Abstract

To truly grasp reasoning ability, a Natural Language Inference model should be evaluated on counterfactual data. TABPERT facilitates this by assisting in the generation of such counterfactual data for assessing model tabular reasoning issues. TABPERT allows a user to update a table, change its associated hypotheses, change their labels, and highlight rows that are important for hypothesis classification. TABPERT also captures information about the techniques used to automatically produce the table, as well as the strategies employed to generate the challenging hypotheses. These counterfactual tables and hypotheses, as well as the metadata, can then be used to explore an existing model’s shortcomings methodically and quantitatively.

1 Introduction

Given the factual evidence, a crucial part of NLP model reasoning capacity is if it can evaluate whether a given hypothesis is an entailment (true), contradiction (false), or neutral (can’t be determined). Current transformers-based models have been shown to outperform humans on these tasks when the evidence is presented as simple unstructured text (Wang et al., 2018, 2019); however, when tested with semi-structured evidence (Gupta et al., 2020; Chen et al., 2019), such as tables, as shown in Figure 1, the very same models struggled to match human accuracy (Neeraja et al., 2021; Wang et al., 2021; Aly et al., 2021).

Furthermore, there can be several reasons for a model’s correct predictions on a particular example. For example, Poliak et al. (2018); Gururangan et al. (2018) show that multiple NLI datasets, such as SNLI and MNLI dataset (Bowman et al., 2015; Williams et al., 2018) exhibit hypothesis-bias, i.e., the hypothesis-only model performs significantly better than the majority label baseline. In the context of tables, Gupta et al. (2020) shows that the right prediction doesn’t always imply reasoning: there can be dataset biases in semi-structured datasets too, such as hypothesis or premise artifacts (spurious patterns) which can wrongly support a particular label.

Furthermore, a model can also ignore the ground evidence and use its pre-trained knowledge for making predictions. These models when deployed in the real world on out-of-domain (different category) or counterfactual (stories tables) examples fail embarrassingly. One way to avoid this inflated performance projection is to test models on several challenging sets before actual deployment. For example, Gupta et al. (2020) evaluate the RoBERTa_{Large} (Liu et al., 2019) models on two additional adversarial sets (hypothesis perturbed and out-of-domain) and observe a significant performance drop. However, manually creating such challenge sets can be tricky, both in terms of the annotation cost involved and the actual annotation process, especially with tabular data of semi-structured nature.

Recently, Ribeiro et al. (2020a) showed that one can deploy simple tricks to semi-automate this process and develop several adversarial counterfactual contrast sets by altering existing data to perform behavioral testing of a model. However, such tricks...
currently only work for unstructured text and cannot be directly adopted for semi-structured text such as tables. To fill this gap, in this work, we present TABPert. TABPert which is an annotation platform especially designed to work on semi-structured tabular data. TABPert supports semi-automatic creation of tabular counterfactual data. Through TABPert annotators can modify tables in several ways such as (a) deleting information: deleting an attribute-value pair or an existing row completely, (b) inserting information: inserting an attribute-value pair for an existing row or creating a fresh row, (c) modifying information: editing the attribute or values cells of an existing row, and (d) modifying hypothesis or label: modifying an existing hypothesis and its inference label.

TABPert also automatically logs the modification operation for each attribute-value of the table with respect to the original table. Furthermore, users can manually log information about the relevant rows and the strategy used for perturbing a table-hypothesis pair, in addition to the gold label, through TABPert. Such metadata is very important in assessing annotated data toughness and can be later utilised to systematically study failure modes of a model.

The contributions of our work can be summarised as below:

1. TABPert can delete, modify, and insert information in semi-structured tabular data for creating counterfactual examples
2. TABPert auto-logs table perturbation metadata, and support manual hypothesis modification and inference labels selection.
3. TABPert assists users in logging metadata including hypothesis-related rows and the perturbation strategy used, which is useful for data and model quantitative analysis
4. We present a case study for TABPert via the generation and evaluation of a counterfactual INFOTABS dataset and models respectively.

The TABPert source code, the annotated counterfactual INFOTABS dataset, along with the RoBERTaLarge model, the annotation instructions and examples set, and all other associated scripts, are available at https://github.com/utahnlp/tabpert. The instruction video describing TABPert usage is accessible at https://www.youtube.com/watch?v=sbCH_zD53Kg.

2 Tables are Challenging

One might argue that creating a counterfactual dataset for tables is not a challenging task, and that table modification can be fully automated by merely ‘shuffling’ or ‘inserting’ attribute values of one table row into another table row (with the same attribute) as long as they are from similar categories, e.g. shuffle ‘producer’ of one film with ‘producer’ of another film). One can extend this further by shuffling rows with different attributes in the same as well as different tables (same category) as long as the name-entity type for values are similar, e.g. shuffle ‘producer’ with the ‘director’ of the same or a different film with each other.

However, this approach does not automate the modification of corresponding hypotheses and their inference labels. Furthermore, such automatic shuffling encourages the violation of certain natural common-sense logical constraints, such as a person’s ‘Birth Date’ must be before their ‘Died Date’, a person’s ‘Marriage Date’ should be after their ‘Birth Date’ and before their ‘Died Date’, an album’s ‘Released Date’ should be after its ‘Recording date’ and so on. Without the enforcement of these constraints, the table will be self-contradictory. While some of these constraints can be automatically satisfied and hence not violated, a majority still slip through because of their sheer variety and variation. \(^1\). Furthermore, enforcing these constraints automatically during perturbation is a challenging job due to its domain-specific nature. However, such automatic perturbations can be a good initialization for our TABPert tables, which can then be manually inspected and modified by human annotators for self-consistency i.e. no natural common sense violation.

3 TABPert Functions, Aspects, and Usability

TABPert is currently supported on common web browsers such as Google Chrome and can be installed to run locally. \(^2\). There are three main steps required for successful annotation, as described below.

3.1 Automatic Initialization

First, we initialise TABPert with original tables and automatic counterfactual tables generated via

\(^1\)In real data, these constraints are naturally satisfied.
\(^2\)Details: https://github.com/utahnlp/tabpert
automatic ‘shuffling’ of table rows or attribute values. Automatic initialization is beneficial as manual table creation is both time-consuming and highly error-plausible. This automatic shuffling operation is stored as a metadata of each attribute-value in the first 4 bits of a 7-bit string, and can be used later to analyse which shuffling was more effective. Table 1 shows the meaning of each of these bits. Counterfactual hypothesis (and label) initialization is done by copying the information from the original table exactly.

### 3.2 Modifying Tables

The automatically perturbed tables from initialization can now be manually modified to create counterfactual examples. All the cells (attributes and values) in the three counterfactual tables can be edited. Table rows can be modified via the dragging and dropping of a value cell from (a) same counterfactual table (cut-paste effect), (b) from another counterfactual table (cut-paste effect), (c) from the original table (copy-paste effect). To minimise errors during this drag-and-drop operation, a type validation check runs in the background, which prevents a drag and drop between different key categories (for example, it is forbidden to drag a Person Name into Date of Birth). To achieve such type-check, keys are automatically grouped using category (entity type) information during initialization.

TABPERT also supports five additional functions for more challenging edits. The ‘Add’ box allows annotators to write text and drag and drop it into a table to create a new value. For deleting a value cell, simply drag and drop the value cell to the ‘Delete’ Box. One can also edit the text for an existing attribute or value via clicking it. Lastly, one can delete any row with the ‘Edit’ option, and also insert a new row and its details using the ‘Add Section’ button. These modification details are also recorded automatically in the last 3 bits of the 7-bit metadata. The 5th bit represents copy-paste from original, the 6th represents a new cell or row addition, and the last 7th bit represents a value update operation. Figure 2a shows the main parts of the TABPERT platform for counterfactual table perturbation.

### 3.3 Hypothesis Modification and Metadata

The text of a hypothesis of a counterfactual table can be edited directly and its corresponding label can also be selected from drop-down menu options. In addition to this, other metadata information is also collected:

1. The strategies used by the annotator to modify the hypothesis. The five main strategies can be selected using the multi-value check-box. The ‘Other’ option corresponds to hypothesis changes that don’t fall into main strategies.

2. All the relevant rows of the table which are necessary for deciding the inference label.

Figure 2b shows the main TABPERT view for hypothesis modification, with hypothesis and inference label. Metadata is inserted by the annotator via clicking ‘+’ symbol on the left side (below label drop-down) for each hypothesis, as shown in Figure 2b. This opens a metadata collection window, as shown in 2c). Here too, we use 6 bits: the initial five for each strategy (bits order is the same as the order in which the strategies are mentioned in TABPERT as shown Figure 2c), and the last one for the ‘Other’ option. We store the relevant rows ‘attribute keys’ in a list (array) for each hypothesis along with the final hypothesis text modification.

**TABPERT Aspects:** The TABPERT web-app’s core tech stack consists of ReactJS and Flask. Here, Flask is used as the main back-end Python web framework, and javascript library ReactJS is used for the front-end. We used Flask because it is easy-to-extend, giving us the ability to easily integrate Python libraries for quick manipulation of JSON and TSV files. We used ReactJS because of

| Bit | Location | Same | Different |
|-----|----------|------|-----------|
| 1   | Dataset  | 0    | 1         |
| 2   | Category | 0    | 1         |
| 3   | Table    | 0    | 1         |
| 4   | Key      | 0    | 1         |

Table 1: First Four Bits of Table Value Metadata. The 1st bit represent the perturb value table location i.e. whether it is coming from the Train set (1) or the Test set (0), the 2nd bit indicates the different (1) or same (0) category, the 3rd bit represents if the value is from the same (0) or different (1) table (for same table, 1st and 2nd bit is always zero), and the 4th represents same (0) or different (1) attribute.

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3 For same table i.e. 3rd bit 0, the 1st and 2nd bits are zero
4 Also to avoid self-contradiction or inconsistency.
5 Original table is fixed to prevent inadvertent edits
6 Keys for which a category information is missing can be dropped without restriction.

7 [https://reactjs.org/](https://reactjs.org/)
8 [https://flask.palletsprojects.com/en/2.0.x/](https://flask.palletsprojects.com/en/2.0.x/)
(a) **Table Perturbation:**
1. **Table Title**
2. **Values**
3. **Key** (table section name)
4. **Edit Section Name or Delete Section**
5. **Add New Value**
6. **Delete Value**
7. **Add New Section**

```
| Original Table | Table A | Table B | Table C |
|----------------|---------|---------|---------|
| **Country of origin** | United States, United Kingdom | Salzburg, Austria | Poland |
| **Introduced** | 2005, 2007 | 2003 | Southern California, 2008 |
| **Manufacturer** | The Coca-Cola Company | Hood River Companies | The Coca-Cola Company |
| **Related products** | Coca-Cola with Lemon | ESB, London Pride, Honey Dew | Related products |
| **Type** | Lime flavoured, citrus flavoured cola Cola | Diet Cola | | Type |
| **Variants** | grape, Kops Fruit | | | | Variants |
| **Table C** | | | | |
| **Country of origin** | | | | |
| **Introduced** | | | | |
| **Manufacturer** | | | | |
| **Related products** | | | | |
| **Type** | | | | |
| **Variants** | | | | |
```

(b) **Hypotheses Perturbation:**
1. **Hypotheses Table Labels**
2. **Label of an Original Hypothesis**
3. **Label of a Counterfactual Hypothesis in Table A**
4. **Original Hypothesis**
5. **Counterfactual Hypothesis**
6. **Select Relevant Rows and Hypothesis Perturbation Strategies**
7. **Submit Button**

```
**Original Hypothesis:** Coca-Cola with Lime/Diet Coke with Citrus Zest was accidentally created when a manager mixed Lime, Tequila, and Coca-Cola together.

**Table A Hypothesis:** Coca-Cola with Lime/Diet Coke with Citrus Zest is only made in the United States.

**Table B Hypothesis:** Coca-Cola with Lime/Diet Coke with Citrus Zest has been introduced more than once.

**Table C Hypothesis:** Coca-Cola with Lime/Diet Coke with Citrus Zest is a British American beverage.

**Select Relevant Rows:**
- Country of origin (United States)
- Introduced (2005, 2007)
- Manufacturer (The Coca-Cola Company)
- Related products (Coca-Cola with Lemon)
- Type (Diet Cola)
- Variants (grape, Kops Fruit)

**Select Strategies:**
- Option to open Modal for Row (checkbox ticked)
- Option to save work

(c) **Selection of Relevant Rows and Hypothesis Perturbation Strategies:**
1. **Hypothesis**
2. **Table Label**
3. **Relevant Row (checkbox ticked)**
4. **Irrelevant Row (checkbox not ticked)**
5. **Option to open Modal for Row (checkbox ticked)**
6. **Submit Button**

```
Coca-Cola with Lime/Diet Coke with Citrus Zest is only made in the United States.

**Select Relevant Rows:**
- Country of origin (unselected)
- Introduced (selected)
- Manufacturer (selected)
- Related products (selected)
- Type (unselected)
- Variants (unselected)

**Select Strategies:**
- Option to open Modal for Row (unselected)
- Option to save work
```
We use the react-beautiful-dnd library\(^9\) essential for simulating the drag-and-drop function.

4 Case Study on INFO_TABS

We use TABPert to create counterfactual data for the INFO_TABS dataset (Gupta et al., 2020). INFO_TABS is a semi-structured natural language inference dataset which consists of entity tables and human-written hypotheses. For this we sampled 47 tables with 423 table-hypothesis pairs taken from the \(\alpha_1\) set of INFO_TABS. INFO_TABS stores each table as a JSON file with key-value as attribute (column 1) - value (column 2) of the table. For initialization we used both the \(Train\) and other \(\alpha_1\) set. Including both set creates more diversity and variation in automatic initialization\(^{10}\).

**Annotation Guidelines:** Following a similar line as earlier works by Ribeiro et al. (2020b); Sakaguchi et al. (2020) for creating challenging adversarial test-sets, we guided the annotators in annotating three counterfactual table (A, B, C) for each original \(\alpha_1\) table. This ensures enough diversity and coverage in the collected counterfactual data. We advised annotators to follow the below strategies for each counterfactual table: (a) For Table A: change the table in a way that it flips entail and contradict labels while keeping the hypothesis same, (b) For Table B: change the hypothesis in a way that it flips entail and contradict labels; modify the table as needed for the same, and (c) For Table C: write a new but related hypotheses with similar reasoning; one can modify table as needed.

Furthermore, for making the neutrals harder we advise annotators to modify them by adding extra ‘true’ information from the same table in the hypotheses. The above discussed procedure ensures that (a) the final label is balanced, (b) hypothesis bias is destroyed by flipped label (Gupta et al., 2020; Chen et al., 2019), and (c) ‘neutrals’ are now closer to ‘entails’ in terms of lexical overlap (Glockner et al., 2018). Finally, after annotation we have 109 counterfactual tables with a total of 982 table-hypothesis pairs, where Table A (141) type having 423, Table B (135) type having 405, and Table C type having 154 (52) pairs.

**Experiment and Analysis** 
To check if the annotated counterfactual data is challenging for existing model, we use INFO_TABS RoBERTa\(_\text{Large}\) ‘para’ representation and hypothesis-only model for making predictions on the original and counterfactual annotated data. Table 2 shows the performance result. The data was represented in ‘para’ form, one with all rows’ sentences (all Rows) and other with just relevant row sentences (coming from the annotation meta-data).

**Performance Analysis:** Clearly the same model struggles with the counterfactual annotated data. Furthermore, better performance with relevant rows for counterfactual data shows that the model is probably using irrelevant rows tokens as artifacts for making predictions (Neeraja et al., 2021). The hypothesis-only model performance on counterfactual data is close to majority-label baselines. Additionally, human find the original and counterfactual data equally challenging, obtaining performance of \(\approx 85\%\) on both sets. \(^{11}\)

| Model Type       | Original | Counterfact |
|------------------|----------|-------------|
| Majority         | 33.33    | 33.33       |
| Hypo Only        | 64.32    | 44.85       |
| All Rows         | 78.91    | 61.26       |
| Relevant Rows    | 74.11    | 65.85       |
| Human            | 84.8     | 85.8        |

Table 2: INFO_TABS RoBERTa\(_\text{Large}\) model with original and counterfactual annotated data.

**Perturbation Analysis:** We also do an analysis using the hypothesis annotation metadata to check which strategies of hypothesis modification is more effective. From Figure 3, it is evident that manual table change (TC) for Label Flip (LF) is more effective than manual hypothesis change (HC) for label flip (TF). Furthermore, strategies involving label flip is more effective then Hypothesis Prompt (Hypo Prompt) and text overlap. We suspect this is because of the ineffectiveness of hypothesis bias with flipped labels. Surprisingly, on new hypotheses, there is marginal performance improvement, indicating simple new data creation is an ineffective approach. Furthermore, there is no significant performance drop with any other perturbation approaches.

We also did a similar analysis on the table perturbation metadata; refer to appendix section A for details. We also show some qualitative example of counterfactual perturbation for each strategy in appendix section C.

\(^9\)https://www.npmjs.com/package/react-beautiful-dnd

\(^{10}\)As discussed earlier, annotators manually fix the constraint violations during annotation

\(^{11}\)No difference in performance between A, B, and C type counterfactual table-example pairs, see appendix Figure 4
Hypothesis Perturbation Strategy

| Other | NewHypo | HypoPrompt | Overlap | HC + LF | TC + LF | TC + HC + LF |
|-------|---------|------------|---------|---------|---------|--------------|
|       | 69.23   | 70.27      | 80.68   | 87.73   | 75.74   | 79.13        |
|       | 72.6    | 69.23      |         |         |         |              |

Accuracy Drop (Relative %)

| Other | NewHypo | HypoPrompt | Overlap | HC + LF | TC + LF | TC + HC + LF |
|-------|---------|------------|---------|---------|---------|--------------|
|       | -10     | 0          | 10      | 20      | 30      | 40            |

Figure 3: Performance drop after counterfactual perturbation with various strategies.

5 TABPERT Utility

Main Platform: TABPERT is a tool designed particularly for annotating counterfactual tabular reasoning data, and as such, it has numerous optimizations, tools, and features that aid in the creation and collection of huge amounts of data, as well as annotating it faster and better. It allows for a broader range of tasks than, perhaps, utilizing spreadsheets or MTurk to modify such data. The drag-and-drop functionality simplifies annotation, making it simple to visualize a complicated job. In tabular form, all of the data may be examined at once. The background type validation reduces mistakes while dragging and dropping.

Other Task Usage: The initialization source code, as well as the platform, are designed to be modular, so that new components can be readily added, deleted, and existing ones may be updated. For example, the ability to reorganize table parts; copying values across table triplets (in addition to cut-paste); and auto-saving work with an undo option\textsuperscript{12}, as well as checkpoints added to reverse mistakes, may all be readily implemented.

Meta-Data: The metadata collected might be used to generate challenging counterfactual adversarial test sets. For example, if a hypothesis comprises of shuffled rows from the train set and the original inference label is inverted, it might be a good candidate for evaluating NLI model overfitting. Furthermore, it is an excellent test for hypothesis artifacts if the hypothesis remains the same but the label is flipped. The hypotheses-specific rows can be used to reduce the table and explain the inference label reasoning. The marked labels can be utilized as the gold standard for existing label verification. Counterfactual tables may also be used to assess pre-trained knowledge overfitting. These are only a few examples of the numerous conceivable application situations.

We also compare and contrast TABPERT with Spreadsheet on effectiveness, visual benefits, and meta-data collection aspects in appendix section B.

6 TABPERT Limitations and Future

During our pilot study, the platform was run locally by the annotators. This was not problematic since the number of annotators was small and the tables were divided between them. We need to host our platform on a central server if we want multiple annotators to be able to make simultaneous edits for large-scale deployment. This is something which we plan to do in the near future. Lastly, the counterfactual data created by making changes had to be manually saved by pressing a button. This was done so that if the user made some mistake the original data would not be lost and the user could store the data after being satisfied with the changes. We wish to add a auto-save feature along with undo options to cater to both these scenarios.

7 Conclusions

We proposed TABPERT, a powerful platform for visualizing semi-structured tabular data and generating counterfactual tabular perturbations. This platform allows researchers to alter tables and hypothesis phrases as well as collect accompanying metadata in order to statistically and methodically examine the shortcomings of their systems. We hope that TABPERT will be useful for academics working on semi-structured data, such as tables. TABPERT may also be used in non-academic industrial settings that demand table change, such as e-commerce product specification tables, financial and tax statements tables, and so on.

\textsuperscript{12}Currently, the Save button must be pressed manually, however it can be pressed several times at different timestamp to save even semi-completed work.
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A Performance vs Perturbation

Figure 4 shows the model performance relative accuracy drop with variable table perturbation strategy. Analysing average accuracy across the A, B, and C counterfactual type, shows no significant difference. We also shows the number of examples for each hypothesis perturbation strategy and the relative accuracy drop in Figure 5 for each strategy.

B TABPERT vs Spreadsheet

Effectiveness: When utilizing spreadsheets for annotation, it becomes quite difficult and time consuming to cut(copy)-paste in numerous rows cells several times. However, the efficient drag(click)-drop with auto checking restrictions in TABPERT makes it a lot easier and faster procedure. Editing and text alteration are also easier than in a spreadsheet. Our study found that it takes around 7 minutes on average to annotate a new table with 9 statements using TABPERT, but the same work in the spreadsheet would take more than 40 minutes.

Visualisation Benefit: Our platform’s table visualisation provides a full data view on a single screen. Seeing the entire picture (table and sentences) is incredibly helpful for quality checking of annotations. It also allows the annotator to quickly follow label and hypothesis changes, which is not feasible with the spreadsheet’s cell type view.

Furthermore, having a single screen focus view on a single counterfactual table makes altering hypotheses even easy. Using this focus feature, it is straightforward to update the labels or add new information to the hypothesis. This focus view is not viable with a spreadsheet; to make appropriate alterations, one must search and navigate to each spreadsheet cell.

Finally, the lack of scrolling required while dragging and dropping on our platform saves annotators time. To discover the relevant cells in a spreadsheet, one must execute numerous scrolling operations to the up, down, left, or right.

Furthermore, in TABPERT, the cell size is automatically set according on the underlying information, but in spreadsheet, this must be handled manually.

Meta-Data Collection: TABPERT also makes it simple to gather information such as methods used to change a hypothesis and rows utilized to answer each hypothesis by simply utilizing a checkbox. In a spreadsheet, this would require 9 columns of check-boxes for each table or manually writing the metadata, which is now automatically done with a single click, thus making the process simpler, efficient and speedier.
### C Qualitative Counterfactual Perturbation Examples

Tables 3, 4, 5, 6, 7 illustrate the five strategies used for counterfactual table-hypothesis perturbation. In the After rows, the 7-bit meta-data associated with each value is also listed. The Automatic Initialisation row explains the meaning of the first four bits of this meta-data, and the Manual Editing row explains the last three bits.

| Premise | Hypothesis | Label | Predicted |
|---------|------------|-------|-----------|
| **Before (T14)** | Box Office 1. $61.3 million Budget 1. $26 million | Flatliners made over double what it cost to make at the box office. | E | E |
| **After (T14A)** | Box Office 1. $140.7 million (1010 010) Budget 1. $85 million (0111 010) | Flatliners made over double what it cost to make at the box office. | C | E |
| **Automatic Initialisation** | 1010: different dataset, same category, different table, same key 0111: same dataset, different category, different table, different key |
| **Manual Editing** | 010: value text edited |

Table 3: Example using Strategy 1
**Strategy:** Change table to flip label

| Premise | Hypothesis | Label | Predicted |
|---------|------------|-------|-----------|
| **Before (T14)** | Box Office 1. $61.3 million Budget 1. $26 million | Flatliners made over double what it cost to make at the box office. | E | E |
| **After (T14B)** | Box Office 1. $13.3 million (1010 010) Budget 1. $5.9 million (0110 010) | Flatliners made over triple what it cost to make at the box office. | C | E |
| **Automatic Initialisation** | 0110: same dataset, different category, different table, same key 1010: different dataset, same category, different table, same key |
| **Manual Editing** | 010: value text edited |

Table 4: Example using Strategy 2
**Strategy:** Change hypothesis to flip label
| Before (T14) | Premise | Hypothesis | Label | Predicted |
|-------------|---------|------------|-------|-----------|
| Produced by 1. Michael Douglas 2. Rick Bieber | Rick Bieber put more money into Flatliners than Michael Douglas did. | N | N |
| Directed by 1. Joel Schumacher | | | |
| After (T14A) | Produced by 1. Rick Bieber (0000 100) 2. Michael Douglas (0000 100) | Rick Bieber put more money into Flatliners directed by Empress Teimei, than Michael Douglas did | N | N |
| Directed by 1. Empress Teimei (1111 000) | | | |

| Automatic Initialisation | 0000: same dataset, same category, same table, same key 1111: different dataset, different category, different table, different key |
| Manual Editing | 000: no change 100: copied from the original table |

| Strategy: Add ‘true’ information from the table to confuse the model, or use text from other places in the table. |

| Before (T14) | Premise | Hypothesis | Label | Predicted |
|-------------|---------|------------|-------|-----------|
| Edited by 1. Robert Brown 2. Peter Filardi | Flatliners was Peter Filardi’s first writing credit. | N | N |
| Written by 1. Peter Filardi | | | |
| After (T14B) | Edited by 1. James Newton Howard (0000 100) 2. Robert Brown (0000 000) | Flatliners was mostly edited by Robert Brown. | N | E. |
| Written by 1. Lee Beom-seon (1110 000) | | | |

| Automatic Initialisation | 0000: same dataset, same category, same table, same key 1110: different dataset, different category, different table, same key |
| Manual Editing | 000: no change 100: copied from the original table |

| Strategy: Use the original hypothesis as a prompt to write a new hypothesis |

| Before (T14) | Premise | Hypothesis | Label | Predicted |
|-------------|---------|------------|-------|-----------|
| Box Office 1. $61.3 million | Flatliners made 50 million over it’s budget at the box office. | C | E |
| Budget 1. $26 million | | | |
| After (T14C) | Box Office 1. US$85.4 million (December 2017) (0111 000) | Flatliners costed around $25 million in making and was a hit. | E | C |
| Budget 1. $26 million (0000 000) | | | |

| Automatic Initialisation | 0000: same dataset, same category, same table, same key 0111: same dataset, different category, different table, different key |
| Manual Editing | 000: no change |

| Strategy: Write a completely new hypothesis |

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Table 5: Example using Strategy 3

Table 6: Example using Strategy 4

Table 7: Example using Strategy 5