Heterogeneous User-Interest Transfer Learning for Cold-Start News Recommendation

Anonymous ACL submission

Abstract

We investigate how to solve the cold start problems commonly present in news recommendation for unseen users in the future. This is a problem where traditional content-based recommendation techniques often fail for cold-start scenarios. Luckily, in real-world recommendation services, some publisher (e.g., Finance news) may have accumulated a large corpus which can be used for a newly deployed publisher (e.g., Sports news). To take advantage of the existing corpus, we propose a transfer learning model for news recommendation (TrNews) to transfer the knowledge from a source domain to a target domain. To tackle the heterogeneity of different user interests and of different word distributions between domains, we design a translator-based transfer-learning strategy to learn a representation mapping between source and target domains. We show through experiments on real-world datasets that TrNews is effective and the translator strategy is necessary.

1 Introduction

News recommendation is key to satisfying users' information need for online services. Some news articles, such as breaking news, are manually selected by publishers and displayed for all users. A huge number of news articles generated everyday make it impossible for editors and users to read through all of them, raising the issue of information overload. Online news platforms provide a service of personalized news recommendation by learning from the past reading history of users, e.g., Google (Das et al., 2007; Liu et al., 2010), Yahoo (Trevisiol et al., 2014; Okura et al., 2017), and Bing news (Lu et al., 2015; Wang et al., 2018).

When a new user uses the system (cold-start users) or a new article is just created (cold-start items), there are too few observations for them to train a reliable recommender system. Content-based techniques exploit the content information of news (e.g., words and tags) and hence new articles can be recommended to existing users (Pazzani and Billsus, 2007). Content-based recommendation, however, suffers from the issue of cold-start users since there is no reading history for them to be used to build a profile (Park and Chu, 2009).

Transfer learning for cross-domain recommendation is a common technique for alleviating the issues of cold-start users (Pan et al., 2010; Cantador et al., 2015; Liu et al., 2018). A user may have access to many websites such as Twitter.com and Youtube.com (Roy et al., 2012; Huang and Lin, 2016), and consume different categories of products such as movies and books (Li et al., 2009). In this case, transfer learning approaches can recommend articles to a new user in the target domain by exploiting knowledge from the relevant source domains for this new user.

A technical challenge for transfer learning approaches is that user interests are quite different across domains. For example, users do not use Twitter for the same purpose. A user may follow up on news about "Donald Trump" because she supports Republican Party, while she may follow up account *@taylorswift13* ("Taylor Swift") because she loves music. Another challenge is that the word distribution and feature space are different across domains. For example, vocabularies are different for describing political news and entertainment news. As a result, the user profile computed from her news history is heterogeneous across domains.

Several strategies have been proposed for heterogeneous transfer learning (Yang et al., 2009). The transferable contextual bandit (TCB) (Liu et al., 2018) learns a translation matrix to translate target feature examples to the source feature space. This linear mapping strategy is also used in collaborative cross networks (CoNet) (Hu et al., 2018a) and deep

dual transfer cross domain recommendation (DDTCDR) (Li and Tuzhilin, 2020). To capture complex relations between source and target domains, some nonlinear mapping strategy is considered in the embedding and mapping cross-domain recommendation (EMCDR) (Man et al., 2017) which learns a supervised regression between source and target factors using a multilayer perceptron. It, however, uses a dilated, large hidden layer which may lead to overfitting since aligned examples between source and target domains are limited.

To tackle challenges of heterogeneous user interests and limited aligned data between domains, we propose a novel transfer learning model (TrNews) for user cold-start news recommendation. TrNews builds a bridge between two base networks (one for each domain, see Section 3.2) through the proposed translator-based transfer strategy. The translator in TrNews captures the relations between source and target domains by learning a nonlinear mapping between them (Section 3.3). It is a general and data-efficient framework by comparing with existing transfer-learning strategies (Section 3.6). TrNews uses the translator to transfer knowledge between source and target networks and the learned translator is used to infer the representations of cold-start users in the future (Section 3.5). By "translating" the source representation of a user to the target domain, TrNews offers an easy solution to create cold-start users' target representations. TrNews outperforms the state-of-the-art recommendation methods on four real-world datasets in terms of four metrics (Section 4.2), while having an interpretability advantage by allowing the visualization of the importance of each news article in the history to the future news (Section 4.7).

2 Related Work

Cold-start recommendation Content-based recommendation exploits the content information about items (e.g., title/body (Yan et al., 2012; Xiao et al., 2019; Ma et al., 2019), tag, vlog (Gao et al., 2010)), builds a profile for each user, and then matches users to items (Lops et al., 2011; Yu et al., 2016; Wu et al., 2019b). It is effective for cold-start items but suffers from cold-start users. DCT (Barjasteh et al., 2015) constructs a user-user similarity matrix from user demographic features including gender, age, occupation, and location (Park and Chu, 2009). NT-MF (Huang and Lin, 2016) constructs a user-user similarity matrix from Twitter texts. BrowseGraph (Trevisiol et al., 2014) addresses the cold-start news recommendation by constructing a graph using URL links between web pages. NAC (Rafailidis and Crestani, 2019) transfers from multiple source domains through the attention mechanism. PdMS (Felício et al., 2017) assumes that there are many recommender models available to select items for a cold-start user, and introduces a multi-armed bandit for model selection. Different from the aforementioned works, we aim to recommending news to cold-start users by transferring knowledge from a source domain.

Transfer learning Transfer learning aims at improving the performance of a target domain by exploiting knowledge from source domains (Pan and Yang, 2009). A special setting is domain adaptation where a source domain provides labeled training examples while the target domain provides instances on which the model is meant to be deployed (Glorot et al., 2011; Li et al., 2019). The coordinate system transfer (CST) (Pan et al., 2010) firstly learns the principle coordinate of users in the source domain, and then transfers it to the target domain in the way of warm-start initialization. This is equivalent to an identity mapping from users' source representations to their corresponding target representations. TCB (Liu et al., 2018) learns a linear mapping to translate target feature examples to the source feature space because there are many labelled data in the source domain. This linear strategy is also used in CoNet (Hu et al., 2018a) and DDTCDR (Li and Tuzhilin, 2020) which transforms the source representations to the target domain by a translation matrix. Nonlinear mapping strategy (Man et al., 2017; Zhu et al., 2018; Fu et al., 2019) is to learn a supervised mapping function between source and target latent factors by using neural networks. SSCDR (Kang et al., 2019) extends them to the semi-supervised mapping setting. Our translator is general to accommodate these identity, linear, and nonlinear transfer-learning strategies.

3 TrNews

3.1 Architecture

The architecture of TrNews is shown in Figure 1, which has three parts. There are a source network for the source domain S and a target network for the target domain T, respectively. The source and target networks are both an instantiation of the base network (Section 3.2). The translator enables knowledge transfer between the two networks (Sec-

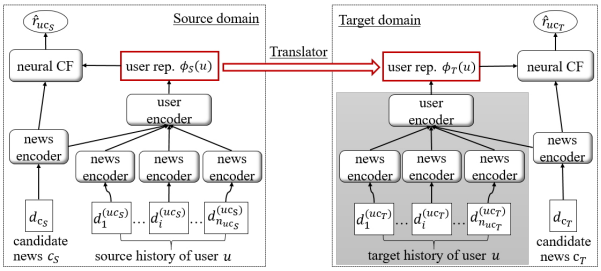


Figure 1: Architecture of TrNews. The translator (Figure 4) enables knowledge transfer between source and target networks both instantiated from the base network (Figure 2). The shaded area in the target network is empty for cold-start users.

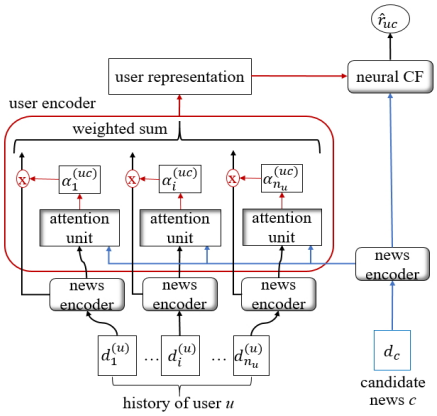


Figure 2: Base network. The base network is used to instantiate the source and target networks.

tion 3.3). We give an overview of TrNews before introducing the base network and the translator.

Target network The information flow goes from the input, i.e., (user u, candidate news c_T) to the output, i.e., the preference score $\hat{r}_{uc_T}$, through the following three steps. First, the news encoder ψ_T computes the news representation from its content. The candidate news representation is $\psi_T(c_T) = \psi_T(d_{c_T})$ where d_{c_T} is c_T's content. The representations of historical news articles $[i]_{i=1}^{n_{uc_T}}$ of the user are $[\psi_T(d_i^{(uc_T)})]_{i=1}^{n_{uc_T}}$ where $d_i^{(uc_T)}$ is i's content and n_{uc_T} is size of the history. Second, the user encoder ϕ_T computes the user representation from her news history by: $\phi_T(u) = \phi_T\left([\psi_T(d_i^{(uc_T)})]_{i=1}^{n_{uc_T}}\right)$. Third, the neural collaborative filtering (CF) module f_T computes the preference score by: $\hat{r}_{uc_T} = f_T([\phi_T(u), \psi_T(c_T)])$. We can denote the target network by a tuple (ψ_T, ϕ_T, f_T).

Source network Similarly to the three-step computing process in target network, we compute preference score $\hat{r}_{uc_S}$ from input (u, c_S) by: $\hat{r}_{uc_S} = f_S([\phi_S(u), \psi_S(c_S)])$ with tuple (ψ_S, ϕ_S, f_S).

Translator The translator $\mathcal{F}$ learns a mapping from the user's source representation to her target representation by $\mathcal{F} : \phi_S(u) \rightarrow \phi_T(u)$.

3.2 Base network for target/source domain

The base network is shown in Figure 2. Similar architectures are widely used in news recommendation (Wu et al., 2019a), product recommendation (Zhou et al., 2018), and hashtag recommendation (Huang et al., 2016). The base network has three modules (ψ, ϕ, f): the news encoder ψ to learn news representations, the user encoder ϕ to learn user representations, and a neural collaborative filtering module f to learn user preferences from reading behaviors.

News encoder The news encoder module is to learn news representation from its content. The news encoder takes a news article c's word sequence $d_c = [w_j]_{j=1}^{n_c}$ (n_c is length of c) as the input, and outputs its representation $\psi(c) \triangleq \psi(d_c) \in \mathbb{R}^D$ where D is the dimensionality. Following (Huang et al., 2016; Hu et al., 2018b), we compute the average of c's word embeddings by: $\psi(d_c) = \frac{1}{|d_c|}\sum_{w \in d_c} e_w$, where e_w is the embedding of w.

User encoder The user encoder module is to learn the user representation from her reading history. The user encoder takes a user's reading history $[\psi(d_i^{(u)})]_{i=1}^{n_u}$ (n_u is length of u's history) as input, and outputs her representation $\phi(u) \triangleq \phi([\psi(d_i^{(u)})]_{i=1}^{n_u}) \in \mathbb{R}^D$ where D is dimensionality.

In detail, given a pair of user and candidate news (u, c), we get the user representation $\phi(u|c)$ as the weighted sum of her historical news articles' representations: $\phi(u|c) = \sum_{i=1}^{n_{uc}} \alpha_i^{(uc)} \psi(d_i^{(u)})$. The weights $\alpha_i^{(uc)}$'s are computed via attention units by: $\alpha_i^{(uc)} = a([\psi(d_i^{(u)}), \psi(d_c)])$ where a is the attention function with parameters to be learned. We use MLP to compute it (Luong et al., 2015; Zhou et al., 2018). For a specific candidate news c, we limit the history news to only those articles that are read before it (Vartak et al., 2017). For notational simplicity, we do not explicitly specify the candidate news when referring to a user representation, i.e., $\phi(u)$ for short of $\phi(u|c)$.

Neural CF The neural collaborative filtering module is to learn preferences from user-news interactions. The module takes concatenated representations of user and news $[\phi(u), \psi(c)]$ as input, and outputs preference score $\hat{r}_{uc} = f([\phi(u), \psi(c)])$ where f is an MLP (He et al., 2017).

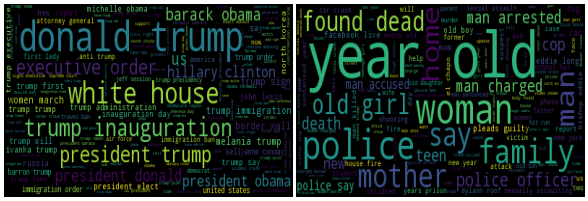


Figure 3: Word clouds of two news corpora.

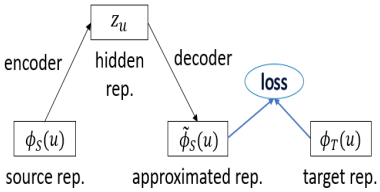


Figure 4: Framework of translator.

3.3 Translator enabling knowledge transfer

The target network suffers from cold-start users who have no reading history. In this section, we propose a transfer learning component (i.e., the translator) to enable knowledge transfer for user cold-start news recommendation. The challenge is that user interests and word distributions are different across domains. For example, we compute the word clouds for two news corpora as shown in Figure 3. We can see that their word distributions are quite different and vocabularies are also different. Hence, user representations computed from their news history are heterogeneous across domains.

We build a translator, $\mathcal{F} : \phi_S(u) \rightarrow \phi_T(u)$, to learn a mapping from a user's source representation to her target representation as shown in Figure 4. This translator captures the relationship and heterogeneity across domains. The translator learns to approximate the target representation from the source representation. We extend an autoencoder-like architecture (Hinton and Salakhutdinov, 2006; Bengio et al., 2007) which is a natural choice for achieving the purpose of mapping.

The translator takes a user's source representation $\phi_S(u)$ as the input, and maps it to a hidden representation z_u via an encoder parameterized by θ, and then gets a approximated representation $\tilde{\phi}_S(u)$ from it via a decoder parameterized by θ'. The parameters $\Theta_{\mathcal{F}} = \{\theta, \theta'\}$ of the translator are optimized to minimize the approximation error:

$$L_{\mathcal{F}} = \frac{1}{|\mathcal{U}_0|} \sum_{u \in \mathcal{U}_0} ||H\tilde{\phi}_S(u) - \phi_T(u)||_2^2, \qquad (1)$$

where $\mathcal{U}_0 = \mathcal{U}_S \cap \mathcal{U}_T$, and $\mathcal{U}_S$ and $\mathcal{U}_T$ are the user sets of source and target domains, respectively. H is to match the dimensions of source and target representations.

Note that, we do not minimize the approximation error between $\phi_S(u)$ and $\tilde{\phi}_S(u)$ as with the standard autoencoder because our goal is to learn a mapping from a user's source representation to her corresponding target representation. After training, the learned mapping function is then used for cold-start users in the target domain (the inference process will be described later in Section 3.5). It fulfills knowledge transfer from the source to the target domain via a supervised learning process.

3.4 Two-stage model learning

We learn TrNews in two stages. First, we train the source network using source training examples D_S and train the target network using target training examples D_T, respectively. Second, we train the translator by pairs of user representations computed on-the-fly from source and target networks. We introduce these two stages in detail.

First, TrNews optimizes the parameters associated with target network $\Theta_T = \{\theta_{\phi_T}, \theta_{\psi_T}, \theta_{f_T}\}$ and source network $\Theta_S = \{\theta_{\phi_S}, \theta_{\psi_S}, \theta_{f_S}\}$ by minimizing the joint cross-entropy loss:

$$\mathcal{L}_{\mathcal{T},\mathcal{S}} = -\sum_{D_T}(r_{uc_T} \log \hat{r}_{uc_T} + (1 - r_{uc_T}) \log(1 - \hat{r}_{uc_T})) - \sum_{D_S}(r_{uc_S} \log \hat{r}_{uc_S} + (1 - r_{uc_S}) \log(1 - \hat{r}_{uc_S})), \qquad (2)$$

where the two terms on the right-hand side are to optimize losses over user-news examples in the target and source domains, respectively. They are related by the word embedding matrix for the union of words of the two domains. We generate D_T and D_S as follows and take the target domain as an example since the procedure is the same for the source domain. Suppose we have a whole news reading history for a user u, say $[d_1, d_2, ..., d_{n_u}]$. Then we generate the positive training examples by sliding over the history sequence: $D_T^+ = \{([d_i]_{i=1}^{c-1}, d_c) : c = 2, ..., n_u\}$. We adopt the random negative sampling technique (Pan et al., 2008) to generate the corresponding negative training examples $D_T^- = \{([d_i]_{i=1}^{c-1}, d'_c) : d'_c \notin [d_1, d_2, ..., d_{n_u}]\}$, that is, we randomly sample a news article from the corpus as a negative sample which is not in this user's reading history.

Second, TrNews optimizes the parameters associated with the translator $\Theta_{\mathcal{F}} = \{\theta, \theta'\}$ by Eq. (1). Since the aligned data is limited, we increase the training pairs by generating them on-the-fly during the training of the two networks.

3.5 Inference for cold-start users

For a new user in the target domain (not seen in the training set $\mathcal{U}_T^{train}$), we do not have any previous history to rely on in learning a user representation for her. That is, the shaded area of the target network in Figure 1 is empty for cold-start users.

TrNews estimates a new user u^*'s target representation by mapping from her source representation using the learned translator $\mathcal{F}$ by:

$$\phi_T(u^*) := \mathcal{F}(\phi_S(u^*)),\ \forall u^* \in \mathcal{U}_S \wedge u^* \notin \mathcal{U}_T^{train},$$

where we compute $\phi_S(u^*)$ using u's latest reading history in the source domain. Then we can predict the user preference for candidate news c^* by: $\hat{r}_{u^*c^*} = f_T([\phi_T(u^*), \psi_T(c^*)])$.

3.6 Relationship to existing approaches

We show that our translator is a general framework by comparing with existing transfer-learning strategies as summarized in Table 1.

Identity mapping CST (Pan et al., 2010) firstly learns the principle coordinate of users in the source domain, and then transfers it to the target domain in the way of warm start. We can formulate CST's transfer learning strategy using our notation as: $\phi_T(u) = \phi_S(u)$. This is equivalent to an identity mapping. Our translator can learn an identity mapping when the dimensionality of the hidden representation is identical to (or larger than) that of input, i.e., achieving a perfect approximation with a zero error (Vincent et al., 2010).

Linear mapping TCB (Liu et al., 2018) learns a translation matrix to translate target feature examples to the source feature space. We can formulate TCB's transfer learning strategy using our notation as: $\phi_T(u) = H\phi_S(u)$ where H is the translation matrix (TCB translates from the target domain to the source domain). The linear mapping strategy is also used in CoNet (Hu et al., 2018a) and DDTCDR (Li and Tuzhilin, 2020). DDTCDR also adds an orthogonal constraint on the translation matrix, i.e., $H^{-1} = H^T$, because orthogonal transformation can preserve the inner product of vectors and hence the similarities of user embeddings across domains. Our translator can learn a linear mapping when the encoder and decoder do not use nonlinear activation functions in the hidden layers.

Nonlinear mapping EMCDR (Man et al., 2017) learns a supervised regression between the source and target latent factors using an MLP. We can formulate EMCDR's transfer learning strategy using our notation as: $\phi_T(u) = \text{MLP}(\phi_S(u))$ where MLP has only one hidden layer and its dimensionality is twice the size of input (and output). Our translator can reduce to MLP where the encoder corresponds to the mapping from the input to the hidden layer and the decoder corresponds to the mapping from the hidden layer to the output.

Approach	Transfer strategy	Formulation
CST (Pan et al., 2010)	Identity mapping	$\phi_T(u) = \phi_S(u)$
TCB (Liu et al., 2018), DDTCDR (Li and Tuzhilin, 2020)	Linear mapping	$\phi_T(u) = H\phi_S(u)$, H is orthogonal
EMCDR (Man et al., 2017)	Nonlinear mapping	$\phi_T(u) = \text{MLP}(\phi_S(u))$

Table 1: Different transfer learning strategies.

Dataset	#user	Target domain			Source domain		
		#news	#reading	#word	#news	#reading	#word
New York	14,419	33,314	158,516	368,000	23,241	139,344	273,894
Florida	15,925	33,801	178,307	376,695	25,644	168,081	340,797
Texas	20,786	38,395	218,376	421,586	29,797	221,344	343,706
California	26,981	44,143	281,035	481,959	32,857	258,890	375,612

Table 2: Statistics of the datasets.

4 Experiment

We evaluate the performance of TrNews and the effectiveness of the translator in this section.

4.1 Dataset and protocol

Dataset We evaluate on four datasets extracted from Cheetah Mobile[1], a large internet company. The information contains news reading logs of users in a large geographical area collected in the whole January of 2017. We consider the top-four subareas, New York, Florida, Texas, and California, as evaluation datasets based on the division of user geolocation. We consider the top two categories of news as the target and source domains. The statistics are summarized in Table 2.

Evaluation We randomly split the whole user set into two parts, training and test sets where the ratio is 9:1. Given a user in the test set, for each news in her history, we follow the strategy in (He et al., 2017) to randomly sample 99 (negative) news items which are not in her reading history and then evaluate how well the recommender can rank this positive news against these negative ones. For each user in the training set, we reserve her last reading news as the valid set. We follow the typical metrics to evaluate top-K news recommendation (Peng et al., 2016; Okura et al., 2017; An et al., 2019) which are hit ratio (HR), normalized discounted cumulative gain (NDCG), mean reciprocal rank

[1] http://www.cmcm.com/en-us/

New York						
Method	HR@5	HR@10	NDCG@5	NDCG@10	MRR	AUC
POP	52.96	67.66	40.34*	45.10	39.89*	77.92
LR	53.24	74.00	36.15	42.86	34.95	91.64
TANR	52.53	71.63	37.24	43.37	36.50	91.35
DeepFM	52.02	73.71	39.17	45.38	39.56	91.79
DIN	57.10*	75.66*	40.23	46.13*	38.65	92.29*
TrNews	**82.60**	**95.15**	**60.78**	**64.83**	**55.70**	**97.28**
Florida						
Method	HR@5	HR@10	NDCG@5	NDCG@10	MRR	AUC
POP	52.45	66.14	39.72*	44.15	39.15*	79.33
LR	54.26*	73.90*	37.15	43.56	35.89	91.79
TANR	49.98	69.46	36.08	42.37	35.95	90.88
DeepFM	52.36	73.02	36.05	42.74	36.29	91.64
DIN	53.98	73.33	37.96	44.18*	36.96	91.86*
TrNews	**81.83**	**94.45**	**62.53**	**66.63**	**58.39**	**97.41**
Texas						
Method	HR@5	HR@10	NDCG@5	NDCG@10	MRR	AUC
POP	54.21	67.87	40.62*	45.03*	39.64*	81.31
LR	55.72*	73.80*	39.24	44.97	37.78	91.74*
TANR	49.87	68.75	35.82	41.89	35.59	90.56
DeepFM	52.19	71.95	35.40	41.92	35.65	91.17
DIN	53.72	72.70	38.47	44.59	37.62	91.53
TrNews	**81.50**	**94.67**	**61.76**	**66.11**	**57.49**	**97.21**
California						
Method	HR@5	HR@10	NDCG@5	NDCG@10	MRR	AUC
POP	58.32*	71.19	44.71*	48.86*	43.44*	83.38
LR	58.82	75.67*	42.16	47.65	40.44	92.37*
TANR	49.87	68.75	35.81	41.88	35.58	90.56
DeepFM	55.58	74.73	38.82	45.16	38.21	92.25
DIN	55.31	73.70	40.14	46.09	39.20	92.03
TrNews	**81.54**	**94.72**	**61.99**	**66.25**	**57.70**	**97.22**

Table 3: Comparison of different recommendation methods.

(MRR), and the area under the ROC curve (AUC). We report the results at a cut-off $K \in \{5, 10\}$.

Implementation We use TensorFlow. The optimizer is Adam (Kingma and Ba, 2015) with learning rate 0.001. The size of mini batch is 256. The neural CF module has two hidden layers with size 80 and 40 respectively. The size of word embedding is 128. The translator has one hidden layer on the smaller datasets and two on the larger ones. The history is the latest 10 news articles and the length of news article cuts off at 30 words. The supplementary material provides more details.

4.2 Performance of recommendation

4.2.1 Baselines

We compare with following recommendation methods which are trained on the merged source and target datasets by aligning with shared users.

POP (Park and Chu, 2009) recommends the most popular news.

LR (McMahan et al., 2013) is widely used in ads and recommendation. The input is the concatenation of candidate news and user's representations.

TANR (Wu et al., 2019a) is a deep news recommendation model using an attention network to learn the user representation. We adopt the news encoder and negative sampling in the same way as TrNews.

DeepFM (Guo et al., 2017) is a deep neural network for the click-through rate (CTR) prediction. We use second-order feature interactions of reading history and candidate news, and the input of deep component is the same as LR.

DIN (Zhou et al., 2018) is a deep interest network for CTR prediction. We use the news content instead of identities.

4.2.2 Results

We have observations from results of different recommendation methods as shown in Table 3. Firstly, considering that breaking and headline news articles are usually read by every user, the POP method gets competitive performance in terms of NDCG and MRR since it ranks the popular news higher than the other news.

Secondly, the neural methods are generally better than the traditional, shallow LR method in terms of NDCG, MRR, and AUC. It may be that neural networks can learn nonlinear, complex relations between the user and the candidate news to capture user interests and news semantics. Considering that the neural representations of user and candidate news are fed as the input of LR, it gets competitive performance in terms of HR.

Finally, the proposed TrNews model achieves the best performance with a large margin improvement over all other baselines in terms of HR, NDCG, and MRR and also with an improvement in terms of AUC. It validates the necessity of accounting for the heterogeneity of user interests and word distributions across domains. This also shows that the base network is an effective architecture for news recommendation and the translator is effective to enable the knowledge transfer from the source domain to the target domain. In more detail, it is inferior by training a global model from the mixed source and target examples and then using this global model to predict user preferences on the target domain, as baselines do. Instead, it is good by training source and target networks on the source and target domains, respectively, and then learning a mapping between them, as TrNews does.

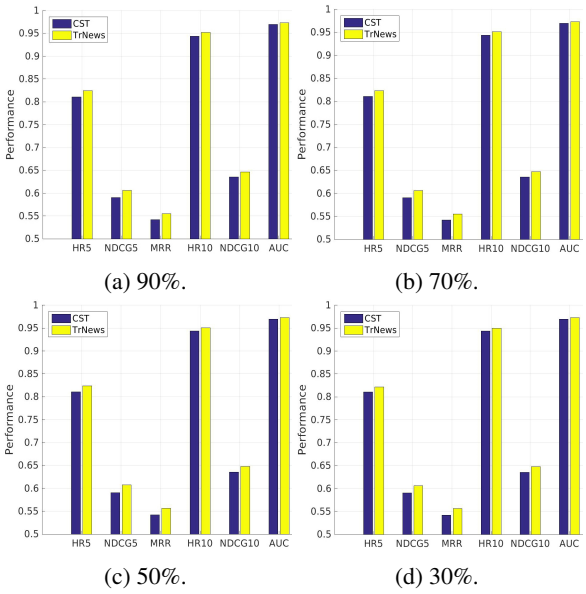
4.3 Effectiveness of translator

4.3.1 Baselines

We compare TrNews with the following transfer learning methods which replace the translator by

New York						
Method	HR@5	HR@10	NDCG@5	NDCG@10	MRR	AUC
CST	81.04	94.37	59.04	63.56	54.19	96.94
TCB	82.18	94.92*	60.36*	64.46*	55.23*	97.28*
DDTCDR	82.27	94.90	59.82	63.90	54.51	97.25
EMCDR	82.44*	94.87	60.35	64.33	55.06	97.24
TrNews	**82.60**	**95.15**	**60.78**	**64.83**	**55.70**	**97.28**
Improved %	+0.51↑	+0.24↑	+0.69↑	+0.57↑	+0.84↑	0.00↔
Florida						
Method	HR@5	HR@10	NDCG@5	NDCG@10	MRR	AUC
CST	79.29	93.91	59.03	63.60	54.74	97.07
TCB	81.51	**94.83**	62.06	66.33*	57.90*	97.40*
DDTCDR	81.39	94.63*	61.76	66.12	57.68	97.37
EMCDR	81.52*	94.47	62.14*	66.23	57.87	97.37
TrNews	**81.83**	94.45	**62.53**	**66.63**	**58.39**	**97.41**
Improved %	+0.38↑	-0.40↓	+0.64↑	+0.44↑	+0.84↑	+0.01↑
Texas						
Method	HR@5	HR@10	NDCG@5	NDCG@10	MRR	AUC
CST	78.74	94.20	58.53	63.48	54.56	96.92
TCB	80.68	94.12	61.06	65.38	56.97	97.10
DDTCDR	81.08	94.57	61.02	65.50	56.87	97.10
EMCDR	81.34*	**94.72**	**61.78**	66.11*	**57.59**	97.16*
TrNews	**81.50**	94.67*	61.76*	**66.11**	57.49*	**97.21**
Improved %	+0.20↑	-0.05↓	-0.03↓	0.00↔	-0.17↓	+0.05↑
California						
Method	HR@5	HR@10	NDCG@5	NDCG@10	MRR	AUC
CST	79.92	93.71*	60.19	64.63	55.97	97.12
TCB	80.90*	93.71*	**62.32**	**66.45**	**58.35**	**97.36**
DDTCDR	80.22	93.47	61.42	65.72	57.44	97.25
EMCDR	80.53	93.33	62.04*	66.18	58.11*	97.30*
TrNews	**81.54**	**94.72**	61.99	66.25*	57.70	97.22
Improved %	+0.79↑	+1.08↑	-0.53↓	-0.30↓	-1.11↓	-0.14↓

Table 4: Comparison of different transfer strategies.



(a) 90%. (b) 70%.

(c) 50%. (d) 30%.

Figure 5: Impact of percentage of shared users used to train the translator.

their corresponding transfer learning strategies (see Section 3.6 and Table 1 for details).

CST (Pan et al., 2010) replaces the translator by CST's transfer strategy, which uses an identity mapping.

TCB (Liu et al., 2018) replaces the translator by TCB's transfer strategy, i.e., learning a linear mapping via a translation matrix.

DDTCDR (Li and Tuzhilin, 2020) replaces the translator by DDTCDR's transfer strategy, i.e., learning a linear mapping via a translation matrix and adding an orthogonal constraint.

EMCDR (Man et al., 2017) replaces the translator by EMCDR's transfer strategy, i.e., learning a nonlinear mapping via an MLP with one hidden layer.

4.3.2 Results

We have observations from results of different transfer learning strategies as shown in Table 4. Firstly, the transfer strategy of identity mapping (CST) is generally inferior to the linear (TCB and DDTCDR) and nonlinear (EMCDR and TrNews) strategies. CST directly transfers the source knowledge to the target domain without adaptation and hence suffers from the heterogeneity of user interests and word distributions across domains.

Secondly, the nonlinear transfer strategy of EMCDR is inferior to the linear strategy of TCB in terms of MRR and AUC on the two smaller datasets. This is probably because EMCDR increases the model complexity by introducing two large fully-connected layers in its MLP component. In contrast, our translator is based on the small-waist autoencoder-like architecture and hence can resist overfitting to some extent.

Finally, our translator achieves the best performance in terms of NDCG, MRR and AUC on the two smaller datasets (New York and Florida), and achieves competitive performance on the two larger datasets (Texas and California), comparing with other four transfer methods. These results validate that our translator is a general and effective transfer-learning strategy to capture the diverse user interests accurately during the knowledge transfer for the user cold-start news recommendation.

4.4 Benefit of knowledge transfer

We vary the percentage of shared users used to train the translator (see Eq. (1)) with $\{90\%, 70\%, 50\%, 30\%\}$. We compare with a naive transfer strategy of CST, i.e., the way of direct transfer without adaptation. The results are shown in Figure 5 on the New York dataset. We can see that it is beneficial to learn an adaptive mapping during the knowledge transfer even when limited aligned examples are available to train the translator. TrNews improves relative 0.82%, 0.77%, 0.67%, 0.64% in terms of HR@10 performance over CST by varying among $\{90\%, 70\%, 50\%, 30\%\}$ respec-

No.	Title	Attention
0	hillary clinton makes a low-key return to washington	0.0421
1	the hidden message in obama's 'farewell' speech	0.1227*
2	here's why sasha obama skipped the farewell address	0.0000
3	donald trump's 'prostitute scandal' was filmed by cameras and recorded with microphones hidden behind the walls	0.0000
4	white house official explains sasha obama's absence at father's farewell speech	0.0000
5	irish bookie puts odds on trump's administration, inauguration and impeachment	0.0059
6	heads are finally beginning to roll at the clinton foundation	0.0001
7	donald trump's incoming administration considering white house without press corps	**0.7691**
8	donald trump says merkel made 'big mistake' on migrants	0.0574
9	controversial clinton global initiative closing its doors for good	0.0024
c	army chief gen. bipin rawat talks about equal responsibility for women in the frontlines. we couldn't agree more	N/A

Table 5: Example I: Some articles matter more while some are negligible. (c is the candidate news)

No.	Title	Attention
0	inauguration fail: the numbers are coming in and donald trump has an unbelievably small crowd	0.0615
1	document found that proves trump right about who created isis	0.0611
2	moments after trump oath, look what disappears from white house website	0.0019
3	breaking: first day in office, trump scores huge victory	0.0114
4	breaking: trump smashes another piece of obama's legacy	0.1413
5	5 signs that donald trump's presidency is already imploding	0.0038
6	local mexicans react to president trump's wall	0.1747*
7	republicans must save the nation from president trump	**0.3255**
8	today was the worst day yet	0.1420
9	trump's executive orders are stretching the limits of presidential power and republicans are pleased	0.0762
c	in defense of a liberal order	N/A

Table 6: Example II: All historical articles are useful.

tively. So we think that the more aligned examples the translator has, the more benefits it achieves.

4.5 Impact of the length of the history

Since we generate the training examples by sliding over the whole reading history for each user, the length of reading history is a key parameter to influence the performance of TrNews. We investigate how the length of the history affects the performance by varying it with $\{3, 5, 10, 15, 20\}$. The results on the New York dataset are shown in Figure 6. We can observe that increasing the size of the sliding window is sometimes harmful to the performance, and TrNews achieves good results for length 10. This is probably because of the characteristics of news freshness and of the dynamics of user interests. That is, the latest history matters more in general. Also, increasing the length of the input makes the training time increase rapidly, which are 58, 83, 143, 174, and 215 seconds when varying with $\{3, 5, 10, 15, 20\}$ respectively.

4.6 Impact of sharing word embeddings

We investigate the benefits of sharing word embeddings between source and target domains. Take the New York dataset as an example, the size of the intersection of their word vocabularies is 11,291 while the union is 50,263. From the results in Table 7 we can see that it is beneficial to share the word embeddings even when only 22.5% words are intersected between them.

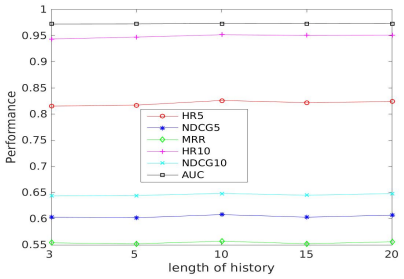


Figure 6: Impact of the length of the history.

Sharing?	HR@5	HR@10	NDCG@5	NDCG@10	MRR	AUC
No	81.31	94.69	59.43	63.72	54.37	97.16
Yes	**82.60**	**95.15**	**60.78**	**64.83**	**55.70**	**97.28**

Table 7: Impact of sharing word embeddings between source and target domains.

4.7 Examining user profiles

One advantage of TrNews is that it can explain which article in a user's history matters the most for a candidate article by using attention weights in the user encoder module. Table 5 shows an example of interactions between some user's history articles 0∼9 and a candidate article $c = 10$, i.e., the user reads the candidate article after read these ten historical articles. We can see that the latest three articles matter the most since the user interests may remain the same during a short period. The oldest two articles, however, also have some impact on the candidate article, reflecting that the user interests may mix with a long-term characteristic. TrNews can capture these subtle short- and long-term user interests. Table 6 shows another pattern that all historical articles contribute to the user preference on the candidate article.

5 Conclusion

We investigate the user cold-start news recommendation via transfer learning. The experiments on real-word datasets demonstrate the necessity of tackling heterogeneity of user interests and word distributions across domains. Our TrNews model and its translator component are effective to transfer knowledge from the source network to the target network. We also shows that it is beneficial to learn a mapping from the source domain to the target domain even when only a small amount of aligned examples are available.

In future works, we will focus on preserving the privacy of the source domain when we transfer its knowledge to the target domain since it may be unavailable and unlawful to share the data.

References

Mingxiao An, Fangzhao Wu, Chuhan Wu, Kun Zhang, Zheng Liu, and Xing Xie. 2019. Neural news recommendation with long-and short-term user representations. In *Proceedings of Annual Meeting of Association for Computational Linguistics*, pages 336–345.

Iman Barjasteh, Rana Forsati, Farzan Masrour, Abdol-Hossein Esfahanian, and Hayder Radha. 2015. Cold-start item and user recommendation with decoupled completion and transduction. In *Proceedings of ACM Conference on Recommender Systems*.

Yoshua Bengio, Pascal Lamblin, Dan Popovici, and Hugo Larochelle. 2007. Greedy layer-wise training of deep networks. In *Advances in neural information processing systems*, pages 153–160.

I. Cantador, I. Fernández, S. Berkovsky, and P. Cremonesi. 2015. Cross-domain recommender systems. In *Recommender systems handbook*.

Abhinandan S Das, Mayur Datar, Ashutosh Garg, and Shyam Rajaram. 2007. Google news personalization: scalable online collaborative filtering. In *Proceedings of World Wide Web*, pages 271–280.

Crícia Z Felício, Klérisson VR Paixão, Celia AZ Barcelos, and Philippe Preux. 2017. A multi-armed bandit model selection for cold-start user recommendation. In *Proceedings of Conference on User Modeling, Adaptation and Personalization*, pages 32–40.

Wenjing Fu, Zhaohui Peng, Senzhang Wang, Yang Xu, and Jin Li. 2019. Deeply fusing reviews and contents for cold start users in cross-domain recommendation systems. In *Proceedings of AAAI Conference on Artificial Intelligence*, pages 94–101.

Wen Gao, Yonghong Tian, Tiejun Huang, and Qiang Yang. 2010. Vlogging: A survey of videoblogging technology on the web. *ACM Computing Surveys*.

Xavier Glorot, Antoine Bordes, and Y. Bengio. 2011. Domain adaptation for large-scale sentiment classification: A deep learning approach. In *Proceedings of international conference on machine learning*.

Huifeng Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, and Xiuqiang He. 2017. Deepfm: a factorization-machine based neural network for ctr prediction. In *Proceedings of International Joint Conference on Artificial Intelligence*, pages 1725–1731.

Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural collaborative filtering. In *Proceedings of world wide web*.

Geoffrey E Hinton and Ruslan R Salakhutdinov. 2006. Reducing the dimensionality of data with neural networks. *Science*, 313(5786):504–507.

Guangneng Hu, Yu Zhang, and Qiang Yang. 2018a. Conet: Collaborative cross networks for cross-domain recommendation. In *Proceedings of ACM International Conference on Information and Knowledge Management*, pages 667–676.

Ziniu Hu, Weiqing Liu, Jiang Bian, Xuanzhe Liu, and Tie-Yan Liu. 2018b. Listening to chaotic whispers: A deep learning framework for news-oriented stock trend prediction. In *Proceedings of ACM International Conference on Web Search and Data Mining*.

Haoran Huang, Qi Zhang, Yeyun Gong, and Xuanjing Huang. 2016. Hashtag recommendation using end-to-end memory networks with hierarchical attention. In *Proceedings of International Conference on Computational Linguistics*, pages 943–952.

Yu-Yang Huang and Shou-De Lin. 2016. Transferring user interests across websites with unstructured text for cold-start recommendation. In *Proceedings of Conference on Empirical Methods in Natural Language Processing*, pages 805–814.

SeongKu Kang, Junyoung Hwang, Dongha Lee, and Hwanjo Yu. 2019. Semi-supervised learning for cross-domain recommendation to cold-start users. In *Proceedings of ACM International Conference on Information and Knowledge Management*.

Diederik P Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *International Conference on Learning Representations*.

Bin Li, Qiang Yang, and Xiangyang Xue. 2009. Can movies and books collaborate? cross-domain collaborative filtering for sparsity reduction. In *International Joint Conference on Artificial Intelligence*.

Pan Li and Alexander Tuzhilin. 2020. Ddtcdr: Deep dual transfer cross domain recommendation. In *Proceedings of ACM International Conference on Web Search and Data Mining*.

Yitong Li, T. Baldwin, and T. Cohn. 2019. Semisupervised stochastic multi-domain learning using variational inference. In *Proceedings of Annual Meeting of Association for Computational Linguistics*.

Bo Liu, Ying Wei, Yu Zhang, Zhixian Yan, and Qiang Yang. 2018. Transferable contextual bandit for cross-domain recommendation. In *AAAI Conference on Artificial Intelligence*.

Jiahui Liu, Peter Dolan, and Elin Rønby Pedersen. 2010. Personalized news recommendation based on click behavior. In *Proceedings of international conference on Intelligent user interfaces*, pages 31–40.

Pasquale Lops, M. De Gemmis, and G. Semeraro. 2011. Content-based recommender systems: State of the art and trends. In *Recommender systems handbook*.

Zhongqi Lu, Zhicheng Dou, Jianxun Lian, Xing Xie, and Qiang Yang. 2015. Content-based collaborative filtering for news topic recommendation. In *Twenty-ninth AAAI conference on artificial intelligence*.

Thang Luong, Hieu Pham, and Christopher D. Manning. 2015. Effective approaches to attention-based neural machine translation. In *Proceedings of Conference on Empirical Methods in Natural Language Processing*, pages 1412–1421.

Ye Ma, Lu Zong, Yikang Yang, and Jionglong Su. 2019. News2vec: News network embedding with subnode information. In *Proceedings of Conference on Empirical Methods in Natural Language Processing*.

Tong Man, Huawei Shen, Xiaolong Jin, and Xueqi Cheng. 2017. Cross-domain recommendation: an embedding and mapping approach. In *Proceedings of International Joint Conference on Artificial Intelligence*, pages 2464–2470.

Brendan McMahan, Gary Holt, David Sculley, Michael Young, Dietmar Ebner, Julian Grady, Lan Nie, Todd Phillips, Eugene Davydov, Daniel Golovin, et al. 2013. Ad click prediction: a view from the trenches. In *Proceedings of ACM SIGKDD international conference on Knowledge discovery and data mining*.

Shumpei Okura, Yukihiro Tagami, Shingo Ono, and Akira Tajima. 2017. Embedding-based news recommendation for millions of users. In *Proceedings of ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.

Rong Pan, Yunhong Zhou, Bin Cao, Nathan N Liu, Rajan Lukose, Martin Scholz, and Qiang Yang. 2008. One-class collaborative filtering. In *IEEE International Conference on Data Mining*, pages 502–511.

Sinno Jialin Pan and Qiang Yang. 2009. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359.

Weike Pan, Evan Wei Xiang, Nathan Nan Liu, and Qiang Yang. 2010. Transfer learning in collaborative filtering for sparsity reduction. In *AAAI conference on artificial intelligence*.

Seung-Taek Park and Wei Chu. 2009. Pairwise preference regression for cold-start recommendation. In *Proceedings of ACM conference on Recommender systems*, pages 21–28.

Michael Pazzani and D. Billsus. 2007. Content-based recommendation systems. In *The adaptive web*.

Hao Peng, Jing Liu, and Chin-Yew Lin. 2016. News citation recommendation with implicit and explicit semantics. In *Proceedings of Annual Meeting of Association for Computational Linguistics*.

Dimitrios Rafailidis and Fabio Crestani. 2019. Neural attentive cross-domain recommendation. In *Proceedings of ACM SIGIR International Conference on Theory of Information Retrieval*, pages 165–172.

Suman Deb Roy, Tao Mei, Wenjun Zeng, and Shipeng Li. 2012. Socialtransfer: cross-domain transfer learning from social streams for media applications. In *Proceedings of ACM international conference on Multimedia*, pages 649–658.

Michele Trevisiol, Luca Maria Aiello, Rossano Schifanella, and Alejandro Jaimes. 2014. Cold-start news recommendation with domain-dependent browse graph. In *Proceedings of ACM Conference on Recommender systems*, pages 81–88.

Manasi Vartak, Arvind Thiagarajan, Conrado Miranda, Jeshua Bratman, and Hugo Larochelle. 2017. A meta-learning perspective on cold-start recommendations for items. In *Advances in neural information processing systems*, pages 6904–6914.

Pascal Vincent, Hugo Larochelle, Isabelle Lajoie, Yoshua Bengio, and Pierre Manzagol. 2010. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. *Journal of machine learning research*.

Hongwei Wang, Fuzheng Zhang, Xing Xie, and Minyi Guo. 2018. Dkn: Deep knowledge-aware network for news recommendation. In *Proceedings of World Wide Web Conference*, pages 1835–1844.

Chuhan Wu, Fangzhao Wu, Mingxiao An, Yongfeng Huang, and Xing Xie. 2019a. Neural news recommendation with topic-aware news representation. In *Proceedings of Annual Meeting of the Association for Computational Linguistics*, pages 1154–1159.

Chuhan Wu, Fangzhao Wu, Mingxiao An, Tao Qi, Jianqiang Huang, Yongfeng Huang, and Xing Xie. 2019b. Neural news recommendation with heterogeneous user behavior. In *Proceedings of Conference on Empirical Methods in Natural Language Processing*.

Wenyi Xiao, Huan Zhao, Haojie Pan, Yangqiu Song, Vincent W. Zheng, and Qiang Yang. 2019. Beyond personalization: Social content recommendation for creator equality and consumer satisfaction. In *Proceedings of ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*.

Rui Yan, Mirella Lapata, and Xiaoming Li. 2012. Tweet recommendation with graph co-ranking. In *Proceedings of Annual Meeting of Association for Computational Linguistics:*.

Qiang Yang, Yuqiang Chen, Gui-Rong Xue, Wenyuan Dai, and Yong Yu. 2009. Heterogeneous transfer learning for image clustering via the social web. In *Proceedings of Annual Meeting of Association for Computational Linguistics*.

Yang Yu, Xiaojun Wan, and Xinjie Zhou. 2016. User embedding for scholarly microblog recommendation. In *Proceedings of Annual Meeting of Association for Computational Linguistics*.

Guorui Zhou, Xiaoqiang Zhu, Chenru Song, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqi Jin, Han Li, and Kun Gai. 2018. Deep interest network for click-through rate prediction. In *Proceedings of ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1059–1068.

Feng Zhu, Yan Wang, Chaochao Chen, Guanfeng Liu, Mehmet Orgun, and Jia Wu. 2018. A deep framework for cross-domain and cross-system recommendations. In *International Joint Conference on Artificial Intelligence*.