The Amazing World of Neural Language Generation

Part II: Neural Network Modeling for Generation

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Basic Architecture of Neural NLG Models

From a (very) high-level viewpoint, neural NLG model can be formulated as with two fundamental components: **encoder** and **decoder**:

$$\text{Input } \boldsymbol{x} \longrightarrow \boxed{\text{Encoder}} \longrightarrow \boxed{\text{Decoder}} \longrightarrow \text{Text } \boldsymbol{y}$$

where

- Input: A sequence of words $\boldsymbol{x} = (x_1, \cdots, x_m)$, m words
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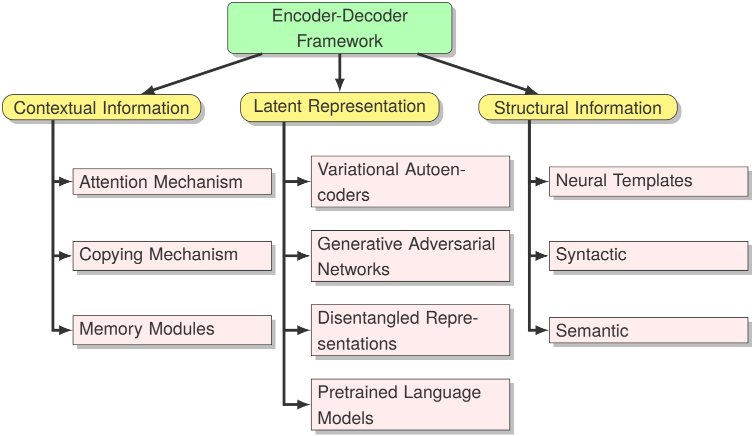
We will try to answer the following three questions with neural network modeling strategies

- How to select *contextual information*?
- How to build better *latent representations*?
- How to incorporate *structural information*?

Roadmap

This part of the tutorial will cover the three major neural network modeling strategies for text generation



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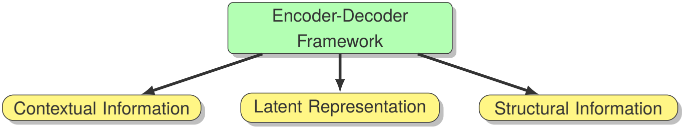
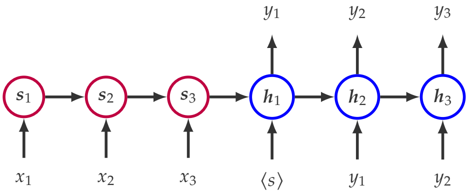


Recurrent Neural Networks as Encoders/Decoders

The simple implementation of the encoder-decoder framework is to realize each component with a recurrent neural network as illustrated in the following



where each $\boldsymbol{s}_{\cdot}/\boldsymbol{h}_{\cdot}$ is a hidden state of the encoder/decoder recurrent neural network.

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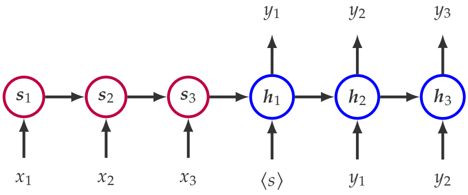

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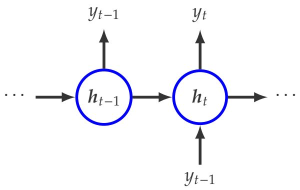
Simple extensions on the encoder side

- Bi-directional RNN
- Stacked LSTM

Recurrent Neural Network Decoder

In general, an decoder can be implemented as an auto-regressive model, with the hidden state computed as

$$\boldsymbol{h}_t = f(\boldsymbol{h}_{t-1}, y_{t-1}) \tag{1}$$



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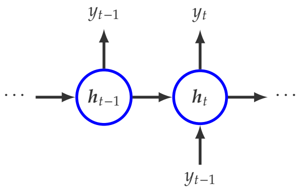

For generation, the probability of the word y_t is computed as

$$p(y) = \text{softmax}(\boldsymbol{W}_o \boldsymbol{h}_t) \tag{2}$$

where $\boldsymbol{W}_o \in \mathbb{R}^{H \times V}$ is a learnable weight matrix for the output layer

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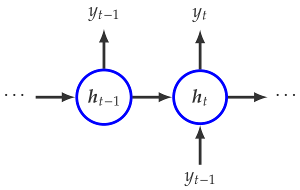

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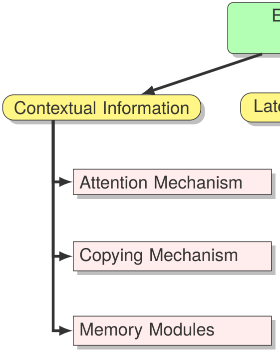
Decoding algorithms will be discussed in the next part of the tutorial.

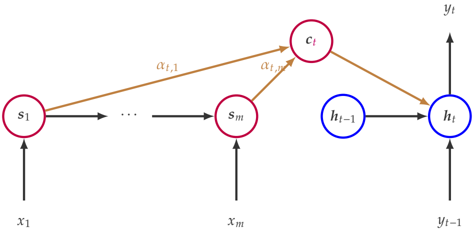
Contextual Information

Roadmap


Encoder-Decoder Framework
Contextual Information
Latent Representation
Structural Information
Attention Mechanism
Copying Mechanism
Memory Modules

Attention Mechanism

Attention mechanism (Bahdanau et al., 2015) provides a way of actively encoding context information from preceding text $\boldsymbol{x} = (x_1, \cdots, x_m)$ via hidden states $(\boldsymbol{s}_1, \ldots, \boldsymbol{s}_m)$



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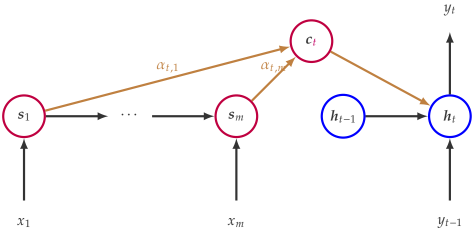

Attention weights

$$\alpha_{t,i} = g(\boldsymbol{s}_i, \boldsymbol{h}_{t-1}) \in (0, 1)$$

$$\boldsymbol{c}_t = \sum_{i=1}^{m} \alpha_{t,i} \cdot \boldsymbol{s}_i$$

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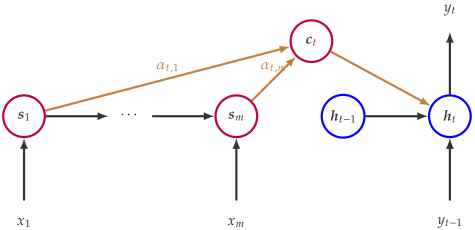

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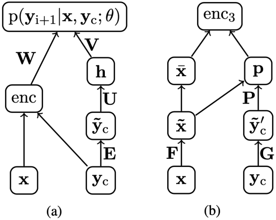
- $\boldsymbol{c}_t$ is a function of $\boldsymbol{h}_{t-1}$, which means it dynamically changes at every time step of decoding
- $\boldsymbol{c}_t$ enables the decoder to be more selective on using contextual information
- Widely used in many text generation tasks: response generation, story generation, and document summarization

Attention Mechanism in FFNs

Rush et al. (2015) use the attention mechanism in a feed-forward neural network for abstractive sentence summarization, where the neural network architecture is constructed as the following



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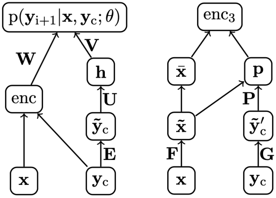


(a) (b)

Diagram (b) represents the attention-based encoder, which use the input x and a fixed context window $y_c = y_{i-c+1:i}$ to compute the attention weights

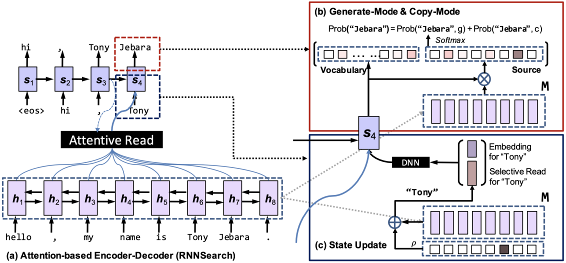
$$\boldsymbol{\alpha} \propto \exp(\tilde{\boldsymbol{x}} \boldsymbol{P} \boldsymbol{y}'_c) \quad \bar{\boldsymbol{x}}_i = \sum_{q=i-Q}^{i+Q} \tilde{\boldsymbol{x}}_i / Q \quad \operatorname{enc}(\boldsymbol{x}, \boldsymbol{y}_c) = \boldsymbol{\alpha}^\top \bar{\boldsymbol{x}} \tag{3}$$

Copying Mechanism: CopyNet

Gu et al. (2016) propose a model called CopyNet to directly copy a phrases from input $\boldsymbol{x}$ to output $\boldsymbol{y}$,

$$p(y_t \mid \boldsymbol{h}_t) = p_g(y_t \mid \boldsymbol{h}_t) + p_c(y_t \mid \boldsymbol{h}_t) \tag{4}$$

where $p_g(y_t \mid \boldsymbol{h}_t)$ is a probability distribution defined on $\mathcal{V}$ and $p_c(y_t \mid \boldsymbol{h}_t)$ is a probability distribution defined only on the input $\boldsymbol{x}$.



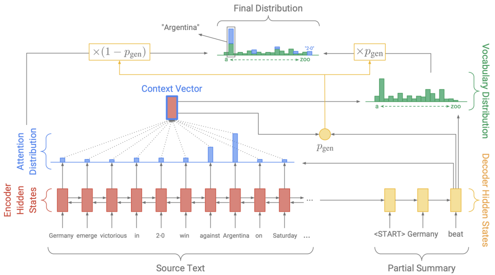
In other words, it defines a mixture model with equal mixture coefficients.

Copying Mechanism: Pointer-Generator Networks

See et al. (2017) propose a similar idea to copy words from input $\boldsymbol{x}$ to output $\boldsymbol{y}$ in text summarization. The probability of $w \in \mathcal{Y}$ being the next word is

$$p(y_t = w \mid \cdot) = \beta p_g(y_t = w \mid \cdot) + (1 - \beta) \sum_{x_i \in \boldsymbol{x}} \delta(w = x_i)\alpha_{t,i} \tag{5}$$

Among the many implementation differences with (Gu et al., 2016), the work uses



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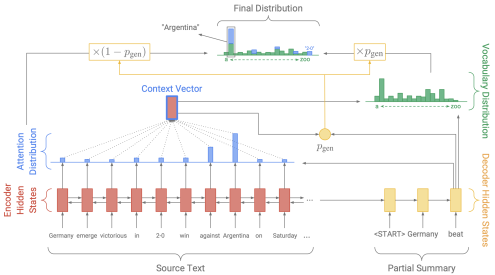

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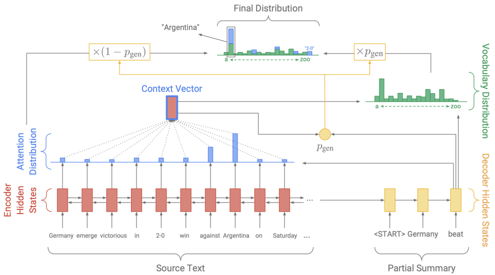
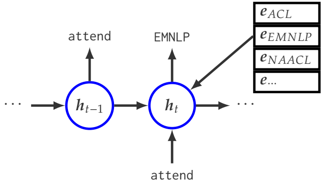
- a soft gate $\beta \in (0,1)$ to decide the probability of generation instead of copying
- the probability of copy a word w is defined by the attention weights associated with it



Memory Modules

One example is proposed in (Clark et al., 2018) for entity-driven text (story) generation, where each memory cell is associated with a particular entity, to encode entity related information from context



where $e_{\cdot}$ is a distributed representation of an entity

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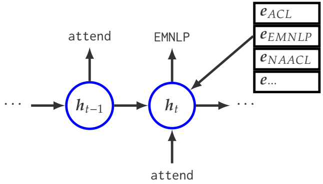

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- Entity prediction $p(e = \mathsf{EMNLP}) \propto \exp(h_{t-1}^{\top} W_e e_{\mathsf{EMNLP}} + w_f f(e))$, where f is the surface feature related to this entity (Ji et al., 2017).

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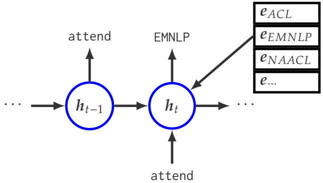

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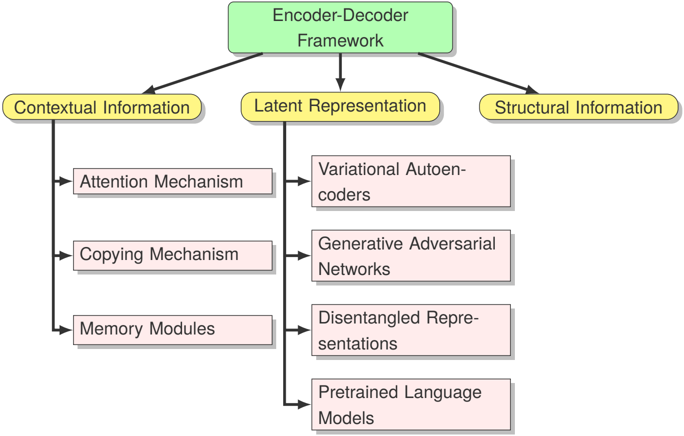
- Dynamic entity updating $\boldsymbol{e}_{\mathsf{EMNLP}}^{(\text{new})} \propto \delta_t \boldsymbol{e}_{\mathsf{EMNLP}}^{(\text{new})} + (1 - \delta_t)\boldsymbol{h}_t$, where $\delta_t \in (0, 1)$ determines how much information should be encoded from $\boldsymbol{e}_{\mathsf{EMNLP}}^{(\text{new})}$.

Latent Representation

Roadmap



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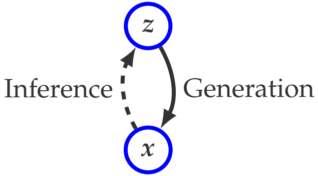
Variational Autoencoders in NLG

One-page summary of variational autoencoder (Kingma and Welling, 2014)



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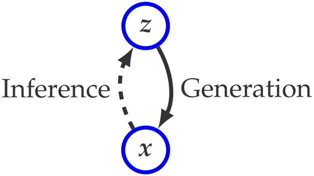

A formulation of variational autoencoders for text generation

$$\begin{aligned} \boldsymbol{h} &= \text{Encoder}(\boldsymbol{x}) && (6) \\ \boldsymbol{z} &= \boldsymbol{h} + \boldsymbol{\epsilon} \quad \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \text{diag}(\boldsymbol{\sigma}^2)) && (7) \\ \tilde{\boldsymbol{x}} &= \text{Decoder}(\boldsymbol{z}) && (8) \end{aligned}$$

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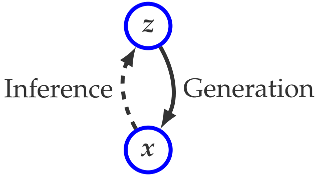

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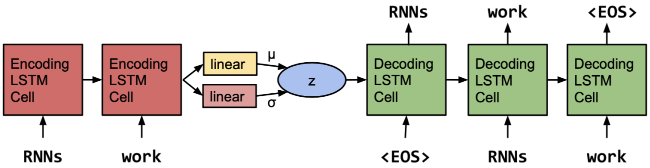
An impact of using VAE is that it (1) produces a robust encoder for input $\boldsymbol{x}$ and (2) enriches the hidden space $\mathcal{H}$.

Variational Seq2seq Models

An example application of variational autoencoder in language generation



(Bowman et al., 2016)

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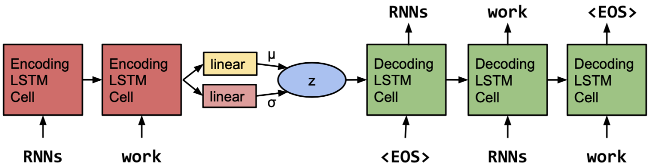

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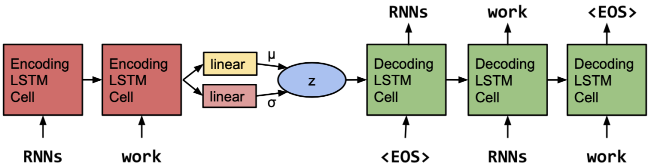
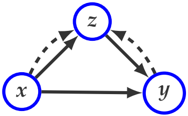


- The mean and variance of latent variable z is computed by the linear transformations of the last hidden states from the RNN encoder s_m
- Other influential ideas from this work are *KL cost annealing* and *adversarial evaluation*

(Bowman et al., 2016)

Conditional VAE

A simple formulation of conditional VAE is proposed by Sohn et al. (2015), which initially was used in computer vision.

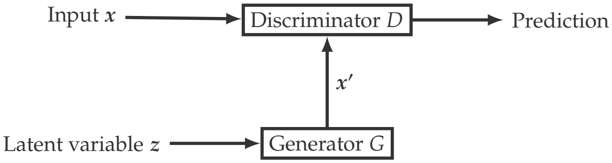


In text generation, consider $\boldsymbol{x}$, $\boldsymbol{y}$ and $\boldsymbol{z}$ are input texts, output texts, and latent representations of input texts

- Generation network: $p_\theta(\boldsymbol{y} \mid \boldsymbol{x}, \boldsymbol{z})$, where $\boldsymbol{z} \sim p_\theta(\boldsymbol{z} \mid \boldsymbol{x})$
- Inference network: $q_\phi(\boldsymbol{z} \mid \boldsymbol{x}, \boldsymbol{y})$
- *Example applications*: in response generation, latent variable $\boldsymbol{z}$ indicates whether the next utterance is a generic response (Shen et al., 2017)

Generative Adversarial Networks

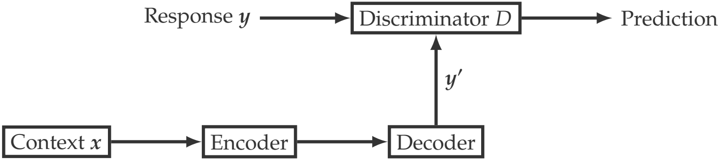
The basic pipeline of GAN is described in the following pipeline



- One goal is to learn a generator G that can generate text x' with the same quality as x (in other words, to "fool" the discriminator)
- Potential applications are to adopt the framework as one component in other task-specific generation tasks (e.g., style transfer)

GANs for Generation

As a straightforward application of adversarial learning is to replace the generator with a sequence-to-sequence model as we discussed before, as proposed by Li et al. (2017)



- The decoder is to generate a response $\boldsymbol{y}'$ based on input context $\boldsymbol{x}$
- The discriminator is to predict whether a response is generated by humans or the decoder

Learning Disentangled Representations

One way to utilize a discriminator is to learn disentangled representations and make sure latent representations encoding the *expected attributes* for generation.

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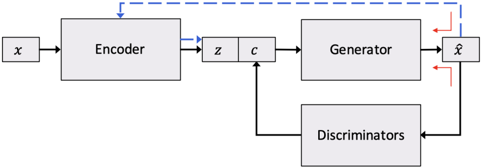
An example of learning disentangled representations is proposed by Hu et al. (2017), with

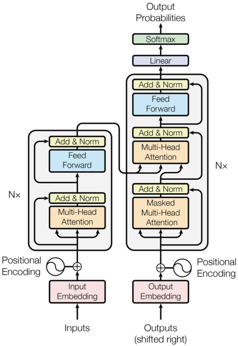
- Encoder
  $(z) = \text{Encoder}(x)$
- Decoder
  $\hat{x} = \text{Decoder}(z, c)$
- Discriminator
  $c = \text{Dis}(\hat{x})$



where c encodes the attributes of a text (e.g., sentiment categories, formality). Other work on learning disentangled representations include (Bao et al., 2019; Cheng et al., 2020)

Transformers

Vaswani et al. (2017): *"Attention mechanism . . . , allowing modeling of dependencies without regard to their distance in the input or output sequences."*



Recent applications of transformers simply use them as basic building blocks, just like the way of using LSTM

Generative Pre-trained Transformers (GPT)

GPT (Radford et al., 2018) is trained simply by predicting the next words with

$$\begin{aligned} \boldsymbol{h}_0 &= \boldsymbol{W}_e \boldsymbol{x}_{t-k:t-1} + \boldsymbol{W}_p \\ \boldsymbol{h}_l &= \text{transformer\_block}(\boldsymbol{h}_{l-1}) \; \forall l \in [1, 12] \\ p(y_t \mid \boldsymbol{h}_n) &= \text{softmax}\,(\boldsymbol{W}_o \boldsymbol{h}_n) \end{aligned} \tag{9}$$

where $\boldsymbol{W}_e$ and $\boldsymbol{W}_p$ are the word and position embeddings.

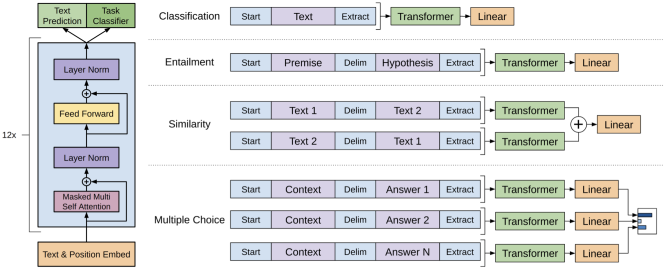
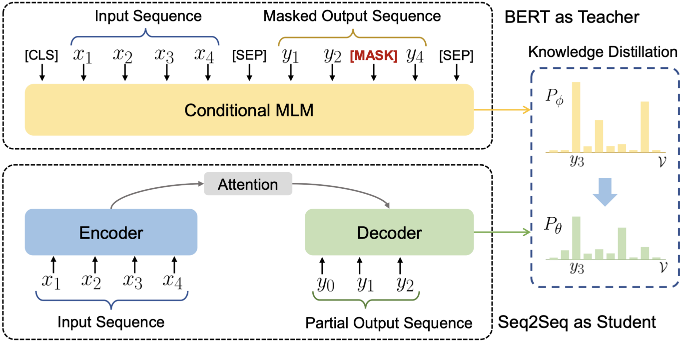


Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

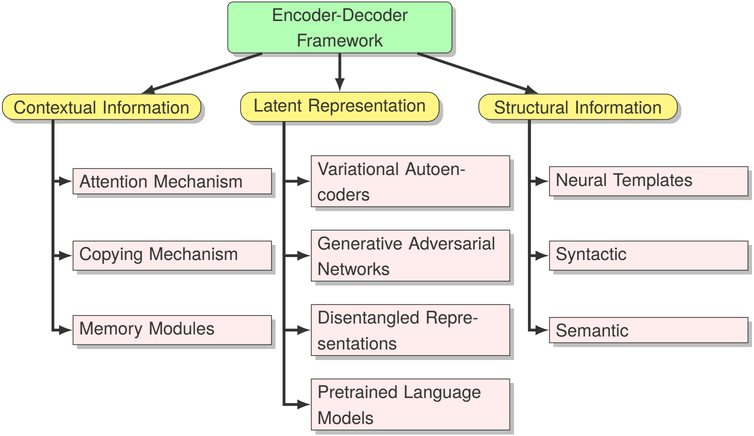
Pre-trained Models as Teachers

Besides the generative models like GPT-2 and its variants, we can also use BERT for text generation. One example from (Chen et al., 2020b) is that BERT can be used as a teacher model to help train a sequence-to-sequence models for better output probability



Structural Information

Roadmap



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Neural Templates
Syntactic
Semantic

Generation with Neural Templates

An extension of variational antoencoders is to incorporate sequential information in latent variables. For example, Wiseman et al. (2018) propose a semi-Markov model on the latent variable sequence $\boldsymbol{z} = (z_1, \ldots, z_n)$ to capture dependency among adjacent words for text-to-data generation.

Source Entity: Cotto

type[coffee shop], rating[3 out of 5], food[English], area[city centre], price[moderate], near[The Portland Arms]

System Generation:

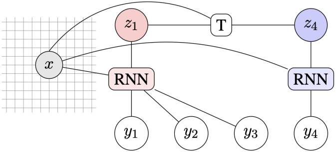
Cotto is a coffee shop serving English food in the moderate price range. It is located near The Portland Arms. Its customer rating is 3 out of 5.

Neural Template:

| The ___ / ___ / ... | is a / is an / is an expensive / ... | ___ | providing / serving / offering / ... | ___ |

| food / cuisine / foods / ... | in the / with a / and has a / ... | ___ | price range / price bracket / pricing / ... | . | It's / It is / The place is / ... |

| located in the / located near / near / ... | ___ | . | Its customer rating is / Their customer rating is / Customers have rated it / ... | ___ | .

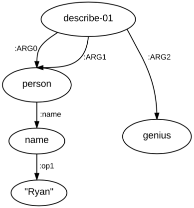


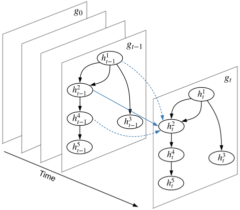
A neural hidden semi-Markov model decoder

- Transition distribution $p(z_{t+1} \mid z_t, \boldsymbol{x})$
- Length distribution $p(l_{t+1} \mid z_{t+1})$
- Emission distribution $p(\boldsymbol{y}_{t-l_t+1:t} \mid z_t = k, l_t = l, \boldsymbol{x})$

Graph-to-Sequence Generation

An example of inputs is an AMR graph, where the task is to generate a text with the same meaning as the input graph.





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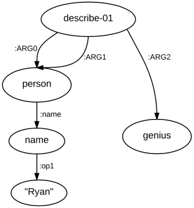

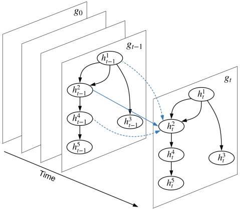

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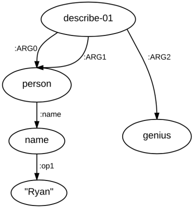

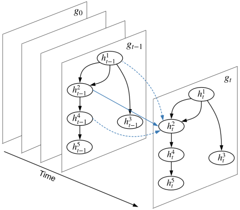

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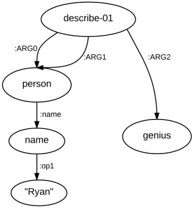

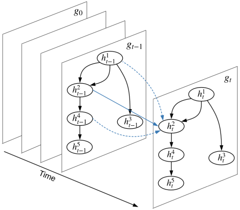

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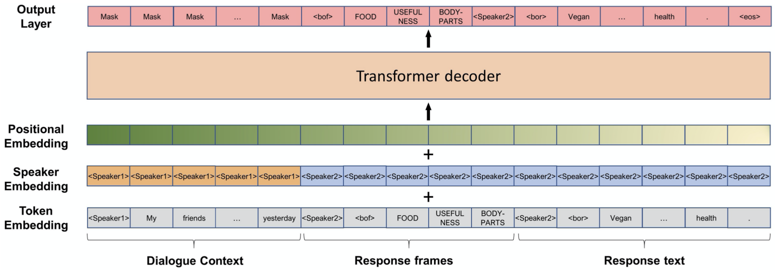
- Other ideas of incorporating AMR graphs: Graph neural network (Chen et al., 2020a)

Dialogue Generation with Semantic Exemplars

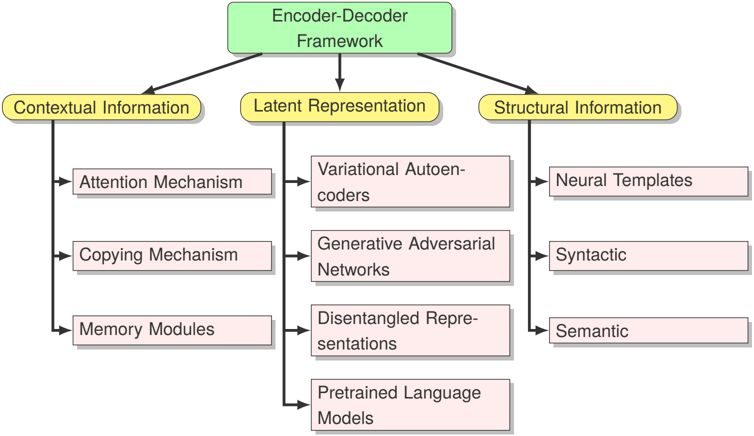
A straightforward application of GPT is the response generation proposed by Gupta et al. (2020). The prediction is still done by word-by-word prediction, where the input sequence and output sequence are [1]

$$\begin{aligned} x &= (\text{Dialogue context}, \text{Response frames}, \text{Response text}) \\ y &= (\langle \text{MASK} \rangle, \text{Response frames}, \text{Response text}) \end{aligned} \tag{10}$$

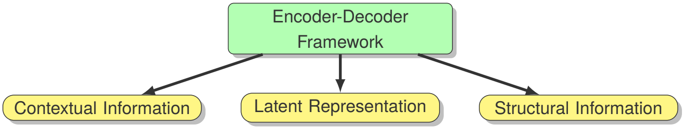


[1] A semantic frame example Perception: `hear, say, see, smell, feel`

Summary


Encoder-Decoder Framework
Contextual Information
Latent Representation
Structural Information
Attention Mechanism
Copying Mechanism
Memory Modules
Variational Autoencoders
Generative Adversarial Networks
Disentangled Representations
Pretrained Language Models
Neural Templates
Syntactic
Semantic

Summary


Encoder-Decoder Framework
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