A Hierarchical Bayesian Model for Unsupervised Induction of Script Knowledge

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Scripts

[...] A script is a predetermined, stereotyped sequence of actions that define a well-known situation.[1]

[1] Schank and Abelson (1975)

Scripts

[...] A script is a predetermined, stereotyped sequence of actions that define a well-known situation.[1]

Example situation: "Eating in a Restaurant"

Look at menu
Order your food
Wait for your food
Eat food
Pay

Event Sequence Description (ESD): explicit instantiation of a script

[1] Schank and Abelson (1975)

Scripts

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Example situation: "Eating in a Restaurant"

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Pay

a way of providing AI/NLP systems with world knowledge

- coherence estimation
- summarization

[1] Schank and Abelson (1975)

Script Characteristics

ESD 1	ESD 2
Look at menu	Check the menu
Order your food	Order the meal
Wait for your food	Wait for meal
	Talk to friends
Eat food	Have meal
Pay	Pay the bill

learn sequential ordering constraints

Script Characteristics

ESD 1	ESD 2
Look at menu	Check the menu
Order your food	Order the meal
Wait for your food	Wait for meal
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learn sequential ordering constraints

learn event types (paraphrases)

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learn sequential ordering constraints

learn event types (paraphrases)

model participant types as latent variables

Event Sequence Descriptions (ESDs)

- from non-expert annotators (web experiments)
- noisy (grammar/spelling)
- variable number and detail of event descriptions
- few ESDs per scenario

"get menucard"
"search for items"
"order items"
"eat items"
"pay the bill"
"quit restaurant"

"enter the front door"
"let hostess seat you"
"tell waitress your drink order"
"tell waitress your food order"
"wait for food"
"eat and drink"
"get check from waitress"
"give waitress credit card"
"take charge slip from waitress"
"sign slip and add in a tip"
"leave slip on table"
"put up credit card"
"exit the restaurant"

Unsupervised Learning of Scripts from Natural Text

Chambers and Jurafsky (2008)

- infer script-like templates from news text ("Narrative Chains")
- learn event sets and ordering information in a 3-step process
  - identification of relevant events
  - temporal classification
  - clustering
- Chambers and Jurafsky (2009) learn events and participants jointly (but no ordering)

- script information often left implicit in natural text (world knowledge)

Unsupervised Learning of Scripts from ESDs

Regneri et al 2010

- collect sets of event sequence description for various scripts
- learn event types and orderings
  - align events across descriptions based on semantic similarity
  - compute graph representation using Multiple Sequence Alignment (MSA)
- Regneri et al. (2011) learn participant types based on those event graphs

- pipeline architecture
- MSA-based graphs cannot encode some script characteristics (e.g. event optionality)

The Proposed Model

(I) A Bayesian Script Model

- joint learning of event types and ordering constraints from ESDs
- generalized Mallows Model for modeling ordering constraints

Bayesian Models of Ordering in NLP

- document-level ordering constraints in structured text (Wikipedia Articles) (Chen et al., 2009)
- integrate a GMM into a standard topic model

The Proposed Model

(II) Informed Prior Knowledge from WordNet

- alleviates the problem of limited training data
- encode correlations between words based on WordNet similarity in the language model priors

Encoding Correlations through a logistic normal distribution

- "The correlated topic model" Blei and Lafferty (2006)

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The Mallows Model (Mallows, 1957)

A probability distribution over permutations of items

- distance measure between two permutations π_1 and π_2: $d(\pi_1, \pi_2)$
- parameters:
  σ, the canonical ordering (identity ordering [1,2,3,...,n])
  $\rho > 0$, a dispersion parameter ($\approx$ distance penalty)

The probability of an observed permutation π

$$P(\pi; \rho, \sigma) = \frac{e^{-\rho * d(\pi,\sigma)}}{\psi(\rho)}$$

The Generalized Mallows Model (Fligner and Verducci, 1986)

Generalization to item-specific dispersion parameters

$\boldsymbol{\rho} = [\rho_1, \rho_2, ...]$ for items in $\boldsymbol{\pi} = [\pi_1, \pi_2, ...]$

$$GMM(\pi; \boldsymbol{\rho}, \sigma) \propto e^{-\sum_i -\rho_i d(\pi_i, \sigma_i)}$$
$$\propto \prod_i e^{-\rho_i d(\pi_i, \sigma_i)}$$

Relation to our model

- items $(\pi_i) \hat{=}$ event types
- model event type-specific temporal flexibility

Contents

Generative Story I: Ordering Generation

for esd d **do**

COOKING PASTA

Generative Story I: Ordering Generation

draw an event type permutation $\boldsymbol{\pi}$

for esd d **do**
  $\boldsymbol{\pi} \sim GMM(\boldsymbol{\rho}, \boldsymbol{\nu})$

COOKING PASTA

$\boldsymbol{\pi}$	
1	get
3	boil
4	put
7	wait
2	grate
5	add
6	drain

Conjugate prior (GMM_0)

Generative Story II: Event Type Generation

realize event type e with success probability θ^e

for esd d **do**

$\pi \sim GMM(\rho, \nu)$

$\mathbf{t} : t_e \sim Binomial(\theta^e)$

Cooking Pasta	
$\boldsymbol{\pi}$	
1	get
3	boil
4	put
$\cancel{7}$	~~wait~~
2	grate
$\cancel{5}$	~~add~~
6	drain

Conjugate prior (*Beta*)

Generative Story II: Event Type Generation

realize event type e with success probability θ^e

for esd d **do**

$\pi \sim GMM(\rho, \nu)$

$\mathbf{t} : t_e \sim Binomial(\theta^e)$

COOKING PASTA

t	
1	get
3	boil
4	put
2	grate
6	drain

Conjugate prior ($Beta$)

Generative Story III: Participant Type Generation

for each event $e \in \mathbf{t}$, realize participant type p with success probability φ_p^e

for esd d **do**

$\pi \sim GMM(\rho, \nu)$

$\mathbf{t} : t_e \sim Binomial(\theta^e)$

for event $e \in$ $\mathbf{t}$ **do**

$\mathbf{u_e} : u_e^p \sim Binomial(\varphi_p^e)$

Cooking Pasta

t	
1	get
3	boil
4	put
2	grate
6	drain

$\mathbf{u_{get}}$	~~pasta~~ ~~water~~ ~~cheese~~ **pot** ~~salt~~ ~~stove~~ ~~strainer~~
$\mathbf{u_{put}}$	**pasta** ~~water~~ ~~cheese~~ ~~pot~~ ~~salt~~ ~~stove~~ ~~strainer~~
...	
$\mathbf{u_{drain}}$	~~pasta~~ **water** ~~cheese~~ **pot** ~~salt~~ ~~stove~~ ~~strainer~~

Generative Story III: Participant Type Generation

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$\mathbf{t} : t_e \sim Binomial(\theta^e)$

for event $e \in$ **t** **do**

$\mathbf{u_e} : u_e^p \sim Binomial(\varphi_p^e)$

Cooking Pasta

t		**u**
1	get	pot
3	boil	water
4	put	pasta
2	grate	cheese
6	drain	water, pot

$\mathbf{u_{get}}$	~~pasta~~ ~~water~~ ~~cheese~~ **pot** ~~salt~~ ~~stove~~ ~~strainer~~
$\mathbf{u_{put}}$	**pasta** ~~water~~ ~~cheese~~ ~~pot~~ ~~salt~~ ~~stove~~ ~~strainer~~
...	
$\mathbf{u_{drain}}$	~~pasta~~ **water** ~~cheese~~ **pot** ~~salt~~ ~~stove~~ ~~strainer~~

Generative Story IV: Lexical Realization

draw a lexical realizations for each realized event and participant

for esd d **do**
  $\pi \sim GMM(\rho, \nu)$
  $\mathbf{t} : t_e \sim Binomial(\theta^e)$
  for event $e \in \mathbf{t}$
    $\mathbf{u_e} : u_e^p \sim Binomial(\varphi_p^e)$
  for $e \in \mathbf{t}$ **do**
    $w_e \sim Mult(\vartheta_e)$
    for $p \in \mathbf{u_e}$ **do**
      $w_p \sim Mult(\varpi_p)$

COOKING PASTA

t		u
1	get	pot
3	boil	water
4	put	pasta
2	grate	cheese
6	drain	water, pot

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      $w_p \sim Mult(\varpi_p)$

COOKING PASTA

“fetch	saucepan”
“boil	water”
“add	noodles”
“grate	cheese“
”drain	water from pot “

Generative Story IV: Lexical Realization

draw a lexical realizations for each realized event and participant

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COOKING PASTA

“fetch	saucepan”
“boil	water”
“add	noodles”
“grate	cheese“
”drain	water from pot “

Informed asymmetric Dirichlet priors

Informed Asymmetric Dirichlet Priors

Tie together the prior values (”pseudo counts“) of semantically related words

Multivariate Normal
$\mathcal{N}(0, \Sigma)$

Informed Asymmetric Dirichlet Priors

Tie together the prior values ("pseudo counts") of semantically related words

Multivariate Normal
$\mathcal{N}(0, \Sigma)$

	saucepan	pot	cheese	noodles	pasta
saucepan	7	6	1	0	1
pot	6	12	0	0	1
cheese	1	0	13	3	3
noodles	0	0	3	7	5
pasta	1	1	3	5	6
...					

Informed Asymmetric Dirichlet Priors

Tie together the prior values ("pseudo counts") of semantically related words

Multivariate Normal
$\mathcal{N}(0, \Sigma)$

semantic similarity:
♯ shared WordNet synsets

	saucepan	pot	cheese	noodles	pasta
saucepan	7	6	1	0	1
pot	6	12	0	0	1
cheese	1	0	13	3	3
noodles	0	0	3	7	5
pasta	1	1	3	5	6
...					

$\delta \sim \mathcal{N}(0, \Sigma)$ $\quad\quad$ $\phi \sim \mathit{Dirichlet}(\delta)$ $\quad\quad$ $w \sim \mathit{Multinomial}(\phi)$

Inference

Collapsed Gibbs Sampling for approximate inference Slice

Sampling for continuous distributions GMM **and** $\mathcal{N}(0, \Sigma)$

Parameters to be estimated (after collapsing)

- latent ESD labels $\mathbf{z} = \{\mathbf{t}, \mathbf{u}, \boldsymbol{\pi}\}$
- GMM dispersion parameter $\boldsymbol{\rho}$
- language model parameters $\boldsymbol{\delta}_{(partic)}, \boldsymbol{\gamma}_{(event)}$

Contents

Data I

Collection of ESDs (Regneri et al., 2010)

- sets of explicit descriptions of event sequences
- created from non-experts via web experiments

Scenario Name	♯ESDs	Avg ♯events
Answer the telephone	55	4.47
Buy from vending machine	32	4.53
Make scrambled eggs	20	10.3
Eat in fast food restaurant	15	8.93
Take a shower	21	11.29
...	...	...

- test set (10 scenarios)
- separate development set (5 scenarios)

Evaluation Setup (Regneri et al., 2010)

Binary event paraphrase classification

- [`get pot` , `fetch saucepan`] ⇒ true
- [`add pasta` , `add water`] ⇒ false

Binary follow-up classification

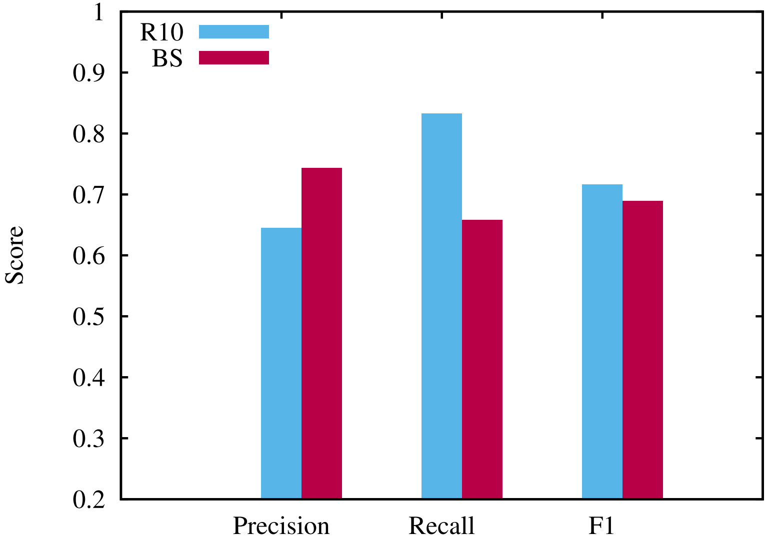
- [`fetch pot` , `put pasta into pot`] ⇒ true
- [`put pasta into pot` , `fetch pot`] ⇒ false

Metric

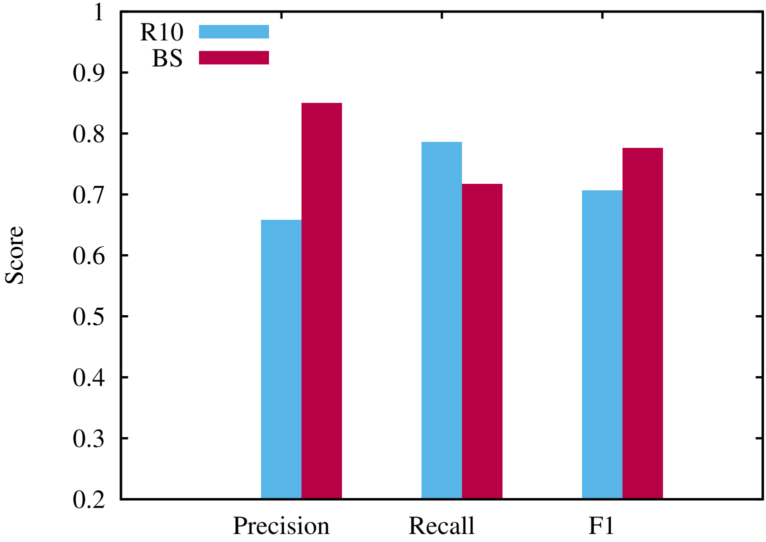
$$precision = \frac{true_{system} \cap true_{gold}}{true_{system}}$$

$$recall = \frac{true_{system} \cap true_{gold}}{true_{gold}} \qquad F = \frac{2 * precision * recall}{precision + recall}$$

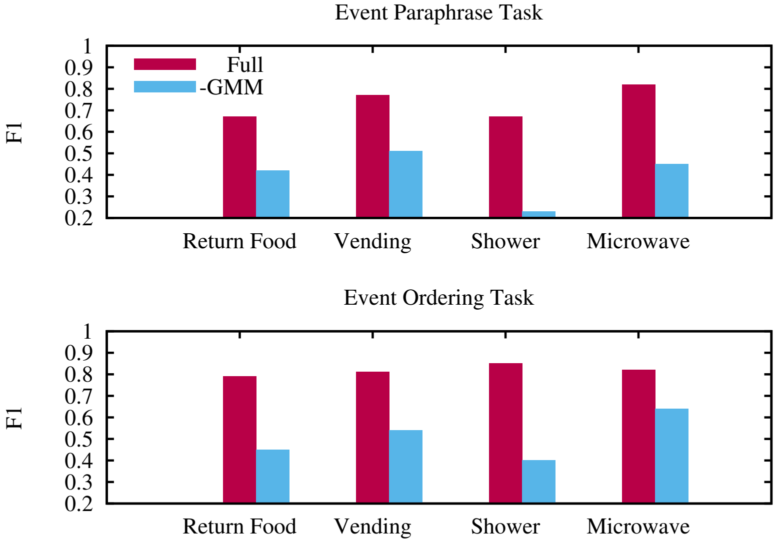
The Event Paraphrase Task



The Event Ordering Task



Influence of Model Components



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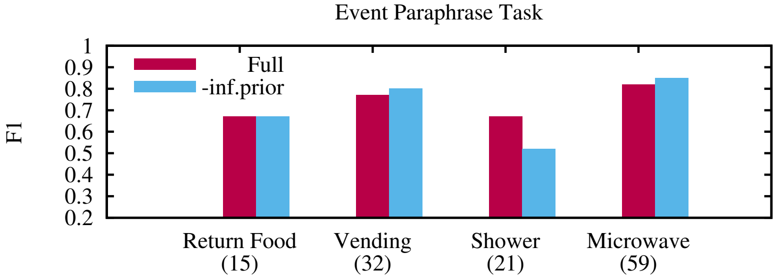

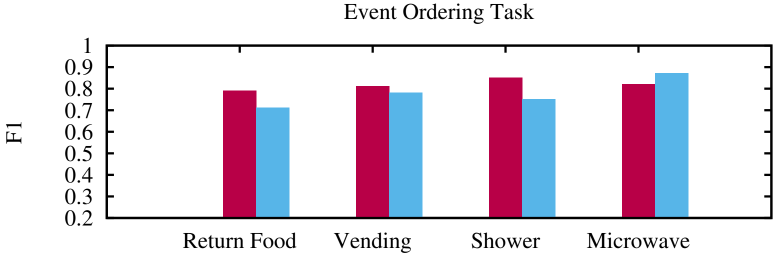

Induced Clustering

Cooking food in the microwave

$\{$get$\}$ $\rightarrow$ $\{$open,take$\}$ $\rightarrow$ $\{$put,place$\}$ $\rightarrow$ $\{$close$\}$

$\rightarrow$ $\{$set,select,enter,turn$\}$ $\rightarrow$ $\{$start$\}$ $\rightarrow$ $\{$wait$\}$

$\rightarrow$ $\{$remove,take,open$\}$ $\rightarrow$ $\{$push,press,turn$\}$

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Conclusion

A hierarchical Bayesian Script model

- joint model of event types and ordering constraints
- competitive performance with a recent pipeline-based model
- inclusion of word similarity knowledge as correlations in the language model priors
- explicitly target apparent script characteristics (event optionality, event type-specific temporal flexibility)
- GMM as an effective model for event ordering constraints

Conclusion

A hierarchical Bayesian Script model

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- competitive performance with a recent pipeline-based model
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Thank you!

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