Word Sense Disambiguation

LING 571 — Deep Processing for NLP November 18, 2020 Shane Steinert-Threlkeld



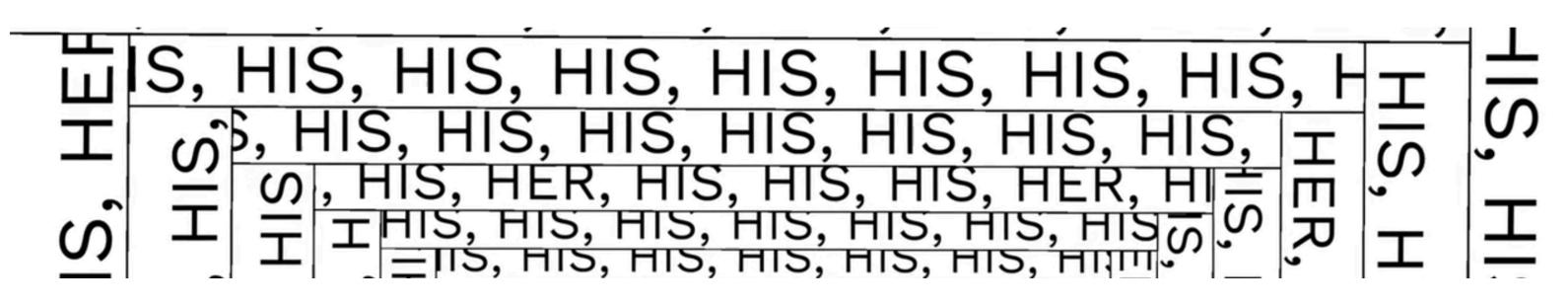




In the News

A.I. Systems Echo Biases They're Fed, Putting Scientists on Guard

Researchers say computer systems are learning from lots and lots of digitized books and news articles that could bake old attitudes into new technology.



https://www.nytimes.com/2019/11/11/technology/artificial-intelligence-bias.html

[includes a quote from CLMS director/faculty Emily Bender]





Ambiguity of the Week

 \sim



Lee Murray @MurrayLeeA

syntax tree of the week

Model who burned down 3,500-year-old tree called 'The Senator' while high on meth avoids jail time

Actually from 2014!

https://www.dailymail.co.uk/news/article-2652104/Model-burned-3-500-year-old-tree-called-The-Senator-high-meth-avoids-jail-time.html

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Distributional Similarity for Word Sense Induction + Disambiguation





- We've looked at how to represent words
 - ...so far, ignored homographs
- Wrong senses can lead to poor performance in downstream tasks
 - Machine translation, text classification
- Now, how do we go about differentiating homographs?

Word Sense Disambiguation







WordNet Sense	Spanish Translation	Roget Category	
bass ⁴	lubina	Fish/Insect	
bass ⁴	lubina	Fish/Insect	
bass ⁷	bajo	Music	
bass ⁷	bajo	Music	

Word Senses

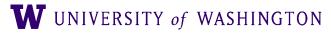
Word in Context

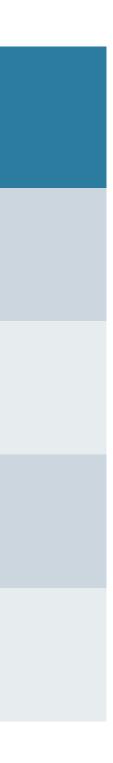
... fish as Pacific salmon and striped **bass** and...

...produce filets of smoked **bass** or sturgeon...

...exciting jazz **bass** player since Ray Brown...

...play **bass** because he doesn't have to solo...









WSD With Distributional Similarity

senses?

• We've covered how to create vectors for *words*, but how do we represent







WSD With Distributional Similarity

- senses?
- *First order* vectors:
 - $\vec{w} = (f_1, f_2, f_3 \dots)$
 - Feature vector of word itself

• We've covered how to create vectors for *words*, but how do we represent







WSD With Distributional Similarity

- senses?
- *First order* vectors:
 - $\vec{w} = (f_1, f_2, f_3 \dots)$
 - Feature vector of word itself
- Second order vectors:
 - Context vector

• We've covered how to create vectors for *words*, but how do we represent







Word Representation

- 2nd Order Representation:
- Identify words in context of w
- For each x in context of w:
 - Compute x vector representation
- Compute centroid of these \vec{x} vector representations







- Compute context vector for each occurrence of word in corpus
- Cluster these context vectors
 - # of clusters = # of senses
- Cluster centroid represents word sense
- Link to specific sense?
 - Pure unsupervised: no sense tag, just ith sense
 - Some supervision: hand label clusters, or tag training

Computing Word Senses





Disambiguating Instances

- To disambiguate an instance t of w:
 - Compute context vector for instance
 - Retrieve all senses of w
 - Assign *w* sense with closest centroid to *t*



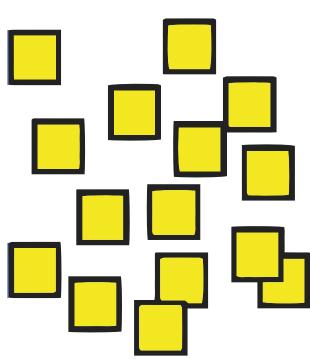




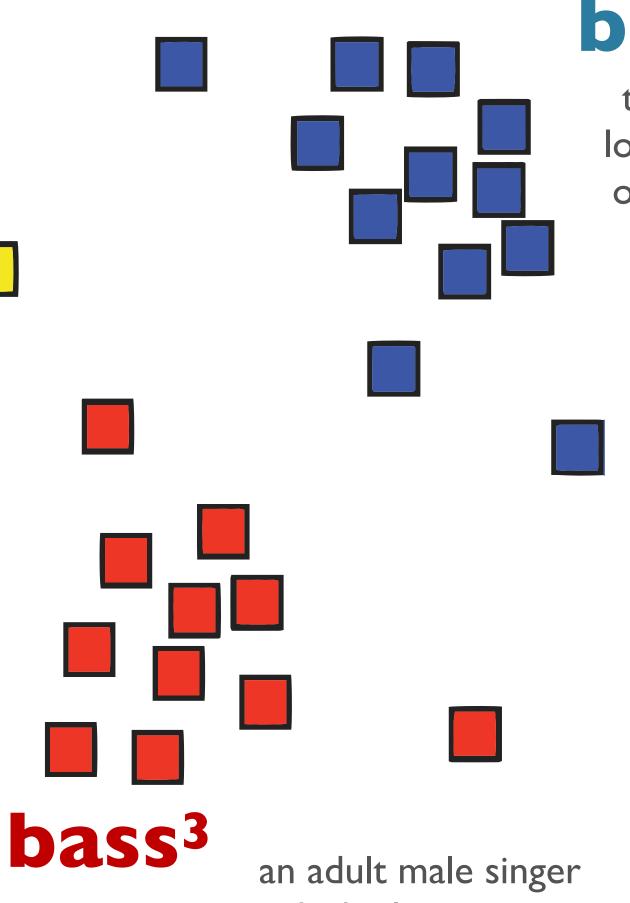




the lean flesh of a saltwater fish of the family Serranidae



Computing Word Senses



bass⁷

the member with the lowest range of a family of musical instruments



with the lowest voice





the lean flesh of a saltwater fish of the family Serranidae



...and the **bass** covered the low notes

Computing Word Senses



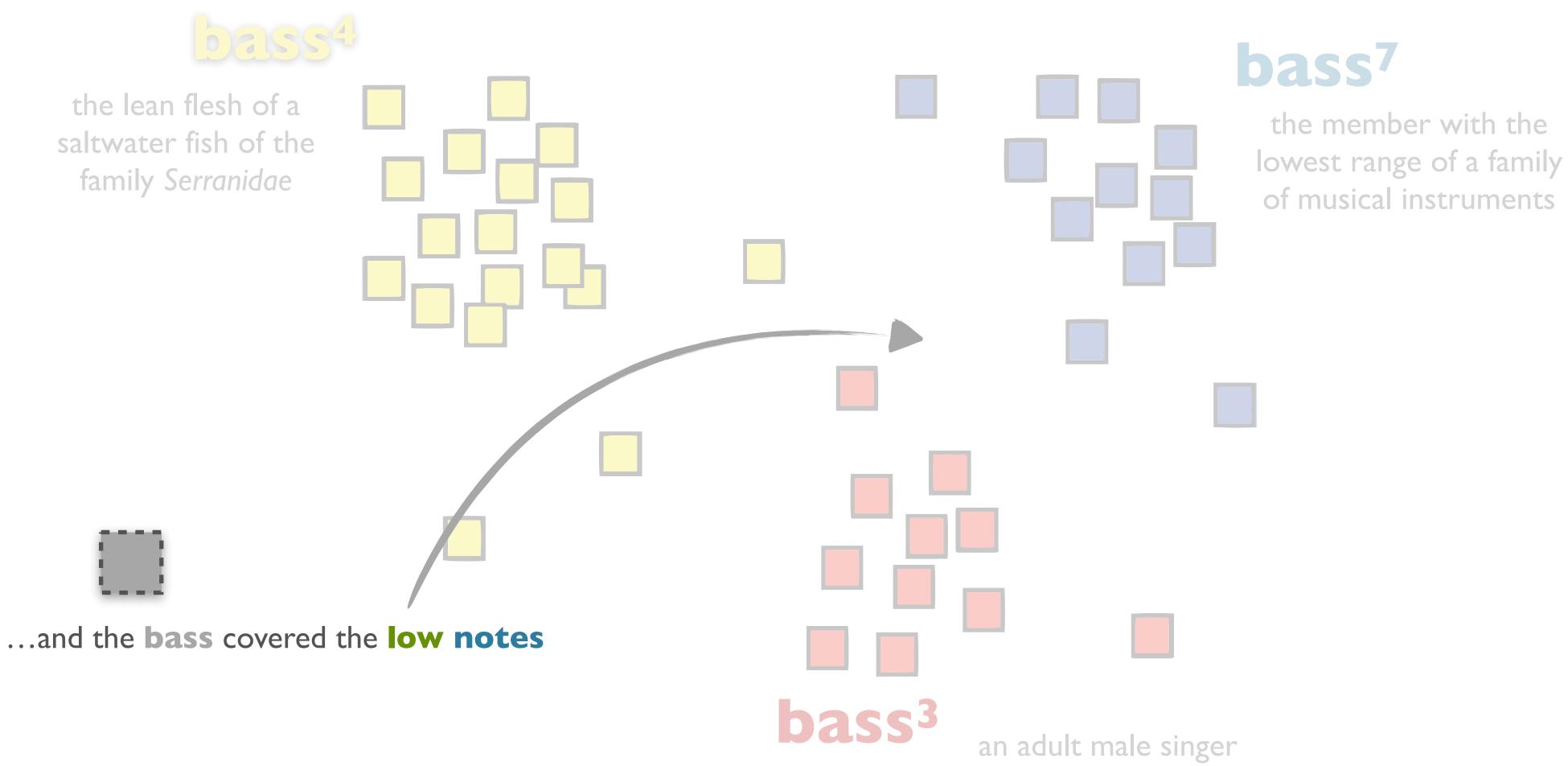
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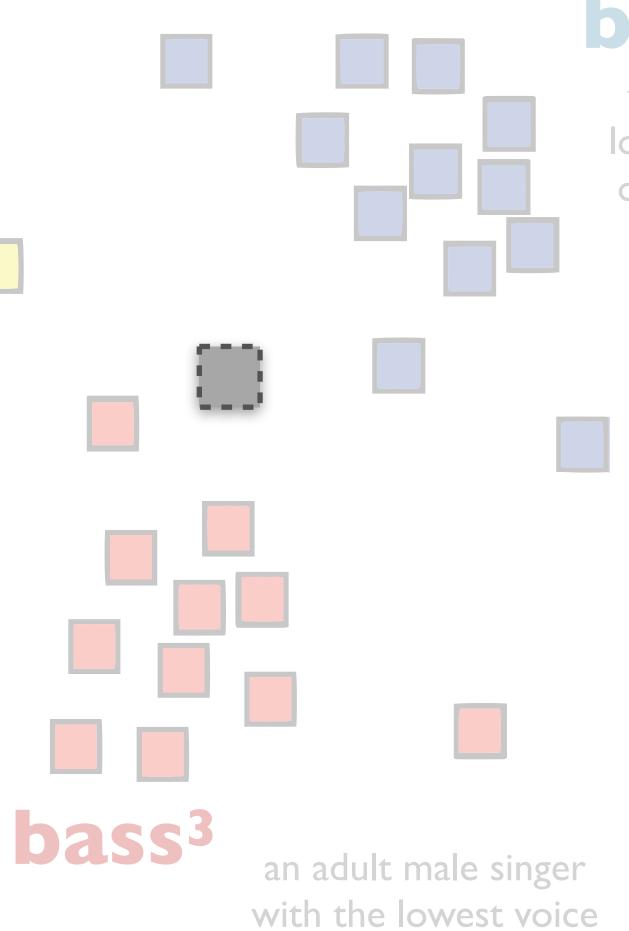




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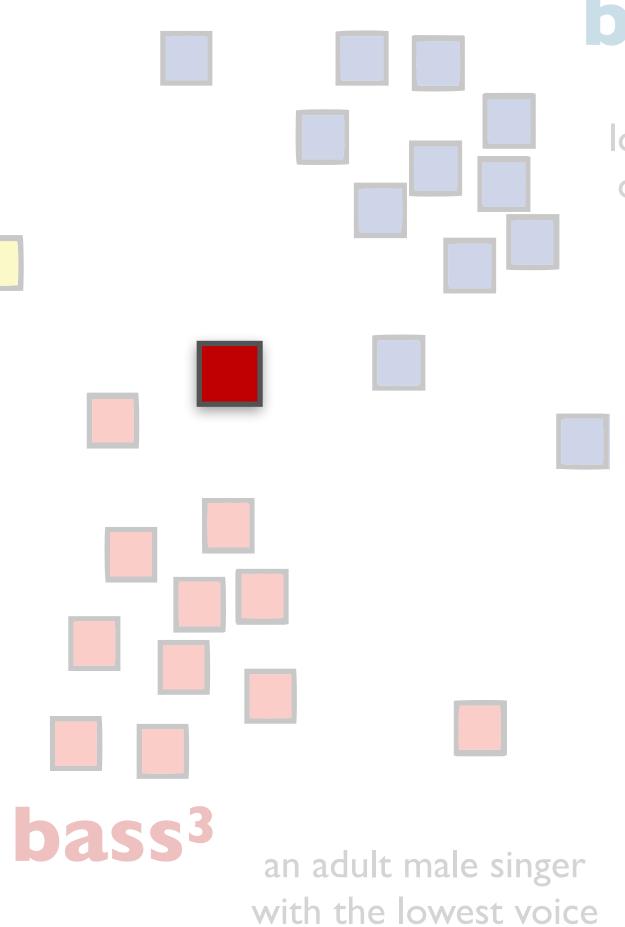




the lean flesh of a saltwater fish of the family Serranidae

...and the **bass**³ covered the low notes

Computing Word Senses



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Local Context Clustering

- "Brown" (aka IBM) clustering [link]
 - Generative, class-based language model over adjacent words
 - class-based:
 - Each w_i has class c_i
 - The distribution for words given a class: P(w|c)
 - Generative:
 - current set of clusters:

$$\log P(corpus | C) = \sum_{i} \log P(w_i | c_i) + \log P(c_i | c_{i-1})$$

• Can estimate the probability of the current set of senses in the corpus, given the





Local Context Clustering • Greedy, hierarchical clustering $\log P(corpus | C) = \sum \log P(w_i | c_i) + \log P(c_i | c_{i-1})$

- - I. Start with each word in own cluster

 - 3. Proceed until all words in one cluster

2. Merge clusters which decrease the likelihood the least — maximize P(corpus)





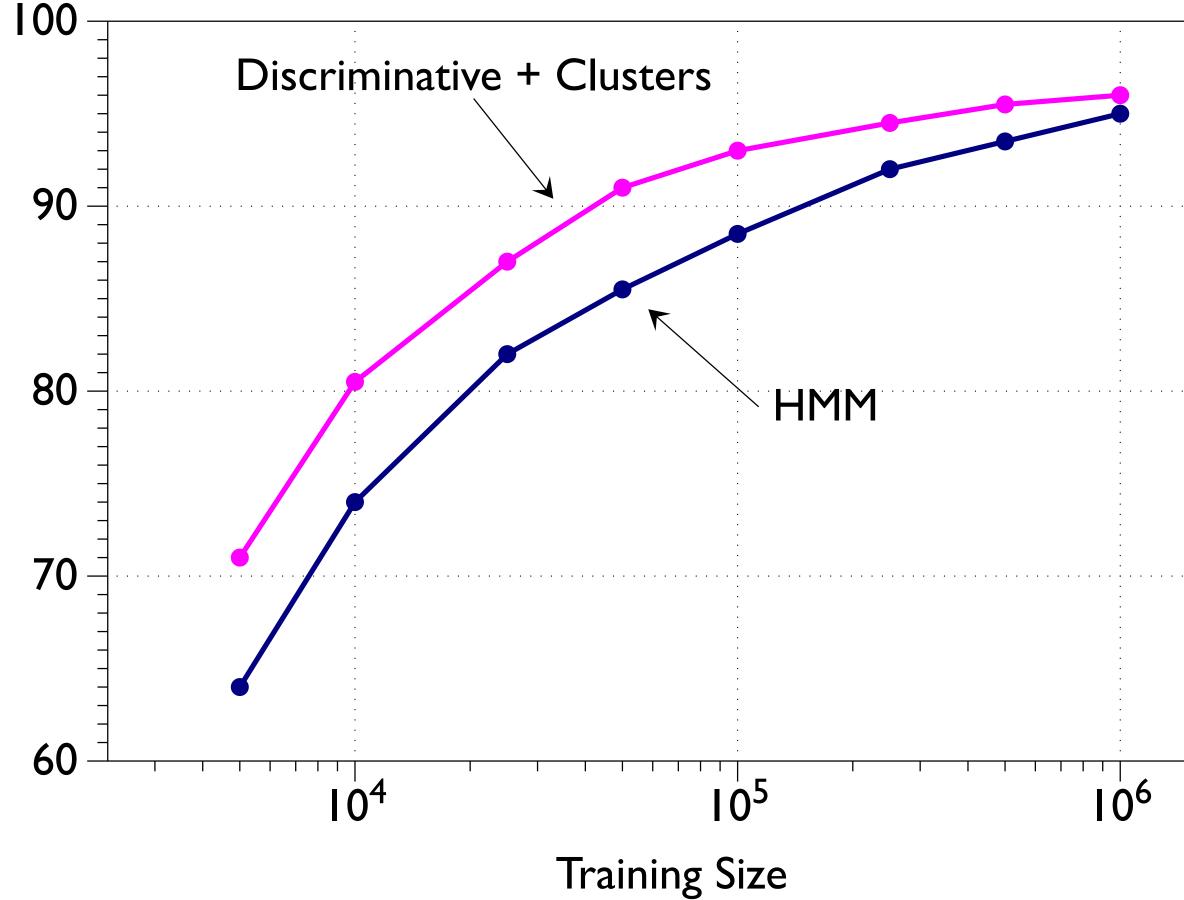




Clustering Impact

- Improves downstream tasks
 - Named Entity Recognition vs. HMM
 - Miller et al '04

F-Measure



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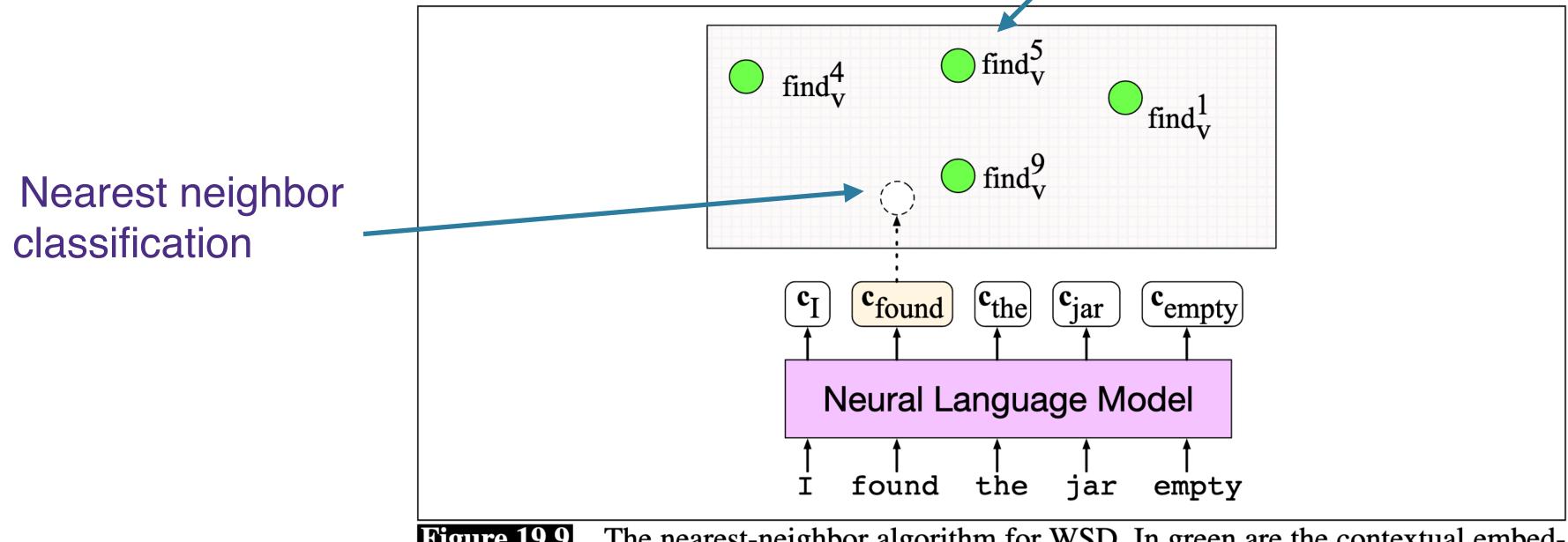








Contextual Embeddings for Disambiguation



The nearest-neighbor algorithm for WSD. In green are the contextual embed-Figure 19.9 dings precomputed for each sense of each word; here we just show a few of the senses for find. A contextual embedding is computed for the target word found, and the and then the nearest neighbor sense (in this case find⁹_n) would be chosen. Figure inspired by Loureiro and Jorge (2019).

Average of all contextual embeddings from dataset with a given sense label [in principle, could be centroid of cluster]

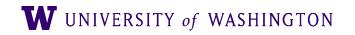








Resource-Based Models





Resource-Based Models

- Alternative to just clustering distributional representations
- What if we actually have some resources?
 - Dictionaries
 - Semantic sense taxonomy
 - Thesauri







- (Simplified) Lesk algorithm
 - "How to tell a pine cone from an ice cream cone" (Lesk, 1986)
- Compute "signature" of word senses:
 - Words in gloss and examples in dictionary

bank (n.)	I	a financial institution that activities. "he cashed a che
	2	sloping land (especially th "they pulled the canoe up o currents."

- t accepts deposits and channels the money into lending neck at the bank,""that bank holds the mortgage on my home."
- he slope beside a body of water). on the bank,""he sat on the bank of the river and watched the





- Compute context of word to disambiguate
- Compare overlap between signature and context
- Select sense with highest (non-stopword) overlap

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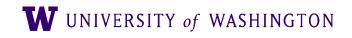
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- "The frog sat on the river **bank**, half in and half out of the water."
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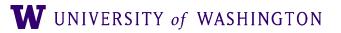
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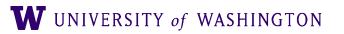
Sense Taxonomy/Thesaurus Approaches







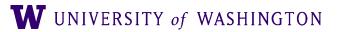
• Widely-used English sense resource







- Widely-used English sense resource
- Manually constructed lexical database

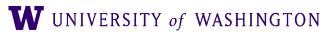






- Widely-used English sense resource
- Manually constructed lexical database
 - 3 tree-structured hierarchies
 - Nouns (117K)
 - Verbs (11K)
 - Adjective+Adverb (27K)





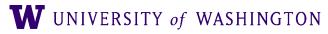




- Widely-used English sense resource
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 - 3 tree-structured hierarchies
 - Nouns (117K)
 - Verbs (11K)
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 - Entries:
 - Synonym set ("synset")
 - Gloss
 - Example usage



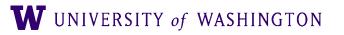








- Relations between entries:
 - Synonymy: in synset
 - Hyponym/Hypernym: *is-a* tree







WordNet

The **noun** "bass" has **8** senses in WordNet. [link]

- 1. **bass**¹ (the lowest part of the musical range)
- 2. **bass**², **bass part**¹ (the lowest part in polyphonic music)
- 3. **bass**³, **basso**¹ (an adult male singer with the lowest voice)
- 4. sea bass¹, bass⁴ (the lean fish of a saltwater fish of the family *Serranidae*)
- 5. freshwater bass¹, bass⁵ (any of various North American freshwater fish with lean flesh (especially of the genus *Micropterus*))
- 6. **bass**⁶, **bass voice**¹, **basso**² (the lowest adult male singing voice)
- 7. **bass**⁷ (the member with the lowest range of a family of musical instruments)
- 8. **bass**⁸ (nontechnical name for any numerous edible marine and freshwater spiny-finned fishes)

The **adjective** "bass" has **1** sense in WordNet. 1. **bass**¹ - deep6 - (having or denoting a low vocal or instrumental range) "a deep voice";" a bass voice is lower than a baritone voice";" a bass clarinet"

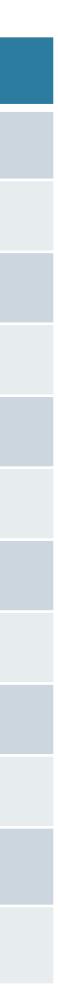






Noun WordNet Relations

Relation	Also Called	Definition	Example
Hypernym	Superordinate	From concepts to superordinates	breakfast ^ı → meal ^ı
Hyponym	Subordinate	From concepts to subtypes	$meal^{I} \rightarrow lunch^{I}$
Instance Hypernym	Instance	From instances to their concepts	Austen ^I \rightarrow author ^I
Instance Hyponym	Has-Instance	From concepts to concept instances	composer ^I → Bach ^I
Member Meronym	Has-Member	From groups to their members	faculty ² → professor ¹
Member Holonym	Has-Part	From members to their groups	copilot → crew
Part Meronym	Part-Of	From wholes to parts	$table^2 \rightarrow leg^3$
Part Holonym		From parts to wholes	course ⁷ → meal ¹
Substance Meronym		From substances to their subparts	water \rightarrow oxygen
Substance Holonym		From parts of substances to wholes	gin ^I → martini ^I
Antonym		Semantic opposition between lemmas	$leader^{I} \iff follower^{I}$
Derivationally Related Form		Lemmas	$destruction^{I} \iff destroy^{I}$





WordNet Taxonomy

```
Sense 3
bass, basso --
(an adult male singer with the lowest voice)
  =>singer, vocalist, vocalizer, vocaliser
    => musician, instrumentalist, player
       => performer, performing artist
         => entertainer
            => person, individual, someone...
              => organism, being
                 => living thing, animate thing
                   => whole, unit
                      => object, physical object
                        => physical entity
                           => entity
              => causal agent, cause, causal agency
                 => physical entity
                   => entity
```







- Key idea:

• The number of "hops" between words in a thesaurus can be a distance measure







- Key idea:

 - The shorter path length in thesaurus, smaller semantic distance

• The number of "hops" between words in a thesaurus can be a distance measure







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 - The number of "hops" between words in a thesaurus can be a distance measure
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 - Words similar to parents, siblings in tree







- Key idea:
 - The number of "hops" between words in a thesaurus can be a distance measure
 - The shorter path length in thesaurus, smaller semantic distance
 - Words similar to parents, siblings in tree
- pathlength = #edges in shortest route through graph between nodes
- $sim_{path} = -\log pathlen(c_1, c_2)$ [Leacock & Chodorow, 1998]

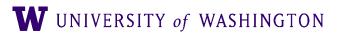






Problem #1

• Rarely know which sense, thus rarely know which node







Problem #1

- Rarely know which sense, thus rarely know which node
- Solution
 - assume most similar senses as an estimate
 - $wordsim(w_1, w_2) = \max sim(c_1, c_2)$

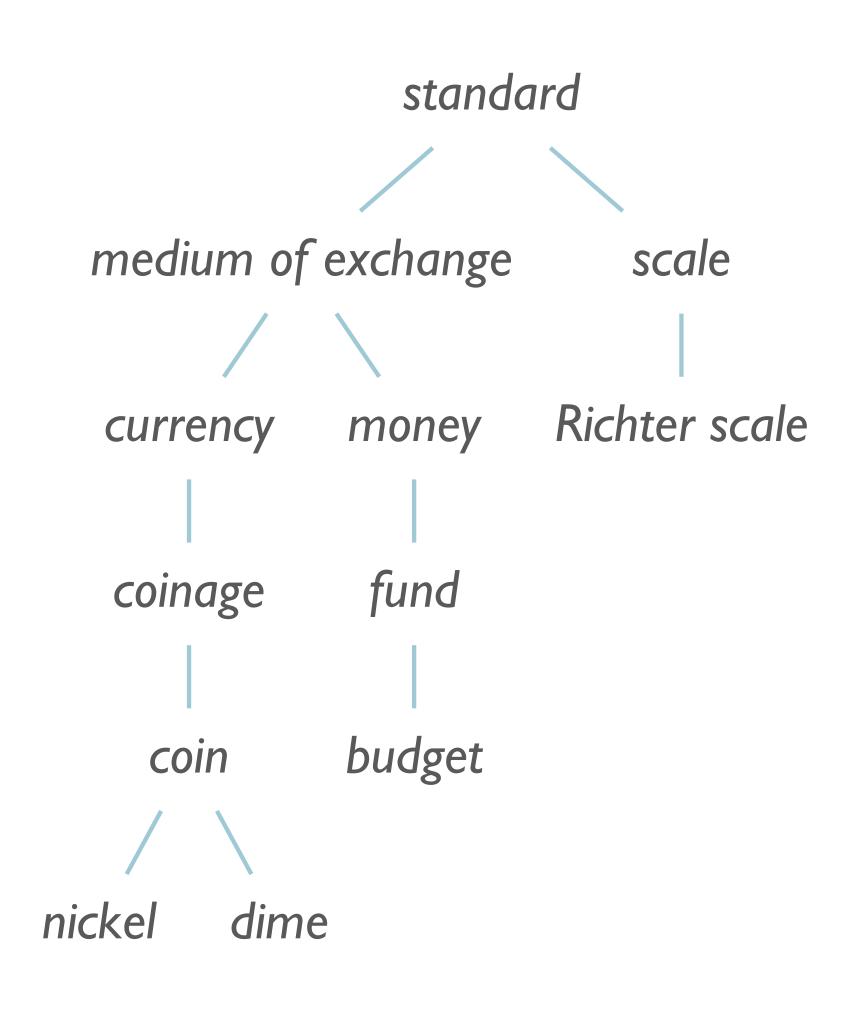






Problem #2

• Links in WordNet not uniformly different







• Links in WordNet not uniformly different • INickel \rightarrow Moneyl = 5

Problem #2 standard medium of exchange scale currency Richter scale money coinage fund budget coin nickel dime









- Links in WordNet not uniformly different
 - INickel \rightarrow Moneyl = 5
 - INickel \rightarrow Standardl = 5

Problem #2 standard medium of exchange scale currency Richter scale money coinage fund budget coin nickel dime









Problem #2 standard medium of exchange scale currency Richter scale money coinage fund budget coin nickel dime

- Links in WordNet not uniformly different
 - INickel \rightarrow Moneyl = 5
 - INickel \rightarrow Standardl = 5
- How to capture?



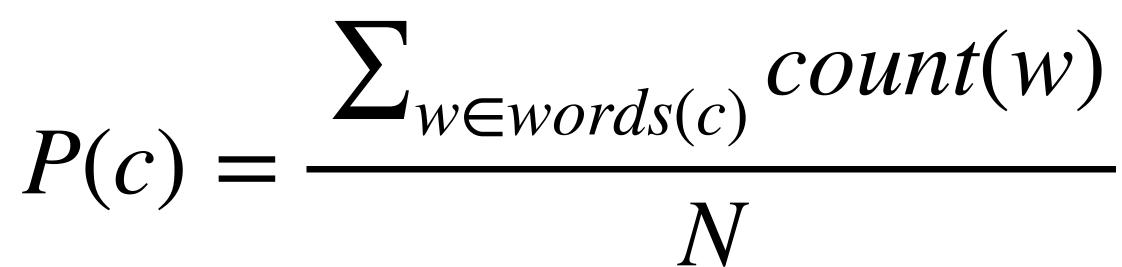






Thesaurus-based Techniques: A Solution

- Add *information content* from a corpus (Resnik, 1995)
- P(c): probability that a word is instance of concept c
- words(c): words subsumed by concept c;
- N: words in corpus







Information Content

Using a sense-tagged corpus (like <u>SemCor</u>)

```
<wf cmd="ignore" pos="IN">in</wf>
<wf cmd="ignore" pos="DT">the</wf>
<wf cmd="done" pos="NN" lemma="united states of america" wnsn="1" lexsn="1:15:00::">United States of America</wf>
<wf cmd="done" pos="VB" lemma="be" wnsn="1" lexsn="2:42:03::">was</wf>
<wf cmd="done" pos="JJ" lemma="gay" wnsn="6" lexsn="5:00:00:homosexual:00">gay</wf>
<punc>,</punc>
<wf cmd="done" pos="JJ" lemma="witty" wnsn="1" lexsn="5:00:00:humorous:00">witty</wf>
<punc>,</punc>
<wf cmd="done" pos="JJ" lemma="mercurial" wnsn="1" lexsn="5:00:00:changeable:00">mercurial</wf>
<punc>,</punc>
<wf cmd="done" pos="JJ" lemma="full" wnsn="1" lexsn="3:00:00::">full</wf>
<wf cmd="done" pos="JJ" ot="notag">of</wf>
<wf cmd="done" pos="NN" lemma="prank" wnsn="1" lexsn="1:04:01::">pranks</wf>
<wf cmd="ignore" pos="CC">and</wf>
<wf cmd="done" pos="NN" ot="foreignword">bonheur</wf>
```

""The Serge Prokofieff whom we knew in the United States of America was gay, witty, mercurial, full of pranks and bonheur—







Concept Probability Example

natural-elevation 0.000113

> hill 0.0000189

```
entity
         0.395
           \uparrow
  inanimate-object
          0.167
           1
    natural-object
         0.0163
            个
geological-formation
         0.00176
                K
       Z
                  shore
                 0.0000836
 \uparrow \qquad \qquad \uparrow
                  coast
                 0.0000216
```







Information Content-Based Similarity Measures

- Information content of node (concept c)
 - $IC(c) = -\log P(c)$
 - As probability of encountering c increases, informativeness decreases







Information Content-Based Similarity Measures

- Information content of node (concept c)
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- Least common subsumer (LCS):
 - Lowest node in hierarchy subsuming 2 nodes







Information Content-Based Similarity Measures

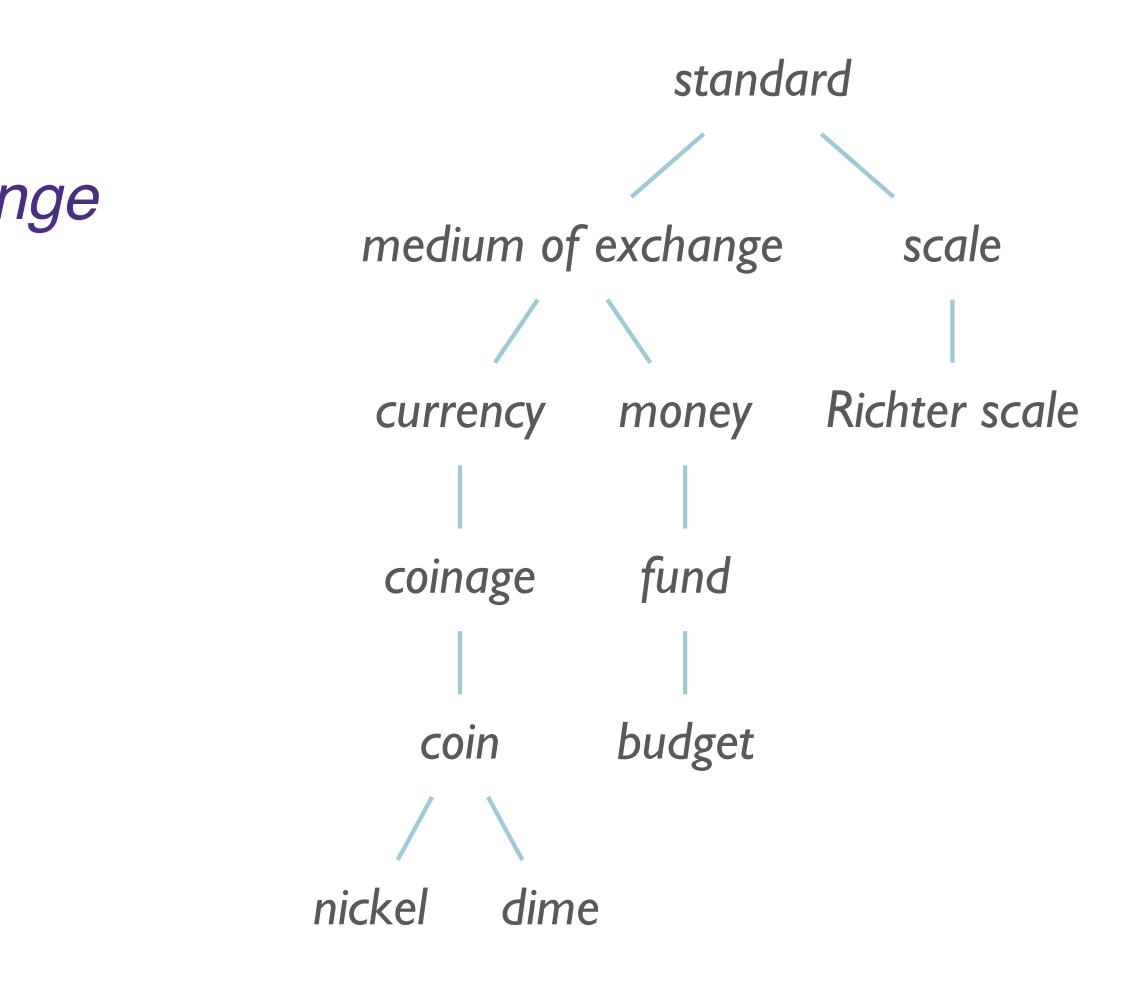
- Information content of node (concept c)
 - $IC(c) = -\log P(c)$
 - As probability of encountering c increases, informativeness decreases
- Least common subsumer (LCS):
 - Lowest node in hierarchy subsuming 2 nodes
- Similarity measure
 - $sim_{resnik}(c_1, c_2) = -\log P(LCS(c_1, c_2))$
 - The more specific the LCS concept, the more similar c_1, c_2 .







- LCS(*nickel*, *dime*) = *coin*
- LCS(nickel, budget) = medium of exchange

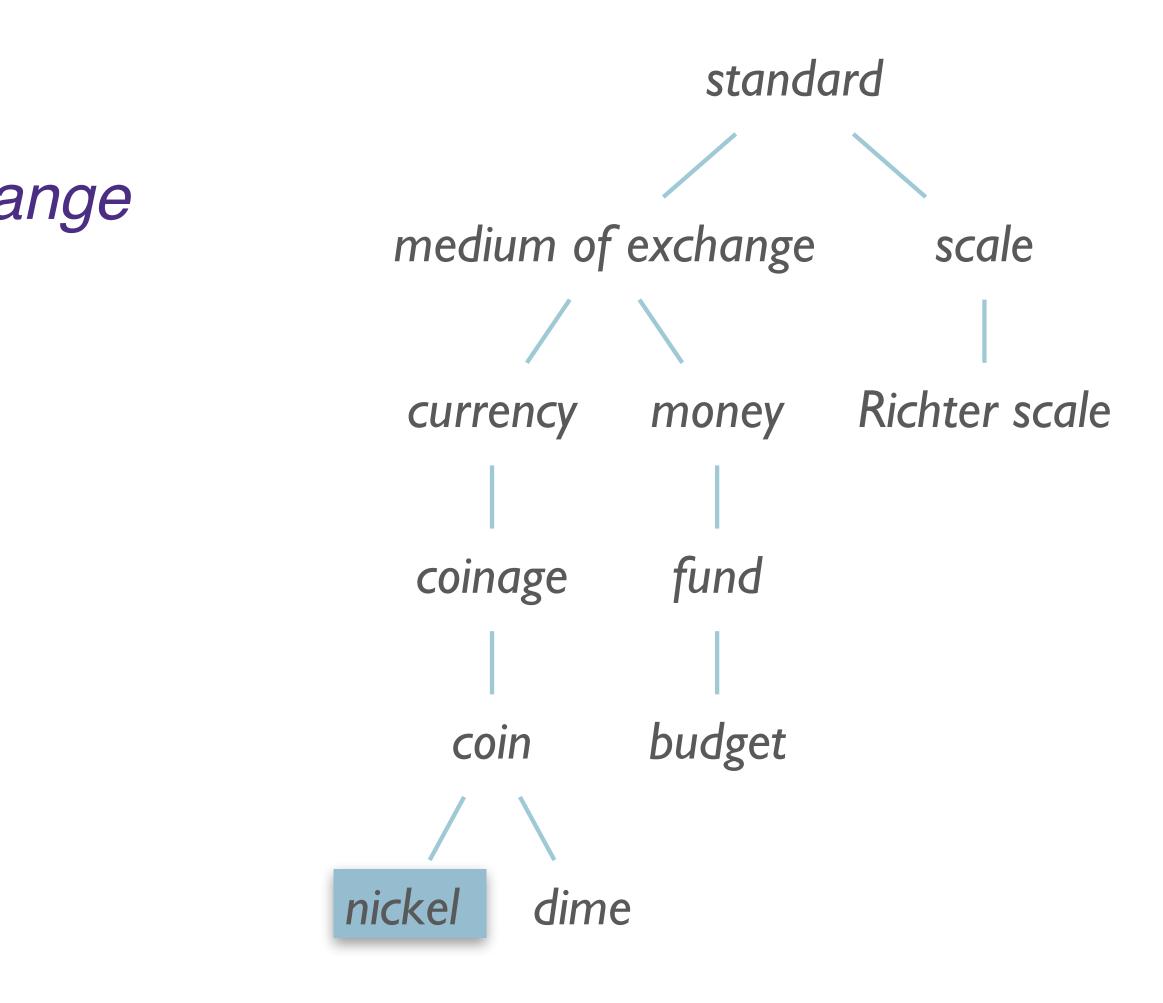








- LCS(*nickel*, *dime*) = *coin*
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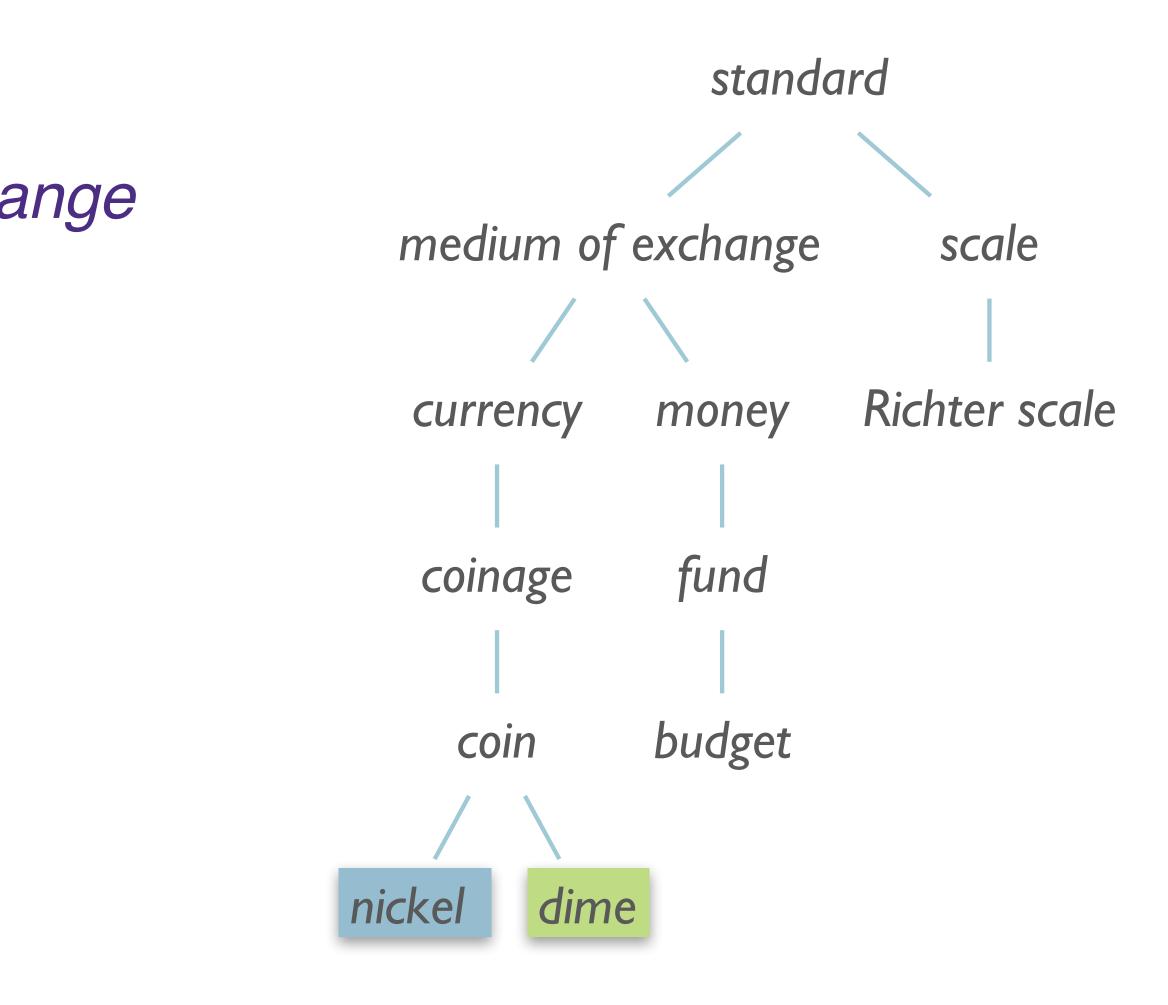








- LCS(*nickel*, *dime*) = *coin*
- LCS(*nickel*, *budget*) = *medium of exchange*

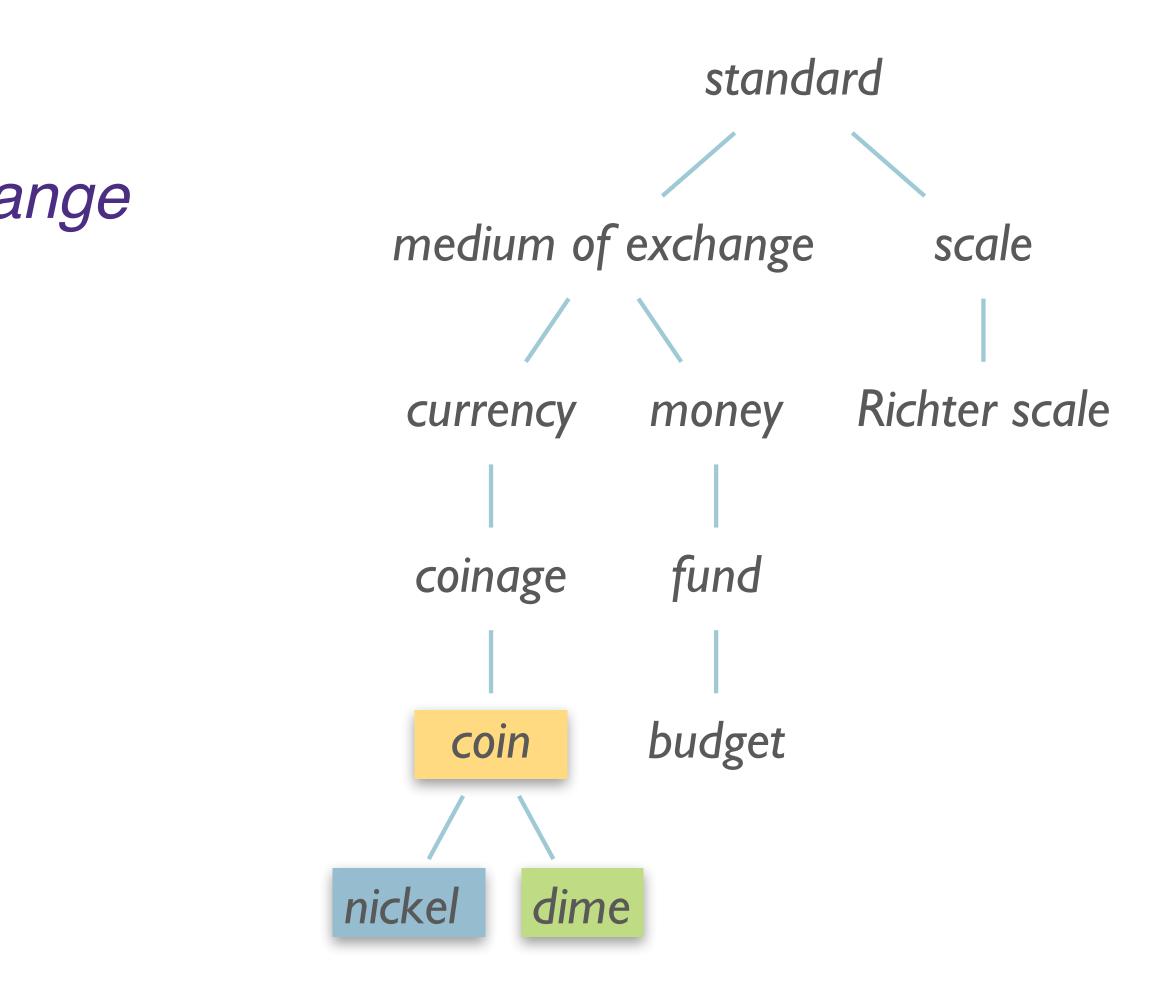








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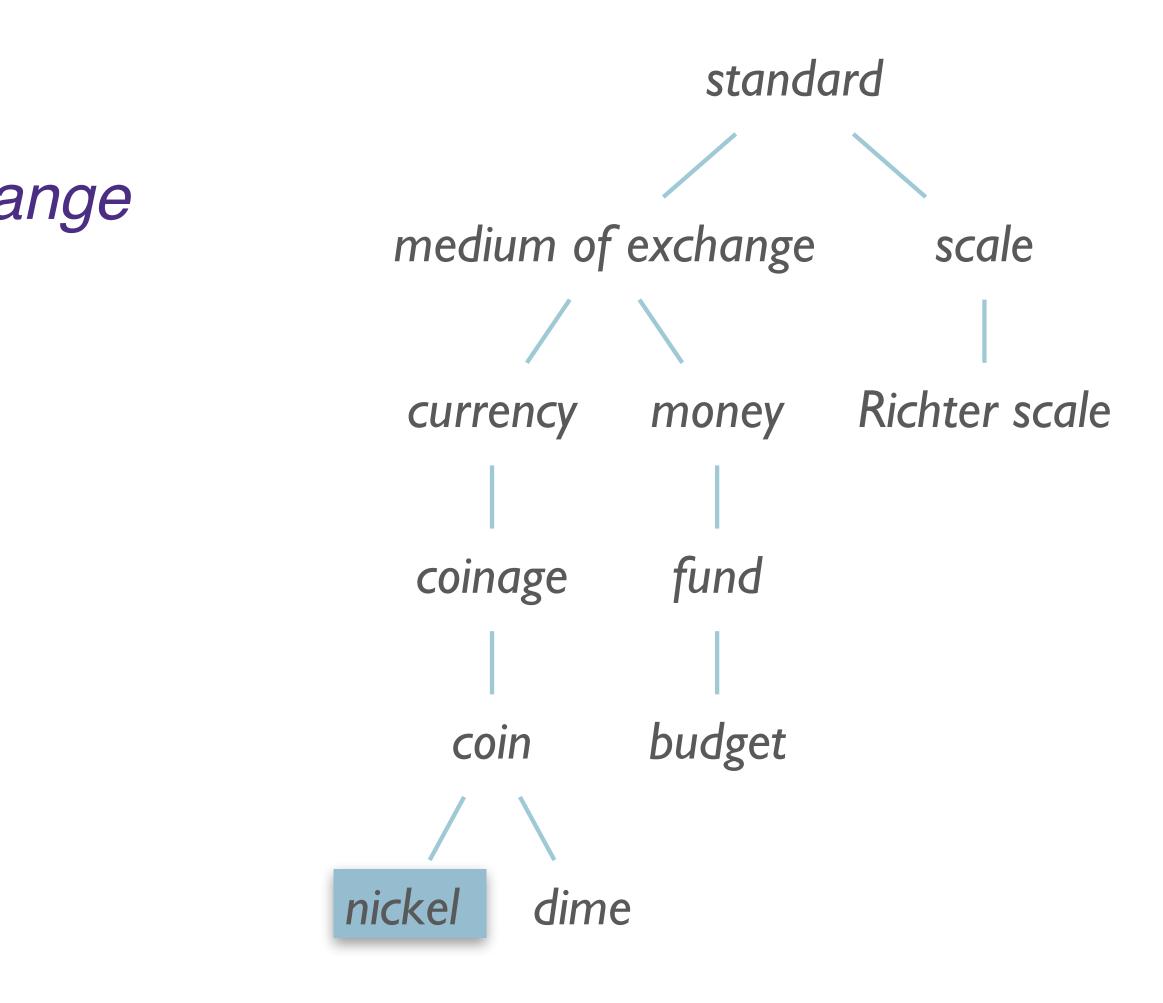








- LCS(*nickel*, *dime*) = *coin*
- LCS(*nickel*, *budget*) = *medium of exchange*

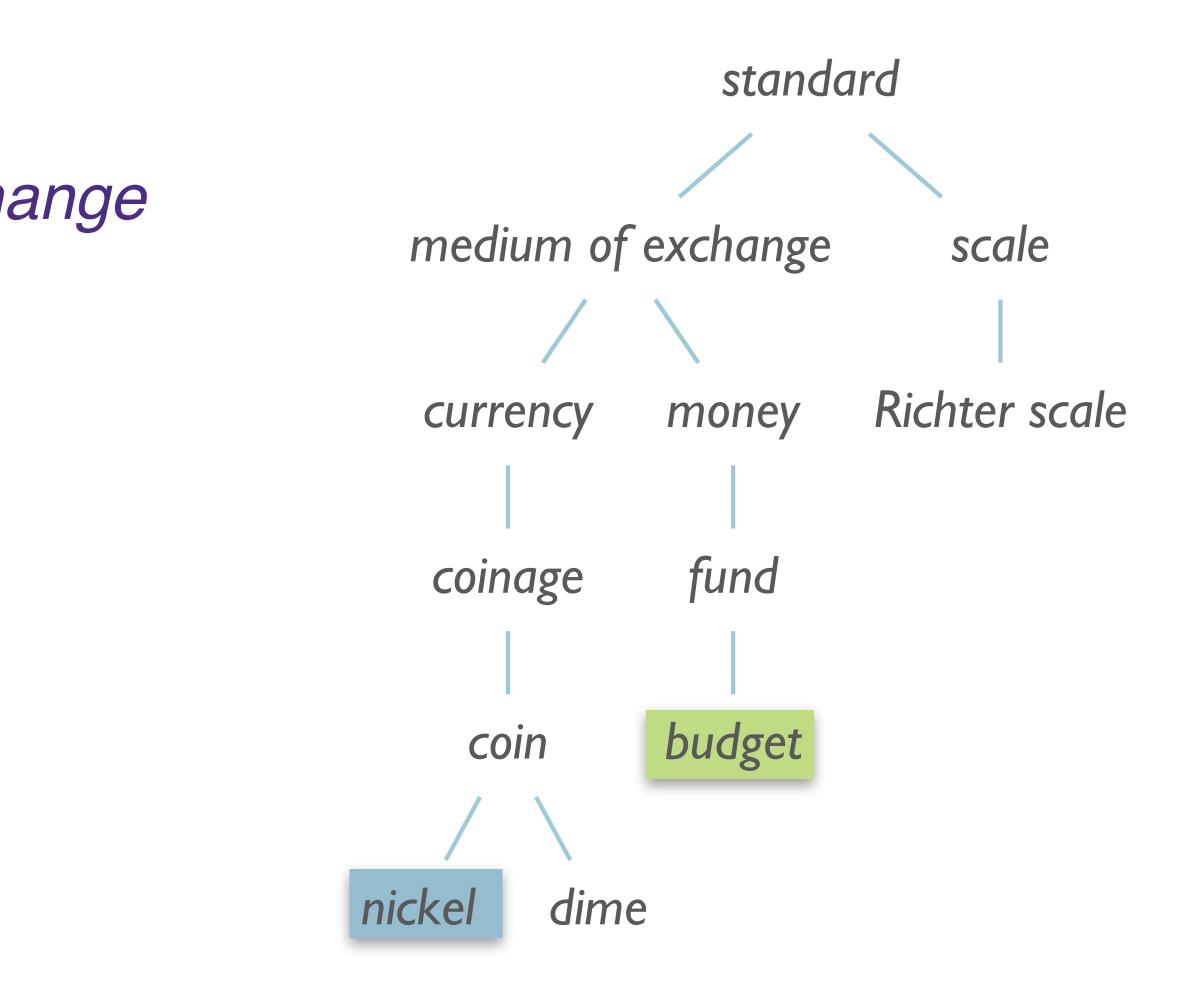








- LCS(*nickel*, *dime*) = *coin*
- LCS(*nickel*, *budget*) = medium of exchange

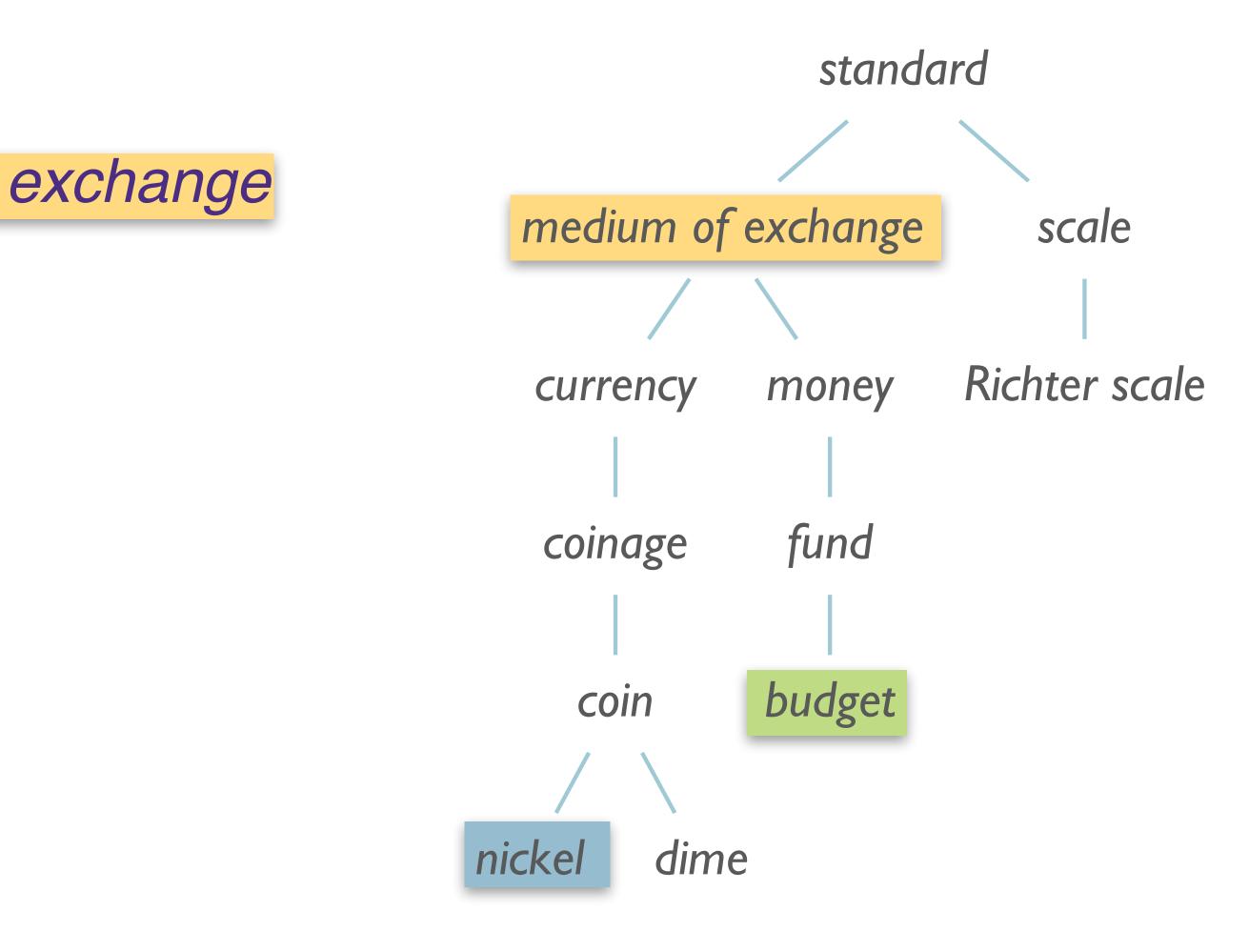








- LCS(*nickel*, *dime*) = *coin*
- LCS(nickel, budget) = medium of exchange









The Plant Example Again

- There are more kinds of plants and animals in the rainforests than discovered.
- with our comprehensive know-how.

anywhere else on Earth. Over half of the millions of known species of plants and animals live in the rainforest. Many are found nowhere else. There are even plants and animals in the rainforest that we have not yet

• The Paulus company was founded in 1938. Since those days the product range has been the subject of constant expansions and is brought up continuously to correspond with the state of the art. We're engineering, manufacturing, and commissioning world-wide ready-to-run plants packed







• Calculate Informativeness

- For each node in WordNet:
 - Sum occurrences of concept and all children
 - Compute Information Content for each node of WordNet

Application to WSD







Application to WSD

Disambiguate with WordNet

- Assume set of words in context: {*animals*, *rainforest*, *species*}
- Find Most Informative Least Common Subsumer
 - for target word, context word
- Increment count for sense subsumed by this concept
- Select sense with highest vote



- 4	

Thesaurus Similarity Issues

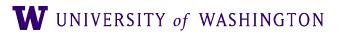
- Coverage:
 - Few languages have large thesauri
 - Few languages have large sense-tagged corpora
- Thesaurus design:
 - Works well for noun *IS-A* hierarchy
 - Verb hierarchy shallow, bushy, less informative







Resnik Similarity







for i and j=1 to n, with i < j $\mathbf{v}_{i,j} = wsim(w_i, w_j)$ for k=1 to num_senses(wi) if **c**_{i,j} is an ancestor of sense_{i,k} for k'=1 to num_senses(w_j) if $c_{i,j}$ is an ancestor of sense_{j,k'} increment normalization[i] by **v**_{i,j} increment normalization[j] by **v**_{i,j} for i=1 to n for k=1 to num_senses(w_i) if (normalization[i] > 0.0) γ_{i,k}=support[i,k]/normalization[i] else $\gamma_{i,k}=1/num_senses[w_i]$

Algorithm

```
Given W = \{w_i, \dots, w_n\}, a set of nouns
   c<sub>i,j</sub>=the most informative subsumer for w<sub>i</sub> and w<sub>j</sub>
          increment support[i,k] by v<sub>i,j</sub>
          increment_support[j,k'] by v<sub>i,j</sub>
```

<u>Resnik 1999, sec 5.1</u> [also on website]







Given $W = \{w_i, \dots, w_n\}$, a set of nouns for i=1 to n, and input word wo $\mathbf{v}_{0,i} = wsim(w_0, w_i)$ for k=1 to num_senses(wi) of $c_{0,i}$ is an ancestor of sense_{i,k} for k'=1 to num_senses(w_0) if $c_{0,i}$ is an ancestor of $sense_{k'}$ increment normalization[i] by **v**_{0,i} for i=1 to n for k=1 to num_senses(w_i) if (normalization[i] > 0.0) else $\gamma_{i,k}=1/\text{num}_\text{senses}[w_i]$

Algorithm

```
c_{0,i}=the most informative subsumer for w_0 and w_i
      increment support[i,k] by v<sub>0,i</sub>
      increment_support[0,k'] by vo,i

γ<sub>i,k</sub>=support[i,k]/normalization[i]
```







 $sim_{word}(w_1, w_2) = \max_{c_1, c_2} \left(sim_{concept}(c_1, c_2) \right)$

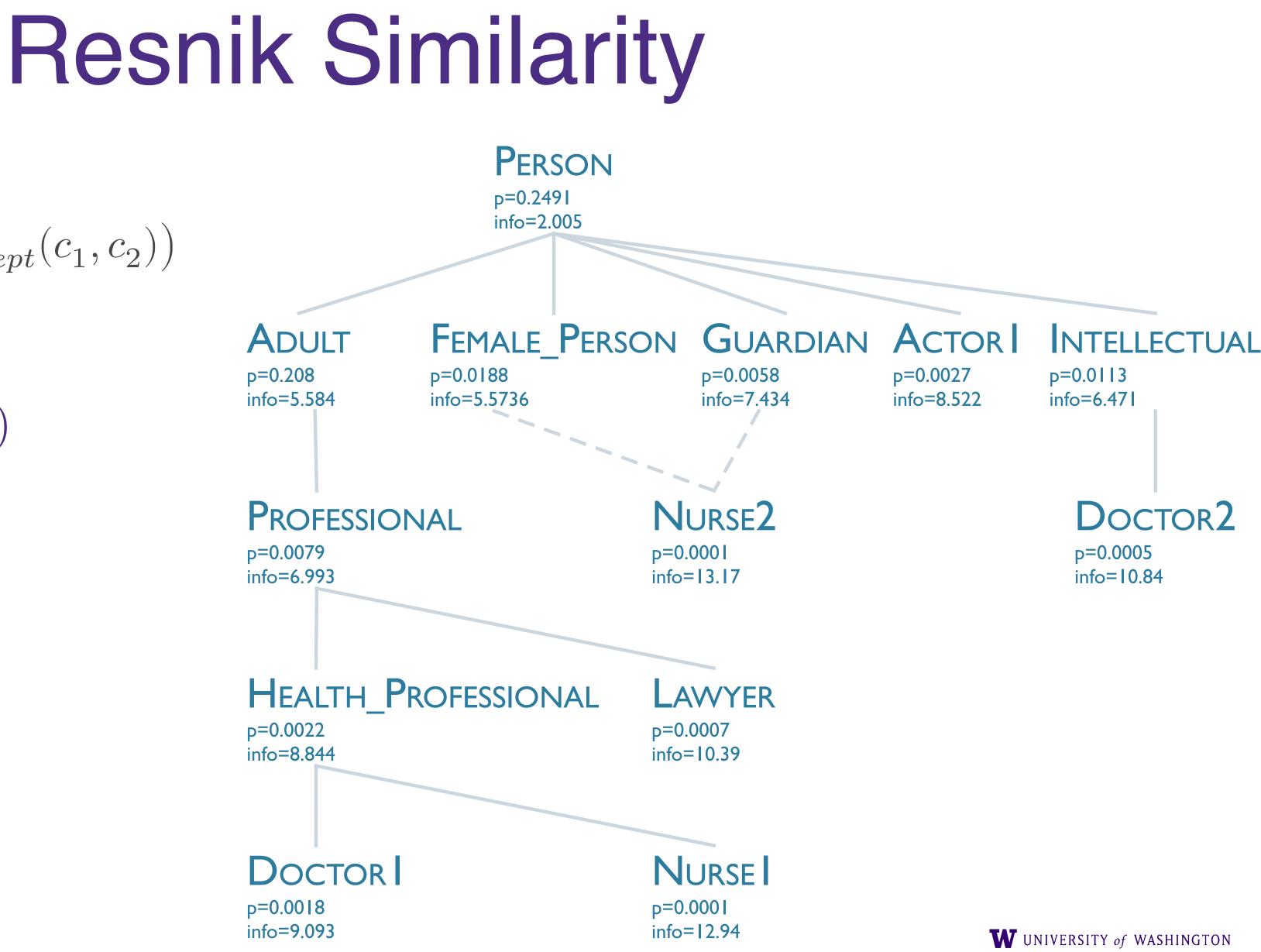
• Let's try

• $sim_{word}(doctor, nurse)$

p=0.208 info=5.584

p=0.0079 info=6.993

p=0.0022 info=8.844











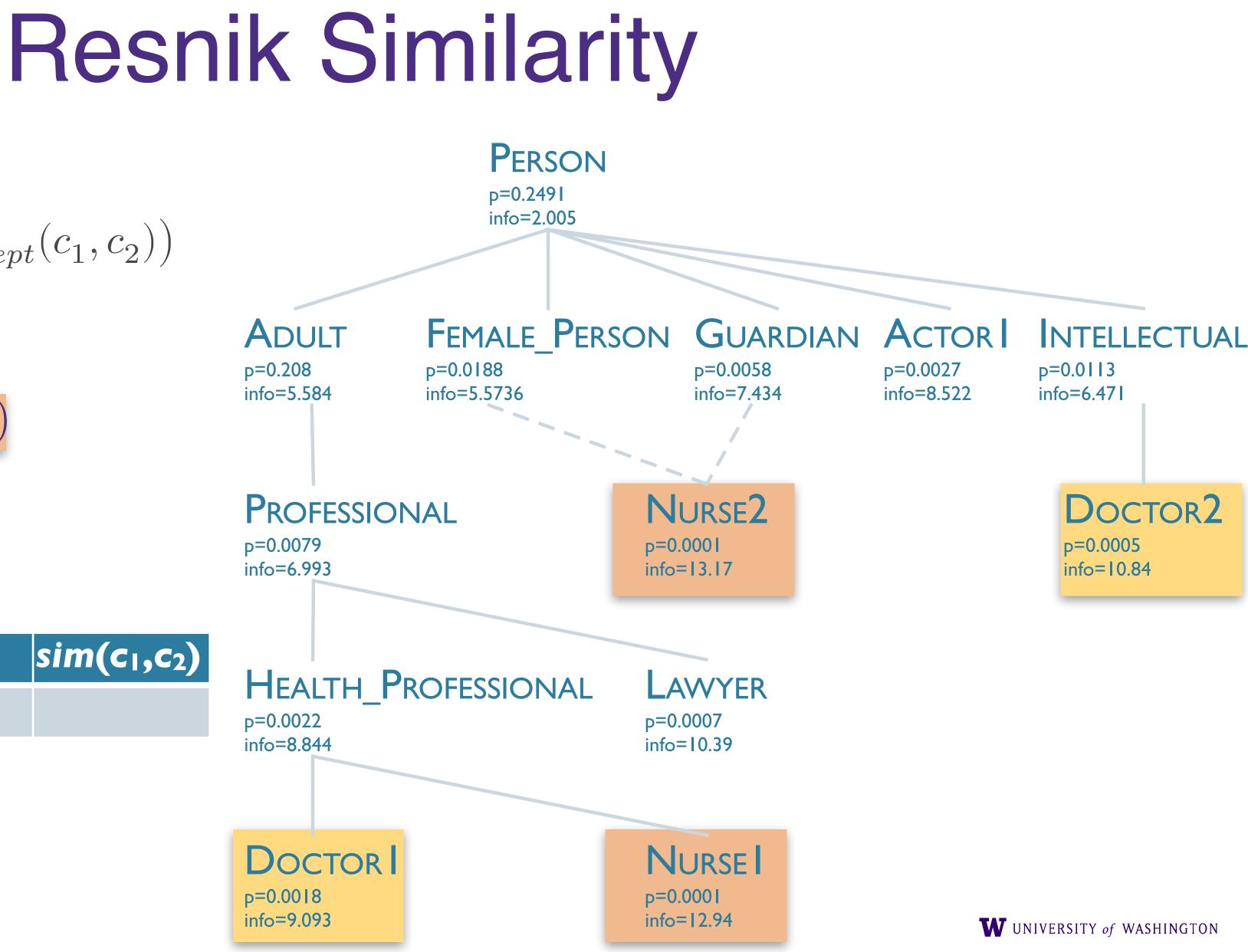
 $sim_{word}(w_1, w_2) = \max_{c_1, c_2} \left(sim_{concept}(c_1, c_2) \right)$

• Let's try

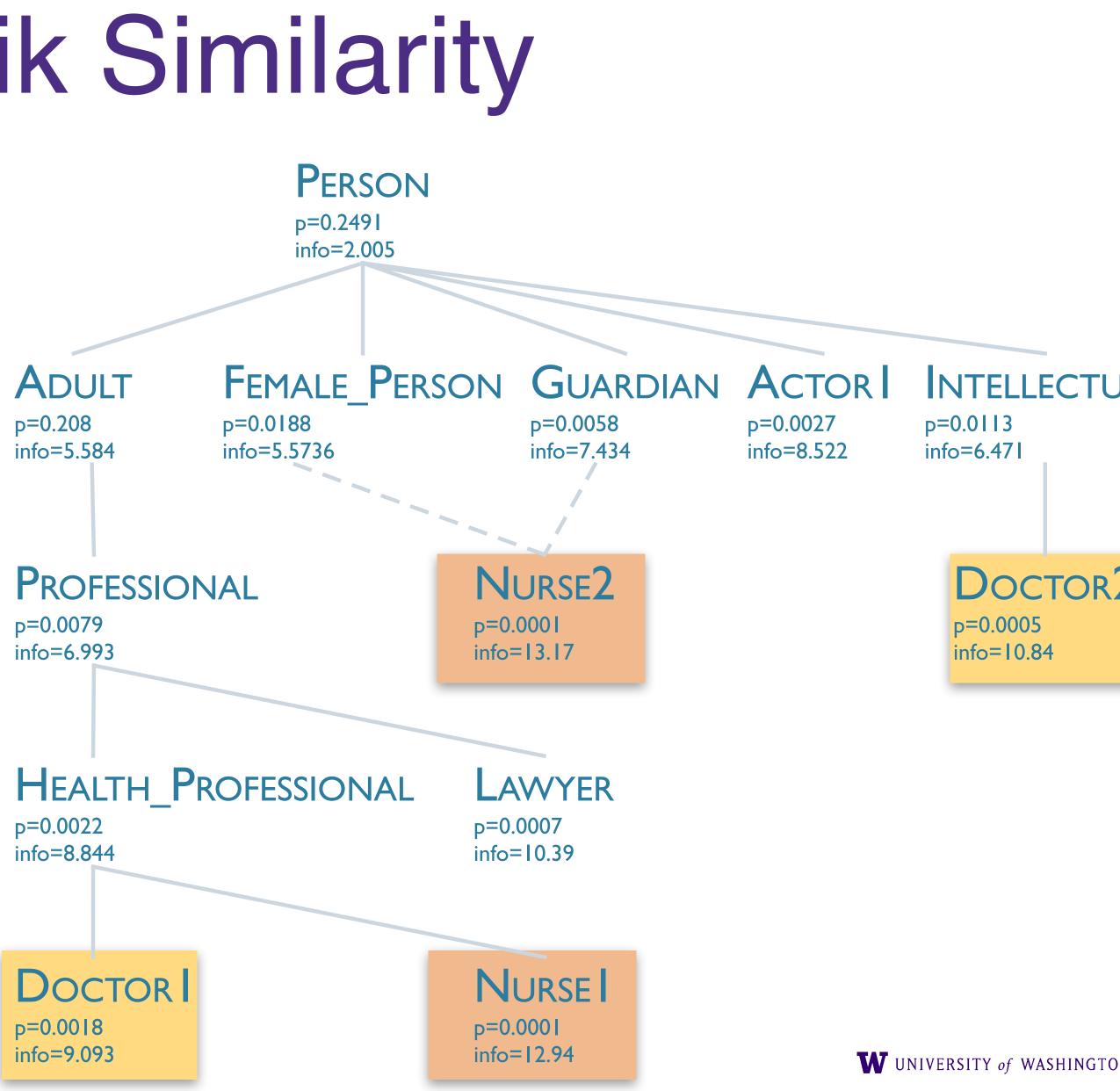
• $sim_{word}(doctor, nurse)$

• $sim_{concept}(c_1, c_2)$

• Get IC of LCS



CI	C 2	LCS	sim(c ₁ ,c ₂)
			P=0







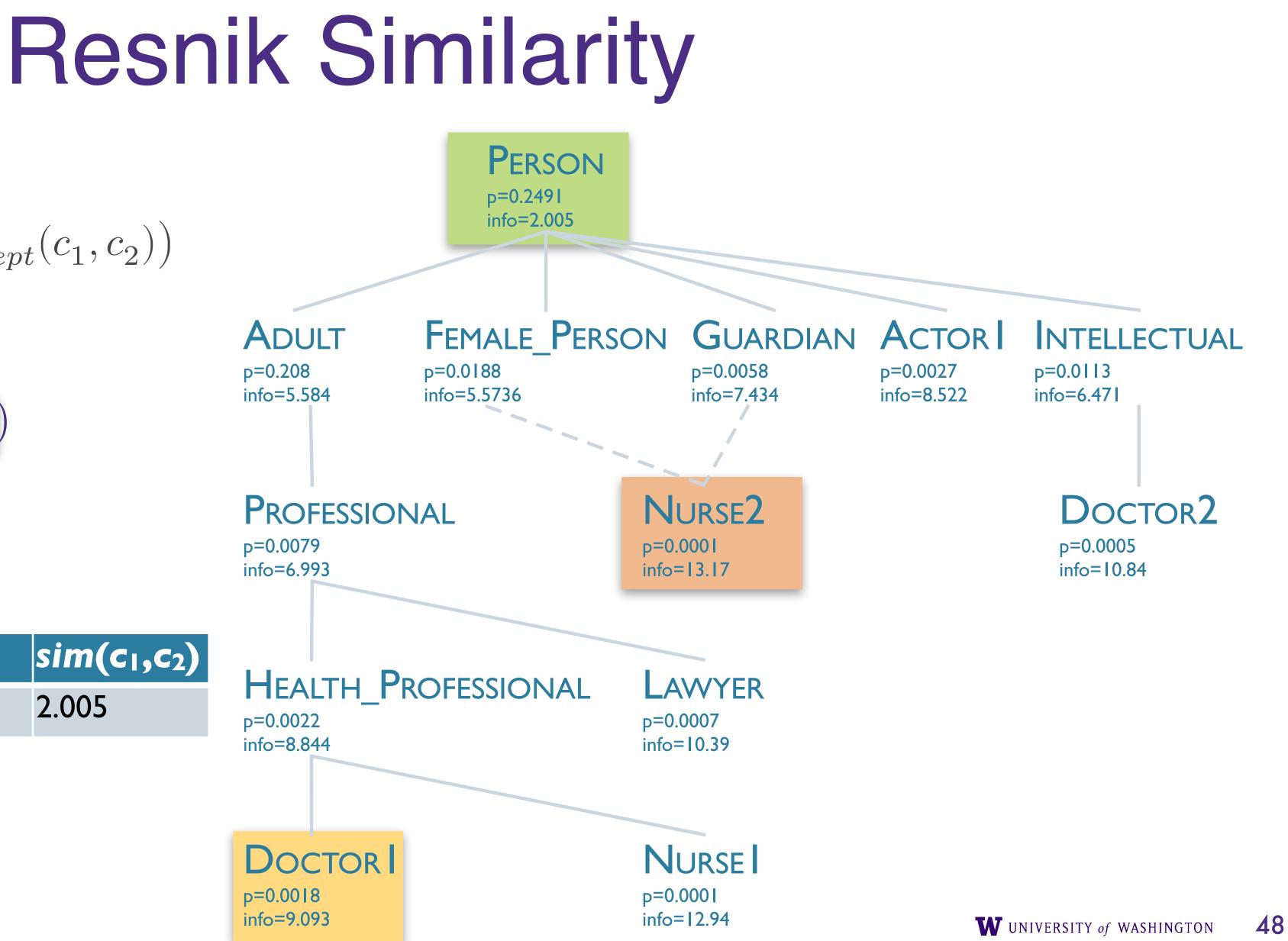
 $sim_{word}(w_1, w_2) = \max_{c_1, c_2} \left(sim_{concept}(c_1, c_2) \right)$

• Let's try

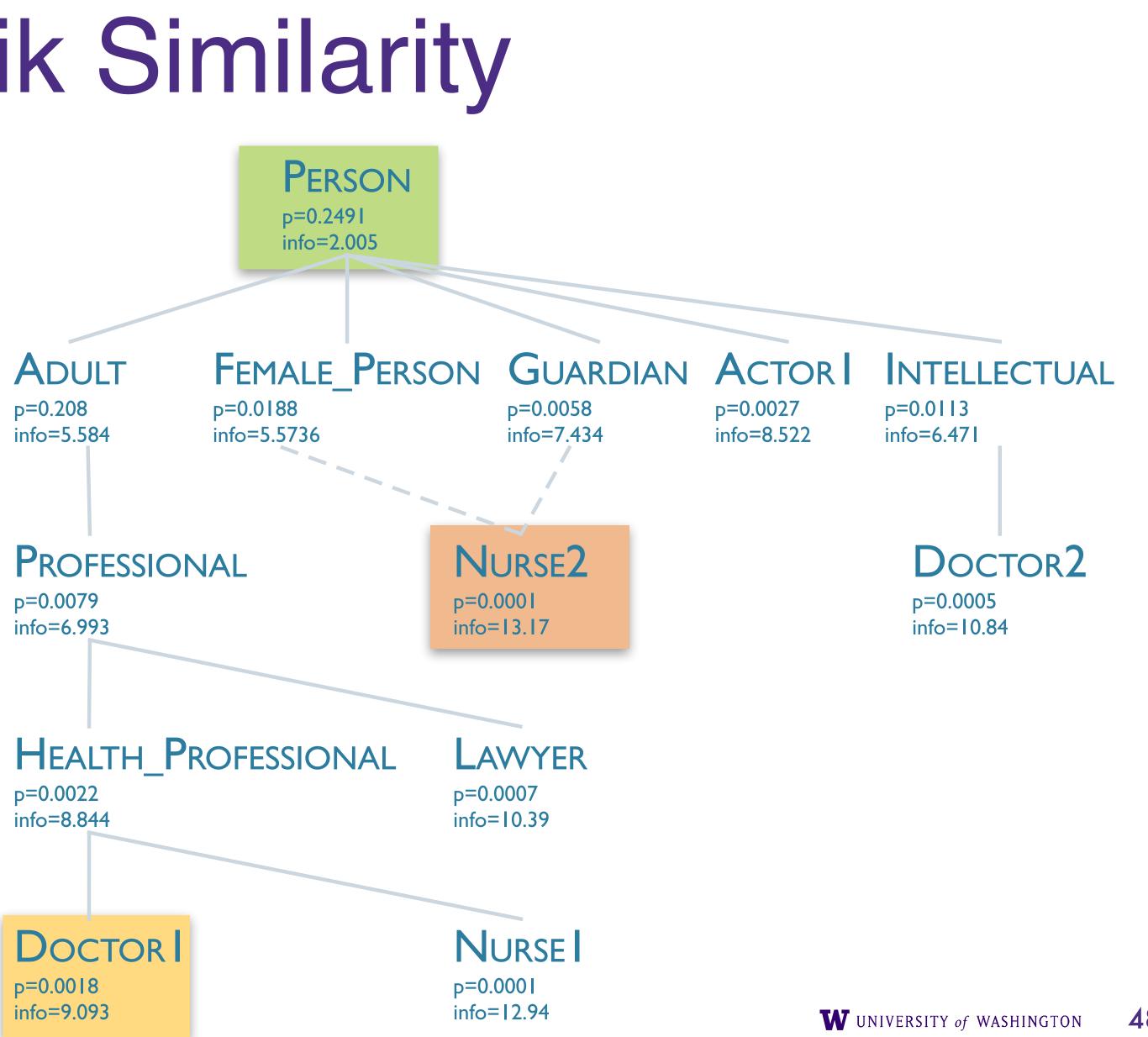
• $sim_{word}(doctor, nurse)$

• $sim_{concept}(c_1, c_2)$

• Get IC of LCS



CI	C 2	LCS	sim(c ₁ ,c ₂)
DOCTOR	NURSE ₂	Person	2.005



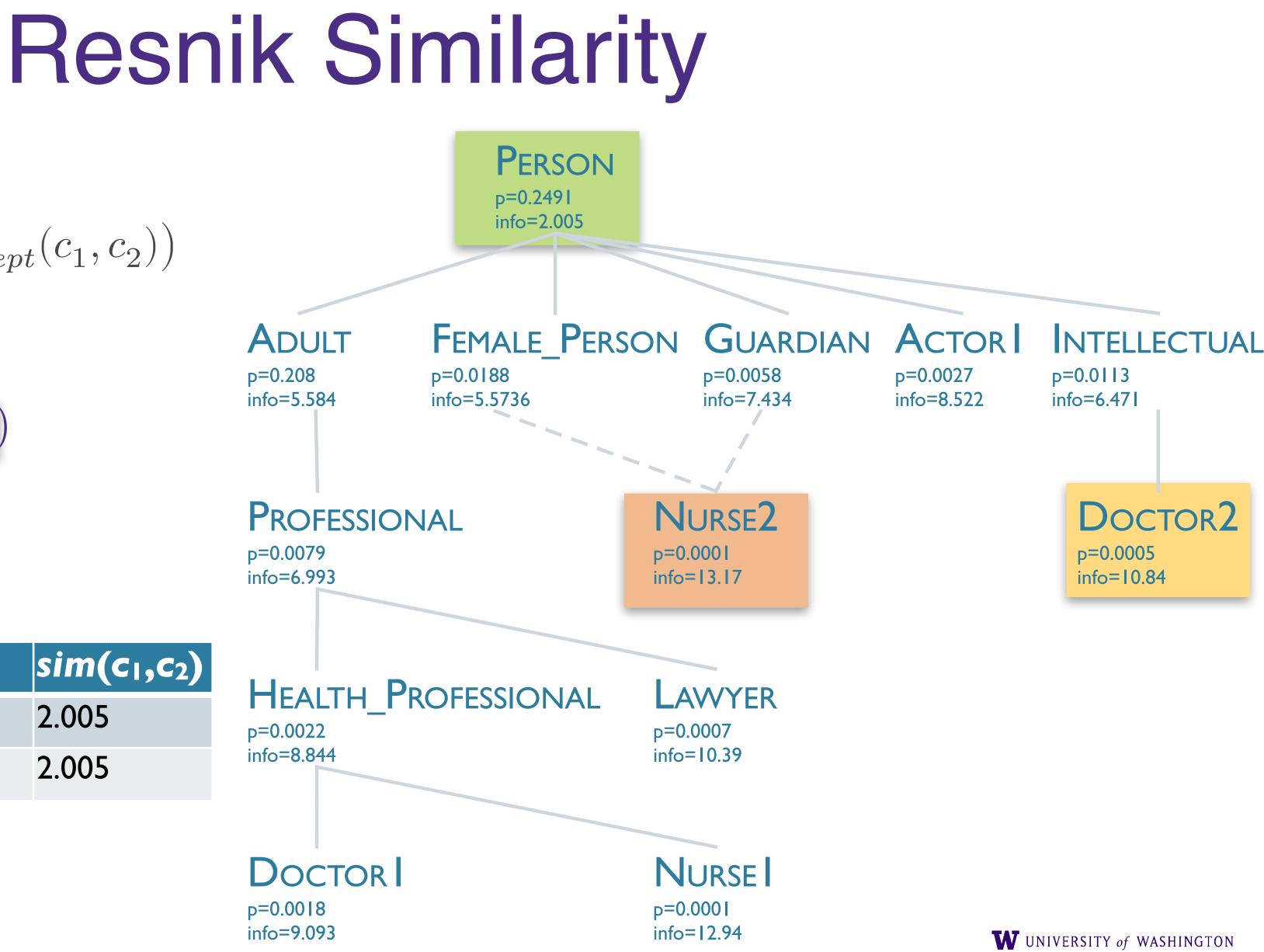
 $sim_{word}(w_1, w_2) = \max_{c_1, c_2} (sim_{concept}(c_1, c_2))$

• Let's try

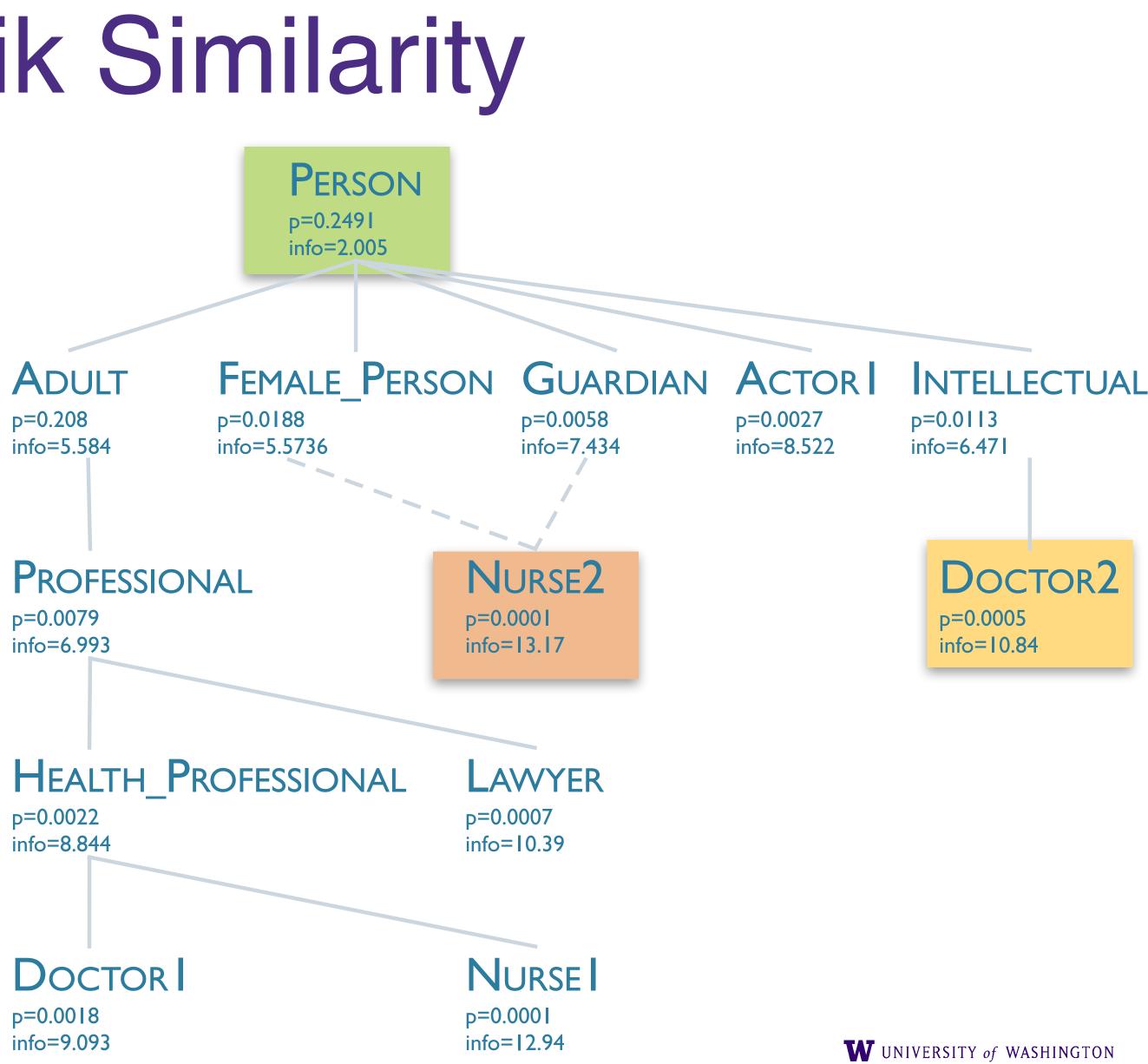
• $sim_{word}(doctor, nurse)$

• $sim_{concept}(c_1, c_2)$

• Get IC of LCS



CI	C2	LCS	sim(c ₁ ,c ₂)	
DOCTORI	NURSE ₂	Person	2.005	Н _Р =0
DOCTOR ₂	NURSE ₂	Person	2.005	info





• Calculate:

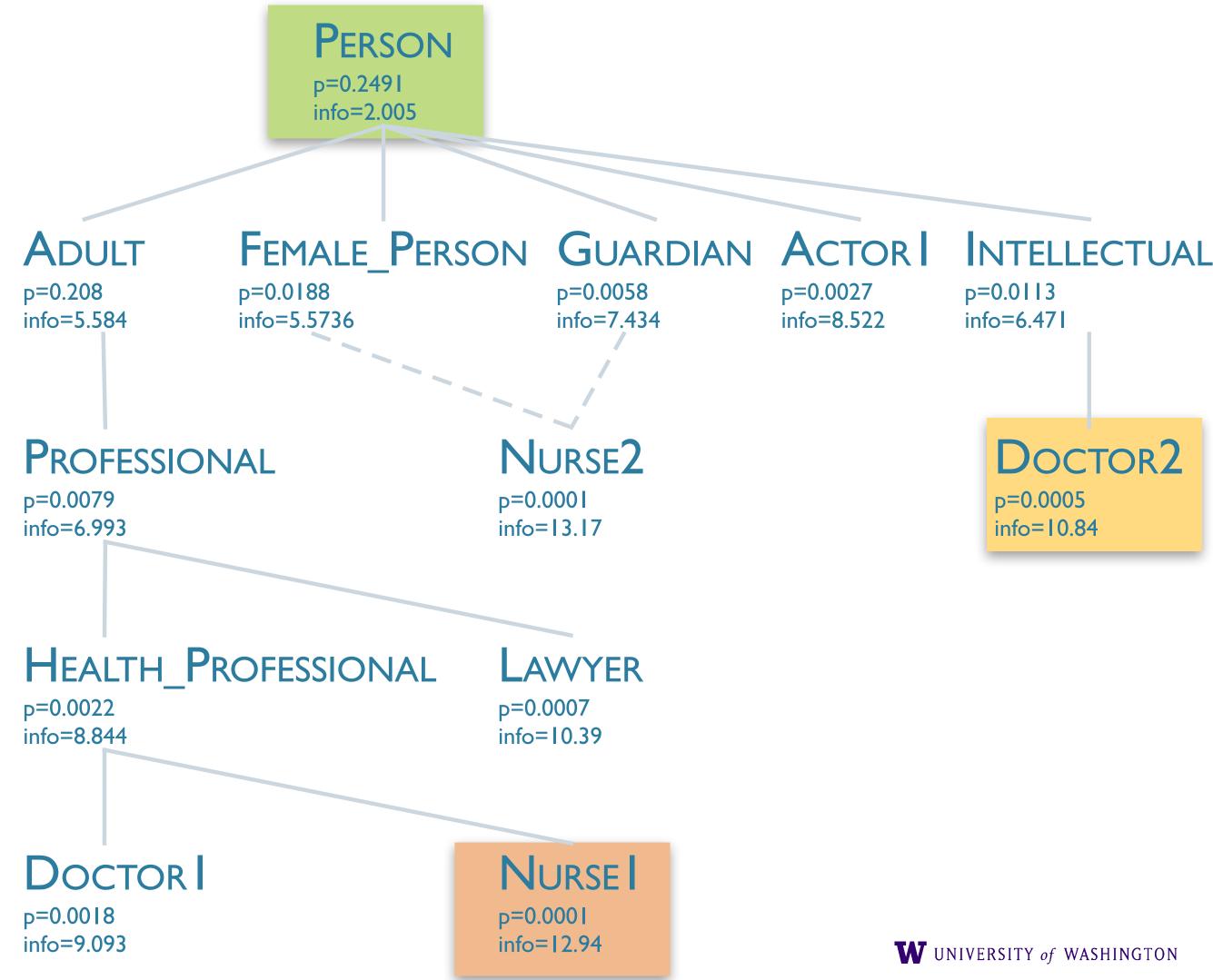
 $sim_{word}(w_1, w_2) = \max_{c_1, c_2} \left(sim_{concept}(c_1, c_2) \right)$

• Let's try

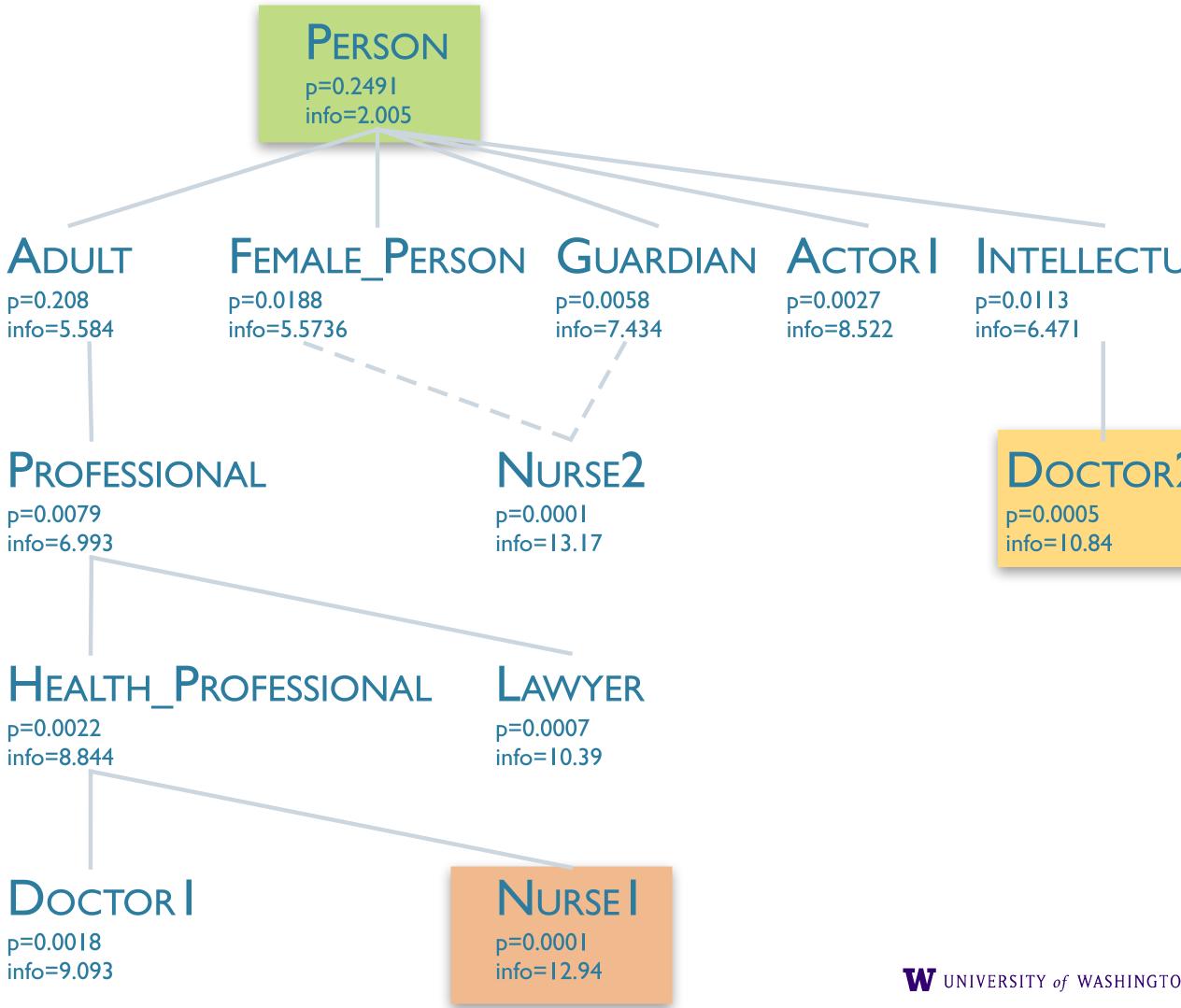
• $sim_{word}(doctor, nurse)$

• $sim_{concept}(c_1, c_2)$

• Get IC of LCS



CI	C2	LCS	sim(c ₁ ,c ₂)
DOCTORI	NURSE ₂	Person	2.005
DOCTOR ₂	NURSE ₂	Person	2.005
DOCTOR ₂	NURSEI	Person	2.005



<u>Via Resnik (1999)</u> — p. 96 **Resnik Similarity**







• Calculate:

 $sim_{word}(w_1, w_2) = \max_{c_1, c_2} \left(sim_{concept}(c_1, c_2) \right)$

• Let's try

• $sim_{word}(doctor, nurse)$

• $sim_{concept}(c_1, c_2)$

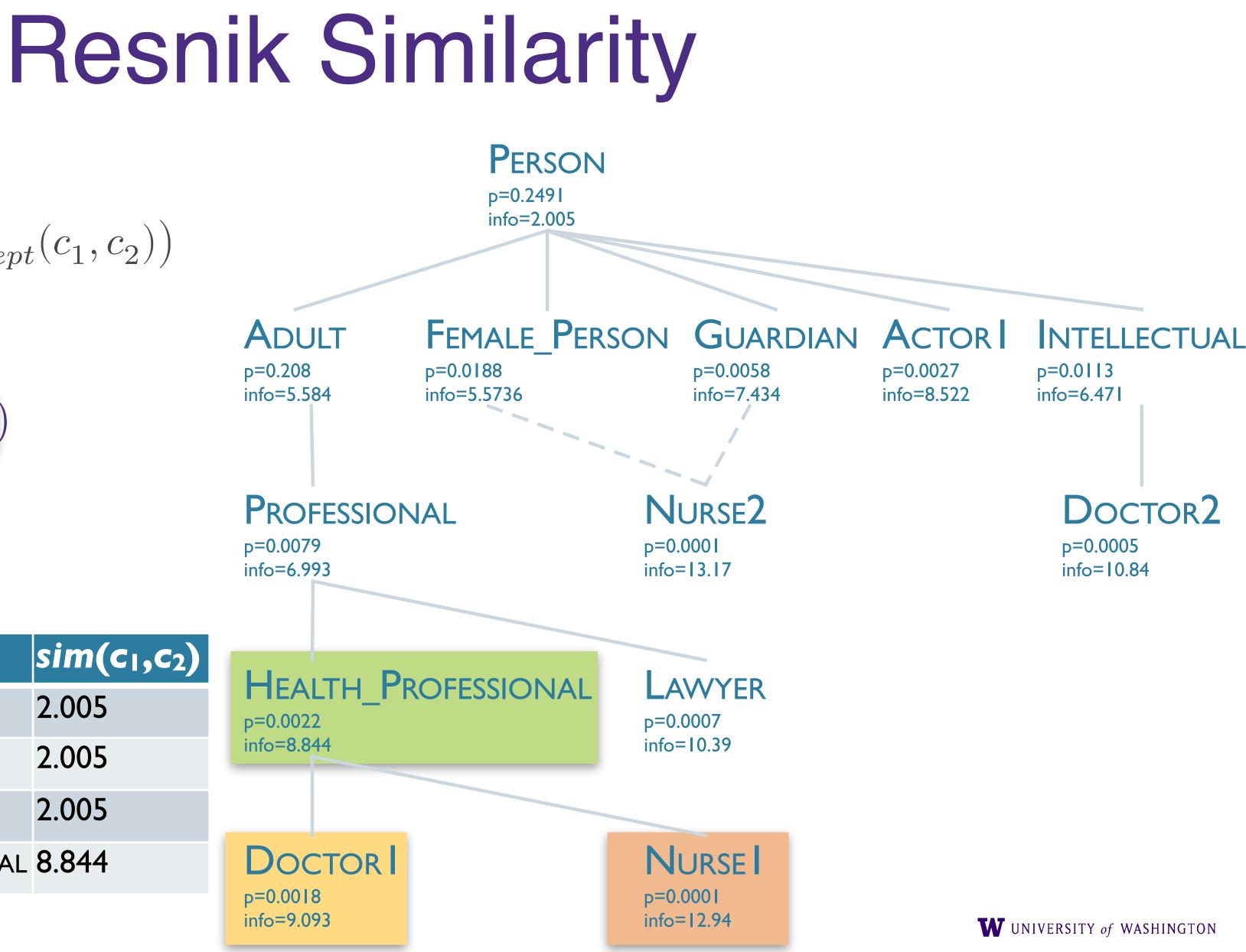
• Get IC of LCS

p=0.208 info=5.584

p=0.0079 info=6.993

CI	C2	LCS	sim(c ₁ ,c ₂)	HEA
DOCTORI	NURSE ₂	Person	2.005	P=0.00
DOCTOR ₂	NURSE ₂	Person	2.005	info=8
DOCTOR ₂	NURSEI	Person	2.005	
DOCTORI	NURSEI	Health_Professional	8.844	

<u>Via Resnik (1999)</u> — p. 96









Resnik WSD: Choosing a Sense

- doctor nurse, lawyer, accountant, scholar, minister
- We'll get:
 - $\{ DOCTOR_I, NURSE_1 \} \subset HEALTH_PROFESSIONAL \}$
 - {**DOCTOR**, LAWYER₁} ⊂ **PROFESSIONAL**
 - {**DOCTOR**_I, ACCOUNTANT₁} \subset **PROFESSIONAL**
 - {**DOCTOR**₂, **S**CHOLAR₁} \subset INTELLECTUAL
 - {**DOCTOR**₂, **MINISTER**₁} \subset **INTELLECTUAL**
- DOCTOR_I with 22.83 of "support"
- DOCTOR₂ with 12.942 of "support"
 - Select **Doctor** by majority vote.

<u>Via Resnik (1999)</u> — p. 96

= 8.844+ 6.993 = 15.837+ 6.993 = 22.83= 6.471+ 6.471 = 12.942







Compositional and Lexical Semantics





The Meaning of "Life"

In the spring of 1976, Terry Parsons and Barbara Partee taught a course on Montague grammar, which i attended. On the second to the final day of class, Terry went around the room asking the students if there were any questions at all that remained unanswered, and promised to answer them on the last day of class. I asked if he really meant ANY question at all, which he emphatically said that he meant. As I had encountered a few questions in my lifetime that remained at least partially unresolved, I decided to ask one of them. What is life? What is the meaning of life? After all, Barbara and Terry had promised to provide answers to any question at all.

On the final day of class Barbara wore her Montague grammar T-shirt, and she and Terry busied themselves answering our questions. At long last, they came to my question. I anticipated a protracted and involved answer, but their reply was crisp and succinct. First Barbara, chalk in hand, showed me the meaning of life.

^<u>life</u>'

Terry then stepped up and showed me what life really is.

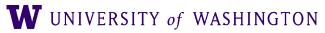
`^<u>}ife</u>'

As we were asked to show on a homework assignment earlier in the year, this is equivalent to: life'.

Leaving me astounded that I had been living in such darkness for all these years, the class then turned to the much stickier problem of pronouns.

Foreword

Carlson 1977







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> ^<u>life</u>' $\w.\x.life(w,x)$

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Foreword

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Two "Approaches" to Meaning

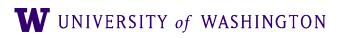
- Compositional / logical semantics:
 - Verb \rightarrow 'booked' { $\lambda W.\lambda z.W(\exists eBooked(e) \land Booker(e,z) \land BookedThing(e,y))$ }
- Lexical semantics:
 - booked: [0.1234, 0.4, 0.269, ...]
- Generating good sentence representations, either by integrating these two approaches or enriching the distributional approach, is a major area of current work in computational semantics.







HW #8







Implementation

- Implement a simplified version of Resnik's "Associating Word Senses with Noun Groupings"
- Select a sense for the probe word, given group
 - Rather than all words as in the algorithm in the paper
- For each pair (probe, noun_i)
 - Loop over sense pairs to find MIS (Most informative sense), similarity value v
 - Update each sense of probe descended from MIS, with v
- Select highest scoring sense of probe
- Repeat noun-pair correlation with Resnik similarity







- Similarity measure:
 - IC:
 - NLTK accessor:
 - Note: Uses WordNet 3.0

/corpora/nltk/nltk-data/corpora/wordnet_ic/ic-brown-resnik-add1.dat

• wnic = nltk.corpus.wordnet ic.ic('ic-brown-resnik-add1.dat')









- >>> from nltk.corpus import *
- >>> brown ic = wordnet ic.ic('ic-brown-resnik-add1.dat')
- >>> wordnet.synsets('artifact')
- [Synset('artifact.n.01')]
- >>> wordnet.synsets('artifact')[0].name 'artifact.n.01'

>>> artifact = wordnet.synset('artifact.n.01') from nltk.corpus.reader.wordnet import information content

>>> information content(artifact, brown ic) 2.4369607933293391







• Hypernyms:

>>>wn.synsets('artifact')[0].hypernyms() [Synset('whole.n.02')]

• Common hypernyms: >>> hat = wn.synsets('hat')[0] >>> glove = wn.synsets('glove')[0] >>> hat.common_hypernyms(glove) [Synset('object.n.01'), Synset('artifact.n.01'), Synset('whole.n.02'), Synset('physical entity.n.01'), Synset('entity.n.01')]







- WordNet API
 - NLTK: Strongly suggested
 - Others exist, but no "warranty"!
- http://www.nltk.org/howto/wordnet.html
- http://www.nltk.org/api/nltk.corpus.reader.html#modulenltk.corpus.reader.wordnet









- You can use supporting functionality, e.g.
 - common_hypernyms, full_hypernyms, etc
- You can NOT just use the built-in
 - resnik similarity
 - least common hypernym, etc
- If unsure about acceptability, just ask!

Note

