Spreading Activation in Soar: Preliminary Work

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1 Problem: Ambiguous Contextualized Retrieval



















The postman[1] mailed [1] the letter [2] .

To disambiguate: *message*, *character*



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How? P(message) > P(character)?



To disambiguate: *message, character*

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Base-Level Activation can serve as prior:

- frequency of access
- recency of access
- learned



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What if we have more information?



Ambiguous Contextualized Retrieval

To disambiguate: *message*, *character*



Ambiguous Contextualized Retrieval



Ambiguous Contextualized Retrieval



Spreading Activation describes a class of methods to solve the ambiguous contextualized retrieval problem by *exploiting Semantic Memory graph structure* to estimate P(C|m).

Problem: Ambiguous Contextualized Retrieval





Spreading Activation: The Naïve Approach



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Spreading Activation: The Naïve Approach

Properties

- Decays with distance from context.
- More connections to a node give higher value.



Problems With The Naïve Approach

Problems



Problems With The Naïve Approach

Problems

• Always recompute from scratch









New context element?

B *P*(*B*|*E*)



New context element?

 $P(A|E) \cdot P(B|E)$



Personalized PageRank

Personalized PageRank: The **probability distribution** describing random walks that randomly restart from context nodes (Page et al., 1999).

• Nonzero for elements on long-term memory graph reachable from a context node.

Personalized PageRank with Monte Carlo Fingerprinting

An efficient way to approximate Personalized PageRank by actually using random walks. (Fogaras & Rácz, 2004)

• Such a collection of walks from a node is a Monte Carlo Fingerprint.

Properties:

- Decays with distance from context.
- More connections to a node give higher value.
- Incremental with context change

Evaluation: Word Sense Disambiguation

D Problem: Ambiguous Contextualized Retrieval

Approach: Spreading Activation Personalized Pagerank

3 Evaluation: Word Sense Disambiguation

Original sentence:

The postman put the letter in the mailbox.

Original sentence:

The postman put the letter in the mailbox.

Corpus annotation:

The postman[1] put[1] the letter[2] in the mailbox[1] .

Original sentence:

The postman put the letter in the mailbox.

Corpus annotation:

The postman[1] put[1] the letter[2] in the mailbox[1] .

```
What the agent receives:
```

postman[?] put[?] letter[?] mailbox[?]

"letter" corresponding to message, not character

Metrics

Task Performance

• How many guesses does it take to get the right word sense? Time

• How long does a processing cycle take?

Data Set - SemCor (Miller et al., 1993):

- Annotated version of a subset of the Brown corpus
- 352 texts of 2000 words each from fiction, nonfiction, books, journals, but no poetry
- >175,000 WordNet 3.0 sense references for nouns and verbs

Semantic Memory - WordNet 3.0 (Fellbaum, 1998):

- WordNet synonyms, antonyms, hypernyms, hyponyms, part-of, derivationally-related
- 270,000 nodes, 900,000 edges
- $\circ \sim .5 \mathrm{GB}$

Working Memory (Context):

Previous words

Random Guessing Perfection PPR Base-level Activation ACT-R's Spreading Activation

Random Guessing

Random Guessing

• Randomly selects a sense for a given word

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Personalized PageRank with Monte Carlo Fingerprinting (PPR)

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- Randomly selects a sense for a given word
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Perfection

- Just a count of how many words there are to disambiguate
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Personalized PageRank with Monte Carlo Fingerprinting (PPR)

• The method focused on in this work

Base-level Activation (BLA)

Base-level Activation (BLA)

• The state of Soar prior to this work

Base-level Activation (BLA)

- The state of Soar prior to this work
- Does not use context

Base-level Activation (BLA)

- The state of Soar prior to this work
- Does not use context
- Based on frequency and recency of access

ACT-R's Spreading Activation



ACT-R's Spreading Activation

- Context influences nodes depth
 - 1 away



ACT-R's Spreading Activation

- Context influences nodes depth 1 away
- "Reverses" edges



Comparison Results (Low is good)



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Future Work

More Analysis on WSD

- Test performance with changes to Semantic Memory graph
- Identify what parts of WordNet and SemCor enable better performance

Other tasks besides WSD

- Context-relevant person retrieval from Wikipedia-based memory
- Connections Quizzes
- John's Construction Grammar parser?

Pair-wise association learning methods

Nuggets

- Context information improves task performance
- Incremental

Coal

- Slower by a factor of 10
- Only preliminary data

References

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 Fogaras, D., & Rácz, B. (2004). Towards scaling fully personalized pagerank. In Algorithms and models for the web-graph. Springer.
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- Page, L., Brin, S., Motwani, R., & Winograd, T. (1999). The pagerank citation ranking: Bringing order to the web.

Independence Assumption

Recall:

$$\arg\max_{m\in M} P(m|C) = \arg\max_{m\in M} \frac{P(C|m)P(m)}{P(C)} = \arg\max_{m\in M} P(C|m)P(m)$$

Assume:

$$rgmax_{m \in M} P(C|m)P(m) = rgmax_{m \in M} \left[\left(\prod_{c \in C} P(c|m)\right) P(m) \right]$$

Task-Performance Zoom



Time Complexity (with respect to memory changes)

Typical Case

- Assume out-degree b > 1
- Assume walk lengths d
- Assume $1 \ll b^d$
- probability of element length d away being in fingerprint $1 - \left(\frac{b^d - 1}{b^d}\right)^n =$ $1 - \left(1 + \left(1 - \frac{b^d - 1}{b^d}\right)\right)^n \approx$

$$n-n\cdot rac{b^d}{b^d}+rac{n}{b^d}=rac{n}{b^d}$$

 number of elements length d away = b^d

Maintaining fingerprints is $O(n \cdot \sum_{i=0}^{d-1} b^{d-i} \cdot \frac{1}{b^{d-i}}) = O(n \cdot d)$

Worst Case: $O(n \cdot |V|)$



A graph with edge where removal or addition forces complete recomputation.