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A Light Transformer-Based Architecture for Handwritten Text Recognition

Killian Barrere Yann Soullard Aurélie Lemaitre Bertrand Couasnon

RFIAP, Vannes
8th July 2022

intuitive
user interaction
for *document* | **intui**
doc

 UMR **IRISA**

IntuiDoc research team, Univ. Rennes, CNRS, IRISA, France

Handwritten Text Recognition



textline image

HTR
→
Model

" The Little Key. "

output text

Transformer for Handwritten Text Recognition

Existing approaches [Kang et al. 2020, Singh et al. 2021]

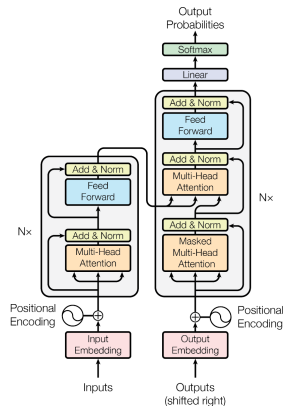
- Transformer layers to model the language
- **Big architectures** to obtain state-of-the-art results

Problem

- Require **a lot of data** to be trained
- Few annotated data in handwritten recognition (10k lines)
- ⇒ **Additional data** to perform well

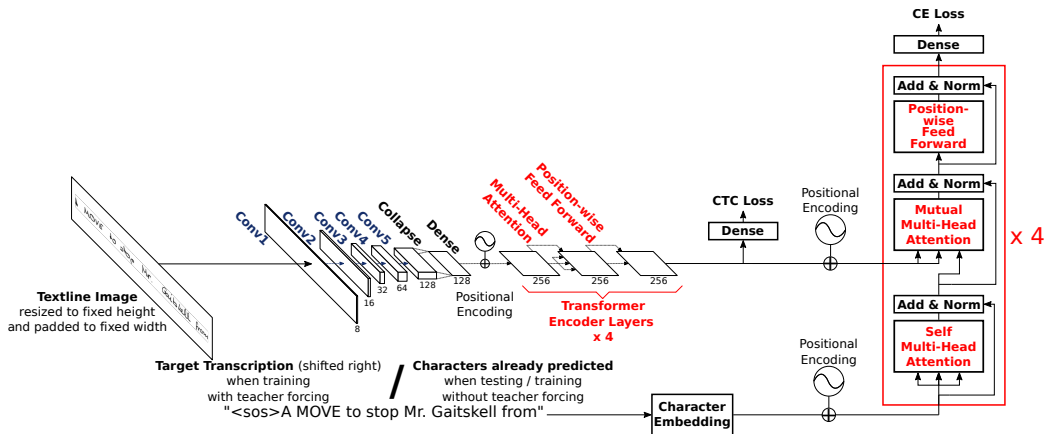
Our proposition

- **Light architecture to perform well with few data**
- Hybrid loss to ease the training

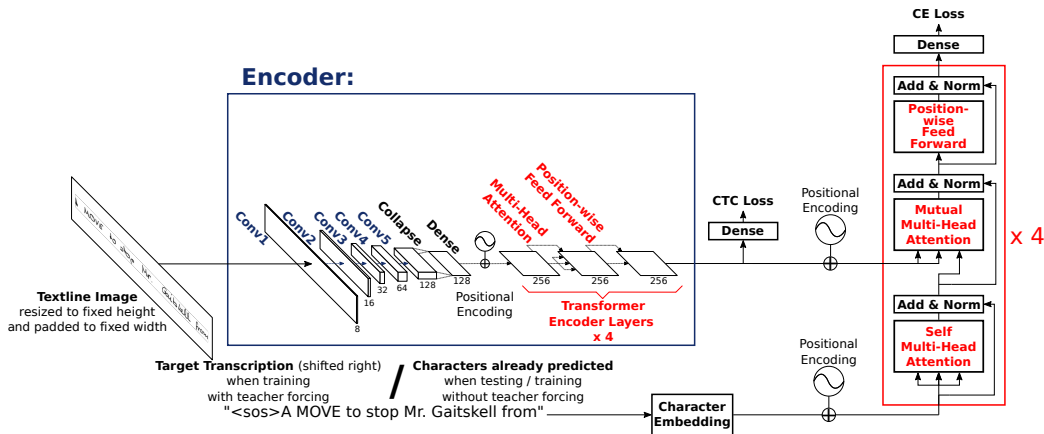


Original Transformer
[Vaswani et al. 2017]

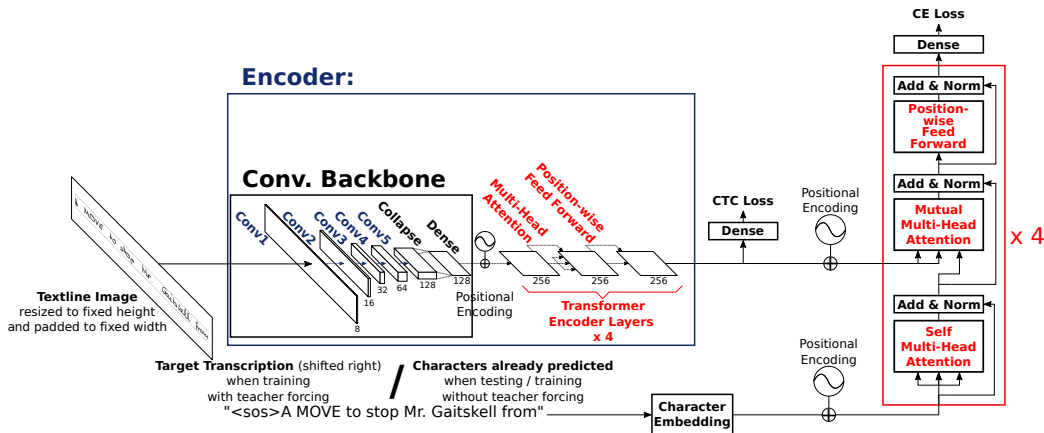
Our Light Transformer Architecture



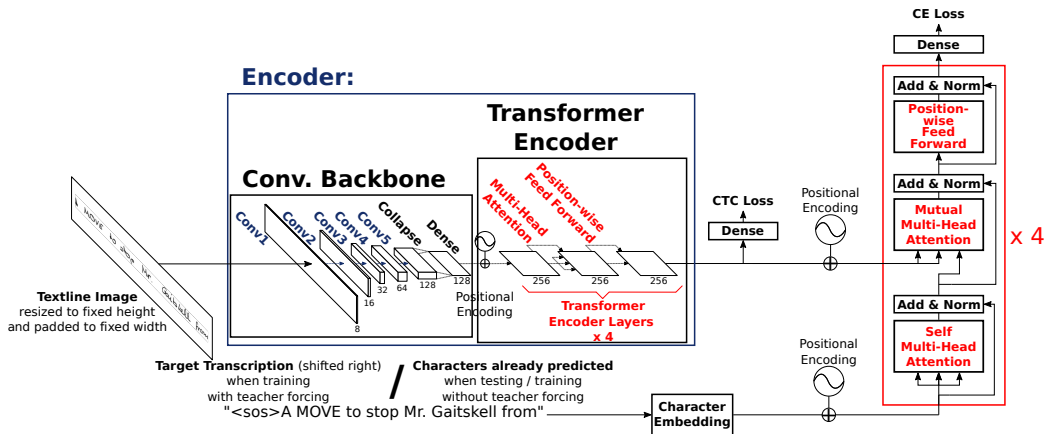
Our Light Transformer Architecture



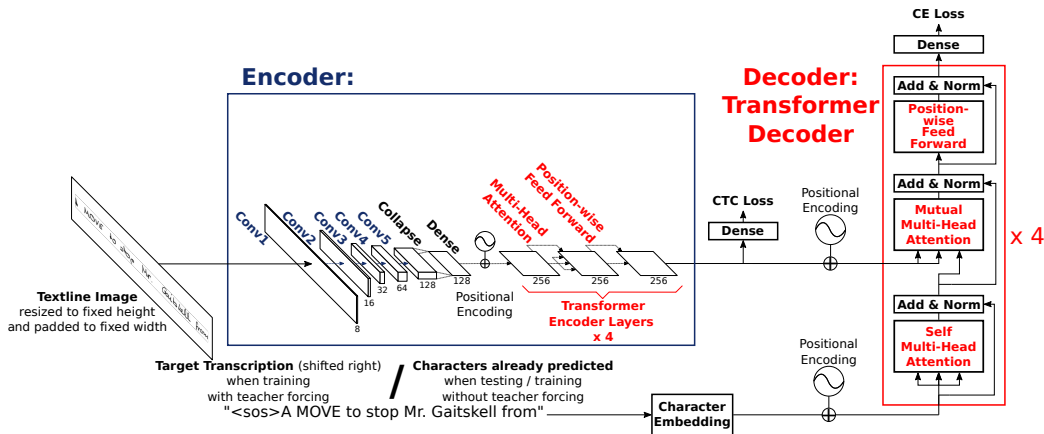
Our Light Transformer Architecture



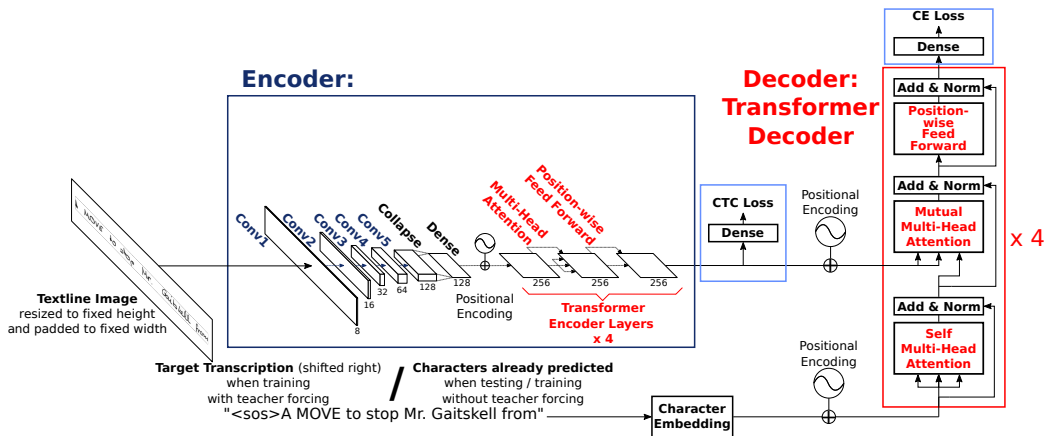
Our Light Transformer Architecture



Our Light Transformer Architecture



Our Light Transformer Architecture



A Light Architecture

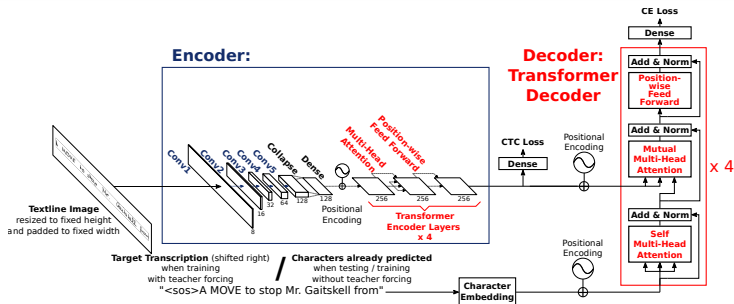
How to make a smaller Transformer

Convolutional backbone

Big backbone (i.e. ResNet18)
⇒ Only 5 convolutional layers

Neurons in Transformer layers

Up to 1,024 neurons
⇒ Only 256 neurons



A Light Architecture

How to make a smaller Transformer

Convolutional backbone

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Neurons in Transformer layers

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⇒ Only 256 neurons

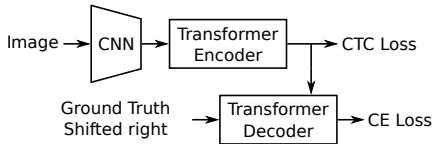
In total

~~100M parameters~~
⇒ **6.9M parameters**

Potential benefits

- **Faster to train** compared to other Transformer-based architecture
- **Does not require additional data** to be trained efficiently

Hybrid Loss



$$\mathcal{L} = \lambda \cdot \mathcal{L}_{CTC} + (1 - \lambda) \cdot \mathcal{L}_{CE}$$

Hybrid loss [Michael et al. 2019]

- Connectionist Temporal Classification (CTC) for the Encoder
- Cross Entropy (CE) for the Decoder

Potential benefits

- Help to train deep layers with gradients from both losses
- Faster convergence

Data used

Real data, without additional data

- IAM dataset (modern English, 10,363 lines, 76k words)
- Data augmentation techniques

a bit earthquake tonight, Trout. I've got a queer
there have been only two occasions on

Our synthetic data (to compare with other transformers)

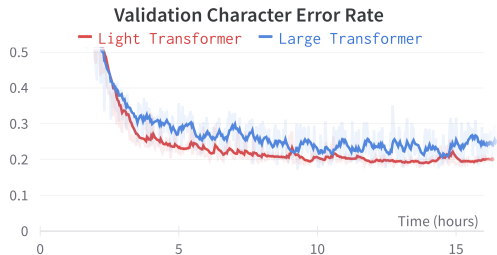
- Articles from Wikipedia (21,350 articles, 66M words)
- Handwritten fonts (32 fonts)
- Random deformations / augmentations

Nearby Loon Mountain has long drawn skiers, and in recent
Justinian I sends a Byzantine army (30,000

Benefits of Using a Light Architecture

Different sizes of our architecture

- **Light Transformer: 6.9M params.**
- **Large Transformer: 28M params.**



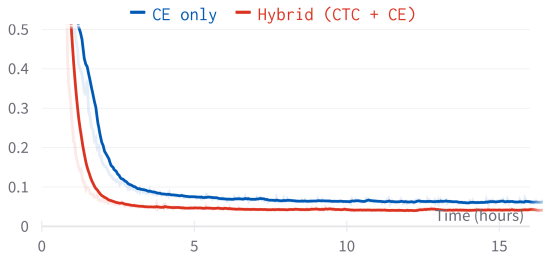
Architecture	IAM		IAM + Synth. Data	
	CER (%)	WER (%)	CER (%)	WER (%)
Our Light Transformer	5.70	18.86	4.76	16.31
Our Large Transformer	5.79	19.67	4.87	17.67

- Our light architecture is **competitive**
- Our light architecture might be **trained faster**

Interest of the Hybrid Loss

- **CE only**: Cross-Entropy loss after the decoder
- **Hybrid**: CTC after the encoder and CE after the decoder

Validation Character Error Rate



Loss Function(s)	IAM		IAM + Synth. Data	
	CER (%)	WER (%)	CER (%)	WER (%)
CE only	10.29	26.36	6.76	19.62
Hybrid (CTC + CE)	5.70	18.86	4.76	16.31

- Faster convergence
- Crucial with few data
- Important with synthetic data

Comparison with the state of the art

Model Architecture	# params.	IAM CER (%)	IAM + Synth. Data CER (%)
CRNN + LSTM [Michael et al. 2019]		5.24	
FCN [Yousef et al. 2020]	3.4M	4.9	
VAN (line level) [Coquenet et al. 2022]	1.7M	4.95	
Transformer [Kang et al. 2020]	100M	7.62	4.67
FPHR Transformer [Singh et al. 2021]	28M		6.5
Forward Transformer [Wick et al. 2021]	13M	6.03	
Bidi. Transformer [Wick et al. 2021]	27M	5.67	
Our Light Transformer-based	6.9M	5.70	4.76

Comparison with the state of the art

Model Encoder	# params.	IAM CER (%)	IAM + Synth. Data CER (%)
CPNN + LSTM [Michael et al. 2019]		5.24	
Compared with other Transformers:	3.4M	4.9	
[Wang et al. 2022]	1.7M	4.95	
Transformer [Kang et al. 2020]	100M	7.62	4.67
FPHR Transformer [Singh et al. 2021]	28M		6.5
Forward Transformer [Wick et al. 2021]	13M	6.03	
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Our Light Transformer-based	6.9M	5.70	4.76

Comparison with the state of the art

Model Encoder	# params.	IAM CER (%)	IAM + Synth. Data CER (%)
CRNN + LSTM [Michael et al. 2019]		5.24	
FCN [Yousef et al. 2020]	3		
VAN (line level) [Coquenet et al. 2022]	1.7		
Transformer [Kang et al. 2020]	100M	7.62	4.67
FPHR Transformer [Singh et al. 2021]	28M		6.5
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**Low error rates
without additional data**

Comparison with the state of the art

Model Encoder	# params.	IAM CER (%)	IAM + Synth. Data CER (%)
CRNN + LSTM [Michael et al. 2019]		5.24	
FCN [Yousef et al. 2020]	3.4M	4.9	State-of-the-art results with synthetic data
VAN (line level) [Coquenet et al. 2022]	1.7M	4.95	
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While being
a light Transformer

Comparison with the state of the art

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Our Light Transformer-based	6.9M	5.70	4.76

Conclusion

Our Contribution

A **light Transformer architecture**, trained with a **hybrid loss**

- **Faster to train** than other Transformers
- **Good results without additional data**
- **State-of-the-art results** with synthetic data

Future Works: Historical Documents

- Ability of Transformers to **model the language** is crucial
- **Very few annotated data** \Rightarrow our light Transformer architecture

Find the paper in

- DAS 2022 (A Light Transformer-Based Architecture for Handwritten Text Recognition)
- HAL: <https://hal.archives-ouvertes.fr/hal-03685976v1>

State of the Art: From RNN to Transformer

Usual approaches: Convolutional Recurrent Neural Networks (CRNN)

- Convolutional layers + recurrent layers

⇒ Lack of parallelism / **slow training speed**

Fully Convolutional Networks [Ingle et al. 2019, Yousef et al. 2020, Coquenot et al. 2021]

- Composed of convolutional layers, no recurrent layers

⇒ Faster training speed, but might be **hard to learn long-range contexts**

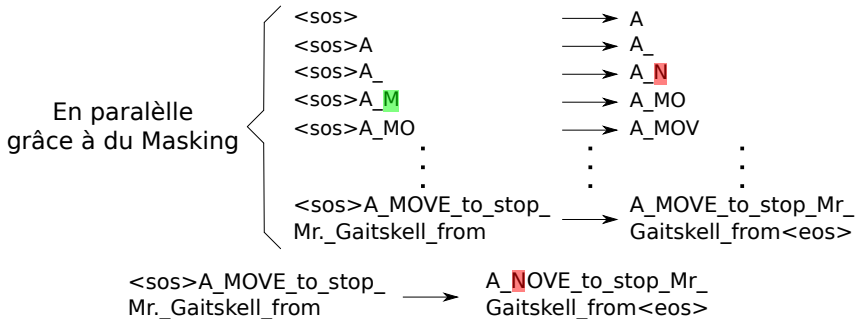
Multi-Head Attention (Transformer layers) [Vaswani et al. 2017]

- Able to **learn long-range context**
- Strong **parallelism**

⇒ **Good alternative** but **require a lot of training data**

A l'entraînement : Decoding en parallèle et Teacher Forcing

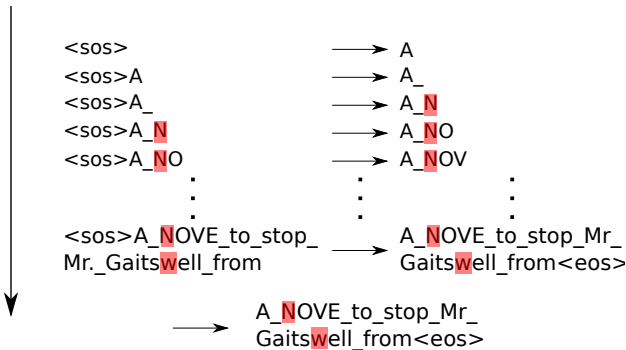
A MOVE to stop Mr. Gaitskell from
 <sos>A MOVE to stop Mr. Gaitskell from



A l'inférence : Decoding séquentiel

A MOVE to stop Mr. Gaitskell from

Decoding
Séquentiel



CER and WER

Definition

- CER: Character Error Rate
- WER: Word Error Rate
- Edit distance between prediction and groundtruth

$$CER = \frac{I+D+S}{N}$$

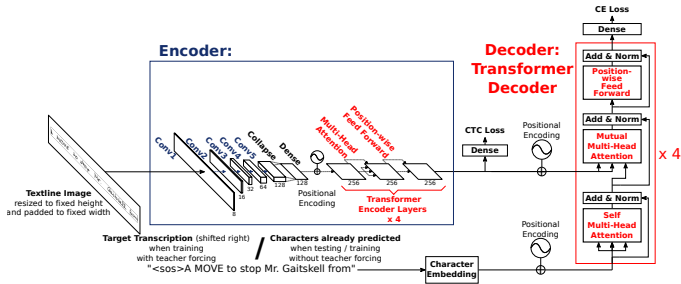
I Number of Insertions

D Number of Deletions

S Number of Substitutions

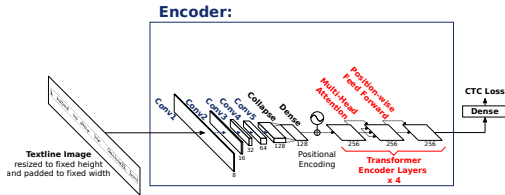
N Length of the ground-truth

Ablation Study: Transformer Layers instead of Recurrent Layers



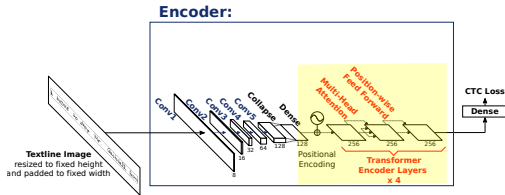
Without the decoder

Ablation Study: Transformer Layers instead of Recurrent Layers



Without the decoder

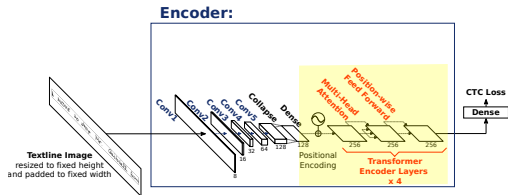
Ablation Study: Transformer Layers instead of Recurrent Layers



Without the decoder

- CRNN with Transformer instead of recurrent layers

Ablation Study: Transformer Layers instead of Recurrent Layers



Without the decoder

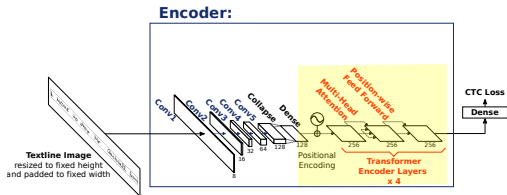
- CRNN with Transformer instead of recurrent layers

Recurrent \Rightarrow Transformer

- More parameters
- Lower error rates
 - Better context

Architecture	# params.	IAM		IAM + Synth. Data	
		CER (%)	WER (%)	CER (%)	WER (%)
CRNN (Baseline)	1.7M	6.14	23.26		
Our Encoder only	3.2M	5.93	22.82		

Ablation Study: Transformer Layers instead of Recurrent Layers



Architecture	# params.	IAM		IAM + Synth. Data	
		CER (%)	WER (%)	CER (%)	WER (%)
CRNN (Baseline)	1.7M	6.14	23.26	5.66	21.62
Our Encoder only	3.2M	5.93	22.82	6.15	24.02

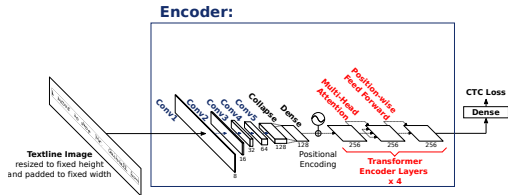
Without the decoder

- CRNN with Transformer instead of recurrent layers

Recurrent \Rightarrow Transformer

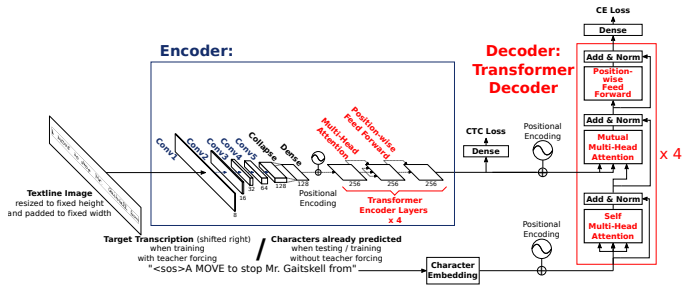
- More parameters
- Lower error rates
 - Better context
- Worse with synthetic data (may not generalize well)

Ablation Study: Decoder



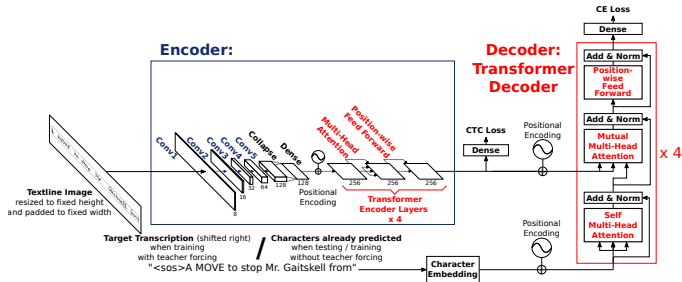
With the decoder

Ablation Study: Decoder



With the decoder

Ablation Study: Decoder



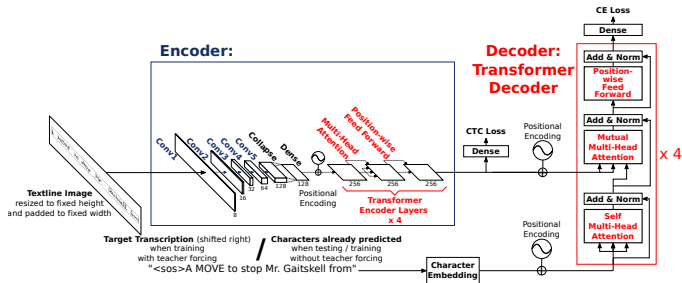
With the decoder

Ability to model the language

- Lower error rates
- Stronger impact on the WER

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Our Light Transformer	6.9M	5.70	18.86		

Ablation Study: Decoder



With the decoder

Ability to model the language

- Lower error rates
- Stronger impact on the WER

Benefits more from synthetic data

- More data to learn the language

Architecture	# params.	IAM		IAM + Synth. Data	
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