

What can we Measure Today, Tomorrow and Which Experiments are Useful for Model Inference, and a Couple of (hopefully) Nice Examples

Dynamic Biological Modeling: Abstractions, Algorithms & Logic

Alejandro Wolf-Yadlin

Department of Genome Science, University of Washington

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The Cell as an Information Processing System

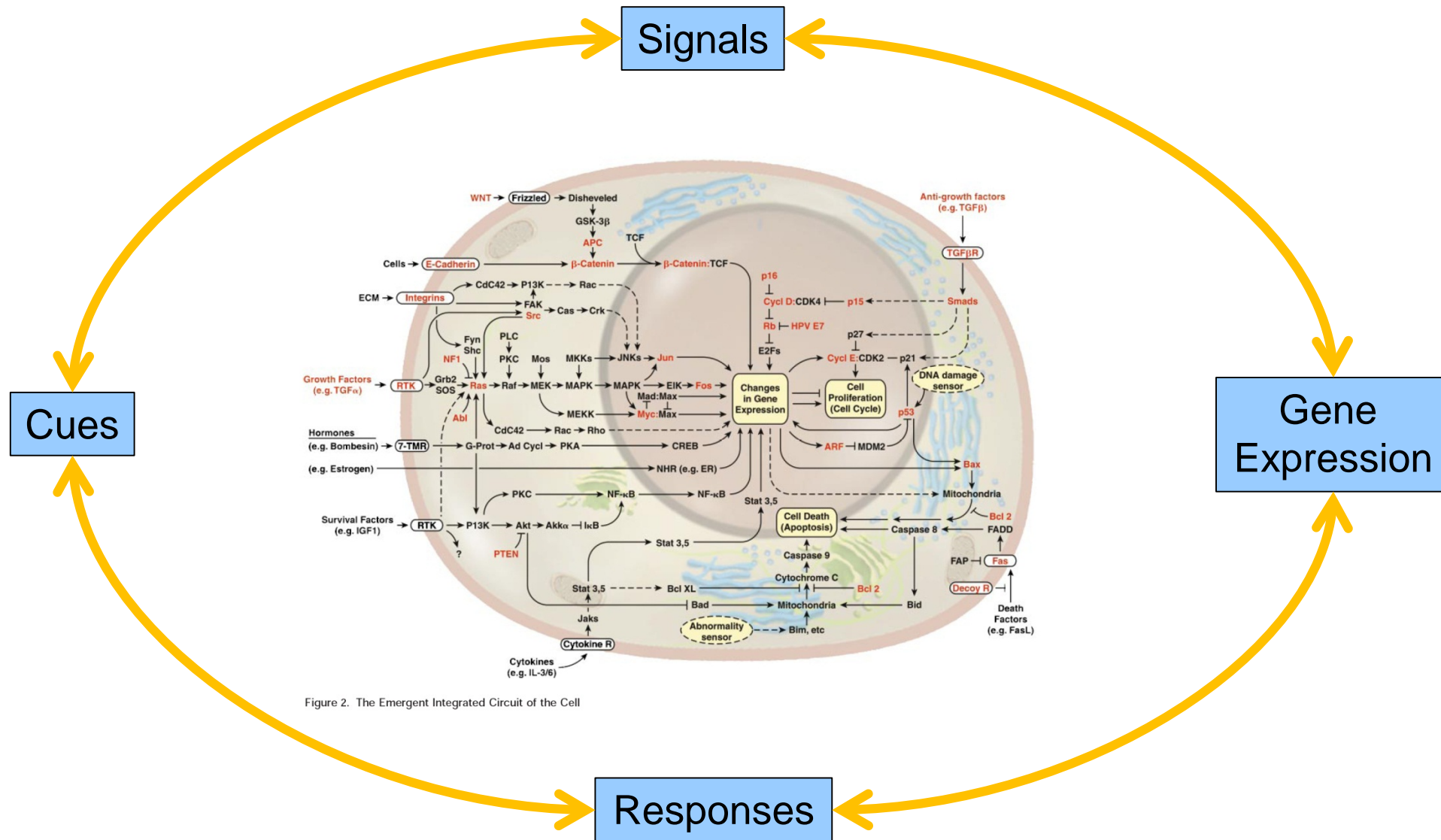
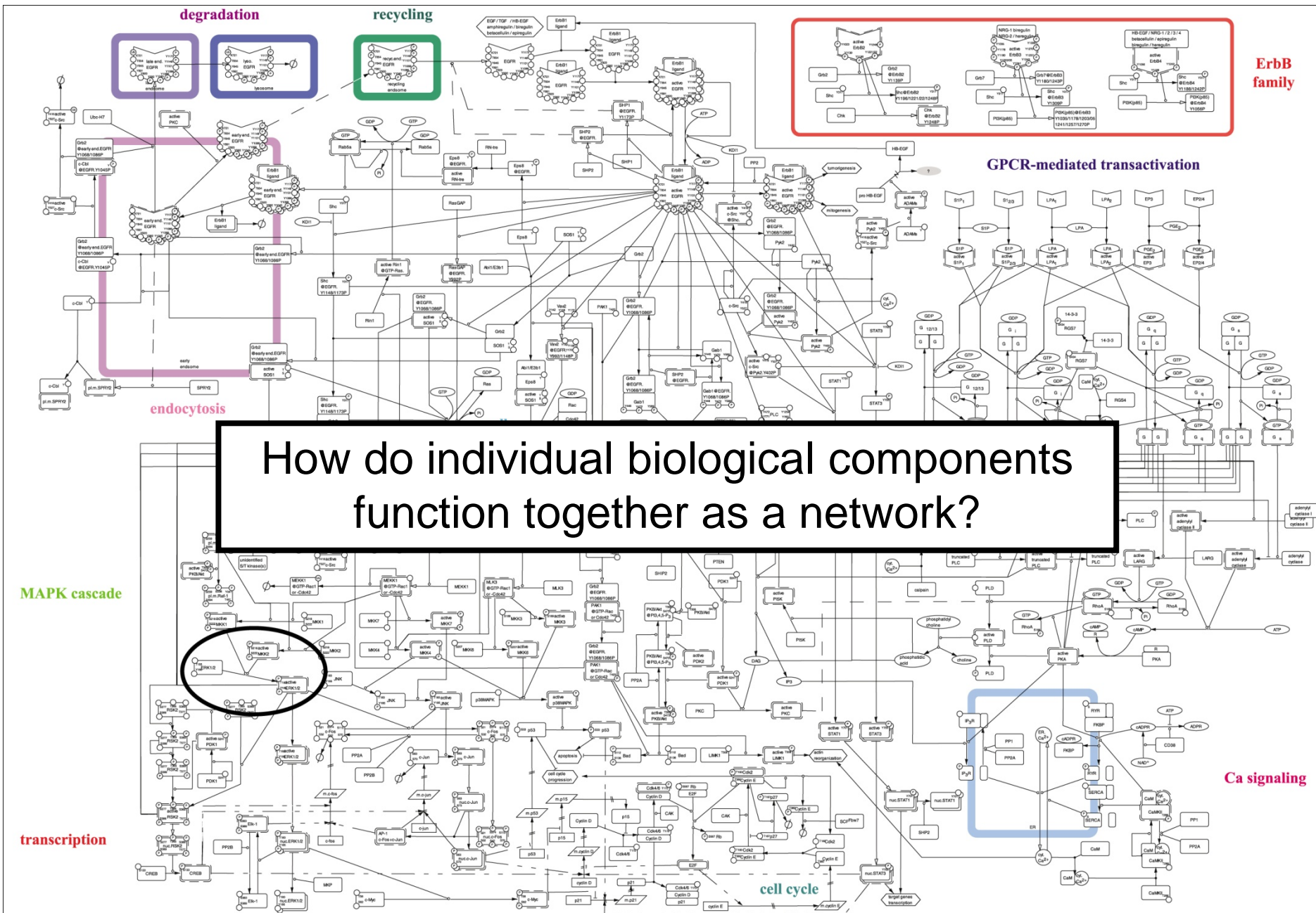
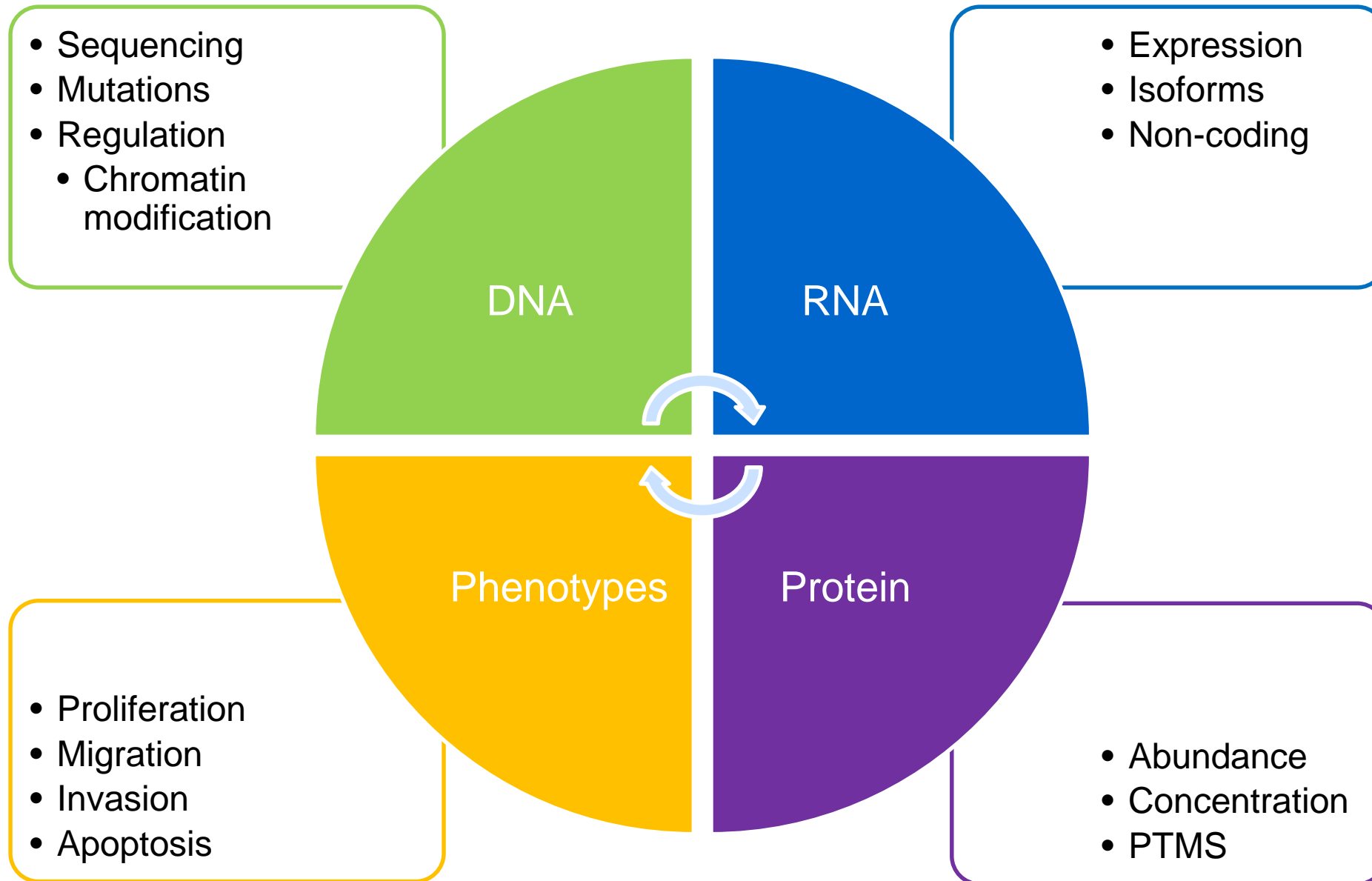


Figure 2. The Emergent Integrated Circuit of the Cell

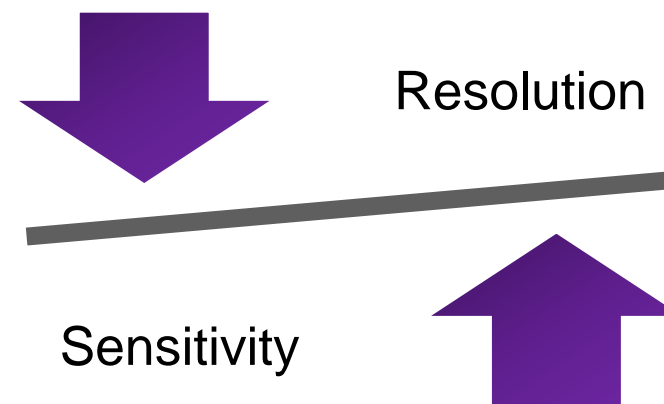
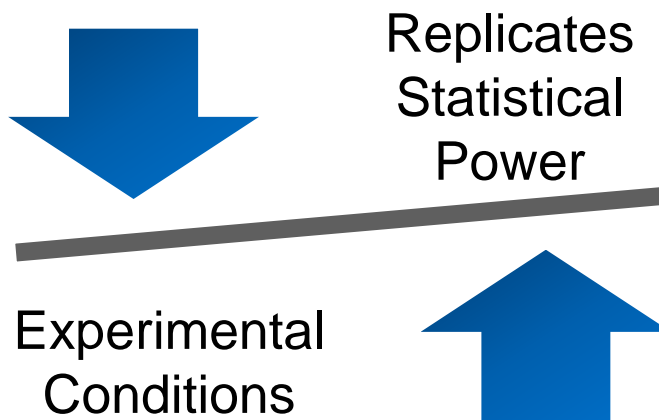
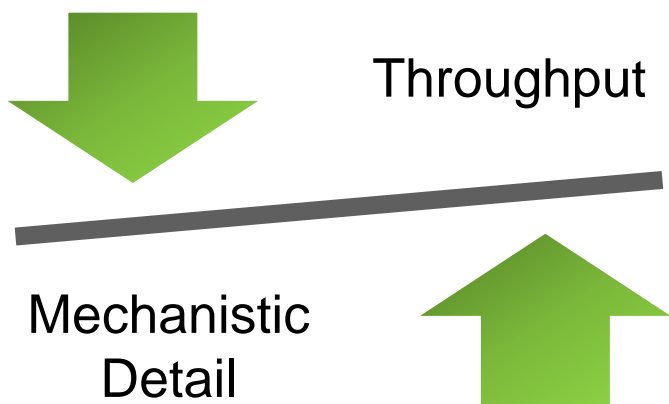
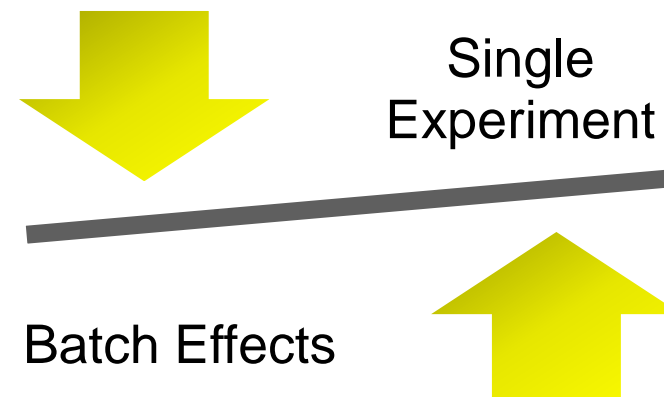
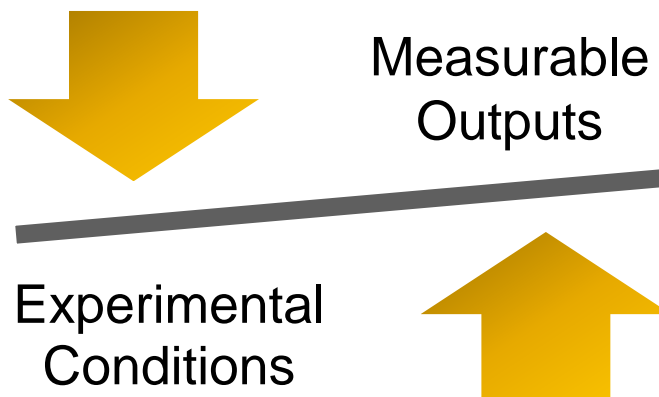
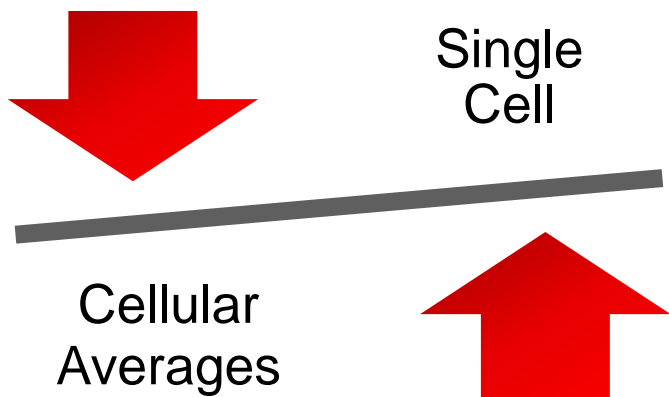


How do individual biological components function together as a network?

What can we measure?

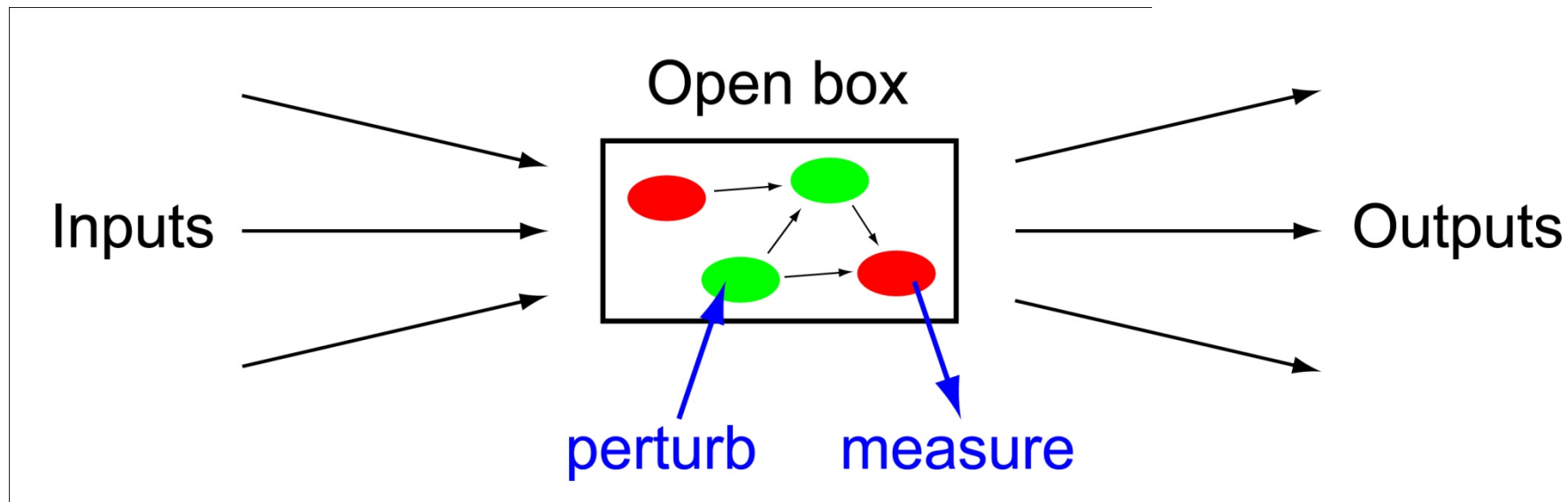
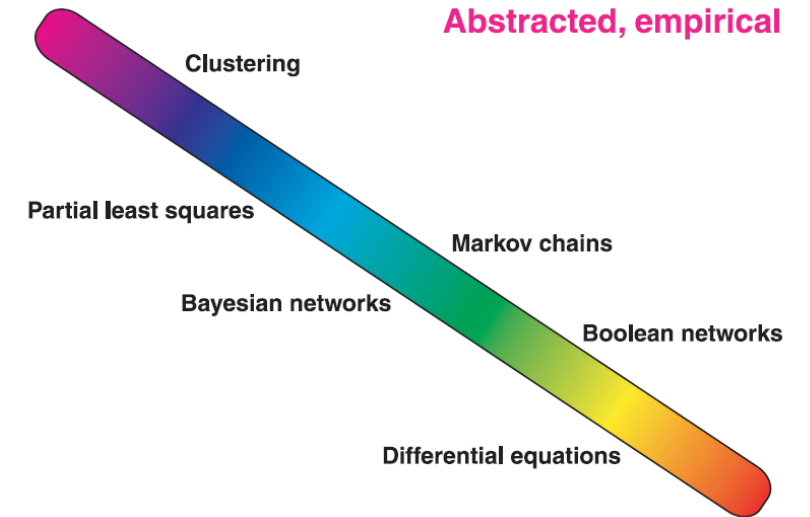


Common Trade offs



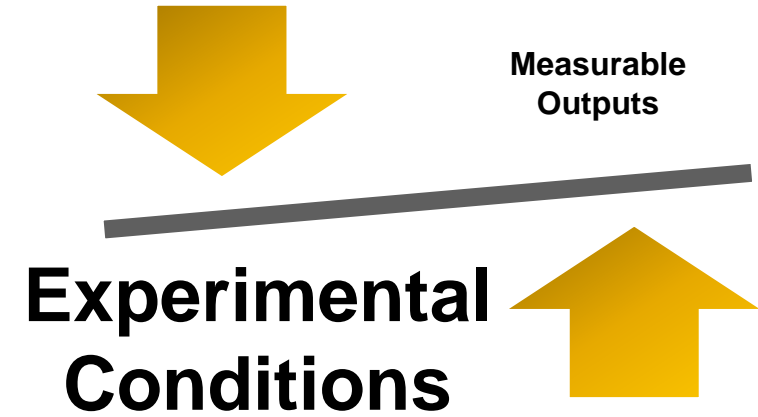
Not all experiments/models are created equally

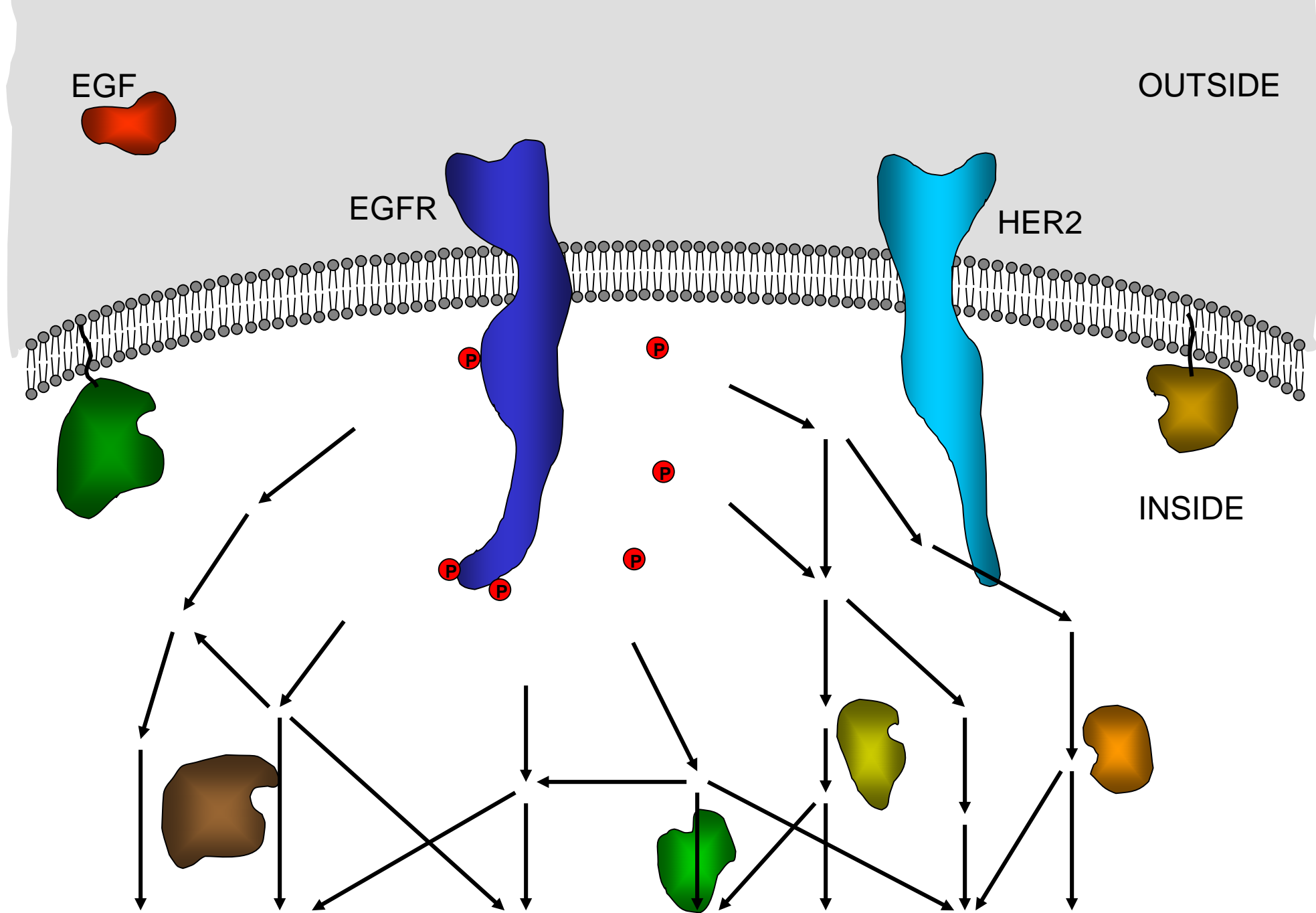
- Talk to your colleagues
 - What model approach fits the problem
- Compare conditions / Perturbations



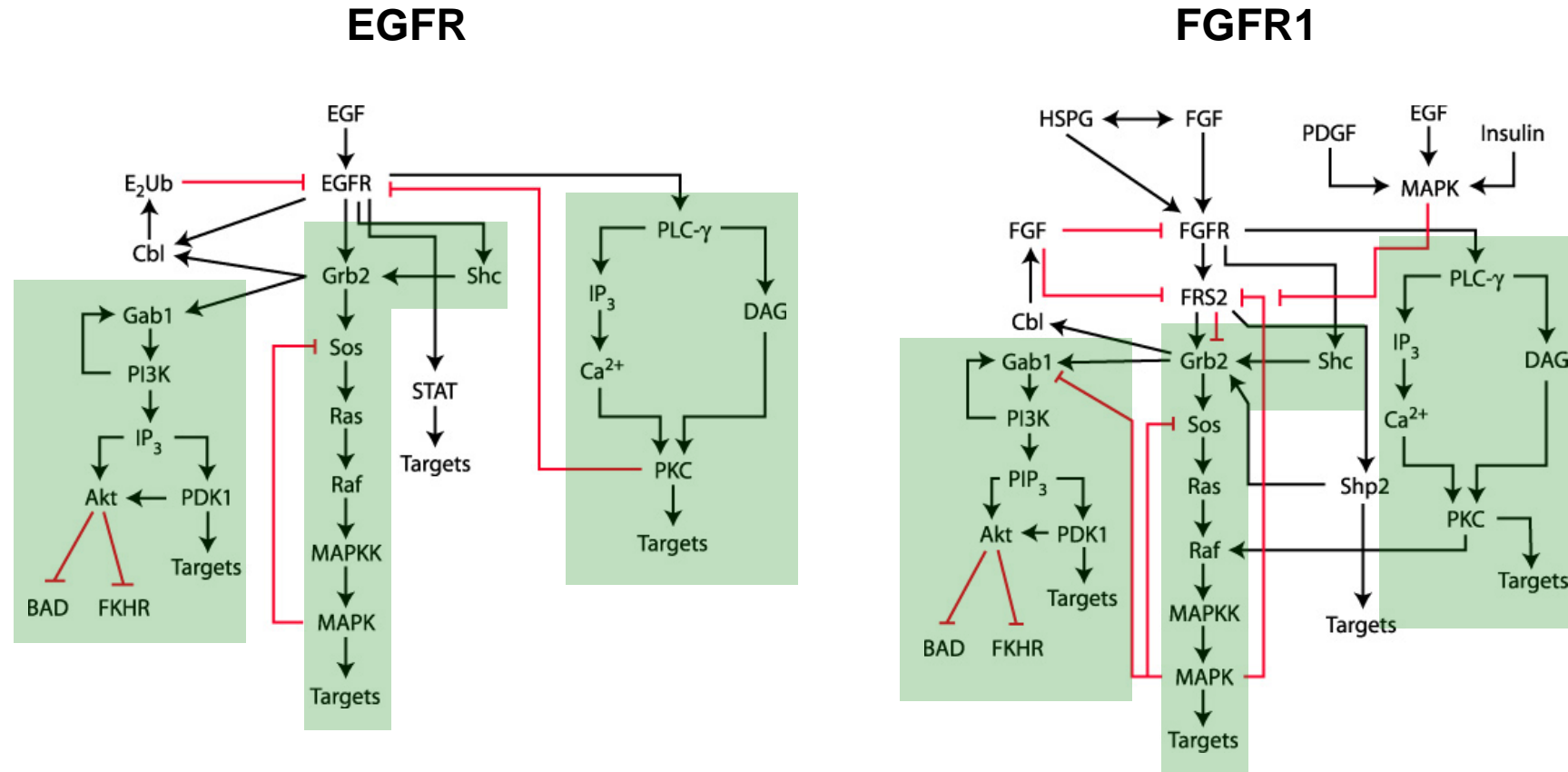
Case Study One: Receptor Tyrosine Kinases

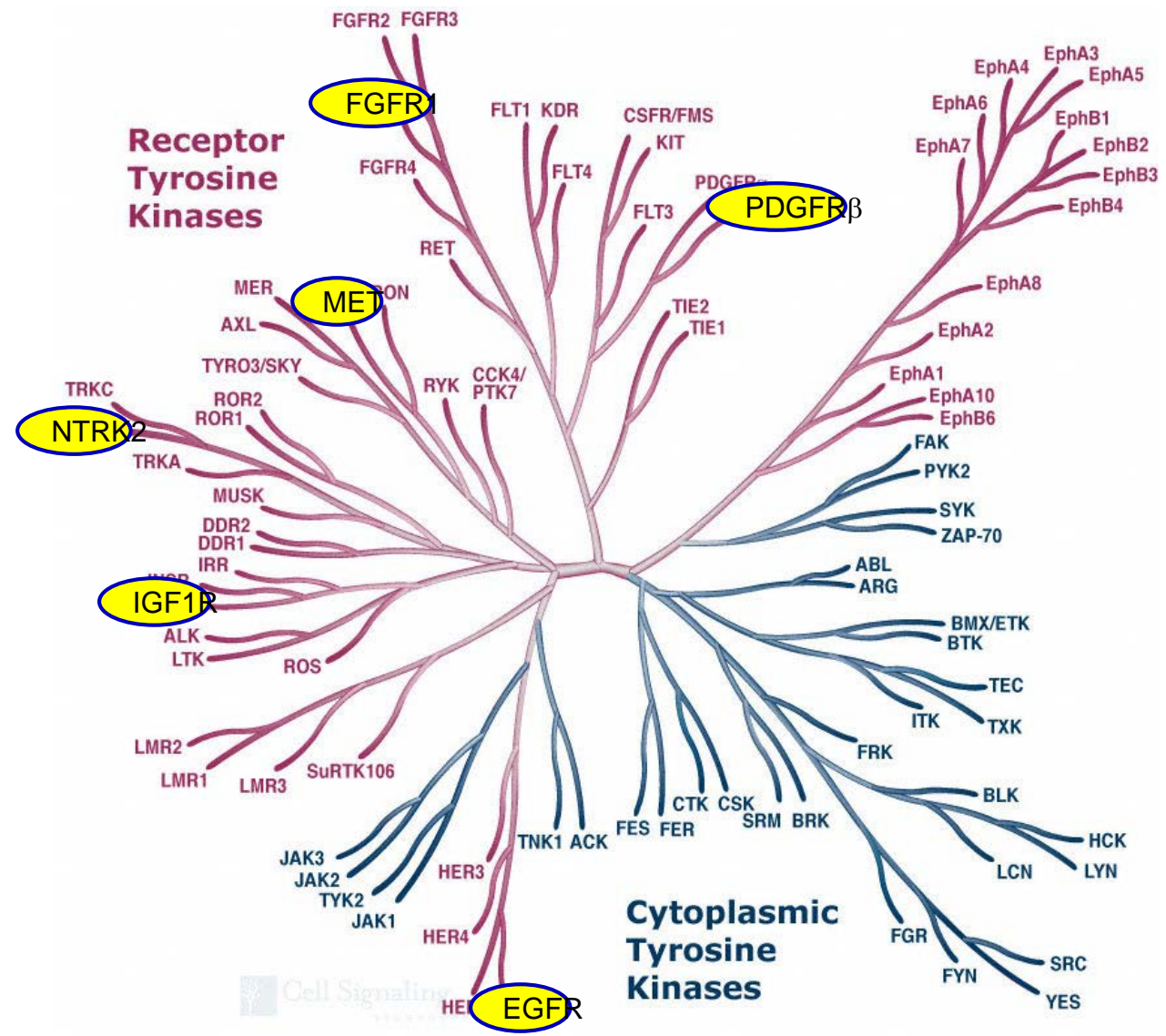
- Determinants of phenotype:
 - Proliferation
 - Migration/Invasio
 - Differentiation
- Deregulation leads to disease
 - Cancer
 - Diabetes
 - Alzheimer's





Binary Wiring Diagrams are Remarkably Similar for Different RTKs

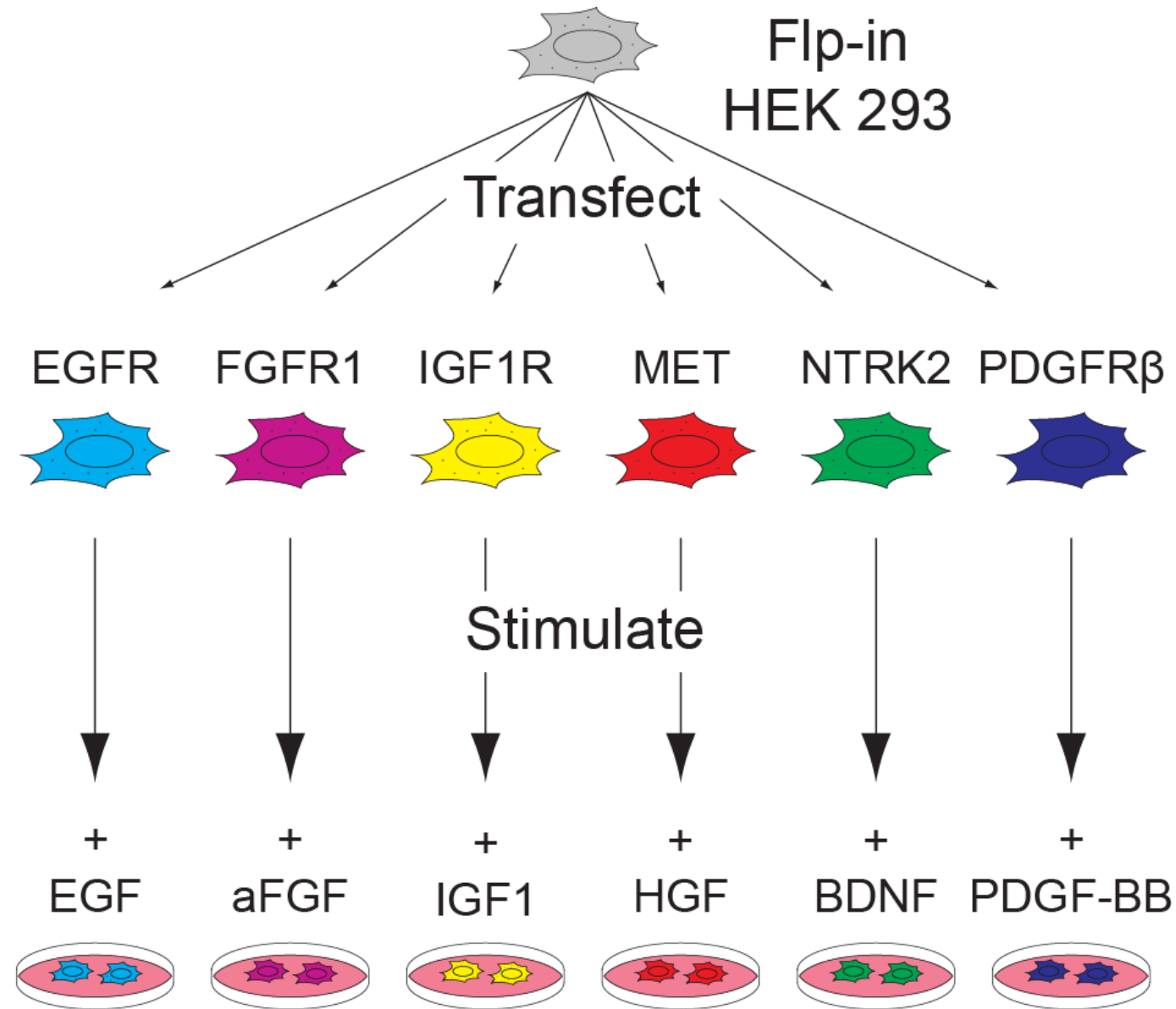




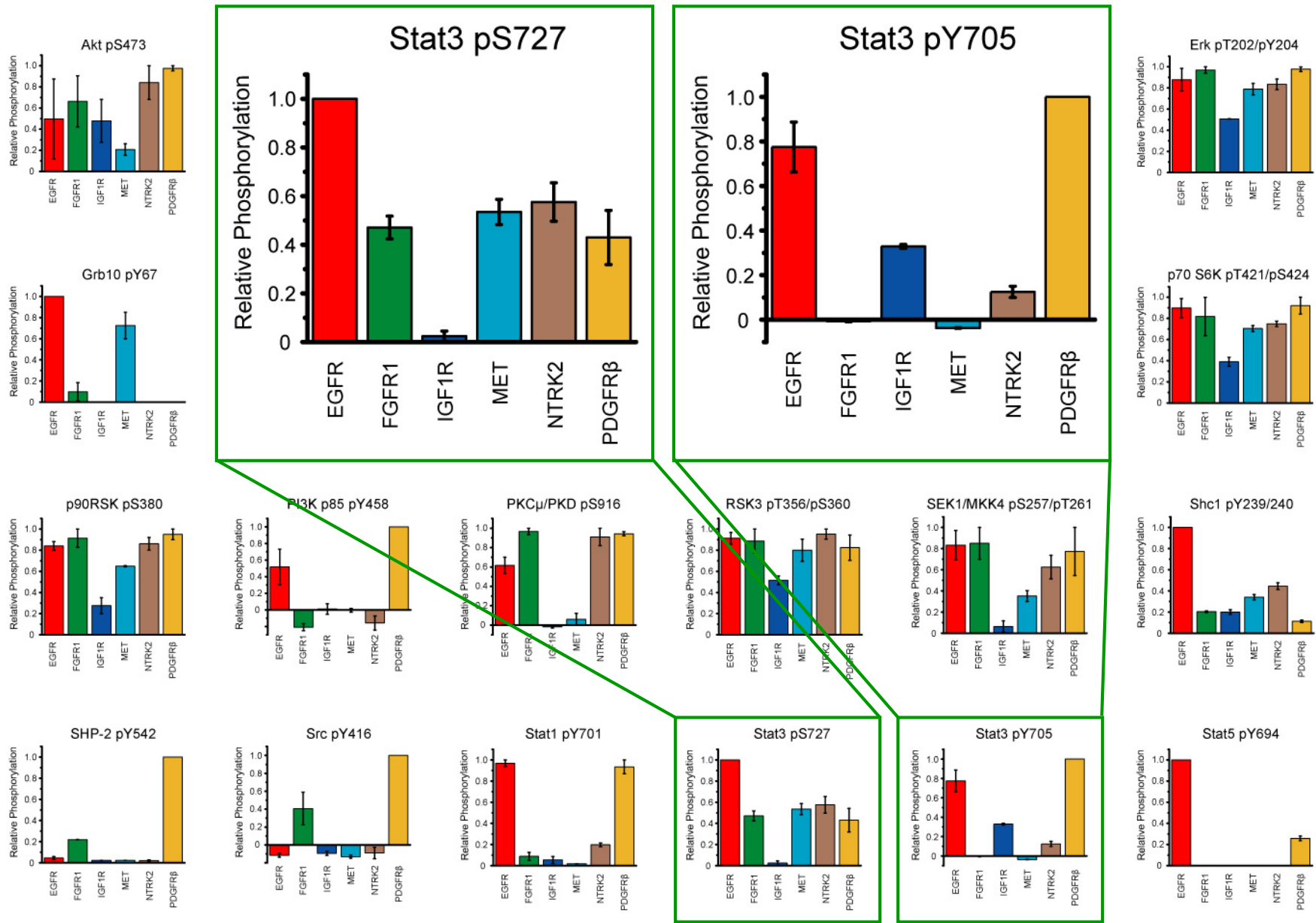
Overview

- We want to understand:
 - Network Connections
 - Network Dynamics
 - Relations among RTKs
 - Relations between RTKs and cancer
- For every RTK we need to:
 - Disrupt the network
 - Measure the network dynamics
- Thousands of samples to collect and measure

Cell Line Treatments

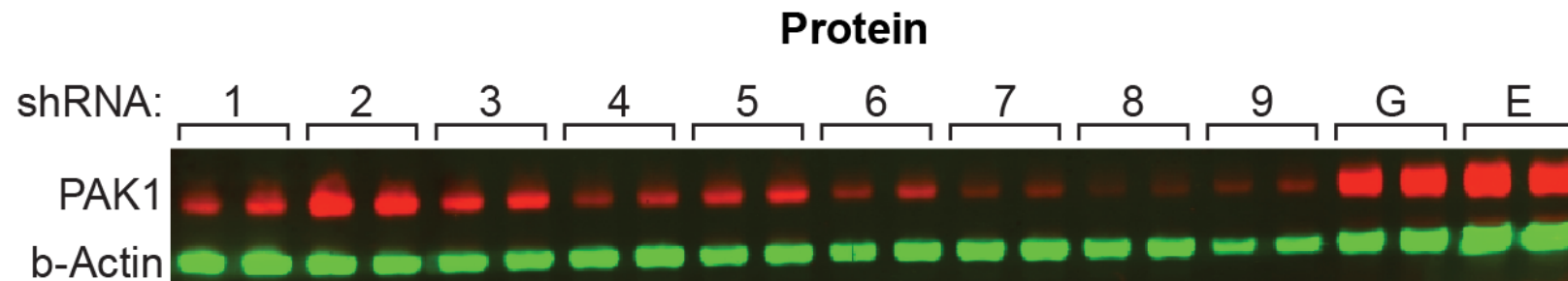
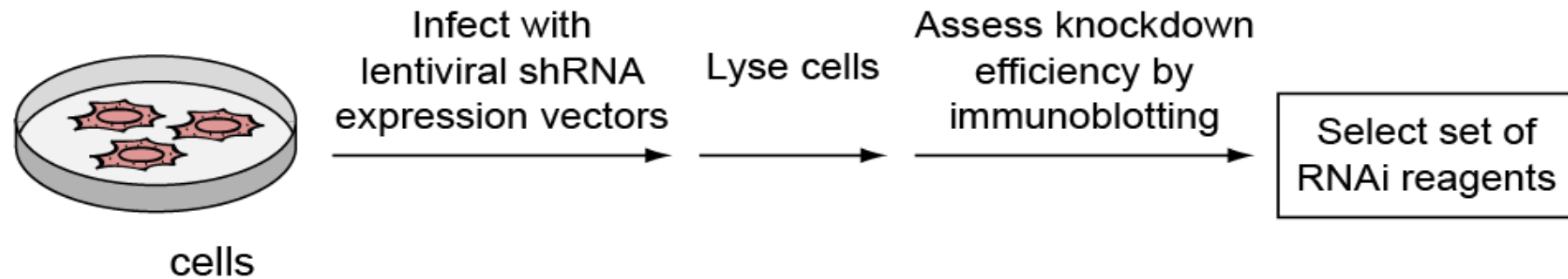


Different RTKs activate different signaling nodes



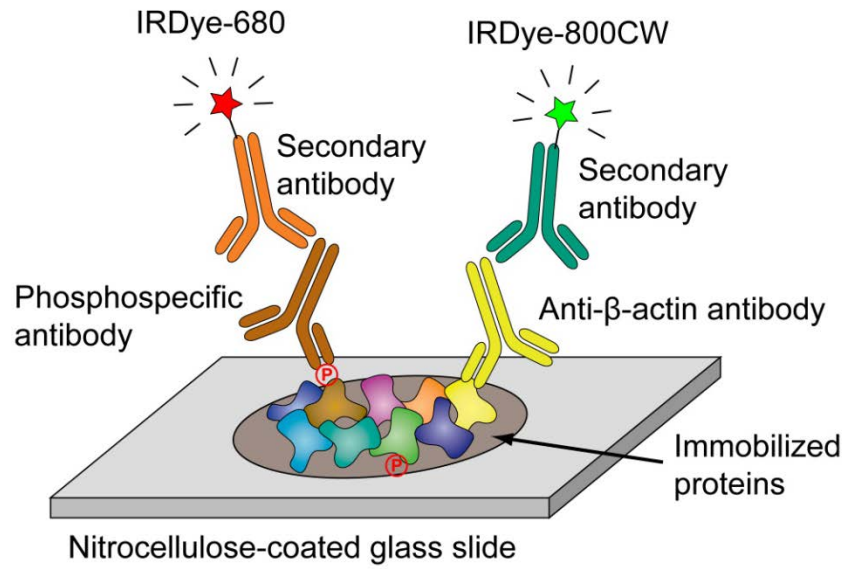
Cellular networks are disrupted using high quality shRNA reagents selected by immunoblotting

Second, we need to validate reagents that will allow us to consistently perturb different cell lines

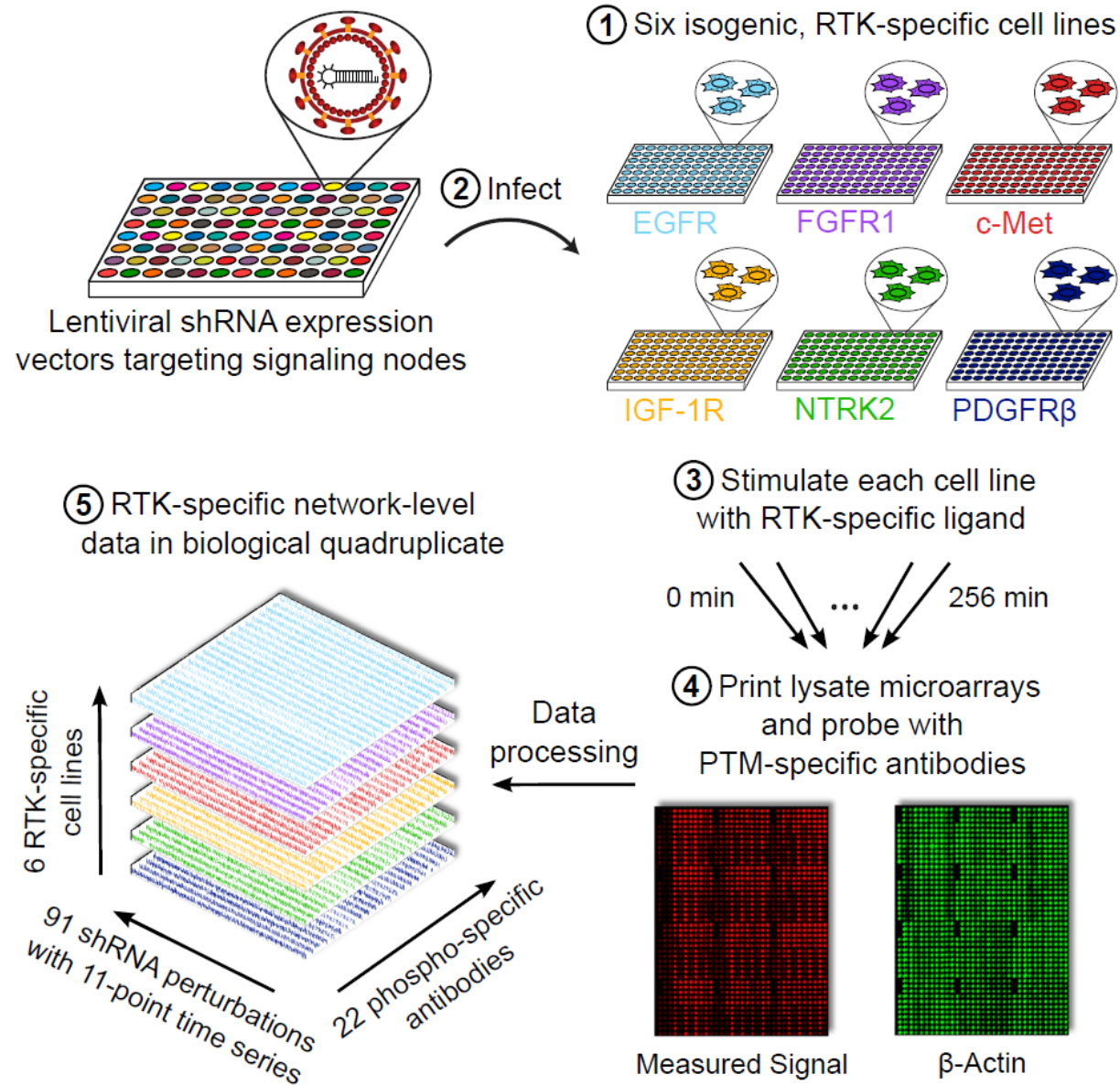


- Test Broad institute library of hairpins for selected signaling nodes
- Chose 2 with highest knockdown efficiency for future work

Detection Method



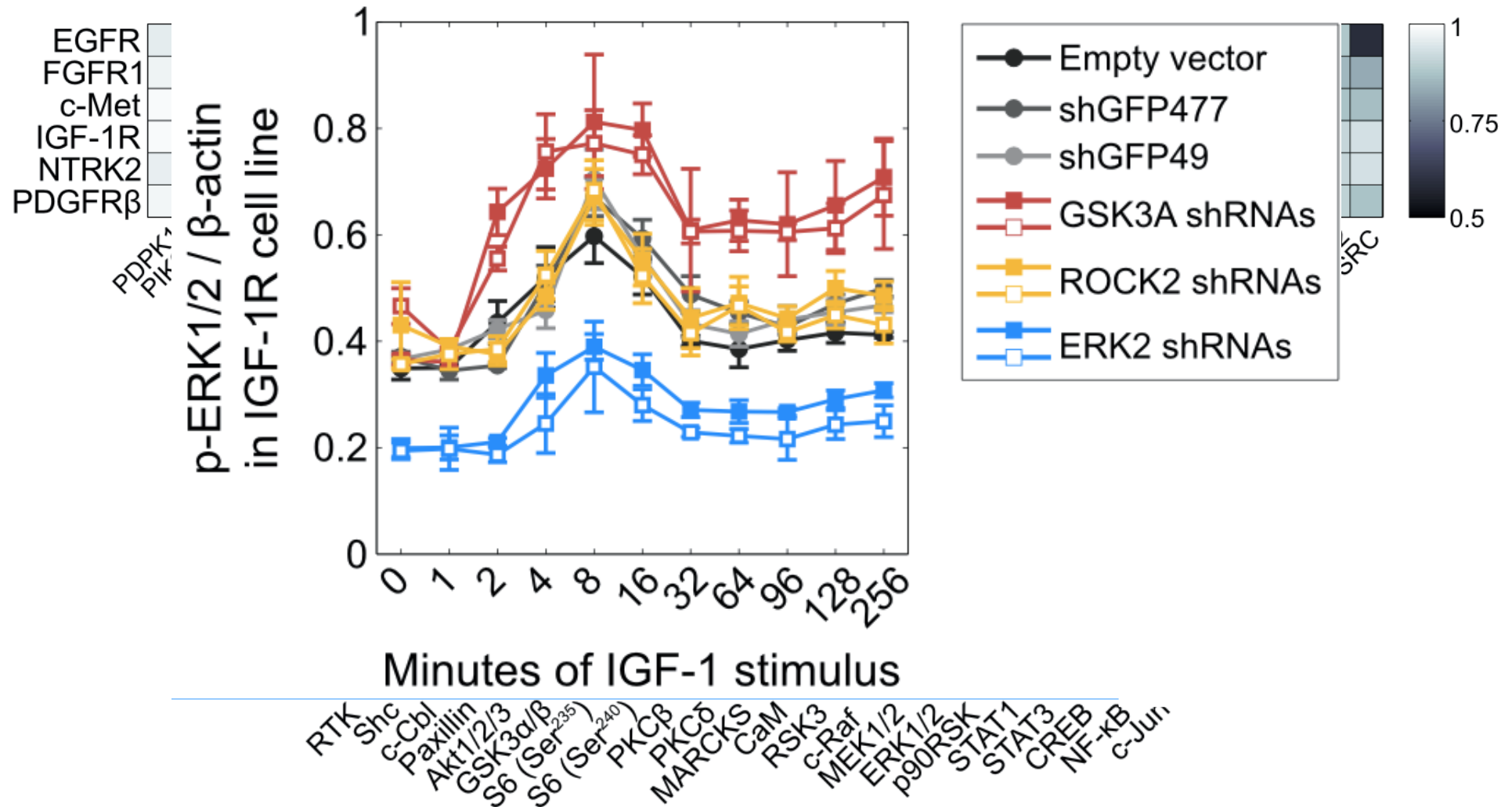
Experimental Design



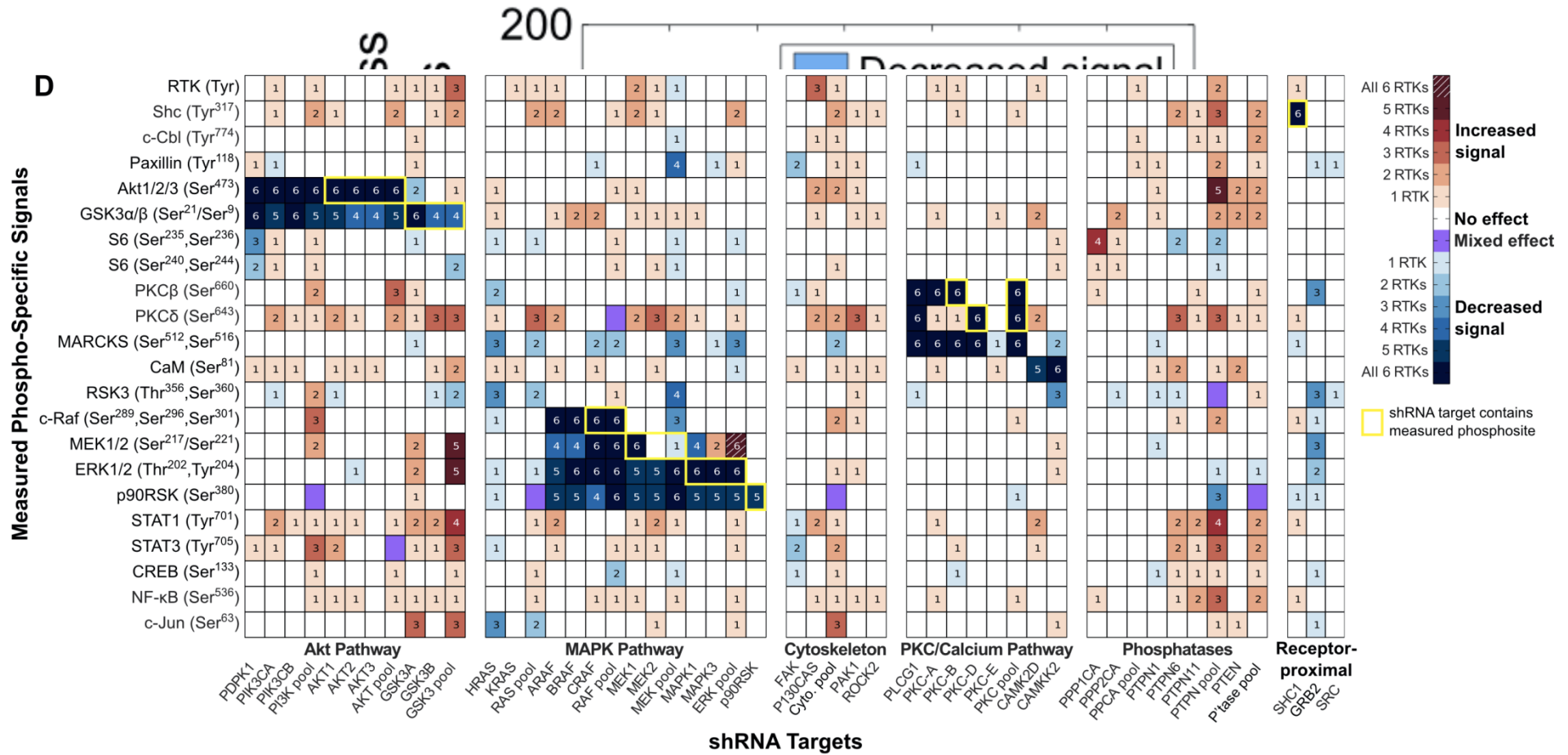
α -phospho-ERK (pT202/pY204)

6 cell lines
x
96 hairpins
x
11 time points
x
4 replicates
=
25344 independent
biological samples

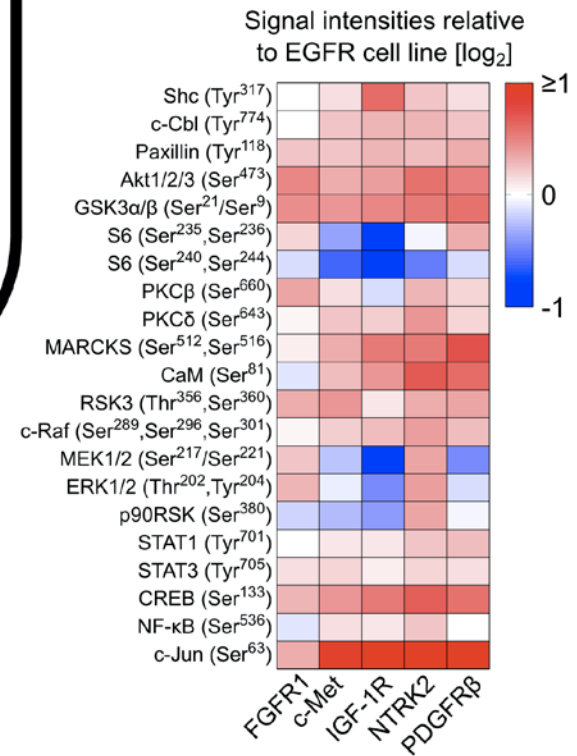
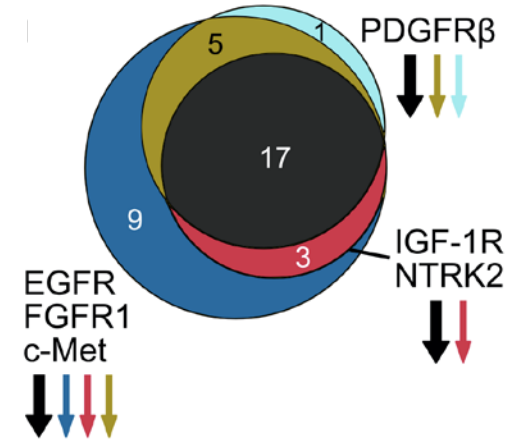
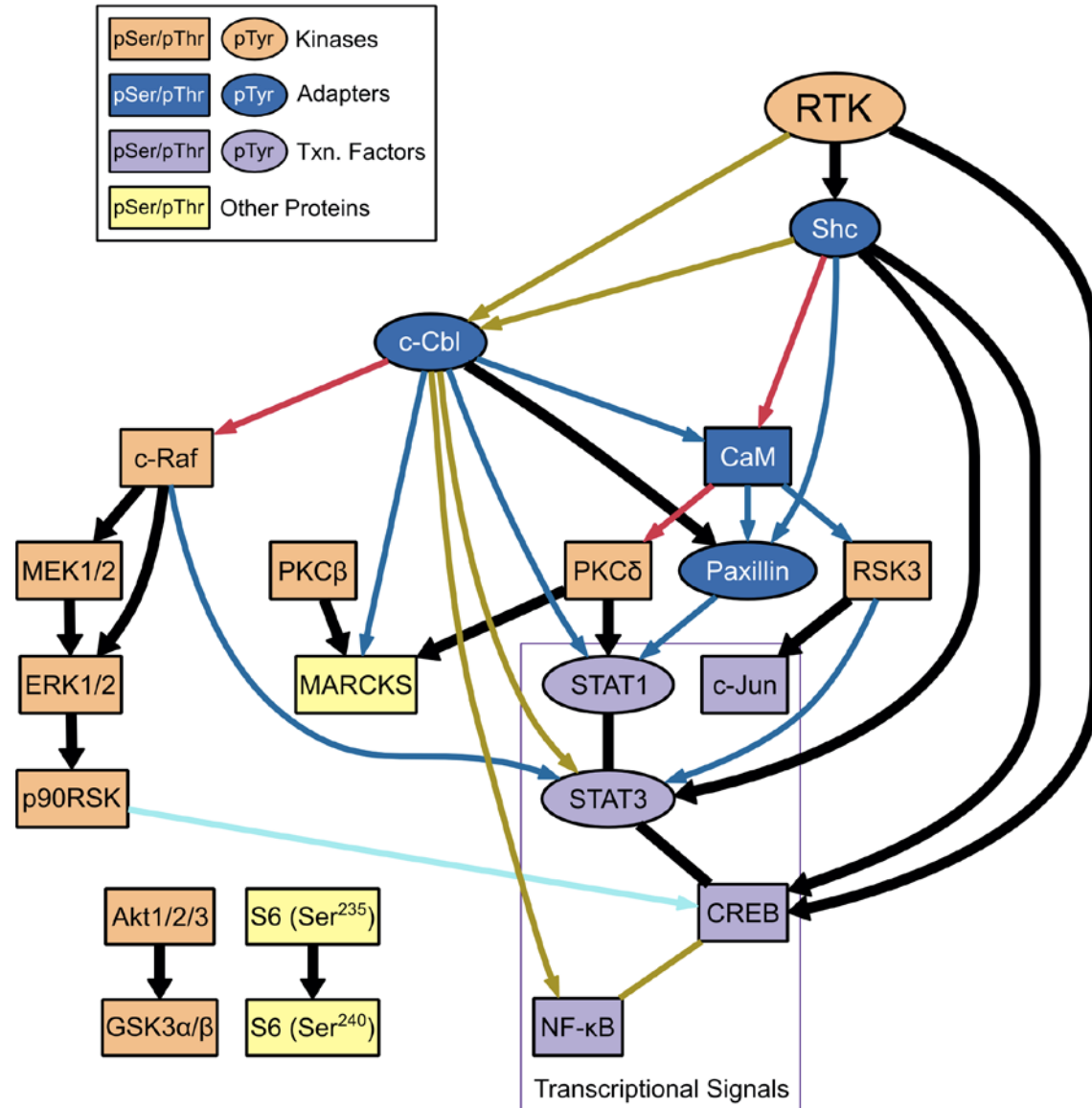
Perturbations reveal specificity in RTK-induced signal transduction



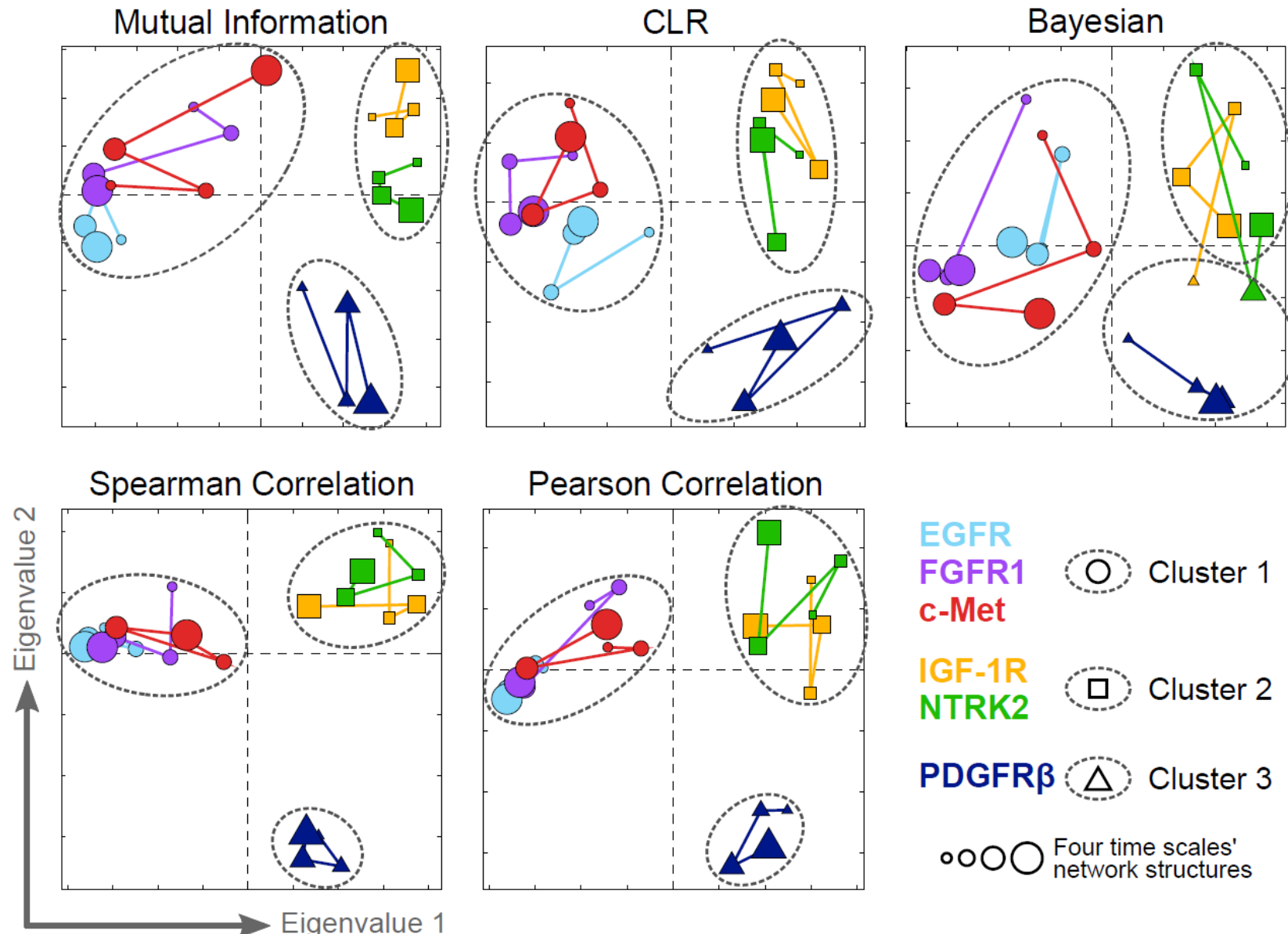
Perturbations reveal specificity in RTK-induced signal transduction



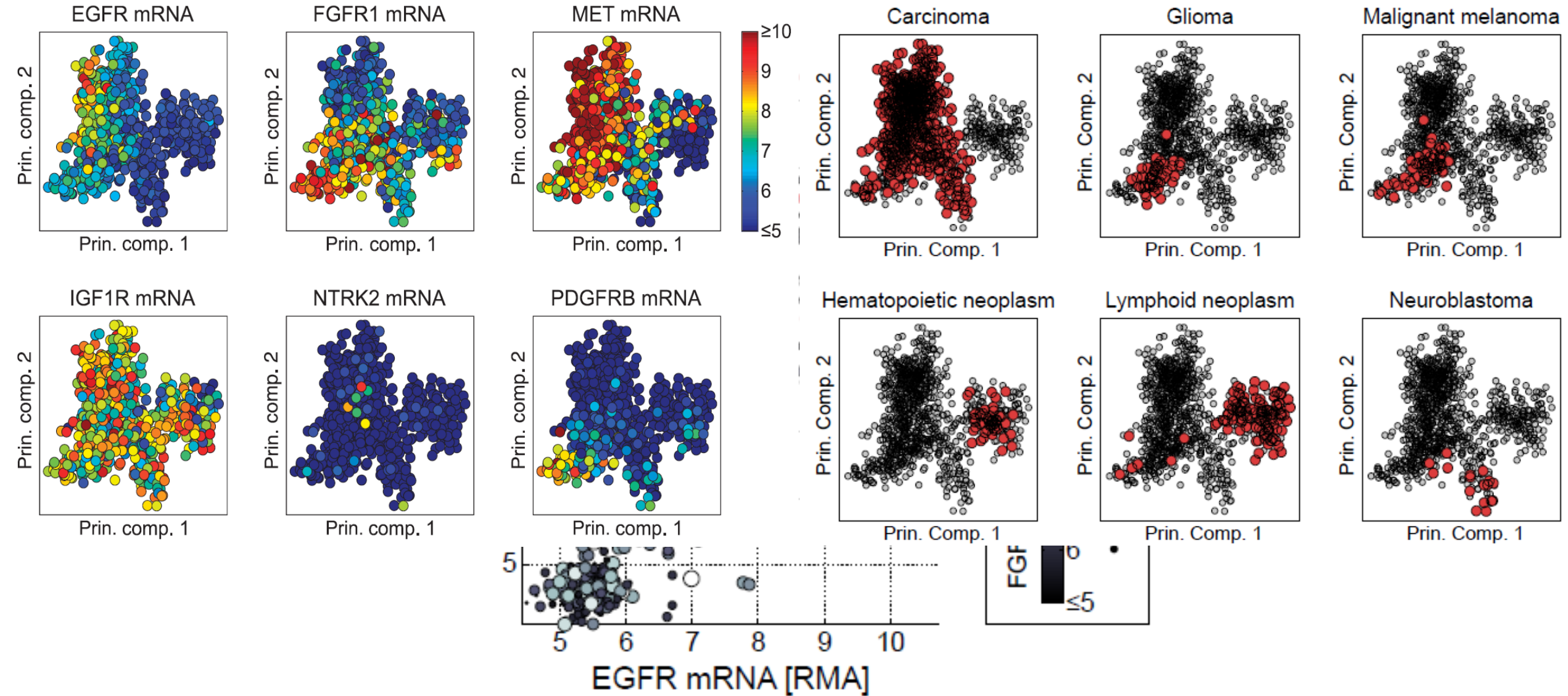
A consensus model for the 6 RTKs reveals a core signaling backbone and class specific interactions



Clustering RTK-specific network models reveals 3 RTK classes.



EGFR, FGFR1 and MET co-expression in CCLE cell lines

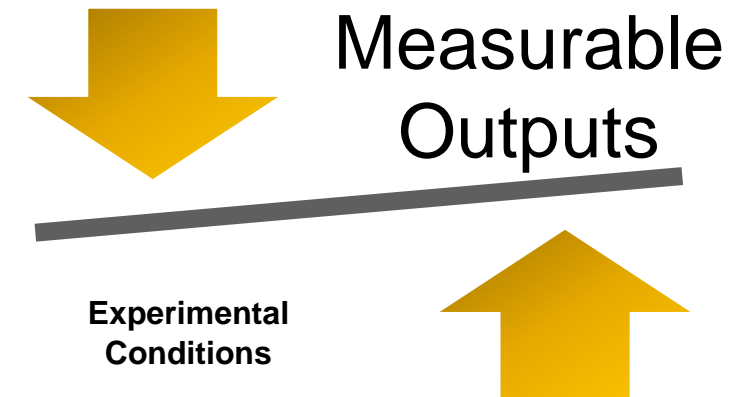
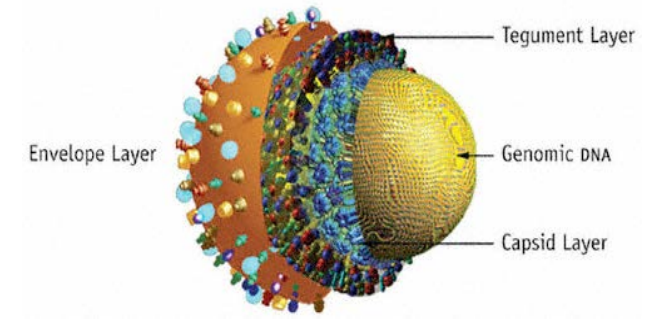


RTK expression correlates with decreased sensitivity to same-class RTK-directed drugs

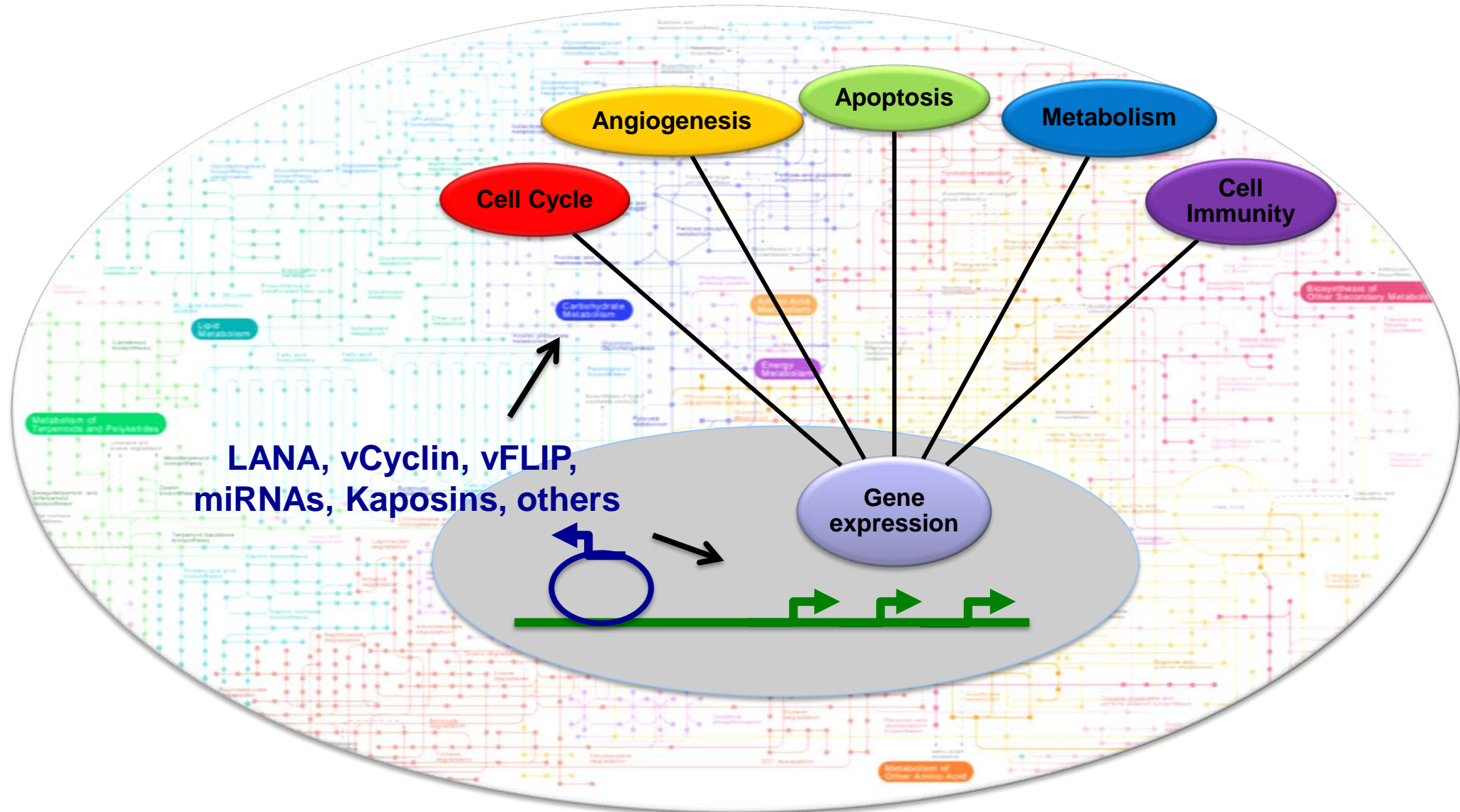
Target/Receptor	EGFR	FGFR1	IGF1R	MET
EGFR (erlotinib)	1.26e-4	9.77e-6	0.15	0.15
FGFR1(TKI258)	4.38e-5	6.39e-3	7.25e-2	1.12e-3
IGF1R (AEW541)	0.105	0.541e-3	1.18e-5	2.72e-2
MET (PHA665752)	1.06e-4	0.14	0.36	0.13

Case Study 2: Kaposi's Sarcoma-associated Herpesvirus (KSHV)

- Human gamma-herpesvirus
- Infectious agent of Kaposi's Sarcoma (KS)
 - Endothelial cell based tumor
 - Highly vascularized tumor
- KSHV presents both lytic and **latent** programs
 - KS tumors are predominantly latently infected
 - Only about 4 viral genes and miRNAs dominate this state



KSHV modulates cell signaling pathways to maintain a latent infection



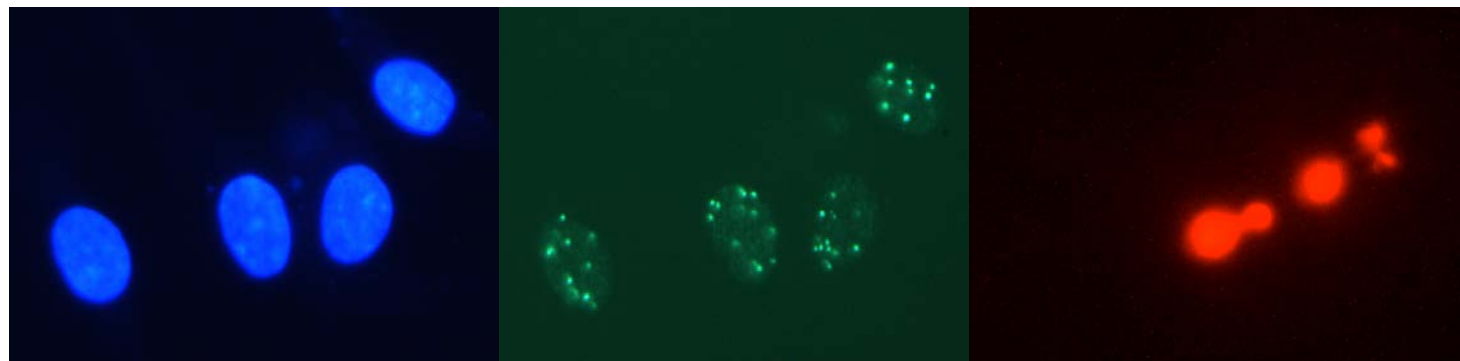
Endothelial cell culture system to study KSHV pathogenesis

- Tert- Immortalized Microvascular Endothelial cells (TIME)
- Human Dermal Microvascular Endothelial Cells (1^o hDMVECs)
- Establishment of latency occurs at 48 hours post infection (hpi)
- KSHV infection rates are detected by Immunofluorescence
 - >90% latent, <1-5% lytic (similar to KS tumors)

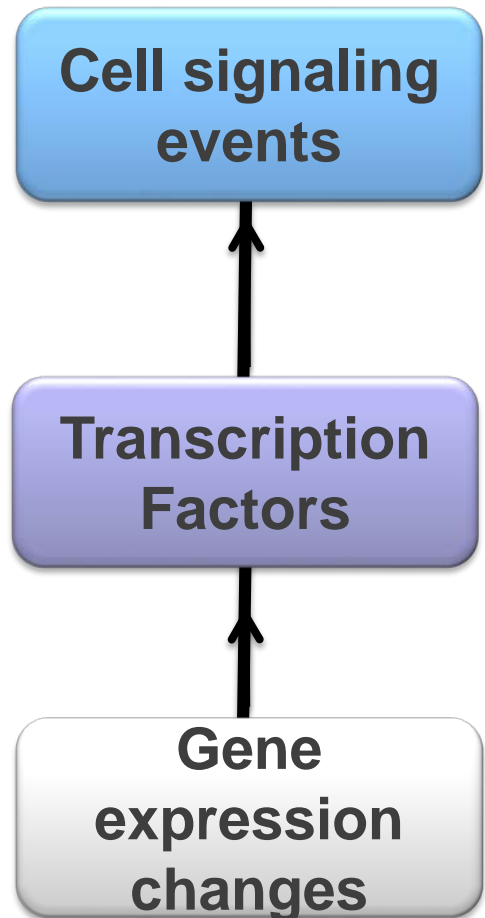
Blue: DAPI
(cell nuclei)

Green: LANA
(Latent protein marker)

Red: ORF59
(Lytic protein marker)

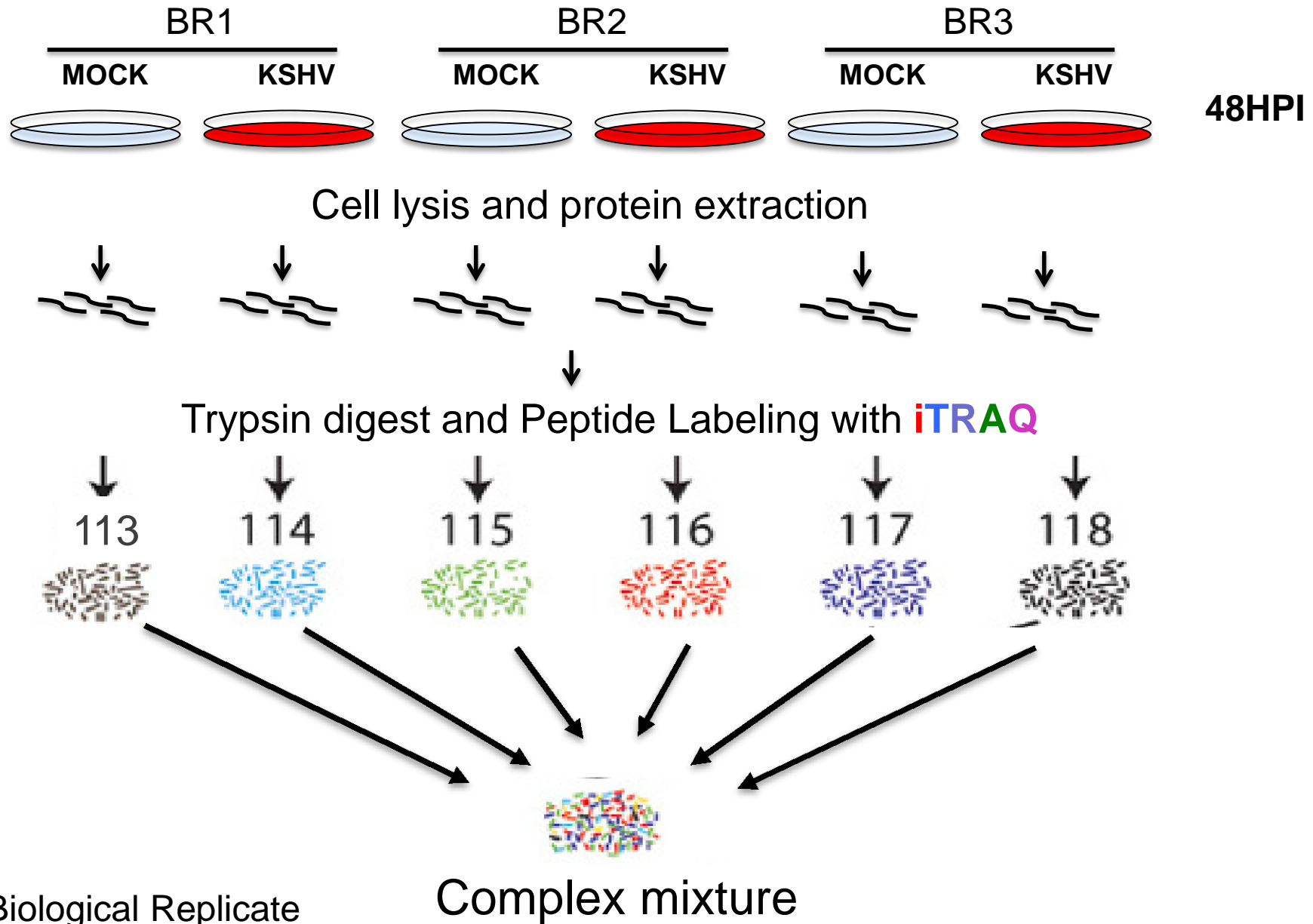


Applying high-throughput technologies to unravel complex signaling networks

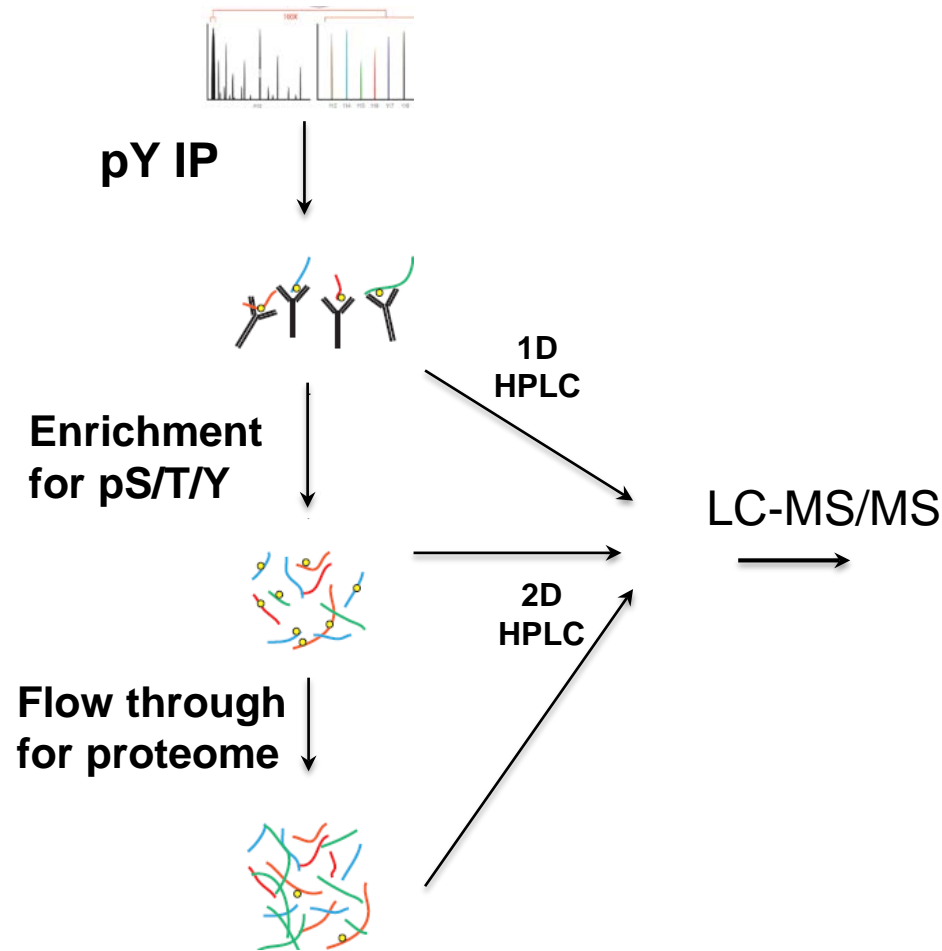


- Quantitative mass spectrometry-based:
 - Proteomics
 - Phosphoproteomics
- Link upstream signaling with gene expression using network inference
 - Steiner Forest algorithm
- Transcriptomics to evaluate differential gene expression
 - Infer Transcription Factor activation changes

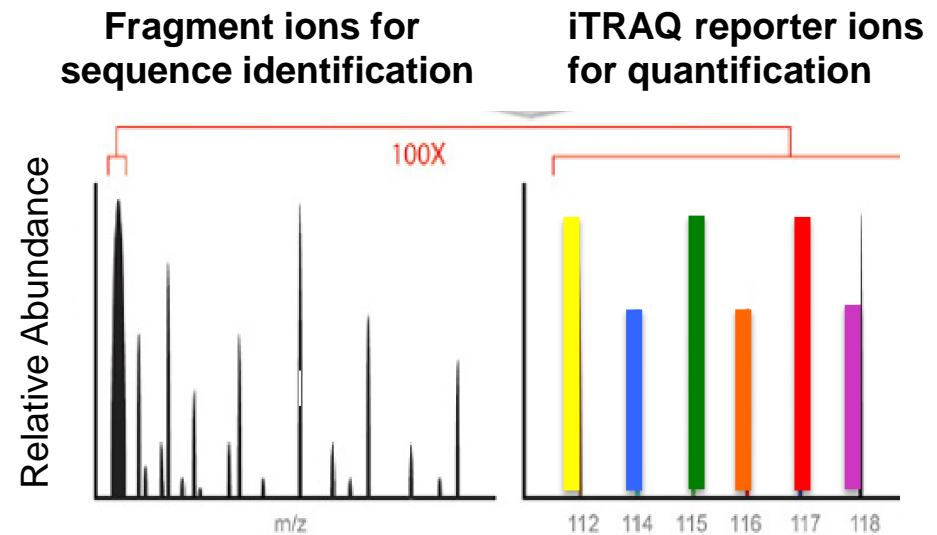
Proteomics workflow using TIME cells



Relative peptide quantification using iTRAQ



3 Biological replicate (samples)
2 Technical replicates (runs)



Data Analysis



A small subset of (phospho)-proteins changes in response to KSHV infection

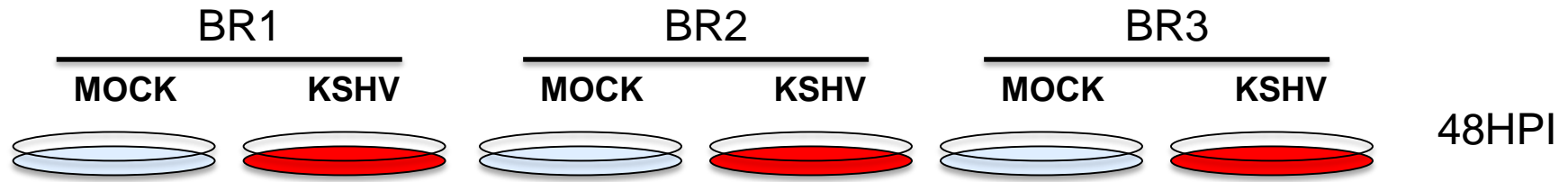
Proteome

SEQUEST FDR 1%		Total # proteins	# of proteins altered
		5304	
p<.01	Upregulated	164	
	Downregulated	125	

Phospho-Proteome

SEQUEST FDR 1%		Total # Unique pProteins	Total # Unique pPeptides
		2963	1469
p<.01	Upregulated	88	
	Downregulated	87	

Transcriptomics workflow using TIME cells



Cell lysis and **RNA** extraction



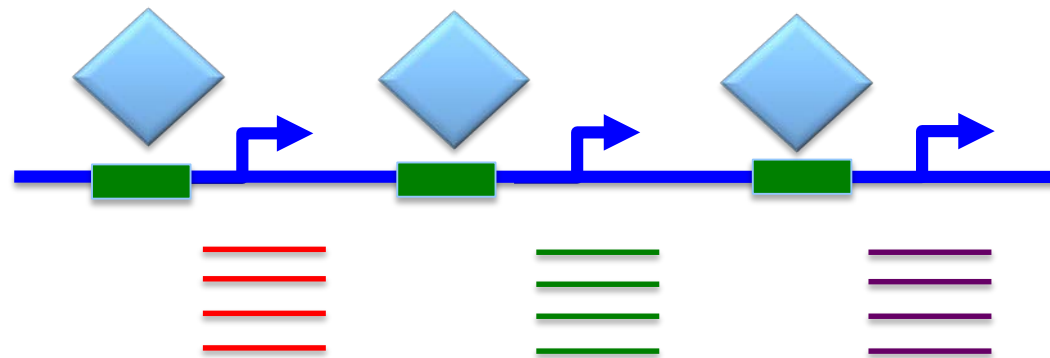
RNA to cDNA

Illumina next-generation sequencing

List > 11,000 genes

BR= Biological Replicate

Using gene expression profiles to predict possible transcription factor binding sites




Transcripts
from RNA-
seq


Predicted TF


TF binding
Motifs

1. Identify the significantly altered transcripts

1. Rank TF binding motif occurrence

- 446 motifs
- 1 Kb from TSS

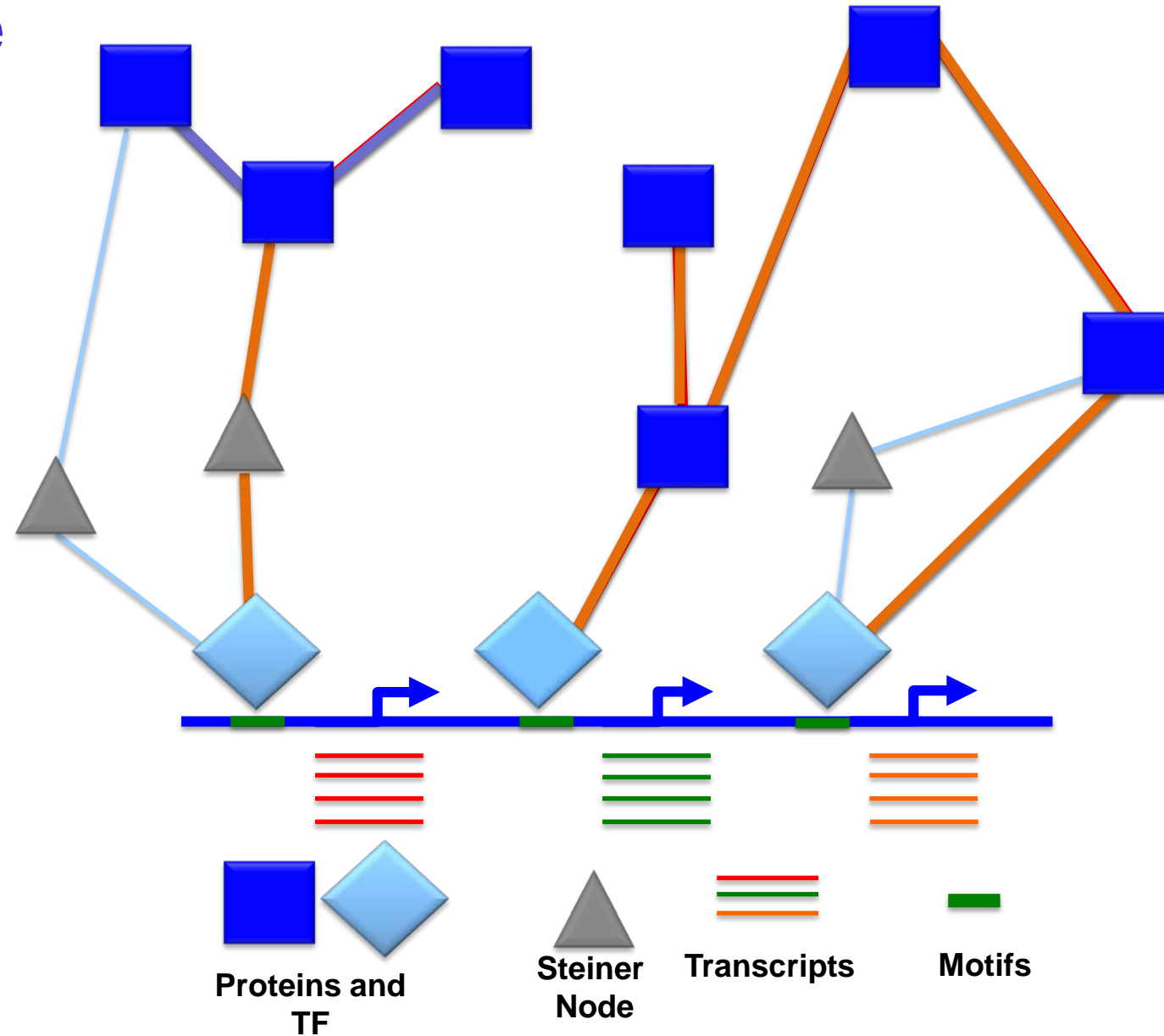
2. Infer active and repressing transcription factor (TF)

Many motifs show significant enrichment of up-regulated flanking transcripts

- Use Wilcoxon Rank sum test to identify cis-regulatory motif enrichment
- 236 TF binding motifs change between mock and KHSV infection (5% FDR)
- 55% of the TF are predicted to be activating

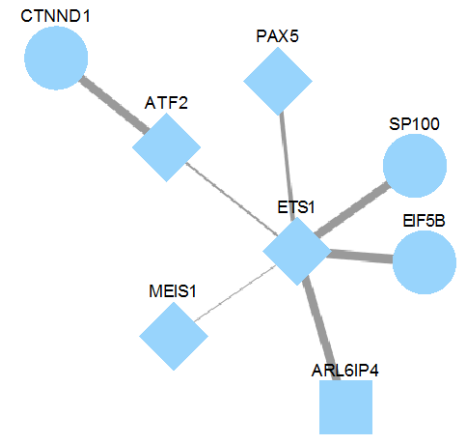
TF	two-tailed pvalue	FDR
S8	5.38E-11	2.39E-08
SRY	3.59E-10	8.00E-08
RSRFC4	8.28E-10	1.23E-07
FOXJ2	3.60E-09	4.00E-07
OCT1	5.32E-09	4.05E-07
LHX3	5.46E-09	4.05E-07
POU6F1	1.01E-08	5.72E-07
MEIS1	1.03E-08	5.72E-07
BACH2	1.24E-08	6.08E-07
HFH1	1.50E-08	6.08E-07
MEF2	1.87E-08	6.92E-07
NKX25	3.94E-08	1.35E-06
GTF2I	5.99E-08	1.90E-06
NRF2	4.00E-03	9.58E-03
ETS1	2.38E-02	4.38E-02
STAT3	3.17E-02	5.76E-02

Integration of Proteomics/Transcriptomic Data Using Steiner Tree

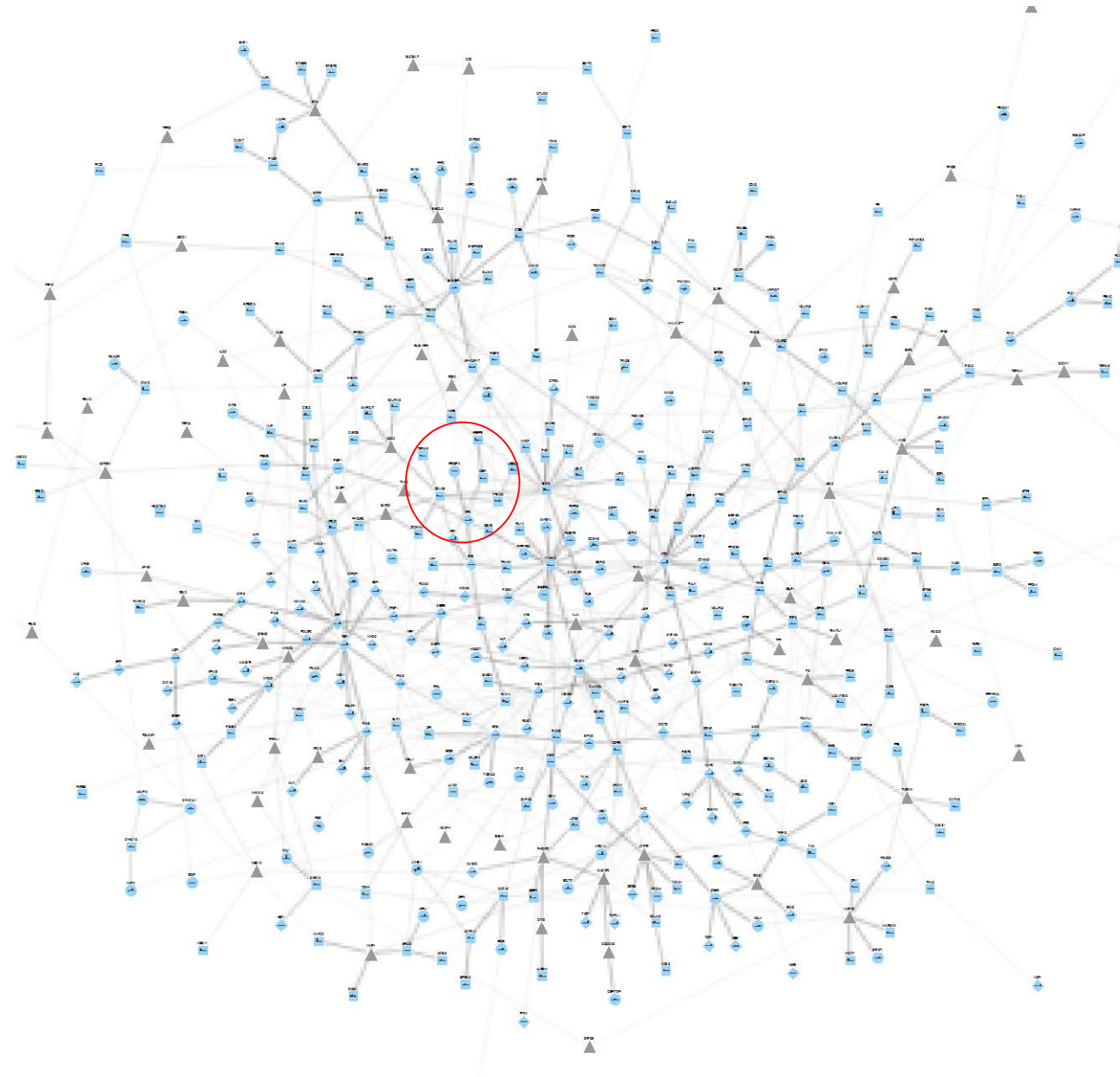
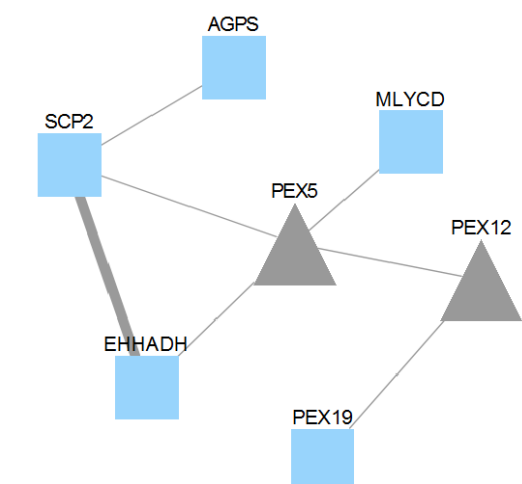


Network of KSHV infected endothelial cells

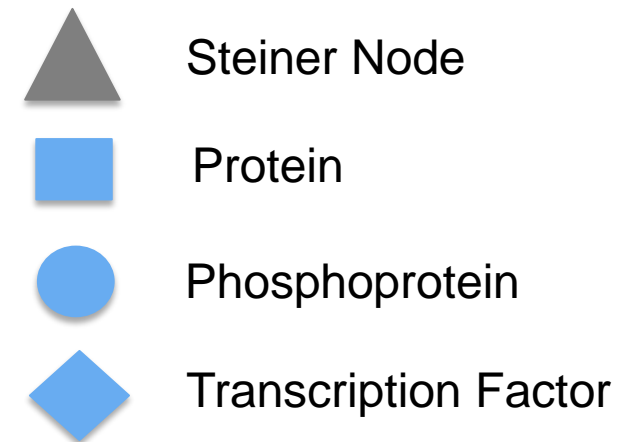
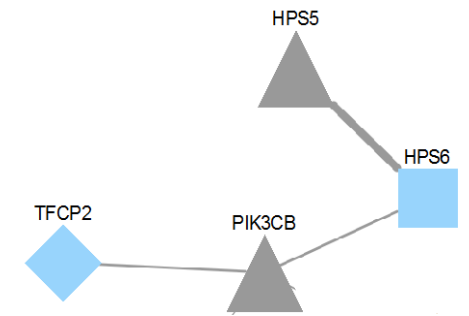
Pluripotency of stem cells and MAPK Signaling



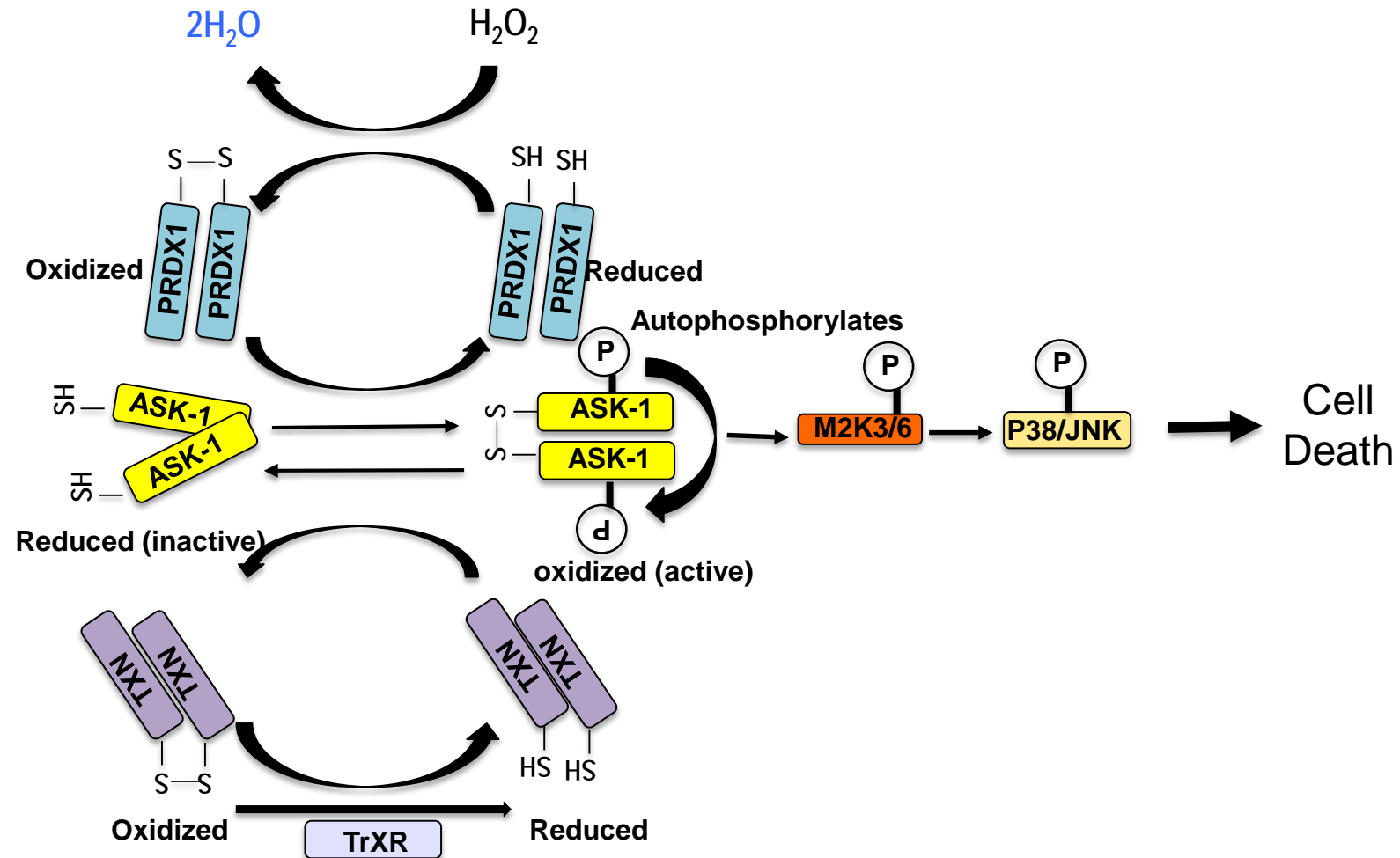
Peroxisome Biogenesis



mTOR and Lysosome synthesis

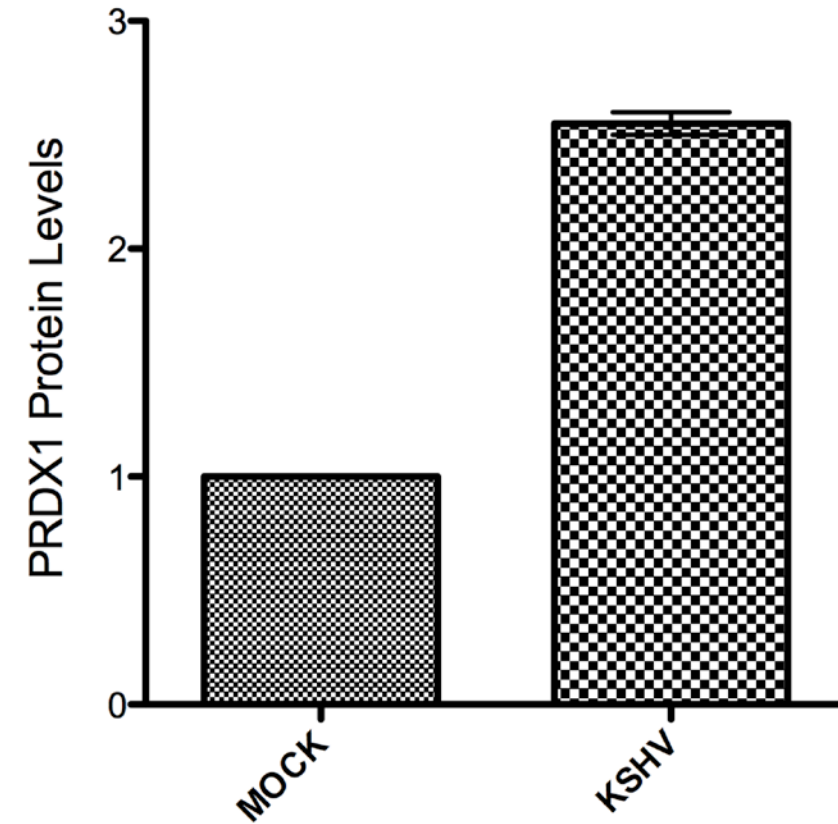
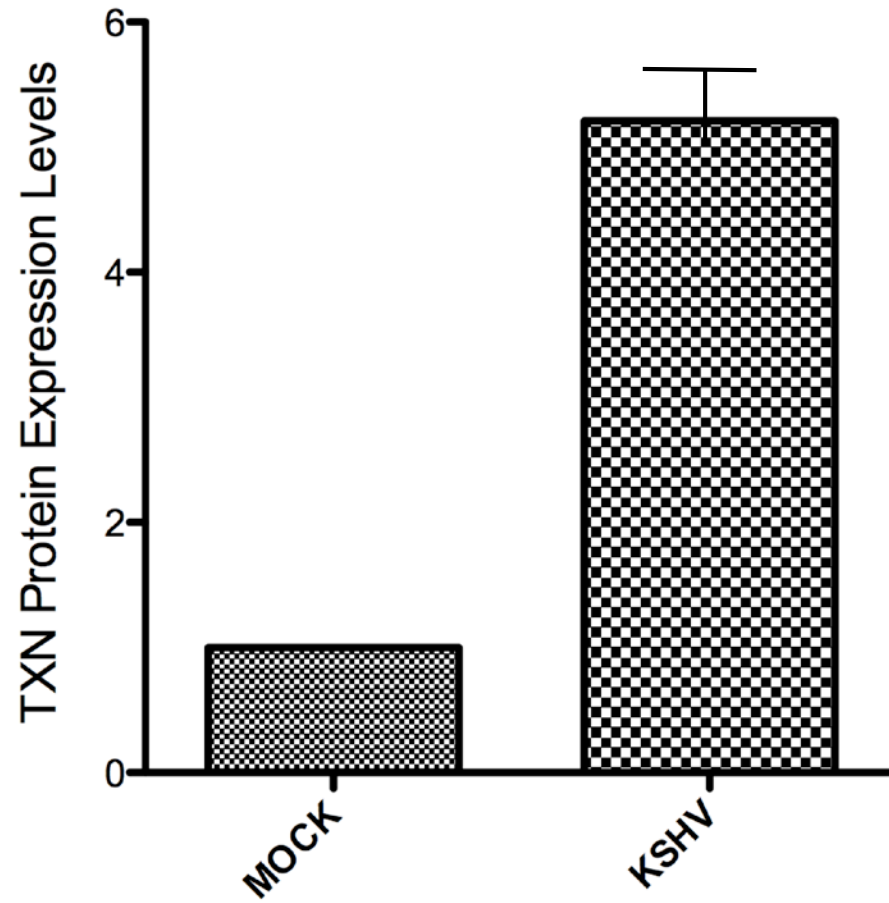


The Thioredoxin System

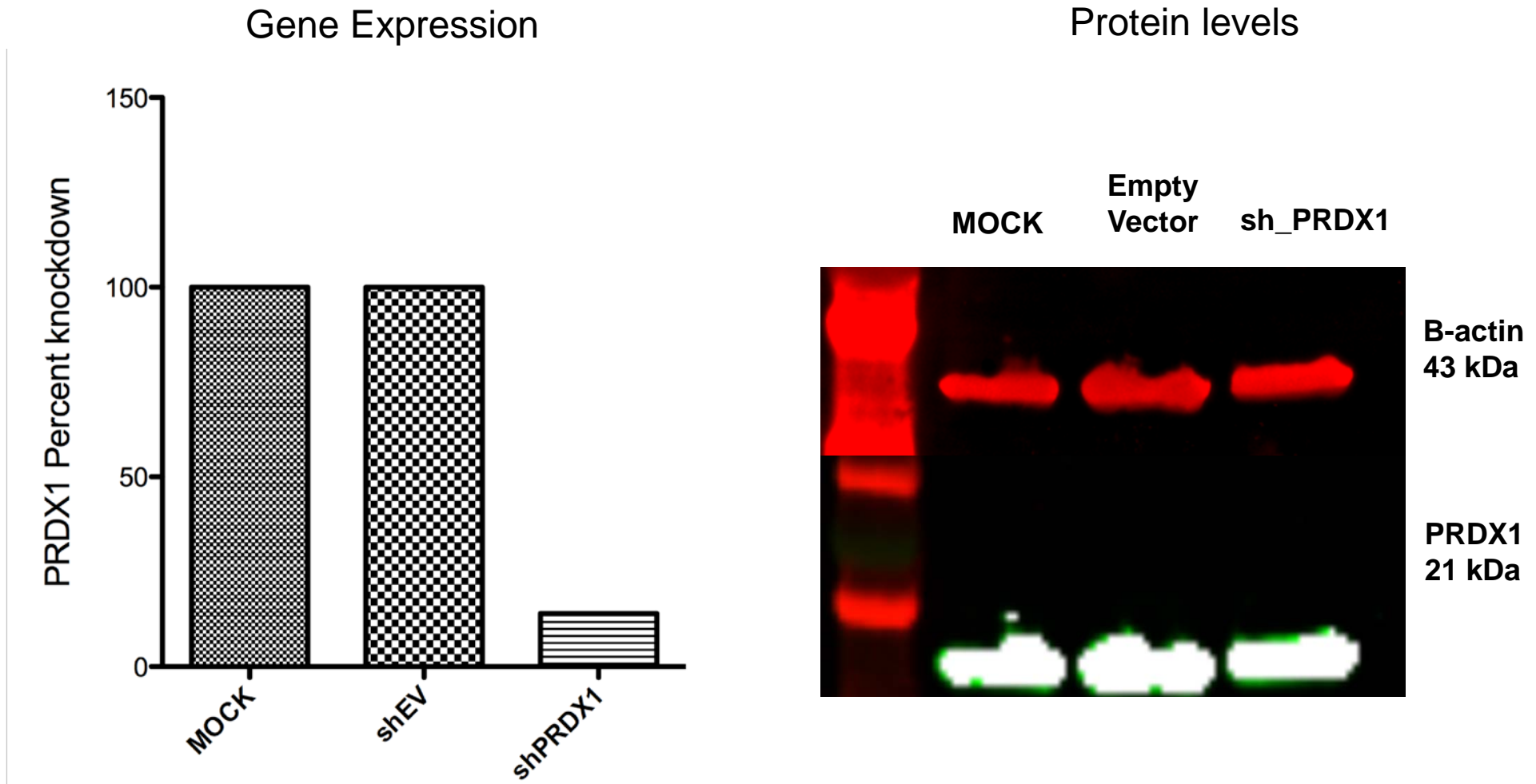


Latent KSHV infection modulates the PRDX/TXN system to regulate hydrogen peroxide and to prevent endothelial cell death

PRDX1 and TXN levels are increased in KSHV infected endothelial cells

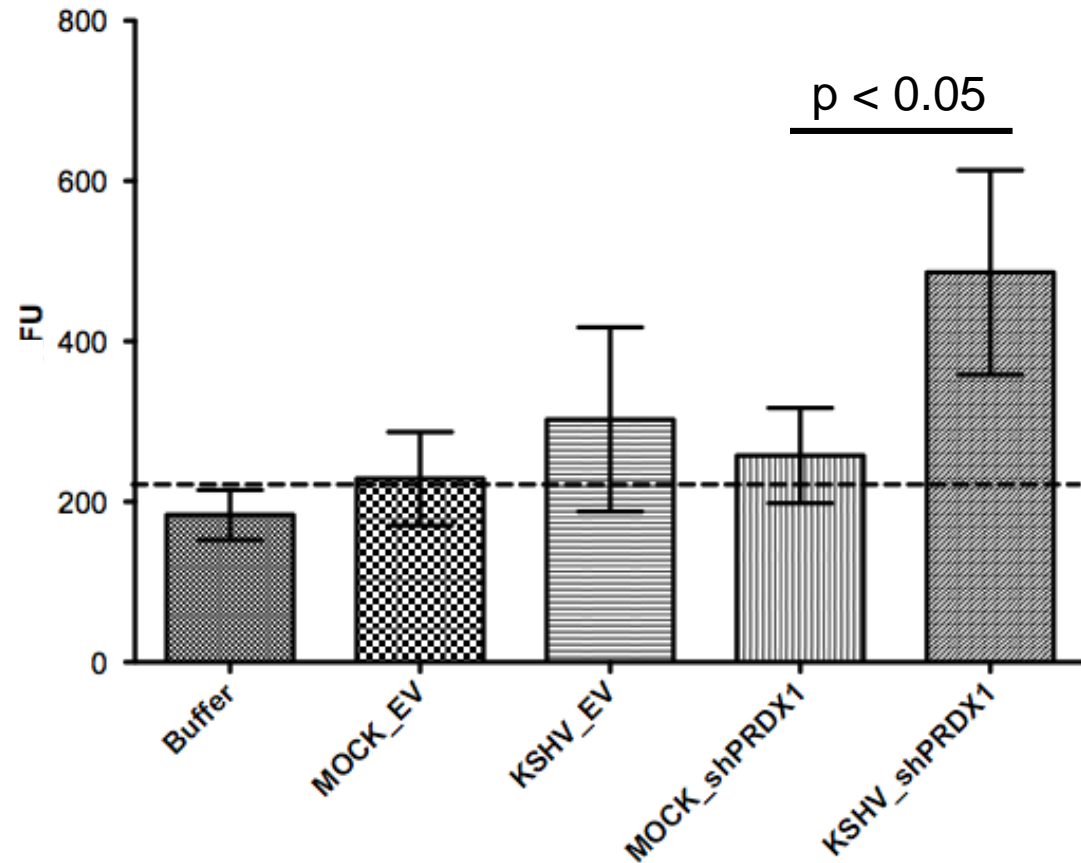
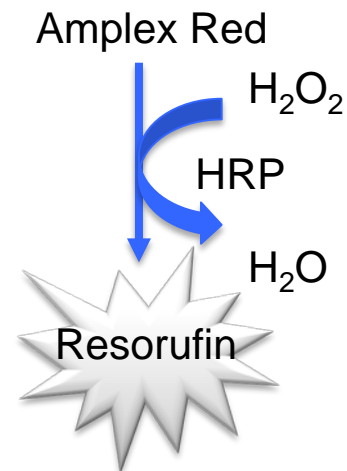
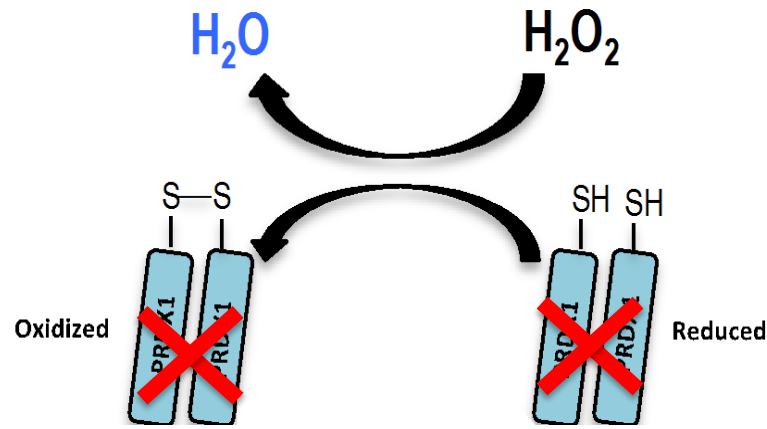


PRDX1 gene and protein expression levels are efficiently silenced



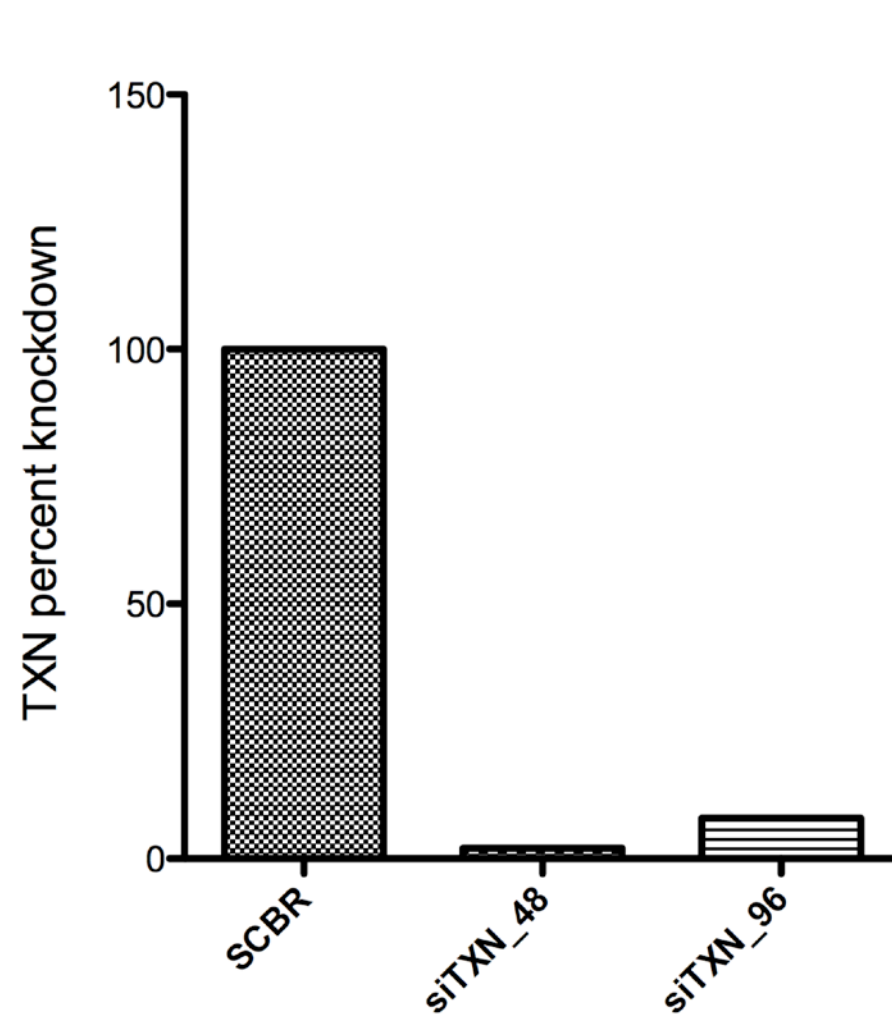
Data was normalized against GAPDH and HPRT

H₂O₂ Levels are increased in the absence of PRDX1 during KSHV infection



Normalized against total number of cells

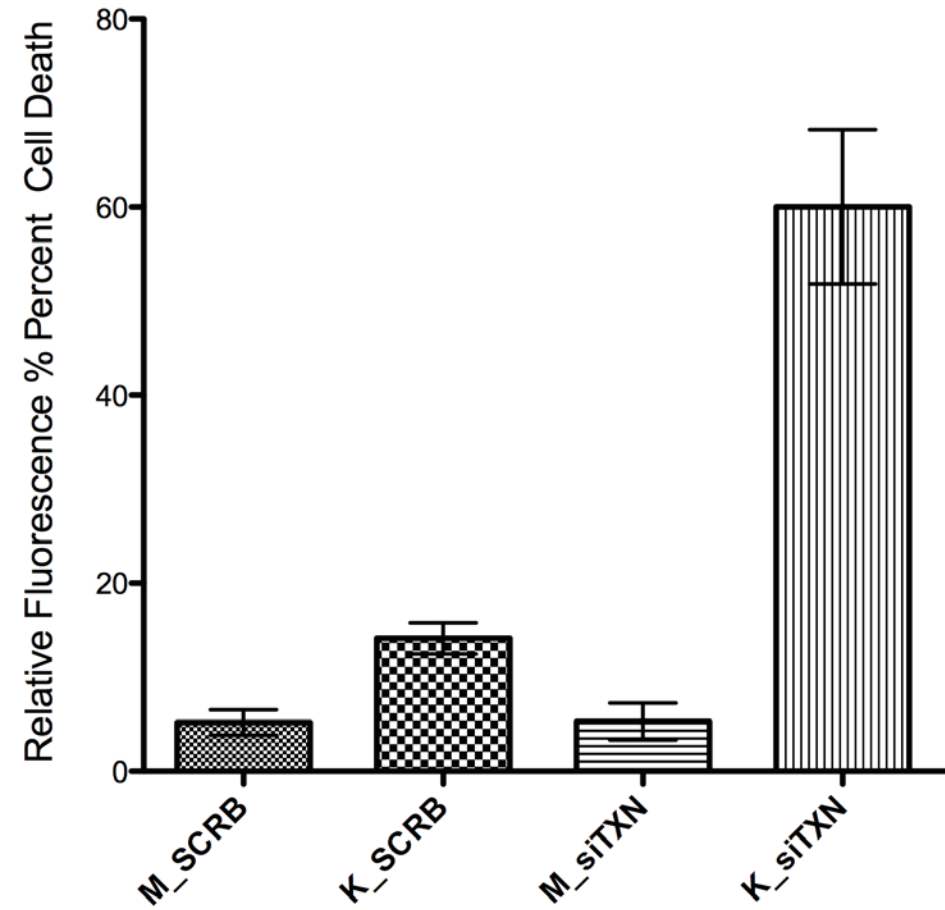
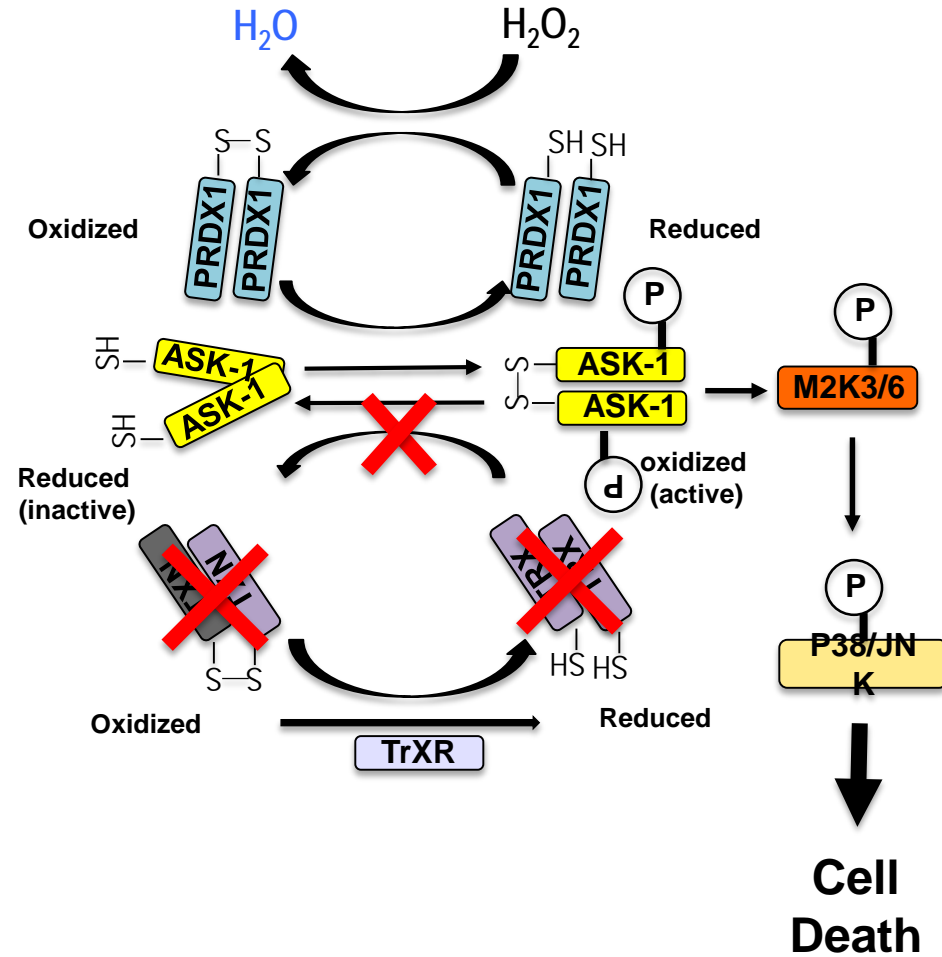
TXN gene expression is efficiently silenced



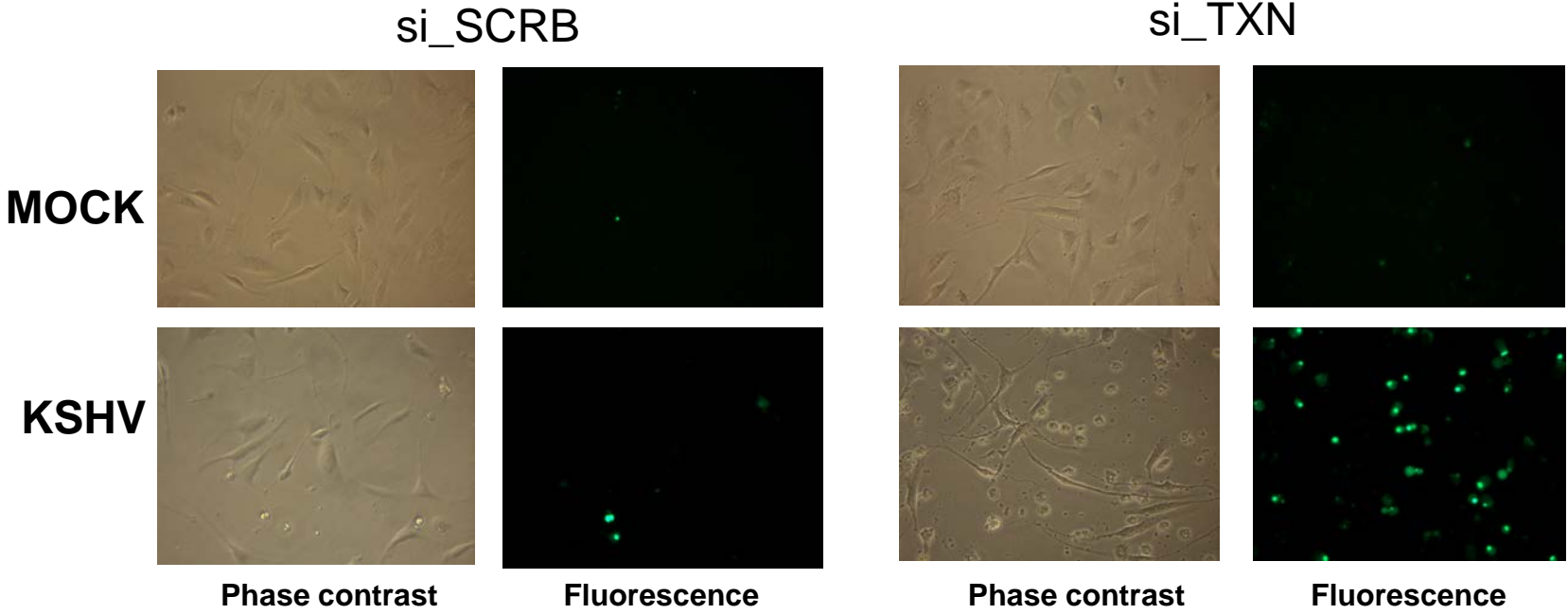
qRT-PCR

Data was normalized against GAPDH and HPRT

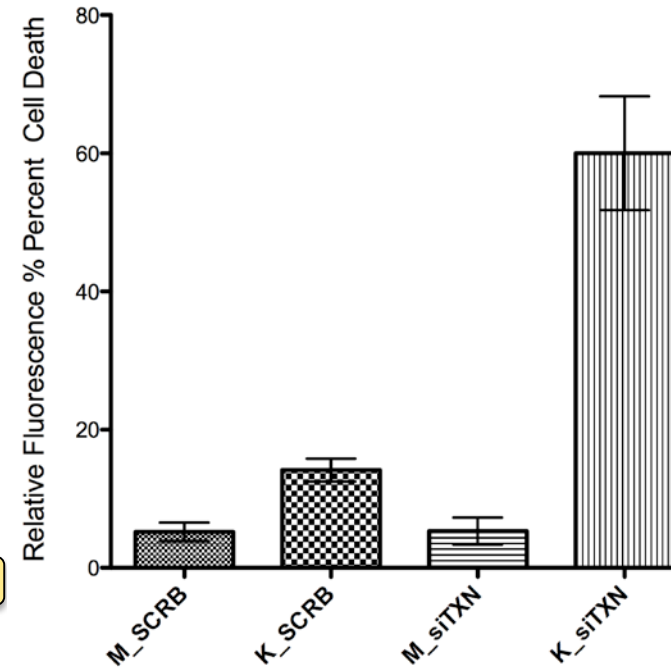
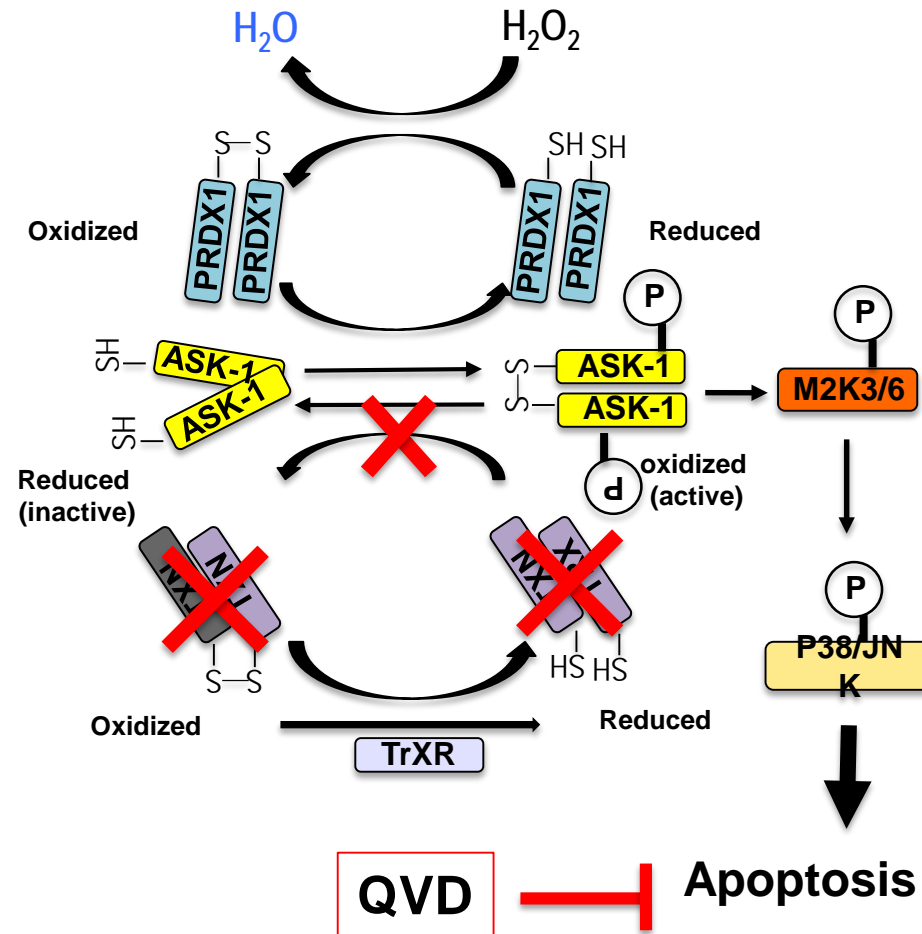
TXN knockdown during latent KSHV infection leads to increase cell death



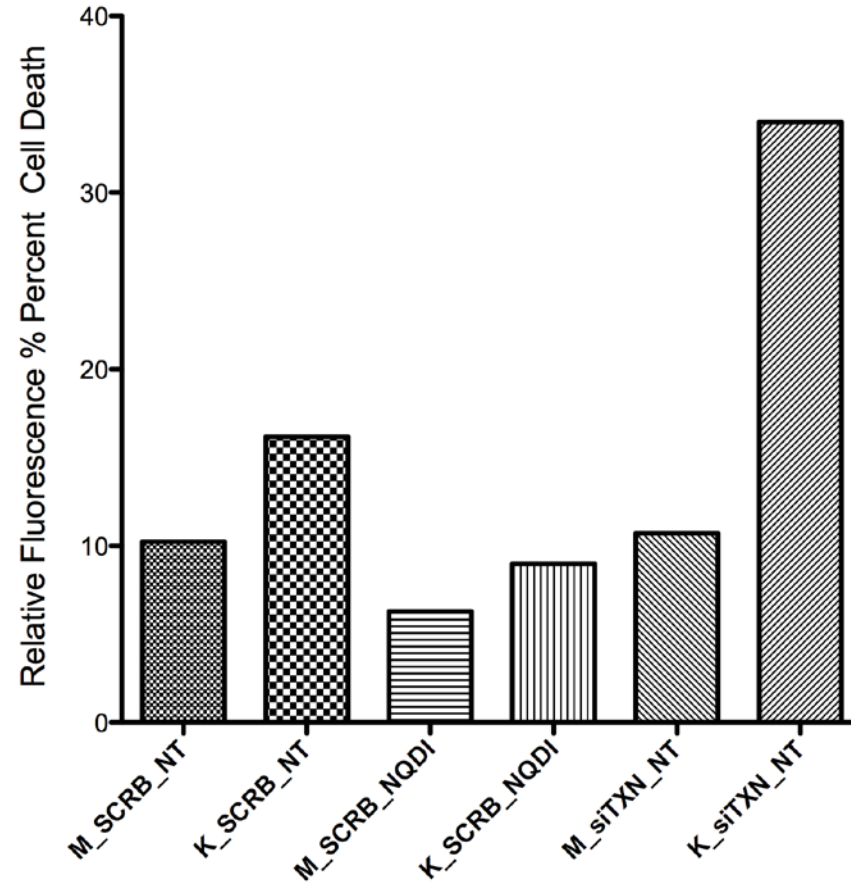
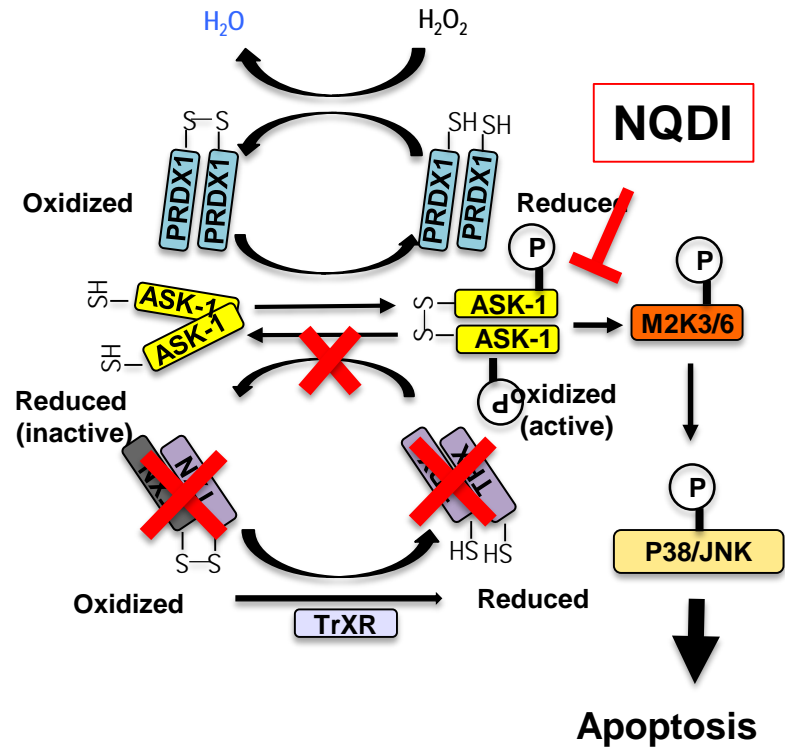
TXN knockdown during latent KSHV infection leads to increase cell death



Cell death seems to occur through apoptosis



Cell death seems to be a function of ASK activity



Acknowledgements

RTK Project

Gavin Macbeath

Doug Lauffenburger

Mark Sevecka

Joel Wagner

KSHV Project

Nathan Camp

Anthony Gitter

Alex Hu

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