CommonGen: A Constrained Text Generation Challenge for Generative Commonsense Reasoning

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Abstract

Recently, large-scale pretrained language models have demonstrated impressive performance on several commonsense benchmark datasets. However, building machines with commonsense to compose realistically plausible sentences remains challenging. In this paper, we present a constrained text generation task, CommonGen[1] associated with a benchmark dataset, to explicitly test machines for the ability of *generative commonsense reasoning*. Given a set of common concepts (e.g., {dog, frisbee, catch, throw}); the task is to generate a coherent sentence describing an everyday scenario using these concepts (e.g., "a man throws a frisbee and his dog catches it").

CommonGen is challenging because it inherently requires 1) relational reasoning using background commonsense knowledge, and 2) compositional generalization ability to work on unseen concept combinations. Our dataset, constructed through a combination of crowdsourcing and existing caption corpora, consists of 30k concept-sets and 50k sentences . Experiments show that there is a large gap between state-of-the-art text generation models (e.g., T5) and human performance (30.6% v.s. 63.5% in SPICE metric). The models struggle at the task, often generating grammatically sound yet realistically implausible sentences – pointing to interesting future research.

Figure 1: An example from our CommonGen dataset. GPT-2 (Radford et al., 2019), UniLM (Dong et al., 2019), BART (Lewis et al., 2019) and T5 (Raffel et al., 2019) are large pre-trained text generation models, fine-tuned on the proposed task.

1 Introduction

Commonsense reasoning, the ability to make acceptable and logical assumptions about ordinary scenes in our daily life, has long been acknowledged as a critical bottleneck of artificial intelligence and natural language processing (Davis and Marcus, 2015). Most recent commonsense reasoning challenges, such as CommonsenseQA (Talmor et al., 2019), SocialIQA (Sap et al., 2019b), WinoGrande (Sakaguchi et al., 2019) and HellaSwag (Zellers et al., 2019b), have been framed as *discriminative* tasks – i.e. AI systems are required to *choose* the correct option from a set of choices based on a given context. While significant progress has been made on these discriminative tasks, we argue that commonsense reasoning in text generation poses a distinct complementary challenge. In this paper, we advance machine commonsense towards *generative* reasoning ability.

Humans acquire the ability to compose sentences by learning to understand and use common concepts that they recognize in their surrounding environment (Tincoff and Jusczyk, 1999). The acquisition of such an ability is regarded as a significant milestone of human development (Moore, 2013). *Can machines acquire such generative commonsense reasoning ability?* To initiate the inveistagtion, we present CommonGen – a novel constrained generation task that requires machines to generate a sentence describing a day-to-day scene

[1]Our code and data can be found at http://inklab.usc.edu/CommonGen/. Work in progress.

using concepts from a given *concept-set*. For example, given a set of concepts: {*exercise*, *rope*, *wall*, *tie*, *wave*}, machines are required to generate a sentence such as "a man in a gym *exercises* by *waving ropes tied* to a *wall*."

To successfully solve the task, models need to incorporate two key capabilities: a) *relational reasoning*, and b) *compositional generalization*. Grammatically sound sentences may not always be realistic as they might violate our commonsense (e.g., "*a dog throws a frisbee ...*" in Fig. 1). In order to compose a plausible sentence that describes an everyday scenario, models need to construct a grammatical sentence while adhering to and reasoning over the commonsense relations between the given concepts. Models additionally need *compositional generalization* ability to infer about unseen concept compounds. This encourages models to reason about a potentially infinite number of novel combinations of familiar concepts – an ability believed to be a limitation of current AI systems (Lake and Baroni, 2017; Keysers et al., 2020).

Therefore, in support of the COMMONGEN task, we present a dataset consisting of 29,599 concept-sets associated with 49,129 sentences. We explicitly design our dataset collection process to capture the key challenges of relational reasoning and compositional generalization described above. We establish comprehensive baseline performance for state-of-the-art language generation models. The best model, based on T5 (Raffel et al., 2019), achieves 36.60% with significant gap compared to human performance of 63.50% in the SPICE metric – demonstrating the difficulty of the task. Our analysis shows that state-of-the-art models struggle at the task, generating implausible sentences – e.g. "dog throws a frisbee ..." , "give massage to a table", etc. – pointing to interesting future research directions for the community.

2 Task Formulation and Challenges

We formulate the proposed COMMONGEN task with mathematical notations and discuss its inherent challenges with concrete examples.

The input is an unordered set of k concepts $x = \{c_1, c_2, \dots, c_k\} \in \mathcal{X}$ (i.e. a concept-set), where each concept $c_i \in \mathcal{C}$ is a common object (noun) or action (verb). We use $\mathcal{X}$ to denote the space of all possible concept-sets and use $\mathcal{C}$ to denote the concept vocabulary (a subset of ConceptNet's single-word concepts). The expected output is a simple, grammatical sentence $y \in \mathcal{Y}$ that describes a common scenario in our daily life, using[2] all given concepts in x. A scenario can depict either a static situation or a short series of actions.

The task is to learn a structured predictive function $f : \mathcal{X} \to \mathcal{Y}$, which maps a concept-set x to a sentence y. The unique challenges of this task come from two major aspects as follows.

Relational Reasoning with Commonsense. Expected generative reasoners should prioritize the most plausible scenes over an infinite number of less plausible scenes. Recall the first illustrative examples in Figure 1, the underlying knowledge are implicit and compositional: (a) dogs love to perform tricks with humans, (b) catching a frisbee is a trick and (c) humans love to play this game with dogs. As for the other example in Section 1 about {*exercise*, *rope*, *wall*, *tie*, *wave*}, we also need to compose the following commonsense facts: (i) doing exercises is to cost energy, (ii) waving a rope can cost energy, and (iii) it is more useful when the rope is tied to a wall.

In order to complete a scenario, a generative commonsense reasoner also needs to reasonably associate additional concepts (e.g., 'gym' and 'man') as agents or environments for completing a natural and coherent scenario in our daily life.

This not only requires understanding underlying commonsense relations between concepts, but also incrementally composing them towards a globally optimal scenario. The underlying reasoning chains are inherently based on a variety of background knowledge such as spatial relations, object properties, physical rules, temporal event knowledge, social conventions, etc. However, they may not be recorded in any existing knowledge bases.

Compositional Generalization. Humans can compose a sentence to describe a scenario about the concepts they may never seen them co-occurring. For example, there is a testing concept-set $\hat{x}$ ={*pear*, *basket*, *pick*, *put*, *tree*}. The concept 'pear' never appear in the training data, and 'pick' never co-occurs with 'basket'. Meanwhile, there are some relevant training examples:

- x_1 ={*apple*, *bag*, *put*} → y_1 ="a boy *puts* an *apple* in a *bag*."
- x_2 ={*apple*, *tree*, *pick*} → y_2 ="a girl *picks* an *apple* from the *tree*."
- x_3 ={*apple*, *basket*, *wash*} → y_3 ="a girl takes an *apple* from the *basket* and *washes* it."

[2] Note that morphological inflections are allowed.

We, humans, can generalize from these seen scenarios and infer that a plausible output: $\hat{y}$ = *"a girl picks some pears from a tree and put them into her basket."* This compositionally generalization ability via analogy, i.e., to make "infinite use of finite means" (Chomsky, 1965), is challenging for machines. This analogical challenge not only requires inference about similar concepts (e.g., 'apple' → 'pear') but also their latent associations.

3 The CommonGen Dataset

We now introduce the construction and analysis of the proposed CommonGen dataset in this section. To ensure that the concepts in each input concept-set are likely to be present together in a everyday scene, we utilize a wide range of existing caption corpora for sampling frequent concept-sets (Section 3.1). We also carefully control the overlap between the training set and development/test set, such that the task is more challenging in terms of compositional generalization. Afterwards, we employ workers on the crowd-sourcing platform AMT for collecting more human-written sentences (Section 3.2), and thus enrich the diversity of development and test set. Finally, we present the statistics of the CommonGen dataset, and utilize ConceptNet as an intermediate tool to investigate the concept connectivity and the distribution of various knowledge types (Section 3.3).

3.1 Collecting Concept-Sets from Captions

It is obviously nonsense if we ask a reasoner to generate a scenario about an arbitrarily concept-set, which is impossible even for humans. The expected concept-sets of our task are supposed to be very likely to co-occur in common, daily-life scenes. Such everyday scenarios are ubiquitous in images and video clips, and this leads us to think about using image/video captioning datasets as a natural resource for collecting concept-sets and sentences.

We therefore collect a large amount of caption sentences from all publicly available visual caption corpora, including image captioning datasets, such as Flickr30k (Young et al., 2014), MSCOCO (Lin et al., 2014), Conceptual Captions (Sharma et al., 2018), and also video captioning datasets such as LSMDC (Rohrbach et al., 2017), ActivityNet (Krishna et al., 2017), and VATEX (Wang et al., 2019).

We first conduct part-of-speech tagging over all sentences in the corpora such that words in sentences can be matched to the concept vocabulary of ConceptNet. Then, we compute the sentence frequency of concept-sets that consist of 3~5 concepts. That is, for each combination of three/four/five concepts in the vocabulary, we know how many sentences are in the corpora covering all concepts.

Towards building a more representative dataset, we expect our selected subset of concept-sets can reflect the distribution in the real world. A straightforward intuition is to directly treat the frequency as the measure of likelihood of concept-sets, and then conduct probabilistic sampling based on this distribution. However, this method tends to sample concept-sets that contain one or two single highly frequent concept, thus leading to corpus-dependent bias. Also, merely using the sentence number can be imprecise to measure the scenario diversity since many images and videos were sampled interdependently. We therefore design a scoring function to weight a concept-set x to incorporate diversity and penalty of inverse set frequency:

$$\text{score}(x) = |S(x)| \frac{|\bigcup_{s_i \in S(x)} \{w | w \in s_i\}|}{\sum_{s_i \in S(x)} Length(s_i)} \rho(x).$$

We denote $S(x)$ as the set of different sentences that contain all its concepts $\{c_1, c_2, \ldots, c_k\} = x$, s_i as one of the sentences, and $|S(x)|$ to be the number of sentences. The second term is to divide the number of unique words in these sentences by the sum of the lengths of all the sentences, which can roughly represent the diversity of the scenes described in these sentences. Then, we times the result with the last term $\rho(x) = |\mathcal{X}| / (\max_{c_i \in x} |\{x' \mid c_i \in x' \text{ and } x' \in \mathcal{X}\}|)$.

The idea is to find the concept in x that has the maximum set frequency (i.e. the number of different concept-sets (with non-zero weight) contains it), and then take the inverse with normalization of the number of all concept-sets. This penalty effectively controls the bias towards highly frequent concepts. With the distribution of such scores, we sample 100k concept-sets as candidate inputs.

3.2 Crowd-Sourcing References via AMT

Although the human-written sentences in the caption corpora can be seen as quality annotations for the CommonGen task as well, they were written with specific visual context (i.e. an image or a video clip). Toward better diversity of the scenes about sampled concept-sets and more rigorous evaluation for systems, crowd-sourcing additional human references is necessary that are written with only

Statistics	Train	Dev	Test
# Concept-Sets	**27,069**	**993**	**1,497**
-Size = 3	20,580	493	-
-Size = 4	4,207	250	747
-Size = 5	2,282	250	750
# Sentences	39,069	4,018	6,042
Average Length	10.85	13.15	13.80
# Unique Concepts	6,643	813	1,351
# Unique Concept-Pairs	47,574	3,982	8,930
# Unique Concept-Triples	38,110	3,786	9,976
% Novel Concepts	-	2.50%	6.01%
% Novel Concept-Pairs	-	64.88%	75.45%
% Novel Concept-Triples	-	95.53%	98.49%

Table 1: The **basic statistics** of the CommonGen data. We highlight the ratios of concept compositions that are unseen in training data, which assures the challenge in compositional generalization ability.

concept-sets as the context. We decide to use the AMT platform for collecting such sentences for covered the top-ranked 2,500 concept-sets in the sampled results, due to the expensive cost of human efforts in writing sentences and the difficulty in verifying the quality of collected sentences. Each of them is assigned to at least three different workers. To encourage workers to write about everyday scenarios about given concept-sets, we ask them to write rationale sentences as well to explain what commonsense facts they have used. Examples of rationales are shown in Figure 4.

We use these 2,500 concept-sets as the dev and test set examples for their higher weights and better diversity of human-written sentences. Furthermore, we use the remaining concept-sets as the training examples, for which we use the associated captions as the target outputs. Note that we explicitly control the overlap between the training and dev/test examples by filtering training concept-sets that have more than two overlapping concepts with any example in the dev/test set.

The basic statistics of the final dataset is shown in Table 1. There are on average four sentences for each example in dev and test sets, which provide a richer and more diverse test-bed for further automatic and manual evaluation. We highlight the ratio of novel concept compositions (i.e., concept, concept-pair, and concept-triple) in dev/test, which never (co-)occur in training examples. This makes CommonGen challenging in terms of compositional generalization ability.

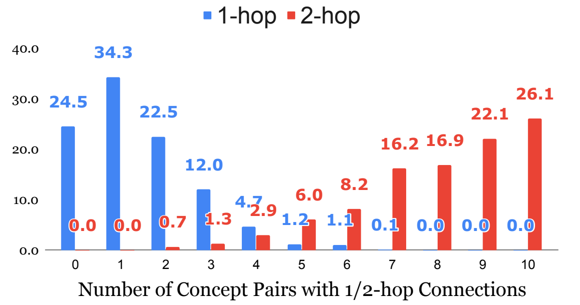

Figure 2: **Connectivity analysis** in 5-size concept-sets in the test set, each of which consists of 10 concept pairs. For example, 12.0 in blue means: there are 12% concept-sets that have 3 concept pairs with one-hop connections on ConceptNet.

3.3 Analysis about Commonsense Knowledge

We here introduce deeper analysis of the dataset by utilizing the largest commonsense knowledge graph (KG), ConceptNet (Speer et al., 2017), as an tool to study connectivity and relation types.

Connectivity Distribution. Obviously, if the concepts inside a given concept-set is more densely connected with each other on the KG, then it is easier to write a scenario about them. In each 5-size concept-set (i.e. a concept-set consists of five concepts), there are 10 unique pairs of concepts, the connections of which we are interested in. As shown in Figure 2, if we look at the one-hop links on the KG, about 60% of the 5-size concept-set have less than one link among all concept-pairs. On the other hand, if we consider two-hop links, then nearly 50% of them are almost fully connected (i.e. each pair of concepts has connections).

These two observations together suggest that the CommonGen has a reasonable difficulty: the concepts are not too distant or too close, and reasoning about the associated scenes is thus neither too difficult nor too trivial.

Relation Distribution. Furthermore, the relation types of such connections can also tell us what kinds of commonsense knowledge are potentially useful for relational reasoning towards generation. We report the frequency of different relation types[3] of the one/two-hop connections among concept-pairs in the dev and test examples in Fig. 3. To better summarize the distributions, we categorize these relations into five major types and present their distribution in Table 2, respectively for one/two-hop connections between concept pairs.

[3]Relation definitions are at `https://github.com/commonsense/conceptnet5/wiki/Relations`.

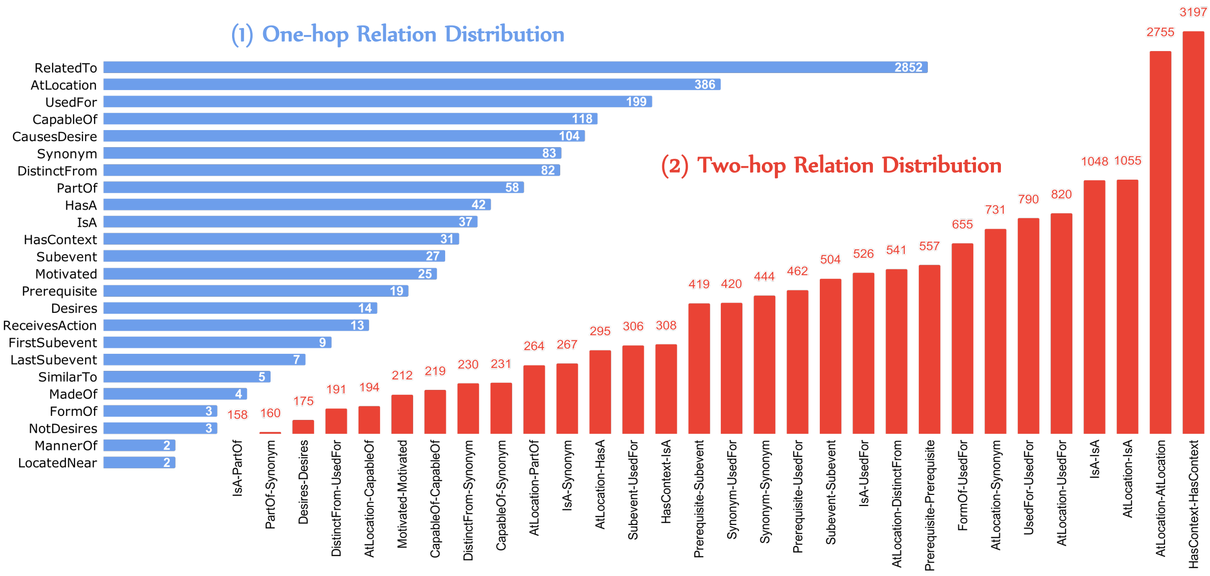

Figure 3: One/two-hop relation frequency in the CommonGen dev.&test sets on ConceptNet.

Category	Relations	1-hop	2-hop
Spatial knowledge	`AtLocation, LocatedNear`	9.40%	39.31%
Object properties	`UsedFor, CapableOf, PartOf, ReceivesAction, MadeOf, FormOf, HasProperty, HasA`	9.60%	44.04%
Human behaviors	`CausesDesire, MotivatedBy, Desires, NotDesires, Manner`	4.60%	19.59%
Temporal knowledge	`Subevent, Prerequisite, First/Last-Subevent`	1.50%	24.03%
General	`RelatedTo, Synonym, DistinctFrom, IsA, HasContext, SimilarTo`	74.89%	69.65%

Table 2: The **distributions of the relation categories** on one/two-hop connections.

4 Methods

In this section, we briefly introduce the adopted baseline methods that are tested on the proposed CommonGen task. As there is no principled approach for the proposed setting, to the best of our knowledge, we mainly consider it as a conditional sentence generation task that can be solved by many sequence-to-sequence frameworks.

Encoder-Decoder Models. Bidirectional RNNs and Transformers (Vaswani et al., 2017) are two most popular architectures for seq2seq learning. We use them with the addition of attention mechanism (Luong et al., 2015) with copying ability (Gu et al., 2016), which are based on an open-source framework OpenNMT-py (Klein et al., 2017). We use `bRNN-CopyNet` and `Trans-CopyNet` denote them respectively. To alleviate the influence from the concept ordering in such sequential learning methods, we randomly permute them multiple times for training and decoding and then get their average performance. To explicitly eliminate the order-sensitivity of inputs, we replace the encoder with a mean pooling-based MLP network (`MeanPooling-CopyNet`).

Non-autoregressive generation. Recent advances (Lee et al., 2018; Stern et al., 2019) in conditional sentence generation have an embeding interest on (edit-based) non-autoregressive generation models, which iteratively refine generated sequences. We assume that these models potentially would have better performance because of explicit modeling on iterative refinements, and thus study the most recent such model Levenshtein Transformer (`LevenTrans`) by Gu et al. (2019).

Pre-trained Language Generation Models. We also employ various pre-trained language generation models, including `GPT-2` (Radford et al., 2019), `UniLM` (Dong et al., 2019), `UniLM-v2` (Bao et al., 2020), `BERT-Gen` (Bao et al., 2020), `BART` (Lewis et al., 2019), and `T5` (Raffel et al., 2019), to tackle this task and test their generative commonsense reasoning ability. We fine-tuned all the above models on our training data with a seq2seq format.

Specifically, to use `GPT-2` for this sequence-to-sequence task, we condition the language model on the format "$c_1\ c_2\ \dots\ c_k\ =\ y$" during fine-tuning, where c_i is a concept in the given concept-set and connects with other concepts with a blank;

Model \ Metrics	ROUGE-2/L		BLEU-3/4		METEOR	CIDEr	SPICE	Coverage
bRNN-CopyNet (Gu et al., 2016)	2.90	19.25	5.50	2.00	12.70	3.99	10.60	42.25
Trans-CopyNet	2.28	14.04	4.30	2.00	9.10	2.31	7.50	24.19
MeanPooling-CopyNet	3.30	19.35	6.60	2.40	13.50	4.34	13.00	44.05
LevenTrans. (Gu et al., 2019)	5.74	21.24	8.80	4.00	13.30	3.72	14.00	36.80
GPT-2 (Radford et al., 2019)	16.47	38.01	28.70	19.40	24.40	11.06	24.50	75.09
BERT-Gen (Bao et al., 2020)	19.78	40.93	33.20	23.10	28.50	13.31	28.30	83.19
UniLM (Dong et al., 2019)	21.57	41.96	**38.30**	**27.50**	29.40	**14.92**	29.90	90.13
UniLM-v2 (Bao et al., 2020)	21.02	**42.41**	34.80	24.30	29.80	14.61	30.00	92.20
BART (Lewis et al., 2019)	**22.38**	41.44	35.10	24.90	**30.50**	13.32	30.10	**96.32**
T5 (Raffel et al., 2019)	21.71	41.79	38.10	27.20	30.00	14.58	**30.60**	95.02
Human Performance	48.88	63.79	48.20	44.90	36.20	43.53	63.50	99.31

Table 3: Experimental results of different baseline methods on the CommonGen test set. The first group of models are non-pretrained models, while the second group is large pretrained models that we have fine-tuned. The best models are **bold** and second best ones are underlined within each metric.

y is a target sentence. For inference, we sample from the fine-tuned GPT-2 model after a prompt of "$c_1\ c_2\ \ldots\ c_k$ =" with beam search and use the first generated sentence as the output sentence.

For BERT-Gen, we use the s2s-ft package[4] to fine-tune them in a sequence-to-sequence fashion similar to the sequence-to-sequence LM objective employed by UniLM.

As for T5, the state-of-the-art text-to-text pretrained model which is pre-trained with a multi-task objective by prepending a task description before the input text, we prepend the input concept set with a simple prompt: "generate a sentence with:" and fine-tune the model with the source sentence on the format "*generate a sentence with* $c_1\ c_2\ \ldots\ c_k$."

5 Evaluation

In this section, we first introduce our metrics for automatic evaluation, then analyze the performance of tested systems, and finally provide qualitative analysis with case studies.

5.1 Metrics

Following other conventional generation tasks, we use several widely-used automatic metrics to automatically assess the performance, such as BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), METEOR (Banerjee and Lavie, 2005), which mainly focus on measuring surface similarities. We report the concept Coverage, which is the average percentage of input concepts that are present in lemmatizatized outputs.

[4] https://github.com/microsoft/unilm

In addition, we argue that it is more suitable to use evaluation metrics specially design for captioning task, such as CIDEr (Vedantam et al., 2015) and SPICE (Anderson et al., 2016). They usually assume system generations and human references use similar concepts, and thus focus on evaluate the associations between mentioned concepts instead of n-gram overlap. For example, the SPICE metric use dependency parse trees as proxy of scene graphs to measure the similarity of scenarios.

To estimate *human performance* within each metric, we treat each reference sentence in dev/test data as a "system prediction" to be compared with all other references, which is equivalent to compute inter-annotator agreement within each metric. Thus, systems that have better generative ability than average crowd-workers should exceed this.

5.2 Experimental Results

Table 3 presents the experimental results of all compared methods in different metrics. We can see that all fine-tuned pre-trained models (the lower group) outperform non-pretrained models (the upper group) with a significant margin. This is not surprising because the their pretraining objectives, including masked language modeling, word ordering, and text infilling which predicts missing words or text spans, are relevant to our task. On the other hand, we find that the key disadvantage of non-pretrained models with CopyNet still falls in the failure of using all given concepts (i.e., low coverage), which results in worse results.

Among them, UniLM, BART, and T5 performs the best, which may be due to its inherent sequence-to-sequence pre-training framework. We found that

[Input concept-set]: { give, lay, massage, table }

[Machine generations]

[bRNN-CpNet]: Lays massage someone table vertical gives on and the water.
[Trans-CpNet]: Massage lays on the kitchen.
[MP-CpNet]: A massage table being calling with an improvisation lay free speaker.
[LevenTrans]: A man chatting at the table.
[GPT-2]: A man gives a massage to a table.
[BERT-Gen]: A woman lays down on a table and gives a massage to a man.
[UniLM]: A woman lays down a massage on a table and gives a massage.
[UniLM-v2]: A woman is laying down and giving a massage on a table.
[BART]: A man lays on a table and gives a massage to a woman laying on the table.
[T5]: Woman lay on a table and gives a massage.

[Human references from AMT]

1. The man lays down on the massage table and the therapist gives him a massage.
[Rationale]: The man must lay down to receive a massage. The therapist is the giver of massages. The table is a massage table.
2. Lay down on the table and the masseuse will give you a neck massage.
[Rationale]: A masseuse is a woman who gives massages professionally. Massages are usually done on tables.
3. The woman gives the man who lays on the table a massage.
[Rationale]: Some massages are done laying down; people like to get massages; tables are used for people to get massages; people lay on tables to get massages.

Figure 4: A case study with a concept-set {*give*, *lay*, *massage*, *table*} for qualitative analysis of machine generations. Human references are collected from AMT and the crowd-workers are required to provide *rationales*. More case studies are shown in Figure 5 in Appendix.

BART has the best concept coverage, which is probably due to its comprehensive pretraining tasks that aim to recover text with noise. The results suggest that further modifying over pre-trained models is a promising direction for generative commonsense reasoning. This also shows that our dataset would be a good test-bed for comparing the commonsense reasoning ability of different pre-trained language models.

Recent work (Lv et al., 2020) finds that the OMCS corpus (Singh et al., 2002), which has derived the ConceptNet, is a valuable resource for retrieving relevant commonsense facts for discriminative reasoning about questions. We follow the same steps to retrieve related facts by querying input concepts. Then, we concatenate them with the original concept-sets as the final input sequence to the above-mentioned methods, mimicking abstractive summarization tasks. However, we only observe very marginal improvement when using retrieved OMCS sentences as additional inputs. We argue that imposing commonsense knowledge with additional graph structures (Lin et al., 2019) between input concepts is a more promising future direction for the COMMONGEN task as graphs are naturally order-insensitive.

5.3 Qualitative Analysis with A Case study

Figure 4 shows the top generations of different models and human references about an input concept-set: {*give*, *lay*, *massage*, *table*}. We find that non-pretrained seq2seq models can successfully use part of given concepts, while the generated sentences are neither grammatical nor coherent. The vanilla LevenTrans model only uses one of the given concepts, although it aims to modeling the edits explicitly and generates syntactically sound sentences. bRNN-CopyNet uses all four concepts with the powerful copy mechanism, but generates nonsensical sentences.

The outputs of fine-tuned pre-trained models are significantly more grammatical and commonsensical. Although they are not equipped with an explicit module for enforcing the use of given concepts, most of them can cover all concepts in their outputs. We can see that the scenarios in the outputs of GPT-2, UniLM-v1/2, and T5 only involve a single person, and the other two models associate their scenarios with two persons. This makes the person doing two contradictory actions in their output scenarios (e.g., 'laying on a table' and 'giving a massage'). GPT-2 creates an even funny nonsensical composition ('gives a massage to a table'), due to this issue. Although BERT-Gen indeed incorporates a second person in its output, it still has the contradiction. The model closet to human references is BART within this case study, if it did not generate the 'lays on a table and' to describe the man. This suggests that a second pass to remove some local optimal generations is necessary for assuring plausibility of the scenario.

6 Related Work

Commonsense benchmark datasets. There are many emerging datasets for testing machine commonsense from different angles, such as commonsense extraction (Xu et al., 2018; Li et al., 2016), next situation prediction (SWAG (Zellers et al., 2018), CODAH (Chen et al., 2019), HellaSWAG (Zellers et al., 2019b)), cultural and social understanding (Lin et al., 2018; Sap et al., 2019a,b), visual scene comprehension (Zellers et al., 2019a), and general commonsense question answering (Talmor et al., 2019; Huang et al., 2019).

Recent studies have shown that simply fine-tuning large pre-trained language models, e.g. RoBERTa (Liu et al., 2019), can yield near-human, or even exceeding-human, performance in these *discriminative reasoning* scenarios such as the SWAG dataset. We argure that the underlying reasons are two-fold: 1) The creation of distractor choices has *annotator bias* (Geva et al., 2019) which can be easily detected by NLU models. 2) Self-supervised training objectives in BERT-like models (Devlin et al., 2019) align well with the multi-choice QA setting; the SWAG task shares almost the same scenario with the Next Sentence Prediction (NSP) task, and because the CSQA task can be viewed as learning to recover missing words that are masked by "wh-words", it can be distantly learned using Masked Language Modeling (MLM). Therefore, these success does not necessarily mean machine reasoners can produce novel assumptions in an open, realistic, generative setting.

Constrained Text Generation. Constrained text generation aims to decode sentences with expected attributes such as sentiment (Luo et al., 2019a; Hu et al., 2017), tense (Hu et al., 2017), template (Zhu et al., 2019), style (Fu et al., 2018; Luo et al., 2019b; Li et al., 2018), topics (Feng et al., 2018), etc. A similar scenario with our task is lexically constrained encoding, which has been mainly studied in the machine translation community (Hasler et al., 2018; Dinu et al., 2019; Hokamp and Liu, 2017). One recent work in this line is the CGMH (Miao et al., 2019) method, which aims to sample sentences with an *ordered* sequence of keywords from language models but cannot be fine-tuned and adopted in our case. Topical story generation (Fan et al., 2018; Yao et al., 2019) is also a related direction, while it targets generating longer, creative stories around the given topics, making it hard to directly adopt them to our task. Additionally, the COMMONGEN task brings some more challenges mentioned in Section 2. Prior constrained generation methods cannot address these issues together in a unified model, and thus we expect COMMONGEN to be also a benchmark dataset for future works in this direction.

Injecting Commonsense for NLG. There are also a few works that incorporate commonsense knowledge in language generation tasks such as essay generation (Guan et al., 2019; Yang et al., 2019a), video storytelling (Yang et al., 2019b), and conversational systems (Zhang et al., 2019). These works suggest that generative commonsense reasoning has a great potential to benefit downstream applications. Our proposed COMMONGEN, to the best of our knowledge, is the very first constrained sentence generation dataset for assessing and conferring generative machine commonsense and we hope it can benefit such applications.

7 Conclusion

Our major contribution in this paper are as follows:

1. we present COMMONGEN, a novel constrained generation task for generative commonsense reasoning, and a large-scale dataset;
2. we carefully analyze the inherent challenges of the proposed task, i.e., a) relational reasoning with latent commonsense knowledge, and b) compositional generalization.
3. our extensive experiments systematically examine recent pre-trained language generation models (e.g., UniLM, BART, T5) on the task , and find that their performance is still far from humans, generating grammatically sound yet realistically implausible sentences.

Our study points to interesting future research directions on modeling commonsense knowledge in language generation process, towards conferring machines with generative commonsense reasoning ability. We hope COMMONGEN would also benefit downstream NLG applications such as conversational systems and storytelling models.

References

Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. 2016. Spice: Semantic propositional image caption evaluation. In *European Conference on Computer Vision*, pages 382–398. Springer.

Satanjeev Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In *Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization*, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Hangbo Bao, Li Dong, Furu Wei, Wenhui Wang, Nan Yang, Xiulei Liu, Yu Wang, Songhao Piao, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2020. Unilmv2: Pseudo-masked language models for unified language model pre-training. *arXiv: Computation and Language*.

Michael Chen, Mike D'Arcy, Alisa Liu, Jared Fernandez, and Doug Downey. 2019. Codah: An adversarially authored question-answer dataset for common sense. *ArXiv*, abs/1904.04365.

Noam Chomsky. 1965. Aspects of the theory of syntax.

Ernest Davis and Gary Marcus. 2015. Commonsense reasoning and commonsense knowledge in artificial intelligence. *Commun. ACM*, 58:92–103.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Georgiana Dinu, Prashant Mathur, Marcello Federico, and Yaser Al-Onaizan. 2019. Training neural machine translation to apply terminology constraints. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3063–3068, Florence, Italy. Association for Computational Linguistics.

Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2019. Unified language model pre-training for natural language understanding and generation. In *Advances in Neural Information Processing Systems*, pages 13042–13054.

Angela Fan, Mike Lewis, and Yann Dauphin. 2018. Hierarchical neural story generation. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 889–898, Melbourne, Australia. Association for Computational Linguistics.

Xiaocheng Feng, Ming Liu, Jiahao Liu, Bing Qin, Yibo Sun, and Ting Liu. 2018. Topic-to-essay generation with neural networks. In *IJCAI*, pages 4078–4084.

Zhenxin Fu, Xiaoye Tan, Nanyun Peng, Dongyan Zhao, and Rui Yan. 2018. Style transfer in text: Exploration and evaluation. In *Thirty-Second AAAI Conference on Artificial Intelligence*.

Mor Geva, Yoav Goldberg, and Jonathan Berant. 2019. Are we modeling the task or the annotator? an investigation of annotator bias in natural language understanding datasets. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 1161–1166, Hong Kong, China. Association for Computational Linguistics.

Jiatao Gu, Zhengdong Lu, Hang Li, and Victor O.K. Li. 2016. Incorporating copying mechanism in sequence-to-sequence learning. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1631–1640, Berlin, Germany. Association for Computational Linguistics.

Jiatao Gu, Changhan Wang, and Junbo Zhao. 2019. Levenshtein transformer. In *Advances in Neural Information Processing Systems*, pages 11179–11189.

Jian Guan, Yansen Wang, and Minlie Huang. 2019. Story ending generation with incremental encoding and commonsense knowledge. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 6473–6480.

Eva Hasler, Adrià de Gispert, Gonzalo Iglesias, and Bill Byrne. 2018. Neural machine translation decoding with terminology constraints. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 506–512, New Orleans, Louisiana. Association for Computational Linguistics.

Chris Hokamp and Qun Liu. 2017. Lexically constrained decoding for sequence generation using grid beam search. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1535–1546, Vancouver, Canada. Association for Computational Linguistics.

Zhiting Hu, Zichao Yang, Xiaodan Liang, Ruslan Salakhutdinov, and Eric P Xing. 2017. Toward controlled generation of text. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 1587–1596. JMLR. org.

Lifu Huang, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2019. Cosmos QA: Machine reading comprehension with contextual commonsense reasoning. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2391–2401, Hong Kong, China. Association for Computational Linguistics.

Daniel Keysers, Nathanael Schärli, Nathan Scales, Hylke Buisman, Daniel Furrer, Sergii Kashubin, Nikola Momchev, Danila Sinopalnikov, Lukasz Stafiniak, Tibor Tihon, Dmitry Tsarkov, Xiao Wang, Marc van Zee, and Olivier Bousquet. 2020. Measuring compositional generalization: A comprehensive method on realistic data. In *International Conference on Learning Representations*.

Guillaume Klein, Yoon Kim, Yuntian Deng, Jean Senellart, and Alexander Rush. 2017. OpenNMT: Open-source toolkit for neural machine translation. In *Proceedings of ACL 2017, System Demonstrations*, pages 67–72, Vancouver, Canada. Association for Computational Linguistics.

Ranjay Krishna, Kenji Hata, Frederic Ren, Li Fei-Fei, and Juan Carlos Niebles. 2017. Dense-captioning events in videos. In *Proceedings of the IEEE international conference on computer vision*, pages 706–715.

Brenden M Lake and Marco Baroni. 2017. Generalization without systematicity: On the compositional skills of sequence-to-sequence recurrent networks. In .

Jason Lee, Elman Mansimov, and Kyunghyun Cho. 2018. Deterministic non-autoregressive neural sequence modeling by iterative refinement. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1173–1182, Brussels, Belgium. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. *ArXiv*, abs/1910.13461.

Juncen Li, Robin Jia, He He, and Percy Liang. 2018. Delete, retrieve, generate: a simple approach to sentiment and style transfer. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1865–1874, New Orleans, Louisiana. Association for Computational Linguistics.

Xiang Li, Aynaz Taheri, Lifu Tu, and Kevin Gimpel. 2016. Commonsense knowledge base completion. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1445–1455, Berlin, Germany. Association for Computational Linguistics.

Bill Yuchen Lin, Xinyue Chen, Jamin Chen, and Xiang Ren. 2019. KagNet: Knowledge-aware graph networks for commonsense reasoning. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2829–2839, Hong Kong, China. Association for Computational Linguistics.

Bill Yuchen Lin, Frank F. Xu, Kenny Zhu, and Seung-won Hwang. 2018. Mining cross-cultural differences and similarities in social media. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 709–719, Melbourne, Australia. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. 2014. Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *ArXiv*, abs/1907.11692.

Fuli Luo, Peng Li, Pengcheng Yang, Jie Zhou, Yutong Tan, Baobao Chang, Zhifang Sui, and Xu Sun. 2019a. Towards fine-grained text sentiment transfer. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2013–2022, Florence, Italy. Association for Computational Linguistics.

Fuli Luo, Peng Li, Jie Zhou, Pengcheng Yang, Baobao Chang, Zhifang Sui, and Xu Sun. 2019b. A dual reinforcement learning framework for unsupervised text style transfer. *arXiv preprint arXiv:1905.10060*.

Thang Luong, Hieu Pham, and Christopher D. Manning. 2015. Effective approaches to attention-based neural machine translation. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1412–1421, Lisbon, Portugal. Association for Computational Linguistics.

Shangwen Lv, Daya Guo, Jingjing Xu, Duyu Tang, Nan Duan, Ming Gong, Linjun Shou, Daxin Jiang, Guihong Cao, and Songlin Hu. 2020. Graph-based reasoning over heterogeneous external knowledge for commonsense question answering. *ArXiv*, abs/1909.05311.

Ning Miao, Hao Zhou, Lili Mou, Rui Yan, and Lei Li. 2019. Cgmh: Constrained sentence generation by metropolis-hastings sampling. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 6834–6842.

Chris Moore. 2013. *The development of commonsense psychology*. Psychology Press.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. *arXiv preprint arXiv:1910.10683*.

Anna Rohrbach, Atousa Torabi, Marcus Rohrbach, Niket Tandon, Christopher Pal, Hugo Larochelle, Aaron Courville, and Bernt Schiele. 2017. Movie description. *International Journal of Computer Vision*, 123(1):94–120.

Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2019. Winogrande: An adversarial winograd schema challenge at scale. *ArXiv*, abs/1907.10641.

Maarten Sap, Ronan Le Bras, Emily Allaway, Chandra Bhagavatula, Nicholas Lourie, Hannah Rashkin, Brendan Roof, Noah A Smith, and Yejin Choi. 2019a. Atomic: An atlas of machine commonsense for if-then reasoning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 3027–3035.

Maarten Sap, Hannah Rashkin, Derek Chen, Ronan Le Bras, and Yejin Choi. 2019b. Social IQa: Commonsense reasoning about social interactions. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 4463–4473, Hong Kong, China. Association for Computational Linguistics.

Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. 2018. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2556–2565, Melbourne, Australia. Association for Computational Linguistics.

Push Singh, Thomas Lin, Erik T Mueller, Grace Lim, Travell Perkins, and Wan Li Zhu. 2002. Open mind common sense: Knowledge acquisition from the general public. In *OTM Confederated International Conferences" On the Move to Meaningful Internet Systems"*, pages 1223–1237. Springer.

Robyn Speer, Joshua Chin, and Catherine Havasi. 2017. Conceptnet 5.5: An open multilingual graph of general knowledge. In *Thirty-First AAAI Conference on Artificial Intelligence*.

Mitchell Stern, William Chan, Jamie Kiros, and Jakob Uszkoreit. 2019. Insertion transformer: Flexible sequence generation via insertion operations. *arXiv preprint arXiv:1902.03249*.

Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. 2019. CommonsenseQA: A question answering challenge targeting commonsense knowledge. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4149–4158, Minneapolis, Minnesota. Association for Computational Linguistics.

Ruth Tincoff and Peter W Jusczyk. 1999. Some beginnings of word comprehension in 6-month-olds. *Psychological science*, 10(2):172–175.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.

Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4566–4575.

Xin Wang, Jiawei Wu, Junkun Chen, Lei Li, Yuan-Fang Wang, and William Yang Wang. 2019. Vatex: A large-scale, high-quality multilingual dataset for video-and-language research. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 4581–4591.

Frank F. Xu, Bill Yuchen Lin, and Kenny Zhu. 2018. Automatic extraction of commonsense LocatedNear knowledge. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 96–101, Melbourne, Australia. Association for Computational Linguistics.

Pengcheng Yang, Lei Li, Fuli Luo, Tianyu Liu, and Xu Sun. 2019a. Enhancing topic-to-essay generation with external commonsense knowledge. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2002–2012, Florence, Italy. Association for Computational Linguistics.

Pengcheng Yang, Fuli Luo, Peng Chen, Lei Li, Zhiyi Yin, Xiaodong He, and Xu Sun. 2019b. Knowledgeable storyteller: a commonsense-driven generative model for visual storytelling. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI*, pages 5356–5362.

Lili Yao, Nanyun Peng, Ralph Weischedel, Kevin Knight, Dongyan Zhao, and Rui Yan. 2019. Plan-and-write: Towards better automatic storytelling. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 7378–7385.

Peter Young, Alice Lai, Micah Hodosh, and Julia Hockenmaier. 2014. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. *Transactions of the Association for Computational Linguistics*, 2:67–78.

Rowan Zellers, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019a. From recognition to cognition: Visual commonsense reasoning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6720–6731.

Rowan Zellers, Yonatan Bisk, Roy Schwartz, and Yejin Choi. 2018. SWAG: A large-scale adversarial dataset for grounded commonsense inference. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 93–104, Brussels, Belgium. Association for Computational Linguistics.

Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019b. HellaSwag: Can a machine really finish your sentence? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4791–4800, Florence, Italy. Association for Computational Linguistics.

Houyu Zhang, Zhenghao Liu, Chenyan Xiong, and Zhiyuan Liu. 2019. Grounded conversation generation as guided traverses in commonsense knowledge graphs. *ArXiv*, abs/1911.02707.

Wanrong Zhu, Zhiting Hu, and Eric P. Xing. 2019. Text infilling. *ArXiv*, abs/1901.00158.

1) [Input concept-set]: { cow, horse, lasso, ride }

[Machine generations]

[bRNN-CpNet]: Someone lowers his horse from the wall and lasso glass by cows.
[Trans-CpNet]: A horse having lasso in the bridal cows.
[MP-CpNet]: Cow in a lasso getting the ride.
[LevenTrans]: A cow rides through a horse.
[GPT-2]: A horse rides on a lasso.
[BERT-Gen]: A cow rides a lasso on a horse.
[UniLM]: A man rides a horse with a lasso at cows.
[UniLM-v2]: A horse rides a cow with a lasso on it.
[BART]: A man rides a horse and a cow on a bridle with a lasso.
[T5]: Lasso to ride a cow on a horse.

[Human references from AMT]

1. When those men ride a horse for the first time and lasso those cows.
`[Rationale]: cowboys ride horses and lasso cows for a living`

2. A cowboy can use a lasso to control a horse or cow in order to ride them.
`[Rationale]: I understand the words and I can read and write English.`

3. The cowboy will lasso the cow while riding on the horse.
`[Rationale]: Have seen it.`

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2) [Input concept-set]: { hand, hold, walk, water }

[Machine generations]

[bRNN-CpNet]: Process of holds at hands under walk on hours.
[Trans-CpNet]: Hands with a walk in the water.
[MP-CpNet]: Walk across the hold to water.
[LevenTrans]: Hand moored at the water.
[GPT-2]: A woman holds a water walker and holds a hand.
[BERT-Gen]: A man walking and holding a hand in water while walking.
[UniLM]: A man holds hands to walk across the water.
[UniLM-v2]: A man is walking and holding a hand in the water.
[BART]: A man walks with a woman holding her hand as they walk through water.
[T5]: Man holds a bottle of water in his hand as he walks along a river.

[Human references from AMT]

1. The couple holds hands as they walk by the water.
`[Rationale]: Couples hold hands when taking walk even by a body of water.`

2. The girl is walking holding in her hand a bottle of water.
`[Rationale]: I see this reading the words`

3. The couple hold hands while they walk by the water.
`[Rationale]: People sometimes hold hands. People Like to walk near water.`

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3) [Input concept-set]: { clean, ladder, squeegee, stand, window }

[Machine generations]

[bRNN-CpNet]: The window stands out a ladder but clean the sun to being squeegee.
[Trans-CpNet]: A brown leather ladder with green eyes.
[MP-CpNet]: Window of the zebra are on a tablecloth.
[LevenTrans]: A man on a a on on the kitchen.
[GPT-2]: Someone grabs a ladder from a window and squeezes it open.
[BERT-Gen]: A woman is cleaning a window with a ladder and a squeegee.
[UniLM]: Someone stands next to a window and stands on a ladder to clean the squeegee.
[UniLM-v2]: A man is standing on a ladder and using a ladder to clean the window.
[BART]: A man with a squeegee and a ladder standing on the ledge of a window is cleaning the window.
[T5]: Squeegee and ladder on a wooden stand to clean windows and windows.

[Human references from AMT]

1. The window cleaner stands on the ladder to clean the window with a squeegee.
`[Rationale]: A squeegee is a tool to clean windows. A ladder is something that people use to reach high places.`

2. The man clean the window on the ladder stand by using squeegee.
`[Rationale]: man need to clean the window by using squeegee on the ladder stand`

3. The man stood beside the ladder and cleaned the window with a squeegee.
`[Rationale]: people can stand next to ladders. People clean windows. Squeegees are used to clean windows.`

Figure 5: Three cases for qualitative analysis of machine generations. References are collected from AMT crowd-workers and they are required to provide rationales. Note that the second one is a positive case showing that some models can successfully generate reasonable scenarios. However, most models perform poorly on the other cases.