A Bayesian Approach to Unsupervised Semantic Role Induction

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Frame Semantics

- Frame semantics and the nature of language (Fillmore, 1977)
- The Berkeley FrameNet Project (Baker et al., 1998)
- Automatic Labeling of Semantic Roles (Gildea and Jurafsky, 2002)
- Frequent task at CoNLL, SensEval/SemEval

What is a frame?

- Structures that describe particular situations, objects, or events

- Each frame contains a set of roles for participating elements

Frame: Ingestion

Michael eats a sandwhich

A sandwich is eaten by Michael

Frame: Ingestion

Michael eats a sandwhich

$[\text{Michael}]_{Ingestor}$ **eats** $[\text{a sandwich}]_{Ingestible}$

A sandwich is eaten by Michael

$[\text{A sandwich}]_{Ingestible}$ **is eaten** $[\text{by Michael}]_{Ingestor}$

A point of confusion!
(And there are many!)

- FrameNet vs. PropBank

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- FrameNet vs. PropBank

FrameNet

<u>Frame</u>: Giving
<u>Frame Elements(Roles)</u>:
Donor
Recipient
Theme
Circumstances
Depictive
Manner
...

PropBank

<u>Frame</u>: Give
<u>Frame Elements(Roles)</u>:
Arg0 (Typically Agent)
Arg1 (Typically Patient)
Arg2
...

Semantic Role Labeling
The Task

2 Stages (Frame Induction)

1. Identification of arguments (Syntax based heuristics)

2. Role labeling (What this paper is all about!)

Semantic Role Labeling

Inputs or how is this unsupervised?

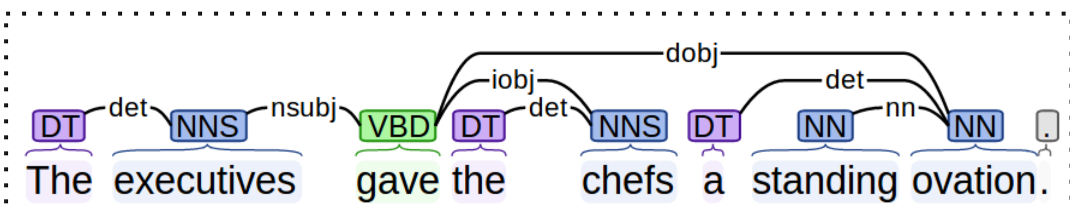
1. A sentence

2. An automatically generated syntactic dependency graph of that sentence

Semantic Role Labeling

An Example

The executives gave the chefs a standing ovation.



Frame: Give

Roles:

- Arg0: giver
- Arg1: thing given
- Arg2: entity given to

Semantic Role Labeling

An Example

The executives **gave** the chefs a standing ovation.

Rel: gave

Frame: Give

Roles:

- Arg0: giver
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Semantic Role Labeling

An Example

{The executives} **gave** {the chefs} {a standing ovation}

Rel: gave

Frame: Give

Roles:

- Arg0: giver
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Semantic Role Labeling

An Example

{The executives} **gave** {the chefs} {a standing ovation}.

Rel: gave

- Arg0: The executives
- Arg1: a standing ovation
- Arg2: the chefs

Frame: Give

Roles:

- Arg0: giver
- Arg1: thing given
- Arg2: entity given to

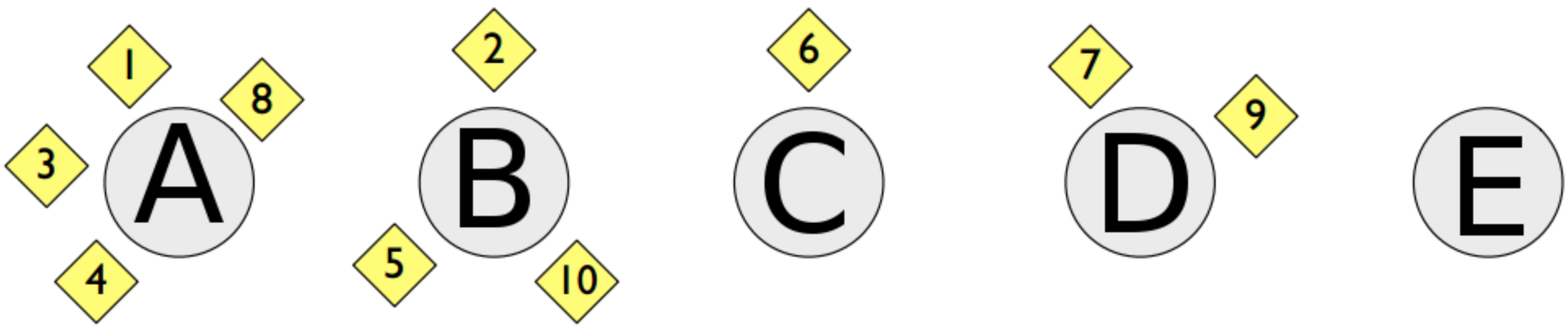
Argument Representation

- Argument Keys
  - Verb Voice (ACT/PASS)
  - Argument position relative to verb (LEFT/RIGHT)
  - Syntactic relation to governor
  - Preposition used for argument (if any)

- Argument Keys for 'Michael' in the sentences:
  a. Michael ate a sandwich.
     - ACT:LEFT:SBJ
  b. The sandwich was eaten by Michael.
     - PASS:RIGHT:LGS->BY

CRP and DD-CRP

- Chinese Restaurant Process



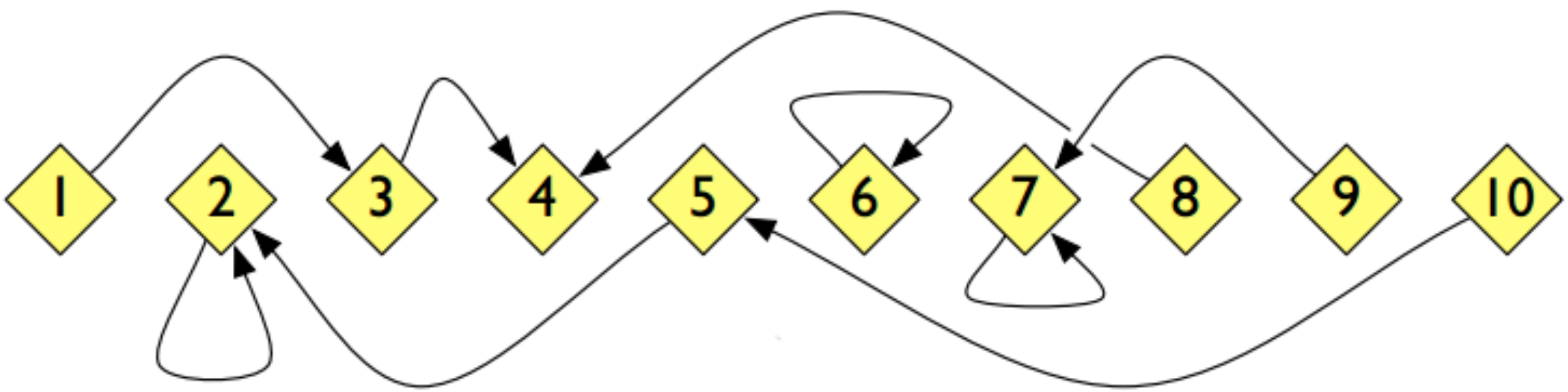
Given $i-1$ customers seated at K tables,

$$\mathbf{Pr}[c_i = k] = \frac{N_k}{i-1+\alpha} \qquad \mathbf{Pr}[c_i = K+1] = \frac{\alpha}{i-1+\alpha}$$

where c_i is table assingment of customer i and N_k is the number of customers already seated at table k.

CRP and DD-CRP

- Distance Dependant Chinese Restaurant Process



Given $i-1$ customers already seated, customer i chooses a partner with probability

$$\mathbf{Pr}[c_i = j | D, \alpha] = \frac{d_{i,j}}{\sum_{j'=1}^{i} d_{i,j'}}$$

where D is the entire similarity graph, $d_{i,j}$ is the similarity between customers i and j, and $d_{i,i} = \alpha$.

Models

Clustering of argument keys:

Factored model:

for each predicate $p = 1, 2, \ldots :$

$B_p \sim CRP(\alpha)$ [partition of arg keys]

Coupled model:

$D \sim NonInform$ [similarity graph]

for each predicate $p = 1, 2, \ldots :$

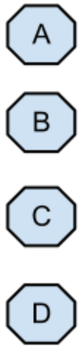
$B_p \sim dd\text{-}CRP(\alpha, D)$ [partition of arg keys]

MAP Search

- A simple greedy procedure
  - Each argument key is assigned to its own cluster
  - On first iteration, choose argument keys by their frequency in the corpus

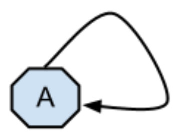
1. Choose an argument key at random
2. (Factored) Assign it to the most probable cluster, including a new cluster
   (Coupled) Assign it to the most probable partner, including itself

MAP Search



Order by frequency and assign seats.

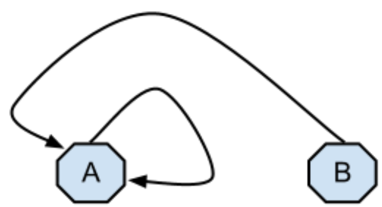
MAP Search

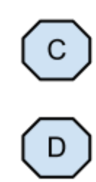


Order by frequency and assign seats.

MAP Search

$$\mathbf{Pr}(c_B = A) > \mathbf{Pr}(c_B = B)$$





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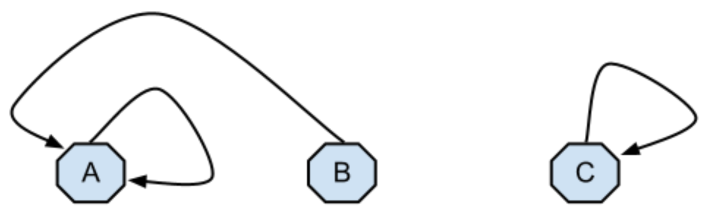

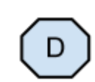

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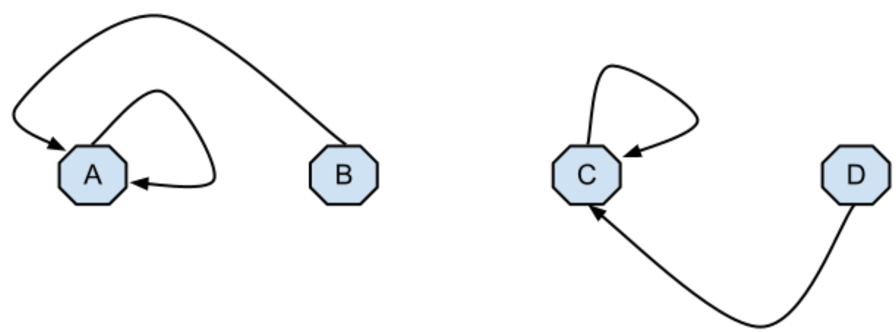

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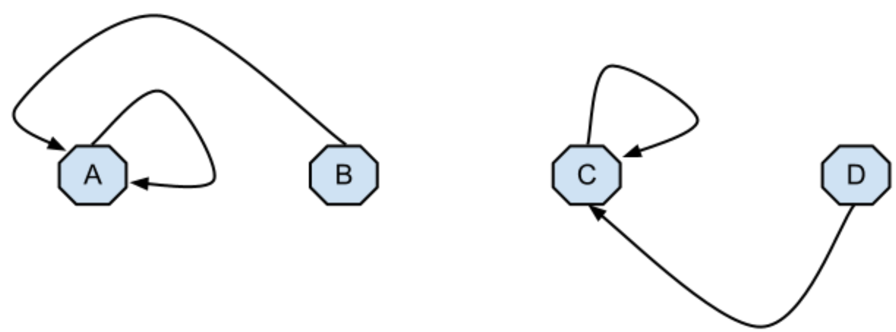
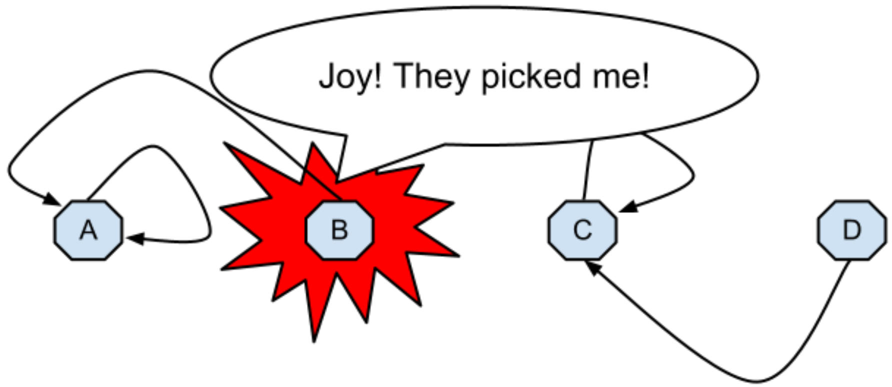


Now randomly select an argument key.

MAP Search



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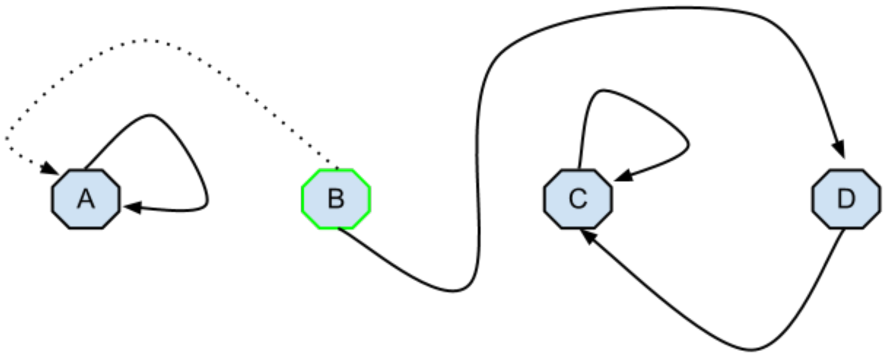

Reassign the argument key to the most probable argument key.

Models

Parameters:

for each predicate $p = 1, 2, \ldots$:
  for each role $r \in B_p$:
    $\theta_{p,r} \sim DP(\beta, H^{(A)})$ [distrib of arg fillers]
    $\psi_{p,r} \sim Beta(\eta_0, \eta_1)$ [geom distr for dup roles]

Data Generation:

for each predicate $p = 1, 2, \ldots$:
  for each occurrence l of p:
    for every role $r \in B_p$:
      if $[n \sim Unif(0,1)] = 1$: [role appears at least once]
        GenArgument(p, r) [draw one arg]
        while $[n \sim \psi_{p,r}] = 1$: [continue generation]
          GenArgument(p, r) [draw more args]

GenArgument(p, r):
  $k_{p,r} \sim Unif(1, \ldots, |r|)$ [draw arg key]
  $x_{p,r} \sim \theta_{p,r}$ [draw arg filler]

Gibbs Sampling for DD-CRP (Blei and Frazier, 2011)

Let model hyperparameters $\eta = \{D, \alpha, f, G_0\}$. $z(\mathbf{c})$ is the partition resultant from seating assignments $\mathbf{c}$.

$$\mathbf{Pr}(c_i^{(\text{new})}|\mathbf{c}_{-i}, \mathbf{x}, \eta) \propto \mathbf{Pr}(c_i^{(\text{new})}|D, \alpha)\mathbf{Pr}(\mathbf{x}|z(\mathbf{c}_{-i} \cup c_i^{(\text{new})}), G_0)$$

$$\begin{array}{rl} \mathbf{Pr}(c_i^{(\text{new})}|D, \alpha) & \text{prior} \\ \mathbf{Pr}(\mathbf{x}|z(\mathbf{c}_{-i} \cup c_i^{(\text{new})}), G_0) & \text{likelihood} \end{array}$$

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$$\mathbf{Pr}(c_i^{(\text{new})} | \mathbf{c}_{-i}, \mathbf{x}, \eta) \propto \begin{cases} \alpha & \text{if } c_i^{(\text{new})} \text{ is equal to } i \\ f(d_{ij}) & \text{if } c_i^{(\text{new})} = j \text{ does not join two tables.} \\ f(d_{ij}) \dfrac{\mathbf{Pr}(\mathbf{x}_{z^k(\mathbf{c}_{-i}) \cup z^\ell(\mathbf{c}_{-i})} | G_0)}{\mathbf{Pr}(\mathbf{x}_{z^k(\mathbf{c}_{-i})} | G_0) \mathbf{Pr}(\mathbf{x}_{z^\ell(\mathbf{c}_{-i})} | G_0)} & \text{if } c_i^{(\text{new})} = j \text{ joins tables } k \text{ and } \ell. \end{cases}$$