

Distributed Representations of Web Browsing Sequences for Ad Targeting

<u>Yukihiro Tagami</u>, Hayato Kobayashi, Shingo Ono, Akira Tajima Yahoo Japan Corporation

- Apply an NLP approach to obtain user representations
 - Words -> URLs
 - Paragraphs -> Web browsing sequences (as user interests)
- Compare our Web page visits data with Wikipedia data
 - Frequencies of relative position in sequences are significantly different
- On the basis of the analysis, we propose Backward PV-DM
 - Achieved better results on two ad-related data sets





- In our work-in-progress paper, we proposed an approach:
 - To obtain distributed representations of users
 - From Web browsing sequences
 - Using Paragraph Vector
- PV learns distributed representations from pieces of text
 - Words -> URLs
 - Paragraphs -> Web browsing sequences (as user interests)

• Y. Tagami, H. Kobayashi, S. Ono, and A. Tajima. Modeling User Activities on the Web using Paragraph Vector. In *WWW Companion*, 2015.

User representations as features of prediction tasks







- Two data are probably generated from different distributions
 - Natural language data / Web page visits data
- In this study,
 - We investigate the difference between these distributions
 - On the basis of the difference, we propose Backward PV-DM
 - Evaluate this method on two ad-related prediction tasks

Similarity between two types of data

- Both distributions look like roughly straight lines
 - Power-law distribution



- The "tail" URLs appear in the latter part of a session
- These URLs are important for user modeling











- Two types of ad-related prediction tasks
 - AdClicker
 - Predict clicked contextual ads by each user among five ads
 - SiteVisitor
 - Predict visited advertisers' sites by each user among five sites
- Obtained users' representations using each vector model
 - One task-independent representation for each user
 - One logistic regression classifier for each prediction task

Web browsing sequence of each user July 24, 2014

Labels corresponding to five candidates





Predict

A set of users which selected at least one among five candidates Multi-label classification is converted into five binary classification problem



- Using Skip-gram, a user is represented as the simple averaging of vectors of URLs in the sequence
- Backward PV-DM achieved better results than PV-DM

	AdClicker				SiteVisitor					
	Ac1	Ac2	Ac3	Ac4	Ac5	Sv1	Sv2	Sv3	Sv4	Sv5
Skip-gram	0.9906	0.8354	0.6562	0.7163	0.7725	0.8017	0.8328	0.7135	0.7931	0.7417
Directed Skip-gram	0.9904	0.8374	0.6533	0.7159	0.7706	0.8019	0.8308	0.7120	0.7914	0.7394
PV-DM	0.9899	0.8151	0.6483	0.7242	0.7633	0.8051	0.8343	0.7180	0.7964	0.7479
Backward PV-DM	0.9902	0.8247	0.6537	0.7345	0.7661	0.8092	0.8366	0.7222	0.8028	0.7491

Values are AUC (Area Under ROC Curve). Larger is better.

- Contextual ads in AdClicker are determined to be displayed by the Web page content as well as user information
- SiteVisitor is the data set based on more complicated user interests

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- Other types of features
 - Search queries and Web page contents
- Other than unsupervised learning
 - Semi-supervised, multi-label or multi-task learning
- Sequence modeling with RNNs (Recurrent Neural Networks)
 - Scalable learning methods for Web scale user data
- Now, we apply LSTM-RNN to user browsing sequences
 - For news article recommendation on smartphones

Thank you! Questions?

Please speak clearly and slowly

Yukihiro Tagami yutagami@yahoo-corp.jp