

# Toxicogenomic Dose Response Analysis to Inform Risk Assessments

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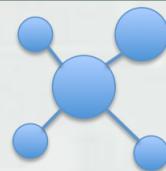
Environmental Laboratory



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AOPXplorer

# Approach Overview

- Preprocessing
  - ▶ Log2 transform
  - ▶ Quantile normalization
- Hypothesis-testing vs Screening
  - ▶ Screening for differentially expressed genes
    - Analyze only probes with at least 1.5x up/down regulation (normal space)
    - Bayesian Region of Practical Equivalence and 95% Highest Density Interval Analysis
  - ▶ Hypothesis-testing
    - Identify probes associated with genes associated with adverse outcome pathway networks of interest
    - Bayesian Region of Practical Equivalence and 95% Highest Density Interval Analysis
- Point of Departure determination
  - ▶ Monotonic dose-response
  - ▶ GRAVEE: Good Risk Assessment Values for Environmental Exposures
  - ▶ <https://github.com/datasciburgoon/gravee>
- Overlay data onto Adverse Outcome Pathway Networks
  - ▶ AOPXplorer: <http://apps.cytoscape.org/apps/aopxplorer>



# Bayesian Analysis to Identify Differentially Expressed Probes/Genes



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# Bayesian Analysis Basics

- Not concerned with “significance”
  - ▶ We don’t deal with p-values
  - ▶ Aside: p-values tell you how well your data fit a particular statistical model – that’s it
- Bayesian statistics are focused on **probability**
  - ▶ What is the probability of some event?
  - ▶ What is the probability the data fit a model?
  - ▶ What is the probability a chemical changes the expression of a gene?



# Bayesian Statistics Without Equations

- Prior probability
  - ▶ Reflects our knowledge of events
    - Probability that a chemical causes Gene X to change
    - Sometimes we don't have prior knowledge
      - ▷ We use uninformative prior probabilities or conjugate priors
      - ▷ More weight is given to the data in this case
- Likelihood
  - ▶ The data we observed
- Posterior probability
  - ▶ Proportional to the Prior probability times the Likelihood
  - ▶ Posterior probability is the probability of an event given conditions using any available prior knowledge (if it exists) and the likelihood
    - The probability that a gene changes in expression given a chemical exposure at a particular dose and time



# Bayesian Statistics Without Equations

- Posterior probability
  - ▶ Usually we get a distribution called Posterior Distribution
  - ▶ The distribution represents our uncertainty
  - ▶ Central tends (median) is typically used to represent the most likely value
  - ▶ Posterior interval represents the range where the posterior probability is likely to exist
    - 95% Posterior Interval represents the region where we have 95% probability where the posterior probability is



# Bayesian Statistics Without Equations

- 95% Highest Density Interval
  - ▶ The values of the distribution from 5% and above
  - ▶ This represents the 95% most likely values
- We typically couple this with decision rules...

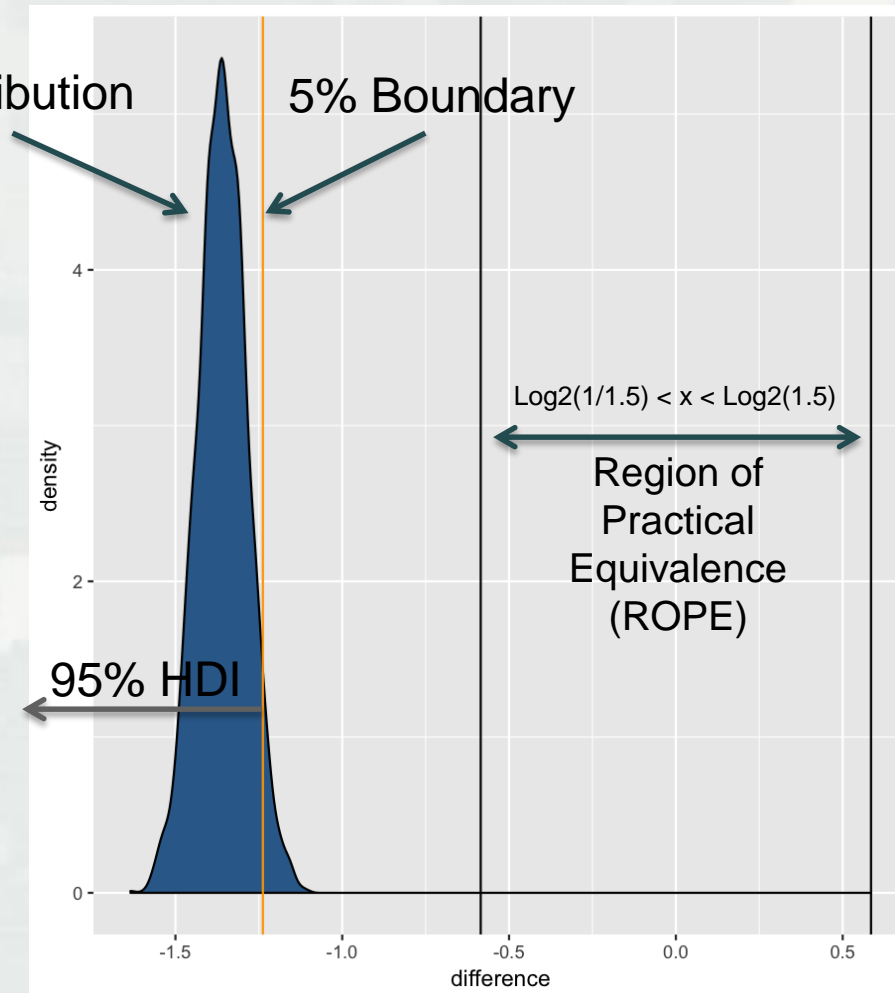




# Bayesian 95% HDI Analysis

Difference Distribution

5% Boundary



**Acyl-coA Synthetase**

Significant  
Difference:

All of the 95% HDI  
is outside the  
ROPE

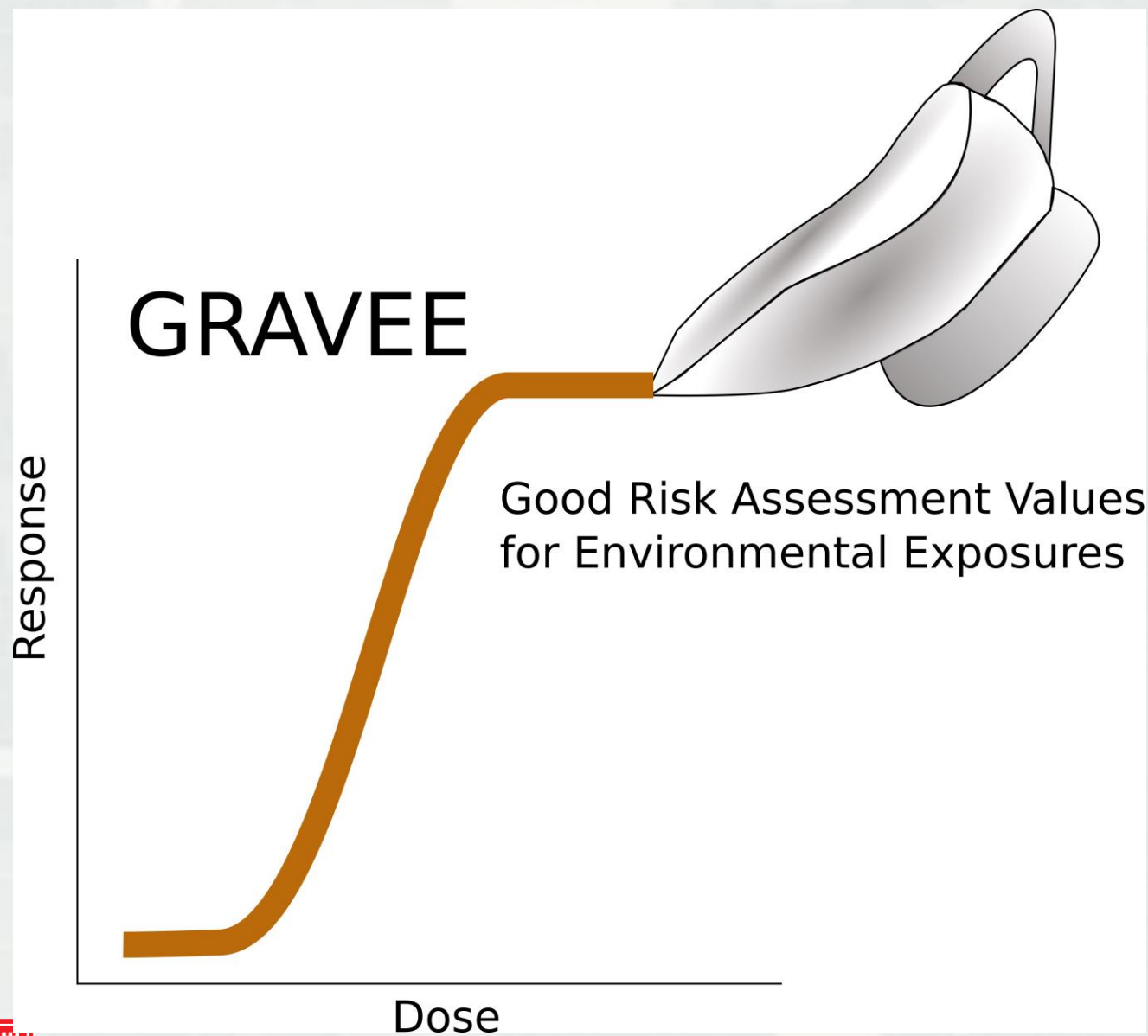


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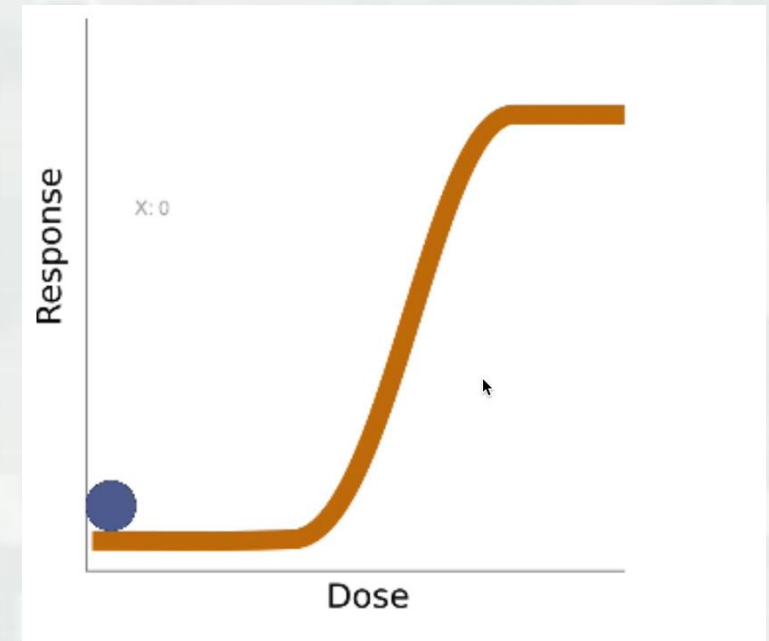
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# How Can We Avoid Needing a Benchmark Response??

- Interpolate curve data
  - ▶ Spline-based metaregression
- Menger Curvature
  - ▶ Measures the curvature of a curve
  - ▶ We identify the point of the maximal Menger Curvature in the interpolated curve
  - ▶ This point is the POD



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# How Do We Get The Uncertainty

- Bootstrap!
  - ▶ Sample with replacement across the dose response dataset to create a lot (let's say 1,000) dose response curves
- So now we have a lot (let's say 1,000) dose response curves
- And now on each of these models we:
  - ▶ Interpolate curve data using spline-based metaregression
  - ▶ Find POD using Menger Curvature
- So now we have a lot (let's say 1,000) of PODs
  - ▶ You can do a lot with a lot (let's say 1,000) of PODs



# Parametric vs Nonparametric Modeling

- Parametric
  - ▶ We “know” the general mathematical family the data follow
  - ▶ Start with predefined mathematical models
    - Hill Model (a variant of a sigmoidal model)
    - Exponential models
    - Polynomial
  - ▶ Example
    - Benchmark Dose Software
- Nonparametric
  - ▶ Does not start with a predefined mathematical model
  - ▶ Lets the data speak for themselves
  - ▶ Example
    - LOESS or LOWESS commonly used in microarray normalization
    - GRAVEE (Good Risk Assessment Values for Environmental Exposures)



# Uncertainty Around Our POD

GRAVEE POD	TNT, in vitro (ug/mL)
POD (5%)	0.60
POD (50%, median, most likely POD)	3.00
POD (95%)	4.80

Uncertainty can be propagated through IVIVE and RfD/RfC calculations



## Revisiting 2,4,6-Trinitrotoluene...A Case Study



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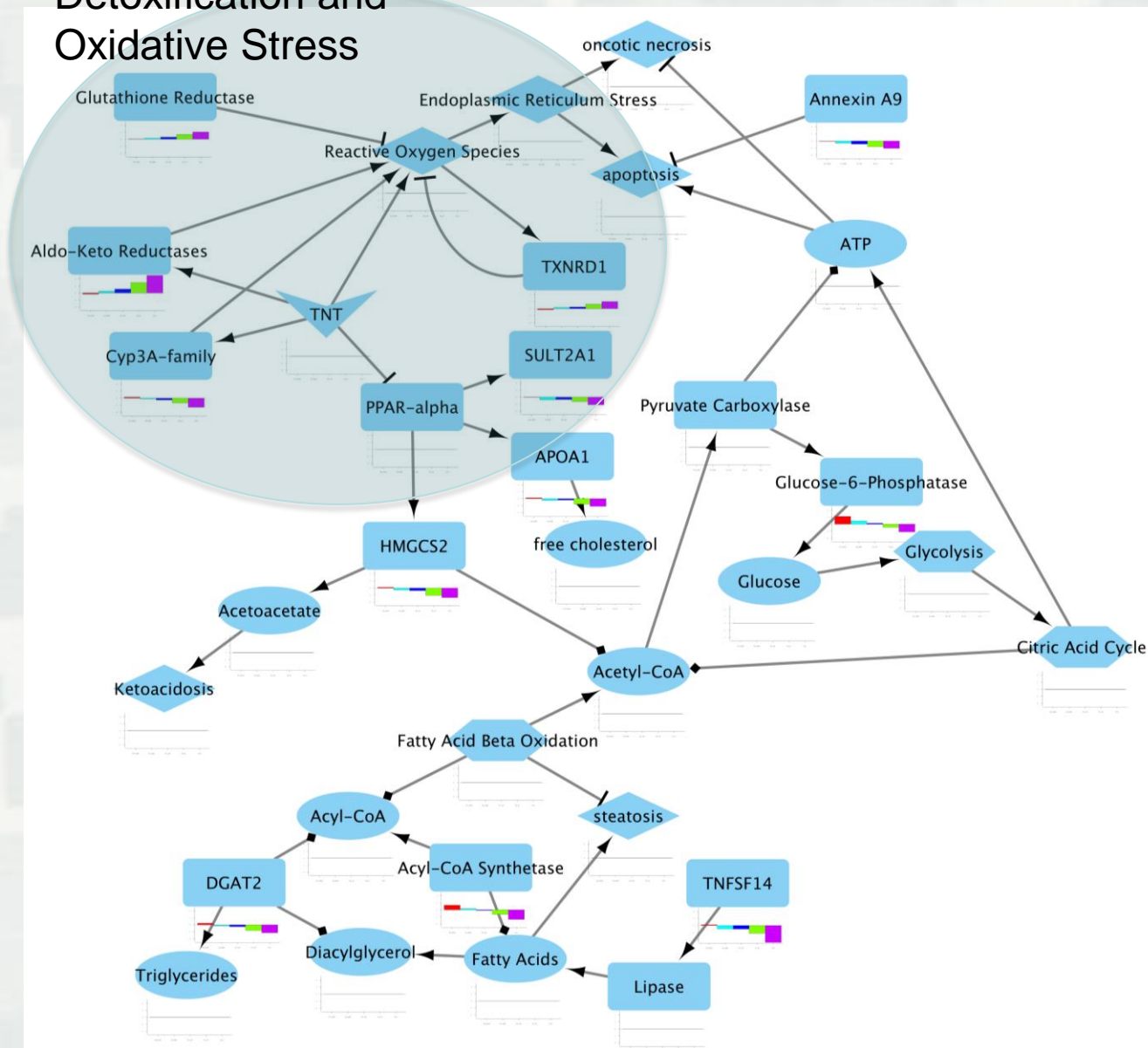
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# Placing Gene Expression in Biological Context

## Detoxification and Oxidative Stress



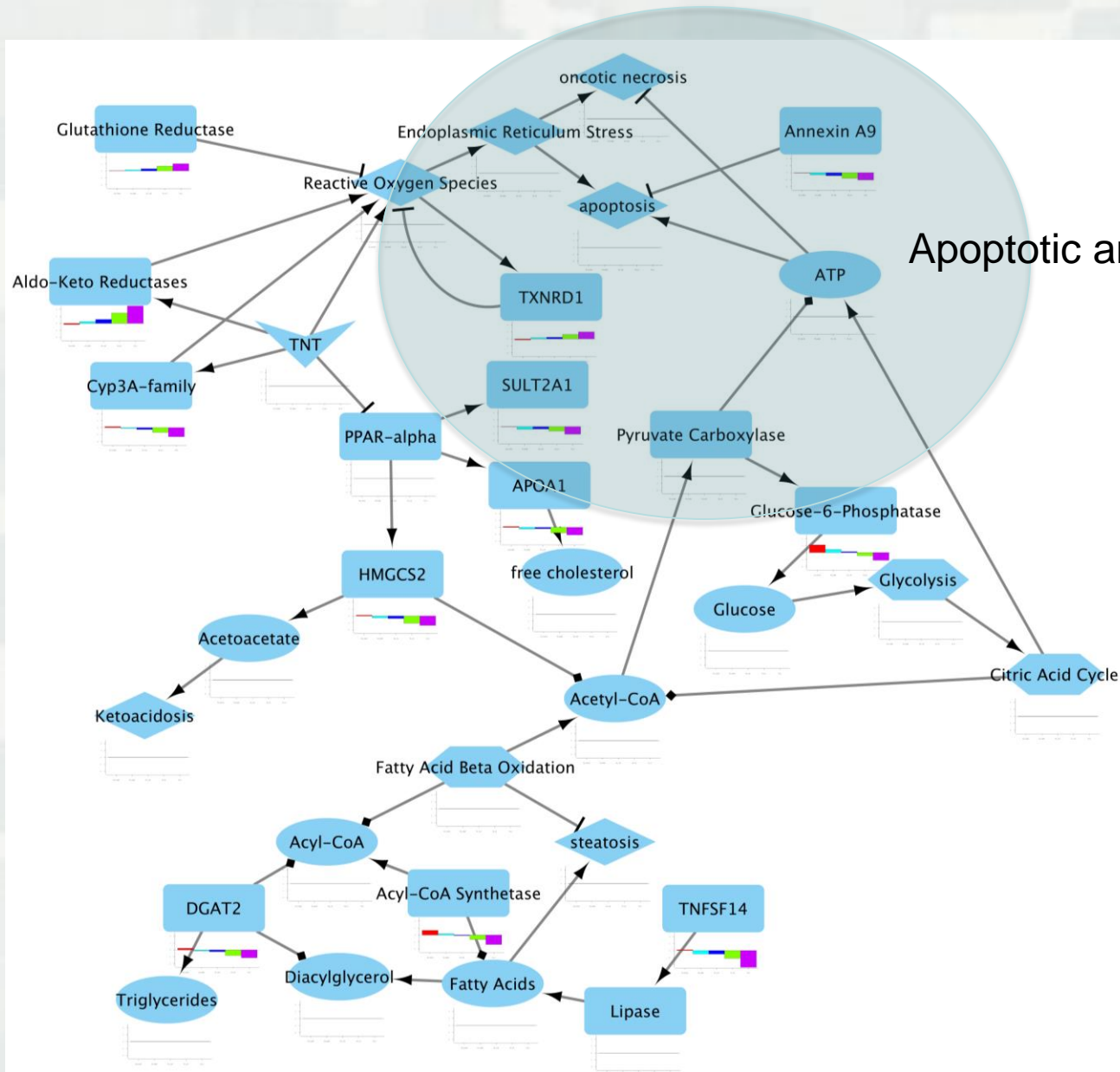
AOPN:  
Steatosis and  
Primary Metabolism

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# Placing Gene Expression in Biological Context



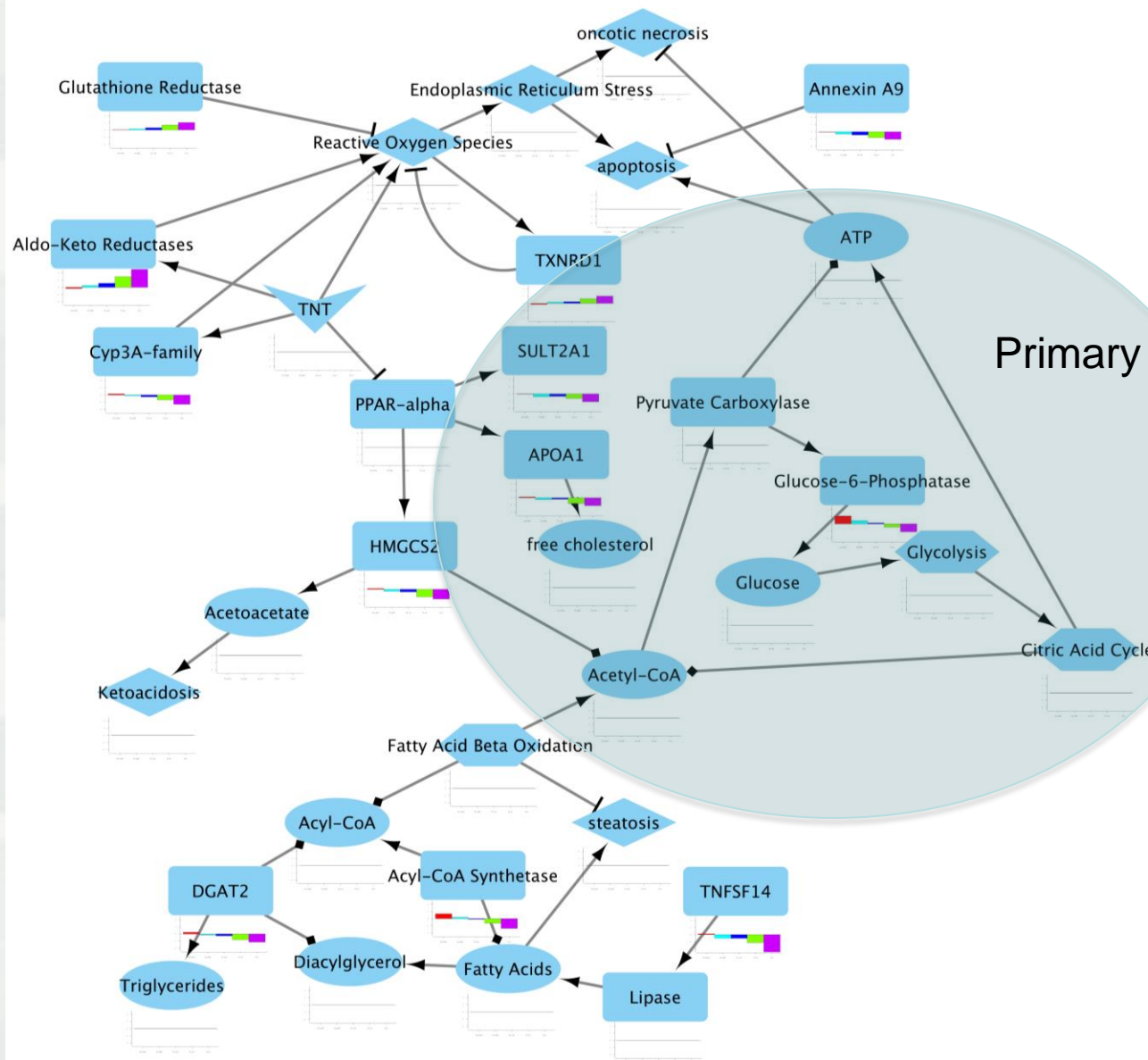
AOPN:  
Steatosis and  
Primary Metabolism

Apoptotic and Oncotic Necrosis

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# Placing Gene Expression in Biological Context



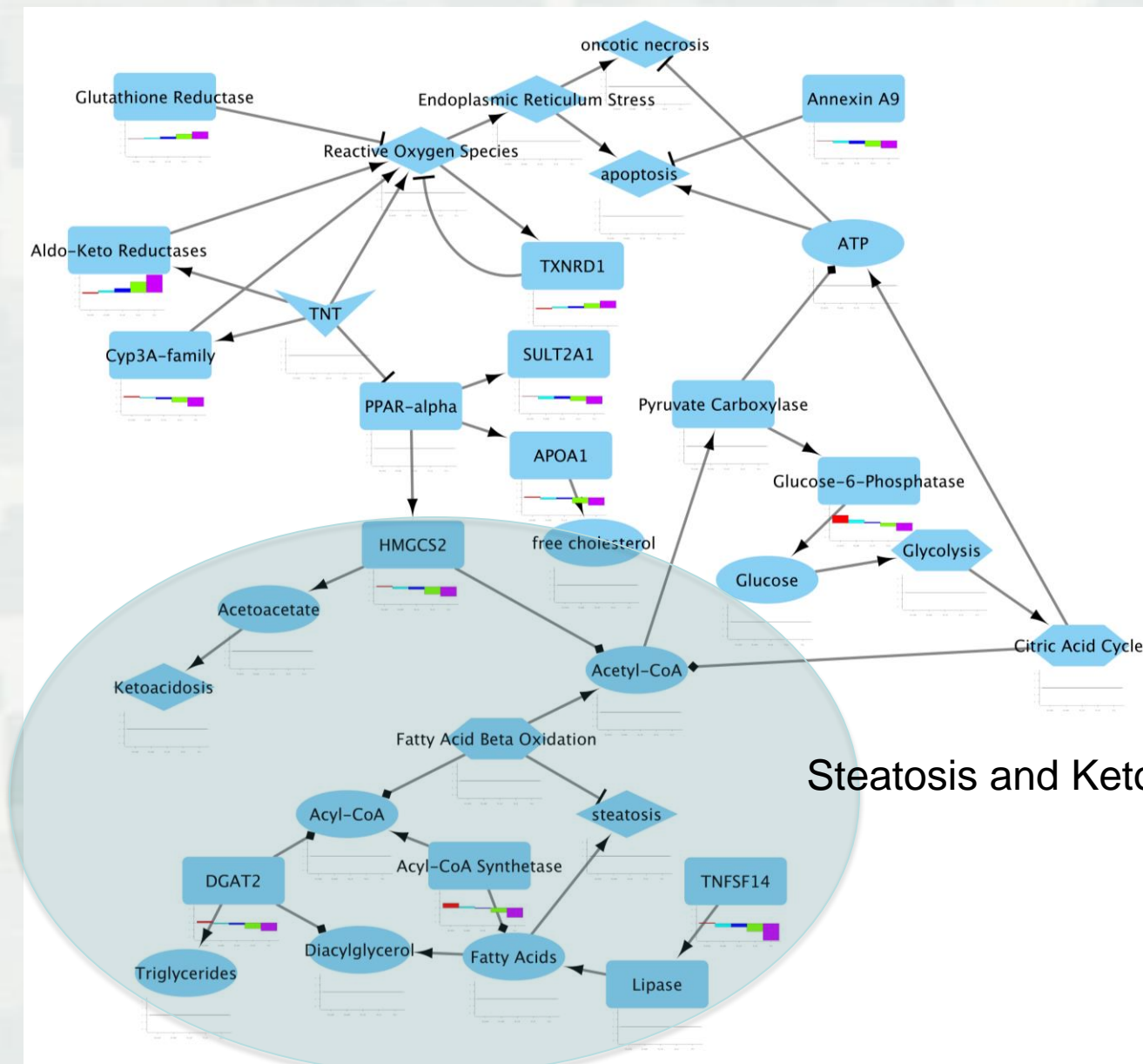
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Primary Metabolism

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# Placing Gene Expression in Biological Context



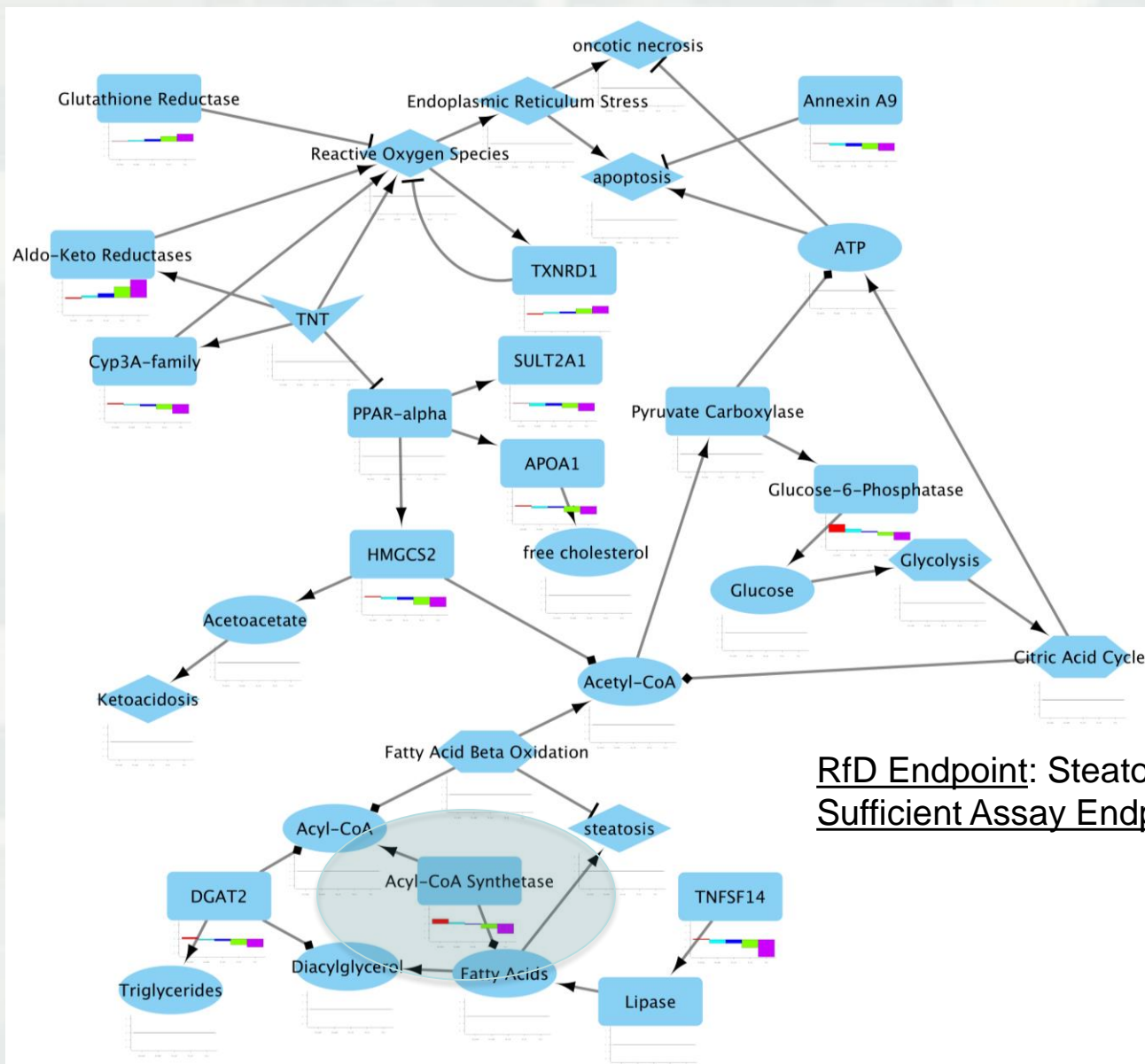
AOPN:  
Steatosis and  
Primary Metabolism

Steatosis and Ketoacidosis

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# Placing Gene Expression in Biological Context



AOPN:  
Steatosis and  
Primary Metabolism

RfD Endpoint: Steatosis  
Sufficient Assay Endpoint: Acyl-CoA Synthetase

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1) Choose your input data file

Data File

Go!

GRAVEE calculates the distribution of predicted PODs using bootstrapping.

POD-50%: This is the median of the POD distribution (the most likely POD value given the data)

Tab-delimited text file. Should look something like this:

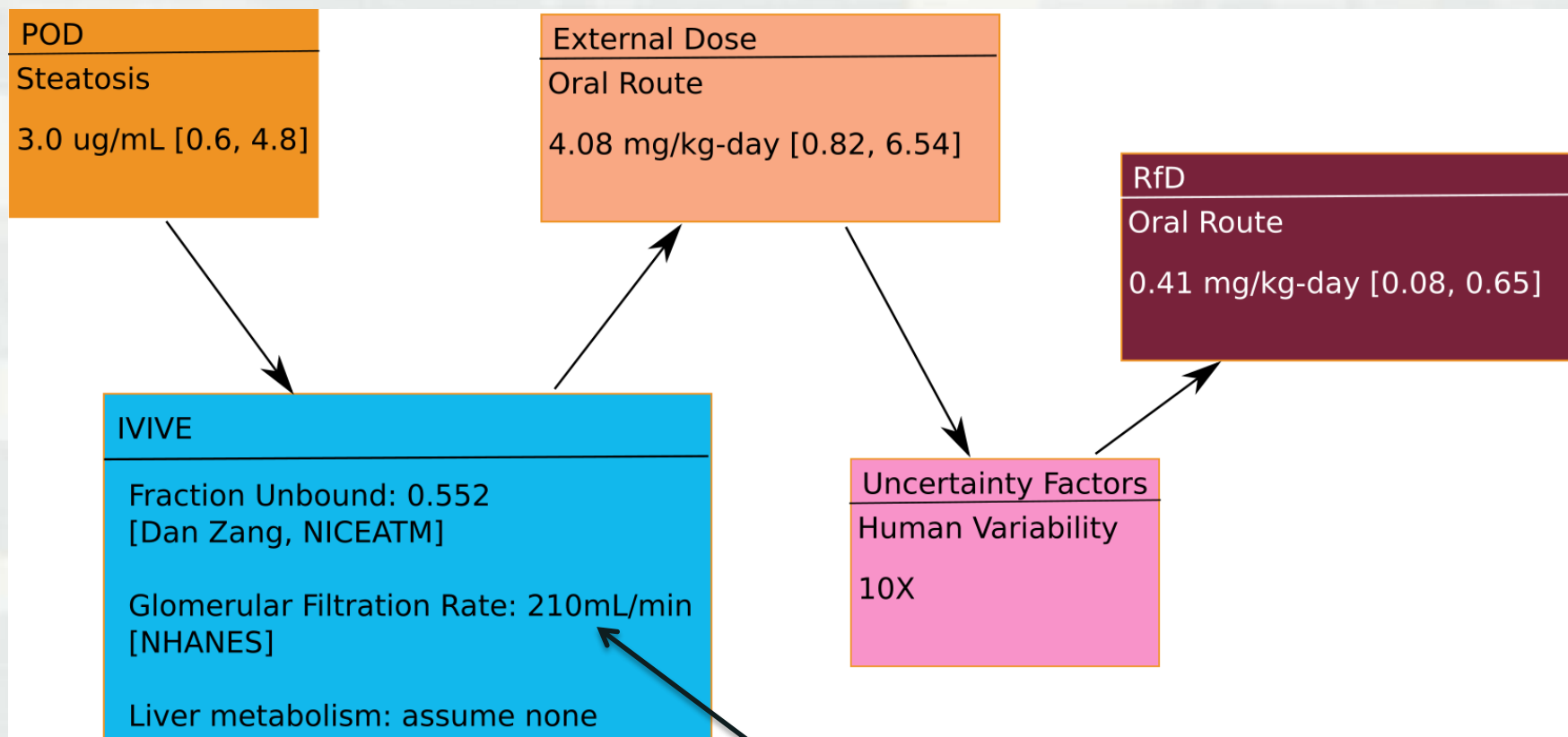
Assay/Gene Name >> Dose 1 >> Dose 2 >> Dose 3 >> Dose 4 >> Dose 5



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# TNT RfD Synthesis for Steatosis



In the future we will consider uncertainty at GFR



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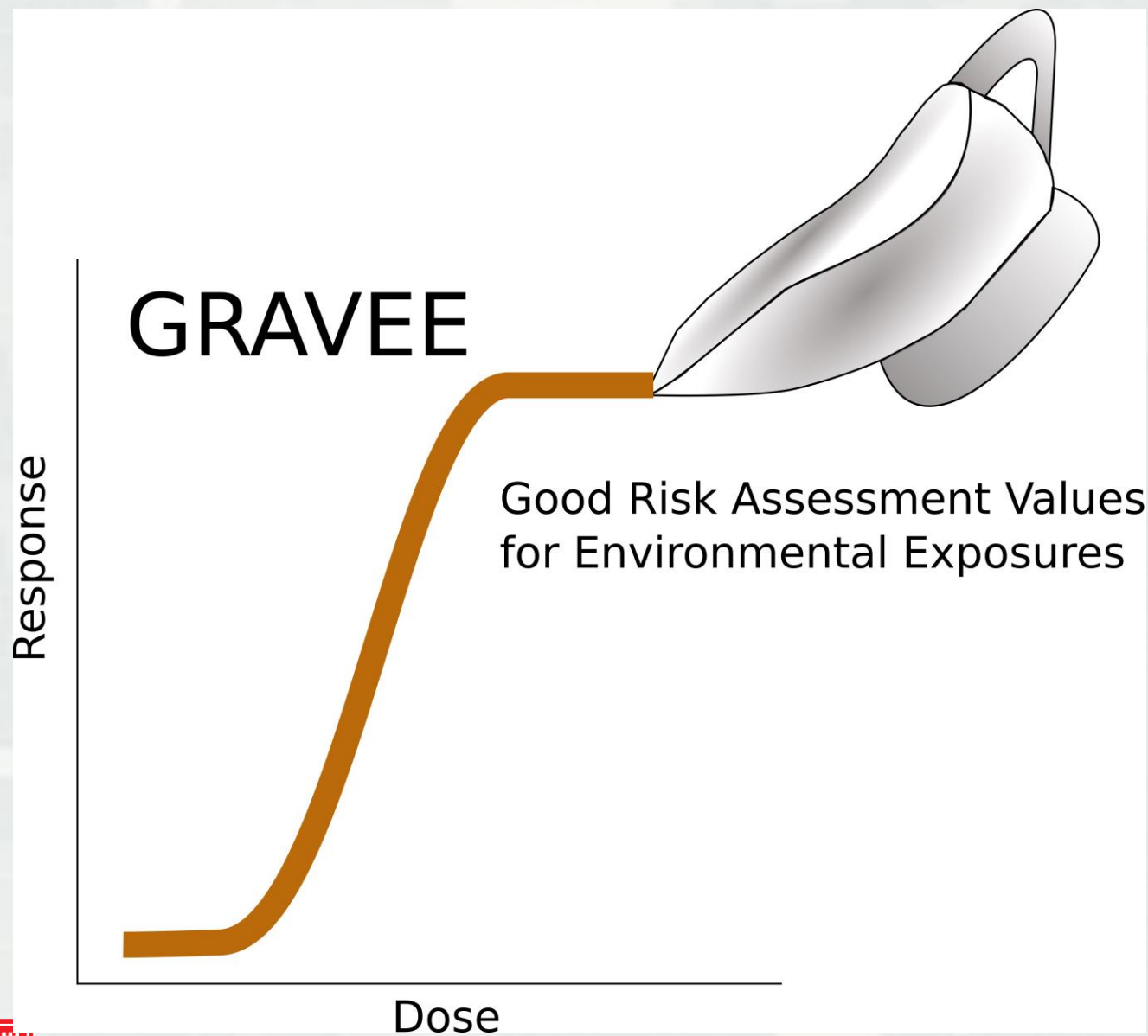


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