



High-Throughput Transcriptomics (HTTr) for Toxicological Testing

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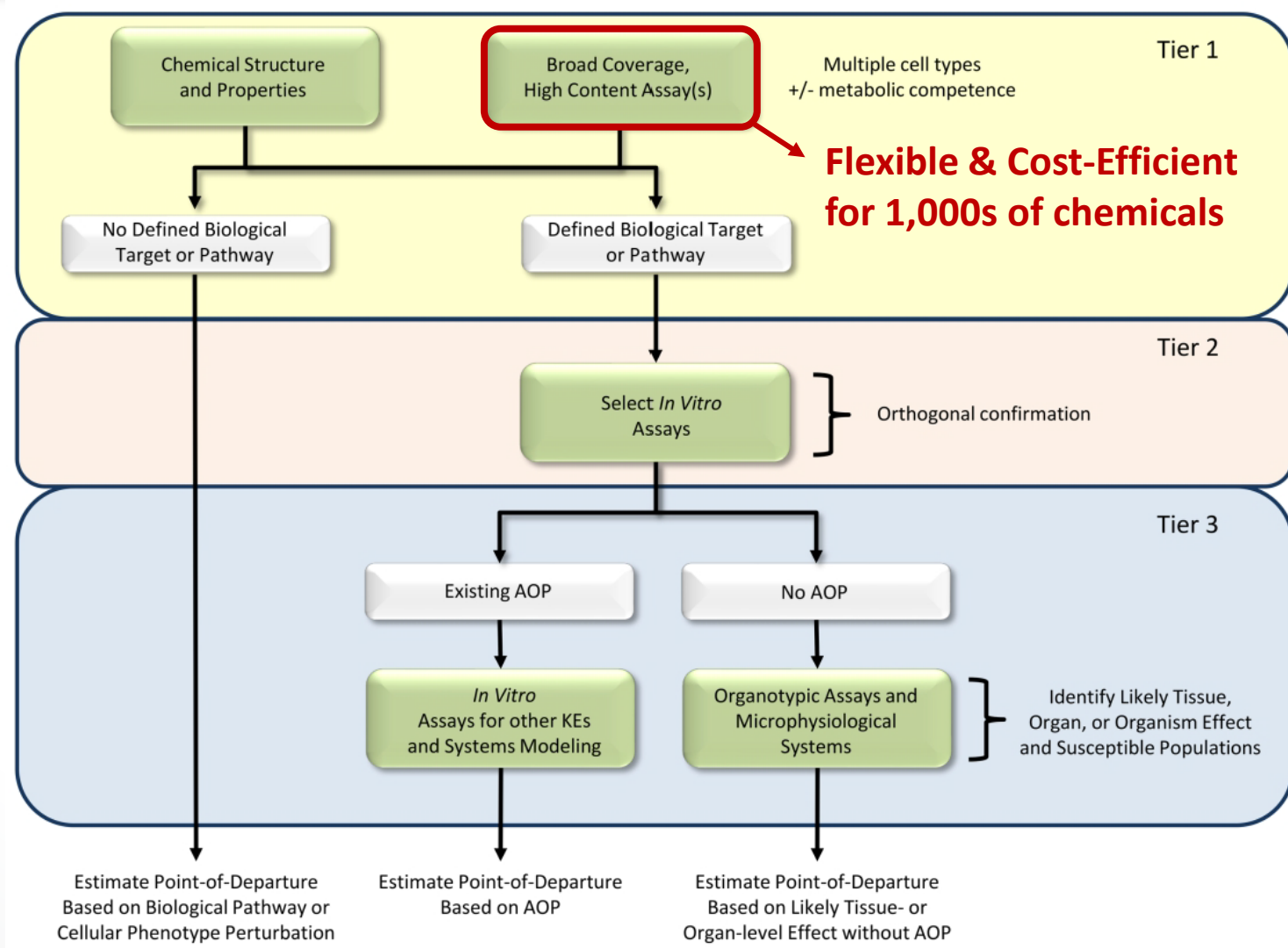
Tiered Chemical Safety Testing Strategy

Tier 1 Primary Goals:

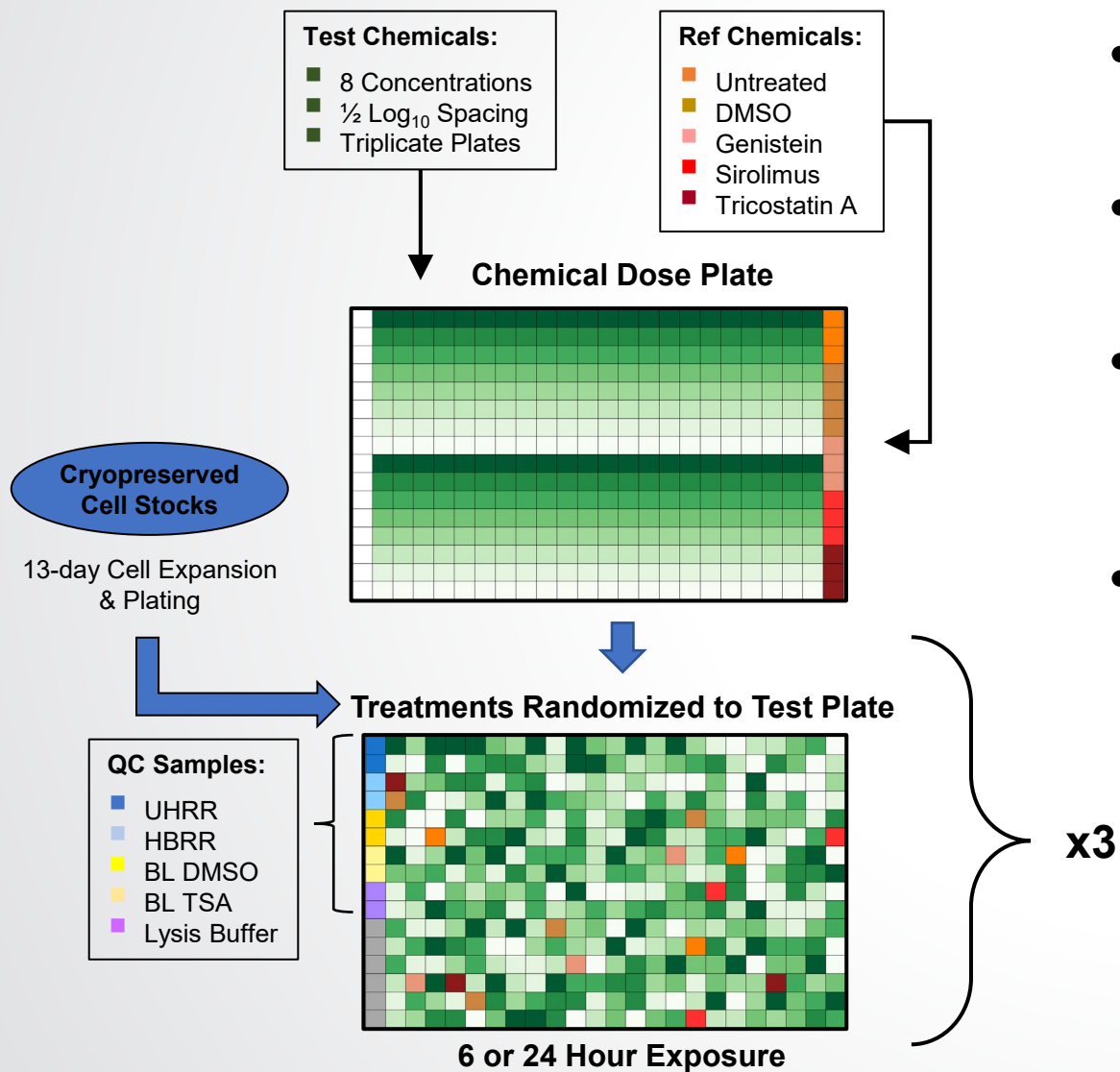
- Prioritize chemicals by bioactivity & potency
- Predict biological targets for chemicals

Key Challenges:

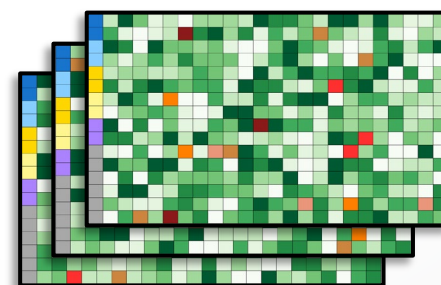
- Curve-fitting on count-based data
- Summarization at pathway/chemical level



HTTr Study Design



- High-throughput *in vitro* screens performed on 384 well plates
- Standardized dilution series for every test sample
- Multiple QC and reference chemicals included on every plate to track assay performance
- Triplicate Test Plates:

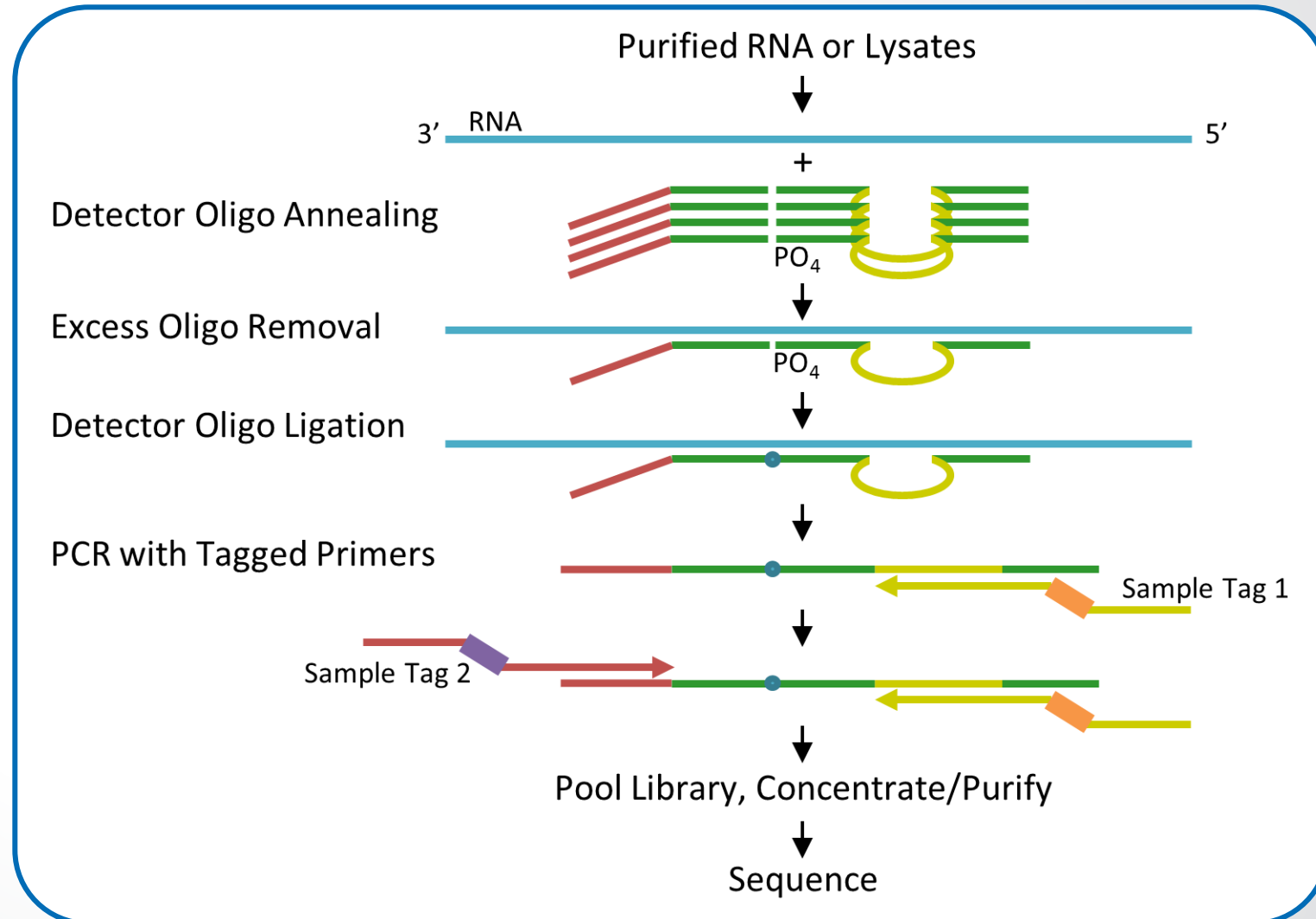


- Randomized independently
- Separate cell culture batches



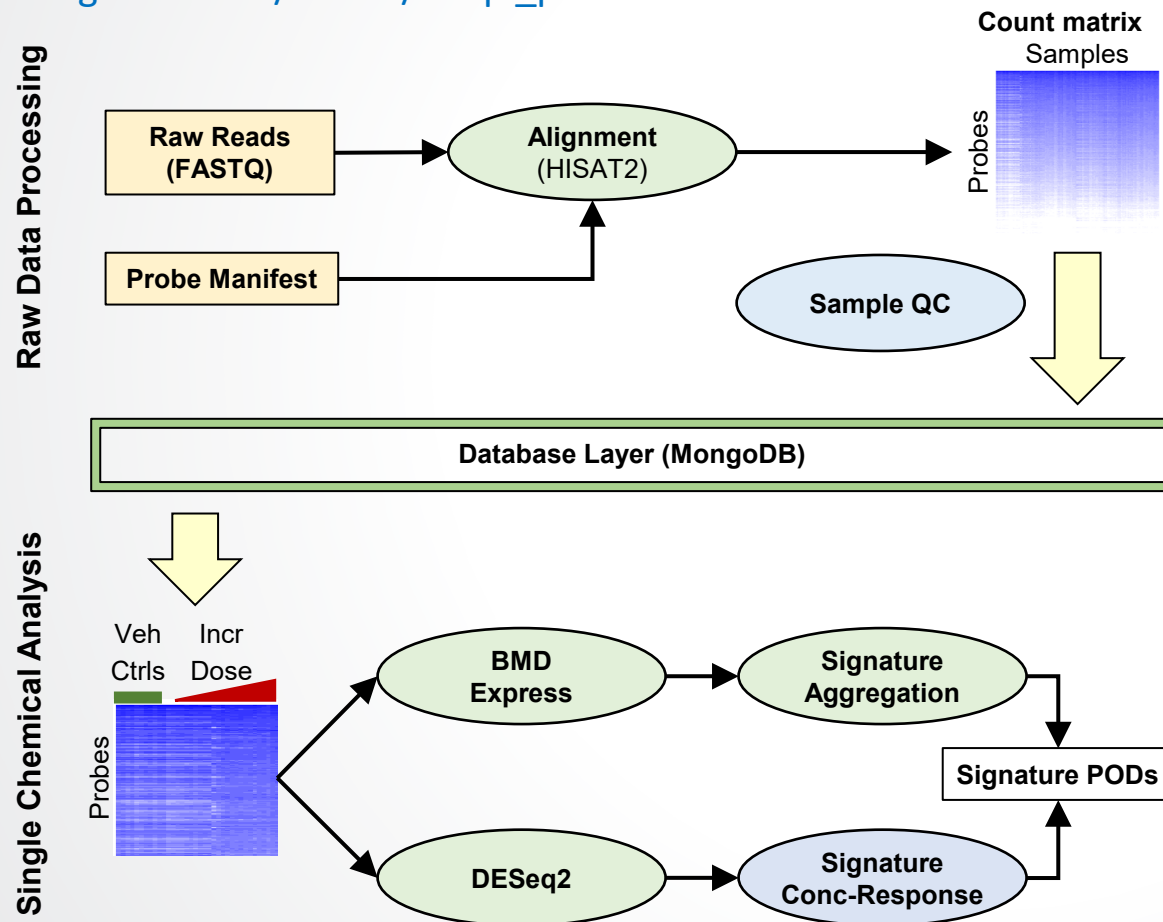
TempO-seq Assay

- Targeted RNA-seq (TempO-seq) enables high-throughput profiling of **cell lysates** or purified RNA
- Probe set for whole human transcriptome targets ~21,000 human genes
- Captures majority of signal with much lower sequencing depth (~3M reads with attenuation)
- Barcoding and pooling allows multiplexing of hundreds of samples



HTTr Bioinformatics Pipeline

github.com/USEPA/httpl_pilot



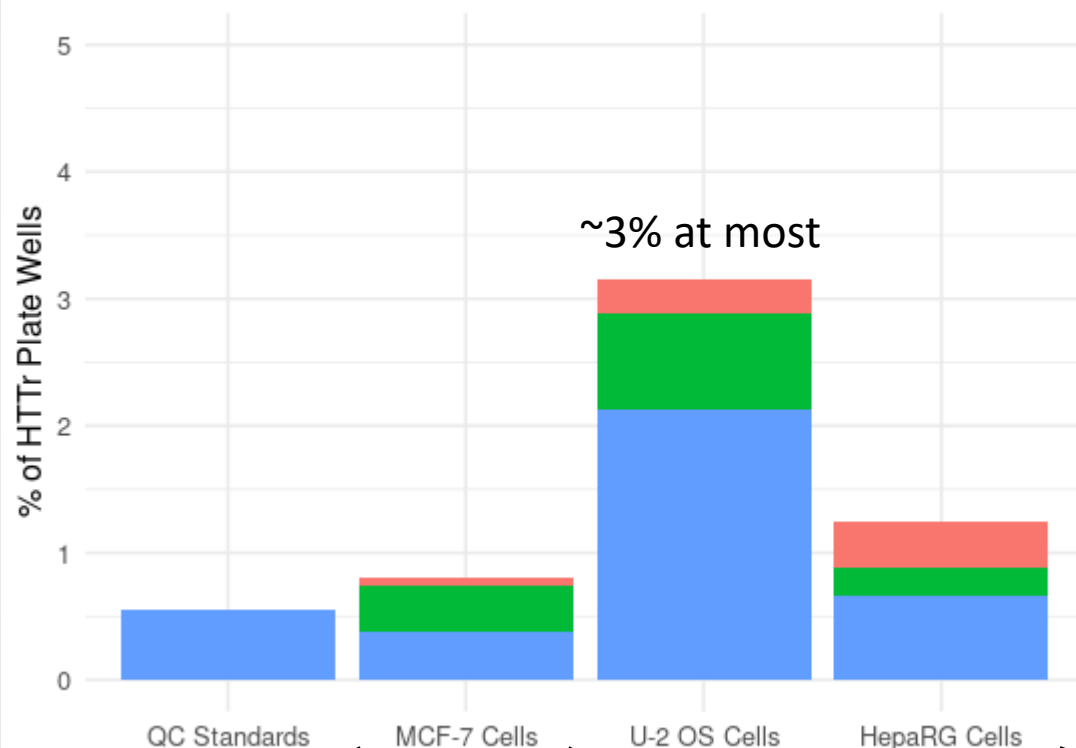
- Rapid processing for large screens
- Many data steps performed independently for each test chemical:
 - Removal of low signal probes
 - Normalization
 - DESeq2 analysis
- Exploring multiple analysis strategies for curve-fitting and signature & chemical-level summarization

github.com/USEPA/CompTox-httrpathway



HTTr Quality Control

QC Failure Rates Across HTTr Screens



~3% at most

QC Issue Type

- Liquid Handling
- Cytotoxicity
- Assay Quality

Acoustic dispenser logs identify problems with chemical handling

Apoptosis/cell viability assays identify >50% cytotoxic concentrations

Bioinformatic QC checks remove:

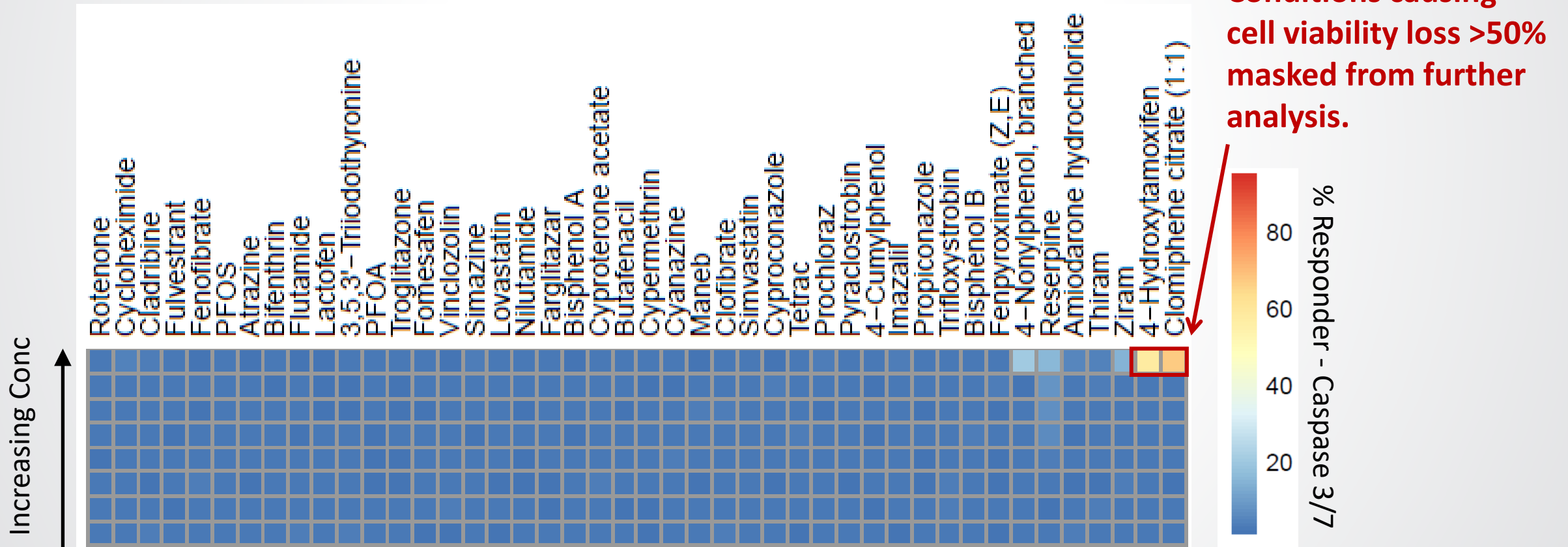
- Low read depth samples
- High rate of alignment failure
- Samples with low gene coverage
- Samples with irregular count distributions

- 44 Chemical Pilot Study
- Screened 1,577 ToxCast chemicals

- Screened 1,201 ToxCast chemicals
- Screened 137 PFAS

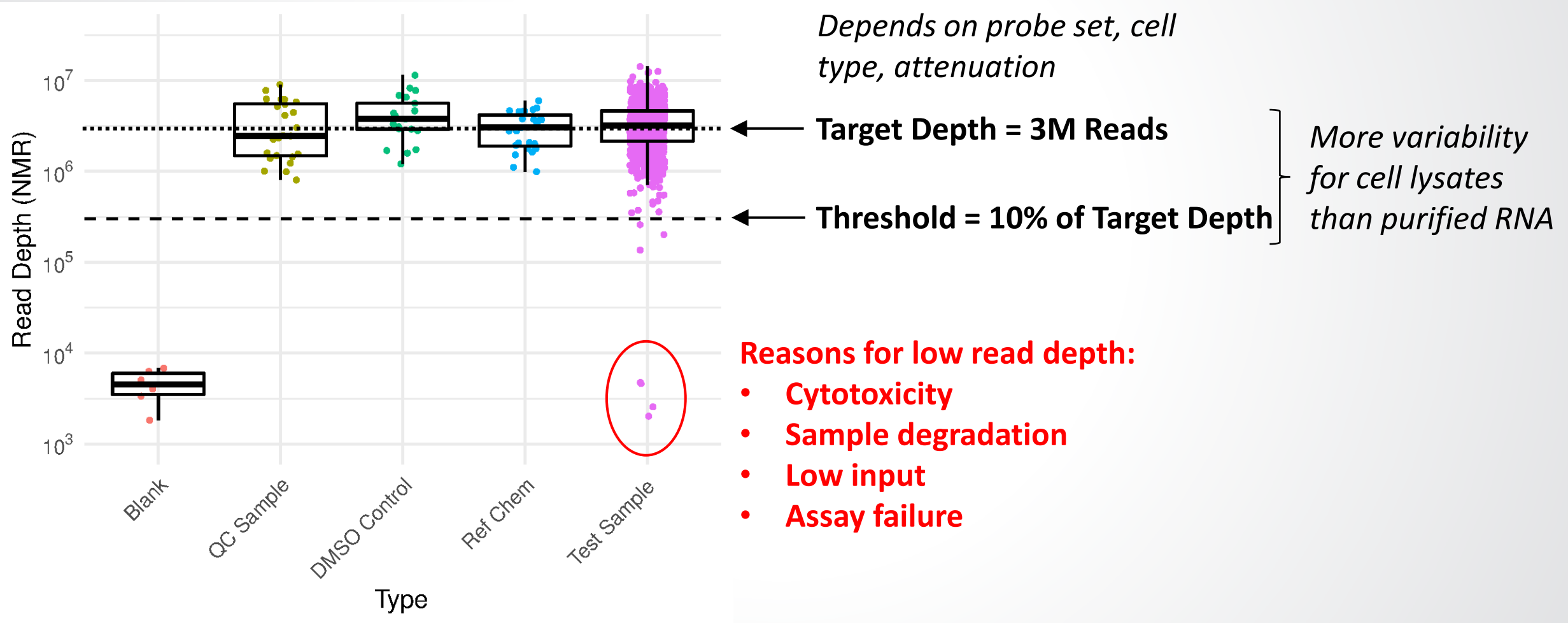


Cell Viability



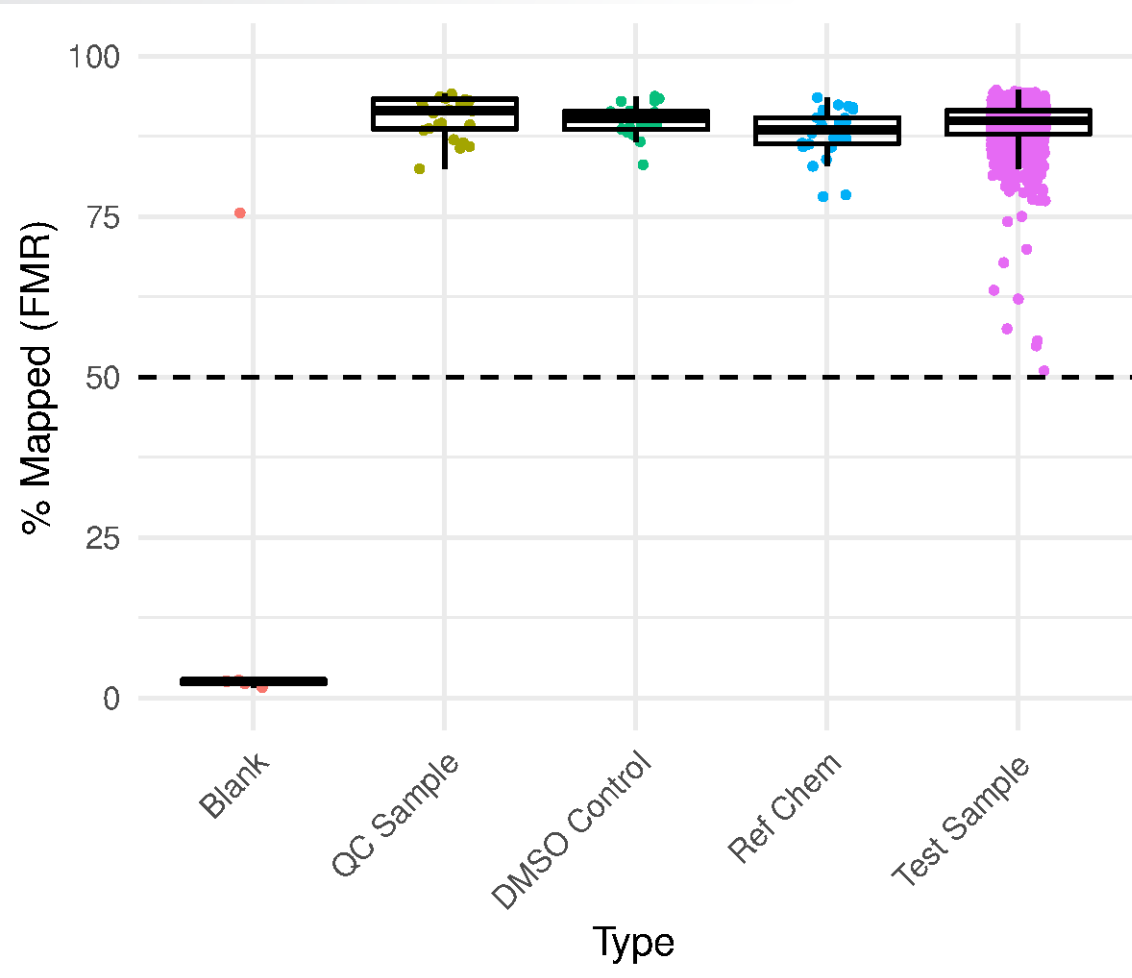


QC Metrics: Read Depth





QC Metrics: Mapping Rate



- Each read mapped to known probe sequences
- Only uniquely mapped reads used for analysis

← **Threshold = 50% Mapping Rate**

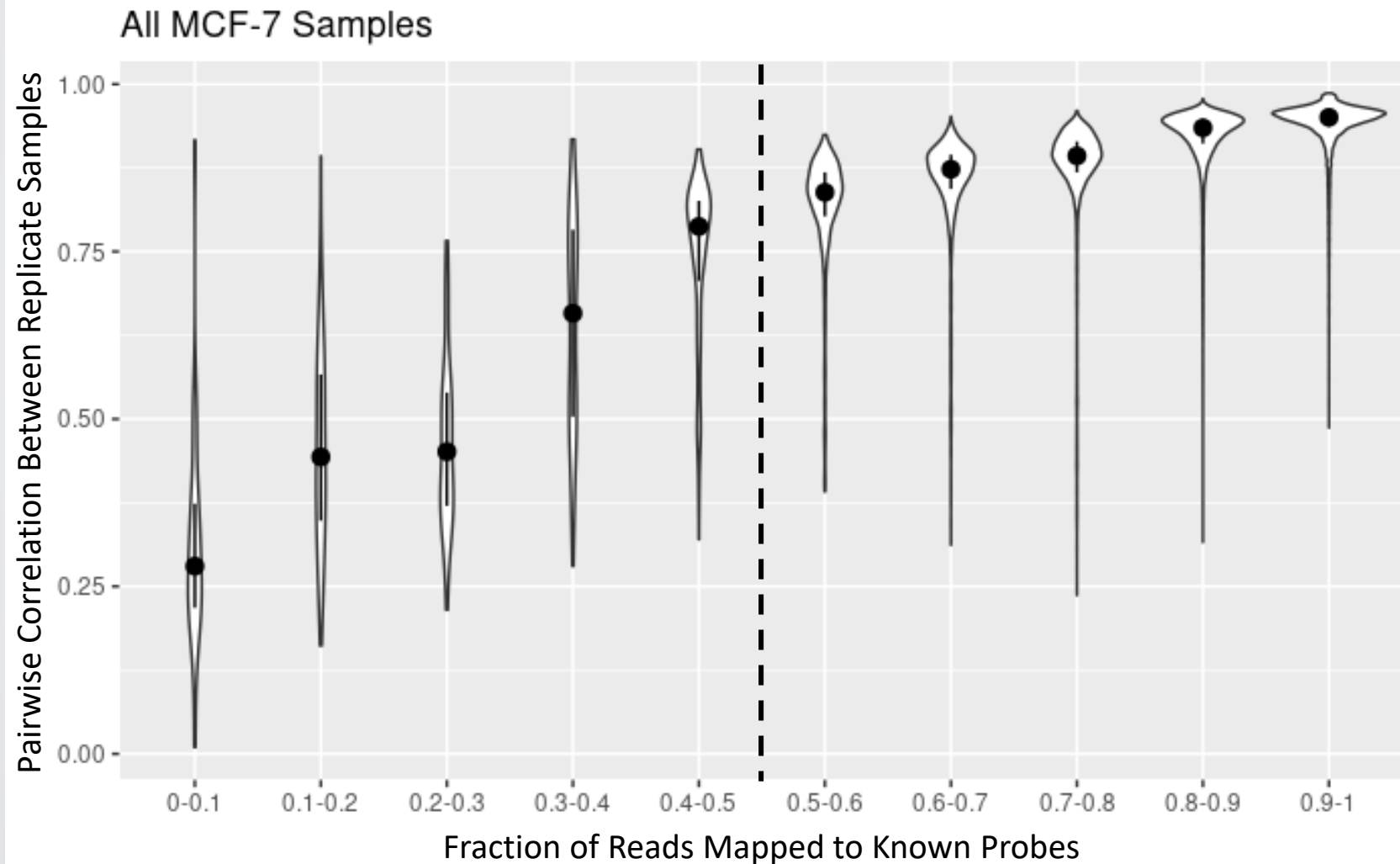
May depend on media/lysate condition, cell type

Reasons for low mapping rate:

- **Cytotoxicity**
- **Sample degradation**
- **Low input**
- **Assay failure**



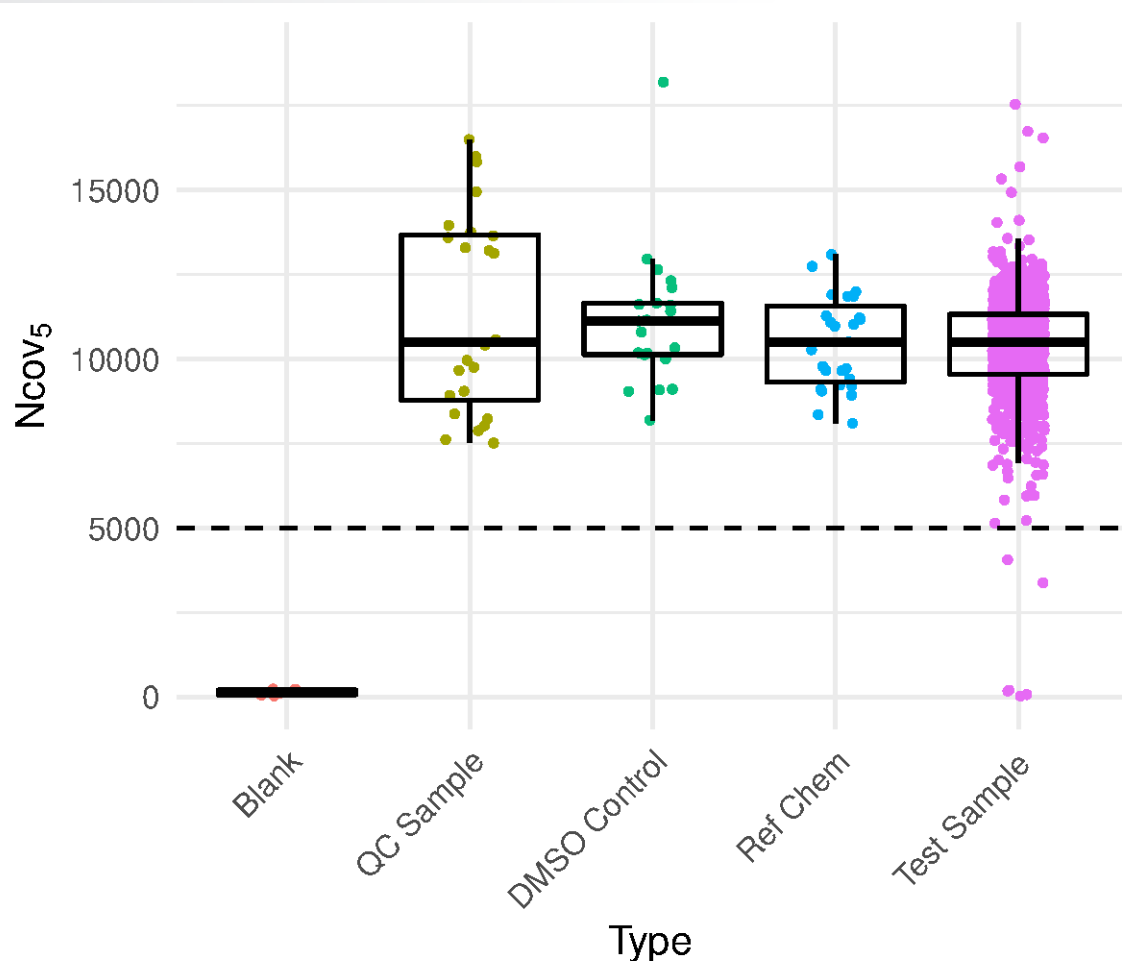
QC Metrics: Mapping Rate



- Replicate correlation drops off when <50% of reads mapped uniquely to probe sequences
- Lower mapping rate leads to lower depth
- May also indicate sample quality issues (e.g. RNA degradation or incomplete cell lysis)



QC Metrics: Transcriptome Coverage



Ncov₅ = # of probes with at least 5 reads

Threshold = 5,000 Probes (MCF-7)

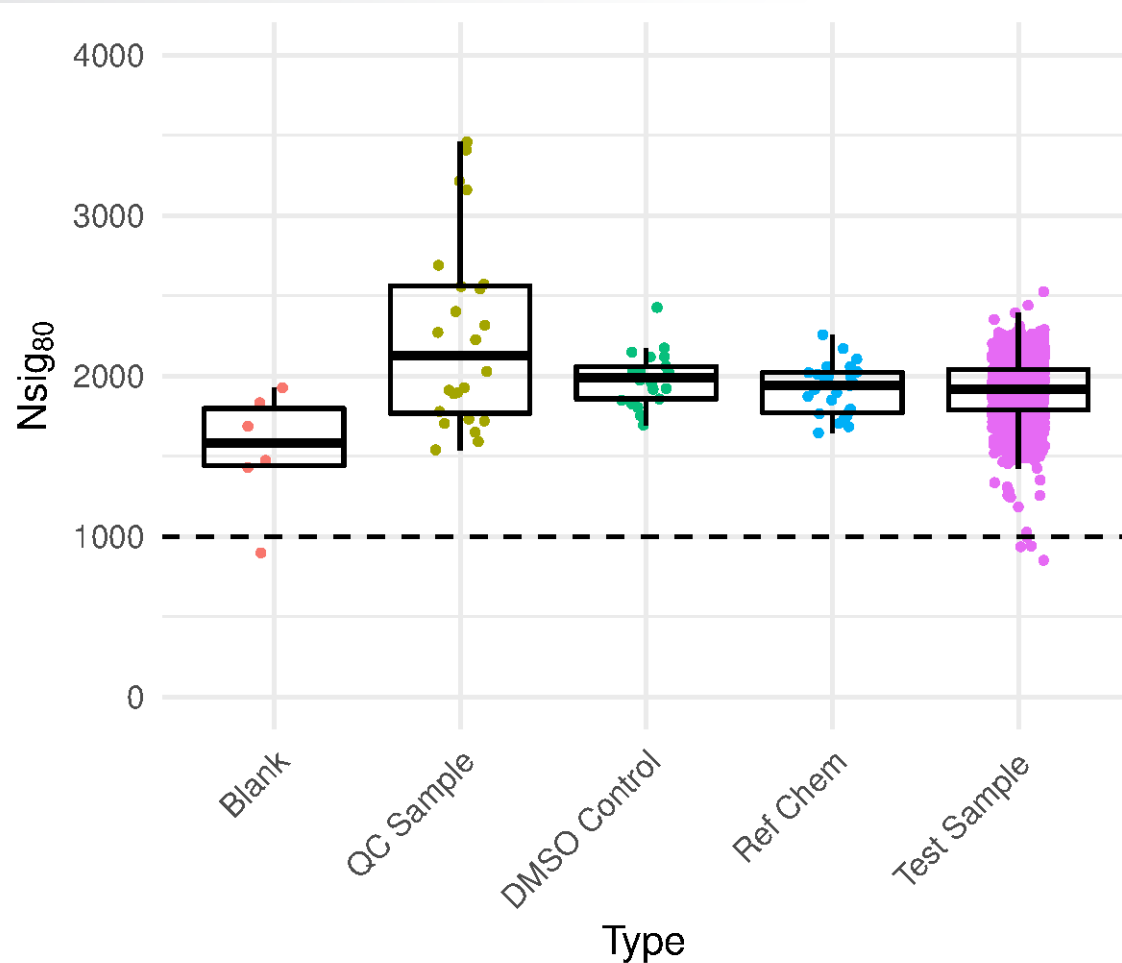
*Based on “outer fence” principle (Tukey, 1976),
Re-evaluated on new cell types, probe sets,
and attenuation strategies*

Reasons for low coverage samples:

- Low read depth
- Sample degradation
- Low input
- Assay failure



QC Metrics: Signal Distribution



- $N_{sig_{80}}$ = # of probes capturing top 80% of signal
- Low values = reads highly concentrated among small number of probes

Threshold = 1,000 Probes (MCF-7)

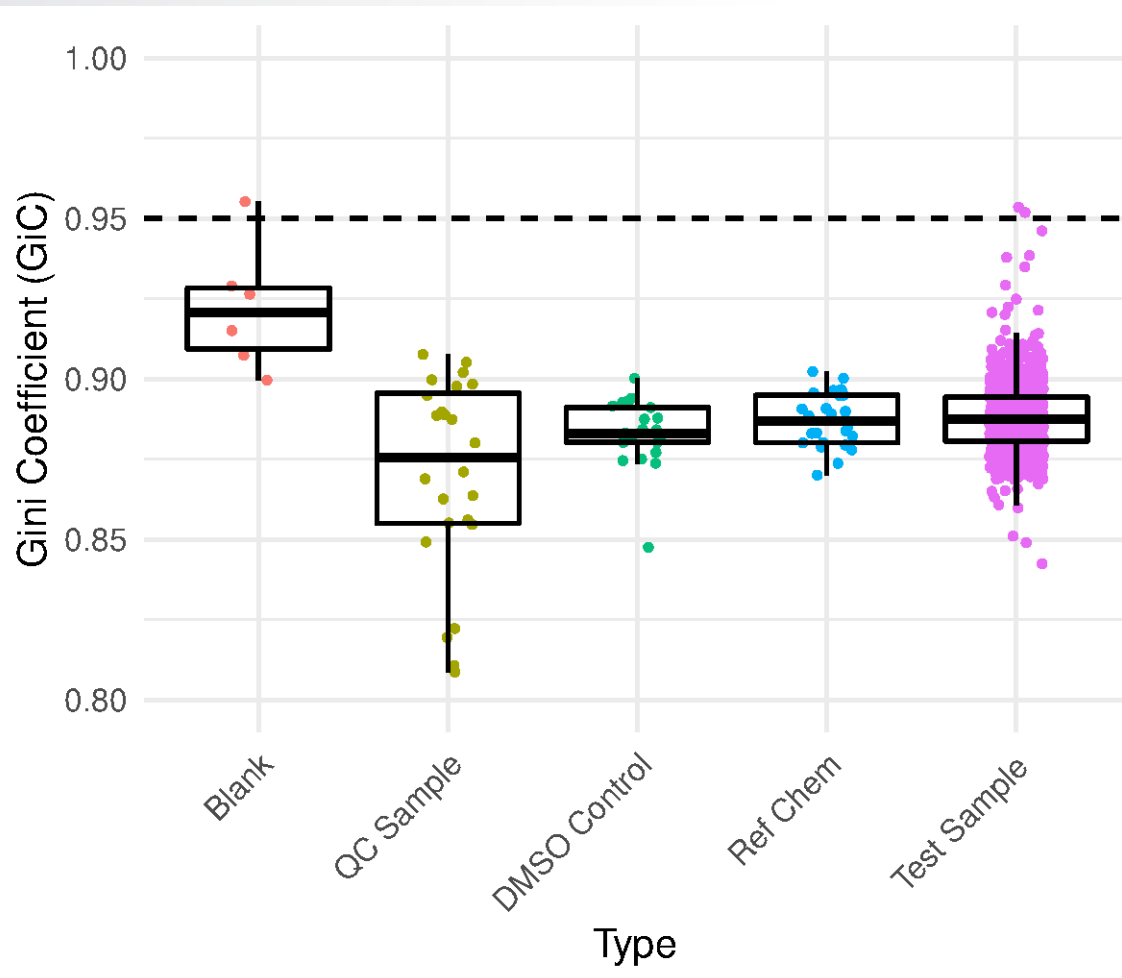
Based on “outer fence” principle (Tukey, 1976)
Should be re-evaluated on new cell types, probe sets, and attenuation strategies

Reasons for low values:

- Sample degradation
- Low input
- Assay failure



QC Metrics: Signal Distribution



Reasons for high values:

- Sample degradation
- Low input

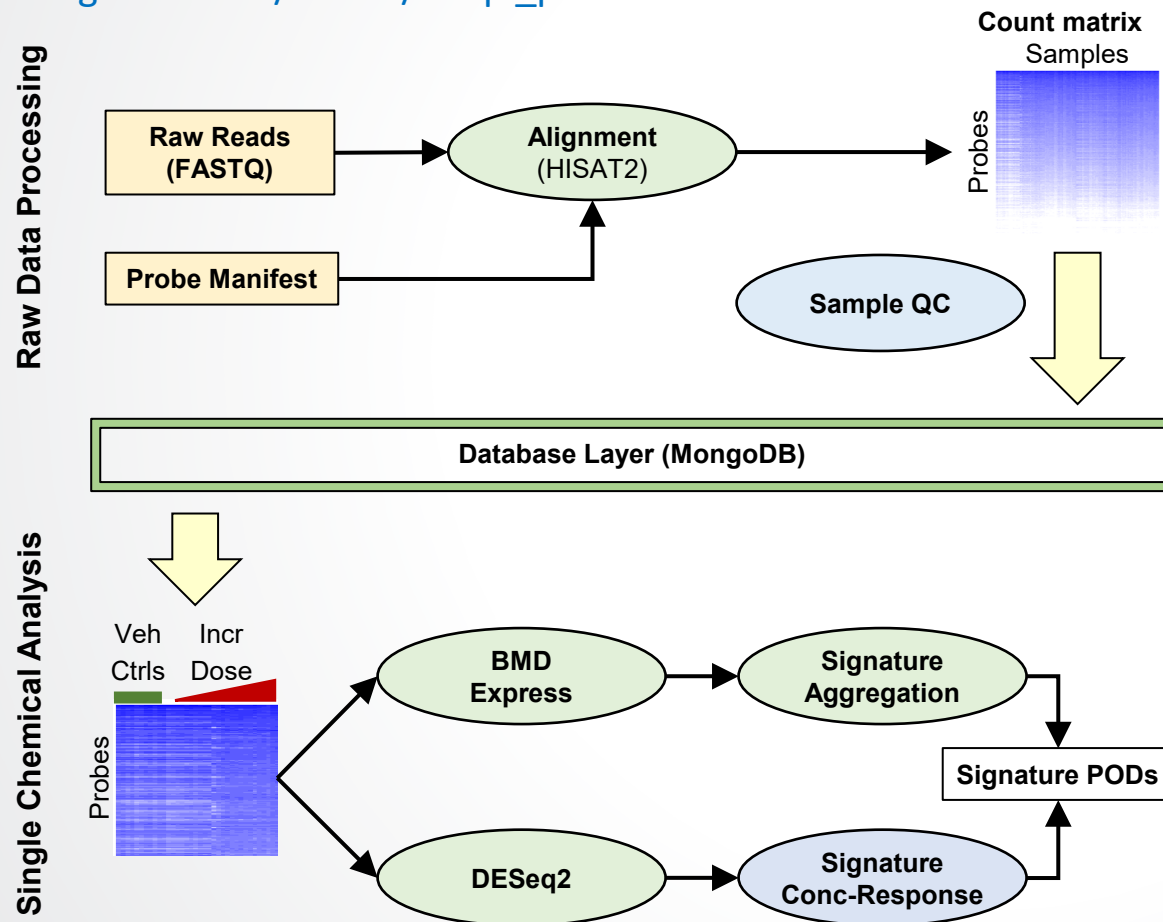
Threshold = 0.95

*Based on “outer fence” principle (Tukey, 1976)
Should be re-evaluated on new cell types, probe sets, and attenuation strategies*

- Gini coefficient = measure of inequality or skewness in a distribution
- High values = most reads coming from few probes (Max 1: All reads from 1 probe)
- Lower values = closer to uniform distribution of reads across all probes (Min 0, not expected for expression data)
- Expect samples from same cell type to be similar

HTTr Bioinformatics Pipeline

github.com/USEPA/httpl_pilot



- Rapid processing for large screens
- Many data steps performed independently for each test chemical:
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github.com/USEPA/CompTox-httrpathway

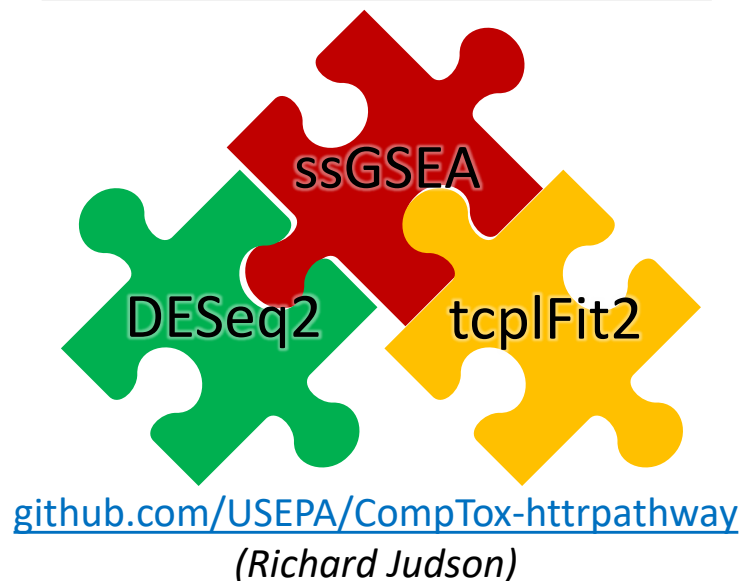


3 Flavors of Bioinformatic Approaches

Gene-First Approaches

- BMDExpress (NTP)
- tcplFit2 (CCTE)
- BIFROST (Unilever)

Signature Conc-Response



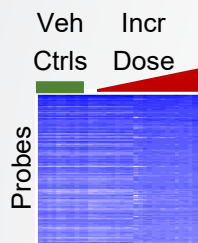
Latent Variable Methods

- Many possible tools, e.g. PLIER, WGCNA
- Identify latent variables in data that capture primary response patterns
- Annotate biological relevance of LVs by gene components
- Perform curve-fitting on LVs
 - Fewer features to fit
 - Compatible with BMDExpress & tcplFit2

Improved integration through HTTr pipeline & database development

Signature Scoring

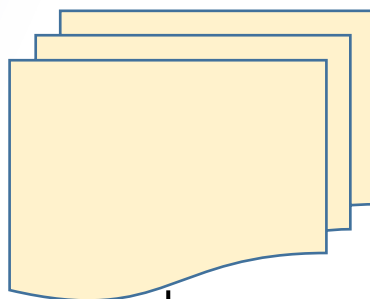
Count data
per chemical



DESeq2

ssGSEA

Catalog of signatures with toxicological relevance,
annotated for known molecular targets



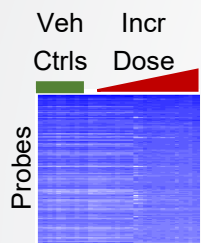
- **Bioplanet** (*Huang, et al. Front Pharmacol 2019*)
- **CMap** (*Subramanian, et al. Cell 2017*)
- **DisGeNET** (*Pinero, et al. Database 2015*)
- **MSigDB** (*Liberzon, et al. Cell Syst 2015*)

Single-Sample Gene Set Enrichment Analysis (ssGSEA) (*Barbie, et al. Nature 2009*)

- Score coordinated responses at each concentration
- Use moderated log2 FC values from DESeq2 as input (no thresholds)
- Null distributions constructed by resampling log2 FC values from whole screen
- Alternate scoring function:
 $\text{mean}(\text{gene set log2FC}) - \text{mean}(\text{background log2FC})$

Signature Scoring

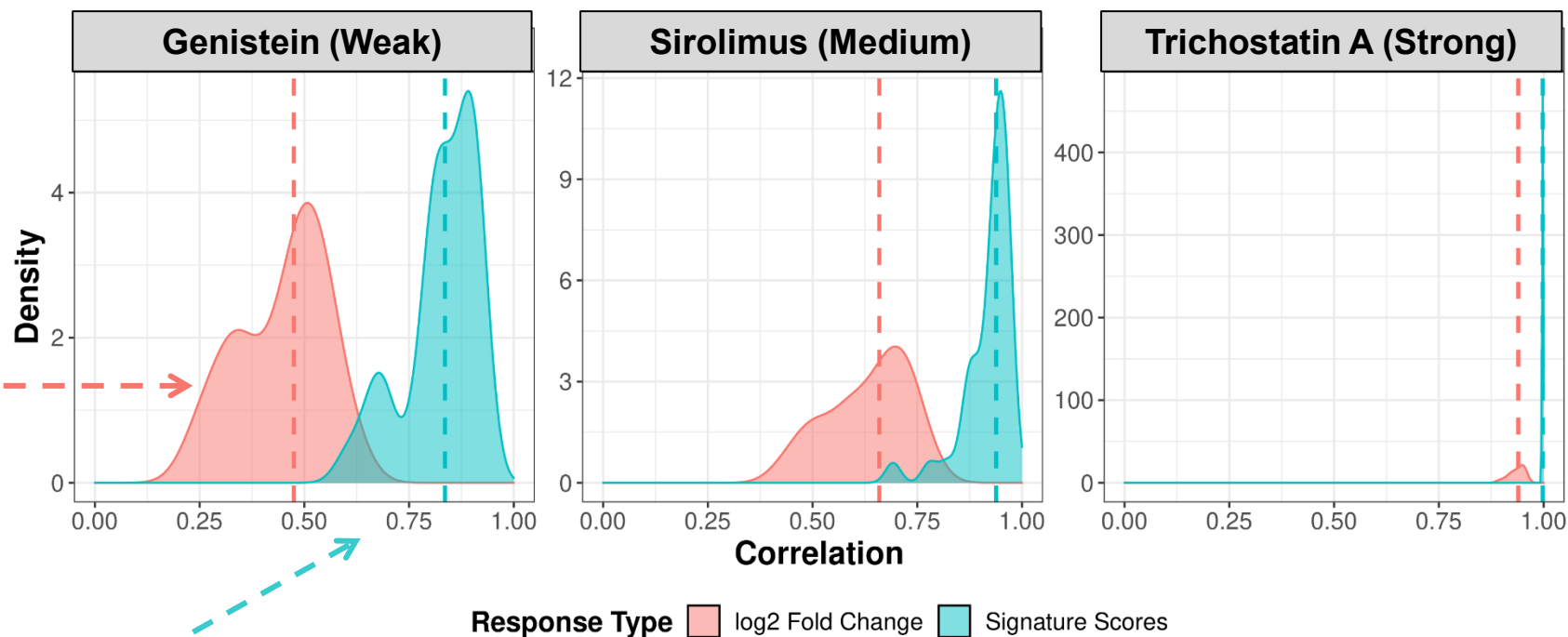
Count data
per chemical



DESeq2

ssGSEA

Reference Chemical (Effect Size)

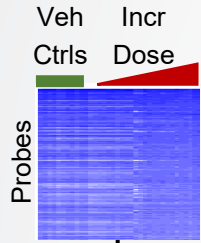


- Differential expression analysis of 3 reference chemicals replicated 37 times (MCF-7 large screen)
- Computed distribution of correlations between each replicate analysis
- **Signature scores have higher reproducibility than fold-changes, especially for weaker effect sizes**



Signature Scoring

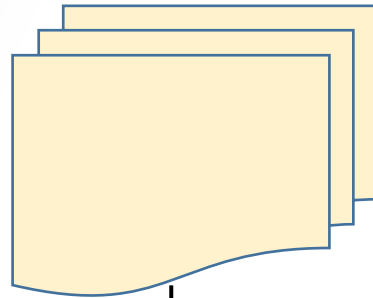
Count data
per chemical



DESeq2

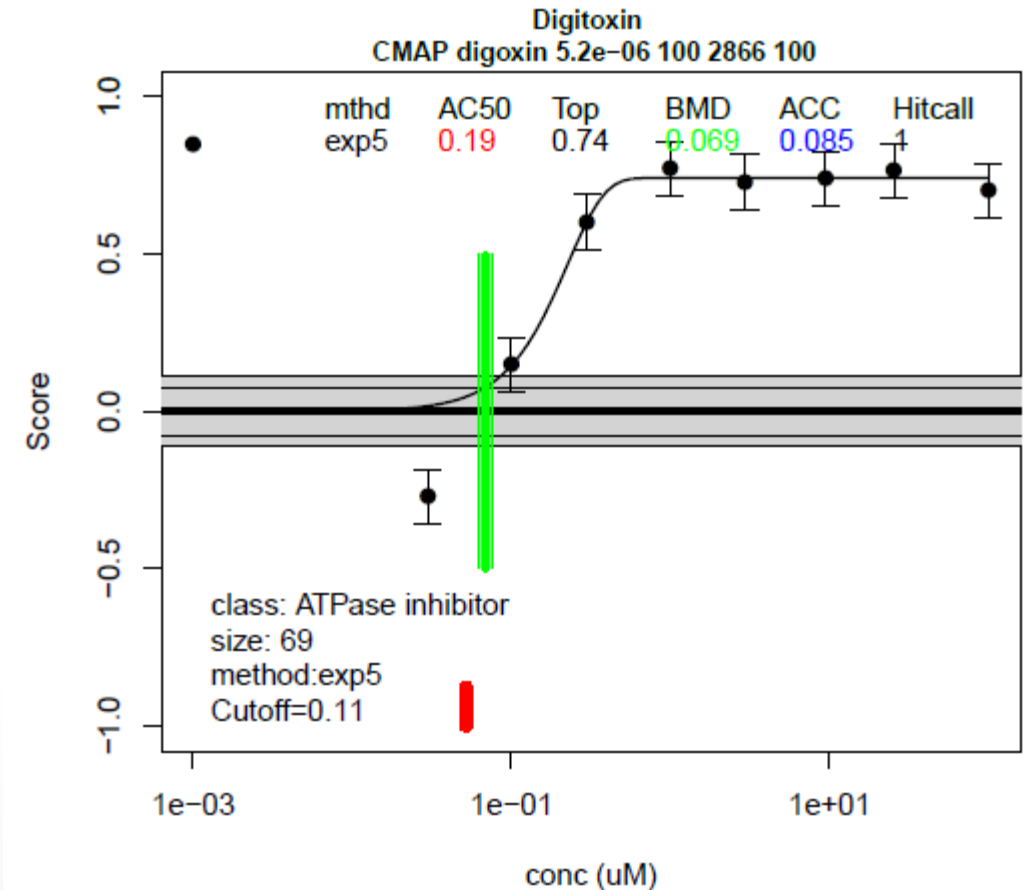
ssGSEA

Catalog of signatures with toxicological relevance,
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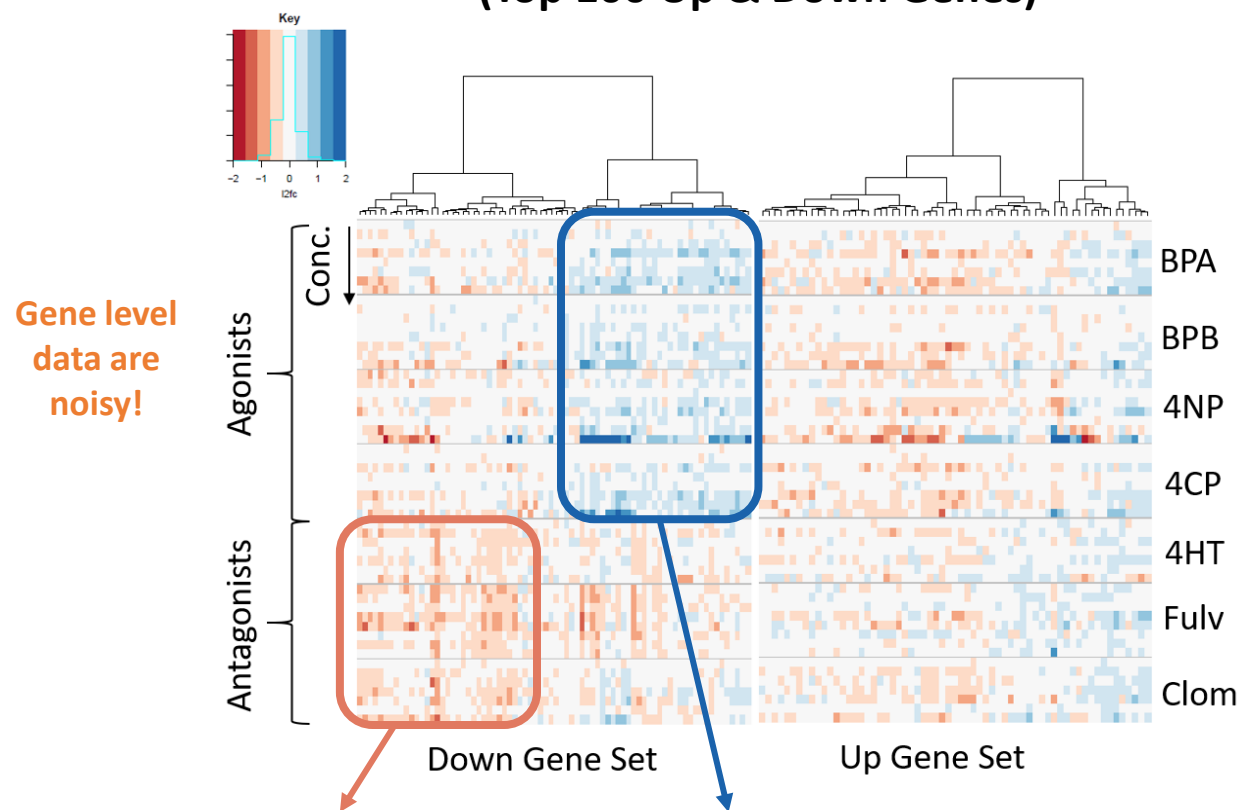
Concentration-Response
Curve Fitting (*tcpIFit2*)

Richard Judson



Directionality of Signature Scores

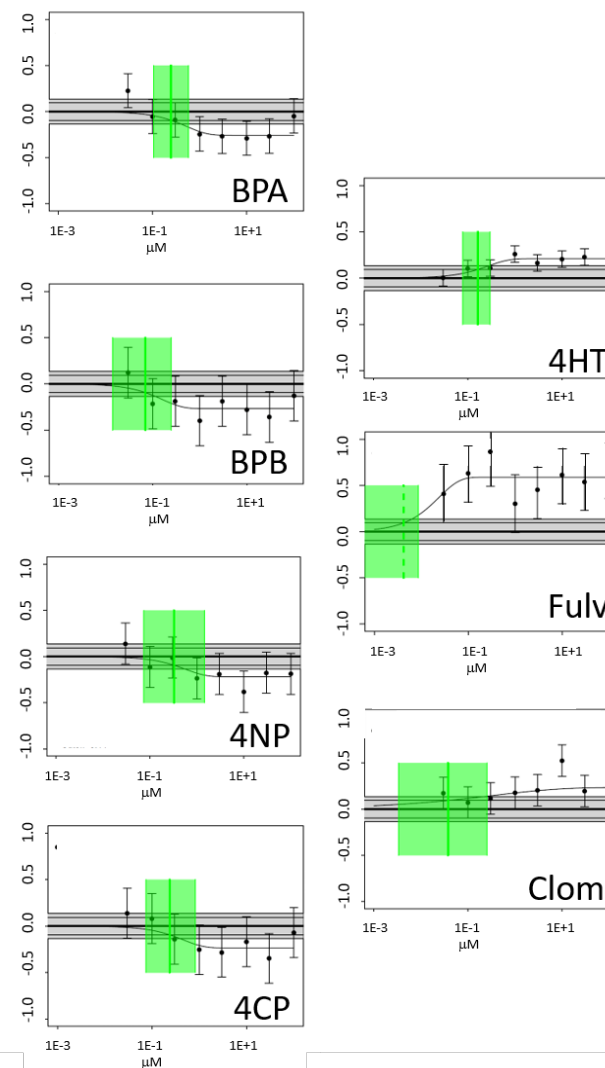
**Fulvestrant Signature from CMap
(Top 100 Up & Down Genes)**



Gene level data are noisy!

The expression of some fulvestrant signature "down" genes goes down following ER antagonist treatment

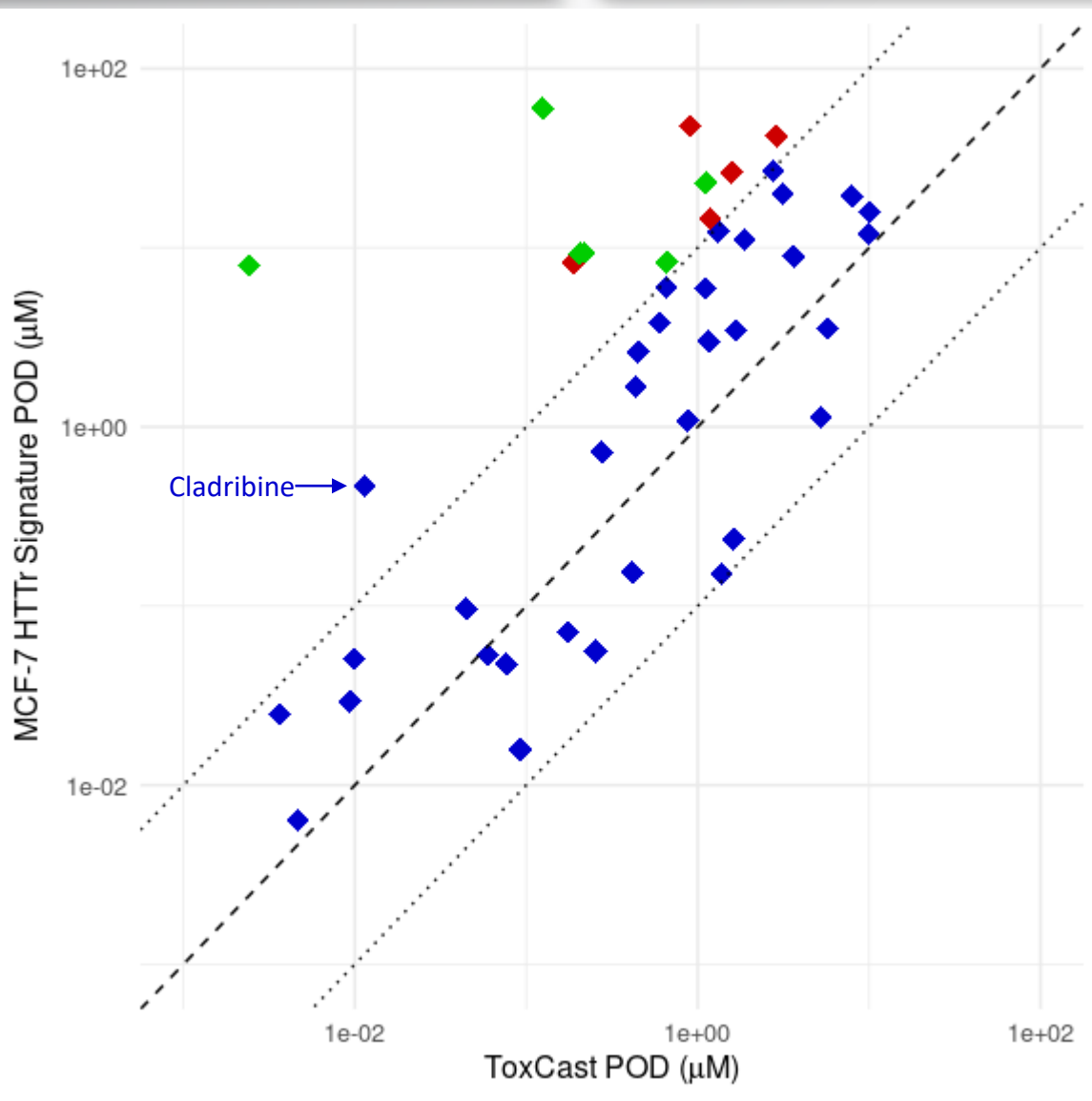
The expression of some fulvestrant signature "down" genes goes up following ER agonist treatment



Signature level results display correct directionality!



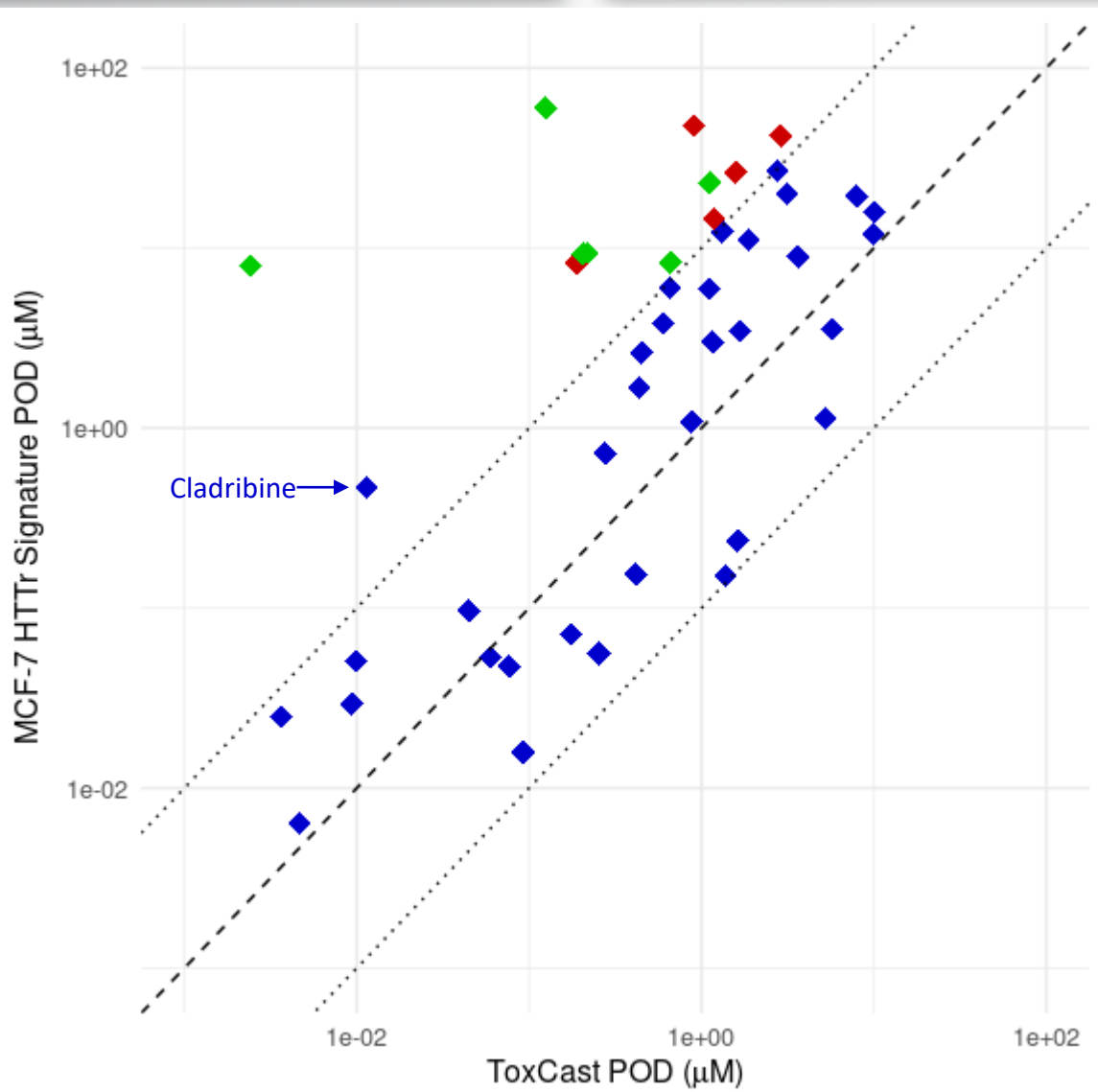
HTTr MCF-7 Pilot Analysis



- Pilot study of 44 well-characterized chemicals in MCF-7 cells, 6h exposure (*Harrill, et al. Toxicol Sci, 2021*)
- Compared HTTr-derived PODs to previous ToxCast HTS assay results (*multiple cell types, assays, and exposure lengths*) (*Paul-Friedman, et al. Toxicol Sci 2020*)
- Signature-based POD are highly concordant with ToxCast results for the majority of test chemicals in pilot study



HTTr MCF-7 Pilot Analysis



- 6 chemicals with targets that have low/absent expression in MCF-7 cells
 - 3,5,3'-triiodothyronine (Thyroid Receptor)
 - Cyproconazole (pan-CYP inhibitor)
 - Butafenacil (pan-CYP inhibitor)
 - Prochloraz (pan-CYP inhibitor)
 - Imazalil (pan-CYP inhibitor)
 - Propiconazole (pan-CYP inhibitor)
- 5 chemicals where most potent assays in ToxCast do not match known target(s)
 - Lovastatin
 - Clofibrate
 - Maneb
 - Lactofen
 - Vinclozolin
- Cladribine (2-chloro-2'-deoxyadenosine) is a DNA synthesis inhibitor
- All other PODs within 1 order of magnitude



Conclusions

- EPA/ORD has developed reliable and cost-efficient workflow for generating HTTr data from thousands of chemicals across multiple cell lines
- Preliminary/pilot analysis demonstrates that overall results are concordant with previous assays (ToxCast/HTS) and known chemical targets
Harrill, et al. Toxicol Sci 2021
- Ongoing research efforts focused on:
 - Methods to summarize signature-level/overall PODs from high-dimensional data
 - Inference of underlying mechanism (e.g. Connectivity Mapping)
 - Comparative evaluation of methods on simulated/synthetic conc-response data



Acknowledgements

Questions?

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Bryant Chambers

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Clinton Willis

Thomas Sheffield

CCTE Leadership

Rusty Thomas

Sid Hunter

Andrew Watkins

John Cowden

Kimberly Slentz-Kesler



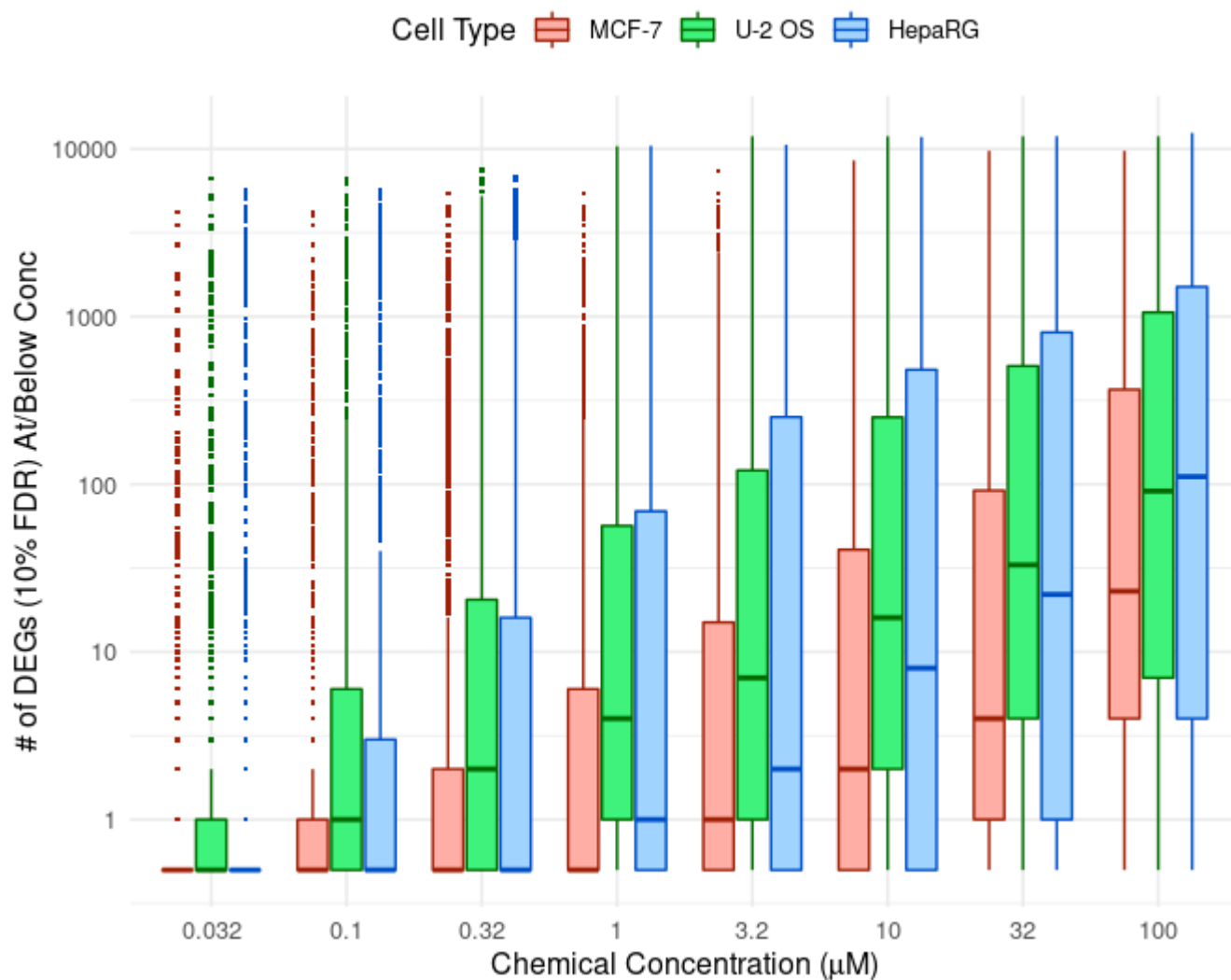
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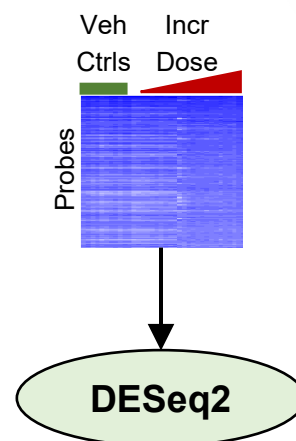


Global View of Bioactivity

Differential Expression per Chemical



Count data for single chemical
(vehicle controls + 8 concs x 3 reps)



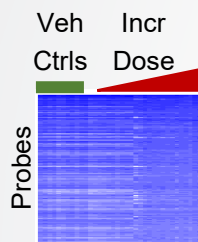
- Statistical model tailored to *-seq data
- Remove plate-level effects
- Smooths noise across depth & expression levels

(Love, et al. *Genome Biol* 2014)

- Each boxplot shows distribution of Differentially Expressed Gene (DEG) count per chemical
- **Primarily interested in transcriptional changes that:**
 - Are coordinated across known pathways/gene sets
 - Fit standard curve-models across all concentrations

Signature Scoring

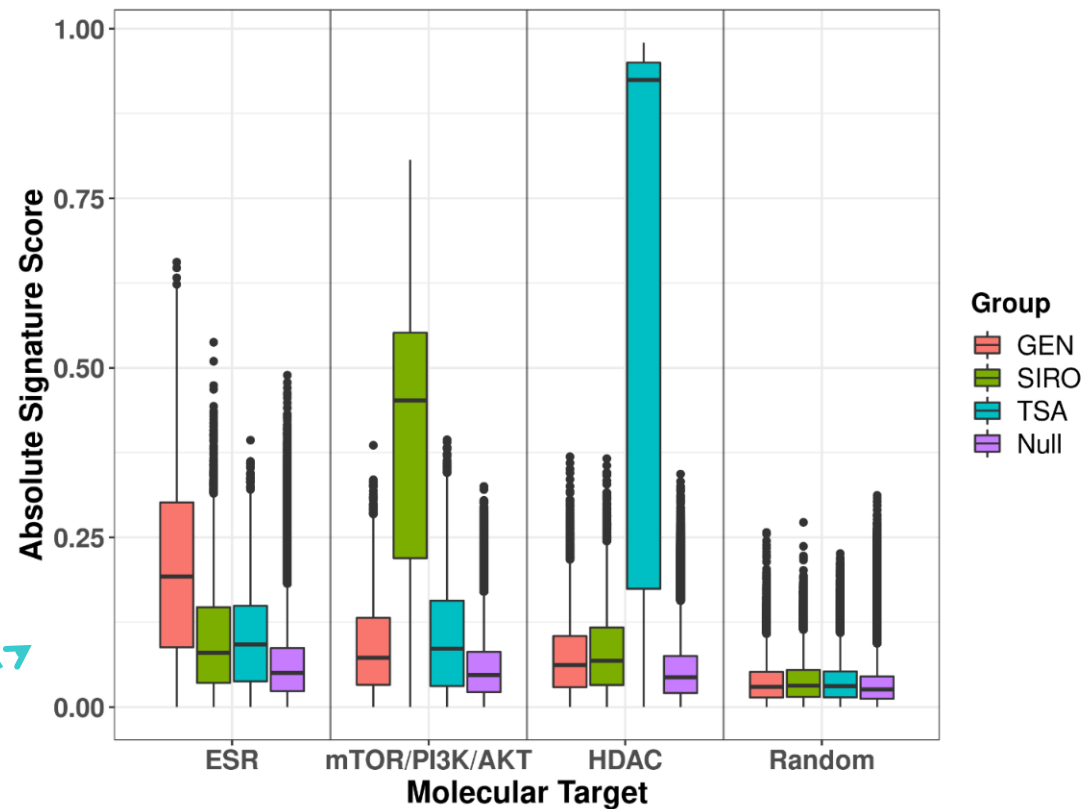
Count data
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DESeq2

ssGSEA

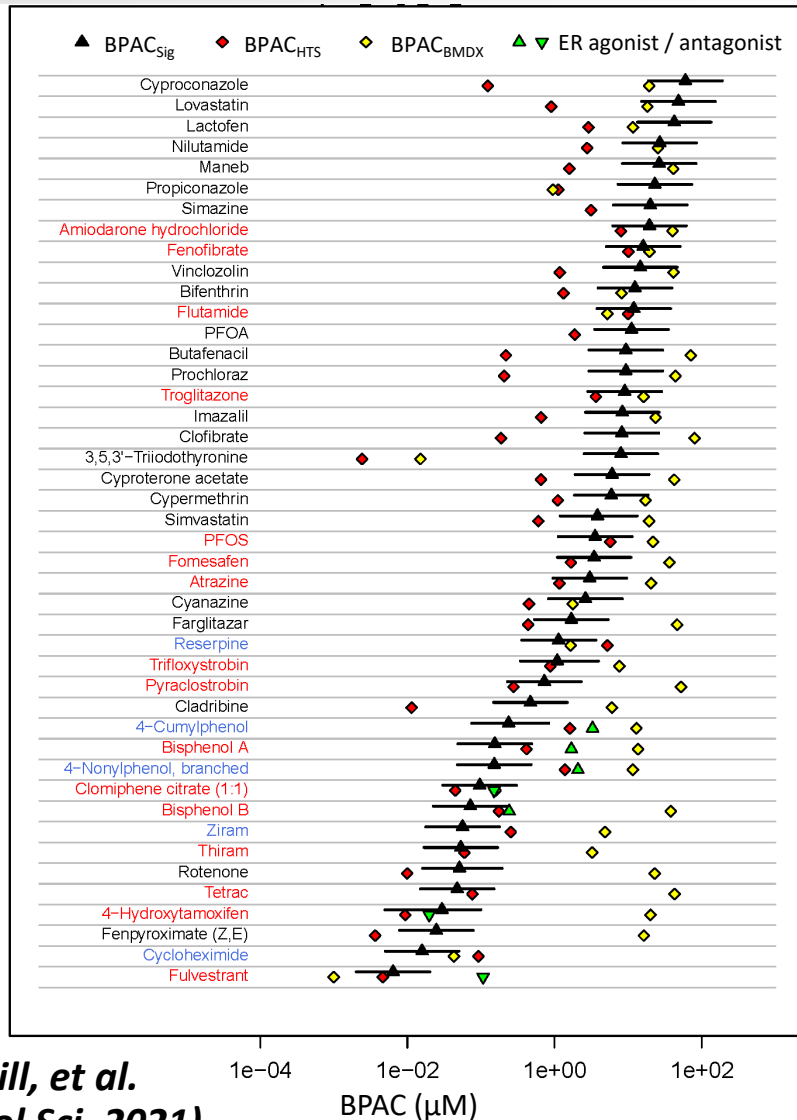
Reference Chemical Signature Specificity



- Higher scores for signatures corresponding to known targets of each reference chemical



HTTr MCF-7 Pilot Analysis

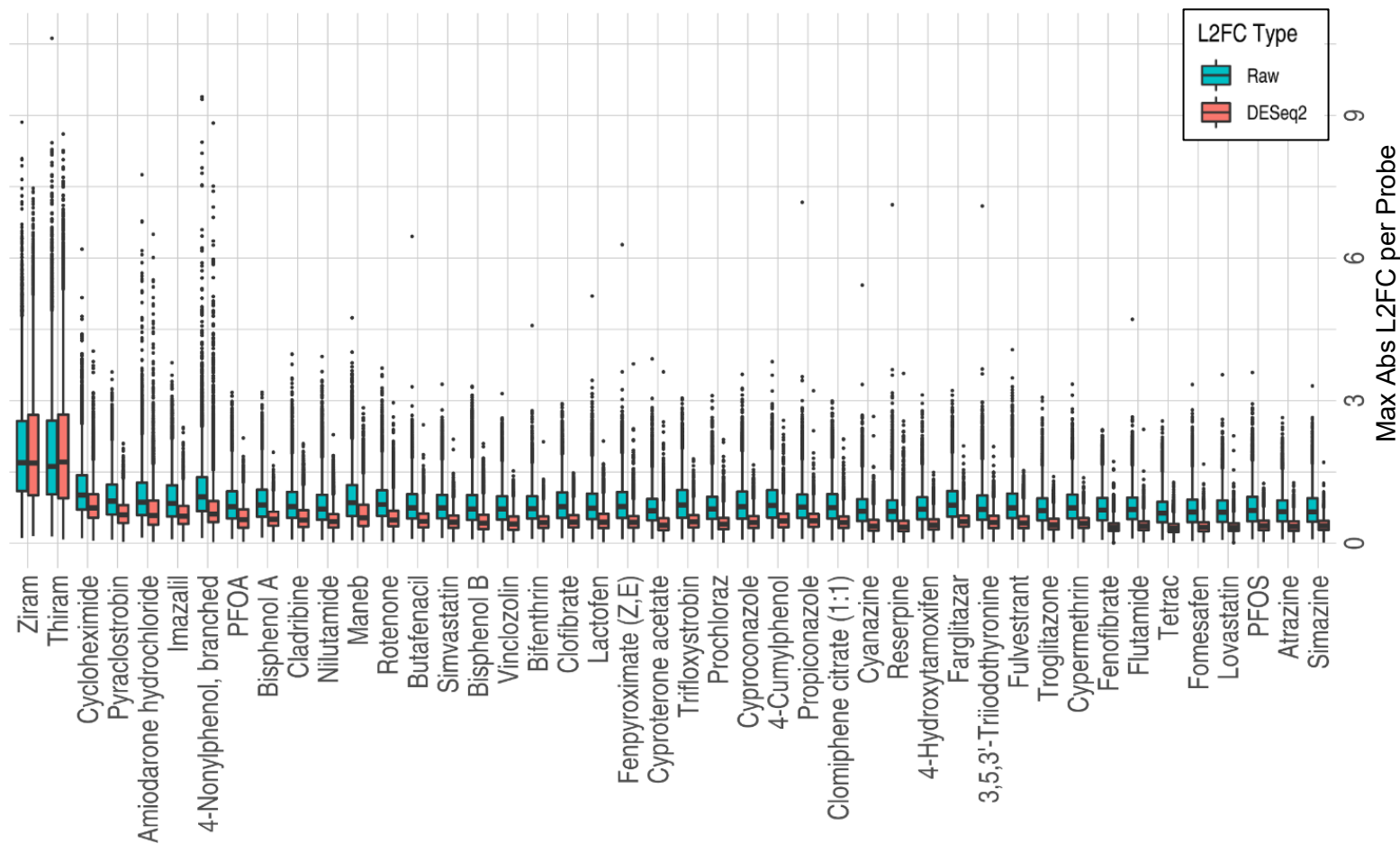


(Harrill, et al.
Toxicol Sci, 2021)

- Also calculated BPAC/PODs using NTP approach with BMDExpress2
(*NTP Research Report 5, 2018; Phillips, et al. 2019*)
- BPAC_{BMDX} (◆) tended to be higher and less concordant with ToxCast PODs
 - Poor signal:noise at gene-level is likely cause
- ***We continue to use BMDExpress for other transcriptomics applications and continue to explore this issue***



HTTr MCF-7 Pilot Analysis



- Majority of differential expression is weak (2-4x) for most chemical treatments
 - DESeq2 dampens these further in most cases
- Consistent with previous studies using MCF-7 cells
- Lower effect size results in lower signal:noise
- Signature-level scores (e.g. GSEA) may perform better than probe-level when this is the case

“Fingerprinting” bioactivity via gene signatures

