Probabilistic Models in Tikz

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Tikz macros and examples for probabilistic models. I use the directed factor graph notation in most figures, but you can use the same macros to draw Bayesian networks.

Chapter 1

Foundations

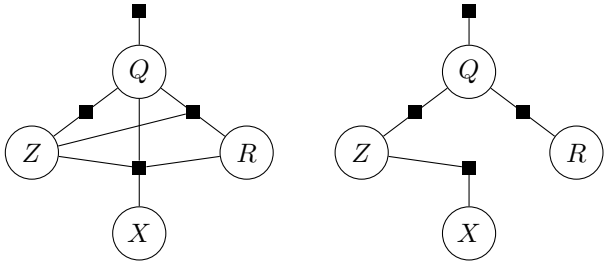

Figure 1.1: Factor graphs for visualizing factorizations of a joint distribution $p(X, Z, R, Q)$. a) General factorization, b) Factorization with conditional independence assumptions.

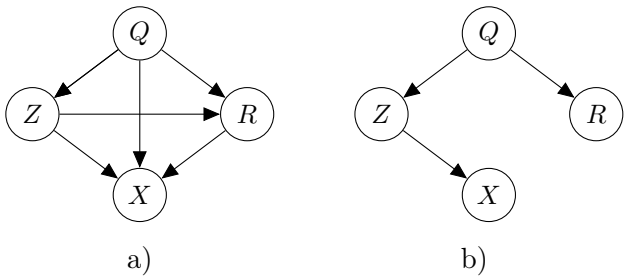

Figure 1.2: Bayesian network visualization for factor graphs in Figure 1.1.

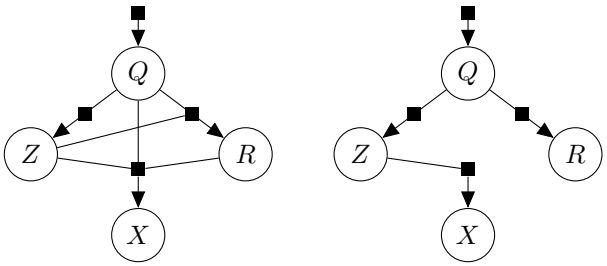

Figure 1.3: Directed factor graph visualization for factor graphs in Figure 1.1.

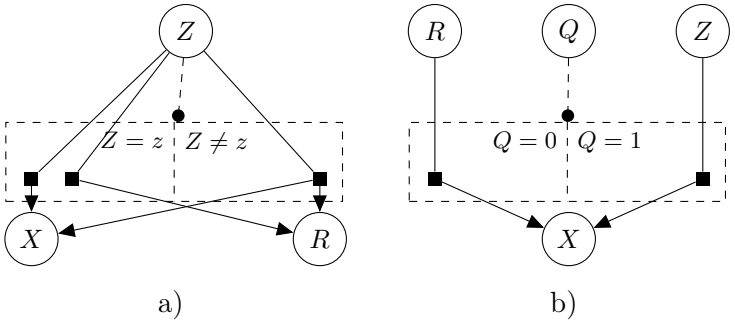

Figure 1.4: Representing context-specific independence by gates (dashed boxes) in factor graphs.

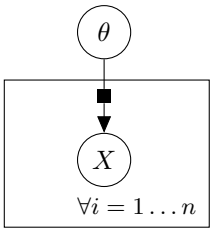

Figure 1.5: Representing repetition of connection templates by plates (solid boxes) in factor graphs.

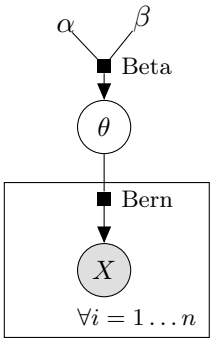

Figure 1.6: Beta-Bernoulli example with hyperparameters.

1.1 Latent Dirichlet Allocation

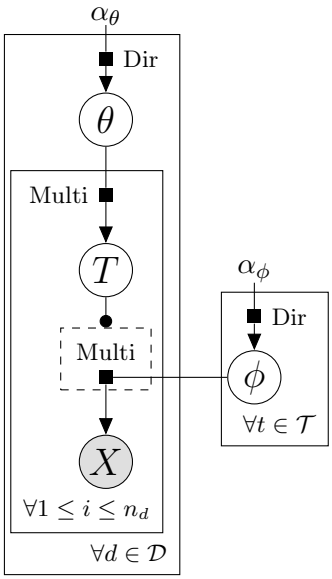

Figure 1.7: Latent Dirichlet allocation as directed factor graph.

Chapter 2

Citation Influence Model

2.1 Plain Citation Influence Model

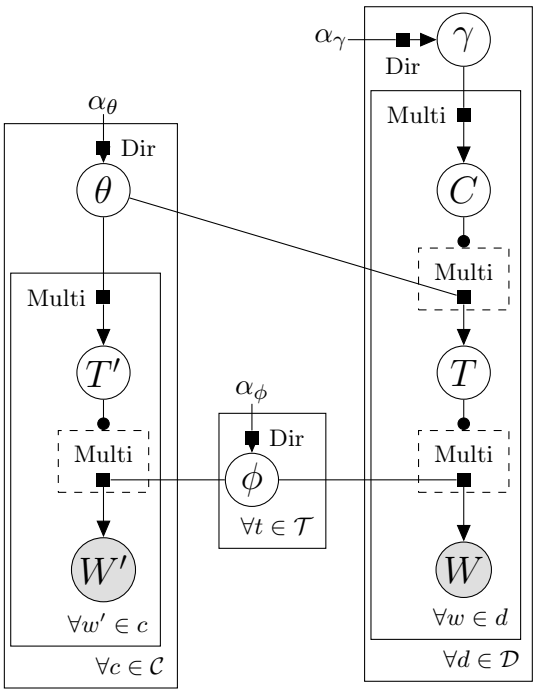

Figure 2.1: Citation influence model in directed factor graph notation.

Algorithm 2.1 Generative process of the plain citation influence model. For a description of each variable see Table 2.1.

for all $t \in \mathcal{T}$ **do**
  draw $\phi_t \sim \mathrm{Dir}(\alpha_\phi)$
for all $c \in \mathcal{C}$ as cited role **do**
  draw $\theta_c \sim \mathrm{Dir}(\alpha_\theta)$
  // Generate content w according to LDA:
  for all words $w'_{c,i} \in c$ **do**
    draw topic $T'_{c,i} \sim \mathrm{Multi}(\theta_c)$
    draw word $W'_{c,i} \sim \mathrm{Multi}(\phi_{T'_{c,i}})$
for all $d \in \mathcal{D}$ as citing role **do**
  draw $\gamma_d \sim \mathrm{Dir}(\alpha_\gamma)$
  for all words $w_{d,i} \in d$ **do**
    draw citation $C_{d,i} \sim \mathrm{Multi}(\gamma_d)$
    draw topic $T_{d,i} \sim \mathrm{Multi}(\theta_{C_{d,i}})$
    draw word $W_{d,i} \sim \mathrm{Multi}(\phi_{T_{d,i}})$

Table 2.1: Notation for the plain citation influence model. Variables in the cited plate are denoted with prime.

Symbol	Description
C, c	cited publication
d	citing publication
θ	shared topic mixture associated with a cited publication
ϕ	characteristic word distribution for each topic
γ	distribution of citation influences
W', W	words in cited, citing publications respectively
T', T	topic assignments of tokens in cited, citing publications respectively
α	Dirichlet / beta parameters of the multinomial / Bernoulli distributions

2.2 Citation Influence Model with Own Topics

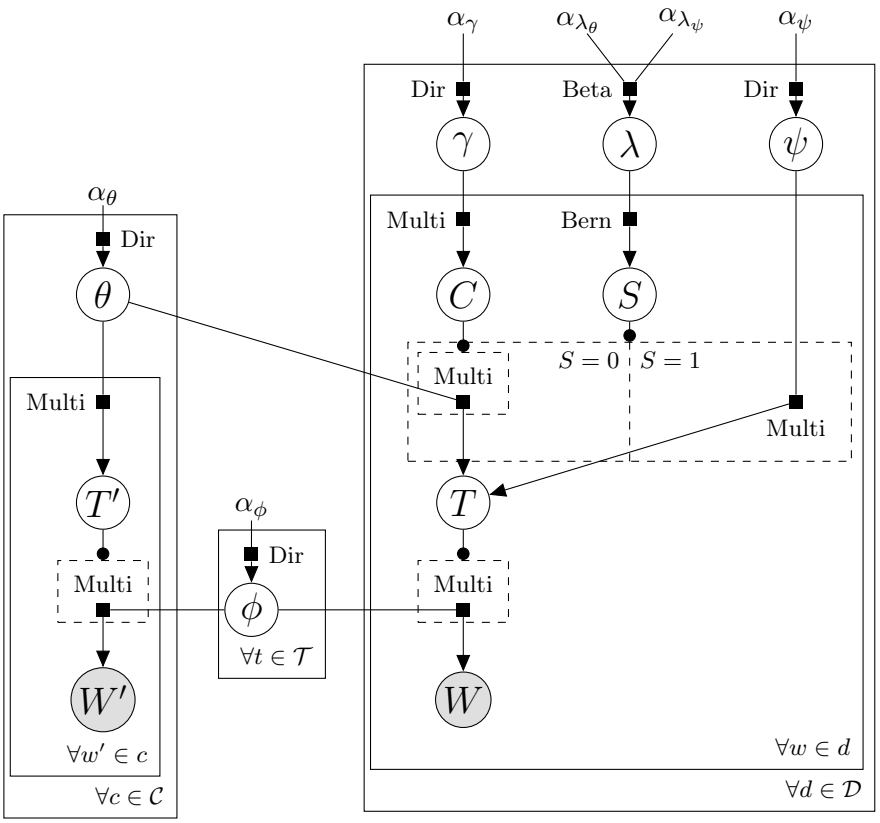

Figure 2.2: Citation influence model with own topics as directed factor graph.

Table 2.2: Further notation used in the citation influence model with own topics.

Symbol	Description
ψ	innovation topic mixture of a citing publication
λ	parameter of the coin flip, choosing to draw topics from θ or ψ
S	indicates whether the topic of a citing publication is drawn from inheritance or innovation

Algorithm 2.2 Generative process of the citation influence model with own topics.

for all $t \in \mathcal{T}$ **do**
  draw $\phi_t \sim \mathrm{Dir}(\alpha_\phi)$ ranging over the vocabulary $\mathcal{V}$.
for all cited $c \in \mathcal{C}$ **do**
  draw topic mixture $\theta_c \sim \mathrm{Dir}(\alpha_\theta)$ ranging over topics $\mathcal{T}$.
  // Generate content w according to LDA:
  for all words $w_{c,i} \in c$ **do**
    draw topic $T'_{c,i} \sim \mathrm{Multi}(\theta_c)$
    draw word $W'_{c,i} \sim \mathrm{Multi}(\phi_{T'_{c,i}})$
for all citing $d \in \mathcal{D}$ **do**
  draw $\gamma_d \sim \mathrm{Dir}(\alpha_\gamma)$ ranging over $L(d)$.
  draw $\lambda_d \sim \mathrm{Beta}(\alpha_{\lambda_\theta}, \alpha_{\lambda_\psi})$
  draw $\psi_d \sim \mathrm{Dir}(\alpha_\psi)$ ranging over topics $\mathcal{T}$.
  for all words $w_{d,i} \in d$ **do**
    draw coin toss $S_{d,i} \sim \mathrm{Bern}(\lambda_d)$
    if $S_{d,i} = 0$ **then**
      // Generate token by inheritance:
      draw a cited publication $C_{d,i} \sim \mathrm{Multi}(\gamma_d)$.
      draw topic $T_{d,i} \sim \mathrm{Multi}(\theta_{C_{d,i}})$ from the cited document's topic mixture.
    else if $S_{d,i} = 1$ **then**
      // Generate token by innovation:
      draw topic $T_{d,i} \sim \mathrm{Multi}(\psi_d)$ from the own topic mixture.
    draw word $W_{d,i} \sim \mathrm{Multi}(\phi_{T_{d,i}})$

Chapter 3

Shared Taste Model

3.1 Plain Shared Taste Model

Symbol	Description
$\lambda_{\{u,f\}}$	Shared topic mixture associated with the undirected edge between users u and f.
T	Topic for items.
ϕ	Item distribution for each topic.
ψ_u	Distribution over friends of user u according to their strength of influence on the user's content.
F	Friend associated with an observed item (if not explained by "own topics").
X	Observed item in contents of the user.
Ω_u	Background topic mixture of the user (the own topics). Alternatively a mixture over own items.
ϵ	Coin parameter deciding on how much content of the user is explained by the "own topics"
E	Boolean indicator, if 1, the observed item is explained by the "own topics" rather than the shared topics.

Table 3.1: Notation for shared taste model with own topics.

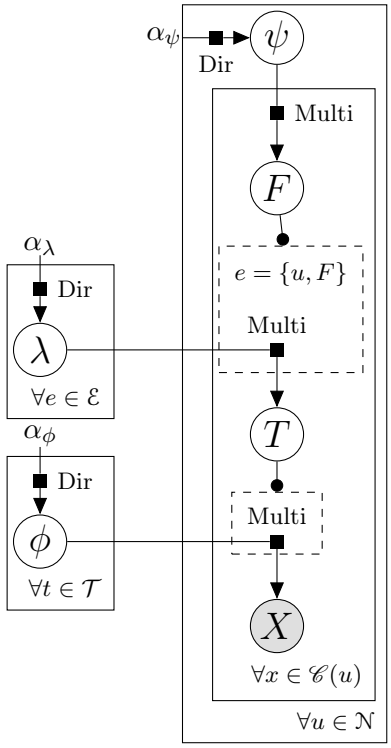

Figure 3.1: Shared taste model as directed factor graph.

Algorithm 3.1 Generative process of the shared taste model.

for all $t \in \mathcal{T}$ **do**
  draw $\phi_t \sim \mathrm{Dir}(\alpha_\phi)$
for all $\{u, f\} \in \mathcal{E}$ **do**
  draw shared topic mixture $\lambda_{\{f,u\}} = \lambda_{\{u,f\}} \sim \mathrm{Dir}(\alpha_\lambda)$.
for all $u \in \mathcal{N}$ **do**
  draw friend mixture $\psi_u \sim \mathrm{Dir}(\alpha_\psi)$ ranging over friends of u.
  for all items $x_{u,i} \in \mathcal{C}(u)$ **do**
    draw friend $F_{u,i} \sim \mathrm{Multi}(\psi_u)$
    draw topic $T_{u,i} \sim \mathrm{Multi}(\lambda_{\{u,F_{u,i}\}})$
    draw item $X_{u,i} \sim \mathrm{Multi}(\phi_{T_{u,i}})$

3.2 Shared Taste Model with Own Topics

Algorithm 3.2 Generative process of the shared taste model with own topics.

for all $t \in \mathcal{T}$ **do**
  draw $\phi_t \sim \mathrm{Dir}(\alpha_\phi)$
for all $\{u, f\} \in \mathcal{E}$ **do**
  draw shared topic mixture $\lambda_{\{f,u\}} = \lambda_{\{u,f\}} \sim \mathrm{Dir}(\alpha_\lambda)$.
for all $u \in \mathcal{N}$ **do**
  draw friend mixture $\psi_u \sim \mathrm{Dir}(\alpha_\psi)$ ranging over friends of u.
  draw background distribution $\Omega_u \sim \mathrm{Dir}(\alpha_\Omega)$
  draw background coin $\epsilon_u \sim \mathrm{Beta}(a_\epsilon, b_\epsilon)$
  for all item $x_{u,i} \in \mathcal{C}(u)$ **do**
    draw coin flip $E_{u,i} \sim \mathrm{Bern}(\epsilon_u)$
    if $E_{u,i} = 0$ **then**
      // Generate from shared topic.
      draw friend $F_{u,i} \sim \mathrm{Multi}(\psi_u)$
      draw topic $T_{u,i} \sim \mathrm{Multi}(\lambda_{\{u,F_{u,i}\}})$ from share topics
    else if $E_{u,i} = 1$ **then**
      // Generate from background.
      draw topic $T_{u,i} \sim \mathrm{Multi}(\Omega_u)$ from own topics
    draw item $X_{u,i} \sim \mathrm{Multi}(\phi_{T_{u,i}})$

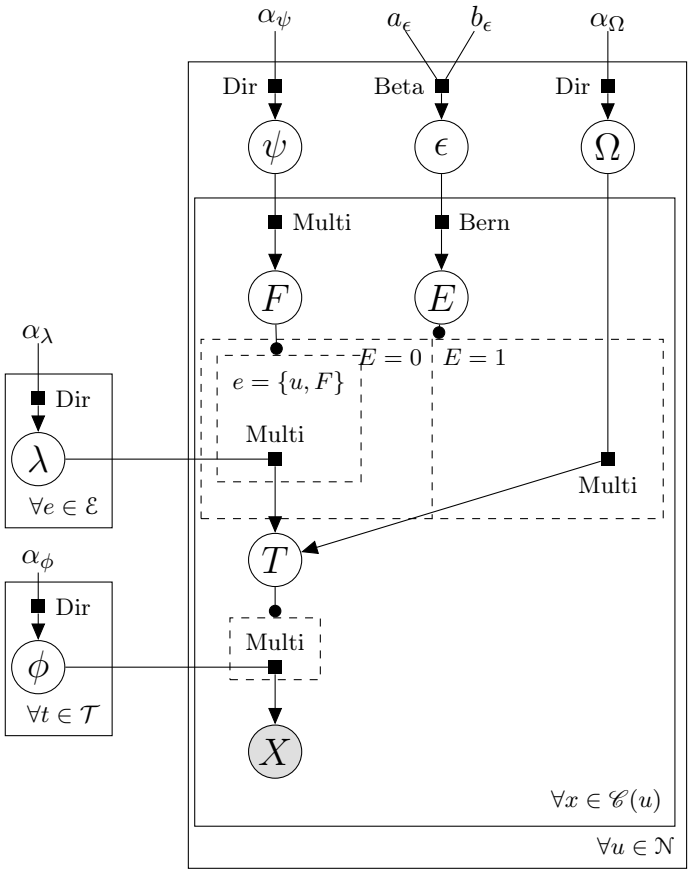

Figure 3.2: Shared taste model with own topics as directed factor graph.

3.3 Pairwise Link LDA model (Nallapati 08)

The original pairwise Link LDA model (Nallapati, Ahmed, Xing, Cohen. Joint latent topic models for text and citations, KDD, 2008) is modified to correct for rarity of interactions (Airoldi, Blei, Fienberg, Xing. Mixed membership stochastic blockmodels, JMLR, 2008).

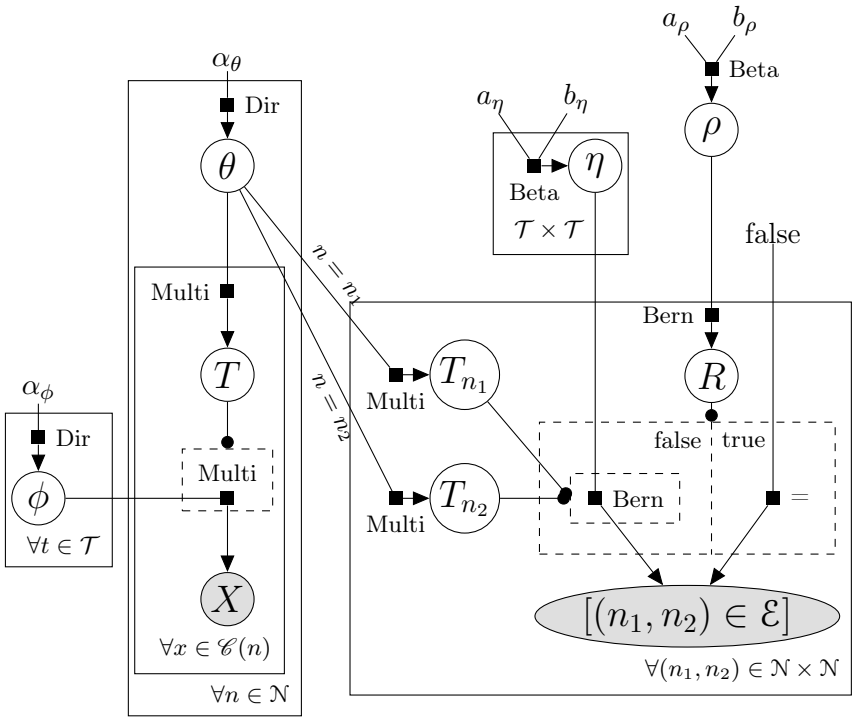

Figure 3.3: Pairwise Link LDA model as directed factor graph.