Recent Advances in Neural Text Generation: A Task-Agnostic Survey

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Abstract

In recent years, considerable research has been dedicated to the application of neural models in the field of natural language generation (NLG). The primary objective is to generate text that is both linguistically natural and human-like, while also exerting control over the generation process. This paper offers a comprehensive and task-agnostic survey of the recent advancements in neural text generation. These advancements have been facilitated through a multitude of developments, which we categorize into four key areas: data construction, neural frameworks, training and inference strategies, and evaluation metrics. By examining these different aspects, we aim to provide a holistic overview of the progress made in the field. Furthermore, we explore the future directions for the advancement of neural text generation, which encompass the utilization of neural pipelines and the incorporation of background knowledge. These avenues present promising opportunities to further enhance the capabilities of NLG systems. Overall, this survey serves to consolidate the current state of the art in neural text generation and highlights potential avenues for future research and development in this dynamic field.

1 Introduction

Natural Language Generation (NLG) is a highly challenging sub-field of Natural Language Processing (NLP) (Reiter and Dale, 2000), which incorporates knowledge (e.g. text, pictures, audio, tables, etc.) and generates corresponding task-oriented text as output, e.g. weather forecast reports. NLG has a range of applications (Gatt and Krahmer, 2018; Santhanam and Shaikh, 2019). NLG is traditionally tackled by symbolic and rule-based approaches, but in recent years deep learning techniques have attracted a great amount of interest (Belinkov and Glass, 2019). Both approaches have their strengths, and it is possible that a neurosymbolic approach will dominate in future. This survey will focus on recent advances in the neural approach.

Existing survey papers usually summarize one of the NLG applications such as Story Generation (Hou et al., 2019; Alhussain and Azmi, 2021; Tang et al., 2022c; Huang et al., 2022), Text summarisation (Suleiman and Awajjan, 2020; El-Kassas et al., 2021), Dialogue (Ni et al., 2021; Tang et al., 2022b; Zhan et al., 2023), Machine Translation (Yang et al., 2020; Dabre et al., 2020), etc (Loakman et al., 2023). Only a few studies (Lu et al., 2018; Chandu and Black, 2020; Jin et al., 2020; Dong et al., 2021) discuss the development of the whole NLG area.

Task-specific surveys are beneficial, but the survey of the whole NLG area could give broader ideas as inspiration for various applications using generative techniques, as the surveys like Belinkov and Glass (2019); Rogers et al. (2020) did. To our knowledge, this is the first comprehensive survey of neural text generation which summarises the commonalities and trends of recent advances.

From the perspective of neural text generation, various NLG applications have task-agnostic commonalities: (i) Unlike traditional systems, neural networks capture features without ad-hoc feature engineering (Belinkov and Glass, 2019); (ii) Various neural generative frameworks mostly use similar encoder-decoder architectures, so they have common modules and training (or inference) strategies; (iii) Evaluation metrics also have good generalization in NLG. Therefore, neural text generation has similar challenges (Chandu and Black, 2020; Thomson and Reiter, 2021) and solutions to analyze.

In this survey, we provide an overview of neural text generation via summarising the papers
mainly published within the last 5 years\textsuperscript{1}. We compartmentalize and analyze the contributions of these papers according to 4 aspects: §2 probes the characteristics of data construction for NLG tasks. §3 summarizes common deep learning techniques used in neural generative frameworks. In §4, we analyze training and inference strategies of neural frameworks. §5 reviews and categorizes existing evaluation metrics for text generation. Following our analysis of recent advances, we discuss the future directions of research on Neural text generation including developing neural pipelines and exploiting background knowledge.

2 Data Construction

Datasets can be divided into benchmarks (for training and evaluating) and resources (usually external to tasks such as ConceptNet (Speer et al., 2017)). A number of papers are devoted to setting up new datasets for NLG tasks, from which we investigate their demands and common approaches.

2.1 The Requirements of Data Construction

2.1.1 Task-oriented Requirements

New innovations in neural text generation often require a new dataset. For example, Rashkin et al. (2020) propose the task of outline-conditioned storytelling, which requires writing stories according to a given plot outline (more reasonable than given a leading context (Fan et al., 2018)), but existing datasets offer no plot outlines. Therefore, they present their datasets and corresponding construction workflow\textsuperscript{2} satisfying the requirements.

Similarly, other requirements e.g. modeling emotions (Huang et al., 2018; Brahman and Chaturvedi, 2020a) or persona (Chandu et al., 2019; Chan et al., 2019b; Wu et al., 2021) all need extra annotations for the new formalization of tasks.

Some tasks also require high-level features (topics, themes, etc.). For example, to support new situations of chatbot detection (Gros et al., 2021), contradiction detection (Nie et al., 2021), personal information leakage detection (Xu et al., 2020c), etc., Dialogue systems are trained on specific corpora to to deal with these task-oriented questions.

2.1.2 Task-agnostic Requirements

As available infrastructures for NLG, there are plenty of benchmarks (Rosenthal et al., 2017; Gardent et al., 2017; Novikova et al., 2017b; Wang et al., 2018) and data resources (Speer et al., 2017; Vrandečić and Krötzsch, 2014; Clarke et al., 2001; Lehmann et al., 2015) offering public resources, and related tools for evaluating, retrieving, constructing for NLG tasks. These are typically updated regularly. For instance, ConceptNet\textsuperscript{3} is a well-known semantic network widely used to pre-train neural networks to capture semantic features, with a first version in 2004 (Liu and Singh, 2004), and most recent version in 2017 (Speer et al., 2017).

According to these updates, we conclude the trends for datasets development as follows:

- **Larger and more comprehensive**: Replenish the corpora e.g. ontology, and facts, or Supplement new knowledge e.g. multilingual translation and commonsense knowledge.
- **More diverse**: Extra tasks and evaluation metrics.
- **Higher quality**: Address existing problems e.g. ambiguities, lack of information.

These trends also reflect the requirements of text generation. To acquire commonsense knowledge, CommonGen (Lin et al., 2020) is released to test the capability of generative commonsense reasoning for NLG systems. Kumar and Black (2020) present a large-scale ClarQ for Clarification Question Generation, clarifying ambiguities existing in current datasets to some extent. XGLUE (Liang et al., 2020b) has more diversified tasks labeled with more languages than GLUE. Akoury et al. (2020) propose STORIUM, a platform\textsuperscript{4} to produce and evaluate long-form stories with richer context than existing datasets.

2.2 Approaches of Data Construction

In this part, we discuss some common approaches of data construction which can cover most NLG

\textsuperscript{1}A tool is built to partly collect high-quality related samples: https://github.com/tangg555/acl-anthology-helper.

\textsuperscript{2}Through RAKE (Rapid Automatic Keyword Extraction), which is a keyword extraction algorithm. https://pypi.org/project/rake-nltk/

\textsuperscript{3}https://conceptnet.io/

\textsuperscript{4}https://storium.com/
tasks we reviewed.

2.2.1 Creating datasets from Public Resources

Processing public resources is the most common way to make a new dataset from scratch, as they are natural and abundant. Plenty of Challenges (Rosenthal et al., 2017; Gardent et al., 2017; Novikova et al., 2017b) and tasks (Agarwal et al., 2021a; Chen et al., 2020a; Wang et al., 2021b) sample plain text, such as descriptive text (e.g. wikipedia), dialogues (e.g. tweet), or structured data (e.g. wikidata (Vrandečić and Krötzsch, 2014)), etc. as the raw material.

Crowdsourcing and automatic pipelines both are commonly used to collect and annotate samples acquired from public resources. CommonGen (Lin et al., 2020) samples frequent concept-sets from existing caption corpora, and employs crowd workers to write corresponding sentences for referenced concept-sets. Chen et al. (2020a) sample from Wikidump and WikiData, and collect data-text pairs through an automatic pipeline.

2.2.2 Adding Extra Annotations to Existing Datasets

Corpora used for text generation are often task-specific, with unique characteristics that make it difficult for them to be shared by other tasks. e.g. Dialogues (datasets for Dialogues Systems) are incompatible with Machine Translation requirements (requiring multilingual corpora). However, similar tasks are able to partially share the datasets. For example, variant tasks of Story Generation (requiring stories as datasets) can make datasets by adding extra annotations of plots (Fan et al., 2018), emotions (Mostafazadeh et al., 2016) or persona (Huang et al., 2016b; Shuster et al., 2020) to existing datasets. This construction approach is more efficient and reliable than constructing from scratch.

2.2.3 Transforming the Representation of Knowledge

Parallel Corpora are a special kind of dataset. As knowledge has a variety of representations (e.g., different languages, or different formats like text, tables, images, etc.), some specific NLG tasks (e.g. Machine Translation or Data-to-text task) which transform one knowledge representation to another (e.g. triples to text) need to be trained on parallel corpora.

These specific tasks are summarized in Figure 1: Image Captions (Sharma et al., 2018; Yoshikawa et al., 2017), Visual Storytelling (Hsu et al., 2019; Chandu et al., 2019), Speech Recognition (Warden, 2018), Data-to-text (Nishino et al., 2020a; Fu et al., 2020; Nishino et al., 2020a; Richardson et al., 2017), Machine Translation (Hasan et al., 2020; Guzmán et al., 2019). In studies of these tasks, parallel corpora are indispensable (Belz and Kow, 2010).

![Figure 1: Special NLG tasks require parallel corpora.](image)

Constructing parallel corpora is more challenging due to potential misalignment (Kuznetsova et al., 2013) and the fact that they do not generally occur naturally (Belz and Kow, 2010). The construction workflow is generally: crawling two types of knowledge, then aligning them manually or automatically, and finally filtering (discarding low-quality samples).

3 Neural Frameworks

The methodologies of neural text can be generally viewed as a framework combining a range of deep learning techniques. There are various alternative deep learning techniques, and most of them can be composed together. However, there is no related study that demonstrated which alternative technique is superior (e.g. theoretically Autoregressive Decoding is more suitable for NLG tasks (Schmidt et al., 2019), but sometimes well-designed Non-autoregressive ones could outperform their Autoregressive counterparts (§3.2)). Thus, we separately analyze these techniques used to build a neural generative framework.
3.1 Encoding Architectures

Encoding processes embed input (text, or image/video, etc.) into continuous representation spaces for neural models, in which knowledge features are converted to the numeric vectors. With respect to text generation tasks, most encoding architectures are mainly based on three techniques: (i) Attention Mechanism e.g. Transformer (Vaswani et al., 2017), (ii) Variational Inference e.g. Seq2Seq Variational Autoencoder (Seq2Seq VAE) (Bowman et al., 2016), and (iii) Adversarial Learning e.g. Sequence Generative Adversarial Nets (SeqGAN) (Yu et al., 2017). To date, no obvious superiority has been demonstrated among these three types of encoder architectures.

Therefore, a number of studies have combined these three techniques, where the combinations had better performance. Tolstikhin et al. (2018) propose Wasserstein Auto-Encoders, which are the combination of (ii) VAEs and (iii) GANs. Bahuleyan et al. (2018) propose a variational attention mechanism applied to (ii) VAE encoder. Zhang et al. (2019a) propose Self-attention Generative Adversarial Networks which combine (i) Attention Mechanism with (iii) GANs.

Derivatives of (i) and (iii) usually keep the vanilla encoder structure but implement different training and inference strategies to encode features. In comparison, encoders of (ii) have flexible encoding architectures, depending on ad hoc choices for probabilistic modeling, driven by task requirements.

Another trend that emerges in several studies is to improve the encoding process by increasing the numbers of encoders which help to encode separate latent-variables, e.g. modeling personalization (Chan et al., 2019b; Wu et al., 2020), discourse coherence (Guan et al., 2021a; Xu et al., 2021b; Yoo et al., 2020), and topology (Huang et al., 2020; Damonte and Cohen, 2019).

3.2 Decoding Architectures

In general, the decoding of neural text generation refers to inferring the text output based on encoded features. Decoding architectures can be divided into (i) Autoregressive and (ii) Non-autoregressive. (Chandu and Black, 2020)

Autoregressive Decoding or Autoregressive Generation (AG) dynamically generates predictions in a recurrent manner. At time step $k$, the output $o_k$ corresponds to the input features $X_k$. At step $k + 1$, the input features $X_{k+1}$ consist of $X_k$ and $o_k$.

This method’s ability to model sequential dependencies when decoding is powerful for generation tasks (Schmidt et al., 2019), but this characteristic also leads to problems (Schmidt et al., 2019; Su et al., 2021) of inability to parallelise, relatively high latency in inference, and train-test discrepancies.

Non-autoregressive Decoding or Non-autoregressive Generation (NAG) has faster inference speed (Guo et al., 2019) than (i). the output text sequence $O$ is directly generated from $X$. In comparison to (i), there is no explicit correlation among outputs. Thus, Non-autoregressive Decoding process also results in two common problems: the fixed length of output and the conditional independence among predictions. These problems mean that existing generation quality of (ii) lags behind (i) (Su et al., 2021).

A number of studies take both decoding methods into consideration in order to alleviate those problems. Schmidt et al. (2019) introduce a conditional random field (CRF) (Sha and Pereira, 2003) to a non-autoregressive baseline (Schmidt and Hofmann, 2018), which “expresses local correlations on the word level but keeps the state evolution non-autoregressive.” Similar approaches (Ma et al., 2019; Zhang et al., 2020a; Chi et al., 2021; Qian et al., 2021) are proposed to deal with the independence assumptions of (ii), which produce a better language model taking advantage of both decoding strategies.

3.3 Reinforcement Learning

Reinforcement Learning (RL) is learning decision-making based on discrete policies (Arulkumaran et al., 2017). Because of the characteristics of learning discrete policies, policy gradient methods are quite suitable to model indifferentiable rewards. Through well designed policy gradient methods (Guo, 2015; Li et al., 2016), RL approaches train generative models towards indifferentiable rewards by minimizing the policy gradient loss (Chan et al., 2019a).

Current trends show rising interest in two directions: (a) Use RL for data augmentation (Nishino 2013) illustrates how Autoregressive decoding works.
et al., 2020b; Liu et al., 2020a; Kedzie and McK-­‐eown, 2019); (b) Design a task-­‐oriented (Yadav et al., 2021; Yao et al., 2020; Liu et al., 2019; Zhou et al., 2019a; Cai et al., 2020) or adaptive (Chan et al., 2019a) reward policy.

Considering the speciality of text generation tasks, in which evaluation metrics have no gold-­‐standard automatic metric (see §5), Pasunuru et al. (2020) showed how to automatically optimize multiple rewards.

3.4 Data Retrieval

In text generation, data retrieval is a technique to retrieve external material by key words. These supplementary data contain rich representations around the key words, helping to augment the training of generative language models. Thus, they are leveraged to implicitly augment (Song et al., 2018; Hua et al., 2019; Fabbri et al., 2020), guide (Cai et al., 2019; Xu et al., 2020b; Gupta et al., 2021), or generalize (Tigunova et al., 2020) the text generation process.

Data retrieval methods were also used as the main framework in generating systems. For example, in the area of conversation systems, retrieval-­‐based systems (Isbell et al., 2000; Ji et al., 2014) can search best-­‐match text as the reply to a user-­‐issued utterance. However, with the rise of deep learning, data retrieval is more often used as an auxiliary module for a neural generator, as mentioned in the previous paragraph. Thus, the recent studies of Data Retrieval mainly focus on supportive tools (Liu et al., 2020b).

3.5 Exploiting Sequential Features

Text can be viewed as a sequence of characters, words, phrases, or other granules. The sequential features of text can be seen as the order among these granules. The phrase "Alice gave Bill" has same words as "Bill gave Alice", but they are totally different. Related work can be divided into the following categories, according to the way in which they model sequential features.

3.5.1 Recurrent Neural Frameworks

Recurrent Neural networks (RNNs) have achieved great success in last couple of years. LSTM (Sundermeyer et al., 2012), GRU (Chung et al., 2014), HRED (Sordoni et al., 2015), VHRED (Serban et al., 2017), RIMs (Goyal et al., 2019) were developed one after another. Furthermore, the mechanism of RNNs also deeply affects the design of current encoders (Fabius et al., 2015; Chien and Wang, 2019) and decoders (Radford et al., 2019). The aforementioned Variational Autoencoder (VAE), for instance, is modified to a Variational Recurrent Autoencoder (VRAE) for text generation (Fabius et al., 2015; Chien and Wang, 2019).

3.5.2 Probabilistic Models

Text sequence generation can be partly viewed as the estimation over conditional probability distributions (the real posterior distribution is intractable) of latent variables with given observations such as words (Zhang et al., 2018; Liao et al., 2020), sentences (Bahuleyan et al., 2019), etc. Linear-­‐chain Conditional Random Field (CRF) (Cai et al., 2017; Gehrmann et al., 2019), for instance, is a typical Markov network to model dependencies among sequence tokens. Furthermore, if we set up variational inference with a neural network to approximate intractable posterior probability and train it with KL loss, this is the mechanism applied in VAE (Kingma and Welling, 2014) and its variants (Bowman et al., 2016; Bahuleyan et al., 2018; Zhang et al., 2019c).

3.5.3 Hierarchical Stacked Framework

The Hierarchical Recurrent Encoder-­‐Decoder (HRED), introduced by Sordoni et al. (2015) for a Query Suggestion task, uses RNNs to encode both session-­‐level and query-­‐level features. The session-­‐level RNN layer can be viewed to be hierarchically on top of the query-­‐level RNN layer. It is a good way to model multi-­‐granule representations in text, and has been improved on in numerous subsequent works (e.g. VHRD (Zeng et al., 2019) and PHVM (Shao et al., 2019)) of this hierarchical stacked structure in dialogues (Serban et al., 2016; Ren et al., 2019), Data-­‐to-­‐text (Gong et al., 2019a; Shao et al., 2019), etc. (Weber et al., 2018).

3.5.4 Memory Network

Inspired by the memorizing mechanism of RNNs, Weston et al. (2015) and Sukhbaatar et al. (2015) proposed the Memory Network, or Memory-­‐argumented Neural Network, to store long-­‐term memory. Instead of training a hidden state to store "memory" of the input sequence, Memory Networks introduce an external memory component which is jointly trained with inference. In this way, neural networks hold the uncompressed sequen-
tial knowledge when doing inference; by keeping a long-term memory it performs better. The Memory Network has been widely used to keep historical information for generation tasks (Zhang et al., 2017; Fu and Feng, 2018; Chen et al., 2019; Tian et al., 2019; Chen et al., 2021; Wu et al., 2021), especially those having a large number of inputs (Jang et al., 2019).

3.5.5 Others

As BERT (Devlin et al., 2019) with Transformer (Vaswani et al., 2017) blocks increased in popularity, the attention mechanism (see §3.1) has also become popular in recent years. Attention mechanisms implement position embeddings to encode sequential features, and encode position embeddings that can be divided into the absolute (Devlin et al., 2019) and the relative (Shaw et al., 2018). We recommend the overview of Dufter et al. (2021) which compares position encoding modules over 30 Transformer-like models to further study position embedding. In addition to position embedding, attention (self-attention) mechanisms can also observe the order between tokens by input embeddings. Thus, some researchers leverage special tokens to encode the order between sentences and utterances (Guan et al., 2021a; Li et al., 2021b; Tang et al., 2022a).

3.6 Leveraging Auxiliary Tasks

Auxiliary tasks can help enhance the representation learning ability of neural models. According to the relationship between auxiliary tasks and the main task, we can apply them in a serial (modules) or parallel (Multi-task Learning) way:

• Multi-task Learning: Based on the hypothesis that correlated tasks have similar representation spaces, Multi-task Learning leverages heterogeneous training data to augment the representation learning ability of neural models. (Zhou et al., 2019b; Ide and Kawahara, 2021; Zhou et al., 2019b; Li et al., 2021a; Xu et al., 2021c). The main task shares part of training parameters with correlated auxiliary tasks to jointly learn how to encode features. Li et al. (2021a), for instance, integrate number ranking (NR) and Importance Ranking (IR) with the data-to-text task to augment encoders when training embeddings. NR and IR are two auxiliary tasks, which help to extract more task-related features from tables.

• Modules in Frameworks: Auxiliary tasks can also be set as the preliminary steps in neural frameworks. Brahman and Chaturvedi (2020b) introduce two Emotion-Reinforced models to track emotions of the protagonist for their generative model of storytelling. Zhao et al. (2020b) design two kinds of auxiliary tasks, "order recovery" and "masked content recovery", to capture sequential and semantic features for their multi-turn dialogue system.

3.7 Hybrid Frameworks

It is well-known that neural networks are unstable and hard to accurately control, because their continuous vector spaces are uninterpretable to humans. In comparison, traditional (non-neural) models are more interpretable but require expertise in feature engineering, whereas neural models do not. Therefore, some studies propose hybrid frameworks to take advantage of both solutions.

We observe two trends behind recent studies in hybrid frameworks: (i) Improving existing traditional frameworks via partially replacing modules with neural networks, for example Luo et al. (2020) build a neural text-stitch module to help their template-based data-to-text system reduce human involvement. Other examples include Manning (2019); Gangadharaiah and Narayanaswamy (2020). (ii) Introducing data-driven non-neural techniques to "guide" neural models. For example, Wang et al. (2021a) use template generated responses as extra input to neural dialogue systems. In a nutshell, (ii) means that through offering higher-level control features (extra inputs to neural models), some auxiliary techniques such as template-based methods (Cao et al., 2018; Peng et al., 2019; Wang et al., 2021a), rule-based methods (Yang et al., 2017), traditional frameworks (Zhai et al., 2019; Goldfarb-Tarrant et al., 2020), etc. can be introduced to guide neural models. Zhai et al. (2019), for instance, introduce a symbolic "agenda generator" to perform text planning, and then use neural models to generate stories according to a produced agenda (script).

4 Training and Inference Strategies

In addition to the framework architecture, good training and inference strategies are also important to the performance of text generation.
4.1 Sampling Strategies

During decoding most generative models compare the likelihood (or unlikelihood (Welleck et al., 2019; Li et al., 2020a; Lagutin et al., 2021)) among sampled candidates to predict the next token. Chandu and Black (2020) summarise three sampling techniques according to the inference process: (i) Random Sampling, (ii) Top-\(k\) Sampling, and (iii) Top-\(p\) Sampling (Holtzman et al., 2020) (selecting a dynamic \(k\) number of works according to a threshold probability value). The Top-\(p\) sampling (iii), also known as Nucleus Sampling, currently claim to be the best available decoding strategy.

Beyond decoding, sampling strategies also have an impact on the training process (i.e. Negative Sampling). Good negative samples have been demonstrated useful when training deep learning models (Goldberg and Levy, 2014; Guan and Huang, 2020a; Ghazarian et al., 2021). Contrastive Learning (CL) (Pan et al., 2021; Liu and Liu, 2021), for instance, aims to maximize that representation gap for machine translation between different languages of randomly collected negative samples.

Through distinguishing high-quality negative samples, neural models can better learn how to optimize related evaluation metrics. Guan and Huang (2020a) train a neural model to measure the overall quality of generated stories by sampling negative samples with commonly observed errors (Repetition, Substitution, Reordering, and Negation Alteration) in existing NLG models. Ghazarian et al. (2021) hypothesize that heuristically generated negative samples are not adequate to reflect implausible texts’ characteristics, so they construct plot-guided adversarial examples, and get better evaluation metrics trained on these samples.

4.2 Masking Strategies

Masking is a common tool widely used in language modeling both in encoding and decoding. For Non-autoregressive Decoding models (See §3.2) masks are used to pad future tokens before being received by the decoder. Note that we consider noising strategies such as token deletion, token replacing, etc as part of masking strategies, because they can also be viewed as "masks" put on the original input.

As for encoding, the encoder reads in a partly masked text sequence, which forces language modeling to learn representations conditioned on incomplete context. A typical use is Masked Language Models (MLM), which train models to restore missing parts (masked tokens) of input text. In order to resist perturbations with contextual features, neural generative models (Fedus et al., 2018; Lewis et al., 2020; Liao et al., 2020; Chen et al., 2020c; Song et al., 2019; Ahmad et al., 2021), e.g. MaskGAN, MASS and BART, train models with an autoregressive decoder to infill the masked tokens in the original data with missing tokens, in which masks can be viewed as the noise to "overcome".

4.3 Adversarial Training

Adversarial Training is a kind of data augmentation strategy, which learns from adversarial samples, and improves the performance and robustness of neural models (Jiang et al., 2020; Bai et al., 2021). As a derivative, Zhou et al. (2021) propose Inverse Adversarial Training (IAT) which trains neural models to be sensitive to perturbations. It encourages neural dialogue systems to capture dialogue history, and avoid generic responses via penalizing the same response under a perturbed dialogue history.

Adversarial training is able to address Adversarial Attacks (Wang et al., 2020), which refers to misleading well-trained models through adding artificial perturbation. The Generative Adversarial Network (GAN) is a typical technique of Adversarial Training, and promising in NLG area (de Rosa and Papa, 2021). GANs train both a generator to generate artificial samples resembling original ones, and a discriminator to resist perturbations on the data’s distribution.

However, as the vanilla GAN only suits continuous and differentiable output while in comparison text generation generates sequences of discrete tokens, many generative frameworks (Yu et al., 2017; Zou et al., 2020; Zhou et al., 2021) implement adversarial training through combining both GAN and Reinforcement Learning (RL) modules (e.g. the aforementioned SeqGAN encoder). There are also other ways (Cui et al., 2019; Wang et al., 2020) to address discrete output for GAN models. Wang et al. (2020), for instance, propose a tree-based auto-encoder embedding discrete tokens into a continuous space.
4.4 Knowledge Distillation

Knowledge Distillation (Stanton et al., 2021; Gou et al., 2021) is a very popular model compression and acceleration technique, which trains a student network to emulate a larger and cumbersome teacher model. In the work of Chen et al. (2020c), they attempt to train an autoregressive model, taught by BERT (Devlin et al., 2019). Haidar and Rezagholizadeh (2019) apply knowledge distillation to GANs for text generation.

To improve knowledge distillation on generative models, Melas-Kyriazi et al. (2019) propose a training approach called "generation-distillation" which leverages data augmentation from an external Seq2Seq model to bridge the gap between "teacher" and "student". Tang et al. (2019) let the student network BiLSTM emulate the distribution of input text instead of the conditional probability distribution of the teacher network.

4.5 Pre-training

Pre-training refers to training a neural language model with large-scale corpora to help it learn parameters, and this method is basically self-supervised and task-agnostic. In order to advance NLG tasks, the Pre-trained Language Models (PLMs) are fine-tuned in task-oriented frameworks with small changes to the workflow and retraining on the datasets.

PLMs are prevalent in current NLG tasks, because they alleviate the lack of training corpora and feature engineering problems (Qiu et al., 2020) for specific tasks. In light of taking advantage of Pre-training techniques, studies consider the improvement on both language models and high-quality corpora.

In the context of NLG, main-stream language models use the encoder-decoder architectures, and transformers (Vaswani et al., 2017) have superseded RNNs (Peters et al., 2018) as basic blocks to build pre-training neural layers. The aforementioned non-autoregressive language model, e.g. BERT (Devlin et al., 2019) and autoregressive language model, e.g. GPT-2 (Radford et al., 2019) both have been widely applied in downstream tasks as baselines or modules learning representations of knowledge. Current trends use training strategies such as mask sampling (See §4.2), multi-task learning (Guan et al., 2020; Xu et al., 2021a), knowledge distillation (Gu et al., 2021), etc. to improve existing language models.

As for the pre-training corpora, some (Su et al., 2020; Liang et al., 2020a; Zhang et al., 2020c; Xu et al., 2020a; Qi et al., 2021) contribute to designing a construction workflow to build large-scale, high-quality, and task-oriented corpora. Su et al. (2020), for instance, construct a high-quality movie dialogue corpus, and experiments show that a simple neural approach trained on this corpus can outperform complex rule-based commercial systems. Adjusting PLMs to heterogeneous knowledge (knowledge graph) (Chen et al., 2020b; Guan et al., 2020; Agarwal et al., 2021b) beyond text is another common approach to feed PLMs. Guan et al. (2020), e.g., let GPT-2 learn commonsense knowledge on natural language sentences transformed by commonsense knowledge graphs.

4.6 Other Methods

There are some other strategies which are fundamental and common in NLG tasks. We list them as follows:

- Multi-task Learning (namely jointly learning). Training multiple correlated neural tasks on shared network layers (introduced in Sec. 3.6).
- Teacher Forcing. Training generative neural can be done in two ways: Free-running and Teacher Forcing. Current training strategies are usually based on these two methods, and we can view them as the variants (Goyal et al., 2016; Goodman et al., 2020; Qi et al., 2020; Zhang et al., 2019b) of Teacher Forcing, e.g. Professor Forcing (Goyal et al., 2016). They attempt to modify sampling strategies to address the Exposure Bias (He et al., 2019) when using the Teacher Forcing strategy.
- Data Augmentation. In general, data augmentation refers to every technique which increases the amount of training data, so we can see it in the aforementioned literature. e.g. Adversarial Training (Wang and Bansal, 2018) creates negative samples to train, so this is also a kind of data augmentation.

5 Evaluation Metrics

Unlike other NLP tasks, NLG is open-ended, so usually NLG tasks have no gold-standard to measure the quality of generated text. Human-centric metrics are unreliable and noisy (Otani et al., 2010).
because they suffer from problems such as being expensive, time-consuming, individual biased and so on. Therefore, currently automatic metrics and human-centric metrics are both applied to evaluate NLG systems, and sometime extra correlation analysis (Guan et al., 2021a; Ghazarian et al., 2021) will be introduced between them e.g. Inter-Annotator Agreement (IAA) (Amidei et al., 2019a). Current NLG systems tend to choose multiple metrics among existing automatic and human-centric metrics to evaluate their results from multiple perspectives.

According to existing studies, we summarize current evaluation metrics (See examples in Table 1.) from two perspectives: the types of evaluators (humans, models or rules), and the data requirement (referenced, unreferenced, or hybrid). We will discuss the characteristics and trends in the following parts.

5.1 Untrained Automatic Metrics

Untrained Automatic Metrics (sometimes abbreviated as Automatic Metrics) are classical methods for NLG tasks. They are mostly based on string handling techniques e.g. N-gram, word matching, string distance, etc. to measure the character-level distribution similarity with a reference text. N-gram based methods (e.g. BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), METEOR (Banerjee and Lavie, 2005), and MS-Jaccard (Alihosseini et al., 2019).) are the most typical referenced methods, which measure similarity via overlaps.

In comparison, unreferenced methods (Zhu et al., 2018; Yao et al., 2019) also calculate content overlaps but the reference is the model generated text. e.g. Self-BLEU (Zhu et al., 2018) is proposed to measure diversity by calculating the average BLEU score between one sentence (as the hypothesis) and others in a generated collection.

Untrained Automatic Metrics are biased, and poorly correlated to human judgements. (Reiter, 2018; Sellam et al., 2020), but they are time-efficient and cheap, so they can be found in most NLG tasks to offer coarse evaluation from different perspectives (Novikova et al., 2017a; Celikyilmaz et al., 2020).

5.2 Machine-Learned Metrics

Letting neural models learn to evaluate generated results is a promising method to overcome the disadvantages of Untrained Automatic Metrics: the coarse measurement and bad correlation to human judgements. When evaluating, machine-learning models map the measurement into a continuous space, so they can generate a more fine-grained real-valued score. In the training process, models learn how to generate or evaluate text as humans, which make the results have better correlation to human judgements.

Referenced Machine-Learned Metrics aim to measure the similarity between machine-generated text with either natural text or its counterparts. Therefore, they are mostly Embedding based methods (e.g. MEANT 2.0 (Lo, 2017), MoverScore (Zhao et al., 2019), and BertScore (Zhang et al., 2020b)), which compare the semantic representations by embedding (Clark et al., 2019). Recent efforts are investigating how to generate more meaningful embeddings, for which we can get some clues from the following: (i) word-level (Huang et al., 2016a) -> phrasal-level (Lo, 2017) -> sentence-level (Clark et al., 2019); (ii) fixture representations -> contextual representations (Zhang et al., 2020b); (iii) coarse input -> fine input (Zhao et al., 2019). However, to measure similarity, the Referenced methods emphasize quality measurement while they neglect diversity measurement.

Unreferenced Machine-Learned Metrics learn how to directly measure the output of generative models without any reference. Since most generative systems are developed to maximize the likelihood of natural language (Yarats and Lewis, 2018), the likelihood of human-written utterances generated by NLG systems (namely perplexity) can be used as the metrics. This kind of Generator based method (Ficler and Goldberg, 2017; Yarats and Lewis, 2018; Guan and Huang, 2020b) is popular to compare a Neural model with its counterparts, but optimizing models only for perplexity may result in bland responses (Celikyilmaz et al., 2020). On the other hand, Discriminator-based metrics (also known as the optimal discriminator) (Bowman et al., 2016; Kannan and Vinyals, 2017; Hu et al., 2017) are trained through constructive learning to distinguish machine-generated text from human-written text. However, training the optimal discriminator needs large-scale human judgements or overfitting may bring a strong bias (Garbacea et al., 2019).

Recently, there is interest in building blended

\[ \text{https://textinspector.com/help/lexical-diversity/} \]
models (e.g. RUBER [Tao et al., 2018], RUBER-BERT [Ghazarian et al., 2019], BLEAURT [Sellers et al., 2020]), which design training strategies to enable end-to-end neural models to incorporate features belonging to the Referenced, Unreferenced or Untrained Automatic Metrics.

5.3 Human-Centric Metrics

Human-Centric Metrics are also called human judgements, which basically rely on the statistics of a crowdsourced collection (e.g. through Amazon Mechanical Turk). Human-centric metrics require the design of surveys. Human-Centric Metrics are important assessment criteria to evaluate NLG systems, but they are quite expensive and time-consuming.

The Unreferenced human-centric metrics (Galley et al., 2018; Ghazarian et al., 2021) require the crowd workers to give a scaled rating score to the generated text. Amidei et al. (2019b) further studied 135 papers with Unreferenced human evaluation, and discuss good practices. On the other hand, the Referenced human-centric metrics (Li et al., 2019; Clark and Smith, 2021; Kiritchenko and Mohammad, 2017; Deriu et al., 2020), which require crowd workers to give a relative rank for given systems (or natural language), are more complicated and domain-oriented (ad-hoc questions). This is due to individual biases (Otani et al., 2016) which make it hard to decide which system is better. Thus, some recent studies (Novikova et al., 2018; Sakaguchi and Van Durme, 2018; Goldfarb-Tarrant et al., 2020) also managed to combine both Referenced and Unreferenced human-centric metrics to establish an evaluation system.

5.4 The Trends of Evaluation Metrics

5.4.1 Combining Multiple Criteria

We summarize the criteria used in the literature of NLG evaluation as follows, and we observe that newly designed evaluation methods tend to cover more metrics.

- **Lexical**: Repetition, Distinctiveness, Perplexity.
- **Linguistic**: Fluency, Sentence Order, Naturalness, Discourse.
- **Semantic**: Coherence, Consistency, Relevance.
- **Overall**: Quality, Diversity, Informativeness, Preference.

Guan and Huang (2020b); Pang et al. (2020); Mehri and Eskenazi (2020); Guan et al. (2021b); Gehrmann et al. (2021) are developing evaluation frameworks and benchmarks to combine multiple metrics.

5.4.2 An End-to-end Evaluation Framework

With the rapid development of deep learning techniques, Machine-Learned Metrics, especially End-to-end neural evaluation models, become a rapidly emerging research direction, because it is an easier way to combine multiple criteria. For example, previous metrics could evaluate either the quality or the diversity, while Semeniuta et al. (2018); Hashimoto et al. (2019); Guan and Huang (2020b); Zhang et al. (2021a) with a language model architecture, can capture both the quality and diversity of the generated samples.

6 Discussion and Further Directions

6.1 Development with Neural Pipeline Frameworks

Neural networks have largely changed the developing directions of generative systems. Traditional generative systems usually break up NLG
tasks into separate stages that work as a pipeline (Reiter and Dale, 1997), e.g. the traditional rule-based system (taken from Reiter (2007)) shown in Figure 2 is a serial pipeline of four separate subdivided tasks: Signal Analysis, Data Interpretation, Document Planning, Microplanning and Realisation. These tasks are separate from each other, which means we could check the intermediate result under generation, and modify rules according to our expectations.

In comparison, neural frameworks are usually end-to-end, in which various modules or techniques (summarized in §3) may take responsibility for separate functions such as encoding inputs (Radford et al., 2019), intents recognition (Pinhanez et al., 2021), emotions tracking (Brahman and Chaturvedi, 2020b), content planning (Goldfarb-Tarrant et al., 2020), and so on.

In Figure 2, we present a typical architecture of neural generative system (used in Gong et al. (2019b); Chang et al. (2021); Zhao et al. (2020a); Chen et al. (2020b)). In a neural end-to-end framework, all kinds of inputs including target generated text are firstly mapped into numeric embeddings, and then neural modules feed forward information layer by layer. Finally the last output of the neural framework is used to generate the target tokens with a decoding strategy, and calculate the losses to optimize parameters. Modules in a framework connect to each other, and learn the inference principles through back propagation of losses between neural networks. This training and inference paradigm means that separate parts in a neural framework cannot be broken up independently. It is hard to directly interfere in the intermediate operations in neural layers, because we do not understand what is in the hidden numeric space of embeddings. We can analyze the numeric embeddings only with indirect approaches, e.g., analyzing the meaning of self-attention outputs by drawing an “attention” heat map among input tokens (Li et al., 2020b; Cui et al., 2020).

On one hand, end-to-end neural frameworks are powerful. They take less manual effort and are widely accepted because of their good performance. On the other hand, end-to-end neural frameworks are not as flexible as traditional pipelines. The implicit features mapped in the numeric space make it harder to analyze and control text generation. Therefore, end-to-end neural frameworks usually have problems of relatively bad generalization, bad robustness, and incomprehensible and uncontrollable working principles.

As discussed above, one of the key limitations of the end-to-end paradigm is the uncontrollable working principles. In contrast, the traditional pipeline approaches e.g. heuristic rules, symbolic systems and template-based methods are more controllable and understandable. To address the

\[12\] Ehud Reiter who has made influential contributions in NLG area has discussed this recently (e.g. Challenges are Same for Neural and Rule NLG [https://ehudreiter.com/2021/11/08/challenges-same-neural-rule-nlg/])
key limitations of the end-to-end paradigm, several new strands of work have been proposed. One strand of work is developing neural pipeline approaches (Castro Ferreira et al., 2019; Nie et al., 2018; Moryossef et al., 2019; Xu et al., 2020b), which introduce separate neural models in a traditional pipeline. Xu et al. (2020b), for instance, set up a pipeline of a Keywords Predictor, Knowledge Retriever, Contextual Knowledge Ranker, and Conditional Generator for story generation. The Keywords Predictor generates keywords for context planning, and then retrieves sentences with high rank from an external knowledge base. These are then sent to the Conditional Generator for story generation. The keywords and retrieved sentences are readable, and can be easily changed by the human designer (more examples seen in §3.7).

Through experiments we can better analyze the advantage of neural pipeline approaches. Castro Ferreira et al. (2019) compared their neural pipeline approach for Data-to-text task with end-to-end counterparts, and draw a conclusion that in most tested circumstances, the pipeline approach generates more fluent and better-quality texts, especially for unseen domains. In addition to worse generalization, end-to-end ones also have the problem of hallucination (Rohrbach et al., 2018) that generates text containing facts not given or not true in the inputs. Thus there have been increasing efforts in developing neural pipeline approaches which use neural models for better representation learning, and explicitly split the generation process for better controllability.

6.2 Exploiting Background Knowledge

One of the major challenges for NLG (and Artificial Intelligence more generally (see e.g. Lake et al. (2016))) is to make effective use of background knowledge. Most NLG systems can train on a specific dataset, and can perform well in generating similar samples. However they have no other background knowledge to help them to deal with examples outside of the distribution. Ideally we would like a system to be like a human: when trained on a specific set of examples they can learn to deal with similar examples, but they also carry a huge amount of background knowledge which they can use to cope with examples outside of the distribution. The kinds of background knowledge that are useful include: general knowledge, conceptual knowledge, and knowledge for dealing with human emotions, personalities, etc.

One way in which this has been tackled is with a task-specific training, which has been summarized in §2.1. For example, more annotations can be added to train neural models to learn how to track emotions, persona, and so on. Sun et al. (2021) add chit-chat to task-oriented datasets to train a chatbot. Experiments show the added chit-chat annotations lead to improved quality of dialogues.

A second approach employs neural frameworks, especially pre-trained models (see §4.5), to acquire background knowledge from external knowledge bases. This has been used for example to acquire conceptual knowledge (Zhang et al., 2021b), commonsense knowledge (Guan et al., 2020; Lin et al., 2020; Ji et al., 2020), semantic knowledge (Ko et al., 2019), multimodal knowledge (Xing et al., 2021), etc. These works use background knowledge to improve their models’ performance on task-oriented requirements, but this knowledge could also be used across various NLG tasks.

Pre-training can alleviate problems of bad generalization and bad robustness, and some advances have been made to address zero-shot (or few-shot) scenarios (Chen et al., 2020b; Antoun et al., 2021). However, the idea behind background knowledge acquisition is to be able to apply it flexibly in new varied scenarios. In this case, fine-tuning pre-trained models does not go far enough, because of the way the knowledge embodied in the models is tied to contexts in which it appears and is implicit. A more human-like background knowledge would need to be more explicit and freed from irrelevant contextual associations (see e.g. Marcus, 2020).

If we compare the artificial neural network (ANN) models and what we know about human processing we can see a contrast: the ANN models embody knowledge implicitly and do a very fast processing (for inference) to generate a result, which may be correct if the implicit knowledge has captured what is required for that particular query, or may be incorrect if not. In contrast humans sometimes do a much slower processing requiring iterative inference (van Bergen and Kriegeskorte, 2020), which may require multiple forward and backward passes to reach a decision. In writing a text humans sometimes produce sentences rapidly, but at other times require deeper thought. The existence of faster and slower pro-
cesses seems to be a general feature of human cognition, and is also evident in other cognitive tasks. In the specific case of visual perception, research has shown that recognising an object in a difficult image (showing part of an object) can take up to two seconds, whereas a straightforward whole object image can be processed in 50ms (Benoni et al., 2020). Benoni et al. propose ‘a prolonged iterative process combining bottom-up and top-down components’. van Bergen and Kriegeskorte note the advantages of recurrence in allowing a network to ‘adjust its computational depth to the task at hand’; i.e. the number of such iterations is not fixed, and can take longer if the situation requires it; we can speculate that this is the case when dealing with more rare or ‘out of training distribution’ samples. In this process background knowledge can participate in the form of contextual knowledge which constrains expectations, or via generative models that embody prior knowledge about the world and can be used in a process of ‘analysis by synthesis’ (van Bergen and Kriegeskorte, 2020).

From Artificial Intelligence a similar message about the need for deeper or more complex processing emerges. For example Davis and Marcus (2015), in analysing the shortcomings of existing AI with respect to common sense, concluded that there is a need for alternative modes of reasoning; they state that “commonsense reasoning involves many different forms of reasoning including reasoning by analogy...”. Analogical reasoning, whether for text or image processing, will require iterative inference including a top-down process (Guerin, 2021).

7 Conclusion

Throughout the paper, we discussed the innovative paradigms behind recent advances from a task-agnostic perspective. From §2 to §5 we mainly summarized and analyzed the commonalities of neural text generation from 4 aspects: data construction, neural frameworks, training and inference strategies, and evaluation metrics. We compartmentalize different techniques or strategies people use to develop their generative systems. Some of them are continually affecting the whole NLG area (e.g. pre-training), and some are topics of much debate (e.g. which is the best encoding and decoding architecture for NLG tasks).

According to the analysis on these commonalities, we give some opinions about the development of neural frameworks from 2 directions in §6: (i) More effort could be taken into exploring neural pipelines. Compared to end-to-end paradigm, neural pipelines take advantage of traditional techniques, and perform better with respect to generalization, interpretability, controllability, and robustness. (ii) Many strands of work aim to make effective use of background knowledge. We highlight some good practices and promising directions to improve neural generative systems.

In this article, we attempt to offer a broad overview of how to create a better neural framework for text generation, and hope to offer some ideas to help solve challenges by building on the results shown by existing recent approaches.

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