Generation based Conversational AI

An Introduction

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Outline

- Introduction
- Building a Conversational Agent
- Summary

Two Main Types of Dialogue Systems

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How is the weather today?

Right now is 21 degrees with cloudy.

Is it good to go out for dinner at 6 pm?

Absolutely, the sky will be clear by 6.

Ok. Then please book me a table for 2 at Sushi Bar at 6 pm

Confirm a table for 2 at 6 pm. Anything else?

That's it. Thanks.

Happy to help

Information consumption

Decision Support

Task completion

[Fung et al., 2020]

Task-oriented conversations

help users achieve some goals/tasks

complete requests with **least turns**

Open-domain chit chat

free-form, open-domain

engage users for long conversations

Conversational AI Applications

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Happy to help

- Lots of applications
  - Personal assistants [Siri, Google, Alexa, Cortana, etc.]
  - Education [Kerry et al., 2008, Mesgar et al., 2019]
  - Health care: therapy chatbot [Fitzpatrick et al., 2017]
  - Customer service: [Cui et al., 2017]
  - ...

Challenges of Generation Dialogue Systems

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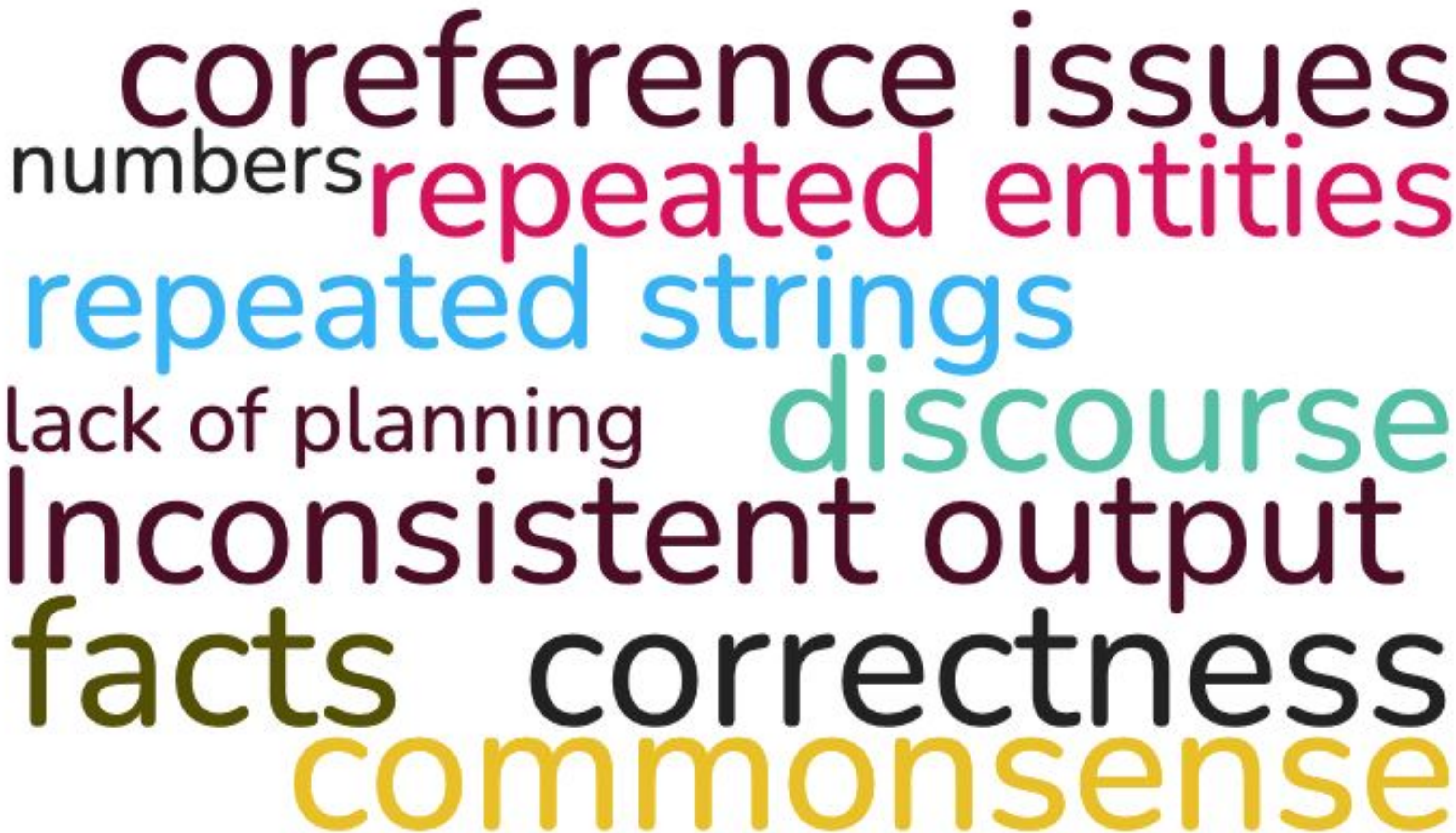

Building a Conversational Agent

4-step recipe
[Fung et al., 2020]

1. Data
2. Model
3. Training
4. Evaluation

Building a Conversational Agent

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Types of Conversational Corpora

- Machine to machine
  - Generated from dialog templates
  - Issues: data quality, naturalness, noises
- Human to machine (MultiWOZ, DSTC)
  - Collected from existing dialog systems
  - Issues: limited domains, biases, noises
- Human to human (Twitter, Reddit, OpenSubtitles, Persona Chat,)
  - Twitter, Reddit, etc.
  - Customer service
  - Issues: small size, limited domains

Some Terms

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4-step recipe
[Fung et al., 2020]

1. Data
2. Model
3. Training
4. Evaluation

Dialogue history

How is the weather today?

Right now is 21 degrees with cloudy.

Is it good to go out for dinner at 6 pm?

Absolutely, the sky will be clear by 6.

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Confirm a table for 2 at 6 pm. Anything else?

That's it. Thanks.

Happy to help

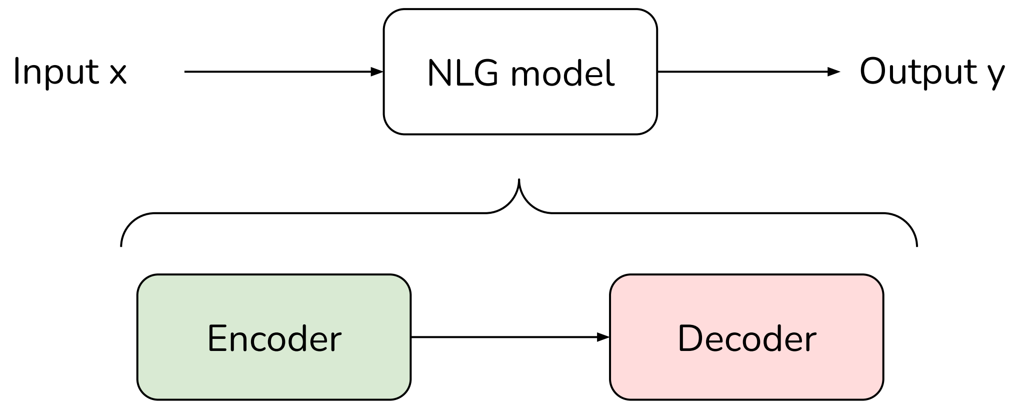
Utterance

Response

Basic Architecture of Generation based Conversational Models

4-step recipe

1. Data
2. Model
3. Training
4. Evaluation

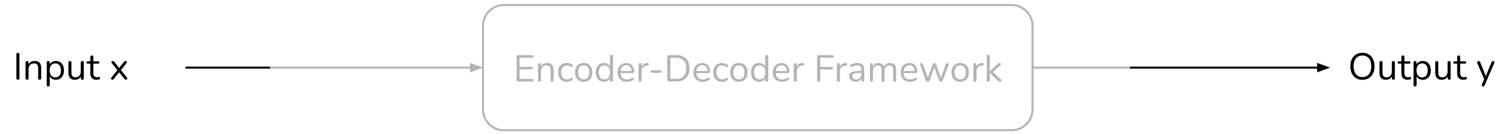


Understanding input (natural language understanding)

Generating the output based on

- the input
- target task

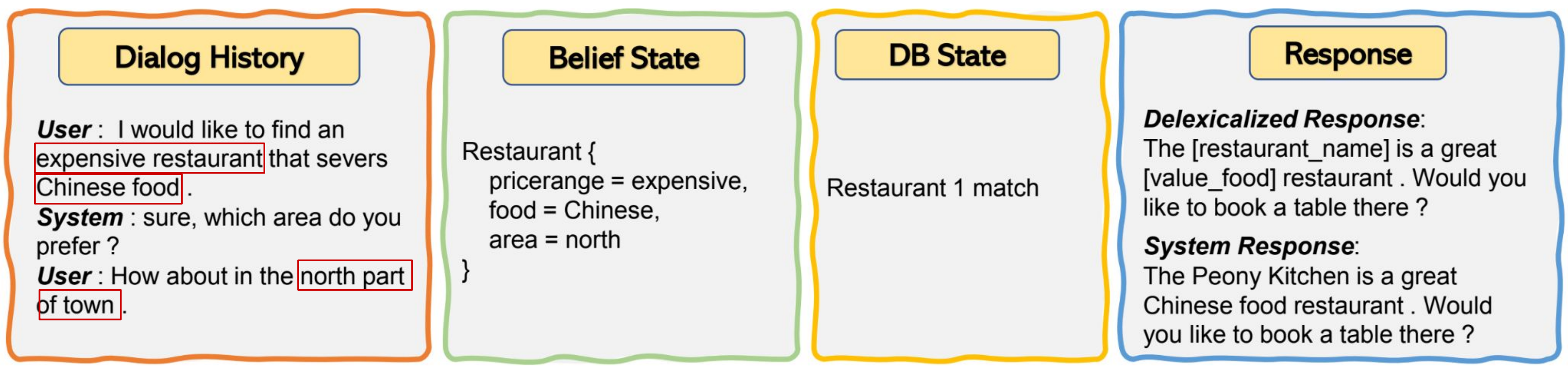
Input and Output



- Open-domain chit chat
  - Input
    - Dialogue history
  - Output
    - Response
- Task-oriented dialogs
  - Input
    - Dialogue history
    - Belief state
    - Database/API results (state)
  - Output
    - Response
    - Belief state
    - Database query
    - API Service

Input and Output: Task Oriented Dialogue Systems

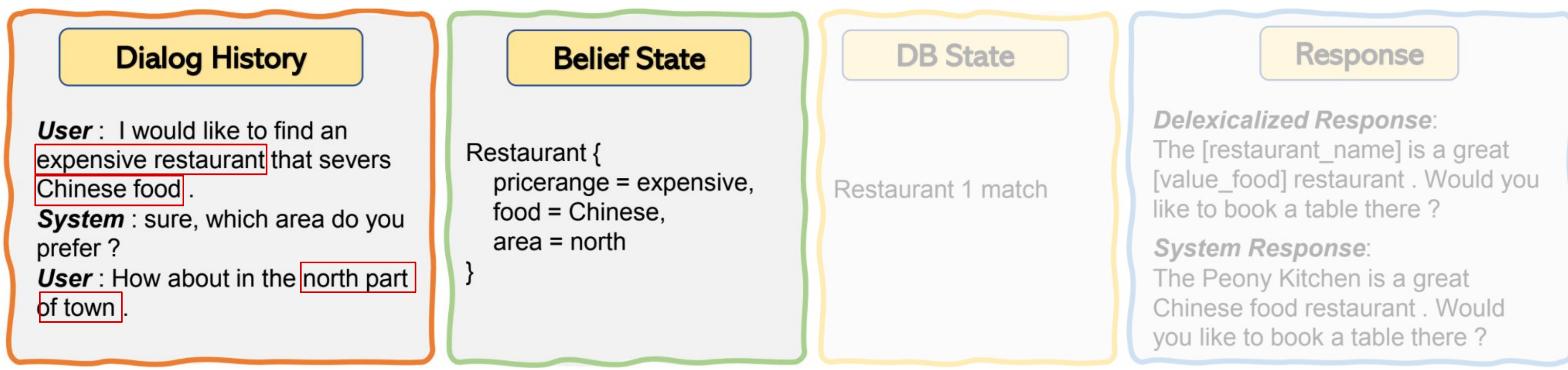
Each input/output is by itself a sequence of tokens



[Peng et al., 2020]

Input and Output: Task Oriented Dialogue Systems

Each input/output is by itself a sequence of tokens



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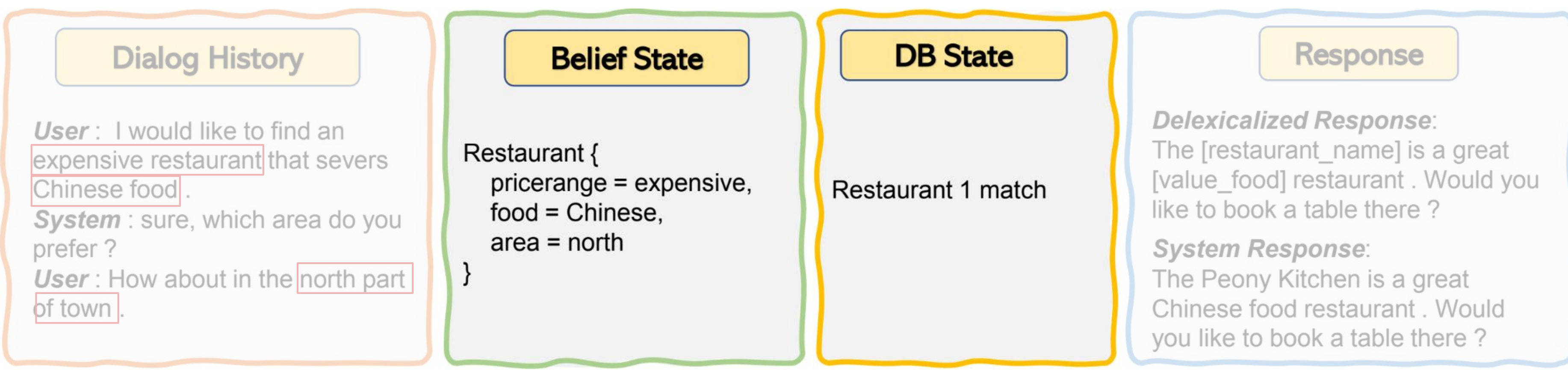
[Peng et al., 2020]

Input and Output: Task Oriented Dialogue Systems

Each input/output is by itself a sequence of tokens



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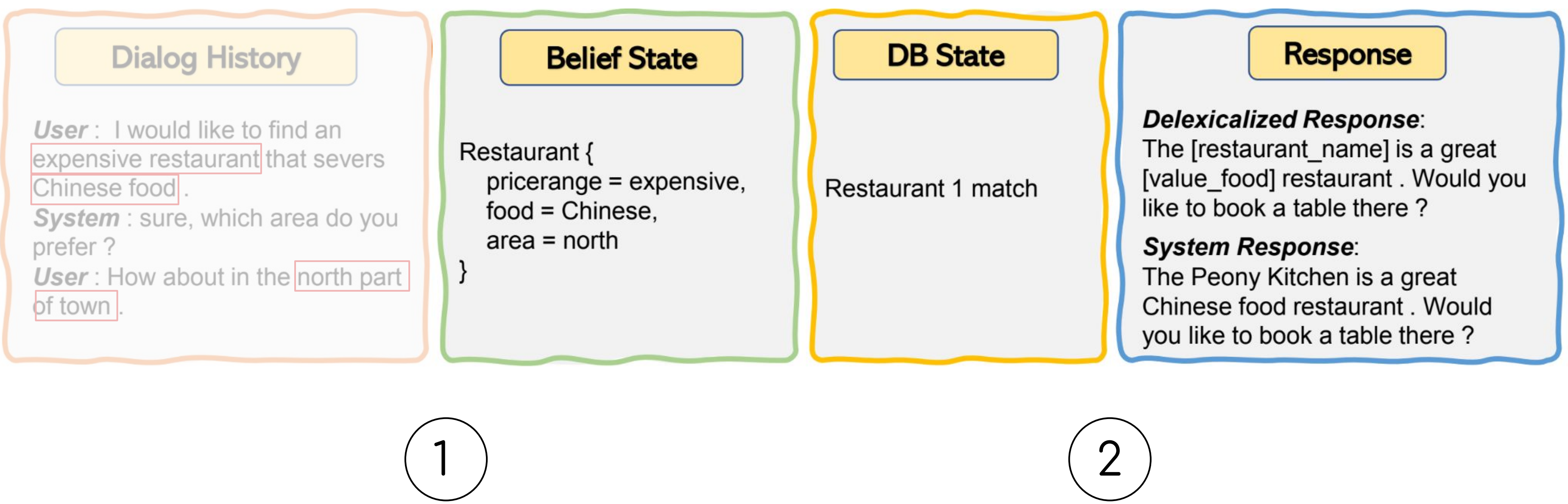
- 0 match
- >1 match

[Peng et al., 2020]

Input and Output: Task Oriented Dialogue Systems

Each input/output is by itself a sequence of tokens

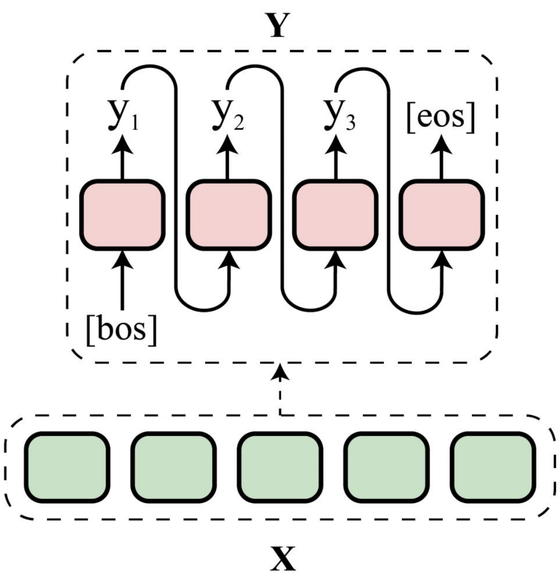


2.1 system action

[Peng et al., 2020]

Encoder-Decoder

Input x → Encoder-Decoder Framework → Output y



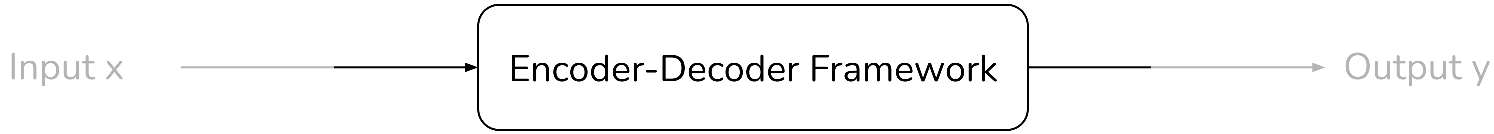
Autoregressive Generation [AG]

Issue with AG

- Error accumulation
  - worse generation at one step → even worse at following steps

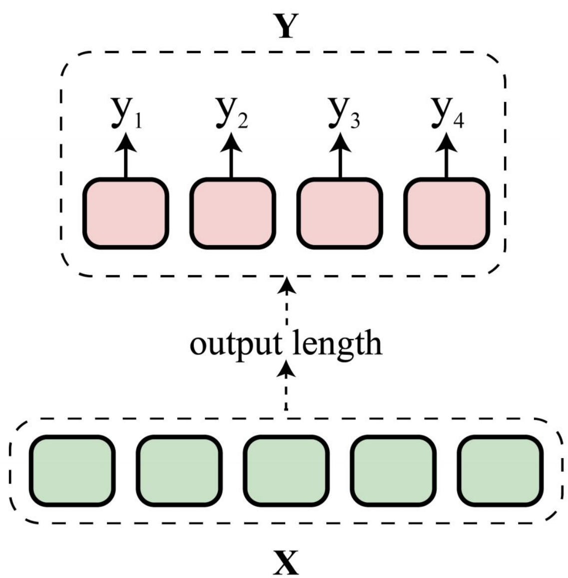
[Su et al., 2021]

Encoder-Decoder



Issues with NAG

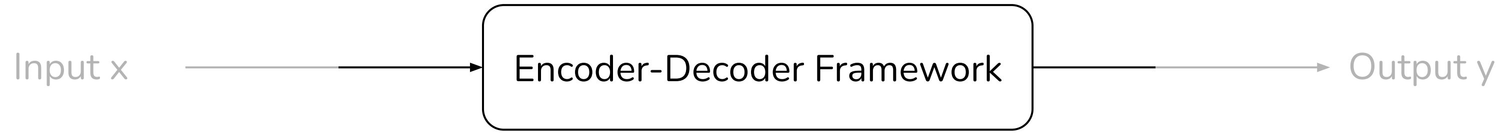
- Need to know target sequence length to generate all words in parallel
- Token repetition: conditional independence
  → repeat high probability tokens

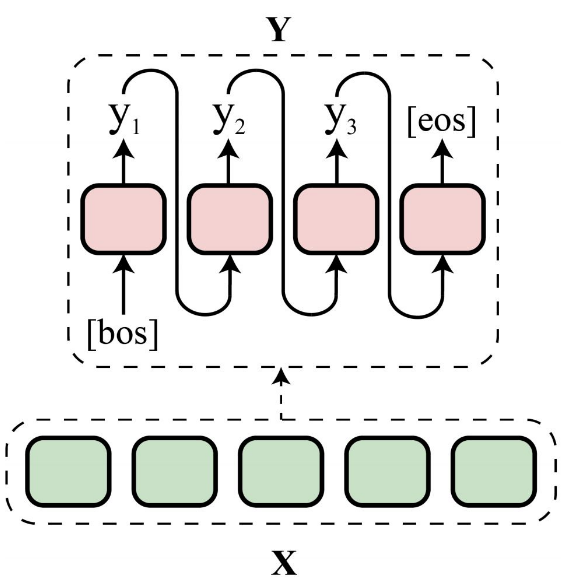


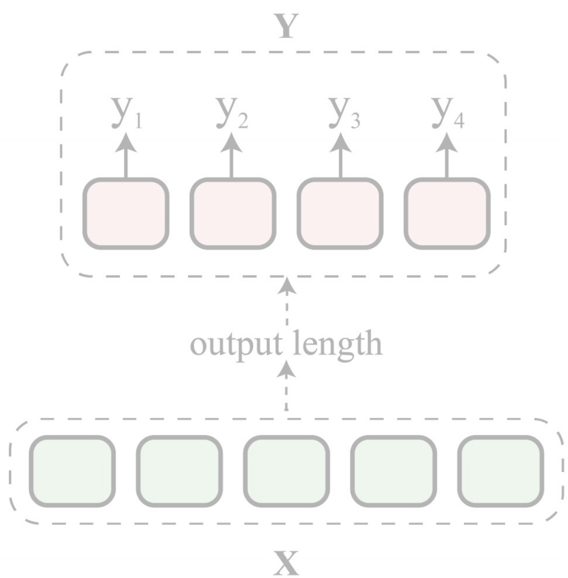
Non-Autoregressive Generation [NAG]

[Su et al., 2021]

Encoder-Decoder







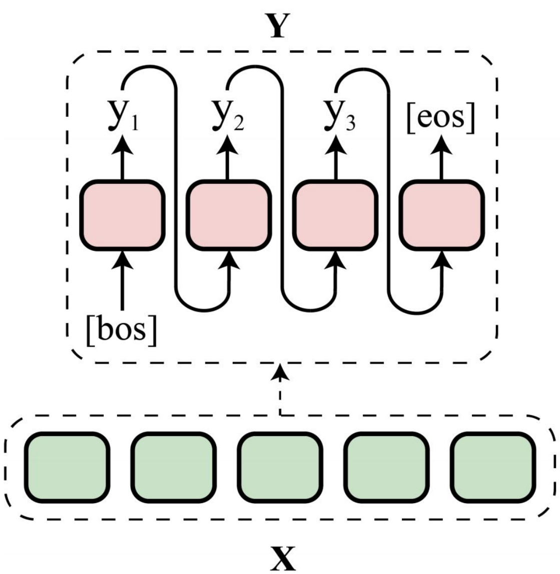
Autoregressive Generation [AG]

Non-Autoregressive Generation [NAG]

[Su et al., 2021]

Output Generation

Input x → Encoder-Decoder Framework → Output y



Autoregressive Generation [AG]

[Su et al., 2021]

- Starts with [bos] (begin-of-sequence)
- At each step
  - take previous generated token
  - generate a distribution over the vocabulary
- Stops by [eos] (end-of-sequence)
  - Terminate when [eos] is predicted
  - Stop when max target sequence length is reached

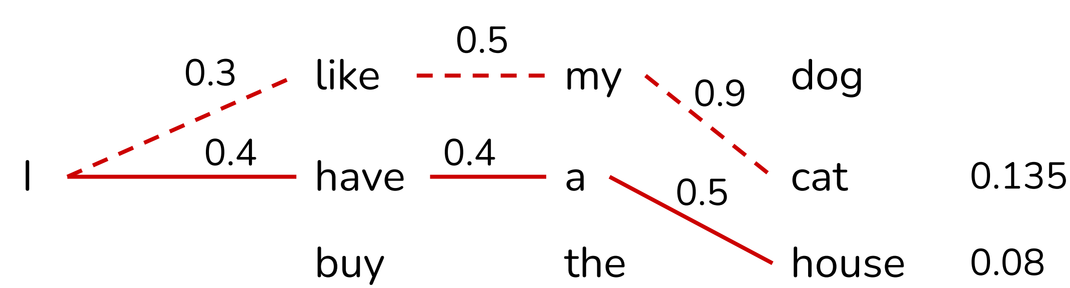
Output Generation: Decoding Strategies

	Greedy	Beam Search	Top-k Sampling	Top-p (Nucleus) Sampling
At each step	Pick the best word	Try a few best words	Random sample from top-k	smallest set with cumulative probability > p
Output	One sequence	Several partial sequences	One sequence	One sequence

Output Generation: Greedy Decoding

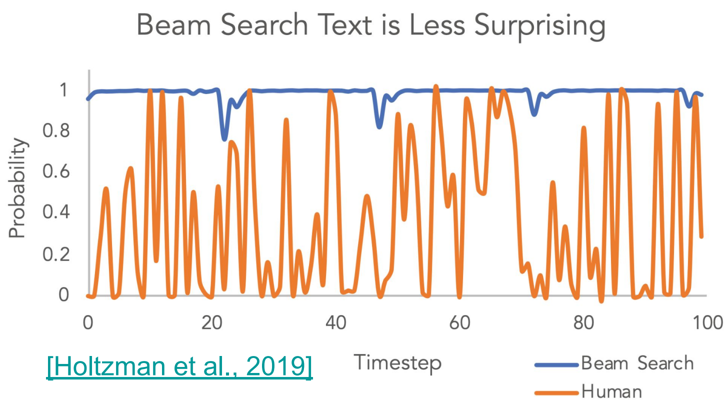
	Greedy	Beam Search	Top-k Sampling	Top-p (Nucleus) Sampling
At each step	Pick the best word	Try a few best words	Random sample from top-k	smallest set with cumulative probability > p
Output	One sequence	Several partial sequences	One sequence	One sequence

Weakness
Repetition as always select the most frequent token



Output Generation: Beam Search

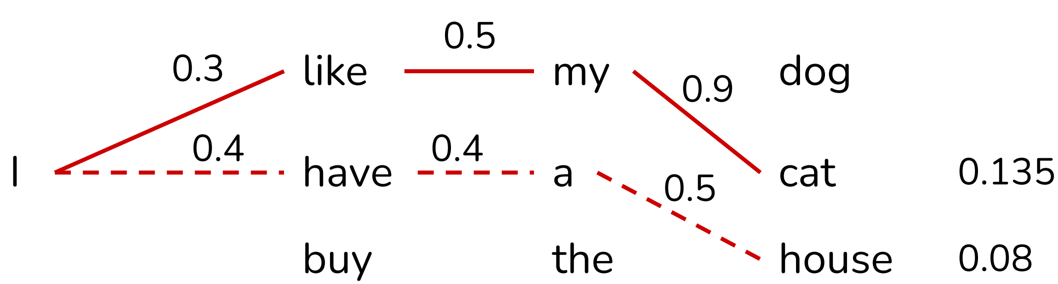
Greedy	Beam Search	Top-k Sampling	Top-p (Nucleus) Sampling
	Try a few best words	Random sample from top-k	smallest set with cumulative probability > p
	Several partial sequences	One sequence	One sequence



[Holtzman et al., 2019]

Common beam: 5 or 10

Weakness
Short sentences
Less diversity

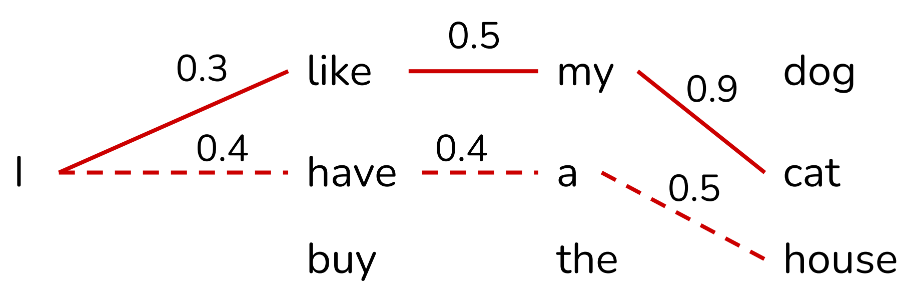


Output Generation: Top-k Sampling

	Greedy	Beam Search	Top-k Sampling	Top-p (Nucleus) Sampling
At each step	Pick the best word	Try a few best words	Random sample from top-k	smallest set with cumulative probability > p
Output	One sequence	Several partial sequences	One sequence	One sequence

Common k: 5, 10, 20

Note
k=1 → Greedy algorithm
↑k → more diverse/risky
↓k → more generic/safe



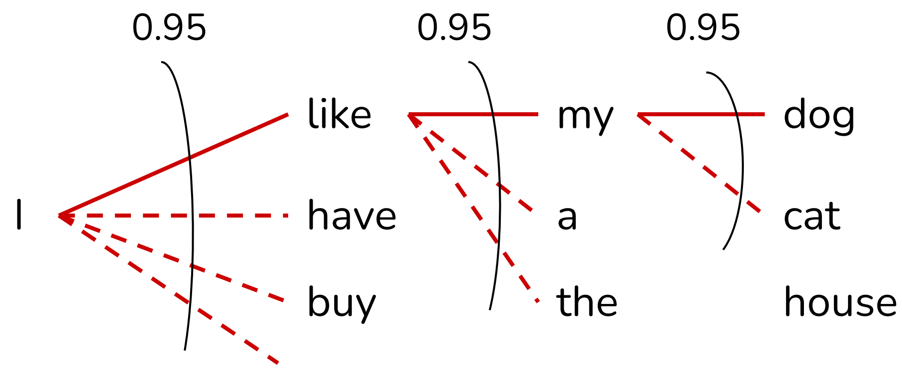
[Holtzman et al., 2019]

Output Generation: Top-p (Nucleus) Sampling

	Greedy	Beam Search	Top-k Sampling	**Top-p (Nucleus) Sampling**
At each step	Pick the best word	Try a few best words	Random sample from top-k	smallest set with cumulative probability > p
Output	One sequence	Several partial sequences	One sequence	One sequence

Common p: 0.95

Weakness
May not include surprising words



[Holtzman et al., 2019]

Output Generation: Decoding Strategies

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	Greedy	Beam Search	Top-k Sampling	Top-p (Nucleus) Sampling
At each step	Pick the best word	Try a few best words	Random sample from top-k	smallest set with cumulative probability > p
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Training

4-step recipe
[Fung et al., 2020]

1. Data
2. Model
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- Teacher forcing: Maximum Likelihood Estimation (MLE)
    - Maximize the conditional probability of target sequence
- Unlikelihood training [Welleck et al., 2020]
    - Minimize likelihood of undesired tokens

What makes a good conversation ?

Human judgment of conversational aspects

Avoiding Repetition	internal repetition; repetition across responses; partner repetition
Interestingness	interesting response: knowledge, engagingness
Making sense	coherent response
Fluency	grammatically correct
Listening	response related to user's utterance
Inquisitiveness	response and ask information about user

[See et al., 2019]

Some Methods to Make a Good Conversation

Input x → Encoder-Decoder Framework → Output y

- Large pretrained models: BART, T5, GPT-1/2/3
  → more **fluent** & **diverse response** thanks to large scale pretraining

- Decoding strategies
  - Top-k sampling, top-p (nucleus) sampling
    → reduce repetition
  - Guided decoding

- Input modification
  - Integrating attribute description

- Type embeddings
  - Using learned attribute embeddings

- Reinforcement learning

Large Scale Pretraining

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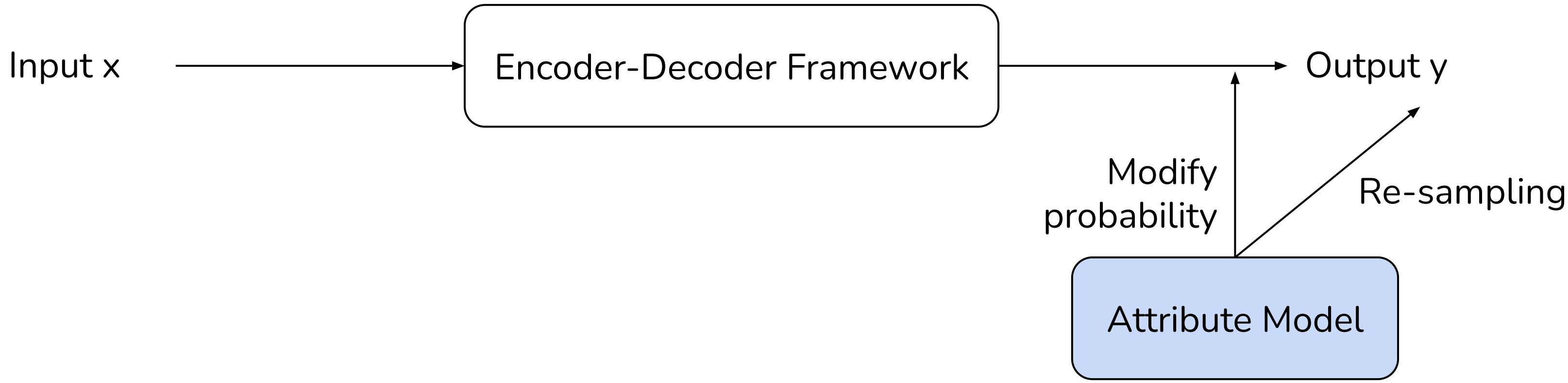
Input x → Encoder-Decoder Framework → Output y

Large pretrained models: BART, T5, GPT-1/2/3 → proposed for general text generation

PLATO	DialoGPT	Meena	BlenderBot	TOD-BERT
Twitter, Reddit (En)	Reddit (En)	public domain social media conversations (En)	Reddit discussions (En)	9 task-oriented datasets (En)
BERT	GPT-2	Evolved Transformer	Poly-encoder Transformer + Seq2seq	BERT
- Response generation - Latent act recognition	- Response generation - Maximum Mutual Information	- Minimize perplexity of next token	- Masked LM - Ranking for retrieval - Response generation - Retrieve & refine - Unlikelihood training	- Masked LM - Response contrastive loss

Guided Decoding



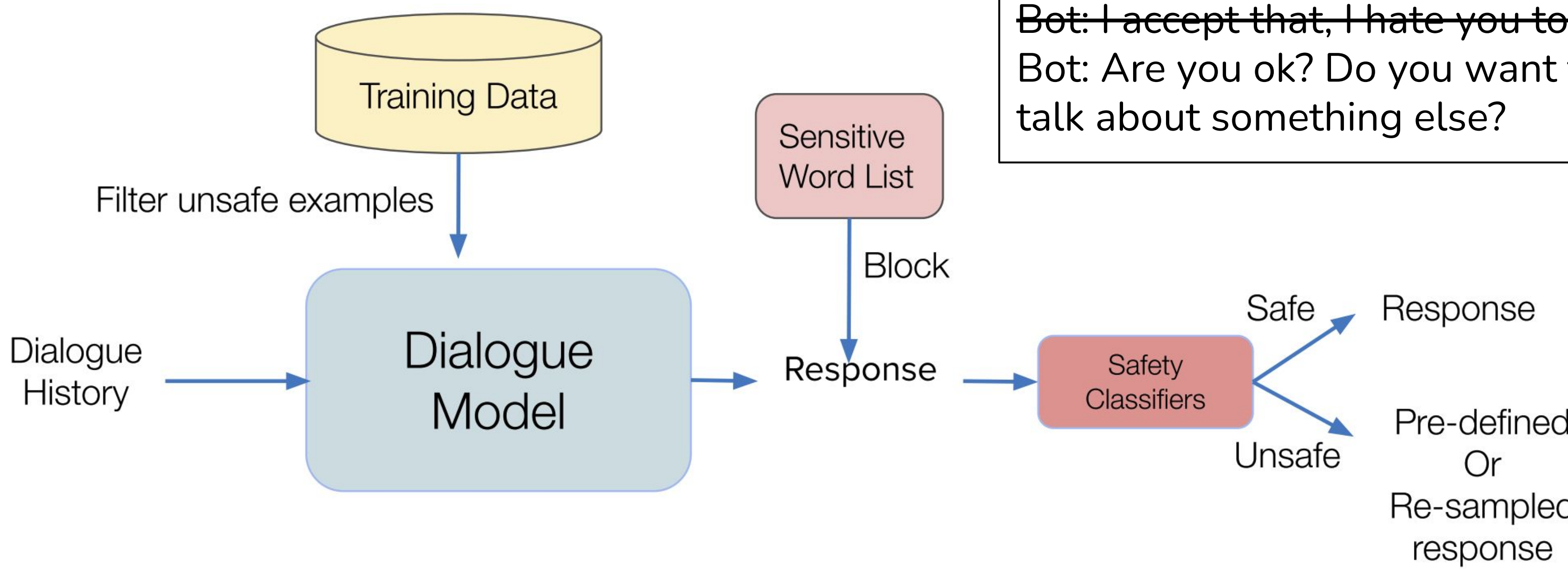
1. Define an attribute model to score the generated sequence
2. Guide the decoding process
    - Re-sampling if not satisfy attribute guide
    - Modify the probability distribution with attribute scores [Madotto et al., 2020]

Guided Decoding

[Safety in Open-domain chatbots](#)

Dialogue systems trained on large scale data may inherit biases from such data
→ may produce toxic, harmful and biased responses
→ bring bad experience to user

Human: I hate everyone. Acceptable?
~~Bot: I accept that, I hate you too.~~
Bot: Are you ok? Do you want to talk about something else?



[Fung et al., 2020]

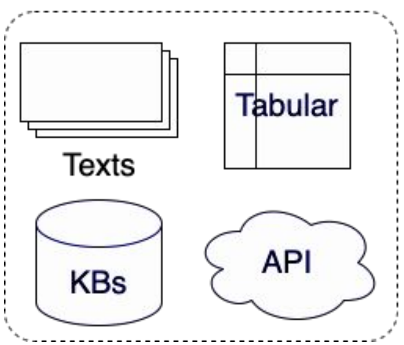
Input Modification

Input x → Encoder-Decoder Framework → Output y

+
Attribute description

E.g., Dialog history + [positive]; [sad] + Dialog history

Knowledge

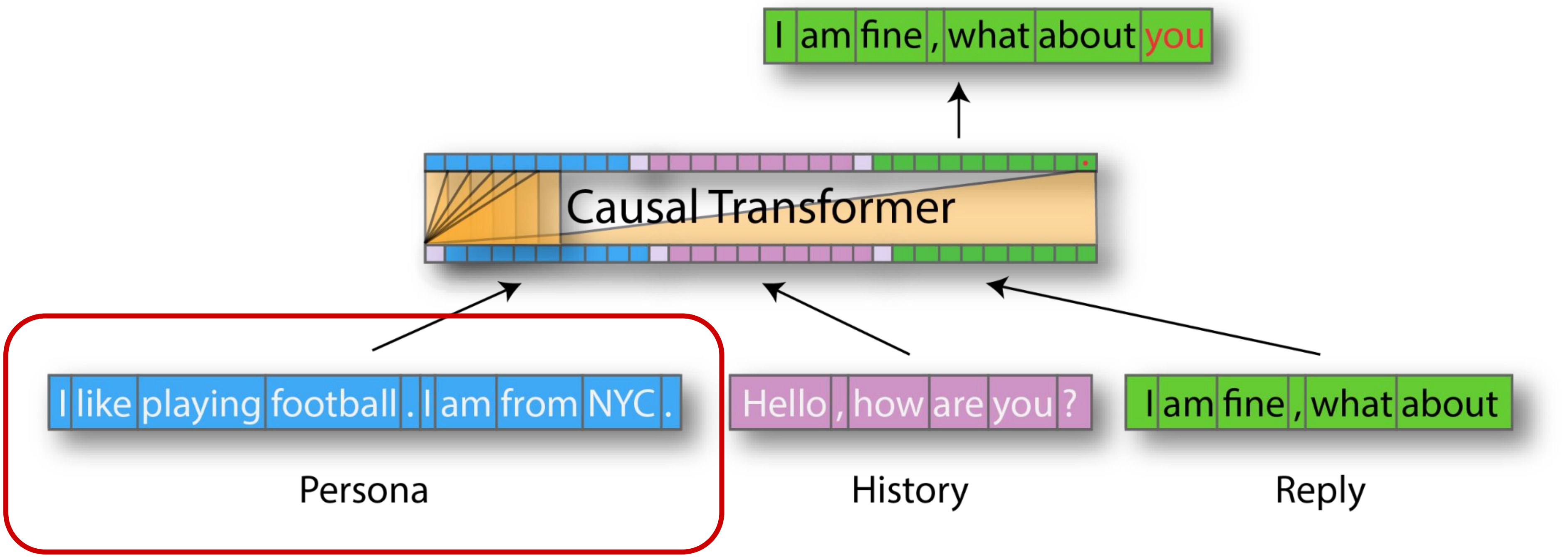


- Retrieval methods:
    - IR systems (TF-IDF, BM25)
    - Neural retriever: dense vectors
    - Generating API query
- Knowledge to text → add to input

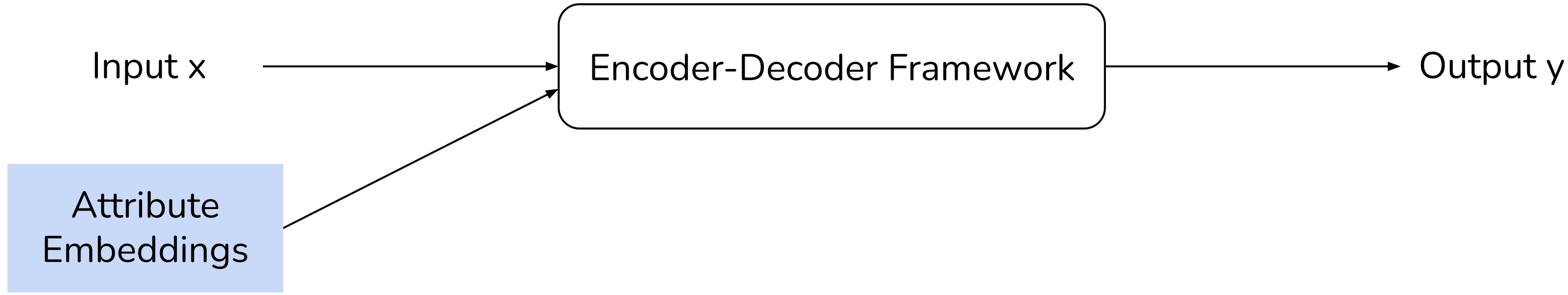
  E.g., “Input” + [restaurant] Sushi Bar

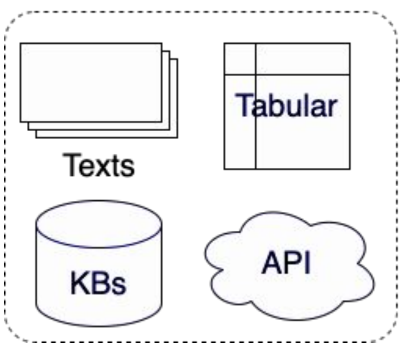
Input Modification

Personalization: TransferTransfo Model



Attribute Embeddings

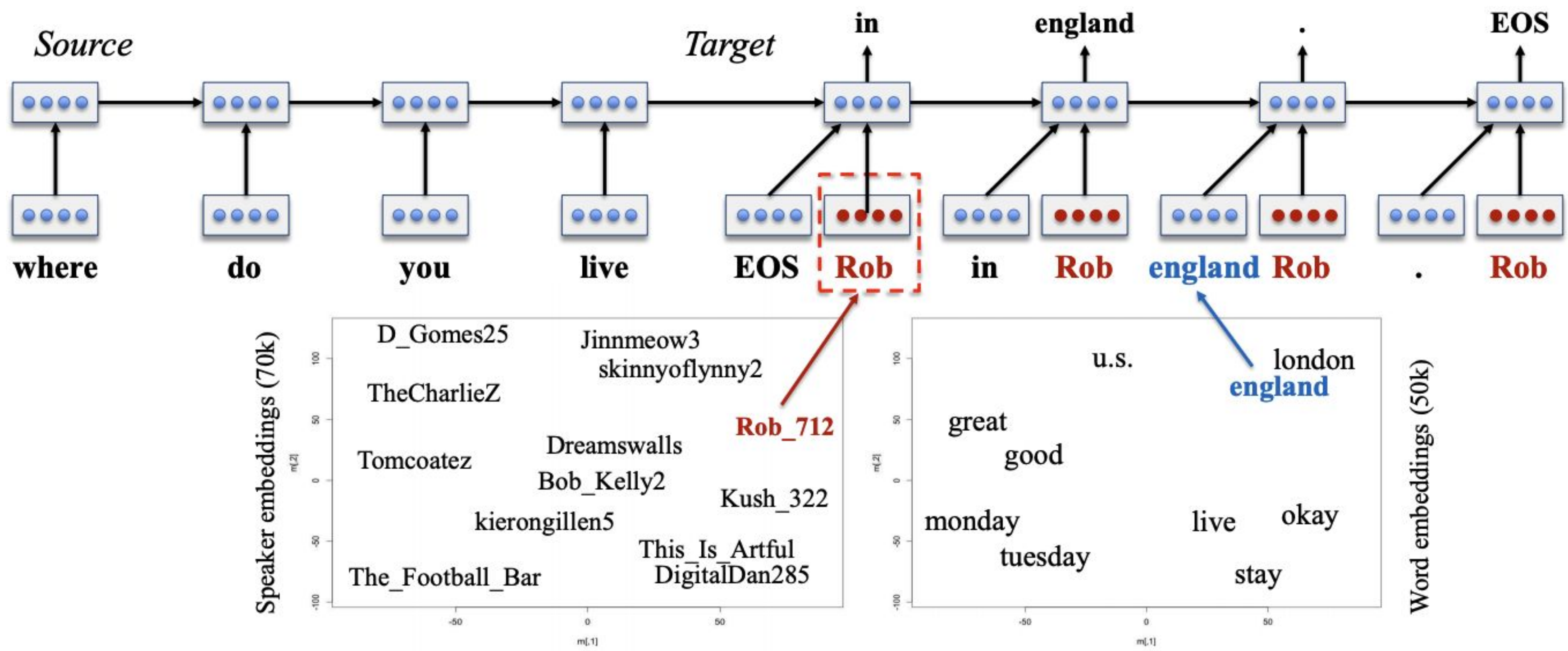




- Embeddings of the target attributes
    - Learned during training the conversational model
    - Obtained from additional methods such as clustering, link prediction for knowledge base integration

Attribute Embeddings

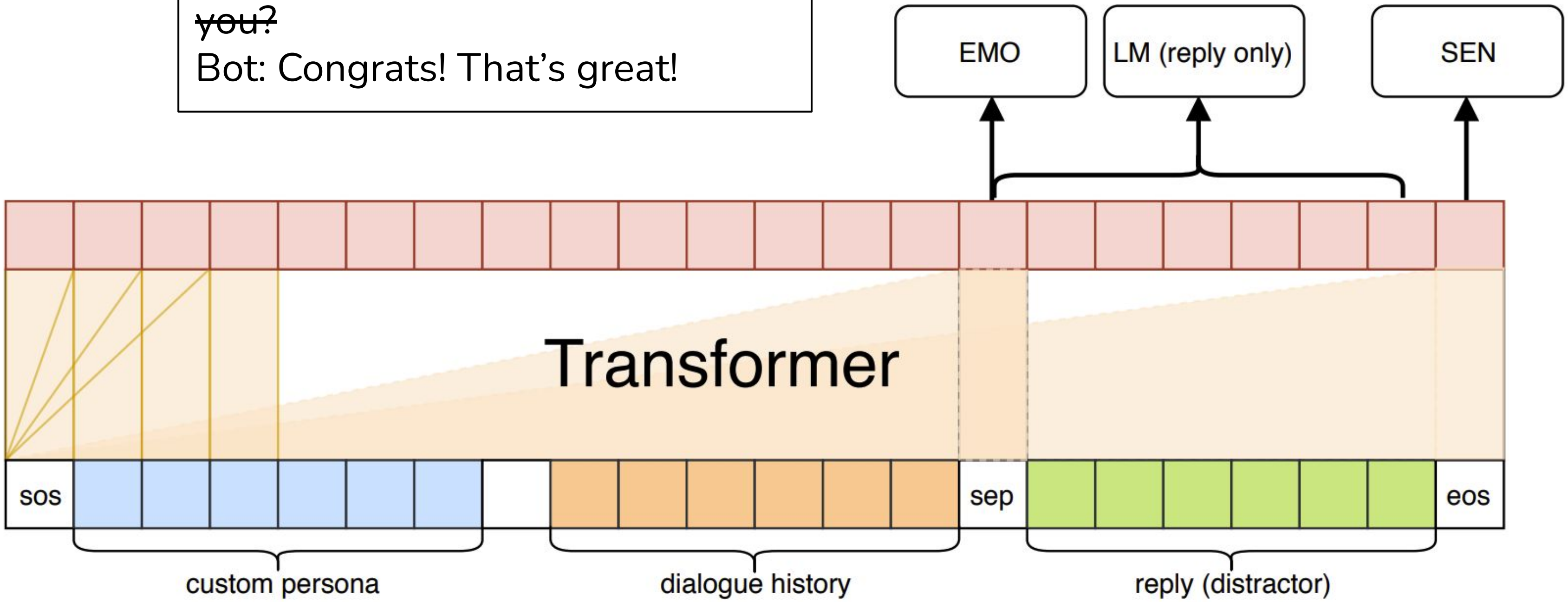
Personalization: Speaker Model



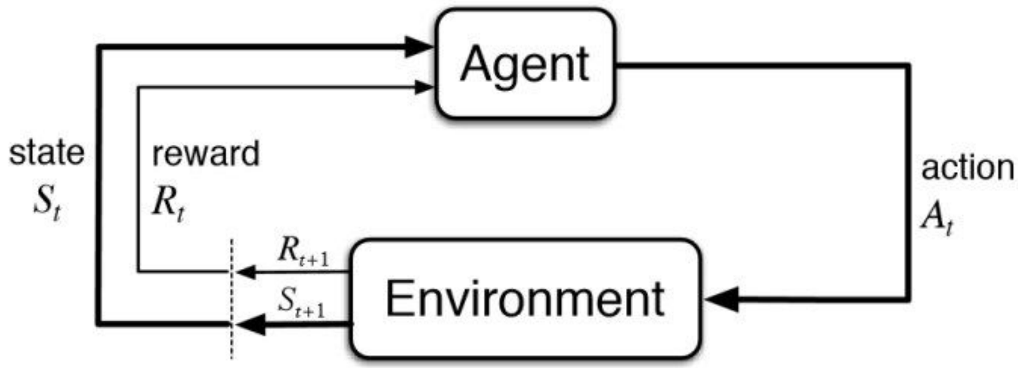
Attribute Embeddings

Empathy: CAiRE

Human: I finally got promoted.
~~Bot: Why would anyone promote you?~~
Bot: Congrats! That's great!



Reinforcement learning



- Reinforcement learning
  - Cast a text generation model as markov decision process
    - *State*: dialog history + previous generated tokens
    - *Actions*: possible tokens
    - *Policy*: conversational model + decoding strategy
    - *Rewards*: attribute models for a good conversation
      - Politeness, sentiment, ..

Reinforcement learning

Personalization:

- Reward function: capture consistency between a response and persona facts
  - Persona consistency
  - Topical coherence
  - Fluency
  - Repeated tokens

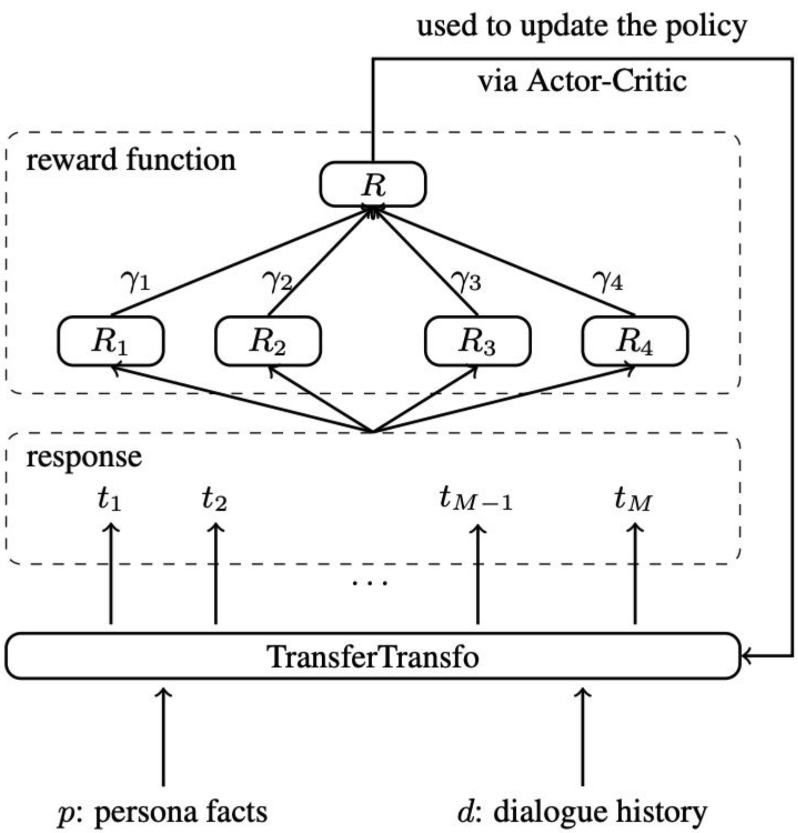


Figure 1: An abstract view of our RL approach.

[Mesgar et al., 2021]

Evaluation

4-step recipe
[Fung et al., 2020]

1. Data
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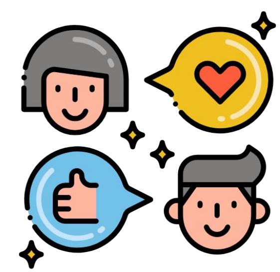
4. Evaluation

System: The brown fox jumps

Reference: The fox

Automatic Evaluation



Human Evaluation

[Ji et al., 2020]

Automatic Evaluation

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- Compare with reference response

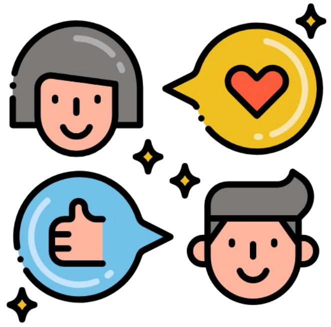
System: The brown fox jumps

Reference: The fox

- Main categories
  - Perplexity: how likely a model generate the reference response
  - N-gram based overlap: BLEU, ROUGE-L
  - Distinct N-gram: diversity
    → Weakness: surface level, correlate poorly with human judgement
  - Model based metrics: BERTScore [Zhang et al., 2020], Adversarial Success [Kannan & Vinyals, 2017; Li et al., 2017]
    → Weakness: not interpretable, not always align with human judgement

Human Evaluation

- Interaction setup
  - Dialogue history, gold response, generated response
  - Directly interact with systems
- Evaluation setup
  - Likert: give ratings according to some criteria, e.g., fluency, consistency, factual etc.
  - Selection preference: select one system among presented systems (usually btw 2)
- Weaknesses
  - Expensive & time consuming
  - Difficult quality control, inconsistency in evaluation



Summary: Evaluation

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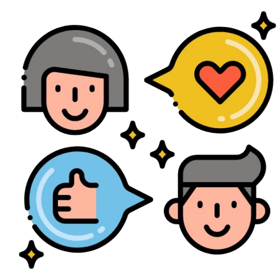
Automatic Evaluation



Human Evaluation

- Improper or offensive language
- Factual consistency

[Ji et al., 2020]

Summary

- A lot efforts have been made
- But still many **improvements** ahead in Conversational AI
- Evaluation remains a huge challenge
  - Need better ways of automatic evaluation
- **Most exciting areas** of NLP!