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News Recommendation System with BERT

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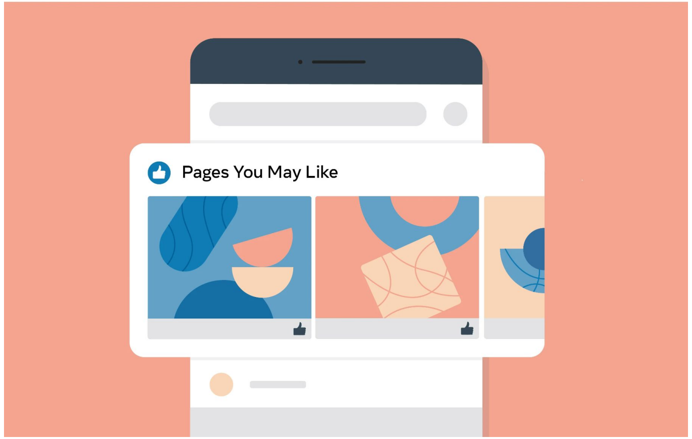
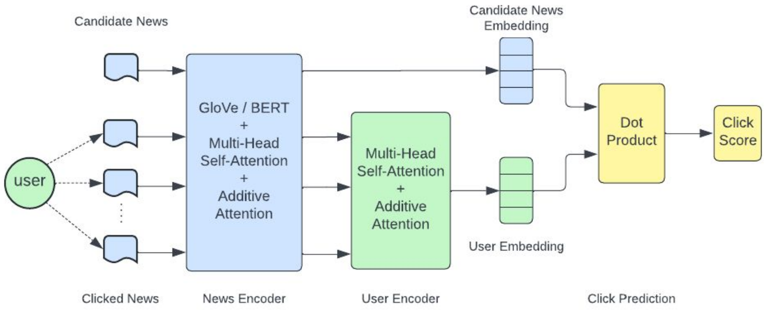
Background



- Previous news recommendation approaches include GRU, CNN, etc.
    - Challenge: learning accurate news and user representations.
- The **NRMS model** (Wu et al., 2019) uses multi-head self-attentions to encode news from news title and users from browsing history.
- The invention of **LLMs** offers the potential to deeply understand textual nuances and user contexts with a better initial point, with a possibility to enhance the recommendation quality.
    - Wu et al. (2021) replaced NRMS' multi-head self-attention with pre-trained **BERT** and fine-tune them with news recommendation task, and achieved better offline results.

NRMS Architecture



Additive Attention: learn more informative news and user representations

Apply **attention mechanism** to capture complex contextual and behavioral interactions.

- **News Encoder**: captures interactions between different words in news titles.
- **User Encoder**: captures the relatedness between news articles browsed by the same user.

Click Prediction: calculates the relevance of the candidates news to users.

Hypothesis

NRMS-BERT achieves higher accuracies in news recommendation than NRMS.

- **Hypothesis 1:** NRMS-BERT can better incorporate features (eg. category, popularity) in news representations than NRMS.

- **Hypothesis 2:** Features captured by model layers in NRMS-BERT can contribute to the effectiveness of news recommendation.

Probing Approaches

- Take the embeddings as feature inputs to classify news categories via a **logistic regression**.

- Use **t-SNE** to reduce news embeddings of the last layer to a two-dimensional space and **visualize** them with respect to specific features, such as news categories.

Experiments

- **Experiment 0**:

  We implement the methods (NRMS & NRMS-BERT) introduced by Wu et al. (2021) by adapting NRMS model to MIND data and empowering it with pre-trained language models.

- **Experiment 1**:

  We aim to employ linear probing techniques to explore whether specific features—news category, popularity, event time—are encoded in embeddings across multi-head attention layers.

- **Experiment 2**:

  We further explore the relationship between our target features and recommendation: “denoise” features from embeddings.

Experiment 0

Model	AUC	MRR	nDCG@5	nDCG@10
NRMS-baseline	0.6655	**0.3210**	0.3474	0.4044
NRMS-BERT	**0.6657**	0.3204	**0.3477**	**0.4055**

Table 1: Results of NRMS-baseline and NRMS-BERT on Test Set

NRMS-BERT generally performs better than NRMS-baseline on most metrics.

- Even though the improvement is not that significant, NRMS-BERT consumes less data to achieve the similar performance as NRMS-baseline. (converges more quickly)

Experiment 1 (News Topic)

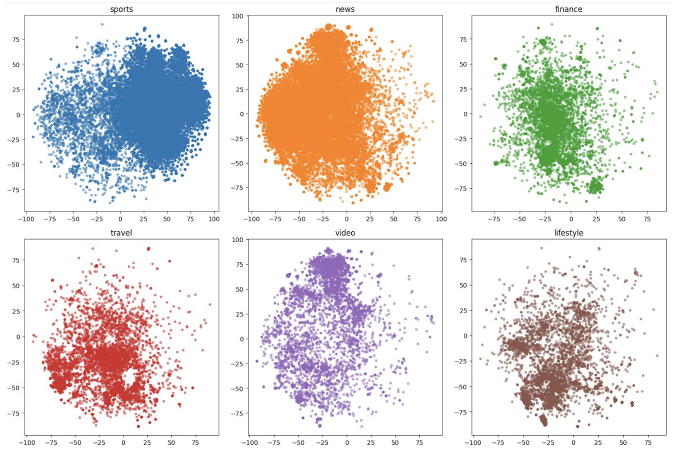
Category	**F1-Score (NRMS)**	**F1-Score (NRMS-BERT)**
Finance	0.44	0.58
Lifestype	0.46	0.56
News	0.73	0.78
Sports	0.87	0.93
Travel	0.37	0.49
Video	0.11	0.28
Overall Accuracy	0.72	0.78

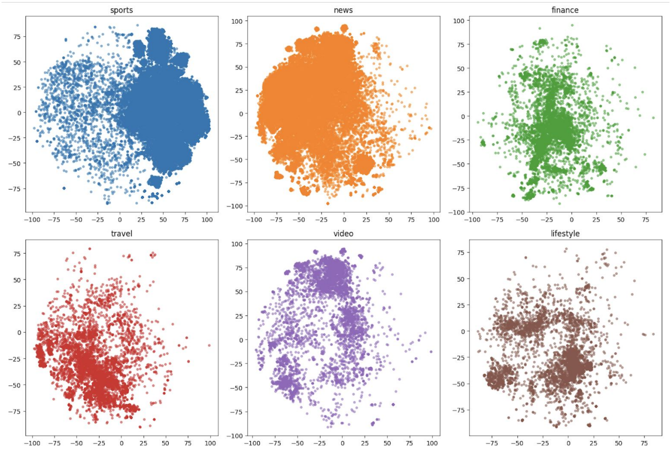
Table 2: Results of Two Embeddings v.s. Categories Using Logistic Regression

Take the embeddings to classify news topics via a logistic regression.

- The results of linear probing further shows the embeddings from NRMS-BERT outperforms the ones from NRMS-baseline in all categories, suggesting that NRMS-BERT is better at capturing category-related information.

Experiment 1 (News Topic)

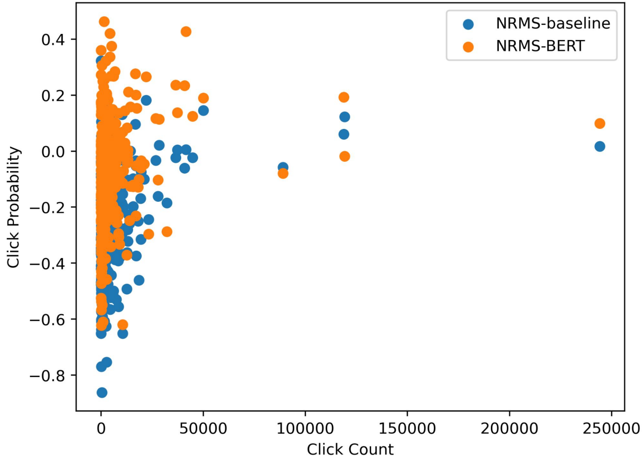




T-SNE visualizations of NRMS-baseline (left) and NRMS-BERT (right) embeddings by news topics:

- NRMS-BERT embeddings are better at differentiating the content inherent to each category as shown in more distinct and compact shapes of the six categories.

Experiment 1 (Popularity)



	Correlation	AUC (New User)
NRMS-baseline	0.23376	0.5843
NRMS-BERT	0.177776	0.5723

Scatter Plot (left) and Correlation (right) of Click Count v.s. Click Probability:

- Both models display no clear correlation between popularity and corresponding prediction of click probability, but both models tend to give relatively higher probability for popular news

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Experiment 2 (TBD)

- **Hypothesis:** News topics captured by model layers in NRMS-BERT can contribute to the effectiveness of news recommendation.

- **Approach:** “Debias” news embeddings and feed them into the model, hypothesis is true if accuracies declined significantly.
    - Subtract the “topic average vector” from each embedding?
    - Use SVM to find a “topic dividing subspace” and project the embeddings onto it?

Discussions & Limitations

- From the two news embedding we identify that the improvement of the news recommendation accuracy may come from the model's improved understanding of news categories.

- Our models only encode information from news titles, which is limited due to their short length and the insufficient clues they provide, even with larger models.

- News recommendation may need to incorporate article content to reach an accuracy breakthrough, but NRMS model alone would be insufficient at that time.

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Thank You Q&A