

Have We achieved Personalized Dialogue Generation yet?

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What is Natural Language Generation?

- What is Natural Language Generation?
 - Data-2-Text

What is Natural Language Generation?

- What is Natural Language Generation?
 - Data-2-Text

- Image Captioning

Input:



Output:

```
<start> a close up of a person  
wearing a bow tie <end>
```

What is Natural Language Generation?

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 - Data-2-Text

- Table to Text

Input:

Denise Margaret Scott	
Born	24 April 1955 Melbourne, Victoria
Nationality	Australian
Other names	Scotty
Occupation	Comedian, actor, television and radio presenter

Output:

Denise Margaret Scott (born 24 April 1955) is an Australian comedian, actor and television presenter.



What is Natural Language Generation?

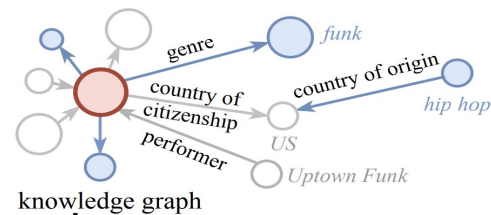
- What is Natural Language Generation?
 - Data-2-Text

- Graph to Text

Input:

Bruno Mars

*retro style, funk,
rhythm and blues,
hip hop music, ...*



knowledge graph

Output:

Peter Gene Hernandez (born October 8, 1985), known professionally as **Bruno Mars**, is an American singer, songwriter, multi-instrumentalist, record producer, and dancer. He is known for his stage performances, *retro* showmanship and for performing in a wide range of musical styles, including *R&B, funk, pop, soul, reggae, hip hop*, and *rock*.

What is Natural Language Generation?

- What is Natural Language Generation?
 - Data-2-Text
 - Text-2-Text
 - Generating a lexicalized human-readable response based on a textual context
 - Traditionally: Converting Mean Representation (a non-linguistic intermediate representation) to a lexicalized output
 - Properties of the Generation output:
 - Correctness
 - Appropriateness
 - Coherent
 - Engaging



What is Natural Language Generation?

- What is Natural Language Generation?
 - Data-2-Text
 - Text-2-Text
 - By Domain:
 - Summarization
 - Abstractive vs. Extractive

Extractive Summarization

Source Text:  Peter and Elizabeth took a taxi to attend the night party in the city.


While in the party, Elizabeth collapsed and was rushed to the hospital.

Summary: Peter

Abstractive Summarization

Source Text: Peter and Elizabeth took a taxi to attend the night party in the city.

While in the party, Elizabeth collapsed and was rushed to the hospital.

Summary: Elizabeth was hospitalized after attending a party with Peter. 



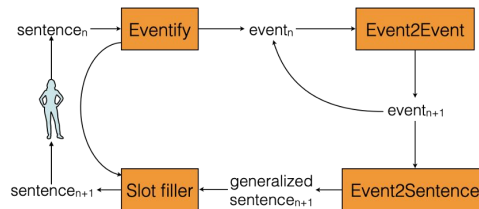
What is Natural Language Generation?

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 - Data-2-Text
 - Text-2-Text
 - By Domain:
 - Story Generation

■ **Context:** Tom and Sheryl have been together for two years. One day, they went to a carnival together. He won her several stuffed bears, and bought her cakes. When they reached the Ferris wheel, he got down on one knee

■ **Prediction:** *Tom asked Sheryl to marry him.*

- Generation



- Selection

Right Ending

Tom asked Sheryl to marry him.

Wrong Ending

He wiped mud off of his boot.

What is Natural Language Generation?

- What is Natural Language Generation?
 - Data-2-Text
 - Text-2-Text
 - By Domain:
 - Response Generation
 - Task-Based
 - Open-Domain
 - Q & A

Passage Sentence

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity.

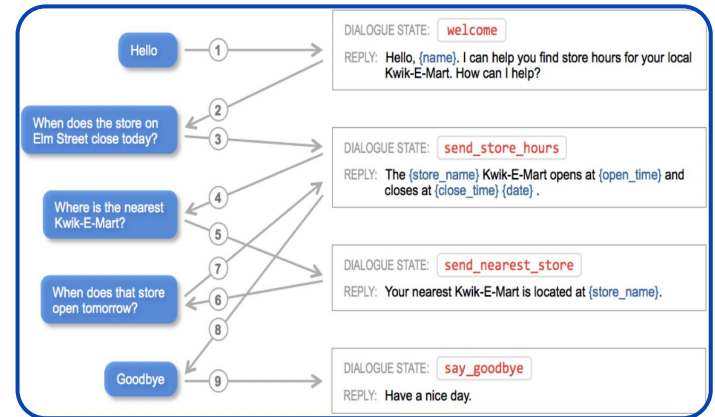
Question

What causes precipitation to fall?

Answer Candidate

gravity

- Between **question** and **answer**
 - cause---gravity
 - precipitation---gravity
 - fall---gravity
 - what---gravity



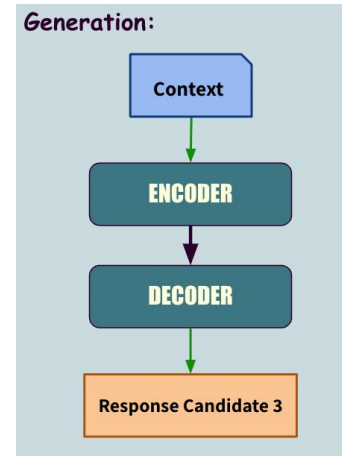
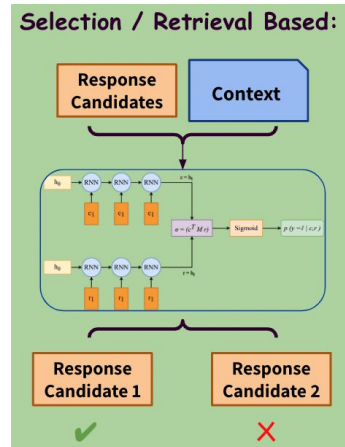
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 - Data-2-Text
 - Text-2-Text
 - By Domain:
 - Summarization
 - Abstractive vs. Extractive
 - Story Generation
 - Response Generation
 - Task-Based vs. Open-Domain vs. Q & A
 - Translation
 - By Policy:
 - Template-based vs. Selection vs. Generation



Generative Vs. Retrieval?

- What is Natural Language Generation?
 - Data-2-Text
 - Text-2-Text
 - By Policy:
 - Template-based vs. Selection vs. Generation



What is Personal Dialogue Generation?

- Personal dialogues are conversations which include user-specific recollections of events, objects, entities and their relations.
 - They may also encompass personal feelings, thoughts, and emotions.
- Personal dialogue generation requires to:
 - 1) Hold dialogues about personal events, relationships, and participants
 - 2) carrying out **multi-session conversations** over extended period of time.
 - 3) obtain the **required knowledge** during each interaction with the user and from her Personal Narratives.



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We need Dialogue Data!

- The acquisition of a dialogue corpus is a key step in the process of training a dialogue model.
- Corpora acquisitions have been designed either for open-domain information retrieval about a finite set of topics (e.g. news, music, weather, games etc.) or slot-filling tasks (e.g. restaurant booking).
- However, neither of the above approaches can address the need for personal conversations which include user-specific recollections of events, objects, entities and their relations.



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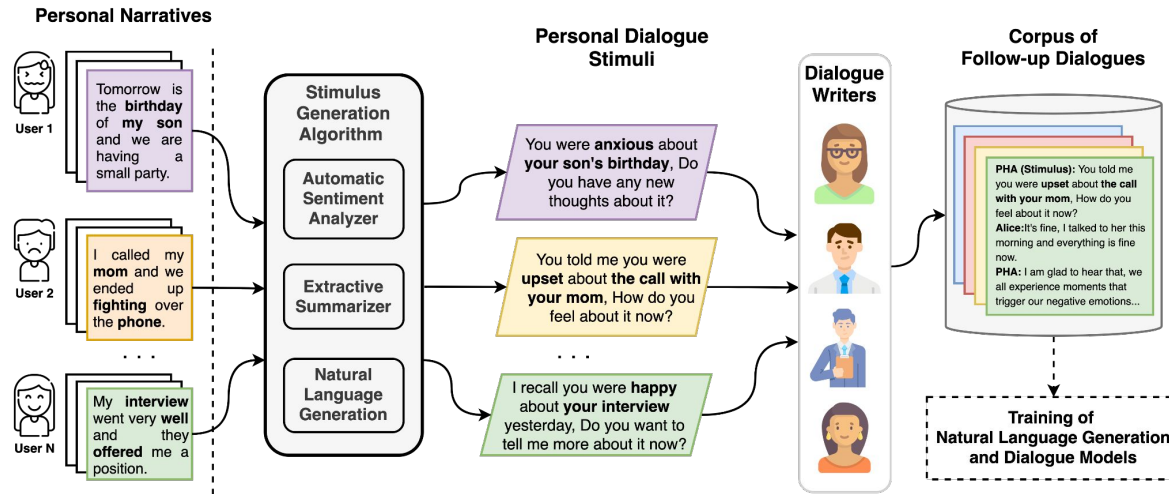
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We Collect Dialogue Data!

- We proposed a novel methodology to collect corpora of personalized follow-up dialogues.¹
 - Dialogue follow-ups are a critical resource for learning about the life events of the narrator as well as his/her corresponding thoughts and emotions in a timely manner.



We need Personal Narrative Understanding!

- We need to obtain the **knowledge** required for responding during each interaction with the user
- A Personal Narrative has a complex structure.
 - It is different than Intent(or Dialogue Act) classification and slot filling.
 - We need to extract personal events, emotions, and participants.
- We need to construct the **Personal Space** of the user from her narratives



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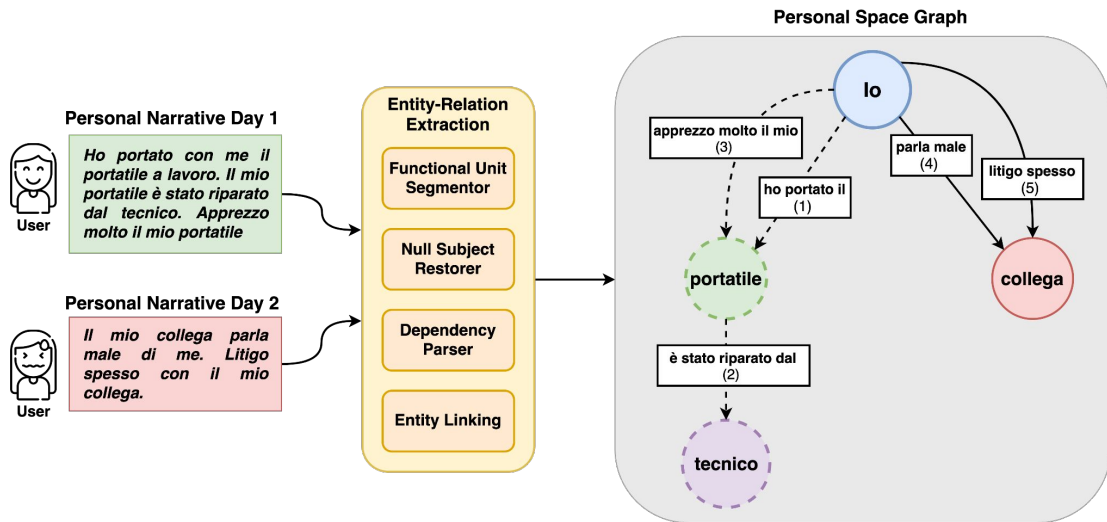
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We develop an Event-Relation Extractor!

- We develop an unsupervised approach to automatically extract personal life-events and participants from the users' narratives and represent them as a personal graph.²
- This personal graph is then updated at each interaction with the patient.



Another Perspective: Emotion Carriers!

- Emotion Carriers (EC) are defined as the persons, objects or actions that explain the emotion felt by the narrator, after recollecting the event³.
- EC tokens clearly convey the activation of the emotional state in the narrator, even though they may not explicitly manifest a sentiment.
- In contrast, emotion-laden words (such as happy, sad, enjoyed, and overwhelmed), explicitly express certain sentiment polarity.

Emotion-laden word *Emotion Carrier*
FU1: I experienced a bit of **distress** **in the office**

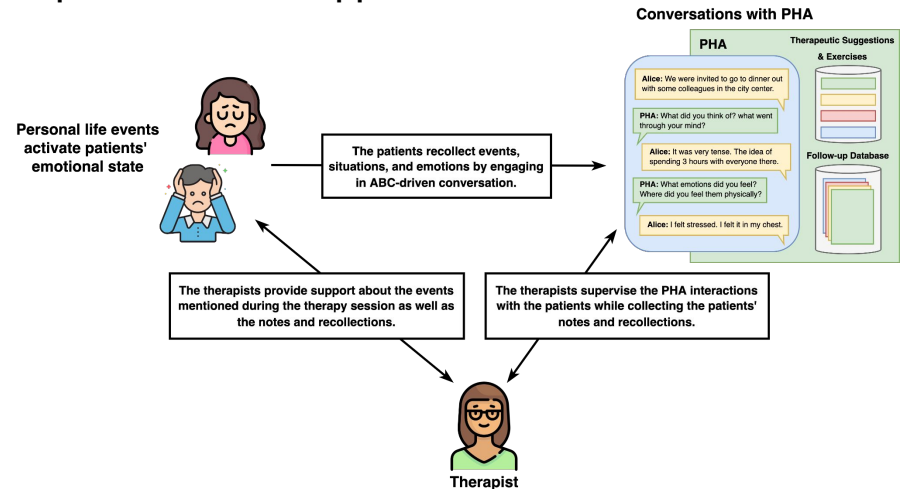
Emotion Carrier *Emotion-laden word*
FU2: because **talking with colleagues** *makes me* **anxious!**

Example: *Emotion-laden words manifest a sentiment explicitly while Emotion Carriers describe the events, persons or objects conveying emotions.*



Lets Try Retrieval Response Models!

- We developed a Retrieval Based PHA for the mental health domain.^{4,5}
- The results show a significant positive trend in the reduction of symptoms related to distress, obsessivity, and compulsivity by the patient group that received support from PHA.
- The therapists engaged in the studies believe the blended intervention may improve the patients' mental health since it results in continuous support provision by the conversational agent.

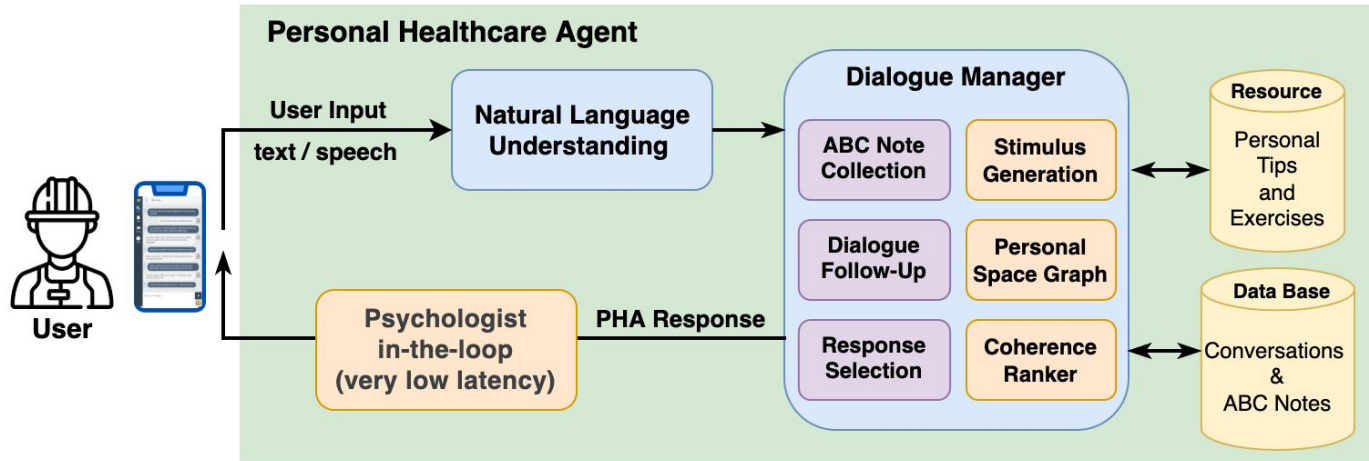


[4] Danieli M, Ciulli T, Mousavi S, Riccardi G. *A Conversational Artificial Intelligence Agent for a Mental Health Care App: Evaluation Study of Its Participatory Design*. JMIR Form Res 2021;5(12)

[5] Danieli M, Ciulli T, Mousavi MS, Silvestri G, Barbato S, Di Natale L, Riccardi G. *TEO: Assessing the Impact of Conversational AI in the Treatment of Stress and Anxiety in Aging Persons: A Randomized Controlled Trial Study*. JMIR Preprints.

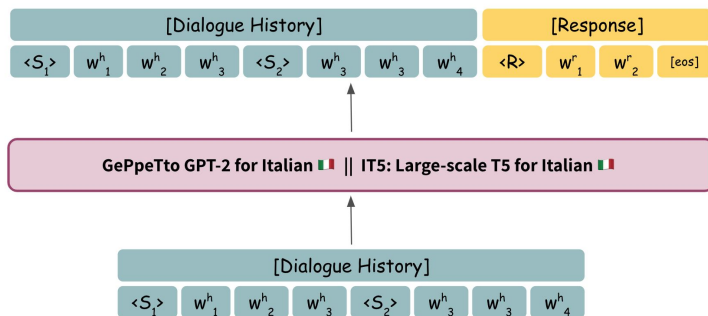
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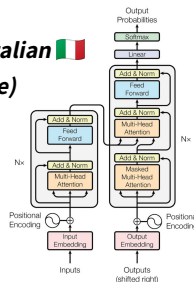



Can we Train now?

- We are experimenting with generative models
- We are currently working on Conversational Fine-Tuning of Pre-Trained Language Models



IT5: Large-scale T5 for Italian 
(small, base, large)



GePpeTto GPT-2 for Italian 
(small)



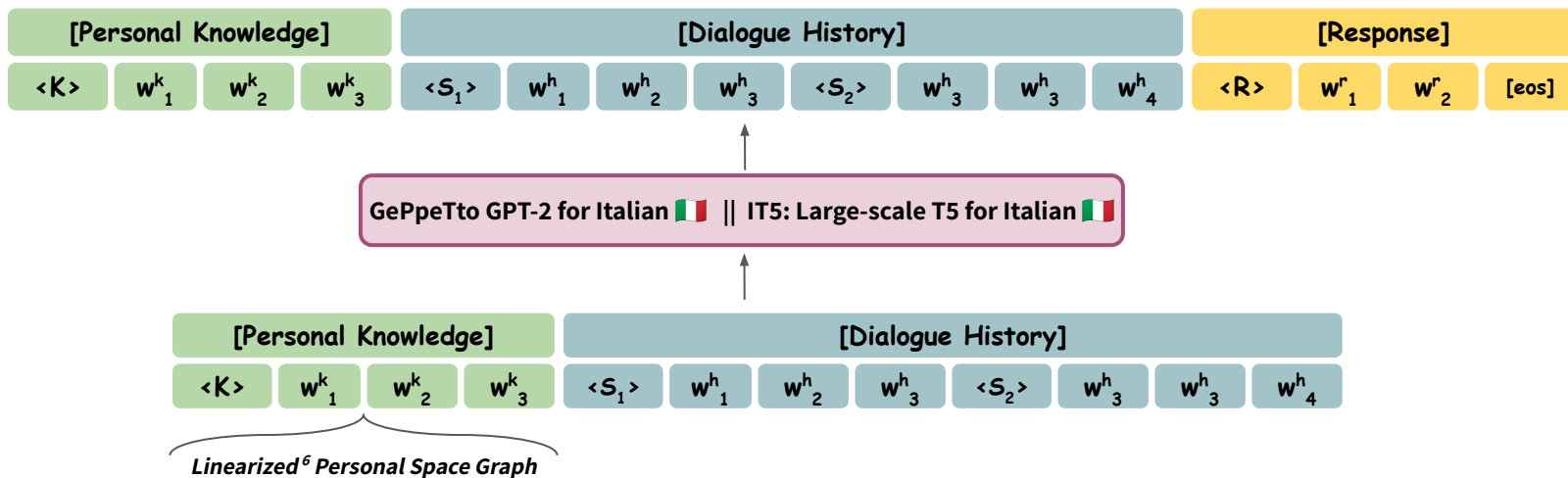
Issues & Challenges

- The design, training and development of a PHAs is strongly subject to factors of accuracy, appropriateness and acceptance by the user and ethical compliance.
- Data-driven conversational models (including GPT-x, T5, ...) suffer from the major issues of generating toxic responses, which are unethical, offensive, biased, and dangerous leading to ethical problems, and are unexplainable due to their nature.
- Meanwhile, detecting and controlling such toxic output in these models are yet not possible due to the nature of such models.
- Personalization of CAs is limited to food preference and pronoun selection.



Can we Train now?

- End-to-End generative models are known for generic and inappropriate response generation
 - We are experimenting the grounded-response generation



Thank You.

