Beyond Bag-of-Words

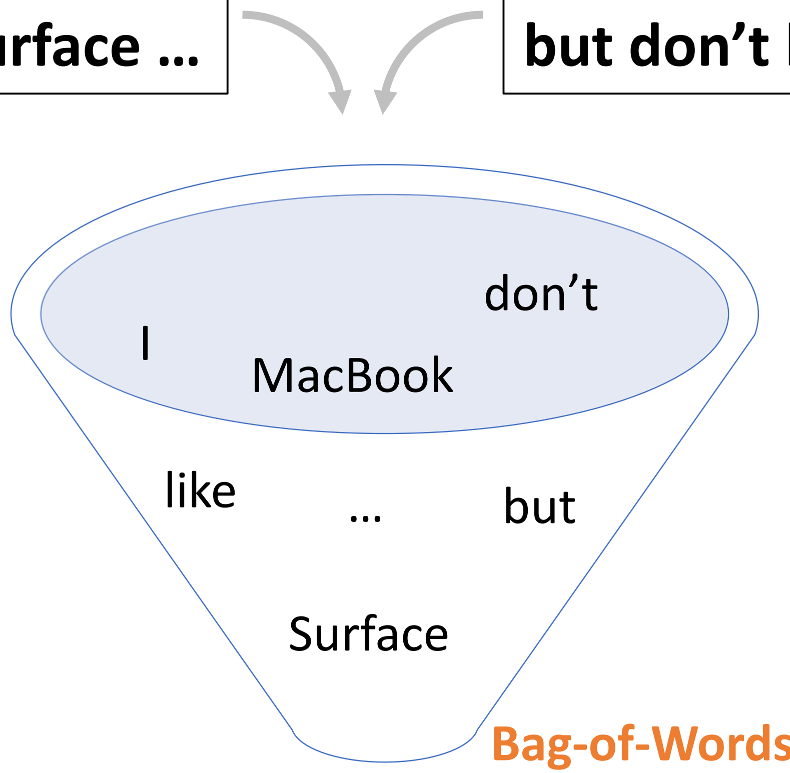
Customer Review Analysis Using Word Embedding Model Considering Text Topics and Sentiments

(work with N. Terui and P.K. Kannan)

Introduction

I like MacBook …
but don’t like Surface …

I like Surface …
but don’t like MacBook…



Word2vec

→単語のベクトル表現を学習するニューラルネットワーク

$$\overrightarrow{w_i} = \{w_{i1}, \ldots, w_{iN}\}$$

Skipgramモデル

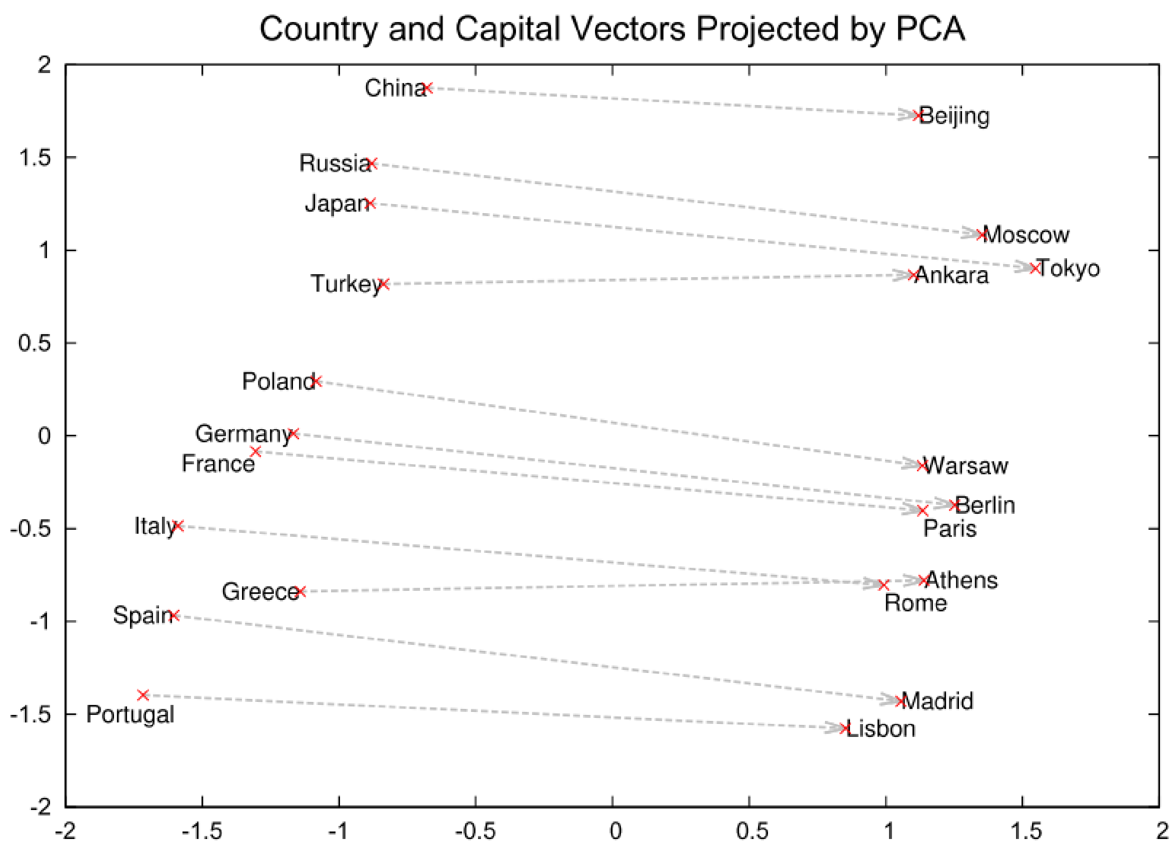
$$p(w_O | w_I) = \frac{\exp(\overrightarrow{w'_O} \cdot \overrightarrow{w_I})}{\sum_v \exp(\overrightarrow{w'_v} \cdot \overrightarrow{w_I})}$$

目的関数

$$\arg\max_{w, w'} p(w_{O1}, \ldots, w_{OC} | w_I) = \prod_{c=1}^{C} \frac{\exp(\overrightarrow{w'_{Oc}} \cdot \overrightarrow{w_I})}{\sum_v \exp(\overrightarrow{w'_v} \cdot \overrightarrow{w_I})}$$

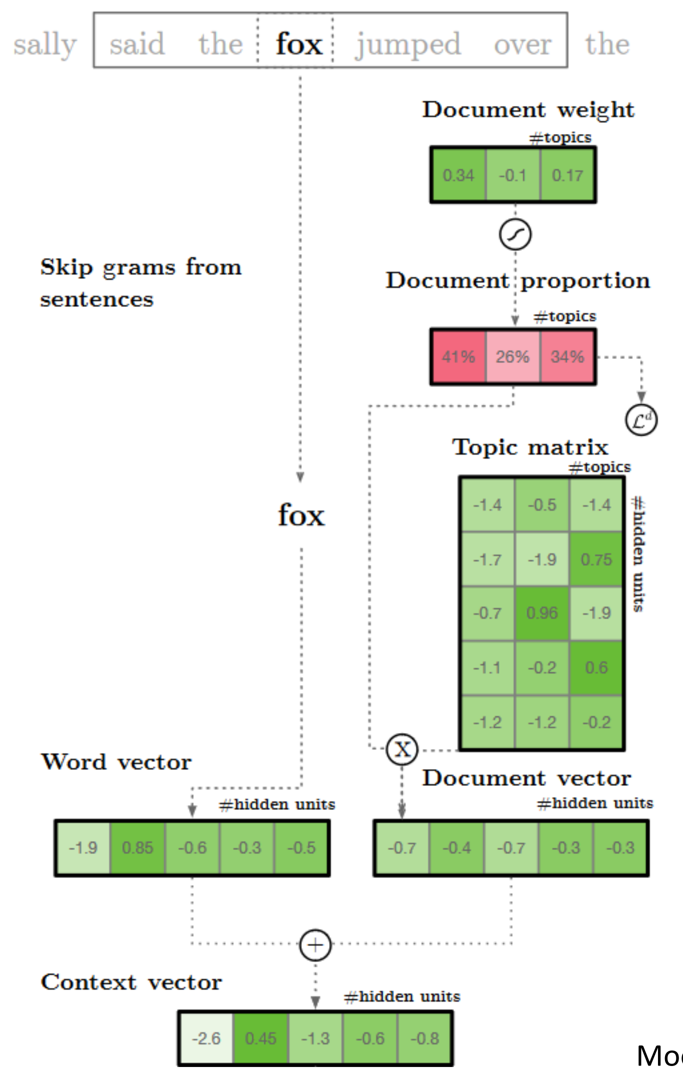
Word2vec

→ローカルな共起関係を考慮して単語をベクトル空間に射影する



Mikolov et al. (2013)

LDA2vec



Moody (2016)

LDA2vec

Context vector

$$\overrightarrow{c_{ih}} = \overrightarrow{w_i} + \overrightarrow{d_h}$$

Document vector

$$\overrightarrow{d_h} = \theta_{h1} \cdot \overrightarrow{t_1} + \cdots + \theta_{hK} \cdot \overrightarrow{t_K}$$

Loss functions

$$L = L^w + L^d$$

$$L^w = \sum_{i,j,h} \left\{ \log \sigma(\overrightarrow{c_{ih}} \cdot \overrightarrow{w_j}) + \sum_{n} \log \sigma(-\overrightarrow{c_{ih}} \cdot \overrightarrow{w_n}) \right\}$$

$$L^d = \sum_{h=1}^{H} \left\{ \lambda(\alpha - 1) \sum_{k=1}^{K} \log \theta_{hk} \right\}$$

LDA2vec with rating regression

Model

$$\overrightarrow{c_{ih}} = \overrightarrow{w_i} + \overrightarrow{d_h}$$
$$\overrightarrow{d_h} = \theta_{h1} \cdot \overrightarrow{t_1} + \cdots + \theta_{hK} \cdot \overrightarrow{t_K}$$
$$y_h = l \quad \text{if } \tau_{l-1} \leq \hat{y}_h < \tau_l, \quad \tau_0 = -\infty, \tau_L = +\infty$$
$$\hat{y}_h = \theta_h^T \beta + \text{other variables}$$

Loss functions

$$L = L^w + L^d + L^y$$
$$L^w = \sum_{i,j,h} \left\{ \log \sigma(\overrightarrow{c_{ih}} \cdot \overrightarrow{w_j}) + \sum_n \log \sigma(-\overrightarrow{c_{ih}} \cdot \overrightarrow{w_n}) \right\}$$
$$L^d = \sum_{h=1}^{H} \left\{ \lambda(\alpha - 1) \sum_{k=1}^{K} \log \theta_{hk} \right\}$$
$$L^y = \sum_{h=1}^{H} \left\{ \sum_{l=1}^{y_h - 1} \psi(-\gamma_{hl}) + \sum_{l=y_h}^{L} \psi(\gamma_{hl}) \right\}, \qquad \psi(\cdot) = \{\text{hinge, logistic, expoential, etc}\}$$

LDA2vec with rating regression

Simulation experiments

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Business	Entertainment	Sports	Technology	Politics
bank	film	match	mobil	parti
growth	award	champion	technolog	labour
profit	actor	cup	user	elect
oil	album	coach	comput	blair
yuko	chart	rugbi	phone	howard
sharehold	nomin	chelsea	softwar	mp
airlin	song	ireland	onlin	lord
stock	oscar	victori	digit	brown
deficit	rock	injuri	blog	lib

LDA2vec with rating regression

Simulation experiments

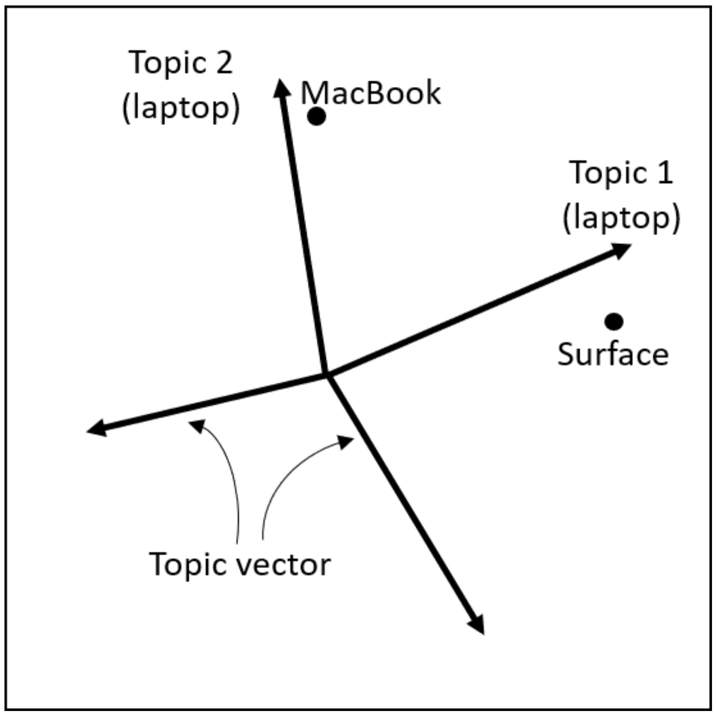
thresholds (τ)	1-2	2-3	3-4	4-5
true	-1.0	0.0	0.8	1.3
estimates	-1.19	-0.47	0.21	1.17

coefficients (β)	business	entertainment	sport	technology	politics
true	2.0	1.0	-1.0	-2.0	1.5
estimates	1.40	0.20	-1.12	-1.75	0.99

		True				
		5	4	3	2	1
Prediction	5	51	0	0	0	0
	4	9	60	0	0	0
	3	0	0	43	0	0
	2	0	0	17	60	6
	1	0	0	0	0	51

Sentiment LDA2vec

LDA2vec
Embedding space



極性を考慮
(positive / negative)

Sentiment LDA2vec

Embedding dimensionをpositiveとnegativeに分割

$$\overrightarrow{w_i} = \{\underbrace{0.23, \ldots, 0.45}_{\text{Positive}}, \underbrace{0.78, \ldots, 0.11}_{\text{Negative}}\}$$

半教師有学習（極性辞書を利用, Lin et al. 2016）

Positive単語 $\{w_{i,1}, \ldots, w_{i,N/2}, 0, \ldots, 0\}$

Negative単語 $\{0, \ldots, 0, w_{i,N/2+1}, \ldots, w_{i,N}\}$

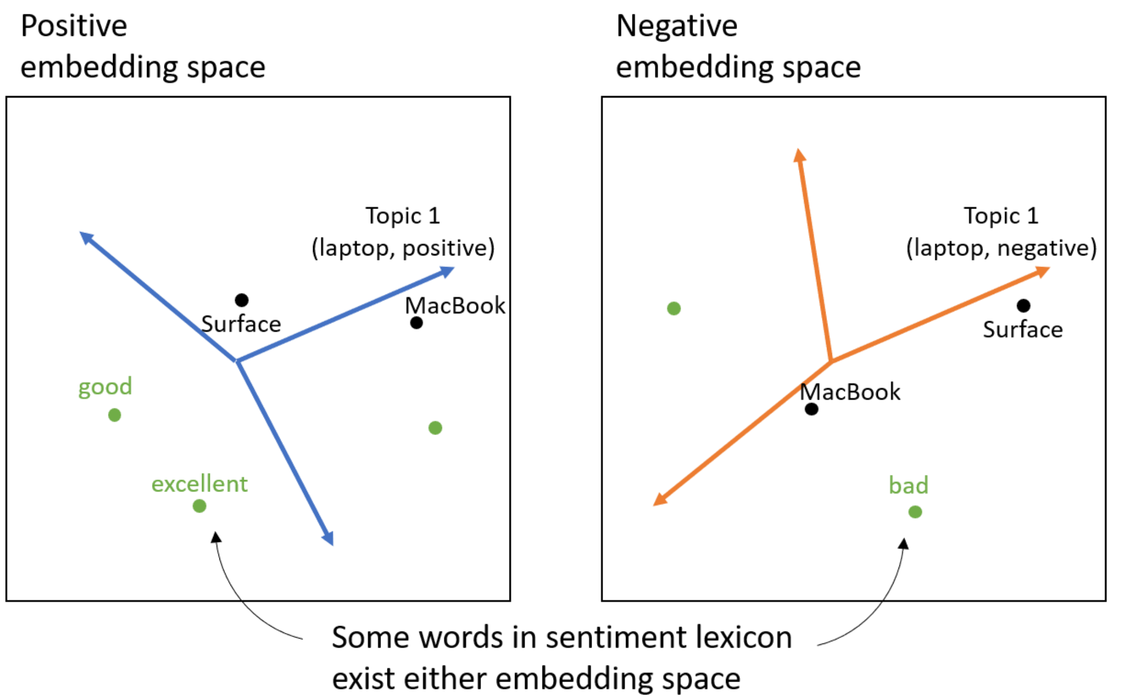
それ以外の単語 $\{w_{i,1}, \ldots, w_{i,N/2}, w_{i,N/2+1}, \ldots, w_{i,N}\}$

Sentiment LDA2vec

Model

$$\overrightarrow{c_{ih}} = \overrightarrow{w_i} + f_h \cdot \overrightarrow{d_{h,pos}} + (1 - f_h) \cdot \overrightarrow{d_{h,neg}}$$

$$\overrightarrow{d_{hm}} = \theta_{hm1} \cdot \overrightarrow{t_{m1}} + \cdots + \theta_{hmK} \cdot \overrightarrow{t_{mK}}, \qquad m \in \{positive, negative\}$$



Sentiment LDA2vec

Rating regression

$$
\begin{aligned}
y_h &= l, \qquad \text{if } \tau_{l-1} \leq \hat{y}_h < \tau_l, \qquad l = 1, \ldots, L \\
\hat{y}_h &= f_h \cdot \theta_{h,pos}^T \beta_{pos} + (1 - f_h) \cdot \theta_{h,neg}^T \beta_{neg} + \text{other variables}
\end{aligned}
$$

Future work

- Simulation experiment
- Bayesian estimation