

Table-LLM-Specialist: Language Model Specialists for Tables using Iterative Generator-Validator Fine-tuning

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ABSTRACT

Language models such as GPT and Llama have shown remarkable ability on diverse natural language tasks, yet their performance on complex table tasks (e.g., NL-to-Code, data cleaning, etc.) continue to be sub-optimal. To improve their performance, task-specific fine-tuning is often needed, which however require expensive human labeling, and is prone to over-fit on a specific training set.

In this work, we propose TABLE-LLM-SPECIALIST, or TABLE-SPECIALIST for short, as a new self-trained fine-tuning paradigm specifically designed for table tasks. Our insight is that for each table task, there often exist two dual versions of the same task, one generative and one classification in nature. Leveraging their duality, we propose a Generator-Validator paradigm, to iteratively generate-then-validate training data from language-models, to fine-tune stronger TABLE-SPECIALIST models that can specialize in a given task, without requiring manually-labeled data.

Our extensive evaluations suggest that our TABLE-LLM-SPECIALIST has (1) *strong performance* on diverse table tasks over vanilla language-models – for example, TABLE-SPECIALIST fine-tuned on GPT-3.5 not only outperforms vanilla GPT-3.5, but can often match or surpass GPT-4 level quality, (2) *lower cost* to deploy, because when TABLE-SPECIALIST fine-tuned on GPT-3.5 achieve GPT-4 level quality, it becomes possible to deploy smaller models with lower latency and inference cost, with comparable quality, and (3) *better generalizability* when evaluated across multiple benchmarks, since TABLE-SPECIALIST is fine-tuned on a broad range of training data systematically generated from diverse real tables.

1 INTRODUCTION

Recent language models, such as GPT [18], Llama [71] and Mistral [39], have shown remarkable abilities to perform diverse natural language tasks [18, 71–73]. Such models show strong generalizability, in that they can be prompted with few-shot examples, to perform across a wide range of language tasks [18, 44].

However, when it comes to complex “table tasks”, such as data transformation [28, 30, 40, 41, 46], and data cleaning [21, 35, 38, 60, 61, 76], where the central object of interest is a *structured relational table* (as opposed to natural language text), even the latest language models can struggle to perform well, despite prompt-level optimizations [47, 70, 90]. This is likely because language models are trained predominately on one-dimensional natural language text, whereas tables are two-dimensional in nature, which are fundamentally different for models to understand and manipulate [47, 66, 70].

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Prior approaches: Fine-tuning for table tasks. To overcome improve language-models performance on table-tasks, various fine-tuning approaches can be used, which we will review below, and show a visual comparison in Figure 1.

Dataset-specific fine-tuning. A common approach to fine-tuning, shown on the left of Figure 1 (marked as ①), is what we refer to as “dataset-specific fine-tuning”. Here, given a particular table-task T (say data-transformation), we start from a vanilla “base” language-model like GPT or Llama (at the lower-right of the figure), and use a labeled dataset D for task T that is usually divided into train/test splits. The training split is then used to fine-tune language-models, which can often lead to significant performance gains when evaluated using the (highly correlated) test-split.

This is a common practice widely used in many of today’s benchmarks for table-tasks, which often come with train/test splits [2, 20, 23, 58, 86, 91, 93], where the expectation is for models to be trained and tested on homogeneous splits of the *same labeled dataset D*.

However, despite their large capacity, large language models fine-tuned on the training-split of one dataset D often do not generalize well to another dataset D' for the same task type T . For instance, Figure 2 shows the result of fine-tuning GPT-3.5-turbo on two table tasks, schema-matching (left) and NL-to-SQL (right). In both cases, we observe that fine-tuned GPT-3.5 using one benchmark dataset D can lead to performance gains on the test-split of the same D (as expected), but significantly lower performance on another benchmark dataset D' of the same task, *compared to the baseline of vanilla GPT-3.5 without fine-tuning*, for both schema-matching and NL-to-SQL.

We argue that the relatively narrow nature of one specific dataset, often manually labeled at a small scale, can lead to poor “generalizability” of fine-tuned language models with “dataset-specific fine-tuning”, which we illustrate along the x-axis of Figure 1.

Given that it is hard to anticipate real test data from real users (e.g., in scenarios like data cleaning or NL-to-SQL, where user tables and queries are often not known *a priori*), we argue that “dataset specific fine-tuning” does not provide a robust way to develop models to handle diverse user requests reliably in practice.

Table-Generalist fine-tuning. A second class of recent fine-tuning techniques, which we refer to as “Table-Generalist”. This class of approaches are inspired by the success of general-purpose chat models like ChatGPT and Llama-Chat, which are fine-tuned from their respective base models (GPT and Llama) [8, 56, 79], and show great

Note that “over-fitting” is a well-known topic studied in the literature [65, 87], especially for small models. Our analysis serves to show that, for the common table-tasks that we care about, over-fitting can still happen even when we fine-tune large language models such as the 175B GPT-3.5 (which have a large capacity and are supposed to be more robust to over-fitting).

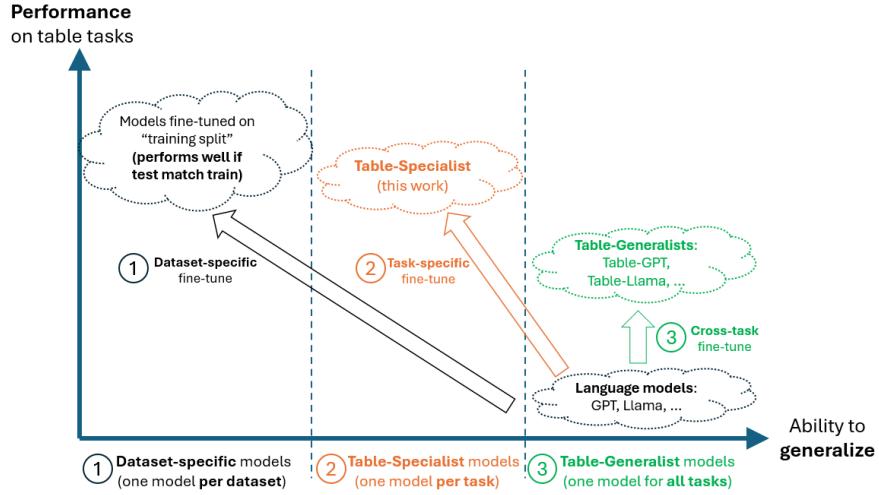


Figure 1: Performance vs. generalizability trade-offs: A visual comparison of different fine-tuning approaches for table-tasks. (1) **Dataset-specific fine-tuning:** models are fine-tuned on benchmark “training split” of one dataset, which performs well on the corresponding “test split” (but may not generalize to a different datasets for the same task type). (2) **Table-Specialist fine-tuning** (this work): we propose to fine-tune one model per table-task (e.g., data cleaning, data transformation, etc.), which generalizes well across datasets for the same task type. (3) **Table-Generalist fine-tuning:** methods that fine-tune one general-purpose model to handle many different table-tasks, which has good generalizability, at the cost of lower-performance on individual tasks.

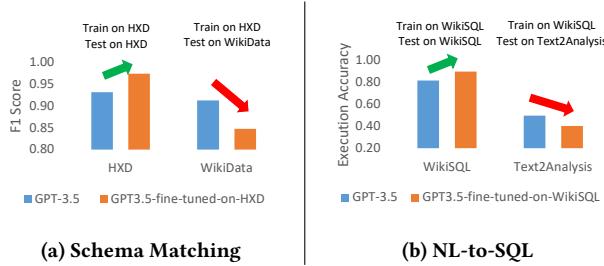


Figure 2: “Dataset-specific fine-tuning” using GPT-3.5 for table-task T : (a) Schema-matching, (b) NL-to-SQL. In both cases, while GPT-3.5 fine-tuned using the training-split of one dataset D lead to performance gains on the test-split of the same D (shown as green arrows pointing up), they also result in significant performance loss on another dataset D' for the same task type T (red arrows down), *relative to un-tuned vanilla GPT-3.5*, suggesting likely over-fitting on D .

generalizability by handling diverse human instructions unseen during training, which we will refer to as “Chat-Generalist”.

Inspired by the success of “Chat-Generalist” models like Chat-GPT, “Table-Generalist” models such as Table-GPT [47] and Table-Llama [90] are developed, which are fine-tuned similarly to Chat-GPT by pooling diverse table-tasks as training data for multi-task table fine-tuning. The resulting “Table-Generalist” models are shown to handle diverse table-tasks, with better performance on a wide range of table tasks than the vanilla language models (GPT and Llama), including on *new and unseen table-tasks* held out during fine-tuning [47, 90].

This class of techniques is depicted on the right of Figure 1 (marked as ③), which shows both strong generalizability (x-axis), and improved table-task performance compared to vanilla language-models (y-axis). However, their cross-task generality comes at a cost of performance, as there is often a performance gap between “dataset-specific fine-tuning” and Table-Generalists, like shown along the y-axis.

TABLE-LLM-SPECIALIST: a new approach to table fine-tuning. In this work, we develop a new fine-tuning approach for table-tasks that aims to close the performance gap, which we call “TABLE-LLM-SPECIALIST”, also referred to as “TABLE-SPECIALIST” for short, shown in the middle of Figure 1 (marked as ②).

In this approach, each TABLE-SPECIALIST model is fine-tuned by design to *focus on one specific type of table task T* (e.g., one model for data transformation, one model for error detection, one model for NL-to-SQL, etc.), which is unlike Table-Generalist models (Table-GPT and Table-Llama) that can handle all types of table tasks.

Importantly, we show that by being more specialized on one task T , TABLE-SPECIALIST can be (1) made much more performant than Table-Generalists (depicted on the y-axis), while (2) still being able to generalize to new and unseen datasets of the same task T (in contrast to “dataset-specific fine-tuning”, where models fine-tuned on D may not generalize to D' , like depicted on the x-axis).

At a high level, our TABLE-SPECIALIST exploits a *duality of table tasks*, where a “*generative table-task*” has a counter-part that is a “*classification table-task*”, and vice versa, forming two dual versions of the same task. Correspondingly, we propose a “Generator-Validator” framework that can iteratively fine-tune a generative model and a classification model for the dual versions of the task, using training data automatically “generated-then-validated” by

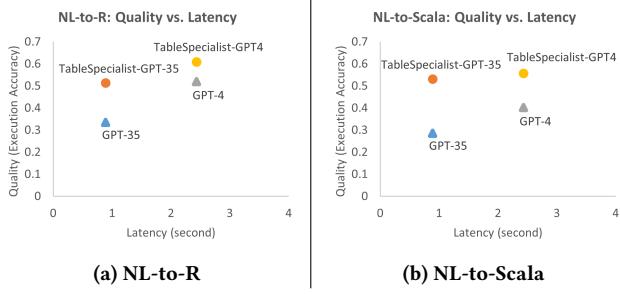


Figure 3: “TABLE-SPECIALIST fine-tuning”: Quality vs. latency comparison on two table-tasks: (a) NL-to-R; (b) NL-to-Scala. In both cases, TABLE-SPECIALIST-GPT-3.5 significantly outperforms vanilla GPT-3.5, and can even outperform vanilla GPT-4 (shown on y-axis), making it possible to deploy TABLE-SPECIALIST-GPT-3.5 over vanilla GPT-4 for these tasks, at substantially lower latency and costs (x-axis).

the two models, leveraging unique characteristics of tables (e.g., permutation-invariance and execution-invariance).

While the notion of dual-learning and dual-tasks is studied for machine-translation tasks (e.g., translating from language A to B, and from B to A) [31, 63, 80] and computer-vision tasks (e.g., transferring from style A to B, and from B to A) [42, 74, 85], it is not explored in the context of tables, as we will review in Section 2.

We show that our approach utilizes diverse real tables to create rich training examples, making the resulting models much more generalizable than baselines such as “dataset-specific fine-tuning”.

Key benefits of TABLE-SPECIALIST. To better illustrate the benefits of TABLE-SPECIALIST, in Figure 3 we highlight our results on two table-tasks, NL-to-R and NL-to-Scala (which are similar to NL-to-SQL but translate natural-language questions to R and Spark-Scala code that can run on tables instead).

In both figures, we can see that vanilla GPT-4 produces higher quality than vanilla GPT-3.5, but have 2-3x higher latency (and also higher financial cost to deploy), which is expected. The proposed TABLE-SPECIALIST fine-tuned on GPT-3.5 and GPT-4 show strong quality gains over vanilla GPT-3.5 and GPT-4, respectively, *without using any training data from the training-split of the test benchmarks*.

More importantly, we can see that in both cases, TABLE-SPECIALIST-GPT-3.5 can match or exceed the quality achieved by vanilla GPT-4. Furthermore, because these TABLE-SPECIALIST-GPT-3.5 are fine-tuned on GPT-3.5, they have similar latency as vanilla GPT-3.5 (shown on x-axis). What this means is that for these table-tasks, *we can deploy smaller specialized models (TABLE-SPECIALIST-GPT-3.5) over larger general models (vanilla GPT-4), with comparable quality, but at significantly lower latency and costs*.

We summarize the key benefits of TABLE-SPECIALIST below:

- **Strong performance.** TABLE-SPECIALIST outperforms vanilla language models such as GPT, as well as generalist models such as Table-GPT and Table-Llama. For example, we show that TABLE-SPECIALIST fine-tuned on GPT-3.5 is not only consistently better than vanilla GPT-3.5, but also often surpasses vanilla GPT-4 for the same table-task, despite being orders of magnitude smaller.

- **Lower cost.** Because TABLE-SPECIALIST achieves GPT-4 level quality using fine-tuned GPT-3.5 models, it is substantially cheaper to deploy, both in terms of latency and financial costs.
- **Better generalizability.** Unlike “dataset-specific fine-tuning”, TABLE-SPECIALIST can reliably generalize to new and unseen datasets for the same task. We show in our experiments that TABLE-SPECIALIST is benchmark-agnostic, and show consistent performance gains on multiple benchmarks of the same task, all *without using any data from the training-split of these benchmarks*.
- **Labeling-free.** Because the “Generator-Validator” framework in TABLE-SPECIALIST leverages language-models to automatically generate-then-validate training data for fine-tuning, it is easier to scale to new table-tasks without expensive human labeling.

2 RELATED WORK

Table tasks. A wide variety of tasks have been studied in the research literature that are centered around tables, which are also increasingly important in practice (e.g., in database and spreadsheet copilots [1, 4–6]). We give a brief overview of tasks considered in this work, and refer readers to surveys like [21, 24, 25] for a more comprehensive treatment of the subject.

Table matching tasks, such as entity-matching [49, 53, 57] and schema-matching [45, 51, 59], address the problem of identifying related rows and columns from tables that refer to the same entity, which are usually framed as binary classification problems [49, 53].

Data cleaning is a broad topic that includes tasks like error-detection [22, 35, 76], that try to identify data errors from tables (which can be seen as a binary classification problem), and error-repair [21, 62], that attempt to identify possible fixes for erroneous table cells (which is generative in nature).

In data transformation, problems like by-example program synthesis [30, 34] have been studied, which aim to generate transformation programs based on user-provided input/output examples in a table, where the generated transformations can target different languages (e.g., SQL, Python, etc.)

NL-to-Code tasks, which translate user natural-language questions into code into different domain-specific languages that can execute on tables, such as NL-to-SQL [83, 86, 93], NL-to-Pandas [33, 50], NL-to-PySpark [3], etc., are also popular topics of research.

We consider all these common table tasks in our study, in order to evaluate the effectiveness of different fine-tuning approaches.

Language models for table tasks. Auto-regressive language models, such as GPT [18] and Llama [71], are capable of performing not only natural-language tasks, but also table-tasks [26, 55].

However, language models still struggle on complex table tasks [47, 67, 68, 88, 90]. This can be attributed to factors such as large table context [67, 70], two-dimensional reasoning [47, 67, 68], as well as possible mismatch between pre-train data (one dimensional text) and test-time tasks (two-dimensional tables) [47, 90].

To improve language models’ performance on table tasks, fine-tuning techniques have been developed, including dataset-specific fine-tuning and table-generalist fine-tuning [47, 90, 95], as discussed in the introduction. In this work, we introduce a new class of “specialist fine-tuning”, with better performance than table-generalists, while still being generalizable across datasets of the same task.

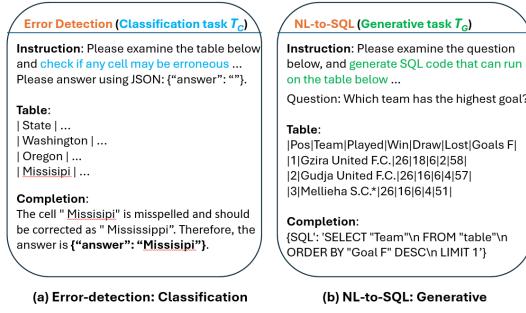


Figure 4: Example table-tasks: Error-detection and NL-to-SQL

Train language models using synthetic data. In this work, we fine-tune models for individual table tasks, using synthetic training data “generated-then-validated” by language models from diverse real tables, which is inspired by the success of using synthetic data to train state-of-the-art small language models [16, 48, 54] and text-embedding models [75], that are also trained using synthetic data generated by language-models. In TABLE-SPECIALIST, we leverage the duality of table tasks, and unique characteristics of tables (e.g., permutation-invariance, and execution-invariance) to validate training data, which are all specific to tables and table tasks.

Validation in table-tasks vs. NLP reasoning tasks. In our Generator-Validator fine-tuning process, we validate table training data based on result consistency (leveraging permutation-invariance and execution-invariance). Our approach can be seen as similar in spirit to consistency-based verification methods used in NLP reasoning tasks, such as “self-consistency” and “tree-of-thoughts” [64, 78, 81, 84], but is tailored specifically for tables.

Teacher-student distillation vs. Self-training. In standard teacher-student distillation, a larger teacher model (e.g., GPT-4) is used to train a smaller student model (e.g., GPT-3.5) for specific tasks [27, 36, 43], where the smaller student model is expected to gain in quality when learning from a more capable teacher model. In our approach, however, both Generator and Validator are symmetric and use the same model (e.g., both are GPT-3.5 to create TABLE-SPECIALIST-GPT-3.5, or both are GPT-4 to create TABLE-SPECIALIST-GPT-4), which is close to a form of “self-training” [32, 82, 94].

Dual learning. Dual learning is a concept in machine-learning where two related tasks are learned together via mutual reinforcement, which are used in machine-translation (where the dual tasks are translating from language A to B, and from B to A) [31, 63, 80], and computer-vision (where the dual tasks can be style-transfers from style A to B, and from B to A) [42, 74, 85]. The duality of table tasks we study in this work is similar in spirit, but not explored in the literature to the best of our knowledge.

3 TABLE-SPECIALIST: OVERVIEW

In this section, we will give a high-level overview of TABLE-SPECIALIST.

Preliminary: Generative and classification table-tasks. Many table-tasks have been studied in the literature. Table 1 shows a list of common table-tasks.

Some of these tasks can be “classification” in nature, where the output has to come from a predefined set of options. Example classification table-tasks include Error-detection (checking whether

any cell in a table may be an error) [22, 35, 76], Schema-matching (checking whether two table columns match) [45, 51, 59], etc.

Note that table tasks may also be “generative” in nature, where new output needs to be generated. Examples here include NL-to-Code (generating code that can execute on a table for a given natural language question) [3, 50, 92, 93], where the generated code can be in a target DSL such as SQL, R, Pandas, and Scala, etc.

Following prior work [47, 90], from the perspective of using language models to solve table tasks, we represent each instance of a table task as an “(instruction, table, completion)” triple:

DEFINITION 1. [Table tasks]. An instance of a table task, denoted by t , is defined as a triplet $t = (Ins, R, C)$, where Ins is the natural language instruction to describe the task, R is the input table on which the task is performed, C is the expected completion by following the instruction Ins and performing the task on table R . \square

We give concrete examples of table tasks below.

EXAMPLE 1. [Table tasks]. Figure 4 (a) shows an instance of the Error detection task, which is a classification task that identifies values in a table column that may be erroneous. Here, we have an “instruction” that describes the task, an actual “table” shown in the middle, and a “completion” that we expect language models to produce, which in this case identifies “Missisipi” (a typo) from the table as a predicted error.

Figure 4(b) shows an example generative table task, NL-to-SQL. In this task, SQL code that can execute on tables needs to be generated in “completion”. Note that this task is generative, as the output is not chosen from a fixed set of options. \square

Goal: Train specialist models that can generalize, using diverse training data generated by language-models. Recall that a key motivation of this work, based on our observation shown in Figure 2, is that it is usually hard to fine-tune models on the training-split of a narrow benchmark dataset D (often manually labeled on a small scale), and hope it can still generalize to diverse test cases beyond the test-split of D .

We would like to build “specialist models” that specialize in a given type of table task T (say NL-to-Code or Error-detection). Crucially, such models need to *generalize to any dataset of the task T* , without being over-fit on a particular dataset D , so that we can build a model once for each task-type T , and then deploy it in production reliably (without needing to fine-tune a new model every time a customer brings in a new dataset D').

Given the success of using language-models (e.g., vanilla GPT-3.5 or GPT-4) to generate synthetic training data, for training small and specialized language models (e.g., code, reasoning, and embedding models) [16, 48, 54, 75], we explore a similar direction to train table-specialist models, by using language-models to generate large amounts of synthetic training data (beyond the scale possible with manual labeling), so that we can hope to fine-tune models for task T that can generalize to diverse test cases in T .

Challenge: Need to validate training data generated by language-models. The obvious challenge, however, is that vanilla language-models, denoted by M , do not automatically generate high quality synthetic training data for task T – in fact, if M already

Table 1: List of table-tasks: classification and generative

Classification table tasks
<ul style="list-style-type: none"> • Error detection (multi-class classification): check if any cell in a table column is erroneous • Schema matching (binary classification): check if a pair of columns in two tables are related • Entity matching (binary classification): check if a pair of rows in two tables refer to the same entity • Column type annotation (multi-class classification): determine the type of a column from a list • Table fact verification (binary classification): check if a statement about a table is true or not
...
Generative table tasks
<ul style="list-style-type: none"> • NL-to-Code (SQL, R, Pandas, ...): translate natural-language questions to executable code on a table • Data transformation by-example (SQL, R, Pandas, ...): generate code for data transformation, based on given input/output examples • Table question answering: answer a natural language question based on a table • Data imputation: fill in missing values in a table, based on table context • Table summarization: summarize a table using natural language
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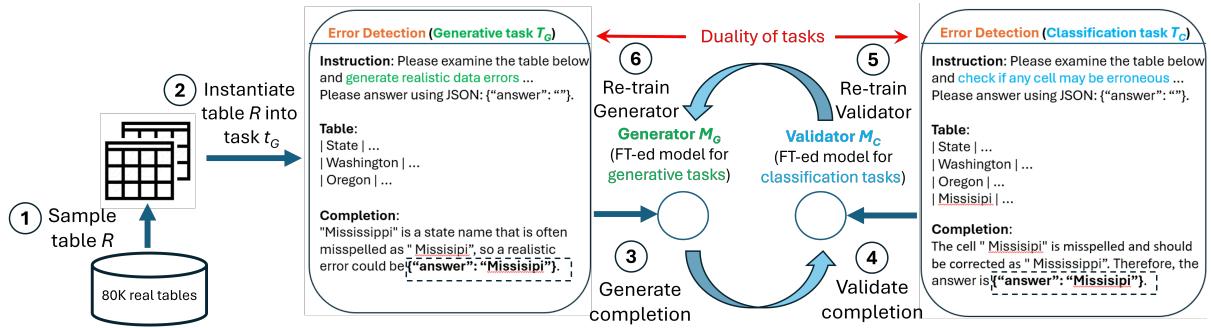


Figure 5: Architecture of TABLE-SPECIALIST using “Generator-Validator” fine-tuning for a given task type T (Error-detection in this example). (1) A real table R is sampled from a corpus of diverse tables; (2) Table R is used to instantiate an instance of the generative table task $T_G(R)$ (left box); (3) A “Generator model” M_G (initially a vanilla language-model) is used to generate completion for $T_G(R)$, in this case a possible typo error “Missisipi”; (4) The completion “Missisipi” is inserted into R , and used to instantiate a classification-version of the Error-detection task T_C (right box), which is validated by a “Validator model” for the classification task M_C (initially also a vanilla language-model). If M_C consistently produces “Missisipi” for T_C , then “Missisipi” is considered validated (i.e., likely a real error); (5-6) Validated training data is then used to re-train the Generator M_G and Validator M_C , for more effective Generator and Validator models. We iteratively fine-tune M_G and M_C , by repeating steps (1)-(6).

understands the task T well enough to consistently generates accurate training data, one could argue that there is no need to fine-tune M for task T in the first place.

We observe that for many table-tasks in Table 1, even state-of-the-art vanilla language models (e.g., GPT-4) still struggle to produce correct answers. This can be because of (1) uncommon DSL: for some code-related tasks (e.g., NL-to-Code), when the target DSL is relatively uncommon (e.g., R or Spark-Scala that are sparse in the pre-training data), language-models may generate incorrect code; (2) unfamiliar task: for tasks like “Data-transformations by-example using code” in Table 1, where the task is to observe input/output examples in a table, and generate transformation code, such tasks are sparse in its pre-training data, and unfamiliar to language-models; (3) challenging task: some tasks are inherently challenging, e.g., Error-detection, which has a strong class imbalance where over 98% of input values can be error-free, and true positives are found in only 2% of the data. such that achieving both high recall and high precision simultaneously is challenging for any predictive models.

Note that even when a table-task T may not be particularly challenging for the aforementioned reasons, the training data directly generated by vanilla language models for T is still often random in nature and far from perfect.

All of these call for a way to “validate” synthetic training data automatically generated by language models, before it can be reliably used to fine-tune specialist models.

Our approach: Validate training data using “task duality”. In order to systematically validate training data, we first observe that there is a natural “duality” in table tasks. Specifically, for each classification table task T_C , we can construct a “dual” generative task T_G , and vice versa, defined as follows:

DEFINITION 2. [Task duality]. Let T_G be a generative table-task, and $T_G(R)$ be an instance of the task T_G instantiated with a table R . Similarly, let T_C be a classification table-task, and $T_C(f(R))$ be an instance of the task T_C , instantiated with table $f(R)$, where f is a deterministic transformation function applied to R . Let M be an oracle model that produces ground-truth completions. The generative task T_G is said to be a *dual task* of T_C , if for any table

R , we always have $M(T_G(R)) \equiv M(T_C(f(R)))$, using some fixed transformation f . \square

Intuitively, a task T_G is the dual of T_C , if for any table R , $M(T_G(R))$ and $M(T_C(f(R)))$ are always expected to produce the same output. For example, we can see that the two tasks constructed for Error-detection in Figure 5, as well as the two tasks constructed for Schema-matching in Figure 7, are expected to produce the same output, as marked in dashed rectangles, making them “dual tasks”.

We illustrate duality and its construction f in more detail below.

EXAMPLE 2. [Task duality]. The task of Error-detection is a multi-class classification task T_C , where the goal is to predict if any value in a given table column is an error, like shown in the right box of Figure 5. We can construct its generative dual, T_G , shown in the left box, which simply asks a model to examine a given table column R and produce a realistic data error.

To see why T_C and T_G are dual tasks, let $T_G(R)$ be an instance of the generative Error-detection task instantiated using a table R , like shown in the left-box of the figure. Let $c = M(T_G(R))$ be its completion, in this example $c = \text{“Missisipi”}$, a realistic typo error. Let $f(R) = \text{insert}(c, R)$ be a transformation that inserts c into R (creating the column on the right that contains the typo “Missisipi”). Now for the task $T_C(f(R))$ (identifying errors in $f(R)$), we expect the same $c = \text{“Missisipi”}$ to always be returned by an oracle model M , ensuring $M(T_G(R)) \equiv M(T_C(f(R)))$, or the two tasks always produce the same output, like shown in the dashed boxes, making the two tasks dual.

As another example, we look at Schema-matching. Recall that Schema-matching is traditionally a classification task T_C , that identifies pairs of columns from two input tables as either match or non-match, shown in Figure 7(b). Like for Error-detection, we can construct its generative dual, T_G , shown in Figure 7(a), which takes a Table-A as input, to generate another Table-B, as well as column mappings between the two tables as output.

To see why the two are also dual tasks, consider a transformation f that combines Table-A and Table-B from T_G in Figure 7(a), as input for T_C in Figure 7(b), we can see that the two tasks T_G and T_C should now always produce the same output, like indicated by dashed boxes in the figure, because under this transformation f , the mappings generated by an oracle model M on T_G should always match that generated by M on T_C . \square

Generator-Validator fine-tuning. Given that two dual tasks are expected to always produce the same output for the same table R (Definition 2), we leverage this duality to automatically “generate-then-validate” training data to fine-tune specialist models.

We give high-level overview of our “*Generator-Validator*” fine-tuning framework, illustrated in Figure 5. Given a target classification task T_C that we want to fine-tune, we first construct its dual generative task T_G (and vice versa), shown as two boxes in the figure. We then iteratively fine-tune: (1) a “*Generator model*”, M_G , for the generative table-task T_G , and (2) a “*Validator model*”, M_C , for the classification table-task T_C , in the middle of the figure.

In Figure 5, in each iteration, we would first (1) sample a real table R from a large corpus to (2) instantiate a task $T_G(R)$, and then (3) invoke M_G (initially a vanilla language model) to generate a

Duality in the other direction for generative-tasks can be defined similarly.

completion $c = M_G(T_G(R))$, which we know is also the expected completion for the corresponding classification task T_C , given the task-duality, which can then be used to “train” the classification model M_C . However, since such training data are not always correct, we (4) invoke M_C (initially also a vanilla language model) to systematically “validate” training data. The resulting validated training data that can then be used to (5) fine-tune M_C for T_C , and (6) fine-tune M_G for T_G , to create increasingly more capable M_G and M_C models.

The validation step in (4) is key to the success of the iterative fine-tuning, where we leverage unique properties of tables, such as “*permutation-invariance*” (reordering rows and columns should not change the semantics of a table), and “*execution-invariance*” (executing semantically equivalent code on sub-samples of a table should always produce identical results), etc., to better validate training data.

In the end, by fine-tuning using diverse training data generated specifically for T_G and T_C , the resulting models M_G and M_C models become more effective “specialist models” in solving T_G and T_C than vanilla language models, which become our TABLE-SPECIALIST models for different table-tasks.

Tasks not suited for Generator-Validator fine-tuning. We want to point out upfront that not all table-tasks are suited for the proposed Generator-Validator fine-tuning. For example, this approach is not directly applicable to tasks that do not have precise “ground-truth”, such as table summarization [19, 29, 89], as the lack of ground-truth makes it hard for perform validation easily.

There are also tasks that naturally come with ample training data, for which Generator-Validator would not be needed. For example, the task of Data-imputation [17, 52] predicts the value for a missing cell in a table, where training data can be easily obtained (by masking out random cells in real tables, and use their ground-truth values for training). For such tasks, it would not be necessary to use of Generator-Validator for fine-tuning.

However, Generator-Validator fine-tuning can apply to tasks with precise ground-truth, and traditionally require careful manual-labeling to generate ground-truth, such as Error-detection, Schema-matching, NL-to-Code, and Data-transformations in Table 1, which we will evaluate in our experiments.

Next, we will describe in more detail our iterative fine-tuning for classification table-task (Section 4) and generative table-tasks (Section 5), respectively.

4 TABLE-SPECIALIST: CLASSIFICATION TASK

Many table tasks studied in the literature are classification in nature, which can be binary-classifications (e.g., Schema-matching, Entity-matching, Table-fact-verification), or multi-class classification (e.g., Error-detection, Column-type-annotation, etc.).

Given a target classification table-task T_C that we want to fine-tune, and its dual generative table-task T_G that we can construct, in this section, we describe how the Generator-Validator framework can fine-tune for T_C .

Algorithm 1 shows the general steps of the Generator-Validator approach. We start by initializing both the generative model M_G for the generative task T_G , and the classification model M_C for the classification task T_C , as a vanilla language model M (Line 1-2). We

Algorithm 1: Generator-Validator fine-tuning

Input: A corpus of real table \mathcal{R} , a vanilla language-model M , a generative table T_G , a corresponding classification table-task T_C

Output: Fine-tuned specialist model M_G for task T_G , and M_C for task T_C

- 1: $M_G \leftarrow M$ // initialize the generative model M_G as vanilla M
- 2: $M_C \leftarrow M$ // initialize the classification model M_C as vanilla M
- 3: **for** i in 1 to k iterations **do**
- 4: $Train_G \leftarrow \{\}$ // initialize the validated training set for T_G
- 5: $Train_C \leftarrow \{\}$ // initialize the validated training set for T_C
- 6: **for** j in 1 to step-size **do**
- 7: Sample $R \in \mathcal{R}$ // sample a real table
- 8: Instantiate $t_G \leftarrow T_G(R)$ // instantiate a generative task t_G using R
- 9: $c \leftarrow M_G(t_G)$ // invoke M_G to compute the completion c for t_G
- 10: Construct $t_C \leftarrow T_C(R, c)$ // construct a classification task t_C with R, c
- 11: // check c is a valid completion of t_G , by calling Validate()
- 12: **if** Validate(M_C, t_C, c) **then**
- 13: $Train_G \leftarrow Train_G \cup (t_G, c)$ // add the validated (t_G, c) into $Train_G$
- 14: $Train_C \leftarrow Train_C \cup (t_C, c)$ // add the validated (t_C, c) into $Train_C$
- 15: Fine-tune M_G using $Train_G$ // fine-tune M_G using validated training data
- 16: Fine-tune M_C using $Train_C$ // fine-tune M_C using validated training data
- 17: **return** M_G, M_C // return fine-tuned models M_G, M_C

then start our iterative fine-tuning (Line 3), by first initializing training set for T_G and T_C as empty sets (Line 4-5). In each fine-tuning iteration, we iteratively perform step-size number of sampled steps (Line 6), where each time, we sample a real table R from the corpus (Line 7), which we use to instantiate an instance of the generative task $t_G = T_G(R)$ (Line 8). We then invoke M_G on t_G , to produce a completion c (Line 9). We use c and R to construct a corresponding classification task t_C (Line 10). At this point, we perform the crucial validation step by calling the Validate() subroutine (Line 11, which calls Algorithm 2 and will be explained next). Once the validation passes, we add (t_G, c) and (t_C, c) as validated training examples for T_G and T_C , respectively, because by duality c will be a correct completion for both t_G and t_C (Line 12-13). After performing step-size number of samples, the validated training data will be used to fine-tune M_G and M_C (Line 14-15), to conclude one iteration of the fine-tuning process. We repeat k such iterations, and return the resulting M_G and M_C as our TABLE-SPECIALIST models.

Algorithm 2: Validate(M_C, t_C, c): validate for classification tasks

Input: A classification model M_C , an instance of classification task t_C , and its expected output c

Output: True or False // validate whether c is the correct completion for t_C

- 1: $R \leftarrow t_C.R$ // get the table R used in task t_C
- 2: **for** i in 1 to N **do**
- 3: $R' \leftarrow \text{Permute}(R)$ // permute row and columns of table R
- 4: $t'_C \leftarrow T_C(R')$ // instantiate a new T_C task, using the permuted R'
- 5: $c' \leftarrow M_C(t'_C)$ // get completion c' for t'_C , using classification model M_C
- 6: **if** $(c' \neq c)$ **then**
- 7: **return** False // Not-validated: unsure if c is correct completion for t_C
- 8: **return** True // Validated: c is likely the correct completion for t_C

Algorithm 2 shows the validation subroutine (Line 11 of Algorithm 1), which is necessary for the following reason. Recall that $c = M_G(t_G)$ is a completion generated by invoking M_G on task t_G , which we expect to also be the completion of the corresponding dual task t_C (by task-duality in Definition 2), such that we can use (t_C, c) as training data to train model M_C for our target classification task T_C . However, M_G is often not perfect in many table-tasks

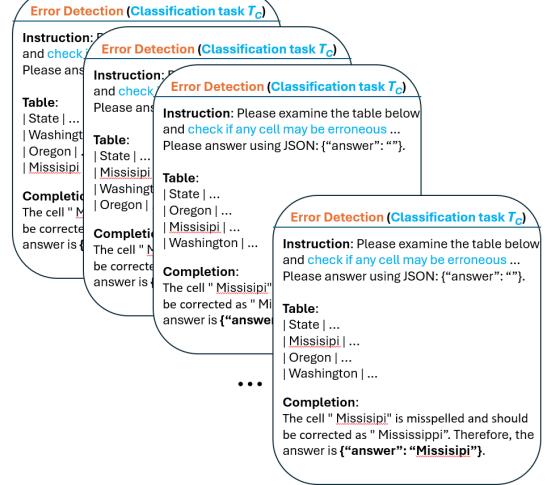


Figure 6: Validate training data by permutation invariance: we permute rows and columns in R , and repeatedly invoke M_C to check whether a consistent completion is produced.

as we discussed, so that $c = M_G(t_G)$ may not be the correct completion for t_G , and thus also not the correct completion for t_C , in which case (t_C, c) pairs should not be used for training. We therefore use the subroutine in Algorithm 2 for this validation.

Here, we use a property unique to tables known as “permutation-invariance” described below, to help validate (t_C, c) .

PROPOSITION 1. [Permutation-invariance]. Given a task T on a table R , let R' be any permuted version of R , whose rows and columns may be reordered. *Permutation-invariance* states that because the permuted R' does not change the semantics of the original table R , we should always have $T(R) \equiv T(R')$. \square

This property is intuitive, and is used in Algorithm 2 as follows. In the pseudo-code, we start by assigning R as the table used in t_C . We then iteratively perform N validations. In each validation iteration, we first permute rows and columns in R to get R' , which we use to instantiate a new task $t'_C = T_C(R')$, that is identical to $t_C = T_C(R)$ except that its table R' is a permuted version of R in t_C . We then invoke M_C on t'_C to get its completion c' . Note that by permutation-invariance, we should have $c = c'$ at this point, but if we verify that $(c' \neq c)$, then we know either c or c' is not a valid completion. Since we are not sure which is valid, we return “False” and discard this data point (t_C, c) . If N repeated validation iterations all pass, we know c is consistently returned as a completion of t_C despite permutations (not due to flukes or randomness from the model’s non-deterministic behavior), and likely a valid answer. We return “True” in such cases, which would make (t_C, c) and (t_G, c) valid training data for M_C and M_G , respectively, in Algorithm 1.

Connecting Algorithm 1 and Algorithm 2 together, we use the following example to illustrate the fine-tuning process end-to-end.

EXAMPLE 3. [Error detection]. We revisit Figure 5, and explain the Error-detection task end-to-end.

First, both the Generator and Validator models, M_G and M_C , are initialized as a vanilla language model M . In each fine-tuning iteration, we sample a real table R and instantiate a generative task

With the exception of tasks that specifically depend on row and column orders, such as “removing the second row”, which however are uncommon (e.g., not seen in Table 1).

$t_G = T_G(R)$, by adding table R into task template T_G , like shown in the box on the left of Figure 5, which in this case, samples a table R with column states, that asks the Generator model M_G to create a realistic error based on R .

Invoking M_G on t_G creates an actual completion, $c = M_G(t_G)$, shown in the lower half of the left box, which in this case is a typo error “Missisipi” that may realistically occur in R .

This completion c is then used to construct a classification-version of Error-detection t_C , where we perform transformation f by inserting the created error “Missisipi” into the original column R , to create the input table for t_C shown in the right box.

Next, we invoke the Validate() subroutine (Algorithm 2), to validate whether c (the completion “Missisipi”) is the correct completion for our t_C . Specifically, like illustrated in Algorithm 2, we would perform repeated “permutation” of the table in task t_C , creating many variants t'_C shown in Figure 6 (note that rows inside each task box in the figure are ordered differently). We then invoke M_C on each t'_C , and we expect the completion c (“Missisipi”) to be consistently produced if c is an actual error. Note that for classification, we would also need negative examples, in this case we directly sample real table column, and perform validation also using Algorithm 2, where the expected c is an empty set.

If a pair (t_C, c) can be consistently validated using M_C with permutation, we treat (t_G, c) and (t_C, c) as good training examples for M_G and M_C , which we add into their respective training sets (in this case, the tasks shown in the left and right box of Figure 6, and their completion “Missisipi”).

We iterate the preceding steps to sample and validate a training data point, for “step-size” number of times (e.g., 3000), and then fine-tune M_G and M_C on validated training data, where the hope is that fine-tuning the resulting M_G and M_C models can be better than the original vanilla models M . We iterate the fine-tuning process for a few iterations (up to 3), and return the resulting models as our specialist models. \square

Note that in the fine-tuning process, because we sample diverse real tables R to construct table-tasks t_C and t_G for training (instead of using a small manually-labeled dataset), the resulting models are less likely to “over-fit”, and are more likely generalize well.

As another example, we explain the end-to-end process for a different task, Schema-matching [45, 51, 59], that takes *two tables* as input (recall that in Schema-matching, our goal is to identify column pairs that refer to the same concept from two input tables).

EXAMPLE 4. [Schema matching]. Figure 7(b) shows the traditional, classification-version of Schema-matching studied in the literature, which is verbalized as a task that requires language-models to inspect two tables, Table-A and Table-B, and produce column-mappings in a JSON list. Exploiting “duality”, we construct its generative-version, shown in Figure 7(a), which takes one table, Table-A, as input, and is asked to produce another table, Table-B, with possible column-mappings between the two tables.

We can then use Figure 7(a) and (b) to replace the two boxes in Figure 5, and similarly perform Generator-Validator fine-tuning.

This is assuming that there are no additional error in the original table – if the original table has other error, then the completion of t'_C would not be consistently c (“Missisipi”), and we will also not validate this (t_C, c) pair for downstream training.

Figure 7: Schema-matching task duality: (a) its generative version; and (b) classification version. We can perform Generator-Validator fine-tuning for Schema-matching, by using these two boxes in Figure 5.

We start by sampling a real table R_A and populate it as Table-A in the generative-version of Schema-matching (Figure 7(a)), to produce an instance of this task t_G . Invoking the Generator model M_G (initially the vanilla model M) produces the completion (lower half of Figure 7(a)), which includes another table T_B and mapping between (T_A, T_B) , denoted by c_m (a completion for mapping), shown as a JSON list at the bottom.

We then construct a corresponding task t_C shown in Figure 7(b), by concatenating (T_A, T_B) as input for Schema-matching (which is the transformation f in Definition 2). By duality, if the generative-task t_G generates c_m correctly, then we expect its classification dual t_C would produce the same c_m as completion, as marked in two rectangle boxes with the same JSON content in the figure.

We therefore repeatedly permute both tables T_A and T_B in task t_C , into a new task t'_C , and invoke $M_C(t'_C)$ to see if we get the expected c_m consistently. If validated, we use the corresponding $(t_G \rightarrow T_B, c_m)$ and $(t_C \rightarrow c_m)$ as training data, to fine-tune M_G and M_C , respectively. \square

With Example 3 and 4, we can see how Generator-Validator fine-tuning in Algorithm 1 can apply to other classification table-tasks. Details of the prompts used in our generative-task T_G and classification-task T_C for Schema-matching and Error-detection, can be found in Appendix A.

5 TABLE-SPECIALIST: GENERATIVE TASKS

In this section, we describe how Generator-Validator fine-tuning can be applied to generative table-tasks (the lower half of Table 1), such as NL-to-Code and Data-transformation, etc. Figure 8 show two generative NL-to-Code tasks on tables, NL-to-Scala and NL-to-SQL, and their respective classification duals.

Our fine-tuning process for generative table-tasks uses the same Generator-Validator approach in Algorithm 1, thanks to the symmetry between generative/classification tasks in our setup.

As additional opportunities, we observe that for a subset of generative table-tasks, such as code-generation (e.g., NL-to-Code and Data-transformations), where the target code can be in languages such as SQL, R, Scala, Pandas, then in addition to using the model-based validation in Line 11 of Algorithm 1 (which invokes

Note that we parse the two JSON lists for order-insensitive equality comparisons, and do not require the two JSON to be identical verbatim.

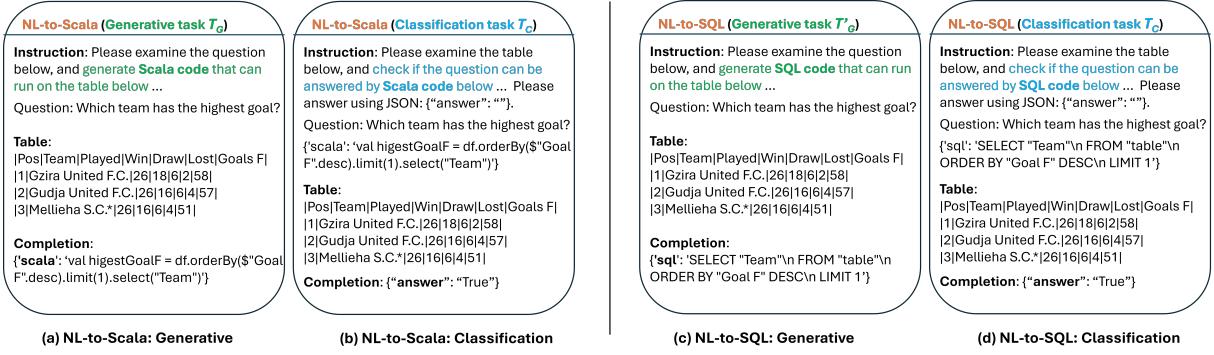


Figure 8: Two example NL-to-Code tasks that translate natural-language questions to code: (a, b) dual versions of the NL-to-Scala task; (c, d) dual versions of the NL-to-SQL task. “Execution-invariance”: observe that in (a) NL-to-Scala, and (c) NL-to-SQL, given the same question, the generated Scala and SQL code should generate identical results when executed on the same input table.

Algorithm 2), we can also leverage a unique property of executing code on tables for validation, that we call “*execution-invariance*” described below.

PROPOSITION 2. [Execution invariance]. Given a task T specified on a table R , let c^L be the generated code in a language L that can execute on R to correctly solve T , and $c^{L'}$ be the generated code in a different language L' that can also solve T . Let $R_S \subseteq R$ be a table with a subset of rows of R , then for any R_S , we have $c^L(R_S) \equiv c^{L'}(R_S)$, meaning that the execution of c^L and $c^{L'}$ on any $R_S \subseteq R$ should always produce identical results. \square

This is intuitive, because given any task T , if the code c^L and $c^{L'}$ generated in two languages can both correctly perform task T , they must be semantically equivalent, and their execution results identical, on R or any of its subsets $R_S \subseteq R$.

EXAMPLE 5. [Execution invariance]. Figure 8(a) and (c) show two generative NL-to-Code tasks, NL-to-Scala and NL-to-SQL, respectively. Given the same question (e.g., “which team has the highest goal”), the generated Scala and SQL code shown at the bottom of the boxes, should always produce the same results when executed on the same table R (or its subset R_S), shown in the figure. \square

The execution-invariance property provides us with an alternative to model-based validation (Algorithm 2), by using execution-based validation, which we explain in Algorithm 3 below.

Algorithm 3: Validate($M_G^L, M_G^{L'}, t_G$): for code-generative tasks

Input: A generative model M_G^L for generating code in a target language L , another generative model $M_G^{L'}$ for generating code in a second language L' , an instance of classification task t_G

Output: True or False

```

1:  $R \leftarrow t_G.R$  // get the table  $R$  used in task  $t_G$ 
2:  $c^L \leftarrow M_G^L(t_G)$  // generate target code  $c^L$  in language  $L$ 
3:  $c^{L'} \leftarrow M_G^{L'}(t_G)$  // generate target code  $c^{L'}$  in language  $L'$ 
4: for  $i$  in 1 to  $N$  do
5:    $R_S \leftarrow \text{Sample}(R)$  // sample rows in table  $R$ 
6:    $r \leftarrow \text{Execute}(c^L, R_S)$  // execute  $c^L$  on table  $R_S$  to get  $r$ 
7:    $r' \leftarrow \text{Execute}(c^{L'}, R_S)$  // execute  $c^{L'}$  on table  $R_S$  to get  $r'$ 
8:   if  $(r \neq r')$  then
9:     return False // Not-validated: unsure if  $c^L$  is correct completion for  $t_G$ 
return True // Validated:  $c^L$  is likely a correct completion for  $t_G$ 

```

In Algorithm 3, we are given a generative model M_G^L that can generate code on tasks t_G in a target language L (e.g., NL-to-Scala). We use a second model $M_G^{L'}$ that generates code for the same task t_G but in a different language L' (e.g., NL-to-SQL), in order to validate code generated by M_G^L .

We start by assigning R as the table used in t_G , then invoke M_G^L and $M_G^{L'}$ (both are initially vanilla language models), to generate code c^L and $c^{L'}$ respectively. Then in N iterations, we repeatedly sample rows to generate $R_S \subseteq R$, and execute c^L and $c^{L'}$ on R_S , to produce results r and r' , respectively. If in any iteration we have $(r \neq r')$, then by execution-invariance we know that c^L and $c^{L'}$ is not semantically equivalent, and at least one of the two is incorrect, which is why we return “False” to signify that c^L cannot be validated so that it will not be used in training later. Otherwise, if we cannot find contradictions in N iterations, we consider (t_G, c^L) a valid training example and return “True” for this data point to fine-tune M_G^L . Note that $(t_G, c^{L'})$ is also a valid training example, so that we can fine-tune $M_G^{L'}$ for a different language L' in parallel.

We illustrate Algorithm 3 using NL-to-Code as an example.

EXAMPLE 6. Consider the task of NL-to-Scala, or generating Scala code that can run on Spark, as shown in Figure 8(a). Like in Figure 5, as pre-processing steps, we would first sample a real table R , and then ask language-models to brainstorm a question relevant to table R , e.g., “which team has the highest goal” for the table in the figure, to create a generative task t_G . The classification version of the task is shown in Figure 8(b), which asks a model to predict whether a code snippet can execute to answer a given natural-language question. With these two tasks, we can already perform Generator-Validator fine-tuning using Algorithm 1 and 2.

Leveraging execution-invariance, we can perform a different type of validation, that invokes Algorithm 3 (in place of Algorithm 2). Specifically, when validating training data (Line 11 of Algorithm 1), we invoke Algorithm 3, where we use the same task, but require code to be generated in a different language – Figure 8(c) shows an NL-to-SQL task that directly corresponds to Figure 8(a) but requires generated code to be in SQL.

Table 2: Table-task and benchmark datasets for evaluation

Table-task group	Evaluation metric	Task category	Dataset	Size
NL-to-Code (NL-to-SQL, NL-to-R, NL-to-Scala)	Execution Accuracy	easy	WikiSQL	1000
			WikiTQ	1000
			Text2Analysis	271
Data transformation (generating SQL, R, Pandas)	Execution Accuracy	hard	TDE	570
			Transform-text	335
			DeepM	42
Schema-matching	F1	easy	WikiData	24
			HxD	468
			Spreadsheet-Tables	1126
Error-detection	F1	hard	Relational-Tables	1081

Let M_G^L be the NL-to-Scala model that we iteratively fine-tune, and $M_G^{L'}$ be a NL-to-SQL model (which can be a vanilla language-model, or another model that we also iteratively fine-tune in lock-step), we can then proceed to invoke Algorithm 3. We first generate code in both Scala and SQL for the same question, like shown in the bottom of Figure 8(a) and (c), and then execute both Scala and SQL repeatedly on sub-samples $R_S \subseteq R$, to compare their execution results. If we cannot find contradictions in any iteration, we consider (t_G, c^L) and $(t_G, c^{L'})$ validated, which we can use to iterative fine-tune M_G^L and $M_G^{L'}$. (This in effect changes the right-half of the architecture in Figure 5, by replacing the mode-based validation, into an execution-based validation). \square

Note that the execution-based validation applies to other generative tasks involving code, such as Data-transformation by-example, or generating code to perform transformations specified by input/output examples, using a target language (e.g., SQL, R, Scala, etc.), which we will also study in our experiments.

Additional details. Details of our fine-tuning, such as task data generation (e.g., using “textbook-like generation” [14, 48], or a curriculum to guide language-models to compose textbook constructs so that they can generate diverse questions of varying levels of difficulty that are relevant to a given table R).

Things we tried but were not effective. In addition to what is reported, we also tried many things that did not turn out to be effective. For example, we tried to extract confidence scores of training examples from language-models (e.g., using log-probabilities) [7, 67, 69], as a form of soft-labels in our self-training, which was not beneficial. We tried to fine-tune using both positive (validated) and negative (invalidated) examples [77], but that was not helpful. We also tried agentic self-reflection style fine-tuning using trajectories, which was also not too beneficial [64].

6 EXPERIMENTS

We perform extensive evaluations to test the quality and efficiency of different methods.

6.1 Experiment Setup

Table-tasks and benchmarks. Table 2 shows the list of table tasks and their corresponding benchmarks used in our evaluation. We use two sets of three generative tasks, NL-to-Code (generating SQL, R, Scala) and Data-transformation (generating SQL, R, Pandas); as well two classification tasks, Error detection and Schema-matching.

NL-to-Code (NL-to-SQL, NL-to-R, NL-to-Scala). The generative NL-to-Code task takes a table and a natural-language question as input, for a model to produce code that can be executed to answer the given question (Figure 8(a) shows an example). We test

generation in three target languages, SQL, R, and Scala, and refer to the corresponding task as NL-to-SQL, NL-to-R, and NL-to-Scala.

We use three benchmarks for NL-to-Code: (1) WikiSQL [93] that is a common benchmark for NL-to-SQL; (2) WikiTableQuestions (WikiTQ) [58] that is a popular table question-answering (QA) benchmark, which we use to test code generation by matching code-execution against QA ground-truth; and (3) Text2Analysis [33] that is a recent benchmark for generating code to perform data analysis intents that are expressed in natural language.

In each task, NL-to-SQL, NL-to-R, and NL-to-Scala, we use all three benchmarks above, and evaluate result quality based on the standard “execution accuracy” [83, 93]. For example, we use the WikiSQL benchmark to evaluate not only NL-to-SQL, but also NL-to-R and NL-to-Scala tasks, by comparing the results of executing generated R and Scala, against the ground-truth execution results.

Data-transformation (generating SQL, R, Pandas). In this generative task, we are given pairs of user-specified input/output examples, and the goal is to synthesize the desired data-transformation program [30, 34]. We generate target programs to be in SQL, R, and Pandas, respectively, as three table-tasks.

We use two benchmarks in the literature for this task, TDE [34] and Transform-Text [13], and report “execution accuracy” by comparing the result of executing generated code with ground truth.

Note that unlike NL-to-Code (a task language-models are familiar with), vanilla language-models struggle with the task of Data-transformation by-example, likely because relevant data is sparsely populated in the pre-training data, and therefore represents a “hard” generative task to test, like shown in Table 2.

Schema matching. Schema matching is the classification task, of predicting whether a pair of columns from two tables refer to the same concept (Figure 7 shows an example). We used three benchmark datasets: DeepM and WikiData from [45], and HxD from [91]. We use the standard F1 score to report the quality of schema matching results [45, 51, 59].

Error detection. Error detection is the classification task of predicting whether any value in a given column is erroneous or not (Figure 4 shows an example). We use two benchmarks, Spreadsheet-Tables and Relational-Tables, with over 1000 columns sampled from real spreadsheet tables and relational tables, respectively. We also report the standard F1 score for result quality [22].

Note that Error-detection has a strong class imbalance (e.g., 98% of real data are error-free), and often have data that is not standard English (e.g., code-names and proprietary vocabularies), which makes it challenging for language-models to produce high precision and high recall. It represents a “hard” classification task in our test.

Methods Compared. We compare with the following methods:

- Vanilla GPT models:
 - GPT-3.5 [18]. We test the quality of all table-tasks, using the vanilla GPT-3.5-turbo-1106 model.
 - GPT-4 [15]. We also test all table tasks using the GPT-4-0613 model, which consistently shows better quality than GPT-3.5 as expected, and is a strong baseline.
- Specialist Fine-Tuning:
 - TABLE-SPECIALIST. This is our proposed approach. We use GPT-3.5 (GPT-3.5-turbo-1106) as both the Generator and Validator,

and then iteratively fine-tune both, which we refer to as TABLE-SPECIALIST-GPT-3.5 (note that no GPT-4 is involved in this setting, as we operate entirely in a self-training fashion). In addition, we also fine-tune using GPT-4 as the base model, but for a subset of tasks for cost reasons, which we refer to as TABLE-SPECIALIST-GPT4.

- FT-no-validation. To see the importance of validation in the Generator-Validator framework, we also test a variant that is the same as TABLE-SPECIALIST, but without the validation step.
- Generalist Fine-Tuning:
 - Table-GPT [47]. This is a Table-Generalist model, trained using a pool of table tasks, and designed to handle new and unseen table tasks. For a fair comparison, we use its released training data [11] to fine-tune a model based on GPT-3.5.
 - TableLlama [90]. This is another Table-Generalist model, and since their release model is small (7B) and not performing well on our tasks, we also use its released training data [12] to re-create TableLlama based on GPT-3.5, for a fair comparison.

We use Lora fine-tuning [37], with learning-rate multiplier of 0.5, and a batch size that is 1% of training-data-size (to ensure that each epoch has 100 steps), which is consistent across all methods.

6.2 Quality Comparisons

Fine-tuning on GPT-3.5. Table 3 shows a detailed comparison on all table-tasks and benchmarks, where we fine-tune GPT-3.5 using TABLE-SPECIALIST and table-generalist fine-tuning.

It can be seen that across generative and classification table tasks, TABLE-SPECIALIST improves over GPT-3.5 on all 20 benchmarks (surpassing vanilla GPT-4 on 7 benchmarks). Importantly, since we *do not use the training-split of any benchmark data during fine-tuning*, it demonstrates that the fine-tuned models are capable of generalizing to multiple unseen benchmarks, which is crucial. TABLE-SPECIALIST is also better than other fine-tuning methods in 19 out of 20 benchmarks. FT-no-validation ranks second in 10 out of 20 benchmarks, but lags behind TABLE-SPECIALIST.

Iterative fine-tuning. Figure 9 and 10 show a comparison of TABLE-SPECIALIST and vanilla GPT models (GPT-3.5 and GPT-4) on generative and classification tasks, respectively. The x-axis here represents intermediate fine-tuned models, where “V1”, “V2” represent models from the first and second fine-tuning iteration, etc., and “V0” represents the base model (vanilla GPT-3.5).

As we can see, TABLE-SPECIALIST on GPT-3.5 demonstrates consistent quality improvement in consecutive iterations (trending up as we move right), matching or surpassing GPT-4-level quality in some cases, which shows the benefit of iterative fine-tuning. In comparison, FT-no-validation is substantially less effective, showing the importance of validation.

Fine-tuning on GPT-4. All fine-tuning experiments reported so far are based on GPT-3.5. To validate the effectiveness of TABLE-SPECIALIST on additional base models, we perform fine-tuning on GPT-4, for a subset of tasks (in light of its fine-tuning cost).

Table 4 shows the results when we fine-tune TABLE-SPECIALIST models on GPT-4, on three NL-to-Code tasks. Across all 3 tasks and 9 benchmarks, TABLE-SPECIALIST fine-tuned on GPT-4 consistently outperforms vanilla GPT-4, validating the effectiveness of TABLE-SPECIALIST even on state-of-the-art frontier models. It is therefore

possible to specialize models to perform even better than frontier models on individual table-tasks, at the same level of cost/latency.

6.3 Latency and Cost Comparisons

In Figure 11, we compare the average latency of TABLE-SPECIALIST models (fine-tuned on GPT-3.5) and GPT-4, on various task, averaged over all benchmark test cases. Because the fine-tuned TABLE-SPECIALIST models are smaller, on average they are 3.42 times faster than vanilla GPT-4 (while still having comparable quality). Figure 3 shows another analysis for NL-to-Code tasks, with similar latency reductions. Since serving online queries and ensuring interactivity is key in many user-facing workloads, this highlights a crucial benefit of TABLE-SPECIALIST as it allows us to employ smaller models to reduce latency significantly.

In Figure 12, we compare the cost of fine-tuning and serving TABLE-SPECIALIST using GPT-3.5, vs. serving directly using vanilla GPT-4, on two table tasks (results for other tasks are similar). The detailed unit price is listed in Table 5. We estimate the cost per API call using the average number of prompt and completion tokens for each tasks, as listed in Table 6.

We can see in Figure 12 that TABLE-SPECIALIST-GPT-3.5 has to pay an upfront cost of fine-tuning, which is why it starts with a non-zero cost (on y-axis) to serve the first query (on x-axis). This however, is amortized over future queries, and takes less than 5000 queries (for Schema-matching) or 10000 queries (for Data-transformation) for TABLE-SPECIALIST to break even with using vanilla GPT-4 directly. We argue that the cost saving in the long run, together with significant latency reductions, makes TABLE-SPECIALIST a viable option, especially in user-facing online settings.

6.4 Sensitivity Analysis

We perform various types of sensitivity analysis in TABLE-SPECIALIST.

Vary the Amount of Training Data. Figure 13a shows TABLE-SPECIALIST quality, when we vary the amount of training data produced by the Generator from 100% to 50%, 25% and 12.5% of the original data (x-axis). We can see that increasing the amount of training data generally has a positive effect on result quality.

Vary Prompt Templates. To test the robustness of TABLE-SPECIALIST, we vary our prompt templates used in each task, by giving our original prompt to ChatGPT and asking it to paraphrase into five different prompts, for the NL-to-SQL and NL-to-Scala tasks. Figure 13b shows that using variants of the prompt (abbreviated as VP in the figure), lead to comparable quality.

Vary the Base Model for Fine-Tuning. We test two alternatives of iterative fine-tuning, where in each iteration, we initialize the base model either as the vanilla model (e.g., GPT-3.5), or the model from the last iteration (continuous fine-tune). Figure 14 shows that using vanilla GPT as the base models are consistently better than using the check-point from the last iteration (continuous fine-tune), for both NL-to-SQL and NL-to-Scala.

6.5 Ablation Studies

We conducted ablation studies to understand the impact of various components in TABLE-SPECIALIST.

We use the published pricing [9] to calculate the cost of fine-tuning and inference.

Table 3: Quality comparisons, between Vanilla GPT models (GPT-3.5, GPT-4), and fine-tuned models. All fine-tuning methods are based on GPT-3.5. We use bold and underlined to indicate first and second place methods that are based on GPT-3.5, respectively, and we use * to indicate fine-tuned GPT-3.5 models that can outperform vanilla GPT-4.

Task Type	Task	Dataset	GPT-3.5	Specialist Fine-tuning (GPT-3.5)		Generalist Fine-tuning (GPT-3.5)		GPT-4
				TABLE-SPECIALIST (ours)	FT-no-validation	TableLlama	Table-GPT	
Classification	Schema Matching	DeepM	0.984	1	0.984	0.990	1	1
		WikiData	<u>0.913</u>	0.918	0.877	0.893	0.832	0.952
		HxD	<u>0.878</u>	0.897	0.860	0.872	0.856	0.924
		Average	0.925	0.938	0.907	0.918	0.896	0.959
	Error Detection	Spreadsheet-Tables	0.180	0.299 *	0.151	0.197	<u>0.209</u>	0.287
		Relational-Tables	0.145	0.347 *	0.136	0.250	<u>0.304</u>	0.278
Generative	NL-to-SQL	Average	0.163	0.323 *	0.144	0.224	<u>0.257</u>	0.282
	NL-to-R	WikiSQL	0.823	0.855	0.828	0.817	0.808	0.869
		WikiTQ	0.421	0.513	<u>0.463</u>	0.424	0.406	0.559
		Text2Analysis	0.498	<u>0.517</u>	0.515	0.520	0.502	0.581
		Average	0.580	0.628	0.602	<u>0.587</u>	0.572	0.670
	NL-to-Scala	WikiSQL	0.567	0.776 *	0.697	0.585	0.306	0.759
		WikiTQ	0.209	0.404	<u>0.318</u>	0.213	0.130	0.416
		Text2Analysis	0.227	0.358	<u>0.336</u>	0.225	0.107	0.382
		Average	0.334	0.513	0.450	0.341	0.181	0.519
	Data-transformation (Pandas)	WikiSQL	0.510	0.794 *	0.729	0.528	0.623	0.745
		WikiTQ	0.109	0.426 *	<u>0.259</u>	0.131	0.136	0.198
		Text2Analysis	0.236	0.373 *	<u>0.347</u>	0.229	0.266	0.258
		Average	0.285	0.531 *	<u>0.445</u>	0.296	0.312	0.401
	Data-transformation (R)	TDE	<u>0.293</u>	0.346	0.277	0.265	0.279	0.418
		Transform-Text	0.227	0.254	<u>0.230</u>	0.218	0.212	0.297
		Average	0.260	0.300	<u>0.254</u>	0.241	0.253	0.357
	Data-transformation (SQL)	TDE	0.200	0.235	0.205	0.212	0.182	0.305
		Transform-Text	0.164	0.215	0.155	<u>0.170</u>	0.134	0.222
		Average	0.182	0.225	0.180	<u>0.191</u>	0.158	0.264

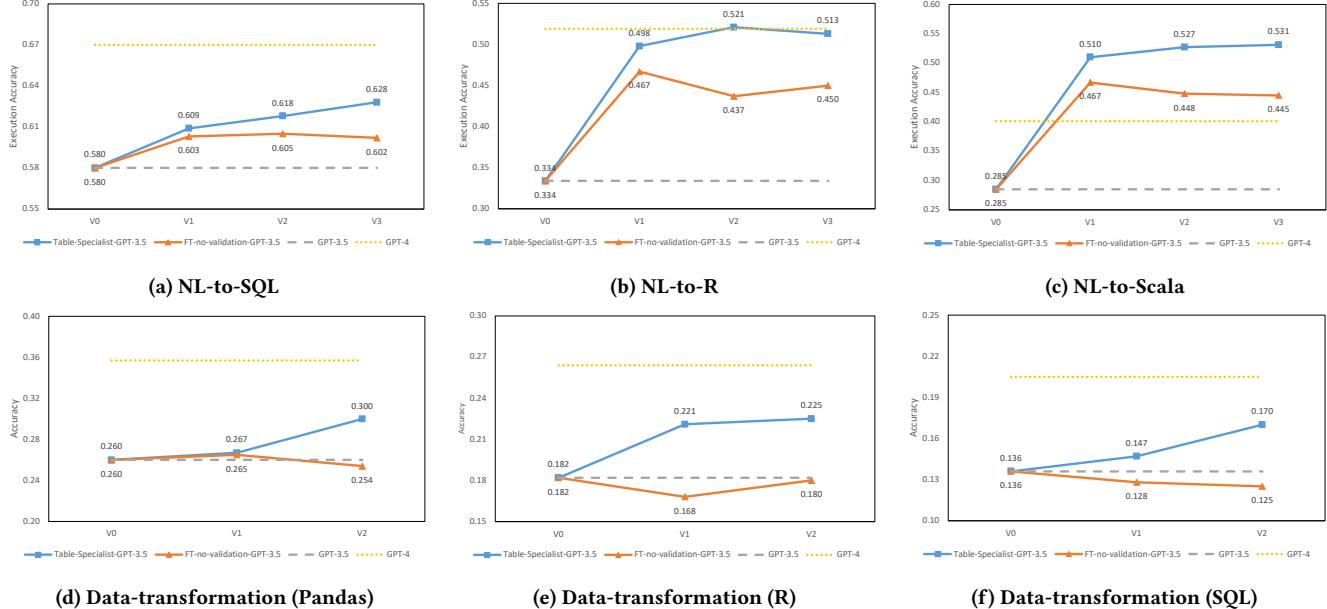


Figure 9: Quality of TABLE-SPECIALIST by Iteration on Generative Tasks

No permutation of tables. Permutation-invariance is an important property we leverage to validate training data. In this ablation, we remove row sampling in NL-to-Code, and row/column shuffling in Error-detection and Schema-matching tasks. Table 7 shows that it leads to clear degradation in result quality.

No fine-tuning of Generator models. In Table 8, we show the quality of not fine-tuning the Generator models in two classification tasks (the vanilla GPT-3.5 is used as the Generator in all iterations).

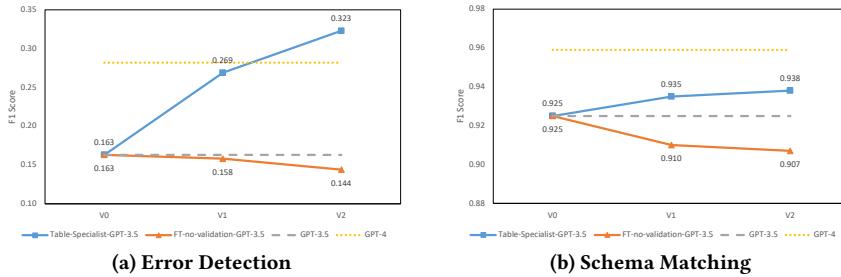


Figure 10: Quality of TABLE-SPECIALIST by iteration on Classification Tasks

Table 4: Quality comparison: TABLE-SPECIALIST (fine-tuned on GPT-4) and vanilla GPT-4, on three NL-to-Code tasks.

Task	Dataset	GPT-3.5	TABLE-SPECIALIST-GPT4 (ours)	GPT-4
NL-to-SQL	WikiSQL	0.823	0.873	0.869
	WikiTQ	0.421	0.594	0.560
	Text2Analysis	0.498	0.583	0.581
	Average	0.580	0.683	0.670
NL-to-R	WikiSQL	0.567	0.827	0.759
	WikiTQ	0.209	0.542	0.416
	Text2Analysis	0.227	0.454	0.382
	Average	0.334	0.608	0.519
NL-to-SparkScala	WikiSQL	0.510	0.812	0.745
	WikiTQ	0.109	0.464	0.198
	Text2Analysis	0.236	0.395	0.258
	Average	0.285	0.557	0.401

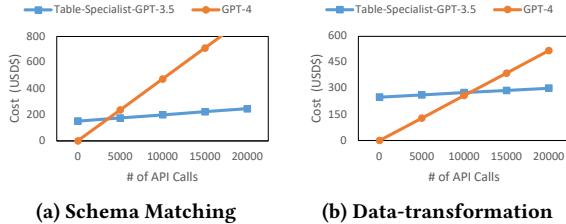


Figure 12: Total Cost Analysis: TABLE-SPECIALIST v.s. GPT-4

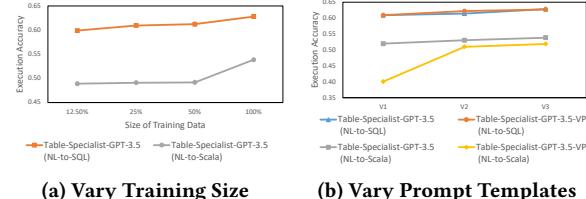


Figure 13: Sensitivity analysis

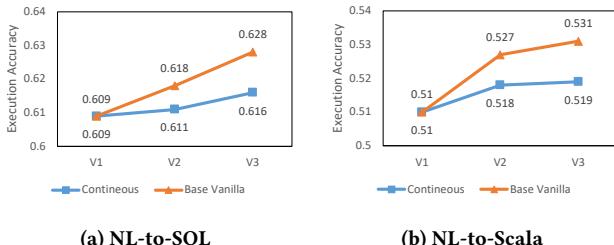


Figure 14: Vary Base Model

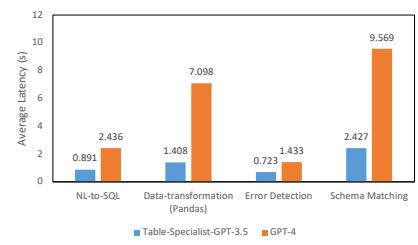


Figure 11: Average Latency of TABLE-SPECIALIST-GPT-3.5 vs. vanilla GPT-4

Table 5: The Unit Price for Inference and Training, Per 1K Tokens, for Vanilla GPT-3.5, GPT-4, and Fine-tuned GPT-3.5. As of July 2, 2024 [10]

Model	Input	Output	Training
GPT-3.5	0.001	0.002	0.008
FT(GPT-3.5)	0.003	0.006	N.A.
GPT-4	0.03	0.06	N.A.

Table 6: Average Number of Prompt and Completion Tokens, and Average Latency for TABLE-SPECIALIST and GPT-4

Task	Average # of Tokens		Average Latency (s)	
	Prompt	Completion	TABLE-SPECIALIST	GPT-4
NS	969	38	0.891	2.436
R2RP	678	92	1.408	7.098
ED	701	10	0.723	1.433
SM	1168	206	2.427	9.569

Table 7: Ablation: No row/column permutation in validation.

Ablation	Error-detect	Schema-match	NL-to-SQL	NL-to-R	NL-to-Scala
TABLE-SPECIALIST-GPT	0.269	0.935	0.609	0.498	0.510
No-Permutation	0.161	0.912	0.613	0.495	0.472
(Vanilla GPT-3.5)	0.163	0.925	0.580	0.334	0.285

Table 8: Ablation: No fine-tuning of Generators (and use vanilla GPT-3.5 as Generators instead), in classification tasks.

Ablation	Error detection	Schema-matching
TABLE-SPECIALIST-GPT-3.5	0.323	0.938
No-Generator-fine-tune	0.225	0.931
(Vanilla GPT-3.5)	0.163	0.925

We can see that this has a negative impact on result quality, suggesting that iterative fine-tuning of both Generator and Validator models are beneficial.

No execution-based validator. In Table 9, we show the result of not using execution-based validation (Algorithm 3), and vanilla model is used for validation instead, for three generative NL-to-Code tasks. We can see that “no-execution-validation” still improves over vanilla GPT-3.5 (suggesting that they are still viable options), but generally has a negative impact on result quality when compared to execution-based validation in TABLE-SPECIALIST-GPT-3.5.

Table 9: Ablation: No execution-based validation (and use language-models as validator instead), in generative tasks.

Ablation	NL-to-SQL	NL-to-R	NL-to-Scala
TABLE-SPECIALIST-GPT-3.5	0.609	0.498	0.510
No-execution-validation	0.608	0.457	0.445
(Vanilla GPT-3.5)	0.580	0.285	0.260

7 CONCLUSIONS AND FUTURE WORK

In this work, we develop a new fine-tuning approach TABLE-SPECIALIST specifically designed for table-tasks. We show that it can fine-tune small models specialized for individual table tasks, while still being performant and generalizable. Future directions include testing the method on additional base models, and tasks beyond table tasks.

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A SAMPLE PROMPTS

Table Question Generation

Task description: Given the input table below, your task is to generate questions that can be answered by the given table with a SQL query.

Input:

Table:

Rank	Country	2016	2013	2012	2011
1	Qatar	0.08%	0.11%	0.10%	0.02%
2	Malta	0.60%	0.61%	0.61%	0.72%
3	Saudi Arabia	1.14%	1.32%	1.31%	1.26%
4	Barbados	1.32%	1.16%	1.15%	2.44%
5	Grenada	1.42%	1.44%	1.46%	2.29%
6	Iceland	1.52%	1.55%	1.53%	1.56%
7	Bahrain	1.69%	1.81%	1.81%	1.66%
8	Kiribati	1.78%	1.78%	1.78%	1.88%
9	United Arab Emirates	1.97%	2.10%	2.07%	4.09%
10	Sweden	2.12%	2.26%	2.15%	2.00%
11	Norway	2.19%	2.35%	2.31%	2.28%
12	Finland	2.21%	2.28%	2.24%	2.06%
13	Singapore	2.27%	2.49%	2.54%	2.85%
14	Egypt	2.29%	2.34%	2.33%	2.38%
15	Israel	2.30%	2.49%	2.43%	2.60%
16	Estonia	2.36%	2.52%	2.50%	2.25%
17	Switzerland	2.37%	2.61%	2.59%	2.55%
18	Luxembourg	2.43%	2.68%	2.65%	2.70%
19	Seychelles	2.55%	2.58%	2.60%	2.68%
20	France	2.62%	2.79%	2.78%	2.76%
21	Oman	2.64%	2.74%	2.72%	2.80%
22	Cyprus	2.68%	2.77%	2.81%	3.46%
23	Denmark	2.89%	3.10%	3.09%	2.86%
24	Lithuania	2.92%	3.18%	3.23%	2.89%
25	Germany	2.95%	3.24%	3.27%	2.96%
26	Ukraine	2.97%	3.14%	3.19%	3.02%
27	Canada	3.01%	3.18%	3.18%	2.57%
28	Spain	3.05%	3.38%	3.40%	3.29%
29	Belgium	3.07%	3.42%	3.48%	3.51%
30	Mongolia	3.08%	3.10%	3.24%	3.43%
31	Belarus	3.11%	3.31%	3.32%	2.98%
32	Poland	3.20%	3.46%	3.53%	3.42%
33	Kuwait	3.28%	3.70%	3.71%	3.71%
34	Latvia	3.31%	3.48%	3.51%	3.09%
35	Czech Republic	3.37%	3.61%	3.67%	4.15%
36	Slovakia	3.39%	3.63%	3.69%	3.38%
37	Austria	3.39%	3.80%	3.75%	3.41%
38	Slovenia	3.41%	3.69%	3.81%	3.72%
39	Portugal	3.45%	3.80%	3.82%	3.62%
40	Paraguay	3.48%	3.85%	3.84%	4.12%
41	United Kingdom	3.54%	3.71%	3.65%	3.61%
42	Kazakhstan	3.56%	3.84%	3.87%	4.04%
43	Argentina	3.56%	3.76%	3.80%	3.77%
44	Russia	3.58%	3.78%	3.83%	3.56%
45	United States	3.76%	3.99%	3.99%	3.72%
46	Libya	3.79%	3.93%	3.80%	3.67%

```
|47|Croatia|3.97%|4.24%|4.35%|3.71%
|48|Uruguay|4.03%|4.09%|4.12%|3.94%
|49|Brazil|4.09%|4.26%|4.30%|4.26%
|50|Bahamas|4.14%|3.99%|4.17%|4.52%
```

Please return one natural language question, and ensure that when your question is answered in SQL, the corresponding SQL would contain all of the below:

- (1) *ONE (1)* number preprocessing step (e.g., extracting numbers from a column for comparisons/sorting)
- (2) *ONE (1)* sorting then take top-K step

Return your answer in the following JSON format: {"question": <QUESTION>}.

Output:

```
{"question": "What are the top 5 countries with the lowest percentage of GDP in 2016?"}
```

NL-to-SQL (Generative)

Task description:

Natural language to SQL, also known as NL2SQL, is the problem of generating a SQL query that can be executed on a input table, for a given natural language question.

You will be given an input table called "table" in the markdown format, as well as a question. Your task is to generate an SQL query that can be executed on the input table to answer the question.

Please ensure that the generated SQL only return relevant columns being specifically asked in the question (e.g., in SQL please don't return more than one columns in SELECT if only one column is needed to answer the given question, and similarly please refrain from using SELECT * unless the entire row is needed to answer the question).

When generating SQL code, please use the SQLite syntax to ensure that your SQL is executable on SQLite3. Use only columns that are present in the table, always use quotes around your column and table names (some column names have punctuation or special characters), and refer to the columns using the column-names exactly as they appear in the table, do not add or remove punctuation (underscore, slash, etc.)

No explanation, return the code only with the following markdown codeblock format : ```sql<SQL CODE>```.

For example:

Input:

Table:

```
|City|Population (2015)|Area|Density|City class|Income class|Province|
|---|---|---|---|---|---|
|Bacolod|561,875|62.81|9,100|Highly urbanized|1st|Negros Occidental|
|Bago|170,981|154.9|1,100|Component|2nd|Negros Occidental|
|Bais|76,291|123.41|620|Component|3rd|Negros Oriental|
|Bayawan|117,900|269.92|440|Component|2nd|Negros Oriental|
|Cadiz|154,723|202.54|750|Component|2nd|Negros Occidental|
|Canlaon|54,509|66.0|830|Component|4th|Negros Oriental|
|Dumaguete|131,377|12.98|10,000|Component|2nd|Negros Oriental|
|Escalante|94,070|74.43|1,300|Component|4th|Negros Occidental|
|Guihulngan|95,969|150.02|650|Component|5th|Negros Oriental|
|Himamaylan|106,880|141.71|750|Component|3rd|Negros Occidental|
|Kabankalan|181,977|269.25|670|Component|1st|Negros Occidental|
|La Carlota|64,469|53.01|1,200|Component|4th|Negros Occidental|
|Sagay|146,264|127.54|1,100|Component|3rd|Negros Occidental|
```

```
|San Carlos|132,536|174.33|750|Component|2nd|Negros Occidental|
|Silay|126,930|82.93|1,500|Component|3rd|Negros Occidental|
|Sipalay|70,070|146.63|470|Component|4th|Negros Occidental|
|Talisay|102,214|77.68|1,300|Component|4th|Negros Occidental|
|Tanjay|80,532|106.58|750|Component|4th|Negros Oriental|
|Victorias|87,933|51.71|1,700|Component|4th|Negros Occidental|
```

question: What is the top-3 most populous city in 2015 in the table?

Output:

```
```sql
SELECT "City"
FROM "table"
ORDER BY CAST(REPLACE("Population (2015)", ',', '') AS INTEGER) DESC
LIMIT 3;
```
```

Input:

Table:

```
Contestant ID	Finalist	Gender
SSJ01	Monisha	Female
SSJ02	Alka Ajith	Female
SSJ03	Balasarangan	Male
SSJ04	Sahana	Female
SSJ05	Manisha	Female
SSJ06	Prasanna Sundar	Male
SSJ07	Sowmya	Female
SSJ08	Oviya	Female
SSJ09	Vishnucharan	Male
SSJ10	Sivaranjani	Female
SSJ11	Nithyashree	Female
SSJ12	Harish	Male
SSJ13	Shri Prasanna	Male
SSJ14	Sanjana	Female
SSJ15	Shravan	Male
SSJ16	Srinisha	Female
SSJ17	Shrihari	Male
SSJ18	Sharath	Male
SSJ19	Roshan	Male
SSJ20	Srikanth	Male
SSJ21	Priyanka	Female
SSJ22	Soundarya	Female
SSJ23	Sathyanaarayanan	Male
SSJ24	Srinidhi	Female
SSJ25	Ponmozhi	Female
```

question: How many female contestants are there in total?

Output:

```
```sql
SELECT COUNT("Contestant ID")
FROM "table"
WHERE "Gender" = 'Female';
```
```

Input:

Table:

| Club | Coach | Replaced Coach | Home stadium |
|--------------------------|------------------------|-------------------|---|
| FC Dynamo Kyiv | Yozhef Sabo | Mykhailo Fomenko | Republican Stadium |
| FC Shakhtar Donetsk | Valery Yaremchenko | Shakhtar Stadium | |
| FC Chornomorets Odessa | Viktor Prokopenko | | Black Sea Shipping Stadium |
| FC Dnipro Dnipropetrovsk | Mykola Pavlov | | Meteor Stadium |
| FC Karpaty Lviv | Myron Markevych | | Ukraina Stadium |
| FC Kryvbas Kryvyi Rih | Volodymyr Brukhtiy | Ihor Nadein | Metalurh Stadium |
| FC Nyva Ternopil | Leonid Buriak | | City Stadium |
| SC Tavriya Simferopol | Anatoliy Zayaev | | Lokomotyv Stadium |
| FC Temp Shepetivka | Leonid Tkachenko | | Temp Stadium |
| FC Nyva Vinnytsia | Yukhym Shkolnykov | | Central City Stadium |
| FC Volyn Lutsk | Roman Pokora | | Avanhard Stadium |
| FC Veres Rivne | Vyacheslav Kobyletskyi | Mykhailo Dunets | Avanhard Stadium |
| FC Torpedo Zaporizhia | Ihor Nadein | Viktor Matviyenko | AvtoZAZ Stadium |
| FC Zorya-MALS | Volodymyr Kobzarev | Anatoliy Shakun | Avanhard Stadium |
| FC Kremien Kremenchuk | Evhen Rudakov | Boris Streltsov | 8 games Tiberiy Korponay 9 games Dnipro Stadium |
| FC Metalurh Zaporizhia | Anatoliy Kuksov | Janis Skredelis | Hryhoriy Vul Metalurh Stadium |
| FC Bukovyna Chernivtsi | Oleksandr Pavlenko | | Bukovyna Stadium |
| FC Metalist Kharkiv | Viktor Kamarzayev | Oleksandr Dovbiy | Yevhen Lemeshko Metalist Stadium |

question: What is the name of the home stadium of the football club FC Kryvbas Kryvyi Rih?"

Output:

```
```sql
SELECT "Home stadium"
FROM "table"
WHERE "Club" = 'FC Kryvbas Kryvyi Rih';
```
```

Input:

Table:

| Title | Year | Director(s) |
|---------------------|------|---|
| "Red Morning Light" | 2003 | Douglas Biro |
| "Molly's Chambers" | 2003 | Honey |
| "Wasted Time" | 2003 | Mark Pellington |
| "The Bucket" | 2004 | Patrick Daughters |
| "Four Kicks" | 2005 | Patrick Daughters |
| "King of the Rodeo" | 2005 | Patrick Daughters |
| "On Call" | 2007 | Adria Petty |
| "Charmer" | 2007 | Robert Hales |
| "Crawl" | 2008 | Nick Wickham |
| "Sex on Fire" | 2008 | Sophie Muller |
| "Use Somebody" | 2008 | Sophie Muller |
| "Notion" | 2009 | Phil Griffin |
| "Radioactive" | 2010 | Sophie Muller |
| "Pyro" | 2010 | Max Goldman, Paul Greenhouse, Casey McGrath |
| "Back Down South" | 2011 | Casey McGrath |
| "Supersoaker" | 2013 | W.I.Z. |
| "Beautiful War" | 2013 | Casey McGrath |
| "Temple" | 2014 | Casey McGrath |
| "Waste a Moment" | 2016 | Dimitri Basil |
| "Walls" | 2016 | Dimitri Basil |
| "Around the World" | 2016 | |

question: What are the names of the directors that have directed movies since 2010, and how many movies have they produced?

Output:

```
```sql
SELECT "Director(s)", COUNT("Title")
FROM "table"
WHERE "Year" >= 2010
GROUP BY "Director(s)";
```
```

Now, for the input table and question below, generate its corresponding SQL query for the natural language question. No explanation, return the code only with the following markdown codeblock format : ```sql<SQL CODE>```.

Input:

Table:

| Date from | Nationality | Name | To | Fee | Ref. |
|--------------|-------------------|--------------|-------------|-----|------|
| --- | --- | --- | --- | --- | --- |
| 1 July 2017 | Fabian Bailey | Free agent | Released | | |
| 1 July 2017 | Lee Camp | Free agent | Released | | |
| 1 July 2017 | Chris Dawson | Free agent | Released | | |
| 1 July 2017 | Joel Ekstrand | Free agent | Released | | |
| 1 July 2017 | Stephen Kelly | Free agent | Released | | |
| 1 July 2017 | Tom Rose | Free agent | Released | | |
| 1 July 2017 | Richard Smallwood | Free agent | Released | | |
| 1 July 2017 | Tom Thorpe | Free agent | Released | | |
| 1 July 2017 | Danny Ward | Cardiff City | Undisclosed | | |
| 1 July 2017 | Kelvin Wilson | Free agent | Released | | |
| 4 July 2017 | Kirk Broadfoot | Kilmarnock | Undisclosed | | |
| 12 July 2017 | Dexter Blackstock | Free Agent | Released | | |

question: Which players were released as free agents on July 1, 2017?

Output:

```
```sql
SELECT "Name"
FROM "table"
WHERE "Date from" = '1 July 2017' AND "Fee" = 'Free agent';
```
```

NL-to-SQL (Classification)

Task description:

Natural language to SQL, also known as NL2SQL, is the problem of generating a SQL query that can be executed on a input table, for a given natural language question. You will be given an input table called "table" in the markdown format below, a question in natural language for this table, and a corresponding SQL query for the natural language question. You need to: (1) determine if the SQL query is grammatically correct, (2) determine if the SQL query can truthfully represent the natural language question being asked. Return your answer in the following JSON format: {"grammarly_correct": <YES or NO>, "SQL-correct": <YES or NO>}

Table:

| Title | Episode # | Writers | Directors | Summary |
|-------|-----------|---------|-----------|---------|
| --- | --- | --- | --- | --- |

- | "That's What Friends Are For" | 125 | Elaine Overbey | Michael Dimich | Robin tries to help her friend Becky (played by Natasha Pearce) overcome her shyness. Songs: "Open Your Eyes", "Big Girls Don't Cry", "Games", "Hold On", "When I See You Smile" *Note*: The episode's title is a reference to the song That's What Friends Are For. |
- | "P*lace Alone" | 108 | ||| Attempting to prove they're "grown up"; Haylie and Robin try to protect the P*lace from a burglar. Songs: "Get Up! (Before the Night Is Over)", "Release Me", "I Can Do Anything", "The Power", "Save Me" |
- | "Secret Agent Girl" | 126 | ||| Haylie gets a spy kit, but when she mistakes a comment the others made about getting rid of a doll and thinks they're talking about her, she threatens to quit. Songs: "Get Ready", "Impulsive", "Read My Mind", "Lies", "More Than Ever" Note: This episode is sometimes called "The Spy Kit." "Secret Agent Girl", the episode's title is a parody of the song Secret Agent Man. |
- | "Breaking Up is Hard to Do" | 115 | Ken Lipman | David Grossman | Ana's father (played by Barry Williams) comes to town on business; and Ana feels neglected when he doesn't spend much time with her. Songs: "Pump Up the Jam", "This Old Heart of Mine (Is Weak for You)", "If You Asked Me To", "Real Love", "Don't Ever Go" |
- | "Music Lessons" | 117 | ||| Kenny attempts to cope with the sudden death of his music teacher. Songs: "Miss You Much", "Dancing Machine", "Power of Love/Love Power", "How Can I Go On", "Tomorrow" |
- | "Earth Day Festival" | 124 | ||| The kids hold a special festival for Earth Day. Songs: "After the Rain", "Yakety Yak", "Please Save Us the World", "This is the Right Time", "Save the Trees" Note: Please Save Us the World would later become the only Kids Incorporated original to appear on a cast member's album when it appeared in Jennifer Love Hewitt's debut album Love Songs Note: The three original songs are the most to appear in a single episode. |
- | "Family Matters" | 113 | ||| Ana's attempts to outdo Robin causes a rift between the two cousins. Songs: "Jealous Again", "You Can't Deny It", "Don't Treat Me Bad", "If You Don't Know Me By Now", "You're the One" |
- | "My Fair Ana" | 120 | ||| Ana develops a crush on a boy she has math class with. Songs: "The Girl I Used to Know", "The Great Pretender", "You Need a New Attitude", "Individuality", "Waiting for Love" |
- | "Pipe Dreams" | 111 | ||| The kids get excited about an upcoming concert until Haylie accidentally loses the tickets. Songs: "U Can't Touch This", "How Can We Be Friends", "Give a Little Love", "Follow it Around", "Voices That Care" |
- | "Teen Spotlight" | 109 | ||| Kids Incorporated is featured in a segment on a teen-oriented show. Songs: "I'm Breaking Free", "Do You Love Me", "If Wishes Came True", "Friends", "I'll Be Good to You" |
- | "History in the Making" | 112 | ||| Eric is having trouble in his history class. Songs: "Don't You Want to Be Mine", "Mercy Mercy Me (The Ecology)", "Two to Make It Right", "History", "I'll Be Your Shelter" |
- | "Five Kids and a Dog" | 121 | ||| Ana takes in a stray dog. Guest appearance by Paul Benvenuti and Foster (as the dog). Songs: "We'll Be Rockin'", "Cherish", "Walkin' the Dog", "Everything", "Downtown Train" |
- | "Flip Out" | 116 | Elaine Overbey | Michael Dimich | When Flip's sneaker fortune runs out; a financial advisor (played by guest star Karla DeVito) suggests making the P*lace a tea room for adults. Songs: "Club at the End of the Street", "(Can't Live Without Your) Love and Affection", "Cry for Help", "Fairweather Friend", "This House" |
- | "New Twist" | 114 | Elaine Overbey | Michael Dimich | The annual tongue-twister contest is approaching at Robin's school; and her classmates name her the school's representative. Songs: "Can't Stop", "Hold On", "I Can Fly", "Get On Your Feet", "Forever Young" |
- | "Double Trouble" | 123 | ||| The kids meet a fun-loving kid new in town and his twin brother. Scott Wolf (credited as Scott Tyler Wolf) guest stars as Billy and Bobby. Songs: "Feels Good", "Lollipop", "How Can We Be Friends", "All Around the World", "Swear to Your Heart" |
- | "While the Cat's Away" | 118 | ||| An urgent meeting forces Flip to leave Kenny and Eric in charge. Songs: "Step by Step", "Let the Good Times Roll", "Here We Go (Let's Rock & Roll)", "All Play and No Work", "Rhythm of My Heart" |
- | "Thirteensomething" | 110 | ||| A girl named Cynthia visits; and Kenny attempts to impress her. Songs: "The Book of Love", "Another Day in Paradise", "Don't Wanna Lose You", "Something Happened on the Way to Heaven", "High Enough" |
- | "A Hard Date's Night" | 107 | ||| Stacy, Devyn, and Richie have left the band. They are replaced by Haylie, Ana, and Eric. Eric, noticing how some girls are paying attention to him, decides to date three of them at once. Songs: "Romeo", "The Shoop Shoop Song (It's in His Kiss)", "It's the Right Time", "Heat of the Moment", "King of Wishful Thinking" Note: The episode's title is a parody of The Beatles song A Hard Day's Night (song) |
- | "Mummy Dearest" | 122 | ||| A mix-up in a delivery leads to a mummy being sent to the P*lace. Songs: "Where There's a Will", "Boris the Spider", "Coming Out of the Dark", "Call It Superstition", "If I Could Turn Back Time" |

```
|"Tall Order"|119|||Haylie becomes self-conscious about being the shortest member of the band. Guest appearance by Mandy Carr and Randy Lathrop. Songs: "Gonna Make You Sweat (Everybody Dance Now)", "Little Darlin'", "When I'm Back on My Feet Again", "Wild Child", "Follow Your Dream"|
```

Question:

Which episodes were directed by Michael Dimich and had the word 'Girl' in the title?

SQL:

```
SELECT "Title"  
FROM "table"  
WHERE "Directors" = 'Michael Dimich' AND "Title" LIKE '%Girl%';
```

Please determine if the SQL query is grammarly correct and if it can truthfully represent the natural language question being asked. Return your answer in the following JSON format: {"grammarly_correct": <YES or NO>, "SQL-correct": <YES or NO>}.

Output:

```
{"grammarly_correct": "YES", "SQL-correct": "YES"}
```

NL-to-R (Generative)

Task description:

Natural language to R script, is a problem of generating R script that can be executed on a input CSV table, for a given natural language question.

You will be given an input table called "table" in the markdown format, as well as a question. Your task is to generate a R script that can be executed on the input table to answer the question.

Please ensure that the generated R script only return relevant columns being specifically asked in the question.

When generating R script, you can assume that the input table is always stored in a file named "data.csv", so always start your R script with the boilerplate prefix:

```
"library(dplyr)  
  
data <- read.csv("data.csv", check.names = FALSE)  
"
```

After you generate R script code to produce results, please always save your final results into a file named "result.csv" with no index column, so your R script should always end with:

```
"write.csv(final_result, "result.csv", row.names = FALSE)"
```

No explanation, return the code only with the following markdown codeblock format : ```r<R CODE>```.

For example:

Input:

Table:

| City | Population (2015) | Area | Density | City class | Income class | Province |
|---------|-------------------|--------|---------|------------------|--------------|-------------------|
| Bacolod | 561,875 | 62.81 | 9,100 | Highly urbanized | 1st | Negros Occidental |
| Bago | 170,981 | 154.9 | 1,100 | Component | 2nd | Negros Occidental |
| Bais | 76,291 | 123.41 | 620 | Component | 3rd | Negros Oriental |
| Bayawan | 117,900 | 269.92 | 440 | Component | 2nd | Negros Oriental |
| Cadiz | 154,723 | 202.54 | 750 | Component | 2nd | Negros Occidental |
| Canlaon | 54,509 | 66.0 | 830 | Component | 4th | Negros Oriental |

| |
|---|
| Dumaguete 131,377 12.98 10,000 Component 2nd Negros Oriental |
| Escalante 94,070 74.43 1,300 Component 4th Negros Occidental |
| Guihulngan 95,969 150.02 650 Component 5th Negros Oriental |
| Himamaylan 106,880 141.71 750 Component 3rd Negros Occidental |
| Kabankalan 181,977 269.25 670 Component 1st Negros Occidental |
| La Carlota 64,469 53.01 1,200 Component 4th Negros Occidental |
| Sagay 146,264 127.54 1,100 Component 3rd Negros Occidental |
| San Carlos 132,536 174.33 750 Component 2nd Negros Occidental |
| Silay 126,930 82.93 1,500 Component 3rd Negros Occidental |
| Sipalay 70,070 146.63 470 Component 4th Negros Occidental |
| Talisay 102,214 77.68 1,300 Component 4th Negros Occidental |
| Tanjay 80,532 106.58 750 Component 4th Negros Oriental |
| Victorias 87,933 51.71 1,700 Component 4th Negros Occidental |

question: What is the top-3 most populous city in 2015 in the table?

Output:

```
```r
library(dplyr)

data <- read.csv("data.csv", check.names = FALSE)

data$`Population (2015)` <- as.numeric(gsub(", ", "", data$`Population (2015)`))

top_3_cities <- data %>%
 arrange(desc(`Population (2015)`)) %>%
 slice(1:3)

final_result <- top_3_cities %>%
 select(City)

write.csv(final_result, "result.csv", row.names = FALSE)
```

```

Input:

Table:

| |
|-------------------------------|
| Contestant ID Finalist Gender |
| --- --- --- |
| SSJ01 Monisha Female |
| SSJ02 Alka Ajith Female |
| SSJ03 Balasarangan Male |
| SSJ04 Sahana Female |
| SSJ05 Manisha Female |
| SSJ06 Prasanna Sundar Male |
| SSJ07 Sowmya Female |
| SSJ08 Oviya Female |
| SSJ09 Vishnucharan Male |
| SSJ10 Sivaranjani Female |
| SSJ11 Nithyashree Female |
| SSJ12 Harish Male |
| SSJ13 Shri Prasanna Male |
| SSJ14 Sanjana Female |
| SSJ15 Shravan Male |
| SSJ16 Srinisha Female |
| SSJ17 Shrihari Male |
| SSJ18 Sharath Male |
| SSJ19 Roshan Male |

```
SSJ20	Srikanth	Male
SSJ21	Priyanka	Female
SSJ22	Soundarya	Female
SSJ23	Sathyanarayanan	Male
SSJ24	Srinidhi	Female
SSJ25	Ponmozhi	Female
```

question: How many female contestants are there in total?

Output:

```
```r
library(dplyr)

data <- read.csv("data.csv", check.names = FALSE)

female_count <- data %>%
 filter(Gender == "Female") %>%
 summarise(Count = n())

write.csv(female_count, "result.csv", row.names = FALSE)
```

```

Input:

Table:

```
Club	Coach	Replaced Coach	Home stadium
FC Dynamo Kyiv	Yozhef Sabo	Mykhailo Fomenko	Republican Stadium
FC Shakhtar Donetsk	Valery Yaremchenko		Shakhtar Stadium
FC Chornomorets Odessa	Viktor Prokopenko		Black Sea Shipping Stadium
FC Dnipro Dnipropetrovsk	Mykola Pavlov		Meteor Stadium
FC Karpaty Lviv	Myron Markevych		Ukraina Stadium
FC Kryvbas Kryvyi Rih	Volodymyr Brukhtiy	Ihor Nadein	Metalurh Stadium
FC Nyva Ternopil	Leonid Buriak		City Stadium
SC Tavriya Simferopol	Anatoliy Zayaev		Lokomotyv Stadium
FC Temp Shepetivka	Leonid Tkachenko		Temp Stadium
FC Nyva Vinnytsia	Yukhym Shkolnykov		Central City Stadium
FC Volyn Lutsk	Roman Pokora		Avanhard Stadium
FC Veres Rivne	Vyacheslav Kobyletskyi	Mykhailo Dunets	Avanhard Stadium
FC Torpedo Zaporizhia	Ihor Nadein	Viktor Matviienko	AvtoZAZ Stadium
FC Zorya-MALS	Volodymyr Kobzarev	Anatoliy Shakun	Avanhard Stadium
FC Kremin Kremenchuk	Evhen Rudakov	Boris Streltsov 8 games Tiberiy Korponay 9 games	Dnipro Stadium
FC Metalurh Zaporizhia	Anatoliy Kuksov	Janis Skredelis Hryhoriy Vul	Metalurh Stadium
FC Bukovyna Chernivtsi	Oleksandr Pavlenko		Bukovyna Stadium
FC Metalist Kharkiv	Viktor Kamarzayev	Oleksandr Dovbiy Yevhen Lemeshko	Metalist Stadium
```

question: What is the name of the home stadium of the football club FC Kryvbas Kryvyi Rih?"

Output:

```
```r
library(dplyr)

data <- read.csv("data.csv", check.names = FALSE)

home_stadium <- data %>%
 filter(Club == "FC Kryvbas Kryvyi Rih") %>%
 select(`Home stadium`)
```

```

write.csv(home_stadium, "result.csv", row.names = FALSE)
```

Input:
Table:
Title	Year	Director(s)
"Red Morning Light"	2003	Douglas Birol
"Molly's Chambers"	2003	Honey
"Wasted Time"	2003	Mark Pellington
"The Bucket"	2004	Patrick Daughters
"Four Kicks"	2005	Patrick Daughters
"King of the Rodeo"	2005	Patrick Daughters
"On Call"	2007	Adria Petty
"Charmer"	2007	Robert Hales
"Crawl"	2008	Nick Wickham
"Sex on Fire"	2008	Sophie Muller
"Use Somebody"	2008	Sophie Muller
"Notion"	2009	Phil Griffin
"Radioactive"	2010	Sophie Muller
"Pyro"	2010	Max Goldman, Paul Greenhouse, Casey McGrath
"Back Down South"	2011	Casey McGrath
"Supersoaker"	2013	W.I.Z.
"Beautiful War"	2013	Casey McGrath
"Temple"	2014	Casey McGrath
"Waste a Moment"	2016	Dimitri Basil
"Walls"	2016	Dimitri Basil
"Around the World"	2016	

question: What are the names of the directors that have directed movies since 2010, and how many movies have they produced?

Output:
```r
library(dplyr)

data <- read.csv("data.csv", stringsAsFactors = FALSE, check.names = FALSE)

movies_since_2010 <- subset(data, Year >= 2010)

director_counts <- aggregate(Title ~ `Director(s)`, data = movies_since_2010, FUN = function(x) length(x))

colnames(director_counts) <- c("Director", "MoviesProduced")

write.csv(director_counts, "result.csv", row.names = FALSE)
```

Now, for the input table and question below, generate its corresponding R code for the natural language question.  

No explanation, return the code only with the following markdown codeblock format : ```r<R CODE>```.
```

Input:

Table:

| Ward | Highest point | Elevation (approx.) |
|--------------------------|-----------------------------------|---------------------|
| West Carleton-March Ward | 2.6 km SSE of Manion Corners | 166m |
| Rideau-Goulbourn Ward | Jinkinson Road, 8 km N of Munster | 153m |
| Kanata South Ward | Glen Cairn Reservoir | 131m |

```

College Ward	Khymer Ct, 1 km N of Fallowfield	129m
Stittsville Ward	Rockson Cres.	128m
Kanata North Ward	Huntsville Dr, Kanata Lakes	126m
Osgoode Ward	1 km SE of Bank Street & Rideau Road, South Gloucester	120m+
Cumberland Ward	Cumberland Ridge Dr, Quigley Hill	120m+
Barrhaven Ward	Cedarview Road, Cedar Hill Estates	120m+
Gloucester-Southgate Ward	Tom Roberts Ave, Macdonald-Cartier International Airport	119m
Knoxdale-Merivale Ward	Cedarview Road at Cedarhill Drive	115m+
River Ward	Carlington Hill, (Carlington Heights Reservoir, Carlington Park) Carlington	115m+
Bay Ward	Corkstown Road, Ottawa - Nepean Tent & Trailer Park	114m
Gloucester-South Nepean Ward	Osgoode Link Pathway (former CPR) & High Rd, 4 km SW of Leitrim	114m
Innes Ward	200m WSW of Forest Ridge Pumping Station	114m
Beacon Hill-Cyrville Ward	Quarry Park, Rothwell Heights	113m
Rideau-Rockcliffe Ward	Foxview Pleasant, Quarries	106m
Alta Vista Ward	Alta Vista (Alta Vista Drive & Randall Ave)	102m
Capital Ward	Bank Street & Alta Vista Drive	96m
Orleans Ward	Clearcrest Cres, Fallingbrook	93m
Kitchissippi Ward	Maitland Avenue Bridge (over the Queensway)	89m
Somerset Ward	Parliament Hill	86m
Rideau-Vanier Ward	Richelieu Park, Vanier	75m+

```

question: What is the highest elevation among all the wards in the table?

Output:

```

```r
library(dplyr)

data <- read.csv("data.csv", stringsAsFactors = FALSE, check.names = FALSE)

data$Elevation <- as.numeric(gsub("[a-zA-Z+]", "", data$`Elevation (approx.)`))

highest_elevation <- data %>%
 summarise(HighestElevation = max(Elevation, na.rm = TRUE))

write.csv(highest_elevation, "result.csv", row.names = FALSE)
```

```

NL-to-R (Classification)

Task description:

Natural language to R script, is a problem of generating R script that can be executed on a input CSV table, for a given natural language question.

You will be given an input table called "table" in the markdown format below, a question in natural language for this table, and a corresponding R code for the natural language question. You need to: (1) determine if the R code is grammatically correct, (2) determine if the R code can truthfully represent the natural language question being asked. Return your answer in the following JSON format: {"grammarly_correct": <YES or NO>, "R -correct": <YES or NO>}

The code is generated with the following iunstructions:

When generating R script, you can assume that the input table is always stored in a file named "data.csv", so always start your R script with the boilerplate prefix:

```
"library(dplyr)
```

```

data <- read.csv("data.csv", check.names = FALSE)
"

After you generate R script code to produce results, please always save your final results into a file named "
result.csv" with no index column, so your R script should always end with:
"write.csv(final_result, "result.csv", row.names = FALSE)"

```

Now, given the following input table, question, and R code, please determine if the R code is grammatically correct and if it can truthfully represent the natural language question being asked. Return your answer in the following JSON format: {"grammarly_correct": <YES or NO>, "R-correct": <YES or NO>}.

Table:

| Episode | Date | Challenging team | Mystery car | Winner |
|---------|-------------|---|------------------------------|-----------------------|
| 3 | March 9 | LDRSHIP Design (Temecula, California) | 1986 Chevrolet El Camino | All Stars |
| 9 | April 27 | Reyes Automotive Customs (South Los Angeles, California) | 2000 Ford Crown Victoria | All Stars |
| 5 | March 23 | SKJ Customs (St. George, Utah) | 1979 Cadillac Coupe de Ville | All Stars |
| 10 | May 1 | A recap of the past nine episodes where the All Stars count down their top 15 moments while the judges name the All-Stars' 1973 Datsun 240Z the Car Warriors Car of the Year. A recap of the past nine episodes where the All Stars count down their top 15 moments while the judges name the All-Stars' 1973 Datsun 240Z the Car Warriors Car of the Year. A recap of the past nine episodes where the All Stars count down their top 15 moments while the judges name the All-Stars' 1973 Datsun 240Z the Car Warriors Car of the Year. | | |
| 12 | March 2 | Danny D. Customs (Chandler, Arizona) | 1999 Ford F-150 | All Stars |
| 7 | April 13 | Gearhead Garage (Sacramento, California) | 1976 Chevrolet Corvette | Gearhead Garage |
| 8 | April 20 | War Machine (Edwards Air Force Base, Edwards, California) | Ford Taurus ARCA stock car | War Machine |
| 4 | March 16 | True Bliss Customs (Burbank, California) | 1973 Datsun 240Z | All Stars |
| 11 | February 23 | Southern Fried D'Lite (Lubbock, Texas) | 1966 Ford Mustang Coupe | Southern Fried D'Lite |
| 6 | March 30 | Wheels (Palmdale, California) | 1969 Volkswagen Beetle | All Stars |

Question:

Which challenging team won the episode on March 30th, 2019 after removing the prefix from the mystery car and counting the total number of episodes so far?

R code:

```

library(dplyr)

data <- read.csv("data.csv", check.names = FALSE)

data$date <- as.Date(data$date, format = "%B %d")

data$mystery_car <- gsub(".*\\"", "", data$mystery_car)

episode_count <- nrow(data)

episode_10_winner <- data %>%
  filter(date == "2019-03-30") %>%
  select(`Challenging team`, mystery_car)

write.csv(episode_10_winner, "result.csv", row.names = FALSE)

```

Output:

```
{"grammarly_correct": "YES", "R-correct": "YES"}
```

```
# Task description:  
Natural language to Spark Scala, is a problem of generating Scala code using the Apache Spark library that can  
be executed on a input CSV table, for a given natural language question.
```

You will be given an input table called "table" in the markdown format, as well as a question. Your task is to generate Scala code using the Apache Spark library that can be executed on the input table to answer the question.

Please ensure that the generated Scala code only return relevant columns being specifically asked in the question.

When generating Scala code, you can assume that the input table is always stored in a file named "data.csv", so always start your Scala code with the boilerplate prefix:

```
"val df = spark.read.option("header", "true").csv("data.csv")"
```

After you generate Scala code to produce results, please always save your final results into a single CSV file named in the "result" directory, so your Scala code should always end with:

```
"finalResult.coalesce(1).write.option("header", "true").csv("result")"
```

No explanation, return the code only with the following markdown codeblock format : ````scala<SPARK SCALA CODE >````.

For example:

Input:

Table:

| City | Population (2015) | Area | Density | City class | Income class | Province |
|------------|-------------------|--------|---------|------------------|--------------|-------------------|
| Bacolod | 561,875 | 62.81 | 9,100 | Highly urbanized | 1st | Negros Occidental |
| Bago | 170,981 | 154.9 | 1,100 | Component | 2nd | Negros Occidental |
| Bais | 76,291 | 123.41 | 620 | Component | 3rd | Negros Oriental |
| Bayawan | 117,900 | 269.92 | 440 | Component | 2nd | Negros Oriental |
| Cadiz | 154,723 | 202.54 | 750 | Component | 2nd | Negros Occidental |
| Canlaon | 54,509 | 66.0 | 830 | Component | 4th | Negros Oriental |
| Dumaguete | 131,377 | 12.98 | 10,000 | Component | 2nd | Negros Oriental |
| Escalante | 94,070 | 74.43 | 1,300 | Component | 4th | Negros Occidental |
| Guihuligan | 95,969 | 150.02 | 650 | Component | 5th | Negros Oriental |
| Himamaylan | 106,880 | 141.71 | 750 | Component | 3rd | Negros Occidental |
| Kabankalan | 181,977 | 269.25 | 670 | Component | 1st | Negros Occidental |
| La Carlota | 64,469 | 53.01 | 1,200 | Component | 4th | Negros Occidental |
| Sagay | 146,264 | 127.54 | 1,100 | Component | 3rd | Negros Occidental |
| San Carlos | 132,536 | 174.33 | 750 | Component | 2nd | Negros Occidental |
| Silay | 126,930 | 82.93 | 1,500 | Component | 3rd | Negros Occidental |
| Sipalay | 70,070 | 146.63 | 470 | Component | 4th | Negros Occidental |
| Talisay | 102,214 | 77.68 | 1,300 | Component | 4th | Negros Occidental |
| Tanjay | 80,532 | 106.58 | 750 | Component | 4th | Negros Oriental |
| Victorias | 87,933 | 51.71 | 1,700 | Component | 4th | Negros Occidental |

question: What is the top-3 most populous city in 2015 in the table?

Output:

```
```scala  
val df = spark.read.option("header", "true").csv("data.csv")
val processedDf = df.withColumn("Population (2015)", regexp_replace($"Population (2015)", " ", "")).cast("int")
val top3PopulousCities = processedDf.orderBy($"Population (2015)".desc).limit(3).select("City")
top3PopulousCities.coalesce(1).write.option("header", "true").csv("result")
```
```

Input:
Table:
|Contestant ID|Finalist|Gender|
|---|---|---|
|SSJ01|Monisha|Female|
|SSJ02|Alka Ajith|Female|
|SSJ03|Balasarangan|Male|
|SSJ04|Sahana|Female|
|SSJ05|Manisha|Female|
|SSJ06|Prasanna Sundar|Male|
|SSJ07|Sowmya|Female|
|SSJ08|Oviya|Female|
|SSJ09|Vishnucharan|Male|
|SSJ10|Sivaranjani|Female|
|SSJ11|Nithyashree|Female|
|SSJ12|Harish|Male|
|SSJ13|Shri Prasanna|Male|
|SSJ14|Sanjana|Female|
|SSJ15|Shravan|Male|
|SSJ16|Srinisha|Female|
|SSJ17|Shrihari|Male|
|SSJ18|Sharath|Male|
|SSJ19|Roshan|Male|
|SSJ20|Srikanth|Male|
|SSJ21|Priyanka|Female|
|SSJ22|Soundarya|Female|
|SSJ23|Sathyaranayanan|Male|
|SSJ24|Srinidhi|Female|
|SSJ25|Ponmozhi|Female|

question: How many female contestants are there in total?

Output:
```scala  
val df = spark.read.option("header", "true").csv("data.csv")  
val finalResult = df.filter(df("Gender") === "Female").select("Gender").groupBy("Gender").count()  
finalResult.select("count").coalesce(1).write.option("header", "true").csv("result")  
```

Input:
Table:
Club	Coach	Replaced Coach	Home stadium
FC Dynamo Kyiv	Yozhef Sabo	Mykhailo Fomenko	Republican Stadium
FC Shakhtar Donetsk	Valery Yaremchenko		Shakhtar Stadium
FC Chornomorets Odessa	Viktor Prokopenko		Black Sea Shipping Stadium
FC Dnipro Dnipropetrovsk	Mykola Pavlov		Meteor Stadium
FC Karpaty Lviv	Myron Markevych		Ukraina Stadium
FC Kryvbas Kryvyi Rih	Volodymyr Brukhiyi	Ihor Nadein	Metalurh Stadium
FC Nyva Ternopil	Leonid Buriak		City Stadium
SC Tavriya Simferopol	Anatoliy Zayaev		Lokomotiv Stadium
FC Temp Shepetivka	Leonid Tkachenko		Temp Stadium
FC Nyva Vinnytsia	Yukhym Shkolnykov		Central City Stadium
FC Volyn Lutsk	Roman Pokora		Avanhard Stadium
FC Veres Rivne	Vyacheslav Kobyletskyi	Mykhailo Dunets	Avanhard Stadium
FC Torpedo Zaporizhia	Ihor Nadein	Viktor Matviienko	AvtoZAZ Stadium

```
|FC Zorya-MALS|Volodymyr Kobzarev|Anatoliy Shakun|Avanhard Stadium|
|FC Kremin Kremenchuk|Evhen Rudakov|Boris Streltsov 8 games Tiberiy Korponay 9 games|Dnipro Stadium|
|FC Metalurh Zaporizhia|Anatoliy Kuksov|Janis Skredelis Hryhoriy Vul|Metalurh Stadium|
|FC Bukovyna Chernivtsi|Oleksandr Pavlenko||Bukovyna Stadium|
|FC Metalist Kharkiv|Viktor Kamarzayev|Oleksandr Dovbiy Yevhen Lemeshko|Metalist Stadium|
```

question: What is the name of the home stadium of the football club FC Kryvbas Kryvyi Rih?"

Output:

```
```scala
val df = spark.read.option("header", "true").csv("data.csv")
val finalResult = df.select("Home stadium").where(df("Club") === "FC Kryvbas Kryvyi Rih")
finalResult.coalesce(1).write.option("header", "true").csv("result")
```

```

Input:

Table:

| Title | Year | Director(s) |
|---------------------|------|---|
| "Red Morning Light" | 2003 | Douglas Biro |
| "Molly's Chambers" | 2003 | Honey |
| "Wasted Time" | 2003 | Mark Pellington |
| "The Bucket" | 2004 | Patrick Daughters |
| "Four Kicks" | 2005 | Patrick Daughters |
| "King of the Rodeo" | 2005 | Patrick Daughters |
| "On Call" | 2007 | Adria Petty |
| "Charmer" | 2007 | Robert Hales |
| "Crawl" | 2008 | Nick Wickham |
| "Sex on Fire" | 2008 | Sophie Muller |
| "Use Somebody" | 2008 | Sophie Muller |
| "Notion" | 2009 | Phil Griffin |
| "Radioactive" | 2010 | Sophie Muller |
| "Pyro" | 2010 | Max Goldman, Paul Greenhouse, Casey McGrath |
| "Back Down South" | 2011 | Casey McGrath |
| "Supersoaker" | 2013 | W.I.Z. |
| "Beautiful War" | 2013 | Casey McGrath |
| "Temple" | 2014 | Casey McGrath |
| "Waste a Moment" | 2016 | Dimitri Basil |
| "Walls" | 2016 | Dimitri Basil |
| "Around the World" | 2016 | |

question: What are the names of the directors that have directed movies since 2010, and how many movies have they produced?

Output:

```
```scala
val df = spark.read.option("header", "true").csv("data.csv")
val processedDf = df.withColumn("Year", df("Year").cast("int"))
val final_rst = processedDf.filter(processedDf("Year") >= 2010).groupBy("Director(s)").agg(count("Title").alias
 ("Movies Produced"))
final_rst.coalesce(1).write.option("header", "true").csv("result")
```

```

Now, for the input table and question below, generate its corresponding Scala code using the Apache Spark library. No explanation, return the code only with the following markdown codeblock format : ``
scala<SPARK SCALA CODE>```.

Input:

Table:

| Title of Book | Author | Year |
|--|--------------------|------|
| An Overview of 100 years of Norway as an Independent State (1905-2005) | Tasneem Sultana | 2006 |
| The Vicissitudes of the Palestinian Quest for Statehood and the European Union | Naveed Ahmad Tahir | 2005 |
| Indo-Russian Relations Since the Collapse of the Soviet Union | Naveed Ahmad Tahir | 1999 |
| The Expansion of the European Union: Problems & Prospects | Naveed Ahmad Tahir | 1995 |
| Muslim Rule in Spain Dr. Affan Seljuq 1991 | | |
| European Press; Tradition and Transition M. Shamsuddin 1990 | | |
| Sweden in Con-temporary World Politics Naveed Ahmad Tahir 1990 | | |
| Austria in World Affairs Naveed Ahmad Tahir 1989 | | |
| Turkey and the Super-powers Rubab Hasan 1989 | | |
| Pakistan-Italian Relations Moonis Ahmar 1989 | | |
| Finland: A Study in Neutrality Naveed Ahmad Tahir 1987 | | |

question: Who is the author of the book 'Muslim Rule in Spain'?

Output:

```
```scala
val df = spark.read.option("header", "true").csv("data.csv")
val finalResult = df.select("Author").where(df("Title of Book") === "Muslim Rule in Spain")
finalResult.coalesce(1).write.option("header", "true").csv("result")
```
```

NL-to-Scala (Classification)

Task description:

Natural language to Spark Scala, is a problem of generating Scala code using the Apache Spark library that can be executed on a input CSV table, for a given natural language question.

You will be given an input table called "table" in the markdown format below, a question in natural language for this table, and a corresponding Spark Scala code for the natural language question. You need to: (1) determine if the Spark Scala code is grammarly correct, (2) determine if the Spark Scala code can truthfully represent the natural language question being asked. Return your answer in the following JSON format: {"grammarly_correct": <YES or NO>, "scala-correct": <YES or NO>}

The code is generated with the following iunstructions:

When generating Scala code, you can assume that the input table is always stored in a file named "data.csv", so always start your Scala code with the boilerplate prefix:
"val df = spark.read.option("header", "true").csv("data.csv")"

After you generate Scala code to produce results, please always save your final results into a single CSV file named in the "result" directory, so your Scala code should always end with:
"finalResult.coalesce(1).write.option("header", "true").csv("result")"

Now, given the following input table, question, and Spark Scala code, please determine if the Scala code is grammarly correct and if it can truthfully represent the natural language question being asked. Return your answer in the following JSON format: {"grammarly_correct": <YES or NO>, "scala-correct": <YES or NO>}.

Table:

| Name | Weight(Start) | Weight(Ranch) | Weight(Final) | Total(lb) | Total(Percent) |
|--|---------------|---------------|---------------|-----------|----------------|
| --- --- --- --- --- | | | | | |
| Red Team Total 1051 964 753 298 28.35% | | | | | |

```

|Sue|170|150|129|41|24.12%
|Al|239|220|200|39|16.32%
|Amy|238|223|179|59|24.79%
|Anita|236|214|184|52|22.03%
|Steve|368|344|258|110|29.89%
|Tony|275|247|187|88|32%
|Amelia|210|194|168|42|20%
|Blue Team Total|907|833|722|185|20.4%
|Ashley|222|205|170|52|23.42%

```

Question:

What is the total weight of the individuals whose weight at the start is greater than 200, weight at the ranch is less than 250, and weight at the final is less than 190, and what is the average total percentage for this group?

Spark Scala Code:

```

val df = spark.read.option("header", "true").csv("data.csv")
val processedDf = df.withColumn("Weight(Start)", df("Weight(Start)").cast("int"))
    .withColumn("Weight(Ranch)", df("Weight(Ranch)").cast("int"))
    .withColumn("Weight(Final)", df("Weight(Final)").cast("int"))
    .withColumn("Total(Percent)", regexp_replace(df("Total(Percent)"), "%", "").cast("float"))

val totalWeight = processedDf.filter(processedDf("Weight(Start)") > 200 && processedDf("Weight(Ranch)") < 250 &&
    processedDf("Weight(Final)") < 190).select(sum("Weight(Start)").alias("Total Weight")).collect()(0)(0)
val averagePercent = processedDf.filter(processedDf("Weight(Start)") > 200 && processedDf("Weight(Ranch)") < 250
    && processedDf("Weight(Final)") < 190).select(avg("Total(Percent)").alias("Average Total Percent")).collect
    ()(0)(0)

val finalResult = sc.parallelize(Seq(("Total Weight", totalWeight), ("Average Total Percent", averagePercent))).toDF("Metric", "Value")
finalResult.coalesce(1).write.option("header", "true").csv("result")

```

Output:

```
{"grammarly_correct": "YES", "scala-correct": "YES"}
```

Transformed Column Generation

Instruction:

You are given a table below with a single column, please produce a derived column that can be generated from the column using a transformation program. In this specific case, your transformation should:

Perform a Numeric transformation that:

Convert into different unit (length, weight, time, etc.)

If the suggested transformation above is not feasible on the table column, please return your transformation plan in a JSON object as {"plan": "NULL"} and then return two empty code blocks for Pandas and R.

If the suggested transformation is feasible on the table column, please (1) first explain your plan in terms of how to transform the values in the column, in a JSON object as {"plan": "<PLAN>"}. Please then (2) return its Python implementation and R implementation, using two *code blocks*. Remember, the new derived column should always be named as "derived_column" in your python Pandas code and R code.

Please produce your Python Pandas code that can run on this table, to generate the derived column. To read this table, you can assume that the input table is always stored in a file named "data.csv", so always start your Python code with the boilerplate prefix:

```

"import pandas as pd
df = pd.read_csv('data.csv')
"

You should always generate your derived column in a column named "derived_column" in the final dataframe. Please
    always save your final dataframe into a file named "result.csv".
Return the final result as a markdown code block, as ```python <PYTHON-CODE>```

Similarly, please also produce your R code that can run on this table, to generate the derived column. To read
    this table, you can assume that the input table is always stored in a file named "data.csv", so always start
        your R code with the boilerplate prefix:
"library(dplyr)

data <- read.csv("data.csv", check.names = FALSE)
"

You should always generate your derived column in a column named "derived_column" in the final dataframe. Please
    always save your final dataframe into a file named "result.csv".
Return the final result as a markdown code block, as ```r <R-CODE>```

**Input table:**
MergedColumn
18,950,15,522
25,367,20,645
19,538,23,868
8,978,15,657
5,304,22,110
36,773,26,000
11,513,16,210
21,306,27,550
24,864,19,107
12,663,28,406

```

If the suggested transformation above is not feasible on the table column, please return your transformation plan in a JSON object as {"plan": "NULL"} and then return two empty code blocks for Pandas and R.

If the suggested transformation is feasible on the table column, please (1) first explain your plan in terms of how to transform the values in the column, in a JSON object as {"plan": "<PLAN>"} . Please then (2) return its Python implementation and R implementation, using two *code blocks*. Remember, the new derived column should always be named as "derived_column" in your python Pandas code and R code.

Output:

```

```json
{"plan": "Convert the values in the MergedColumn from the current format to a new format by replacing the comma
 with period (for decimal) and removing the other commas."}
```

```python
import pandas as pd

Read the input table
df = pd.read_csv('data.csv')

Perform the transformation

```

```

df['derived_column'] = df['MergedColumn'].str.replace(',', '').str.replace('.', ',')

Save the final dataframe into a file named "result.csv"
df.to_csv('result.csv', index=False)
```

```r
library(dplyr)

Read the input table
data <- read.csv("data.csv", check.names = FALSE)

Perform the transformation
data <- data %>% mutate(derived_column = gsub(", ", "", MergedColumn),
 derived_column = gsub("\\.", ", ", derived_column))

Save the final dataframe into a file named "result.csv"
write.csv(data, file = "result.csv", row.names=FALSE)
```

```

Data Transformation Pandas (Generative)

Task description: The task of row-to-row transformation using examples, is to perform data transformation using table columns, to produce a new "DERIVED_COLUMN" in the table.

The task of "program-by-example" or "transform data by-example", is to use a few given example output values in the new "DERIVED_COLUMN", to infer the underlying transformation program that was used to derive the given output values in the "DERIVED_COLUMN". This is also known as program-synthesis or program-by-example in the research literature.

Given the **Input table** shown below, we want to perform data transformations on this Input Table, to produce a **Desired Output Table**, with the new "DERIVED_COLUMN" shown as the rightmost column of the **Desired Output Table**.

Please inspect the given output examples in the "DERIVED_COLUMN" of the **Desired Output Table**, to identify the transformation program that can be used to produce the "DERIVED_COLUMN" using columns in the **Input table**. Please generate Python Pandas code for the transformation that can execute on the **Input table**, to produce an output column that can exactly match the given output examples in the "DERIVED_COLUMN".

Please pay close attention to the format and the details of the given output examples in the "DERIVED_COLUMN", to make sure that your code will generate output values exactly matching the given examples, in terms of style, format, and casing.

To read this table, you can assume that the input table is always stored in a file named "data.csv", and always read everything as string (using "dtype=str"). So always start your Python code with the boilerplate prefix:

```

import pandas as pd
df = pd.read_csv('data.csv', dtype=str)
"
```

For numerical computation, please use Python Decimal class to avoid floating point precision issues, so always include "from decimal import Decimal" at the beginning of your code.

Please do not hard code your transformation program (e.g., if row id == 1, return output-value-1, etc.). Please produce transformation programs that can *generalize* to new data rows from the same table, that are not shown below in the interest of space.

Your Python Pandas code should always generate your target column in a column named "DERIVED_COLUMN" in the final dataframe. Please always save your final dataframe with this "DERIVED_COLUMN" into a file named "result.csv" with header and no index column.

Input table:

```
MergedColumn
0.1666
0.15
0.131
```

Desired Output Table:

```
MergedColumn	DERIVED_COLUMN
0.1666	0.17
0.15	0.15
0.131	0.13
```

No explanation, return the final result as a markdown code block, as ```python <PYTHON-CODE>```.
Output:

```
```python
import pandas as pd
from decimal import Decimal

df = pd.read_csv('data.csv', dtype=str)
df['DERIVED_COLUMN'] = df['MergedColumn'].apply(lambda x: str(Decimal(x).quantize(Decimal('0.01'))))
df.to_csv('result.csv', index=False)
```
```

Data Transformation R (Generative)

Task description: The task of row-to-row transformation using examples, is to perform data transformation using table columns, to produce a new "DERIVED_COLUMN" in the table.

The task of "program-by-example" or "transform data by-example", is to use a few given example output values in the new "DERIVED_COLUMN", to infer the underlying transformation program that was used to derive the given output values in the "DERIVED_COLUMN". This is also known as program-synthesis or program-by-example in the research literature.

Given the **Input table** shown below, we want to perform data transformations on this Input Table, to produce a **Desired Output Table**, with the new "DERIVED_COLUMN" shown as the rightmost column of the **Desired Output Table**.

Please inspect the given output examples in the "DERIVED_COLUMN" of the **Desired Output Table**, to identify the transformation program that can be used to produce the "DERIVED_COLUMN" using columns in the **Input table**. Please generate R code for the transformation that can execute on the **Input table**, to produce an output column that can exactly match the given output examples in the "DERIVED_COLUMN".

Please pay close attention to the format and the details of the given output examples in the "DERIVED_COLUMN", to make sure that your code will generate output values exactly matching the given examples, in terms of style, format, and casing.

When you generate R code to read the input table, you can assume that the input table is always stored in a file named "data.csv", so always start your R code with the boilerplate prefix:

```
"library(dplyr)
```

```

data <- read.csv("data.csv", check.names = FALSE)
"

Please do not use case_when statements, or anything that is like CASE/IF/ELSE, to hard code your transformation
program (e.g., if row id == 1, return output-value-1, etc.). Please produce transformation programs that can
*generalize* to new data rows from the same table, that are not shown below in the interest of space.

Your R code should always generate your target column in a column named "DERIVED_COLUMN" in the final dataframe.
Please always save your final dataframe with this "DERIVED_COLUMN" into a file named "result.csv" with
header and no index column. No explanation, Return the final result as a markdown code block, as ```r<R
CODE>```.

**Input table:**  

|MergedColumn|  

|---|  

|Gary Payton|  

|Alonzo Mourning|  

|Shareef Abdur-Rahim|  

**Desired Output Table:**  

|MergedColumn|DERIVED_COLUMN|  

|---|---|  

|Gary Payton|GaryPayton|  

|Alonzo Mourning|AlonzoMourning|  

|Shareef Abdur-Rahim|ShareefAbdur-Rahim|  

No explanation, return the final result as a markdown code block, as ```r<R CODE>```.  

Output:  

```r
library(dplyr)

data <- read.csv("data.csv", check.names = FALSE)

data <- data %>%
 mutate(DERIVED_COLUMN = gsub(" ", "", MergedColumn))

write.csv(data, "result.csv", row.names=FALSE)
```

```

Data Transformation SQL (Generative)

```

# Task description: The task of "program-by-example" or "transform data by-example", is to use a few given
example output values in the new "DERIVED_COLUMN", to infer the underlying transformation program that was
used to derive the given output values in the "DERIVED_COLUMN". This is also known as program-synthesis or
program-by-example in the research literature.

```

Given the **Input table** shown below, we want to perform data transformations on this Input Table, to produce a **Desired Output Table**, with the new "DERIVED_COLUMN" shown as the rightmost column of the **Desired Output Table**.

Please inspect the given output examples in the "DERIVED_COLUMN" of the **Desired Output Table**, to identify the transformation program that can be used to produce the "DERIVED_COLUMN" using columns in the **Input table**. Please generate SQL code for the transformation that can execute on the **Input table**, to produce an output column that can exactly match the given output examples in the "DERIVED_COLUMN".

Please pay close attention to the format and the details of the given output examples in the "DERIVED_COLUMN", to make sure that your code will generate output values exactly matching the given examples, in terms of style, format, and casing.

For numerical computation, please use SQL Decimal class to avoid floating point precision issues, so always do "CAST(<computation> AS DECIMAL) AS DERIVED_COLUMN" if numbers are involved.

Also, to perform string concatenation in SQL using "||", always remember to cast both sides of "||" from number to string before performing concatenation, so always do "CAST(CAST(<computation> AS DECIMAL) AS TEXT) || " some string"", before you return your results.

Please do not use CASE statements, or anything that is like CASE/IF/ELSE, to hard code your transformation program (e.g., if row id == 1, return output-value-1, etc.). Please produce transformation programs that can *generalize* to new data rows from the same table, that are not shown below in the interest of space.

Your SQL code should always generate your target column in a column named "DERIVED_COLUMN" in your final result. You can assume that your SQL code will be executed on a SQLite3 database and on a table called "table".

No explanation, Return the final result as a markdown code block, as `sql<SQL CODE>`.

Input table:
|MergedColumn|
|---|
|WR UFA Tennessee Titans|
|LB UFA Saskatchewan Roughriders (CFL)|
|LS UFA Omaha Nighthawks (UFL)|

Desired Output Table:
|MergedColumn|DERIVED_COLUMN|
|---|---|
|WR UFA Tennessee Titans|WR UFA Tennessee Titans|
|LB UFA Saskatchewan Roughriders (CFL)|LB UFA Saskatchewan Roughriders CFL|
|LS UFA Omaha Nighthawks (UFL)|LS UFA Omaha Nighthawks UFL|

No explanation, Return the final result as a markdown code block, as `sql<SQL CODE>`.

Output:

```
```sql
SELECT
 MergedColumn,
 REPLACE(MergedColumn, ' (', ' ') AS DERIVED_COLUMN
FROM
 table;
```
```

Error Detection (Generative)

Instruction:

Task Description: Given the table column <Column> below, please brainstorm an erroneous cell <CELL> that is NOT compatible with the <Column>, which if added to the <Column>, would be considered as a data error.

For example:

- (1) When the <Column> has a list of string-valued names, an error <CELL> can be a number as a special placeholder such as "99999" or "0".
- (2) When the <Column> has a list of numbers, an error <CELL> can be is a string.
- (3) An error <CELL> can also be placeholder punctuation like "?", "!", "***" and "--"
- (4) An error <CELL> can also be of a semantic type that is obviously not compatible with the rest of the <Column>, e.g., <CELL> is an email address while the <Column> has a list of URLs, or <CELL> is a phone number while <Column> has a list of countries, etc.

Please brainstorm an **ERROR** cell <CELL> **NOT** compatible with the <Column>.

```
**DO** generate <CELL> using realistic strings
** NEVER ** generate fake <CELL> like "123 Main Street".
** NEVER ** generate fake <CELL> like "123456789"
** NEVER ** generate fake <CELL> like "12345"
** NEVER ** generate fake <CELL> like "ABC"
** NEVER ** generate fake <CELL> like "ABCD"
** NEVER ** generate fake <CELL> like "john.doe@example.com"
```

Return a JSON in the format {"ERROR": "<CELL>"}.

```
## Input:
```

```
|11:43.1|
|10:30.1|
|10:54.7|
|23:03.1|
|11:01|
|11:27.4|
|08:24.6|
|13:44.4|
```

```
## Output:
```

```
{"ERROR": "new zealand"}
```

```
## Input:
```

```
|Mens 100m butterfly|
|Womens 100m freestyle|
|Mens 200m breaststroke|
|Womens 200m backstroke|
```

```
## Output:
```

```
{"ERROR": "Olivia.Mcbath@gmail.com"}
```

Input:

```
|Jefferson|
|Benton|
|Franklin|
|Faulkner|
|Madison|
|Garland|
|Poinsett|
|Craighead|
|Crawford|
|Lonoke|
|Lincoln|
|Pulaski|
|Crittenden|
|Miller|
|Cleveland|
```

Output:

```
{"ERROR": "99999"}
```

Input:

```
|2|
|4|
|1|
|6|
|29|
```

Output:

```
{"ERROR": "$129.00"}
```

Input:

```
|$70,000|
|$40,000|
|$90,000|
|$80,000|
|$60,000|
|$100,000|
|$130,000|
|$150,000|
|$50,000|
```

```
|$120,000|  
|$160,000|  
|$170,000|  
|$110,000|  
|$30,000|  
|$10,000|  
|$20,000|  
  
## Output:  
  
{ "ERROR": "+1 800-425-1829" }
```

```
## Input:
```

```
|James Smith|  
|Chris White|  
|Jane Doe|  
|Bill Gates|  
|Steve Jobs|
```

```
## Output:
```

```
{ "ERROR": "***" }
```

```
## Input:
```

```
|Labrador Retriever|  
|French Bulldog|  
|Golden Retriever|  
|Poodle|  
|German Shepherds|
```

```
## Output:
```

```
{ "ERROR": "---" }
```

```
## Input:
```

```
|(41) 9635-0575|  
|(47) 9285-3910|  
|(15) 6518-6603|  
|(91) 2727-6856|  
|(61) 4425-1329|  
|(78) 4464-7756|  
|(23) 1443-9130|
```

```
|(94) 6570-4540|  
|(54) 4294-8441|  
|(62) 4022-2429|  
|(29) 3528-8592|  
|(72) 4078-7452|  
|(12) 8805-7156|
```

Output:

```
{"ERROR": "?"}
```

Input:

```
|#ffd66a|  
|#fbc527|  
|#ff9212|
```

Output:

```
{"ERROR": "2025"}
```

Input:

```
|$100,000 to $250,000|  
|$60,000 to $80,000|  
|$80,000 to $100,000|  
|$40,000 to $60,000|  
|$20,000 to $40,000|  
|less than $20,000|  
|more than $250,000|
```

Output:

```
{"ERROR": "-"}  
-----
```

Input:

```
|108 lakeside court|  
|2947 vine lane|  
|620 woodside ct.|  
|9539 glenside dr|  
|101 candy rd.|  
|6369 ellis street|  
|9495 limewood place|  
|5980 icicle circle|
```

Output:

```

{"ERROR": "RGB(255, 87, 51)"}

-----
## Input:

|1899-12-30 10:00:00.000|
|1899-12-30 14:00:00.000|
|1899-12-30 08:00:00.000|
|1899-12-30 12:00:00.000|
|1899-12-30 09:00:00.000|


## Output:

{"ERROR": "MD-192038"}


-----
## Input:

|2017-wk19|
|2017-wk20|
|2017-wk21|
|2017-wk23|
|2017-wk24|
|2017-wk25|
|2017-wk26|
|2017-wk28|
|2017-wk29|
|2017-wk30|
|2017-wk31|


## Output:

{"ERROR": "g79"}


-----
## Input:

|lonnie brien pol / lonnie.b.pol2@uscg.mil|
|shirley kraft / shirley.kraft@bpd.treas.gov|
|paulette anne swann / paulette.a.swann@uscg.mil|
|nekiesha michel bone-williams / nekiesha.m.edler@uscg.mil|
|alyssa chevalier / alyssa.chevalier@bpd.treas.gov|
|jeff hoge / jeffrey.hoge@fms.treas.gov|
|william stimmel / william.stimmel1@dhs.gov|
|james d. rapley / james.rapley@dhs.gov|
|/ kelly.rapley@dhs.gov|


## Output:

{"ERROR": "[4.72|2022-12-23 00:00:00|2022-12-23 00:00:00|Delivery]"}

```

Now given the input column below:

Input:

```
|2012-2013|  
|2011-2012|  
|2010-2011|  
|2009-2010|  
|2008-09|  
|2007-08|  
|2006-07|  
|2005-06|  
|2004-05|  
|2003-04|  
|2002-03|  
|2001-02|  
|2000-01|  
|1999-00|  
|1998-99|  
|1997-98|  
|1996-97|  
|1995-96|  
|1994-95|  
|1993-94|  
|1992-93|  
|1991-92|  
|1990-91|  
|1989-90|  
|1988-89|  
|1987-88|
```

Please brainstorm an **ERROR** cell <CELL> **NOT** compatible with the <Column>.

```
**DO** generate <CELL> using realistic strings  
** NEVER ** generate fake <CELL> like "123 Main Street".  
** NEVER ** generate fake <CELL> like "123456789"  
** NEVER ** generate fake <CELL> like "12345"  
** NEVER ** generate fake <CELL> like "ABC"  
** NEVER ** generate fake <CELL> like "ABCD"  
** NEVER ** generate fake <CELL> like "john.doe@example.com"
```

Output:

```
{"ERROR": "2022-wk23"}
```

Error Detection (Classification)

Task Description: The table column below is a high-quality real data column. In the unlikely event that you see any one cell that is clearly a data error, either because the cell is a typo/misspelling (e.g., Mississippi that is a misspelling of Mississippi), or because it is a semantic outlier that does not fit in the context of this column (e.g., a city name mixed in a column with country names, etc.), please point it out.

*** Please be aware that cell values that appear unusual are often NOT ERRORS, such as code values (e.g., "mdl -1023"), abbreviations (e.g., "MDX"), out-of-vocabulary words (e.g., foreign languages, or proprietary terminologies), etc.. In all those cases, simply DO NOT make any prediction. Users will be very angry if they see incorrect predictions. ***

Please return {"obvious_error": "NULL"} if you believe the column is a high-quality column. Otherwise, please return any error cell you identified in JSON {"obvious_error": "<CELL>"}, ONLY IF you are ABSOLUTELY SURE that <CELL> is erroneous. We will manually verify and you will be punished if it turns out that <CELL> is not erroneous.

Input:

```
|Tortimer|
|Bowsser|
|Devan Shell|
|The Giant Turtle|
|Bowser|
|Tiptup|
|Shen-zin Su|
|Koopa Troopa|
|Valluta|
|Ghido|
|Bentley|
```

*** Please be aware that cell values that appear unusual are often NOT ERRORS, such as code values (e.g., "mdl -1023"), abbreviations (e.g., "MDX"), out-of-vocabulary words (e.g., foreign languages, or proprietary terminologies), etc.. In all those cases, simply DO NOT make any prediction. Users will be very angry if they see incorrect predictions. ***

Please return {"obvious_error": "NULL"} if you believe the column is a high-quality column. Otherwise, please return any error cell you identified in JSON {"obvious_error": "<CELL>"}, ONLY IF you are ABSOLUTELY SURE that <CELL> is erroneous. We will manually verify and you will be punished if it turns out that <CELL> is not erroneous.

Output:

```
{"obvious_error": "NULL"}
```

Schema Matching (Generative)

Instruction:

Given the Table A shown below, please generate a new table Table B, so that *some* (but not all) of the generated columns in Table B can "map" to *some* (but not all) of columns in Table A, in the sense that they will refer to the same semantic concepts, such that they can "map" to each other.

When you generate new column names in Table B, please make sure that the new column names are different from the original column names in Table A.

When you generate new data values in Table B, please also make sure that you generate new data values not found in Table A.

After you generate Table B, please show how columns in Table A can map to columns in Table B. For each column in Table A, specify the corresponding column in Table B. If a column in A has no corresponding column in Table B, you can map it to None. Represent each column mapping using a pair of column headers in a list, i.e., [Table A Column, Table B column or None]. Provide the mapping for each column in Table A and return all mappings in a list. Return the final result as JSON in the format {"column_mappings": "<a list of column pairs>"}.

```

## Input:

Table A:
Material collected	Pages	Publication Date
NYX #1-7	208	July 2011
NYX #1-7 & NYX: NO WAY HOME #1-6	392	July 2016
NYX #1-7 and X-23 Vol. 1, #1-6	352	November 2005
X-23 and the unrelated Firestar, Lady Deadpool, Namora, Valkyrie, Rescue, Sif, Spitfire, Galacta, Women of		
Marvel #1-2	352	February 2011
X-23 Vol. 1 #1-6	144	April 2006
X-23: Target X #1-6	160	August 2007
X-23 vol. 2 #1-6 and material from All-New Wolverine Saga	152	November 2011
Daken: Dark Wolverine #5-9, X-23 (Vol. 2) #7-9 And Material From Wolverine: Road To Hell.	200	February 2012
X-23 vol. 2 #10-16	152	July 25, 2012
X-23 vol. 2 #17-21	112	December 2012


Please first return Table B in markdown format.

Please then return the column mapping result between Table A and Table B, using the following JSON format {"column_mappings": "<a list of column pairs>"}.

## Output:

Table B:
Collected Material	Total Pages	Publishing Date
X-23 #1-7	215	August 2010
X-23: NO WAY HOME #1-6	380	June 2015
X-23 #1-7 and X-24 Vol. 1, #1-6	345	October 2004
X-24 and the unrelated Firestar, Lady Deadpool, Namora, Valkyrie, Rescue, Sif, Spitfire, Galacta, Women of		
Marvel #1-2	345	March 2010
X-23 Vol. 1 #1-6	140	May 2005
X-23: Target X #1-6	155	July 2006
X-24 vol. 2 #1-6 and material from All-New Wolverine Saga	148	October 2010
Daken: Dark Wolverine #5-9, X-24 (Vol. 2) #7-9 And Material From Wolverine: Road To Hell.	195	January 2011
X-24 vol. 2 #10-16	148	June 20, 2011
X-24 vol. 2 #17-21	110	November 2011


## Column Mapping:
>{"column_mappings": [["Material collected", "Collected Material"], ["Pages", "Total Pages"], ["Publication Date", "Publishing Date"]]}

```

Schema Matching (Classification)

Task Description: Please identify the matching columns between Table A and Table B. For each column in Table A, specify the corresponding column in Table B. If a column in A has no corresponding column in Table B, you can map it to None. Represent each column mapping using a pair of column headers in a list, i.e., [Table A Column, Table B column or None]. Provide the mapping for each column in Table A and return all mappings in a list. Return the final result as JSON in the format {"column_mappings": "<a list of column pairs>"}.

```

## Input:
Table A:
First elected	Councillor	Communities	Ward

```

| |
|---|
| 2010 Doug Shipley Little Lake, East Bayfield 3 |
| 2012 Arif Khan Allandale, South Shore, Painswick North 8 |
| 2003 Barry Ward Sunnidale, West Bayfield, Northwest 4 |
| 2014 Sergio Morales Painswick South 9 |
| 2014 Rose Romita Wellington, Queen's, City Centre, Lakeshore 2 |
| 2003 Michael Prowse Ardagh 6 |
| 2006 (Councillor); 2010 (Mayor) Jeff Lehman At-large Mayor |
| 2010 Bonnie Ainsworth Georgian Drive, Grove East, Codrington, North Shore 1 |
| 2010 Peter Silveira Letitia Heights, Sandy Hollow, Edgehill Drive 5 |
| 2006 2016 John Brassard (until 2015) Andrew Prince (after 2016) Holly 7 |
| 2014 Mike McCann Innishore, Bayshore 10 |

Table B:

| Year elected | Representative | District | Neighborhoods |
|--|----------------|----------|---------------|
| --- | --- | --- | --- |
| 2016 David Thompson B Hillcrest, Sunnyside | | | |
| 2012 Samantha Smith A Downtown, Riverdale | | | |
| 2010 Emily White C West End, Parkside | | | |

Return the final result as JSON in the format {"column_mappings": "<a list of column pairs>"}.

Output:

```
```json
{"column_mappings": [
 ["First elected", "Year elected"],
 ["Councillor", "Representative"],
 ["Communities", "Neighborhoods"],
 ["Ward", "None"]
]}
```
```

```