



Using High-Throughput Transcriptomics to Analyze Chemical Safety

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Computational Toxicology
NCCT

Workshop on “TempO-Seq data analysis”
4-5 October 2018, Leiden, the Netherlands



The views expressed in this presentation are those of the author[s] and do not necessarily reflect the views or policies of the U.S. Environmental Protection Agency.

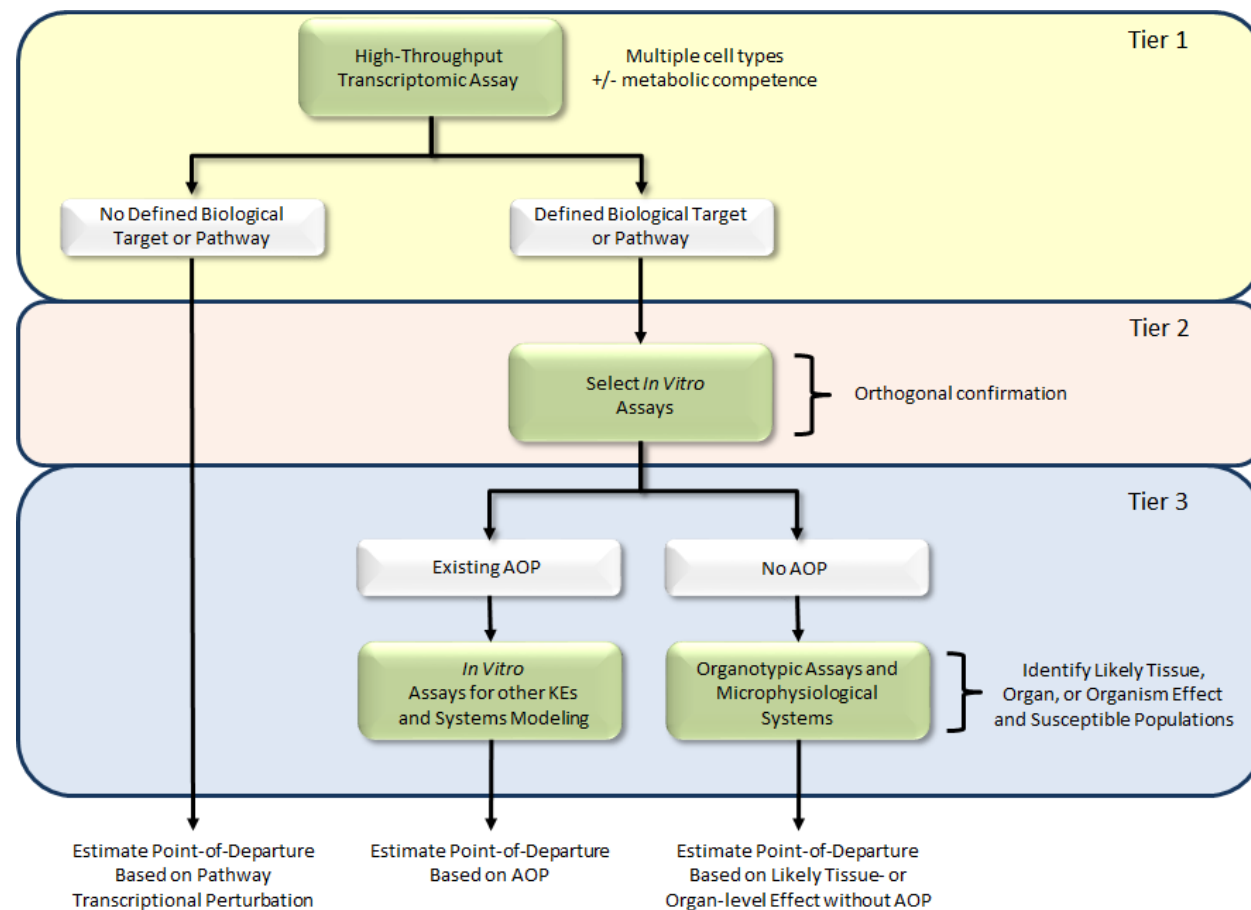
Outline

- Why NCCT is using high-throughput transcriptomics
- Overall workflow and team
- Experimental analysis
- Computational analysis
 - Overview of different computational workflows / use-cases
 - NCCT HTTr workflow
 - Evaluate Data quality
 - Identify concentration-dependent effects of chemicals
 - Analyze putative molecular / pathway targets of chemicals

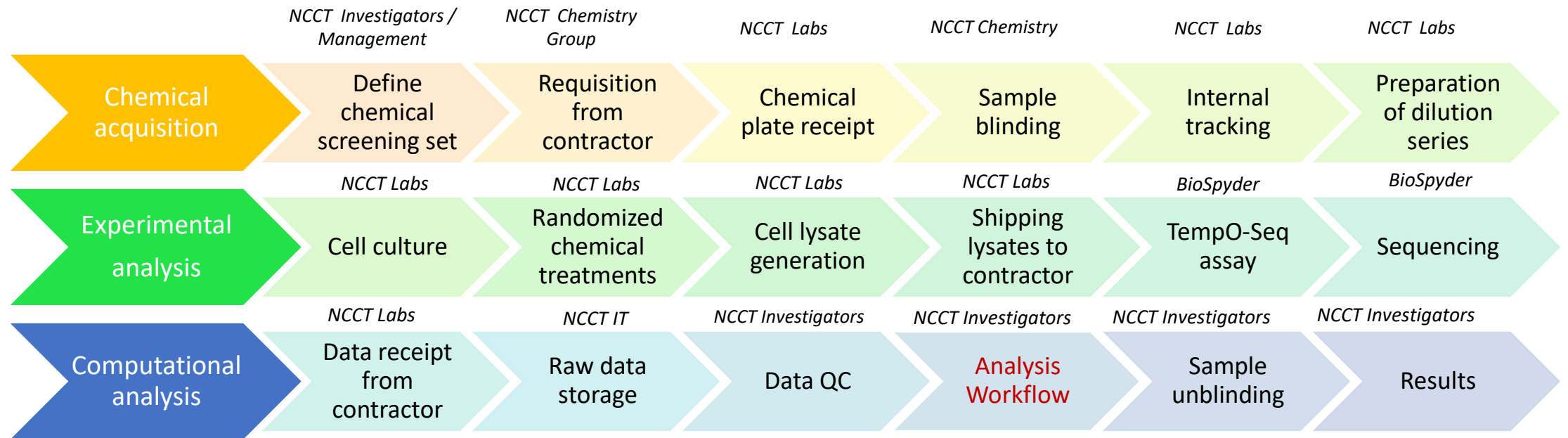
Objectives

- A flexible, portable and cost efficient platform to comprehensively evaluate the potential biological pathways and processes impacted by chemical exposure
→ High-throughput transcriptomics (HTTr)
- Identify the concentration at which biological pathways/processes begin to be impacted
- Predict biological targets for chemicals with specific modes-of-action

A strategic vision and operational road map for computational toxicology at the U.S. Environmental Protection Agency [DRAFT]



HTTr Workflow





NCCT HTTr Project Team

National Center for Computational Toxicology



**Joshua
Harrill**
Toxicologist



**Clinton
Willis**
NSSC (JH)



**Imran
Shah**
*Computational
Systems Biologist*



**R. Woodrow
Setzer**
*Mathematical
Statistician*



**Derik
Haggard**
ORISE Fellow



**Richard
Judson**
Bioinformatician



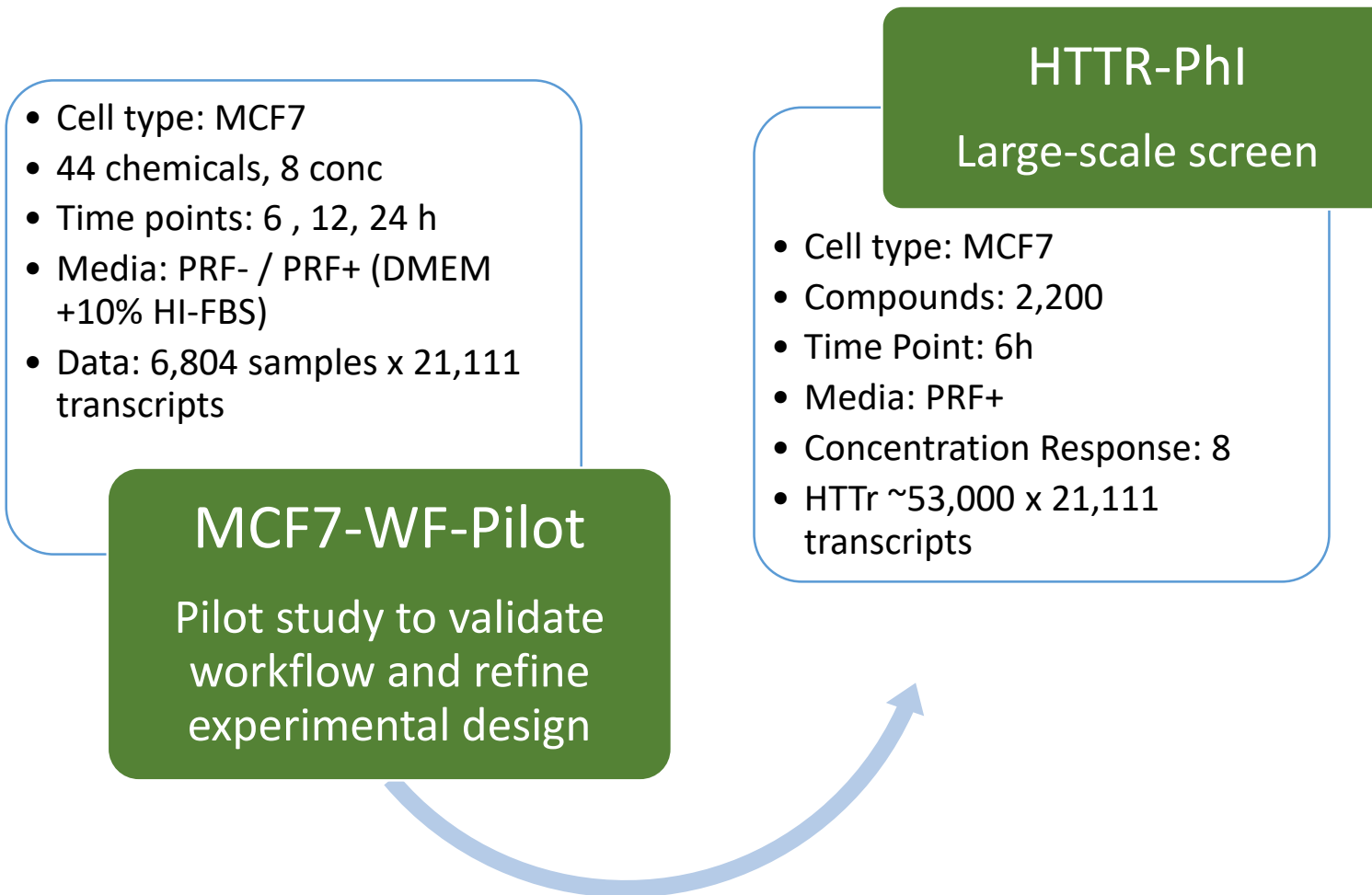
**Russell
Thomas**
Director

Experimental

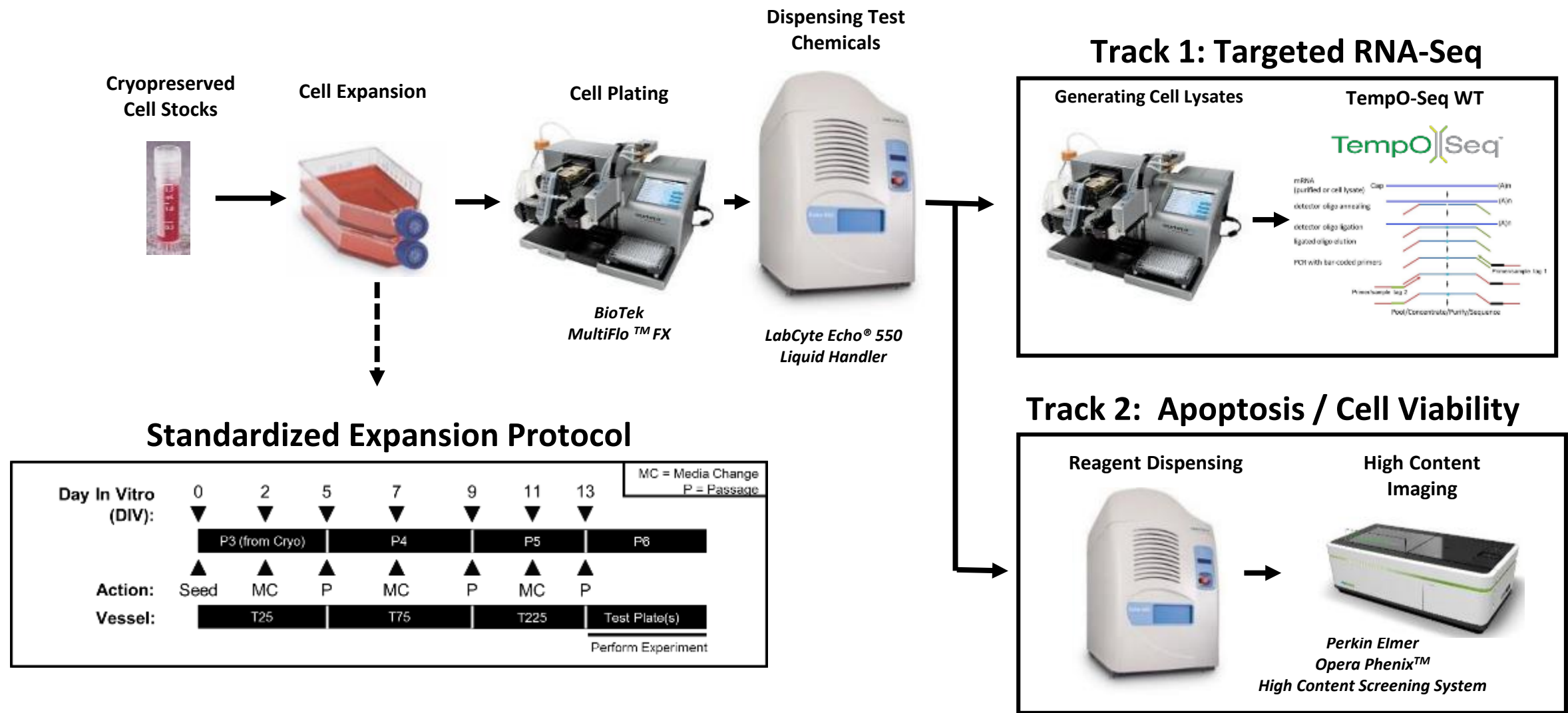
Computational

Experimental Analysis

Two Main HTTr Experiments (so far)



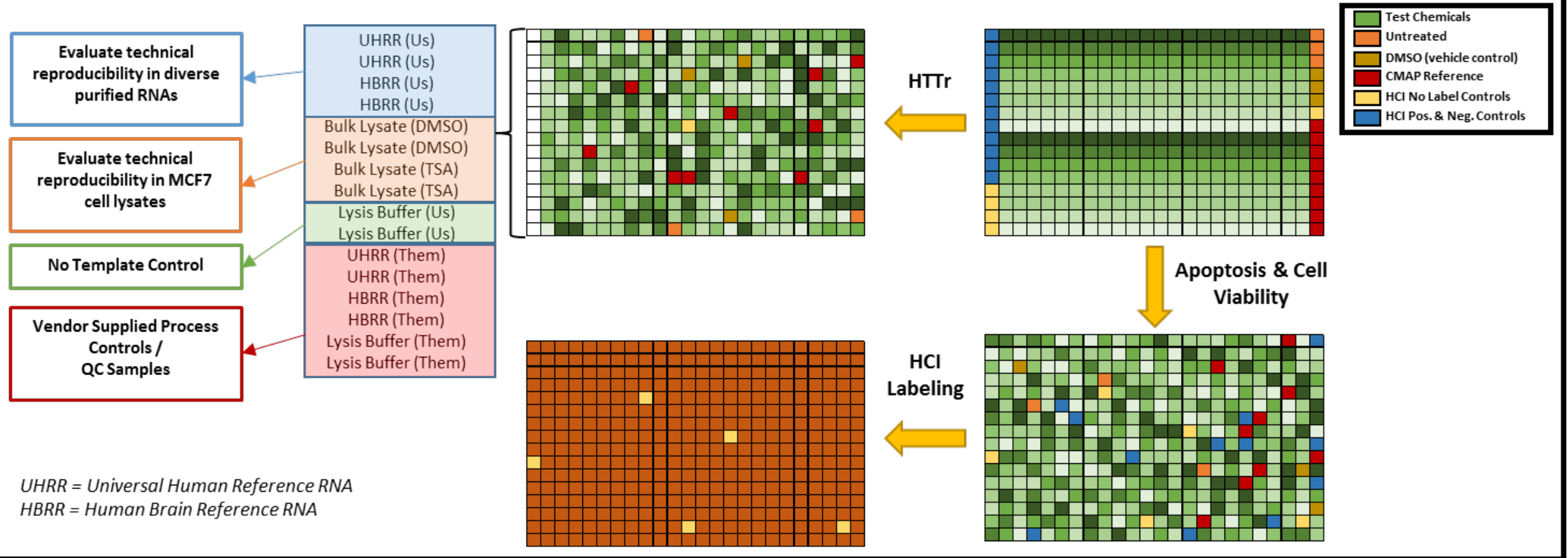
Lab Workflow



Quality Control Samples and Reference Standards for Performance-Based Validation

Treatment Randomization: *Each test plate uniquely randomized with respect to treatment.*

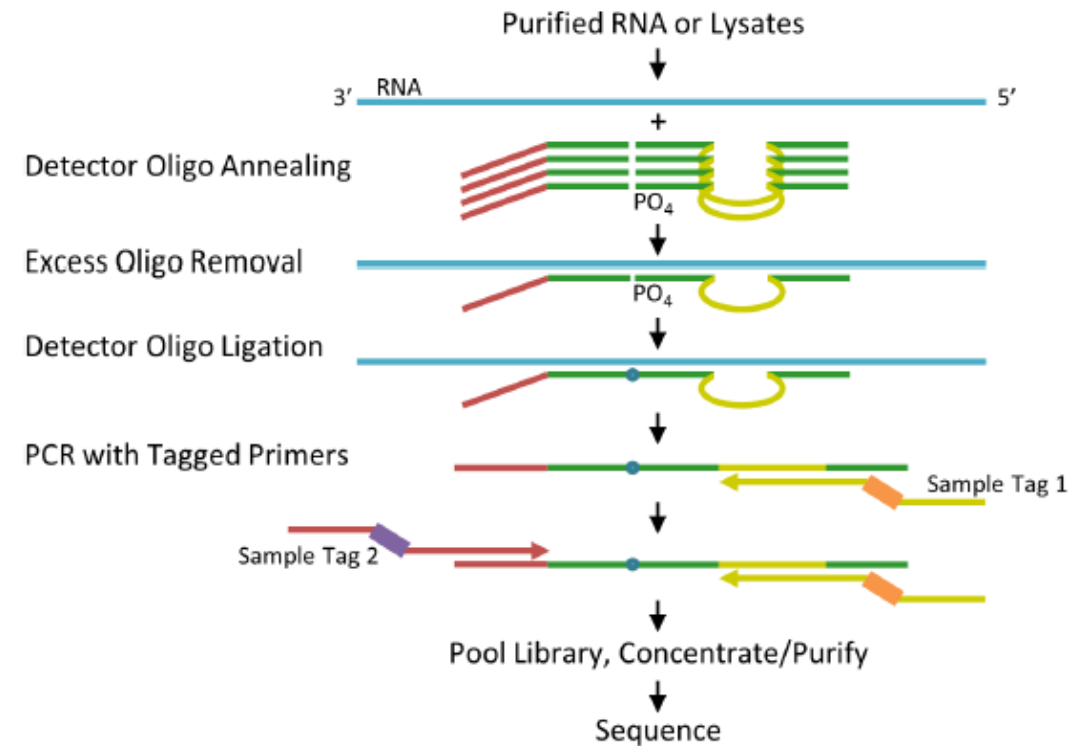
QC Samples: *Quality Control samples included on each plate*



TempO-Seq for HTTr

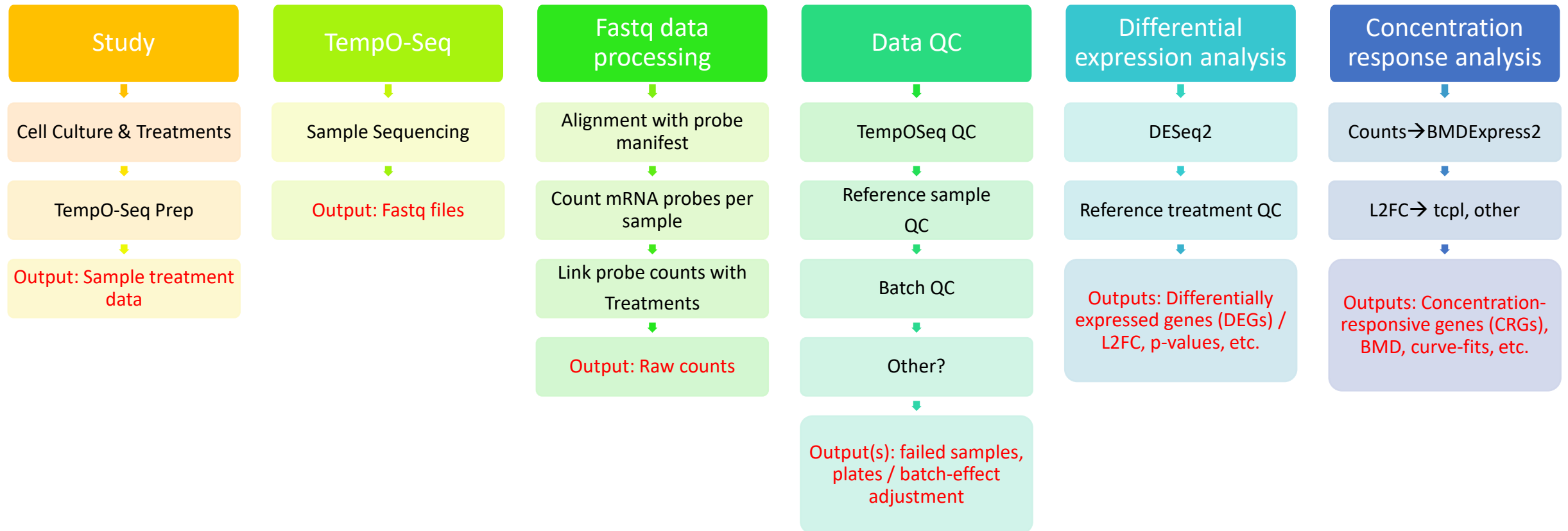
- The **TempO-Seq** human whole transcriptome assay measures the expression of ~21,100 transcripts.
- Requires only picogram amounts of total RNA per sample.
- Compatible with purified RNA samples or **cell lysates**.
- Transcripts in cell lysates generated in 384-well format barcoded to well position
- Scalable, targeted assay:
 - Measures transcripts of interest
 - Greater throughput and requires lower read depth than RNA-Seq
 - Ability to attenuate highly expressed genes

TempO-Seq Assay Illustration

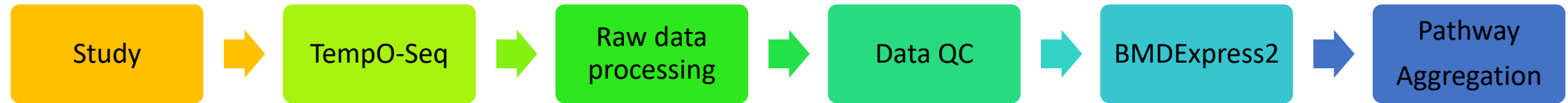


Computational Analysis Overview

HTTr Computational Analysis Steps

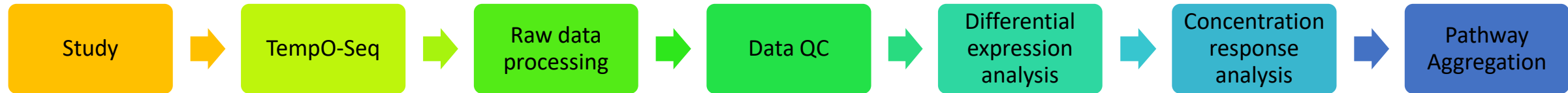


Basic HTTr Analysis Workflow



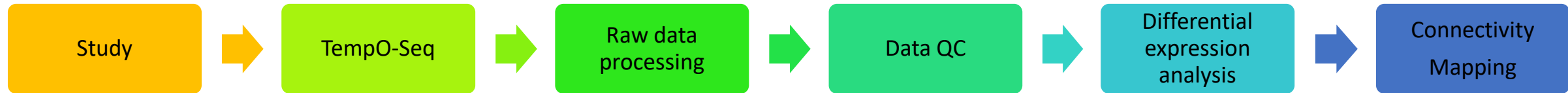
- Use-case: identify the most sensitive pathway perturbations
- Study design: One cell type, multiple chemicals, multiple conc, single time point
- Approach:
 - TempO-Seq HTTr data generation
 - Process raw data to generate probe level counts
 - Conduct TempO-Seq QC (read depth, mapped fraction, etc.)
 - Filter probes by average/maximum/median count (to exclude very low level counts)
 - Normalise counts for each sample (e.g by read-depth scale to 3×10^6)
 - Conc-response analysis using BMDExpress2 (choice of filters, fits, and thresholds output conc-responsive probes and BMD values)
 - Pathway level aggregation by genes and BMD values (summarised as accumulation plots)

Intermediate HTTr Analysis Workflow



- Use-case: identify the most sensitive pathway perturbations
- Study design: One cell type, multiple chemicals, multiple conc, single time point
- Approach:
 - TempO-Seq HTTr data generation
 - Process raw data to generate probe level counts
 - Conduct TempO-Seq QC (read depth, mapped fraction, etc.)
 - Filter probes by average/maximum/median count (to exclude very low level counts)
 - Differential expression analysis using DESeq2 (produces L2FC, p-values, mean-counts, etc.)
 - Concentration response analysis using L2FC data and tcpl (ToxCast curve-fitting pipeline)
 - Pathway level aggregation of conc-responsive genes using BMD₁₀

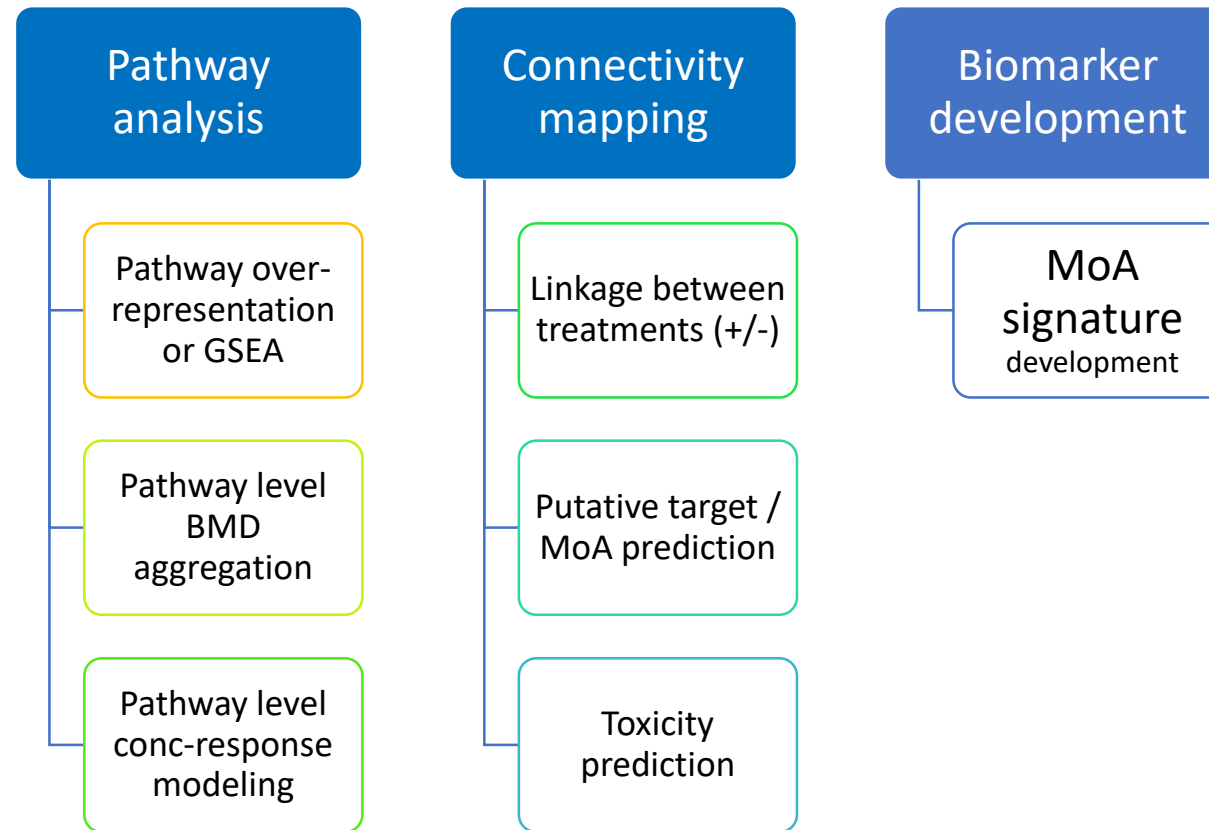
Intermediate HTTr Analysis Workflow



- Use-case: identify the putative molecular targets of chemicals
- Study design: One cell type, multiple chemicals, multiple conc, single time point
- Approach:
 - TempO-Seq HTTr data generation
 - Process raw data to generate probe level counts
 - Conduct TempO-Seq QC (read depth, mapped fraction, etc.)
 - Filter probes by average/maximum/median count (to exclude very low level counts)
 - Differential expression analysis using DESeq2 (produces L2FC, p-values, mean-counts, etc.)
 - Generate DEG signatures for GSEA analysis with CMap reference database
 - Link CMap hits to putative targets

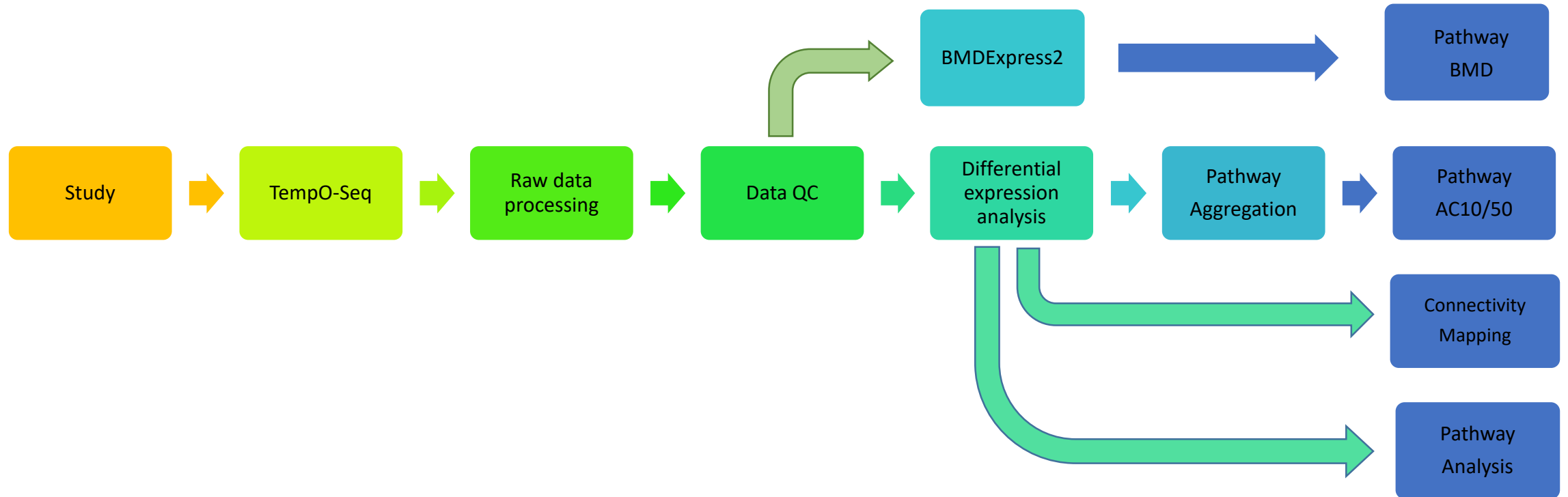
Interpretation – many options

Some interpretation options that can use either CRGs or DEGs



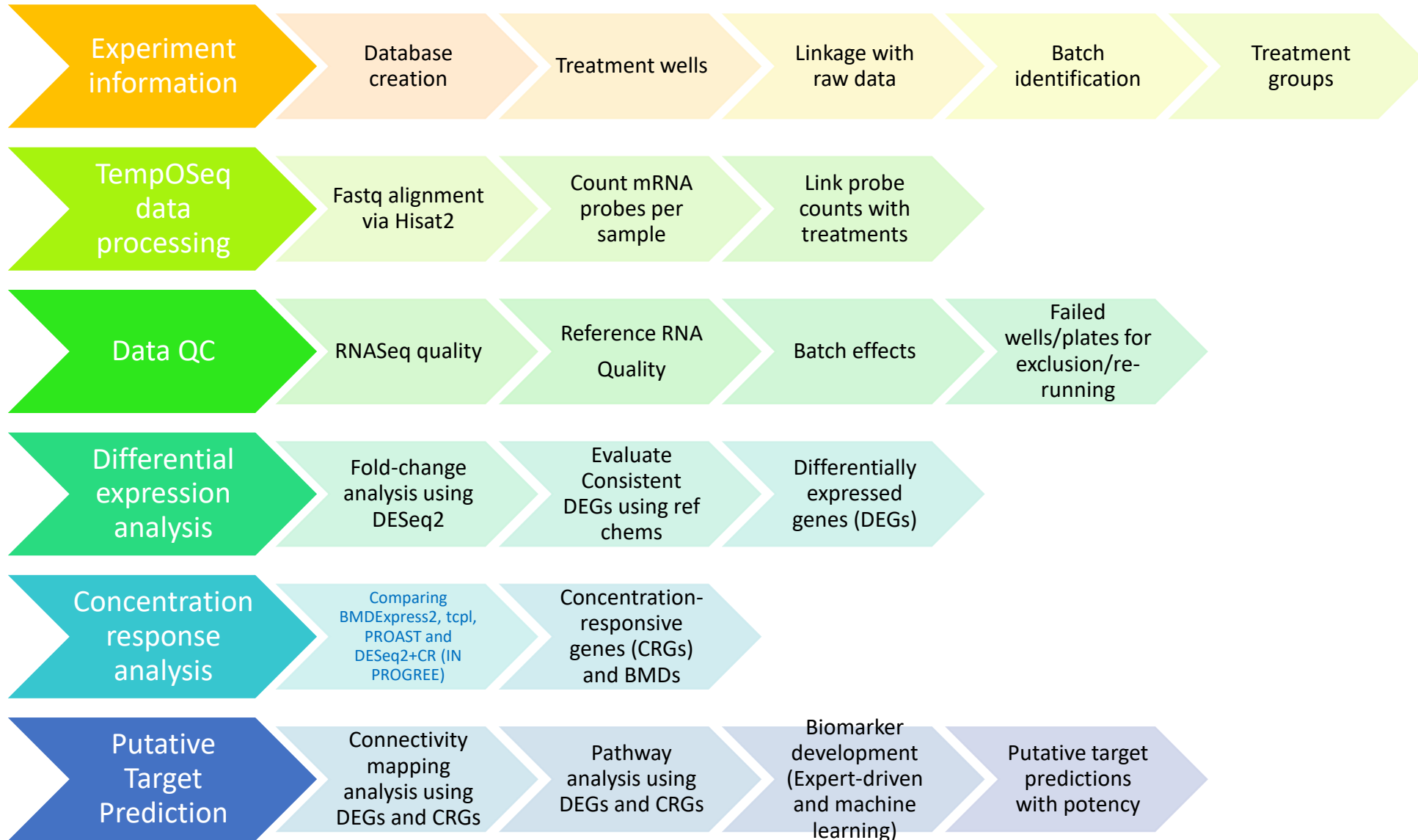
NCCT HTTr Analysis Workflow

NCCT HTTr Analysis Workflow



- Use-case: **Evaluate chemical potency, putative targets and pathways using HTTr**
- Study design: MCF7 cells, 2100 chemicals, 8 conc, 6 h time point
- Approach: “Exploratory”

Analysis Pipeline (June 2018)



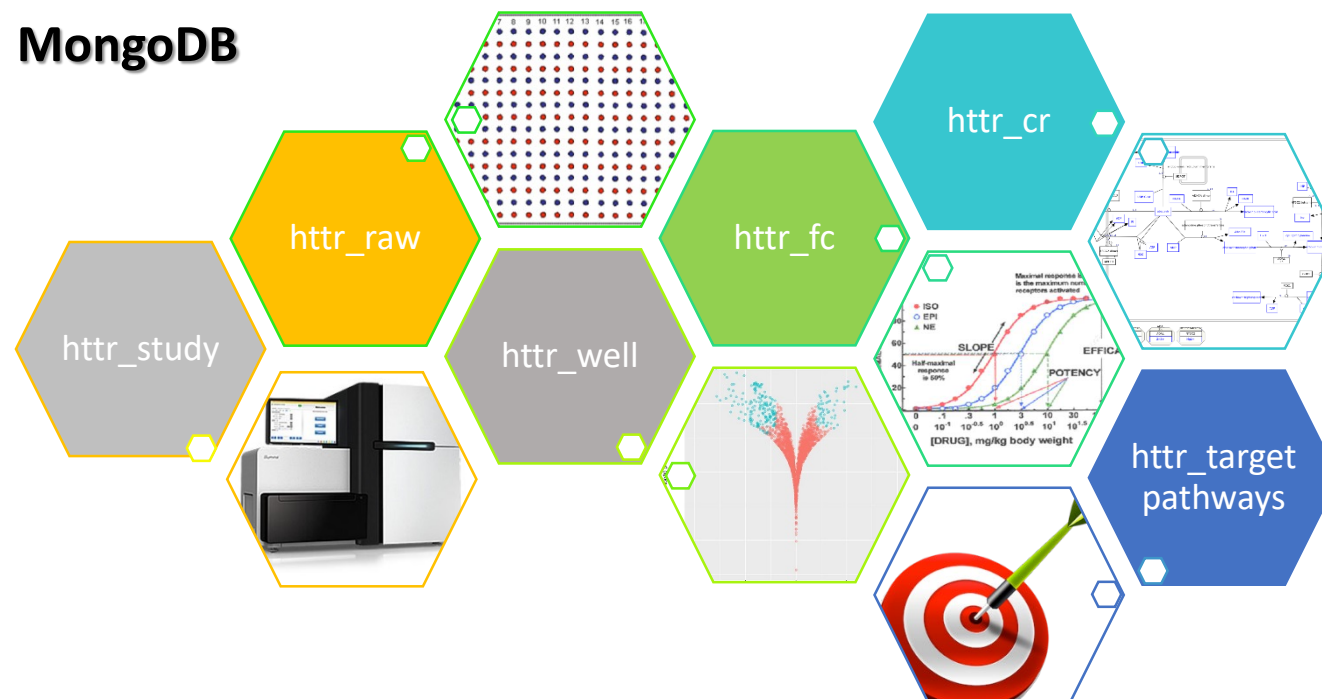
HTTr Analysis, Storage and Dissemination

(Internal EPA)

Python & R analysis pipeline

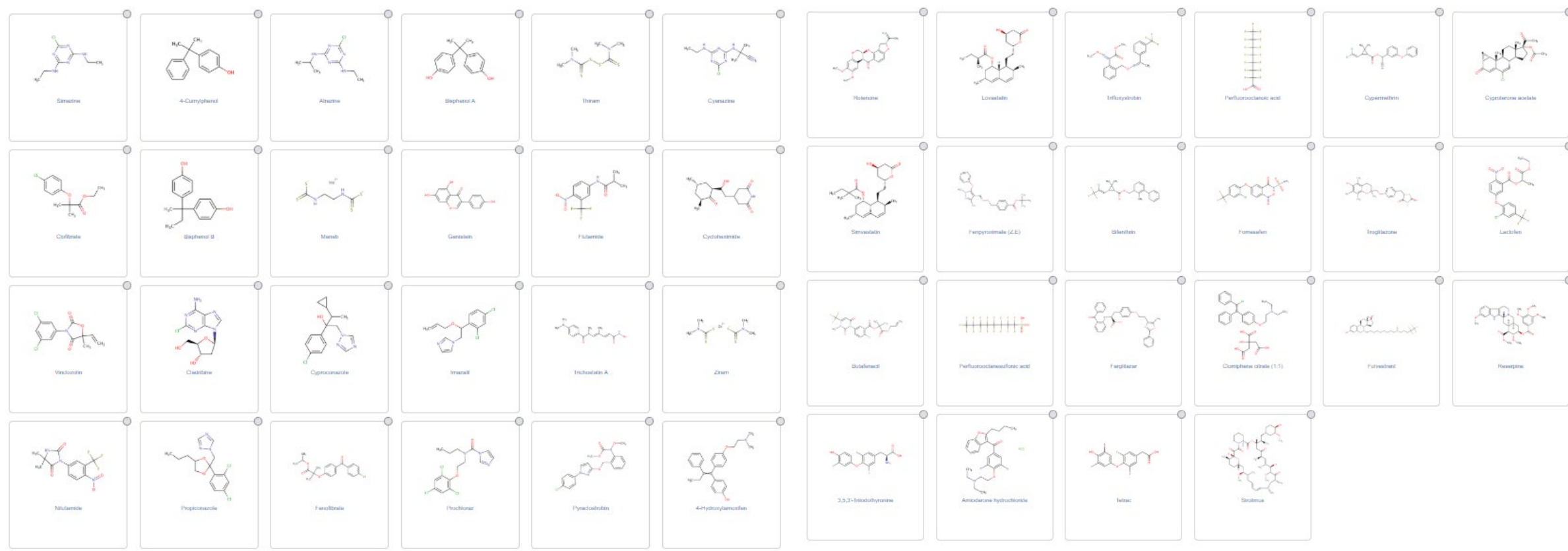


MongoDB



REST API

MCF7 Pilot Study Chemicals



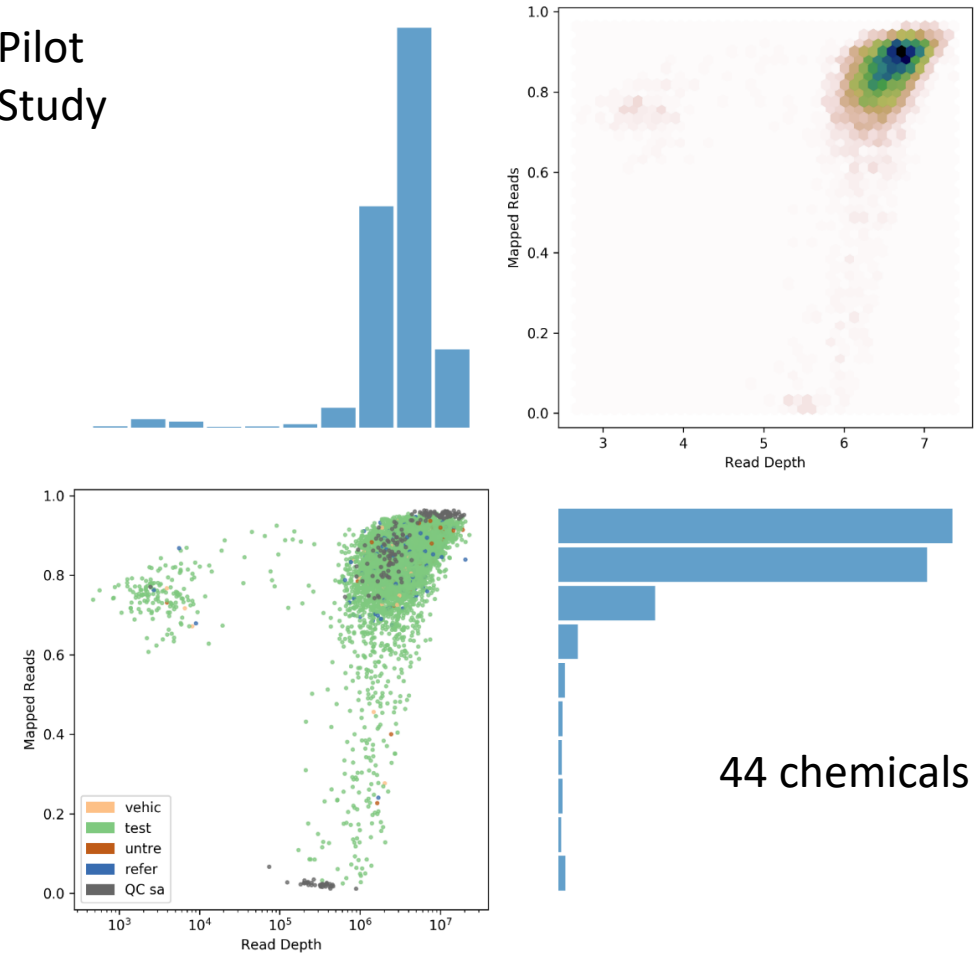
Data Quality

TempO-Seq Quality

Quality metrics:

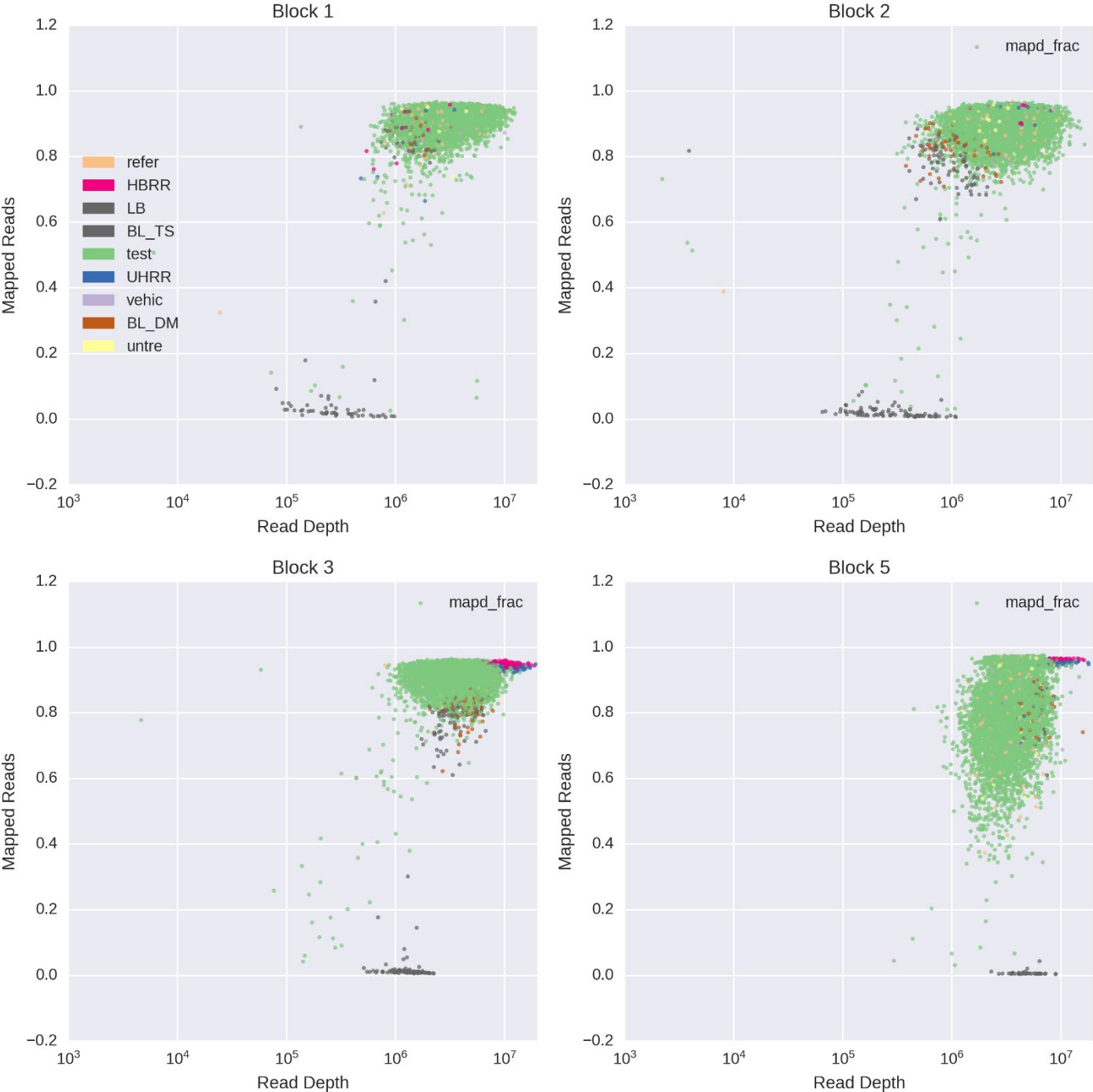
- Read depth: number of mRNAs sequenced
 - Ideal value = 3×10^6
- Mapped reads: fraction of sequenced mRNAs that map to a specific probe/gene
 - Ideal value = 100%

Pilot Study

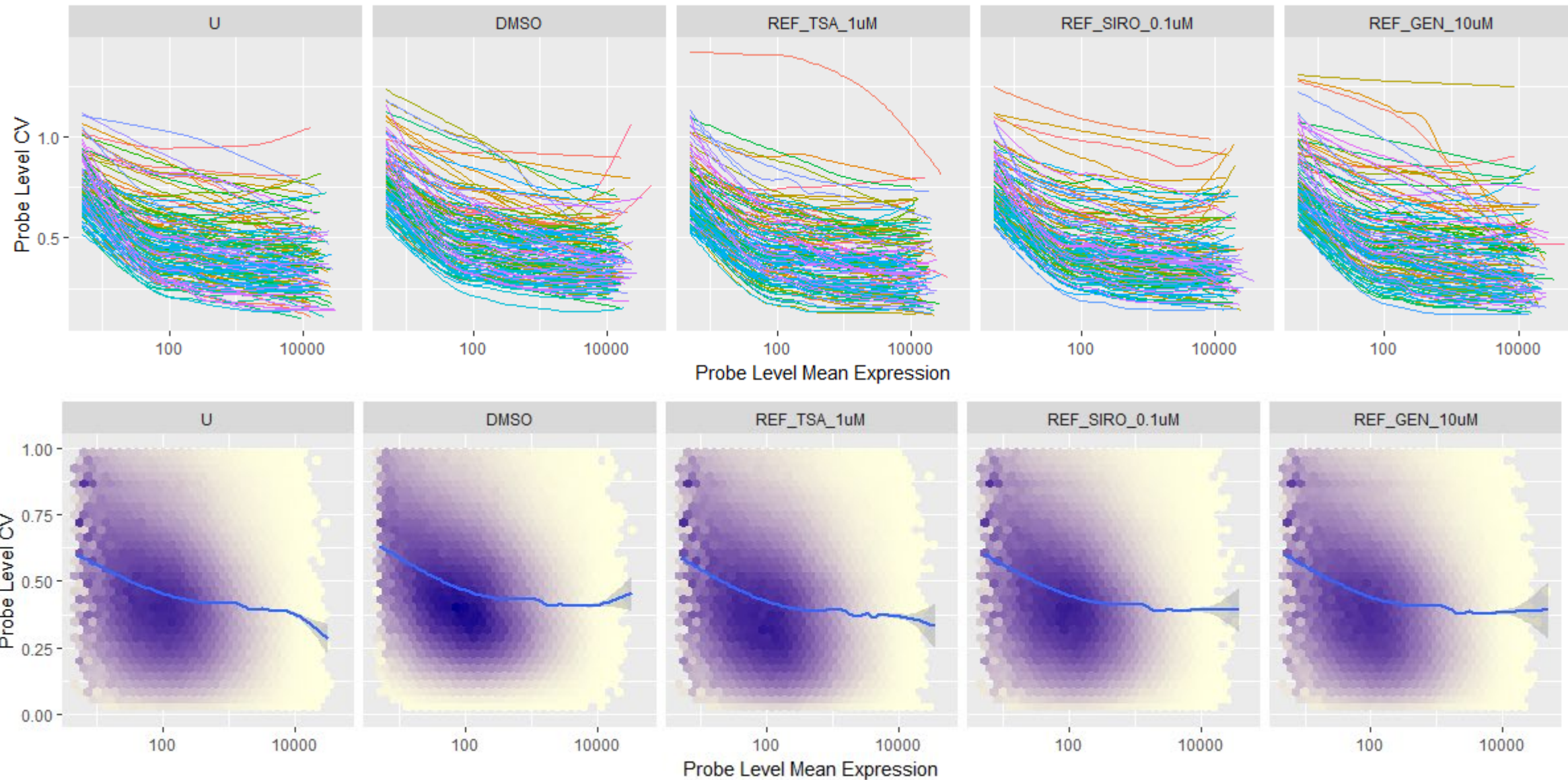


TempO-Seq quality

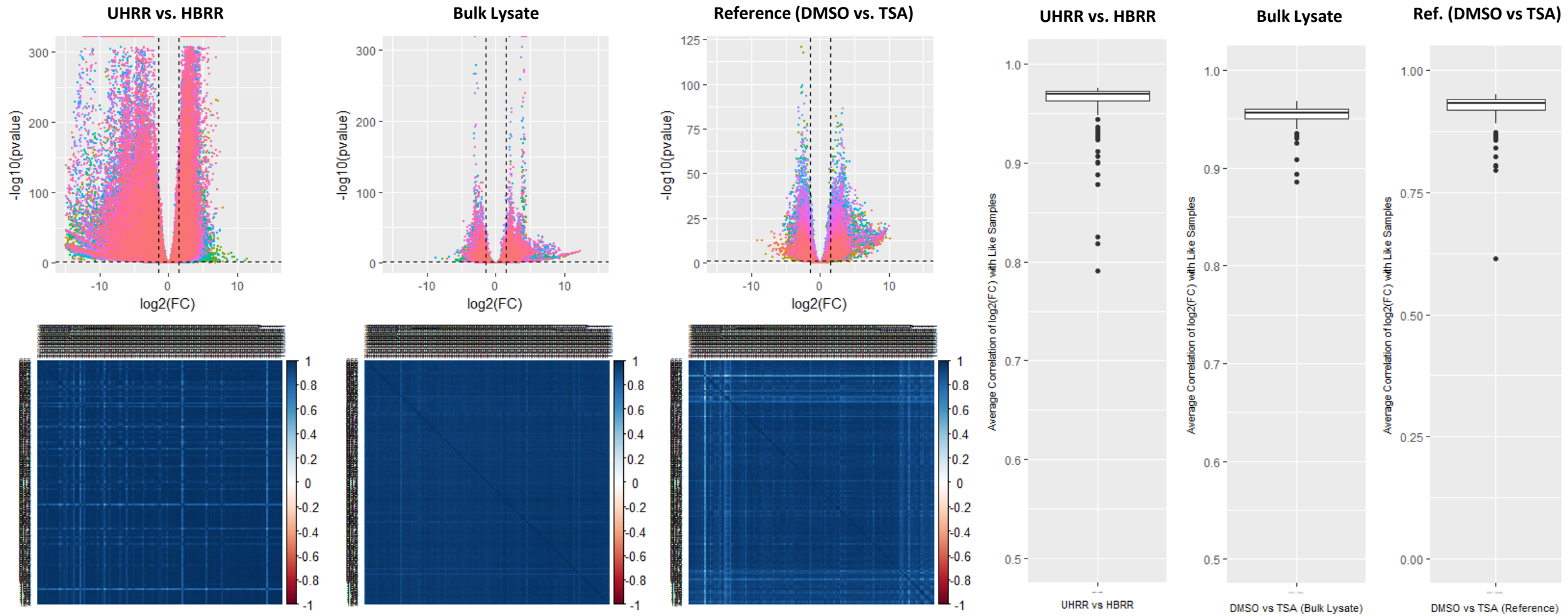
block_id	Mapped %		Read depth	
	mean	std	mean	std
1	0.908	0.077	3.33E+06	1.60E+06
2	0.892	0.078	3.53E+06	1.64E+06
3	0.909	0.076	3.72E+06	1.56E+06
5	0.797	0.124	3.77E+06	1.64E+06



Coefficient of Variation Vs. Transcript Abundance



Reproducibility of $\text{Log}_2(\text{FC})$ Estimates



- High correlation of $\log_2 \text{FC}$ estimates across plates and screening blocks.

Concentration-Response Analysis

BMDEpress2

Benchmark Dose Modeling



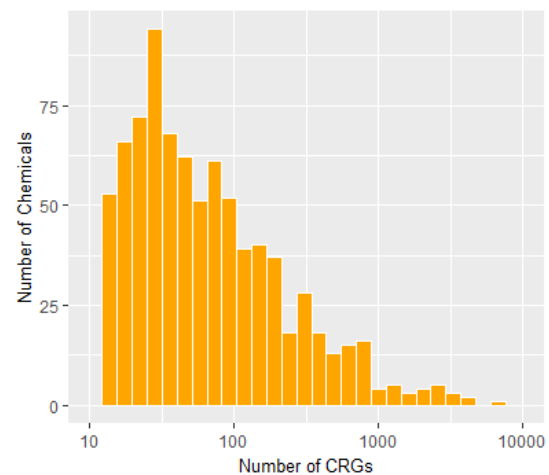
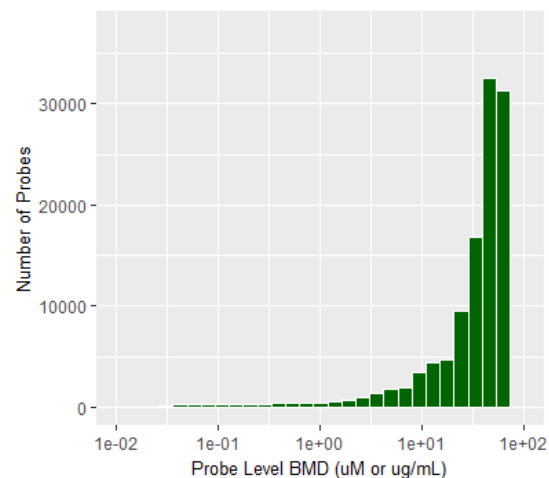
Parameter	Criteria ^a
Pre-filter:	Williams trend test
Models	Hill, Exponential 2, <i>poly2</i> , <i>power</i> , <i>linear</i>
BMR Factor:	1.349 (10 %)
Best Model Selection:	Lowest AIC
Hill Model Flagging ^b :	'k' < 1/3 Lowest Positive Dose Retain Flagged Models
Pathway Analysis:	Genes with BMD ≤ Highest Dose ≥ 3 ≥ 1% Gene Set Coverage
Gene Set Collections ^c :	MSigDB_C2 MSigDB_H Reactome BioPlanet KEGG

^a Exploratory analysis – modeling criteria not finalized

^c Gene Set Collections:

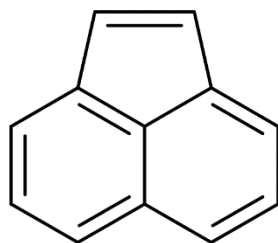
- **MSigDB_C2:** Curated gene sets from online pathway databases, publications and knowledge of domain experts (n = 4738).
- **MSigDB_H:** Coherently expressed signatures derived by aggregating many MSigDB gene sets to represent well-defined biological states or processes (n = 50).
- **Reactome:** Open-source, curated and peer reviewed pathway database with hierarchical pathway relationships in specific domains of biology. (n = 1764). Some pathways included in MSigDB_C2.
- **BioPlanet** (n = 1700): Curated pathway set developed by National Toxicology Program.

Benchmark Dose Modeling Summary & Inducible Genes



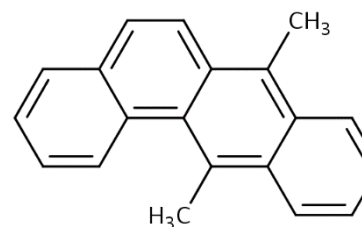
CYP1A1_10775
(n = 473)

Acenaphthylene
208-96-8 | DTXSID3023845



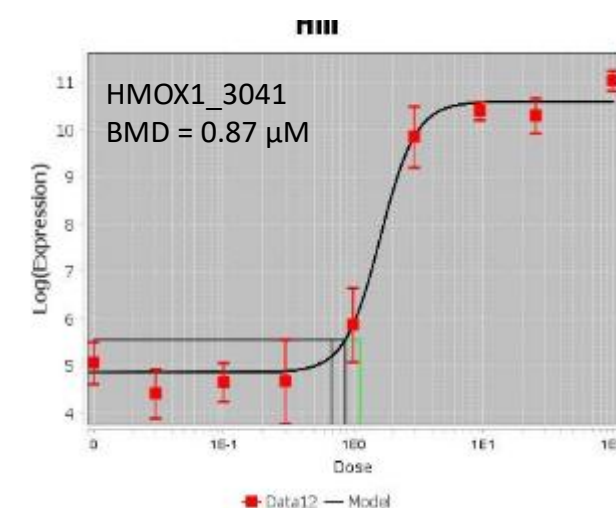
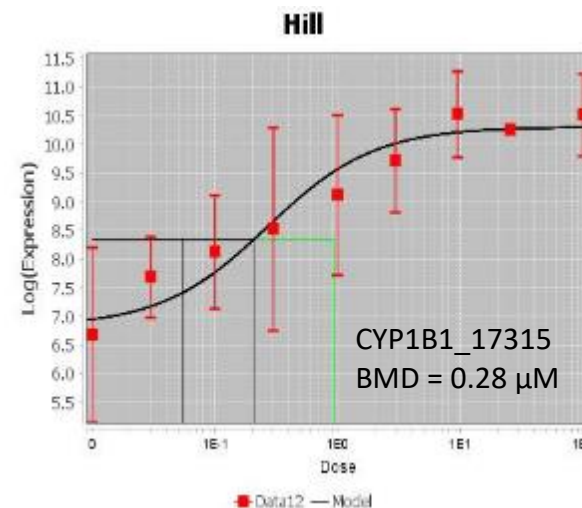
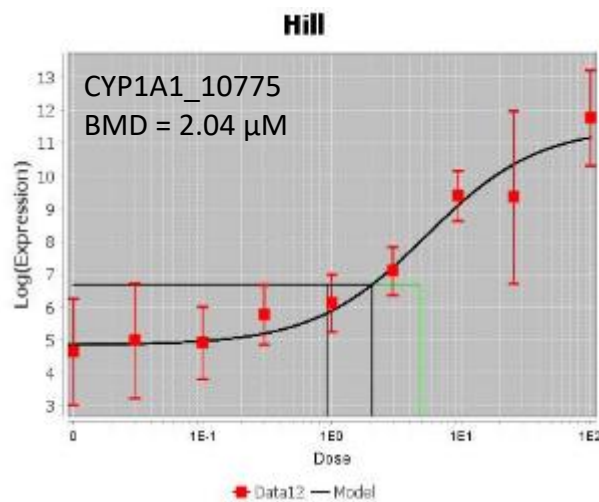
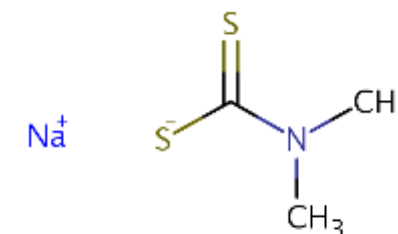
CYP1B1_17315
(n = 279)

7,12-Dimethylbenz(a)anthracene
57-97-6 | DTXSID1020510

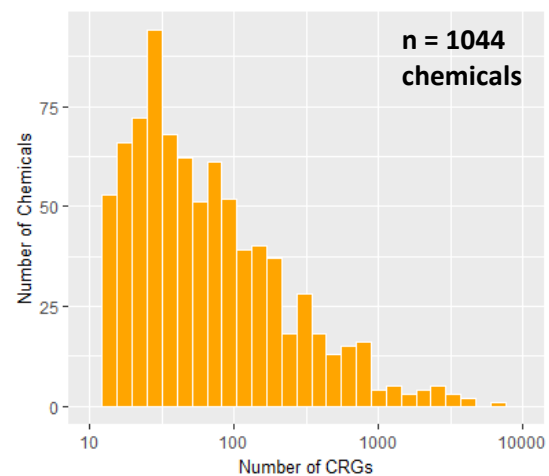
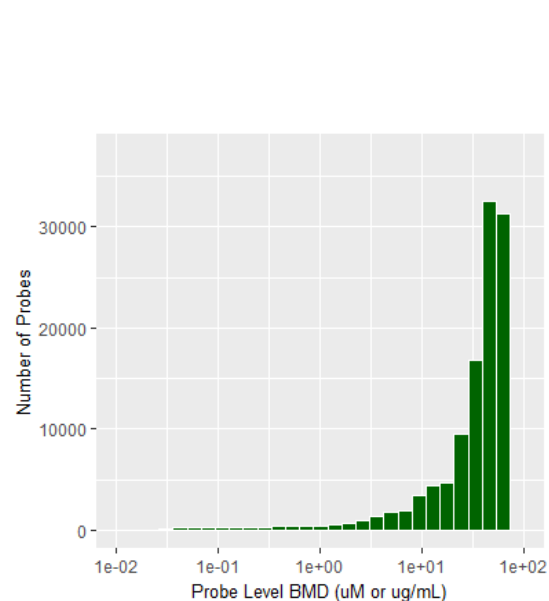


HMOX1_3041
(n = 174)

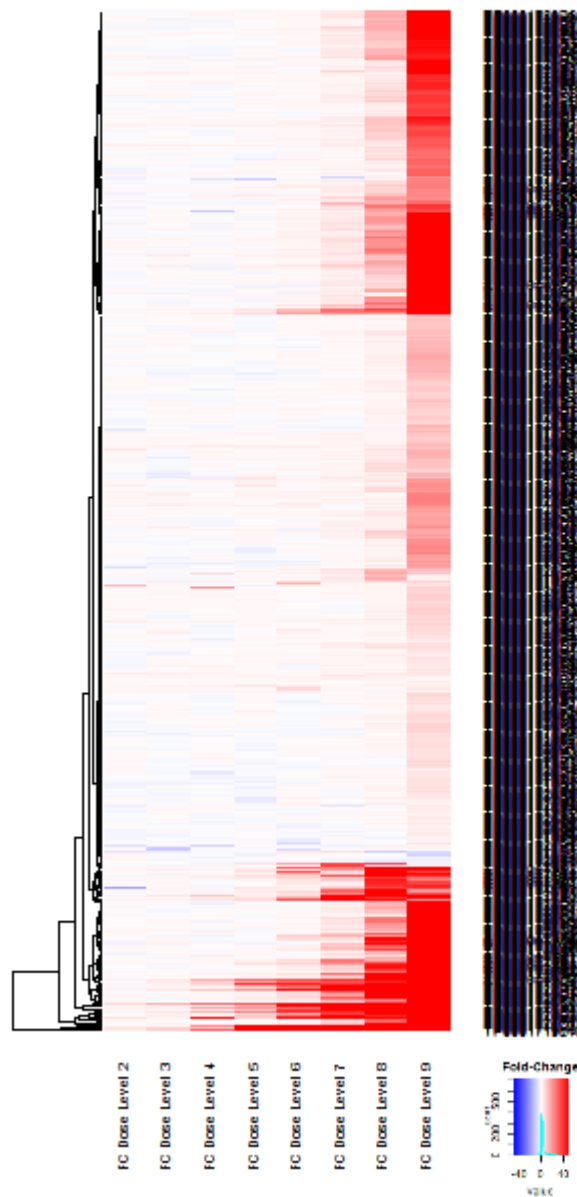
Sodium
dimethyldithiocarbamate
128-04-1 | DTXSID6027050



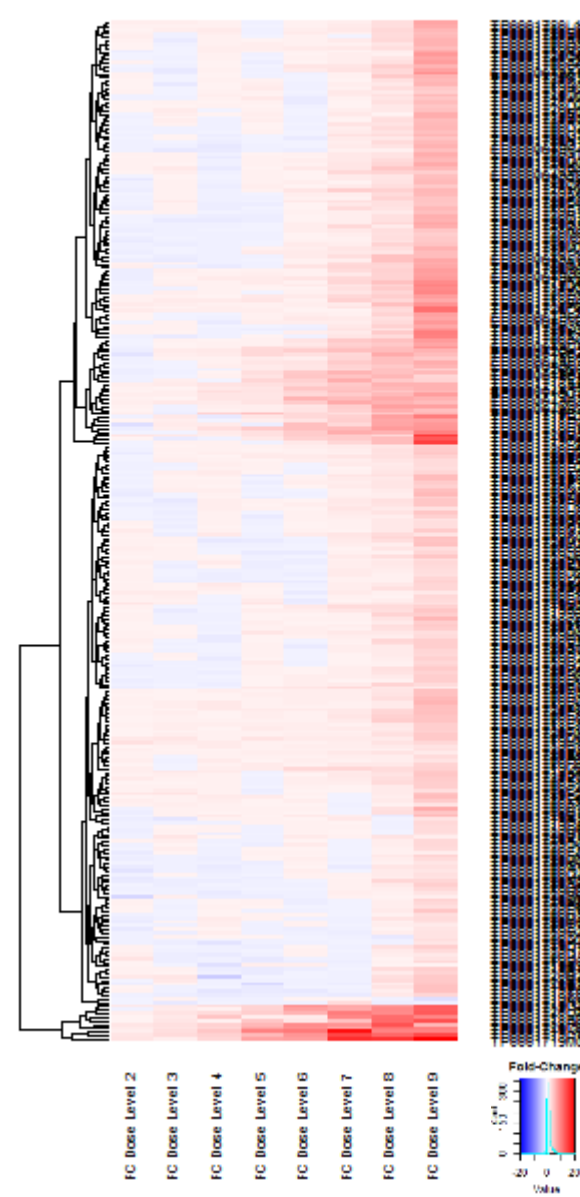
Benchmark Dose Modeling Summary & Inducible Genes



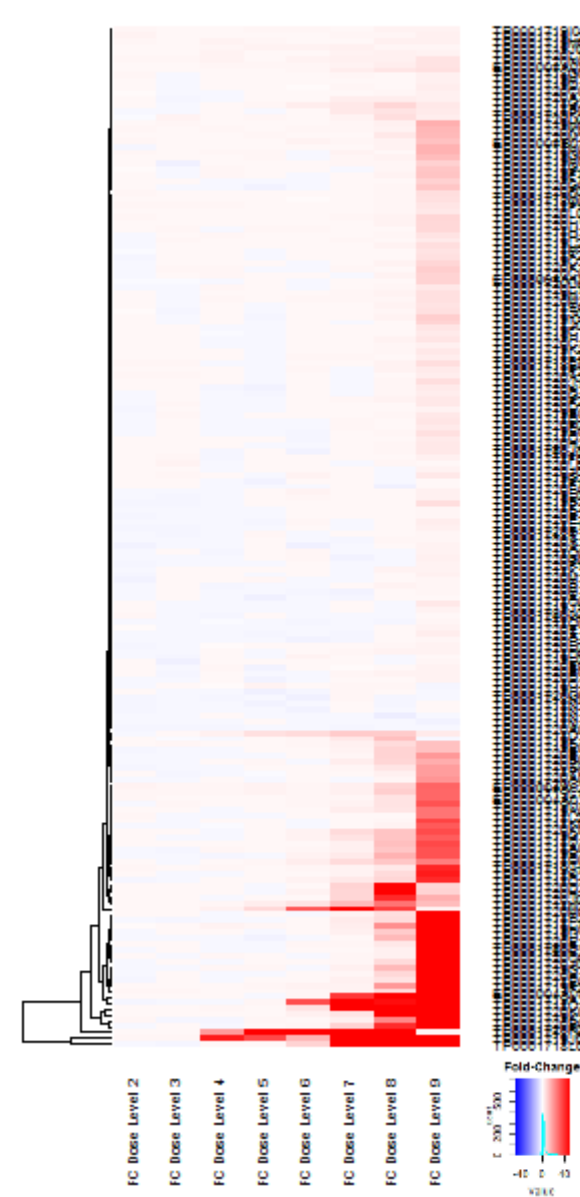
CYP1A1_10775
(n = 473)



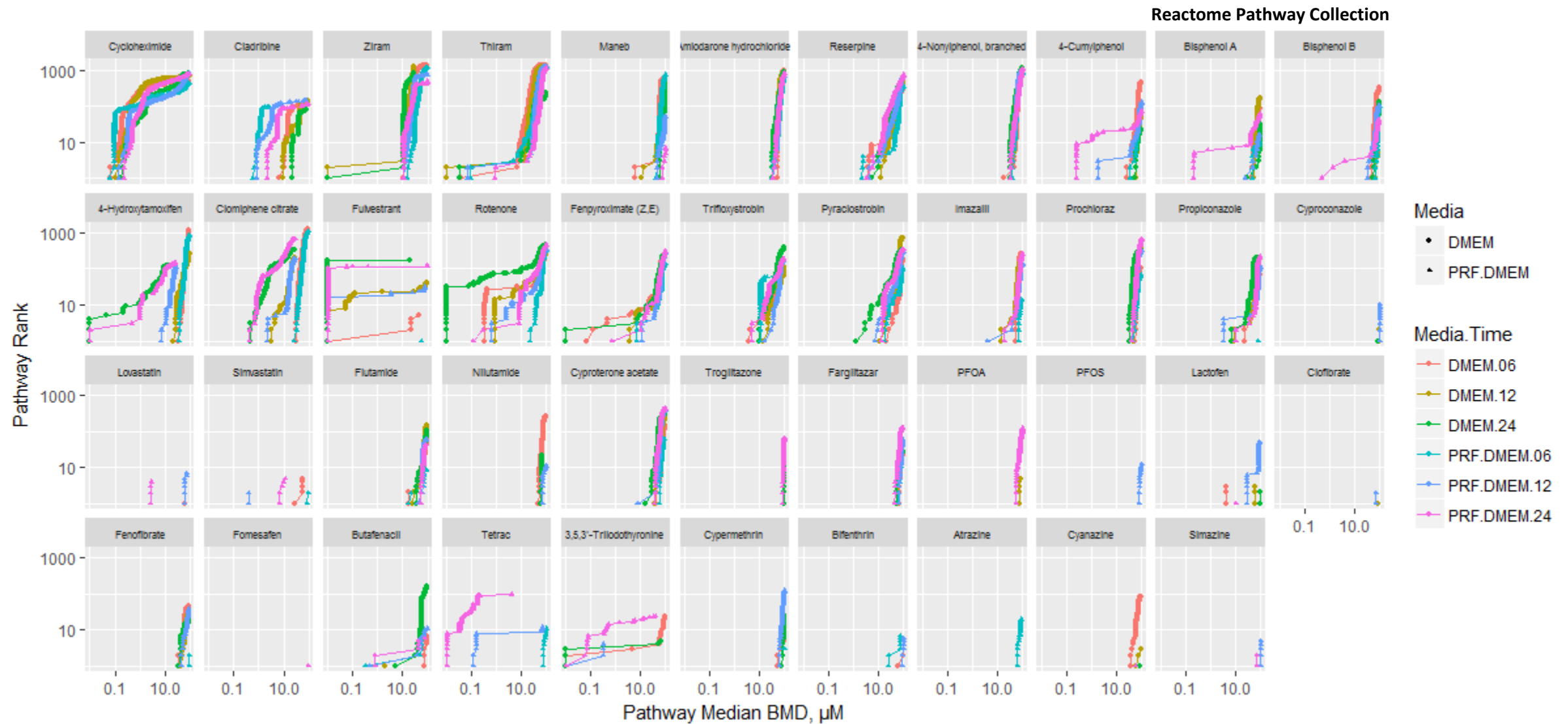
CYP1B1_17315
(n = 279)



HMOX1_3041
(n = 174)



Gene Set Accumulation Plots (1) *log₁₀ x-axis scaling*



- Identification of the most sensitive gene set / pathway (or lower %ile of affected pathways) is a common way to identify bioactivity thresholds in transcriptomics data.
- Some chemicals affect many pathways across a broad concentration range (i.e. cycloheximide, ziram).
- Other affect a comparatively smaller number of pathways within a narrow concentration range (i.e. flutamide, prochloraz).

No affected pathways identified for Vinclozolin

Concentration-Response Analysis of Pathways

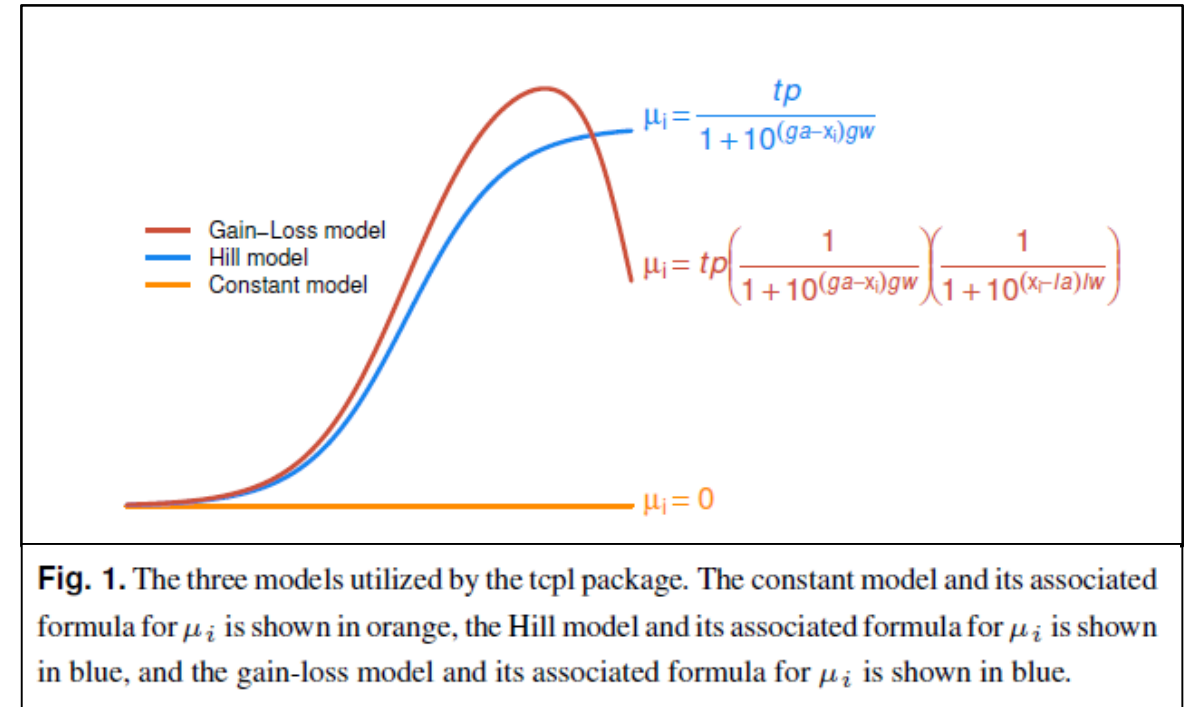
Concentration Response Modeling

ToxCast Pipeline (tcpl):

- Originally developed for CR modeling of high-throughput targeted screening assays.
- Fits 3 Models:
 - Constant
 - Hill
 - Gain-Loss
- Winning model = Lowest AIC
- “Hits” are defined as curves where:
 - The Hill or Gain-Loss wins
 - Response surpasses an efficacy threshold
- Modified to handle both upwards and downwards trending concentration-response curves.

Applications in HTTr:

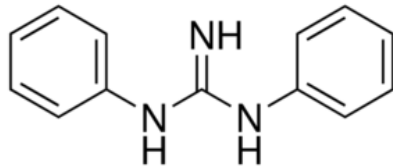
- Gene level concentration-response modeling of DESeq2 FC estimates.
- Pathway level concentration-response modeling



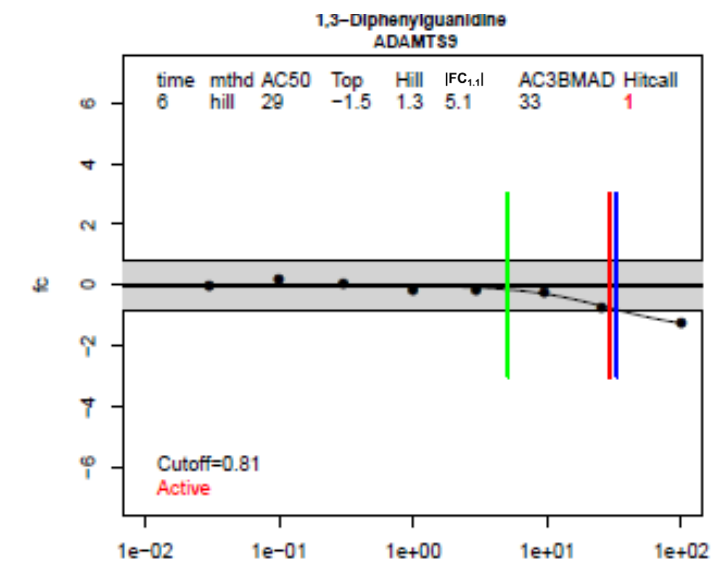
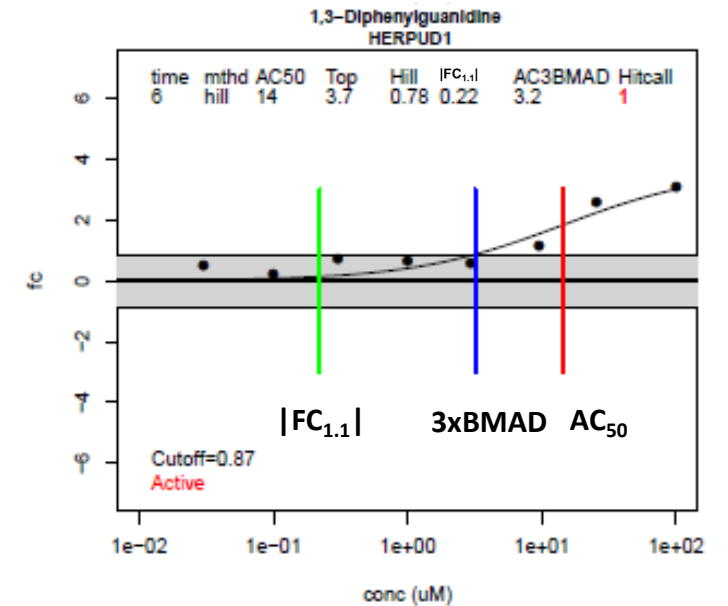
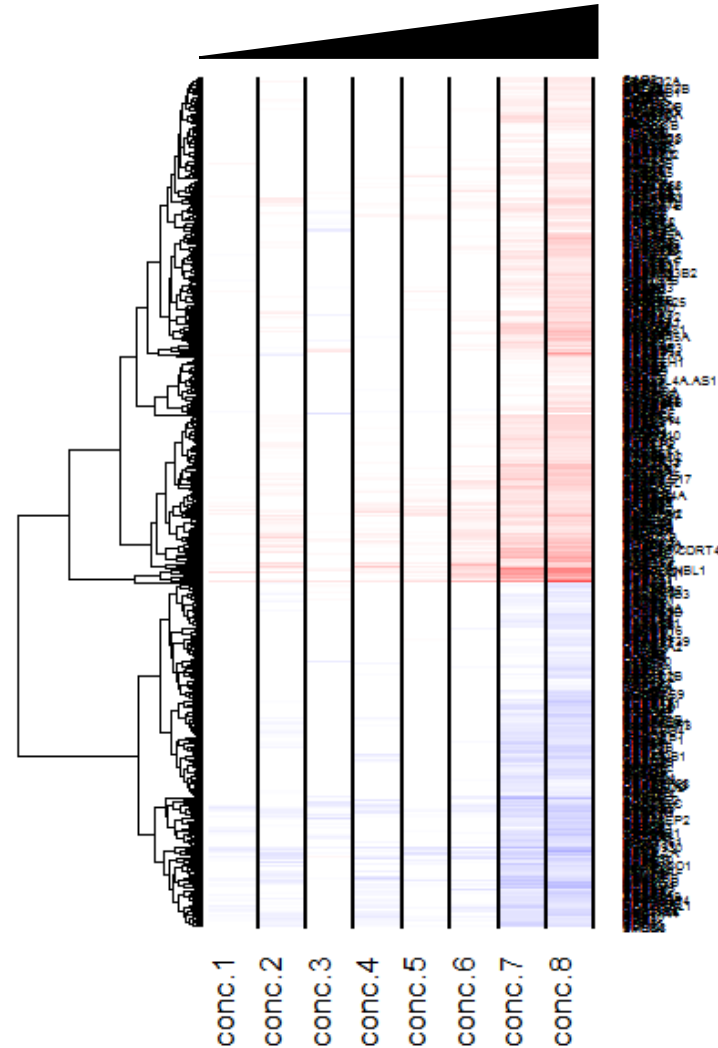
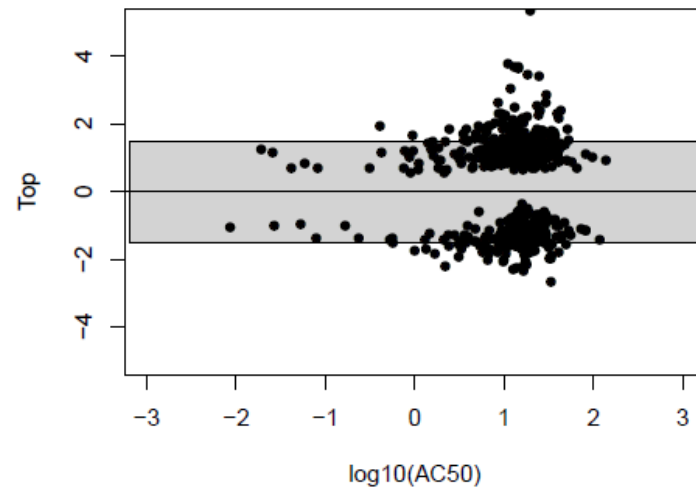
Filer et al. (2017)

Gene Level CR Modeling Example

1,3-Diphenylguanidine
102-06-7 | DTXSID3025178



1,3-Diphenylguanidine (568)



Gene Set Level Concentration Response Modeling

Step 1: Calculate Response

- A gene set is a list / bag of genes
- Under one condition (chemical x dose) calculate “gene set response” separately for genes in the set and out of the set:

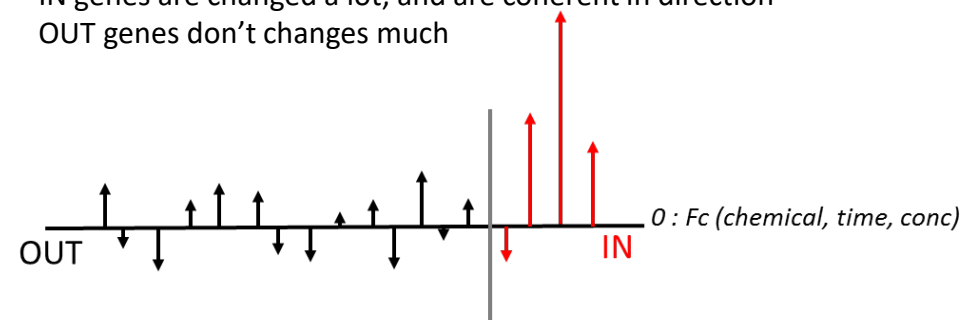
$$M = \sum_{i=1}^{ngene} f c_i$$

$$R = M_{in} - M_{out}$$

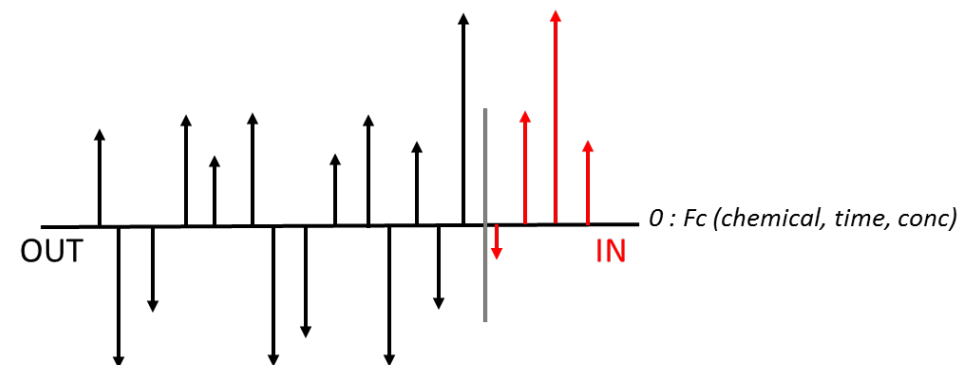
Step 2: CR Modeling

- For each chemical, fit using tcplFit
 - Constant, Hill , Gain-Loss methods
 - BMAD(pathway) = MAD of response for the pathway across the two lowest concentrations across all chemicals and times
- Hitcall:
 - tcplFit calls a hit
 - Top > 3*BMAD

- IN genes are changed a lot, and are coherent in direction
- OUT genes don't change much



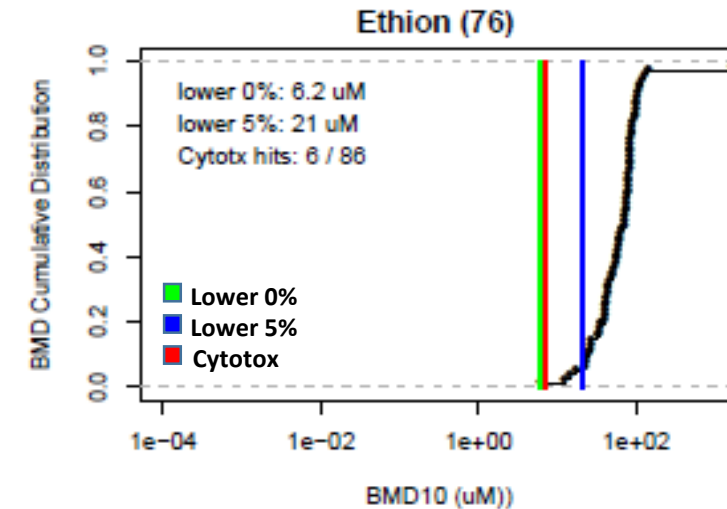
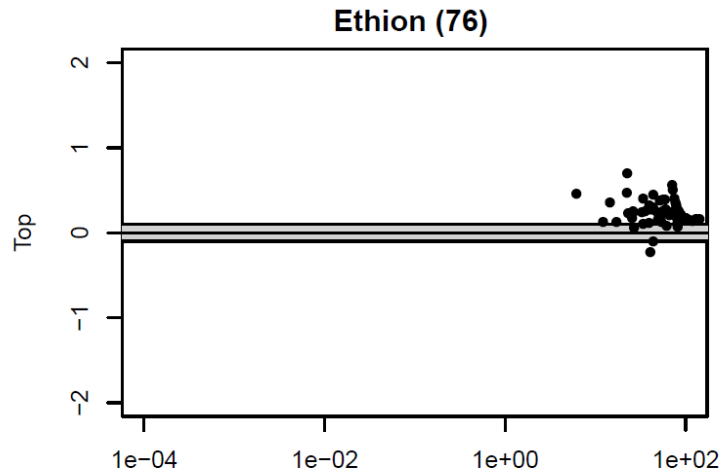
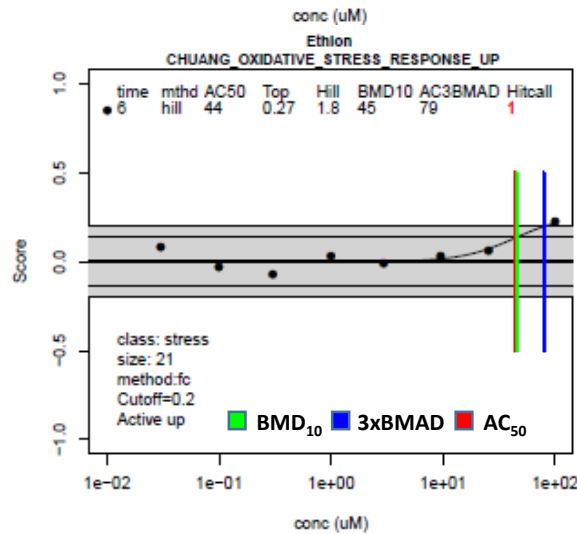
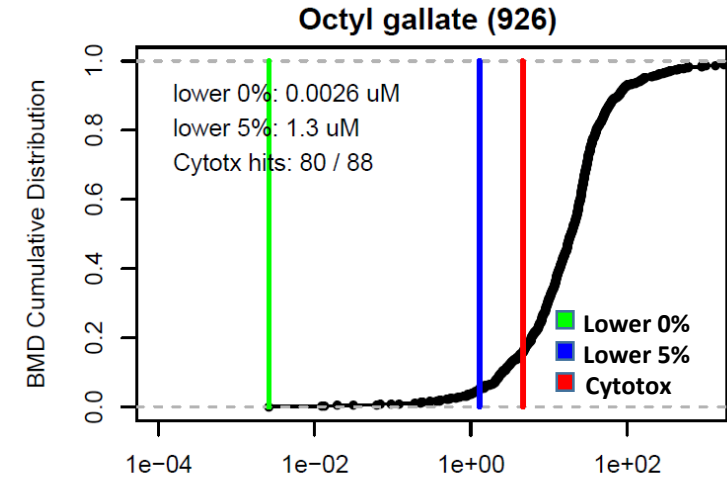
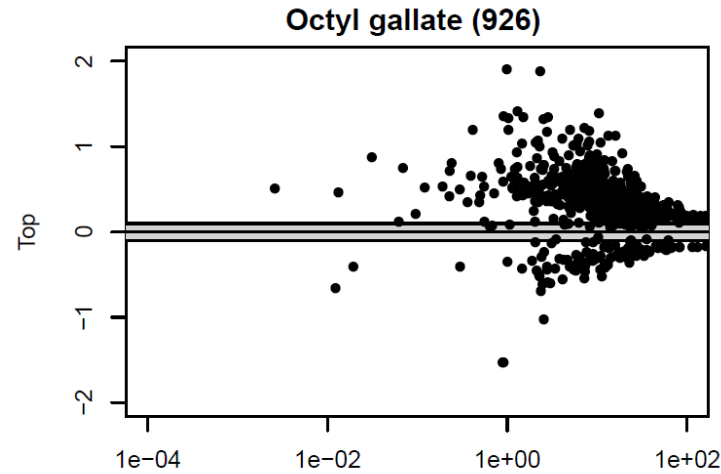
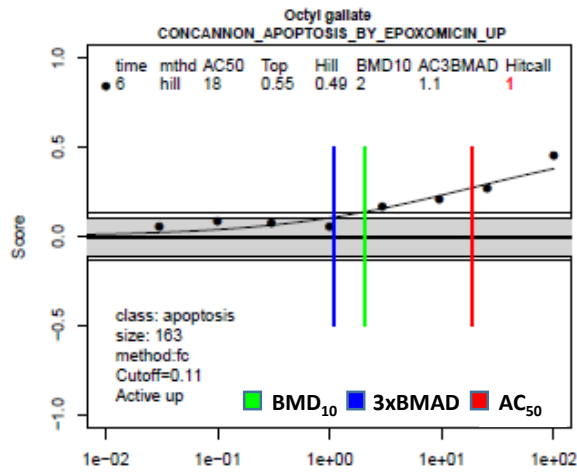
- IN genes are changed a lot, and are coherent in direction
- OUT genes change a lot but are not coherent (mean ~ 0)



Gene Set Collections:

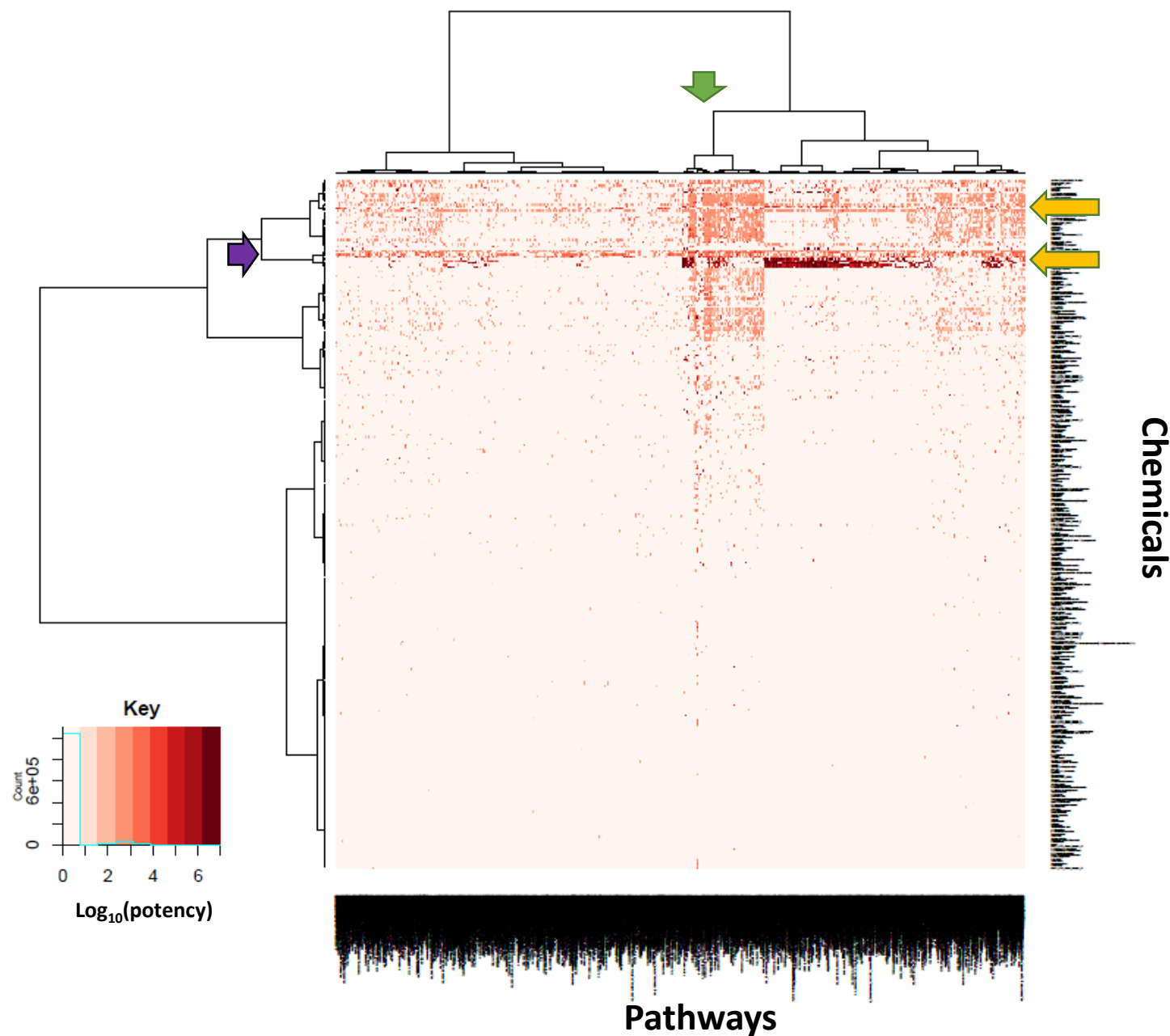
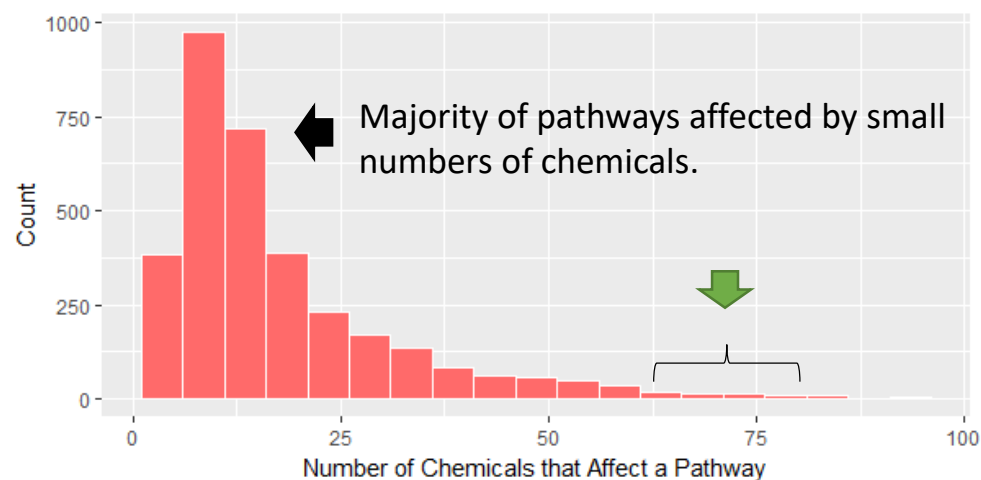
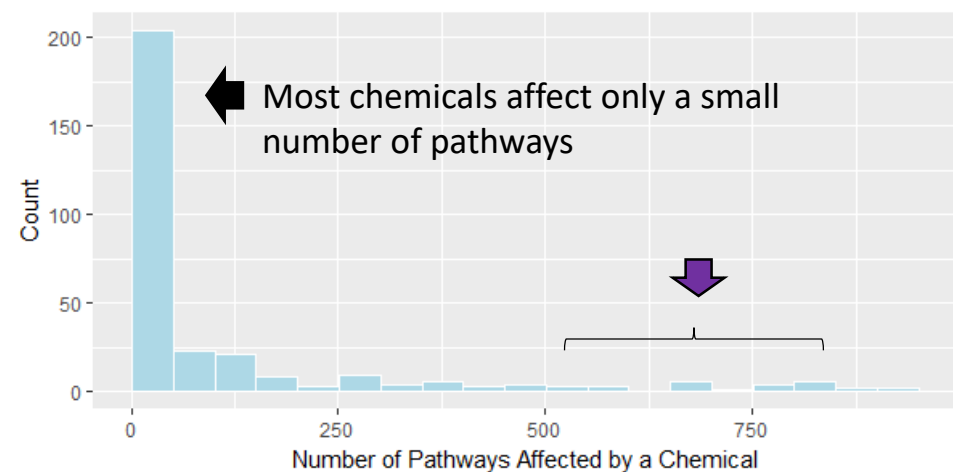
- **MSigDB_C2**: Curated gene sets from online pathway databases, publications and knowledge of domain experts (n = 4738).
- **BioPlanet**: Curated pathway set developed by National Toxicology Program (n = 1700).

Gene Set Level CR Modeling Examples



- **Top Row:** Chemical produced effects on biological pathways at concentrations **below** cytotoxicity.
- **Bottom Row:** Chemical produced effects on biological pathways at or **above** the cytotoxicity threshold.

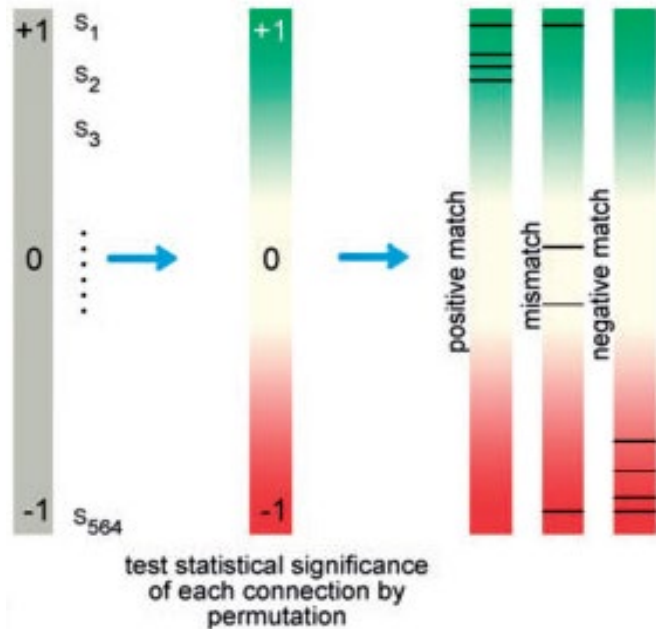
Gene Set Level CR Summary



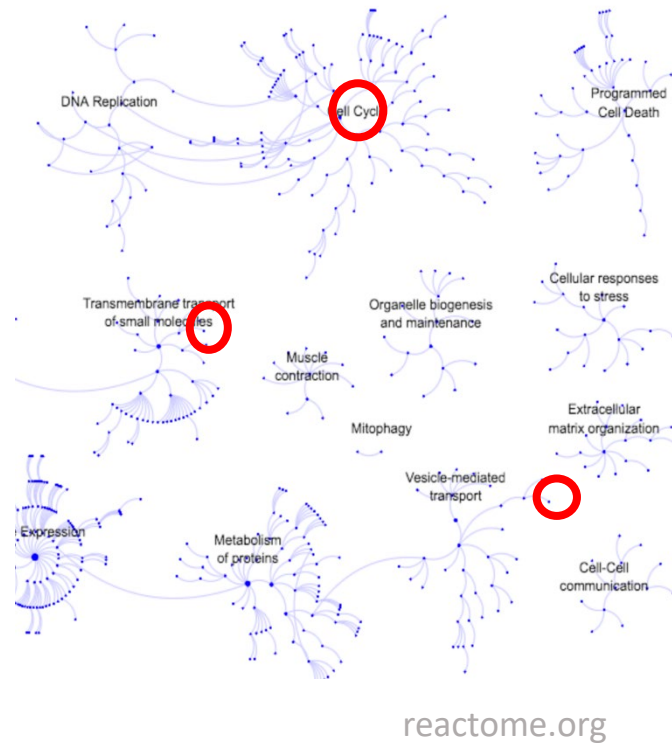
Putative Target Prediction

Putative Molecular Target Prediction

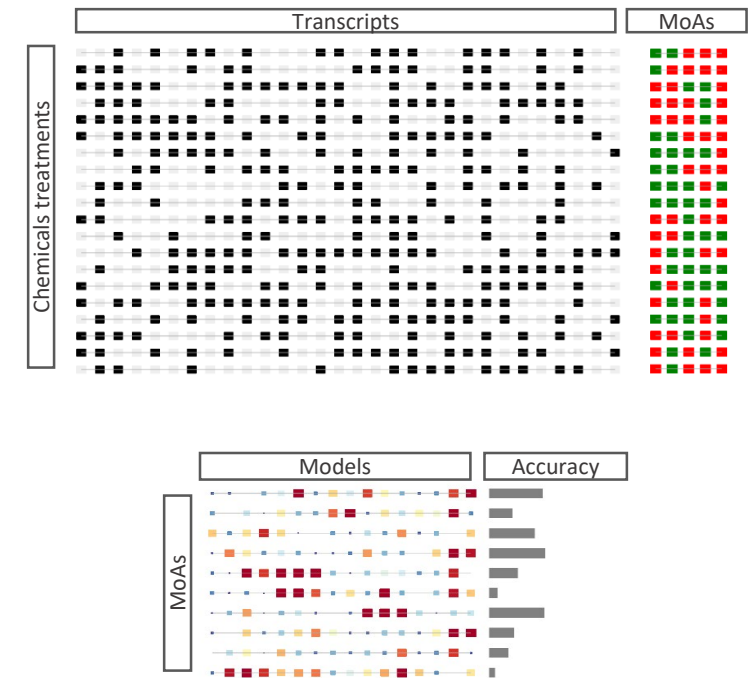
Connectivity mapping
analysis using DEGs and CRGs



Pathway / Network analysis
using DEGs and CRGs

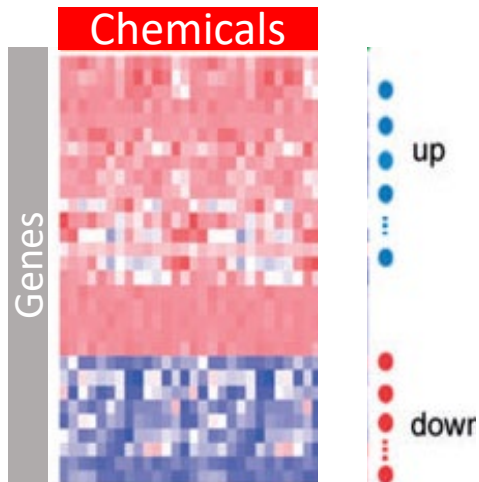


Machine learning to build
Target-specific models



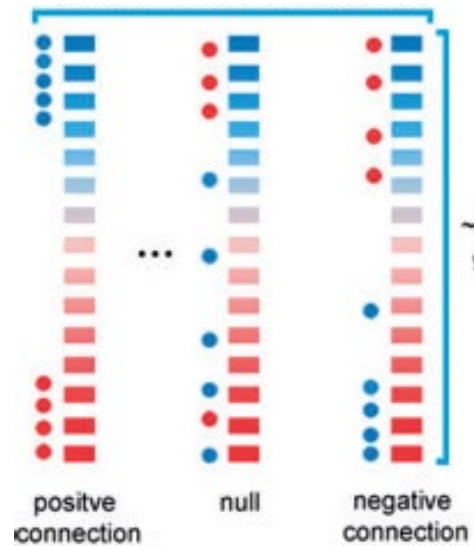
Connectivity Mapping

Input DEGs or
CRGs

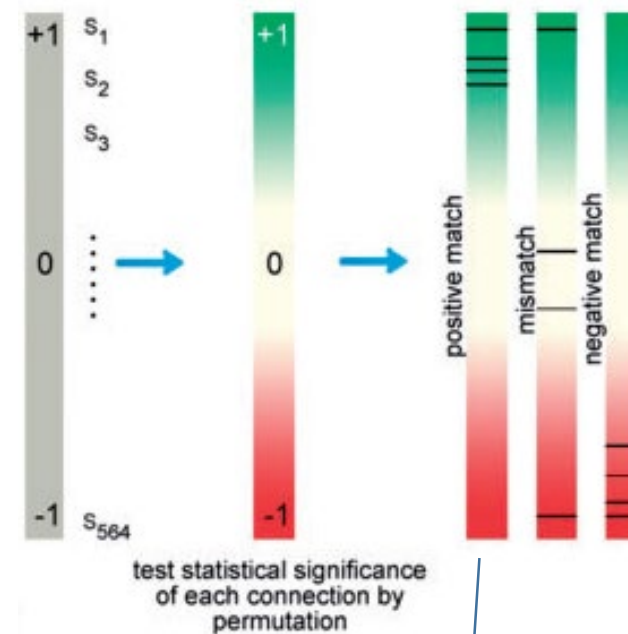


BioSpyder HTTr (BSP)

Query Signature DB
CMap or BSP



Find best positive matches



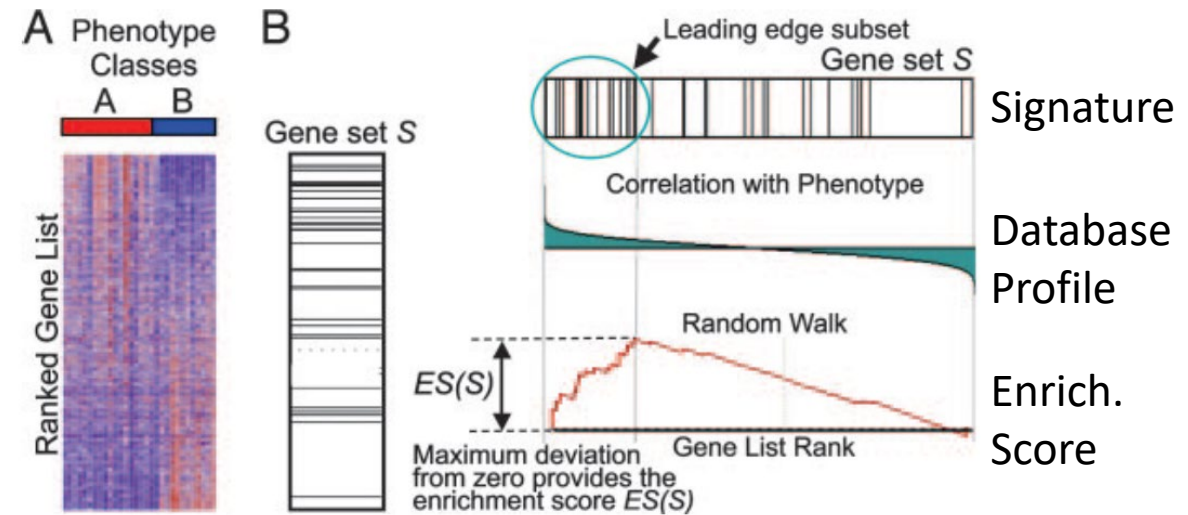
Infer Tox/MoA by
best match

Issues

- Translating DEG/CRG to signature
- Many measures of similarity
- Only as good as reference chemical MoA annotation
- Highly sensitive but not very specific
- Chemicals that cause global perturbations “hit” all classes – how do we distinguish signal from noise ?

“Connectivity” Scoring

- Connectivity mapping is a similarity metric based on transcriptional descriptors
- Gene Set Enrichment Analysis (GSEA): Calculate score of signature with highly up or down regulated genes in reference profiles using KS statistics
- Many alternatives
 - ssCMap: subspace connectivity mapping based on DEGs
 - ProbCMap: probabilistic scoring based on latent factors
 - XCos: Cosine similarity based on overlapping genes
- We used GSEA in this analysis



Subramanian et al. 2005

Reference Database and Signatures

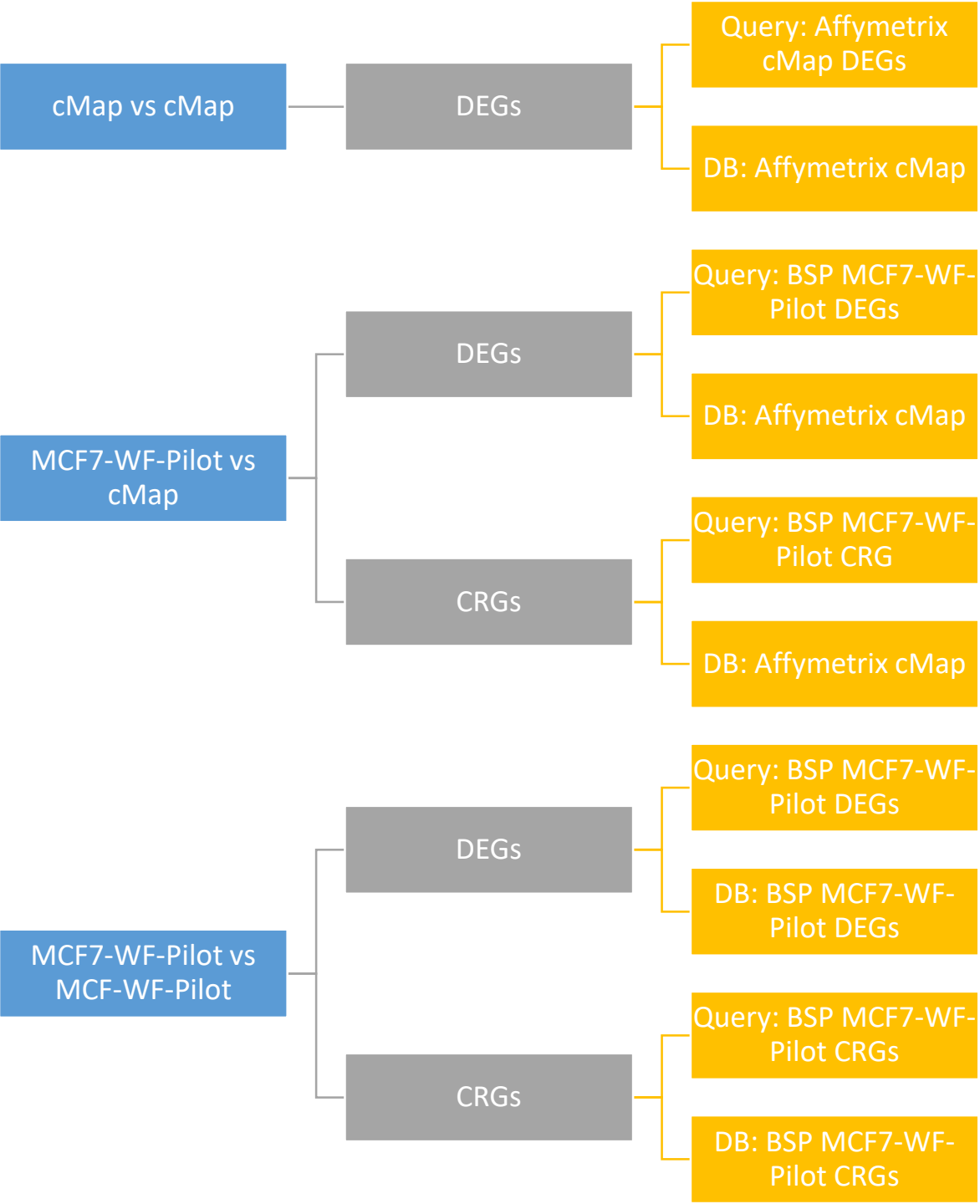
CMap Build 02

- CMap DB
 - Use CMap v2 database: Affymetrix data on 1176 chemicals, 5 cell lines
 - RMA Normalize CEL files
 - L2FC using treatment vs. matched DMSO
- Signatures (DEG)
 - Translate FC profiles in up/down profiles (signatures)
 - Convert L2FC data to Z-scores
 - DEG: For $z_0=1,2,3$ create discrete Z where value = 1 if $Z > z_0$ and -1 where $Z < z_0$

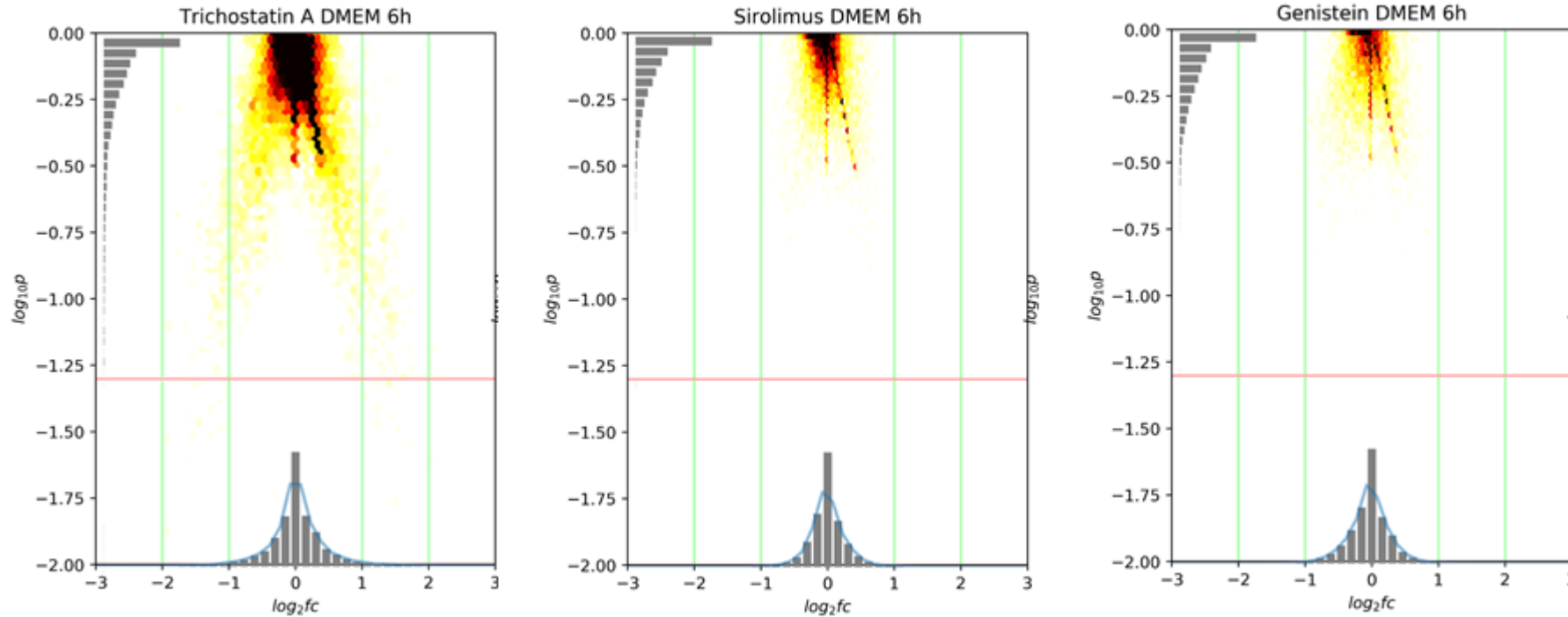
MCF7-WF-Pilot BSP

- BSP DB
 - Use 44 chemicals x 8 conc x 3 times x 2 media combinations
 - Exclude probes with ave count < 5
 - L2FC using DESeq2 (by chemical x 8 conc, time, media vs matched DMSO)
- Signatures (DEG & CRG)
 - Convert L2FC data to Z-scores
 - $|L2FC| \geq 0.6$ & $p < 0.05$ for at least one conc
 - DEG: For $z_0=1,2,3$ create discrete Z where value = 1 if $Z > z_0$ and -1 where $Z < z_0$
 - CRG: Calc 1-way ANOVA on L2FC $p < 0.05$

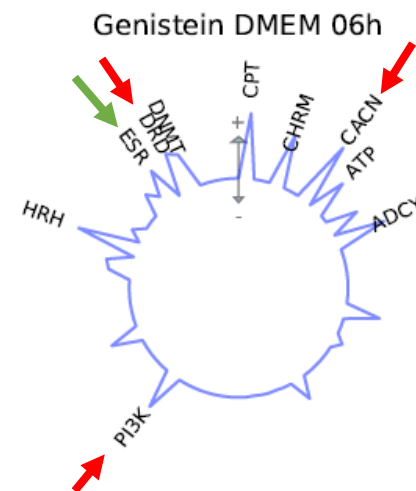
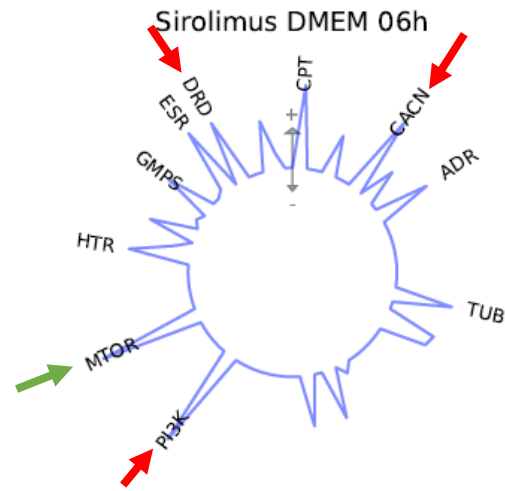
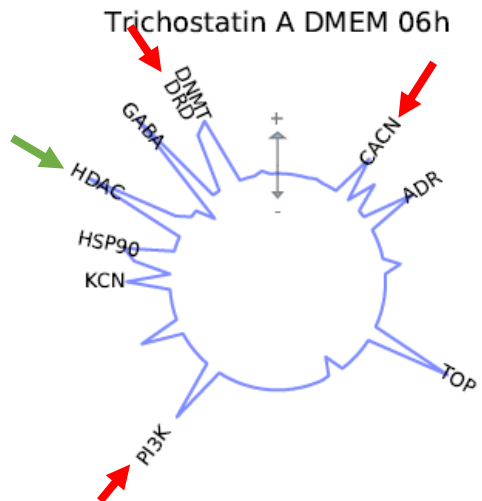
Connectivity Mapping Comparisons



Connectivity Mapping (MCF7-Pilot vs CMap)

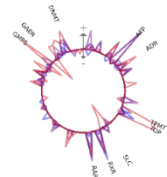


- Differential gene expression observed with reference chemicals.
- Putative targets identified using Connectivity Mapping
- Large degree of promiscuity of predicted targets observed.
- Currently evaluating additional methods for MIE prediction

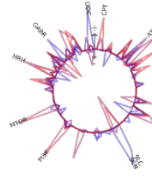


- Putative target
- Promiscuous Target Mapping

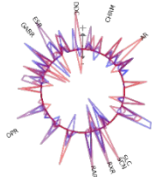
3,5,3'-Triiodothyronine



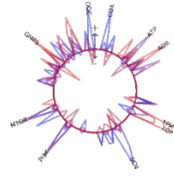
4-Cumylphenol



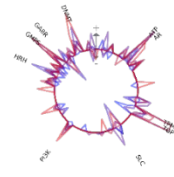
4-Hydroxytamoxifen



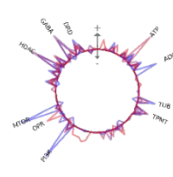
4-Nonylphenol, branched



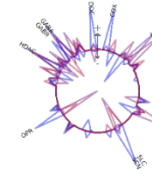
Amiodarone hydrochloride



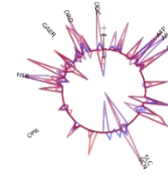
Atrazine



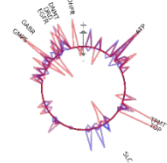
Bifenthrin



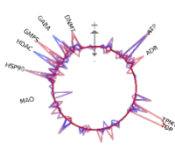
Bisphenol A



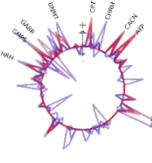
Bisphenol B



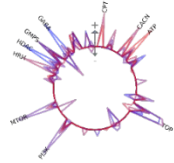
Butafenacil



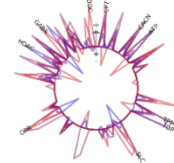
Cladribine



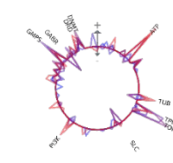
Clofibrate



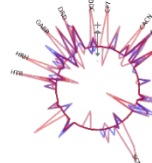
Clomiphene citrate (1:1)



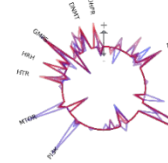
Cyanazine



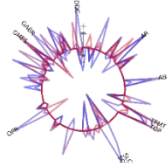
Cycloheximide



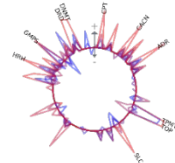
Cypermethrin



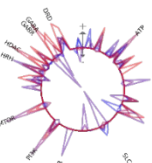
Cyproconazole



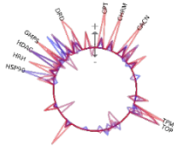
Cyproterone acetate



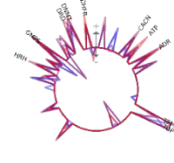
Farglitazar



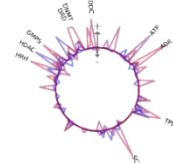
Fenofibrate



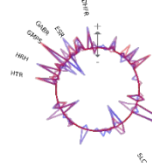
Fenpyroximate (Z,E)



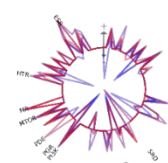
Flutamide



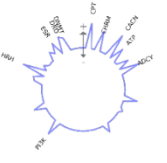
Fomesafen



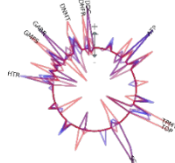
Fulvestrant



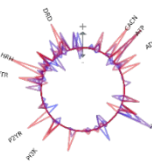
Genistein



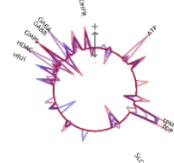
Imazalil



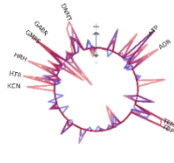
Lactofen



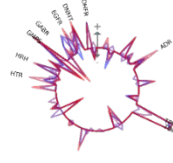
Lovastatin



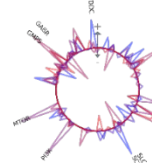
Maneb



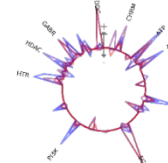
Nilutamide



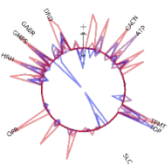
PFOA



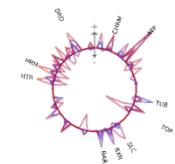
PFOS



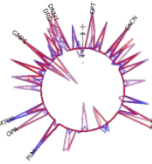
Prochloraz



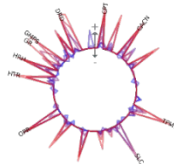
Propiconazole



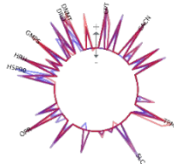
Pyraclostrobin



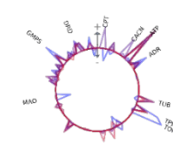
Reserpine



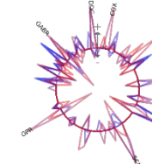
Rotenone



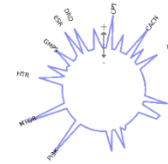
Simazine



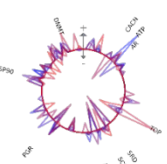
Simvastatin



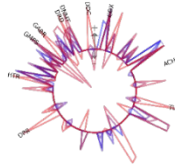
Sirolimus



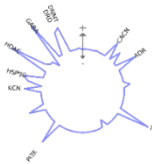
Tetrac



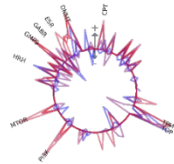
Thiram



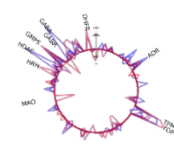
Trichostatin A



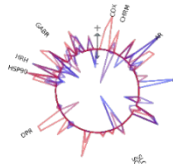
Trifloxystrobin



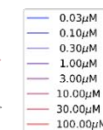
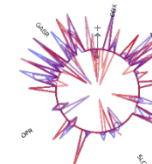
Troglitazone



Vinclozolin



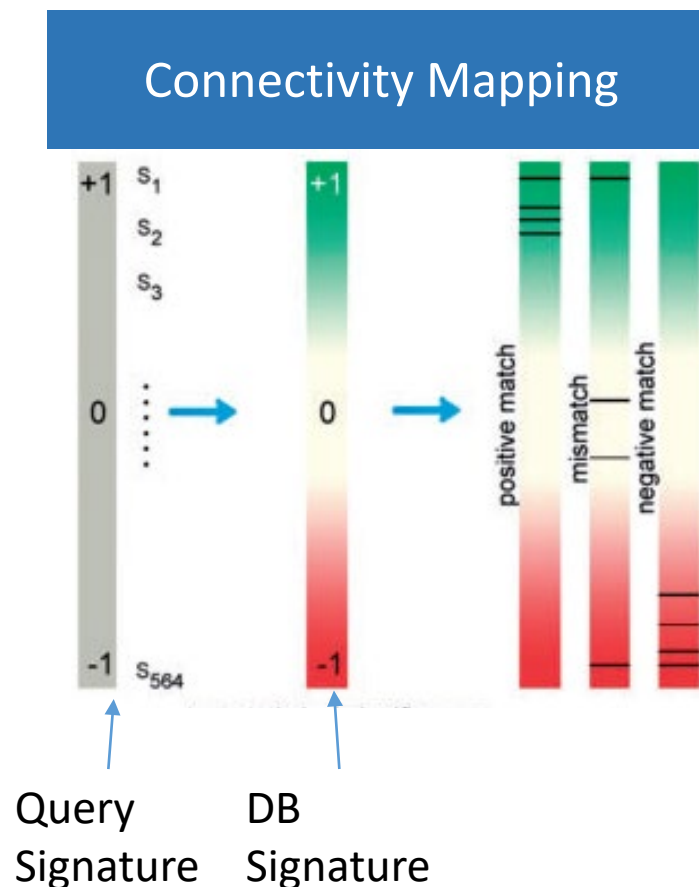
Ziram



Quantifying Performance

Conduct Leave-one-out (LOO) evaluation of hits:

1. Annotate CMap chemicals with classes
 - Classes: 143 (Putative targets)
 - Chemicals: 614
2. Search “hits” by connectivity with score = ϑ
 - If $\vartheta > \vartheta_0$
 - if query.target == hit.target:
pred = TP
 - elif query.target != hit.target:
pred = FP
 - If hit $\vartheta < \vartheta_0$
 - if query.target == hit.target:
pred = FN
 - elif query.target != hit.target:
pred = TN
3. Measure sensitivity, specificity, BA



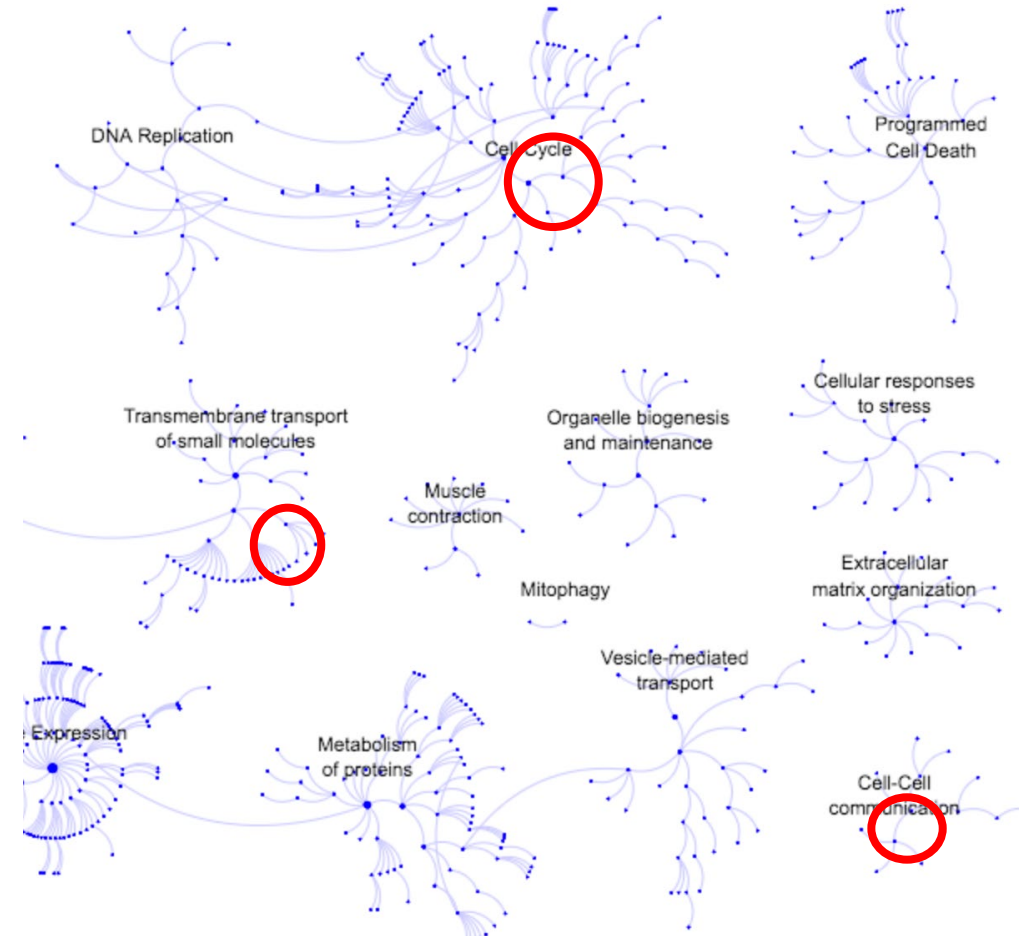
cMap 2.0 vs cMap 2.0

MoA	pos	neg	pos_annot	BA	Sn	Sp	th0
GABAT	2	117	2	0.85	1.00	0.71	0.19
HDAC	3	144	6	0.84	1.00	0.69	0.16
RAR	2	63	2	0.83	1.00	0.66	0.13
TUB	5	172	5	0.83	1.00	0.65	0.14
FKBP	2	41	2	0.82	1.00	0.63	0.33
HPRT	2	77	2	0.81	1.00	0.63	0.09
OPR	5	157	6	0.81	1.00	0.63	0.23
DNMT	2	32	2	0.81	1.00	0.63	0.28
DDC	2	84	2	0.81	1.00	0.62	0.17
TPO	2	78	3	0.81	1.00	0.62	0.04
DAT	2	73	3	0.81	1.00	0.62	0.03
PLG	2	71	3	0.81	1.00	0.62	0.13
DHFR	3	97	3	0.81	1.00	0.62	0.20
PTGER	4	113	4	0.81	1.00	0.62	0.07
NFKB	2	104	2	0.81	1.00	0.62	0.03
TR	2	82	2	0.81	1.00	0.62	0.14
ADORA	5	165	5	0.81	1.00	0.62	0.10
CHRN	4	139	6	0.81	1.00	0.62	0.06
TYMS	3	101	3	0.81	1.00	0.61	0.10
SRD	2	88	2	0.81	1.00	0.61	0.09

Pathway Analysis

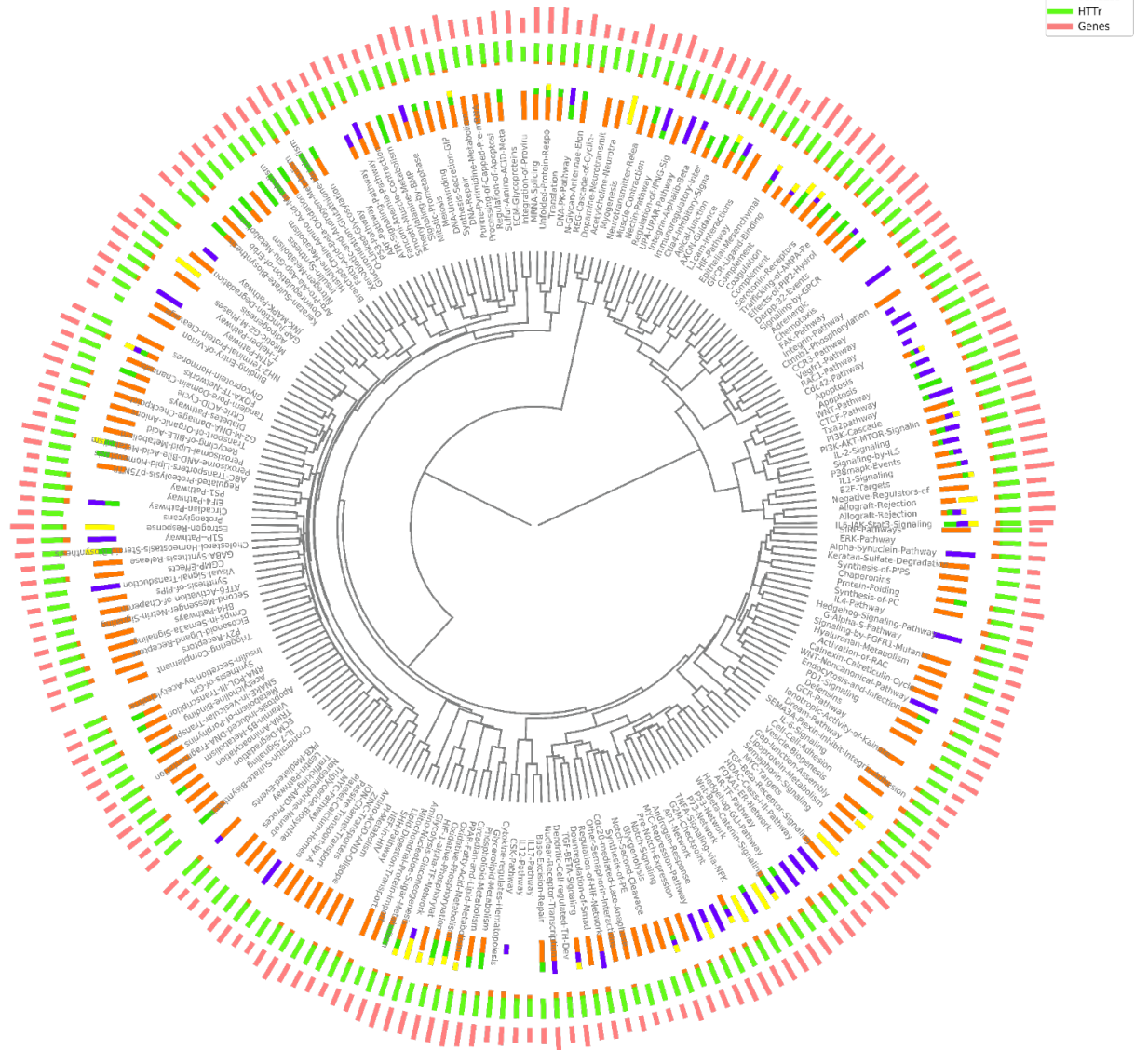
Predicting Tox/MoA via Networks & Pathways

- Transcriptional perturbations of key pathways/interactions predicts Tox/MoA
- Pathway analysis
 - Select DEGs or CRGs to identify enriched pathways
 - Link enriched pathways to Tox/MoA
- Network analysis
 - Select DEGs or CRG to identify critical interactions
 - Link interactions to upstream or downstream targets
- Issues
 - Choice of pathway database
 - Scoring pathway/interaction enrichment
 - How do we objectively evaluate predictive accuracy
 - Effectively using signaling and genetic-regulatory network information
 - Linking pathways/interactions → MoA?



“Super-Pathways”

- Cluster Hallmark and canonical pathways (Reactome, KEGG, PID and BioCarta) from MSigDB V6 using genes
- Use hierarchical agglomerative clustering to organize super-pathways by similarity
- Each clade in the dendrogram shows groups of functionally related pathways
- Concentric rings show information about the source of information, HTTr coverage, and # of genes in each super-pathway



Pathway Analysis

- The HTTr profiles for chemical treatments were searched against 224 super-pathways.
- Pathways were scored using different metrics that used the entire HTTr profile (e.g. enrichment scores), and just DEGs.
- The significance of scores was estimated by simulation.

