Text Representations for Scrutable Recommendations

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ABSTRACT

Traditional recommender systems rely on high-dimensional (latent) embeddings for modeling user-item interactions, often resulting in opaque representations that lack interpretability. Moreover, these systems offer limited control to users over their recommendations, without consuming additional items. Inspired by recent work, we introduce *TExtual latent Auto-encoders for Recommender Systems* (TEARS) to address these challenges. Instead of representing a user's interests through latent embeddings, TEARS encodes them in natural text, providing transparency and allowing users to edit them. Drawing inspiration from the autoencoder literature, a pre-trained large language model (LLM) encodes the user preferences into a user summary. We find modern LLMs capable of generating summaries that uniquely capture user preferences. The method then decodes the summary to provide personalized recommendations. In practice, we find that aligning the summaries' representations with the representation of a standard VAE for collaborative filtering provides user-controllable recommendations that surpass the performance of the standalone VAE. This is true across two popular VAEs methods. We further analyze the controllability of TEARS through a simulated user task to evaluate the impact of large changes in the summary. We also show that TEARS can be guided to provide contextual recommendations with minimal summaries. We make our code and all user-summaries available on GitHub [1].

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CCS CONCEPTS

• **Information systems** → *Retrieval models and ranking*.

KEYWORDS

Transparent Recommendation, Explainable AI, Recommender Systems, Large Language Models

[1]https://github.com/Emilianopp/TEARS

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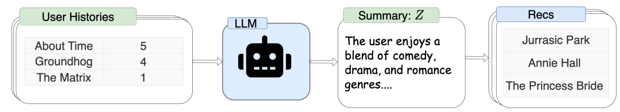

Figure 1: General scrutable recommendations framework proposed by Radlinski et al. [35]. Our work implements this framework while also addressing its limitations.

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1 INTRODUCTION

Recommender systems are a crucial component of the online ecosystem, providing personalized content by modeling user preferences. Every day, rather than parsing through a large collection of items, users rely on recommender systems to infer their preferences and surface relevant items.

Recommender systems often employ collaborative filtering (CF) models, such as those discussed in [15, 47, 52], which are particularly effective for users with extensive interaction histories (e.g., clicks or ratings). These models derive latent *user representations* from observed preferences to generate recommendations. However, these representations are encoded using high-dimensional numeric vectors, which are inaccessible to users and, anyway, lack interpretability. Further, these CF systems offer limited control to users, who can influence them only through coarse item-level interactions, such as clicks or ratings, without understanding the precise impact of such actions on recommendations.

To address these limitations, we introduce a recommender system that represents users with *natural text* summaries. Such user representations are easily understandable and directly editable [35]. Previous attempts at designing controllable recommender systems have generally restricted user profiles to broad tags or rigid templates [13]. These methods provide limited customization options, as users might find the available tags too numerous and the templates overly restrictive. Instead, text-based representations offer users a clear insight into how the model interprets their historical behavior (preferences) and allow them to modify these interpretations, thereby directly influencing the recommended outcomes they receive.

Our work implements the framework developed by Radlinski et al. [35], illustrated in Figure 1. This framework suggests transitioning from black-box user representations to more interpretable ones using *scrutable (natural) language*. They define scrutable language as being both short and clear enough for someone to review and edit directly (such that the edits impact the downstream recommendations). This approach provides several key benefits. First, it enhances transparency in the recommendation process by basing recommendations on user summaries and clarifying the system's inferred preferences. Additionally, it allows users to edit their summaries, thus giving them control over their recommended content. However, this framework assumes that text summaries can encapsulate all the information typically contained in rich numerical latents, which we find is generally not the case in practice, potentially leading to a substantial drop in performance (see Table 1).

We develop TExtual latent Auto-encoders for Recommender Systems (TEARS) to obtain high-quality recommendations and scrutable user representations.

TEARS uses an optimal transport (OT) regularizer to align black-box feedback representations with summary-based representations. The aligned representations are then merged using a convex combination. Changing the interpolation coefficient allows the system designer or its users to guide their recommendations further. For example, users can choose recommendations based entirely on their user summaries, adhering to the principles of Radlinski et al. [35], opt for more black-box-based recommendations for optimal performance, or select a blend of both from text adjustments.

In our empirical evaluations, we explore three key aspects of TEARS: user summaries, recommendation performance, and controllability. We begin by testing whether modern pre-trained LLMs can generate distinctive, appropriately sized user summaries. Next, we demonstrate that aligning feedback and summary-based embeddings improves recommendation performance. Due to the lack of standard metrics for controllability, we introduce new metrics and benchmark tasks, designed to evaluate how user edits influence the system. These tasks are built around the principle that there are two primary types of user edits: large-scope and small-targeted edits, with additional changes simply being repetitions or a combination of these. For instance, we assess large changes by instructing GPT to "flip" user preferences, swapping favorite and least favorite genres and measuring the change in the recommendations. Targeted edits are evaluated using GPT to make minor adjustments to the summary to boost the rank of a poorly rated movie. Finally, we test a combined approach where the user first deletes their summary (large change) and then uses a short phrase (small-targeted change) to guide recommendations. Our findings indicate that TEARS is controllable across all scenarios. Additionally, in App. J we perform ablation studies on key design choices of TEARS.

2 RELATED WORK

We now review related work in two key areas: enhancing the scrutability of recommender systems and applying LLMs to recommender systems.

2.1 Scrutable Recommender Systems

Latent-variable models are useful to build recommender systems from implicit data [41]. Choosing to represent users in a numerical latent space makes building a transparent and scrutable recommender system challenging. The two primary avenues explored to alleviate this issue are by designing models that provide explanations or justifications for their generated recommendations [42]. There is a key distinction to be made between justifications and explanations. The former aims to give a post hoc interpretation of why certain recommendations were generated (e.g. "this movie has a lot of action"). The latter directly addresses what qualities make an item suitable for recommendation (e.g. "you are interested in character study movies with a backbone of action").

While justifications provide insight into what qualities may make an item attractive to the user, they are post hoc interpretations of the model's decisions and do not directly explain the decision making process itself. This is a key limitation in justification-based systems, such as those that provide generated justifications based on reviews [4, 12, 24, 25], or using general knowledge acquired by LLMs [7] as they do not give deeper insights into the inner workings of the model. On the other hand, explainable recommender systems have been very limited in flexibility, as they have primarily been explored by providing explanations through the use of keywords [7], tags/tag clouds [8, 11, 45]. Overall, these systems are largely limited in the context of controllability, as a user must parse through large amounts of tags or keywords.

Few works have explored more scrutable recommender systems. Balog et al. [3] explore explaining user recommendations through natural text-based templates. They first generate a set of user-specific weighted tags, which encode the preferences based on the user history. Then, they can use these relevant tags alongside premade templates to expose the inferred preferences as simple text. While they provide a form of scrutability in their recommendations, they do not fully address the mentioned limitations. Specifically, constraining user representations to a predefined set of templates is limiting and does not allow for a personalized experience as different users can obtain the same representation, even with varying histories. Additionally, controllability is restricted as the user can only select from a sampled subset of generated templates and cannot freely alter their representation. More recently, Sanner et al. [37] conducted a user study showing the benefits of using user-summaries to generate zero/few-shot recommendations using a frozen LLM. This study shows that under certain settings, by levering user-summaries LLMs are competitive with black-box models under the cold start settings. Mysore et al. [31] introduce LACE, the most comparable method to TEARS as they both aim to align user concept and feedback embeddings. LACE is primarily limited by how it exposes user preferences as dataset-specific sets of concepts that users can then add or remove to alter their recommendations. This design is similar to the mentioned tag/keyword-based systems, so LACE inherits the same limitations. We build TEARS to specifically address these common limitations by making scrutable user summaries from natural text that are customizable/editable without constraints.

2.2 Large Language Models for Recommendations Systems

Enhancing recommender systems with textual attributes is widely recognized for improving both performance and robustness [2, 21, 32, 53]. The integration of LLMs into recommender systems can generally be categorized into two approaches: utilizing LLMs as

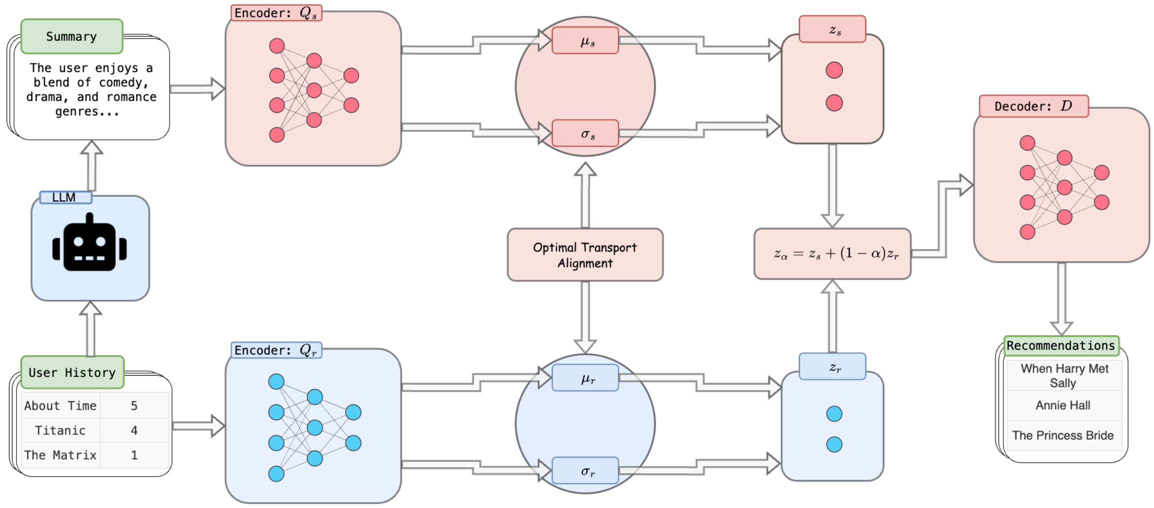

Figure 2: We illustrate the general TEARS. TEARS produces recommendations based on a convex combination of aligned summary and feedback representations, allowing users to interpolate between transparent text-based recommendations and black-box methods. All figures in blue indicate frozen weights, while red indicates a trainable procedure.

standalone recommender systems and enhancing existing systems with LLM-generated text.

Studies have shown that LLM-generated text can significantly improve recommendation quality by providing item or user-specific content [1, 43, 49]. Such approaches leverage the descriptive power of LLMs to enrich the contextual understanding of user preferences and catalog items. Meanwhile, other approaches deploy LLMs directly as recommender systems. This can be done either in a zero-shot manner, where the model makes recommendations based on general pre-training [27, 50], or through fine-tuning the model on specific recommendation tasks [27]. While LLM zero-shot or few-shot methods might offer scrutability since they rely purely on natural text, they suffer from inconsistencies and are limited by confabulations and incomplete catalogue coverage [29]. We further validate this in Table 1, where we evaluate GPT-4-turbo's performance on strong generalization. On the other hand, fine-tuning can enhance the quality of recommendations by integrating new item-specific or user-specific tokens into the LLM's vocabulary [9, 10, 20]. However, it may compromise the model's ability to comprehensively navigate the full item catalogue due to the added tokens not appearing during general pre-training. While these approaches show that one can enhance performance using textual attributes, they do not focus on the development and evaluation scrutable systems, which is the main focus of this work.

3 TEARS

We introduce TEARS, a method with user-interpretable and controllable representations. We begin by contrasting TEARS with standard latent-based CF methods. Then, we introduce the components of TEARS, starting with a prompting pipeline to summarize the user preferences using an LLM. These summaries are then used to predict recommendations. To achieve this, we use two AE models: a text representation-based model, which transforms text summaries into recommendations, and a (black-box) VAE model. We propose aligning the space of the text representations model with the space of a standard recommendation VAE using optimal transport (OT). We find this alignment crucial for obtaining high-quality recommendations while preserving the controllability of the text user summaries (see App. J.1).

3.1 Motivation

Traditional collaborative-filtering-based recommender systems rely on a user's history to provide recommendations. A user wanting to obtain better recommendations, e.g. if current recommendations do not appear satisfying, faces a tedious process with unclear outcomes since they must interact with (e.g., consume or at least rate) items that better reflect their preferences with the hope of obtaining better recommendations. This is even more impractical in domains where users' preferences evolve rapidly or if users have *short-term* preferences in a given context.

In contrast, TEARS allows users to adjust their recommendations by adapting or even deleting their summary and creating a new one more aligned with their (current) preferences. This process is immediate and transparent. It allows users to correct representational mistakes (e.g. add a missing genre) or adapts them to better suit their evolving preferences and the current context. Additionally, we introduce an interpolation coefficient, α, between a user's summary and feedback representations. Setting $\alpha = 1$ puts all the weight on text representations, while $\alpha = 0$ favors feedback representations. This gives users extra control over how their recommendations are influenced (details in Section 3.4).

3.2 Background

Autoencoder models have proven highly effective for collaborative-filtering recommender systems, consistently outperforming counterparts across various tasks [26, 38, 40]. With this in mind, we design TEARS to be compatible with existing VAE-based models and refer to the combination as TEARS VAE models. We study

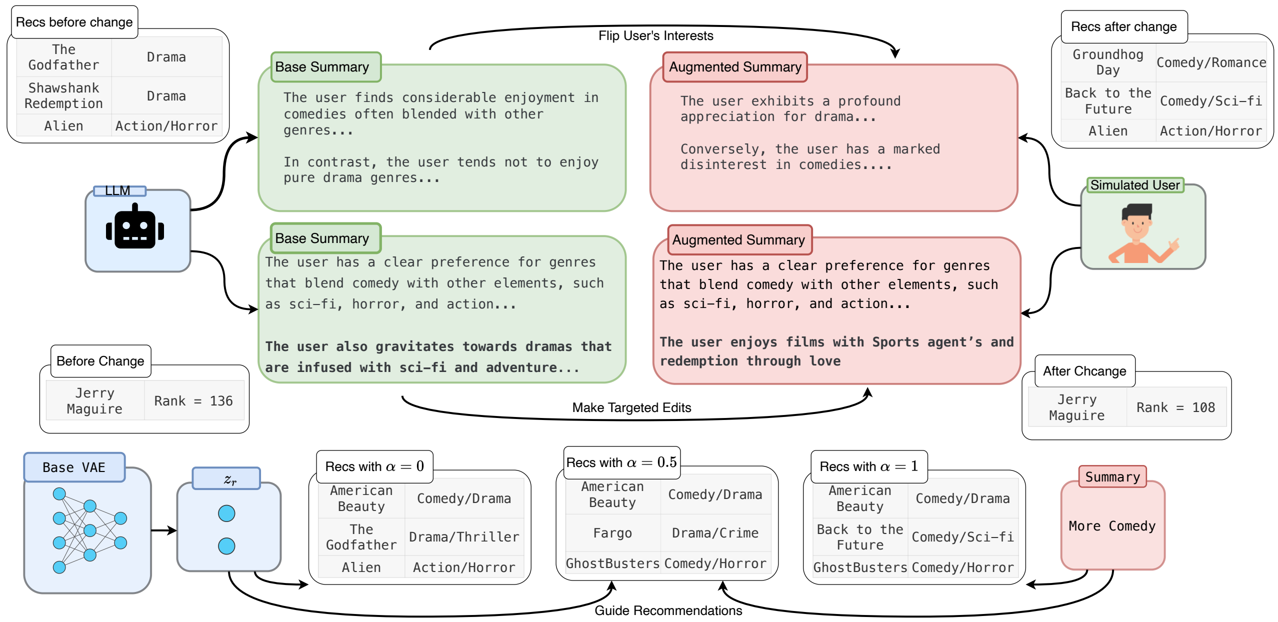

Figure 3: We visualize controllability experiments: large-scope changes (top), fine-grained edits (middle), and guided recommendations (bottom). Red indicates changed summaries, green represents their base summaries, and blue denotes models. Summaries and examples are paraphrased. Refer to App. A for more summaries, App. B for large-scope examples, and App. C for fine-grained examples.

specific VAEs, and we denote their combinations using their names, e.g. TEARS RecVAE.

The auto-encoder framework involves representing user-item feedback matrix $\mathbf{X} \in \mathbb{N}^{U \times I}$, where each entry represents a rating given by a user u to an item i. Our focus is on predicting users' implicit preferences $\mathrm{Y} \in \{0,1\}^{U \times I}$ (e.g. identifying items that a user has rated above a specified threshold r as positive targets). These models prescribe learning an encoding function $Q : \mathbf{X} \to \mathbf{Z}$ to compress input data into a lower-dimensional latent space, followed by a decoding function $D : \mathbf{Z} \to \mathbf{Y}$ to map it to the target.

3.3 Summary Design

Creating scrutable summaries for controllable recommender systems presents unique difficulties. Manual summary creation is impractical due to scalability and inconsistency, while the quality of earlier machine-generated summaries was low [6]. However, LLMs like the recent GPTs have significantly improved capabilities across natural language tasks [17, 51], offering a tool for generating high-quality user summaries.

We propose designing user summaries by leveraging GPTs. While these generative models provide an efficient way to obtain summaries, ensuring their quality and consistency is non-trivial.

We believe each summary should contain enough information to be decodable into good recommendations but short enough to be easy to understand and control by users. In that sense, it should describe the user's preferences sufficiently and uniquely. We note that these design choices may also vary by domain, and in this work, we focus on the movie and book recommendation domain.

Given the above criteria, we identify preference attributes that a user may wish to edit and that are essential in providing good recommendations. For each attribute, we also pinpoint relevant prompting information:

- **Inferred Preferences**: What users like and dislike, prompted with user ratings.
- **High-Level Attributes**: Preferences for genres, prompted with item metadata.
- **Fine-Grained Details**: Specifics such as plot or theme, prompted with the title.

GPT models have been shown to encode significant knowledge over various movie and book datasets [16, 18, 46]. As such, we believe they should be able to encode appropriate item information conditioned on titles and genres alone. To verify this, we conducted preliminary experiments using GPT-3.5, GPT-4-turbo, and GPT-4 via the OpenAI API, finding that GPT-3.5 generated poor summaries, while there was no significant difference between GPT-4 and GPT-4-turbo. We select GPT-4-turbo[2] to generate summaries and refer to it as GPT for the remainder of the text.

While GPTs have shown impressive capabilities in text summarization [6], we find that free-style prompting without adherence to a specific structure can make summaries generic and vary in quality. On the other hand, GPTs have excelled in instruction-based tasks [33]. With this in mind, we design a prompt asking for summaries to include the desirable characteristics mentioned to enforce consistency and quality. Consistent summaries will also likely help train a decoder and obtain high-quality recommendations. Our resulting

[2]We specifically use gpt-4-1106-preview

prompting strategy is in Figure 6. We explicitly direct the model to avoid stating titles and rating information to prevent over-reliance on such details and encourage summaries to be more expressive. By design, GPT's responses are non-deterministic. As such, we found in early experiments that summary generation can vary, with two output summaries being significantly different for the same user. We observed higher variability in users with extensive histories, leading us to limit the number of items used for each summary (to a maximum of 50 items in our studies). Note that the number of items used for each summary, m_u, is user-dependent, with some having less than this maximum threshold. Finally, our prompt also contains the expected length of the summaries. Which we set to 200 words which we find short enough to not incur heavy cognitive loads, but can be detailed enough.

3.4 Methodology

In this section, we define the TEARS model and its training process. With user summaries $\mathbf{S}$ and feedback data $\mathbf{X}$, our goal is to obtain a pair of encoding functions $Q_s : \mathbf{S} \rightarrow Z_s$ and $Q_r : \mathbf{X} \rightarrow Z_r$ which we can constrain to map the representations z_s^u and z_r^u to a common space. We obtain Q_r from a trained auto-encoder. After that, we aim to decode a convex combination of the representations $z_c^u = \alpha z_s^u + (1-\alpha) z_r^u$ onto recommendations using a shared decoder $D : Z_c \rightarrow \mathbf{Y}$. When $\alpha = 1$, the recommendations are generated solely using the summary embeddings; this means the downstream recommendations are controllable through simple text edits. On the other hand, when $\alpha = 0$, the recommendations are based purely on the backbone recommender system and only leverage the user feedback data. Other α values lead to a combination of these, making it such that a user can guide their recommendations through text edits but still use their historical data, which may be richer in information, making the changes less drastic but more personalized. Overall, our training objective is composed of three components, which are detailed below.

Alignment through Optimal Transport. While the shared decoder architecture should naturally incentivize both the text and feedback embeddings to be naturally aligned, in practice we find that training without additional constraints is not enough (see App. J.5). Rather, we align these embeddings using optimal transport techniques which measure the cost of shifting the mass from one probability measure to another. This is achieved by calculating a cost function that reflects the underlying geometry of the distributions, known as the Wasserstein distance. Unlike other distance metrics such as KL-divergence, the Wasserstein distance is symmetric, making it particularly suitable as an optimization target for aligning two distributions. Computing this distance is straightforward with Gaussian distributions, where the cost has a closed-form solution [23]. To make use of these properties, we use encoders Q_r and Q_s that map inputs onto Gaussian-distributed latent encodings, as is traditional for VAEs [22, 26, 39], $Z_r \sim N(\mu_r, \sigma_r \mathbf{I})$ and $Z_s \sim N(\mu_s, \sigma_s \mathbf{I})$. This parameterization allows for direct computation of the minimal transportation cost between Gaussian distributions to align the two embeddings effectively:

$$\mathcal{L}_{OT} = ||\mu_s - \mu_r||_2^2 + \mathrm{Tr}\{\Sigma_s + \Sigma_r - 2(\Sigma_r^{\frac{1}{2}} \Sigma_S \Sigma_r^{\frac{1}{2}})^{\frac{1}{2}}\}. \tag{1}$$

Other optimal transport techniques, like Sinkhorn's algorithm [5], are applicable to non-Gaussian distributions, we reserve these methods for future exploration.

Objective for Recommendation. For Q_s, in practice, we use a T5-base model [36], which we fine-tune using low-rank adaptors (LoRA) [19], to obtain an embedding of the text summaries and train an MLP head to obtain μ_s, σ_s, we then use the reparametrization trick to obtain Z_s:

$$\mu_s, \sigma_s = \mathrm{MLP}\big(\text{T5-Encoder}(S)\big), \tag{2}$$

$$Z_s = \mu_s + \sigma_s \circ \epsilon, \epsilon \sim N(0, \mathbf{I}). \tag{3}$$

Thanks to the OT alignment, Z_r, Z_s and Z_c share a common space and thus a shared decoder, D alongside the softmax function Ψ can be used to produce a distribution over items for each user with each of these latent spaces:

$$\hat{\mathbf{Y}}_{\mathbf{c}} = \Psi\big(D(Z_c)\big),\ \hat{\mathbf{Y}}_{\mathbf{r}} = \Psi\big(D(Z_r)\big),\ \hat{\mathbf{Y}}_{\mathbf{s}} = \Psi\big(D(Z_s)\big). \tag{4}$$

We use these distributions to optimize the multinomial likelihood of each representation.

During training, we fix $\alpha = 0.5$ to optimize for performance on the merged representations but note that α can be changed at any time during inference. The model is learning using the binary cross-entropy of trained-autoencoder (r), TEARS (s), and their combination:

$$\mathcal{L}_R = \sum_{k \in \{c,s,r\}} \sum_{i \in I, u \in U} y_{ui} \log(\hat{y}_{ui,k}). \tag{5}$$

Constraint of Gaussian Priors. Additionally, we impose a standard Gaussian prior $P(Z) \sim N(\mathbf{0}, \mathbf{I})$ on Z_s which has been shown to help improve performance [26]. Enforcing this constraint can be expressed as optimizing the KL-divergence between that prior and its inferred value:

$$\mathcal{L}_{KL} = DKL\big(Q_s(Z \mid S) || P(Z)\big)$$

Our overall training objective is a weighted sum of the above three objectives, formulated as below:

$$\mathcal{L} = \mathcal{L}_R + \lambda_1 \mathcal{L}_{OT} + \lambda_2 \mathcal{L}_{KL}, \tag{6}$$

where λ_1 and λ_2 are weighing parameters for their respective losses. In practice, we initialize D with the base model's decoder and update its weights whilst training, and keep Q_r's weights frozen.

4 DATASETS

We conduct experiments on subsets of the MovieLens-1M (ML-1M)[3], Netflix[4], and Goodbooks[5] datasets. As is common in other studies, we filter out cold-start items for all datasets [14, 47]. Additionally, due to the cost of using the GPT API, for each dataset, we use a subset of users with enough ratings to provide a comprehensive summary. For the Netflix and Goodbooks datasets, we filter out users with less than 100 interactions and items with less than twenty. Due to being a smaller dataset for ML-1M, we only filter out users with less than twenty interactions and items with less than 5. After filtering, we have 6,014 users and 2,081 items for ML-1M, 9,978 users and 3,081 items for Netflix, and 9,990 users and

[3]https://grouplens.org/datasets/movielens/1m/
[4]https://www.kaggle.com/datasets/netflix-inc/netflix-prize-data
[5]https://github.com/zygmuntz/goodbooks-10k

Table 1: Comparison of model performance across the ML-1M and Netflix datasets on NDCG and recall at $k \in \{20, 50\}$. Each model is evaluated using five different seeds. We report both mean values and standard deviations. Here, TEARS Base is the model most closely aligned with the framework proposed by Radlinski et al. [35]. Best results are denoted in bold, and a * indicates statistical significance ($p < 0.05$) in a two-way t-test between the TEARS-based model to its respective base model (in grey in the row immediately above).

	ML-1M				Netflix				GoodBooks			
Model	Recall@20	NDCG@20	Recall@50	NDCG@50	Recall@20	NDCG@20	Recall@50	NDCG@50	Recall@20	NDCG@20	Recall@50	NDCG@50
GPT-4-turbo	0.043	0.043	0.045	0.030	0.034	0.037	0.045	0.040	0.015	0.012	0.013	0.011
EASE [40]	0.359	0.348	0.403	0.345	0.428	0.393	0.447	0.411	0.173	0.180	0.193	0.182
Multi-DAE [26]	0.392 ± 0.002	0.359 ± 0.002	**0.445 ± 0.005**	0.355 ± 0.002	0.473 ± 0.002	0.487 ± 0.004	0.428 ± 0.002	0.445 ± 0.002	0.151 ± 0.002	0.155 ± 0.002	0.173 ± 0.001	0.160 ± 0.001
TEARS Base	0.349 ± 0.016	0.324 ± 0.016	0.390 ± 0.016	0.318 ± 0.014	0.438 ± 0.010	0.463 ± 0.013	0.384 ± 0.010	0.410 ± 0.011	’ 0.145 ± 0.001	0.153 ± 0.002	0.158 ± 0.002	0.153 ± 0.002
Multi-VAE [26]	0.367 ± 0.003	0.350 ± 0.002	0.423 ± 0.002	0.350 ± 0.003	0.493 ± 0.005	0.515 ± 0.004	0.436 ± 0.003	0.461 ± 0.002	0.159 ± 0.001	0.163 ± 0.001	0.186 ± 0.001	0.170 ± 0.001
TEARS Multi-VAE	0.385 ± 0.003*	0.372 ± 0.001*	0.444 ± 0.006*	0.366 ± 0.002*	0.499 ± 0.002*	0.523 ± 0.001*	0.437 ± 0.002*	0.463 ± 0.002*	0.171 ± 0.002	0.178 ± 0.002	0.187 ± 0.003	0.178 ± 0.002
MacridVAE [28]	0.367 ± 0.011	0.346 ± 0.016	0.421 ± 0.022	0.345 ± 0.017	0.496 ± 0.018	0.514 ± 0.018	0.443 ± 0.012	0.465 ± 0.013	0.168 ± 0.001	0.170 ± 0.001	**0.196** ± 0.001*	0.178 ± 0.001
TEARS MacridVAE	**0.396 ± 0.005***	0.372 ± 0.004*	0.433 ± 0.006*	0.363 ± 0.003*	0.519 ± 0.002*	0.544 ± 0.003*	0.454 ± 0.001*	0.482 ± 0.002*	0.171 ± 0.002	0.175 ± 0.002	0.195 ± 0.002	0.180 ± 0.001
RecVAE [39]	0.385 ± 0.006	0.372 ± 0.003	0.437 ± 0.009	0.366 ± 0.002	0.520 ± 0.006	0.543 ± 0.006	0.457 ± 0.003	0.484 ± 0.004	0.171 ± 0.001	0.176 ± 0.001	0.191 ± 0.002	0.179 ± 0.001
TEARS RecVAE	0.393 ± 0.002*	**0.379 ± 0.003***	0.444 ± 0.008*	**0.373 ± 0.003***	**0.527 ± 0.003***	**0.551 ± 0.003***	**0.459 ± 0.001***	**0.488 ± 0.001***	**0.175** ± 0.002	**0.181** ± 0.002	0.193 ± 0.000	**0.183**± 0.001

8,093 items for Goodbooks. Further descriptive statistics such as sizes of train/validation/test splits are in Appendix F.

We construct $\mathbf{Y}$ using $\mathbf{X}$, with $r = 4$, that is we train the model to predict implicit feedback where the rating is positive ($y_{ui} = 1$) if the item is rated four and above and a negative ($y_{ui} = 0$) otherwise [30]. We evaluate under a strong generalization setting where we reserve 500 users for the validation and testing splits (250 each) for ML-1M and Netflix. With this setup, we initially found a large discrepancy between the validation and testing splits for Goodbooks (not observed in the other two dataset), thus to get a more robust estimate of performance, we hold out 2,000 users (split evenly across testing and validation sets) for evaluation. All summaries are constructed using GPT with the prompt in Figure 6, where we only feed in a maximum of 50 items to construct the summaries and use the rest for evaluation. For users that rate less than fifty items, we retain the most recent two for evaluation and generate the summary with the remaining.

5 USER SUMMARY PROPERTIES

We first assess the scrutability and uniqueness of user summaries. We evaluate scrutability by analyzing the average length of summaries, which contain an average of 171.41±4.93 words across all datasets. This indicates that the summaries are concise enough to be easily editable yet comprehensive enough to reflect detailed information about the user, as seen in the recommendation performance (see §6). For uniqueness, we use pairwise edit distance and the BLEU score [34], which measures the overlap of n-grams between two texts. Across all datasets, we find an average edit distance of 169.03±20.2 words and an average BLEU score of 0.050±0.02. The low BLEU score suggests minimal n-gram overlap, indicating diverse phrasing between summaries. The edit distance, close to the average summary length, further confirms that the summaries are distinct, enhancing personalization. A more comprehensive view and additional statistics are provided in Appendix E, along with examples for each dataset in Appendix A.

6 RECOMMENDATION QUALITY

Since the user summaries largely contribute to the quality of recommendations, we use recommendation performance as a proxy to measure of the quality of user summaries. We use Multi-VAE [26], RecVAE [39], MacridVAE [28], EASE [40] and Multi-DAE [26] as baselines. We train TEARS models with Multi-VAE, RecVAE and MacridVAE as they are Gaussian-based variational auto-encoders. For TEARS-VAE models, we report the metrics on the test set using the value of α which had the highest recommendation performance on the validation set. Additionally, we compare against TEARS without a backbone model, which is trained only using S without any alignment strategy. We refer to this model as TEARS Base. TEARS Base is the closest model to the framework outlined by Radlinski et al. [35] and visualized in Figure 1. Furthermore, we benchmark GPT on few-shot recommendations under strong generalization, to evaluate the possibility of using vanilla LLMs as recommender systems. We detail the procedure in App H. For fair evaluation, we only use the input ratings used to create each user summary. We then predict $\hat{\mathbf{Y}}$ using D. We highlight that, unlike the typical approach of binarizing auto-encoder inputs, we use ratings directly as input. This approach improves the performance of auto-encoders compared to binarized inputs. It also offers a fair comparison with TEARS, where summaries specifically contain positive and negative sentiments as provided by the ratings. Additionally, we find that normalizing the input rating $r \in [0, 1]$ yields improved performance for EASE and report metrics using this procedure.

For evaluating unseen users (strong generalization), we use the same items that were used to generate user summaries as input into baseline models and calculate metrics using the rest.

We assess the quality of recommendations using two popular top-k ranking metrics recall@k and Normalized Discounted Cumulative Gain at k (NDCG@k), with k denoting the number of items recommended.

Table 1 reports the results for recommendations averaged over five different seeds and for $k = \{20, 50\}$. We observe that TEARS-VAE models significantly improve recommendation performance against their respective backbone models in all but two instances. This indicates that the generated text summaries alone have useful information not found within the feedback data used by the aligned embeddings GPT's performance is low in this setting, highlighting the necessity of adaptation to the recommendation task.

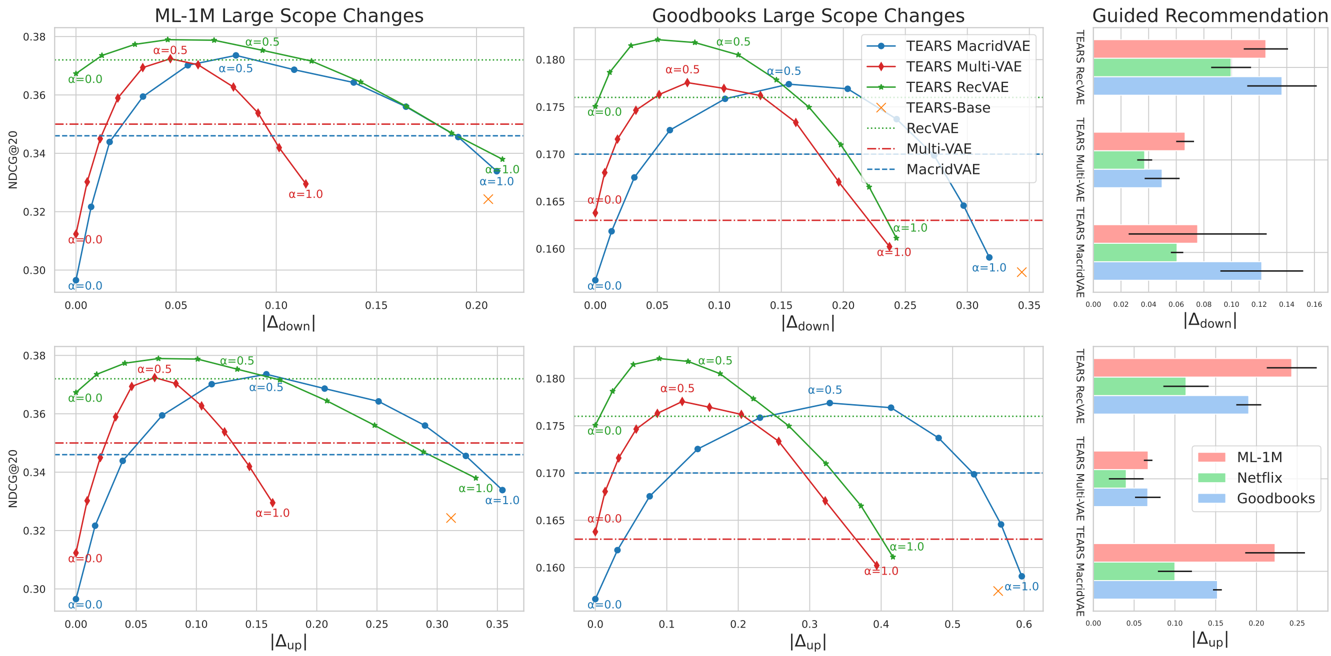

Figure 4: Tradeoff between recommendation performance (y-axis) and large scope controllability (x-axis) for ML-1M (left) and Goodbooks (middle). Netflix results are in Figure 7. The x-axis represents $|\Delta_{\text{up/ down}}|$ as α increases. We observe RecVAE-TEARS and MVAE-TEARS show good levels of controllability while outperforming TEARS-Base. Additionally, RecVAE-TEARS and MVAE-TEARS can outperform their backbone models while being controllable. The two-rightmost bar plots showcase results for guided recommendations, where all models can consistently guide the feedback embeddings in the correct direction.

7 CONTROLLABILITY THROUGH TEXT EDITS

We now study the controllability of user text representations, which is the ability of users to edit and readjust their representation to (better) align the system's recommendations with their preferences. This is one of the main advantages of text representations compared to latent representations.

Given the lack of evaluation metrics for scrutable recommendations, we create three tasks to evaluate the controllability of scrutable recommender systems. These tasks can be benchmarked and easily compared across methods. To do so, we design scenarios that would lead users to update their text summaries.

The posit and evaluate three types of edits. First, *large-scope changes*, for example, to correct significant inaccuracies in a user profile. Second, finer or *small-scope* changes aim to readjust minor discrepancies in a user summary. Other changes can be seen as an interpolation between these two cases where a large change is simply many aggregate small edits. Third, we test the ability of summaries to guide personalized recommendations. This tests a different type of user interaction where the summary is used as an instruction (e.g., in a particular context). This evaluates a model's capacity to interpolate between historical behavior and a context.

7.1 Evaluating Large Scope Changes

We first evaluate how well TEARS can react to a large change in a user's interest. To simulate, such a change we prompt GPT to "flip" a user's interest. We do so by first prompting it to identify a user's most and least favored genre. Using these genres, we prompt GPT to make the user's favorite genre into its least favorite and vice-versa, effectively inducing a large shift in the user's preference. We show the complete prompting strategy and its effect on an example summary in App. B.

To evaluate how effective TEARS is at modeling such changes we design the genre-wise Discounted Cumulative Gains at k ($\text{DCG}_g@k$), which measures how favored a specific genre, ρ, is within the user's top-k recommendations. The intuition is that items from a newly-favored genre should rank higher than in the original ranking—we can use the difference in DCG_g to measure that.

Below, we define $\text{DCG}_g@k$, where $\omega(i)$ maps the i-th item to its corresponding set of genres (in our context, items can have multiple genres):

$$\text{DCG}_g@k(\rho) = \sum_{i=1}^{k} \frac{\mathbf{I}(\rho \in \omega(i))}{\log_2(i+1)}. \tag{7}$$

We normalize $\text{DCG}_g@k$ using the Idealized Discounted Gains (IDCG) to obtain the genre-wise NDCG ($\text{NDCG}_g@k$). To assess the effectiveness of the changes, we measure the $\Delta@k$ change in $\text{NDCG}_g@k$ between the original (denoted with a superscript O) and augmented summary (denoted with superscript A):

$$\Delta@k(\rho) = \text{NDCG}_g^{\text{O}}@k(\rho) - \text{NDCG}_g^{\text{A}}@k(\rho). \tag{8}$$

We evaluate each summary using two metrics: $|\Delta_{\text{up}}@k|$, which assesses TEARS' ability to elevate the rankings of the initially least

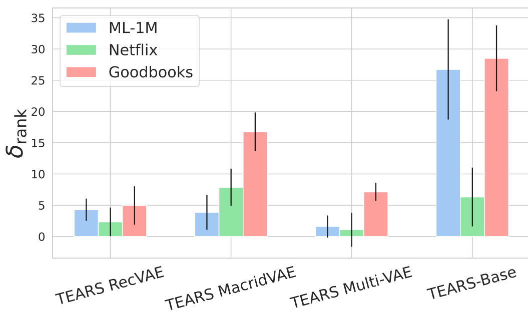

Figure 5: Maximum rank changes in target item rank after fine grained changes. Here the Y-axis represents δ_{rank} = New rank - Old Rank

favored genre (ρ = least favorite), and $|\Delta_{\text{down}}@k|$, which gauges its proficiency in lowering the rankings of the initially favored genre (ρ = favorite), where k denotes the number of items considered. Additionally, we explore how the parameter α influences controllability, highlighting the trade-off between recommendation performance and controllability.

We prompt GPT to obtain the altered summaries for all test users and use those to examine shifts in genre preferences. Figure 4 illustrates the NDCG@20 calculated using the **original summaries** compared to $|\Delta_{\text{up}}@20|$ and $|\Delta_{\text{down}}@20|$ for the range of α values, averaged over five different seeds, for ML-1M and Goodbooks (Netflix in App B.1). This plot displays the trade-off between recommendation performance and controllability as α increases. Our findings indicate that at high values of α, all TEARS VAE variants demonstrate high levels of controllability across both datasets. Remarkably, TEARS VAEs maintain satisfactory controllability even at reduced values of α. We find that TEARS MacridVAE is consistently the best method for controllability, consistently outperforming TEARS Base while also outperforming all AE based methods in NDCG@20 for multiple values of α.

7.2 Fine-Grained Changes

We now evaluate smaller edits to user summaries by simulating a task where a user may want to increase the rank of a single target item by making small edits to their summary. While we could do such a simulation by putting in the item's name, actors, or description, we are not interested in such use cases which other systems, such as search engines, are better suited for. Rather, we simulate summary changes alluding to higher-level characteristics such as plot points or themes, that could be linked to many items. To achieve this, we first sample an item from the evaluation set, that is ranked between positions 100 and 500. This range was picked as it indicates the summary may not capture certain attributes for that specific item that could be included to raise its rank. We make sure the item is within this range for all models within all values of α. With these sampled items, we task GPT with two tasks: first, to "summarize the item in 5 words while only referring to plot points/themes", and then to replace an existing sentence in the summary with one including these plot points and themes. Using this, we measure δ_{rank} = original rank - rank after change. We note some users do not have an item that satisfies such criteria, thus we filter them out. In total, we examine 76 users for ML-1M, 125 for Netflix, and 351 for Goodbooks.

Figure 5 visualizes the rank differences between the augmented and original summaries. We observe that for all datasets, all models can push the target item in a positive direction with minor changes to the summary. Moreover, we find TEARS Base and TEARS MacridVAE are the most consistent across datasets, with Multi-VAE being the weakest, a finding consistent with the results of §7.1. Across all datasets and models, we can consistently move a target item, even with small changes within summaries. We report the changes for $\alpha = 0.5$ and provide a complete overview alongside the prompting procedure, and example changes in App. C.

7.3 Guided Recommendations

We design a task to assess if users can augment their summaries into short instructions to guide their recommendations. This change is particularly interesting for TEARS-VAE models as they can use an $\alpha \neq 1$ to effectively guide their feedback embeddings with a small amount of text, for instance, a user might request that the system include "more action movies" in its current recommendations. To evaluate if TEARS can effectively deliver such targeted recommendations, we design an experiment where we measure $\Delta_{\text{up/down}}$ where $NDCG@20_g^O$ is measured using purely the feedback embeddings (i.e. $Z_{\alpha=0}$) and $NDCG@20_g^A$ is calculated using $Z_{\alpha=0.5}$, where the summary is a simple guidance prompt indicating "More {genre} {item_type}." Here using $Z_{\alpha=0.5}$ suggests that adding a genre preference should yield personalized recommendations favouring that genre, as the representation still has to adhere to the base feedback representations. Similarly, we aim to simulate moving target genres down, which initial analysis showed is a much harder task, as merely mentioning a genre was sufficient to elevate related items when no other summary information was provided. To address this, we adjusted the model by subtracting negative text representations from feedback representations, $Z_{-\alpha=0.5} = \frac{Z_r - Z_s}{2}$. For this experiment, $NDCG@20_g^A$ is calculated using the rankings generated by $Z_{-\alpha=0.5}$.In practice, this procedure could be adopted given the effectiveness of modern sentiment classifiers [48]. We evaluate these changes for all test users using the ten genres with the most corresponding items in each dataset.

The rightmost plots of Figure 4 display the results for the guided recommendation experiment over the three datasets. We note that the $|\Delta|$ changes we see are expected to be smaller as we use an $\alpha = 0.5$ for this setting. Nonetheless, we see that even with summaries composed of simple phrases, we are able to guide recommendations in the desired direction. Moreover, these changes in recommendations are more personalized as they are a combination of the base feedback embeddings and the altered summary. This procedure, as well as the latents of the feedback embeddings, are further visualized in Appendix D.

8 CONCLUSION AND DISCUSSION

We present TEARS, a method for constructing controllable recommender systems using natural-text user representations. By aligning user-summary and feedback embeddings through OT techniques, we demonstrate that the system provides higher-quality recommendations and is controllable. For the latter, we identify three types of changes users can make to their summaries to impact their downstream recommendations: *large-scope changes*, *fine-grained edits* and *guided recommendations*. To evaluate the controllability of TEARS under these changes, we design evaluation metrics and simulated tasks. The results show that TEARS models are controllable in each task. These tasks are reproducible and can be benchmarked in future work. While creating a user interface for TEARS and designing experiments to enable user studies is out of scope, it presents opportunities for future work. Overall, this work shows that scrutability can contribute to performance and leads to a new class of recommender systems that are more transparent and controllable. This work also opens new ways for users to interact with recommender systems, which we hope future work will develop.

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A EXAMPLE SUMMARIES

We provide example generated summaries for all three datasets as well as visualize the prompting scheme in Figure 6.

A.1 ML-1M Summaries

MovieLens ID	Summary
3,850	The user enjoys action-packed narratives with adventurous undertones, marked by the intersection of science fiction and fantasy elements. They appreciate the thrill of survival scenarios and extraordinary quests that involve fantastical creatures or post-apocalyptic landscapes. Plot points involving action heroes overcoming extreme obstacles or engaging in spectacular battles are particularly appealing. On the romantic front, the user enjoys comedy-dramas where relationships and humorous circumstances intertwine, and the journey towards love often involves quirky plot twists. However, the user does not enjoy films that primarily focus on horror without an accompanying thriller or action component. Plots that delve into supernatural hauntings or monsters without a layer of mystery or a crime to solve are less favored. While some audiences might be drawn to the tension and fears associated with horror or slasher films, the user prefers when a horror element is part of a larger, more complex narrative, such as a horror-thriller with a mystery to unravel or a science fiction with a horror twist.
1,488	The user shows a clear preference for films containing action, horror, sci-fi, and thriller elements, particularly those with high-intensity plot points such as survival scenarios, advanced technology, encounters with supernatural or extraterrestrial beings, and characters navigating high-stakes situations. On the other hand, the user does not favor romantic narratives as much, especially those that are more traditional or conventional in their portrayal of relationships, without the addition of other elements such as comedy or fantasy. While some users appreciate drama and character-driven plot points that delve into romantic entanglements and emotional depth, these seem to be less appealing to the user unless they are interwoven with tension or an element of the unexpected found in other genres they enjoy.
5,965	The user enjoys a variety of genres including action, adventure, drama, fantasy, crime, romance, and science fiction. They are particularly inclined towards films involving complex narratives such as those found in action-adventure with fantastical elements or sci-fi thrillers with intricate plot developments. They appreciate character-driven dramas with emotional depth or themes of war and crime that provide a gritty portrayal of human experiences. The user also values intelligent humor and is fond of comedies that feature romantic elements or musical components. Conversely, the user does not enjoy certain comedic movies, particularly those that may be considered low-brow or slapstick. While other users might find enjoyment in lighthearted, easy-going comedy films, these do not seem to resonate as well with this particular user. They also tend to steer clear of thrillers and action movies that are less cerebral or lack significant character development, preferring more substance and intricacy in the plot points of the films they watch.
4,737	The user has a predilection for films that blend genres of crime, drama, and thriller, often appreciating complex narratives that delve into moral intricacies and showcase character development, such as those found in high-stakes criminal underworlds or intense psychological studies. They also show a strong favoritism towards science fiction with immersive world-building, futuristic concepts, and often a mix of action and adventure, indicating a desire for escapism, innovation, and adrenaline-pumping sequences. On the other hand, the user does not resonate with movies that centralize on the fantasy genre or standard war narratives, suggesting a disinterest in the conventional tropes of medieval quests or military glorification. Additionally, plot points involving comedy as a central theme, aside from dark or dry humor occasionally found within crime thrillers, and stories that revolve around historical warfare without substantial personal drama or unique storytelling angles, seem to not engage the user. However, such genres and plot elements have an established fan base that appreciates the whimsical diversion of fantasy or the heroic and strategic aspects of war depicted in action comedies.
2,488	The user has a predilection for gripping narratives interwoven with suspense; they enjoy thrillers that often incorporate crime and mystery, along with instances of action that heighten the tension. They demonstrate an affinity for comedies, particularly those that are intricately crafted with elements of drama or romance, suggesting an appreciation for nuanced humor blended with meaningful storylines or character relationships. Scenarios that play with conventions, like action-adventure comedies that offer a satirical take on familiar genres, or animated and sci-fi films that cleverly subvert expectations, resonate well with the user. Contrarily, the user is not inclined towards horror films, especially when they lean more into the domain of thrillers without additional genre elements to broaden the appeal. They show limited interest in dramas that lack a substantial thrilling or comedic aspect. Pure adventure dramas that aim for a more traditional storytelling approach those without the infusion of either substantial humor or thought-pro

A.2 Netflix Summaries

Netflix ID	Summary
1,033,930	Summary: The user gravitates towards a variety of film genres that typically blend elements of drama, comedy, and romance. They appreciate intricate narratives that intertwine crime and mystery into compelling thrillers, which suggests a predilection for suspenseful plot twists and cerebral storytelling. Action-packed tales with a strong dramatic core, as well as historical dramas that incorporate romance and biography are also favored, indicating a taste for depth and character development within the context of excitement and tension. The user does not prefer straightforward horror, particularly when it dips into the extreme or grotesque, leaning away from overwhelming suspense that prioritizes shock over story. Similarly, movies that might rely heavily on special effects or fantastical elements within science fiction without substantial narrative support appear to resonate less. It’s evident that the viewer enjoys films with robust and emotionally driven narratives, preferring engaging storylines over straightforward genre tropes that might sacrifice character depth for thematic clichés.
647,979	Summary: The user enjoys films that span across multiple genres, appreciating drama, film-noir, mystery, and thrillers, as well as documentaries, biographical pieces, action-adventure movies, and animated features. High engagement is found in plots that involve historical narratives, sporting events, and tales of personal or societal challenges. They also seem to have a penchant for fantasy and science fiction when paired with adventure. Additionally, action-comedy and animated family comedies resonate well with the user, especially when they incorporate elements of fantasy. Conversely, the user does not enjoy primarily horror-themed movies, consistently rating them low regardless of their inclusion of fantasy, thriller, or comedy elements. Even when horror films incorporate other genres like mystery or crime, the user’s disinterest remains. Plots that lean heavily towards simplistic or formulaic horror, including recurring supernatural or slasher themes, don’t capture the user’s interest. Other viewers may find value in the suspense, fear, and iconic characters that genre offers, but these qualities don’t align with this user’s preferences.
2,514,777	Summary: The user shows a clear preference for genres infused with humor and family-oriented themes, often grading animation, adventure, comedy, and family genres highly. Plots revolving around whimsical adventures, humorous interactions, and family dynamics are particularly enjoyable. Comedies with a romantic twist also receive positive feedback, suggesting an affinity for lighthearted and uplifting narratives. In contrast, the user does not favor intense dramas, including those with sport themes, nor do they gravitate towards darker genres such as horror, mystery, and certain thrillers. Plot points that delve into serious biographical accounts or historical recounts are not well-received. Psychological tension, pervasive mystery, and thrillers that are more cerebral or unsettling seem to resonate less, though they may be appreciated by audiences seeking more complex or thought-provoking cinematic experiences.
1,370,564	Summary: The user exhibits a preference for dynamic narratives, often enveloped in genres such as Action, Adventure, and Thriller, with occasional forays into Comedy. They show an inclination toward plot points that invoke high-stakes scenarios, including hostage situations, family-oriented adventures with fantastical elements, and crime-driven storylines with mysterious undertones. Sporting dramas also seem to resonate, alongside poignant biographies and animations that blend humor with exciting escapades. The enjoyment seems amplified when these narratives fuse multiple genres, creating complex and multifaceted movie-going experiences. Conversely, the user demonstrates a distaste for certain dramatic films and romantic comedies that may lack a certain depth or innovative storytelling flair. Plot points focusing predominantly on romance, drama grounded in everyday scenarios without an enticing hook, or comedies that don’t blend well with the user’s taste in humor are not well-received. Horror, especially when combined with mystery, does not seem to elicit much enthusiasm, nor do sci-fi dramas that might lean more toward introspection rather than action. Other users, however, may find the slow-burn intensity of such films, the exploration of human relationships, or the suspenseful ambiance of horror appealing, even if these elements do not align with this particular user’s preferences.
2,554,745	Summary: The user shows a consistent preference for dramas, often connecting with emotionally rich narratives that explore complex relationships and personal growth. They appreciate intricate character studies and plots that delve into the human experience, manifesting as an appreciation for biographies that bring historical or noteworthy figures’ stories to the screen. The user also gravitates toward comedic elements, particularly those blended with other genres such as action or adventure, suggesting a taste for dynamic storytelling with levity. The appeal extends to animation and family-oriented offerings, highlighting a versatility in the user’s tastes that includes a fondness for imaginative worlds. Conversely, the user does not resonate with most horror films, indicating a potential disinterest in the typical tension and scares that define this genre. Similarly, crime thrillers, especially when they are heavy on action without substantive narrative depth, seem to be less favored. Pure romance movies without additional genre blending are not amongst the user’s preferences, possibly due to a perception of predictability or a lack of engaging conflict. Films that lean heavily on thrills or supernatural elements, especially those that are perceived to prioritize spectacle over storytelling, also do not align with the user’s interests, as do documentaries and period pieces that might be considered too niche or specific in their historical context.

A.3 Goodbooks Summaries

Goodbooks ID	Summary
5,428	The user enjoys genres such as fantasy, particularly with complex world-building and elements of high stakes and epic battles, as seen in the elaborately crafted realms and adventures. They favor intricately plotted tales with deep mythology and a clear moral conflict. Additionally, the user appreciates historical and political dramas, along with classic literature featuring existential themes and rich character development. They also show an affinity for poignant social commentaries, both in novels and dramatic works, that explore the human condition and societal issues. The user seems to enjoy plot points involving heroes overcoming great odds, elaborate fantasy quests, and narratives intertwined with deep mythological lore. They also appreciate stories that examine personal and societal dilemmas, focusing on individual struggles within a broader social context, often set against a richly detailed historical or fantastical backdrop. The user does not enjoy straightforward adventure genres or stories focused primarily on exploration without significant character development or moral questions. They tend to be less engaged with narratives that are overly episodic and those that revolve around more whimsical, juvenile themes without a darker or more substantial undertone. The user does not enjoy repetitive series that lack depth or narratives that feel overly drawn out and predictable, even if other users find them humorous or light-hearted.
2,522	The user enjoys a diverse array of genres including classic literature, fantasy, science fiction, and psychological novels. They seem to appreciate intricate world-building and complex character studies. Their preferred plot points often involve deep emotional and psychological development, such as in stories of personal growth, dystopian societies, and sweeping epic tales of good versus evil. The user does not enjoy romance-centric genres or overly political narratives. They tend to be less interested in books with heavily experimental writing styles or dark, cynical views of society and human nature, which other users might find compelling. Additionally, the user seems to avoid stories that revolve primarily around mundane, everyday life events without a significant overarching plot or character transformation.
2,726	The user enjoys genres such as fantasy, historical fiction, mystery, and psychological thrillers. They are particularly drawn to intricate storylines involving supernatural elements, like those found in wizarding worlds, vampire lore, and dark mysteries. Large, complex family sagas and stories with strong character development and emotional depth are also appealing to the user. The user enjoys plot points that feature strong, well-developed characters and complex relationships. Intriguing mysteries, unexpected plot twists, and richly detailed worlds captivate their attention. They appreciate stories that delve into the psychological, moral, and existential dilemmas of the characters. The user does not enjoy romance-focused genres or overly sentimental stories as much, particularly those with predictably emotional outcomes. Simple, straightforward storylines without much complexity or depth do not appear to engage them. The user does not enjoy plot points that are overly melodramatic, excessively focused on romance, or lacking in substantial character development and depth, which other users might find appealing. They prefer stories with a significant amount of conflict and complexity over those with a lighter, more predictable narrative arc.
7,062	The user enjoys a diverse array of genres, including literary classics, science fiction, psychological thrillers, and children's literature. They appreciate deep explorations of human nature, moral quandaries, and the complexities of society's structure. The user seems particularly drawn to narratives that feature profound character development, intricate plotting, and philosophical undertones. Elements that involve a dark or gothic atmosphere, exploration of existential themes, and introspective journeys resonate well with them, as do imaginative adventures and whimsical tales. Conversely, the user does not show an explicit preference against any particular genres, suggesting a broad appreciation for many storytelling styles. However, they might not be as enthusiastic about contemporary romance or light-hearted slice-of-life narratives that lack a deeper, more reflective component. While other readers may enjoy stories with straightforward, linear plots and predictable outcomes, the user seems to favor complex narratives with significant emotional and intellectual depth.
1,704	The user enjoys books across a variety of genres, showing a particular affinity for classic literature, historical fiction, dystopian novels, and stories that explore human emotions and ethical dilemmas. In terms of plot points, the user seems to favor narratives featuring strong, complex characters dealing with social and moral issues, coming-of-age stories, and tales with significant historical or political contexts. They also seem to appreciate elements of magical realism and introspective narratives that delve into human nature and cultural relations. The user does not enjoy genres such as fantasy and certain types of speculative fiction as much; although these novels are popular among others, it indicates a lower preference for intricate world-building and magical systems over more realistic and emotionally charged storytelling. Additionally, they do not favor books with overly technical or philosophically heavy content that veers away from emotional and character-driven narratives.

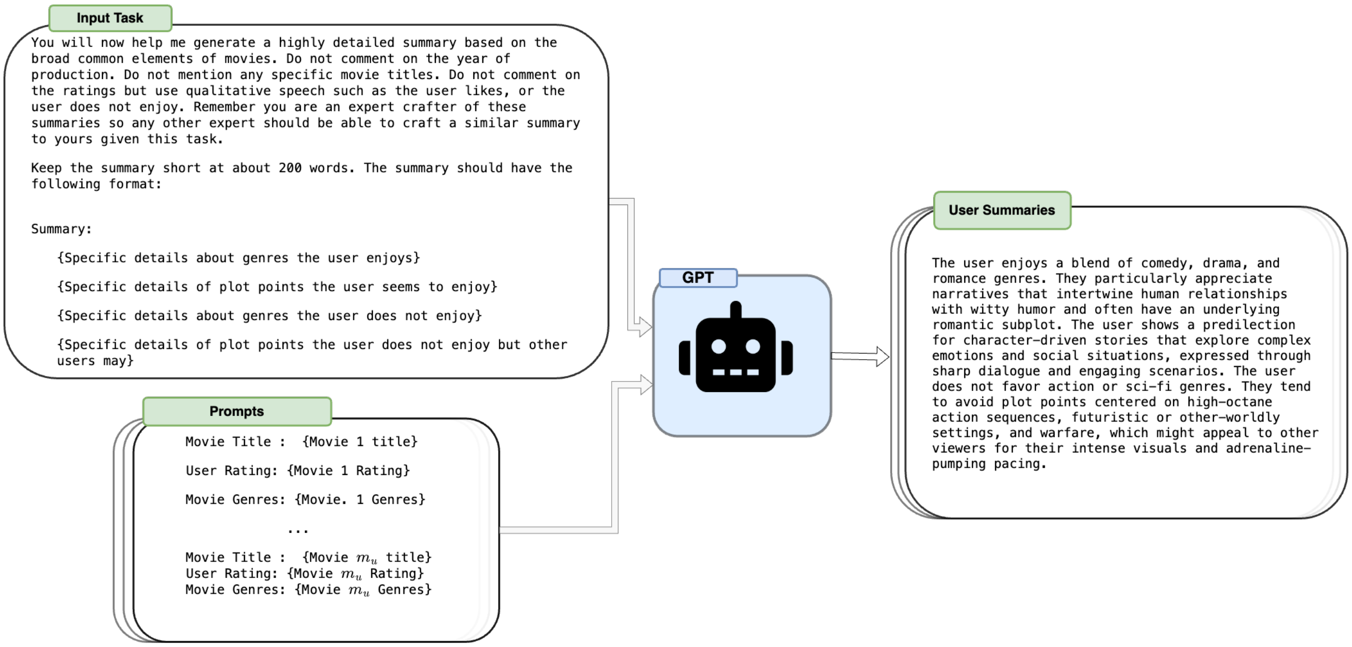

Figure 6: Illustration of the prompting strategy used to generate user summaries. .

A.4 Summary Generation Prompts

Aspect	Value
Prompt for Movies	Task: You will now help me generate a highly detailed summary based on the broad common elements of movies. Do not comment on the year of production. Do not mention any specific movie titles or actors. Do not comment on the ratings but use qualitative speech such as the user likes, or the user does not enjoy. Remember you are an expert crafter of these summaries so any other expert should be able to craft a similar summary to yours given this task. Keep the summary short at about 200 words. The summary should have the following format: Summary: {Specific details about genres the user enjoys}. {Specific details of plot points the user seems to enjoy}. {Specific details about genres the user does not enjoy}. {Specific details of plot points the user does not enjoy but other users may}. {title$_1$}, {rating$_1$}, {genre$_1$} ... {title$_n$}, {rating $_n$}, {genre $_n$ } Do not comment on the ratings or specific titles but use qualitative speech such as the user likes, or the user does not enjoy Do not comment mention any actor names
Prompt for Books	Task: You will now help me generate a highly detailed summary based on the broad common elements of books. Do not comment on the year of release. Do not mention any specific book titles or authors. Do not comment on the ratings but use qualitative speech such as the user likes, or the user does not enjoy. Remember you are an expert crafter of these summaries so any other expert should be able to craft a similar summary to yours given this task. Keep the summary short at about 200 words. The summary should have the following format: Summary: {Specific details about genres the user enjoys}. {Specific details of plot points the user seems to enjoy}. {Specific details about genres the user does not enjoy}. {Specific details of plot points the user does not enjoy but other users may}. {title$_1$}, {rating$_1$}, {genre$_1$} ... {title$_n$}, {rating $_n$}, {genre $_n$ } Do not comment on the ratings or specific titles but use qualitative speech such as the user likes, or the user does not enjoy Do not comment or mention any author names

B LARGE-SCOPE CHANGES

B.1 Netflix Results

We visualize the large-scope changes for the Netflix dataset in this appendix. Figure 10 shows the details. Our findings are consistent with those of §7.1 where we find TEARS-MacridVAE can consistently outperform TEARS-Base and TEARS-Multi-Vae performs poorest on controllability tasks.

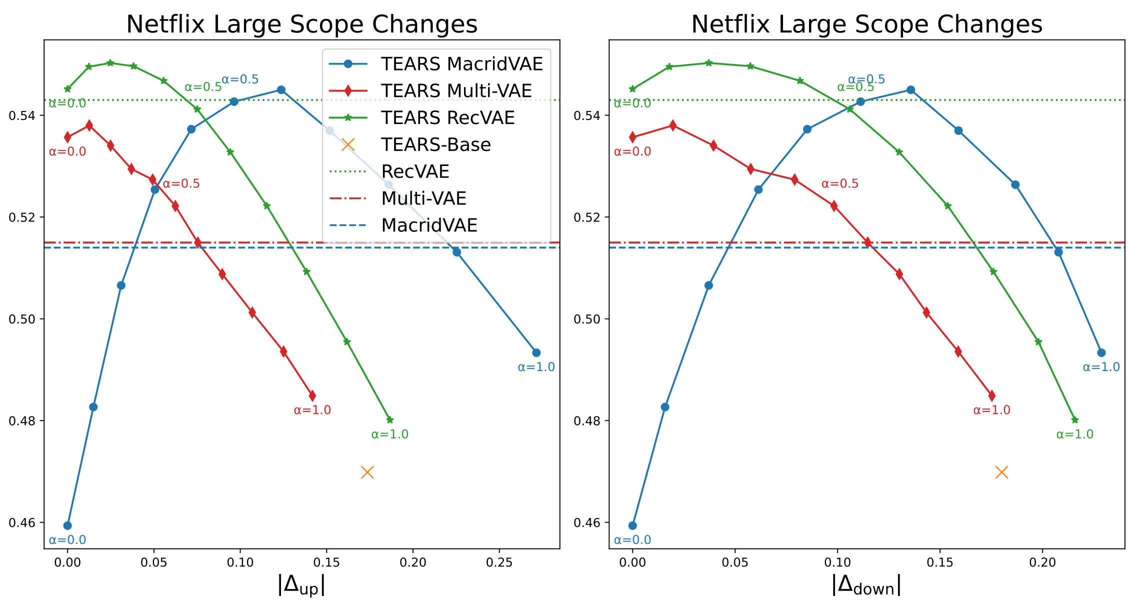

Figure 7: Tradeoff between recommendation and controllability for the Netflix dataset. The x-axis represents $|\Delta_{\text{up/ down}}|$ as α decreases. We find results to be consistent with those observed in ML-1M and Goodbooks

B.2 Examples

Aspect	Value
MovieLens ID	929
Input prompt	Summary: The user enjoys a blend of drama, romance, and inspirational true stories, often favoring narrative depth and emotional arcs that showcase personal growth, complex relationships, or historical significance. Plots that revolve around overcoming adversity, exploring human connections, or facing moral dilemmas tend to resonate well. The user also has a strong appreciation for action and war dramas where the stakes are high, and characters must showcase heroism or make profound sacrifices. However, the user does not enjoy certain horror and animated films, particularly those with a darker, more disturbing premise or themes that might be deemed as too intense or mature, and animated features that perhaps skew towards a younger audience or do not present as complex or emotionally engaging stories. Plots that incorporate extreme violence or psychological terror, as well as those that lack the depth of character development found in dramas, are generally less appreciated, despite their popularity among other audiences who may enjoy the thrill and suspense they provide.
Genre Identification Prompt	You are a professional editor please identify the user-preferred genres from the following: {genre_set}
Favourite Genre	Drama
Least Favourite Genre	Horror
User Prompt	Please identify the user's most favorite genre from the following summary and the least favorite genre in the format Favorite: [genre]Least Favorite: [genre] {user_sumary}.
Least Favourite Genre	Horror
Editing Prompt	Now using this setup write a new summary in the same style that reflects that {favorite_genre} is your least favorite and {least_favorite_genre} is your favorite. Only output the full summary, keep the format and length the same.
Output	The user has a profound affinity for the suspenseful and chilling narratives that horror films provide, often seeking out stories that delve into the supernatural, psychological terror, or the macabre. They appreciate the adrenaline rush and the exploration of darker themes that challenge their fears and push the boundaries of comfort. The user is particularly drawn to horror films that cleverly twist reality and offer innovative scares or thought-provoking premises. They also enjoy the high stakes and intense scenarios found in action-packed horror where survival is a key element. Conversely, the user finds little interest in drama, as they tend to avoid films that focus heavily on emotional arcs, personal growth, and the intricacies of human relationships. They perceive these narratives as lacking the excitement and visceral engagement they crave. Dramas that emphasize historical significance or moral dilemmas do not captivate their attention in the same way that a thrilling, heart-pounding horror story does. The user is less moved by stories of overcoming adversity or exploring complex relationships unless they are framed within the context of a horror setting.
Δ_{Down}@50	0.461
Δ_{Up}@50	-0.730

C FINE GRAINED EXPERIMENTS SUPPLEMENTAL

C.1 Prompting Procedure for Fine-Grained Controllability

Table 2: Prompting Scheme for fine-grained experiment. We note we specifically ask for the identified words to be inserted into the summary together, but explicitly ask to replace a sentence in the summary.

First Prompt	You are a professional editor. Please summarize the `{item_type}` into 5 words only, referring to plot points/themes: `{item}`.
Second Prompt	Now, using this, edit those 5 words into this summary. Replace a sentence where it makes sense. Only output the summary. `{summary}` only output the new summary, making sure the 5 new comma-separated words are in a new sentence, replacing an old one somewhere together in the new summary.

C.2 Breakdown by value of α

Figure 8 visualizes the relationship between the fine grained changes and the value of α. We generally observe that higher levels of alpha lead to higher levels of controllability, with some exceptions. Importantly we see that for all models in all datasets, there is a value of α that can be attributed to a positive δ_{rank}.

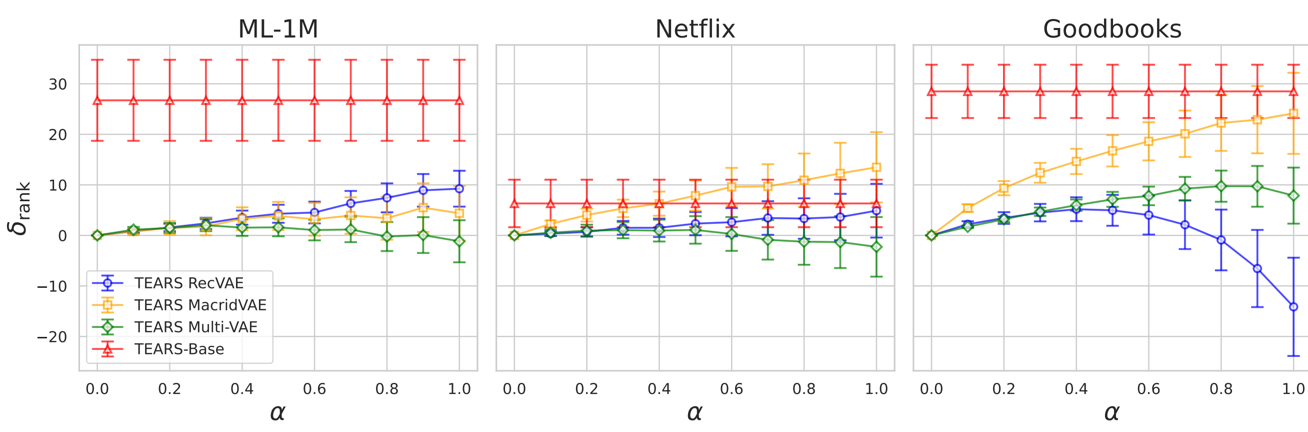

Figure 8: δ_{rank} broken down by α for each dataset with error bars representing the standard error. We observe for all models there is a value of α for which we are able to increase the rank of the target item.

C.3 ML-1M Examples

Dataset	ML-1M
Original Summary	Summary: The user enjoys a variety of genres with a strong preference for comedy, often blended with elements of romance, drama, and action. Bent towards comedies that deliver a mix of witty dialogue, quirky characters, and situations that lead to both heartwarming and humorous outcomes is evident. The user appreciates horror when it is juxtaposed with humor, and thrillers that contain supernatural or fantastical elements are particularly enjoyable. **Storylines involving personal growth, unconventional relationships, and comedic misadventures also resonate well.** Conversely, the user does not enjoy certain actions and science fiction films as much, especially if they lack a comedic element or deeper narrative. Plots that focus heavily on conventional action sequences, with less emphasis on character development or innovative storytelling, are less favorable. The user might be less interested in sci-fi adventures that are more serious and lacking the playful or satirical tone found in more favored titles. While tension and suspense are appreciated in certain contexts, straightforward action-driven thrillers without substantial plot twists or character complexity may not capture the user's interest.
Augmented Summary	The user enjoys a variety of genres with a strong preference for comedy, often blended with elements of romance, drama, and action. Bent towards comedies that deliver a mix of witty dialogue, quirky characters, and situations that lead to both heartwarming and humorous outcomes is evident. The user appreciates horror when it is juxtaposed with humor, and thrillers that contain supernatural or fantastical elements are particularly enjoyable. **Self-worth, community, sacrifice, redemption, family resonate well.** Conversely, the user does not enjoy certain actions and science fiction films as much, especially if they lack a comedic element or deeper narrative. Plots that focus heavily on conventional action sequences, with less emphasis on character development or innovative storytelling, are less favorable. The user might be less interested in sci-fi adventures that are more serious and lacking the playful or satirical tone found in more favored titles. While tension and suspense are appreciated in certain contexts, straightforward action-driven thrillers without substantial plot twists or character complexity may not capture the user's interest.
Target Item	It's a Wonderful Life (1946)
Original Rank	259
New Rank	235
δ_{rank}	24
Dataset	ML-1M
Original Summary	Summary: The user has a clear preference for genres that blend comedy with other elements, such as sci-fi, horror, and action. They particularly enjoy comedic films that explore the dynamic interplay between humor and speculative fiction, most likely appreciating how these genres can satirize or comment on society and our relationship with technology. **The user also gravitates towards dramas that are infused with sci-fi and adventure, often valuing intricate plots that weave in elements of thrill and suspense, and possibly favoring storylines that involve exploration, the supernatural, and high stakes situations.** Conversely, the user does not enjoy animations as much, especially those targeted primarily at children. This suggests a lesser interest in stories that are perceived as being too simplistic or juvenile. Furthermore, the user seems disinterested in musicals and fantastical adventures that prioritize whimsy over mature humor or complex storytelling. While other users might appreciate the innocence and escapism offered by these genres, this user shows a predilection for more sophisticated narratives found in films that provide a mix of laughter with thought-provoking or action-driven content.
Augmented Summary	Summary: The user has a clear preference for genres that blend comedy with other elements, such as sci-fi, horror, and action. They particularly enjoy comedic films that explore the dynamic interplay between humor and speculative fiction, most likely appreciating how these genres can satirize or comment on society and our relationship with technology. **Sports agent's redemption through love.** Conversely, the user does not enjoy animations as much, especially those targeted primarily at children. This suggests a lesser interest in stories that are perceived as being too simplistic or juvenile. Furthermore, the user seems disinterested in musicals and fantastical adventures that prioritize whimsy over mature humor or complex storytelling. While other users might appreciate the innocence and escapism offered by these genres, this user shows a predilection for more sophisticated narratives found in films that provide a mix of laughter with thought-provoking or action-driven content.
Target Item	Jerry Maguire (1996)
Original Rank	136
New Rank	108
δ_{rank}	28

C.4 Netflix Examples

Dataset	Netflix
Original Summary	Summary: The user exhibits a preference for films that blend action with elements of comedy, crime, and drama, demonstrating an appreciation for multifaceted narratives that weave a sense of humor into high-stakes scenarios. **Plot points that center around clever heists, adventurous undertakings, and historical events that are thrilling and engaging seem to resonate with the user.** The user does not favor documentary genres or those that pertain solely to heavy drama or explicit themes. Specifically, plot points involving political commentary, intense emotional struggles without interspersed levity, or horror that primarily aims to shock rather than developing a multi-layered story are less appealing, although they might be favored by audiences seeking realism or intense psychological experiences.
AUgmented Summary	Summary:The user exhibits a preference for films that blend action with elements of comedy, crime, and drama, demonstrating an appreciation for multifaceted narratives that weave a sense of humor into high-stakes scenarios. **Survival, isolation, resilience, hope, return.** The user does not favor documentary genres or those that pertain solely to heavy drama or explicit themes. Specifically, plot points involving political commentary, intense emotional struggles without interspersed levity, or horror that primarily aims to shock rather than developing a multi-layered story are less appealing, although they might be favored by audiences seeking realism or intense psychological experiences.
Target Item	Cast Away
Original Rank	114
New Rank	73
δ_{rank}	41

Dataset	Netflix
Original Summary	Summary: The user has a strong preference for films in the genres of biography, drama, and thriller, especially when these elements are combined. These films often have rich character development, complex storylines, and emotionally charged narratives, highlighting important historical events, psychological tension, or crime puzzles to be solved. **The user appreciates plot points that involve intricate mysteries, biographical tales of significant figures, and intense dramatic moments that challenge characters' moral and emotional fortitude.** Conversely, the user does not enjoy comedies as much, particularly those with a slapstick or overtly absurd sense of humor. Also, horror films that lean primarily on supernatural elements or shock value seem to be of lesser interest. Despite these personal preferences, such plot points can be appealing to other viewers who relish jump scares, paranormal activities, or light-hearted comedic relief that lampoons various aspects of society or plays with incongruent and ludicrous situations for entertainment.
Augmented Summary	Summary: The user has a strong preference for films in the genres of biography, drama, and thriller, especially when these elements are combined. These films often have rich character development, complex storylines, and emotionally charged narratives, highlighting important historical events, psychological tension, or crime puzzles to be solved. **Multiple personalities, murder mystery, twist.** Conversely, the user does not enjoy comedies as much, particularly those with a slapstick or overtly absurd sense of humor. Also, horror films that lean primarily on supernatural elements or shock value seem to be of lesser interest. Despite these personal preferences, such plot points can be appealing to other viewers who relish jump scares, paranormal activities, or light-hearted comedic relief that lampoons various aspects of society or plays with incongruent and ludicrous situations for entertainment.
Target Item	Identity
Original Rank	105
New Rank	67
δ_{rank}	38

C.5 Goodbooks Examples

Dataset	Goodbooks
Original Summary	Summary: The user enjoys genres that feature elements of horror, psychological thrillers, and dark fantasy. They seem to appreciate complex, multi-layered plot points that involve supernatural occurrences, personal trauma, and intricate world-building. The blending of horror with psychological depth, as well as epic quests interwoven with a sense of dark fate, appears to resonate well with the user. Conversely, the user does not enjoy genres that lean heavily into slower-paced or overly introspective narratives. Plot points involving excessive domestic or romantic issues, as well as those that delve too deeply into the protagonist's internal monologue without substantial action, are not particularly appealing to them. The user seems to favor more externally driven plots and might find tales that lack significant conflict or supernatural elements less engaging.
Augmented Summary	Summary: The user enjoys genres that feature elements of horror, psychological thrillers, and dark fantasy. They seem to appreciate complex, multi-layered plot points that involve supernatural occurrences, personal trauma, and intricate world-building. The blending of horror with psychological depth, as well as epic quests interwoven with a sense of dark fate, appears to resonate well with the user. **Time travel, medieval rescue mission.** Conversely, the user does not enjoy genres that lean heavily into slower-paced or overly introspective narratives. Plot points involving excessive domestic or romantic issues, as well as those that delve too deeply into the protagonist's internal monologue without substantial action, are not particularly appealing to them. The user seems to favor more externally driven plots and might find tales that lack significant conflict or supernatural elements less engaging.
Target Item	Identity
Original Rank	101
New Rank	145
δ_{rank}	44

Dataset	Goodbooks
Original Summary	Summary: The user enjoys genres that include urban fantasy, dystopian fiction, paranormal romance, historical fiction, and young adult fantasy. They seem to appreciate complex plots involving strong female protagonists, political intrigue, supernatural elements, and intricate relationships. The user's interests align with stories that combine elements of suspense, moral dilemmas, and emotionally charged narratives with immersive world-building. The user does not enjoy literary fiction or non-genre specific dramas as much. Additionally, they are less likely to favor books that focus heavily on introspective or slow-paced narratives without significant external conflicts or supernatural components. Other users may enjoy these genres, which often feature more nuanced human interactions and deep existential themes but are not aligned with this user's preferences for action and fantasy-driven storytelling.
Augmented Summary	Summary: The user enjoys genres that include urban fantasy, dystopian fiction, paranormal romance, historical fiction, and young adult fantasy. They seem to appreciate complex plots involving strong female protagonists, political intrigue, supernatural elements, and intricate relationships. **Secret society, Vatican, antimatter, conspiracy**. The user's interests align with stories that combine elements of suspense, moral dilemmas, and emotionally charged narratives with immersive world-building. The user does not enjoy literary fiction or non-genre specific dramas as much. Additionally, they are less likely to favor books that focus heavily on introspective or slow-paced narratives without significant external conflicts or supernatural components. Other users may enjoy these genres, which often feature more nuanced human interactions and deep existential themes but are not aligned with this user's preferences for action and fantasy-driven storytelling.
Target Item	Angels & Demons
Original Rank	127
New Rank	103
δ_{rank}	24

D GUIDED RECOMMENDATION

We further visualize the process of generating guided recommendations for three different genres in the ML-1M dataset using TEARS RecVAE. To accomplish this, we employ t-SNE [44] to visualize two types of embeddings: the mean latent of the feedback embeddings (displayed in red) and the mean latent for the text embeddings (displayed with a color gradient). Our observations reveal that guiding the recommendations has a personalized effect for each user. Individual user representations move towards the genre representation in unique ways. This personalization can be attributed to changes in recommendations that suggest items belonging to the target genre while still aligning with the individual user's preferences.

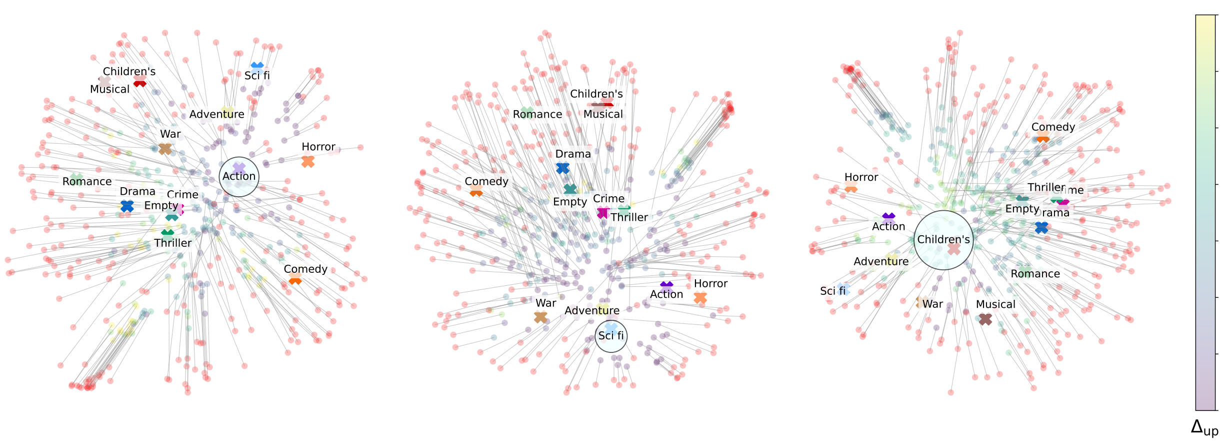

Figure 9: Rank changes in target item rank after fine grained changes. Y-axis represents δ_{rank} = New rank - Old Rank

E SUMMARY CHARACTERISTICS

Table 3 displays various qualities of the generated summaries. Overall we find that the average summary length is under 200 words, demonstrating the conciseness of the generated content. However, despite GPT's general adherence to instructions, we observe that the variance in summary lengths is greater than ideal, with some summaries exceeding the expected 200-word limit. For future work, we recommend more refined prompt engineering and potentially fine-tuning the LLM for summary construction to enhance consistency in summary length and adherence to target constraints.

Table 3: Summary length statistics. We compute average statistics for each dataset. We find GPT on average adheres to instructions, but has high variance in its output. We observe that the BLUE scores are quite low, and edit distances are comparable to the average summary length. Both these findings suggest the summaries are distinct between users enhancing personalization.

Statistics	ML-1M	Netflix	GoodBooks
Max Length	262 ±26.13	263 ±27.23	246 ±27.6
Minimum Length	91	43	79
90th Percentile Length	209	209	197
10th Percentile Length	144	141	125
Average Length	175.64	174.11	164.5
Edit Distances	172.9 ±20.50	172.45 ±21.18	161.72 ±18.92
BLEU scores	0.041 ±0.029	0.041 ±0.030	0.066 ±0.02

F DATASET STATISTICS

Table 4: Dataset Statistics

	Number of Train users	Validation Users	Test users	Number of Items	Average rating	Sparsity
ML-1M	5,514	250	250	2,081	3.63	0.943
Netflix	9,478	250	250	3,081	3.60	0.904
Goodbooks	7,980	1,000	1,000	8,093	3.97	0.988

G TRAINING DETAILS

For our proposed models, we use the ADAMW optimizer while for AE models we use ADAM. For TEARS models we train for 100 epochs using a batch size of 32, we do not use early stopping, but choose the best checkpoint across the 100 epochs. For TEARS Base the best checkpoint is chosen on NDCG@50 while for TEARS-VAEs we use the average NDCG@50 evaluated at $\alpha = \{0, 0.5, 1\}$. For AE models we train for 200 epochs with a batch size of 500. We choose the best checkpoint based on NDCG@50. TEARS models were trained using a single Nvidia RTX-8000 GPU, with an average runtime of about 2 hours to complete the 100 epochs, although we observe TEARS converges with much less than 100 epochs depending on the learning rate. AE models are also trained using a single GPU and took on average 10-20 minutes (depending on the model) to complete the full 200 epochs.

- *TEARS*: For TEARS-VAEs and TEARS-Base, we tune dropout $\in \{0.1, 0.2, 0.4\}$ the learning rate (LR) $\in \{0.001, 0.0001\}$. Aditionally, For TEARS-VAEs we tune $\lambda_1 \in \{0.1, 0.5, 1\}$. We choose to not tune λ_2 and use an annealing schedule up to $\lambda_2 = 0.5$
- *Multi-VAE* : We tune dropout $\in \{0.1, 0.2, 0.4\}$ the learning rate $\in \{0.001, 0.0001, 0.00001\}$ and $\beta \in \{0.1, 0.3, 0.5\}$ with a standard annealing schedule found in [26].
- *Multi-DAE* We tune dropout $\in \{0.1, 0.2, 0.4\}$ and the learning rate $\in \{0.001, 0.0001, 0.00001\}$.
- *RecVAE* We tune dropout $\in \{0.1, 0.2, 0.4\}$, LR $\in \{0.001, 0.0001, 0.00001\}$ and $\gamma \in \{.0035, .004, .005\}$. We additionally use the loss function provided by the authors [39], only for this model specifically.
- *MacridVAE* We tune dropout $\in \{0.1, 0.2, 0.4\}$, LR $\in \{0.001, 0.0001, 0.00001\}$ and the number of concepts $k \in \{2, 4, 8, 16\}$.
- EASE We tune λ over 50 values ranging between $[1, 10, 000]$ spread evenly.

G.1 TEARS-MacridVAE

MacridVAE decomposes the user representation into multiple disentangled concept representations which are normalized across the concept dimensions, thus, to be able to properly interpolate between the feedback and summary embeddings we do the same procedure for TEARS-MacridVAE such that:

$$z_{u,r} = \left[z_{u,r}^{(1)}, z_{u,r}^{(2)}, ..., z_{u,r}^{(K)}\right] \tag{9}$$

$$\mu_{\text{normalized},u,r}^{(k)} = \frac{\mu_{u,r}^{(k)}}{||\mu_{u,r}^{(k)}||_2} \tag{10}$$

$$z_{u,s} = \left[z_{u,s}^{(1)}, z_{u,s}^{(2)}, ..., z_{u,s}^{(K)}\right] \tag{11}$$

$$\mu_{\text{normalized},u,s}^{(k)} = \frac{\mu_{u,s}^{(k)}}{||\mu_{u,s}^{(k)}||_2} \tag{12}$$

$$\tag{13}$$

Additionally, MacridVAE's first layer representations, often thought of as analogous to the item representations in AE recommender models, are shared with the last layer's representations. Since we freeze the encoder model at the beginning of training, we found that making a copy of MacridVAE's input representations, freezing them, and then allowing the final layers representations to be trained led to the best results and highest consistency in logic with other models.

H FEW-SHOT PROMPTING GPT FOR RECOMMENDATIONS

Table 5 displays the prompting strategy used to obtain GPT-4Turbo recommendation metrics in Table 1. We post-process the GPT output it is successfully in the requested format. If there is a failure we file the request again, for up to 10 times, after which we declare it as a failure and record the respective metrics as 0. We overall have 78 failures for the Netflix dataset and 24 failures for ML-1M. We do not include failures when calculating the metrics in 5, which is favorable for GPT.

Table 5: Prompting strategy for few-shot recommendations

Aspect	Value
Input Prompt	User summary: {user summary} Here are the available {item_type}: {All {item_type} in the catalog in ID: Title format} Important, do not recommend the following movies as they have already been seen by the user: {Seen {item_type} by user} Please only output the top 100 {item_type}. Simply print their id do not use the title output the movies in the format: id1, id2, ... idn}

I CONTROLLABILITY BREAKDOWN

Table 6 shows the controllability results for the large-scope and guided recommendation experiments averaged over five different seeds. Overall, we observe TEARS MacridVAE consistently outperforms other models and even TEARS BASE when it comes to controllability at an $\alpha = 1$. Overall, we find TEARS MacridVAE to be the best-performing model, having better recommendation performance than baselines for some value of α in all datasets while also excelling in the controllability tasks.

Table 6: Comparison of controllability performance across different datasets and models. Each model is evaluated using five different seeds.

Dataset	Model	Best α	Large Scope $\lvert\Delta_{\text{up},\alpha=1}\rvert$	Large Scope $\lvert\Delta_{\text{up},\alpha=0.5}\rvert$	Large Scope $\lvert\Delta_{\text{down},\alpha=1}\rvert$	Large Scope $\lvert\Delta_{\text{down},\alpha=0.5}\rvert$	Genre $\lvert\Delta_{\text{up},\alpha=0.5}\rvert$	Genre $\lvert\Delta_{\text{down},\alpha=0.5}\rvert$
ML-1M	TEARS MacridVAE	0.475	0.354 ± 0.229	0.158 ± 0.116	0.210 ± 0.138	0.080 ± 0.082	0.223 ± 0.050	0.076 ± 0.037
	TEARS Multi-VAE	0.420	0.163 ± 0.063	0.065 ± 0.013	0.115 ± 0.031	0.047 ± 0.011	0.067 ± 0.006	0.066 ± 0.005
	TEARS RecVAE	0.700	0.332 ± 0.046	0.134 ± 0.011	0.213 ± 0.020	0.093 ± 0.014	0.243 ± 0.016	0.125 ± 0.031
	TEARS-Base	N/A	0.312 ± 0.258	N/A	0.206 ± 0.168	N/A	N/A	N/A
Netflix	TEARS MacridVAE	0.500	0.271 ± 0.011	0.096 ± 0.002	0.229 ± 0.008	0.111 ± 0.003	0.100 ± 0.004	0.061 ± 0.021
	TEARS Multi-VAE	0.933	0.142 ± 0.010	0.062 ± 0.005	0.175 ± 0.001	0.098 ± 0.005	0.040 ± 0.005	0.037 ± 0.021
	TEARS RecVAE	0.800	0.187 ± 0.009	0.075 ± 0.006	0.216 ± 0.014	0.106 ± 0.009	0.114 ± 0.014	0.100 ± 0.028
	TEARS-Base	N/A	0.174 ± 0.098	N/A	0.180 ± 0.071	N/A	N/A	N/A
Goodbooks	TEARS MacridVAE	0.620	0.597 ± 0.024	0.328 ± 0.014	0.318 ± 0.023	0.156 ± 0.015	0.152 ± 0.030	0.122 ± 0.005
	TEARS Multi-VAE	0.620	0.394 ± 0.054	0.122 ± 0.015	0.237 ± 0.024	0.074 ± 0.006	0.067 ± 0.013	0.050 ± 0.016
	TEARS RecVAE	0.840	0.417 ± 0.043	0.175 ± 0.011	0.243 ± 0.026	0.115 ± 0.010	0.191 ± 0.025	0.137 ± 0.015
	TEARS-Base	N/A	0.564 ± 0.088	N/A	0.344 ± 0.049	N/A	N/A	N/A

J ABLATIONS

We perform a variety of ablations to assess the efficacy of the proposed method, using the hyperparameters from the best-performing TEARS RecVAE model.

J.1 Pooling and Optimal Transport

We compare mean-pooling with concatenation, another popular pooling method [49]. We assess NDCG_s, that is recommendations built purely on text-embeddings, $NDCG_\alpha$, where the mean pooling methods refer to $\alpha = 0.5$, while for concatenations we use a simple MLP to map concatenated embeddings onto the correct dimensions and report the recommendations on those. For controllability, we assess Δ_{up}@20 and Δ_{down}@20 when the recommendations are generated purely on Z_s (which yields the best controllability). Additionally, we assess whether the OT objective is beneficial. Table 7 shows that mean pooling without OT yields comparable recommendations, but at the cost of controllability, moreover, recommendations purely based on the text NDCG@50_s are a lot weaker when compared to models trained with OT. We find that the prior results are consistent when using concatenation, $\text{NDCG}_{\alpha=0.05}$ is higher when using concatenation with OT, additionally we see that OT again makes the model much more controllable. Overall, we find that mean-pooling with OT is superior to the presented alternatives.

J.2 Loss Function Configurations

Table 8 shows different configurations for $\mathcal{L}_R$. In practice, we optimize $\mathcal{L}_R = \mathcal{L}_r + \mathcal{L}_\alpha + \mathcal{L}_s$, that is we optimize for both recommendations based purely on feedback representations, purely on summary representations and a mixture of the two. We aim to investigate which of these loss components has the most effect on performance and controllability. We find that $\mathcal{L}_r$ is specifically responsible for improving recommendation performance but it alone even when optimizing alongside $\mathcal{L}_\alpha$ does not yield controllability. Additionally, we find that optimizing $\mathcal{L}_s$ is important for controllability. Most interestingly we find that optimizing $\mathcal{L}_r$ and $\mathcal{L}_s$ without $\mathcal{L}_\alpha$ yields the worst performance

Table 7: Ablation on different pooling and optimization strategies. We find the mean w OT is the most optimal in both recommendation performance and controllability

	NDCG@20$_\alpha$	NDCG@20$_s$	$\lvert\Delta_{\text{down}}$@20$\rvert$	$\lvert\Delta_{\text{up}}$@20$\rvert$
Mean w OT	**0.378**	**0.350**	**0.239**	**0.355**
Mean w.o OT	0.357	0.307	0.014	0.004
Concat w OT	0.359	0.334	0.145	0.258
Concat w.o OT	0.372	0.304	0.004	0.001

without controllability, this indicates that training on a combination of the representations is essential in obtaining the desired properties of TEARS.

Table 8: Comparison of metrics across different configurations

$\mathcal{L}_r$	$\mathcal{L}_\alpha$	$\mathcal{L}_s$	NDCG@50	$\lvert\Delta_{\text{down}}$@20$\rvert$
x	x	x	**0.378**	**0.238**
x	x		0.374	0.216
	x	x	0.377	0.205
x		x	0.374	0.216

J.3 What weights to train

We run ablations on what weights one should and should not update when training TEARS. Table 9 showcases different combinations of training regimens. An x here indicates that the model encoder weights are trained, for all methods we train decoder weights. Interestingly we find that when training both models, instabilities seem to arise not allowing the model to converge properly and yielding both worse recommendations and no controllability. Furthermore we observe that keeping the text encoder frozen but training the AE yields improved recommendations and some controllability, we imagine in this case, the AE is learning to more closely align to the text-encoders representations. Finally, our proposed training regimen of only updating the text-encoder's weights outperforms the prior two methods.

Table 9: Performance metrics based on training components

Train AE-encoder	Train text-encoder	NDCG@50	$\lvert\Delta_{\text{down}}$@20$\rvert$
x	x	0.303	0.001
x		0.320	0.057
	x	**0.378**	**0.238**

J.4 Using TEARS to initialize the text-encoder

We aim to investigate if pre-initializing the backbone text-encoder as a trained TEARS model is a viable strategy when training aligned models. Table 10 showcases the results of this experiment. Interestingly, we find that pre-initializing the text-encoder does not yield benefits. We hypothesize this is because the model has learned to map the summary embeddings far away from the feedback embeddings, adding complexity to the optimization process. In comparison, directly training the text-encoder to directly align to the feedback embeddings seems stabilize the training procedure.

Table 10: Performance metrics of different model configurations

Model	NDCG@50	$\lvert\Delta_{\text{down}}$@20$\rvert$
TEARS$_{\text{pre-initialized}}$-RecVAE	0.303	0.000
TEARS-RecVAE	**0.378**	**0.238**

J.5 Effect of λ_1 on Controllability and Recommendation Performance

We analyze the impact of λ_1, the scaling parameter for the optimal transport loss, has on overall performance and controllability. We take a similar approach to visualizing controllability and display the recommendation performance and controllability of models trained with varying values of λ_1 over varying α.

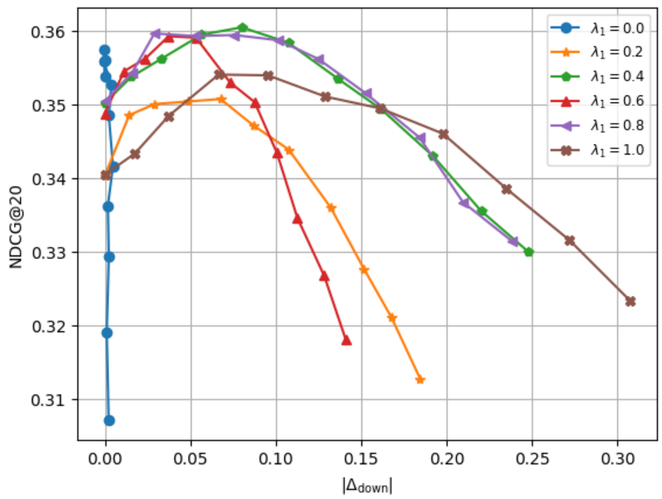

Figure 10: Visualization of controllability (x-axis) and recommendation performance (y-axis) for varying α (increasing left to right) with models trained with different values of λ_1

We observe that generally as λ_1 increases we are able to get both higher recommendation performance, as well as higher controllability. We do see that a $\lambda_1 = 1.0$ has worse recommendation performance than $\lambda_1 = 0.8$ but trades that off with higher controllability. Overall this indicates that training with a higher value of λ_1 generally yields better performance on both recommendation and controllability when compared with lower values $i.e\lambda_1 < 0.4$.

K STOCHASTICITY IN GPT GENERATED SUMMARIES

As mentioned in §3.3, GPT's output is non-determinstic by design. As such, we analyze the effect this has on the performance of TEARS. We generate five summaries using five different seeds and measure the variation on NDCG@20 for the ML-1M and Netflix datasets.

Table 11: Averaged performance and standard deviations of TEARS models over five different summaries. We observe when $\alpha = 1$ the variation is higher and observe smaller variances when $\alpha = 0.5$.

	ML-1M		Netflix	
	$\alpha = 1$	$\alpha = 0.5$	$\alpha = 1$	$\alpha = 0.5$
TEARS RecVAE	0.341 ± 0.006	0.376 ± 0.001	0.479 ± 0.006	0.552 ± 0.001
TEARS MacridVAE	0.329 ± 0.004	0.371 ± 0.001	0.492 ± 0.003	0.547234 ± 0.005
TEARS MVAE	0.327 ± 0.004	0.369 ± 0.003	0.488 ± 0.005	0.521 ± 0.002
TEARS Base	0.321 ± 0.004	N/A	0.476	N/A

Table 11 displays the averaged values and standard deviations of NDCG@20 over the five generated summaries. As can be seen, this has the largest variation when $\alpha = 1$ where TEARS only uses the summary embeddings. Additionally, we observe when $\alpha = 0.5$ we observe much less variation, indicating TEARS can consistently extract important information from the summaries.

L COLD START EXPERIMENT

We analyze the effect of using varying amounts of items as input to the models to assess which users may benefit the most from TEARS. For this we gather a subset of users with more than 100 items, for each of these users we create summaries with varying amounts of items, 10, 25, 50, 75, and 100. We then use these newly created summaries to assess the performance on NDCG@20. We note we specifically evaluate all these methods on the set of items that are left after the initial 100 items that were used to create the subset. This means that in all scenarios, we evaluate on the same set of items with the only thing changing being the input items. Figure 11 showcases the effect of using different amounts of input items on NDCG@20. We generally observe that as the number of items used to make the summaries increases, we get a slight increase in the performance of the summaries, indicating the summary quality is still able to improve as more items are fed in. Interestingly, after 50 items, we see RecVAE can overtake TEARS RecVAE on recommendation performance, indicating black box models are specifically good the more interactions the user has. Overall, we observe that TEARS RecVAE is much more efficient when there is less information to work with while RecVAE is better as more items are used.

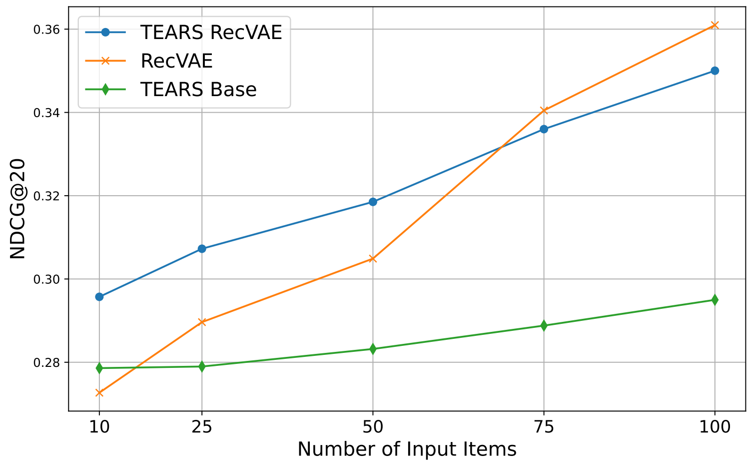

Figure 11: Plots showcasing the impact of different numbers of input items NDCG@20 for the 78 users in the Netflix dataset. We observe that the information provided by the summaries is specifically important within colder users, while the RecVAE seems to get better the more items that are used. All results for TEARS RecVAE are using the best α according to the validation set.

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