Dissecting the components and factors of Neural Text Generation

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Abstract

Neural text generation metamorphosed into several critical natural language applications ranging from text completion to free form narrative generation. Generating natural language has fundamentally been a human attribute and the advent of ubiquitous NLP applications and virtual agents marks the need to impart this skill to machines. There has been a colossal research effort in various frontiers of neural text generation including machine translation, summarization, image captioning, storytelling etc., We believe that this is an excellent juncture to retrospect on the directions of the field. Specifically, this paper surveys the fundamental factors and components relaying task agnostic impacts across various generation tasks such as storytelling, summarization, translation etc., In specific, we present an abstraction of the imperative techniques with respect to learning paradigms, pretraining, modeling approaches, decoding and the key challenges. Thereby, we hope to deliver a one-stop destination for researchers in the field to facilitate a perspective on where to situate their work and how it impacts other closely related tasks.

1 Introduction

Text Generation is the task of producing written or spoken narrative from structured or unstructured data. The overarching goal is the seamless human-machine communication by presenting a wealth of data in a way we can comprehend. With respect to the modeling approaches, there are three main paradigms in generating text based on the schema of input and output: (i) Text-to-Text (ii) Data-to-Text (iii) None-to-Text. Table 1 presents the categorization of different tasks based on this paradigm. These several tasks deserve undivided attention and accordingly they have been heavily dissected, studied and surveyed in the recent past. For instance, independent and exclusive surveys are periodically conducted on summarization (Lin and Ng, 2019; Allahyari et al., 2017; Nenkova and McKeown, 2012; Tas and Kiyan), knowledge to text generation DBLP:conf/inlg/GardentSNP17, DBLP:conf/naacl/Koncel-Kedziorski19, machine translation (Chu and Wang, 2018; Dabre et al., 2019; Chand, 2016; Slocum, 1985), dialog response generation (Liu et al., 2016; Montenegro et al., 2019; Ramesh et al., 2017; Chen et al., 2017), storytelling, narrative generation (Tong et al., 2018; Togelius et al., 2011), image captioning (Hossain et al., 2018) etc., to dig deeper into task specific approaches that are foundational as well as in the bleeding edge of research. While these are extremely necessary, often the focus on techniques that are beneficial to other tightly coupled tasks are overlooked. The goal of this survey is to focus on these key components that are task agnostic to improve the ensemble of tasks in neural text generation.

There have been several studies conducted on surveying text generation. Perera and Nand (2017) present a detailed overview of information theory based approaches. Iqbal and Qureshi (2020) primarily focus on core modeling approaches, especially VAEs (Kingma and Welling, 2014) and GANs (Goodfellow et al., 2014). Gatt and Krahmer (2018) elaborated on tasks such as captioning, style transfer etc., with a primary focus on data-to-

| Generation Paradigm | Task                | Input                                                      | Output                                     |
|---------------------|---------------------|------------------------------------------------------------|--------------------------------------------|
| Text-to-Text        | Dialog              | Conversation History Source Language                      | Text Response Source Language             |
|                     | Machine Translation | Style 1 Text                                              | Target Language                           |
|                     | Style Transfer      | Single/Multiple Documents                                 | Style 2 Text                              |
|                     | Summarization       |                                                           | Summary                                    |
| Data-to-Text        | Image Capturing     | Image                                                     | Descriptive Text                          |
|                     | Speech Recognition  | Audio                                                     | Text                                       |
|                     | Table to Text       | Table                                                     | Text                                       |
|                     | Knowledge Bases to Text | Knowledge Bases              | Text                                       |
| None-to-Text        | Language Modeling   | Null                                                      | Sequence of Text                           |

Table 1: Paradigms of Tasks in Text Generation. For the purposes of compactness, we include ‘Knowledge-to-text’ paradigm within ‘Data-to-text’.
text tasks. Controllability aspect is explored by Prabhumoye et al. (2020). The work closest to this is by Lu et al. (2018) who perform an empirical study on the core more modeling approaches only. In contrast to these, this paper focuses on task agnostic components and factors capable of pushing the ensemble of tasks forward. Figure 1 presents the various components and factors that are important to study in neural text generation which are elaborated in this paper.

2 Modeling Approaches

2.1 Core Modeling Paradigms

Supervised Learning: Most generation approaches in this setting use maximum likelihood objective for training sequence generation with a sequential multi-label cross entropy.

$$-\sum_{t=1}^{T} \log p(y_t|X,y_{<t}; \theta)$$

However, there is an inherent inconsistency in exposure to ground truth text between training and inference stages when using teacher forcing during training. This leads to the problem of exposure bias (Ranzato et al., 2016). During training, the token in the current time step is predicted conditioned on ground truth prefix correcting the course irrespective of what word is predicted by the model. However, during inference, the same is conditioned on generated prefix in the absence of ground truth prefix. This problem becomes severe with the increasing length of the output. A solution to address this issue is scheduled sampling (Bengio et al., 2015) which mixes teacher forced embeddings and model predictions from previous time step.

Reinforcement Learning: The main issue with the supervised learning approach for text generation is the mismatch between maximum likelihood objective that is optimized and metrics for text quality. Reinforcement learning addresses this mismatch by directly optimizing end metrics which could be non-differentiable. Typically, policy gradient algorithms are used to optimize for BLEU score directly via Reinforce. The objective is shown below which is the sum of log probabilities multiplied by the reward score. The reward score itself is computed as the expected BLEU score.

$$-\sum_{t=1}^{T} R_t \log P(y_t|y_{<t}, X)$$ (1)

However, computing BLEU before every update is not computationally efficient to incorporate in the training procedure. Another problem is the inherent inefficiency of the metric itself i.e BLEU is not the best measure to evaluate text quality. In practice, usually, the policy network is usually pretrained with maximum likelihood objective before optimizing for BLEU score.

Adversarial Learning: The third paradigm is adversarial learning comprising of competing objectives. The mismatch in training and inference stages is addressed using Professor Forcing (Lamb et al., 2016) with adversarial domain adaptation to bring the behavior of the training and sampling close to each other. This is done by sharing the parameters between teacher forcing network and
the free running network. Apart from this the two main components are a generator and a discriminator. Discriminator here is optimized to correctly classify the sequence as belonging to free running behavior or teacher forced behavior. The generator has two goals: (i) maximize the likelihood of the data (ii) fool the discriminator. There are two options with respect to keeping one fixed and bringing the other closer to the first. This can be done with respect to either of teacher forcing network or free running network. Empirically, professor forcing also plays the role of a regularizer. Generative Adversarial Networks (GAN) also gained popularity with respect to this in the recent times. The core idea is that the gradient of the discriminator guides how to alter the generated data and by what margin in order to make it more realistic. This slight change is apparent in continuous values in comparison to language which is a discrete space. There are several variants adopted to address specific problems such as SeqGAN to assess partially generated sequence (Yu et al., 2017), MaskGAN to improve sample quality using text filling (Fedus et al., 2018) and LeakGAN to model long term dependencies by leaking discriminator information to generator (Guo et al., 2018). The three main challenges researched in this area are:

- **Discrete Sampling**: The sampling step selecting argmax in language is a non-differentiable function. One solution is to replace it with a continuous approximation by adding Gumbel noise which is negative log of negative log of a sample from uniform distribution, also known as Gumbel Softmax.

- **Mode Collapse**: GANs typically face the issue of sampling from specific tokens to cheat discriminator, known as mode collapse. In this way, only a subspace of target distribution is learnt by the generator. DP-GAN addresses this using an explicit diversity promoting reward (Xu et al., 2018b).

- **Power dynamics between Generator and Discriminator**: Another problem arises when the discriminator is trained faster than the generator. This is most often the case, the gradient from discriminator vanishes leading to no real update to generator.

2.2 Pre-training

Recent couple of years have seen a major surge in interest for pre-training techniques. While they are primarily focused on language understanding tasks, there has been some work targeted for pre-training for generation as well. UniLM (UNIfied pre-trained Language Model, (Dong et al., 2019a)) is proposed as a pre-training mechanism for both natural language understanding and natural language generation tasks. Fundamentally, the previously widely used ELMo (Peters et al., 2018) constitutes a language model that is left to right and right to left. While GPT (Radford et al.) has an autoregressive left to right language model, BERT (Devlin et al., 2019) has a bidirectional language model. UniLM is optimized jointly for all of the above objectives along with an additional new seq2seq LM which is bidirectional encoding followed by unidirectional decoding. Depending on the use case, UniLM can be adopted to use Unidirectional LM (left to right), Bidirectional LM (attention on all tokens) and Seq2seq LM (attention on all tokens in previous segment and left context in the current segment). With a similar goal in mind, MASS (Song et al., 2019) modified masking patterns in input to achieve this. BERT and XLNet (Yang et al., 2019) pre-train an encoder and GPT pretrains a decoder. This is a framework introduced to pretrain encoder-attention-decoder together. Encoder masks a sequence of length k and the decoder predicts the same sequence of length k and every other token is masked. While the idea of jointly training the encoder-attention-decoder remains the same as in UniLM, the interesting contribution here is the way masking is utilized to bring out the following advantages. (i) The tokens masked in decoder are the tokens that are not masked in encoder. This complementary masking encourages joint training of encoder-decoder. (ii) Encoder supports decoder by extracting useful information from the masked fragments which improves the understanding or NLU capabilities of the model. (iii) Since a sequence of length k is decoded consecutively, NLG capability is improved as well. Note that when k is 1, the model is closer to BERT which is biased to an encoder and when k is the length of sentence, the model is closer to GPT which is biased to decoder. Similar to UniLM, BART (Lewis et al., 2019) has a bidirectional encoder and an autoregressive decoder. The underlying model is standard transformer (Vaswani et al., 2017) based neural MT framework. The main difference of BART from MASS is that the tokens masked here are not necessarily consecutive. The main idea and the second difference is to corrupt text with arbitrary noise and reconstruct original text. The input is corrupted with the following
transformations: token masking, token deletion, token infilling, sentence permutation and document rotation. Following this, Raffel et al. (2019) proposed T5 as a unifying framework that ties all NLP problems as text generation tasks with a text-in and text-out paradigm. Recently, Dathathri et al. (2020) introduced plug and play language models capable of efficiently training fewer parameters to control a huge underlying pretrained model. Finetuning these vast models for generative tasks has been studied in style transformers (Sudhakar et al., 2019) and conversational agents (Dinan et al., 2019).

2.3 Decoding Strategies

The natural next step after pre-training and training is decoding. The distinguishing characteristic of generation is the absence of one to one correspondence between time steps of input and the output, thereby introducing a crucial component which is decoding. Primarily, they can be categorized as (i) autoregressive and (ii) non-autoregressive.

**Autoregressive decoding:** Traditional models with this strategy correspond well to the true distributions of words. This mainly comes from respecting the conditional dependence property from left to right. The autoregressive techniques can be further viewed as sampling and search techniques. The main disadvantage of this strategy is throttling transformer based models that fail short in replicating their training advantages as training can be non-sequential and inference holds to be sequential with autoregressive decoding.

**Non-autoregressive decoding:** This line of work primarily addresses two problems that are associated with autoregressive decoding. First, by definition, there is a conditional independence property that holds. This leads to the multimodality problem, where each time step considers different variants with respect to the entire sequence and these conditions compete with each other. Second, the main advantage is the reduction in latency during real time generation. Guo et al. (2020) addressed this problem in the context of neural machine translation using transformers by copying each of the source inputs to the decoder either uniformly or repeatedly based on their fertility counts. This is done to address varying sequence lengths between source and target texts. These fertilities are predicted using a dedicated neural network to reduce the unsupervised problem to a supervised one and thereby enabling it to be used as a latent variable. This invariable replications based on fertilities may lead to duplication of words. Closely followed by this, van den Oord et al. (2018) took a different approach by introducing probability density distillation by modifying a convolutional neural network using a pre-trained teacher network to score a student network attempting to minimize the KL divergence between itself and the teacher network. Both these works set the trend of using latent variables to capture the interdependence between different time steps in the decoder. Following this work, Lee et al. (2018) use iterative refinement by denosing the latent variables at each of the refinement steps. This idea of iterative decoding inspired way to more avenues by combining the benefits of cloze style mask prediction objectives from Bert (Devlin et al., 2019). Some of them include insertion based techniques (Gu et al., 2019), repeated masking and regenerating (Ghazvininejad et al., 2019) and providing model predictions to the input (Ghazvininejad et al., 2020).

Wang et al. (2019) proposed an alternative approach to address repetition (observed in (Gu et al., 2020)) and completeness using regularization terms for each. Repetition is handled by regularizing similarity between consecutive words. Completeness is addressed by enabling reconstruction of source sentence from hidden states of the decoder, based on the duality of translation tasks between source to target and target to source. Concurrently, Guo et al. (2019) also address these issues by improving the inputs to decoder using additional phrase table information and sentence level alignment between source and target word embeddings.

**Sampling and Search Techniques:**

1. Random Sampling: The words are sampled randomly based on the probability from the entire distribution without pruning any of the mass.

   \[ P(y_t = w_i | y_{<t}, x) = \frac{\exp(z_{t,i})}{\sum_{j \in V} \exp(z_{t,j})} \]  

2. Greedy Decoding: This technique simply boils down to selecting argmax of the probability distribution. As you keep selecting argmax everywhere, the problem is that it limits the diversity of generation. Note that this may not result in the best output as there may be an alternate hypothesis comprising of a path that does not have to select
the most probable word at each time step.

\[
\hat{y}_t = \text{argmax}_y_t \left( \frac{\exp(z_{t,i})}{\sum_{j \in V} \exp(z_{t,j})} \right) \tag{3}
\]

A major disadvantage of greedy decoding is that there is no mechanism to correct the course if a mistake is made. This accumulates errors for the following time steps. It is monotonous with more predictable texts. This is alleviated by the next techniques and beam search. This is also worked out for discrete settings using gumbel-greedy decoding (Gu et al., 2018). Variants of this were also studied by Zarrieß and Schlangen (2018).

3. Beam Search: Beam search introduces a course correction mechanism in approximation of the argmax by selecting a beam size number of beams at each time step. When beam size is 1, this is the same as greedy decoding and when beam size is the size of the vocabulary, it is computationally very expensive. It has been relatively well studied in task agnostic objectives (Wang et al., 2014) for instance, including social media text (Wang and Ng, 2013), error correction (Dahlmeier and Ng, 2012). Small beam sizes may lead to ungrammatical sentences, they get more grammatical with increasing beam size. Similarly small beam sizes may be less relevant with respect to content but get more generic with increasing beam size. There are several varieties within beam search:

(a) Noisy Parallel Approximate Decoding: This method (Cho, 2016) introduces some noise in each hidden state to non-deterministically make it slightly deviate from argmax.

(b) Beam Blocking: Repetition is one of the problems we see in NLG and this technique (Paulus et al., 2018) combats this problem by blocking the repeated n-grams. It essentially adjusts the probability of any repeated n-gram to 0.

(c) Iterative Beam Search: In order to search a more diverse search space, another technique (Kulikov et al., 2019) was introduced to iteratively perform beam search several times. And for each current time step, we avoid all of the partial hypotheses encountered until that time step in the previous iterations based on soft or hard decisions on how to include or exclude these beams.

(d) Diverse Beam Search: One problem with beam search is that most times the decoded sequence still tends to come from a few highly significant beams thereby suppressing diversity. The moderation by (Vijayakumar et al., 2016) adds a diversity penalty computed (for example using hamming distance) between the current hypothesis and the hypotheses in the groups to readjust the scores for predicting the next word.

(e) Clustered Beam Search: The goal is prune unnecessary beams. At each time step, Tam (2020) get the top 2b candidates and embed them by using averaged Glove representations. Cluster them using k-means to get k clusters. And then, they pick the top b/k candidates from each cluster to get b candidates in total for that time step.

(f) Clustering Post Decoding: The above approaches modify decoding step itself. This technique (Kriz et al., 2019) clusters after decoding is done. Sentence representations from any of the diversity promoting beam search variants are obtained. These are then clustered and the sentence with high log likelihood is selected from the cluster.

4. Top-k sampling: This technique by Fan et al. (2018) randomly samples from the k most probable candidates from this distribution. This means that we are confining the model to select from a truncated probability mass.

\[
P'(y_t | y_{<t}) = \begin{cases} 
\sum_{y \in V^k} P(y_t | y_{<t}) & \text{if } y_t \in V^k \\
0 & \text{otherwise}
\end{cases} \tag{4}
\]

If k is the size of vocabulary, then it is random sampling and if k is 1 then it is greedy decoding. High valued k results in dicey words but are non-monotonous and low valued k results in safe outputs which are monotonous. The problem however is that k is limited to the same value in all scenarios.

5. Top-p sampling: The aforementioned problem of a fixed value of k is addressed by top-p sampling. This is also known as nucleus sampling (Holtzman et al., 2020), which instead of getting rid of the unspecified probability mass in top-k sampling, importance is shifted to the amount of probability mass preserved. This addresses scenarios where there could be broader set of reasonable options and sometimes a narrow set of options. It is achieved by selecting a dynamic k number of words from a cumulative probability distribution of words until a threshold probability value is attained.

\[
\sum_{y_t \in V^k} P(y_t | y_{<t}) >= p \tag{5}
\]
3 Key Challenges

For each of the challenges, this section provides a list of solutions. The pitfalls of these solutions are also described there by encouraging research to address these key challenges.

1. Fluency: There are a couple of detrimental factors that affect the fluency of text generation, which are repetition and coherence.
   • Solution - Beam blocking: Blocking beams containing previously generated n-grams from subsequent generation combats repetition and encourages diversity. There are multiple options to perform this including cutting the beam stream or select from the rest of the n-grams (Klein et al., 2017; Paulus et al., 2018) etc..
   - Problem: However, sometimes beams with natural kind of repetition done for instance in order to emphasize something, that is naturally done by humans are also blocked. Selecting the number of beams is often a problem since it is natural for a function word to repeat more often.
   - Solution to problem: Massarelli et al. (2019) extensively studied the variants of introducing beam blocking which is also referred to as n-gram blocking by applying delays in beam search.
   • Solution - Unlikelihood objective: Welleck et al. (2020) argue that there is a fundamental flaw in the objective of likelihood. The main idea is to decrease the probability of unlikely or negative candidates. The negative candidates are selected from the previous contexts either at token or at sequence levels which are essentially n-grams. This way, we are simultaneously optimizing for both likelihood with unlikelihood by discouraging the repetition of previous outputs.
   - Problem: This may not seem a major issue, however, selecting negative contexts is tricky and needs to be beyond selection of simple n-gram sequences that occurred previously.
   • Solution - Coverage penalty: This discourages the attention mechanism to attend the same word repeatedly (See et al., 2017). Navigating through each of the time step in the source, if across different time steps of the decoded output, the attention weights are higher for that particular source timestep, then that timestep is covered and hence the coverage penalty would be log(1) which is 0. Otherwise coverage penalty would be the attention probability mass on that source time step.
   • Solution - Static and Dynamic Planning: This addresses coherence in terms of layout or structural organization of the text (Yao et al., 2019). A schema of static or dynamic plans are used to form an abstract flow of the text from which the actual text is realized.

- Problem: However, underlying language models are capable of taking over, leading to hallucinations and thereby compromising the fidelity of text.

2. Length of Decoding: One factor that distinguishes generation from rest of the seq2seq family of tasks is the variability in the length of the generated output. The main problem here is that as the length of the sequence increases, the sum of the log probability scores decrease. This means that models prefer shorter hypotheses. Some solutions to combat this problem are the following.
   • Solution - Length Normalization or Penalty: The generated output is scored by normalizing or dividing with length. (Wu et al., 2016) explore a different variation of the normalization constant. This is pretty standard when the dataset has high variance in lengths.
   • Solution - Probability Boosting: This technique multiplies the probability with a fixed constant at every time step. This alleviates the diminishing score problem.
   • Solution - Bias: Incorporate bias in the model based on empirical relations on lengths in source and target sentences in the training data.

3. Content Selection: Certain tasks demand copying over the details in the input such as rare proper nouns for instance in news articles etc., This is especially needed in tasks like summarization which can demand a combination of extractive and abstractive techniques.
   • Solution - Copy Mechanism: Copy mechanism can take various forms such as pointing to unknown words (Gulcehre et al., 2016) based on attention (See et al., 2017) or a joint or a conditional copy mechanism (Gu et al., 2016; Puduppully et al., 2019). It maybe based on attention that copies segments from input into the output. The problem is that sometimes, this technique boils down from a combination of being extractive and abstractive to sort of an extractive system.
   • Solution - Hierarchical Modeling: This technique maintains a global account of the content. This is often modeled using hierarchical techniques or dual stage models (Martin et al., 2018; Xu et al., 2018a; Gehrmann et al., 2018) where the first stage
pre-selects relevant keywords for generation in the following stage.

- Problem: Such models possibly take a hit on fluency while connecting dots between selected content and generation. This means that Rouge-1 can be good because the right words are extracted but Rouge-2 may decrease as it affects the fluency.

4. Optimization Objective: Similar to the observation earlier in Section 2, there is an inherent mismatch in the between the objective function which is maximum likelihood and the end metrics which are BLEU, Rouge etc;

  • Solution - Reinforcement Learning: A common solution for this problem is using reinforcement learning to optimize end metrics such as Rouge. Often, a combination of MLE and RL objectives are used (Hu et al., 2020; Wang et al., 2018).

  • Problem: However, this is still a problem since these end metrics do not directly correlate to human judgements. Hence optimizing for BLEU or Rouge does not ensure human quality text.

  • Solution - Maximum Mutual Information: The idea is to incorporate pairwise information of source and target instead of only one direction which is usually target given source (Li et al., 2016). The target probability is subtracted from target given source probability to diminish the probability of generic sentences. A viable extension to this is conditioning on personality for consistency.

  • Solution - Distinguishability: Hallucinations in abstractive generation are unwanted byproducts of optimizing log loss. To combat this, several researchers explored optimizing for minimized distinguishability with human generated text (Hashimoto et al., 2019; Theis et al., 2016). Following similar path, Kang and Hashimoto (2020) proposed truncating loss to get rid of unwanted samples.

5. Speed: Practical applications call for generating text in real time without time lag in decoding in addition to chasing the state of the art results. Model compression plays a crucial part in demonstrating an increase in the speed of generation. Cheng et al. (2017) exhaustively surveyed the different techniques to perform model compression. While there are techniques in the hardware side, there are certain modeling approaches that can handle this problem as well (Gonzalvo et al., 2016). Most of this work is studied in the context of real time interpretation of speech (Fügen et al., 2007; Yarmohammadi et al., 2013; Grissom II et al., 2014). Recently, Deng and Rush (2020) proposed a cascaded decoding approach introducing Markov Transformers to demonstrating high speed and accuracy.

  • Quantization: Quantizing (Roy et al., 2018; Gray, 1984) the weights i.e sharing the same weight value when they belong to a bin also proved helpful in improving the speed. This also facilitates the computations of gradients only once per bin.

  • Distillation: It can be performed with a teacher and a smaller student network that tries to replicate the performance of the teacher with fewer parameters (Chen et al., 2019).

  • Pruning: This technique thresholds and prunes all the connections that have weights lesser than the predetermined threshold and then we can retrain the network in order to adjust the weights of the remaining connections.

  • Real time: Gu et al. (2017) trained an agent that learns to decide between the actions of reading by discarding a candidate or writing by accepting a candidate. The policy network is optimized with a combination of quality evaluated with BLEU and delay evaluated by number of consecutive words in reading stage which increases wait time.

  • Caching: Another trick is to cache some of the previous computations to avoid repetition.

4 Evaluation

Similar to other generative modeling, text generation also faces crucial challenges in evaluation (Reiter and Belz, 2009; Reiter, 2018). van der Lee et al. (2019) present some of the best practices of evaluating automatically generated text. The main hindrance to standardize or evaluate NLG like other standard tasks is that it is often a sub-component of other tasks. This means that the input can be in varied forms such as tables, images and text. In certain settings such as diverse image captioning, we would need more objects or entities. Sometimes in dialog, we would need pronouns to have a natural coherence instead of repeating nouns.

Desiderata of Text: It is crucial to define the factors contributing to the quality of good text. Some of the factors include relevant content, appropriate structure in terms of coherence and suitable surface forms. In addition, fluency, grammaticality, believability and novelty in some scenarios are crucial factors.

Intrinsic and Extrinsic: Evaluation in subjective scopes such as text generation can be performed
intrinsically or extrinsically. Intrinsic evaluation is performed internally with respect to the generation itself and extrinsic evaluation is typically performed on the metric used to evaluate a downstream task in which this generation is used. The quality can also be judged using automatic metrics and human evaluation.

(a) Automatic Metrics: Here, we outline the broad categories of metrics along with their advantages and disadvantages. These metrics can be classified into the following categories:

• **Word overlap based metrics:** These are based on the extent of word overlap, which means that they capture replication of words. The problem with such measures is that they do not focus on semantics but rather just the surface form of words and alone. This includes precision for n-grams (BLEU (Papineni et al., 2002)), improved weighting for rare n-grams (NIST (Doddington, 2002)), recall for n-grams (ROUGE (Lin and Hovy, 2002)), F1 equivalent of n-grams (METEOR (Banerjee and Lavie, 2005)), tf-idf based cosine similarity for n-grams (CiDER (Vedantam et al., 2015)). In extension to this, we also have specific metrics to evaluate content selection by measuring summarization content units using PYRAMID (Nenkova and Passonneau, 2004) and parsed scene graphs with objects and relations using SPICE (Anderson et al., 2016). Stanojevic and Sima’an (2014) proposed BEER to address this as a ranking problem with character n-grams along with words.

• **Language Model based metrics:** This includes perplexity (Brown et al., 1992). Such metrics are good in commenting about the language model itself. It sort of gives the average number of choices each random variable has. However, it does not directly evaluate the generation itself, for instance a decrease in perplexity does not imply a decrease in the word error rate. It just means that intrinsically, the LM is good enough to select the right next word for that corpus. The human likeness is also measured by training a model to discriminate between human and machine generated text such as an automatic turing test (Lowe et al., 2017; Cui et al., 2018; Hashimoto et al., 2019).

• **Embedding based metrics:** This has the advantage of being able to capture semantics. MEANT 2.0 (Lo, 2017) and YISI-1 (Lo et al., 2018) computes structural similarity with shallow semantic parses being definitely and discretionarily used respectively along with word embeddings. Recently, contextualized embeddings have been extensively used to capture this, such as BertScore (Zhang et al., 2020) and BLEURT (Sellam et al., 2020). Metrics based on a combination of different embeddings are also proposed (Shimanaka et al., 2018; Ma et al., 2017). However the problem of not correlating to human judgements still persists.

(b) Emulated Automatic Metrics: These metrics check for the intended behavior in generation based on the sub-problem the modeling approach is addressing. To check correctness or fidelity or loyalty with respect to source document, we can apply inference. Diversity can be evaluated by computing corpus based distributions on number of distinct entities (Fan et al., 2019; Dong et al., 2019b; Clark et al., 2018) and so on. Recently, (Wang et al., 2020) worked on identifying factual inconsistencies generated summaries. The idea is that when a question is posed, the source document and the summary should result in same or similar answers.

(c) Human Evaluation: There are broadly two mechanisms in conducting subjective evaluations which is a challenging component of text generation. The first is preference testing and the second is scoring. Some studies have shown that preference based testing is prone to less variance compared to absolute scoring. Here are some important points to keep in mind during conducting human evaluation. *(i)* They are very expensive to conduct and hence not feasible to check the model by repeated examination. *(ii)* There are no standard universally agreed upon guidelines to setup such tasks. In other words, conducting subjective evaluation itself is subjective in nature. *(iii)* Scores tend to vary based on the nature of scales whether the judgements are binary, discrete integer values or continuous. *(iv)* It is observed that human preferences are inconsistent. They are biased with personal and demographic conditions. In such cases, it is important to measure inter-annotator agreement as well. *(v)* Some people might be lenient and others more strict which is not scaled across people. *(vi)* Framing the task in an unambiguous way to elicit the right information and maintain reproducibility. Having critically discussed human evaluation, this is still really the best we got. It is absolutely crucial to perform human evaluation in most NLG tasks. So, these problems need to be
taken merely as cautions to develop more rational and systematic testing conditions. Comparisons between automatic and human evaluation systems (Belz and Reiter, 2006) are also studied actively in order to bring human evaluation closer to automatic metrics.

5 Conclusion

The past decade witnessed text generation dribbling from niche scenarios into several mainstream NLP applications. This urges the need for a snapshot to retrospect the progress of varied text generation tasks in unison. This paper is written with the goal of presenting a one-stop destination for task agnostic components and factors in text generation for researchers foraging to situate their work and guage their impact in this vast field. Moving forward, we envision that there are some of the crucial directions to focus for impactful innovation in text generation. These include (i) generation in real time (ii) non-autoregressive decoding (iii) consistency with situated contexts in real and virtual environments and games (iv) consistency with personality with opinions especially for virtual agents (v) conditioning on multiple modalities together with text and data (vi) investigation is still ongoing on finding better metrics to evaluate NLG with better correlated human judgements (vii) creative text generation. We believe this is the right time to extend advancements in any particular task to other tightly coupled tasks to revamp improvements in text generation as a holistic task.

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