

# Toward Unsupervised Text Content Manipulation

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## Abstract

Controlled generation of text is of high practical use. Recent efforts have made impressive progress in generating or editing sentences with given textual attributes (e.g., sentiment). This work studies a new practical setting of *text content manipulation*. Given a structured record, such as (*PLAYER: LeBron, POINTS: 20, ASSISTS: 10*), and a reference sentence, such as *Kobe easily dropped 30 points*, we aim to generate a sentence that *accurately* describes the full content in the record, with the *same* writing style (e.g., wording, transitions) of the reference. The problem is unsupervised due to lack of parallel data in practice, and is challenging to minimally yet effectively manipulate the text (by rewriting/adding/deleting text portions) to ensure fidelity to the structured content. We derive a dataset from a basketball game report corpus as our testbed, and develop a neural method with unsupervised competing objectives and explicit content coverage constraints. Automatic and human evaluations show superiority of our approach over competitive methods including a strong rule-based baseline and prior approaches designed for style transfer.

## 1 Introduction

Generating natural language text to describe structured content, such as a database record or a table, is of ubiquitous use in real-life applications including data report generation (Wiseman et al., 2017), article writing (Lebret et al., 2016; Kiddon et al., 2016), dialog systems (Wen et al., 2015; Yang et al., 2016), and many others. Recent efforts have developed many techniques to improve *fidelity* to the source content, such as new powerful neural architectures (Gu et al., 2016; See et al., 2017), hybrid generation and retrieval (Hashimoto et al., 2018; Weston et al., 2018), and so forth, most of which are applied in supervised context.

Language is rich with variation—given a data record, there are diverse possible ways of saying the same content<sup>1</sup>, with different word choices, expressions, transitions, tone, etc<sup>2</sup>. Previous data-to-text work has largely focused only on content fidelity, while ignoring and lacking control over the rich stylistic properties of language. It can be practically useful to generate text that is not only describing the conditioning content, but also following a designated writing style, e.g., as provided in a piece of reference text.

In this work, we study the new yet practical problem in which we aim to express given content with a sentence and mimic the writing style of a reference sentence (Table 1). More specifically, we are given a structured data record containing the content to describe, along with a sentence about a similar but different matter. Our goal is to generate a new sentence that precisely depicts all content in the record, while at the same time using as much of the writing style of reference sentence as possible. As above, the problem differs critically from the supervised data-to-text (Wiseman et al., 2017) or retrieval-and-rewriting work (Hashimoto et al., 2018; Weston et al., 2018) as we have imposed an additional goal of preserving the reference text style. The resulting problem is typically *unsupervised* due to lack of parallel data.

<sup>1</sup>[https://en.wikipedia.org/wiki/Variation\\_\(linguistics\)](https://en.wikipedia.org/wiki/Variation_(linguistics))

<sup>2</sup>We refer to these characteristics that are independent of the desired content as *writing style*.

Content Record	<b>PLAYER</b> LeBron_James	<b>PT</b> 32	<b>RB</b> 4	<b>AS</b> 7	<b>PLAYER</b> Kyrie_Irving	<b>PT</b> 20
Reference Sentence	Jrue_Holiday led the way with 26 points and 6 assists , while Goran_Dragic scored 23 points and pulled down 8 rebounds .					
Desired Output	LeBron_James led the way with 32 points , 7 assists and 4 rebounds , while Kyrie_Irving scored 20 points .					

**Table 1:** An example input (content record and reference sentence) of text content manipulation and its desired output. Text portions that fulfill the writing style are highlight in blue.

The problem also differs in important ways from the emerging task of *text style transfer* (Hu et al., 2017; Shen et al., 2017) which assumes an existing sentence of certain content, and modifies single or multiple textual attributes of the sentence (e.g., transferring negative sentiment to positive) without changing the content. Our task, on the contrary, assumes abstract style is encoded in a reference sentence and attempts to modify its concrete content to express new information from the structured record. The different setting can lead to different application scenarios in practice, and pose unique technical challenges. In particular, though the most recent style transfer research (Subramanian et al., 2019; Logeswaran et al., 2018) has controlled multiple categorical attributes which are largely independent or loosely correlated to each other, a content record in our task, in comparison, can contain *varying* number of entries which are of different types (e.g., player, points, defensive/offensive rebounds, etc), having many possible values (e.g., hundreds of players), and are structurally coupled (e.g., 32 points by LeBron). A model must understand the content structure, and minimally yet sufficiently manipulate the reference sentence by rewriting, adding, or deleting text portions, with necessary polishing for grammatical correctness and fluency. We name the problem *text content manipulation*. Our empirical studies show the most recent models designed for style transfer fail to perform well in the task.

In this paper, we first develop a large unsupervised dataset as a testbed of the new task. The dataset is derived from an NBA game report corpus (Wiseman et al., 2017). In each data instance, besides a content record and a reference sentence as the problem inputs, we also collect side information useful for unsupervised learning. Specifically, each instance has an auxiliary sentence that was originally written by human reporters to describe the content record without seeing (and thus stylistically irrelevant to) the reference sentence. We also provide the structured record of the reference sentence. The side information can provide valuable clues for models to understand the content structure and text semantics at training time. We do not rely on the side information at test time.

We then propose a neural method to tackle the problem. With a hybrid attention and copy mechanism, the model effectively encodes the reference and faithfully copies content from the record. The model is learned with two competing objectives of reconstructing the auxiliary sentence (for content fidelity) and the reference sentence (for style preservation). We further improve the model with an explicit content coverage constraint which encourages to precisely and fully convey the structured content.

For empirical study, we devise automatic metrics to measure content fidelity and style preservation, respectively. We also perform human evaluations to compare different approaches. Results demonstrate the proposed method significantly improves over others, including a strong rule-based baseline and the recent style transfer models.

## 2 Related Work

Generating text conditioning on structured input has been widely studied in recent work, such as (Wen et al., 2015; Lebre et al., 2016; Yang et al., 2016; Wiseman et al., 2017). Those methods are based on neural sequence to sequence models and trained with supervised data. This line of work has focused primarily on generating more accurate description of the given data, while does not study the problem of controlling the writing style of outputs. Our task takes a step forward to *simultaneously* describing desired content and controlling stylistic properties. Furthermore, our task

is challenging due to its unsupervised setting in practice.

Beyond generating text from scratch, there is another line of work that first retrieves a similar sentence and then rewrites it to express desired information (Weston et al., 2018; Hashimoto et al., 2018; Li et al., 2018; Guu et al., 2018). For example, Weston et al. (2018) used the framework to generate response in dialogues, while Hashimoto et al. (2018) studied programming code generation. The goal of the work is to manifest useful information from neighbors, usually in a supervised context, without aiming at controlling writing characteristics, and thus has fundamentally different assumptions to ours.

Recently, there has been growing interest in text style transfer, in which many techniques for controlled text generation are developed (Hu et al., 2017; Shen et al., 2017; Yang et al., 2018; Prabhunoye et al., 2018; Tian et al., 2018; Subramanian et al., 2019; Logeswaran et al., 2018). The main idea underlying those models is to learn disentangled representations of text so as to modify textual attributes or style of interest. Those papers used different objectives to encourage learning disentangled representations. Hu et al. (2017) used pre-trained classifiers as the supervision. Shen et al. (2017) used a GAN-based approach in which binary classifiers were used as discriminators. Yang et al. (2018) proposed to use more structured discriminators such as language models to provide better supervision to the generator. Prabhunoye et al. (2018); Subramanian et al. (2019) further augmented prior work using back-translation technique to incorporate cycle-consistency loss. Both (Subramanian et al., 2019) and (Logeswaran et al., 2018) generalized the task to controlling multiple categorical attributes at the same time. Our work differs from those in that we assume an existing sentence to provide the source of style and a structured record as the source of content. The input content record in our task is also more structured than the style attributes which are typically loosely connected and of a pre-fixed number. The resulting content manipulation setting poses unique challenges in controlling, as discussed more in the empirical study.

### 3 Task and Dataset

We first formally define the problem of unsupervised text content manipulation, and establish the notations. We then present a large dataset for the task.

#### 3.1 Task Definition

Without loss of generality, consider a content record  $\mathbf{x} = \{\mathbf{x}_i\}_{i=1}^{L_x}$ , where each element  $\mathbf{x}_i$  is a data tuple which typically includes a data type (e.g., points), a value (e.g., 32), and other information (such as the associated player, e.g., *Lebron\_James*).  $L_x$  is the number of tuples in record  $\mathbf{x}$ , which can vary across different records. We are also given a reference sentence  $\mathbf{y}'$  which is assumed to describe content that has a similar but not exact the same structure with that of the record  $\mathbf{x}$ . For example, in Table 1, both the content record and the reference sentence involve two players, respectively, but the number of associated data tuples as well as the types are different (e.g., *Lebron\_James* in the record has 3 box-score entries, while *Jrue\_Holiday* in the reference has only 2).

We may also have access to other side information at training time. For example, in the dataset developed below, each content record  $\mathbf{x}$  is associated with an auxiliary sentence  $\mathbf{y}_{\text{aux}}$  that was originally written to describe  $\mathbf{x}$  without following the reference  $\mathbf{y}'$ . Each reference sentence  $\mathbf{y}'$  also has its corresponding record  $\mathbf{x}'$  containing the content information. The side information can provide valuable clues for models to understand the content structure and text semantics at training time. For example, the auxiliary sentence provides a hint on how the desired content can be presented in natural language, though it is stylistically irrelevant to the reference sentence. Note that, at test time, a solution to the task should only rely on the inputs  $(\mathbf{x}, \mathbf{y}')$  without using the side information.

The goal of the task is to generate a new realistic sentence  $\hat{\mathbf{y}}$  that achieves **(1) content fidelity** by accurately describing the full content in  $\mathbf{x}$ , and at the same time **(2) style preservation** by retaining as much of the writing style and characteristics of reference  $\mathbf{y}'$  as possible. The task is unsupervised as there is no ground-truth sentence for training.

	Train	Dev	Test
#Instances	31,751	6,833	6,999
#Tokens	1.64M	0.35M	0.36M
Avg Sentence Length	25.90	25.87	25.99
#Data Types	34	34	34
Avg Record Length	4.88	4.88	4.94

**Table 2:** Data Statistics.

### 3.2 Dataset

We now present a dataset developed for the task. Our dataset is derived from a recent large table-to-document corpus (Wiseman et al., 2017) which consists of box-score tables of NBA basketball games and associated documents as game reports. The corpus is originally used for studying supervised game report generation which has attracted increasing research interest (Nie et al., 2018; Wiseman et al., 2017).

To obtain our data, we first split each game report into individual sentences, and, for each sentence, find its corresponding data in the box-score table as the content record. A record can contain a varying number of tuples, with each tuple containing three fields, namely a data type, a value, and an associated player or team, e.g., (*team\_points*, *106*, *Lakers*). As the original corpus is already largely clean, we found some simple rules are sufficient to obtain high-quality results in this step. Please see the supplementary materials for more details. Each of the resulting record-sentence pairs is treated as a pair of  $(\mathbf{x}, \mathbf{y}_{\text{aux}})$ , namely (content record, auxiliary sentence). The next step is to find a suitable reference sentence  $\mathbf{y}'$  for each content record  $\mathbf{x}$ . As defined above, the reference sentence should cover similar but not the same content as in record  $\mathbf{x}$ . We achieve this by retrieving from the data another record-sentence pair using  $\mathbf{x}$ , where the retrieved record is designated to have a slightly different structure than that of  $\mathbf{x}$  by having less or more tuples and different data types. More details of the retrieval method are deferred to supplements. The retrieved record-sentence pair thus plays the role of  $(\mathbf{x}', \mathbf{y}')$  and is paired with  $(\mathbf{x}, \mathbf{y}_{\text{aux}})$  to form an instance.

Table 2 summarizes the statistics of the final dataset. The vocabulary size is 8.4K. We can see that the training set contains over 31K instances. Each content record contains around 5 tuples, each of which takes one of the 34 data types.

## 4 Model

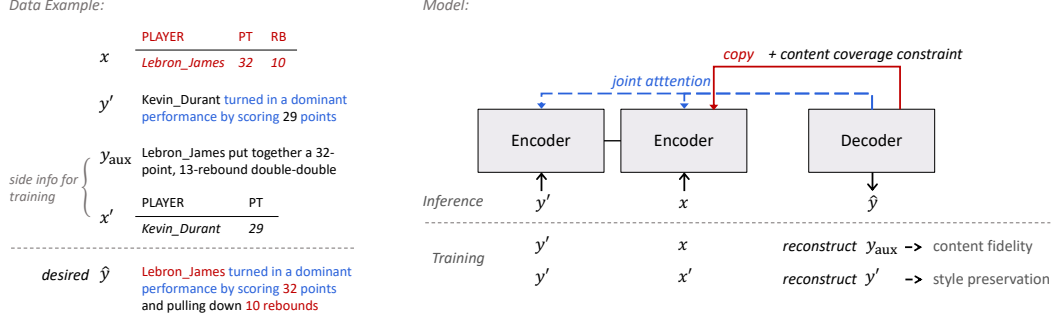
We next develop methods to tackle the problem. As shown in the empirical study (section 5), a simple rule-based method that matches  $\mathbf{x}$  with  $(\mathbf{x}', \mathbf{y}')$  and performs text replacement would fail in terms of content fidelity due to the different structures between  $\mathbf{x}$  and  $\mathbf{x}'$ . Previous approaches for (multi-attribute) style transfer do not apply well either, because of the different underlying task assumptions and the rich content structures of records with varying lengths.

In the following, we present a new neural approach that addresses the challenges of text content manipulation. We first describe the model architecture, then develop unsupervised learning objectives, and finally add a content coverage constraint to improve learning. Figure 1 provides an illustration of the proposed approach.

Let  $p_{\theta}(\hat{\mathbf{y}}|\mathbf{x}, \mathbf{y}')$  denote the model that takes in a record  $\mathbf{x}$  and a reference sentence  $\mathbf{y}'$ , and generates an output sentence  $\hat{\mathbf{y}}$ . Here  $\theta$  is the model parameter.

### Hybrid Attention-Copy Mechanism

As shown in the figure, the architecture of our neural model consists of two encoders and one decoder. The first encoder is used to extract representation of the reference sentence  $\mathbf{y}'$ . The second encoder is applied to content records. Specifically, for each data tuple in a record, we first concatenate the embedding vectors of all fields in the tuple, and feed the combined embedding to the encoder. There is no need to specify a particular order of the tuples as their fields have specified the associated player or team.



**Figure 1:** A (simplified) data example (left) and the model overview (right).

The decoder is to generate the output sentence, with a hybrid attention-copy mechanism at each decoding step. In particular, the decoder applies a joint attention (Luong et al., 2015) over both  $y'$  and  $x$ , and applies a copy mechanism (Gu et al., 2016) only on the record  $x$ . More specifically, at each step  $t$ , the decoder first attends jointly to the hidden states of both encoders and obtains a decoding hidden state  $h_t$ . The decoder then computes the output distribution over words with

$$p_{out}^{(t)} = g_t \cdot p_V^{(t)} + (1 - g_t) \cdot p_x^{(t)}, \quad (1)$$

where  $g_t$  is the probability of generating a token from the vocabulary;  $p_V^{(t)}$  is the generation distribution over the whole vocabulary; while  $p_x^{(t)}$  is the copy distribution over the data values in the content record. All the quantities are computed based on the post-attention hidden state  $h_t$ .

Note that we have allowed copying only from the content record but not the reference sentence  $y'$ , since we found empirically that, with a copy path from  $y'$ , the model trained with the objectives below tends to quickly collapse to directly copying the whole reference sentence. The attention layer serves as a more moderate way for the decoder to access and truly ingest the information of the reference sentence. Besides, intuitively, the attention layer helps with the generation-copy decision, as a high attention on the content record part tends to turn down  $g_t$  and promote copying from the record. Finally, the copy mechanism over content record enables us to devise an explicit coverage constraint, as detailed shortly.

### Competing Learning Objectives

As defined in section 3.1, the task has two simultaneous goals, namely data fidelity and style preservation. The two goals are in a sense competitive with each other (e.g., describing the new designated content would usually change the expressions in reference sentence to some extent). We base our unsupervised learning on this competitive relation.

We make use of the side information  $(y_{aux}, x')$  during training. Specifically, as the auxiliary sentence  $y_{aux}$  was originally written by human to describe the content  $x$  and thus can be seen to have the maximum data fidelity, we devise the first objective that reconstructs  $y_{aux}$  given  $(x, y')$ :

$$\mathcal{L}_{content}(\theta) = \log p_{\theta}(y_{aux}|x, y'). \quad (2)$$

We call it the content fidelity objective.

To fulfill the second goal of preserving the style of reference  $y'$ , we want to encourage the model to generate sentences in a similar form of  $y'$ . We further notice that, if we feed the model with the reference sentence  $y'$  and its corresponding record  $x'$  (instead of  $x$ ), the ground truth output of the case is indeed  $y'$  itself (as  $y'$  describes content  $x'$ , and is of course in the same style of itself). We thus can specify the second objective that reconstructs  $y'$  given  $(x', y')$ :

$$\mathcal{L}_{style}(\theta) = \log p_{\theta}(y'|x', y'). \quad (3)$$

We call it the style preservation objective. The objective essentially treats the reference sentence encoder and the decoder together as an auto-encoding module, and effectively drives the model to absorb the characteristics of reference sentence and apply to the generated one.

The above two objectives are coupled together and train the model to achieve the desired goals:

$$\mathcal{L}_{joint}(\theta) = \lambda \mathcal{L}_{content}(\theta) + (1 - \lambda) \mathcal{L}_{style}(\theta), \quad (4)$$

where  $\lambda$  is the balancing parameter.

### Content Coverage Constraint

As shown in the empirical study (section 5), the above learning can yield reasonably good performance, but sometimes can still fall short of accurately expressing the desired content. We thus devise an additional learning constraint based on the nature of content description—each data tuple in the content record should usually be mentioned *exactly once* in the generated sentence.

The copy mechanism over content record  $\mathbf{x}$  enables a simple yet effective way to encourage the behavior. Intuitively, we want each tuple to be copied once and only once on average. We thus minimize the following L2 constraint that drives the aggregated copy probability of each data tuple to be 1:

$$\mathcal{C}(\theta) = \left\| \sum_t \mathbf{p}_{\mathbf{x}}^{(t)} - \mathbf{1} \right\|^2, \quad (5)$$

where  $\mathbf{p}_{\mathbf{x}}^{(t)}$ , as defined in Eq.(1), denotes the copy distribution over all data tuples at decoding step  $t$ ; and  $\mathbf{1}$  is a vector with all ones. It is still possible that tokens of the content values “leak” from the generation distribution  $\mathbf{p}_V^{(t)}$  in Eq.(1). We disable the leakage by masking out relevant words (particularly numbers) for each instance from the vocabulary.

We note that prior work in other context, especially machine translation, has also explored the idea of *coverage* through either architecture augmentation (Tu et al., 2016) or inference penalty (Wu et al., 2016). We tried these techniques but did not obtain noticeable improvement. As shown in the experiments, the proposed explicit coverage constraint over copy mechanism leads to significant performance gains.

The full training objective of the proposed model with the constraint is thus written as:

$$\mathcal{L}(\theta) = \mathcal{L}_{joint}(\theta) - \eta \cdot \mathcal{C}(\theta), \quad (6)$$

where  $\eta$  is the weight of the constraint.

## 5 Experiments

We conduct both automatic and human evaluations to assess the model performance. For automatic evaluation, we use two metrics to measure content fidelity and style preservation, respectively. Results show our model balances well between the two goals, and outperforms a variety of comparison methods. All code will be released soon.

### 5.1 Experimental Setup

#### Comparison Approaches

We compare with a diverse set of approaches:

- **AttnCopy-S2S.** We first evaluate a base sequence-to-sequence (Sutskever et al., 2014) model with the above attention-copy mechanism, which takes in record  $\mathbf{x}$  and generates its descriptive sentence  $\mathbf{y}_{aux}$ . The evaluation provides a sense of the difficulty in describing desired content.
- **Rule-based Method.** A straightforward way for text content manipulation is to match between  $\mathbf{x}$ ,  $\mathbf{x}'$  and  $\mathbf{y}'$  with certain rules, and replace corresponding portions in  $\mathbf{y}'$  with those in  $\mathbf{x}$ . Specifically, we first build a mapping between the tuples of  $\mathbf{x}$  and  $\mathbf{x}'$  through their data types, and a mapping between  $\mathbf{x}'$  and  $\mathbf{y}'$  through data values, types and indicative tokens (e.g., “12 points” in  $\mathbf{y}'$  indicates 12 is of type player points or team\_points). The two mappings connect  $\mathbf{x}$  and  $\mathbf{y}'$ , enabling us to swap appropriate text in  $\mathbf{y}'$  to express content  $\mathbf{x}$ .

In theory, rule-based method sets the best possible style preservation performance, as it only replaces content related tokens (particularly numbers) without modifying other parts of the reference sentence. The output, however, tends to miss or contain extra content compared to the content record of interest.

- **Multi-Attribute Style Transfer (MAST)** (Subramanian et al., 2019). We compare with the most recent style transfer approach that models multiple attributes. To apply to our setting, we treat content record  $\mathbf{x}$  as the attributes. The method is based on back-translation (Sennrich et al., 2015)



that first generates a target sentence  $\hat{y}$  conditioning on  $(x, y')$ , and then treat it as the reference to reconstruct  $y'$  conditioning on  $(x', \hat{y})$ . Auxiliary sentence  $y_{aux}$  is used in an extra auto-encoding loss.

- **Adversarial Style Transfer (AdvST)** (Logeswaran et al., 2018). As another latest style transfer approach capable of handling more than one attributes, the model also mixes back-translation with auto-encoding as the above method, and additionally uses adversarial training to disentangle content and style representations.
- **Ours w/o Coverage.** For ablation study, we compare with a model variant that omits the content coverage constraint. That is, the model is trained by maximizing only Eq.(4).

### Model Configurations

We use single-layer LSTM RNNs in all encoders and decoders, and use the Luong attention (Luong et al., 2015). Both the embedding dimensions and hidden dimensions are set to 384. During training, we first set  $(\lambda = 0, \eta = 0)$  and pre-train the model to convergence so that the model captures the full characteristics of the reference sentence. We then set  $(\lambda = 0.2, \eta = 1.0)$  for full training. We apply Adam optimization (Kingma and Ba, 2014) with an initial learning rate of 0.001 and gradient norm clipping of 15. For inference we use beam search with beam-width 5. The maximum decoding length is set to 50.

## 5.2 Automatic Evaluation

As no ground truth annotations are available, we first set up automatic metrics for quantitatively measuring the key aspects of model performance.

### Metrics

We use separate metrics to evaluate in terms of the two primary goals of the task, namely content fidelity and style preservation, respectively. A desired solution should balance and excel on both metrics.

- **Content fidelity.** Following the table-to-document task (Wiseman et al., 2017) where our dataset is derived from, we use an information extraction (IE) approach to measure content fidelity. That is, given a generated sentence  $\hat{y}$  and the conditioning content record  $x$ , we extract data tuples from  $\hat{y}$  with an IE tool, and compute the precision and recall against  $x$ . We use the IE model provided in (Wiseman et al., 2017) and re-train with  $(x, y_{aux})$  pairs in our dataset. The IE model achieves around 87% precision and 76% recall on the test set, which is comparable to the one used in (Wiseman et al., 2017).
- **Style preservation.** A generated sentence is desired to retain stylistic properties, such as word choice and expressions, of the input reference sentence. Inspired by the text style transfer literature (Yang et al., 2018; Subramanian et al., 2019), we measure the BLEU score between generated and reference sentences. To reduce the influence of new content, we first mask in both sentences all obvious content tokens, including player/team names and numbers, by replacing them with a special token  $\langle M \rangle$ , and then compute the BLEU score. In this way, the above rule-based method has a maximum BLEU score of 100, which is consistent with our intuition above.

## Results

We now compare the performance of different methods in terms of the above metrics. Table 3 shows the results.

The first block shows the two baseline models providing reference performance. The AttnCopy-S2S model only concerns about content fidelity, and achieves a high content precision score (but a low recall). However, its style BLEU is particularly low, which verifies the rich variation in language and that direct supervised learning is incapable of controlling the variation. We can see that the rule-based method achieves reasonably good precision and recall, setting a strong baseline for content fidelity. As discussed above, the rule-based method can reach the maximum BLEU (100) after masking out content tokens. To improve over the strong rule-based baseline, we would expect a method that provides significantly higher precision/recall, while keeping a high BLEU score. The two style transfer methods (MAST and AdvST) fail the expectation, as their content fidelity performance is greatly inferior or merely comparable to the rule-based method. This is

	Model	Content		Style
		Precision%	Recall%	BLEU
1	AttnCopy-S2S	88.71 $\pm$ 2.45	60.64 $\pm$ 1.31	39.15 $\pm$ 5.48
	Rule-based	62.63	63.64	100
2	MAST	33.15 $\pm$ 0.78	31.09 $\pm$ 0.63	<b>95.29<math>\pm</math>2.53</b>
	AdvST	66.51 $\pm$ 1.08	56.03 $\pm$ 0.56	72.22 $\pm$ 1.47
3	Ours w/o Cover.	75.61 $\pm$ 1.03	62.93 $\pm$ 0.53	75.09 $\pm$ 2.17
	Ours	<b>78.31<math>\pm</math>0.94</b>	<b>65.64<math>\pm</math>0.47</b>	80.83 $\pm$ 1.89

**Table 3:** Model Performance under Automatic Evaluation. Results are averaged over 3 runs  $\pm$  one standard deviation. Models in the first block (AttnCopy Seq2seq and Rule-based) represent two baselines for reference performance. We have highlighted the best results in blocks 2 and 3 under different metrics. Our model achieves significant higher content precision and recall compared to both rule-based and style transfer methods, and reaches a high BLEU score in style preservation.

Model	Content Fidelity	Style Preserv.	Fluency
Rule-based	2.79	<b>5.00</b>	<b>4.96</b>
AdvST	2.88	4.00	4.09
Ours w/o Cover.	3.43	4.13	4.59
Ours	<b>3.88</b>	4.53	4.45
	Ours Better	No Prefer.	Ours Worse
Rule-based	<b>67.5%</b>	17.5%	15.0%
AdvST	<b>68.8%</b>	17.5%	13.8%
Ours w/o Cover.	<b>51.3%</b>	32.5%	16.3%

**Table 4:** Human Evaluation Results. **Top:** Humans are asked to score the model outputs in terms of content fidelity, style preservation, and fluency, respectively, from 1 (strongly bad) to 5 (strongly good). As expected, the rule-based method reaches the maximum possible scores in terms of style preservation and fluency, but a much lower score in terms of content fidelity. Our model is more balanced across all aspects, and performs significantly better in accurately describing desired content. **Bottom:** Humans are asked to rank a pair of generated sentences in which one is from our model and the other from the comparison method. Our model wins on more than 50% instances compared to each of other models.

partially because these models are built on a different task assumption (i.e., modifying independent textual attributes) and cannot manipulate content well. In comparison, our proposed model achieves better content precision/recall, substantially improving over other methods (e.g., with a 15-point precision boost in comparison with the rule-based baseline) except for AttnCopy-S2S which has failed in style control. Our method also manages to preserve a high BLEU score of over 80. The superior performance of the full model compared to the variant Ours-w/o-Coverage demonstrates the usefulness of the content coverage constraint (Eq.5). By explicitly encouraging the model to mention each of the data tuples exactly once—a common pattern of human-written descriptions—the model achieves higher content fidelity with less style-preservation ability “sacrificed”.

### 5.3 Human Evaluation

We also carried out human evaluation for a more thorough and accurate comparison. Following the experimental settings in prior work (Subramanian et al., 2019; Logeswaran et al., 2018; Shen et al., 2017), we undertook two types of human studies: (1) We asked human turkers to score generated sentences in three aspects, namely content fidelity, style preservation, and sentence fluency. Each score is from 1 (strongly bad) to 5 (strongly good); (2) We present to annotators a pair of generated sentences, one from our model and the other from a comparison method. We then ask the annotators to rank the two sentences by considering all the criteria. Annotators can also choose “no preference” if the sentences are equally good or bad. For each study, we evaluate on 80 test instances, and



<b>Content x</b>	<b>TEAM</b> Bulls	<b>WINS</b> 29	<b>LOSSES</b> 16	<b>TEAM-PTS</b> 102	<b>TEAM</b> Mavericks	<b>WINS</b> 30	<b>LOSSES</b> 14	<b>TEAM-PTS</b> 98	<b>TEAM</b> Dallas
<b>Reference y'</b>	The Pistons ( 22 - 33 ) held off the Bulls ( 34 - 21 ) 100 - 91 in Detroit on Friday night .								
Rule-based	The <b>Mavericks ( 30 - 14 )</b> held off the <b>Bulls ( 29 - 16 )</b> <b>98 - 102</b> in Dallas on Friday night .								
AdvST	The Bulls ( 29 - 16 ) held off the Mavericks ( 30 - 14 ) <b>100 - 100</b> in Dallas on Friday night .								
Ours w/o Cover.	The Bulls ( 29 - 16 ) held off the <b>Bulls ( 29 - 16 )</b> 102 - 98 in Dallas on Friday night .								
Ours	The Bulls ( 29 - 16 ) held off the Mavericks ( 30 - 14 ) 102 - 98 in Dallas on Friday night .								
<b>Content x</b>	<b>PLAYER</b> Gerald_Henderson	<b>PTS</b> 17	<b>FGM</b> 6	<b>FGA</b> 13	<b>FG3M</b> 1	<b>FG3A</b> 2	<b>FTM</b> 4	<b>FTA</b> 4	<b>AST</b> 5
<b>Reference y'</b>	Kawhi_Leonard also had a solid offensive game , scoring 16 points ( 7 - 13 FG , 0 - 1 3Pt , 2 - 5 FT ) and adding 5 assists and 5 rebounds .								
Rule-based	Gerald_Henderson also had a solid offensive game , scoring 17 points ( 6 - 13 FG , 1 - 2 3Pt , 4 - 4 FT ) and adding 5 assists and 5 rebounds .								
AdvST	Gerald_Henderson also had a solid offensive game , scoring 13 points ( 13 - 13 FG , 2 - 2 3Pt , 4 - 4 FT ) and adding 5 assists and 5 rebounds .								
Ours w/o Cover.	Gerald_Henderson also had a solid offensive game , scoring 17 points ( 6 - 13 FG , 1 - 2 3Pt , 4 - 4 FT ) and adding 5 assists and 5 rebounds .								
Ours	Gerald_Henderson also had a solid offensive game , scoring 17 points ( 6 - 13 FG , 1 - 2 3Pt , 4 - 4 FT ) and adding 5 assists .								
<b>Content x</b>	<b>PLAYER</b> Zach_Randolph	<b>PLAYER</b> Andrew_Harrison	<b>PLAYER</b> Troy_Daniels	<b>PTS</b> 10					
<b>Reference y'</b>	Both J.J. Hickson and Timofey_Mozgov reached double - figures , scoring 10 and 15 points respectively .								
Rule-based	Both Zach_Randolph [...] and Andrew_Harrison reached double - figures , scoring 10 and 10 points respectively .								
AdvST	Both <b>J.J. Hickson [...]</b> and Troy_Daniels reached double - figures , scoring 10 and 15 points respectively								
Ours w/o Cover.	Both Zach_Randolph [...] and Andrew_Harrison reached double - figures , scoring 10 and 10 points respectively								
Ours	<b>Both</b> Zach_Randolph , Troy_Daniels and Andrew_Harrison reached double - figures , scoring 10 and points respectively								

**Table 5:** Example Outputs by Different Models. Text of erroneous content is highlighted in red, where [...] indicates desired content is missing. Text portions in the reference sentences and the generated sentences by our model that fulfill the stylistic characteristics are highlighted in blue. Please see the text for more details.

compare our model with the rule-based method, AdvST style transfer model (which has shown better performance on the task than the other style transfer model MAST), and the model variant without coverage constraint.

Table 4 shows the human evaluation results. From the top block of the table, as expected and discussed above, the rule-based method sets the records of style preservation and fluency scores, as it only conducts lightweight token replacement on reference sentences. However, its content fidelity score is very low. In contrast, our model achieves a reasonably high content score of 3.88, which is much higher than those of other methods. The model is also more balanced across the three criteria, achieving reasonably high scores in both style preservation and language fluency. The fluency of the full model is slightly inferior to the variant without coverage constraint, which is not unexpected since the full model has modified more portions of reference sentence in order to better describe the desired content, which would tend to introduce more language mistakes as well.

The bottom block of Table 4 shows the results of ranking sentence pairs. We can see that our model consistently outperforms the comparison methods with over 50% wins.

<b>Content x</b>	<b>PLAYER</b> <b>FGM</b> <b>FGA</b> <b>FG3M</b> <b>FG3A</b> <b>PTS</b> <b>MIN</b> Johnson   6   9   4   5   16   20
<b>Reference y'</b>	Rudy_Gay led his team , with 16 points ( 6 - 12 FG , 4 - 6 3Pt ) and 7 rebounds , in 27 minutes .
Ours	Johnson led his team , with 9 points ( 6 - 9 FG , 4 - 5 3Pt ) and 16 rebounds , in 20 minutes .
Desired Output	Johnson led his team , with 16 points ( 6 - 9 FG , 4 - 5 3Pt ) in 20 minutes .

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<b>Content x</b>	<b>TEAM</b> <b>TEAM-FG_PCT</b> <b>TEAM-FG3_PCT</b> <b>TEAM-FT_PCT</b> Kings   55   50   88
<b>Reference y'</b>	Portland allowed the Spurs to shoot a scorching 50 percent from the field and 60 percent from beyond the arc .
Ours	The Kings allowed the Kings to shoot a scorching 55 percent from the field and 88 percent from beyond the arc [...].
Desired Output	Kings shot a scorching 55 percent from the field, 50 percent from beyond the arc, and 88 percent from the free throw line .

**Table 6:** Example Erroneous Outputs. Text of erroneous content is highlighted in red. Missing content is denoted with [...]. We also show the desired correct outputs. In the first example, the model was confused by the data types; while in the second example, the model fails to understand there is only one team in the content record x and the number 88 is the free-throw percentage.

## 5.4 Qualitative Study

We take a closer look at the model performance by studying generated sentences from different models.

Table 5 shows example outputs on three test cases given content record x and reference sentence y'. We can see that, in general, the proposed full model can manipulate the reference sentence more accurately to express the new content. For example, in the first case, the rule-based method was confused between the winning and losing teams, due to its incapacity of understanding the semantics of text such as "held off". The style transfer model AdvST failed to comprehend the content record well and generated irrelevant data "100 - 100". The simplified variant without explicit coverage constraint copied the content of Bulls twice. In contrast, the full model successfully generates the desired sentence. Similarly, in the second and third cases, other methods tend to keep irrelevant content originally in the reference sentence (e.g., "and 5 rebounds" in the second case), or miss necessary information in the record (e.g., one of the player names was missed in the third case). The proposed model performs better in properly adding or deleting text portions for accurate content descriptions, though sometimes it can yield sentences of lower language quality (e.g., in the third case).

Table 6 shows some failure cases by the proposed model along with the respective desired outputs. Despite the enhanced performance over other methods, the model can still get confused in presence of complicated content records or non-straightforward correspondence between the semantic structures of content record and reference sentence. It is desirable to further improve the modeling of both content and reference to better understand the underlying semantics and achieve better manipulation results.

## 6 Conclusions

We have proposed a new and practical task of text content manipulation which aims to generate a sentence that describes desired content from a structured record (content fidelity) and meanwhile follows the writing style of a reference sentence (style preservation). To study the unsupervised problem, we derived a new dataset, and developed a method with competing learning objectives and an explicit coverage constraint. For empirical study, we devised two automatic metrics to measure different aspects of model performance. Both automatic and human evaluations showed superiority of the proposed approach.

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