Train Once, Use Flexibly: A Modular Framework for Multi-Aspect Neural News Recommendation

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Abstract

Recent neural news recommenders (NNRs) extend content-based recommendation (1) by aligning additional *aspects* (e.g., topic, sentiment) between candidate news and user history or (2) by diversifying recommendations w.r.t. these aspects. This customization is achieved by "hardcoding" additional constraints into the NNR's architecture and/or training objectives: any change in the desired recommendation behavior thus requires retraining the model with a modified objective. This impedes widespread adoption of multi-aspect news recommenders. In this work, we introduce MANNeR, a modular framework for *multi-aspect* neural news recommendation that supports on-the-fly customization over individual aspects at inference time. With metric-based learning as its backbone, MANNeR learns aspect-specialized news encoders and then *flexibly* and *linearly* combines the resulting aspect-specific similarity scores into different ranking functions, alleviating the need for ranking function-specific retraining of the model. Extensive experimental results show that MANNeR consistently outperforms state-of-the-art NNRs on both standard content-based recommendation and single- and multi-aspect customization. Lastly, we validate that MANNeR's aspect-customization module is robust to language and domain transfer.

1 Introduction

Neural content-based recommenders, trained to infer users' preferences from their click history, represent the state of the art in news recommendation (Li and Wang, 2019; Wu et al., 2023). While previously consumed content clearly indicates users' preferences, *aspects* (i.e., news features) other than content alone, i.e, category (e.g., *sports*), contribute to their news consumption decisions. Accordingly, some neural news recommenders (NNRs) leverage information on these aspects in addition to text content, be it (i) directly as model input (Wu et al., 2019a; Liu et al., 2020) or (ii) indirectly, as auxiliary training tasks (Wu et al., 2019c, 2020a).

Increased personalization is often at odds with *diversity* (Pariser, 2011). NNRs optimized to maximize congruity to users' preferences tend to produce suggestions highly similar in content to previously consumed news (Liu et al., 2021; Wu et al., 2020a; Sertkan and Neidhardt, 2023). Another strand of work thus focuses on increasing diversity of recommendations w.r.t. aspects other than content (e.g., sentiment). To this effect, prior work either (i) re-ranks content-based recommendations to decrease the aspectual similarity between them (Rao et al., 2013; Gharahighehi and Vens, 2023), or (ii) trains the NNR model by combining a content-based personalization objective with an aspect-based diversification objective (Wu et al., 2020a, 2022b; Shi et al., 2022; Choi et al., 2022).

Different users assign different importance to various news aspects (e.g., following developing events requires maximization of content-based overlap with the user's recent history; in another use-case, a user may prefer content-wise diversification of recommendations, but within the same topic of interest). Moreover, with personalization and diversification as mutually conflicting goals, users should be able to seamlessly define their own optimal trade-offs between the two. The existing body of work is ill-equipped for such multi-aspect customization, because each set of preferences – i.e., to personalize or diversify for each aspect – requires a different NNR model to be trained from scratch. Put differently, forcing global assumptions on personalization and diversification preferences (i.e., same for all users) into the model design and training prevents customization at inference time.

Contributions. We propose a *modular* framework for *Multi-Aspect* Neural News Recommendation (MANNeR) to address this limitation. It leverages metric-based contrastive learning to induce a dedicated news encoder for each aspect, starting from a pretrained language model (PLM). This way, we obtain linearly-combinable aspect-specific similarity scores for pairs of news, allowing us to define ad-hoc at inference a custom ranking function for each user, reflecting their preferences across all aspects. MANNeR's modular design allows customization for any recommendation objective specified over (i) standard (i.e., content-based) personalization, (ii) aspect-based diversification, and (iii) aspect-based personalization. It also makes MANNeR easily extendable: to support personalization and diversification over a new aspect (e.g., news outlet), one only needs to train the aspect-specific news encoder for that aspect. Through extensive experiments on two established benchmarks, with *topical categories* and *sentiment* as the additional aspects next to content itself, we find that MANNeR outperforms state-of-the-art NNRs on standard content-based recommendation. Thanks to its module-specific outputs being *linearly composable* between objectives, we show – without training numerous models with different objectives – that depending on the recommendation goals, one can either (i) vastly increase aspect diversity (e.g., over topics and sentiment) of recommendations or (ii) improve aspect-based personalization, while retaining much of the content-based personalization performance. Finally, we demonstrate that MANNeR with a multilingual PLM is robust to the (cross-lingual) transfer of aspect-based encoders.

2 Related Work

Personalized NNR. Neural content-based models have become the main vehicle of personalized news recommendation, replacing traditional recommenders relying on manual feature engineering (Wu et al., 2023). Most NNRs consist of a dedicated (i) news encoder (NE) and (ii) user encoder (UE) (Wu et al., 2023). The NE transforms input features into news embeddings (Wu et al., 2023, 2019d,b), whereas UEs create user-level representations by aggregating and contextualizing the embeddings of clicked news from the user's history (Okura et al., 2017; An et al., 2019; Wu et al., 2022c). The candidate's recommendation score is computed by comparing its embedding against the user embedding (Wang et al., 2018; Wu et al., 2019a). NNRs are primarily trained via point-wise classification objectives with negative sampling (Huang et al., 2013; Wu et al., 2021). Exploiting users' past behavior as NNR supervision leads to recommendations that are content-wise closest to previously consumed news, in contrast to methods based on non-personalized criteria (Son et al., 2013; Chen et al., 2017; Ludmann, 2017). More recent NNRs seek to augment content-based personalization by considering other aspects, such as categories, sentiment, emotions (Sertkan and Neidhardt, 2022), entities (Iana et al., 2024), outlets, or recency (Wu et al., 2023). These are incorporated in the NNR either as additional input to the NE (Wang et al., 2018; Gao et al., 2018; Wu et al., 2019a; Liu et al., 2020; Sheu and Li, 2020; Lu et al., 2020; Qi et al., 2021a; Xun et al., 2021), or in the form of an auxiliary training objective for the NE (Wu et al., 2019c, 2020a; Qi et al., 2021b).

Diversification. Personalized NNR reduces exposure to news dissimilar from those consumed in the past. Recommending "more of the same" constrains access to diverse viewpoints and information (Freedman and Sears, 1965; Heitz et al., 2022) and leads to homogeneous news diets and "filter bubbles" (Pariser, 2011), in turn reinforcing users' initial stances (Li and Wang, 2019). Consequently, a significant body of work attempts to diversify recommendations, either by re-ranking them to increase some measure of diversity (e.g. intra-list distance (Zhang and Hurley, 2008)) or by resorting to multi-task training (Gabriel De Souza et al., 2019; Wu et al., 2020a; Shi et al., 2022; Wu et al., 2022b; Choi et al., 2022; Raza, 2023), coupling the primary content-based personalization objective with auxiliary objectives that force aspect-based diversification.

Current NNR Limitations. Critically, existing approaches, by "hardcoding" aspectual requirements (i.e., personalization or diversification for an aspect) into the NNR's architecture and/or training objectives, cannot be easily adjusted for varying recommendation goals. Since even minor changes in the recommendation objective require retraining the NNR, current models are generally limited to fixed single-aspect recommendation scenarios (e.g., content-based personalization with topical diversification), and ill-equipped for multi-aspect customization. In this work, we rethink personalized news recommendation and propose a novel, modular multi-aspect recommendation framework that allows for ad-hoc creation of recommendation functions over aspects at inference time. This enables fundamentally different recommendation:

one that lets each user define their own custom recommendation function, choosing the amount of personalization or diversification for each aspect.

3 Methodology

Personalized news recommendation produces for each candidate news n^c and user u with corresponding click history $H = \{n_1^u, n_2^u, ..., n_N^u\}$, a relevance score $s(n^c, u)$ that quantifies the candidate's relevance for the user. We define an *aspect* A_p as a categorical variable that encodes a news attribute (e.g. its category), where each news n_i can belong only to one value of A_p (e.g. if A_p is the topic, then n_i may take exactly one value from {*politics*, *sports*, ...}). As discussed in §2, aspects are additional dimensions next to content over which to tailor recommendations, whether by (i) personalizing or (ii) diversifying over them. In line with earlier work, we define *aspect-based personalization* as the level of homogeneity between a user's recommendations and clicked news w.r.t. the distribution of aspect A_p. In contrast, we define *aspect-based diversity* as the level of uniformity of aspect A_p's distribution among the news in the recommendation list.

We next introduce our proposed *modular framework* MANNeR, illustrated in Fig. 1. Starting from a PLM, during (1) training, we reshape the PLM's representation space via contrastive learning, independently for each aspect; this results in one specialized NE for each aspect; at (2) inference, we can, depending on the recommendation task, aggregate the resulting aspect-specific similarity scores to produce a final ranking function.

3.1 News Encoder

We adopt a dual-component architecture for the NE coupling (i) a text and (ii) an entity encoder (Qi et al., 2021b,c). The former, a PLM, transforms the text input (i.e., concatenation of news title and abstract) into a text-based news embedding $\mathbf{n}_t$, given by the PLM's output `[CLS]` token representation. The latter learns an entity-level news embedding $\mathbf{n}_e$ by contextualizing pretrained embeddings of named entities (i.e., extracted from title and abstract) in a layer that combines multi-head self-attention (Vaswani et al., 2017) and additive attention (Bahdanau et al., 2014). The final news embedding $\mathbf{n}$ is the concatenation of $\mathbf{n}_t$ and $\mathbf{n}_e$.

3.2 Modular Training

MANNeR comprises two module types, each with a dedicated NE, responsible for content-based (`CR-Module`) and aspect-based (`A-Module`) recommendation relevance, respectively. We train both by minimizing the supervised contrastive loss (SCL, Eq. 1) which aims to reshape the NE's representation space so that embeddings of same-class instances become mutually closer (cf. a distance/similarity metric) than instances of different classes (Khosla et al., 2020; Gunel et al., 2020). To this end, we contrast the similarity score of a positive example (pair of same-class instances) against scores of corresponding negative examples (paired instances from different classes):

$$\mathcal{L} = -\sum_{i=1}^{N} \frac{1}{N_{y_i} - 1} \sum_{\substack{j \in [1,N] \\ i \neq j, y_i = y_j}} \log \frac{e^{(\mathbf{n}_i \cdot \mathbf{n}_j / \tau)}}{\sum_{\substack{k \in [1,N] \\ i \neq k}} e^{(\mathbf{n}_i \cdot \mathbf{n}_k / \tau)}} \quad (1)$$

with y_i as news n_i's label, N the batch size, N_{y_i} the number of batch instances with label y_i, and $\tau > 0$ the temperature hyperparameter controlling the extent of class separation. We use the dot product as the similarity metric for both module types.

CR-Module. Our `CR-Module` is a modification of the common content-based NNR architecture (Wu et al., 2023). Concretely, we encode both candidate and clicked news with a dedicated NE. However, following Iana et al. (2023b), we replace the widely used UEs (i.e., early fusion of clicked news representations) with the simpler (and non-parameterized) mean-pooling of dot-product scores between the candidate embedding $\mathbf{n}^c$ and clicked news embeddings $\mathbf{n}_i^u$: $s(\mathbf{n}^c, u) = \frac{1}{N} \sum_{i=1}^{N} \mathbf{n}^c \cdot \mathbf{n}_i^u$ (i.e., late-fusion). We thus reduce the computational complexity of the standard approaches with elaborate parameterized UEs. We then update `CR-Module`'s encoder (i.e., fine-tune the PLM) by minimizing SCL, with clicked candidates as positive and non-clicked news as negative examples for the user. As there are many more non-clicked news, we resort to negative sampling (Wu et al., 2022a).

A-Module. Each `A-Module` trains a specialized NE for one aspect other than content. Via the metric-based objective, we reshape the PLM's representation space to group news according to aspect classes. Given a multi-class aspect, we first construct the training set from the union of all news in the dataset. Sets of news with the same aspect label form the positive samples for SCL; we obtain the corresponding negatives by pairing the same news from positive pairs with news from other aspect classes (e.g., for topical category as A_p, a news from *sports* is paired with the news from *politics*

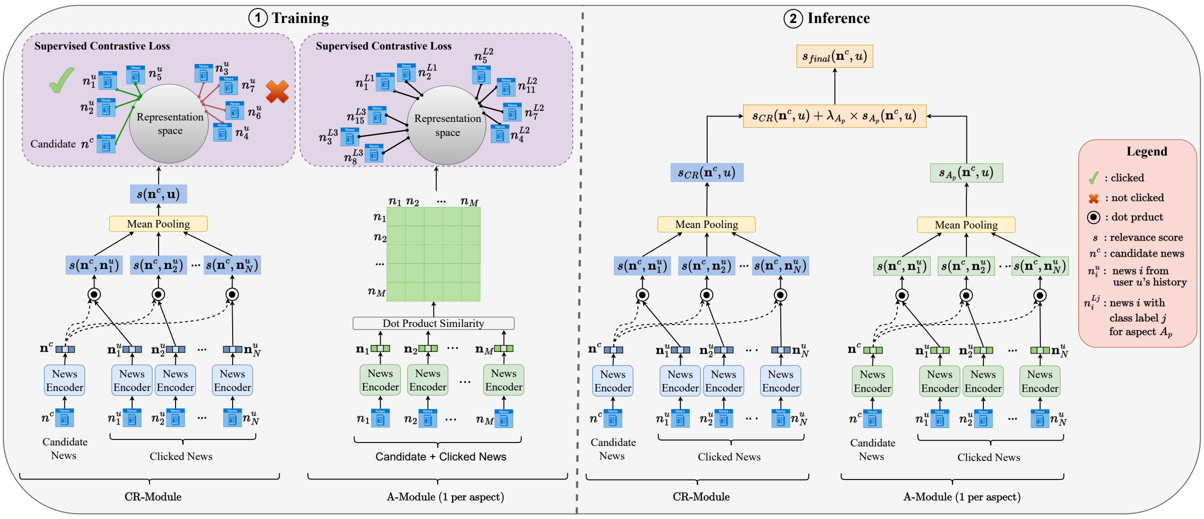


Figure 1: Illustration of the MANNeR framework. ① We train aspect-specialized NEs (i.e. `CR-Module` for content-based personalization, `A-Module` for aspect-based similarity) with metric-based contrastive learning. ② Inference: we linearly aggregate aspect-specific similarity scores between candidate and clicked news for final ranking.

and/or *weather*). For each aspect, we independently fine-tune a separate copy of the same initial PLM. Note that the resulting aspect-specific NE encodes no information on user preferences: it only encodes the news similarity w.r.t. the aspect in question. Importantly, this implies that extending MANNeR to support a new aspect amounts to merely training an additional `A-Module` for that aspect.

3.3 Inference: Custom Ranking Functions

At inference time, the NEs of the `CR-Module` and of each of the `A-Modules` are leveraged identically: we encode the candidate news as well as the user's clicked news with the respective NE, obtaining their module-specific embeddings $\mathbf{n}^c$ and $\mathbf{n}_i^u$ – their dot product $s = \mathbf{n}^c \cdot \mathbf{n}_i^u$ quantifies their similarity according to the module's aspect (or content for `CR-Module`'s NE). As different NEs produce similarity scores of different magnitudes, we z-score normalize each module's scores per user. The final ranking score constitutes a *linear* aggregation of the content s_{CR} and aspect s_{A_p} similarity scores:

$$s_{final}(\mathbf{n}^c, u) = s_{CR} + \sum_{A_p \in A} \lambda_{A_p} s_{A_p} \tag{2}$$

where λ_{A_p} is the scaling weight for the aspect score, and A the set of all aspects of interest. This linear composability of aspect-specific similarity scores allows not only generalization to multi-aspect recommendation objectives, but also different ad-hoc realizations of the ranking function that match custom recommendation goals: (i) with $\lambda_{A_p} = 0$, MANNeR performs standard content-based personalization, (ii) for $\lambda_{A_p} > 0$ it recommends based on both content- and aspect personalization, whereas (iii) for $\lambda_{A_p} < 0$ it simultaneously personalizes by content but diversifies for the aspect(s).

4 Experimental Setup

We compare MANNeR against state-of-the-art NNRs on a range of single- and multi-aspect recommendation tasks. We experiment with two aspects: *topical categories* (*ctg*) and news *sentiment* (*snt*).

Baselines. We evaluate several NNRs trained on classification objectives. We follow Wu et al. (2021) and replace the original NEs of all baselines that do not use PLMs (instead, contextualizing word embeddings with convolution or self-attention layers) with the same PLM used in MANNeR.[1] We include two models optimized purely for content personalization: (1) NRMS (Wu et al., 2019d), and (2) MINER (Li et al., 2022). We further evaluate seven NNRs that inject aspect information. Thereof, five incorporate *topical categories*, i.e., (3) NAML (Wu et al., 2019a), (4) LSTUR (An et al., 2019), (5) MINS (Wang et al., 2022), (6) CAUM (Qi et al., 2022), (7) TANR (Wu et al., 2019c), and two the news *sentiment*: (8) SentiRec (Wu et al., 2020a), and (9) SentiDebias (Wu et al., 2022d). For more details, see Appendix A.

Data. We carry out the evaluation on two prominent monolingual news recommendation benchmarks: MINDlarge (denoted MIND) (Wu et al., 2020b) with news in English and Adressa-1 week

[1]The only exception is the final text embedding, where Wu et al. (2021) pool tokens with an attention network.

(Gulla et al., 2017) (denoted Adressa) with Norwegian news. We provide further details about dataset usage and statistics in Appendix B. As Adressa contains no disambiguated named entities, we use only the news title as input to MANNeR' NE, while on MIND we use all news features as NE input.

Evaluation Metrics. We report performance with AUC, MRR, nDCG@k ($k = \{5, 10\}$). We measure aspect-based diversity of recommendations at position k as the normalized entropy of the distribution of aspect A_p's values in the recommendation list:

$$D_{A_p}@k = -\sum_{j \in A_p} \frac{p(j) \log p(j)}{\log(|A_p|)} \tag{3}$$

where $A_p \in \{ctg, snt\}$, and $|A_p|$ is the number of A_p classes. If aspect-based personalization is successful, aspect A_p's distribution in the recommendations should be similar to its distribution in the user history. We evaluate personalization with the generalized Jaccard similarity (Bonnici, 2020):

$$PS_{A_p}@k = \frac{\sum_{j=1}^{|A_p|} \min(\mathcal{R}_j, \mathcal{H}_j)}{\sum_{j=1}^{|A_p|} \max(\mathcal{R}_j, \mathcal{H}_j)}, \tag{4}$$

where R_j and H_j represent the probability of a news with class j of A_p to be contained in the recommendations list R, and, respectively, in the user history H. As all metrics are bounded to $[0, 1]$, we measure the trade-off between content-based personalization (nDCG@k) and either aspect-based diversity $D_{A_p}@k$ or aspect-based personalization $PS_{A_p}@k$ with the harmonic mean. We denote this $\mathrm{T}_{\mathrm{A_p}}@k$ for single-aspect. For multi-aspect evaluation, i.e., when ranking for content-personalization by diversifying simultaneously over topics and sentiment, we adopt as evaluation metric the harmonic mean between nDCG@k, $\mathrm{D}_{\mathrm{ctg}}@k$ (topical category), and $\mathrm{D}_{\mathrm{snt}}@k$ (sentiment), denoted $\mathrm{T}_{\mathrm{all}}@k$.

Training Details. We use RoBERTa Base (Liu et al., 2019) and NB-BERT Base (Kummervold et al., 2021; Nielsen, 2023) in experiments on MIND and Adressa, respectively. We set the maximum history length to 50. We tune the main hyperparameters of all NNRs. We train all models with mixed precision, the Adam optimizer (Kingma and Ba, 2014), the learning rate of 1e-5 on MIND, 1e-6 on Adressa, and 1e-6 for the sentiment `A-Module` on both datasets. In `A-Module` training, we sample 20 instances per class,[2] while in `CR-Module` training we sample four negatives per positive example.

[2]For M class instances, we obtain $\frac{M^2-M}{2}$ positive pairs for that class for SCL.

We find the optimal temperature of 0.36 on MIND, and 0.14 on Adressa, for the `CR-Module`, and of 0.9 for all `A-Modules` on both datasets. We train all baselines and the `CR-Module` for 5 epochs on MIND and 20 epochs on Adressa, with a batch size of 8. We train each `A-Module` for 100 epochs, with the batch size of 60 for sentiment and 360 for topics. We repeat runs five times with different seeds and report averages and standard deviations for all metrics. We refer to Appendices C.1 - C.2 for further details about model sizes and hyperparameters.

5 Results and Discussion

We first discuss MANNeR's content personalization performance. We then analyze its capability for single- and multi-aspect (i) diversification and (ii) personalization. In the aspect customization setups, we treat MANNeR's `CR-Module` as a baseline. Lastly, we evaluate its ability to re-use pretrained aspect-specific modules in cross-lingual transfer.

5.1 Content Personalization

Table 1 summarizes the results on content personalization. Since the task does not require any aspect-based customization, we evaluate the MANNeR variant that uses only its CR-Module at inference time (i.e., $\lambda = 0$). MANNeR consistently outperforms all state-of-the-art NNRs in terms of both classification and ranking metrics on both datasets. Given that MANNeR's `CR-Module` derives the user embedding by merely averaging clicked news embeddings, these results question the need for complex parameterized UEs, present in all the baselines, in line with the findings of Iana et al. (2023b).

We ablate `CR-Module`'s content personalization performance for (i) different inputs to the NE and (ii) alternative architecture designs and training objectives. We find that all groups of features (e.g., abstract, named entities) contribute to the overall performance (cf. Fig. 5a). Moreover, we confirm the findings of Iana et al. (2023b) that (i) late fusion outperforms a parameterized UE (i.e., early fusion), and that (ii) SCL better separates classes than cross-entropy loss, in line with other similarity-oriented NLP tasks (Reimers and Gurevych, 2019).

5.2 Single-Aspect Customization

Diversification. Table 2 summarizes the results on aspect diversification tasks. Most baselines (including MANNeR's `CR-Module` without aspect diversification) obtain similar diversification scores ($\mathrm{D}_{\mathrm{ctg}}$

Model	MIND AUC	MIND MRR	MIND nDCG@5	MIND nDCG@10	Adressa AUC	Adressa MRR	Adressa nDCG@5	Adressa nDCG@10
NRMS-PLM	63.0±1.5	35.5±0.6	33.4±0.7	39.9±0.6	72.3±3.3	43.0±2.7	44.3±2.8	51.3±2.3
MINER	63.1±1.2	35.5±1.1	33.7±1.1	40.0±1.0	70.1±4.9	37.3±4.1	38.5±5.1	46.3±4.1
NAML-PLM	60.6±3.4	37.6±0.4	35.9±0.4	42.2±0.4	50.0±0.0	45.0±5.0	47.2±5.5	52.5±4.1
LSTUR-PLM	54.6±3.0	33.3±1.5	31.7±1.8	38.3±1.7	65.0±7.2	43.1±1.7	44.8±2.6	51.2±2.0
MINS-PLM	61.3±2.7	36.2±0.3	34.5±0.4	40.8±0.3	74.3±3.2	44.2±2.9	47.3±3.3	53.0±3.4
$\text{CAUM}_{\text{no entities}}$-PLM	66.2±3.0	36.6±2.0	34.6±2.0	41.0±1.9	76.5±1.2	43.6±1.3	46.9±1.3	52.0±1.2
CAUM-PLM	66.4±3.1	36.2±1.2	34.3±1.3	40.8±1.3	–	–	–	–
TANR-PLM	63.3±1.1	37.0±1.0	35.2±1.0	41.6±0.9	50.0±0.0	43.8±1.0	45.6±1.3	51.4±0.6
SentiRec-PLM	62.2±0.7	35.7±0.4	33.9±0.4	40.5±0.4	67.6±2.7	33.1±2.4	32.9±3.8	40.8±2.4
SentiDebias-PLM	55.0±2.5	27.8±1.9	25.5±1.9	32.2±2.0	67.4±2.4	35.7±3.4	36.4±4.2	44.2±2.9
MANNeR (`CR-Module`)	**69.7±0.9**	**38.6±0.6**	**37.0±0.6**	**43.2±0.6**	**79.4±1.7**	**47.0±2.4**	**48.9±2.8**	**54.3±2.5**
Improvement (%)	+ 5.4	+ 2.8	+ 3.1	+ 2.3	+ 3.7	+ 4.6	+ 3.3	+ 2.5

Table 1: Content-based recommendation performance. We average results across five runs, and report the relative improvement over the best baseline. The best results per column are highlighted in bold, the second best underlined.

Model	MIND nDCG@10	MIND D_{ctg}@10	MIND T_{ctg}@10	MIND D_{snt}@10	MIND T_{snt}@10	MIND T_{all}@10	Adressa nDCG@10	Adressa D_{ctg}@10	Adressa T_{ctg}@10	Adressa D_{snt}@10	Adressa T_{snt}@10	Adressa T_{all}@10
NRMS-PLM	39.9±0.6	50.0±1.1	44.3±0.4	66.4±0.5	49.8±0.5	49.9±0.3	51.3±2.3	31.8±1.0	39.2±0.5	61.5±0.5	55.9±1.2	44.6±0.5
MINER	40.0±1.0	49.4±1.2	44.2±0.4	65.7±0.9	49.7±1.0	49.6±0.5	46.3±4.1	31.1±0.6	37.1±1.6	60.9±0.5	52.5±2.8	42.7±1.5
NAML-PLM	42.2±0.4	47.3±0.3	44.6±0.3	65.1±0.4	51.2±0.3	49.9±0.3	52.5±4.1	30.6±2.4	38.6±2.1	61.6±0.6	56.7±2.6	44.0±1.9
LSTUR-PLM	38.3±1.7	50.0±1.2	43.4±0.7	65.6±0.3	48.4±1.3	48.9±0.5	51.2±2.0	29.9±4.6	37.7±5.2	61.4±0.5	55.8±1.2	43.2±3.8
MINS-PLM	40.8±0.3	49.1±1.0	44.6±0.3	66.3±0.9	50.5±0.1	50.0±0.4	53.0±3.4	33.6±1.7	41.0±1.0	61.8±0.6	57.0±1.8	46.2±0.9
$\text{CAUM}_{\text{no entities}}$-PLM	41.0±1.9	47.4±1.0	43.9±0.9	65.8±1.2	50.5±1.3	49.4±0.6	52.0±1.2	34.4±0.3	**41.4±0.4**	62.1±0.5	56.6±0.7	**46.6±0.3**
CAUM-PLM	40.8±1.3	47.8±0.9	44.0±1.0	66.1±0.5	50.6±1.0	49.6±0.9	–	–	–	–	–	–
TANR-PLM	41.6±0.9	48.9±0.9	45.0±0.3	66.1±0.8	51.1±0.7	50.3±0.3	51.4±0.6	32.9±1.7	40.1±1.1	61.8±0.7	56.1±0.2	45.4±1.0
SentiRec-PLM	40.5±0.4	49.4±0.4	44.5±0.1	67.0±0.6	50.4±0.4	50.1±0.2	40.8±2.4	**35.6±0.6**	38.0±1.1	**68.5±0.2**	51.1±1.9	44.6±1.0
SentiDebias-PLM	32.2±2.0	**52.0±2.2**	39.7±1.1	68.6±1.2	43.8±1.8	46.2±1.0	44.2±2.9	32.3±1.0	37.3±1.2	61.2±0.2	51.3±2.0	42.9±1.1
MANNeR (`CR-Module`)	**43.2±0.6**	49.3±0.3	46.0±0.3	65.4±0.6	52.0±0.4	51.1±0.2	**54.3±2.5**	31.7±0.2	40.0±0.7	61.4±0.3	57.6±1.5	45.3±0.6
MANNeR ($\lambda_{ctg} = -0.2/-0.3$, $\lambda_{snt} = 0$)	42.0±0.6	51.5±0.3	**46.2±0.3**	65.6±0.6	51.2±0.4	51.3±0.3	50.9±2.5	34.1±0.3	40.8±0.8	61.9±0.3	55.8±1.6	46.0±0.7
MANNeR ($\lambda_{ctg} = 0$, $\lambda_{snt} = -0.3/-0.2$)	42.8±0.7	49.8±0.2	46.0±0.4	**68.7±0.3**	**52.7±0.4**	**51.7±0.3**	53.8±2.5	32.4±0.2	40.4±0.7	63.0±0.3	**58.0±1.5**	45.9±0.6

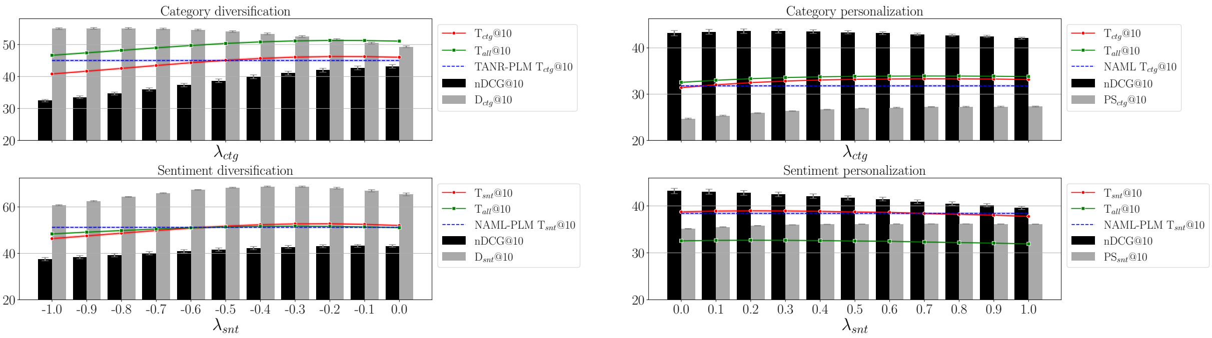
Table 2: Single-aspect diversification. For MANNeR, we list the best results (cf. T_{A_p}) of single-aspect diversification as λ_{A_p} (MIND/Adressa). The best results per column are highlighted in bold, the second best underlined.

and D_{snt}). The sentiment-aware SentiRec-PLM, with an explicit auxiliary sentiment diversification objective, yields the highest sentiment diversity on Adressa; this comes at the expense of content personalization quality (lowest nDCG). On MIND, the sentiment-specific SentiDebias-PLM achieves the highest sentiment diversity, but also exhibits lower content personalization performance. Overall, these results point to a trade-off between content personalization and aspectual diversity: models with higher D_{A_p} tend to have a lower nDCG.

Unlike all other models, MANNeR can trade content personalization for diversity (and vice-versa) with different values of the aspect coefficients λ_{A_p}. Fig. 2a illustrates its performance in single-aspect diversification tasks for different values of λ_{ctg} and λ_{snt} on MIND. The steady drop in nDCG together with the steady increase in D_{A_p} indeed indicate the existence of a trade-off between content personalization and aspect diversification. For topical categories we observe a steeper decline in content personalization quality with improved diversification than for sentiment. Sentiment diversity reaches peak performance for $\lambda_{snt} = -0.4$, whereas category diversity continues to increase all the way to $\lambda_{ctg} = -0.9$. Intuitively, content-based recommendation is more aligned with the topical than with the sentiment consistency of recommendations. The best trade-off (i.e., maximal performance w.r.t. T_{A_p}@10) is achieved for $\lambda_{ctg} = -0.2$ for topics, and $\lambda_{snt} = -0.3$ for sentiment. We report analogous results on Adressa in Appendix D.2. We attribute these effects to the representation spaces of the `A-Modules`. Fig. 3 shows the 2-dimensional t-SNE visualizations (Van der Maaten and Hinton, 2008) of the news embeddings produced with category-specialized encoders trained on MIND (see Fig. 7 for sentiment). The results confirm that the latent representation space of the encoder was reshaped to group same-class instances. The separation of classes, however, is less prominent for representation spaces of the encoders trained on Adressa (cf. Fig. 8) than for those learned on MIND (e.g., the effect is stronger on the category-shaped embedding space).[3]

Personalization. Table 3 displays the results on aspect personalization tasks. TANR, trained with an auxiliary topic classification task, underperforms

[3] We believe that this is because Adressa has 10 times fewer news than MIND (and contrastive learning, naturally, benefits from more news pairs), with over half of the topical categories in Adressa being represented with fewer than 100 examples.



(a) Single-aspect diversification. (b) Single-aspect personalization.

Figure 2: Results of single-aspect customization for MANNeR and the best baseline on MIND.

	MIND						Adreesa					
Model	nDCG@10	PS_{ctg}@10	T_{ctg}@10	PS_{snt}@10	T_{snt}@10	T_{all}@10	nDCG@10	PS_{ctg}@10	T_{ctg}@10	PS_{snt}@10	T_{snt}@10	T_{all}@10
NRMS-PLM	39.9±0.6	23.9±0.2	29.9±0.3	35.1±0.1	37.3±0.3	31.5±0.2	51.3±2.3	34.3±0.4	41.1±1.0	41.8±0.1	46.1±1.0	41.3±0.7
MINER	40.0±1.0	23.9±0.4	29.9±0.5	35.0±0.2	37.3±0.4	31.5±0.4	46.3±4.1	34.4±0.2	39.4±1.5	42.0±0.0	43.9±1.8	40.2±1.0
NAML-PLM	42.2±0.4	25.5±0.2	31.8±0.2	35.1±0.2	38.4±0.2	32.8±0.2	52.5±4.1	36.1±0.8	42.7±1.7	41.8±0.1	46.5±1.7	42.4±1.1
LSTUR-PLM	38.3±1.7	24.0±1.0	29.5±1.2	34.8±0.3	36.5±0.9	31.1±1.0	51.2±2.0	35.1±2.1	41.6±1.0	41.8±0.1	46.0±0.8	41.7±0.7
MINS-PLM	40.8±0.3	25.0±0.3	31.0±0.3	34.7±0.2	37.5±0.2	32.1±0.3	53.0±3.4	33.9±0.7	41.3±1.4	41.8±0.1	46.7±1.3	41.5±1.0
$CAUM_{no\ entities}$-PLM	41.0±1.9	24.8±0.6	30.9±1.0	35.0±0.2	37.8±0.9	32.2±0.7	52.0±1.2	33.5±0.2	39.6±1.1	40.8±0.4	46.3±0.5	41.1±0.3
CAUM-PLM	40.8±1.3	25.1±0.3	31.1±0.4	35.0±0.1	37.7±0.6	32.3±0.3	–	–	–	–	–	–
TANR-PLM	41.6±0.9	25.2±0.5	31.4±0.6	35.0±0.2	38.0±0.4	32.5±0.5	51.4±0.6	34.0±0.5	41.0±0.5	41.8±0.1	46.1±0.3	41.2±0.4
SentiRec-PLM	40.5±0.4	24.2±0.3	30.3±0.3	34.6±0.0	37.3±0.2	31.6±0.2	40.8±2.4	32.4±0.3	36.1±1.0	39.3±0.1	40.0±1.2	37.1±0.7
SentiDebias-PLM	32.2±2.0	20.8±1.3	25.2±1.5	34.1±0.3	33.1±1.2	27.6±1.2	44.2±2.9	34.1±0.6	38.5±1.3	41.8±0.1	42.9±1.4	39.5±1.0
MANNeR (CR-Module)	**43.2±0.6**	24.7±0.1	31.4±0.2	35.1±0.1	38.7±0.2	32.6±0.2	**54.3±2.5**	34.5±0.1	42.2±0.8	42.0±0.1	47.3±0.9	42.1±0.5
MANNeR ($\lambda_{ctg} = 0.7/0.4$, $\lambda_{snt} = 0$)	42.9±0.3	**27.2±0.1**	**33.3±0.1**	35.2±0.0	38.7±0.1	**33.9±0.1**	53.6±1.9	**36.2±0.1**	**43.2±0.7**	42.1±0.1	47.2±0.7	**42.9±0.4**
MANNeR ($\lambda_{ctg} = 0$, $\lambda_{snt} = 0.2/0.1$)	42.8±0.5	24.7±0.1	31.3±0.2	**35.8±0.1**	**39.0±0.2**	32.7±0.1	54.1±2.4	34.7±0.1	42.2±0.8	**42.2±0.1**	**47.4±0.9**	42.2±0.5

Table 3: Single-aspect personalization. For MANNeR, we list the best results (cf. T_{A_p}) of single-aspect diversification as λ_{A_p} (MIND/Adressa). The best results per column are highlighted in bold, the second best underlined.

NAML, which uses topical categories as NE input features, in category personalization on both datasets . MANNeR's CR-Module alone (i.e., without any aspect customization) yields competitive category personalization performance. We believe that this is because (i) the CR-Module is best in content personalization and (ii) category personalization is well-aligned with content personalization (i.e., news with similar content tend to belong to the same category). Fig. 2b explores the trade-off between content and aspect personalization, for different positive values of λ_{A_p} on MIND (see Fig. 6b for Adressa). The best topical category personalization (PS_{ctg}), obtained for $\lambda_{ctg} > 0.7$, comes at the small expense of content personalization: too much weight on the category similarity of news dilutes the impact of content relevance. Increased sentiment personalization, however, is much more detrimental to content personalization. Intuitively, users do not choose articles based on sentiment. Tailoring recommendations according to the sentiment of previously clicked news thus leads to more content-irrelevant suggestions.

5.3 Multi-Aspect Customization

We further explore the trade-off between content personalization and multi-aspect diversification, i.e. diversifying simultaneously over both topical categories and sentiments, for different values of the aspect coefficients λ_{ctg} and λ_{snt}. We achieve the highest T_{all} for $\lambda_{ctg} = -0.2$ and $\lambda_{snt} = -0.25$ on MIND (cf. Fig. 9a). In line with results on single-aspect diversification, we observe that improving diversity in terms of topical categories rather than sentiments has a more negative effect on content personalization quality, i.e. steeper decline in T_{all}. Overall, these results confirm that MANNeR can generalize to diversify for multiple aspects at once by weighting individual aspect relevance scores less than in the single-aspect task. This can be explained by the fact that weighting several aspects higher at the same time acts as a double discounting for content personalization, diluting content relevance disproportionately. Similarly, for multi-aspect personalization, we achieve the best multi-aspect trade-off on MIND (cf. Fig. 9b) for $\lambda_{ctg} = 0.45$ and $\lambda_{snt} = 0.25$. Stronger enforcing of alignment of candidate news with user's history is needed for topical categories than for sentiment (i.e., $\lambda_{ctg} > \lambda_{snt}$). This is because sentiment exhibits low variance within topical categories (e.g., *politics* news are mostly negative) and enforcing categorical personalization thus partly also achieves sentiment personalization.

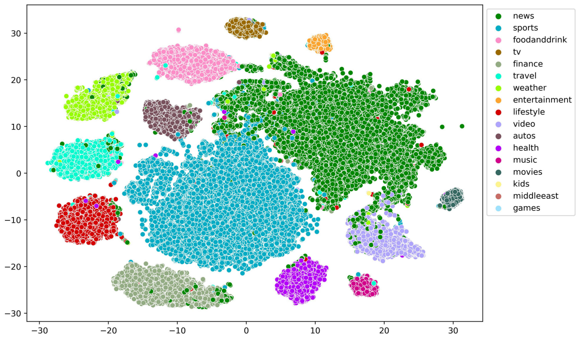


Figure 3: t-SNE plot of the category-shaped embedding space of the news in the test set of MIND.

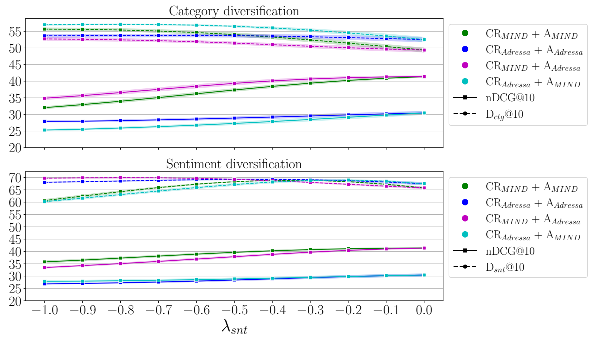


Figure 4: Cross-lingual transfer results in single-aspect diversification for MANNeR, with modules trained on different (combinations of) source-language datasets and evaluated on the target-language dataset MIND. The line style indicates the metric, the line color denotes the source-language datasets used in training.

5.4 Cross-Lingual Transfer

Lastly, we analyze the transferability of MANNeR across datasets and languages in single-aspect customization experiments.[4] Concretely, we train the `CR-Module` and `A-Modules` on both MIND (i.e., in English) and Adressa (i.e., in Norwegian), respectively. At inference, we evaluate all combinations of pretrained `CR-Module` and `A-Modules` on the test set of MIND. We replace the monolingual PLMs used in MANNeR's NE with a multilingual DistilBERT Base (Sanh et al., 2019) to enable cross-lingual transfer (`XLT`). Fig. 4 summarizes the `XLT` results for single-aspect diversification. We refer to Appendix D.4 for similar results on single-aspect personalization and on Adressa as target-language dataset. As expected, MANNeR trained fully on Adressa suffers a large drop in content personalization performance, compared to the counterpart trained on MIND. In contrast, transferring only the `A-Module`, i.e., training the `CR-Module` on MIND and the `A-Module` (for topics and sentiment) on Adressa, yields performance comparable to that of complete in-language training (i.e., both `CR-Module` and `A-Module` trained on MIND). This is particularly the case for the sentiment `A-Module`, since the sentiment labels between the datasets are more aligned than those for topical categories. These results indicate that the plug-and-play of `A-Modules` enables zero-shot `XLT`, as modules trained on the much smaller Norwegian Adressa transfer well to the large English MIND. This suggests that, coupled with multilingual PLMs, MANNeR can be used for effective news recommendation in lower-resource languages, where training data and aspectual labels are scarce. Furthermore, the results demonstrate that the `A-Modules` could be trained on general-purpose classification datasets (e.g. topic or sentiment classification datasets), alleviating the need for aspect-specific annotation of news stories.

[4] We evaluate only the title-based version of MANNeR, as the full version cannot be trained on Adressa.

6 Conclusion

We proposed MANNeR, a modular framework for multi-aspect neural news recommendation. It learns aspect-specialized news encoders with supervised contrastive learning, and linearly combines the corresponding aspect-specific similarity scores for final ranking. MANNeR's modular design allows defining ad-hoc multi-aspect ranking functions (i.e. diversification or personalization) at inference time. MANNeR can be seamlessly extended to new aspects, without the need to train dedicated models for changes in the recommendation objective. Our experiments show that MANNeR consistently outperforms state-of-the-art NNRs on (i) standard content-based recommendation, as well as on single- and multi-aspect (ii) diversification and (iii) personalization of recommendations. Our detailed analyses show that, by weighing the importance of individual aspects, we can identify on-the-fly optimal trade-offs between content-based recommendation performance and aspect-based customization. Lastly, we show that, if equipped with a multilingual PLM, MANNeR can successfully cross-lingually transfer aspect-specific news encoders. This supports use cases where aspect-specific labels (e.g., sentiment) are not available for news in the target languages of interest. We hope that our work stimulates more research towards modular, easily extendable, and reusable news recommenders.

Limitations

MANNeR targets exclusively content-based neural news recommendation and leverages solely textual features. In practice, recommender systems may incorporate content features from various other modalities (e.g., image, video), as well as similarities between users in a collaborative filtering manner. While in this work we experimented only with textual inputs (e.g., titles, named entities, topical categories), we believe that MANNeR can easily be extended to handle multi-modal content (e.g., either as additional input to the news encoder or as a dedicated `A-Module`), as well as collaborative user relations (e.g., by training an `A-Module` to group together users who consume similar articles).

Our framework fully fine-tunes a PLM per aspect-specific module (either for content-relevance in the `CR-Module` or for aspect similarity in the `A-Module`). As all modules share the same PLM as backbone, parameter efficient fine-tuning (PEFT), e.g. LoRA (Hu et al., 2021), would bypass the need to repeatedly load the entire PLM per module into memory. PEFT has been shown to closely meet the performance of full fine-tuning. This represents a key advantage for deploying MANNeR in real-world applications. We however fully fine-tuned models to avoid PEFT as a confounding factor in our experiments. We further chose base-sized PLMs as the backbone of the news encoder in all models due to computational constraints. While in fine-tuning they remain competitive to large language models (LLMs), the latter may capture richer semantics, which can prove particularly useful for cross-lingual transfer applications. With a PEFT approach, MANNeR could easily leverage LLMs without a corresponding increase in computational resources.

Lastly, there exist varied approaches for measuring both the descriptive (Castells et al., 2021), as well as the normative (Vrijenhoek et al., 2023) diversity of recommendations. While some of these metrics can be tailored to support arbitrary aspects (i.e., to measure the diversity of recommendations w.r.t. to a particular categorical feature), we opted to quantify aspect-based diversity as generally as possible, leveraging only the distribution of an aspect's values in the recommendation list. We leave exploration of further diversity metrics to future work.

Ethical Considerations

We consider several ethical considerations that arise when working with recommender systems and open benchmark datasets. On the one hand, any biases or misinformation that might exist in the news and user data provided in the public datasets could be propagated through the recommendation pipeline. Similarly, the PLMs used as the recommenders' backbone could contain social biases captured from the training data. On the other hand, the `A-Modules` in MANNeR could be abused to reduce the diversity of recommendations by overweighting the aspectual-similarity with the user's history, particularly for sensitive aspects such as news stance. This, in turn, could lead to reinforcing the users' existing worldviews and stances (Li and Wang, 2019). Therefore, safeguards should be incorporated in the recommendation models to ensure not only that the outputs are accurate and truthful, but also that the systems are not misused to constrain access to diverse viewpoints.

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A Baselines

We compare MANNeR against the following content-based NNRs, in which we replace the original NEs of all baselines that do not use PLMs with the same PLM employed in MANNeR:

1. NRMS (Wu et al., 2019d) encodes only the news title, and learns user representations with an encoder combining multi-head self-attention and additive attention.

2. MINER (Li et al., 2022) employs a poly attention scheme to extract multiple user interest vectors for the users' representations using additive attention layers.

3. NAML (Wu et al., 2019a) leverages information about topical categories, in addition to textual content from the news title and abstract, as input to the NE. It learns user representations from the clicked news embeddings with a user encoder based on additive attention.

4. LSTUR (An et al., 2019) also incorporates category information in the NE, next to title and abstract. It learns user representations via recurrent neural networks, and differentiates between short-term user preferences encoded with a GRU (Cho et al., 2014), and long-term embeddings, consisting of a randomly initialized and fine-tuned component.

5. MINS (Wang et al., 2022) embeds both textual features (i.e, title, abstract), as well as categories. It employs a UE which combines multi-head self-attention, multi-channel GRU-based recurrent network, and additive attention to generate user embeddings.

6. CAUM (Qi et al., 2022) leverages not only titles and corresponding named entities, but also topical categories as input to the NE. In contrast to the other baselines, it combines a candidate-aware self-attention network with a candidate-aware convolutional neural network to learn candidate-aware user representations.

7. TANR (Wu et al., 2019c) injects information on topical categories by jointly optimizing the NE for content-based personalization and topic classification. Its UE is analogous to that of NAML.

	MIND (large)		Adressa (one week)	
Statistic	Train	Test	Train	Test
# News	101,527	72,023	11,207	11,207
# Users	698,365	196,444	96,801	68,814
# Impressions	2,186,683	365,201	218,848	146,284
# Categories	18	17	18	18
Avg. history length	33.7	33.6	13.9	15.6
Avg. # candidates / user	37.4	37.4	21.0	21.0

Table 4: MIND and Adressa dataset statistics.

8. SentiRec (Wu et al., 2020a) adds regularization for sentiment diversity to its primary content personalization objective, and encodes users similarly to NRMS.

9. SentiDebias (Wu et al., 2022d) uses sentiment-debiasing based on adversarial learning to reduce the NNR's sentiment bias (originating from the user data) and generate sentiment-diverse recommendations.

B Datasets

We conduct our experiments on two public news recommendation datasets: MINDlarge (denoted MIND) (Wu et al., 2020b) and Adressa-1 week (denoted Adressa) (Gulla et al., 2017). Since Wu et al. (2020b) do not release test labels for MIND, we use the provided validation portion for testing, and split the respective training set into temporally disjoint training (first four days of data) and validation portions (the last day). Following established practices on splitting the Adressa dataset (Hu et al., 2020; Xu et al., 2023), we use the data of the first five days to construct user histories and the clicks of the sixth day to build the training dataset. We randomly sample 20% of the last day's clicks to create the validation set, and treat the remaining samples of the last day as the test set.[5] Since Adressa contains only positive samples (i.e., no data about users' seen but not clicked news), we randomly sample 20 news as negatives for each clicked article to build impressions following Yi et al. (2021). Table 4 summarizes the statistics of both datasets.

Regarding aspects, the topical category annotations are provided in both datasets. As no sentiment labels exist in neither MIND nor Adressa, we use a multilingual XLM-RoBERTa Base model (Conneau et al., 2020) trained on tweets and fine-tuned for sentiment analysis (Barbieri et al., 2022) to classify news into three classes: positive (pos), neutral, and negative (neg). We compute real-valued scores

[5]Note that during validation and testing, we reconstruct user histories with all the samples of the first six days of data.

		MIND		Adressa	
Model	Non-trainable	Trainable	Total	Trainable	Total
NRMS-PLM	56.7	73	129	126	182
MINER	56.7	68.2	124	121	178
NAML-PLM	56.7	70.8	127	124	180
LSTUR-PLM	56.7	633	690	200	257
MINS-PLM	56.7	73.3	130	126	183
CAUM$_{\text{no entities}}$-PLM	56.7	73.2	129	126	183
CAUM-PLM	56.7	74.9	131	–	–
TANR-PLM	56.7	70.6	127	123	180
SentiRec-PLM	56.7	73	129	126	182
SentiDebias-PLM	56.7	73.3	130	126	183
MANNeR (CR-Module$_{\text{title}}$ / A-Module$_{\text{title}}$) – monolingual	56.7	67.9	124	121	177
MANNeR (CR-Module / A-Module) – monolingual	56.7	70.3	126	–	–
MANNeR (CR-Module$_{\text{title}}$ / A-Module$_{\text{title}}$) – multilingual	0	134	134	134	134

Table 5: Number of model parameters (in millions). CR-Module$_{\text{title}}$ / A-Module$_{\text{title}}$ denote the MANNeR modules trained with only the news title as input to the NE.

using the model's confidence scores s_i for class i, and the predicted sentiment class label $\hat{l}$ as follows:

$$s_{sent} = \begin{cases} (+1) \times s_{pos}, \text{ if } \hat{l} = pos \\ (-1) \times s_{neg}, \text{ if } \hat{l} = neg \\ (1 - s_{neutral}) \times (s_{pos} - s_{neg}), \text{ otherwise} \end{cases} \quad (5)$$

C Reproducibility Details

C.1 Model Parameters.

Table 5 lists the number of model parameters, in millions, for both datasets.

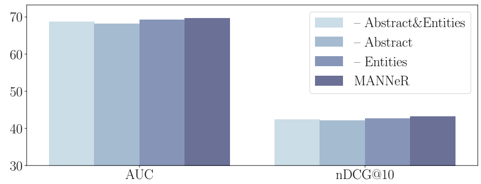
C.2 Hyperparameters and Implementation

Hyperparameter Optimization. We use RoBERTa Base (Liu et al., 2019) and NB-BERT Base (Kummervold et al., 2021; Nielsen, 2023) as the backbone PLMs of all models, in experiments on MIND and Adressa, respectively. In both cases, we fine-tune only the PLM's last four layers.[6] In the cross-lingual transfer experiments from §5.4, we fine-tune all of the 6 layers of DistilBERT. We use 100-dimensional TransE embeddings (Bordes et al., 2013) pretrained on Wikidata as input to the entity encoder in the NE of the knowledge-aware NNRs. We perform hyperparameter tuning on the main hyperparameters of MANNeR and the baselines using grid search. Table 6 lists the search spaces for all the optimized hyperparameters, as well as the best values. We repeat each experiment five times with the seeds ($\{42, 43, 44, 45, 46\}$) set with PyTorch Lightning's `seed_everything`.

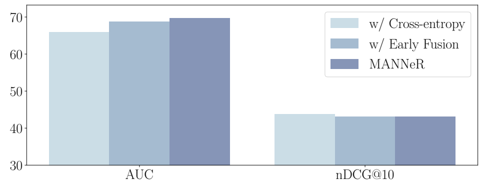
Code. We train MANNeR, as well as all the baselines, using the implementations provided in the NewsRecLib library (Iana et al., 2023a).

Infrastructure and Compute. We conduct all experiments on a cluster with virtual machines.

[6]In preliminary results, we did not see significant differences between full fine-tuning of all layers and fine-tuning only the last four layers. In the interest of computational efficiency, we thus froze the first eight layers of the transformer.



(a) Input features for the News Encoder (NE).



(b) `CR-Module` design/training alternatives.

Figure 5: Effect of different (a) NE inputs and (b) model design/training choices on MANNeR's content-based personalization performance.

We train MANNeR on both datasets, as well as the baselines on the MIND dataset, on a single NVIDIA A100 40GB GPU. We train the baselines on the Adressa dataset on a single NVIDIA Tesla V100 32GB GPU.

D Additional Results

D.1 Content Personalization

Fig. 5a shows MANNeR's performance on MIND for different inputs to the NE. We note that even the `CR-Module` exposed to titles only (i.e., no abstract or entity information) outperforms all of the baselines on content recommendation. Fig. 5b illustrates MANNeR's performance for alternative architecture designs and training objectives, as discussed in §5.1.[7]

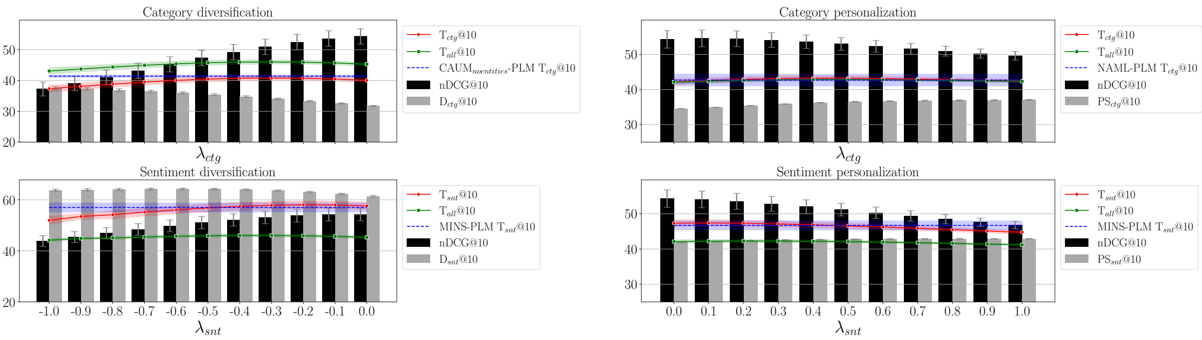
D.2 Single-Aspect Customization

Figure 6a illustrates MANNeR's performance in single-aspect diversification tasks for different values of λ_{ctg} and λ_{snt} on Adressa. Sentiment diversity reaches peak performance for $\lambda_{snt} = -0.6$, while category diversity continues to increase all the way to $\lambda_{ctg} = -1.0$. The best trade-off (i.e., maximal performance w.r.t. $\mathrm{T}_{\mathrm{A_p}}$@10), is achieved for $\lambda_{ctg} = -0.3$ for topical categories, and $\lambda_{snt} = -0.2$ for sentiment. Similarly, Fig. 6b explores the trade-off between content and aspect personalization, for different positive values of λ_{A_p} on the Adressa dataset. We obtain the best topical

[7]For brevity, we report results on MIND; findings on Adressa exhibit identical trends.

	`lr`	`num`$_{\text{heads}}$	`query`$_{\text{dim}}$	`UE agg`	K	`score agg`	λ	μ	α	$\tau_{CR-Module}$	$\tau_{A-Module}$
Search Space	$[1e^{-4}, 1e^{-6}]$	{8, 12, 16, 24, 32}	[50, 200]	{ini, con}	{8, 16, 32, 48}	{mean, max, weighted}	[0.1, 0.3]	[5, 15]	[0.05, 0.2]	[0.1, 0.5]	[0.1, 0.9]
Step	$1e^{-1}$	–	50	–	–	–	0.05	5	0.05	0.02	0.05
NRMS-PLM	$1e^{-5}$ / $1e^{-6}$	32 / 8	150 / 200	–	–	–	–	–	–	–	–
MINER	$1e^{-5}$ / $1e^{-6}$	–	–	–	32 / 48	mean / mean	–	–	–	–	–
NAML-PLM	$1e^{-5}$ / $1e^{-6}$	16 / 8	200 / 200	–	–	–	–	–	–	–	–
LSTUR-PLM	$1e^{-5}$ / $1e^{-6}$	24 / 8	150 / 50	ini / ini	–	–	–	–	–	–	–
MINS-PLM	$1e^{-5}$ / $1e^{-6}$	32 / 12	100 / 200	–	–	–	–	–	–	–	–
CAUM-PLM	$1e^{-5}$ / $1e^{-6}$	16 / 16	50 / 150	–	–	–	–	–	–	–	–
TANR-PLM	$1e^{-5}$ / $1e^{-6}$	32 / 8	150 / 50	–	–	–	0.3 / 0.15	–	–	–	–
SentiRec-PLM	$1e^{-5}$ / $1e^{-6}$	32 / 8	200 / 200	–	–	–	–	5 / 5	–	–	–
SentiDebias-PLM	$1e^{-5}$ / $1e^{-6}$	8 / 12	100 / 150	–	–	–	–	–	0.15 / 0.15	–	–
MANNeR	$1e^{-5}$ / $1e^{-6}$	–	200 / 200	–	–	–	–	–	–	0.36 / 0.14	0.9 / 0.9

Table 6: Search spaces used for hyperparameter optimization and best values found for all models. We report the optimal values in the format *value*$_{MIND}$ / *value*$_{Adressa}$. We use the following abbreviations: `lr` = learning rate, `num`$_{\text{heads}}$ = number of attention heads, `query`$_{\text{dim}}$ = dimensionality of the query vector in additive attention, `UE agg` = aggregation method used to combine the long-term and the short-term user representations into a final user embedding in LSTUR (An et al., 2019), K = number of context codes in MINER (Li et al., 2022), `score agg` = aggregation function for the final user click score calculation in MINER (Li et al., 2022), λ = weight of the topic classification task in TANR (Wu et al., 2019c), μ = weight of the sentiment diversity regularization loss in SentiRec (Wu et al., 2020a), α = adversarial loss coefficient in SentiDebias (Wu et al., 2022d), τ = temperature parameter in SCL in MANNeR, *ini* = initialize, *con* = concatenate, *categ* = category.



(a) Single-aspect diversification.

(b) Single-aspect personalization.

Figure 6: Results of single-aspect customization for MANNeR and the best baseline on Adressa.

category personalization (PS$_{\text{ctg}}$) for $\lambda_{ctg} > 0.4$.

Fig. 7 shows the 2-dimensional t-SNE visualizations (Van der Maaten and Hinton, 2008) of the news embeddings produced with sentiment-specialized encoders trained on MIND. Fig. 8 shows analogous visualizations (Van der Maaten and Hinton, 2008) of the news embeddings produced with aspect-specialized encoders trained on the Adressa dataset: (a) for topical categories, and (b) for sentiment.

D.3 Multi-Aspect Customization

Fig. 9 explores the trade-off between content personalization and multi-aspect diversification, for different values of the aspect coefficients λ_{ctg} and λ_{snt}, on MIND and Adressa, respectively.

D.4 Cross-Lingual Transfer

Fig. 10 summarizes the cross-lingual transfer results for single-aspect personalization on the target-language dataset MIND. Fig. 11 summarizes the cross-lingual transfer results for single-aspect diversification and personalization, respectively, on the target-language dataset Adressa.

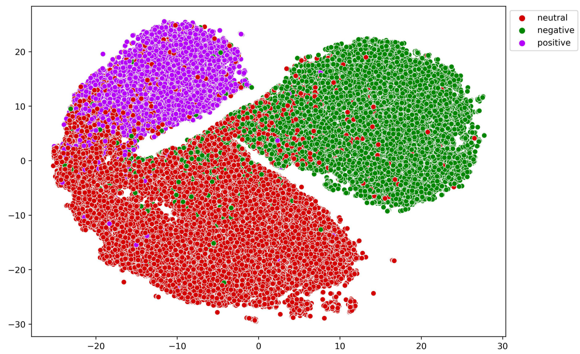
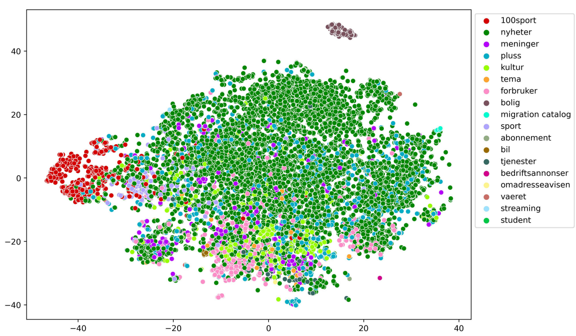
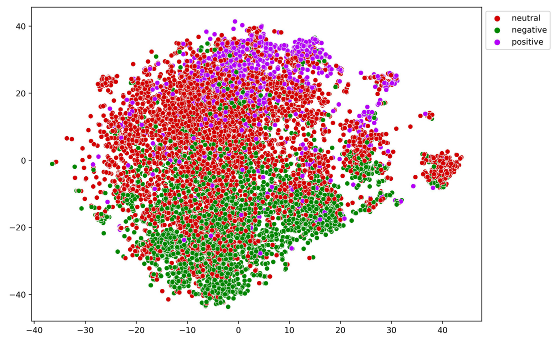


Figure 7: t-SNE plot of the sentiment-shaped embedding space of the news in the test set of MIND.

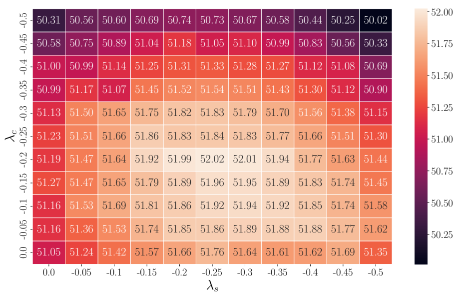


(a) Category-shaped embedding space.

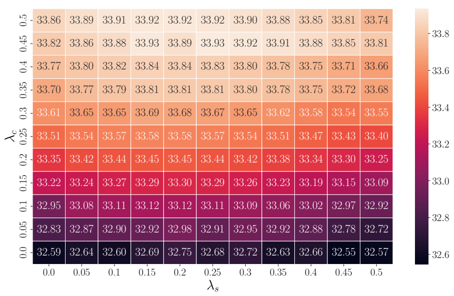


(b) Sentiment-shaped embedding space.

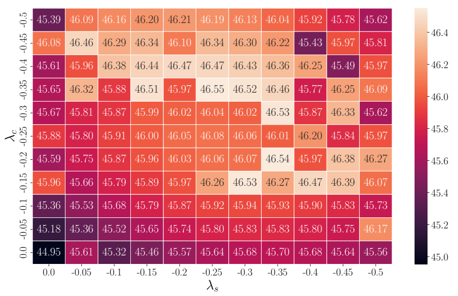
Figure 8: t-SNE plots of the news embeddings in the test set of Adressa.



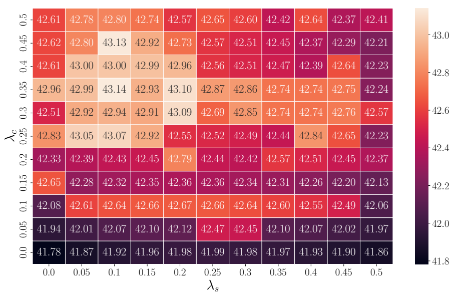
(a) Multi-aspect diversification on MIND.



(b) Multi-aspect personalization on MIND.



(c) Multi-aspect diversification on Adressa.



(d) Multi-aspect personalization on Adressa.

Figure 9: Results of multi-aspect customization for MANNeR on MIND, and Adressa, respectively.

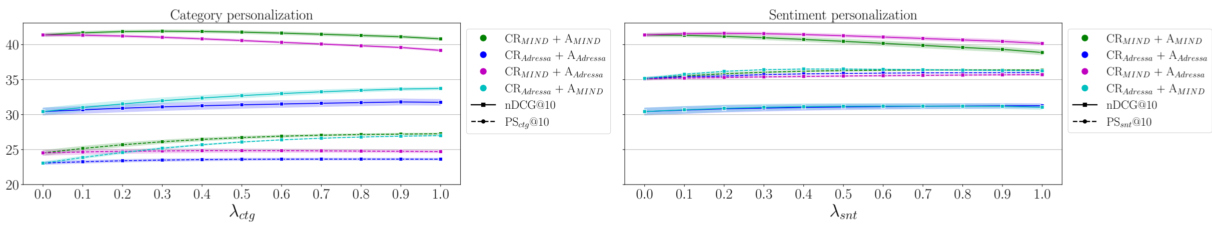
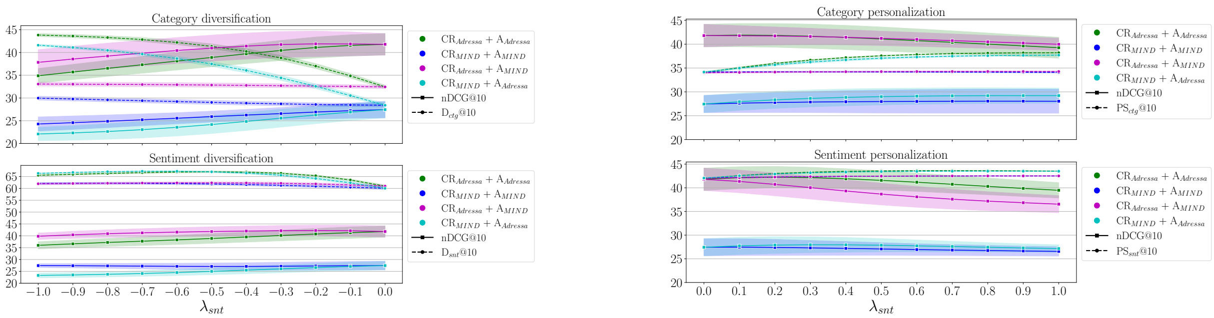


Figure 10: Cross-lingual transfer results in single-aspect personalization for MANNeR, with modules trained on different (combinations of) source-language datasets and evaluated on the target-language dataset MIND. The line style indicates the metric, the line color denotes the source-language datasets used in training.



(a) Single-aspect diversification.

(b) Single-aspect personalization.

Figure 11: Cross-lingual transfer results in single-aspect customization for MANNeR, with modules trained on different (combinations of) source-language datasets and evaluated on the target-language dataset Adressa. The line style indicates the metric, whereas the line color denotes the source-language datasets used in training.