

Mitigating the Filter Bubble while Maintaining Relevance: Targeted Diversification with VAE-based Recommender Systems

Zhaolin Gao
University of Toronto
Toronto, ON, Canada
zhaolin.gao@mail.utoronto.ca

Tianshu Shen
University of Toronto
Toronto, ON, Canada
tina.shen@mail.utoronto.ca

Zheda Mai
Optimy AI
Toronto, ON, Canada
zheda.mai@mail.utoronto.ca

Mohamed Reda Bouadjenek
Deakin University
Geelong, VIC, Australia
reda.bouadjenek@deakin.edu.au

Isaac Waller
University of Toronto
Toronto, ON, Canada
walleris@cs.toronto.edu

Ashton Anderson
University of Toronto
Toronto, ON, Canada
ashton@cs.toronto.edu

Ron Bodkin
Vector Institute for Artificial
Intelligence
Toronto, ON, Canada
ron.bodkin@vectorinstitute.ai

Scott Sanner*
University of Toronto
Toronto, ON, Canada
ssanner@mie.utoronto.ca

ABSTRACT

Online recommendation systems are prone to create filter bubbles, whereby users are only recommended content narrowly aligned with their historical interests. In the case of media recommendation, this can reinforce political polarization by recommending topical content (e.g., on the economy) at one extreme end of the political spectrum even though this topic has broad coverage from multiple political viewpoints that would provide a more balanced and informed perspective for the user. Historically, Maximal Marginal Relevance (MMR) has been used to diversify result lists and even mitigate filter bubbles, but suffers from three key drawbacks: (1) MMR directly sacrifices relevance for diversity, (2) MMR typically diversifies across all content and not just targeted dimensions (e.g., political polarization), and (3) MMR is inefficient in practice due to the need to compute pairwise similarities between recommended items. To simultaneously address these limitations, we propose a novel methodology that trains Concept Activation Vectors (CAVs) for targeted topical dimensions (e.g., political polarization). We then modulate the latent embeddings of user preferences in a state-of-the-art VAE-based recommender system to diversify along the targeted dimension while preserving topical relevance across orthogonal dimensions. Our experiments show that our Targeted Diversification VAE-based Collaborative Filtering (TD-VAE-CF) methodology better preserves relevance of content to user preferences across a range of diversification levels in comparison

to both untargeted and targeted variations of Maximum Marginal Relevance (MMR); TD-VAE-CF is also much more computationally efficient than the post-hoc re-ranking approach of MMR.

CCS CONCEPTS

• **Information systems** → **Information retrieval diversity**; **Recommender systems**; • **Computing methodologies** → *Neural networks*.

KEYWORDS

Recommendation Systems, Filter Bubble, Diversity

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1 INTRODUCTION

Online recommender systems are prone to create filter bubbles [11], where over time users may be increasingly recommended content narrowly aligned with their historical interests due to a feedback loop between data collection and recommendation processes. While the impacts of these recommendation feedback loops are somewhat nuanced (e.g., in some cases they can increase homogeneity due to popularity bias in recommender systems [3, 4]), in the case of media recommendation, it is observed that filter bubble effects arising from feedback loops may restrict user perspectives and viewpoints [1, 10]. As a case in point, we consider the row for VAE-CF (a state-of-the-art recommender system [8]) in Figure 1, which shows a Republican shifted distribution of politically polarized Reddit community content recommendations (details in Section 3) for a user that has historically consumed Republican-oriented content.

*Affiliate to Vector Institute of Artificial Intelligence, Toronto

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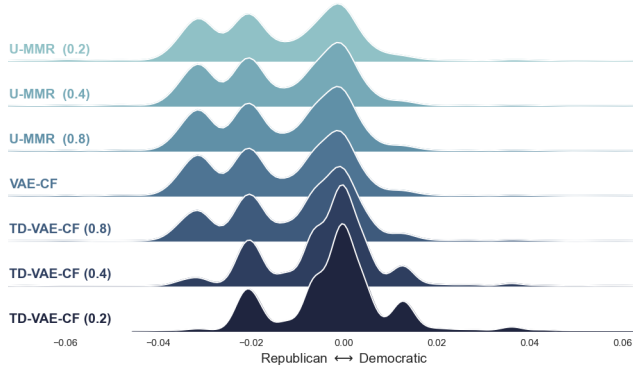


Figure 1: Top 50 recommendations for Republicans using Reddit dataset. X-axis represents the political spectrum of the recommendations. The scores are computed by projecting the item embeddings on the Concept Activation Vector (CAV). The recommendations for TD-VAE-CF and U-MMR are computed using 3 different λ diversity levels (0.2, 0.4, 0.8).

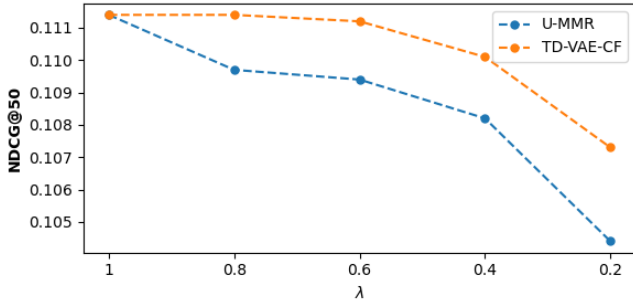


Figure 2: NDCG@50 vs. λ for TD-VAE-CF and U-MMR. λ values are taken from (1, 0.2, 0.4, 0.6, 0.8).

However, considering that topical content such as “the economy” may be represented in a variety of Reddit communities spanning the political spectrum, one might ask whether it is possible to mitigate this filter bubble effect by shifting the political coverage distribution to a more neutral position while preserving recommendation relevance for the user?

Historically, Maximal Marginal Relevance (MMR) [2] (cf. Section 2) has been used to diversify content rankings, including recent methods aiming to mitigate filter bubble effects [9]. While such result list diversification may decrease quantitative metrics of recommendation performance, user studies have shown that diversity can also improve overall satisfaction with recommendation lists [17]. However, the drawback of post-hoc reranking methods like MMR is their independent treatment of relevance and novelty [16] that inherently trades off relevance for diversity. Furthermore, MMR typically diversifies across all content and not just targeted dimensions (e.g., political polarization) and its post-hoc reranking approach has quadratic time complexity in terms of the ranked list size.

In this paper, we propose a simple but empirically effective approach to address all of the aforementioned deficiencies of MMR. Our Targeted Diversification VAE-CF (TD-VAE-CF) methodology

intrinsically dovetails with the latent user and item representations in state-of-the-art VAE-based collaborative filtering (VAE-CF) [8]. Specifically, we train Concept Activation Vectors (CAVs) [5] for targeted topical dimensions (e.g., political polarization) and use these to modulate latent embeddings of user preferences in VAE-CF to diversify along that targeted dimension while preserving topical relevance across orthogonal dimensions.

One can observe in Figure 1 that TD-VAE-CF clearly shifts the political polarization distribution to a more neutral range as diversification strength increases (λ decreases) in comparison to standard untargeted MMR (U-MMR), which is unable to shift the political spectrum; later we will see that a targeted version of MMR (T-MMR) performs even worse. Furthermore, as evidenced in Figure 2, the NDCG measure of recommendation relevance does not drop as steeply for TD-VAE-CF as it does for U-MMR when diversification strength is increased. We present more comprehensive experiments in Section 4 that confirm these results in a variety of additional settings, where we additionally show that the latent modulation approach of TD-VAE-CF induces low computation overhead in comparison to the quadratic time complexity of MMR.

In summary, TD-VAE-CF combines CAVs with VAE-based Collaborative Filtering to enable a novel targeted diversification approach to recommendation that can selectively mitigate filter bubble effects while maintaining relevance without sacrificing efficiency.

2 MAXIMAL MARGINAL RELEVANCE (MMR)

As one of the most popular ranked list diversification methods in the literature and our baseline for comparison, we briefly review Maximal Marginal Relevance (MMR) [2] as it applies to the recommendation setting. Given a set \mathcal{I} of items to select $s_i \in \mathcal{I}$, we aim to build an optimal subset of items $S_k^* \subset \mathcal{I}$ (where $|S_k^*| = k$ and $k < |\mathcal{I}|$) relevant to a given user u . For computational efficiency, we will build S_k^* in a greedy manner by choosing the next optimal selection s_k^* given the previous set of optimal selections $S_{k-1}^* = \{s_1^*, \dots, s_{k-1}^*\}$ and recursively defining with $S_k^* = S_{k-1}^* \cup \{s_k^*\}$. MMR greedily populates the result set according to the following criteria:

$$s_k^* = \underset{s_k^* \in \mathcal{I} \setminus S_{k-1}^*}{\operatorname{argmax}} [\lambda \operatorname{Sim}_1(u, s_k) - (1 - \lambda) \operatorname{Sim}_2(s_i, s_k)] \quad (1)$$

Here, similarity metric Sim_1 measures user-item relevance (i.e., recommendation score), metric Sim_2 measures item-item similarity, and the parameter $\lambda \in [0, 1]$ trades off relevance and diversity. In the case of s_1^* , the maximization term is vacuous ($=0$).

From an inspection of Equation 1, one can easily identify the key weaknesses of MMR that we seek to address in this work: (1) it directly sacrifices relevance to achieve diversity [16]; (2) in its standard form, the item diversification Sim_2 is generic and untargeted (U-MMR) [9] though we later define a targeted variant (T-MMR) for additional comparison; (3) it requires a quadratic complexity computation of pairwise similarity measures between items.

3 METHODOLOGY

VAEs for Collaborative Filtering: The impressive generalization and reconstruction ability of the VAE model is particularly attractive to the recommendation community and has inspired many recent deep learning-based recommendation models [7, 8, 13]. Figure 3(a) shows the basic VAE-CF model for recommendation, where

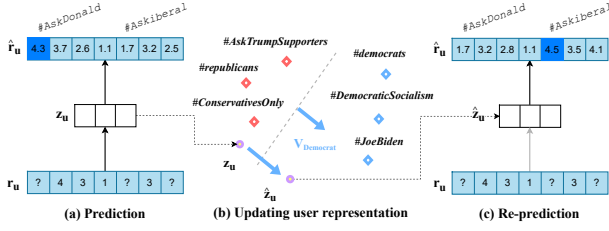


Figure 3: Step-by-step flow of TD-VAE-CF architecture. (a) We first obtain the user latent preference representation from the off-the-shelf VAE-CF model. (b) Next we find the CAV of two subtopics and update the user latent representation. (c) Re-predict to obtain CAV-shifted user preference ratings.

a (sparse) vector of user preferences \vec{r}_u over n items are encoded by the VAE [6] into a Gaussian-distributed latent preference embedding \vec{z}_u of width d . \vec{z}_u is then stochastically decoded to a (dense) reconstruction \hat{r}_u that generalizes user preferences to unobserved items. Formally, VAE-CF optimizes the following objective over the respective parameters ϕ and θ of the encoder and decoder:

$$\sum_u \log p(\vec{r}_u) \geq \sum_u [E_{q_\phi(\vec{z}_u|\vec{r}_u)} [\log p_\theta(\vec{r}_u|\vec{z}_u)] - KL[q_\phi(\vec{z}_u|\vec{r}_u) || p(\vec{z}_u)]], \quad (2)$$

In practice, the approximation of user distribution $q_\phi(\vec{z}_u|\vec{r}_u)$ is usually a Normal distribution with learned parameters μ_u and Σ_u .

In our implementation, we use a one-layer decoder such that the weights of the decoder can be directly used as item embeddings, $\mathbb{X}^{n \times d}$, where the i^{th} vector \vec{x}_i is the i^{th} weight of the decoder that corresponds to the i^{th} item and n is the number of items. From the latent embedding space, we can obtain the user embeddings as $\mathbb{Z}^{m \times d}$ where the u^{th} vector \vec{z}_u is the latent preference embedding \vec{z}_u of user u and m is the number of users.

Concept Activation Vectors: Existing work for conversational recommender systems [14] leveraged the CAV [5] methodology with the VAE-CF framework to determine the alignment of keyphrase embeddings with user embeddings and applied a Bayesian update to user beliefs after each critique [14].

Here, we propose two methods for generating CAVs: I-CAVs and U-CAVs. We define a CAV as the normal to a hyperplane that separates two opposing subtopics (e.g. Republican vs. Democratic) in the embedding space as shown in Figure 3(b). For I-CAVs, we sample k items from each subtopic to form two subsets of items, \mathcal{I}_k^1 and \mathcal{I}_k^2 , from decoder matrix $\mathbb{X}^{n \times d}$. To obtain the activation vector $\vec{v}_i \in \mathbb{R}^d$, multiple linear classifiers are trained to distinguish \mathcal{I}_k^1 and \mathcal{I}_k^2 and the averaged classifier is used as \vec{v}_i . U-CAVs sample from the user embeddings, $\mathbb{Z}^{m \times d}$, to form two subsets of users, \mathcal{U}_k^1 and \mathcal{U}_k^2 . Similarly, the activation vector, \vec{v}_u , is generated using the averaged linear classifier between \mathcal{U}_k^1 and \mathcal{U}_k^2 .

Targeted Diversification VAE-CF (TD-VAE-CF): TD-VAE-CF applies a targeted CAV direction to update the user-embeddings from VAE-CF in the latent space. After we generate CAV \vec{v} using either user or item embeddings, we update a user-embedding by subtracting its projection on the CAV with a parameter λ :

$$\hat{\vec{z}}_u = \vec{z}_u - (1 - \lambda) \frac{\vec{z}_u \cdot \vec{v}}{\|\vec{v}\|^2} \vec{v} \quad (3)$$

Table 1: Dataset statistics.

Dataset	#User	#Item	#Interactions	Density
Yelp	7,000	4,997	151,456	0.433%
Reddit Politics	9849	9,892	449,660	0.462%
Reddit Gender	9779	9,892	365,307	0.377%

where $\hat{\vec{z}}_u$ is the updated user embedding for user u . As shown in Figure 3(b), the updated user embedding moves closer to the hyperplane that separates two subtopics. The parameter λ is taken from $[0, 1]$ which controls the degree of update. Finally, the updated user-embedding is decoded using the one-layer decoder in VAE-CF to the (dense) reconstruction, $\hat{\hat{r}}_u$, where the user preference rating for the opposing subtopic would increase as shown in Figure 3(c).

4 EXPERIMENTS

We now experimentally compare the recommendation and diversification quality of our proposed TD-VAE-CF with a baseline VAE-CF model (i.e., TD-VAE-CF with $\lambda = 1$) and MMR-diversified variants of VAE-CF to address the following research questions:

- **RQ1 – Relevance vs. Diversity:** Is TD-VAE-CF able to maintain relevance and achieve diversity better than MMR?
- **RQ2 – Targeted Diversification:** Does TD-VAE-CF effectively distribute items in the targeted latent direction?
- **RQ3 – Running Time:** Is TD-VAE-CF efficient vs. MMR?

4.1 Datasets

We conduct experiments on two datasets: **Reddit** for recommendation of communities, and **Yelp** for recommendation of restaurants. We follow the same preprocessing steps as in previous work [12, 15] and randomly select 80% for training, 10% for validation, and 10% for testing. For Reddit, we select two spectra to diversify along with two subtopics for each spectrum: politics (*Republican* vs. *Democratic*) and gender (*Men* vs. *Women*). Since the Reddit communities are sparse and there are, on average, less than ten communities corresponding to one subtopic, U-CAVs are used for Reddit by selecting the users that have interacted exclusively with the communities within one subtopic in the spectrum (e.g., *DemocraticSocialism* for Democratic and *Republicans* for Republican). Similarly, the two spectra we choose for Yelp are health (*Deep Fried* vs. *Salad*) and meat consumption (*Vegetarian* vs. *BBQ*). The labels for each restaurant are generated using the ten most common key phrases in the user reviews (e.g. *DeepFried*, *BBQ*, etc.). We use I-CAVs for Yelp since there is a sufficient number of items for each subtopic to generate a representable CAV. Since there is no need to perform targeted diversification on users who haven’t interacted with the targeted direction, we used two subsets of Reddit dataset on politics and gender. The statistics for the datasets are summarized in Table 1.

4.2 Metrics

We evaluate the relevance of top-k ranking performance using Normalized Discounted Cumulative Gain (NDCG) as done in previous work [8, 13]. The diversity of top-k items along the targeted spectrum is evaluated using S-Precision [16] and Harmonic Mean of

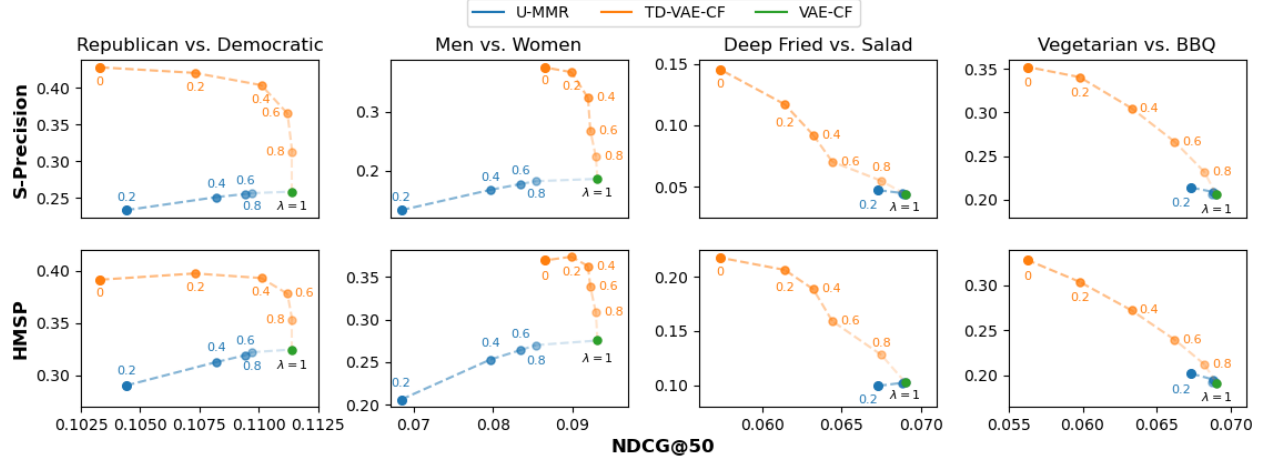


Figure 4: NDCG@50 vs. S-Precision and HMSP for four spectra of two datasets. λ values for TD-VAE-CF and U-MMR are (0, 0.2, 0.4, 0.6, 0.8, 1) and (0.2, 0.4, 0.6, 0.8, 1) respectively. Smaller λ values (higher diversity) are marked with higher opacity.

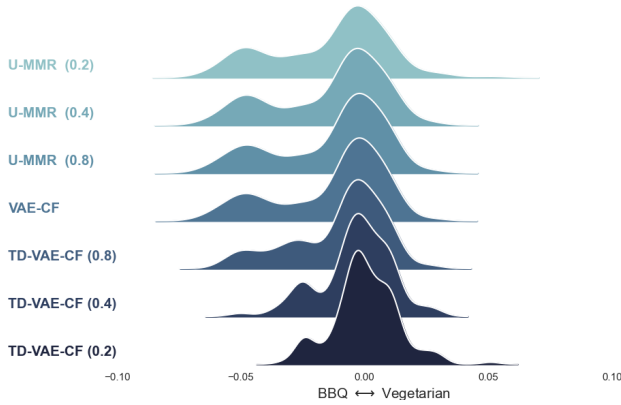


Figure 5: Top 50 recommendations for BBQ lovers using Yelp dataset. X-axis represents the meat consumption spectrum of the recommendations. The scores are computed by projecting the item embeddings on the Concept Activation Vector (CAV). The recommendations for TD-CAE-CF and U-MMR are computed using three different λ values (0.2, 0.4, 0.8).

Subtopic Probabilities (HMSP) since these two metrics can capture the distribution difference of the two ends of the targeted spectrum.

NDCG: NDCG is a measure of ranking quality using Discounted Cumulative Gain (DCG). Formally, it is defined as:

$$DCG@K = \sum_{i=1}^K \frac{rel_i}{\log_2(i+1)} \quad NDCG@K = \frac{DCG@K}{IDCG@K} \quad (4)$$

where rel_i is the graded relevance score of the i^{th} item and $IDCG@K$ is ideal discounted cumulative gain.

S-Precision: S-Precision reflects the number of subtopics covered in the recommended items and is derived from S-Recall that measures the number of subtopics covered among the top-k items:

$$S-Recall@K \equiv \frac{|\cup_{i=1}^K subtopics(d_i)|}{n_A}, \quad (5)$$

where n_A is the number of subtopics. If S is a recommendation system, we define $minRank(S, r)$ as the minimal rank K at which the ranking produced by S has S-Recall r . Then, we can define:

$$S-Precision@r \equiv \frac{minRank(S_{opt}, r)}{minRank(S, r)}, \quad (6)$$

where S_{opt} is a system that produce the optimal ranking (i.e., $minRank(S_{opt}, r)$ is the smallest K for a S-Recall r). Since we focus on two subtopics, we use $S-Precision@1$ such that the $minRank(S, r)$ would be the minimum rank that covers both subtopics.

Harmonic Mean of Subtopic Probabilities (HMSP): Harmonic Mean of Subtopic Probabilities (HMSP) measures the prevalence of each subtopic in the recommendation list; we choose the Harmonic mean since it is strictly greater than or equal to the minimum subtopic probability. Given empirical probabilities p_A and p_B of subtopics A and B in the recommendation list, $HMSP = \frac{2p_A p_B}{p_A + p_B}$.

4.3 Methods Compared

We compare the following (diversified) recommendation methods:

- **TD-VAE-CF:** Our Targeted Diversification VAE-CF as defined in Section 3 with U-CAVs (Reddit) and I-CAVs (Yelp). Gaussian negative log-likelihood loss is used for VAE-CF. 100 CAVs are generated using 10 embeddings for each of the two subtopics which are randomly sampled and the final CAV is the mean of the 100 CAVs.
- **VAE-CF:** The undiversified baseline collaborative filtering system defined in Section 3 (VAE-CF = TD-VAE-CF @ $\lambda = 1$). Gaussian negative log-likelihood loss is used.
- **U-MMR:** Untargeted MMR defines Sim_1 as the VAE-CF user-item embedding dot product and Sim_2 as VAE-CF item-item embedding dot product (VAE-CF = U-MMR @ $\lambda = 1$).
- **T-MMR:** To see if we can achieve a Targeted MMR, we first project the user and item embeddings on the CAV to obtain their preference scores in the targeted spectrum. Then, the similarity metrics Sim_1 and Sim_2 are computed by taking

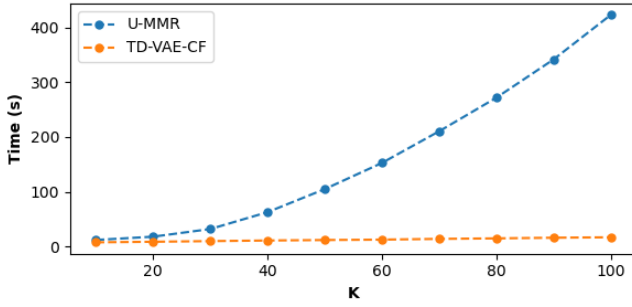


Figure 6: Time for generating top-K recommendations.

the negative absolute value of the difference between the user-item and item-item scores, respectively.

4.4 Performance Evaluation

RQ1 – Relevance vs. Diversity: Overall, the targeted variation of MMR (T-MMR) demonstrates relevance scores that are extremely low (0.0043 for Yelp, 0.0036 for Reddit Politics, and 0.0038 for Reddit Gender on NDCG@50). *Therefore, in the remaining results, we omit T-MMR and only report results of the three other methods that have reasonable relevance.* The results of relevance and diversity on TD-VAE-CF, VAE-CF, and U-MMR are shown in Figure 4. For any fixed level of NDCG recommendation performance (x-axis), the TD-VAE-CF method *strictly dominates* U-MMR’s diversity metrics. Since U-MMR performs untargeted diversification while the metric for diversity is measured along the targeted direction, U-MMR’s diversity and relevance maybe both decrease for some datasets.

RQ2 – Targeted Diversification: The distribution of recommended items on the target CAV are shown in Figure 1 and 5. We see a clear shift of the distribution from one side to the middle, showing the diversified recommendations are well-balanced between the two targeted subtopics of the spectrum, unlike U-MMR.

RQ3 – Running Time: Empirical running times for TD-VAE-CF and U-MMR are shown in Figure 6 (T-MMR would be identical to U-MMR). U-MMR reranks items according to Equation 1. At the K th rank selection step U-MMR compares all non-selected items with $K - 1$ selected items. Therefore, the time complexity for U-MMR is $O(mnK^2)$ where m is the number of users, n is the number of items, and K is the number of recommendations to generate. For TD-VAE-CF, the time complexity can be divided into two parts: the user embedding update requires $O(m)$, and user-item rating generation and sorting need $O(mn)$ to generate the ratings and $O(m(K + K \log(K)))$ to select and sort the top- K ratings. Then, the total time complexity for TD-VAE-CF is:

$$O(m + mn + m(K + K \log(K))) = O(m(K + K \log(K) + n)), \quad (7)$$

Since the complexity of U-MMR has a quadratic growth with respect to K while TD-VAE-CF has a dominant term of $K \log(K)$ growth, the time difference of each increases drastically with higher K .

Conclusion: Overall, in comparison to MMR-based diversification, these results collectively confirm that our novel TD-VAE-CF can

mitigate filter bubble effects through targeted diversification while maintaining relevance without sacrificing efficiency.

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A ALTERNATIVE METHODS

A.1 Targeted Diversification with Posterior Updating

In Section 3, we update the user-embeddings from VAE-CF in the latent space by subtracting its projection. We can achieve the same effect with a closed-form Bayesian update with CAV \vec{v} . From VAE-CF, we obtain the approximation of user distribution $q_\phi(\vec{z}_u|\vec{r}_u)$ with parameters μ_u and Σ_u which serves as an informed prior over u 's latent space. Then, we can get the posterior distribution of the user using \vec{v} :

$$\hat{\Sigma}_u = (\Sigma_u^{-1} + \beta \vec{v}^T \vec{v})^{-1} \quad (8)$$

$$\hat{\mu}_u = \hat{\Sigma}_u (\Sigma_u^{-1} \mu_u + \beta \vec{v} y)^{-1} \quad (9)$$

where β is a hyperparameter and y is the likelihood with distribution $\mathcal{N}(\vec{v} \vec{z}_u^T, \beta^{-1})$. Since we want to reduce the user preference in the targeted direction, we take $y = 0$. The updated user-embedding would be:

$$\hat{\vec{z}}_u = \hat{\Sigma}_u (\Sigma_u^{-1} \mu_u)^{-1} \quad (10)$$

Since the performance of this method is similar to the one we discussed in Section 3, we will skip the experimental results.

A.2 Flatten the Filter Bubble with Gaussian Noise

One side effect of diversifying with TD-VAE-CF is that only a few extreme items (i.e. heavily toward one side of the spectrum) are recommended. We can observe this effect in Figure 1 and 5: while the distributions of the items recommended shifted to the middle, the range of the distributions decrease. We can flatten the distribution with Gaussian noises.

First, we update the user-embeddings following the same method in Section 3 with $\lambda = 0$ which would totally remove the preference information of the user in the targeted direction. Then, we remap the user n times along the targeted direction by adding $\alpha \vec{v}$. α is sampled from $\mathcal{N}(0, \sigma)$ and, during each remapping, a new α is sampled. Finally, the n remapped user-embeddings are decoded to produce n reconstructions and we take the average to produce the final reconstruction of the user preference.

The resulting distributions are shown in Figure 7 and the results of relevance and diversity are shown in Figure 8. When $\sigma = 0$, the remapping process does not change the user-embeddings and it is the same methods as Section 3 with $\lambda = 0$. We can clearly see that the distribution is flattened with higher σ and a wider range of items are covered along the targeted direction. The diversity continue to increase with higher σ while the relevance decreases.

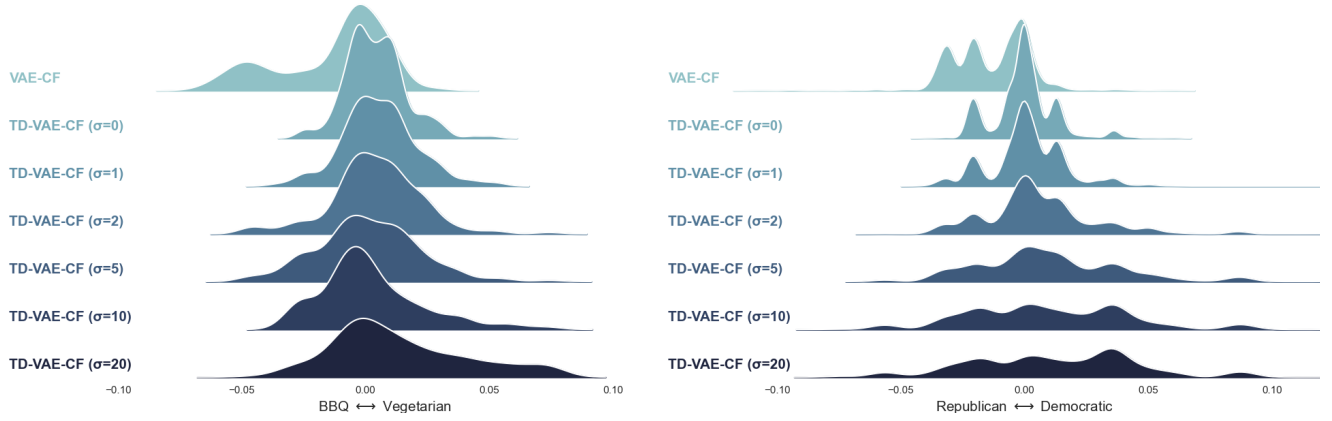


Figure 7: Top 50 recommendations for Republicans and BBQ lovers using Reddit and Yelp dataset respectively. X-axis represents the political spectrum or the meat consumption spectrum of the recommendations. The scores are computed by projecting the item embeddings on the Concept Activation Vector (CAV). The recommendations for TD-CAE-CF and U-MMR are computed using three different σ values (0, 1, 2, 5, 10, 20).

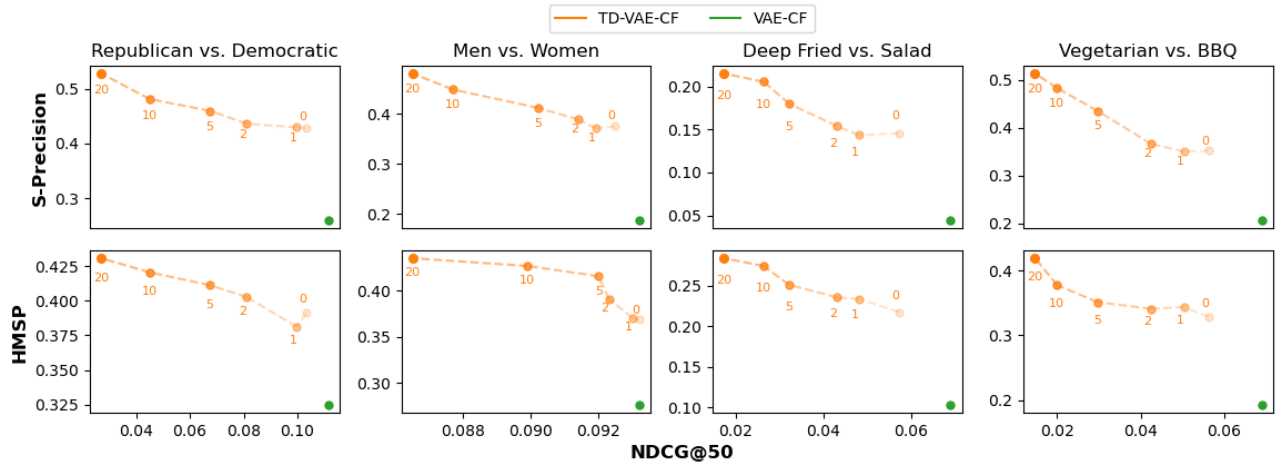


Figure 8: NDCG@50 vs. S-Precision and HMSP for four spectra of two datasets with different σ values (0, 1, 2, 5, 10, 20). Higher σ values (higher standard deviation) are marked with higher opacity.