Learning Random Walk Models for Inducing Word Dependency Distributions

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Outline

- Markov Chains
- Prepositional Phrase Attachment Problem
- Random Walks

Markov Chains

- Markov Distribution
  - States $\mathcal{S}$
  - Initial distribution: $p_0(S)$ over all $S \in \mathcal{S}$
  - State transition probabilities: $p(S_t|S_{t-1})$

Markov Chains

- Generating a Markov Chain
  - Generate initial state, S_0, based on p_0
  - Generate remaining states, S_t, based on transition probabilities

- Stationary distribution (if the limit exists):

$$\pi(s) = \lim_{t \to \infty} P(S_t = s)$$

Markov Chains

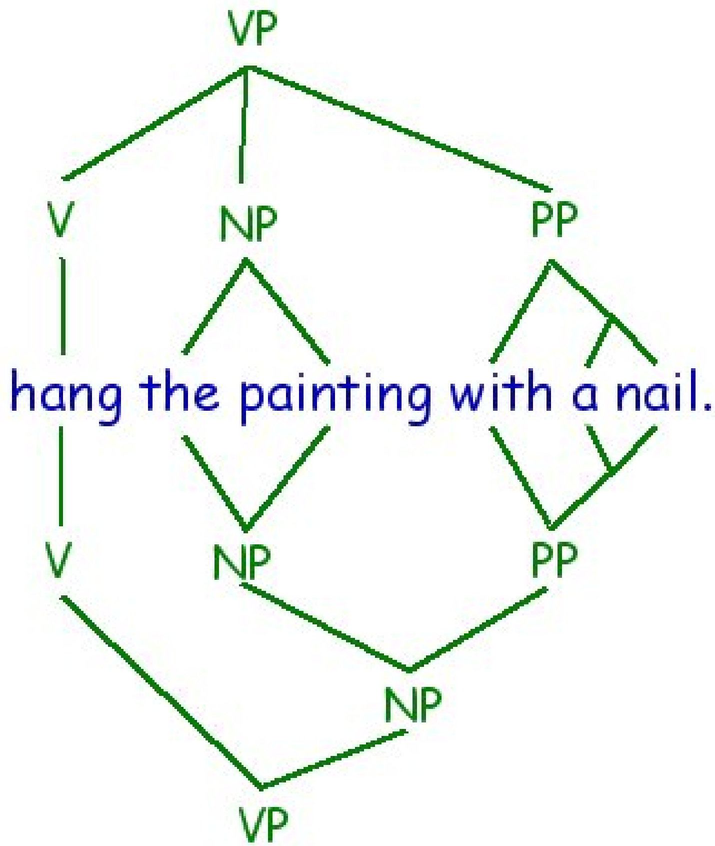
- How to ensure a stationary distribution?
  - Include probability $\gamma > 0$ of resetting to initial distribution p_0
  - New state transition distribution:

$$p(S_t|S_{t-1}) = \gamma p_0(S_t) - (1-\gamma)p'(S_t|S_{t-1})$$

  - Stationary distribution (can be approximated) becomes:

$$\pi(s) = \gamma \sum_{t=0}^{\infty} (1-\gamma)^t P(S_t = s)$$

PP Attachment Problem



PP Attachment Problem

- ⋆ v:hang n_1:painting p:with n_2:nail

- ⋆ $P(V, N_1, P, N_2, Att) \Rightarrow P(Att|V, N_1, P, N_2)$

  - ⋆ $Att = va$ (verb attachment) or na (noun attachment)

  - ⋆ $P(v, n_1, p, n_2, va) =$

    $$P(p, va)P(v|p, va)P(n_1|p, va, v)P(n_2|p, \mathbf{v}, va)$$

  - ⋆ $P(v, n_1, p, n_2, na) =$

    $$P(p, na)P(v|p, na)P(n_1|p, na, v)P(n_2|p, \mathbf{n_1}, na)$$

Random Walks

- $\star$ But how to generate the probabilities?
  - $\star$ Random Walks!

- $\star$ $\mathcal{S} = \mathcal{W} \times \{0, 1\}$
  - $\star$ $\mathcal{W}$ = all words, 0 = head state, 1 = dependent state
  - $\star$ nail = {nail, 1}, hang = {hang, 0}

- $\star$ $p_0(verb, 0) = 1$

Random Walks

- ⋆ Separate graphs for each probability distribution (e.g. $P(N_2|p, v, va)$)

- ⋆ Separate transition matrics (graphs) for each p

- ⋆ "Short" walks away are likely related; "long" walks are not as likely

Transition types

- ⋆ Empirical transitions: What was seen in the training set

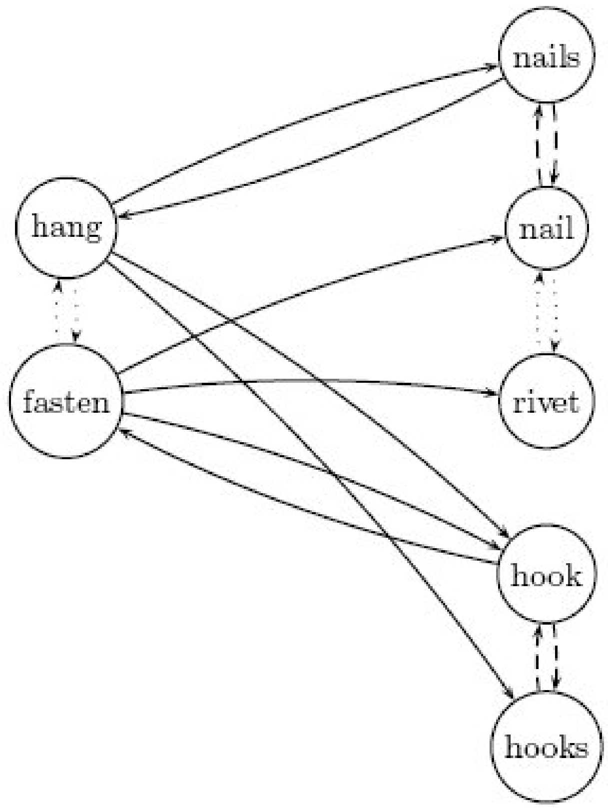
- ⋆ Morphology: Words with same root and same marker (nail vs. nails)

- ⋆ WordNet Synsets: Semantically similar words (nail vs. rivet)

Transition types

- External Corpus: Similar to empirical transition, but includes noisy data (from a statistical parser)
- $V \rightarrow V$: Verbs that take similar dependents (hang vs. fasten)
- $N \rightarrow V$: Nouns with similar heads (nail vs. rivet)

Random Walks



State space for learning $P_{with}(n_2, v)$

Experiments

- ⋆ Penn Treebank WSJ for training and test set
- ⋆ BLLIP corpus for noisy data (1.8 million sentences; Charniak parser)
  - ⋆ 567,582 ambiguous PP tuples extracted
- ⋆ Run the Markov chain d time steps (degree)
- ⋆ Try different types of links

Results

Model	Degree	Accuracy
Baseline	1	85.86%
Baseline+stem verbs	1	86.02%
Morph Verbs	2,3	86.08%
Morph Verbs and Nouns	2,3	86.18%
Morph & Synonyms	2,3	86.53%
Sim_{JS_β}	2,3	86.44%
Final	2,3	87.54%

⋆ Baseline: run chain for one step (linear interpolation)

Conclusions

- Random walk models provide general framework for similarity based smoothing

- Random walk of step 1 is just linear interpolation (baseline)

- Gives high performance in prepositional phrase attachment
  - Can be applied to other problems as well