KnowVrDU: A Unified Knowledge-aware Prompt-Tuning Framework for Visually-rich Document Understanding

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Introduction

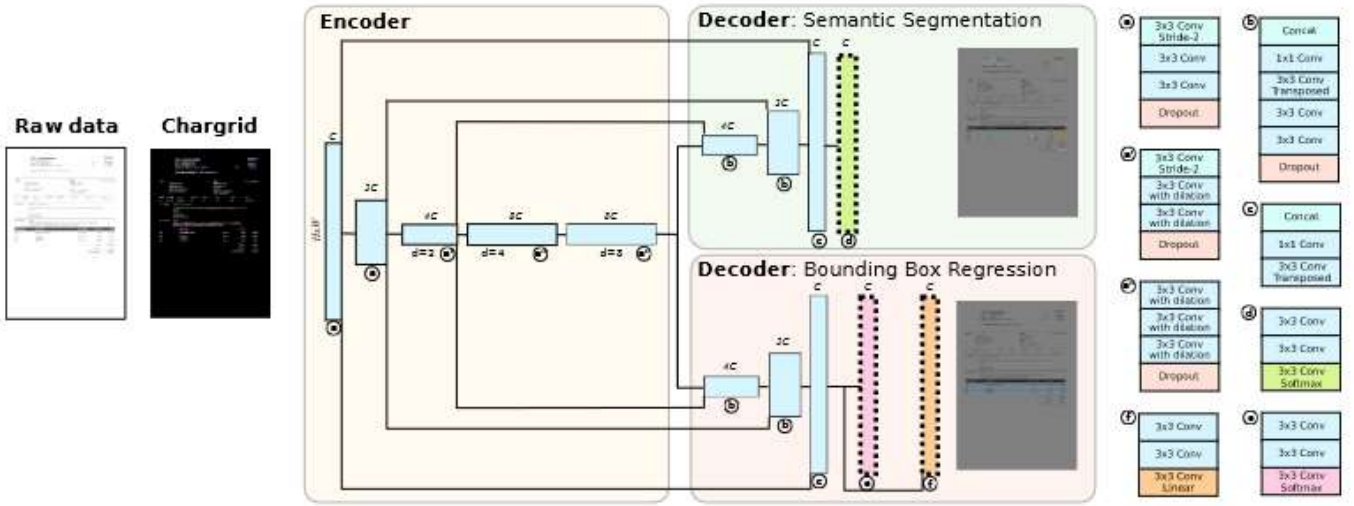
- Visually-rich Document Understanding(VrDU)
  - Automatically analyze and extract significant factual texts from image or digital-born documents
  - Subtasks: document information extraction, document visual question answering and document image classification[1]

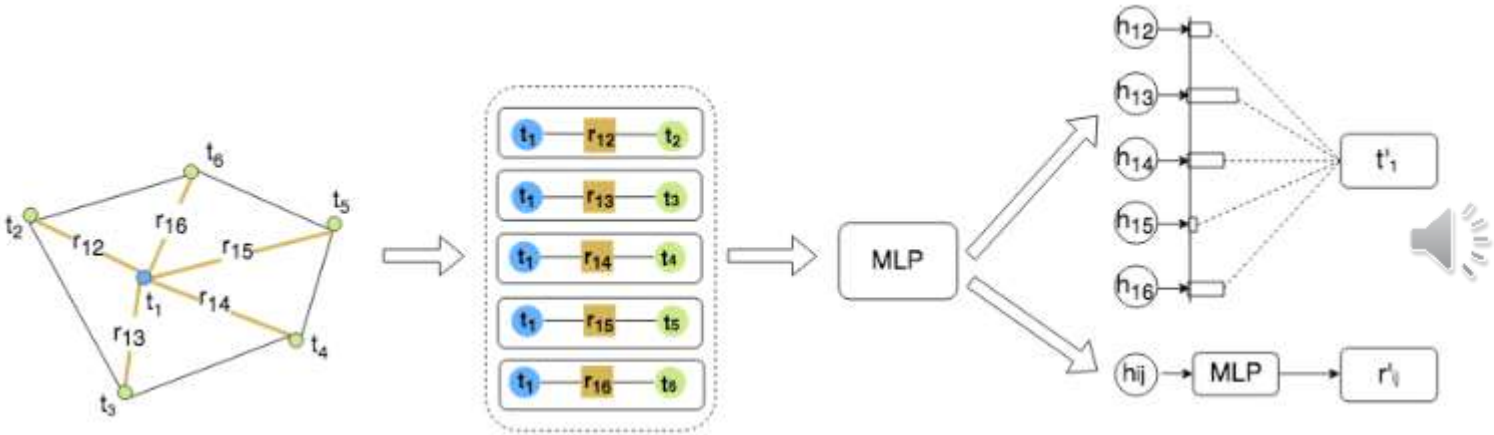
Introduction

- Critical multi-modal task
  - Cross-modal alignment learning
- Recent work
  - Learning the multi-modal interactions between text, image and layout modalities.
  - Neural network-based approaches: designing suitable network architectures
  - Pre-train and fine-tune approaches : designing objectives used at both the pre-train and fine-tune stages

Related Work

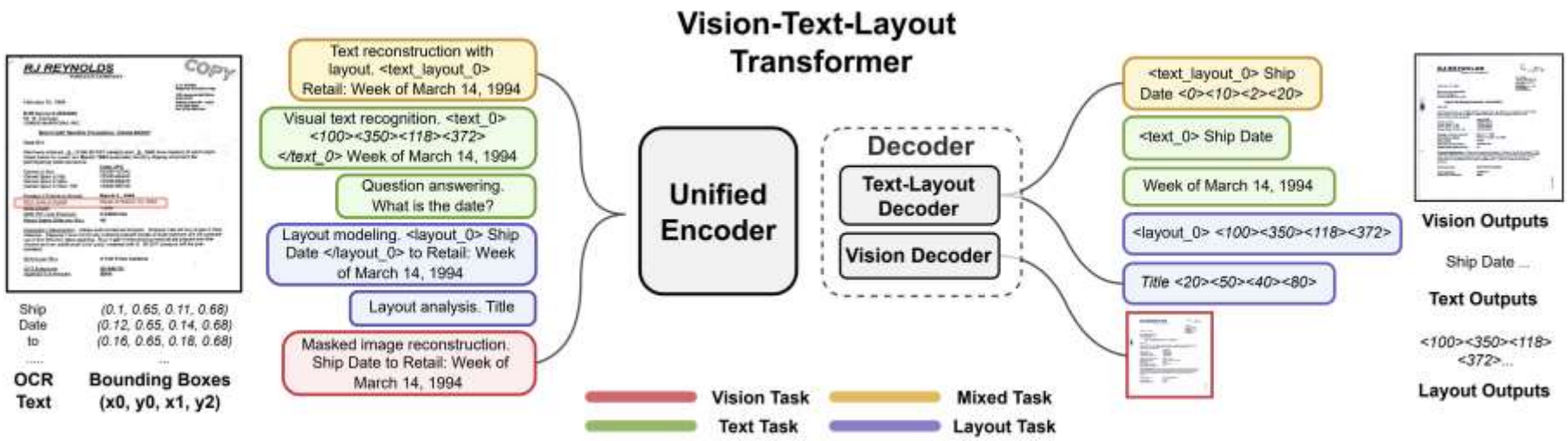
- Neural network-based approaches
  - CharGrid[2], GCN[3]





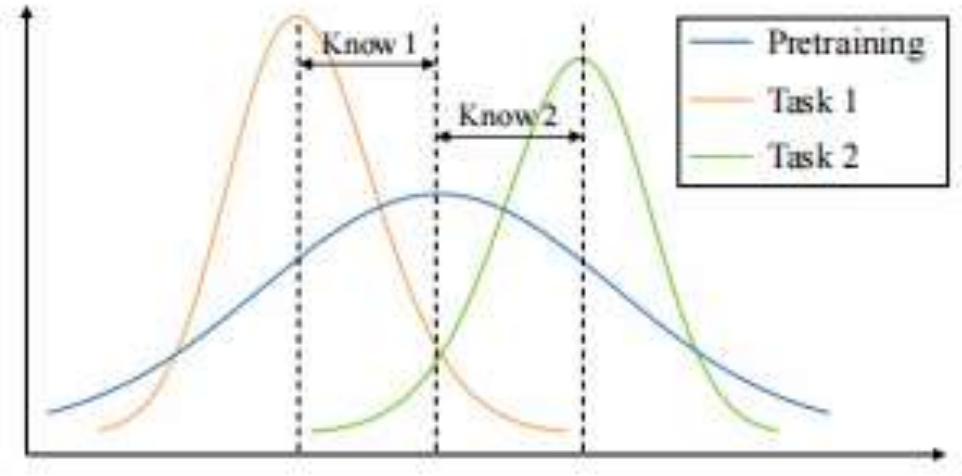
Related Work

- Pre-train and fine-tune approaches
  - Layoutlmv3[4], UDOP[5]



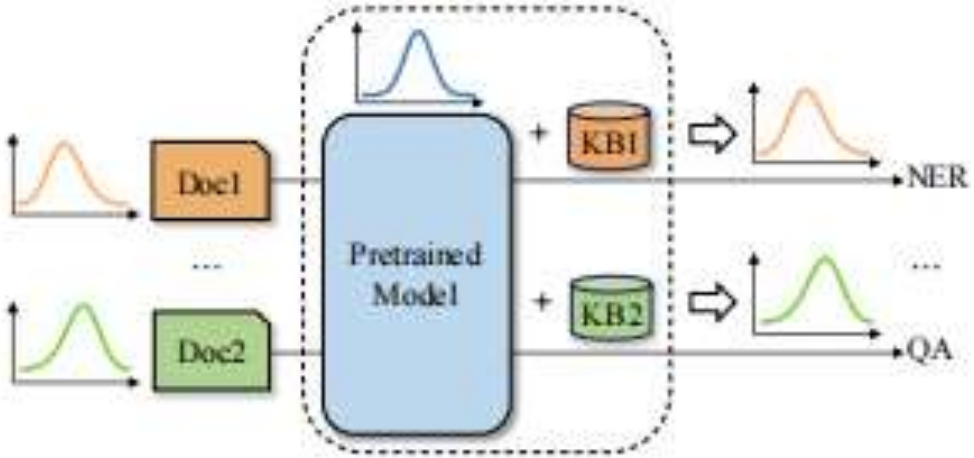
Problems

- Existing methods [6] relied on huge demands of designing dedicated architectures and annotating task-specific samples to fine-tune pretrained models.
- Significant knowledge distribution gaps between the pre-training task and VrDU tasks.
- Limited annotations are insufficient and ineffective in capturing refined task expertise [7].



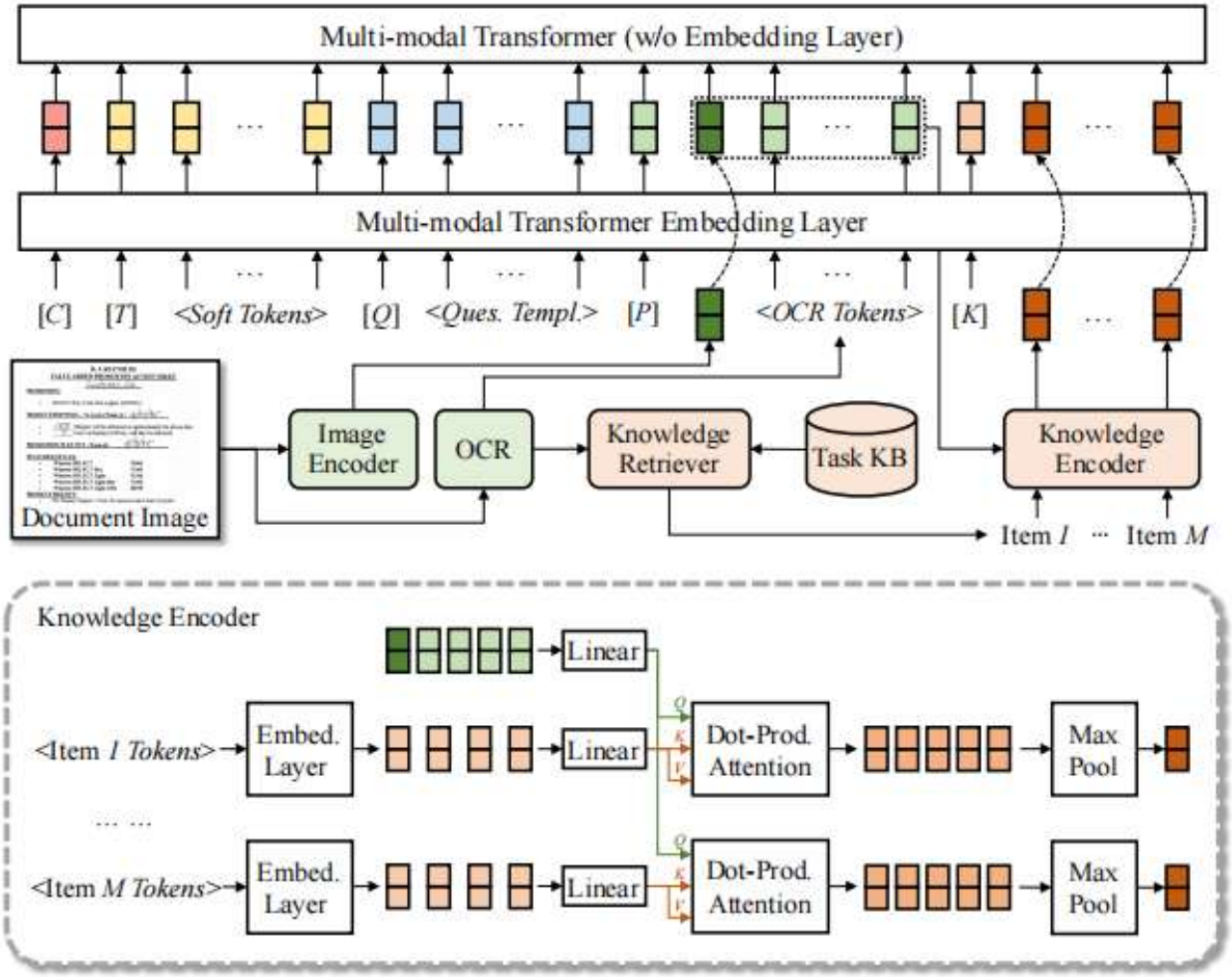
Motivation

- Recent research of natural language processing uniformly model various tasks, including information extraction and document classification, with Question Answering (QA) format.
- The lack of task-specialized knowledge caused by limited labeled data in few-shot scenarios can be compensated with large-scale knowledge bases.



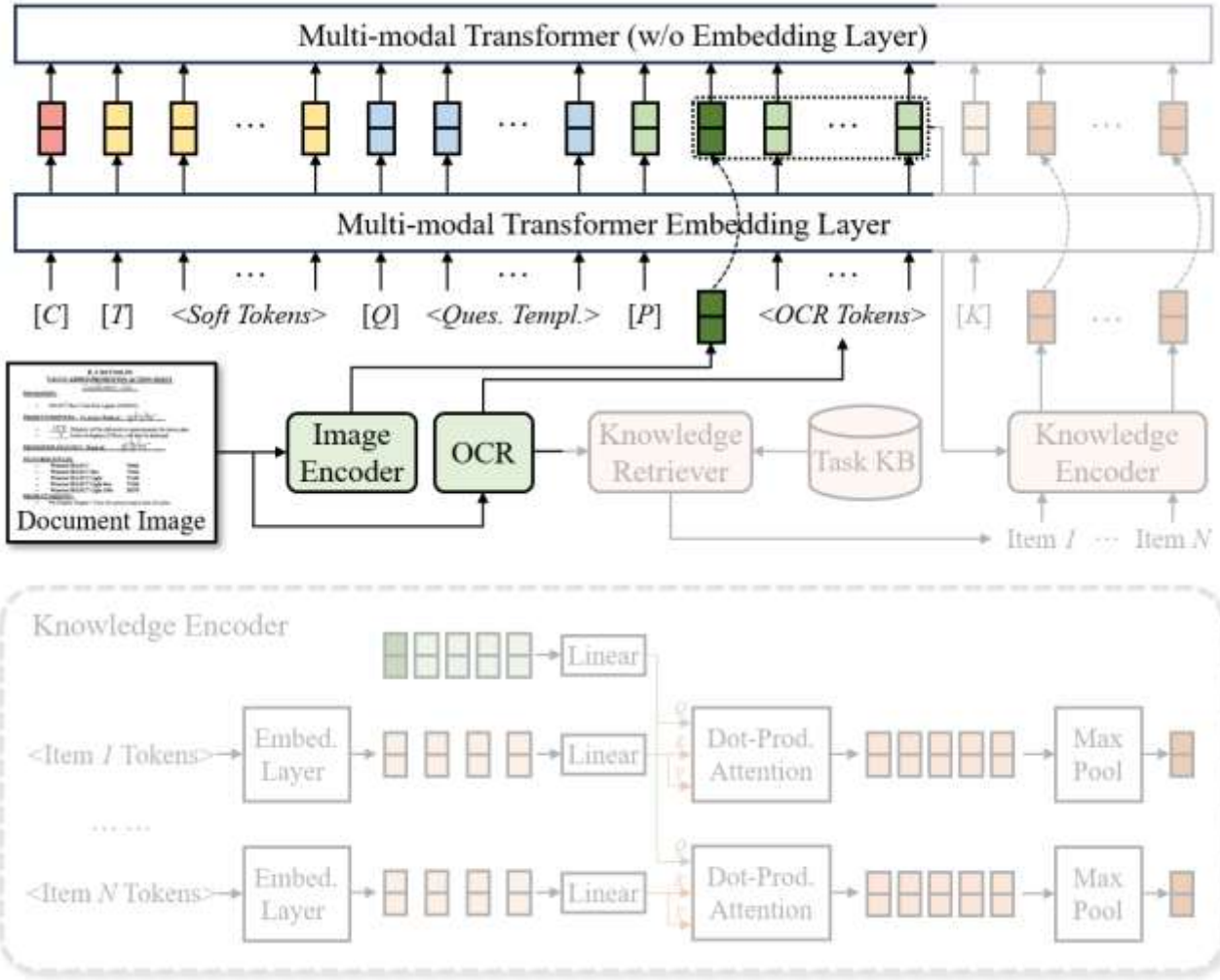
Our Approach

- Overall Framework



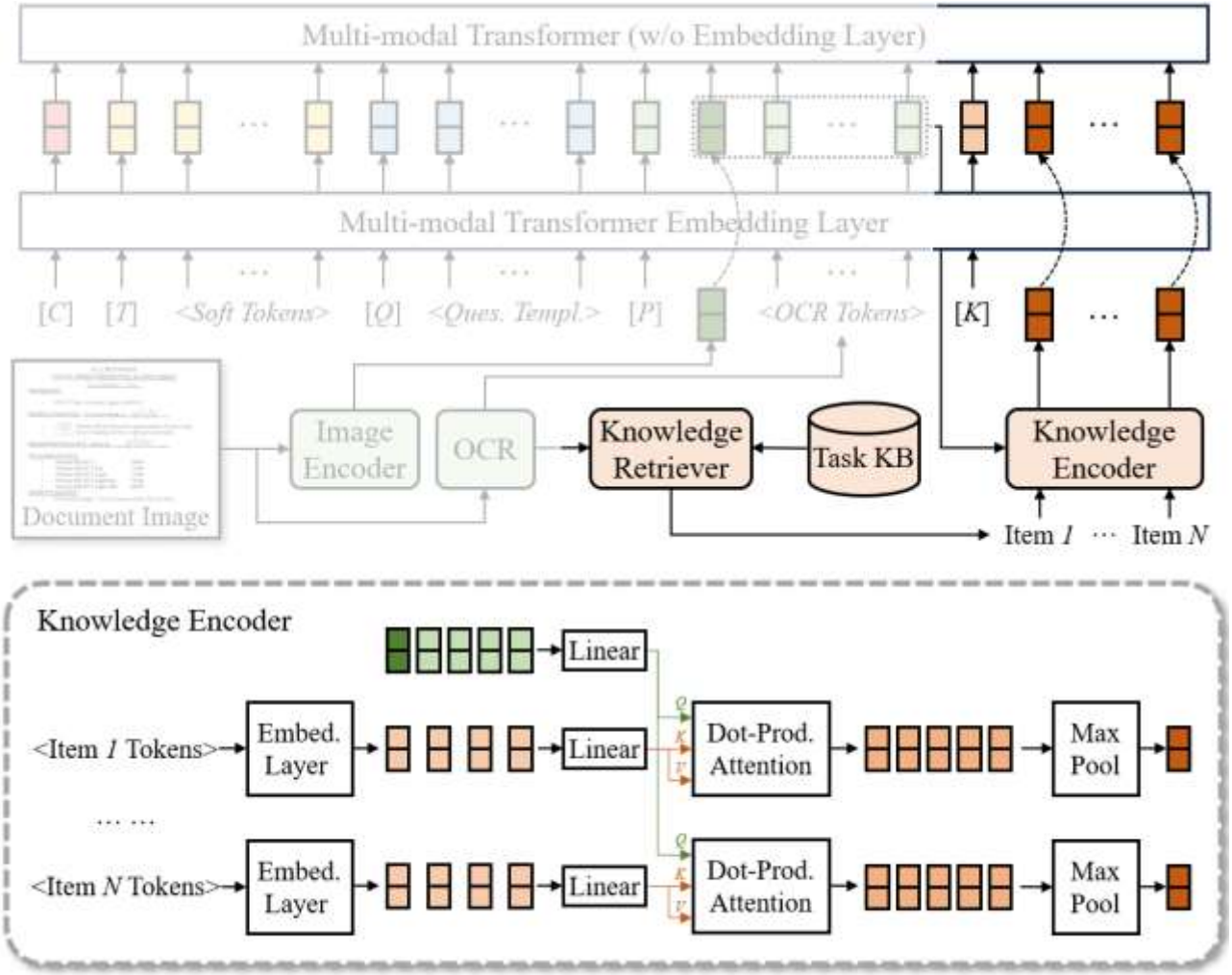
Our Approach

- Uniform Prompts Generation



Our Approach

- External Knowledge Injection



Experiments

- Datasets
  - FUNSD: 199 documents
  - CORD: 1000 documents
  - RVL-CDIP: 400000 documents
  - DocVQA:12767 documents

Dataset	Field	Train	Vaild	Test
FUNSD	4	149	-	50
CORD	30	800	100	100
RVL-CDIP	16	320k	40k	40k
DocVQA	-	10,104	1,286	1,287

- Evaluation
  - Document Information Extraction: Precision, Recall, F_1
  - Document Image Classification: Accuracy
  - Document Question Answering: ANLS

Experiments

- Performance Evaluation on FUNSD and CORD

N	Method	FUNSD			CORD		
		Precision	Recall	F_1	Precision	Recall	F_1
2	RoBERTa	21.64±1.64	33.43±4.24	26.68±1.76	34.96±6.73	45.70±7.17	39.59±7.03
	LASER	30.40±4.89	35.20±7.20	32.36±5.14	-	-	-
	LayoutLMv3$_{BASE}$	44.29±6.14	58.96±7.20	50.43±6.03	47.21±6.25	58.99±4.94	52.41±5.85
	†LAGER$_{BASE}$	49.82±6.06	59.55±8.91	54.09±6.54	48.68±5.72	60.19±4.23	53.79±5.24
	KnowVrDU$_{BASE}$	50.37±5.85	59.61±6.26	54.42±6.13	49.36±5.96	59.84±3.28	54.29±4.75
	KnowVrDU$_{LARGE}$	**54.28±4.77**	**64.09±6.34**	**58.67±5.82**	**52.27±5.31**	**66.15±4.53**	**57.73±4.97**
4	RoBERTa	27.53±2.92	42.83±2.68	33.48±2.83	45.89±7.84	55.04±8.69	50.05±8.25
	LASER	44.91±2.42	50.25±3.26	47.36±2.18	-	-	-
	LayoutLMv3	65.32±3.89	77.97±2.26	71.06±3.04	54.18±5.01	64.92±3.76	59.04±4.53
	†LAGER$_{BASE}$	67.86±3.30	78.73±2.57	72.86±2.69	56.28±4.24	66.47±3.29	60.94±3.86
	KnowVrDU$_{BASE}$	69.20±3.03	78.51±2.64	73.67±2.31	56.69±4.13	68.16±4.05	62.24±5.01
	KnowVrDU$_{LARGE}$	**72.87±4.49**	**79.61±3.11**	**76.15±3.47**	**58.58±3.87**	**72.31±3.84**	**64.79±3.40**
6	RoBERTa	33.75±2.19	47.20±2.54	39.32±2.06	52.88±4.84	61.41±4.86	56.82±4.82
	LASER	48.64±2.14	53.54±2.10	50.96±1.95	-	-	-
	LayoutLMv3	71.19±3.75	80.83±1.09	75.68±2.58	60.91±3.51	69.16±2.76	64.76±3.16
	†LAGER$_{BASE}$	72.71±3.41	81.53±1.98	76.84±2.58	61.80±5.14	70.00±3.75	65.63±4.53
	KnowVrDU$_{BASE}$	72.23±3.26	83.25±1.16	77.31±2.36	63.27±2.76	72.90±4.68	67.59±3.38
	KnowVrDU$_{LARGE}$	**73.49±2.31**	**85.02±2.40**	**78.60±1.77**	**66.43±3.64**	**73.41±2.57**	**69.62±3.05**
8	RoBERTa	37.30±3.55	49.52±4.89	42.52±4.89	57.38±1.86	65.32±1.54	61.08±1.57
	LASER	-	-	-	-	-	-
	LayoutLMv3	74.31±2.19	81.75±2.60	77.85±2.29	64.49±3.24	72.21±2.17	68.12±2.77
	†LAGER$_{BASE}$	76.27±1.44	83.41±1.73	79.66±1.14	64.89±4.38	72.22±3.19	68.35±3.84
	KnowVrDU$_{BASE}$	78.14±1.68	84.65±1.29	81.44±1.42	66.17±2.83	72.99±3.71	69.23±3.16
	KnowVrDU$_{LARGE}$	**81.52±1.78**	**87.23±1.36**	**84.04±1.30**	**70.19±3.49**	**75.41±4.44**	**72.51±3.63**

Experiments

- Performance on Document Image Classification and Document Question Answering tasks

Ratio	Model	RVL-CDIP	DocVQA
1%	LayoutLMv3	29.70	16.84
	KnowVrDU$_{BASE}$	38.53	20.91
	KnowVrDU$_{LARGE}$	**45.31**	**25.42**
5%	LayoutLMv3	52.47	28.03
	KnowVrDU$_{BASE}$	56.90	31.78
	KnowVrDU$_{LARGE}$	**61.27**	**35.23**
10%	LayoutLMv3	71.14	42.11
	KnowVrDU$_{BASE}$	75.70	45.52
	KnowVrDU$_{LARGE}$	**78.22**	**49.67**
20%	LayoutLMv3	80.25	67.46
	KnowVrDU$_{BASE}$	84.03	69.81
	KnowVrDU$_{LARGE}$	**85.89**	**72.43**

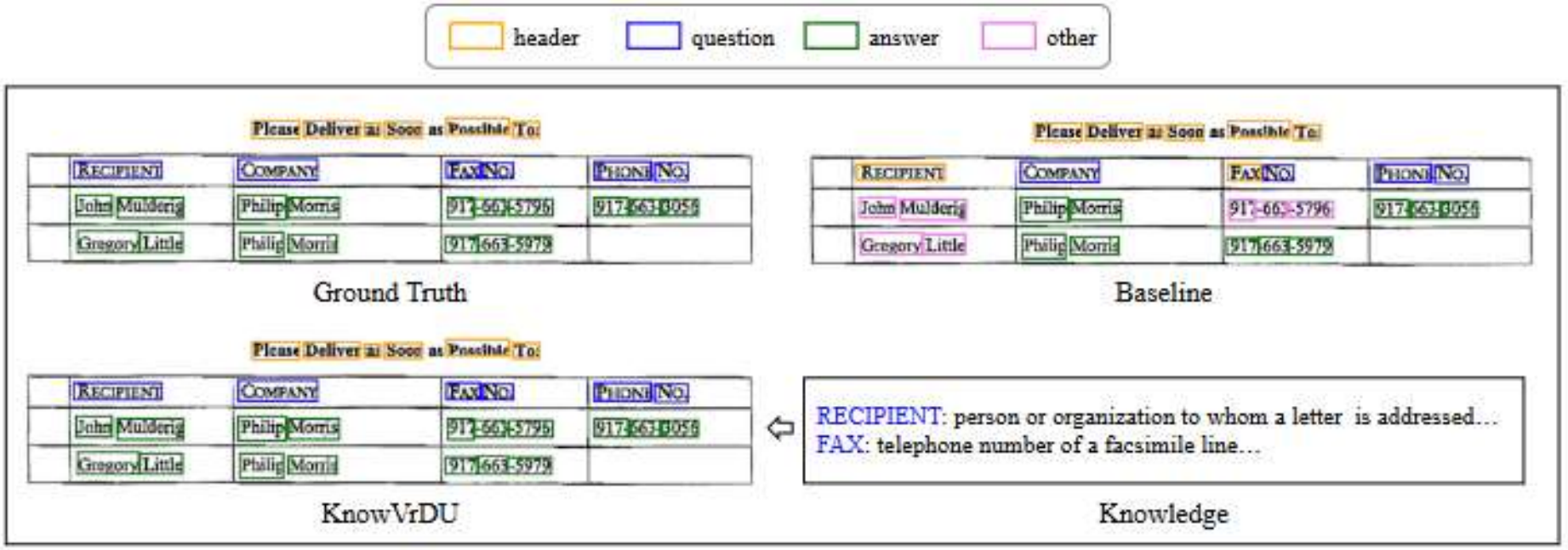
Experiments

- An ablation study of the KnowVrDU model on the CORD dataset.

Method	Prec.	Rec.	F_1
KnowVrDU$_{BASE}$	**78.14**	**84.65**	**81.44**
w/o Attention	76.41	82.27	79.23
w/o Knowledge	74.92	81.66	78.14
w/o Soft Prompts	77.10	83.49	80.16
w/o All	74.31	81.75	77.85

Experiments

- Case Study



Conclusion

- We propose a unified knowledge-aware framework for a wide applications of various downstream VrDU tasks.
- We propose to model heterogeneous VrDU structures through reformulating all tasks into extractive question answering tasks with task-specific prompts.
- We propose to reduce the knowledge gap through integrating external open-source knowledge to incorporate external knowledge bases.
- Experimental results in few-shot settings demonstrate the effectiveness of our method on a wide variety of downstream VrDU tasks.

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Thanks for Listening!