# I. INTRODUCTION

Recommendation systems are very useful because they can help users find products according to their preferences. Traditional recommendation systems often face the problem of data sparsity, which is the lack of information in a dataset that reduces prediction accuracy. In addition, the cold-start problem is also an important problem because each new user does not have enough interaction and makes it difficult for the system to provide recommendations [1].

To overcome this problem is to use Cross-Domain Recommendation (CDR). By using knowledge from a domain, CDR can enrich the existing information. In CDR, knowledge in the source domain is used to improve prediction performance in the target domain. In this way, the CDR model can overcome the problem of data sparsity.

The main challenge in CDR is the transfer of knowledge from the source domain to the target domain. To transfer knowledge, overlapping entities are required between the two domains used. These entities can be users or overlapping items [1]. EMCDR is a CDR method that has been proven effective and is commonly used. EMCDR consists of the embedding and mapping processes. Embedding will produce latent representations of users and items in the source domain and target domain. The latent representation of users will be mapped from the source domain to the target domain to optimize the transfer process [2].

There are two types of mapping available, namely linear and non-linear mapping. Linear mapping as developed by Mikolov et al. [3] is done by using a simple mapping to change the representation vector from the source domain to the target domain. Linear mapping is able to work well and efficiently if the data used between the two domains has a similar structure. This linear mapping has the disadvantage that it is difficult to capture complex relationships between two different domains [3].

Another mapping is non-linear mapping that uses neural networks such as Multilayer Perceptron (MLP). This mapping allows more complex modeling to be performed. Non-linear mapping is able to capture non-linear patterns, which makes this mapping suitable for data with high variation, such as the Amazon Review dataset. The disadvantages of this mapping are the potential for overfitting and large computational resources [4].

In previous research, we have not found any research that discusses hyperparameter tuning in the EMCDR method, especially on the Amazon Review dataset. This study aims to address evaluate the hyperparameter configuration in the EMCDR method. The embedding process was carried out using Matrix Factorization and non-linear mapping with MLP. To simulate CDR, we use Amazon Fashion as source domain and All Beauty and the target domain. Through this study, it will be seen how hyperparameter variations affect prediction performance within the CDR.