

MARec: Metadata Alignment for Cold-start Recommendation

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ABSTRACT

For many recommender systems the primary data source is a historical record of user clicks. The associated click matrix which is often very sparse, however, as the number of users \times products can be far larger than the number of clicks, and such sparsity is accentuated in cold-start settings. The sparsity of the click matrix is the reason matrix factorization and autoencoders techniques remain highly competitive across collaborative filtering datasets. In this work, we propose a simple approach to address cold-start recommendations by leveraging content metadata, Metadata Alignment for cold-start Recommendation (MARec). We show that this approach can readily augment existing matrix factorization and autoencoder approaches, enabling a smooth transition to top performing algorithms in warmer set-ups. Our experimental results indicate three separate contributions: first, we show that our proposed framework largely beats SOTA results on 4 cold-start datasets with different sparsity and scale characteristics, with gains ranging from +8.4% to +53.8% on reported ranking metrics; second, we provide an ablation study on the utility of semantic features, and proves the additional gain obtained by leveraging such features ranges between +46.8% and +105.5%; and third, our approach is by construction highly competitive in warm set-ups, and we propose a closed-form solution outperformed by SOTA results by only 0.8% on average.

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1 INTRODUCTION

Recommender systems have been a hot topic of interest in the research community, even more so since we interact with large-scale recommender systems in our daily lives. Significant effort has been dedicated to surpass the performance of state-of-the-art methods on public datasets, focusing on learning the best representation of the sparse user-item interaction matrix. Less interest has been vested on solving the different yet practical problem of cold-start

recommendation which consists of providing relevant recommendations for new users and items as soon as they appear on the platform.

Cold-start is a significant challenge for recommender systems as traditional collaborative filtering techniques rely heavily on past user interactions which are not available for new users or items. As a result, existing systems that are optimized for warm (previously seen) users may generalize poorly, if at all, to the cold-start scenario. As recommender systems constantly experience flurry of new items and users, high quality cold-start recommendations are essential for a great user experience and long-term engagement. It is important to highlight that the cold-start scenario extends beyond just looking at the ranking performance on new items (or users); relevant recommendations are required for the mixed scenarios as well i.e. with a blend of warm and cold items (users) with varying amount of historical data.

Amongst early works on cold-start recommendation modeling figure the works of [14, 29] which respectively map metadata features to Matrix factorization latent factors, and leverage item metadata reconstruction for regularization. More recent techniques for cold-start modeling include meta learning to combine user history with item representation [42], Variational AutoEncoders [47], and the novel idea of content-aware hashing [48]. However, while current approaches for cold-start modeling demonstrate good performance in cold-start scenarios, their effectiveness tends to decline significantly when applied to warm-start settings. In an industrial setup, managing separate models for cold-start and warm-start proves cumbersome. This not only adds to the overhead of maintaining multiple models in production but also poses a challenge to ensure a consistent and high-quality pool of recommendations for users when they transition between the cold and warm regime. In this paper, we present MARec (Metadata Alignment for cold-start Recommendation), a new approach that excels beyond current methods in cold-start recommendation all the while being competitive with state-of-the-art (SOTA) techniques for warm-start recommendation.

Our approach builds upon the existing body of literature in particular the hybrid approaches of merging content-based and collaborative filtering techniques [21, 23] as well as the recent works on retrieval-augmented systems [7]. However, our core contribution is a novel yet simple idea of aligning item-item similarities estimated from user clicks and from the item metadata features via a regularization term that pushes the cold-start items onto the same similarity space. In this way, we leverage SOTA models for

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warm-start recommendation to learn an alignment of the feature-based similarities to the user-item interaction similarities and learn a high-performing cold-start recommender.

1.1 Contributions

To the best of our knowledge, the alignment framework we propose differs from the existing body of literature, as it can augment any top performing Matrix Factorization and (variational) autoencoders approaches, it makes the most of any additional metadata features we can leverage across modalities (image, categorical, textual), and yet it achieves impressive results despite its simplicity. We present the following contributions:

- (1) We present a novel algorithm (MAREC) for cold-start recommendation that achieves state-of-the-art performance on several benchmarking datasets. Our algorithm combines embeddings learned from item and customer metadata with the user-item click matrix and gives closed-form update equations.
- (2) We show that MAREC beats SOTA techniques on four cold-start benchmarking datasets with different sparsity and scale characteristics, with gain ranging from +8.4% to +53.8% on standard ranking metrics. MAREC achieves this performance while being orders of magnitude faster, in terms of training time, compared to the best performing baseline.
- (3) We provide a study on the utility of Large Language Models (LLMs) embeddings and demonstrate that the additional gain obtained by leveraging semantic features ranges between +46.8% and +105.5%.
- (4) Finally, MAREC enables a transition to near-SOTA performance in warm set-ups, and we introduce a closed-form solution outperformed by SOTA results on warm datasets by only 0.8% on an average.

2 RELATED WORKS

The historical way to perform collaborative filtering with click datasets is via neighbourhood methods which consists of computing similarities across items or users, where the similarity is evaluated as a dot product based on click behaviour, and possibly item and user metadata [17]. The Netflix competition and subsequent research works on available public datasets have shown that SLIM [28] and matrix factorization techniques tend to outperform neighbourhood methods [22, 40]. A push for neural approximations of matrix factorization took place [10, 16], with the later concluding that the proposed MLP architectures fail to learn a better nonlinear variant of the dot product and are outperformed by careful implementations of matrix factorization [11, 35, 36].

More recently, some neural approaches have obtained SOTA results. The variational autoencoder approach [24] is amongst the most competitive neural approaches but the least squares approximation of SLIM, i.e., a linear autoencoder with projections to ensure the zero diagonal constraint (EASE) [38, 40], still beat it on 2 out of 3 public datasets. It was shown in [20] that augmenting the VAE approach with flexible priors and gating mechanisms led to SOTA performance. The VAE approach was also refined and ensembled with a neural EASE to achieve SOTA [41] on MovieLens20M and Netflix. Differently to the autoencoders family of models, sequential

models have also achieved SOTA results on the less sparse MovieLens1M dataset with the SAS-Rec transformer architecture [18] and its SSE-PT improvement [45] which allows for personalization through the utilisation of stochastic shared embeddings [46]. The success of Deep Cross Networks on learning to rank tasks [32] also showed the importance of explicitly encoding the dot product in the network architecture.

Comparatively, less research has been done on the benefits of incorporating metadata information and on the usefulness of the SOTA collaborative filtering algorithms for cold-start recommendations [42]. An early effort to incorporate item metadata into the SLIM family of models was the one of [29], where it is shown that adding a regularization term encoding the feature information matrix could help achieve gain on some datasets. Early methods addressed this fusion problem by proposing hybrid models merging neighborhood and collaborative filtering methods [21, 23, 31]. A meta learning algorithm deployed in a production system was proposed in [42] to combine user history representation with item representation. Another recent work [44] relies on maximizing the mutual information between user-item collaborative embeddings and it is shown that the presented technique beats a number of previous approaches [15], [13]. The variational framework of [24] is adapted in [47] for addressing cold-start in particular to obtain reasonable priors so that to IDs with the similar attributes can naturally cluster together in the latent embedding space. In [48], a content-aware hashing approach named Discrete Deep Learning (DDL), which first relies on building a user-item preference model based on hash codes, is proposed to alleviate data sparsity and cold-start item problem. A hybrid model is proposed in [6] where a neural model is trained to learn feature embeddings and item similarities from the similarities pre-learned from a collaborative filtering model, e.g. SLIM, and it is shown that the approach largely beats the baselines on 4 public datasets.

Ensembling complementary models remains a possibility for boosting cold-start recommendations, e.g., the winning solution of the 2018 ACM challenge on a cold-start music recommendation dataset was the score ensembling of a content-aware deep cross network and a gradient boosted decision tree [5]. It is also worth mentioning retrieval-augmented models outside of the recommender systems domain, e.g. in [19] where they achieved SOTA on Wikitext-103 by linearly interpolating a pre-trained LLM with a k-nearest neighbors model, in [7] where they use a chunked cross-attention mechanism to condition the training of the language model to encoded neighbours, and in [25] where a retrieval module to return the top-k text descriptions associated to the image helps achieves SOTA results for visual long tail classification.

3 COLD-START RECOMMENDATION

Let \mathcal{U} and \mathcal{I} denote the set of users and items respectively. We assume that the data is available as a sparse matrix $\mathbf{X} \in \mathbb{R}^{|\mathcal{U}| \times |\mathcal{I}|}$ where X_{ij} denotes the interaction (click, rating) between user $i \in \mathcal{U}$ and item $j \in \mathcal{I}$. A value of 1 in X_{ij} indicates that the user interacted with the item while a value of 0 implies that no interaction has been observed. We use the shorthand notation \mathbf{X}_i and \mathbf{X}_j to denote the i^{th} row and j^{th} column of \mathbf{X} . Similarly, we use x_i to denote the i^{th} element of a vector x .

For each item, we have access to a list of N attributes representing metadata associated with each item such as item name, description, brand, etc. We assume that the k^{th} attribute across all items has a compact feature representation $\mathbf{F}^{(k)} \in \mathbb{R}^{|I| \times n_k}$ where n_k is the dimension of the feature space. The feature representation may be obtained via one-hot encoding of categorical attributes, e.g., brand, or embedding of text attributes, e.g., item description. Finally, $\mathbf{F} \in \mathbb{R}^{|I| \times K}$ represents the feature vector of items with $K = \sum_{k=1}^N n_k$.

3.1 MAREC

MAREC consists of three components: 1) a backbone model f^B which is an encoder-decoder network that learns a low-dimensional representation of the interaction data \mathbf{X} and its reconstruction, 2) an embedding model f^E that encodes a dense representation of the item metadata and 3) an alignment model f^A that aligns the metadata representation with the click history. This aligned representation can then be fused with the backbone model to reconstruct the click history. The backbone model $f^B : \mathbb{R}^{|U| \times |I|} \rightarrow \mathbb{R}^{|U| \times |I|}$ can be chosen among the well-performing collaborative filtering algorithms of matrix factorization and autoencoder families, e.g., [20, 38]. Below we describe each component in detail.

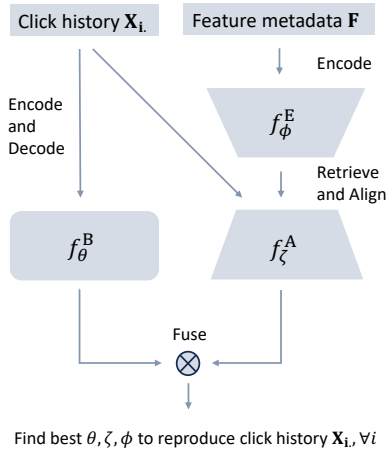


Figure 1: Simplified architecture of MAREC. The embedding model f_ϕ^E embeds each item metadata in a joint embedding space, and the alignment function f_ζ^A retrieves and aligns the similar items to the similarity space provided by the backbone model f_θ^B . The architecture is trained with a reconstruction loss on the click history.

The embedding model $f^E : \mathbb{R}^{|F| \times |I|} \rightarrow \mathbb{R}^{|E| \times |I|}$ learns a dense representation of item metadata so that items with similar interaction pattern are mapped closer in the embedding space. The alignment model $f^A : \mathbb{R}^{|U| \times |I|} \times \mathbb{R}^{|E| \times |I|} \rightarrow \mathbb{R}^{|U| \times |I|}$ is responsible for aligning interaction data with the item-item similarity estimated via the embedding model f^E . Figure 1 presents the high-level overview of MAREC.

The model is learned by minimizing a weighted combination of the backbone model loss and the alignment loss:

$$\min_{\theta, \phi, \zeta} L(\mathbf{X}, f_\theta^B(\mathbf{X})) + \gamma \cdot L(f_\theta^B(\mathbf{X}), f_\zeta^A(\mathbf{X}, f_\phi^E(\mathbf{F}))) \quad (1)$$

where $\gamma > 0$ is a hyper-parameter that balances the two loss terms and θ, ϕ, ζ are the model parameters of individual components of MAREC. Note that L can be any loss function e.g. L_2 , cross entropy, cosine, multinomial likelihood etc possibly augmented with regularization terms and constraints, as in the case of autoencoders to prevent overfitting [39]. While the first term of the loss function is the familiar one leveraged in matrix factorization and autoencoder techniques, the second term can be understood as a regularization to push the collaborative filtering similarities towards the learned metadata embeddings. This is particularly beneficial for cold-start items as they are under-represented in the interaction data. It is to be noted that MAREC modifies only the training objective by adding a regularization term. Once trained, the backbone model can be used for inference as usual. MAREC can be seen as a generalization of the merging of collaborative and content-based filtering techniques and admits a closed-form solution with appropriate choice of the components.

3.2 Embedding Model

The embedding model can be either the identity function $f^E = \mathbf{I}$, keeping the encoded metadata features \mathbf{F} as they are, or a Siamese network [8] trained on the processed click data \mathbf{X} which aims at learning joint metadata embeddings. We follow a similar process to [27] to train the Siamese network. For each item $I_j \in \mathcal{I}$, we select k items with the highest cosine similarity $\mathbf{X}_{j^+}^T \mathbf{X}_j$ and assign them a label of one. Similarly, we sample k items with cosine similarity of 0 and label them as zero. This gives us a dataset of similar and dissimilar pairs of the form $(\mathbf{F}_j, S_j^+, S_j^-)$ where S_j^+ is the set of positive pairs and S_j^- is the set of negative pairs. We then train the network by minimizing the contrastive loss [43]:

$$\sum_j \sum_{k^+ \in S_j^+} \left[-\log \frac{\exp(z_{k^+}^T \cdot z_j / \tau)}{\exp(z_{k^+}^T \cdot z_j^T / \tau) + \sum_{k^- \in S_j^-} \exp(z_{k^-}^T \cdot z_j^T / \tau)} \right] \quad (2)$$

where $z_j = f^E(\mathbf{F}_j)$, $z_{j^+} = f^E(\mathbf{F}_{j^+})$, $z_{j^-} = f^E(\mathbf{F}_{j^-})$ are the latent representations learned by the embedding model and $\tau > 0$ is a temperature hyper-parameter. The embedding layer presents the benefit of directly optimizing for the (dis)similarities of items which in turn is leveraged by the alignment model.

3.3 Alignment Model

The alignment layer is a critical component of MAREC with the objective of aligning the observed click matrix \mathbf{X} with an item-item similarity measure defined over the metadata embeddings encoded by the embedding layer f^E . The item-item similarity can be captured via a smoothed cosine transform [11] $g : \mathbb{R}^{|I| \times |E|} \rightarrow \mathbb{R}^{|I| \times |I|}$,

$$g(f^E(\mathbf{F})) = \mathbf{G}, \quad G_{ij} = \frac{z_i^T \cdot z_j}{\|z_i\| \cdot \|z_j\| + \delta}, \quad i, j \in \mathcal{I} \quad (3)$$

where $\delta > 0$ is a smoothing term used to lower the similarity between items with only few interactions [11]. When the embedding

model is the identity function, the smoothed cosine transform simply computes similarities by taking the complete feature vector \mathbf{F} as input, and this is known as itemKNN [12]. However, it is expected that some attributes in the metadata are more predictive of item similarity than others. Hence an alternative is to compute embedding of each attribute $\mathbf{F}^{(k)}$ separately, and then weigh attribute representations at a later stage. More specifically, starting from the encoded representation of the k^{th} attributes, $z_j^{(k)} = f^E(F_{.j}^{(k)})$, we define item-item similarity based on the k^{th} attribute as

$$G_{ij}^{(k)} = \frac{z_i^{(k)} \cdot z_j^{(k)}}{\|z_i^{(k)}\| \cdot \|z_j^{(k)}\| + \delta}, \quad i, j \in \mathcal{I}. \quad (4)$$

This leads to N similarity matrices which are mixed via a quadratic form:

$$g(f^E(\mathbf{F})) = \sum_{k < l} (\mu_k \cdot \mathbf{G}^{(k)} + \mu_{kl} \cdot \mathbf{G}^{(k)} \cdot \mathbf{G}^{(l)}), \quad (5)$$

where the scalar coefficients $\mu_k \geq 0$ and $\mu_{kl} \geq 0$ are model parameters that learn importance of first and second order similarities across the feature subspaces. Finally, we define the alignment function as,

$$f^A(\mathbf{X}, f^E(\mathbf{F})) = \alpha \cdot \mathbf{X} \cdot g(f^E(\mathbf{F})) \cdot \mathbf{D}^R \quad (6)$$

where $\alpha \in \mathbb{R}_+^*$ is a scaling coefficient, $\mathbf{D}^R = [d_j]_{j \in [|\mathcal{I}|]} \in \mathbb{R}_+^{|\mathcal{I}| \times |\mathcal{I}|}$ is a regularizing diagonal matrix that weights the importance of the metadata embeddings as a function of the number of clicks per item. The entries in \mathbf{D}^R are set as $d_j = h(\sum_j X_{.j})$, with $h: \mathbb{N} \rightarrow \mathbb{R}^+$, a non-negative monotone decreasing linear or exponential function. Note that a monotone decreasing function is used to mitigate the popularity bias problem [50], thereby giving more importance to cold-start items during model training. The significance of popular items is nevertheless captured in the backbone model that we describe next.

3.4 Backbone Model

Our framework supports any model of the autoencoder and matrix factorization families as we aim to align the item embeddings with the learned similarities from the click matrix itself. We consider 3 competitive baselines in this work, the multi-VAE model of [24], a collective version of the EASE model [29, 38], and a modified SLIM model that we introduce.

Variational autoencoders. For each user $i \in \mathcal{U}$, the model samples a K -dimensional latent representation ξ_i from a standard Gaussian prior. The latent representation ξ_i is then passed to a multilayer perceptron $f_\theta(\xi_i)$ to produce a probability distribution over the set of items $\pi(\xi_i)$ from which the click history \mathbf{X}_i is assumed to have been drawn. For each user i , we then adapt the multinomial log-likelihood to be maximized and the global objective of equation (1) can be modified to:

$$\min_{\theta} -\log p_\theta(x_i | \xi_i) = \sum_{j \in \mathcal{I}} -X_{ij} \log(\pi(\xi_i)) - b_j \log(\pi(\xi_i)), \quad (7)$$

$$\mathbf{b} = f^A(\mathbf{X}_i, f^E(\mathbf{F})).$$

To learn the parameters θ of the generative model, we need to approximate the intractable posterior distribution $p(\xi_i | X_i)$ and may

use variational inference as in [20, 24, 47]. We note that the second term added to the objective takes care of both the alignment and fusion by adapting the learned probability distribution over items to the metadata-based estimates. Here, the multi-VAE model of [24] was considered but we can readily consider its recent enhancements, H+Vamp [20] and VASP [41], which now occupy the first 2 slots of the MovieLens20M and Netflix leaderboards.

EASE. We adapt the EASE model [38] to our global objective of equation (1) which becomes:

$$\min_{\Theta} \|\mathbf{X} - \mathbf{X}\Theta\|_F^2 + \lambda_1 \|\Theta\|_F^2 + \|\mathbf{X}\Theta\mathbf{D}^R - f^A(\mathbf{X}, f^E(\mathbf{F}))\|_F^2 \quad (8)$$

$$\text{s.t. } \text{diag}(\Theta) = 0,$$

with $\Theta \in \mathbb{R}^{|\mathcal{I}| \times |\mathcal{I}|}$ and $\beta \in \mathbb{R}$ a scalar coefficient. Note that we may add the collective term $\lambda_0 \|\mathbf{F} - \mathbf{F}\Theta\|_F^2$ to the objective function as in [29]. This optimization policy admits a closed formed solution via the use of a Lagrangian multiplier heuristics that sets $\text{diag}(\Theta)$ to zero [38] and the solution is written:

$$\mathbf{P} = (\mathbf{X}^T \mathbf{X} + \lambda_0 \mathbf{F}^T \mathbf{F} + \lambda_1 \mathbf{I} + \mathbf{X}^T f^A(\mathbf{X}, f^E(\mathbf{F})))^{-1},$$

$$\tilde{\Theta} = \mathbf{P} (\mathbf{X}^T \mathbf{X} + \lambda_0 \mathbf{F}^T \mathbf{F} + \mathbf{X}^T f^A(\mathbf{X}, f^E(\mathbf{F}))), \quad (9)$$

$$\Theta = \tilde{\Theta} - \mathbf{P} \frac{\text{diag}(\tilde{\Theta})}{\text{diag}(\mathbf{P})}.$$

Modified SLIM. We do observe that the least squares framework of [38] could be further improved for two reasons: first, by giving less weight to negative samples, as we observe that matrix factorization results in [35] were boosted by a simple negative subsampling strategy; second, by relaxing the projection heuristics used to enforce the $\text{diag}(\Theta) = 0$ constraint. We can then write a constraint-free optimisation policy and the backbone model loss of equation (1) becomes:

$$\min_{\Theta} \sum_i \|\mathbf{W}_i^{\frac{1}{2}} (\mathbf{X}_{.i} - \mathbf{X}\Theta_{.i})\|_F^2 + \lambda_1 \|\Theta_{.i}\|_F^2 + \gamma_1 |\Theta_{ii}|^2, \quad (10)$$

where $\mathbf{W}_i \in \mathbb{R}^{|\mathcal{U}| \times |\mathcal{U}|}$, $i \in \mathcal{I}$, are the diagonal matrices of the weights w_0 and w_1 for positive and negative samples, and $\gamma_1 \sum_i |\Theta_{ii}|^2$ is the new regularization term that relaxes the constraint $\text{diag}(\Theta) = 0$ but serves the same goal of penalising the trivial $\Theta = \mathbf{I}$ solution. The closed-form solution to the global objective of equation (1) is now written, $\forall i \in \mathcal{I}$:

$$\Theta_{.i} = (\mathbf{X}^T \mathbf{W}_i \mathbf{X} + \mathbf{X}^T \mathbf{W}_i \mathbf{B} + \lambda_1 \mathbf{I} + \Gamma^{(i)})^{-1} (\mathbf{X}^T \mathbf{W}_i \mathbf{X}_{.i} + \mathbf{X}^T \mathbf{W}_i \mathbf{B}_{.i}),$$

$$\mathbf{B} = f^A(\mathbf{X}, f^E(\mathbf{F})), \quad (11)$$

with $\Gamma^{(i)}$ the diagonal matrix made of zeros except at position i where $\Gamma_{ii}^{(i)} = \gamma_1$, and $\mathbf{B}_{.i}$ the i^{th} column of the alignment matrix.

4 EXPERIMENTS

We leverage cold and warm dataset splits used in previous works where SOTA results were reported, for reproducibility reasons.

4.1 Datasets

Cold splits. Experimental evaluation of MARec requires datasets with varying sparsity level, and where item metadata can be leveraged for cold-start recommendations. We select popular dataset splits, as shown in Table 1, explored in the cold-start recommendation literature [6, 44].

| | # users | # items | # item features | Interactions (%) |
|------------------------|---------|---------|-----------------|------------------|
| Amazon Video Games [6] | 33858 | 12463 | 5 | 0.06 |
| Netflix [3] [6] | 469986 | 9503 | 6 | 1.19 |
| MovieLens10M [2] | 55485 | 5986 | 5 | 1.34 |
| MovieLens Hetrec [6] | 2107 | 6234 | 6 | 3.10 |

Table 1: Characteristics of cold-start data splits used in our experiments ordered by sparsity level.

The dataset splits were generated to reproduce a cold-start item scenario as per the procedure described in the initial work of [37]. For the Amazon Video Games and MovieLens Hetrec datasets, we leverage the publicly available splits¹ of [6], for which 60% of items are kept for training, 20% for validation and 20% for test. Models are trained on the training set with hyper-parameter optimization achieved on the validation set. The metrics are averaged over 10 different random splits of train, validation and test sets. For the MovieLens10M and the Netflix datasets, 20% of cold-start items are sampled and they are split into the cold validation and test sets. Then we proceed with a random 80%, 10%, 10% split on the rest of the click matrix to get the train, warm validation and test sets.

The hybrid validation and test sets are obtained after combining the cold and warm validation and test sets. Regarding item metadata, we take the same set of attributes used in [6, 44]. For Amazon Video Games, we use *title name*, *description*, *feature description*, *brand* and *categories*. For MovieLens Hetrec, we use *movie years*, *genres*, *actors*, *directors*, *countries*, and *locations*. For MovieLens10M, we use *title*, *description*, *genres*, *actors*, and *directors*. For Netflix, we use *title*, *genres*, *actors*, *directors*, *producers*, and *composers*. For the Netflix dataset, we join the titles of the Netflix prize dataset with the titles of the IMDb non-commercial dataset [1].

| | # users | # items | Interactions (%) |
|------------------|---------|---------|------------------|
| Pinterest [16] | 55187 | 9916 | 0.27 |
| MovieLens1M [16] | 6040 | 3706 | 4.47 |

Table 2: Characteristics of the warm data splits used in experiments ordered by sparsity level.

Warm splits. We also present our analysis on publicly available data splits² for warm-start recommendation that received a lot of attention in the literature [11, 16, 35]. The dataset characteristics are summarized in Table 2. The splits were generated by selecting users with at least 20 ratings and using the leave-one-out evaluation, ranking the last click together with 100 randomly drawn negative samples. The validation set is generated from the training set using the same protocol as in [35].

¹<https://github.com/cesarebernardis/NeuralFeatureCombiner>

²https://github.com/hexiangnan/neural_collaborative_filtering

4.2 Metrics and statistical significance

We leverage standard metrics reported in recommendation literature [24] namely, hit rate (hr@k) and normalized discounted cumulative gain (ndcg@k). Given a validation or test set containing a set of users $\mathcal{U}' \subseteq \mathcal{U}$, let $\mathcal{I}_u \subseteq \mathcal{I}$ be the set of items clicked by user u . The metric hr@k is defined as:

$$\text{hr@k} = \frac{1}{|\mathcal{U}'|} \sum_{u \in \mathcal{U}'} \frac{\sum_{i \in \mathcal{I}_u} \mathbb{I}(r_{ui} \leq k)}{\min(k, |\mathcal{I}_u|)}, \quad (12)$$

where \mathbb{I} is the indicator function and r_{ui} the predicted rank of item i for user u . The ndcg@k is defined as:

$$\text{ndcg@k} = \frac{1}{|\mathcal{U}'|} \sum_{u \in \mathcal{U}'} \left(\sum_{i \in \mathcal{I}_u} \frac{\mathbb{I}(r_{ui} \leq k)}{\log_2(1 + r_{ui})} \right) / \left(\sum_{j \in K'} \frac{1}{\log_2(1 + j)} \right), \quad (13)$$

where the set K' is defined as $K' = \{1, \dots, \min(k, |\mathcal{I}_u|)\}$.

In the rest of the paper, we report average gain observed across all users in the test datasets. We also performed bootstrapping analysis to assess the significance of our results by sampling 20% of the users in each test dataset and repeating the process 500 times, in order to compute 95% confidence intervals, and we indicate when our results achieve statistical significance.

4.3 Results for Cold Splits

We now report ndcg@k and hr@k metrics on the cold data splits. We first focus on incorporating item features with the same featureization policy as in [6, 44]. A study into more sophisticated ways to encode the item metadata features is also conducted. We discuss embeddings and alignment strategies to achieve the best results with item metadata features only. Finally, we explore the incorporation of more item metadata features and discuss the lifts obtained. Regarding the baselines considered, we largely make use of the code repository³ of [6] for hyper-parameter tuning, training and scoring. We train the baselines and our proposed approach on an ml.p3.2xlarge EC2 instance.

Baselines: We report the results for several competitive baselines: NFC [6], ItemKNNCF [26], Wide and Deep [9], and FM [34]. NFC is the hybrid model that learns feature embeddings and item similarities from the similarities pre-learned via a collaborative filtering model, e.g. SLIM [28]. In [6] it was reported to largely beat SOTA for cold item recommendations. ItemKNNCF is an item content-based k-nearest neighbour approach which was proven to be competitive across a variety of tasks despite its simplicity [11]. Wide and Deep consists of training jointly wide linear models and deep neural networks to combine the benefits of memorization and generalization for recommender systems. Finally, Factorization Machines (FM) is a classic competitive baselines when dealing with cold-start recommendations [30] and explicitly model first and second order interactions of feature and click embeddings. We also experimented with CLCRec [44], which is a contrastive optimization framework that combines the mutual information between user and item collaborative embeddings on one end and between feature and collaborative embedding on the other end, and CVAR [49], which proposes a method to warm-up cold item embeddings by modelling the relationship between item id and side information

³<https://github.com/cesarebernardis/NeuralFeatureCombiner>

in the latent space. However, we could not reproduce the results of [44] and the code repository of [49] did not scale to the size of our datasets. Hence these results are excluded from Table 3.

| | MovieLens Hetrec | | | |
|---------------|--------------------|---------------|---------------|---------------|
| | hr@10 | ndcg@10 | hr@25 | ndcg@25 |
| NFC | 0.1904 | 0.2076 | 0.1748 | 0.1866 |
| ItemKNNCF | 0.1175 | 0.1335 | 0.1130 | 0.1214 |
| Wide and Deep | 0.1555 | 0.1762 | 0.1479 | 0.1588 |
| FM | 0.1790 | 0.1946 | 0.1808 | 0.1842 |
| MAREC (Eq 9) | 0.2928 | 0.3071 | 0.2717 | 0.2826 |
| Lift | +53.8%* | +47.9%* | +49.7%* | +51.4%* |
| | Amazon Video Games | | | |
| | hr@10 | ndcg@10 | hr@25 | ndcg@25 |
| NFC | 0.1231 | 0.0785 | 0.2099 | 0.1040 |
| ItemKNNCF | 0.1187 | 0.0786 | 0.1842 | 0.0980 |
| Wide and Deep | 0.0103 | 0.0060 | 0.0200 | 0.0088 |
| FM | 0.0080 | 0.0134 | 0.0129 | 0.0302 |
| MAREC (Eq 9) | 0.1568 | 0.1047 | 0.2433 | 0.1305 |
| Lift | +27.4%* | +33.2%* | +15.9%* | +25.5%* |
| | MovieLens10M | | | |
| | hr@10 | ndcg@10 | hr@25 | ndcg@25 |
| NFC | 0.0322 | 0.0379 | 0.0342 | 0.0366 |
| ItemKNNCF | 0.0961 | 0.0865 | 0.1525 | 0.1054 |
| Wide and Deep | 0.0576 | 0.0571 | 0.0864 | 0.0654 |
| FM | 0.0718 | 0.0634 | 0.1064 | 0.0737 |
| MAREC (Eq 9) | 0.1094 | 0.0938 | 0.1956 | 0.1236 |
| Lift | +13.8%* | +8.4%* | +28.3%* | +17.3%* |
| | Netflix | | | |
| | hr@10 | ndcg@10 | hr@25 | ndcg@25 |
| NFC | 0.1087 | 0.1098 | 0.1278 | 0.1114 |
| ItemKNNCF | 0.1081 | 0.1115 | 0.1249 | 0.1127 |
| Wide and Deep | 0.0188 | 0.0146 | 0.0250 | 0.0180 |
| FM | 0.0586 | 0.0483 | 0.0990 | 0.0651 |
| MAREC (Eq 9) | 0.1369 | 0.1412 | 0.1574 | 0.1411 |
| Lift | +25.9%* | +26.6%* | +23.2%* | +25.2%* |

Table 3: Baseline comparison of MAREC across benchmarking datasets on cold-start recommendation. Top performing and second best scores are respectively in bold and underlined. Lift is reported between MAREC and best performing baseline and * indicates whether the lift is statistically significant.

Baseline Comparison. For fair comparison, we adopt the same featurization strategies reported in [6, 44] to produce the feature matrix \mathbf{F} , that is, the text features are embedded through tf-idf with 1000 as vocabulary size and the categorical features through multi-hot encoding. For the non-negative decreasing function h used in the regularization term \mathbf{D}^R of equation (6), we use a step linear decreasing function. We take the 10th percentile p of the distribution of the number of ratings per item $r^{(i)} = \sum_l X_{li}$ and the linear

function is written $h(r^{(i)}) = k(p - r^{(i)})$ if $r^{(i)} \leq p$, $h(r^{(i)}) = 0$ if $r^{(i)} \geq p$, with $k = \beta/p$. We keep $f_\phi^E = I$ for the embedding model and for the alignment model f_ζ^A we used equation (5), and optimize for the first and second order scalar terms. For the backbone model f_θ^B , we used equation (9) which is the fastest to run.

Table 3 shows the lifts obtained by MAREC on the MovieLens Hetrec, Amazon Video Games, MovieLens10M, and Netflix datasets, all with very significant margins. For the MovieLens Hetrec dataset, the hyperparameters obtained on the validation sets are $\delta = 20$ (equation 5), $\lambda_1 = 1$ (equation 9), $\alpha = 1$ (equation 6), $\beta = 100$ (term \mathbf{D}^R in equation 6). For the Amazon Video Games dataset, the hyperparameters obtained on the validation sets are $\delta = 50$, $\lambda_1 = 1$, $\alpha = 10$, $\beta = 100$. We note that learning the first and second order coefficients in the alignment function of (5) did not lead to improvements, which we relate to the high sparsity observed in the data (click percentage of 0.06%, see Table 1). For the MovieLens10M dataset, the hyperparameters obtained on the validation set are $\delta = 50$, $\lambda_1 = 700$, $\alpha = 1$, $\beta = 60$. Finally, for the Netflix dataset, the hyperparameters obtained on the validation set are $\delta = 100$, $\lambda_1 = 500$, $\alpha = 1$, $\beta = 100$.

4.4 Ablation Studies

Here we focus on MovieLens10M dataset although similar observation was made on other datasets as well and those results are not presented for sake of brevity.

Discussion on the encoding and embeddings functions. We have showed that our proposed approach can outperform competitive baselines on a variety of cold-start dataset splits. This can be further improved by utilising better embeddings and leveraging more features. As a result, we are first interested in the recommendation quality we get without the fusion term, by only considering item metadata.

| | MovieLens10M | | | |
|---------------------------------|---------------|---------------|---------------|---------------|
| | hr@10 | hr@25 | hr@50 | hr@100 |
| ItemKNN | 0.0071 | 0.0137 | 0.0241 | 0.0449 |
| MAREC (Eq 5, 1st order) | 0.0326 | 0.0484 | 0.0757 | 0.1235 |
| MAREC (Eq 5) | 0.0329 | 0.0487 | 0.0776 | 0.1302 |
| MAREC (Eq 5, Falcon7B) | 0.0373 | 0.0612 | 0.1007 | 0.1545 |
| MAREC (Eq 5, Falcon7B (all)) | 0.0344 | 0.0541 | 0.0905 | 0.1448 |
| MAREC (Siamese, Falcon7B (all)) | 0.0357 | 0.0537 | 0.0820 | 0.1280 |
| MAREC (Eq 5, ST) | 0.0378 | 0.0626 | 0.1028 | 0.1602 |

Table 4: Ablation study on using metadata information on the MovieLens10M dataset split.

Table 4 presents the results of different encoding, and embeddings strategies to get to metadata-based recommendations. The first step we tried was to replace the text tf-idf embeddings with pretrained Large Language Models (LLMs) embeddings: we experimented with Falcon-7B [4] and Sentence Transformers (ST) [33] embeddings. We also experimented with learning the first order coefficients μ_i , $i \in \{1, \dots, N\}$ vs learning first and second order coefficients μ_i, μ_{ij} , with $i, j \in \{1, \dots, N\}$, $j > i$ of equation (5). First, we notice that LLM pre-trained embeddings largely outperformed

the tf-idf embeddings for $hr@k$ and $ndcg@k$, for instance ST embeddings led to an increase of +22.8% for $hr@100$ with respect to tf-idf embeddings. Second, we notice that learning scalar weights for second order terms, as per equation (5), brings a clear gain in ranking metrics. The second and third rows of Table 4 show a consistent benefit over ranking metrics and a gain of 5.4% for $hr@100$. This is because the multiplication of cosine similarities enable to model nonlinear interactions between sub-feature spaces.

Finally, we also report results on converting the categorical features (actors, directors, genres) into numeric representations with Falcon7B, indicated as "Falcon7B (all)" in Table 4. This led to a small decrease in performance over using multi-hot encoded features, e.g., -6.8% for $hr@100$. However this helped when training the Siamese network, and the best results on cold-start splits were reported using Falcon embeddings across all features. For the Siamese network, we used 1 projection layer followed by 1 cross attention layer between text and categorical features and 2 dense layers. We noticed that feeding categorical features to the Siamese network was leading the network to learn id associations between multi-hot encoded features and items, instead of semantic ones. The results we report here show that the Siamese network fall short of the best reported results, e.g., -6.6% for $recall@10$.

Fusion performance, and variational vs linear autoencoder. The previously presented results give an indication of the performance of the fusion approaches (equations 7 and 9), that we present in Table 5.

| | MovieLens10M | | | |
|----------------------------|---------------|---------------|---------------|---------------|
| | hr@10 | hr@25 | hr@50 | hr@100 |
| MAREC (Eq 9, BoW) | 0.1094 | 0.1956 | 0.2866 | 0.4203 |
| MAREC (Siamese+equation 9) | 0.0910 | 0.1601 | 0.2457 | 0.4109 |
| MAREC (Eq 9, ST) | 0.1385 | 0.2240 | 0.3286 | 0.4692 |
| MAREC (Eq 7, ST) | 0.0779 | 0.2037 | 0.3831 | 0.5072 |

Table 5: Ablation study on the MovieLens10M dataset comparing different fusion strategies.

First, the Siamese approach which was trailing best results on the metadata-based learning task is also trailing after fusion. It falls behind the alignment function leveraging first and second order cosine similarities, as per equation (5), by 2.3% on $recall@100$. As future work, we will explore improving the joint representation learning of item metadata with the Siamese network, by e.g., including external data to further help with the adaptation of the pre-trained embeddings, which could be in the form of either additional click data or generated data through LLMs. Second, we report the performance of our network with the 2 backbone models of equations (7) and (9). The multi-VAE network was trained with one encoding and one decoding layer similarly to [24] and after hyperparameter turning, we trained the network over 20 epochs, with a embedding dimension of 200, and D^A in equation (6) chosen such that $\beta = 50$. Our observation is that equation (7) struggles with ranking metrics for low values of k , falling -44.8% and -9.1% behind (9) for $hr@10$ and $hr@25$, while largely outperforming (9) for high values of k , with a gain of +16.6% for $hr@50$ and +8.1% for $hr@100$. We interpret that this is caused by the needs for deeper

representations with more than one hidden layer, combined with the inaccuracy of the sampling Gaussian prior. As future work, we will consider flexible priors and regularization techniques such as in the work of [20]. Finally, we note that this difference in performance with the two backbone models was also appreciated by the work of [41], which focused on warm conditions, where they proposed a late fusion ensemble between a multi-VAE branch with focal loss with a neural EASE branch, by simply multiplying the softmax probabilities obtained. In future work, we will experiment with similar ensembling techniques to bring the best out of the backbone models.

Adding images, and tags. We explore the incorporation of additional metadata into our framework. Table 6 presents the results when we incorporated image embeddings and item tags to the metadata signals.

| | MovieLens10M | | | |
|---------------------------------|--------------|--------|--------|--------|
| | hr@10 | hr@25 | hr@50 | hr@100 |
| MAREC (Eq 9, ST) | 0.1385 | 0.2240 | 0.3286 | 0.4692 |
| MAREC (Eq 9, ST + images) | 0.1401 | 0.2267 | 0.3315 | 0.4721 |
| MAREC (Eq 9, ST + images, tags) | 0.2194 | 0.3540 | 0.4808 | 0.6168 |

Table 6: Results for the cold-start MovieLens10M dataset split on introducing additional metadata to our framework.

The MovieLens10M images were pulled from the Kaggle poster repository⁴. We used the a pretrained CLIP model (ViT-H/14 - LAION-2B⁵) to get image embeddings. We relied on this model as we also tried to generate keywords and captions from these images by leveraging the BLIP2-2.7b architecture but this did not lead to improvements in ranking metrics. On the contrary, Table 6 shows clear benefits in adding the image embeddings to the framework, with gains ranging from 0.5% to 1.4% on the $recall@k$ metrics. Finally, we also made use of the MovieLens tags provided as part of the MovieLens dataset and we simply encoded them through multi-hot encoding, after merging similar tags together, which led to a vocabulary of 2504 words. This is an informative feature, e.g., the movie "Dumb ad Dumber" would come with the following tags: "Jim Carrey", "Jeff Daniel", "stupid", "comedy", "infantil", "hilarious".

The inclusion of such tags led to a very significant additional improvement in ranking metrics, e.g. +30.7% for $hr@100$. We also get to an impressive cold-start performance of 0.6168 for $hr@100$, which after checking is only 15.1% behind the $hr@100$ we get on the warm split. In general, the inclusion of semantic features, i.e. LLM embeddings, image embeddings, and tags metadata, have led to a gain of 105.5% on $hr@10$ and +46.7% on $hr@100$ with respect to training the same model with BoW representation. Under the MovieLens set-up, the tags are coming from user entries, hence this does not make their use strictly correct in a cold-start set-up. However, tags essentially extract relevant semantic features from items and we believe the process of tagging items could be repeated by a ML system utilising the world knowledge hence removing the needs for an user input. We leave this as future work.

⁴<https://www.kaggle.com/datasets/ghrzarea/movielens-20m-posters-for-machine-learning?select=MLP-20M>

⁵laion/CLIP-ViT-H-14-laion2B-s32B-b79K

Results for transitioning from cold to warm conditions. Finally, we report the capability of the proposed approach to provide relevant recommendations for situations in which there is a mix of cold and warm items. Table 7 presents the results in the 3 test scenarios:

| | MovieLens10M | | | | | |
|------------------|---------------|---------------|---------------|---------------|---------------|---------------|
| | Warm | | Cold | | All | |
| | hr@10 | ndcg@10 | hr@10 | ndcg@10 | hr@10 | ndcg@10 |
| NFC | 0.0945 | 0.0736 | 0.0322 | 0.0379 | 0.0833 | 0.0767 |
| ItemKNNCF | 0.0499 | 0.0476 | <u>0.0962</u> | <u>0.0865</u> | 0.0509 | 0.0565 |
| Wide and Deep | 0.1204 | 0.0907 | 0.0576 | 0.0571 | 0.0879 | 0.0752 |
| FM | <u>0.1461</u> | <u>0.1206</u> | 0.0718 | 0.0634 | <u>0.1012</u> | <u>0.0947</u> |
| MAREC (Eq 5, ST) | 0.0558 | 0.0494 | 0.0378 | 0.0384 | 0.0618 | 0.0662 |
| MAREC (Eq 9, ST) | 0.3513 | 0.2890 | 0.1385 | 0.1150 | 0.2443 | 0.2283 |

Table 7: Results on the MovieLens10M dataset under different evaluation scenarios with warm, mixed, and cold items.

warm items only, cold and warm items, and cold items only, against the 2 best performing approaches reported in [44]. We have seen that MAREC was largely beating SOTA results on cold-start splits and here we confirm its efficacy for warm and mixed situations. As for the hyperparameters, we get $\lambda_1 = 700$, $\alpha = 1$, $\beta = 0.5$, for the mixed split and $\lambda_1 = 500$, $\alpha = 1$, $\beta = 0$, for the warm split. For the mixed and warm situations, it largely beats the baselines as our approach converges to the backbone model without fusion, and we repeat that our approach provides the flexibility to choose the backbone model from the top performing collaborative filtering techniques of the matrix factorization and autoencoder families.

A note on time complexity. We note that the training process can be done either in sequential steps by first learning the best metadata representations (equations 3, 5) and then training the backbone and fusion part of the network (equations 7, 9, 11), or in an end-to-end fashion. The sequential implementation enables not to pass all the metadata feature matrix F at test time but rather the user specific generated embeddings. We report the training times of the approaches: on MovieLens10M, 0.43 seconds for ItemKNNCF, 5.3e3 seconds for Wide and Deep, 1.3e3 seconds for FM, 1.3e4 seconds for NFC, 230 seconds for (7), and 34 seconds for (9); and on Amazon Video Games, 2 seconds for ItemKNNCF, 190 seconds for Wide and Deep, 27 seconds for FM, 8.2e3 seconds for NFC, 440 seconds for equation (7), and 92 seconds for equation (9). The gain in training time over the second best performing approach (NFC) is of one order of magnitude for the VAE backbone and two orders of magnitude for the EASE backbone. We note that the matrix implementation of (9) will suffer the curse of dimensionality in the user space, however equation (7) scales well as it trains across batch of users.

4.5 Experiments on Warm-start Datasets

We also put a focus on warm dataset splits to evaluate the merit of our proposed optimization strategy of equation (10), and its closed form solution presented in equation (11), where the alignment term can be removed as we are in warm conditions. As for the weight matrices we use $w_0 = 1$ for positive labels and tunable parameter w_1 for negative labels. Hence the 3 parameters to optimise are w_1 , λ_1 , and γ_1 . For the weight matrices we use $w_0 = 1$ for positive labels and tunable parameter w_1 for negative labels. Hence the 3 parameters

to optimise are w_1 , λ_1 , and γ_1 . Hyperparameter optimization is done via grid search on the validation set optimising for both ndcg@10 and recall@10, where the grids are defined with parameters such as $w_1 \in \{0, 0.5, \dots, 1\}$, $\lambda_1 \in \{0, 100, \dots, 2000\}$, and $\gamma_1 \in \{0, 100, \dots, 2000\}$. We get $w_1 = 0.25$, $\lambda_1 = 300$, $\gamma_1 = 800$ for MovieLens1M, $w_1 = 0.05$, $\lambda_1 = 300$, $\gamma_1 = 100$ for Pinterest. We implement our approach with a batch array job with on-demand AWS Fargate resources and 1 vCPU of 8 GB of memory per job, which runs in 1 min for the MovieLens dataset and 7 min for the Pinterest dataset.

| | MovieLens1M | | Pinterest | |
|---------------|---------------|---------------|---------------|---------------|
| | hr@10 | ndcg@10 | hr@10 | ndcg@10 |
| Popularity | 0.4535 | 0.2543 | 0.2740 | 0.1409 |
| iALS | 0.711 | 0.4383 | 0.8762 | 0.5590 |
| NeuMF | 0.7093 | 0.4039 | 0.8777 | 0.5576 |
| SLIM | 0.7162 | 0.4468 | 0.8679 | 0.5601 |
| MF | <u>0.7294</u> | <u>0.4523</u> | 0.8895 | 0.5794 |
| EASE | 0.7184 | 0.4494 | 0.8634 | 0.5616 |
| MAREC (Eq 10) | 0.7301 | 0.4560 | <u>0.8748</u> | <u>0.5683</u> |
| Lift | +0.1% | +0.8%* | -1.5% | -1.9%* |

Table 8: Baseline comparison of MAREC on warm-start benchmarking datasets. Top and second best performing metrics are respectively in bold and underlined. Lift is reported between MAREC and the best performing baseline and * indicates whether the lift is statistically significant.

In Table 8, we report the competitive baselines already reported in [35], to which we add the EASE model [38] and our optimization strategy (11). The baselines are the neural matrix factorization (NMF) approach of [16], the implicit alternating least squares (iALS) collaborative filtering method [36], the original SLIM model [28], and the matrix factorization (MF) implementation of [35] which is the reported SOTA result on the 2 datasets. It is interesting to note that weighted least squares beats matrix factorization for the least sparse dataset (average margin +0.5%) and fails to beat it for the sparse dataset (average margin -1.7%). Another remark is that we consistently beat SLIM (+2.0%, +1.1%), and EASE (+1.5%, +1.3%), meaning that our closed-form weighted least squares should always be considered as strong baseline.

5 CONCLUSION

We introduce Metadata Alignment for cold-start Recommendation (MAREC), a novel algorithm to enhance cold start recommendations by integrating semantic information. This was achieved by combining similarities derived from user click actions and metadata features using a regularization term, aligning cold-start items with the collaborative filtering space. Experimental results demonstrated that MAREC significantly outperformed reported SOTA results on cold-start datasets with varying sparsity and metadata characteristics, showing improvements ranging from +8.4% to +53.8% on hr@k and ndcg@k metrics while being competitive on warm-start recommendation datasets. Moreover, MAREC achieved these results while being one order of magnitude faster to train compared to the second-best performing baseline. The inclusion and utilization of

semantic features led to substantial gains ranging from +46.8% to +105.5% compared to Bag-of-Words (BoW) representations. Future work will focus on refining joint metadata embeddings by incorporating external data sources and multi-modal embeddings, and exploring generative models for informative keyword generation, as well as investigating more advanced end-to-end training and merging mechanisms within the framework.

REFERENCES

- [1] [n. d.]. IMDb Non-Commercial Datasets. <https://developer.imdb.com/non-commercial-datasets/>.
- [2] [n. d.]. MovieLens 10M Dataset. <https://grouplens.org/datasets/movielens/10m/>.
- [3] [n. d.]. Netflix Prize data. <https://www.kaggle.com/datasets/netflix-inc/netflix-prize-data>.
- [4] Ebtesam Almazrouei, Hamza Alobeidli, Abdulaziz Alshamsi, Alessandro Cappelli, Ruxandra Cojocaru, M  rouane Debbah,   tienne Goffinet, Daniel Hesslow, Julien Launay, Quentin Malartic, Daniele Mazzotta, Badreddine Noun, Baptiste Pannier, and Guilherme Penedo. 2023. The Falcon Series of Open Language Models. *arXiv:2311.16867* [cs.CL]
- [5] Bing Bai and Yushun Fan. 2017. Incorporating field-aware deep embedding networks and gradient boosting decision trees for music recommendation. In *11th ACM International Conference on Web Search and Data Mining (WSDM)*. ACM, London, England, Vol. 7.
- [6] Cesare Bernardis and Paolo Cremonesi. 2021. NFC: a deep and hybrid item-based model for item cold-start recommendation. *User Modeling and User-Adapted Interaction* (2021), 1–34.
- [7] Sebastian Borgeaud, Arthur Mensch, Jordan Hoffmann, Trevor Cai, Eliza Rutherford, Katie Millican, George Bm Van Den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, et al. 2022. Improving language models by retrieving from trillions of tokens. In *International conference on machine learning*. PMLR, 2206–2240.
- [8] Jane Bromley, Isabelle Guyon, Yann LeCun, Eduard S  ckinger, and Roopak Shah. 1993. Signature Verification Using a "Siamese" Time Delay Neural Network. In *Proceedings of the 6th International Conference on Neural Information Processing Systems* (Denver, Colorado) (NIPS'93). Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 737–744.
- [9] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishy Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ipsir, et al. 2016. Wide & deep learning for recommender systems. In *Proceedings of the 1st workshop on deep learning for recommender systems*. 7–10.
- [10] Paul Covington, Jay Adams, and Emre Sargin. 2016. Deep neural networks for youtube recommendations. In *Proceedings of the 10th ACM conference on recommender systems*. 191–198.
- [11] Maurizio Ferrari Dacrema, Paolo Cremonesi, and Dietmar Jannach. 2019. Are we really making much progress? A worrying analysis of recent neural recommendation approaches. In *Proceedings of the 13th ACM Conference on Recommender Systems*. 101–109.
- [12] Mukund Deshpande and George Karypis. 2004. Item-Based Top-N Recommendation Algorithms. *ACM Trans. Inf. Syst.* 22, 1 (jan 2004), 143–177. <https://doi.org/10.1145/963770.963776>
- [13] Xiaoyu Du, Xiang Wang, Xiangnan He, Zechao Li, Jinhui Tang, and Tat-Seng Chua. 2020. How to learn item representation for cold-start multimedia recommendation?. In *Proceedings of the 28th ACM International Conference on Multimedia*. 3469–3477.
- [14] Zeno Gantner, Lucas Drumond, Christoph Freudenthaler, Steffen Rendle, and Lars Schmidt-Thieme. 2010. Learning attribute-to-feature mappings for cold-start recommendations. In *2010 IEEE international conference on data mining*. IEEE, 176–185.
- [15] Xue Geng, Hanwang Zhang, Jingwen Bian, and Tat-Seng Chua. 2015. Learning Image and User Features for Recommendation in Social Networks. In *2015 IEEE International Conference on Computer Vision (ICCV)*. 4274–4282. <https://doi.org/10.1109/ICCV.2015.486>
- [16] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural collaborative filtering. In *Proceedings of the 26th international conference on world wide web*. 173–182.
- [17] Yifan Hu, Yehuda Koren, and Chris Volinsky. 2008. Collaborative Filtering for Implicit Feedback Datasets. In *2008 Eighth IEEE International Conference on Data Mining*. 263–272. <https://doi.org/10.1109/ICDM.2008.22>
- [18] Wang-Cheng Kang and Julian McAuley. 2018. Self-attentive sequential recommendation. In *2018 IEEE international conference on data mining (ICDM)*. IEEE, 197–206.
- [19] Urvashi Khandelwal, Omer Levy, Dan Jurafsky, Luke Zettlemoyer, and Mike Lewis. 2019. Generalization through memorization: Nearest neighbor language models. *arXiv preprint arXiv:1911.00172* (2019).
- [20] Daeryong Kim and Bongwon Suh. 2019. Enhancing VAEs for collaborative filtering: flexible priors & gating mechanisms. In *Proceedings of the 13th ACM Conference on Recommender Systems*. 403–407.
- [21] Yehuda Koren. 2008. Factorization meets the neighborhood: a multifaceted collaborative filtering model. In *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*. 426–434.
- [22] Yehuda Koren, Robert Bell, and Chris Volinsky. 2009. Matrix factorization techniques for recommender systems. *Computer* 42, 8 (2009), 30–37.
- [23] Xuan Nhat Lam, Thuc Vu, Trong Duc Le, and Anh Duc Duong. 2008. Addressing cold-start problem in recommendation systems. In *Proceedings of the 2nd international conference on Ubiquitous information management and communication*. 208–211.
- [24] Dawen Liang, Rahul G Krishnan, Matthew D Hoffman, and Tony Jebara. 2018. Variational autoencoders for collaborative filtering. In *Proceedings of the 2018 world wide web conference*. 689–698.
- [25] Alexander Long, Wei Yin, Thalaisyasingam Ajanthan, Vu Nguyen, Pulak Purkait, Ravi Garg, Alan Blair, Chunhua Shen, and Anton van den Hengel. 2022. Retrieval augmented classification for long-tail visual recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 6959–6969.
- [26] Pasquale Lops, Marco De Gemmis, and Giovanni Semeraro. 2011. Content-based recommender systems: State of the art and trends. *Recommender systems handbook* (2011), 73–105.
- [27] Julian McAuley, Christopher Targett, Qinfeng Shi, and Anton Van Den Hengel. 2015. Image-based recommendations on styles and substitutes. In *Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval*. 43–52.
- [28] Xia Ning and George Karypis. 2011. Slim: Sparse linear methods for top-n recommender systems. In *2011 IEEE 11th International Conference on Data Mining*. IEEE, 497–506.
- [29] Xia Ning and George Karypis. 2012. Sparse linear methods with side information for top-n recommendations. In *Proceedings of the sixth ACM conference on Recommender systems*. 155–162.
- [30] Feiyang Pan, Shuokai Li, Xiang Ao, Pingzhong Tang, and Qing He. 2019. Warm up cold-start advertisements: Improving ctr predictions via learning to learn id embeddings. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 695–704.
- [31] Alexandrin Popescul, Lyle H Ungar, David M Pennock, and Steve Lawrence. 2013. Probabilistic models for unified collaborative and content-based recommendation in sparse-data environments. *arXiv preprint arXiv:1301.2303* (2013).
- [32] Zhen Qin, Le Yan, Honglei Zhuang, Yi Tay, Rama Kumar Pasumarthi, Xuanhui Wang, Mike Bendersky, and Marc Najork. 2021. Are Neural Rankers still Outperformed by Gradient Boosted Decision Trees? (2021).
- [33] Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics. <https://arxiv.org/abs/1908.10084>
- [34] Steffen Rendle. 2010. Factorization machines. In *2010 IEEE International conference on data mining*. IEEE, 995–1000.
- [35] Steffen Rendle, Walid Krichene, Li Zhang, and John Anderson. 2020. Neural collaborative filtering vs. matrix factorization revisited. In *Fourteenth ACM Conference on Recommender Systems*. 240–248.
- [36] Steffen Rendle, Walid Krichene, Li Zhang, and Yehuda Koren. 2022. Revisiting the performance of ials on item recommendation benchmarks. In *Proceedings of the 16th ACM Conference on Recommender Systems*. 427–435.
- [37] Mohit Sharma, Jiayu Zhou, Junling Hu, and George Karypis. 2015. Feature-based factorized bilinear similarity model for cold-start top-n item recommendation. In *Proceedings of the 2015 SIAM International Conference on Data Mining*. SIAM, 190–198.
- [38] Harald Steck. 2019. Embarrassingly shallow autoencoders for sparse data. In *The World Wide Web Conference*. 3251–3257.
- [39] Harald Steck. 2020. Autoencoders that don't overfit towards the identity. *Advances in Neural Information Processing Systems* 33 (2020), 19598–19608.
- [40] Harald Steck, Maria Dimakopoulou, Nickolai Riabov, and Tony Jebara. 2020. ADMM SLIM: Sparse Recommendations for Many Users. In *Proceedings of the 13th International Conference on Web Search and Data Mining*. 555–563.
- [41] Vojtěch Van  ura and Pavel Kord  k. 2021. Deep variational autoencoder with shallow parallel path for top-N recommendation (VASP). In *Artificial Neural Networks and Machine Learning–ICANN 2021: 30th International Conference on Artificial Neural Networks, Bratislava, Slovakia, September 14–17, 2021, Proceedings, Part V* 30. Springer, 138–149.
- [42] Manasi Vartak, Arvind Thiagarajan, Conrado Miranda, Jeshua Bratman, and Hugo Larochelle. 2017. A meta-learning perspective on cold-start recommendations for items. *Advances in neural information processing systems* 30 (2017).
- [43] Tongzhou Wang and Phillip Isola. 2020. Understanding Contrastive Representation Learning through Alignment and Uniformity on the Hypersphere. In *Proceedings of the 37th International Conference on Machine Learning (ICML'20)*. JMLR.org, Article 921, 11 pages.

- [44] Yinwei Wei, Xiang Wang, Li Qi, Liqiang Nie, Yan Li, Xuanqing Li, and Tat-Seng Chua. 2021. Contrastive Learning for Cold-start Recommendation. In *Proceedings of the 29th ACM International Conference on Multimedia*.
- [45] Liwei Wu, Shuqing Li, Cho-Jui Hsieh, and James Sharpnack. 2020. SSE-PT: Sequential recommendation via personalized transformer. In *Proceedings of the 14th ACM Conference on Recommender Systems*. 328–337.
- [46] Liwei Wu, Shuqing Li, Cho-Jui Hsieh, and James L Sharpnack. 2019. Stochastic shared embeddings: Data-driven regularization of embedding layers. *Advances in Neural Information Processing Systems* 32 (2019).
- [47] Xiaoxiao Xu, Chen Yang, Qian Yu, Zhiwei Fang, Jiaying Wang, Chaosheng Fan, Yang He, Changping Peng, Zhangang Lin, and Jingping Shao. 2022. Alleviating Cold-start Problem in CTR Prediction with A Variational Embedding Learning Framework. In *Proceedings of the ACM Web Conference 2022*. 27–35.
- [48] Yan Zhang, Hongzhi Yin, Zi Huang, Xingzhong Du, Guowu Yang, and Defu Lian. 2018. Discrete deep learning for fast content-aware recommendation. In *Proceedings of the eleventh ACM international conference on web search and data mining*. 717–726.
- [49] Xu Zhao, Yi Ren, Ying Du, Shenzheng Zhang, and Nian Wang. 2022. Improving item cold-start recommendation via model-agnostic conditional variational autoencoder. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2595–2600.
- [50] Ziwei Zhu, Yun He, Xing Zhao, Yin Zhang, Jianling Wang, and James Caverlee. 2021. Popularity-Opportunity Bias in Collaborative Filtering. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining (Virtual Event, Israel) (WSDM '21)*. Association for Computing Machinery, New York, NY, USA, 85–93. <https://doi.org/10.1145/3437963.3441820>