Auto-Test: Learning Semantic-Domain Constraints for Unsupervised Error Detection in Tables

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Data cleaning is a long-standing challenge in data management. While powerful logic and statistical methods have been developed to detect and repair data errors in tables, existing methods predominantly rely on domain-experts to first manually specify data-quality constraints specific to a given dataset. In this work, we observe that there is an important class of data-quality constraints that we call *Semantic-Domain Constraints*, which can be automatically applied to *any tables*, without requiring domain-experts to manually specify on a per-table basis.

We develop a principled framework to systematically learn such constraints from table corpora using large-scale statistical tests, which can further be distilled into a core set of constraints using our optimization framework, with provable quality guarantees. Extensive evaluations show that this new class of constraints can both (1) directly detect errors on real tables in the wild, and (2) augment existing data-cleaning techniques as a new class of complementary constraints. Our code and data are available in https://github.com/qixuchen/AutoTest for future research.

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1 INTRODUCTION

Data cleaning is a long-standing challenge in the data management community. While there is a long and fruitful line of research that developed powerful techniques using *data-quality constraints* (e.g., FD, CFD, etc.) to detect and repair data errors in tables [11, 16, 25, 35, 35, 41, 55, 67], existing methods largely depend on domain-experts to first specify data-quality constraints that are specific to a given table, before data-cleaning algorithms can be performed (while constraint discovery

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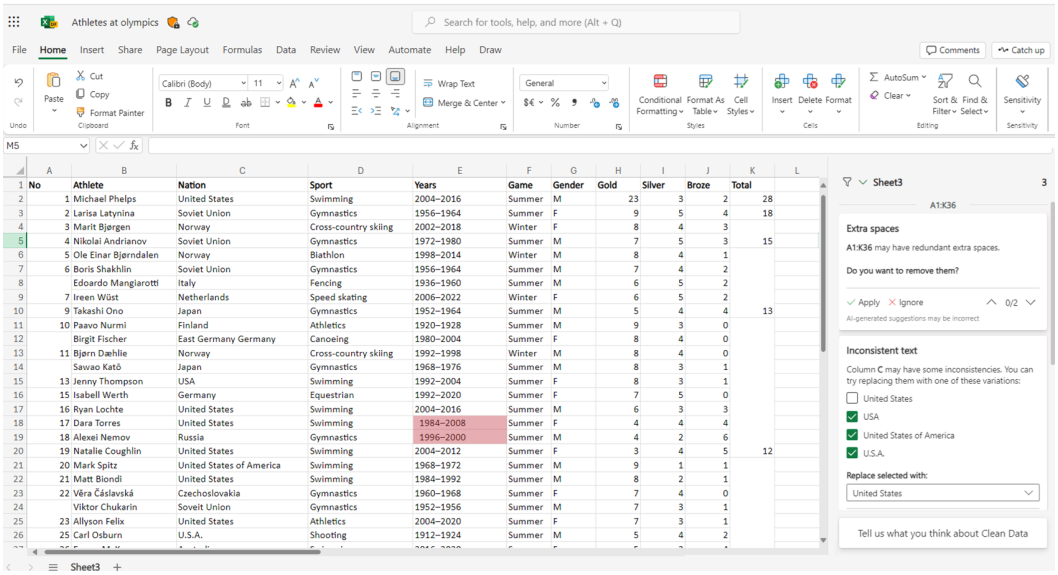


Fig. 1. Data cleaning feature for non-technical end-users in Excel. Each automatically detected data-quality issue in user table is shown as a "suggestion cards" on the side-pane (right), which users only need to review and accept. [This link] gives an end-to-end demo of how users can stay in control while leveraging capabilities like SDC to clean data automatically.

methods also exist, they are mainly intended to discover *candidate rules* that still require humans to verify [10, 17, 23, 29, 66]). We term this class of sophisticated and powerful approaches as "*expert-driven data cleaning*".

	C1 (country)	C2 (state code)	C3 (month)	C4 (city)	C5 (fiscal year)	C6 (unit)	C7 (date)	C8 (url)
2	Germany	FL	january	mankato	fy17	12 oz	12/3/2020	https://twitter.com/#!/nyctbus/status/803706869944565760
3	Austria	AZ	febuary	st peter	fy18	9.8 oz	11/5/2020	https://twitter.com/#!/jrwolfson/status/799056736661475328
4	France	CA	march	seattle	fy19	0.05%	2/5/2021	https://twitter.com/#!/bmrbreakingnews/status/799061681750110208
5	Liechstein	OK	april	saint paul	fy20	28 oz	10/23/2020	_/status/799512626703323140
6	Italy	Germany	may	shakopee	fy definition	1.5 oz	10/7/2020	https://twitter.com/#!/polmsted/status/799087394884636672
7	Switzerland	AL	june	phoenix	fy21	30 oz	new facility	https://twitter.com/#!/yoadamboy/status/799108555869655046
8	Porland	GA	july	farimont	fy22	18 oz	3/26/2021	https://twitter.com/#!/yoadamboy/status/799108523535859712
9	...	...	...	...	...	...	...	...

Fig. 2. Real examples of table columns, each representing a distinct "semantic domain" (annotated in the column header). Each column C_i has a real data error (which may be a typo, or semantically incompatible value), that is detected by a corresponding "semantic domain constraint" r_i in Table 1, which are constraints automatically learned from running Auto-Test.

While such expert-driven approaches to data cleaning are extremely powerful, when experts are available to inspect each table and define relevant constraints, we observe that there is an emerging class of "*end-user data-cleaning*" use cases that aim to democratize data-cleaning for the average non-technical users, by working out-of-the-box and without requiring experts to be involved.

For example, in end-user spreadsheet tools such as Microsoft Excel [6] and Google Sheets [5], that are used by billions of non-technical users, there is a growing need to automatically detect and repair data errors in user tables out-of-the-box, *without requiring users to define constraints or provide labeled data first.*

Table 1. Example Semantic-Domain Constraints (SDCs), instantiated using CTA-classifiers (in r_1, r_2), text-embedding (r_3, r_4), regex-patterns (r_5, r_6), and program functions (r_7, r_8), all sharing the same SDC structure. Each SDC has a (a) Pre-condition: if matching-percentage% of column values in column C, evaluated using a domain evaluation function satisfy inner-distance threshold, we recognize that constraint r should apply to column C, and (b) Post-condition: any value evaluated using the same domain evaluation function satisfy outer-distance threshold, are predicted as data errors. Each example constraint r_i in this table would trigger the detection of a real data error shown in column C_i of Figure 2. All color-coded components (matching-percentage, evaluation function, etc.) are parameters to SDC that are learned using Auto-Test.

ID	Type	Pre-condition P: (on what columns should this constraint apply)	Post-condition S: (what values will be predicted as errors)	Conf.
r_1	CTA	85% column values have their *country-classifier* scores > 0.75	values whose *country-classifier* scores < 0.01	...
r_2	CTA	90% column values have their *state-classifier* scores > 0.55	values whose *state-classifier* scores < 0.05	...
r_3	Embedding	85% column values have their *Glove* distances to "january" < 4.0	values whose *Glove* distances to "january" > 5.5	...
r_4	Embedding	80% column values have their *S-BERT* distances to "seattle" < 1.2	values whose *S-BERT* distances to "seattle" > 1.35	0.88
r'_4	Embedding	90% column values have their *S-BERT* distances to "seattle" < 1.1	values whose *S-BERT* distances to "seattle" > 1.4	0.93
r_5	Pattern	95% column values match pattern "\[a-zA-Z]+\d+" (match = 1)	values not matching pattern "\[a-zA-Z]+\d+" (match = 0)	...
r_6	Pattern	95% column values match pattern "\d+ \[a-zA-Z]+" (match = 1)	values not matching pattern "\d+ \[a-zA-Z]+" (match = 0)	...
r_7	Function	98% column values return true on function *validate_date()* (ret = 1)	values that return false on function *validate_date()* (ret = 0)	...
r_8	Function	99% column values return true on function *validate_url()* (ret = 1)	values that return false on function *validate_url()* (ret = 0)	...

Figure 1 shows a screenshot of such a feature in Excel, where automatically detected data-quality issues are presented as "suggestion cards" on the side-pane, which users can easily review and accept with the click of a button (without needing the specialized knowledge to define any constraints first). Google Sheets has a similar feature for error-detection [4]. (Note that users always stay "in control" in these situations, as they choose to apply or ignore data cleaning suggestions that are presented to them).

In this work, we study a new class of data-quality constraints previously overlooked in the literature, which we call *Semantic-Domain Constraints (SDC)*. Importantly, such constraints can be reliably applied to in a generic fashion to relevant tables, without needing human experts, making them suitable for both "end-user data cleaning" (e.g., in spreadsheets), and "expert-driven data cleaning" (as they serve as a new class of constraints to complement existing constraints).

Intuition: leverage "semantic domain" for error detection. The new class of constraints we study in this work are based on the intuitive notion of "*semantic domains*". Specifically, given any relational table, values in the same column are expected to be *homogeneous* and drawn from a "domain" of same semantics, such as date, url, city-name, address, etc. Figure 2 shows an example table, where the semantics of each column can then be inferred by humans from its values (annotated in column-headers to assist readability).

The semantics of a column often implicitly define the "domain" of valid values that can appear in this column – values falling outside of the "domain" can be picked up by humans as possible data errors, like the example in Figure 2 would show.

Given that we as humans can reliably infer column semantics, and then use the underlying "domain of valid values" to identify likely errors in Figure 2 (without needing specialized knowledge to understand the specifics of a table), the question we ask in this work is whether algorithms mimic the human intuition, by codifying it into precise, executable data-quality constraints that can automatically detect data errors.

"Column-type detection": insufficient for error detection. There is a large literature on the related topic of "column-type detection", where the goal is to predict the semantic column type for a given column C, from a pre-defined list of column types (e.g., people-names, locations, phone-numbers, etc.). The problem has been studied in different settings, leading to a range techniques tailored to different types of tabular data.

For example, for natural-language-oriented data columns (e.g., people-names, company-names, address, etc.), this is typically studied as a multi-class classification problem, also known as "column type annotation" (CTA) [24, 30, 31, 39, 45, 59, 60, 69, 70], where techniques based on machine learning (ML)-classifiers and text embedding (e.g., Glove [51] and SentenceBERT [54]) are developed to predict column types.

On the other hand, for machine-generated data columns that are often number-heavy, and with strong regularity (e.g., ip-address, upc code, time-stamps, etc.), techniques based on (synthesized and curated) regex-patterns and program-functions, are used to detect such columns in tables [1, 8, 50, 68].

While "column-type detection" is closely related to our goal of using "semantic domain" to detect errors, we observe that applying column-type detection directly to the task of error detection is insufficient, because column-type detection focuses on the *macro-level prediction* of whether a column C belongs to a type T, without being calibrated to make *fine-grained, micro-level predictions* of whether a value-instance $v \in C$ must be an error or not in the context of C and type T.

Auto-Test: Learn reliable "semantic domain constraints". In this work, we propose a new class of data-quality constraints called "Semantic-Domain Constraints (SDC)", that builds upon and unifies diverse prior techniques for column-type detection, for our new task of error detection.

Table 1 shows examples of SDC constraints. Briefly, each SDC r consists of a "pre-condition" that tests whether a given column C is in the relevant semantic domain for r to apply, and if so, a "post-condition" would calibrate the confidence of predicting $v \in C$ as an error, mirroring our fuzzy intuition of using "semantic domains" for error detection, but codified in precise constraints. The exact parameters (color-coded components in the table), can be automatically learned from large table corpora using statistical tests in our proposed Auto-Test, which is the focus of this work.

Note that SDC unifies prior techniques for column-type detection, using an abstraction we call "domain evaluation functions" (marked in purple in Table 1), as they can be instantiated using diverse column-type detection, such as CTA-classifiers, text embedding, patterns, and functions, like shown in Table 1.

Extensive evaluations, using benchmarks with real spreadsheet and relational tables in the wild, show that Auto-Test can reliably learn high-quality SDC constraints for accurate error-detection.

Overall, our proposed Auto-Test has the following key features:

(1) Consistently more accurate than alternative methods, including language models such as GPT-4 and even fine-tuned GPT-4 (we give a detailed analysis of why language models may not be a good fit for the error-detection task in our experiments);

(2) Generalizable to new and unseen datasets, making it possible to auto-apply SDC on diverse tables without domain experts;

(3) Extensible to new and different types column-type detection techniques, which are unified in the same Auto-Test framework;

(4) Highly efficient to detect errors even on large tables, with negligible runtime and memory overhead compared to alternatives;

(5) Explainable to humans, as our constraints leverage the natural notion of "semantic domains", which are not black-box models.

2 RELATED WORK

Data Cleaning. Data cleaning is a long-standing challenge in the data management community, with an influential line of research developing constraint-based techniques, including functional dependency (FD), conditional functional dependency (CFD), denial constraints (DC), etc., to detect and repair data errors in tables [11, 16, 25, 35, 41, 55, 67]. Differential dependencies [58] and Metric FD [38] are additional powerful examples that can effectively relax equality constraints using distance functions.

While existing data cleaning techniques are both flexible and powerful, they generally rely on complex data-quality constraints (e.g., in first-order logic) to be first defined by experts. Constraint discovery methods have also been studied, though they are generally designed to discover *candidate rules* that still require human experts to verify, in order to ensure accuracy [10, 17, 23, 29, 66].

Outlier detection. There is a large literature of outlier detection methods in the machine learning and data mining literature, as reviewed in [15, 43, 44], which are conceptually related to the problem we study. However, classical outlier detection methods predominantly operate only on *local statistical features* (e.g., value distribution *within a single target column* in our context) to determine outliers, without considering more *global corpus-level information* (e.g., inferred semantic types and global data distributions) that our proposed method specifically leverages for the error detection task on tabular data. We will show in experiments that this gives our method a unique edge, which substantially outperforms 6 top-performing outlier detection methods (selected based on a benchmark study [21]).

3 PRELIMINARY: SEMANTIC COLUMN TYPES

Since our SDC constraints are based on "*semantic types*", we start with an overview of semantic types, and techniques to detect them.

Semantic column-type detection methods. As humans, we read tables columns not as string vs. numbers (primitive types), instead, we interpret the semantics of columns (column types), as `date`, `url`, `people-name`, `address`, etc., as shown in Figure 2.

"*Column-type detection*" refers techniques to identify the "semantic types" for a given column C. Diverse techniques have been developed, including ML-classifiers and NL-embedding that are effective for natural-language data (e.g., `people name`, `address`, etc.), and regex-like patterns or program-functions that are suitable for machine-generated data with syntactic structures (e.g., `ip address`, `time-stamps`, etc.).

We survey existing column-type techniques, and summarize them into four broad categories below.

(1) CTA-based methods [31, 59, 69]. In Column Type Annotation (CTA), column-type detection is treated as an ML problem of multi-class classification, that predicts a semantic type from a fixed set of options. Various ML-classifiers have been developed for this problem, such as *Sherlock* [31] classifiers that can detect 78 semantic types ("`type-city`", "`type-country`", etc., from DBPedia), and *Doduo* [59] can further detect 121 semantic types (based on Freebase).

At a conceptual level, a CTA classifier for a semantic type t_i (say "type-country")[1], can be viewed as a function f_{cta}, that given a value v (say "Germany") as input[2], can produce a classifier score CTA-classifier(t_i, v) in the range of $[0, 1]$, to indicate the likelihood of v in type t_i, written as:

$$f_{\text{cta}}(t_i, v) = \text{CTA-classifier}(t_i, v)$$

For example, we may get $f_{\text{cta}}(\text{"type-country"}, \text{"Germany"}) = 0.8$, and $f_{\text{cta}}(\text{"type-city"}, \text{"Germany"}) = 0.1$, from CTA-classifiers.

Observe that $f_{\text{cta}}(t_i, v)$ measures "similarity" between type t_i and value v. To unify CTA with other column-type detection methods, we standardize f_{cta} into a "distance function", written as f^d_{cta}:

$$f^d_{\text{cta}}(t_i, v) = 1 - f_{\text{cta}} \tag{1}$$

With this distance function, we can equivalently write $f^d_{\text{cta}}(\text{"type-country"}, \text{"Germany"}) = 0.2$, and $f^d_{\text{cta}}(\text{"type-city"}, \text{"Germany"}) = 0.9$, etc., where a smaller distance indicates a closer association between value v and type t_i.

(2) Embedding-based methods [51, 54]. Text embedding, such as *Glove* [51] and *SentenceBERT* [54], are popular vector-based representations of text in NLP. In the embedding space, texts with similar semantic meanings (e.g., month-names like "january", "feburary", etc.) tend to cluster closely together, while those with unrelated meanings (e.g., "january" and color-names like "yellow") are positioned further apart [46, 51, 54].

Such embedding provides an effective method to detect semantic types. Specifically, it is natural to select a "*centroid*", say "january", to represent the semantic-type we want to detect (in this case month-name), and for a given a column C, if most or all values $v \in C$ fall within a small radius of "january", we may predict column C as type month-name (implied by the centroid "january").

We view text-embedding as providing another function, $f^d_{\text{emb}}(c_i, v)$, that calculates the "distance" between a given value v, and a centroid c_i (representing a semantic-type):

$$f^d_{\text{emb}}(c_i, v) = \text{dist}(\text{emb}(c_i), \text{emb}(v)) \tag{2}$$

For example, let c = "january" be a centroid, we may have $f^d_{\text{emb}}(c, \text{"february"}) = 0.1$, indicating the close proximity of the two values. Alternatively, let c' = "yellow" be another centroid (for color-name), and we may have $f^d_{\text{emb}}(c', \text{"february"}) = 0.7$, showing that "february" is likely not in the same type as "yellow". Note that f^d_{emb} is already a distance-function, like f^d_{cta} (Equation 1).

(3) Pattern-based methods [32, 48, 57]. For machine-generated data with clear syntactic structures (e.g., date, email, timestamp, etc.), regex-like patterns can often detect semantic types [32, 48, 57]. For example, if most values in C_7 of Figure 2 follow the pattern "\d{1,2}/\d{1,2}/\d{4}", we may predict the column as type date.

Similar to CTA and embedding, given a semantic type implied by pattern p_i (e.g., "\d{1,2}/\d{1,2}/\d{4}" for date), and a value v, we can view the pattern-based detection as a different "similarity" function $f_{\text{pat}}(p_i, v)$ between value v, and a type represented by p_i:

$$f_{\text{pat}}(p_i, v) = \begin{cases} 1, & \text{if } v \text{ matches } p_i \\ 0, & \text{if } v \text{ does not match } p_i \end{cases}$$

We also normalize $f_{\text{pat}}(p_i, v)$ into a distance-function, f^d_{pat}:

$$f^d_{\text{pat}}(p_i, v) = 1 - f_{\text{pat}}(p_i, v) \tag{3}$$

[1]While some CTA-classifiers such as Sherlock are framed as multi-class classification, they can be equivalently interpreted as multiple binary-classifications (one for each type), to simplify our discussions.

[2]Note that while some CTA-classifiers take an entire column C as input, they also produce valid scores for individual values $v \in C$ (since CTA-classifiers need to make predictions for single-value columns such as $C' = \{v\}$ too).

For example, let p = "\d{1,2}/\d{1,2}/\d{4}", v_1 = "12/3/2020" and v_2 = "new facility" in Figure 2. We have $f^d_{\text{pat}}(p, v_1) = 0$, indicating "distance= 0" between type p and a compatible value v_1; and $f^d_{\text{pat}}(p, v_2) = 1$, indicating "distance = 1" between p and an incompatible value v_2.

(4) Function-based methods [1, 8, 50, 68]. Finally, various "validation-functions" (in python and other languages) have been developed, to validate rich semantic types. For example, credit-card-number and UPC-code are not just random-numbers, but have internal check-sums and can be validated using special validation-functions[3] (e.g., Luhn's checksum [2]). Similarly, date and timestamps can also be validated precisely with functions (in place of simple patterns)[4]. Such "validation functions" are curated in popular open-source repositories like *DataPrep* [50] and *Validators* [8], to reliably detect semantic column types.

For each validation-function f_i (to validate a semantic-type), we similarly view it as a function $f_{\text{fun}}(f_i, v)$, that measures the "similarity" between value v and a type represented by f_i:

$$f_{\text{fun}}(f_i, v) = \begin{cases} 1, & \text{if } f_i(v) \text{ returns true} \\ 0, & \text{if } f_i(v) \text{ returns false} \end{cases}$$

which can again be standardized into a distance-function, f^d_{fun}:

$$f^d_{\text{fun}}(f_i, v) = 1 - f_{\text{fun}}(f_i, v) \tag{4}$$

where a distance $f^d_{\text{fun}}(f_i, v) = 0$ indicates that a value v is validated true by function f_i. For example, let f_i be the *validate_date()* function. Then for C_7 in Figure 2, we have $f^d_{\text{fun}}(f_i, \text{"12/3/2020"}) = 0$, and $f^d_{\text{fun}}(f_i, \text{"new facility"}) = 1$.

Observe that different column-type detection methods can have *overlapping coverage* in the types they detect – for example, different CTA-classifiers (e.g., from Sherlock, Doduo, Sato, etc.) all have their own implementations to detect the same semantic type (e.g., type-city). Similarly, both pattern-based and function-based methods can detect similar types (e.g., timestamps). We do not attempt to manually determine which method is the best for a type t – we simply ingest all type-detection methods into our framework, which can be reasoned consistently to automatically select suitable SDC constraints, which is a salient feature of Auto-Test.

Domain-evaluation function. Note that we intentionally characterize all column-type detection methods as distance functions between value v and a type t (e.g., f^d_{cta}, f^d_{emb}, f^d_{pat}, and f^d_{fun} in Equation (1)-(4)), so that they can be reasoned consistently. Specifically, to quantify whether a value v may be "in" vs. "out of" type t_i for error-detection, we use a notion of "*domain-evaluation functions*" that naturally generalizes these distance-functions.

Definition 1. [**Domain-evaluation function**]. Given a semantic type t_i defined by an underlying column-type detection method (CTA, embedding, etc.), a *domain-evaluation function* $f(t_i, v)$ measures the "distance" between type t_i and value v, where f can be instantiated as f^d_{cta}, f^d_{emb}, f^d_{pat}, and f^d_{fun} in Equation (1)-(4).

As a distance function, a smaller $f(t_i, v)$ naturally indicates that v is likely "in" the domain of type t_i, while a larger $f(t_i, v)$ indicates v to be likely "out" of type t_i.

[3]For example, https://yozachar.github.io/pyvalidators/stable/api/card/ for "credit-card-number", and https://pypi.org/project/barcodenumber/ for "UPC-code"

[4]For example, https://docs.dataprep.ai/user_guide/clean/clean_date.html and https://gurkin33.github.io/respect_validation/rules/DateTime/ for "date" and "timestamp".

4 SEMANTIC-DOMAIN CONSTRAINTS

Given the domain-evaluation functions $f(t_i, v)$ in Section 3, which we will henceforth write as $f_{t_i}(v)$ for simplicity, we now describe a new class of data-quality constraints called Semantic-Domain Constraints (SDC) we propose in this work.

Definition 2. [**Semantic-Domain Constraints**] A Semantic-Domain Constraint (SDC), denoted as $r_t = (P, S, c)$ for semantic type t, is a 3-tuple that consists of a *pre-condition* P, a *post-condition* S, and a *confidence-score* c, where:

- The pre-condition P: it determines whether the SDC described in r should apply to an input column C, defined as:

$$P(C, f_t, d_{in}, m) = \begin{cases} \text{true} & \text{if } \frac{|\{v|v \in C, f_t(v) \leq d_{in}\}|}{|\{v|v \in C\}|} \geq m, \\ \text{false} & \text{otherwise.} \end{cases}$$

  When the fraction of values $v \in C$ with domain-evaluation function $f_t(v)$ no greater than an *inner-distance threshold* d_{in}, denoted as $\frac{|\{v|v \in C, f_t(v) \leq d_{in}\}|}{|\{v|v \in C\}|}$, is over a *matching-percentage* m, the pre-condition P evaluates true (in which case r_t applies to C), .
- The post-condition S: if the pre-condition P evaluates true, it will be used to detect values $v \in C$ as errors, whose domain-evaluation function $f_t(v)$ evaluates to be greater than an *outer-distance threshold*, d_{out}, written as:

$$S(C, f_t, d_{out}) = \{v|v \in C, f_t(v) > d_{out}\}$$

- The confidence $c \in [0, 1]$: indicates the confidence of the errors detected by the post-condition S above.

The pre-condition $P(C, f_t, d_{in}, m)$ checks whether a given column C is in the semantic domain of the type t (before r_t can apply). Specifically, it uses the domain-evaluation function $f_t(v)$ for type t, to calculate the fraction of values $v \in C$ that, when evaluated using $f_t(v)$, fall within the inner ball of radius d_{in} (indicating that they belong to type t), written as $\frac{|\{v|v \in C, f_t(v) \leq d_{in}\}|}{|\{v|v \in C\}|}$.

The post-condition $S(C, f_t, d_{out})$ would then check whether there are any values $v \in C$ that fall substantially farther away from the inner ball, to be outside of the outer ball, written as $S = \{v|v \in C, f_t(v) > d_{out}\}$. If such values exist in C, values in S will be predicted as *errors*, with a confidence score c.

Parameters. Note that three parameters, d_{in}, d_{out}, m, are used in each constraint r_t. These are clearly hard to set manually, especially when there are many semantic-types, where each type t has its own optimal parameters. A key technical challenge in this work is to automatically learn these parameters from real tables, both efficiently and with quality-guarantees (Section 5).

Why this design of SDC. We design SDC with this structure for the following reasons. First, it mimics the human intuition of identifying data errors – given a table in Figure 2, humans would read values in a column, to first identify its semantic type (e.g., `city` vs. `date`, which is a "pre-condition"), before using a fuzzy notion of "domain" of each type to identify errors (post-conditions). Our design of SDC mimics the reasoning process, by imposing a inner-ball/outer-ball "structure" as a strong "prior" to restrict the search space of constraints, such that the problem reduces to learning good parameters (d_{in}, d_{out}, m), which is more tractable.

Because SDC is based on semantic-domains, the resulting constraints are "explainable" as they are often associated with types (e.g., the prediction of "`germany`" in C_2 can be explained using the CTA-classifier for `state`), making predictions interpretable.

Finally, the SDC framework is extensible to different column-type detection methods, and it is easy to add/remove constraints in a white-box fashion, making it easy to deploy and operationalize.

Problem Statement: Learning SDC. In this work, we want to "learn" high-quality SDCs with appropriate parameters from a large table corpus, so that they can cover diverse semantic-types (e.g., in Table 1), and be readily applicable to new and unseen tables.

We leverage a large corpus of tables C (e.g., millions of tables crawled from the web and enterprises), and model them as a collection of individual columns $C = \{C\}$. Ideally, we want to leverage C to learn a set of high-quality SDCs, denoted by R, such that:

(1) the *recall* of R is maximized, or R should detect as many true-errors as possible on an unseen test set C_{test}.
(2) the *false positive rate (FPR)* of R is minimized (or high precision), for R should trigger few false-positives on C_{test};
(3) the *size* of R is not exceedingly large for latency and efficiency reasons (e.g., the size of Table 1 should be limited).

We give a high-level sketch of our problem below, which will instantiate into concrete problem variants in later sections.

Definition 3. [**Learning Semantic-Domain Constraints**]. Given a corpus C, a size constraint B_{size}, and a FPR threshold B_{FPR}, find a set of SDCs R that maximizes Recall(R), while satisfying $|R| \leq B_{size}$ and $FPR(R) \leq B_{FPR}$, written as:

$$\max_{R} \text{Recall}(R) \tag{5}$$

$$\text{s.t. } |R| \leq B_{size} \tag{6}$$

$$FPR(R) \leq B_{FPR} \tag{7}$$

Note that in balancing the three requirements, we want to bound FPR (e.g., false-positive rate should not exceed $B_{FPR} = 1\%$, for scenarios like Figure 1 has strict precision requirements), and the size of R (e.g., $|R|$ should not exceed $B_{size} = 10000$) to limit its memory footprint and make inference efficient, while maximizing recall as much as possible.

5 AUTO-TEST: LEARN SDC USING TABLES

We now describe our proposed Auto-Test that learns high-quality SDCs from a large table corpus C in an unsupervised manner.

The offline training has three steps, which we will describe in turn below. At a high level, we will first generate a set of SDC candidates (Section 5.1), and assess their quality using principled statistical tests (Section 5.2), before we perform holistic optimization of the problem stated in Definition 3, to select an optimal set of SDCs with quality guarantees (Section 5.3).

5.1 SDC Candidate Generation

Our first step in offline training is a preprocessing step that generates a large collection of SDCs candidates.

Recall that in Definition 2, each SDC has four parameters: domain-evaluation function f_t, inner-distance d_{in}, outer-distance d_{out}, and matching-percentage m (all colored-coded in example SDCs in Table 1 for readability).

Note that f_t may be instantiated using different "domain-evaluation functions" (Definition 1) for different column-type detection methods, namely f^d_{cta}, f^d_{emb}, f^d_{pat} and f^d_{fun} in Equation (1)-(4), for CTA, embedding, patterns, and functions, respectively. Specifically, we use the following instantiations of f_t:

- CTA. We use the 78 classifiers in *Sherlock* [31] (designed to semantic-types in DPBpedia), and the 121 classifiers in *Doduo* [59] (for semantic-types in Freebase), for a total of 199 f^d_{cta} functions.

Table 2. A contingency table for an example SDC r, on which we perform statistical tests to determine r's efficacy.

	cols covered by r ("in domain" columns)	cols not covered by r ("out of domain" columns)
cols triggered by r (error detected)	$\left\|C^r_{C,T}\right\| = 10$	$\left\|C^r_{\overline{C},T}\right\| = 160,000$
cols not triggered by r (no error detected)	$\left\|C^r_{C,\overline{T}}\right\| = 990$	$\left\|C^r_{\overline{C},\overline{T}}\right\| = 40,000$

- Embed. We use the *Glove* [51] and *SentenceBERT* [54] embedding, and randomly sample 1000 values as centroids (which may be values like "`seattle`" and "`january`" shown in Table 1), to create a total of 2000 f^d_{emb} functions.
- Pattern. We generate common patterns observed in our corpus C, for a total of 45 f^d_{pat} functions.
- Function. We use validation-functions in *DataPrep* [50] and *Validators* [8], for a total of 8 f^d_{fun} functions.

For parameters d_{in}, d_{out}, and m, we perform grid-search and enumerate parameters using fixed step-size (e.g., the matching-percentage m is enumerated with a step-size of 0.05, or $m \in \{1.0, 0.95, 0.9, \ldots\}$, and d_{in}/d_{out} are enumerated similarly). This generates a total of over 100K SDCs as candidates.

Since these SDC candidates are enumerated in an exhaustive manner, only a small fraction of appropriately parameterized SDCs are suitable for error-detection, which we will identify using (1) statistical tests and (2) principled optimizations, explained below.

5.2 SDC Quality Assessment by Statistical Tests

In this section, we take all SDC candidates, and use statistical hypothesis tests to assess the quality of each candidate r.

Given an SDC $r = (P, S, c)$, where $r.P$ is its pre-condition, $r.S$ its post-condition, and $r.c$ its confidence, from Definition 2. We say a column C is "*covered by*" r, if $r.P(C) =$ true (i.e., more than m fraction of values in C fall inside the inner-ball with radius d_{in}), in which case C is regarded as "in the semantic domain" specified by the pre-condition $r.P$.

Similarly, we say a column C is "*triggered by*" r, if $r.S(C) =$ true, meaning that the post-condition $r.S$ is producing non-empty results as detected errors in C (i.e., there exists some $v \in C$ that fall outside of the outer-ball with radius d_{out}).

Given a large corpus $\mathcal{C}$ and r, we can analyze r's behaviour on $\mathcal{C}$, using a *contingency table* [22, 33] shown in Table 2, where:

- $\left|C^r_{C,T}\right| = \{C | C \in \mathcal{C}, r.P(C) = \text{true}, r.S(C) = \text{true}\}$ denotes the number of columns in $\mathcal{C}$ that are both covered by and triggered by r (C is "in the semantic domain" of r, with errors detected).
- $\left|C^r_{C,\overline{T}}\right| = \{C | C \in \mathcal{C}, r.P(C) = \text{true}, r.S(C) = \text{false}\}$ denotes the the number of columns in $\mathcal{C}$ that are covered by, but not triggered by r (C is "in domain" for r, with no errors detected).
- Similarly, $\left|C^r_{\overline{C},T}\right|$ and $\left|C^r_{\overline{C},\overline{T}}\right|$ correspond to the number of columns in $\mathcal{C}$ that are not covered by r (C is "not in domain" for r), but with and without detection in the post-condition $r.S(C)$, respectively.

Note that the subscript C and T in these notations would correspond to "cover" and "trigger", respectively. We can see that the top-left entry of Table 2 (covered and triggered), corresponds to set of columns that would be predicted as having errors by r.

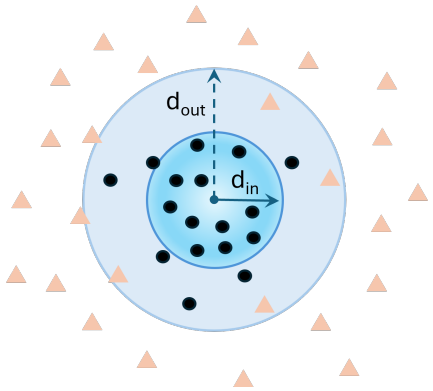


Fig. 3. A visualization of inner/outer-balls that find "natural separation" of semantic-domains, in the universe of all values. Black-dots represent "in-domain" values, triangles represent "out-of-domain" values.

Using the contingency table, we perform statistical analysis to: (1) find suitable inner/outer-balls in r that can naturally separate "in-domain" vs. "out-of-domain" columns, and (2) set each r's confidence by the percentage of false-positives it reports among the covered columns. We will explain each in turn below.

(1) Find suitable inner/outer-balls using effect-size (Cohen's h). Recall that in Section 5.1, we exhaustively enumerate SDC candidates with different parameters (inner/outer-ball, centroid, etc.), and the hope is that using an unsupervised analysis of the corpus C, we can identify good SDC that are suitably parameterized.

As we analyze these candidates, we know that a good SDC r for a semantic domain t should ideally have an inner-ball with radius d_{in} tightly enclose most "in-domain" values, and an outer-ball with radius d_{out} that can filter out most "out-of-domain" values, like visualized in Figure 3, where dots and triangles represent in-domain and out-of-domain values, respectively.

More specifically, given a table corpus C, when we compute the contingency table for a candidate r using C, like shown in Table 2, an ideal r with a suitable inner-ball/outer-ball should "cover" a good number of columns in C (e.g., a domain like "`city`" will cover many columns in C), reflected by a large $\left|C^r_{C,T}\right| + \left|C^r_{C,\overline{T}}\right|$ on the left of the contingency table, and at the same time should rarely "trigger" on columns in C, reflected by a small $\left|C^r_{C,T}\right|$ at top-left of the table (r should rarely trigger on columns in C, because the columns we harvested from relational sources are generally clean and error-free – our manual analysis suggests that over 98% columns in C are without errors). In effect, we are looking for r whose ratio $\rho(r) = \left|C^r_{C,T}\right| / \left(\left|C^r_{C,T}\right| + \left|C^r_{C,\overline{T}}\right|\right)$ is small.

In contrast, if the inner/outer-ball are too small or too large (compared to the ideal balls in Figure 3), the separations between "in-domain" vs. "out-of-domain" are no longer clean, and the ratio $\rho(r)$ will be indistinguishable from the same ratio for the vast majority of columns that are "out-of-domain" (the two entries on the right of Table 2), written as: $\overline{\rho}(r) = \left|C^r_{\overline{C},T}\right| / \left(\left|C^r_{\overline{C},T}\right| + \left|C^r_{\overline{C},\overline{T}}\right|\right)$.

Motivated by this observation, we perform statistical tests on $\rho(r)$ and $\overline{\rho}(r)$ in the contingency table (Table 2), to test their *effect size* [34], which is a principled measure of the magnitude of difference between $\rho(r)$ and $\overline{\rho}(r)$ – namely, the larger the difference between the two ratios, the better $\rho(r)$ can "stand out" from the background noise ratio $\overline{\rho}(r)$, indicating a clean in-domain vs. out-of-domain separation using r. Specifically, we use *Cohen's h* [19] to evaluate the effect size of r,

defined as:

$$h(r) = 2\left(\arcsin\sqrt{\rho(r)} - \arcsin\sqrt{\overline{\rho}(r)}\right) \tag{8}$$

Cohen's h has precise statistical interpretations, where $h \geq 0.8$ indicates large effect size [19], which we use to identify SDC candidates with suitably parameterized inner/outer-balls that would correspond to natural domains (e.g., Figure 3).

Furthermore, we perform "*statistical significance test*" (complementary to effect size in what is known as power-analysis [20]), using the standard Chi-squared tests [52] on the contingency table (Table 2). We discard r whose p value is not significant at 0.05 level.

(2) Estimate r's confidence (Wilson's score intervals). Recall that each SDC $r = (P, S, c)$ has a confidence score c (shown with examples in the last column of Table 1), which is the probability of r not producing false-positives among the "in-domain" columns it covers, that we calibrate using C with precise statistical interpretations as follows.

Specifically, note that the ratio $\hat{c} = \left|C^r_{C,\overline{T}}\right| / \left(\left|C^r_{C,T}\right| + \left|C^r_{C,\overline{T}}\right|\right)$ calculated from our contingency table is exactly an unbiased estimator of c. However, because both $\left|C^r_{C,T}\right|$ and $\left|C^r_{C,\overline{T}}\right|$ (the left two entries of Table 2) can be "rare events" with small counts, whose $\hat{c}$ ratio is therefore susceptible to over- and under-estimation on small samples. In order to guard against this, we produce a "safe" lower-bound of c (as it is better to under-estimate c than over-estimate it, to avoid false-positives), using binomial confidence interval of $\hat{c}$, and specifically we use *Wilson score interval* [65] to produce a lower-bound estimate[5] of the confidence c of a candidate r as:

$$c = 1 - \frac{\left|C^r_{C,T}\right| + \frac{1}{2}z^2}{|C^r_C| + z^2} - \frac{z}{|C^r_C| + z^2}\sqrt{\frac{\left|C^r_{C,T}\right| \cdot \left|C^r_{C,\overline{T}}\right|}{|C^r_C|} + \frac{z^2}{4}} \tag{9}$$

where $|C^r_C| = \left|C^r_{C,T}\right| + \left|C^r_{C,\overline{T}}\right|$, and $z = 1.65$ is the normal interval width at 95% confidence level.

Discussion. We note that while heuristic estimates (e.g., directly using $\hat{c}$ to estimate c) can still be used in our end-to-end optimization framework, we confirm in our ablation studies that adopting a more principled statistical analysis (Wilson's interval to lower-bound confidence, and Cohen's h for effect-size) does provide quality benefits over heuristic estimates.

5.3 SDC Optimizations by LP-Relaxation

Let R_{all} be the set of all candidate SDCs that meet the statistical tests performed in Section 5.2 (still a large set in tens of thousands, with overlapping coverage and varying degrees of quality). We now describe the key final step in offline-training, where we perform holistic optimization like sketched in Definition 3, to select an optimal set $R \subseteq R_{all}$ with FPR and recall guarantees.

We will first describe how to estimate FPR(r) and recall(r) below.

Estimating FPR. Recall that the FPR of a constraint r is defined as $\text{FPR}(r) = \frac{\text{r-false-positive-columns}}{\text{total-negative-columns}}$, or the number of false-positives r produces, over the total number of negative (error-free) columns. While we don't have labeled data to count these events for r precisely (which would be hugely expensive if we were to label each r), we can approximate these events using a large corpus C in an unsupervised data-driven manner.

Specifically, since C is extracted from relational sources, its columns are generally clean and free of errors (for instance, in our manual analysis of a sample of 2400 table columns randomly

[5]Note that because the corpus C is not completely clean, the true number of false-triggers among covered columns is bound to be smaller than the current estimate of $\left|C^r_{C,T}\right|$ using C. However, because this is in the denominator of $\rho(r)$, it does not affect our lower-bound analysis, as an over-estimate of $\left|C^r_{C,T}\right|$ still leads to a conservative lower-bound of c, which is what we want.

sampled from spreadsheets and relational tables, we found the error rate of C to be around 2%, like we will explain in Section 6.1). We can therefore use $|C|$ to approximate the number of total negative columns in $|C|$. Also recall that we can estimate false-positives of r, based on $C^r_{C,T}$ in the contingency table (estimated using C), so putting the two together we can then estimate FPR(r) as $\frac{|C^r_{C,T}|}{|C|}$.

Estimating recall. The recall of a r, written as Recall(r), is the total number of true-positive errors that r can detect.[6] Since we also don't have labeled data to estimate recall for each r, we use *distant-supervision* [28, 47, 61] to approximate it.

Specifically, we construct a synthetic corpus for that purpose, written as $C_{syn} = \{C(v^e) = C \cup \{v^e\} | C \in \mathcal{C}, C' \in \mathcal{C}, v^e \in C'\}$, where each column in C_{syn} is constructed as $C(v^e) = C \cup \{v^e\}$, with C being a randomly sampled column in $\mathcal{C}$, v^e being a randomly sampled value from a different column C', such that when v^e is inserted into C to produce $C(v^e)$, v^e is likely an error in the context of $C(v^e)$. Like in distant supervision [28, 47, 61], this then allows us to compute the set of errors that r can detect in C_{syn}, as

$$D(r) = \{C(v^e) | C(v^e) \in C_{syn}, r(C(v^e)) = v^e\} \tag{10}$$

where $r(C(v^e)) = v^e$ indicates that r can detect the same v^e as constructed in column $C(v^e)$. We then simply use Recall(r) = $|D(r)|$, as the estimated recall of r. Although there is a small chance that v^e might not be an actual error in the context of $C(v^e)$, in practice, it leads to only a very small difference in recall estimation. For example, in a manual examination of 100 randomly sampled synthetic columns, we identify only 3 cases where v^e could not be identified as an error/outlier, confirming our assumption that inaccuracies so introduced is minimal (e.g., 3%), which have negligible impact for the final SDCs selected by the algorithm as we will show empirically in our experiments.

Coarse-grained SDC Selection (CSS). We are now ready to instantiate the high-level problem sketched in Definition 3 as follows.

Definition 4. [**Coarse-grained SDC Selection (CSS)**]. Given all SDC candidates R_{all}, find a set $R \subseteq R_{all}$ such that its recall Recall(R) is maximized, subject to a constraint that the FPR(R) should not exceed B_{FPR}, and a cardinality constraint that the size of R should not exceed B_{size}, written as:

$$\text{(CSS)} \quad \max_{R \subseteq R_{all}} \left| \bigcup_{r \in R} D(r) \right| \tag{11}$$

$$\text{s.t. } |R| \leq B_{size} \tag{12}$$

$$\sum_{r \in R} \text{FPR}(r) \leq B_{FPR} \tag{13}$$

Note that in the objective function Equation (11), we use Recall(R) = $|\bigcup_{r \in R} D(r)|$ to instantiate the objective function of the original problem in Definition 3 (Equation (5)), since Recall(R) over a set of constraints R can be calculated as the union of errors detected by each $r \in R$.

Observe that because individual $r \in R_{all}$ can often have overlapping coverage (e.g., different embedding methods, and different CTA-classifiers that can detect columns of a type, say "`city`", are all present in R_{all}), this union term in Equation (11) can therefore take the overlaps of recall into consideration when we optimize for the best solution set R.

Also note that in Equation (13), we use $\sum_{r \in R}$ FPR(r) in place of FPR(R) in Equation (7) of Definition 3, because it can be verified that FPR(R) $\leq \sum_{r \in R}$ FPR(r) (using an argument similar to

[6] We use the absolute version of recall over the relative version for its simplicity, the two versions differ only by a universal denominator (the total-number-of-positive-columns), and are therefore equivalent in our context.

union-bound), so that imposing the constraint in Equation (13) esures that the original constraint $\text{FPR}(R) \leq B_{FPR}$ is also satisfied.

We show that the CSS problem in Definition 4 is hard and hard to approximate, using a reduction from maximum coverage. A proof of this can be found in [3].

Theorem 5.1. *The CSS problem is NP-hard and cannot be approximated with a factor of* $(1 - 1/e)$*, unless* $NP \subseteq DTIME(n^{O(\log \log n)})$.

Despite its hardness, we develop Coarse-Select to solve CSS using LP-relaxation and randomized rounding [53], which has an approximation ratio of $(1 - 1/e)$ (matching the inapproximability result). Specifically, we first transform CSS into a CSS-ILP problem:

$$\text{(CSS-ILP) maximize} \sum_{C_j \in C_{syn}} y_j \tag{14}$$

$$\text{s.t.} \sum_{r_i \in R_{all}} x_i \leq B_{size} \tag{15}$$

$$\sum_{r_i \in R_{all}} \text{FPR}(r_i) \cdot x_i \leq B_{FPR} \tag{16}$$

$$\sum_{r_i \in K_j} x_i \geq y_j \quad \forall C_j \in C_{syn} \tag{17}$$

$$x_i, y_j \in \{0, 1\} \tag{18}$$

Here, we use an indicator variable x_i for each $r_i \in R_{all}$, where $x_i = 1$ indicates r_i is selected into R, and 0 otherwise. Let $D(R) = \bigcup_{r \in R} D(r)$ be the union of all errors detected by R. We use another indicator variable y_j for each column $C_j \in C_{syn}$, where $y_j = 1$ indicates $C_j \in D(R)$, and 0 otherwise. Finally, for each $C_j \in C_{syn}$, we define $K_j \subseteq R_{all}$ as the set of constraints that can detect the error constructed in C_j. It can be shown that the CSS-ILP problem so constructed, has the same solution as the original CSS problem.

From CSS-ILP, we construct its LP-relaxation [53], referred to as CSS-LP, by dropping its integrality constraint in Equation (18). The resulting CSS-LP is a linear program that can be solved optimally in polynomial-time, yielding *fractional solution* for each x_i. Finally, we perform randomized-rounding to turn the fraction x_i into integral solutions R.

Fine-grained SDC Selection (FSS). While CSS reduces R_{all} into R from the perspective of set-based optimization, we find in our evaluation, that the confidence produced by the solution $R \subseteq R_{all}$ from CSS, to deviate substantially from the true calibrated confidence (Equation (9) in Section 5.2), if we use the entire R_{all}. This is because CSS only focuses on the set-based optimization, without considering how well the selected R can approximate the calibrated confidence from the original R_{all}, which leads to poor confidence ranking of predicted results, that negatively affects the result quality (e.g., when evaluated using area under precision-recall curves).

To address this inadequacy, we propose an improved version of CSS that ensures confidence approximation in the selection process, which we call *Fine-grained SDC Selection (FSS)*. Define $\text{diff}(C, R, R_{all}) = \text{conf}(C, R_{all}) - \text{conf}(C, R)$ as the difference in predicted confidence for any $C \in C_{syn}$, between using R_{all} and R. We define FSS as follows:

Definition 5. [**Fine-grained SDC Selection (FSS)**]. Given all SDC candidates R_{all}, find a set $R \subseteq R_{all}$ to maximize the number of columns detected in $D(R)$, whose predicted confidence using R does not deviate from its true confidence by δ (or $\text{diff}(C, R, R_{all}) \leq \delta$), subject to a constraint that

Table 3. Quality comparisons, reported as (F1@P=0.8, and PR-AUC) for each method, on ST-Bench and RT-Bench.

		Spreadsheet-Table-Bench (ST-Bench)				Relational-Table-Bench (RT-Bench)			
	Method	real	+5% syn err.	+ 10% syn err.	+20% syn err.	real	+5% syn err.	+10% syn err.	+20% syn err.
Ours	All-Constraints	0.23, 0.38	0.36, 0.39	0.47, 0.57	0.50, 0.66	**0.21**, **0.34**	**0.30**, 0.36	**0.36**, 0.48	0.36, 0.54
	Fine-Select	**0.34**, **0.45**	**0.38**, **0.52**	**0.48**, **0.62**	**0.53**, **0.68**	**0.21**, **0.34**	**0.30**, **0.46**	**0.36**, **0.56**	**0.40**, **0.62**
	Coarse-Select	0.25, 0.43	0.35, 0.52	0.41, 0.60	0.52, 0.67	0.05, 0.31	0.25, 0.43	0.28, 0.53	0.39, 0.61
Column-type detection methods	Sherlock	0, 0.04	0, 0.05	0, 0.10	0.01, 0.21	0, 0.03	0, 0.06	0, 0.14	0, 0.22
	Doduo	0.04, 0.06	0.06, 0.09	0.09, 0.17	0.08, 0.31	0, 0.03	0, 0.05	0, 0.10	0, 0.20
	Glove	0, 0.10	0.03, 0.18	0.07, 0.26	0.06, 0.35	0.05, 0.10	0.06, 0.13	0.03, 0.18	0.03, 0.28
	SentenceBERT	0.08, 0.14	0.12, 0.18	0.11, 0.23	0.18, 0.36	0.09, 0.09	0.14, 0.18	0.11, 0.19	0.09, 0.28
	Regex	0.04, 0.25	0.06, 0.30	0.09, 0.41	0.27, 0.51	0, 0.14	0.03, 0.28	0.01, 0.38	0.11, 0.48
	DataPrep	0.08, 0.22	0.09, 0.25	0.10, 0.38	0.12, 0.49	0.05, 0.14	0.06, 0.24	0.03, 0.40	0.03, 0.50
	Validators	0.04, 0.29	0.03, 0.29	0.01, 0.31	0.01, 0.44	0, 0.03	0, 0.05	0, 0.30	0.03, 0.44
Data-cleaning	AutoDetect	0, 0.18	0, 0.17	0, 0.18	0, 0.25	0, 0.09	0, 0.12	0, 0.15	0.01, 0.25
	Katara	0, 0.04	0, 0.05	0, 0.10	0, 0.20	0, 0.03	0, 0.05	0, 0.10	0, 0.19
Outlier detection methods	SVDD	0.04, 0.04	0.06, 0.06	0.09, 0.10	0.09, 0.15	0.05, 0.04	0.06, 0.06	0.03, 0.07	0.03, 0.12
	DBOD	0, 0.15	0, 0.23	0, 0.35	0, 0.46	0, 0.12	0, 0.29	0, 0.40	0, 0.51
	LOF	0, 0.08	0, 0.12	0, 0.18	0, 0.24	0, 0.04	0, 0.12	0, 0.16	0, 0.22
	RKDE	0.04, 0.20	0.06, 0.24	0.09, 0.31	0.24, 0.40	0.05, 0.11	0.06, 0.21	0.03, 0.27	0.12, 0.35
	PPCA	0, 0.14	0, 0.15	0, 0.19	0.17, 0.26	0, 0.06	0, 0.12	0, 0.15	0, 0.20
	IForest	0, 0.13	0, 0.15	0, 0.19	0.11, 0.25	0, 0.05	0, 0.13	0.11, 0.17	0.12, 0.22
GPT	few-shot-with-COT	0, 0.20	0, 0.30	0, 0.38	0, 0.56	0, 0.16	0, 0.33	0, 0.48	0, 0.53
	few-shot-no-COT	0, 0.20	0, 0.32	0, 0.38	0, 0.56	0, 0.10	0, 0.22	0, 0.44	0, 0.56
	zero-shot-with-COT	0, 0.15	0, 0.28	0, 0.34	0, 0.53	0, 0.16	0, 0.26	0, 0.43	0, 0.52
	zero-shot-no-COT	0, 0.11	0, 0.23	0, 0.25	0, 0.43	0, 0.08	0, 0.21	0, 0.40	0, 0.46
Commercial	Vendor-A	0, 0.18	0, 0.20	0, 0.22	0, 0.27	0, 0.02	0, 0.05	0, 0.11	0, 0.21
	Vendor-B	0, 0.02	0, 0.05	0, 0.10	0, 0.21	0, 0.02	0, 0.05	0, 0.11	0, 0.21

the FPR(R) should not exceed B_{FPR}, and the size of R should not exceed B_{size}, written as:

$$\text{(FSS)} \quad \max_{R \subseteq R_{all}} |\{C \mid C \in D(R), \text{diff}(C, R, R_{all}) \leq \delta\}|$$
$$\text{s.t. } |R| \leq B_{size}$$
$$\sum_{r \in R} \text{FPR}(r) \leq B_{FPR}$$

Observe that when we set $\delta = 1$, FSS reduces to CSS because the confidence approximation requirement of $\text{diff}(C, R, R_{all}) \leq \delta$ is trivially satisfied, making it an advanced variant of CSS.

We propose algorithm Fine-Select to solve FSS, also with quality guarantees. The pseudo-code for Fine-Select is similar to that of Coarse-Select, with two key modifications: (1) for each column $C_j \in \mathcal{C}_{syn}$, its indicator variable $y_j = 1$ if $C_j \in \{C \in D(R) \mid \text{diff}(C, R, R_{all}) \leq \delta\}$, and 0 otherwise; (2) for each $C_j \in \mathcal{C}_{syn}$, we set $K_j \subseteq R_{all}$ as the set that can detect the error constructed in C_j, with the required confidence approximation specified by δ.

We will show in our technical report [3] that the Fine-Select approach has a $(1 - 1/e)$ approximation ratio in expectation, with all constraints also satisfied in expectation, like stated below.

Theorem 5.2. *Let $R \subseteq R_{all}$ be the solution produced by Fine-Select, and $E(\cdot)$ denote expectation. Then the following hold: $E(|R|) \leq B_{size}$, $E(\sum_{r \in R} FPR(r)) \leq B_{FPR}$, and $E(|\{C \in D(R) \mid diff(C, R, R_{all}) \leq \delta\}|) \geq (1 - 1/e)OPT$ where OPT is the optimal value.*

We will test both Fine-Select and Coarse-Select and compare their effectiveness in our experiments.

6 EXPERIMENT

We perform extensive evaluations using real errors from real data. Our code, data, and labelled benchmarks are available in [3].

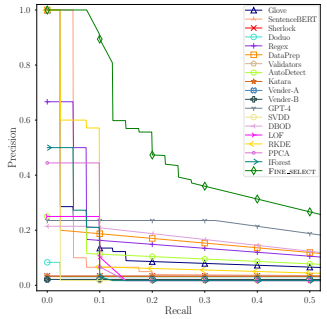


Fig. 4. PR curves on the 1200-column RT-Bench, trained on Relational-Tables.

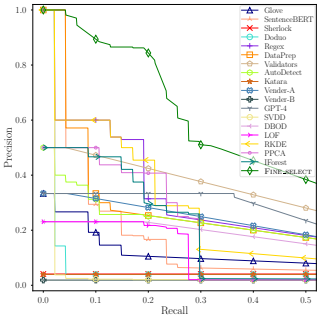


Fig. 5. PR curves on the 1200-column ST-Bench, trained on Relational-Tables.

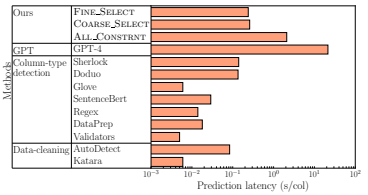


Fig. 6. Online prediction latency: average time to process one column (all methods)

6.1 Experimental Setup

Benchmarks. To test the effectiveness of different algorithms on real tables "in the wild", we focus on real relational tables and spreadsheet tables in our evaluation, and create two benchmarks containing real errors from real tables, described below.

Spreadsheet-Table-Bench (ST-Bench). We randomly sample 1200 spreadsheet columns, extracted from real spreadsheets (`.xlsx` files crawled from the web), as our ST-Bench test set.[7] Each column is carefully labelled and cross-checked by human-labellers, as either *clean* (no data errors are present); or *dirty*, in which case all erroneous values in the column are marked in ground-truth for evaluation. A total of 22 columns (1.8%) contain real errors.

Relational-Table-Bench (RT-Bench). We also sample 1200 relational table columns from real tables extracted from BI models (`.pbix` files crawled from the web), as our second test set. Each column is similarly labeled as clean, or dirty, with erroneous values identified in the ground-truth. A total of 25 columns (2.1%) are identified to contain errors.

Existing data-cleaning benchmarks. To test the applicability of learned SDCs on existing data-cleaning benchmarks, we further compile 9 commonly-used datasets from prior studies [26, 41, 42, 49], which are: *adults*, *beers*, *flights*, *food*, *hosptial*, *movies*, *rayyan*, *soccer* and *tax*. We reuse existing ground-truth in our evaluation.

Evaluation metrics. We evaluate the quality of different algorithms, using standard precision/recall, where precision $P = \frac{\text{num-of-correct-predicted-errors}}{\text{num-of-total-predicted-errors}}$, and recall $R = \frac{\text{num-of-correct-predicted-errors}}{\text{num-of-total-true-errors}}$.

Since each algorithm have different score thresholds to make predictions at different confidence levels, we plot precision-recall curves (PR-Curves) of all algorithms, and summarize the overall quality of PR-Curves using two standard metrics:

(1) Precision-Recall Area-Under-Curve (PR-AUC) [9], which measures the area under the PR-curve, where higher is better;

(2) F1-score at Precision=0.8 (F1@P=0.8) [12], which measures the F1 score (the harmonic mean of precision and recall) at high precision ($P = 0.8$). Note that a high level of precision is crucial in our setting (e.g., to win user trust in end-user data cleaning), which is why we use this metric to complement PR-AUC.

[7]We sample non-numerical columns for testing only, since it is usually trivial to identify non-conforming values (e.g., strings) in numerical columns.

Table 4. Quality and latency comparison for FINE-SELECT, as we vary the constraint count budget (B_{size})

	ST-BENCH					RT-BENCH				
Constraint count budget (B_{size})	100	200	500	1000	ALL-CONSTRAINTS (26673)	100	200	500	1000	ALL-CONSTRAINTS (26673)
Quality: F1@P=0.8	0.29	0.31	0.34	**0.35**	0.23	0.09	0.11	**0.21**	**0.21**	**0.21**
Quality: PR-AUC	0.42	0.41	0.44	**0.46**	0.38	0.22	0.27	**0.34**	0.31	**0.34**
Latency: second per column	0.13	0.16	0.21	0.23	1.44	0.12	0.18	0.24	0.26	2.10

Table 5. Ablation study: contribution of each type of method, reported as (F1@P=0.8, and PR-AUC).

	ST-BENCH	RT-BENCH
FINE-SELECT	**0.34**, **0.45**	**0.21**, **0.34**
no-CTA	0.34, 0.45	0.17, 0.32
no-embedding	0.29, 0.43	0.13, 0.30
no-pattern	0.22, 0.40	0.18, 0.34
no-function	0.15, 0.38	0.17, 0.32

Table 6. Ablation study: contribution of the Wilson score interval and Cohen's h, reported as (F1@P=0.8, and PR-AUC).

	ST-BENCH	RT-BENCH
ALL-CONSTRAINTS	**0.23**, **0.38**	**0.21**, **0.34**
no Wilson score interval	0.12, 0.36	0.18, 0.31
no Cohen's h	0.23, 0.35	0.21, 0.32

6.2 Methods Compared

We compare with the following methods on quality and efficiency.

- **Column-type detection methods**. Our first group of baselines directly invoke existing column-type detection methods. For each method below, we compute the domain evaluation score $f_t(v)$ of type t (Definition 1), for each value v in column C, and use the standard z-score on the resulting distribution of $f_t(v)$ to identify potential errors [27]. We vary the z-score threshold to plot PR-curves for each method.
  - CTA methods: *Sherlock* [31], *Doduo* [59]. We use the CTA-classifier as domain evaluation function $f_t(\cdot)$ to compute a score distribution for each column C.
  - Embedding domains: *Glove* [51], *Sentence-BERT* [54]. We use the embedding distance as the domain evaluation function $f_t(\cdot)$ to compute a score distribution.
  - Function domains: *DataPrep* [1], *Validator* [8]. We use the boolean result returned by a type-validation function (true=1, false=0) as the domain evaluation function $f_t(\cdot)$.
  - Pattern domains: *Regex*. We use whether a value v matches an inferred regex pattern of a column C (match = 1, non-match = 0) as the domain evaluation function $f_t(\cdot)$.
- **GPT-4**. Language models such as GPT have shown strong abilities in diverse tasks [14]. Since our task can also be formulated as a natural-language task, we invoke GPT-4[8] with extensive prompt optimization, including (1) select few-shot examples [14]; and (2) use chain of thought (COT) [64] (to require GPT-4 to reason about its detection with possible repairs, so that it can stay truthful with fewer false-positives). We report 4 variants here based on prompts used, which are: few-shot-with-COT, few-shot-no-COT, zero-shot-with-COT, and zero-shot-no-COT.
- **Katara** [18]. Katara performs data cleaning by mapping table columns to Knowledge-Bases (KB) like YAGO, to identify columns of type `city`, `country`, etc., so that errors can be detected. This is

[8]Version gpt-4-0125, accessed via OpenAI API in 2024-06.

col_header	data_vals
movie_id	['tt0054215', 'tt0088993', 'tt0032484', 'tt0889671', 'tt1325014', 'tt0065112', 'tt0074512', 'tt0092796', 'tt0090021', 'tt0102733', 'tt0102741', 'tt1045642', 'tt0265666', 'tt0440963', 'tt
contract no.	['b50005237', 'b50005238', 'b50002613', 'b50003343', 'b50004853', 'b50003298', 'b50003292', 'b50004499', 'b50004017', 'b50003446', 'b50004085', 'b50002318', 'b50004162', 'b
article number	['1-15-80-00-30-spp', '1-20-10-60-00-pek', '1-20-10-62-00-pek', '1-25-50-10-00-kvs', '1-25-50-32-00-ppv', '1-25-50-32-00-wiv', '1-30-50-10-00-kst', '1-30-51-00-00-ksv', '1-40-10-0
commbuys mbpo link	['po-17-1080-osd03-osd03-10332', 'po-17-1080-osd03-osd03-10324', 'po-17-1080-osd03-osd03-10816', 'po-17-1080-osd03-osd03-10336', 'po-17-1080-osd03-src02-10355', 'po-
ordernum	['num000002', 'num000003', 'num000004', 'num000005', 'num000006', 'num000007', 'num000008', 'num000009', 'num000010', 'num000011', 'num000012', 'num000013', 'num
primary funding agreement	['12-ec-002', '13-hqjdf-004', '13-hqjtc-018', '12-100-004', '14-hqjdf-025', '12-130-021', '13-hqjdf-003', '12-ez-016', '14-ez-007', '12-ez-012', '14-hqjdf-009', '13-ez-013', '14-hqjdf-0

Fig. 7. Examples columns with specialized meanings, but are still "covered" by SDCs: each row here corresponds to a real data column, with its column-header and data-values listed. Many of these columns convey specialized meanings (e.g., specialized contract no., article number, etc.), which are nevertheless covered by our pattern-based SDCs, as our method learns a generalized notation of what a reliable pattern-domain may look like, which transcends specific meanings in each column.

Table 7. Sensitivity to different training corpora

	Spreadsheet-Table-Bench (ST-Bench)				Relational-Table-Bench (RT-Bench)			
	real	+5% syn err.	+ 10% syn err.	+20% syn err.	real	+5% syn err.	+10% syn err.	+20% syn err.
Relational-Tables	0.34, 0.45	0.38, 0.52	0.48, 0.62	0.53, 0.68	0.21, 0.34	0.30, 0.46	0.36, 0.56	0.40, 0.62
Tablib	0.15, 0.45	0.34, 0.54	0.45, 0.61	0.53, 0.68	0.13, 0.41	0.37, 0.54	0.40, 0.56	0.46, 0.60
Spreadsheet-Tables	0.05, 0.30	0.18, 0.43	0.28, 0.52	0.45, 0.64	0.02, 0.29	0.25, 0.43	0.25, 0.47	0.27, 0.55

similar in spirit to ours, but is limited to symbolic knowledge-bases, and are based on heuristic mapping with static thresholds (not trained/calibrated).

- **Auto-Detect** [28]. This approach detects errors due to incompatible data patterns, based on co-occurrence statistics. While it also leverages a corpus to produce predictions, it is only applicable to patterns, limiting its coverage.
- **Outlier detection methods**. There is a large literature on outlier detection, we select *RKDE* [36], *PPCA* [63] and *IForest* [40] for comparison, which are shown to be the best-performed methods in an empirical study [21]. We also include three classical methods: *SVDD* [62], *DBOD* [37] and *LOF* [13], that compared with in an earlier study [28] similar to our problem setting.
- **Commercial**. We also test our benchmarks on two commercial software targeting non-technical end-users, that can automatically detect errors in tables. We refer to these two systems as Vendor-A and Vendor-B in our experiments.
- **Auto-Test**. This is our proposed method. We report 3 variants of Auto-Test, which are (1) All-Constraints, which uses the entire set of candidate constraints R_{all} after quality-based pruning (Section 5.2), (2) Coarse-Select (Section 5.3), and (3) Fine-Select (Section 5.3).
  We invoke the solver in SciPy [56] to solve our LP. By default, we set B_{size} to 500, B_{FPR} to 0.1, and δ in Fine-Select to 10^{-3}.
  For training, we use three corpora: (i) 247K relational table columns extracted from real BI models, henceforth referred to as Relational-Tables, and (ii) 297K real spreadsheet table columns extracted from real spreadsheets, referred to as Spreadsheet-Tables, and (iii) 298K real table columns extracted from a publically available corpus Tablib [7]. We kept Relational-Tables and Spreadsheet-Tables completely separate from RT-Bench and ST-Bench. To test generalizability, we also train on one corpus (e.g., Relational-Tables) and test on the benchmark from a different source (e.g., ST-Bench).

All experiments are run on a Linux machine with a 64-core, 2.4 GHz CPU and 512 GB memory.

6.3 Quality Comparisons

Quality comparison with real errors. In Figure 4 and 5, we compare the PR-curves of all methods, on two benchmarks Relational-Table-Bench (RT-Bench) and Spreadsheet-Table-Bench (ST-Bench), respectively. To avoid clutter in these figures, we show the best method Fine-Select from

Table 8. Quality results of applying SDCs learned in Auto-Test on existing data-cleaning benchmarks. Note that the cell-level precision (reported in the last line) is evaluated by strictly comparing our detection, vs. the ground-truth "clean" version of the benchmarks, which however underestimates the true precision, because the current ground-truth labels in some of the benchmarks are incomplete that "miss" real errors. We therefore also report adjusted precision in parenthesis "()" – for example, our 9-dataset aggregate precision is "95% (97%)", meaning that precision is 95% (174/183) if strictly using existing ground-truth, which however increases to 97% (179/183) if we use augmented ground-truth that is manually labeled and shared at [3].

		9-dataset overall	*adults*	*beers*	*flights*	*food*	*hosptial*	*movies*	*rayyan*	*soccer*	*tax*
Dataset statistics	# of total categorical cols	85	9	6	6	10	16	14	8	8	8
	# of cols covered by existing ground-truth	36	1	3	4	1	12	0	8	1	6
Quality: column-level	Coverage: # of cols with new constraints by using SDC	**17**	2	2	0	3	4	2	1	2	1
	Precision: % of new SDCs that are correct	**94%**	100%	67%	-	100%	100%	100%	100%	100%	100%
Quality: cell-level	True-positives: # of detected data errors using SDCs	**183**	0	5	0	3	13	161	1	0	0
	Precision: % of detected data errors that are correct	**95% (97%)**	-	40% (60%)	-	0% (33%)	92% (100%)	99% (100%)	0% (100%)	-	-

the Auto-Test family, trained using Relational-Tables (additional results can be found in our full technical report [3]). Similarly, for methods in GPT-4 family, we also only show few-shot-with-COT since it performs the best, as can be seen in Table 3.

The proposed Fine-Select substantially outperforms all other methods. It is worth noting that Fine-Select trained using Relational-Tables not only performs well on RT-Bench, but also on ST-Bench, demonstrating strong generalizability to tables of different characteristics (spreadsheet vs. relational tables).

Among all baselines, SentenceBERT, DataPrep, and Regex perform better than other domain-based baselines, while RKDE performs better than other outlier detection baselines, but these methods still lag significantly behind the proposed Fine-Select. Note that while GPT-4 can detect many data errors (around 80%), it also produce a large number of false-positives (especially on columns involving code-names, abbreviations, and proprietary vocabularies that are not standard English), which affects its quality.

In Table 3, we further summarize the PR-curves using two metric numbers: (1) F1@P=0.8, and (2) PR-AUC, both of which show a picture similar to what we observe on the PR-curves, where Fine-Select outperforms alternatives methods.

Quality comparison with real and synthetic errors. In addition to testing on the real RT-Bench and ST-Bench, we further report 3 settings for each of the benchmark in Table 3, where we inject synthetic errors (using values randomly sampled from other columns), at 5%/10%/20% levels, on top of real errors. We observe that Fine-Select continues to dominate all other methods, confirming its effectiveness across a spectrum of error rates.

Coverage of specialized content. In addition to precision/recall, a question we want to explore is whether the generated SDCs only cover well-known concepts commonly represented on the web. Figure 7 shows a sampled analysis, with examples of real columns that have specialized meanings and structures (corresponding to contract-number, article-number, etc.), some of which are likely unique to a specialize domain or few datasets. Our pattern-based SDCs can nevertheless reliably install pattern-based SDCs for such columns, as the method learns a generalized notation of what a reliable domain-pattern should look like, which transcends specific meanings conveyed in the data, therefore providing "coverage" even when the underlying domains may be highly specialized.

Additional results, such as training using different corpora (Spreadsheet-Tables), can be found in [3] in the interest of space.

Table 9. Details of real SDC that are automatically applied on existing data-cleaning benchmarks, using Auto-Test. Many of these SDC constraints here offer new mechanisms to identify data errors, that are not possible using existing constraints from these benchmark data (e.g., note that existing constraints from these benchmark data do not cover many columns marked as "-", or existing constraints identify errors using complementary mechanisms, such as "2 letters" for `state` columns, while our SDC use ML-based CTA "state-classifiers" from Sherlock and Doduo, which are more fine-grained in detecting subtle errors).

Dataset	Column	Example values	Existing constraints in benchmark data	Auto-Test: New SDC constraints (pre-condition)	Auto-Test: New SDC constraints (post-condition)	New errors SDC can identify if present (not by existing constraints)
adult	race	white, black, others, ...	-	80% column values have their *Glove* distances to "red" < 5.5	values whose *Glove* distances to "red" > 7.5	(Typo): wite, blaack, ... (Incompatible): seattle, male, ...
adult	sex	female, male	-	80% column values have their *Glove* distances to "male" < 7.0	values whose *Glove* distances to "male" > 9.5	(Typo): femele, malle, ... (Incompatible): masculina, finnish, ...
beers	city	san francisco, columbus, louisville, ...	brewery id → city	80% column values have their *Glove* distances to "hawaii" < 6.0	values whose *Glove* distances to "hawaii" > 11.0	(Typo): louisvilla, seettle, ... (Incompatible): maine, 9th ave., ...
beers	state	or, in, ca, fl, ...	brewery id → state, state (2 letters)	80% column values have their *Sherlock state-classifier* scores > 0.5	values whose *Sherlock state-classifier* scores ≤ 0	(Typo): ax, xk, ... (Incompatible): us, xl, ...
food	facility type	restaurant, school, grocery store, ...	-	80% column values have their *Doduo type-classifier* scores > 4	values whose *Doduo type-classifier* scores < -1	(Typo): childern's service, koisk, ... (Incompatible): asia, dummy_type, ...
food	city	chicago, schaumburg, lake zurich, ...	-	80% column values have their *Glove* distances to "berlin" < 5.5	values whose *Glove* distances to "berlin" > 8.0	(Typo): chiago, buffolo, ... (Incompatible): upenn, mcdonald, ...
food	state	il, ilxa	city → state	80% column values have their *Doduo state-classifier* scores > 4	values whose *Doduo state-classifier* scores < -2	(Typo): xx, nt, ... (Incompatible): usa, tottenham, ...
hospital	sample	0 patients, 107 patients, 5 patients, ...	-	93% column values match pattern "\d+ \[a-zA-Z]+"	values not matching pattern "\d+ \[a-zA-Z]+"	(Typo): x patients, 3x patients,... (Incompatible): empty, sample_size, ...
hospital	state	al, ak	zip → state, county → state, state (2 letters)	80% column values have their *Sherlock state-classifier* scores > 0.5	values whose *Sherlock state-classifier* scores ≤ 0	(Typo): ax, xk, ... (Incompatible): us, xl, ...
hospital	hospital type	acute care hospitals	condition, measure name → hospital type	80% column values have their *Doduo category-classifier* scores > 4.5	values whose *Doduo category-classifier* scores < -1.5	(Typo): acute caer, clinix, ... (Incompatible): london, co. kildare, ...
hospital	emergency service	yes, no	zip → emergency service	80% column values have their *Glove* distances to "no" < 5.5	values whose *Glove* distances to "no" > 7.0	(Typo): yxs, nao, ... (Incompatible): emergency, 95503, ...
movie	id	tt0054215, tt0088993, tt0032484, ...	-	85% column values match pattern "\[a-zA-Z]+\d+"	values not matching pattern "\[a-zA-Z]+\d+"	(Incompatible): iron_man_3, dark_tide, ...
movie	duration	109 min, 96 min, 120 min, ...	-	93% column values match pattern "\d+ \[a-zA-Z]+"	values not matching pattern "\d+ \[a-zA-Z]+"	(Incompatible): 2 hr 30 min, nan, ...
rayyan	article created_at	[1/1/71, 4/2/15, 12/1/06, ...]	-	90% column values return true on function *validate_date()*	values that return false on function *validate_date()*	(Incompatible): nan, june, ...
soccer	position	defender, midfield, goalkeeper, ...	-	80% column values have their *Sherlock position-classifier* scores > 0.1	values whose *Sherlock position-classifier* scores ≤ 0	(Typo): strikor, forwrad, ... (Incompatible): difensore, goleiro, ...
soccer	city	cardiff, dortmund, munich, ...	-	80% column values have their *Sentence-BERT* distances to "panama" < 1.2	values whose *Sentence-BERT* distances to "panama" > 1.375	(Typo): cardif, munihei, ... (Incompatible): fl, 744-9007, ...
tax	state	ma, nv, ar, ...	zip → state, area code → state, state (2 letters)	80% column values have their *Sherlock state-classifier* scores > 0.5	values whose *Sherlock state-classifier* scores ≤ 0	(Typo): ax, xk, ... (Incompatible): us, xl, ...

6.4 Efficiency Analysis

Online prediction latency. Figure 6 shows the average latency of making predictions for one column. The proposed Fine-Select takes around 0.2 seconds on average, which is interactive and suitable for user-in-the-loop scenarios. All-Constraints in comparison, is an order of magnitude slower, showing the benefit Fine-Select in compressing and selecting most beneficial SDCs. GPT-4 is the slowest as it takes over 20 seconds for one column on average.

Additional results on latency, including offline latency analysis, can be found in our technical report [3].

Table 10. Examples of new errors detected by SDCs, marked in underline, that are not known or labeled as errors in existing benchmark ground-truth. For example, in the "hospital" dataset, a cell with value "empty" in the "sample" column (with typical values like "0 patients", "107 patients") are not marked in ground-truth; in the "food" dataset, a cell with misspelled "childern" is not marked in the ground-truth, etc. This shows that SDCs can complement and enhance existing constraint-based cleaning to identify additional errors.

Dataset	Column	Example column values	Existing constraints in benchmark data	New SDC constraint (pre-condition)	New SDC constraint (post-condition)	New errors detected by SDC (not known in ground-truth)
hospital	sample	[0 patients, 107 patients, 5 patients, ...]	-	93% column values match pattern "\d+ \[a-zA-Z]+"	values not matching pattern "\d+ \[a-zA-Z]+"	"empty"
food	facility type	[restaurant, grocery store, catering, ...]	-	80% column values have their *Doduo type-classifier* scores > 4	values whose *Doduo type-classifier* scores < -1	"childern's service facility"
rayyan	article created_at	[1/1/71, 4/2/15, 12/1/06, ...]	-	90% column values return true on function *validate_date()*	values that return false on function *validate_date()*	"nan"

6.5 Sensitivity Analysis

We analyze the sensitivity of Auto-Test to different parameters.

Sensitivity to the number of constraints. Table 4 shows the effect of varying the number of constraints B_{size} in Fine-Select, using All-Constraints (with 26673 constraints) and GPT-4 as reference points. Fine-Select shows strong efficiency benefit (7-10x faster) over All-Constraints, while having the same or even better quality with just 500 constraints (e.g., Fine-Select shows even higher PR-AUC and F1@P=0.8 than All-Constraints on RT-Bench, likely because it is forced to select high-quality SDCs).

Sensitivity to training corpora. We summarize the performance of using Relational-Tables, Spreadsheet-Tables and Tablib as the training corpus in Table 7. Our results show that the performance with Relational-Tables and Tablib follows a similar trend, both are better than Spreadsheet-Tables. This can be attributed to the fact that Spreadsheet-Tables are crawled from human-generated spreadsheet tables, which tend to be noisier than the machine-generated tables in Relational-Tables and Tablib. This observation suggests that the quality of the training corpus plays a critical role in the effectiveness of mined SDCs.

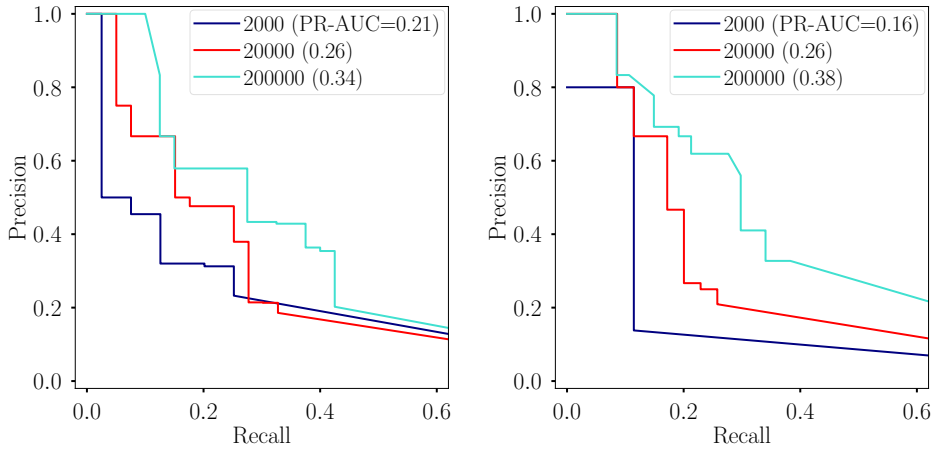
Sensitivity to training corpus size. We study the effect of varying training corpus size from 2,000 to 200,000 columns in Figure 8. On both benchmarks, quality improves with more training data, showing the effectiveness of our data-driven approach.

Robustness to low-quality SDC candidates. To test whether Auto-Test is robust to low-quality SDCs, we study the effect of injecting 1000 random hashing SDCs candidates (in Section 5.1). Specifically, a random hashing SDC has a domain-evaluation function $f^d_{hash}(h_i, v) = h_i(v)$ where h_i is a hash function that randomly maps v to a real number between 0 and 1. Since hash functions do not correspond to any meaningful domain, these SDCs are inherently of low quality. We found that all adversarial SDC candidates are rejected by our statistical test, and consequently have no effect on our final results (e.g., with no false positive detections produced).

Additional results such as sensitivity to FPR budget, size budget, Cohen's h, and Wilson, can be found in [3] in the interest of space.

6.6 Quality on data-cleaning benchmarks

In addition to testing using large-scale real benchmarks collected in the wild (ST-Bench and RT-Bench), we also test SDCs learned using Auto-Test against 9 existing data-cleaning datasets used



(a) RT-Bench (b) ST-Bench

Fig. 8. Sensitivity to training corpus size

in prior work [11, 16, 25, 35, 41, 55], listed in Table 8. Our goal of this experiment is to test whether our learned SDCs can identify new constraints to complement existing constraints in these datasets, thereby augmenting existing data cleaning algorithms.

Table 8 reports our results in terms of (1) column-level coverage, or new constraints that we discover using SDCs not in existing ground-truth, (2) column-level precision, or the fraction of new SDCs constraints judged as correct, (3) cell-level true-positives, or the number of erroneous cells that the new SDCs can detect, and (4) cell-level precision, or the fraction of erroneous cells detected by SDCs that are correct.

Column-level results. We can see that our approach can indeed discover new SDC constraints on 16 columns (not known in existing benchmark ground-truth), from a total of 81 columns, in which 94% new constraints are correct.

Table 9 lists all new SDCs found automatically on existing Data-cleaning benchmarks. Observe that some of these columns do not originally have applicable constraints in benchmark ground-truth (marked by "-"), in which case our SDCs auto-applied on such columns would clearly provide value, by enabling new mechanisms for error detection. While for the rest of the columns existing constraints do exist, our SDC can nevertheless still augment them. For example, on column "`city`" in dataset "`beers`", although there is an FD constraint between "`brewery id`" and "`city`", there are still many errors that cannot be reliably detected by the FD alone – e.g., the FD constraint cannot find errors for rows with a unique brewery id in the table, while SDC can help to detect errors such as typos (e.g., "`seatle`") and incompatible values (e.g., "`9th ave`") in such cases.

Cell-level results. At the cell-level, we can see from Table 8 that these automatically-installed new SDCs alone (without using any other constraints in benchmark ground-truth, which typically require human experts to program), can already identify 183 data values as errors, with an overall precision of 95%, when evaluated against the ground-truth clean data.

Interestingly, using these new SDCs enable us to uncover *new errors not known or labelled in existing ground-truth*, some of the example errors, and their corresponding SDCs, are shown in Table 10. Note that no constraints are programmed on these example columns in the existing benchmarks (indicated by "-" in the table), but the SDCs we automatically apply, can find typos (misspelled "`childern`"), and incompatibility (strings like

"empty" and "nan" mixed in data columns) that are not known in existing ground-truth. We believe this demonstrates that SDC has the potential to augment existing data-cleaning methods, to identify new and complementary data errors not covered by existing constraints.

We want to stress that in expert-driven data-cleaning scenarios and with experts in the loop, existing data-cleaning algorithms and powerful formalism such as denial constraints are still way more powerful, such that *SDCs are not meant to outperform or replace existing methods in such settings* – this particular experiment is only meant to show that SDCs can serves as a new class of constraints (auto-applied to relevant table columns), that may complement and augment existing data cleaning methods.

7 CONCLUSIONS AND FUTURE WORK

In this work, we propose a new class of data-quality constraints that we argue are overlooked in the literature. We show that such constraints can unify diverse column-type detection methods in the same framework, and once learned from large table corpora using Auto-Test, can reliably apply to new and unseen tables.

Future directions include integrating SDCs with existing integrity constraints, and study how they may complement constraint-driven data cleaning in the expert-driven scenarios. Testing the coverage of our proposed method on specialized domains and corpora, is another direction of future work.

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