Frustratingly Easy Edit-based Linguistic Steganography with a Masked Language Model

Honai Ueoka  Yugo Murawaki  Sadao Kurohashi
Graduate School of Informatics, Kyoto University
hueoka@icn.cce.i.kyoto-u.ac.jp
{murawaki,kuro}@i.kyoto-u.ac.jp

Abstract

With advances in neural language models, the focus of linguistic steganography has shifted from edit-based approaches to generation-based ones. While the latter’s payload capacity is impressive, generating genuine-looking texts remains challenging. In this paper, we revisit edit-based linguistic steganography, with the idea that a masked language model offers an off-the-shelf solution. The proposed method eliminates painstaking rule construction and has a high payload capacity for an edit-based model. It is also shown to be more secure against automatic detection than a generation-based method while offering better control of the security/payload capacity trade-off.

1 Introduction

Steganography is the practice of concealing a message in some cover data such that an eavesdropper is not even aware of the existence of the secret message (Simmons, 1984; Anderson and Petitcolas, 1998). While images, videos, and audio have been dominant cover media (Fridrich, 2009), natural language is a promising choice, thanks to the omnipresence of text (Bennett, 2004).

Formally, the goal of linguistic steganography is to create a steganographic system (stegosystem) with which the sender Alice encodes a secret message, usually in the form of a bit sequence, into a text and the receiver Bob decodes the message, with the requirement that the text is so natural that even if transmitted in a public channel, it does not arouse the suspicion of the eavesdropper Eve. For a stegosystem that creates the text through transformation, we refer to the original text as the cover text and the modified text as the stego text. A stegosystem has two objectives, security and payload capacity. Security is the degree of how unsuspicious the stego text is while payload capacity is the size of the secret message relative to the size of the stego text. The two objectives generally exhibit a trade-off relationship (Chang and Clark, 2014).

Edit-based approaches used to dominate the research on linguistic steganography. Arguably, the most effective approach was synonym substitution (Chapman et al., 2001; Bolshakov, 2005; Taskiran et al., 2006; Chang and Clark, 2014; Wilson and Ker, 2016), where a bit chunk was assigned to each member of a synonym group, for example, ‘0’ to marry and ‘1’ to wed. The cover text She will marry him was then modified to the stego text She will wed him such that the latter carried the secret bit sequence ‘1’.

This conceptual simplicity was, however, overshadowed by the complexity of linguistic phenomena such as part-of-speech ambiguity, polysemy, and context sensitivity. For this reason, edit-based approaches were characterized by the painstaking construction of synonym substitution rules, which were tightly coupled with acceptability checking mechanisms (see Chang and Clark (2014) for a review and their own elaborate method). With all these efforts, edit-based stegosystems suffered from low payload capacity, for example, 2 bits per sentence (Chang and Clark, 2014).

With advances in neural language models (LMs), edit-based approaches have been replaced by generation-based ones (Fang et al., 2017; Yang et al., 2019; Dai and Cai, 2019; Ziegler et al., 2019; Shen et al., 2020). In these approaches, bit chunks are directly assigned to the conditional probability distribution over the next word estimated by the LM, yielding impressive payload capacities of 1–5 bits per word (Shen et al., 2020).

However, it remains challenging for an LM to generate so genuine-looking texts that they fool both humans and machines (Ippolito et al., 2020) even if they do not encode secret messages. It is also worth noting that generation-based stegosystems do not necessarily cut out the need for cover texts, as Ziegler et al. (2019) and Shen et al. (2020)
2 Proposed Method

2.1 Masked LM

The essential ingredient of the proposed edit-based stegosystem is a masked LM. It was first introduced along with BERT (Devlin et al., 2019) as an effective pretraining strategy for the Transformer-based (Vaswani et al., 2017) neural net. The pre-trained model is usually fine-tuned on downstream tasks, but for our purpose we keep it intact.

In this paper, we revisit edit-based linguistic steganography. Our key idea is that a masked language model (masked LM), which was first introduced with BERT (Devlin et al., 2019), offers an off-the-shelf solution. Usually treated as an intermediate model with no direct application, the masked LM drastically simplifies an edit-based stegosystem. It eliminates painstaking rule construction because it readily offers a list of words applicable in the context. As illustrated in Figure 1, all Alice and Bob have to share is the masking and encoding strategies in addition to the masked LM.

In our experiments, we showed that the proposed method had a high payload capacity for an edit-based model. As expected, the amount was far smaller than those of generation-based models, but the proposed method offers better control of the security/payload capacity trade-off. We also demonstrated that it was more secure against automatic detection than a generation-based method although it was rated slightly lower by human adversaries.

Our code is available at https://github.com/ku-nlp/steganography-with-masked-lm.
the same tokens. In this paper, we present a simple strategy. As a general rule, we mask every one in $f$ tokens in the input, but we skip tokens if they match any of the following criteria:

1. A punctuation or number.
2. A stopword.
3. A non-initial subword, which BERT’s standard tokenizer marks with the initial “##”.

Editing subwords is dangerous because there is no 100 percent guarantee that Bob’s subword tokenization reproduces Alice’s original segmentation. For example, if “##break” in the word “un ##break ##able” is replaced with “##us”, the subword tokenizer would segment the new word into “un ##us-able”, distorting the masking positions. We will revisit this problem in Section 3.4.

The hyperparameter $f$ is expected to control the security/payload capacity trade-off. A large $f$ lowers the payload capacity but is likely to increase the difficulty of detection. We also anticipate that since the tokens we decide to skip do not have many good alternatives, not masking them is good for the stego text quality.

2.3 Encoding Strategy

We use block encoding for simplicity. For each masked token, we select and sort items whose probabilities are greater than $p$. To avoid distorting masking positions, we drop items that are to be skipped in the masking phase. Let $n$ be the largest integer that satisfies $2^n \leq c$, where $c$ is the number of the remaining items. Each item is given a unique bit chunk of size $n$. Coding is an active research topic (Dai and Cai, 2019; Ziegler et al., 2019; Shen et al., 2020) and is orthogonal to our core proposal.

3 Experiments

We tested the proposed method with several configurations and compared it with a generation-based method. To assess security, we employed automatic discriminators and human adversaries.

3.1 Models and Data

**BERT** For the proposed edit-based method, we used BERT (Devlin et al., 2019) as the masked LM. Specifically, we used Google’s BERT$_{Base}$, Cased model and Hugging Face’s transformers package (Wolf et al., 2020) with default settings. Given a random bit sequence as the secret message and a paragraph as the cover text, the model encoded bit chunks on a sentence-by-sentence basis. When the bit chunks reached the end of the secret message, the process was terminated, discarding the remaining sentences in the given paragraph. The last bit chunk usually exceeded the limit, and the remainder was filled with zeros.

**GPT-2** Ziegler et al. (2019) built a state-of-the-art generation-based model on top of the GPT-2 neural LM (Radford et al., 2019). We used their original implementation\(^1\) to encode random bit sequences. We set the option $\text{finish\_sent}$ to true to avoid terminating generation at the middle of a sentence. We tested the temperature parameter $\tau = \{0.4, 0.7, 1.0\}$. Since the generation was conditioned on context sentences, we supplied the first three sentences of a paragraph.

**Data** We extracted paragraphs from the English part of the CC-100 dataset (Wenzek et al., 2020) and used them as the cover texts for BERT and as the contexts for GPT-2.\(^2\) For each stegosystem, we also extracted texts that were comparable to the corresponding stego texts in terms of length. We refer to them as real texts.

3.2 Automatic Detection

We trained discriminators to distinguish stego texts from real texts. This corresponds to a situation unusually favorable to Eve as she has access to labeled data, though not to secret messages. A practical reason for this is that after all, we cannot build discriminators without training data. Besides, a stegosystem’s performance is deemed satisfactory if it manages to fool the discriminator even under such disadvantageous conditions.

For each stegosystem, we fine-tuned the same BERT$_{Base}$, Cased model on the binary classification task. The details are explained in Appendix A.

3.3 Human Evaluation

We asked Amazon Mechanical Turk\(^3\) workers to give 5-point scale ratings on the stego and real

\(^{1}\)https://github.com/harvardnlp/NeuralSteganography

\(^{2}\)Ziegler et al. (2019) used the CNN/Dailymail (Hermann et al., 2015; Nallapati et al., 2016) as the contexts.

We found, however, that the resulting stego texts were excessively easy for automatic discriminators to distinguish from real news articles, presumably due to domain mismatch with a web corpus on which GPT-2 had been trained. That is why we chose CC-100, a web corpus, in our experiments. Note that this setting may have worked slightly against the proposed method because BERT was mainly trained on Wikipedia.

\(^{3}\)https://www.mturk.com/
texts according to naturality and correctness. Since we found a consistent bias toward shorter texts, we tuned each stegosystem’s hyperparameters to generate stego texts with comparable length. The details are explained in Appendix B.

### 3.4 Results

Table 1 shows the result of automatic detection. As expected, the proposed method, BERT, had a much lower payload capacity than the generation-based GPT-2 although it was high for an edit-based method. In practical situations, however, security is given priority over payload capacity. In this respect, BERT’s performance was remarkable as its stego texts were nearly indistinguishable from real texts. By contrast, GTP-2’s stego texts were easily detectable for the discriminator even though they were much shorter than BERT’s.

Figure 2 shows the effect of the masking interval parameter $f$, with $p = 0.02$. We can observe a clear trade-off between the two objectives.

Figure 3 indicates the effectiveness of the mask skipping heuristics explained in Section 2.2. With $f = 4$ and $p = 0.02$, masking stopwords and subwords not only raised detection accuracy but also lowered payload capacities. Because these tokens did not have many good alternatives, they consumed only small bit chunks and simply damaged the stego text quality.

As we briefly discussed in Section 2.2, editing subwords may cause distortion in mask positions, leading to decoding failures. We quantified the risk, with the hyperparameter settings of $p = 0.02$ and $f = 3$. We found that 1.41% of the masked tokens had substitution candidates that did not reproduce the original segmentations. Although this danger applies equally to generation-based steganography built on top of subword LMs (Dai and Cai, 2019; Ziegler et al., 2019; Shen et al., 2020), to our knowledge, we are the first to point it out.

Figure 4 shows the effect of the probability threshold $p$. Lowering the threshold increases the payload capacity because the number of alternative tokens increases. It did sacrifice detection accuracy, but not as much as we expected.

As for human evaluation, Table 3 summarizes the results with average ratings. Overall, both methods achieved high average ratings, almost equal to that of the real texts. However, BERT slightly underperformed GPT-2. We conjecture that the quality of the cover texts affected the edit-based method more directly than the generation-based method. Following Ziegler et al. (2019), we initially used news articles for cover/real texts but switched to web texts because we noticed that the discriminator appeared to exploit the domain mismatch with a web corpus on which GPT-2 had been trained. Considering the massive quality improvement efforts given to GPT-2’s training data, however, there seems to be much room to improve the quality of CC-100 (Wenzek et al., 2020).

Table 2 shows good and bad stego texts produced by the BERT-based method. In the first example, BERT successfully suggested context-aware words,
Switzerland also has an amazing scientific community that includes Geneva University and CERN, which is one of the top research institutes in the world and is home to the world’s largest particle physics laboratory.

Switzerland also has an international scientific community that includes Basel University and CERN, which is one of the top physics institutes in the world and is home to the world’s largest particle physics laboratory.

Allowing local authorities to increase that charge puts the negative political feedback, particularly in areas where compliance is less, like Donegal, on to the local councils and protects the central government.

Allowing local authorities to file that charge puts the negative negative feedback, particularly in areas where opposition is less, like Donegal, on to the local government and protects the central government.

Table 2: Two examples of stego texts produced by the proposed edit-based method. The last column indicates average ratings by crowdworkers.

| Cover text                                                                 | Stego text                                                                 | Rating |
|---------------------------------------------------------------------------|---------------------------------------------------------------------------|--------|
| Switzerland also has an amazing scientific community that includes Geneva University and CERN, which is one of the top research institutes in the world and is home to the world’s largest particle physics laboratory. | Switzerland also has an international scientific community that includes Basel University and CERN, which is one of the top physics institutes in the world and is home to the world’s largest particle physics laboratory. | 5.0    |
| Allowing local authorities to increase that charge puts the negative political feedback, particularly in areas where compliance is less, like Donegal, on to the local councils and protects the central government. | Allowing local authorities to file that charge puts the negative negative feedback, particularly in areas where opposition is less, like Donegal, on to the local government and protects the central government. | 2.8    |

Table 3: The results of human evaluation. The ratings range from 1 to 5, and higher is better.

| BERT | GPT-2 | Real texts |
|------|-------|------------|
| 4.32 ± 0.97 | 4.43 ± 0.89 | 4.54 ± 0.78 |

Ethical Considerations

This paper works on steganography. Unlike cryptography, steganography conceals the fact that a secret message is being transmitted as well as its contents. Steganography can be just fun, but it usually involves a conflict of interest between two parties: those who want to censor media and those who want to evade detection. Depending on value judgments, either one or both can be evil. Steganography is an effective tool to counter censorship in countries where encryption is illegal and visibly encrypted messages may be incriminating. However, it can also be used to transfer malicious data. As such, steganography can be seen as a dual-use technology.

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4 Conclusions

In this paper, we demonstrated that the masked language model could revolutionize edit-based linguistic steganography. The proposed method is drastically simpler than existing edit-based methods, has a high payload capacity, and allows easy control of the security/payload capacity trade-off.

The masked language model is a general framework adopted by many BERT-like models, of which attempts to handle longer texts (Beltagy et al., 2020; Wang et al., 2020) are particularly relevant to steganography. Tailoring the training procedure to steganography is also an interesting research direction.
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A Details of Automatic Detection

The edit-based and generation-based methods differ considerably in the amount of text needed to encode a secret message because the latter has a higher payload capacity by design. For a fair comparison, we chose to encode bit sequences of equal size, meaning that the proposed method yielded longer stego texts. Specifically, we used random 32-bit sequences. The sequence of sentences was given to the discriminator at once. For GPT-2, we discarded the contexts and only fed stego texts into the discriminator.

For the binary classification task, we prepared the training, development and test sets with 8,000, 1,000, and 1,000 paragraphs, respectively. Each set had the same amount of stego and real texts, and they were comparable with respect to length. The discriminators were trained for 20 epochs, with the batch size of 32. We applied early stopping if the validation loss did not drop five times in a row. The model snapshots were saved for every 250 steps, and the one with the lowest validation loss was chosen. We used Adam (Kingma and Ba (2017)) as the optimizer with the learning late of $10^{-6}$.

B Details of Human Evaluation

For the proposed edit-based method, we used the same masking and encoding strategies used for automatic detection. The hyperparameters were as follows: $p = 0.02$, and $f = 4$, stopwords and subwords were skipped. We used random 6-bit sequences as secret messages.

For the generation-based method, the temperature parameter $\tau$ was set to 0.7. We used random 45-bit sequences as secret messages.

We designed a MTurk HIT (human intelligence task) following Abdelnabi and Fritz (2020). Workers were asked to rate texts (each question had 5 texts) with a Likert scale from 1 (lowest) to 5 (highest). As shown in Table 4, the ratings were described with the instructions ranging from “This sentence is completely understandable, natural, and grammatically and structurally correct” to “This sentence is completely not understandable, unnatural, and you cannot get its main idea”. Each HIT had 5 texts, with stego texts from both methods and real texts of comparable length appearing in a random order. The questions also had a simple attention check and if the answer to the attention check was wrong, the corresponding HIT was discarded. We have set the reward per assignment at $0.3.

We observed that human raters strongly favored shorter texts. To verify the observation, we performed linear regression analysis with the number of words as a parameter. We found that it indeed had a statistically significant negative impact on the ratings with $p < 10^{-3}$ for the t-statistic.

| Rating | Description |
|--------|-------------|
| 5      | The text is understandable, natural, and grammatically and structurally correct. |
| 4      | The text is understandable, but it contains minor mistakes. |
| 3      | The text is generally understandable, but some parts are ambiguous. |
| 2      | The text is mainly not understandable, but you can get the main ideas. |
| 1      | The text is completely not understandable, unnatural, and you cannot get the main ideas. |

Table 4: Ratings explanations given in the human evaluation.