Faithfulness in Natural Language Generation: A Systematic Survey of Analysis, Evaluation and Optimization Methods

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Abstract

Natural Language Generation (NLG) has made great progress in recent years due to the development of deep learning techniques such as pre-trained language models. This advancement has resulted in more fluent, coherent and even properties controllable (e.g. stylistic, sentiment, length etc.) generation, naturally leading to development in downstream tasks such as abstractive summarization, dialogue generation, machine translation, and data-to-text generation. However, the faithfulness problem that the generated text usually contains unfaithful or non-factual information has become the biggest challenge, which makes the performance of text generation unsatisfactory for practical applications in many real-world scenarios. Many studies on analysis, evaluation, and optimization methods for faithfulness problems have been proposed for various tasks, but have not been organized, compared and discussed in a combined manner. In this survey, we provide a systematic overview of the research progress on the faithfulness problem of NLG, including problem analysis, evaluation metrics and optimization methods. We organize the evaluation and optimization methods for different tasks into a unified taxonomy to facilitate comparison and learning across tasks. Several research trends are discussed further.

Figure 1: Four aspects of the NLG challenge. Faithfulness has become the biggest challenge in modern natural language generation.
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1 Introduction

Natural Language Generation (NLG) is the process of producing a natural language text from a textual or non-textual input in order to meet specified communicative goals (Gatt and Krahmer 2018). The input of NLG varies with different task settings, however, the output is always readable natural language text. According to the type of input, the tasks of NLG can be mainly categorized into: text-to-text generation, data-to-text generation, and multimodality-to-text generation.

The text-to-text generation tasks take existing texts as input, and automatically produce a new, coherent text as output. The most common applications include: text summarization (Allahyari et al. 2017), dialogue generation (Li et al. 2016b), machine translation (Koehn 2009), question generation (Du et al. 2017), paraphrase generation (Li et al. 2017) etc. The data-to-text generation tasks automatically generate text from numerical or structured data such as table, key-value lists, and tuples. The example applications include: table-to-text generation (Liu et al. 2018b), KG-to-text generation (Ke et al. 2021), meaning-to-text generation (e.g. AMR-to-text) (Song et al. 2018) etc. The multimodality-to-text generation tasks transfer the semantics in multimodal input such as images or videos, into natural language texts. Typical tasks include image caption (Vinyals et al. 2015), visual storytelling (Huang et al. 2016), and video summarization (Ma et al. 2002).

From the perspective of input-output information transformation, the tasks of NLG can be divided into open-ended language generation and non-open-ended language generation. Open-ended language generation tasks refer to tasks that the input is incomplete and the output semantics are not contained by the input. For example, story generation is a classical open-ended language generation task, which tends to generate a complete story based on some leading sentences or keywords. Obviously, the model needs to create new information to completing storyline planning and generating meaningful stories. One of the greatest characteristics of the open-ended language generation tasks is that the information mapping between input and output is usually one-to-many. The same input can produce many outputs with different meanings.

By contrast, for non-open-ended language generation tasks, the input usually provides complete or even more information for the output. Machine translation is one typical non-open-ended language generation task where the input provides complete semantics for the output. Paraphrase generation can be regarded as an equivalent transformation of information, where the input and output semantics are exactly the same, but the language expression is different. In text summarization, input usually provides more information than output, so the summarization model needs to select salient information to produce summary output.

Table 1 lists some common NLG tasks as well as their characteristics.

Table 1: Categories of common natural language generation tasks.

| Tasks                | Category            | Information Mapping |
|----------------------|---------------------|---------------------|
| Text Summarization   | Text-to-Text        | Non-open-ended      |
| Machine Translation  | Text-to-Text        | Non-open-ended      |
| Sentence Simplification | Text-to-Text    | Non-open-ended      |
| Paraphrase Generation | Text-to-Text      | Non-open-ended      |
| Dialogue Generation  | Text-to-Text        | Open-ended          |
| Question Generation  | Text-to-Text        | Non-open-ended      |
| Story Generation     | Text-to-Text        | Open-ended          |
| Essay Generation     | Text-to-Text        | Open-ended          |
| News Generation      | Text-to-Text        | Open-ended          |
| Poetry Generation    | Text-to-Text        | Open-ended          |
| Table-to-Text Generation | Data-to-Text  | Non-open-ended      |
| AMR-to-Text Generation | Data-to-Text   | Non-open-ended      |
| Image Caption        | Multimodality-to-Text | Non-open-ended    |
| Video Caption        | Multimodality-to-Text | Non-open-ended    |
| Visual Storytelling  | Multimodality-to-Text | Open-ended       |
Table 2: Four paradigms in natural language generation.

| Paradigm   | Engineering                      | Main Problems         |
|------------|----------------------------------|-----------------------|
| Template-based | Manual Rules (Content Planning, Sentence Planning, Text Realization) | Fluency, Informativeness |
| Statistical-based | Statistic Language Model (e.g. N-gram, Smoothing, Perplexity) | Fluency, Informativeness |
| Neural-based | Neural Architecture (e.g. RNN, LSTM, CNN, Transformer) | Controllability, Faithfulness |
| Pretraining-based | Pretraining Objectives (e.g. BERT, T5, GPT3, BART, CTRL) | Faithfulness |

1.1 Developing of NLG

The research on NLG has a long history, starting from 1950s. The developing of NLG approaches can be mainly divided into four stages: template-based, statistical-based, neural-based and pretraining-based, as shown in Table 2.

- **Template-based.** The earliest natural language generation system adopted the method of rules and templates to design different modules for text generation, which reflected the linguistic knowledge of vocabulary, grammar, syntax and even pragmatics designed by many experts. They usually consists of several different components including content planning, sentence planning and text realization, each performing a specified function.

- **Statistical-based.** Statistical language model further proposes a new idea of language modeling from the perspective of probability and statistics, which encodes the dependency between vocabulary and context in conditional probability. N-gram language model is the most popular statistical language model, which is usually coupled with template-based methods for re-ranking and selecting fluent generated texts.

- **Neural-based.** With the development of deep learning, the neural-based end-to-end methods have gradually occupied a dominant position, which can better model the statistical co-occurrence relationship between vocabulary and context through end-to-end training, thus significantly improves the performance of text generation. Various neural architectures have been explored for NLG, such as Recurrent Neural Network (RNN) (Graves, 2013; Zaremba et al., 2014), Convolutional Neural Network (CNN) (Kalchbrenner et al., 2014) and self-attention Transformer network (Vaswani et al., 2017).

- **Pretraining-based.** Most recently, the pre-trained language generation model based on the Transformer architecture can better capture the linguistic knowledge of vocabulary, syntax and semantics, which greatly promotes the development of natural language generation. The rise of pre-trained language models (Brown et al., 2020; Devlin et al., 2018; Liu et al., 2019) has led to strong text generation models for applications including text summarization (Dong et al., 2019; Liu and Lapata, 2019; Zhang et al., 2020b), dialogue generation (Bao et al., 2020; Zhang et al., 2019), data-to-text generation (Chen et al., 2020b), and machine translation (Liu et al., 2020). However, while these models generate fluent and grammatical text, they are prone to making factual errors that contradict the input text (Cao et al., 2017).

**Challenges and Issues**  
NLG faces four main challenges and issues at different development stages: fluency, informativeness, controllability and faithfulness, as shown in Figure 1.

- The **fluency** problem refers to whether the generated text is fluent, grammatical, and coherent.
• The **informativeness** problem refers to that the model generates redundant, meaningless, and general content, and the generated text is significantly insufficient in informativeness, diversity, and specificity.

• The **controllability** problem means that the generated text cannot satisfy the pre-given constraints, such as text style, attributes and content.

• The **faithfulness** problem means that the generated content is inconsistent with the input information, has hallucinations or non-factual information.

Traditional template-based methods can usually generate reliable and faithful texts, but limited by the diversity and generality of rules, the generated texts usually face the problems of fluency and informativeness. Benefiting from end-to-end training on large corpus, the neural-based methods can generate fluent and informative texts. However, due to the introduction of the probability sampling mechanism, they need to sample from the probability distribution estimated by the model each time. Considering that the vocabulary is very large, generally in the order of 1000～50000, the probability distribution inevitably contains a large number of long-tail words with low probability of occurrence, coupled with the randomness of probability sampling itself, the controllability and faithfulness of the neural-based NLG model is particularly serious. In the pre-training era, through self-supervised training on large-scale unlabeled corpora, the model generated text is outstanding in terms of fluency, informativeness and even controllability, but it still cannot solve the faithfulness problem.

1.2 The Faithfulness Problem

The faithfulness problem has become the biggest challenge in NLG, which largely limits the applicability of NLG algorithms in practical scenarios. For example, the researches on abstractive text summarization show that about 30% of summaries generated by state-of-the-art models have faithfulness issues [Cao et al., 2017; Falke et al., 2019; Krysciński et al., 2019; Pagnoni et al., 2021]. This brings serious problems to the credibility and usability of abstractive summarization systems.

Table 3: Examples of unfaithful errors for several common NLG tasks. **Red color** denotes factual errors.

| Tasks                      | Source                                                                 | Output                                                                 |
|----------------------------|------------------------------------------------------------------------|------------------------------------------------------------------------|
| Abstractive Summarization  | The first vaccine for Ebola was approved by the FDA in 2019 in the US, five years after the initial outbreak in 2014. To produce the vaccine, scientists had to sequence the DNA of Ebola, then identify possible vaccines, and finally show successful clinical trials. Scientists say a vaccine for COVID-19 is unlikely to be ready this year, although clinical trials have already started. | The first vaccine for Ebola was rejected in 2019. Scientists say a vaccine for Ebola is unlikely to be ready this year. |
| Dialogue Generation        | **Persona**: I have two cats. I work as a teacher at a middle school. My favorite color is yellow. I dislike country music. **Dialogue**: hi, do you have any pets? I do not have any pets. Do you play any sports? |                                                                          |
| Machine Translation        | 迈克周日去书店。*(Michael goes to the bookstore on Thursday.)*               | Mike happily goes to the bookstore on Thursday with his friend.         |
| Table-to-Text Generation   | Name: Frank Lino; Caption: FBI surveillance photo; Birth date: October 30, 1938; Birth place: Gravesend, Brooklyn, New York, United States; | Frank Lino (born October 30, 1938 in Brooklyn) is an American criminal defense attorney. |
The faithfulness problem is widely existed in nearly all NLG tasks, such as text summarization, dialogue generation, machine translation and table-to-text generation. Unfaithful examples of several popular tasks are shown in Table 3. For the non-open-ended NLG tasks and open-ended NLG tasks, the definitions of faithfulness problem are different.

**Faithfulness in Non-open-ended NLG** For non-open NLG tasks, NLG models generate text based on the input which provides complete or even more information for the output text. The faithfulness problem in non-open NLG tasks is defined as whether the generated content is factually consistent with the input information, often referred to as factual consistency. For example, faithfulness in text summarization is whether the generated summary is factually consistent with and faithful to the input document. If the summary has hallucinations that not contained by the input document, then it’s unfaithful to the input document. Similarly, faithfulness in machine translation is whether the translation is consistent with and faithful to the original language.

**Faithfulness in Open-ended NLG** For Open-ended NLG tasks, the model needs to leverage knowledge in Knowledge Graph or corpus to create new content that not contained by the input. The faithfulness problem in open-ended NLG tasks is defined as whether the generated content is factually consistent with the world knowledge or commonsense, often referred to as factual correctness. For example, the faithfulness in news article generation is whether the facts in the generated article actually exists or happen in the real world. One relevant research topic is fake news detection (Shu et al., 2017; Zhang and Ghorbani, 2020).

To address the faithfulness problem, a lot of automatic faithfulness evaluation metrics and meta evaluations for these metrics have been proposed. Besides, much effort has been devoted to optimizing faithfulness for different NLG tasks. The framework of existing researches is demonstrated in Figure 2. Since the research on faithfulness mainly focuses on non-open-ended tasks, such as text summarization, machine translation, knowledge-grounded dialogue generation and data-to-text generation, this paper mainly studies the faithfulness (i.e. factual consistency) in non-open-ended tasks. We conduct a comprehensive survey of existing researches on faithfulness, including problem analysis, evaluation metrics, and optimization approaches.

**1.3 Structure of This Survey**

The content typology of this survey is shown in Figure 3.

In Section 2, we give a systematic analysis on the faithfulness problem in NLG, including categorization of unfaithful errors, manual annotations, challenges for evaluating and optimizing faithfulness, cause analysis, and relations with other aspects.

In Section 3, we organize the various evaluation metrics proposed for faithfulness evaluation, and combine the meta-evaluations for these metrics to facilitate future research on faithfulness evaluations.

In Section 4, we summarize different optimization methods from both the perspective of tasks and methodology, and detail their relative advantages.
## Faithfulness

### Problem Analysis
- **Definition & Categorization**
  - Model Analysis
  - Evaluation Problem
  - Annotation Problem
  - Data Divergence
  - Exposure Bias
  - Poor Representation

### Challenges & Issues
- **Model Analysis**
- **Evaluation Problem**
- **Annotation Problem**
- **Data Divergence**
- **Exposure Bias**
- **Poor Representation**

### Cause Analysis

### Evaluation Metrics
- **Meta Evaluation**
  - FRANK
  - SUMMAC
  - BEGIN
- **NLI-based Metrics**
  - DAE
  - FactCC
  - DialogNLI
- **QA-based Metrics**
  - QAGS
  - FEQA
  - Q2
  - QUALS
- **Fact-based Metrics**
  - EntityAlign
  - SimAlign
  - PARENT
  - PARENT-T
  - TripleAlign
  - ArcsAlign
- **Other Metrics**
  - BARTScore
  - COCO
  - TokenCLS

### Optimization Methods
- **Abstractive Summarization**
  - Keyword
  - Sentence
  - Relation
- **Dialogue Generation**
  - Implicit
  - Extractive
  - Retrived
- **Data-to-Text Generation**
  - SANA
  - Segment
  - Entity
- **Entailment**
  - QA
  - Others
- **NLI-reranking**
  - NLI-RL
- **Entity Matching**
  - FocusAttn
- **Machine Translation**
  - FENMT
  - WordAlignment
- **Abstractive Summarization**
  - SpanFact
  - FactCorrect
- **Dialogue Generation**
  - GDR
  - NeuralPathHunter

### Auxiliary Tasks
- **Abstractive Summarization**
- **Dialogue Generation**
- **Entity Matching**
- **Machine Translation**
- **Post-Editing**
### Problem Analysis

In general, the task of natural language generation (NLG) targets at finding an optimal sequence \( y_{<T+1} = (y_1, y_2, \ldots, y_T) \) that satisfies:

\[
\begin{align*}
y_{<T+1} & = \arg \max_{y_{<T+1} \in S} \sum_{t=1}^{T} \log P_{\theta}(y_t | y_{<t}, x) \\
& = \arg \max_{y_{<T+1} \in S} \sum_{t=1}^{T} \log P_{\theta}(y_t | y_{<t}, x)
\end{align*}
\]

where \( T \) represents the number of tokens of the generated sequence, \( S \) represents a set containing all possible sequences, and \( P_{\theta}(y_t | y_{<t}, x) \) is the conditional probability of the next token \( y_t \) based on its previous tokens \( y_{<t} = (y_1, y_2, \ldots, y_{t-1}) \) and the source sequence \( x \) with model parameters \( \theta \).

#### 2.1 Definition and Categorization

We define the output sequence as being unfaithful if it has a span \( y_i, \ldots, y_j \), that is not supported by the input sequence \( x \). The faithfulness issues, i.e. factual inconsistent with source sequence, can be divided into two categories:

- **Intrinsic Error**: the fact that is contradicted to the source sequence \( x \) due to synthesizing content using information present in \( x \), which is also referred to “intrinsic hallucination” in Maynez et al. (2020).
Table 4: Hierarchical typology of unfaithful errors. Examples of text summarization are shown. The source input is the same as the first line in Table 3.

| Categorization | Examples |
|----------------|----------|
| **Intrinsic Error** | |
| **Semantic Frame Errors** | Predicate Error (PredE) The Ebola vaccine was rejected by the FDA in 2019. |
| | Entity Error (EntE) Scientists say a vaccine for Ebola is unlikely to be ready this year. |
| | Circumstance Error (CircE) The first vaccine for Ebola was approved by the FDA in 2014. |
| **Discourse Errors** | Co-reference Error (CorefE) The first vaccine for Ebola was approved in 2019. They say a vaccine for COVID-19 is unlikely to be ready this year. |
| | Discourse Link Error (LinkE) To produce the vaccine, scientists have to show successful human trials, then sequence the DNA of the virus. |
| **Extrinsic Error** | Factual China has already started clinical trials of the COVID-19 vaccine. |
| | Non-Factual China didn’t start clinical trials of the COVID-19 vaccine. |

- **Extrinsic Error**: the fact that is neither supported nor contradicted by the source, which is also referred to “extrinsic hallucination” in Maynez et al. (2020).

Frank (Pagnoni et al., 2021) defines a fine-grained typology of factual errors for text summarization, which is theoretically grounded in frame semantics (Fillmore et al., 1976; Palmer et al., 2005) and linguistic discourse analysis (Brown et al., 1983). It can also be applied to other non-open-ended NLG tasks, such as dialogue generation, machine translation and table-to-text generation.

The fine-grained categories of factual errors mainly include:

1. **Semantic Frame Errors** capture factual errors in frame semantic and its core and non-core frame elements, including:
   - Predicate Error (PredE) denotes errors where the predicate is inconsistent with the source text;
   - Entity Error (EntE) denotes errors where the primary arguments (like entities) of the predicate are wrong or have the wrong attributes;
   - Circumstance Error (CircE) denotes errors where the arguments and predicates interact (e.g. location, time, manner, direction, modality) are wrong.

2. **Discourse Errors** capture erroneous links between discourse segments, including:
   - Co-reference Error (CorefE) denotes errors where pronouns and other types of references to previously mentioned entities either are incorrect or have no clear antecedents;
   - Discourse Link Error (LinkE) denotes incorrect discourse link between different statements.

3. **Content Verifiable Errors** capture erroneous information that cannot be verified against the source text, which are mainly caused by:
   - Out of Article Error (OutE) denotes information that cannot be deduced by from the original text (the same as extrinsic hallucinations (Maynez et al., 2020));
   - Grammatical Error (GramE) denotes not well formed statements that make their meaning incomprehensible or ambiguous and cannot be verified against the source.

Despite all extrinsic errors are assumed incorrect, Cao et al. (2021) and Maynez et al. (2020) find that much hallucinated content is factual, namely consistent with world knowledge. Factual hallucinations...
referring to content that is verifiable by world knowledge but not inferable from source text. For example, in text summarization, they find that more than half of the hallucinated entities are factual with respect to the source document and world knowledge. These factual hallucinations can be beneficial in a summary by providing useful background information. Thus, the extrinsic errors or OutEs can be further categorized into factual hallucinations and non-factual hallucinations.

Combining these definitions and categorization, we define a more thorough hierarchical typology of the faithfulness problems, as shown in Table 4. This typology provides us with the means to categorize the types of errors made by generation models, helping us gain deeper insights than simply categorizing content as faithful or unfaithful.

### 2.2 Challenges and Issues

**Model Analysis**  A lot of researches make annotations with different granularity to analyze the faithfulness performance of existing language generation models. The results show that even the most powerful pertaining models suffer from serious unfaithful problems. Take the abstractive summarization task for example, the annotation results of the ratio of unfaithful summaries generated by several popular models including T5 (Raffel et al., 2019), BART (Lewis et al., 2019) and PEGASUS (Zhang et al., 2020b), are shown in Table 5. The annotation results are combined from Pagnoni et al. (2021) and Cao and Wang (2021).

| System      | XSum   | CNN/DM |
|-------------|--------|--------|
| TransS2S    | 96.9%  | 74.8%  |
| BERTSum     | 83.7%  | 27.2%  |
| T5          | 82.0%  | 26.7%  |
| BART        | 66.7%  | 24.7%  |
| PEGASUS     | 60.7%  | 13.3%  |

The above results show that all systems generate over 60% unfaithful summaries on the XSum dataset. Also, on the CNN/DM dataset, T5 and BART generate over 20% unfaithful summaries. On the one hand, the above results show the severity of the faithfulness problem of current models, and on the other hand, it also shows that the impact of different datasets is also very large. We will analyze the influence of dataset in Section 2.3.

**Evaluation**  Common automatic evaluation metrics for text generation based on n-gram overlap – BLEU, ROUGE, and METEOR (Banerjee and Lavie, 2005; Lin, 2004; Papineni et al., 2002) – are insufficient to measure the faithfulness of the generated text. Kryściński et al. (2019) and Fabbri et al. (2021a) find that they have low correlation with human judgements of factuality, as shown in Table 6. So, a lot of new evaluation methods are proposed to evaluate the faithfulness of generated text for different tasks. We will describe them in Section 3.

**Annotation**  Faithfulness annotation of NLG models is very difficult. Most existing work consider faithfulness as a binary concept, annotating generated text as faithful or unfaithful (Maynez et al., 2020). However, Falke et al. (2019) showed relatively low crowd–expert agreement, indicating the presence of subjectivity in the annotation process. Pagnoni et al. (2021) annotated the faithfulness of summarization systems in a more fine-grained manner, however, the inter-annotator agreement is also low. They collect human annotations from three independent annotators. The inter-annotator agreement in terms of Fleiss Kappa (Fleiss, 1971) is 0.58 for faithful or not, and 0.39 for specific unfaithful error types shown in Table 4, which all indicate low inter-annotator agreement. Tang et al. (2021) compared the reliability of ranking and rating-based human annotations of faithfulness in summarization models and found that ranking-based Best-Worst Scaling annotations are largely reliable than rating-based annotations.
Table 6: The Person and Spearman correlation between different n-gram based metrics and human annotation of faithfulness on CNN/DM dataset, XSum dataset and their combination.

| Metrics   | All data | CNN/DM | XSum |
|-----------|----------|--------|------|
|           | Person   | Spearman | Person | Spearman | Person | Spearman |
|           | $\rho$   | $p$-val | $\gamma$ | $p$-val | $\rho$ | $p$-val | $\gamma$ | $p$-val |
| BLEU      | 0.10     | 0.00    | 0.07    | 0.00    | 0.14   | 0.00    | 0.20    | 0.00    |
| METEOR    | 0.14     | 0.00    | 0.11    | 0.00    | 0.15   | 0.00    | 0.10    | 0.00    |
| Rouge-1   | 0.14     | 0.00    | 0.10    | 0.00    | 0.15   | 0.00    | 0.09    | 0.01    |
| Rouge-2   | 0.12     | 0.00    | 0.08    | 0.00    | 0.17   | 0.00    | 0.14    | 0.00    |
| Rouge-L   | 0.13     | 0.00    | 0.09    | 0.00    | 0.16   | 0.00    | 0.10    | 0.00    |

2.3 Cause Analysis

Many factors can affect the faithfulness of model-generated results, such as dataset, training method, and model expressiveness.

**Data divergence between source and reference.** The divergence between source and reference is one of the main reasons for extrinsic hallucinations during generation. For example, in text summarization, summaries were usually written by journalists as introductions to the news articles they precede. These summaries, therefore, often have true additional information not found in the document. Such divergence issue between source and target is not uncommon in conditional text generation (Dhingra et al., 2019; Kryscinski et al., 2019; Wiseman et al., 2017). The divergence may be a product of heuristic data collection, or it may be inevitable due to the nature of some NLG tasks, such as table-to-text generation and dialogue generation.

Existing models are usually agnostic to the source-reference divergence, making them vulnerable to hallucinations. Thus, models can generate texts that are not consistent with the input, yet would likely have reasonable model log-likelihood. This is the main reason why the same model performs differently on different datasets, such as the difference in summarization performance on the XSum dataset and the CNN/DM dataset. The XSum dataset is collected heuristically by simply taking the introductory sentence prefacing each article as its reference summary, so reference summaries often contain hallucinations. Maynez et al. (2020) reported that 76.9% of reference summaries contained unfaithful content. In contrast, the reference summaries of the CNN/DM datasets are all human-written with less hallucinations. Therefore, the faithfulness of the summarization model on the CNN/DM dataset is much better than that on the XSum dataset.

**Exposure bias between training and inference.** Wang and Sennrich (2020) state that exposure bias (Ranzato et al., 2015), a discrepancy between training and inference, is partially to blame for hallucinations. Specifically, the standard teacher-forcing training algorithm (Williams and Zipser, 1989) used by most existing work can lead to a discrepancy between what the model sees during training and test time, resulting in degenerate outputs with factual hallucinations (Maynez et al., 2020). Furthermore, the model is also only optimized to maximize the log-likelihood of the reference summary at the word-level, which does not necessarily reward models for being faithful.

**Poor text representation.** A model with poor input text representation will fail to do document level inference, often required for abstraction and generation, and will be vulnerable to such errors. For example, in text summarization, the percentage of system summaries with intrinsic hallucination was much higher than in gold summaries. This phenomenon particularly revealed the models’ tendency to misrepresent information in the document due to the lack of document-level understanding and inference. To improve text representation, it is a common practice to leverage large pre-trained models for downstream NLG tasks. Pre-training can improve text generation, due to its exposure to vast amount of text through pretraining, allowing it to integrate background knowledge with generation. However, Longpre et al. (2021) have discovered that such models usually over-rely on the parametric
Table 7: Categorization of Evaluation Metrics.

| Categories      | Methods | Target Tasks                      |
|-----------------|---------|-----------------------------------|
| Entailment-based| DAE     | Summarization, Paraphrasing       |
|                 | Goyal and Durrett (2021)         |                                    |
|                 | RankNLI (Falke et al., 2019)    | Summarization                      |
|                 | SummaC (Laban et al., 2021b)    | Summarization                      |
|                 | DialogNLI (Welleck et al., 2019c)| Dialogue Generation               |
|                 | FactCC (Kryściński et al., 2019)| Summarization                      |
|                 | RCDG    | Dialogue Generation               |
|                 | (Song et al., 2020c)            |                                    |
|                 | KvPi    | Dialogue Generation               |
|                 | (Song et al., 2020a)            |                                    |
|                 | CI-ToD  | Dialogue Generation               |
|                 | (Qin et al., 2021)              |                                    |
|                 | DECODE  | Dialogue Generation               |
|                 | (Nie et al., 2021)              |                                    |
|                 | SentenceNLI (Mishra et al., 2021)| Summarization                   |
| QA-based        | QAGS    | Summarization                      |
|                 | (Wang et al., 2020a)            |                                    |
|                 | FEQA    | Summarization                      |
|                 | (Durmus et al., 2020)           |                                    |
|                 | QAFactEval (Fabbri et al., 2021a)| Summarization                   |
|                 | QuestEval (Scialom et al., 2021)| Summarization                   |
|                 | \(Q^2\) (Honovich et al., 2021) | Dialogue Generation               |
|                 | QUALS   | Summarization                      |
|                 | (Nan et al., 2021a)             |                                    |
| Fact-based      | SimAlign (Sabet et al., 2020)   | Machine Translation               |
|                 | EntityAlign (Nan et al., 2021b) | Summarization                      |
|                 | TripleAlign (Goodrich et al., 2019)| Summarization                   |
|                 | PARENT  | Table-to-Text                      |
|                 | (Dhingra et al., 2019)          |                                    |
|                 | PARENT-T | Table-to-Text                    |
|                 | (Wang et al., 2020b)            |                                    |
| Others          | COCO    | Summarization                      |
|                 | (Xie et al., 2021)              |                                    |
|                 | TokenLevelCLS (Zhou et al., 2021)| Machine Translation, Summarization|
|                 | BARTScore (Yuan et al., 2021)   | 16 NLG tasks                      |
|                 | ShannonScore (Egan et al., 2021) | Summarization                   |

knowledge learned from large scale corpus over the provided input. Also, the dominant language model usually prompts the decoder generates common words to make sure outputs are fluent.

3 Automatic Evaluation Metrics

Recently, there has been wide empirical success in text summarization, machine translation, dialogue response generation, and other text generation tasks. For evaluation, these models generally rely on metrics like ROUGE (Recall-Oriented Understudy for Gisting Evaluation) (Lin, 2004), BLEU (Bilingual Evaluation Understudy) (Papineni et al., 2002) and METEOR (Metric for Evaluation of Translation with Explicit ORdering) (Banerjee and Lavie, 2005) that measure locally constrained n-gram overlap. However, these metrics cannot evaluate the faithfulness of generated text.

Recently, much work focus on evaluating the factual consistency of generated text and propose various new metrics for different NLG tasks. We categorize these metrics into 4 types: Entailment-based, QA-based, Fact-based, and Others, as shown in Table 7.
3.1 Entailment-based Metrics

One of the most popular methods is to apply NLI (Natural Language Inference) to access the faithfulness of generated texts, that is whether the generated text is entailed, neutral, or conflicting with a given input, as shown in Figure 4. The basic hypothesis is that the content of generated texts should be entailed by or at least not conflict with the source text. Though an NLI model usually predicts three different scores for entailment, neutral, and contradiction, most work only utilize entailment score to evaluate faithfulness. Formally, given a source text $x$ as a premise, a generated text $y$ as a hypothesis, an NLI model $N$ predicts the entailment score as $N(x, y)$. The larger the $N(x, y)$ is, the more faithful $y$ given $x$. For evaluating the proposed metrics, most works report their correlations with human judgements, while some other works, especially entailment-based metrics, also propose ranking-based downstream tasks to demonstrate performances. We will also introduce these ranking tasks in the following.

Sentence-level NLI  

Traditional NLI tasks predict entailment scores between sentences. However, in the text generation scenario, the input text $x$ takes various forms and often contains multiple sentences that severely challenge the application of NLI. Earlier attempts directly apply NLI classifiers to access the factual consistency between input text $x$ and output text $y$. They study how NLI models trained on traditional NLI datasets like MNLI (Williams et al., 2018) perform. Falke et al. (2019) proposed to aggregate entailment scores between sentences of $x$ and $y$ to calculate the faithfulness score between $x$ and $y$, namely RankNLI. Given sentences $s_y \in y, s_x \in x$, RankNLI formalizes faithfulness between $y$ and $x$ as:

$$\frac{1}{|y|} \sum_{s_y \in y} \max_{s_x \in x} N(s_x, s_y)$$

(2)

They found that while entailment prediction should help with this problem, out-of-the-box NLI models performed poorly on this task. Falke et al. (2019) also proposes a summary re-ranking task to evaluate the performance of RankNLI. In this task, a better metric should help the summarization model to select more faithful summaries during the reranking process of beam search. They further analyze how different architectures of the NLI model $N$, such as ESIM (Chen et al., 2017), BERT (Devlin et al., 2018), affect the summary ranking task.

Maynez et al. (2020) applied a much simpler strategy by directly using NLI models trained on MNLI to predict entailment score $N(x, y)$. Barrantes et al. (2020) further found that applying ANLI dataset instead of MNLI dataset in Falke et al. (2019) to train the NLI classifier is more suitable for faithfulness evaluation. SummaC (Laban et al. 2021a) comprehensively revisits sentence-level NLI for accessing faithfulness. They apply a CNN module to aggregate the entailment score matrix between document and summary sentences, and demonstrate the potential of sentence-level NLI on various benchmarks.

Annotation-based  

The major problem of sentence-level NLI metrics is that they are inconsistent with their downstream tasks, which often require the evaluator to predict paragraph-level entailment scores. Some work attempted to directly train an NLI classifier between source text $x$ and target output $y$. A straightforward solution is to annotate a certain scale of samples for training the classifier. In text summarization, Aralikatte et al. (2021) and Gehrmann et al. (2021) finetuned NLI classifier on hundreds of (around 500) manual annotated samples for faithfulness evaluation and reported a good performance of this simple metric.
In dialog generation, Welleck et al. (2019b) constructed a Dialog NLI dataset (DialogNLI) for factual consistency evaluation. To save human labor, they annotate the relation triples of dialogue sentences instead. Based on relation triples, they infer the NLI labels by certain rules. Welleck et al. (2019b) also propose an utterance ranking task, which is often applied to evaluate the factual consistency of a dialogue model. In this task, given history utterances $u_{<t}$, a dialogue model is asked to select the next utterance $u_t$ with the lowest perplexities from a set of candidate utterances $U$:

$$u_t = \arg \min_{u \in U} - \log p(u|u_{<t}), \quad \text{where} \quad U = (U^+, U^-, U^{rand})$$

(3)

where the generation probability $p$ is calculated by the dialogue model. $U^+, U^-, U^{rand}$ represent the set of utterances that are entailed with $u_{<t}$, conflicted with $u_{<t}$ or randomly selected, respectively. The higher probability the model selects a $u_t$ from $U^+$, the better factual consistency it has.

Song et al. (2020a) proposed a human-annotated dataset, namely Key-value Profile Identification (KvPI), with single-turn conversations and corresponding attribute profiles. They further labeled NLI relations between each conversation and structured profile. With the NLI labels, they trained a classifier to predict entailment relations between structured attributes and generated utterances. Qin et al. (2021) proposed a human-annotated dataset CI-ToD, which incorporates NLI labels between various types of inputs including dialogue history, user query and the corresponding knowledge base. They propose a uniform model to assess all the factual consistency relations above. Nie et al. (2021) proposed a multi-domain dataset DECODE for evaluating consistency of dialogue. DECODE balances human-written contradicting dialogues with an equal number of non-contradicting dialogues from several public datasets. NLI models trained on DialogNLI or DECODE can be used for assessing the faithfulness of dialogues. Gupta et al. (2021) proposed a benchmark DialFact to evaluate and check knowledge errors in open domain dialog generation. They proposed a fact-checking pipeline for this benchmark, in which an NLI component is applied to check whether the generated utterance is supported by the retrieved evidences.

**Weak Supervision** Because it is difficult to annotate a large-scale document-level NLI dataset, several recent works apply weakly supervised methods for training. Some work applied data augmentation methods to construct synthetic datasets. FactCC (Kryściński et al., 2019) constructed positive entailment samples by different heuristic methods for weak supervised training. For constructing various positive samples, they swap, delete or insert textual units like entities, pronouns, numbers, etc. To better explain this metric, FactCC also provides an additional version, FactCCX, which highlights spans of evidence in source documents. Dziri et al. (2021b) introduced a new benchmark BEGIN for evaluating factual consistency of knowledge grounded dialogue systems. For the evaluation metric, they also proposed a NLI classifier by constructing adversarial samples similar to FactCC. SetenceNLI (Mishra et al., 2021) suggested that the major bottleneck in the utility of NLI models is that traditional NLI datasets do not exhibit long premises. To solve this problem, they convert multiple-choice reading comprehension datasets into two-class NLI datasets using data augmentation methods. In addition to similar rule-based methods, they also applied text generation models to generate higher-quality samples.

**Fine-grained Prediction** Some works utilize fine-grained features to assess faithfulness. They convert direct predictions of $N(x, y)$ into sequentially labeled fine-grained features in the generated text. DAE (Goyal and Durrett, 2020) applies a new formulation of entailment that decomposes it at the level of dependency arcs. Instead of making decisions at the sentence level, DAE sequentially predicts the entailment scores of each dependency arc in the generated sentence and aggregates them to obtain the final faithfulness score. Goyal and Durrett (2021) further explores the difference in error distribution between synthetic and human written summaries, and investigates how fine-grained supervision information can benefit faithfulness evaluation.

### 3.2 QA-based Metrics

Because assessing faithfulness requires logical inference over factual information, it is natural to utilize the reasoning ability of Question Answering (QA) models. Several recent works proposed QA-based factual evaluation metrics. As shown in Figure 5, these metrics often include two components: a question generation (QG) module and a QA module. The core idea of these metrics is to predict the matching score between source answers (key information units from source text) and target answers...
Figure 5: The framework of QA-based metrics.

(key information units from generated text). The overall procedure of these metrics are summarized as following:

1. **Answer Selection**: Extract information units from the generated text, which is viewed as target answers.
2. **Question Generation**: Conditioned upon the selected target answers, the QG module generates questions using the generated text as context.
3. **Question Answering**: The QA module answers the questions with the source text as context to retrieve source answers.
4. **Answer Alignment Evaluation**: Calculate the matching score between source and target answers by an answer alignment metric to output the final evaluation score.

QAGS (Wang et al., 2020a) and FEQA (Durmus et al., 2020) are the earliest QA-based factual evaluation metrics. These two metrics share similar model architectures and processing procedures introduced above. In the procedure 1, QAGS extracted n-grams as the information units for target answers while FEQA extracted entities. In procedure 2-4, they both applied BERT-based QA modules, BART-based QG modules and token-level F1 as answer alignment metrics.

Several QA-based metrics followed the framework of QAGS and FEQA with moderate modifications. QuestEval [Seralom et al., 2021] extended this framework by adding an extra procedure to measure the recall-oriented performance. The additional procedure generated question-answer pairs from the source document and answered the questions from the generated text. In contrast to QuestEval, QUALS [Nan et al., 2021a] simplified the above procedure 1-3 by only one neural language model (QAGen). QUALS employs QAGen as proposed in (Shakeri et al., 2020), to generate both the questions and answers from the generated text. In particular, given a summary \( y \), QAGen outputs a question-answer (q-a) pair jointly, separated by a special token `<a>`. Let \( LL_y(q, a) \) be the average log likelihood of generating the q-a pair from the given summary \( y \). Then given the input document \( x \), QUALS simply evaluates the average log likelihood of the QAGen model producing the same q-a pairs, denoted as \( LL_x(q, a) \). Formally, given a summary \( y \) and input document \( x \), QUALS score is computed as follows:

\[
QUALS(x, y) = \frac{1}{M} \sum_{(q, a) \in y} (LL_x(q, a) - LL_y(q, a))
\]

(4)

where \( M \) is the number of q-a pairs selected on the summary \( y \). This simplification largely decreases the computational time and memory of the original QAGS.

QAFactEval [Fabbri et al., 2021a] conducted extensive comparisons of QA-based metrics and demonstrated that carefully choosing the components of a QA-based metric is critical to performance. The optimized settings of QAFactEval in each procedure are listed in the following:

1. Select NP chunks as the textual units as target answers;
2. Apply BART-QA2D (Demszky et al., 2018) for the QG module and filter low quality generated questions;
3. Apply Electra-large (Clark et al., 2020) for QA;
4. Apply LERC (Chen et al., 2020a) score as the answer alignment metric.

With these carefully selected settings, Fabbri et al. (2021a) boosted the performance of QA-based metric to a new level.

In addition to the factual metrics in text summarization listed above, Honovich et al. (2021) proposed a QA-based metric $Q^2$ for evaluating factual consistency in open-domain dialogue generation. They utilized the entailment score predicted by an NLI model as the alignment metric for answer spans.

### 3.3 Fact-based Metrics

The most intuitive way to evaluating faithfulness is to count the fact overlap between generated text and source document, as shown in Figure 6. Facts can be represented in different forms, such as entities, n-grams and relation triples (subject, relation, object).

Factual inconsistency can occur at either the entity or the relation level. At the entity level, a model generated text may contain named entities that never appeared in the source document. At the relation level, the entities indeed exist in the source document but the relations between them are not in the source document.

#### 3.3.1 Entity-based

**EntityAlign** Nan et al. (2021b) proposed an entity-based metrics that rely on off-the-shelf tools to perform Named-Entity Recognition (NER). Let $N(x)$ and $N(y)$ denote the number of named-entities in the source (input document) and target (generated text), respectively. $N(y \cap x)$ denotes the number of entities found in the generated text that can find a match in the source document. If a named entity in the generated text consists of multiple words, it is considered a match as long as any n-gram of the named-entity can be found in the source document. The degree of faithfulness with respect to the source text is quantified: $\text{prec} = \frac{N(y \cap x)}{N(y)}$.

**SimAlign** For machine translation, Sabet et al. (2020) proposed to leverage multilingual word embeddings – both static and contextualized – for word alignment between source language and translated language.

#### 3.3.2 Ngram-based

**PARENT** For table-to-text generation task, Dhingra et al. (2019) modeled facts as n-grams, and developed a metric PARENT (Precision And Recall of Entailed Ngrams from the Table) which aligns n-grams from the reference and generated texts to the semi-structured data before computing their precision and recall. When computing precision, PARENT effectively uses a union of the reference and table, to reward correct information missing from the reference. When computing recall, it uses an intersection of the reference and the table, to ignore extra incorrect information in the reference. The union and intersection are computed with the help of an entailment model to decide if a text n-gram is entailed by the table. The entailed precision and recall are combined into an F-score to give the PARENT metric for one instance. The system-level PARENT score for a model is the average of instance-level PARENT scores across the evaluation set.
PARENT-T  PARENT-T (Wang et al., 2020b) is a table-focused version of PARENT. When computing precision, PARENT-T considers an n-gram to be correct if it has a high probability of being entailed by the table. PARENT-T uses the word overlap model for computing entailment probability. For recall, PARENT-T only computes it against table to ensure that texts that mention more information from the table get higher scores. The system-level PARENT-T score for a model is the average of instance-level PARENT-T scores across the evaluation set.

3.3.3 Relation-based

**TripleAlign**  Facts are usually represented by relation triples (subject, relation, object), where the subject has a relation to the object. To extract triples, Goodrich et al. (2019) first try to use OpenIE tool (Yates et al., 2007). However, OpenIE extracts triples with an unspecified schema instead of a fixed schema. In unspecific schema extraction, relation is extracted from the text between subject and object. In fixed schema extraction, a relation is predicted from a pre-defined relations set, which could be viewed as a classification task. Unspecific schema extraction makes the extracted triples hard to compare with each other. To resolve this problem, Goodrich et al. (2019) change to use relation extraction tools with fixed schema, which helps extracted triples easier to compare.

3.4 Other Metrics

Recently, there are some work evaluate faithfulness of text generation from other perspectives.

**BARTScore**  Yuan et al. (2021) conceptualize the evaluation of generated text as a text generation problem, modeled using pre-trained sequence-to-sequence models, directly evaluating text through the lens of its probability of being generated from or generating other textual inputs and outputs. The general idea is that models trained to convert the generated text to/from a reference output or the source text will achieve higher scores when the generated text is better. They operationalize this idea using BART (Lewis et al., 2019), an encoder-decoder based pre-trained model, and propose a metric BARTScore with a number of variants that can be flexibly applied in an unsupervised fashion to evaluation of text from different perspectives (e.g. informativeness, fluency, or factuality).

\[
BARTScore = \sum_{t=1}^{m} w_t \log p(y_t|y_{<t}, x, \theta)
\]  

(5)

To evaluate faithfulness, they propose to compute the probability from source document to hypothesis \(p(y|x, \theta)\). This direction measures how likely it is that the hypothesis \(y\) could be generated based on the source text \(x\).

**TokenLevelCLS**  Zhou et al. (2021) propose a general-purpose method for token level hallucination detection for conditional sequence generation tasks. Given the source input \(x\), they first formulate the task of token-level hallucination detection as a sequence labeling problem where a binary label is predicted at each position of the generated text. They train a model with synthetic training data in the form of \(((x, y), L_y)\) where \(L_y\) are the labels at every position of \(y\) that indicate if each word is a hallucinated one or not. They leverage the BART model (Lewis et al., 2019) to mapping a corrupted sentence back to the original text it was derived from, without providing it any access to the source sentence, thereby encouraging it to insert new content as needed to ensure fluency. Then, they finetune a pre-trained language model (LM) on the synthetic data to help detect the token level hallucinations in various conditional sequence generation tasks.

**CoCo**  CoCo (Xie et al., 2021) is proposed to evaluate the faithfulness of summarized texts via counterfactual estimation. They point out that the effect of language prior can be blamed to cause factual inconsistency. The intuition is that when texts are generated more relying on the source document rather than the language prior, they should be more likely to be faithful w.r.t. the source documents. They adopt the probabilities of the tokens of evaluated summaries to implement the automatic evaluation metric. Specifically, given the source document \(x\) and model-generated summary \(y\), several key tokens \(y’\) are first selected from \(y\), then the source document \(x\) is masked according \(y’\) to produce a masked version \(x’\). \(x\) and \(x’\) are feed into the same scoring model respectively to generate the probability of each token in \(y’\), i.e., \(P(y_i|x, y_{<i})\) and \(P(y_i|x’, y_{<i})\), \(\forall y_i \in y’\). The CoCo
value is defined as:

$$\text{CoCo} = \frac{1}{|y'|} \sum_{y_i \in y'} P(y_i|x, y_{<i}) - P(y_i|x', y_{<i})$$  \hspace{1cm} (6)

**ShannonScore** [Egan et al. (2021)] proposed a reference-free metric ShannonScore to evaluate the quality of generated summary via Shannon Game. The Shannon information content of event $E$ with the probability $p(E)$ of happening is defined as $I(E) = -\log p(E)$. The ShannonScore performs the Shannon Game with a language model such as GPT-2 [Radford et al. (2019)]. The main assumption of this metric is that if $y$ is a satisfactory summary of $x$, then $I(x|y) < I(x)$, as documents that have little to do with the summary should be much less likely than documents that are relevant to the summary after conditioning the language model. Thus they define an Information Difference metric of summary quality as:

$$ID(x, y) = I(x) - I(x|y)$$ \hspace{1cm} (7)

They further define the ShannonScore as the normalized Information Difference:

$$s(x, y) = \frac{I(x) - I(x|y)}{I(x) - I(x|x)}$$ \hspace{1cm} (8)

where $I(x|x)$ is the lower bound of $I(x|y)$.

### 3.5 Meta Evaluation

As there are a lot of new metrics proposed to evaluate the faithfulness of language generation, they perform differently on different tasks. To verify the effectiveness of the above metrics, these work usually report the correlations between their own metrics and human-annotated factual consistency scores. However, it is difficult to compare each metric by the diversity of annotating settings in different works and disagreement among different annotators. To directly compare the effectiveness of different kinds of faithfulness metrics, several work (Gabriel et al., 2021b; Koto et al., 2021) proposed benchmarks to conduct meta-evaluations of faithfulness metrics. For example, the popular benchmarks of evaluating the faithfulness metrics for abstractive summarization include FRANK (Pagnoni et al., 2021), SUMMAc (Laban et al., 2021b), QAGS (Wang et al., 2020a), FEQA (Durmus et al., 2020) and CoCo (Xie et al., 2021). Table 8 combines these benchmarks, showing the Pearson correlations between different types of faithfulness evaluation metrics and human annotations. To facilitate reliable evaluation metrics for grounded dialogue generation, Dziri et al. (2021b) also proposed a benchmark BEGIN for evaluation of grounded dialogue generation systems.

Table 8 shows that the meta-evaluation results in different benchmarks differ greatly. The same metric can also performs very different on different datasets. Overall, the QA-based metrics achieve better performance on most datasets and benchmarks. However, the correlations with human evaluations are not more than 0.6. Therefore, the faithfulness evaluation remains an open question of exploration.

### 4 Optimization Methods

A lot of optimization methods for the faithfulness problem have been proposed for different tasks, including abstractive summarization, dialogue generation, data-to-text generation and machine translation. However, most of these methods are general for different tasks. They can be categorized as factual guidance, auxiliary tasks, learning methods, post-editing, constrained decoding and others. In the following, we will organize the optimization methods for each task into the above categories to facilitate comparing and learning of different methods, as shown in Figure 3.

#### 4.1 Faithfulness in Abstractive Summarization

The faithfulness problem has attracted more and more attention in abstractive summarization. A lot of mitigation methods have been studied, many of which also can be applied to other NLG tasks. In the following, we will introduce the main types of optimization methods for abstractive summarization.

##### 4.1.1 Factual Guidance

Factual guidance is an intuitive and effective method for boosting faithfulness and informativeness in summarization tasks. Guidance can be defined as some signals which are fed into the model as
Table 8: Meta evaluations on several popular benchmarks. The results are Pearson correlations between different types of faithfulness evaluation metrics and human annotations.

| Metrics     | FRANK benchmark | QAGS benchmark | FEQA benchmark | CoCo benchmark |
|-------------|-----------------|----------------|---------------|---------------|
|             | CNN/DM | XSum | CNN/DM | XSum | CNN/DM | XSum | CNN/DM | XSum | SUMMEVAL |
| N-gram based|        |      |        |      |        |      |        |      |          |
| ROUGE-1     | 0.12    | 0.15 | 0.29   | 0.13 | 0.12   | -0.03| 0.29   | 0.13 | 0.20     |
| ROUGE-2     | 0.08    | 0.17 | 0.18   | 0.09 | 0.13   | -0.06| 0.18   | 0.09 | 0.17     |
| ROUGE-L     | 0.11    | 0.16 | 0.24   | 0.09 | 0.13   | -0.06| 0.23   | 0.08 | 0.19     |
| BLEU        | 0.08    | 0.14 | 0.21   | 0.06 | 0.12   | -0.07| 0.18   | 0.03 | 0.11     |
| METEOR      | 0.12    | 0.15 | 0.27   | 0.10 | -      | -    | 0.26   | 0.11 | 0.17     |
| BERTScore   | 0.02    | -0.04| 0.28   | 0.03 | 0.11   | 0.10 | 0.37   | 0.11 | 0.19     |
| Entailment-based |     |      |        |      |        |      |        |      |          |
| ENT         | -       | -    | -      | -    | 0.03   | -0.06| -      | -    | -        |
| DAE         | 0.25    | 0.04 | -      | -    | -      | -    | -      | -    | -        |
| FactCC      | 0.36    | 0.07 | -      | -    | -      | -    | -      | -    | -        |
| QA-based    |        |      |        |      |        |      |        |      |          |
| FEQA        | -0.01   | 0.02 | -      | -    | 0.32   | 0.26 | -      | -    | -        |
| QAGS        | 0.13    | -0.02| 0.55   | 0.17 | -      | -    | 0.31   | 0.15 | 0.18     |
| QuestEval   | -       | -    | -      | 0.33 | -      | -    | 0.49   | 0.07 | 0.37     |
| Others      |        |      |        |      |        |      |        |      |          |
| OpenIE      | 0.16    | 0.00 | -      | -    | 0.09   | 0.02 | -      | -    | -        |
| CoCo        | -       | -    | -      | -    | -      | -    | 0.59   | 0.24 | 0.42     |
Figure 7: The framework of factual guidance. Usually, we use an oracle method to select guidance during training and use automatically extracted guidance at test time.

additional inputs to the source document. Within this framework, the crucial points are what kind of information we need to feed into the model and how to feed it. Figure 7 shows a simple seq2seq based factual guidance framework in which two encoders process origin source and extra guidance signals respectively, then a decoder generates final summaries considering the hidden states of both two encoders. Here, the guidance signals could be keywords, important sentences or other structures such as relations or semantic graphs. According to the types of guidance signals, factual encoders could be a Transformer network (for signal of sequence structure) or a Graph Attention Network (for signal of graph structure) [Velickovic et al. (2017)]. GSum [Dou et al. (2021)] is such a general and extensible framework that can take different kinds of external guidances as extra inputs to mitigate the unfaithful problems. We follow the basic classifications of guidance signals of GSum and then make an extension by supplying some different but effective ones. We divide guidance signals into three types: keywords, sentences and relations.

**Keyword Guidance** Keywords reflect the crucial information of the source text in a simplest way. They help the summarization models to focus on the most important parts of the source text and result in less factual errors. [Li et al. (2018a)] propose a Key Information Guide Network which encodes the keywords into the key information representation, to guide the process of generation. Firstly, they extract keywords from the text by using TextRank algorithm, then encode keywords by Bi-RNN network, and guide the generation process by cooperating keyword representations in both attention mechanism and the pointer mechanism. [Saito et al. (2020)] further combine pre-trained seq2seq model with token-level saliency models called CIT, in which a saliency model (Transformer encoder with feed-forward layer) produces a score for each token in order to select important ones which are denoted as $K$. Then a combined text $\hat{X} = \text{concat}(K, X)$ is given to the seq2seq model as the input.

**Sentence Guidance** Keywords convey limited information of the source text, so some works turn to sentence-level guidance which contains more abundant information including keywords and the connections among them. [Cao et al. (2018)] propose Re3Sum which retrieves existing summary sentences as candidate templates, and then uses an extended seq2seq framework to jointly conduct template reranking and template-aware summary generation. Specifically, both the source text $X$ and the soft template $R$ are converted into hidden states with a RNN encoder. In the Rerank module, they measure the saliency of $R$ according to its hidden state relevance to $X$. In the Rewrite module, a RNN decoder combines the hidden states of $X$ and $R$ to generate a summary $Y$. [Song et al. (2020d)] exploit PORL-HG model following the extract-then-rewrite framework. PORL-HG firstly selects some attractive sentences from the article by an extractor, then rewrites these sentences by a seq2seq-based abstractor. The model combines the extractor with the abstractor by a reinforcement learning network which regards the popularity score and ROUGE scores as rewards to make sure generated headlines are both attractive and faithful.

**Relation Guidance** [Dou et al. (2021)] argue that if we utilize full sentence as guidance signals, it may contain much unnecessary and irrelevant information which is not crucial in a summary and could distract the model from focusing on the actual important parts of the source text. To address this problem, some works use relation information in the form of relational triples as factual guidance. [Cao et al. (2017)] leverage open information extraction and dependency parsing techniques to extract
they propose a dual-attention seq2seq framework to force the generation conditioned on both the source text and the extracted fact descriptions. Huang et al. (2020) present ASGARD framework which enhances the regular document encoder with an independent graph-structured encoder which improves upon Graph Attention Networks (Veličković et al., 2017) to maintain the global context and local characteristics of entities. They utilize <subject, predicate, object> triples extracted by OpenIE to construct a knowledge graph, then use the hidden states of input tokens represented by RoBERTa (Liu et al., 2019c) to initialize the graph nodes. During decoding, both the representations of source tokens and graph nodes are incorporated into each generation step via cross-attention mechanism. In this way, the knowledge graph can be used as an extra factual guidance during summary generation.

Most works use OpenIE to extract relations from source documents, then represent them as graph structures to improve seq2seq models. However, these OpenIE-based graphs only contain sparse relations between partial words, which cannot cover the overall semantic meaning of the source article. Wu et al. (2021a) propose BASS which firstly introduce an unified semantic graph to enhance the performance of multi-document summarization. To construct the semantic graph, they extract phrases and their relations from sentences by a two-stage merging in which tokens are firstly merged into phrases based on dependency parsing trees, then co-referent phrases are merged into graph nodes according to co-reference chains. Finally, the model encodes graph structures both in encoding and decoding processes, by applying the graph adjacent matrix as self-attention mask and using an graph-propagate attention mechanism to guide the decoding process.

4.1.2 Auxiliary Tasks

Unlike guidance methods which improve factual consistency explicitly, auxiliary task-based methods combine extra tasks which are correlative with factual correctness to boost the performance of summarization systems in an implicit way. There are three widely used frameworks that can easily involve auxiliary task into summarization task, which are reinforcement learning (RL) framework, multi-task learning framework and re-ranking framework, as shown in Figure 8. In the RL framework, it is common to design a score model for generated summaries to obtain a reward which will optimize the factual consistency of summarization models. As for the multi-task framework, a task-specific layer will be stacked over the shared-weight encoder. In this way, the summarization model and auxiliary model share the same semantic representations but have different learning objectives. The related auxiliary task can be seen as a supplement to the summarization task and will improve the performance of the original summarization system. As for the re-ranking framework, it firstly generates several candidate summaries, then a score model based on auxiliary tasks produces a score for each candidate, and finally the best one is selected as the summary. In the following, we will describe several common auxiliary tasks to improve faithfulness of abstractive summarization.

Entailment Task Natural Language Inference (NLI), in which a hypothesis sentence is classified as either entailed by, neutral or contradicting a premise sentence. Previous works (Barrantes et al., 2020; Fabbri et al., 2021b; Falke et al., 2019; Laban et al., 2021b; Li et al., 2018b) have proved that NLI tasks can improve faithfulness of summarization models. It can be incorporated into summarization models by multi-task learning, or acting as a RL reward, or utilized to re-ranking summary candidates.
Li et al. (2018b) is the first work which incorporates entailment knowledge into abstractive summarization. They argue that a correct summary is semantic entailed by the source document. They propose an entailment-aware encoder under a multi-task learning framework, and an entailment-aware decoder under an RL framework with entailment rewards. In particular, they use shared weight encoders trained on both the summarization task (i.e. encoder+decoder) and the entailment task (i.e. encoder+classifier). Entailment prediction is regarded as an auxiliary task for summary generation. When decoding, they treat the entailment score as a special reward and combine the reward with a maximum likelihood training process by RL.

Following the idea that all information in a summary should be entailed by the source document, Falke et al. (2019) propose a re-ranking approach to select summaries with less unfaithful errors by entailment prediction models. They design a score function mentioned in Equation 2 to measure the entailment score of a generated summary $y$ given its source document $x$. The candidate summary with the highest score $\sigma(y)$ is selected as the model output after reranking. Barrantes et al. (2020) follow this idea and make a further step by applying the adversarial NLI dataset to train the NLI model. More accurate NLI model has more potential of selecting faithful summaries. Fabbri et al. (2021a) propose query-based summarization model which apply NLI score as one of the reinforcement learning rewards to improve factual consistency.

**Question answering Task** Generating factual consistent summaries not only needs the overall understanding of source text but also the discrimination between crucial and useless parts. Thus, it is a natural way to check a summarization model’s comprehension and distinction abilities by a QA model. The QA-based methods mainly calculate a QA score by measuring the overlap degree of answers extracted from source text and from the generated summaries, then use the QA score as the reward in the RL framework or the reranking framework. The key procedures of QA-based tasks are mentioned in the Section 3.2. Following this idea, Nan et al. (2021a) incorporate a QA model (Equation 4) into the seq2seq architecture by a novel contrastive learning method. They firstly produce some candidate summaries, then sort them into positive samples and negative samples according to the QA score, finally improve faithfulness of models through contrastive learning over them (specifically introduced in Section 4.1.3).

**Other Tasks** Zhang et al. (2020d) develop a concise framework to quantify factual correctness of a generated summary using an information extraction model. They take a structured vector $v$ to represent facts in the reference summaries. Each dimension of vector $v$ is a binary variable which describes whether an event or an entity is present or not in the text.

$$v = f(y) = (v_1, \ldots, v_m)$$

(9)

Given the reference summary fact vector $v$ and generated summary fact vector $\hat{v}$, a factual accuracy score $s$ can be computed as:

$$s(\hat{v}, v) = \sum_{i=1}^{m} 1[v_i = \hat{v}_i]$$

(10)

Finally, they combine factual score with rouge score as reward via a reinforcement learning framework.

Nan et al. (2021b) propose a series of simple but effective entity-level methods to improve factual consistency of abstractive summarization, including data filtering, multi-task learning, and joint entity and summary generation. For data filtering, they first apply Spacy NER (Honnibal and Montani, 2017) on reference summary to identify all named-entities. If any entities cannot find a match in the source document, they consider this sample as a noisy data and discard the sentence that contains the entity from the ground truth summary to make sure that there is no hallucination in the dataset. They also add a classification layer after the encoder of BART to identify summary-worth entities. As for decoding, they train the BART model to first generate the sequence of summary-worth entities and then the summary so that the salient named-entities can be incorporated into the cross-attention of the decoder.

**4.1.3 Learning Methods**

**Contrastive Learning** Cao and Wang (2021) observed that the commonly used maximum likelihood training method showed weak ability of distinguishing references from incorrect generations. Therefore, a potential solution is to design new learning objectives to improve the preference of
factual summaries over inconsistent ones. Contrastive learning (CL) is such a paradigm which is first proposed in visual tasks and recently utilized in many NLP tasks. The main idea of contrastive learning shown in Figure 9 is to learn representations of similar samples staying close to each other, while dissimilar ones keeping away. The key point of CL is how to generate positive and negative samples. In visual tasks, it is common to construct positive samples by rotating, resizing, distorting the origin picture, and consider other images as negative samples. In this section, we will introduce several effective methods to construct positive and negative samples in summarization task, and how to involve them into the contrastive learning framework.

Cao and Wang (2021) design a task-specific contrastive learning formulation (CLIFF) that teaches a summarizer to expand the margin between factually consistent summaries and incorrect peers. CLIFF uses three methods to construct positive samples, including paraphrasing with synonym substitution, randomly replacing words, and back-translation. As for negative samples, previous works often treat other samples in the same batch as negative ones. However, Cao and Wang (2021) argue that such negative samples are easy to distinguish because they are totally different from positive ones. It will be more effective to construct negative samples by making a small but crucial change based on the original references, so that the model can focus on the real important parts of the source text and enhance the ability of differentiating factual and non-factual summaries. Following this idea, CLIFF designs four strategies to create negative samples:

- **Entity swap imitates intrinsic errors**: swapping named entities in the references with other randomly selected entities of the same entity type in the source text.
- **Mask-and-fill with BART**: replacing each named entity in a reference with a [MASK], then let BART generates new entities.
- **Source-conditioned regeneration**: for each entity in the reference, feeding the text before it along with the origin source into BART, then combining the text before the entity with the generated text as a negative sample.
- **System generation**: selecting system generated summaries with low probability as negative samples.

After constructing positive samples (denoted as $P$) and negative samples (denoted as $N$), CLIFF optimizes the contrastive learning objective in Equation 11 and combines it with typical cross-entropy loss to form the final training objective shown in Equation 12, where $h_i$, $h_j$, $h_k$ are representations for summary $y_i$, $y_j$, $y_k$. $\text{sim}$ calculates the cosine similarity between summary representations.

$$L_{CL} = - \frac{1}{\binom{|P|}{2}} \sum_{y_i, y_j \in P, y_i \neq y_j} \log \frac{\exp(\text{sim}(h_i, h_j)/\tau)}{\sum_{y_k \in P \cup N, y_k \neq y_i} \exp(\text{sim}(h_i, h_k)/\tau)}$$

$$L = L_{CE} + \lambda L_{CL}$$

Except for entity-level replacement, Liu et al. (2021c) make a further step by switching the sentiment of some sentences by adding negation words or replacing opposite meaning words to generate more diverse negative samples.

Liu et al. (2021b) argue that previous works (Cao and Wang, 2021; Liu et al., 2021c) mainly focus on entity faithfulness which is not equal to summary faithfulness. Thus, they propose a contrastive summarization framework CO2Sum and a span-level negative samples construction.
method LFN based on pre-trained language model. Specifically, they delete or disturb factual fragments in sentences and observe the language model probability of predicting the context based on these sentences in an iterative way to distinguish which fragments are important to the source text. After detecting most influential factual spans, they replace the fragment in the gold summary with embedding-similar article words to construct negative samples. They involve contrastive learning in both encoder and decoder. In the encoding procedure, they apply contrastive learning between source text and summaries by making the representations of the article and the ground truth summary closer, and make that of the article and the factual inconsistent summaries apart. The CL loss $L_{Enc}$ for the encoder is similar to Cao and Wang (2021). As for the decoder, CO2Sum applies contrastive learning between summaries with a max-margin loss (Yang et al., 2019) $L_{Dec}$ to force the model to increase the decoding probabilities of ground truth summaries while decrease the decoding probabilities of negative summaries. The margin loss $L_{Dec}$ and the final training objective $L$ are shown as following.

$$L_{Dec} = \max \left\{ \frac{1}{R} \sum_{i \in R} (P_s(T_{neg}, i) - P_s(T_{gold}, i)) + \eta, 0 \right\}$$  \hspace{1cm} (13)$$

$$L = L_{CE} + \lambda_{Enc} L_{Enc} + \lambda_{Dec} L_{Dec}$$ \hspace{1cm} (14)$$

where $R$ means replaced positions with inconsistent facts, $T_{neg}$ and $T_{neg}$ denote the negative summary and ground truth summary respectively, $P_s(T, i)$ denotes the generation probability of the $i$-th position in sequence $T$. $\lambda_{Enc}$ and $\lambda_{Dec}$ denote the loss weights of the constrastive learning objectives in the encoder side and decoder side, respectively.

Most works construct negative samples by simply replacing some non-target sequences. Lee et al. (2021) argue that these explicit negative samples are suboptimal, since they are easily distinguishable from the correct output, especially when models are pre-trained with large corpus. Within the simple and explicit sample construction framework, models barely learn nothing. Thus, they propose a principled method called CLAPS to construct positive and negative samples implicitly by adding perturbations to the input sequence. To generate a negative example, they add a small perturbation (hard sample) to the hidden representation of target sequence, then minimize its conditional likelihood. As for positive examples, they adding a large perturbations while enforcing the model to have a high conditional likelihood. This will yield a negative example that is very close to the original representation of target sequence in the embedding space but is largely dissimilar in the semantics, while the generated positive example is far away from the original input sequence but has the same semantic as the target sequence. It could generate hard examples which the model might be difficult to discriminate, helping it learn more meaningful representations.

### 4.1.4 Post-Editing

Above methods require modification of model structures or extra sample construction processes to improve factual consistency, which may affect the informativeness (e.g. ROUGE scores) of summary results. Post-editing based methods improve factual consistency by adding an corrector to system-generated summaries. They consider generated summaries as drafts, and correct factual errors to form the final summaries. This process is quite similar to the human writing process, where people write a first draft, then review and edit it to make it better. Figure [10] shows the general framework of post-editing methods.
Dong et al. (2020) propose SpanFact, a suite of two factual correction models that leverage knowledge learned from question answering models to correct system-generated summaries through span selection and correction. SpanFact takes into account entity-level corrections and make them iteratively. Specifically, assume that the system summary has $N$ entities. At time step $i$, they mask the $i$-th entity and use this masked sequence as a query to the QA model. The QA model will replace the wrong entities with the correct ones based on the source document. The corrected entity will then form an updated summary for use in the next step. Human evaluation demonstrates that SpanFact is able to correct about 26% unfaithful summaries, while barely destroying any otherwise correct summaries.

Cao et al. (2020) simplify the post-editing procedures by directly training a seq2seq rewrite model on artificial unfaithful summaries as a corrector. They create a weakly-supervised training dataset based on the text transformations following Kryscinski et al. (2019) which replace entities, numbers, numerals and pronouns in source documents with other tokens of the same type. The goal of the corrector is to generate correct summaries based on the unfaithful summaries and source documents. As a standalone module, post-editing methods have been shown to be effective in improving the faithfulness of abstractive summarization systems while preserving their informativeness. However, it’s more of an indirect solution than a fundamental solution to factual inconsistencies.

4.1.5 Constrained Decoding

Lexically constrained or guided decoding is a modification of beam search that enforces the inclusion of pre-specified words and phrases in the output. This is a general way to control specific tokens in the generated output without modifying the model structure or additional training data.

Mao et al. (2020) propose CAS (Constrained Abstractive Summarization) to improve the factual consistency of summary systems by constructing constrained token sets during dynamic beam search decoding. It only allows the generation process to end when all constraints are met. They focus on entities and noun phrases and select these types of words that are not present in the summaries generated by the unconstrained system to form constrained sets. Therefore, the model will generate more correct and faithful tokens during the inference process, effectively improving the faithfulness of abstractive summarization. Aralikatte et al. (2021) introduce the Foucs Attention Mechanism (FAME) for the transformer-based seq2seq architecture. FAME combines a standard contextual representation with a dynamic source-conditioned lexical bias layer, which encourages the decoder to actively generate tokens that are faithful to the input document.

4.1.6 Other Methods

Zhao et al. (2020a) propose HERMAN which learns to recognize and verify quantity entities in candidate summaries, in order to re-rank the candidate summaries to select the one whose quantity terms are supported by the original text. During the training process, they use a BiLSTM-CRF decoder as a verification model to tag sequence labels and finally predict an overall label that indicates whether the output summary is faithful to the source input or not. At the test time, the same verification model is applied to rerank the candidate summaries, then select the best one with less hallucinations.

Gabriel et al. (2021a) proposed Co-opNet, a generator-discriminator framework to do fact-checking for text generation. In this framework, the generator outputs a series of candidate summaries. Then the discriminator scores the factuality of these summaries using one of the following objectives: the overlap between the introduction of a scientific article and the predicted evidence spans in summaries, the ordering of predicted discourse roles, the coverage of predicted discourse roles, or the likelihood of adjacency between generated sentences. The best summary is selected by combining the scores of the generator and the discriminator.

Cao et al. (2021) propose an interesting method to detect factual errors by using the prior and posterior predicted probabilities of each token. They assume that if an entity is a factual error, giving the source should not provide more evidence for it, resulting in only small changes in the probabilities between the prior (i.e. without source) and the posterior (i.e. given source) language models. Based on this assumption, they use prior and posterior probabilities as key features of a classifier to predict the factuality of entities.
### Table 9: Different types of source that dialogue generation models should be faithful to in different tasks.

| Source Type                      | Methods                                      |
|----------------------------------|----------------------------------------------|
| History Dialogue                 | DialogNLI (Welleck et al., 2019b), Gao et al. (2019) |
|                                  | Arun et al. (2020), Ghazvininejad et al. (2018) |
|                                  | DECODE (Nie et al., 2021), CI-ToD (Qin et al., 2021) |
|                                  | TransferTransfo (Mesgar et al., 2021), UL (Li et al., 2020a) |
|                                  | Blender (Roller et al., 2021), Balakrishnan et al. (2019) |
|                                  | Nye et al. (2021), Kim et al. (2020)          |
| Persona Facts                    | Li et al. (2016a), Zhang et al. (2018)        |
|                                  | DialogNLI (Welleck et al., 2019b), DECODE (Nie et al., 2021) |
|                                  | KvBERT (Song et al., 2020a), RCDG (Song et al., 2020c) |
|                                  | TransferTransfo (Mesgar et al., 2021), UL (Li et al., 2020a) |
|                                  | GDR (Song et al., 2020b), Kim et al. (2020)   |
| Unstructured Knowledge (e.g. Wikipedia Documents) | Rashkin et al. (2021), Wu et al. (2021b) |
|                                  | Dinan et al. (2019), Shuster et al. (2021)    |
| Structured Knowledge (e.g. Knowledge Graph) | KvBERT (Song et al., 2020a), CI-ToD (Qin et al., 2021) |
|                                  | NPH (Dziri et al., 2021a)                    |
| User Query (i.e. task-oriented dialogue) | CI-ToD (Qin et al., 2021)                    |

### 4.2 Faithfulness in Dialogue Generation

Recently, the area of dialogue generation has made significant progress with end-to-end neural networks and large-scale pre-training (Bao et al., 2020; Roller et al., 2021). However, a long standing problem, faithfulness, still challenges current best dialog systems and attracts an increasing amount of attention. In general, the generated utterance should be faithful to its history utterances (Vinyals and Le, 2015). Different from other generation tasks like text summarization, various forms of dialog generation tasks include a diversity of background or knowledge inputs, with which the generated utterances should also be consist. In Table 9, we summarize different forms of inputs that have been studied in dialogue faithfulness. The optimization methods for dialogue faithfulness are similar to abstractive summarization, which consists of six types of methods. Some of them can also be utilized in summarization tasks.

#### 4.2.1 Factual Guidance

Several works utilized various guidance information to improve factual consistency of dialogues. These methods incorporate relevant guidance information into the training or inference process of dialogue models. As shown in Figure 7, we categorize theses guidance into three types: implicit guidance, which is the guidance in vector representations; extracted guidance, which is the relevant textual information extracted from source inputs; retrieved guidance, which is information retrieved from open-domain knowledge.

**Implicit Guidance** Implicit guidance is usually representations that are automatically learned before or during the training process of a dialogue model. Li et al. (2016a) inject implicit speaker information into a LSTM-based model to improve the personality consistency. In each generation
step of their model, they fuse the embedding of the speaker into the text encoder. Zhang et al. (2018) present the PERSONA-CHAT dataset which provides persona profiles for each speaker. They also propose a memory-augmented dialogue system where persona profiles were saved and updated in memory. Guided by the profile memory, the generated dialogues are more consistent in personality. Gao et al. (2019) combine dialog generation with style-transfer for a more stylized and context-relevant chatbot. They fuse conversation modeling and non-parallel style transfer method by sharing a structured latent space to guide the decoding process.

**Extractive Guidance** Extractive guidance is often the important information extracted from the source input, which helps the model focus on the important parts of the input. Ghazvininejad et al. (2018) propose a knowledge-grounded conversation model, which extracts factual sentences from history dialog and utilizes them as factual guidance in the decoding process. Arun et al. (2020) extract tree-based meaning representations to improve the faithfulness of generated responses for task-oriented dialog systems. The extract structural knowledge efficiently guided the model to generate correct information. Rashkin et al. (2021) utilize control codes to encourage the model to generate responses that are faithful to the provided evidence. They apply three types of control codes, including entailment, objective voice and lexical precision, which are calculated during data pre-processing. Wu et al. (2021b) further construct fine-grained control codes by using lexical phrases as factual guidance. Based on these phrases, the generated responses are more relevant and faithful to the input.

**Retrieved Guidance** Retrieved guidance is usually from external knowledge. Dinan et al. (2019) create an open-domain dialogue dataset Wow, where each topic in the conversation is connected to Wikipedia articles. Then they design a memory network based dialog system which is enhanced by retrieved knowledge from Wikipedia. Augmented by knowledge guidance, their model is able to generate more precise responses. Shuster et al. (2021) propose a retrieval-augmented neural architectures, in which dialogues are generated grounded on retrieved knowledge. Specially, they apply a learnable retriever and designed a fine-grained interactions between history dialogue and knowledge.

### 4.2.2 Auxiliary Tasks

Many work utilize the auxiliary task of Natural Language Inference (NLI) to improve the factual consistency of dialogue systems. The main approaches include leveraging entailment scores to rerank candidate texts, or treating entailment as a reward for reinforcement learning, which are similar to the entailment-based methods for text summarization (described in Section 4.1.2).

**Reranking-based** Several works apply entailment score predicted by an NLI model to the reranking process for selecting more faithful generated text. As discussed in Section 5.1, several works (Nie et al. 2021; Qin et al. 2021; Song et al. 2020a; Welleck et al. 2019b) propose their factual evaluation metrics based on entailment. They utilize entailment scores predicted by their proposed metrics in
the re-ranking process to improve faithfulness of dialogue models. For example, in Welleck et al. (2019b), given a persona $P$, previous utterances $u_{<t}$, and the dialogue model outputs the score of a next-utterance candidate $s_{t+1}$, the new score $s_{t+1}^{re-rank}$ after incorporating NLI relation is:

$$s_{t+1}^{re-rank} = s_{t+1} + \lambda s_{t+1}^{contradict}$$  

where $s_{t+1}^{contradict}$ is the highest contradiction score between $s_{t+1}$ and persona sentences in $P$, hyper-parameter $\lambda$ controls the NLI model’s influence in re-ranking.

### Reinforcement Learning

Another type of methods incorporate entailment scores as a part of the reinforcement learning (RL) rewards, similar to Figure 8. Song et al. (2020c) propose a RL-based model RCDG for generating persona consistent dialogues. Similar to the architecture of GANs (Generation Adversarial Neural Networks), RCG is composed of a generator and two evaluators to estimate the quality and consistency of generated utterances, respectively. The consistency evaluation is based on an NLI classifier to compute the entailment score. Mesgar et al. (2021) also propose an RL-based model TransferTransfo-RL for improving consistency between generated responses and personas. Differently, TransferTransfo-RL take advantage of Actor-Critic (Mnih et al. 2016) learning approach, which also utilizes the entailment score as reward.

### Learning Methods

As unfaithful generation relates to the deficiencies of training strategy, several works improve factual consistency of dialogue models by refining the training procedures. Li et al. (2020a) extend unlikelihood training to address various problems in generating dialogues, including over copying, repetitions, overuse frequent words, and factual inconsistency. Besides training with common maximum likelihood estimation (MLE), they apply unlikelihood loss (UL) to alleviate these problems. In the time step $i$ during training, given an input-output pair $(x, y)$, a dialogue model $p_\theta$ and a set $C$ containing sentences contradicting with $y$ which the model should avoid to generate, the UL is defined as:

$$L_{UL}(p_\theta, C, x, y) = -\sum_{t=1}^{T} \sum_{y_c \in C} \beta(y_c) (1 - p_\theta(y_c | x, y_{<t}))$$

where $\beta(y_c)$ is the weighting parameter for every $y_c \in C$. Roller et al. (2021) followed this method for training a large-scale chatbot.

### Constrained Decoding

Some works also focus on designing decoding strategies to improve consistency. Especially, these works apply constrained decoding during inference. These methods usually require the generated utterance to be semantically consistent with inputs based on certain semantic structure. Balakrishnan et al. (2019) apply a tree-structured meaning representations (MR) in dialog systems. Comparing to common flat MR, which is a flat list of key-value pairs, their MR is able to represent more fine-grained relations. Based on the proposed MR, they design a constrained decoding strategy on beam search which requires the MR of generated text not conflicting with the input. Similarly, Nye et al. (2021) propose a dual-system approach for faithful text generation, where the “system 1” is a common model for generation, and the “system 2” constrains and controls the generated sentences to be factually correct. The essence of this method is that it applies GPT-3 (Brown et al. 2020) to parse text into clear and correct logical symbols that are easy for “system 2” to check. During decoding, “system 2” selects correct candidates that are faithful to the given context.

### Post-Editing

Several works focus on refining the generated dialogues without modifying the original model. These works mainly design an extra refining module to correct the factual errors in the generated dialogues. These models usually consist of three steps: generate, delete, and rewrite, similar to the summarization task shown in Figure 10. In the first step, the dialogue model normally generates utterances. In the second step, the rewrite module removes the incorrect contexts in the generated utterances, and then the third step rewrites them to the correct contexts.
Song et al. (2020b) propose a post-editing based dialogue model, GDR, following the three steps introduced above. After the normal text generation procedure “Generate” in the first stage, GDR identifies and deletes conflict words in the second stage “Delete”. Then GDR recovers the deleted words by a generation module in the last stage “Rewrite”. Through the three stages above, GDR refines factual errors in the generated utterance. Dziri et al. (2021a) apply the similar strategy on knowledge grounded dialogue system. Different from GDR, their refining module NPH needs to rewrite based on knowledge graph. After deleting potential incorrect entities in the generated text, NPH based on graph neural network retrieves correct entities in the grounded knowledge graph for refining.

4.2.6 Other Methods

Kim et al. (2020) propose a dialogue system based on Rational Speech Act framework (Frank and Goodman, 2012), which enforces dialogue agents to refrain from uttering contradiction. The proposed model endows dialogue agents with public self-consciousness, helping them maintain consistency across each generation step by reflecting the distribution of imagined listeners across roles.

4.3 Faithfulness in Machine Translation

Neural machine translation (NMT) has achieved great success due to the ability to generate high-quality sentences. Compared with human translations, one of the drawbacks of current NMT is that translations are not usually faithful to the input, e.g., omitting information or generating unrelated fragments, which inevitably decreases the overall quality, especially for human readers. The optimization methods for faithfulness in machine translation mainly include: incorporating auxiliary tasks like word alignment (4.3.1), improving learning methods like minimum risk training (4.3.2), utilizing constrained decoding methods like grid beam search (4.3.3), etc.

4.3.1 Auxiliary Tasks

Wang et al. (2020b) propose a multi-task learning paradigm with two auxiliary tasks, including marked language model task and word alignment task, for building a faithfulness enhanced NMT (named FENMT). On the encoder side, FENMT employs a masked language model (MLM) task (Devlin et al., 2018) to infer the input words didn’t be correctly translated. This task can enhance the ability of modeling the whole input sentence and give the decoder accurate and complete representations. On the decoder side, FENMT further uses a word alignment task to improve the alignment accuracy of the encoder decoder cross-attention to help the decoder to capture correct contextual representation. Furthermore, along with the NMT objective, an auxiliary max-margin objective based on contrastive learning is introduced in all decoding timesteps which prompts the decoder to translate fluent and faithful sentences.

To improve the ability of the decoder, Tu et al. (2017) propose to introduce a reconstruction loss to make translation can reconstruct the input sentence. Kong et al. (2019) propose to use a coverage difference ratio metric as a reward to train NMT. Feng et al. (2020), Garg et al. (2019), Zhang et al. (2021) propose to introduce word alignment information in Transformer to improve translation accuracy.

4.3.2 Learning Methods

Minimum Risk Training Wang and Sennrich (2020) hypothesise that exposure bias (Ranzato et al., 2015), a discrepancy between training and inference, is partially to blame for hallucinations, and that training with Minimum Risk Training, which avoids exposure bias, can mitigate this. Minimum Risk Training (MRT) is a sequence level objective that avoids this problem. Specifically, the objective function of MRT is the expected loss (risk) with respect to the posterior distribution:

$$R(\theta) = \sum_{(x,y) \in D} \sum_{\hat{y} \in Y(x)} P(\hat{y}|x; \theta) \Delta(\hat{y}; y)$$

in which the loss $\Delta(\hat{y}; y)$ indicates the discrepancy between the gold translation $y$ and the model prediction $\hat{y}$. Due to the intractable search space, the posterior distribution $Y(x)$ is approximated by
where they use the negative log translation probability to estimate
where $\alpha$ is a hyperparameter to control the sharpness of the subspace. Random sampling was used
to generate candidate translations, and the reference translation was not added to the subspace. They
find that Minimum Risk Training, which does not suffer from exposure bias, reduces the number of
hallucinations substantially, and makes beam search with large beams more stable.

Adversarial Learning NMT models are still susceptible to input sentence perturbations and tend
to produce hallucinatory outputs in the presence of some source perturbations (Lee et al., 2018).
For example, Belinkov and Bisk (2017) find that NMT models can be immensely brittle to small
perturbations applied to the inputs. Even if these perturbations are not strong enough to alter the
meaning of an input sentence, they can nevertheless result in different and often incorrect translations.
Belinkov and Bisk (2017) and Karpukhin et al. (2019) study how to use some synthetic noise and/or
natural noise. Cheng et al. (2018) propose adversarial stability training to improve the robustness
on arbitrary noise type including feature-level and word-level noise. Liu et al. (2018a) examine the
homophonic noise for Chinese translation.

Formally, a set of adversarial examples $Z(x; y)$ is generated with respect to a training sample $(x; y)$
by solving an optimization problem:

$$\{x'| R(x', x) \leq \epsilon, \arg\max_{x'} J(x', y; \theta)\}$$

where $J(.)$ measures the possibility of a sample being adversarial, and $R(x'; x)$ captures the degree
of imperceptibility for a perturbation. Although it is difficult to give a precise definition of the degree
of imperceptibility $R(x'; x)$, $l_\infty$ is usually used to bound the perturbations in image classification
(Goodfellow et al., 2014).

Following Ebrahimi et al. (2017); Goodfellow et al. (2014); Miyato et al. (2016), the white-box
method to generate adversarial example stightly guided by the training loss. Given a parallel sentence
pair $(x; y)$, a set of adversarial examples $A(x; y)$ specific to the NMT model are generated by:

$$\{x'| R(x', x) \leq \epsilon, \arg\max_{x'} - \log P(y|x'; \theta)\}$$

where they use the negative log translation probability to estimate $J(.)$. The formula constructs adversarial examples that are expected to distort the current prediction and retain semantic similarity bounded by $R$.

Cheng et al. (2019) propose a gradient-based adversarial learning approach, called AdvGen, to
construct adversarial examples and use these examples to both attack as well as defend the NMT
model to improving the robustness of NMT models, which consists of two parts: (1) attack the
translation model with adversarial source examples; (2) defend the translation model with adversarial
target inputs to improve its robustness against the adversarial source inputs. For the generation of
adversarial inputs, they propose a gradient-based method to craft adversarial examples informed by
the translation loss over the clean inputs.

Robust Learning on Noisy Corpus Corpus-level noise in NMT parallel corpora tends to produce
significant hallucinatory patterns (Raunak et al., 2021). NMT models also have a propensity to
hallucinate more frequently under out-of-domain inputs (Müller et al., 2019). Several techniques
can be used to improve learning robustness to corpus-level noise in NMT. Kang and Hashimoto
(2020) propose a loss truncation method to reduce the impact of noisy references in sequence-to-
sequence training. Li et al. (2020a) propose a modification of expected risk minimization (ERM),
namely Tilted-ERM, to reduce the effect of outliers during training. Corpus-level noise filtering that
incorporating heuristics or filters Junczys-Dowmunt (2018) to remove invalid source-target pairs is also effective in reducing NMT hallucinations.

4.3.3 Constrained Decoding

One interesting method is lexically constrained decoding, a modification to beam search that allows
the user to specify words and phrases that must appear in the system output. Three algorithms
have been proposed for this: grid beam search (Hokamp and Liu, 2017), constrained beam search
(Anderson et al., 2017) and dynamic beam allocation (Post and Vilar, 2018). These papers showed that these algorithms do a good job automatically placing constraints and improving results in tasks such as simulated post-editing, domain adaptation, and caption generation.

Grid Beam Search (GBS), an algorithm which extends beam search to allow the inclusion of pre-specified lexical constraints while still taking advantage of the distribution learned from training data. The algorithm can be used with any model that generates a sequence $\hat{y} = y_0, \ldots, y_T$, by maximizing $p(y|x) = \prod_t p(y_t|x; y_0, \ldots, y_{t-1})$. Lexical constraints take the form of phrases or words that must be present in the output sequence. This is a very general way to incorporate additional knowledge into a model’s output without requiring any modification of the model parameters or training data, thus can improve faithfulness of translation output.

The computational complexities of grid beam search (Hokamp and Liu, 2017) are linear and constrained beam search are exponential in the number of constraints. Post and Vilar (2018) present a more efficient algorithm for lexically constrained decoding with a complexity of $O(1)$ in the number of constraints.

4.3.4 Other Methods

Some work design special mechanism for using source representation more effectively. In the RNN-based NMT, Tu et al. (2016) and Mi et al. (2016) propose a coverage mechanism to improve the accuracy of translation outputs. Weng et al. (2020a) propose to model global representation in the source side to improve the source representation. Zheng et al. (2019) propose a capsule based module to control the source representation dynamically in the decoding process. Feng et al. (2020) propose a faithfulness part to optimize the contextual representation before feeding into the decoder. Weng et al. (2017) propose a bag-of-words loss to constrain decoding process.

4.4 Faithfulness in Data-to-Text Generation

Data-to-text generation (or table-to-text generation) has been widely studied for decades. Recently, deep neural networks have been successfully adopted in this task. However, the problem of unfaithfulness in data-to-text methods remains a significant challenge (especially in long-form text generation). In the data-to-document generation dataset (e.g., Rotowire (Wiseman et al., 2017) and MLB (Puduppully et al., 2019)), obvious gaps exist in the record generation (RG) precision between recent methods and faithful templated-based baselines. Moreover, the issue of generating unfaithful text remains a serious problem for noisy datasets constructed automatically (e.g., WikiBio (Lebret et al., 2016) and WikiPerson (Wang et al., 2018)). In WikiBio, almost two-thirds of the training instances contain unfaithful descriptions (Dhingra et al., 2019).

4.4.1 Factual Guidance

Compared to other text generation tasks, factual information is highly structured and exists explicitly in data-to-text tasks. Therefore the two-stage method, which plans the subset of input data to be described and then generates text from the plan, is popular in this research field. If a method explicitly considers the issue of faithfulness in the plan-to-text generation step, we categorize it into factual guidance optimization methods.

Wang et al. (2021) propose a two-stage table-to-text generation method SANA. SANA firstly constructs a skeleton using an autoregressive pointer network to select contents from the source table. SANA expands the skeleton to the final output in the second stage, considering the source table with an edit-based non-autoregressive model. Therefore, SANA could generate more faithful because the input of the second stage is directly extracted from the input table as strong factual guidance.

Shen et al. (2020) model the table-to-text task as a segment-by-segment generation procedure and every segment is generated in two-stage. Firstly, proper data records are selected as factual guidance. Secondly, text corresponding to the plan is generated by paying attention only to the selected input data records.

4.4.2 Auxilary Tasks

Liu et al. (2021a) extend the two-stage table-to-text generator to an augmented plan-based method. They create a pseudo training corpus for the plan-to-text phase, which covers all entities in the target
description. In this way, there is no hallucinated entity in the training phase of the plan-to-text generating. Therefore the noise in the original corpus does not affect the plan-to-text generating step.

4.4.3 Learning methods

Neural sequence-to-sequence learning-based data-to-text models are often trained by maximum likelihood loss optimization. However, this kind of model suffers from the noise of the training data and leads to unfaithful output (also called divergence).

Wang et al. (2020b) extend the maximum likelihood loss of attention-based Transformer with two additional losses. The first one is a latent matching disagreement loss which measures the distance between embeddings of the input table and the output text. The second one is an entity matching optimal-transport loss to measure the entity matching of the table and the output. Reinforcement learning (RL) based methods could directly optimize the faithfulness of data-to-text generation.

Liu et al. (2019b) propose a force attention method to encourage the model to focus on uncovered data records. Then they adopt RL for information richness to generate more faithful descriptions for the input data. Rebuffel et al. (2020) propose an RL-based approach relying on the PARENT metric to reduce the issue of unfaithfulness.

4.4.4 Constrained Decoding

Tian et al. (2019) propose a confident decoding method to detect and avoid unfaithful generation in the decoder. For each decoder position, a confidence score consists of attention and a dedicated language model that only gives higher scores to common words. Therefore, the confidence score could be utilized to detect the generating of a word conveying source information without paying enough attention to the source data. Tian et al. (2019) believe that lower confidence scores indicate higher risks of generating unfaithful text. In the training time, a variational Bayes training framework is designed to ensure the model generates high confidence results. In the inference time, tokens generated with low confidence scores would be marked and skipped.

Filippova (2020) treats faithful data-to-text as a controllable text generation problem. In the training corpus, a prefix measuring the amount of noise is appended to the input sequence. Although data-to-text models are trained without modification, we still categorize this method into constrained decoding because the controlling prefix guides the decoding. Rebuffel et al. (2022) extend the controllable text generation method to the fine-grained level. Word alignment labels are calculated through dependency parsing, and the labels guide the proposed weighted multi-branch neural decoder.

4.4.5 Other Methods

Considering that noise in the training corpus is critical to the faithfulness of data-to-text generation, pre-processing datasets is a direct and reasonable method. Nie et al. (2019) propose a neural data refinement method to reduce unaligned noise from original datasets. Wang (2019) observe that only 60% of the output contents in RotoWire could be grounded to the input records. They purify and enlarge the original dataset to a new RotoWire-FG dataset.

4.5 Faithfulness in Other NLG Tasks

Faithfulness is a common problem in NLG tasks. There are also some researches on faithfulness for other tasks, such as image caption, image-to-text radiology report generation and general factual language model. The methods for improving faithfulness include: factual guidance by knowledge graph, constrained decoding, and incorporating auxiliary tasks (e.g. entailment, word/entity alignment), etc.

4.5.1 Factual Language Model

Some work design language models that are conditioned on external, structured knowledge source to generate factual text. Logan IV et al. (2019) introduce the knowledge graph language model (KGLM), a neural language model with mechanisms for selecting and copying information from an external knowledge graph. The KGLM maintains a dynamically growing local knowledge graph, a subset of the knowledge graph that contains entities that have already been mentioned in the text, and their related entities. When generating entity tokens, the model either decides to render a new entity that is
Figure 12: An illustration example of the factual language model (Logan IV et al., 2019). It maintains a dynamically growing localized knowledge graph containing facts that are (possibly) conveyed in the sentence above. The graph is built by iteratively linking each detected entity to Wikidata, then adding any relations to previously mentioned entities.

absent from the local graph, thereby growing the local knowledge graph, or to render a fact from the local graph. When rendering, the model combines the standard vocabulary with tokens available in the knowledge graph, thus supporting numbers, dates, and other rare tokens.

An example is shown in Figure 12. Initially, the graph is empty and the model uses the entity “Super Mario Land” to render the first three tokens, thus adding it and its relations to the local knowledge graph. After generating the next two tokens (“is”, “a”) using the standard language model, the model selects “Super Mario Land” as the parent entity, “Publication Date” as the relation to render, and copies one of the tokens of the date entity as the token (“1989” in this case). The factual completion capabilities of KGLM, which predicts the next word after a factual sentence (e.g., “Barack is married to”), is significantly more accurate. KGLM is able to generate accurate facts for rare entities, and can be controlled via modifications on the knowledge graph.

4.5.2 Factuality Detection

Factuality detection is an important task in practical applications. Hansen et al. (2020) build an ensemble learner that predicts news headline factuality using only eye-tracking measurements as they find that false headlines receive statistically significantly less visual attention than true headlines. Meng et al. (2020) propose a gradient-based adversarial training on transformer networks to the task of detecting check-worthy claims. Zhong et al. (2020) propose a graph-based reasoning approach utilizing factual structure of text for deepfake detection. Zellers et al. (2020) propose a controllable text generation model Grover to defend against fake news, which can generate fake news that are more trustworthy than human-written disinformation. Counterintuitively, the best defense against Grover turns out to be Grover itself, with 92% accuracy versus 73% from best discriminators. As an important factuality detection task, fake news detection has been widely explored in the literature (Jain and Kasbe, 2018; Reis et al., 2019; Shu et al., 2017, 2019).

4.5.3 Constrained Text Generation

Generating text under specific lexical constraints is challenging, which can help generate more faithful and factual texts. Constrained text generation broadly falls into two categories, depending on whether inclusion of specified keywords in the output is mandatory.

In soft-constrained generation (Qin et al., 2019; Tang et al., 2019), keyword-text pairs are typically first constructed (sometimes along with other conditioning information), and a conditional text
generation model is trained to capture their co-occurrence, so that the model learns to incorporate the constrained keywords into the generated text. While soft constrained models are easy to design, keywords are apt to be lost during generation, especially when multiple keywords must be included, or the keywords are less correlated. Soft enforcing algorithms such as attention and copy mechanisms (Bahdanau et al., 2014; Gu et al., 2016) can be helpful in preserving keywords, but do not guarantee that constraints will be included in the output sentence.

Hard-constrained generation (Hokamp and Liu, 2017; Hu et al., 2019; Miao et al., 2019; Post and Vilar, 2018; Welleck et al., 2019a), on the other hand, requires that all the lexical constraints be present in the output sentence. This approach typically involve sophisticated design of network architectures. Hokamp and Liu (2017) construct a lexical-constrained grid beam search decoding algorithm to incorporate constraints. However, Hu et al. (2019) observe that a naive implementation of this algorithm has a high running time complexity. Miao et al. (2019) introduces a sampling-based conditional generation method, where the constraints are first placed in a template, then words in a random position are either inserted, deleted or updated under a Metropolis-Hastings-like scheme. However, individually sampling each token result in slow convergence, as the joint distribution of all the tokens in a sentence is highly correlated. Welleck et al. (2019a) propose a tree-based text generation scheme, where a token is first generated in an arbitrary position, and then the model recursively generates words to its left and right, yielding a binary tree. However, the constructed tree may not reflect the progressive hierarchy/granularity from high-level concepts to low-level details. Further, the time complexity of generating a sentence using this approach is O(n), like standard auto-regressive generation methods.

Zhang et al. (2020c) propose a novel non-autoregressive model for hard-constrained text generation, called POINTER (PrOgressive INsertion based TTransformER). Given lexical constraints, POINTER first generates high-level words (e.g., informative nouns, verbs and adjectives) that bridge the keyword constraints, then these words are used as pivoting points at which to insert details of finer granularity. This process iterates until a sentence is finally completed by adding the least informative words (typically pronouns and prepositions).

Anderson et al. (2017) uses constrained beam search to force the inclusion of selected tag words in image caption, and fixed, pre-trained word embeddings to facilitate vocabulary expansion to previously unseen tag words. Constrained beam search is an approximate search algorithm capable of enforcing any constraints over resulting output sequences that can be expressed in a finite-state machine.

4.5.4 Image Caption

Image caption is an important type of multimodality-to-text generation. Image captioning models are prone to “hallucinating” objects that are not actually in a scene. Several examples are shown in Figure 13. The standard evaluation metrics only measure similarity to ground truth captions and cannot fully capture image relevance. Rohrbach et al. (2018) propose a image relevance metric to evaluate image captioning models with veridical visual labels and assess their rate of object hallucination. Anderson et al. (2017) use constrained beam search to force the inclusion of selected tag words in the output, and fixed pre-trained word embeddings to facilitate vocabulary expansion to previously unseen tag words. Constrained beam search is an approximate search algorithm capable of enforcing any constraints over resulting output sequences that can be expressed in a finite-state machine.

Image-to-Text radiology report generation is a new type of image caption, which is an important application of natural language generation (NLG). It is to build assistive systems that take X-ray images of a patient and generate a textual report describing clinical observations in the images (Boag et al., 2020; Chen et al., 2020c; Jing et al., 2017; Li et al., 2018c; Liu et al., 2019a). This is a clinically important task, offering the potential to reduce radiologists’ repetitive work and generally improve clinical communication (Kahn Jr et al., 2009). However, the automatic generated reports by neural models are not always factually complete or consistent. They usually face the issues of factual incompleteness and inconsistency (Boag et al., 2020; Liu et al., 2019a).

Miura et al. (2021) show that existing image-to-text radiology report generation systems can be substantially improved by replacing widely used NLG metrics with simple alternatives. They propose two new simple rewards that can encourage the factual completeness and consistency of the generated reports. First, they propose the Exact Entity Match Reward (factENT) which captures the completeness of a generated report by measuring its coverage of entities in the radiology domain, compared with a reference report. The goal of the reward is to better capture disease and anatomical
knowledge that are encoded in the entities. Second, they propose the Entailing Entity Match Reward (factENTNLI), which extends factENT with a natural language inference (NLI) model that further considers how inferentially consistent the generated entities are with their descriptions in the reference. They add NLI to control the overestimation of disease when optimizing towards factENT. They directly optimizes these two rewards with RL, showing that the proposed approach substantially improves performance on factual consistency and completeness.

5 Discussion

The faithfulness problem is the most critical challenge in modern NLG. As described above, we have discussed evaluation metrics and optimization methods for different NLG tasks. In the following, we discuss some of the limitations of current evaluation and optimization methods, and provide several research directions worth investigating in the general NLG.

5.1 Fine-grained and General Evaluation

Most existing faithfulness evaluation metrics measure the faithfulness of the generated text as a score, such as entailment score or QA matching score. They cannot distinguish between different types of factual errors and cannot locate specific error spans, which are detrimental to robust evaluation and repair. Moreover, most of them mainly focus on specific tasks, rather than be general to all NLG tasks. More fine-grained and general evaluation methods are needed to drive further developments in the field of NLG.

Intrinsic and Extrinsic  Most of the existing evaluation metrics measure intrinsic and extrinsic factual errors as a unified metric without distinguishing them. We argue that intrinsic and extrinsic factual errors should be evaluated separately, as they have different definition and reference. The reference for the intrinsic error is the source text, however, the reference for the extrinsic error include the source text and world knowledge. As the extrinsic hallucinations contains both factual and non-factual information, it is necessary to distinguish them as the non-factual extrinsic hallucinations are harmful while the factual extrinsic hallucinations are usually beneficial for NLG tasks, such as
dialogue generation. The field of fact checking is promising to help detect non-factual extrinsic hallucinations.

**Fine-grained Error Types** None of existing evaluation metrics can locate specific error spans and their fine-grained error types, such as predicate error, entity error, circumstance error or discourse link error. Fine-grained error types can help post-editing methods to fix unfaithful content and also provide richer insight to the researchers.

**General Evaluation** Existing evaluation metrics are mainly designed for specific tasks, such as text summarization or table-to-text generation. Although some of them can be applied to other NLG tasks, task-agnostic general metrics and evaluation benchmarks are lacking. Although the source and output texts of different tasks come in various forms, it is worth exploring the relationship between them and propose a general and fine-grained metric to evaluate faithfulness. Task-agnostic metrics with cross-domain robustness can help the research community to establish a unified benchmark, which is important and meaningful to help collaborate and standardize evaluation metrics for NLG tasks.

### 5.2 Reasoning-based Optimization

Most intrinsic errors are caused by misunderstanding the facts in the source context. Besides NLU-based pre-training on large scale corpus, to help models understand the facts correctly requires reasoning over the input context or world knowledge.

**Numerical Reasoning** The correctness of the numerals in the generated texts such as date, quantity and scalar are important for readers to get the correct information. As existing models usually model numerals in the same way as textual tokens, such as splitting numerals into sub-words or byte-pairs, they are more vulnerable to numerical errors. However, most of the existing optimization methods do not focus on the faithfulness of numerals. Tasks with quantities such as table-to-text generation, require numerical reasoning. Therefore, adding reasoning ability to numerical modeling is crucial for faithfulness optimization.

**Grounded Language Representation** The expressiveness of language generation models are vital to the faithfulness of the generated results. A model with poor input text representation will fail to do document-level understanding and inference. Language grounding is an active field aiming at enriching textual representations with visual information, which has been shown to improve performance on a variety of core NLP tasks (Baroni, 2016; Bruni et al., 2014; Kiela, 2017). Some recent work also propose unified-modal models for language understanding and generation UNIMO (Li et al., 2020c). Learning grounded language representation is a promising direction for improving the expressiveness of NLG models, thus improving the faithfulness of their generated texts.

**Incorporating Causal Inference** Existing language models are mostly correlation prediction models, where predictions are due to correlation rather than causal inference. Therefore, these correlational predictive models are not credible and may lead to errors in out-of-distribution or long-tailed situations. Clearly, the lack of causality is one of the main reasons for poor model generalization and faithfulness. Incorporating causal inference into language model may be the fundamental method to solve the faithfulness of NLG models.

### 6 Conclusion

In this survey, we conduct a systematic overview of the faithfulness problem across different NLG tasks. We organize and discuss the faithfulness analysis, evaluation metrics and optimization methods in a combined manner under a general categorization standard. The evaluation metrics for different NLG tasks are categorized into four types: Entailment-based, QA-based, Fact-based and Others. The optimization methods are categorized into six types: Factual Guidance, Auxiliary Task, Post-Editing, Learning Method, Constrained Decoding and Others. All the evaluation metrics and optimization methods are discussed and compared to facilitate both task-specific and task-agnostic understanding of the faithfulness problem. In addition, we propose potential future directions according to the
challenges of this problem and the current research status of evaluation metrics and optimization methods.

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