Inference and Reasoning on Semi-Structured Tables

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Semi-structured tables are a ubiquitous feature in various domains, including e-commerce product listings, finance annual reports, sports score tables, scientific articles, etc. Despite their varied contexts, these tables share some common characteristics. One notable attribute is their succinct nature, enabling them to efficiently contain a substantial amount of information in a compact form. Thus, making them an ideal tool for comparative analysis and finding information. Additionally, tables require complex reasoning and inference to understand the implicit connections across table cells.

Neural network models have significantly advanced in processing unstructured text, like sentences and paragraphs. Yet, their ability to effectively manage semi-structured text remains somewhat unknown. This knowledge gap restricts a comprehensive understanding of these models' reasoning powers, a challenge that persists even among NLP experts. **I believe that studying semi-structured data is essential for understanding model reasoning ability on textual information.** Therefore, my research focuses on *semi-structured tabular data* (cf. Figure 1). While working with tables, I addressed the following questions:

Q1. How do models designed for unstructured text adapt to (semi-)structured data?(§1) Unstructured text explicitly mentions connection between the entities in the sentence/paragraph. However, in (semi-)structured text (e.g. tables) these relationships are latent due to its underlying implicit structure. Furthermore, tables hold information in succinct form, which makes information navigation in the cluttered world challenging (Neeraja et al., 2021; Gupta et al., 2022b).

Q2. How does one incorporate knowledge into tabular models?(§2) AI programs that are trained on tables might not understand certain words and phrases, which can make it hard to interpret the tabular information correctly. For example, in a table that lists music albums, the label "*Length*" might not make sense without more information about the context of the table.

Q3. How to ensure that the model is doing correct evidence-based reasoning?(§3) AI models suffer from a lack of output trustworthiness, making it difficult to be deployed in the real world. Recent studies show that AI systems are brittle and memorize spurious patterns such as annotation artefacts, often amplify societal biases (Bolukbasi et al.; Zhao et al., 2017; Poliak et al., 2018; Niven and Kao, 2019; Yu et al., 2023; Zhang et al., 2023; Ji et al., 2023). I studied these structural biases for tables using logical probes (Gupta et al., 2022a).

Breakfast in America		Relevance
Released[4]	29 March 1979[4]	H3
Recorded[3,4]	May-December 1978[3,4]	H2, H3
Studio	The Village Recorder in Los Angeles[3]	
Genre	Pop, Art Rock, Soft Rock	
Length[2]	46:06[2]	H1
Label	A&M	
Producer[1]	Peter Henderson, Supertramp[1]	H1

H1: Supertramp produced[1] an album that was less than an hour long[2].
H2: Most of Breakfast in America was recorded[3] in the last month of 1978[3].
H3: Breakfast in America was released[4] the same month recording[4] ended.

Figure 1: A semi-structured premise (the table 'Breakfast in America') example from InfoTabS. The table displays three hypotheses, with H1 entailed, H2 neither entailed nor contradictory, and H3 contradictory. Relevant rows are highlighted in color (and superscript), and the "Relevance" column indicates which hypotheses use each row for reasoning.

1 How do models designed for unstructured text adapt to (semi-)structured data?

To study this questions we created INFOTABS (Gupta et al., 2020), a semi-structure tabular inference dataset. INFOTABS consists of human-written textual hypotheses based on premises extracted from Wikipedia info-boxes. Figure 1 shows an example from the INFOTABS dataset, a table with three hypotheses. The dataset contains $2,540$ distinct infoboxes ($\approx$ 24K pairs) representing a variety of domains. INFOTABS incorporates several diverse kinds of reasoning (numerical, temporal, knowledge and common sense etc.) several adapted from the Glue (Wang et al., 2018) and SuperGlue (Wang et al., 2019) benchmarks, which are typically missing in earlier natural language inference (NLI) datasets. For example, in Figure 1, consider the hypothesis sentence H1. To determine whether the hypothesis entails the premise, one needs to look up multiple rows (*'Length'* and *'Producer'*), conclude that *'Length'* in Album terms denotes the total length of the album's songs (i.e. Album Singles), and *'46:06'* where the album length is in minutes rather than an hour (using common sense). In addition to the regular training and development sets, to differentiate models' true learning ability from learning spurious correlated patterns in the data (artifacts), we created three challenge test sets of equal size. The α_1 set (200 tables, 1800 table-hypothesis pair) represents a standard test set that is topically and lexically similar to the training

data. In the α_2 set, hypotheses are designed to be lexically adversarial, and the α_3 tables are from topics not present in the training set.

We also created the first set of baselines on INFOTABS dataset. The third row (Universal Encoding) of Figure 2 table presents the performance of the model trained on training data. The table also shows the hypothesis-only baseline (Poliak et al., 2018; Gururangan et al., 2018) and human agreement on the labels. We found that existing inference models, e.g., RoBERTa-LARGE, underperform on INFOTABS compared to the majority human agreement performance, suggesting that reasoning about tables can pose a difficult modeling challenge. Since its publication, the INFOTABS has emerged as a standard benchmark for evaluating tabular reasoning capabilities in NLP models. Numerous studies have utilized INFOTABS to test and enhance their models' ability to comprehend and reason with semi-structured data (Zhao et al., 2023b; Akhtar et al., 2023a; Zhao et al., 2023c; Ye et al., 2023; Petrak et al., 2023; Lu et al., 2023; Zhao and Yang, 2022; Zhao et al., 2023a; Kurosawa and Yanaka, 2022, and others).

Model	α_1	α_2	α_3
Human	**84.04**	**83.88**	**79.33**
Hypothesis Only	60.48	48.26	48.89
Universal Encoding	74.88	65.55	64.94
Type-Base Encoding	75.29	66.50	64.26
+++Knowledge	**78.42**	**71.97**	**70.03**

Figure 2: Results on INFOTABS representation with RoBERTa$_L$ model, hypothesis-only baseline and majority human agreement. Table also show accuracy with the proposed modifications (§2).

Recently, we also extend the INFOTABS to it's multilingual version XINFOTABS (Minhas et al., 2022; Agarwal et al., 2022), which consist of 10 languages, belonging belong to seven distinct language families (seven continent, 2.76 billion speakers) and six unique writing scripts. To create XINFOTABS, we leverage machine translation models and developed an effective translation pipeline which provide high-quality translations of tabular data.

2 How do we incorporate knowledge into tabular reasoning models?

Tabular data typically does not provide the necessary context to explain the relationship between different elements, like table attributes and values. As a result, models trained on tables often have difficulty with correct reasoning. To overcome this issue, one approach is to incorporate knowledge through preprocessing (Neeraja et al., 2021).

(a.) **Type-based representation.** A model should understand implicit relationship between table entries. The table does not explicitly state the relationship between the attributes and values. We saw above (§1) that the use of a universal template to address this, but this leads to most sentences being incoherent and ungrammatical, e.g., "*The recorded of Breakfast in America is 29 March 1998.*". Incoherent sentences can often limit a model's ability to understand information. To address this, we propose using entity-type specific templates by using value entity types DATE or MONEY or CARDINAL or BOOL. The final sentence now become grammatically correct, e.g., "*Breakfast in America was recorded on March 29th, 1998.*". Furthermore, we also add category-specific information, e.g., "*Breakfast in America is an album.*".

(b.) **Adding lexical knowledge.** Model's should be able to decipher the diverse lexical constructions. A accurate model can distinguish differences between word meanings, such as *"less than*" in H1 and *"most of*" in H2. However, limited training data often affects the model interpretation of *synonyms*, *antonyns*, *hypernyms*, *hyponyns*, and *co-hyponyms* of words such as "fewer", "over", "more than", "less than", "over", "under", "negations", and others. We find that pre-training on a large Natural Language Inference dataset helps expose the model to diverse lexical constructions and make model representation tuned to the NLI task. So firstly, we intermediately pre-train with MNLI data **(implicit knowledge)** and then subsequently fine tune on the tabular inference INFOTABS dataset.

(c.) **Removing distracting information.** A good model should be able to select the pertinent evidence for accurate reasoning. Only select rows are relevant for a given hypothesis. For example, the key *'Recorded'* is relevant for the hypothesis H2 and H3 but irrelevant for the hypothesis H3. Models can struggle with selecting the right evidence due to the vast amount of surrounding information. To handle this we propose, **distracting row removal**, where we select only rows relevant to the hypothesis. For this, we adopt the Alignment based retrieval algorithm with fastText vectors as detailed in Yadav et al. (2019). For example, we prune the table with only rows *'Length'* and *'Producer'* for hypothesis H1. We also explore the sensitivity to extraction method and introduce *trustworthy tabular inference* (Gupta et al., 2022b). In, *trustworthy tabular inference*, we split the NLI task into two causal sequential tasks: evidence extraction and inference on extracted evidence. We utilize several supervised and unsupervised methods for the evidence extraction.

(d.) **Adding domain knowledge.** The model needs to understand what the table attribute means in respect to table domain. For example, in H1, the *"Length*" attribute should be understood as *"the total playtime of a music album*", not as *"the size of the larger side of a portrait*", which would be the meaning

in a *"painting*" domain. To help the model, we provide extra information **(explicit knowledge)** that explains the correct meaning of the attribute. This extra knowledge helps the model to choose the right meaning of the table attribute. We use BERT (Devlin et al., 2019) attribute embeddings to compare wordnet examples with the table premise and add the correct definition as extra context to the premise.

Our proposed knowledge addition approach (+++ knowledge) lead to substantial improvements in prediction quality, especially on adversarial α_2 and α_3 test sets as shown in Figure 2 Table. Definitions can be long and sometimes add unnecessary information, causing confusion. To solve this problem, we suggest using structured knowledge from factual and commonsense knowledge graphs like DBpedia (Auer et al., 2007), ATOMIC (Sap et al., 2019), and ConceptNet (liu, 2004). Our proposed solution, TransKBLSTM (Varun et al., 2022), combines Bi-LSTM with transformer to efficiently incorporate knowledge within the model. This approach can also be used for question answering and generation tasks that involve both tabular and textual inputs. This work received recognition as the best paper at the DeeLIO-2022 workshop.

3 How to ensure that the model is doing correct evidence-based reasoning?

Merely achieving high accuracy is not sufficient evidence of reasoning: the model may arrive at the right answer for the wrong reasons leading to inadequate generalization over unseen data. "Reasoning" is a multi-faceted phenomenon, and fully characterizing it is almost impossible. However, one can probe for the *absence* of evidence-grounded reasoning i.e. *reasoning failures* via model responses to carefully constructed inputs and their variants. For example there are certain pieces of information in the premise (irrelevant to the hypothesis) when changed, should not impact the outcome, thus making the outcome *invariant* to these changes. For example, deleting irrelevant rows from the premise should not change the model's predicted label. Contrary to this is the relevant information (*evidence*) in the premise. Changing these pieces of information should vary the outcome in a predictable manner, making the model *covariant* with these changes. For example, deleting relevant evidence rows should change the model's predicted label to NEUTRAL[1]. Overall, the guiding premise for this (in-/co-)variants perturbation work is:

> *Any "Evidence-based reasoning" systems should respond predictably to controlled input changes.*

Directly checking for such property there would require a lot of labeled data—a big practical impediment. Fortunately, in the case of tabular semi-structured data, the (in-/co-)variants associated with these dimensions allow controlled and semi-automatic edits to the inputs leading to predictable variation of the expected output. We instantiate the above knowledge along three dimensions to introduce specific probes, described below using example in Figure 1.

(a.) Avoiding Annotation Artifacts A model must not depend on incidental lexical correlations for making predictions. For instance, in the context of a Natural Language Inference (NLI) task, the model should not be capable of determining the label solely based on the hypothesis. Lexical differences in closely related hypotheses should produce predictable changes in the inferred label. For example, in the hypothesis H1 of Figure 1 if the token "less than" is replaced with "more than", the model prediction should change from ENTAIL to CONTRADICT. To create such probe, we identify a set of reasoning categories and characterize the relationship between a tabular premise and a hypothesis.

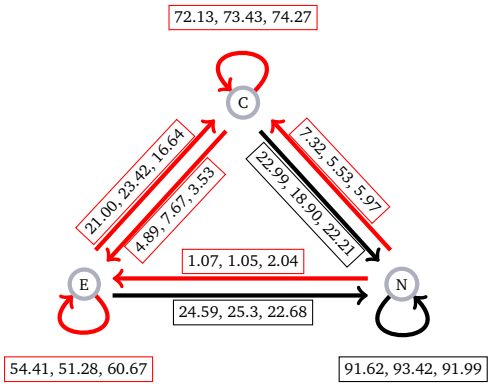

Figure 3: Changes in model predictions after deletion of relevant rows. Directed edges are labeled with transition percentages from the source node label to the target node label. The number triple corresponds to α_1, α_2 and α_3 test sets respectively and for each source node, adds up to 100% over the outgoing edges. Red lines represent invalid transitions while **black** lines represent valid transitions.

From the analysis of the artifact probes, we found that the model heavily relies on correlations between a hypothesis' sentence structure and its label. Thus, models should be systematically evaluated on adversarial sets like α_2 for robustness and sensitivity. This observation is concordant with multiple studies that probe deep learning models on adversarial examples in a variety of non-tabular tasks such as question answering, sentiment analysis, document classification, natural language inference, etc. (e.g. Ribeiro et al., 2020; Richardson et al., 2020; Goel et al., 2021; Lewis et al., 2021; Tarunesh et al., 2021).

(b.) Evidence Selection A model should use the correct evidence in the premise for determining the hypothesis label. For example, ascertaining that the hypothesis H1 is entailed requires the *Length* and

[1] This strategy has been either explicitly or implicitly also employed for recent non-tabular work (Ribeiro et al., 2020; Gardner et al., 2020).

Producer rows of Figure 1. To better understand the model's ability to select evidence in the premise, we use two kinds of controlled edits: (a) **automatic edits** without any information about relevant rows, and, (b) **semi-automatic edits** using knowledge of relevant rows via manual annotation. We define four types of table modifications that are agnostic to the relevance of rows to a hypothesis: (a) **row deletion**, i.e. deleting information, (b) **row insertion**, i.e. inserting new information, (c) **row-value update**, i.e., changing existing information, and (d) **row permutation**, i.e., reordering rows. Each modification allows certain desired (valid) changes to model predictions.[2] Overall from evidence-selection probing, we found the model does not look at correct evidence (Figure 3) for correct reasoning and rather leverages spurious patterns and statistical correlations to make predictions. A recent study by Lewis et al. (2021) on non-tabular question-answering shows that models indeed leverage spurious patterns to answer a large fraction (60-70%) of questions.

(c.) Robustness to Counterfactual Changes A model's prediction should be *grounded* in the provided information even if it contradicts the real world, i.e., to counterfactual information. For example, if the month and year of the *Released* date changed to "December" and "1978" respectively, then the model should change the label of H3 in Figure 1 to ENTAIL from CONTRADICT. Since this information about release date contradicts the real world, the model cannot rely on its pre-trained knowledge, say from Wikipedia. For the model to predict the label correctly, it needs to reason with the information in the table as the primary evidence. Although the importance of pre-trained knowledge cannot be overlooked, it must not be at the expense of primary evidence. We used similar techniques for synthetic and counterfactual tabular augmentation data generation (Kumar et al., 2022) to enhance tabular reasoning.

From counterfactual probes, we found that the model relies on knowledge of pre-trained language models than on tabular evidence as the primary source of knowledge for making predictions. This is in addition to the spurious patterns or hypothesis artifacts leveraged by the model. Similar observations are made by Clark and Etzioni (2016); Jia and Liang (2017); Kaushik et al. (2020); Huang et al. (2020); Gardner et al. (2020); Tu et al. (2020); Liu et al. (2021); Zhang et al. (2021); Wang et al. (2021) for unstructured text. We refer the reader to the Gupta et al. (2022a) for probes details and more results. Additionally, we also released a interactive annotation platform (Jain et al., 2021) for generating effective tabular perturbations. Recently, we're assessing the reasoning capabilities of Large Language Models (LLMs) on numerical and mathematical data (Akhtar et al., 2023a) in semi-structured tables, and examining their concurrent robustness to multiple input perturbations (Gupta et al., 2023a).

4 Future Work

In today's world, where data is growing in volume and complexity, understanding semi-structured data is more important than ever. This form of data, prevalent in diverse domains such as e-commerce (product listings), finance (annual reports), sports (score tables), and scientific research (research articles), bridges the gap between the rigidity of structured data and the fluidity of unstructured data. Its succinct nature allows it to hold large and diverse amounts of information in a compact form. However, this also introduces challenges in interpretation, especially in understanding implicit connections between entries. For an NLP model to effectively handle this, it must possess the capability to analyze structural information across multiple rows and columns. Furthermore, the model should be adept at integrating this data with a vast array of world knowledge, utilizing diverse reasoning techniques to do so. Building upon our current understanding, for the future, I envision to explore reasoning over (a.) dynamic, (b.) multilingual, and (c.) multi-modal information, in context of semi-structured data. This expansion is crucial to address the evolving complexities and ensure comprehensive data utilization in a globally interconnected and technologically advanced landscape. In particular, I wish to explore the following questions:

(a.) **Dynamic Temporal Reasoning.** Numerous data pieces about an entity evolve and change throughout time. For instance, a city's population, geographical coverage or its official representatives change frequently. ***How do models reason about dynamic, particularly temporally varying, information?*** To enable consistent reasoning across time, robust models must consider these temporal variations. I aim to address this challenge by developing methods that leverage time-sensitive language models. Evaluating language model for static temporal reasoning over paragraph and knowledge graph is studied in the past (Zhou et al., 2021; Neelam et al., 2022; Saxena et al., 2021; Jia et al., 2018; Dhingra et al., 2022; Ning et al., 2018; Wen et al., 2021; Chen et al., 2021, and soon). In this direction, we introduce TEMPTABQA a dataset for temporal question answering over static entity tables (Gupta et al., 2023b).

(b.) **Reducing Information Gaps.** Tables across different languages often have significant information gaps, such as the variation in an entity infoboxes between English and French. ***How can models close the information gap across multilingual tables?*** To address this challenge, I propose utilizing information editing techniques, including information alignment and updating, which can be achieved through the use of large language models. Recently related problems of information editing are explored for article

[2] In performing these modifications, we ensure that the modified table does not become inconsistent or self-contradicting.

updating (Iv et al., 2022), news editing (Spangher et al., 2022), headline updation (Panthaplackel et al., 2022), and sentence updation (Shah et al., 2020; Dwivedi-Yu et al., 2022). To study this, as a first step, we recently introduced a new dataset INFOSYNC and a two-step baseline for tabular synchronization (Khincha et al., 2023), as first step.

(c.) **Navigating Multi-modal Information.** My current work involves studying unimodal tables with simple text. However, I'm keen to expand my research to include multimodal tables with text, symbols, images, and complex nested structures. ***How can model reason on complex multimodal tables?*** I aim to address this question by working with pre-trained models that can analyze both visual and textual information. The model should also account for visual variations, such as highlights, color changes, and font variations. Recently efforts are been made to for similar work specifically on chart-table QA/generation (Liu et al., 2022b; Lee et al., 2022; Liu et al., 2022a), QA on infographicVQA (Mathew et al., 2022; Tanaka et al., 2023), and image-table-text generation (Gatti et al., 2022; Talmor et al.). In this direction, we recently publish CHARTCHECK (Akhtar et al., 2023b), a dataset for real-world fact checking on charts.

By tackling the broader problems of dynamic, multilingual, and multi-modal information in semi-structured data, I hope to contribute to the development of novel methods for reasoning with changing information, and ultimately advance our understanding of these complex data types, which extend beyond traditional free text and necessitate specialized handling.

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