DCAN: Diversified News Recommendation with Coverage-Attentive Networks

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ABSTRACT Self-attention based models are widely used in news recommendation tasks. However, previous Attention architecture does not constrain repeated information in the user’s historical behavior, which limits the power of hidden representation and leads to some problems such as information redundancy and filter bubbles. To solve this problem, we propose a personalized news recommendation model called DCAN. It captures multi-grained user-news matching signals through news encoders and user encoders. We keep updating a coverage vector to track the history of news attention and augment the vector in 4 types of ways. Then we fed the augmented Coverage vector into the Multi-headed Self-attention model to help adjust the future attention and added the Coverage regulation to the loss function (CRL), which enabled the recommendation system to consider more about differentiated information. Extensive experiments on Microsoft News Recommendation Dataset (MIND) show that our model significantly improve the diversity of news recommendations with minimal sacrifice in accuracy.

INDEX TERMS Coverage vector, Diversity, Positional Embedding, Self-attention, News Recommendation

I. INTRODUCTION

THENews Recommender System (NRS) has been widely used in online news websites [14], [31]. It helps users to find news of interest in huge amounts of data. In most studies, accuracy is the primary or even the only goal of news recommendation. However, improving the diversity of recommended content is essential for enhancing [1], [48], [37] user experience. The excessive pursuit of accuracy indirectly leads to information redundancy in recommended content [39], users’ boredom [23], [25] and filter bubbles [17], [35], [46], which have many negative effects on society.

To address these issues, some studies [1], [48] have used diversity to improve user engagement and user satisfaction in recommendation scenarios. However, many existing diversity-oriented news recommendation methods [21], [41], [45] perform poorly, and only a few methods [36], [43] have achieved good results. Moreover, most of these algorithms ignore the use of the Coverage mechanism to improve recommendation diversity. The Coverage mechanism is common to machine translation and has achieved satisfactory results. Since the Coverage vector contains historical information, it can be used to model the information that is different from the historical behaviour in candidate news and improve the diversity of recommendation.

In this paper, we propose Deep Coverage Attentive Networks (DCAN), which integrates the Coverage attributes into recommendations in an end-to-end and extensible way. Specifically, we model user behaviour as a Coverage sequence in the latent space, and then augment the Coverage sequence to mine multi-view Coverage information. Afterwards, multiple augmented Coverage sequences are embedded into different self-attention headers of the model. Finally, we also configure the corresponding regularizer for the target function according to the different Coverage sequences. Experiments show that our work can effectively improve the diversity of news recommendations with minimal loss of accuracy. Experiments show that our work can effectively improve the diversity of news recommendations with minimal sacrifice in accuracy. Our contributions are as follows.

1. We propose a novel DCAN model, which is a news recommendation model combining diversification and relevance.
2. Coverage mechanism in machine translation is used to improve multiple self-attention mechanisms and objective functions.
3. Experiments on news datasets demonstrate the effective-
ness of our model. We also investigate the impact of various novel modules in the model through ablation experiments.

II. RELATED WORK
A. NEWS RECOMMENDATION
The core problem of news recommendation is learning the representation of news and users and ranking candidate news based on their representation [41]. Modeling news representations are generally from the title, category, entity, keyword, abstract, tag, etc, while the information of modeling users includes news click, user ID, Time, Location, Non-click, Finish, Quick Close, Share, Dislike, etc. [55]. In recent years, several news recommendation methods based on deep learning techniques have been proposed and achieved better performance than traditional methods. DKN [31] NPA [18] and [45], [55], [51] use CNN and personalized attention for representation learning. NRMS [34] use self-attentional networks for news representation, Plm-nr [15] UNBERT [52] uses the pre-trained BERT model for feature representation. Slightly different from these methods, our model learns news representations through transformers and forms user representations using multi-head self-attention with Coverage embedding.

B. DIVERSITY RECOMMENDATION
Diversity recommendation is often regarded as a bi-criteria optimization problem, which seeks to maximize the relevance of the recommended list while minimizing the redundancy among the recommended items [5]. Diversity recommendations usually have two solutions: aggregate-level diversity [5] and individual diversity. The former aims to increase the differentiation of all recommended content and exposure to long-tail content [4], [16], [9], while the latter aims to improve the intra-user diversity [22], [24]. Our work focuses on the latter.

The diversity recommendation methods can be divided into two categories: offline optimization and online optimization. Offline non-interactive methods usually generate recommendations based on user historical interactions and then rank them. These include post-processing methods based on heuristics [42] and determinantal Point Process [16] [29] [47], and Learning to Rank (LTR) [28] [27] generation ranking methods. Online approaches are to update recommendation policies based on real-time interactions between users and recommendation systems, such as contextual bandits [9], [10] and deep reinforcement learning [57].

C. COVERAGE MECHANISM
Coverage mechanisms are generally used to mitigate over-translation and under-translation problems in neural machine translation. [32] summed the attention distribution during decoding to obtain a Coverage vector. This vector was used to track the attention history and to compute a new attention distribution at the next time step. [19] proposed a Coverage based loss function to penalize attentional repetition in text summarization during optimization. Coverage mechanisms play a role in enhancing diversity in recommender systems. [11] proposed a Coverage method based on a probability model for diversity reordering algorithm. [2] represents news as nodes in a similarity graph, and improves recommendation diversity by recommending subsets of news that are positively rated by users and have low Coverage values.

III. OUR APPROACH
In this section, we first formulate the problem of news recommendation, then detail our DCAN including the News Encoder, User Encoder and the prediction module(Figure 1), and finally elaborate on a model training method.

A. PROBLEM STATEMENTS
For a given user u and candidate news v, we denote the history of news clicks for user u as \( V_u = [v_1^u, \ldots, v_{|V_u|}^u] \). Our goal is to predict the next news that user u is likely to interact with based on the given history \( V_u \) and to maximize the diversity of recommended content. The output of DCAN is a matching score, which represents the probability that user u will click on the candidate news.

B. NEWS ENCODER
The news encoder is used to learn news representations from features such as news title, entity, abstract, category, etc. This article only uses the feature of the news title, which consists of a series of words. As shown in Figure 2, for any news \( v_i^u = [w_1^u, \ldots, w_n^u] \), \( w_i^u \) represents the jth word. Inspired by the news encoder [34], we first use a word embedding layer to convert word sequences in news titles into the embedding vector sequence \( E^u = [e_1^u, e_2^u, \ldots, e_{|V_u|}^u] \). Then we use Transformer [6] encoder to capture the context of words and build a d-dimensional vector to represent the news. We denote the sequence of news clicks learned by the news encoder as \( R_u = [r_1^u, r_2^u, \ldots, r_{|R_u|}^u] \), and the candidate news representations are denoted as \( r_c \).

C. USER ENCODER
The User Encoder module is used to learn the user’s representation from the news that the user browses. It consists of five parts.

1) User Encoder Input Layer
After \( V_u \) has been converted into \( R_u \) by news encoder, we feed \( R_u \) into the model. As in previous work [8], [30], our User Encoder is a fixed-length model with length N. Therefore, \( R_u \) needs to be converted to \( R^u = [r_1^u, r_2^u, \ldots, r_{|R_u|}^u | \text{mask} ] \in \mathbb{R}^{N \times d} \). If the history is less than N-1, it will be padded with a special token [PAD].

2) Coverage Feature representation module
In this part, we constructed the Coverage feature representation sequence \( Cov^u = [c_1^u, c_2^u, \ldots, c_{|Cov^u|}^u] \) based on \( R_u \).
and satisfied $c_i^u = r_i^u$, $c_i^u = c_{i-1}^u + r_i^u$ and $c_i \in \text{Cov}_i$.
For a fixed-length model of length $N$, the Coverage sequence is $\text{Cov}_u = [c_1^u|\text{Cov}_u|_{-N+1}, \ldots, c_i^u|\text{Cov}_u|_{-1}, c_i^u|\text{Cov}_u|_{1\text{ mask}}] \in \mathbb{R}^{N \times d}$.

3) Coverage Augmentation Module
To obtain different views of the Coverage properties, we take four types of data augmentation: Decay, Circle, Log, Gamma.

The first one is the Decay encoder ($C^\text{Decay}$), which converts $c_i^u$ to $c_i^{Decay}$ using the following equation.

$$c_i^{Decay} = r_i + \eta r_{i-1} + \eta^2 r_{i-2} + \ldots + \eta^{i-1} r_1, \eta \in [0, 1]$$  \hspace{0.5cm} (1)

The Circle encoder ($C^\text{Circle}$) converts the $c_i^u$ into hidden vectors $c_i^{\text{circle}} = \{c_i^{\text{sin}}, c_i^{\text{cos}}\} \in \mathbb{R}^d$ by the following formula.

$$c_i^{\text{sin}} = \sin(\frac{c_i^{2a_1} \times \pi}{\text{freq}}), c_i^{\text{cos}} = \sin(\frac{c_i^{2a_1+1} \times \pi}{\text{freq}})$$  \hspace{0.5cm} (2)

where $c_i^{2a_1}$ the $a$th value of the $c_i$ vector and freq is an adjustable parameter. The Log encoder ($C^\text{Log}$) and Gamma encoder ($C^\text{Gamma}$) convert $c_i^u$ to $c_i^{\text{log}}$ and $c_i^{\text{Gamma}}$ by the following equations, respectively.

$$c_i^{\text{log}} = \log\left(1 + \frac{|c_i^u|}{\text{freq}}\right), c_i^{\text{Gamma}} = \beta c_i^{a} e^{(-\beta c_i^u)}$$  \hspace{0.5cm} (3)

Where $\beta$ is the scale hyperparameter. After augmentation, the $c_i^{\text{circle}}$ vector makes it more focused on recent news. The Log can alleviate the problem that large values have too much influence on the results. Finally, the Gamma encoder keeps the best Coverage value in a moderate range.

4) Coverage embedded Self-Attention Structure
There are several options for embedding encoding functions into attention headers. Self-attention based Models [7], [44], [8] take the sum of $R_u$ and position encoding $C^{\text{position}}$ as the input of [Query] [Key] [Value]. Advanced transformers [30] position encoding is replaced by features and only [key] is embedded, or the feature of representations are embedded in [query] and [key] [30]. In our work, we first divided the vectors $C_i^\text{Circle}, C_i^\text{Decay}, C_i^\text{Log}, C_i^\text{Gamma}$ by the historical click times $i$ to calculate the average value, then inserted the obtained vectors into [Value] as shown in Figure 3. Since Coverage can track attention history, the [Value] used for decoding learns information that is different from historical behaviour.

5) Stacking Self-Attention Blocks
The part after self-attention is similar to [8], [30]. We feed the self-attention output into a feed-forward network (FFN), and then stack the self-attention and FFN $L$ times. Like [8], [44], we build a residual connection for each stacking module and then use layer normalization [26] to facilitate training.

$$y = \text{layerNorm}(x + \text{Dropout}(\text{Attention}(x)))$$

$$y = \text{layerNorm}(y + \text{Dropout}(\text{FFN}(y)))$$  \hspace{0.5cm} (4)

Where $\text{GELU} = \frac{\sigma(x) + x}{2}$ is the Gaussian Error Linear Unit and $x \in \mathbb{R}^{1 \times d}$ is the output of the Coverage embedded multi-head Attention (CMA). $M^1 \in \mathbb{R}^{d \times 4d}, b^1 \in \mathbb{R}^{4d}, M^2 \in \mathbb{R}^{d \times 4d}$ and $b^2 \in \mathbb{R}^{d \times 4d}$ is a learnable parameter.

D. PREDICTION MODULE
Given the output $O = [o_1, \ldots, o_i, \ldots, o_N] \in \mathbb{R}^{N \times d}$ of the last layer, we obtain the news score distribution for each position by using the following equation.

$$P(V \mid r, c) = \text{softmax} \left(\text{GELU} \left(\alpha_i M^p + b^p\right) M^T + b^o\right)$$  \hspace{0.5cm} (5)

Where $M \in \mathbb{R}^{d \times d}, b^p \in \mathbb{R}^{d}$ and $b^o \in \mathbb{R}^{|R|}$ are the learnable parameters, and $M^T \in \mathbb{R}^{d \times |r_i|}$ is the candidate news embedding. $P(r_i = r| r, c)$ is the probability that an news at position $i$ is news $r$.

E. MODEL TRAINING
Overall, to provide recommendations with both accuracy and diversity, we calculate the following mixed loss functions to train the DCAN model.

$$L = L_{\text{main}} + \gamma L_{\text{diverse}}$$  \hspace{0.5cm} (6)

where $L_{\text{main}}$ is the click prediction loss function, and $L_{\text{diverse}}$ is a Coverage-based diversification-oriented regularization loss (DOR).

1) Main loss
We train the model using the techniques in [8], [19]. We feed $V_u$ into news encoder to generate $R_u$ and $C_u$. We sample the news subsequence $R_u^{\text{main}} \in R_u$ and $C_u^{\text{main}} \in C_u$ respectively and convert $R_u^{\text{main}}$ to $R_u^{\text{main}}$ by randomly masking $R_u^{\text{main}}$ with probability $\rho$. Finally, we feed $R_u^{\text{main}}$ and $C_u^{\text{main}}$ to our model and get the probability that news at position $i$ is $R_u^{\text{main}}$. We calculate the loss as follows:

$$L_{\text{main}} = -\sum_{R_u^{\text{main}} \text{ is masked}} \log P(R_u^{\text{main}} \mid R_u^{\text{main}}, C_u^{\text{main}})$$  \hspace{0.5cm} (7)

2) Diverse-Oriented Regularization
Finding differentiated recommendation information is an effective way to diversify recommended content, but in fact, it is difficult to estimate the feature distribution of diverse information. To solve this problem, the training objective is to enlarge the distance between the output feature distribution and Coverage feature distribution. We add a regular function based on the Coverage mechanism to the original loss function. Specifically, the Coverage vector $c_i^u$ is augmented to $C_i^\text{Decay}, C_i^\text{Circle}, C_i^\text{Log}, C_i^\text{Gamma}$ according to the Coverage
To verify the effectiveness of our method, we compared it lines in accuracy and diversity. We expect to increase model designed to have larger values when ground truth news ranks higher in the top-K list. We compare our models with base-

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A. DATASETS

We evaluated our model on the real-world news recommendation dataset MIND \[31\], which consists of anonymous behaviour logs from Microsoft News. There are two versions of the MIND datasets named MIND-large and MIND-small. Where MIND-small is a small version of MIND-large by randomly sampling daily behaviour with equal probability. The basic statistics for these two datasets are shown in Table 1. For these two data sets, we generate training samples from
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time \[31\]. We grouped the interactions according to user ids and then sorted them according to timestamps, forming a sequence for each user.

B. ASSESSMENT

To evaluate the performance of the recommendation model, we keep the last news of each user’s click sequence as test data, which is widely used in \[33\], \[40\], \[44\]. The item just before the last item is considered to be validation data. We train with the rest of the news. We use the rest of the news as a training set. Inspired by \[8\], \[30\], \[44\], \[49\], the model takes 100 randomly sampled news that users have not yet interacted with as negative samples and pairs them with ground truth. Negative sampling correlates with popularity. To score the ranking list, we use three metrics: Accuracy (AUC), Normalized Discounted Cumulative Gain (NDCG), and Diversity Score(DIV). We set diversity as the difference of news pairs under a certain cutoff \((k)\) in a user’s recommendation list. Thus, we use the intra-column similarity (ILS) \[22\], \[24\]as the diversity metric. AUC, NDCG@K, and DIV@K are all designed to have larger values when ground truth news ranks higher in the top-K list. We compare our models with baselines in accuracy and diversity. We expect to increase model diversity while maintaining as much accuracy as possible.

C. BASELINE MODEL AND IMPLEMENTATION DETAILS

To verify the effectiveness of our method, we compared it with the following representative baselines: MMR \[24\] DPP

IV. EXPERIMENTS

A. DATASETS

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Squared Error:

\[ \text{Coverage vector } C_i = \phi_i \text{Decay} + \phi_i \text{Circle} + \phi_i \text{Log} + \phi_i \text{Gamma} \]

\[ (8) \]

We calculated the L2 norm \[26\] of the output vector \(o_i\) and Coverage vector \(C_i^{COV}\).

\[ \hat{o}_i = \frac{o_i}{\|o_i\|_2} - \frac{C_i^{COV}}{\|C_i^{COV}\|_2} \]

\[ (9) \]

Then we define the diverse loss with the help of Mean Squared Error:

\[ L_{\text{diverse}} = -\|\hat{o}_i - \frac{C_i^{COV}}{\|C_i^{COV}\|_2}\|^2 \]

\[ (10) \]

D. RESULTS

Table 2 shows the results for all models on two datasets (mind-small and mind-large). It also shows the comparison between our model and the strongest baseline. Overall, our model achieves the best performance on all diversity metrics, while the click prediction accuracy (AUC) and recommendation accuracy (NDCG) losses are within a reasonable range (-1. 55% and -3. 38% on average). For the evaluation of DIV@10, DIV@20 and DIV50, our model achieved 4. 36%, 3. 7% and 2. 5% improvement over the strongest baseline, respectively. We observe that the overall performance of the attention-based methods is better than the traditional recommenders. Since most of our baseline models utilize the multi-head attention mechanism, we also find that the performance improvement comes from our proposed novel Coverage embedding multi-head attention and Diverse-Oriented Regularization loss function.

In order to analyze the impact of different Coverage embedding and regularization functions in our model, we conduct an ablation study on the MIND-small dataset. We unified all the other hyperparameters. Table 3 shows the performance of our default DCAN method and its variants. DCAN consists of 4 kinds of coverage vectors include \(C_{\text{Decay}}, C_{\text{Circle}}, C_{\text{Log}}, C_{\text{Gamma}}\) and 4 kinds of DORs includes \(\text{DOR}_{\text{Decay}}, \text{DOR}_{\text{Circle}}, \text{DOR}_{\text{Log}}, \text{DOR}_{\text{Gamma}}\). Our model variants are named DCAN. When we remove some side information, we use a minus sign in front of the coverage vectors and DORs, e.g. \(-C_{\text{Decay}} - \text{DOR}_{\text{Decay}}\) is DCAN without \(-C_{\text{Decay}}\) and \(-\text{DOR}_{\text{Decay}}\). The results show that the importance of each kind of embedding seems to be different. In general, the performance of multiple embedding is generally greater than that of individual embedding. The Circle embedding seems to have a greater impact on the DIV than other kinds of embedding. This suggests that although
users have relatively fixed reading preferences for news, there are inherent differences in short-term news browsing (within one day), so the modeling effect of short-term Coverage embedding such as Decay and Gamma is not significant. This suggests that diversity modeling needs to take into account the reading habits of users and flexibly select different Coverage embedding.

In addition, the further analysis of self-attention showed that with the increase of the number of heads, $h = \{8, 10, 20, 25\}$, the diversity fluctuated continuously with no obvious trend. It can be seen that the types of embedding vector and loss function play an important role in the training process, while the variation of attention heads does not significantly improve diversity performance.

V. CONCLUSION
In this paper, we propose a novel method named Deep Coverage Attentive Networks for diversified news recommendations. The core of our method is to provide unique position embedding for the self-attention module by using multiple augmentation methods of Coverage information in the user encoder and adding a corresponding Coverage regularizer into the objective function at the same time. Experiments on real datasets show that our model outperforms state-of-the-art baselines in diversity recommendation. Through extensive ablation studies, we also found that the Coverage augmentation embedding scheme needs to fully consider user preferences. In the future, we will improve our method in the following directions. First, we’ll try embedding the Coverage attribute into other Transformer variants to see what happens. Second, we consider introducing more features (such as news types, news sentiment, etc.) and techniques (such as contrast learning) to improve diversity. We will study the diversity feature representation method. Finally, we will further study the diversity representation method (such as GNN).

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FIGURE 1. Model Architecture

FIGURE 2. The framework of news encoder.
FIGURE 3. Brief overview of the User encoder with coverage embedded multi-headed attention structure.

| Datasets     | News | Users | Train impression | Val impression | Test impression |
|--------------|------|-------|------------------|----------------|-----------------|
| MIND-small   | 161,013 | 50,000 | 199,998.00       | 50,002.00      | 100,000.00      |
| MIND-large   | 161,013 | 100,000 | 223,274.80      | 376,471.00     | 237,072.70      |

FIGURE 4. Basic statistics of the datasets.

| Metrics     | MIND-small | MIND-large |
|-------------|------------|------------|
| AUC         | 0.586      | 0.585      |
| NDCG10      | 0.457      | 0.456      |
| DIV@10      | 0.456      | 0.456      |
| DIV@20      | 0.455      | 0.456      |
| DIV@50      | 0.454      | 0.455      |

FIGURE 5. The accuracy and diversity performance comparison.
| Variant     | NDCG@10 | DIV@20  | DIV@50  |
|-------------|---------|---------|---------|
| OURS        | 0.5306  | 0.5369  | 0.5245  |
| -C^Decay -DOR^Decay | 0.4976  | 0.5142  | 0.4990  |
| -C^Circle -DOR^Circle | 0.4894  | 0.5049  | 0.4897  |
| -C^Log -DOR^Log     | 0.5007  | 0.5175  | 0.5023  |
| -C^Gamma -DOR^Gamma | 0.5021  | 0.5183  | 0.5031  |
| -C^Decay          | 0.5222  | 0.5251  | 0.5248  |
| -C^Circle         | 0.5067  | 0.5096  | 0.5095  |
| -C^Log            | 0.5222  | 0.5233  | 0.5231  |
| -C^Gamma          | 0.5209  | 0.5229  | 0.5228  |

**FIGURE 6.** NDCG@10, DIV@20 and DIV@50 score of the DCAN variants.