# Machine learning with ontologies

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

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

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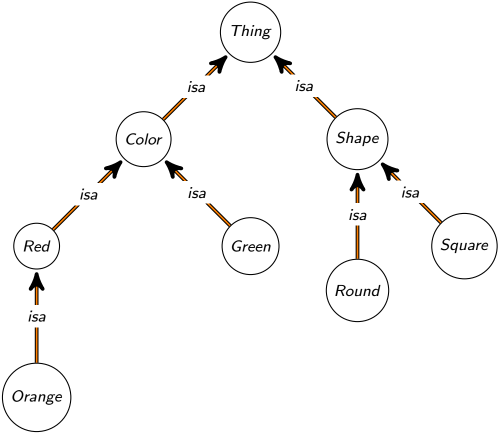

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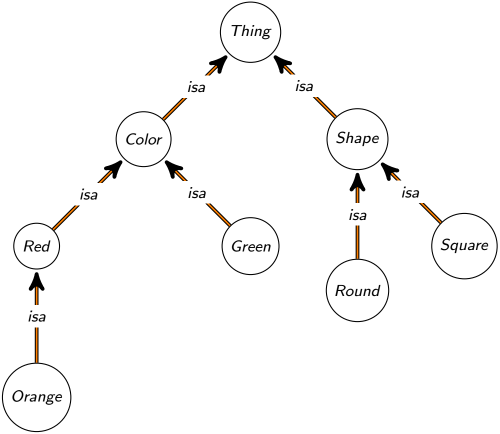


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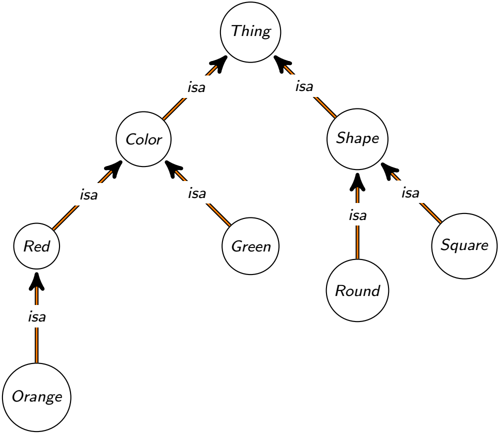


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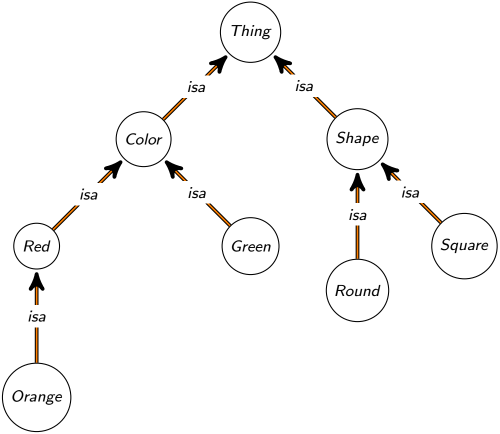


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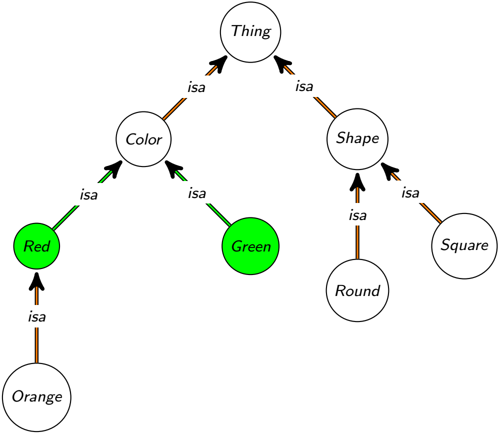


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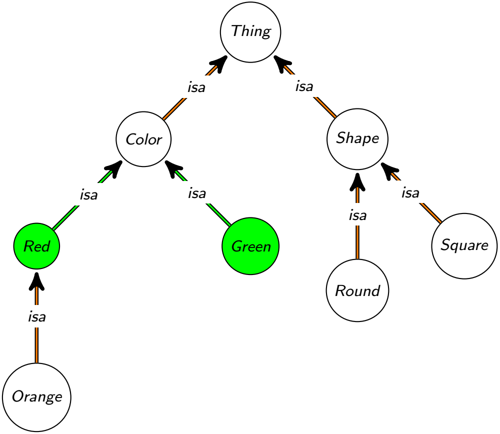


- distance on shortest path
- distance(green, red) $= 2$
- $sim_{Rada}(green, red) = \frac{1}{3}$

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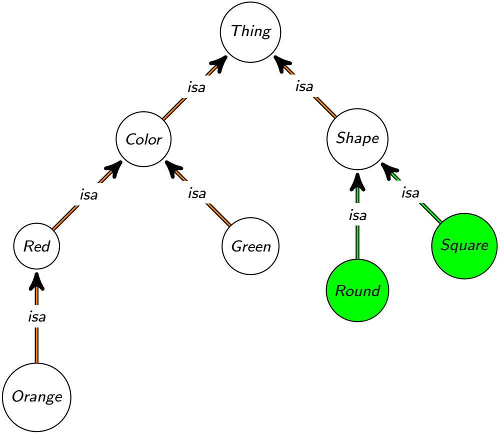


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- distance(square, round) = 2
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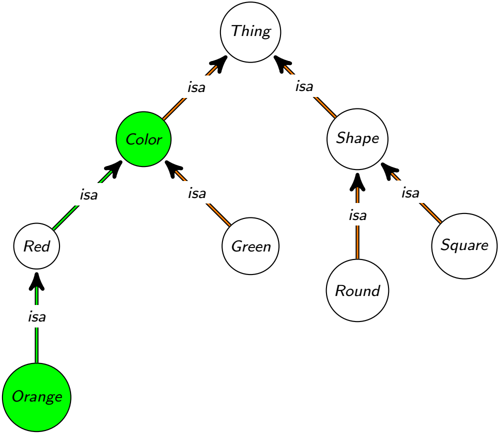


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- distance(orange, color) $= 2$
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- *density* of a branch in the ontology
  - number of siblings
  - information content
- account for different edge types
  - non-uniform edge weighting

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  - $\sigma(x) = f(A(x))$ (for ancestors $A(x)$)
  - $\sigma(x) = f(D(x))$ (for descendants $D(x)$)
  - many more, e.g., Zhou et al.:
    $\sigma(x) = k \cdot \left(1 - \frac{\log |D(x)|}{\log |C|}\right) + (1-k)\frac{\log \mathit{depth}(x)}{\log \mathit{depth}(G_T)}$

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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: $eIC_{Resnik}(x) = -\log p(x)$ (with $p(x) = \frac{|I(x)|}{|I|}$)
    - in biology, one of the most popular specificity measure when annotations are present

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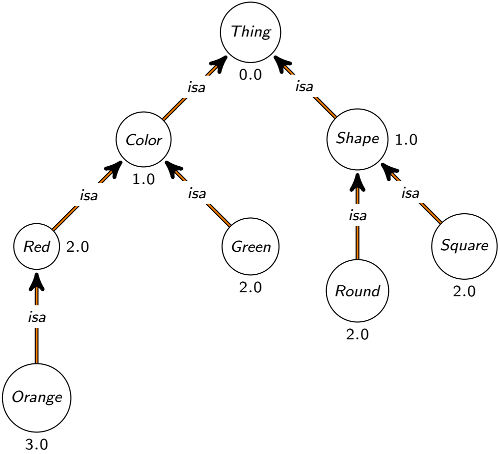


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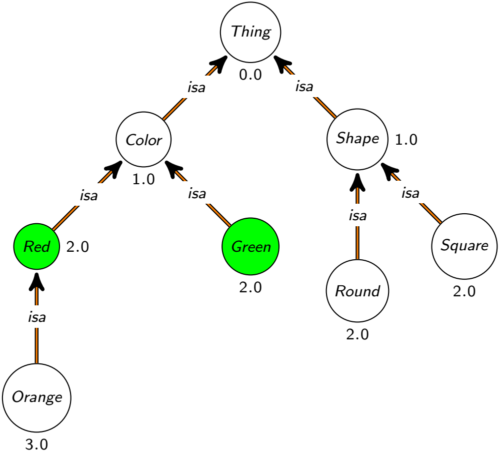


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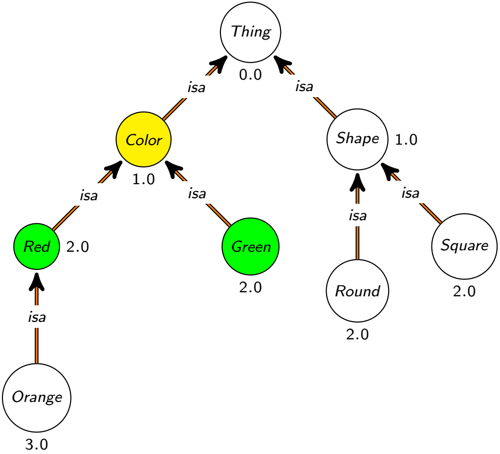


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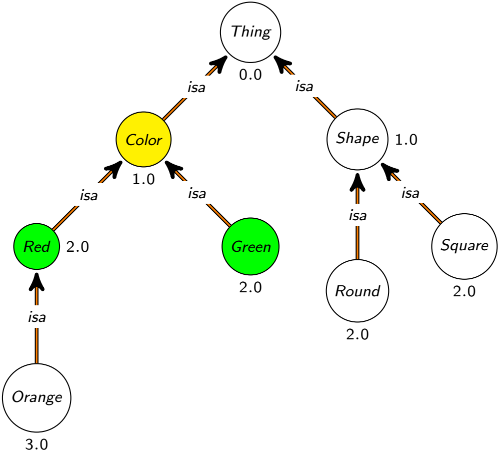


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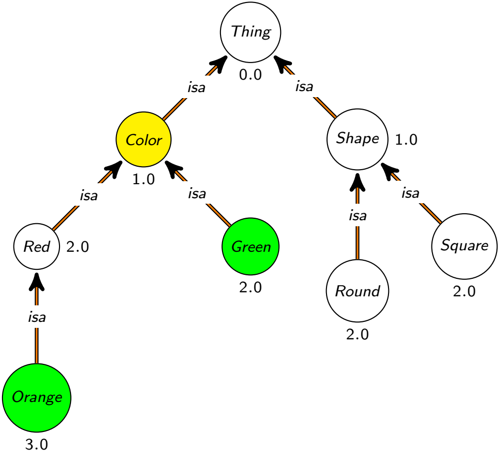


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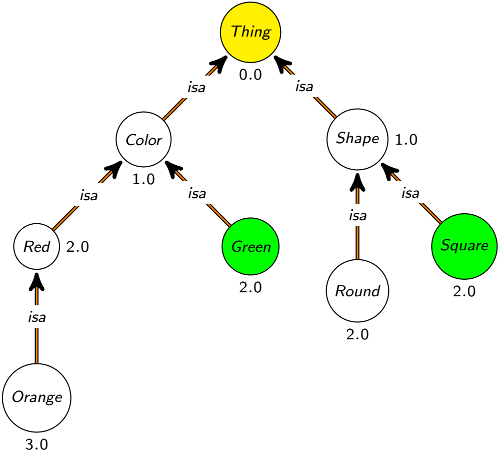


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- $sim_{Resnik}(Square, Orange)$ 0.0

# How to measure similarity?

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

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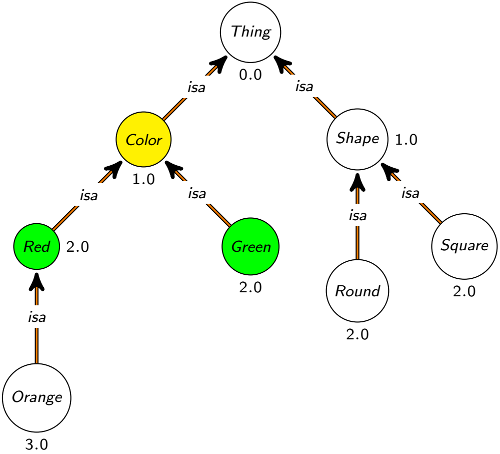


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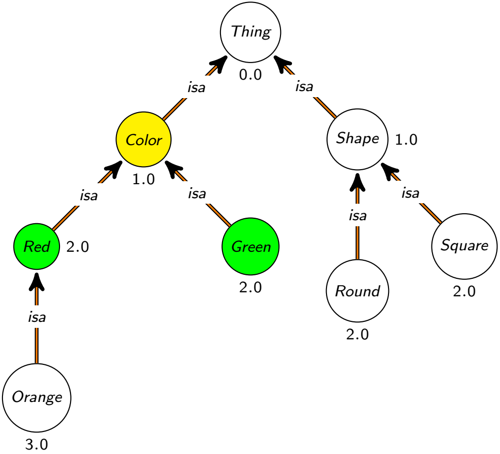


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- $sim_{Lin}(Green, Red) = 0.5$

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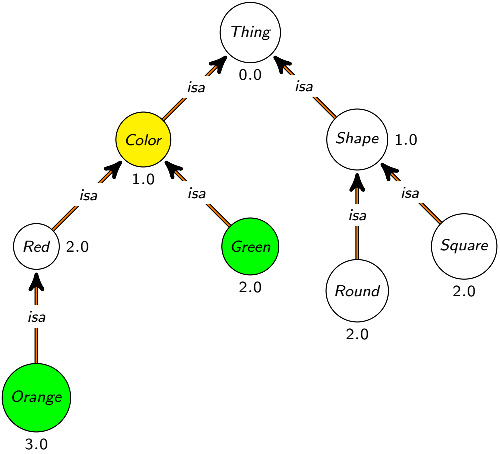


- Lin 1998: $sim_{Lin}(x, y) = \frac{2 \cdot IC(MICA(x,y))}{IC(x)+IC(y)}$
- $sim_{Lin}(Green, Orange) = 0.4$

# 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

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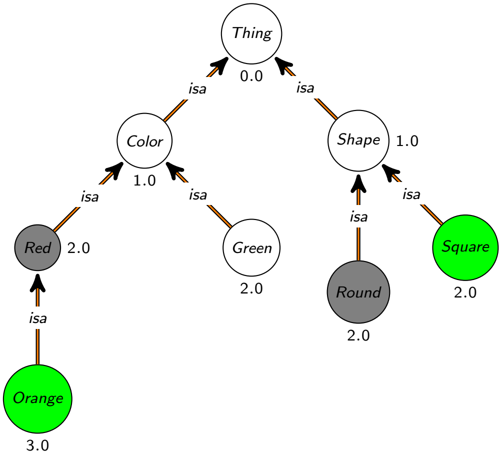


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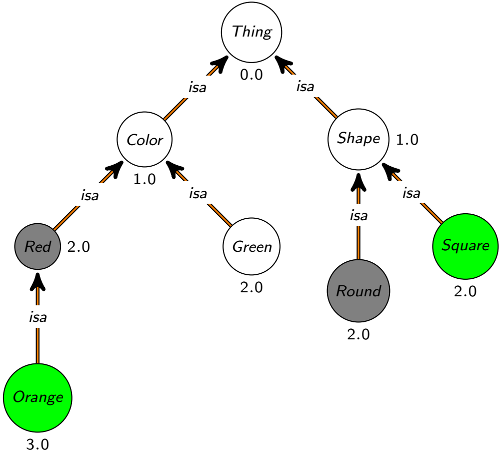


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- Pesquita et al., 2007: $simGIC(X, Y) = \frac{\sum_{c \in A(X) \cap A(Y)} IC(c)}{\sum_{c \in A(X) \cup A(Y)} IC(c)}$

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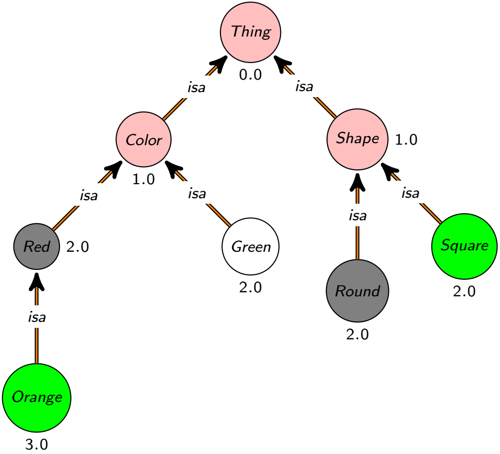


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- $simGIC(so, rr) = \frac{2}{11}$

# 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

- 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 (normalized)
- 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
- $\Rightarrow$ but there are many exceptions
  - similar location $\Rightarrow$ use location subset of GO
  - developmental phenotypes $\Rightarrow$ use developmental branch of phenotype ontology