

Gene expression biomarkers as tools to interpret high-throughput transcriptomics data streams

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Research Triangle Park, NC**

**Scitovation
Durham, NC
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Disclaimer

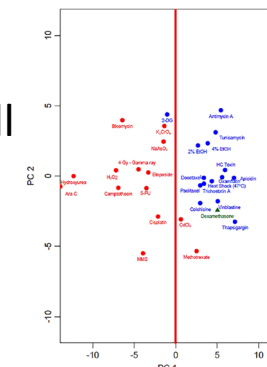
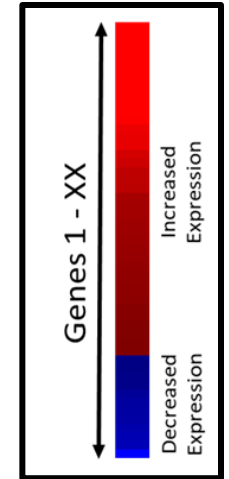
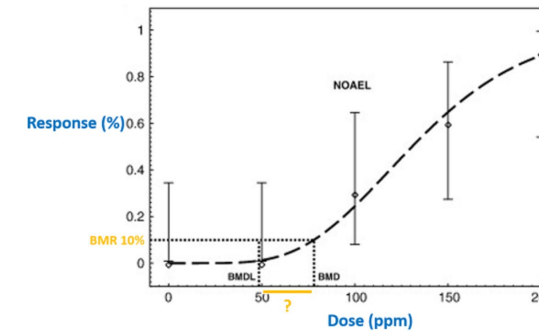
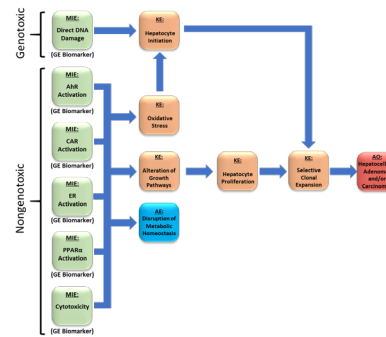
- The views expressed are those of Dr. Chris Corton and do not reflect US-EPA policy or product endorsement by the US-EPA.

Outline

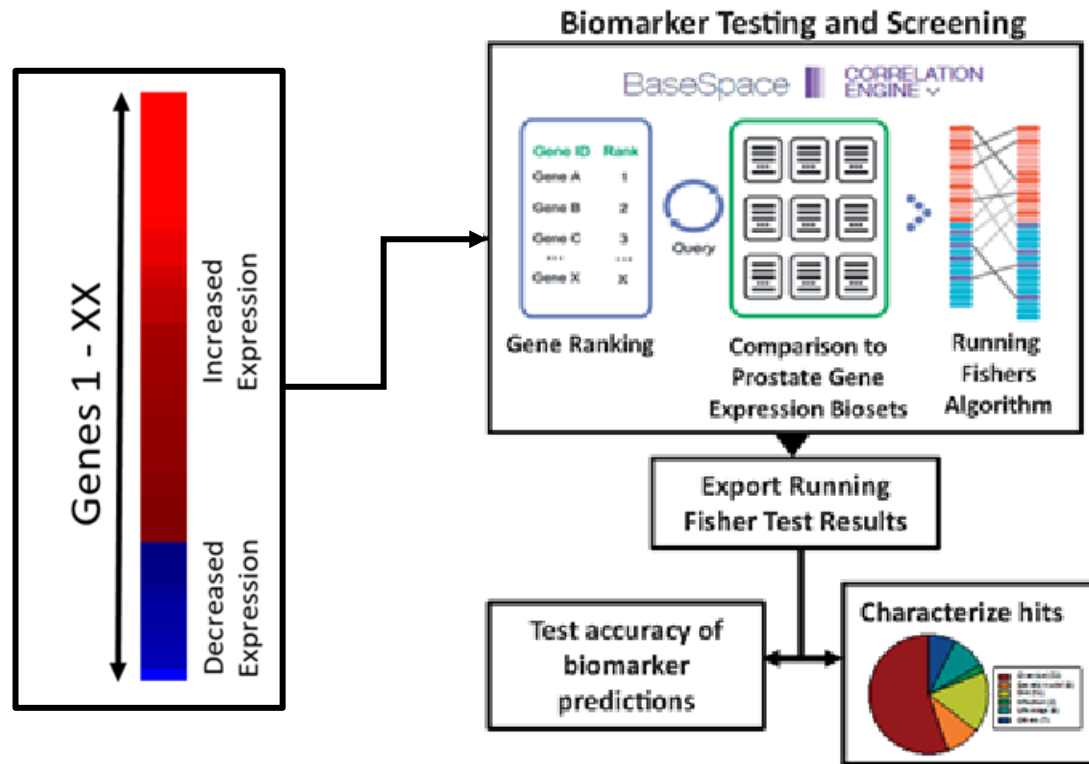
- Gene expression biomarkers
 - General information
 - Methods used for
 - Testing for predictive accuracy
 - Screening chemicals
- Biomarkers for screening transcript profiles generated in mice
 - Identification of mode of action
- Biomarkers for screening transcript profiles generated in rats to reduce 2-year bioassay
 - Identification of mode of action
 - Identification of chemical doses that would cause cancer
- Biomarkers for Tier 1 screening in high-throughput transcriptomics (HTTr) profiling
 - E.g., identification of estrogen receptor modulators

Gene expression biomarkers – moving towards regulatory acceptance

- Biomarker defined as “a characteristic that is objectively measured and evaluated as an indicator of normal biological processes, pathogenic processes, or pharmacologic responses to a therapeutic intervention.” (1998, the National Institutes of Health Biomarkers Definitions Working Group)
- A gene expression biomarker is a short list of genes and associated fold-change values or ranks used to predict the activity of a factor important in mediating effects of chemicals or toxicity
- Can be used to
 - Identify mode of action
 - Predict tumorigenic potential
 - (Determine a benchmark dose)
- Very few examples of well characterized gene expression biomarkers with known accuracies
 - Signature/pathway analysis often used as hypothesis generators
- Only two biomarkers have been considered for regulatory acceptance
 - GARDskin/GARDpotency – used to identify skin sensitizers in human myeloid dendritic-like cell line; accepted for regulatory studies (OECD TGP 4.106)
 - TGx-DDI biomarker – used to identify DNA damage-inducing chemicals in TK6 cells; under review by the FDA

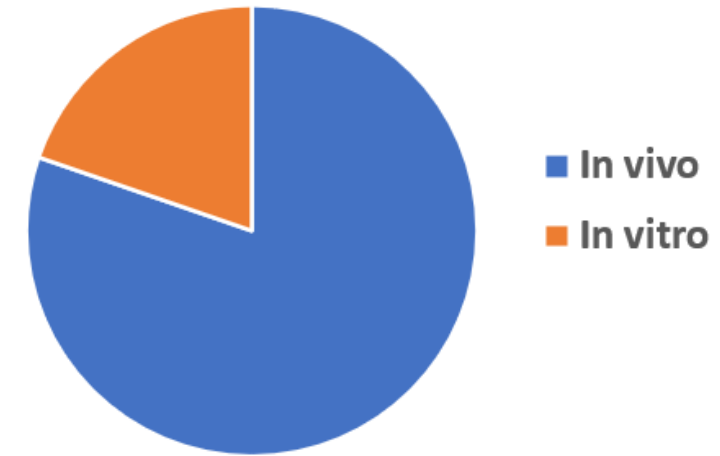


Comparing gene lists in BaseSpace Correlation Engine

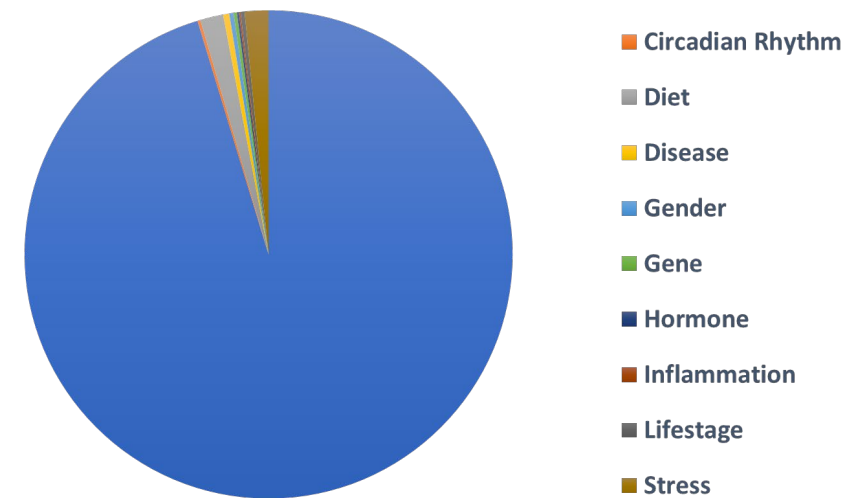


- Utilize Illumina's BaseSpace Correlation Engine
- Contains ~140,000 microarray lists of statistically significant genes
- Valuable computational tools
- Compares all microarray comparisons to each other in a pairwise fashion using a Running Fisher test
- For each pair-wise comparison: generates the number of overlapping genes, correlation direction and p-value

Total Number of Biosets = ~10,260



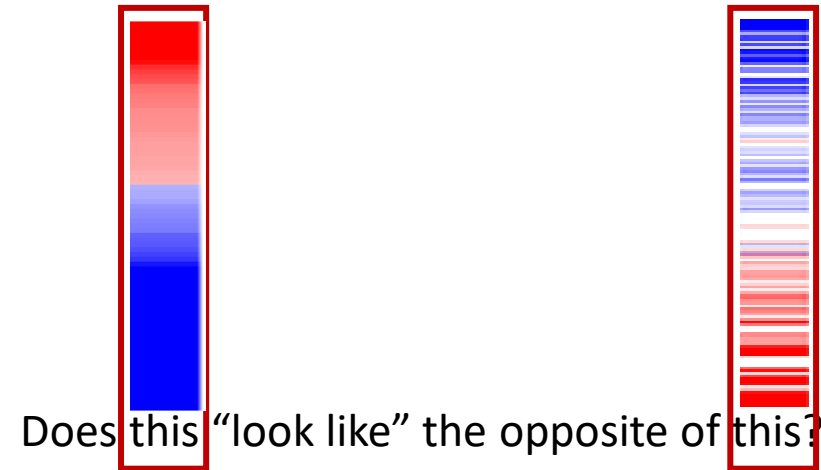
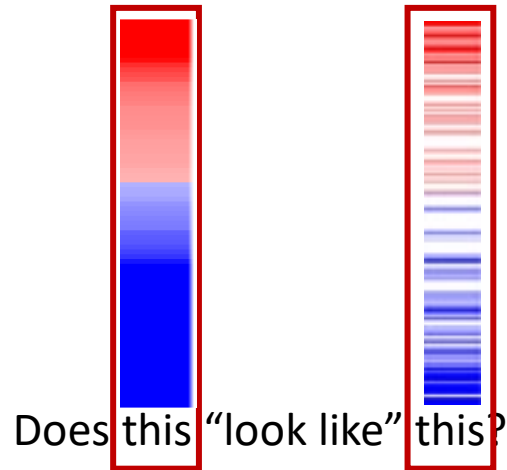
Total Number of In Vivo Biosets = 8233



- Greatly accelerated construction and analysis of rat biomarkers

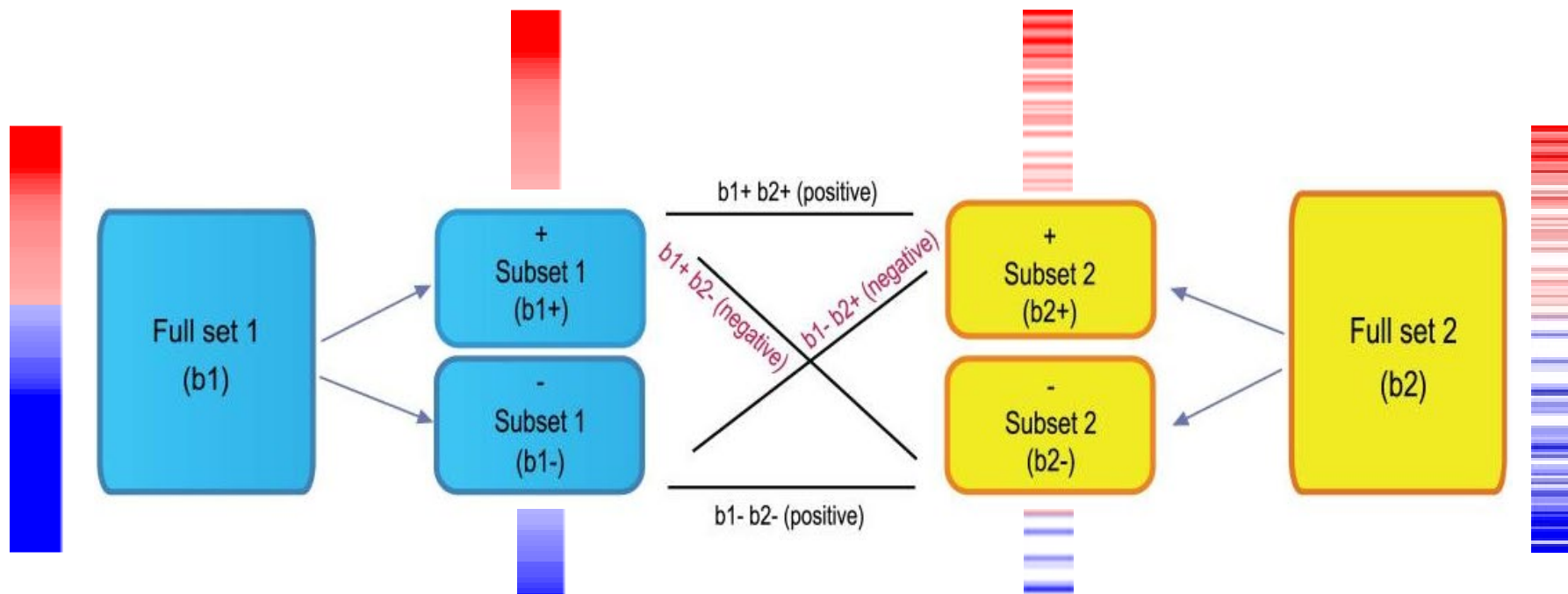
Correlation analysis using the Running Fisher Test

- Identification of factors (chemicals, hormones, diets, genes, etc.) that “look” like your gene list



- Correlation can be determined computationally using the Running Fisher test in BSCE

Computing directionality and final correlation scores between two gene lists



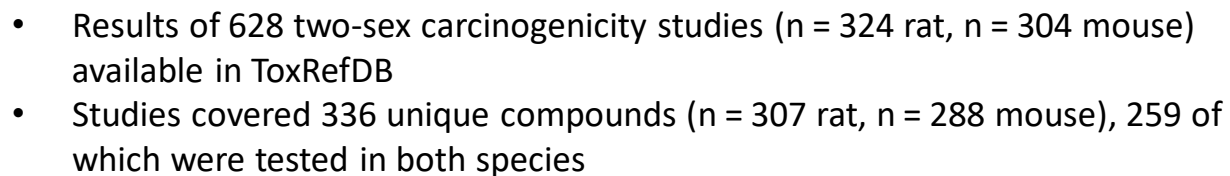
- $\text{Score}(b1, b2) = \text{sum}(b1+b2+, b1+b2-, b1-b2+, b1-b2-)$
- Running Fisher Test p-value
- Direction of the correlation

- The Running Fisher test p-value is a useful metric of correlation between gene sets

Liver



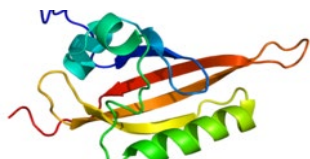
Liver



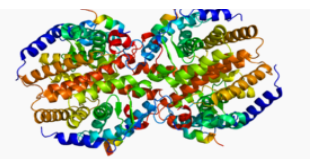
From Hill et al. Toxicol Sci. 2017 Jan; 155(1):157-169

Biomarkers that predict key events in the livers of mice and rats

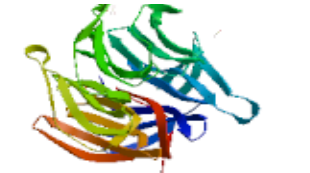
AhR



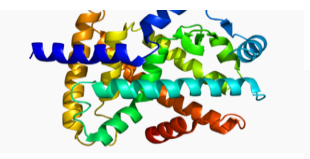
CAR



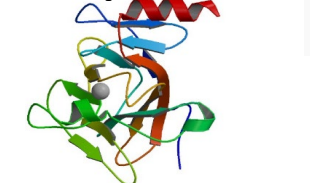
NRF2



PPAR α



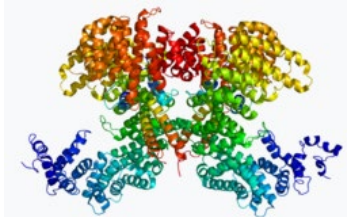
p53



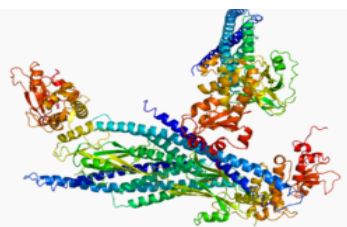
Estrogen
Receptor α



SREBP

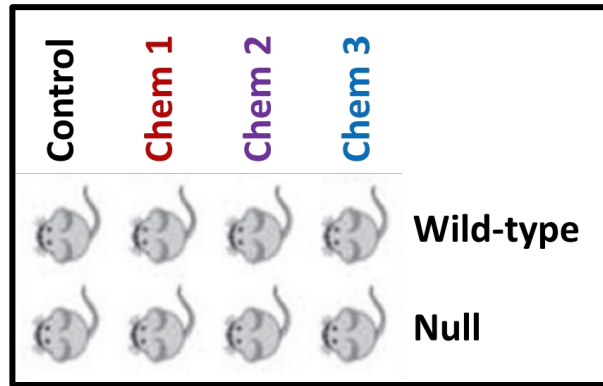


STAT5b



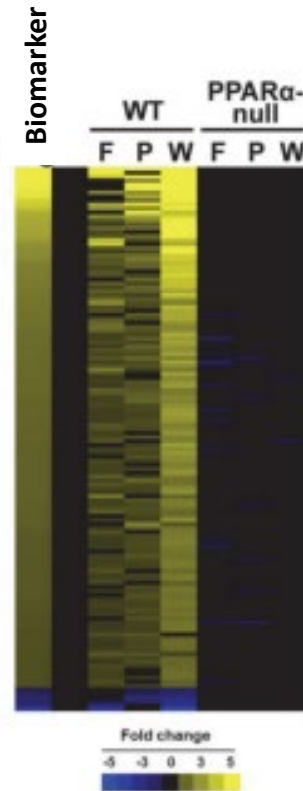
- Oshida et al. (2015). Identification of Modulators of the Nuclear Receptor Peroxisome Proliferator-Activated Receptor α (PPAR α) in a Mouse Liver Gene Expression Compendium. PLoS One. 10(2):e0112655.
- Oshida et al. (2015). Identification of Chemical Modulators of the Constitutive Activated Receptor (CAR) in a Mouse Liver Gene Expression Compendium. Nuclear Receptor Signaling. 13:e002.
- Oshida et al. (2015). Screening a Mouse Liver Gene Expression Compendium Identifies Effectors of the Aryl Hydrocarbon Receptor (AhR). Toxicology. 336:99-112.
- Oshida et al. (2015). Disruption of STAT5b-Regulated Sexual Dimorphism of the Liver Transcriptome by Diverse Factors Is a Common Event. PLoS One. 11(3):e0148308.
- Oshida et al. (2015). Chemical and Hormonal Effects on STAT5b-Dependent Sexual Dimorphism of the Liver Transcriptome. PLoS One. 2016 11(3):e0150284.
- Rosen et al. (2017). PPAR α -independent transcriptional targets of perfluoroalkyl acids revealed by transcript profiling. Toxicology. 387:95-107.
- Rooney et al. (2017). Genomic Effects of Androstenedione and Sex-Specific Liver Cancer Susceptibility in Mice. Toxicol Sci. 160(1):15-29.
- Rooney et al. (2018) Activation of Nrf2 in the liver is associated with stress resistance mediated by suppression of the growth hormone-regulated STAT5b transcription factor. PLoS One. 13(8):e0200004.
- Rooney et al. (2018). Activation of CAR leads to activation of the oxidant-induced Nrf2. Toxicol Sci. 167:172-189.
- Rooney et al. (2018). Adverse outcome pathway-driven identification of rat liver tumorigens in short-term assays. Toxicol Appl Pharmacol. 356:99-113.
- Corton (2019). Frequent Modulation of the Sterol Regulatory Element Binding Protein (SREBP) by Chemical Exposure in the Livers of Rats. Comput. Toxicol. 10:113-129.

Construction of mouse biomarkers using wild-type vs. nullizygous comparisons



- Identified genes that were regulated in wild-type mice but not null mice
- Genes had to be similarly regulated across the three chemicals (2 or 3 out of 3) in wild-type but not the same direction in null mice

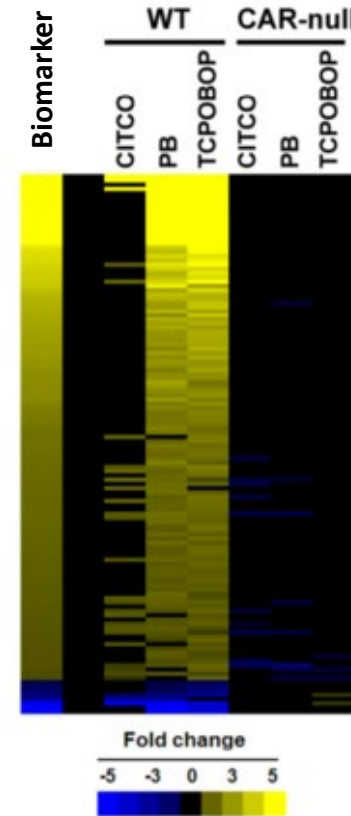
PPAR α



F=fenofibrate
P=PFOA
W=Wy-14,643

Oshida et al. PLoS One.
2015 10(2):e0112655

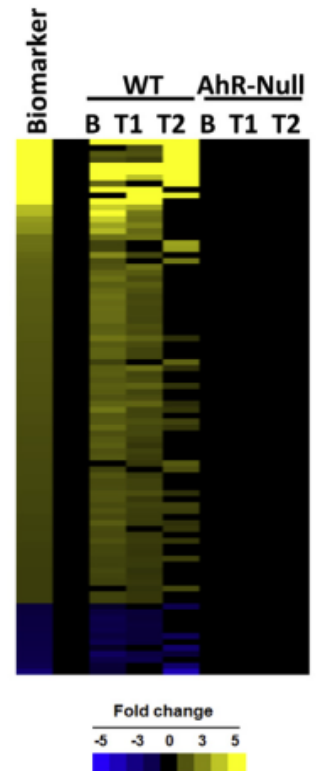
CAR



PB=phenobarbital

Oshida et al. Nucl
Recept Signal. 2015
13:e002

AhR

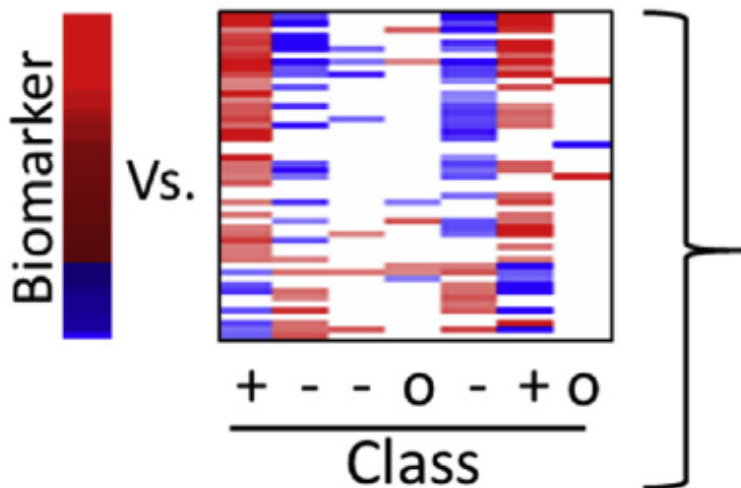


B=BaP
T1,T2=TCDD

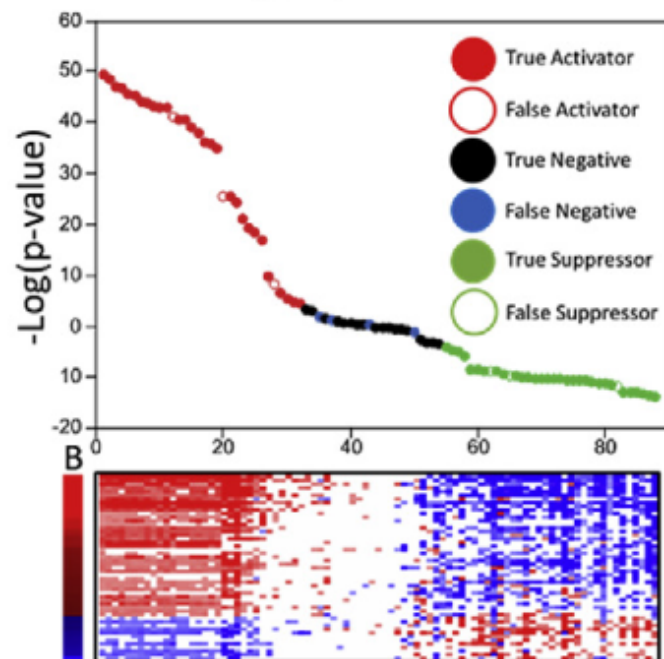
Oshida et al.
Toxicology. 2015
336:99-112

Determination of biomarker accuracy using chemical-induced profiles

Comparison of biomarker to
chemical profiles with known
outcomes



Ranking by Correlation



Accuracy
Determination

- Sensitivity
- Specificity
- Positive predictive value
- Negative predictive value
- Balanced accuracy

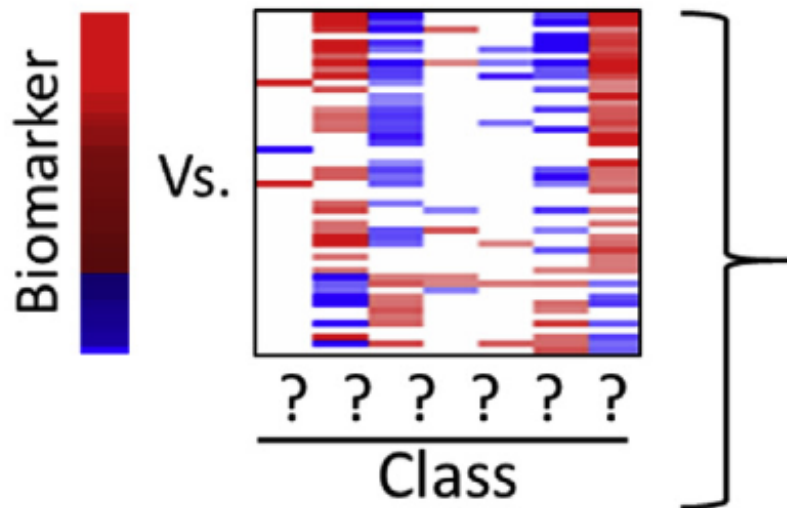
- Defining activation as $-\log(p\text{-value}) \geq 4$ and suppression as $-\log(p\text{-value}) \leq -4$

The mouse biomarkers have excellent predictive accuracy

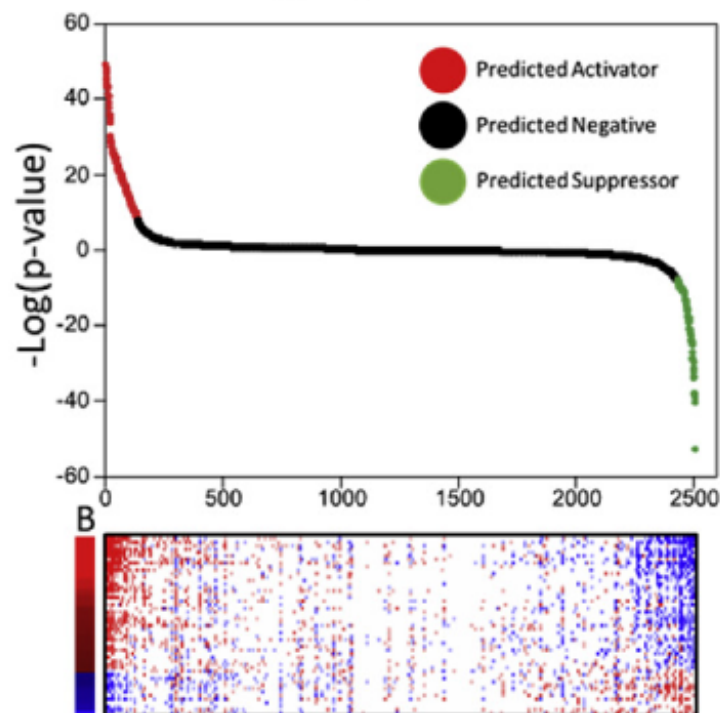
| Mouse Biomarker | Number of Genes | Mutant mice used | Predictive Accuracy for Activation | Publication |
|-----------------|-----------------|---------------------------------------|------------------------------------|----------------------------------|
| PPARalpha | 131 | <i>Ppara</i> | 98% | PLoS One. 2015 10(2):e0112655 |
| CAR | 83 | <i>Nr1i3</i> | 97% | Nucl Recept Signal. 2015 13:e002 |
| AhR | 63 | <i>Ahr</i> | 95% | Toxicology. 2015 336:99-112 |
| Nrf2 | 48 | <i>Nfe2l2, Keap1</i> | 96% | PLoS One 2018 13(8):e0200004 |
| Stat5b | 144 | <i>Stat5b</i> | 97% | PLoS One 2016 11(3):e0150284 |
| Srebp | 99 | <i>Srebf1a, Srebf1c, Srebf2, Scap</i> | 94% | Comp Tox 10 (2019) 63-77 |

Use of biomarkers in chemical screening

Comparison of biomarker to
uncharacterized chemicals



Ranking by Correlation

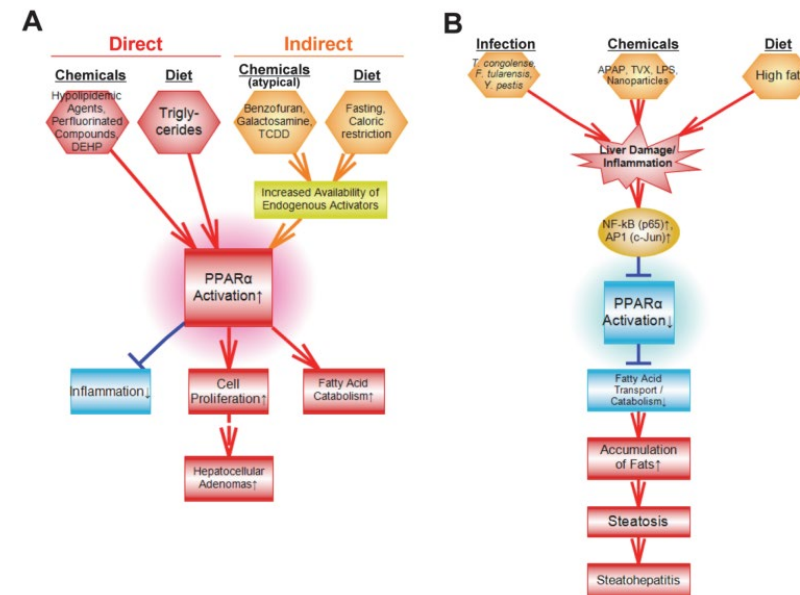


Characterize Hits

- Confirm positives
- Determine mechanism of modulation

Use of mouse biomarkers for screening

- Expanded and confirmed the factors that modulate PPAR α
 - Oshida et al. PLoS One. 2015 10(2):e0112655.

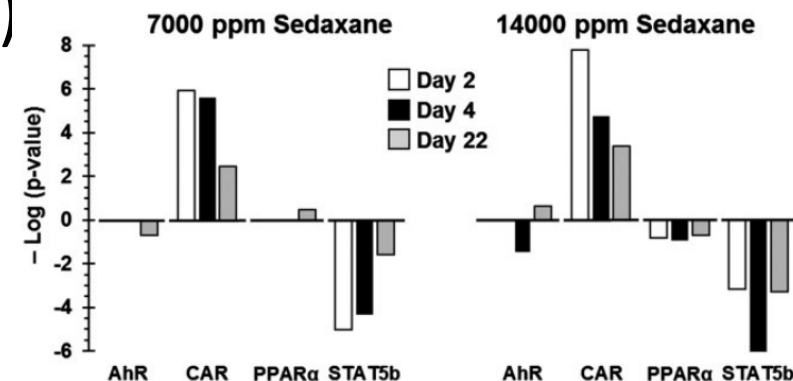


- Predict mode of action of a chemical (sedaxane) that causes mouse liver tumors

- Peffer et al. Toxicol Sci. 2018 162(2):582-598.

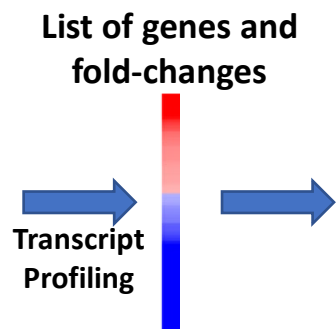
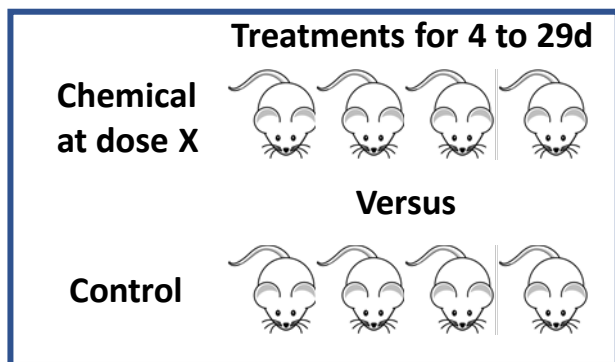
- Database of mouse profiles was limited

- No opportunity to make predictions of chemical-dose conditions that would lead to induction of cancer



NAM: Prediction of rat liver tumor induction using toxicogenomics analysis of short-term exposures

Would a chemical candidate at dose X cause increases in liver tumors in chronic studies?



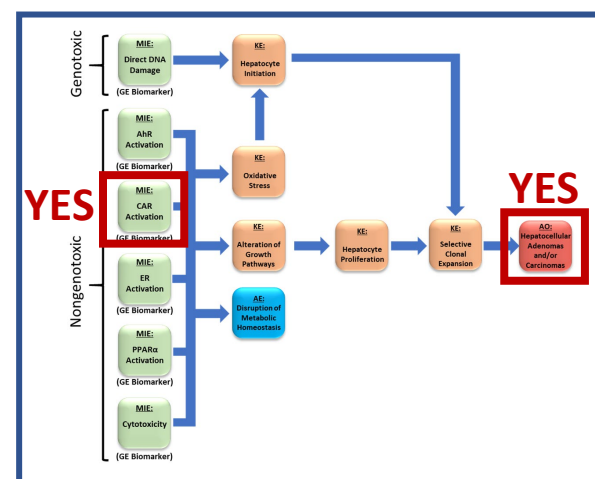
Data Used to Construct the Model

- Microarray data
 - TG-GATES
 - DrugMatrix
- 2-year cancer data
 - Lhasa carcinogenicity database

NAM Computational Model



Network of Liver Cancer AOPs



- Is the dose tumorigenic?
- Which mode(s) of action is activated?
- Is the mode(s) of action human irrelevant?
- Is a waiver for testing appropriate?

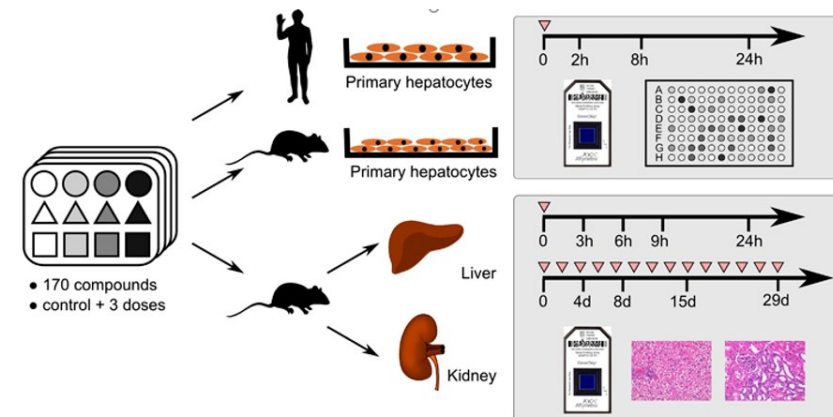
When to use the NAM:

- Screening chemicals in short-term exposures
- After a (sub)chronic study when liver is found to be a tissue with histopath findings of concern

Data Used to Construct the Model

- TG-GATES microarray data
 - ~130 chemicals, 8 time points, 3 doses
- DrugMatrix microarray data
 - >600 chemicals, 4 time points, 2 doses
- Carcinogenicity Potency Database
 - Carcinogenicity data on >1500 chemicals in rats and mice
 - Used data to categorize the hepatotumorigenic potential of chemical-dose comparisons in TG-GATES and DrugMatrix
 - Used the data to identify thresholds for tumorigenicity

Open TG-GATES



DrugMatrix/ToxFX



Predictive Accuracies of Six Gene Expression Biomarkers

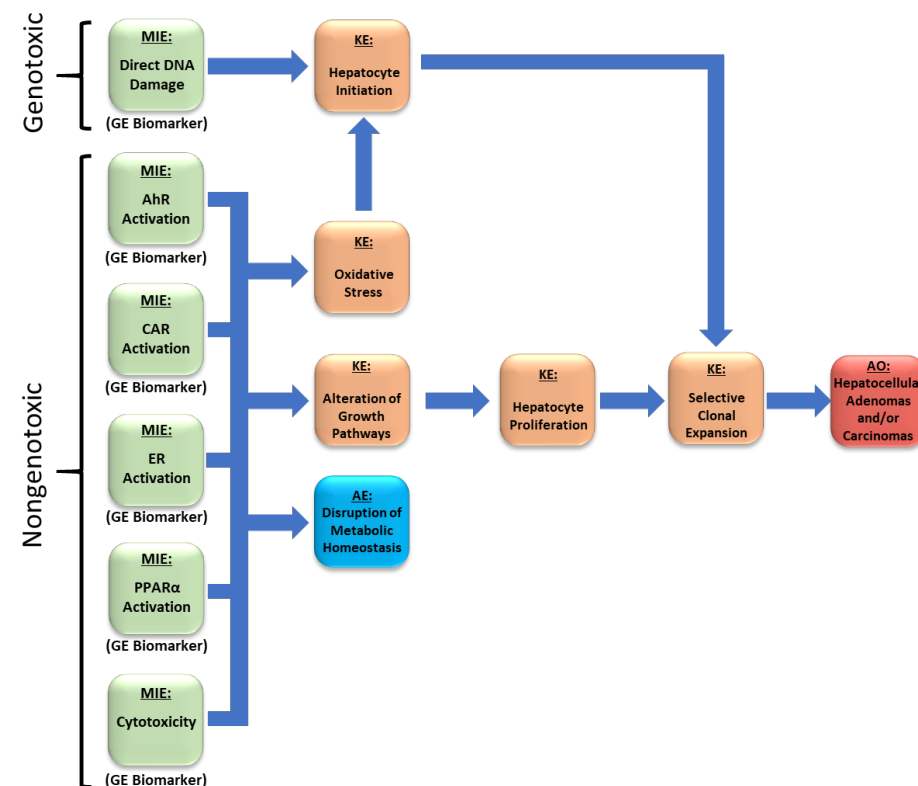
- Context of use: Male rat liver
- All biomarkers have balanced accuracies above 90%
- Genes identified are known to be regulated by the MIE
 - Rooney et al., (2018) *Tox Appl Pharm* 356:99–113
 - Corton et al. (2020). A Set of Gene Expression Biomarkers Identify Rat Liver Tumorigens in Short-Term Assays. *Tox Sci.* 177(1):11-26



| | | Balanced Accuracies | Examples of Biomarker Genes | Number of Genes |
|--------------|---|---------------------|-----------------------------------|-----------------|
| Genotoxic | <div>MIE: Direct DNA Damage</div> <div>(GE Biomarker)</div> | 92% | <i>Cdkn1a, Bax, Ccng1</i> | 7 |
| | <div>MIE: AhR Activation</div> <div>(GE Biomarker)</div> | 91% | <i>Cyp1a1, Cyp1a2, Aldh1a1</i> | 63 |
| Nongenotoxic | <div>MIE: CAR Activation</div> <div>(GE Biomarker)</div> | 91% | <i>Cyp2b1, Ugt2b1, Ces2c</i> | 113 |
| | <div>MIE: ER Activation</div> <div>(GE Biomarker)</div> | 96% | <i>Shp, Lifr, Gdf15</i> | 35 |
| | <div>MIE: PPARα Activation</div> <div>(GE Biomarker)</div> | 98% | <i>Cyp4a1, Cpt1b, Lpl</i> | 58 |
| | <div>MIE: Cytotoxicity</div> <div>(GE Biomarker)</div> | 96% | <i>Bcl2a1a, S100a4, Tnfrsf12a</i> | 10 |

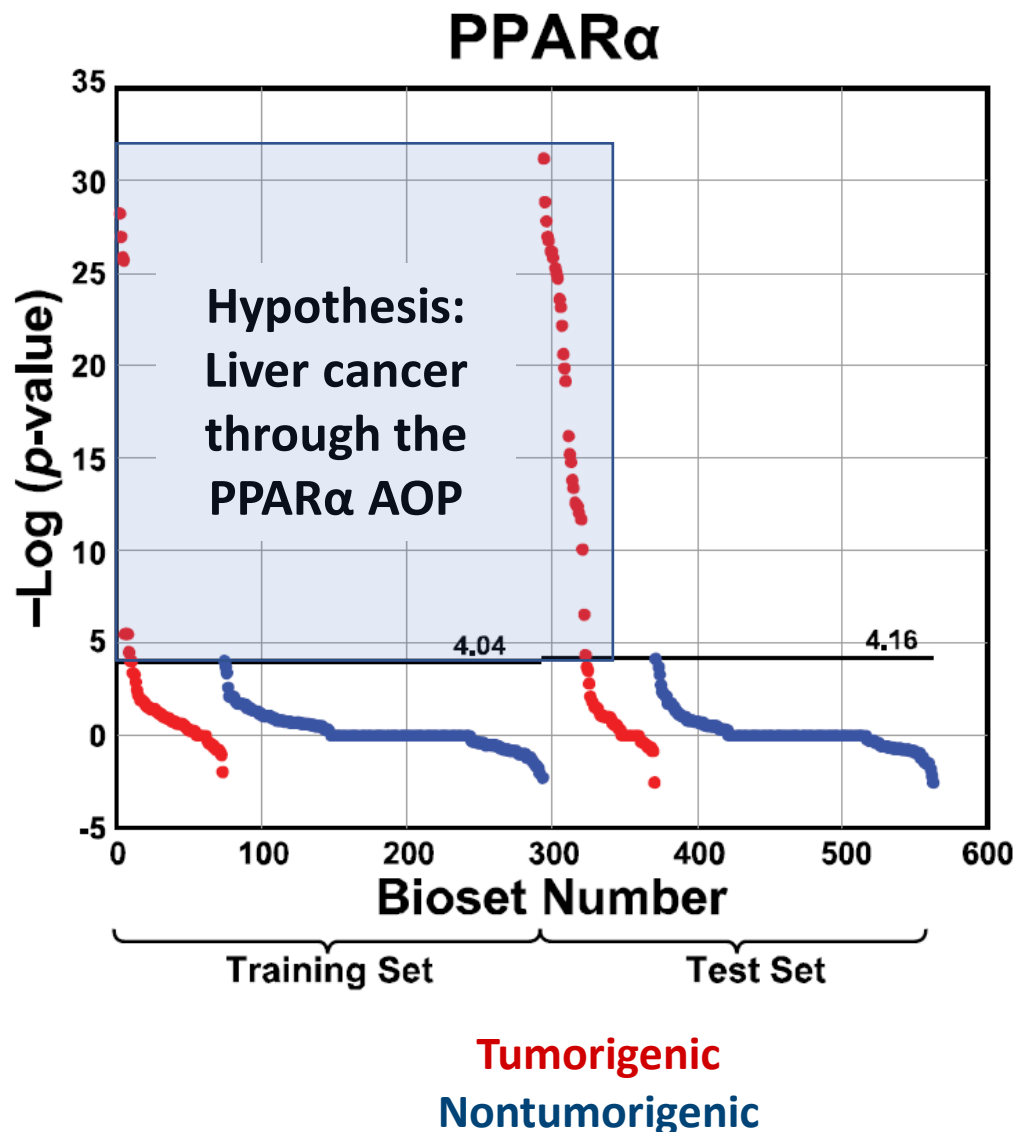
Defining biological activation levels for liver cancer

- Central premise of AOP framework: Key events are necessary but not sufficient
 - Induction of an AO depends on the degree or amount of disruption of preceding key events
- Can we define activation levels associated with liver tumor induction for each of the MIEs?
- Defined the tumorigenic activation levels for the 6 biomarkers



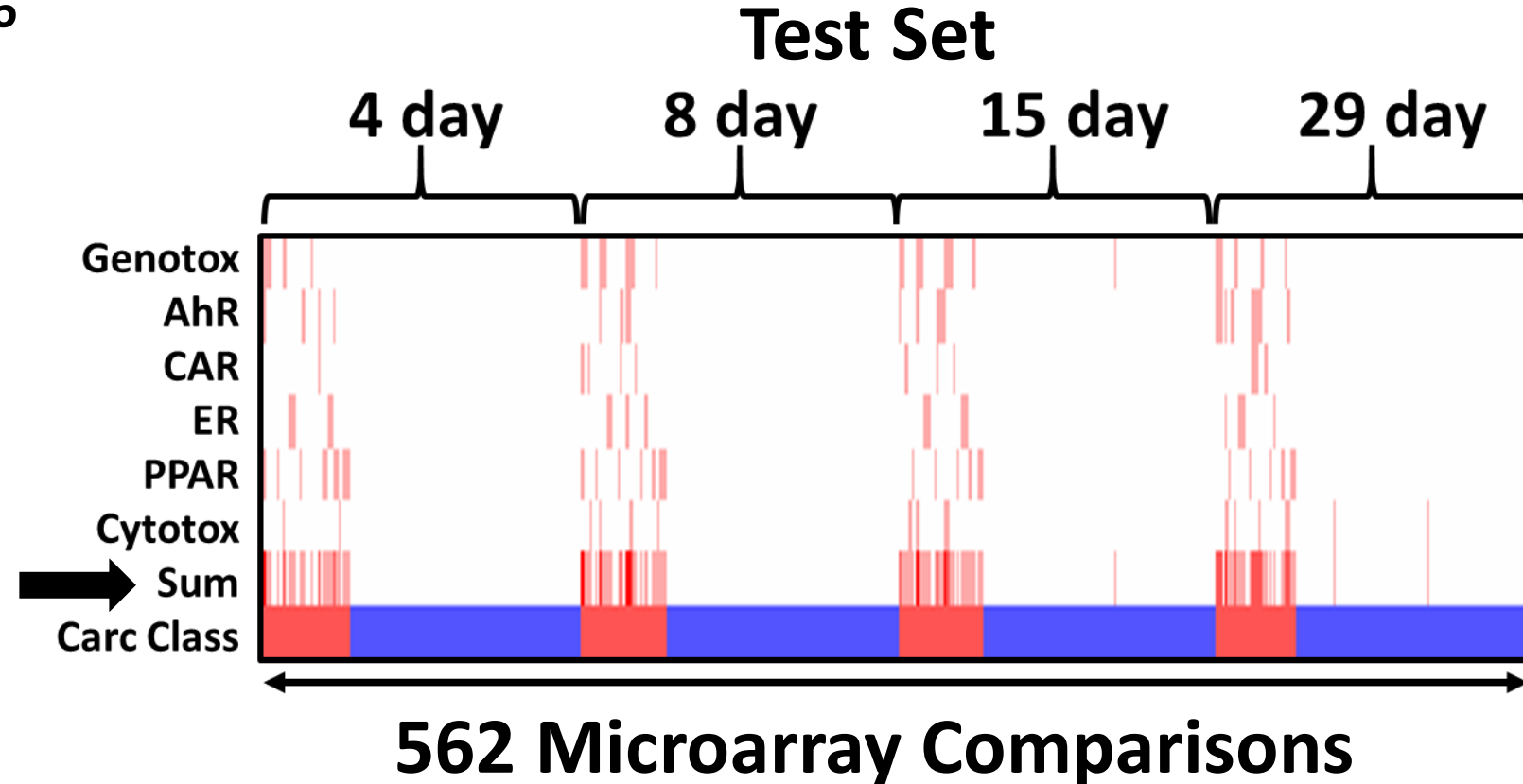
Identification of tumorigenic activation levels for gene expression biomarkers

- Divided the chemical-dose conditions
 - Tumorigenic and nontumorigenic groups
 - Training and test sets
- Thresholds defined as the maximum value in the nontumorigenic group
 - Reach an upper limit for activation that would not cause liver cancer
- Generated tumorigenic activation levels for all 6 MIEs
- Levels were similar between the training and test sets



Biomarker Activation Levels Accurately Predict Liver Tumors

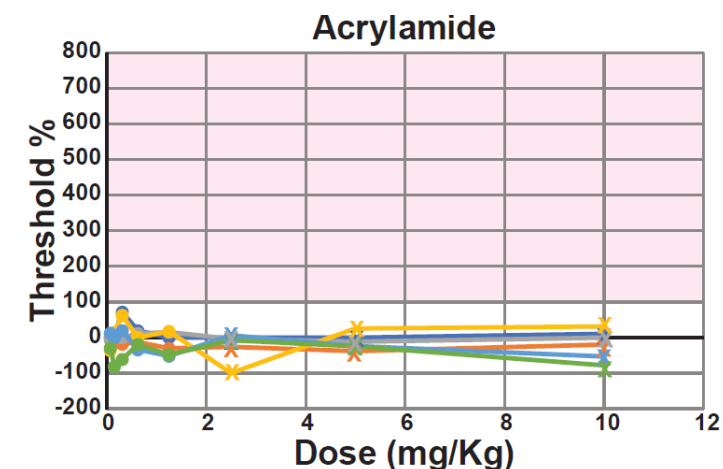
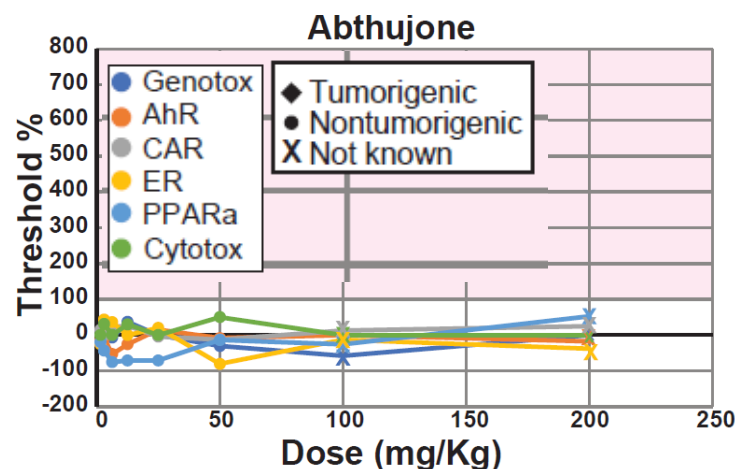
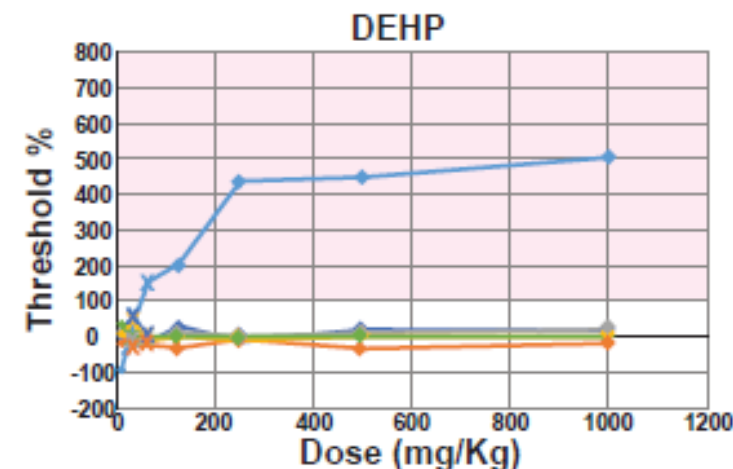
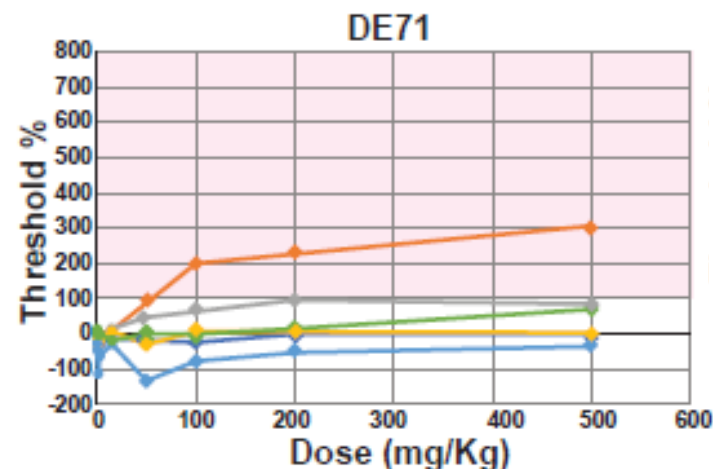
- Identified activation levels for the 6 biomarkers associated with tumor induction from the TG-GATES training set and then applied to a test set
- Each red line is a chem-dose condition in which the biomarker tumorigenic level is surpassed
- Almost all of the tumorigenic conditions exceeded one or more of the 6 activation levels
- Tumorigenic activation levels were rarely exceeded in any of the nontumorigenic conditions



- Test set: 100% sensitivity, 93% specificity, and a balanced accuracy of 97%

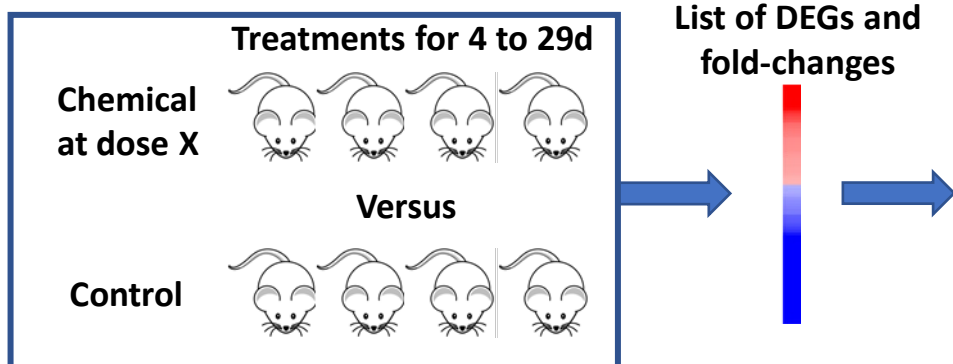
NAM identifies chemical-dose pairs that are tumorigenic in the liver using TempO-Seq

- Examined 16 chemicals at up to 10 doses; 5d exposures (Gwinn et al., 2021 ToxSci)
- Liver gene expression analyzed using full genome TempO-Seq
- Model correctly identified all tumorigenic chemicals
- Balanced accuracies = 74-91% depending on the tumorigenic activation level used and whether individual chem-doses were considered or all doses for a chemical



NAM: Prediction of rat liver tumor induction using toxicogenomics analysis of short-term exposures

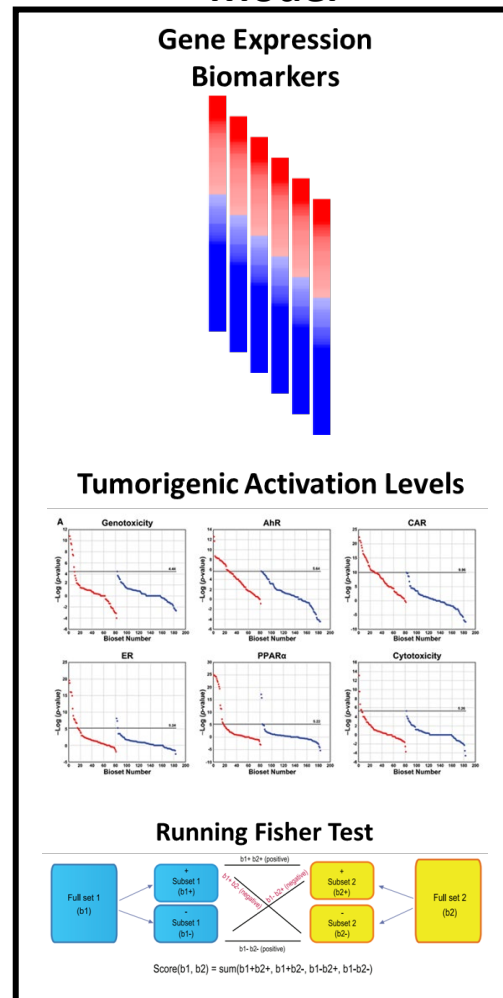
Will a chemical candidate at dose X cause increases in liver tumors in chronic studies?



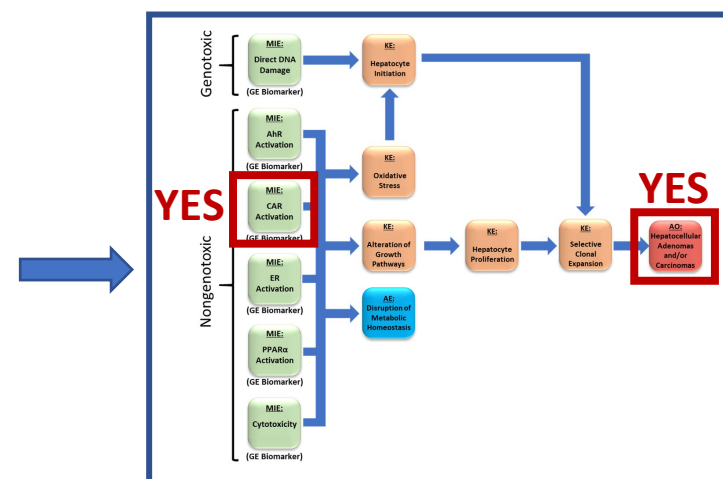
Questions still to be addressed:

- Can we improve accuracy by incorporating
 - More data?
 - A greater diversity of chemicals?
 - Wild-type and null rat comparisons?

NAM Computational Model



Network of Liver Cancer AOPs



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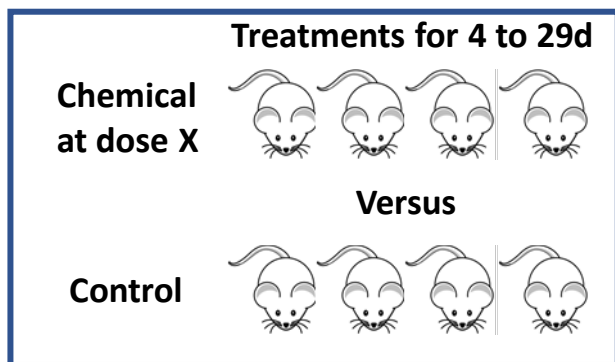
Emerging Systems Toxicology for the Assessment of Risk (eSTAR) Committee

Future Studies:

- Studies conducted through the HESI eSTAR Carcinogenomics Workgroup

NAM: Prediction of rat liver tumor induction using toxicogenomics analysis of short-term exposures

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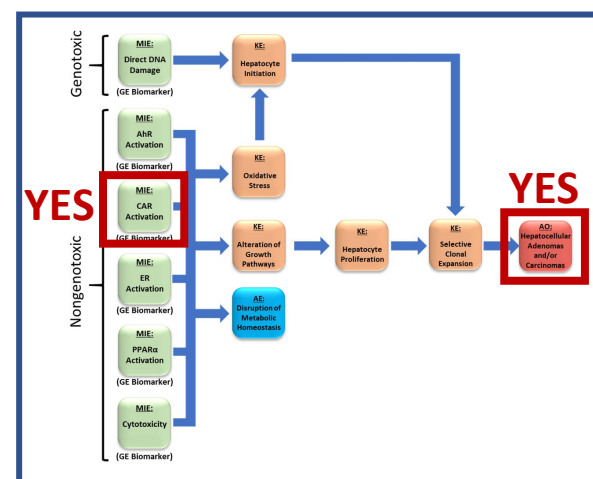


List of genes and fold-changes

Transcript Profiling

NAM Computational Model

Network of Liver Cancer AOPs



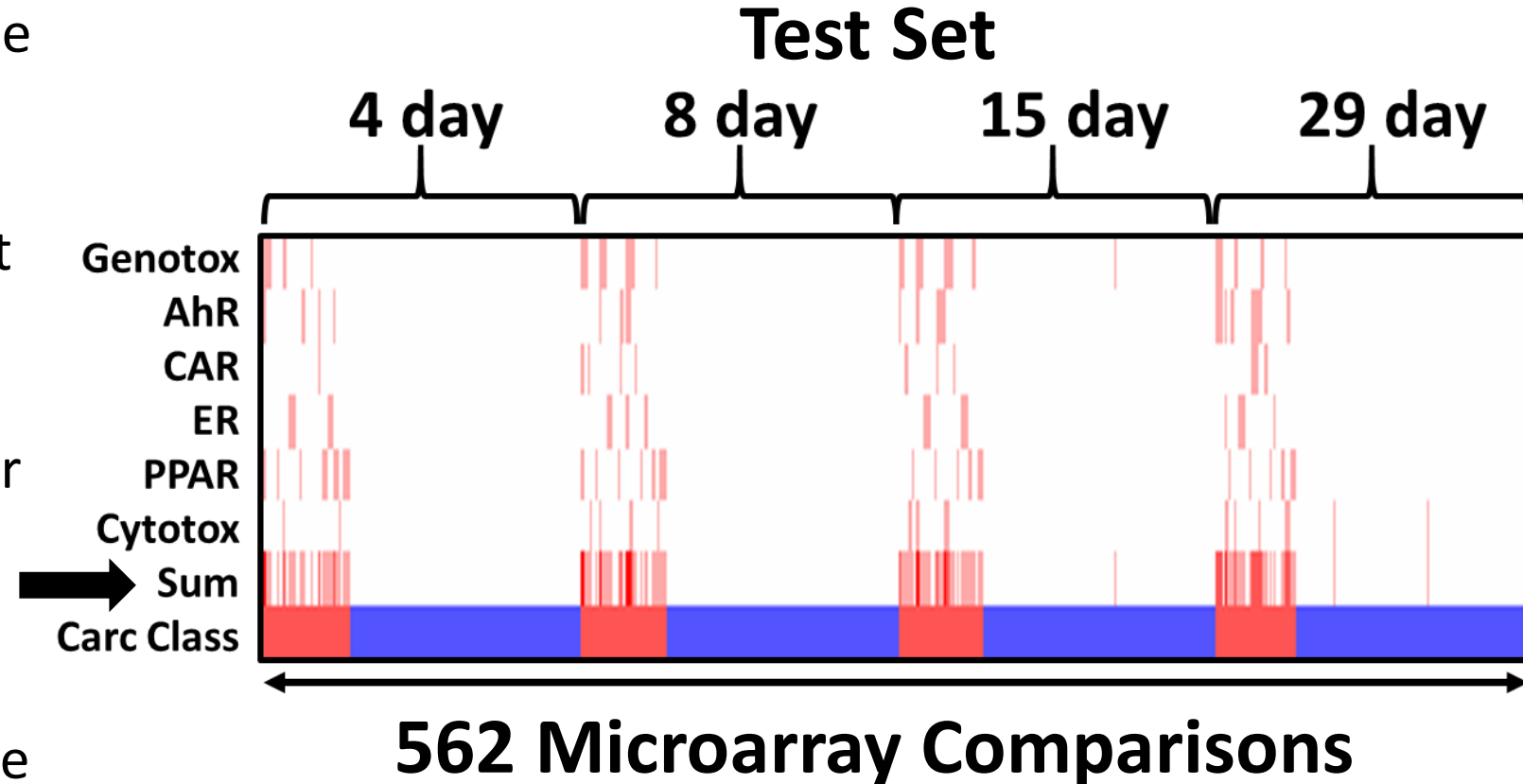
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When to use the NAM:

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Biomarker Activation Levels Accurately Predict Liver Tumors

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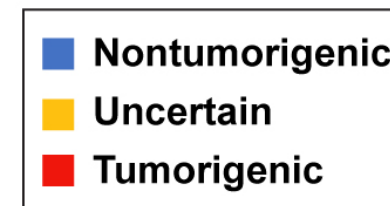
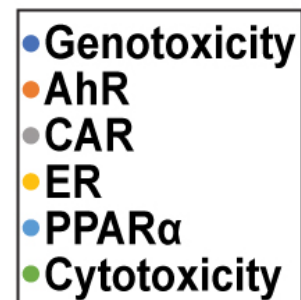
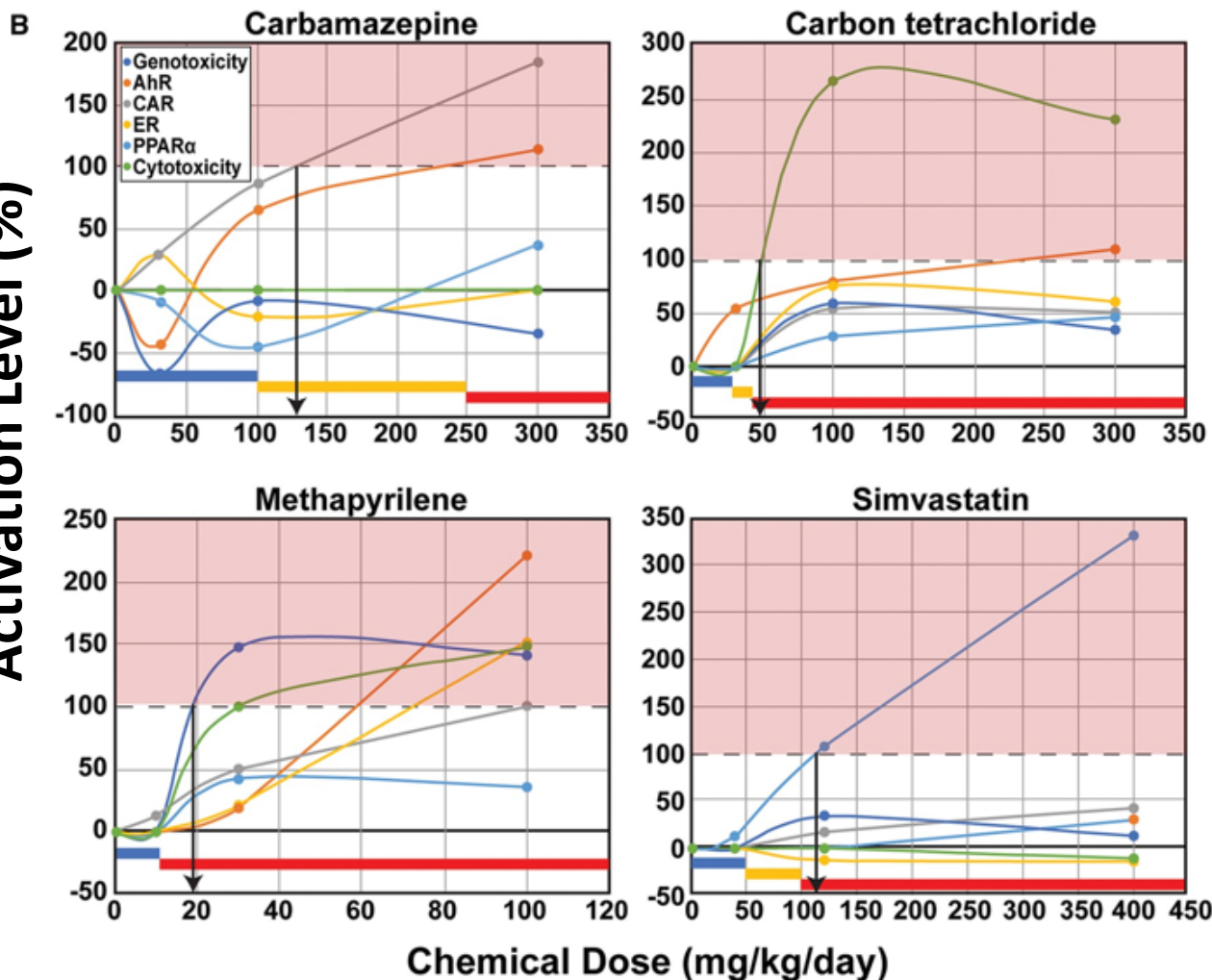
- **Test set: 100% sensitivity, 93% specificity, and a balanced accuracy of 97%**

Tumorigenic
Nontumorigenic

Application of Biomarkers and Activation Levels to Liver Tumorigens

- Chemicals examined in the TG-GATES study in male rats for 15d at 3 doses

Biomarker Tumorigenic
Activation Level (%)



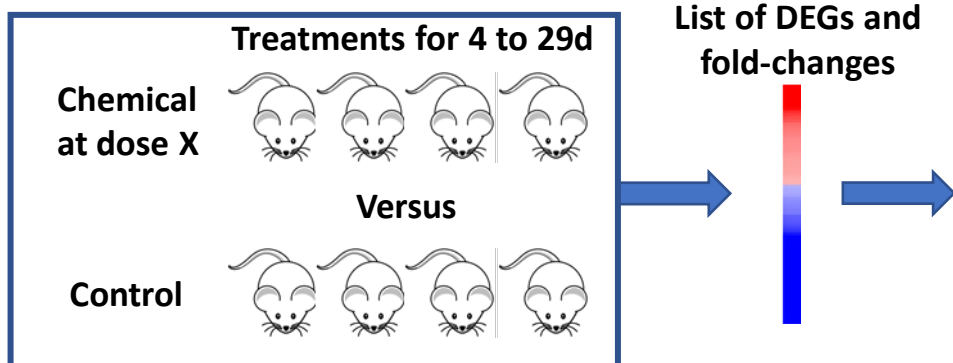
Pink = conditions predicted to be tumorigenic

- Approach identifies the MOA and the lowest tumorigenic dose
- Confidence would increase with greater numbers of doses examined

From Hill et al. (2020) ToxSci 177(1):41-59

NAM: Prediction of rat liver tumor induction using toxicogenomics analysis of short-term exposures

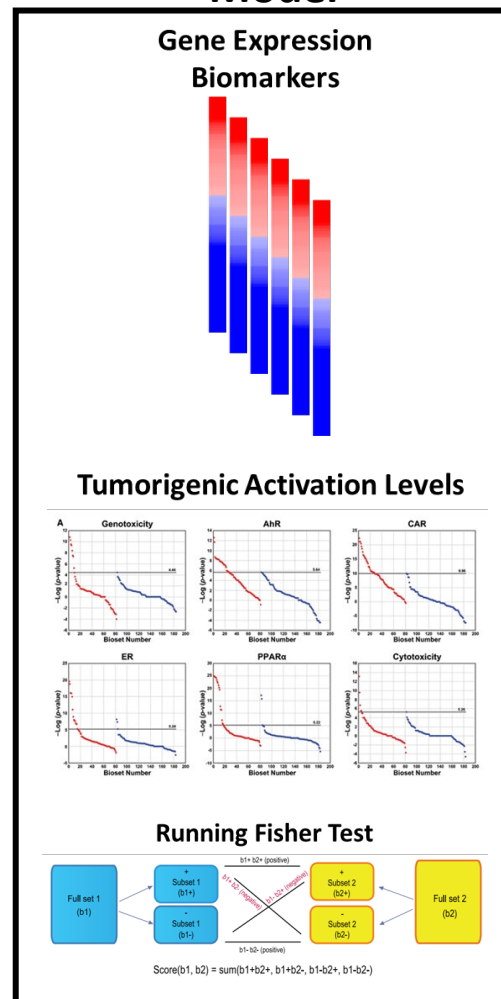
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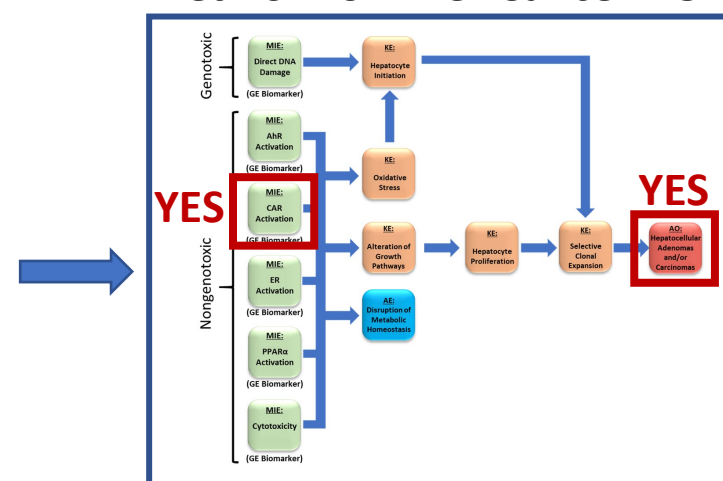
Questions still to be addressed:

- Can the methods be used for (targeted) RNA-Seq?
- Can we make predictions using in vitro models?

NAM Computational Model



Network of Liver Cancer AOPs



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the Assessment of Risk (eSTAR)
Committee

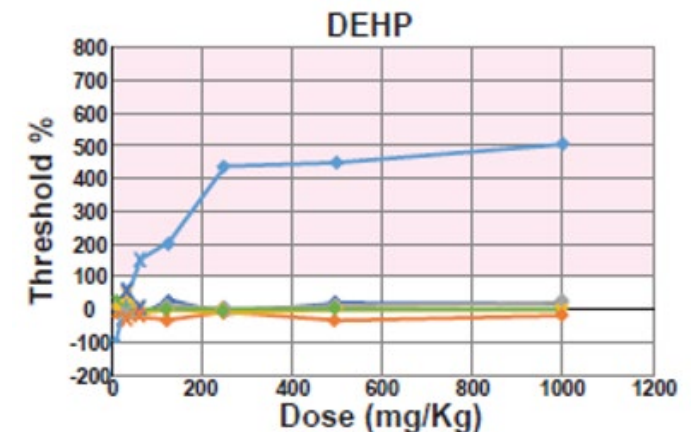
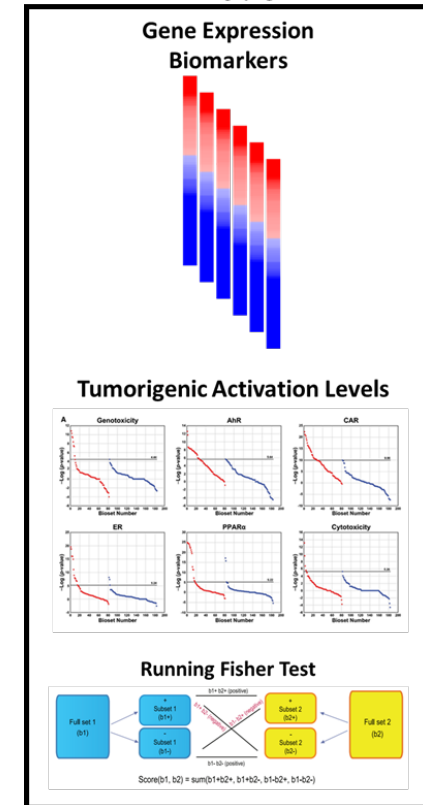
Future Studies:

- Studies conducted through the HESI eSTAR Carcinogenomics Workgroup

Summary (First Part)

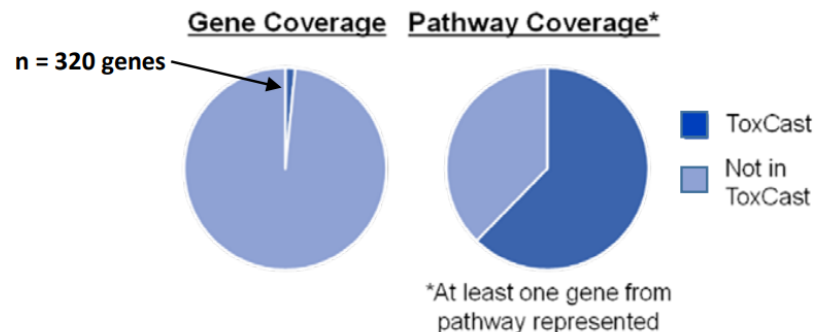
- The NAM can be used to identify liver tumorigens
 - Identification of mode of action
 - Identification of chemical doses that would cause cancer
- In multiple studies have examined ~250 chemicals (~50 caused liver tumors)
 - Accuracy was ~75-95% depending on the dataset used
 - Accuracy is independent of platform used to assess gene expression
 - Missed only two positives
 - Acetamide
 - Ethionine
 - Provides opportunities to build additional biomarkers for prediction

NAM Computational Model



High-throughput toxicity testing

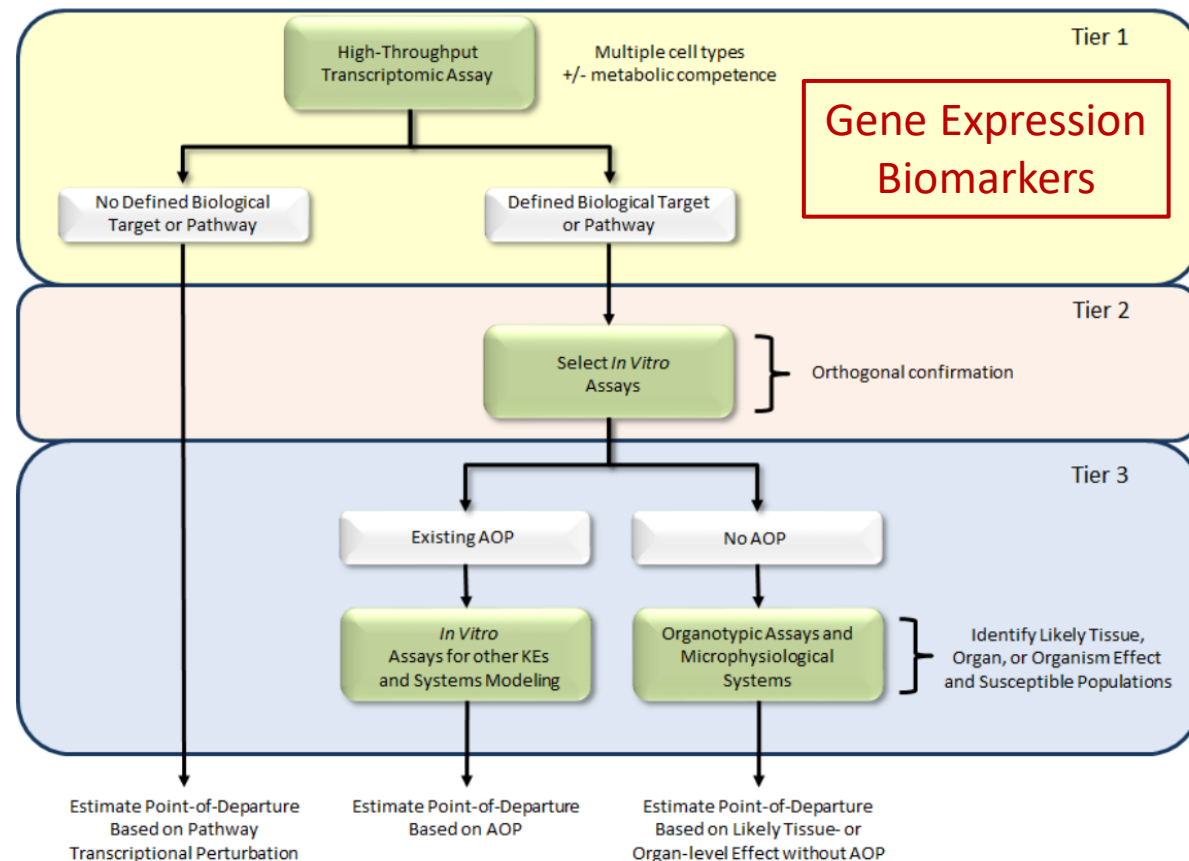
- ToxCast assays cover many genes and pathways, but do not provide complete coverage of biological space.



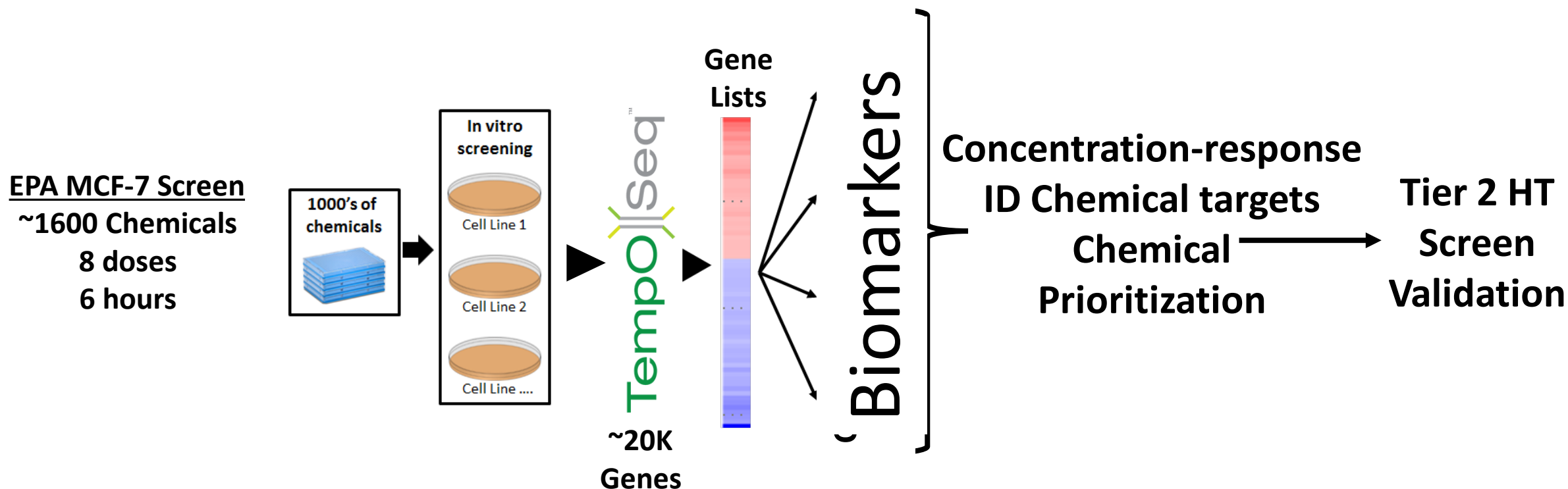
USEPA Strategic Vision and Operational Roadmap:

- Tier 1 strategy must cast the broadest net possible for capturing hazards associated with chemical exposure.
- Global gene expression provides a robust and comprehensive evaluation of chemically induced changes in biological processes.
- Increasing efficiency and declining cost of generating whole transcriptome profiles has made high-throughput transcriptomics (HTTr) a practical option for determining bioactivity thresholds in *in vitro* models.

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

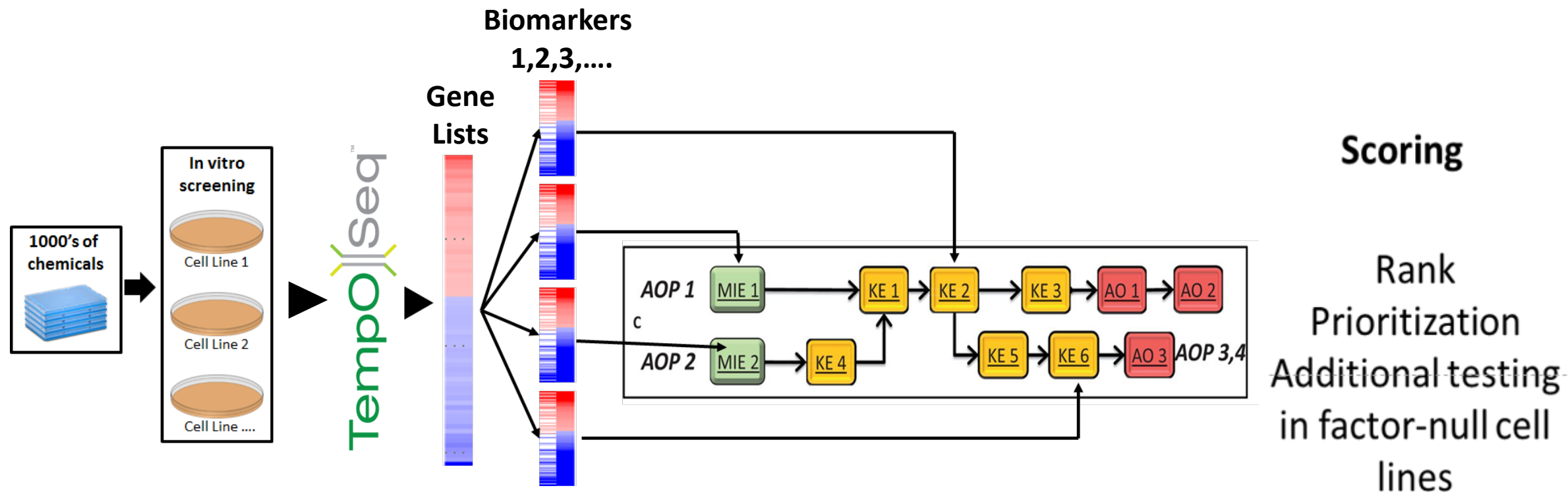


Using gene expression biomarkers to identify molecular targets of chemicals in transcriptomic studies



- Use predictions for
 - Chemical prioritization as part of Tier 1 screening
- Followed up with short-term tests in organotypic cultures or animals

Using gene expression biomarkers to identify molecular targets of chemicals in transcriptomic studies



- Use predictions for
 - Chemical prioritization as part of Tier 1 screening
 - Predict molecular initiating events and key event perturbations in adverse outcome pathways
- Followed up with short-term tests in knockout/knockdown cell lines, organotypic cultures or animals
- **Ultimate Goal: Move from hypothesis generation to final predictions to minimize further testing**

Biomarkers that predict key events in human cells in vitro

Used genetic profiles to develop the biomarker

Endocrine disruption

- Ryan et al. (2016). Moving Toward Integrating Gene Expression Profiling Into High-Throughput Testing: A Gene Expression Biomarker Accurately Predicts **Estrogen Receptor α** Modulation in a Microarray Compendium. Toxicol Sci. 151(1):88-103.
- Androgen receptor: Rooney et al. (2018). Identification of **Androgen Receptor** Modulators in a Prostate Cancer Cell Line Microarray Compendium. Toxicol Sci. 166:146-162.
- Robarts et al. (2023). Characterization of a 50-gene estrogen receptor biomarker. In preparation.

DNA Damage Response – TGx-DDI Biomarker

- Corton et al. (2018). Using a gene expression biomarker to identify **DNA damage-inducing agents** in microarray profiles. Environ Mol Mutagen. 59:772-784.
- Cho et al. (2019). Assessment of the performance of the TGx-DDI biomarker to detect **DNA damage-inducing agents** using quantitative RT-PCR in TK6 cells. Environ Mol Mutagen. 60:122-133.
- Corton JC, Witt KL, Yauk CL. (2019). Identification of **p53 Activators** in a Human Microarray Compendium. Chem Res Toxicol. 32(9):1748-1759.

Epigenetic effects – HDACi and BRDi

- Corton et al. A Gene Expression Biomarker Identifies Inhibitors of Two Classes of **Epigenome Effectors** in a Human Microarray Compendium. Chemico-Biological Interactions. 365:110032.

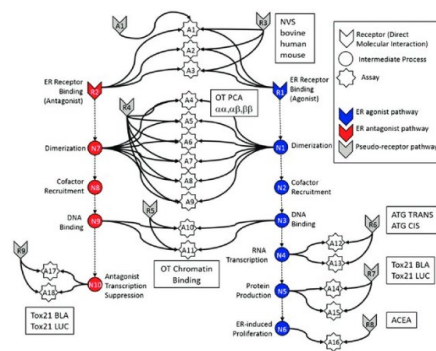
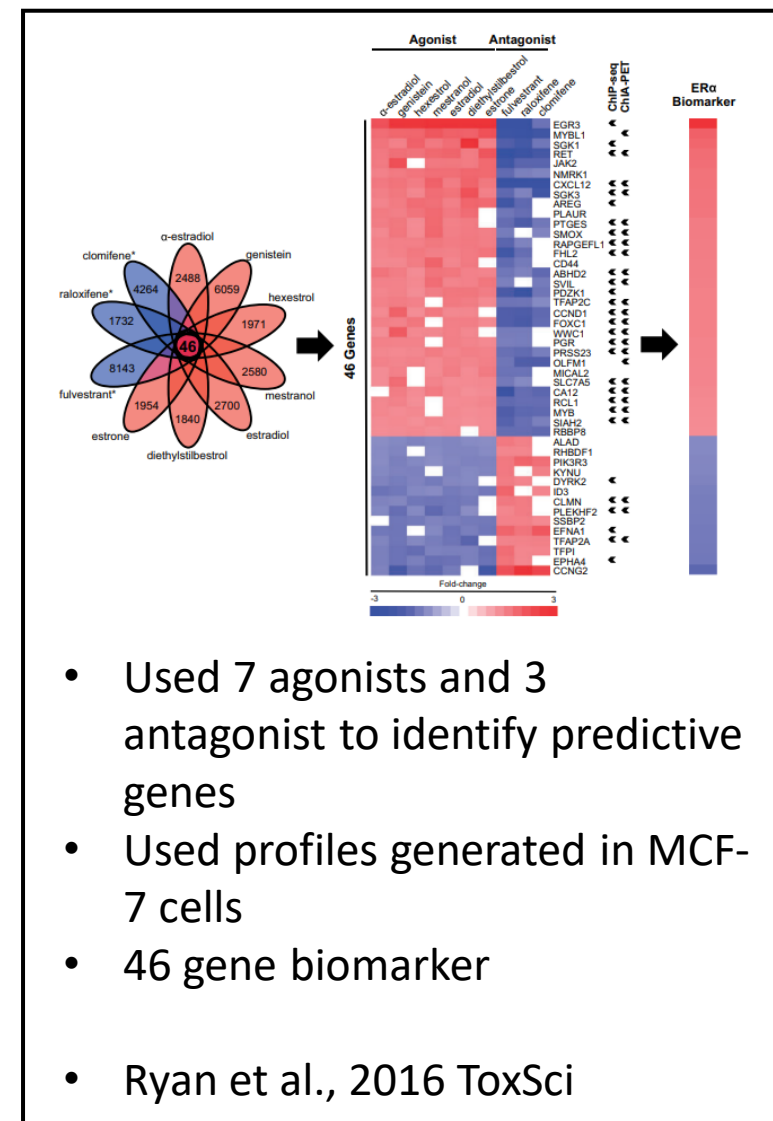
Stress factors

- Cervantes PW, Corton JC. (2021). A Gene Expression Biomarker Predicts **Heat Shock Factor 1** Activation in a Gene Expression Compendium. Chem Res Toxicol. 2021 34(7):1721-1737.
- Jackson AC, Liu J, Vallanat B, Jones C, Nelms MD, Patlewicz G, Corton JC. (2020). Identification of novel activators of the **metal responsive transcription factor (MTF-1)** using a gene expression biomarker in a microarray compendium. Metallomics. 12(9):1400-1415.
- Korunes KL, Liu J, Huang R, Xia M, Houck KA, Corton JC. (2022). A gene expression biomarker for predictive toxicology to identify chemical modulators of **NF- κ B**. PLoS One. 17(2):e0261854.
- Rooney JP, Chorley B, Hiemstra S, Wink S, Wang X, Bell DA, van de Water B, Corton JC. (2020). Mining a human transcriptome database for chemical modulators of **NRF2**. PLoS One. 15(9):e0239367.

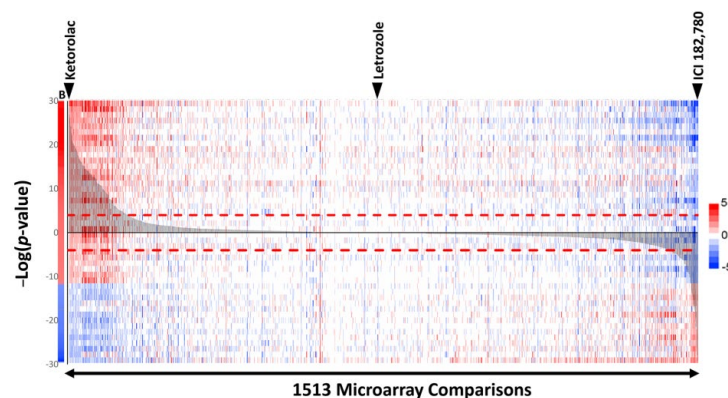
In progress

- HIF1a, Unfolded Protein Response (ATF4, ATF6, XBP1), Cell Proliferation, AhR, Epigenome Effectors

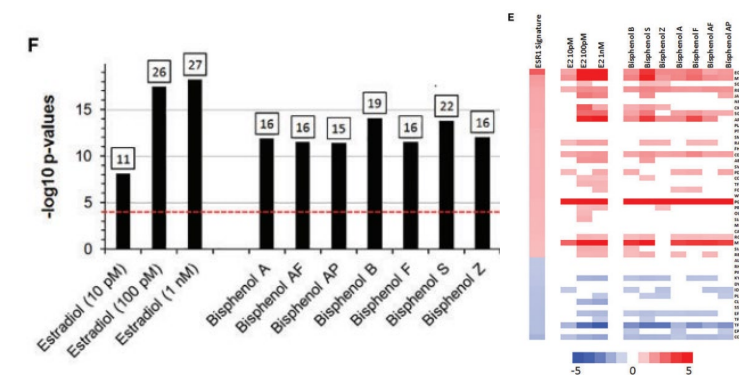
Use of an estrogen receptor biomarker to identify ER modulators in human cells in vitro



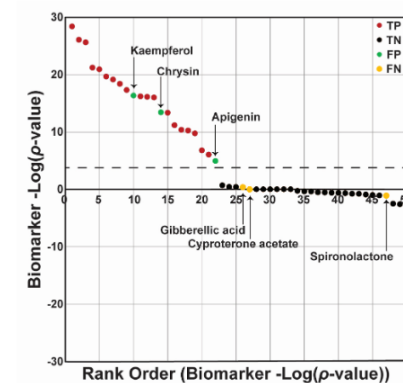
- Accurately replicates the predictions of the ToxCast ER Model based on 18 HTS assays (Ryan et al. Toxicol Sci. 2016 151(1):88-103)



- Used in screening in an MCF-7 compendium (Rooney et al. Chem Res Toxicol. 2021 34(2):313-329)

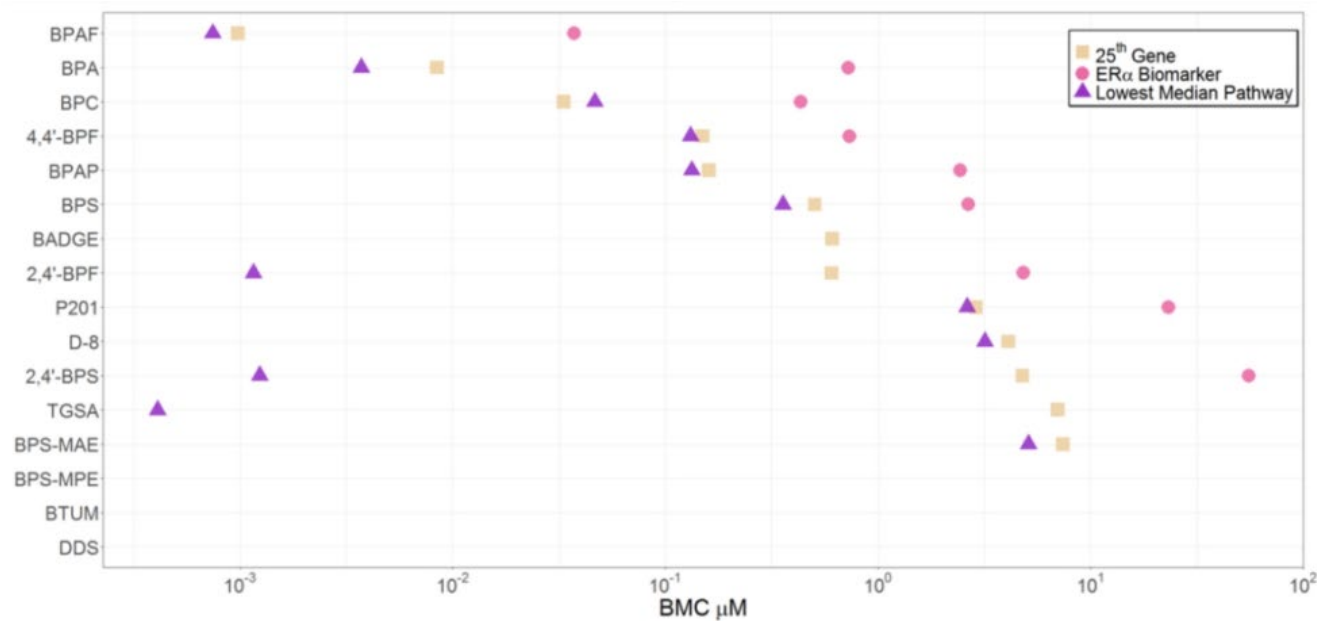
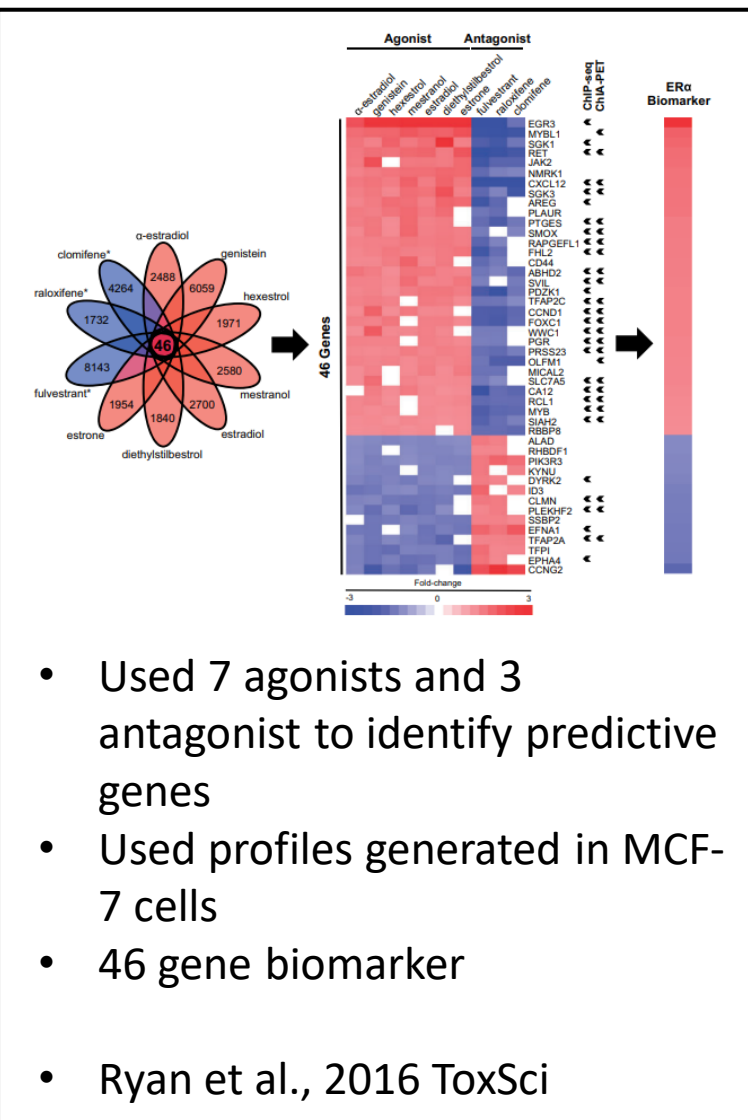


- Used to identify BPA alternatives with estrogenic activity (Mesnage et al. Toxicol Sci. 2017 158(2):431-443)



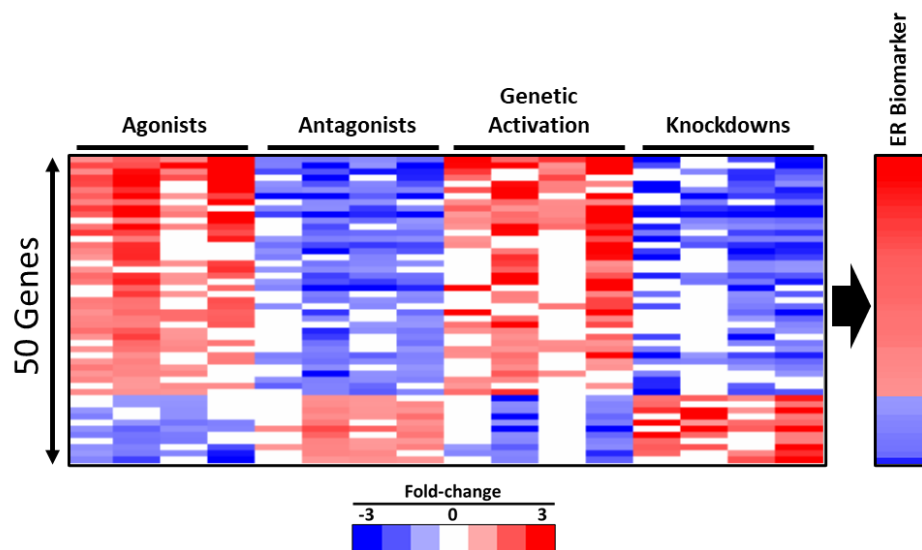
- Methods could be used to identify positives in the rodent uterotrophic assay (Corton et al., Chem Biol Interact. 2022 363:109995)

Use of an estrogen receptor biomarker to identify ER modulators in human cells in vitro



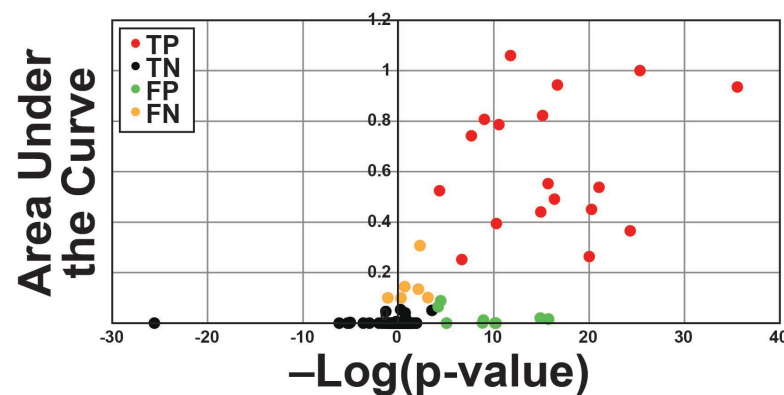
- Used the ER biomarker to derive potencies for data-poor BPA alternatives (Matteo et al., ToxSci. 2023. In press.

Use of an estrogen receptor biomarker to identify ER modulators by high-throughput transcriptomics (HTTr) screening



50-gene biomarker built from profiles of

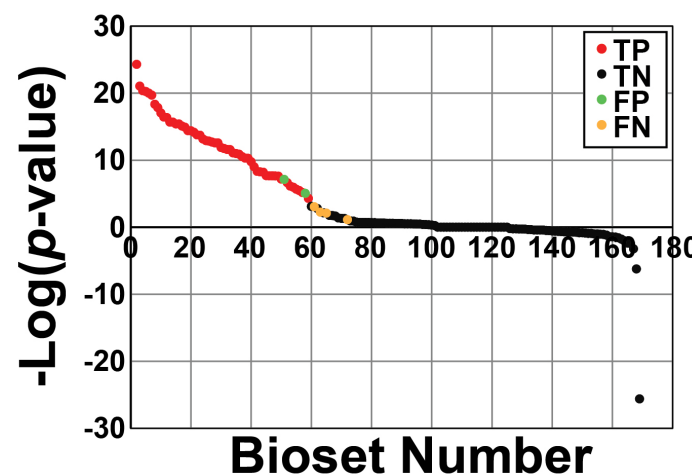
- 4 ER agonists
- 4 ER antagonists
- 4 constitutively active ER mutants
- 4 knockdowns of *ESR1* expression



Using the ToxCast ER model as the reference data set:

- Sensitivity = 75%
- Specificity = 90%
- Balanced accuracy = 82%

- Replicates the predictions of the ToxCast ER Model based on 18 HTS assays



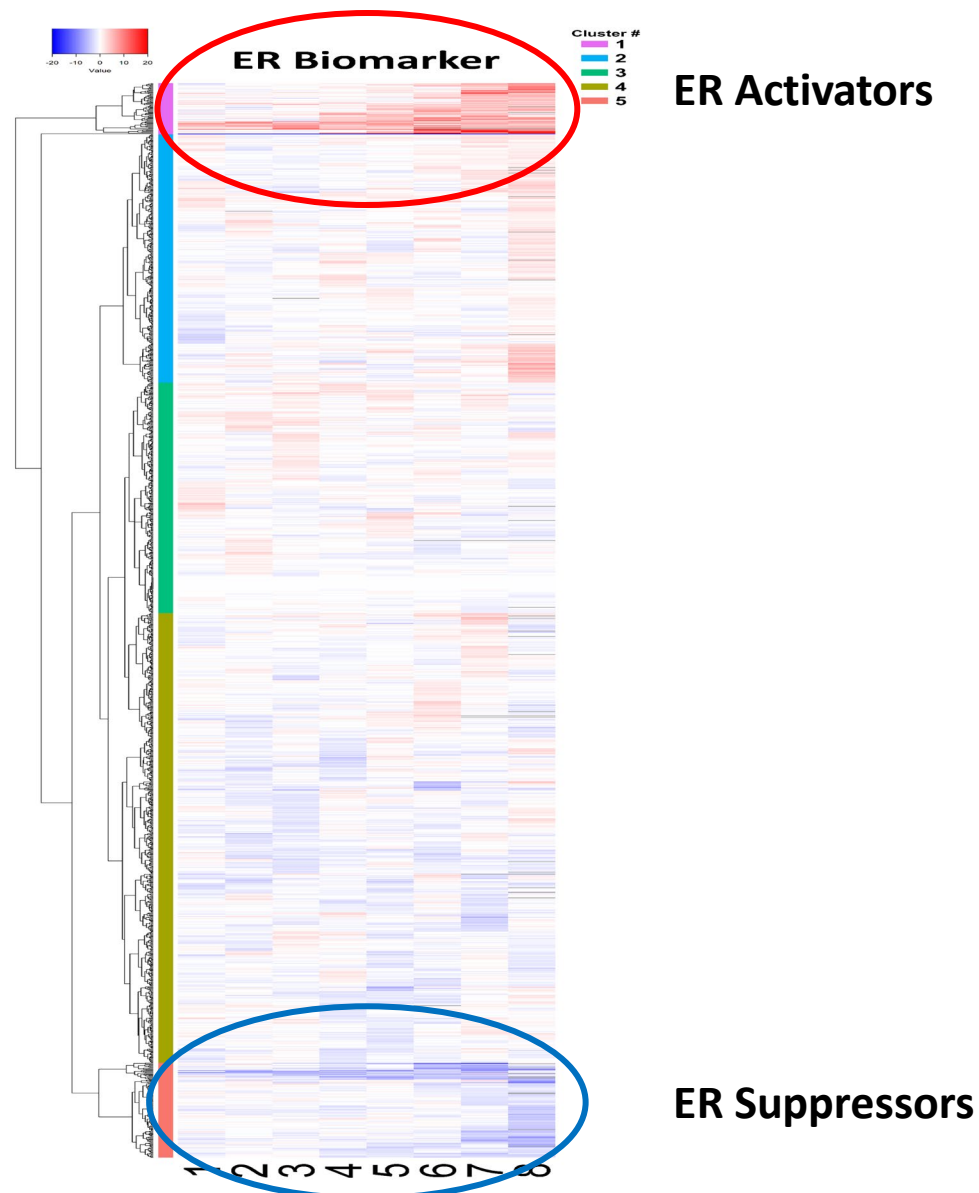
Using the NCATS Tox21 ER trans-activation assays as the reference data set:

- Sensitivity = 93%
- Specificity = 98%
- Balanced accuracy = 96%

- Excellent predictive accuracy with HTTr TempO-Seq data (Robarts et al., in prep)

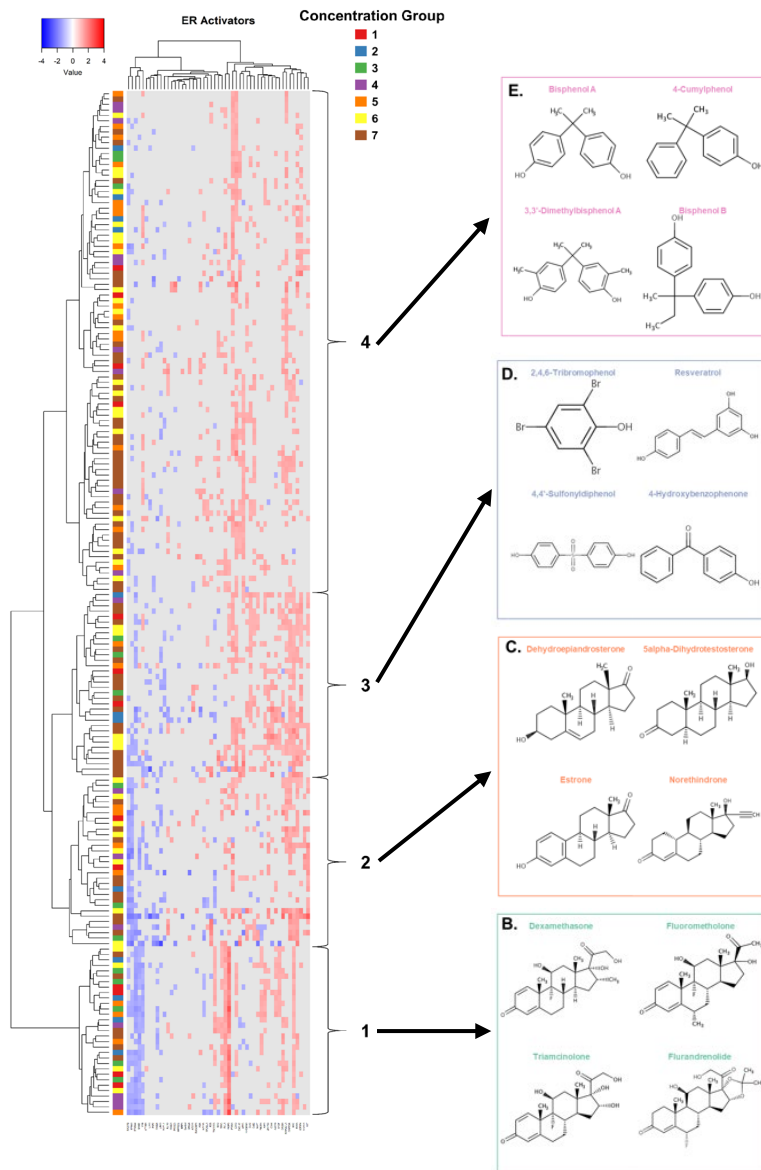
Identification of ER modulators using an estrogen receptor biomarker in MCF-7 cells

- Examined transcript changes in MCF-7 cells treated with ~1600 chemicals at 8 concentrations (~12,800 comparisons)
- Compared the profiles to the 50-gene estrogen receptor (ER) biomarker
- 2D hierarchical clustering of chemicals across 8 concentrations



ER activators regulate ER biomarker genes in a structure-dependent manner

- Examined transcript changes in MCF-7 cells treated with ~1600 chemicals at 8 concentrations (~12,800 comparisons)
- Compared the profiles to the 50-gene estrogen receptor (ER) biomarker
- 2D hierarchical clustering of ~120 chem-concentration pairs that activated ER

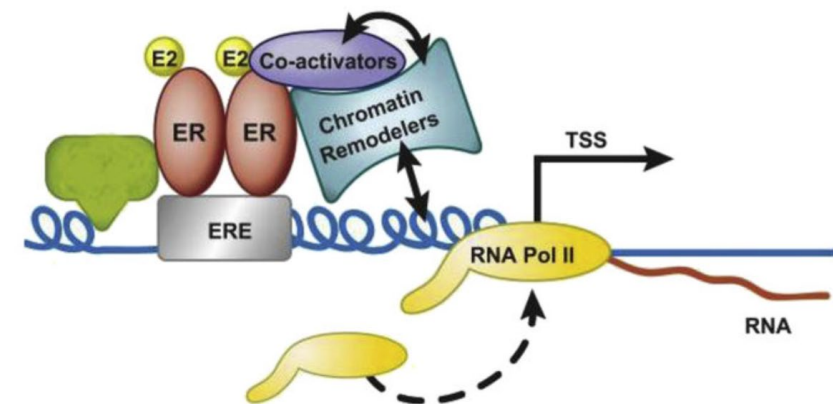


Bisphenols

Misc
activators

Classical
estrogens

GR and PR
agonists



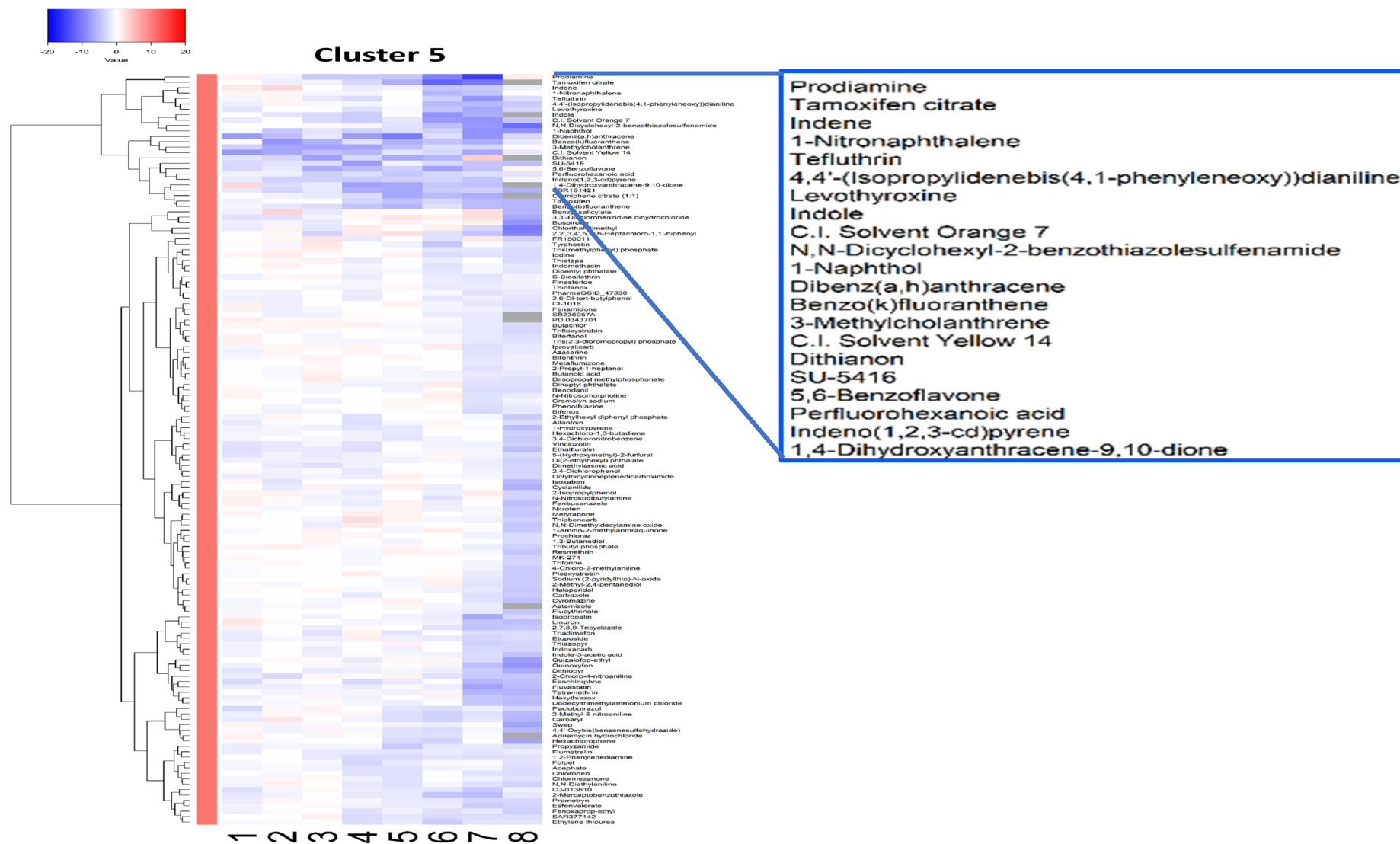
Results consistent with

- Agonists induce different conformations of the receptor
- ER conformation determines which co-activators interact
- ER-co-activator complexes determine which genes are activated

Robarts et al., in preparation

Many ER suppressors appear to be AhR activators

- Examined transcript changes in MCF-7 cells treated with ~1600 chemicals at 8 concentrations (~12,800 comparisons)
- Compared the profiles to the 50-gene estrogen receptor (ER) biomarker
- 2D hierarchical clustering of chemicals across 8 concentrations

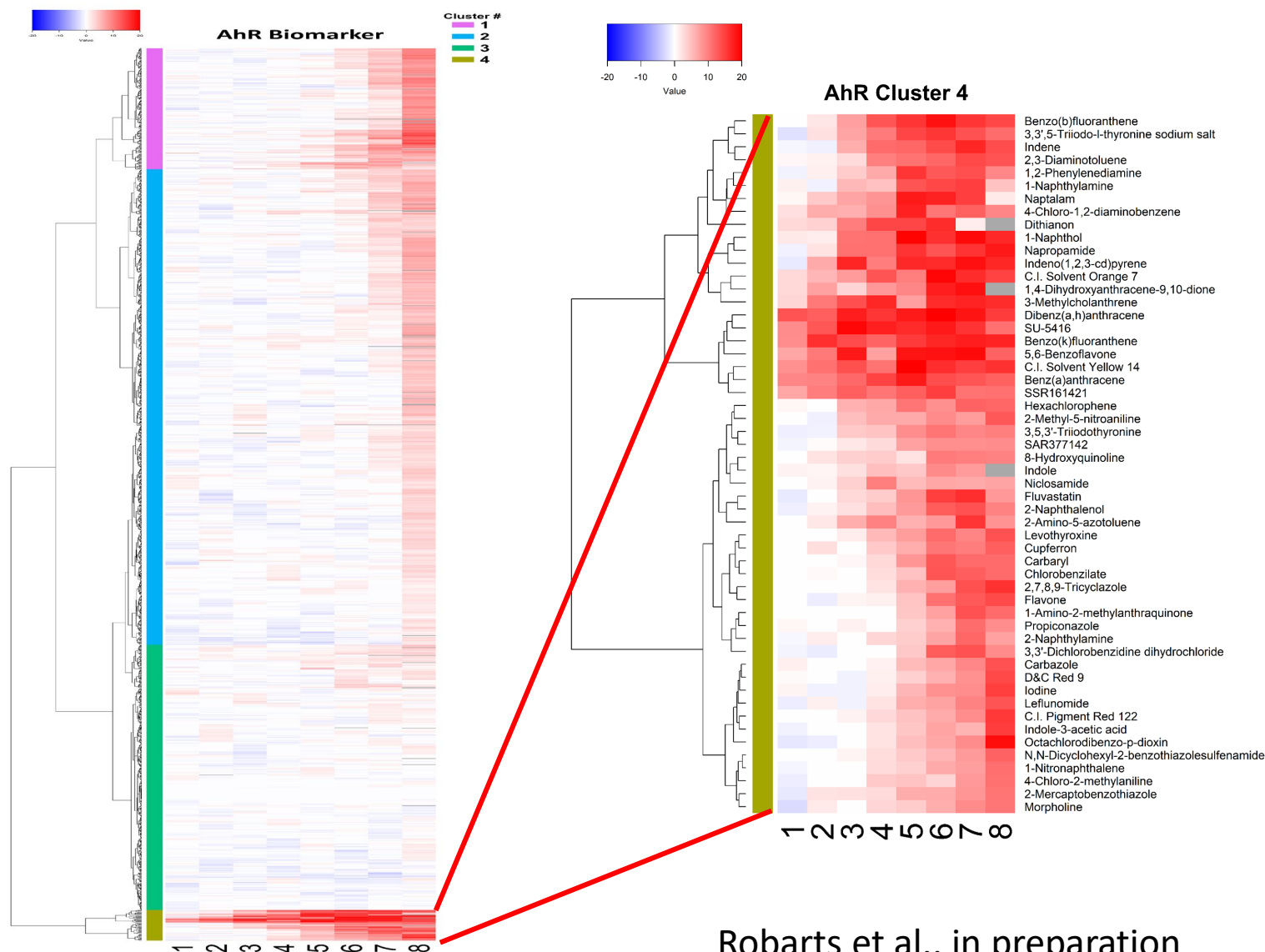


Robarts et al., in preparation

Identification of AhR activators in an HTTr screen in MCF-7 cells

- Built and characterized a gene expression biomarker to identify AhR activators in MCF-7 cells
- 16 genes consistently regulated by 12 AhR activators and in the opposite direction by knockdown of AhR using gene-specific siRNA
- Compared predictions to NCATS Tox21 AhR transactivation assay carried out in HepG2 cells
 - Sensitivity = 73%
 - Specificity = 59%
 - Balanced accuracy = 66%
- 7 out of the 29 were positive in the ToxCast ATG_Ahr-Cis_up assay carried out in HepG2 cells.

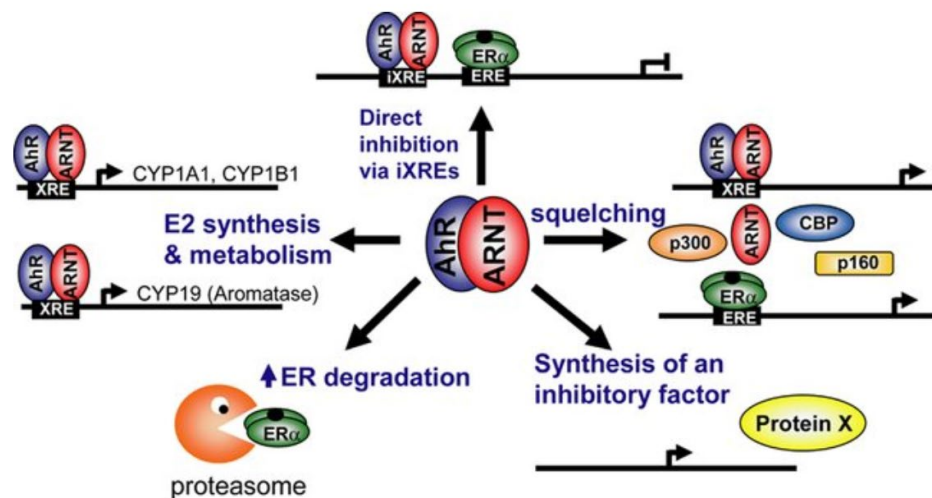
- Compared the ~12,800 profiles to the AhR biomarker



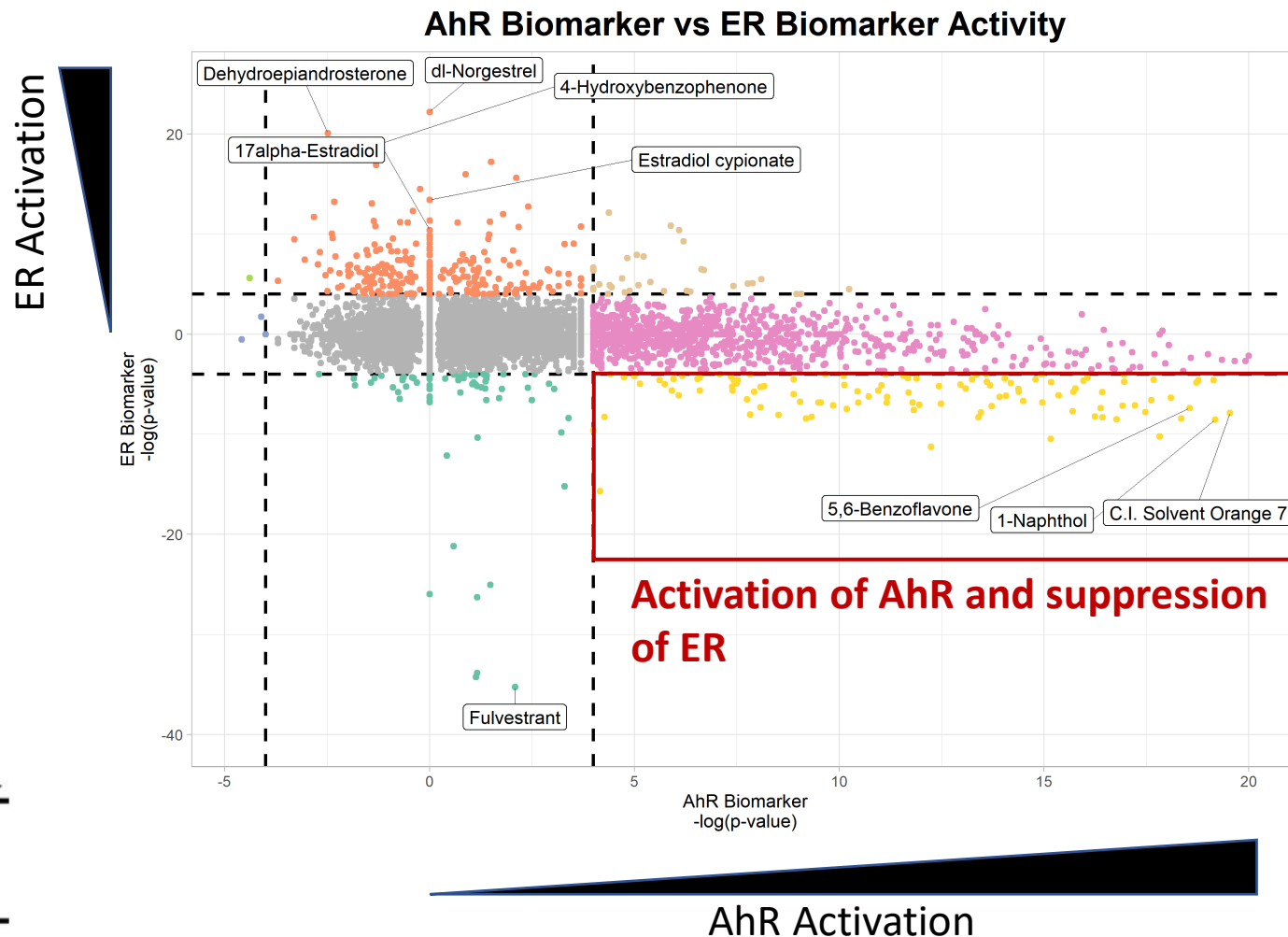
Robarts et al., in preparation

AhR activators suppress ER responses

- Examined transcript changes in MCF-7 cells treated with ~1600 chemicals at 8 concentrations
- Compared the profiles to the estrogen receptor (ER) and aryl hydrocarbon receptor (AhR) biomarkers



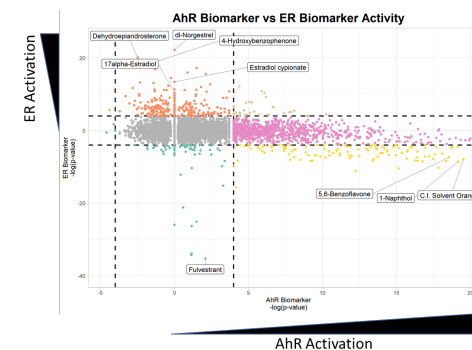
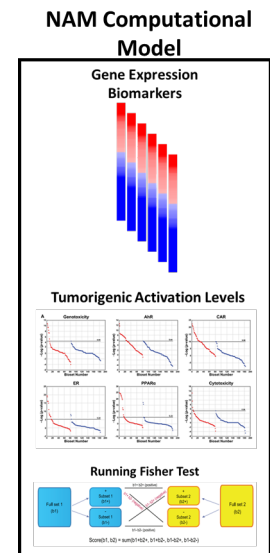
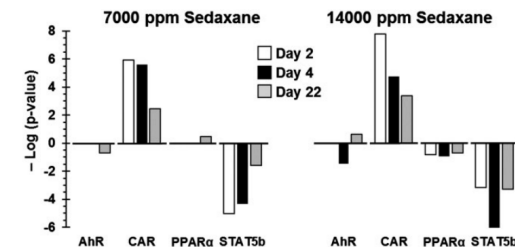
From Nuclear Receptor Signaling 4(1):e016



Robarts et al., in preparation

Summary

- Gene expression biomarkers have multiple uses
- Biomarkers for screening in mice
 - Identification of mode of action
- Biomarkers for screening in rats to reduce unnecessary testing
 - Identification of mode of action
 - Identification of chemical doses that would cause cancer
- Biomarkers for Tier 1 screening in high throughput transcript profiling
 - Estrogen receptor biomarker
 - Used to identify MIE modulation
 - Potential for replacing HTS assays
 - Potential for replacing the uterotrophic assay
 - Uncovers interesting biology
 - Biomarker gene expression pattern determined by chemical structure
 - Identified AhR-ER interactions



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