



## Linguistic Steganography



Two objectives

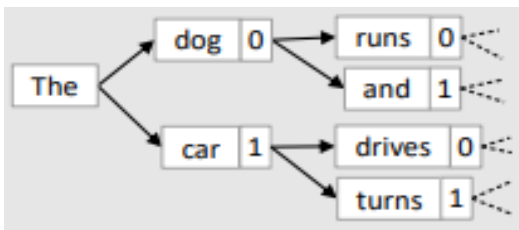
**Context Coherency** How the stego text makes sense through the organization of its content so it does not seem suspicious.

**Payload Capacity** The size of secret text relative to size of the stego text.

## Proposed Methods

### 1. GPT2 (Generation-based method)

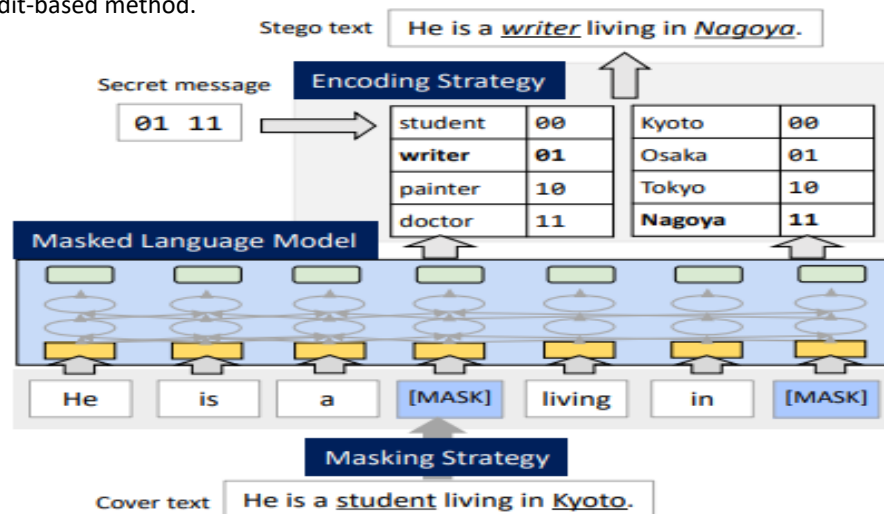
- Directly assign bit chunks to the output of language models (LMs).
- Secret message can be of any size (no limitations)
- Words generation continues until reaching specified length of steganographic text.
- Remains challenging to produce accurate and context coherent steganographic text.



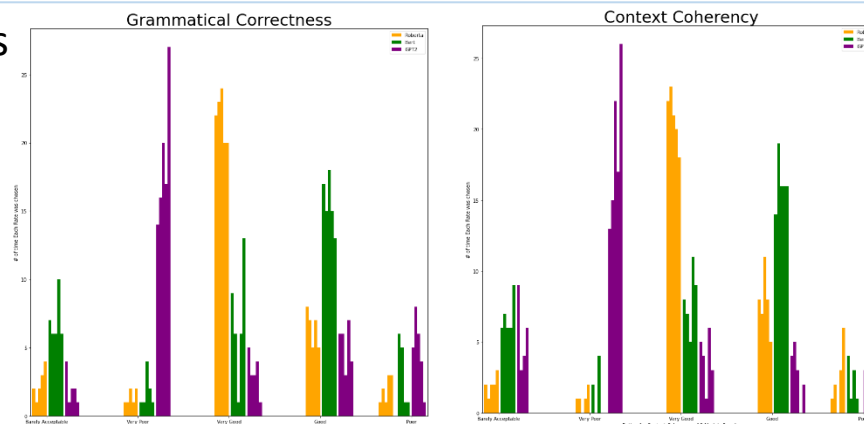
Generation-based method - **GPT2** approach example. Message "10..." is encoded to "The car drives..."

### 2. BERT and RoBERTa (Edit-based method)

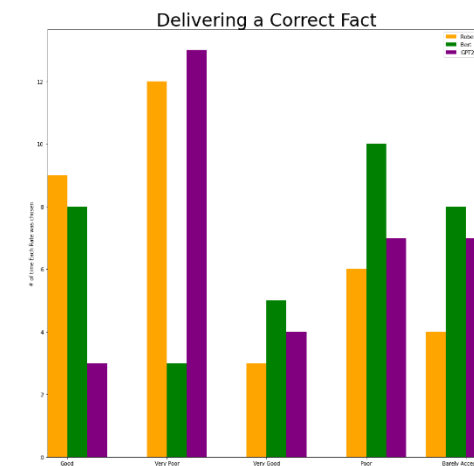
- The cover text is being masked by masking strategy shared between Alice and Bob.
- The LM predicts the substitution candidates.
- The suitable candidate is chosen using secret message bit sequence
- Due to some modifications on BERT, RoBERTa has been proposed for outperforming BERT as edit-based method.



## Results



## Human Evaluation Results



- Generation-based stego texts were easily detectable due to its poor context coherency and grammatically incorrectness.
- RoBERTa** has shown best results in all but of lower payload capacity than that of the generation-based method, but it's high for an edit-based method due to its Dynamic Masking.

## Conclusion

- RoBERTa, a modified BERT version has shown the best results among the three proposed models.
- It is **not advisable** to use proposed models in political domain due to sensitivity and criticalness of information used as cover.
- Different Tokenizers can affect meaning of stego text.
- Masking up to 40% of input tokens can outperforms the 15% baseline masking process. However, more than 40% can cause context corruption of stego text.