An Unsupervised Joint System for Text Generation from Knowledge Graphs and Semantic Parsing

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Abstract

Knowledge graph (KG) schemas can vary greatly from one domain to another. Therefore supervised approaches to graph-to-text generation and text-to-graph knowledge extraction (semantic parsing) will always suffer from a shortage of domain-specific parallel graph-text data, while adapting a model trained on a different domain is often impossible due to little or no overlap in entities and relations. This situation calls for an approach that (1) does not need large amounts of annotated data and (2) is easy to adapt to new KG schemas. To this end, *we present the first approach to fully unsupervised text generation from KGs and KG generation from text.* Inspired by recent work on unsupervised machine translation, we serialize a KG as a sequence of facts and frame both tasks as sequence translation. By means of a shared sequence encoder and decoder, our model learns to map both graphs and texts into a joint semantic space and thus generalizes over different surface representations with the same meaning. We evaluate our approach on WebNLG v2.1 and a new benchmark leveraging scene graphs from Visual Genome. Our system outperforms strong baselines for both text↔graph tasks without any manual adaptation from one dataset to the other. In additional experiments, we investigate the impact of using different unsupervised objectives.[1]

1 Introduction

Knowledge graphs (KGs) are a general-purpose approach for storing information in a structured, machine-accessible way (Van Harmelen et al., 2008). They are used in various fields and domains to model knowledge about topics as different as lexical semantics (Fellbaum, 2005; van Assem et al., 2006), common sense (Speer et al., 2017; Sap et al., 2019), biomedical research (Wishart et al., 2018) and visual relations in images (Lu et al., 2016).

This ubiquitousness of KGs necessitates interpretability because diverse users – both experts and non-experts – work with them. Even though a KG is human-interpretable in principle, non-experts may have difficulty making sense of it. Thus, there is a need for methods such as automatic natural language generation that support them.

Semantic Parsing, i.e., the conversion of natural language to a KG, is equally important because it automatically makes information that only exists in text form accessible for machines, assisting expert knowledge base engineers in KG creation or completion.

As KGs are flexible tools to express various kinds of knowledge, schemas in separately created KGs vary a lot. This unavoidably leads to a shortage of training data for both of the aforementioned tasks. We therefore propose an unsupervised model that (1) can easily be adapted to new KG schemas and (2) only requires unlabeled (i.e., non-parallel) texts and graphs from the relevant domain, together with a small number of fact extraction heuristics, but no manual annotation.

To show the effectiveness of our approach, we conduct experiments on the latest release (v2.1) of the WebNLG corpus (Shimorina and Gardent, 2018) and on a new benchmark we derive from *Visual Genome* (Krishna et al., 2016). While both of these datasets contain enough annotations to train supervised models, we evaluate our unsupervised approach by ignoring these annotations. The datasets are particularly well-suited for our evaluation as both graphs and texts are completely human-generated. Thus for both our tasks, models are evaluated with natural, i.e., human-generated targets.

Concretely, we make the following contributions: (1) We present the first unsupervised non-template approach to text generation from

[1]We will make our code and the new benchmark available upon publication.

KGs (graph→text). (2) We jointly develop a new unsupervised approach to semantic parsing that automatically adjusts to a target KG schema (text→graph). (3) In contrast to prior unsupervised graph→text and text→graph work, our model neither requires manual adaptation to new domains nor any language-specific preprocessing. (4) We provide a thorough analysis of the impact of using different unsupervised objectives, especially the ones we newly introduce for text↔graph conversion. (5) We create a new large-scale dataset for text↔graph transformation tasks in the visual domain.

2 Related Work

graph → text. Our work is the first attempt at fully unsupervised text generation from KGs. In this respect it is only comparable to traditional rule- or template-based approaches (Kukich, 1983; McRoy et al., 2000). In contrast to these approaches, however, which need to be manually adapted to new domains and KG schemas, our method is generally applicable to all kinds of data without modification.

There is a large body of literature about supervised text generation from structured data, notably about the creation of sports game summaries from statistical records (Robin, 1995; Tanaka-Ishii et al., 1998). Recent efforts make use of neural encoder-decoder mechanisms (Wiseman et al., 2017; Puduppully et al., 2019). Although text creation from relational databases is related and our unsupervised method is, in principle, also applicable to this domain, in our work we specifically address text creation from graph-like structures such as KGs.

One recent work on supervised text creation from KGs is (Bhowmik and de Melo, 2018). They generate a short description of an entity, i.e., a single KG node, based on a set of facts about said entity. We, however, generate a description of the whole KG, which involves multiple entities and their relations.

Koncel-Kedziorski et al. (2019) also generate texts from whole KGs. They, however, do not evaluate on human-generated KGs but instead rely on automatically generated ones from the scientific information extraction tool SciIE (Luan et al., 2018). Their supervised model is based on message passing through the topology of the incidence graph of the KG input. Such graph neural networks (Kipf and Welling, 2017; Veličković et al., 2018) have been widely adopted in supervised graph-to-text tasks (Beck et al., 2018; Damonte and Cohen, 2019; Ribeiro et al., 2019, 2020).

Even though Marcheggiani and Perez-Beltrachini (2018) report that graph neural networks can make better use of graph input than RNNs for supervised learning, for unsupervised learning we follow the line of research that uses RNN-based sequence-to-sequence (seq2seq) models (Cho et al., 2014; Sutskever et al., 2014) operating on serialized triple sets (Gardent et al., 2017b; Trisedya et al., 2018; Gehrmann et al., 2018; Castro Ferreira et al., 2019; Fan et al., 2019). We make this choice because learning a common semantic space space for both texts and graphs by means of a shared encoder and decoder is a central component of our model and because it is a nontrivial, separate research question whether and how encoder-decoder parameters can effectively be shared for models working on sequential and non-sequential data. We thus leave the adaptation of our approach to graph neural networks for future work.

text → graph. Converting a text into a KG representation, our method is an alternative to prior work on open information extraction (Niklaus et al., 2018) – with the additional advantage that the extractions, though trained without labeled data, automatically adjust to the schema of the KGs used for training. It is therefore also related to relation extraction in the unsupervised (Yao et al., 2011; Marcheggiani and Titov, 2016; Simon et al., 2019) and distantly supervised setting (Riedel et al., 2010; Parikh et al., 2015). However, these systems merely predict a single relation between two given entities in a single sentence, whereas our approach can translate a whole text into a KG with potentially multiple facts.

Although its typical use case is converting a question into a KG or database query and our method converts statements into KG facts, semantic parsing (Kamath and Das, 2019) is most closely related to our knowledge extraction task. Poon and Domingos (2009) were the first to propose an unsupervised approach. They, however, still needed an additional KG alignment step, i.e., were not able to directly adjust to a target KG schema. Other approaches overcame this limitation but only in exchange for the inflexibility of manually created domain-specific lexicons (Popescu et al., 2004; Goldwasser et al., 2011). Poon (2013)'s approach is more flexible but still relies on preprocessing

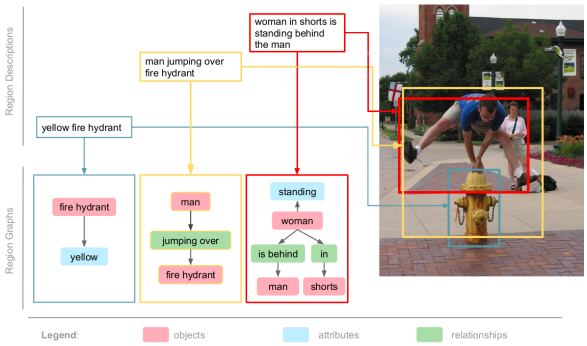


Figure 1: Region graphs and textual region descriptions in Visual Genome, a unique collection of millions of completely human-generated texts and graphs. Image regions served as common reference for text and graph creation but are disregarded in our work. We solely focus on the pairs of corresponding texts and graphs. Illustration adapted from (Krishna et al., 2016).

by a dependency parser, which generally means language-specific annotations to train such a parser are needed. Our approach is end-to-end, i.e., does not need any language-specific preprocessing and only depends on a POS tagger in the rule-based text→graph system that is used to bootstrap our model during training.

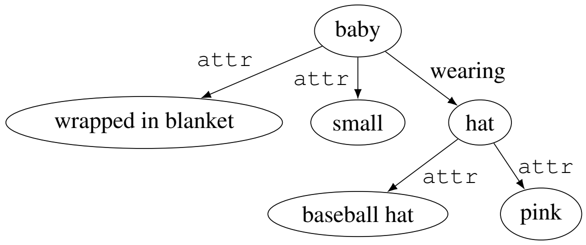
Unsupervised seq2seq training. The way we train our model for both text ↔ graph conversion tasks is inspired by (Lample et al., 2018b). They identified self-supervised pretraining and back-translation as important principles for unsupervised translation from one language to another. We adapt these principles and their noise model to the tasks of text ↔ graph conversion, introducing two new noise functions specific to our tasks.

3 Preliminaries

3.1 Data structure

A KG can be formalized as a labeled directed multi-graph (V, E, s, t, l) where entities constitute the set of nodes V and the set of edges E represent relations between the entities. The lookup functions $s, t : E \to V$ assign to each edge its source and target node. The labeling function l assigns labels to nodes and edges, where node labels are simply entity names and edge labels typically come from a predefined set R of relation types.

An equivalent representation of a KG is the set of its facts. A fact is a triple consisting of an edge's source node (the subject), the edge itself (the predicate), and its target node (the object). So the set of



(a) Reference text	a baseball cap on a baby's head
(b) Graph2text-rule	baby is small and baby is wrapped in blanket and hat is pink and hat is baseball hat and baby wearing hat
(c) Unsuperv. neural model	small baby wrapped in blanket with pink baseball hat
(d) Superv. neural model	baby wearing a pink hat

Figure 2: Example graph from Visual Genome and text generated by different systems.

facts $\mathcal{F}$ of a KG can be obtained from its edges:

$$\mathcal{F} := \{ (s(e), e, t(e)) \mid e \in E \} .$$

Applying l to all triple elements and writing out $\mathcal{F}$ in an arbitrary order generates a serialization that makes the KG accessible to sequence models otherwise used only for text. This has the advantage that we can train a sequence encoder to embed text and KGs in the same semantic space. Specifically, we serialize a KG by writing out its facts separated with end-of-fact symbols (`EOF`) and elements of each fact with special `SEP` symbols. We thus define our task as a seq2seq task.

3.2 Scene Graphs

The VG repository is a large collection of images with associated manually annotated **scene graphs**; see Fig. 1. A scene graph formally describes image objects with their attributes, e.g., (hydrant, `attr`, yellow), and their relations to other image objects, e.g., (woman, in, shorts). Each scene graph is organized into smaller subgraphs, known as **region graphs**, representing a subpart of a more complex larger picture that is interesting on its own. Each region graph is associated with a textual **region description**. Neither texts nor graphs were automatically produced from the other, but both were collected from crowdworkers who were presented an image region and then generated text and graph. So although the graphs were not specifically designed to closely resemble the texts, they describe the same image region. This semantic correspondence makes scene graph ↔ text conversion an

noise function	behavior
`swap`	applies a random permutation σ of words or facts with $\forall i \in \{1, \ldots, n\}, \|\sigma(i) - i\| \leq k$; $k = 3$ for text, $k = +\infty$ for knowledge graphs.
`drop`	removes each fact/word with a probability of p_{drop}.
`blank`	replaces each fact/word with a probability of p_{blank} by a special symbol `blanked`.
`repeat`	inserts repetitions with a probability of p_{repeat} in a sequence of facts/words.
`rule`	generates a noisy translation by applying Graph2text-rule to a graph or Text2graph-rule to a text.

Table 1: Noise functions and their behavior on graphs and texts.

interesting and challenging problem because text and graph are not simple translations of each other.

Scene graphs can easily be formalized in the same way as other sorts of KGs: V now consists of image objects and their attributes and R contains all types of visual relationships as well as a special label `attr` for edges between attribute and non-attribute nodes. Fig. 2 shows an example.

VG scene graphs have been used before for traditional KG tasks, such as KG completion (Wan et al., 2018), but, to the best of our knowledge, we are the first to create a text↔graph conversion dataset from them.

4 Approaches

4.1 Rule-based systems

We propose two rule-based systems as unsupervised baselines for graph→text and text→graph.

Graph2text-rule. From a KG serialization, we remove `SEP` symbols and replace `EOF` symbols by the word *and*. The special label `attr` is translated as *is*. This corresponds to a template-based enumeration of all KG facts. See Fig. 2 for an example.

Text2graph-rule. After preprocessing a text using NLTK's default POS tagger (Loper and Bird, 2004) and removing stop words, we apply two simple heuristics to identify facts: (1) Each verb becomes a new predicate; occurrences of *is* create facts with predicate `attr`. Subject and object are identified as the content words directly before and after such a predicate word. (2) All adjectives a form an attribute, i.e., build facts of the form $(X, \texttt{attr}, a)$, where X is filled with the first noun after a (see Table 7 for an example).

4.2 Neural sequence-to-sequence systems

Our main system is a neural seq2seq architecture. We adapt the standard encoder-decoder model with attention (Bahdanau et al., 2014) and a copy mechanism (Gu et al., 2016). Allowing the model to directly copy from the source to the target side is beneficial in data to text generation (Wiseman et al., 2017; Puduppully et al., 2019). The encoder (resp. decoder) is a bidirectional (resp. unidirectional) LSTM (Hochreiter and Schmidhuber, 1997). Dropout (Hinton et al., 2012) is applied at the input of both encoder and decoder (Britz et al., 2017). We combine this model with the following concepts:

Multi-task model. In unsupervised machine translation, systems are trained for both translation directions (Lample et al., 2018b). In the same way, we train our system for both conversion tasks text↔graph, i.e., both for the task of text generation from KGs and KG fact extraction from texts, sharing encoder and decoder. To tell the decoder which type of output should be produced (text or graph), we initialize the cell state of the decoder with an embedding of the desired output type. The hidden state of the decoder is initialized with the last state of the encoder as usual.

Noisy source samples. Lample et al. (2018a) introduced denoising auto-encoding as pretraining and auxiliary task to train the decoder to produce well-formed output and make the encoder robust to noisy input. The training examples for this task consist of a noisy version of a sentence as source and the original sentence as target. We adapt this idea and propose the following noise functions for the domains of graphs and texts: `swap`, `drop`, `blank`, `repeat`, `rule`. Table 1 describes their behavior. `swap`, `drop` and `blank` are direct adaptations from (Lample et al., 2018a), but facts in graph serializations take the role of words in text. As order should not matter at all for a set of facts, we drop the locality constraint in the permutation in `swap` for graphs by setting $k = +\infty$.

For `repeat`, the intuition is that a graph serialization should not contain repetitions. Denoising samples generated by `repeat` requires to learn to remove redundant information in a set of facts. In the case of text, `repeat` mimics a behavior often

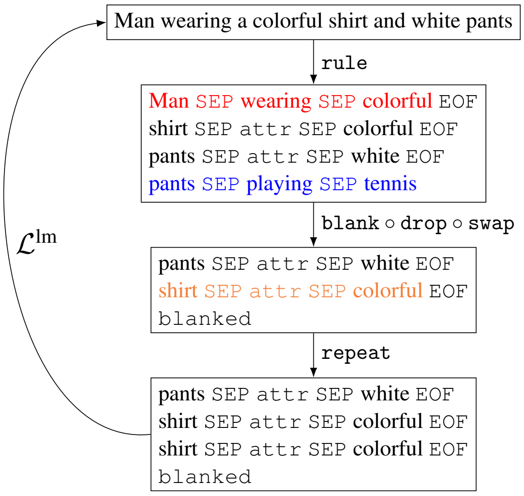


Figure 3: Example noisy training instance for the task of text generation from graphs in the composed noise setting. The fact highlighted in red is removed by `drop`, the one in blue is replaced with `blanked` by `blank`, the one in orange is repeated by `repeat`.

observed with insufficiently trained neural models, i.e., repeating words considered important.

Unlike the other noise functions, `rule` does not aim to perturb its input on purpose but rather attempts a noisy backtranslation. We will see in Section 7 that bootstrapping our method with these noisy translations is essential for its success.

We consider two fundamentally different noise injection regimes: (1) The **composed noise** setting is an adaptation of Lample et al. (2018a)'s noise model (`blank`∘`drop`∘`swap`) where our newly introduced noise functions `rule` and `repeat` are added to the start and end of the pipeline, i.e., all data samples are treated equally with the same noise function $C_{\text{comp}} := \texttt{repeat}\circ\texttt{blank}\circ\texttt{drop}\circ\texttt{swap}\circ\texttt{rule}$. Figure 3 shows an example. (2) In the **sampled noise** setting, we do not use all noise functions at once but sample a single one per data instance.

4.3 Training regimes

We denote the sets of graphs and corresponding texts by $\mathcal{G}$ and $\mathcal{T}$. The set of available supervised examples $(x, y) \in \mathcal{G} \times \mathcal{T}$ is called $\mathcal{S} \subset \mathcal{G} \times \mathcal{T}$. P_g and P_t are probabilistic models that generate, conditioned on any input, a graph (g) or a text (t).

4.3.1 Unsupervised training

Our setup is similar to (Lample et al., 2018b). We first obtain a language model for both graphs and text by training for one epoch using only the denoising auto-encoder objective $\mathcal{L}^{\text{denoise}}$:

$$\mathcal{L}^{\text{denoise}} = \mathop{\mathbb{E}}_{x\sim\mathcal{G}}[-\log P_g(x|C(x))] + \mathop{\mathbb{E}}_{y\sim\mathcal{T}}[-\log P_t(y|C(y))]$$

where $C \in \{C_{\text{comp}}\}$ for composed noise and $C \in \{\texttt{swap}, \texttt{blank}, \texttt{drop}, \texttt{repeat}, \texttt{rule}\}$ for sampled noise. In this pretraining epoch only, we use all possible noise functions individually on all available data. As sampled noise incorporates five different noise functions and composed noise only one, this results in five times more pretraining samples for sampled noise than for composed noise.

In subsequent epochs, we additionally consider $\mathcal{L}^{\text{back}}$ as training signal:

$$\begin{aligned}\mathcal{L}^{\text{back}} &= \mathop{\mathbb{E}}_{x\sim\mathcal{G}}[-\log P_g(x|z^*(x))] + \mathop{\mathbb{E}}_{y\sim\mathcal{T}}[-\log P_t(y|w^*(y))]\\ z^*(x) &= \arg\max_z P_t(z|x)\\ w^*(y) &= \arg\max_w P_g(w|y)\end{aligned}$$

This means that, in each iteration, we apply the current model to backtranslate a text (graph) to obtain a potentially imperfect graph (text) that we can use as noisy source with the clean original input being the target. This gives us a pseudo-parallel training instance for the next iteration – recall that we address unsupervised generation, i.e., without access to parallel data.

The total loss in these epochs is $\mathcal{L}^{\text{back}} + \mathcal{L}^{\text{denoise}}$, where now $\mathcal{L}^{\text{denoise}}$ only samples one possible type of noise independently for each data instance.

4.3.2 Supervised training

Our intended application is an unsupervised scenario. For our two datasets, however, we have labeled data (i.e., a "parallel corpus") and so can also compare our model to its supervised variant. Although supervised models should unsurprisingly outperform their unsupervised counterparts, supervised performance can serve as a reference point and thus give us an idea of the impact of supervision as opposed to other factors like model architecture and hyperparameters. The supervised loss is simply defined as follows:

$$\mathcal{L}^{\text{sup}} = \mathop{\mathbb{E}}_{(x,y)\sim\mathcal{S}}[-\log P_t(y|x) - \log P_g(x|y)]$$

	VG	VG_{ball}	WebNLG
#instances in train	2,412,253	151,790	12,876
#instances in val	323,478	21,541	1,619
#instances in test	324,664	20,569	1,600
#relation types	36,506	5,167	373
avg #facts in graph	2.7	2.5	3.0
avg #tokens in text	5.4	5.5	22.8
avg % text tokens in graph	49.3	50.6	49.4
avg % graph tokens in text	52.3	54.7	75.6

Table 2: Statistics of WebNLG v2.1 and our newly created benchmark VG; VG_{ball} is a subset of VG representing images from ball sports events.

5 Experiments

5.1 Data

For our experiments, we randomly split the VG images 80/10/10 into train/val/test. Then we remove all graphs from train that also occur in one of the images in val or test. Finally, we unify graph duplicates with different textual descriptions to single instances with multiple reference texts for graph→text and proceed analogously with text duplicates for text→graph. For WebNLG v2.1, we use the data splits as provided. Following previous work on an older version of WebNLG (Gardent et al., 2017a), we resolve the camel case of relation names and remove underscores from entity names in a preprocessing step. Because of VG's enormous size and limited computation power, we additionally create a closed-domain subset of VG, called VG_{ball}, which we can use to quickly conduct additional experiments (see Section 7). With the domain of ball sports events in mind, we identify all images where at least one region graph contains at least one fact that mentions an object ending with *ball* and take all the regions from them (keeping data splits the same). In contrast to alternatives like random subsampling, we consider this domain-focused construction more realistic. Table 2 shows relevant statistics for all datasets.

While VG and WebNLG have similar statistics overall, VG is around 200 times larger than WebNLG, which makes it a very interesting benchmark for future research, both supervised and unsupervised. Apart from size, there are only two important differences: (1) The VG graph schema has been freely defined by crowd workers and thus features a very large variety of different relations. (2) The average percentage of graph tokens that can be found in the text, a measure important for the text→graph task, is lower for VG than for WebNLG. This suggests that, on average, VG graphs contain more details than their corresponding texts, which is a characteristic feature of the domain of image captions: they mainly describe salient parts of images.

5.2 Training details

We train our models using the Adam optimizer (Kingma and Ba, 2015) with a learning rate of 10^{-4}, word embeddings of size 300, an LSTM hidden size of 250, a dropout rate of 0.2 and a batch size of 10. Following Lample et al. (2018b), we set $p_{\text{blank}} = p_{\text{repeat}} = 0.2$, $p_{\text{drop}} = 0.1$ (cf. Table 1). For inference, we decode greedily with a maximum number of 40 decoding steps. We use these same settings for all experiments.

We train all models for a maximum number of 30 epochs. We apply early stopping to supervised models with a patience of 10 epochs. Unsupervised models on VG are stopped after 5 iterations because of its big size and limited computational resources. We train with homogeneous batches of one target output type (text or graph) at a time. In the unsupervised setting, we use the same graphs and texts as in the supervised setting, but we ignore the gold target sides. This makes supervised and unsupervised training more directly comparable. Our implementation is based on AllenNLP (Gardner et al., 2017).

6 Results and Discussion

6.1 Text generation from graphs

Model selection. Table 4 shows how the performance of our unsupervised model changes at every backtranslation iteration, measured in BLEU (Papineni et al., 2002), a common evaluation metrics for natural language generation. For model selection, we adopt the two methods proposed by Lample et al. (2018b), i.e., a small validation set (we take a 100-sized random subset of val, called $\mathcal{V}_{100}$) and a fully unsupervised criterion ($\mathcal{U}$) where BLEU compares an unlabeled sample with its back-and-forth translation. We confirm their finding that $\mathcal{U}$ is not reliable for neural text generation models whereas $\mathcal{V}_{100}$ correlates better with performance on the larger test sets. We therefore use $\mathcal{V}_{100}$ for model selection in the rest of this paper.

Quantitative observations. Table 3 compares the best unsupervised models with our rule baseline Graph2text-rule, which is in many cases, i.e., if

graph → text	Visual Genome						WebNLG					
	BLEU		METEOR		CHRF++		BLEU		METEOR		CHRF++	
	val	test	val	test	val	test	val	test	val	test	val	test
Graph2text-rule	5.9	5.9	28.2	28.1	43.4	43.3	18.3	18.3	33.5	33.6	55.0	55.2
Ours w/ sampled noise	19.8	19.5	31.4	31.2	50.9	50.7	**39.1**	**37.7**	**35.4**	**35.5**	**61.9**	**62.1**
Ours w/ composed noise	**23.2**	**23.2**	**33.0**	**32.9**	**53.7**	**53.6**	30.8	30.5	30.2	30.0	53.1	52.8
Ours *supervised*	26.5	26.4	32.3	32.2	53.7	53.6	35.1	34.4	39.6	39.5	64.1	64.0

Table 3: Detailed analysis of unsupervised text generation models and our model trained with supervision. Note that training a supervised model on millions of labeled samples is usually not an option. Best unsupervised models are identified by best BLEU on $\mathcal{V}_{100}$. BLEU and METEOR are computed with scripts from (Lin et al., 2018).

#	sampled noise				composed noise			
	$\mathcal{U}$	$\mathcal{V}_{100}$	val	test	$\mathcal{U}$	$\mathcal{V}_{100}$	val	test
1	**80.4**	7.8	10.1	9.9	**72.2**	15.9	19.8	19.7
2	50.7	7.2	9.2	9.1	41.2	14.0	15.2	15.1
3	67.6	19.5	19.4	19.2	61.0	22.7	**23.5**	**23.4**
4	56.4	**21.2**	**19.8**	**19.5**	51.9	22.2	21.4	21.3
5	62.9	20.0	19.6	19.4	60.5	**24.5**	23.2	23.2

Table 4: BLEU scores on VG for our unsupervised models evaluated for graph→text at different iterations. $\mathcal{U}$ is calculated on all unlabeled data used for training. $\mathcal{V}_{100}$ is a 100-size random sample from val. All results are computed with scripts from (Lin et al., 2018).

#	sampled noise				composed noise			
	$\mathcal{U}$	$\mathcal{V}_{100}$	val	test	$\mathcal{U}$	$\mathcal{V}_{100}$	val	test
1	19.1	1.0	1.2	1.2	17.0	2.0	2.2	2.2
2	**71.0**	**21.7**	**19.1**	**18.8**	49.3	**22.1**	**22.1**	**21.7**
3	58.2	19.3	18.6	18.3	45.9	18.7	19.7	19.4
4	62.3	18.3	**19.1**	**18.8**	**54.4**	19.9	20.8	20.5
5	63.7	19.8	19.0	18.7	49.0	18.8	19.0	18.8

Table 5: F1 scores on VG for our models from Table 4 evaluated on text→graph at different iterations.

parallel graph-text data are scarce, the only alternative. For this final evaluation, we also measure METEOR (Banerjee and Lavie, 2005) and CHRF++ (Popović, 2017). First, it is interesting to see that Graph2text-rule performs much better on WebNLG, indicating that our new benchmark poses a tougher challenge. Second, we observe that our unsupervised models consistently outperform this baseline on all metrics and on both datasets, showing that our method produces textual descriptions that are much closer to human-generated ones and therefore easier to read and interpret.

Interestingly, noise composition, the general default in unsupervised machine translation, does not always perform better than noise sampling. So it can be worthwhile to try different noise settings for new tasks or datasets.

To our surprise, the performance gap between unsupervised and supervised models is very small. Real supervision does not seem to give much better guidance in training than our unsupervised regime, as measured by our three metrics on two different datasets. It is remarkable that some metric-dataset combinations even favor one of the unsupervised models. As different metrics measure different aspects of generated text, this suggests that unsupervised training results in qualitatively different generations than supervised training.

Qualitative observations. Taking a look at example generation (Fig. 2), we also see qualitatively how much easier it is to grasp the content of our natural language summarization than reading through a simple enumeration of KG facts. We find that the unsupervised model (c) seems to output the KG information in a more complete manner than its supervised counterpart (d). The supervision probably introduces a bias present in the training data that textual descriptions of images tend to focus on the salient part of an image and therefore the supervised model is encouraged to omit information. As it never sees a corresponding text-graph pair together, the unsupervised model cannot draw such a conclusion.

6.2 Graph extraction from texts

We evaluate knowledge extraction (text→graph) performance by computing the micro-averaged F1 score of extracted facts. In the presence of multiple reference graphs, an extracted fact is considered correct if it occurs in at least one reference graph. For the ground truth number of facts that should be extracted from a given text, we take the maximum number of facts in its reference graphs.

Model selection. Table 5 shows that – compared to text generation quality – $\mathcal{U}$ is a more reliable

text → graph	VG		WebNLG	
	val	test	val	test
Text2graph-rule	13.4	13.1	0.0	0.0
Stanford SG Parser	19.5	19.3	0.0	0.0
Ours w/ sampled noise	19.1	18.8	**38.5**	**39.1**
Ours w/ composed noise	**22.1**	**21.7**	32.5	33.1
Ours *supervised*	23.5	23.0	52.8	52.8

Table 6: F1 scores of facts extracted by the best unsupervised semantic parsing (text→graph) systems and our model trained with supervision.

indicator for text→graph performance. For sampled noise, it correctly identifies the best iteration, whereas for composed noise it chooses second best. In both noise settings, $\mathcal{V}_{100}$ perfectly identifies the best model.

Quantitative observations. Table 6 shows a comparison of our best unsupervised models with our rule-based Text2Graph-rule, the highly domain-specific rule-based Stanford Scene Graph Parser (Schuster et al., 2015), and our model trained in the supervised setting. While the Stanford Scene Graph Parser was not optimized to match the scene graphs from VG, its rules were still engineered to cover typical idiosyncrasies encountered in textual image descriptions and corresponding scene graphs. Furthermore it consistently uses lemmata as predicates. So we evaluate it with lemmatized reference graphs. All this gives it a major advantage over the other presented systems.

It is nevertheless outperformed by our best unsupervised model – even on VG. This shows that our method has a potential use as an unsupervised semantic parsing system that performs on par with hand-crafted domain-specific rules.

Its biggest advantage, however, is revealed when we compare results on WebNLG. Text2graph-rule picks single tokens from the text as subject, predicate and object of its extracted facts. This never matches any WebNLG fact completely either because entities and relations consist of multiple tokens or because they are not mentioned verbatim in the text. The highly domain-adapted Stanford Parser probably fails for similar reasons. Although our system uses Text2graph-rule during training and was similarly not adapted from one dataset to the other, it performs significantly better.

Supervised training boosts performance more on WebNLG than on VG. We hypothesize that this is due to the handicap of Text2graph-rule's worse performance on WebNLG.

Input sentence	Man wearing a colorful shirt and white pants playing tennis
Reference (RG)	(shirt, `attr`, colorful) (pants, `attr`, white) (man, wearing, shirt) (man, wearing, pants)
Text2graph-rule	(Man, wearing, colorful) (shirt, `attr`, colorful) (pants, `attr`, white) (pants, playing, tennis)
Stanford Scene Graph Parser	(shirt, play, tennis), (pants, play, tennis), (shirt, `attr`, colorful), (pants, `attr`, white)
Unsuperv. model w/ composed noise	(pants, `attr`, colorful) (pants, `attr`, white) (man, wearing, shirt) (man, playing, tennis)
Superv. model	(shirt, `attr`, colorful) (pants, `attr`, white) (Man, wearing, shirt) (Man, wearing, pants)

Table 7: Example fact extractions and evaluation wrt reference graph (RG). Green: correct ($\in$ RG). Yellow: acceptable fact, but $\notin$ RG. Red: incorrect ($\notin$ RG).

Qualitative observations. Table 7 shows example facts extracted by different systems. The rule-based systems are both fooled by the proximity of the noun *pants* and the verb *play*, whereas our system correctly identifies *man* as the subject. For some reason, however, it fails to identify shirt as an object and instead associates the two attributes *colorful* and *white* to *pants*. Only the supervised system produces perfect output.

7 Noise Ablation Study

As the types of noise injection define our unsupervised objectives and thus are critical for our unsupervised training regime, we examine their impact in a noise ablation study. Table 8 shows results for text→graph and graph→text on the validation splits of VG_{ball} and WebNLG.

First, we notice that – irrespective of the dataset or task – introducing variation via noise functions is crucial for the success of unsupervised learning. The model without noise (i.e., $C(x) = x$) fails completely as do all models lacking `rule` as type

	VG_{ball}		WebNLG	
	g→t BLEU	t→g F1	g→t BLEU	t→g F1
No noise	0.9	0.0	14.8	0.0
sample all noise funs	**19.9**	17.3	**39.1**	**38.5**
compose all noise funs	19.6	**19.0**	30.8	32.5
use only `rule`	**19.5**	**18.5**	37.4	**31.0**
use only `swap`	0.9	0.0	13.1	0.0
use only `drop`	0.9	0.0	**39.9**	30.1
use only `blank`	0.9	0.0	14.9	0.0
use only `repeat`	1.1	0.0	15.7	0.0
sample all but `rule`	0.9	0.0	14.9	0.0
sample all but `swap`	19.2	17.0	39.6	**37.3**
sample all but `drop`	19.5	16.0	39.2	35.3
sample all but `blank`	19.9	**17.5**	**41.0**	37.0
sample all but `repeat`	**20.4**	16.6	36.7	37.1
comp. all but `rule`	0.9	0.0	13.5	0.0
comp. all but `swap`	20.2	16.3	35.9	40.8
comp. all but `drop`	21.5	18.6	36.4	41.1
comp. all but `blank`	20.2	16.3	34.8	40.4
comp. all but `repeat`	**21.1**	**20.1**	**38.5**	**42.3**

Table 8: Ablation study of our models on val of VG_{ball} and WebNLG v2.1. Models selected based on $\mathcal{V}_{100}$. Bold: best performance per column and block. Underlined: worse than corresponding rule-based system.

of noise, the only exception being the only-`drop` system on WebNLG. Even though `drop` seems to work equally well in this one case, the simple translations delivered by our rule-based systems clearly provide the most useful information for the unsupervised models – notably in combination with other noise functions: removing `rule` and keeping all other types of noise (cf. "sample all but `rule`" and "comp. all but `rule`") performs much worse than leaving out `drop`.

It is also noteworthy that the unsupervised training regime manages to improve on the rule-based systems even when `rule` is the only type of noise: graph→text performance increases from BLEU 6.2/18.3 to 19.5/37.4 on VG/WebNLG and text→graph F1 from 14.4/0.0 to 18.5/31.0.

Finally, our ablation study makes clear that there is no best noise model for all datasets and tasks. We therefore recommend experimenting with both different sets of noise functions and noise injection regimes (sampled vs. composed) to best match the desired target data distribution.

8 Conclusion

We presented the first fully unsupervised approach to text generation from knowledge graphs and a flexible approach to unsupervised semantic parsing that automatically adapts to a target KG schema. We showed the effectiveness of our approach on two datasets, the newest version (v2.1) of WebNLG and a new text↔graph benchmark in the domain of scene graphs, which we derived from Visual Genome. We provided both quantitative and qualitative analysis of our method's performance on text↔graph conversion and explored the impact of different unsupervised objectives in an ablation study. Based on said study, we find that our newly introduced unsupervised objective using rule-based translations is essential for the success of unsupervised learning.

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