Catalog Integration of Low-quality Product Data by Attribute Label Ranking

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Abstract: The integration of product data from heterogeneous sources and manufacturers into a single catalog is often still a laborious, manual task. Especially small- and medium-sized enterprises face the challenge of timely integrating the data their business relies on to have an up-to-date product catalog, due to format specifications, low quality of data and the requirement of expert knowledge. Additionally, modern approaches to simplify catalog integration demand experience in machine learning, word vectorization, or semantic similarity that such enterprises do not have. Furthermore, most approaches struggle with low-quality data. We propose Attribute Label Ranking (ALR), an easy to understand and simple to adapt learning approach. ALR leverages a model trained on real-world integration data to identify the best possible schema mapping of previously unknown, proprietary, tabular format into a standardized catalog schema. Our approach predicts multiple labels for every attribute of an input column. The whole column is taken into consideration to rank among these labels. We evaluate ALR regarding the correctness of predictions and compare the results on real-world data to state-of-the-art approaches. Additionally, we report findings during experiments and limitations of our approach.

1 INTRODUCTION

The success of an e-commerce company depends on displaying and selling products on its platform. To do so, all customers who want to offer products on this platform have to provide the corresponding product data. Small to medium sized enterprises (SMEs) are not able to force every customer to comply with their standards. Hence, they have to deal with various data formats from different sources and extract relevant information to display on their platform.

A typical workflow to integrate heterogeneous data from multiple sources includes steps like format unification, schema matching, and information extraction. Due to the complexity of these tasks, data integration requires manual corrections, since tools often fail to automate extract-transform-load (ETL) data pipelines on non-standard or low-quality data.

Enabling an automated data integration pipeline allows employees to process complex datasets with reduced effort and domain knowledge. Schema matching is a critical operation in this process, especially for data warehouses or e-commerce. In order to integrate one product catalog into the other, corresponding entries in both catalogs need to be identified, or attributes need to be matched to their representatives.

However, relations between attributes of an input catalog and the target schema are unknown if the names of attributes change frequently. Even if the input schema is known from a previous catalog, another manufacturer could use the same naming differently. Since tabular data with product attributes are the most common way to handle these data in SMEs, we can only rely on attribute names and attribute representatives to identify possible matches.

In this paper, we present an approach to integrate tabular catalog data with previously unknown column names and column count from different manufacturers into a single catalog based on labeling each representative of an attribute. After labeling each attribute representative, we aggregate the label predictions to rank among all label candidates of a column and use this ranking as a recommendation to simplify the process of catalog integration for SMEs.

We conducted this research in a collaboration

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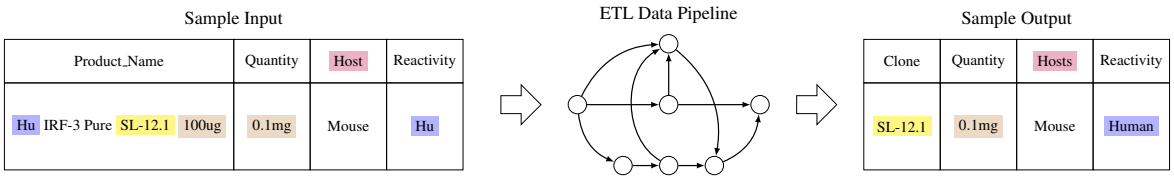


Figure 1: A typical integration workflow for e-commerce data: An industry partner delivers a tabular semi-structured input file, which might look like the sample input. Then, an ETL pipeline handles these data. Every node in the data pipeline represents a task that might include manual actions or is entirely automated. After meeting quality objectives, output data have a unified schema and semantic concepts as well as standardized attribute contents.

project with an e-commerce SME from the bioscience domain. Therefore, we evaluate our approach with real-world product catalogs from this domain.

The main contributions of this paper are:

1. We introduce a dataset specifically designed to target the challenge of catalog integration and column labeling. This dataset includes real-world data collected during manual integration tasks.[1]
2. We propose Attribute Label Ranking (ALR), an approach for catalog integration based on attribute labeling by learning from attribute representatives through combining features from meta-information and content language analysis.
3. We compare the performance of using one-hot vectors of words or n-grams as language features on catalog integration.

The remainder of this paper is structured as follows: Section 2 emphasizes the importance of handling low-quality data in automatic integration approaches for SMEs in e-commerce. Subsequently, Section 3 provides an overview of related approaches and previous work. In Section 4, we review the data we work on before we present our approach to integrating low-quality data in Section 5. Based on the dataset for catalog integration of antibody product data in Section 6, we evaluate our work in Section 7 before we conclude the paper with a summary and a brief outlook in Section 8.

2 MOTIVATING EXAMPLE

This section provides a motivating example, demonstrating the economic importance of automatic integration of low-quality data, especially for SMEs in e-commerce. We present a simplified data integration workflow of an SME, providing antibodies to researchers.

Figure 1 illustrates a typical workflow for such an e-commerce company after format unification. Prior to this workflow, antibody manufacturers deliver product data in any format. After format unification, additional data processing tasks are required to integrate the product catalog. Often, an ETL pipeline handles these tasks with or without manual interaction. Typical tasks that require manual actions are:

- **Schema Matching.** An employee has to match the schema from an input file to the target schema, on which other processes rely. Automating this task is easy if the two schemas are identical. However, SMEs cannot force their customers to comply with their schema, format, or semantic concept naming due to the lack of market power. Problem classes for identifying semantic concepts, such as using synonyms, misspelling, plural, splitting characters, identified by Paulus et al. (Paulus et al., 2018), apply here as well (c.f. Figure 1, *Host* expands to *Hosts*). Although transformations once implemented for a single manufacturer are in theory reusable, the reality shows that the input schema changes regularly.
- **Identifying Additional Information.** Some manufacturers add information to a semantic concept that misses elsewhere. An employee needs to identify those entities, to extract them (e.g., via unique regular expressions), and finally matches them to the correct concept. This task requires very much time and is error-prone due to the use of regular expressions for information extraction. For example, in Figure 1, the clone is extracted from the product name, since the input schema misses a clone property.
- **Resolving Duplicated Information.** The same information might occur in multiple attributes. An employee needs to decide which information to use. The input file in Figure 1 contains the product quantity in multiple attributes. The quantity is identical in both attributes, but the unit of measurement differs (including a misspelling).
- **Resolving Synonyms and Abbreviations.** Different antibody manufacturers might use their synonyms and abbreviations in input files. These

[1] https://github.com/oschmi/antibody-catalog-integration-dataset

need to be standardized and resolved to use a consistent vocabulary in the webshop (c.f. Figure 1, *Hu* expands to *Human*).

Failing a single task may create product data in the shop that are incorrect. Hence, a review by a highly educated domain specialist is required to guarantee the product data quality. In the worst case, an employee has to run the integration pipeline multiple times until fulfilling quality goals. Avoiding to integrate a single file of product data multiple times saves time and money for a SME, depending on the amount of manual work required.

Considering that antibody manufacturers change their schema frequently, reducing the effort to integrate product data becomes economically relevant. In addition to regular schema changes, some manufacturers try to hide that they are reselling other manufacturers' products and obfuscate product data.

Hence, it is desirable to improve automatic data integration for e-commerce data by predicting multiple labels for given attributes and thus simplifying schema matching and identifying additional information to assist employees on manual tasks.

3 RELATED WORK

The task of data integration closely relates to schema matching, data labeling, and finding similar semantic concepts in multiple datatsets. In this section, we present recent work from corresponding fields.

While schema matching has a long history of approaches, it typically relies on the similarity between attribute names (Comito et al., 2006; Schmidts et al., 2019) or similarity of their values (Kirsten et al., 2007; Bernstein et al., 2011; de Carvalho et al., 2013). Advanced approaches that resulted in major matching frameworks like CUPID (Madhavan et al., 2001), COMA++ (Aumueller et al., 2005), or ORCHID (Dessloch et al., 2008) use a combination of both and add further steps like synonym and abbreviation resolution to match between two schemas. However, these approaches focus on a general-purpose solution to unify schemas and often use structural information derived from hierarchies (Shvaiko and Euzenat, 2005).

Integrating and matching product data into a single catalog relies on tabular data in which product attributes are most commonly stored. Approaches motivated by the semantic web, focus on entity matching to find related products in two tabular datatsets. Foley et al. shows that learning from low-quality data can improve search results (Foley et al., 2015). Ristoski et al. and Bizer et al. demonstrate how a deep learning model can predict matching products (Ristoski et al., 2018; Bizer et al., 2019). Nevertheless, these approaches rely on a unified schema for all input data. Gu et al. combine schema matching and record matching through likelihood estimation. This approach works well on datatsets that overlap for some records and attributes, and it works only well if one entity in a table matches with no more than one entity in the other table (Gu et al., 2017).

Recent research focuses on predicting labels or semantic concepts by content analysis (Chen et al., 2018) or combining attribute names and representatives (Pham et al., 2016; Pomp et al., 2019). Chen et al. leverage a deep learning model to predict labels to columns based on multiple features, such as cell length, character ratio, and character unigramms. They consider the labeling problem as a multi-class classification where every label represents a single class. For a data integration task, we need to extend this approach to a multi-label problem where every column can have multiple labels. Otherwise, the model can solely recognize 1:1 relations, which is not desirable for a product catalog integration. Additionally, their approach works best on Bag of Words (BoW) columns. However, columns concerning product specifications frequently contain text.

Pham et al. and Pomp et al. determine similar concepts based on different similarity measures, for instance, value distribution through a column. Utilizing the value distribution is not possible in catalog integration. For instance, one manufacturer produces antibodies with mice as host, and another manufacturer uses mice and rabbits as host. As a consequence the distribution of class representatives differ. Knowledge graphs can further improve matching results after enriching with enough concept representatives (Anam et al., 2016; Pomp et al., 2019). They find similar concepts (labels) in a knowledge base based on different classifiers (e.g., rule and histogram) and metrics. These approaches perform well on BoW and numerical columns, but lack accuracy on textual representatives.

4 REVIEW OF PRODUCT CATALOG DATA

Before we started to design a learning model, we reviewed original data from integration processes in the antibody product domain to identify challenges and to measure the usual quality of data from manufacturers. We limited this review to CSV files since it is the most common format to integrate on our partners' platform. However, our review also applies to any file

format that allows hierarchical attributes and thus can express relations between attributes. We reviewed a total number of 50 files before and after integration from different manufacturers containing a range from three up to 230.000 products of multiple types. Due to the specialized domain, the product standards of schema.org are not applicable in this context.[2] To integrate data effectively, we analyzed the content of the columns and categorized them into the following classes:

- **Bag of Words (BoW).** A column that contains a limited amount of words (e.g., a host is always one of 22 animals). We can find the attribute to integrate by analyzing the content if the BoW is unique in both schemas. However, BoWs are not unique for antibodies. For example, an animal can be a host or describes the reactivity of the antibody. In this case, the attribute name always defines the context of this class. A BoW mostly refers to a 1:1 relation between two schemas.
- **Unstructured Text (UT).** This class contains either a list of words or full sentences up to paragraphs of multiple sentences. Typical examples for this class are product names or descriptions, where the product name contains a list of words, and the description contains multiple paragraphs. Nevertheless, this class is not limited to these two attributes. The UT class can refer either to a 1:1 relation (e.g., description) or a 1:n if the content holds more than one concept of a finer-grained target schema despite not mentioning this concept in the column or attribute name.
- **URLs.** Some attributes include URLs to different targets like pictures, detailed product specification sheets, or the UniProt database.[3]

BoW and UT classes suffer from similar problem classes as the naming of attributes such as misspelling and encoding errors. Depending on the manufacturer, different synonyms and abbreviations are used, which require a transformation to a standard naming in a subsequent process.

Pomp et al. identified further data classes, such as ID and numerical values (Pomp et al., 2019). However, these classes are not as relevant in catalog integration as in a more general context. For example, if an attribute contains prices, a manufacturer may use the plain number in the corresponding column or use the number with an additional currency symbol. Hence, we handle these cases as plain text, to avoid mistakes based on class confusion because of additional (or missing) symbols or characters.

[2]https://schema.org/Product

[3]https://www.uniprot.org/

5 ATTRIBUTE LABEL RANKING

In this section, we present Attribute Label Ranking (ALR) to integrate products from different manufacturers into a unified catalog through mutli-label classification ranking.

5.1 Problem Statement

We follow the problem definition of Chen et al. on finding schema labels based on content analysis of tabular data and extend it to catalog integration. We consider an input file of the format (Chen et al., 2018) as product catalog:

$$P^{in} = \begin{bmatrix} L_1^{in} & L_2^{in} & \cdots & L_n^{in} \\ c_{1,1}^{in} & c_{1,2}^{in} & \cdots & c_{1,n}^{in} \\ \vdots & \vdots & \ddots & \vdots \\ c_{m,1}^{in} & c_{m,2}^{in} & \cdots & c_{m,n}^{in} \end{bmatrix}$$

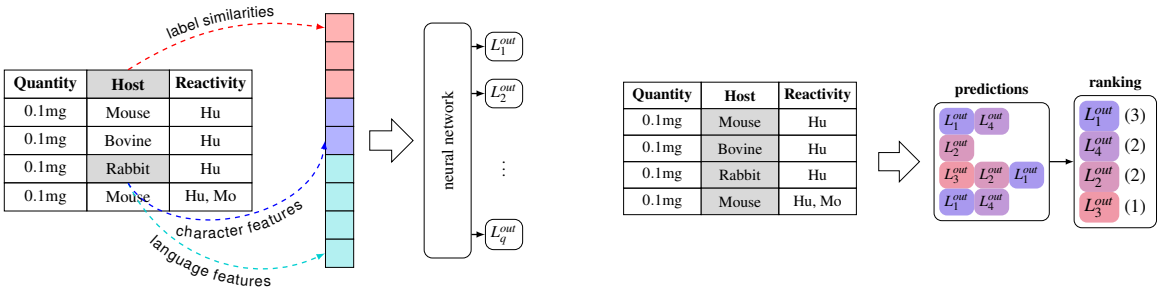
Based on this product catalog, we introduce the following naming conventions:

- **input schema labels** (or attribute names)**:** L_i^{in}, where i ($i \in [1,n]$) is the input label index.
- **output schema labels:** L_k^{out}, where k ($k \in [1,q]$) is the input label index.
- **input catalog content** (or attribute representatives)**:** $c^{in} = [c_{1,1}^{in}, \ldots, c_{m,n}^{in}]$ where $c_{j,i}^{in}$ is a single representative.
- **column:** $C_i^{in} = [L_i^{in}, c_{1,i}^{in}, \ldots, c_{m,i}^{in}]$.
- **product** (or row)**:** $P_j^{in} = [c_{j,1}^{in}, \ldots, c_{j,n}^{in}]$.

With these conventions, we define catalog integration as a task, where we try to integrate multiple catalogs into the fixed schema L^{out} of a target catalog. An optimal result would match each column to the correct target schema label. This approach corresponds to the approach of Chen et al. for columns matching exactly one label (1:1 relation) (Chen et al., 2018). However, an input column may refer to multiple target labels. We leverage a multi-label classification model to also obtaining 1:n relations while preserving the performance on 1:1 relations. By considering multiple input columns from C^{in} that target the same L_k^{out}, we further address n:1 relations.

5.2 Approach Overview

ALR relies on two consecutive steps, as pictured in Figure 2, while making no assumptions about the schema and content of an input catalog except both are part of the same context (e.g., antibody products).



(a) The feature vector contains character and language features based on an attribute representative as well as label similarities between the corresponding input header and target label. Hereafter, a neural network predicts multiple possible labels for a single attribute representative.

(b) The network predicts labels for each representative of a column. After that, the count of occurrences determines the label ranking for that column. The more often a label occurs, the higher is the ranking. For example, L_1^{out} receives the highest ranking with three occurrences.

Figure 2: Overview of our approach consisting of two parts. Figure 2a illustrates how we generate feature vectors from attribute representatives. In Figure 2b the results of the neural network define the final label ranking for the complete column.

The first step considers different features for each attribute representative with its corresponding input label to determine possible target labels. Figure 2a illustrates the process of feature selection at different levels for the attribute representative *Rabbit*. From this attribute representative, we extract character- and language-based features. Besides, we utilize available meta-information, such as the similarity between the corresponding input label (e.g., *Host* in Figure 2a) and all target labels. The next section provides more details on feature selection. After determining these features, we aggregate and feed them into a neural network, which predicts multiple labels for each attribute.

After predicting target labels for all attribute representatives of a column, we count occurrences per target label. Based on the occurrence count, we build a ranking among all predicted target labels. In Figure 2b target labels for the column *Host* were predicted. The target label L_1^{out} counts three occurrences and therefore receives the highest rank before L_4^{out} and L_2^{out} with two occurrences. The relative ranking score is the final result of ALR. In Figure 2b L_1^{out} receives a final score of $\frac{3}{8} = 0.375$.

5.3 Feature Selection

Modern research approaches perform well in predicting labels on numerical-, BoW-, and ID-based attributes (Chen et al., 2018; Pomp et al., 2019). However, a product catalog contains multiple textual attributes, such as a description or usage information. Additionally, a textual attribute might contain information that misses in an explicit product specification by manufacturers but is available in a more general schema. Consequently, we use the following features based on label similarity, language, attribute content

Table 1: List of features for multi-label classification.

ID	Length	Description
1	len(L^{out})	target label similarity
2	1	ltd., norm., cell length
3	1	% of alphabetic chars
4	1	% of numeric chars
5	1	% of symbolic chars
6	len(vocab)	one-hot tokens
7	1	a token is a URL

(c.f. Table 1 and Figure 2a) to predict multiple labels for an attribute representative:

- **Label Similarity Features:** We utilize the label similarity between L_i^{in} and each L_k^{out} as meta-information of a representative. The similarity vector is calculated by applying the cos-similarity of character bi- and trigrams to a single input label and each target label:

$$cos\_sim(L_i^{in}, L_k^{out})$$

  As a result, the feature length is $q = len(L^{out})$.
- **Character Features:** We use the count of characters, limited to a maximum of 1024 characters per attribute, and normalize the value to [0,1]. Besides, we use the percentages of numeric, alphabetic, and symbolic characters of an attribute. These features are particularly useful to predict the labels of IDs (Chen et al., 2018) and antibodies or gene sequences in the context of our products.
- **Language Features:** To improve results on labeling text attributes, we use different text vectorizing techniques. These may include one-hot word vectors, character n-grams of word tokens (sub-word n-grams), or any other word vectorization technique, such as word embeddings. In this paper, we only consider one-hot word vectors

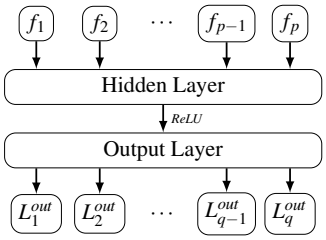


Figure 3: Neural network architecture for attribute labeling.

and sub-word n-grams since we would need specialized embeddings for antibody product data. Building these embeddings is not feasible for SMEs because of hardware and knowledge limitations. The used vocabulary determines the feature-length for one-hot vectors. Additionally, we added a binary URL recognizer, which is either set to 1 if a URL is present or 0 if not.

5.4 Multilayer Network

Figure 3 shows a similar network architecture, as Joulin et al. used in their approach to efficient text classification. They advise using flat neural networks to gain fast and accurate results on text classification tasks (Joulin et al., 2016). Therefore, we use a multilayer approach with a single hidden layer that is close to their network architecture. The feature size defines the size of the input layer. We use a layer of 400 nodes as a hidden layer, which is fully connected by rectified linear units (ReLUs) to the output layer. The size of the output layer depends on the number of labels to predict for an attribute.

Our model optimizes the Binary Cross Entropy (BCE) with logits loss through ADAGRAD (better performance on multi-label classification (Nam et al., 2014)) to handle the multi-label classification. With this loss function, we can use binary labels as a target or any value in $[0,1]$. In the prediction step, we consider every target value greater than 0 as a positive label prediction.

6 CREATING A CATALOG INTEGRATION DATATSET

With ALR, we provide an approach to tackle catalog integration. However, commonly used tabular datasets do not include information about how the data were integrated. In this section, we introduce an annotated dataset for product catalog integration. We gathered this dataset by analyzing logs from manual labeling actions in our partners' ETL pipeline.

6.1 Data Collection and Annotation

We collected files at two stages of our partners' integration pipeline. Firstly, we gathered product catalog data after the format unification in the CSV format, where each file contains original attribute names and contents of a manufacturer. Secondly, we gathered the corresponding data after the last human interaction before transferring the product information into a database. These files have a unified tabular target schema.

Between these stages, data of some input columns were adopted entirely into the target file. These attributes identify by matching strings before and after integration. We consider an exact match as a 1:1 relation between the two files. However, other attribute representatives from the input file have been transformed during the integration process: Information was extracted from strings into one or multiple target columns, units of measurement were standardized, synonyms and abbreviations might have been resolved. Nevertheless, we only know for sure the relation among exact string matches, since we have no information about the matching process (input label to target label).

To identify unknown relations as well, we used a tokenizer for biomedical data (Neumann et al., 2019). We determined the cosine similarity (ignoring stopwords) of tokens between an attribute representative from the manufacturers' file and all representatives of the corresponding product in the integrated file.

After that, we annotated $c_{j,i}^{in}$ with the tuple of the associated L_k^{out} and the similarity score $(cos\_sim(c_{j,i}^{in}, c_{j,k}^{out}))$. With this method, an exact string match receives a similarity score of 1.0. We consider a target label annotated with a similarity score of 1.0 as the primary label of that attribute representative. If a representative has no primary label after the annotation, we can only assume that the representative was integrated into the target label with the highest score.

This approach allows using the same dataset for different problem definitions. For example, solely considering 1:1 relations, where the similarity equals 1.0, leads to a multi-class classification problem, since the content can only match to a single concept. Utilizing lower similarities leverages a multi-label approach, where the content may correspond to multiple concepts.

6.2 Properties and Format

We assembled 19 files from integration jobs for the dataset, containing a total of ca. 420.000 antibody

Table 2: Properties of the catalog integration dataset.

Total Files	19
Total Products	ca. 420.000
Products per File	3 – ca. 230.000
Manufacturers	12
Input Attribute Range	14 – 65

```
{
 'content': ...
 'labels': [
    'label_1': 0.1,
    'label_2': 1.0,
    ...
    'label_q': 0.5
    ]
 'header_similarity': {
    'original_header':  L_1^in,
    'headers': [
        'label_1': cos_sim(L_1^out, L_1^in),
        'label_2': cos_sim(L_2^out, L_1^in),
        ...
        'label_q': cos_sim(L_q^out, L_1^in)
        ]
}
```

Listing 1: Format of the catalog integration dataset.

products (c.f. Table 2).[4] The number of products contained in a single file ranges from 3 up to ca. 230.000 products of 12 manufacturers and different product types (e.g., ELISA Kits, Primary Antibodies, etc.). Depending on the product type and manufacturer, the number of attribute names per catalog ranges from 14 to 65 names that were integrated into a target schema with 94 labels.

Listing 1 shows the structure of the annotated dataset in a JSON-format based on attribute representatives. The property *content* refers to a single attribute representative of a product catalog. The unsorted list of *labels* contains all possible target labels with the annotations. Additionally, we include the bi- and trigram cos-similarity mentioned in Section 5.3. However, the only mandatory attributes in this dataset are *content* and *labels*. Other properties are added and pre-calculated for convenience. To keep track of manufacturers, we pseudonymized their name and replaced it with a sha256-hash in the file name. Additionally, we split all files into smaller chunks.

6.3 Limitations

The integrated data contain quality issues despite the manual actions and review. For example, there are encoding errors, spelling errors, and fragments of regular expressions. These errors made the annotation process more prone to errors for uncertain matches without a primary label. Furthermore, the integrated dataset only contains resolved synonyms and abbreviations, which might lead to a missing primary label in a small number of cases.

Furthermore, we removed URL-attributes from the published datatset to prevent manufacturers from being exposed.

7 EXPERIMENTAL EVALUATION

In this section, we evaluate the performance of ALR regarding different aspects as correctness, performance, and explain limitations. We also compare our results to recent research approaches and present mentionable findings.

7.1 Scenario

In this experimental scenario, we use a subset of antibody products from our dataset (c.f. Section 6) split in train and test datasets. The training dataset consists of ca. 50.000 products from 7 manufacturers with different product types (e.g., ELISA Kits, Primary Antibodies, etc.). The testing dataset contains ca. 25.000 products from 5 manufacturers, which are not present in the training dataset. Every manufacturer uses an individual schema for its products ranging from 14 attributes to 65 attributes that shall be integrated into 94 attributes of the integration schema.

We evaluate the performance of our approach by trying to integrate the product catalogs from the testing set after our model was trained through the training set. We study the model performance with two different language features (one-hot word vectors and combined one-hot sub-word bi- and trigram vectors) while retaining character features and label similarity features.

Additionally, we trained the models with three thresholds (0.0, 0.5, 0.9) that determine target labels from the annotated dataset. A model trained with a threshold of 0.9 means to only consider almost exact matches of attribute representatives between columns of an input dataset and the associated integrated dataset during the training phase. Regarding our scenario, the models with a threshold of 0.9 were trained with exact string matches of attribute representatives only. A model that was trained with a threshold of 0.5 additionally considers uncertain string matches in the training phase, while a model trained without a threshold (0.0) respects every kind

[4] https://github.com/oschmi/antibody-catalog-integration-dataset

of similarity between attribute representatives to predict a target label during training.

For models trained with the thresholds of 0.5 and 0.9, we determine the annotated target labels by transforming the raw annotated label score from the dataset into a one-hot ground truth vector, where an annotation value greater than 0.5 (0.9) is transformed into 1 and otherwise into 0. A target vector may contain more than one target label, especially for the threshold of 0.5.

The models trained with a threshold of 0.0 use the annotated label score as ground truth. This ground truth is not transformed into a one-hot multi-label target vector. For the rest of the paper, we refer to the models as $word_t$ concerning one-hot word vector based models, where t is followed by the threshold used, and $ngram_t$ respectively if the used model was trained with sub-word bi- and trigrams.

7.2 General Performance

Before evaluating the applicability of ALR to catalog integration, we analyze the performance of the model trained on one-hot word vectors with a threshold of 0.0 by analyzing the Label Ranking Average Precision (LRAP), which evaluates the average fraction of labels ranked above a particular label (Tsoumakas et al., 2010), concerning the label cardinality and the content type (either BoW or text) on the testing dataset. The label cardinality describes the average number of labels of the examples in a dataset (Tsoumakas et al., 2010).

Figure 4 illustrates the influence of the ground truth label cardinality per target label to the LRAP score. Most instances of BoW have a cardinality lower than 4. However, the LRAP significantly drops after two labels in the examples for BoWs and rises again after four. The label cardinality of text instances ranges from 1 to 14 with no recognizable focus. The LRAP drops slowly from 0.8 to 0.7 at six labels while almost staying constant after more than six labels. These observations show that most BoW instances have a clear label ranking, which is learnable by the model. On the other hand, label ranking of text instances seems more challenging to learn. Additionally, a higher label cardinality reduces the models' performance since there are more labels to learn combined with the simple structure of the model. Applying thresholds to the ground truth reduces the label cardinality – a threshold of 0.5 results in a maximum ground truth cardinality of 5.

Figure 5 pictures the LRAP concerning the content type of full columns using the same model as in Figure 4. Comparing BoW and text attributes, BoW

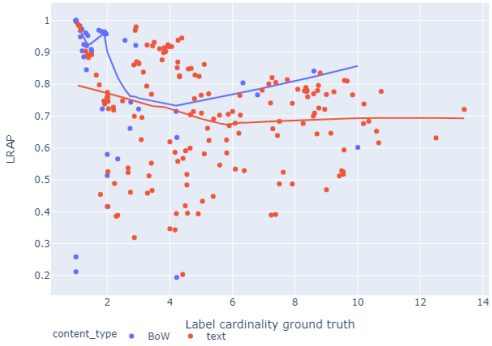


Figure 4: Model performance concerning the label cardinality. $word_{t0.0}$ needs to predict a maximum of 14 labels.

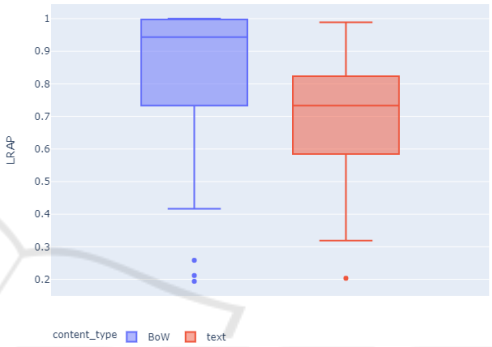


Figure 5: LRAP comparing text and BoW columns for $word_{t0.0}$.

clearly gains higher LRAP scores with some minor outliers. These results should also be visible in the following evaluations.

7.3 Multi-class Evaluation

We evaluate the performance predicting the labels for complete columns in two different aspects. Firstly, we measure the Mean Reciprocal Rank (MRR) (Craswell, 2009) to examine the usability of ALR as a recommendation engine. We consider a prediction of ALR as correct if the highest-ranked label of a column matches the target label of the column since MRR does not apply to multi-label classifications. Secondly, we measure precision, recall, and f1-score concerning the highest-ranked label to compare our approach with recent research results.

7.3.1 Recommendation Results

Table 3 illustrates the MRR of predictions of ALR based on the different models from the scenario for 1:1 relations with no modification during the integration process (target label threshold of 0.9). Therefore, we precisely know the associated columns.

Table 3: MRR of ALR with models trained on different ground truth thresholds on 1:1 relations. Bold font indicates the best performance.

	MRR		
	all	BoW	text
Model			
$word_{t0.0}$	0.7212	0.7678	0.7030
$word_{t0.5}$	0.7641	0.7857	0.7558
$word_{t0.9}$	0.7075	0.7678	0.6840
$ngram_{t0.0}$	0.7679	0.8125	0.7506
$ngram_{t0.5}$	**0.8208**	**0.8393**	**0.8137**
$ngram_{t0.9}$	0.7467	0.8214	0.7176

Comparing word-based ALR to n-gram-based ALR, we can see that every ALR based on n-grams gains higher scores than the corresponding ALR based on text. The ALR that uses an n-gram model trained with a threshold of 0.5 performs best in all categories. It reaches an MRR of 0.8208 overall while performing better on BoW (0.8393) than on text (0.8137).

The other configurations show a similar characteristic: In general, the performance on BoW is better than on text. Additionally, the gap between BoW and text of the ALR based on $ngram_{t0.5}$ is significantly smaller than other approaches except for $text_{t0.5}$. Considering word and n-gram-based ALRs individually, models trained with a threshold of 0.5 perform best in each category. We can explain the better performance of n-gram based ALRs by vocabulary misses and low quality of attribute representatives. For instance, the word vocabulary does not contain *96test* due to the missing whitespace. If the whole column contains only unknown words, a word-based model possibly cannot predict a target label if other features are not significant as well. An n-gram-based approach at least gets partial matches if the vocabulary contains the trigrams of *test* (tes, est).

Although our scenario and the dataset is not fully comparable to the datasets Pomp et al. evaluated their approach with, our results for the MRR indicate that we perform in the same range of MRR scores overall (Pomp et al., 2019). They report maximum MRRs for BoW of 0.783 (soccer dataset) and 0.764 (museum dataset), we reach a maximum value of 0.839. Concerning text attributes, their approach varies depending on the dataset from 0.783 (museum) up to 0.983 (soccer). With the consideration that the museum dataset contains more complex data than the soccer dataset, we perform at least on even on complex and low-quality data.

7.3.2 Classification Results

To evaluate the classification results of ALR, we used the same setup as for the recommendations. We again consider 1:1 relations with no modification during the integration process (target label threshold of 0.9) and treat the predicted label with the highest rank as a classification result. We take columns, where ALR could not make a prediction, into account as false negatives. Therefore, unpredicted columns modify recall and f1-score but not the precision.

Table 4 shows the classification performance of ALR depending on the model used and the attribute class. The overall precision score of ALR remains over 0.8 for all models, reaching the maximum (bold) of 0.893 with the $word_{t0.5}$ model, followed by $ngram_{t0.5}$ (0.8766) and $word_{t0.9}$ (0.8735). Additionally, $ngram_{t0.5}$ achieves the highest recall (0.805) and f1-score (0.8393) followed by $word_{t0.5}$ with a recall of 0.75 and an f1-score of 0.8153.

Concerning the performance of BoW attribute representatives, all approaches gain precision scores of higher (or equal) than 0.9. Again $word_{t0.5}$ achieves the highest precision (0.9778). Contrary to the overall performance, word-based models work significantly better than n-gram-based models concerning the precision, while the f1-score is almost on even for all models (maximum of 0.8713 for $word_{t0.5}$). N-gram-based models constantly achieve a recall of 0.8 or better outperforming word-based models again, where $ngram_{t0.5}$ reaches the highest value of 0.8393.

Chen et al. report a micro f-score of 0.23 or 0.20 for strings depending on the features used (Chen et al., 2018). ALR outperforms their approaches by at least 0.5. This result shows the effectiveness of using subword bi- and trigrams or words instead of character unigrams for strings.

Even if we consider uncertain 1:1 integrations, where we do not exactly know which columns were matched during the integration process due to ambiguousness, ALR almost perseveres its precision (c.f. Table 5). Both models trained on a threshold of 0.5 still perform well. As before, ALR with $ngram_{t0.5}$ achieves higher recall scores than the $word_{t0.5}$. However, Table 5 shows that the achieved recall scores drop by at least 0.1 for n-grams (0.8 to 0.69, 0.84 to 0.7, 0.79 to 0.68, rounded). $word_{t0.5}$ achieves higher precision scores except for text, where n-grams outperform other approaches. Nevertheless, the loss in precision of $word_{t0.5}$ is relatively small (0.89 to 0.87, 0.98 to 0.98, 0.87 to 0.85, rounded). The range of this loss applies to n-gram-based ALR as well. The results on the f-scores show again that ALR outperforms the approach of Chen et al. on strings by at least 0.5.

Table 4: Multi-class classification weighted avg. performance of ALR considering 1:1 relations of exact string matches between input and integrated files. Bold font indicates the best performance.

	all			BoW			text		
	precision	recall	f1	precision	recall	f1	precision	recall	f1
Model									
word$_{t0.0}$	0.8130	0.6750	0.7376	0.9773	0.7679	0.8600	0.7585	0.6389	0.6936
word$_{t0.5}$	**0.8930**	0.7500	0.8153	**0.9778**	0.7857	**0.8713**	0.8681	0.7361	0.7967
word$_{t0.9}$	0.8735	0.7050	0.7803	0.9356	0.7679	0.8434	0.8543	0.6806	0.7576
ngram$_{t0.0}$	0.8368	0.7400	0.7854	0.9320	0.8036	0.8631	0.8186	0.7153	0.7635
ngram$_{t0.5}$	0.8766	**0.8050**	**0.8393**	0.9020	**0.8393**	0.8695	**0.8992**	**0.7917**	**0.8420**
ngram$_{t0.9}$	0.8595	0.7014	0.7724	0.9000	0.8214	0.8589	0.8681	0.7014	0.7759

Table 5: Multi-class classification weighted avg. performance of ALR considering 1:1 relations and uncertain matches between input and integrated files. Bold font indicates the best performance.

	all			BoW			text		
	precision	recall	f1	precision	recall	f1	precision	recall	f1
Model									
word$_{t0.5}$	**0.8652**	0.6320	0.7304	**0.9787**	0.6301	**0.7666**	0.8509	0.6327	0.7258
ngram$_{t0.5}$	0.8418	**0.6877**	**0.7570**	0.8098	**0.6986**	0.7501	**0.8733**	**0.6837**	**0.7669**

7.4 Multi-label Evaluation

ALR is not only able to predict the primary label for a column, but it also aims to detect as many labels as possible to identify possibly ambiguous columns. For instance, a product name often contains more information. In Figure 1, the product's name contains information about the reactivity, quantity, and the clone of the product. If these data miss in other columns, practitioners need an indication, where they can find these data. Consequently, ALR predicts 1:n relations for uncertain matches.

We evaluate the performance considering multi-label classification by evaluating the Area Under the Receiver Operating Characteristic Curve (AUROC) score (Hand and Till, 2001). The AUROC score describes a models' ability to distinguish between classes. A score of 1.0 means that the model correctly identifies all classes. On the opposite, a model achieving a score of 0.5 is not capable of separating the classes.

Table 6 describes the ability of ALR based on different models to distinguish between classes, which are the different target labels in our case. ALR based on $ngram_{t0.5}$ overall achieves the best results with an AUROC of 0.7464. Additionally, it gains the highest result on text (0.7571). Considering BoW $ngram_{t0.0}$ (0.7129) performs slightly better than $ngram_{t0.5}$ (0.7071). These results show that ALR cannot perfectly distinguish different labels but can do so for most of them. While analyzing the results in more detail, we found some classes that could not be separated at all (*Antigen, Characteristic, Epitope, Principle, proteinType, reactivityPredicted*), lowering the average score. Those classes need further investigation in future approaches. Furthermore, we could identify ambiguous classes, which humans may confuse as well without deep expert knowledge (*Storage, storageComment, storageShipping*). However, the majority of investigated target labels achieve results close to 1.

Table 6: Weighted mean AUROC of ALR for multi-label classification. Bold font indicates the best performane.

	AUROC		
	all	BoW	text
Model			
word$_{t0.0}$	0.7324	0.6910	0.7400
word$_{t0.5}$	0.7105	0.6807	0.7190
ngram$_{t0.0}$	0.7271	**0.7129**	0.7304
ngram$_{t0.5}$	**0.7464**	0.7071	**0.7571**

7.5 Limitations

The major limitation of ALR is relying entirely on single columns, not taking co-occurrences of input labels and context of the product into account to handle ambiguous predictions. Hence, an imbalanced dataset may restrict our evaluation. Besides to unbalanced target labels, columns contain duplicates, especially attribute representatives from BoW. Additionally, our dataset includes a wide range of attributes and products (c.f. Table 2), but only a limited amount of different manufacturers.

We designed ALR to also work with low-quality data, which our real-world dataset requires: The qual-

ity varies from clean data to attribute representatives without whitespaces (e.g., *96test* instead of *96 test*), representatives with misspellings or worse, representatives containing encoding errors and arbitrary strings or numbers (e.g., *™* instead of ™, *ug* instead of µg). These quality issues may negatively affect the presented results due to uncertain matches in the ground-truth data and more frequent out of vocabulary errors. Out of vocabulary issues are the most common reason for ALR not predicting a target label.

Another limitation of ALR is depending on a fixed schema: All products need the same context or domain to apply ALR since we only learn a single target schema. Therefore, we need to retrain the model if the target schema changes. However, changes in the target schema are rare, considering SMEs.

7.6 Experiences of Practitioners

We integrated a research prototype into the production systems of our partner as a recommendation engine. We applied this strategy because, according to interviews with our partners and reviews of their use case, a single wrong, fully automatic prediction in the production system would lead to mistrust. Furthermore, an unrecognized false prediction might cause incorrect product data displayed to customers. According to the results of our evaluation, the risk is too high.

We applied ALR with $ngram_{t0.5}$ due to its performance in MRR in our evaluation. Despite not being able to (always correctly) predict every label, ALR reduced the manual effort from minutes to seconds if the correct prediction occurred in the top 3 labels, which is the case in 86%. This feedback validates the economic benefit of ALR in practice.

8 CONCLUSION

The results of our evaluation show that ALR outperforms the approach of Chen et al., and ALR at least performs on even compared to Pomp et al., with better results on BoW attribute representatives. Furthermore, we verified the better performance of language features compared to character and column distribution features for catalog integration.

Although we used simple language features (one-hot vectors), we were able to produce results on low-quality data that impact and simplify the daily business of practitioners. Using sophisticated embeddings instead of one-hot vectors could further improve our results as they did in natural language processing (NLP) tasks like named entity recognition (NER). It has to be considered that these embeddings need to be specialized in the catalog domain.

Due to the imbalanced labels and attribute instances of the dataset used, further research needs to investigate the performance on other datasets or evaluate ALR over a more extended period in production systems with feedback from practitioners and analysis of their manual corrections. To adapt ALR onto other domains, a model needs to learn from an integration dataset, which contains at least attribute representatives with corresponding target labels of a fixed schema. Since log files of integration processes contain these data, adapting ALR to another domain is simple.

Finally, future research should address the major limitation of ALR: Since ALR relies only on single columns, it does not take co-occurrences of labels into account to handle ambiguous labels. Handling these labels could further extend the use case of ALR.

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