Donut: Document Understanding Transformer without OCR

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Introduction

Optical Character Recognition (OCR)

> 사람이 쓰거나 기계로 인쇄한 문자의 이미지를 이미지 스캐너로 획득하여 기계가 읽을 수 있는 문자로 변환하는 것

- Text Detection + Text Recognition

Visual Document Understanding (VDU)

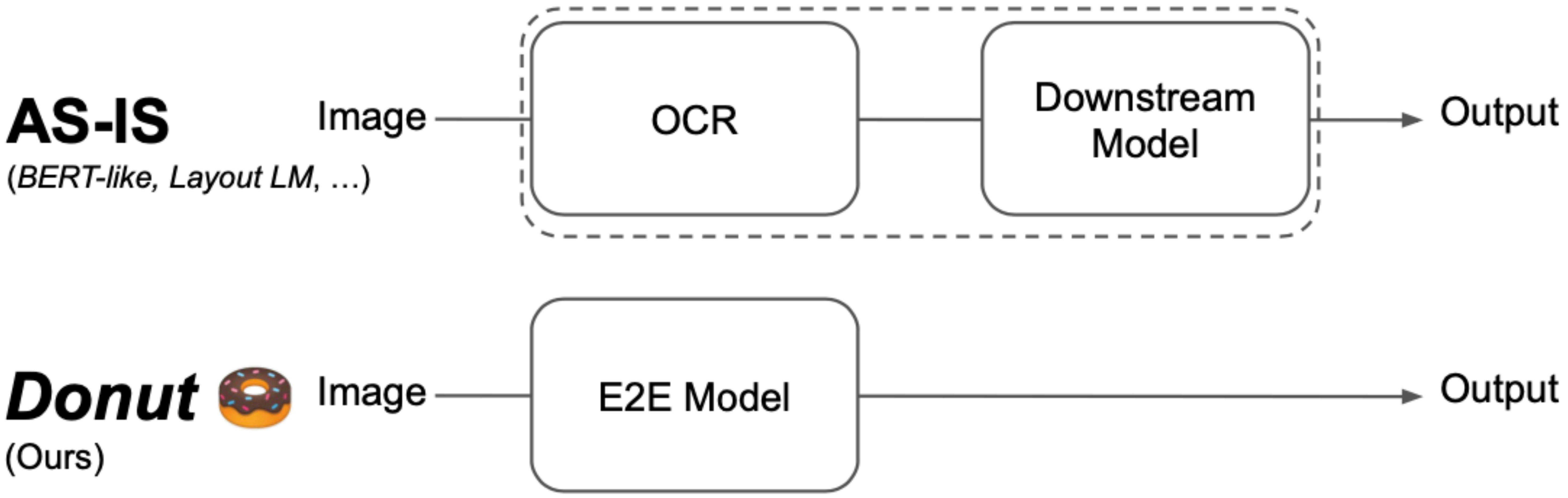
> 다양한 Formats, Layouts, Contents를 가진 Document Image를 이해하는 것이 목적
>
> e.g. Document Classification, Parsing, Visual Question Answering(VQA)

- Invoices, Receipts, Business Card와 같은 Semi-Structured Document를 주로 활용
- Semi-Structured Document는 Digital Files, Scanned Images, Photographs로 존재함

Introduction

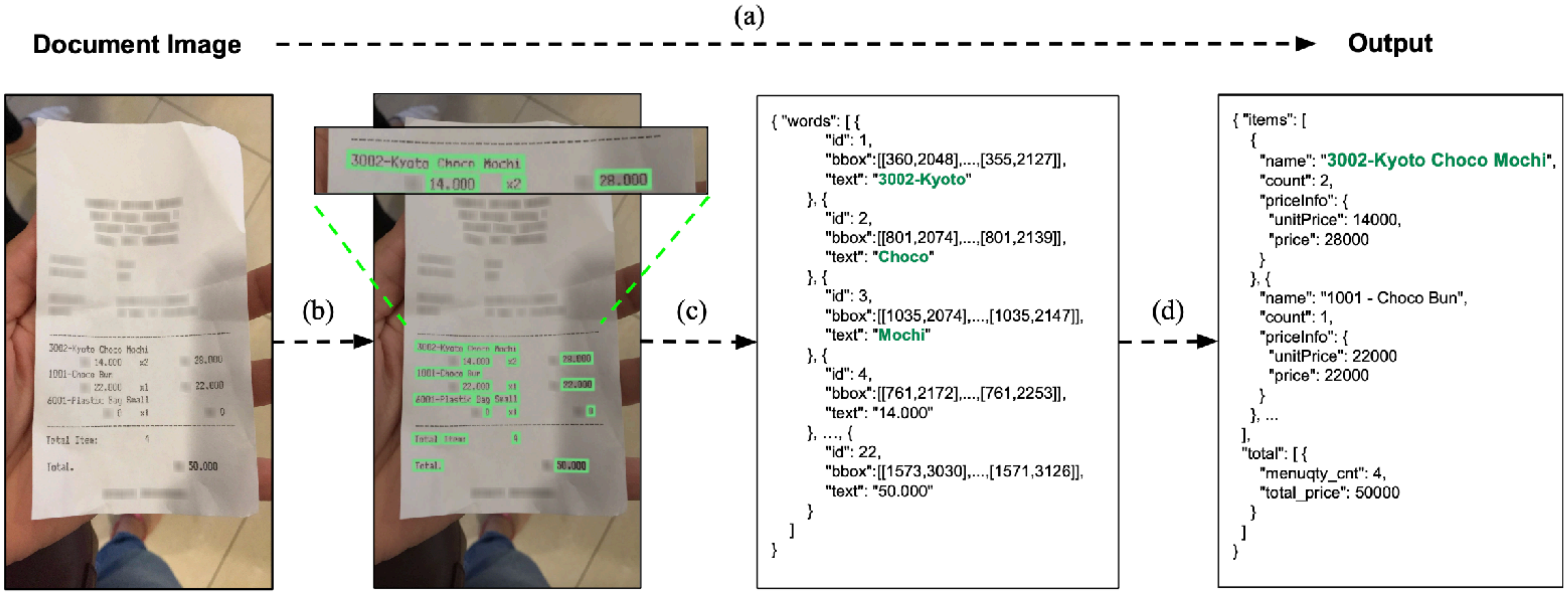
기존의 OCR-based 방법의 문제점

- Expensive Computational Costs
- Performance Degradation due to the OCR Error Propagation



Introduction

기존의 OCR-based 방법의 문제점



Introduction

기존의 OCR-based 방법의 문제점

- Expensive Computational Costs

✓ Own OCR Model의 학습을 위해서는 추가적인 Supervision과 Large-Scale Dataset이 필요함

✓ 최근의 Model은 학습을 위해 비싸고, 유지 비용을 증가시키는 GPU를 필요로 함

✓ 기존의 OCR Engine을 활용하여 비용을 줄일 수 있지만, Target Domain의 성능은 보장하지 못함

Introduction

기존의 OCR-based 방법의 문제점

- Performance Degradation due to the OCR Error Propagation

  ✓ OCR Model에서 발생하는 Error는 Subsequent Processes에 부정적인 영향을 미침

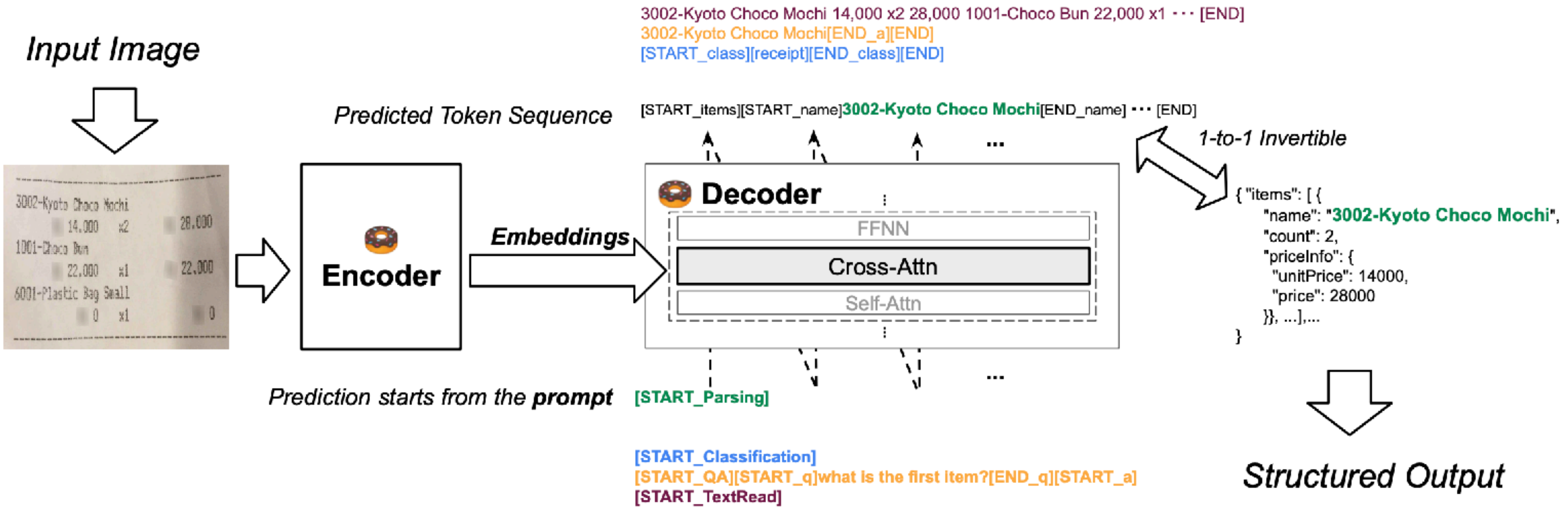
  ✓ 이는 복잡하고 큰 Character Sets를 가진 언어(e.g. Korean, Japanese)에서는 심각함

  ✓ 별도의 Post-OCR Correction Module을 활용할 수는 있지만, 전체 시스템의 크기와 유지 보수 비용 문제 때문에 실질적으로 좋은 방법이 아님

Introduction

Donut: A Simple OCR-free Transformer Architecture (End-to-End Manner)

SynthDoG: Synthetic Document Generator



Method

Document Understanding Transformer

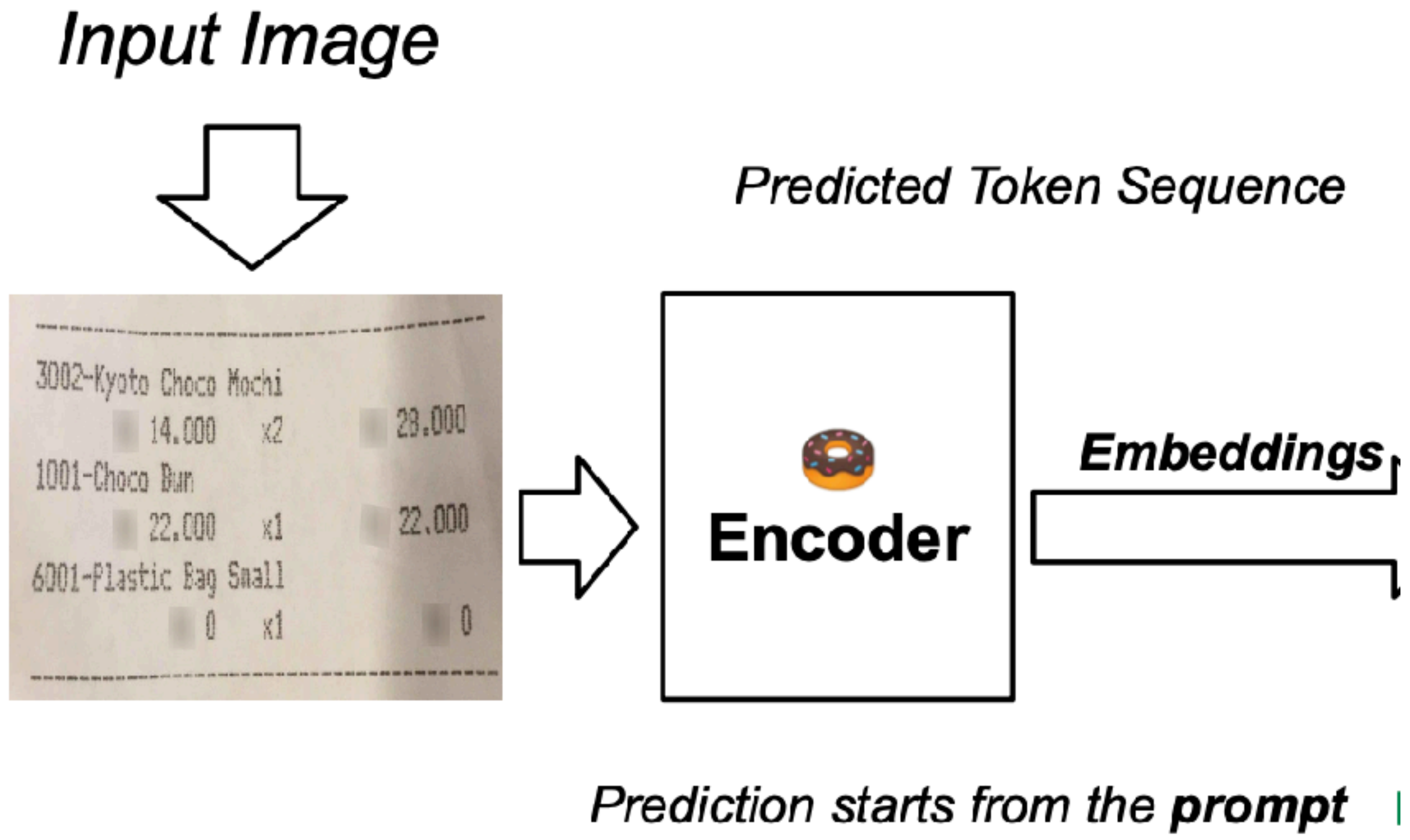
Encoder: Swin Transformer

Input_Image $\mathbf{x} \in \mathbb{R}^{H \times W \times C}$

Encoder_I/O $\{\mathbf{z}_i | \mathbf{z}_i \in \mathbb{R}^d, 1 \leq i \leq n\}$,

n : Feature Map Size or Number of Image Patches

d : Dimension of the Latent Vectors



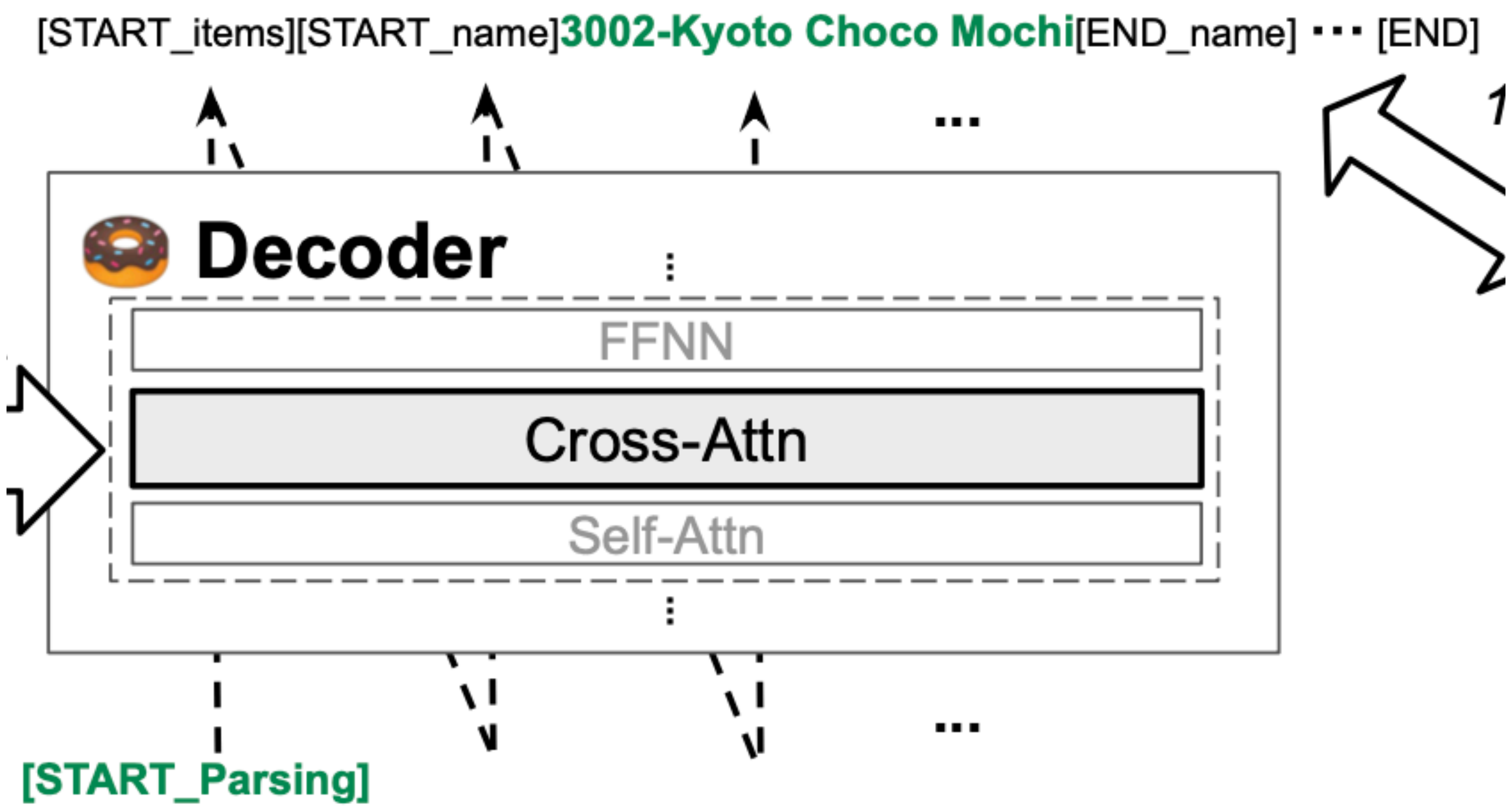
Method

Document Understanding Transformer

Decoder: Multilingual BART Decoder (use the first 4 layers)

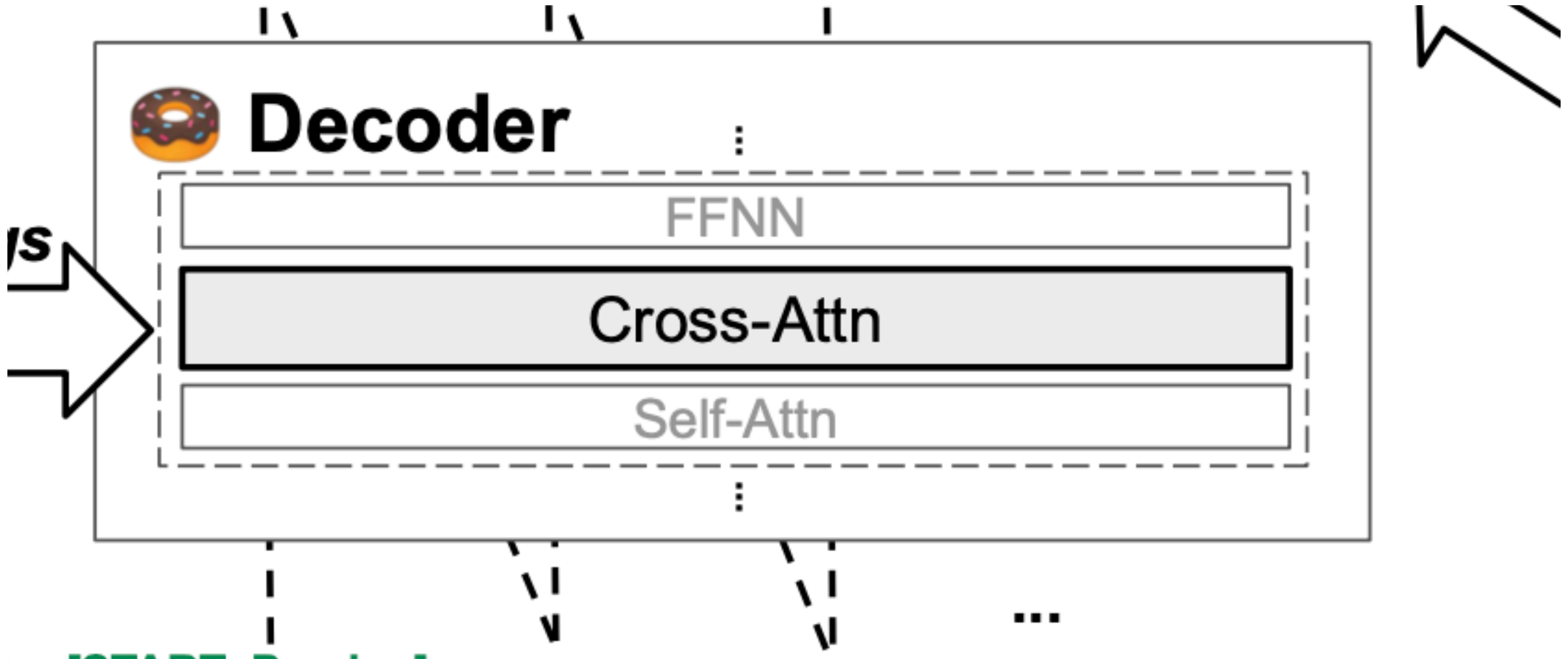
Decoder_Output $(\mathbf{y}_i)_1^m,\ \mathbf{y}_i \in \mathbb{R}^v$

i : One – hot Vector for the Token
v : Size of Token Vocabulary
m : HyperParameter



Method

Document Understanding Transformer



Model Input

[START_Parsing]

[START_Classification]
[START_QA][START_q]what is the first item?[END_q][START_a]
[START_TextRead]

Train Phase: Teacher Forcing Manner

Test Phase: Prompt/Special Tokens for Each Downstream Task (Like GPT-3)

Method

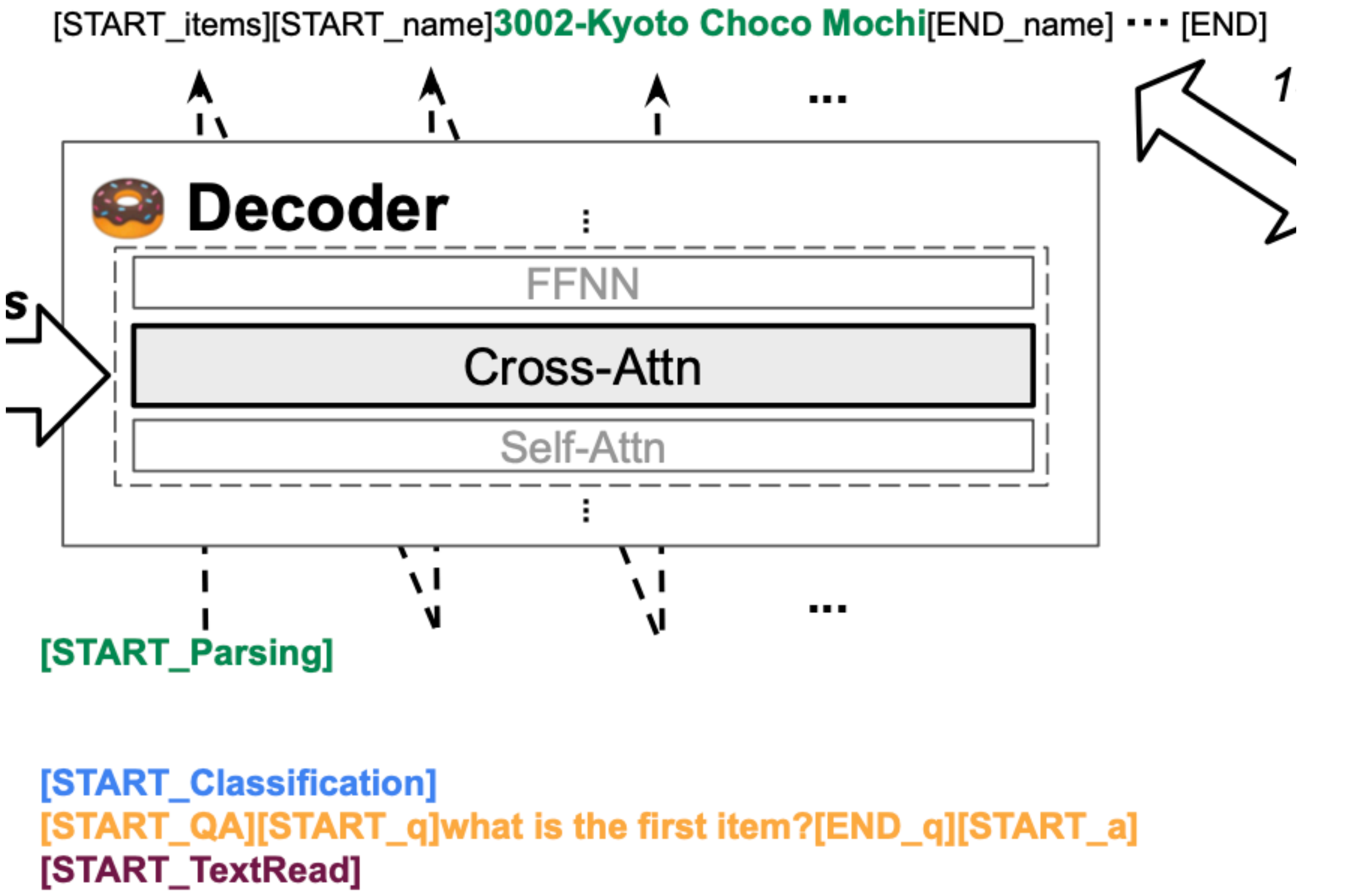
Document Understanding Transformer

<u>Output Conversion</u>

JSON Format

Special Token: [START_*] and [END_*]

[START_name]은 있는데, [END_*]이 없으면 Regular Expression을 통해
name field는 손실되었다고 가정



Method

Pre-Training - How to Read

<u>Synthetic Document Generator (SynthDog)</u>

1.2M Synthetic Document Images 생성

Wikipedia(English, Korean, Japanese)에서 추출된 Corpus 활용

각 언어마다 400K Images 생성

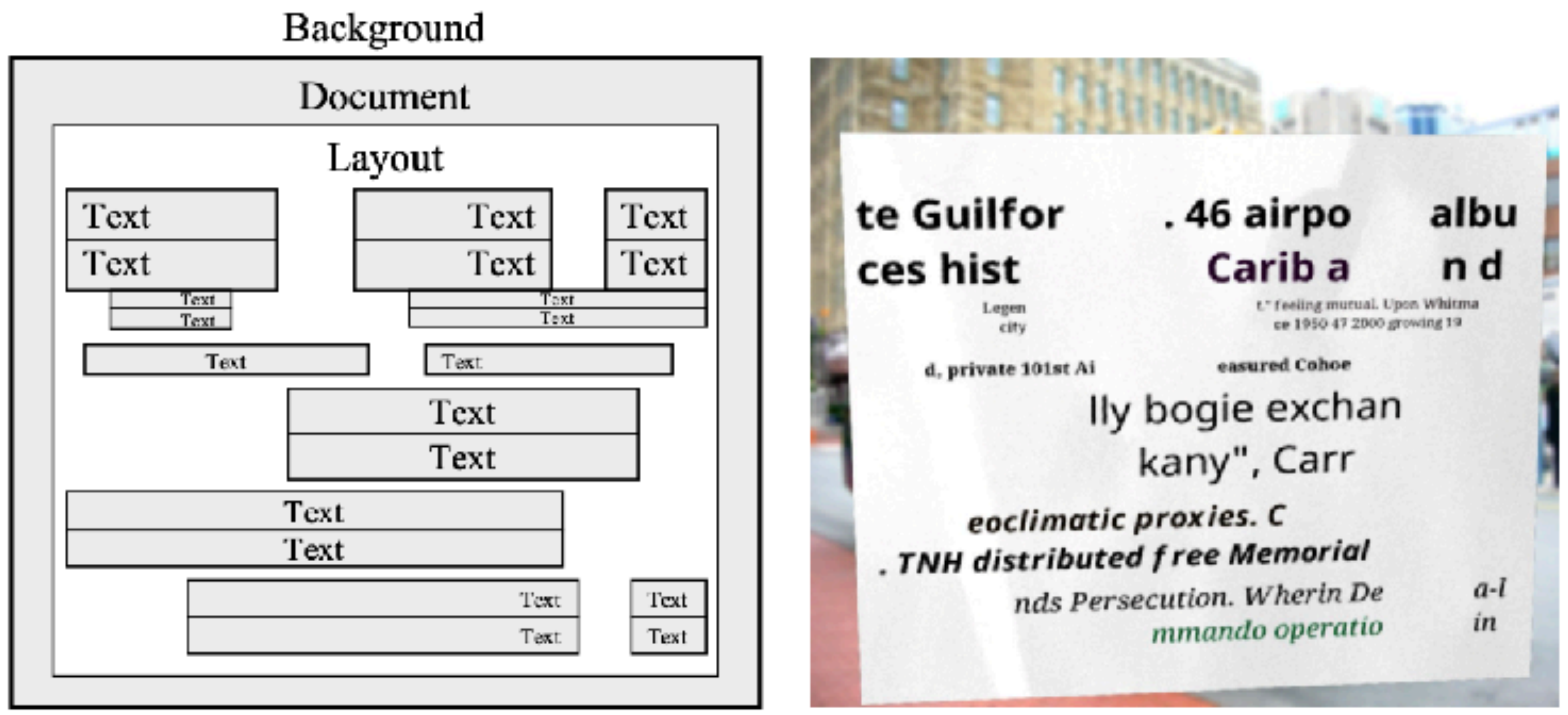
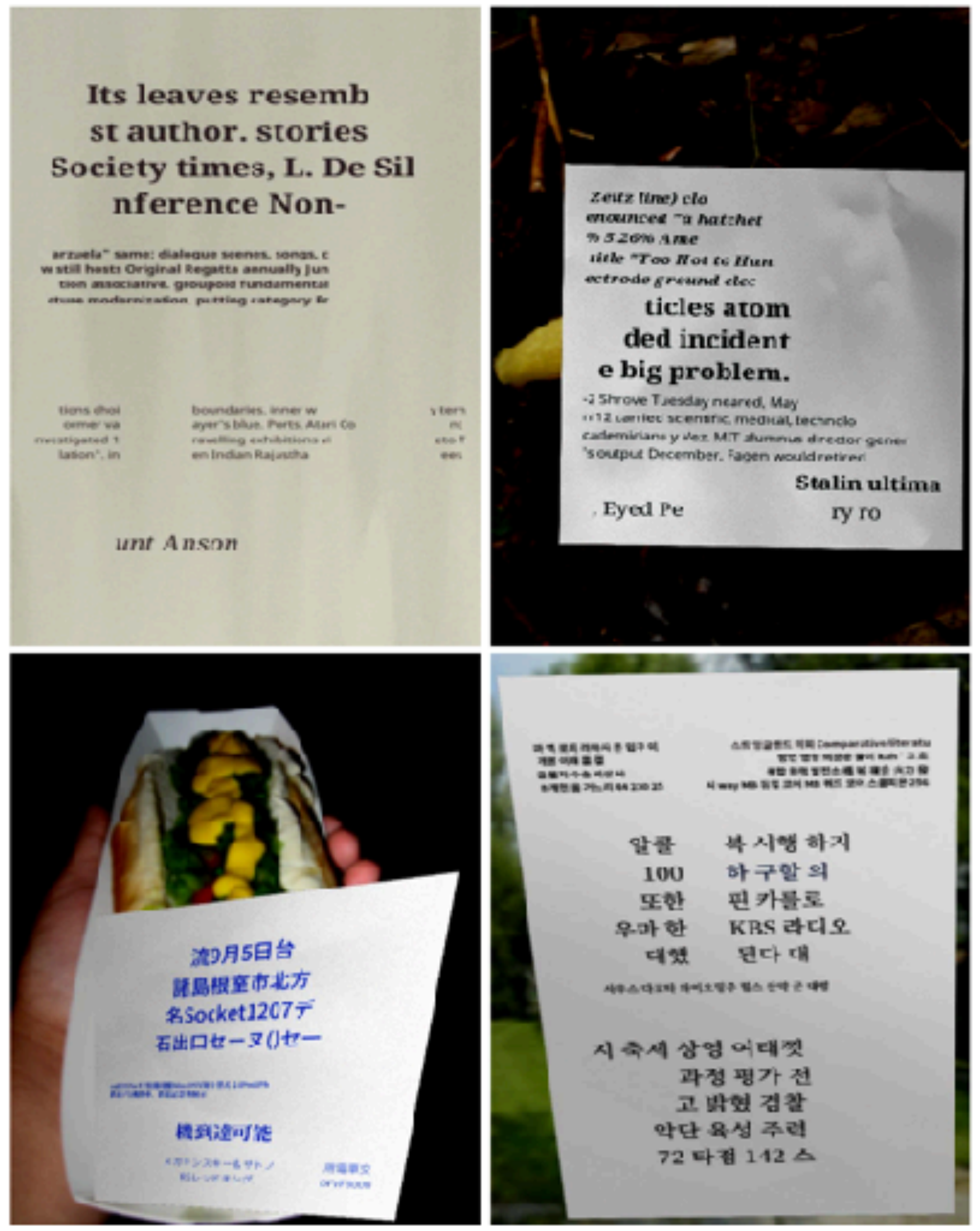
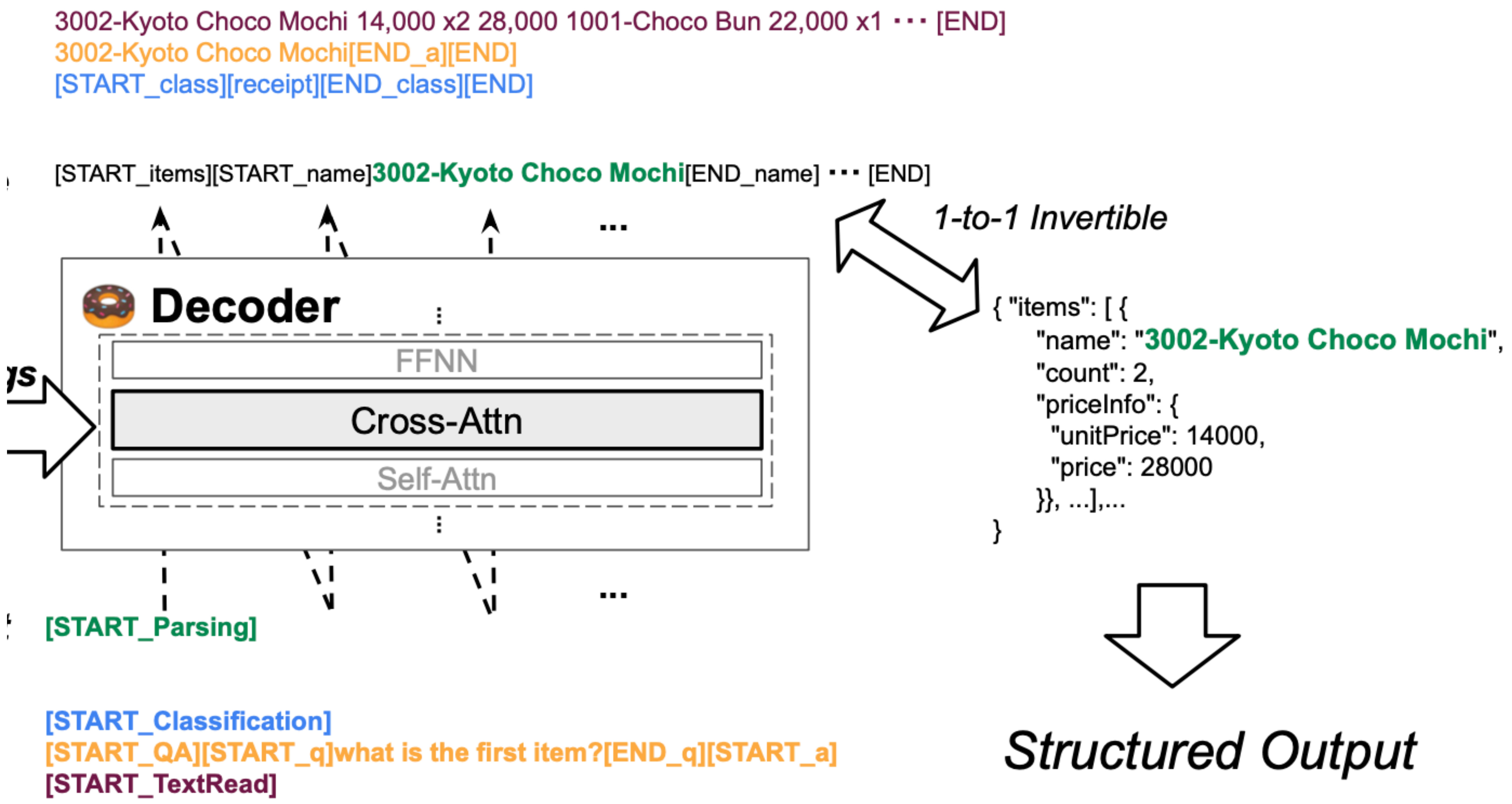


Figure 4: The components of **SynthDoG**.



Method

Application (i.e. Fine-Tuning) - How to Understand



Experiments

Downstream Tasks and Datasets

Document Classification	RVL-CDIP
Document Parsing	Indonesian Receipts Japanese Business Cards Korean Receipts
Document VQA	DocVQA

Experiments

Document Classification

	use OCR	#Params	Time(ms)	Accuracy (%)
$\text{BERT}_{\text{BASE}}$	✓	110M + n/a†	1392	89.81
$\text{RoBERTa}_{\text{BASE}}$	✓	125M + n/a†	1392	90.06
$\text{UniLMv2}_{\text{BASE}}$	✓	125M + n/a†	n/a	90.06
$\text{LayoutLM}_{\text{BASE}}$ (w/ image)	✓	160M + n/a†	n/a	94.42
$\text{LayoutLMv2}_{\text{BASE}}$	✓	200M + n/a†	1489	**95.25**
Donut (Proposed)		156M	**791**	94.50

† Parameters for OCR should be considered for the non-E2E models.

Experiments

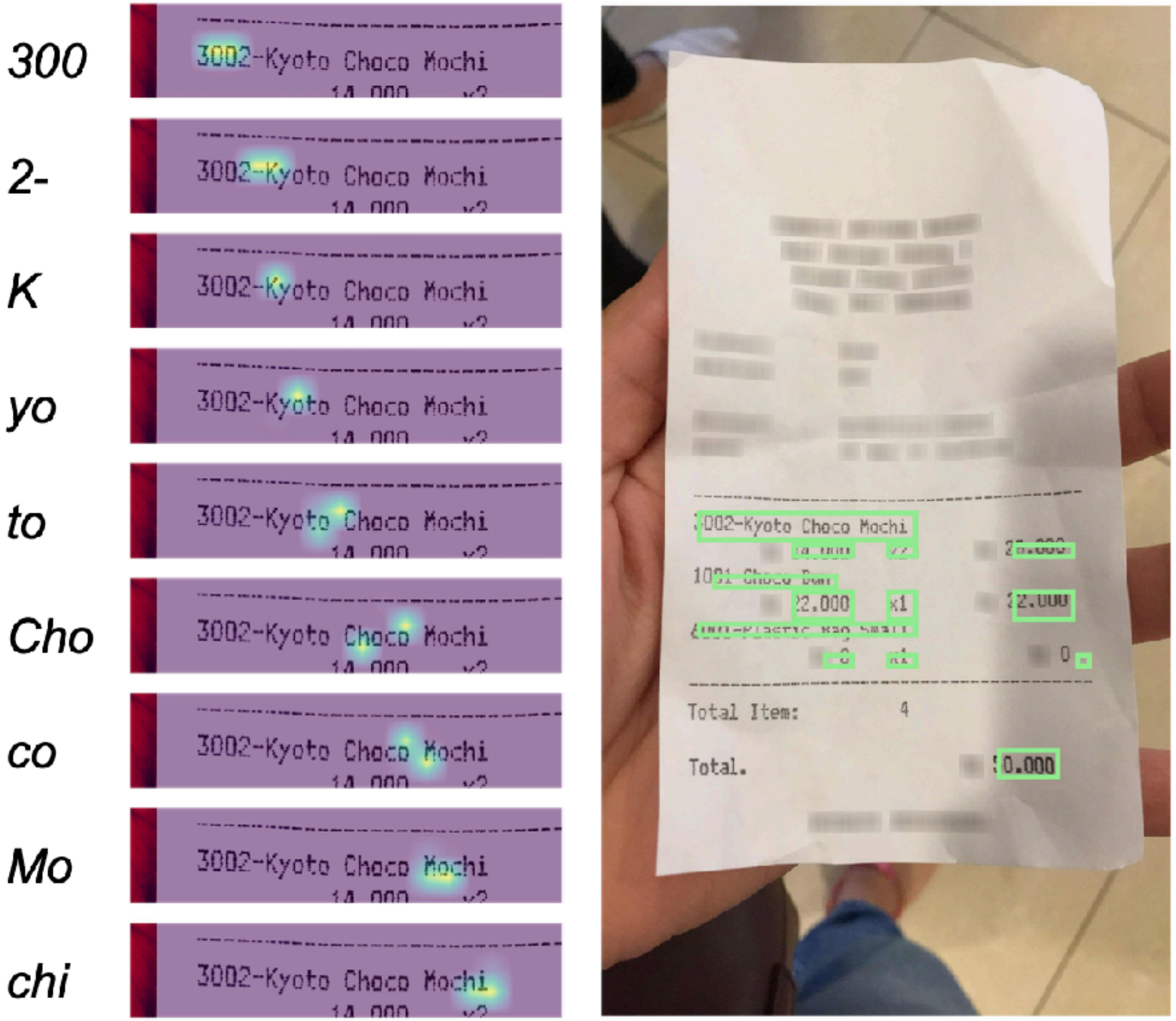
Document Parsing

	use OCR	Params	Indonesian Receipt		Korean Receipt		Japanese Business Card	
			Time (s)	nTED	Time (s)	nTED	Time (s)	nTED
BERT-based Extractor*	✓	86M† + n/a‡	0.89 + 0.54	11.3	1.14 + 1.74	21.67	0.83 + 0.50	9.56
SPADE (Hwang et al., 2021b)	✓	93M† + n/a‡	3.32 + 0.54	10.0	6.56 + 1.74	21.65	3.34 + 0.50	9.77
Donut (Proposed)		156M†	1.07	**8.45**	1.99	**5.87**	1.39	**3.70**

* Our currently-deployed model for parsing business cards and receipts in our real products. The pipeline is based on Hwang et al. (2019).
† Parameters for token (vocabulary) embeddings are omitted for a fair comparison.
‡ Parameters for OCR should be considered for non-E2E models.

Experiments

Document Parsing



Experiments

Document VQA

	OCR	Params‡	Time (ms)	ANLS
LoRRA	✓	∼223M	n/a	11.2
M4C	✓	∼91M	n/a	39.1
$\text{BERT}_{\text{BASE}}$	✓	110M	n/a	57.4
CLOVA OCR	✓	n/a	$\gtrsim$ 3226	32.96
UGLIFT v0.1	✓	n/a	$\gtrsim$ 3226	44.17
$\text{BERT}_{\text{BASE}}$	✓	110M + n/a†	1517	63.54
$\text{LayoutLM}_{\text{BASE}}$	✓	113M + n/a	1519	69.79
$\text{LayoutLMv2}_{\text{BASE}}$	✓	200M + n/a	1610	78.08
Donut		∼207M	809	47.14
+ 10K imgs of trainset				53.14

† Parameters for OCR should be considered for non-E2E models.
‡ Token embeddings for English is counted for a fair comparison.

Conclusion

Donut (End-to-End Method for VDU)

- maps an input document image into a desired structured output
- does not depend on OCR and large-scale real document images (unlike traditional)

SynthDoG (Synthetic Document Generator)

- important role in pre-training of the model
- gradually trained the model from how to read to how to understand