Factorization Machines (FMs) are generic factorization models for Collaborative Filtering (CF) that offer several advantages compared to the conventional CF models. They are expressive and general models that can mimic several CF problems, their accuracy is state-of-the-art, and their linear complexity makes them fast and scalable. Factorization Machines however, are optimized for datasets with explicit feedback (such as ratings) and they are not very effective for datasets with implicit feedback. Although FMs can also be used for datasets with implicit feedback by a trivial mapping of implicit feedback to explicit values, but we will empirically show that such trivial mapping is not optimized for ranking. In this work, we propose FM-Pair, an adaptation of Factorization Machines with a pairwise loss function, making them effective for datasets with implicit feedback. The optimization model in FM-Pair is based on the BPR (Bayesian Personalized Ranking) criterion, which is a well-established pairwise optimization model. FM-Pair retains the advantages of FMs on generality, expressiveness and performance and yet it can be used for datasets with implicit feedback. We also propose how to apply FM-Pair effectively on two collaborative filtering problems, namely, context-aware recommendation and cross-domain collaborative filtering. By performing experiments on different datasets with explicit or implicit feedback we empirically show that in most of the tested datasets, FM-Pair beats state-of-the-art learning-to-rank methods such as BPR-MF (BPR with Matrix Factorization model). We also show that FM-Pair is significantly more effective for ranking, compared to the standard FMs model. Moreover, we show that FM-Pair can utilize context or cross-domain information effectively as the accuracy of recommendations would always improve with the right auxiliary features. Finally we show that FM-Pair has a linear time complexity and scales linearly by exploiting additional features.

Categories and Subject Descriptors: C.2.2 [Artificial Intelligence]: Learning

General Terms: Design, Algorithms, Performance

Additional Key Words and Phrases: Factorization Machines, Collaborative Filtering

1. INTRODUCTION

The role of Recommender Systems (RS) as a tool to provide personalized content for users is becoming more and more important. Among different techniques that have been introduced for recommender systems in the past two decades, Collaborative Filtering (CF) has become the most successful and widely-used technique. Early CF techniques were mainly based on neighborhood approaches [Resnick et al. 1994] while recently model-based techniques such as Matrix Factorization (MF) [Salakhutdinov and Mnih, 2008] attracted more attention due to their superior performance and scalability [Koren et al. 2009]. Matrix factorization techniques generally learn a low-dimensional representation of users and items by mapping them into a joint latent space consisting of latent factors. Recommendations are then generated based on the similarity of user and item factors.
Factorization Machines (FMs) [Rendle 2010] are general factorization models that not only learn user and item latent factors, but also the relation between users and items with any auxiliary features. This is done by also factorizing auxiliary features to the same joint latent space. In contrast to the conventional factorization techniques where the training data is represented by a matrix, the input data for FMs are feature vectors just similar to the input data for the other supervised learning methods such as Support Vector Machines or regression models. This creates a great flexibility for FMs by allowing them to incorporate any additional information in terms of auxiliary features. Thanks to the flexibility of FMs on representing the data, FMs can mimic other factorization models by feature engineering without the need to change the underlying model. In [Rendle 2012] Rendle shows how several factorization model such as Matrix Factorization [Koren et al. 2009], Attribute-Aware models [Gantner et al. 2010] and SVD++ [Koren 2008] can be mimic by FMs. Factorization Machines have been successfully applied in different collaborative filtering problems including context-aware recommendation [Rendle et al. 2011], cross-domain collaborative filtering [Loni et al. 2014] and social recommendation [Zhang et al. 2013]. Factorization Machines have linear time complexity and thus are scalable for large datasets. They have been shown [Rendle et al. 2011] to be significantly faster than tensor factorization [Karatzoglou et al. 2010], a popular context-aware CF method. Moreover, an effective parallel optimization method for FMs has been developed [Juan et al. 2016], reporting significant speed-up in training time compared to the standard training models.

Despite the great advantages of Factorization Machines, the FMs model is not optimized for data with implicit user feedback. All the aforementioned studies have been developed for datasets with explicit feedback. Implicit user feedback (such as clicks) are typically unary or positive-only feedback, and thus there are no explicit real-valued scores for user-item interactions. A trivial approach to train FMs with such datasets, is to map positive feedback to a real-value number such as +1. Negative examples can be sampled from unobserved interactions and can be assigned a real-valued label of 0 or -1. The model can then be trained just like the standard FMs model. However, such mapping methods are associated with two problems: firstly, the sampled interactions with negative labels might not be a real negative feedback as the user might not have the chance to observe the item [Rendle et al. 2009]. Secondly, due to the point-wise optimization techniques in FMs, the model learns to correctly predict +1s and -1s, which is not necessarily the optimal model for ranking. We experimentally show that such trivial mapping is not an accurate model for learning from implicit feedback.

The existing work on FMs with implicit feedback is limited and the scope of existing experimental studies is narrow. In a recent work, Guo et al. [2016] introduce PRFM (Pairwise Ranking Factorization Machines), where they adapt a pairwise optimization technique to learn from implicit feedback. This work however, has not fully exploited one of the main advantages of FMs, namely the ability to encode additional information as auxiliary features. In PRFM, contextual information has been exploited to adapt the sampling stage of the learning method and thus the model needs to be re-adapted for different types of auxiliary information. Furthermore, PRFM was only tested on one explicit dataset. In Guo et al. [2016], explicit feedback was mapped to unary positive-only feedback, and thus it is not clear how PRFM performs on datasets with inherent implicit feedback. In another work, Nguyen et al. [2014] introduced Gaussian Process Factorization Machines (GPFM), a non-linear adaptation of Factorization Machines.

We use the term “auxiliary” for any additional information that is available next to the user-item matrix. Auxiliary features can be user and item attributes, context, content, information from other domains and so on.
In GPFM, interactions between users, items and context are captured with non-linear Gaussian kernels. They also introduced a pairwise optimization model for GPFM for datasets with implicit feedback and used it for context-aware recommendations. However, GPFM is not linearly scalable as the underlying optimization method relies on calculating the inverse of Gaussian kernels, which is a computationally-intensive task. Furthermore, the GPFM model is dependent on the choice of kernel, thus making it more complex compared to the standard FMs model. Nevertheless, we empirically compare the performance of GPFM with our method based on the training time and recommendations accuracy, in Section 5.

In this work we consolidate previous work on FMs and introduce a generic Factorization Machines framework for datasets with implicit feedback. Similar to [Guo et al. 2016], we adapt a pairwise optimization method based on BPR (Bayesian Personalized Ranking) criterion [Rendle et al. 2009]. BPR is an state-of-the-art learning-to-rank method for collaborative filtering that learns to correctly rank pairs of items with respect to a user. BPR has been successfully applied for datasets with implicit feedback and it has been shown [Rendle et al. 2009] to be more effective than other learning-to-rank methods such as Weighted Regularized Matrix Factorization (WRMF) [Hu et al. 2008]. Unlike [Guo et al. 2016], our proposed training model does not depend on the sampling method. We adapt the optimization model of BPR based on the existing auxiliary information that are represented as additional features. We refer to our implementation as FM-Pair since we are using a pair-wise optimization method for FMs. FM-Pair is a linear model that can exploit additional information as auxiliary features just like the standard FMs, without requiring any adaptation to the underlying model. We further propose two applications of FM-Pair on context-aware and cross-domain collaborative filtering problems. We test FM-Pair on four implicit and explicit datasets with different tasks. We find that by using the right data, FM-Pair outperforms state-of-the-art methods for learning from implicit feedback data. We also show that FM-Pair is significantly more effective than the trivial implicit-to-explicit mapping method. Furthermore, we empirically demonstrate the effectiveness of FM-Pair on exploiting auxiliary features (i.e., context or cross-domain information). We also empirically show that FM-Pair scales linearly by increasing dimensionality of factorization or number of auxiliary features.

FM-Pair is publicly available as a part of WrapRec2, an open-source evaluation framework for recommender systems and can be used simply on different datasets.

The contributions of this work can be summarized as follows:

— An extension to Factorization Machines is introduced that allows the use of FMs for datasets with implicit feedback. Inspired by BPR [Rendle et al. 2009], FM-Pair is implemented with a pairwise loss function without requiring explicit feedback for user-item interactions.

— We propose to apply FM-Pair to exploit context and provide context-aware recommendations for datasets with implicit feedback. Similarly, we propose a method to apply FM-Pair for the task of cross-domain collaborative filtering.

— We release the implementation of FM-Pair as a part of WrapRec, an evaluation framework for recommender systems. The usage of WrapRec framework is briefly described in this work.

In the remainder of this paper we first provide a brief introduction to FMs and discuss some background and related work. In Section 3, we introduce FM-Pair and its pairwise optimization method in detail. In Section 4, we propose two applications of FM-Pair for context-aware and cross-domain collaborative filtering. In Section 5 we
describe the datasets, our evaluation method and the experiments that we performed in this work and further elaborate on the results of those experiments. We conclude the paper by summarizing the contributions and discussing about possible extensions in Section 6.

2. BACKGROUND AND RELATED WORK

In this section we briefly introduce the model of Factorization Machines for explicit feedback datasets and explain how the input data is represented in FMs. We also review the related work on Factorization Machines in more details.

Factorization Machines represent each user-item interaction by a real-valued feature vector $x$ with a corresponding output value of $y$. Typically the feature vectors are binary vectors with two non-zero features corresponding to user and item. In case of explicit user feedback, the output value $y$ would be the actual rating given by the user. Figure 1 illustrates how the user-item rating matrix can be modeled by the feature vectors $x$ and output values $y$. Each rating in the user-item matrix is represented by a feature vector. The feature vectors indicate which user rated which item and if auxiliary information (such as context) is available for the user-item interactions, it is represented by real-valued auxiliary features.

More specifically, let us assume that the input data is represented by a set $S$ of tuples $(x,y)$ where $x = (x_1, \ldots, x_n) \in \mathbb{R}^n$ is a $n$-dimensional feature vector and $y$ is its corresponding output value. Factorization Machines learn a model based on the interaction between features. The FM model with the order of 2, where the interactions up to order of 2 (i.e., pairs) are considered, is represented as follows:

$$f(x) = w_0 + \sum_{j=1}^{n} w_j x_j + \sum_{j=1}^{n} \sum_{j'=j+1}^{n} w_{j,j'} x_j x_{j'}$$

where $w_j$ are first order interaction parameters and $w_{j,j'}$ are second order factorized interaction parameters and are defined as $w_{j,j'} = \langle v_j, v_{j'} \rangle$ where $v_j = (v_{j,1}, \ldots, v_{j,k})$ is a $k$-dimensional factorized vector for feature $j$. In fact, FMs factorize any feature that is represented in a feature vector $x$ and consider the terms $x_j x_{j'}$ as weight parameters for the pairwise interactions between the factorized parameters. As you might notice, the FM model is similar to a polynomial regression model. However, FMs differ from a standard polynomial regression model by the fact that the parameters $w_{j,j'}$ are not independent parameters as they are inner product of two factorized vectors. This makes

![Fig. 1: An overview of data representation in Factorization Machines.](image)

ACM Transactions on Intelligent Systems and Technology, Vol. x, No. x, Article xx, Publication date: October 2018.
the total number of parameters much lower (compared to the regression model) and makes FMs favorable for problems with sparse and high dimensional data such as collaborative filtering. For a FM with \( n \) as the dimensionality of feature vectors and \( k \) as the dimensionality of factorization, the model parameters that need to be learned are 
\[
\Theta = \{ w_0, w_1, \ldots, w_n, v_1, \ldots, v_{n,k} \}.
\]

Rendle [2012] proposes three learning methods to learn the parameters of FMs: Stochastic Gradient Descent (SGD), Alternating Least-Squares (ALS) and Markov Chain Monte Carlo (MCMC) method. In principal all the three methods find the optimal parameters by optimizing the same objective function but they use different techniques to solve the optimization problem. The objective function is defined by summing up the losses of individual samples in the training set. A regularization term is also added to the objective function to prevent over-fitting. The objective function \( L \) with square loss over training set \( S \) is defined as:
\[
L(\Theta, S) = \sum_{(x,y) \in S} (f(x|\Theta) - y)^2 + \sum_{\theta \in \Theta} \lambda_\theta \theta^2
\]
(2)

where \( \theta \in \Theta \) are model parameters and \( \lambda_\theta \) is regularization value for parameter \( \theta \). The optimal parameters \( \Theta_{OPT} \) are found by minimizing the objective function, i.e., \( \Theta_{OPT} = \arg\min_{\Theta} L(\Theta, S) \). Rendle [2012] showed that all three learning methods has the same time complexity. The advantage of MCMC over the other two optimization techniques is that it is insensitive to hyper-parameters (such as regularization values) which can avoid time-consuming search for hyper-parameters. On the other the advantages of the SGD technique are its simplicity and lower storage complexity. Details about the optimization techniques can be found in Rendle [2012].

Factorization Machines have several advantages compared to other factorization methods:

---
**Generalization:** Factorization Machines are general factorization models. Despite other factorization models (such as matrix factorization) where specific entities (e.g. user, item) are factorized, in FMs any dimension that can be represented in terms of a feature can be factorized to a low-dimensional latent space. In matrix factorization, predictions are generated by taking into account the interaction between user and item, but in FMs the predictions are generated by taking into account the pairwise interaction between any pair of features (including user and item). FMs can even take into account higher order interactions between features.

---
**Expressiveness:** The fact that the input data in FMs are represented by feature vectors, not only makes FMs easy to use but also makes it possible to mimic several collaborative filtering methods such as Tensor Factorization [Karatzoglou et al. 2010] by feature engineering. This obviate the need to introduce a new prediction and inference methods for such cases. Other example of CF methods that can be represented by FMs are SVD++ [Koren 2008], Attribute-Aware matrix factorization [Gantner et al. 2010] and Joint Matrix Factorization [Shi et al. 2013].

---
**Performance and Scalability:** The complexity of prediction and inference in FMs are linear in terms of number of latent factors and the number of non-zero features [Rendle 2012] and thus FMs can be scaled for large datasets. Furthermore, a parallel implementation of FMs with shared-memory architecture has been proposed [Juan et al. 2016] that can achieve noticeable training speed-up on large datasets.

## 3. LEARNING FACTORIZATION MACHINES FROM IMPLICIT FEEDBACK

In this section we introduce FM-Pair, an adaptation of Factorization Machines with a pairwise optimization methods. Previous studies [Rendle et al. 2009; Shi et al. 2014].
Nguyen et al. [2014] have reported better performance for pairwise learning-to-rank methods compared to point-wise methods for datasets with implicit feedback. While FM-Pair benefits from the effectiveness of pairwise learning-to-rank, it can also leverage the arbitrary auxiliary features that might be available in the input data.

The optimization technique in FM-Pair is inspired by the BPR [Rendle et al. 2009] optimization criterion. The BPR method comes with an assumption that all observed positive feedback is preferred over the missing preferences. The training data in BPR consist of a user and a pair of items where the first item, referred as the positive item, is chosen from the user positive feedback and the second item, referred as the negative item, is sampled from the unobserved interactions. More specifically, the training data in BPR would be a set of tuples \( S_P = \{(u, i, j) | i \in I_u^+ \land j \in I \setminus I_u^+\} \) where \( I_u^+ \) is set of all positive feedback from user \( u \), \( i \) is an item with positive feedback from \( u \) and \( j \) is a missing item for that user which is sampled uniformly from the unobserved items. The BPR optimization technique learns to correctly rank the items in any given pair of items, with respect to a given user.

In FM-Pair arbitrary information can be represented by auxiliary features and thus the pairwise learning method should be able to exploit those features. Let us assume that \( z(u, i) \) are the auxiliary features associated with user \( u \) and item \( i \). Then the tuple \((u, i, j) \in S_P\) indicates user \( u \) prefers item \( i \) over item \( j \) under the observed auxiliary features \( z(u, i) \). Auxiliary features can be user features, item features, context or additional information about user-item interaction. FM-Pair finds the optimal parameters \( \Theta \) by maximizing the following likelihood function:

\[
\prod_{(u, i, j) \in S_P} p(i > u, x, j | \Theta)\tag{3}
\]

where \( i > u, x, j \) indicates item \( i \) is preferred over \( j \) by user \( u \) under auxiliary features \( x = z(u, i) \). Similar to the BPR model, the probability \( p(i > u, x, j | \Theta) \) is defined by mapping a utility function \( g_x(u, i, j) \) to a value between 0 and 1. This can be done by the sigmoid function \( \sigma(x) = \frac{1}{1 + e^{-x}} \). Therefore:

\[
p(i > u, x, j | \Theta) = \sigma(g_x(u, i, j | \Theta))\tag{4}
\]

The utility function \( g \) captures the interaction between user \( u \), item \( i \) and item \( j \) with presence of auxiliary features \( z(u, i) \). Similar to BPR, the utility function \( g \) is defined by calculating the difference between the utility of individual interactions. FM-Pair calculates the utility of individual interactions by taking into account the auxiliary features \( z(u, i) \). We define the utility function \( g \) as:

\[
g_x(u, i, j | \Theta) = f_x(u, i | \Theta) - f_x(u, j | \Theta)\tag{5}
\]

The utility of individual interactions \( f_x(u, i | \Theta) \) can be calculated using equation (1). In this case the input feature vector \( x \) is a sparse vector in which features corresponding to user \( u \), item \( i \) and \( z(u, i) \) are non-zero. Thus the vector \( x \) can be represented with the following sparse form:

\[
x(u, i, z) = x_{u, i, z} = \{(u, x_u), (i, x_i), \{(z, x_z) | z \in z \}\}
\]

where \( x_z \) is the value of feature \( z \) and can be a real value number. The parameters \( x_u \) and \( x_i \) are considered to be 1 to indicate the corresponding user and item of a feedback (see Figure 1 for clarity). By replacing \( x_{u, i, z} \) in equation (1), and expanding \( w_{j,j'} \), the individual utility function \( f_x(u, i | \Theta) \) can be written as:
\[ f(z(u, i|\Theta)) = w_0 + w_u + w_i + \sum_{z \in \mathcal{Z}} v_z x_z + \sum_{f=1}^{k} v_{u,f} v_i,f \]

By replacing (7) in (5), the pairwise utility function \( g \) can be written as:

\[ g(z(u, i, j|\Theta)) = w_i - w_j + \sum_{f=1}^{k} v_{u,f} (v_i,f - v_j,f) + \sum_{z \in \mathcal{Z}} v_{z,f} (v_i,f - v_j,f) \]

Now we define the FM-Pair objective function by taking the logarithm of the likelihood function in equation (3) and adding regularization terms:

\[ L(\Theta, S_p) = \sum_{(u, i, j) \in S_p} \ln \sigma(g(z(u, i, j|\Theta))) - \sum_{\theta \in \Theta} \lambda_\theta \theta^2 \]

Since the FM-Pair objective function is based on likelihood, the optimal parameters are found by maximizing this function, i.e., \( \Theta_{OPT} = \arg\max_{\Theta} L(\Theta, S_p) \).

To find the optimal parameters, optimization is done with Stochastic Gradient Descent (SGD) technique. First the parameters are initialized and then they are updated by iterating over the tuples \((u, i, j) \in S_p\) using the following update rule:

\[ \theta \leftarrow \theta - \eta \frac{\partial L(\Theta, S_p)}{\partial \theta} \]

where \( \eta \) is the learning rate. By replacing (9) in (10), the update rule would be:

\[ \theta \leftarrow \theta + \eta \left( \frac{e^{g(z)}}{1 + e^{g(z)}} \frac{\partial g(z)}{\partial \theta} + \lambda_\theta \theta \right) \]

Based on equation (8), the gradients of \( g(z) \) with respect to \( \theta \) is defined as:

\[ \frac{\partial g(z)}{\partial \theta} = \begin{cases} 
1 & \text{if } \theta = w_i, \\
-1 & \text{if } \theta = w_j, \\
v_{i,f} - v_{j,f} & \text{if } \theta = v_{u,f}, \\
v_{u,f} + \sum_{z \in \mathcal{Z}} x_z v_{z,f} & \text{if } \theta = v_{i,f}, \\
v_{u,f} - \sum_{z \in \mathcal{Z}} x_z v_{z,f} & \text{if } \theta = v_{j,f}, \\
x_z (v_{i,f} - v_{j,f}) & \text{if } \theta = v_{z,f}, \\
0 & \text{otherwise}
\end{cases} \]

The parameters \( w_i \) are typically initialized by 0 and the factorization parameters \( v_{*,f} \) should be initialized by a zero-mean normal distribution with standard deviation \( \sigma_0 \) for a better performance. The parameter \( \sigma_0 \) is one of the hyper-parameters of SGD that typically is tuned by cross-validation or by using a validation set.

The SGD algorithm typically iterates over the entire training data and updates the parameters according to the update rule. [Rendle et al. 2009] suggests to draw the positive feedback from the input data by bootstrapping with replacement to prevent consecutive updates on a same user or item for faster convergence. FM-Pair first draws a positive feedback \((u, i, z_{u,i})\) from the input dataset \( D \) and then samples a negative item...
1: **procedure** LEARN FM-PAIR(D)
2:    initialize \( \Theta \)
3:    repeat
4:        sample \((u, i)\) from \(D\) and create \(x_{u,i,z}\)
5:        sample \(j\) from \(I \setminus I_u^+\) create \(x_{u,j,z}\)
6:        let \(g_{z}(u, i, j|\Theta) = f(x_{u,i,z}|\Theta) - f(x_{u,j,z}|\Theta)\)
7:        update \(\Theta\) according update rule (11)
8:    until convergence
9:    return \(\Theta\)
10: **end procedure**

Fig. 2: Learning FM-PAIR with Stochastic Gradient Descent.

3.1. Computational Complexity

FM-PAIR have a linear learning and prediction time complexity. The main effort in the FM-PAIR SGD algorithm is to calculate \(g_{z}(u, i, j)\) (line 6 in Figure 2). According to (8), this can be done in \(O(k + |z|k)\). Sampling positive pairs \((u, i)\) and negative items \(j\) (lines 4 and 5 in Figure 2) can be done efficiently [Rendle and Freudenthaler 2014] in \(O(1)\). Updating the parameters are done according to (11) and (12). For each point \((u, i, j, z)\) in the training data only the parameters corresponding to that point is updated since the gradient of the other parameters are 0. Thus the complexity of updating the parameters for each training point (line 7 in Figure 2) is \(O(|z|k)\) according to (12). Putting it all together, the complexity of one iteration in FM-PAIR SGD algorithm is \(O(k(|z| + 1))\) and the complexity of a full iteration on the entire training data \(D\) is \(O(k(|z| + 1)|D|)\). Therefore, the computational complexity of FM-PAIR is linear in terms of number of latent factors \(k\) and number of auxiliary features \(z\). In the experiments section we empirically demonstrate the training time of FM-PAIR based on \(k\) and \(z\).

3.2. Analogy Between FM-PAIR and BPR-MF

FM-PAIR can mimic other factorization methods with feature engineering, similar to the standard Factorization Machines. A specific model that can be represented with FM-PAIR is BPR-MF (BPR with Matrix Factorization utility) [Rendle et al. 2009]. The matrix factorization model calculates the utility of a user-item interaction as the inner product of the user and item factors, that is, \(f_{MF}(u,i) = \sum_{f=1}^{k} v_{u,f} v_{i,f}\). By considering \(f_{MF}\) as the utility function of matrix factorization model, the utility of triples \((u, i, j)\) in BPR-MF is defined as:

\[
g_{MF}(u, i, j) = \sum_{f=1}^{k} v_{u,f} (v_{i,f} - v_{j,f})
\]  

(13)

By comparing the above equation with (8), one can notice that \(g_{MF}\) is a special case of \(g_{z}(u, i, j)\) where \(z = \emptyset\) (i.e., no auxiliary features) and the parameters \(w_i\) and \(w_j\) are 0. In fact when there are no auxiliary features, FM-PAIR, compared to BPR-MF, learns two additional parameters \(w_i\) and \(w_j\) that can be regarded as global item biases for positive and negative items.
4. IMPROVED RECOMMENDATIONS WITH AUXILIARY DATA

A great advantage of Factorization Machines as mentioned earlier, is that they are capable of exploiting arbitrary information as auxiliary features to improve recommendations. In this section, we propose to apply FM-Pair for the context-aware and cross-domain collaborative filtering for datasets with implicit feedback.

4.1. Context-Aware Recommendation with FM-Pair

Context is a dynamic set of parameters describing the state of the user at the moment of experience. Some studies also consider user and item attributes as a type of context [Adomavicius and Tuzhilin 2011]. Context-aware recommendation relies on these additional information to better learn from the interactions between users and items. In FM-Pair, context can be considered as one type of auxiliary features for user-item interactions. We represent the context of a user feedback with the following sparse representation:

$$z(u, i) = \{(z, x_z) | x_z \neq 0\}$$

(14)

where \(z\) is a context and \(x_z\) is its corresponding value. For example if available context of an interaction \((u, i)\) are user mood (e.g. “happy”) and movie genre (e.g. “action”), then we can represent the context of interaction with \(z(u, i) = \{(\text{happy}, 1), (\text{action}, 1)\}\). By expanding the feature vector \(x\) with context features, the feature vector \(x\) would have the following sparse form:

$$x(u, i, z) = x_{u,i} = \{(u, x_u), (i, x_i)\} \cup z(u, i)$$

(15)

and the following expanded form:

$$x_{u,i,z} = (0, \ldots, 0, x_u, 0, \ldots, 0, 0, \ldots, 0, x_i, 0, \ldots, 0, x_{z_1}, \ldots, x_{z_m})$$

(16)

where \(Z\) is the set of contextual feature and \(m = |Z|\). The parameters \(x_u, x_i\) and \(x_z\) are the actual values of features, which be seen as weight parameters specifying the strength of features. The parameters \(x_u\) and \(x_i\) are typically considered to be 1 to just indicate the presence of features. The parameters \(x_z\) can be assigned with any real-values to control the weight of contextual features. For the categorical context such as user mood typically binary values are used similar to \(x_u\) and \(x_i\). However, the binary values can also be replaced with real values. If the features are continues by their nature (e.g. user age, time of the day and number of clicks), a real value can be considered as the value of the feature. According to [Rendle et al. 2011] it is often desirable that the value of auxiliary features sum up to 1. Continuous features can also be mapped to categorical features by forming several bins. With our preliminary experiments we found that mapping continuous context to categorical features results to better accuracy. In Section 5 we describe our feature mapping on the two datasets with contextual features.

4.2. Cross-Domain Recommendations

Cross-Domain Collaborative Filtering (CDCF) methods exploit additional information from source domains to improve recommendations in a target domain. The main idea of CDCF is that a user’s taste in one domain (e.g., movie) can be exploited to better learn user’s taste on another domain (e.g., music). Different methods for the problem of CDCF have been proposed. A great overview of the existing solutions can be found

\[\text{source domains} \]
in [Cantador et al. 2015]. Among different techniques that have been developed for cross-domain CF, in an earlier study [Loni et al. 2014] we proposed a method for the problem of CDCF with Factorization Machines for the rating prediction problem. In this section, we propose a similar technique that has been adapted for FM-Pair and thus can be applied for datasets with implicit feedback.

Thanks to the flexibility of Factorization Machines in exploiting additional features, the information from source domains can be translated to auxiliary features to expand the feature vectors in the target domain. The expanded feature vectors can be then used as the input data for FM-Pair to train a model. With the same assumption as the case of context-aware recommendation, the extra features can enrich the feature vectors to better learn the user preferences. We refer to our proposed cross-domain CF method with FM-Pair as FM-Pair-CD. The advantage of FM-Pair-CD is that it does not require any adaptation to the underlying FM-Pair model and thus the model can be used out-of-the-box. FM-Pair-CD proposes a simple and yet effective way to exploit features from source domains in order to improve the performance of recommendations in the target domain. Here the domain refers to the type of item that user interacted with. For example if user provides a feedback for a movie, the domain is “movies”.

To understand how FM-Pair-CD represents the auxiliary features, suppose $p$ is the number of source domains and $I_j(u)$ is the set of items in domain $j$ that user $u$ interacted with. FM-Pair-CD proposes to use one auxiliary feature for every item that user interacted with in the source domains. Therefore, the feature vectors $x$ in the target domain can be represented with the following sparse form consisting of both target and source domain features:

$$x(u, i) = \{ (u, 1), (i, 1), \bigcup_{j=1}^p \{ (z, x_z(u, j)) \mid z \in I_j(u) \} \}$$ (17)

where $x_z(u, j)$ is the value of feature $z$, i.e., the weight that should be considered for the interaction of user $u$ with item $z$ in the source domain $j$. We propose the following two approaches to define the feature values $x_z(u, j)$:

— Binary indicator: In this case similar to the representation of user and item, the presence of an source domain feature is specified by indicator value of 1. We denote $x^B_z(u, j)$ as binary representation of features. In other words, in this case, with binary values we indicate which items have been rated by the user in the source domains.

— Normalized by count: In this case the values of source domain features are normalized by the number of feedback that user provided in the source domain. The normalized value $x^C_z(u, j)$ is defined by:

$$x^C_z(u, j) = \frac{1}{|I_j(u)|}$$ (18)

The auxiliary features in the FM-Pair-CD method, are in fact the items in source domains with feedback from the user. The normalization of auxiliary features ensures that the target features are not dominated by auxiliary features. Figure 3 illustrates how FM-Pair-CD represents feature vectors for input data. In this example the target domain is the “movie” domain and source domain is the “music” domain. The music items that same user has interacted with are considered as auxiliary features for the interactions in the target domain. As you might notice from Figure 3 the total number of auxiliary features is the number of items in source domains. We found that using only a fraction of user feedback from source domains results in almost same improvement compared to the case that all user feedback from source domains are used. Such feature selection makes the size of feature vectors smaller and thus the training and prediction become faster. The selected features can be based on most popular items,
highly rated items, or just randomly chosen items. In fact, by applying this feature selection method, the auxiliary features in (17) can be represented as:

$$\bigcup_{j=1}^{P} \{ (z, x_z(u, j)) | z \in I_j(u) \land z \in I^S(u) \}$$

(19)

where $I^S(u)$ are the selected features. Since finding the most informative items from source domains is not the focus of this work, we just consider $I^S(u)$ to be random items from source domains.

5. DATASETS, EXPERIMENTS AND EVALUATION

In this section we first introduce the datasets that we used in this work, then we describe our evaluation method and then we explain our experiments.

5.1. Datasets

We used the following four datasets in this work, ranging from the popular MovieLens dataset to a recent industry dataset of XING. These datasets are chosen so that we can test different scenarios with auxiliary features and to cover both implicit and explicit feedback scenarios.

— **MovieLens 100K**: The MovieLens 100K dataset is a popular benchmark dataset for recommender systems with explicit feedback consisting of 100K user rating on the scale of 1 to 5. This dataset also contains several user and item attributes that can be used as auxiliary features in FM-Pair.

— **Amazon**: The Amazon dataset [Leskovec et al. 2007] consists of user ratings on the products on the Amazon website. The ratings are on the same scale as the MovieLens dataset. The products belong to four different domains: Books, Music CDs, Video tapes and DVDs. This dataset has been used for some previous work on cross-domain CF [Lon et al. 2014; Hu et al. 2013].

— **Frappe**: Frappe is a context-aware mobile app discovery tool. It logs number of time users run an application on their mobile phone. It also logs several contexts such as time, date, location and weather. The Frappe dataset [Baltrunas et al. 2015] consists

http://grouplens.org/datasets/movielens/
Table I: Statistics of the dataset used in this work

| Dataset       | #Users | #Items | #Feedback | Sparsity(%) | Scale |
|---------------|--------|--------|-----------|-------------|-------|
| MovieLens 100K| 943    | 1,682  | 100K      | 93.74       | 1-5   |
| Amazon        | 15,994 | 84,508 | 270K      | 99.98       | 1-5   |
| Frappe        | 957    | 4,082  | 96K       | 97.54       | Implicit |
| XING          | 9,751  | 9,821  | 223K      | 99.76       | Implicit |

of 100K implicit positive feedback. An observation is considered as a positive feedback if user runs an application at least one time. We used this dataset because of the presence of several contextual features. This dataset has also been used in one of the related work [Nguyen et al. 2014].

— XING: XING is a professional social network and a job discovery platform. This dataset is a subset of the RecSys 2016 challenge and consists implicit user feedback on job postings. Users can either click on a job posting, bookmark it or apply for it. We consider any user action on a job posting as a positive feedback. Since the original dataset was extremely sparse, we densified the dataset by considering users and items with at least 20 interactions.

Table I list the statistics of the three datasets that we used in this work.

5.2. Experiments Setup and Evaluation

All experiments in this work are done with four-fold cross-validation to make sure the hyper-parameters are not tuned for one particular test set. FM-Pair is implemented as a part of the WrapRec [Loni and Said 2014] open source project. WrapRec can be used as a command line tool in different platforms. The source code and documentation can be found in http://wraprec.crowdrec.eu/.

5.2.1. Evaluation Method: The performance of our experiments are evaluated with two ranking metrics namely Recall and NDCG (Normalized Discounted Cumulative Gain). To calculate these metrics on datasets with positive-only feedback, typically for each user in the test set a rank list is created. The metrics are then calculated based on the presence of test feedback on top of the list. However, when auxiliary features such as context are available for the feedback, this strategy is not suitable as it is not clear based on which context the scores (i.e., the utility of a user-item interaction) should be generated. To make an unbiased estimation of performance when auxiliary features are available, we applied the approach known as One-plus-random [Cremonesi et al. 2010; Bellogin et al. 2011] where the following procedure is applied: For every user-item interaction in the test set (which is a positive feedback with possible auxiliary features), 1000 random items which are not observed with that user are scored based on the same user and auxiliary features. Then a ranked list including the target item is created. The position of the target item in the ranked list is used to calculate the metrics. If the targeted test point appears in the top N positions of the list, then it would be considered as a hit. In case of a hit, the recall of a single test point would be 1 and otherwise it would be 0. The overall metric is calculated by averaging on all points. That is:

\[
\text{Recall}@N = \frac{1}{|T|} \sum_{i=1}^{|T|} I(r_i \leq N)
\] (20)

http://www.xing.com/
http://2016.recsyschallenge.com/
where \( r_i \) is the rank of the \( i \)th test sample in the generated list, \( I \) is the indicator function and \( |T| \) is the size of test set. The above metric can be interpreted as the hit rate of the test samples where a hit is defined as presence of the relevant test point in the top \( N \) positions of the ranked list.

Based on the one-plus-random evaluation method, we also adopted the MRR metric as follows:

\[
MRR@N = \frac{1}{|T|} \sum_{i=1}^{|T|} \frac{1}{r_i} I(r_i \leq N)
\]  

(21)

We use the MRR metric since it also takes into account the position of the relevant item in the list. Note that these metrics are not absolute metrics [Bellogin et al. 2011] and their value does not reflect the real performance of the system. However, they are reliable metric to compare the performance of different experiments.

5.3. Comparison of FM-Pair with Other Methods

The proposed FM-Pair algorithm is compared with several methods on the four datasets. In this experiment no auxiliary or context features are used and the methods are compared only based on the positive feedback in the user-item matrix. The following setups have been tested in this experiment:

— **Most-Popular**: This is a baseline method where the most popular items are recommended to the users.

— **FM-Map**: In this setup the training is done similar to the FMs for rating prediction. For the positive feedback in the training set the output value of +1 is considered. Same number of unobserved interactions are sampled uniformly and they are considered as negative feedback with output value of -1. The positive and sampled negative feedback is used to train the FMs model. To resemble the experiment for datasets with explicit feedback, the ratings higher than user's average were mapped to +1 and negative feedback were sampled in the same way as the implicit feedback datasets.

— **BPR-MF**: This method is an implementation of BPR method with Matrix Factorization as the utility function [Rendle et al. 2009]. With this method there is no possibility to incorporate auxiliary information.

— **FM-Pair**: This is the proposed method in this work. The FM-Pair algorithm is listed in Figure 2. For the two datasets of MovieLens and Amazon with explicit feedback, the ratings above user’s average rating is considered as positive feedback.

5.3.1. Hyper-parameters and Experimental Reproducibility. The three datasets of MovieLens, Amazon and Frappe are publicly available. For the experiments in this section, the number of factors (parameter \( k \)) is set to 10 and the number of iteration of the SDG algorithm on the training data is set to 300. The standard deviation of the normal distribution for initialization (parameter \( \sigma_0 \)) is set to 0.1. The learning rate of the SGD algorithm (parameter \( \lambda \)) varies per dataset. The following learning rates are used for each dataset: XING: 0.075, Frappe and MovieLens: 0.005, Amazon: 0.001. The two hyper-parameters of \( \sigma_0 \) and \( \lambda \) are found with a grid search with our four-fold cross-validation experiments. That is, the hyper-parameters that result to the best performance on the average of all folds are chosen, thus they are not optimized for one particular test set.
Table II: Comparison of different learning-to-rank methods on the four dataset based on Recall@10. The numbers in parentheses are standard deviations of the results in the four folds.

| Method / Dataset       | XING          | Frappe        | Amazon        | MovieLens     |
|------------------------|---------------|---------------|---------------|---------------|
| Most-Popular           | 0.0306 (0.0005) | 0.1643 (0.0087) | 0.0222 (0.0010) | 0.1180 (0.0012) |
| FM-Map                 | 0.0287 (0.0015) | 0.1230 (0.0260) | 0.0348 (0.0014) | 0.0728 (0.0036) |
| BPR-MF                 | 0.2925 (0.0030) | 0.1428 (0.0167) | 0.0962 (0.0056) | 0.2278 (0.0024) |
| FM-Pair (this work)    | 0.2920 (0.0077) | 0.1816 (0.0161) | 0.0972 (0.0030) | 0.2357 (0.0016) |

5.3.2. Description of the Results. Table II lists the performance of the above five methods on the four datasets based on Recall@10 metric[^7]. As it can be seen from the table, in three out of the four datasets, the FM-Pair is performing better than the other baselines. In the XING dataset, BPR-FM is slightly performing better than FM-Pair. It is worth mentioning that when there are no auxiliary features (such as this experiment) the underlying model of FM-Pair is very similar to BPR-MF (see Section 3.2). This can explain the close performance of the two methods. Nevertheless, the additional parameters of FM-Pair contribute to some accuracy gain in three out of the four datasets. Another observation that you can see in this table, is that the FM-Map method is not really effective for ranking compared to the two pairwise methods in our experiments. This can be explained by the fact that the standard FMs optimization method is a pointwise method that in principle learns to correctly predict the mapped scores and it is not optimized for ranking. Note that we also tried to map the sampled unobserved feedback to other values than -1, but in practice the result were very similar. For the two datasets of Amazon and MovieLens with explicit feedback, we did an additional experiment where the model is trained with the standard FM with original ratings. The ranked lists are then generated based on the predicted ratings. For this experiment we achieved a Recall of 0 for Amazon and 0.001 for the MovieLens dataset. This shows that even for datasets with explicit feedback, ranking based on predicting ratings is not really effective. Previous studies [Balakrishnan and Chopra 2012; Cremonesi et al. 2010] also showed the ineffectiveness of pointwise methods for ranking.

5.3.3. Comparison with GPFM. In addition to the methods listed in Table II we also compare the performance of FM-Pair with the pairwise method of GPFM [Nguyen et al. 2014] since it is very close to our work as it also adapted a pairwise optimization technique for FMs. We tested the GPFM method on Frappe and MovieLens datasets. For the Frappe dataset we achieved a Recall@10 of 0.1615 and for the MovieLens a Recall@10 of 0.1562 was achieved, both less than the performance of FM-Pair (See Table II). However, the remarkable advantage of FM-Pair compared to GPFM is that the computational complexity of FM-Pair is significantly lower than GPFM. Figure 4 compares the epoch time (the time of a full iteration on dataset) of the three methods of BPR-MF, GPFM and FM-Pair on two datasets of Frappe and MovieLens. The numbers are represented in the log scale due to the significant difference between the epoch time of GPFM with the other two methods. The epoch time of FM-Pair is slightly higher than the epoch time of BPR-MF due to the presence of two additional parameters (see Section 3.2). The GPFM method on the other hand, is significantly slower that the other two methods due to the fact that GPFM need to calculate the inverse of the covariance matrix of the preference kernels [Nguyen et al. 2014]. This introduces a significant computational complexity in the training of GPFM.

[^7]: Other ranking metrics such as MRR and NDCG are also calculated, but due to the high correlation between the values, we only report Recall@10 for this experiment.
Fig. 4: Comparison of the epoch time (the time of a full iteration on the dataset in milliseconds) of three pairwise learning-to-rank methods on the log scale.

Due to the high space complexity of GPFM, running the experiment on the larger datasets of XING and Amazon was not even possible on our testing machine. Since the complexity of GPFM is significantly higher than the other methods, we did not further investigate on testing GPFM on our larger datasets.

We used the Matlab implementation of GPFM that was released with that work to train the model but the evaluation was done in the same way as other methods, as described in Section 5.2, to have a fair comparison between the methods. The kernel of the Gaussian process is chosen to be the RBF kernel, the recommended kernel of the model.

5.4. FM-Pair with Auxiliary Data

In the second set of our experiments, we test the performance of FM-Pair with auxiliary information. We use FM-Pair for the two scenarios that we described in Section 4: context-aware recommendation and cross-domain collaborative filtering.

5.4.1. FM-Pair with Context. Among the four datasets that we use in this work the two datasets of Frappe and MovieLens have several context and attributes. The final context and attributes that are used in the experiments are found with a naive greedy method, where the top performing features are combined. For the Frappe dataset the following contexts are used: daytime (with seven possibilities of sunrise, morning, noon, afternoon, sunset, evening, night), weekday (day of the week), isweekend (with two values of workday or weekend) and homework (with three values of unknown, home, work). For the MovieLens dataset, we used the genre of movies as auxiliary features in FM-Pair. Each movie in this dataset has one or more genres from the 17 genres that exists in this dataset.

Table 1 compares the performance of FM-Pair with context or attributes as auxiliary features (FM-Pair-Context), with the original FM-Pair without any auxiliary features. We reported Recall@10 and MRR@10 for the two setups in this experiment. The results show that the FM-Pair can clearly exploit context or auxiliary attributes if they are present in a dataset.

The experiments are run on a machine with 8 GB of memory and an Intel i5 processor with 4 CPU cores.

http://trungngv.github.io/gpfm/
Table III: Performance of FM-Pair with context compared to the standard FM-Pair without auxiliary features.

| Method / dataset | Recall@10 | MRR@10 |
|------------------|-----------|--------|
| FM-Pair          | Frappe    | MovieLens |
|                  | 0.1816    | 0.2357 |
| FM-Pair-Context  | 0.2064    | 0.2601 |

5.4.2. Cross-Domain Recommendation with FM-Pair. To test the performance of FM-Pair for cross-domain collaborative filtering, we use the dataset of Amazon where the items come from four different domains. We use the two domain of books and music as target domains and use other domains as source domains. The experiments are done with four-fold cross-validation and on each fold only the interactions from the target domain are evaluated. The source domains are used to generate auxiliary features, as described in Section 4.2. Figure 5 illustrates our four-fold cross-validation splitting method on the Amazon dataset with one target domain and three source domains. The design choices and hyper-parameters of the experiment are the same as the ones described in Section 5.3.1 except that for the books domain, the learning rate of the SGD algorithm is set to 0.001 due to its faster convergence.

The following three setups are used to demonstrate the performance of the FM-Pair method for cross-domain recommendations. In all setups, the evaluation is done for the target domain.

— **FM-Pair**: In this setup FM-Pair is only applied on the target domain and source domains are not exploited.

— **FM-Pair-All**: In this setup the source domains are used as additional training samples. Thus, no auxiliary features are generated.

— **FM-Pair-CD**: In this setup source domains are exploited to generate auxiliary features for the training feature vectors in the target domain. In fact, the number of training samples in this setup is the same as the first setup but the feature vectors are expanded with auxiliary features. The value of auxiliary features are defined based on equation (18) and for each user we take at most five feedback from each source domain to avoid large feature vectors.

Table IV lists the performance of the above three setups on the Amazon dataset where domains of books and music are used as target domains. First of all, as you can see in this table, the FM-Pair-CD outperform the other two methods on the accuracy of recommendations. The second interesting observation is that when recommendations are generated for a target domain, using only interactions from that particular domain (setup FM-Pair) is better than using the entire dataset for training (setup FM-Pair-All). Similar effect has been shown in a previous study as well [Loni et al. 2015]: using a sensible subset of data can perform better than using the entire dataset. In fact exploiting the source domains by means of auxiliary features in FM-Pair has a better effect than blindly combining all samples from all domains in one big dataset.

Table IV lists the performance of the above three setups on the Amazon dataset where domains of books and music are used as target domains. First of all, as you can see in this table, the FM-Pair-CD outperform the other two methods on the accuracy of recommendations. The second interesting observation is that when recommendations are generated for a target domain, using only interactions from that particular domain (setup FM-Pair) is better than using the entire dataset for training (setup FM-Pair-All). Similar effect has been shown in a previous study as well [Loni et al. 2015]: using a sensible subset of data can perform better than using the entire dataset. In fact exploiting the source domains by means of auxiliary features in FM-Pair has a better effect than blindly combining all samples from all domains in one big dataset.

![Fig. 5: Illustration of the cross-validation splitting method for the cross-domain recommendation experiment with FM-Pair on the Amazon dataset.](image-url)
Table IV: Performance of cross-domain recommendation with the FM-Pair-CD method compared to the single-domain training scenarios.

| Method / Target Domain | Recall@10 | MRR@10 |
|------------------------|-----------|--------|
|                        | Books     | Music  |
| FM-Pair (Target-only)  | 0.1058    | 0.0966 |
| FM-Pair-All            | 0.0831    | 0.0855 |
| FM-Pair-CD             | 0.1238    | 0.1060 |

5.5. Convergence and Complexity of FM-Pair

In this section we further analyze the convergence and complexity of FM-Pair by monitoring the performance of FM-Pair with different number of iterations (of the training algorithm) and different dimensions of factorization. Figure 6 compares the performance of FM-Pair, FM-Pair-Context and BPR-MF on different number of epochs on the two datasets of Frappe and MovieLens. In Figure 7, we illustrate the performance of cross-domain recommendations with FM-Pair-CD compared to the two setups of FM-Pair and FM-Pair-All on different number of epochs. The models are evaluated on every 10 epoch with Recall@10.

As you can see in Figure 6, on the Frappe and MovieLens dataset all models converge rather fast due to the density of datasets. However, an interesting observation on the Frappe dataset is that FM-Pair and FM-Pair-Context already achieve a high recall after the first few epochs whereas the BPR-MF algorithm converge later and yet cannot achieve FM-Pair’s performance even with higher number of epochs. A closer examination of Section 3.2 and Table II can explain this result. The high recall of the popularity algorithm on the Frappe dataset exhibits a high tendency on popular items in this dataset. On the other hand the presence of bias parameters $w_i$ and $w_j$ in the FM-Pair model can learn such biases, that turns to be very effective on training the model in popularity-skewed datasets such as Frappe. The effectiveness of such bias parameters on CF models have also been shown in previous studies (e.g. [Koren et al. 2009]).

On the two datasets of Amazon, as you can see in Figure 7, the FM-Pair-All converge faster, most likely due to the larger number of training samples, but fails to reach the performance of FM-Pair and FM-Pair-CD. The FM-Pair-CD performs better that the other two methods even with smaller number of epochs and thus it is an effective model to leverage cross-domain auxiliary feature.

In Section 3.1 we showed that the complexity of FM-Pair is linear in dimensionality of factorization (parameter $k$) and the number of auxiliary features ($|z|$). Experimental results also confirms the linearity of FM-Pair. Figure 8 illustrates the influence of the two parameters $k$ (left chart) and $|z|$ (right chart) on the epoch time of different datasets (the effect of parameter $|z|$ is only illustrated on the Frappe datasets since this is the only dataset with multiple context features). The reported epoch time is the average epoch time on four-fold cross-validation experiments and the bars indicate the standard deviation of the four folds. As you can see in the two charts for both parameters the epoch time grows linearly (with small errors) and thus the linearity of FM-Pair can be confirmed.

5.6. Using WrapRec

The implementation of this work is published in the WrapRec toolkit. WrapRec is an open source evaluation framework for recommender systems that can wrap algorithms from different frameworks and evaluate them under same setup. WrapRec is written in C# and can be used in multiple platforms. WrapRec can be used as a command-

ACM Transactions on Intelligent Systems and Technology, Vol. x, No. x, Article xx, Publication date: October 2018.
Fig. 6: Empirical comparison of the convergence of FM-Pair (with or without context) with BPR-MF on the two datasets with auxiliary features.

Fig. 7: Empirical comparison of the convergence of cross-domain CF with FM-Pair compared to the single-domain models on two domains of the Amazon dataset.

Fig. 8: Empirical comparison of the training time of different datasets based on the dimensionality of factorization (left chart) and number of auxiliary features (right chart).

line tool. To use WrapRec all setting need to be defined in one configuration file. The
configuration file specifies the model and its parameters, how the dataset should be read and split, and how the evaluation should be done. The command-line tool can be downloaded from the WrapRec website[10] and can be simply used as:

— (Windows): WrapRec.exe [path-to-config-file]
— (Linux and Mac): mono WrapRec.exe [path-to-config-file]

Details about the format of the configuration file and usage of WrapRec can be found in the WrapRec website. The experiments on this paper can be reproduced by using the configuration file that is defined for the experiments[11].

6. CONCLUSION AND FUTURE WORK

In this work we introduce FM-Pair, an adaptation of Factorization Machines with a pairwise learning-to-rank optimization technique. In contrast to the original model of Factorization Machines, FM-Pair can be used effectively for datasets with implicit feedback, thus addressing a wider range of problems in recommender systems. In this work we show that for ranking problems, FM-Pair is more effective than the standard FMs even on datasets with explicit feedback. FM-Pair leverages a pairwise learning-to-rank method inspired by the Bayesian Personalized Ranking (BPR) criterion, which optimizes the model parameters for ranking. Similar to the standard Factorization Machines, FM-Pair can exploit additional features such as context, user and item attributes, cross-domain information and any discrete or real-valued auxiliary features. In this work we also propose to apply FM-Pair for context-aware and cross-domain collaborative filtering problems. Experimental results on four datasets with implicit or explicit feedback showed the effectiveness of FM-Pair for datasets with implicit or explicit feedback with or without auxiliary features. We showed that when no auxiliary features are exploited FM-Pair is at least as accurate as state-of-the-art methods such as BPR-MF, if not more. However, FM-Pair shines with its ability to easily exploit additional features without any effort to adapt the underlying model. For the two task of context-aware and cross-domain CF we show that FM-Pair is effective on exploiting such features. The model can be trained without much of overhead on training time while considerable improvement can be achieved by exploiting additional features. Comparison of FM-Pair with GPFM, which is also capable of exploiting context features, exhibits superiority of FM-Pair in terms of accuracy and complexity.

In this work we also observed that the trivial implicit-to-explicit mapping is not an effective way of using FMs for learning-to-rank from datasets with implicit feedback. In fact, the standard FMs are not optimized for ranking and even for datasets with explicit feedback, standard FMs are not effective for ranking problems.

We also analyzed the convergence and complexity of FM-Pair in the tested datasets. An interesting observation was the ability of FM-Pair to leverage item biases that turns to be very effective for the Frappe dataset, which is a popularity-skewed dataset. We also empirically show that FM-Pair scales linearly on dimensionality of factorization and number of features.

As a future work, the proposed methods for context-aware and cross-domain CF can be further investigated by studying the effect of selected features on the performance of the recommendations. For example, for the task of cross-domain CF, as we mentioned earlier, the features from source domain can be transferred with several possibilities. In this work the features correspond to items in the source domains. The number and characteristics of the selected items in source domains is subject to further studies.

10 http://wraprec.crowdrec.eu/
11 The configuration file will be release in the WrapRec website.
Similarly, for the task of context-aware recommendation, the contribution of different context features can be adjusted by feature engineering.

In this work we adapted a pairwise optimization technique for Factorization Machines. Further studies can be done to apply other optimization techniques such as list-wise learning-to-rank methods for Factorization Machines.

ACKNOWLEDGMENTS

This work is supported by funding from EU FP7 project under grant agreements no. 610594 (CrowdRec)

REFERENCES

Gediminas Adomavicius and Alexander Tuzhilin. 2011. Context-aware recommender systems. In Recommender systems handbook. Springer, 217–253.

Suhrid Balakrishnan and Sumit Chopra. 2012. Collaborative Ranking. In Proceedings of the Fifth ACM International Conference on Web Search and Data Mining (WSDM ’12). ACM, New York, NY, USA, 143–152. DOI: http://dx.doi.org/10.1145/2124295.2124314

Linas Baltrunas, Karen Church, Alexandros Karatzoglou, and Nuria Oliver. 2015. Frappe: Understanding the Usage and Perception of Mobile App Recommendations In-The-Wild. CoRR abs/1505.03014 (2015). http://arxiv.org/abs/1505.03014

Alejandro Bellogin, Pablo Castells, and Ivan Cantador. 2011. Precision-oriented Evaluation of Recommender Systems: An Algorithmic Comparison. In Proceedings of the Fifth ACM Conference on Recommender Systems (RecSys ’11). ACM, New York, NY, USA, 333–336. DOI: http://dx.doi.org/10.1145/2043932.2043996

Iván Cantador, Ignacio Fernández-Tobías, Shlomo Berkovsky, and Paolo Cremonesi. 2015. Cross-Domain Recommender Systems. Springer US, Boston, MA, 919–959. DOI: http://dx.doi.org/10.1007/978-1-4899-7637-6_27

Paolo Cremonesi, Yehuda Koren, and Roberto Turrin. 2010. Performance of Recommender Algorithms on Top-n Recommendation Tasks. In Proceedings of the Fourth ACM Conference on Recommender Systems (RecSys ’10). ACM, New York, NY, USA, 39–46. DOI: http://dx.doi.org/10.1145/1864708.1864721

Z. Gantner, L. Drumond, C. Freudenthaler, S. Rendle, and L. Schmidt-Thieme. 2010. Learning Attribute-to-Feature Mappings for Cold-Start Recommendations. In Data Mining (ICDM), 2010 IEEE 10th International Conference on. 176–185. DOI: http://dx.doi.org/10.1109/ICDM.2010.129

Weiyu Guo, Shu Wu, Liang Wang, and Tieniu Tan. 2016. Personalized ranking with pairwise Factorization Machines. Neurocomputing 214 (2016), 191 – 200. DOI: http://dx.doi.org/10.1016/j.neucom.2016.05.074

Liang Hu, Jian Cao, Guangdong Xu, Longbing Cao, Zhiping Gu, and Can Zhu. 2013. Personalized recommendation via cross-domain triadic factorization. In Proceedings of the 22nd international conference on World Wide Web (WWW ’13). International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, Switzerland. http://dl.acm.org/citation.cfm?id=2488388.2488441

Yifan Hu, Yehuda Koren, and Chris Volinsky. 2008. Collaborative Filtering for Implicit Feedback Datasets. In Proceedings of the 2008 Eighth IEEE International Conference on Data Mining (ICDM ’08). IEEE Computer Society, Washington, DC, USA, 263–272. DOI: http://dx.doi.org/10.1109/ICDM.2008.22

Yuchin Juan, Yong Zhuang, Wei-Sheng Chin, and Chih-Jen Lin. 2016. Field-aware Factorization Machines for CTR Prediction. In Proceedings of the 10th ACM Conference on Recommender Systems (RecSys ’16). ACM, New York, NY, USA, 43–50. DOI: http://dx.doi.org/10.1145/2959100.2959134
Alexandros Karatzoglou, Xavier Amatriain, Linas Baltrunas, and Nuria Oliver. 2010. Multiverse Recommendation: N-dimensional Tensor Factorization for Context-aware Collaborative Filtering. In Proceedings of the Fourth ACM Conference on Recommender Systems (RecSys ’10). ACM, New York, NY, USA, 79–86. DOI: http://dx.doi.org/10.1145/1864708.1864727

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 (KDD ’08). ACM, New York, NY, USA, 426–434. DOI: http://dx.doi.org/10.1145/1401890.1401944

Yehuda Koren, Robert Bell, and Chris Volinsky. 2009. Matrix Factorization Techniques for Recommender Systems. Computer 42, 8 (Aug. 2009), 30–37. DOI: http://dx.doi.org/10.1109/MC.2009.263

Jure Leskovec, Lada A. Adamic, and Bernardo A. Huberman. 2007. The dynamics of viral marketing. ACM Trans. Web 1, 1, Article 5 (May 2007). DOI: http://dx.doi.org/10.1145/1232722.1232727

Babak Loni, Martha Larson, Alexandros Karatzoglou, and Alan Hanjalic. 2015. Recommendation with the Right Slice: Speeding Up Collaborative Filtering with Factorization Machines. In RecSys Posters.

Babak Loni and Alan Said. 2014. WrapRec: An Easy Extension of Recommender System Libraries. In Proceedings of 8th ACM International Conference of Recommender Systems (RecSys ’14).

Babak Loni, Yue Shi, Martha Larson, and Alan Hanjalic. 2014. Cross-Domain Collaborative Filtering with Factorization Machines. In Proceedings of the 36th European Conference on Information Retrieval (ECIR ’14).

Trung V. Nguyen, Alexandros Karatzoglou, and Linas Baltrunas. 2014. Gaussian Process Factorization Machines for Context-aware Recommendations. In Proceedings of the 37th International ACM SIGIR Conference on Research & Development in Information Retrieval (SIGIR ’14). ACM, New York, NY, USA, 63–72. DOI: http://dx.doi.org/10.1145/2600428.2609623

S. Rendle. 2010. Factorization Machines. In Data Mining (ICDM), 2010 IEEE 10th International Conference on. DOI: http://dx.doi.org/10.1109/ICDM.2010.127

Steffen Rendle. 2012. Factorization Machines with libFM. ACM Trans. Intell. Syst. Technol. 3, 3, Article 57 (May 2012), 22 pages. DOI: http://dx.doi.org/10.1145/2168752.2168771

Steffen Rendle and Christoph Freudenthaler. 2014. Improving Pairwise Learning for Item Recommendation from Implicit Feedback. In Proceedings of the 7th ACM International Conference on Web Search and Data Mining (WSDM ’14). ACM, New York, NY, USA, 273–282. DOI: http://dx.doi.org/10.1145/2556195.2556249

Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2009. BPR: Bayesian Personalized Ranking from Implicit Feedback. In Proceedings of the Twenty-Fifth Conference on Uncertainty in Artificial Intelligence (UAI ’09). AUAI Press, Arlington, Virginia, United States, 452–461. http://dl.acm.org/citation.cfm?id=1795114.1795167

Steffen Rendle, Zeno Gantner, Christoph Freudenthaler, and Lars Schmidt-Thieme. 2011. Fast context-aware recommendations with factorization machines. In Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval (SIGIR ’11). ACM, New York, NY, USA. DOI: http://dx.doi.org/10.1145/2009916.2010002

Paul Resnick, Neophytos Tacovou, Mitesh Suchak, Peter Bergstrom, and John Riedl. 1994. GroupLens: An Open Architecture for Collaborative Filtering of Netnews. In Proceedings of the 1994 ACM Conference on Computer Supported Cooperative Work (CSCW ’94). ACM, New York, NY, USA, 175–186.
Ruslan Salakhutdinov and Andriy Mnih. 2008. Probabilistic Matrix Factorization. In Advances in Neural Information Processing Systems, Vol. 20.

Yue Shi, Martha Larson, and Alan Hanjalic. 2013. Mining Contextual Movie Similarity with Matrix Factorization for Context-aware Recommendation. ACM Trans. Intell. Syst. Technol. 4, 1, Article 16 (Feb. 2013), 19 pages. DOI: http://dx.doi.org/10.1145/2414425.2414441

Yue Shi, Martha Larson, and Alan Hanjalic. 2014. Collaborative Filtering Beyond the User-Item Matrix: A Survey of the State of the Art and Future Challenges. ACM Comput. Surv. 47, 1, Article 3 (May 2014), 45 pages. DOI: http://dx.doi.org/10.1145/2556270

Yu Zhang, Xiaomin Zhu, and Qiwei Shen. 2013. A recommendation model based on collaborative filtering and factorization machines for social networks. In Broadband Network Multimedia Technology (IC-BNMT), 2013 5th IEEE International Conference on. 110–114. DOI: http://dx.doi.org/10.1109/ICBNMT.2013.6823925