InfoTabS: Inference on Tables as Semi-structured Data

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Abstract

In this paper, we observe that semi-structured tabulated text is ubiquitous; understanding them requires not only comprehending the meaning of text fragments, but also implicit relationships between them. We argue that such data can prove as a testing ground for understanding how we reason about information. To study this, we introduce a new dataset called InfoTabS, comprising of human-written textual hypotheses based on premises that are tables extracted from Wikipedia info-boxes. Our analysis shows that the semi-structured, multi-domain and heterogeneous nature of the premises admits complex, multi-faceted reasoning. Experiments reveal that, while human annotators agree on the relationships between a table-hypothesis pair, several standard modeling strategies are unsuccessful at the task, suggesting that reasoning about tables can pose a difficult modeling challenge.

Dressage	
Highest governing body	International Federation for Equestrian Sports (FEI)
Characteristics	
Contact	No
Team members	Individual and team at international levels
Mixed gender	Yes
Equipment	Horse, horse tack
Venue	Arena, indoor or outdoor
Presence	
Country or region	Worldwide
Olympic	1912
Paralympic	1996

H1: Dressage was introduced in the Olympic games in 1912.
H2: Both men and women compete in the equestrian sport of Dressage.
H3: A dressage athlete can participate in both individual and team events.
H4: FEI governs dressage only in the U.S.

Figure 1: A semi-structured premise (the table). Two hypotheses (H1, H2) are entailed by it, H3 is neither entailed nor contradictory, and H4 is a contradiction.

1 Introduction

Recent progress in text understanding has been driven by sophisticated neural networks based on contextual embeddings—e.g., BERT (Devlin et al., 2019), and its descendants—trained on massive datasets, such as SNLI (Bowman et al., 2015), MultiNLI (Williams et al., 2018), and SQuAD (Rajpurkar et al., 2016). Several such models outperform human baselines on these tasks on the benchmark suites such as GLUE (Wang et al., 2019b). Reasoning about text requires a broad array of skills—making lexical inferences, interpreting the nuances of time and locations, and accounting for world knowledge and common sense. *Have we achieved human-parity across such a diverse collection of reasoning skills?*

In this paper, we study this question by proposing an extension of the natural language inference (NLI) task (Dagan et al., 2005, and others). In NLI, which asks whether a premise entails, contradicts or is unrelated to a hypothesis, the premise and the hypothesis are one or more sentences. Understanding the premise requires understanding its linguistic structure and reasoning about it. We seek to separate these two components. Our work stems from the observation that we can make valid inferences about *implicit* information conveyed by the mere juxtaposition of snippets of text, as shown in the table describing *Dressage* in Figure 1.

We introduce the InfoTabS dataset to study and model inference with such semi-structured data. Premises in our dataset consist of info-boxes that convey information implicitly, and thus require complex reasoning to ascertain the validity of hypotheses. For example, determining that the hypothesis H2 in Figure 1 entails the premise table requires looking at multiple rows of the table, un-

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derstanding the meaning of the row labeled *Mixed gender*, and also that *Dressage* is a sport.

INFOTABS consists of 23,738 premise-hypothesis pairs, where all premises are info-boxes, and the hypotheses are short sentences. As in the NLI task, the objective is to ascertain whether the premise entails, contradicts or is unrelated to the hypothesis. The dataset has 2,540 unique info-boxes drawn from Wikipedia articles across various categories, and all the hypotheses are written by Amazon's Mechanical Turk workers. Our analysis of the data shows that ascertaining the label typically requires the composing of multiple types of inferences across multiple rows from the tables in the context of world knowledge. Separate verification experiments on subsamples of the data also confirm the high quality of the dataset.

We envision our dataset as a challenging testbed for studying how models can reason about semi-structured information. To control for the possibility of models memorizing superficial similarities in the data to achieve high performance, in addition to the standard train/dev/test split, our dataset includes two additional test sets that are constructed by systematically changing the surface forms of the hypothesis and the domains of the tables. We report the results of several families of approaches representing word overlap based models, models that exploit the structural aspect of the premise, and also derivatives of state-of-the-art NLI systems. Our experiments reveal that all these approaches underperform across the three test sets.

In summary, our contributions are:

1. We propose a new English natural language inference dataset, INFOTABS, to study the problem of reasoning about semi-structured data.
2. To differentiate models' ability to reason about the premises from their memorization of spurious patterns, we created three challenge test sets with controlled differences that employ similar reasoning as the training set.
3. We show that several existing approaches for NLI underperform on our dataset, suggesting the need for new modeling strategies.

The dataset, along with associated scripts, are available at https://infotabs.github.io/.

2 The Case for Reasoning about Semi-structured Data

We often encounter textual information that is neither unstructured (i.e., raw text) nor strictly structured (e.g., databases). Such data, where a structured scaffolding is populated with free-form text, can range from the highly verbose (e.g., web pages) to the highly terse (e.g. fact sheets, information tables, technical specifications, material safety sheets). Unlike databases, such semi-structured data can be heterogeneous in nature, and not characterized by pre-defined schemas. Moreover, we may not always have accompanying explanatory text that provides context. Yet, we routinely make inferences about such heterogeneous, incomplete information and fill in gaps in the available information using our expectations about relationships between the elements in the data.

Understanding semi-structured information requires a broad spectrum of reasoning capabilities. We need to understand information in an ad hoc layout constructed with elements (cells in a table) that are text snippets, form fields or are themselves substructured (e.g., with a list of elements). Querying such data can require various kinds of inferences. At the level of individual cells, these include simple lookup (e.g., knowing that *dressage takes place in an arena*), to lexical inferences (e.g., understanding that *Mixed Gender* means both men and women compete), to understanding types of text in the cells (e.g., knowing that the number 1912 is a year). Moreover, we may also need to aggregate information across multiple rows (e.g., knowing that *dressage is a non-contact sport that both men and women compete in*), or perform complex reasoning that combines temporal information with world knowledge.

We argue that a true test of reasoning should evaluate the ability to handle such semi-structured information. To this end, we define a new task modeled along the lines of NLI, but with tabular premises and textual hypotheses, and introduce a new dataset INFOTABS for this task.

3 The Need for Multi-Faceted Evaluation

Before describing the new dataset, we will characterize our approach for a successful evaluation of automated reasoning.

Recent work has shown that many datasets for NLI contain annotation biases or artifacts (e.g. Poliak et al., 2018). In other words, large models trained on such datasets are prone to learning spurious patterns—they can predict correct labels even with incomplete or noisy inputs. For instance, *not* and *no* in a hypothesis are correlated with contradictions (Niven and Kao, 2019). Indeed, classifiers trained on the hypotheses only (ignoring the premises completely) report high accuracy; they exhibit *hypothesis bias*, and achieving a high predictive performance does not need models to discover relationships between the premise and the hypothesis. Other artifacts are also possible. For example, annotators who generate text may use systematic patterns that "leak" information about the label to a model. Or, perhaps models can learn correlations that mimic reasoning, but only for one domain. With millions of parameters, modern neural networks are prone to overfitting to such imperceptible patterns in the data.

From this perspective, if we seek to measure a model's capability to understand and reason about inputs, we cannot rely on a single fixed test set to rank models. Instead, we need multiple test sets (of similar sizes) that have controlled differences from each other to understand how models handle changes along those dimensions. While all the test sets address the same task, they may not all be superficially similar to the training data.

With this objective, we build three test sets, named α_1, α_2 and α_3. Here, we briefly introduce them; §4 goes into specifics. Our first test set (α_1) has a similar distribution as the training data in terms of lexical makeup of the hypotheses and the premise domains.

The second, *adversarial test set (α_2)*, consists of examples that are also similar in distribution to the training set, but the hypothesis labels are changed by expert annotators changing as few words in the sentence as possible. For instance, if *Album X was released in the* 21^{st} *century* is an entailment, the sentence *Album X was released before the* 21^{st} *century* is a contradiction, with only one change. Models that merely learn superficial textual artifacts will get confused by the new sentences. For α_2, we rewrite entailments as contradictions and vice versa, while the neutrals are left unaltered.

Our third test set is the *cross-domain (α_3)* set, which uses premises from domains that are not in the training split, but generally, necessitate similar types of reasoning to arrive at the entailment decision. Models that overfit domain-specific artifacts will underperform on α_3.

Note that, in this work, we describe and introduce three different test sets, but we expect that future work can identify additional dimensions along which models overfit their training data and construct the corresponding test sets.

4 The InfoTabS Dataset

In this section, we will see the details of the construction of InfoTabS. We adapted the general workflow of previous crowd sourcing approaches for creating NLI tasks (e.g., Bowman et al., 2015) that use Amazon's Mechanical Turk.[1]

Sources of Tables Our dataset is based on $2,540$ unique info-boxes from Wikipedia articles across multiple categories (listed in Appendix D). We did not include tables that have fewer than 3 rows, or have non-English cells (e.g., Latin names of plants) and technical information that may require expertise to understand (e.g., astronomical details about exoplanets). We also removed non-textual information from the table, such as images. Finally, we simplified large tables into smaller ones by splitting them at sub-headings. Our tables are isomorphic to key-value pairs, e.g., in Figure 1, the bold entries are the keys, and the corresponding entries in the same row are their respective values.

Sentence generation Annotators were presented with a tabular premise and instructed to write three self-contained grammatical sentences based on the tables: one of which is true given the table, one which is false, and one which may or may not be true. The turker instructions included illustrative examples using a table and also general principles to bear in mind, such as avoiding information that is not widely known, and avoiding using information that is not in the table (including names of people or places). The turkers were encouraged not to restate information in the table, or make trivial changes such as the addition of words like *not* or changing numerical values. We refer the reader to the project website for a snapshot of the interface used for turking, which includes the details of instructions.

We restricted the turkers to be from English-speaking countries with at least a Master's qualification. We priced each HIT (consisting of one table) at $50¢$. Following the initial turking phase, we removed grammatically bad sentences and rewarded workers whose sentences involved multiple rows in the table with a 10% bonus. Appendix C gives additional statistics about the turkers.

Data partitions We annotated $2,340$ unique tables with nine sentences per table (i.e., three turkers

[1] Appendix A has more examples of tables with hypotheses.

Data split	# tables	# pairs
Train	1740	16538
Dev	200	1800
α_1 test	200	1800
α_2 test	200	1800
α_3 test	200	1800

Table 1: Number of tables and premise-hypothesis pairs for each data split

Dataset	**Cohen's Kappa**	**Human Accuracy**	**Majority Agreement**
Dev	0.78	79.78	93.52
α_1	0.80	84.04	97.48
α_2	0.80	83.88	96.77
α_3	0.74	79.33	95.58

Table 2: Inter-annotator agreement statistics

per table).[2] We partitioned these tables into training, development (Dev), α_1 and α_2 test sets. To prevent an outsize impact of influential turkers in a split, we ensured that the annotator distributions in the Dev and test splits are similar to that of the training split.

We created the α_2 test set from hypotheses similar to those in α_1, but from a separate set of tables, and perturbing them as described in §3. On an average, ~ 2.2 words were changed per sentence to create α_2, with no more than 2 words changing in 72% of the hypotheses. The provenance of α_2 ensures that the kinds of reasoning needed for α_2 are similar to those in α_1 and the development set. For the α_3 test set, we annotated 200 additional tables belonging to domains not seen in the training set (e.g., diseases, festivals). As we will see in §5, hypotheses in these categories involve a set of similar types of reasonings as α_1, but with different distributions.

In total, we collected 23,738 sentences split almost equally among entailments, contradictions, and neutrals. Table 1 shows the number of tables and premise-hypothesis pairs in each split. In all the splits, the average length of the hypotheses is similar. We refer the reader to Appendix D for additional statistics about the data.

Validating Hypothesis Quality We validated the quality of the data using Mechanical Turk. For each premise-hypothesis in the development and the test sets, we asked turkers to predict whether the hypothesis is entailed or contradicted by, or is unrelated to the premise table. We priced this task at 36¢ for nine labels.

The inter-annotator agreement statistics are shown in Table 2, with detailed statistics in Appendix F. On all splits, we observed significant inter-annotator agreement scores with Cohen's Kappa scores (Artstein and Poesio, 2008) between 0.75 and 0.80. In addition, we see a majority agreement (at least 3 out of 5 annotators agree) of range between 93% and 97%. Furthermore, the human accuracy agreement between the majority and gold label (i.e., the label intended by the writer of the hypothesis), for all splits is in range 80% to 84%, as expected given the difficulty of the task.

[2] For tables with ungrammatical sentences, we repeated the HIT. As a result, a few tables in the final data release have more than 9 hypotheses.

5 Reasoning Analysis

To study the nature of reasoning that is involved in deciding the relationship between a table and a hypothesis, we adapted the set of reasoning categories from GLUE (Wang et al., 2019b) to table premises. For brevity, here we will describe the categories that are not in GLUE and defined in this work for table premises. Appendix B gives the full list with definitions and examples. *Simple look up* refers to cases where there is no reasoning and the hypothesis is formed by literally restating what is in the table as a sentence; *multi-row reasoning* requires multiple rows to make an inference; and *subjective/out-of-table* inferences involve value judgments about a proposition or reference to information out of the table that is neither well known or common sense.

All definitions and their boundaries were verified via several rounds of discussions. Following this, three graduate students independently annotated 160 pairs from the Dev and α_3 test sets each, and edge cases were adjudicated to arrive at consensus labels. Figures 2a and 2b summarizes these annotation efforts. We see that we have a multifaceted complex range of reasoning types across both sets. Importantly, we observe only a small number of simple lookups, simple negations for contradictions, and mere syntactic alternations that can be resolved without complex reasoning. Many instances call for looking up multiple rows, and involve temporal and numerical reasoning. Indeed, as Figures 2c and 2d show, a large number of examples need at least two distinct kinds of reasoning; on an average, sentences in the Dev and α_3 sets needed 2.32 and 1.79 different kinds of reasoning, respectively.

We observe that semi-structured premises forced annotators to call upon world knowledge and common sense (KCS); 48.75% instances in the Dev set require KCS. (In comparison, in the MultiNLI data, KCS is needed in 25.72% of examples.) We conjecture that this is because information about the entities and their types is not explicitly stated in tables, and have to be inferred. To do so, our annotators relied on their knowledge about the world including information about weather, seasons, and widely known social and cultural norms and facts. An example of such common sense is the hypothesis that *"X was born in summer"* for a person whose date of birth is in May in New York. We expect that the INFOTABS data can serve as a basis for studying common sense reasoning alongside other recent work such as that of Talmor et al. (2019),

Neutral hypotheses are more inclined to being subjective/out-of-table because almost anything subjective or not mentioned in the table is a neutral statement. Despite this, we found that in all evaluations in Appendix E (except those involving the adversarial α_2 test set), our models found neutrals almost as hard as the other two labels, with only an $\approx 3\%$ gap between the F-scores of the neutral label and the next best label.

The distribution of train, dev, α_1 and α_2 are similar because the premises are taken from the same categories. However, tables for α_3 are from different domains, hence not of the same distribution as the previous splits. This difference is also reflected in Figures 2a and 2b, as we see a different distribution of reasonings for each test set. This is expected; for instance, we cannot expect temporal reasoning from tables in a domain that does not contain temporal quantities.

6 Experiments and Results

The goal of our experiments is to study how well different modeling approaches address the INFOTABS data, and also to understand the impact of various artifacts on them. First, we will consider different approaches for representing tables in ways that are amenable to modern neural models.

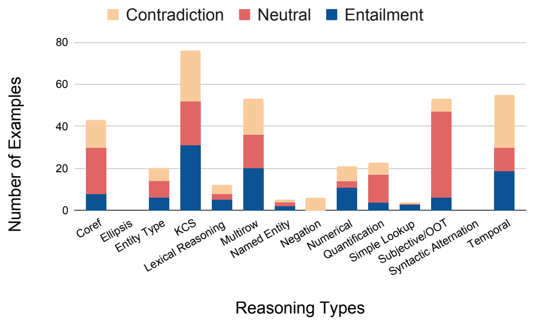
6.1 Representing Tables

A key aspect of the INFOTABS task that does not apply to the standard NLI task concerns how premise tables are represented. As baselines for future work, let us consider several different approaches.

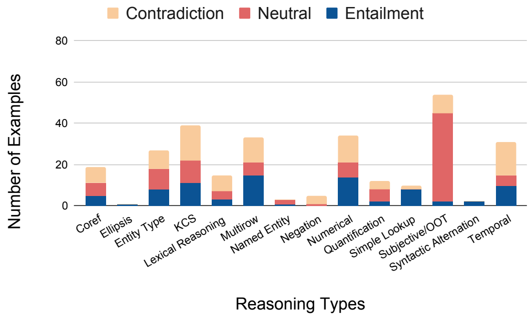
1. **Premise as Paragraph (Para)**: We convert the premise table into paragraphs using fixed template applied to each row. For a table titled `t`, a row with key `k` and value `v` is written as the sentence *The* `k` *of* `t` *are* `v`. For example, for the table in Figure 1, the row with key *Equipment* gets mapped to the sentence *The equipment of Dressage are horse, horse tack.* We have a small number of exceptions: e.g., if the key is *born* or *died*, we use the following template: `t` *was* `k` *on* `v`.
The sentences from all the rows in the table are concatenated to form the premise paragraph. While this approach does not result in grammatical sentences, it fits the interface for standard sentence encoders.
2. **Premise as Sentence (Sent):** Since hypotheses are typically short, they may be derived from a small subset of rows. Based on this intuition, we use the word mover distance (Kusner et al., 2015) to select the closest and the three closest sentences to the hypothesis from the paragraph representation (denoted by WMD-1 and WMD-3, respectively).
3. **Premise as Structure 1 (TabFact)**: Following Chen et al. (2020), we represent tables by a sequence of `key : value` tokens. Rows are separated by a semi-colon and multiple values for the same key are separated by a comma.
4. **Premise as Structure 2 (TabAttn)**: To study an attention based approach, such as that of Parikh et al. (2016), we convert keys and values into a contextually enriched vectors by first converting them into sentences using the Para approach above, and applying a contextual encoder to each sentence. From the token embeddings, we obtain the embeddings corresponding of the keys and values by mean pooling over only those tokens.

6.2 Modeling Table Inferences

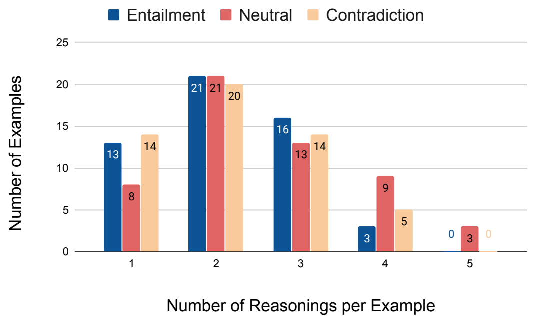
Based on the various representations of tables described above, we developed a collection of models for the table inference problem, all based on standard approaches for NLI. Due to space constraints,



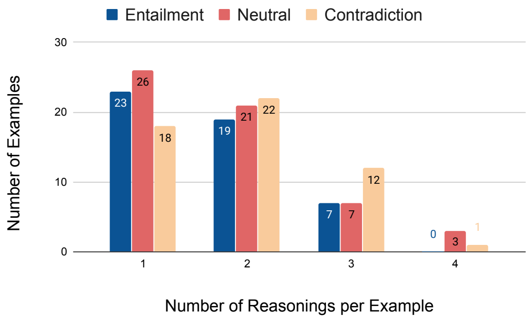
(a) Number of examples per reasoning type in the Dev set



(b) Number of examples per reasoning type in the α_3 set



(c) Number of reasonings per example in the Dev set



(d) Number of reasonings per example in the α_3 set

Figure 2: Distribution of the various kinds of reasoning in the Dev and α_3 sets. The labels OOT and KCS are short for out-of-table and Knowledge & Common Sense, respectively.

we give a brief description of the models here and refer the interested reader to the code repository for implementation details.

For experiments where premises are represented as sentences or paragraphs, we evaluated a feature-based baseline using unigrams and bigrams of tokens. For this model (referred to as *SVM*), we used the LibLinear library (Fan et al., 2008).

For these representations, we also evaluated a collection of BERT-class of models. Following the standard setup, we encoded the premise-hypothesis pair, and used the classification token to train a classifier, specifically a two-layer feedforward network that predicts the label. The hidden layer had half the size of the token embeddings. We compared RoBERTa$_L$ (Large), RoBERTa$_B$ (Base) and BERT$_B$ (Base) in our experiments.

We used the above BERT strategy for the TabFact representations as well. For the TabAttn representations, we implemented the popular decomposable attention model (Parikh et al., 2016) using the premise key-value embeddings and hypothesis token embeddings with 512 dimensional attend and compare layers.

We implemented all our models using the PyTorch with the transformers library (Wolf et al., 2019). We trained our models using Adagrad with a learning rate of 10^{-4}, chosen by preliminary experiments, and using a dropout value of 0.2. All our results in the following sections are averages of models trained from three different random seeds.

6.3 Results

Our experiments answer a series of questions.

Does our dataset exhibit hypothesis bias? Before we consider the question of whether we can model premise-hypothesis relationships, let us first see if a model can learn to predict the entailment label without using the premise, thereby exhibiting an undesirable artifact. We consider three classes of models to study hypothesis bias in INFOTABS.

Hypothesis Only (hypo-only): The simplest way to check for hypothesis bias is to train a classifier using only the hypotheses. Without a premise, a classifier should fail to correlate the hypothesis and the label. We represent the hypothesis in two ways a) using unigrams and bigrams for an SVM, and b) using a single-sentence BERT-class model. The results of the experiments are given in Table 3.

Model	Dev	α_1	α_2	α_3
Majority	33.33	33.33	33.33	33.33
SVM	59.00	60.61	45.89	45.89
BERT$_B$	62.69	63.45	49.65	50.45
RoBERTa$_B$	62.37	62.76	50.65	50.8
RoBERTa$_L$	60.51	60.48	48.26	48.89

Table 3: Accuracy of hypothesis-only baselines on the INFOTABS Dev and test sets

Dummy or Swapped Premise: Another approach to evaluate hypothesis bias is to provide an unrelated premise and train a full entailment model. We evaluated two cases, where every premise is changed to a (a) *dummy* statement (*to be or not to be*), or (b) a randomly *swapped* table that is represented as paragraph. In both cases, we trained a RoBERTa$_L$ classifier as described in §6.2. The results for these experiments are presented in Table 4.

Premise	Dev	α_1	α_2	α_3
dummy	60.02	59.78	48.91	46.37
swapped	62.94	65.11	52.55	50.21

Table 4: Accuracy with dummy/swapped premises

Results and Analysis: Looking at the Dev and α_1 columns of Tables 3 and 4, we see that these splits do have hypothesis bias. All the BERT-class models discover such artifacts equally well. However, we also observe that the performance on α_2 and α_3 data splits is worse since the artifacts in the training data do not occur in these splits. We see a performance gap of $\sim 12\%$ as compared to Dev and α_1 splits in all cases. While there is some hypothesis bias in these splits, it is much less pronounced.

An important conclusion from these results is that the baseline for all future models trained on these splits should be the best premise-free performance. From the results here, these correspond to the *swapped* setting.

How do trained NLI systems perform on our dataset? Given the high leaderboard accuracies of trained NLI systems, the question of whether these models can infer entailment labels using a linearization of the tables arises. To study this, we trained RoBERTa$_L$ models on the SNLI and MultiNLI datasets. The SNLI model achieves an accuracy of 92.56% on SNLI test set. The MultiNLI model achieves an accuracy of 89.0% on matched and 88.99% on the mismatched MultiNLI test set. We evaluate these models on the WMD-1 and the Para representations of premises.

Premise	Dev	α_1	α_2	α_3
Trained on SNLI				
WMD-1	49.44	47.5	49.44	46.44
Para	54.44	53.55	53.66	46.01
Trained on MultiNLI				
WMD-1	44.44	44.67	46.88	44.01
Para	55.77	53.83	55.33	47.28

Table 5: Accuracy of test splits with structured representation of premises with RoBERTa$_L$ trained on SNLI and MultiNLI training data

Results and Analysis: In Table 5, all the results point to the fact that pre-trained NLI systems do not perform well when tested on INFOTABS. We observe that full premises slightly improve performance over the WMD-1 ones. This might be due to a) ineffectiveness of WMD to identify the correct premise sentence, and b) multi-row reasoning.

Does training on the paragraph/sentence representation of a premise help? The next set of experiments compares BERT-class models and SVM trained using the paragraph (Para) and sentence (WMD-n) representations. The results for these experiments are presented in Table 6.

Premise	Dev	α_1	α_2	α_3
Train with SVM				
Para	59.11	59.17	46.44	41.28
Train with BERT$_B$				
Para	63.00	63.54	52.57	48.17
Train with RoBERTa$_B$				
Para	67.2	66.98	56.87	55.36
Train with RoBERTa$_L$				
WMD-1	65.44	65.27	57.11	52.55
WMD-3	72.55	70.38	62.55	61.33
Para	75.55	74.88	65.55	64.94

Table 6: Accuracy of paragraph and sentence premise representation reported on SVM, BERT$_B$, RoBERTa$_B$ and RoBERTa$_L$

Results and Analysis: We find that training with the INFOTABS training set improves model performance significantly over the previous baselines, except for the simple SVM model which relies on unigrams and bigrams. We see that RoBERTa$_L$ outperforms its base variant and BERT$_B$ by around $\sim 9\%$ and $\sim 14\%$ respectively. Similar to the earlier observation, providing full premise is better than selecting a subset of sentences.

Importantly, α_2 and α_3 performance is worse than α_1, not only suggesting the difficulty of these data splits, but also showing that models overfit both lexical patterns (based on α_2) or domain-specific patterns (based on α_3).

Does training on premise encoded as structure help? Rather than linearizing the tables as sentences, we can try to encode the structure of the tables. We consider two representative approaches for this, TabFact and TabAttn, each associated with a different model as described in §6.2. The results for these experiments are listed in Table 7.

Premise	Dev	α_1	α_2	α_3
	Train with BERT$_B$			
TabFact	63.67	64.04	53.59	49.05
	Train with RoBERT$_B$			
TabFact	68.06	66.7	56.87	55.26
	Train with RoBERTa$_L$			
TabAttn	63.63	62.94	49.37	49.04
TabFact	77.61	75.06	69.02	64.61

Table 7: Accuracy on structured premise representation reported on BERT$_B$, RoBERTa$_B$ and RoBERTa$_L$

Results and Analysis: The idea of using this family of models was to leverage the structural aspects of our data. We find that the TabAttn model, however, does not improve the performance. We assume that this might be due to the bag of words style of representation that the classifier employs. We find, however, that providing premise structure information helps the TabFact model perform better than the RoBERTa$_L$+Para model. As before model performance drops for α_2 and α_3.

How many types of reasoning does a trained system predict correctly? Using a RoBERTa$_L$, which was trained on the paragraph (Para) representation, we analyzed the examples in Dev and α_3 data splits that were annotated by experts for their types of reasoning (§5). Figure 3 shows the summary of this analysis.

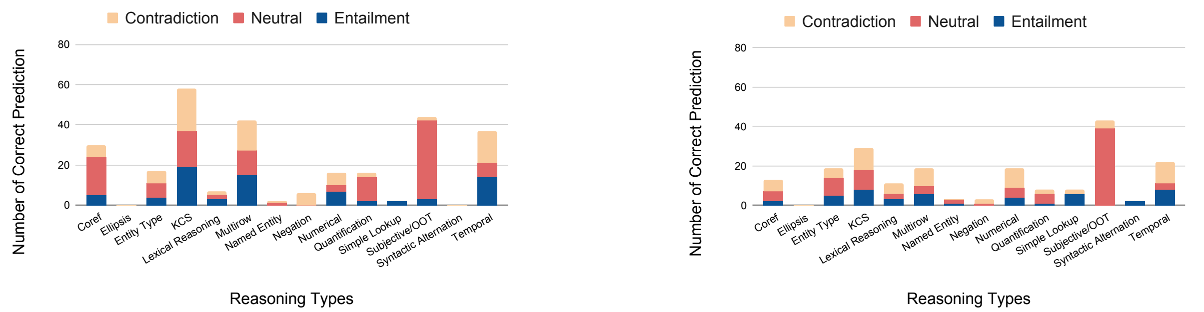
Results and Analysis: Figures 3a and 3b show the histogram of reasoning types among correctly predicted examples. Compared to Figures 2a and 2b, we see a decrease in correct predictions across all reasoning types for both Dev and α_3 sets. In particular, in the Dev set, the model performs poorly for the knowledge & common sense, multi-row, coreference, and temporal reasoning categories.

Discussion Our results show that: 1) INFOTABS contains a certain amount of artifacts which transformer-based models learn, but all models have a large gap to human performance; and 2) models accuracies drop on α_2 and α_3, suggesting that all three results together should be used to characterize the model, and not any single one of them. All our models are significantly worse than the human performance (84.04%, 83.88% and 79.33% for α_1, α_2 and α_3 respectively). With a difference of $\sim 14\%$ between our best model and the human performance, these results indicate that INFOTABS is a challenging dataset.

7 Related Work

NLI Datasets Natural language inference/textual entailment is a well studied text understanding task, and has several datasets of various sizes. The annual PASCAL RTE challenges (Dagan et al., 2005, *inter alia)* were associated with several thousands of human-annotated entailment pairs. The SNLI dataset (Bowman et al., 2015) is the first large scale entailment dataset that uses image captions as premises, while the MultiNLI (Williams et al., 2018) uses premises from multiple domains. The QNLI and WNLI datasets provide a new perspective by converting the SQuAD question answering data (Rajpurkar et al., 2016) and Winograd Schema Challenge data (Levesque et al., 2012) respectively into inference tasks. More recently, SciTail (Khot et al., 2018) and Adversarial NLI (Nie et al., 2019) have focused on building adversarial datasets; the former uses information retrieval to select adversarial premises, while the latter uses iterative annotation cycles to confuse models.

Reasoning Recently, challenging new datasets have emerged that emphasize complex reasoning. Bhagavatula et al. (2020) pose the task of determining the most plausible inferences based on observation (abductive reasoning). Across NLP, a lot of work has been published around different kinds of reasonings. To name a few, common sense (Talmor et al., 2019), temporal (Zhou et al., 2019), numerical (Naik et al., 2019; Wallace et al., 2019b) and



(a) Number of correct predictions per reasoning type in the Dev set

(b) Number of correct predictions per reasoning type in the α_3 test set

Figure 3: Number of correct predictions per reasoning type in the Dev and α_3 splits.

multi-hop (Khashabi et al., 2018) reasoning have all garnered immense research interest.

Tables and Semi-structured data Tasks based on semi-structured data in the form of tables, graphs and databases (with entries as text) contain complex reasoning (Dhingra et al., 2019; Chen et al., 2020). Previous work has touched upon semantic parsing and question answering (e.g., Pasupat and Liang, 2015; Khashabi et al., 2016, and references therein), which typically work with tables with many entries that resemble database records.

Our work is most closely related to TabFact (Chen et al., 2020), which considers database-style tables as premises with human-annotated hypotheses to form an inference task. While there are similarities in the task formulation scheme, our work presents an orthogonal perspective: (i) The Wikipedia tables premises of TabFact are homogeneous, i.e., each column in a table has structural redundancy and all entries have the same type. One can look at multiple entries of a column to infer extra information, e.g., all entries of a column are about locations. On the contrary, the premises in our dataset are heterogeneous. (ii) TabFact only considers entailment and contradiction; we argue that inference is non-binary with a third "undetermined" class (neutrals). (iii) Compared to our multi-faceted reasonings, the reasonings of the hypotheses in TabFact are limited and mostly numerical or comparatives. (iv) The α_2 and α_3 sets help us check for annotation and domain-specific artifacts.

Artifacts Recently, pre-trained transformer-based models (Devlin et al., 2019; Radford et al., 2019; Liu et al., 2019, and others) have seemingly outperformed human performance on several NLI tasks (Wang et al., 2019b,a). However, it has been shown by Poliak et al. (2018); Niven and Kao (2019); Gururangan et al. (2018); Glockner et al. (2018); Naik et al. (2018); Wallace et al. (2019a) that these models exploit spurious patterns (artifacts) in the data to obtain good performance. It is imperative to produce datasets that allow for controlled study of artifacts. A popular strategy today is to use adversarial annotation (Zellers et al., 2018; Nie et al., 2019) and rewriting of the input (Chen et al., 2020). We argue that we can systematically construct test sets that can help study artifacts along specific dimensions.

8 Conclusion

We presented a new high quality natural language inference dataset, InfoTabS, with heterogeneous semi-structured premises and natural language hypotheses. Our analysis showed that our data encompasses several different kinds of inferences. InfoTabS has multiple test sets that are designed to pose difficulties to models that only learn superficial correlations between inputs and the labels, rather than reasoning about the information. Via extensive experiments, we showed that derivatives of several popular classes of models find this new inference task challenging. We expect that the dataset can serve as a testbed for developing new kinds of models and representations that can handle semi-structured information as first class citizens.

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A Examples of Data

Figure 4 shows two additional examples of table premises and their corresponding hypotheses available in the development set of INFOTABS.

Kamloops	
Type	Elected city council
Mayor	Ken Christian
Governing body	Kamloops City Council
MP	Cathy McLeod
MLAs	Peter Milobar, Todd Stone

H1: Kamloops has a democracy structure.
H2: If Ken Christian resigns as Mayor of Kamloops then Cathy McLeod will most likely replace him.
H3: Kamloops is ruled by a president.

Jefferson Starship	
Origin	San Francisco California
Genres	Rock, hard rock, psychedelic rock, progressive rock, soft rock
Years active	1970 - 1984, 1992 - present
Labels	RCA Grunt Epic
Associated acts	Jefferson Airplane Starship, KBC Band, Hot Tuna
Website	www.jeffersonstarship.net

H1: Jefferson Starship was started on the West Coast of the United States.
H2: Jefferson Starship won many awards for its music.
H3: Jefferson Starship has performed continuously since the 1970s.

Figure 4: Two semi-structured premises (the tables), and three hypotheses (H1: entailment, H2: Neutral, and H3: contradiction) that correspond to each table.

B Reasoning for INFOTABS

Our inventory of reasoning types is based on GLUE diagnostics (Wang et al., 2019b), but is specialized to the problem of reasoning about tables. Consequently, some categories from GLUE diagnostics may not be represented here, or may be merged into one category.

We assume that the table is correct and complete. The former is always true for textual entailment, where we assume that the premise is correct. The latter need not be generally true. However, in our analysis, we assume that the table lists all the relevant information for a field. For example, in a table for a music group as in Figure 4, if there is a row called **Labels**, we will assume that the labels listed in that row are the only labels associated with the group.

Note that a single premise-hypothesis pair may be associated with multiple types of reasoning. If the same reasoning type is employed multiple times in the same pair, we only mark it once.

Simple lookup This is the simple case where there is no reasoning, and the hypothesis is formed by literally restating information in the table. For example, using the table in Figure 5, *Femme aux Bras Croisés is privately held.* is a simple lookup.

Multi-row reasoning Multiple rows in the table are needed to make an inference. This has the strong requirement that without multiple rows, there is no way to arrive at the conclusion. Exclude instances where multiple rows are used only to identify the type of the entity, which is then used to make an inference. The test for multi-row reasoning is: If a row is removed from the table, then the label for the hypothesis may change.

Entity type Involves ascertaining the type of an entity in question (perhaps using multiple rows from the table), and then using this information to make an inference about the entity.

This is separate from multi-row reasoning even if discovering the entity type might require reading multiple rows in the table. The difference is a practical one: we want to identify how many inferences in the data require multiple rows (both keys and values) separately from the ones that just use information about the entity type. We need to be able to identify an entity and its type separately to decide on this category. In addition, while multi-row reasoning, by definition, needs multiple rows, entity type may be determined by looking at one row. For instance, looking at Figure 5, one can infer that the entity type is a *painting* by only looking at the row with key value **Medium**. Lastly, ascertaining the entity type may require knowledge, but if so, then we will not explicitly mark the instance as Knowledge & Common Sense. For example, knowing that SNL is a TV show will be entity type and not Knowledge & Common Sense.

Femme aux Bras Croisés	
Artist	Pablo Picasso
Year	1901-02
Medium	Oil on canvas
Dimensions	81 cm 58 cm (32 in 23 in)
Location	Privately held

Figure 5: An example premise

Lexical reasoning Any inference that can be made using words, independent of the context of the words falls. For example, knowing that dogs are animals, and alive contradicts dead would fall into the category of lexical reasoning. This type of reasoning includes substituting words with their synonyms, hypernyms, hyponyms and antonyms. It also includes cases where a semantically equivalent or contradicting word (perhaps belonging to a different root word) is used in the hypothesis., e.g., replacing understand with miscomprehend. Lexical reasoning also includes reasoning about monotonicity of phrases.

Negation Any explicit negation, including morphological negation (e.g., the word *affected* being mapped to *unaffected*). Negation changes the morphology without changing the root word, e.g., we have to add an explicit *not*.

This category includes double negations, which we believe is rare in our data. For example, the introduction of the phrase *not impossible* would count as a double negation. If the word *understand* in the premise is replaced with *not comprehend*, we are changing the root word (understand to comprehend) and introducing a negation. So this change will be marked as both Lexical reasoning and Negation.

Knowledge & Common Sense This category is related to the World Knowledge and Common Sense categories from GLUE. To quote the description from GLUE: "...the entailment rests not only on correct disambiguation of the sentences, but also application of extra knowledge, whether it is concrete knowledge about world affairs or more common-sense knowledge about word meanings or social or physical dynamics."

While GLUE differentiates between world knowledge and common sense, we found that this distinction is not always clear when reasoning about tables. So we do not make the distinction.

Named Entities This category is identical to the Named Entities category from GLUE. It includes an understanding of the compositional aspect of names (for example, knowing that the *University of Hogwarts* is the same as Hogwarts). Acronyms and their expansions fall into this category (e.g., the equivalence of *New York Stock Exchange* as *NYSE*).

Numerical reasoning Any form of reasoning that involves understanding numbers, counting, ranking, intervals and units falls under this group. This category also includes numerical comparisons and the use of mathematical operators to arrive at the hypothesis.

Temporal reasoning Any inferences that involves reasoning about time fall into this category. There may be an overlap between other categories and this one. Any numerical reasoning about temporal quantities and the use of knowledge about time should be included here. Examples of temporal reasoning:

- 9 AM is in the morning. (Since this is knowledge about time, we will only tag this as Temporal.)
- 1950 is the 20^{th} century.
- 1950 to 1962 is twelve years.
- Steven Spielberg was born in the winter of 1946. (If the table has the date—18th December, 1946—and the location of birth—Ohio, this sentence will have both knowledge & Common Sense and temporal reasoning. This is because one should be able to tell that the birth location is in the northern hemisphere (knowledge) and December is part of the Winter in the northern hemisphere (temporal reasoning)).

Coreference This category includes cases where expressions refer to the same entity. However, we do not include the standard gamut of coreference phenomena in this category because the premise is not textual. We specifically include the following phenomena in this category: Pronoun coreference, where the pronoun in a hypothesis refers to a noun phrase either in the hypothesis or the table. E.g., *Chris Jericho lives in a different state than he was born in.* A noun phrase (not a named entity) in the hypothesis refers to a name of an entity in the table. For example, the table may say that *Bob has three children, including John* and the hypothesis says that *Bob has a son*. Here the phrase *a son* refers to the name *John*.

If there is a pronoun involved, we should not treat it as entity type or knowledge even though knowledge may be needed to know that, say, *Theresa May* is a woman and so we should use the pronoun *she*.

To avoid annotator confusion, when two names refer to each other, we label it only as the Named Entities category. For example, if the table talks about *William Henry Gates III* and the hypothesis describes *Bill Gates*, even though the two phrases do refer to each other, we will label this as Named Entities.

Quantification Any reasoning that involves introducing a quantifier such as every, most, many, some, none, at least, at most, etc. in the hypothesis. This category also includes cases where prefixes such as multi- (e.g., *multi-ethnic*) are used to summarize multiple elements in the table.

To avoid annotator confusion, we decide that the mere use of quantifiers like most and many is quantification. However, if the quantifier is added after comparing two numerical values in the table, the sentence is labeled to have numerical reasoning as well.

Subjective/Out of table Subjective inferences refer to any inferences that involve either value judgment about a proposition or a qualitative analysis of a numerical quantity. Out of table inferences involve hypotheses that use extra knowledge that is neither a well known universal fact nor common sense. Such hypotheses may be written as factive or implicative constructions. Below are some examples of this category:

- Based on a table about Chennai: *Chennai is a very good city.*
- If the table says that John's height is 6 feet, then the hypothesis that *John is a tall person.* may be subjective. However, if John's

height is 8 feet tall, then the statement that *John is tall.* is no longer subjective, but common sense.

- If the table only says that John lived in Madrid and Brussels, and the hypothesis is *John lived longer in Madrid than Brussels.* This inference involves information that is neither well known nor common sense.

- Based on the table of the movie Jaws, the hypothesis *It is known that Spielberg directed Jaws* falls in this category. The table may contain the information that Spielberg was the director, but this may or may not be well known. The latter information is out of the table.

Syntactic Alternations This refers to a catch-all category of syntactic changes to phrases. This includes changing the preposition in a PP, active-passive alternations, dative alternations, etc. We expect that this category is rare because the premise is not text. However, since there are some textual elements in the tables, the hypothesis could paraphrase them.

This category is different from reasoning about named entities. If a syntactic alternation is applied to a named entity (e.g., *The Baltimore City Police* being written as *The Police of Baltimore City*), we will label it as a Named Entity if, and only if, we consider both phrases as named entities. Otherwise, it is just a syntactic alternation. Below are some examples of this category:

- *New Orleans police officer* being written as *police officer of New Orleans*.

- *Shakespeare's sonnet* being written as *sonnet of Shakespeare*.

Ellipsis This category is similar in spirit to the category Ellipsis/Implicits in GLUE: "An argument of a verb or another predicate is elided in the text, with the reader filling in the gap." Since in our case, the only well-formed text is in the hypothesis, we expect such gaps only in the hypothesis. (Compared to GLUE, where the description makes it clear that the gaps are in the premises and the hypotheses are constructed by filling in the gaps with either correct or incorrect referents.). For example, in a table about Norway that lists the per capita income as $74K, the hypothesis that *The per capita income is $74K.* elides the fact that this is about citizens of Norway, and not in general.

C INFOTABS Worker Analysis

Figure 6 shows the number of examples annotated by frequent top-n workers. We can see that the top 40 annotators annotated about 90% of the data. This observation is concordant with other crowd-sourced data annotation projects such as SNLI and MultiNLI (Gururangan et al., 2018).

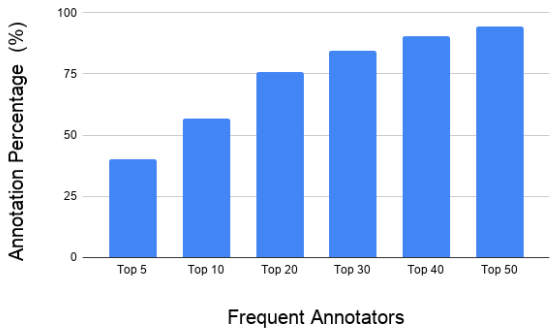

Figure 6: Number of annotations by frequent annotators

D INFOTABS Dataset Statistics

In this section, we provide some essential statistics that will help in a better understanding of the dataset.

Table 8 shows a split-wise analysis of premises and annotators. The table shows that there is a huge overlap between the train set and the other splits except α_3. This is expected since α_3 is from a different domain. Also, we observe that tables in α_3 are longer. In the case of annotators, we see that most of our dataset across all splits was annotated by the same set of annotators.

Table 9 presents information on the generated hypotheses. The table lists the average number of words in the hypotheses. This is important because a dissimilar mean value of words would induce the possibility of length bias, i.e., the length of the sentences would be a strong indicator for classification.

Table 10 shows the overlap between hypotheses and premise tables across various splits. Stop words like *a, the, it, of,* etc. are removed. We observe that the overlap is almost similar across labels.

Table 11 and 12 show the distribution of table categories in each split. We accumulate all the categories occurring for less than 3% for every split into the "Other" category.

Split	Train	Dev	α_1	α_2	α_3
Number of Unique Keys	1558	411	466	332	409
Number of Unique Keys Intersection with Train	-	334	312	273	94
Average # of keys per table	8.8	8.7	8.8	8.8	13.1
Number of Distinct Annotators	121	35	37	31	23
Annotator Intersection with Train	-	33	37	30	19
Number of Instances annotated by a Train annotator	-	1794	1800	1797	1647

Table 8: Statistics of the premises and annotators across all discussed train-test splits

Label	Train	Dev	α_1	α_2	α_3
Entail	9.80	9.71	9.90	9.33	10.5
Neutral	9.84	9.89	10.05	9.59	9.84
Contradict	9.37	9.72	9.84	9.40	9.86

Table 9: Mean length of the generated hypothesis sentences across all discussed train-test splits (standard deviation is in range 2.8 to 3.5)

Label	Train	Dev	α_1	α_2	α_3
Entail	0.52	0.47	0.45	0.46	0.48
Neutral	0.46	0.44	0.44	0.49	0.46
Contradict	0.44	0.43	0.45	0.44	0.46

Table 10: Mean statistic of the hypothesis sentences word overlapped with premises tables across all discussed train-test splits (standard deviation is in range 0.17 to 0.22)

Category	Train	Dev	α_1	α_2
Person	23.68	27	28.5	35.5
Musician	14.66	19	18.5	22.5
Movie	10.17	10	9	11.5
Album	9.08	7	3.5	4.5
City	8.05	8.5	8	7
Painting	5.98	4.5	4	3.5
Organization	4.14	2	1	0.5
Food / Drinks	4.08	4	4	3
Country	3.74	6	9	3.5
Animal	3.56	4.5	4	4
Sports	4.6	3.5	2.5	0.0
Book	2.18	0.5	3	2.5
Other	6.07	8.00	5.00	2.00

Table 11: Categories for all data splits (excluding α_3) in percentage (%). Others ($< 3\%$) include categories such as University, Event, Aircraft, Product, Game, Architecture, Planet, Awards, Wineyard, Airport, Language, Element, Car

E F1 Score Analysis

The F1 scores per label for two model baselines are in Table 13. We observe that neutral is easier than entailment and contradiction for both baseline, which is expected as neutrals are mostly associated with subjective/out-of-table reasonings which makes them syntactically different and easier to predict correctly. Despite this, we found that in all evaluations in (§6) (except for α_2 test set), our models found neutrals almost as hard as the other two labels, with only an $\sim 3\%$ gap between the F-scores of the neutral label and the next best label. For α_2 test set neutral are much easier than entailment and contradiction. This is expected as entailment and contradiction in α_2 were adversarially flipped; hence, these predictions become remarkably harder compared to neutrals. Furthermore, α_3 is the hardest data split, followed by α_2 and α_1.

Category	α_3 (%)
Diseases	20.4
Festival	17.41
Bus / Train Lines	14.93
Exams	8.46
Element	4.98
Air Crash	3.98
Bridge	3.98
Disasters	3.48
Smartphone	3.48
Other	18.9

Table 12: Categories for α_3 datasplit. Others ($< 3\%$) include categories such as Computer, Occupation, Restaurant, Engines, Equilibrium, OS, Cloud, Bus/Train Station, Coffee House, Cars, Bus/Train Provider, Hotel, Math, Flight

Premise as Paragraph			
Split	Entailment	Neutral	Contradiction
Dev	76.19	79.02	72.73
α_1	74.69	77.85	69.85
α_2	57.06	80.36	62.14
α_3	65.27	66.06	61.61
Premise as TabFact			
Split	Entailment	Neutral	Contradiction
Dev	77.69	79.45	74.77
α_1	76.43	80.34	73.07
α_2	55.34	80.83	64.44
α_3	65.92	67.28	63.57

Table 13: F1 Score (%) with various baselines. All models are trained with RoBERTa$_L$

F Statistics of InfoTabS Verification

Table 14 shows the detailed agreement statistics of verification for the development and the three test splits. For every premise-hypothesis pair, we asked five annotators to verify the label. The table details the verification agreement among the annotators, and also reports how many of these majority labels match the gold label (i.e., the label intended by the author of the hypothesis). We also report individual annotator label agreement by matching the annotator's label with the gold label and majority label for an example. Finally, the table reports the Fleiss Kappa (across all five annotation labels) and the Cohen Kappa (between majority and gold label) for the development and the three test splits.

We see that, on average, about 84.8% of individual labels match with the majority label across all verified splits. Also, an average of 75.15% individual annotations also match the gold label across all verified splits.

From Table 14, we can calculate the percentage of examples with at least 3, 4, and 5 label agreements across 5 verifiers for all splits. For all splits, we have very high inter-annotator agreement of >95.85% for at-least 3, > 74.50% for at-least 4 and 43.91% for at-least 5 annotators. The number of these agreements match with the gold label are: >81.76% for at-least 3, > 67.09% for at-least 4 and 40.85% for at-least 5 for all splits.

Exact agreement between annotators		
Dataset	**Number**	**Gold/Total**
Dev	3	350 / 469
	4	529 / 601
	5	550 / 605
	no agreement	116
α_1	3	184 / 292
	4	459 / 533
	5	863 / 922
	no agreement	45
α_2	3	245 / 348
	4	453 / 537
	5	812 / 857
	no agreement	58
α_2	3	273 / 422
	4	441 / 524
	5	706 / 765
	no agreement	79
Individual agreement with gold / majority label		
Dataset	**Statistics**	**Agreement (%)**
Dev	Gold	71.12
	Majority	81.65
α_1	Gold	78.52
	Majority	87.24
α_2	Gold	77.74
	Majority	86.32
α_3	Gold	73.22
	Majority	84.01
Average	Gold	75.15
	Majority	84.8
Kappa values across splits		
Dataset	**Fleiss**	**Cohen**
Dev	0.4601	0.7793
α_1	0.6375	0.7930
α_2	0.5962	0.8001
α_3	0.5421	0.7444

Table 14: Exact, Individual and Kappa values for verification's statistics.