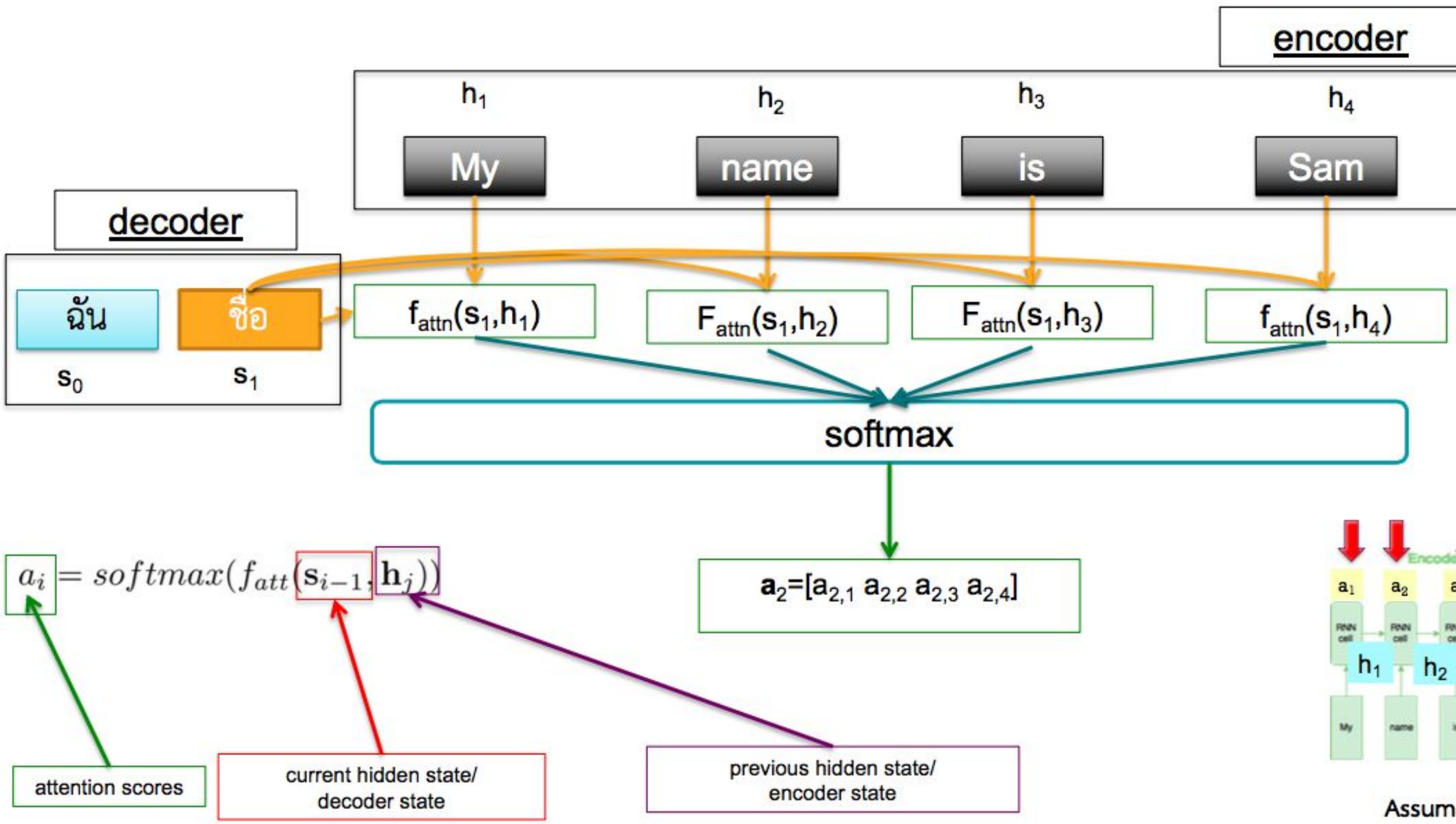
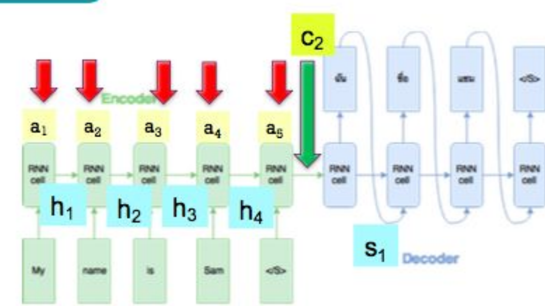
Text gen and QA2

Transformer and others

Attention Calculation Example (1): Attention Scores

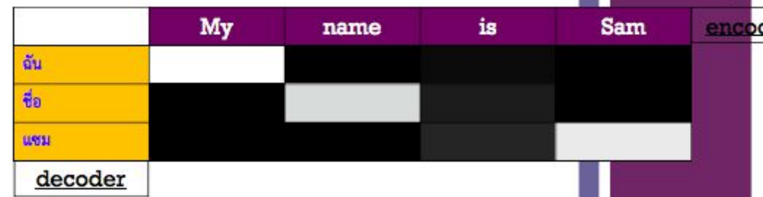




Assume now try to translate "ชื่อ"
to give high weight at "name"

$$\boxed{a_i = softmax(f_{att}(\mathbf{s}_{i-1}, \mathbf{h}_j))}$$

Type of Attention mechanisms



(Remember that there are many variants of attention function $\mathbf{f}_{\text{attn}}$)

Additive attention: The original attention mechanism (Bahdanau et al., 2015) uses a one-hidden layer feed-forward network to calculate the attention alignment:

$$f_{attn}(\mathbf{s}_{i-1}, \mathbf{h}_j) = tanh(\mathbf{W}_a[\mathbf{s}_{i-1}; \mathbf{h}_j])$$

Multiplicative attention: Multiplicative attention (Luong et al., 2015) simplifies the attention operation by calculating the following function:

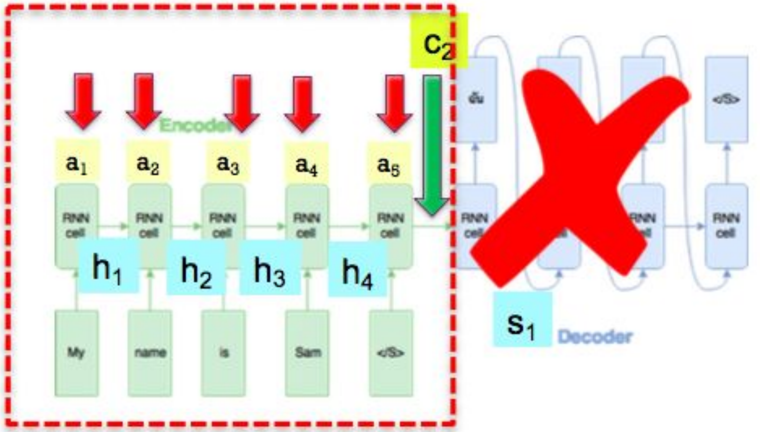
$$f_{attn}(\mathbf{s}_{i-1}, \mathbf{h}_j) = \mathbf{s}_{i-1}^{\top} \mathbf{W}_a \mathbf{h}_j$$

Self-attention: Without any additional information, however, we can still extract relevant aspects from the sentence by allowing it to attend to itself using self-attention (Lin et al., 2017)

$$\mathbf{a} = softmax\boxed{(\mathbf{w}_{s_2} tanh(\mathbf{W}_{s_1} \mathbf{H}^T))}$$

Key-value attention: key-value attention (Daniluk et al., 2017) is a recent attention variant that separates form from function by keeping separate vectors for the attention calculation.

Self attention



Assume now try to translate “ชื่อ”
to give high weight at “name”

No need for additional information in order to select where to attend

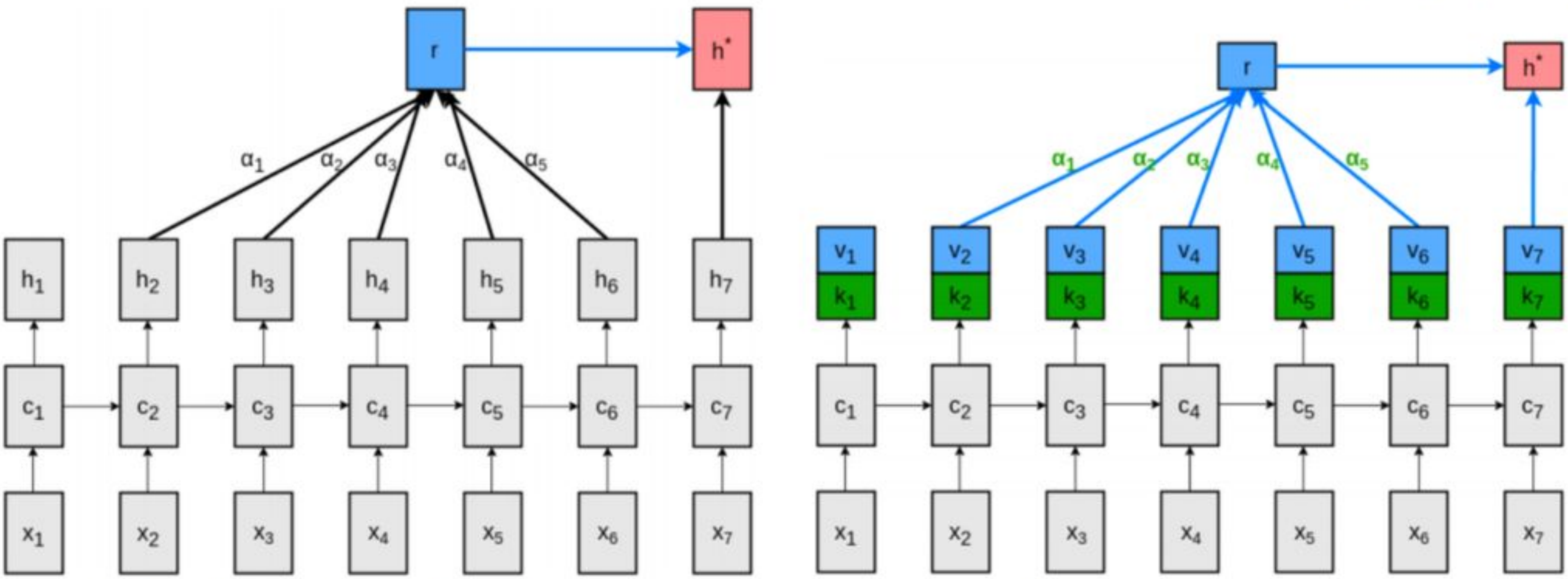
Similar to CNN in flow

https://nlp.stanford.edu/seminar/details/lkaiser.pdf

Key-value attention

Normal attention use the same vector to find the position and use as values

Use key to find the position, and use the values as information



(a) Neural language model with attention. (b) Key-value separation.

Overview

- Techniques
  - Transformer
  - Beam search
  - GAN for text
- Applications
  - Grammar correction
  - QA

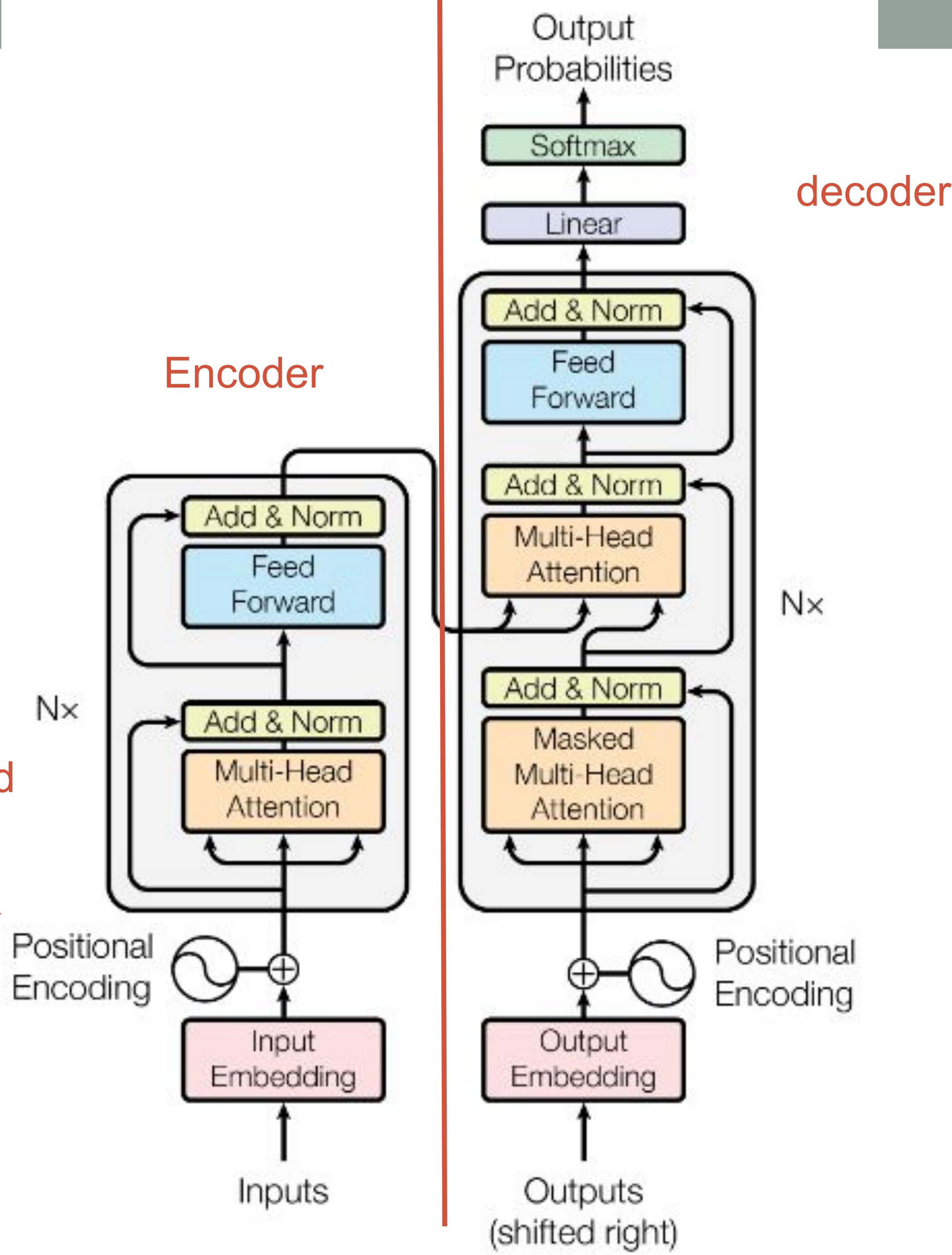
Attention is all you need

Abstract

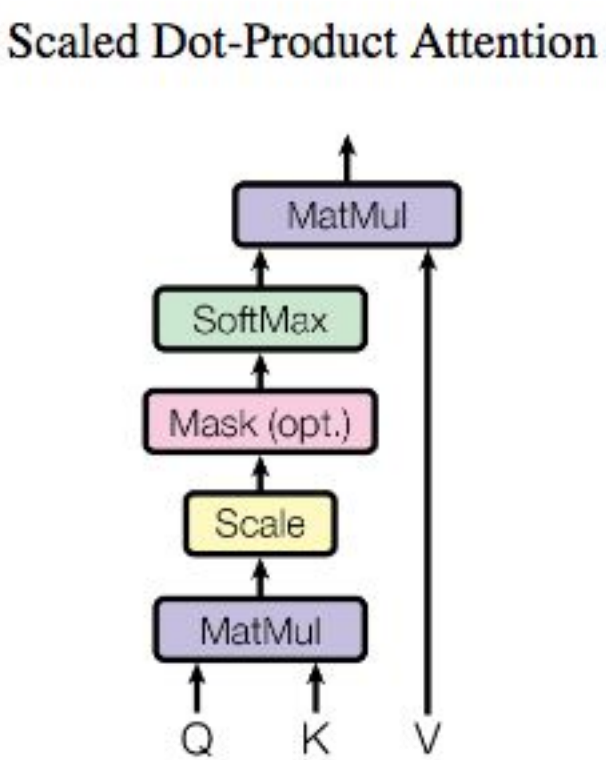
The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

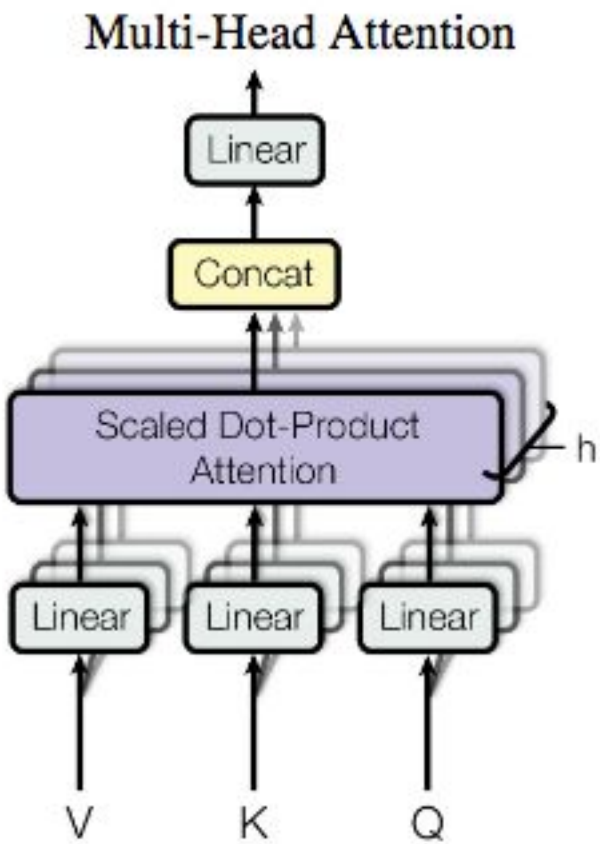
https://arxiv.org/pdf/1706.03762.pdf

To eliminate GRU which remembers time, encode position instead



Multi-head attention





What's this????

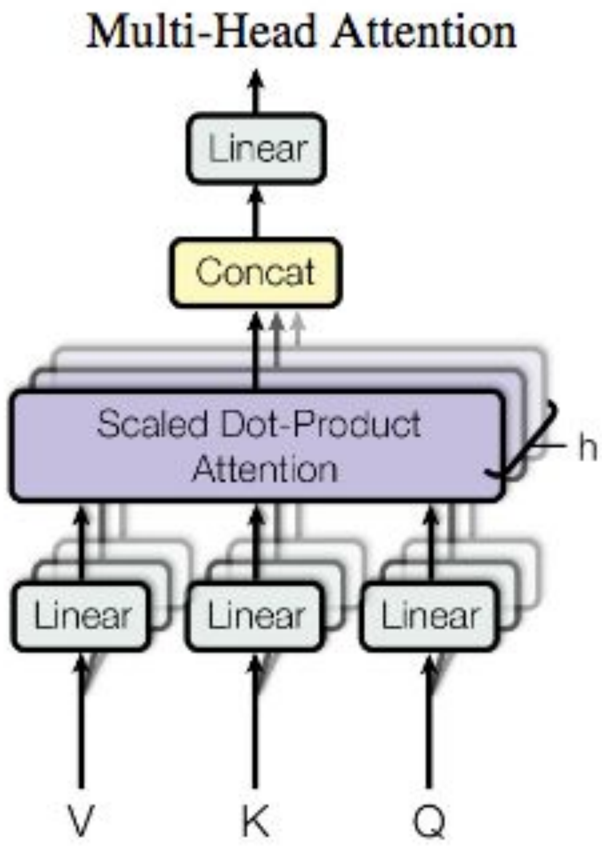
Query – used with Key to determine the position
Value – used as the information after determining the position

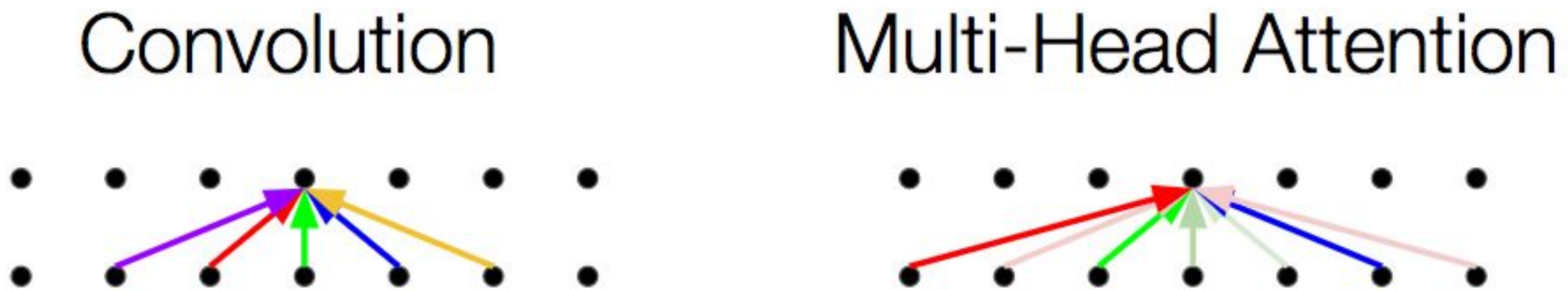
Attention drawback

- Convolution: weights * input. Each weights are different. So position is encoded.
- Self-attention: a weighted average. Position information is lost at the output

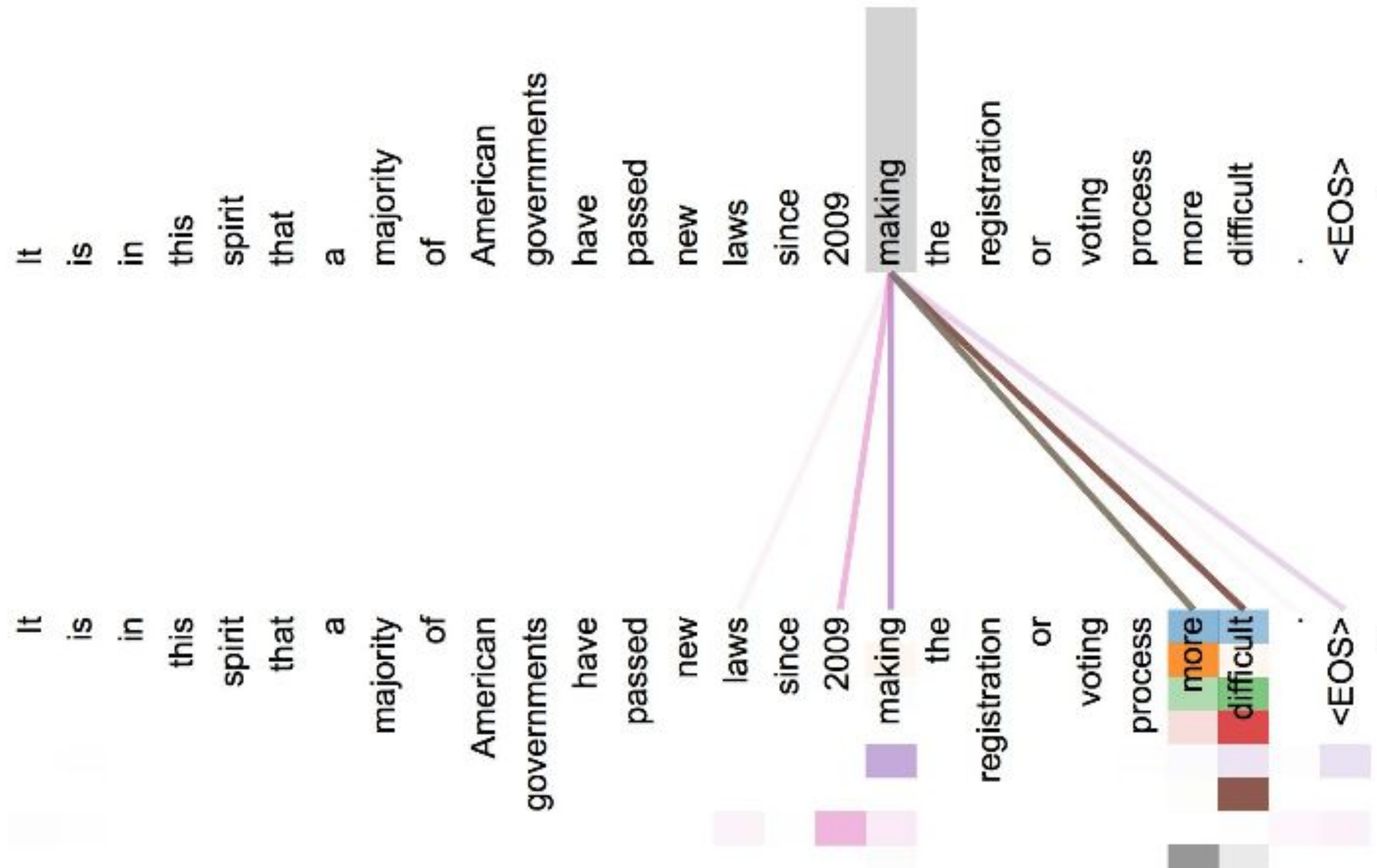
Multi-head attention

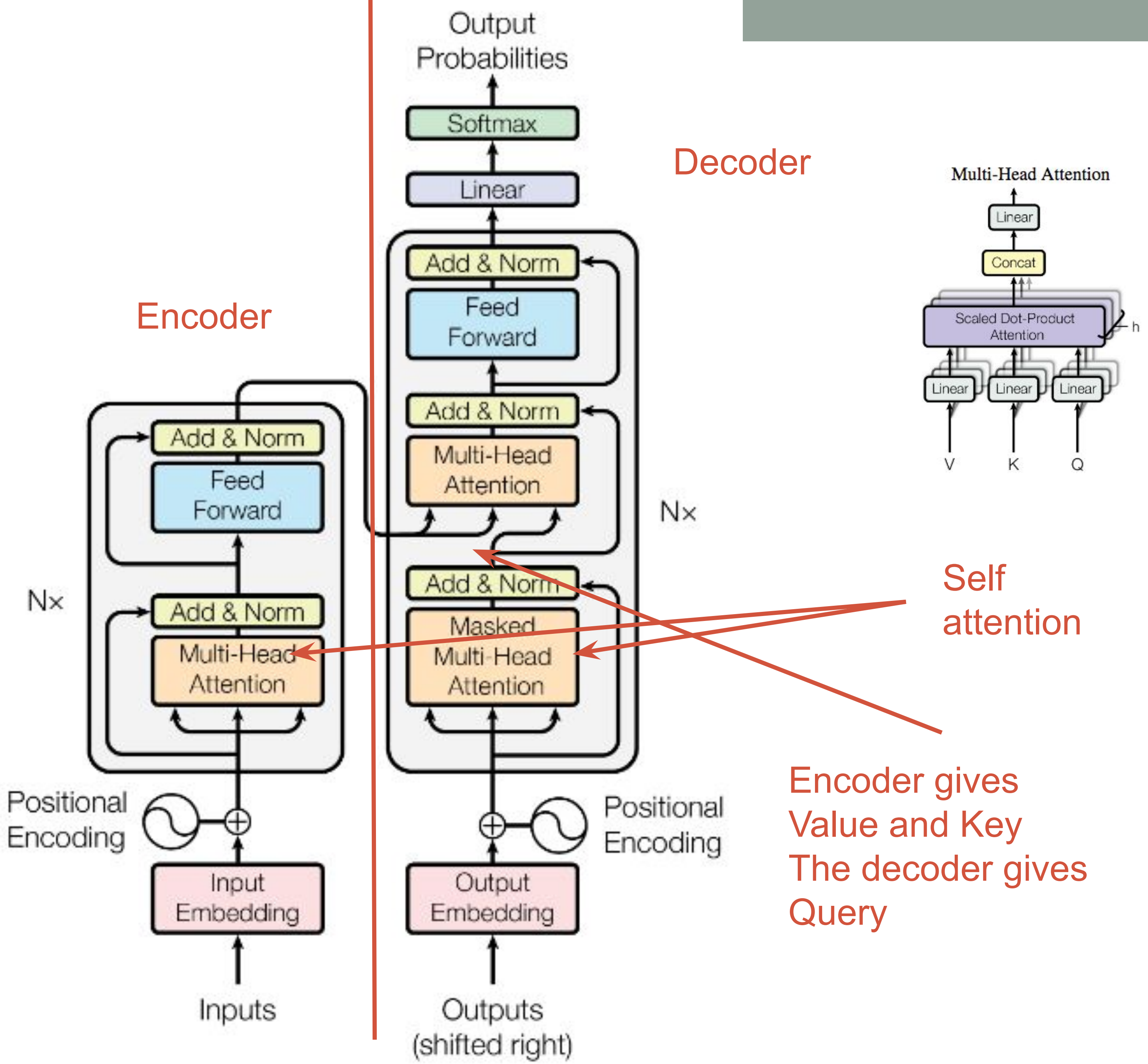
- Multiple attention layers (heads) that run in parallel
- Each head use different weights
- Each head can learn different relationship



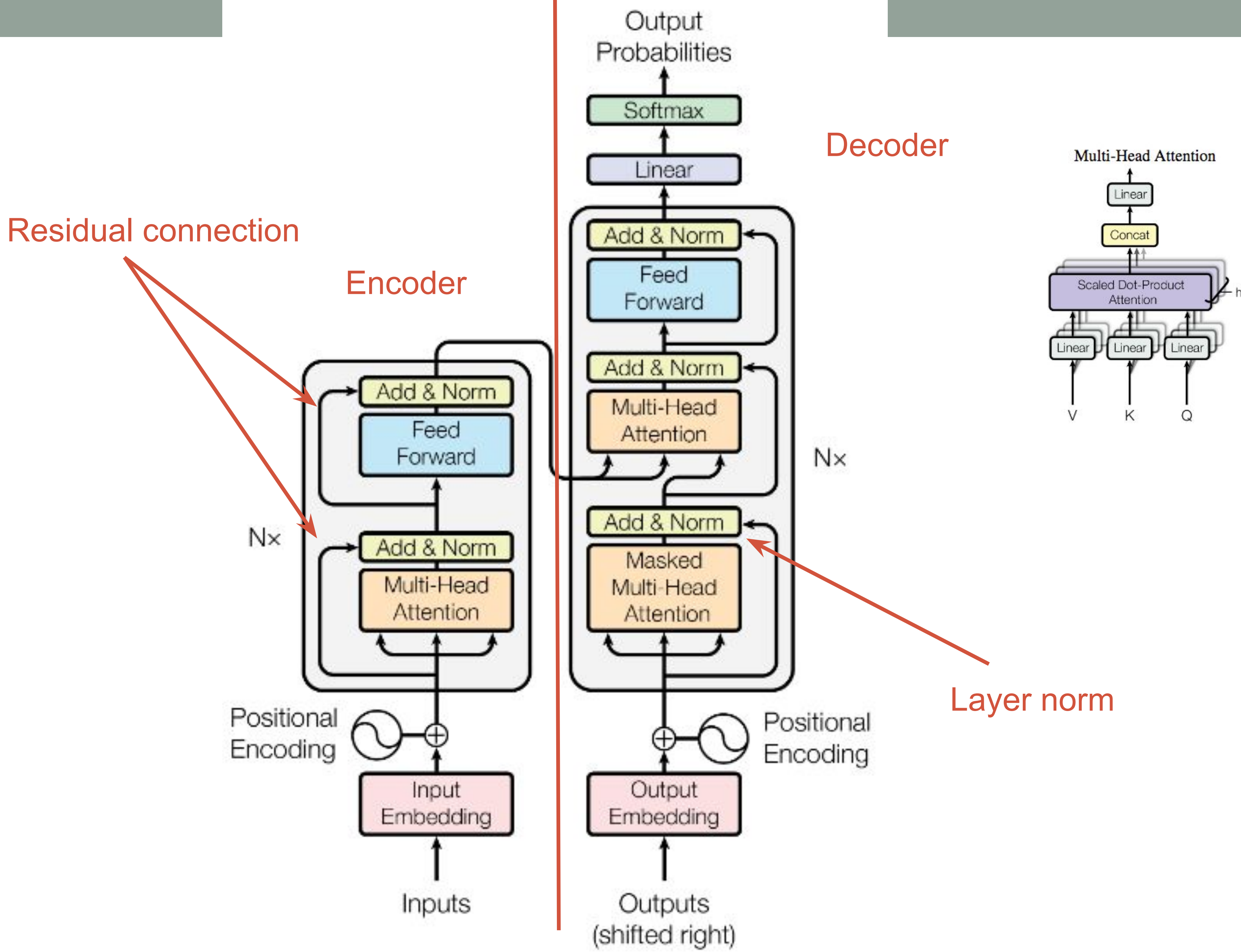


Multi-head visualization





Output Probabilities
Softmax
Linear
Decoder
Multi-Head Attention
Linear
Concat
Scaled Dot-Product Attention
h
Linear
Linear
Linear
V
K
Q
Encoder
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Nx
Self attention
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Encoder gives Value and Key
The decoder gives Query
Inputs
Outputs (shifted right)

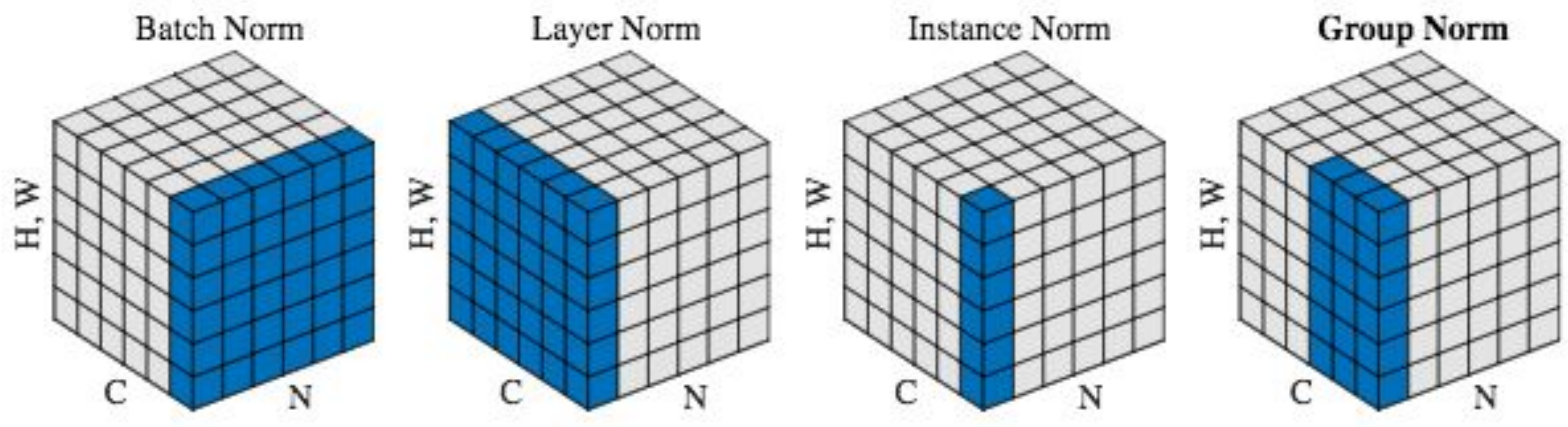


Residual connection
Encoder
Decoder
Layer norm
Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Positional Encoding
Input Embedding
Inputs
Positional Encoding
Output Embedding
Outputs (shifted right)
Multi-Head Attention
Linear
Concat
Scaled Dot-Product Attention
h
Linear
Linear
Linear
V
K
Q

Layer norm

- Normalize the mean and SD
- Batch norm vs layer norm vs Instance norm vs group norm

Group is used to distributed models into multiple GPUs

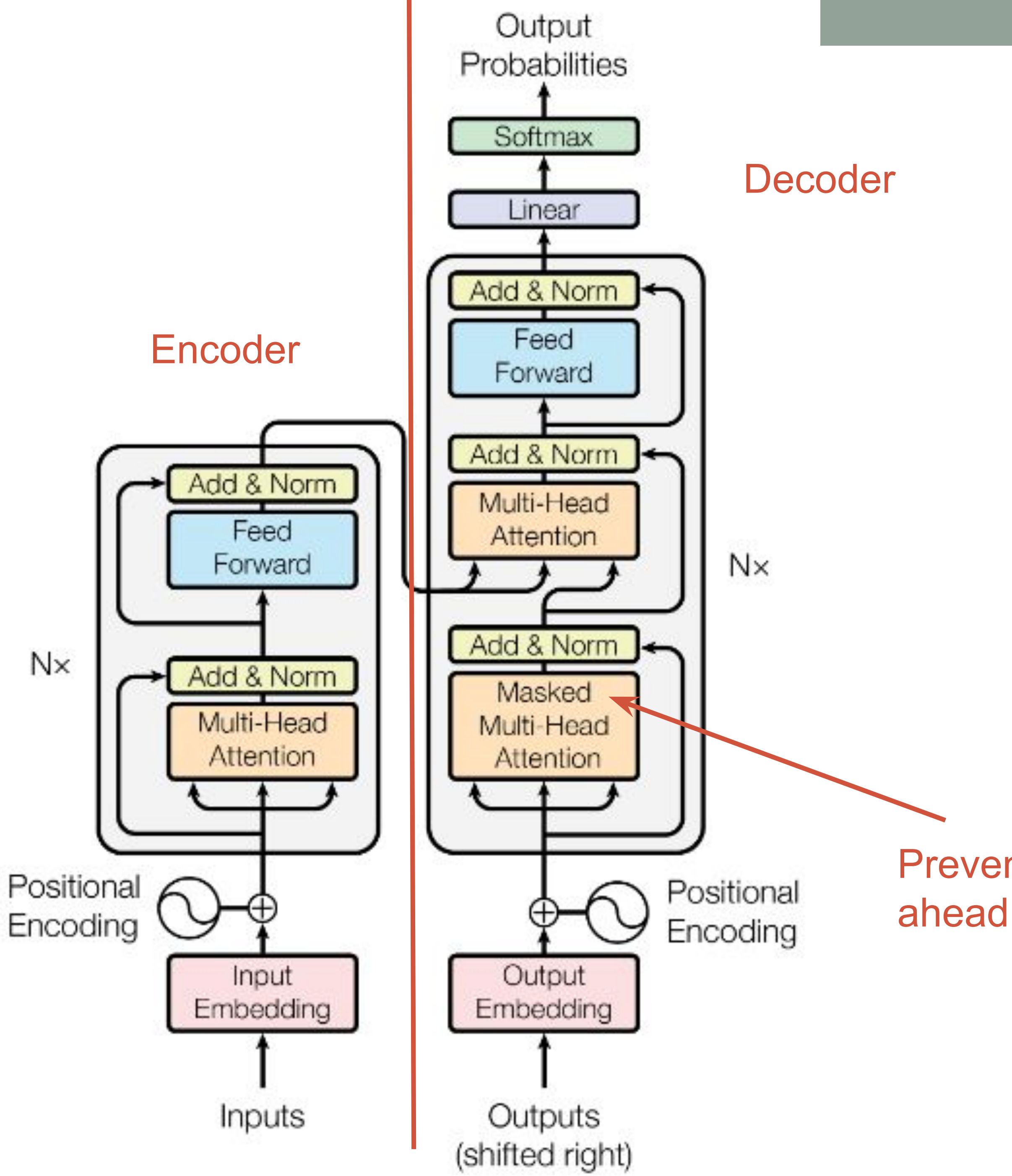


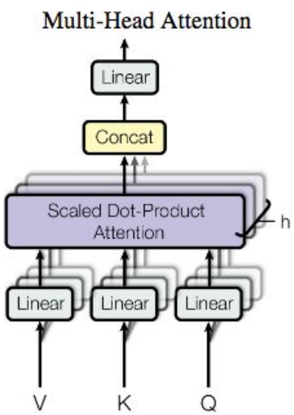
N – example in mini batch
C – Channel output
H,W – spatial coordinates (x,y)

Box is output tensor from CNN

BN and GN are usually best, GN is better when batch size is small (Vision task)

https://arxiv.org/abs/1803.08494


Output
Probabilities
Softmax
Linear
Decoder
Encoder
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Nx
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Nx
Add & Norm
Masked
Multi-Head
Attention
Prevent looking
ahead (cheating)
Positional
Encoding
Positional
Encoding
Input
Embedding
Output
Embedding
Inputs
Outputs
(shifted right)


Multi-Head Attention
Linear
Concat
Scaled Dot-Product
Attention
h
Linear
Linear
Linear
V
K
Q

MT results

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

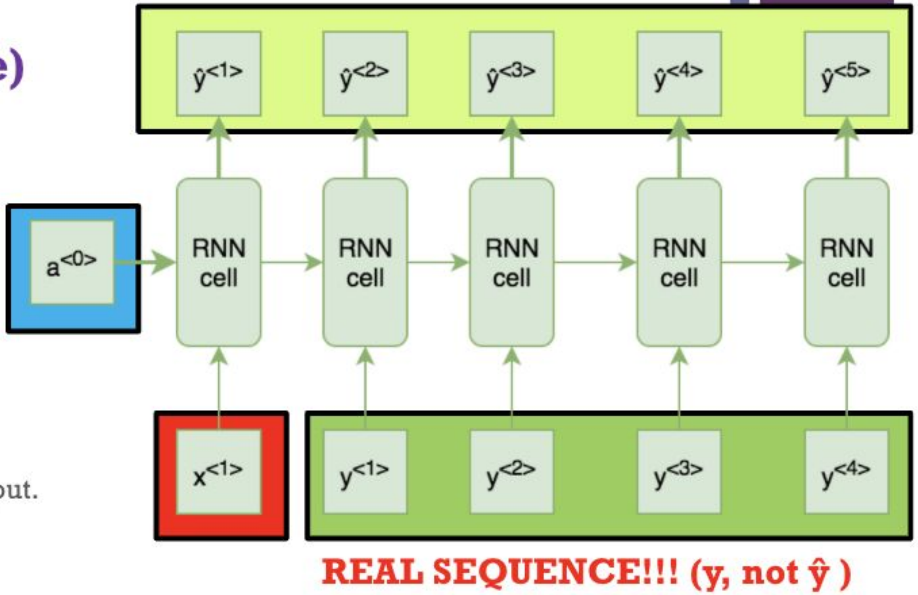
Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

Can use for other tasks, like ASR, parsing, etc.

Text generation model (training)

- **One-to-Many RNN (autoregressive)**
  - The only real input is $\mathbf{x}^{<1>}$
  - $a^{<0>}$ is the initial hidden state.
  - $\hat{y}$ is the predicted output.
  - y is an actual output.
  - During **the training phase**, instead of using the predicted output to feed into the next time-step, we use the actual output.

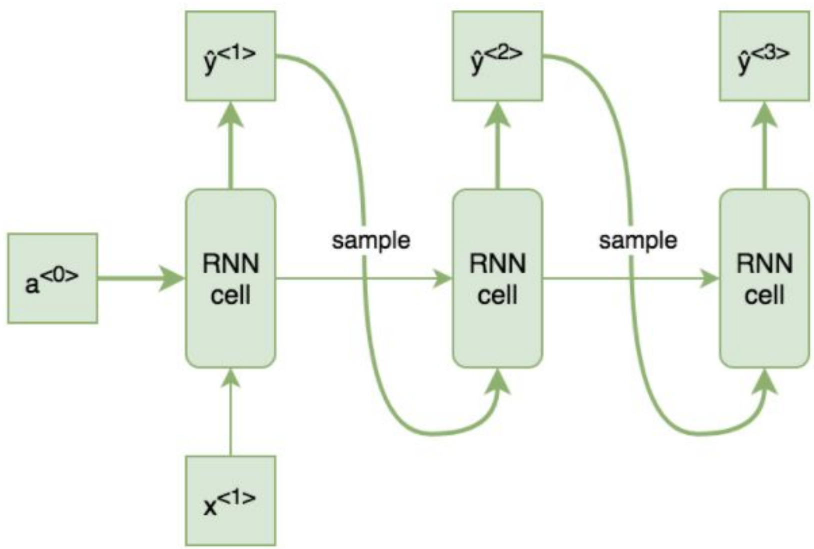
$$a^{<t>} = \boxed{Wa^{<t-1>}} + \boxed{Wx^{<t>}} + \boxed{b}$$



+ Text generation model (inference)

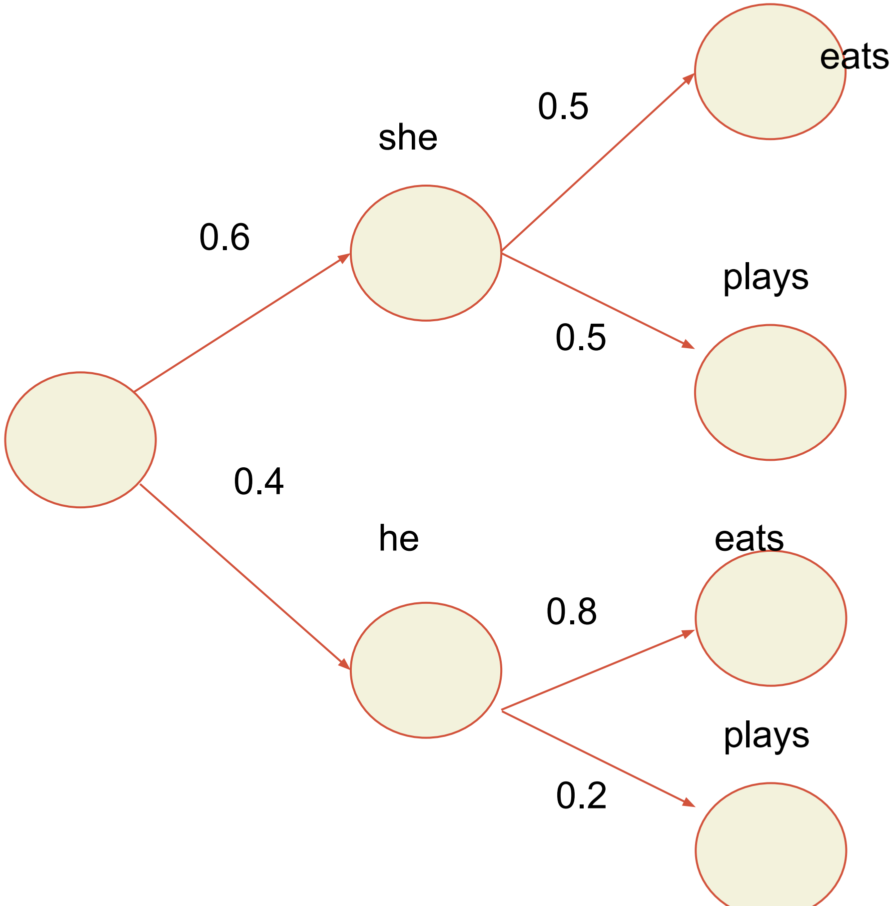
Training
Inference

- To generate a novel sequence, the inference model (testing phase) randomly samples an output from a softmax distribution.



Beam search

Autoregressive requires making a decision even though it might not be optimal for the whole sequence



However, expanding the tree will be exponential

P(he eats) = 0.32
P(she eats) = 0.30

Beam search

Beam search keeps a list of n options at all times

Problems

Longer sentences have lower probabilities.

- Normalize by length
- See homework

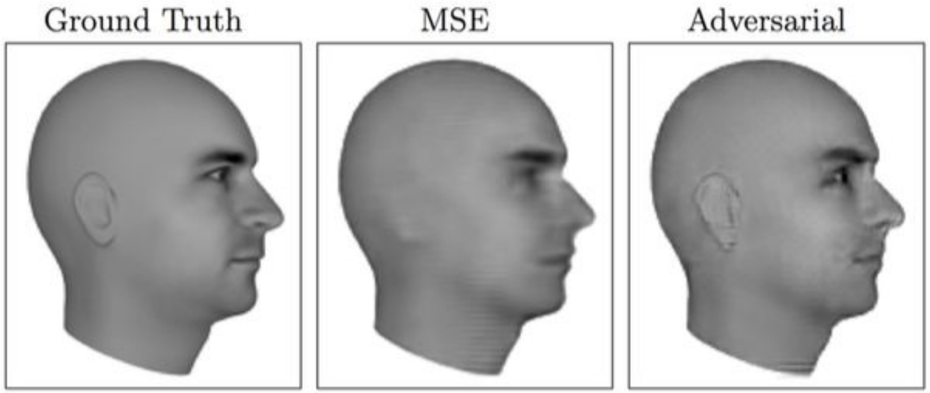
Generative Adversarial Networks (GANs)

Learning distributions

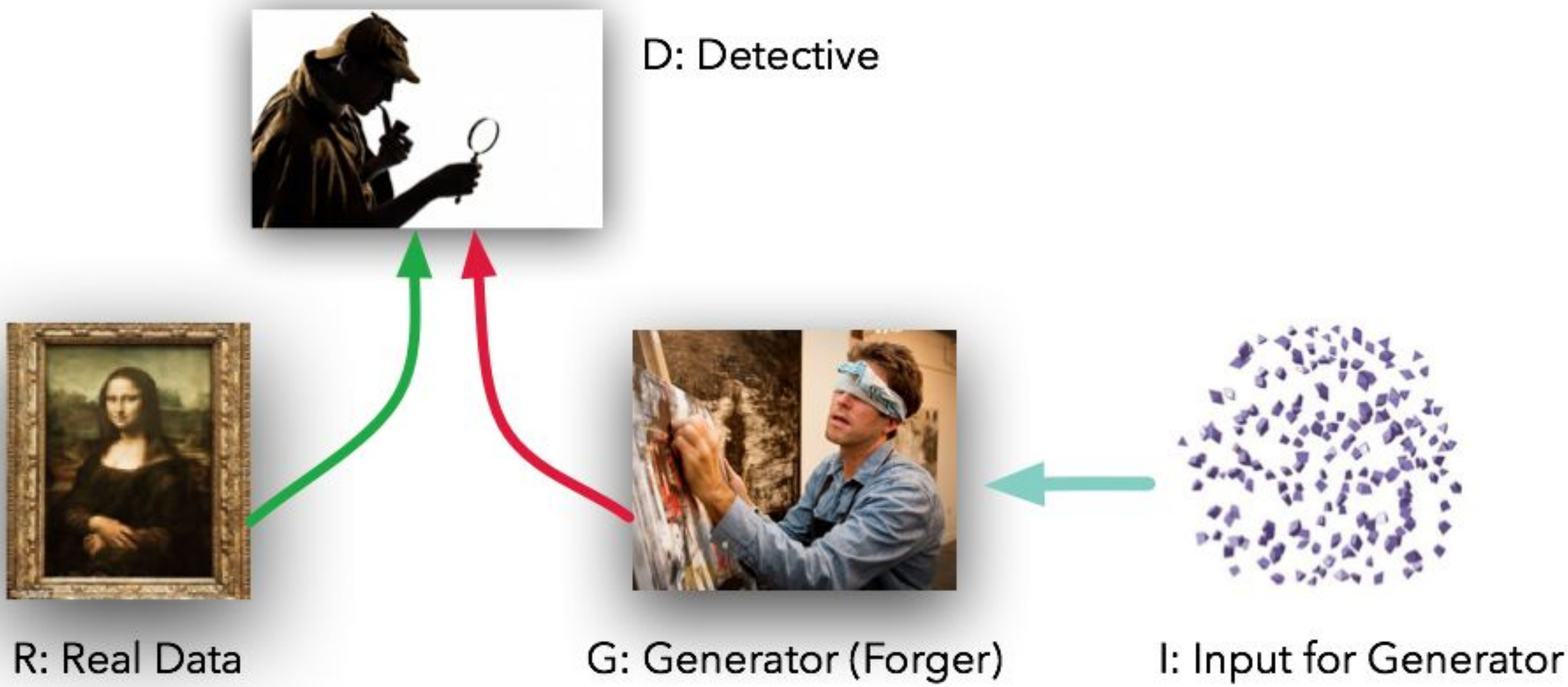
- Supervised learning tasks usually have one correct answer

Learning distributions

- Supervised learning tasks usually have one correct answer
- Sometimes there are more than one possibility
  - What is the next frame of a video?
  - What is the missing pixels in an image?
  - What word is missing from the blank?
    - I eat ____



https://arxiv.org/abs/1701.00160



https://medium.com/@devnag/generative-adversarial-networks-gans-in-50-lines-of-code-pytorch-e81b79659e3f

Generative Adversarial Networks (GANs)

0.1, -0.3, .. → Generator →  → Discriminator → Real or Fake

z

x

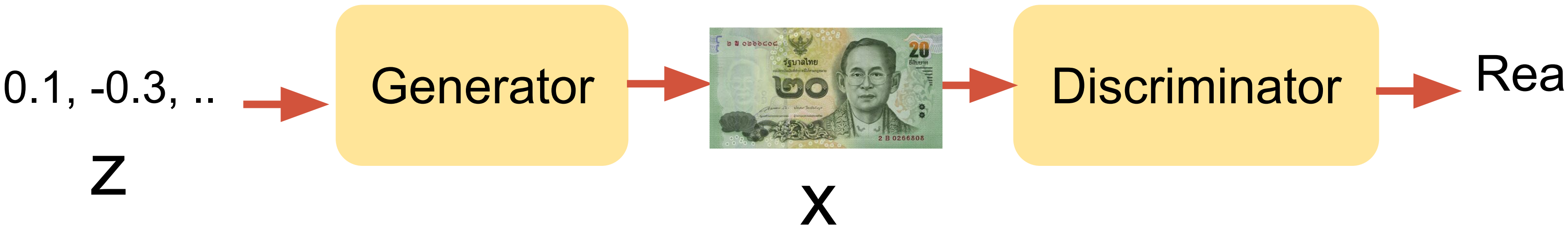
Y=f(x)

Consider a money counterfeiter

- He wants to make fake money that looks real
- There's a police that tries to differentiate fake and real money.

The counterfeiter is the adversary and is generating fake inputs. – Generator network

The police is try to discriminate between fake and real inputs. – Discriminator network


0.1, -0.3, ..
z
Generator
x
Discriminator
Real

0.1, -0.3, ..

z

Generator

x

Discriminator

Fake

real x

Discriminator

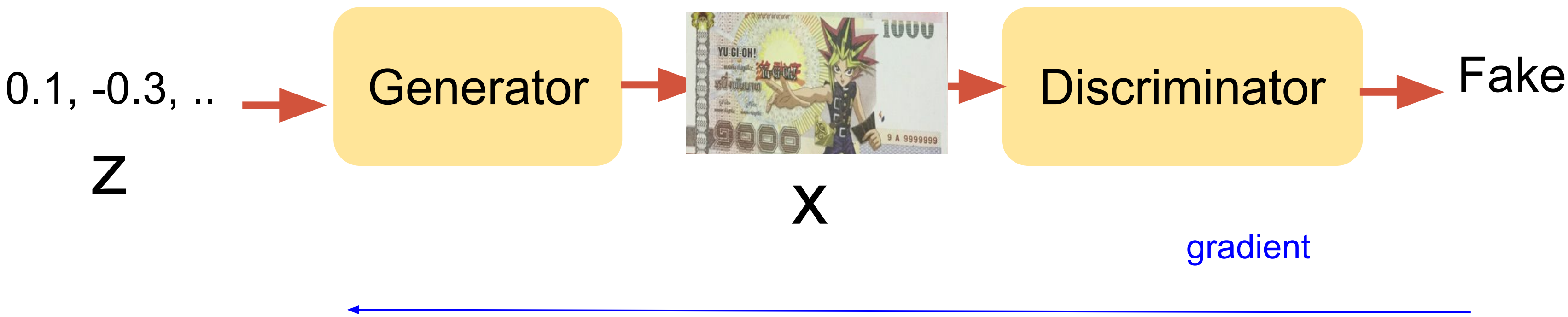
Real

gradient

fake x

The discriminator learns to differentiate real and fake data

Learns by backpropagation



The generator learns to be better by the gradient given by the discriminator

Generative Adversarial Networks (GAN)

0.1, -0.3, .. → Generator →  → Discriminator → Real or Fake

z x $Y=f(x)$

- Generator (Money Faker):
  - Maximize Y

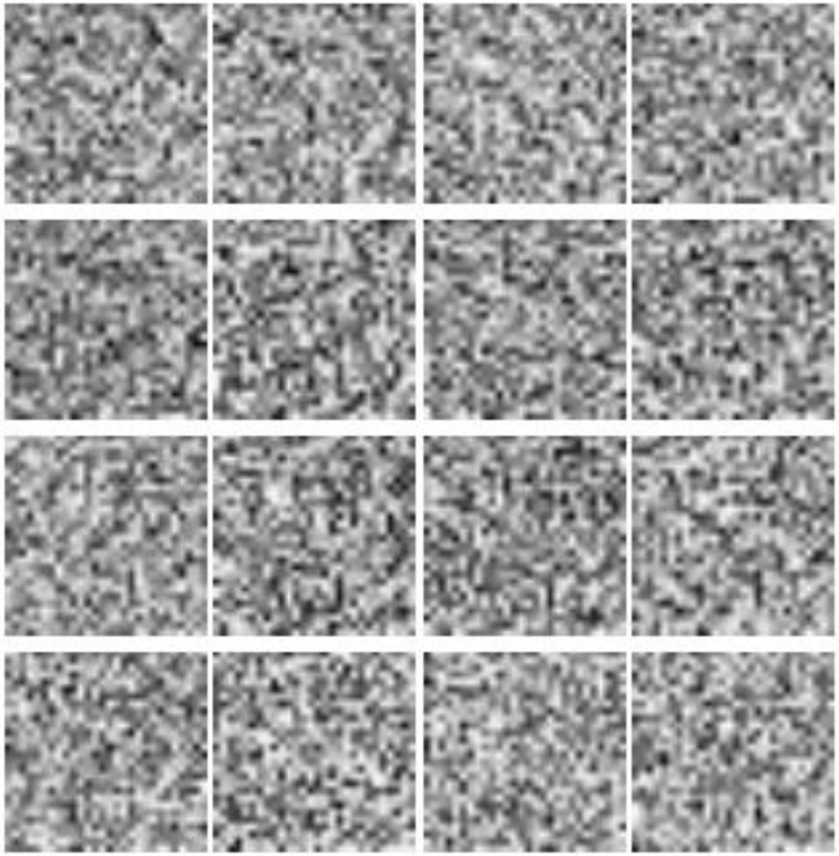
$$\min_{G} \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z}))]$$

- Discriminator (Police):
  - For real images => Maximize Y
  - For generated images from the faker => Minimize Y

$$\max_{D} \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z}))] + \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}}[\log(D(\mathbf{x}))]$$

GAN example

Generator output starts from random noise and gets better as we train.



https://wiseodd.github.io/techblog/2016/09/17/gan-tensorflow/

GANs Loss Formulations

$$\max_D \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z}))] + \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}}[\log(D(\mathbf{x}))]$$

$$\min_G \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z}))]$$

Discriminator

Generator

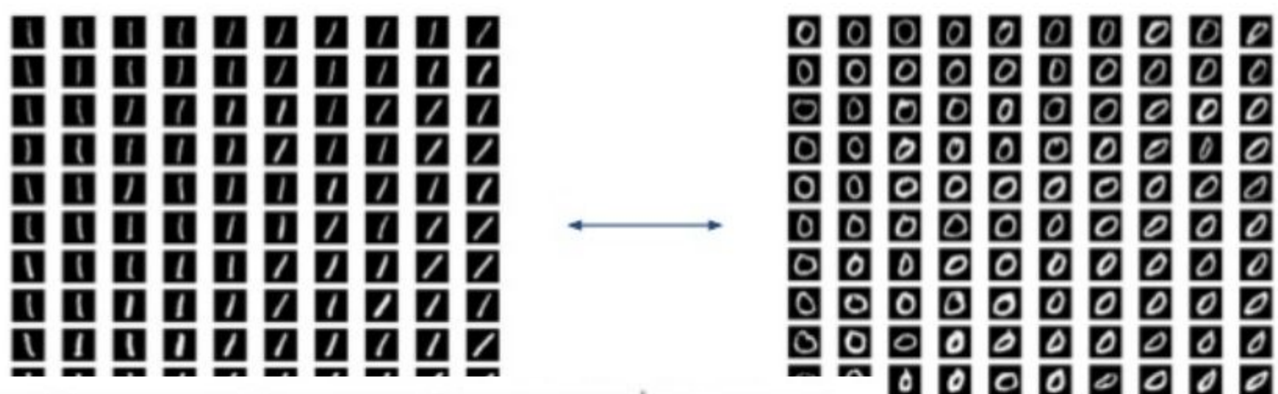
GAN	Discriminator Loss	Generator Loss
MM GAN	$\mathcal{L}_{\text{D}}^{\text{GAN}} = -\mathbb{E}_{x\sim p_d}[\log(D(x))] - \mathbb{E}_{\hat{x}\sim p_g}[\log(1 - D(\hat{x}))]$	$\mathcal{L}_{\text{G}}^{\text{GAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\log(1 - D(\hat{x}))]$
NS GAN	$\mathcal{L}_{\text{D}}^{\text{NSGAN}} = -\mathbb{E}_{x\sim p_d}[\log(D(x))] - \mathbb{E}_{\hat{x}\sim p_g}[\log(1 - D(\hat{x}))]$	$\mathcal{L}_{\text{G}}^{\text{NSGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[\log(D(\hat{x}))]$
WGAN	$\mathcal{L}_{\text{D}}^{\text{WGAN}} = -\mathbb{E}_{x\sim p_d}[D(x)] + \mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$	$\mathcal{L}_{\text{G}}^{\text{WGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$
WGAN GP	$\mathcal{L}_{\text{D}}^{\text{WGANGP}} = \mathcal{L}_{\text{D}}^{\text{WGAN}} + \lambda\mathbb{E}_{\hat{x}\sim p_g}[(\lvert\lvert\nabla D(\alpha x + (1-\alpha\hat{x})\rvert\rvert_2 - 1)^2]$	$\mathcal{L}_{\text{G}}^{\text{WGANGP}} = -\mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$
LS GAN	$\mathcal{L}_{\text{D}}^{\text{LSGAN}} = -\mathbb{E}_{x\sim p_d}[(D(x)-1)^2] + \mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})^2]$	$\mathcal{L}_{\text{G}}^{\text{LSGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[(D(\hat{x}-1))^2]$
DRAGAN	$\mathcal{L}_{\text{D}}^{\text{DRAGAN}} = \mathcal{L}_{\text{D}}^{\text{GAN}} + \lambda\mathbb{E}_{\hat{x}\sim p_d+\mathcal{N}(0,c)}[(\lvert\lvert\nabla D(\hat{x})\rvert\rvert_2 - 1)^2]$	$\mathcal{L}_{\text{G}}^{\text{DRAGAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\log(1 - D(\hat{x}))]$
BEGAN	$\mathcal{L}_{\text{D}}^{\text{BEGAN}} = \mathbb{E}_{x\sim p_d}[\lvert\lvert x - \text{AE}(x)\rvert\rvert_1] - k_t\mathbb{E}_{\hat{x}\sim p_g}[\lvert\lvert\hat{x} - \text{AE}(\hat{x})\rvert\rvert_1]$	$\mathcal{L}_{\text{G}}^{\text{BEGAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\lvert\lvert\hat{x} - \text{AE}(\hat{x})\rvert\rvert_1]$

Another problem: Mode collapsing

Are GANs Created Equal? A Large-Scale Study [Lucic et al. 2018]

GAN problems

- Hard to tune
  - Loss is not meaningful (model evaluation is hard)
  - Prone to initialization
  - “An art” to tune
- Mode collapse



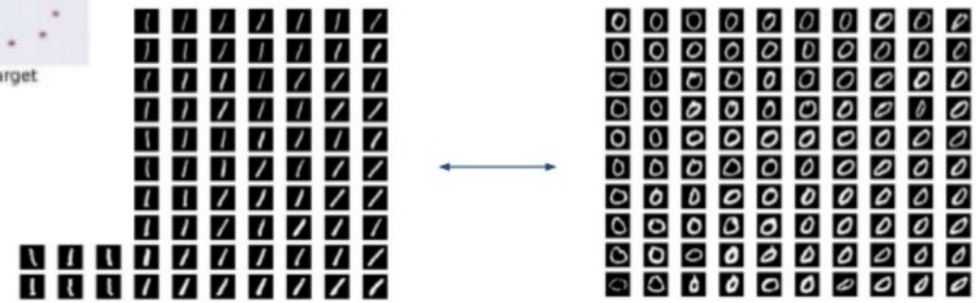
mode collapsing

https://www.slideshare.net/ssuser77ee21/generative-adversarial-networks-70896091

Mode collapse

Model only learn a couple types (modes) of inputs

mode collapsing

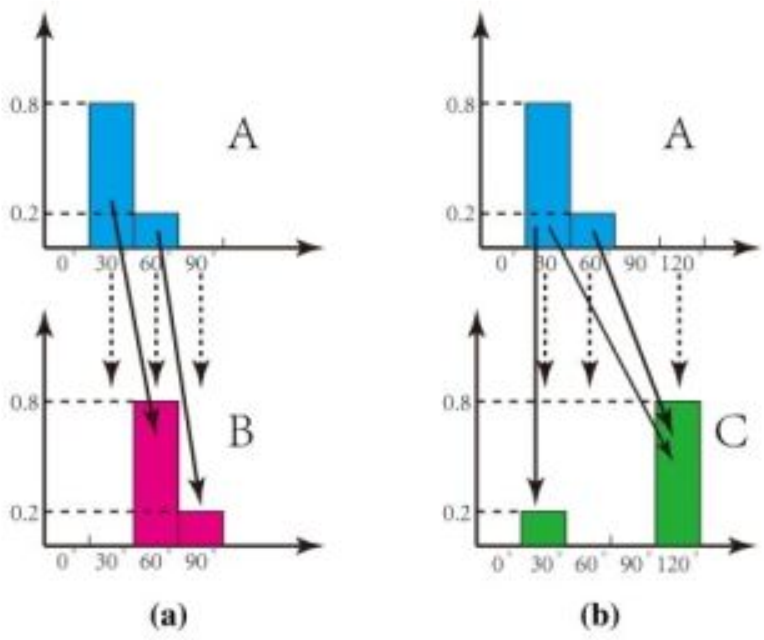


https://arxiv.org/pdf/1701.07875.pdf

Wasserstein GAN (WGAN)

Wasserstein distance? (Earth mover distance)

Energy required to move mass to make two distributions look the same



WGAN

Discriminator to a critic (no fake/real sigmoid) but output a score

WD has better gradient and convergence

	Discriminator/Critic	**Generator**
GAN	$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right]$	$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)$
WGAN	$\nabla_w \frac{1}{m} \sum_{i=1}^{m} \left[f\left(x^{(i)}\right) - f\left(G\left(z^{(i)}\right)\right)\right]$	$\nabla_\theta \frac{1}{m} \sum_{i=1}^{m} f\left(G\left(z^{(i)}\right)\right)$

WGAN

WGAN requires the critic model to be a k-Lipschitz function

k-Lipschitz?

- Bounded in slope of k
- $|f(a) - f(b)| < k| a - b |$

Example

- $f(x) = 5x$ is 5-Lipschitz

WGAN to WGAN-GP

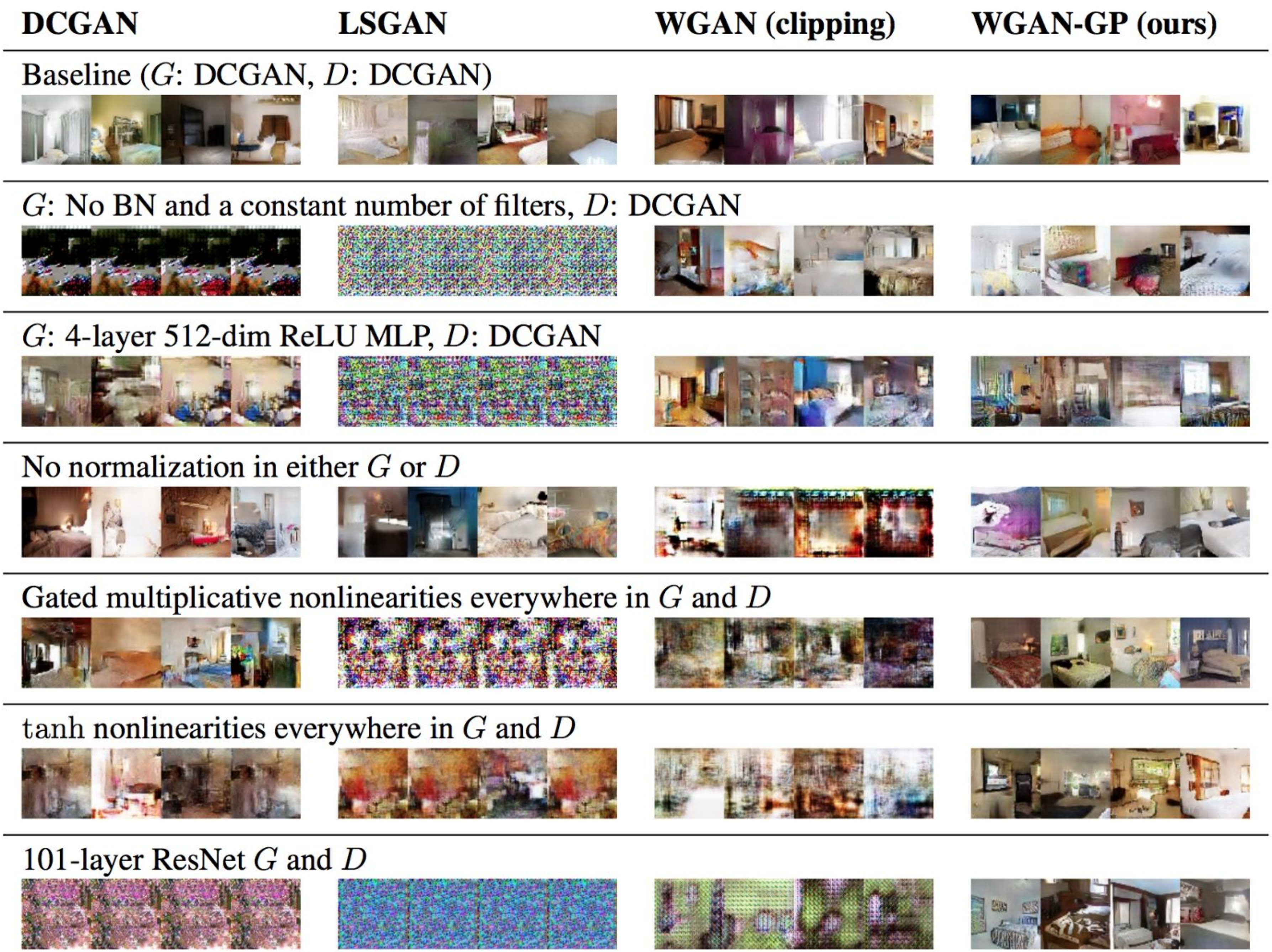
To make k-Lipschitz

WGAN caps the weights of all layers to 1

WGAN-GP improves and add Gradient Penalty to reduce the weights instead

A differentiable function f is 1-Lipschtiz if and only if it has gradients with norm at most 1 everywhere.

$$L = \underbrace{\underset{\tilde{\boldsymbol{x}} \sim \mathbb{P}_g}{\mathbb{E}} \left[D(\tilde{\boldsymbol{x}}) \right] - \underset{\boldsymbol{x} \sim \mathbb{P}_r}{\mathbb{E}} \left[D(\boldsymbol{x}) \right]}_{\text{Original critic loss}} + \underbrace{\lambda \underset{\hat{\boldsymbol{x}} \sim \mathbb{P}_{\hat{\boldsymbol{x}}}}{\mathbb{E}} \left[\left(\| \nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}}) \|_2 - 1 \right)^2 \right]}_{\text{Our gradient penalty}} .$$


DCGAN
LSGAN
WGAN (clipping)
WGAN-GP (ours)
Baseline (G: DCGAN, D: DCGAN)
G: No BN and a constant number of filters, D: DCGAN
G: 4-layer 512-dim ReLU MLP, D: DCGAN
No normalization in either G or D
Gated multiplicative nonlinearities everywhere in G and D
tanh nonlinearities everywhere in G and D
101-layer ResNet G and D

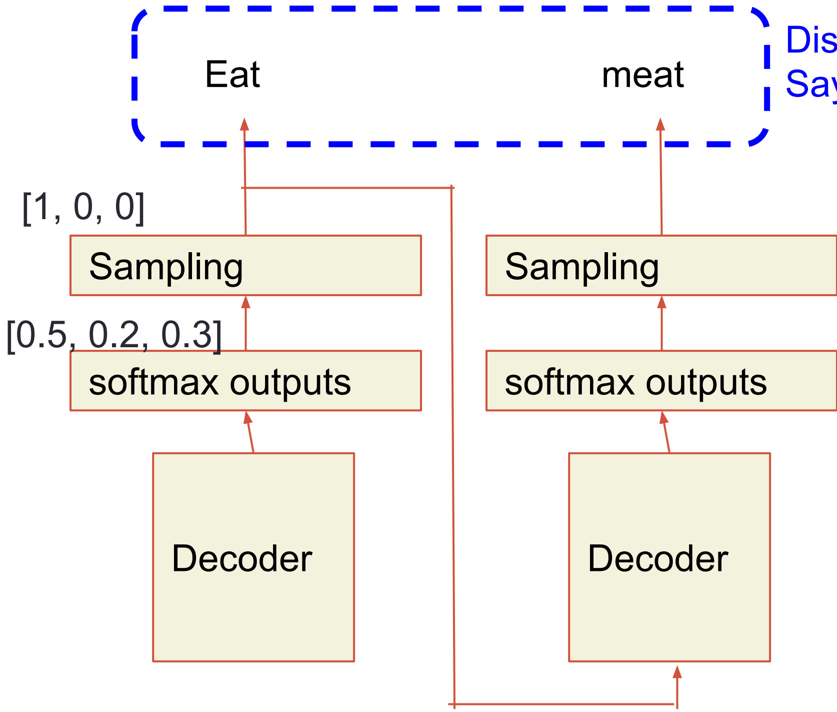
WGAN makes things easier

- With WGAN many people start exploring usage of GANs in more domains

GAN for text generation

Autoregressive decoding includes a sampling process

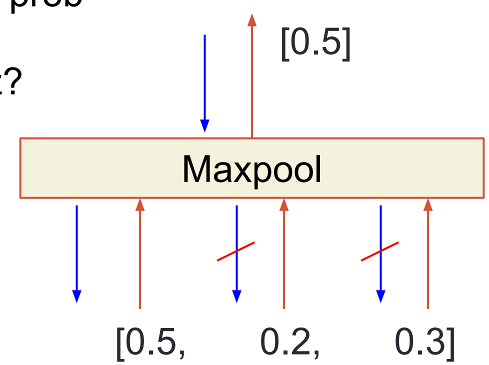
Cannot gradient descent



Discriminator sees the sampled sentence.
Says it's good or bad

softmax prob [0.3 0.4 0.1 0.2] -> word index z
Pick the max
Pick randomly based on prob

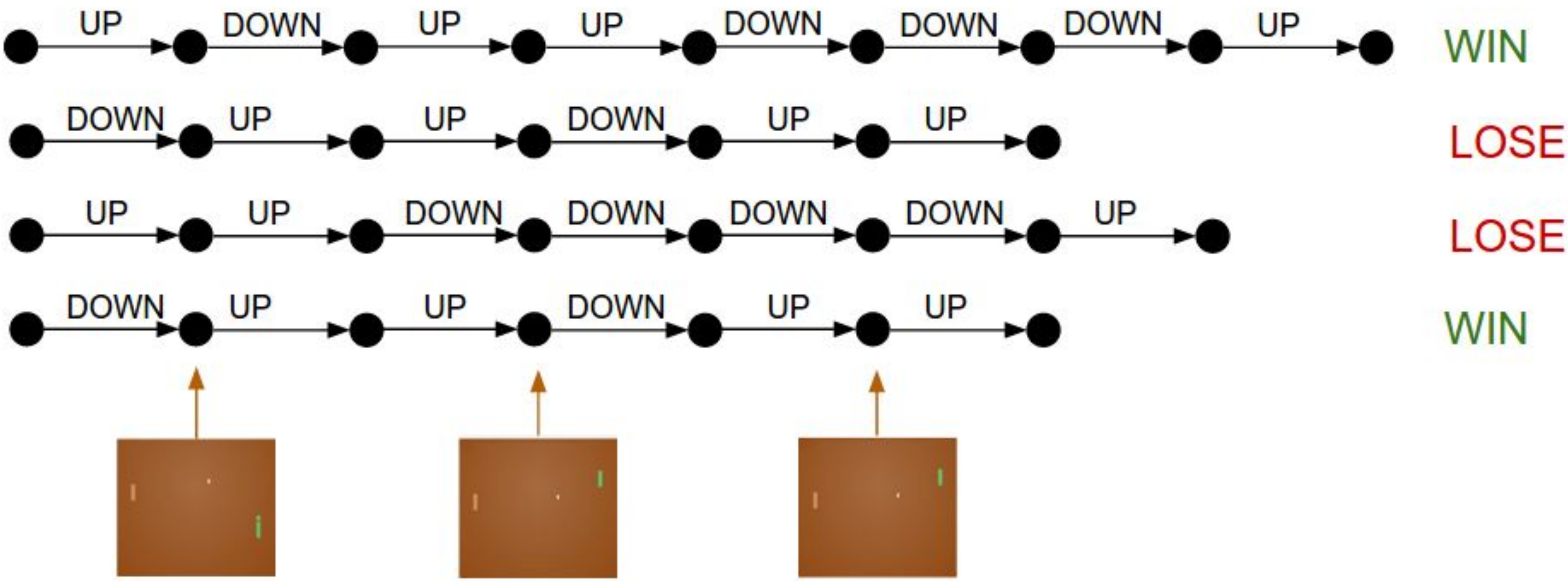
What is the gradient of z?



Two popular methods: REINFORCE, Gumbel-Softmax approximation (https://arxiv.org/abs/1611.01144)

RL and policy gradients

- Credit assignment problem in reinforcement learning



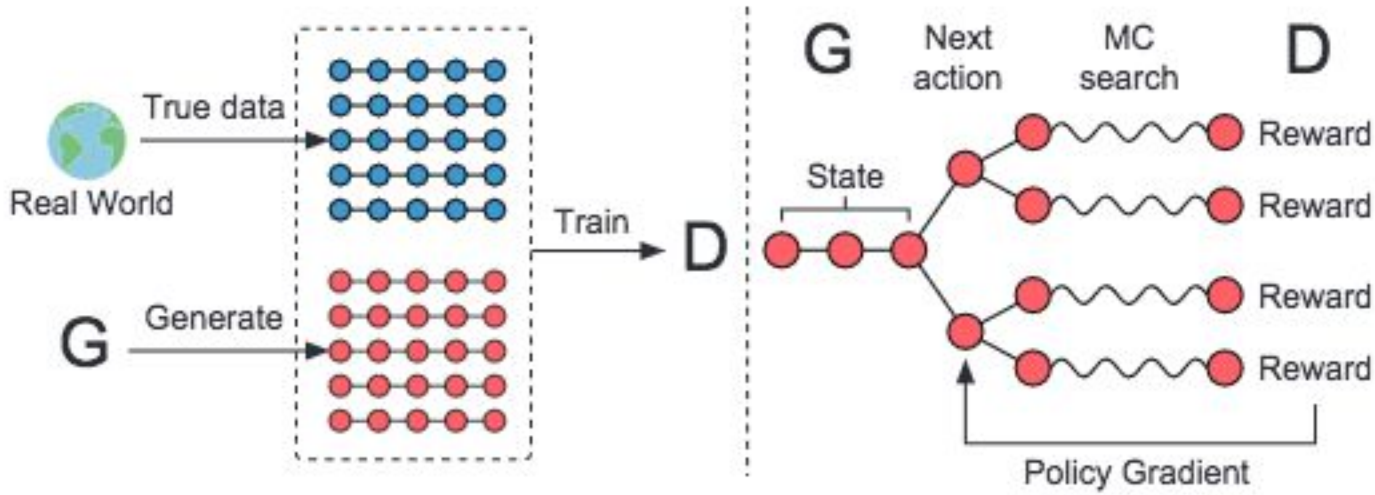
which move makes you win?

For RL with policy gradients, we increase the probability of every move that results in a win (REINFORCE algorithm)

http://karpathy.github.io/2016/05/31/rl/

GAN with text generation (SeqGAN)

- Use policy gradient to update the generator (the agent in RL setting)
- The discriminator (critic) gives the reward



How is this different from our previous text generation? (Maximum likelihood)
Want to generate exact vs Want to generate “real” sentences

https://arxiv.org/pdf/1609.05473.pdf

Table 2: Chinese poem generation performance comparison.

Algorithm	Human score	p-value	BLEU-2	p-value
MLE	0.4165	0.0034	0.6670	$< 10^{-6}$
SeqGAN	**0.5356**		**0.7389**	
Real data	0.6011		0.746	

Table 3: Obama political speech generation performance.

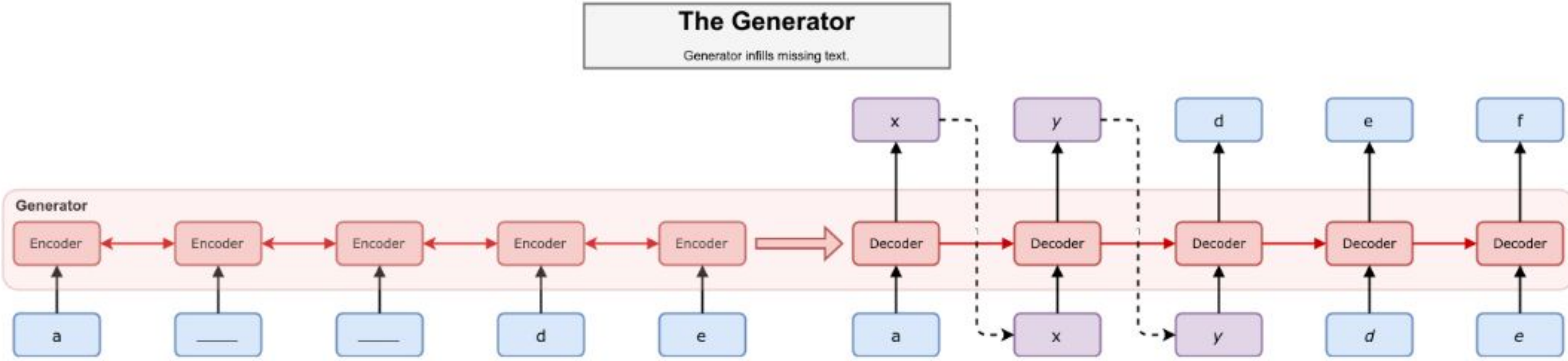
Algorithm	BLEU-3	p-value	BLEU-4	p-value
MLE	0.519	$< 10^{-6}$	0.416	0.00014
SeqGAN	**0.556**		**0.427**	

Table 4: Music generation performance comparison.

Algorithm	BLEU-4	p-value	MSE	p-value
MLE	0.9210	$< 10^{-6}$	22.38	0.00034
SeqGAN	**0.9406**		**20.62**	

MaskGAN

- GAN to fill in the blank. Encoder - Decoder



https://arxiv.org/pdf/1801.07736.pdf

MaskGAN

- GAN to fill in the blank. Encoder - Decoder

Ground Truth	**Pitch Black was a complete shock to me when I first saw it back in 2000 In the previous years I**
MaskGAN	Pitch Black was a complete shock to me when I first saw it back in 1979 I was really looking forward
	Pitch Black was a complete shock to me when I first saw it back in 1976 The promos were very well
	Pitch Black was a complete shock to me when I first saw it back in the days when I was a
MaskMLE	Black was a complete shock to me when I first saw it back in 1969 I live in New Zealand
	Pitch Black was a complete shock to me when I first saw it back in 1951 It was funny All Interiors
	Pitch Black was a complete shock to me when I first saw it back in the day and I was in

https://arxiv.org/pdf/1801.07736.pdf

Gumbel Softmax

From softmax prob [0.3 0.4 0.1 0.2] -> word index z

Pick randomly based on prob (sampling)

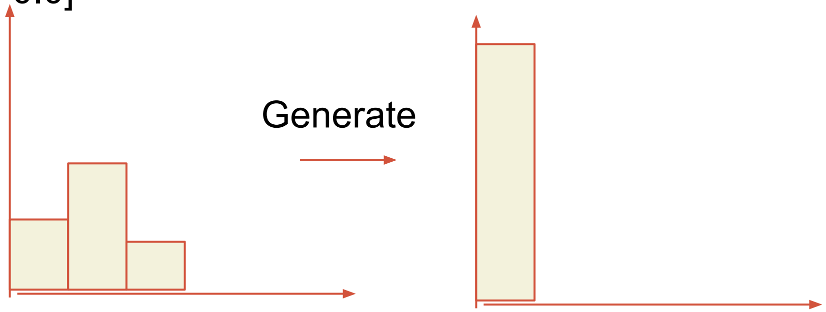
random value generated from Gumbel dist.

$$z = \texttt{one\_hot}\left(\arg\max_i \left[g_i + \log \pi_i\right]\right)$$

prob values from softmax
[1.0, 0.0, 0.0]

index for each word

prob values from softmax
[0.3, 0.5, 0.2]



https://arxiv.org/pdf/1611.01144.pdf

Gumbel Softmax

From softmax prob [0.3 0.4 0.1 0.2] -> word index z
Pick randomly based on prob

random value generated from Gumbel dist.

$$z = \texttt{one\_hot}\left(\boxed{\arg\max_i \left[g_i + \log \pi_i\right]}\right)$$

prob values from softmax

index for each word

estimate using Gumbel trick

$$\boxed{y_i} = \frac{\exp((\log(\pi_i) + g_i)/\tau)}{\sum_{j=1}^{k} \exp((\log(\pi_j) + g_j)/\tau)} \qquad \text{for } i = 1, \ldots, k.$$

Gumbel Softmax

From softmax prob [0.3 0.4 0.1 0.2] -> word index z
Pick randomly based on prob

random value generated from Gumbel dist.

$$z = \mathtt{one\_hot}\left(\arg\max_i \boxed{[g_i + \log \pi_i]}\right)$$

prob values from softmax

index for each word

Not a one hot

Temperature parameter

$$\boxed{y_i} = \boxed{\frac{\exp((\log(\pi_i) + g_i)/\tau)}{\sum_{j=1}^{k} \exp((\log(\pi_j) + g_j)/\tau)}} \quad \text{for } i = 1, ..., k.$$

This rescales the distribution

Gumbel Softmax

Temperature can be scaled
y can be back propagated through

Gumbel softmax

Regular argmax

Small T

large T

Not a one hot

Temperature parameter

$$\boxed{y_i} = \boxed{\frac{\exp((\log(\pi_i) + g_i)/\tau)}{\sum_{j=1}^{k} \exp((\log(\pi_j) + g_j)/\tau)}} \quad \text{for } i = 1, \ldots, k.$$

This rescales the distribution

GAN readings

- 1) GAN tutorial: https://arxiv.org/pdf/1701.00160.pdf
- 2) WGAN: https://arxiv.org/abs/1701.07875
  - 2.1) Blog explanation: https://www.alexirpan.com/2017/02/22/wasserstein-gan.html Read 2) and 2.1) together section by section.
- 3) WGAN-GP: https://arxiv.org/abs/1704.00028
- 4) On how GANs are hard to train stil: https://arxiv.org/abs/1711.10337

Overview

- Techniques
  - Transformer
  - Beam search
  - GAN for text
- Applications
  - Grammatical Error Correction
  - QA

Grammatical Error Correction

Fix grammar and spelling errors.

For English, mostly grammatical errors in the data

Input

She see Tom is catched by policeman in park at last night.

Output

She saw Tom caught by a policeman in the park last night.

Encoder-decoder (Seq2seq) with attention

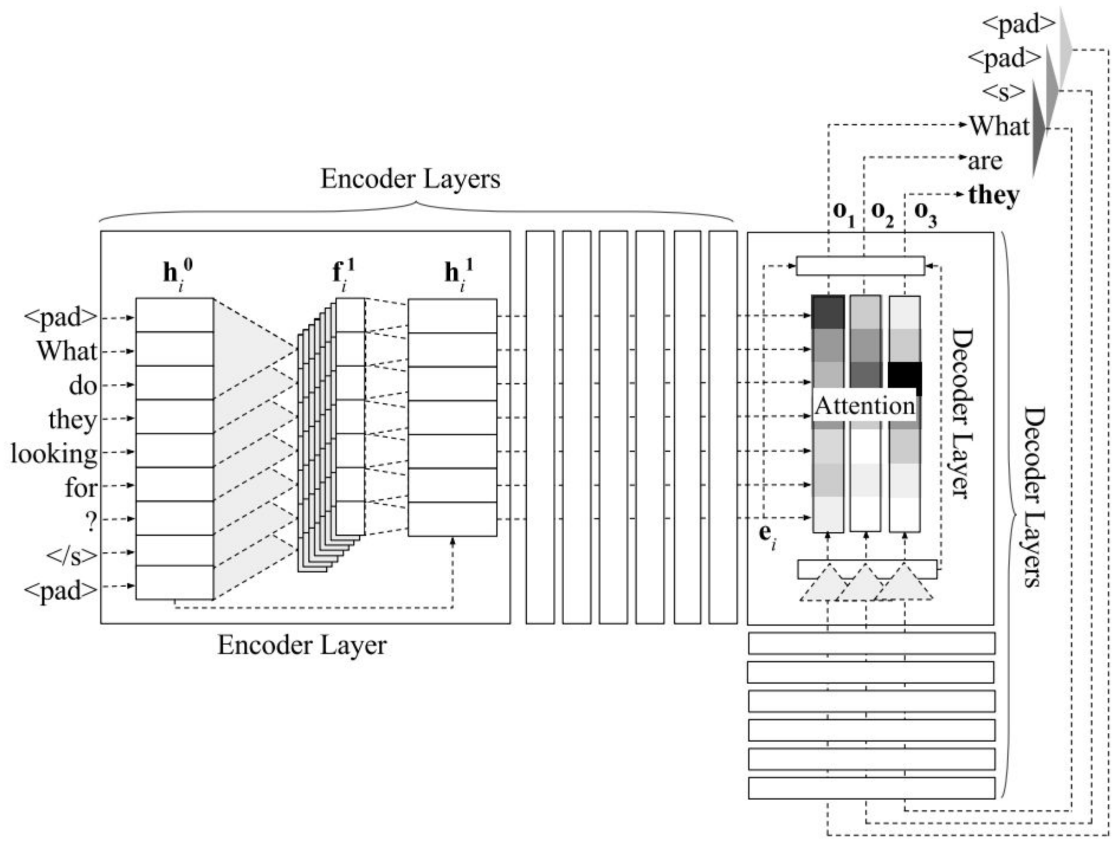


Figure 1: Architecture of our multilayer convolutional model with seven encoder and seven decoder layers (only one encoder and one decoder layer are illustrated in detail).

A Multilayer Convolutional Encoder-Decoder Neural Network for Grammatical Error Correction 2018

Handling OOV

Need some way to handle oov tokens

Intput

I went Don Muang airport

I went <oov> <oov> airport

Output

I went to <oov> <oov> Airport

Unlike MT, we need some way to copy words from the input.

Seq2seq with copy-augmented

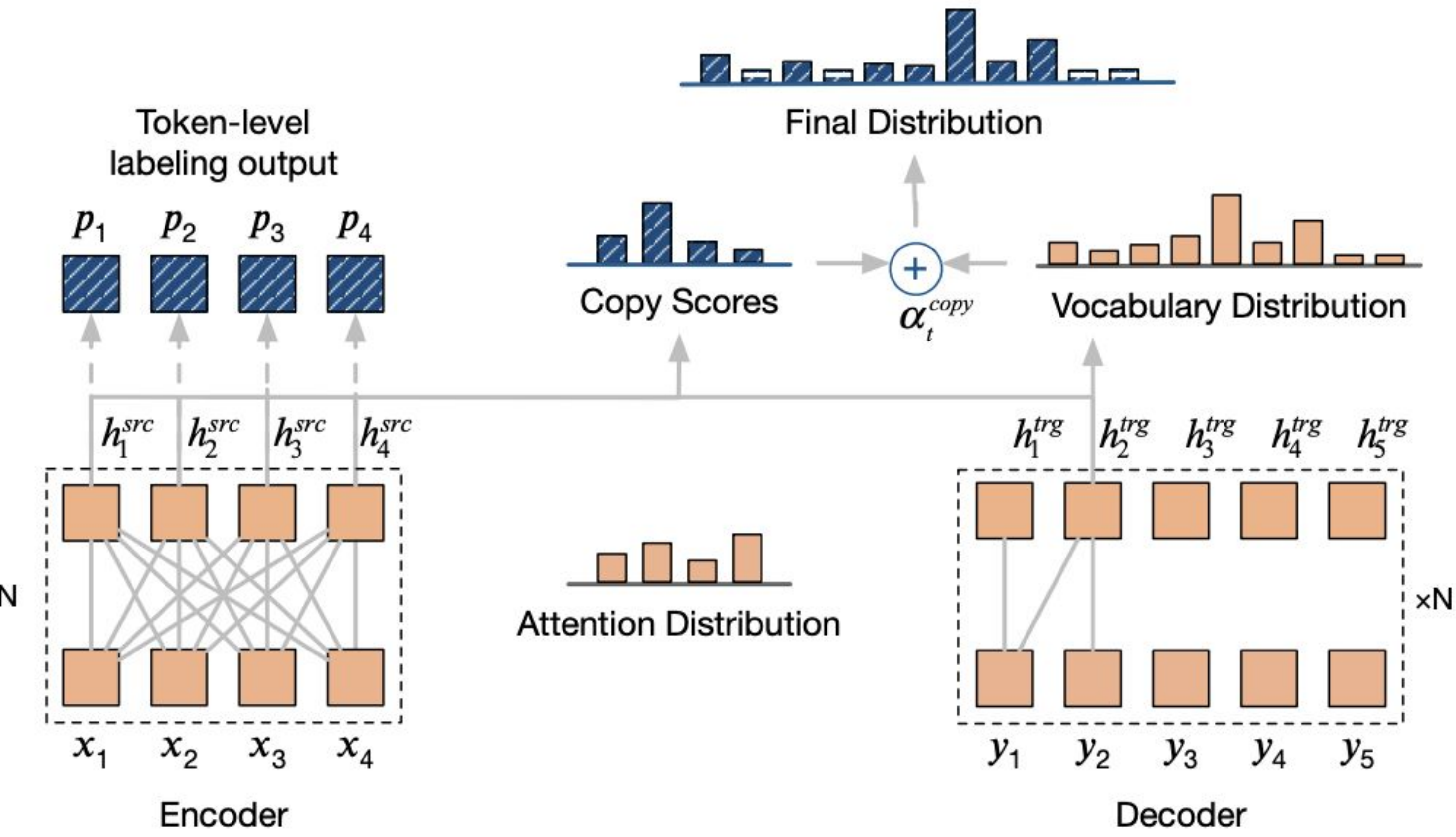


Figure 1: Copy-Augmented Architecture.

Also useful for text summarization

Improving Grammatical Error Correction via Pre-Training a Copy-Augmented Architecture with Unlabeled Data 2019

Model	Year	CoNLL-14			JFLEG GLEU	Dict
		Pre.	Rec.	$F_{0.5}$		
SMT (with LM)	2014	41.72	22.00	35.38	-	word
SMT Rule-Based Hybird (with LM)	2014	39.71	30.10	37.33	-	word
SMT Classification Hybird (with LM)	2016	60.17	25.64	47.40	-	word
Neural Hybird MT (with LM)	2017	-	-	45.15	53.41	char/word
CNN + EO (4 ens. with LM)	2018	65.49	33.14	54.79	57.47	bpe
Transformer + MIMs (4 ens. with LM)	2018	63.00	38.90	56.10	59.90	bpe
NMT SMT Hybrid (4 ens. with LM)	2018	66.77	34.49	56.25	61.50	bpe
Our Model						
Copy-augmented Model (4 ens.)	-	68.48	33.10	**56.42**	59.48*	word
+ DA, Multi-tasks (4 ens.)	-	71.57	38.65	**61.15**	61.00*	word
Model Trained with Large Non-public Training Data						
CNN + FB Learning (4 ens. with LM)	2018	74.12	36.30	61.34	61.41	bpe

Improving Grammatical Error Correction via Pre-Training a Copy-Augmented Architecture with Unlabeled Data
2019

Thai misspellings

Thai poorly written text are mostly due to misspellings rather than grammar

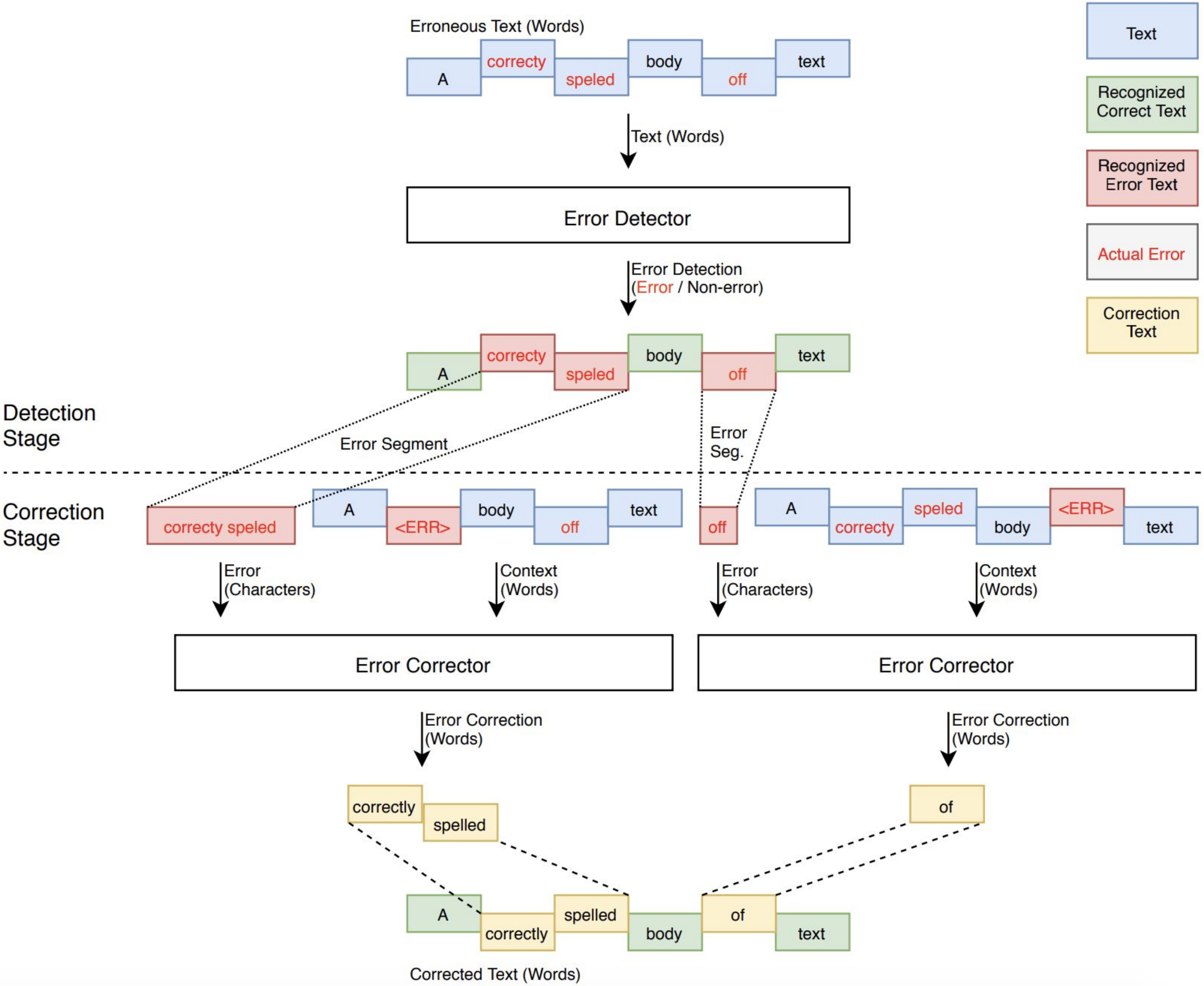
Prone to error in word segmentation.

One word might become two word or multiple words might become one word.

Type of errors in Thai social

Table 1: Examples of different types of errors and their respective correction.

Type of Error	Occurrence (%)	Error	Correction
Misspelling	61.38	ทุ๊กคน	ทุกคน
		คว่ำบัตร	คว่ำบาตร
Morphed	24.00	ครัช	ครับ
		ตั๊ลล๊าคคคค	น่ารัก
Abbreviation	15.00	มค	ม.ค.
		พน	พรุ่งนี้
Spoonerism	0.14	พับกบ	พบกับ
Slangs	0.08	ตีเนียน	No correction
		อ้อย	ทอดสะพาน
Other	5.63	โรบินสัน	No correction



Erroneous Text (Words)
A
correcty
speled
body
off
text
Text (Words)
Error Detector
Error Detection
(Error / Non-error)
Detection Stage
Error Segment
Error Seg.
Correction Stage
correcty speled
<ERR>
Error (Characters)
Context (Words)
Error Corrector
Error Correction (Words)
correctly
spelled
of
Corrected Text (Words)
Text
Recognized Correct Text
Recognized Error Text
Actual Error
Correction Text

Error detector

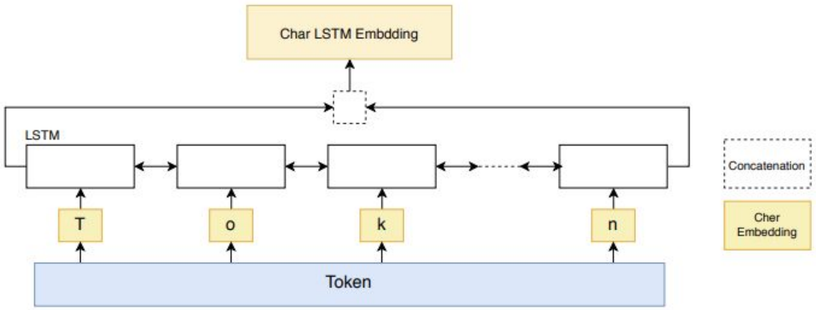


Figure 3: Character LSTM embedding layer encoding a word token.

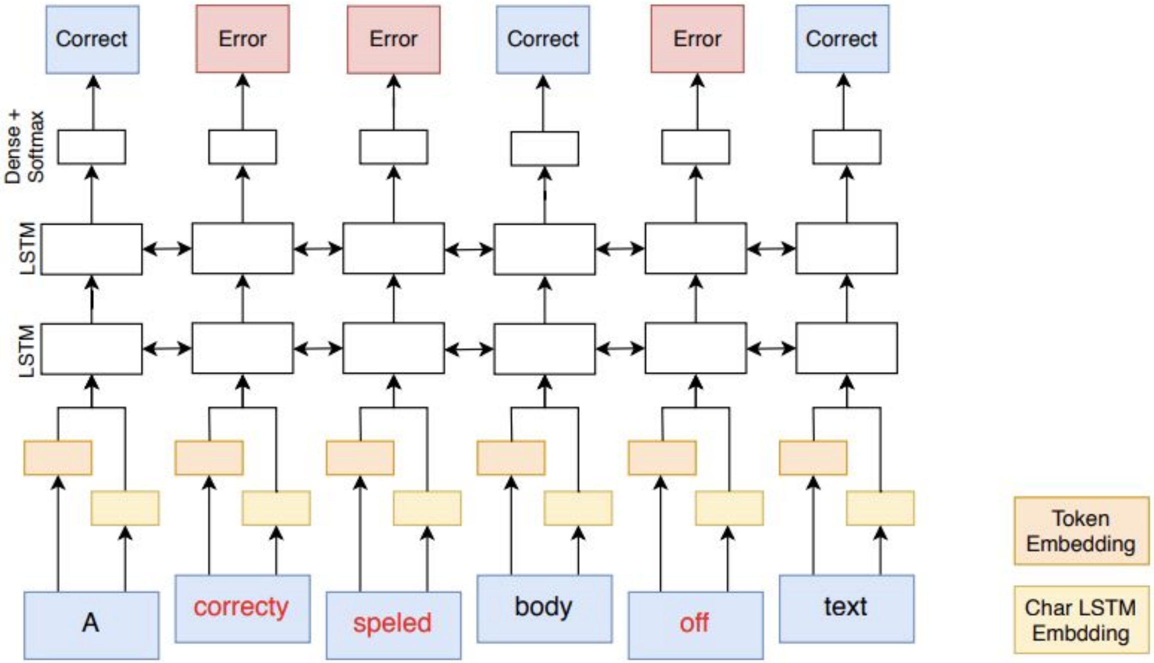
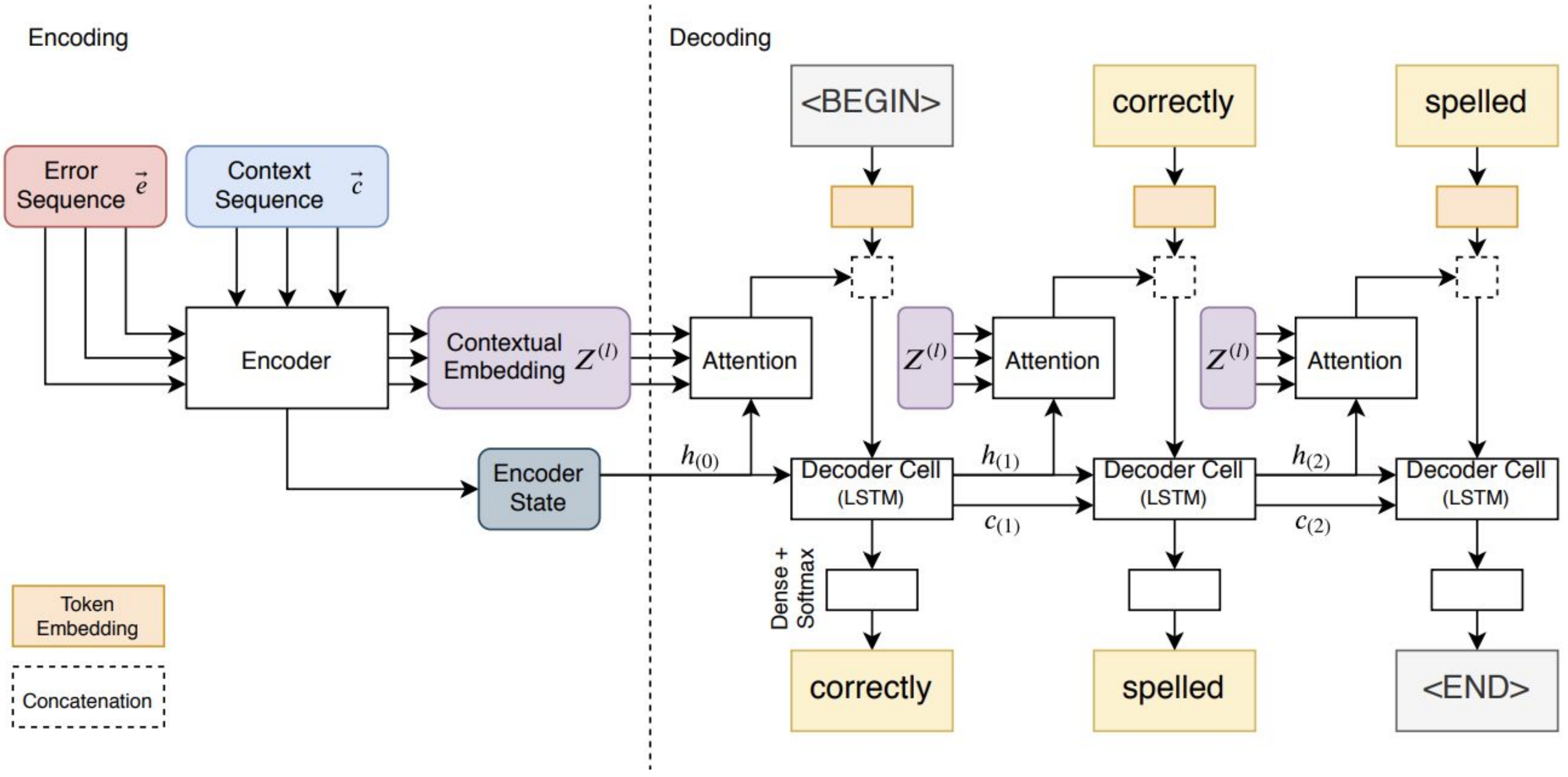


Figure 2: Error Detector operating on a sequence.

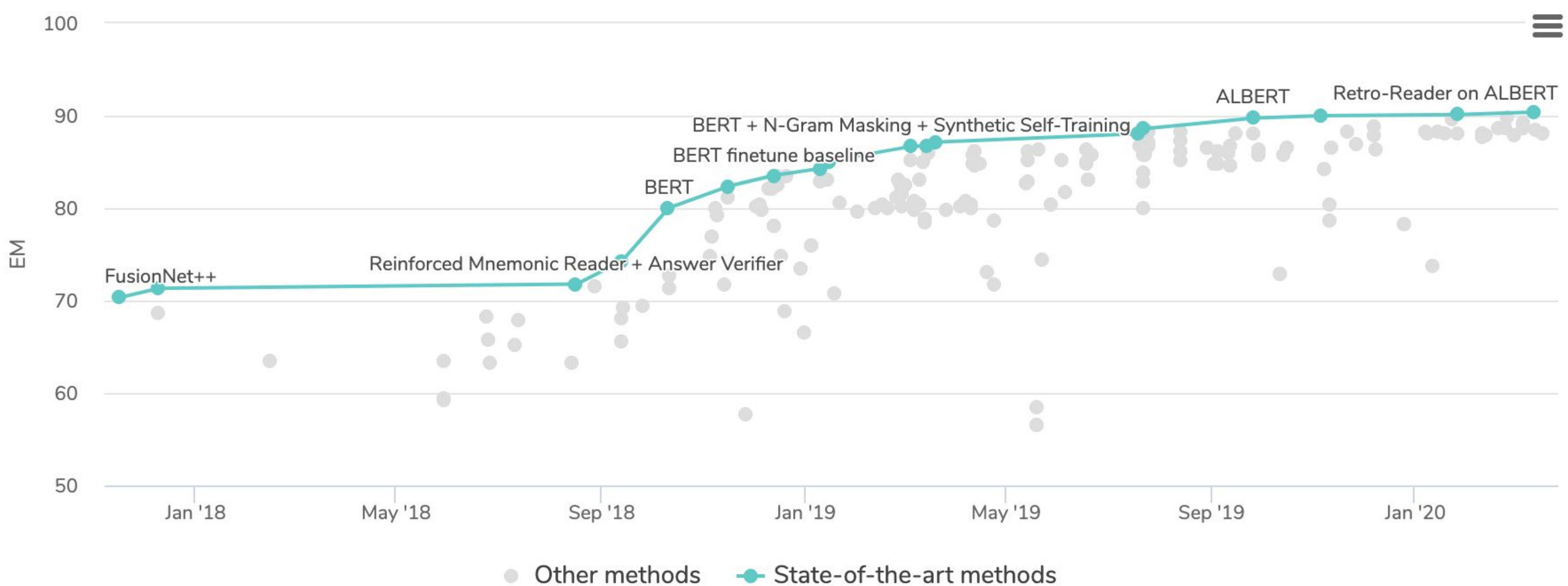
Error corrector



QA2

Current advances in QA comes from more sophisticated text representations (Transformer-based)

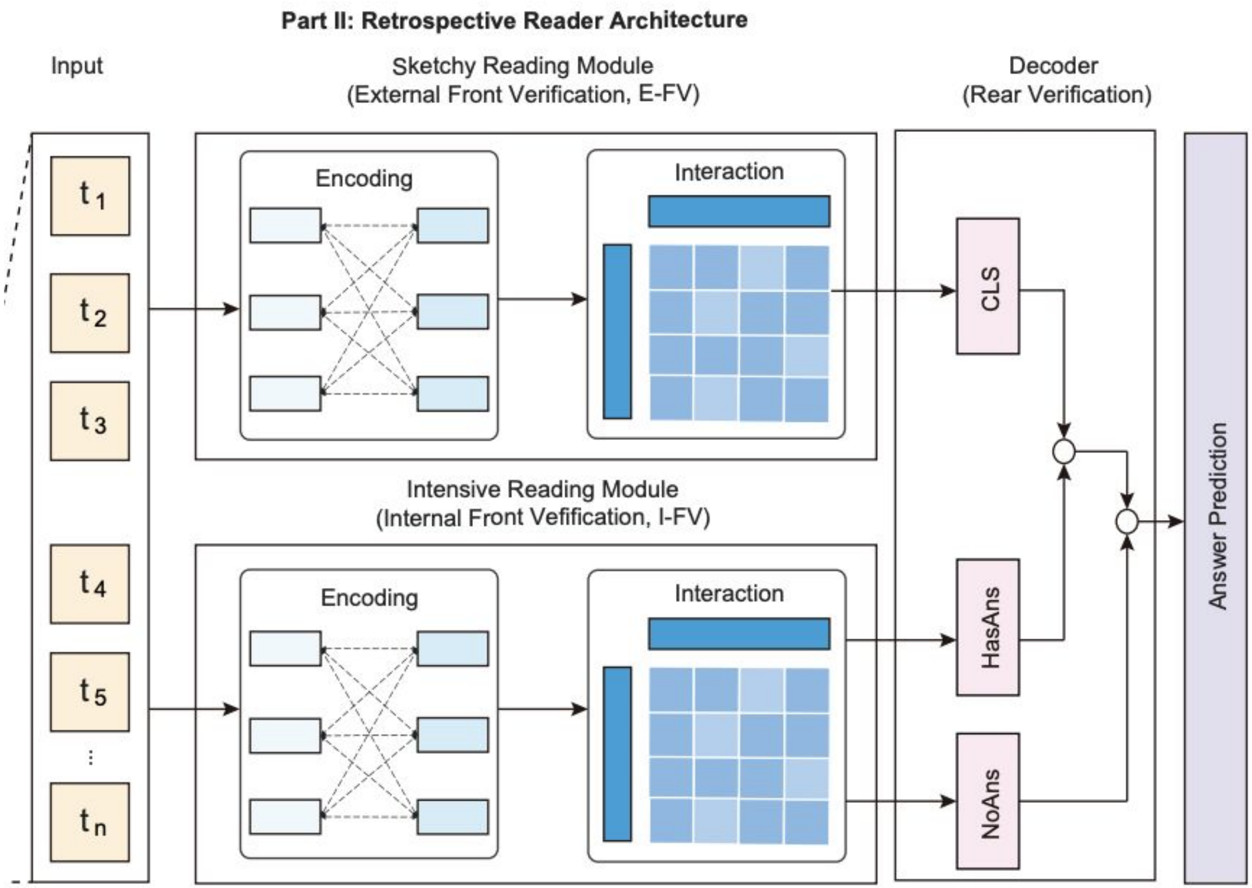
Question Answering on SQuAD2.0



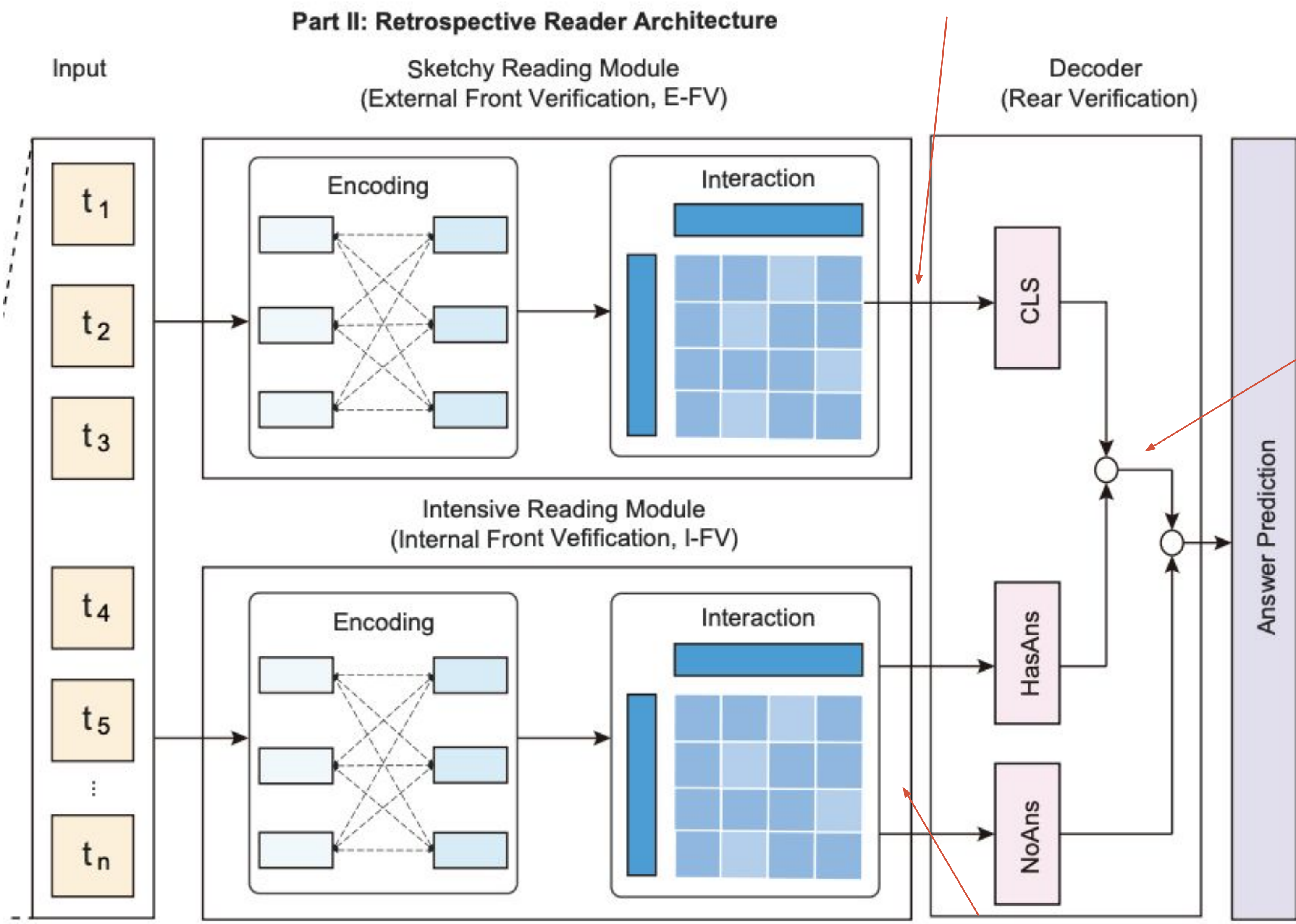
https://paperswithcode.com/sota/question-answering-on-squad20

Retro-reader

Main idea: skim and scan



Retrospective Reader for Machine Reading Comprehension, 2020 simple feed forward model for skim mode

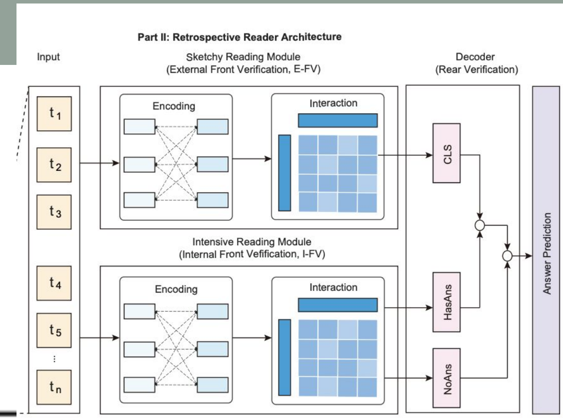


additive
just like
copy-augment
ed

Another set of bi-directional attentions for scan mode

Model	Dev		Test	
	EM	F1	EM	F1
Regular Track				
Joint SAN	69.3	72.2	68.7	71.4
U-Net	70.3	74.0	69.2	72.6
RMR + ELMo + Verifier	72.3	74.8	71.7	74.2
Top results on the leaderboard				
Human	-	-	86.8	89.5
XLNet [Yang *et al.*, 2019]	86.1	88.8	86.4	89.1
RoBERTa [Liu *et al.*, 2019]	86.5	89.4	86.8	89.8
UPM†	-	-	87.2	89.9
XLNet + SG-Net Verifier++†	-	-	87.2	90.1
ALBERT [Lan *et al.*, 2020]	87.4	90.2	88.1	90.9
ALBERT+ DA Verifier†	-	-	87.8	91.3
albert+verifier†	-	-	88.4	91.0
ALBERT (+TAV)	87.0	90.2	-	-
Retro-Reader over ALBERT	**87.8**	**90.9**	**88.1**	**91.4**

Table 2: The results (%) from single models for SQuAD2.0 challenge. The results except ours are obtained by the online evaluation server and the corresponding literatures. † refers to the results without a published literature citation. Our model results are in bold face. Our model is significantly better than all the baselines with p-value < 0.05. TAV: threshold based answerable verification (Section 2.3)



Method	HasAns		NoAns		All	
	EM	F1	EM	F1	EM	F1
BERT	78.9	85.4	77.0	77.0	78.0	81.2
+ E-FV	79.1	85.7	77.4	77.4	78.2	81.5
+ I-FV (Class.)	77.7	84.5	79.6	79.6	78.6	82.0
+ I-FV (Reg.)	78.0	84.6	78.9	78.9	78.5	81.7
+ both FVs (RV)	78.0	84.0	80.7	80.7	79.3	82.4
ALBERT	82.6	89.0	91.4	91.4	87.0	90.2
+ E-FV	82.4	88.7	92.4	92.4	87.4	90.6
+ I-FV (Class.)	81.7	87.9	92.7	92.7	87.2	90.3
+ I-FV (Reg.)	82.4	88.5	92.3	92.3	87.3	90.4
+ both FVs (RV)	83.1	89.4	92.4	92.4	87.8	90.9

Table 4: Results (%) with different answer verification methods on the SQuAD2.0 dev set. *Class.* and *Reg.* are short for the classification and regression loss defined in Section 2.2.

HOW TO READ A SCIENTIFIC ARTICLE

2 Paper types

- Review article/tutorial
  - Give insights about the field
  - Useful for learning about a new field
  - Read multiple to avoid the author’s bias
  - Title usually has “review” or “tutorial”
- Primary research article
  - More details on the experiments and results

Parts of an article

- Abstract
- Introduction
- Methods
- Results and discussion
- Conclusion
- Reference

Things to look for before reading an article

- Publication date
- Author names
  - Previous and newer publications
- Keywords
- Acknowledgements and funding sources

Zero-Shot Entity Linking by Reading Entity Descriptions

Lajanugen Logeswaran[†*] **Ming-Wei Chang**[‡] **Kenton Lee**[‡] **Kristina Toutanova**[‡]
Jacob Devlin[‡] **Honglak Lee**[‡,†]

[†]University of Michigan, [‡]Google Research

{llajan,honglak}@umich.edu,
{mingweichang,kentonl,kristout,jacobdevlin,honglak}@google.com

https://arxiv.org/pdf/1906.07348.pdf

Getting the big picture

- Read the abstract
- Read the introduction
  - What is the research question?
  - What is the method?
  - What had been done? How is it different from other work?
- Look at figures and results

Tip: keep track of terms you don’t understand

First reading

- Reread the introduction
- Skim methods
- Read results and discussion
  - Does the figures make sense now?
- Write on the article!

Understanding the article

- Reread the article (until you get what you want)
- Check references for parts you don't understand
- Reread the abstract
  - Does your understanding match the abstract?
- Note down important points. This might come in handy when you write you paper/thesis!

Evaluating the article

- Does the method make sense?
  - What are the limitations that the authors mention?
  - Are there other limitations?
  - Can it be used in other situations?
- Are the experiments legitimate?
  - The sample size is big enough?
  - What kind of dataset is used? How big?
  - The evaluation criterion is sound?
- Have these results been reproduced?
  - Look for articles that cite this paper

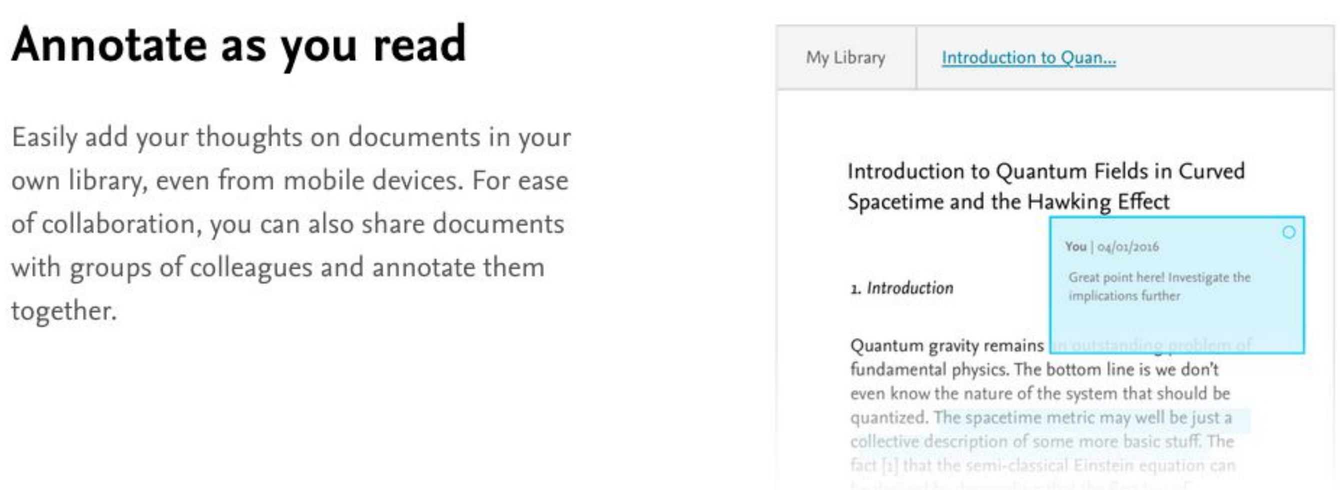
ML paper checklist

- What is being done?
- How is it being done?
  - How is it different from previous work
- What is the dataset?
  - Nature of dataset
  - How many training/testing samples? How many classes/vocab size?
- Evaluation metric
  - What are the baselines?
- Practicality
  - Prone to parameter tuning?
  - Computing resource
  - Runtime (training and testing)

Useful tools

- https://scholar.google.com
  - For finding other articles by the same authors or paper that cites the article

- https://www.mendeley.com/
  - Reference manager



Summary

Transformer

Beam search

GAN

Grammatical Error Correction

QA

Project

Max 5 people per group

Freestyle project related to NLP

https://www.youtube.com/watch?v=gfNBZYf4gKc