# Semantic similarity and machine learning with ontologies

Robert Hoehndorf and Maxat Kulmanov

#### 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
- ullet  $\Rightarrow$  reduce all of this to similarity between classes

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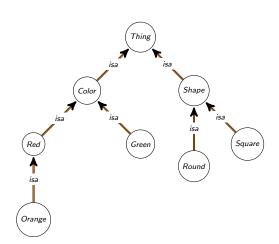
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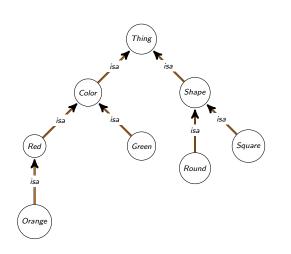
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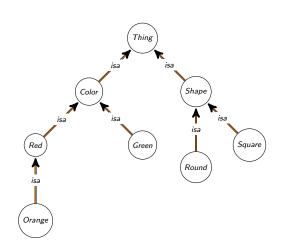
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- ullet sim is a normalized similarity measure if it has values in [0,1]

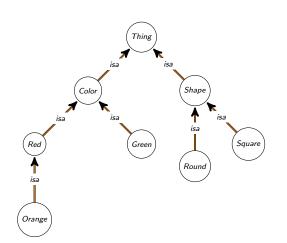




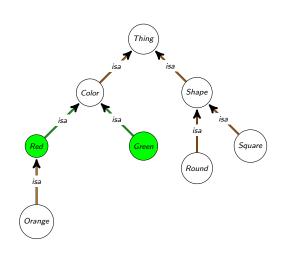
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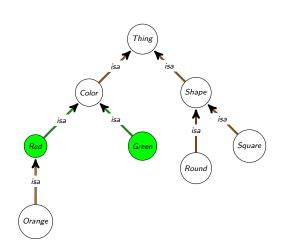
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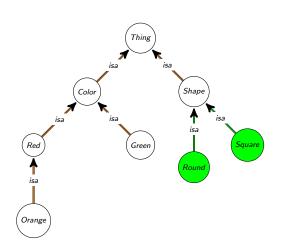
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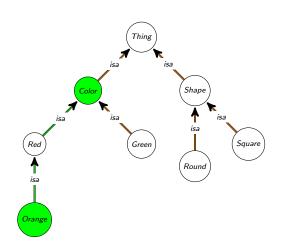
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- distance on shortest path
- distance(green, red)2
- $sim_{Rada}(green, red) = \frac{1}{3}$



- 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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- account for different edge types
  - non-uniform edge weighting

• term specificity measure  $\sigma: C \mapsto \mathbb{R}$ :

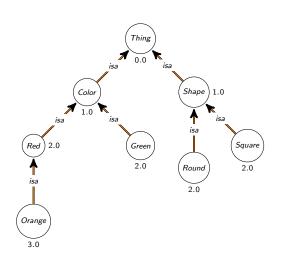
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- intrinsic:
  - $ightharpoonup \sigma(x) = f(depth(x))$
  - $ightharpoonup \sigma(x) = f(A(x))$  (for ancestors A(x))
  - $\sigma(x) = f(D(x))$  (for descendants D(x))
  - many more, e.g., Zhou et al.:

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

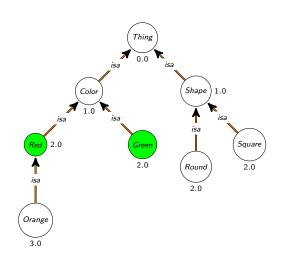
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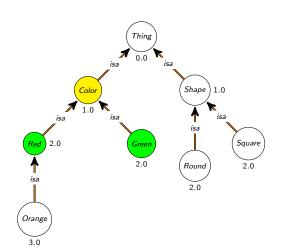
- extrinsic:
  - $ightharpoonup \sigma(x)$  defined as a function of instances (or annotations) I
    - note: the number of instances monotonically decreases with increasing depth in taxonomies
  - ► Resnik 1995:  $elC_{Resnik}(x) = -\log p(x)$  (with  $p(x) = \frac{|I(x)|}{|I|}$ )
    - in biology,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



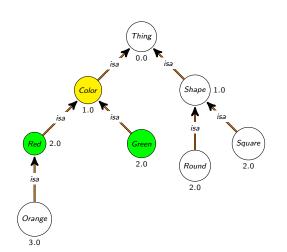
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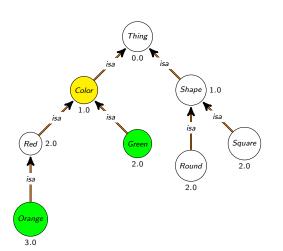
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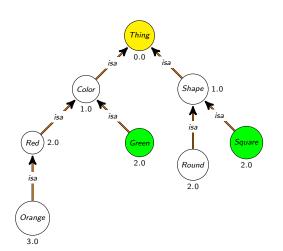
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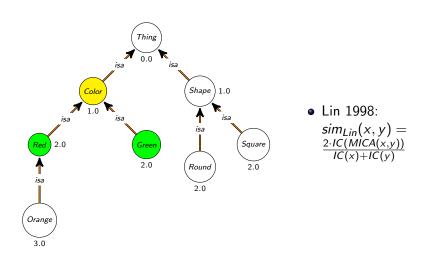


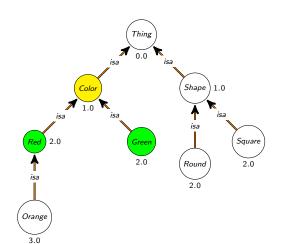
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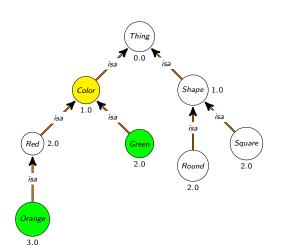
- Resnik 1995: similarity between x and y is the information content of the most informative common ancestor
  - $sim_{Resnik}(Square, Orange) \ 0.0$

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





- Lin 1998:  $sim_{Lin}(x, y) = \frac{2 \cdot IC(MICA(x,y))}{IC(x) + IC(y)}$
- $sim_{Lin}(Green, Red) = 0.5$

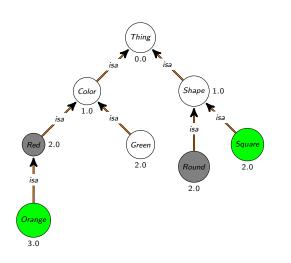


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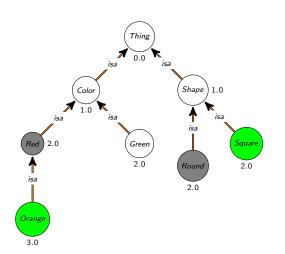
 $sim_{Lin}(Green, Orange) = 0.4$ 

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

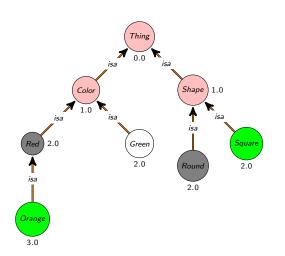
- we only looked at comparing pairs of classes
- mostly, we want to compare sets of classes
  - set of GO annotations
  - set of signs and symptoms
  - set of phenotypes
- two approaches:
  - compare each class individually, then merge
  - directly set-based similarity measures



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

- 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)

### Applications of semantic similarity

- no obvious choice of similarity measure
- depends on application
  - e.g., predicting PPIs in different organisms through similarity 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:

- use Resnik's information content measure
- use Resnik's similarity
- use Best Match Average
- use the full ontology
- classify your ontology using an automated 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