

USING THE LIBRARY OF INTEGRATED NETWORK-BASED CELLULAR SIGNATURES (LINCS) TO CHARACTERIZE THE MECHANISM OF ACTION OF SMALL-MOLECULE THERAPEUTICS,

1. LINCS Center for Transcriptomics (data)
2. LINCS-BD2K Center (analysis)

ARAVIND SUBRAMANIAN

MAY 28, 2015

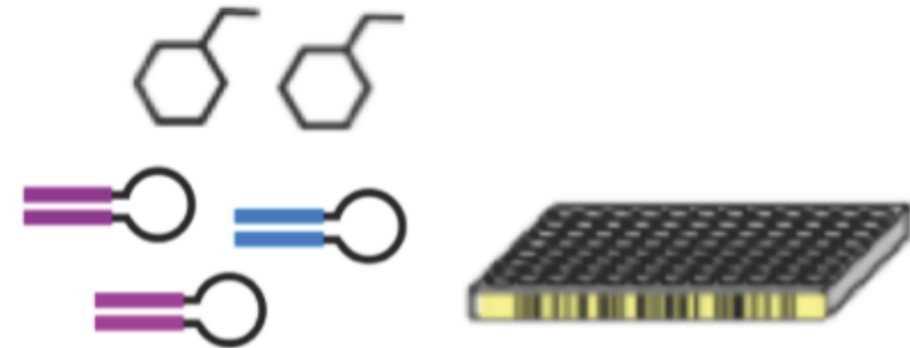
BROAD INSTITUTE OF MIT AND HARVARD

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LINCS experiment

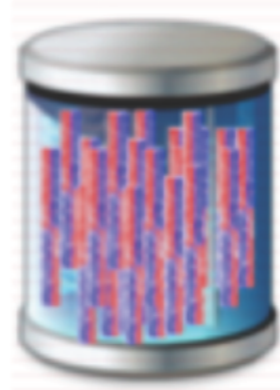
1. Perturbagen

e.g compound, shRNA, CRISPR



3. Read-out

e.g mRNA



Typical applications

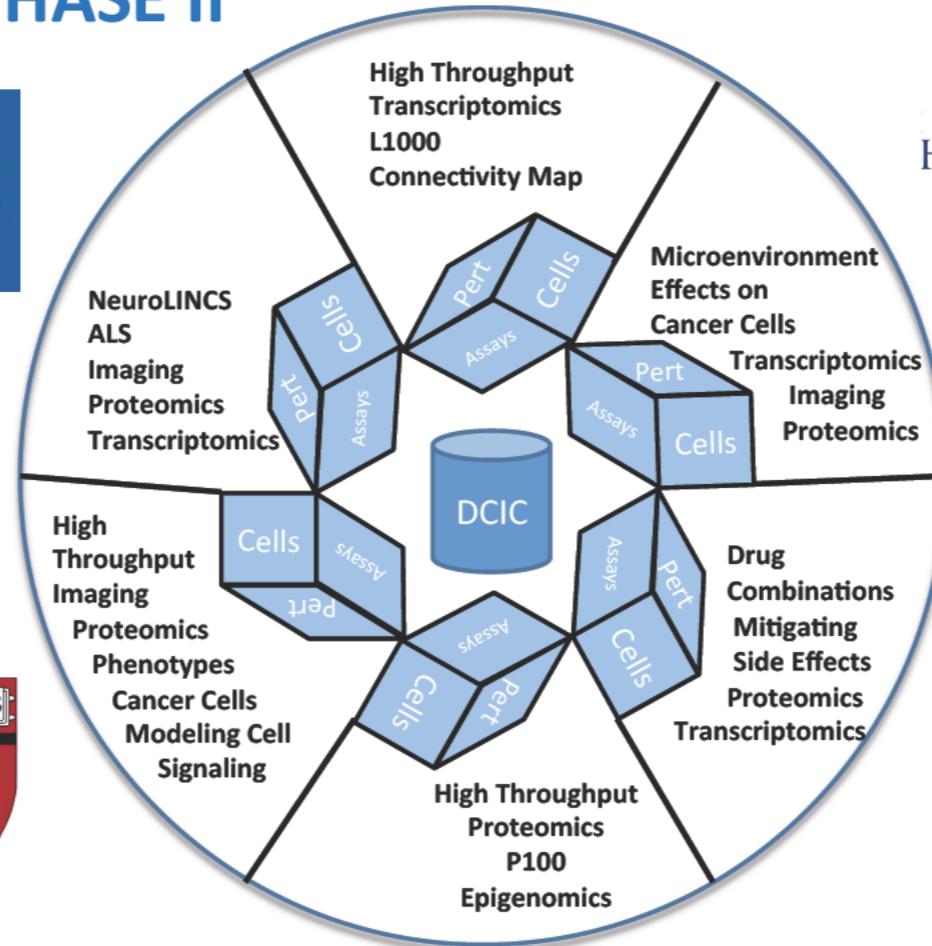
- Mechanism of Action (MoA) of compounds and drugs
- Structure-activity relationships
- Functional annotation of genes
- Functional annotation of genetic variants
- Parsing Lists into “complimentation groups” of related function

Library of Integrated Network Based Cellular Signatures (LINCS)

LINCS PHASE II



New NIH Program
(launched FY2015)



Broad Institute - Connectivity Map (CMap)

a resource of perturbational profiles

Aim 1

Construct a **comprehensive reference database** of perturbational signatures

Aim 2

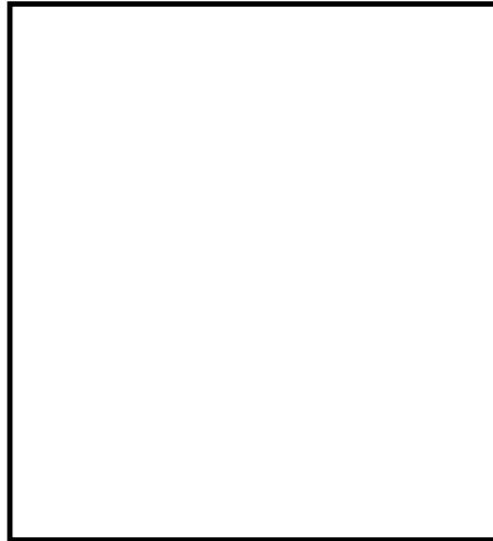
Develop **algorithms and software** to make these data and results accessible to the entire biomedical community

Aim 3

Utilize these resources to make **biological and therapeutic discoveries**

The Connectivity Map

Connecting disease to genes and drugs



mRNA Expression Database



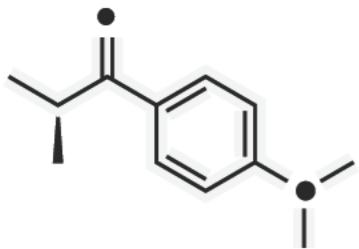
PILOT

564 Affymetrix profiles 16,000+ users
164 drugs 916 citations

(build02 expanded to ~7,000 profiles)

LINCS - desired dataset (~10M profiles)

- **CMap is limited by profiling cost**
- **low-cost, high-throughput method would enable ...**



small-molecule compounds

Drugs, tool compounds, natural products, diverse synthesized libraries



genes (knock-down and gain-of-function)

shRNAs, CRISPRs, cDNAs, variants (natural and synthetic)



cellular contexts

diverse, multiple lineages, culture conditions, genetics



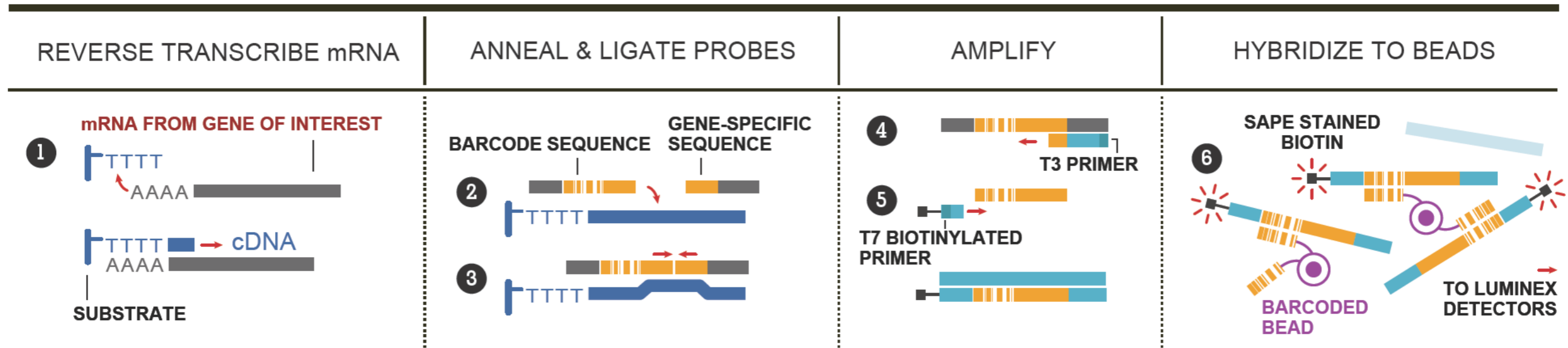
treatment parameters contexts

concentrations, durations, combinations

L1000 ASSAY

The L1000 Assay

ligation-mediated 1000-plex amplification



Measure 1,000 transcripts with 500-color Luminex beads

384-well plate format compatible with HTS

Cell lysates (not purified RNA)

Dramatic cost reduction

Reduced representation of transcriptome using 'landmarks' to infer the rest

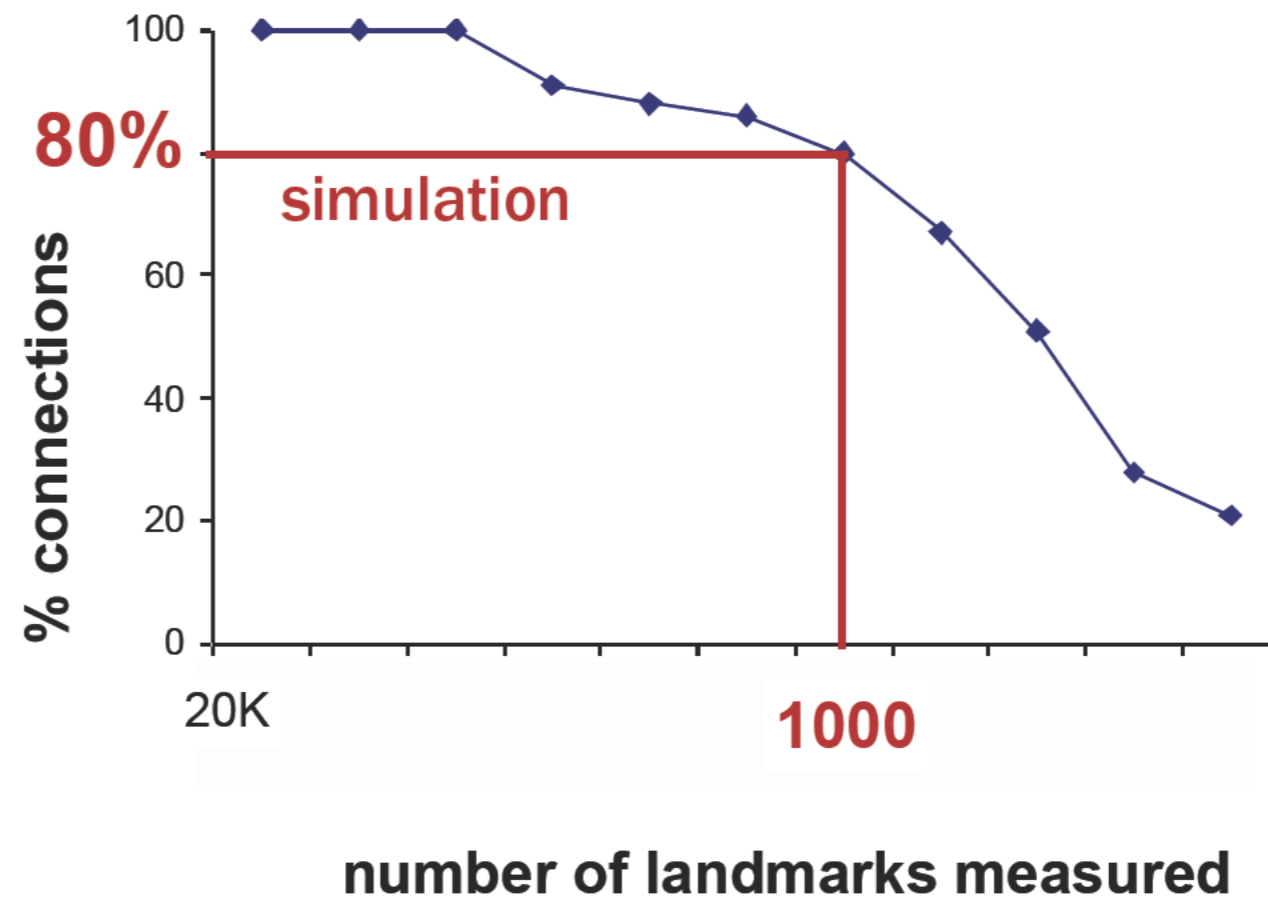
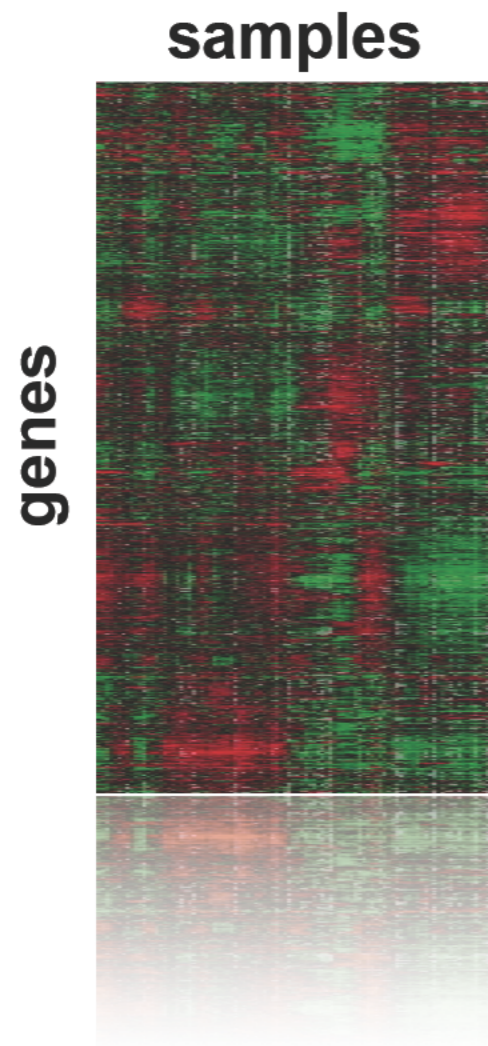
Reduced representation
of transcriptome
"Landmark genes"

+

Computational
inference model

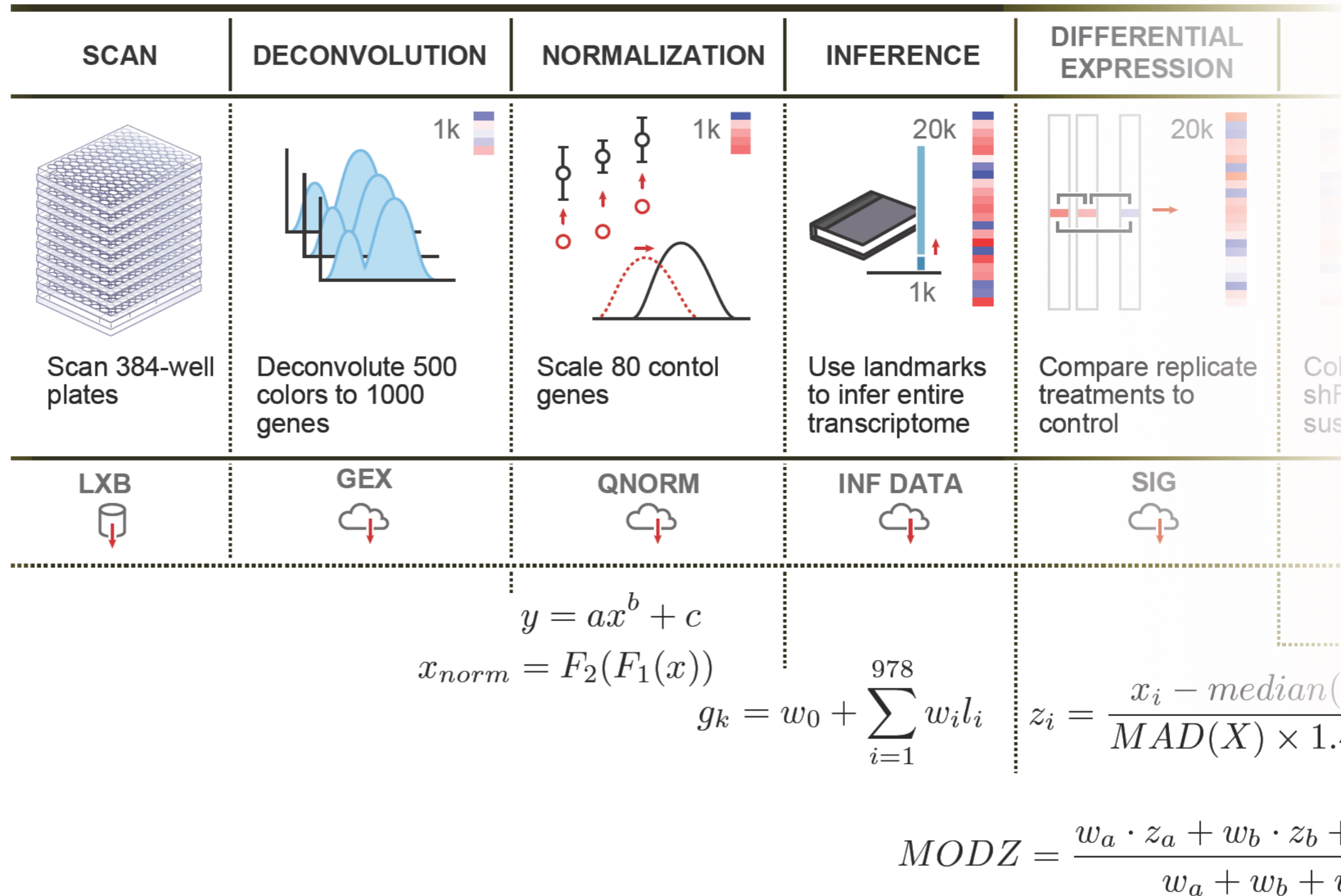
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Genome wide
expression



Processing L1000 data

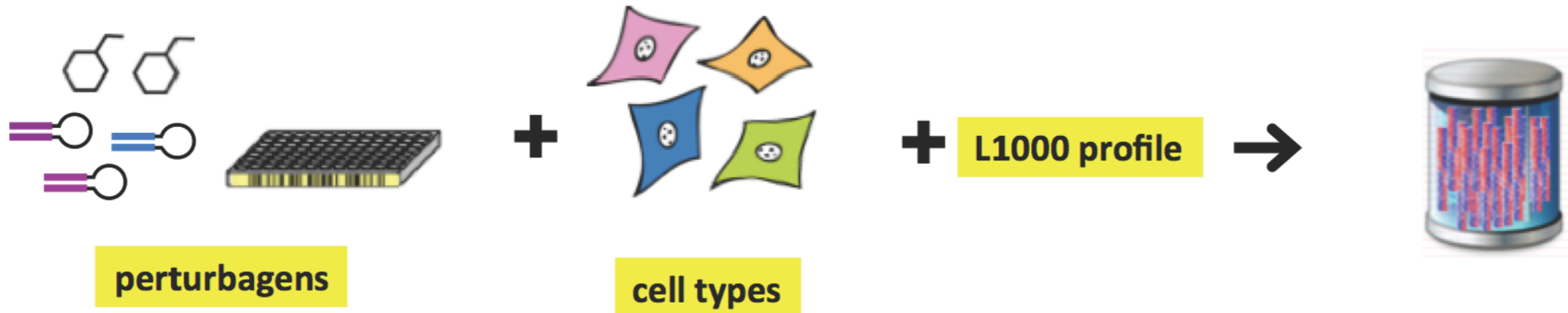
Data flow: from scans to signatures



Signature generation

raw profiles to differentially expressed, ranked gene lists

Experiment



Signature

1 perturbagen in 1 cell type at 1 dose and for 1 duration of treatment

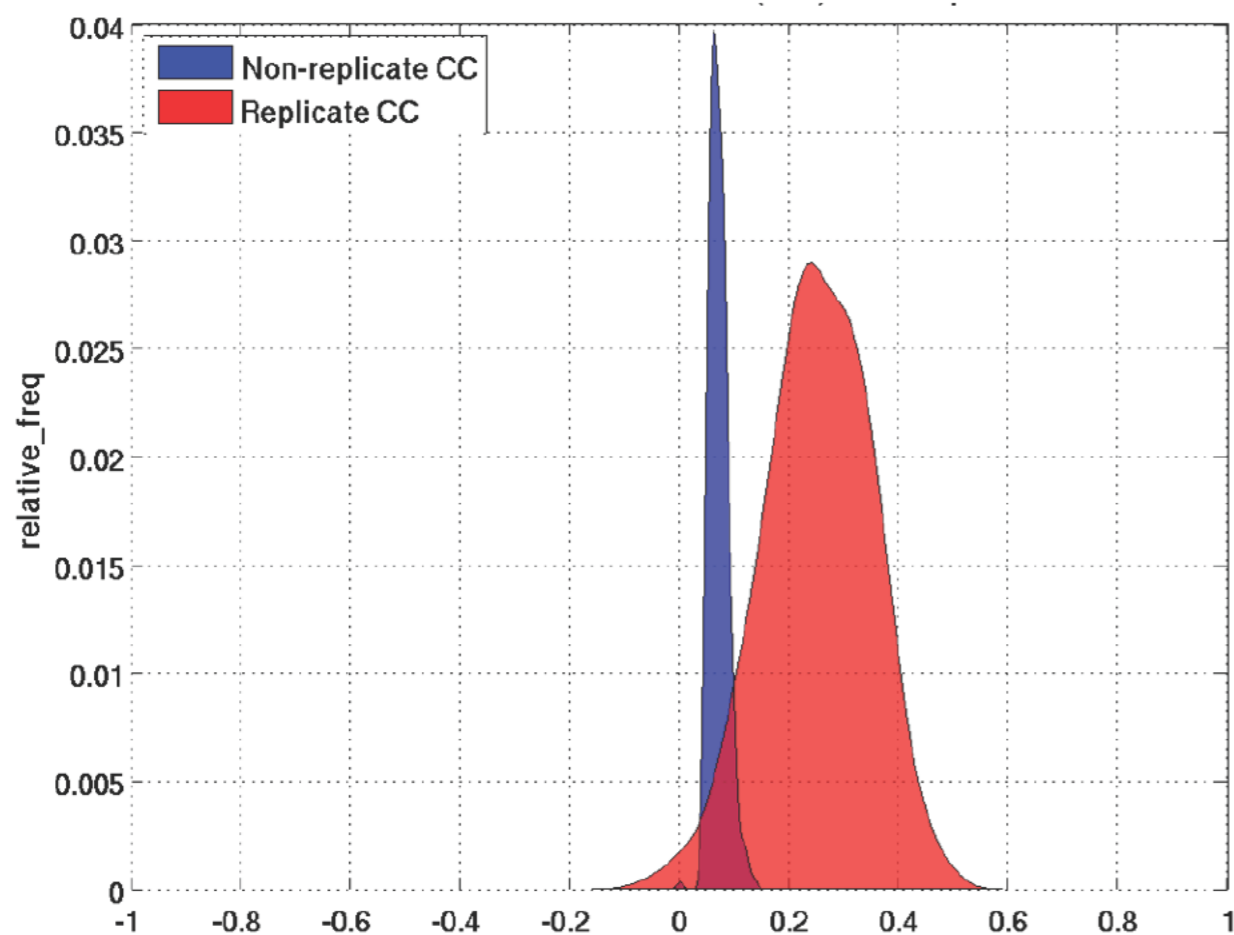
Database

Perturbagen	Cell Types	Doses	Duration	Replicates	# signatures
Compound 1	12	6	1	3	$12 \times 6 = 72$
Compound 2	12	6	1	3	$12 \times 6 = 72$
Compound 3	12	6	1	3	$12 \times 6 = 72$
...					
Compound 348	12	6	1	3	$12 \times 6 = 72$
TOTAL					$72 \times 348 = 25,056$

L1000 performance - over batches

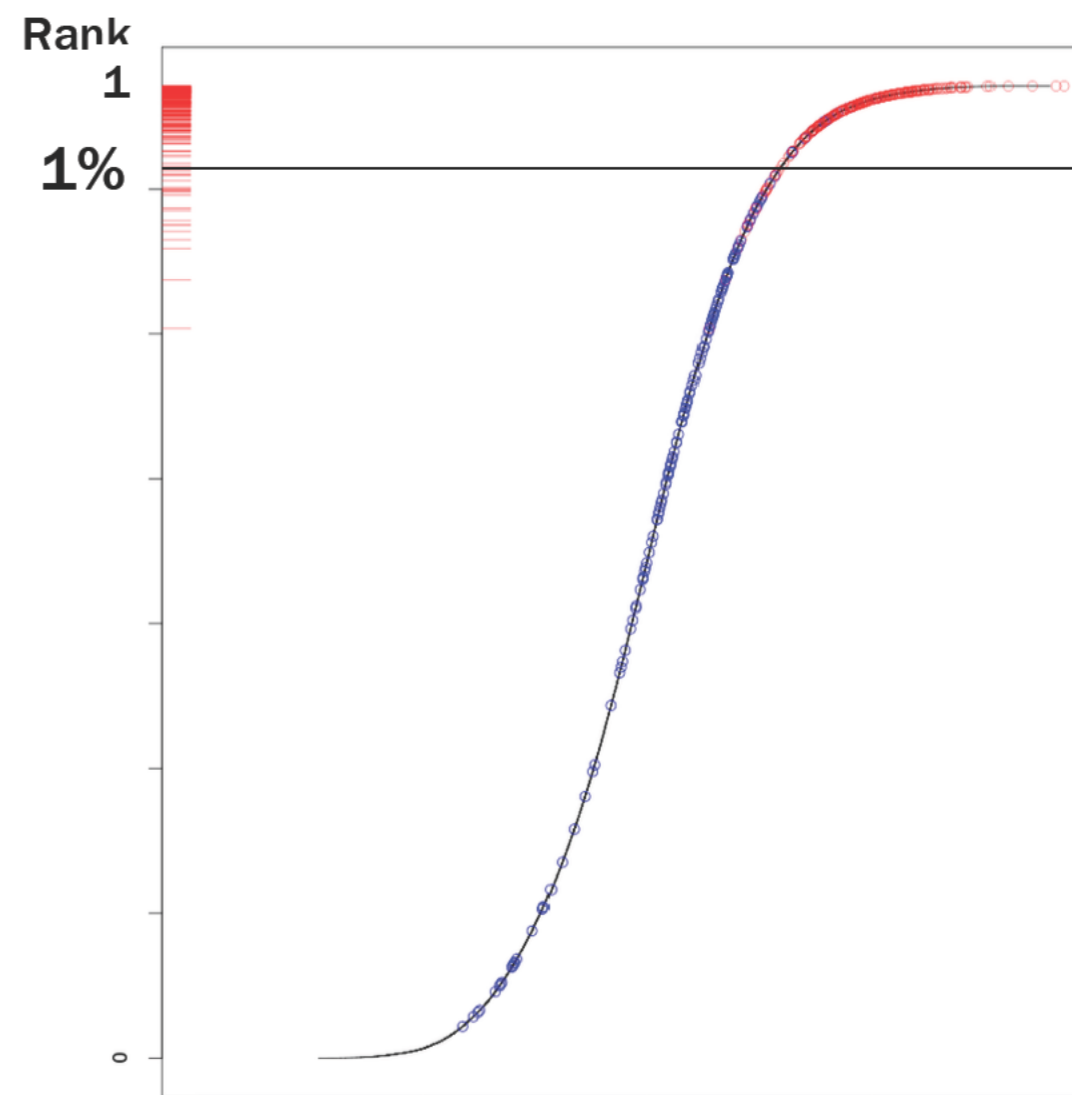
High connectivity between past & new profiles - data is robust

Query space: 1 plate
(384 profiles)



Spearman rank correlation

Query space: Full database
(1.3M profiles)



Connectivity Score

L1000 performance - compared to Affymetrix experimental L1000 data (not simulation)

79 connections from 7200 Affymetrix profiles

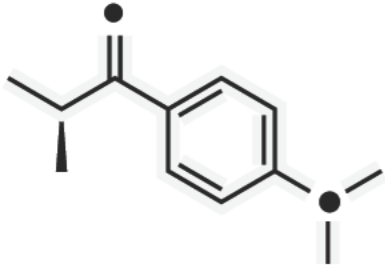


Repeat Affymetrix profiles on L1000



71/79 (90%) connections recovered

Current CMap dataset (2M (...10M) profiles)



~5,000 Compounds

- FDA approved drugs
- Bioactive tool compounds
- Screening hits



~3,000 Genes (shRNA & cDNA)

- Targets/pathways of approved drugs
- Candidate disease genes (e.g. recurrent from TCGA)
- Community nominations



15 Cell types

- Banked primary cell types
- Cancer cell lines (8)
- Primary hTERT-immortalized
- Patient-derived iPS cells

ANALYSIS METHODS

Design goals of L1000 data and analytics

- **Comprehensive**
- **Information-rich readouts (not optimized to particular questions)**
- **Easy to look things up (like Google)**
- **Easy to compare to non-L1000 data**
- **Accessible to biologists and computationalists**



Query



Match user-defined gene sets to L1000 signatures

[take a tour](#)

Name your query

+ Enter **Up-regulated** genes

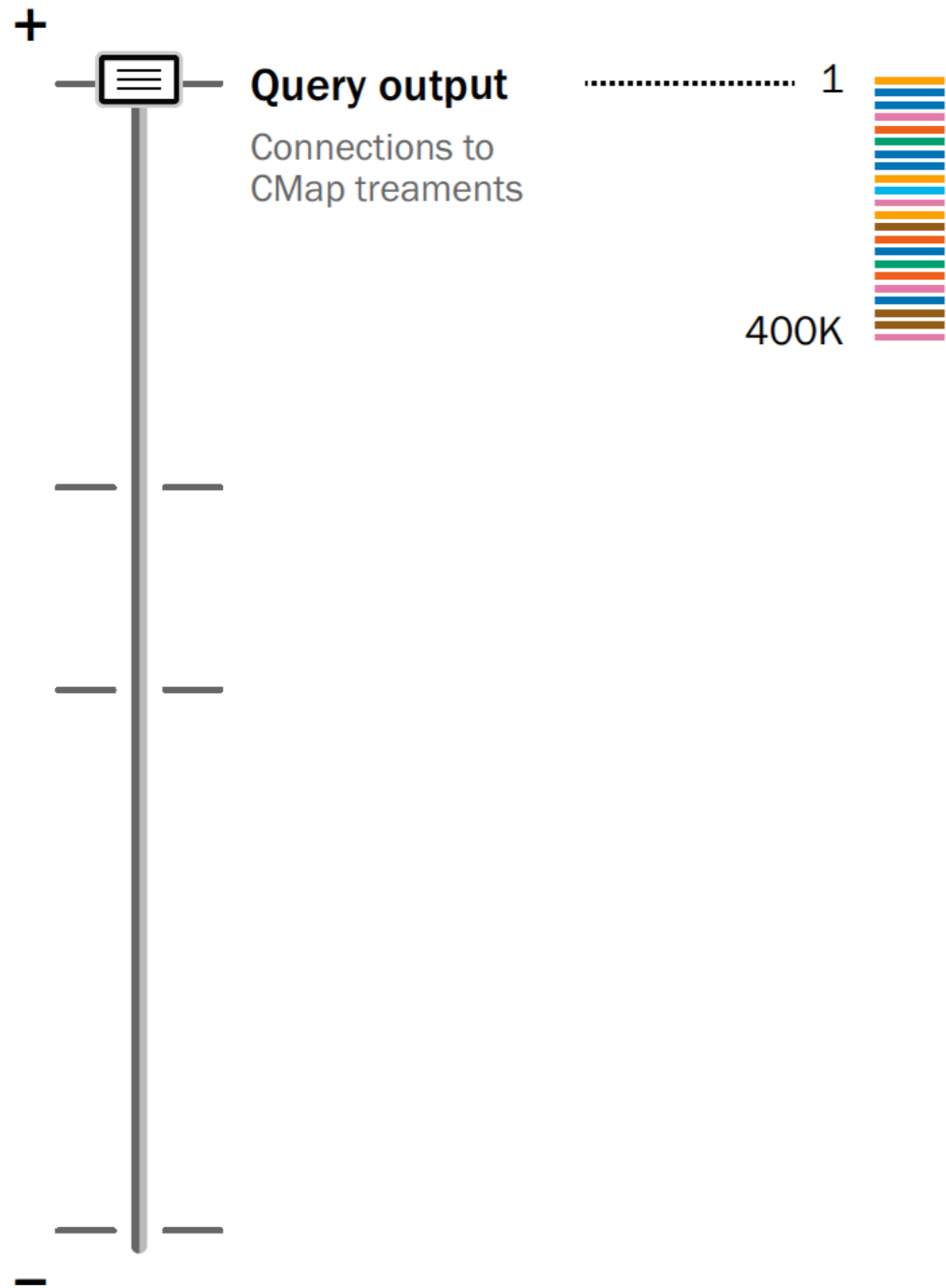
Enter one gene symbol or Affymetrix U133A probe ID per line or drag and drop a plain text file here.

- Enter **Down-regulated** genes

Enter one gene symbol or Affymetrix U133A probe ID per line or drag and drop a plain text file here.

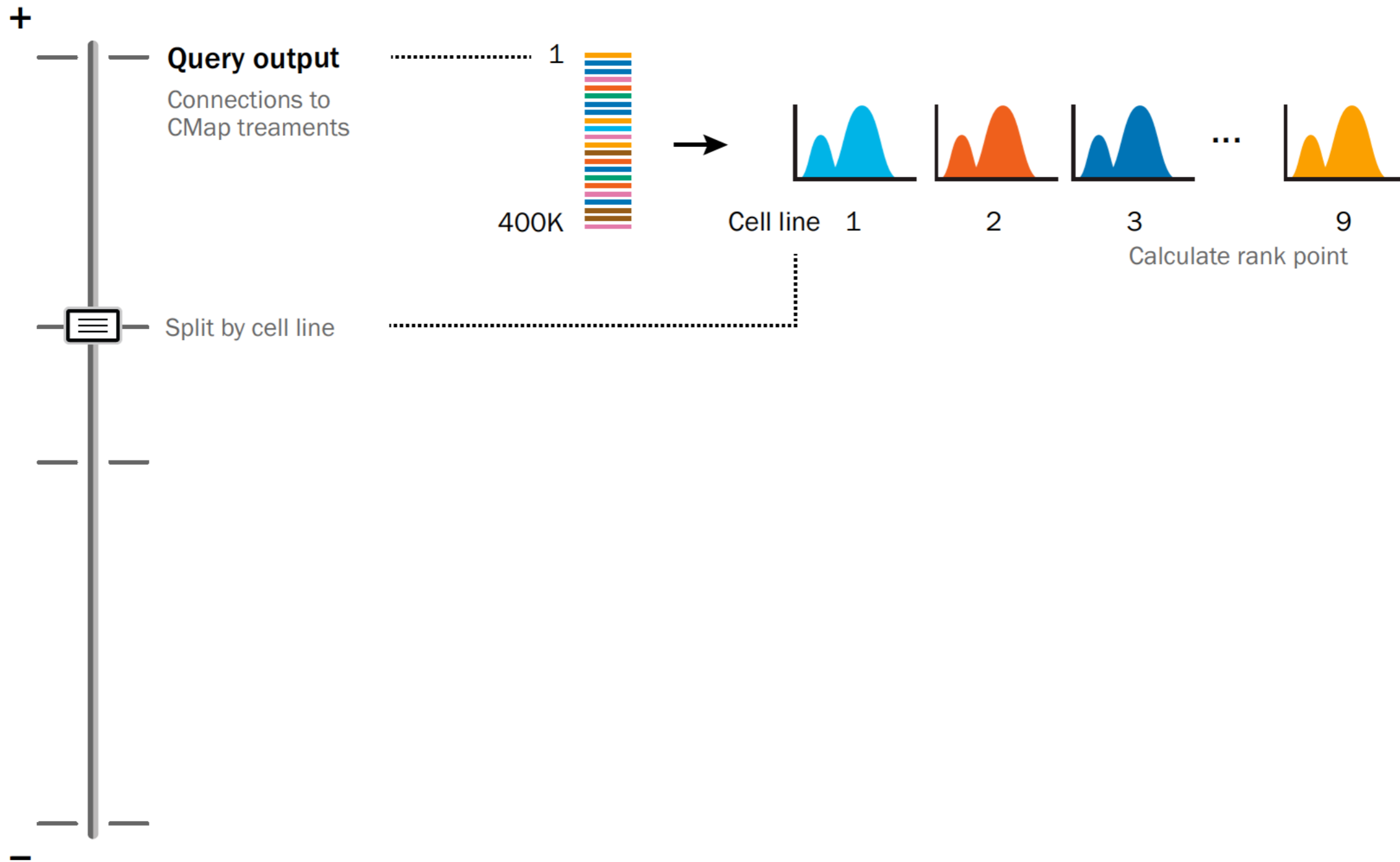
CMap result analysis

Many views of a single query



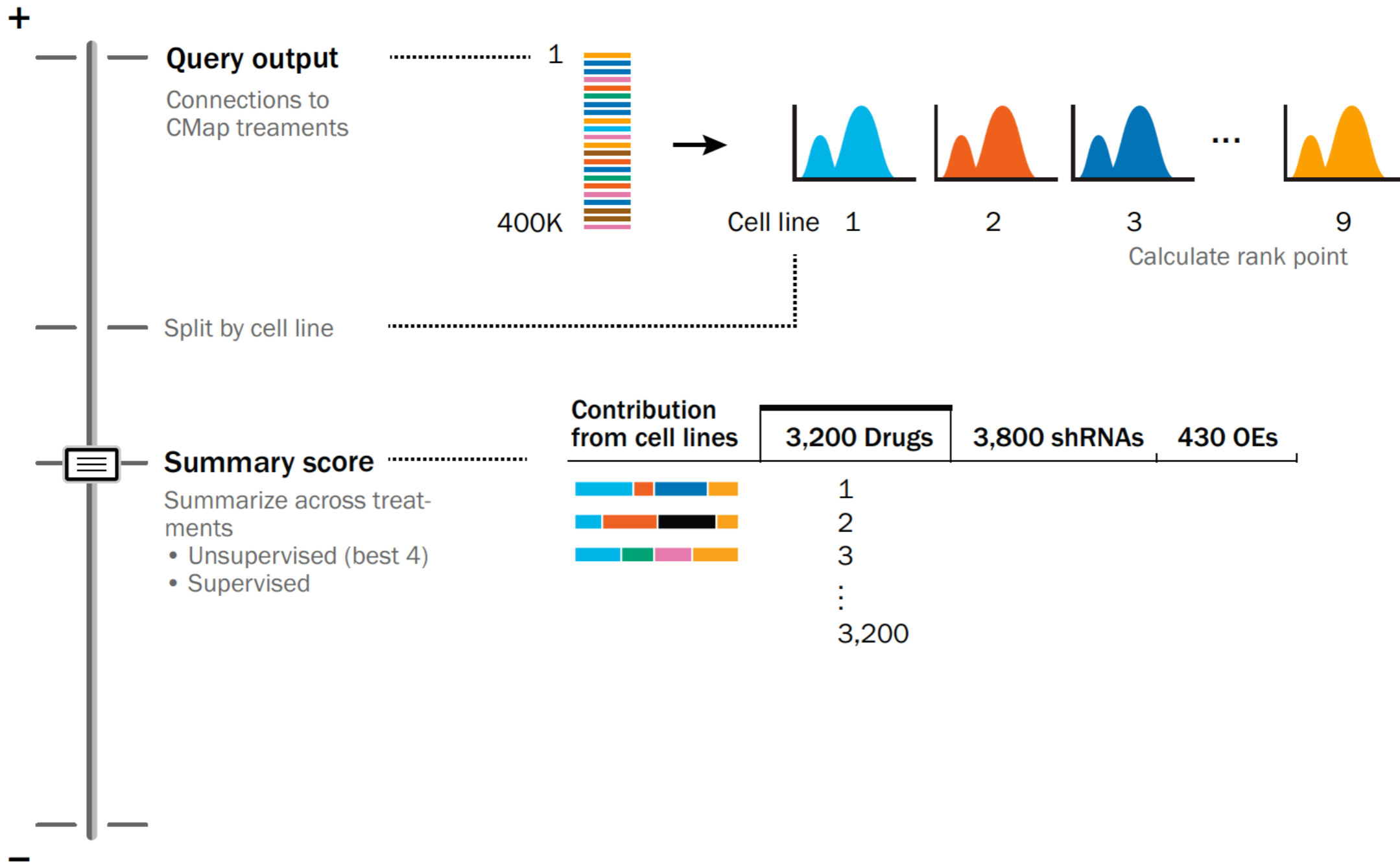
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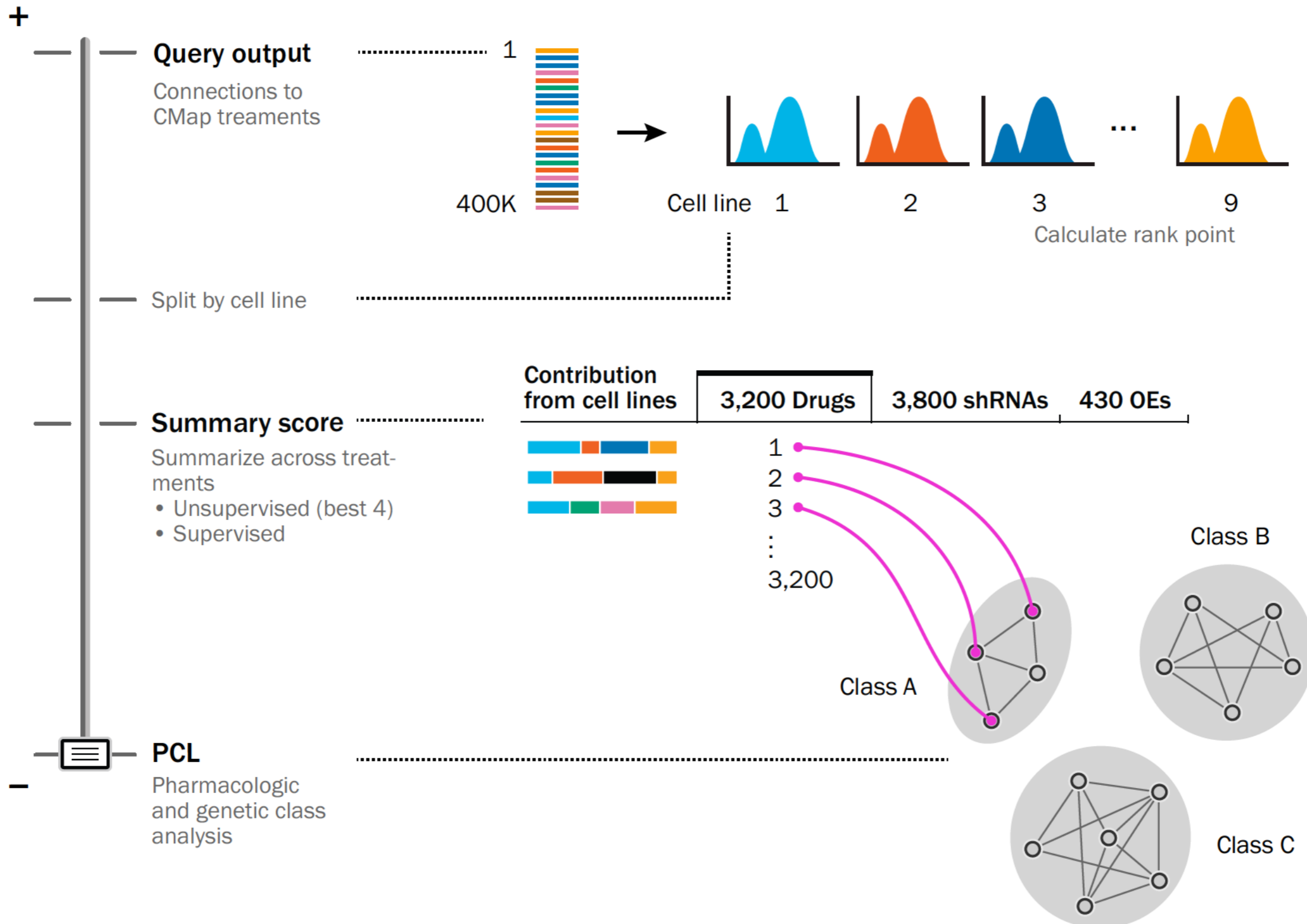
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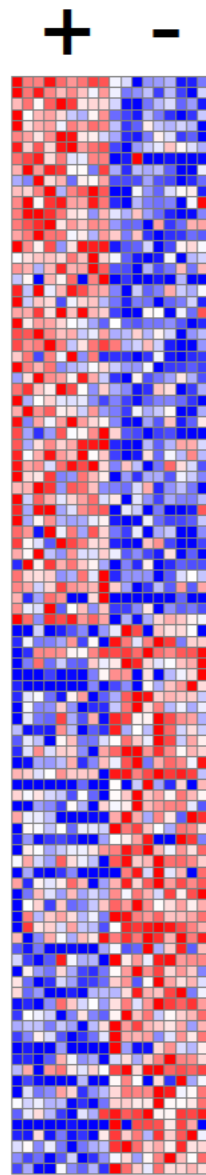
CMap result analysis

Many views of a single query



Query example

GEO Signature: HUVEC cells treated with pitavastatin



Rank	Compound
1	lovastatin
2	simvastatin
3	mevastatin
10	atorvastatin
29	pitavastatin
36	fluvastatin

⋮

3,200

Results

Given the mRNA expression signature of a TEST perturbagen

1. BIOACTIVITY

Does the perturbagen elicit a gene expression response?

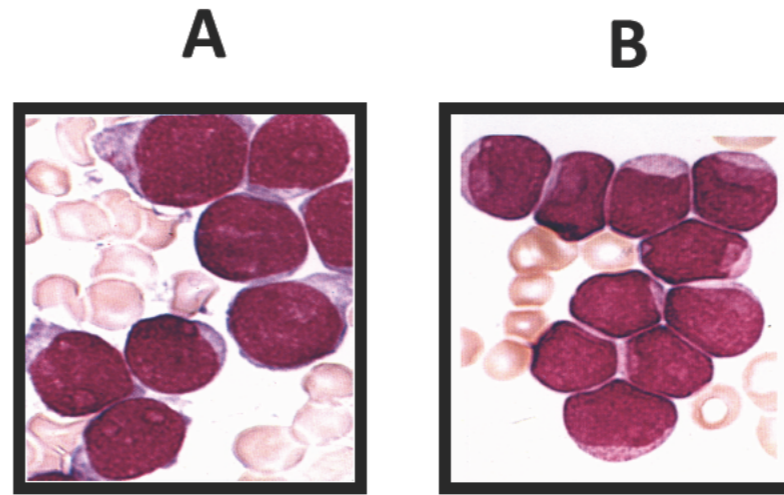
2. PATHWAYS

What gene pathways (or “networks”) are modulated?

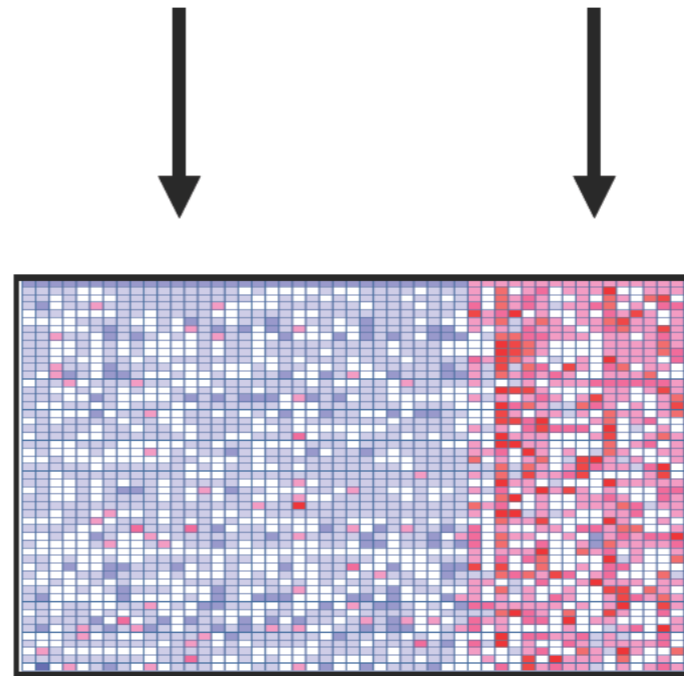
3. PHARMACOLOGICAL CLASSES

Which (previously characterized) pharmacological activities match the test perturbagen?

Biological States



mRNA signature



Interpretation

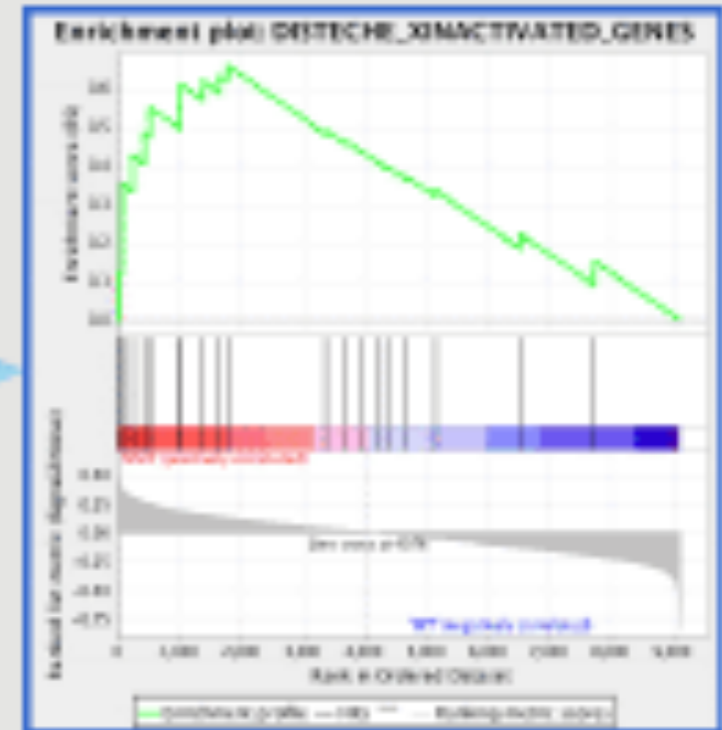
Molecular Profile Data



Gene Set Database

Run
GSEA

Enriched Sets



key challenge: Better gene sets

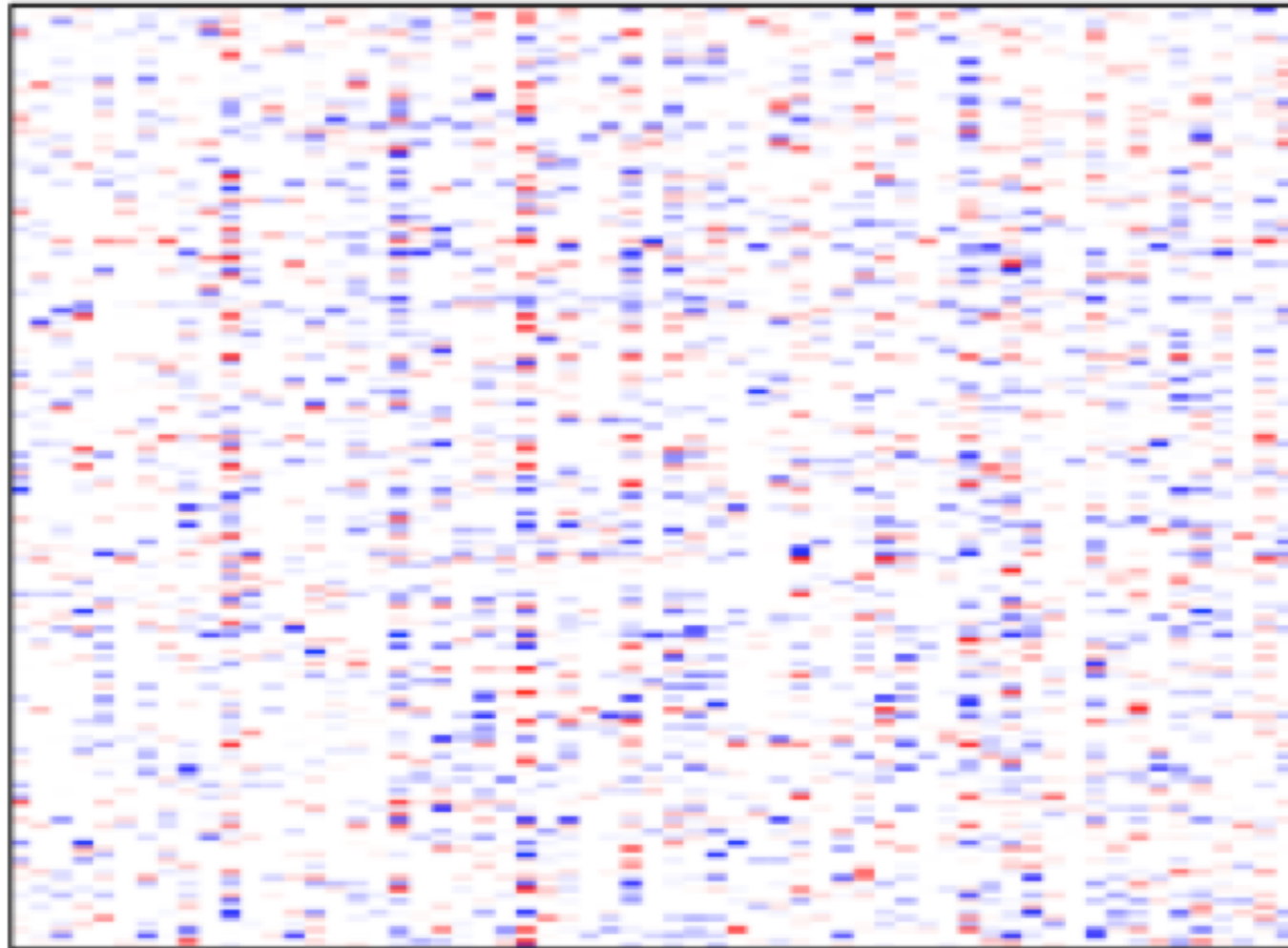
Solution: Systematic Known-down and over-expression of all genes

20,000 gene KDs
(e.g. shRNAs)

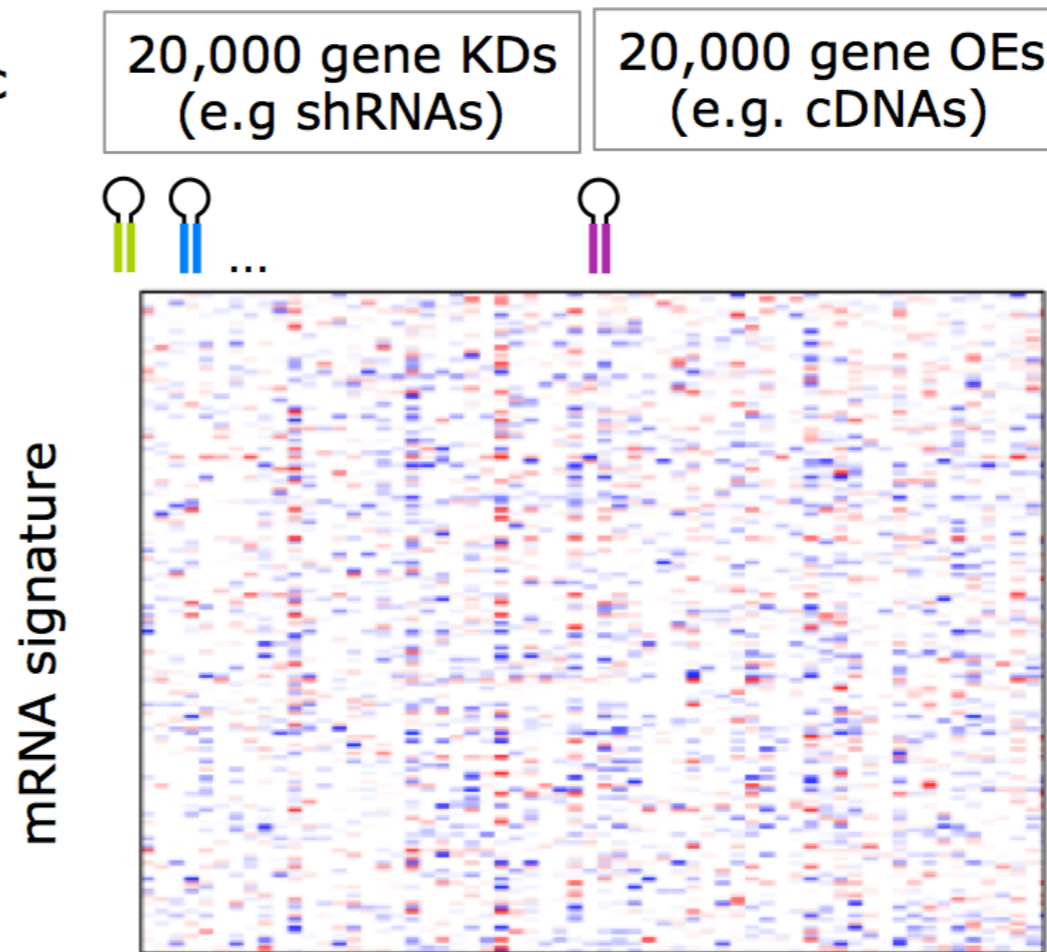
20,000 gene OEs
(e.g. cDNAs)



mRNA signature



Hypothesis: Creating a systematic dataset of gene knock-down and over-expression signatures



Would be useful for:

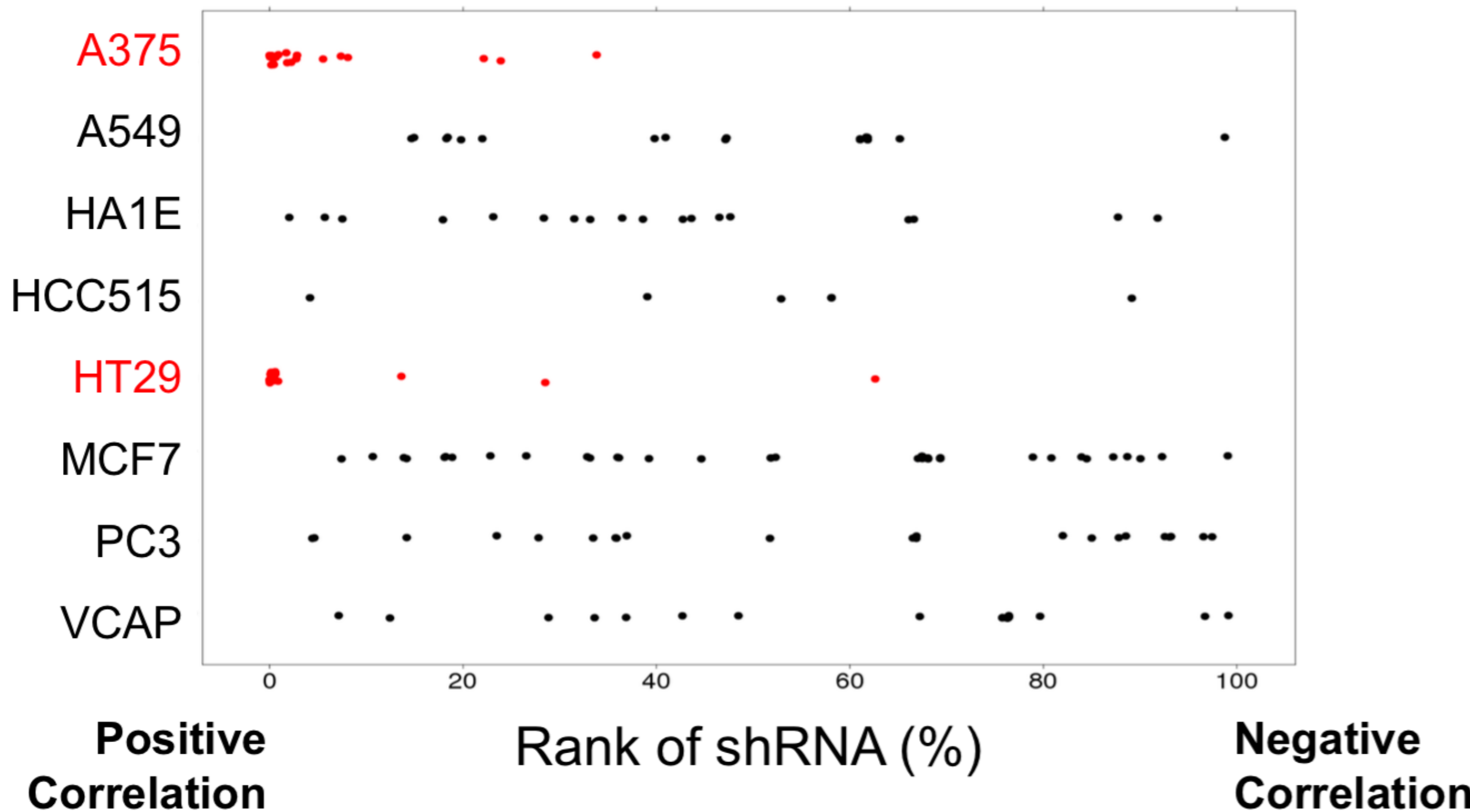
- 1) defining the "**core signature**" of a gene's function
- 2) identifying **gene-gene** functional connections
- 3) identifying **pathway** members
- 4) identifying **targets/pathways of small-molecules**

20,000 GENES x 2 (KD+OE) x replicates x cell types (10-20)
=> **5M** profiles (~1M so far)

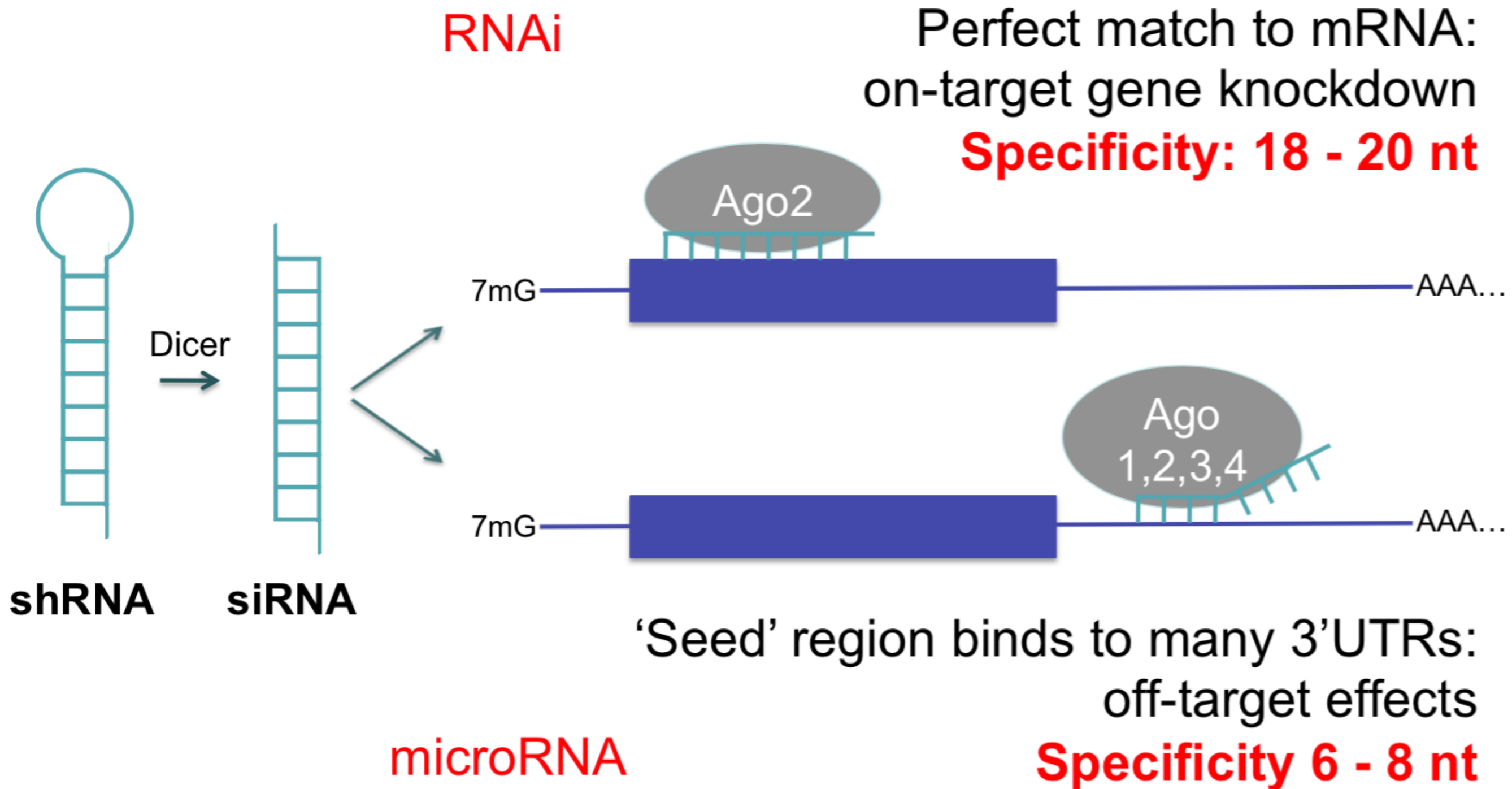
Query with Vemurafenib, a small molecule inhibitor of BRAF



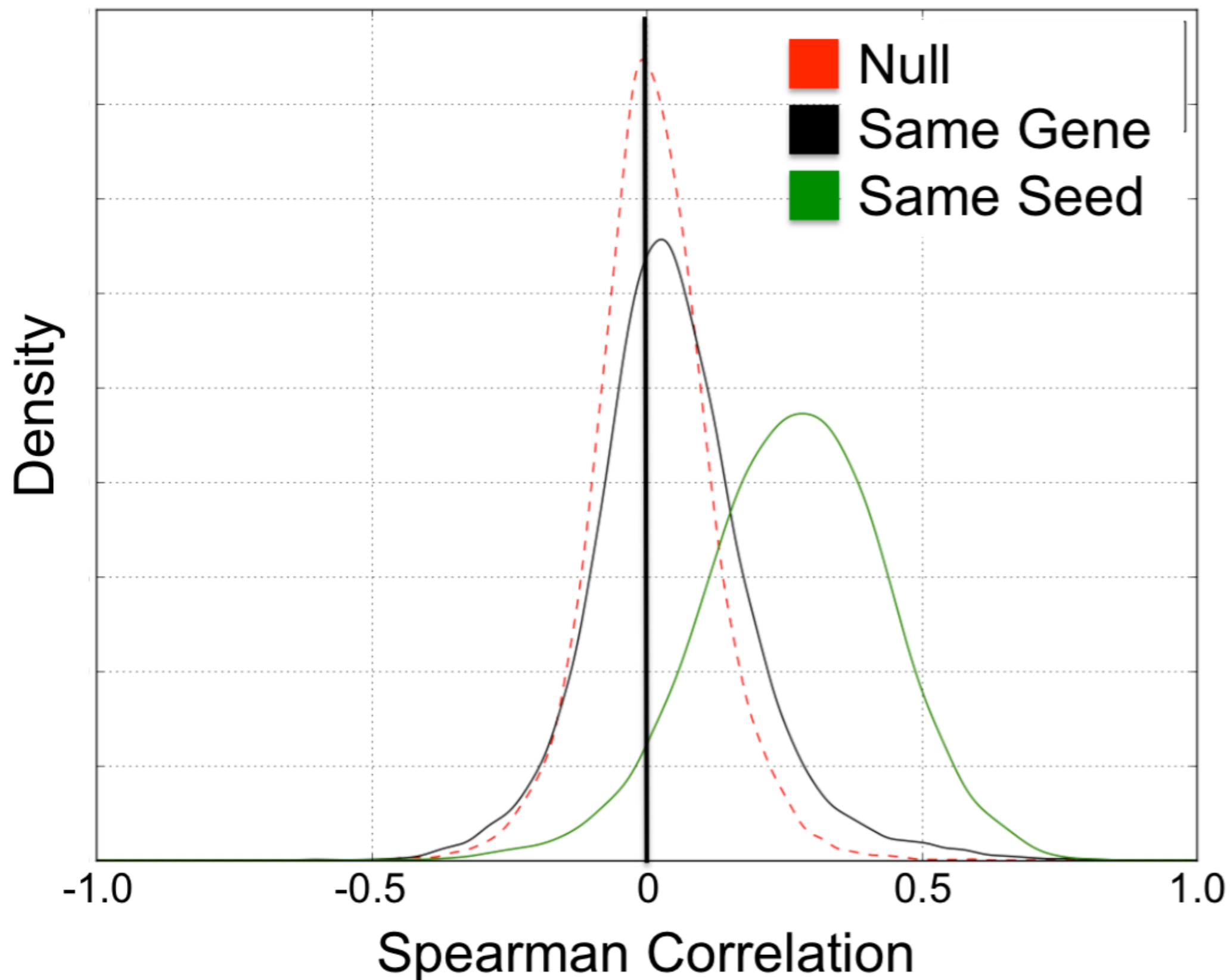
Each dot is an individual shRNA targeting BRAF



Two paths for shRNAs: how important are off-target effects?



shRNAs sharing a seed sequence correlate better than same-gene shRNAs

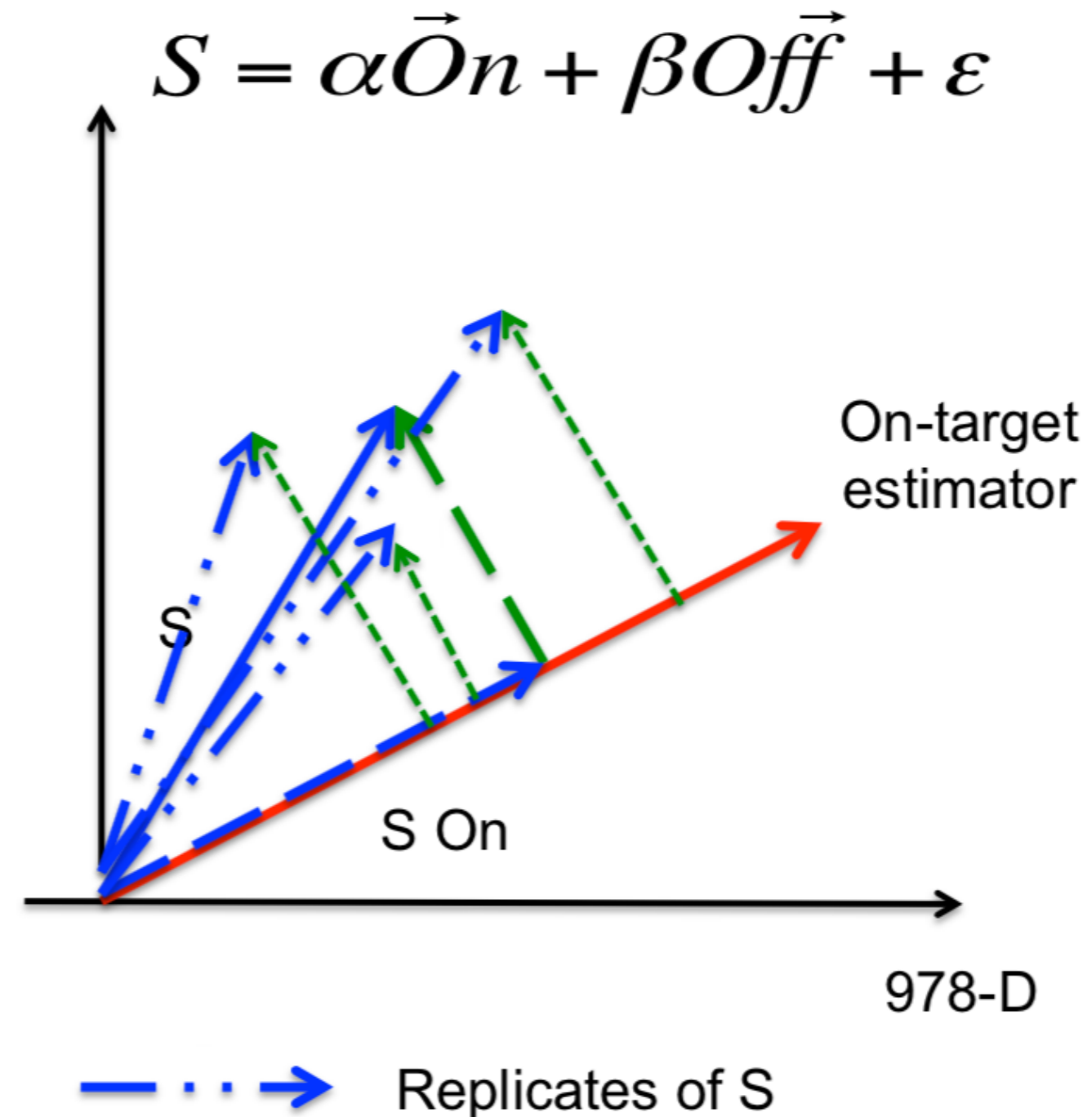


Projection Method decomposes on- and off-targets without prior knowledge of off-target mechanism

Method: Projection

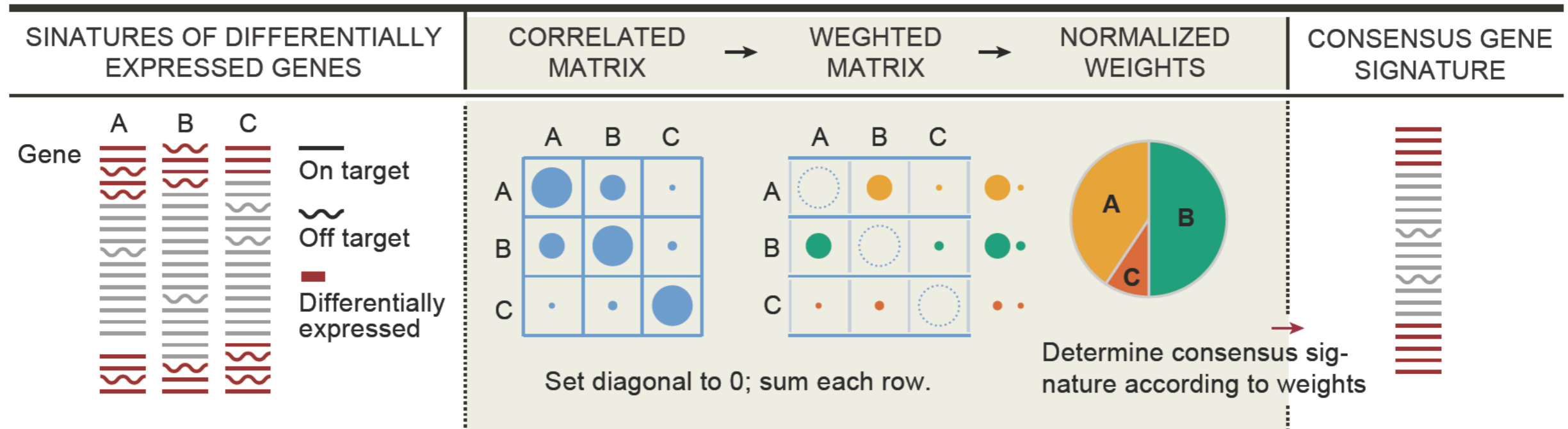
All signatures are a combination of:

- Assay noise
 - Model with technical replicates
- On-target effects
 - Model with Consensus Gene Signature
- Off-target effects
 - Whatever is left

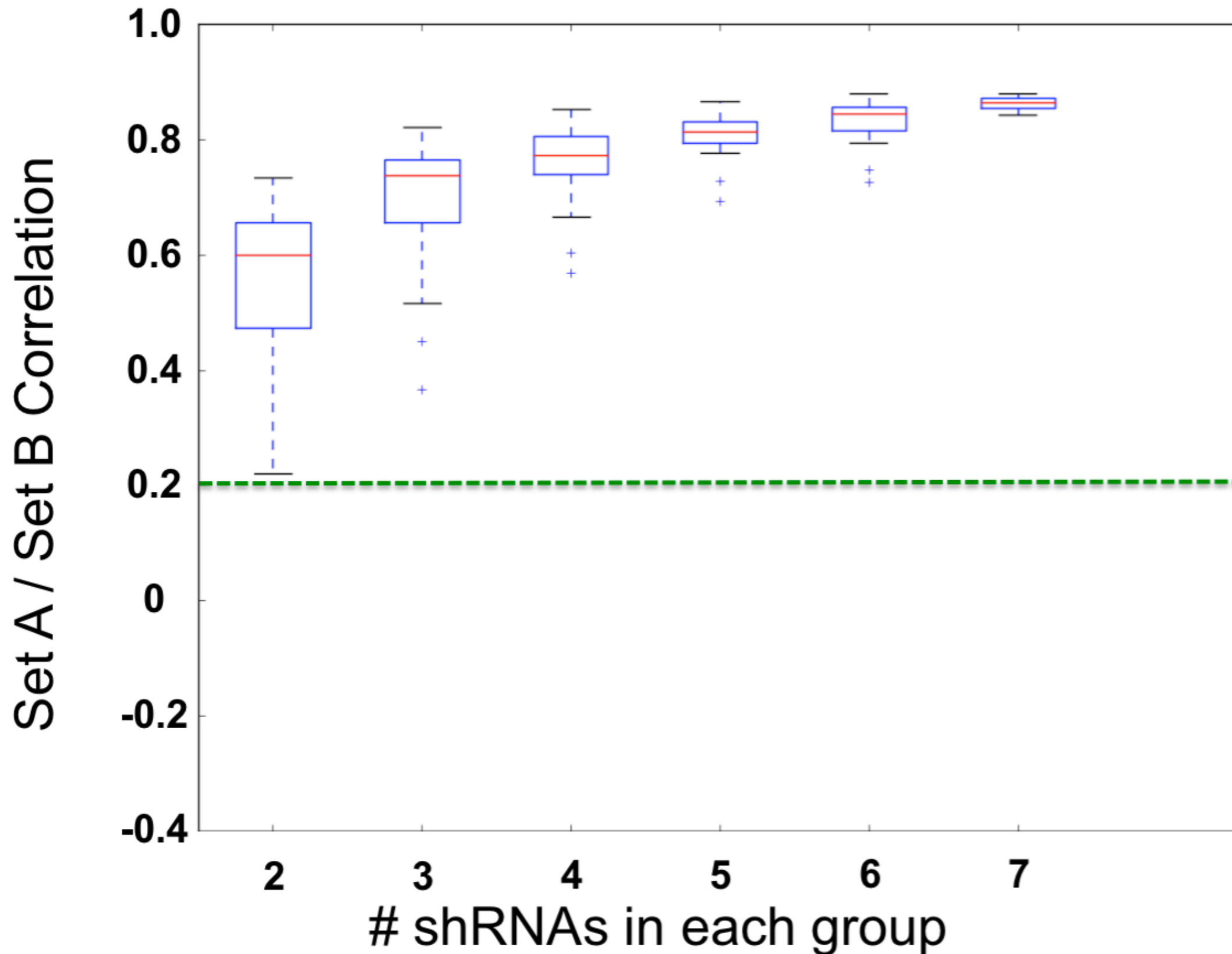


Consensus gene signatures (CGS)

Moderated Z procedure

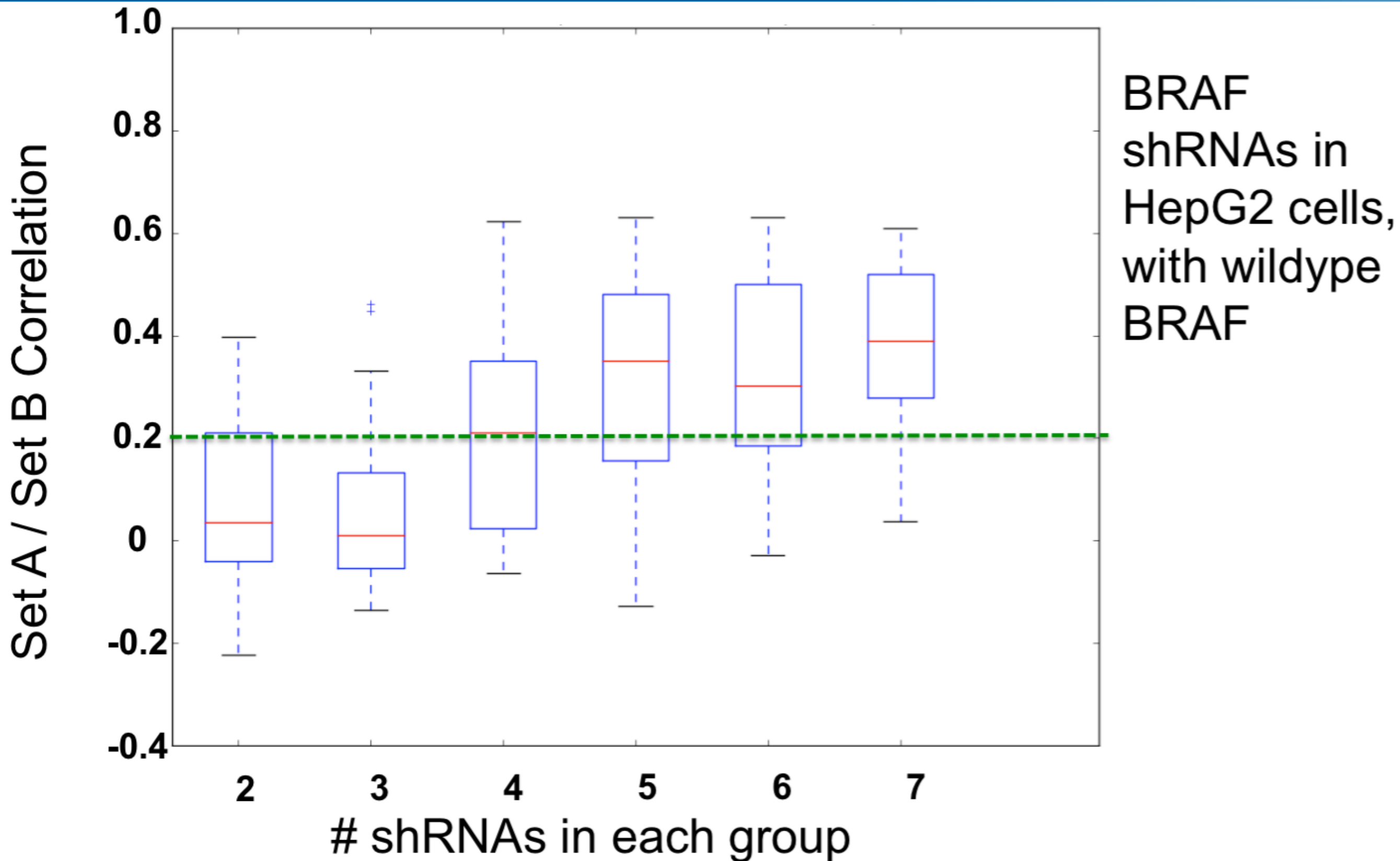


BRAF shRNAs converge in HT29 cell



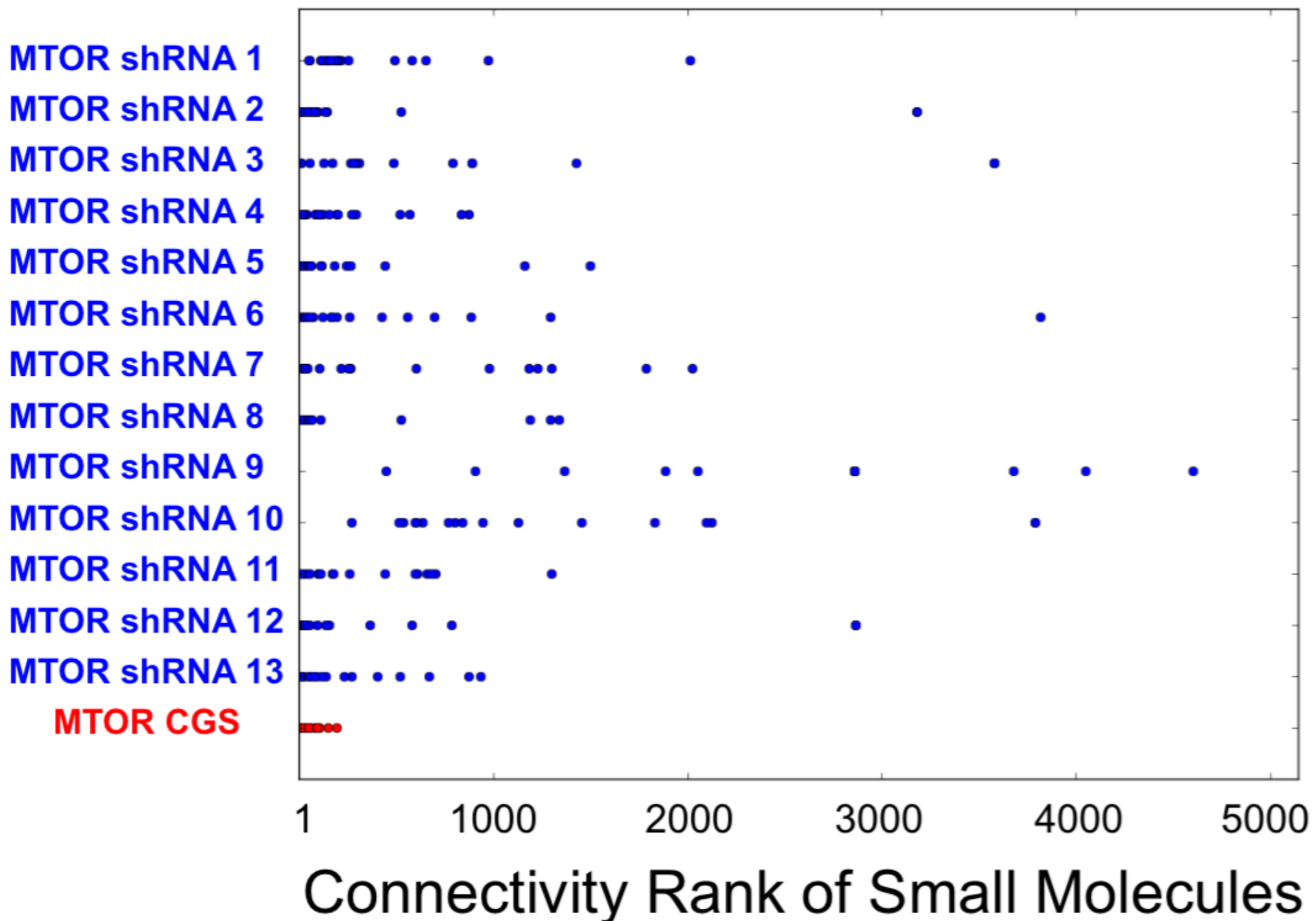
BRAF
shRNAs in
HT29 cells,
with BRAF
V600E
mutation

But not in HEPG2 cells (BRAF wt)



Combining information from multiple shRNAs improves connections to compounds

Each dot is a dose / timepoint of rapamycin



Compound-knockdown connections

BEZ235 (PI3K/MTOR inhibitor) treatment

Compounds

rank	compound	target
1	AZD-8055	MTOR
2	KU-0063794	MTOR
3	PP-110	PI3K
4	BEZ235	MTOR, PI3K
5	PI-103	MTOR, PI3K
6	PI-828	PI3K
7	TGX-115	PI3K
9	WYE-354	MTOR
10	PIK-90	PI3K
12	OSI-027	MTOR
13	GDC-0941	PI3K
14	temsirolimus	MTOR
18	wortmannin	PI3K
19	GSK-1059615	MTOR, PI3K
20	WYE-125132	MTOR

•
•
•
3,200

Knockdown

rank	gene
1	MTOR
3	RPTOR
6	SGK1
12	KRAS

•
•
•
3,800

Compound-knockdown connections

Trametinib (MEK inhibitor) treatment

Compounds

rank	compound	target
1	selumetinib	MEK
3	PD-0325901	MEK
4	U0126	MEK
5	PD-0325901	MEK
6	MEK1-2-inhibitor	MEK
7	AS-703026	MEK
8	AZ-628	BRAF, RAF1
9	U-0126	MEK
11	PD-184352	MEK
15	ERK-inhibitor-11E	ERK
16	U-0126	MEK
18	neratinib	EGFR, ERBB2
23	PD-198306	MEK

•
•
•
3,200

Knockdown

rank	gene
3	MEK
7	KIT
21	EGFR
27	KRAS

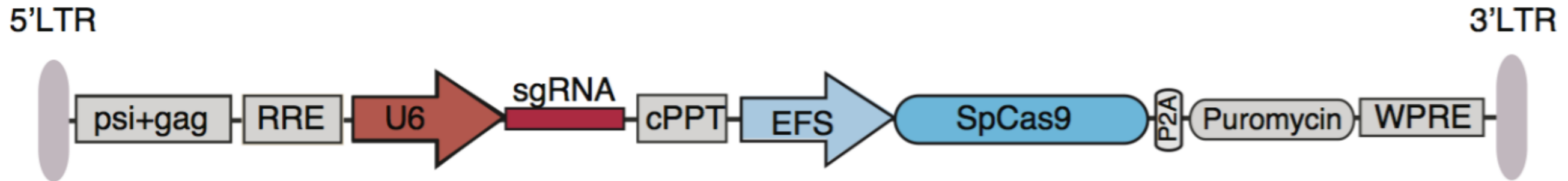
•
•
•
3,800

Overexpression

rank	gene
2	DUSP4
3	DUSP6
419	RAF1
423	IGF2
430	SRC

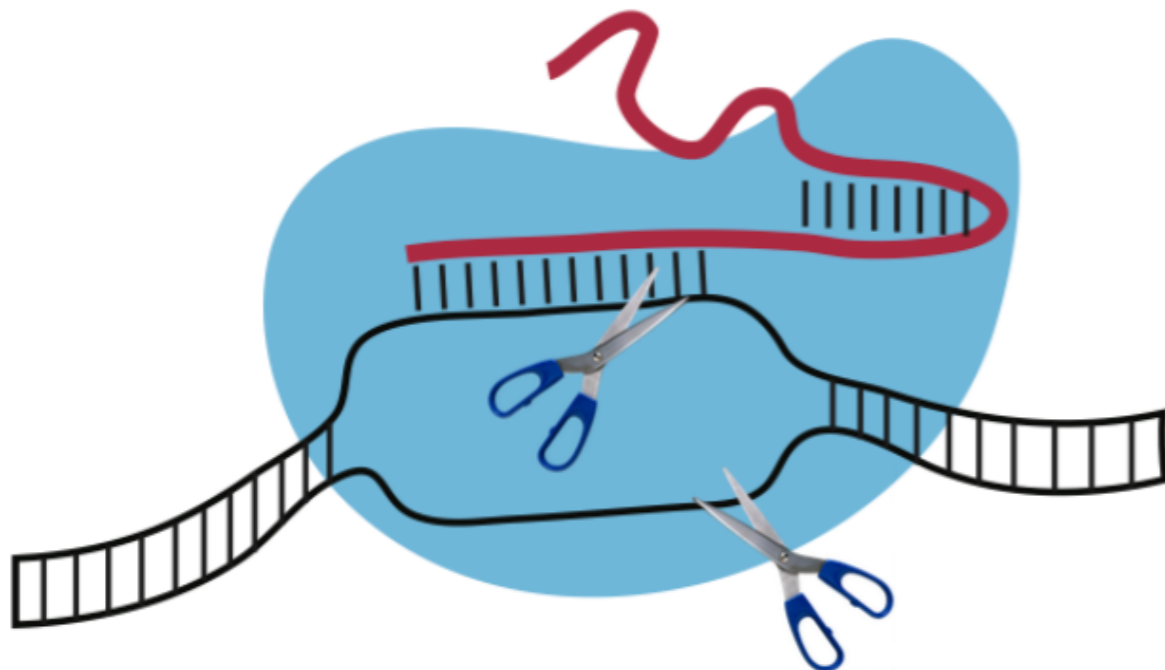
430

CRISPR system for lentiviral-based loss of function screening

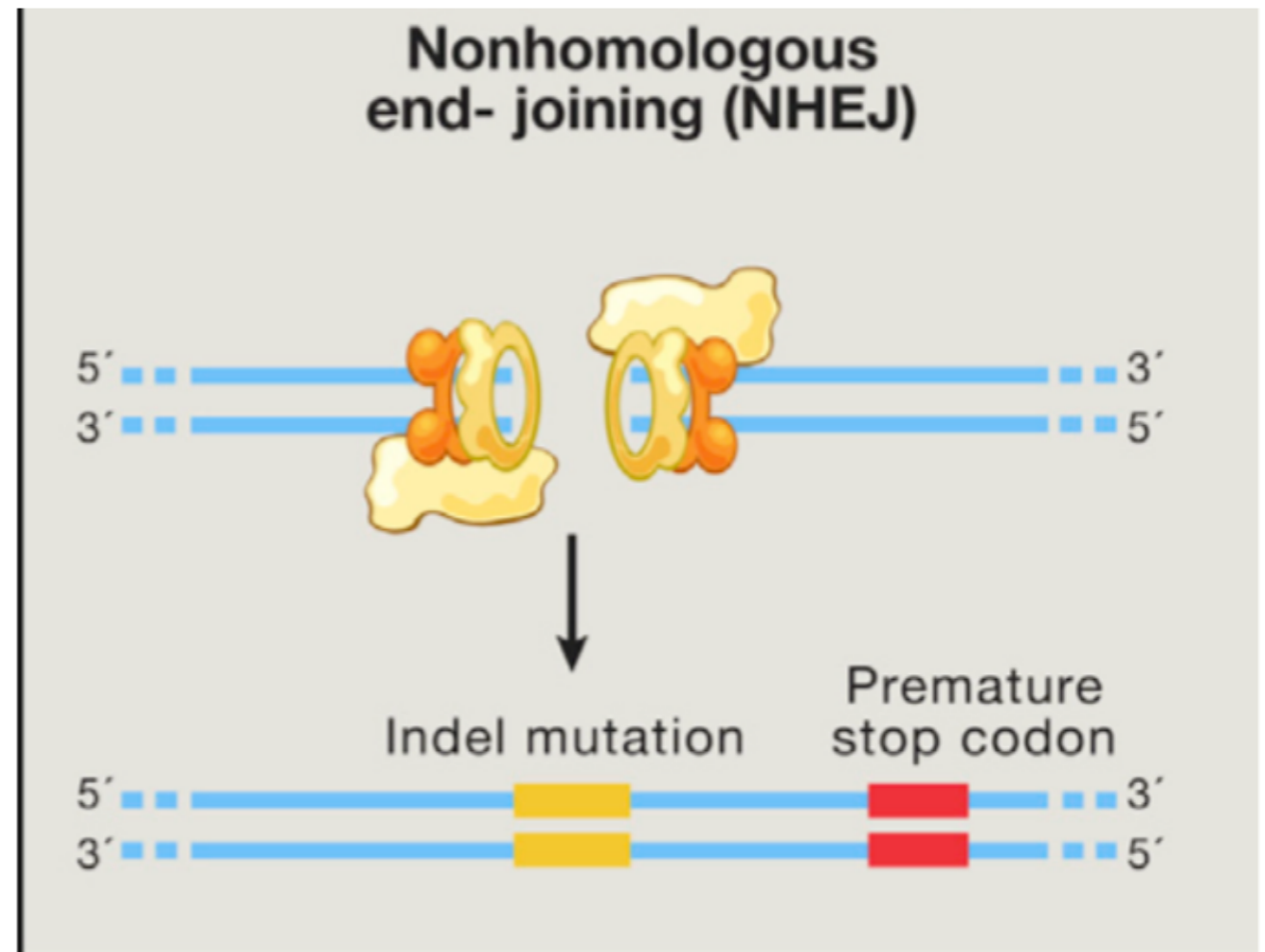


sgRNA: crRNA & tracrRNA

Program with 20nts of specificity
Binds Cas9



Cas9 endonuclease



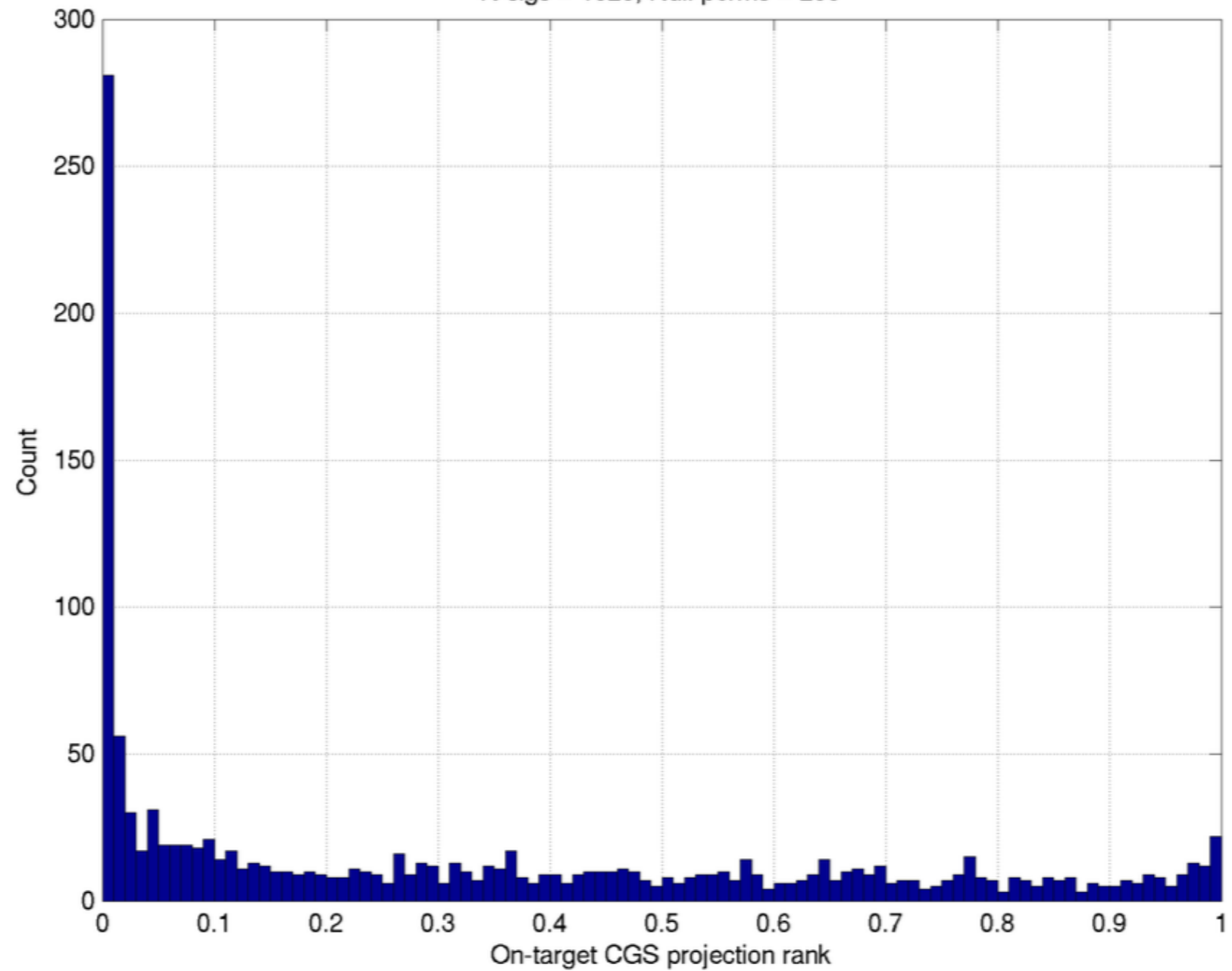
sgRNA On-target projection ranks

Validating the projection method: About 25% of CRISPR signatures find their on-target CGS

Procedure:

- Project sgRNA signature onto CGS
- Find rank CGS projection relative to 200 null CGS projections
- 257 of 1320 sgRNA signatures rank their CGS in the top 1%

Distribution of on-target projection ranks relative to null, xpr_ngg_rep_test
N sigs = 1320, Null perms = 200



Proper use of shRNAs



- Combine information from multiple shRNAs targeting a gene to reach conclusions
- shRNAs have off-target effects due to seed
 - More widespread than generally appreciated
 - All screens can benefit from explicitly examining and correcting for seed effects
- Combination of on-target effects and seed-based effects explain a very high percentage of shRNA activity
 - **We understand the proper use and analysis of these reagents**
- Explicit seed-matched controls can be used at small-scale to confirm on-target efficacy
 - Stop using your ‘favorite’ EGFP shRNA as a control!
- Orthogonal reagents to validate phenotype, e.g. cDNAs, CRISPRs

PHARMACOLOGICAL CLASSES

Given the mRNA expression signature of a TEST perturbagen

1. BIOACTIVITY

Does the perturbagen elicit a gene expression response?

2. PATHWAYS

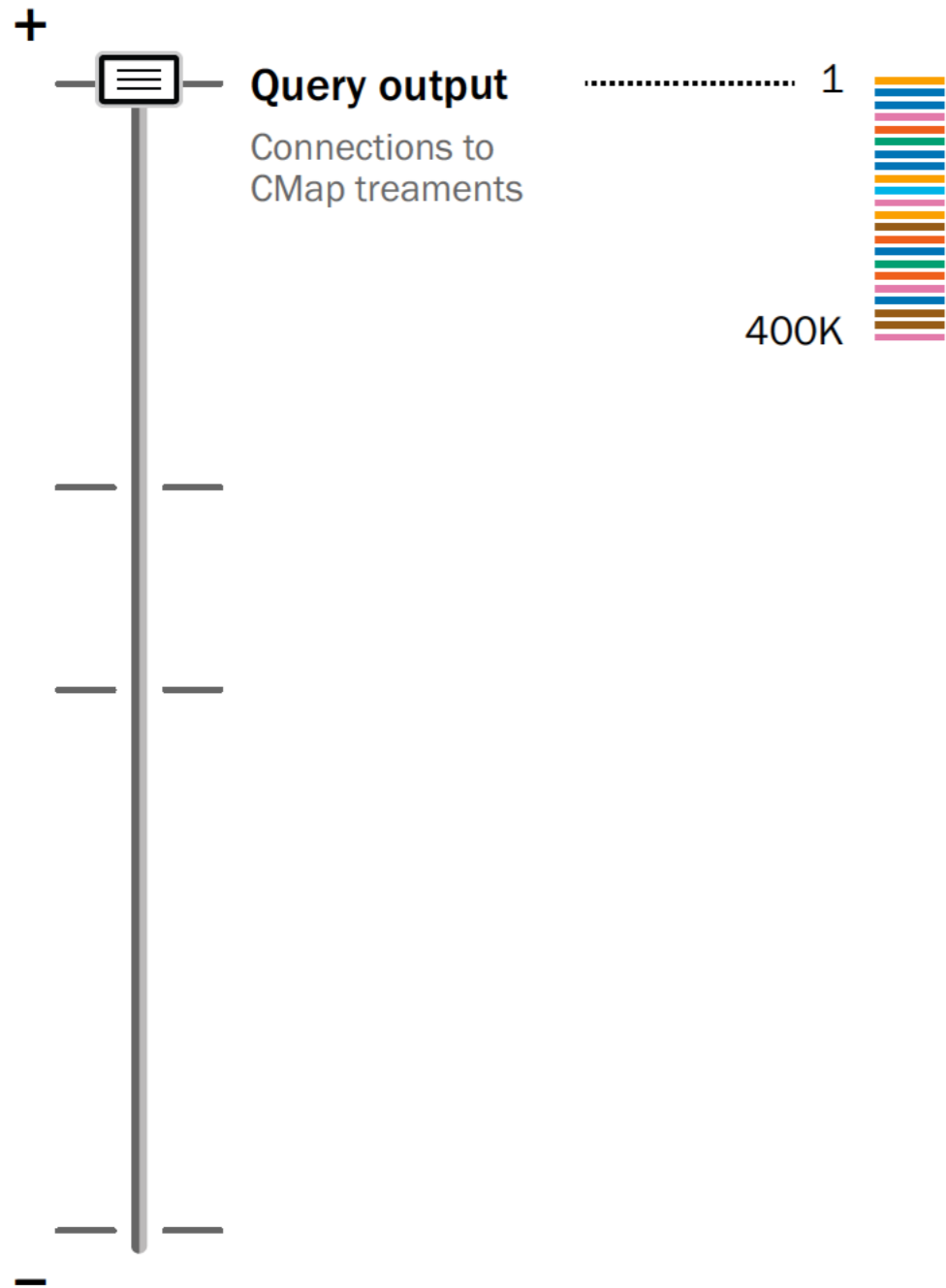
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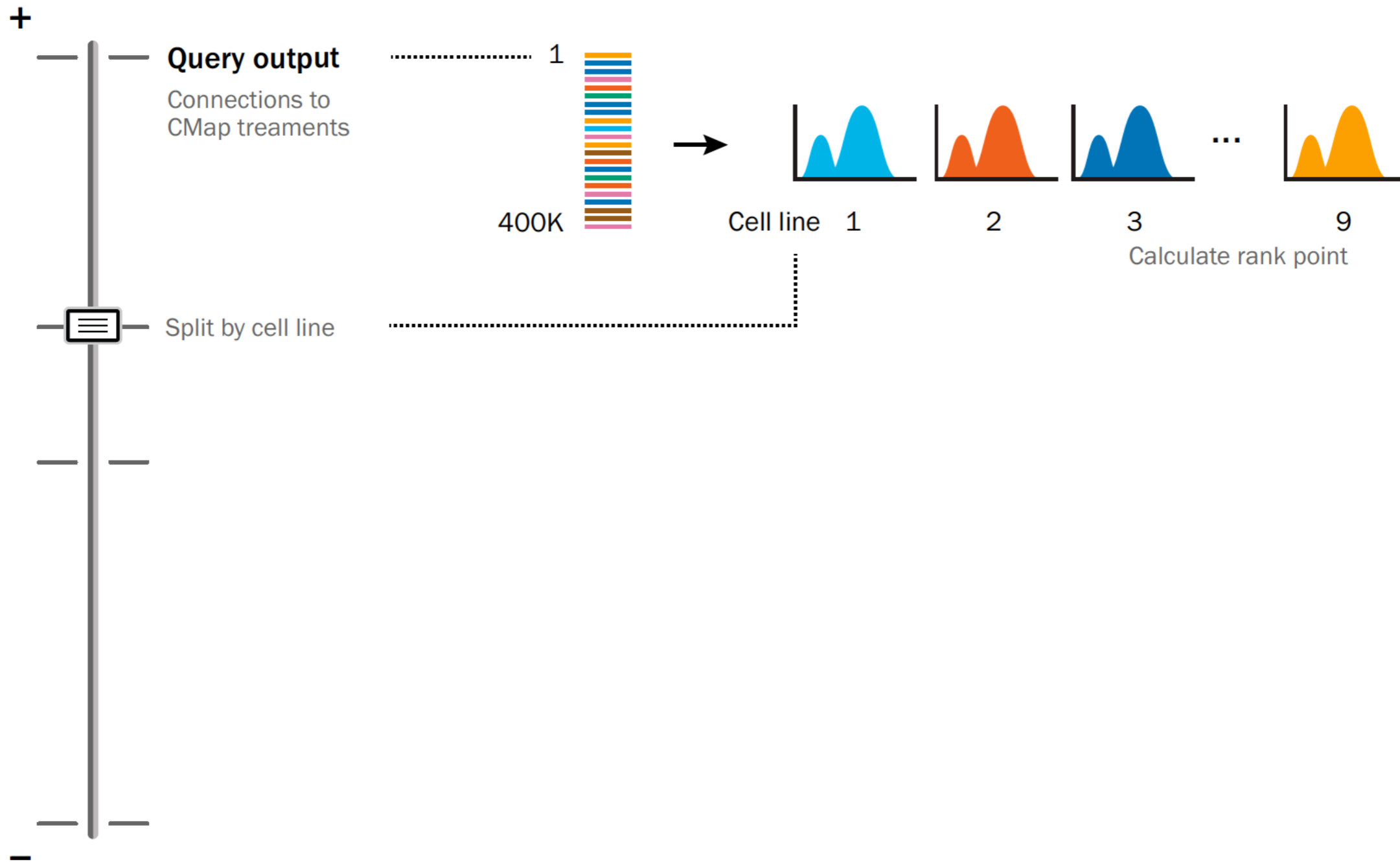
CMap result analysis

Many views of a single query



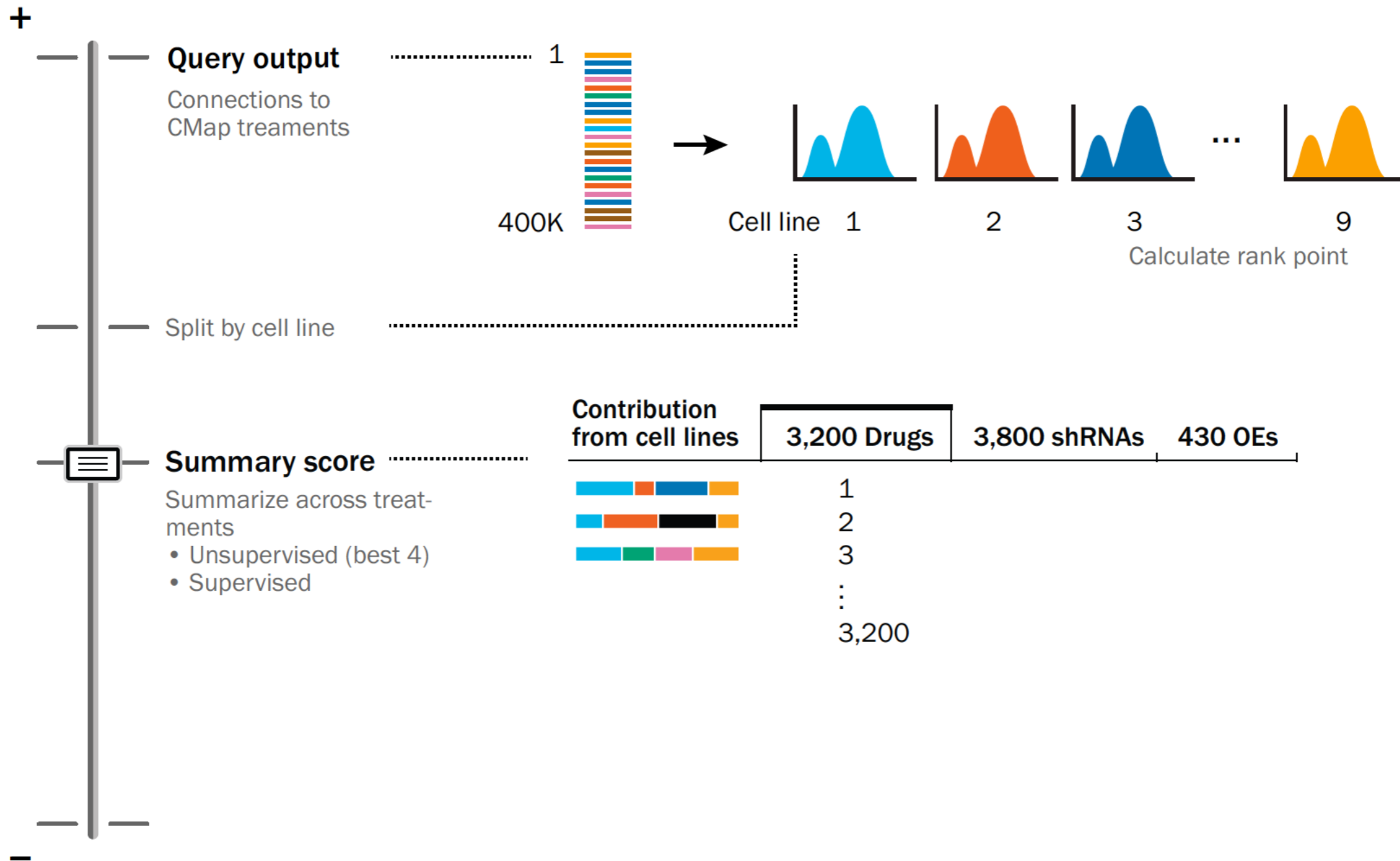
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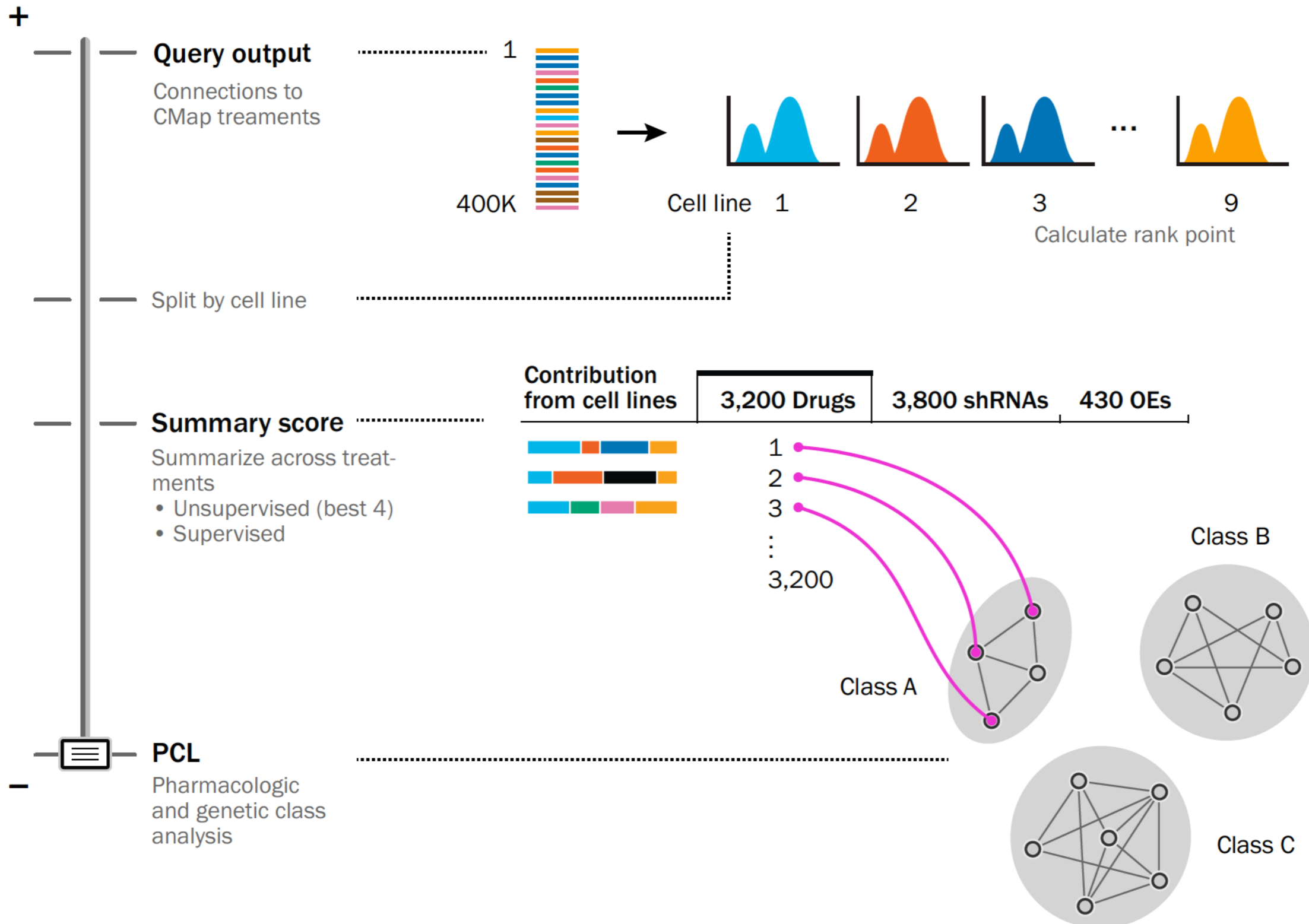
CMap result analysis

Many views of a single query



CMap result analysis

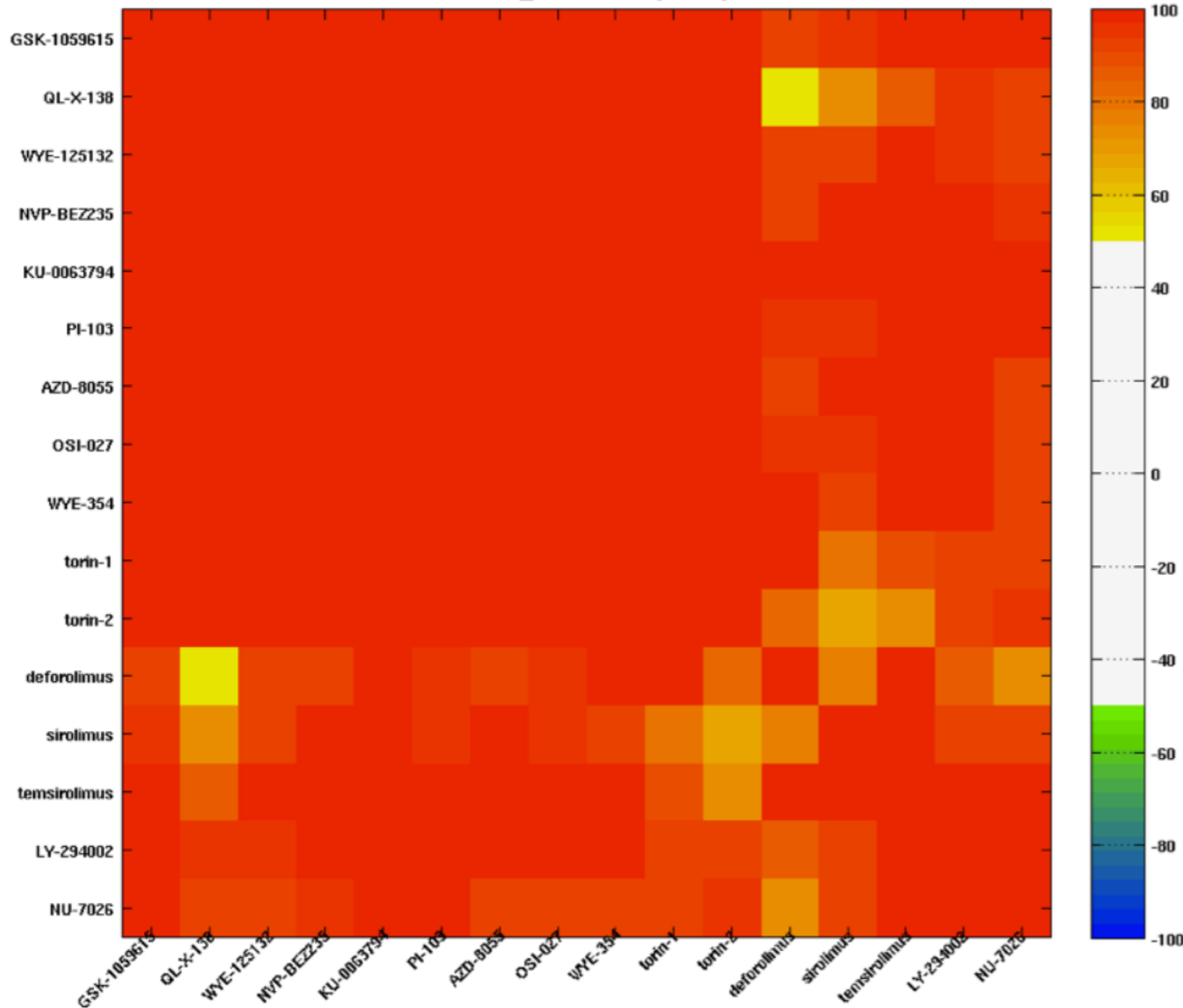
Many views of a single query



Robust PCI example

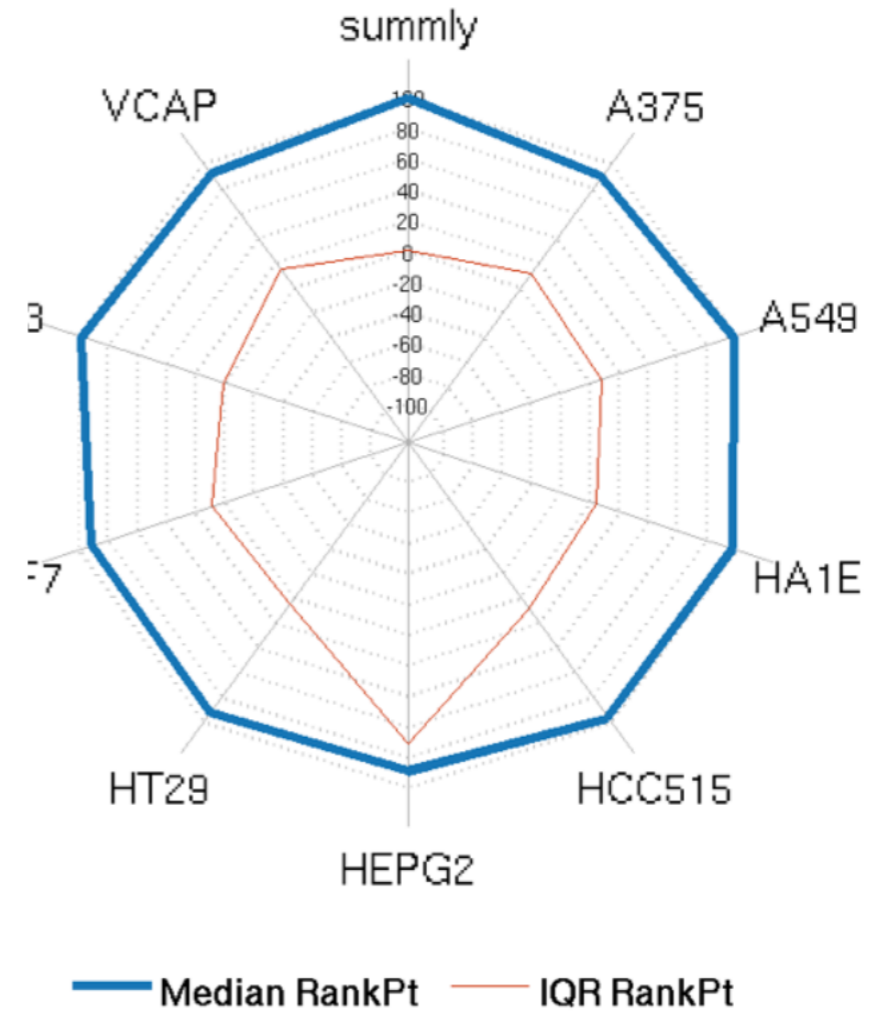
MTOR inhibitors

MTOR_inhibitor (n=16)



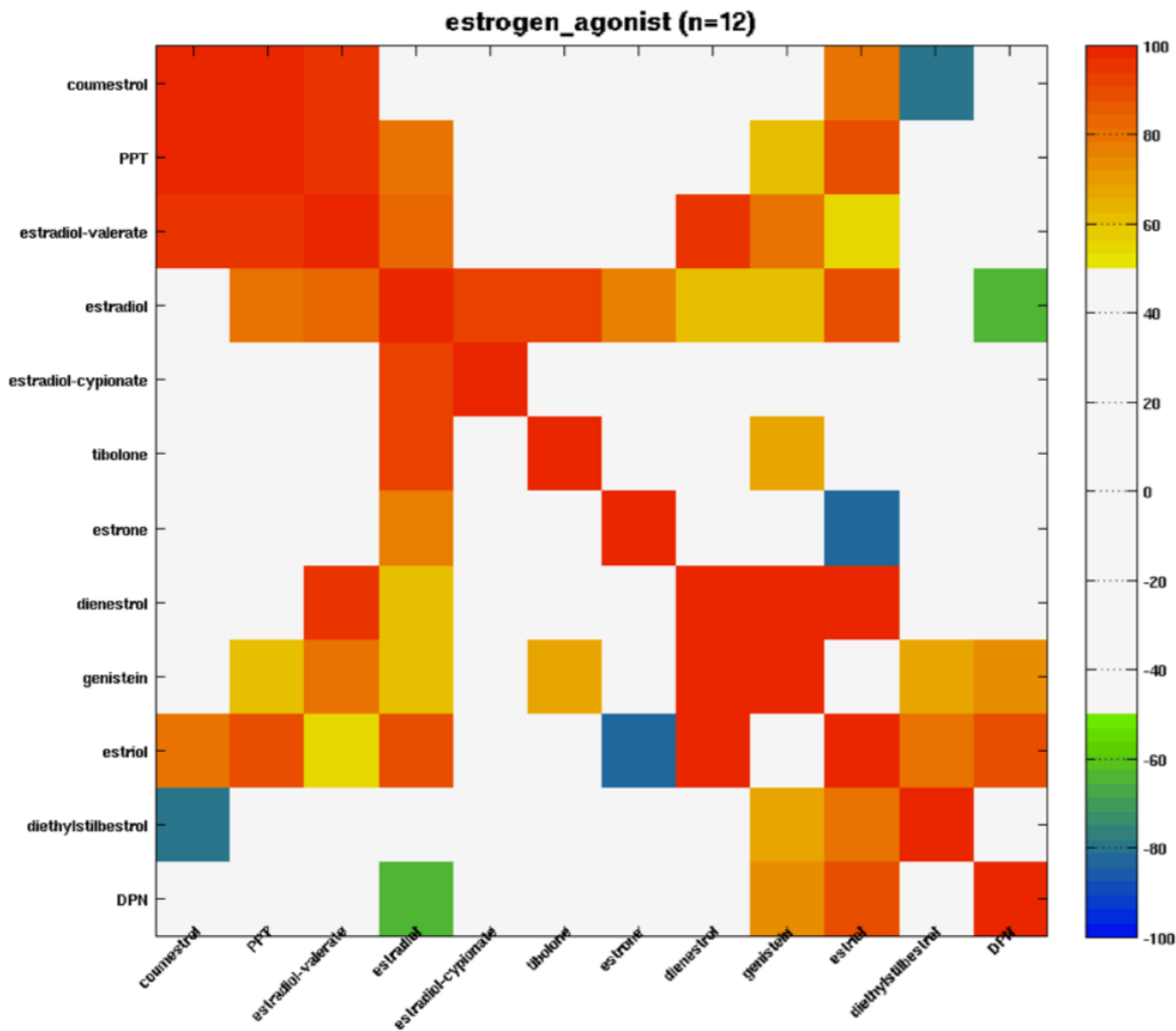
Across all cell lines

MTOR_inhibitor (n=16)

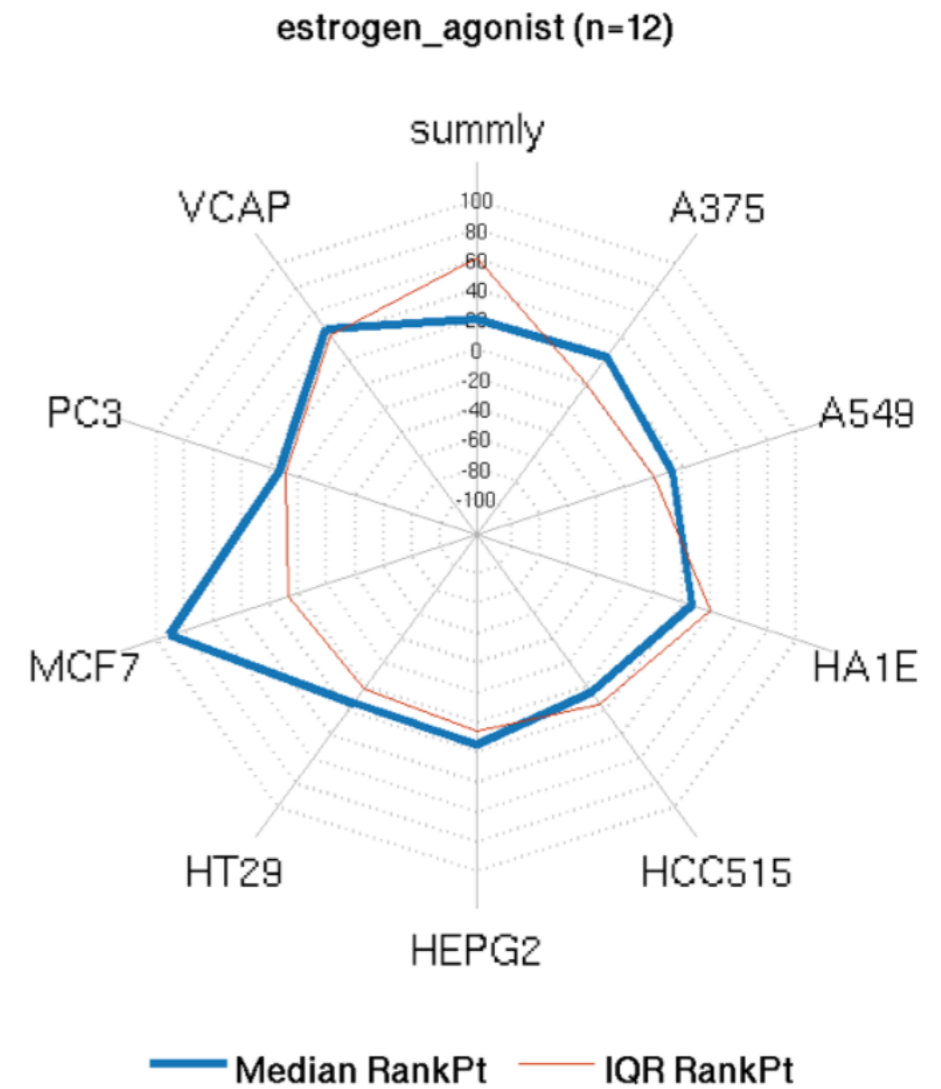


Cell type-specific PCI example

Estrogen signaling

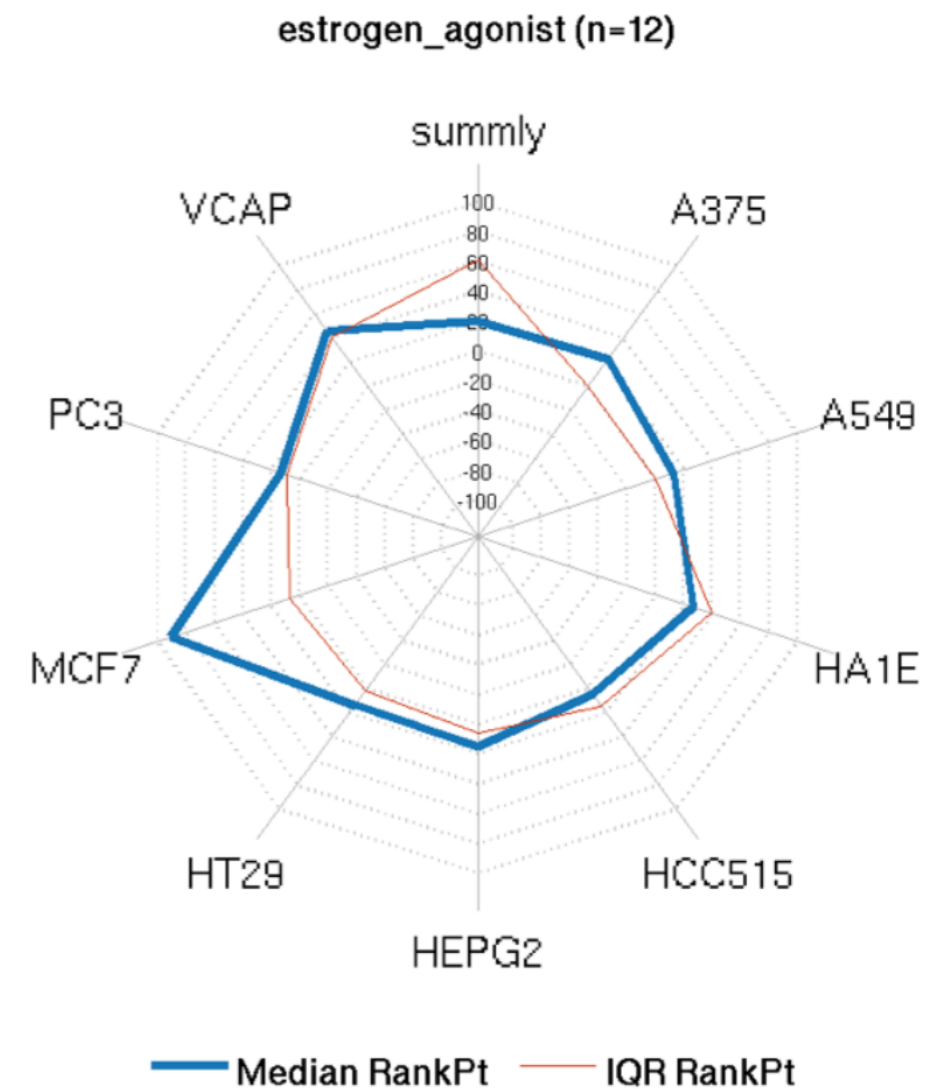
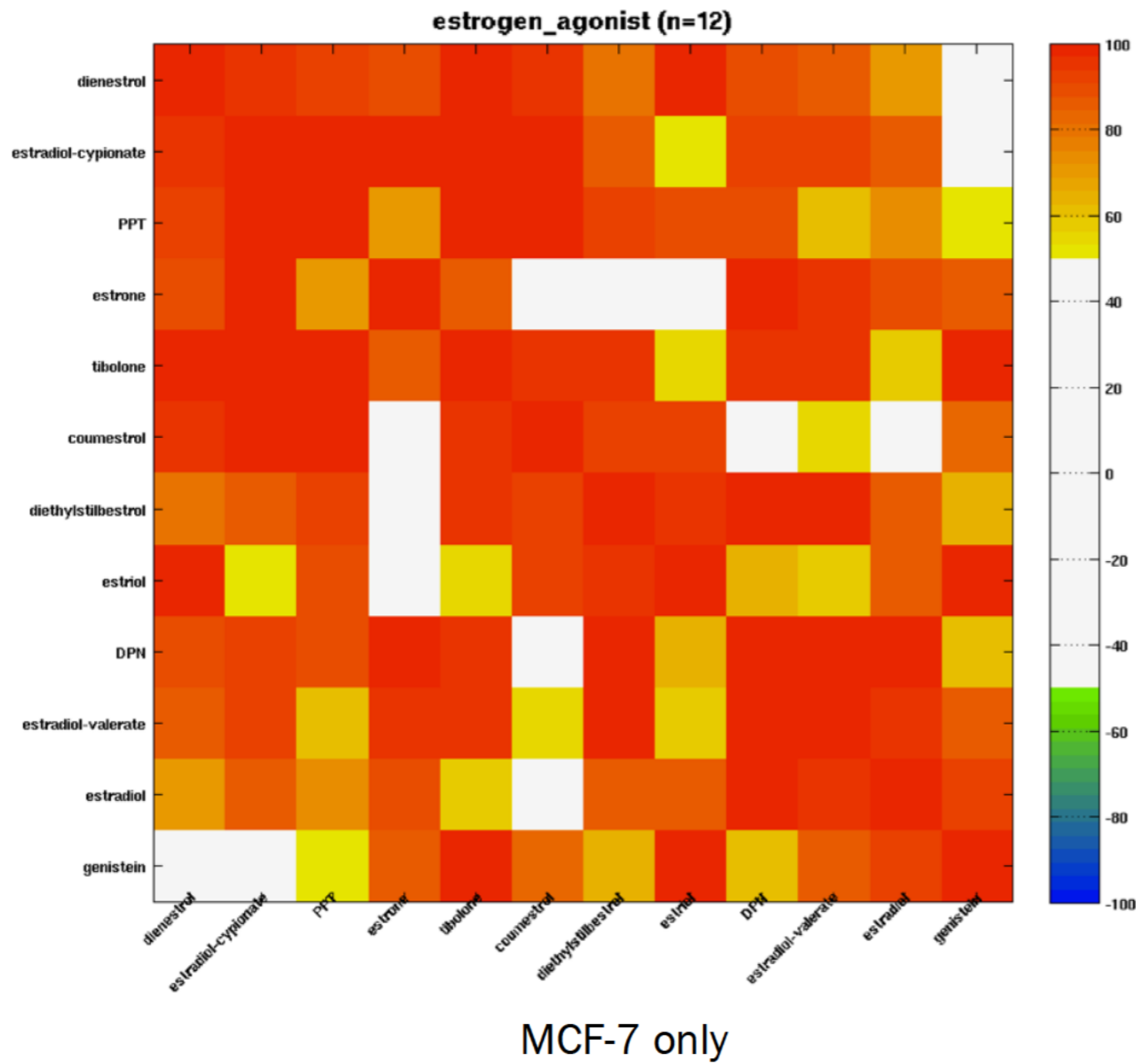


Across all cell lines



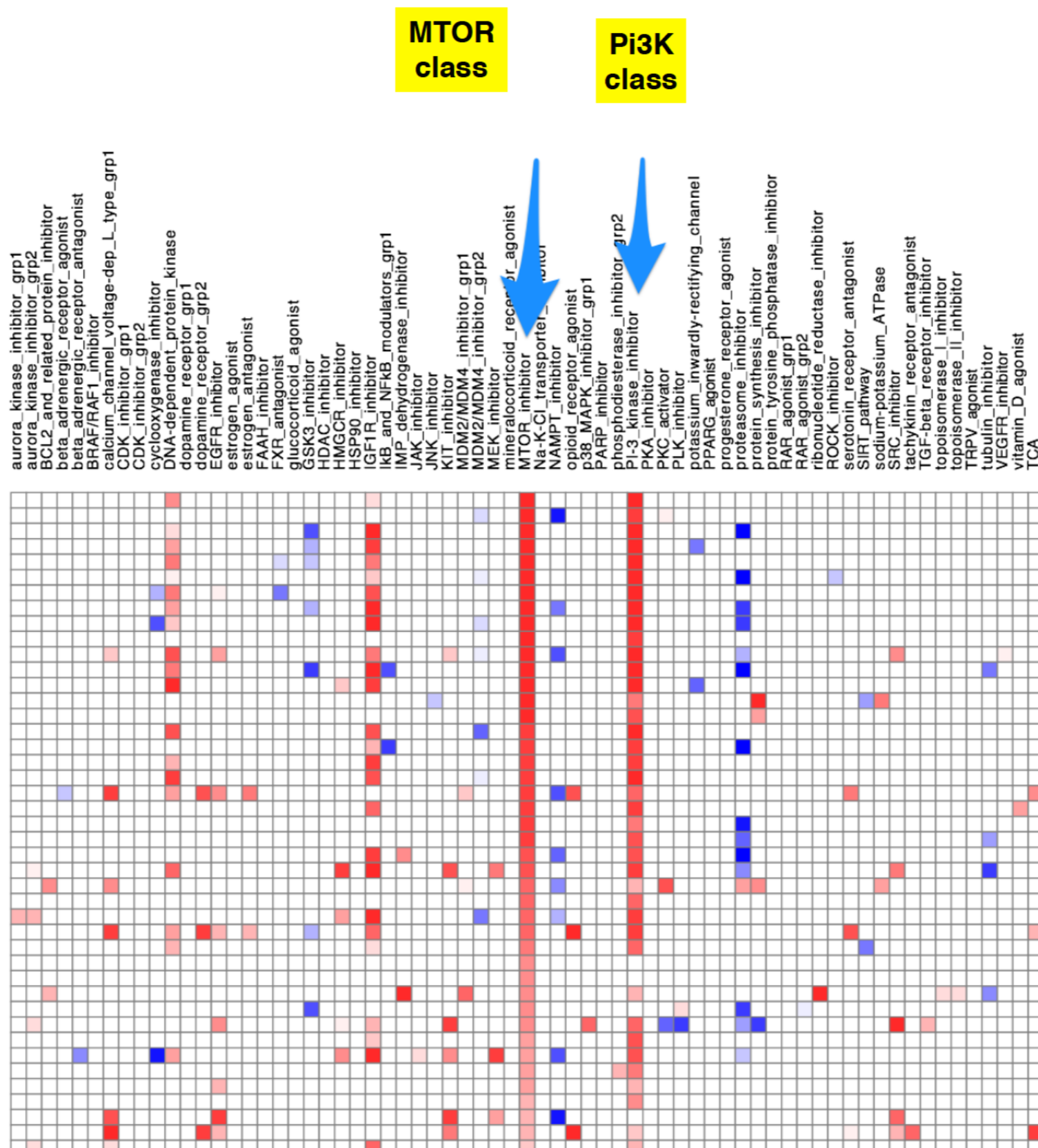
Cell type-specific PCL example

Estrogen signaling



example result: Connectivity to 67 pharmacological classes - compounds sorted by matches to MTOR / PI3K inhibitors

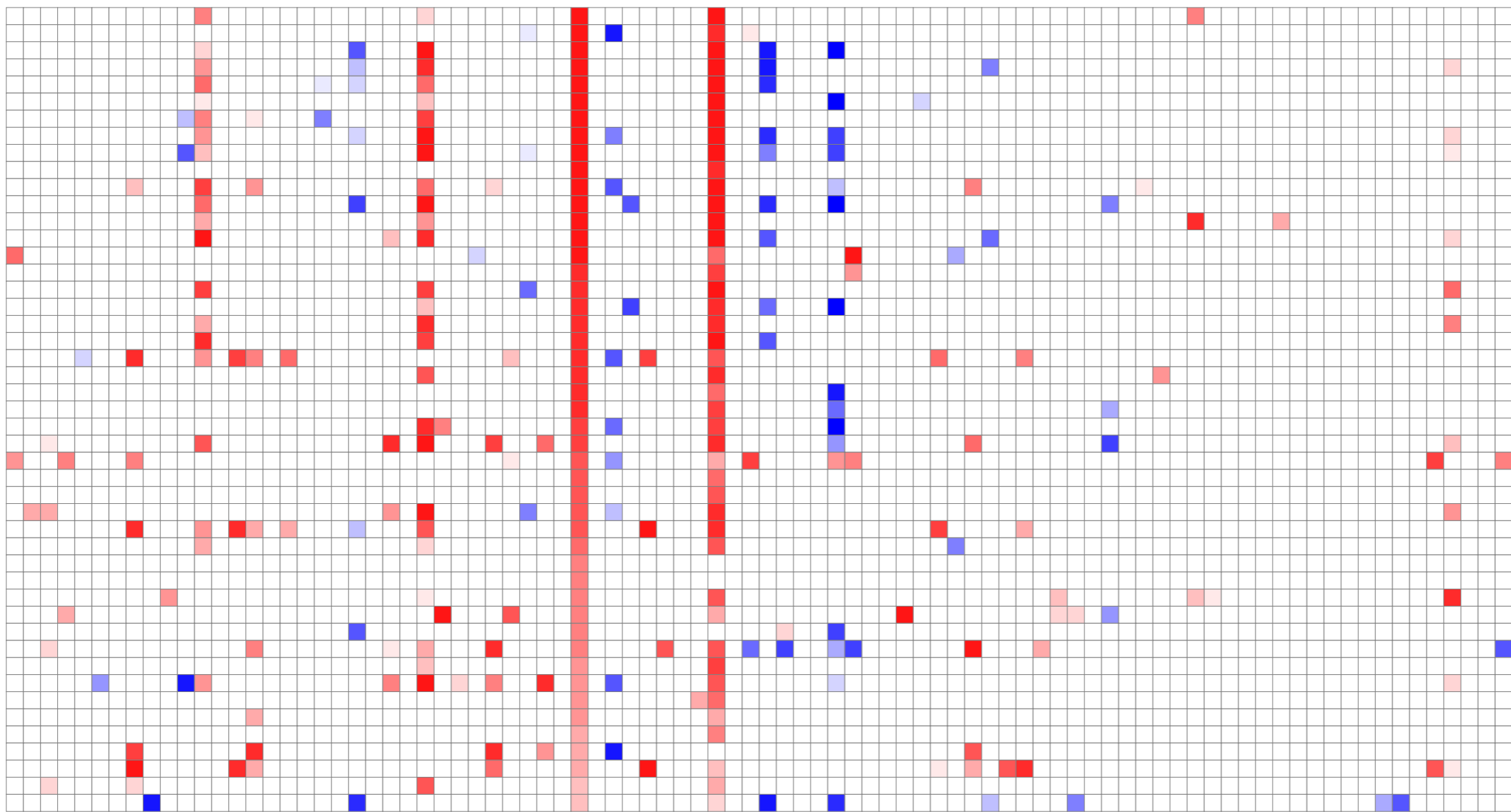
Columns:
Pharmacological classes



Rows:
Top 20
Compounds -
know and novel
(out of 4,000+
columns)



Class	Type
CP	CP_ATPASE_INHIBITOR
CP	CP_AURORA_KINASE_INHIBITOR_GRP1
CP	CP_AURORA_KINASE_INHIBITOR_GRP2
CP	CP_BCL2_AND_RELATED_PROTEIN_INHIBITOR
CP	CP_BETA_ADRENERGIC_RECEPTOR_AGONIST
CP	CP_BETA_ADRENERGIC_RECEPTOR_ANTAGONIST
CP	CP_BRAF_RAF1_INHIBITOR
CP	CP_CALCINIUM_CHANNEL_INHIBITOR
CP	CP_CDK_INHIBITOR_GRP1
CP	CP_CDK_INHIBITOR_GRP2
CP	CP_CYCLOOXYGENASE_INHIBITOR
CP	CP_DNA_DEPENDENT_PROTEIN_KINASE
CP	CP_DOPAMINE_RECEPTOR_GRP1
CP	CP_DOPAMINE_RECEPTOR_GRP2
CP	CP_EGFR_INHIBITOR
CP	CP_ESTROGEN_AGONIST
CP	CP_ESTROGEN_ANTAGONIST
CP	CP_FAAH_INHIBITOR
CP	CP_FXR_ANTAGONIST
CP	CP_GLUCOCORTICOID_AGONIST
CP	CP_GSK3_INHIBITOR
CP	CP_HDAC_INHIBITOR
CP	CP_HMGR_INHIBITOR
CP	CP_HSP90_INHIBITOR
CP	CP_GF1R_INHIBITOR
CP	CP_IMP_DEHYDROGENASE_INHIBITOR
CP	CP_JAK_INHIBITOR
CP	CP_JNK_INHIBITOR
CP	CP_KIT_INHIBITOR
CP	CP_MDM2_MDM4_INHIBITOR_GRP1
CP	CP_MDM2_MDM4_INHIBITOR_GRP2
CP	CP_MEK_INHIBITOR
CP	CP_MINERALOCORTICOID_AGONIST
CP	CP_MTOR_INHIBITOR
CP	CP_NA-K-CL_TRANSPORTER_INHIBITOR
CP	CP_NAMPT_INHIBITOR
CP	CP_NFKB_PATHWAY_INHIBITOR
CP	CP_OPIOID_RECEPTOR_AGONIST
CP	CP_P38_MAPK_INHIBITOR_GRP1
CP	CP_PARP_INHIBITOR
CP	CP_PHOSPHODIESTERASE_INHIBITOR
CP	CP_PI3K_INHIBITOR
CP	CP_PKA_INHIBITOR
CP	CP_PKC_ACTIVATOR
CP	CP_PKC_INHIBITOR
CP	CP_PLK_INHIBITOR
CP	CP_PPARG_AGONIST
CP	CP_PROGESTERONE_AGONIST
CP	CP_PROTEASOME_INHIBITOR
CP	CP_PROTEIN_SYNTHESIS_INHIBITOR
CP	CP_RAR_AGONIST_GRP1
CP	CP_RAR_AGONIST_GRP2
CP	CP_RIBONUCLEOTIDE_REDUCTASE_INHIBITOR
CP	CP_ROCK_INHIBITOR
CP	CP_SEROTONIN_RECEPTOR_ANTAGONIST
CP	CP_SIRT_PATHWAY
CP	CP_SRC_INHIBITOR
CP	CP_SULFONYLUREA
CP	CP_TACHYKININ_ANTAGONIST
CP	CP_TCA
CP	CP_TGF_BETA_INHIBITOR
CP	CP_TOPOISOMERASE_II_INHIBITOR
CP	CP_TOPOISOMERASE_I_INHIBITOR
CP	CP_TRPV_AGONIST
CP	CP_TUBULIN_INHIBITOR
CP	CP_TYROSINE_PHOSPHATASE_INHIBITOR
CP	CP_VEGFR_INHIBITOR
CP	CP_VITAMIN_D_AGONIST
KD	KD_AHSP_PATHWAY
KD	KD_AKT_SIGNALING
KD	KD_ALDO_KETO_REDUCTASE
KD	KD_BMP_SIGNALING
KD	KD_DNA_REPLICATION
KD	KD_EIF_PROTEINS
KD	KD_G2_M_CHECKPOINT
KD	KD_IL4_PATHWAY
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KD	KD_NUCLEOPORIN
KD	KD_PI3K_SIGNALING
KD	KD_PROTEASOME_PATHWAY
KD	KD_RIBOSOMAL_40S_SUBUNIT
KD	KD_RNA_POLYMERASE_ENZYMES
KD	KD_TUBULIN
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OE	OE_GPCR_SUBSET
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AZD-8055	CP
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torin-1	CP
GDC-0941	CP
PIK-90	CP
MTOR	trt_sh.cgs
PI-828	CP
QL-X-138	CP
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TGX-115	CP
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AZD-6482	CP
PP-30	CP
PP-110	CP
JW-7-24-1	CP
RPTOR	trt_sh.cgs
epoxycholesterol	CP
BMS-754807	CP
MK-2206	CP
TGX-221	CP
molsidomine	CP
BRD-K64835161	CP
MYC	trt_sh.cgs
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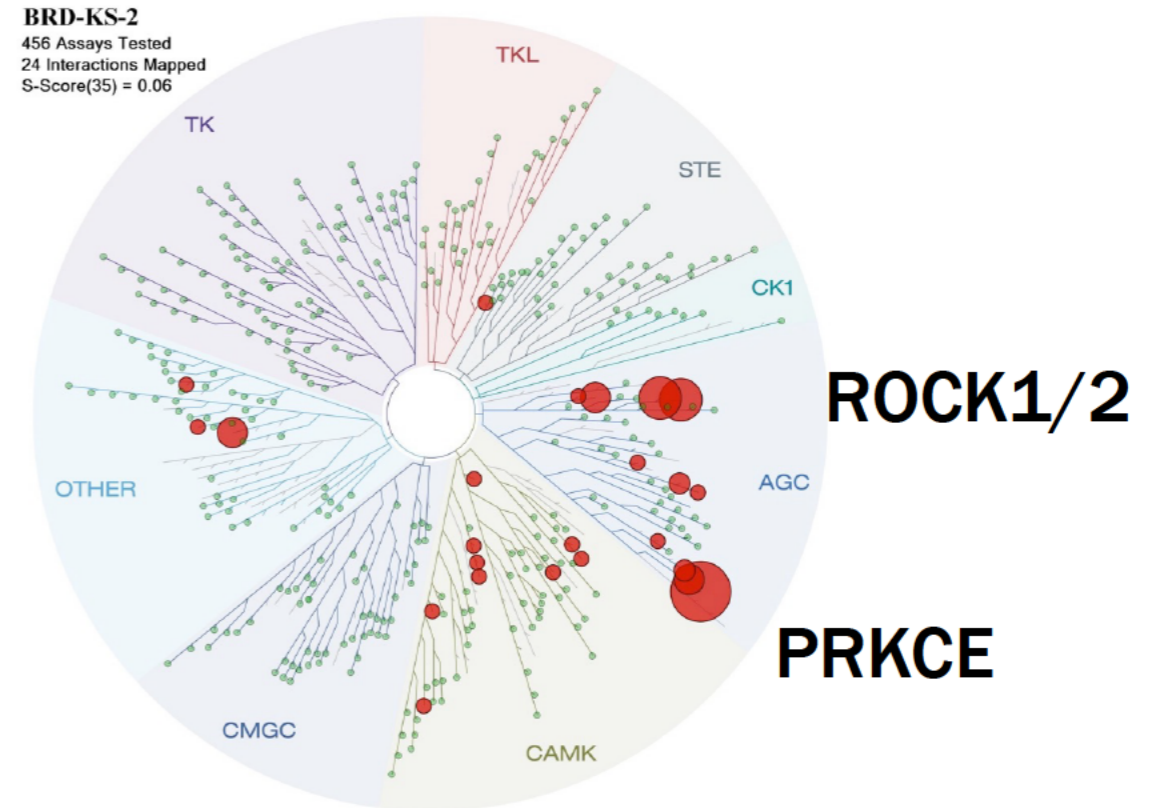
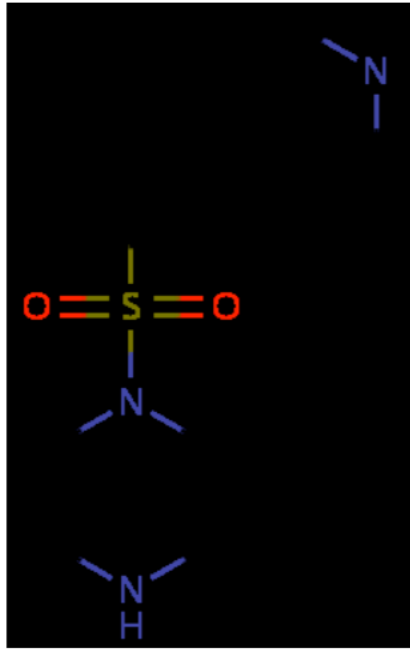
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AZD-6482	CP
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PP-110	CP
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RPTOR	trt_sh.cgs
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BMS-754807	CP
MK-2206	CP
TGX-221	CP
molsidomine	CP
BRD-K64835161	CP
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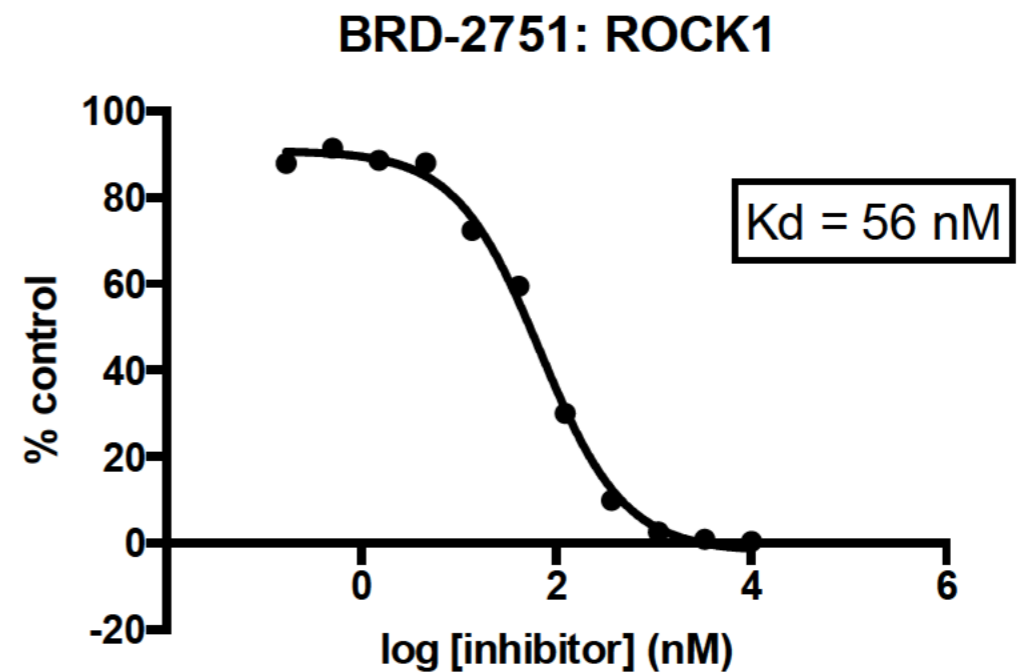
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torin3	CP
BRD-K63425657	CP
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PP-110	CP
JW-7-24-1	CP
RPTOR	trt_sh.cgs
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BMS-754807	CP
MK-2206	CP
TGX-221	CP
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linsitinib	CP
WZ-4-145	CP
paroxetine	CP
crizotinib	CP
deforolimus	CP

BRD-2751

Confirmed ROCK1/2 inhibitor



Class	Type
CP_CP_JAK_INHIBITOR	
CP_CP_PKA_INHIBITOR	
CP_CP_GSK3_INHIBITOR	
CP_CP_CDK_INHIBITOR_GRP1	
CP_CP_ROCK_INHIBITOR	

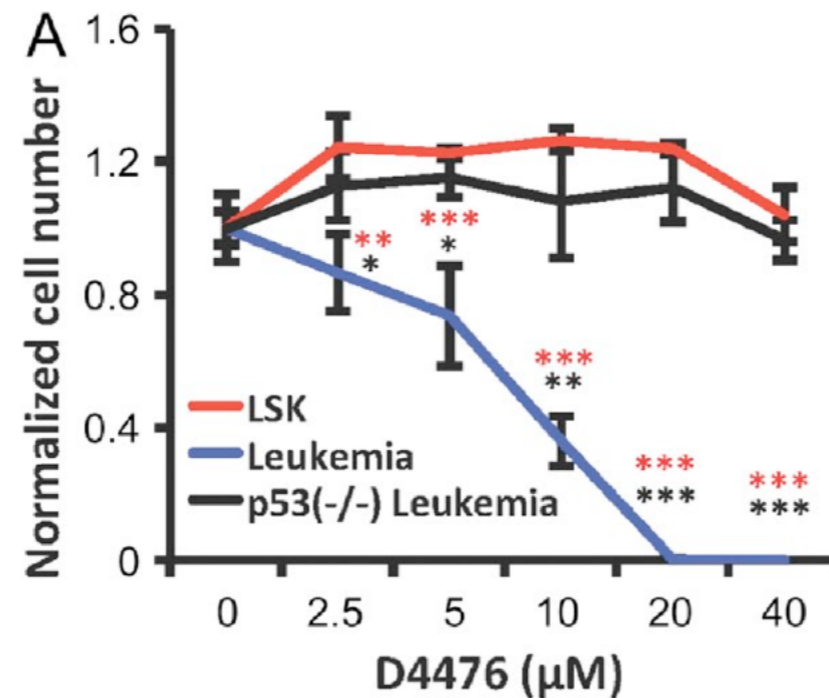


CSNK1A1 disease relevance

Investigated for pathogenic role in MDS and AML

Published March 10, 2014

JEM



Csnk1a1 inhibition has p53-dependent therapeutic efficacy in acute myeloid leukemia

Marcus Järås,^{1,2} Peter G. Miller,¹ Lisa P. Chu,¹ Rishi V. Puram,¹ Emma C. Fink,¹ Rebekka K. Schneider,¹ Fatima Al-Shahrour,¹ Pablo Peña,² L. Jordan Breyfogle,¹ Kimberly A. Hartwell,^{1,3} Marie E. McConkey,¹ Glenn S. Cowley,³ David E. Root,³ Michael G. Kharas,^{4,5} Ann Mullally,¹ and Benjamin L. Ebert^{1,3}

CSNK1A1 inhibitor: unmet clinical need

Predicted CMap inhibitors

rank	compound
1	BRD-1868
2	BRD-8715
3	azithromycin
4	BRD-4657
5	BRD-1433
6	BRD-1742
7	phenazopyridine
8	caffeine
9	tivozanib
10	BRD-0220

rank	compound
1	BRD-1868
2	BRD-4657
3	ENMD-2076
4	LY-456236
5	salmeterol
6	BRD-4053
7	RS-102895
8	BMS-754807
9	MBCQ
10	DM-55-3

Query CSNK1A1 shRNA

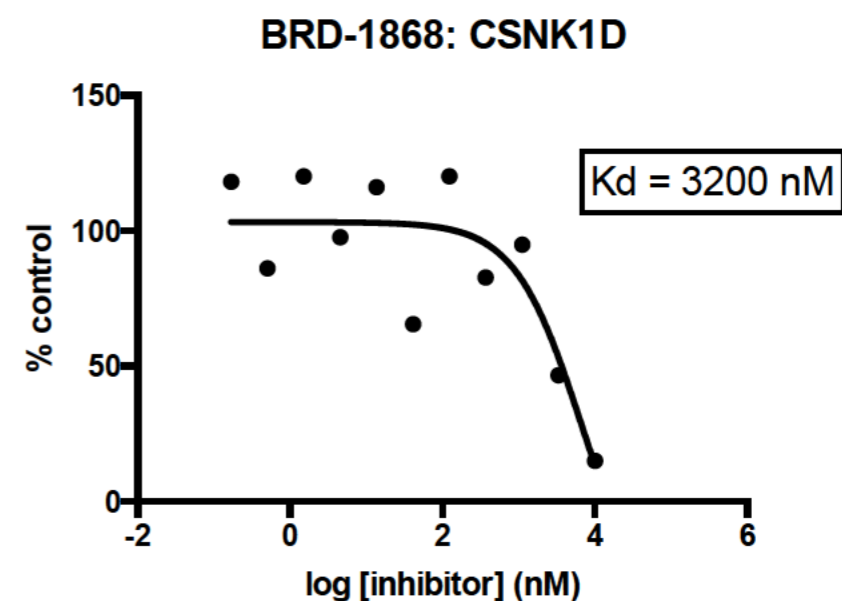
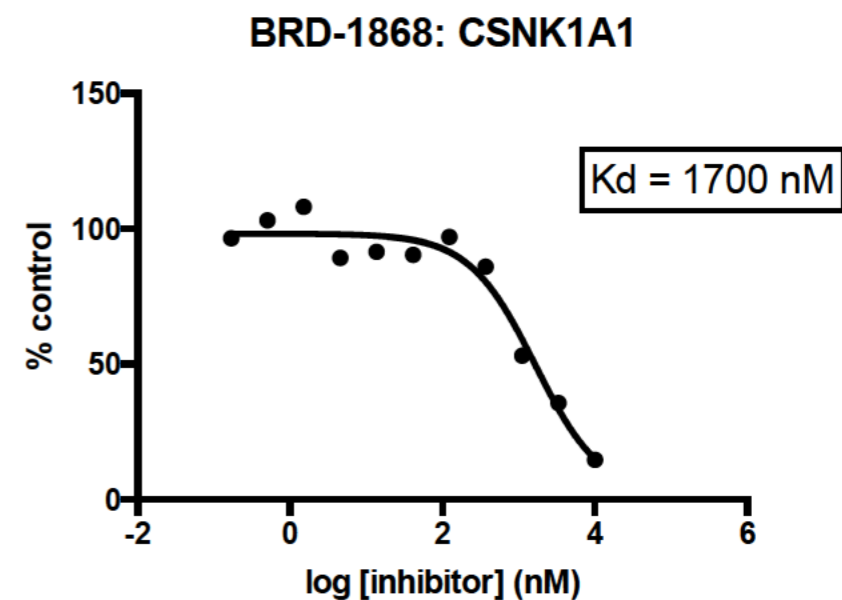
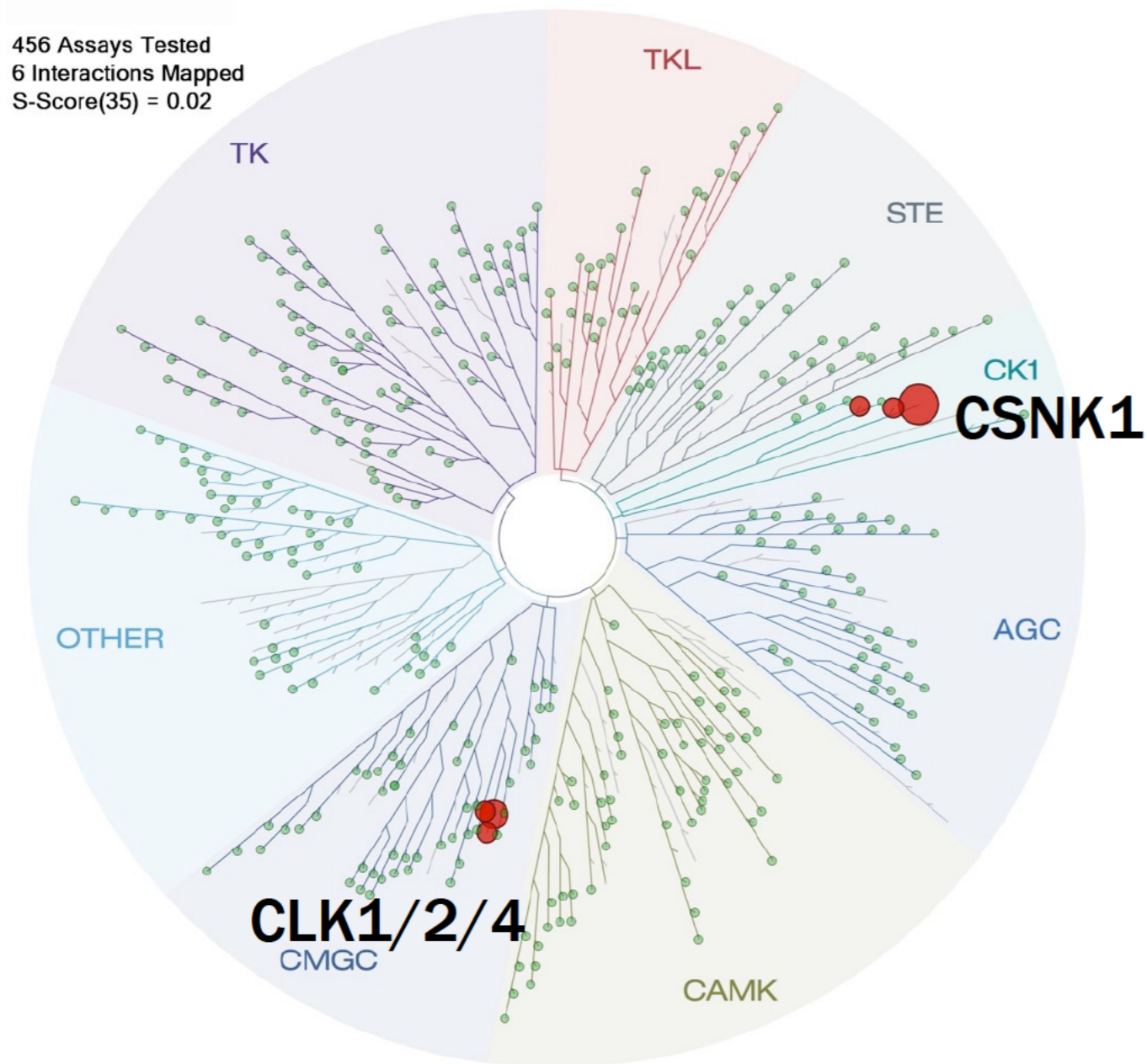
Result Compound rank

All compounds

CSNK1A1 rank

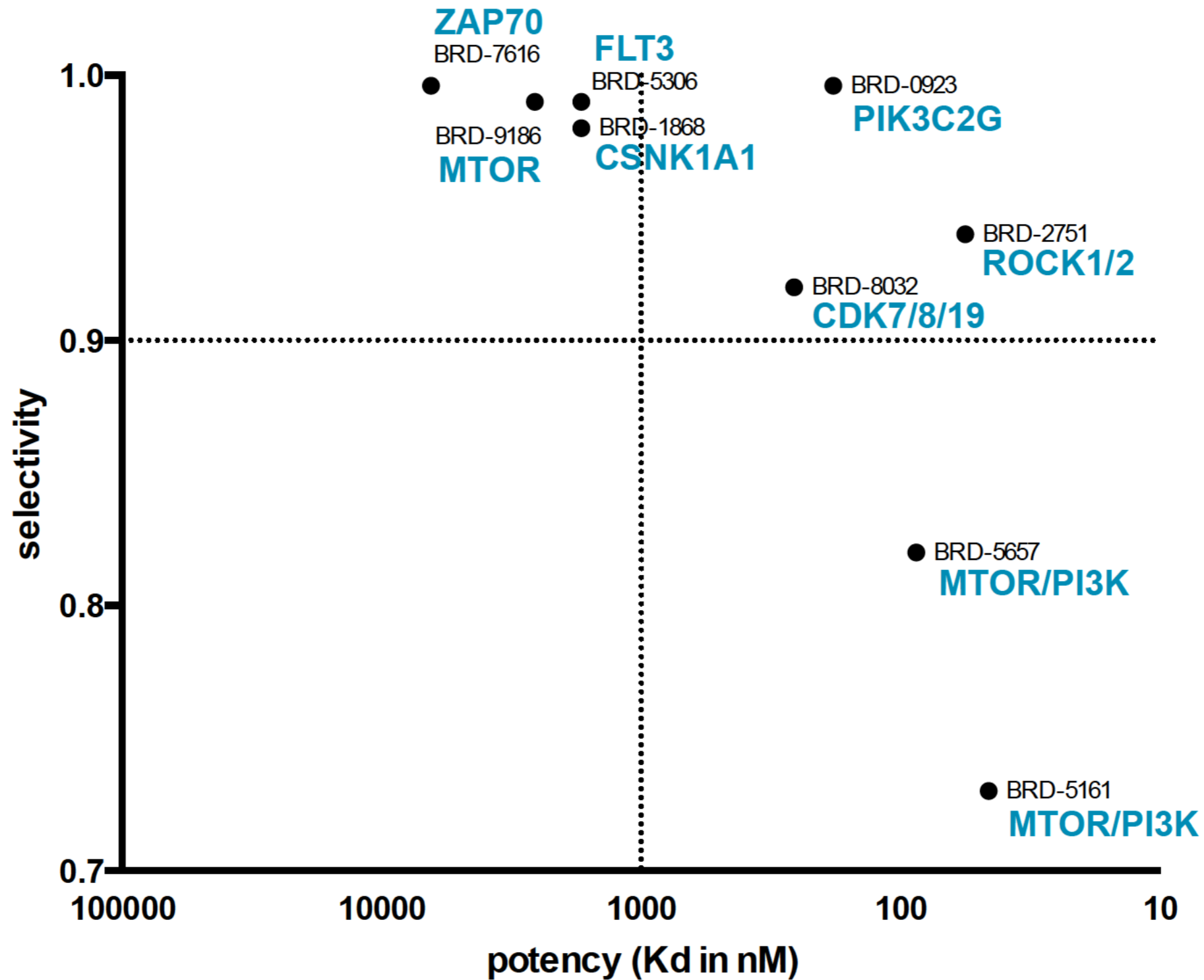
Discovery of novel CSNK1A1 inhibitor

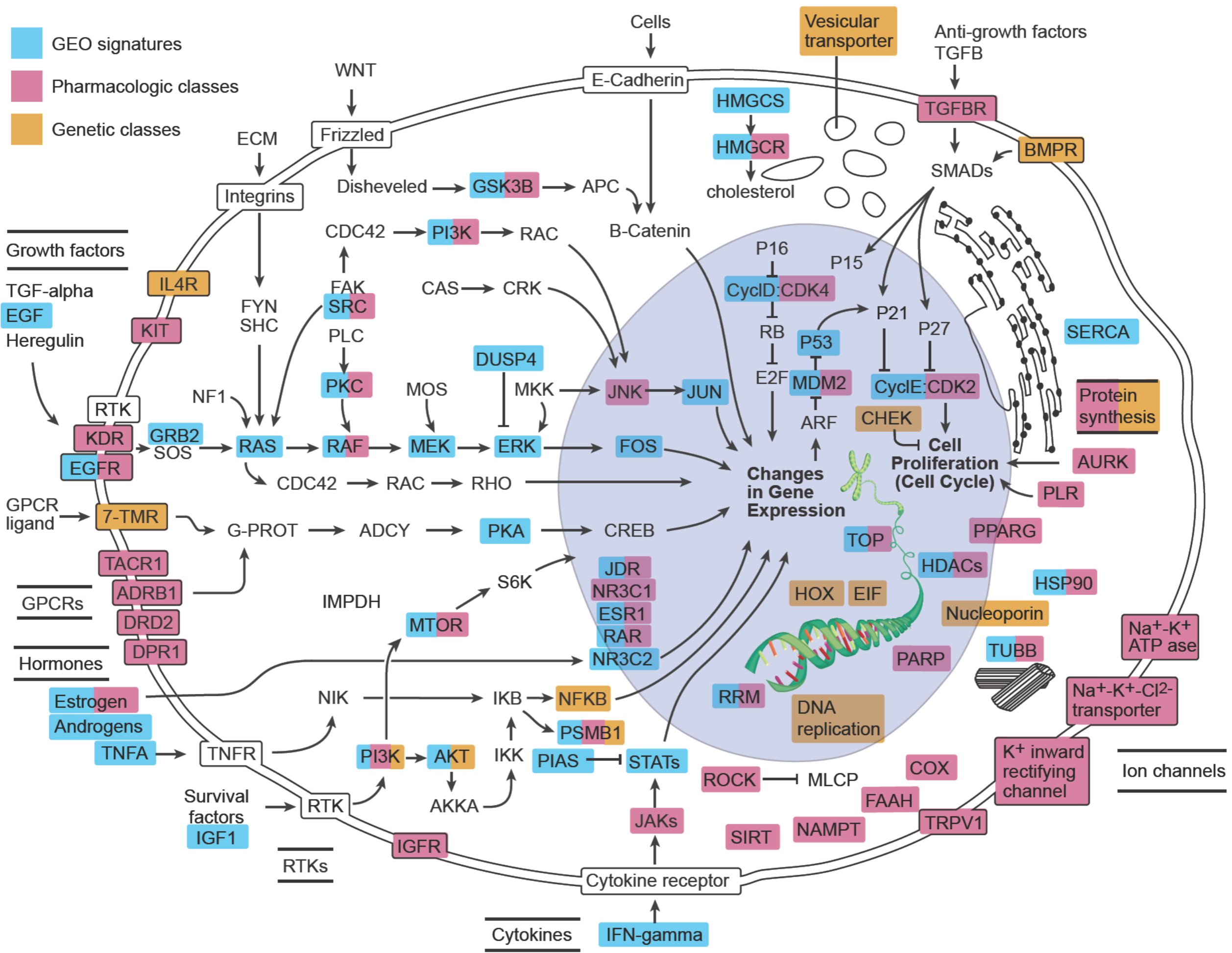
CMap prediction confirmed



Kinase inhibitor hits

Potency vs selectivity





METHODS & RESOURCES

Assay: L1000

- Measure 978 transcripts with 500-color Luminex beads
- 384-well plate format compatible with HTS
- Cell lysates (not purified RNA)
- Dramatic cost reduction

Algorithms and tools
(under development)



<http://lincsproject.org>
<http://lincs-dcic.org/>
<http://lincscloud.org>

Why repurpose existing drugs?

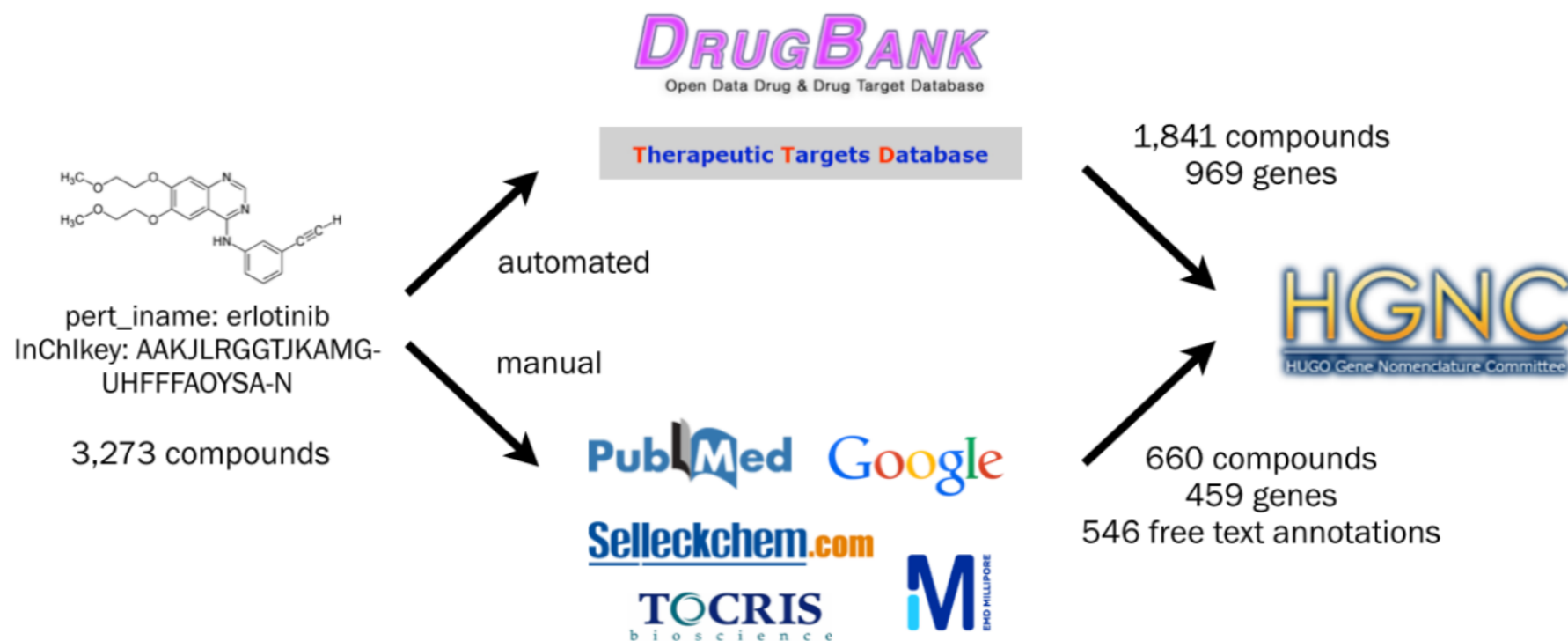
Motivation

- **Bioactive compounds have long been known to act on multiple targets, potentially enabling additional uses and explaining toxicities**
- **Developing a new drug takes up to 10-15 years and several hundred million dollars**
- **Thousands of “orphan” or rare diseases exist where the market size alone may not justify a dedicated discovery program**

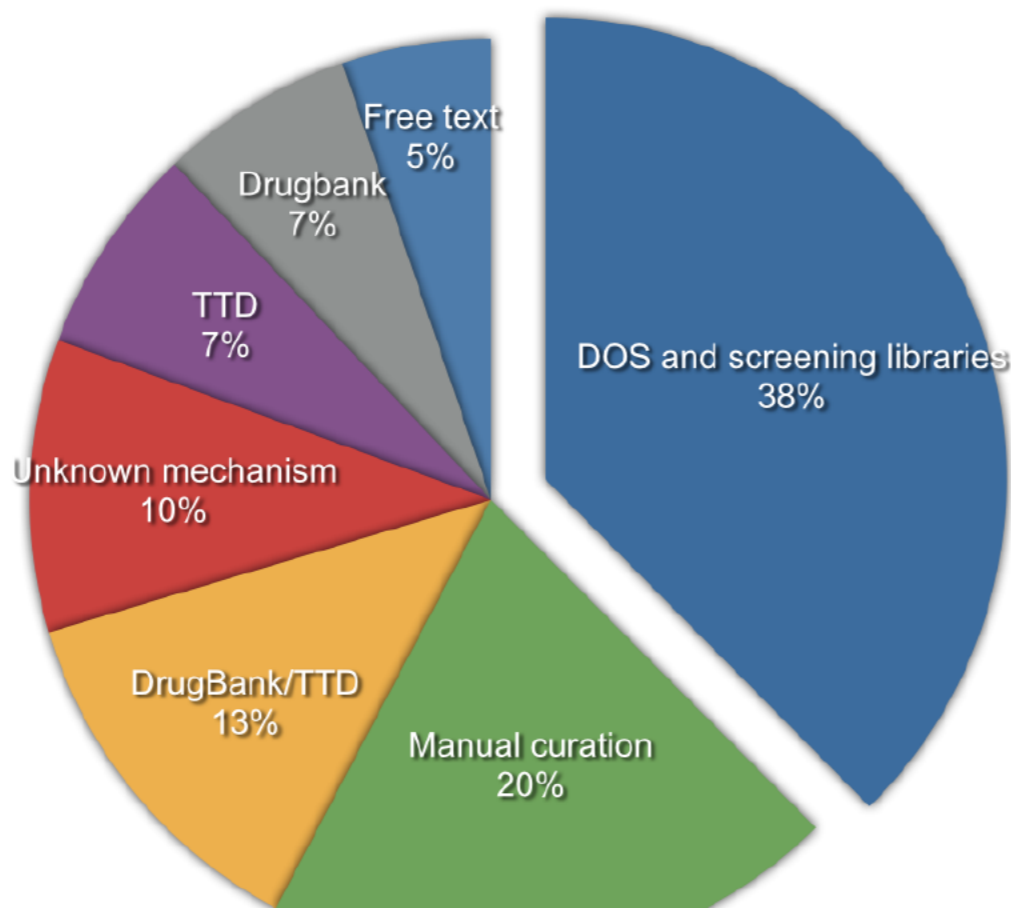
Compound annotation

Integrating high-quality source information

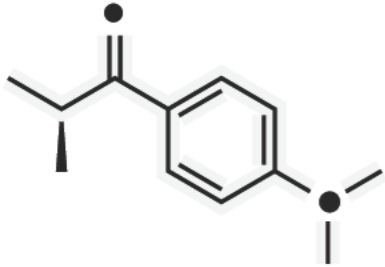
Curation process



Current Database



Current CMap dataset (2M profiles)



~5,000 Compounds

- FDA approved drugs
- Bioactive tool compounds
- Screening hits



~3,000 Genes (shRNA & cDNA)

- Targets/pathways of approved drugs
- Candidate disease genes (e.g. recurrent from TCGA)
- Community nominations



15 Cell types

- Banked primary cell types
- Cancer cell lines (8)
- Primary hTERT-immortalized
- Patient-derived iPS cells

Design goals of CLUE

Cloud-based

No need to download data (tools to data)
Elastic compute (fast, scale-on-demand)

Harmonized

Centralized annotations and meta data
Interoperable with other perturbational datasets (e.g PRISM, P100)

Reproducible

Prepackaged Box with - all of the data + pre-processing pipeline + analysis tools

Customizable

Detach'able from Broad infrastructure
Companies can securely mix proprietary datasets with public data

Access at: clue.io
(early access phase till July 2015; full version in August)

Looking forward

resources coming soon ...

- Genome-scale perturbations
- CRISPR/Cas9 knock-outs
- Small-molecule analogs and libraries
- Multiple readouts at scale
- Diverse cell types
- Patient-derived iPS cells
- Next generation biologist-focused tools
- **Data integration (GTEx, GEO, Tox21)**

Team @Broad Institute

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Josh Bittker
Steven Corsello
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John Davis
John Doench
Oana Enache
Corey Flynn
Joshua Gould
Jodi Hirschman
David Lahr

Daniel Lam
Xiaodong Lu
Federica Piccioni
Rajiv Narayan
Ted Natoli
David Peck
Jackie Rosains
Ian Smith
Bang Wong

David Root
Stuart Schreiber
Lucienne Ronco

Todd Golub

Questions?

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