Transfer Learning on User Behaviors for Multi-lingual eCommerce Systems

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1 EXTENDED ABSTRACTS

Verizon Media (Yahoo) Taiwan office is leading the thriving eCommerce business in Taiwan for more than 15 years. One of the key success pillars is to adopt machine learning in various user facing modules. Among those modules, recommender systems based on user behaviors models have been built and proven to increase the revenue significantly, such as personalized recommendation, product to product recommender system and trending product. Those systems are designed from tens of millions of product listings and millions of active users on a daily basis, and several approaches have been developed to represent the complex eCommerce challenges from data. From building the inferred user understanding data pipeline to composing a product network architecture by capturing hundreds of thousands of user behaviors (e.g. co-view, co-buy).

As the company re-engaging eCommerce business in other markets (starting from the Yahoo! U.S. eCommerce), it encounters the cold start challenge since there is not enough user data to build a confident recommendation system. And if the learnt knowledge from Taiwan eCommerce systems can be leveraged (e.g., "Headsets" are often bought with "iPhone", “Nitendo Switch” is very popular in the past period), the loss caused by cold start could be relieved substantially.

With this motivation, this paper proposes a novel lingual-independent knowledge transfer framework to give an end-to-end solution. Multilingual product representation by its title tokens is first introduced to diminish the barrier caused by language differences between markets[3][5][7] Our solution is proposing QR-AdvRefine(QRAR), which use a semi-supervised learning to develop a word embedding space between the source language and the target by the anchor words mapping, which not only leverage the accuracy of multilingual product embeddings, but also increase the efficiency and effectiveness in editor support. The experiment shows good improvement on recall@10 when anchord word size is small than Adv-Refine [3] (Figure 1).

Figure 1: Recall@10 for AR and QRAR

Anchor Number (n)	English to Chinese		Chinese to English		French to English		English to French	
	AR	QRAR	AR	QRAR	AR	QRAR	AR	QRAR
300	0.423	0.552	0.420	0.51	0.811	0.860	0.831	0.862
500	0.465	0.584	0.445	0.524	0.823	0.874	0.839	0.871
1000	0.521	0.606	0.481	0.546	0.844	0.887	0.852	0.875
2000	0.582	0.618	0.532	0.568	0.870	0.889	0.875	0.894
3000	0.631	0.642	0.561	0.575	0.877	0.903	0.894	0.900
4000	0.644	0.649	0.574	0.579	0.898	0.910	0.908	0.906

Figure 2: The nearest words in different embedding spaces

Word	iPhone		Toothbrush		Dog	
	Semantic	**Co-view**	**Semantic**	**Co-view**	**Semantic**	**Co-view**
1	iPad	iPad	brushbrush	toothpaste	puppy	feed
2	smartphone	airpods	toothpaste	toothpicks	sheepdog	canned
3	iPod	bumper	toothpowder	mouthwash	dachshund	puppy
4	iphonehacks	gorilla	toothing	floss	poodle	cesar
5	iOS	dock	shaving	brushbrush	chickenhound	skin
6	android	hoda	toothpicks	Whitening	coonhound	leash
7	iphonesoft	moshi	mouthwash	lipsticks	doberman	litter
8	app	charging	lipsticks	oralb	hound	richell
9	handsets	applewatch	hairbrush	mouth	bullmastiff	dewarm
10	AppStore	lightning	razors	dental	terrier	bone

Next, we provide two models to build up the product to product recommendation [1] [2] [4] [6]and trending product respectively from Taiwan eCommerce data for U.S. eCommerce, utilizing the the multilingual product representation. For the product to product recommendation, we transfer the the multilingual product embeddings into a co-view product embedding space, which is learnt from product co-view data in Taiwan, by a transformation model. In this co-view product embedding space, the product embedding will be closed if 2 products are usually view together (co-view), see the example of the closest word set between multilingual product embeddings (semantic embeddings) and co-view product embedding on Figure 2. The closet word set for “iPhone” by co-view embedding are much likely including eCommerce product words. However, it emerges another problem - location issues, that is, the products or customers vary across different countries. For instance, there is a word hoda in the related words of iPhone. The word hoda is a company name which sells the screen protection products, but the brand may not be recognized in several countries. We put the issue as our future work.

The experiment result of product to product showed on Figure 3, The fraction parameter ranges from 0.01 to 0.9. This parameter is introduced to simulate the richness of a dataset. The result shows when k is small, KT model outperforms other methods since it gets benefits from the knowledge transfer. While Random Walk, a Collaborative Filtering model, performs very poor in this cold-start case, i.e., little training data. It is because the user behaviors are too sparse to get the reliable relations of co-buy. on the online environment, this methods for product to product shows 34% improvement on Click-Though-Rate than the recommendations of top click items.

For the trending product, a GBDT model is trained on Taiwan eCommerce dataset, we predict the product Click-Through-Rate

Figure 3: Knowledge transfer models with different fraction of training and testing dataset

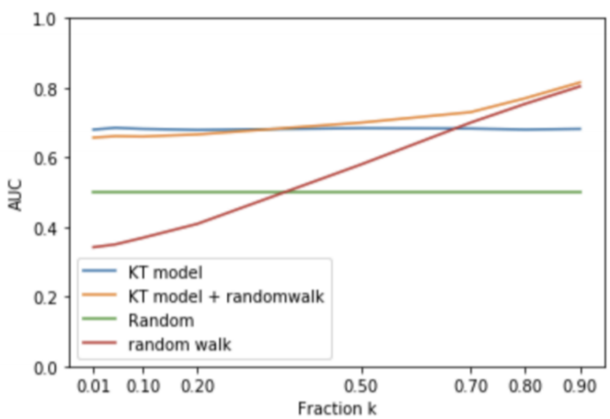

Figure 4: RMSE of the CTR/CVN prediction

RMSE	CTR		CVN	
	HK	TW	HK	TW
KT model	0.21	0.25	0.08	0.13
random	0.41	0.38	0.56	0.57

(CTR) and Conversion Rate(CVN) in target domain according to multilingual product embeddings, price, and other metadata. Since we don't have much CTR/CVN data in the U.S. eCommerce, we simulate the experiment on Yahoo Hong Kong eCommerce dataset.Root-mean-square error (RMSE) is considered as the target metric for training and testing experiments. The result is promising and shown on Figure 4.

In General, our strategy is transferring the user behaviors from source domain a.k.a. Taiwan eCommerce through the unified multi-language product representation, we proposed a semi-supervised solution to build the representation, and demonstrate how to transfer the co-view behaviors and trending products on this multi-language product representation. The result showed the method did help cold-start markets. In the future, this research attempts to get the convergence of human purchasing actions, especially for online eCommerce activities. Though location is still the dominant factor in the virtual world, studies have suggested great potential that we could model the purchasing questions and adopt transfer learning with domain discriminators to different product categories. We will investigate how regional behaviors affect eCommerce operations and what transferred model should be adapted when emerged markets grow.

REFERENCES

[1] Oren Barkan and Noam Koenigstein. 2016. Item2Vec: Neural Item Embedding for Collaborative Filtering. arXiv:cs.LG/1603.04259

[2] Yuri M Brovman, Marie Jacob, Natraj Srinivasan, Stephen Neola, Daniel Galron, Ryan Snyder, and Paul Wang. 2016. Optimizing similar item recommendations in a semi-structured marketplace to maximize conversion. In *Proceedings of the 10th ACM Conference on Recommender Systems*. 199–202.

[3] Alexis Conneau, Guillaume Lample, Marc'Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. 2017. Word Translation Without Parallel Data. arXiv:cs.CL/1710.04087

[4] G. Linden, B. Smith, and J. York. 2003. Amazon.com recommendations: item-to-item collaborative filtering. *IEEE Internet Computing* 7, 1 (2003), 76–80.

[5] Tomas Mikolov, Quoc V. Le, and Ilya Sutskever. 2013. Exploiting Similarities among Languages for Machine Translation. arXiv:cs.CL/1309.4168

[6] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. 2001. Item-based collaborative filtering recommendation algorithms. In *Proceedings of the 10th international conference on World Wide Web*. 285–295.

[7] Chao Xing, Dong Wang, Chao Liu, and Yiye Lin. 2015. Normalized Word Embedding and Orthogonal Transform for Bilingual Word Translation. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. Association for Computational Linguistics, Denver, Colorado, 1006–1011. https://doi.org/10.3115/v1/N15-1104