Adaptive Multi-view Rule Discovery for Weakly-Supervised Compatible Products Prediction

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ABSTRACT

On e-commerce platforms, predicting if two products are compatible with each other is an important functionality to achieve trustworthy product recommendation and search experience for consumers. However, accurately predicting product compatibility is difficult due to the heterogeneous product data and the lack of manually curated training data. We study the problem of discovering effective labeling rules that can enable weakly-supervised product compatibility prediction. We develop AMRule, a multi-view rule discovery framework that can (1) adaptively and iteratively discover novel rulers that can complement the current weakly-supervised model to improve compatibility prediction; (2) discover interpretable rules from both structured attribute tables and unstructured product descriptions. AMRule adaptively discovers labeling rules from large-error instances via a boosting-style strategy, the high-quality rules can remedy the current model’s weak spots and refine the model iteratively. For rule discovery from structured product attributes, we generate composable high-order rules from decision trees; and for rule discovery from unstructured product descriptions, we generate prompt-based rules from a pre-trained language model. Experiments on 4 real-world datasets show that AMRule outperforms the baselines by 5.98% on average and improves rule quality and rule proposal efficiency.

CCS CONCEPTS

• Computing methodologies → Rule learning; • Applied computing → Online shopping.

KEYWORDS

Rule Discovery, Weak Supervision, Compatible Products

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1 INTRODUCTION

The prevalence of bundle items on e-commerce and content platforms makes identifying compatible products become an important task. The product compatibility prediction problem aims to predict if two products are functionally compatible with each other. Figure 1 shows a concrete example on The Home Depot online platform. To ensure a chandelier and a bulb are compatible, it is required that their lighting technologies are matched and the wattage is within-range—all such information needs to be inferred from their product data. Accurate compatible products recommendation is critical to e-commerce platforms, as this functionality is key to ensuring trustworthy and reliable customer experiences in product search recommendation.

Despite the importance of this task, accurate product compatibility prediction is challenging due to two key reasons: 1) the lack of manually curated data to train an accurate classifier; and 2) the heterogeneity of product data. First, we typically do not have
clean labeled data for learning a product compatibility predictor. Manually labeling compatible products is very time-consuming, because the annotators need to inspect the high-dimension product attributes and compare multiple entries between anchor products and recommendation products. Although one may resort to user behaviors such as co-purchase records as pseudo-positive labels, these data could be noisy because co-purchase behavior does not always reflect compatibility of two items. Second, the representation of products includes both structured product attributes and unstructured product descriptions, where product attributes have high cardinality, and the product description is not an ideal source for mining the buried compatibility. In practice, the compatibility rules are written by domain experts in The Home Depot. Although more efficient than labeling individual data points, the process of developing rules still requires intensive human labor, and most of the human-written rules just consider one product attribute while ignoring high-order association of product attributes.

Compatible product prediction is mainly related to two lines of work in literature. One line of work is weakly-supervised learning (WSL), which has shown promising results in addressing label scarcity in various tasks including text classification [1, 28, 37, 44], dialogue systems [26], and fraud detection [39]. However, the performance of WSL approaches is often hindered by the low quality of the initial rules and the static learning process [42]. For the initial rules, either the human-written rules [12, 29] requires tedious and time-consuming creation, or the automatically discovered rules [32] are restricted to frequent patterns and predefined types which are inadequate for training an accurate model. For the static learning process used in [28, 29, 44], the performance of these methods largely depends on the quality of the initial weak sources. When the quality of the weak labels is poor, the incorrect weak labels can result in error propagation and deteriorate the model’s performance. To improve the quality of the rules, interactive rule discovery [2, 9, 15] has been explored to iteratively refine the rule set using human guidance. However, [2] only discover simple rules with a repetitive structure given by a pre-defined rule family, and [9] uses an enumerating-pruning approach to search rules, which is inapplicable for large corpus.

The second line is pattern-based classification [5, 6, 30]. Classical approaches construct a pattern pool based on pattern frequency and then select the most discriminative patterns via heuristics [5, 8]. However, the large pattern pool makes the computation inefficient, and the number of selected patterns limits the interpretability. To tackle the drawbacks, Shang et al. [30] proposes to generate prefix paths in tree-based models and further compress the number of patterns by selecting the most effective ones. Liu et al. [20] prune unnecessary features from tree ensembles using a weighted LASSO-based method. Although these methods improve the interpretability and efficiency, they have not explored the weakly supervised settings, under which we aim to discover compatibility rules and perform compatible products prediction.

We propose an adaptive multi-view rule discovery framework AMRULE for weakly-supervised compatible products prediction. Our approach overcomes the aforementioned challenges with the following key designs:

- To address the label scarcity issue of product compatibility prediction, we leverage user behavior data as the supervision source to generate weakly labeled instances. Specifically, we use co-purchase data to generate positive labels and randomly sample product pairs from the anchor categories and the recommendation categories as negative labels.
- To avoid error propagation caused by the imperfect initial weak source, we design a boosting strategy to iteratively target rule discovery on difficult instances. In each iteration, we reweigh data by boosting error to enforce the rule discovery module to focus on larger-error instances. We prevent enumerating massive possible rules and post-filtering for novel rules, but directly propose rules based on large-error instances to provide complementary information to the current model.
- To handle the complex input of products, we propose a multi-view rule discovery framework, where we integrate two rule representations based on structured and unstructured data. Specifically, we design a decision tree-based rule generation method where the key product attributes are selected to form a composable rule. As the product attributes are high-cardinality and not consistent between product pairs, we further leverage product description to generate a fallback rule, where the rules are generated by prompting pre-trained language models (PLMs) to capture the hidden semantics in the unstructured text-format description.

We conduct extensive experiments on the Home Depot real datasets across four categories of products. The results show that 1) the proposed method outperforms all the baselines, including static approaches and iterative approaches; 2) The boosting strategy is effective in discovering novel rules by targeting hard instances iteratively; 3) The multi-view rule discovery design is effective, and the rules generated from structured attributes and unstructured descriptions can complement each other; 4) Our rule discovery pipeline improves the interpretability and annotation efficiency.

Our main contributions can be summarized as follows: 1) a user behavior-based approach for weakly supervised compatible product prediction; 2) a multi-view rule discovery design integrating structured and unstructured data representation; 3) an iterative and adaptive rule discovery framework via model boosting; 4) comprehensive experiments on real-world datasets verifying the efficacy of our method.

2 RELATED WORK

Weakly Supervised Learning. The weak supervision learning (WSL) frameworks provided a solution to truly reduce the efforts of annotation [29]. Specifically, in WSL, users encode weak supervision sources, e.g., heuristics, knowledge bases, and pre-trained models, in the form of labeling functions (LFs), which are user-defined programs that each provide labels for some subset of the data, collectively generating a large set of training labels [41]. Weak supervision methods have been widely applied in various domains including text classification [1, 28, 36, 40, 43], dialogue systems [26].

The success of the WSL paradigm has attracted much attention from the industry. For example, Tang et al. [31] deploy an image understanding system in Facebook Marketplace, where the user
interactions in search logs serve as weak supervision sources for linking text-format queries to images and enables the curation of a large-scale image understanding task. However, they focus on how to leverage the weak signals in the user interaction data without denoising the weak supervision source. Xiao et al. [34] study weakly supervised query rewriting and semantic matching for e-commerce platforms, they also leverage search logs to build an unlabeled dataset. They propose a co-training framework where two models for different tasks generate weak labels for each other to boost their performance simultaneously. Zhan et al. [38] explore multi-modal product retrieval on e-commerce dataset. They generate pseudo-labels for the image-text pairs by a copy-and-paste data augmentation approach, and overcome the fuzzy correspondence between modalities via contrastive learning. Despite the successful deployment of these methods, they are tailored for specific applications and thus cannot be transformed to the compatibility prediction task. Their end-to-end learning paradigm also sacrifices the interpretability of the framework, but in our task, we aim for model performance improvement and also interpretability of the weakly labeled data.

**Rule Discovery.** Most work of WSL relies on the human-written rules as weak sources, but manually designing the rules can be tedious and time-consuming. To alleviate human efforts in the rule discovery process, a few works attempt to discover rules from data. For example, Snuba [32] automatically generates rules using a small labeled dataset to create weak labels for another large, unlabeled dataset; TagRuler [7] also proposes an automatic creation of labeling functions based on the human demonstration for span-level annotation tasks. However, these methods constrain the rules to task-specific types and the rule set cannot be modified once proposed. Instead, we integrate multiple views of rules for the heterogeneous data and design an adaptive rule discovery framework, which iteratively complements the existing rule set. Two works have studied interactive WSL [2, 9] as in our problem. However, they either use simple n-gram-based rules [2] that are not applicable to our problem, or suffer from a huge searching space for context-free grammar rules [9]. Although [42] also leverage prompt for rule generation, it mainly focuses on textual data, and cannot be well applied to our scenarios where both the structured and unstructured features exist. In contrast, our proposed multi-view rules consider both structured and unstructured information of products, and the adaptive rule discovery process avoids enumerating all possible rules and performing post-filtering for novel rules.

**Prompting Methods for Pre-trained Language Models.** The rule discovery component in our work is also related to prompting methods for PLMs. The prevailing prompting methods modify the original input text into a string with unfilled slots, from which the final prediction can be derived [3, 21]. It enables PLMs to adapt to new scenarios with few or no labeled data [4, 11, 16, 18, 19]. Recent works explore learning implicit prompt embedding via tuning the original prompt templates [10, 22, 23, 33]. Instead of tuning prompts to achieve optimal performance for the original task, we leverage prompts and PLMs to assist the multi-view rule discovery. Moreover, none of these works studied prompting to generate weak labels for WSL as we have.

### 3 PRELIMINARIES

Compatible products prediction underpins the recommendation of sale bundles on e-commerce websites. We first introduce the representation of products here. Given a product category $X_a$ and a specific product $x_a \in X_a$, the representation of $x_a$ includes two parts: the structured product attributes $w_a = \{w_{a,1}, w_{a,2}, \cdots, w_{a,n}\}$, and the unstructured product description $r_a$. For a product category $X_a$, there is an attribute set $W_a$, such that $\forall x_a \in X_a, w_a \in W_a$.

Besides, we leverage the item-level co-purchase data as the weak supervision source. Each entry in the item-level co-purchase data is a tuple $(x_a, x_b, v)$, where $v$ is the co-purchase times. Note that the records in co-purchase data are not necessarily compatible products, users could purchase two items together for other reasons rather than compatibility. Now we give definitions of the task:

**Definition 3.1 (Compatible products prediction).** For two mutually exclusive product corpus $X_a$ and $X_b$, given an anchor product $x_a \in X_a$ and a recommendation product $x_b \in X_b$, we aim to predict the label $y \in \{1, -1\}$ indicating whether the product pair can be functionally used together without conflict.

Because the dataset curation involves user behavior data as weak supervision signals, it is necessary to generate more high-quality labeled data via a reliable source to suppress the noise in the initial dataset. For the compatible product prediction task, compatibility rules (labeling rules) are a reasonable way to capture the relevance between the product attributes of the product pairs. We formally introduce labeling rules in this problem here.

**Definition 3.2 (Labeling rules).** Given an unlabeled product pair $(x_a, x_b)$, a labeling rule $r(\cdot)$ maps it into an label space: $r(x_a, x_b) \rightarrow y \in Y \cup \{0\}$. Here $Y = \{1, -1\}$ is the original label set for the task, and $\{0\}$ is a special label indicating $(x_a, x_b)$ is unmatchable by $r(\cdot)$. We also perform conjunction operation over atomic rules, which yields higher-order rules to capture the composable patterns.

**Problem Formulation.** We have an unlabeled dataset $D_u$ and a weakly labeled dataset $D_t$, where $D_t$ is generated from user behavior data thus could be noisy and incomplete. Our goal is to iteratively discover labeling rules from $D_t$ to improve the weakly supervised model performance. In each iteration $t$, the high-quality rules $R_t$ are used to create new weakly labeled instances $D_t$ from $D_u$. Using the augmented weakly labeled dataset $D_t \cup D_t$, we train a model $m_t : (X_a, X_b) \rightarrow Y$. We aim to obtain a final model $f_0(\cdot) : (X_a, X_b) \rightarrow Y$ from the preceding models $\{m_t\}_{t=1}^T$ and provide interpretability by the generated rules $\{R_t\}_{t=1}^T$.

### 4 METHODOLOGY

In practice, the clean data for compatible products prediction are often unavailable, and we rely on user behavior data to generate the weakly labeled dataset $D_t$. Considering the noise and incompleteness of $D_t$, training a machine learning model directly on $D_t$ will yield suboptimal results. To this end, we design a boosting-style rule proposal framework to target the hard instances iteratively and propose rules adaptively. For the rule representation, we leverage information from structured product attributes and unstructured product descriptions. Such a multi-view rule generation will improve the coverage of rules while maintaining a high-precision matching.
4.1 Adaptive Rule Proposal via Boosting

We adaptively target the candidate rule generation on hard instances via a boosting-style [13] strategy. The intuition of the adaptive rule proposal is two-fold: First, the co-purchase data includes false positive samples for compatibility prediction because the frequently co-purchased product pairs are not necessarily compatible products. We aim to summarize compatibility rules from such a weak source and implement a more precise matching on the unlabeled data to improve the quality of the training set. Second, the model could be weak in certain feature regimes, we thus iteratively check such regimes by updating the data weights and propose candidate rules accordingly.

As Figure 2 shows, the adaptive rule discovery is enabled by identifying hard instances on the labeled dataset $D_l$. Through the identified hard instances where the model tends to make cumulative mistakes during the iterative learning, the discovered rules can complement the current rule set $R$ and suppress the noise in the initial weak source by adding more high-quality rule-matched data, so the next model $m_{t+1}$ trained on the refined weakly labeled dataset can be improved adaptively.

Specifically, we start from the weights initialization of the instances in $D_l$ as

$$w_i = 1/|D_l|, \quad i = 1, 2, \ldots, |D_l|.$$  

During the iterative model learning process, each $w_i$ is updated as the model’s weighted loss on instance $x_i \in D_l$. In iteration $t \in \{1, \ldots, T\}$, we first compute a weighted error rate $\text{err}_t$ on $D_l$ by

$$\text{err}_t = \frac{\sum_{i=1}^{|D_l|} w_i \cdot \mathbb{1}(y_i \neq m_t(x_i))}{\sum_{i=1}^{|D_l|} w_i},$$  

(2)

(3)

(4)

(5)

(6)

(7)

Figure 2: The boosting strategy used in AMRule for adaptive rule proposal. The current model $m_t$ identifies the large error instances from the labeled dataset.

4.2 Multi-View Rule Generation

AMRule generates rules from two views: 1) the structured product attributes and 2) the unstructured product descriptions. Product attributes provide a better alignment between product pairs being judged for compatibility. When the product attributes are filled relatively completely (i.e., with just a few missing values), it is ideal to apply attribute-based rules to obtain a precise match of compatible product pairs. However, the product attributes are of high-cardinality — If the unlabeled instances miss some product attributes, it will make rule matching difficult. We thus further leverage product description to generate fallback rules. This view complements product attributes by providing text-format descriptions, where we use the sparse product attributes to construct prompt templates in the expectation of obtaining supplementary information from product descriptions via prompting pre-trained language models. Although the single use of prompt-based rules may be noisy to capture the compatibility, it can serve as a fallback to improve the rule coverage when the attribute-based rules are unmatched.

4.2.1 Rule Discovery from Structural Attributes with Decision Trees.

To handle the categorical attributes and numerical attributes in the structural representation of products, we first design three prototypes to capture the compatibility: 1) exact matched categorical values, 2) within-range numerical values 3) stand-alone attribute. Table 1 shows concrete examples of these rules. To express such relations among product attributes, we naturally construct a concatenated input $x$ from the pairwise anchor products $x_a$ and recommendation products $x_b$:

$$x = [x_a \oplus x_b \oplus (x_a' - x_b')],$$

(5)

where $x_a', x_b'$ are the shared features of two products, i.e., the product attributes names in $x_a', x_b'$ are the same.

We first base the decision tree generation on the large-error instances identified by the updated data weights:

$$D_t = \{x_j\}_{j=1}^n \quad \text{s.t.} \quad \{w_j\}_{j=1}^n = \text{Top-n } w_i.$$  

(6)

To select features as the atomic unit of rules, we compute the permutation importance of each feature. We denote the $i$-th feature of the input $x$ as $f_i$, and we have a evaluation metric $\phi(m_t, D_t)$ to measure the performance of model $m_t$ on dataset $D_t$. For each $k$ in 1, $\ldots$, $K$, where $K$ is the repeat times, we first compute the $k$-th score using the same evaluation metric:

$$\phi_{k,t} = \phi(m_t, D_{t,k}).$$  

(7)
Here $D_{t,i'}$ indicates the dataset $D_t$ with the $i$-th column randomly shuffled. Then the permutation importance of feature $f_i$ can be computed by:

$$\mu_i = \phi(m_t, D_{t}) - \frac{1}{K} \sum_{k=1}^{K} \phi_{k,i}.$$  

(8)

Such permutation importance indicates whether a feature should be selected as the atomic unit of the rules, and we select the top-$b$ features according to the permutation importance to form the rules. The selected candidate rules will be evaluated in the following stage. For example, for the features belonging to $(x_{a}^t - x_{b}^t)$, we examine if the categorical values equal to 0, which indicates an exact match as one of the rule prototypes. For the numerical values, we output an inequality sign during rule-level annotation. We introduce details in Section 4.3.

Though low-bias, the generated decision trees could be highly variant on the small size of identified error instances. Thus the candidate rules consisted of important nodes on the trees need to be further evaluated by humans. Moreover, the selected features may correspond to some sparse product attributes. When a quite number of features are filled with placeholder values, it is hard to summarize insightful information from the product attributes. Even we generate rules from such features, only a few unlabeled instances can be matched with these rules. To this end, we introduce the following prompt-based rules to handle the sparse but important product attributes.

### 4.2.2 Rule Discovery from Unstructured Descriptions with Prompting

Although decision tree-based rules are capable of matching unlabeled instances by checking product attributes, the high cardinality of attributes makes the rule generation and rule matching process sometimes nontrivial. In this case, we further leverage product descriptions to propose prompt-based rules as fallback rules. Specifically, we construct rule templates based on the sparse product attributes selected from the previous step. For example, we denote the selected sparse feature as $f'$, the product names of product A and B are $n_a, n_b$, and the product description of them are $\text{Desc}_a, \text{Desc}_b$. Then the rule prompt can be constructed from a template, where the original product descriptions and the selected product attribute are connected by some template words. We show a concrete example in Table 2.

In this way, we provide the context from the product description and prompt the PLMs to fill the $\text{[MASK]}$ token. By filling the masked slot in the prompt, PLMs propose candidate keyword-based rules for topic classification. Different from the rules extracted from surface patterns of the corpus (e.g., $n$-gram rules), such a prompt-based rule proposal can generate words that do not appear in the original inputs—this capability is important to model generalization.

Given the selected sparse feature $f'$ and a large-error instance $x_e \in D_t$ such that $x_e$ miss a original value for the feature $f'$, we first convert it into a prompt $x_p$ by the rule template above, which consists of product descriptions of the original input pair and the compatibility label, as well as a $\text{[MASK]}$ token to be predicted by a PLM $M$. To complete the rule, we feed $x_p$ to $M$ to obtain the probability distribution of the $\text{[MASK]}$ token over the vocabulary $\mathcal{V}$:

$$p(\text{MASK} = \hat{v} | x_p) = \frac{\exp (\hat{v} \cdot M(x_p))}{\sum_{v \in \mathcal{V}} \exp (v \cdot M(x_p))},$$

(9)

where $M(\cdot)$ denotes the output vector of $M$. We use the prediction with highest $p(\text{MASK} = \hat{v} | x_p)$ to form the candidate rules. By filling the rule template of $x_e$ with its prompt prediction, we obtain a candidate prompt-based rule. Integrated with the proceeding decision tree-based rules, we obtain the rule set in iteration $t$, denoted as $R_t = \{r_j\}_{j=1}^b$. Here the number $b$ is same as the number of selected features. In other words, for each selected important feature, we generate a rule either by the decision tree or the prompt.

### 4.3 Rule Annotation and Rule Matching

The candidate rule set $R_t$ is just one step away from the rule matching stage. Note that the selected features just specify the column on the product attribute table, so we need a concrete value for each feature to complete the rule. AMRULE thus presents $R_t$ to humans for evaluation, which can yield a set of positive rules. Specifically, for each candidate rule $r_j \in R_t$, humans can make a decision from the following options: 1) Exact match: This operation is set for the features belonging to $(x_{a}^t - x_{b}^t)$. For example, the base code of chandelier and lighting bulb should be an exact match to be compatible. 2) Range: This operation is set for the features in $(x_{a}^t \oplus x_{b}^t)$. For example, the bulb wattage should be lower than the maximum wattage. 3) Contain: This operation is set for the features in $(x_{a}^t \oplus x_{b}^t)$. It does not require a pairwise relation between the product pair, but requires the selected attribute of one product to have its original value instead of a filled placeholder. 4) Abstain: Human annotators can reject this rule due to its poor quality.

After the rule-level annotation, the accepted rules will be used for weak label generation via rule matching. We compute a matching score weighted by the feature importance to decide if an unlabeled product pair should be assigned a weak positive label. The matching score is computed in two steps. First, for the decision tree-base

| Dataset | Anchor Category | Rec. Category | Rule Example 1 | Rule Example 2 |
|---------|-----------------|--------------|----------------|----------------|
| Lighting | Lighting Fixture | Light Bulbs | Compatible Bulb Type = Lighting Technology | Maximum Bulb Wattage >= Wattage |
| Appliance | Refrigerator | Water Filter | Walter Filter Replacement Model# = Model# | Brand Name = Brand Compatibility |
| Bathroom | Vanities | Faucets | Color Family = Color Family | Faucet Not Included |
| Tools | Power Tools | Batteries | Battery Power Type = Battery Power Type | Voltage <= Voltage |

Table 1: The examples of decision tree-based rules. The rules typically consist of two product attributes, one from the anchor product and another from the recommendation product. For example, "Battery Power Type = Battery Power Type" indicates a categorical equivalence for two attributes with the same name; "Maximum Bulb Wattage >= Wattage" indicates a numerical range for two different attributes. We also present a case where only one product attribute is considered. As the rule example 2 of Bathroom shows, when the "Faucet Not Included" attribute is true for vanities, we do not match it with other faucets.
rules, we only need to check the hard match of the specific product attributes. If matched, the score will be accumulated with the corresponding feature importance:

\[ s^d_{t,j} = \mu_j \delta(r_j = f^w_{j}), \]

where \( f^w_{j} \) is the \( j \)-th feature of the unlabeled instance.

However, as we mentioned above, some attributes could be sparse among the corpus, thus resulting in difficulty for matching. As a fallback, the prompt-based rules are exactly proposed for this situation by checking the semantic similarity in the product descriptions. The integration of the both views of rules is enabled by the computation of prompt matching score. We first feed \( r(x^u_{t}) \) into the prompting model (Equation 9) and use the to obtain the prompt of instance \( x^u_{t} \). Then we compute the prompt matching score:

\[ s^{p}_{t,j} = \mu_j \frac{e^u_{t} \cdot e^f_{j}}{\|e^u_{t}\| \cdot \|e^f_{j}\|}, \]

where \( e^u_{t} \) is the prompt embedding of \( x^u_{t} \) and \( e^f_{j} \) is the rule embedding of \( r_j \), both embeddings are obtained from a PLM encoder. Next, we compute the final matching score by merging decision tree-based rules and the prompt-based rules:

\[ s_{t,j} = \sum_{j=1}^{b} (s^d_{t,j} + s^{p}_{t,j}) = \sum_{j=1}^{b} \mu_j \delta(1(r_j = f^w_{j}) + \frac{e^u_{t} \cdot e^f_{j}}{\|e^u_{t}\| \cdot \|e^f_{j}\|}). \]

### 4.4 Model Learning and Ensemble

Figure 3 shows how we proceed from rule matching to the model learning and ensemble. Specifically, in iteration \( t \), with the new rule-matched dataset \( D_t \), we fit a weak model \( m_t \) on \( D_t \) by optimizing:

\[ \min_{\theta} \frac{1}{|D_t|} \sum_{(x_i, y_i) \in D_t} \ell_{CE} (m_t(x_i), \hat{y}_i), \]

where \( \hat{y}_i \) is the weak label for instance \( x_i \), and \( \ell_{CE} \) is the cross entropy loss.

Finally, we incorporate the newly trained weak model into the ensemble model. The final model is a weighted ensemble of the proceeding models:

\[ f_0() = \sum_{t} a_t m_t, \]

### 5 EXPERIMENTS

#### 5.1 Experiment Setup

##### 5.1.1 Data

We create four benchmarks for compatible product prediction from real-world data obtained from homedepot.com. Each dataset consists of 5k product pairs sampled from a specific anchor product category and a specific recommendation product category.

To provide a comprehensive evaluation, the product categories covered in the four datasets are selected as diverse as possible, including 1) Lighting: Lighting Fixture and Light Bulbs; 2) Appliance: Refrigerators and Water Filters; 3) Bathroom: Vanities and Faucets; 4) Tools. Power Tools and Batteries. To avoid the expensive human annotation process, we use co-purchase data as the weak source to sample positive instances. Given the specific category pair, we can query the compatible products from the highly-frequent co-purchase product pairs. For the negative instances, we randomly sample product pairs from the same category, but use the co-purchase data to filter out those possible compatible products. Although such a process can introduce noise, our annotators with domain expertise The Home Depot, the co-purchase data can be regarded as a reliable weak source.

##### 5.1.2 Evaluation Protocol

For the 5k weakly labeled dataset generated from co-purchase data, we use the ratio 7:1:5:1.5 to split
train, validation and test set. Besides, we have a hold-out 5k dataset for querying labels in AL settings or matching unlabeled instances by AMRule. To make a convincing test set, we use a higher co-purchase score to distinguish the data quality between the test set and the training set, thus making the test set derived from user behavior data, though weakly supervised, still a reasonable proxy for measuring compatibility. We use classification accuracy as the evaluation metric.

5.1.3 Baselines. We compare our method with the following baselines: **MLP**: A multi-layer perceptron classifier with 2 hidden layers. **DPClass-F** [30]: It implements pattern-based classification by mining discriminative patterns from the prefix paths in random forest. It selects patterns with the biggest improvement of the training classification accuracy. **DPClass-L** [30]: A variant of DPClass. Its pattern selection is based on an L1 regularization term. **Self-training** [17]: It is the vanilla self-training method that generates pseudo labels for unlabeled data. **Entropy**-based active learning [14, 35]: It is an uncertainty-based method that acquires annotations on samples with the highest predictive entropy. **CAL** [27] is the most recent AL method for pre-trained LMs. It calculates the uncertainty of each sample based on the KL divergence between the prediction of itself and its neighbors’ prediction.

5.1.4 Implementation Details. We use a MLP with 2 hidden layers as the classifier in all experiments. For the optimizer, we use AdamW [25] and choose learning rate from $\{2 \times 10^{-3}, 1 \times 10^{-4}, 5 \times 10^{-5}\}$. For the decision tree, we search the depth between $[3, 10]$ with an interval of $1$. For the PLM, we choose RoBERTa-base [24] for rule discovery with prompting. We keep the number of iterations as $10$ for all the tasks and the annotation budget $b = 10$ in each iteration. For iterative baselines, we query $300$ data points in each iteration. We set the repetition time $K = 10$ for the feature importance calculation.

5.2 Main Result

Table 3 reports the performance of AMRule and the baselines on the 4 benchmarks. The results demonstrate AMRule consistently outperforms baselines on all the four datasets. AMRule significantly outperforms its underlying MLP, the improvement on four datasets are $7.33\%$, $5.85\%$, $5.55\%$, $5.22\%$, respectively. Compared to the strongest interactive learning baseline CAL, AMRule still holds a $0.93\%$ lead averaged on the four datasets. The performance improvement to self-training baseline ranges from $1.00\%$ ~ $2.34\%$, which demonstrates the advantage of our adaptive rule discovery for enhancing WSL over the vanilla weak label generation paradigm.

We present the iterative performance in Figure 4, compared with the baselines that also feature iterative learning. We observed AMRule outperforms the other iterative methods consistently in each iteration. It is worth noting that AMRule also reduces much annotation cost compared to the iterative baselines, which adopt the instance-level annotation. For the rule-level annotation in AMRule, it takes each annotator nearly $100$ seconds to annotate $10$ candidate rules, which is just $2\%$ of the instance-level annotation time for $500$ unlabeled points in each iteration.

We notice that the performance improvement varies by product category. For the Bathroom dataset, the baseline CAL performs closely to AMRule, while the performance on other datasets presents a large margin between AMRule and baselines. It is because compatibility rules vary by product category. For example, the Bathroom dataset takes vanities and faucets as the anchor and recommendation product category. During the rule discovery process, we find the candidate rules focus on a few product attributes, which describe colors and dimensions. In contrast, when the rule discovery provides a diverse candidate rule set where different product attributes are covered, more unlabeled instances will be covered during the rule matching stage, thus the end model presents a stronger performance over the baselines.

5.3 Analysis of the Multi-view Rules

In this set of experiments, we study the effect of different views of rules in AMRule. Figure 5 verifies the advantage of the multi-view rule design, when both views of rules are considered, the model...
presents the best prediction capability. When we implement a single-
view rule discovery, we found the rules generated from structured
attributes work better than the rules generated from unstructured
descriptions. It can be explained by the high relevance between
the product attributes and product compatibility. The structured at-
tributes can precisely match with unlabeled product pairs, because
it excludes those incompatible products via hard filtering. However,
as shown in Figure 5, only proposing rules based on the structured
attributes will fall behind the multi-view approach significantly
after several iterations. When the selected features become increas-
ingly sparse with the iteration increases, the attribute-only rules
can hardly match enough unlabeled instances to further improve
the model. At this time, the product descriptions can serve as a
complementary source for rule discovery. It undertakes the task
of rule discovery from the sparse attributes by prompting PLMs
to mine the semantic hint in the unstructured descriptions. In this
way, it supplements the attribute view by matching unlabeled in-
stances in a soft manner, where we use prompts for the descriptions
of unlabeled instances and then compute a similarity score. The
results demonstrate both views of rules do complement each other
and yield the best performance when integrated.

5.4 Effect of different components

Figure 6 presents the ablation study to verify the effect of different
components in AMRule, our findings are as follows:

1) Adaptive rule discovery by targeting hard instances is effective.

Figure 5: A closer look at the effect of multi-view rules. AM-
Rule is the complete method where we discover rules from
both the structured attributes and the unstructured descrip-
tions. ‘Only attributes’ and ‘Only description’ denote we only
consider a single view of rule. ‘Only boosting’ means the im-
plementation does not discover any rules but only iteratively
train weak models and ensemble model.

In Figure 6, the “w/o ensemble” setting shows the adaptive strategy
contributes to the final performance. Specifically, we fix the annota-
tion budget \( b \) but discover candidate rules from large-error samples
in one iteration. We compare AMRule with this “w/o ensemble”
curve and observed a 1.53% performance gain, which comes from
that the complete method iteratively identifies the hard instances
and proposes rules based on these instances accordingly. Such an
adaptive process helps the model to check its weaknesses and refine
them by discovering new rules, thus yielding more effective rules
than static rule discovery under the same annotation budget.

2) Ensemble alone without new rule discovery is not as effec-
tive. For the “w/o rule” variant, we do not propose new rules, but
ensemble multiple self-trained weak classifiers instead. The final
performance drops significantly under this setting by 1.75%. It
demonstrates the newly proposed rules provide complementary
weak supervision to the model. Although simply ensembling mul-
tiple weak classifiers also helps WSL, it is not as effective as training
multiple complementary weak models as in AMRule.

5.5 Case Study

We use a case study to illustrate the rule discovery process. Here the
anchor category is power tools and the recommendation category
is batteries. In iteration 1, AMRule first select the features based on
the permutation importance. The selected features include \{battery
power type, brand name, \ldots, number of total batteries included\}. For
the battery type which belongs to \( (x'_a = x'_b) \) in Equation 5, the
human annotator can implement the operation "Exact match" indi-
cating this product attributes should be associated with a condition
of categorical equivalence. For example, the battery power type of
the anchor and recommendation products are both "Lithium Ion",
and it is a reasonable compatibility hint. For the next candidate
brand name, it is a sparse attribute under this category pair, so
we leverage product descriptions to generate a prompt-based rule.
As Table 2 shows, we can get a rule by prompting a PLM. For the
last candidate \textit{number of total batteries included} which is a stand-
alone and irrelevant feature, the human annotator can choose the
"Abstain" operation to reject this rule.

6 CONCLUSION

To solve the compatible products prediction task, we propose an
adaptive rule discovery framework AMRule to predict compatibil-
ity from weakly labeled data. We leverage user behavior data to
construct a weakly supervised setting, which avoids cumbersome
annotation engineering. From the heterogeneous nature of the prod-
uct representation, we design the multi-view rules to incorporate
both structured product attributes and unstructured product descriptions. Through the decision tree-based and prompt-based rule generation, AMRULE discovers multi-view rules that complement each other to improve the weakly supervised model. Moreover, the boosting strategy enables identifying hard instances for rule discovery, so the new rules iteratively refine where the model accumulates mispredictions. Experiments on real-world benchmarks demonstrate AMRULE significantly improves weakly-supervised compatible products prediction and provides interpretable predictions by discovering compatibility rules.

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