VSR: A Unified Framework for Document Layout Analysis combining Vision, Semantics and Relations

Peng Zhang[1]
Can Li[1]
Liang Qiao[1]
Zhanzhan Cheng[2,1]
Shiliang Pu[1]
Yi Niu[1]
Fei Wu[2]

1. Hikvision Research Institute, Hangzhou, China
2. Zhejiang University, Hangzhou, China

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Outline

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- Background
- Method
- Experiments

Background

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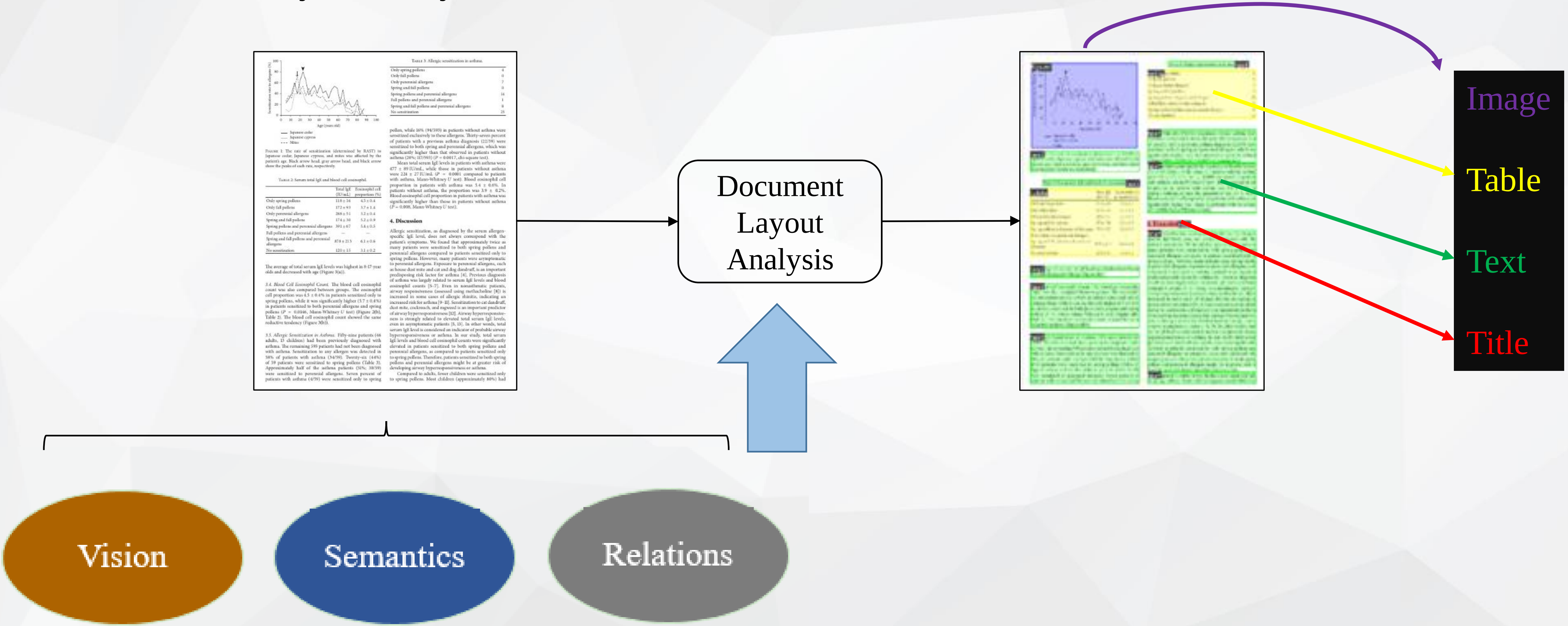
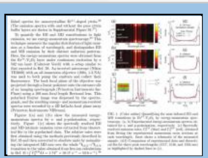
◆ Document Layout Analysis



Background

◆ **Multimodal document layout analysis frameworks**

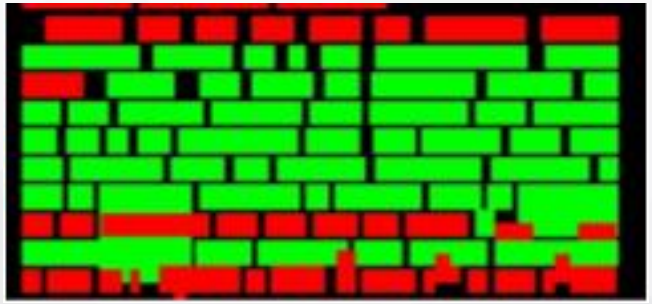
➢ **NLP-based framework**



Image+Text → ***Components generation:*** (e.g. PDF parsing) → ***Feature Extraction:*** vision + semantics → ***Relation Module:*** Sequence labeling →

Limitations:

- Insufficient capabilities in layout modeling



Text Figure Caption

Background

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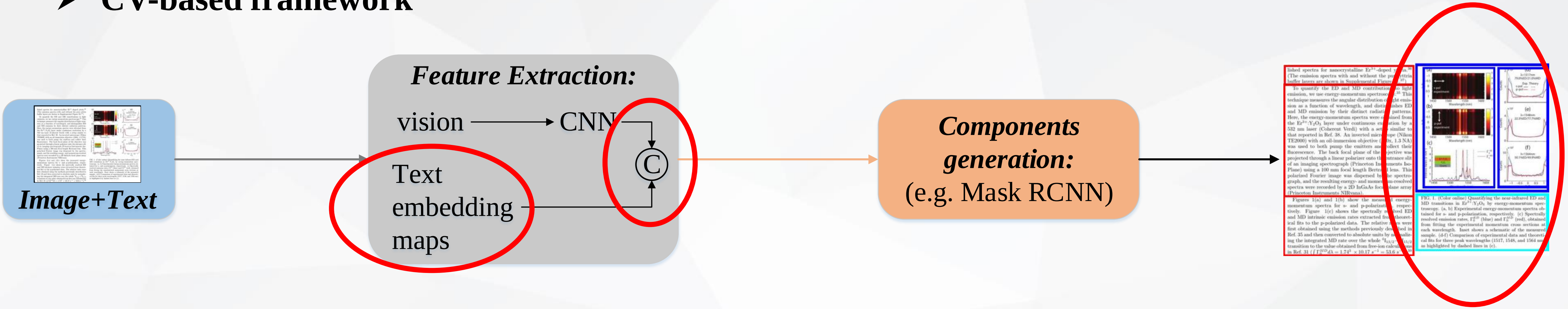
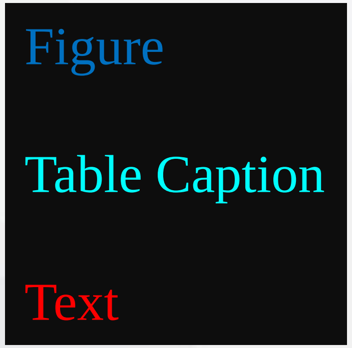
- **Multimodal document layout analysis frameworks**
  - **CV-based framework**



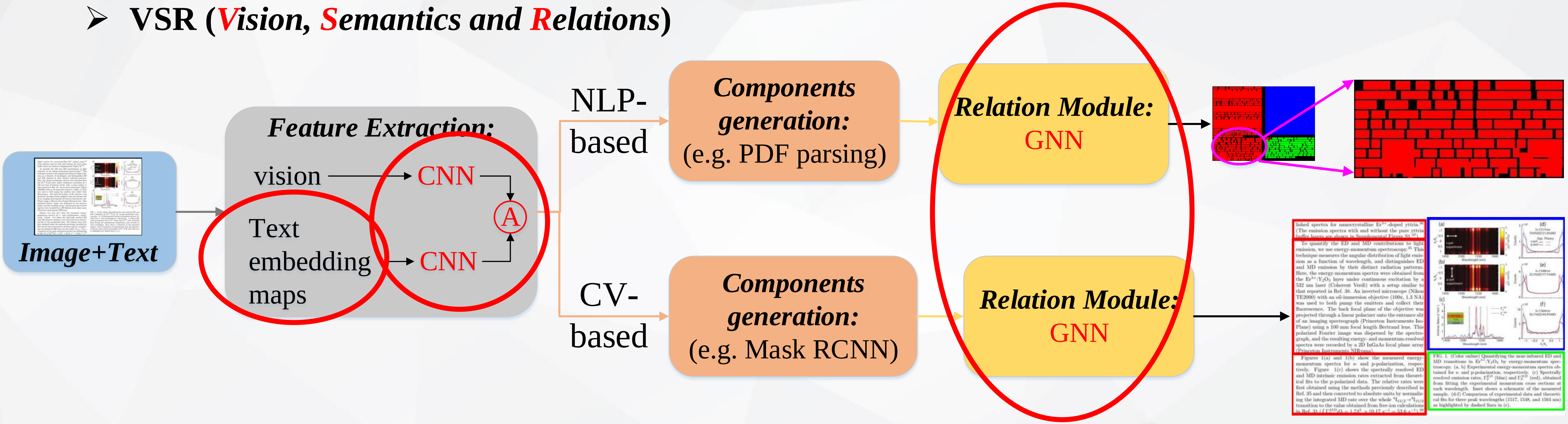
Limitations:

- Limited semantics
- Simple and heuristic modality fusion strategy
- Lack of relation modeling between components



Background

- **Multimodal document layout analysis frameworks**
  - **VSR (*Vision, Semantics and Relations*)**



Advantages:

- Semantics at multiple granularities (*Character & Sentence*)
- Two-stream network and adaptive aggregation module to exploit *vision and semantics* effectively
- A GNN-based relation module to support relation modeling in both *NLP- and CV-based methods*

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Method

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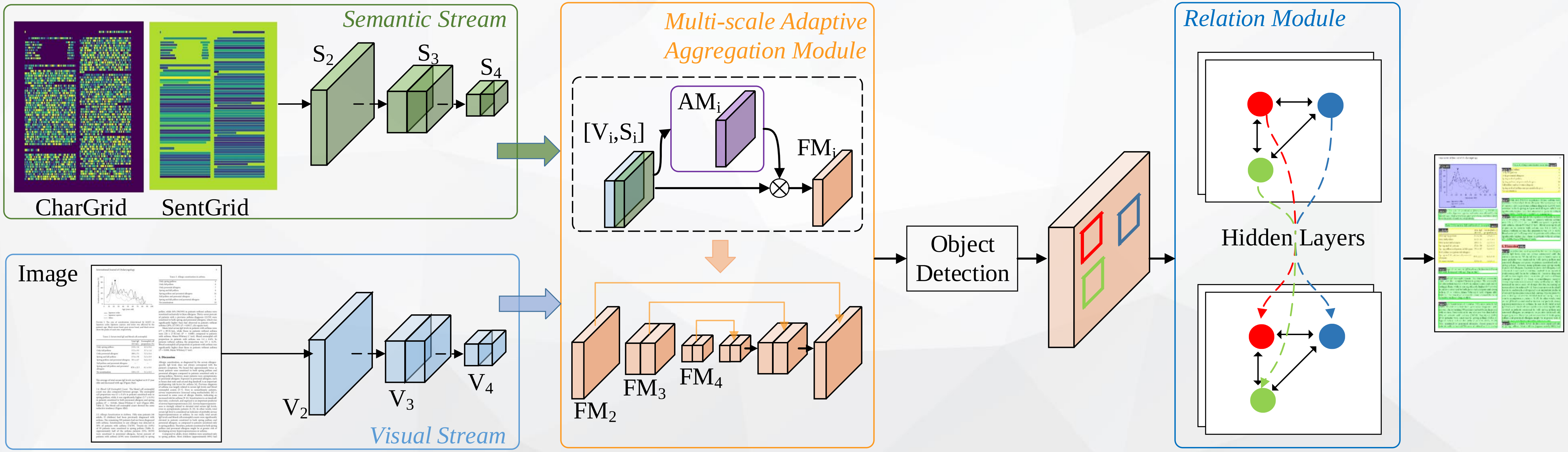
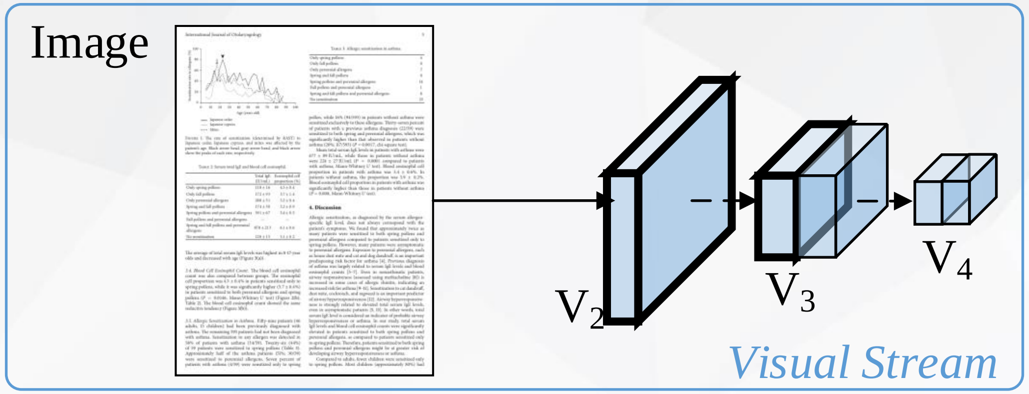
- Two-stream ConvNets
- Multi-scale Adaptive Aggregation
- Relation Module



System Architecture

Method

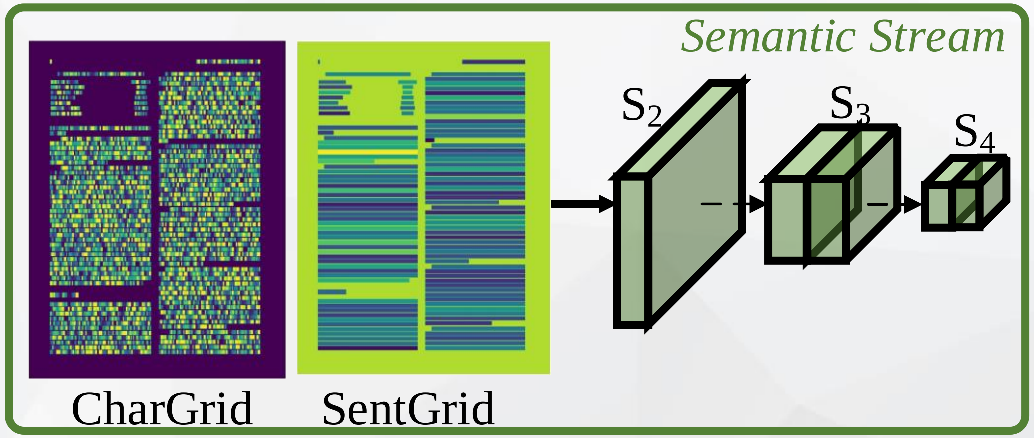
- Two-stream ConvNets



input (document image): $V_0 = x \in R^{H \times W \times 3}$

output (multi-scale *visual* features):

$$\{V_2, V_3, V_4\} \quad V_i \in R^{\frac{H}{2^i} \times \frac{W}{2^i} \times C_i^V}$$



input (text embedding maps):

$$S_0 = LayerNorm(Chargrid + Sentgrid) \in R^{H \times W \times C_0^S}$$

character granularity

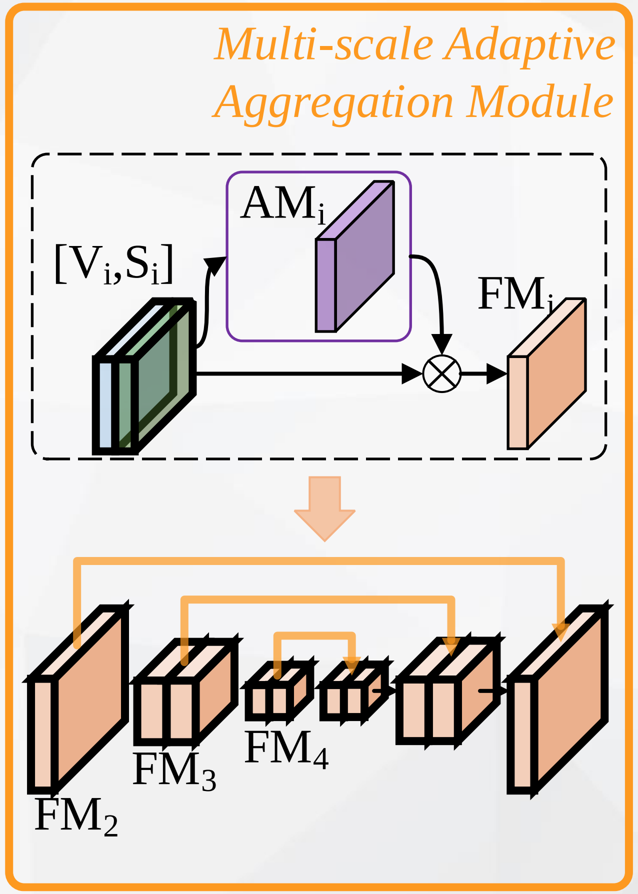
sentence granularity

output (multi-scale *semantic* features):

$$\{S_2, S_3, S_4\} \quad S_i \in R^{\frac{H}{2^i} \times \frac{W}{2^i} \times C_i^V}$$

Method

- Multi-scale Adaptive Aggregation



$\{V_2, V_3, V_4\}$ $V_i \in R^{\frac{H}{2^i} \times \frac{W}{2^i} \times C_i^V}$

$\{S_2, S_3, S_4\}$ $S_i \in R^{\frac{H}{2^i} \times \frac{W}{2^i} \times C_i^V}$

$$AM_i = h\left(g\left([V_i, S_i]\right)\right)$$

$$FM_i = AM_i \odot V_i + (1 - AM_i) \odot S_i$$

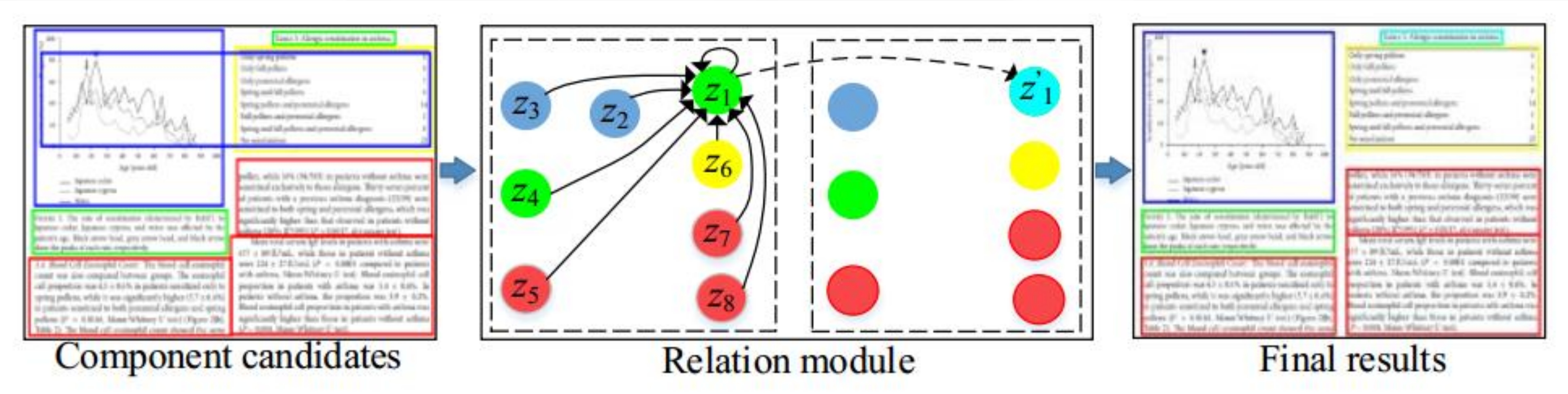
$\{FM_2, FM_3, FM_4\}$

FPN

$\{FM_2, FM_3, FM_4\}$

$[\ \cdot]$: concatenation
g : convolutional layer
h : activation function

- Relation Module



Nodes: $Z = \{z_1, \cdots, z_N\}$ → self-attention → Updated Nodes: $Z' = \{z'_1, \cdots, z'_N\}$

node features: $z_j = LayerNorm(f_j + e_j^{pos}(b_j))$

visual features: $f_j = RoIAlign(FM, b_j)$

position embeddings: $e_j^{pos}(b_j)$

probabilities: $\widetilde{p_j^c} = Softmax(Linear_{cls}(z'_j))$

regression coordinates: $\widetilde{b_j} = Linear_{reg}(z'_j)$

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Experiment

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- Datasets

Dataset	Num of Samples	Metric	Classes	Support tasks
Article Regions	822	mAP	Title, Authors, Abstract, Body, Figure, Figure Caption, Table, Table Caption, References	CV-based method
PubLayNet	360K	AP@IOU 0.5-0.95	Text, Title, List, Figure, Table	
DocBank	500K	F1-score mAP	Abstract, Author, Caption, Equation, Figure, Footer, List, Paragraph, Reference, Section, Table, Title	CV-based method + NLP-based method

Experiment

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- **SOTA results**
  - Article Regions

Table 1. Performance comparisons on Article Regions dataset

Method	Title	Author	Abstract	Body	Figure	Figure Caption	Table	Table Caption	Reference	mAP
Faster RCNN [31]	-	1.22	-	87.49	-	-	-	-	-	46.38
Faster RCNN *w/ context* [31]	-	10.34	-	93.58	-	-	-	30.8	-	70.3
Faster RCNN *reimplement*	100.0	51.1	94.8	98.9	94.2	91.8	97.3	67.1	90.8	87.3
Faster RCNN *w/ context* [31] *reimplement*	100.0	60.5	90.8	98.5	**96.2**	91.5	**97.5**	64.2	91.2	87.8
VSR	**100.0**	**94**	**95**	**99.1**	95.3	**94.5**	96.1	**84.6**	**92.3**	**94.5**

Note: missing entries are because those results are not reported in their original papers.

Experiment

- **SOTA results**
  - PubLayNet

Table 2. Performance comparisons on PubLayNet dataset.

Method	Dataset	Text	Title	List	Table	Figure	AP
Faster RCNN [43]	val	91	82.6	88.3	95.4	93.7	90.2
Mask RCNN [43]		91.6	84	88.6	96	94.9	91
VSR		**96.7**	**93.1**	**94.7**	**97.4**	**96.4**	**95.7**
Faster RCNN [43]	test	91.3	81.2	88.5	94.3	94.5	90
Mask RCNN [43]		91.7	82.8	88.7	94.7	95.5	90.7
DocInsightAI		94.51	88.31	94.84	95.77	97.52	94.19
SCUT		94.3	89.72	94.25	96.62	97.68	94.51
SRK		94.65	89.98	**95.14**	**97.16**	**97.95**	94.98
SiliconMinds		96.2	89.75	94.6	96.98	97.6	95.03
VSR		**96.69**	**92.27**	94.55	97.03	97.90	**95.69**

Experiment

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- **SOTA results**
  - DocBank

NLP-based:

Table 3. Performance comparisons on DocBank dataset in F1 Score.

Method	Abstract	Author	Caption	Equation	Figure	Footer	List	Paragraph	Reference	Section	Table	Title	Macro Average
$BERT_{base}$	92.94	84.84	86.29	81.52	100.0	78.05	71.33	96.19	93.10	90.81	82.96	94.42	87.70
$RoBERTa_{base}$	92.88	86.18	89.44	82.48	100.0	80.14	73.53	96.46	93.41	93.37	83.89	95.11	88.91
$LayoutLM_{base}$	98.16	85.95	95.97	89.47	100.0	89.57	89.48	97.88	93.38	95.98	86.33	95.79	93.16
$BERT_{large}$	92.86	85.77	86.50	81.77	100.0	78.14	69.60	96.19	92.84	90.65	83.20	94.30	87.65
$RoBERTa_{large}$	94.79	87.24	90.81	83.70	100.0	83.92	74.51	96.65	93.34	94.07	84.94	94.61	89.88
$LayoutLM_{large}$	97.84	87.83	95.56	89.74	**100.0**	91.46	90.04	97.90	93.32	95.96	86.79	95.52	93.50
X101	97.17	82.27	94.35	89.38	88.12	90.29	90.51	96.82	87.98	94.12	83.53	91.58	90.51
X101+$LayoutLM_{base}$	98.15	89.07	**96.69**	94.30	99.90	92.92	93.00	98.43	94.37	96.64	88.18	95.75	94.78
X101+$LayoutLM_{large}$	98.02	89.64	96.66	94.40	99.94	93.52	92.93	98.44	94.30	96.70	88.75	95.31	94.88
VSR	**98.29**	**91.19**	96.32	**95.84**	99.96	**95.11**	**94.66**	**98.66**	**95.05**	**97.11**	**89.24**	**95.63**	**95.59**

CV-based:

Table 4. Performance comparisons on DocBank dataset in mAP.

Models	Abstract	Author	Caption	Equation	Figure	Footer	List	Paragraph	Reference	Section	Table	Title	mAP
Faster RCNN	96.2	88.9	93.9	**78.1**	85.4	**93.4**	86.1	67.8	89.9	76.7	77.2	**95.3**	86.3
VSR	**96.3**	**89.2**	**94.6**	77.3	**97.8**	93.2	**86.2**	**69.0**	**90.3**	**79.2**	**77.5**	94.9	**87.6**

Experiment

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➢ **Ablation results**
  ➢ Effects of multi-granularity semantic features

Table 5. Effects of semantic features at different granularities.

Vision	Semantics		Title	Author	Abstract	Body	Figure	Figure Caption	Table	Table Caption	Reference	mAP
	Char	Sentence										
√			100.0	51.1	94.8	98.9	94.2	91.8	97.3	67.1	90.8	87.3
√	√		100.0	71.4	**96.5**	98.9	95.6	**93.6**	96.9	68.6	89.9	90.2
√		√	100.0	60.2	95.5	**99.0**	**97.8**	93.2	98.9	**73.0**	91.2	89.8
√	√	√	**100.0**	**84.3**	96.1	98.7	95.7	92.5	**99.4**	71.4	**92.4**	**92.3**

Experiment

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- **Ablation results**
  - Effects of two-stream network with adaptive aggregation

Table 6. Effects of two-stream network with adaptive aggregation.

Method		Title	Author	Abstract	Body	Figure	Figure Caption	Table	Table Caption	Reference	mAP	FPS
Single-stream at input level	R101	94.7	58.7	82.7	98.1	97.9	**96.3**	91.8	63.7	91.5	86.2	19.07
	R152	100.0	50.5	85.3	97.9	**98.0**	94.4	93.3	62.6	90.5	85.8	18.15
Single-stream at decision level	R101	99.5	67.6	95.1	98.8	95.0	93.2	96.6	70.7	91.3	89.8	**19.79**
	R152	100.0	80.2	91.0	**99.4**	96.0	92.4	98.3	**73.8**	91.7	91.4	16.43
VSR	R101	**100.0**	**84.3**	**96.1**	98.7	95.7	92.5	**99.4**	71.4	**92.4**	**92.3**	13.94

Experiment

- **Ablation results**
  - Effects of relation module

Table 7. Effects of relation module.

Method		Title	Author	Abstract	Body	Figure	Figure caption	Table	Table caption	Reference	mAP
Faster RCNN	w/o RM	1	51.1	94.8	98.9	**94.2**	91.8	97.3	67.1	90.8	87.3
	w/ RM	**1**	**88.4**	**99.1**	**99.1**	85.4	**92.6**	**98.0**	**79.2**	**91.6**	**92.6**
VSR	w/o RM	1	84.3	**96.1**	98.7	**95.7**	92.5	**99.4**	71.4	**92.4**	92.3
	w/ RM	**1**	**94**	95	**99.1**	95.3	**94.5**	96.1	**84.6**	92.3	**94.5**

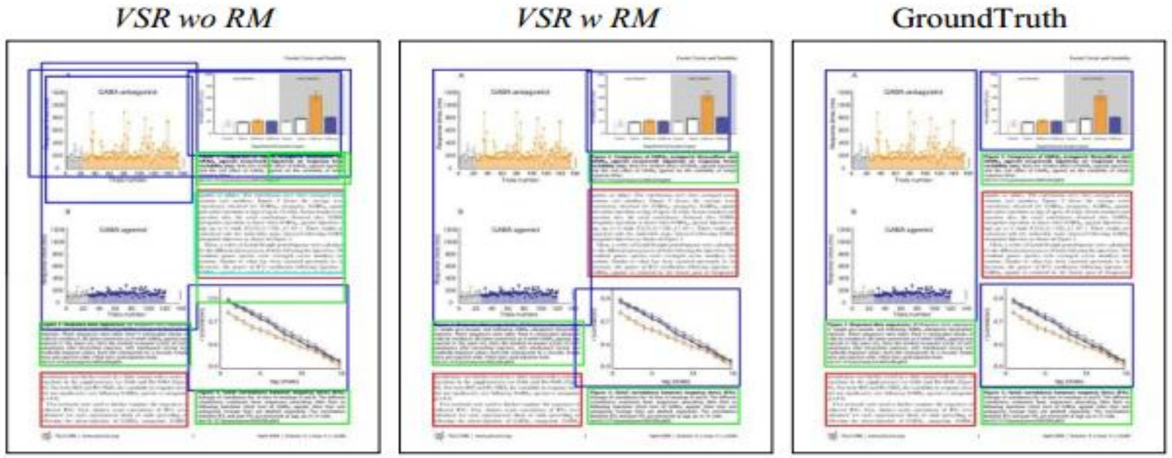
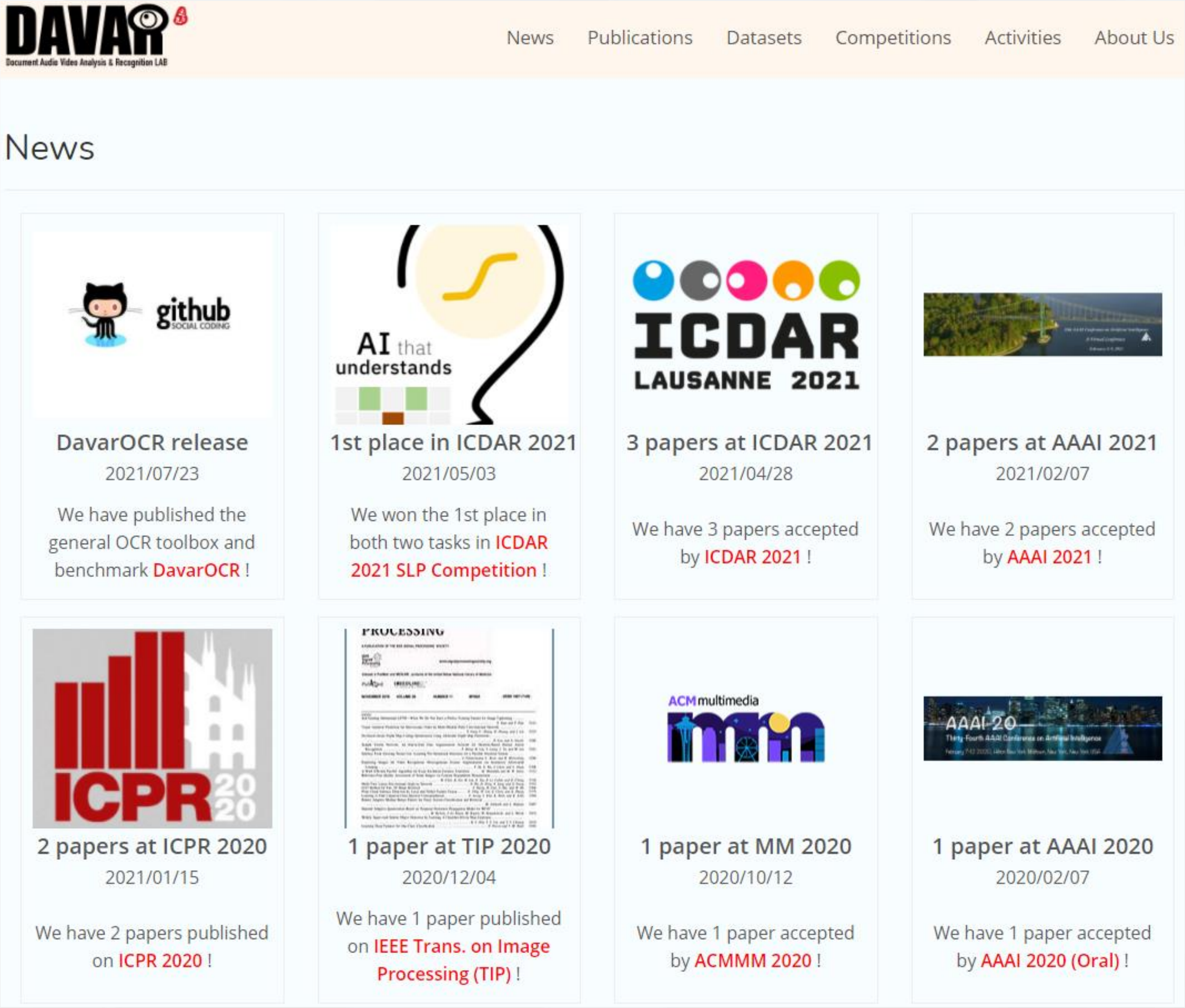


Fig. 4. Qualitative comparison between *VSR w/wo RM*. Introducing *RM* effectively removes duplicate predictions and provides more accurate detection results (both labels and coordinates). The colors of semantic labels are: Figure, Body, Figure Caption.

https://davar-lab.github.io/index.html



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