Semantic Labeling Using a Deep Contextualized Language Model

Mohamed Trabelsi  
Lehigh University  
Bethlehem, PA, USA

Jin Cao  
Nokia Bell Labs  
Murray Hill, NJ, USA

Jeff Hefflin  
Lehigh University  
Bethlehem, PA, USA

ABSTRACT

Generating schema labels automatically for column values of data tables has many data science applications such as schema matching, and data discovery and linking. For example, automatically extracted tables with missing headers can be filled by the predicted schema labels which significantly minimizes human effort. Furthermore, the predicted labels can reduce the impact of inconsistent names across multiple data tables. Understanding the connection between column values and contextual information is an important yet neglected aspect as previously proposed methods treat each column independently. In this paper, we propose a context-aware semantic labeling method using both the column values and context. Our new method is based on a new setting for semantic labeling, where we sequentially predict labels for an input table with missing headers. We incorporate both the values and context of each data column using the pre-trained contextualized language model, BERT, that has achieved significant improvements in multiple natural language processing tasks. To our knowledge, we are the first to successfully apply BERT to solve the semantic labeling task. We evaluate our approach using two real-world datasets from different domains, and we demonstrate substantial improvements in terms of evaluation metrics over state-of-the-art feature-based methods.

CCS CONCEPTS

• Information systems → Data mining; • Computing methodologies → Artificial Intelligence; Knowledge representation and reasoning.

KEYWORDS

semantic labeling; pretrained language model; data table

1 INTRODUCTION

In this era of Big Data, various datasets are publicly available for users to explore vast amounts of information in multiple fields. Among all types of publicly available datasets, data tables represent the most prevalent form of data. A data table has multiple rows and columns. Each column can be seen as a variable described by a schema label in order to distinguish between the variables. Some of these data tables are pre-processed, for example, those found in repositories such as UCI machine learning repository\(^1\), kaggle\(^2\), and OpenML \([42]\). Governments also store their data in a tabular format, like data.gov\(^3\). In addition to that, vast amounts of information that are related to scientific, political, and cultural topics, are found on the Web. Some others require extraction such as those HTML

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\(^1\)Mohamed Trabelsi’s work was done during a summer internship in Nokia Bell Labs.

\(^2\)http://archive.ics.uci.edu/ml/index.php

\(^3\)https://www.kaggle.com/

\(^3\)https://www.data.gov/
[11, 36, 47] tasks. Different from traditional word embeddings, the pre-trained neural language models are contextual with the representation of a token is a function of the entire sentence. This is mainly achieved by the use of a self-attention structure called transformer [43]. Here, we integrate BERT into our proposed method, denoted by SeLaB (Semantic Labeling with BERT), to solve the schema generation task. We train a single BERT model that makes an initial prediction for the column’s label using only data values, and then updates its prediction by incorporating both data values and predicted contexts of the column. SeLaB is trained end-to-end for feature extraction and model building, which reduces the significant human effort that is needed in prior methods, and gives the model the ability to capture specific features that are better than the hand-crafted ones for semantic labeling. In addition to that, by incorporating the context, we are able to predict labels in a richer and more fine-grained set of vocabulary unlike the limited classes that are used to describe the semantic labels. SeLaB doesn’t assume that the column values match an existing KB, and therefore SeLaB generalizes to table collections from multiple domains.

In summary, we make the following contributions:

- We propose a new context-aware semantic labeling approach. Our method presents a new setting in which the input to our model is a data table with missing headers, and we sequentially generate schema labels for each data table.
- We demonstrate that by incorporating the predicted contexts of an attribute into the model, we can more accurately infer its context-aware schema label.
- We are the first to integrate BERT into the semantic labeling task. In particular, we incorporate data values and predicted contexts using BERT, which is trained end-to-end for feature extraction and label prediction. This reduces human effort in the semantic labeling.
- We experiment on two datasets (public and internal data table corpus), and demonstrate that our new method outperforms the state-of-the-art baselines, and generalizes to table collections from multiple domains.

2 RELATED WORK

2.1 Semantic Labeling

Existing approaches [16, 35, 41] in the semantic labeling consist of classifying data values into a predefined set or categories known as semantic labels. These approaches rely on a multiclass classification setup where the labels are manually defined and curated. Commercial tools, like tableau[4] and Trifacta[5], are proposed for semantic type detection. Only a limited set of semantic types are predicted using these tools. Hulsebos et al. [16] extend the set of semantic types by considering 275 DBpedia [1] properties. These manually defined concepts, like Birth place, Continent, and Product, represent the semantic types that are frequently found in datasets. In order to infer the semantic type of a column using data values, the authors define four categories of features which are: global statistics, character distributions, pretrained word embedding, and trained paragraph embedding. Each feature category has different performance and noise level, so that the authors propose a multi-input neural networks model, instead of simply concatenating all features, and feeding the resulting feature vector to a single-input neural network. The multi-input neural networks model is composed of multiple identical subnetworks without weights sharing. Each subnetwork consists of two fully connected hidden layers with batch normalization, rectified linear unit (ReLU) activation functions, and dropout. Knowledge Base based methods [8, 9] integrate DBpedia [1] to predict semantic labels, where entities from DBpedia that match all the column cells are used as additional information for a given column values.

Semantic types use a limited set of vocabulary, and can restrict the number of categories that can be considered when inferring the label of a given column. In practice, the predefined set of semantic types may not apply for new datasets. Chen et al. [10] proposed a schema label generation task, in which the objective is to infer the schema label, and not only the semantic type. This setting can be
seen as a multiclass classification task, where each column’s label in the training set represents a possible semantic label. Generating schema labels is more challenging as the number of possible labels is large compared to the predefined set of semantic types. The authors extract hand-crafted features from data values to predict schema labels. The set of features include content and unique content ratio [15], and the content histogram which is a 20-dimensional vector extracted using fast Fourier transform (FFT). Random forest classifier is used to predict schema labels from the curated features.

Schema matching is related to semantic type detection where the objective is to find correspondence between attributes in different schemas. Existing data on the Web, such as WebTables [5], and knowledge bases, such as DBPedia [1] and Freebase [4], are used in schema matching. Syed et al. [40] use headers and data values to predict the class of a column in the target ontology or knowledge base. The data values provide additional information that can disambiguate between the possible candidates. Limaye et al. [22] associate one or more types from YAGO [37] with each attribute or column in the table using a probabilistic graphical model. Another probabilistic approach, that is based on the maximum likelihood hypothesis, is introduced by Venetis et al. [44]. The best label is chosen to maximize the probability of the values given the class label for a given column. The authors showed that class labels that are automatically extracted from the web provide more coverage for column’s labeling than using manually created knowledge bases like YAGO [37] and Freebase [4].

Matching functions are used to infer the correct semantic labels for data values. Pham et al. [31] solve the semantic labeling as a combination of many binary classification problems. After extracting similarity metrics features from a pair of attributes, each feature vector is given a True/False label, where True means that the attributes have the same semantic type, and False indicates that the attributes are not sharing the same semantic type. Logistic Regression and Random Forests are used to predict the matching score. For the similarity metrics features, the authors investigated multiple metrics, such as Jaccard similarity [26], cosine similarity of the product of term frequency (TF) and inverse document frequency (IDF), known as TF-IDF [26], Kolmogorov-Smirnov test (KS test) [21], and Mann-Whitney test (MW test) [21]. Mueller and Smola [27] proposed a neural network embeddings for data values to predict the matching score of two sets of data values. The matching score is estimated using the distance between the embeddings of two sets of data values. The score is adjusted using the output of another neural network to distinguish two columns that are different but their data values are identically distributed.

Semantic types prediction is formalized as a ranking problem in the approach proposed by Ramnandan et al. [34]. Training data values are considered as documents, and the previously-unseen data values are considered as queries. So, in the prediction phase, the objective is to extract the top k candidate semantic labels for the new data values by ranking semantic labels in decreasing order using cosine similarity between query feature and every document feature in training data. The authors distinguished between textual and numeric data. For textual data, the feature vector is a weighted bag of words with TF-IDF. For numerical data, the authors used a statistical hypothesis testing to analyze the distribution of numerical data values that corresponds to a given semantic label. The statistical hypothesis test is performed between each sample in the training data and the testing sample. The returned p-values are then ranked in descending order to predict the top k candidate semantic labels for the testing data values.

Our proposed method is based on the multiclass classification setting because the schema labels are easily collected from data table corpus, unlike matching based strategy that requires additional human effort to define pairs of attributes that have similar semantic type.

### 2.2 BERT

BERT [14] is a deep contextualized language model that contains multiple layers of transformer [43] blocks. Each transformer block has a multi-head self-attention structure followed by a feed-forward network, and it outputs contextualized embeddings or hidden states for each token in the input. BERT is trained on unlabeled data over two pre-training tasks which are the masked language model, and next sentence prediction. Then, BERT can be used for downstream tasks on single text or text pairs using special tokens ([SEP] and [CLS]) that are added into the input. For single text classification, BERT special tokens, [CLS] and [SEP], are added to the beginning and the end of the input sequence, respectively. For applications that involve text pairs, BERT encodes the text pairs with bidirectional cross attention between the two sentences. In this case, the text pair is concatenated using [SEP], and then treated by BERT as a single text.

The sentence pair classification setting is used to solve multiple tasks in information retrieval including document retrieval [13, 29, 46], frequently asked question retrieval [36], passage re-ranking [28], and table retrieval [11]. The single sentence setting is used for text classification [38, 48]. BERT takes the final hidden state \( h_0 \) of the first token [CLS] as the representation of the whole input sequence, where \( \theta \) denotes the parameters of BERT. Then, a simple softmax layer, with parameters \( W \), is added on top of BERT to predict the probability of a given label \( l: p(l | h_0) = \text{softmax}(Wh_0) \). The parameters of BERT, denoted by \( \theta \), and the softmax layer parameters \( W \) are fine-tuned by maximizing the log-probability of the true label.

The organization of the rest of the paper is as follows. Section 3 formalizes the semantic labeling as a multiclass classification problem; Section 4 proposes a new context-aware semantic labeling approach that is based on the deep contextualized language model, BERT; and Section 5 illustrates data table collections that are used in our approach, and compares baselines and our algorithm in the semantic labeling task.

### 3 PROBLEM STATEMENT

Our goal is to generate schema labels or semantic types for tables columns using data values, and predicted contexts in order to resolve the ambiguity problem in the prediction phase. As we mentioned before, we use the multiclass classification setting to solve schema labeling. The training data consists of a table corpus \( \mathcal{T} = \{ T_1, T_2, \ldots, T_n \} \), with \( n \) is the total number of data tables. Each table \( T_k \) has a set of \( m \) columns \( A_1, A_2, \ldots, A_m \), where each column \( A_j \) has a schema label \( l_j \) (column’s header), and a set of data values \( V_i = \{ v_{i1}, v_{i2}, \ldots, v_{ir} \} \), where \( r \) is the number of rows in \( T_k \). The set
of all possible schema labels is denoted by $L$. Resolving ambiguity when predicting schema labels requires the whole table as input to the model, instead of only using independent column’s values. Therefore, our setting consists of table inputs that have missing headers, and our objective is to predict schema labels for all columns of the input table.

We denote our proposed model by $M = N \circ F$, with $F$ is the feature extractor function (Contextual input block in Figure 1), and $N$ is the classification layer (Model block in Figure 1). The input to $M$ is a table $T_k$ with missing schema labels, and the output of our model is a sequence of predicted schema labels $\hat{A}_1, \hat{A}_2, \ldots, \hat{A}_m$. Our method learns both features and model simultaneously leading to significant reduction in human’s effort spent in the feature engineering phase.

4 CONTEXT PREDICTION FOR SEMANTIC LABELING

In this section, we introduce our context-aware method for schema label generation. We formally define the contextual information of each column, which is combined with column’s data values to improve the performance of semantic labeling.

4.1 Column’s context

The set of data values $V_i$ for a given column $A_i$ in a table $T_k$ are not sufficient to have accurate schema label prediction. For example in Figure 1, both columns nationality (A3 in the left table) and location (A4 in the right table) contain values from class country, but they refer to different labels. In this case, if we know that $A_3$ (in the left table) occurs in a table that contains player, team, position, and birth date attributes, hence it is more probable that $A_3$ is related to nationality rather than location. Therefore, we argue that the attributes $A_1, A_2, \ldots, A_{i-1}, A_{i+1}, \ldots, A_m$ provides a rich contextual information for $A_i$. However, as we explained in our setting, the input to our model is a table that has missing headers, which means that we cannot directly incorporate the context into our model.

To solve that, we propose incorporating predicted context instead of the ground truth context. In other words, our model has two passes for predicting schema labels. During the first pass, given a table $T_k$ with missing headers, only data values are used to make initial predictions for semantic labels, denoted by $A_1', A_2', \ldots, A_m'$. The initial predictions are context-free, as they only capture data values. For the second pass, we incorporate both data values $V_i$ and the predicted context $A_1', A_2', \ldots, A_{i-1}', A_{i+1}', \ldots, A_m'$ of $A_i$ to make the final context-aware prediction, denoted by $\hat{A}_i$.

4.2 Semantic labeling with BERT (SeLaB)

We incorporate data values and predicted contexts of a given attribute using the contextualized language model BERT. So, for our proposed model $M = N \circ F$, denoted by SeLaB, $F$ is equivalent to BERT with parameters $\theta$, as we use the hidden state of [CLS] token from the last transformer block to compute the embedding of the input sentence. $N$ denotes the softmax layer with parameters $W$ that is used to produce the probability distribution of a given sequence over all schema labels from $L$. The general form of input to $M$ for an attribute $A_i$, denoted by contextual input, is the sequence $[CLS] + V_i + [SEP] + \text{context}(A_i) + [SEP]$, where context($A_i$) is the predicted context of $A_i$. For first pass prediction, where context($A_i$) is missing, the input sequence form, denoted by only values, becomes $[CLS] + V_i + [SEP] + [SEP]$. Next, we describe the training and testing phases.

4.2.1 Training phase. The steps of training phase are shown in Algorithm 1. The inputs to training phase are: table corpus $T = \{T_1, T_2, \ldots, T_k\}$ where semantic labels $l_1, l_2, \ldots, l_m$ are available for all attributes $A_1, A_2, \ldots, A_m$ of a given table $T_k \in T$, set of possible semantic labels $L$, and pre-trained BERT model as a feature extractor $F$. The compact notation of table $T_k$, that is used in algorithms, is $T_k = [\{A_1, V_1\}, \{A_2, V_2\}, \ldots, \{A_m, V_m\}]$.

The training process has three phases. The first phase consists of predicting an initial label for each column using only values input form as shown in Lines 4–9 of Algorithm 1. The output of the first phase is a sequence $A_1', A_2', \ldots, A_m'$ of initial predicted labels. During the second phase (Lines 10–15), we construct the predicted context context($A_i$) for each attribute $A_i$, which is the set of predicted labels $\{A_j'; j \in [1, m] \}$ in each column. In order to avoid the true label leakage in context($A_i$), we remove $l_i$ from context($A_i$) if $l_i \in$ context($A_i$). We also remove duplicates from context($A_i$) as most of data tables contain unique headers. The final phase (Lines 16–21) computes the context-aware predictions by using contextual input form. The output of $M$ is the probability distribution $\hat{p}_i$ over all labels in $L$, for every $A_i \in T_k$. These probability distributions are used to calculate the cross entropy loss, and to update the parameters of $M$ as indicated in Lines 22–23. In addition to incorporating the context of column for schema labeling, our model has the ability to accept two forms of sequence inputs (only values and contextual input),

Algorithm 1 Training phase

1. Input: tables collection $T = \{T_1, T_2, \ldots, T_k\}$, set of labels $L$.
2. for $T_k$ in $T$ do
   3. the schema labels of $T_k$, $l_1, l_2, \ldots, l_m$, are available
   4. % First phase: Values based prediction phase
   5. for $[A_i, V_i]$ in $T_k$ do
      6. input to BERT for $A_i$: $I_i(A_i) = [CLS] + V_i + [SEP] + [SEP]$
      7. compute values based probability, $p_i = M(I_i(A_i))$
      8. $A_i' = \text{argmax}_{c \in \mathbb{L}} p_i(c)$
   9. end for
   10. % Second phase: Compute contexts of each attribute
   11. for $[A_i, \ldots]$ in $T_k$ do
      12. Context of $A_i$: $\text{context}(A_i) = A_1' + A_2' + \ldots + A_i' + \ldots + A_m'$
      13. avoid true label leakage in context: remove $l_i$ from context($A_i$) if $l_i \in$ context($A_i$)
      14. remove duplicates from context($A_i$)
   15. end for
   16. % Third phase: compute final predictions
   17. for $[A_i, \ldots]$ in $T_k$ do
      18. input to BERT for $A_i$: $I_i(A_i) = [CLS] + V_i + [SEP] + \text{context}(A_i) + [SEP]$
      19. compute context-aware probability, $\hat{p}_i = M(I_i(A_i))$
      20. $A_i = \text{argmax}_{c \in \mathbb{L}} \hat{p}_i(c)$
   21. end for
   22. loss($T_k$) = CrossEntropy($[\hat{p}_1, \hat{p}_2, \ldots, \hat{p}_m]$, $[l_1, l_2, \ldots, l_m]$)
   23. update $M$ parameters ($\theta, W$) by minimizing loss($T_k$)
   24. end for
25. Output: A Trained context-aware model $M$.
which significantly reduces the number of parameters compared to the case where a separate model is needed to handle each type of input sequence.

In contrast to [31, 34] which have a pre-processing step to distinguish between string and numerical attributes, our BERT-based feature extractor F is able to process string and numerical texts by taking advantage of BERT tokenizers. In contrast to [10, 16] where the feature extraction and model building steps are decoupled, our model M = N ◦ F is trained end-to-end to jointly optimize the feature extractor F, and the classification layer N. Unlike [8, 9] that integrate external KB in semantic labeling with a strong assumption that the column’s values match the KB entities, SeLaB needs only BERT embeddings that is fine-tuned on target table corpus to extract the feature of each column, and therefore generalizes to data tables from multiple domains. We train SeLaB for E epochs.

Algorithm 2 Testing phase

1: Input: testing table \( T_k \), set of headers labels L, trained M model, Boolean: unique_headers and topsc. 
2: First phase: Values based prediction phase 
3: Second phase: Compute contexts of each attribute 
4: % Third phase: compute final predictions 
5: predicted_attributes = ∅, seen_columns = ∅ 
6: for it in [1, m] do 
7: for \((A_i, V_i)\) in \( T_k \) do 
8: input to BERT for \( A_i \): \( I(A_i) = [CLS] + V_i + [SEP] + context(A_i) + [SEP] \) 
9: compute context-aware probability, \( \hat{p}_i = M(I(A_i)) \) 
10: \( \hat{A}_i = \text{argmax}_{\ell \in L} \hat{p}_i[\ell], \quad \hat{p}_{\text{max}} = \text{max}_{\ell \in L} \hat{p}_i[\ell] \) 
11: end for 
12: if unique_headers then 
13: \( h, \text{chosen_label} = \text{UniqueHeaders}(\{\hat{p}_1, \hat{p}_2, \ldots, \hat{p}_m\}, \text{tops}_{\text{c}}, \text{predicted_attributes}) \) 
14: \( \hat{A}_h = \text{chosen_label} \) 
15: else 
16: \( h = \text{argmax}_{i \in [1, m-\text{it+1}] \in \text{it+1}} p^s \) 
17: end if 
18: \( \text{predicted_attributes}.\text{append}(\hat{A}_h) \), \( \text{seen_columns}.\text{append}(h) \) 
19: \( T_k.\text{delete}(\{A_h, V_h\}) \) 
20: update contexts with new predicted attribute \( \hat{A}_h \): replace \( A'_h \) by \( \hat{A}_h \) in context(Ai), \( i \in [1, m] \setminus \text{seen_columns} \) 
21: end for 
22: Output: A label for each header in the testing table.

4.2.2 Testing phase. The steps of the testing phase are shown in Algorithm 2. The inputs to the testing phase are: a testing table \( T_k \) that has missing headers (\( l_1, l_2, \ldots, l_m \), are not available), set of possible semantic labels L, trained model M, and two parameters unique_headers and topsc, that we will describe later.

The testing process has three phases. The first and second phases (Lines 2–3) are similar to the training process, where initial predictions are computed using only values input form, and then used to produce the context of each attribute. During the third phase, the final predicted labels for the testing data table are generated sequentially as shown in Lines 4–22. For a given table \( T_k \), initially all schema labels are missing, and the set of predicted attributes, denoted by predicted_attributes, is empty. Given that the prediction is done sequentially, \( m \) passes are needed to obtain a predicted schema label for each column in \( T_k \). For the \( j \)-th pass, the predicted_attributes has \( j-1 \) labeled headers, and \( m-j+1 \) columns in \( T_k \), denoted by \( S_j \), are still missing the predicted labels. We predict the probability distribution \( \hat{p}_i \) and a schema label \( \hat{A}_i \) for each column \( A_i \in S_j \) using our model M with contextual input sequence. The confidence of prediction for \( A_i \in S_j \) is given by \( p_{\text{max}} = \text{max}_{\ell \in L} \hat{p}_i[\ell] \). The unique_headers is a Boolean variable that we set to True to force the unique headers constraint for a given table. When predicting duplicate headers is allowed, the column \( h \), that we choose to predict from \( S_j \) in the \( j \)-th pass, is given by \( h = \text{argmax}_{i \in [1, m-\text{it+1}]} p^s \) as shown in Lines 15–16.

Algorithm 3 UniqueHeaders

1: Input: probability distributions \( \hat{p}_1, \hat{p}_2, \ldots, \hat{p}_m, \text{tops}_{\text{c}}, \text{already predicted headers set} \( \text{Ps} \) 
2: \( p^s_{\text{c}} \): select topsc probabilities of \( \hat{p}_i, i \in [1, l_m] \) 
3: \( \hat{A}_h \): argmax of topsc probabilities of \( \hat{p}_i, i \in [1, l_m] \) 
4: repeat 
5: \( c = \text{argmax}_{i \in [1, l_m]} p^s_{\text{c}}[i] \) 
6: \( \text{chosen_label} = \hat{A}^c_{\text{c}}[1] \) 
7: \( p^s_{\text{c}}[1 : l_m-1] = p^s_{\text{c}}[2 : l_m], \quad p^s_{\text{c}}[l_m] = -1 \) 
8: \( \hat{A}_h^c[1 : l_m-1] = \hat{A}_h^c[2 : l_m], \quad \hat{A}_h^c[l_m] = -1 \) 
9: until \( \text{chosen_label} \notin \text{Ps} \) or \( p^s_{\text{c}} \) contains only -1, for \( i \in [1, l_m] \) 
10: if \( \text{chosen_label} \notin \text{Ps} \) then 
11: return \( \text{chosen_label} \) from first pass in repeat loop 
12: end if 
13: Output: \( c \): chosen column for prediction, \( \text{chosen_label} \)

On the other hand, when unique headers constraint is required for a given data table, we propose a routine, called UniqueHeaders, that resolves the duplicate headers problem as shown in Algorithm 3. The inputs to this routine are: the probability distributions \( \hat{p}_i \) for \( A_i \in S_j \), topsc which denotes the number of top confidences per attribute that are used to find the label, and the set predicted_attributes that contains the \( j = 1 \) semantic labels that are already assigned to \( j-1 \) columns of \( T_k \). The objective of the function UniqueHeaders is to find the label chosen_label with the highest confidence value, with respect to the unique headers constraint that requires \( \text{chosen_label} \notin \text{predicted_attributes} \). For time complexity efficiency, we limit the depth of search by choosing \( \text{topsc} \ll ([L] \cdot \text{it+1}) \). By limiting the depth of search, UniqueHeaders can produce a duplicate header. In this case, we use a heuristic that returns the label that corresponds to the maximum confidence score. UniqueHeaders is called in Lines 12–14 of Algorithm 2.

We remove the chosen column \( h \) from \( S_j \) to obtain \( S_{j+1} \) (the columns of \( T_k \) that are still missing labels after the \( j \)-th pass), and we add the chosen column \( h \) to seen_columns set, and the predicted label \( \hat{A}_h \) to predicted_attributes set (Lines 18–20). We finish the \( j \)-th pass by updating context(Ai), where \( A_i \in S_{j+1} \), using the predicted label \( \hat{A}_h \) from the \( j \)-th pass as shown in Line 21. The objective of the context update step is to replace the only values predicted label by the contextual input inferred schema label, as the latter is more accurate than the former. For the \( j \)-th pass, we select the best schema label from \( m-j+1 \) predicted labels. The increase in the number of predictions is justified by the sequential nature of
the testing algorithm where context is updated in each pass, and the most confident prediction is selected.

5 EVALUATION

5.1 Data collections

5.1.1 WikiTables. This dataset is composed of the WikiTables corpus [2] which contains over 1.6M tables that are extracted from Wikipedia. Since a lot of tables have unexpected formats, we preprocess tables so that we only keep tables that have enough content with at least 3 columns and 50 rows. We further filter the columns whose schema labels appear less than 10 times in the table corpus, as there are not enough data tables that can be used to train the model to recognize these labels. We experiment on 15,252 data tables, with a total number of columns equal to 82,981. The total number of schema labels is equal to 1088.

5.1.2 Log Tables from Network Equipment. Our work is motivated by the business need to automatically generate schema labels for the data tables extracted from log files of network equipment. Network logs files contain computer-generated event records, such as authentication attempts, process assessment calls and information output of network equipment, and are instrumental for network performance monitoring and fault diagnosis.

For the purpose of schema label auto-generation, we shall utilize the existing data tables that have already been collected in an internal platform used by network care engineers from parsing log files. In the current pipeline, engineers design a parser for each type of log files, and these parsers generate the tables. We have collected 329 tables from this platform with logs files coming from products on wireless equipment such as base station, Radio Access Network and Radio Network Controllers. To evaluate our methods on header prediction, we removed tables that have less than 10 rows and cleaned up columns that have mostly invalid values (such as NULL, empty string, or NA). The remaining set contains 248 tables. The number of rows of these tables have a very skewed distribution with quantiles being 138 (25%), 551 (50%) and 1954 (75%), while the number of columns ranges from 3 to 48 columns with many tables having in the neighbourhood of 10 columns. For our purpose, we focus on 87 headers from these tables that have more than 3 instances.

Figure 2 shows the cumulative frequency distribution for the headers from the two datasets, from the most to the least popular. There is a small set of labels that are much more frequently occurring in WikiTables. One reason that the labels in log tables are more scattered is because the tables are manually collected from diverse products as we would like to understand the performance of our algorithm in various situations.

5.2 Baselines

We compare the performance of our proposed model with feature-based baselines [10, 16], and a variation of our model where only data values (without context) are used. We describe the five categories of features that are extracted from the data values of each column. There are five categories of features as shown in Table 1. Four categories are previously used in feature-based methods: global statistics [10, 16], character distributions [10, 16], word embeddings

| ID | Category type          | Dimension |
|----|------------------------|-----------|
| 1  | Global statistics      | 52        |
| 2  | Character distributions| 960       |
| 3  | Character embeddings   | 400       |
| 4  | Word embeddings        | 401       |
| 5  | Paragraph embeddings   | 400       |
The dimension of embedding is 100, so that after computing statistics, the dimension of the concatenated feature vector equals 400. As in [16], an additional binary feature is appended to the final word embedding feature vector, and it indicates if there is at least one value from $V_i$ that belongs to Glove vocabulary.

The use of pre-trained embedding is suitable for table collections, such as WikiTables, that have common values with the vocabulary of the pre-trained embedding. This is not the case for log tables from network equipment, where the number of out of vocabulary (OOV) tokens is large, and this leads to poor performance for pre-trained word embedding. To solve this problem, we train a word embedding on the table corpus $T$, where the sentences are rows and columns from $T_i \in T$. Instead of using Glove, we train a fastText [3] model to produce word embeddings. The use of character-level n-grams in fastText allows word embeddings to be created even for terms that have not been seen before, and reduces the negative effect of OOV tokens. Given that having long strings is common for log data, we use BERT tokenizer to preprocess values before training fastText embeddings.

### 5.2.5 Paragraph embeddings
Each column $A_i$ can be seen as a paragraph that contains the set of values $V_i = \{v_1, v_2, \ldots, v_r\}$. The paragraph embedding, that is based on the distributed bag of words [20], is trained to map each column into an embedding with dimension equals to 400.

### 5.2.6 Sherlock
Hulsebos et al. [16] uses global statistics, character distributions, word embeddings, and paragraph embeddings with a multi-input neural networks architecture.

### 5.2.7 All features
This baseline extends Sherlock [16] features by adding our character embeddings to cover three different levels of embeddings (character, word, and paragraph).

### 5.2.8 BERT with only values
This baseline can be seen as a variation of our proposed method SeLaB, where only data values are used to predict schema labels. So, for training, the first phase predictions are used to update the parameters of the model. For testing, the first phase predictions are used to evaluate the performance of the model. The input data values sequence to the model has only values input form.

We note that we do not compare to external KB based methods [8, 9] because there is a vocabulary mismatch between log tables from network equipment and DBpedia, and an important aspect of our evaluation is to show generalization to data tables from multiple domains (not only tables from Wikipedia and Web tables).

### 5.3 Experimental Setup
In our proposed model, we use the BERT-base-uncased for the feature extractor $F$. For each column, we shuffle data values and randomly select a subset of values to reduce the complexity of the model. Given that the majority of log tables have more rows than WikiTables, we randomly choose 200 values for each column in a given log table, and 100 values for columns from WikiTables. In general, shuffling the predicted context can reduce overfitting. For WikiTables collection, the majority of tables that have both attributes home team and away team (these attributes have similar data values), report home team column before away team column (same for birth date which occurs before death date) for a left-to-right sequential order. In this case, we can resolve the ambiguity of predicting home team and away team by keeping the sequential order of the predicted context. We train our model for 10 epochs, and we set $top_k$ of UniQueHeaders routine to 5.

The model is implemented using PyTorch, with Nvidia GeForce GTX 1080 Ti. We use Adam [19] optimizer for gradient descent to minimize the cross entropy loss function and update the weights of our model. We report results for our method and baselines using a random split of the entire table corpus, where 80% of tables are used for training, and 20% for testing. For the baselines, BERT with only values is also trained for 10 epochs. For the feature-based baselines (except for Sherlock), random forest is trained for prediction.
5.4 Experimental results

We evaluate the performance of SeLaB and baselines on the schema labeling task using macro-averaged and micro-averaged precision (P), recall (R) and F-score of predictions on the testing set. In the multiclass classification problem, the micro-average precision, recall and F-score are the same, so we only report the Micro-F score. We also report the Mean Reciprocal Rank (MRR) [23], as the rank of the true class is an important measure for evaluation. In addition to that, we calculate the top-\(k\) accuracy that shows the fraction of testing samples where the true label is within the top \(k\) predicted confidences.

5.4.1 Semantic labeling results. Table 3(a) shows the performance of different approaches on the WikiTables collection. We show that our proposed method SeLaB outperforms the baselines for all evaluation metrics. The context, which is incorporated into our model, solves the ambiguity in predictions and leads to an increase in evaluation metrics compared to baselines that generate schema labels solely on the basis of data values. Among all the five categories of features (global statistics, character distributions, character embeddings, word embeddings, paragraph embeddings) that are used in the feature-based approaches, our character embeddings feature achieves higher performance for all evaluation metrics. So, a generative model with a character granularity is able to capture the distributions of data values drawn from different variables or attributes. Figure 3(a) shows the top-\(k\) accuracy results where our method SeLaB outperforms the baselines. BERT with only values, Sherlock, and all features baselines have close performance. So, the BERT-based embedding, which is trained by using only data values, is as good as the hand-crafted features. While extracting the hand-crafted features requires significant human effort to compute the global statistics, character distributions and three types of embeddings (character, word, and paragraph), BERT embeddings are trained jointly with the classification layer with minimal preprocessing which reduces the human effort.
Table 3(b) and Figure 3(b) show the performance of different approaches on the Log tables from network equipment. Consistent with WikiTables, our results on the log tables corpus show the importance of a column’s context in improving the semantic labels prediction, especially for top-1 accuracy as shown in Figure 3(b). The top-5 accuracies for SeLaB, BERT with only values, and all semantic labels are missing for a given data table. This can be seen as an extreme case. A common scenario for tables extraction is to have a percentage of missing or false headers. To better understand how SeLaB deals with such tables, we randomly mask a percentage of headers from tables in the testing set, and we compute the top-1 accuracy function of the percentage of masked headers as shown in Figure 4. For each table, we run the masked headers for five times with a randomly selected headers, and we compute mean and standard deviation (std) for each percentage of masked headers. 100% masked headers means that all labels are missing which is the most difficult and the main setting for SeLaB.

As reported in Figure 4, the maximum std (vertical bar) is 0.01 for Log tables and 0.005 for WikiTables. Figure 4 shows that when the percentage of masked headers decreases, there is an increase in the mean of top-1 accuracy for predicted masked headers. This means that the attribute’s context is more accurate given that the labels of the non-masked headers are groundtruth labels. However, comparing the fully predicted context in 100% masked headers with the partially predicted context in 20% masked headers, there is only a small improvement (mainly for WikiTables) which indicates that the predicted context in the extreme case is as good as groundtruth context.

5.4.3 String vs Numeric columns analysis. We evaluate the performance of SeLaB for two categories of columns which are numeric and string. As shown in Figure 5, we report top-k accuracy of numerical and string columns for Log tables and WikiTables. In both datasets, semantic labeling of string columns outperforms numerical columns. So, generating an exact schema label for numerical data values is more ambiguous than string values, as numerical columns contain similar values.

5.4.4 Predicted labels examples. To better understand how SeLaB works, we show examples of predicted schema labels from WikiTables testing set in Table 4. Each row corresponds to a testing table where we show the ground truth attributes, first phase predictions, and the final predicted schema labels. For example, for the first row, there are three wrong predictions (year instead of season, division instead of section, and finish instead of position) from first phase predictions which are based only on data values. After incorporating context for each attribute, SeLaB updates the predicted label for each column, and the new context-aware semantic labels that match the ground-truth labels are shown in bold in Table 4. For the first example, we obtain the third phase predictions which are identical to the ground truth labels after three corrections from context-aware representation for each column. For the sixth row, the table’s attributes contain home team and away team. Both attributes are predicted home team after first phase predictions. SeLaB learns that away team occurs with home team so that the predictions are corrected after the third phase.

5.4.5 Effect of the Number of Training Samples. To understand how the number of training samples for each semantic label affects the accuracy of SeLaB predictions in the test data, in Figure 6, for each label in the testing set, we plot the indicator values of correct SeLaB prediction against the number of samples for each label in the training set as black circles (i.e. 1 indicates the predicted column header is the same as the ground truth). Local smoothing [12] was performed to obtain the average accuracy curve for SeLaB predictions (yellow line). As a reference, we also added a similar local smoothing curve representing the accuracy curve from predictions obtained using “Bert with only values” (pink line).

Figure 6 clearly demonstrates that overall speaking, as the number of samples for each label in the training set increases, both SeLaB and “Bert with only values” are performing better. However, SeLaB appears to perform much better when there is sufficient number of samples.
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| Table attributes | First phase predictions | Third phase predictions |
|------------------|-------------------------|-------------------------|
| season, level, division, section, position | year, level, division, division, finish | season, level, division, section, position |
| pos, rider, bike, pts | year, title, developer, developer, setting, system | year, title, developer, publisher, setting, system |
| pos, class, no, team, drivers, car, laps, qual pos | pos, group, rank, driver, driver, car, deaths, rank | pos, class, no, entrant, drivers, car, laps, grid |
| senator, party, years, term, electoral history date, time, home team, away team site, location, year, description | representative, party, years, wins, electoral history date, time, home team, home team site, province, year, description | representative, party, years, term, electoral history date, time, home team, away team name, location, year, description |
| land area, latitude, longitude | area, latitude, geographic coordinate system | land area, latitude, longitude |
| title, director, cast, genre, notes | film, role, cast, genre, notes | role, director, cast, genre, notes |
| county, location, exit number, destinations, notes | county, location, notes, notes, notes | county, location, exit, destinations, notes |

Table 4: Example of predicted schema labels from Wikitables testing set

| Figure 6: Accuracy vs. Number of training samples per label |
|-------------------------------------------------------------|
| ![Graph](image1.png) ![Graph](image2.png) |

(a) Log tables
(b) WikiTables

of samples per label (e.g. more than 20 instances). There is a slight dip for the SeLab curve for those columns when the corresponding number of samples in the training set becomes the largest. Upon close inspection, it does not seem to imply that the performance of SeLab is deteriorating. For example, in Wikitables, the column header with the largest number of instances is in fact a generic label name (with 3064 instances in training data). In the testing set, SeLab sometimes predicts name as player, swimmer, representative, etc, depending on the context of the table, thus potentially yielding more appropriate header names.

6 CONCLUSIONS
We have shown that a context-aware model that combines data values and column’s context outperforms approaches that predict semantic labels only on the basis of data values. Our method has been evaluated on two real-world datasets from multiple domains: WikiTables extracted from Wikipedia and Log tables from network equipment. We have shown that the attribute’s predicted context, which is incorporated into our model SeLab, solves the ambiguity in semantic labels predictions. Our model is trained end-to-end for both feature extraction and label prediction which reduces the human effort in semantic labeling.

Future work includes looking at how to incorporate metadata of each data table, such as table caption and description, into SeLab, and how to select the best subset of data values for each column to improve semantic labeling results.
