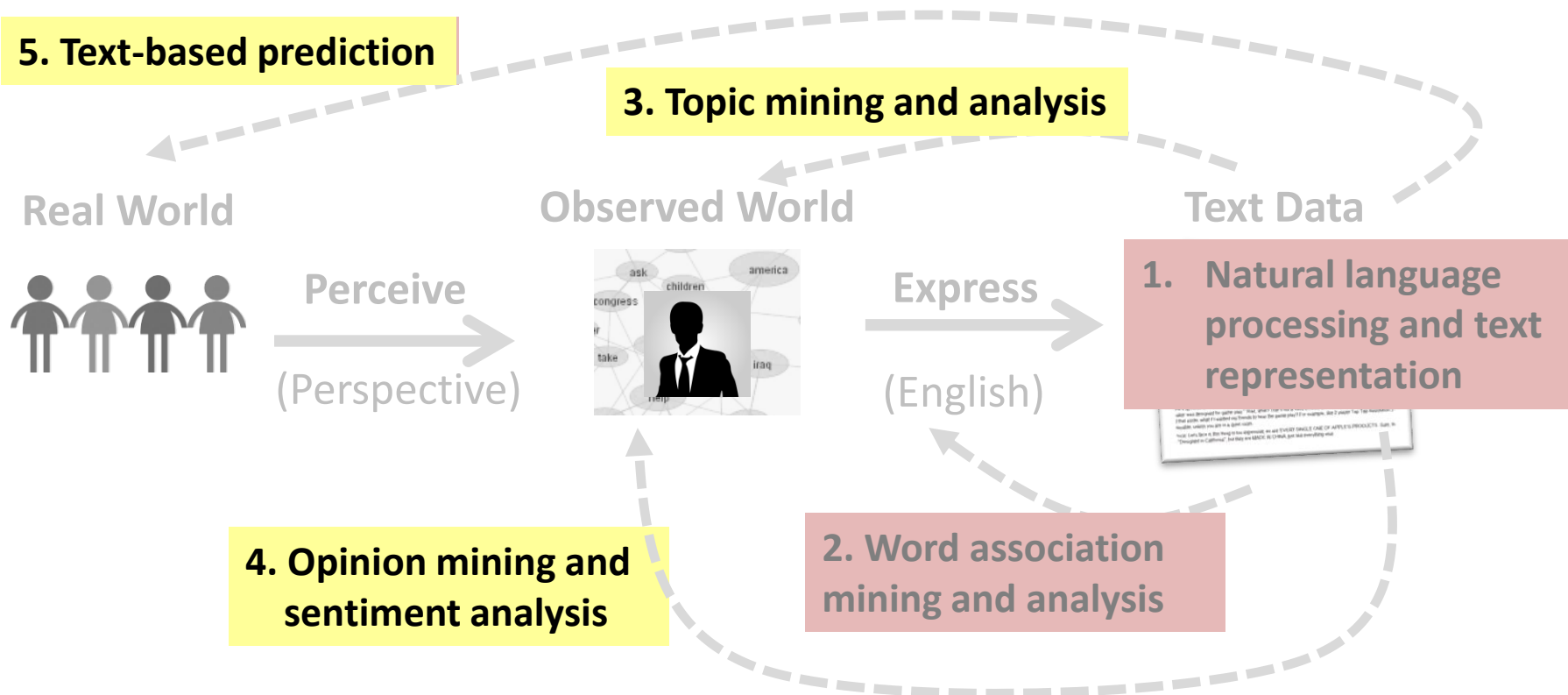




Contextual Text Mining: Mining Topics with Social Network Context

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Contextual Text Mining: Mining Topics with Social Network as Context



Topic Analysis with Network Context

- The **context** of a text article can form a **network**, e.g.,
 - Authors of research articles may form **collaboration networks**
 - Authors of social media content form **social networks**
 - Locations associated with text can be connected to form a **geographic network**
- **Benefit of joint analysis** of text and its network context
 - Network imposes **constraints** on topics in text (**authors connected in a network tend to write about similar topics**)
 - Text helps **characterize** the content associated with each subnetwork (e.g., difference in opinions expressed in two subnetworks?)

Network Supervised Topic Modeling: General Idea

[Mei et al. 08]

- Probabilistic topic modeling as optimization: maximize likelihood

$$\Lambda^* = \arg \max_{\Lambda} p(\text{TextData} \mid \Lambda)$$

- Main idea: network imposes constraints on model parameters Λ
 - The text at two adjacent nodes of the network tends to cover similar topics
 - Topic distributions are smoothed over adjacent nodes
 - Add network-induced regularizers to the likelihood objective function

Any generative model

Any network

$$\Lambda^* = \arg \max_{\Lambda} f(p(\text{TextData} \mid \Lambda), r(\Lambda, \text{Network}))$$

Any way to combine

Any regularizer

Instantiation: NetPLSA [Mei et al. 08]

Network-induced prior: Neighbors have similar topic distribution

Modified objective function

Text collection

PLSA log-likelihood

$$O(C, G) = (1 - \lambda) \cdot \left(\sum_d \sum_w c(w, d) \log \sum_{j=1}^k p(\theta_j | d) p(w | \theta_j) \right) + \lambda \cdot \left(-\frac{1}{2} \sum_{\langle u, v \rangle \in E} \frac{w(u, v)}{\sum_{j=1}^k (p(\theta_j | u) - p(\theta_j | v))^2} \right)$$

Network graph

Influence of network constraint

Weight of edge (u,v)

Quantify the difference in the topic coverage at node u and v

蓝号, 累加, 后边.

Mining 4 Topical Communities: Results of PLSA

Can't uncover the 4 communities (IR, DM, ML, Web)

Topic 1		Topic 2		Topic 3		Topic 4	
term	0.02	peer	0.02	visual	0.02	interface	0.02
question	0.02	patterns	0.01	analog	0.02	towards	0.02
protein	0.01	mining	0.01	neurons	0.02	browsing	0.02
training	0.01	clusters	0.01	vlsi	0.01	xml	0.01
weighting	0.01	stream	0.01	motion	0.01	generation	0.01
multiple	0.01	frequent	0.01	chip	0.01	design	0.01
recognition	0.01	e	0.01	natural	0.01	engine	0.01
relations	0.01	page	0.01	cortex	0.01	service	0.01
library	0.01	gene	0.01	spike	0.01	social	0.01

Mining 4 Topical Communities: Results of NetPLSA

Uncovers the 4 communities well

Information Retrieval		Data Mining		Machine Learning		Web	
retrieval	0.13	mining	0.11	neural	0.06	web	0.05
information	0.05	data	0.06	learning	0.02	services	0.03
document	0.03	discovery	0.03	networks	0.02	semantic	0.03
query	0.03	databases	0.02	recognition	0.02	services	0.03
text	0.03	rules	0.02	analog	0.01	peer	0.02
search	0.03	association	0.02	vlsi	0.01	ontologies	0.02
evaluation	0.02	patterns	0.02	neurons	0.01	rdf	0.02
user	0.02	frequent	0.01	gaussian	0.01	management	0.01
relevance	0.02	streams	0.01	network	0.01	ontology	0.01

Text Information Network

- In general, we can view text data that naturally “lives” in a rich information network with all other related data
- Text data can be associated with
 - Nodes of the network
 - Edges of the network
 - Paths of the network
 - Subnetworks
 - ...
- Analysis of text should be using the entire network!

Suggested Reading

- **[Mei et al. 08]** Qiaozhu Mei, Deng Cai, Duo Zhang, and ChengXiang Zhai. 2008. Topic modeling with network regularization. In *Proceedings of the 17th international conference on World Wide Web (WWW 2008)*. ACM, New York, NY, USA, 101-110. DOI=10.1145/1367497.1367512