ComptoxAI:

An artificial intelligence toolkit for knowledge discovery in computational toxicology

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NIEHS EHSCC Early Stage Investigators Webinar Series
Presented January 12, 2022







The role of Al in toxicology

- Al should help basic toxicologists by:
 - Predicting new associations between chemicals and endpoints of toxicity
 - Explaining mechanisms that may underlie those predictions
- It does not replace experimental validation; rather, it helps us to focus our time and effort

Outline

- ComptoxAl overview
- ComptoxAI: Data access and information retrieval
- ComptoxAI: GraphML to improve QSAR models

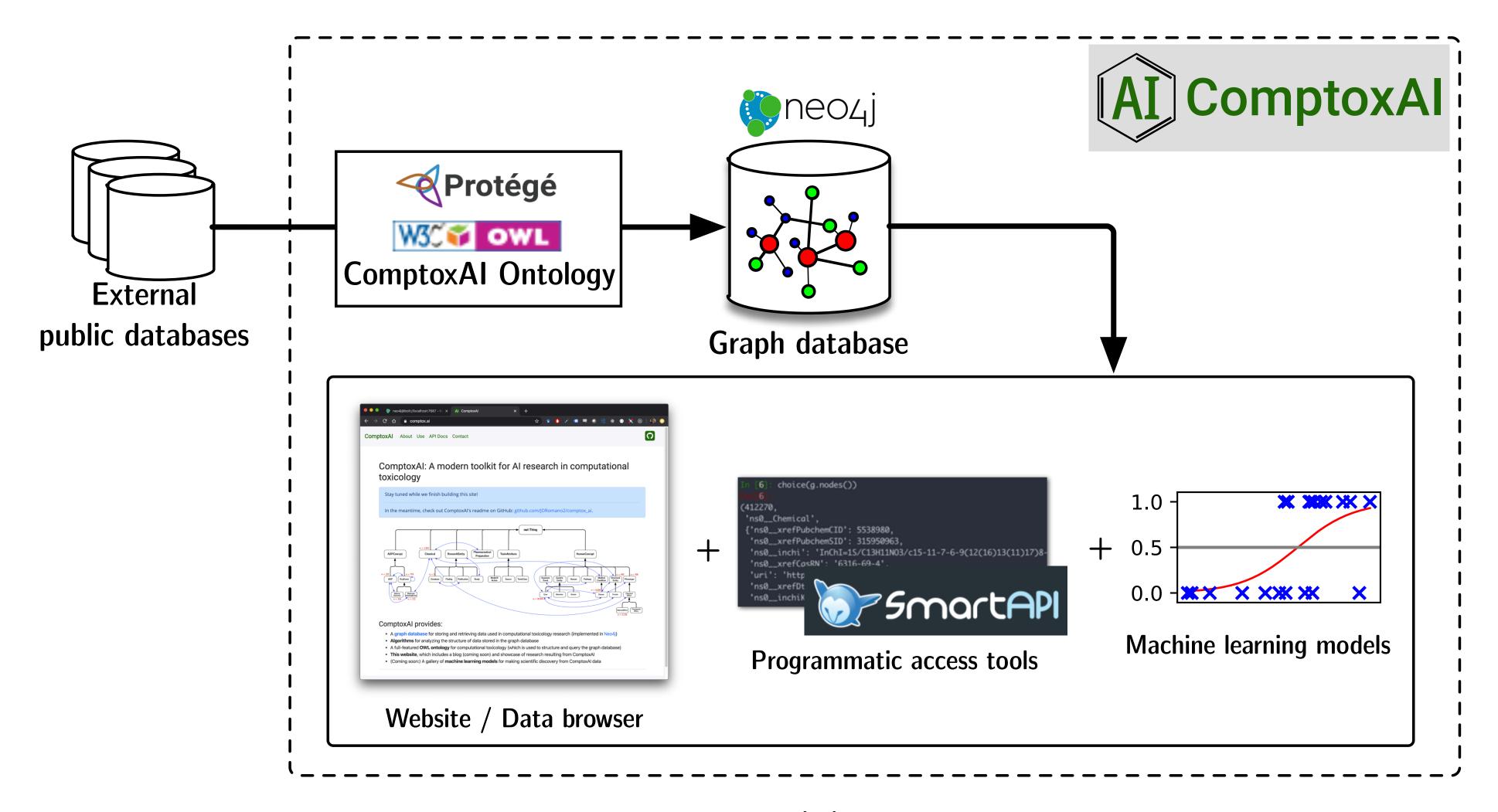
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Toxicology

- Study of the adverse effects of chemicals on living organisms
 - Environmental toxicology focuses on environmental exposures
 - Occupational toxicology focuses on workplace exposures
 - Can also focus on toxic effects of pharmaceutical compounds
- Predictive toxicology: Use of computational and statistical techniques to predict (previously unobserved) toxic effects of specific chemicals

ComptoxAl



https://comptox.ai

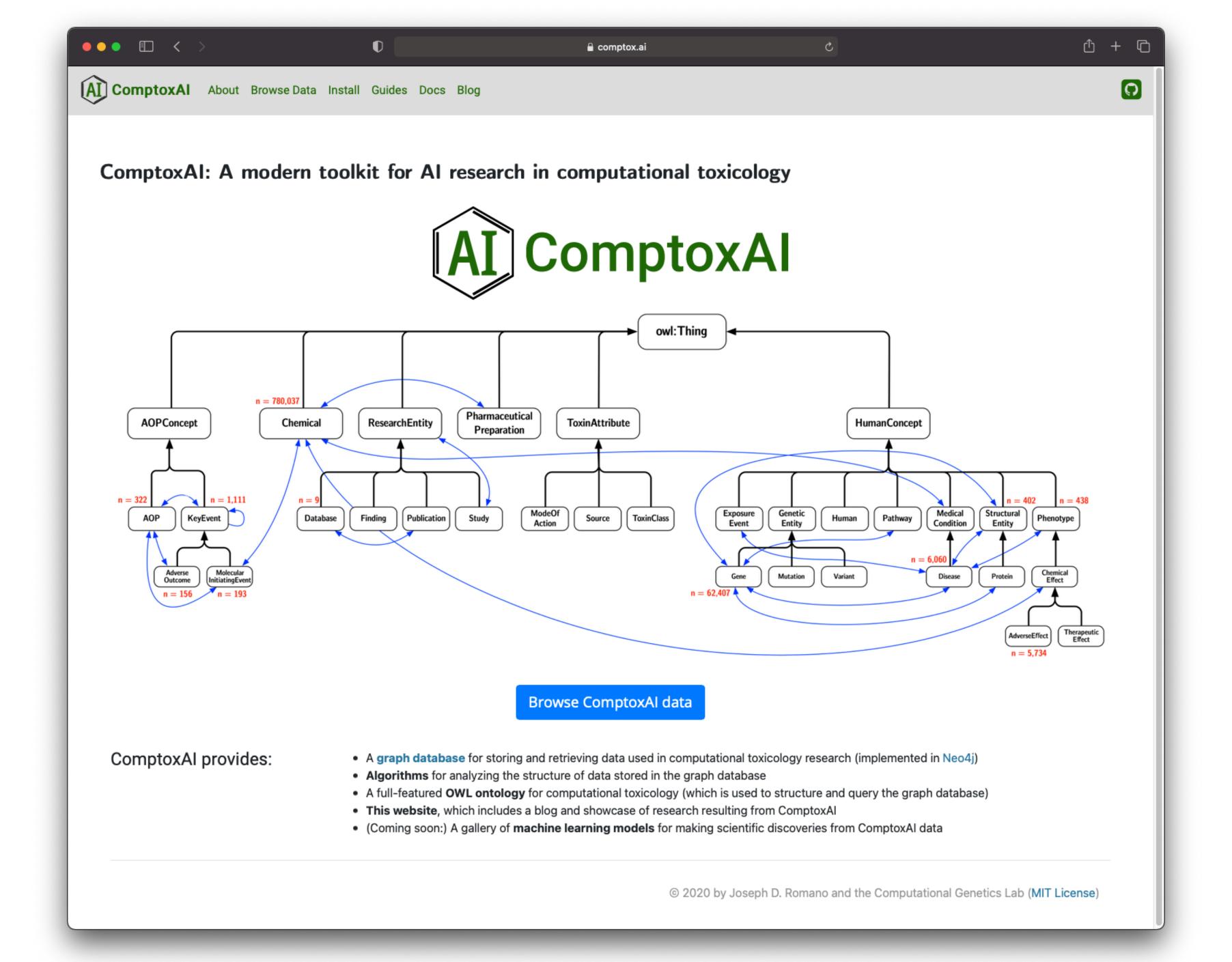
Data vs. Knowledge

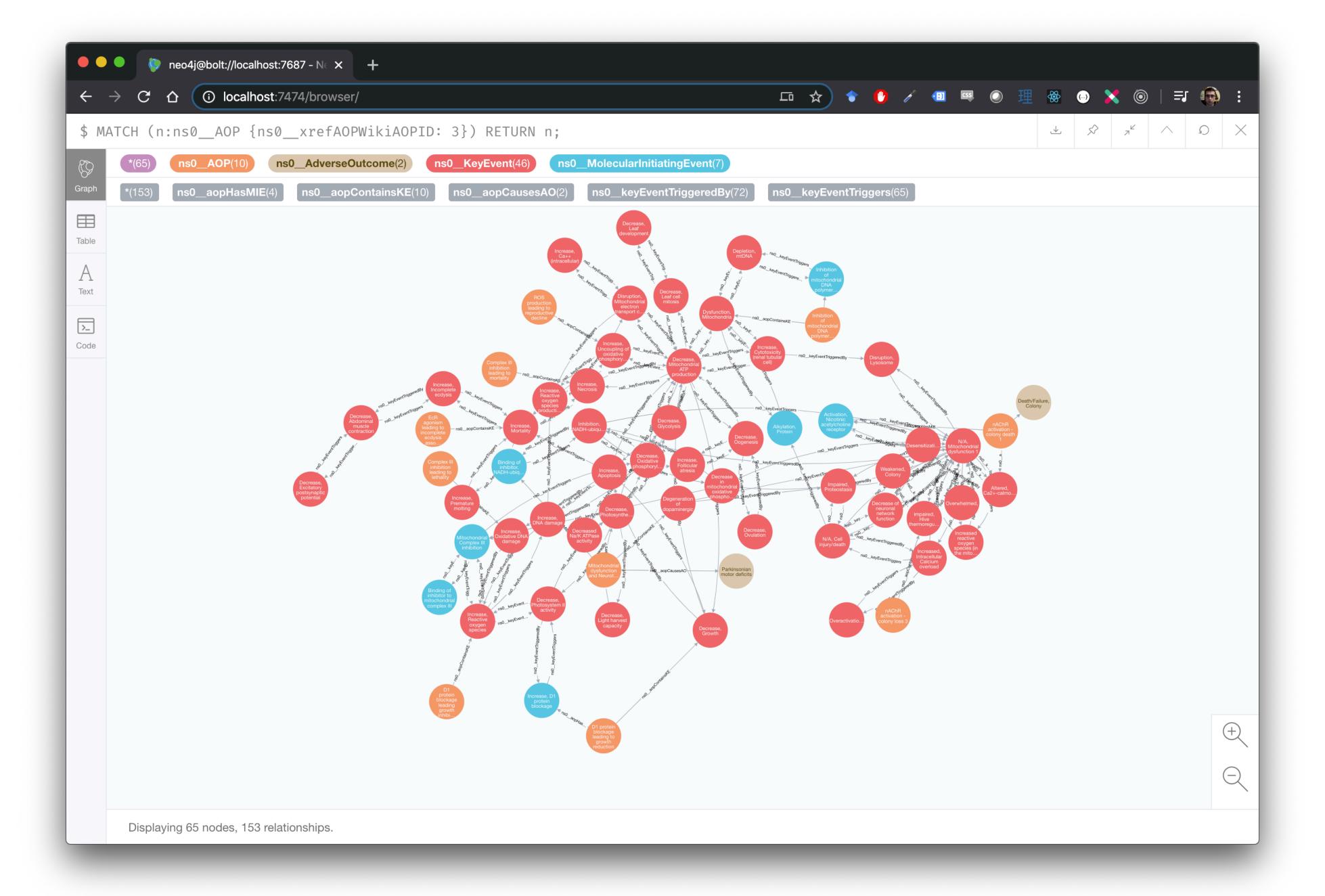
- Data:

- Raw observations
- Often (usually?) quantitative
- E.g., specific gene expression measurements

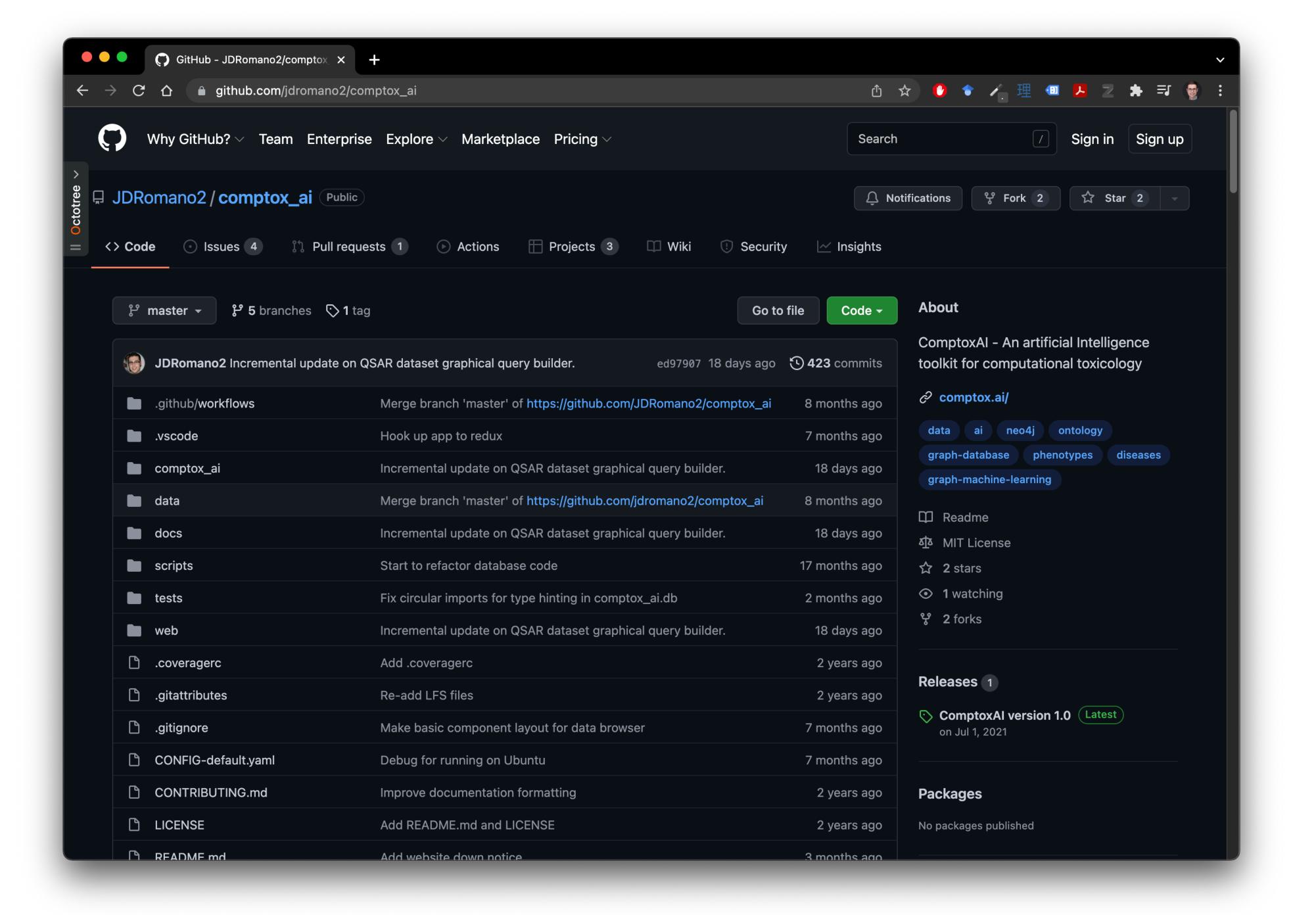
- Knowledge:

- Meaningful understanding of phenomena
- Often results from analysis of many points of data
- Typically represents
- E.g., "Chemical [X] upregulates expression of gene [Y]"





Entity type	n
Chemical	780,037
Gene	$62,\!407$
Pathway	4,570
Key Event	1,111
Chemical List	311
Adverse Outcome Pathway	280
Molecular Initiating Event	193
Adverse Outcome	156
Assay	68



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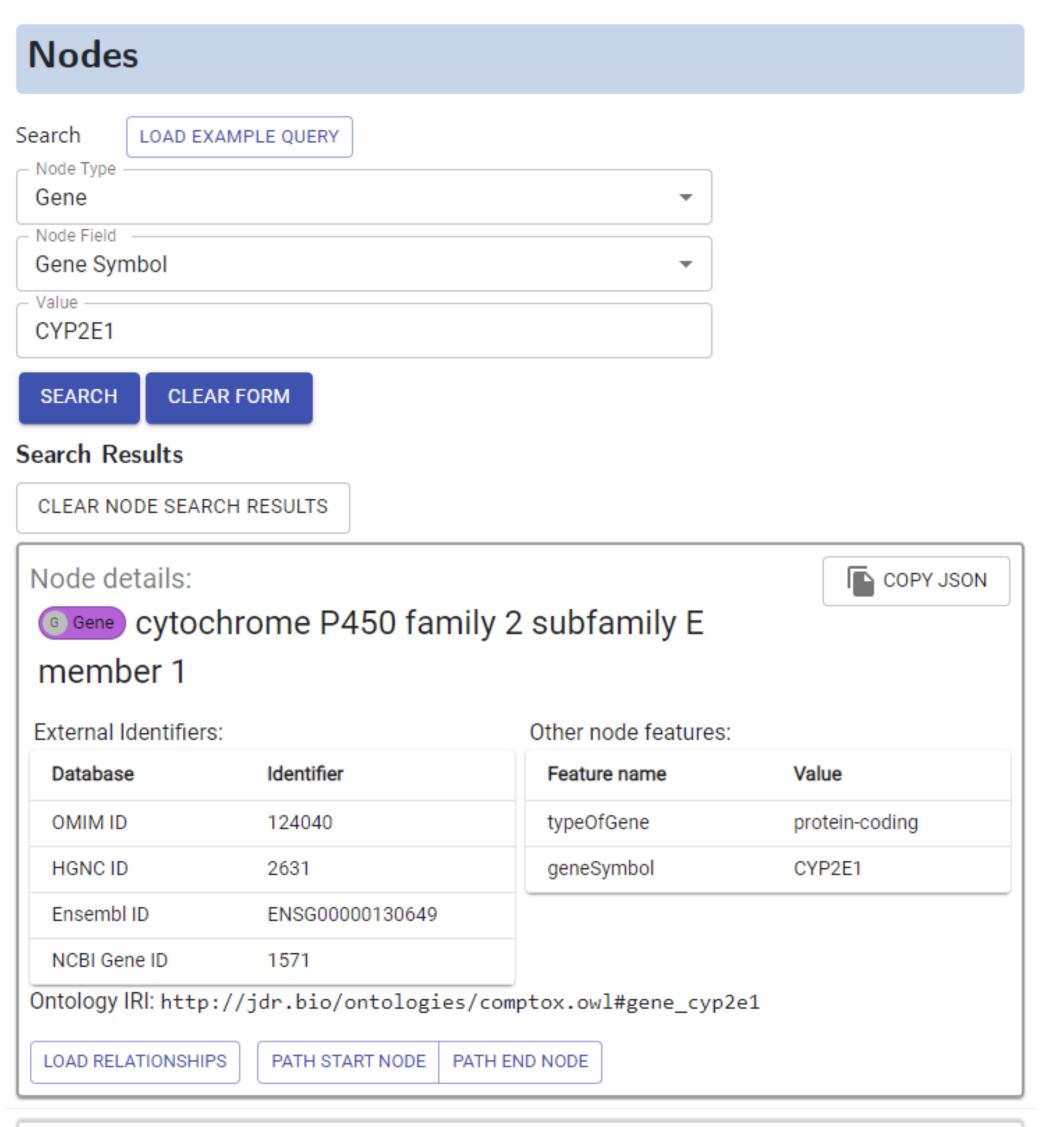
ComptoxAI: Data Interfaces

- Data browser / dataset generator tools on website
- Direct access to graph database (local or remote)
- Web API (Programmatic access to data)
- Python package (Access data and construct machine learning models from the Python programming language)

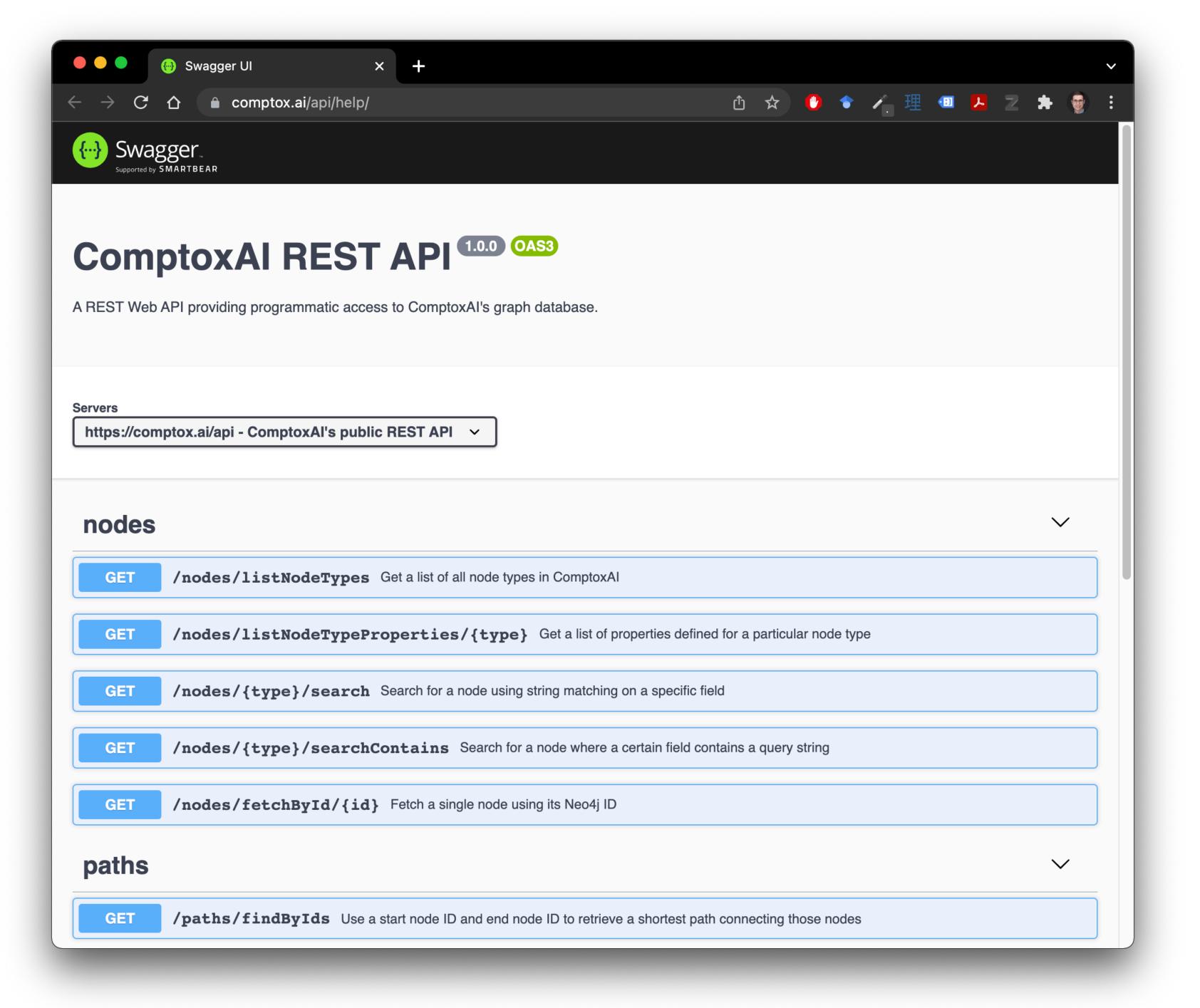
ComptoxAl interactive data portal

From this page, you can search for individual entities (nodes) in ComptoxAI's graph database. When you select a query result, adjacent nodes (related data elements) are loaded and displayed below.

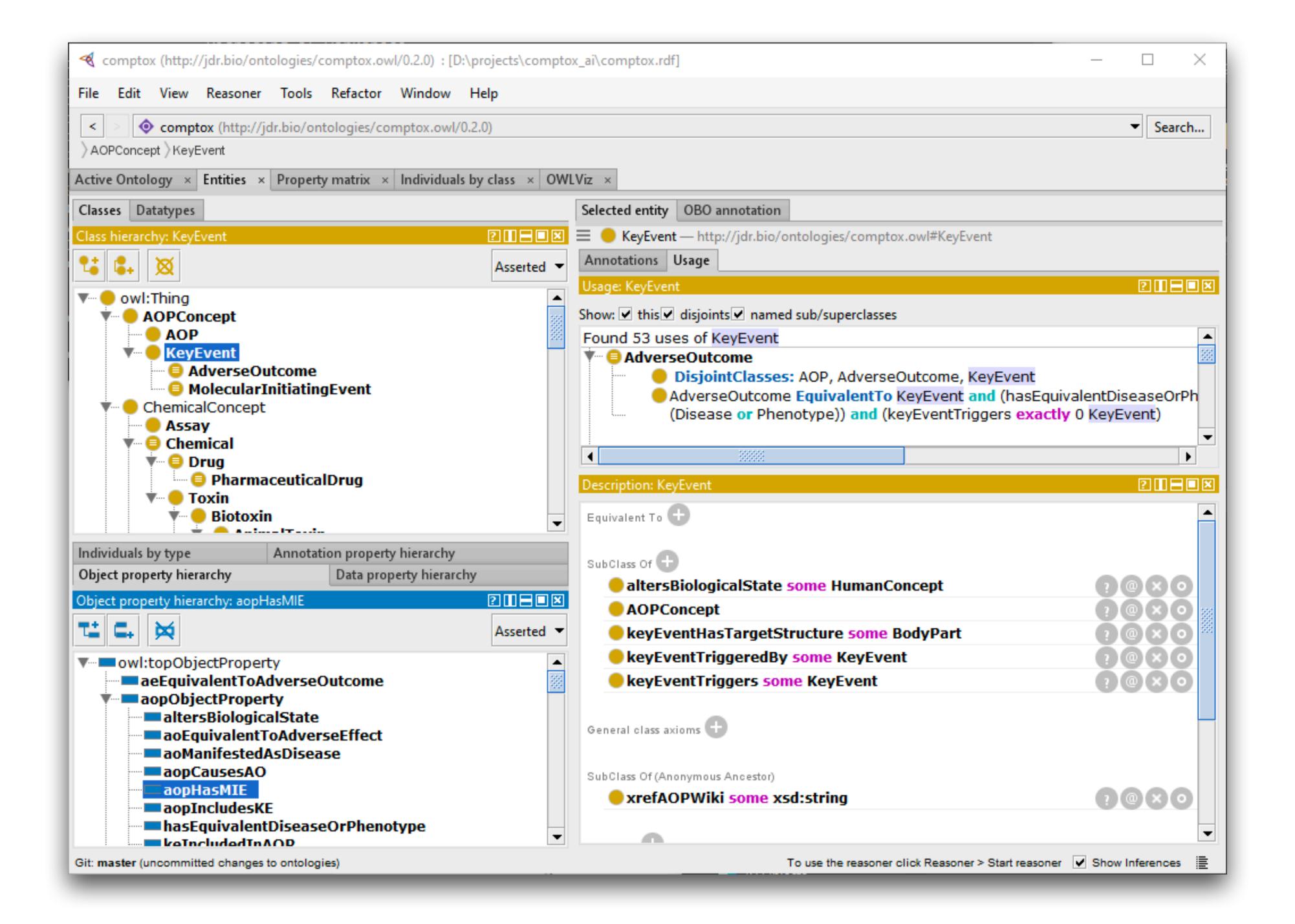
For detailed usage instructions, please see this page.





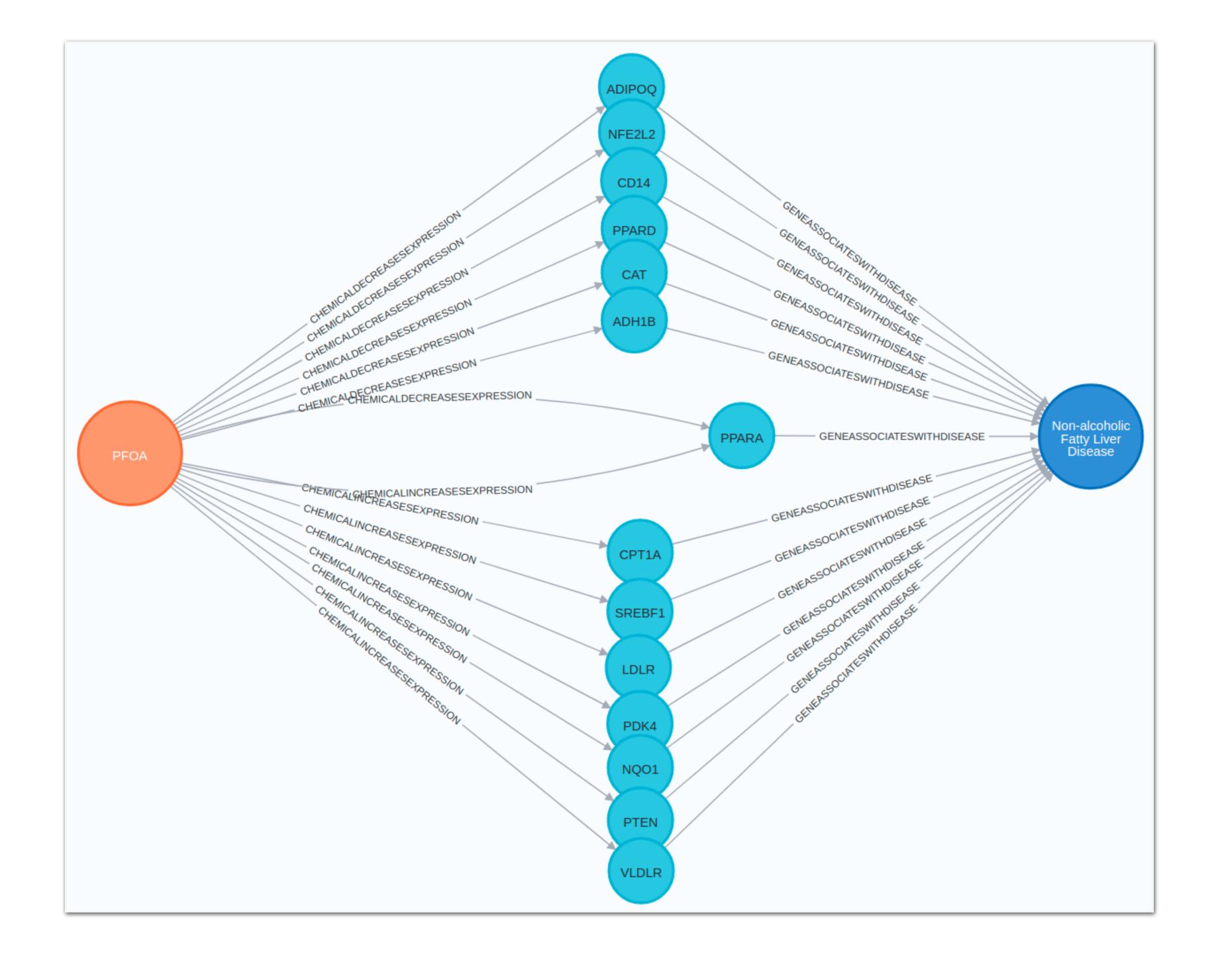


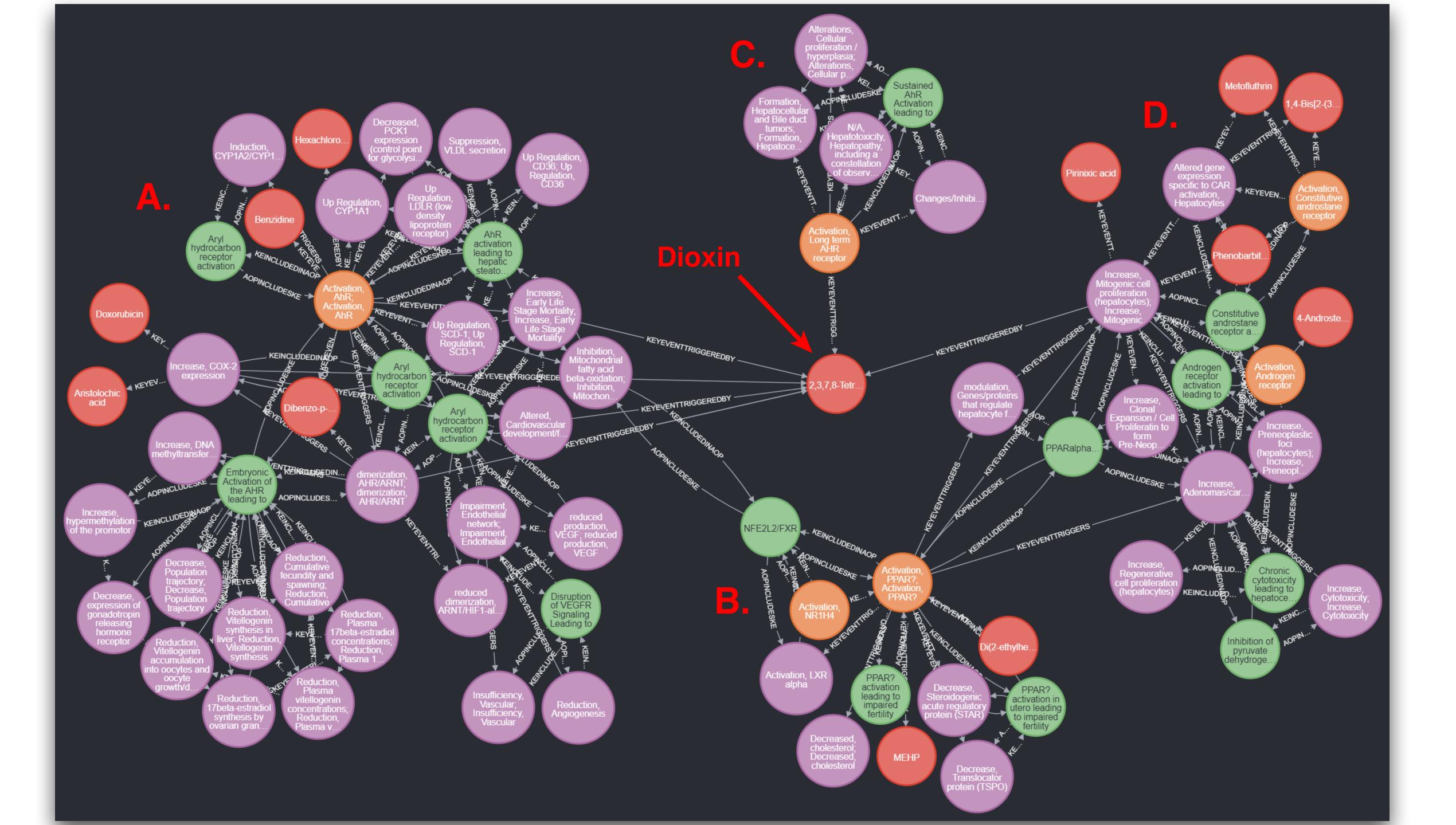
```
Curl
                                                                                                                            curl -X GET "https://comptox.ai/api/nodes/listNodeTypeProperties/Chemical" -H "accept: */*"
Request URL
 https://comptox.ai/api/nodes/listNodeTypeProperties/Chemical
Server response
Code
            Details
200
            Response body
                "property": "commonName",
                "type": "STRING"
                 "property": "maccs",
                "type": "LIST"
                "property": "xrefMeSH",
                "type": "STRING"
                "property": "xrefDrugbank",
                "type": "STRING"
                "property": "xrefPubchemSID",
                "type": "STRING"
                "property": "xrefDTXSID",
                                                                                                                     Download
                "type": "STRING"
           Response headers
              access-control-allow-credentials: true
              access-control-allow-headers: Origin, X-Requested-With, Content-Type, Accept, Authorization
              access-control-allow-methods: GET, HEAD, OPTIONS, POST, PUT, DELETE
              access-control-allow-origin: *
              connection: keep-alive
              content-length: 372
              content-type: application/json; charset=utf-8
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```



IR Tools

- "Shortest Path" Identifies the most direct mechanistic routes linking two (or more) entities
- "Expand Network" Shows an entity in the context of a network of nearby 'neighbor' entities
- "QSAR Dataset Generator" Dynamically builds tabular datasets for predicting a toxic endpoint using fingerprints for a list of chemicals





Important Caveats

- Information retrieval is limited to what we already know and what is already in the source databases
- Advanced users might get more mileage (e.g., by constructing graph queries by hand)
 - New 'entry-level' features will be continuously in development!
- Running complex queries can be (a little bit) slow

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> Pac Symp Biocomput. 2022;27:187-198.

Improving QSAR Modeling for Predictive Toxicology using Publicly Aggregated Semantic Graph Data and Graph Neural Networks

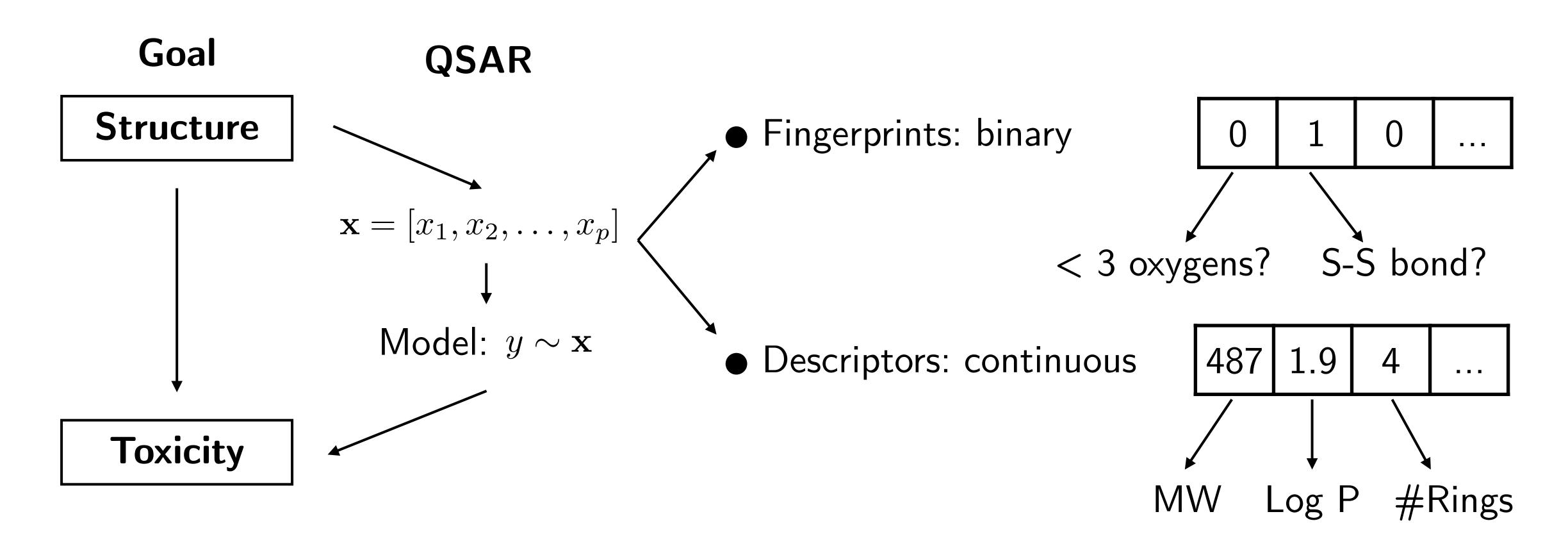
Joseph D Romano ¹, Yun Hao, Jason H Moore

Affiliations + expand

PMID: 34890148 PMCID: PMC8714189

Free PMC article

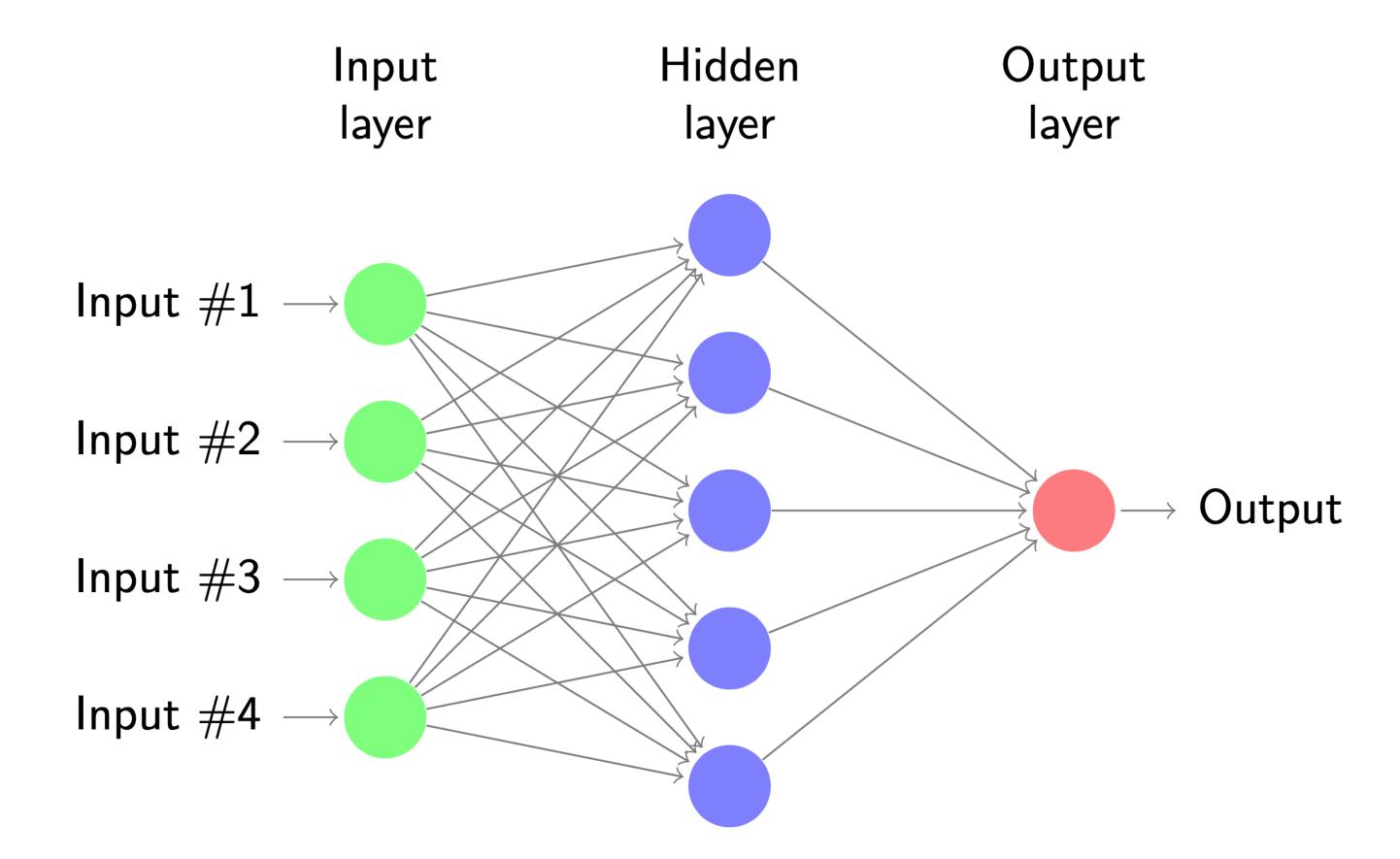
QSAR

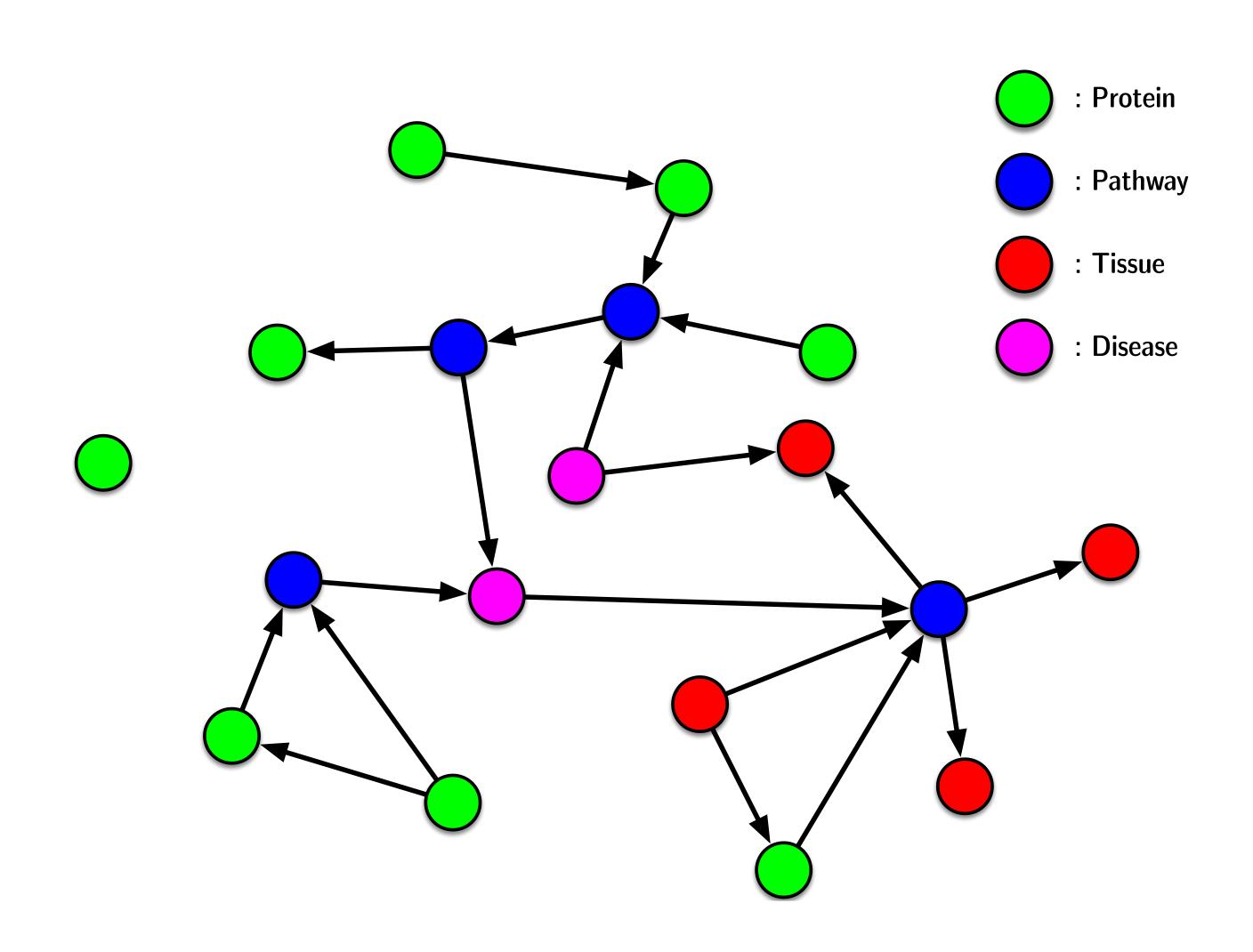


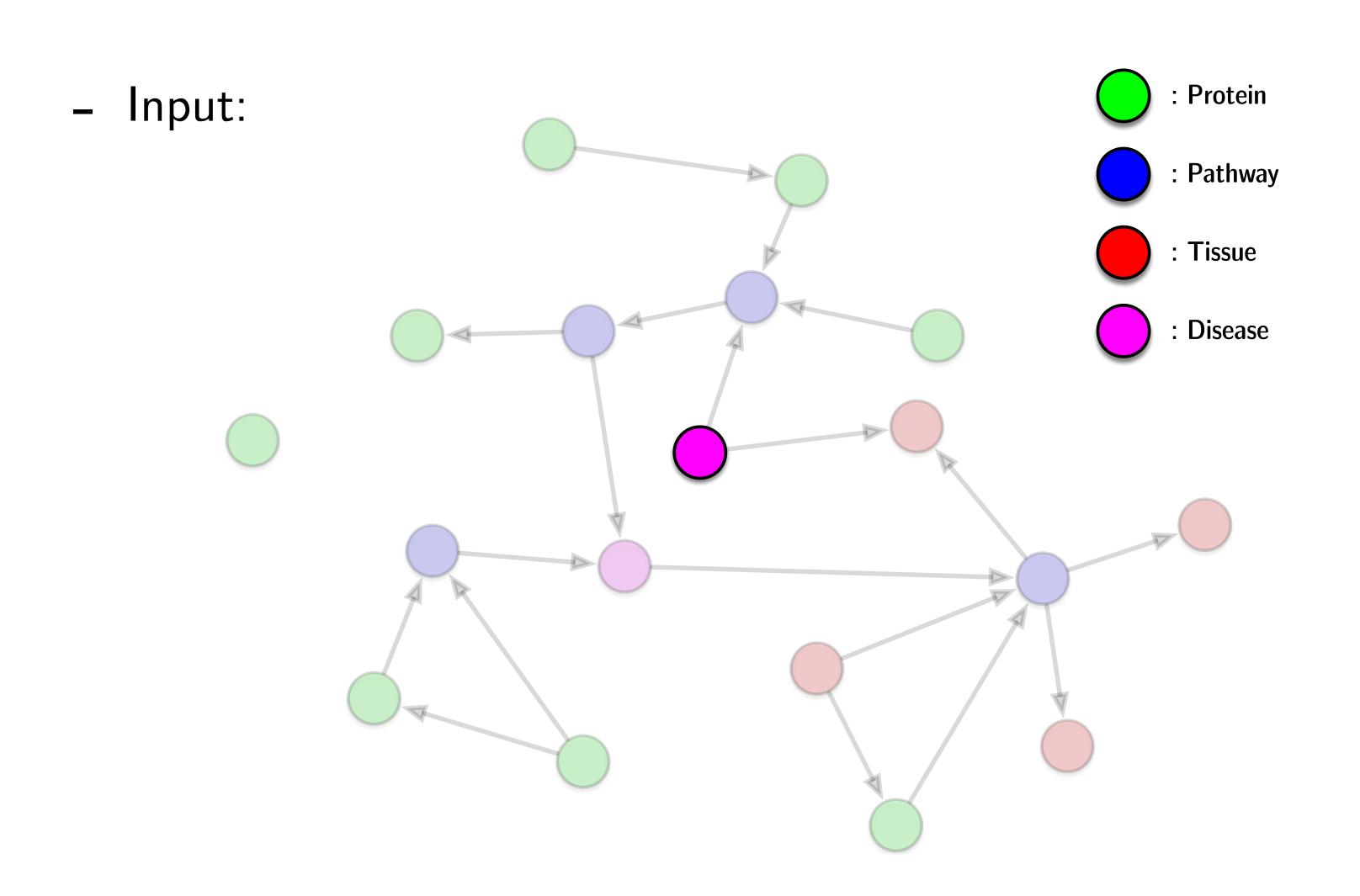
- QSAR: Quantitative Structure-Activity Relationship

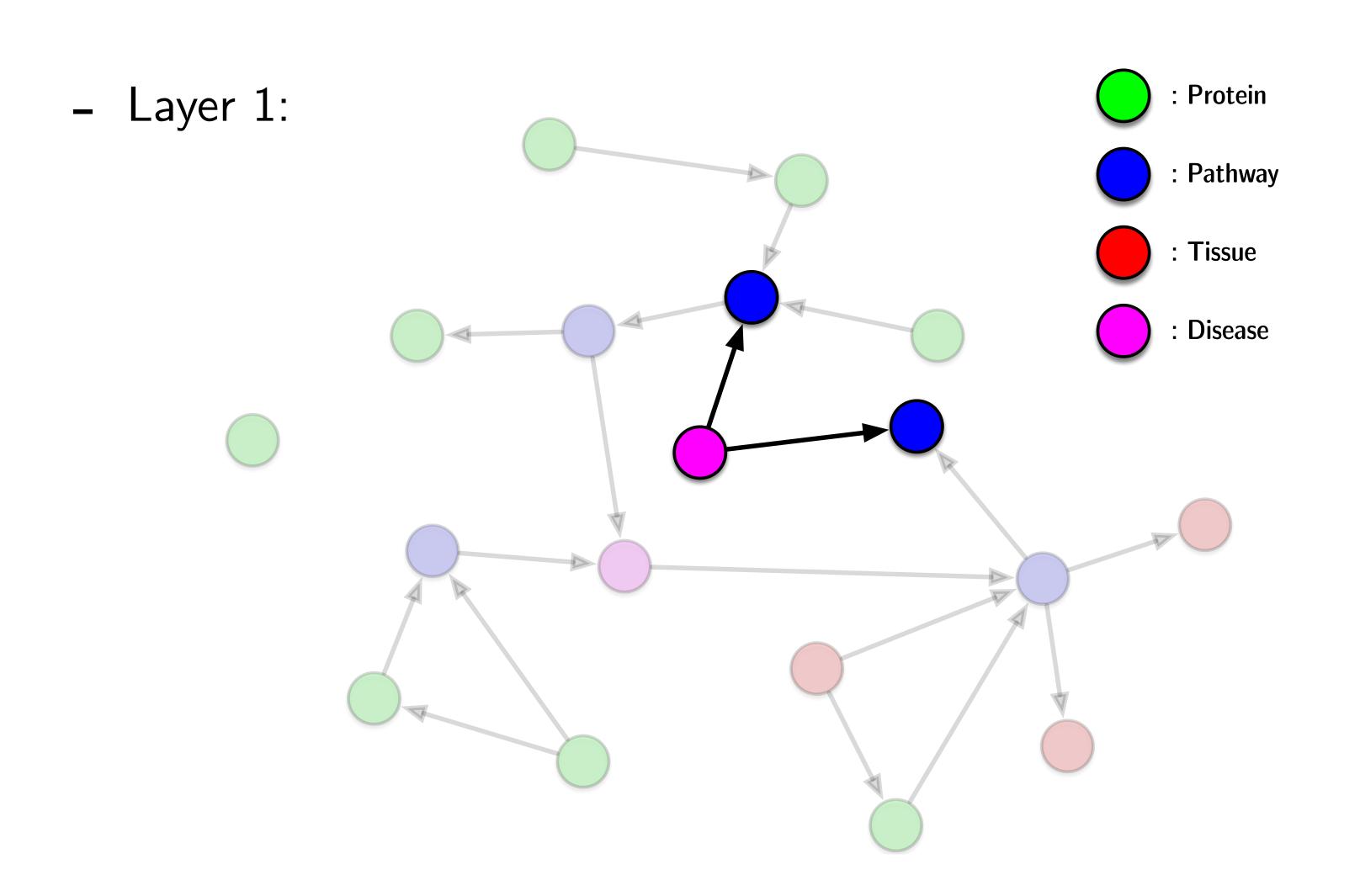
(Artificial) Neural Networks

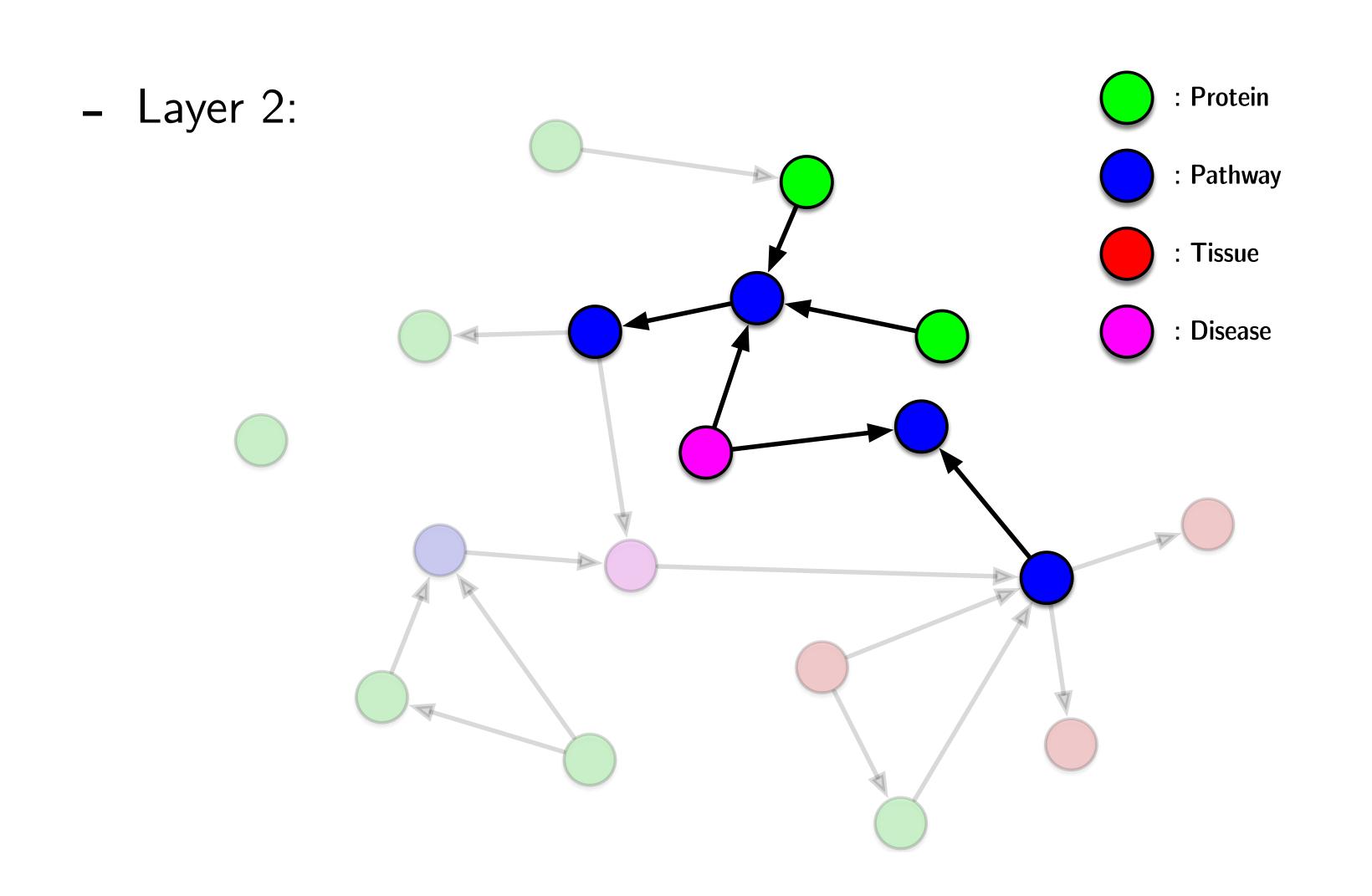
- Consist of nodes organized into layers, which are usually stacked
- Deep learning —> NN with tens or hundreds of layers

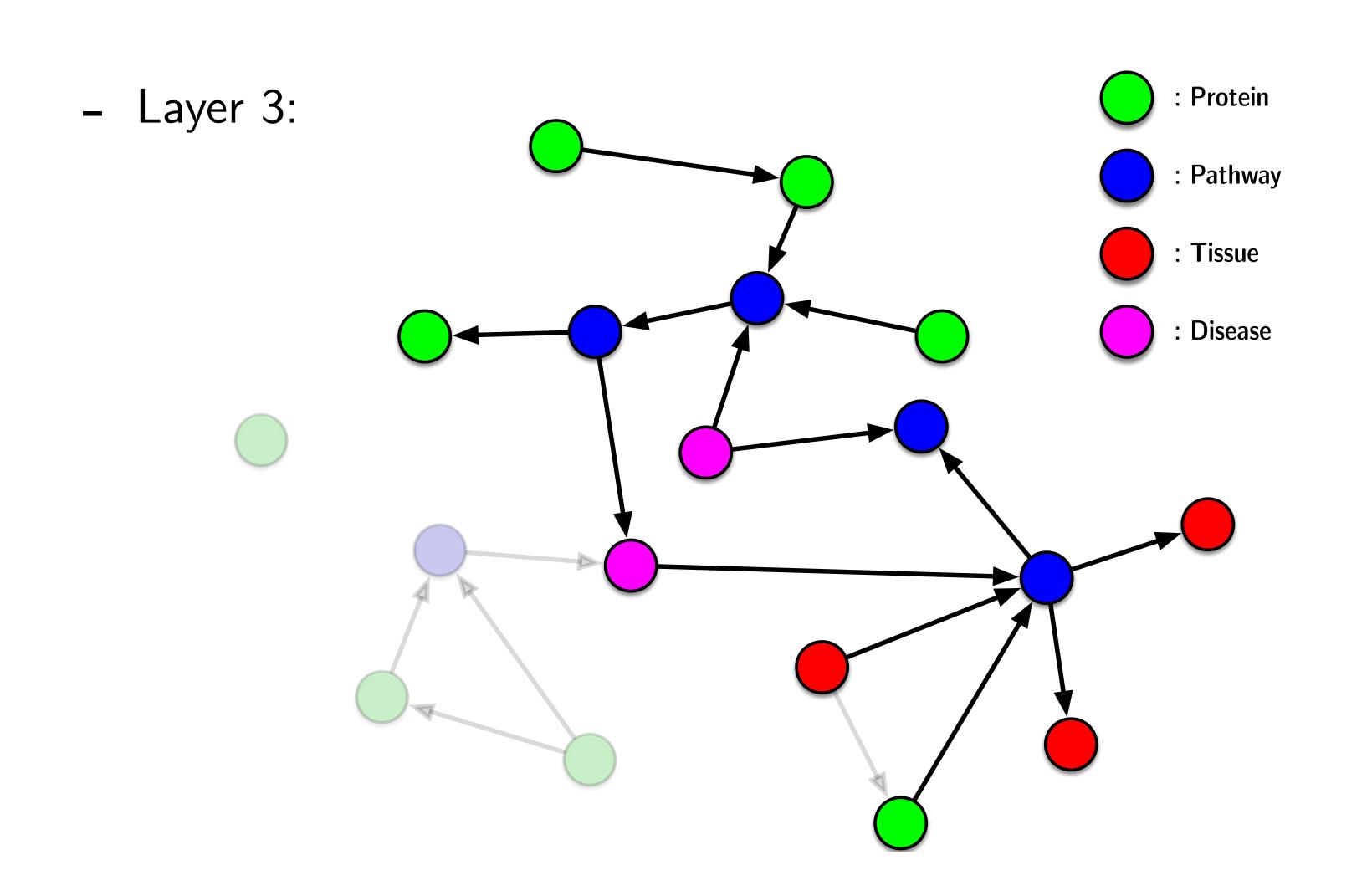




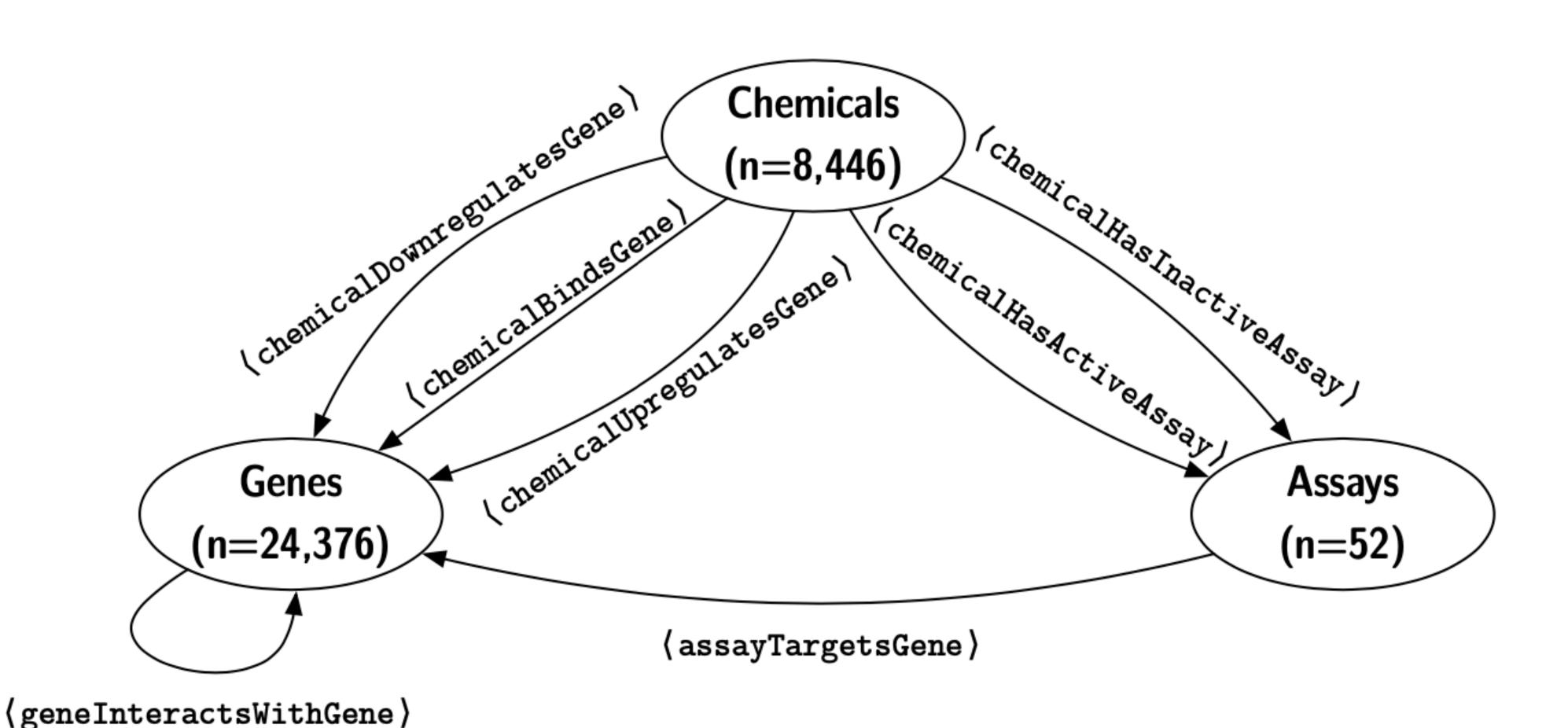




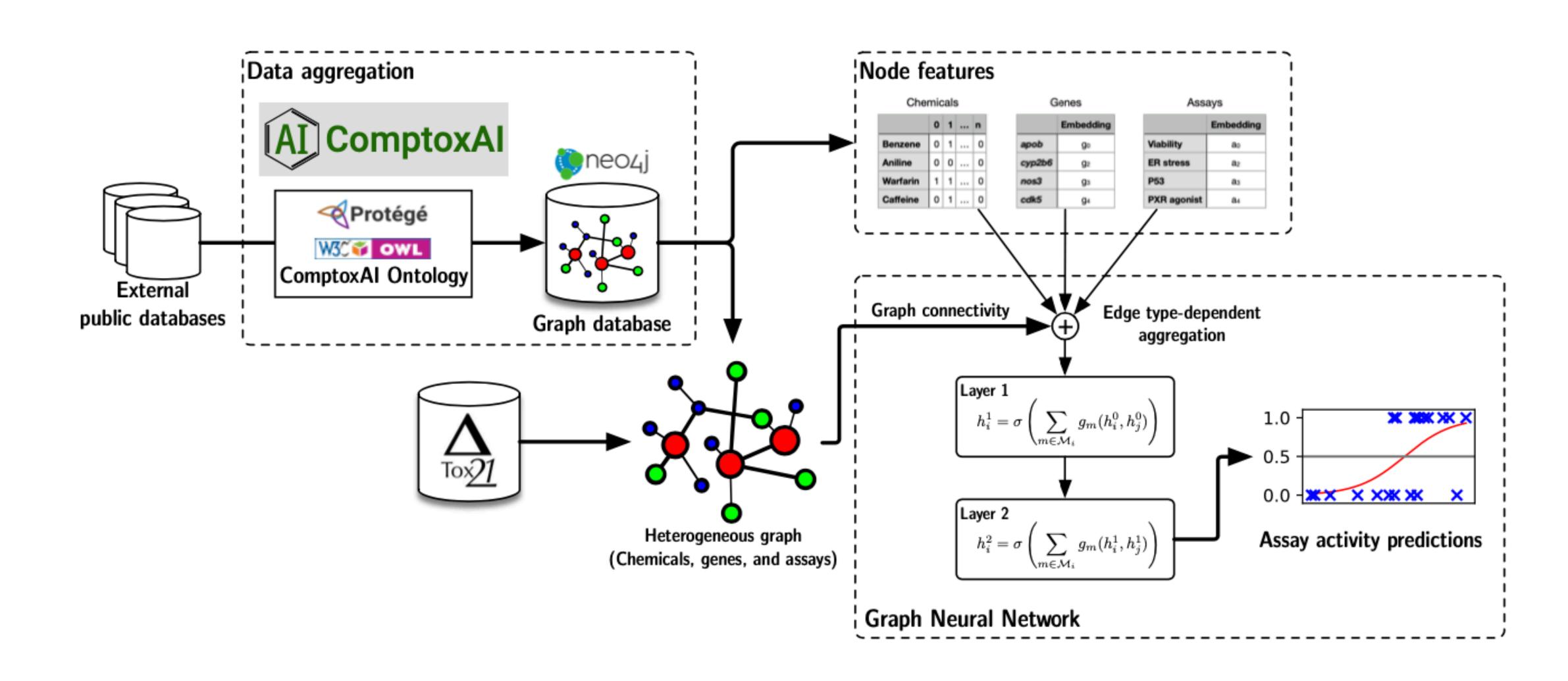




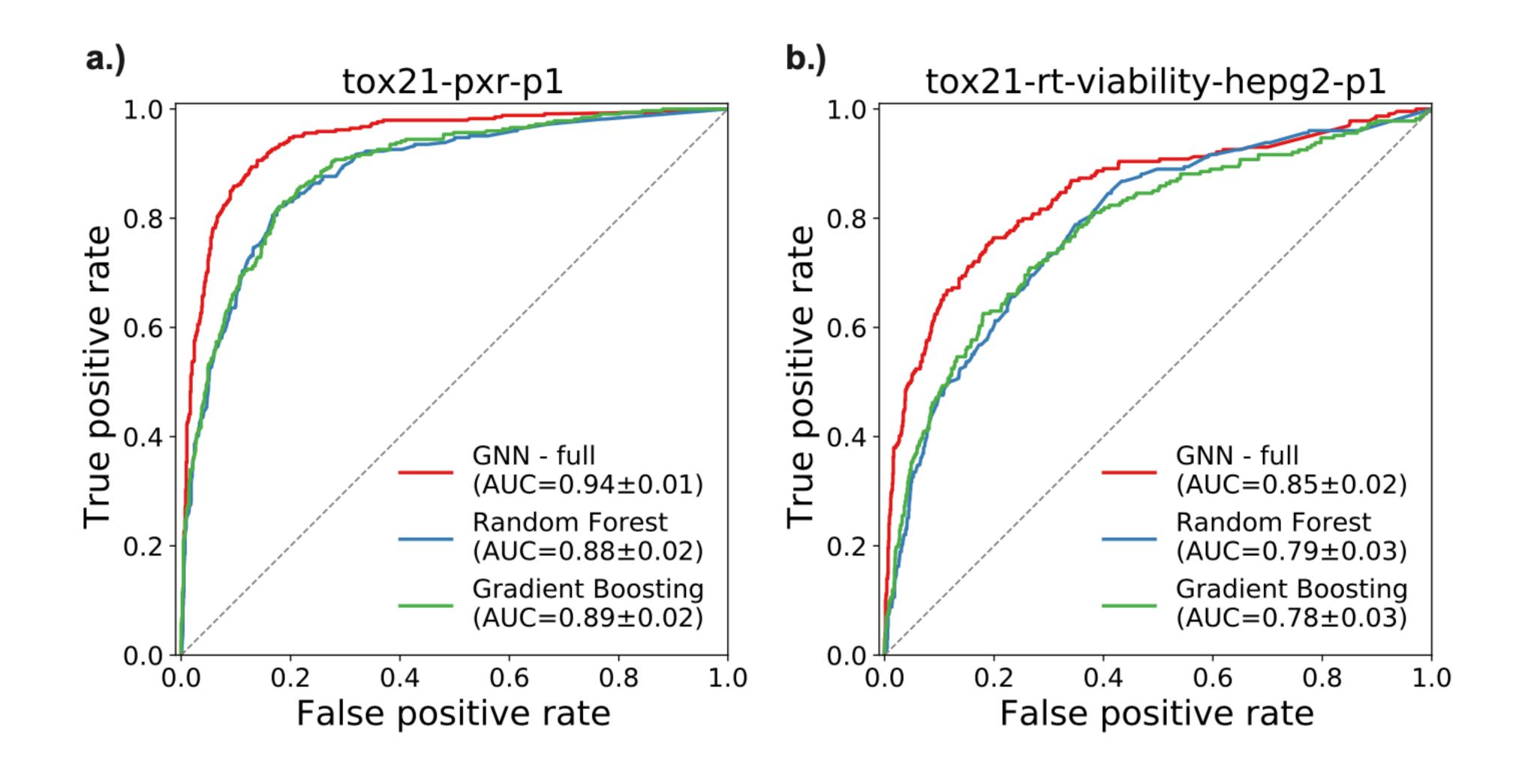
QSAR Subgraph



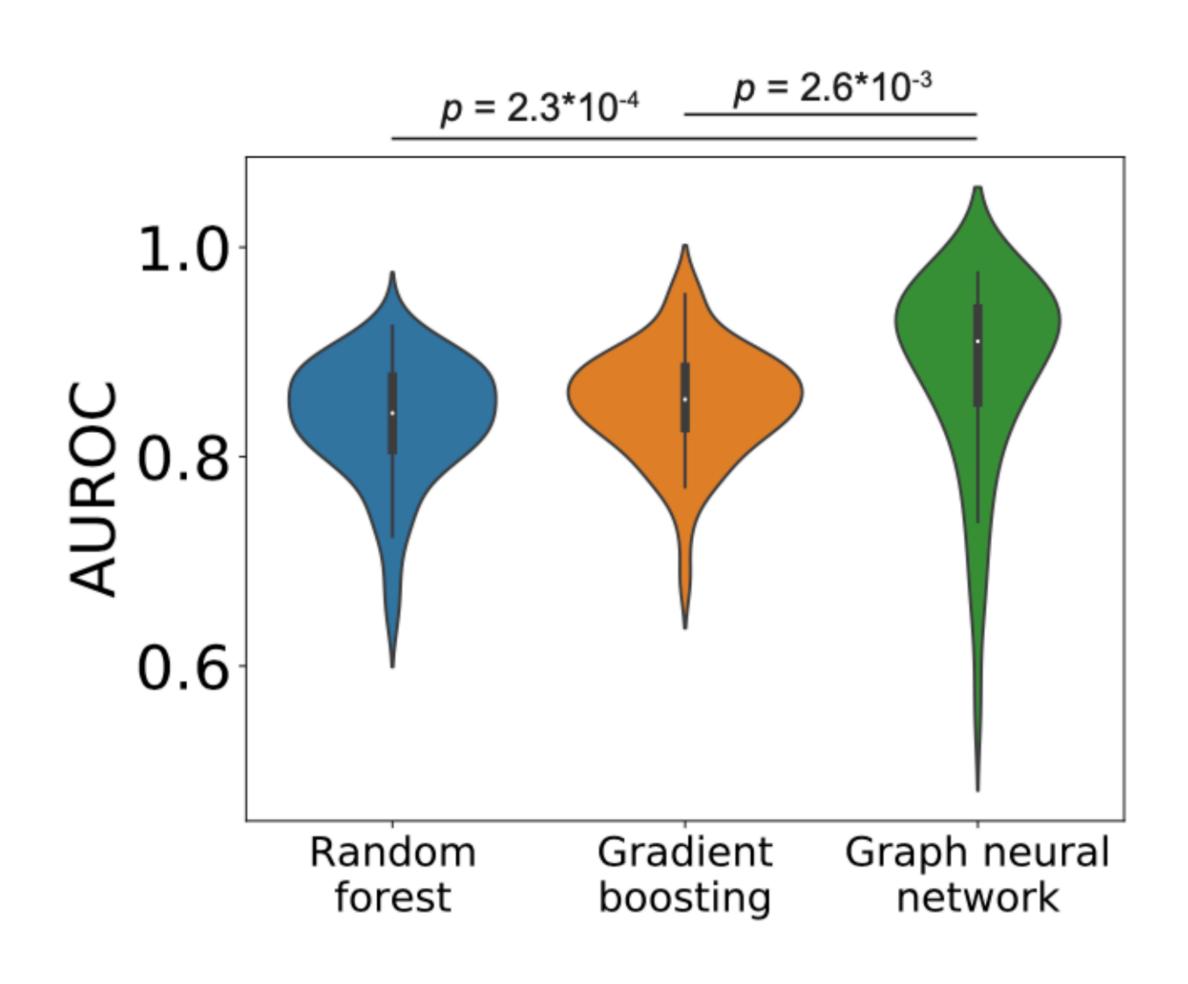
GNN Pipeline



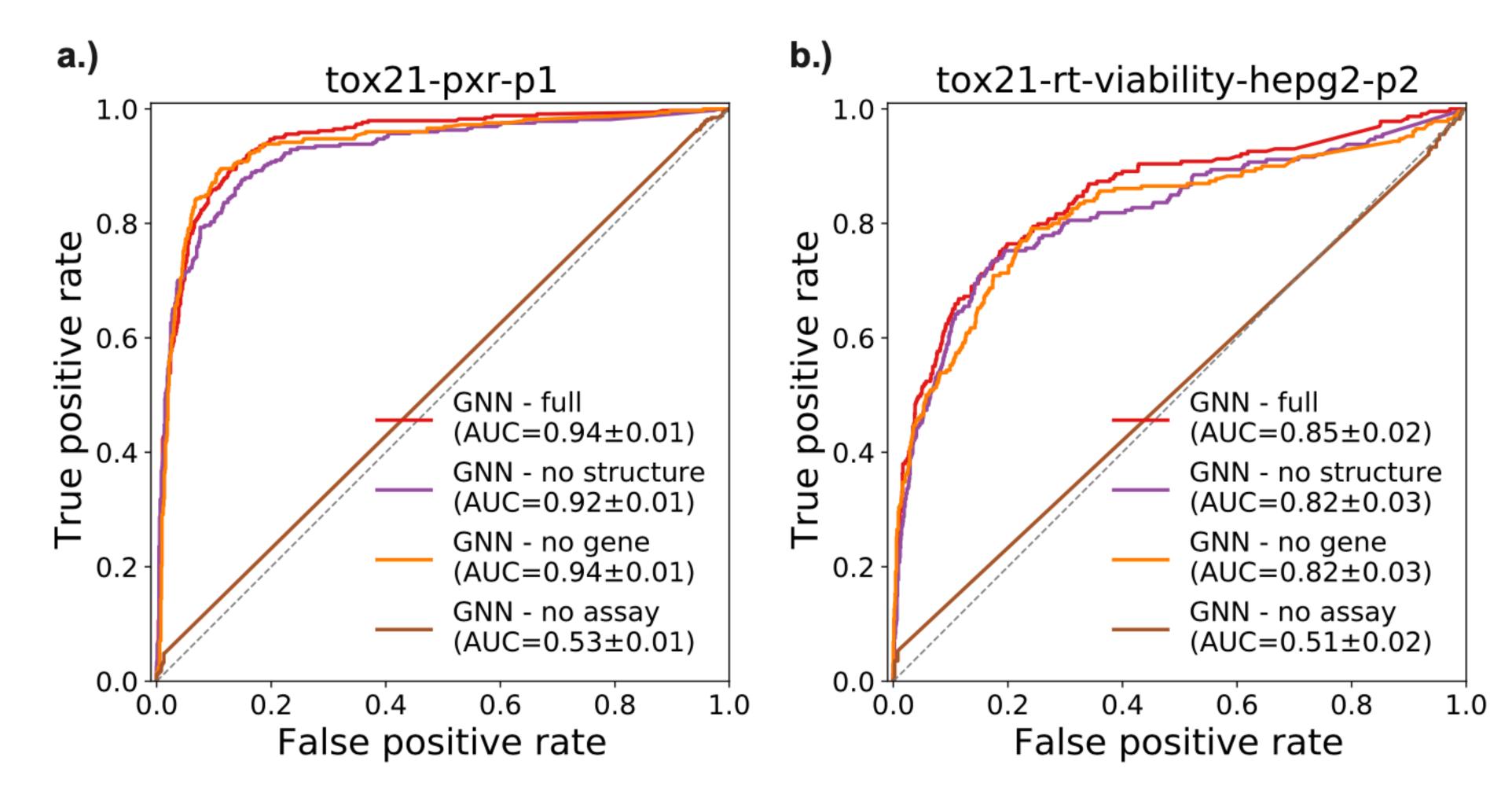
QSAR Performance



QSAR Performance



Why do the GNNs perform so much better?



Potential for model explainability

- Each relationship in the graph conveys semantic meaning based on node types and relationship types
- For any given assay's GNN, edge weights are proportional to their influence on the final prediction
- Example: HepG2 cell viability assay activity prediction
 - Top weighted "other" assays:
 - HepG2 Caspase-3/7 mediated cytotoxicity
 - NIH/3T3 Sonic hedgehog antagonism
 - The first makes obvious sense; is there a mechanistic explanation for the other?

Future work

- Expand on the concept types included in the subgraph (i.e., add diseases, pathways, cell types, etc.)
- Test continuous endpoints (IC₅₀, etc.)
- Evaluate more complex network architectures:
 - Link prediction models
 - Use regularization to better utilize information from non-Assay nodes (important for Graph ML in heterogeneous networks)
 - Deeper networks? May be useful as the network grows
- Develop easy-to-use graphical tools to lower the barrier for diverse user types
 - Use ontology reasoning to further improve explainability

- Let us know if you use ComptoxAl in your research! We will be happy to give you a plug on our website.
 - joseph.romano@pennmedicine.upenn.edu
- We're always happy to take suggestions, questions, and contributions (data, code, documentation, etc.)
- Check back in a few weeks for a more complete feature set including everything described in this talk (and more!)

Acknowledgements

- Yun Hao (Penn)
- Jason Moore (Cedars-Sinai)
- Trevor Penning (Penn)
- Li Shen (Penn)

- Grant funding:
 - K99-LM013646 (Romano)
 - R01-LM010098,
 R01-LM012601,
 R01-AI116794,
 UL1-TR001878,
 - T32-ES019851,P30-ES013508 (Penning)

UC4-DK112217 (Moore)





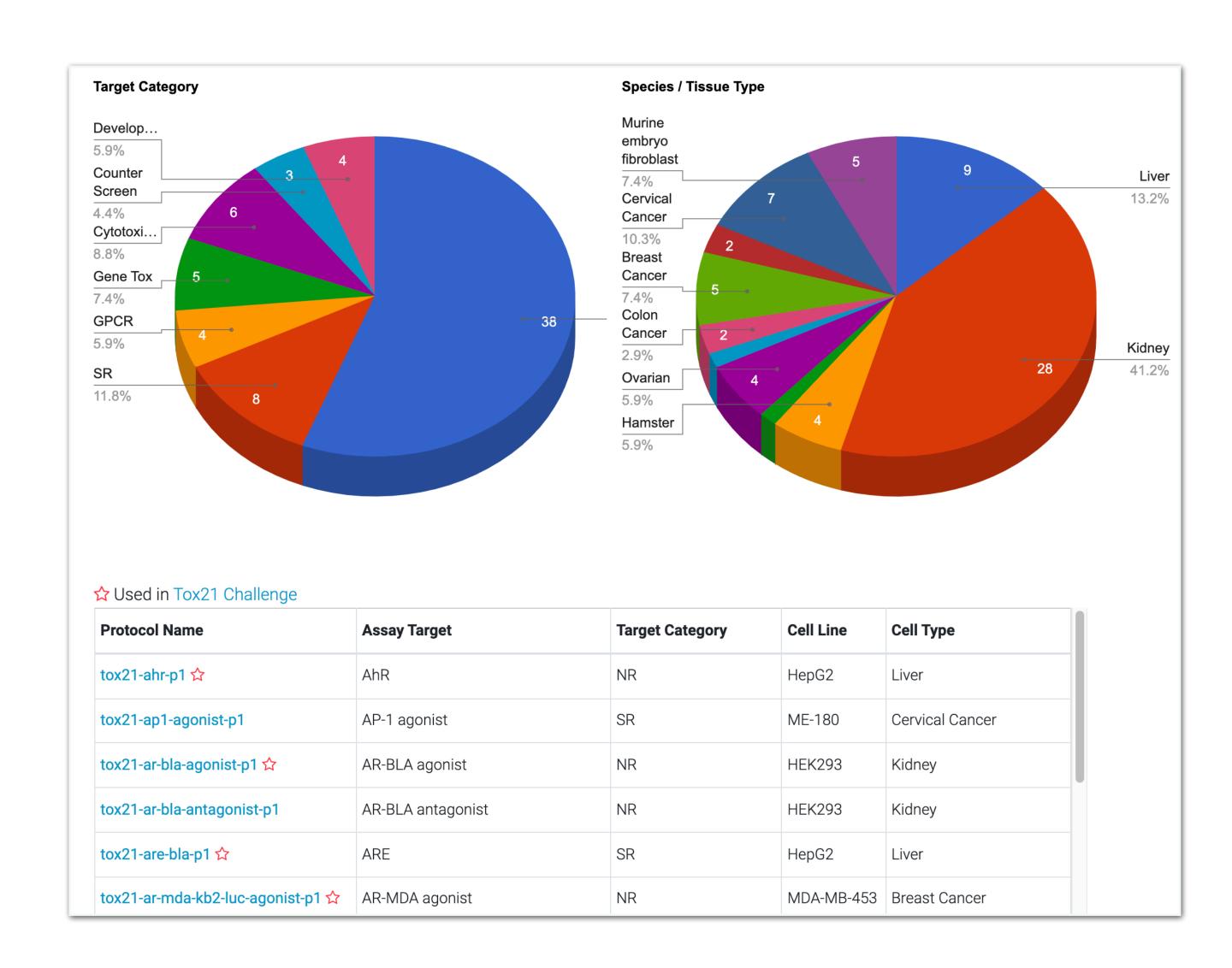






Tox21 screening dataset

- Tox21: "Toxicology in the 21st
 Century" dataset for high-throughput chemical screening
 - ~ 60 specific toxicology-focused biochemical assays
 - ~ ~8,000 chemicals evaluated on those assays



Node classification labeling algorithm

- To build a training dataset for a single assay:
 - Look at the edge linking each chemical to the assay of interest
 - If edge is "chemicalHasActiveAssay", label the chemical "1"
 - If edge is "chemicalHasInactiveAssay", label the chemical "0"
 - If there is no edge, don't label the chemical
 - Remove the node (and incident edges) for the assay of interest to prevent information leakage

GCN Architecture details

Each layer of the network is defined as an edge-wise aggregation of adjacent nodes:

$$h_i^{(l)} = \sigma \left(\sum_{r \in \mathcal{R}} \rho_{j \in \mathcal{N}_i^r} \left(W_r^{(l-1)} h_j^{(l-1)} + W_0^{(l-1)} h_i^{(l-1)} \right) \right). \tag{A.1}$$

where h_i^l is the hidden representation of node i in layer l, $\mathcal{N}(i)$ is the set of immediate neighbors of node i, and σ is a nonlinear activation function (either softmax or leaky ReLU, as explained in **Appendix B**). ρ can be any differential 'reducer' function that combines messages passed from incident edges of a single type; in the case of this study we use summation. Since our graph contains relatively few edge types, regularization of the weight matrices W is not needed.

Node Classification details

For classifying chemicals as active or inactive with regards to an assay of interest, we stack 2 GCN layers in the form given by (A.1), with a leaky ReLU activation between the two layers and softmax applied to the second layer's output. Since we only classify chemical nodes, we ignore outputs for all other node types (and for chemicals with undefined labels); labels are generated via **Algorithm 1** We train the network by minimizing binary cross-entropy between the network's softmax outputs and true activity values:

$$\mathcal{L} = -\sum_{i \in \mathcal{Y}} \ell(h_i^{(0)}) \cdot \ln h_i^{(2)} + (1 - \ell(h_i^{(0)})) \cdot \ln(1 - h_i^{(2)}).$$
(B.1)

where \mathcal{Y} is the set of all labeled nodes, $\ell(h_i^{(0)})$ is the true label of node i, and $h_i^{(2)}$ is the final layer output of node i.

The relatively shallow architecture of the network allows us to optimize the model using the Adam algorithm applied to the entire training data set, but the model can be adapted to mini-batch training when appropriate or necessary.