Benchmark: Extracting Table Information from Scientific Documents

Valda Seminar

Marijan Soric

May 16, 2025

Outline

Project Context

Inria Valda (Inria Paris, DI ENS, CNRS) Topics: management of complex data, data generated by human activity

Inria Cedar (Inria Saclay, LIX, CNRS) Topics: Cloud-scale analysis of rich data

BRGM (*Bureau de Recherches Géologiques et Minières*) French National Geological Survey: Earth science applications for managing soil and subsoil resources and risks

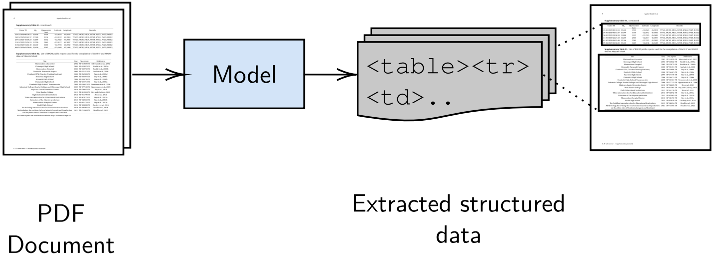
Working environment

- GéolAug project collaboration Inria & BRGM
- Helping geologists prepare their missions, facilitating access to knowledge
- Thesis: "Exploitation and Structuring of Heterogeneous Geological Data and Knowledge"
- Heterogeneous data:
  - Geological maps, diagrams
  - Databases
  - Text
  - Tables

Outline

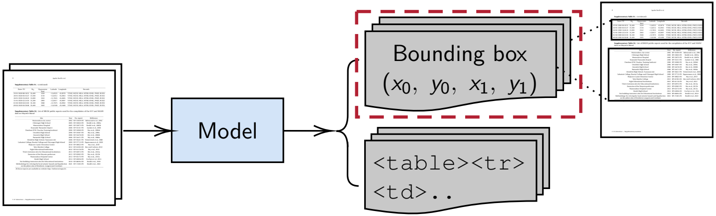
Definitions

Automatic structured table extraction from PDF documents



Task definition (1/2)

Table Detection: Find all tables within a document



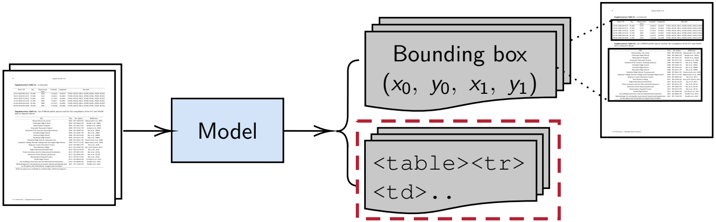
PDF Document

Tables as bounding box and HTML mark-up

Hard: various table styles (with or without borders)

Task definition (2/2)

Table Structure Recognition: Extract content from tables while keeping their structures



PDF
Document

Tables as bounding box
and HTML mark-up

Hard: various cell styles (empty, alignement. . .)

Table Extraction: Detection + Structure

Outline

Baseline

PdfPlumber	Python library, PDF parser, rule-based heuristics
Camelot	Python library, rule-based heuristics

Baseline

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GROBID	PDF parser, used in HAL https://hal.science

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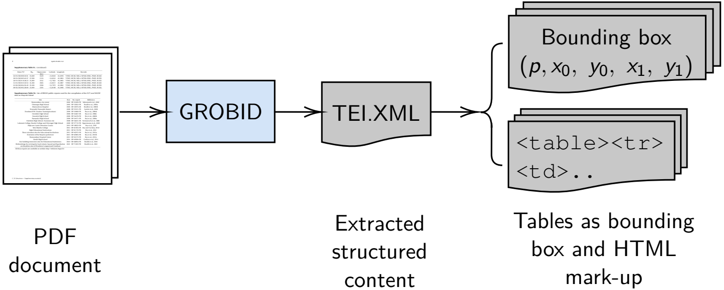
PdfPlumber	Python library, PDF parser, rule-based heuristics
Camelot	Python library, rule-based heuristics
GROBID	PDF parser, used in HAL https://hal.science
LLM-Vision	GPT-4o-mini with OpenAI API

GROBID

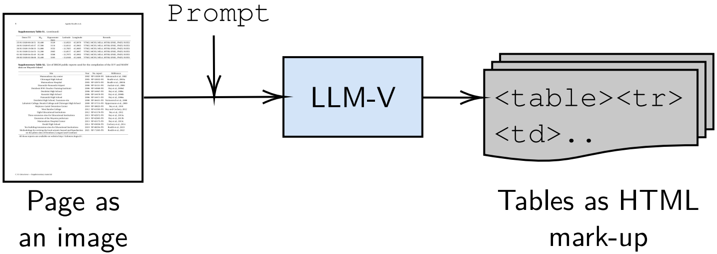
GROBID (Lopez, 2008) PDF parser, used in HAL[1].



[1] https://hal.science

LLM-Vision

LLM-Vision GPT-4o-mini with OpenAI API



Note: LLM-Vision does not output coordinates

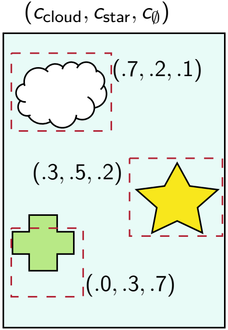
Outline

Object detection

Object detection: detect the instances in an image

Instance: Objet to find ("table", "column", "row", "cell").

Detection: Locations (bounding boxes) + probability distribution on labels (confiance score).



Object detection: instances (cloud, star, no object)

Baseline methods do not output confidence scores.

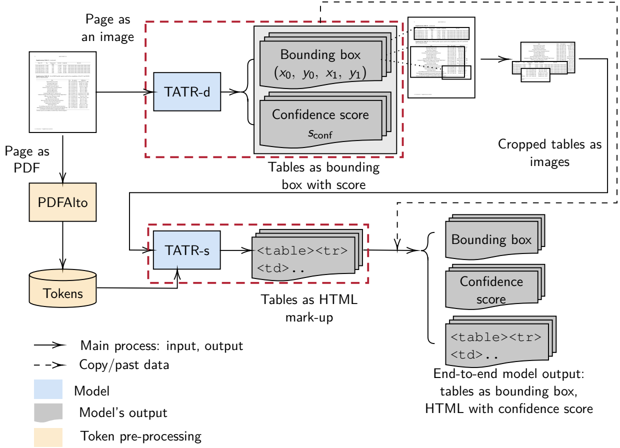
Two-step extraction method

Specialized models are assembled for each task.

Table Extraction Method	Table Detection	Table Structure Recognition
TATR-extract (Smock et al., 2022)	TATR-detect	TATR-structure
VGT+TATR-structure	VGT (Da et al., 2023)	TATR-structure
XY+TATR-extract	XY+TATR-detect	TATR-structure

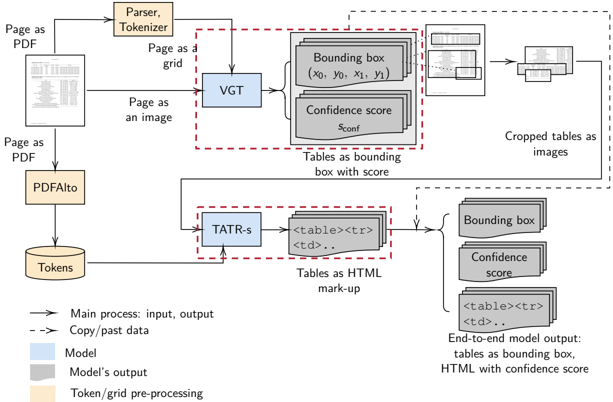
Extraction method (1/3)

TATR-extract is composed of two models: TATR-detect and TATR-structure, using DETR (Carion et al., 2020) (transformer encoder-decoder) architecture.



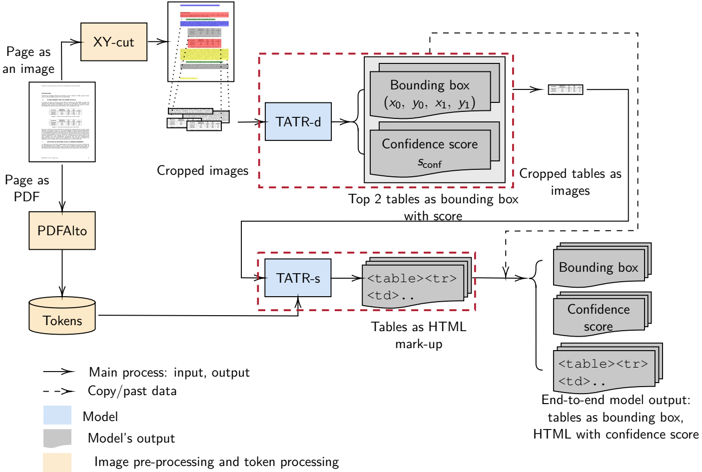
Extraction method (2/3)

VGT+TATR-structure uses VGT for table detection: specialized in document layout detection (including TD). VGT is multimodal: it operates on visual and textual content.



Extraction method (3/3)

XY+TATR-extract adds pre-processing with X-Y cut algorithm (Ha et al., 1995).



Outline

Table Detection

Usual metrics: Precision, Recall, based on *positive* predictions

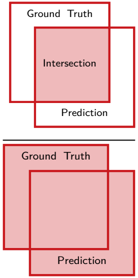
Positive	"There is a table"
True Positive (TP)	Table correctly identified
False Positive (FP)	Detected table is not real
False Negative (FN)	True table not detected

$$P = \frac{TP}{TP + FP} \qquad R = \frac{TP}{TP + FN}$$

TP and FP (with bounding boxes)

We decide if a positive (prediction) is a TP or a FP using Intersection-over-Union (IoU) with a threshold θ_J.

$$\mathrm{IoU} = \frac{\text{area of overlap}}{\text{area of union}} =$$



If $\mathrm{IoU} > \theta_J$ then the positive is a TP, otherwise a FP.

TP and FP (without bounding boxes)

We decide if a positive (prediction) is a TP or a FP using Jaccard-index according with a threshold θ_J.

$$\text{Jaccard}(S_P, S_{GT}) = \frac{|S_P \cap_{\text{multi}} S_{GT}|}{|S_P \cup_{\text{multi}} S_{GT}|}$$

Where S are multisets of 2-grams, where tokens are 2-characters (non-empty) strings from table content (HTML tags not included).
If $\mathrm{J} > \theta_J$ then the positive is a TP, otherwise a FP.

Metrics

Precision	P_{θ_J} mesures how precise the model is in its predictions
Recall	R_{θ_J} mesures how much the model misses real tables

But these metrics are sensitive to the choice of threshold θ_J, that is why we use metrics aggregating $\mathbb{E}_{\theta_J}[X_{\theta_J}]$ w.r.t $\theta_J \sim f$.

Average Precision	Area under the Precision–Recall curve for models with confidence scores.
Model miscalibration	Makes sure that confiance scores are probabilities.

Expected metrics

Before: binary value

$$TP^i = \mathbb{1}_{[\mathrm{IoU}_i > \theta_J]}$$

After: score

$$\widetilde{TP}^i = \mathbb{E}_{\theta_J}[\mathbb{1}_{[\mathrm{IoU}_i > \theta_J]}]$$

Expected metrics

Before: binary value

$$TP^i = \mathbb{1}_{[\mathrm{IoU}_i > \theta_J]}$$

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Example:

$$\mathbb{E}_{\theta_J}[P_{\theta_J}] = \frac{1}{|\mathcal{P}|} \sum_{i \in \mathcal{P}} \mathbb{E}_{\theta_J}[\mathbb{1}_{[\mathrm{IoU}_i > \theta_J]}]$$

With $f(\theta_J) \propto \theta_J$ and $f(\theta_J) \propto \theta_J \mathbb{1}_{[0.5,1]}$

Outline

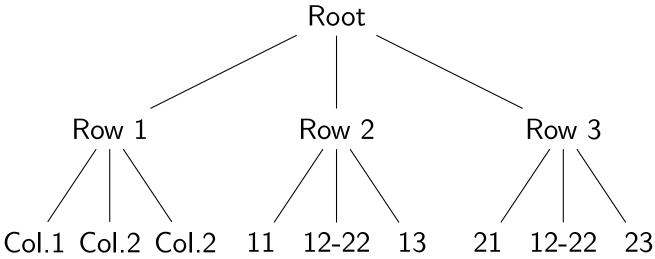
Table Structure Recognition

- Available metrics:
  - Structure absolute coordinates (rows, columns, cells) as we did for TD.
  - Cells relative positions and global structure, like TEDS (Li et al., 2020) and GriTS (Smock et al., 2023).
- Evaluation of extraction methods as a whole: the TSR part depends on the TD part.

Metrics (1/2)

TEDS measures the similarity of tables viewed as trees

<table>
<tr><th>Col.1</th><th>Col.2</th><th>Col.3</th></tr>
<tr><td>11</td><td rowspan="2">12-22</td><td>13</td></tr>
<tr><td>21</td><td>23</td></tr>
</table>



$$\mathrm{TEDS}(T_P, T_{GT}) = 1 - \frac{\mathrm{EditDist}(T_P, T_{GT})}{\max(|T_P|, |T_{GT}|)}$$

Metrics (2/2)

GriTS represents tables as matrices and computes different similarity types

GriTS Content

$$\begin{pmatrix} \text{Col.1} & \text{Col.2} & \text{Col.3} \\ 11 & 12-22 & 13 \\ 21 & 12-22 & 23 \end{pmatrix}$$

GriTS Topology

$$\begin{pmatrix} (0,0,1,1) & (0,0,1,1) & (0,0,1,1) \\ (0,0,1,1) & (0,0,1,2) & (0,0,1,1) \\ (0,0,1,1) & (0,-1,1,1) & (0,0,1,1) \end{pmatrix}$$

$$\mathrm{GriTS}_f(T_P, T_{GT}) = 2\frac{\sum_{i,j} f(\widetilde{T}_{P,i,j}, \widetilde{T}_{GT,j})}{|T_P| + |T_{GT}|}$$

With 2D most similar substructures $(\widetilde{T}_P, \widetilde{T}_{GT}) = \text{2D-MSS}_f(T_P, T_{GT})$

Outline

Table Extraction Metrics

Need to evaluate end-to-end methods on TE (not TD and TSR independently)
Before: binary value

$$TP^i = \mathbb{1}_{[\mathrm{IoU}_i > \theta_J]}$$

After: score

$$\widetilde{TP}^i = s_i^{\mathrm{TSR}} \mathbb{1}_{[\mathrm{IoU}_i > \theta_J]}$$

Table Extraction Metrics

Need to evaluate end-to-end methods on TE (not TD and TSR independently)
Before: binary value

$$TP^i = \mathbb{1}_{[\mathrm{IoU}_i > \theta_J]}$$

After: score

$$\widetilde{TP}^i = s_i^{\mathrm{TSR}} \mathbb{1}_{[\mathrm{IoU}_i > \theta_J]}$$

Finally,

$$P_{\theta_J}^{\mathrm{TSR}} = \frac{1}{|\mathcal{P}|} \sum_{i \in \mathcal{P}} s_i^{\mathrm{TSR}} \mathbb{1}_{[\mathrm{IoU}_i > \theta_J]}$$

$$R_{\theta_J}^{\mathrm{TSR}} = \frac{1}{|\mathcal{G}|} \sum_{i \in \mathcal{P}} s_i^{\mathrm{TSR}} \mathbb{1}_{[\mathrm{IoU}_i > \theta_J]}$$

Outline

Datasets

Table-BRGM manually annotated, PDF from geological reports from BRGM[2]

PubTables scientific articles from PubMed Central Open Access[3]

Table-arXiv synthetically generated from arXiv[4] paper source code. Use anchor and LaTeXML[5]

Dataset	# Pages	# Tables
Table-BRGM	499	124
PubTables	46 942	55 990
Table-arXiv	36 869	6 308

[2] https://infoterre.brgm.fr/rechercher/
[3] https://pmc.ncbi.nlm.nih.gov/tools/openftlist/
[4] https://arxiv.org
[5] http://dlmf.nist.gov/LaTeXML/

Outline

Confidence scores

Baseline	No confidence scores. $\mathcal{P}^+ = \mathcal{P}$. We can compute $P, R \dots$
Object detection	With confidence scores. We have to define a set of positive predictions $\mathcal{P}^+_{\theta_c}$ from $\mathcal{P}$. We can then compute $P, R \dots$

We use a threshold θ_c to define *positive* predictions from models with confidence scores.

$$\mathcal{P}^+_{\theta_c} := \{\hat{y} \mid (\hat{y}, c) \in \mathcal{P},\ c_{\text{table}} > \theta_c\}$$

Then we obtain tuples $\left(P^{\theta_c}, R^{\theta_c}\right)_{\theta_c}$

Precision–Recall curves with bounding boxes

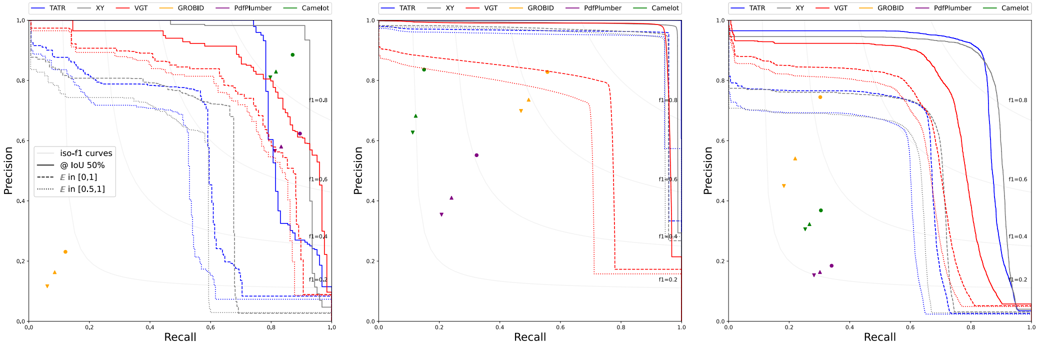


Figure: Table-BRGM, PubTables, Table-arXiv

Precision–Recall curves without bounding boxes

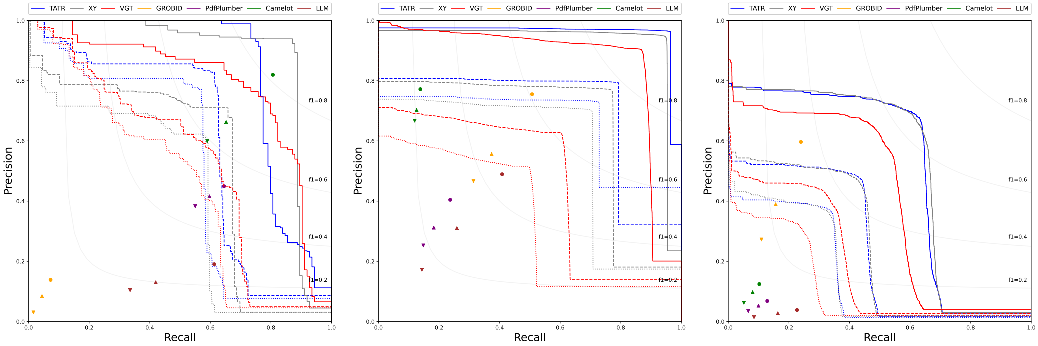
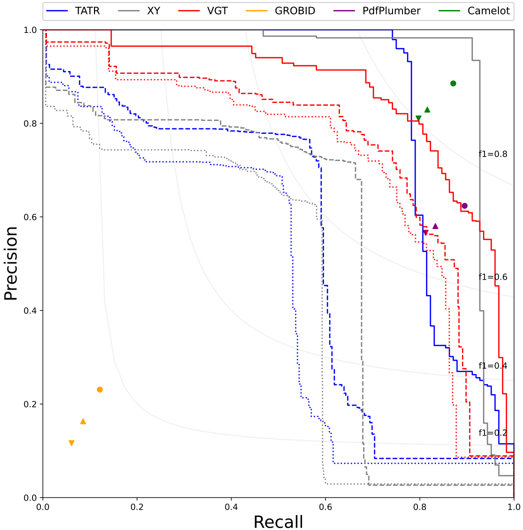
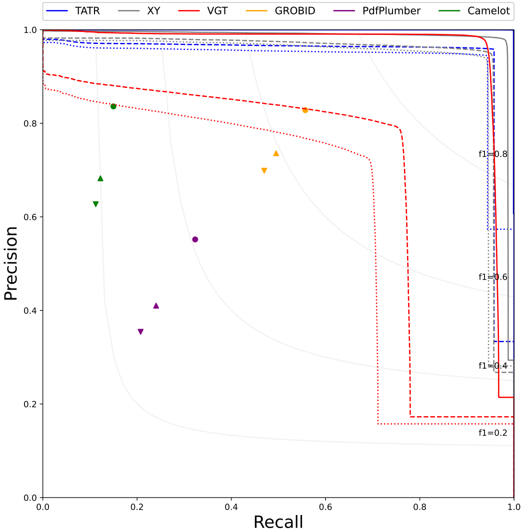


Figure: Table-BRGM, PubTables, Table-arXiv

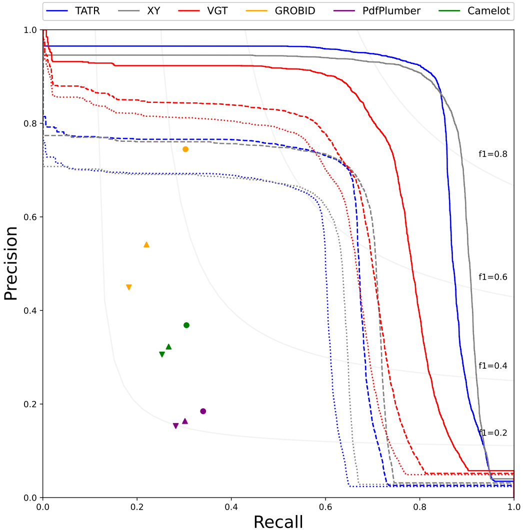
Precision–Recall curves with bboxes (Table-BRGM)



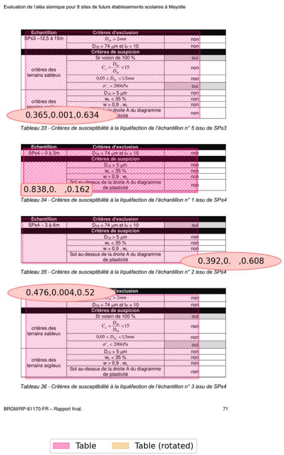
Precision–Recall curves with bboxes (PubTables)

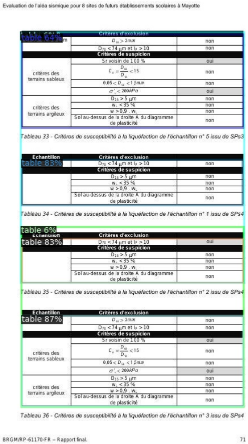


Precision–Recall curves with bboxes (Table-arXiv)



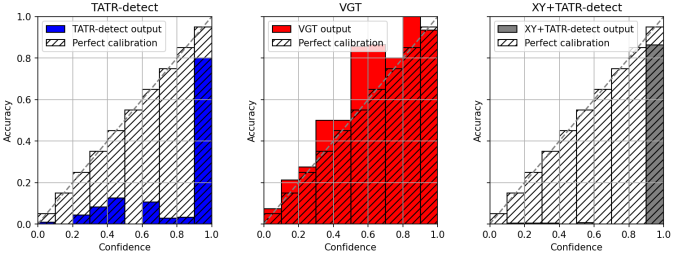
Example: comparison TATR-detect / VGT





Model calibration

Should we trust confidence scores from models?



Reliability diagramms (Niculescu-Mizil & Caruana, 2005)

Outline

On which dataset should we evaluate TSR?

- The TSR part depends on the TD for evaluation.
- We decided to compute average TSR score on the set of *True Positive*: tuples (predicted table, ground truth table), setting with IoU @ 50%.

TSR histograms scores

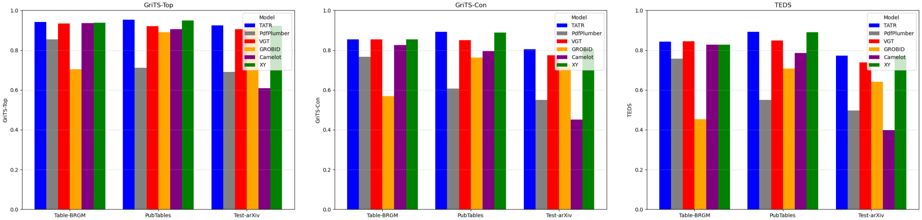
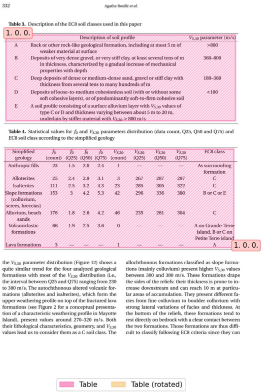
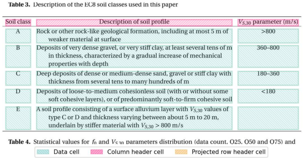


Figure: GriTS Topology, GriTS Content and TEDS.

Example: End-to-end extraction with TATR-extract



(a) TATR-detect



(b) TATR-structure

Soil class	Description of soil profile	V S,30 parameter (m/s)
A	Rock or other rock-like geological formation, including at most 5 m of weaker material at surface	>800
B	Deposits of very dense gravel, or very stiff clay, at least several tens of m in thickness, characterized by a gradual increase of mechanical properties with depth	360–800
C	Deep deposits of dense or medium-dense sand, gravel or stiff clay with thickness from several tens to many hundreds of m	180–360
D	Deposits of loose-to-medium cohesionless soil (with or without some soft cohesive layers), or of predominantly soft-to-firm cohesive soil	<180
E	A soil profile consisting of a surface alluvium layer with V S,30 values of type C or D and thickness varying between about 5 m to 20 m, underlain by stiffer material with V S,30 > 800 m/s	

(c) Extracted table (HTML)

Outline

TE Precision–Recall curves with bboxes (Table-BRGM)

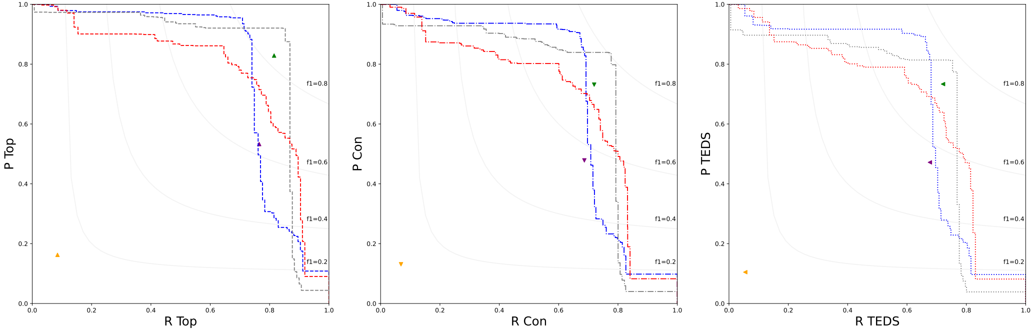
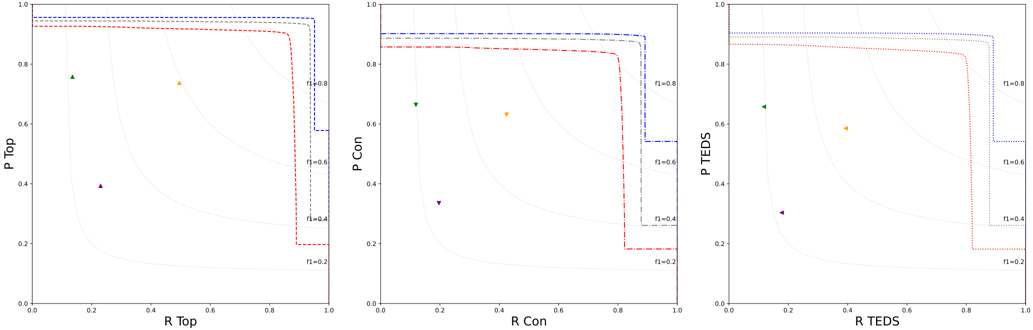


Figure: $P^{\mathrm{TSR}} - R^{\mathrm{TSR}}$ curves for GriTS Topology, GriTS Content and TEDS.

TE Precision–Recall curves with bboxes (PubTables)



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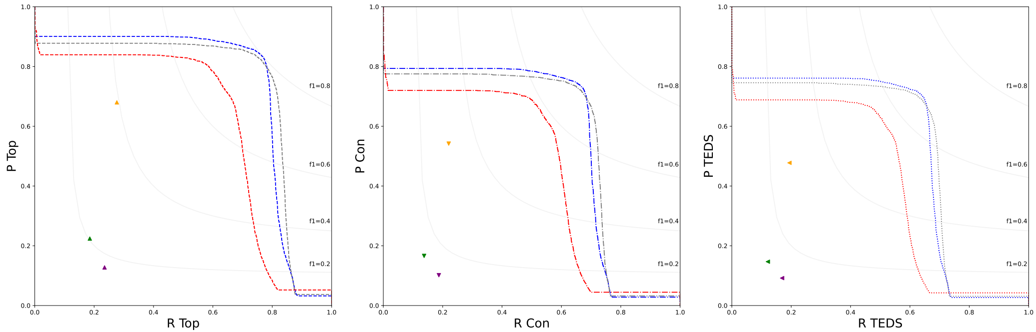

Figure: $P^{\mathrm{TSR}} - R^{\mathrm{TSR}}$ curves for GriTS Topology, GriTS Content and TEDS.

TE evaluation for models with scores

	Models	AP	AP^{Top}	AP^{Con}	AP^{TEDS}
BRGM	TATR	0.84	0.77	0.69	0.66
	VGT	0.86	0.76	0.67	0.65
	XY	**0.92**	**0.83**	**0.71**	**0.67**
PubTab	TATR	**1.00**	**0.91**	**0.80**	**0.80**
	VGT	0.96	0.81	0.69	0.70
	XY	0.97	0.88	0.78	0.78
arXiv	TATR	0.84	**0.73**	**0.56**	**0.52**
	VGT	0.73	0.60	0.44	0.40
	XY	**0.85**	**0.73**	**0.56**	0.51

TE evaluation for models without scores

	Models	F_1	F_1^{Top}	F_1^{Con}	F_1^{TEDS}
BRGM	Camelot	**0.88**	**0.82**	**0.73**	**0.73**
	GROBID	0.16	0.11	0.09	0.07
	PdfPlumber	0.73	0.63	0.56	0.56
PubTab	Camelot	0.25	0.23	0.20	0.20
	GROBID	**0.67**	**0.59**	**0.51**	**0.47**
	PdfPlumber	0.41	0.29	0.25	0.22
arXiv	Camelot	0.33	0.20	0.15	0.13
	GROBID	**0.43**	**0.39**	**0.31**	**0.28**
	PdfPlumber	0.24	0.17	0.13	0.12

Conclusion

- Problem not solved
- We developed new framework for TE evaluation, built datasets and compared various methods
- In downstream tasks, two choices:
  - Use a threshold θ_c in order to define $\mathcal{P}^+$
  - Trust confidence scores

Outlook

This work:

- Semantize tables through their content, context and captions
- Perform Q/A on tables

My thesis:

- Focus on other data types
- Exploite heterogeneous data through multi-modal methods
- Locate knowledge spatially and temporally

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Ha, J., Haralick, R., & Phillips, I. (1995).Recursive x-y cut using bounding boxes of connected components. *Proceedings of 3rd International Conference on Document Analysis and Recognition*, *2*, 952–955 vol.2. https://doi.org/10.1109/ICDAR.1995.602059

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- Smock, B., Pesala, R., & Abraham, R. (2022).Pubtables-1m: Towards comprehensive table extraction from unstructured documents. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 4634–4642.

Smock, B., Pesala, R., & Abraham, R. (2023). Grits: Grid table similarity metric for table structure recognition. https://arxiv.org/abs/2203.12555