

# Know Your Dataset

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## ABSTRACT

It has become very easy to obtain a large dataset for experimental analysis. But most of these datasets are unlabeled or poorly labeled. Absence of labels, leads to difficulty in accessing the data.

We propose the design of a system LOKI, which would serve as a knowledge base for storing column-naming heuristics, as well as an interactive tool: the LOKI editor for populating the knowledge-base.

Poonam:paraphrase, taken from HILDA paper

The LOKI editor primes the knowledge base by learning from example data (e.g., from open data portals), and assists domain experts in reviewing and refining the resulting heuristic naming schemes. We identify specific issues arising from training and show how the LOKI editor streamlines the process of manually repairing these issues.

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## 1. MOTIVATION

Big datasets are available in abundance and are being used by data scientists and database community for research purpose. These datasets are often curated, analyzed and forgotten without any documentation about the dataset itself. We propose to end this cycle by designing a system with a central goal of inferring column names by creating a knowledge base, which would store a collection of rules and column-naming heuristics (LOKI: Label Once and Keep It), as well as help start the documentation for a dataset (DOKI: Document Once and Keep It).

So when presented a new dataset our system would start with creating LOKI and DOKI. LOKI would help an analyst in inferring the column names for new datasets and using DOKI the analyst can start documenting the dataset. Apart from creating a knowledge base LOKI also provides an interactive tool for populating the knowledge base.

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## 2. RESEARCH QUESTIONS

Given a dataset the user wants to analyze, the system performs two steps (1) create LOKI and (2) create DOKI. Once a dataset is documented the analyst can save the documentation for future use.

The first step is to create LOKI which helps in streamlining the process of developing schemas for unlabeled or poorly labeled datasets. LOKI provides users with two modes of interaction: (1) A labeling interface that assists users in assigning names to existing columns of data, and (2) A discovery interface that helps users to search for columns representing particular concepts of interest. These interfaces are supported by a knowledge-base that combines expert-provided heuristics, learned characteristics, as well as historical feedback gathered from users about already-loaded datasets. Once the user has labeled or discovered a sufficient set of columns, LOKI generates appropriate data loading/initialization code (e.g., a CREATE TABLE or Spark DataFrame initializer).

Once LOKI is created, the next step is to create DOKI. 1 illustrates the different components of dataset that DOKI helps store.

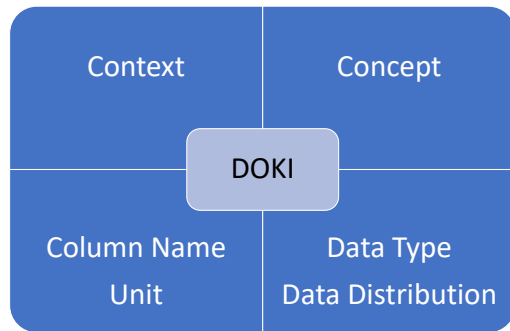


Figure 1: Document Once and Keep It overview

Context stores the details of the domain to which the dataset belongs. Concepts correspond to names. Since the same name may be used in different contexts, multiple concepts can use the same column name. Similarly, a single concept may be associated with multiple names. Unit refers to the mathematical unit associated with a column. e.g. Kilogram, Hectares, etc. Name stores the column name. Type of data present in the dataset whether it is numerical, categorical, datetime etc are stored as data type. Data distribution refers to the distribution that best describes a column. e.g Normal, uniform, zipfian etc.

EXAMPLE 2.1. *This is an example*

Col1	Col2	Col2	Col3
1	6	87837	787
2	7	78	5415
3	545	778	7507
4	545	18744	7560
5	88	788	6344

analyst can reuse it without any difficulty. The analyst does not have to document the dataset again, and is well versed with the dataset through the information stored in knowledge base(data type, data distribution). The knowledge base would store expert inputs and feedback

Explain.What do you mean by expert inputs and feedback?

and also help the analyst in identifying schema names for new datasets. The system named LOKI serves as a knowledge base and an interactive tool for populating the knowledge base. When a user first points LOKI at a new tabular data set, LOKI proposes a schema

just schema?

for it. It then collects feedback, both learning and also preserving schema metadata for later use.

Poonam:rewrite, taken from HILDA paper

In short, LOKI will allow users to assemble schemas on-demand, both (re-)discovering and incrementally refining schema definitions in response to changing data needs.

However, to accomplish this, we first need a knowledge-base of heuristics, domain knowledge, and dirty tricks. In principle, we might implement such a knowledge base as a neural network, train it on example data, and use it to suggest schemas. However, this approach suffers from a host of limitations: (1) Lack of generality: A neural network tuned for use with one type of training data may need to be retuned for other scenarios. (2) Lack of extensibility: Adding new training data or knowledge network misclassifies a column name, it can be hard to debug and refine the result. Instead, we opt for an interactive approach. We present the LOKI knowledge-base, a flexible, extensible infrastructure for collecting schema-naming heuristics. We show how simple, efficient off-the-shelf techniques can be used to quickly prime the knowledge-base using example data. Then, we introduce an interactive editor that we are designing as part of LOKI to allow domain experts to refine the knowledge-base. In particular, we focus on our preliminary work to streamline manual refinement of knowledge learned from one type of example data. We show how, the editor can be used to help experts to quickly identify and resolve errors and ambiguity in the LOKI knowledge-base. Concretely, the contributions of this paper include: (1) We introduce LOKI in Section 2 and detail the structure of its knowledge- base in Section 3. (2) We illustrate how the LOKI editor pre-populates the knowledge-base by learning from example data in Section 4. (3) We identify specific errors that arise in the training process and show how the LOKI editor facilitates efficient detection and manual repair of the error in Section 5.

Documentation would consist of storing the following information about the dataset:

- Context: Domain to which the column belongs.

- Concept: Noun that describes a column.
- Unit: Mathematical unit associated with the column. e.g. Kilogram, Hectares, etc.
- Name: String name associated with the column. e.g. A column containing patients blood pressure might be named BP.
- Signature: Parameters used to describe a column. It is a combination of context, Range, Distribution, set of values and the type of data.
- Column:
- Data type:
- Data distribution:

## 2.1 Challenges

1. Column might match on multiple signatures
2. Similar concepts with different signatures
3. Similar signatures for different concepts
4. Insufficient signal for signature based matching. -types of signature insufficient
5. different signatures combine differently to id concepts
6. performance

## 3. RELATED WORK

Poonam:rewrite, taken from HILDA paper

Data distributions have been used for similar purposes in other work. For example GestureQuery [4] uses data similarity between two attributes to select candidate attributes for an equi-join. To maximize the join arity, the system counts the number of times each value from one attribute appears in the other and a histogram is constructed from the counts for all of the values.

Wrangler [3] and Potter’s wheel [6] detect data domains through inclusion functions (e.g. regular expressions). Wrangler in particular infers the data type of a column and highlights errors based on inconsistent data types. Wrangler also has several operators like split and unfold that create new columns. The split operator decomposes composite data values into component distributions. The unfold operator reverses a table pivot, collapsing data laid out as key-value pairs into columns. A useful application of the LOKI knowledge-base that we hope to explore in future work is using it to detect opportunities for applying such operators.

An orthogonal approach to modeling and matching columns is to use ontologies, which express entities, facts, relations between facts and properties of relations. Ontologies like Yago [1] could be used to identify semantic properties that relate columns.

A data summary called the data describer is used in [5]. The data types, correlations and distributions of the attributes in a private dataset are listed. Each attribute is categorized into either numerical or non-numerical. If non-numerical attribute cannot be parsed as datetime then it is considered to be a string.

Data describer takes in a CSV file and infers the data types and domains. The attribute datatypes are parsed as numerical, datetime or string. We are inferring the datatypes as well. When run in correlated attribute mode, data describer provides correlation between attributes. We could use this functionality in LOKI.

PADS [2] helps users to understand the layout and meaning of data by designing syntactic descriptions of the data. Based on the syntax, accumulators track the number of good values, the number of bad values, and the distribution of legal values. This technique could be used in LOKI to help capture expert knowledge.

There is an increasing number of datasets in which well-structured attributes (with or without a name) can be identified, each containing a set of values called a domain. There is lack of schema description in most of the datasets. LSH Ensemble is used in [7] to find domains that maximally contain a query dataset, which can help to find datasets that best augment a given set of data.

## 4. EXPERIMENTS

Poonam:rewrite, taken from HILDA paper

Describe how KB was created for datasets. System design from HILDA paper

## 5. RESEARCH PLAN

We plan several extensions as future work focused on building and refining a knowledge-base for storing column-naming heuristics. Use of contextual information: Contextual information such as ontologies, units and data domains could be used to augment the LOKI knowledge base (KB). We could use a network of semantic relations such as Babel-Net strengthen data models for training the KB as well as providing curation recommendations to experts. [2] Recommendation of columns for query: Concepts in the KB could be used to recommend columns that could be in a query based on the columns that are already present. Smarter Matchers: We would develop matchers which recognize a wider spectrum of data. For example, regular expression matchers could be used to detect geolocation data. Matchers which can identify synonymous labels could help experts in the curation process.

Poonam:for reference

To overcome the assumptions and limitations of the current framework we propose the following research plan: (1) We want to generalize candidate questions to include non-boolean atoms. In this way, same incomplete data in different candidate questions can be confirmed in one confirmation round. (2) The current framework assumes the probability distributions for incomplete data are given. However, this is not always feasible. We want to make use of the existing reliable data to estimate the probability distribution of incomplete data. (3) In many domains, there exist models that can be utilized to increase query result accuracy without consulting users. Currently, in the UDL component, we mainly utilized the user-defined models to preprocess incomplete data at no cost. We want to explore how to learn models from system-user interactions. For instance, in data integration, possible schema matches are candidate models, one of which is a correct match. We can treat each candidate model as probabilistically related to the real model. We can

integrate these candidate models with our current framework and adjust the confidence of a model on confirmation. The probability will converge on true model. This learned model will be utilized adaptively in subsequent queries. (4) Our current framework considers user feedback is always correct. However, humans may make mistakes. In crowdsourcing, humans may provide incorrect answers to tasks accidentally or on purpose. In medical expert systems, user feedback is obtained based on test results by machines. The test results may not be 100% a user profile to record the credibility of user feedback. We need to decide how to integrate this profile with our framework and based on the correctness of the decisions made

## 6. CONCLUSION

Poonam:for reference

This paper proposes the design of a system which would help build a knowledge base along with an interactive tool for populating the knowledge base.

Mention Query model?

## 7. ACKNOWLEDGMENTS

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