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OCR-free Document Understanding Transformer

Geewook Kim[1] *, Teakgyu Hong[4], Moonbin Yim[2], Jeongyeon Nam[1], Jinyoung Park[5], Jinyeong Yim[6], Wonseok Hwang[7], Sangdoo Yun[3], Dongyoon Han[3], Seunghyun Park[1]

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[1]NAVER CLOVA [2]NAVER Search [3]NAVER AI Lab [4]Upstage [5]Tmax [6]Google [7]LBox

This is a slide for a paper “OCR-free Document Understanding Transformer”

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which will be presented at

ECCV EUROPEAN CONFERENCE ON COMPUTER VISION TEL AVIV 2022 October 23-27, 2022, Tel Aviv

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Agenda

1. Introduction: Background and Motivation
2. Proposal: Document Understanding Transformer (Donut 🍩)
3. Experiments and Analyses
4. Conclusions

This is the table of contents. Let’s start from the Introduction.

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Visual Document Understanding (VDU)

VDU Model

Useful Information

VDU aims to extract useful information from the document image. For example,

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Example 1: Document Classification

VDU Model

{ "class": "receipt" }

A document classifier aims to extract a category information from the image.

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Example 2: Document Parsing

VDU Model


```
{ "menu": [
    {
      "nm": "3002-Kyoto Choco Mochi",
      "unitprice": "14.000",
      "cnt": "x2",
      "price": "28.000"
    }, … }
```


For another example, a document parser aims to get a data in a format, such as, JSON or XML, that contains full information.

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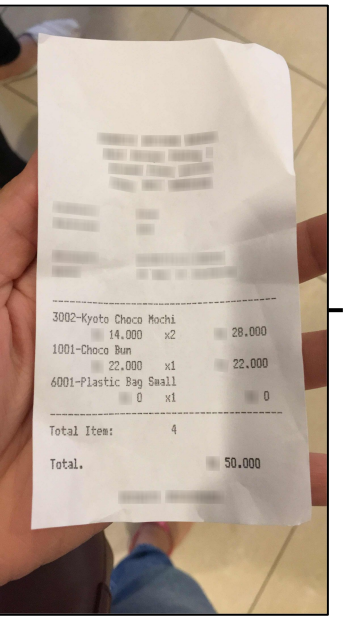
Conventional VDU Model

Input



Output


```
{ "items": [
    {
      "name": "3002-Kyoto Choco Mochi",
      "count": 2,
      "priceInfo": {
        "unitPrice": 14000,
        "price": 28000
      }
    }, {
      "name": "1001 - Choco Bun",
      "count": 1,
      "priceInfo": {
        "unitPrice": 22000
        "price": 22000
      }
    }, ...
  ],
  "total": [ {
      "menuqty_cnt": 4,
      "total_price": 50000
    }
  ]
}
```


Here, we show a representative pipeline of visual document parsing.

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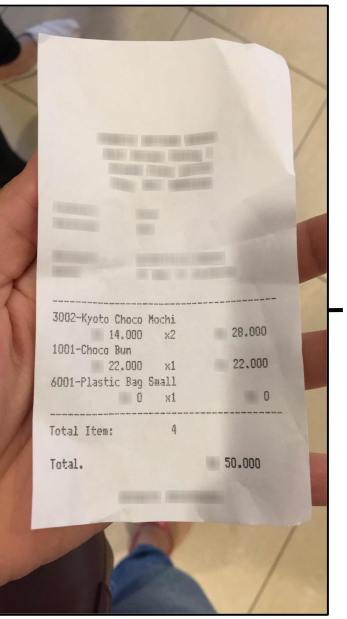
Conventional VDU Model

Input



Output


```
{ "items": [
    {
      "name": "3002-Kyoto Choco Mochi",
      "count": 2,
      "priceInfo": {
        "unitPrice": 14000,
        "price": 28000
      }
    }, {
      "name": "1001 - Choco Bun",
      "count": 1,
      "priceInfo": {
        "unitPrice": 22000
        "price": 22000
      }
    }, ...
  ],
  "total": [ {
      "menuqty_cnt": 4,
      "total_price": 50000
    }
  ]
}
```


Most conventional VDU methods share a similar pipeline.

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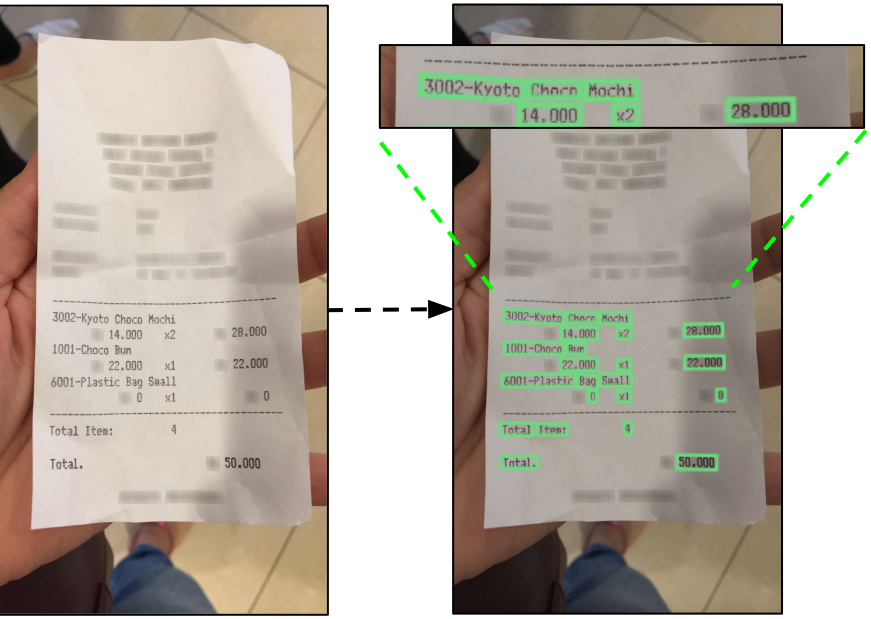
Conventional VDU Model



Detection!

First, a text detector finds all text boxes.

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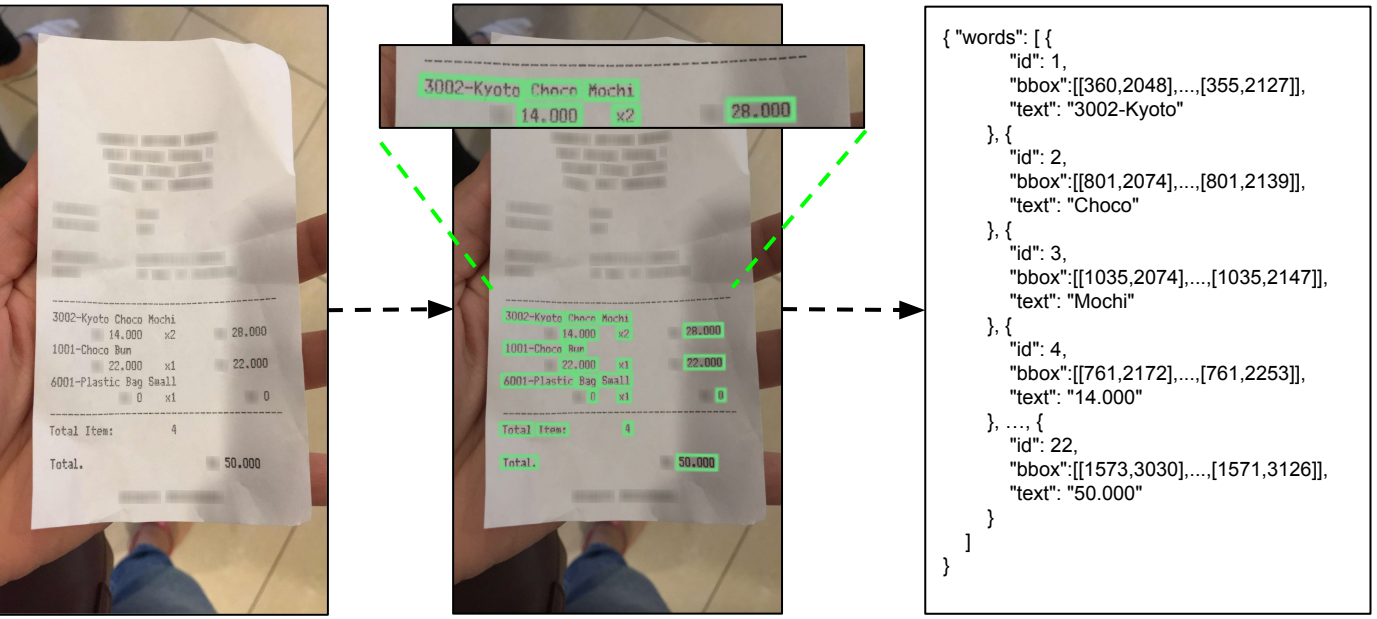
Conventional VDU Model



Detection! Recognition!

And then, a text recognizer reads all texts in the extracted boxes.

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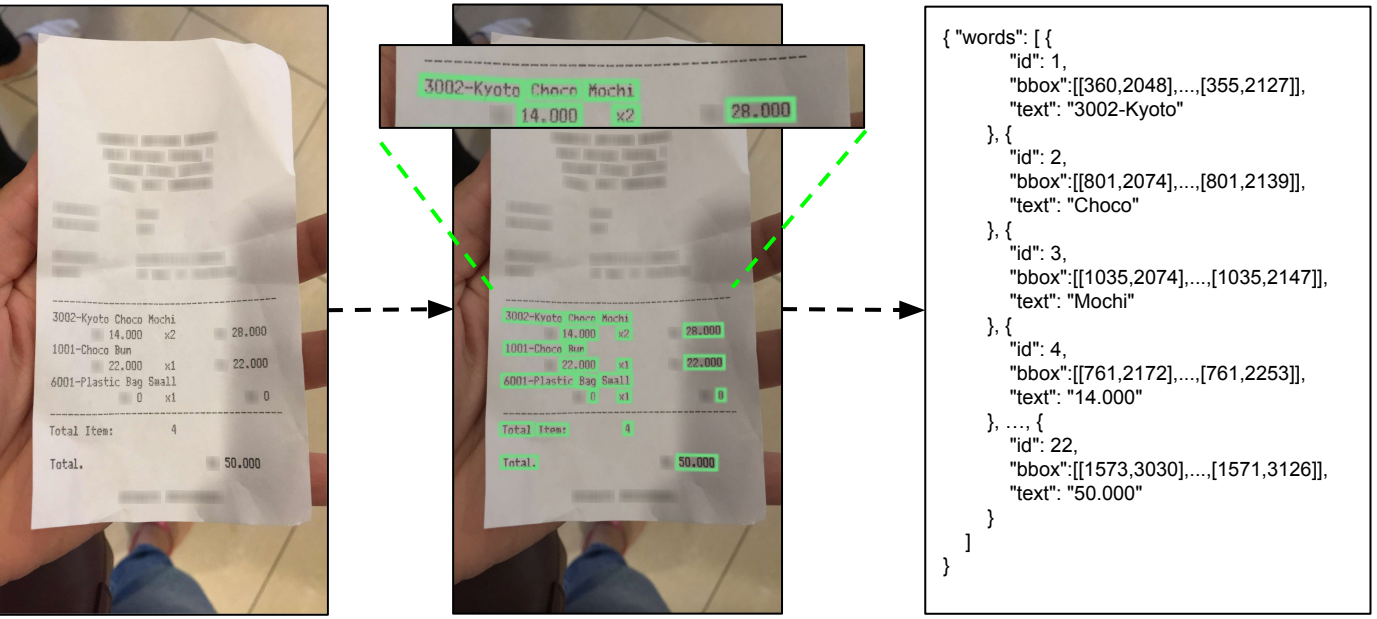
Conventional VDU Model




```
{ "words": [ {
        "id": 1,
        "bbox":[[360,2048],...,[355,2127]],
        "text": "3002-Kyoto"
    }, {
        "id": 2,
        "bbox":[[801,2074],...,[801,2139]],
        "text": "Choco"
    }, {
        "id": 3,
        "bbox":[[1035,2074],...,[1035,2147]],
        "text": "Mochi"
    }, {
        "id": 4,
        "bbox":[[761,2172],...,[761,2253]],
        "text": "14.000"
    }, …, {
        "id": 22,
        "bbox":[[1573,3030],...,[1571,3126]],
        "text": "50.000"
    }
  ]
}
```


Detection! Recognition!

OCR

This two parts are also called as Optical Character Recognition (OCR).

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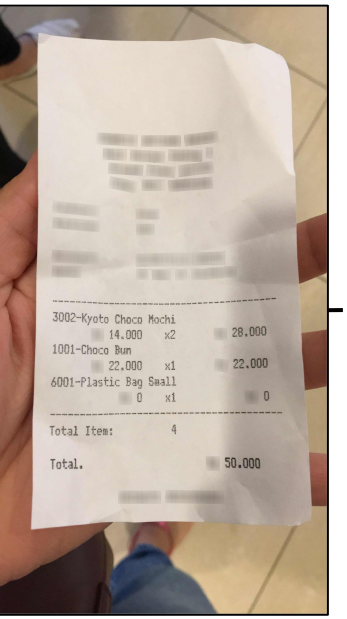
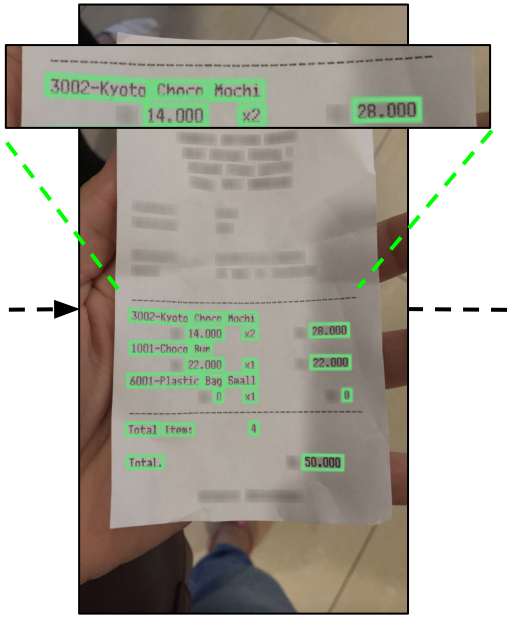
Conventional VDU Model






```
{ "words": [ {
        "id": 1,
        "bbox":[[360,2048],...,[355,2127]],
        "text": "3002-Kyoto"
    }, {
        "id": 2,
        "bbox":[[801,2074],...,[801,2139]],
        "text": "Choco"
    }, {
        "id": 3,
        "bbox":[[1035,2074],...,[1035,2147]],
        "text": "Mochi"
    }, {
        "id": 4,
        "bbox":[[761,2172],...,[761,2253]],
        "text": "14.000"
    }, …, {
        "id": 22,
        "bbox":[[1573,3030],...,[1571,3126]],
        "text": "50.000"
    }
  ]
}
```



```
{ "items": [
   {
    "name": "3002-Kyoto Choco Mochi",
    "count": 2,
    "priceInfo": {
     "unitPrice": 14000,
     "price": 28000
    }
   }, {
    "name": "1001 - Choco Bun",
    "count": 1,
    "priceInfo": {
     "unitPrice": 22000
     "price": 22000
    }
   }, ...
  ],
  "total": [ {
    "menuqty_cnt": 4,
    "total_price": 50000
   }
  ]
}
```


Detection! Recognition! Parsing!

OCR

Finally, the OCR results are fed to a following module to get full information of the document.

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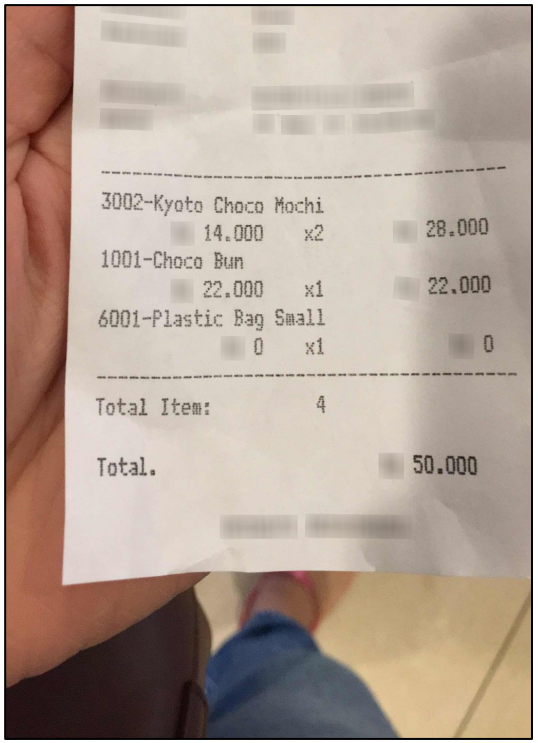
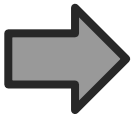
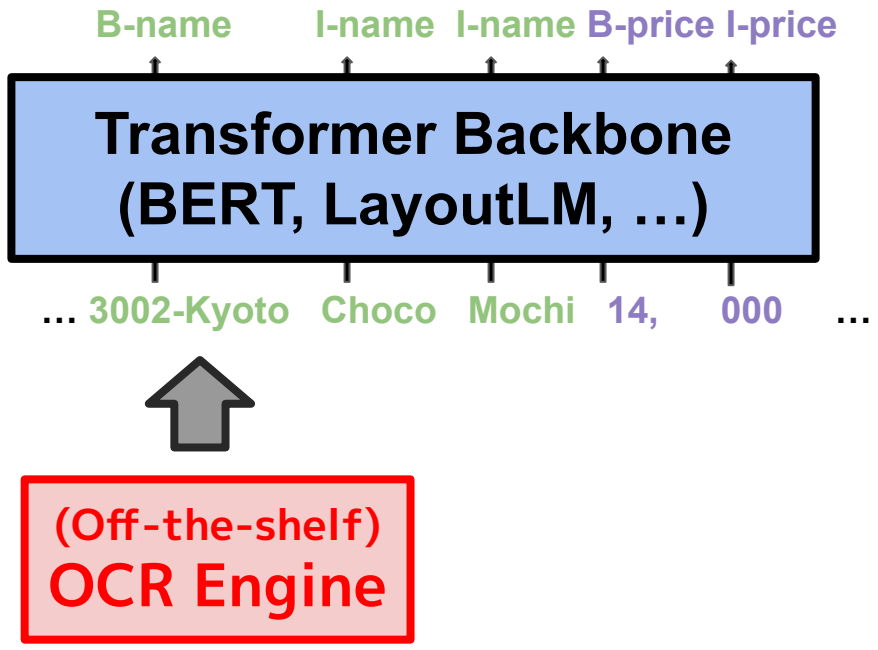
Conventional VDU Model: Details of the Parsing Stage







For example, in most methods, BIO-tags are predicted by a backbone.

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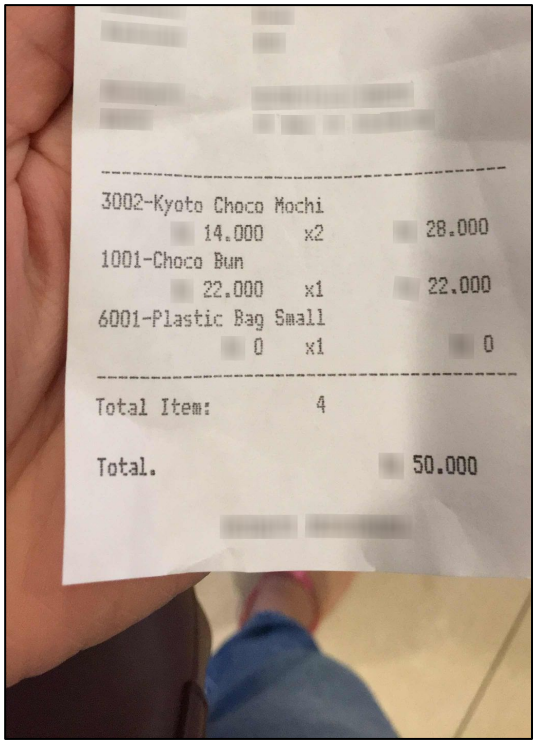
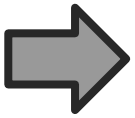
Conventional VDU Model: Details of the Parsing Stage





(Off-the-shelf)
OCR Engine

… 3002-Kyoto Choco Mochi 14, 000 …

Transformer Backbone
(BERT, LayoutLM, …)

B-name I-name I-name B-price I-price

```
{ "menu": [
   {
    "nm": "3002-Kyoto Choco Mochi",
    "unitprice": "14.000",
    "cnt": "x2",
    "price": "28.000"
   }, … }
```

Then, the tag sequence is converted into a final data format (e.g., JSON).

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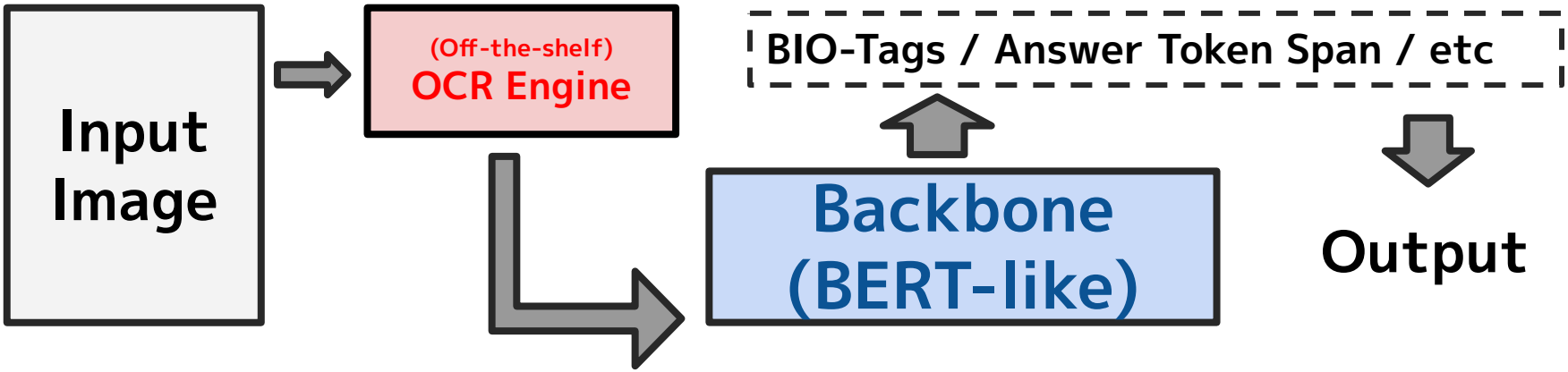
Conventional VDU Model: Overview



Overall, the conventional VDU methods can be summarized as shown in the figure.

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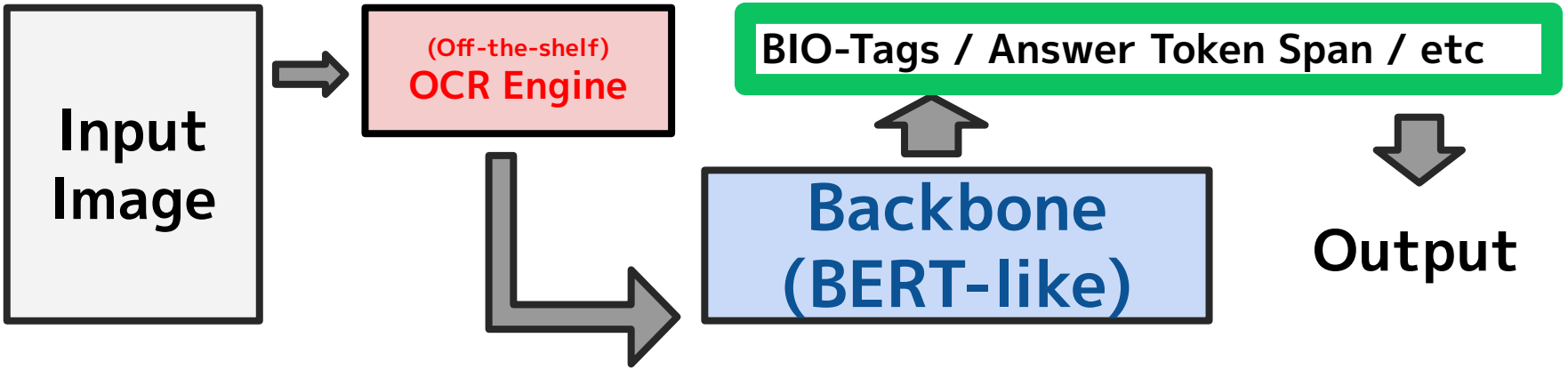
Conventional VDU Model: Overview



For each task, the backbone predicts a desired set of tokens/tags.

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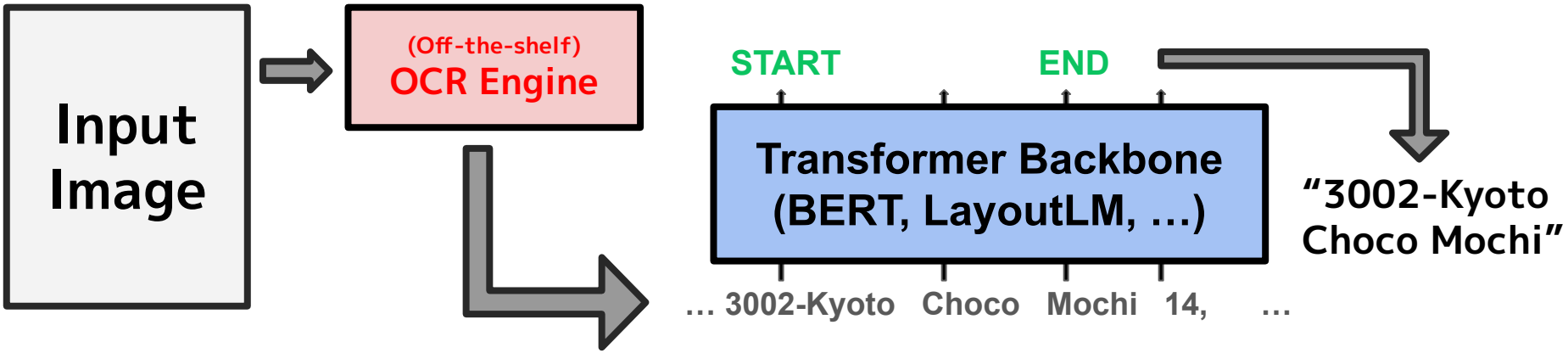
Conventional VDU Model: Overview



For example, in order to conduct VQA,
a span is predicted over the OCR-ed text tokens.

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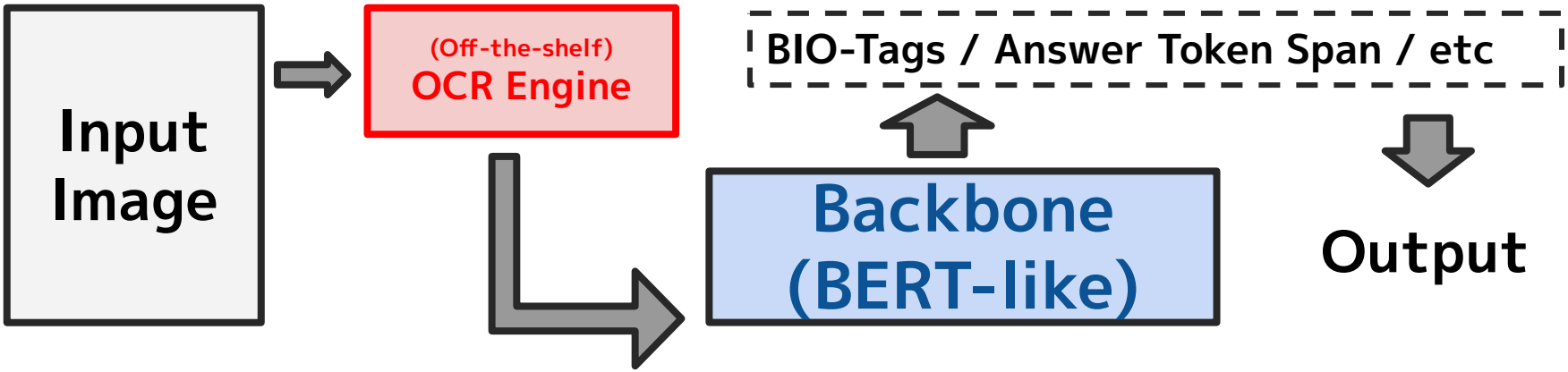
Conventional VDU Model: Overview



Although such OCR-based approaches have shown promising performance, they have several problems induced by OCR.

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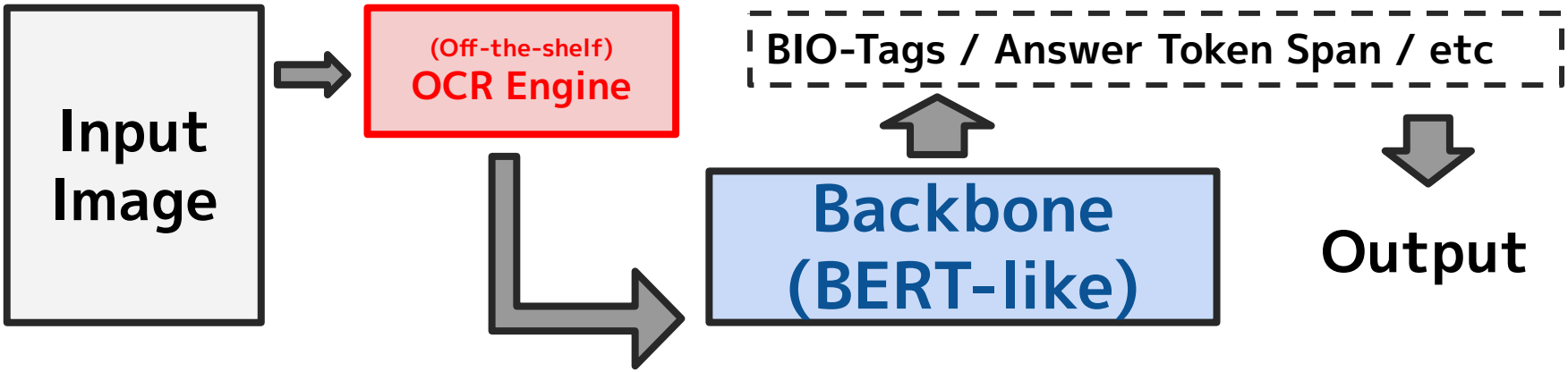
Conventional VDU Model: Overview



Although such OCR-based approaches have shown promising performance, they have several problems induced by OCR.

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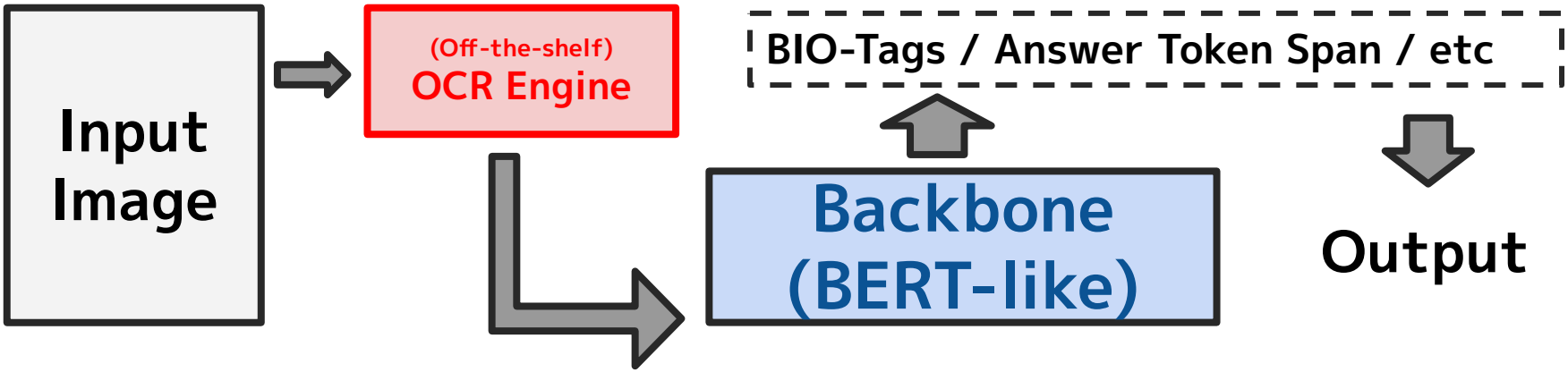
Conventional VDU Model: Overview



- high computational costs

First, OCR increase computational costs.

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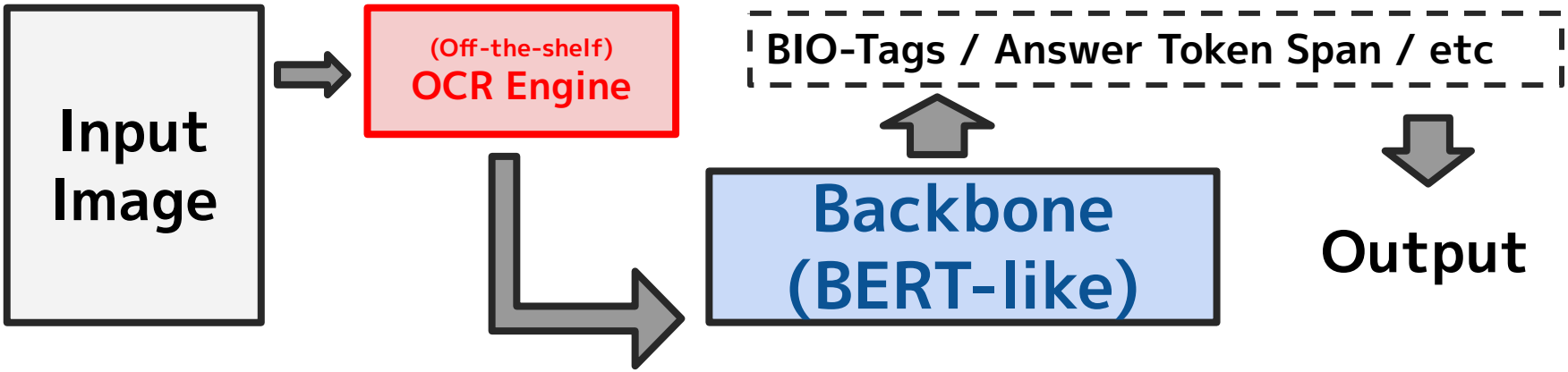
Conventional VDU Model: Overview



- high computational costs
- inflexibility of OCR on languages or document type

Second, OCR makes it hard to handle various languages/types of documents.

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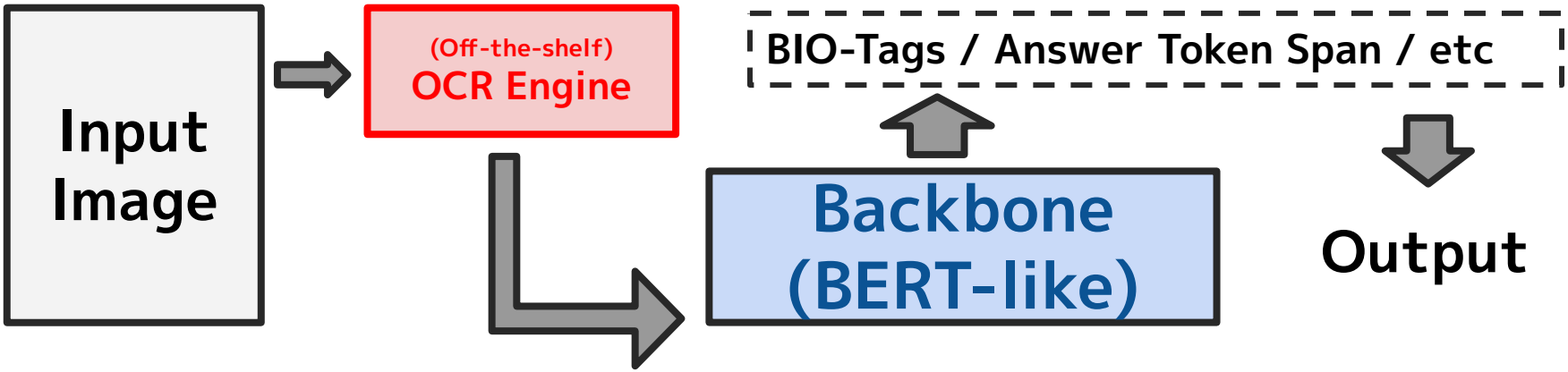
Conventional VDU Model: Overview



- high computational costs
- inflexibility of OCR on languages or document type
- OCR error propagation

Lastly, OCR errors are propagate to the subsequent process.

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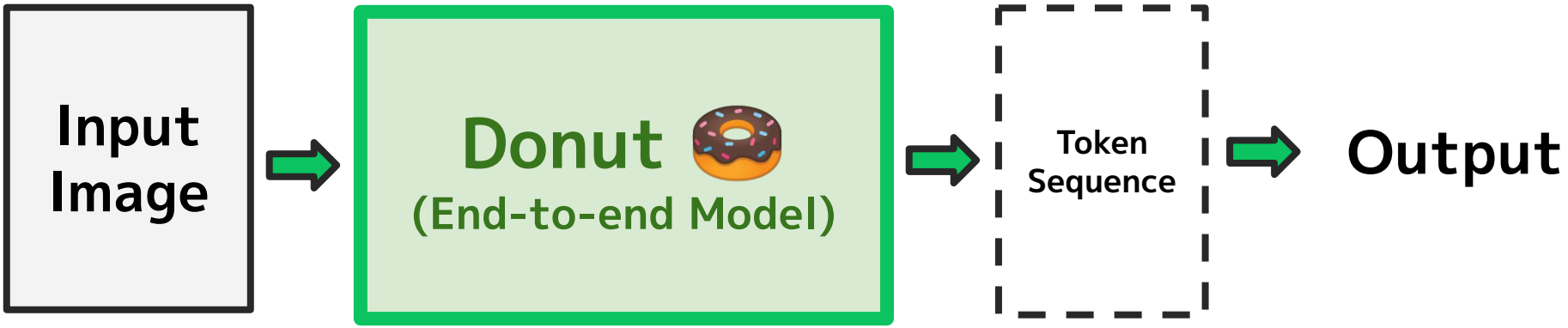
Proposal: OCR-free Approach



To address the issues, we introduce a novel OCR-free VDU model, Donut.

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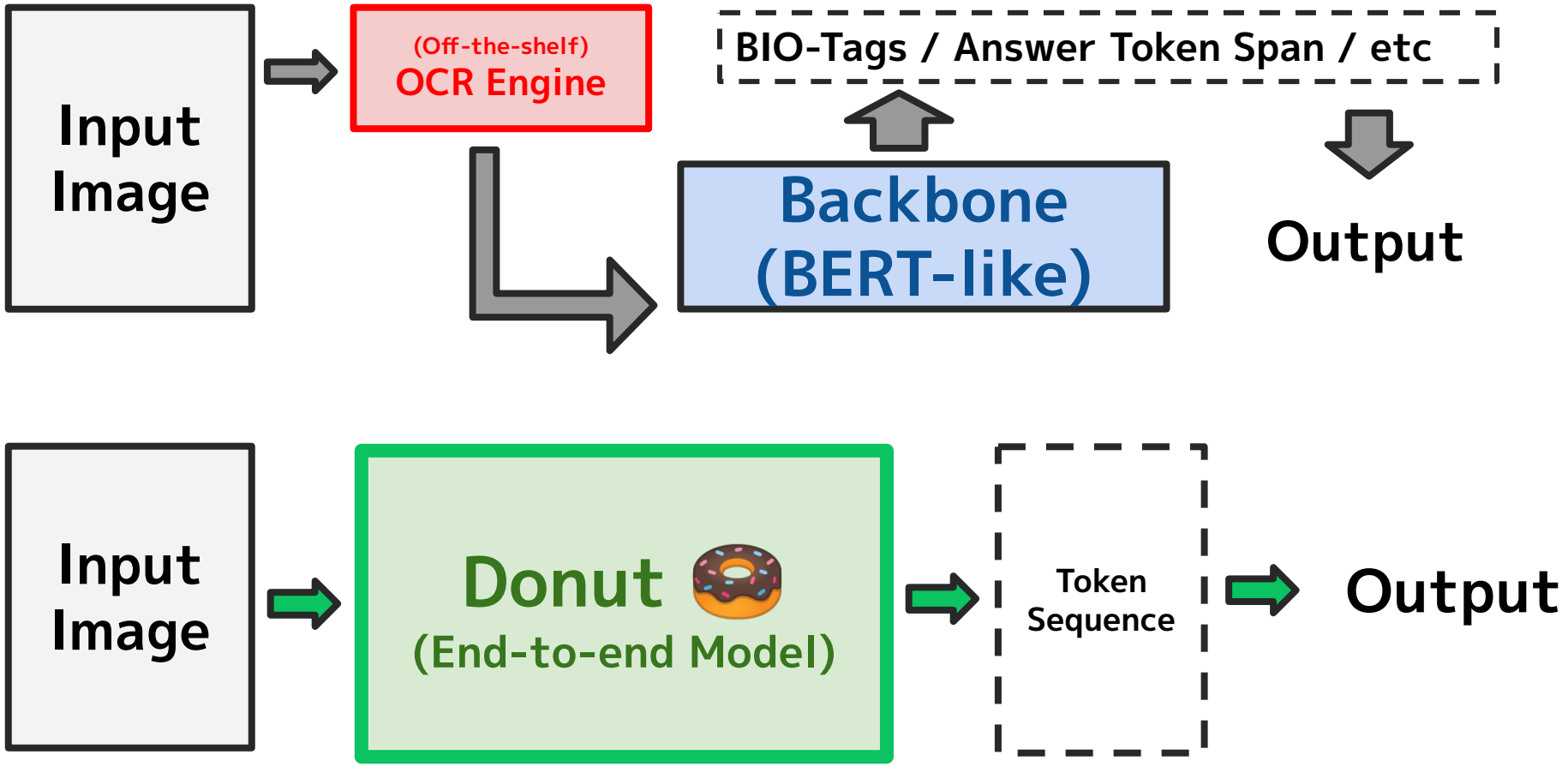
AS-IS v.s. TO-BE



Without OCR, Donut directly processes the input image
and gets an output that contains desired types of information.

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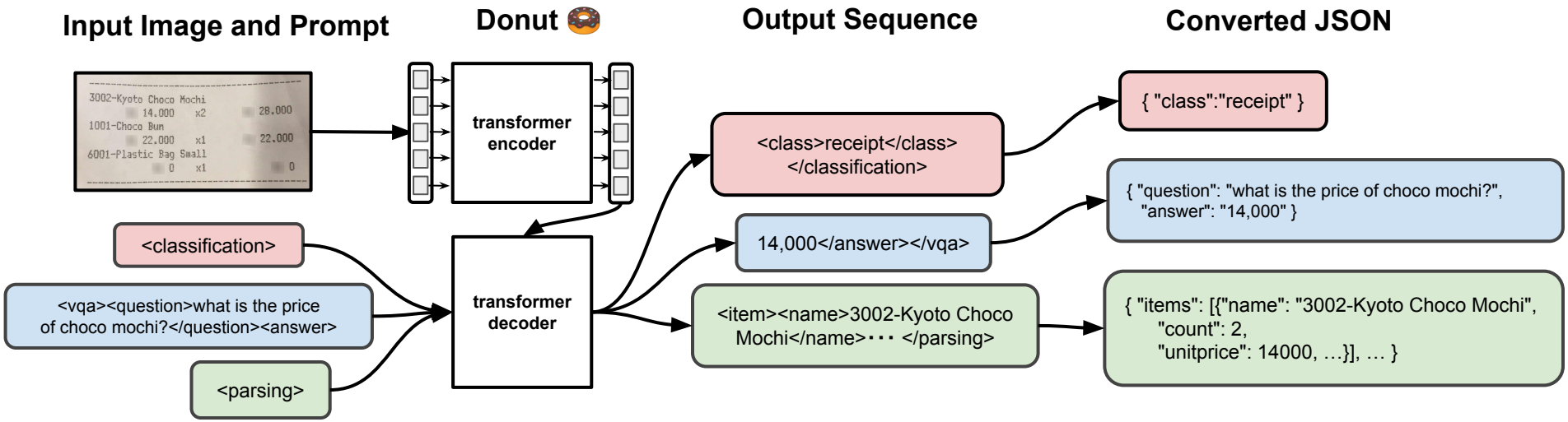
Overview



This is the overview of Donut.

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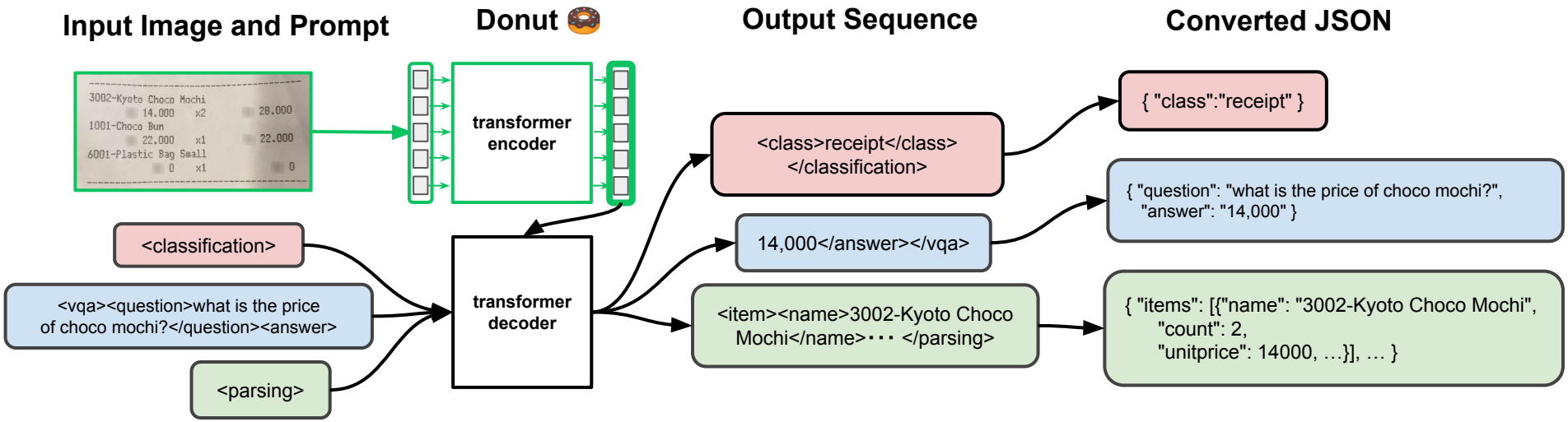
Overview



The visual encoder maps the input image into a set of embeddings.

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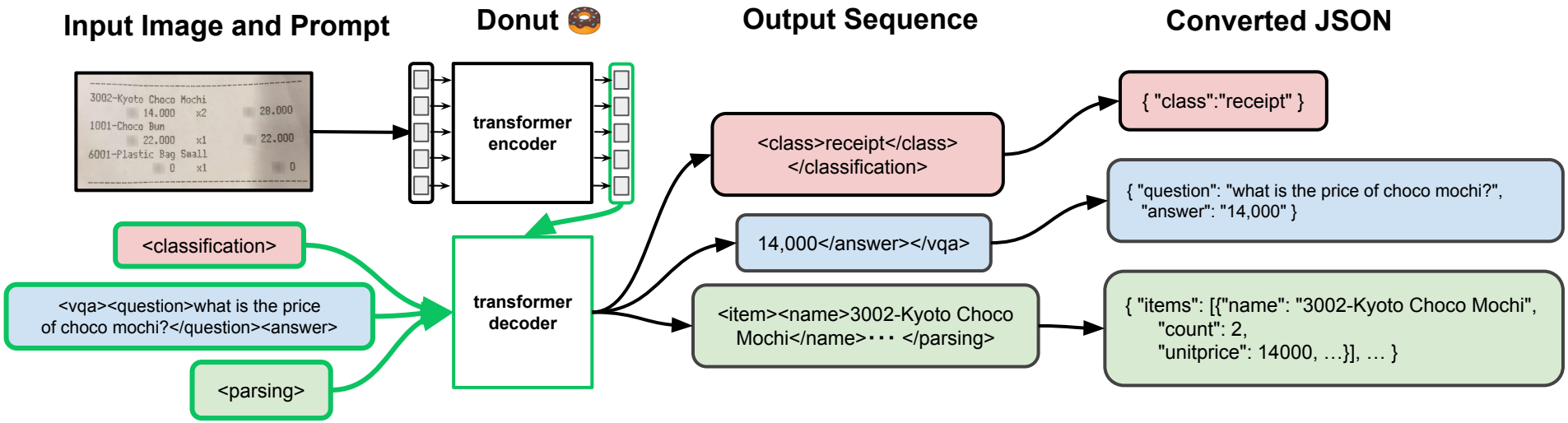
Overview



The textual decoder processes the image embeddings and prompt tokens.

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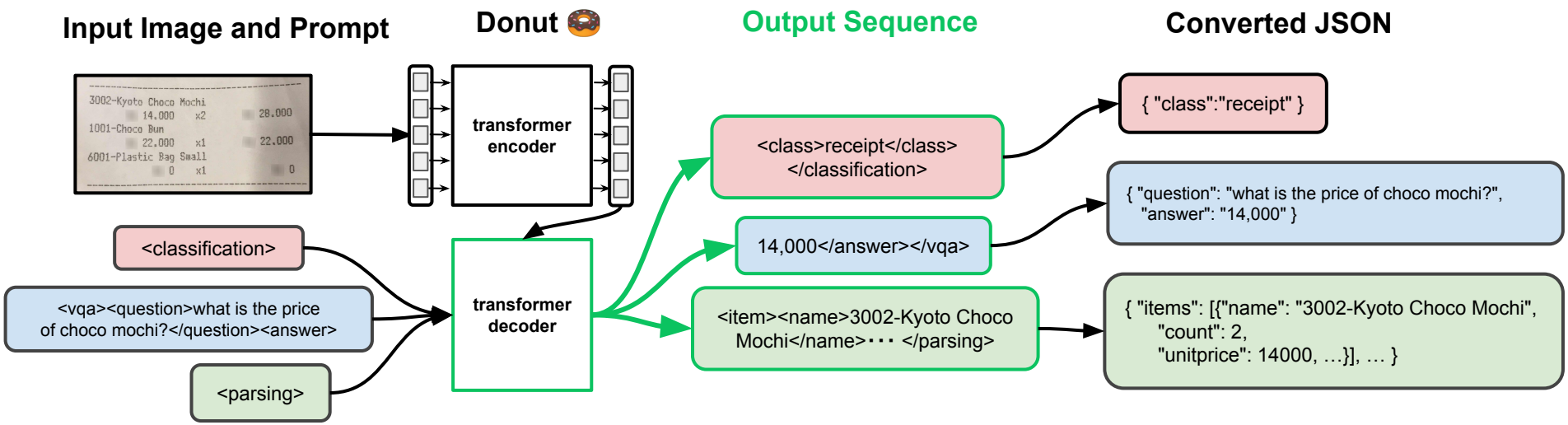
Overview



Then, the decoder outputs token sequences,

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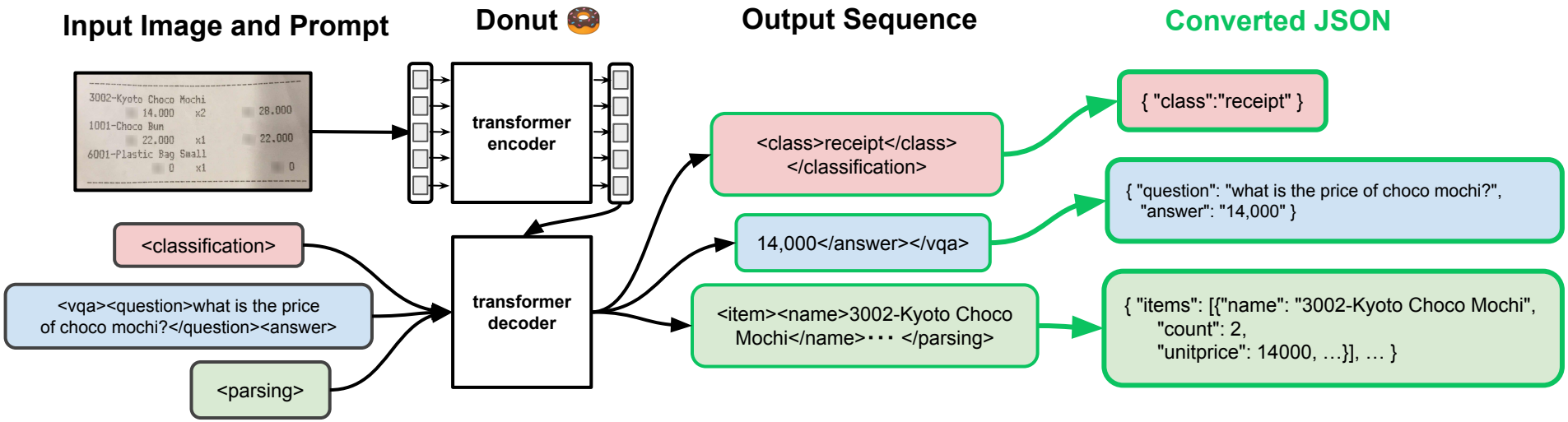
Overview



that can be converted into a desired data format, such as, a JSON format.

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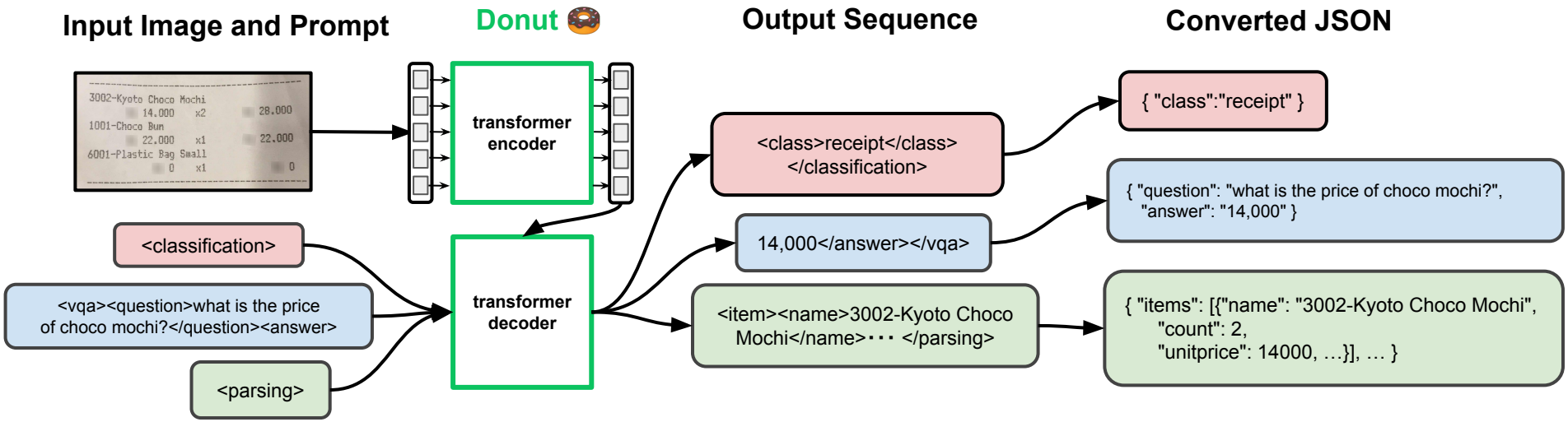
Overview: Model Architecture



Swin Transformer and BART are used as an encoder and decoder, respectively.
More details can also be found in the manuscript.

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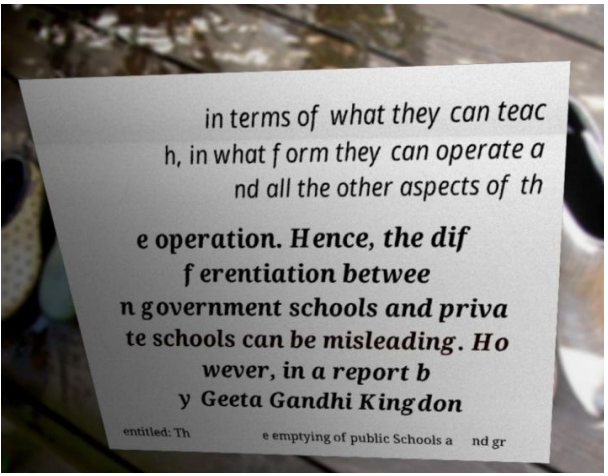
Pre-training Task



Donut 🍩
(End-to-end Model)

In terms of what that can teach, in what from …

To train Donut, we propose a simple pre-training task.

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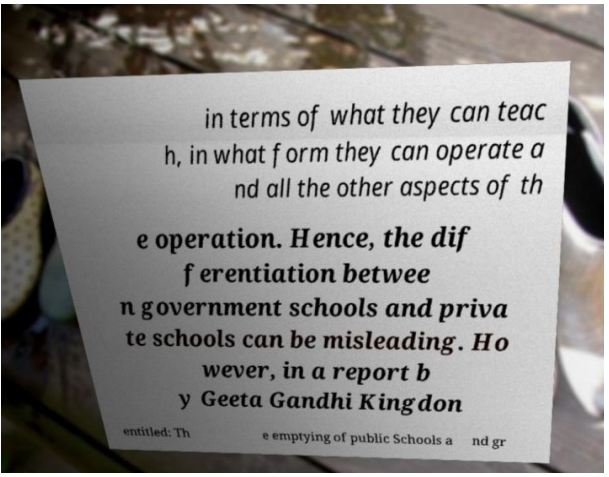
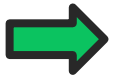
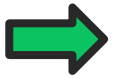
Pre-training Task





Donut 🍩
(End-to-end Model)



In terms of what that can teach, in what from …

The objective is to read all texts from the top-left to bottom-right.
This task can be interpret as a pseudo OCR task.

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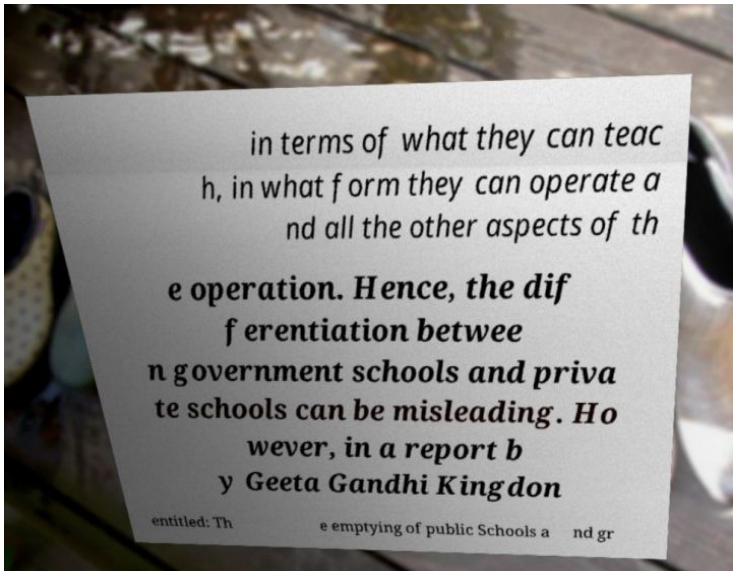
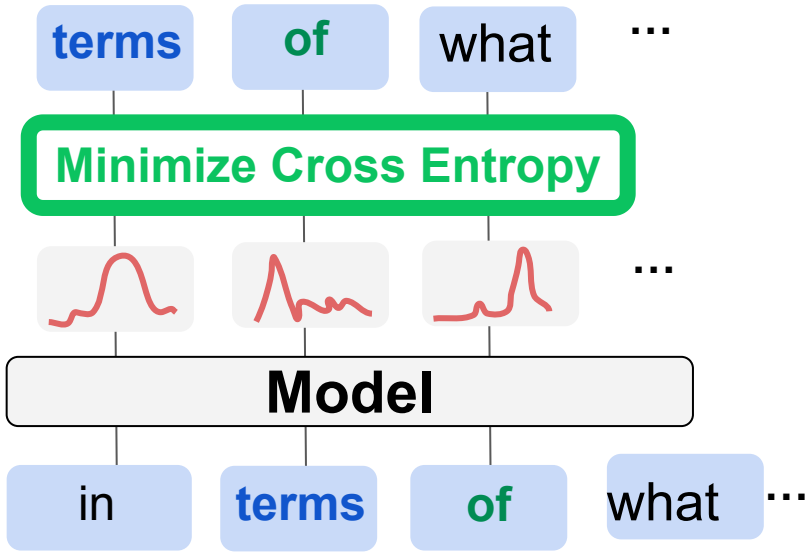
Training Strategy: Teacher-forcing Scheme





This can be interpret as a token classification at each step.

Following the original Transformer, the model training is done with Teacher-forcing scheme. More details can also be found in the manuscript.

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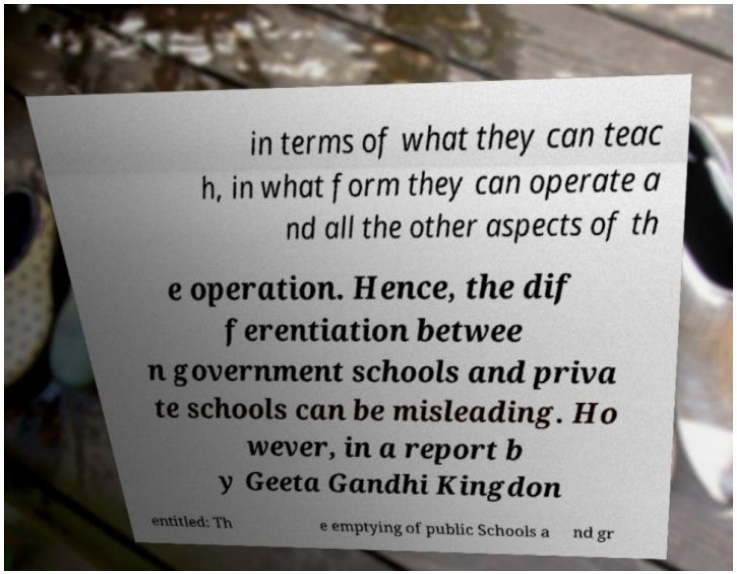
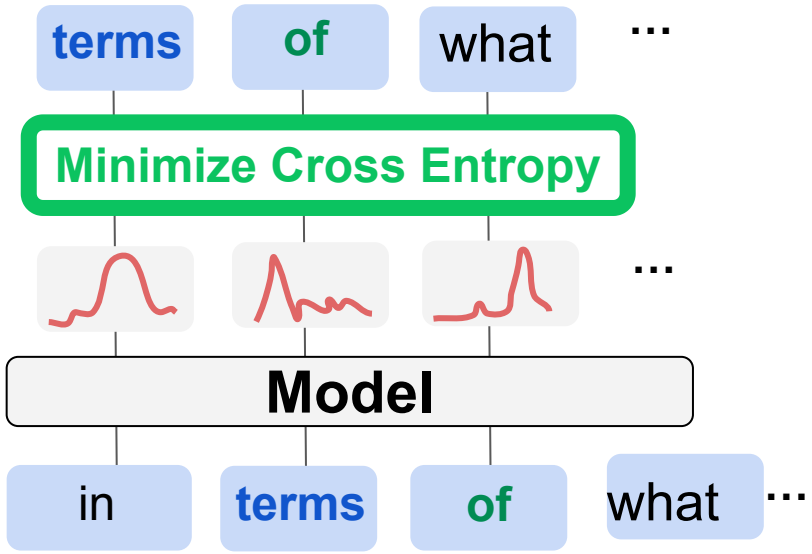
Training Strategy: Teacher-forcing Scheme





This can be interpret as a token classification at each step.

Following the original Transformer, the model training is done with Teacher-forcing scheme. More details can also be found in the manuscript.

Slide

SynthDoG 🐶:Synthetic Document Generator

For the pre-training of Donut, we also present a data generator, SynthDoG 🐶.

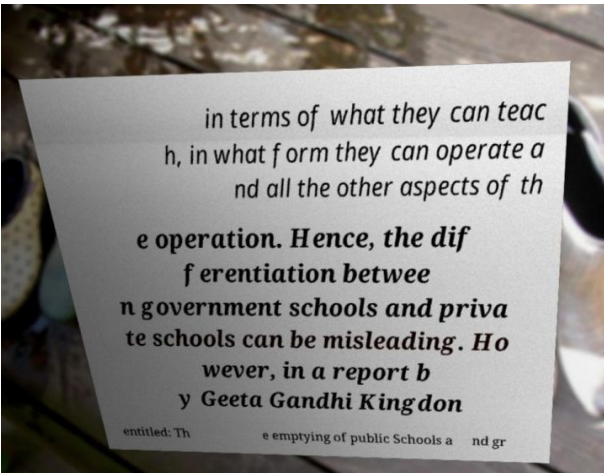
Slide

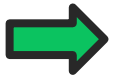
SynthDoG 🐶:Synthetic Document Generator

SynthDoG alleviates the dependency on large-scale real document images and enables the extension to a multilingual setting.

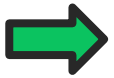
Slide

Pre-training Task





Donut 🍩
(End-to-end Model)

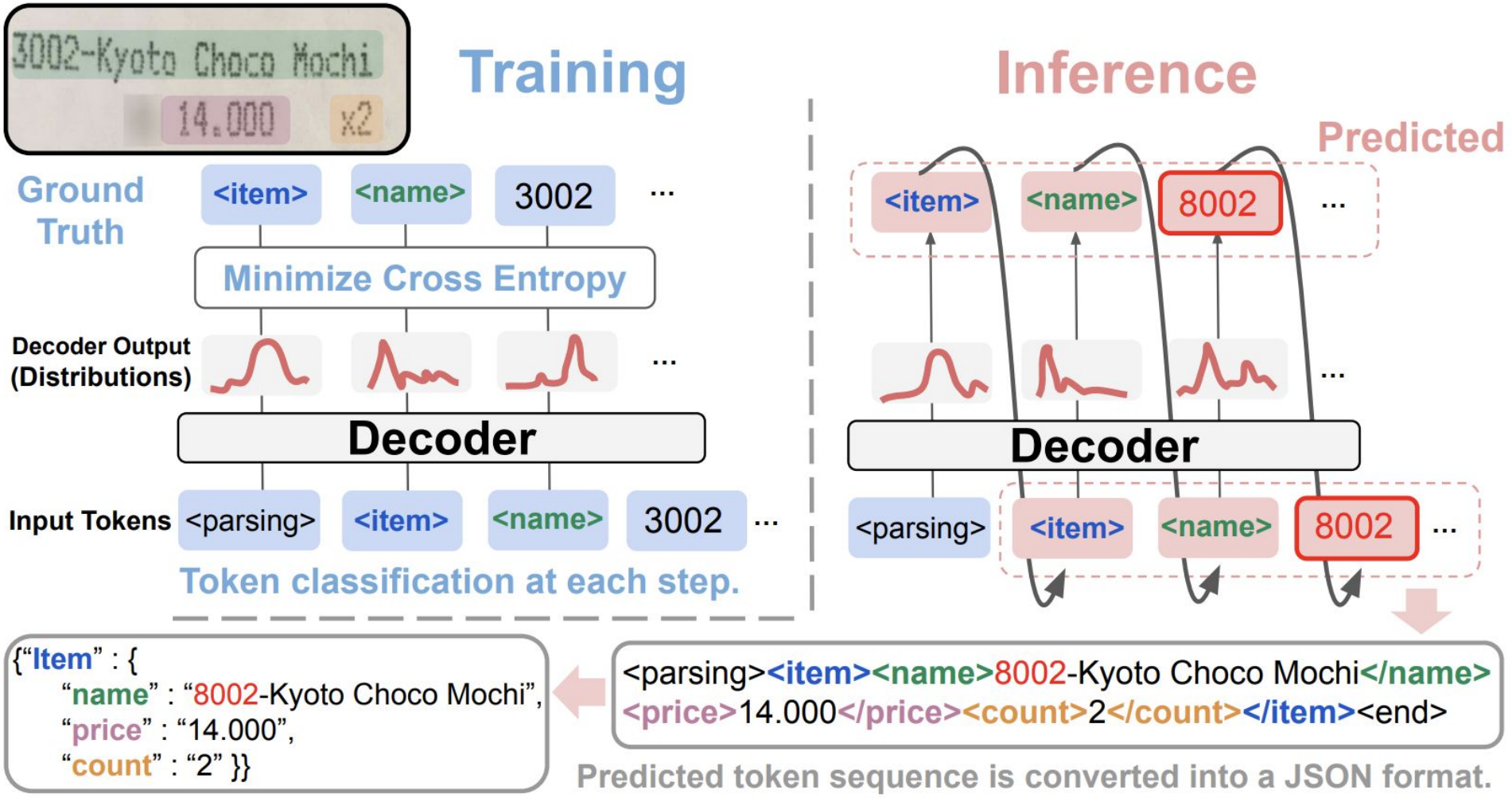


In terms of what that can teach, in what from …

After the model learns “how to read”,

Slide

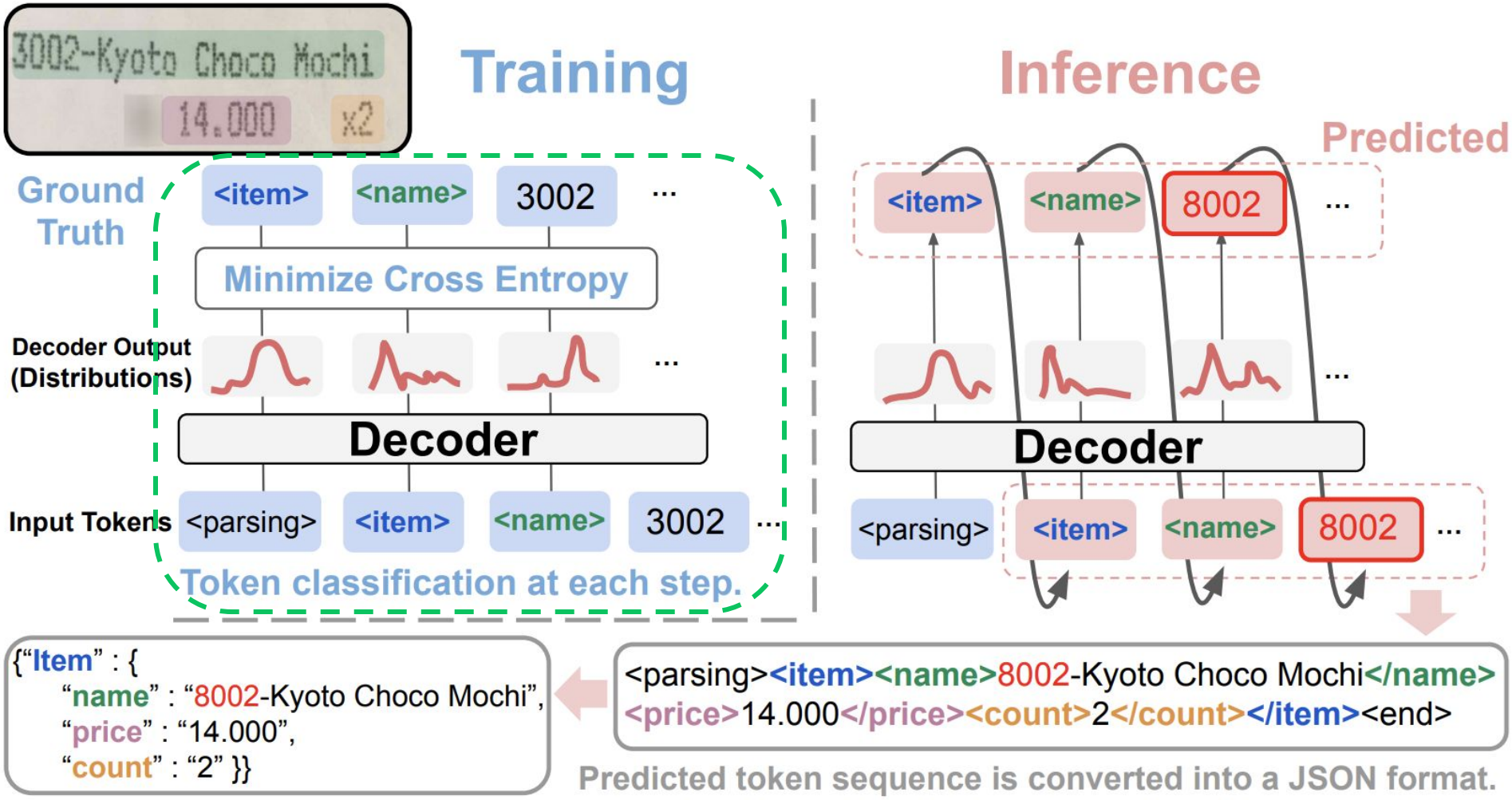
Model Fine-tuning and Inference Overview



in the fine-tuning, we teach the model "how to understand".

Slide

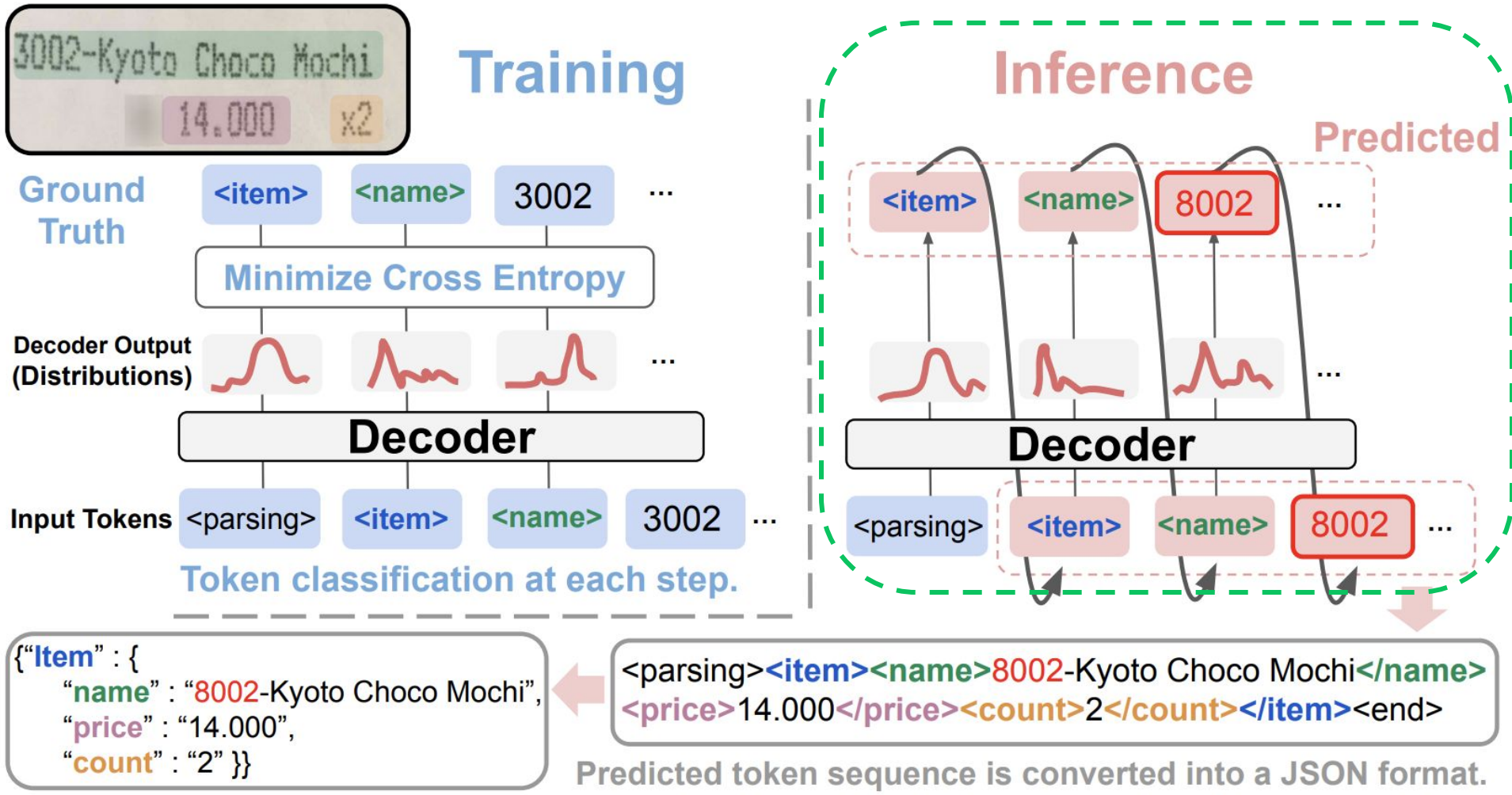
Model Fine-tuning and Inference Overview



The prediction target is set to a desired downstream token sequence, including some special tokens.

Slide

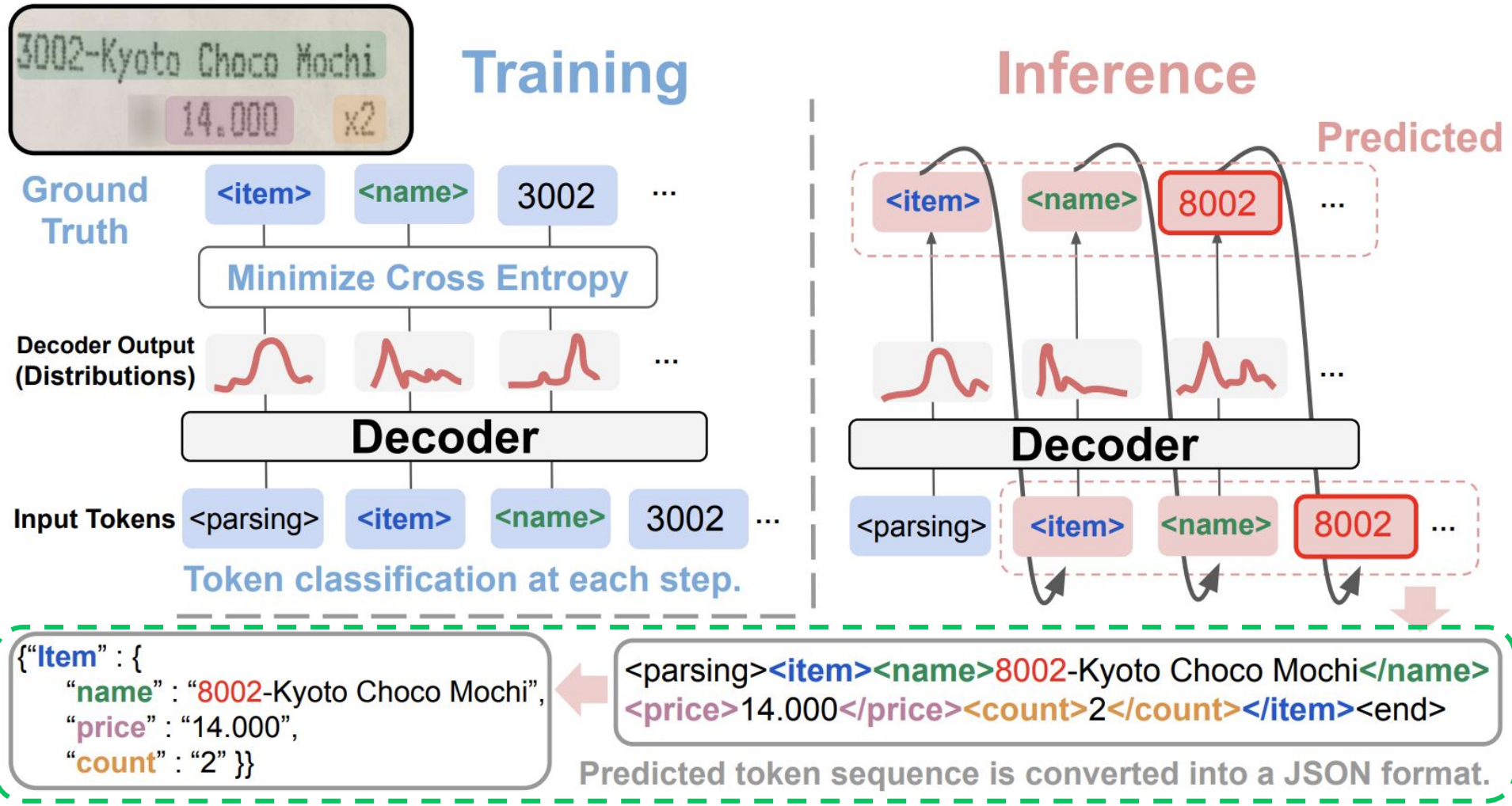
Model Fine-tuning and Inference Overview



At inference, the predicted token from the last step is fed to the next.

Slide

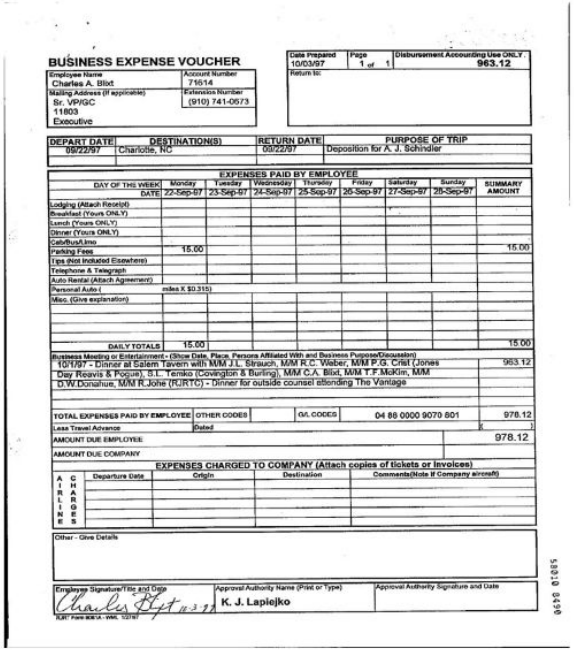
Model Fine-tuning and Inference Overview



The predicted sequence is converted into a JSON format.

Slide

Experiments: Samples of Downstream Datasets



Q: What is the Extension Number as per the voucher?
A: (910) 741-0673

We conducts 3 VDU applications on 6 different datasets. Some samples are shown.

Slide

Experiments: Document Classification

To see whether the model can distinguish across different types of documents, we test a classification task.

Slide

Experiments: Document Classification

	OCR	#Params	Time (ms)	Accuracy (%)
BERT	✓	110M + $\alpha^{\dagger}$	1392	89.81
RoBERTa	✓	125M + $\alpha^{\dagger}$	1392	90.06
LayoutLM	✓	113M + $\alpha^{\dagger}$	1396	91.78
LayoutLM (w/ image)	✓	160M + $\alpha^{\dagger}$	1426	94.42
LayoutLMv2	✓	200M + $\alpha^{\dagger}$	1489	95.25
Donut (Proposed)		143M	**752**	**95.30**

This is the results on the RVL-CDIP dataset.
Donut achieves state-of-the-are scores with reasonable speed and efficiency.

Slide

Experiments: Document Classification

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This is the results on the RVL-CDIP dataset.
Donut achieves state-of-the-are scores with reasonable speed and efficiency.

Slide

Experiments: Document Parsing

input_img

output

copy to clipboard

```
{
  menu:  [
    0:  {
      nm:  "0571-1854 BLUS WANITA",
      unitprice:  "@120,000",
      cnt:  "1",
      price:  "120,000"
    } ,
    1:  {
      nm:  "1002-0060 SHOPPING BAG",
      cnt:  "1",
      price:  "0"
    }
  ],
  total:  {
    total_price:  "120,000",
    changeprice:  "0",
    creditcardprice:  "120,000",
    menuqty_cnt:  "1"
  }
}
```

Next, to see the model fully understands the complex layouts and contexts, we test document parsing tasks.

Slide

Experiments: Document Parsing

			CORD [45]			Ticket [12]			Business Card			Receipt		
	OCR	#Params	Time (s)	F1	Acc.	Time (s)	F1	Acc.	Time (s)	F1	Acc.	Time (s)	F1	Acc.
BERT* [22]	✓	$86^{\dagger}_{\mathrm{M}} + \alpha^{\ddagger}$	1.6	73.0	65.5	1.7	74.3	82.4	1.5	40.8	72.1	2.5	70.3	54.1
BROS [18]	✓	$86^{\dagger}_{\mathrm{M}} + \alpha^{\ddagger}$	1.7	74.7	70.0									
LayoutLM [65]	✓	$89^{\dagger}_{\mathrm{M}} + \alpha^{\ddagger}$	1.7	78.4	81.3									
LayoutLMv2* [64,66]	✓	$179^{\dagger}_{\mathrm{M}} + \alpha^{\ddagger}$	1.7	78.9	82.4	1.8	87.2	90.1	1.6	52.2	83.0	2.6	72.9	78.0
Donut		$143^{\dagger}_{\mathrm{M}}$	**1.2**	**84.1**	**90.9**	**0.6**	**94.1**	**98.7**	**1.4**	**57.8**	**84.4**	**1.9**	**78.6**	**88.6**
SPADE* [25]	✓	$93^{\dagger}_{\mathrm{M}} + \alpha^{\ddagger}$	4.0	74.0	75.8	4.5	14.9	29.4	4.3	32.3	51.3	7.3	64.1	53.2
WYVERN* [21]	✓	$106^{\dagger}_{\mathrm{M}} + \alpha^{\ddagger}$	1.2	43.3	46.9	1.5	41.8	54.8	1.7	29.9	51.5	3.4	71.5	82.9

For all domains, Donut showed the best with significantly faster inference

Slide

Experiments: Document Parsing

			CORD [45]			Ticket [12]			Business Card			Receipt		
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BERT* [22]	✓	$86^{\dagger}_{\mathrm{M}} + \alpha^{\ddagger}$	1.6	73.0	65.5	1.7	74.3	82.4	1.5	40.8	72.1	2.5	70.3	54.1
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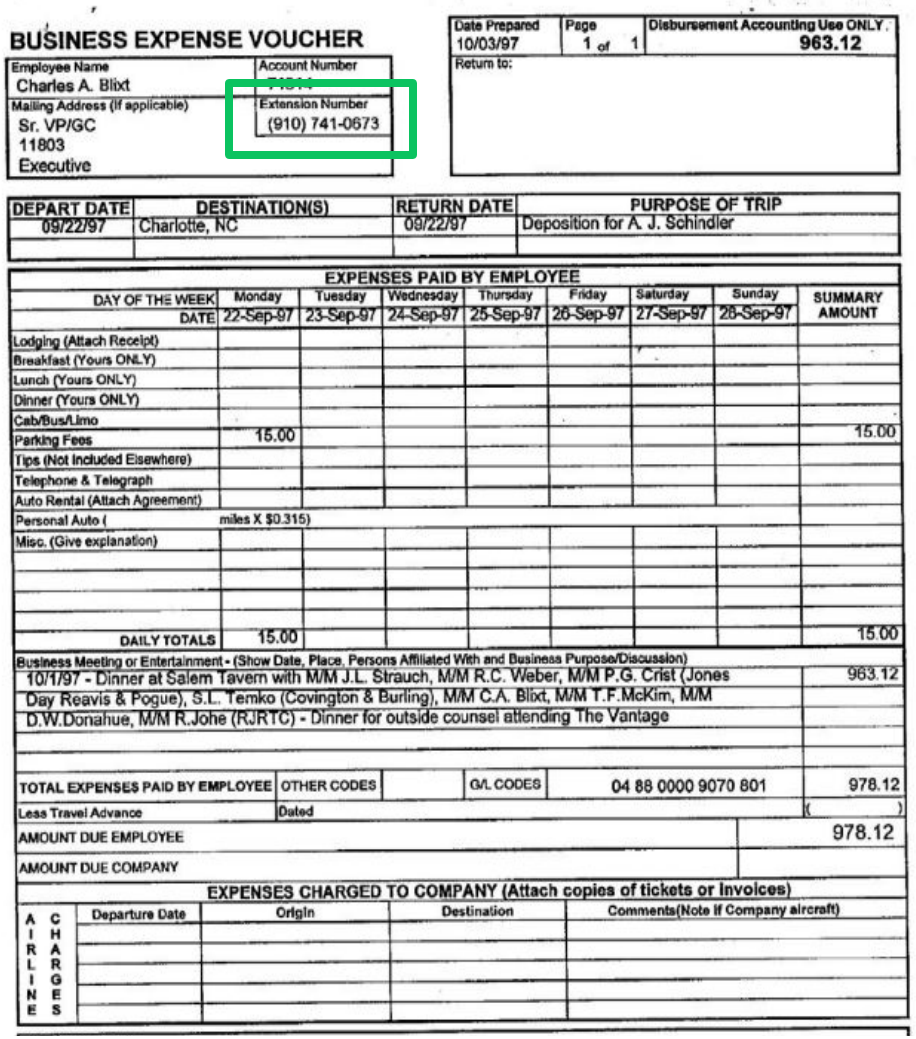
For all domains, Donut showed the best accuracies with significantly faster inference speed.

Slide

Experiments: Document VQA



BUSINESS EXPENSE VOUCHER

Date Prepared	Page	Disbursement Accounting Use ONLY
10/03/97	1 of 1	963.12

Return to:

Employee Name: Charles A. Blixt
Account Number: 71311
Mailing Address (If applicable): Sr. VP/GC 11803 Executive
Extension Number: (910) 741-0673

DEPART DATE	DESTINATION(S)	RETURN DATE	PURPOSE OF TRIP
09/22/97	Charlotte, NC	09/22/97	Deposition for A. J. Schindler

EXPENSES PAID BY EMPLOYEE

DAY OF THE WEEK	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	SUMMARY AMOUNT
DATE	22-Sep-97	23-Sep-97	24-Sep-97	25-Sep-97	26-Sep-97	27-Sep-97	28-Sep-97	
Lodging (Attach Receipt)								
Breakfast (Yours ONLY)								
Lunch (Yours ONLY)								
Dinner (Yours ONLY)								
Cab/Bus/Limo								
Parking Fees	15.00							15.00
Tips (Not Included Elsewhere)								
Telephone & Telegraph								
Auto Rental (Attach Agreement)								
Personal Auto (miles X $0.315)								
Misc. (Give explanation)								
DAILY TOTALS	15.00							15.00

Business Meeting or Entertainment - (Show Date, Place, Persons Affiliated With and Business Purpose/Discussion)

10/1/97 - Dinner at Salem Tavern with M/M J.L. Strauch, M/M R.C. Weber, M/M P.G. Crist (Jones Day Reavis & Pogue), S.L. Temko (Covington & Burling), M/M C.A. Blixt, M/M T.F.McKim, M/M D.W.Donahue, M/M R.Johe (RJRTC) - Dinner for outside counsel attending The Vantage — 963.12

TOTAL EXPENSES PAID BY EMPLOYEE	OTHER CODES		G/L CODES	04 88 0000 9070 801	978.12
Less Travel Advance	Dated				( )
AMOUNT DUE EMPLOYEE					978.12
AMOUNT DUE COMPANY					

EXPENSES CHARGED TO COMPANY (Attach copies of tickets or Invoices)

AIRLINE CHARGES	Departure Date	Origin	Destination	Comments(Note if Company aircraft)

Q: What is the Extension Number as per the voucher?

A: (910) 741–0673

To validate the further capacity of the model, we test a document VQA task.

Slide

Experiments: Document VQA

	Fine-tuning set	OCR	#Params†	Time (ms)	ANLS test set	ANLS* handwritten
BERT [64]	train set	✓	110M + $\alpha^{\ddagger}$	1517	63.5	n/a
LayoutLM[65]	train set	✓	113M + $\alpha^{\ddagger}$	1519	69.8	n/a
LayoutLMv2[64]	train set	✓	200M + $\alpha^{\ddagger}$	1610	78.1	n/a
Donut	train set		176M	**782**	67.5	**72.1**
LayoutLMv2-Large-QG[64]	train + dev + QG	✓	390M + $\alpha^{\ddagger}$	1698	**86.7**	67.3

For VQA, Donut showed a high score on the handwritten documents which are known to be challenging.

Slide

Experiments: Document VQA

	Fine-tuning set	OCR	#Params†	Time (ms)	ANLS test set	ANLS* handwritten
BERT [64]	train set	✓	110M + $\alpha^{\ddagger}$	1517	63.5	n/a
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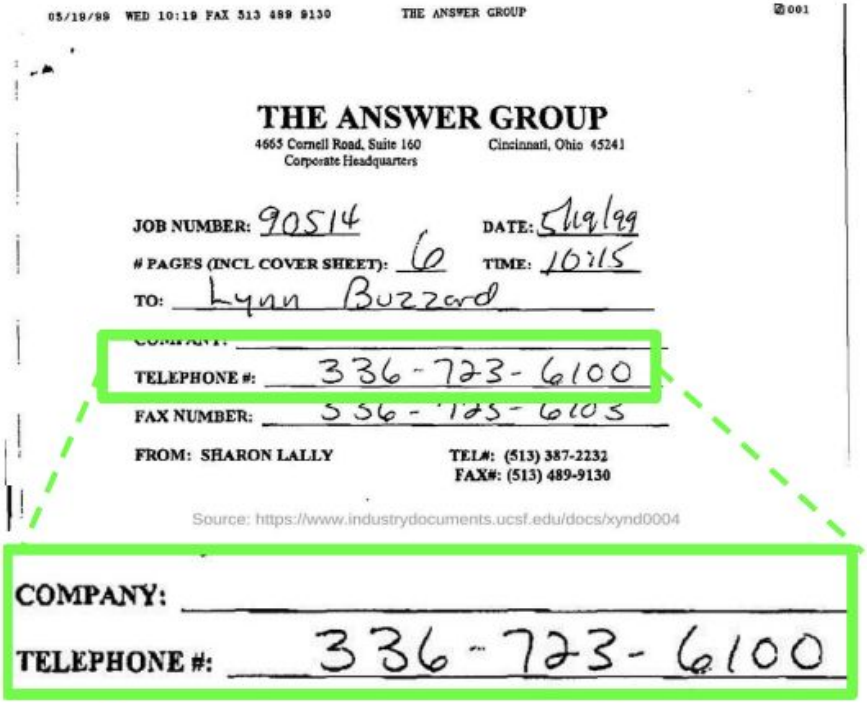
Donut	train set		176M	**782**	67.5	**72.1**
LayoutLMv2-Large-QG[64]	train + dev + QG	✓	390M + $\alpha^{\ddagger}$	1698	**86.7**	67.3

For VQA, Donut showed a high score on the handwritten documents which are known to be challenging.

Slide

Analysis: VQA on Handwritten Documents

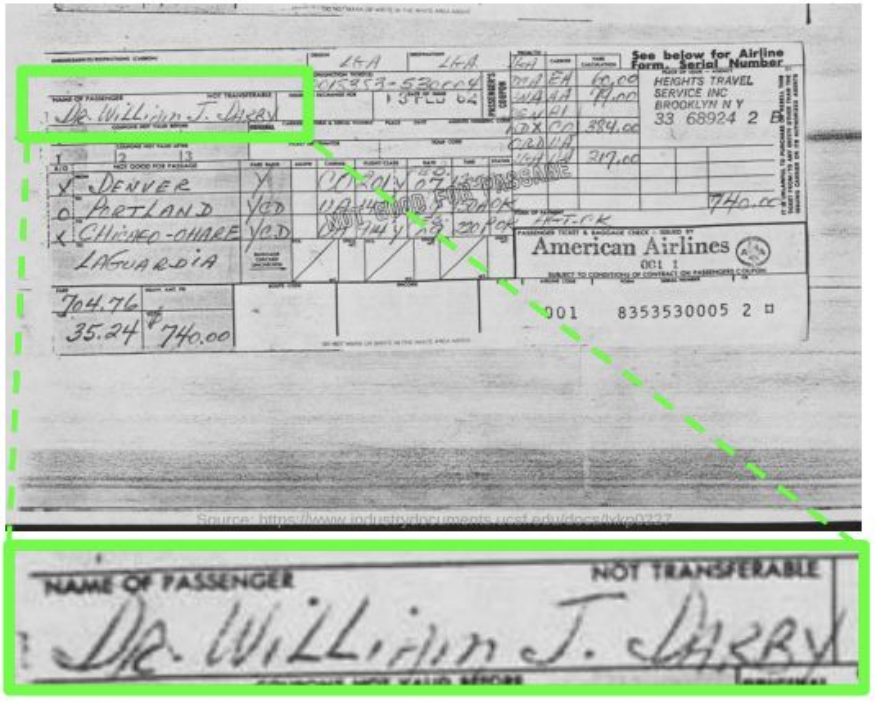


Q: What is the phone number given?

Answer: 336-723-6100

Donut: 336-723-6100

LayoutLMv2-Large-QG: **336-723- 4100**



Q: What is the name of the passenger?

Answer: DR. William J. Darby

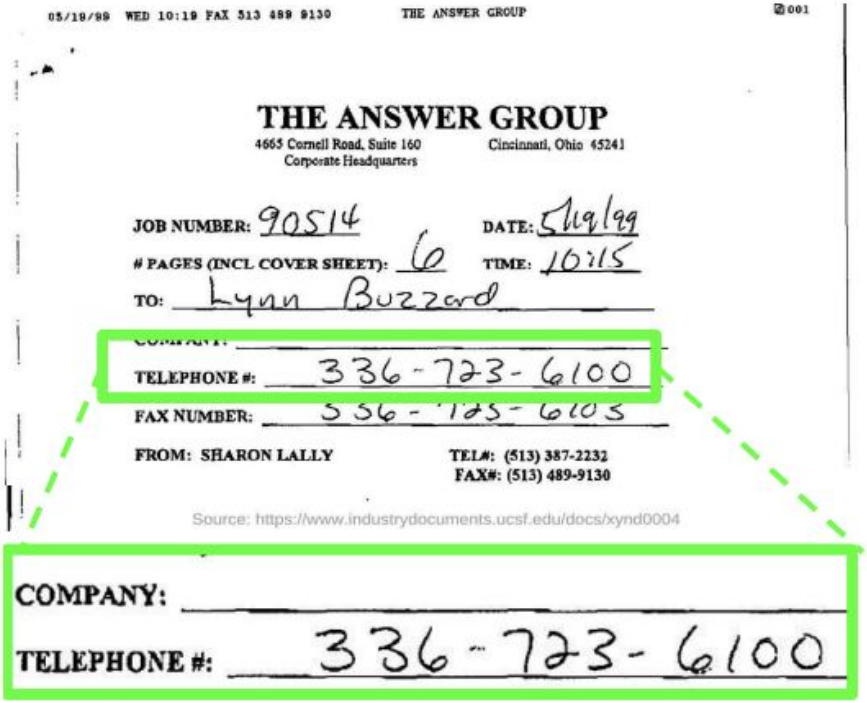
Donut: DR. William J. Darby

LayoutLMv2-Large-QG: **DR. William J. Jarry**

As can be seen, the OCR errors make the performance upper-bound for the conventional baselines.

Slide

Analysis: VQA on Handwritten Documents

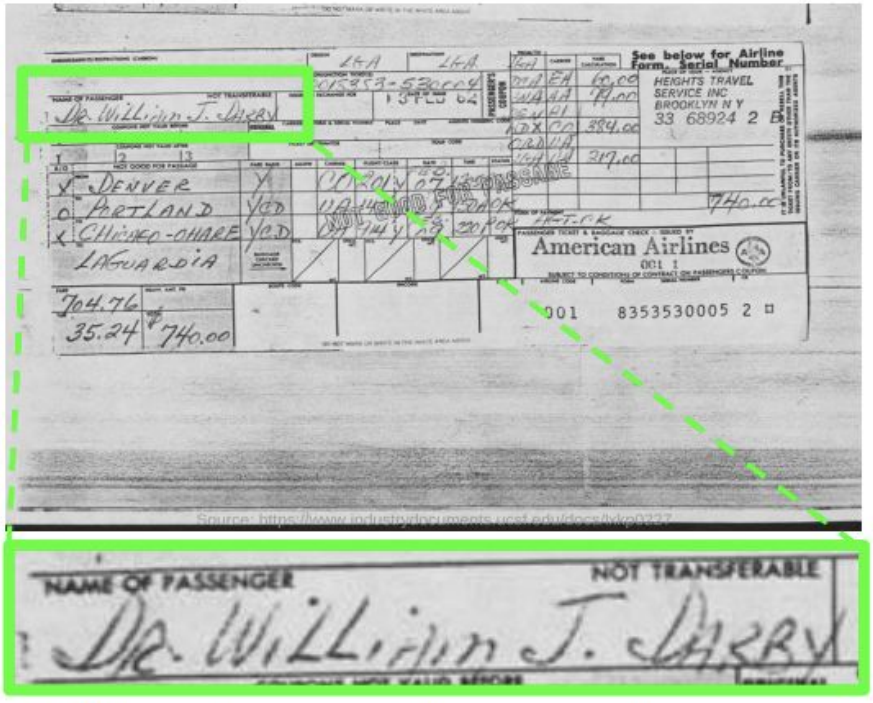


Q: What is the phone number given?

Answer: 336-723-6100

Donut: 336-723-6100

LayoutLMv2-Large-QG: **336-723- 4100**



Q: What is the name of the passenger?

Answer: DR. William J. Darby

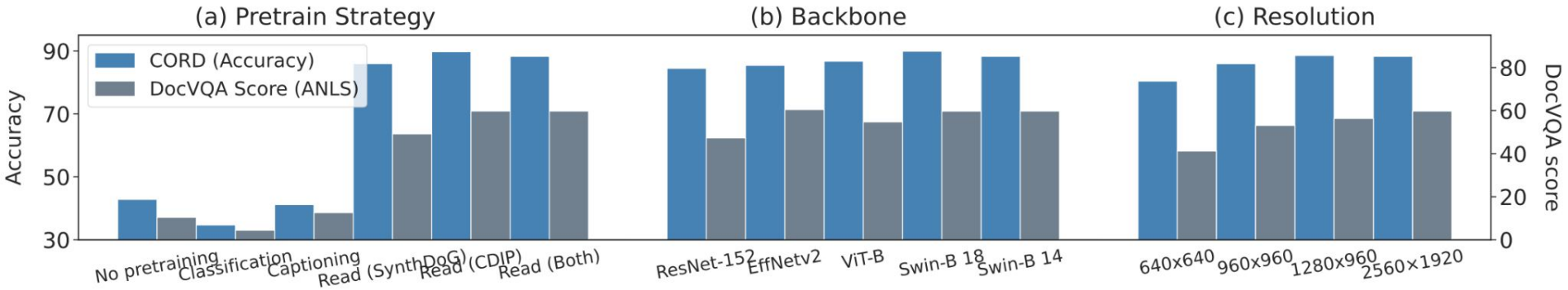
Donut: DR. William J. Darby

LayoutLMv2-Large-QG: **DR. William J. Jarry**

On the other hand, Donut seems robust to the handwritten documents.

Slide

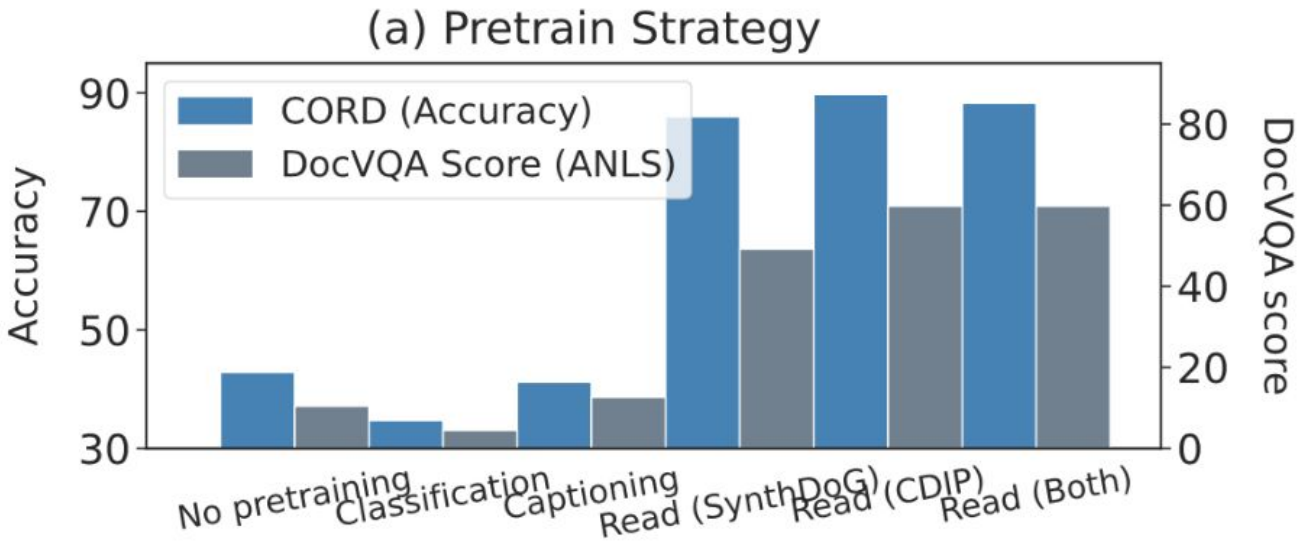
Analysis



Next, we show some main results of our analysis on Donut.

Slide

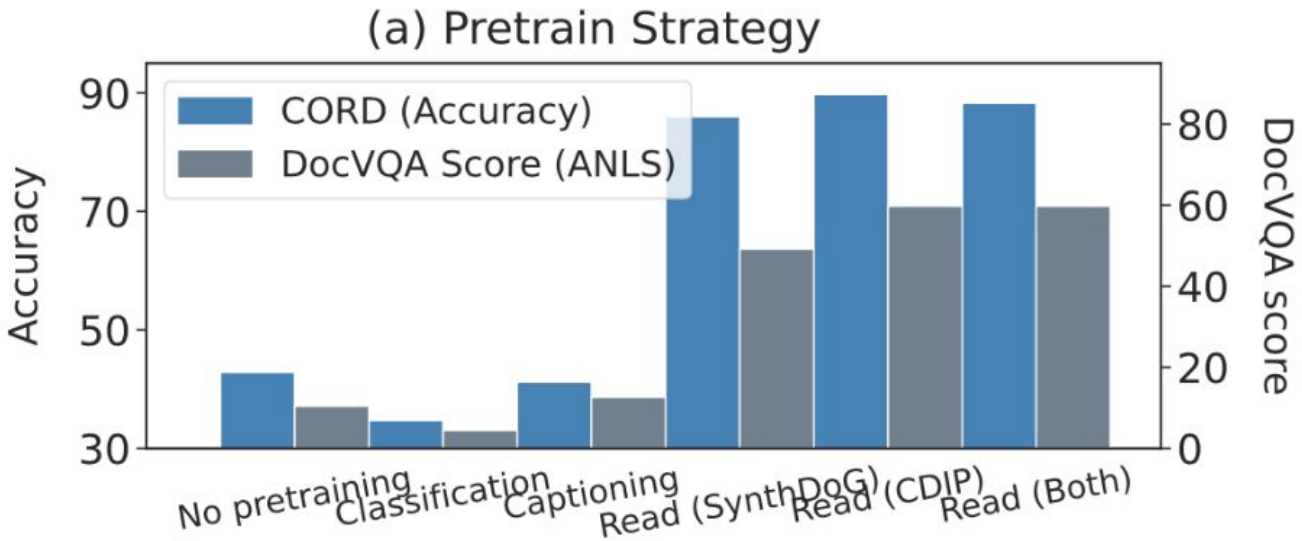
Analysis: Pre-training Strategies



We tested several pre-training tasks.
We found that the proposed task is the most simple yet effective approach.

Slide

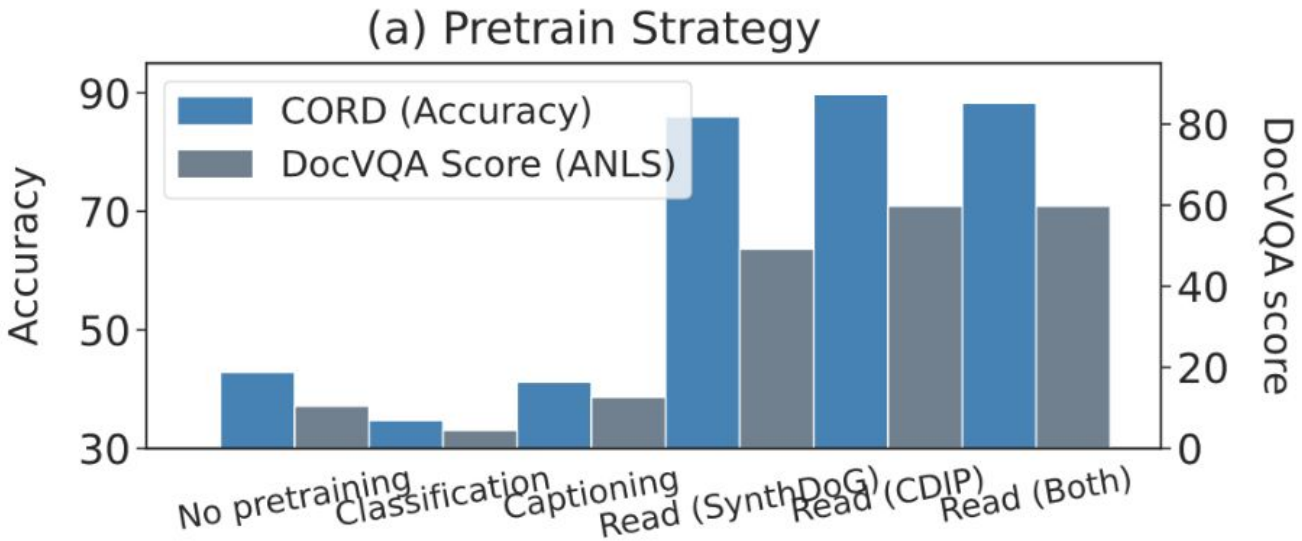
Analysis: Pre-training Strategies



Other tasks that impose a general knowledge of images and texts on models show little gains in the fine-tuning tasks.

Slide

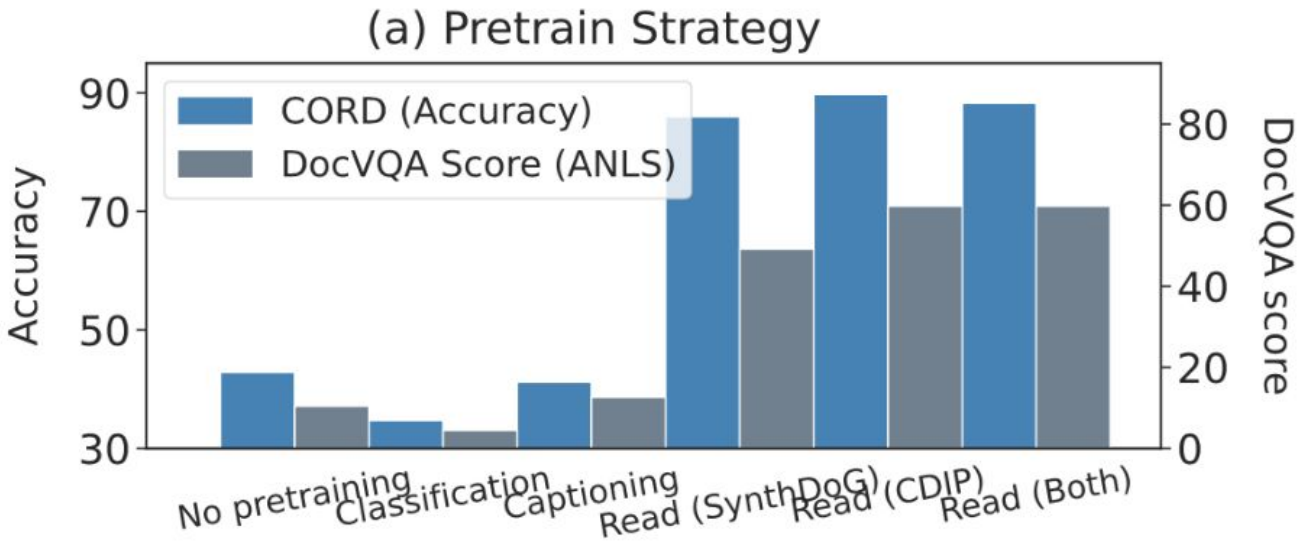
Analysis: Pre-training Strategies



For the text reading task, synthetic images were enough for the CORD task.

Slide

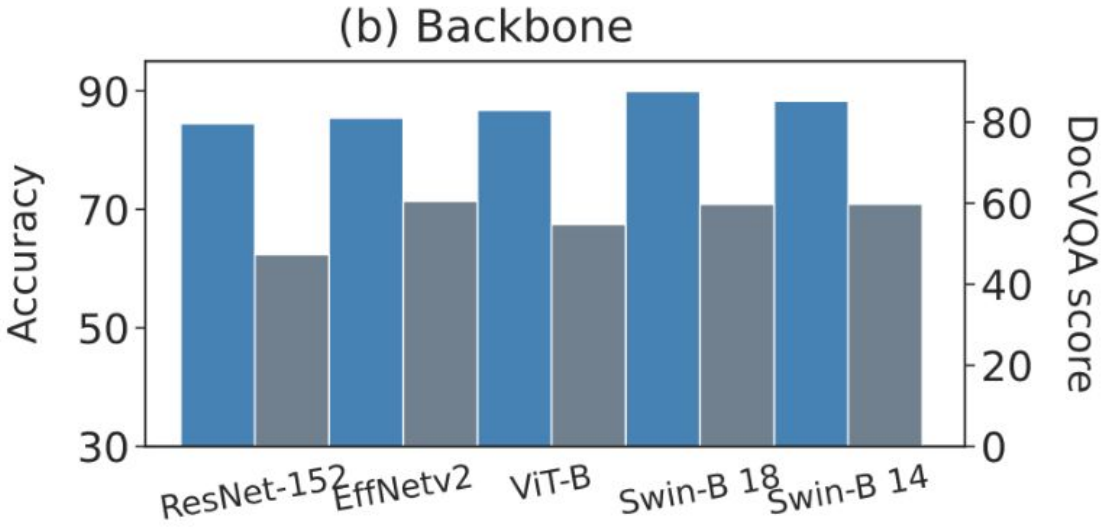
Analysis: Pre-training Strategies



But, in the DocVQA task, it was important to see the real images.

Slide

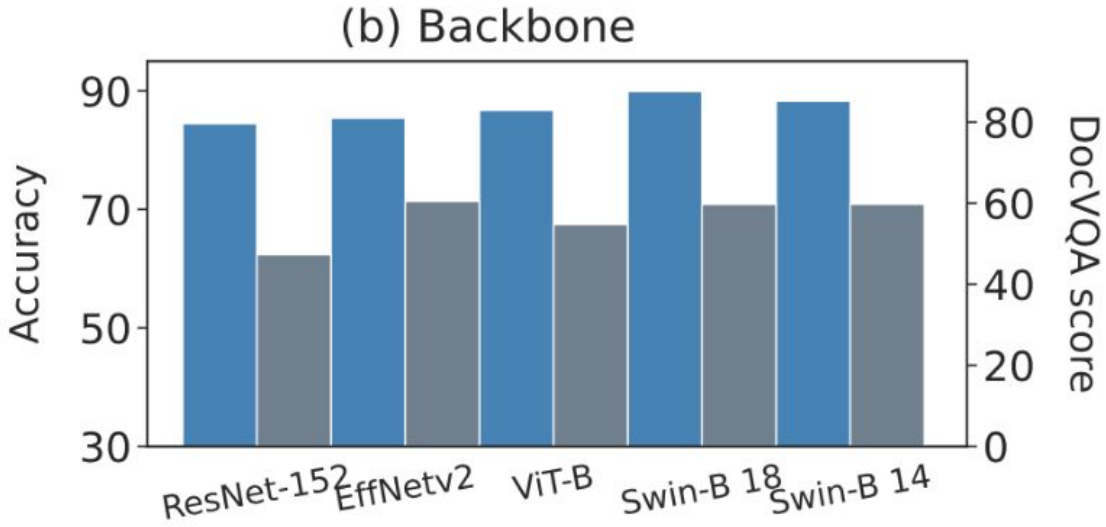
Analysis: Image Backbones



Next, we study popular image classification backbones.

Slide

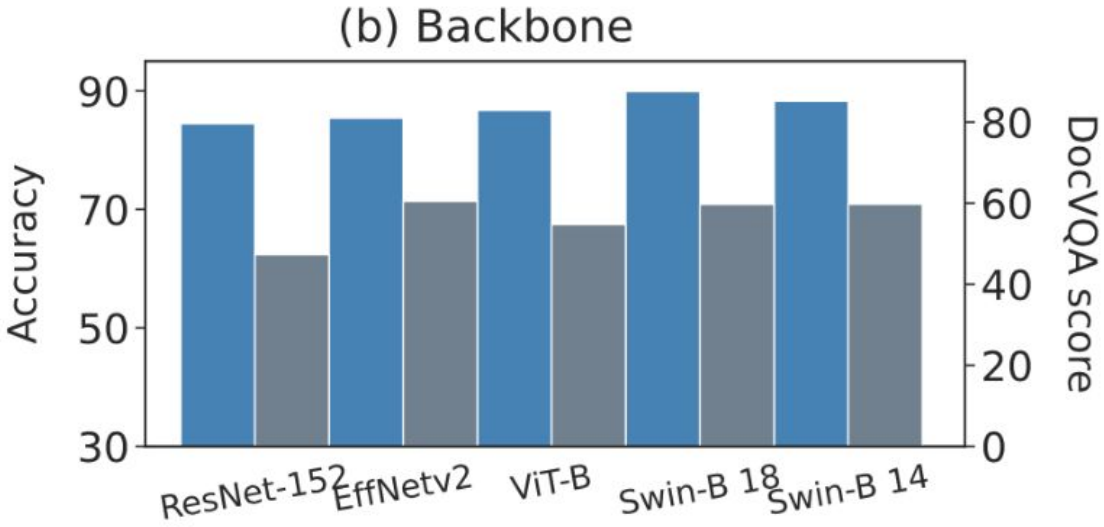
Analysis: Image Backbones



Overall, EfficientNetV2 and Swin Transformer outperform the others.

Slide

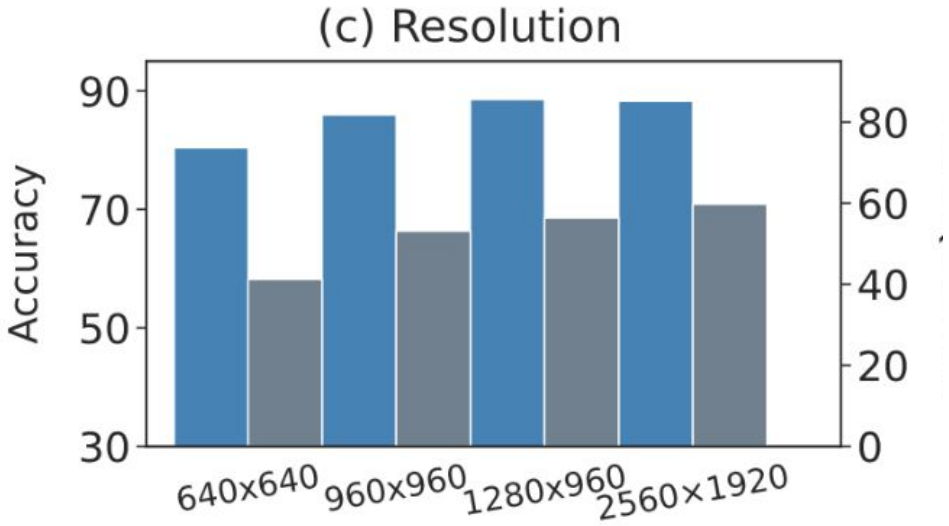
Analysis: Image Backbones



We choose Swin Transformer due to the high scalability and performance.

Slide

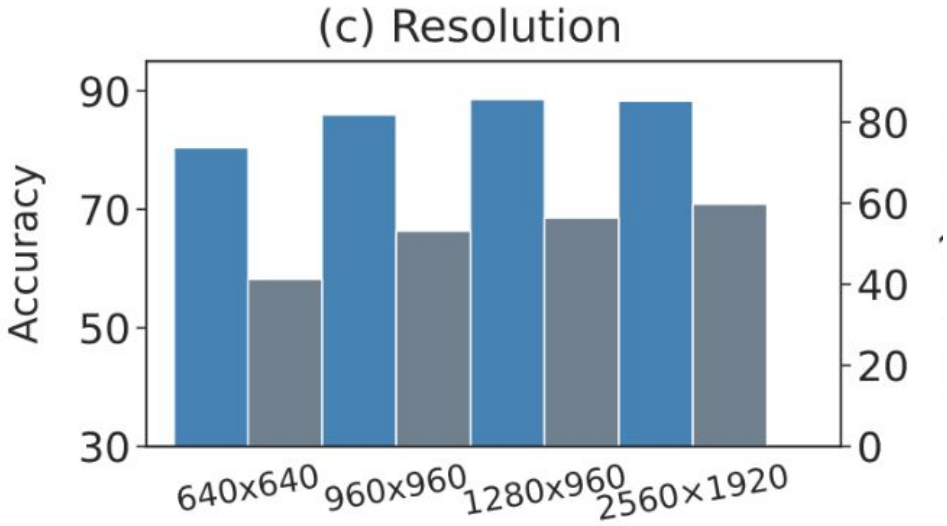
Analysis: Input Resolution



We observed that Donut grows rapidly as we set a larger input size.

Slide

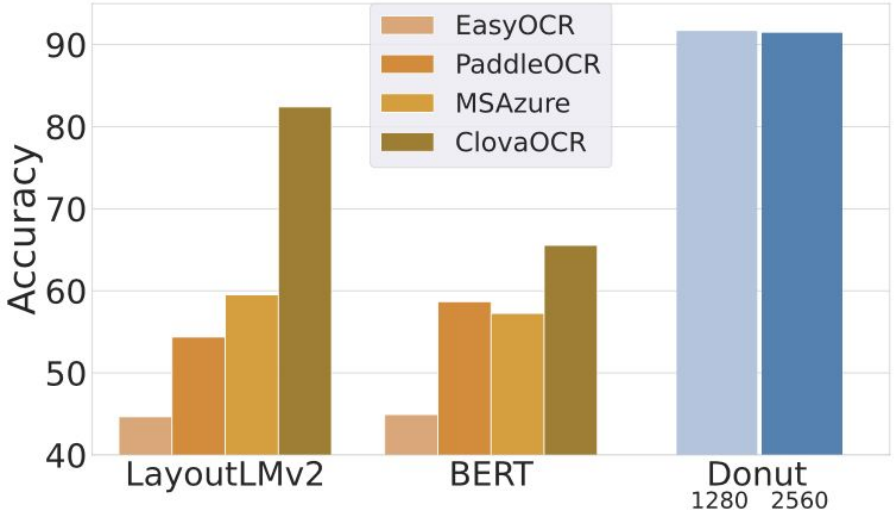
Analysis: Input Resolution

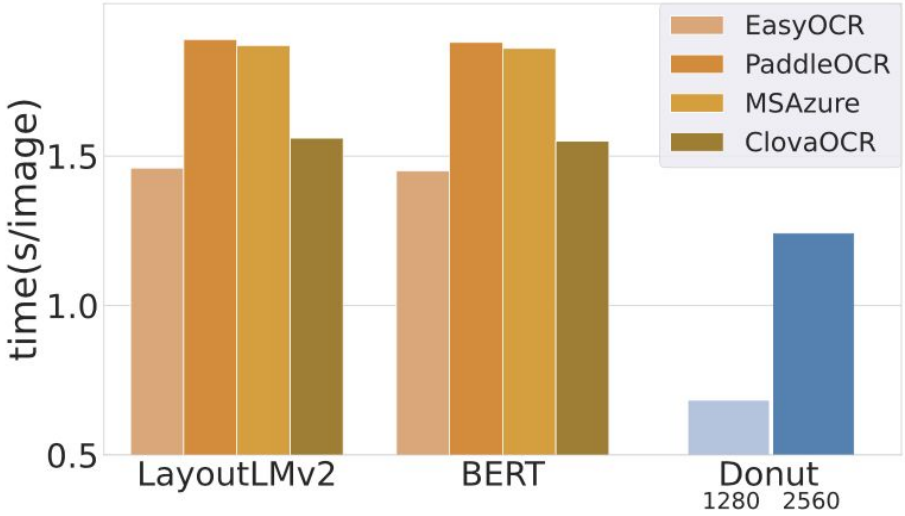


This gets clearer in the DocVQA where the images are larger with many tiny texts.

Slide

Analysis: OCR Engines

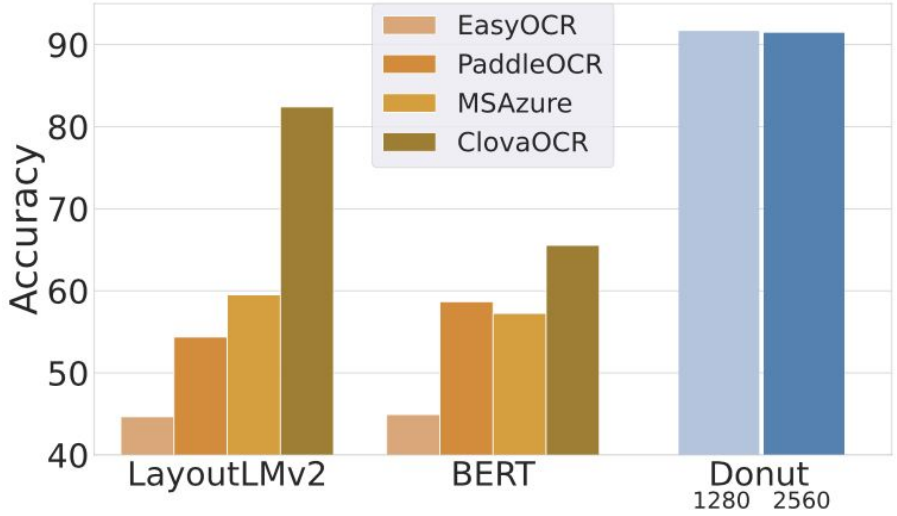


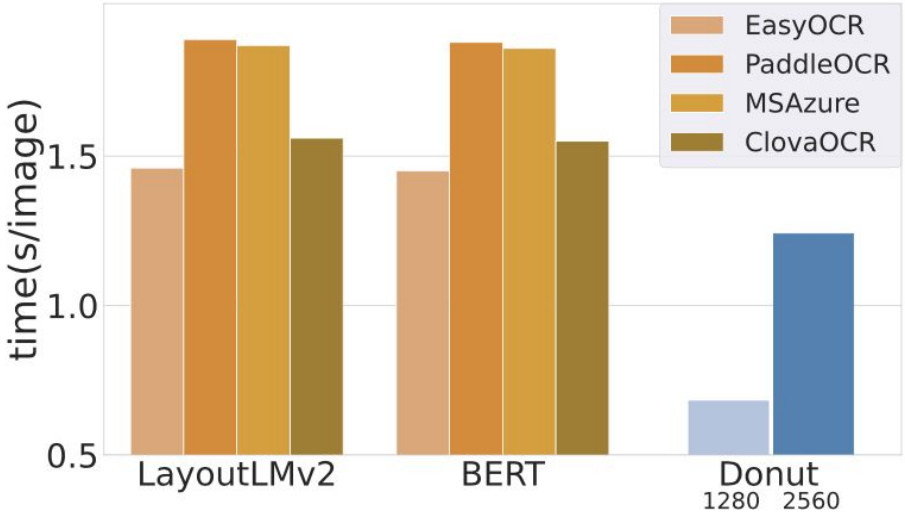


Next, we study the effects of OCR engines on the traditional baselines. We test four widely-used public engines.

Slide

Analysis: OCR Engines





We observed that the scores heavily rely on the OCR engine.

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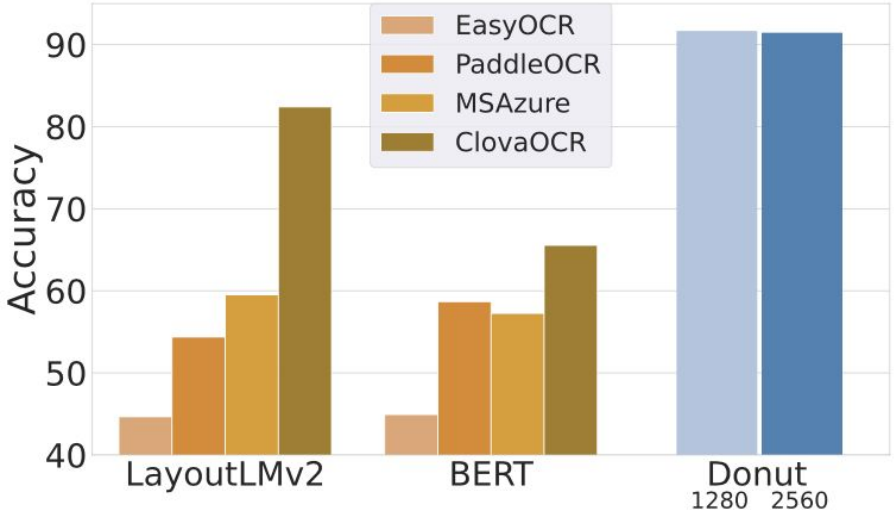

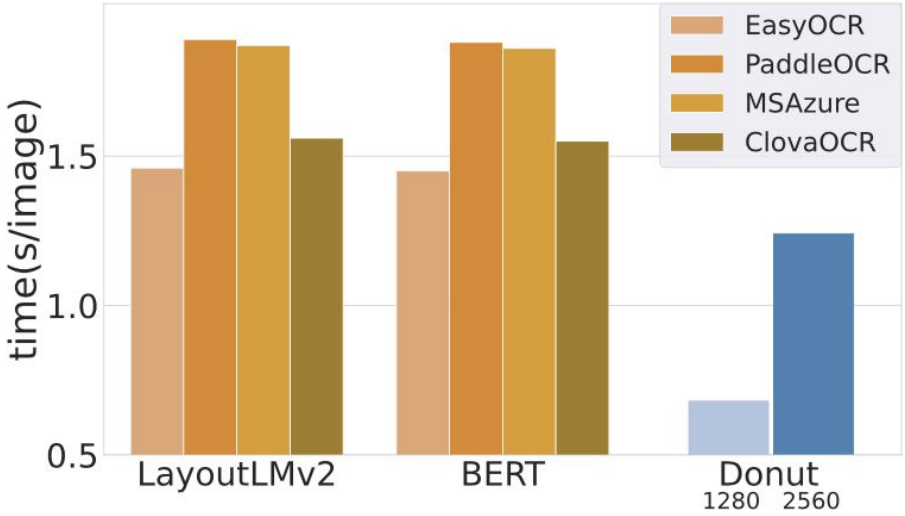

This shows why we need an OCR-free method.

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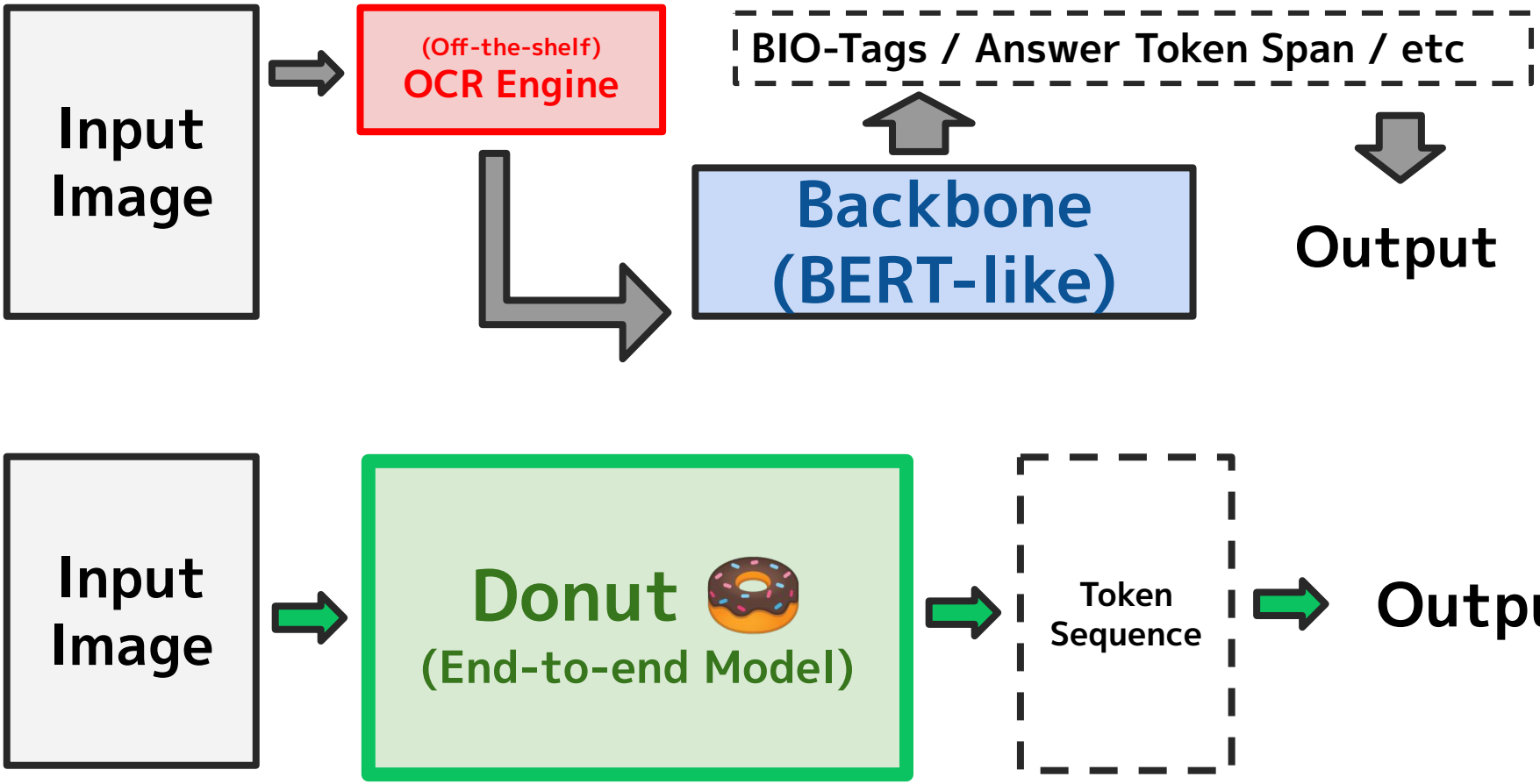
Conclusions



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More experiments and analysis can be found in the manuscript.

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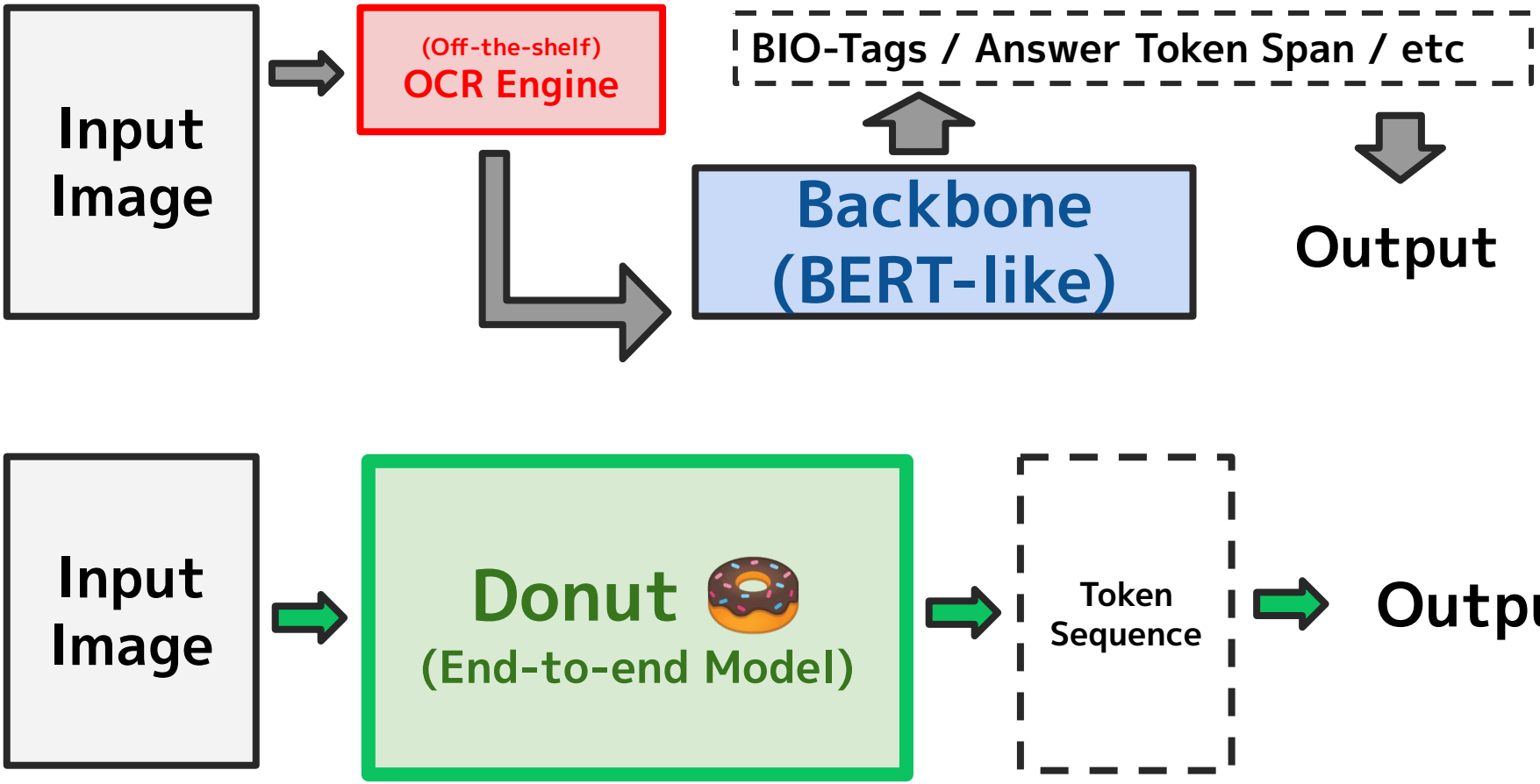
Conclusions



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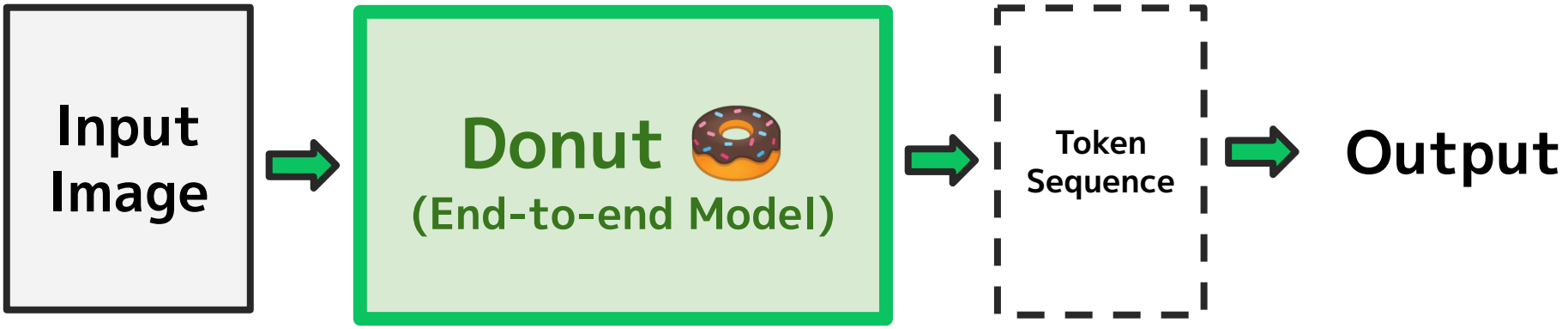

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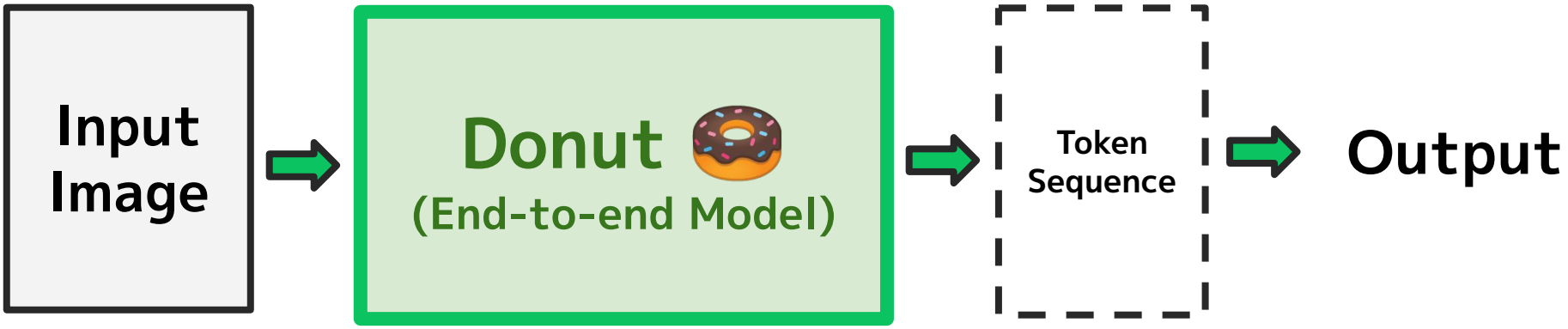

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Thank you!

Contact: gwkim.rsrch@gmail.com

If you have any questions please feel free to contact me :)
Thank you!