Part 1: Ontologies and semantic similarity

Robert Hoehndorf

Before the tutorial

See https://github.com/bio-ontology-research-group/ontology-tutorial:

- ▶ install Docker (e.g.: apt-get install docker)
- ► docker run -i -t -p 8888:8888 leechuck/ai-biomed-summer-school
- ▶ in your browser, connect to localhost:8888

Learning goals

- brief overview of ontologies in biomedicine
- semantic similarity with ontologies
- machine learning with ontologies as features (or background knowledge)
- unsupervised or supervised:
 - ► here: mostly unsupervised *feature* learning
 - "deep" learning
- focus on existing tools and methods
 - Jupyter Notebooks and code examples
- not covered:
 - learning ontologies (axioms, definitions) from data
 - ► (most) natural language processing
 - reasoning with ontologies
 - ► learning on "knowledge graphs"
 - machine learning theory

Learning goals

Biomedical questions:

- diagnosing rare disease
- ► finding functionally similar proteins
- ► relying on heterogeneous data integration
 - ► from different databases
 - model organisms

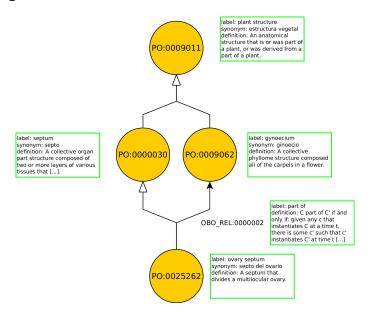
Agenda

- ► Introduction: ontologies and graphs
- ► Semantic similarity
- ► Machine learning:
 - syntactic
 - ► graph-based
 - ► model-theoretic

Ontologies, machine learning, and Al

- ontologies are ubiquitous in biomedical research
- ► rich formal characterization (axioms)
- ▶ how can they be used for (predictive) data analysis?
 - "fuzzy", similarity-based search
 - background knowledge in machine learning

Ontologies



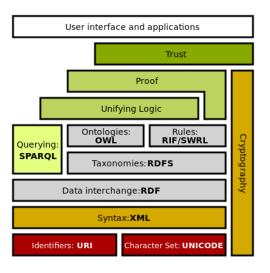
Ontologies for data integration

- ► standard identifiers (IRIs)
- ► labels of classes and relations
- ► human-readable descriptions
- axioms

Ontologies provide domain knowledge

Overview	Browse	DLQuery Download		
Annotation	1	Value		
label		B cell apoptotic process		
definition		Any apoptotic process in a B cell, a lymphocyte of B lineage with the phenotype CD19-positive and capable of B cell mediated immunity.		
class		http://purl.obolibrary.org/obo/GO_0001783		
ontology		GO-PLUS		
Equivalent		apoptotic process and (occurs in some B cell)		
SubClassOf		occurs in some B cell, lymphocyte apoptotic process		
Id		GO:0001783		
has_obo_name	espace	biological_process		

The Semantic Web



Manchester OWL Syntax

DL Syntax	Manchester Syntax	Example
$C \sqcap D$	C and D	Human and Male
$C \sqcup D$	C or D	Male or Female
$\neg C$	not C	not Male
∃ <i>R</i> . <i>C</i>	R some C	hasChild some Human
∀R.C	R only C	hasChild only Human
$(\geq nR.C)$	R min n C	hasChild min 1 Human
$(\leq nR.C)$	R max n C	hasChild max 1 Human
(= nR.C)	R exactly n C	hasChild exactly 1 Human
$\{a\} \sqcup \{b\} \sqcup$	{a b}	{John Robert Mary}

Reasoning with ontologies

- ▶ 'B cell apoptosis' EquivalentTo: apoptosis and 'occurs in' some 'B cell'
- ▶ 'lymphocyte apoptosis' EquivalentTo: apoptosis and 'occurs in' some lymphocyte
- ▶ 'B cell' SubClassOf: lymphocyte

Reasoning with ontologies

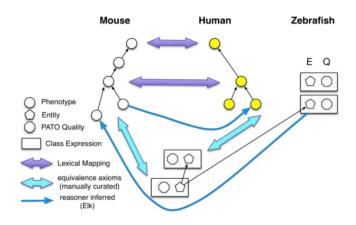
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- ▶ 'B cell apoptosis' SubClassOf: 'lymphocyte apoptosis'

Reasoning with phenotype ontologies

Phenotype ontology:

- ► A phenotype is a quality that inheres in its bearer:
 - ▶ Enlarged heart: $Enlarged(x) \land \exists y (inheresIn(x, y) \land Heart(y))$
 - ▶ in DL: *Enlarged* □ ∃*inheresIn.Heart*
 - ► Enlarged: reuse an ontology of qualities (PATO)
 - ► Heart: reuse ontology of (human, mammalian) anatomy

UberPheno, PhenomeNET



BLAST-like search over phenotypes

Using ontologies and reasoning, we can

- 1. describe phenotypes computationally
 - morphology
 - ► function
 - ightharpoonup \Rightarrow ontologies
- 2. integrate/compare phenotypes within and between species (to overcome limitations in phenotype data)
 - homologous organ structures
 - related/identical function
 - ► ⇒ ontologies and automated reasoning
- 3. measure phenotypic similarity
 - ► use morphological or functional similarity
 - similarity in attribute values
 - → semantic similarity, machine learning

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- ▶ Does functional similarity correlate with phenotypic similarity?

Ontologies and graphs

- semantic similarity measures can be graph-based, feature-based, or model-based
- we may need to generate graphs from ontologies
 - remember: ontologies are sets of axioms
 - subclass axioms are easy
 - how about more complex axioms?
- solution: define relational patterns

Relations as patterns

```
► X SubClassOf: Y: X \xrightarrow{\text{is-a}} Y

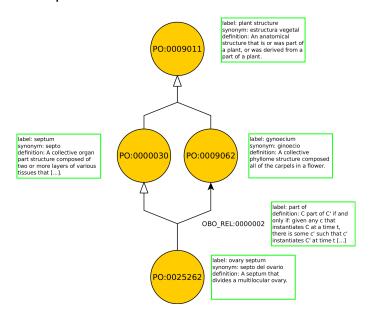
► X SubClassOf: part-of some Y: X \xrightarrow{\text{part-of}} Y

► X SubClassOf: regulates some Y: X \xrightarrow{\text{regulates}} Y

► X DisjointWith: Y: X \xleftarrow{\text{disjoint}} Y

► X EquivalentTo: Y: X \xleftarrow{\equiv} Y, \{X, Y\}
```

Relations as patterns



Semantic similarity

- ► We want to use background knowledge in ontologies to
 - ► determine similarity between classes,
 - ► instances,
 - and entities with ontology annotations

- ► semantic similarity measures similarity between classes
- semantic similarity measures similarity between instances of classes
- semantic similarity measures similarity between entities annotated with classes
- ► ⇒ reduce all of this to similarity between classes

What properties do we want in a similarity measure? A function $sim : D \times D$ is a similarity on D if, for all $x, y \in D$, the function sim is:

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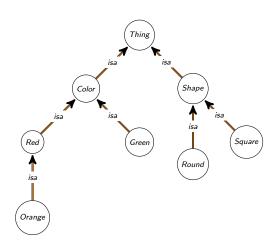
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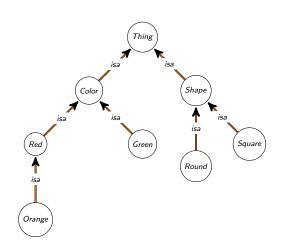
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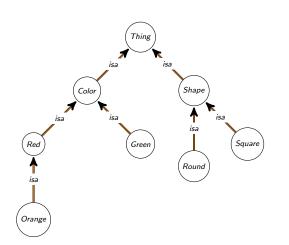
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- ightharpoonup sim is a normalized similarity measure if it has values in [0,1]

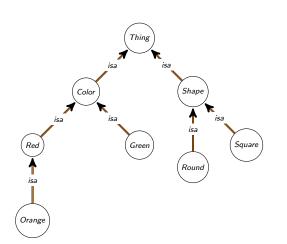




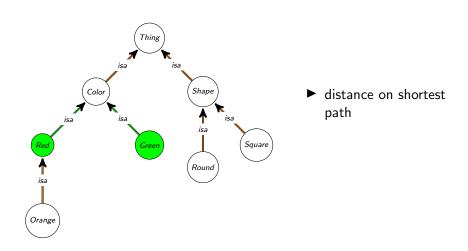
► distance on shortest path (Rada *et al.*, 1989)

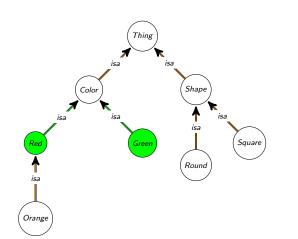


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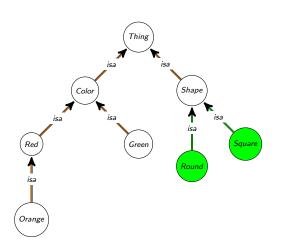


- ► distance on shortest path (Rada *et al.*, 1989)
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- $\sum_{\substack{\text{dist}_{Rada}(u,v)+1}} sim_{Rada}(u,v) =$

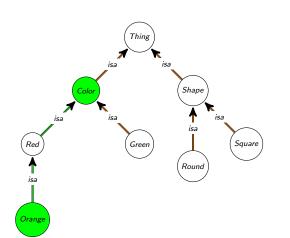




- distance on shortest path
- ▶ distance(green, red)
 = 2
- $sim_{Rada}(green, red) = \frac{1}{3}$



- distance on shortest path
- distance(square, round) = 2
- $sim_{Rada}(square, round) = \frac{1}{3}$



- distance on shortest path
- distance(orange, color) = 2
- $sim_{Rada}(orange, color) = \frac{1}{3}$

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- we need a way to determine specificity of a class
 - number of ancestors
 - number of children
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- density of a branch in the ontology
 - number of siblings
 - information content
- account for different edge types
 - non-uniform edge weighting

- ▶ term specificity measure $\sigma: C \mapsto \mathbb{R}$:
 - $x \sqsubseteq y \to \sigma(x) \ge \sigma(y)$

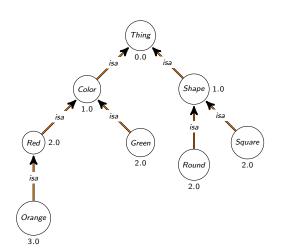
- ▶ term specificity measure $\sigma: C \mapsto \mathbb{R}$:
 - $ightharpoonup x \sqsubseteq y o \sigma(x) \ge \sigma(y)$
- ► intrinsic:
 - $ightharpoonup \sigma(x) = f(depth(x))$
 - $ightharpoonup \sigma(x) = f(A(x))$ (for ancestors A(x))
 - $ightharpoonup \sigma(x) = f(D(x))$ (for descendants D(x))
 - ▶ many more, e.g., Zhou et al.:

$$\sigma(x) = k \cdot \left(1 - \frac{\log |D(x)|}{\log |C|}\right) + (1 - k) \frac{\log depth(x)}{\log depth(G_T)}$$

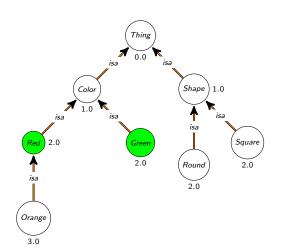
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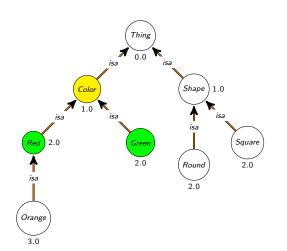
- extrinsic:
 - $ightharpoonup \sigma(x)$ defined as a function of instances (or annotations) I
 - ► note: the number of instances monotonically decreases with increasing depth in taxonomies
 - Resnik 1995: $elC_{Resnik}(x) = -\log p(x)$ (with $p(x) = \frac{|I(x)|}{|I|}$)
 - in biology, one of the most popular specificity measure when annotations are present



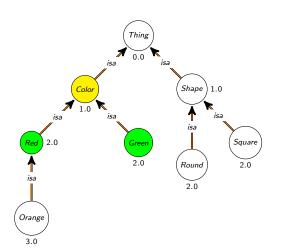
► Resnik 1995: similarity between *x* and *y* is the information content of the *most* informative common ancestor



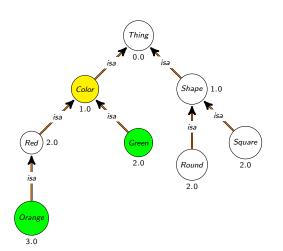
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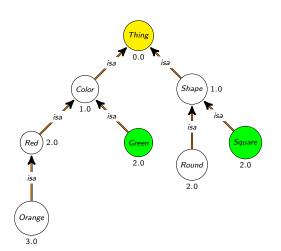
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 - $sim_{Resnik}(Green, Red) = 1.0$

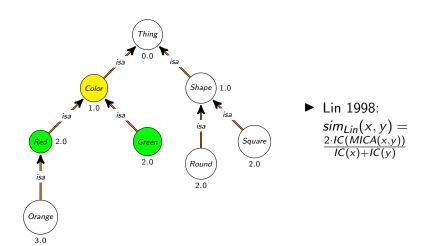


- ► Resnik 1995: similarity between *x* and *y* is the information content of the *most* informative common ancestor
 - sim_{Resnik} (Green, Orange) = 1.0

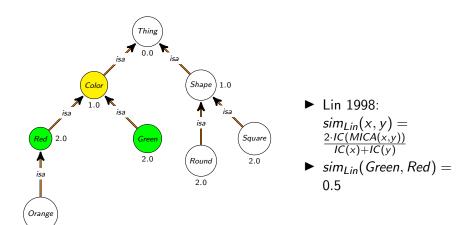


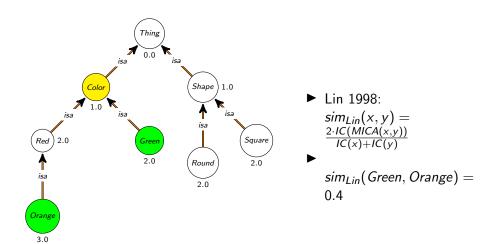
- ► Resnik 1995: similarity between *x* and *y* is the information content of the *most* informative common ancestor
 - sim_{Resnik} (Square, Orange)
 0.0

- ► (Red, Green) and (Orange, Green) have the same similarity
- ▶ need to incorporate the specificity of the compared classes



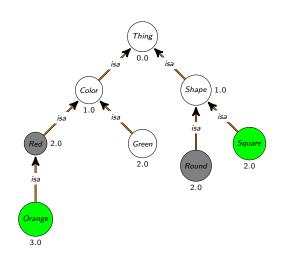
3.0



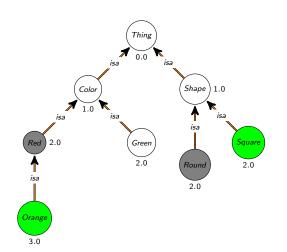


- ► many(!) others:
 - ► Jiang & Conrath 1997
 - ► Mazandu & Mulder 2013
 - ► Schlicker et al. 2009
 - ▶ ..

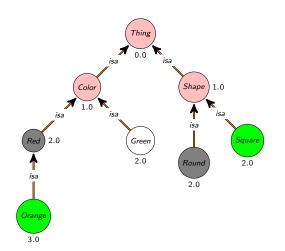
- we only looked at comparing pairs of classes
- ▶ mostly, we want to compare *sets* of classes
 - set of GO annotations
 - set of signs and symptoms
 - set of phenotypes
- two approaches:
 - compare each class individually, then merge
 - directly set-based similarity measures



 similarity between a square-and-orange thing and a round-and-red thing



- similarity between a square-and-orange thing and a round-and-red thing
- Pesquita et al., 2007: $simGIC(X, Y) = \sum_{c \in A(X) \cap A(Y)} IC(c) \sum_{c \in A(X) \cup A(Y)} IC(c)$



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- $\blacktriangleright \ simGIC(so, rr) = \frac{2}{11}$

- alternatively: use different merging strategies
- ► common: average, maximum, best-matching average

▶ Average:
$$sim_A(X, Y) = \frac{\sum_{x \in X} \sum_{y \in Y} sim(x, y)}{|X| \times |Y|}$$

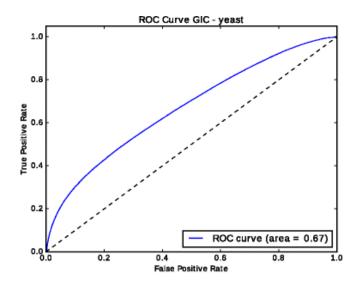
- ► Max average: $sim_{MA}(X, Y) = \frac{1}{|X|} \sum_{x \in X} max_{y \in Y} sim(x, y)$
- ▶ Best match average: $sim_{BMA}(X, Y) = \frac{sim_{MA}(X, Y) + sim_{MA}(Y, X)}{2}$

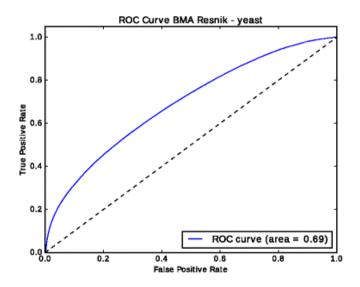
- ► Semantic Measures Library:
 - comprehensive Java library
 - ► http://www.semantic-measures-library.org/
- R packages: GOSim, GOSemSim, HPOSim, LSAfun, ontologySimilarity,...
- ► Python: sematch, fastsemsim (GO only)

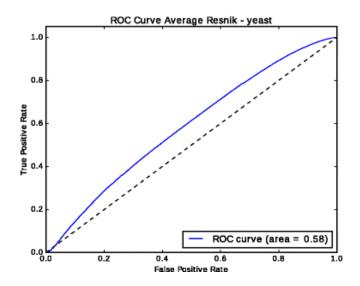
Hypothesis

Proteins with similar functions are more likely to interact.

- relies on background knowledge about functions (encoded in GO)
- "similarity" can mean:
 - ▶ part of the same pathway
 - siblings of a common super-class
 - ▶ located in the same location
- set-based comparison of GO functions
 - ► single GO hierarchy or all?
 - which similarity measure?







- ▶ no obvious choice of similarity measure
- ► depends on application
 - predicting PPIs in different organisms may benefit from a different similarity measure!
- different similarity measures may react differently to biases in data
- ► needs some testing and experience

Recommendations for using semantic similarity::

- ▶ use Resnik's information content measure
- ► use Resnik's similarity
- use Best Match Average
- ► use the full ontology
- classify your ontology using a reasoner before applying semantic similarity
 - ► although many ontologies come pre-classified
- ▶ ⇒ but there are many exceptions
 - ► similar location ⇒ use location subset of GO
 - ▶ developmental phenotypes ⇒ use developmental branch of phenotype ontology

- choice of ontology determines the kind of similarity
- functional similarity: Gene Ontology
- ▶ anatomical, structural similarity: anatomy ontologies (Uberon, MA, FMA, etc.)
- ▶ phenotypic similarity: phenotype ontology (HPO, MP, etc.)
- chemical structural similarity: ChEBI

- phenotypic similarity used to:
 - diagnosis: similarity between patient phenotypes and disease phenotypes
 - ► also between patient phenotypes, e.g., Phenomizer: http://compbio.charite.de/phenomizer/
 - disease modules: similarity between disease and disease
 - clustering/stratification: similarity between patient and patient
 - disease gene discovery: similarity between patient/disease phenotypes and gene-phenotype associations
 - ▶ in humans
 - ► in model organisms
 - drug repurposing: side-effect similarity; similarity between side effect profile and gene-disease associations

- comparing entities annotated with different ontologies/vocabularies of the same (or related) domains
 - ▶ medical: UMLS, HPO, DO, ORDO, NCIT, ICD, SNOMED CT, MeSH, ...
 - ▶ phenotype: HPO, MP, CPO, WBPhenotype, FBCV, MeSH, ...
 - ► chemical: ChEBI, MeSH, DrOn, RXNorm, DrugBank, ...

- ▶ needs mapping, alignment, or integration
 - mapping: given a term t, find corresponding class in ontology O
 - ► can be 1:1, 1:n, n:1, n:m
 - ▶ t can be from ontology, vocabulary, database, or text
 - ► use *O* for analysis
 - ▶ alignment: given two ontologies or vocabularies O_1 and O_2 , find all mappings between classes/terms in O_1 and O_2
 - applicable to ontologies and vocabularies
 - ightharpoonup use O_1 or O_2 for analysis
 - ▶ integration: given two ontologies O_1 and O_2 , combine both ontologies into a single ontology O
 - ► maintain meaning of classes
 - ▶ use O for analysis

- lexical mappings: use class labels (and synonyms) to find matches
 - ▶ hypertension (HP:0000822) and hypertension (MP:0000231)
- semantic mappings: use class axioms to find matches
 - ▶ pulmonary valve stenosis (MP:0006182) and Pulmonic stenosis (HP:0001642)
 - ▶ both definitions based on constricted (PATO:0001847) and pulmonary valve (UBERON:0002146)
- ▶ hybrid: combine lexical and semantic mappings

tools for ontology mapping, matching, integration:

- ► AgreementMaker Light:
 - https://github.com/AgreementMakerLight/AML-Jar
 - structural (semantic) and lexical matches
 - ► can use domain-specific background knowledge
- ► LogMap: https:

//github.com/ernestojimenezruiz/logmap-matcher

- structural (semantic) and lexical matches
- biology-themed versions
- ► NCBO Annotator:

https://bioportal.bioontology.org/annotator

- ► lexical matches only
- can annotate full text
- recent tools and comprehensive ongoing evaluation:
 - ► OAEI: http://oaei.ontologymatching.org/

Hands-on part: diagnosing rare disease using mouse phenotypes

- ► run the "Semantic Similarity" notebook
 - ► then find the mouse genotype with the most similar set of phenotypes to "Tetralogy of Fallot" (OMIM:187500)
 - or: use the data from https://hpo.jax.org/app/download/annotation to add more diseases and query by disease (hint: a disease is really just a set of phenotypes)