Topic Mining and Analysis: Probabilistic Topic Models

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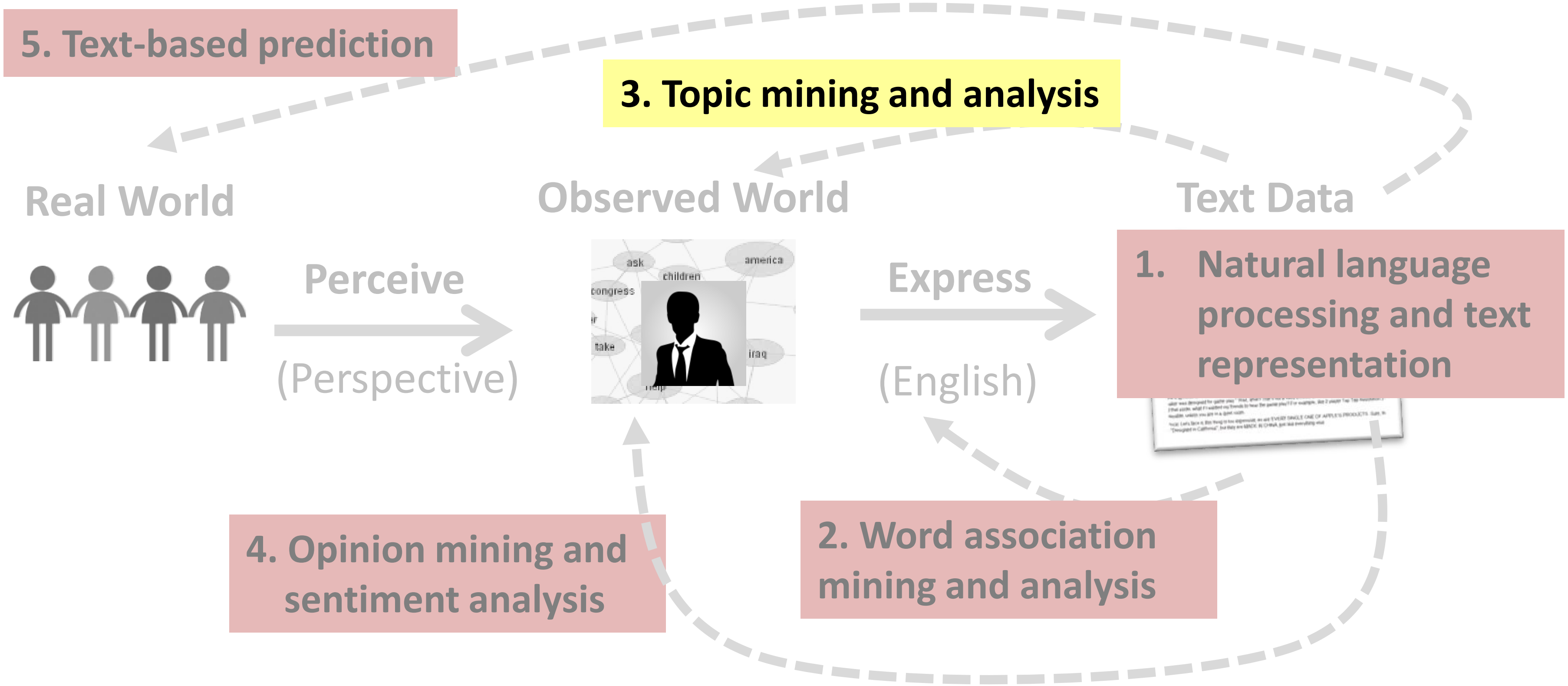


5. Text-based prediction

3. Topic mining and analysis

Real World

Observed World

Text Data

Perceive

(Perspective)

Express

(English)

1. Natural language processing and text representation

4. Opinion mining and sentiment analysis

2. Word association mining and analysis

Problems with “Term as Topic”

- Lack of expressive power

  ➔ Topic = {Multiple Words}

  – Can only represent simple/general topics

  – Can’t represent complicated topics

- Incompleteness in vocabulary coverage

  + weights on words

  – Can’t capture variations of vocabulary (e.g., related words)

- Word sense ambiguity

  ➔ Split an ambiguous word

  – A topical term or related term can be ambiguous (e.g., basketball star vs. star in the sky)

A probabilistic topic model can do all these!

Improved Idea: Topic = Word Distribution

θ_1 "Sports"

$P(w|\theta_1)$

词汇表.

sports	0.02
game	0.01
basketball	0.005
football	0.004
play	0.003
star	0.003
…	
nba	0.001
…	
travel	0.0005
…	

θ_2 "Travel"

$P(w|\theta_2)$

travel	0.05
attraction	0.03
trip	0.01
flight	0.004
hotel	0.003
island	0.003
…	
culture	0.001
…	
play	0.0002
…	

所有词的概率都不为0.

●●●

θ_k "Science"

$P(w|\theta_k)$

science	0.04
scientist	0.03
spaceship	0.006
telescope	0.004
genomics	0.004
star	0.002
…	
genetics	0.001
…	
travel	0.00001
…	

$$\sum_{w \in V} p(w|\theta_i) = 1$$

Vocabulary Set: V={w1, w2,….}

Probabilistic Topic Mining and Analysis

- Input
  - A **collection** of **N** text documents **$C=\{d_1, \ldots, d_N\}$**
  - **Vocabulary set: $V=\{w_1, \ldots, w_M\}$**
  - **Number of topics**: **k**
- Output
  - **k topics, each a word distribution**: **$\{ \theta_1, \ldots, \theta_k \}$**
  - **Coverage of topics in each d_i**: **$\{ \pi_{i1}, \ldots, \pi_{ik} \}$**
  - π_{ij}=prob. of d_i covering topic θ_j

$$\sum_{w \in V} p(w \mid \theta_i) = 1$$

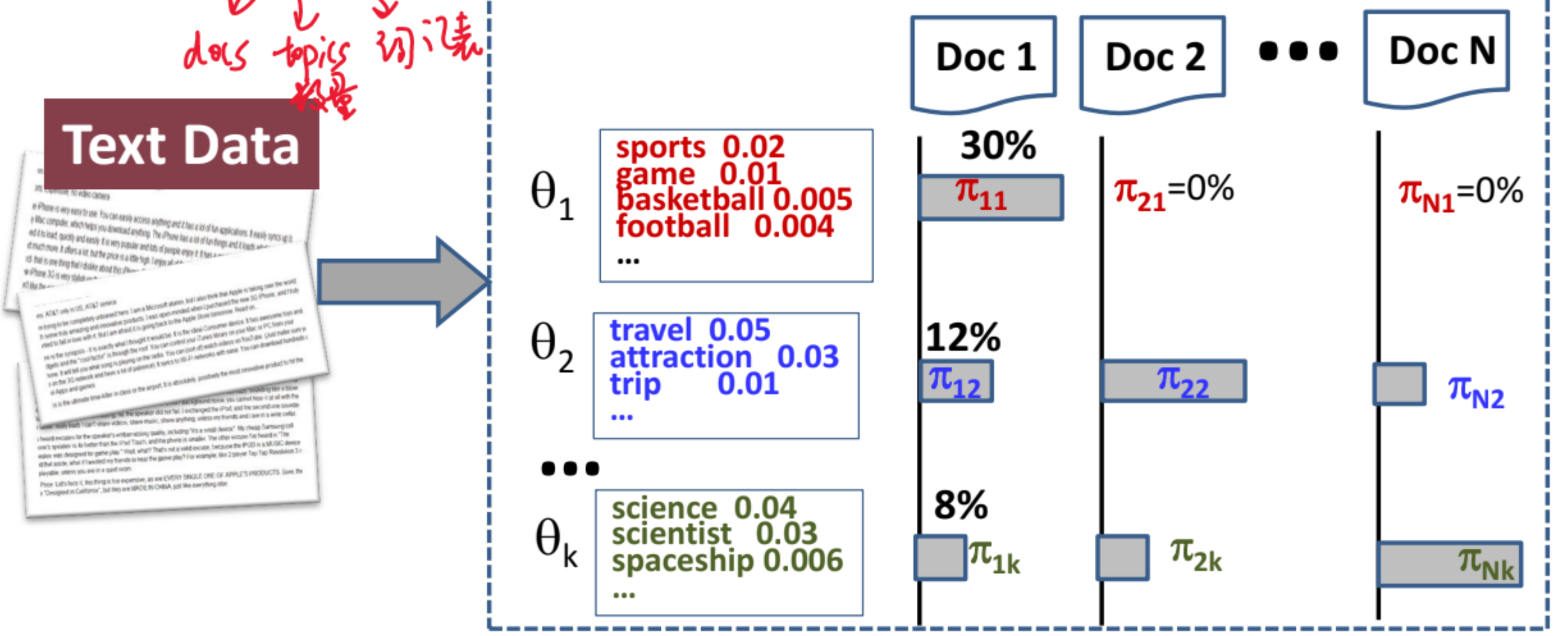
$$\sum_{j=1}^{k} \pi_{ij} = 1$$

The Computation Task

INPUT: C, k, V

docs topics 数量 词汇表

OUTPUT: { θ_1, …, θ_k }, { π_{i1}, …, π_{ik} }



Generative Model for Text Mining

Modeling of Data Generation: P(Data |Model, Λ)

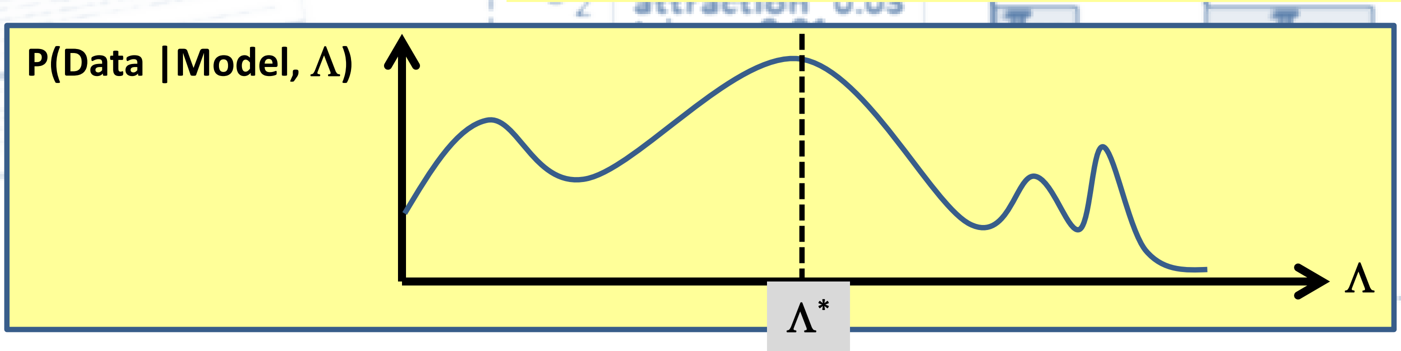
$\Lambda=(\{\theta_1, \dots, \theta_k\}, \{\pi_{11}, \dots, \pi_{1k}\}, \dots, \{\pi_{N1}, \dots, \pi_{Nk}\})$

Text Data

How many parameters in total?

Parameter Estimation/ Inferences

$\Lambda^* = \text{argmax}_{\Lambda}\, p(\text{Data} \mid \text{Model}, \Lambda)$



Summary

- Topic represented as word distribution
  - Multiple words: allow for describing a complicated topic
  - Weights on words: model subtle semantic variations of a topic
- Task of topic mining and analysis
  - Input: collection C, number of topics k, vocabulary set V
  - Output: a set of topics, each a word distribution; coverage of all topics in each document

$$\Lambda=(\{ \theta_1, \ldots, \theta_k \}, \{ \pi_{11}, \ldots, \pi_{1k} \}, \ldots, \{ \pi_{N1}, \ldots, \pi_{Nk} \})$$

$$\forall j \in [1,k], \sum_{w \in V} p(w \mid \theta_j) = 1$$

$$\forall i \in [1,N], \sum_{j=1}^{k} \pi_{ij} = 1$$

Summary (cont.)

- **Generative model** for text mining
  - **Model data generation** with a prob. model: **P(Data |Model, Λ)**
  - **Infer the most likely parameter values Λ^*** given a particular data set**:** **Λ^* = argmax $_\Lambda$ p(Data| Model, Λ)**
  - **Take Λ^* as the "knowledge"** to be mined for the text mining problem
  - **Adjust** the design of the model to discover different knowledge