

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 pull coolmaksat/embeddings:latest`
- ▶ `docker run -i -t -p 8888:8888 coolmaksat/embeddings /bin/bash -c "jupyter notebook --notebook-dir=/home/borg/ontology-tutorial/ --ip='0.0.0.0' --port=8888 --no-browser --allow-root"`

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

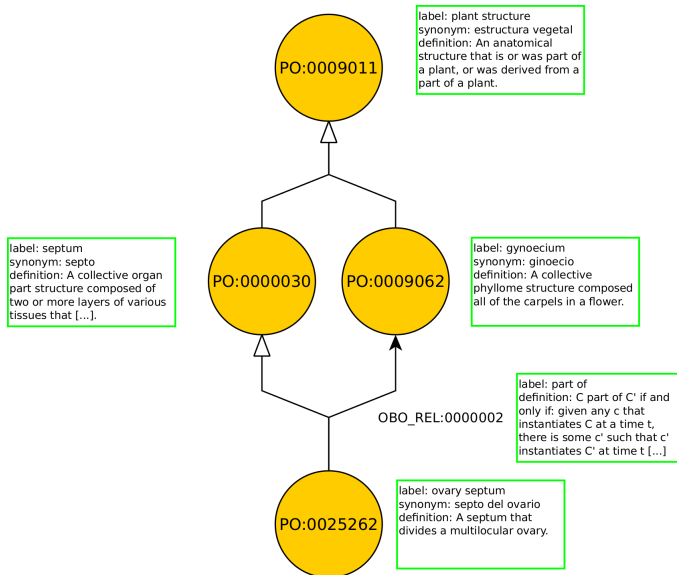
Agenda

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

Ontologies, machine learning, and AI

- ▶ 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

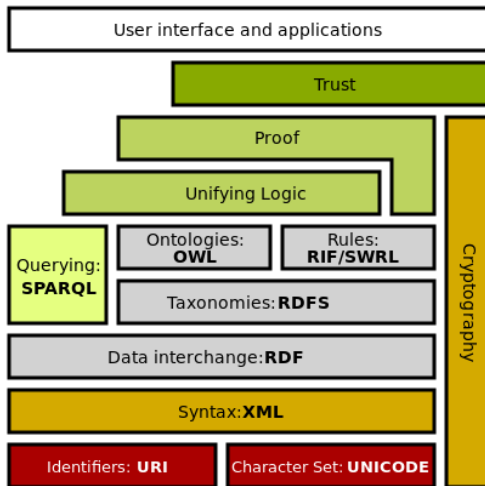
- ▶ standard identifiers (IRIs)
- ▶ labels of classes and relations
- ▶ human-readable descriptions
- ▶ axioms

Ontologies provide domain knowledge

[Overview](#)
[Browse](#)
[DLQuery](#)
[Download](#)

Annotation	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_namespace	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
$\exists R.C$	R some C	hasChild some Human
$\forall R.C$	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
$\{a\} \sqcup \{b\} \sqcup \dots$	{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

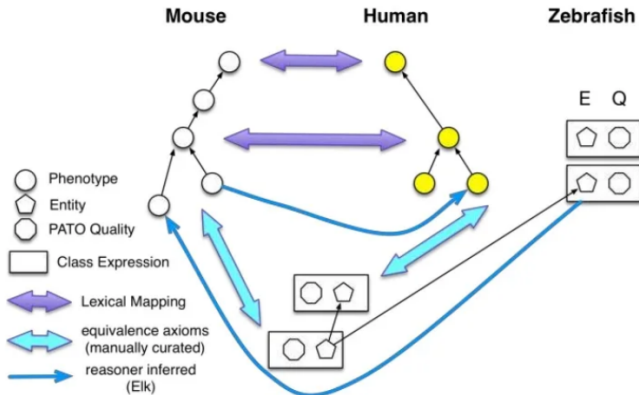
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Reasoning with phenotype ontologies

Phenotype ontology:

- ▶ A phenotype is a quality that inheres in its bearer:
 - ▶ Enlarged heart: $Enlarged(x) \wedge \exists y (inheresIn(x, y) \wedge Heart(y))$
 - ▶ in DL: $Enlarged \sqcap \exists inheresIn. Heart$
 - ▶ 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
 - ▶ \Rightarrow ontologies
2. integrate/compare phenotypes *within and between species* (to overcome limitations in phenotype data)
 - ▶ homologous organ structures
 - ▶ related/identical function
 - ▶ \Rightarrow ontologies and automated reasoning
3. measure phenotypic similarity
 - ▶ use morphological or functional similarity
 - ▶ similarity in attribute values
 - ▶ \Rightarrow semantic similarity, machine learning

Other questions we want to answer

- ▶ Are cyclin dependent kinases *functionally* more similar to lipid kinases or to riboflavin kinases? How about *phenotypically*?

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- ▶ Does functional similarity correlate with phenotypic similarity?

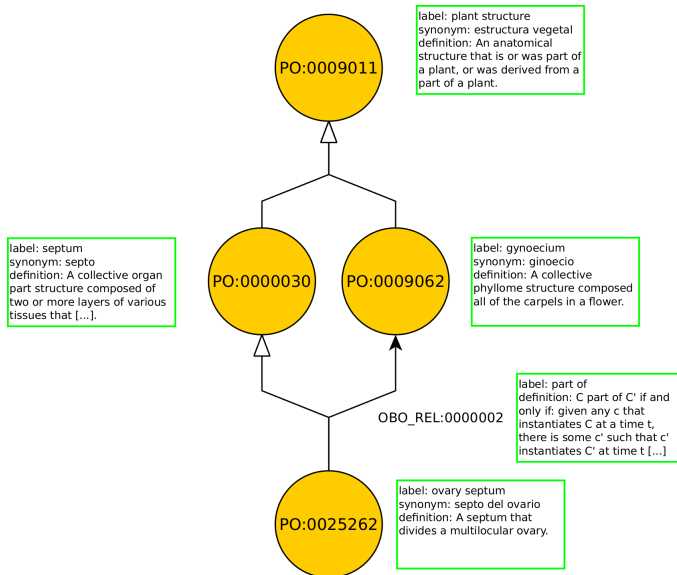
Ontologies and graphs

- ▶ 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

- ▶ $X \text{ SubClassOf } Y: X \xrightarrow{\text{is-a}} Y$
- ▶ $X \text{ SubClassOf } \text{part-of some } Y: X \xrightarrow{\text{part-of}} Y$
- ▶ $X \text{ SubClassOf } \text{regulates some } Y: X \xrightarrow{\text{regulates}} Y$
- ▶ $X \text{ DisjointWith } Y: X \xleftrightarrow{\text{disjoint}} Y$
- ▶ $X \text{ EquivalentTo } Y: X \xleftrightarrow{\equiv} Y, \{X, Y\}$

Relations as patterns



Semantic similarity

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

How to measure similarity?

- ▶ semantic similarity measures similarity between classes
- ▶ semantic similarity measures similarity between instances of classes
- ▶ semantic similarity measures similarity between entities *annotated* with classes
- ▶ \Rightarrow reduce all of this to similarity between classes

How to measure similarity?

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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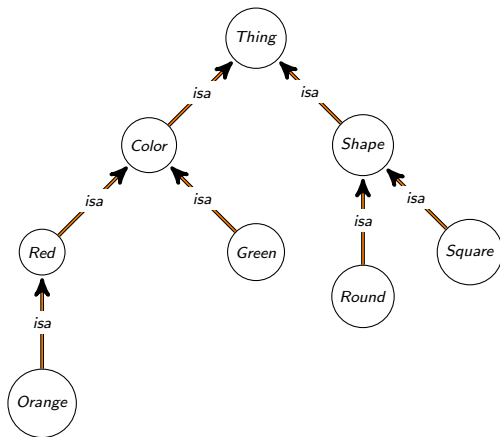
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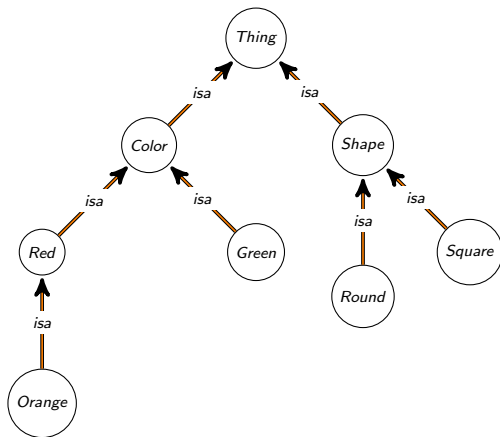
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- ▶ $sim(x, x) > sim(x, y)$ for $x \neq y$
- ▶ sim is a *normalized* similarity measure if it has values in $[0, 1]$

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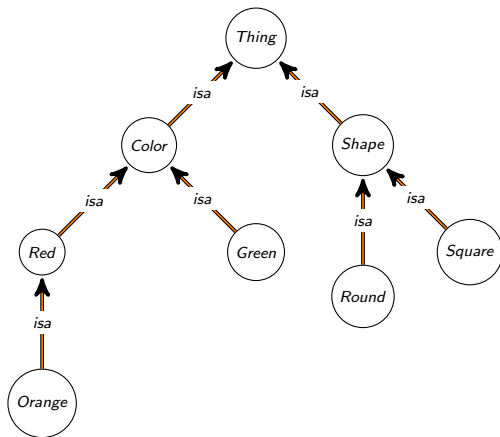


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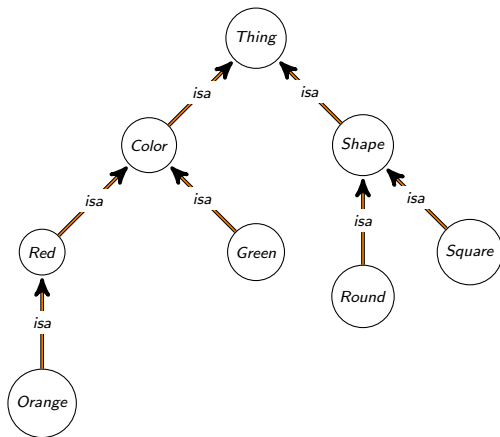
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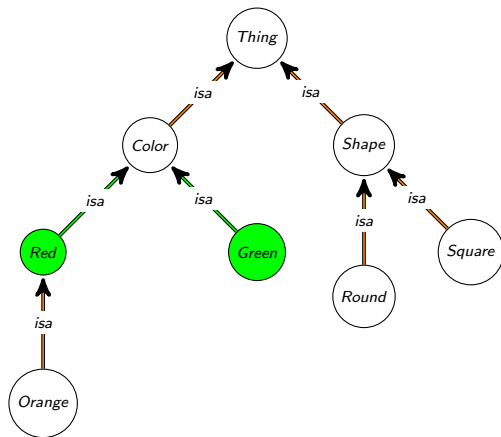
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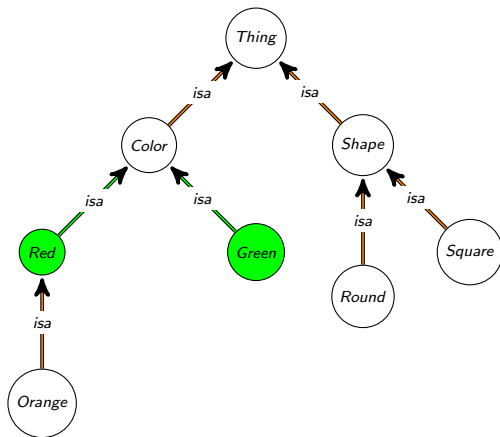
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- ▶ $sim_{Rada}(u, v) = \frac{1}{dist_{Rada}(u, v) + 1}$

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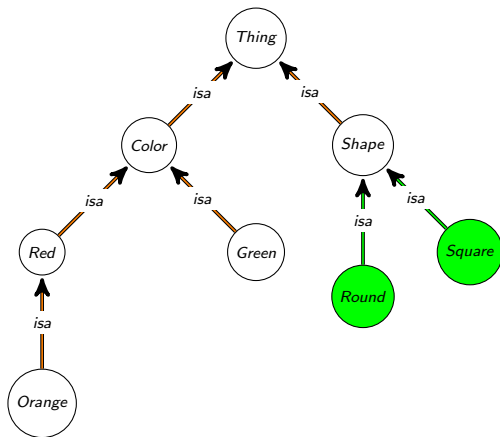
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How to measure similarity?



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

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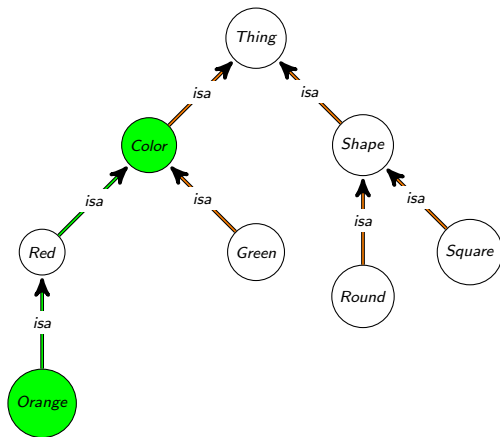
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►

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How to measure similarity?



► distance on shortest path

► $\text{distance}(\text{orange}, \text{color}) = 2$

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$$\text{sim}_{\text{Rada}}(\text{orange}, \text{color}) = \frac{1}{3}$$

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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

How to measure similarity

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

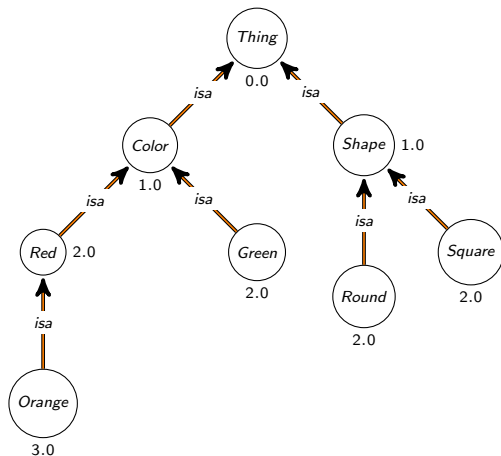
How to measure similarity

- ▶ term specificity measure $\sigma : C \mapsto \mathbb{R}$:
 - ▶ $x \sqsubseteq y \rightarrow \sigma(x) \geq \sigma(y)$
- ▶ intrinsic:
 - ▶ $\sigma(x) = f(\text{depth}(x))$
 - ▶ $\sigma(x) = f(A(x))$ (for ancestors $A(x)$)
 - ▶ $\sigma(x) = f(D(x))$ (for descendants $D(x)$)
 - ▶ many more, e.g., Zhou et al.:
$$\sigma(x) = k \cdot \left(1 - \frac{\log |D(x)|}{\log |C|}\right) + (1 - k) \frac{\log \text{depth}(x)}{\log \text{depth}(G_T)}$$

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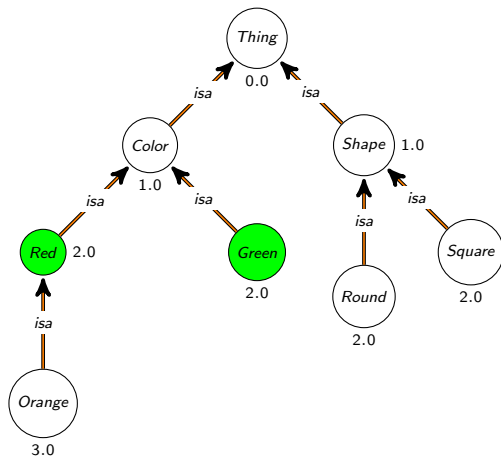
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- ▶ extrinsic:
 - ▶ $\sigma(x)$ defined as a function of instances (or annotations) I
 - ▶ note: the number of instances monotonically decreases with increasing depth in taxonomies
 - ▶ Resnik 1995: $eIC_{\text{Resnik}}(x) = -\log p(x)$ (with $p(x)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

How to measure similarity?



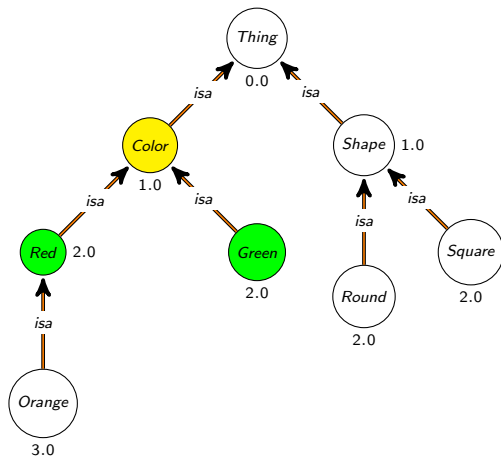
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similarity between x and y is the information content of the *most informative common ancestor*

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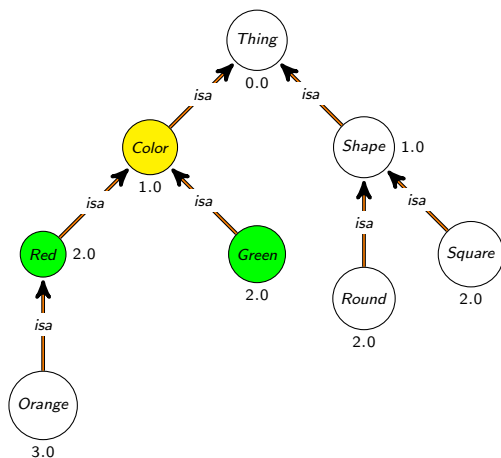
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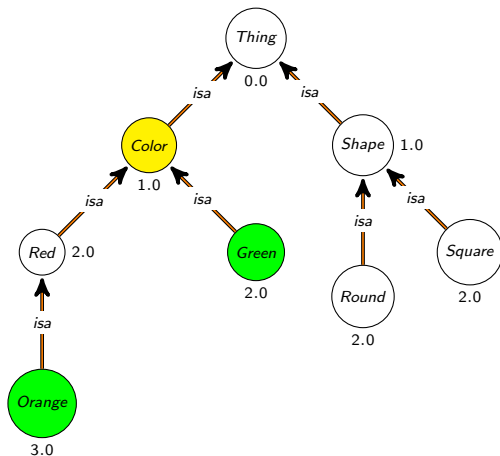
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- ▶
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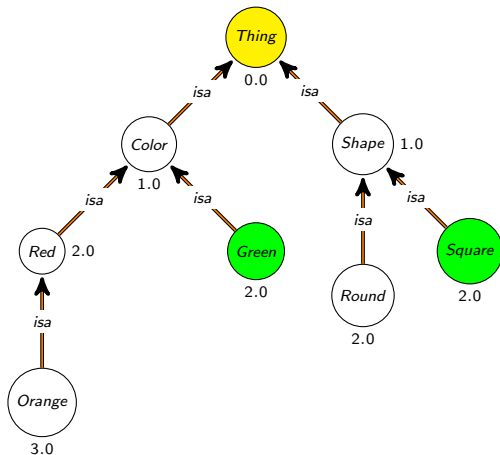
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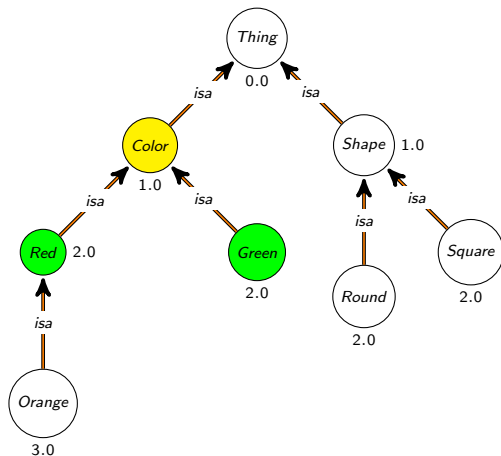
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- ▶ $sim_{Resnik}(Square, Orange)$
0.0

How to measure similarity?

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

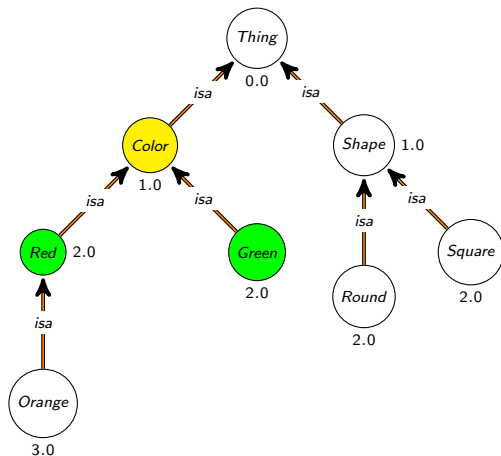
How to measure similarity?



► Lin 1998:

$$sim_{Lin}(x, y) = \frac{2 \cdot IC(MICA(x, y))}{IC(x) + IC(y)}$$

How to measure similarity?

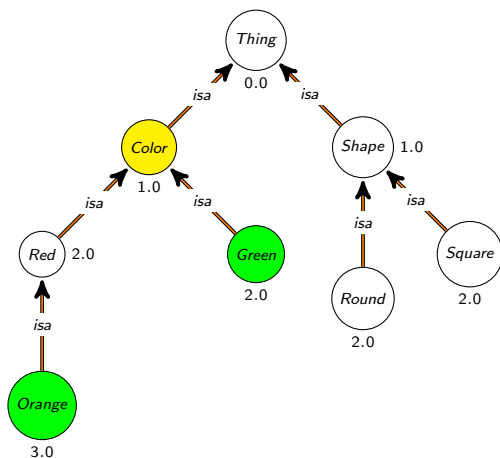


► Lin 1998:

$$sim_{Lin}(x, y) = \frac{2 \cdot IC(MICA(x, y))}{IC(x) + IC(y)}$$

► $sim_{Lin}(Green, Red) = 0.5$

How to measure similarity?



► Lin 1998:

$$sim_{Lin}(x, y) = \frac{2 \cdot IC(MICA(x, y))}{IC(x) + IC(y)}$$

►

$$sim_{Lin}(Green, Orange) = 0.4$$

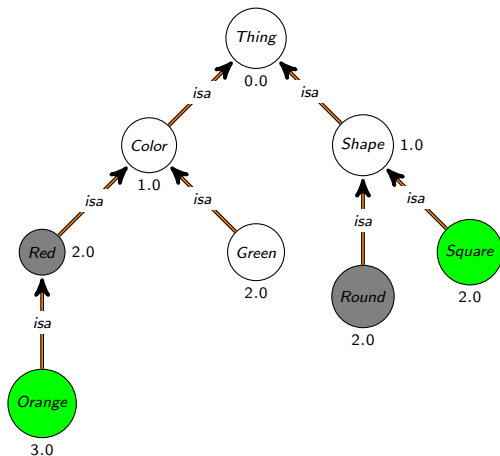
How to measure similarity?

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

How to measure similarity?

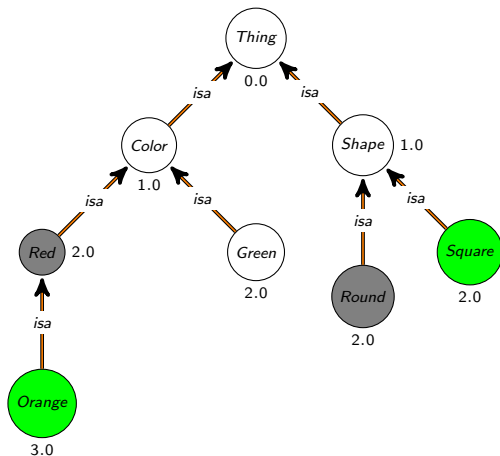
- ▶ we only looked at comparing pairs of classes
- ▶ mostly, we want to compare *sets* of classes
 - ▶ set of GO annotations
 - ▶ set of signs and symptoms
 - ▶ set of phenotypes
- ▶ two approaches:
 - ▶ compare each class individually, then merge
 - ▶ directly set-based similarity measures

How to measure similarity?



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

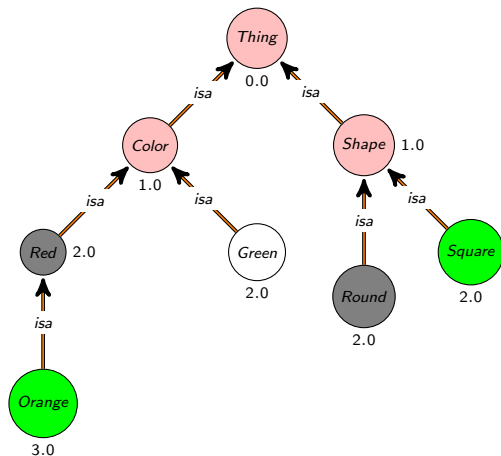
How to measure similarity?



- ▶ similarity between a square-and-orange thing and a round-and-red thing
- ▶ Pesquita et al., 2007:

$$\text{simGIC}(X, Y) = \frac{\sum_{c \in A(X) \cap A(Y)} IC(c)}{\sum_{c \in A(X) \cup A(Y)} IC(c)}$$

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

How to measure similarity?

- ▶ 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: $sim_{BMA}(X, Y) = \frac{sim_{MA}(X, Y) + sim_{MA}(Y, X)}{2}$

How to measure similarity?

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

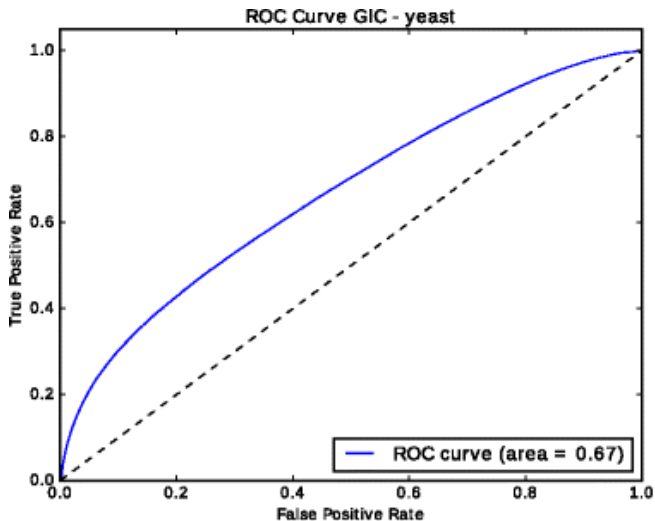
Applications of semantic similarity

Hypothesis

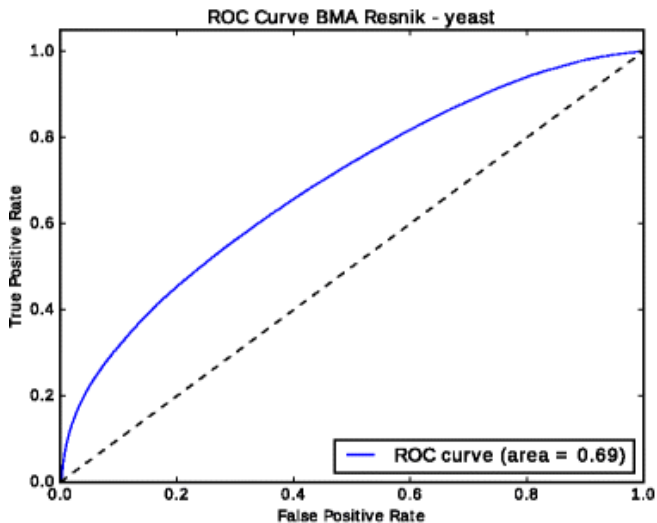
Proteins with similar functions are more likely to interact.

- ▶ 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?

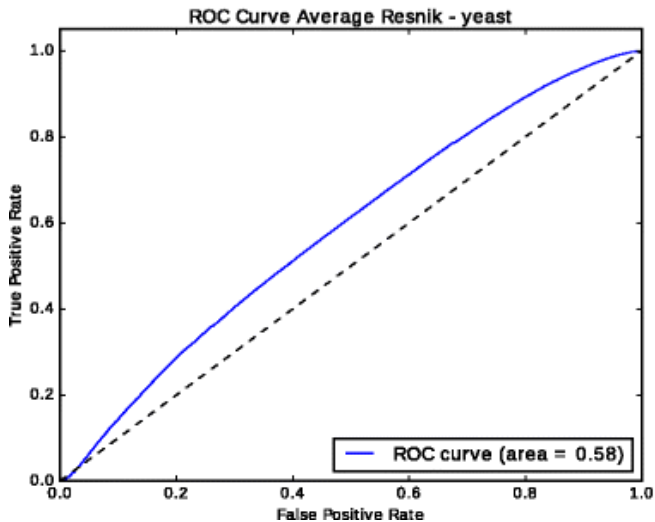
Applications of semantic similarity



Applications of semantic similarity



Applications of semantic similarity



Applications of semantic similarity

- ▶ 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

Applications of semantic similarity

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
- ▶ \Rightarrow but there are many exceptions
 - ▶ similar location \Rightarrow use location subset of GO
 - ▶ developmental phenotypes \Rightarrow use developmental branch of phenotype ontology

Applications of semantic similarity

- ▶ 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

Applications of semantic similarity

- ▶ 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

Applications of semantic similarity

- ▶ 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, ...

Applications of semantic similarity

- ▶ 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
 - ▶ 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

Applications of semantic similarity

- ▶ 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

Applications of semantic similarity

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://oei.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)