

# Integrating Topics and Syntax

Paper Presentation

CSC 665 – Advanced Topics in Probabilistic Graphical Models

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# Outline

- Introduction
- Background
- Model
- Inference
- Results

# Introduction

- Word dependencies
  - Short-range (syntax)
  - Long-range (context)
- Generative Model
  - Both kinds of dependencies
  - Syntactic classes and semantic topics
    - no representation beyond statistical dependency

# Background

- Syntactic Class

- Short-range
- Syntax
- Span words within the limit of a sentence
- Function Words
- Handled by Hidden Markov Model

- Semantic Topic

- Long-range
- Context
- Span words throughout the document (similar words)
- Content Words
- Handled by topic model

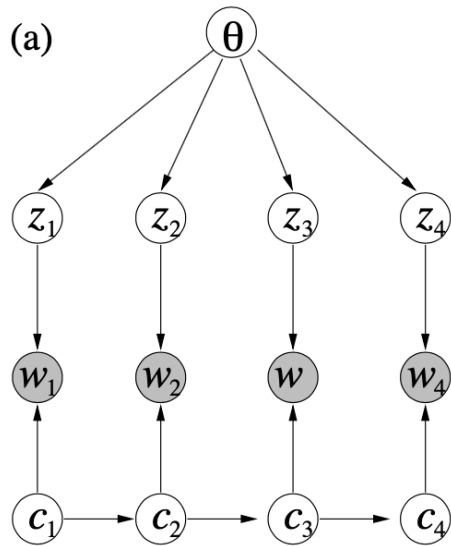
# Model

- Captures the interaction between the two components
  - Modularity
- Identify the role that words play in a document
  - Organizes words into syntactic and semantic classes
- Combination of two models
  - Each sensitive to one kind of dependency
- Mixture: either short- or long-range dependencies
- Product: both short- and long-range dependencies
- Asymmetry captured in a **composite** model

# Composite Model

- The syntactic model
  - HMM
  - when to emit a content word, and
- The semantic model to choose
  - Topic model
  - which word to emit.
- Three sets of variables:
  - A sequence of words  $w = \{w_1, \dots, w_n\}$
  - A sequence of topic assignments  $z = \{z_1, \dots, z_n\}$
  - A sequence of classes  $c = \{c_1, \dots, c_n\}$ 
    - One class  $c_i = 1$  is designated the “semantic” class.

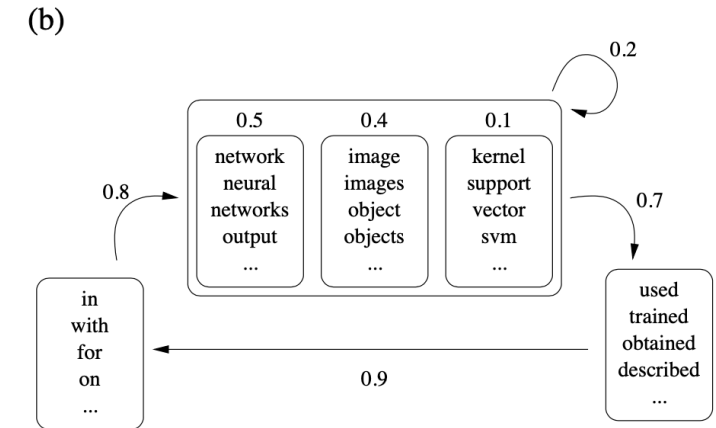
# Composite Model



- a distribution over words  $\phi^{(z)}$
- each class  $c \neq 1$  is associated with a distribution over words  $\phi^{(c)}$
- $d$  has a distribution over topics  $\theta^{(d)}$
- transitions between classes  $c_{i-1}$  and  $c_i$  follow a distribution  $\pi^{(c_{i-1})}$
- Document generation:
  - 1) Sample  $\theta^{(d)}$  from a Dirichlet ( $\alpha$ ) prior
  - 2) For each word  $w_i$  in document  $d$ 
    - Draw  $z_i$  from  $\theta^{(d)}$
    - Draw  $c_i$  from  $\pi^{(c_{i-1})}$
    - If  $c_i = 1$ , then draw  $w_i$  from  $\phi^{(z_i)}$  (**semantic**), else draw  $w_i$  from  $\phi^{(c_i)}$  (**syntactic**)

# Composite Model

- Phrase generation
- Three-class HMM
  - Multinomial distributions over words ( $c_i \neq 1$ )
  - Topic model containing three topics ( $c_i = 1$ )
- Probabilities in semantic class
  - to choose a topic when the HMM transitions to the semantic class
  - generate sentences with the same syntax but different content





# Inference

- $\theta$ : Dirichlet( $\alpha$ ) distribution
- $\phi^{(z)}$ : Dirichlet( $\beta$ ) distribution
- rows of the transition matrix: HMM Dirichlet( $\gamma$ ) distribution
- $\phi^{(c)}$ : Dirichlet( $\delta$ ) distribution
- All Dirichlet distributions are symmetric (uniform vector of reals)
- Gibbs Sampling
  - Draw topic and class assignment
  - Collapsed Gibbs Sampling (HMM)

# Results

- Syntactic classes and semantic topics
  - HMM allocates content words into semantic class
  - Assigned to topics
- Identifying function and content words
  - Factorization of words between the two components
- Marginal Probabilities
  - LDA outperforms on smaller corpora compared to HMM model
- **Part-of-speech tagging**
  - Focus on identifying the syntactic class of a word
- **Document Classification**
  - Grouping documents according to context