Fact-Enhanced Synthetic News Generation

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Abstract

The advanced text generation methods have witnessed great success in text summarization, language translation, and synthetic news generation. However, these techniques can be abused to generate disinformation and fake news. To better understand the potential threats of synthetic news, we develop a novel generation method FACTGEN to generate high-quality news content. The majority of existing text generation methods either afford limited supplementary information or lose consistency between the input and output which makes the synthetic news less trustworthy. To address these issues, FACTGEN retrieves external facts to enrich the output and reconstructs the input claim from the generated content to improve the consistency among the input and the output. Experiment results on real-world datasets demonstrate that the generated news contents of FACTGEN are consistent and contain rich facts. We also discuss an effective defending technique to identify these synthetic news pieces if FACTGEN was used to generate fake news.

Introduction

With the success of natural language process such as recurrent neural networks (RNNs) (Rumelhart and McClelland 1987) and self-attentive (SA) language models (Vaswani et al. 2017; Radford et al. 2019), there has been a significant performance improvement in text generation applications, like document summarization (Gehrmann, Deng, and Rush 2018), machine translation (Johnson et al. 2016) and synthetic news generation (Leppänen et al. 2017a).

These advanced methods are able to generate readable and realistic text. For example, one can use the generative adversarial network (GAN) (Aghakhani et al. 2018) or sequence-to-sequence (seq2seq) model (Yang et al. 2019b) to generate human-like comments. One recent approach named Grover (Zellers et al. 2019a) aims to generate news pieces based on multiple attributes such as headlines, authors, and website domains, showing some promising early results.

However, these methods can also be abused to generate and amplify disinformation and fake news. For example, the machine generated fake review threaten business reputations and virtual characters sends generated story to spread propaganda. The wide dissemination of synthetic disinformation and fake news will bring new challenges to the news ecosystem. Therefore, it becomes critical to understand synthetic fake news for further achieving accurate detection.

In the real-world scenario, fake news deliberately imitates the writing styles of real news, which makes it hard to be identified by human and computational detection methods (Shu et al. 2020). Both fake and real news usually contain additional facts that are consistent and supplementary to the news claims. For example, in Table 1, the news mainly focuses on framework agreement with Iran, and provide additional facts like the location and time of the agreement. To eventually identify synthetic disinformation, from an adversarial perspective, we attempt to build a powerful synthetic news generation model by closing the inherent factual discrepancies between human and machine-generated text. Existing methods on generating synthetic news may fall short with the following limitations: (1) factual inconsistency, indicating the generated news contradict or refute the news claims; and (2) factual scarcity, meaning the generated news content may miss essential details to supplement the claim. However, directly using or fine-tuning language models does not provide a good solution.

Table 1: Example claim and the beginning part of a news pieces from CNN/DailyMail dataset. The black bold sentence fragments are the consistent word and Italic red fragment is the supplementary information.

| Claim | The united states and its negotiating partners reached a very strong framework agreement with iran in lausanne, switzerland, on thursday that limits iran’s nuclear program in such a way as to effectively block it from building a nuclear weapon. The debate that has already begun since the announcement of the new framework will likely result in more heat than light. It will not be helped by the gathering swirl of dubious assumptions and doubtful assertions. |
|-------|---------------------------------------------------------------------------------------------------------------|
| Content | The united states and its negotiating partners reached a very strong framework agreement with iran in lausanne, switzerland, on thursday that limits iran’s nuclear program in such a way as to effectively block it from building a nuclear weapon. The debate that has already begun since the announcement of the new framework will likely result in more heat than light. It will not be helped by the gathering swirl of dubious assumptions and doubtful assertions. |

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not help as it is non-trivial to enhance factual consistency and richness on a language model directly. Therefore, in this study, we aim to address the following challenges in synthetic news generation: (1) how to generate news content related to a given claim/context; and (2) how to ensure that the generated content contains supplemental fact information.

Our solution to these challenges results in a novel framework FACTGEN (Fact-Enhanced Synthetic News Generation). FACTGEN consists of three major components: (1) Pseudo-Self-Attentive (PSA) Language Model (Ziegler et al. 2019), where the customized encoder deceptively injects source information (claims and external facts) into pre-trained decoder for the generation. The adapted deceptive injection mechanism can resolve the mismatch between the untrained encoder and the well-trained decoder; (2) Fact Retriever, which heuristically retrieves the supplemental information from external fact corpus to provide more candidate facts during generation; and (3) Claim Reconstructor, a randomly initialized masked language model (Devlin et al. 2019) which enhances the output consistency by reconstructing the masked claim tokens from both the representation of the generated content and the unmasked claim tokens. During training, the PSA Language Model takes the news claim and the retrieved facts from the Fact Retriever as input, then generates highly consistent news content by incorporating the Claim Reconstructor into the generation process. In this way, the proposed framework can generate both fact-consistent and fact-enriched news content. To summarize, our main contributions are as follows:

• We study a novel problem of fact-enhanced synthetic news generation, which aims to generate consistent and fact-enriched news content.

• We propose a principled framework FACTGEN generates realistic synthetic news by retrieving external facts and reconstructing the input claim.

• We conduct experiments on real-world datasets using quantitative and qualitative metrics to demonstrate the effectiveness of FACTGEN for synthetic news generation and its defense.

Methodology

Our goal is to incorporate external facts into news generation that are consistent with the news claim. Given a sequence of tokens from the claim $X = \{x_1, x_2, \ldots, x_N\}$, the fact retriever retrieves related fact information $F = \{f_1, f_2, \ldots, f_K\}$ by semantic similarity, then the language model generates the news content $Y = \{y_1, y_2, \ldots, y_M\}$ based on claim $X$ and $F$. It should be noticed that the length of $Y$ is much larger than $X$, which is $M >> N$, and $x_i, y_i, f_i$ are words. Figure 1 illustrates the architecture of our proposed model and the objective functions. The causal language loss $L_{CLL}$, which heuristically retrieves the supplemental information on the language model output and the unmasked claims. This has a twofold benefit. Initially, the pre-trained decoder and the retrieved facts will bring unrelated information. This technique encourages the generated content to cover the input claim and provides a regularization effect. In addition, it is fully differentiable so we can minimize the objective function end-to-end. Overall, we minimize:

$$L = L_{CCLL} + \lambda L_{MLL}$$ (1)

where $\lambda$ is the hyperparameter to control the contribution of claim reconstruction. The formulas of $L_{CCLL}$ and $L_{MLL}$ are in Eq. 5 and Eq. 6 respectively.

Preliminary

Self-attentive (SA) language models (Devlin et al. 2018; Radford et al. 2019; Song et al. 2019) have achieved impressive performance gains in various language generation tasks. These models are stacks of several SA blocks which encode the input $X = \{x_1, \ldots, x_i, \ldots, x_N\}$ into key-value pairs $(K, V) = \{(k_1, v_1), \ldots, (k_i, v_i), \ldots, (k_N, v_N)\}$ and query $Q = \{q_1, \ldots, q_i, \ldots, q_N\}$. The next output is produced by taking the weighted sum of values $v_i$, where the weight assigned toward each value is the dot-product of the query $Q$ with all the keys $K$. The formula of SA is:

$$K = H_X W_k, \quad V = H_X W_v, \quad Q = H_X W_q$$ (2)

$$SA(X) = \text{softmax}(QK^T) V$$ (3)

where $H_X \in \mathbb{R}^{N \times D}$ is the hidden representation of the input $X$, $D$ is the hidden dimension, and $W_k, W_v, W_q \in \mathbb{R}^D \times D$ are the parameters to map the hidden representation of tokens $H_X$ into key, value and query space, respectively.

Proposed Method

Pseudo-Self-Attentive Language Model: Although the fine-tuned self-attentive language models like GPT-2 (Radford et al. 2019) have been applied to many text generation tasks, the application of using GPT-2 for the synthetic news generation may not be satisfactory. Since the GPT-2 is an autoregressive model, it will lose partial information from the input by only encoding the forward information. Besides, without a specific encoder, GPT-2 cannot capture the dependency relationship between the news claim and the retrieved facts which will hurt the performance of the decoder (Edunov, Baevisk, and Auli 2019). Therefore, we need...
a new encoder to capture bi-directional information and dependency among the input. We follow (Ziegler et al. 2019)’s setting, employing a pseudo-self-attentive(PSA) language model, where the "pseudo" is that the encoder deceptively extends the decoder’s key-value pairs by the encoder’s pairs, and the decoder predicts the next token not only based on previous output but also from the input. To model the dependency between claim and retrieved facts, we wrap them with "[Claim]" and "[Fact]" separately, and especially all the retrieved facts are contacted together without any special separation token. The architecture of the language model is shown in Figure 2, and the formula of PSA is:

$$PSA(Y, X, F) = \text{softmax} \left( Q_Y \left[ \begin{array}{c} K_Y \\ K_X \\ K_F \end{array} \right] \left[ \begin{array}{c} V_Y \\ V_X \\ V_F \end{array} \right]^T \right)$$

(4)

Note that $K_X, K_F, V_X,$ and $V_F$ are using different projection matrix $W_e$ and are randomly initialized. The objective function of the language model is:

$$L_{CLL} = - \sum_{i=1}^{M} \log P(y_i|y_1, \ldots, y_{i-1}; X, F)$$

(5)

Fact Retriever: Directly training a sequence to sequence model on $(X, Y)$ often results in fact scarcity. One main reason is that facts from the input are extremely insufficient compared to the output. Thus, the language model is more likely to generate repeated sentences. Our solution towards the facts imbalance between the input and output is to increase the facts in the source side by retrieving related facts and considers them as part of the input. Our fact retriever (FR) heuristically retrieves external facts in two steps. Firstly, to omit the computation limitation, we retrieve the related document based on the tf-idf vectors’ cosine similarity between the claim and the document. Here we only keep the $top-k_1$ similar documents. Secondly, to accurately identify related sentences in the document, we utilize the pretrained BERT (Devlin et al. 2018) to encode all sentences presented in the picked documents and choose the $top-k_2$ most similar sentences based on the cosine similarity.

Claim Reconstructor: Since the aforementioned modules FR and PSA language model will bring inconsistency during the generation, and high-quality news content is consistent with the news claims, to improve the content consistency, we propose to reconstruct the masked claim from the generated content and the unmasked claims. The existing reconstruction approaches for the input text consistence require the prior knowledge of the input, like the topic label to learn a topic consistent reward function (Yang et al. 2019a), key-entities for multi-classification on the hidden states to entail these entities in the generated content (Wiseman, Shieber, and Rush 2017). Our claim reconstructor (CR) does not require any prior knowledge about the input. It reconstructs the masked claim $X_{[Masked]}$ based on the mean pooling of output hidden representation $h_Y$ and unmasked sentence fragments $X_{[Unmasked]}$. We mask claim’s tokens with probability $P_{mask}$ and we follow the pseudo-self-attention (Ziegler et al. 2019) projecting $h_Y$ into CR’s key-value pairs to predict the masked sentence fragment, $X_{[Masked]}$. The objective function of CR is:

$$L_{MCLL} = \sum_{x \in X_{[Masked]}} - \log P(x|X_{[Unmasked]}, h_Y)$$

(6)

Training Schedule

Since FACTGEN need to guarantee that two improvements will not contradict each other, we cannot directly train the model via minimizing eq(1). We then train FACTGEN in two-stages. The overview of the training procedure is summarized in Algorithm 1. The joint training can align the latent space of these two modules. The two stages of training bring several advantages: firstly, it allows us to start the PSA language model and CR warmly, omitting the gradient explosion problem during training; secondly, because the claim is the main idea of the generated text and the retrieved facts are the auxiliary information during the generation, this order can help the decoder understand the importance of different input source. The following experiment result also stipulates the efficiency of this training schedule.
Algorithm 1 Training Procedure of FACTGEN

Input: The source claims, relevant facts and target news pieces corpus $S = \{(X,F,Y)\}$; the masked and unmasked claims $D = \{(X_{\text{[Masked]}},X_{\text{[Unmasked]}})\}$; first and second stage epoch number $epochs_1$ and $epochs_2$.

Output: PSA language model and claim reconstructor

- For $CR$:
  1. Initialize $PSA_{\text{encoder}}$ and $CR$ with random weights
  2. Pre-train the $PSA$ via minimizing eq(5) on $\{(X,Y)\}$; Pre-train the $CR$ by minimizing $\text{eq}(6)$ on $D$.
  3. for $epochs_1 = 1$ to $epochs_1$ do
     4. Jointly training $PSA$ and $CR$ via minimizing $\text{eq}(5)$ on $\{(X,Y)\}$ and $D$; $\triangleright$First Stage
  5. end for
  6. for $epochs_2 = 1$ to $epochs_2$ do
     7. Jointly training $PSA$ and $CR$ via minimizing $\text{eq}(5)$ on $S$ and $D$; $\triangleright$Second Stage
  8. end for

Experiments

In this section, we conduct experiments on two real-world news dataset to demonstrate the effectiveness of FACTGEN for news generation. Specifically, we aim to evaluate the quality of the generated news pieces in terms of fluency, Consistency, richness, and trustworthiness.

Dataset

We utilize two news dataset in our experiment. The first dataset is a widely used fake news detection dataset collected from a fact-checking website, GossipCop (Shu et al. 2018). Each sample contains the news’ claim, content, metadata, label, and social engagements. The average lengths of the claim and content are 30 words and 250 words respectively. The second dataset is the CNN/DailyMail news highlight dataset (Hermann et al. 2015) which contains the news content and selected highlight. In contrary to the text summarization, we use the highlight sentence as the source claim and the news content as the target text. On average, the claim has 56 tokens and the content has 790 tokens. As for prepossessing, we truncate the news claim longer than 100 words and content longer than 300 words in both datasets. For the dataset splitting, we randomly sample 75% training set, 15% validation set, and 10% test set in the GossipCop dataset and follow the same splitting setting in (See, Liu, and Manning 2017). Datasets’ statistical information is listed in Table 2.

| Dataset       | # of train | # of val | # of test |
|---------------|------------|----------|-----------|
| GossipCop     | 7,331      | 1,459    | 974       |
| CNN/DailyMail | 278,408    | 11,490   | 13,368    |

Table 2: The statistical information of the datasets.

In this paper, we consider the factual sentences in the training dataset as our external fact corpus. This brings two advantages: firstly, utilizing several sentences instead of whole news pieces can avoid the model learning from copy the information from the source to the target side; secondly, the fact sentences from the training dataset can omit the data leakage problem during testing. Here we focus on external facts as the format of the text, though it can be extended to tabular data or knowledge graph.

Experiment Settings

We implement FACTGEN on OpenNMT (Klein et al. 2017). We tune the hyper-parameter $\lambda$ on the validation set. The encoder of FACTGEN is 4 blocks of SA block with 12 attention heads and 3072 hidden units. The weight of the decoder is initialized with the median pre-trained GPT-2 (Radford et al. 2019) model. The claim reconstruction module is 3 blocks of SA block with 4 attention heads and 256 hidden sizes. The optimizer is Adam (Kingma and Ba 2014) with $\beta_1 = 0.9$ and $\beta_2 = 0.998$. It should be noticed that the learning rate for the encoder is $1e-3$, for the decoder is $1e-5$, and $5e-5$ for the claim reconstruction. The number of retrieved documents $k_1$ and sentences $k_2$ is set to 10 and 5 respectively. The $epochs_1$ and $epochs_2$ in the training schedule are set to 4 and 2 respectively. During decoding we used Nucleus Sampling (top-$p$) with $p=0.9$.

Evaluation Metrics

Automatic Evaluation The traditional text generation metrics like BLEU (Papineni et al. 2002) and ROUGE (Lin 2004) which are focus on the overlap between the generated content and the reference text which is not enough to reflect the claim-content consistency and the richness of the generated content. To remedy this, we develop two new evaluation metrics to measure the quality from different perspectives.

- **Fluency**: we report the BLEU score of different methods.
- **Consistency**: The ideal news content should support its claim. Therefore, we propose a stance detection model to detect whether the content is in favor of the claim or against it. Given the claim and the generated news content $\{X,Y\}$, the stance detection model will output the relation of the text pair in (Agrees, Disagrees, Discusses, Unrelated). We utilize the Fake News Challenge dataset to fine-tune RoBERTa (Liu et al. 2019). This approach achieves a 0.93 accuracy score on the test dataset of the Fake News Challenge. We report the ratio of the “agrees”:

  \[
  \text{Consistency} = \frac{\# \text{of agrees samples}}{\# \text{of all samples}}
  \]

- **Richness**: The richness of the output can be evaluated by the number of unique name entities in the generated text (Fan, Lewis, and Dauphin 2019). We utilize spaCy\(^5\) to extract the named entity from the output.

Human Evaluation We distribute the 100 generated samples in CNN/DailyMail dataset to 2 annotators with a linguistic background. They have no advanced knowledge about the source of the generated content. They are asked to evaluate the generated content from fluency, richness, consistency, and Trustworthiness, 4 different perspectives\(^6\). So

\(^5\)http://www.fakenewschallenge.org/
\(^6\)https://spacy.io/
\(^7\)The details of human evaluation questions are in Appendix.
totally, there are 7,200 evaluation questions in our human evaluation. The annotator should answer each question from a score of 1 to 3 (3 being the best, 1 being the worst).

Baseline Methods
To demonstrate the quality of the generated text, we compare our proposed model on content quality with the following text generation models:

- CopyTransformer [See, Liu, and Manning 2017]: a sequence-to-sequence transformer with a pointer network that can copy the word from the source to the target.
- Conv Seq2Seq [Fan, Lewis, and Dauphin 2018]: a seq2seq convolution neural network to generate claim consistent stories.
- PPLM [Dathathri et al. 2019]: a topic and content controlled language model. It can directly control the pre-trained language model without fine-tuning.
- GPT-2 [Radford et al. 2019]: a large pre-trained language model which is the decoder part of the transformer. For a fair comparison, we utilize the median size of the model.
- Grover [Zellers et al. 2019a]: generating news text conditioned on the news title, authors, and website domains. It uses the same architecture as GPT-2.

Experimental Results
The automatic and human evaluation results are shown in Table 3 and 4, respectively. We evaluate the quality of the text generation with the following perspectives:

- **Fluency**: From the human evaluations on fluency in CNN/DailyMail dataset and BLEU scores in two datasets, we can find that our model achieves the best performance. In the meantime, we find that the pre-trained language model achieves better human evaluation results than the model trained from scratch (PPLM, GPT-2, Grover > CopyTransformer, Conv Seq2Seq). This indicates the importance of incorporating the large pre-trained language model in the synthetic news generation. Besides, FACTGEN’s performance indicates the pseudo-self attention properly connecting the randomly initialized encoder and the pre-trained decoder.
- **Consistency**: The consistent result in both human evaluation and automatic evaluation demonstrates the effectiveness of our approach. Especially, in the GossipCop dataset, our approach achieves 42% performance improvement over the best baseline in automatic metric, and in CNN/DailyMail, the human evaluation also shows that our approach achieves 6% performance improvement compared with the best baseline method. The main reason for the increase is reconstructing the claim increases the coverage of the output on the input information.
- **Richness**: Our approach achieves the best performance in CNN/DailyMail dataset and the second performance in the GossipCop dataset. The reason for the ordinary performance in GossipCop is that the size of the candidate documents in GossipCop is much smaller than the CNN/DailyMail (7,331 < 278,408). The FR cannot retrieve enough related facts from the external corpus and CR will reject the inconsistent facts during generation. This indicates that FR can bring rich facts in generation.

  - **Trustworthiness**: Human evaluation of the Trustworthiness of synthetic news content indicates that overall, FACTGEN can generate high-quality text content. This helps us to understand the difference between machine-generated news content and true news in the future.

Case Study
One case study of the generated samples is listed in Table 5. We only reveal the output from the model with pre-trained language models and we have several observations: (i) Our model mainly talks about the agreement of nuclear weapons in Iran and includes the supplemental information about Iraq and UK’s action toward nuclear weapons. This brings more context information about the news claims and makes the generated news more convincing. (ii) Although Grover mentions much additional factual information, it is unrelated to the nuclear agreement with Iran. (iii) The outputs of GPT-2 and PPLM mainly discuss the nuclear agreement without supplemental information about the agreement.

Ablation Study
**Impact of \( \lambda \)**: To learn the impact of the hyper-parameter \( \lambda \) in our objective function in Eq. 1, we change \( \lambda \) from \{0.001, 0.01, 0.1, 1, 10\} and calculating all the automatic evaluation metrics. From Figure 4 we can find that \( \lambda = 0.001 \) achieves the best performance across all the automatic evaluations and with the increase of \( \lambda \), the fact richness has been greatly decreased. This is because the CR will constrain the coverage of the generated content and cause the language model to only generated content around the input, which will reduce the richness of the generated content.

![Figure 4: Impact of hyper-parameter \( \lambda \) in CNN/DailyMail.](image)

**Impact of Model Components**: To evaluate the importance of each key components, we set up three different ablation studies of FACTGEN: without claim reconstruction (w/o CR), without Fact Retriever (w/o FR) and without these two components (w/o CR and FR). It should be noticed that all versions of the model have been pre-trained on \( \{X, Y\} \). The automatic and human evaluation in Table 6 and Table 7 show that the performance decrease in all ablation study. However, an interesting finding is that there seems to have a contradiction between the CR and FR. From Table 6 we find that w/o
This stipulates the effectiveness of our training schedule.

Impact of Training Schedule: To understand the effectiveness of our two-stage training schedule, we compare it with single-stage training where the model directly takes the claims and external fact information in the first stage. From the automatic and human evaluation result in Table 6 and 7, we can find that two stages training schedule achieve better performance in all categories compared with single-stage. These results indicate the effectiveness of CR and FR in improving the richness and consistency in the generation.

Further Analysis

Defending Against Synthetic Fake News

To detect the new synthetic fake news, we follow (Zellers et al. 2019b) develop a defending method FACTGEN def based on the checkpoint of FACTGEN at iteration 20k. This setting can reduce the parameters overlap between the generator and the discriminator. We also use hV as the final representation of the input, synthetic fake news or human written real news, and add a full connection layer to classify whether the input is fake or real. We utilize 300 synthetic fake news content and the same amount of human written real news to fine-tune FACTGEN def. The result in Table 8 shows FACTGEN def achieves the best accuracy score. This is because FACTGEN def can learn a better representation of the input. We thus conclude that while the synthetic content is hard to be identified by existing methods, it still can be detected by FACTGEN def.

Related Work

Synthetic News Generation Most synthetic news generation systems used in the newsroom are heavily rule-based and template-based. The neural synthetic news generation like Grover (Zellers et al. 2019a) utilizes an autoregressive language model to learns the dependency among news metadata fields include the domain, date, authors, title, and body. Sam and et. al (Wiseman, Shieber, and Rush 2017) propose a structured data to text challenge which is to generate a sport news piece of sports games from the associated box- or line-score data. To better capture the input data, (Wiseman, Shieber, and Rush 2017) employs...
The deep learning models engineering or latent features extracted by deep neural network methods often leverage features from the feature detection methods (Perez-Rosas et al. 2017). The synthetic fake news detection methods fluency, richness, and fact-consistency.

### Table 5: Samples of generated fake news with different fake news generation methods. 

| Methods | Fluency | Richness | Consistency |
|---------|---------|----------|-------------|
| Full Model | 2.17 | 2.28 | 2.12 | 2.18 |
| single-stage | 2.01 | 2.22 | 2.10 | 2.14 |
| w/o CR | 2.15 | 2.31 | 2.09 | 2.15 |
| w/o FR | 1.93 | 2.28 | 2.03 | 1.98 |
| w/o CR and FR | 2.09 | 2.19 | 2.03 | 2.10 |

### Table 6: Results of automatic evaluation of model components ablation study in CNN/DailyMail dataset.

| Methods | BLEU | Fluency | Richness | Consistency |
|---------|------|---------|----------|-------------|
| Full Model | 4.7 | 16.8 | 0.76 |
| single-stage | 4.6 | 16.6 | 0.74 |
| w/o CR | 3.4 | 17.7 | 0.73 |
| w/o FR | 5.1 | 11.7 | 0.75 |
| w/o CR and FR | 4.0 | 12.9 | 0.73 |

### Table 7: Results of human evaluation of model components ablation study in CNN/DailyMail dataset.

| Methods | Fluency | Richness | Consistency | Trustworthiness |
|---------|---------|----------|-------------|-----------------|
| Full Model | 2.17 | 2.28 | 2.12 | 2.18 |
| single-stage | 2.01 | 2.22 | 2.10 | 2.14 |
| w/o CR | 2.15 | 2.31 | 2.09 | 2.15 |
| w/o FR | 1.93 | 2.28 | 2.03 | 1.98 |
| w/o CR and FR | 2.09 | 2.19 | 2.03 | 2.10 |

### Table 8: Results of synthetic fake news content detection.

|       | EANN | MWSS-CNN | RoBERTa | FACTGEN-def |
|-------|------|----------|---------|-------------|
| Accuracy | 0.64 | 0.58 | 0.74 | **0.82** |

Conclusion and Future Work

In this paper, we propose a synthetic news generation method FACTGEN to ensure fact-consistency and fact-richness. From the automatic and human evaluation of the content quality, FACTGEN is more effective than existing methods. Simultaneously, we discuss the difficulty of detecting synthetic fake news content by current SOTA fake news and human-machine detection methods. For social good, we propose a defending method FACTGEN-def that achieves outstanding performance in detecting synthetic fake news content. In the future, we would like to include other formats of facts like tabular or knowledge graph. This can help us retrieve up-to-date fact information during generation. Since fake news often contains propaganda and more likely to widely spread on the social network, we would like to explore the style control of the generated content to make it prone to be spread.
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Appendices on Reproducibility

In this section, we provide more details about the human evaluation questions, experimental settings and hyperparameter configuration to enable the reputationability of our work.

Human Evaluation Question

To evaluate the quality of FACTGEN, we ask human workers to answer four different questions. For each question, human worker need to give a score from 1 to 3 (1 means low quality and 3 is high quality).

• (Fluency) Is the output article written by human?
• (Richness) Does the text provide extra information not listed in the input claim?
• (Consistency) Is the output consistent with the input?
• (Trustworthiness) Do you trust the output content?

Synthetic News Generation

In Section 4, we compare FACTGEN with 5 baseline methods, including Conv Seq2Seq, CopyTransformer, PPLM, fine-tuned GPT-2 and Grover.

For the dataset, GossipCop is available in the dataset section of the submission and CNN/DailyMail is available at https://github.com/yaqingwang/EANN-KDD18. The description of the Fact Retriever as follows:

• $\text{top} - k_1$: the number of documents we retrieved based on the tf-idf cosine similarity, we rank it from the biggest to the smallest. We set $\text{top} - k_1$ to 10 for both datasets.
• $\text{top} - k_2$: the number of sentences we retrieved from the $\text{top} - k_1$ Documents. We set it 5 for both datasets.

The parameters for evaluating the semantic similarly are the same as RoBERTa.

Synthetic News Detection

The two fake news detection models EANN, MWSS can be obtained online. EANN: it is publicly available at https://github.com/yaqingwang/EANN-KDD18. MWSS: CNN: it is available at https://github.com/microsoft/MWSS.

The hyper parameters for human written and machine generated content detection RoBERTa are as follows:

• Epochs: fine-tuning Epochs the RoBERTa model, 10.
• Patience: the number of epochs to wait before early stop if no progress on the validation set, 3.
• Batch size: number of samples in one iteration, 10.
• Learning Rate: model fine-tuning learning rate, 5e-5.
• Max Length: we pad the input sentence into 300 tokens.

Appendices on Ethics Statement

To better understand the characteristics of synthetic fake news, we propose a fact-enriched synthetic news generation method to generate high quality news pieces. From the automatic and human evaluation results, we find that FACTGEN can generate human-like and convincing news pieces. In this paper, we also discuss a possible solution to defend this attack, which is to use the checkpoint of FACTGEN. We are discussing the further usage of FACTGEN and ethical concerns as follows:

Journalism Assistants: Since our method retrieves the external fact information and generate fact-consistent and fact-enriched news pieces, the journalists can utilize FACTGEN to automatically generate news by providing additional factual information and the claim. However, it still needs manually checking (Leppänen et al. 2017b).

Synthetic Disinformation Detection: In this paper, we shortly discuss the defending method, FACTGEN$_{def}$, and prove the effectiveness of it. However, like the Grover (Zellers et al. 2019a), this method mainly relies on semantic information rather than the veracity of the information (Schuster et al. 2019). Future work should verify the factual correctness of the text in the following pipeline: check-worthy sentence extraction, the verified claim matching, and prediction (Adair et al.).

Release Policy: Since FACTGEN can generate human-like and convincing news content, we need to critically release the code and the model parameters. We propose to publicly release the code including generator and discriminator. However, as for the checkpoints of both models, we will only share for academic usage.

8https://github.com/harvardnlp/sent-summary