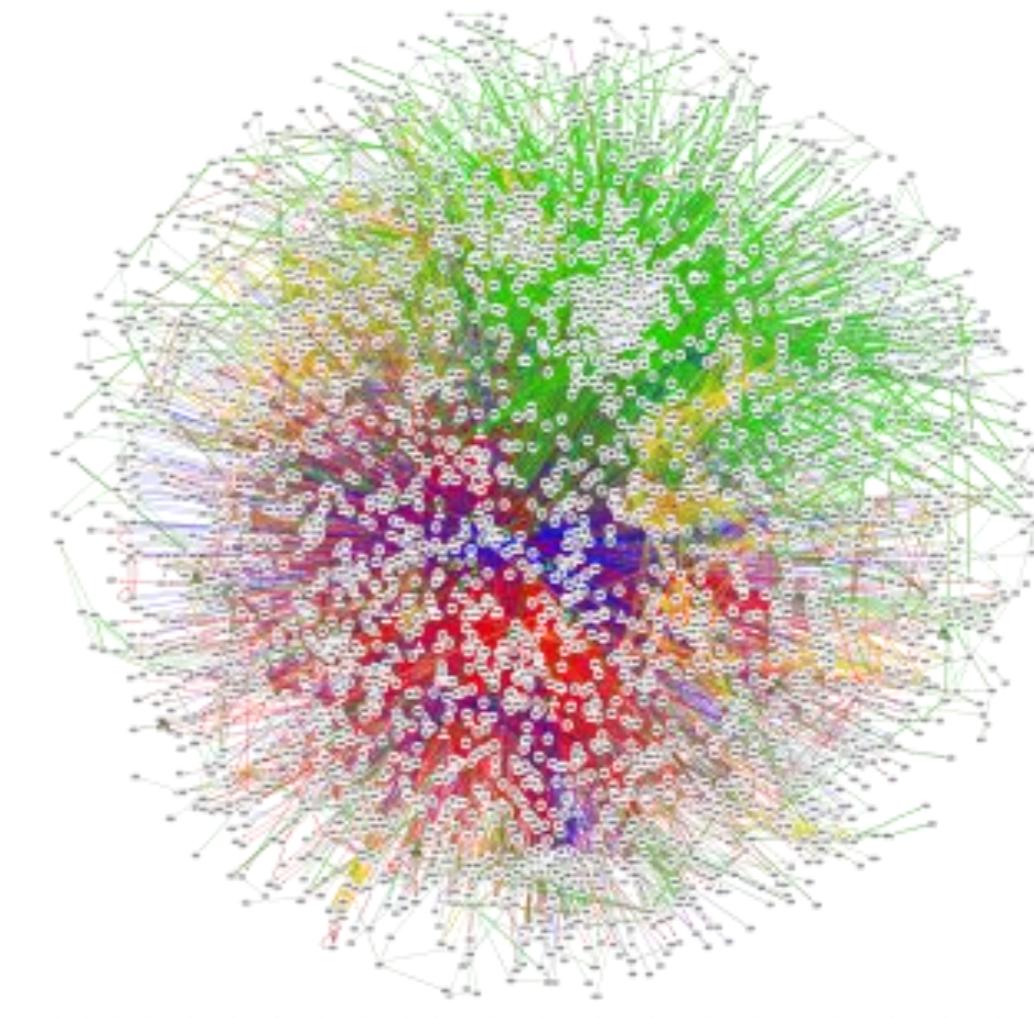
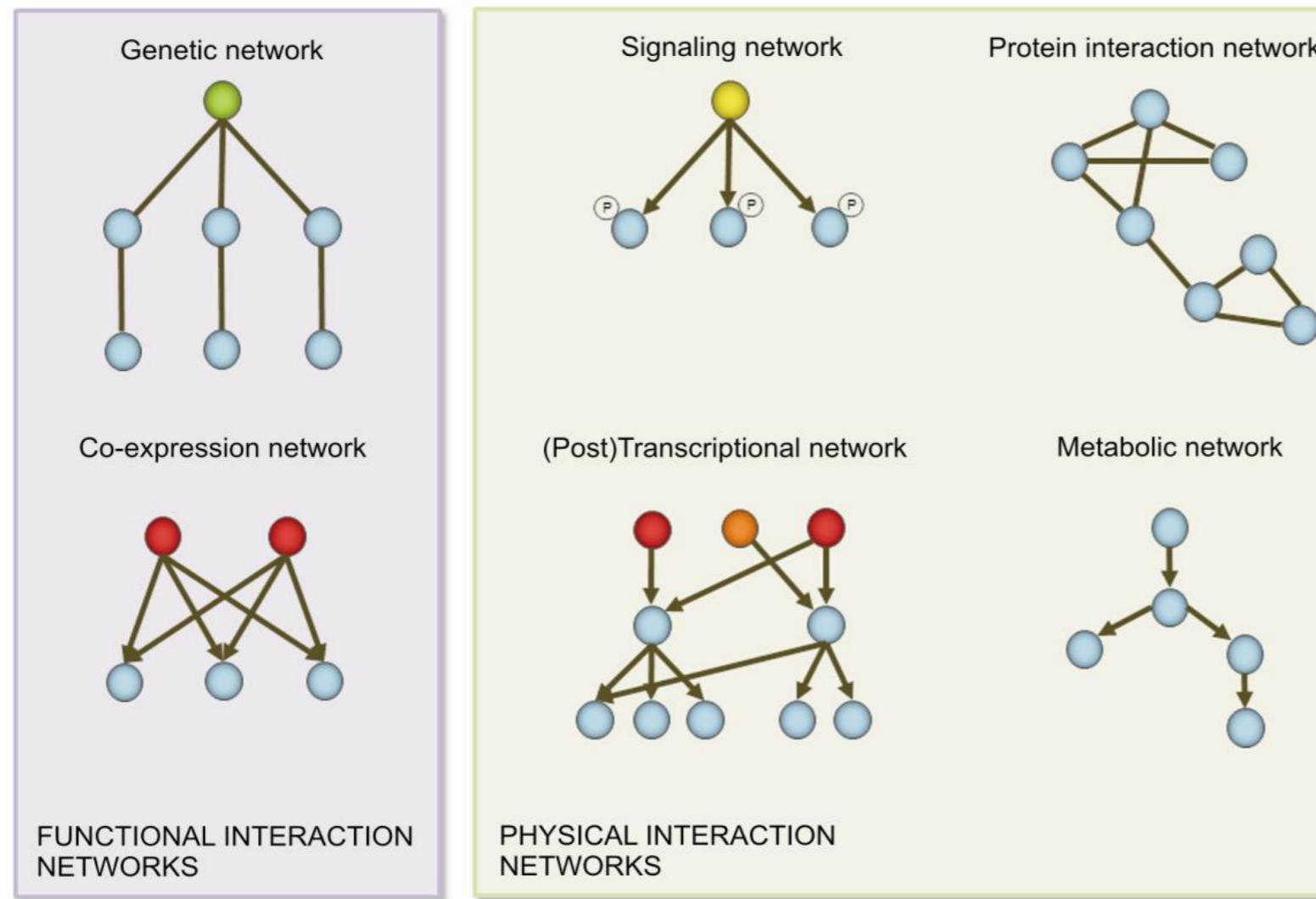
# Omics data integration is statistically ill defined

## Multivariate approaches: ANOVA (QTL, eQTL)



# Network-based analysis of omics data

Networks increase the power of the analysis



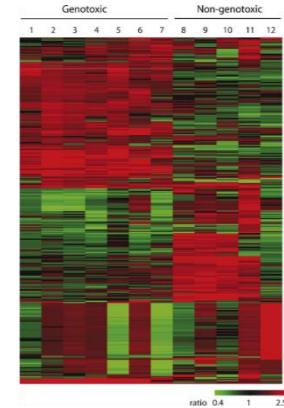
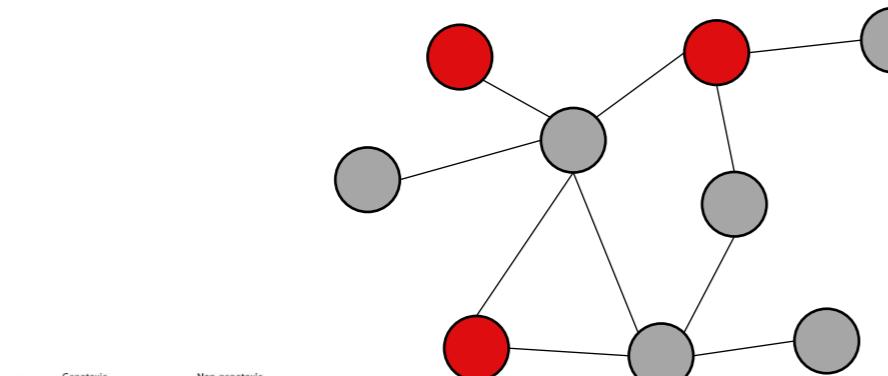
Exploit prior information on molecular interactions as a scaffold to drive the analysis

- Steers the solution of the data-integration problem to the most biologically relevant one

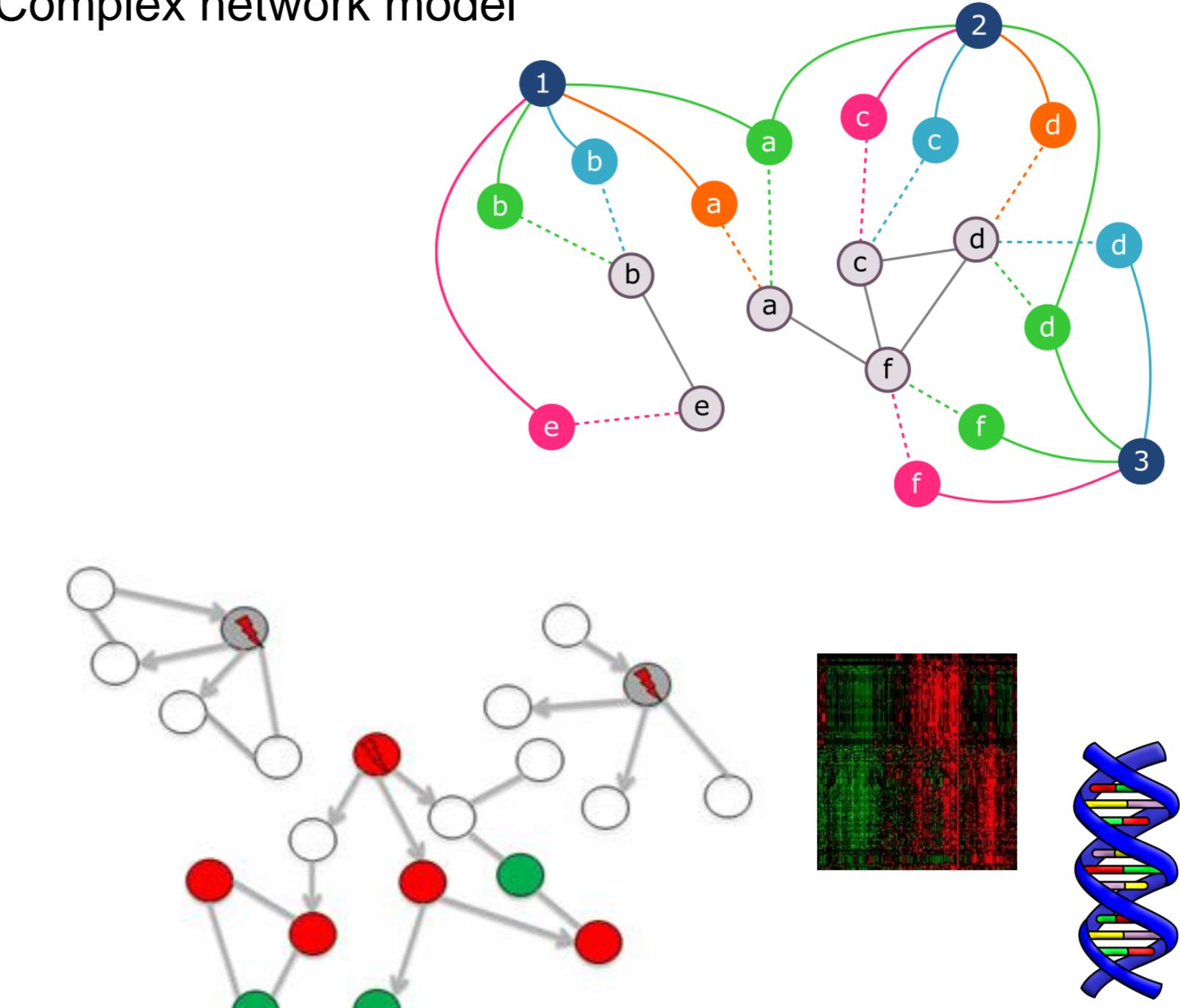
# Network-based analysis of omics data

Networks provide an intuitive scaffold to integrate data

Simple network model

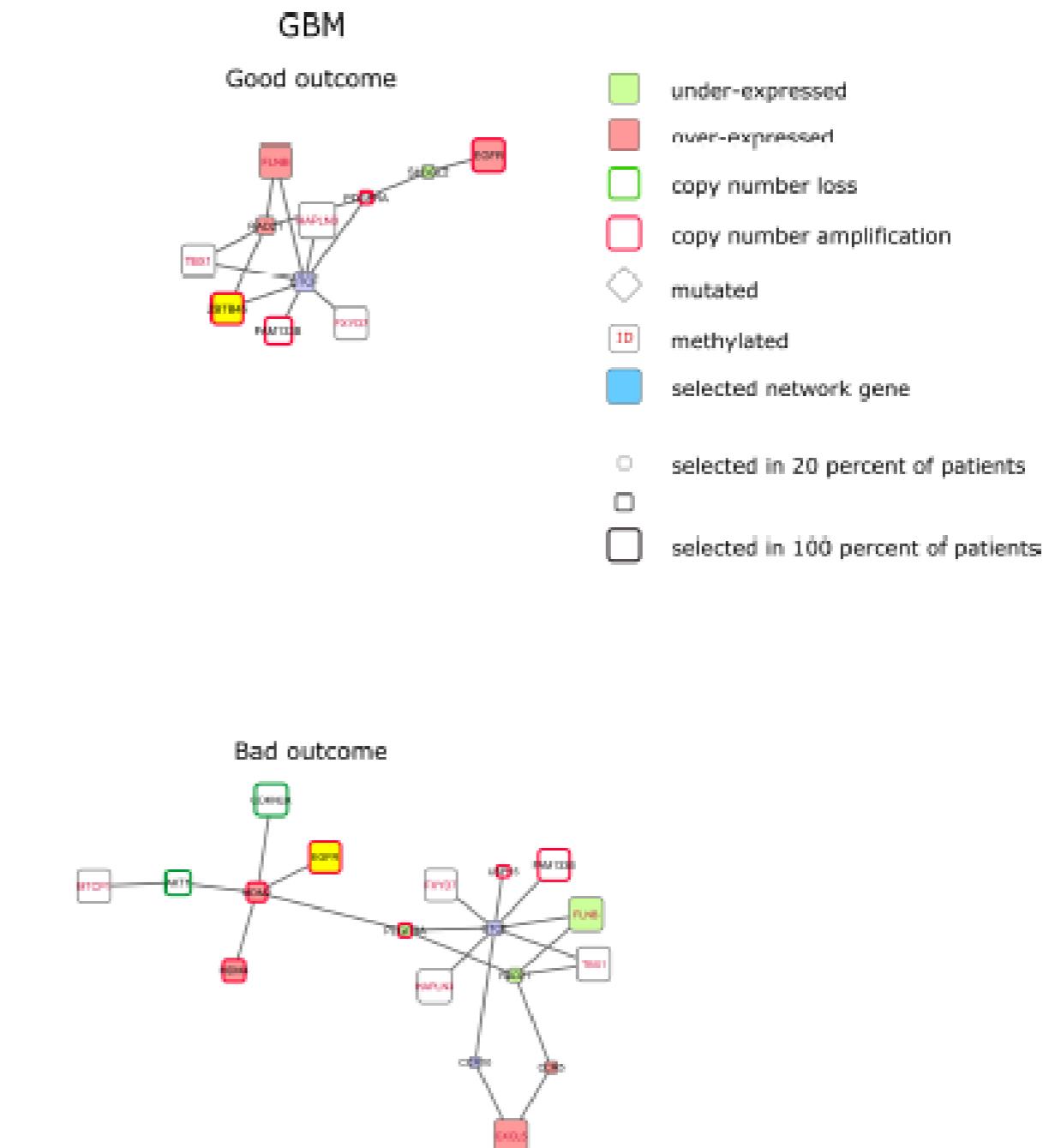
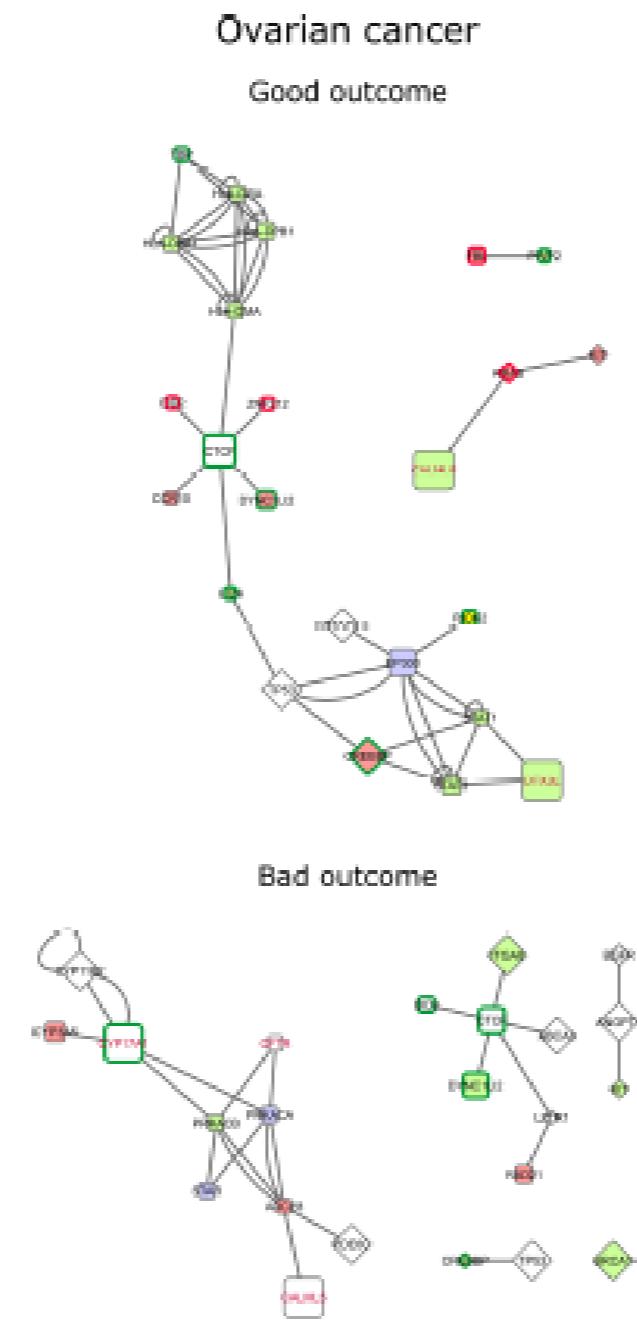
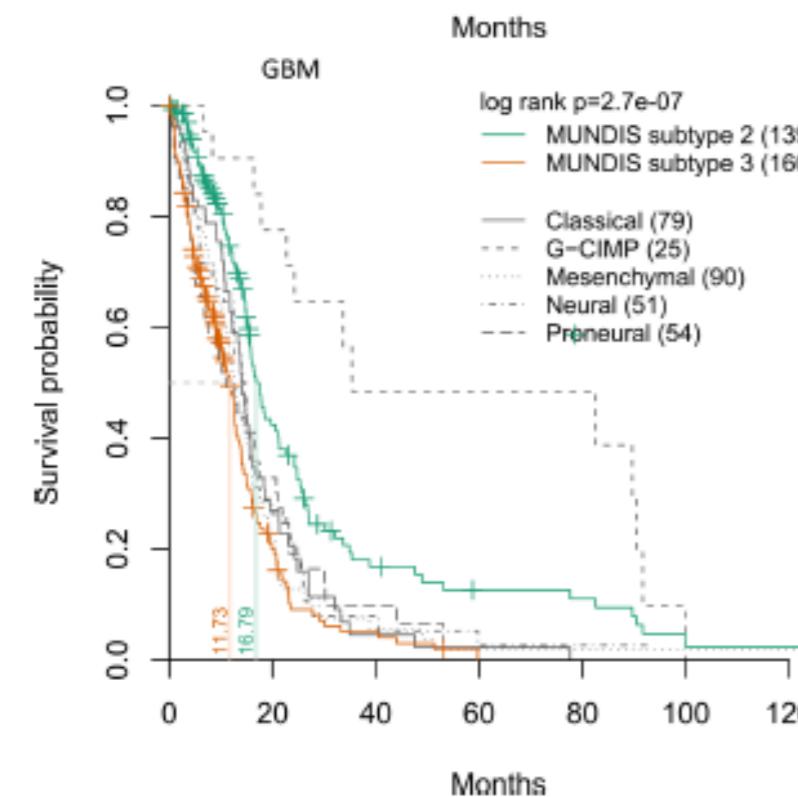
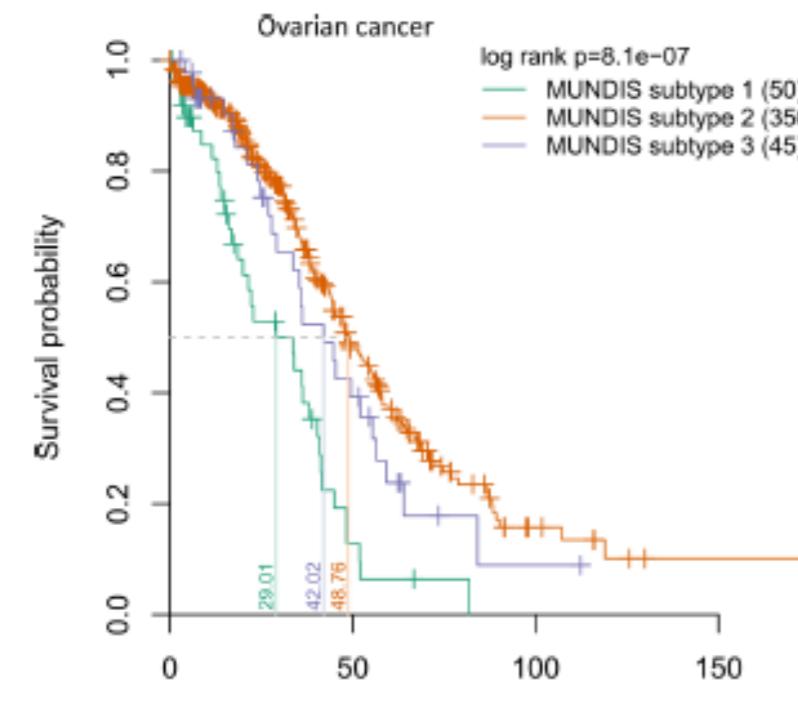


Complex network model



# Network-based analysis of omics data

Results provide insight in the mechanism of the disease

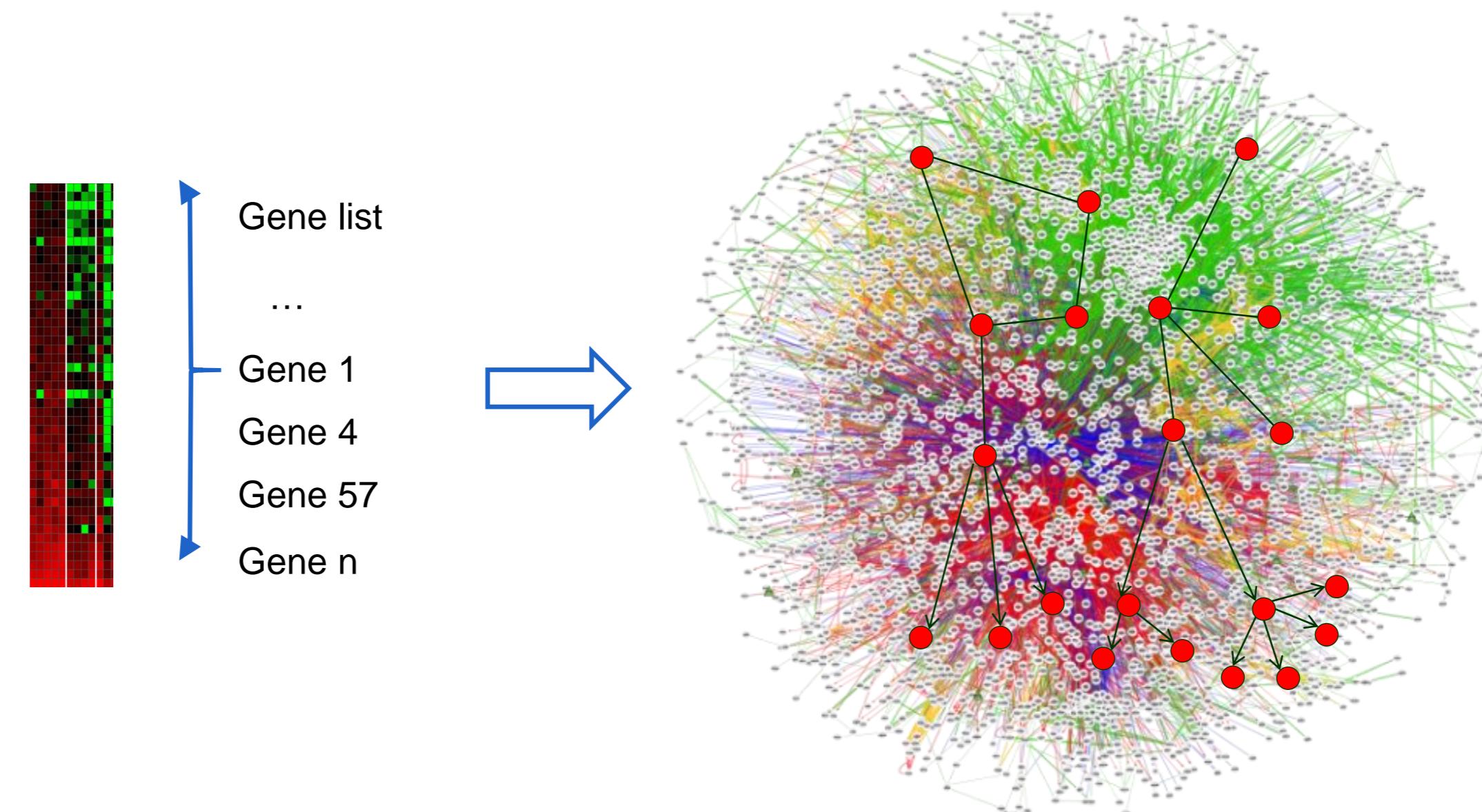


# Network-based analysis of omics data

Network  
model

Network model	Gene centric information	Gene set information	Network properties	
Network propagation	Mutation Epigenetic Expression	Mutual exclusivity	undirected, simple undirected, simple undirected, simple undirected, complex undirected, complex	
Significance area extraction	DriverNet <sup>2, 3</sup> NetSig <sup>2</sup> SSA.ME <sup>2</sup> MEMO <sup>2</sup> MUTEX <sup>2</sup> MEMCOVER <sup>2</sup>	✓ ✓ ✓ ✓ ✓ ✓	✓ ✓ ✓ ✓ ✓ ✓	undirected, complex undirected, simple undirected, simple undirected, simple undirected, simple undirected, simple
(Probabilistic) path-finding	PARADIGM* FAME Phenetic	✓ ✓ ✓	✓ ✓ ✓	directed, complex undirected, simple directed, simple

# Case 1: Network-guided data interpretation

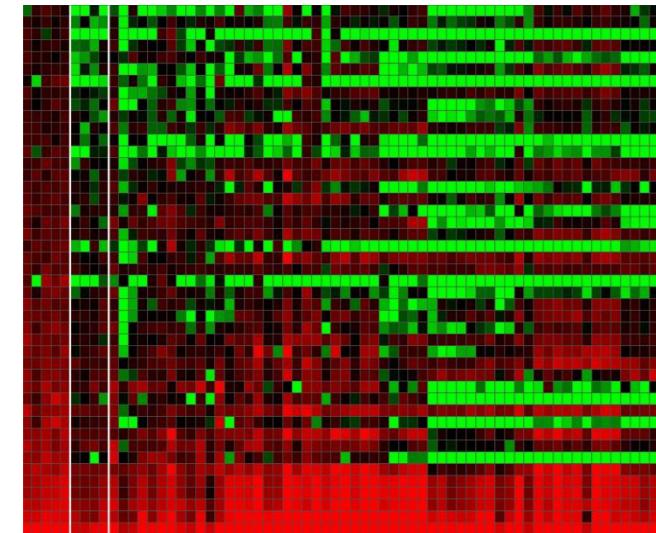


- Map the genes on the interaction network
- Connect the genes on the interaction network and extract relevant edges

} Non trivial because the network is overconnected

# Case 1: Network-guided data-interpretation

## Phenetic: probabilistic subnetwork selection

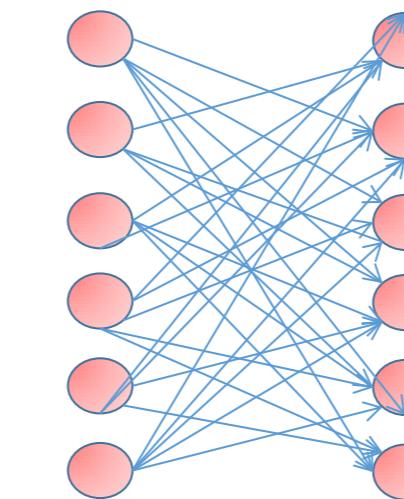


Entity List

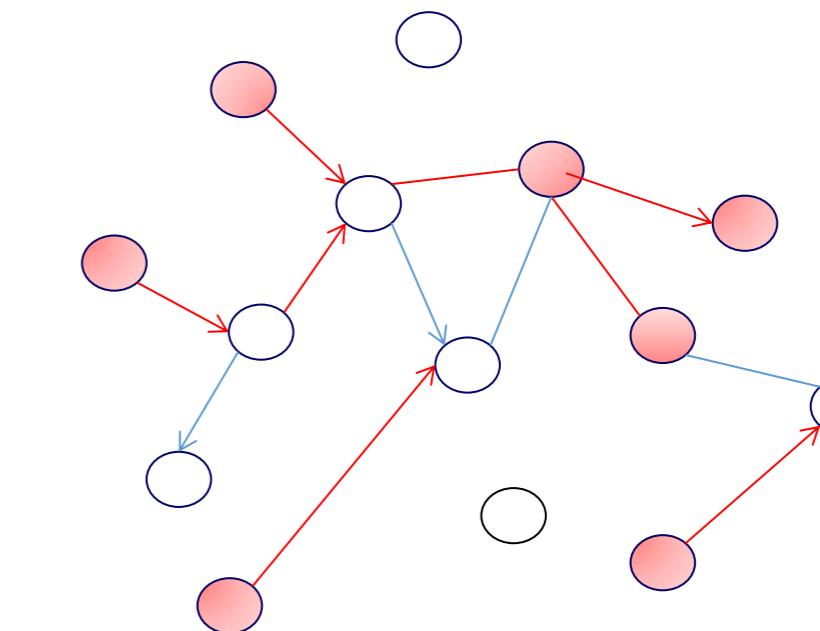
gene 1  
gene 2  
...  
gene n



Entity pairs



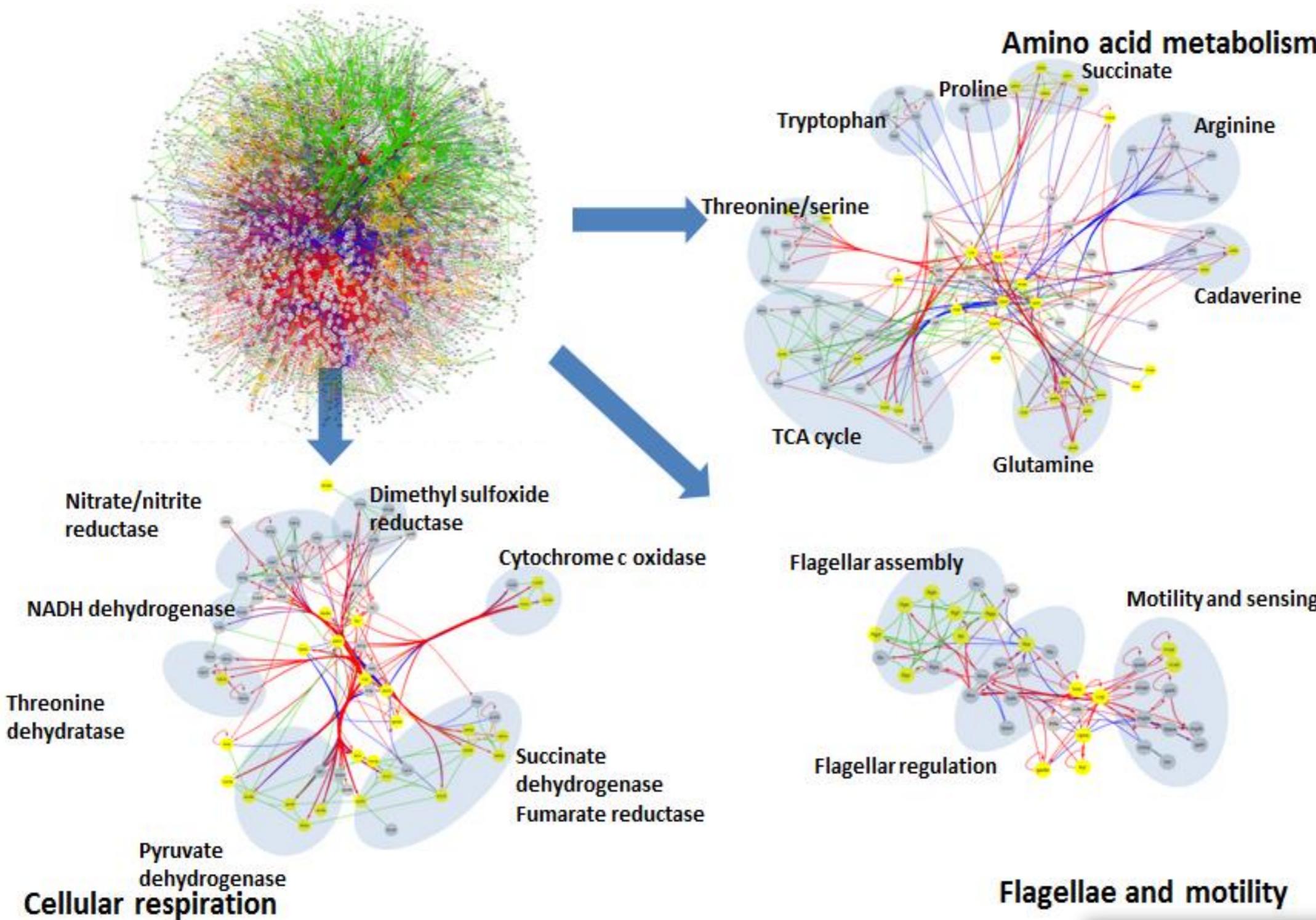
Entity pairs linked over interaction network



$$S(K) = \sum_i^n (\sum_j^l (P(path(C_{i,j}, A_i) | Q_i, K))) - |K| * x_e$$

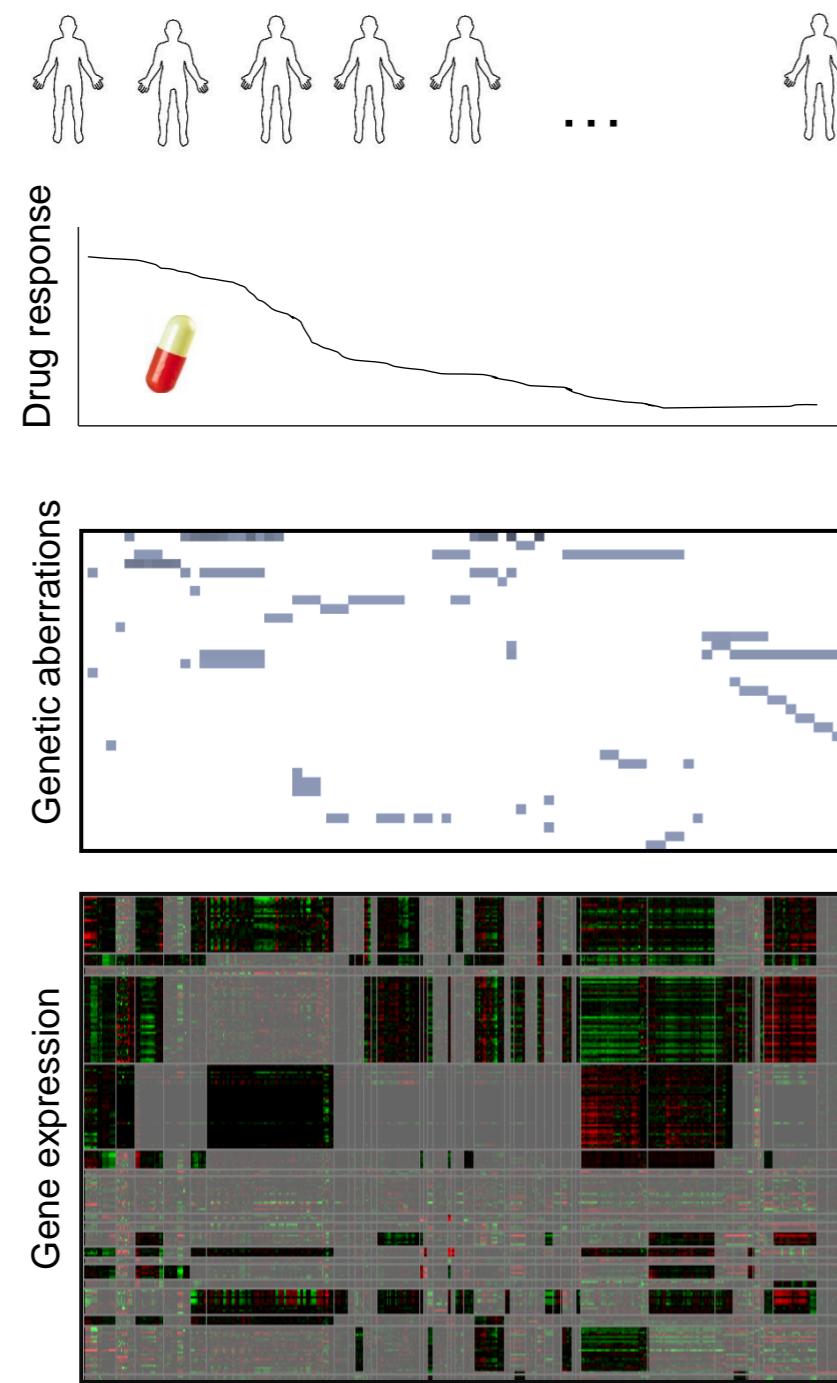
# Case 1: Network-guided data-interpretation

## Phenetic: probabilistic subnetwork selection

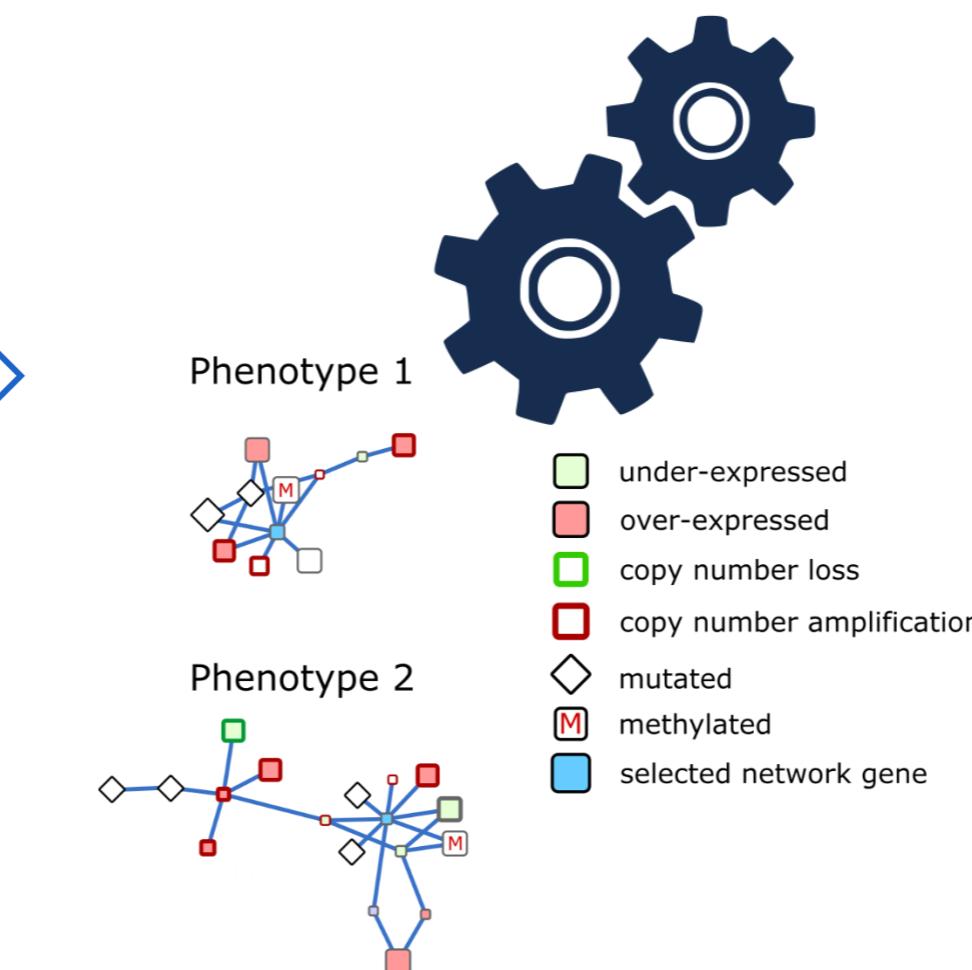


# Case 2: Identifying pathway signatures

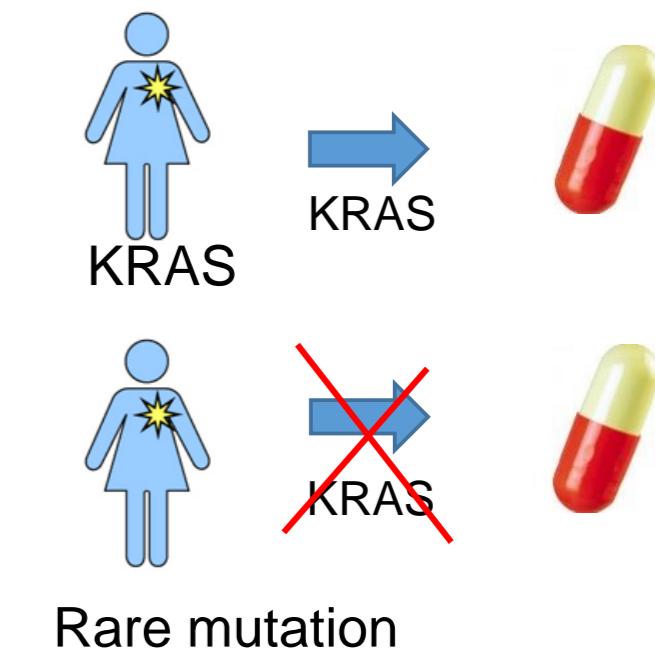
Cohort data



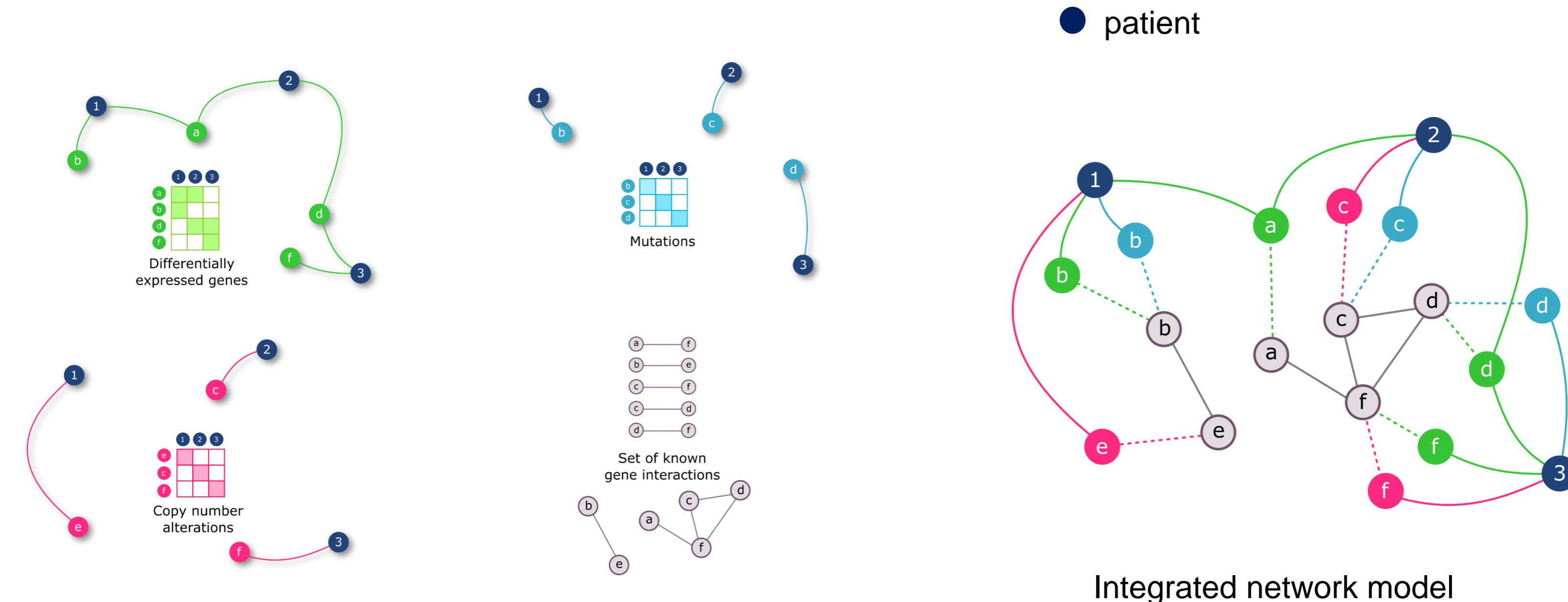
Network-based data integration



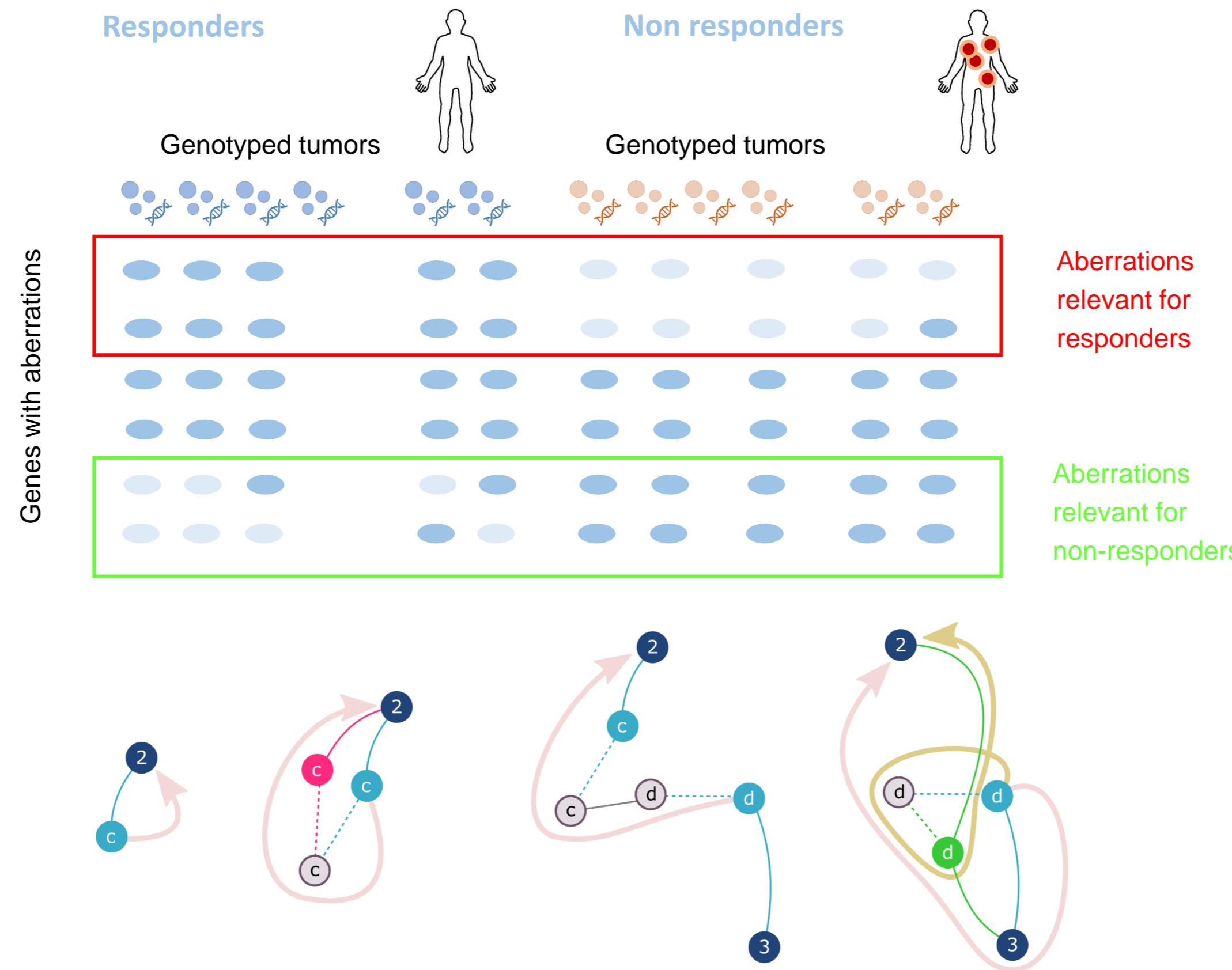
Biomarkers for improved patient stratification



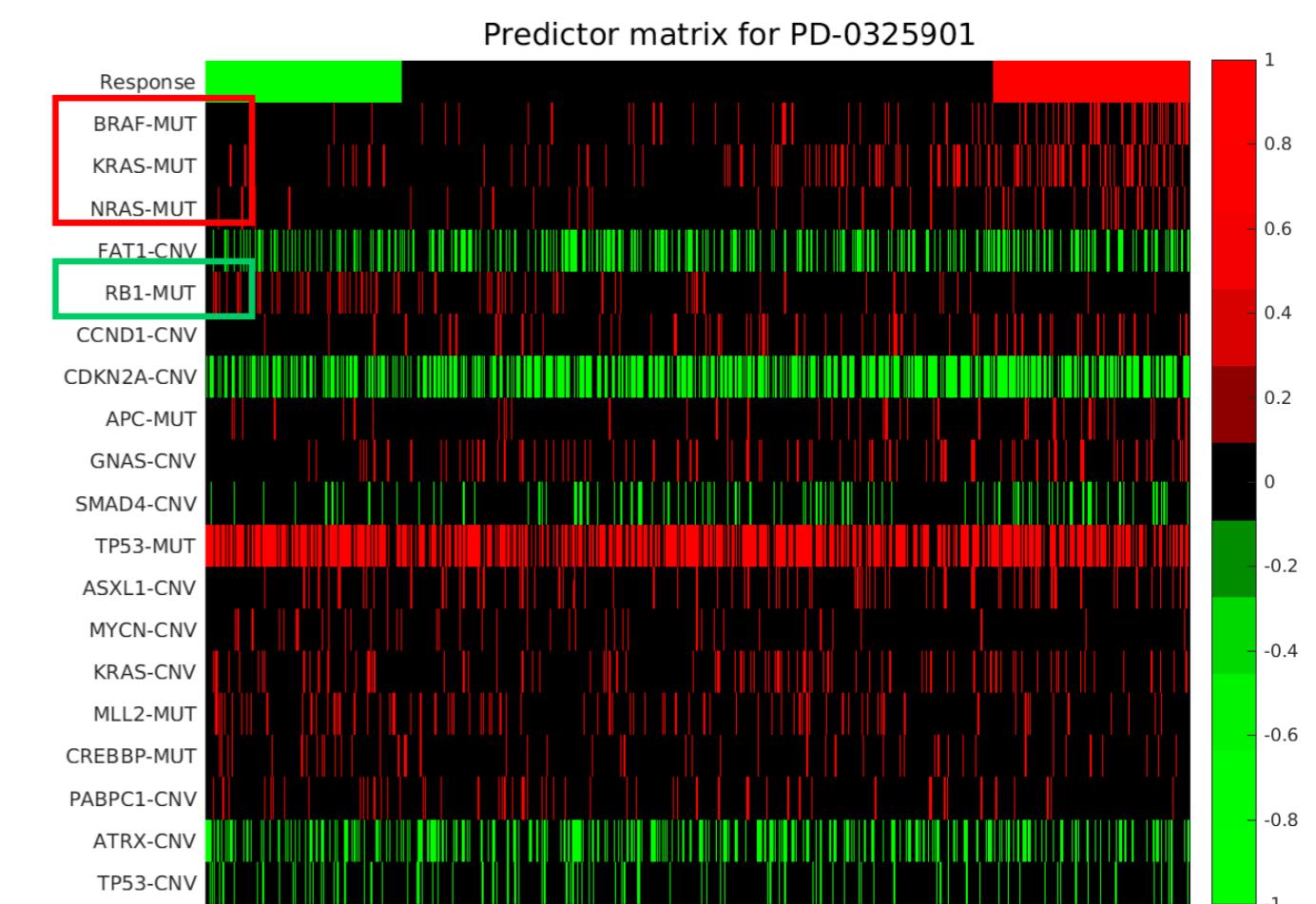
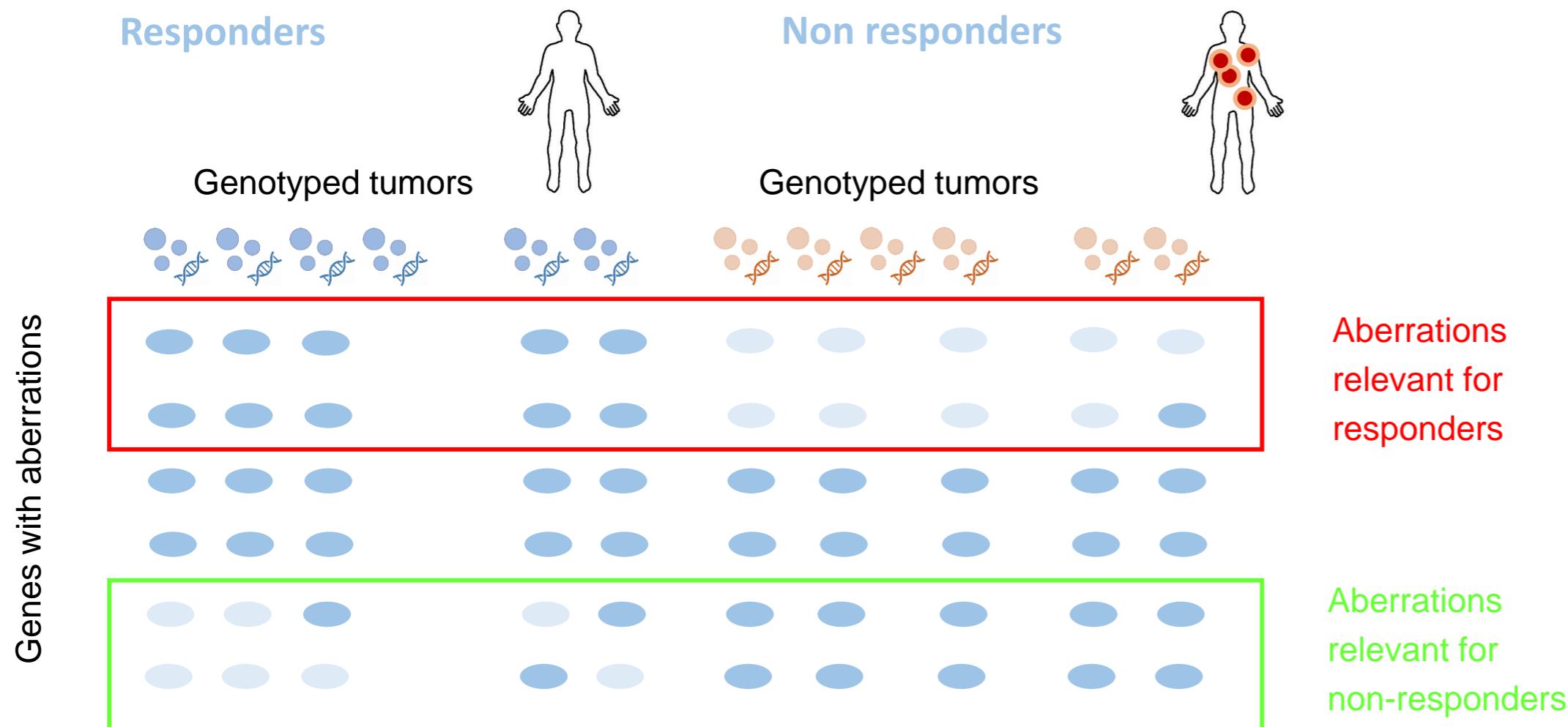
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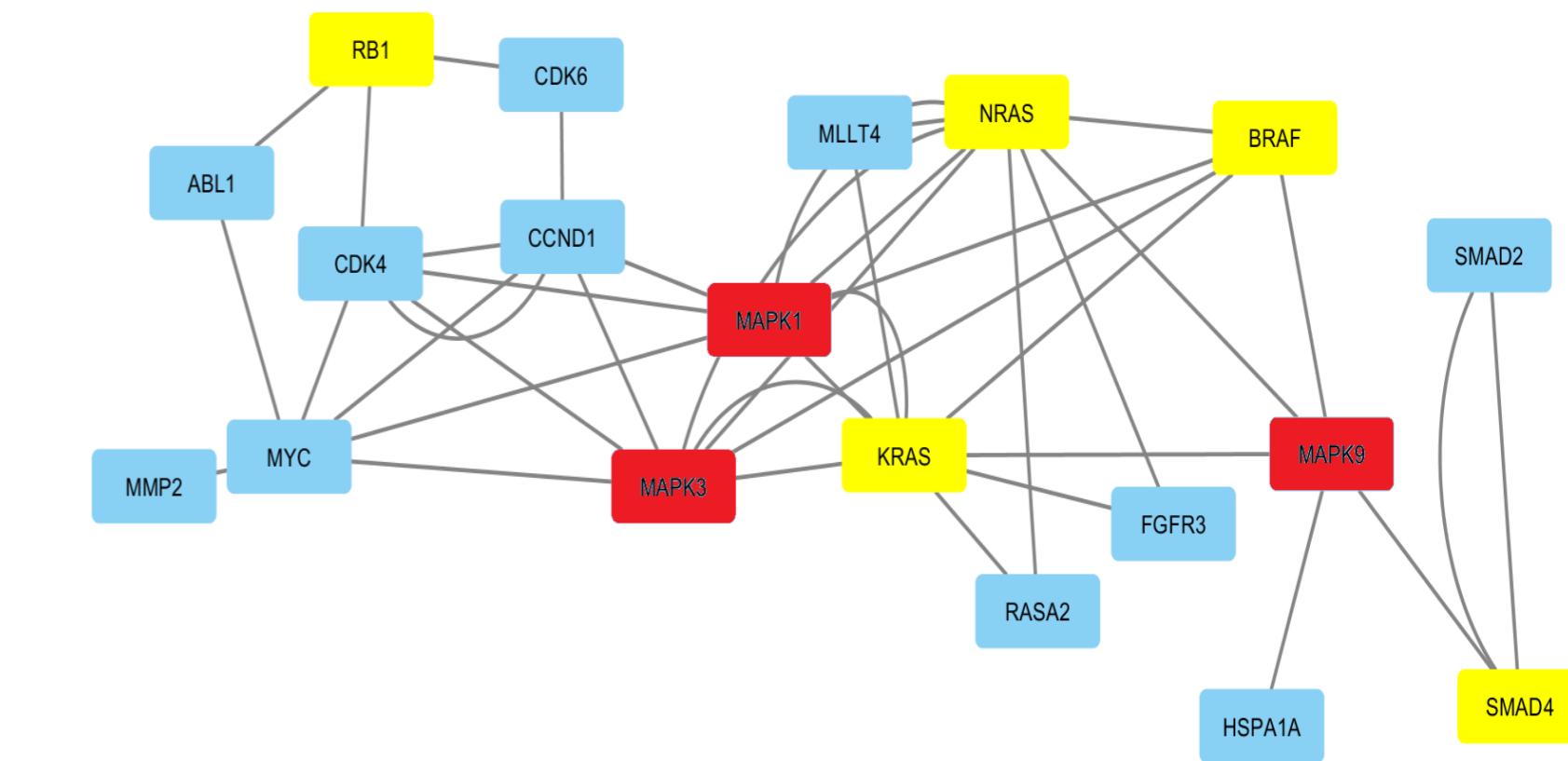
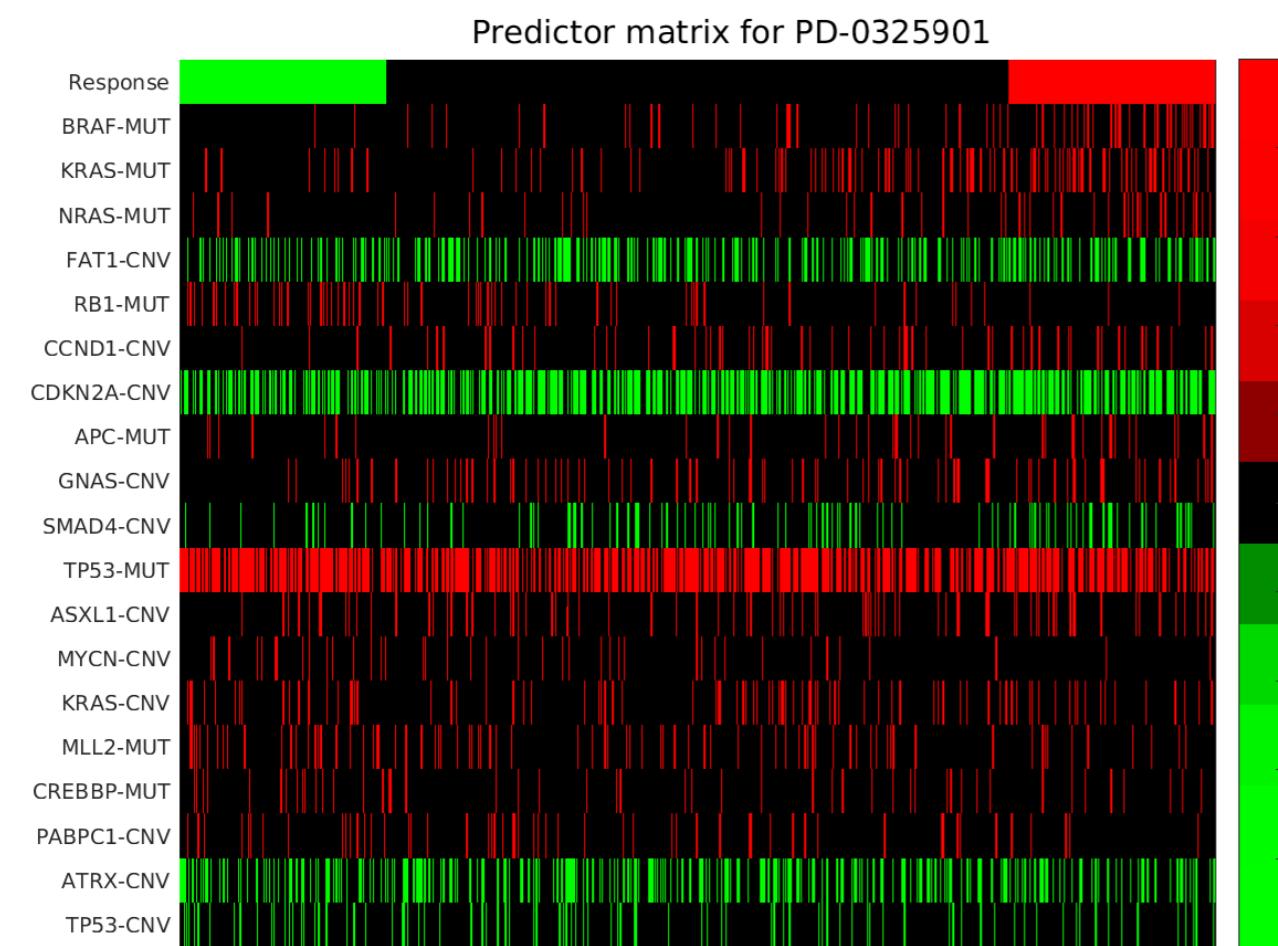


# Case 2: Identifying pathway signatures



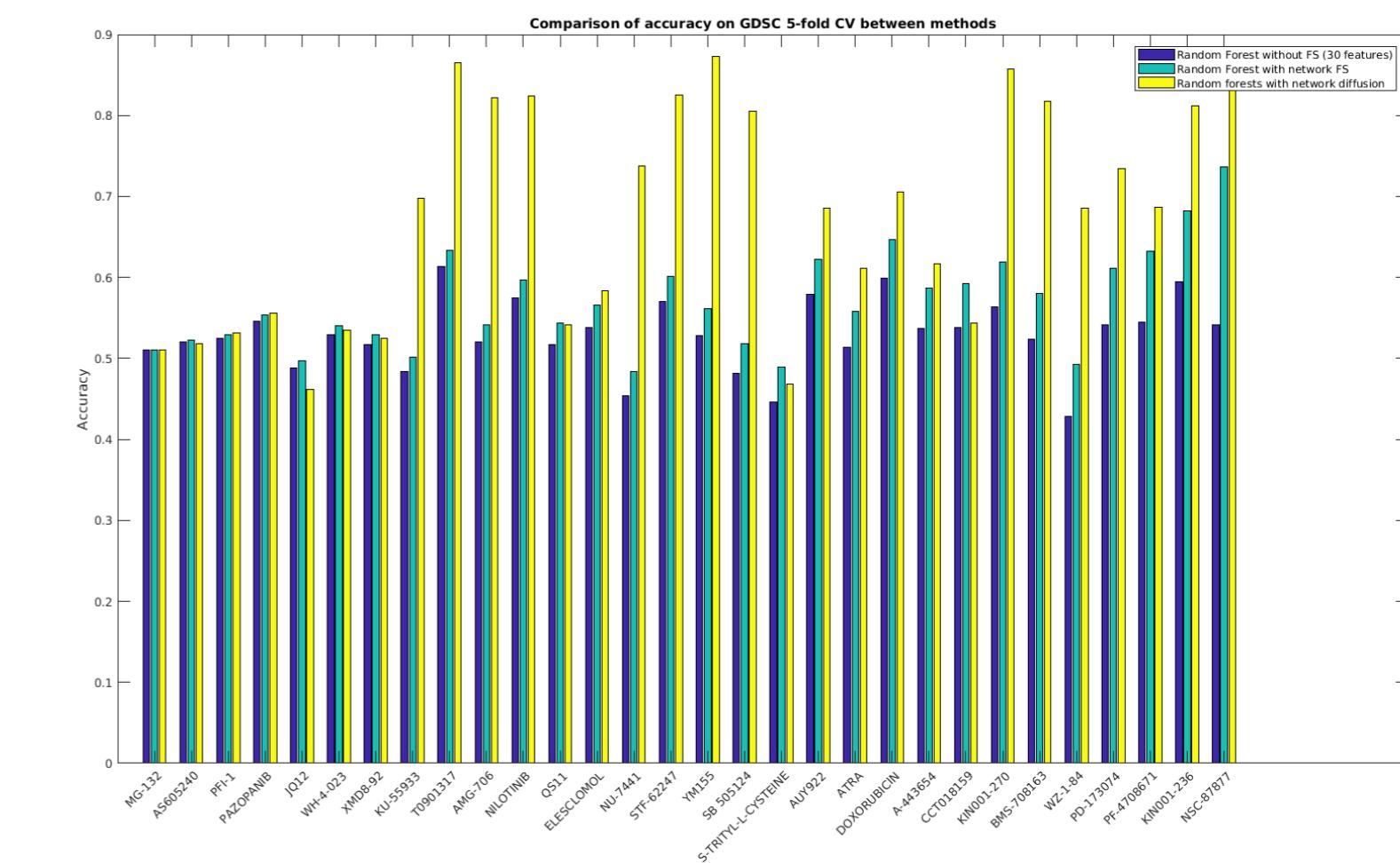
# Case 2: Identifying pathway signatures

Pathway-based biomarkers: network relevant to drug response



# Case 2: Identifying pathway signatures

Drug Name	Target	Pathway	Feature	Sign	Network ranking	Predictor Ranking
AC220	FLT3	RTK signaling	FLT3-MUT	+	9 (MUTP)	3
AFATINIB	ERBB2, EGFR	EGFR signaling	EGFR-AMP	+	5 (CNVP)	4
AMG-706	VEGFR, RET, c-KIT, PDGFR	RTK signaling	PDGFRA-AMP	+	2 (CNVP)	2
BOSUTINIB	SRC, ABL, TEC	ABL signaling	BCR-ABL-MUT	+	2 (MUTP)	1
DABRAFENIB	BRAF	ERK MAPK signaling	BRAF-MUT	+	1 (MUTP)	1
DASATINIB	ABL, SRC, KIT, PDGFR	ABL signaling	BCR-ABL-MUT	+	3 (MUTP)	2
GDC0941	PI3K (class 1)	PI3K signaling	PIK3CA-MUT	+	1 (NETP)	2
GEFINITIB	EGFR	EGFR signaling	EGFR-MUT	+	1 (NETP)	4
GEFINITIB	EGFR	EGFR signaling	EGFR-AMP	+	1 (NETP)	5
GSK690693	AKT	PI3K signaling	PIK3CA-MUT	+	2 (MUTP)	4
GSK690693	AKT	PI3K signaling	PTEN-MUT	+	1 (MUTP)	6
IMATINIB	ABL, KIT, PDGFR	ABL signaling	BCR-ABL-MUT	+	1 (MUTP)	1
LAPATINIB	ERBB2, EGFR	EGFR signaling	ERBB2-AMP	+	3 (CNVP)	-
MITOMYCIN C	DNA crosslinker	DNA replication	TP53-MUT	+	1 (NETP)	3
NILOTINIB	ABL	ABL signaling	BCR-ABL-MUT	+	1 (MUTP)	1
NUTLIN-3	MDM2	p53 pathway	TP53-MUT	-	1 (NETN)	1
OLAPARIB	PARP1, PARP2	Genome integrity	EWSR1-FLI1-MUT	+	1 (MUTP)	1
PD-0332991	CDK4, CDK6	cell cycle	RB1-DEL	-	1 (CNVN)	3
PLX4720	BRAF	ERK MAPK signaling	BRAF-MUT	+	1 (MUTP)	1
TRAMETINIB	MAP2K1 (MEK1), MAP2K2 (MEK2)	ERK MAPK signaling	BRAF-MUT	+	2 (MUTP)	1
TRAMETINIB	MAP2K1 (MEK1), MAP2K2 (MEK2)	ERK MAPK signaling	KRAS-MUT	+	1 (MUTP)	2
TRAMETINIB	MAP2K1 (MEK1), MAP2K2 (MEK2)	ERK MAPK signaling	NRAS-MUT	+	8 (NETP)	3



# Conclusion

- Omics data integration offers a huge potential for phenotypic analysis, but data-analysis is not trivial
- Network-based data integration methods are tuned towards the integration of molecular data by using biologically relevant assumptions
  - Increases the power of the analysis
  - Insight into the mode of action
  - Intuitive scaffold to integrate omics data

# Acknowledgements

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