Data Augmentation for Conversational AI

Fundamentals and Advances

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It should be mentioned that we are still working on these slides and they are not the final version

Tutorial website: https://dataug-convai.github.io

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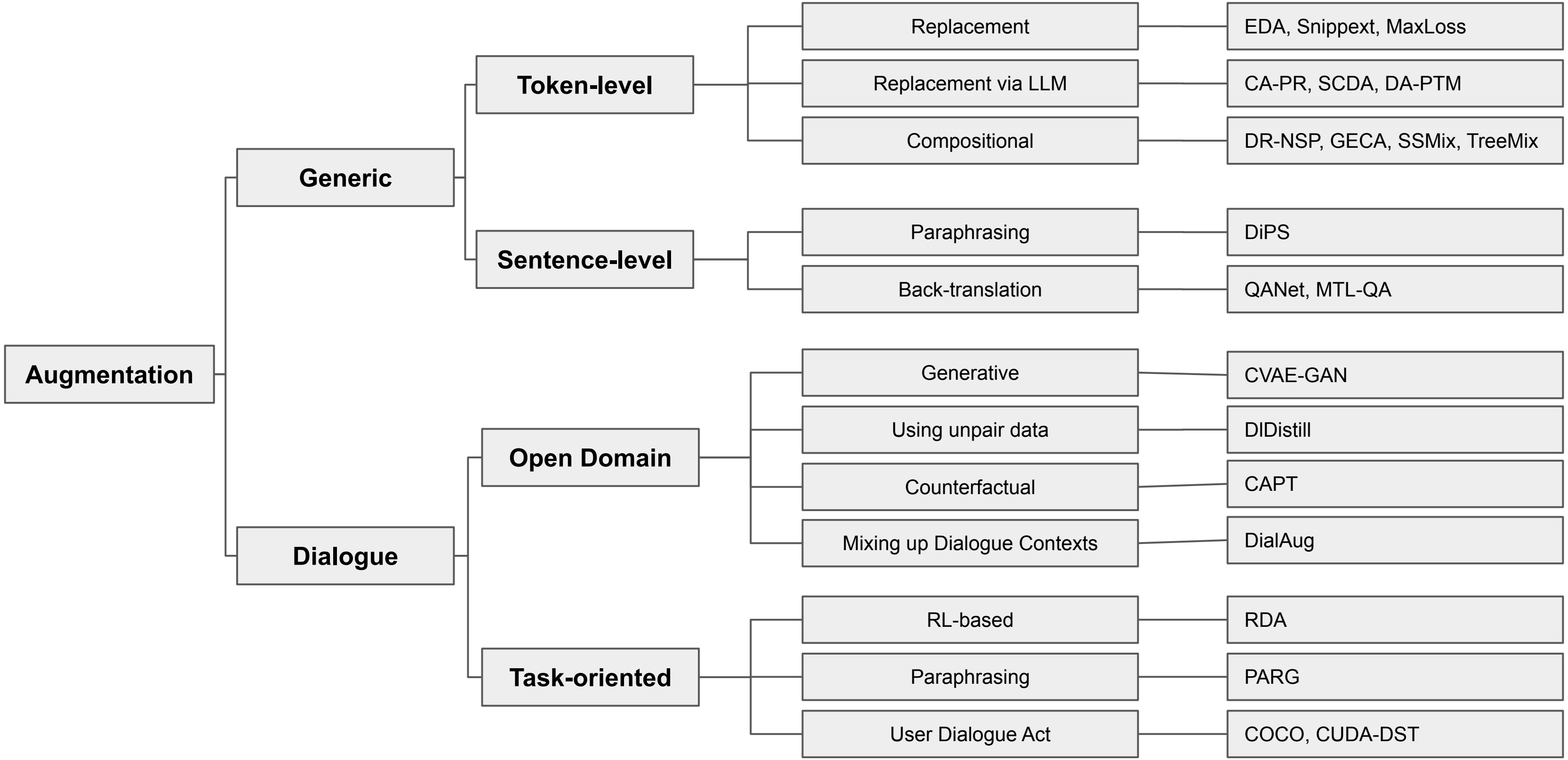
Agenda

- **Introduction (10 min)**
  - Conversational Systems
    - Open-domain
    - Task-oriented
  - Problem of Data Scarcity
  - Data Augmentation
    - Augmenting with Existing Conversations Data
    - Augmenting with Conversation Generation
- **Conversation Augmentation (30 min)**
  - Generic Token-level & Sentence-level Augmentation
  - Dialogue Data Augmentation
- **Conversation Generation: Open Domain (80 min)**
  - Single-turn QA Pair Generation
  - Multi-turn Dialogue Generation
  - Topic-aware Dialogue Agent
    - One-turn Topic Transitions
    - Target-oriented Dialogue Systems
- **Conversation Generation: Task-oriented (40 min)**
  - Schema-guided Generation
  - Simulator-agent Interaction
  - E2E Dataset Creation
- **Evaluation (10 min)**
- **Conclusion and Future Direction (10 min)**

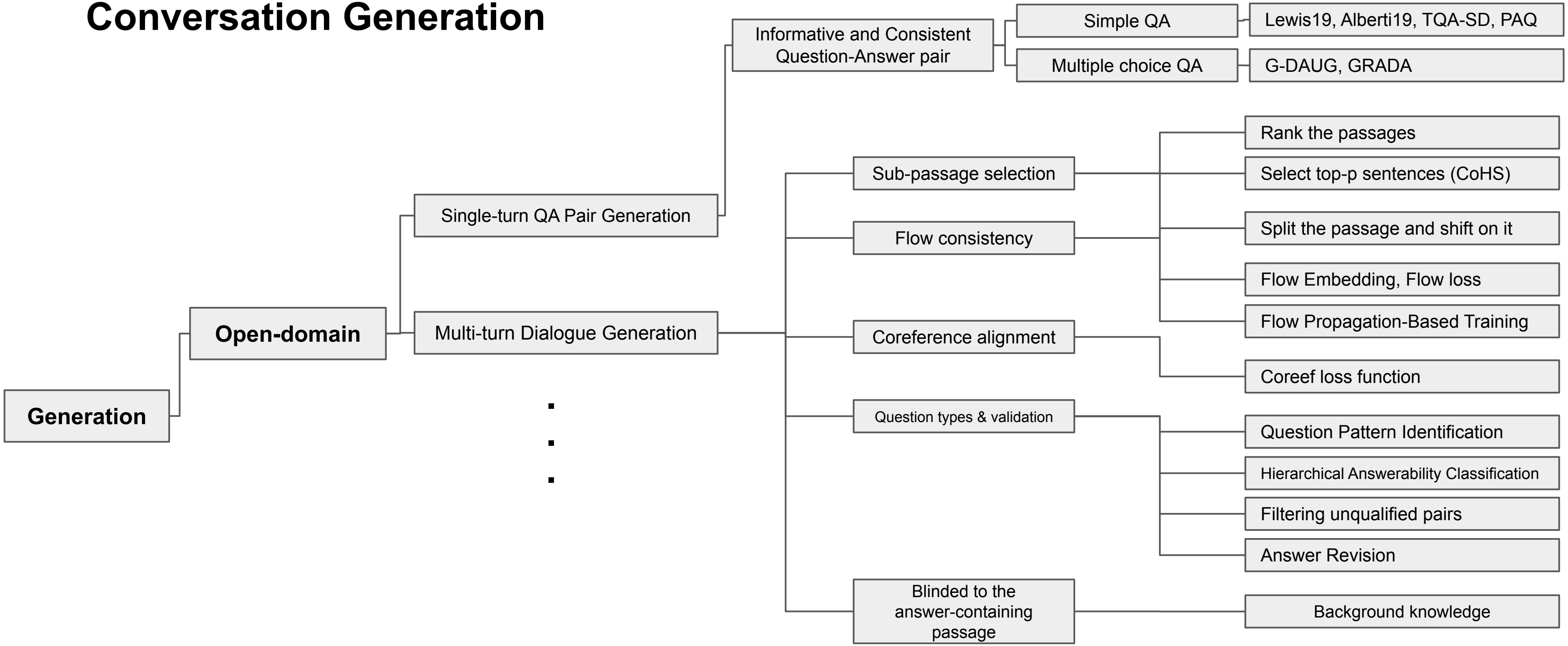
Tutorial overview

Conversation Augmentation



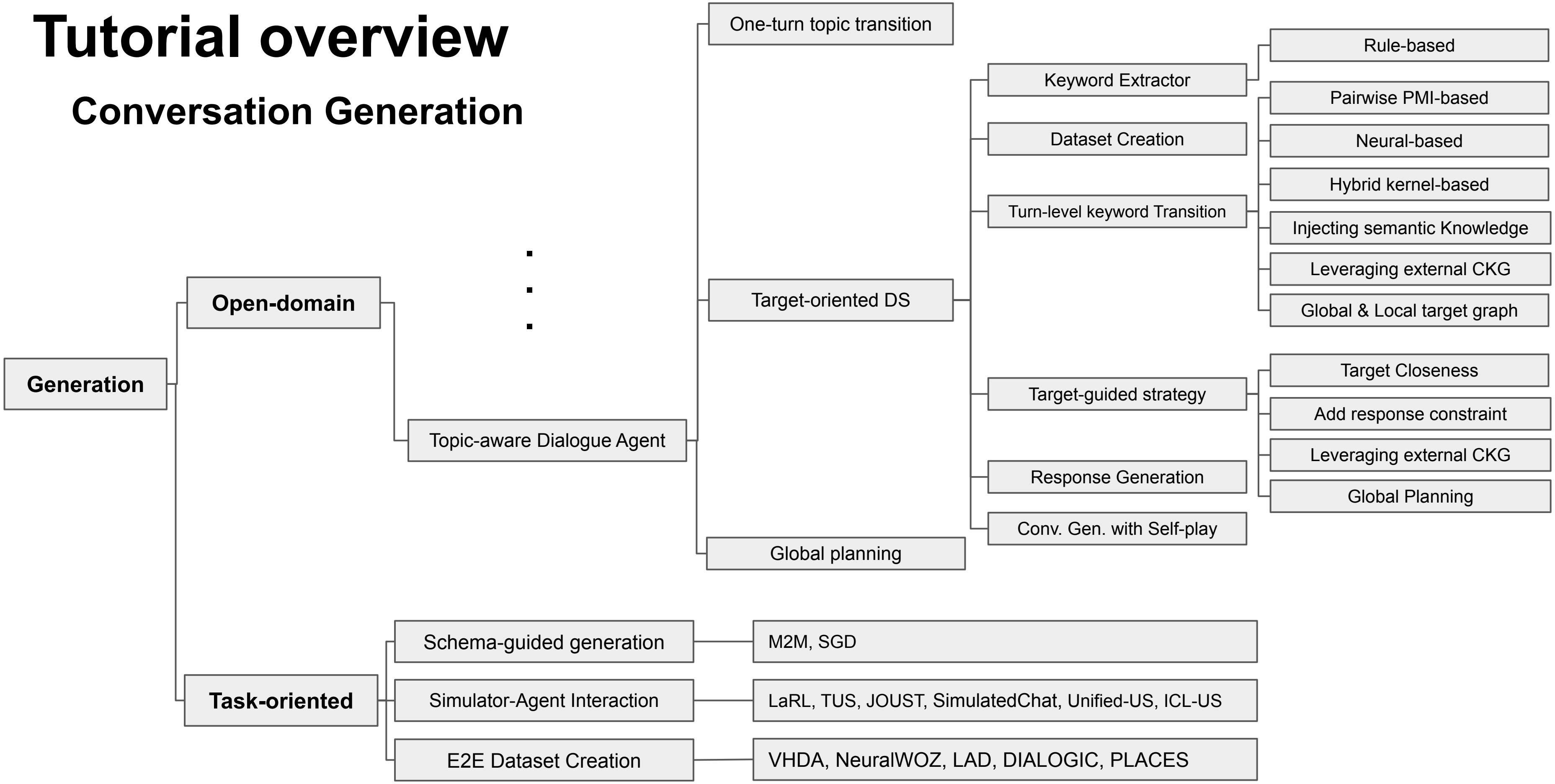
Tutorial overview

Conversation Generation



Tutorial overview

Conversation Generation



List of all papers

Table 1: List of current works for Dialogue Augmentation

Paper	Year	tr. Method	Level	Type	Challenges	Approach	Input
Aug: Generic Token-level & Sentence-level Augmentation							
MTL-QA [3]	2021-05	–	Sentence			Back-translation	
QANet [66]	2018-08	–	Sentence			Back-translation	
DiPS [22]	2019-06	–	Sentence		Inducing diversity	Paraphrasing	
TreeMix [68]	2022-07	–	Token		Meaningfulness, Diversity	Compositional	–
SSMix [65]	2021-08	–	Token		Meaningfulness, Diversity	Compositional	–
GECA [2]	2020-07	–	Token		Meaningfulness, Diversity	Compositional	–
DR-NSP [16]	2016-08	–	Token		Meaningfulness, Diversity	Compositional	–
DA-PTM [23]	2020-12	–	Token		Meaningfulness, Diversity	Replacement (LM)	–
SCDA [8]	2019-07	–	Token		Meaningfulness, Diversity	Replacement (LM)	–
CA-PR [21]	2018-06	–	Token		Meaningfulness	Replacement (LM)	–
Snippext [35]	2020-04	–	Token		Meaningfulness	Replacement (all)	–
EDA [54]	2019-11	–	Token		Meaningfulness	Replacement (all)	–
MaxLoss [17]	2019-03	–	Token		Meaningfulness	Replacement (Synonym)	–
Aug: Dialogue Data Augmentation							
DialAug [42]	2022-10	Generative	Dialogue	Open-domain	Diversity		
CAPT [40]	2022-10	Generative	Dialogue	Open-domain	Diversity	Counterfactual	H, CQ, CA
DlDistill [69]	2020-11	Both Ret. & Gen.	Dialogue	Open-domain	Diversity	Unpair data	–
CVAE-GAN [27]	2019-01	Generative	Dialogue	Open-domain	Diversity	Generative model	H, CQ, CA
CUDA-DST [24]	2022-09	Generative	Dialogue	Task-oriented	Generalization, Diversity	User Dialogue Act (UDA)	H
COCO [28]	2021-03	Retrieval	Dialogue	Task-oriented	Generalization, Diversity	UDA, Counterfactual	H
PARG [9]	2020-07	Generative	Dialogue	Task-oriented	Diversity	Paraphrasing	H, CA
RDA [63]	2020-04	Generative	Dialogue	Task-oriented	Quantity, Diversity	RL-based	P, CQ, CA

Table 2: List of current works for Dialogue Generation: Open-Domain

Paper	Year	tr. Method	Level	Type	Challenges	Approach	Input
ODD Gen: Single-turn generation							
GRADA [33]	2022-10	Generative, Augmentation	QA pair	Open-domain	Informative, Diverse	2, 3, 4	KG
G-DAUG [60]	2020-11	Generative	QA pair	–		2, 3, 4	–
PAQ [26]	2021	Hybrid-GR	QA pair	Open-domain		1, 2, 3, 4	KB
TQA-SD [43]	2020-02	Generative	QA pair	–		2, 3, 4	–
Alberti19 [1]	2019-07	Generative	QA pair	–		2, 3, 4	P
Lewis19 [25]	2019-07	Generative	QA pair	–		2, 3, 4	P
ODD Gen: Multi-turn generation							
Baize [56]	2023-04	Prompting	Dialogue	Open-domain			
SIMSEEK [18]	2022-12	Generative	Dialogue	Open-domain	Blinded to the answer-containing passage, rely on background information B	2, 3, 4	H, B, P
GCN [32]	2022-09	Hybrid-GR, RL	Dialogue	Open-domain	Real scenarios	1, 2, 3, 4	
DG2 [55]	2022-09	Generative	Dialogue	Open-domain	Consistency, Sub passage selection	1, 2, 3, 4	P, H
MultiCQAG [14]	2022-11	Generative	Dialogue	Open-domain	Consistency, Question Types	1, 2, 3, 4	H, P
CQAG-AR [15]	2022-10	Generative	Dialogue	Open-domain	Consistency, Answer revision	2, 3, 4	H, P
CoHS-CQG [6]	2022-10	Generative	Dialogue	Open-domain	Consistency, Sub Passage/History selection	1, 2, 3, 4	H, P
ChainCQG [11]	2021-04	Generative	Dialogue	Open-domain	Consistency	1, 2, 3, 4	H
SHSF [44]	2020-11	–	–	Open-domain		–	–
AU-CQG [37]	2019-11	Hybrid-GR	Dialogue	Open-domain	Consistency, Sub passage selection	1, 3, 4	H, P
ReDR [41]	2019-07	Generative	Dialogue	Open-domain	Consistency, Coreference alignment	2, 3	H
CFNet [10]	2019-07	Generative	Dialogue	Open-domain	Consistency, Coreference alignment	1, 3, 4	H, P
ODD Gen: Target-oriented dialogue systems							
COLOR [53]	2023-05	Generative	Dialogue	Target-oriented	Consistency, target achievement	1, 2, 3	H, Ext.KG, G
HiTKG [38]	2022-10	Generative	Dialogue	Target-oriented	Consistency, target achievement	1, 2, 3	H, Ext.KG, G
EGRL [57]	2021-01	Generative	Dialogue	Target-oriented	Consistency, target achievement	1, 2, 3	H, Ext.KG, G
KnowHRL [58]	2020-04	Generative	Dialogue	Target-oriented	Consistency, target achievement	1, 2, 3	H, Ext.KG, G
TopKG [62]	2022-10	Generative	Dialogue	Target-oriented	Consistency, target achievement	1, 2, 3	H, Ext.KG, G
CKC [71]	2021-12	Generative	Dialogue	Target-oriented	Consistency, target achievement	1, 2, 3	H, Ext.KG, G
DKRN [45]	2020-06	Retrieval	Dialogue	Target-oriented	Consistency, target achievement	1, 2, 3	H, Int.KG, G
TGODC [49]	2019-07	Retrieval	Dialogue	Target-oriented	Consistency, target achievement	1, 2, 3	H, Int.KG, G
TGCP [20]	2022-10		1-turn Dialogue	Target-oriented			
CRG [12]	2022-07		1-turn Dialogue	Target-oriented			
OTTers [47]	2021-08		1-turn Dialogue	Target-oriented			

Table 3: List of current works for Dialogue Generation: Task-oriented

Paper	Year	tr. Method	Level	Type	Challenges	Approach	Input
ToD Gen: Schema-guided generation							
SGD [46]	2020-06	Generative	Dialogue	Task-oriented	Task completion	–	–
M2M [48]	2018-01	Generative	Dialogue	Task-oriented	Task completion	–	–
ToD Gen: Simulator-Agent Interaction							
ICL-US [50]	2023-06	In-Context	Dialogue	Task-oriented	Task completion, Diversity	–	–
Unified-US [52]	2022-12	Generative	Dialogue	Task-oriented	Task completion	–	–
SimulatedChat [36]	2021-11	Hybrid-GR	Dialogue	Task-oriented	Task completion	–	–
JOUST [51]	2021-08	Generative	Dialogue	Task-oriented	Task completion	–	–
TUS [31]	2021-07	Generative	Dialogue	Task-oriented	Task completion	–	–
LaRL [70]	2019-06	Generative	Dialogue	Task-oriented	Task completion	–	–
ToD Gen: E2E dataset creation							
PLACES [4]	2023-05	In-context	Dialogue	Task-oriented	Multi-party conversations		
DIALOGIC [29]	2022-12	In-context	Dialogue	Task-oriented	Controllable Gen.		
LAD [34]	2022-09	Prompting	Dialogue	Task-oriented	ZSH. Generalisation, Diversity		
NeuralWOZ [19]	2021-08	Retrieval	Dialogue	Task-oriented	Task completion, Unseen domain	–	–
VHDA [64]	2020-11	Generative	Dialogue	Task-oriented	Task completion	–	–

Part 1: Introduction

1.1 Conversational Systems

1.2 Problem of Data Scarcity

1.3 Data Augmentation

Duration: 10 min

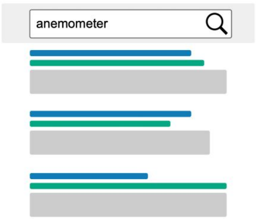
Presenter: —

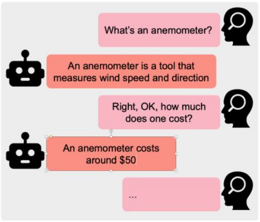
Conversational System

- Age of information explosion
- Conversation applications
  - Seeking relevant information
  - Need ongoing feedback from an agent
  - Engage in conversations for casual chit-chat
  - Engage in conversations for negotiating

Photo: Flight with query

Photo: Flight with Conversation





Types of Dialogue Systems

Open Domain Dialogue System (ODD)

- Aim to perform chit-chat with users without the task and domain restriction
- Engage in conversations with users across a wide range of topics and domains
- Task: generate meaningful and coherent responses based on the user's input and dialogue history
- Challenges:
    - Context awareness: response coherence
    - Response diversity: Avoid making dull responses
    - Controllable generation
        - Conversation topic
        - Mixed-initiative conversation
    - Informative responses: knowledge-grounded system

Types of Dialogue Systems

Task-oriented Dialogue System (ToD)

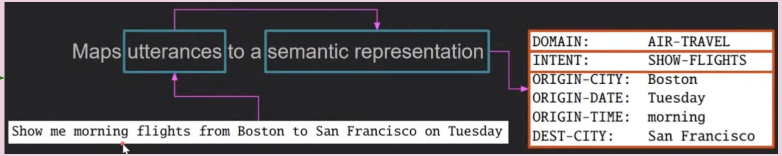
- Accomplish user-requested tasks
  - by accurately understanding the user's intent
  - providing suitable responses
- Domains:
  - Flight ticket / Restaurant / Hotel / Taxi / Movie ticket booking
  - Weather, navigation and scheduling domain
  - Customer service delivery
- Approaches: 1) Pipeline, 2) End-to-end

Goal: You want to book a taxi. The taxi should go to anatolia and should leave after 22:00. The taxi should depart from kymmoy. Make sure you get car type and contact number.
User: i need a taxi to |anatolia|>. **System:** what time would you like to leave? **User:** i would like to leave after |22:00|>. **System:** there are |9|> options available to you. where would you like to leave from? **User:** i 'd like to leave from |kymmoy|>. **System:** the fare estimate is |9.78|>. do you want to book this taxi now? **User:** no, i would like the contact number if possible. **System:** the contact number is |07356725299|> **User:** thank you very much for your help. **System:** you are welcome. do you need anything else today

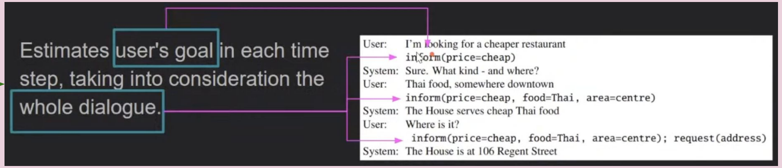
Table 1: A dialogue generated by our model with corresponding natural language user goal. The "|*anatolia*|>" with special tag indicates that the word is a value.

ToD: Pipeline approach

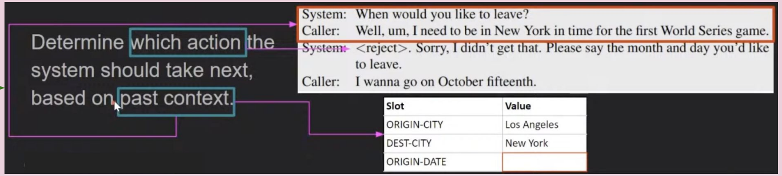
- 1) Natural Language Understanding (NLU)
    - Domain classification
    - Intent classification
    - Slot value Extraction (tagging)



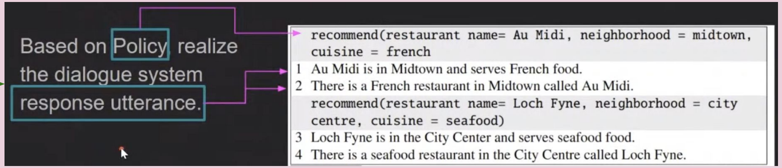
- 2) Dialogue management
    - Dialog state tracking
        - Conducts KB Query, make API calls
        - Provide feedback to DM in order to construct system response



    - Dialog policy optimization
        - RL framework:
            - The DM is the agent
            - The user is the environment
            - NLU are observations made by Agent
            - NLG are actions conducted by Agent
            - Agent tries to maximize Expected Future Rewards



- 3) Natural Language Generation (NLG)
    - Generated response:
        - Adequacy, fluency, readability, variation
    - Generate clarification question: instead of reject response



Problem of data scarcity

- Rapid development of conversation-based models
- Deep learning based
  - High number of trainable parameters
  - Requires a significant amount of training data
- Crowd-sourcing approach
  - Expensive and time-consuming
  - Hard to scale up to new domains
  - Human-authored data possess weaker performance on out of distribution samples
  - Do not necessarily consider the full diversity of question types
- Specific domain / language

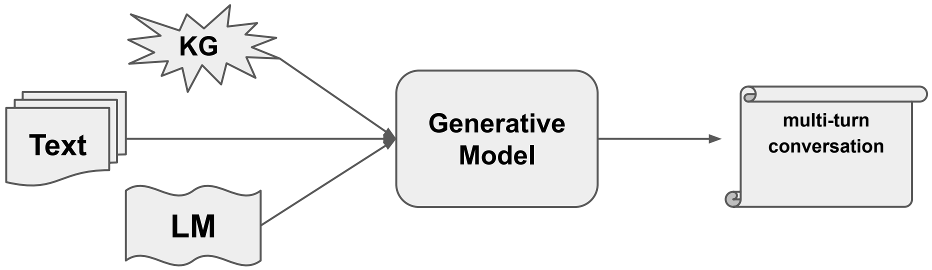
Learning from limited data

- Unsupervised learning: Training with unlabeled data
- Semi-supervised learning: Training with both labeled and unlabeled data
- Transfer learning: Leverage data from a different-but-related task
- Multi-task learning: Use information learned on different tasks for mutual benefit
- Few/Zero shot learning: Generalize to new tasks after seeing a few (or no) examples
- **Data augmentation:** Modify labeled data to with class-preserving transformations

[Chen, et al., 2022]

Data Augmentation (DA)

- Definition: A technique that increases the amount of training data
  - by either slightly modifying existing data or generating new synthetic
- DA Advantages
  - Increase amount of training data
  - Improve the diversity of the dataset
  - Dealing with the overfitting problem
- Data Generation
  - Using external and various resource



Part 2: Conversation Augmentation

2.1 Generic Token-level & Sentence-level Augmentation

2.2 Dialogue Data Augmentation

Duration: 30 min

Presenter: —

Generic Token-level & Sentence-level Augmentation

Overview

- Involve the replacement of original tokens or sentences with relevant alternatives
- Token-level: Modifying a few local words
  - Replacement: Random word, Synonym, Insertion, Deletion, Swapping, MixDA
  - Replacement via LM: Contextual augmentation
  - Compositional Augmentation
- Sentence-level: Modifying an entire sentence at once
  - Paraphrasing
  - Back-Translation

Token-level: Replacement

- **EDA:** Consists of four simple but powerful operations
  - Synonym Replacement (SR)
  - Random Insertion (RI)
  - Random Swap (RS)
  - Random Deletion (RD)
- **Sniptext**: Replacement analysis
- Problems:
  - A naive application of swap or delete may leave the sequence with an inconsistent state of tags
  - Replace or insert can change the meaning of tokens and make the original tags invalid

Operation	Sentence
None	A sad, superior human comedy played out on the back roads of life.
SR	A ***lamentable***, superior human comedy played out on the ***backward*** road of life.
RI	A sad, superior human comedy played out on ***funniness*** the back roads of life.
RS	A sad, superior human comedy played out on ***roads*** back ***the*** of life.
RD	A sad, superior human out on the roads of life.

Table 1: Sentences generated using EDA. SR: synonym replacement. RI: random insertion. RS: random swap. RD: random deletion.

[] EDA: Easy Data Augmentation Techniques for Boosting Performance on Text Classification Tasks, EMNLP-IJCNLP, 2019

Token-level: Replacement

Operator	Description
TR	Replace **non-target token** with a new token.
INS	Insert before or after a **non-target token** with a new token.
DEL	Delete a **non-target token**.
SW	Swap two **non-target tokens**.
SPR	Replace a **target span** with a new span.

- **MIXDA:** Augment and Interpolate
- Types of tokens: 1) Target spans, 2) Non-target tokens
- Sampling & Post-sampling step: Determine a new token (or span) to insert or replace the original one
  - Uniform sampling
  - Importance-based sampling
  - Semantic Similarity (post-sampling only)

$$
\begin{aligned}
\mathrm{BERT}(x') &= \lambda \cdot \mathrm{BERT}(x_1) + (1-\lambda) \cdot \mathrm{BERT}(x_2) \\
y' &= \lambda \cdot y_1 + (1-\lambda) \cdot y_2
\end{aligned}
$$

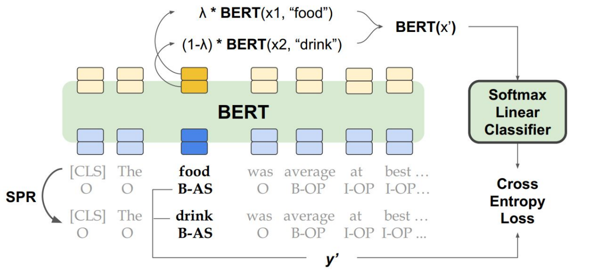
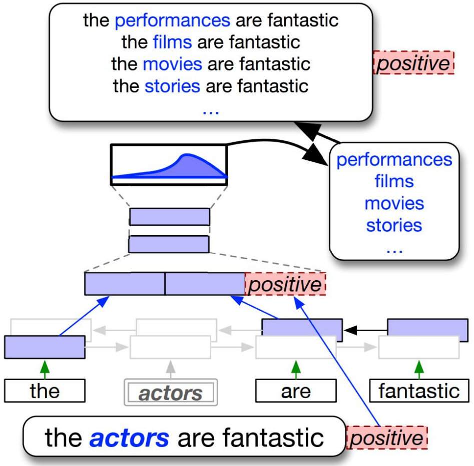


Figure 5: MixDA augments by interpolating over the BERT encoding.

[] Snippext: Semi-supervised Opinion Mining with Augmented Data, WWW, 2020

Token-level: Replacement via LLM

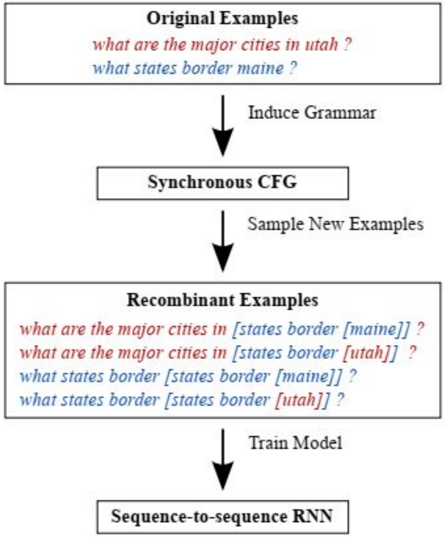
- Contextual augmentation: Replace the sampled words given their context
- Instead of the synonyms, we use words that are predicted by a LM given the context surrounding the original words to be augmented
- Conditional DA using Pre-trained LM [DA-PTM]
- Hard sampling [CA-PR]
- Soft sampling [SCDA]



Contextual augmentation: Data augmentation by words with paradigmatic relations, NAACL, 2018
Soft Contextual Data Augmentation for Neural Machine Translation, ACL, 2019

Token-level: Compositional

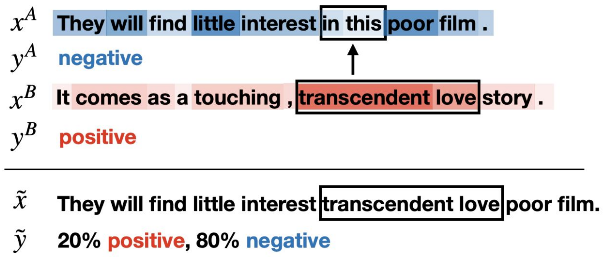
- Recombining various fragments from different sentences
- Requires more carefully designed rules
- Potential to greatly improve the generalization abilities to out-of-distribution data
- Methods:
  - Synchronous Context-Free Grammar (SCFG) [DR-NSP]
  - lexical environment [GECA]

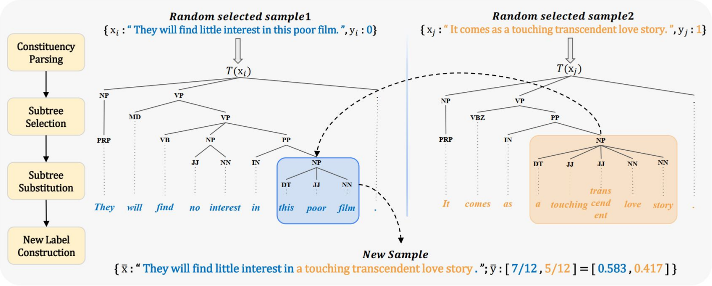


An Empirical Survey of Data Augmentation for Limited Data Learning in NLP, ACL, 2021

Token-level: Compositional

- Saliency-Based Span Mixup (SSMix)
  - Performed on input text rather than on hidden vectors
- TreeMix
  - Constituency parsing tree
    - Decompose sentences into constituent sub-structures
  - Mixup data augmentation technique
    - Recombine them to generate new sentences

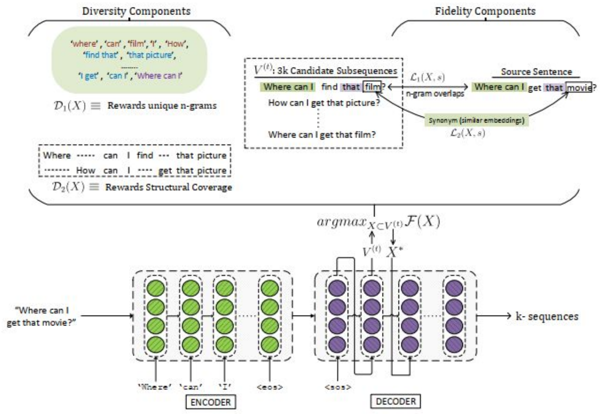




SSMix: Saliency-Based Span Mixup for Text Classification, ACL-IJCNLP 2021
TreeMix: Compositional Constituency-based Data Augmentation for Natural Language Understanding, NAACL, 2022

Sentence-level: Paraphrasing

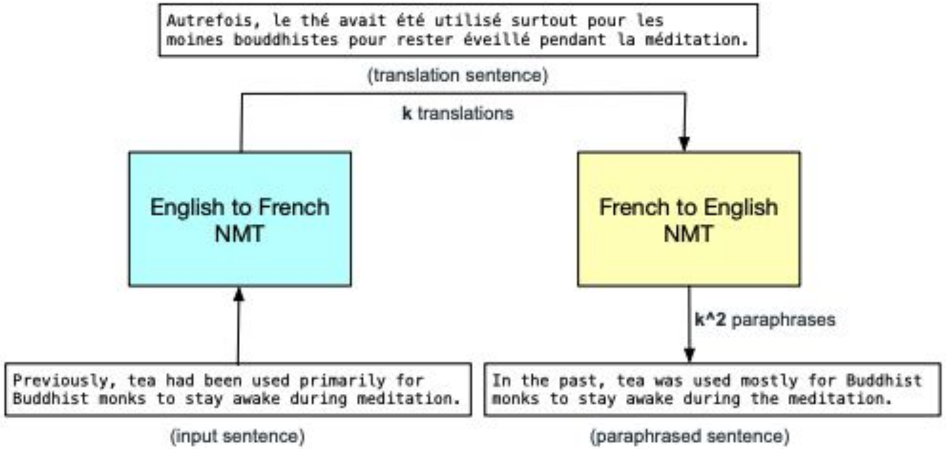
- Paraphrasing: Directly training end-to-end models to generate paraphrases
  - Generating semantically similar paraphrases, paying little attention towards diversity [top-k beam search]
  - Diverse Paraphraser using Submodularity [DiPS]



Submodular Optimization-based Diverse Paraphrasing and its Effectiveness in Data Augmentation, NAACL, 2019
Multilingual Transfer Learning for QA using Translation as Data Augmentation, AAAI, 2021

Sentence-level: Back-translation

- Translates a sentence into another language and then back again



Multilingual Transfer Learning for QA using Translation as Data Augmentation, AAAI, 2021

Dialogue Data Augmentation (DDA)

Overview

- Open Domain dialogue system
  - Generative: Generating different questions and answers given a dialogue data [CVAE]
  - Using unpair data: Dialogue Distillation
  - Counterfactual: [CAPT]
  - Mixing up Dialogue Contexts [DialAug]
- Task-oriented dialogue system
  - RL-based: Augmentation for dialogue state tracking (DST) module [RDA]
  - Paraphrasing: Response generation [PARG]
  - User Dialogue Act: Controllable user dialogue act augmentation [CoCo, CUDA-SDT]

DDA: Generative approach

- Type of dialogue: Open-domain, Query-Response
- CVAE: generating sufficient alternative expressions
- Discriminator: improve the relevance of each augmented query-response pair
- Distillation strategy: filter repetition query-response pairs
- Three different schemes for enhancing dataset
  - One-to-many (1-n)
  - Many-to-one (n-1)
  - Many-to-many (n-n)

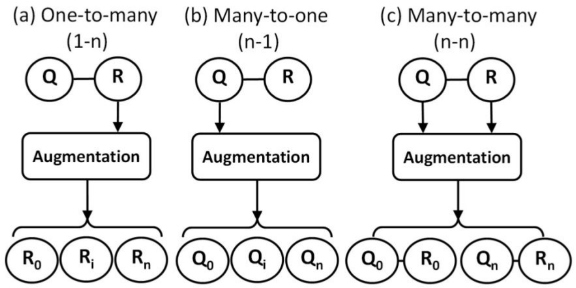
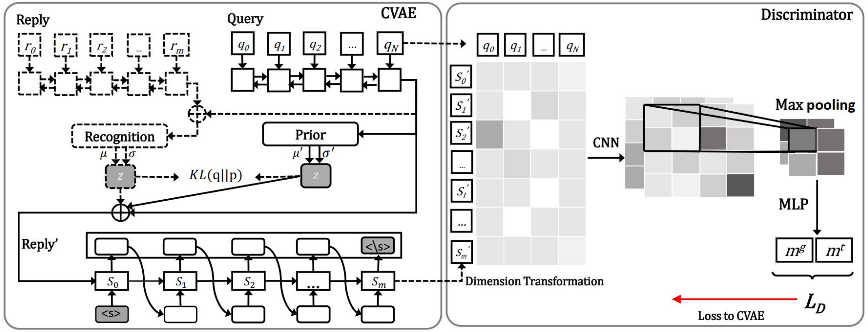


Figure 4 Three different paradigms of data augmentation for open-domain dialogue generation

Insufficient Data Can Also Rock! Learning to Converse Using Smaller Data with Augmentation, AAAI, 2019

DDA: Generative approach (cont.)

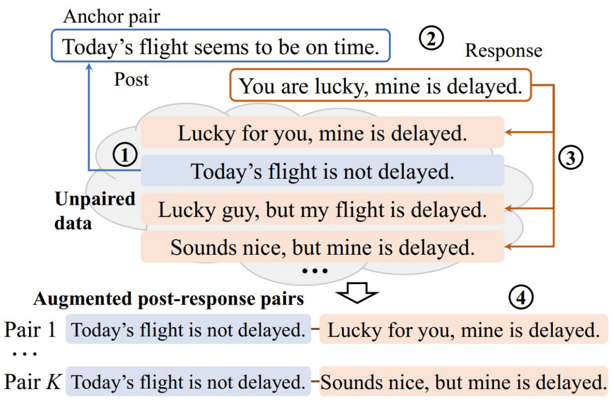
- Generator CVAE:
  - Encoder $(x, c) \mapsto z$. $q_\theta(z \mid x, c)$
  - Decoder $(z, c) \mapsto x$. $p_\theta(x \mid z, c)$,
- Discriminator
  - calculate the interaction (or matching) matrix
  - (CNN) to extract features
  - an adversarial fashion for training
- Filtering: Jaccard distance
  - depict the word-level semantic similarity



Insufficient Data Can Also Rock! Learning to Converse Using Smaller Data with Augmentation, AAAI, 2019

DDA: Using unpair data

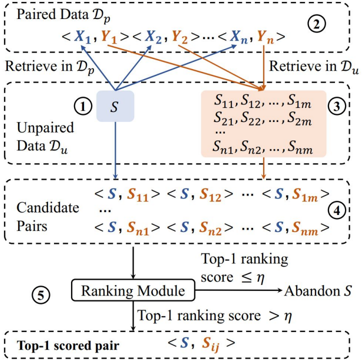
- Type of dialogue: Open domain, post-response pairs
- High-quality unpaired data are generally easier to collect
- The method involves two phases of distillation
  - Data level: constructs post-response pairs by matching sentences retrieved from a set of unpaired data
  - Model-level: distills a teacher model using the augmented data



Dialogue Distillation: Open-Domain Dialogue Augmentation Using Unpaired Data, EMNLP, 2020

DDA: Using unpair data, Data-level

- Constructing a set of new post-response pairs
- 1) Constructing candidate pairs
    - 1) The sentence S is randomly selected in the unpaired data Du.
    - 2) A set of posts X1; : : : ; Xn that are similar to S are retrieved from the paired data Dp
    - 3) Each corresponding response Yi is then used to retrieve m sentences Si1; : : : ; Sim that are similar to Yi from Du.
    - 4) Then n × m candidate pairs can be formed by grouping S with each sentence: hS; Siji, (i = 1; : : : ; n,
    - j = 1; : : : ; m)
- 2) Filtering low-quality candidates
    - ranking module is used to rank these candidate pairs
    - score function as a text matching model
    - only extract the top-1 scored pair hS; Siji among all its n × m candidate pairs



Dialogue Distillation: Open-Domain Dialogue Augmentation Using Unpaired Data, EMNLP, 2020

DDA: Using unpair data, Model-level

- Training with both original and augmented data
- The augmented pairs in Da might not be as high-quality as these human-crafted pairs in Dp.
- Prevent the dialogue models from being affected by the noise in Da
- Retrieval-based Dialogue Model
  - A matching function that predicts whether a response Y matches a given post X
    - Optimizing a negative log likelihood (NLL) loss

$$\mathcal{L}_{m-nll}(\theta) = -(1-l)\log\mathcal{P}_\theta(0|X,Y) - l\log\mathcal{P}_\theta(1|X,Y)$$

  - A teacher model
    - Teacher model is fixed
    - Used to compute a knowledge distillation (KD) loss

$$\mathcal{L}_{m-kd}(\theta) = -\sum_{i=0}^{1}\mathcal{P}_{\theta_t}(i|X,Y)\cdot\log\mathcal{P}_\theta(i|X,Y)$$

  - The final matching model is trained on the following loss

$$\mathcal{L}_M(\theta) = \mathcal{L}_{m-nll}(\theta) + \alpha_m\mathcal{L}_{m-kd}(\theta),$$

- Generation-based Dialogue Model
  - Try to capture the distribution of the response sentences Y given the post sentence X

Dialogue Distillation: Open-Domain Dialogue Augmentation Using Unpaired Data, EMNLP, 2020

DDA: Counterfactual

- Type of dialogue: Open domain, post-response pairs
- RQ: Given an observed dialogue, what the response would happen if we change the reply perspective, while keeping the current environment unchanged?
- Background: Structural Causal Model
    - Definition
    - Intervention
    - Counterfactual Inference

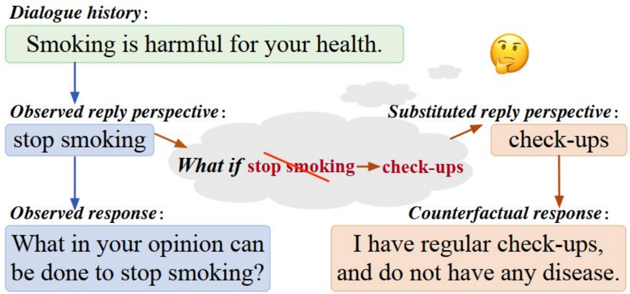
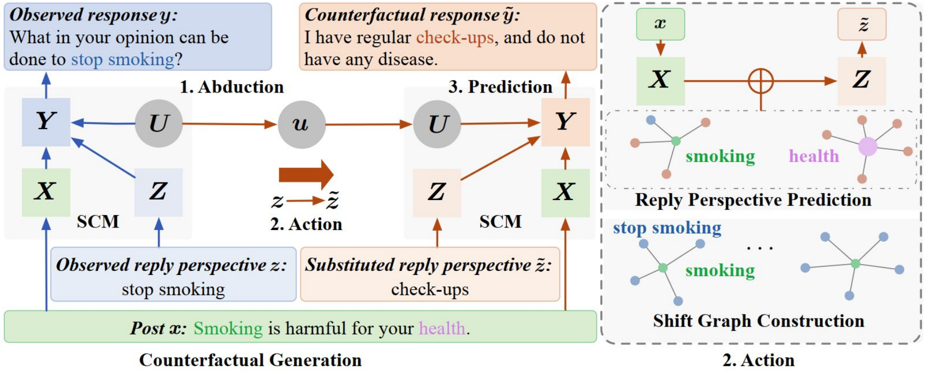


Figure 1: An example of a counterfactual response, which is a semantically different response re-inferred by changing the observed reply perspective.

Counterfactual Data Augmentation via Perspective Transition for Open-Domain Dialogues, EMNLP, 2022

DDA: Counterfactual (cont.)

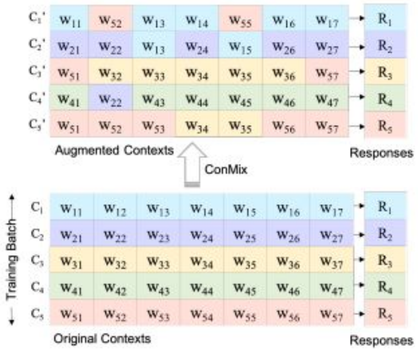
- Counterfactual Generation via Perspective Transition
  - Abduction: Estimate the unobserved variable given the observed sample
  - Action: Replace the observed reply perspective z with a substituted reply perspective
  - Prediction: Generate the counterfactual response given the posterior sample
  - Model Training: Reply perspective predictor and the counterfactual generator

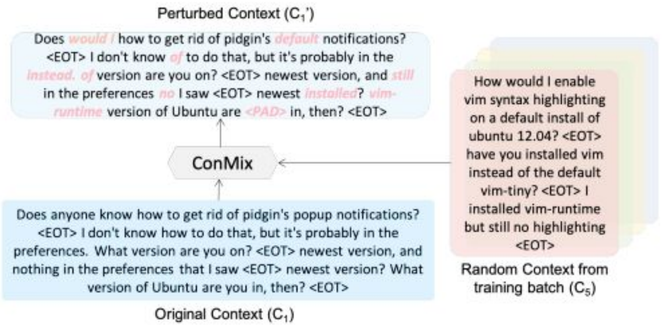


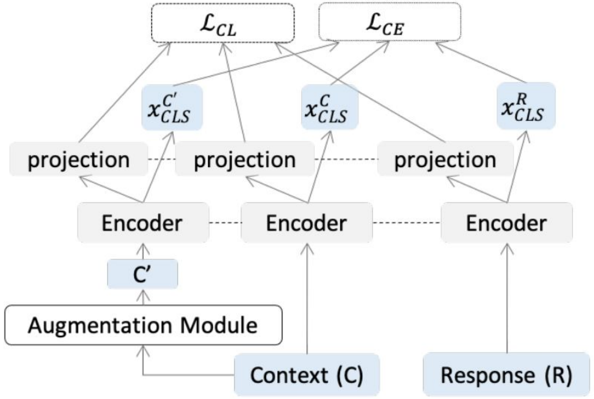
Counterfactual Data Augmentation via Perspective Transition for Open-Domain Dialogues, EMNLP, 2022

DDA: Mixing up Dialogue Contexts

- ConMix DA method: creates augmentations through dynamic mixing of words from other contexts in the batch
- Adapt the Bernoulli MixUp approach



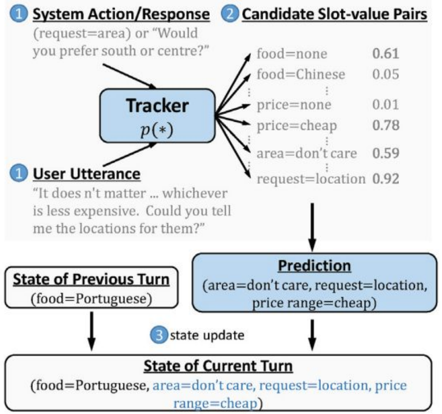




DialAug: Mixing up Dialogue Contexts in Contrastive Learning for Robust Conversational Modeling, COLING, 2022

DDA: RL-based

- Tracker Module: Track the user's goal during the dialog process
- Generator Module: Formulate DA as an optimal text span replacement problem
- Reward Design
  - Bag-level reward: Re-train the Tracker with each sampled bag
  - Instance-level reward: Evaluate each generated instance in the bag

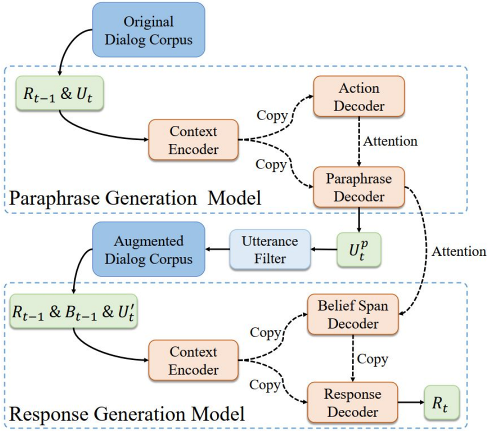


Dialog State Tracking with Reinforced Data Augmentation, AAAI, 2020

DDA: Paraphrasing

- Type of dialogue: Task-oriented, Augmenting next user utterance
- PARG model:
  - 1) Paraphrase Data Construction
  - 2) Paraphrase Augmented Response Generation
    - Paraphrase Generation Model
    - Paraphrase Filter
    - Response Generation Model

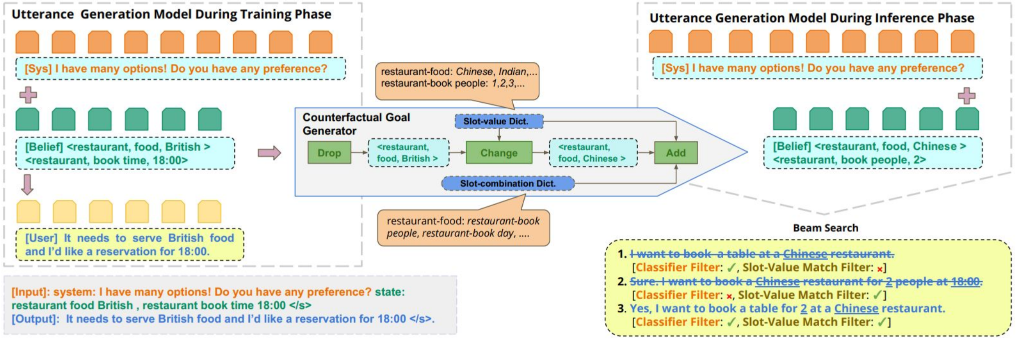
$$loss = loss_a + loss_p + loss_b + loss_r$$



Paraphrase Augmented Task-Oriented Dialog Generation, ACL, 2020

DDA: User Dialogue Act, counterfactual approach

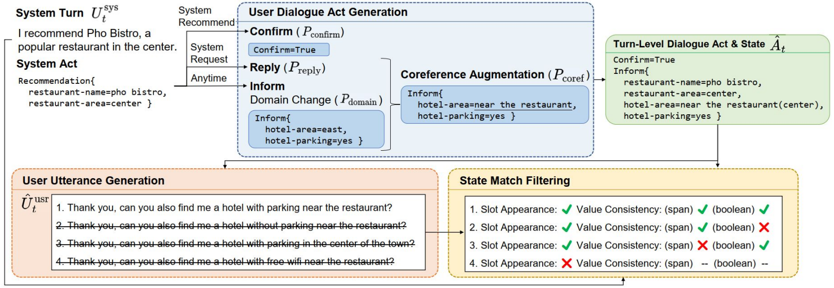
- Type of dialogue: Task-oriented, Augmenting next user act
- COCO consists of three main pillars:
  - Value Substitution
  - Controllable Counterfactual Generation
    - Operation
    - Slot-Value Dictionary
    - Slot-Combination Dictionary
  - Filtering
    - Slot-Value Match Filter
    - Classifier Filter

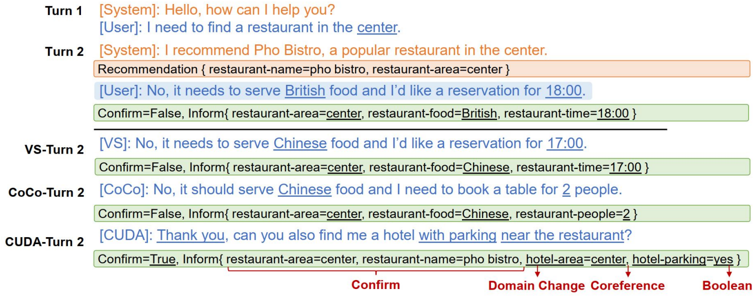


CoCo: Controllable Counterfactuals for Evaluating Dialogue State Trackers, ICLR, 2021

DDA: User Dialogue Act, user’s behavior

- Type of dialogue: Task-oriented, Augmenting next user act
- A user dialogue act represents the core meaning of the user’s behavior
- Controllable User Dialogue Act Augmentation (CUDA)
  - User Dialogue Act Generation
  - User Utterance Generation
  - State Match Filtering





Controllable User Dialogue Act Augmentation for Dialogue State Tracking, SIGDIAL, 2022

Token-level & Sentence-level Shortcomings

- Provide variety to the training data without greatly altering the semantics of the original sentences
  - Consistency between turns and coreference
- Only operate on the existing dialogue data
  - Fail to take advantage of the available external resources
  - Not suitable for low-resource languages and domains
- No Control on conversation flow
  - Cannot generate different forms of questions
    - Open-ended / Close-ended / unanswerable
  - Clarification question
- Next Idea: Using Generation process

Part 3: Conversation Generation, ODD

3.1 Single-turn QA Pair Generation

3.2 Multi-turn Dialogue Generation

3.3 Topic-aware Dialogue Agent

Duration: 80 min
Presenter: —

Single-turn QA pair Generation

Overview

Input (C)		... in 1903, boston participated in the first modern world series, going up against the pittsburgh pirates ...
(1)	$C \rightarrow A$	1903
(2)	$C, A \rightarrow Q$	when did the red sox first go to the world series
(3)	$C, Q \rightarrow A'$	1903
(4)	$A \stackrel{?}{=} A'$	Yes

Table 1: Example of how synthetic question-answer pairs are generated. The model's predicted answer (A') matches the original answer the question was generated from, so the example is kept.

- Creating new Question-Answer pair based on Passage
- Main goal: Informative and Consistent Question-Answer pair
- Principles of Pipeline method
  - Passage selection: identifying passages which humans are likely to ask questions about
  - Answer Extraction: an answer is extracted from the selected passage
  - Question Generation: generating a question based on the passage C and the extracted answer
  - Filtering: to ensure the accuracy and quality of the generated question-answer pair

Synthetic QA Corpora Generation with Roundtrip Consistency, ACL, 2019

Passage Selection

- Used to find passages that are likely
  - To contain information that humans may ask about,
  - Make good candidates to generate questions from
- Dense Passage Retrieval" method
  - Training passage and question Encoders
  - At run-time, calculate the similarity
  - For training the encoder: Metric learning

$$\mathrm{sim}(q, p) = E_Q(q)^\intercal E_P(p).$$

$$L\left(q_i, p_i^+, p_{i,1}^-, \cdots, p_{i,n}^-\right) = -\log \frac{e^{\mathrm{sim}\left(q_i, p_i^+\right)}}{e^{\mathrm{sim}\left(q_i, p_i^+\right)} + \sum_{j=1}^{n} e^{\mathrm{sim}\left(q_i, p_{i,j}^-\right)}}$$

Dense Passage Retrieval for Open-Domain Question Answering, EMNLP, 2020
PAQ: 65 Million Probably-Asked Questions and What You Can Do With Them, TACL, 2021

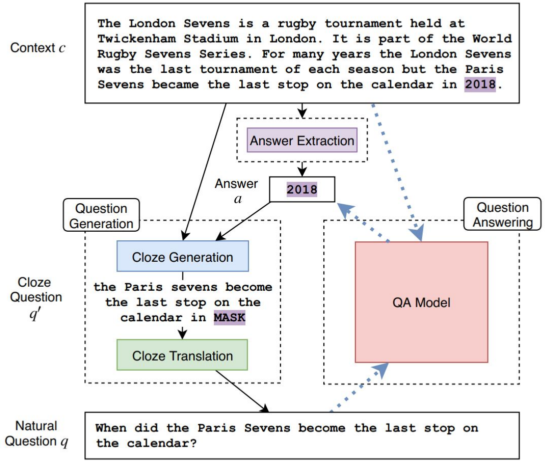
Answer Extraction

- Given a passage, identify spans that are likely to be answers to questions
- Types:
    - Question Unconditional Extractive [Alberti]
    - Question Conditional Extractive [Alberti]
    - NER answer extractor [PAQ][Lewis]

PAQ: 65 Million Probably-Asked Questions and What You Can Do With Them, TACL, 2021
Synthetic QA Corpora Generation with Roundtrip Consistency, ACL, 2019

Question Generation

- Given a passage and an answer, generate likely questions with that answer
- Types:
    - As a left-to-right language model [Alberti][PAQ]
    - By Cloze Translation [Lewis19]



Unsupervised question answering by cloze translation, ACL, 2019
Synthetic QA Corpora Generation with Roundtrip Consistency, ACL, 2019

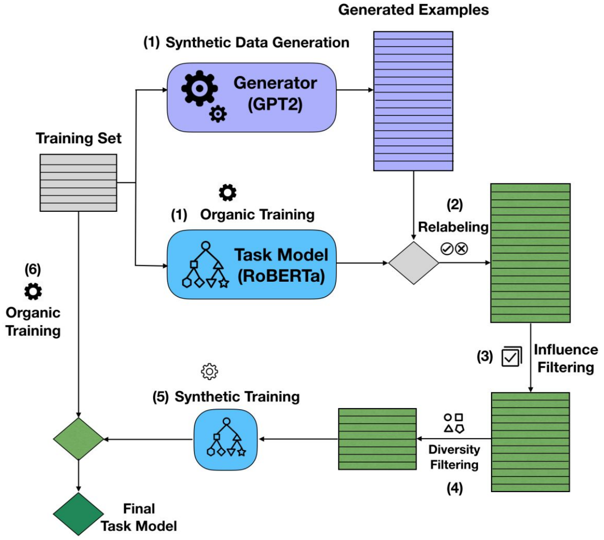
Filtering

- Improves the quality of generated questions
  - By ensuring that they are consistent
  - The answer they were generated is likely to be a valid answer to the question
- Types:
  - Local filtering [Alberti, RTQA]
    - Based on the selected passage ot sub-passage
    - will not remove questions that are ambiguous
  - Global filtering [PAQ]
    - Based on the whole corpus

PAQ: 65 Million Probably-Asked Questions and What You Can Do With Them, TACL, 2021
Synthetic QA Corpora Generation with Roundtrip Consistency, ACL, 2019

Multiple choice QA

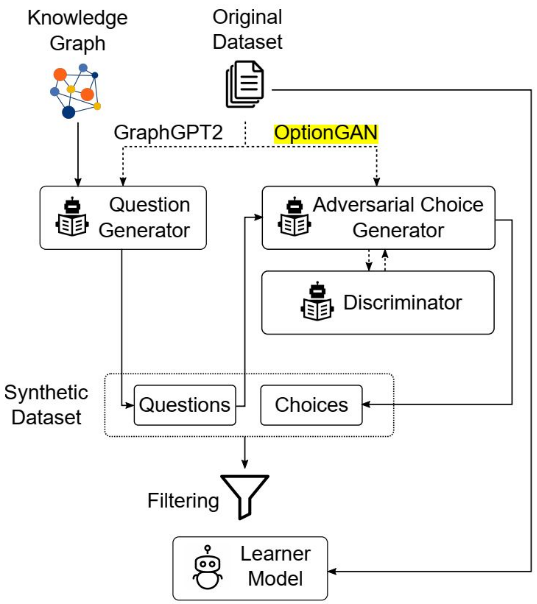
- Selects the most informative and diverse set of examples for data augmentation
- Synthetic Training Data Generation
  - Generating Synthetic Questions
  - Generating Synthetic Answers and Distractors
  - Data Relabeling
- Filtering: Synthetic Data Selection
  - Filtering with Influence Functions
  - Selecting Diverse Examples
- Training with Synthetic Data
  - Synthetic Training
  - Organic Training



Generative Data Augmentation for Commonsense Reasoning, EMNLP, 2020

Multiple choice QA (KG-based)

- GRADA: a graph-generative data augmentation framework
    - To synthesize factual data samples from knowledge graphs
    - For commonsense reasoning datasets
- Graph-to-Text Generation
    - Linearized Graph Input
    - GraphGPT2 for Structure-aware Graph Input
- Answer & Distractor Generation
- Filtering and Selection of Samples

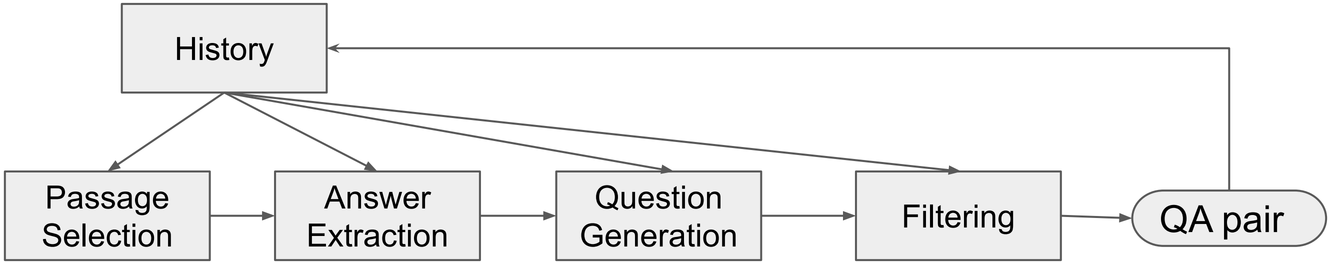


GRADA: Graph Generative Data Augmentation for Commonsense Reasoning, COLING, 2022

Multi-turn Conversation Generation

Overview

- Differences with single-turn QA
  - The history of the conversation are also fed to model
  - The generated QA is added to conversation history
  - The use of some components has been slightly changed
- Additional challenges
  - deeper understanding of the context and the dialogue history
  - specific challenges unique to conversational settings, such as coreference alignment and conversation flow



Passage Selection

- Modified to selecting a sub passage
- 1) Rank the passages [DG2]: A document can often be very long
    - Contrastive loss
- 2) Shortening the context and history for the model
    - Highlight a sentence of the given passage that contains answer rationale, in answer-aware [ChainCQG]
    - Context and History Selection (CoHS) [CoHS-CQG]
        - Naive solution: only simply selected the last k turns
        - CoHS: select the top-p of sentences and QA pairs from C and Hn

$$minimize(u + k)$$

$$\sum_{i=v-u}^{v-1} \sum_{j=n-k}^{n-1} \mathbf{T}[i][j] \geq p$$

$$(q_{n-1}, a_{n-1}) \in H_{sub}, c_s \in C_{sub}$$

Passage Selection (cont.)

- 3) Guarantee & Control the flow of the generated conversation
  - Assumption: A passage usually starts with some general concepts and as going through, it gets in details
  - Split the passage in some chunks [CFNet, AU-CQG]
  - Document Positional Information [DG2]

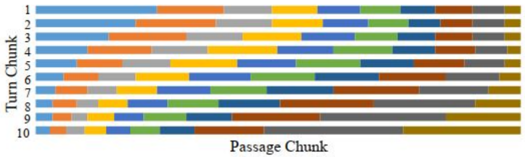
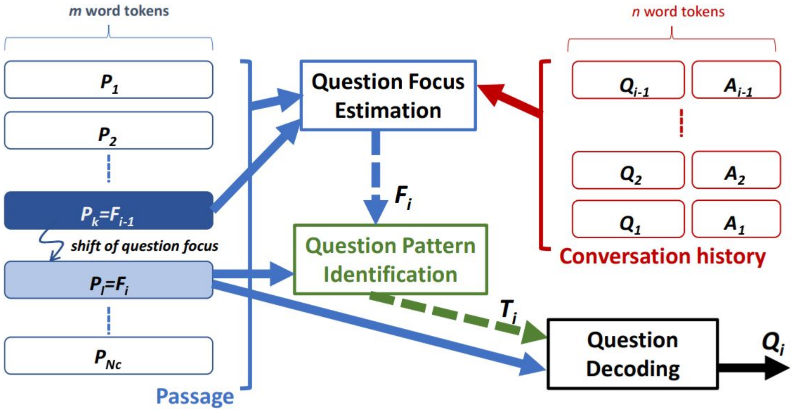


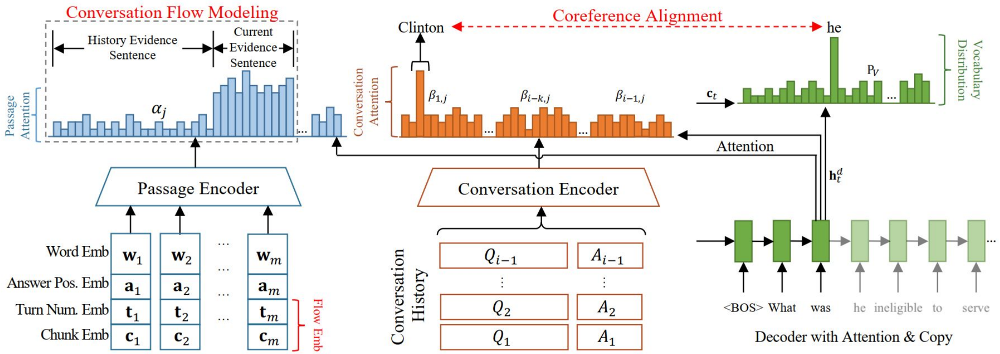
Figure 1: Passage chunks of interest for each turn chunks. Each row contains 10 bands distinguished by different colors. Each band represents a passage chunk. The width of a passage chunk indicates the concentration of conversation in that turn. The y-axis indicates turn chunk number. Same passage chunks share the same color across different turn chunks. *(Best viewed in color)*



Conversation Flow

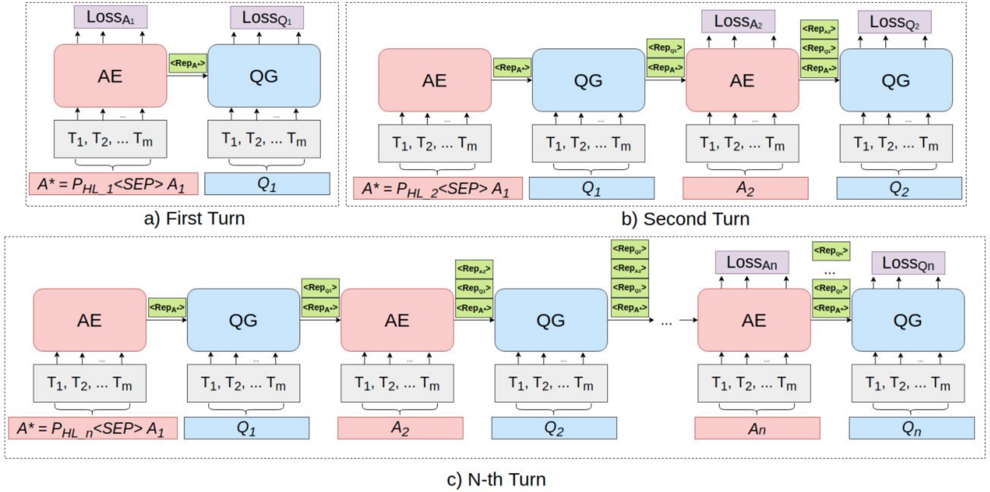
- Mainly by filtering sub-module
- Flow embedding [CFNet]
- Flow loss [CFNet]
- Conversation Flow Modeling Analysis [CFNet]

$$\mathcal{L}_{\text{flow}} = -\lambda_3 \log \frac{\Sigma_{j:w_j \in \mathtt{CES}} \alpha_j}{\Sigma_j \alpha_j} + \lambda_4 \frac{\Sigma_{j:w_j \in \mathtt{HES}} \alpha_j}{\Sigma_j \alpha_j}$$



Conversation Flow (Cont.)

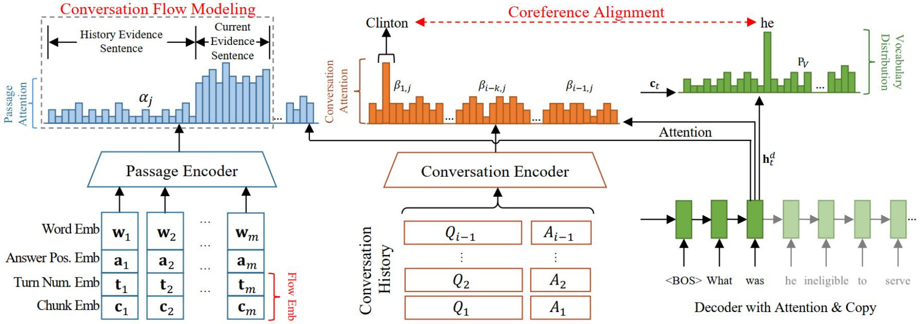
- Flow Propagation-Based Training [ChainCQG]



Coreference Alignment

- Coref loss function
- History as an input
- Coreference Alignment Analysis

$$\mathcal{L}_{\text{coref}} = -(\lambda_1 \log \frac{\Sigma_j \beta^c_j}{\Sigma_{k,j} \beta_{i-k,j}} + \lambda_2 \log p_{\text{coref}}) * s_c,$$



Passage: … however , mccain has a very different life story . he grew up in a navy family and was a pilot during the vietnam war in the 1960s …

Conversation History:

<q>	what	war	was	mccain	in	?
0.0000	0.0001	0.0049	0.0138	0.7710	0.0055	0.0069
<a>	vietnam	war				
0.0000	0.0140	0.0095				
<q>	was	he	in	the	army	?
0.0000	0.0045	0.1303	0.0005	0.0139	0.0001	0.0250
<a>	no					
0.0000	0.0000					

Question (Human): what was his job ?

Question (Our Model): what was his job ?

Passage: … incumbent democratic president bill clinton was ineligible to serve a third term due to term limitations in the 22nd amendment of the constitution …

Conversation History:

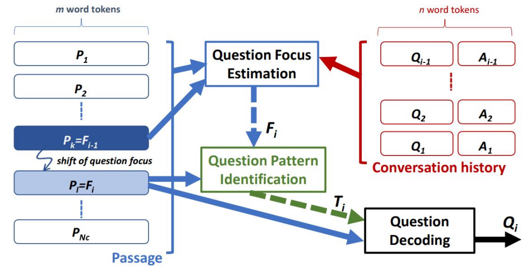
<q>	what	political	party	is	clinton	a
0.0000	0.0000	0.0002	0.0063	0.0045	0.9260	0.0430
member	of	?	<a>	democratic		
0.0008	0.0006	0.0026	0.0000	0.0160		

Question (Human): what was he ineligible to serve ?

Question (Our Model): what was he ineligible for ?

Question Types

- Question Pattern Identification [AU-CQG]
  - Question Pattern Classification
  - Question Pattern Generation



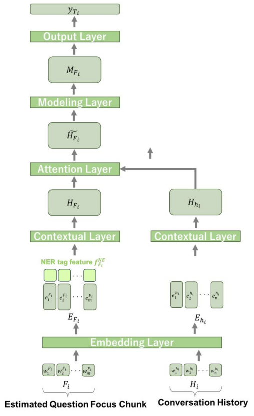


Figure 3: Question pattern classification model.

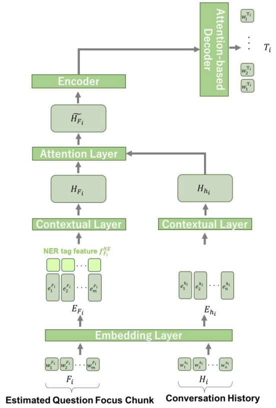


Figure 4: Question pattern generation model.

Question Types (cont.)

- Hierarchical Answerability Classification [MultiCQAG]
    - filters out invalid Q–A pairs and acquires unanswerable questions
    - determines whether a question can be answered based on the passage
    - If not, the module replaces the answer of an unanswerable question with "unknown"
- Classify synthetic questions into three categories:
    - 1) Answerable in correct context
    - 2) Answerable in different context
    - 3) Unanswerable question
- Modeling

Filtering unqualified pairs & Answer Revision

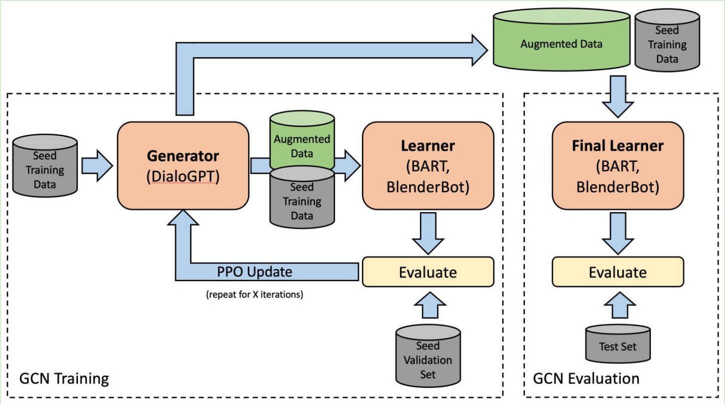
- Discarding unqualified pairs
  - Question Filtering [CoHS-CQG]
  - Roundtrip Filtration for CQA [SIMSEEK]
- Revision module:
  - First considers that the extracted answer span is proper for use as an answer
  - Then modifies it if it is inappropriate
- Two negative sampling techniques:
  - To collect improper answer spans from proper ones
  - Generating Negative Samples
    - 1) Answer Span Expansion
    - 2) Answer Span Reduction
  - Modeling

Blinded to the answer-containing passage

- Rely on background information B [SIMSEEK]
- Two opposite ways to simulate synthetic conversations from unlabeled documents
  - SimSeek-sym
  - SimSeek-asym

Generative and RL based

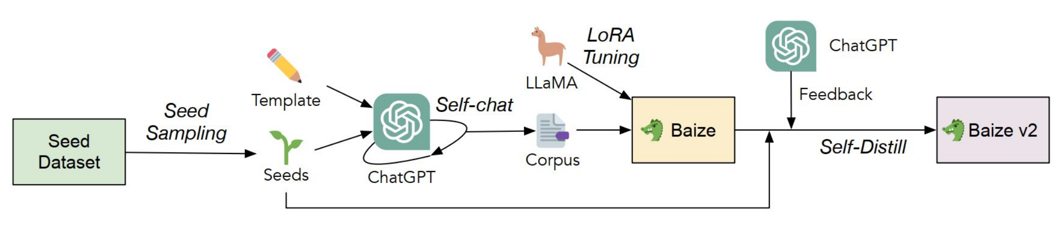
- T



Knowledge-Grounded Conversational Data Augmentation with Generative Conversational Networks, SIGDIAL, 2022

Prompting

- T



Baize: An Open-Source Chat Model with Parameter-Efficient Tuning on Self-Chat Data, EMNLP, 2023

Multi-turn Dialogue Generation: Summary

- The main challenges:
  - Sub-passage selection
  - Flow consistency
  - Coreference alignment
  - Question types & validation
  - Blinded to the answer-containing passage
- Text-based approach
- No annotation needed
  - Just the consistency and correctness are evaluated

Topic-aware Dialogue Agent

- No controllability in the pipeline method
- Proactive dialogue systems
  - Add more control over the conversations
  - Proactiveness: the agent introducing new elements into the conversation
- How can this type of dialogue system be beneficial in generating full conversations?
  - Having a high-level plan or strategy
  - Planning techniques that involve defining paths on a knowledge graph
- Tasks
  - Incorporating mix-initiative in control flow & facilitating topic shifting
  - asking clarifying questions,
  - suggesting useful search queries,
  - integrating chit-chat with task-oriented interactions,

One-turn Topic Transition

- Task definition: Identifying a bridging path of entities to link the context and the target
- OTTers
    - Incorporates a reasoning module
    - Connects the two sentences using a Knowledge Graph (KG) path
        - The outputs can be more controlled and interpretable
- Sub-task for mixed-initiative dialogue system

User A	**Source Topic**:	I spend a lot of time **outside**.
User B	**Transition**:	I like the outdoors as well, especially **gardening**. It destresses me.
	Target Topic:	I enjoy relaxing and getting **flowers**.
	Entity Path:	**outside** - **garden** - **flower**
User A	**Source Topic**:	I like **seafood** a lot.
User B	**Transition**:	Since you like seafood, is **Swedish fish** a candy that you might enjoy?
	Target Topic:	I have no self control when it comes to **candy**.
	Entity Path:	**seafood** - **Swedish fish** - **candy**
User A	**Source Topic**:	I think I am getting **engaged** soon.
User B	**Transition**:	I have two children from a previous **marriage**
	Target Topic:	My **children** are my life.
	Entity Path:	**engagement** - **marriage** - **child**

OTTers: One-turn Topic Transitions for Open-Domain Dialogue,

Commonsense Path and Data

- Two approaches for the transition response generation task
  - 1) Commonsense-guided response generation (CRG)
  - 2) Data augmentation to tackle data sparsity

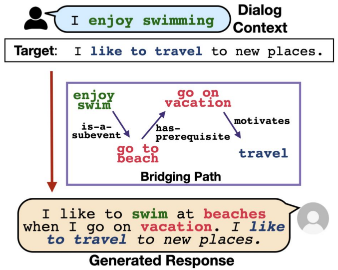
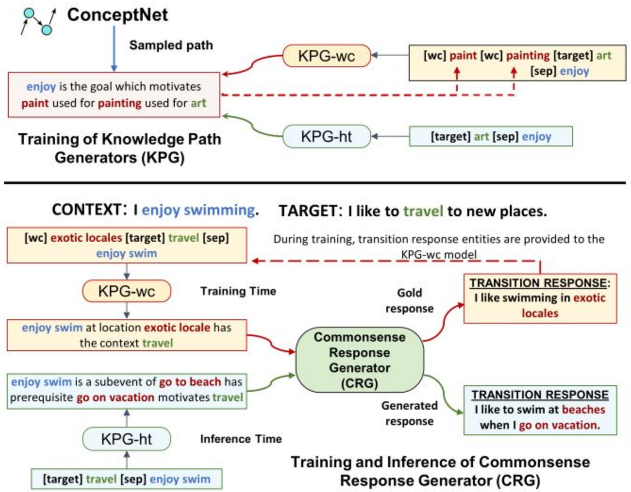


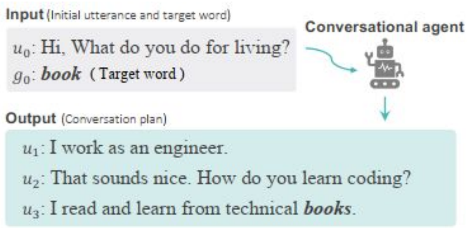
Figure 1: Given a dialogue context and a target sentence, our goal is to generate a dialogue response that smoothly transitions the conversation from context towards the target. Our proposed approach involves identifying a bridging path of entities to link the context and the target.

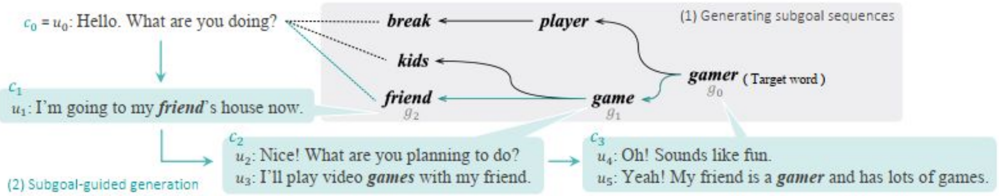


Target-Guided Dialogue Response Generation Using Commonsense and Data Augmentation

Target-Guided Open-Domain Conversation (TGCP)

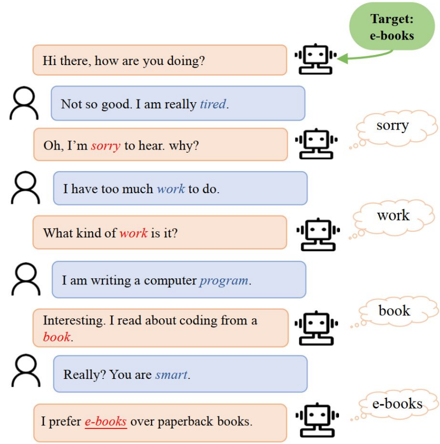
- Definition: Evaluate whether neural conversational agents have goal-oriented conversation planning abilities





Target-Guided Dialogue Response Generation Using Commonsense and Data Augmentation

Target-oriented Dialogue System



- Task Definition
  - Chat naturally with human
  - Proactively guide the conversation to a designated target subject
- Types of goal
  - Designated target topic: A word (an named entity, or a common noun)
  - Pre-defined topic thread
- The challenge of this problem: how to balance the tradeoff between
  - Transition smoothness: maximizing transition smoothness between turns in the dialogue
  - Target achievement: minimizing the number of turns taken to reach the target
- Sub-problems:
  - Next turn keyword selection
  - Keyword-augmented response retrieval / generator
- Dataset problem for this task
  - Add the proposed challenge to existed dataset

Target-Guided Open-Domain Conversation, ACL, 2019

Keyword Extractor

- Rule-based keyword extractor
  - Combines TF-IDF and Part-Of-Speech features for scoring word salience
- Steps:
  - 1) Regards each utterance in a conversation as a document
    - each word as a term to calculate the TF-IDF value of each word
  - 2) Ignores the words
    - Appearing less than 10 times in all corpus
    - Have been mentioned in the former utterance of the current conversation
  - 3) Sets different weights to distinguish the importance of each part of speech
  - 4) Multiplies the TF-IDF value with the part-of-speech weight
  - 5) Considers the words left as the keywords of an utterance in an conversation
- Pros:
  - Simplicity and interpretability
- Cons:
  - Data sparsity
  - Perform poorly with a priori unseen transition pairs

Target-Guided Open-Domain Conversation, ACL, 2019

Dataset Creation

Dialog	**A:** I spend a lot of time **outside**. **B:** I like the outdoors as well, especially **gardening** . **A:** Wow! I used to have a **garden** too. **B:** I love sipping coffee while enjoying **flowers** in my garden. **A:** Flowers are always beautiful and **colorful** ! **B:** I like anything with **art**, especially colorful things.
Entity Path	**Outside-Garden-Flower-Color-Art**
Target	**Art**

Table 1: A target-oriented example dialog in TGConv

- Target-Guided Conversation (TGC) [TGODC]
  - is constructed from Persona-Chat
  - The conversations cover a broad range of topics such as work, family, personal interest, etc
  - the discussion topics change frequently during the course of the conversations
- Chinese Weibo Conversation(CWC) [DKRN]
  - derived from a public multi-turn conversation corpus1 crawled from Sina Weibo
  - covers rich real-world topics in our daily life, such as shopping, disease, news, etc
- Reddit-based [CKC]
  - collected from casual chats on the CasualConversation and CasualUK subreddits,
    - where users chat freely with each other in any topic
  - use TF-IDF and part-of-speech (POS) features to extract keywords, same as TGC
- TGConv [TopKG]
  - from chit-chat corpus ConvAI2
  - a consistent reasoning path of words linking all the utterances in their order in the dialog
  - is distinguished into "easy-to-reach/hard-to-reach" targets

A survey on Proactive Dialogue Systems: Problems, Methods, and Prospects, Arxiv, 2023

Component 1: Turn-level keyword transition module

- Task: Guarantee the smooth transition
- Approaches
  - A) Pairwise PMI-based transition [TGODC]
  - B) Neural-based prediction [TGODC]
  - C) Hybrid kernel-based method [TGODC]
  - D) Inject semantic knowledge relations among candidate keywords [DKRN]
  - E) Leverage external commonsense knowledge graphs (CKG) as an another input [CKC]
  - F) Global-target graph and local-target graph as external inputs [TopKG]

Component 1: Turn-level keyword transition module

A) Pairwise PMI-based transition

- Construct a keyword pairwise matrix
- Characterizes the association between keywords in the observed conversation data
- Pointwise mutual information (PMI)
  - Computes likeliness
  - p(wi|wj) is the ratio of transitioning to wi in the next turn given wj in the current turn
  - p(wi) is the ratio of wi occurrence
  - Both quantities can be directly counted from the conversation data beforehand

$$\mathrm{PMI}(w_i, w_j) = \log p(w_i|w_j)/p(w_i),$$

Component 1: Turn-level keyword transition module

B) Neural-based prediction

- Steps:
  - Use a recurrent network to encode the conversation history
  - Feed the resulting features to a prediction layer to obtain a distribution over keywords for the next turn
- Pros:
  - Straightforward
- Cons:
  - Rely on a large amount of data for learning

Target-Guided Open-Domain Conversation, ACL, 2019

Component 1: Turn-level keyword transition module

C) Hybrid Kernel-based Method

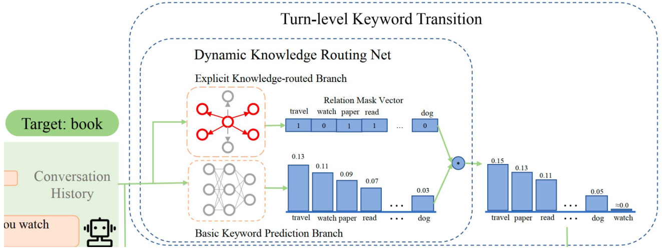
- Combines neural feature extraction with pairwise closeness measuring
- Steps:
  - 1) Measuring the cosine similarity of their normalized word embeddings
  - 2) Feeding the quantity to a kernel layer consisting of K RBF kernels
  - 3) The output of the kernel layer is a K-dimension kernel feature vector
    - Fed to a single-unit dense layer for a candidate score
  - 4) The score is finally normalized across all candidate keywords to yield the candidate probability distribution
  - 5) If the current turn has multiple keywords
    - The corresponding multiple K-dimension kernel features are first summed up before feeding to the dense layer
    - The intermediate kernel layer serves as a soft aggregation mechanism to account for multiple-to-one keyword transition

Target-Guided Open-Domain Conversation, ACL, 2019
End-to-end neural ad-hoc ranking with kernel pooling, SIGIR, 2017

Component 1: Turn-level keyword transition module

D) Inject semantic knowledge relations among candidate keywords

- Previous methods' limitation
  - Considering semantic or factual knowledge relations among candidate topics/keywords
- There are two branches in our DKRN
  - Basic keyword prediction branch
  - Explicit knowledge routing branch
- Mask those keywords that are uncorrelated directly to the conversation context/history

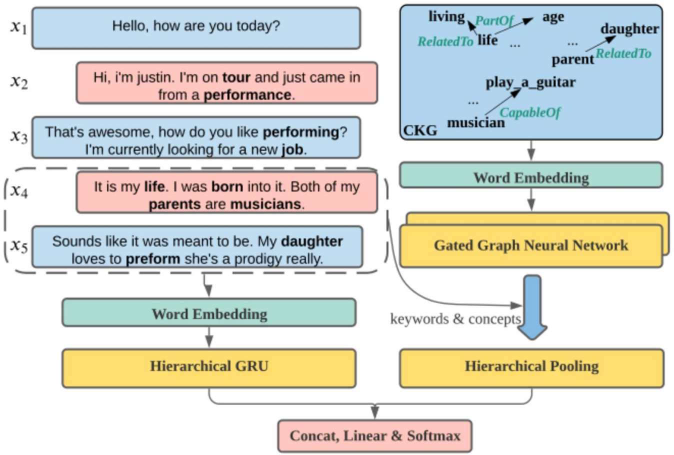


Dynamic Knowledge Routing Network For Target-Guided Open-Domain Conversation, AAAI, 2020

Component 1: Turn-level keyword transition module

F) Leverage external commonsense knowledge graphs (CKG)

- A multi-label classification problem
- Steps:
  - 1) Utterance Representation
  - 2) CKG Graph Representation
  - 3) Keyword and Concept Representation
  - 4) Classification

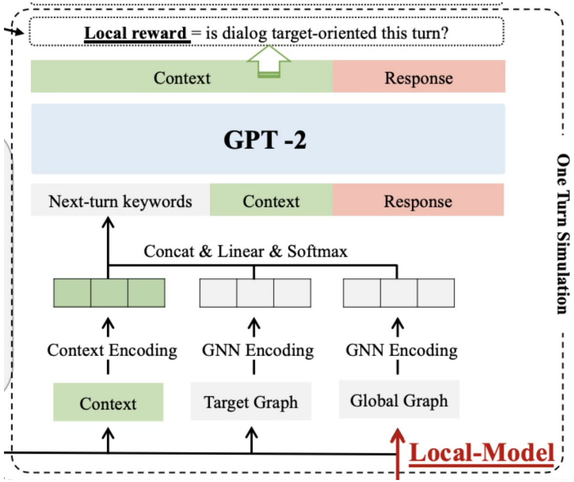


Keyword-guided neural conversational model, AAAI, 2021

Component 1: Turn-level keyword transition module

E) Global-target graph and local-target graph as external inputs

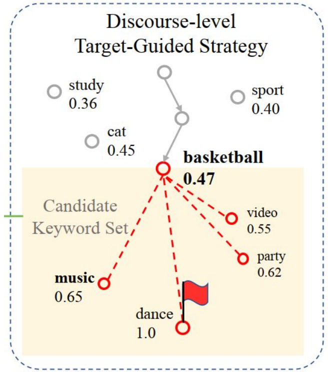
- Previous methods shortcoming:
  - They adopt a short-sighted and greedy strategy
  - instead of global planning to optimize the process towards the global target
- Steps:
  - Graph-based Encoder
  - Conversation Context Encoder
  - Classification



TopKG: Target-oriented Dialog via Global Planning on Knowledge Graph, COLING, 2022

Component 2: Discourse-level Target-Guided Strategy module

- Task: Taking an effective step towards the target
- Approaches:
- A) Calculate the closeness between keywords candidates and the target [TGODC]
    - Higher target closeness as a constraint, cosine similarity
- B) Dual Discourse-level Target-Guided Strategy [DKRN]
    - Not only constrains the keyword but also constrains the next chosen response (retrieval model)



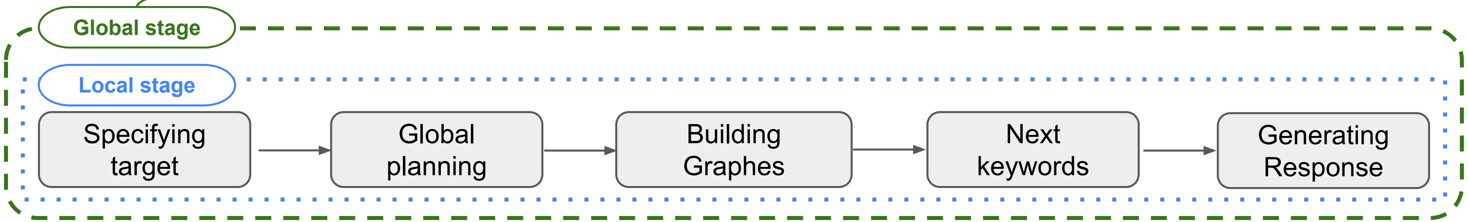
Component 2: Discourse-level Target-Guided Strategy module…

- Approaches:
- C) Leverage external commonsense knowledge graphs (CKG) as an another input
    - The distance between keywords is measured as the weighted path length between keywords on the CKG
    - Computed by the **Floyd-Warshall algorithm**
    - The edge weights on ConceptNet correlate positively with concept relatedness
        - we apply a reciprocal operation to the weights before computing path lengths

Component 2: Discourse-level Target-Guided Strategy module…

- Approaches:
- D) Global planning:
  - Leveraging RL based global-model
  - Dialogue Policy Learning

Guide with RL:
- State: G_global, G_local, Context
- Action: The next turn keyword
- Action space: The potential paths obtained by global planning
- Reward:
  - Local: Encourages the contextual consistency at each turn of dialog
  - Global: Encourages the global target-oriented response
- Policy: Proximal Policy Optimization



TopKG: Target-oriented Dialog via Global Planning on Knowledge Graph, COLING, 2022

Component 3: Keyword-augmented Response Retrieval/Generator

- Produce a response
  - Conditioning on both the conversation history and the predicted keyword
- Approaches:
  - 1) Retrieval based [TGODC]
    - Recurrent networks to encode the input conversation history and keyword, and each of the candidate responses
  - 2) The sequential matching network (SMN) + the Hadamard product [DKRN]
  - 3) Retrieval + matching score [CKC]
  - 4) Keyword Augmented GPT [TopKG]

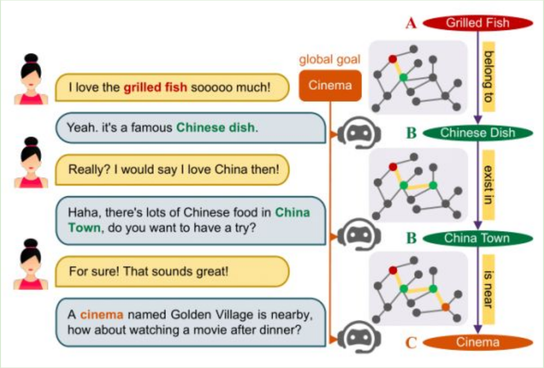
Multi-turn Conversation Generation by Self-play

- To simulate the process of two virtual agents taking turns talking with each other
- For global evaluation
    - To assess that does the model reach the target
- The base Retrieval/Generator agent to play the role of human
    - Retrieves/Generates a response without knowing the end target
- The simulator randomly picks a keyword as the end target, and an utterance as the starting point

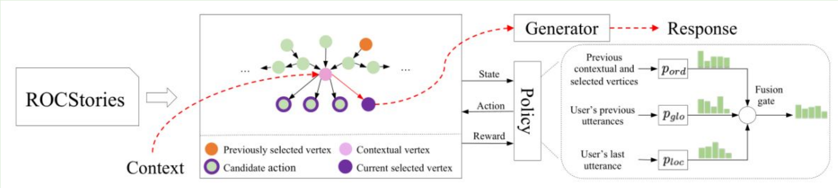
Deal or No Deal? End-to-End Learning of Negotiation Dialogues, EMNLP, 2017

Global Planning

- Enhance multi-turn consistency
- Mainly KG-based: Generating more informative responses
- Guide the response/conversation generation flow toward the target



Event Graph Grounded Content Planning



Multi-Hierarchy Learning

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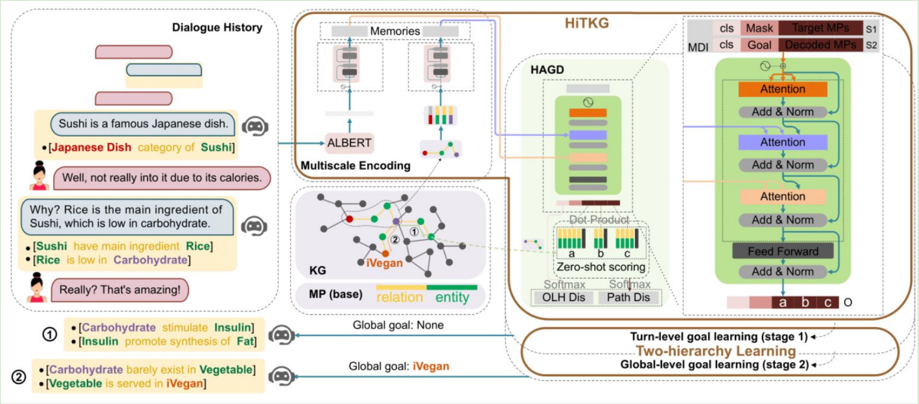

Brownian Bridge Stochastic Process

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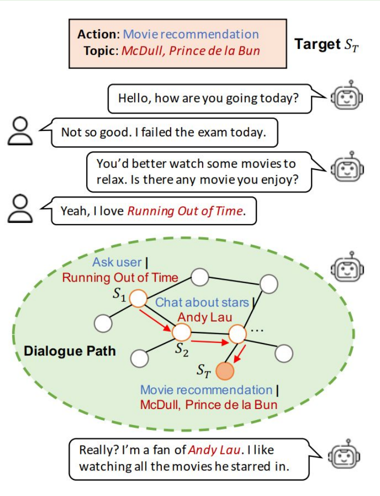


Topic-aware dialogue agent: Summary

- Add new responsibility to dialogue agent
- Improve the controllability on dialogue generation
- The dialogue is annotated by
  - Initial sentence and keyword, and final Target
  - The full transition keyword path
- Using a knowledge graph seems to be effective in guiding the conversation towards the Target
  - Unlike most dialog system models that use KG to generate informative responses
- Using the self-play tool completes the process of conversation generation
  - Although the main purpose of the topic-aware conversation agent is not to create a conversation dataset

Part 3: Conversation Generation, TOD

3.1 Schema-guided Generation

3.2 Simulator-Agent Generation

3.3 E2E Dataset Creation

Duration: 40 min

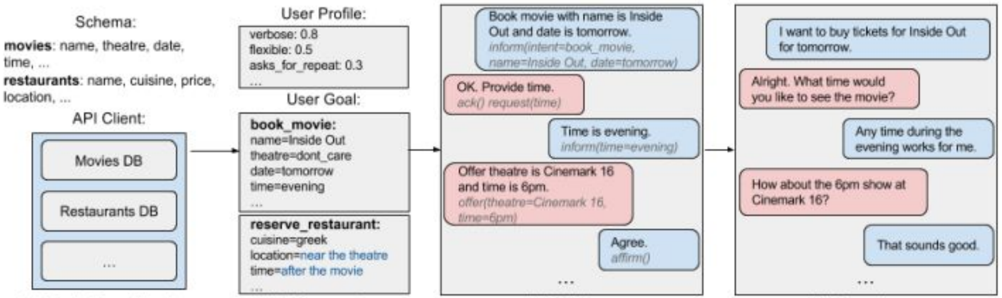
Presenter: —

Introduction

- Human2Human: MultiWOZ
- Schema-guided Generation: M2M, SGD
  - Combining automation and crowdsourcing
  - Generate outline or schema by simulator
  - Paraphrase template utterances into more natural sounding utterances by crowdsourcing
- Simulator-Agent Interaction
  - The dialogue system (DS) and user simulator (US) discourse with each other
  - A domain-independent (general) user simulator with transformers [TUS]
  - Interaction between a prompt-based user simulator and a dialog system [ICL-US]
  - The context encoder is shared between the two agents [JOUST]
- E2E dialogue generation
  - A model generates a whole dialogue

Schema-guided Generation: M2M

- A framework combining automation and crowdsourcing
- Machine-to-Machine:
  - 1) Generate dialogue templates
    - Creating an environment with a simulated user
  - 2) These templates can be mapped to a natural language
- self-play
- user simulator: employ an agenda-based
- system agent: a finite state machine based



(a) Task Specification (b) Scenario (c) Outline (d) Paraphrase

A

Schema-guided Generation: SGD

- Schema-guided paradigm for task-oriented dialogue
  - simplifies the integration of new services and APIs with large scale virtual assistants
- Crowdsourcing: to paraphrase template utterances into more natural sounding utterances
- Steps:
  - 1) Services and APIs
  - 2) Dialogue Simulator Framework
  - 3) Dialogue Paraphrasing

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Simulator-Agent Interaction: LaRL

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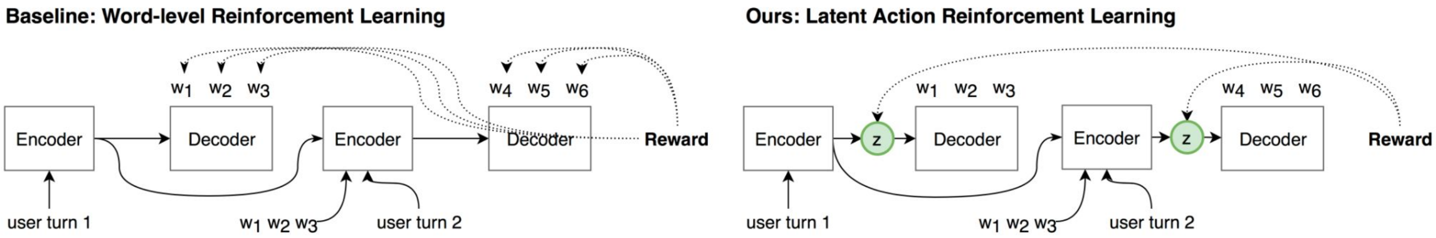

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Simulator-Agent Interaction: TUS

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Simulator-Agent Interaction: JOUST

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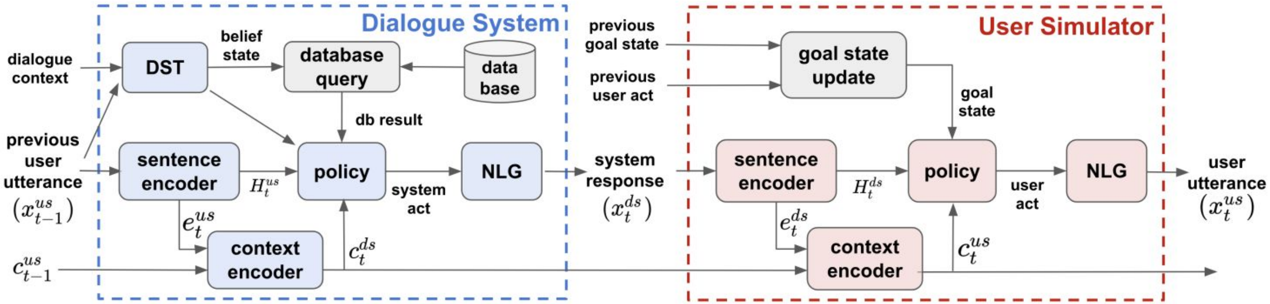

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Simulator-Agent Interaction: SimulatedChat

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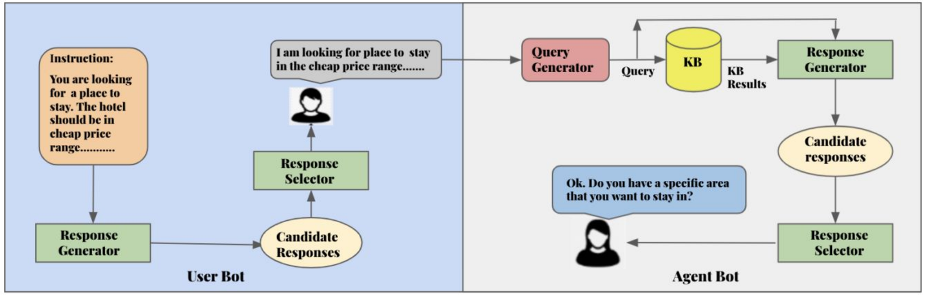

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Simulator-Agent Interaction: Unified-US

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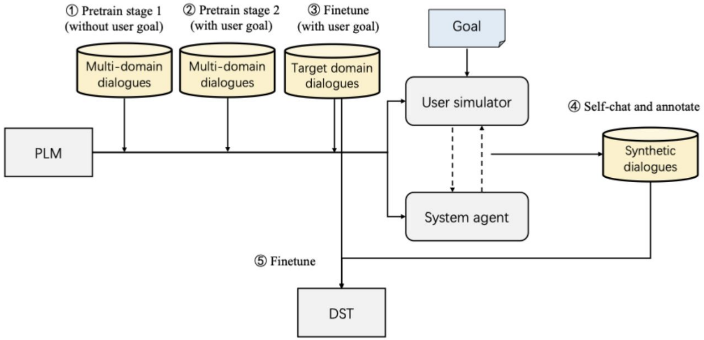

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Simulator-Agent Interaction: ICL-US

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E2E Dataset Creation: VHDA

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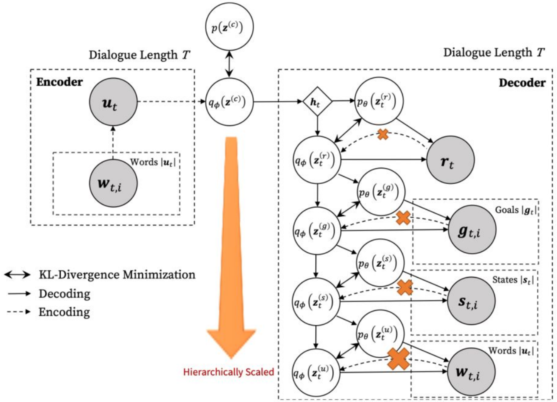

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E2E Dataset Creation: NeuralWOZ

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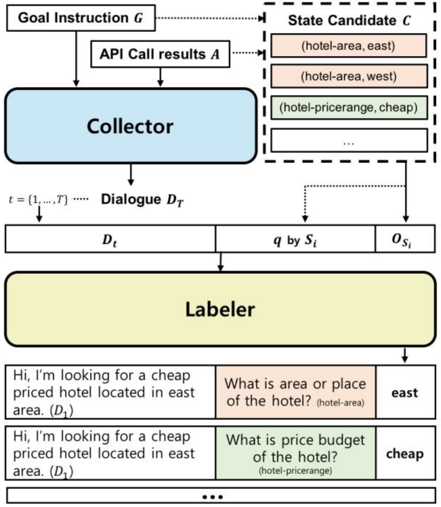

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E2E Dataset Creation: LAD

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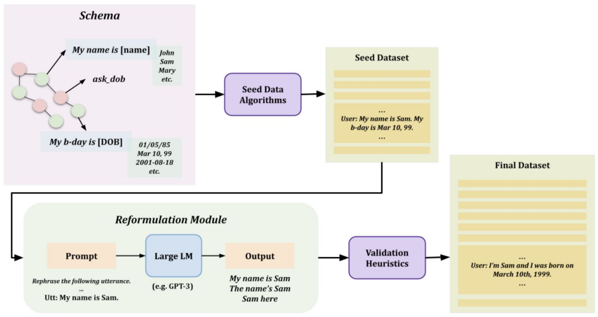

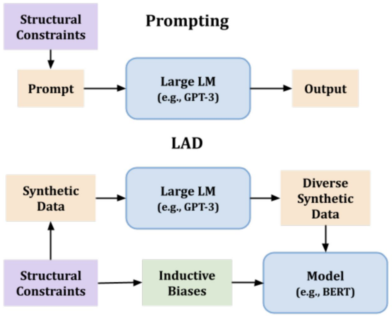

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E2E Dataset Creation: DIALOGIC

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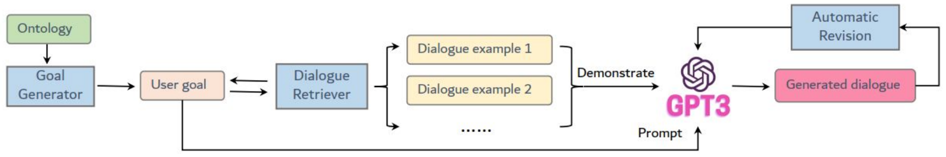

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E2E Dataset Creation: PLACES

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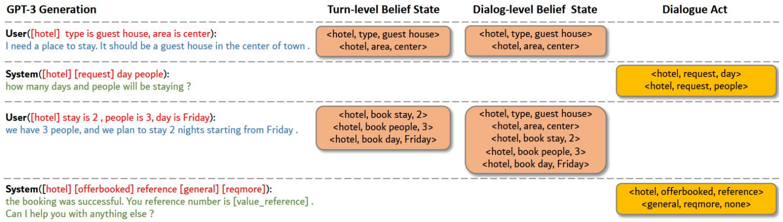

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Part 3: Evaluation

How to evaluate

- Open-domain Dialogue system
    - Measure response correctness
        - Automatic Evaluation metrics:
            - F1_score, EM, BLEU, ROUGE, METEOR, Perplexity, BERTscore, MoverScore
    - Measure the whole conversation
        - Human Evaluation
            - Naturalness, Relevance, Coherence, Richness, Fluency, Informativeness
    - For models that generate conversation indirectly
        - Make conversation with human or user simulator
            - Evaluate the generated conversation with
                - Automatic Evaluation metrics
                - Human Evaluation
    - TARGET-COHERENCE [CRG]

How to evaluate …

- Task-oriented Dialogue system
  - Automatic Evaluation metrics
  - Human Evaluation
    - Consistency, Grammar, Fluency
  - Use of generated data in End-task
    - End-to-end dialogue modeling (E2E)
    - Dialogue state tracking (DST)
    - Metrics:
      - Inform, Success, BLEU,
      - An overall metric Combined Score: BLEU +0.5×(Inform+Success)

Part 4: Limitations and Future work

Open Challenges

- Generate More challenging and realistic dataset
  - With clarification questions
  - Mixed Initiative dialogues
  - Real-world scenarios, Negotiation and Persuasion dialogues
- Define strategies grounded on external resource
  - Use them for generating full conversation
- How to evaluate the added challenges
- For task-oriented dialogue system:
  - Out of domain generation
  - Multi domain dialogue generation

Building and evaluating open-domain dialogue corpora with clarifying questions, EMNLP, 2021

Why we generate new data

- [GCN] many challenges still remain
    - Handling idioms, humour, expressing empathy, processing unstructured knowledge
    - One big factor for this is the lack of large and rich conversational data that include these complex aspects of human communication
    - These expensive data collections usually target a single phenomenon at a time, and hence do not necessarily scale to the richness of human conversations
    - Another challenge, privacy, preventing the use of much of the publicly available conversational data
- [Baize] Fine-tune chat models to be specialized in specific areas, such as
    - healthcare or finance
- [Baize] Enhance the knowledge and ability of the chat model for a specific domain
    - One could use questions or phrases extracted from a domain-specific dataset, medical domain
    -

Conclusion

- We introduce approaches, tools, … that can be a part of full conversation generation process
- Study different user behaviour
- Adding more challenges to the conversation
    - (i.e. user satisfaction, clarification question)
- Multimodal dialogue systems

References