**COCO: Coherence-Enhanced Machine-Generated Text Detection Under Low Resource With Contrastive Learning**

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**Abstract**

Machine-Generated Text (MGT) detection, a task that discriminates MGT from Human-

Written Text (HWT), plays a crucial role in preventing misuse of text generative models, which excel in mimicking human writing style recently. The latest proposed detectors usually take coarse text sequences as input and fine- tune pre-trained models with standard cross- entropy loss. However, these methods fail to consider the linguistic structure of texts. More- over, they lack the ability to handle the low- resource problem, which could often happen in practice considering the enormous amount of textual data online. In this paper, we present a **co**herence-based **co**ntrastive learning model named COCO to detect the possible MGT un- der the low-resource scenario. To exploit the linguistic feature, we encode coherence infor- mation in the form of graph into the text rep- resentation. To tackle the challenges of low data resources, we employ a contrastive learn- ing framework and propose an improved con- trastive loss for preventing performance degra- dation brought by simple samples. The exper- iment results on two public datasets and two self-constructed datasets prove our approach outperforms the state-of-the-art methods signif- icantly. Also, we surprisingly find that MGTs originated from up-to-date language models could be easier to detect than these from pre- vious models, in our experiments. And we propose some preliminary explanations for this counter-intuitive phenomena. All the codes and datasets are open-sourced[.1](#bookmark2)

**1 Introduction**

Thriving progress in the field of text generative models (TGMs) [(Yang et al.,](#bookmark3)[2019;](#bookmark4)[Kenton and](#bookmark5) [Toutanova,](#bookmark6)[2019;](#bookmark7)[Liu et al.,](#bookmark8)[2019;](#bookmark9)[Keskar et al.,](#bookmark10)

[2019;](#bookmark11)[Lewis et al.,](#bookmark12)[2020;](#bookmark13)[Brown et al.,](#bookmark14)[2020;](#bookmark15)[Gao](#bookmark16)

[1Codes are available at -https://github.com/YichenZW/Coh](#bookmark17) [MGT-Detection and datasets are at](#bookmark18) [https://huggingface.co/datasets/ZachW/MGTDetect\_CoCo.](#bookmark19)

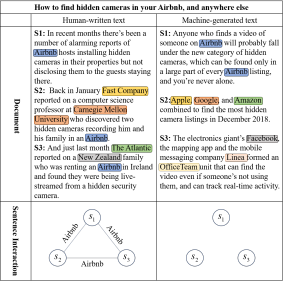


Figure 1: Illustration of sentence-level structure differ- ence between HWT and MGT, the MGT is generated by GROVER [(Zellers et al.,](#bookmark20)[2019)](#bookmark21). HWT is more coherent than MGT as the sentences share more same entities with each other.

[et al.,](#bookmark22)[2021a;](#bookmark23)[Madotto et al.,](#bookmark24)[2021;](#bookmark25)[Ouyang et al.,](#bookmark26) [2022;](#bookmark27)[Touvron et al.,](#bookmark28)[2023;](#bookmark29)[Anil et al.,](#bookmark30)[2023)](#bookmark31), *e.g.*, [ChatGPT2](#bookmark32)and GPT-4 [(OpenAI,](#bookmark33)[2023)](#bookmark34), enables ev- eryone to produce MGTs massively and rapidly. However, the accessibility to high-quality TGMs is prone to cause misuses, such as fake news gen- eration [(Zellers et al.,](#bookmark35)[2019;](#bookmark36)[Yanagi et al.,](#bookmark37)[2020;](#bookmark38) [Huang et al.,](#bookmark39)[2022)](#bookmark40), product review forging [(Ade-](#bookmark41) [lani et al.,](#bookmark42)[2020)](#bookmark43), and spamming [(Tan et al.,](#bookmark44)[2012)](#bookmark45), etc. MGTs are hard to distinguish by an untrained human for their human-like writing style [(Ippolito](#bookmark46) [et al.,](#bookmark47)[2020)](#bookmark48) and the excessive amount [(Grinberg](#bookmark49) [et al.,](#bookmark50)[2019)](#bookmark51), which calls for the study of reliable automatic MGT detectors.

Previous works on MGTs detection mainly con- centrate on sequence feature representation and classification [(Gehrmann et al.,](#bookmark52) [2019;](#bookmark53) [Solaiman](#bookmark54)

[2https://chat.openai.com](#bookmark55)

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*Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 16167–16188 December 6-10, 2023 ©2023 Association for Computational Linguistics

[et al.,](#bookmark56)[2019;](#bookmark57)[Zellers et al.,](#bookmark58)[2019;](#bookmark59)[He et al.,](#bookmark60)[2023;](#bookmark61) [Mitchell et al.,](#bookmark62)[2023)](#bookmark63). Recent studies have shown the good performance of automated detectors in a fine-tuning fashion [(Solaiman et al.,](#bookmark64) [2019;](#bookmark65) [Mireshghallah et al.,](#bookmark66)[2023)](#bookmark67). Although these fine- tuning-based detectors have demonstrated their ef- fectiveness, they still suffer from two issues that limit their conversion to practical use: (1) Existing detectors treat input documents as flat sequences of tokens and use neural encoders or statisticalfea- tures (*e.g.*, TF-IDF, perplexity) to represent text as the dense vector for classification. These fine- tuning-based methods rely much on the token-level distribution difference of texts in each class, which ignores high-level linguistic representation of text structure. (2) Compared with the enormous number of online texts, the annotated dataset for training MGT detectors is rather low-resource. Constrained by the amount of available annotated data,tradi- tional detectors sustain frustrating accuracy and even collapse during the test stage.

The defect in the coherence of LMs in generat- ing long text has been revealed by previous works. [Malkin et al.](#bookmark68)[(2022)](#bookmark69) mentions that long-range se- mantic coherence remains challenging in language generation. [Sun et al.](#bookmark70) [(2020)](#bookmark71) also provides ex- amples of incoherent MGTs. As shown in Fig.[1,](#bookmark1) MGTs and HWTs exhibit differences in terms of co- herence traced by entity consistency. Accordingly, we propose that coherence could be an entry point forMGT detection via the perspective of high-level linguistic structure representation, where MGTs could be less interactive than HWTs. Specifically, we propose an entity coherence graph to model the sentence-level structure of texts based on the thoughts of Centering Theory [(Grosz and Sidner,](#bookmark72) [1986)](#bookmark73), which evaluates text coherence by entity consistency. The entity coherence graph treats enti- ties as nodes and builds edges between entities in the same sentences and the same entities among dif- ferent sentences to reveal the text structure. Instead of treating text as a flat sequence, coherence mod- eling helps to introduce distinguishable linguistic features at the input stage and provides explainable differences between MGTs and HWTs.

To alleviate the low-resource problem in the sec- ond issue, inspired by the resurgence of contrastive learning [(He et al.,](#bookmark74)[2020;](#bookmark75)[Chen et al.,](#bookmark76)[2020)](#bookmark77), we utilize the proper design of sample pair and con- trastive process to learn fine-grained instance-level features under low resource. However, it has been

proven that the easiest negative samples are un- necessary and insufficient for model training in contrastive learning [(Cai et al.,](#bookmark78)[2020)](#bookmark79). To circum- vent the performance degradation brought by the easy samples, we propose a novel contrastive loss with the capability to reweight the effect of nega- tive samples by difficulty score to help the model concentrate more on hard samples and ignore the easy samples. Extensive experiments on multiple datasets (GROVER, GPT-2, GPT-3.5) demonstrate the effectiveness and robustness of our proposed method. Surpirsingly, we find that the GPT-3.5 datasets are easier for all the detectors compared with datasets of smaller and older models (GPT-2 and GROVER) under our setting. We take a small step to exploring why the GPT-3.5 dataset is overly simple by probing statistical cues, including per- spective from token spans and individual tokens.

In summary, our contributions are summarized as follows:

• **Coherence Graph Construction:** We model the text coherence with entity consistency and sentence interaction while statistically proving its distinctiveness in MGT detection, and we further introduce the linguistic feature at the input stage.

• **Improved Contrastive Loss:** We propose a novel contrastive loss in which hard negative samples are paid more attention to improve the detection accuracy of challenging samples.

• **Outstanding Performance:** We achieve state- of-the-art performance on four MGT datasets in both low-resource and high-resource set- tings. Experimental results verify the effec- tiveness and robustness of our model.

**2 Related Work**

**Machine-generated Text Detection.** Machine- generated texts, also named deepfake or neural fake texts, are generated by language models to mimic human writing style, making them perplexing for humans to distinguish [(Ippolito et al.,](#bookmark80)[2020)](#bookmark81). Gen- erative models like GROVER [(Zellers et al.,](#bookmark82)[2019)](#bookmark83), GPT-2 [(Radford et al.,](#bookmark84)[2019)](#bookmark85), GPT-3 [(Brown et al.,](#bookmark86) [2020)](#bookmark87), and emerging GPT-3.5-turbo (also known as ChatGPT) have been evaluated on the MGT detec- tion task and achieve good results [(Gehrmann et al.,](#bookmark88) [2019;](#bookmark89)[Mireshghallah et al.,](#bookmark90)[2023)](#bookmark91). [Bakhtin et al.](#bookmark92) [(2019)](#bookmark93) train an energy-based model by treating the

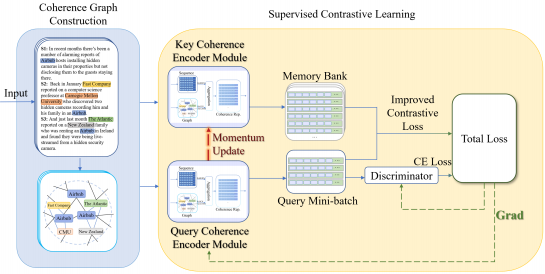


Figure 2: Overview of COCO. Input document is parsed to construct a coherence graph [(3.1)](#bookmark95), the text and graph are utilized by a supervised contrastive learning framework [(3.2)](#bookmark96), in which coherence encoding module is designed to encode and aggregate to generate coherence-enhanced representation [(3.2.3)](#bookmark97). After that, we employ a MoCo based contrastive learning architecture in which key encodings are stored in a dynamic memory bank [(3.2.4)](#bookmark98) with improved contrastive loss to make final prediction [(3.2.5)](#bookmark99).

output of TGMs as negative samples to demonstrate the generalization ability. Deep learning models incorporating stylometry and external knowledge are also feasible for improving the performance of MGT detectors [(Uchendu et al.,](#bookmark100)[2019;](#bookmark101)[Zhong et al.,](#bookmark102) [2020)](#bookmark103). Our method differs from the previous work by analyzing and modeling text coherence as a dis- tinguishable feature and emphasizing performance improvement under low-resource scenarios.

**Coherence Modeling.** For generative models, co- herence is the critical requirement and vital target [(Hovy,](#bookmark104)[1988)](#bookmark105). Previous works mainly discuss two types of coherence, local coherence [(Mellish et al.,](#bookmark106) [1998;](#bookmark107)[Althaus et al.,](#bookmark108)[2004)](#bookmark109) and global coherence [(Mann and Thompson,](#bookmark110)[1987)](#bookmark111). Local coherence focus on sentence-to-sentence transitions [(Lapata,](#bookmark112) [2003)](#bookmark113), while global coherence tries to capture com- prehensive structure [(Karamanis and Manurung,](#bookmark114) [2002)](#bookmark115). Our method strives to represent both local and global coherence with inner- and inter-sentence relations between entity nodes.

**Contrastive Learning.** Contrastive learning in NLP demonstrates superb performance in learn- ing token-level embeddings [(Su et al.,](#bookmark116)[2022)](#bookmark117) and sentence-level embeddings [(Gao et al.,](#bookmark118)[2021b)](#bookmark119) for natural language understanding. With an in-depth study of the mechanism of contrastive learning, the hardness of samples is proved to be crucial in the

training stage. [Cai et al.](#bookmark120)[(2020)](#bookmark121) define the dot prod- uct between the queries and the negatives in nor- malized embedding space as hardness and figured out the easiest 95% negatives are insufficient and unnecessary. [Song et al.](#bookmark122)[(2022)](#bookmark123) propose a difficulty measure function based on the distance between classes and apply curriculum learning to the sam- pling stage. Differently, our method pays more attention to hard negative samples for improving the detection accuracy of challenging samples.

**3 Methodology**

The workflow of COCO mainly contains coher- ence graph construction and supervised contrastive learning discriminator. Fig. [2](#bookmark94)illustrates its over- all architecture. The pseudocode of the training process is shown in Algorithm[1.](#bookmark124)

**3.1 Coherence Graph Construction**

In this part, we illustrate how to construct coher- ence graph to dig out the coherence structure of the text by modeling sentence interaction.

According to Centering Theory [(Grosz and Sid-](#bookmark125) [ner,](#bookmark126)[1986)](#bookmark127), the coherence of texts could be mod- eled by sentence interaction around center enti- ties. To better reflect text structure and avoid se- mantic overlap, we propose to construct an undi- rected graph with entities as nodes. Specifically, we first implement the ELMo-based NER model





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|  |  |  |
| TagLM |

Graph

Construction

RoBERTa



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Relation

-Aware

GCN

Att. LSTM

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| S2 | **+** |  |  |
| S3 | **+** | **+** |  |

Node Rep. Initialization



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Text Sequence

Concatenation

Entity Graph

*Embeddings*

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| S4 … |

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| S5 … |

Embeddings **Coherence Enhanced Represent**

*[CLS]*



*Token*

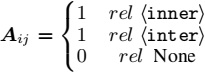
Sentence Rep.

*Entities*

Coherence Rep.

Figure 3: Illustration of CEM. It encodes and fuses the coherence graph and text sequence to generate coherence- enhanced representation of document.

TagLM [(Peters et al.,](#bookmark128)[2017)](#bookmark129) with the help of the [NER toolkit AllenNLP3](#bookmark130)to extract the entities from document. A relation < inter > is constructed between the same entities in different sentences and nodes within the same sentences are connected by relation < inner > for their natural structure relevance. Formally, the mathematical form of the coherence graph’s adjacent matrix is defined as follows:



vi,a  vj,b , a = b

vi,a = vj,b , a  b

others

where vi,a represents i-th entity in sentence a, which is regarded as node incoherence graph. We verify how MGT and HWT separate through static analysis on coherence graph in Appendix[I.](#bookmark131)

**3.2 Supervised Contrastive Learning**

**3.2.1 Model Overview**

The training process is illustrated in Fig.[2.](#bookmark94) Each en- try in the dataset is documented with its coherence graph. The entries in the training set are sampled randomly into keys and queries. Two coherence encoder modules (CEM) fk and fq, are initialized the same to generate coherence-enhanced represen- tation **D**k and **D**q for key and query. A dynamic memory bank with the size of all training data is initialized to store all key representation and their annotations for providing enough contrastive pairs in low-resource scenarios. In every training step, the newly encoded key graphs update the memory bank following the First In First Out (FIFO) rule to keep it updated and the training process consistent.

3<https://demo.allennlp.org/named-entity-recognition>

A novel loss composed of improved contrastive loss and cross-entropy loss ensures the model’s ability to achieve instance-level intra-class com- pactness and inter-class separability while main- taining class-level distinguishability. A lineardis- criminator takes query representations as input and generates prediction results.

**3.2.2 Positive/Negative Pair Definition**

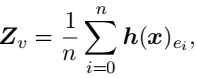
In the supervised setting, where we have access to label information, we define two samples with the same label as positive pairs and those with differ- ent labels as negative pairs for incorporating label information into the training process.

**3.2.3 Encoder Design**

In this part, we introduce the structure of graph neural network structure, an innovative coherence encoder module(CEM), which is utilized to inte- grate coherence information into a semantic repre- sentation of text by propagating and aggregating information from different granularity. The work- flow is illustrated in Fig.[3.](#bookmark132)

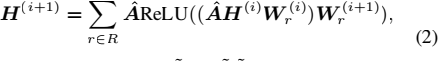
**Node Representation Initialization.** We initialize the representation of entity nodes with the pow- erful pre-trained model RoBERTa for its superior ability to encode contextual information into text representation.

Given an entity e with a span of n tokens, we utilize RoBERTa to map input document **x** to em- beddings**h**(**x**). The contextual representation of e is calculated as follows:

 (1)

where ei is the absolute position where the i-th token ine lies in the whole document.

**Relation-aware GCN.** Based on the vanilla Graph Convolutional Networks [(Welling and Kipf,](#bookmark133)[2016)](#bookmark134), we propose a novel method to assign different weight **W**r for inter and inner relation r with Relation-aware GCN. Relation-aware GCN con- volute edges of each kind of relation in the coher- ence graph separately. The final representation is the sum of GCN outputs from all relations. We use two-layer GCN in the model because more lay- ers will cause an overfitting problem under low resources. We define the relation set as R, and the calculation formula is as follows:



= **D** −  −  ,

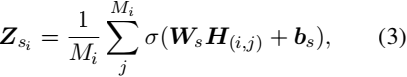
where **H**˜ (i) ∈ **R**N×d is node representation in i-th

layer. **A** = **A**+**I**, **A** is the adjacency matrix of the

coherence g˜raph, is the normalized Laplacian

matrix of **A**, **W**r is the relation transformation matrix for relation r.

**Sentence Representation.** Afterward, we aggre- gate updated node representation from the last layer of Relation-aware GCN into sentence-level rep- resentation to prepare for concatenation with se- quence representation from RoBERTa. The aggre- gation follows the below rule:



where Mi represents the number of entities in i-th sentence, **H**(i,j) represents the embedding of j-th entity in i-th sentence, **Ws** is weight matrix and **b**s is bias. All the sentence representations within the same document are concatenated as sentence matrix **Z**s.

**Document Representation with Attention LSTM.** We design a self-attention mechanism for discovering the sentence-level coherence between one sentence and other sentences, and apply LSTM with the objective to track the coherence in continuous sentences and take the last hidden state of LSTM for aggregated document representation containing comprehensive coherence information. The calculation is described as follows:



where **K** , **Q**, **V** are linear transformations of **Z**s with matrix **W**k, **W**q, **W**v , dZ is the dimension of representation **Z**s, and γ is a hypergammar- parameter for scaling.

Finally, we concatenate **Z**c and the sequence representation **h**([CLS]) from the RoBERTa’s last layer to generate document coherence-enhanced representation **D**.

**3.2.4 Dynamic Memory Bank**

The dynamic memory bank is created to store as much as key encoding **D**k to form adequate posi- tive and negative pairs within a batch. The dynamic memory bank is maintained as a queue so that the newly encoded keys can replace the outdated ones, which keeps the consistency between the key en- coding and the current training step.

**3.2.5 Loss Function**

Following the definition of positive pairs and nega- tive pairs above, traditional supervised contrastive loss [(Gunel et al.,](#bookmark138)[2021)](#bookmark139) treats all positive pairs and negative pairs equally. However, with a recogni- tion that not all negatives are created equal [(Cai](#bookmark140) [et al.,](#bookmark141)[2020)](#bookmark142), our goal is to emphasize the informa- tive samples to help the model differentiatediffi- cult samples. Thus, we propose an improved con- trastive loss that dynamically adjusts the weight of negative pair similarity according to the hardness of negative samples. To be specific, the hard negative samples should be assigned a larger weight to stim- ulate the model to pull the same classes together and push different classes away. The improved contrastive loss is defined as:





Sij = exp(**DD**/τ),

(5)

where P(i) is the positive set in which data has the same label with qi and N(i) is the negative set in which data has a different label from qi.

Apart from instance-level learning mechanism, a linear classifier combined with cross-entropy loss LCE is employed to provide the model with class- level separation ability. LCE is calculated by

LCE =  Σ −[yi log(pi )+(1−yi )log(1−pi )], (6)

where pi is the prediction probability distribution of i-th sample. The final loss Ltotal is a weighted average of LICL and LCE as:

Ltotal = αLICL + (1 − α)LCE , (7)

where the hyperparameter α adjusts the relative balance between instance compactness and class separability.

**3.2.6 Momentum Update**

The parameters of query encoder fq and the clas- sifier can be updated by gradient back-propagated from Ltotal. We denote the parameters offq as θq , the parameters of fk as θk, The key encoder fk’s parameters are updated by the momentum update mechanism:

θk ← βθk+ (1 − β)θq , (8) where the hyperparameter β is momentum coeffi- cient.

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| **Algorithm 1** Algorithm of COCO | |
| **Input:** Input X , consisting of documents D and correspond- ing coherence graph G, hyper-parameters such as the size of dynamic memory bank M and batch size S, labels Y  **Output:** A learned model COCO, consisting of key encoder fk with parameters θk , query encoder fq with parameters θq , classifierfc with parameters θc  1: Initialize θk = θq , θc | |
| 2: | Initialize dynamic memory bank with fk (x1 , x2...xM ), where xi is randomly sampled from X. |
| 3: | Freeze θk |
| 4: | epoch ← 0 |
| 5: | **while** epoch ≤ epochmax **do** |
| 6: | n ← 0 |
| 7: | **while** n ≤ nmax **do** |
| 8: | Randomly select batch **b**k , **b**q |
| 9: | **D**q = fq (**b**q ), **D**k = fk (**b**k ) |
| 10: | p- = fc (**D**q ) |
| 11: | Calculate LICL with equation [5,](#bookmark135) calculate LCE with equation[6,](#bookmark136) calculate Ltotal with equation[7](#bookmark143) |
| 12: | Backward on Ltotal and update θq , θc based on AdamW gradient descent with an adjustable learn- ing rate |
| 13: | Momentum update θk with equation[8](#bookmark144) |
| 14: | Update dynamic memory bank queue with enqueue(queue, **D**k ), dequeue(queue) |
| 15: | k ← k + 1 |
| 16: | **end while** |
| 17: | **if** Early stopping **then** |
| 18: | **break** |
| 19: | **else** |
| 20: | epoch ← epoch + 1 |
| 21: | **end if** |
| 22: | **end while** |
| 23: | **return** A trained model COCO |

**4 Experiments**

**4.1 Datasets**

We evaluate our model on the following datasets:

**GROVER Dataset** [(Zellers et al.,](#bookmark146)[2019)](#bookmark147) is a News-style dataset in which HWTs are collected from RealNews, a large corpus of news from Com- mon Crawl, and MGTs are generated by Grover- Mega (1.5B), a transformer-based news generator.  **GPT-2 Dataset** is a Webtext-style dataset pro- vided by OpenA[I4](#bookmark148)with HWTs adopted from Web- Text and MGTs produced by GPT-2 XLM-1542M.

**GPT-3.5 Dataset** is a News-style open-source dataset constructed by us based on the text-davinci- 00[35](#bookmark149)model (175B) of OpenAI, which is one of the most capable GPT-3.5 models so far and can gen- erate longer texts (maximum 4,097 tokens). The GPT-3.5 model refers to various latest newspapers (Dec. 2022 - Feb. 2023) whose full texts act as the HWTs part, and the model generates by imita- tion. We design two subsets: **mixed-** and **unmixed-** provenances, whose details are explained in Ap- pendix [B.](#bookmark150) The brand-new datasets ensure no ex- isting models have been pre-trained on the corpus, which accounts for the fairness of comparison.

The statistics of datasets are summarized in Ap- pendix [A.](#bookmark151) We randomly sample 500 examples as training data for low-resource settings. As for the full dataset setting, we utilize all training data. The implementation details are in Appendix[D.](#bookmark152)

**4.2 Comparison Models**

We compare COCO to state-of-the-art detection methods to reveal the effectiveness. We mainly divide comparison methods into two categories, **model-based** and **metric-based** methods. The metrics-based methods detect based on specific sta- tistical text-evaluation metrics and logistic regres- sion while the model-based methods learn features via fine-tuning a model.

The **model-based** baselines are as follows:

**GPT-2** [(Radford et al.,](#bookmark153)[2019)](#bookmark154), **RoBERTa** [(Liu](#bookmark155) [et al.,](#bookmark156)[2019)](#bookmark157), **XLNet** [(Yang et al.,](#bookmark158)[2019)](#bookmark159) are power- ful transformers-based models fine-tuned on the binary classification task, implementing GPT-2 small(124M), RoBERTa-base(110M) and XLNet- base(110M).

**CE+SCL** [(Gunel et al.,](#bookmark160)[2021)](#bookmark161), a state-of-the-art supervised contrastive learning method in various downstream task. We train the detector with Cross- Entropy loss (CE) and supervised contrastive loss (SCL) calculated within a mini-batch.

**DualCL** [(Chen et al.,](#bookmark162)[2022)](#bookmark163), a contrastive learn-

4<https://github.com/openai/gpt-2-output-dataset> 5<https://platform.openai.com/docs/models/gpt-3-5>

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| --- | --- | --- |
| **Dataset** | **GROVER** | **GPT-2** |
| **Size** | Limited Dataset (500 examples) Full Dataset | Limited Dataset (500 examples) Full Dataset |
| **Metric** | ACC F1 ACC F1 | ACC F1 ACC F1 |
| GPT2 | 0.5747 ± 0.0217 0.4394 ± 0.0346 0.8274 ± 0.0091 0.8003 ± 0.0141 | 0.5380 ± 0.0067 0.4734 ± 0.0182 0.8913 ± 0.0066 0.8839 ± 0.0078 |
| XLNet | 0.5660 ± 0.0265 0.4707 ± 0.0402 0.8156 ± 0.0079 0.7493 ± 0.0073 | 0.6551 ± 0.0083 0.5715 ± 0.0095 0.9091 ± 0.0091 0.9027 ± 0.0111 |
| RoBERTa | 0.6621 ± 0.0133 0.5895 ± 0.0231 0.8772 ± 0.0029 0.8171 ± 0.0048 | 0.8223 ± 0.0088 0.7978 ± 0.0085 0.9402 ± 0.0039 0.9384 ± 0.0044 |
| DualCL | *0.5835* ± *0.0857 0.4628* ± *0.1076 0.7574* ± *0.0855 0.6388* ± *0.1300* | *0.6039* ± *0.1367 0.5435* ± *0.0903 0.8023* ± *0.1120 0.8046* ± *0.1530* |
| CE+SCL | 0.6870 ± 0.0142 0.5961 ± 0.0197 0.8782 ± 0.0044 0.8202 ± 0.0057 | 0.8355 ± 0.0046 0.8127 ± 0.0067 0.9408 ± 0.0006 0.9390 ± 0.0009 |
| GLTR | 0.3370 0.4935 0.6040 0.5182 | 0.7755 0.7639 0.7784 0.7691 |
| DetectGPT | 0.5910 0.4258 0.6142 0.5018 | 0.7941 0.6982 0.7939 0.7002 |
| COCO | **0.6993** ± **0.0119 0.6125** ± **0.0159 0.8826** ± **0.0018 0.8265** ± **0.0036** | **0.8530** ± **0.0019 0.8410** ± **0.0018 0.9457** ± **0.0004 0.9452** ± **0.0004** |
| **Dataset** | **GPT-3.5 Unmixed** | **GPT-3.5 Mixed** |
| **Size** | Limited Dataset (500 examples) Full Dataset | Limited Dataset (500 examples) Full Dataset |
| **Metric** | ACC F1 ACC F1 | ACC F1 ACC F1 |
| GPT2 | 0.9023 ± 0.0095 0.8920 ± 0.0073 0.9917 ± 0.0056 0.9905 ± 0.0042 | 0.8898 ± 0.0094 0.8914 ± 0.0084 0.9910 ± 0.0046 0.9910 ± 0.0033 |
| XLNet | 0.9107 ± 0.0068 0.9037 ± 0.0064 0.9620 ± 0.0043 0.9634 ± 0.0068 | 0.8925 ± 0.0106 0.8922 ± 0.0089 0.9513 ± 0.0052 0.9505 ± 0.0039 |
| RoBERTa | 0.9670 ± 0.0084 0.9681 ± 0.0077 0.9928 ± 0.0035 0.9913 ± 0.0040 | 0.9565 ± 0.0103 0.9583 ± 0.0092 0.9923 ± 0.0017 0.9901 ± 0.0024 |
| CE+SCL | 0.9823 ± 0.0053 0.9703 ± 0.0070 0.9944 ± 0.0023 0.9943 ± 0.0031 | 0.9628 ± 0.0077 0.9686 ± 0.0062 0.9932 ± 0.0017 0.9905 ± 0.0038 |
| GLTR | 0.9255 0.9287 0.9350 0.9358 | 0.9175 0.9181 0.9210 0.9212 |
| DetectGPT | 0.9220 0.8744 0.9245 0.8991 | 0.8980 0.8814 0.9113 0.9041 |
| COCO | **0.9889** ± **0.0044 0.9791** ± **0.0062 0.9972** ± **0.0015 0.9957** ± **0.0020** | **0.9701** ± **0.0069 0.9735** ± **0.0086 0.9932** ± **0.0019 0.9937** ± **0.0028** |

Table 1: Results of the model comparison. It should be noticed that DualCL is easily affected by random seed, which may be caused by its weakness in understanding long texts. We do not present the experiment results for DualCL on GPT-3.5 dataset because the documentsin GPT-3.5 dataset is so long that DualCL completely fails.

ing method with the addition of label representa- tions for data augmentation.

The **metric-based** baselines are as follows:

**GLTR** [(Gehrmann et al.,](#bookmark165)[2019)](#bookmark166), a supporting tool for facilitating humans to recognize MGTs with visual hints. We follow the settings of [(Guo et al.,](#bookmark167) [2023)](#bookmark168) and select the Test-2 feature, which counts the top-k tokens ranking from GPT-2 medium (355M) predicted probability distributions as features for training a logistic regression classi- fier.

**DetectGPT** [(Mitchell et al.,](#bookmark169)[2023)](#bookmark170), a contem- poraneous metric-based method utilizing the dif- ference of model’s log probability after text per- turbations. We use T5-3B to perturb texts, and Pythia-12B [(Biderman et al.,](#bookmark171)[2023)](#bookmark172) for scoring in the model. A logistic regression classifieristrained to make predictions.

**4.3 Performance Comparison**

As shown in Table [1,](#bookmark164) COCO surpasses the state- of-the-art methods in MGT detection task by **at least 1.23%** and **1.64%**, **1.75%** and **2.83%** on the GROVER, GPT-2 limited datasets in terms of Accuracy and F1-Score, respectively. And COCO achieves comparable performance with the most ca- pable detectors in the complete dataset setting. The result indicates the utility of contrastive learning and the rationality of coherence representation.

Moreover, it should be noticed that compared with metric-based methods, model-based methods usually tend to achieve better results. This can be explained because metric-based methods can only concern and regress on a few features, which are over-compressed and under-represented for the de- tection task. Also, metric-based methods mainly use the pre-trained model for token probability in- stead of fine-tuning the whole model. And with more training samples involved, the performance of model-based methods improves drastically, while metric-based methods do not benefit much from more training examples. It reveals that logistic re- gression is not strong enough to take in many texts with diverse semantics. Meanwhile, COCO outper- forms CE+SCL and DualCL regardless of the size of the training set, which suggests the success of improved contrastive loss to solve the performance degradation problem brought by simple negative samples.

We also find GROVER Dataset is the hardest to detect. It is because the GROVER generator is trained in an adversarial heuristic with the objec- tive of deceiving the verifier, which endows the generator with a deceptive nature. To our surprise, the GPT-3.5 dataset is overly simple for all detec- tors. The result is also in accord with conclusions in recent works [(Mireshghallah et al.,](#bookmark173)[2023;](#bookmark174)[Chen](#bookmark175) [et al.,](#bookmark176)[2023)](#bookmark177). We conduct extensive experiments on

different self-constructed and published GPT-3.5 datasets generated by a series of prompts, validat- ing this thundering conclusion. The experiment details and results are in Appendix[C.](#bookmark178) We also im- plement experiments and discussions to explore further explanations in Sec.[4.5.2.](#bookmark179)

Notably, a **more comprehensive comparison experiment** with 8 datasets [(Pu et al.,](#bookmark180)[2023)](#bookmark181) and 12 methods is presented in Appendix[E,](#bookmark182) which sub- stantiates the advantage of COCO.

**4.4 Ablation Study**

To illustrate the necessity of components of COCO, we conduct ablation experiments on 1,000-example GROVER dataset. The ablation models’ structure is as follows:

|  |  |  |
| --- | --- | --- |
| **Model** | **ACC** | **F1** |
| COCO (Plain) | 0.7697 | 0.6428 |
| COCO (Sentence Nodes) | 0.7733 | 0.6379 |
| COCO (Coherence) | 0.7777 | 0.6463 |
| COCO (Coherence+LSTM) | 0.7787 | 0.6471 |
| COCO (Coherence+LSTM+SCL) | 0.7827 | 0.6609 |
| **COCO** | 0.7843 | 0.6684 |

Table 2: Results of the ablation study on 1,000-example GROVER dataset.

**COCO (Plain)** removes graph information and en- codes only by RoBERTa parts. The model removes contrastive learning and only uses CE loss.

**COCO (Sentence Nodes)** treats sentences (instead of entities) as nodes and establishes edges between sentences that share the same entities. Node repre- sentation is initialized by RoBERTa embedding and mean-pooling operation. Document representation is obtained by one CEM discarding sentence rep- resentation and attention LSTM part in Sec.[3.2.3.](#bookmark137) Document representation is calculated by mean- pooling operation on sentence node representations. A linear classification head with cross-entropy loss is used for detection.

**COCO (Coherence)** incorporates the coherence graph into the representation of document and de- ploys the sentence representation of Sec.[3.2.3.](#bookmark137) The rest are the same with COCO (Sentence Nodes).

**COCO (Coherence+LSTM)** uses attention LSTM for document-level aggregation, and the rest is the same as COCO (Coherence).

**COCO (Coherence+LSTM+SCL)** utilizes the contrastive learning framework, but the loss func-

tion is traditional supervised contrastive loss (SCL) instead of the improved contrastive loss.

As shown in Table [2,](#bookmark184) coherence information and the contrastive learning framework greatly con- tribute to the development of model performance, especially in F1-Score. Replacing entity nodes in the coherence graph with sentences impairs the de- tector, which could be caused by semantic overlap between graph representation and text sequence representation. The attention LSTM also plays an important role in preserving the coherence infor- mation during sentence aggregation. Lastly, the results show the advantage of improved contrastive loss over standard supervised contrastive loss.

Furthermore, we also conduct ablation studies on other scenarios, including GPT-2, GPT-3.5- Unmixed, and GPT-3.5-Mixed datasets. More de- tailed results are discussed in the Appendix [G,](#bookmark185) which clearly stands for the performance gain of COCO components. Moreover, the helpfulness of contrastive learning is verified to be orthogonal to the helpfulness of coherence information.

**4.5 Discussion**

**4.5.1 Model Robustness to Perturbation**

To validate the robustness of COCO to various per- turbations, we train COCO on the GROVER dataset in the low-resource setting and perturb the test set with four different operations: **Delete** (randomly delete tokens in each entry), **Repeat** (randomly select tokens and repeat them twice in the text), **Insert** (add random tokens from the vocabulary of the pre-trained model into random positions in the text), **Replace** (randomly replace tokens with ran- domlyselected tokens from the vocabulary). The perturbation scale is set to 15%. The experiment result is shown in Table[3.](#bookmark186)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model RoBERTa COCO  Metric Acc F1 Acc F1 | | | | |
| Original | 0.6635 | 0.5901 | **0.6993** | **0.6125** |
| **Delete** | 0.5736 (-0.0899) | 0.5545 (**-0.0356**) | **0.6363** (**-0.0630**) | **0.5703** (-0.0422) |
| **Repeat** | 0.6320 (-0.0315) | 0.5743 (-0.0158) | **0.6732** (**-0.0261**) | **0.6004** (**-0.0121**) |
| **Insert** | **0.6325** (**-0.0310**) | 0.4881 (**-0.1020**) | 0.6286 (-0.0707) | **0.4970** (-0.1155) |
| **Replace** | 0.5554 (-0.1081) | 0.4814 (**-0.1087**) | **0.6367** (**-0.0626**) | **0.5023** (-0.1102) |
| Average | 0.5984 (-0.0651) | 0.5246 (**-0.0655**) | **0.6437** (**-0.0556**) | **0.5425** (-0.0700) |

Table 3: Model robustness to different perturbations.

Despite the structural complexity, COCO keeps outperforming the baseline during perturbations. COCO’s performance fluctuations are as minor as the baseline. And COCO maintains **4.53%** better in

|  |  |  |
| --- | --- | --- |
| N-gram Coverage | MGT | HWT |
| γ1 | 0.6659 | 0.6377 |
| γ2 | 0.4250 | 0.3630 |
| γ3 | 0.2883 | 0.2076 |
| γ4 | 0.2019 | 0.1372 |
| γ5 | 0.1425 | 0.0935 |

Table 4: N-gram Coverage in GPT-3.5 Mixed Dataset.

|  |  |  |
| --- | --- | --- |
| Token | Productivity | Coverage |
| according | 0.6923 | 0.3126 |
| where | 0.6842 | 0.1998 |
| they | 0.6316 | 0.3837 |

Table 5: Individual tokens with top-3 productivity.

accuracy and **1.79%** better in F1-score on average, which stands for its robustness.

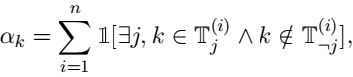
**4.5.2 Statistic Cues for Detectable Feature in**

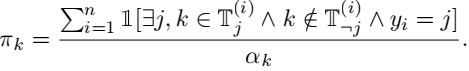
**GPT-3.5**

To further investigate the rationale behind the easy- to-detect nature of GPT-3.5 generated texts, we utilize Transformers-Interpre[t6 ,](#bookmark189) a tool for evaluat- ing feature attribution in predictions based on In- tegrated Gradients [(Sundararajan et al.,](#bookmark190)[2017)](#bookmark191), for discovering the supporters and opponents (tokens) in the decision-making stage. We probe the statis- tical cues of the GPT-3.5 mixed dataset from two perspectives: spans of tokens and individual tokens.

We define spans of tokens coverage γn as n-gram supporters for true positives Pn , *i.e.*, n consecutive tokens all contribute positively to the correct pre- diction, over all n-gram tokens in true positives An , which could be formulated as γn =  .

Moreover, we apply productivity πk and cover- age ϵk of statistic cue k [(Niven and Kao,](#bookmark192)[2019)](#bookmark193) on the GPT-3.5 mixed dataset to find out if there are individual tokens acting as common and strong signals contribute to model predictions. Formally, productivity πk is defined as:





(9) Here, Tj(i) is the set of tokens for text i with label j. And the coverage ϵk is the portion that all appli-

cable cues over the total number of data points.

We fine-tune the RoBERTa-base model with a

classification head on the GPT-3.5 mixed dataset

6<https://github.com/cdpierse/transformers-interpret>

and quantify how tokens in GPT-3.5 mixed test data affect the model predictions with the criteria mentioned above. The results are shown in Table[4](#bookmark187) and Table[5.](#bookmark188) It could be noticed that although γ1 for MGT and HWT is about the same, the gap widens from γ2 to γ5 , indicating that more consecutive spans of tokens act as an indicator for MGT than HWT. Table[5](#bookmark188)shows that "according", "where", and "they" are top-3 strongest tokens for detection. However, we could not reach any valid conclusions from their semantics. Meanwhile, these tokens only cover a small portion of the total number of data points (less than 0.4), leading to the weak strength of the signal they provide. Therefore, we come up with a hypothesis that the easy-to-detect nature of GPT-3.5 does not originate from specific token but from certain language patterns (could be demon- strated by a span of tokens). The reason might be that advanced LLMs fit extremely well to the cor- pus so that it generates more general expressions, which could be much easier to be expected by fine- tuned detectors. A case study for token importance illustration is shown in Appendix[H.2.](#bookmark194)

Further, we discuss more topics in the Appendix, *e.g.*, the effect of hyper-parameters [(F)](#bookmark195), case study [(H)](#bookmark196), static geometric analysis on coherence graph [(I)](#bookmark197), and exploration on imbalanced data [(J)](#bookmark198).

**5 Conclusion**

In this paper, we propose COCO, a coherence- enhanced contrastive learning model for MGT de- tection. We construct a novel coherence graph from the document and implement a MoCo-based contrastive learning framework to improve model performance in low-resource settings. An innova- tive encoder composed of relation-aware GCN and attention LSTM is designed to learn the coherence representation from the coherence graph, which is further incorporated with the sequence repre- sentation of the document. To alleviate the effect of unnecessary easy samples, we propose an im- proved contrastive learning loss to force the model to pay more attention to hard negative samples. COCO outperforms all detection tasks generated by GROVER, GPT-2, and GPT-3.5, respectively, in both low-resource and high-resource settings. We also find the outputs from the advanced GPT- 3.5 are more detectable and explore the rationale behind the phenomena through the perspective of spans of tokens and individual tokens.

**Limitations**

In this work, we step forward to better distinguish- ing MGTs under the low-resource setting. How- ever, several limitations still exist for the broader applications of this detector. Firstly, MGTs are easier to generate and collect than HWTs, which may cause an imbalanced label distribution in the dataset. And COCO literally corrupts in extremely imbalanced data distribution condition, as shown in[J.](#bookmark199) Future work could build upon the contrastive learning method of COCO with innovation on sam- pling strategy for harsh low-resource and imbal- anced data settings. Secondly, our method artifi- cially generates a coherence graph for every entry, which is not efficient for larger datasets. What’s more, short text, codes, and mathematical proofs, which are hard to generate coherence graphs, are also limitedly detected by CoCo. More distinctive and easy-to-calculate features are worth exploring for generating distinguishable representations for texts with efficiency while better understanding the essence of TGMs. Thirdly, with instruct-based generation and human-in-loop fine-tuning models prevailing, the strategy and defect of TGMs change slightly but constantly. The entity relation with the same semantic granularity and concretization in this paper would not be enough to detect the high-quality content by TGMs in the future. More generative and adaptive detection models should be considered.

**Ethical Considerations**

We provide insight into the potential weakness of TGMs and publish the GPT-3.5 news datasets. We understand that the discovery of our work can be viciously used to confront detectors. And we under- stand that malicious users can copy the contents of our GPT-3.5 news dataset to disguise real news and publish them. However, with the purpose of calling for attention to detecting and controlling possible misuse of TGMs, we believe our work will inspire the advancement of the stronger detector of MGTs and prevent all potential negative uses of language models.

Our work complies with the sharing & publi- cation policy of OpenA[I7](#bookmark202)and all data we collect is in the public domain and licensed for research purposes.

7<https://openai.com/api/policies/sharing-publication/>

**Acknowledgements**

We thank all the reviewers, the area chair, Kevin Yang (UC Berkeley), and Prof. Pietro Liò (Univ. of Cambridge) for their helpful feedback, which aided us in greatly improving the paper. This work is sup- ported by National Natural Science Foundation of China (62272371, 62103323, U21B2018), Initia- tive Postdocs Supporting Program (BX20190275, BX20200270), China Postdoctoral Science Founda- tion (2019M663723, 2021M692565), Fundamental

Research Funds for the Central Universities under grant (xhj032021013), and Shaanxi Province Key Industry Innovation Program (2021ZDLGY01-02).

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**A Basic Statistics of Datasets**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dataset** | **Class** | Train | Valid | Test |
| GROVER | HWT | 5,000 | 2,000 | 8,000 |
| MGT | 5,000 | 1,000 | 4,000 |
| GPT-2 | HWT | 25,000 | 5,000 | 5,000 |
| MGT | 25,000 | 5,000 | 5,000 |
| GPT-3.5 | HWT | 3,454 | 1,000 | 1,000 |
| Unmixed | MGT | 3,454 | 1,000 | 1,000 |
| GPT-3.5 | HWT | 3,032 | 1,000 | 1,000 |
| Mixed | MGT | 3,032 | 1,000 | 1,000 |

Table 6: Basic statistics of datasets.

**B Details of GPT-3.5 Dataset**

GPT-3.5 Dataset for COCO is our latest dataset for the MGT detection task. There are two subsets in the self-made dataset for easy analysis of the impact of provenance and writing styles: unmixed- and mixed provinces. We use the text-davinci-003 model of OpenAI to generate MGT examples. The maximum length of HWTs is 1,024 tokens, and the target generation length is set as 1,024 tokens. Here is an example of the MGT data.

"title": "On Eve of World Cup, FIFA Chief Says,

‘Don’t Criticize Qatar; Criticize Me . ’",

"text": "DOHA, Qatar . The president of world soccer’s governing body on Saturday sought to blunt mounting concerns about the World Cup in Qatar with a strident defense of both the host country’s reputation and FIFA’s authority over its showpiece championship. . . . . . . Citing statistics, history and even childhood to bolster his case, he at one point likened his own experience as a redheaded child of immigrants to Switzerland to the assimilation problems of gays in the Middle East, and defended the laws, customs and honor of the host country.",

"authors": ["Tariq Panja"],

"publish\_date": "2022-11-19 00:00:00", "source": "The New York Times",

"url": "<https://www.nytimes.com/2022/11/19/sports/> soccer/world-cup-gianni-infantino-fifa.html"

And the following data shows the corresponding MGT in the dataset.

|  |
| --- |
| "title": "On Eve of World Cup, FIFA Chief Says,  ‘Don’t Criticize Qatar; Criticize Me . ’",  "text": "The 2022 FIFA World Cup in Qatar is fast approaching, and its organizing committee’s president, Gianni Infantino, is speaking out about the lingering criticism of the country hosting the event. . . . . . . he said. “It is a once-in-a-lifetime opportunity for the region to show the world its values and aspirations, and it is vital that this event is seen as a celebration of football and a celebration of the region.”",  "authors": "machine",  "source": "The New York Times",  "matched\_hwt\_id": 202, "label": "machine"" |

**B.1 Human Written Texts**

**Unmixed Subset.** The HWTs of the unmixed sub- set are all from The New York Time[s8](#bookmark215)to exclude the impact of writing style. The time span of our data is Nov 1, 2022 - Dec 25, 2022, making sure that no pre-trained model has learned them. We develop the crawler based on news-crawle[r9 .](#bookmark216)

**Mixed Subset.** The HWTs of the mixed subset come from various sources, listed as Table[7.](#bookmark217) The time span of the data is Jan 1, 2022 - Jan 7, 2023. We develop the crawler based on Newspaper3k[10 .](#bookmark218) The dataset is specifically designed for MGTs detection and improving generation models. The contents of dataset are obtained from official news websites and the names of indicidual people are

not mentioned maliciously. And we strongly reject using our dataset to create offensive content or peek at private information.

8<https://www.nytimes.com/>

9<https://github.com/LuChang-CS/news-crawler> 10<https://github.com/codelucas/newspaper>

|  |  |
| --- | --- |
| **Name** | **Website** |
| Kotaku | <https://kotaku.com> |
| The Daily World | <https://www.thedailyworld.com> |
| CNN | <https://edition.cnn.com> |
| BBC | <https://www.bbc.com> |
| NBC News | <https://www.nbcnews.com> |
| Reuters | <https://www.reuters.com> |
| Huffpost | <https://www.huffpost.com> |
| Pando | <http://pandodaily.com> |
| Yahoo | <https://news.yahoo.com> |
| Sun Times | <https://chicago.suntimes.com/news> |
| Sfgate | <https://www.sfgate.com> |
| New Republic | <https://newrepublic.com> |
| Time | <https://time.com> |
| Pcmag | <http://www.pcmag.com> |
| CNBC | <https://www.cnbc.com/world/> |
| News | <https://www.news.com.au/> |
| The Atlantic | <https://www.theatlantic.com/latest/> |

Table 7: Data sources for the mixed subset.

**B.2 Machine Generated Texts**

As the GPT-3.5 and ChatGPT model need prompts to generate, we write hints for the generation mod- els to generate texts that meet our news-style long text generation. The hints format is as follows, and the content is related to HWTs.

|  |
| --- |
| Write a news more than 1000 words.  The news is written by {Authors} from {Source} in {date} . Title is {title} . |

**C GPT-3.5 Dataset Generated by**

**Different Prompts and Experiment Results**

To further validate the conclusion that GPT-3.5 gen- erated texts are easier to detect, we utilize CNN news as a reference and design different prompts for GPT-3.5 generation. The principle is to pro- vide as much information as possible to GPT-3.5 to alleviate the possible gap in semantics and in length.

**Keywords as Prompt (KP).** We extract the key- words and entities with GPT-3.5-turbo and provide examples in original news to form the prompt for generation. The prompt format is as follows.

Example prompt for generation.

|  |
| --- |
| "role": "system", "content": "Extract all the keywords, entities, and examples in the following passage:"  "role": "user", "content": {text} |

Example prompt for generation.

|  |
| --- |
| Generate a news passage .  The news is written by {Authors} from {Source} in {date} .  Title: Lionel Messi isn’t expected to be back with PSG until early January after World Cup success  Keywords: exploring, mountains, space, Poorna Malavath, Kavya Manyapu, NASA, Mount Everest, Project Shakthi, girls’ education, Ladakh, India, virgin peak, climbing, altitude sickness, safety, motivation, empowerment, education, gender gap, Mount Aconcagua, sponsorship.  Entities: CNN, Poorna Malavath, Kavya Manyapu, NASA, Mount Everest, Project Shakthi, Ladakh, India, Mount Aconcagua, South America, World Bank .  Examples: designing space suits, youngest ever woman to summit Mount Everest, climbed a 6,012m virgin peak, raise money to fund girls’ education, difficulties of climbing a virgin peak, experiences of altitude sickness, purpose of Project Shakthi, India’s Right to Education Act, sponsorship for underprivileged school children, scaling Mount Aconcagua, expanding sponsorship globally.  The target length for generation is 731 tokens. Add as much details and examples as you can .  News: |

**Summary as Prompt (SP).** We employ GPT-3.5- turbo to summarize the original texts. The com- pression ratio is set to [0.3, 1.0], which means the summary is required to be longer than 0.3 of the length of original text and shorter than whole origi- nal text. The generated summary is used as prompt and the format is as follows:

|  |
| --- |
| Generate a news based on the following abstract:  Paris Saint-Germain’s coach Christophe Galtier has stated that Lionel Messi is not expected to join the team until early January as he is spending time in Argentina following the World Cup . Kylian Mbappé, Neymar Jr . and Achraf Hakimi, who played for their respective national teams at Qatar 2022, could return to the team as long as they are physically and mentally fit. . . The news is written by Matias Grez from CNN in 2022-12-28 00:00:00 .  Title: Lionel Messi isn’t expected to be back with PSG until early January after World Cup  success News: |

**Outline as Prompt (OP).** We also outline the skele- ton of original texts by GPT-3.5-turbo and feed the outline into GPT-3.5 text-davinci-003. The prompt format is as follows:

Prompt for extraction.

|  |
| --- |
| "role": "system", "content": "Write a hierarchical multi-point outline for the paragraph. "  "role": "user", "content": {text} |

Example prompt for generation.

|  |
| --- |
| News Title: There’s a shortage of truckers, but TuSimple thinks it has a solution: no driver needed  The news is written by Jacopo Prisco, CNN from CNN in 2021-07-15 02:46:59 .  Outline:  I. TuSimple’s plan for fully autonomous truck tests  A . Reliability of software and hardware needs to improve  B . Fully autonomous tests without human safety driver planned by end of year  C . Results will determine if company can launch trucks by 2024  D . 7,000 trucks reserved in US alone II. TuSimple’s competition  A . . . .  Add more details and examples. News: |

We first remove the HWTs that do not have de- sired length (i.e., 200-1024 tokens). And we take half of the selected HWTs as references to formu- late different prompts mentioned above and feed it into GPT-3.5 to get MGTs. TheMGTs are sampled by Gaussion Distribution of their lengths. To avoid the possible label leakage brought by text length, we directly filter the no-reference HWTs according to the Gaussion Distribution of MGT lengths.

Besides the self-constructed datasets, we also utilize the published GPT-3.5 dataset TuringBench benchmark (abbraviate as GPT-3.5 (TB)) [(Uchendu](#bookmark211) [et al.,2020)](#bookmark211) to validate the deceptiveness of GPT- 3.5. The statistics of datasets we use is in Table [8.](#bookmark219)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Dataset | | Train | Valid | Test | # of tokens |
| GPT-3.5(KP) | HWT | 446 | 148 | 148 | 427.96 ± 45.49 |
| MGT | 446 | 148 | 148 | 403.88 ± 75.63 |
| GPT-3.5(SP) | HWT | 446 | 148 | 148 | 427.96 ± 45.49 |
| MGT | 446 | 148 | 148 | 415.72 ± 66.54 |
| GPT-3.5(OP) | HWT | 446 | 148 | 148 | 427.96 ± 45.49 |
| MGT | 446 | 148 | 148 | 429.34 ± 78.62 |
| GPT-3.5(TB) | HWT | 5,964 | 975 | 1915 | 236.17 ± 72.96 |
| MGT | 5,507 | 894 | 1763 | 147.29 ± 70.15 |

Table 8: Statistics of GPT-3.5 datasets.

We conduct experiments with 3 random seeds and the average results are shown in Table[9.](#bookmark220) Coun- terintuitively, even if we elaborate the prompts and eliminate the length difference between MGTs and HWTs, the detection results are still superior, even on outdated baselines like GPT-2. The conclusion might be counterintuitive, but texts generated by the most advanced and popular GPT-3.5 model are the easiest to detect.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset  **Metric** | **GPT-3.5 (KP)** | | **GPT-3.5 (SP)** | | **GPT-3.5 (OP)** | | **GPT-3.5 (TB)** | |
| ACC(val/test) | F1(val/test) | ACC (val/test) | F1 (val/test) | ACC (val/test) | F1 (val/test) | ACC (val/test) | F1 (val/test) |
| GPT2 | 0.9914/0.9916 | 0.9916/0.9918 | 0.9890/0.9893 | 0.9885/0.9889 | 0.9925/0.9928 | 0.9923/0.9924 | 0.9884/0.5422\* | 0.9880/0.6335\* |
| RoBERTa | 0.9946/0.9950 | 0.9950/0.9952 | 0.9935/0.9941 | 0.9933/0.9937 | 0.9946/0.9943 | 0.9942/0.9940 | 0.9962/0.6406\* | 0.9960/0.7273\* |
| COCO | 0.9955/0.9950 | 0.9942/0.9945 | 0.9938/0.9941 | 0.9936/0.9940 | 0.9942/0.9943 | 0.9942/0.9943 | 0.9966\* | 0.9970\* |

Table 9: Experiment of different detectors on different GPT-3.5 Dataset. \* : The great performance difference between validation set and test set on GPT-3.5 (TB) are because the test set randomly sample 50% of the words of each article in the dataset [(Uchendu et al.,2021)](#bookmark212). We do not test COCO on GPT-3.5 (TB) for the reason that such operation greatly influences the coherence in texts. We provide an example of this in Table[10.](#bookmark221)

**GPT-3.5 (TB) GPT-3.5 (OP)**

|  |  |  |
| --- | --- | --- |
| |  | | --- | | ’.video : morne morkel press conference \* cricbuzz.video : eng- land cricbuzz.bevan leads scotland ’s 21-man squad for their first ever test match against pakistan in edinburgh icc.chris rogers retires after champions trophy defeat : australian cricketer an- nounces international retirement the sun.icc super eight teams : odi ranking results.bahrain host oman on sunday kitply hans vohra gold cup gulf today.icc results.new zealand series history : india v new zealandyazan mohsen qawasma : how bahrain caught | | Recent changes to key international indexes have resulted in the unprecedented exclusion of Russian stocks at a “zero” price, causing further losses in Moscow’s already-dismal stock ex- change. This exclusion has made Russia no longer an option for investors, prompting a shift to other emerging markets.\n\nThe dramatic shift was made in early March, when FTSE Russell and MSCI announced the removal of Russian stocks from their indexes due to the country’s escalating economic and geopoliti- cal problems. Shortly after, the Moscow Exchange suspended trading, sending ripples through the market.\n\nThe possible de- fault on Russian debt has Western investors further reconsidering their investments in Russia... |

Table 10: A comparison example between texts in test set of GPT-3.5 (TB) and GPT-3.5 (OP). The GPT-3.5 (TB) text shows great disorder while GPT-3.5 (OP) text is neat.

**D Implementation Details**

This part mentions the implementation details and hyper-parameter settings of all the methods in the experiment. To imitate the situation of low data-resources, we randomly sample 500 en- tries from the datasets as limited dataset (posi- tive:negative=1:1), which will test models together with the complete datasets. And we conduct ex- periments on 10 different seeds and report the av- erage test accuracy, F1-Score, and standard devia- tion only for model-based methods because metric- based methods would not be affected by random seeds.

We use RoBERTa base model to initialize the embedding of our representation and optimize the model using AdamW [(Loshchilov and Hutter,](#bookmark207) [2018)](#bookmark207) optimizer with a 0.01 weight decay. We set the initial learning rate to 10−5 and the batch size to 8 for all datasets based on experiences.

We utilize packages, namely transformers, py- torch, and allennlp to implement COCO. And the GPT-3.5 datasets and ChatGPT case is generated by OpenAI API and websites. We spend $300 for API costs, including development and final gen- eration costs. We train and do experiments on 8 NVIDIA A100 GPUs on 2 Ubuntu-based servers.

The total budget for training 20 epochs, dev, and testing on the GROVER dataset is 2.5 hours. On GPT-2 dataset is 12 hours, and on GPT-3.5 dataset is 1.5 hours. We will publish our code and dataset recently.

**E More Comparison Experiments**

Provisioning empirical evidence to claim effective- ness is a relatively broad topic, and in Table[1](#bookmark164)we have shown COCO outperforms on 4 datasets (8 set- tings) compared with 6 models, including Roberta and CE+SCL, the SOTA of the model-based meth- ods, and DetectGPT, the SOTA of the metric-based methods. Moreover, our model is outperforming on very wide scenarios. Due to the limitation of pages, we do not post all the results in the main text, so we would love to share with you a more comprehensive result here.

**Dataset.** Following[Pu et al.(2023)](#bookmark181), we use Real-

News dataset [(Raffel et al.,2020)](#bookmark208) as human-written

texts, and the machine-generators are the most

representative models nowadays, namely GPT-[2](#bookmark222)

(medium and xl) [(Radford et al.,](#bookmark154) [2019)](#bookmark154), GPT-[3](#bookmark223)

(text-davinci-003) [(Ouyang et al.,2022)](#bookmark157), GPT-[4](#bookmark224)

[(OpenAI,](#bookmark206) [2023)](#bookmark206), GPT-Neo (2.7B) [(Black et al.,](#bookmark200)

[2022)](#bookmark200), GPT-J [(Wang and Komatsuzaki,2021)](#bookmark213), and

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Type** | **Dataset Generator Method** | ***GPT-2 md***  ACC AUROC | | ***GPT-2 xl***  ACC AUROC | | ***GPT-3***  ACC AUROC | | ***GPT-4***  ACC AUROC | |
| probability metric-based | GLTR | 0.7840 0.8536 | | 0.7360 0.8098 | | 0.2780 0.1930 | | 0.4320 0.3990 | |
| Rank | 0.6680 0.7200 | | 0.6160 0.6723 | | 0.4520 0.4304 | | 0.5120 0.5203 | |
| LogRank | 0.8080 0.8837 | | 0.7600 0.8374 | | 0.2800 0.1988 | | 0.4220 0.3885 | |
| perturbed | DetectGPT-10d | 0.8620 0.8400 | | 0.8020 0.8896 | | 0.3100 0.2349 | | 0.4020 0.3601 | |
| metric-based | DetectGPT-10z | 0.8480 0.8331 | | 0.8200 0.8977 | | 0.3120 0.2330 | | 0.4020 0.3585 | |
| off-the-shelf | OpenAI-detector | 0.8460 0.8341 | | 0.7740 0.8680 | | 0.4400 0.4263 | | 0.4200 0.3936 | |
| model-based | ChatGPT-detector | 0.4760 0.4957 | | 0.4900 0.5156 | | 0.9280 0.9764 | | 0.8640 0.9013 | |
| fine-tuned model-based | OpenAI-GPT BERT-base GPT-2  RoBERTa-base Electra-base  **CoCo** | 0.8050 0.8480 0.6680 0.8940 0.8710  **0.9067** | 0.8278 0.8480 0.7896 0.8941 0.8726  **0.9123** | 0.8170 0.8540 0.7300 0.8970 0.8720  **0.9063** | 0.8189 0.8543 0.7247 0.8978 0.8727  **0.9063** | 0.8450 0.8570 0.9920 0.9840 0.8880  **0.9936** | 0.8460 0.8599 0.9920 0.9840 0.8940  **0.9938** | 0.9020 0.9260 0.8990 0.9630 0.9350  **0.9787** | 0.9026 0.9275 0.9010 0.9630 0.9351  **0.9786** |
| **Type** | **Dataset Generator Method** | ***GPT-Neo lg***  ACC AUROC | | ***GPT-J***  ACC AUROC | | ***LLaMA 7B***  ACC AUROC | | ***LLaMA 13B***  ACC AUROC | |
| probability metric-based | GLTR | 0.7240 0.8044 | | 0.6940 0.7574 | | 0.5980 0.6086 | | 0.5840 0.6082 | |
| Rank | 0.6660 0.7329 | | 0.6420 0.6923 | | 0.5760 0.6114 | | 0.5660 0.6106 | |
| LogRank | 0.7580 0.8449 | | 0.7480 0.8300 | | 0.6160 0.6465 | | 0.6160 0.6468 | |
| perturbed | DetectGPT-10d | 0.6900 0.7545 | | 0.7560 0.8271 | | 0.5640 0.5877 | | 0.5300 0.5481 | |
| metric-based | DetectGPT-10z | 0.6860 0.7483 | | 0.7560 0.8434 | | 0.5740 0.5931 | | 0.5320 0.5570 | |
| off-the-shelf | OpenAI-detector | 0.7620 0.8615 | | 0.7200 0.7904 | | 0.6140 0.6712 | | 0.5940 0.6453 | |
| model-based | ChatGPT-detector | 0.8400 0.8798 | | 0.8500 0.8875 | | 0.8440 0.8845 | | 0.8480 0.8880 | |
| fine-tuned model-based | OpenAI-GPT BERT-base GPT-2  RoBERTa-base Electra-base  **CoCo** | 0.7480 0.7390 0.8940 0.9270 0.7880  **0.9462** | 0.7611 0.7690 0.8954 0.9326 0.8320  **0.9353** | 0.6720 0.7200 0.8970 0.9220 0.7740  **0.9326** | 0.6720 0.7277 0.8990 0.9290 0.7816  **0.9414** | 0.6100 0.6460 0.7960 0.9180 0.6690  **0.9321** | 0.6142 0.6462 0.8046 0.9254 0.6920  **0.9313** | 0.6330 0.6430 0.9050 0.9240 0.7060  **0.9455** | 0.6335 0.6595 0.9100  **0.9669**  0.7063 0.9602 |

Table 11: Comprehensive experimental results on wide scenarios. The same as the limited setting in Sec.[4.1,](#bookmark145) which uses 500 examples for these models to fine-tune.

LLaMA (7Band 13B) [(Touvron et al.,2023)](#bookmark21).

**Comparison Models.** More detailed, current de- tection methods can be categorized into four types: probability metric-based, perturbed metric-based, off-the-shelf model-based, and fine-tuned model- based. Our model COCO is in the fine-tuned model- based category.

• **Probability metric-based methods:** GLTR [(Gehrmann et al.,2019)](#bookmark166), *i.e.*, using token log- likelihood; Rank [(Solaiman et al.,2019)](#bookmark107) and LogRank [(Ippolito et al.,2020)](#bookmark205), *i.e.*, using the rank/log-rank of token likelihood.

• **Perturbed metric-based methods:** Detect- GPT [(Mitchell et al.,2023)](#bookmark170), in the nomencla- ture of Table[11,](#bookmark225) the number ‘10’ means the number of perturbation samples. The letter ‘d’ means not normalized on distribution, while ‘z’ means normalized.

• **Off-the-shelf model-based model:** OpenAI- detector [(Solaiman et al.,2019)](#bookmark107), built by Ope- nAI mainly for GPT-2 detection based on the RoBERTa model; ChatGPT-detector [(Guo](#bookmark168) [et al.,2023)](#bookmark168), made based on SimpleAI based on the HC3 dataset.

• **Fine-tuned model-based methods:** All the models we use have the same level of size,*i.e.*, around 110M parameters, including OpenAI- GPT, Bert-base-uncased, GPT-2, RoBERTa- base, Google Electra-base discriminator, and COCO.

Table[11](#bookmark225)reveals the outstanding performance of COCO in almost all the scenarios. Moreover, We also find the following phenomenon:

• It follows the intuitive notion that off-the-shelf models are only competitive in their designed scenario. OpenAI-detector performs well on

GPT-2s and GPT-Neo datasets. And ChatGPT- detector, in reverse, excels on GPT-3, GPT-4, Llamas, GPT-J, and GPT-Neo.

• Probability metric-based methods rely on the likelihood from the generation model, which is mainly designed for white-box machine- generated detection. For white-box models like GPT-2, GPT-Neo, and GPT-J, their perfor- mance is relatively good. But when applied to totally black-box models, these methods could easily fail. DetectGPT, the perturbed metric- based method, shares the same limitation with a similar mechanism.

• Among all the fine-tuned model-based meth- ods, RoBERTa-base shows the best perfor- mance average on all datasets compared to other base models. Thus, it supports our claim that recognizing RoBERTa as SOTA for this category, and further built CL methods and COCO based on RoBERTa.

**F Effect of Hyper-Parameters**

**F.1 Contrastive Learning Parameters**

We evaluate the influence of contrastive learning hyper-parameters α and τ with experiments on dif- ferent combinations of them. The result is shown in Fig.[4.](#bookmark226) Considering the discovering that smaller τ leads to better hard negative mining ability [(Wang](#bookmark214) [and Liu,2021)](#bookmark214), we select α from {0.1, 0.2, ..., 0.9} and τ from {0.1, 0.2, 0.3}. We find that the ex- treme α value causes the performance degrada- tion and the best hyper-parameter combination is α,τ = 0.6, 0.2. Our analysis is that large α forces the model to concentrate on the instance-level con- trast and small α lets class separation objective take control. Both will reduce the generalization performance of the detector on test set.

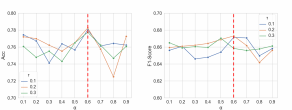


Figure 4: Effect of parameters α and τ on model perfor-

mance.

**F.2 Graph Parameters**

We further investigate the effect of max node num- ber and max sentence number on model perfor-

mance. The result is shown in Fig. [5.](#bookmark227) We se- lect max node number from {60, 90, 120, 150} and max sentence number from {30, 45, 60, 75}. The detector performs best when max node number is 90 and max sentence number is 45. The experi- ment results prove that the large node and sentence number are not necessary for the improvement of detection accuracy. We infer that even though set- ting large node and sentence number includes more entity information, excessive nodes bring noise to the model and impair the distinguishability of co- herence feature.

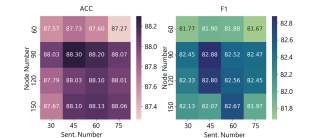


Figure 5: Performance of COCO with different graph parameters.

**G Ablation Study**

In Sec.[4.4,](#bookmark183) we mainly show the performance gain on the GROVER dataset. To further verify the effectiveness of COCO across other scenarios. We also do the ablation study on 500-example GPT-2, GPT-3.5-Unmixed, and GPT-3.5-Mixed datasets. The result is shown in Table[12.](#bookmark228)

Here, we add a new ablated setting, COCO (ICL), which applies the improved contrastive learning we proposed but does not include any part of the coher- ence graph representation model (*i.e.*, Coherence and LSTM).

By comparing COCO (Coherence) with COCO (Plain), we can evaluate the effectiveness of the coherence model. It shows an average improve- ment of 1.14% accuracy and 1.54% F1 on the plain version. Furthermore, if we add attention LSTM for concatenation, it can achieve 1.26% accuracy enhancement.

Moreover, by comparing COCO (ICL) and COCO, we further show the effectiveness of the coherence model based on the ICL model. There’s a gap of 0.86% accuracy and 0.61% F1 between with Coherence model and w/o it. The result shows the effectiveness of the coherence model compo-

nent doesn’t heavily overlap with the effectiveness of the ICL method component. In conclusion, both

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Dataset Metric** | **GPT-2** | | **GPT-3.5 Unmixed** | | **GPT-3.5 Mixed** | | **Avg. Increase** | |
| ACC | F1 | ACC | F1 | ACC | F1 | ACC | F1 |
| COCO (Plain) | 0.8223 | 0.7978 | 0.9670 | 0.9681 | 0.9565 | 0.9583 | - | - |
| COCO (Coherence) | 0.8325 | 0.8217 | 0.9778 | 0.9785 | 0.9698 | 0.9704 | ↑ 0.0114 | ↑ 0.0154 |
| COCO (Coherence + LSTM) | 0.8356 | 0.8274 | 0.9778 | 0.9787 | 0.9703 | 0.9710 | ↑ 0.0126 | ↑ 0.0176 |
| COCO (ICL) | 0.8417 | 0.8319 | 0.9798 | 0.9779 | 0.9646 | 0.9654 | ↑ 0.0134 | ↑ 0.0170 |
| **COCO** | 0.8530 | 0.8410 | 0.9889 | 0.9791 | 0.9701 | 0.9735 | ↑ 0.0220 | ↑ 0.0231 |

Table 12: Results of ablation study on 500-example GPT-2, GPT-3.5-Unmixed, and GPT-3.5-Mixed datasets.

two components of COCO function effectively and cooperate with the other beneficially.

**H Case Study**

**H.1 Coherence Graph Difference**

In this subsection, we conduct a case study with HWT and MGT produced by sensational ChatGPT with the same metadata. As illustrated in Fig. [6,](#bookmark229) we parse two news as coherence graphs. And we observe that although ChatGPT expresses fluently, it is not coherent from the perspective of coher- ence graph. Hence, COCO utilizes the distinctive coherence feature and makes correct predictions. However, RoBERTa fails to discriminate the MGT without noticing the coherence difference. This reflects even the most popular and advanced lan- guage model could suffer from weak coherence and be detected by COCO.

|  |  |  |
| --- | --- | --- |
| **Shabab Al Ahli Dubai have task cut out** | | |
|  | HWT: Gulf News | MGT: ChatGPT |
| **Document** | Dubai: Shabab AlAhli Dubai willcontinue  pushing towards the top while keeping an eye on  chasing AlAin as the 20th round of the Arabian  Gulf League (AGL) is playedout this weekend. The team from Deira climbed into secondplace for the first time last weekfollowing their 3-1 win over  Dibba and a 5-1 thrashing of AlAin by AlJazira. Shabab AlAhli Dubai now remain tiedon 38  points with defending champions AlAin, while unbeaten Sharjah are at the top with 47points. | Shabab AlAhli Dubai FC, the Dubai-basedfootballclub, have a difficult task ahead of them as they gear up for the upcoming season. The team, which plays in the UAE Pro League, is facing a number of challenges, both on and off the field, that will need to be overcome if they hope to be successful in the coming months. In the off-season, several of the team‘stop performers, including star striker Ahmed Khalilandmidfieldmaestro Omar Abdulrahman, left the club to join teams in other countries. |
| **Coherence Graph** |  |  |
|  | CoCo: [0.9233, 0.0767]  RoBERTa:[0.9085, 0.0915] | CoCo: [0.1038, 0.8962]  RoBERTa:[0.7354, 0.2646] |

Figure 6: An illustration for case study of our method. Entities in documents are colored green. The blue solid box indicates the sentence. The orange dashed lines are inner edges and green dashed lines are inter edges. Numbers in red indicate the probability of predicted label.

**H.2 Token Importance in GPT-3.5 Detection**

As shown in Fig. [7,](#bookmark230) we take segments from two text pairs consisting of HWT and its corresponding MGT in GPT-3.5 mixed and GROVER dataset. It

could be noticed that consecutive spans in text gen- erated by GPT-3.5 tend to contribute more to the model decision. However, in HWTs, model pays more attention to individual tokens. Following this observation, we infer that with the improvement of model scale, LLMs fit extremely well to the cor- pus so that it generates more general expressions compared with HWTs, which follows certain pat- terns (always demonstrated by a span of tokens) that could be expected by fine-tuned models. Thus, barely all the methods show nearly perfect perfor- mance on GPT-3.5 dataset.

As for GROVER dataset, more tokens contribute negatively to the model prediction, even if the pre- diction is correct. This reflects the deceptive nature of GROVER and explains the reason why it is the hardest dataset in our experiment to some extent.

**I Static Geometric Analysis on Coherence** **Graph**

We have witnessed performance enhancement by applying the graph-based coherence model to the detection model, but how does the coherence graph help detection? In this subsection, we apply static geometric features analysis to coherence graph we construct to evaluate the distinguishable difference between HWTs and MGTs with explanation. In the following discussion, we take the dataset of GROVER into the analysis. Some basic metrics of data and the corresponding graph are shown in Table[13.](#bookmark231)

|  |  |  |
| --- | --- | --- |
| **Metric** | **HWT** | **MGT** |
| Sample Num. | 4994 | 4991 |
| Avg. Num. of Token | 463.2 | 456.0 |
| Avg. Num. of Vertex | 43.60 | 32.37 |
| Avg. Num. of Edge | 107.4 | 65.44 |

Table 13: Basic metrics of texts and corresponding graphs.

Though HWTs and MGTs have approximately the same number of tokens in every text, coher-

  **“Help, I Can’t Stop Staring at My Face”**

**1 1 1 9.96**



**0 0 0 3.21**



**1 1 1 5.82**

**“Le Wagon launches part-time coding bootcamps – TechCrunch”**

**0 0**

**0 8.15**



Figure 7: Visualization of token attributions. The first text pair is sampled from GPT-3.5 mixed dataset and the second text pair is from GROVER dataset. The tokens in green represent contributing positively to the predicted label, while those in red contribute negatively. Label "0" represents HWT, and Label "1" represents MGT.

|  |  |
| --- | --- |
| **Metric** | **Avg. Degree** |
| **HWT** | 2.980 |
| **MGT** | 2.591 |

Table 14: Average of degree (whole dataset).

ence graph for HWTs has larger scale than MGTs’ with **34.7%** more vertexes and **64.1%** more edges, which shows that HWTs have more complex se- mantic relation structures than MGTs.

**I.1 Degree Distribution**

Semantically, degree of coherence graph measures the co-occurrence and TF-IDF feature of keywords. Moreover, degree distribution shows global coher- ence because high-degree nodes devote to the main topic and low-degree nodes are the extension.

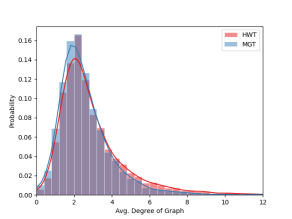


Figure 8: Distribution of average degree of graphs.

As shown in Table[14,](#bookmark232) The degree of the graph representation of HWTs is **2.980**, which is **15.0%**

larger than MGTs (**2.591**), which shows dispari- ties of MGTs to form coherent interaction between sentences. Fig.[8](#bookmark233)measures the distribution of each graph’s average nodes’ degree, showing that the distribution of HWTs has a longer tail than MGTs.

Furthermore, we analyze the distinguishability of degree features when impacted by other factors. One most considerable influences is the style and genre of different provenance. We chose around 60 articles from The Sun[11](#bookmark234)and Boston[12 .](#bookmark235) Then we use GROVER to mimic their style to generate similar topic news. Fig.[9](#bookmark236)shows the degree distribution of HWTs and MGTs of both provenances.

We use the Jensen–Shannon divergence to eval- uate the similarity of the degree distribution. The JS-divergence of MGTs mimicking The Sun and Boston is **0.029**, while the JS-divergence of MGTs and HWTs in Boston is **0.050**, in The Sun is **0.061**. The apparent gap shows that degree distribution can robustly detect MGTs and HWTs when impacted by provenance differences.

**I.2 Aggregation**

Aggregation is a shared metric for complex net- works and linguistics, depicting how closely the whole is organized around its core. We propose two metrics to evaluate the aggregation of graph- based text representation in our coherence model, the size of the largest connected subgraph and the clustering coefficient.

In our representation, not all sentences have en- tities related to others. Hence the graph is an un- connected one. The average number of nodes in

11<https://www.thesun.co.uk/> 12<https://www.boston.com/>

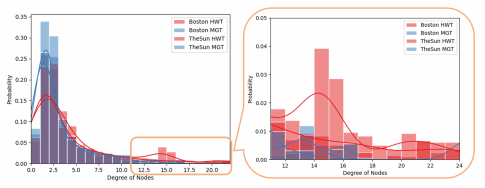


Figure 9: Distribution of degree with different provenance.

subgraphs of MGTs is **4.49** and of HWTs is **4.84**. We propose that the size of the largest connected subgraph shows the contents which are closely or- ganized around the topic. Moreover, the size of graphs may be an unfair factor, so we use the por- tion of nodes in the largest connected subgraph to reflect its size. The average portion in HWTs is **0.6725** and in MGTs is **0.6458**. Fig.[10](#bookmark236)shows the distribution of the portion of graphs, and HWTs distribute more high-portion ones than MGTs.

The clustering coefficient representshow nodes tend to cluster. For the entities of texts, clustering evaluateshow the author narrates around the cen- tral theme. The larger the clustering coefficient is, the tighter the semantic structure is. The average cluster coefficient of the graphs of HWTs is **0.2213** and of MGTs is **0.1983**, HWTs is **11.6%** better than MGTs. Fig.[11](#bookmark236)shows the distribution.

**I.3 Core & Degeneracy**

The degeneracy of a graph is a measure of how sparse it is, and the k-core is the subgraph corre- sponding to its significance in the graph. We pro- pose that, in our graph representation, the degen- eracy process of graphs equals summarizing texts semantically. The maximum of core-number shows the complexity of hierarchical structure in texts. Furthermore, the distribution of the core-number reflects the overall sparse and is a graph-perspective N-gram module. Based on experiments, the aver- age core-number of HWTs is **5.772** while MGTs with **4.458**. HWTs are **29.5%** ahead. Fig.[12](#bookmark237)is the distribution of the core-number.

**I.4 Entropy**

Entropy is a scientific concept to measure a state of disorder, randomness, or uncertainty. The well- known Shannon entropy is the core of the informa-

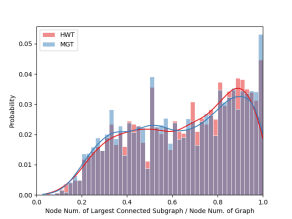


Figure 10: Portion of the largest connected subgraph.

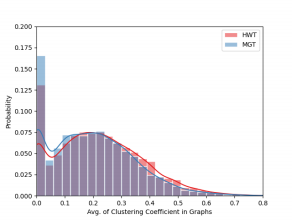


Figure 11: Distribution of clustering coefficient.

tion theory, measuring the self-information content. For the graph data, network structure entropy de- fined as the following can examine the information amount of the graph structure.

Entropy = − Ii lnIi = −  ki ln( ki )

i=1 i=1 Σ kj Σ kj ,

(10)

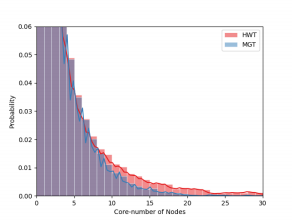


Figure 12: Core-number of nodes in graphs

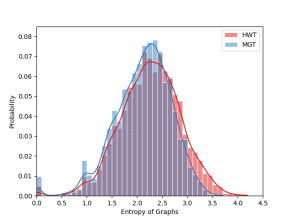


Figure 13: Structure entropy of graphs

where Ii is the information content represented by the degree distribution, N is the number of nodes, and ki is the degree of the i-th node.

Global coherence, from our perspective, equals refining more information inside the semantic struc- ture of the whole text, which matches to structure entropy of our graph representation. From our ex- periments, the structure entropy of HWTs (2.263) is **6.80%** larger than MGTs (2.119),which means HWTs obtain more structured information because their semantic information is globally organized. We show the network structure entropy distribution in Fig.[13.](#bookmark238)

**J Exploration on Imbalanced Data**

Imbalanced distribution in data is another crucial limitation in the task of MGTs detection, which is similar to the low resource limitation. It is imag- inable that, with the development of generation technology, MGTs will overwhelmingly dominate low-quality articles since they are easier and faster to generate than human writing. The detection

model will face training resources with MGTs as the main part and HWTs as the small part. We test the current models in the imbalanced limitation and find the dramatic decline in accuracy when the ratio of HWTs is less than 30%, as shown in the Fig.[14.](#bookmark239) The test is based on the 10% GROVER dataset.

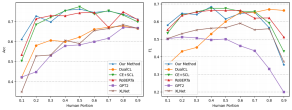


Figure 14: Model comparison results on DL dataset with 9 different human-generated text portions.

All models show poor performance at low HWTs ratios. With a percentage of HWTs of 0.1 (only 100 HWTs in the training set in this case), most of the models have an accuracy below 50%, which performance is close to random and reflects intol- erance for extreme cases. Besides, we find that a high proportion of HWTs also cause a decrease in F1 score to some extent.

**K Related Work: Graph-based Text Representation**

Graph-of Words (GoW) Model [(Turney,2002;](#bookmark101)[Mi-](#bookmark209)

[halcea and Tarau,2004)](#bookmark209) is a type graph representa-

tion method in which each document is represented

by a graph, whose nodes correspond to terms and

edges capture co-occurrence relationships between

terms. Using GoW, keywords can be extracted

by retaining the document graph [(Turney,2002)](#bookmark101).

Thus, graph representation is sensible to apply in

tasks like information retrieval [(Blanco and Lioma,](#bookmark201)

[2011)](#bookmark201), categorization [(Malliaros and Skianis,2015)](#bookmark208)

and sentiment classification tasks [(Huang and Car-](#bookmark204)

[ley,2019;](#bookmark204)[Hou et al.,2021)](#bookmark203).

Most models enhance classification or detection performance by combining graph representation with neural networks. Text-GCN [(Yao et al.,2019)](#bookmark210) first builds a single large graph for the whole cor- pus, followed by Tensor-GCN [(Liu et al.,2020)](#bookmark206) with tensor representation. Also, the relation be- tween words varies, and should be treated as differ- ent edges. COCO matches keywords PLM embed- ding to nodes and sentence representation, consid- ers dealing inner- and inter-sentence relation differ- entlyin GCN, and merges the structure graph and flat sequence representation to predict accurately.