Are LLMs Any Good for Scientific Leaderboard Extraction?

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10th of September, 2024, Grenoble, France







What are Scientific Leaderboards?

- Compare Scientific Results
 - Task
 - Dataset
 - Metric
- Find best models for given task
- Currently manually curated





Example: "Efficient Adaptive Ensembling for Image Classification"

Task: Image Classification (from title)

Dataset: CIFAR-10, CIFAR-100, ...

Metric: Accuracy, Improvement

Score: 99.5%, 99.612%, 0.112%, ...

→ Manually extract these TDMS combinations for leaderboards

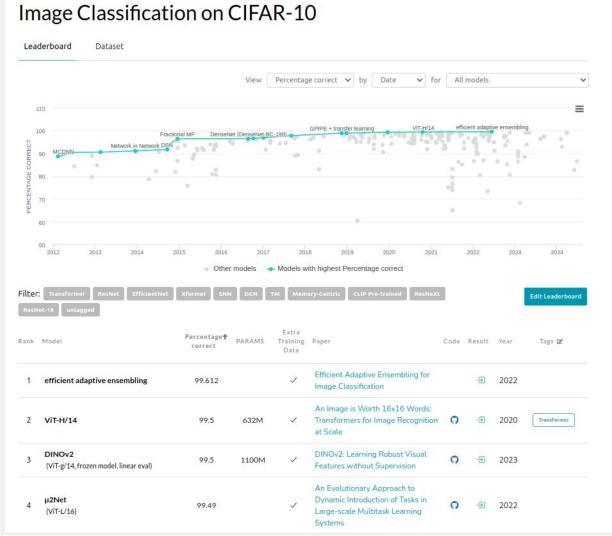
Dataset	SOTA accuracy	Our accuracy	Improvement
CIFAR-10 [30]	99.500%	99.612%	0.112%
CIFAR-100 [31]	96.080%	96.808%	0.728%
Cars [32]	96.320%	96.868%	0.548%
Food-101 [31]	96.180%	96.879%	0.699%
Flower102 [33]	99.720%	99.847%	0.127%
CINIC-10 [34]	94.300%	95.064%	0.764%
Pets [31]	97.100%	98.220%	1.120%

In order to stress our method, we also provide a different combination of weak classifiers: specifically, we show the results of an ensemble of five weak models. For demonstration purposes we report the results obtained only for the CIFAR-100 and CIFAR-10 datasets. In the case of CIFAR-100, while the ensemble using 2 weak models obtained an accuracy of 96.808%, the new one obtained an accuracy of 84.930%. This result was expected, since each weak model had to be trained on a third of the images of the previous case according to the data splitting procedure described in Section 4.6 in order to avoid the use of the same images. In the case of CIFAR-10, while the ensemble using 2 weak models obtained an accuracy of 99.612%, the new one obtained an accuracy of 96.640%





Example: "Efficient Adaptive Ensembling for Image Classification"

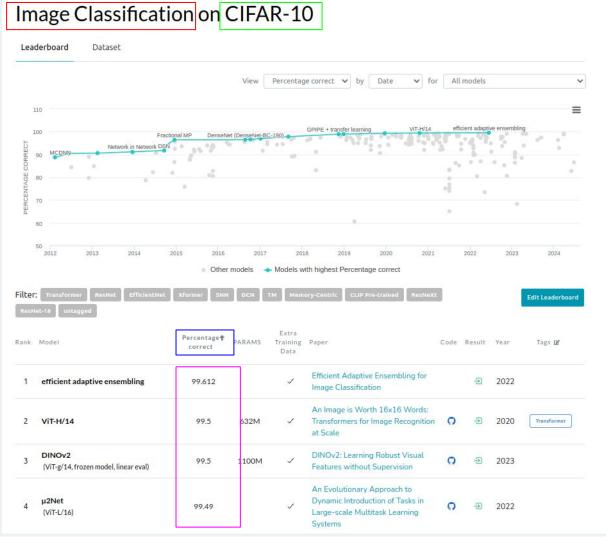


https://paperswithcode.com/sota/image-classification-on-cifar-10





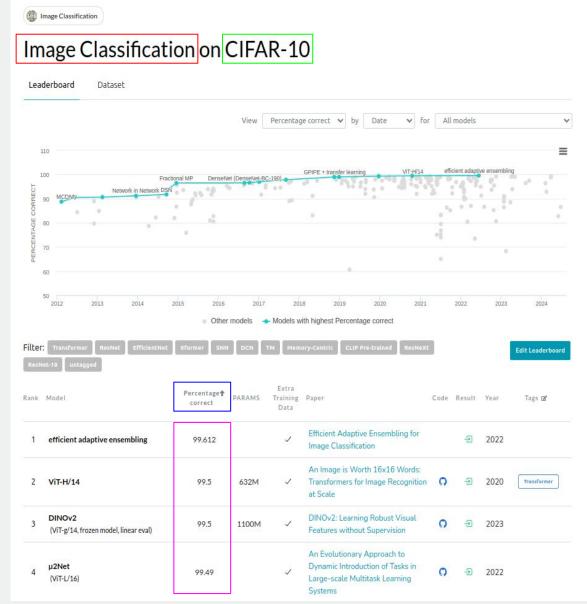
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In order to stress our method, we also provide a different combination of weak classifiers: specifically, we show the results of an ensemble of five weak models. For demonstration purposes we report the results obtained only for the CIFAR-100 and CIFAR-10 datasets. In the case of CIFAR-100, while the ensemble using 2 weak models obtained an accuracy of 96.808%, the new one obtained an accuracy of 84.930%. This result was expected, since each weak model had to be trained on a third of the images of the previous case according to the data splitting procedure described in Section 4.6 in order to avoid the use of the same images. In the case of CIFAR-10, while the ensemble using 2 weak models obtained an accuracy of 99.612%, the new one obtained an accuracy of 96.640%

https://arxiv.org/pdf/2206.07394v3





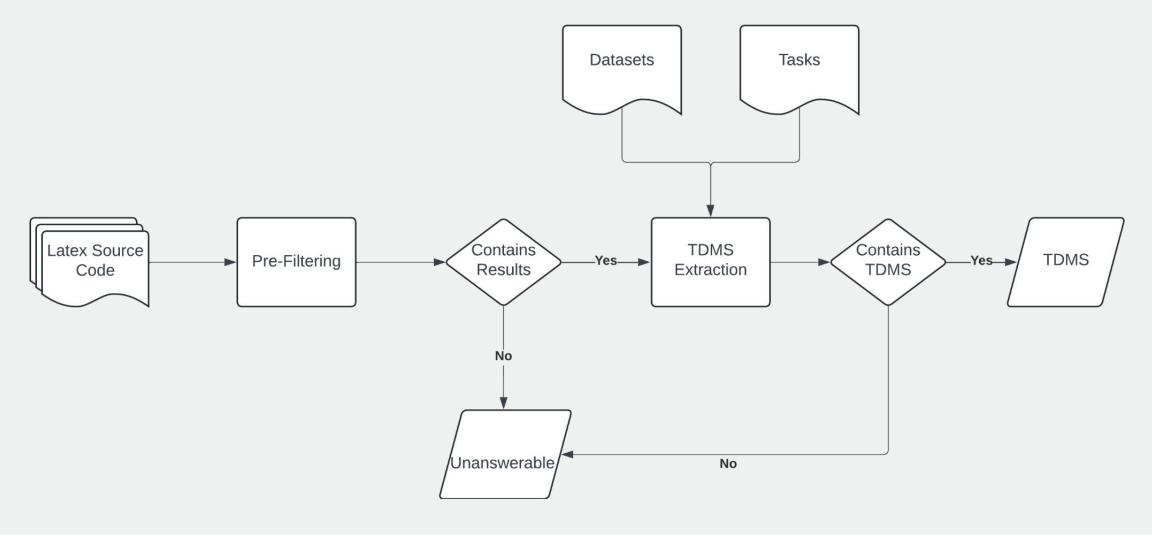


Task

Develop a machine learning model that can distinguish whether a scholarly article provided as input to the model reports a TDMS or not. And for articles reporting TDMSs, extract all the relevant ones.



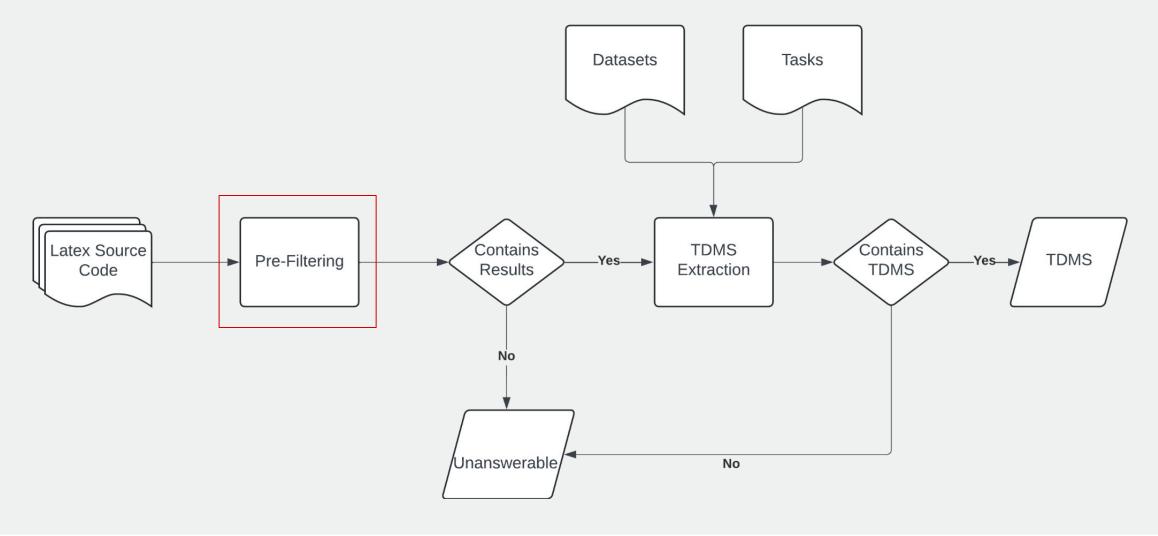
Process







Process







Rule Based Pre-Filtering

- Rule-based binary classifier → LaTeX source code structures
- Avoid complex models for simple tasks
- Recall-Oriented

Method

Result Section Exists
Result Section Exists with add. terms
Result Table Exists





Rule Based Pre-Filtering

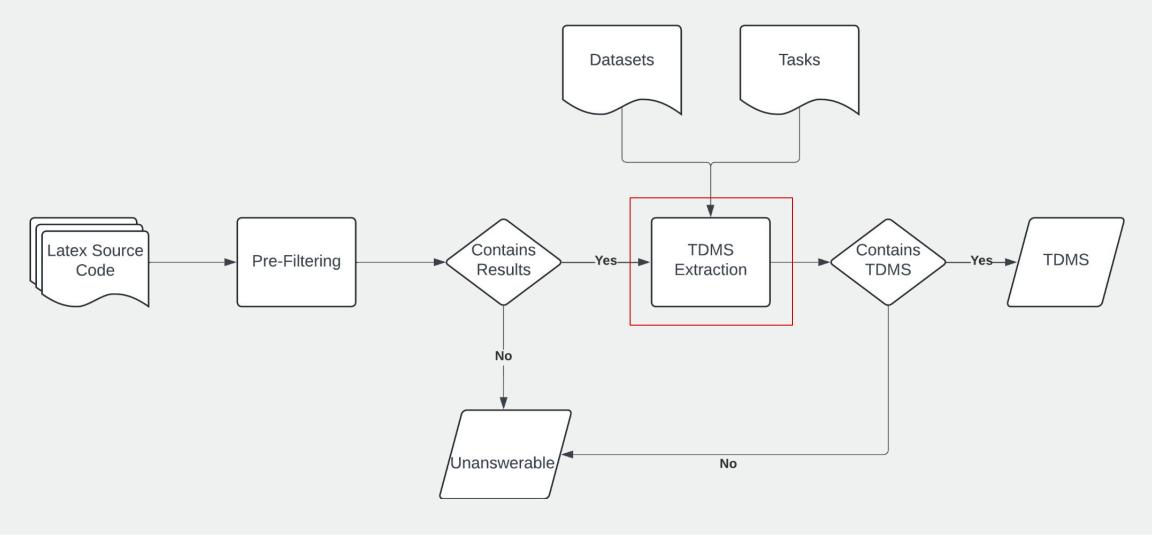
- Rule-based binary classifier → LaTeX source code structures
- Avoid complex models for simple tasks
- Recall-Oriented

Method	Precision	Recall	Accuracy
Result Section Exists	0.685	0.96	0.76
Result Section Exists with add. terms	0.67	0.98	0.75
Result Table Exists	0.85	0.80	0.83





Process







Type	ld	Name	Filtered	zero- or few-shot	fulltext or az	PwC information
Baseline	1	AxCell	\ \	2 1	fulltext	X

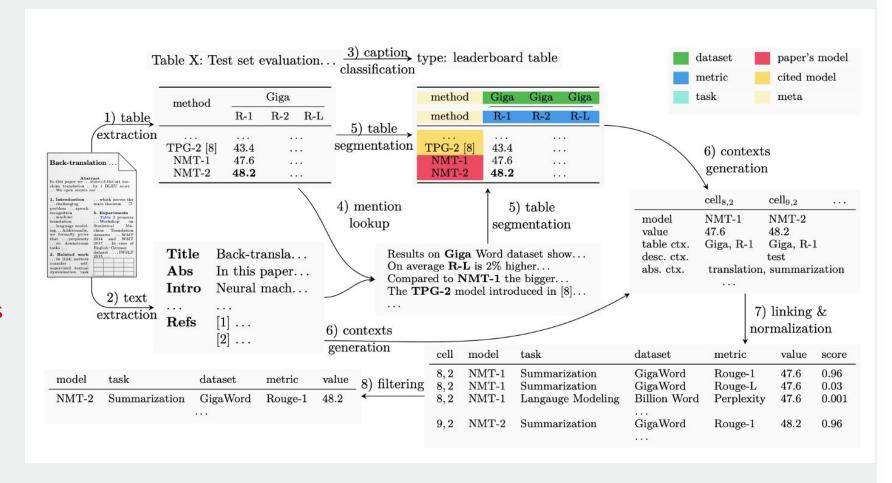


Type	ld	Name	Filtered	zero- or few-shot	fulltext or az	PwC information
Baseline	1	AxCell	/	4 9	fulltext	×
	2	GPT35-zero	X	zero	fulltext	X
	3	GPT35-fil-zero	1	zero	fulltext	X
	4	GPT35-few	X	few	fulltext	X
	5	GPT35-fil-few	1	few	fulltext	X
LLMs	6	GPT35-info-few	X	few	fulltext	✓
	7	GPT35-az-few	X	few	az	X
	8	GPT35-az-info-few	X	few	az	✓
	9	Mistral-fil-zero	1	zero	fulltext	X
	10	Mistral-fil-info-zero	1	zero	fulltext	✓





- ML Pipeline
 - Table Extraction
 - Text Extraction
- Result Merging
- Uses Arxiv as source →
 overlap in the collections







Type	ld	Name	Filtered	zero- or few-shot	fulltext or az	PwC information
	2	GPT35-zero	X	zero	fulltext	×
	3	GPT35-fil-zero	1	zero	fulltext	X
	4	GPT35-few	Х	few	fulltext	X
	5	GPT35-fil-few	1	few	fulltext	X
LLMs	6	GPT35-info-few	X	few	fulltext	/
	7	GPT35-az-few	X	few	az	X
	8	GPT35-az-info-few	X	few	az	✓
	9	Mistral-fil-zero	/	zero	fulltext	X
	10	Mistral-fil-info-zero	1	zero	fulltext	/

zero shot

few shots





Type	ld	Name	Filtered	zero- or few-shot	fulltext or az	PwC information
	2	GPT35-zero	×	zero	fulltext	×
	3	GPT35-fil-zero	/	zero	fulltext	X
	4	GPT35-few	X	few	fulltext	X
	5	GPT35-fil-few	1	few	fulltext	X
LLMs	6	GPT35-info-few	X	few	fulltext	✓
	7	GPT35-az-few	X	few	az	X
	8	GPT35-az-info-few	X	few	az	✓
	9	Mistral-fil-zero	/	zero	fulltext	X
	10	Mistral-fil-info-zero	1	zero	fulltext	1

unanswerable filtered



Type	ld	Name	Filtered	zero- or few-shot	fulltext or az	PwC information
	2	GPT35-zero	×	zero	fulltext	×
	3	GPT35-fil-zero	1	zero	fulltext	X
	4	GPT35-few	X	few	fulltext	X
	5	GPT35-fil-few	1	few	fulltext	X
LLMs	6	GPT35-info-few	X	few	fulltext	✓
	7	GPT35-az-few	X	few	az	X
	8	GPT35-az-info-few	X	few	az	✓
	9	Mistral-fil-zero	/	zero	fulltext	X
	10	Mistral-fil-info-zero	/	zero	fulltext	/

results and experiments sections (Argumentative Zoning)





Type	ld	Name	Filtered	zero- or few-shot	fulltext or az	PwC information
	2	GPT35-zero	×	zero	fulltext	×
	3	GPT35-fil-zero	/	zero	fulltext	X
	4	GPT35-few	X	few	fulltext	X
	5	GPT35-fil-few	/	few	fulltext	X
LLMs	6	GPT35-info-few	X	few	fulltext	✓
	7	GPT35-az-few	X	few	az	X
	8	GPT35-az-info-few	X	few	az	/
	9	Mistral-fil-zero	/	zero	fulltext	X
	10	Mistral-fil-info-zero	/	zero	fulltext	✓

PwC additional information





Results

The Accuracy and Summary results of our Phase 2 submissions

Model	A a a u ra a u		Su	mmary	
Model	Accuracy	Rouge 1	Rouge 2	Rouge L	Rouge Lsum
AxCell	83.4	75.25	4.56	74.85	73.7
GPT35-fil-zero	67.05	66.61	0.11	66.54	66.44
GPT35-few	85.93	73.72	6.07	72.72	72.57
GPT35-fil-few	69.07	68.81	0.14	68.76	68.66
GPT35-info-few	72.75	59.22	2.48	59.06	58.99
GPT35-az-few	79.09	71.07	3.56	70.82	70.62
GPT35-az-info-few	75.41	71.59	1.71	71.46	71.35
Mistral-fil-zero	75.79	68.92	2.18	67.51	66.48
Mistral-fil-info-zero	71.23	56.63	3.7	55.14	53.09

Drop because misleading information



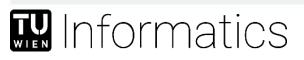


Results

The overall results of all TDMS for our Phase 2 submissions

AA o d o l		Exact			Inexact	
Model	Р	R	F1	P	R	F1
AxCell	36.36	6.21	10.6	40.85	6.97	11.9
GPT35-fil-zero	2.63	0.15	0.29	3.08	0.18	0.34
GPT35-few	12.82	9.89	11.16	16.74	12.81	14.52
GPT35-fil-few	4.04	0.15	0.3	4.04	0.15	0.3
GPT35-info-few	4.46	2.24	2.99	6.82	3.43	4.56
GPT35-az-few	11.78	3.77	5.71	18.16	5.7	8.68
GPT35-az-info-few	13.45	1.38	2.5	23.12	2.33	4.23
Mistral-fil-zero	8.05	4.42	5.71	10.74	5.89	7.61
Mistral-fil-info-zero	11.64	8.37	9.74	14.62	10.5	12.22

Increase because valuable information





Manual Analysis

Data source	Task-Dataset-Metric-Score
Ground Truth	Image Classification - CIFAR-10 - Percentage correct - 95.02 Image Classification - CIFAR-100 - Percentage correct - 76.85
AxCell	Image Classification - CIFAR-10 - Percentage error - 4.98 Image Classification - CIFAR-100 - Percentage error - 20.7 Semantic Segmentation - KITTI Semantic Segmentation - Mean IoU (class) - 89.08
GPT35-zero	Image classification - CIFAR-10, CIFAR-100 - Accuracy - 96.74% Image classification - CIFAR-10, CIFAR-100 - AUC - 0.9803 Stability analysis of Bayesian Neural Networks - CIFAR-10 - Epoch Divergence - None OOD detection - CIFAR-10, CIFAR-100 - ECE - 0.0520 Semantic segmentation - StreetHazards, BDD-Anomaly - mIoU - 56.12%





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Conclusion

- No reliable results yet
 - → Repeat runs
- Test data needs improvement
 - Standardized naming
 - All results should be included
- External knowledge beneficial for TDMS extraction
 - → Cause hallucinations in classification task
- Only <60% of TDMS values are in preprints
 - → How does the coverage change for the actual papers?







Any Questions?

