Backup slides

Ethics and Bias Case Study in NLP

Janelle Shane @JanelleCShane · 1d

Predictive policing algorithms don't predict who commits crime. They predict who the police will arrest.

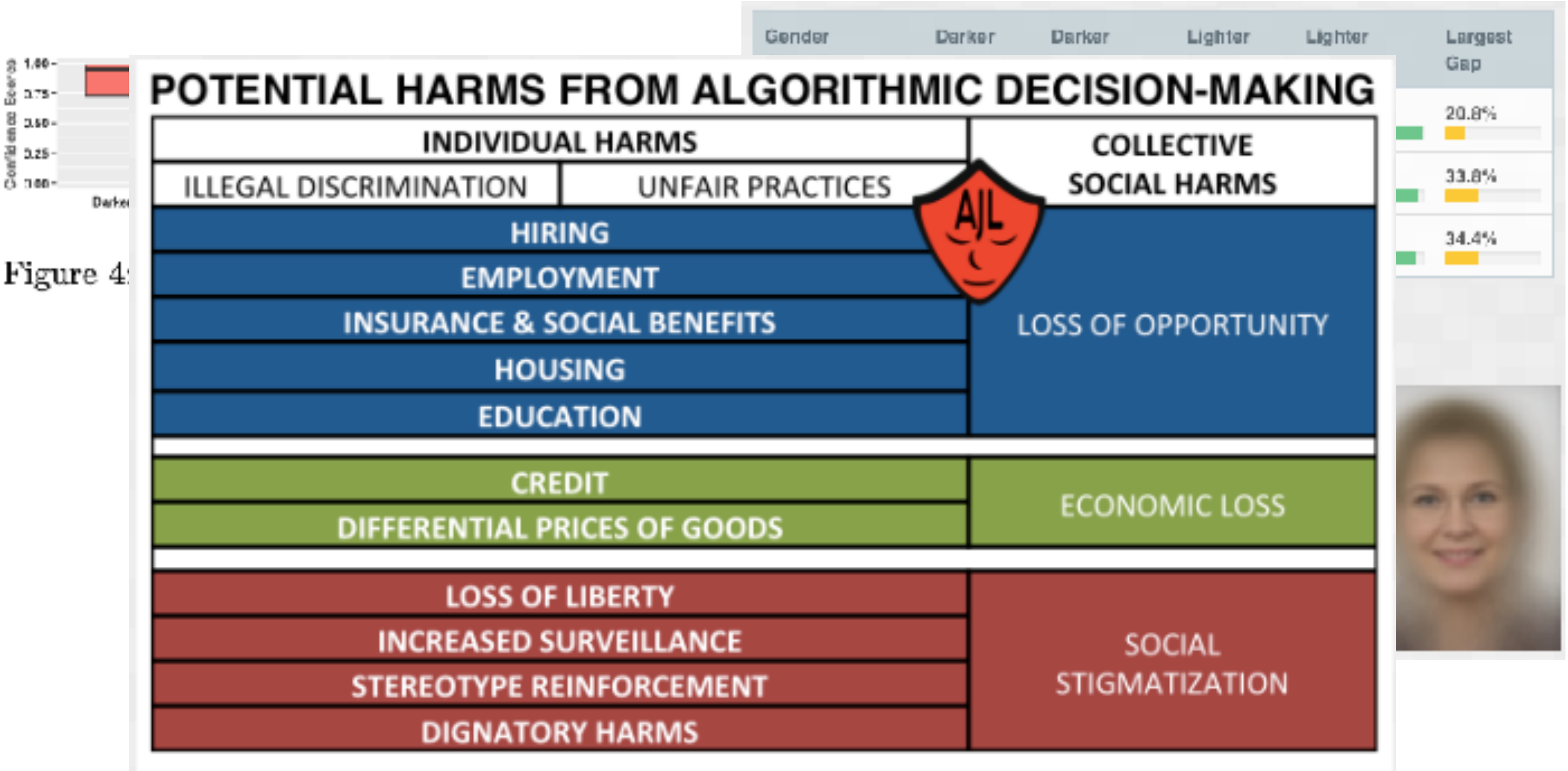
So of course the algorithm points toward people that are already overpoliced - it's trying to predict racism. Don't explicitly tell it race & it will just use other proxies.

Timnit Gebru @timnitGebru

I'm sick of this framing. Tired of it. Many people have tried to explain, many scholars. Listen to us. You can't just reduce harms caused by ML to dataset bias.

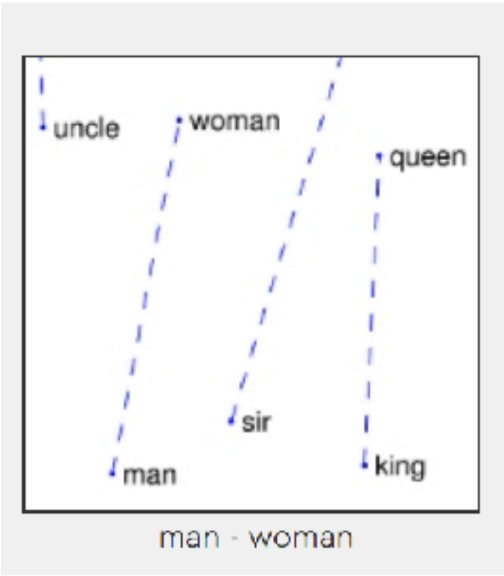
> **Yann LeCun** @ylecun · 19h
>
> ML systems are biased when data is biased. This face upsampling system makes everyone look white because the network was pretrained on FlickFaceHQ, which mainly contains white people pics....

Timnit Gebru: Gender Shades



http://proceedings.mlr.press/v81/buolamwini18a/buolamwini18a.pdf

Back to RNNs: Word Embedding Analogy



$$W(\text{``woman''}) - W(\text{``man''}) \simeq W(\text{``aunt''}) - W(\text{``uncle''})$$

$$W(\text{``woman''}) - W(\text{``man''}) \simeq W(\text{``queen''}) - W(\text{``king''})$$

$$\overrightarrow{\text{man}} - \overrightarrow{\text{woman}} \approx \overrightarrow{\text{computer programmer}} - \overrightarrow{\text{homemaker}}.$$

Trained on New York Times

Extreme *she* occupations

1. homemaker	2. nurse	3. receptionist
4. librarian	5. socialite	6. hairdresser
7. nanny	8. bookkeeper	9. stylist
10. housekeeper	11. interior designer	12. guidance counselor

Extreme *he* occupations

1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. figher pilot	12. boss

https://nlp.stanford.edu/projects/glove/

Bolukbasi et al., NeurIPs 2016
https://arxiv.org/pdf/1607.06520.pdf

ConceptNet

en cooking dinner

An English term in ConceptNet 5.7

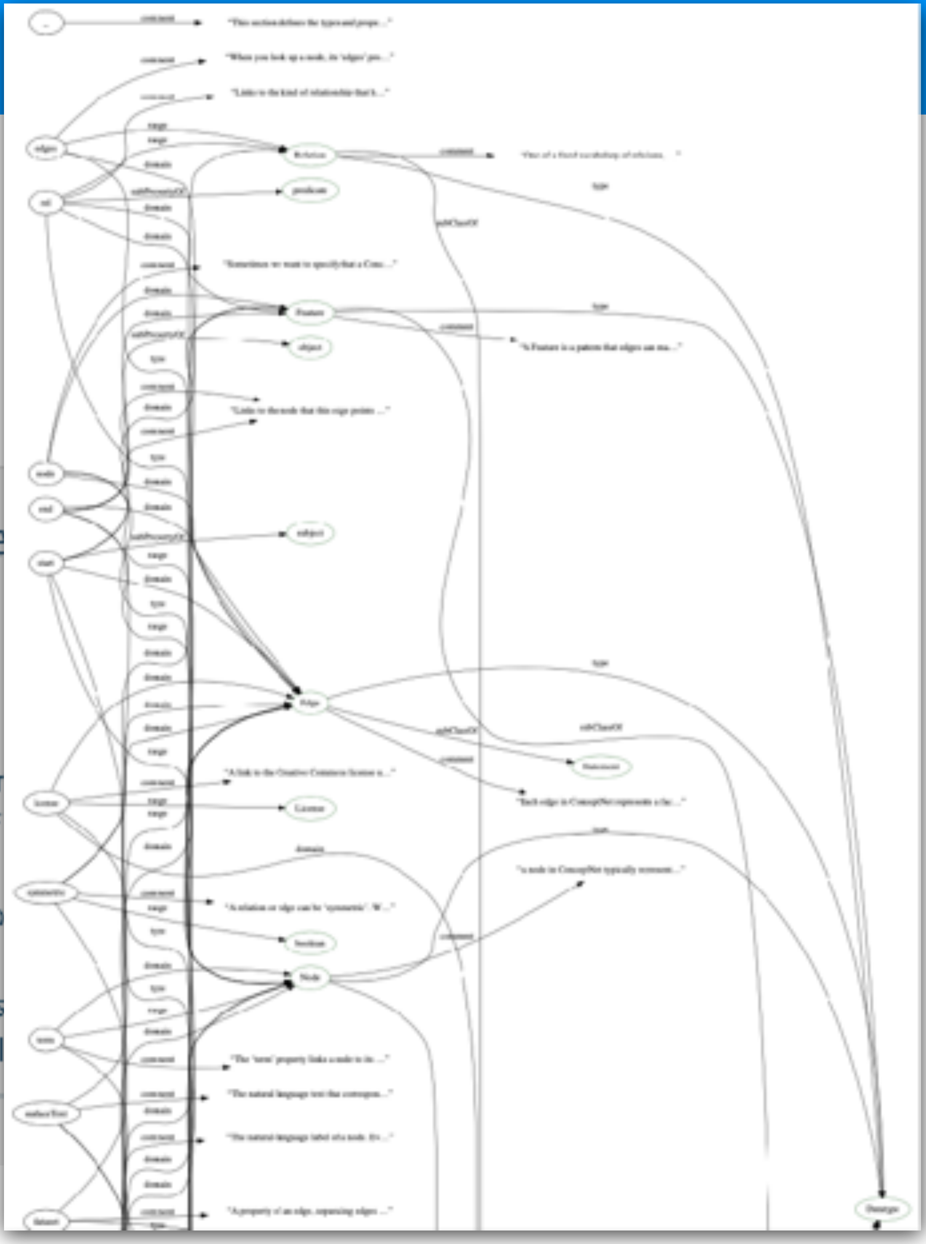
Source: Open Mind Common Sense contributors
View this term in the API

cooking dinner is a subevent of...

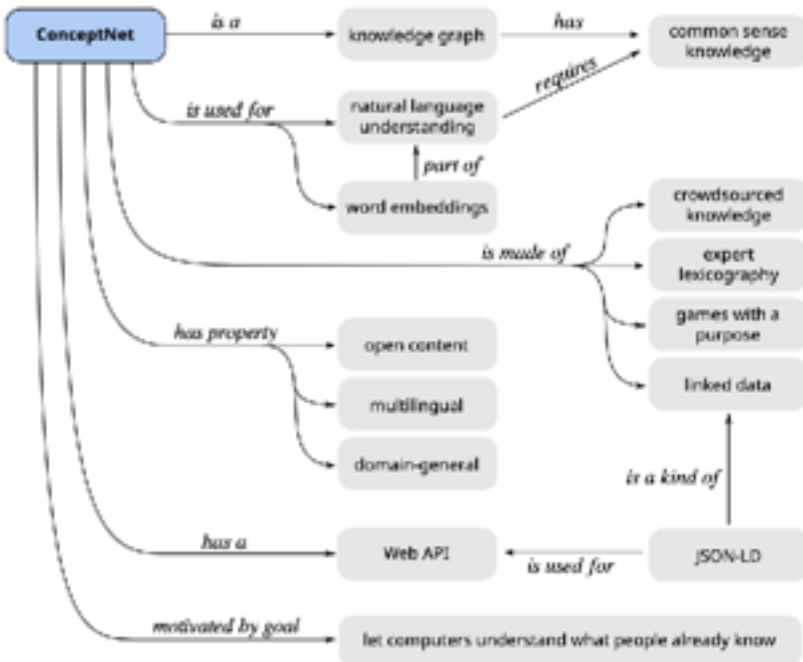
- en boiling water →
- en it burns →
- en preheat the oven →
- en taste the food →
- en boil salt water →
- en boil water →
- en brown the hamburger →
- en chop a vegetable →
- en defrost →
- en a fire →
- en the fire alarm might go off →

cooking dinne for...

- en feeding a family
- en TO EAT →
- en entertaining com
- en feeding yourself
- en anyone →
- en avoiding fast foo
- en being a cook →
- en caring for others
- en cheering yoursel
- en creative people
- en eating →



ConceptNet Numberbatch



- Create with a Knowledge Graph (from multiple sources with relations like *UsedFor*, *PartOf*, *etc*.)
- Based on this KG, perturb existing embeddings (like GloVe) to optimize:

$$\Psi(Q) = \sum_{i=1}^{n} \left[\alpha_i \| q_i - \hat{q}_i \|^2 + \sum_{(i,j)\in E} \beta_{ij} \| q_i - q_j \|^2 \right]$$

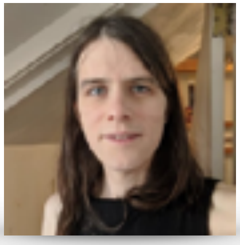
new embed — old embed — neighbors from KG

(keep similar to original) — (make similar according to other knowledge)

- Easy to optimize the objective by averaging neighbors in the ConceptNet KG
- Multiple embeddings achieved by merging through “retrofitting” which projects onto a shared matrix space (with SVD)

ConceptNet 5.5: An Open Multilingual Graph of General Knowledge, Speer et al., 2017

How to Make a Racist AI without Really Trying



Robyn Speer, 2017

http://blog.conceptnet.io/posts/2017/how-to-make-a-racist-ai-without-really-trying/

Debiasing: Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

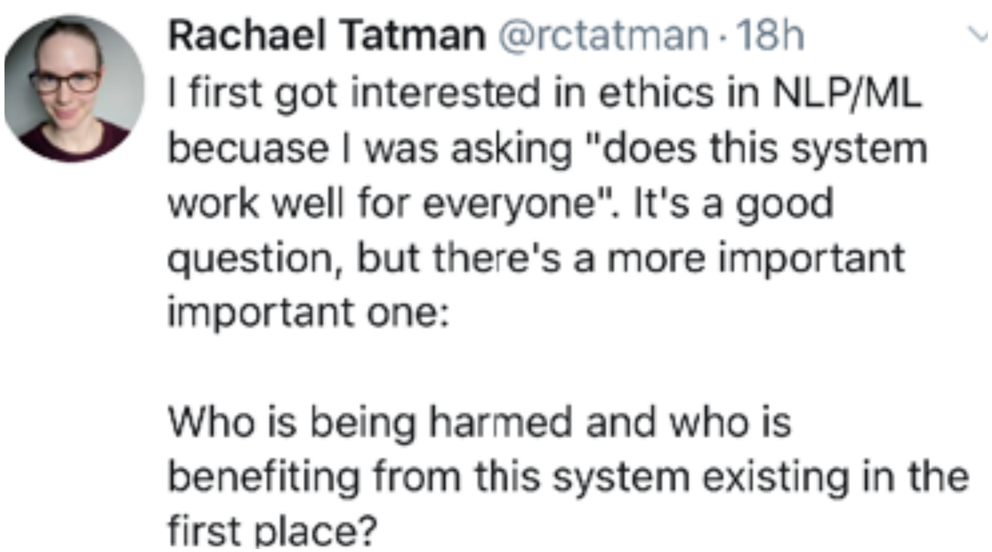
Bolukbasi et al., NeurIPs 2016

https://arxiv.org/pdf/1607.06520.pdf

ConceptNet 5.5: An Open Multilingual Graph of General Knowledge

Speer et al., AAAI 2017

https://arxiv.org/pdf/1612.03975.pdf



Lecture Notes for

Machine Learning in Python

Professor Eric Larson

Seq-2-Seq and Transformers

Archived

Lecture Agenda

- Logistics
  - RNNs due **During Finals Time**
- Agenda
  - Sequence to sequence
  - Transformers

Last Time

- LSTM prototype

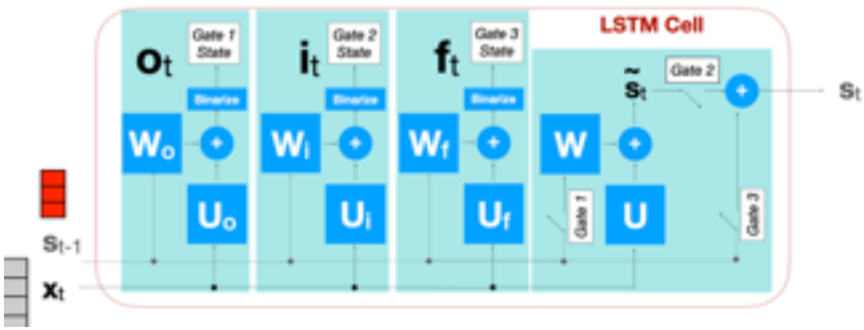
Selectivity controls (**gates, 0 or 1**)

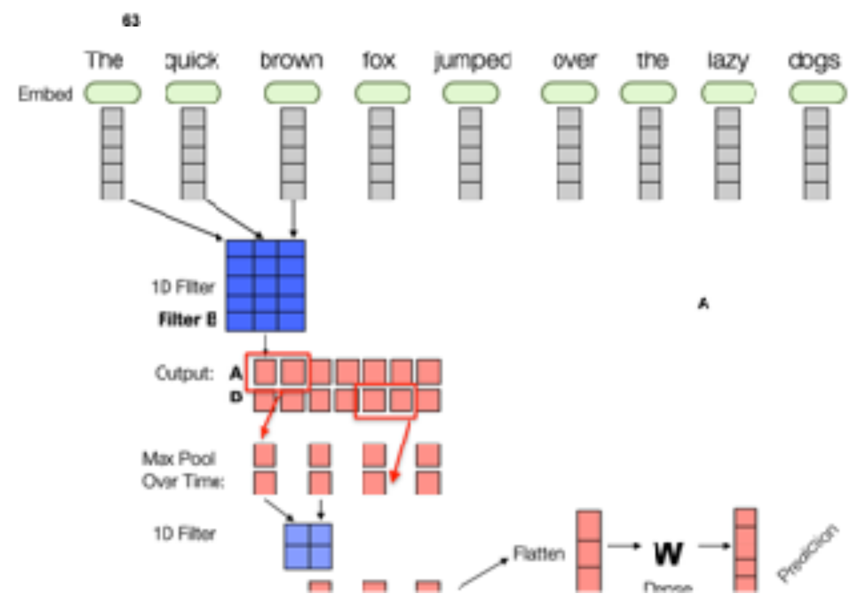
$$o_t = \sigma(W_o s_{t-1} + U_o x_t + b_o)$$
$$i_t = \sigma(W_i s_{t-1} + U_i x_t + b_i)$$
$$f_t = \sigma(W_f s_{t-1} + U_f x_t + b_f)$$

selectively remember past — with influence

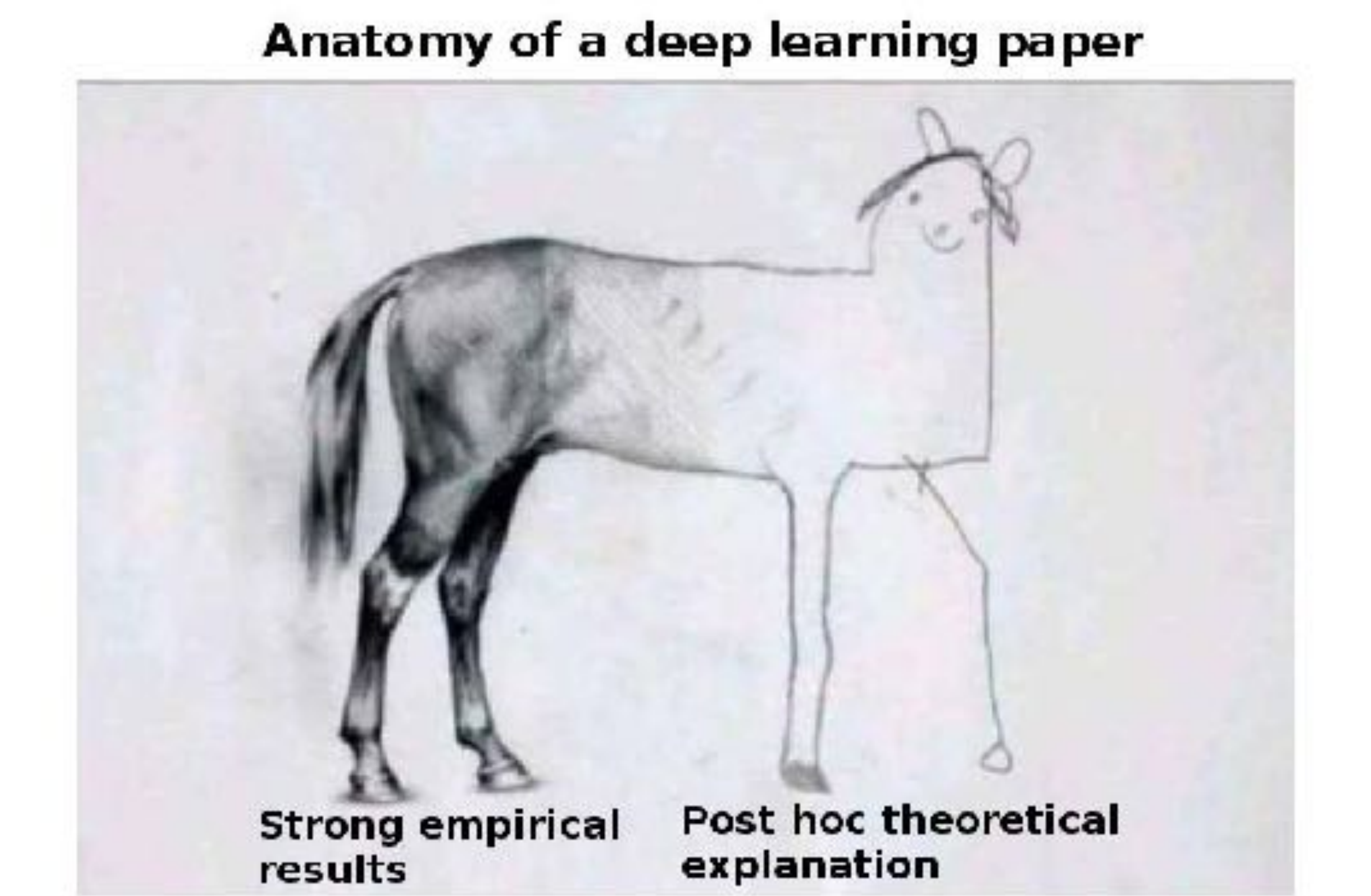
$$\tilde{s}_t = \phi(W\boxed{o_t \odot s_{t-1}}) + \boxed{U x_t + b}$$
$$s_t = \boxed{f_t \odot s_{t-1}} + \boxed{i_t \odot \tilde{s}_t}$$

selectively remember past — with past weighted influence



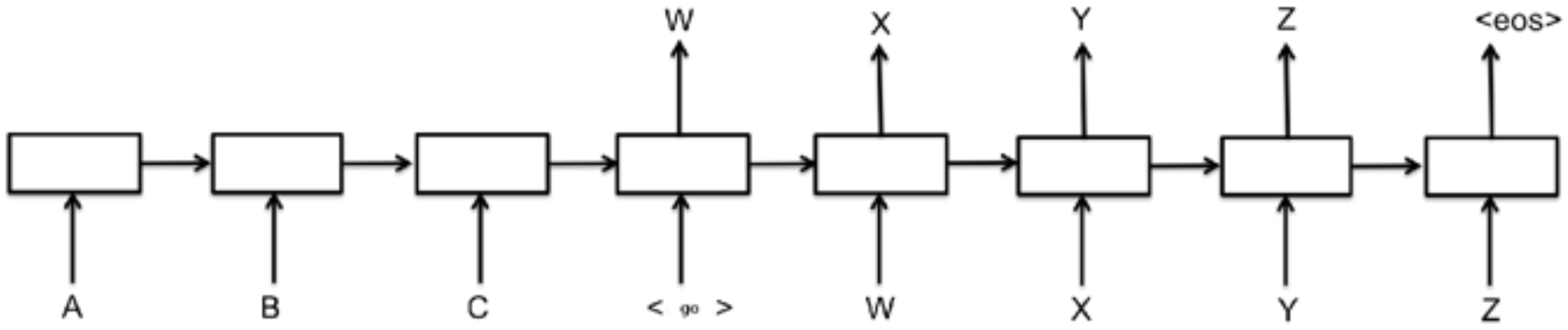


Sequence to Sequence



Modeling Sequence to Sequence

Need to translate outputs of unknown size.



- Additional Vocabulary Special Casing:
  - <UNKNOWN>, for unknown input or characters not included in vocabulary
  - <EOS>, end of sentence
  - <GO>, start output sequence
  - <DONTCARE>, outputs before <GO> command

Sutskever et al. Sequence to Sequence Learning with Neural Networks, arXiv. 2014
https://arxiv.org/pdf/1409.3215.pdf

Modeling Sequence to Sequence

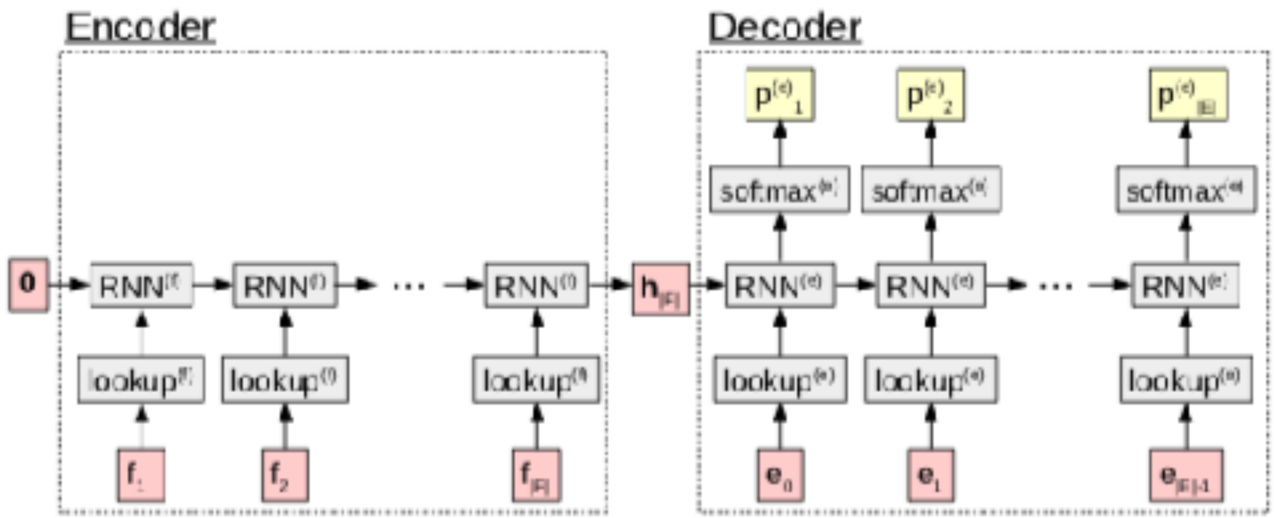


Figure 21: A computation graph of the encoder-decoder model.

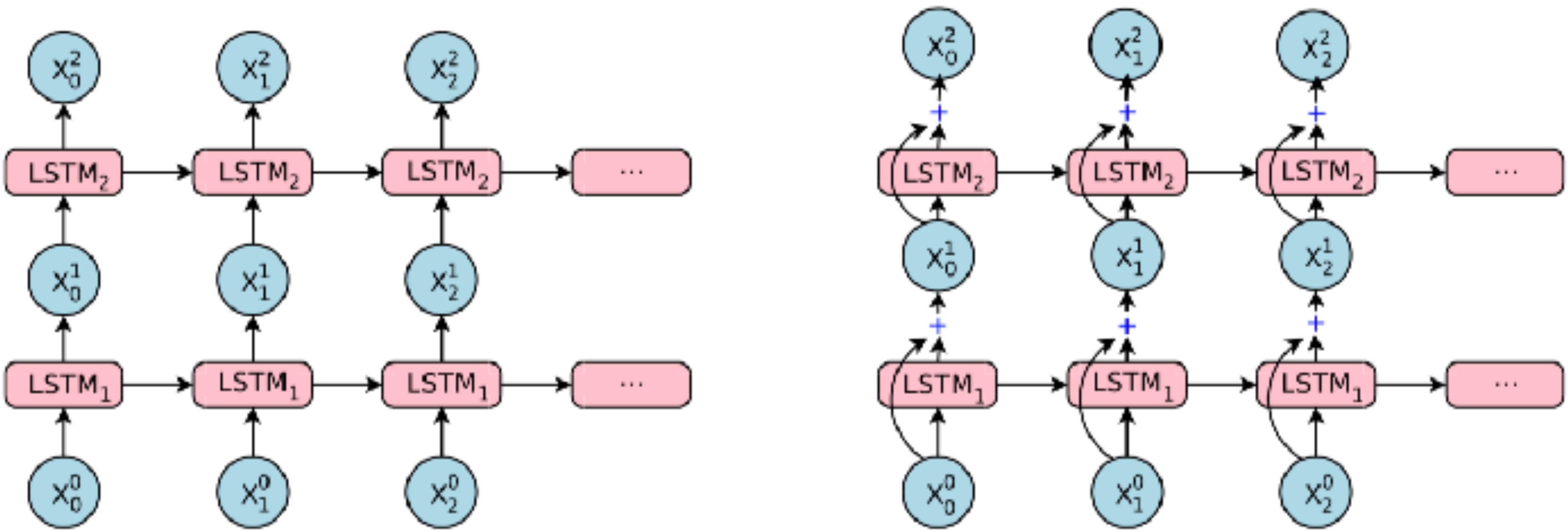
- **Training Process**: Give actual decoded letters for predicting next token
- **Decoding Process** can alter reliability of results:
  - Greedy Search, always choose most likely “next” symbol, seed
  - Keep list of “best” predictions for seeding (i.e., Beam Search)

Graham Neubig. 2017
Neural Machine Translation and
Sequence-to-sequence Models: A Tutorial
https://arxiv.org/pdf/1703.01619.pdf

https://github.com/m2dsupsdlclass/lectures-labs/blob/master/labs/07_seq2seq/Translation_of_Numeric_Phrases_with_Seq2Seq_rendered.ipynb

GNMT: Residuals

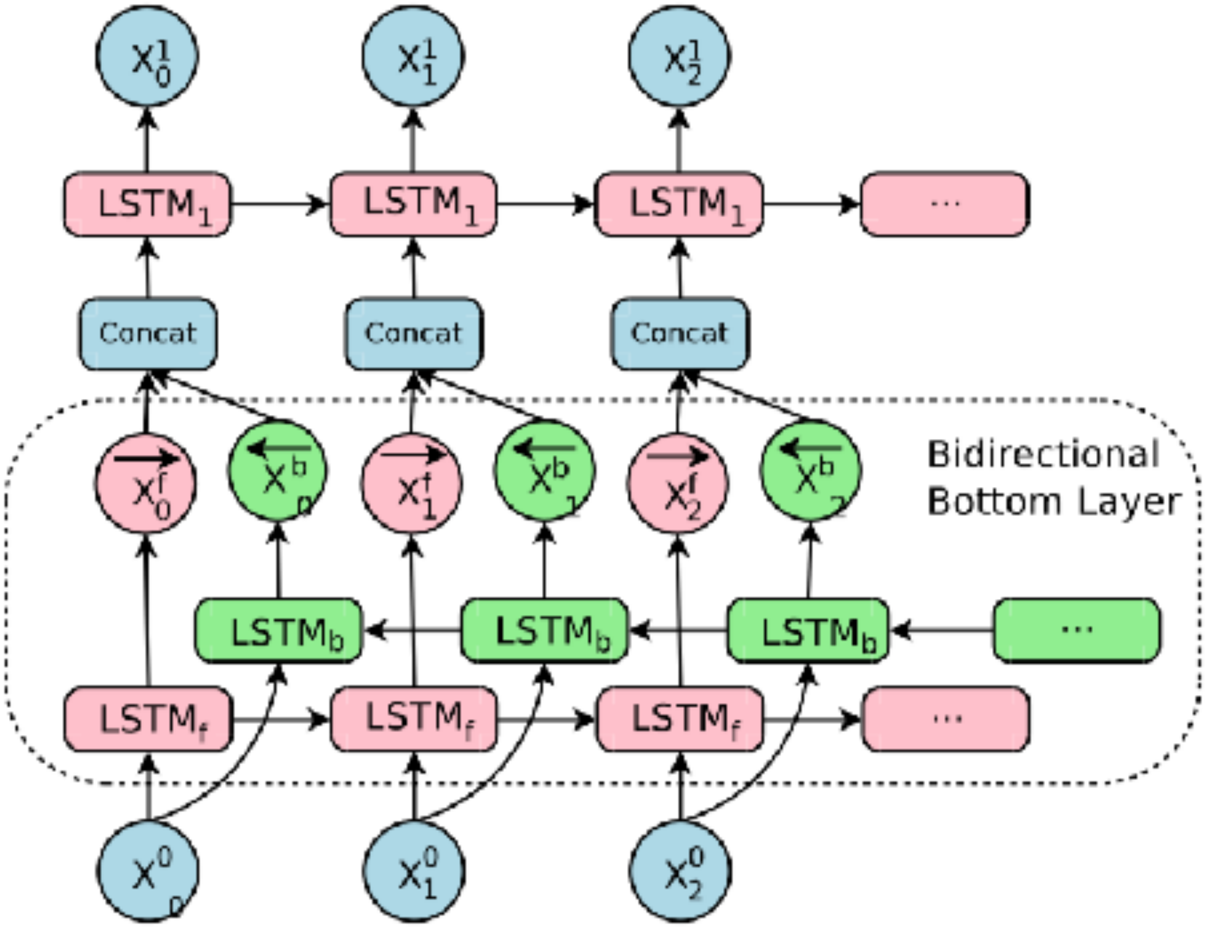
- Google, 2016



Google's Neural Machine Translation:
https://arxiv.org/pdf/1609.08144.pdf

GNMT: Bidirectionality

- Google, 2016



Google Neural Machine Translation:
https://arxiv.org/pdf/1609.08144.pdf

GNMT: Attention

- Google, 2016

$$s_t = AttentionFunction(\mathbf{y}_{i-1}, \mathbf{x}_t) \quad \forall t, \quad 1 \le t \le M$$

$$p_t = \exp(s_t) / \sum_{t=1}^{M} \exp(s_t) \qquad \forall t, \quad 1 \le t \le M$$

$$\mathbf{a}_i = \sum_{t=1}^{M} p_t . \mathbf{x}_t$$

where $\mathbf{x}_t$ is state of the t^{th} encoder
$\mathbf{y}_{i\text{-}1}$ is the state of the previous decoder
and $\mathbf{a}_i$ is the input for the i^{th} decoder

Google Neural Machine Translation:
https://arxiv.org/pdf/1609.08144.pdf

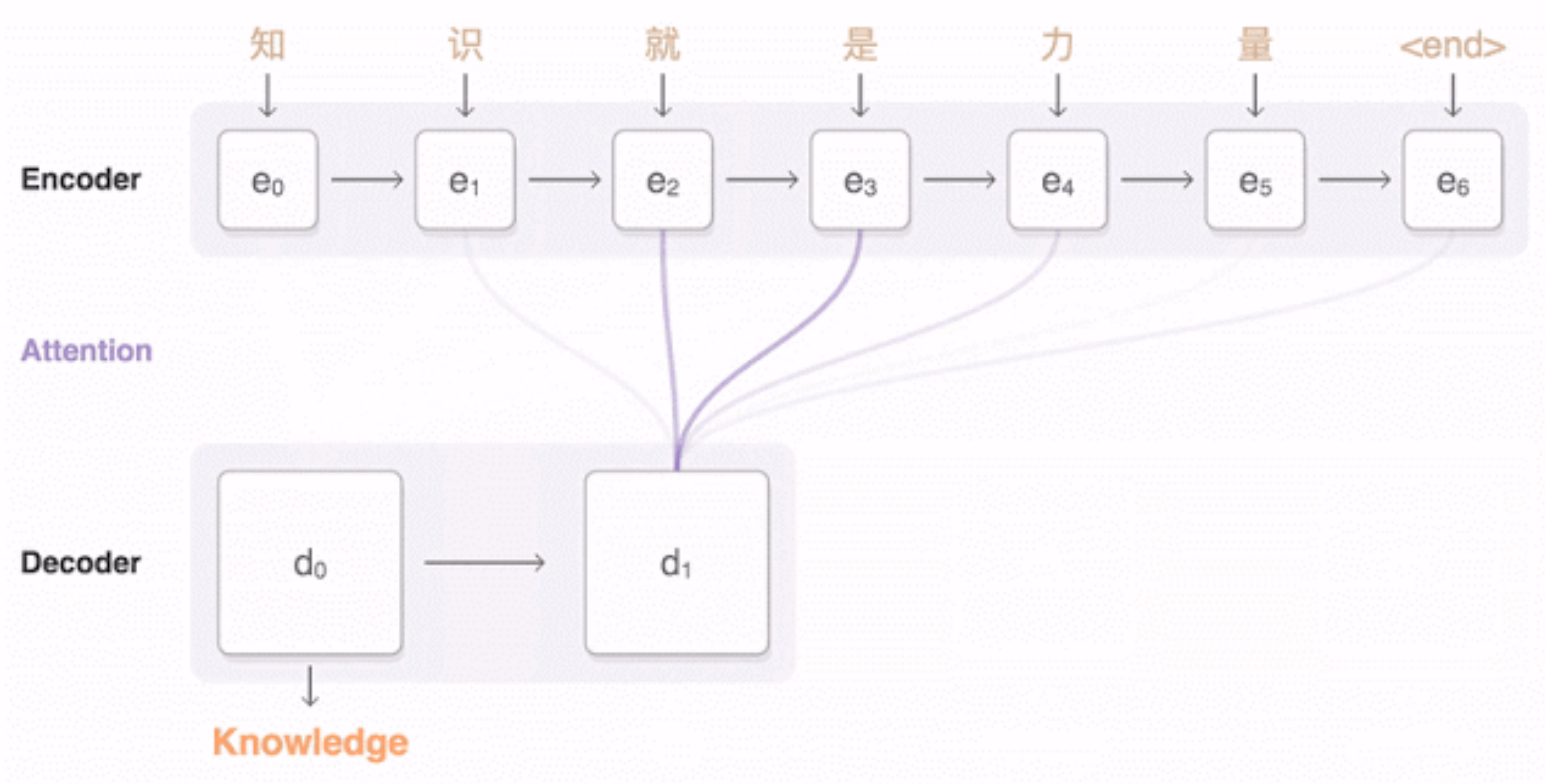
GNMT: Attention

- Google, 2016

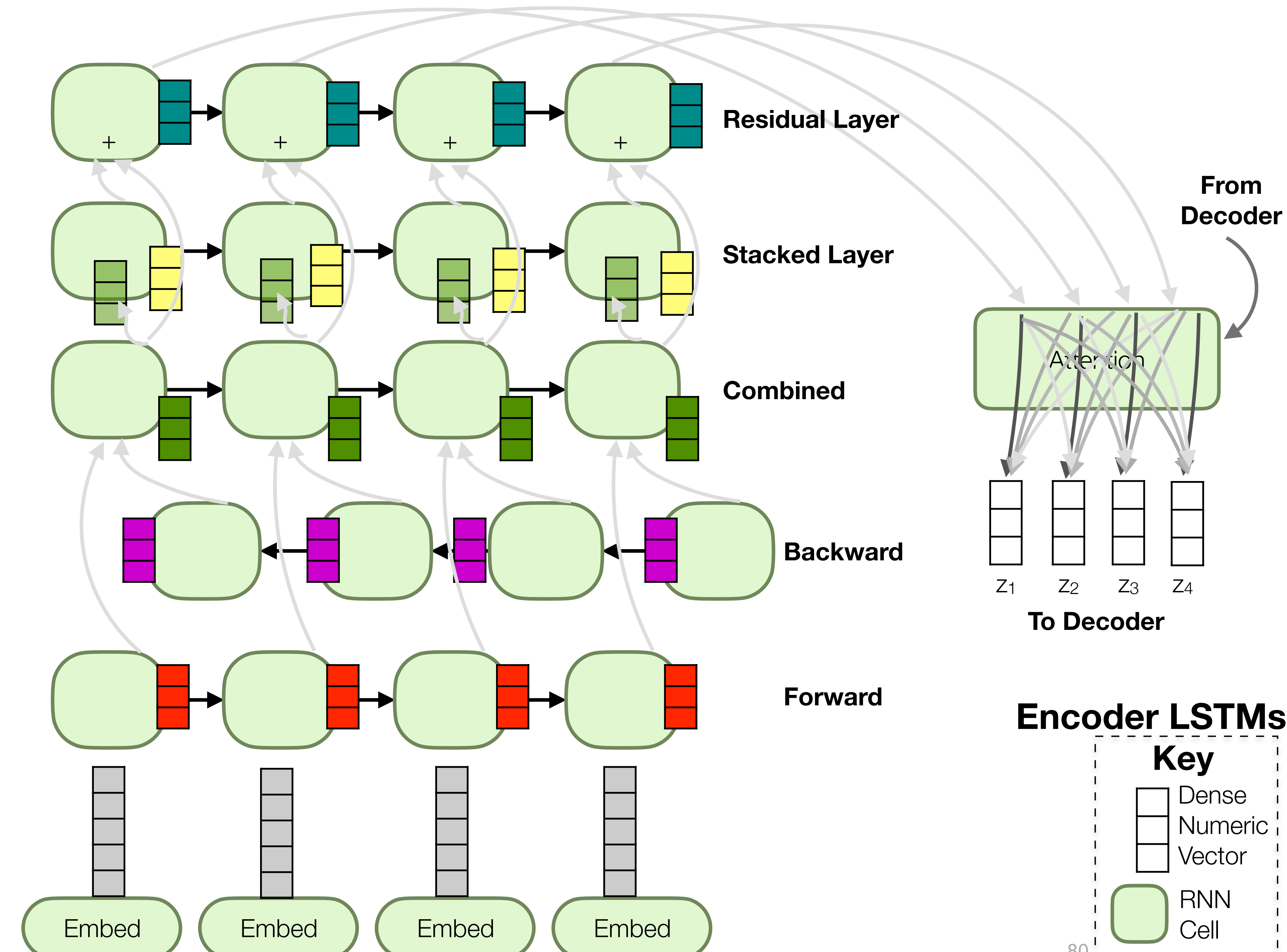
$$s_t = AttentionFunction(\mathbf{y}_{i-1}, \mathbf{x}_t) \quad \forall t, \quad 1 \le t \le M$$

$$p_t = \exp(s_t) / \sum_{t=1}^{M} \exp(s_t) \qquad \forall t, \quad 1 \le t \le M$$

$$\mathbf{a}_i = \sum_{t=1}^{M} p_t . \mathbf{x}_t$$

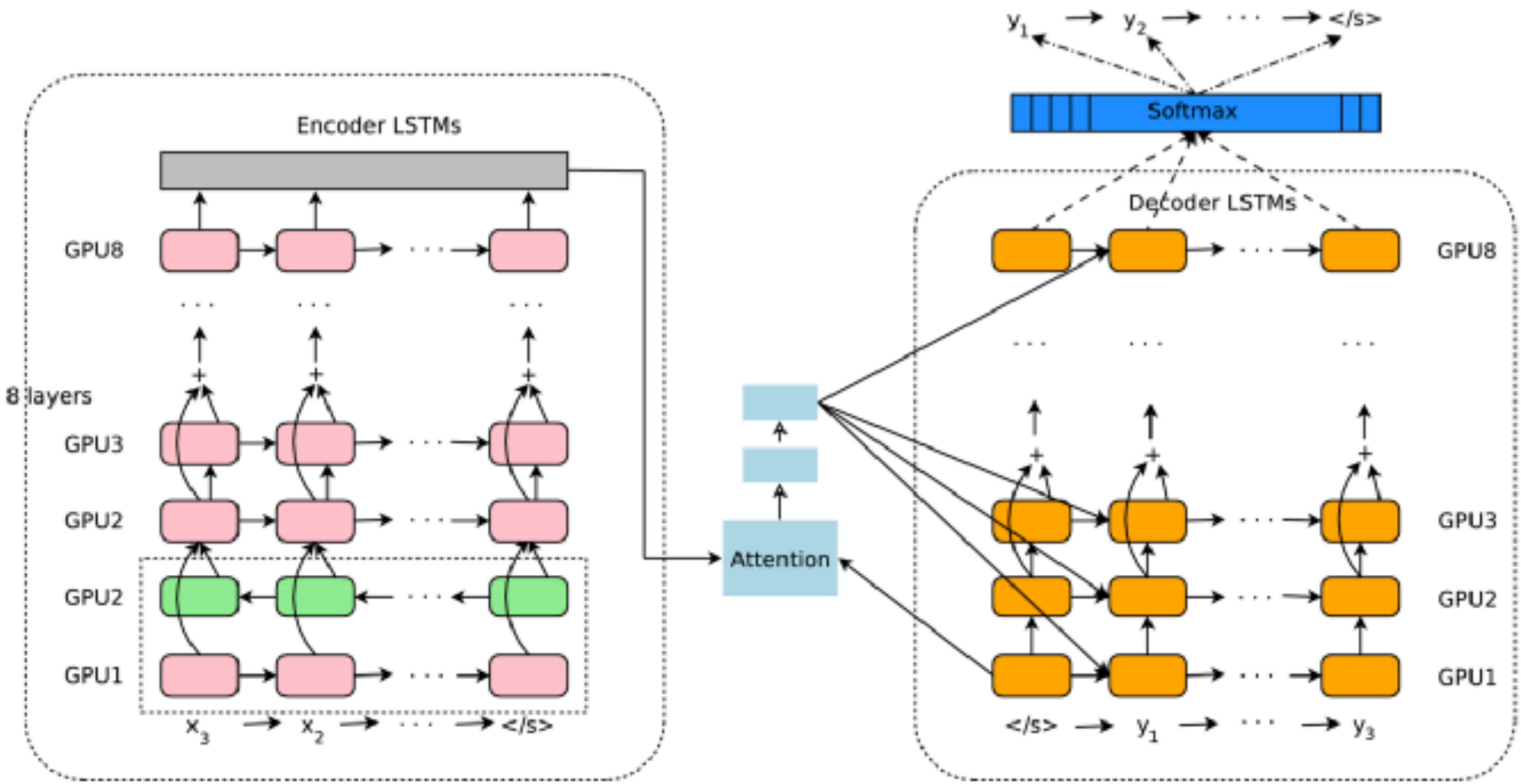


Google Neural Machine Translation:
https://arxiv.org/pdf/1609.08144.pdf
https://medium.com/@Synced/history-and-frontier-of-the-neural-machine-translation-dc981d25422d


Residual Layer
Stacked Layer
Combined
Backward
Forward
Embed
Embed
Embed
Embed
From Decoder
Attention
Z_1
Z_2
Z_3
Z_4
To Decoder
Encoder LSTMs
Key
Dense Numeric Vector
RNN Cell

GNMT: Putting it All together

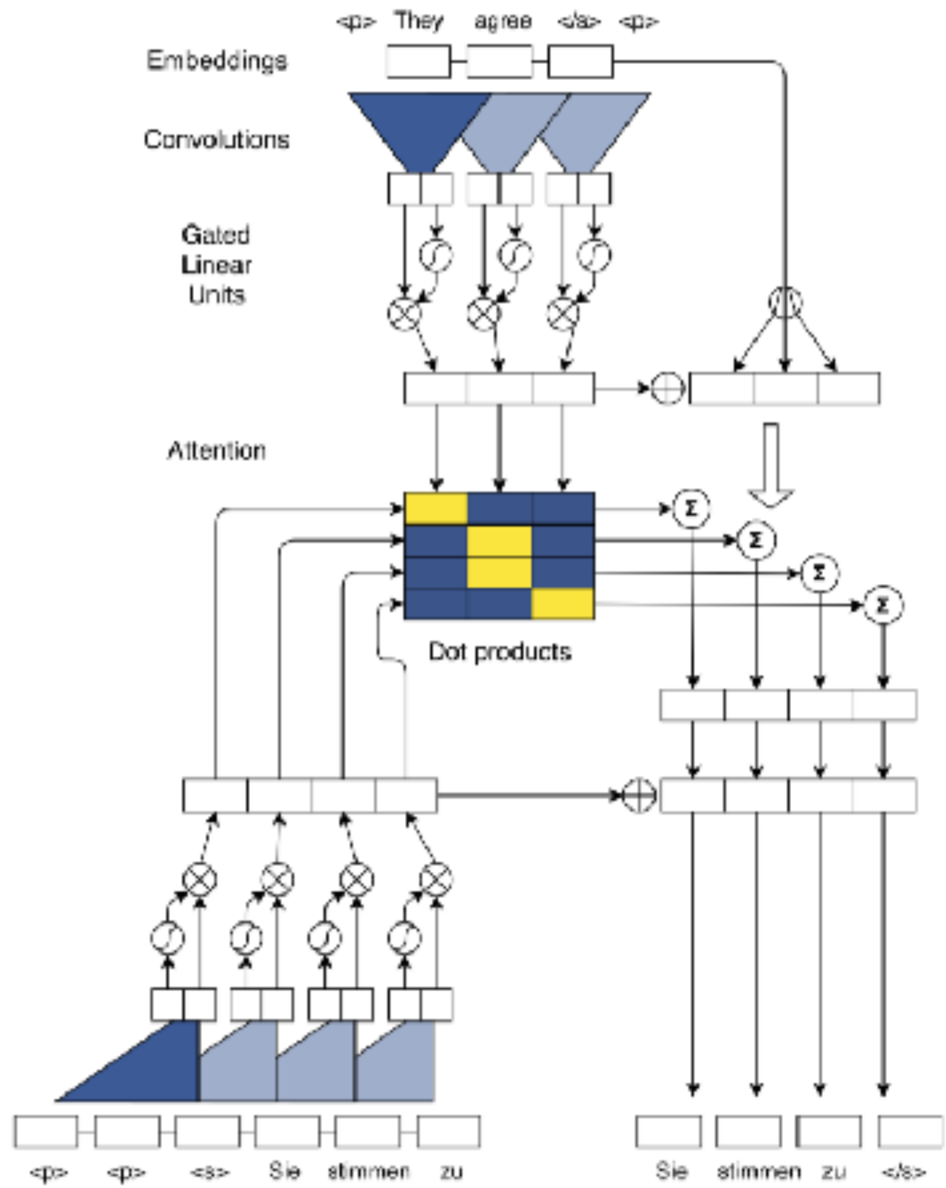
- Google, 2016



Google Neural Machine Translation:
https://arxiv.org/pdf/1609.08144.pdf

CNNs and RNNs

- Can translation also be done using only CNNs?
  - Yes, Facebook AI already did it,
  - 9 times faster than GNMT
  - Similar Performance
  - July, 2017



https://arxiv.org/pdf/1705.03122.pdf

Demo, if time

… from Olivier Grisel

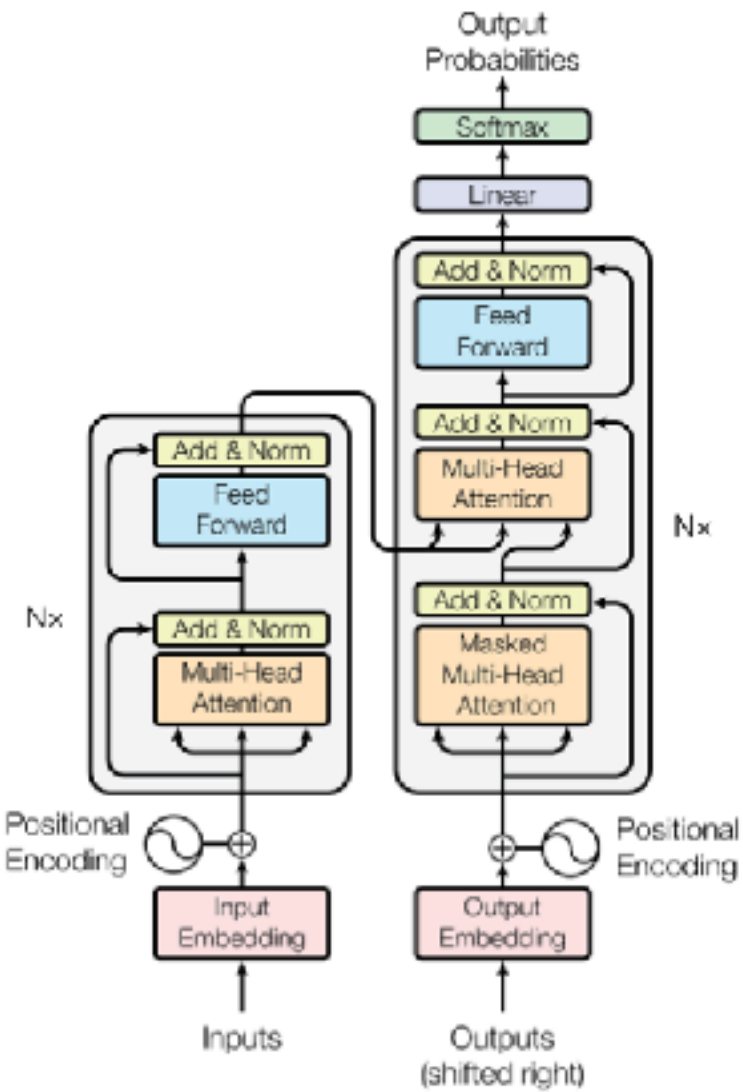
https://github.com/m2dsupsdlclass/lectures-labs/blob/master/labs/07_seq2seq/Translation_of_Numeric_Phrases_with_Seq2Seq_rendered.ipynb

Transformers

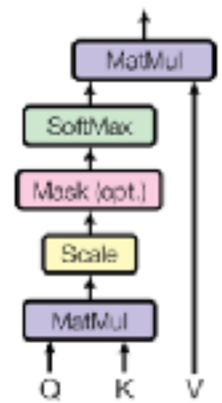
Attention is All You Need

- Well, its a good paper title, but not exactly accurate
- Problem: recurrent networks are not inherently parallelized or efficient at remembering
- Convolution needs many examples from all different word positions (after flattening)
- Filters are not resilient to long-term relationships
- Transformer Solution:
  - Build attention into model from the **beginning**
  - Compare all words to each other through **multi-headed** attention
  - Define a notion of “**position**”in the sentence

Transformer



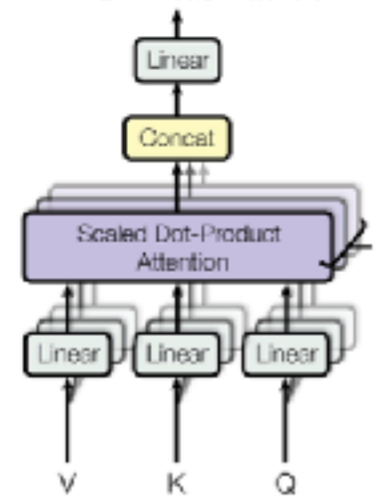
Scaled Dot-Product Attention



for each word

$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Multi-Head Attention

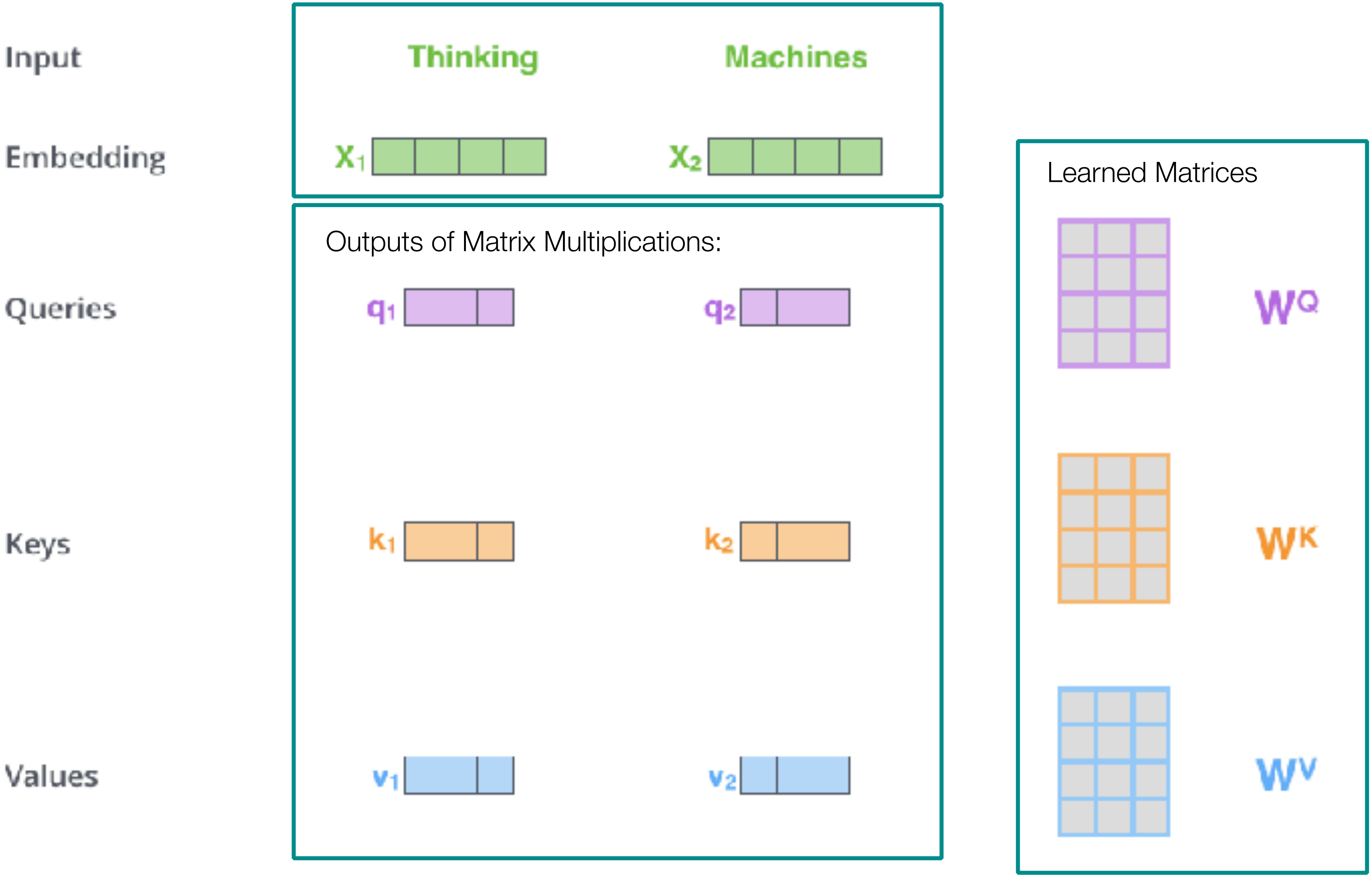


more than one
Q,K,V use in document

$$\mathrm{MultiHead}(Q,K,V) = \mathrm{Concat}(\mathrm{head}_1, ..., \mathrm{head}_h)W^O$$
$$\text{where } \mathrm{head}_i = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

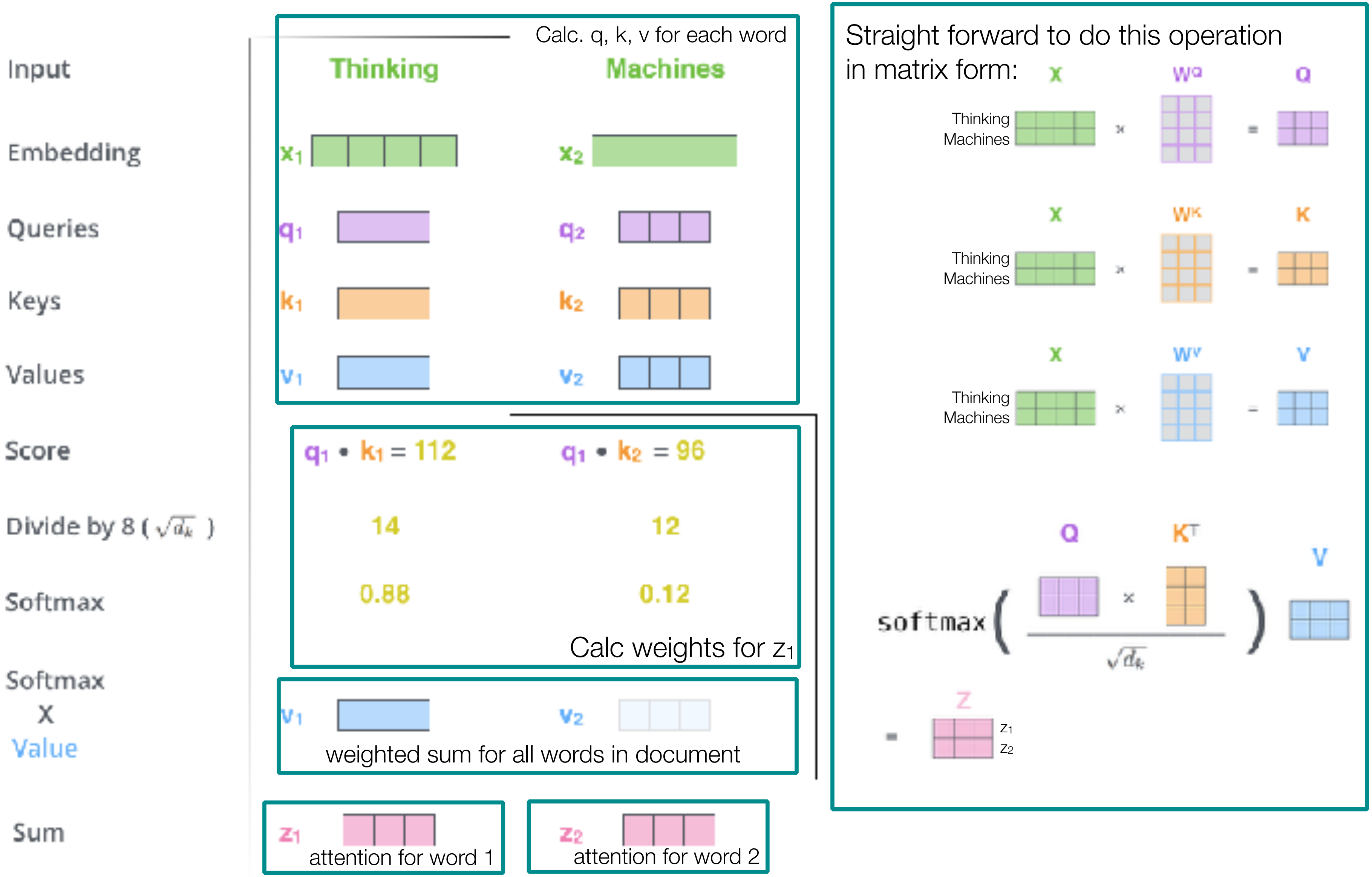
https://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf

Transformer: in more detail



Excellent Blog on Transformers: http://jalammar.github.io/illustrated-transformer/

Transformer: in more detail



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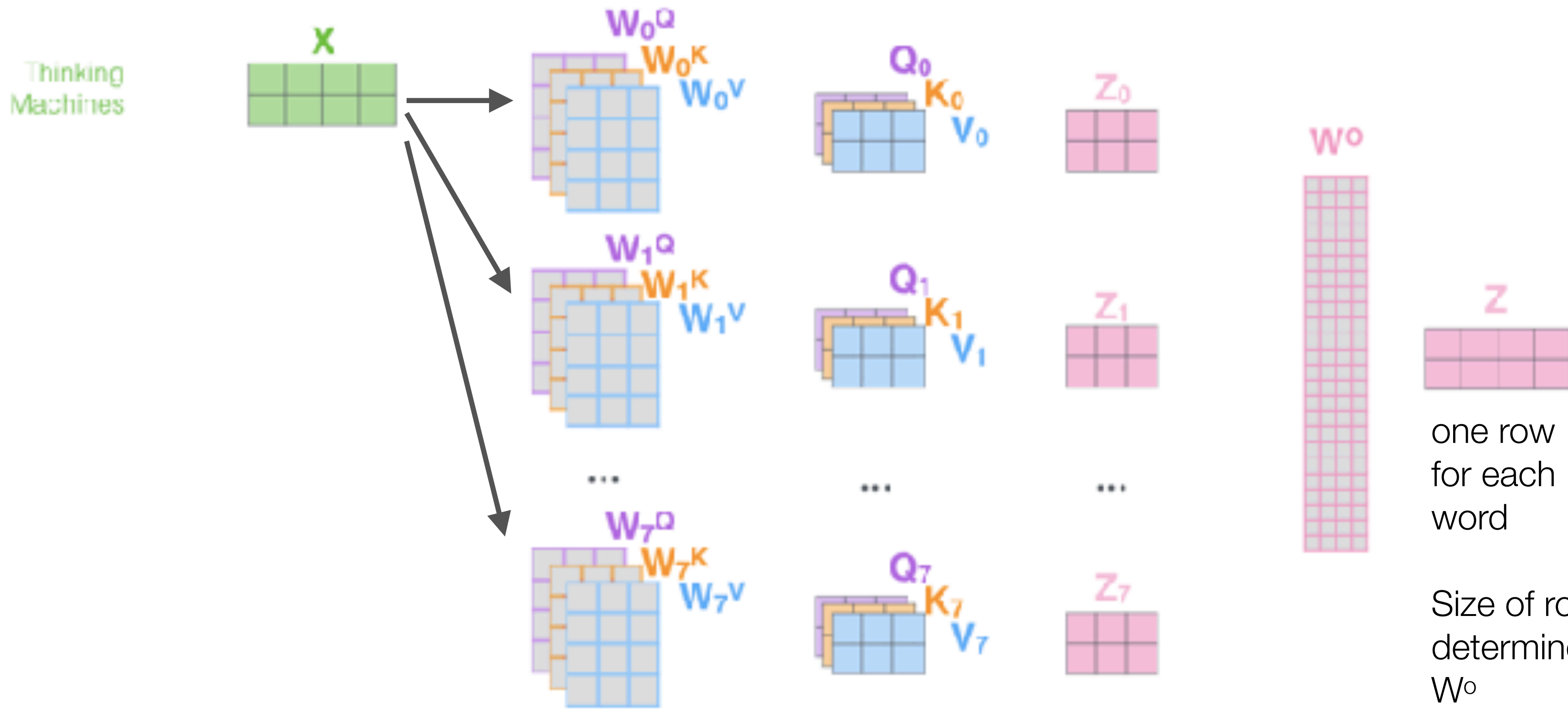
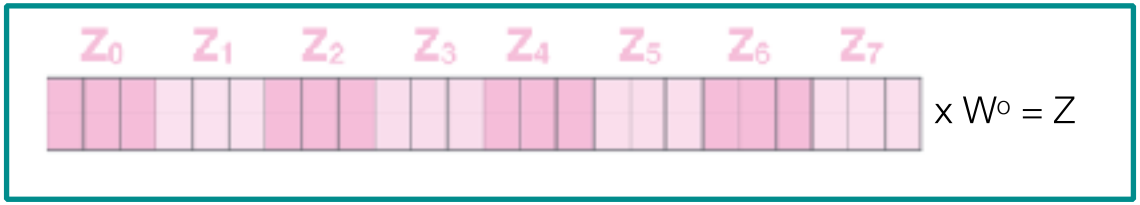
Transformer: Multi-headed Attention



one row for each word

Size of row determined by W^O



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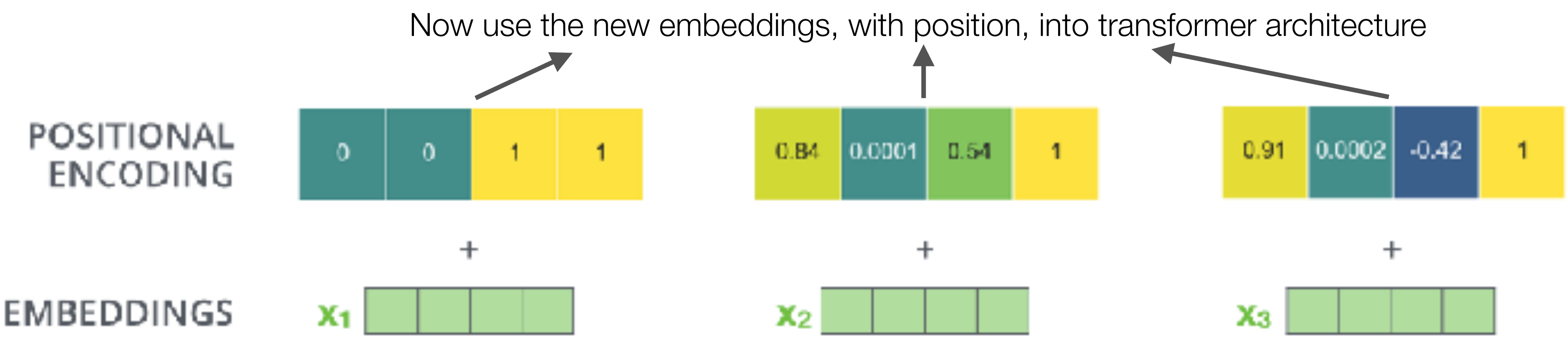
Transformer: Positional Encoding

- Objective: add notion of position to embedding
- Attempt in paper: add sin/cos to embedding
- But could be anything that encodes position

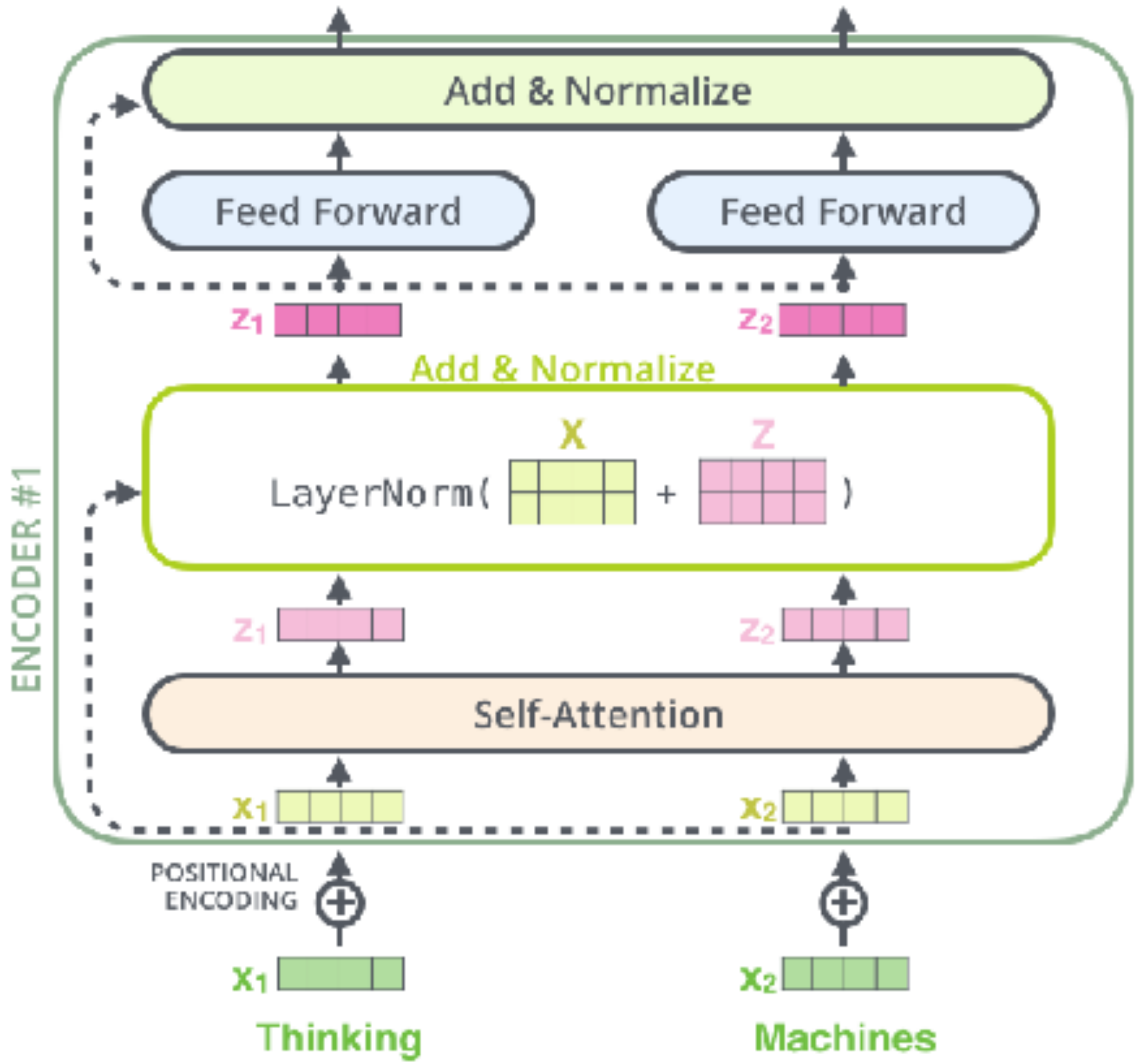
$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$



Hypothesis: Now the word proximity is encoded in the embedding matrix, with other pertinent information. Well, it does help… so it could be true that this is a good way to do it.

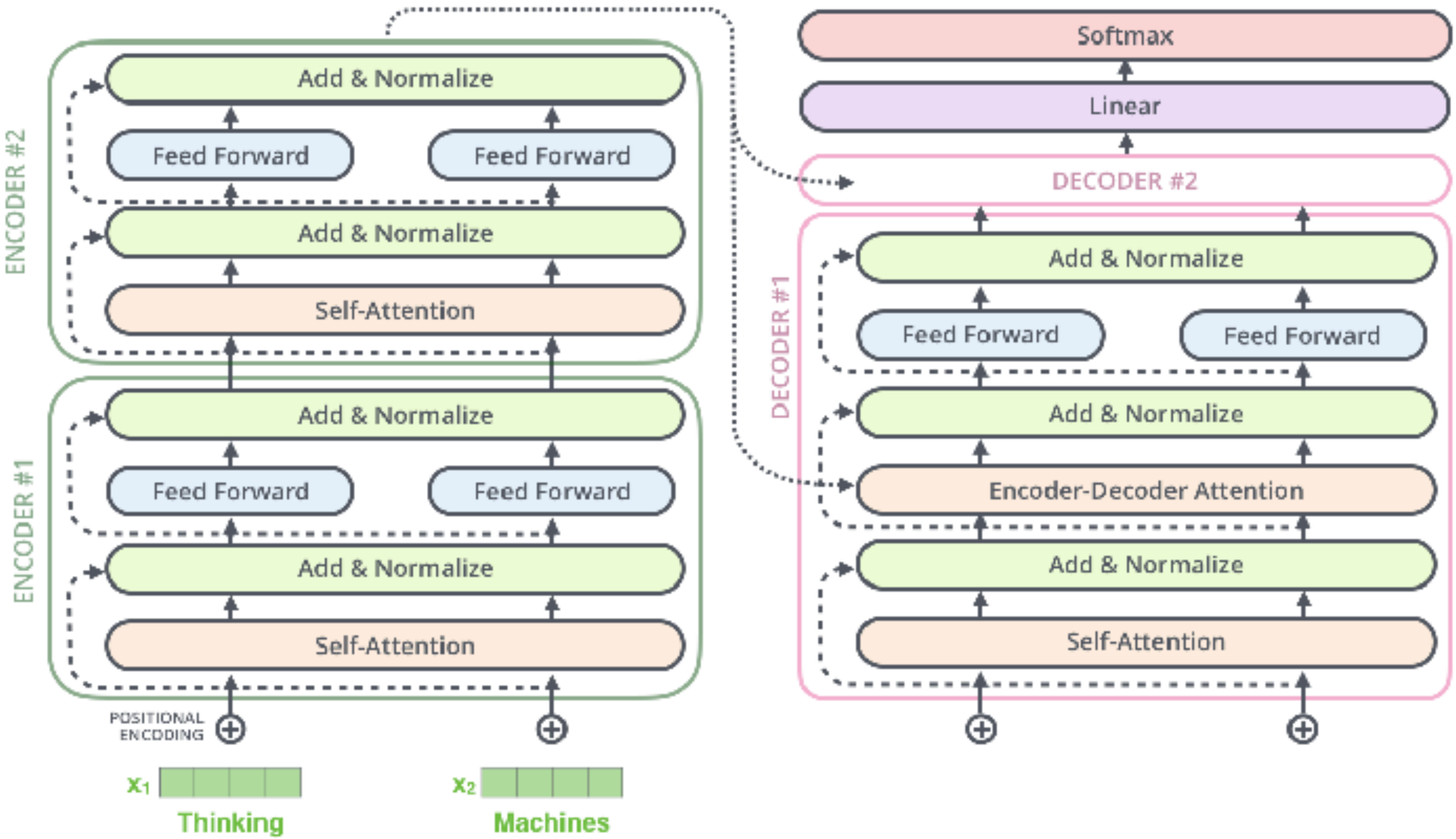
Excellent Blog on Transformers: http://jalammar.github.io/illustrated-transformer/

Transformer: Residual Connections



Excellent Blog on Transformers: http://jalammar.github.io/illustrated-transformer/

Transformer: Putting it all together



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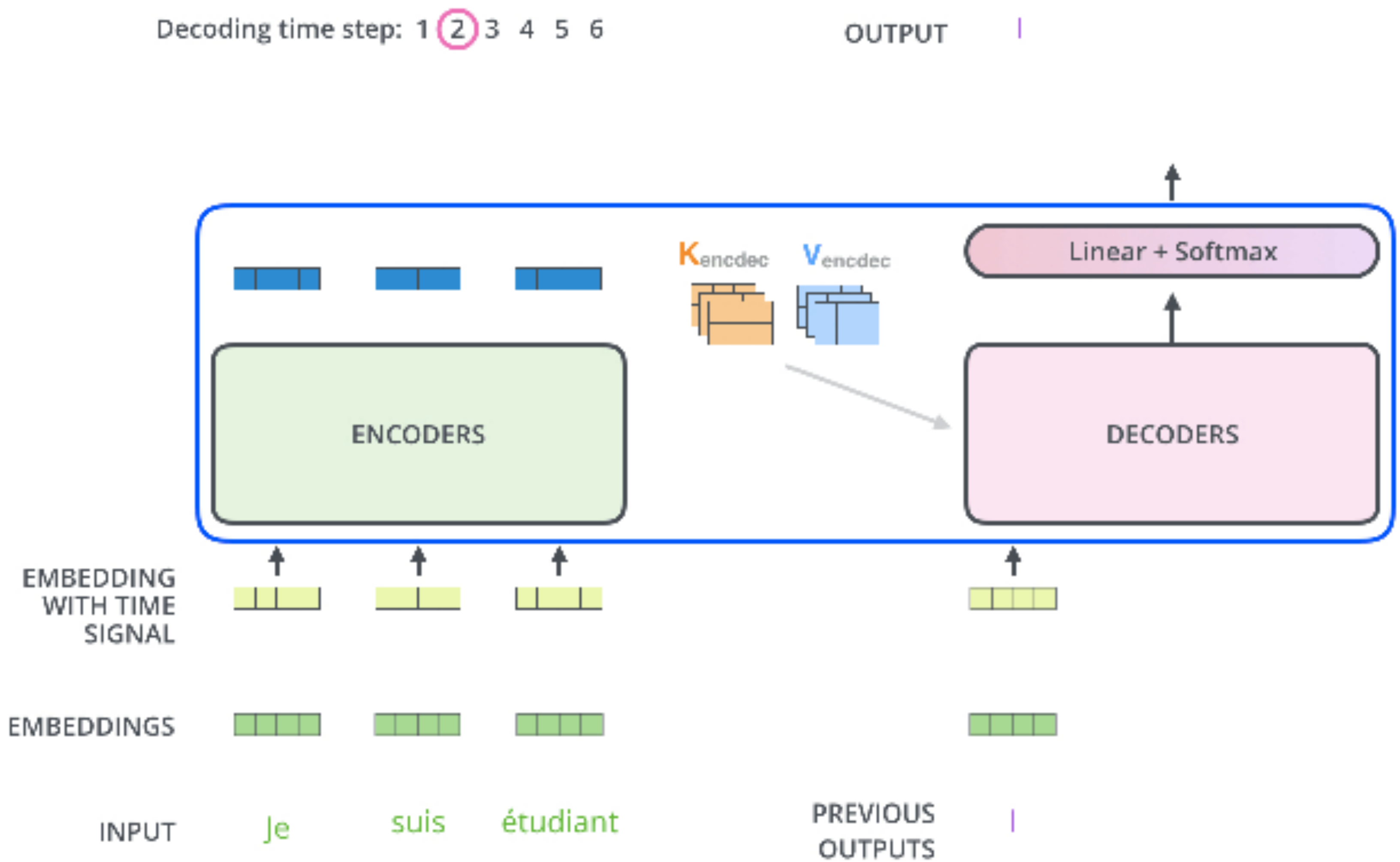
Transformer: Putting it all together



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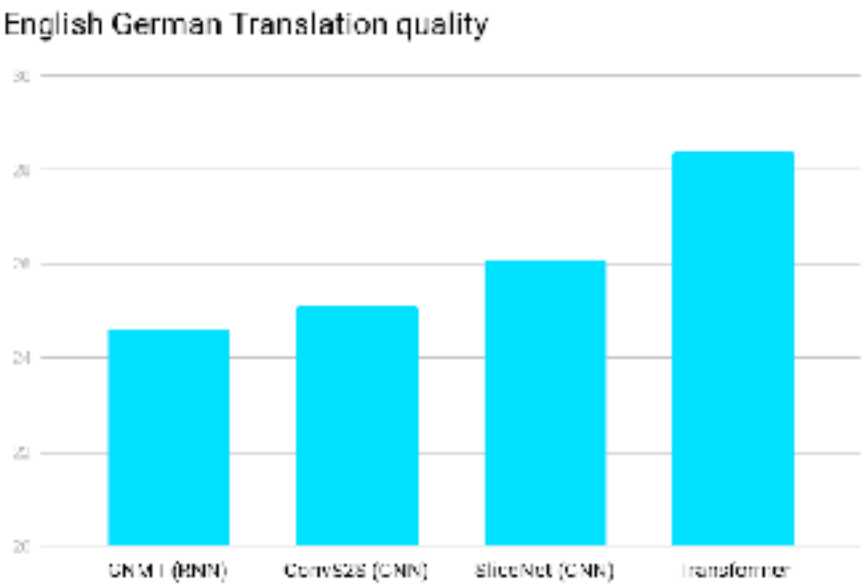
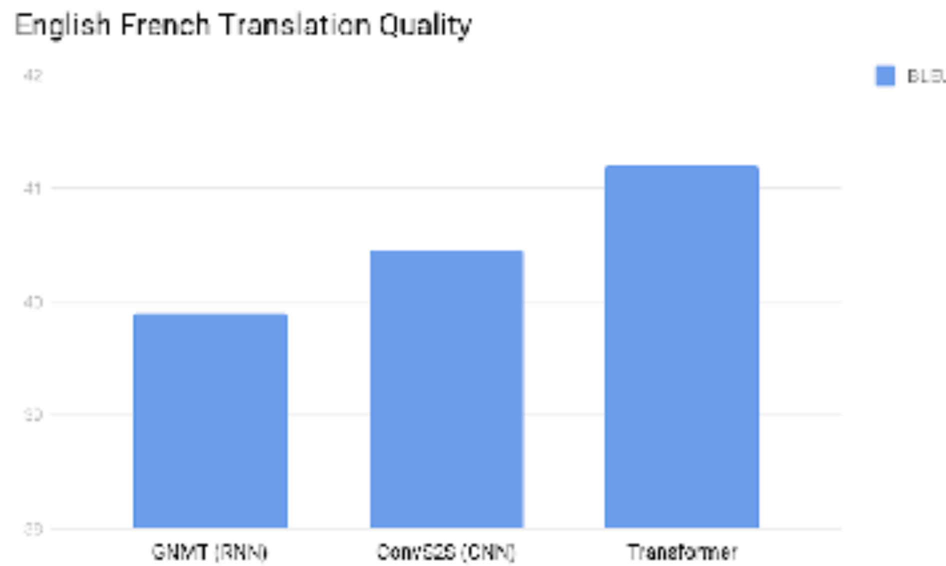
Results





https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

Implementations:

- Not Native to Keras or Tensorflow, but many Open Source Implementations Exist
- Is Native to PyTorch

TensorFlow

http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html

```
with tf.variable_scope('rnn_cell'):
    W = tf.get_variable('W', [num_classes + state_size, state_size])
    b = tf.get_variable('b', [state_size], initializer=tf.constant_initializer(0.0))

def rnn_cell(rnn_input, state):
    with tf.variable_scope('rnn_cell', reuse=True):
        W = tf.get_variable('W', [num_classes + state_size, state_size])
        b = tf.get_variable('b', [state_size], initializer=tf.constant_initializer(0.0))
    return tf.tanh(tf.matmul(tf.concat(1, [rnn_input, state]), W) + b)

state = init_state
rnn_outputs = []
for rnn_input in rnn_inputs:
    state = rnn_cell(rnn_input, state)
    rnn_outputs.append(state)
final_state = rnn_outputs[-1]

#logits and predictions
with tf.variable_scope('softmax'):
    W = tf.get_variable('W', [state_size, num_classes])
    b = tf.get_variable('b', [num_classes], initializer=tf.constant_initializer(0.0))
logits = [tf.matmul(rnn_output, W) + b for rnn_output in rnn_outputs]
predictions = [tf.nn.softmax(logit) for logit in logits]

# Turn our y placeholder into a list labels
y_as_list = [tf.squeeze(i, squeeze_dims=[1]) for i in tf.split(1, num_steps, y)]

#losses and train_step
losses = [tf.nn.sparse_softmax_cross_entropy_with_logits(logit,label) for \
          logit, label in zip(logits, y_as_list)]
total_loss = tf.reduce_mean(losses)
train_step = tf.train.AdagradOptimizer(learning_rate).minimize(total_loss)
```

http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html

```
def train_network(num_epochs, num_steps, state_size=4, verbose=True):
    with tf.Session() as sess:
        sess.run(tf.initialize_all_variables())
        training_losses = []
        for idx, epoch in enumerate(gen_epochs(num_epochs, num_steps)):
            training_loss = 0
            training_state = np.zeros((batch_size, state_size))
            if verbose:
                print("\nEPOCH", idx)
            for step, (X, Y) in enumerate(epoch):
                tr_losses, training_loss_, training_state, _ = \
                    sess.run([losses,
                              total_loss,
                              final_state,
                              train_step],
                                  feed_dict={x:X, y:Y, init_state:training_state})
                training_loss += training_loss_
                if step % 100 == 0 and step > 0:
                    if verbose:
                        print("Average loss at step", step,
                              "for last 250 steps:", training_loss/100)
                    training_losses.append(training_loss/100)
                    training_loss = 0

    return training_losses
```

TensorFlow

http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html

```
def train_network(num_epochs, num_steps, state_size=4, verbose=True):
    with tf.Session() as sess:
        sess.run(tf.initialize_all_variables())
        for idx, epoch in enumerate(gen_epochs(num_epochs, num_steps)):
            training_state = np.zeros((batch_size, state_size))
            for X, Y in epoch:
                tr_losses, training_loss_, training_state, _ = \
                    sess.run([losses,
                              total_loss,
                              final_state,
                              train_step],
                             feed_dict={x:X, y:Y, init_state:training_state})
```

TensorFlow (simplified)

http://r2rt.com/recurrent-neural-networks-in-tensorflow-i.html

```
cell = tf.nn.rnn_cell.BasicRNNCell(state_size)
rnn_outputs, final_state = tf.nn.rnn(cell, rnn_inputs, initial_state=init_state)
```

```
loss_weights = [tf.ones([batch_size]) for i in range(num_steps)]
losses = tf.nn.seq2seq.sequence_loss_by_example(logits, y_as_list, loss_weights)
```

```
x = tf.placeholder(tf.int32, [batch_size, num_steps], name='input_placeholder')
y = tf.placeholder(tf.int32, [batch_size, num_steps], name='labels_placeholder')
init_state = tf.zeros([batch_size, state_size])

x_one_hot = tf.one_hot(x, num_classes)
rnn_inputs = tf.unpack(x_one_hot, axis=1)

cell = tf.nn.rnn_cell.BasicRNNCell(state_size)
rnn_outputs, final_state = tf.nn.rnn(cell, rnn_inputs, initial_state=init_state)
```

```
with tf.variable_scope('softmax'):
    W = tf.get_variable('W', [state_size, num_classes])
    b = tf.get_variable('b', [num_classes], initializer=tf.constant_initializer(0.0))
logits = [tf.matmul(rnn_output, W) + b for rnn_output in rnn_outputs]
predictions = [tf.nn.softmax(logit) for logit in logits]

y_as_list = [tf.squeeze(i, squeeze_dims=[1]) for i in tf.split(1, num_steps, y)]

loss_weights = [tf.ones([batch_size]) for i in range(num_steps)]
losses = tf.nn.seq2seq.sequence_loss_by_example(logits, y_as_list, loss_weights)
total_loss = tf.reduce_mean(losses)
train_step = tf.train.AdagradOptimizer(learning_rate).minimize(total_loss)
```