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Background and Approaches

Background

- High throughput in vitro assays like those developed for ToxCast/Tox21 and L1000 provide a valuable source of data for a wide range of biological functions
- Direct use of all high throughput endpoints is not effective, especially with a small sample size
- The adverse outcome pathway (AOP) framework provides a convenient way to encode and communicate mechanistic knowledge
- We aim to integrate mechanistic knowledge with multiple *in vitro* assay data sources to develop predictive models for the risk of drug induced liver injury (DILI)

Approaches

- Map drugs with known DILI properties to AOPs using information in DrugBank
- Build high-dimensioial predictive models for DILI risk with predictors selected with the aid of AOP networks

Build predictive models with high throughput assays and AOP networks

Selection of predictors aided by AOP networks

- Liver toxicity related AOPs in AOPwiki and literature were used to identify 64 potential predictors, including endpoints for nuclear receptor binding, gene expression and cellular function
- These were matched to 12 assays in Tox21 and 31 gene expression measures from L1000
- Three drug properties for daily dose, logP, and reactive metabolite (RM) formation are also included for a total of 46 predictors

Logistic regression model with elastic net penalty

• The response (y) indicates either most-DILI-concern (92 drugs) or no-DILI concern (64 drugs). The vector x encode the 56 predictors

•
$$log \frac{P(y=1|X=x)}{P(y=0|X=x)} = \beta_0 + \beta^T x$$

The penalty parameter λ is selected by cross-validation

$$(\hat{\beta}_0, \hat{\beta}) = \min_{(\beta_0, \beta)} -\frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \sum_{i=1}^{N} \left[y_i(\beta_0 + x_i^T \beta) - \log\left(1 + e^{\beta_0 + x_i^T \beta}\right) \right] + \lambda \left[\frac{(1-\alpha) \|\beta\|_2^2}{2} - \frac{1}{N} \sum_{i=1}^{N} \sum_{i=1$$

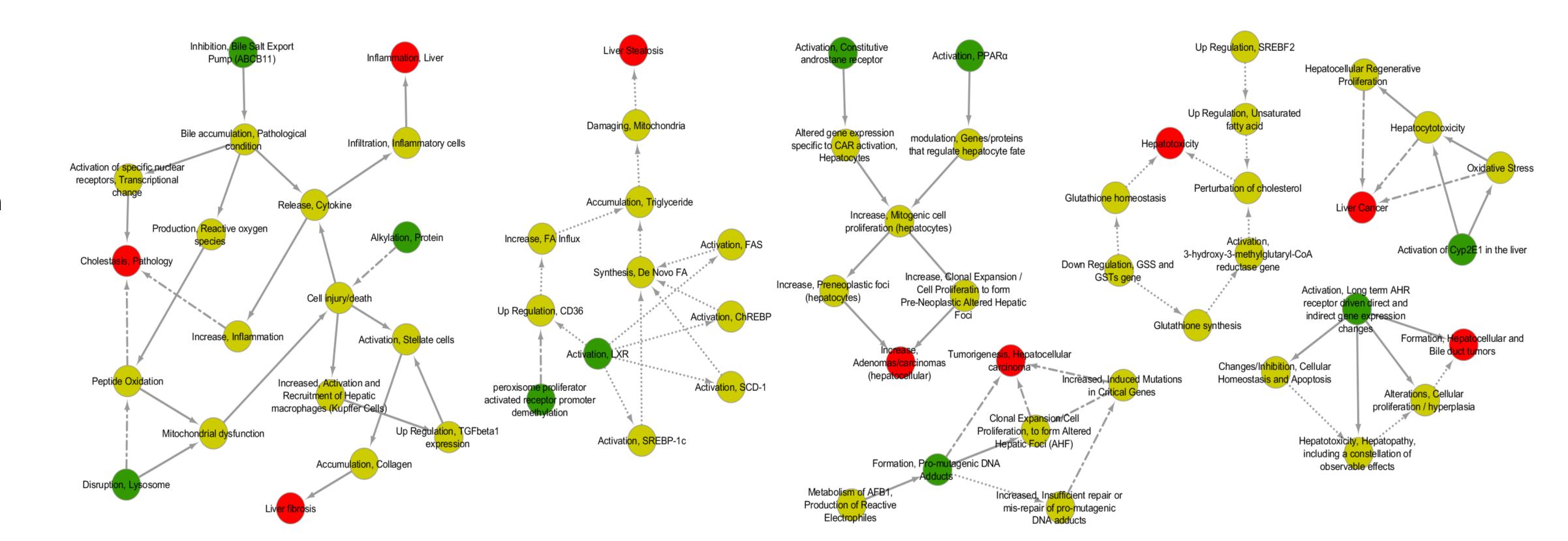
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Integrating Adverse Outcome Pathways (AOPs) and High Throughput in vitro Assays for Better **Risk Evaluations, a Study with Drug Induced Liver Injury (DILI)**

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AOPs with hits by most-DILI-concern drugs



- AOPs with hits by most-DILI-concern drugs form seven distinctive AOP networks
- (MIEs), and the yellow nodes are key events (KEs)

Performance of the penalized logistic regression aided by AOP networks

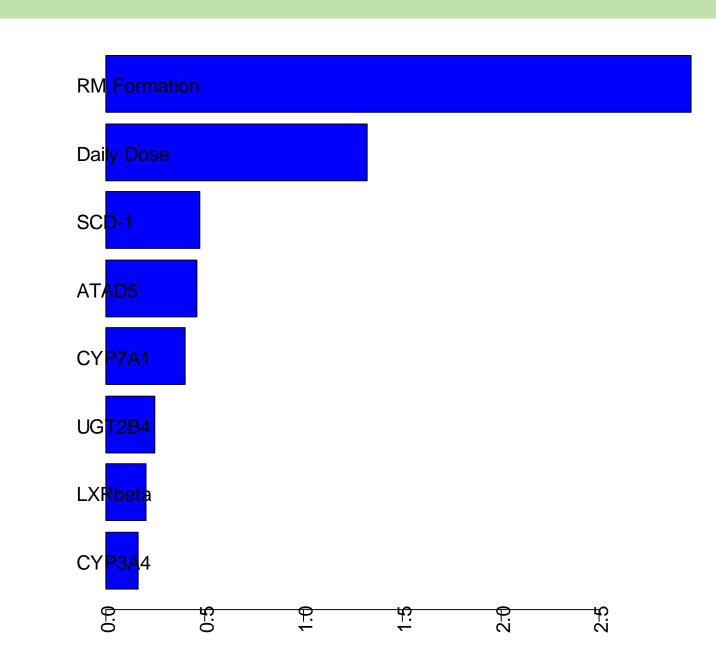
Model Fit		Actual	
		No-DILI-	Most-DILI-
		Concern	Concern
	No-DILI-		
	Concern	45	4
Fitted	Most-DILI-		
	Concern	9	88

Cross-validation		Actual	
		No-DILI-	Most-DILI-
		Concern	Concern
	No-DILI-		
	Concern	39	11
Predicted	Most-DILI-		
	Concern	15	81

- On model fit, the penalized regression model obtained a sensitivity of 0.96, a specificity of 0.83, with the accuracy being 0.91.
- being 0.82.
- logistic regression model using all selected predictors (0.91).

 $+ \alpha \|\beta\|_1$

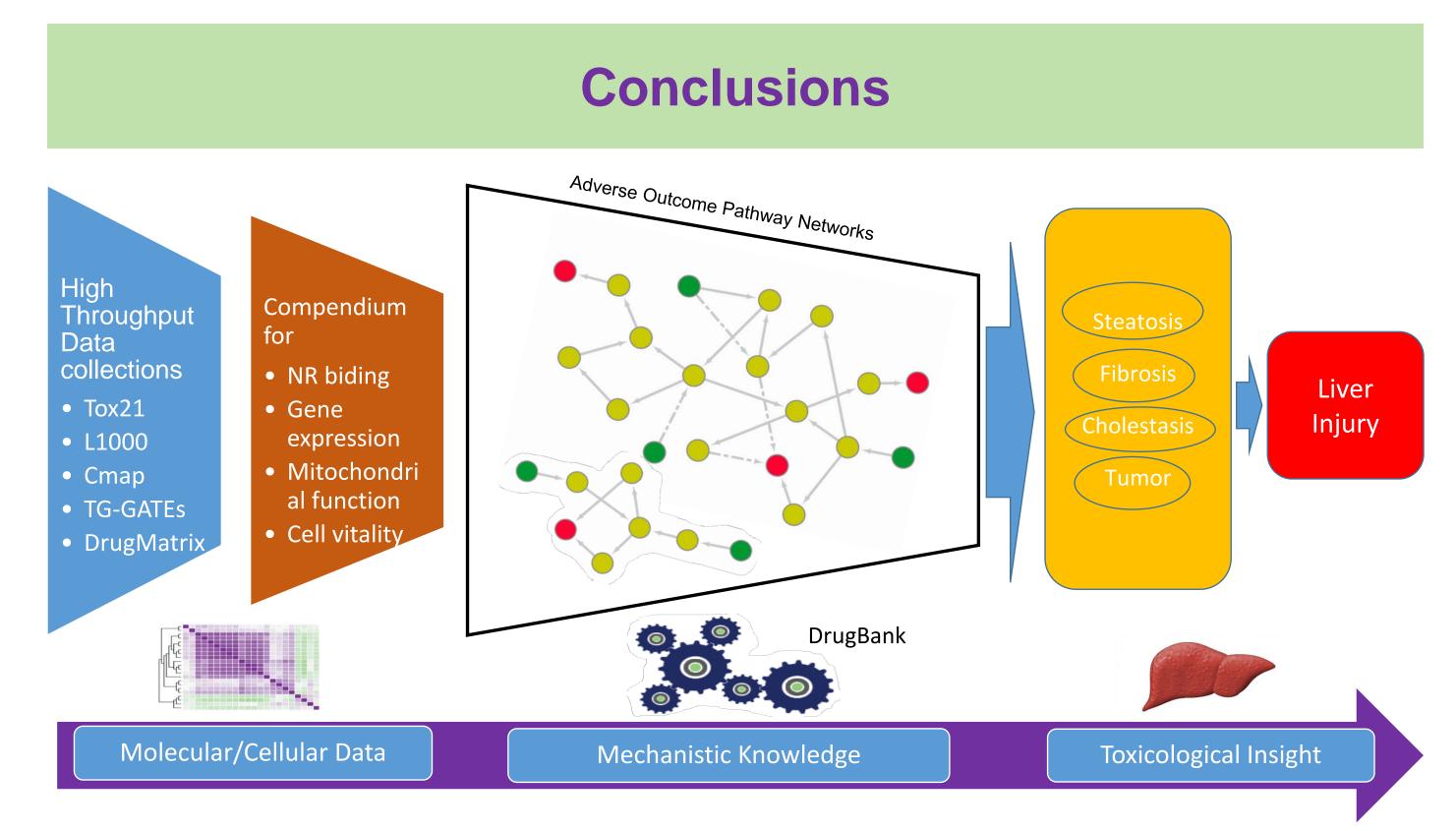
• The red nodes are adverse outcomes (AOs), the green nodes are molecular initiating events



Predictors with the largest coefficients in the penalized logistic regression model

• Under cross-validation, it obtained a sensitivity of 0.88 and a specificity of 0.72, with the accuracy

• In comparison, the model fit accuracy using only three drug properties (daily dose, logP, and RM) formation) is 0.84, that using only in vitro assays is 0.63. Both are lower than that of the penalized



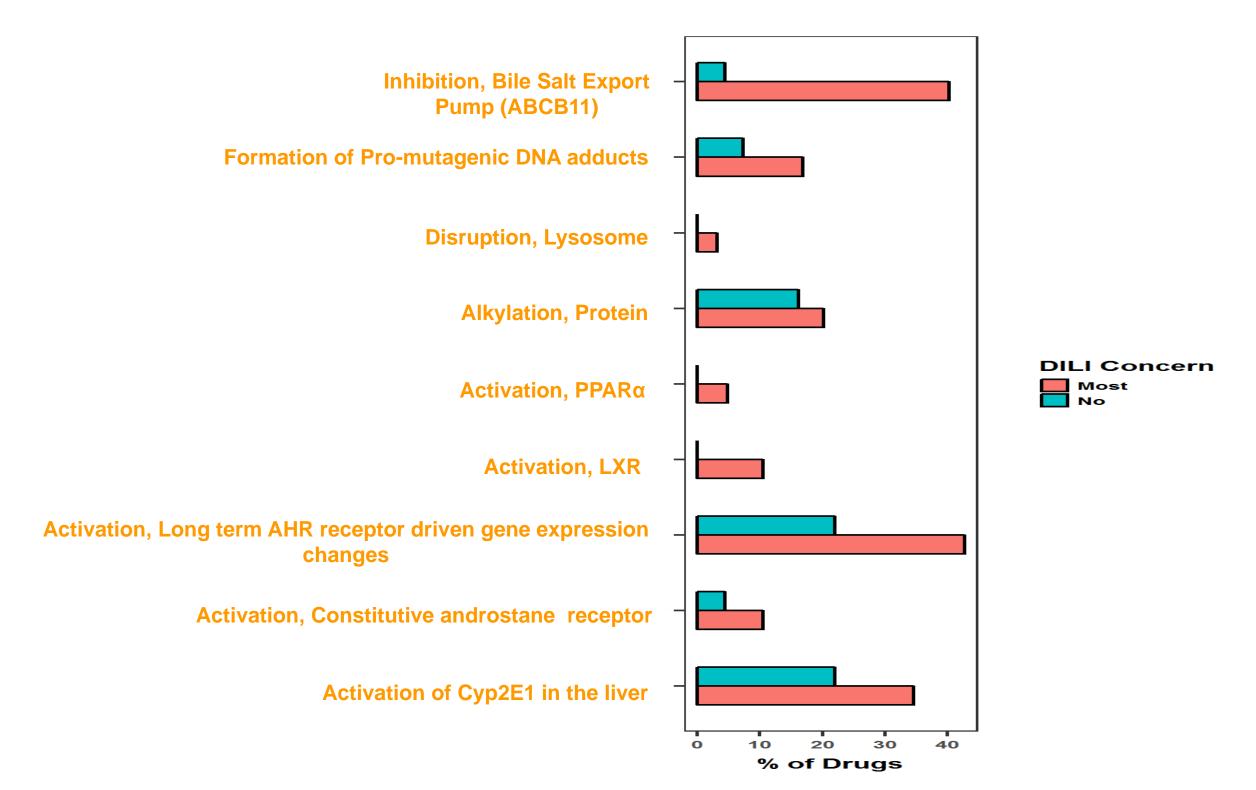
- Mechanistic knowledge is of critical importance even with the availability of high throughput in vitro data

- Integrating multiple data sources with AOPs is promising • The linear score for DILI potential has been shown to be significantly associated with higher reporting rates in the FAERS data

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ADMINISTRATION

Frequency of hits by Most-DILI-concern and no-**DILI-concern drugs**



Liver toxicity related AOPs have varying frequencies of hits by most-DILI- concern and no-DILI-concern drugs

- Our results confirmed the utility of AOPs as a easily accessible source of mechanistic knowledge
- AOPs can be effectively utilized to select endpoints from in vitro assays as a dimension-reduction tool