

arXiVeri: Automatic table verification with GPT

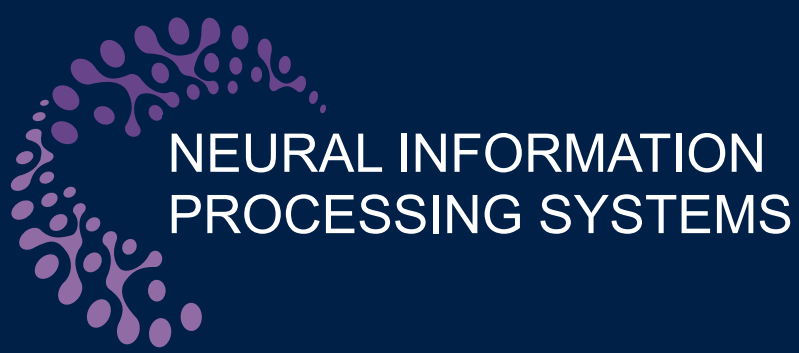
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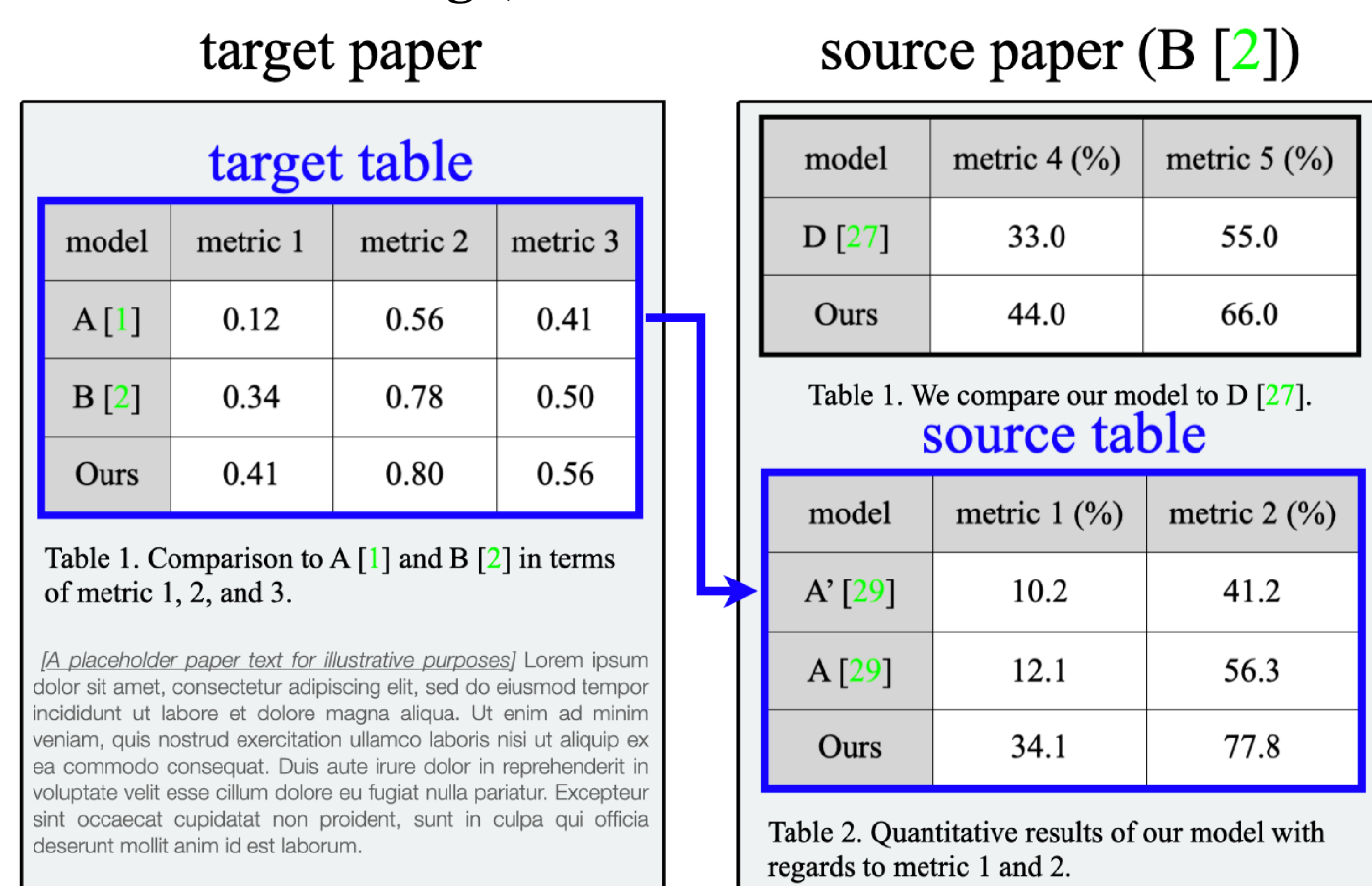
³Shanghai AI Laboratory, China

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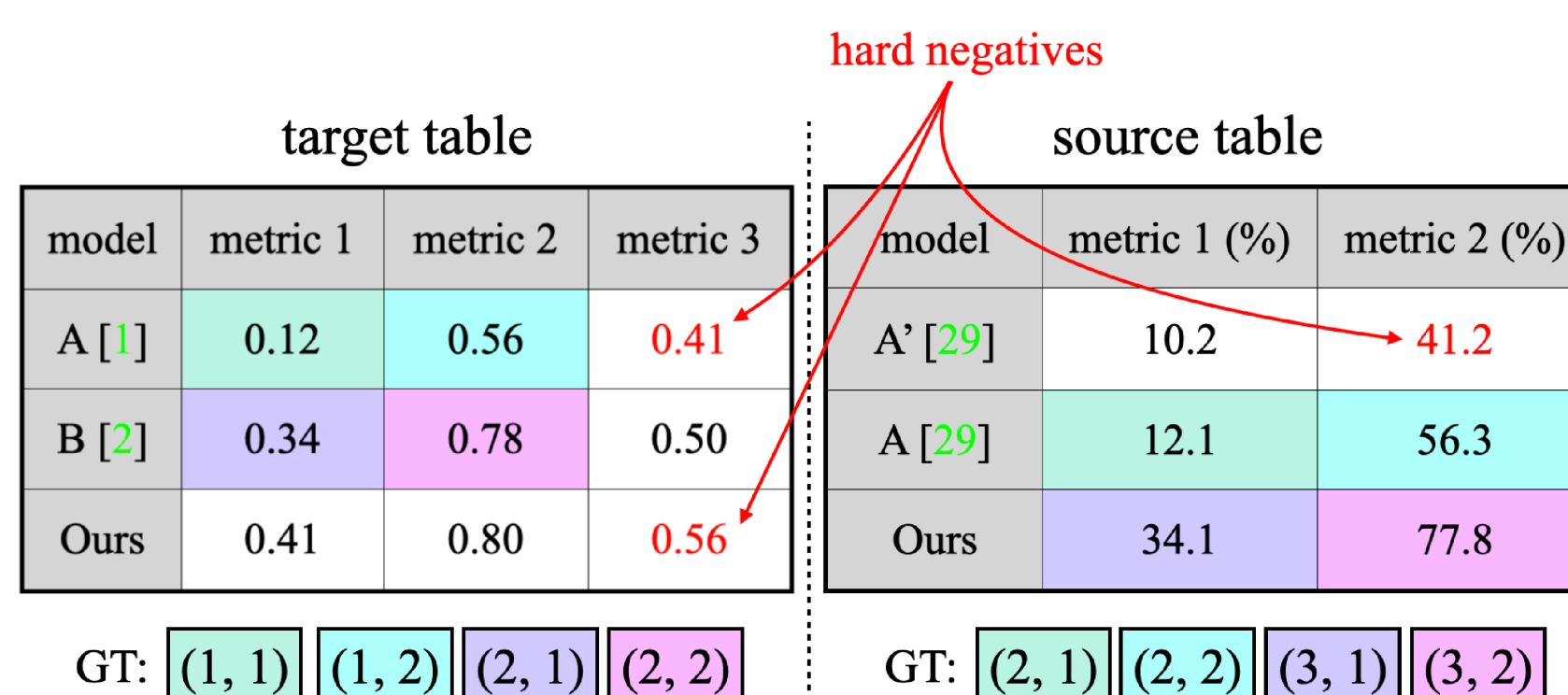


Automatic table verification Task

Researchers often manually transfer performance metrics between academic papers, a practical but error-prone process. To meet this challenge, automatic table verification aims to verify the numerical data in tables by cross-referencing cited sources.

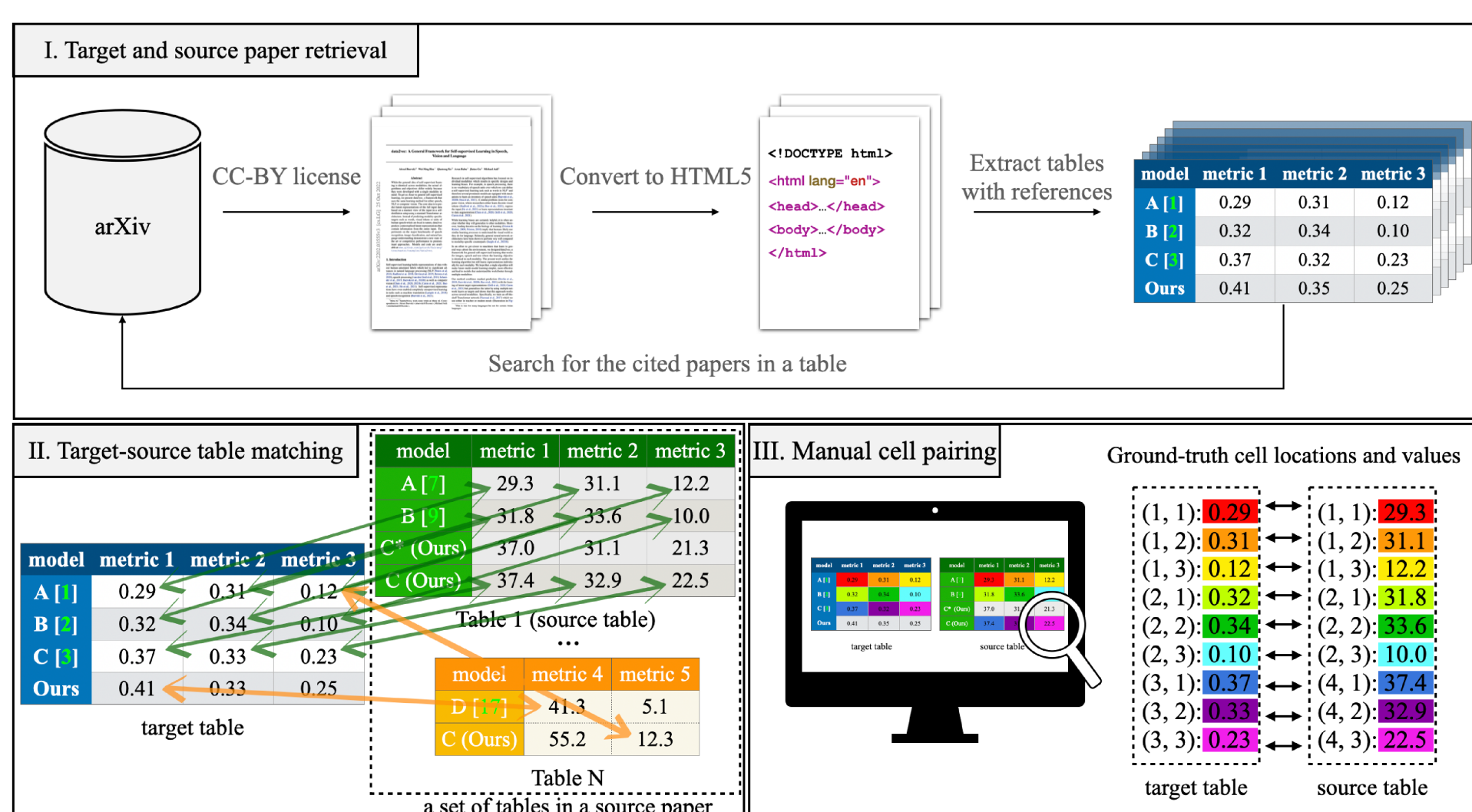


I. Table matching



II. Cell matching

arXiVeri benchmark



Metrics

- **Table matching accuracy** evaluates the verifier's ability to accurately identify a source table that matches a given target table, or to determine that no such source table exists in the cited document.
- **Cell matching recall** quantifies the percentage of target-source cell matches that are accurately identified (i.e., true positives) among a ground-truth set of cell matches across a source table and a target table.
- **Cell matching precision** measures how many target-source cell pairs are true positives among all the detected target-source cell pairs.

Text prompt for cell matching

Target-source cell matching

Input a target table (target_table), a source table (source_table)

System You are a helpful assistant.

User Compare the following target and source tables and identify cells that contain floating point numbers with the same meaning present in both tables. Return the matched cells in a Python dictionary with the following format:

```
{
  (target_table_row_index, target_table_column_index):
  (source_table_row_index, source_table_column_index),
  ...
}
```

Use 0-based indexing, including headers, rowspan, and colspan attributes. Locate as many matching cell pairs as possible. If no matches are found, return an empty dictionary ({}).

The target table and its caption: {target_table}

The source table and its caption: {source_table}

GPT-4 Answer

Qualitative example

Method	Supervised Metrics				Unsupervised Metrics		
	B@4	M	C	S	CLIP-S ^{Ref}	CLIP-S	PP
VinVL [60]	0.41	0.311	1.409	0.252	0.63	0.780	24.16
ZeroCap [47]	0.029	0.12	0.131	0.055	0.778	0.970	25.737
MAGIC [44]	0.29	0.174	0.493	0.113	0.763	0.787	37.126
Ours	0.22	0.127	0.172	0.073	0.798	0.885	19.049

Table 2: Quantitative results for image captioning methods. We evaluate supervised metrics that measure text correspondence to human references and unsupervised metrics that are computed without referring to the human annotation.

Method	Supervised Metrics				Diversity Metrics		
	B@4	M	C	S	Vocab	%Novel	CLIP-S
ClipCap [51]	32.5	27.0	108.85	20.12	0.8	1650	66.4%
CLIP-VL [64]	2.6	11.5	14.6	5.5	0.82	2464	85.1%
VinVL [78]	41.0	31.3	140.9	25.3	0.83	1125	77.9%
Ours	2.6	11.5	14.6	5.5	0.79	8681	100%

Table 1: For each method, we report supervised metrics (i.e., ones requiring human references): B@4 = BLEU-1, M = METEOR, C = CIDEr, S = SPICE. We also report diversity metrics, which measures the vocabulary size (Vocab), and the number of novel sentences w.r.t the training set (%Novel). Finally, we report semantic relatedness to the image (CLIP-S), and to the human references (CLIP-S^{Ref}) based on CLIP's embeddings.

Cells marked in green denote accurate correspondences, while those highlighted in orange indicate mismatches.

Links



Paper



Code & benchmark

Conclusion

- We address the critical task of ensuring numerical data accuracy in academic documents by introducing a novel task —**automatic table verification**—leveraging the capabilities of large language models.
- We presented **arXiVeri**, a benchmark comprising tabular data from arXiv papers, and proposed metrics for evaluating verification performance.
- Despite the sophistication of advanced models like GPT-4, our findings underline the inherent complexity of the task, underscoring the necessity for further research in this field.