Final project

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Abstract

RoBERTector detects AI-generated sentences with high precision and recall, and performs efficiently with early convergence. In this paper, we provide a novel tool based on the RoBERtector (RoBEREctor) for the detection of artificially generated sentences.

Introduction

Research Question: To what extent did ChatGPT contribute to official U.S. Senate press releases? Generative models like ChatGPT suffers from hallucination, generating false and misleading information. While U.S. Senate press must have transparency and accountability, meaning AI generated texts can be dangerous. Thus we aim to ensure trust in public communication, and maintain transparency and accountability in Senate press releases by classifying AI generated text in U.S. senate press.

The original idea on this project was using Sentence Transformers(SBERT, for reference view https://sbert.net/) embedding to classify, human and AI generated text. However this attempt was unsuccessful because features that were extracted from SBERT failed to capture any significant information as shown in t-SNE plot below. Seeing this, choose to fine tune pretrained LLM RoBERTa.

Theoretical Background

Perceptrons and Deep Models

Perceptrons are the fundamental building block of neural networks, which is introduced by Frank Rosenblatt in 1957. It computes z values using weights, variables, bias like equation below and applies threshold function.

$$z = \sum_i w_i x_i + b$$

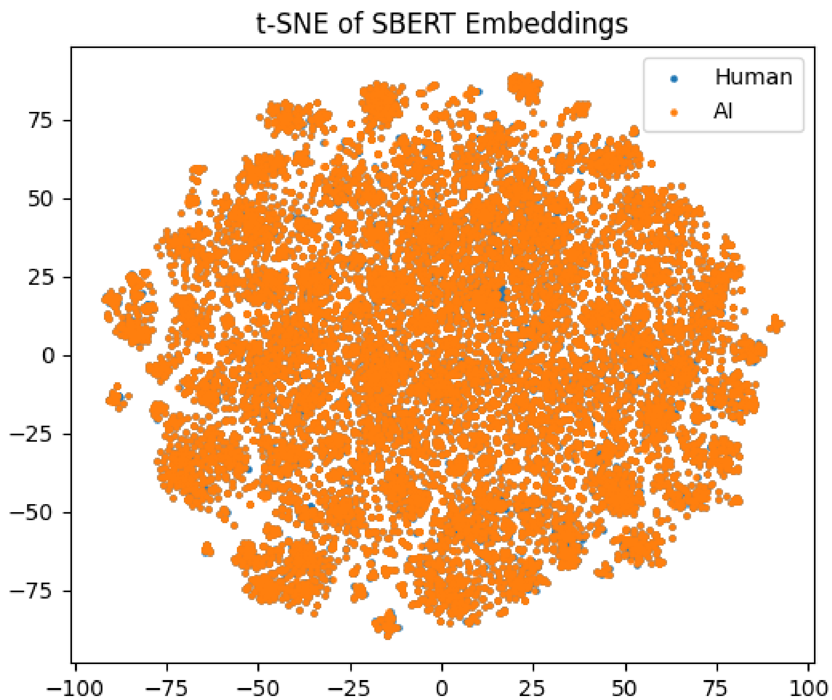
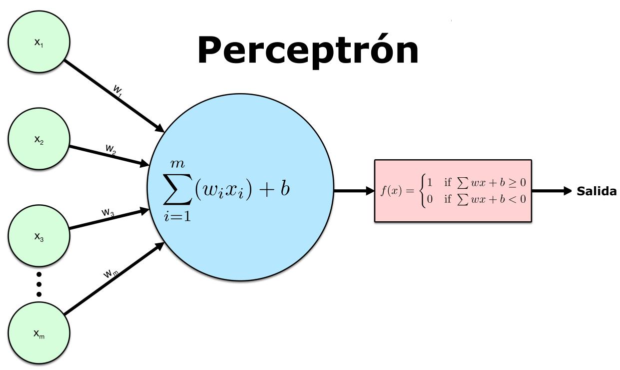


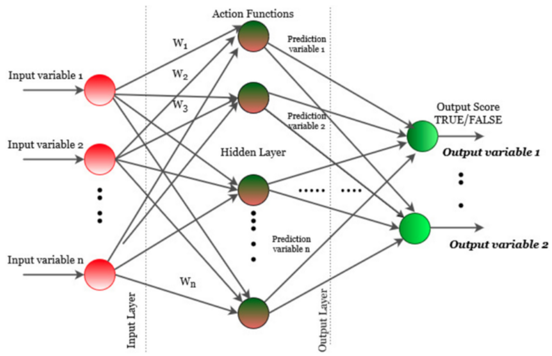
Figure 1: t-SNE plot of SBERT feature



| Then it works with linear threshold limit, that implements a binary classifier using a linear decision boundary. Also, it updates weights based on prediction errors and gradient descent rules. | Deep models are artifical intelligence models that uses artifical neural networks, which is composed of perceptrons. It shows a high performance in linear separable problems, and it is a highly-discussed models among artificial intelligence models.

MLP, Back propagation and fine tuning

MLP is a deep model that extend single perceptrons by adding hidden layers with nonlinear activation functions. MLPs with sufficient hidden units can approximate any continuous function.



| Fine-tuning is a supervised adaptation to specific tasks, where a pretrained model is further trained on labeled data to specialize in a narrower domain or objective.

Transformers and attention mechanism

Attention mechanism is an text interpretation mechanism that focuses on relevant parts of input sequences dynamically. It selectively focuses on important information, computes attention weights that reflect the relative importance. Also, it uses three matrices to compute attention scores and weighted representations.

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})$$

| Transformers is an sequence modeling system that relys entirely on attention mechanisms, which allows the models to attend to different positions in the input sequence simultaneously. | It uses encoder-decoder architecture, which consists of both encoder and decoder components, though variations exist. In addition, transformer's don't have inherent sequential processing, so positional information is added via endcodings in transformer.

LLM, BERT and RoBERTa

Large Language Model(LLM)is a class of neural networks trained on vast amounts of text data to understand and generate human language. It is build on the transformer model with self-attention mechanisms. Also, it uses autoregressive generation, which predicts the next token in a sequence based on previous tokens. LLM training is held through pre-training(unsupervised learning on large text corpora), fine-tuning(supervised adaptation to specific tasks), in-context learning(learning from examplex provided in the input).
BERT is an LLM, large language model that represents a paradigm shift in natural language processing by introducing bidirectional training for language representations. BERT also uses masked language modeling(MLM), by using a novel pre-trained objective where some tokens are randomly masked and the model predicts them. In addition, BERT utilizes transformer encoder architecture and transfer learning to enhance its performance.
RoBERTa (Robustly Optimized BERT Pretraining Approach) is an enhanced version of BERT that builds on the transformer architecture with these several key improvements:
Dynamic Masking: Unlike BERT's static masking, RoBERTa uses dynamic masking to generate different masked tokens for the same sentence during training, allowing the model to learn from various input sequences.
Removal of Next Sentence Prediction (NSP): RoBERTa eliminates the NSP task, focusing solely on the Masked Language Modeling (MLM) objective.
Larger Training Data and Batch Sizes: Uses much larger mini-batches and learning rates with significantly more training data.
Byte-level Byte Pair Encoding (BPE): Implements the same tokenization as GPT-2, using a smaller vocabulary that requires fewer computational resources.

Theoretical Background: Integrated Gradients

To interpret the predictions made by deep neural networks, we apply **Integrated Gradients (IG)** — a method introduced to attribute a model's prediction to its input features. IG helps identify which tokens or sentences contribute most to the final classification outcome.

Formally, for a model F and an input x, the integrated gradient of the i-th feature is defined as:

$$\mathrm{IG}_i(x) = (x_i - x'_i) \times \int_{\alpha=0}^{1} \frac{\partial F(x' + \alpha \cdot (x - x'))}{\partial x_i} \, d\alpha$$

where x' is a baseline input (e.g., zero embedding), and the integral computes the average gradient of the model output with respect to the input along the path from x' to x.

By aggregating gradients across interpolated inputs, IG provides a more stable and theoretically justified measure of feature importance compared to raw gradients. This is particularly useful in our context of AI-text detection, as it allows us to visualize and explain which words or sentences influenced the model's decision.

RoBERTector

RoBERTector is finetuned RoBerta that specify on AI detection on sentence level. it's predeictive abilitwes were Accuracy: 0.8648 F1 Score: 0.8644 on validation set.

Architecture

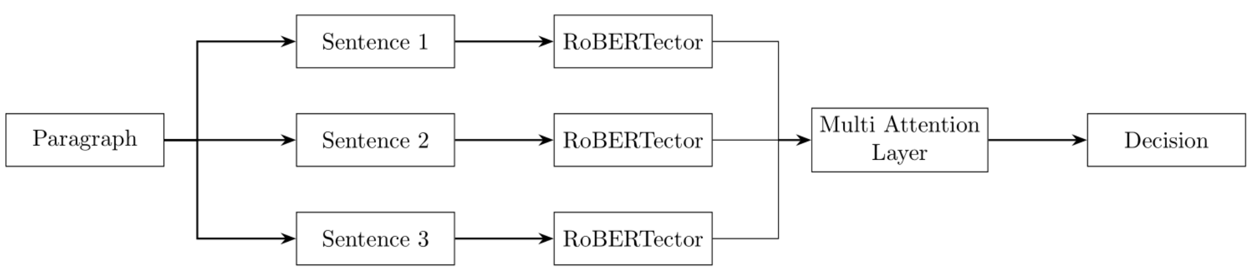


Figure 2: Architecture

A paragraph's "main content" is concentrated in a small subset of its sentences, and by assigning higher attention weights to those key sentences (and down-weighting the rest), the model can accurately classify the paragraph as AI-generated vs. human-written. This main content is valid because of various point of view, psycholingustics, cognitive science, deep-learning.

Psycholingustics Perspective

People tend to focus on main point of view instead of remembering all details. This is because gist information is more efficiently encoded, thereby being meaningful into memory. People prefer the most meaningful portion of the text, so people usually remember the main idea most. Also, according to Van Dijk and Kintsch's discourse comprehension theory, people are reported to remember contents by compressing and generalizing to macro-level semantic structure (gist).

Cognitive Science Perspective

It is proved in cognitive science fields that people get their attention on main ideas. Our cognitive system processes and emphasizes data selectively rather than catching full context at once. For example, when we write essays, people usually loads the most information, main idea, into the first sentence or paragraph instead of spreading contexts into paragraph or full text.

Deep-Learning Perspective

Attention mechanism, which is utilized in this research, is a technology that aimed to weigh more on main factors. This is inspired by selective cognition mechanism of people, and led to optimization in model efficiency by lowering the burden to encode long text at once.
In special, Multi-Head Attention uses lots of attention heads, so it collects complex main information in parell. Through this mechanism, attention layer assigns high value in most informative sentences while considering sentence-sentence interactions. So, in summry, the model creates embedding that represents full meaning by focusing main sentences in the text.

Our model begins by **splitting each paragraph** into at most 16 sentences. We scan for sentence delimiters (`.`, `?`, `!`), trim whitespace, and discard empty fragments. If a paragraph produces fewer than 16 sentences, we pad the remainder with dummy tokens; if it exceeds 16, we simply truncate after the 16th. This approach guarantees every input tensor has a fixed shape `(batch_size × 16 × max_length)`, which simplifies batching and avoids dynamic control-flow overhead.

Next, each of these up to 16 sentence slots is **encoded independently** by RoBERTector(a RoBERTa model that was previously fine-tuned on sentence-level AI vs. human text classification). By freezing all of RoBERTector's parameters, we preserve its robust ability to capture subtle stylistic and lexical cues (word choice, phrasing patterns, function-word frequencies) without risking over-fitting on our comparatively small paragraph dataset. From each sentence's transformer output we extract the `CLS` token embedding (a 768-dimensional vector), producing a tensor of shape `(batch_size, 16, 768)`.

These 16 sentence embeddings are then fed into a **multi-head self-attention layer** (four heads, embed_dim=768). Because the Query, Key, and Value all derive from the same set of sentence embeddings, the attention mechanism learns to assign higher weights to the most informative sentences—thesis statements, topic transitions, or discourse markers—while down-weighting less relevant ones. The attended outputs are mean-pooled across the sentence axis, yielding a single 768-dimensional "paragraph embedding" that fuses both micro-level sentence cues and macro-level discourse structure.

Finally, a **lightweight classification head** (a two-layer MLP with ReLU and dropout) maps this paragraph embedding to a single logit. We apply `BCEWithLogitsLoss` during training—combining sigmoid activation and binary cross-entropy in a numerically stable way—and use a 0.5 threshold on the sigmoid probability to make the AI vs. human decision. We train only the attention and MLP head (leaving RoBERTector frozen), save model checkpoints after every epoch, and evaluate on an 80/10/10 train/val/test split of our ~20 000-paragraph dataset (with test performed just once at the end).

By **reusing** a specialized sentence encoder, **learning** which sentences truly matter via attention, and **regularizing** most of the model by freezing, this architecture achieves high accuracy and generalization while remaining interpretable: attention weights can be visualized to show exactly which sentences drove each classification.

Training

Set up python enviroment

Install packages

Fine tune RoBERTa

Load data and split paragraphs into sentences

```
import pandas as pd
df=pd.read_csv('ai_press_releases.csv')
df=df.dropna()
human=df['non_chat_gpt_press_release']
ai=df['chat_gpt_generated_release']
hu=[]
a=[]
for i in human:
    l=list(i.split('. '))
    hu.extend(l)
for i in ai:
    l=list(i.split('. '))
    a.extend(l)

ap=a.copy()
a.extend(hu)
texts=a
labels=[0 if i<len(ap) else 1 for i in range(len(texts))]
from sklearn.model_selection import train_test_split

#split train, test and validation data.
texts_train_val, texts_test, labels_train_val, labels_test = train_test_split(
    texts,
    labels,
    test_size=0.2,       # 20% of the entire dataset
    random_state=42,
    stratify=labels      # Maintain label distribution
)

# 2) Split train_temp again into train (75% of temp → 60% of the total) and val (25% of temp → 20% of t
texts_train, texts_val, labels_train, labels_val = train_test_split(
    texts_train_val,
    labels_train_val,
    test_size=0.25,      #25% of train_temp → 0.2 of total
    random_state=42,
    stratify=labels_train_val
)

print(f"Train: {len(texts_train)} samples")
print(f"Valid: {len(texts_val)} samples")
print(f"Test : {len(texts_test)} samples")
```

Load Roberta and fine tune

```python
import torch
from torch.utils.data import DataLoader
from transformers import AutoTokenizer, AutoModelForSequenceClassification
from torch.optim import AdamW
from datasets import Dataset
from tqdm.auto import tqdm
from sklearn.metrics import accuracy_score, f1_score

# Load pretrained tokenizer
tokenizer = AutoTokenizer.from_pretrained("roberta-base")

# Function to prepare batch inputs
def collate_fn(batch):
    enc = tokenizer(
        [x["text"] for x in batch],  # Extract texts
        padding="longest",           # Pad to the longest in batch
        truncation=True,             # Truncate if too long
        max_length=256,              # Limit to 256 tokens
        return_tensors="pt"          # Return PyTorch tensors
    )
    enc["labels"] = torch.tensor([x["label"] for x in batch], dtype=torch.long)
    return enc

# Convert to HuggingFace Dataset format
train_ds = Dataset.from_dict({"text": texts_train, "label": labels_train})
val_ds   = Dataset.from_dict({"text": texts_val,   "label": labels_val})
test_ds  = Dataset.from_dict({"text": texts_test,  "label": labels_test})

# Create PyTorch DataLoaders
train_loader = DataLoader(train_ds, batch_size=16, shuffle=True, collate_fn=collate_fn)
val_loader   = DataLoader(val_ds,   batch_size=32, shuffle=False, collate_fn=collate_fn)
test_loader  = DataLoader(test_ds,  batch_size=32, shuffle=False, collate_fn=collate_fn)

# Model and optimizer configuration
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")  # Use GPU if available
model  = AutoModelForSequenceClassification.from_pretrained("roberta-base", num_labels=2).to(device)  #
optim  = AdamW(model.parameters(), lr=2e-5)  # Use AdamW optimizer

num_epochs = 8  # Train for 8 epochs

# Training loop
for epoch in range(1, num_epochs+1):
    # 1) Training phase
    model.train()
    train_loop = tqdm(train_loader, desc=f"Epoch {epoch}/{num_epochs} [TRAIN]")  # Show progress
    for batch in train_loop:
        batch = {k: v.to(device) for k, v in batch.items()}  # Move to GPU
        outputs = model(**batch)  # Forward pass
        loss    = outputs.loss
        optim.zero_grad()  # Reset gradients
        loss.backward()  # Backpropagation
```

```
        optim.step()  # Update weights
        gpu_mem = torch.cuda.memory_allocated(device) // (1024**2)  # Monitor GPU memory
        train_loop.set_postfix(loss=f"{loss.item():.4f}", gpu_mem=f"{gpu_mem}MiB")

    # 2) Validation phase
    model.eval()
    all_preds, all_labels = [], []
    val_loop = tqdm(val_loader, desc=f"Epoch {epoch}/{num_epochs} [VAL]  ")
    with torch.no_grad():  # Disable gradient tracking
        for batch in val_loop:
            batch = {k: v.to(device) for k, v in batch.items()}
            logits = model(**batch).logits
            preds  = torch.argmax(logits, dim=-1).cpu().tolist()
            labels = batch["labels"].cpu().tolist()
            all_preds += preds
            all_labels += labels
    val_acc = accuracy_score(all_labels, all_preds)  # Compute accuracy
    val_f1  = f1_score(all_labels, all_preds, average="weighted")  # Compute weighted F1
    print(f"→ Validation | Acc: {val_acc:.4f}, F1: {val_f1:.4f}")

    # 3) Test phase (for monitoring)
    all_preds, all_labels = [], []
    test_loop = tqdm(test_loader, desc=f"Epoch {epoch}/{num_epochs} [TEST] ")
    with torch.no_grad():
        for batch in test_loop:
            batch = {k: v.to(device) for k, v in batch.items()}
            logits = model(**batch).logits
            preds  = torch.argmax(logits, dim=-1).cpu().tolist()
            labels = batch["labels"].cpu().tolist()
            all_preds += preds
            all_labels += labels
    test_acc = accuracy_score(all_labels, all_preds)
    test_f1  = f1_score(all_labels, all_preds, average="weighted")
    print(f"→ Test       | Acc: {test_acc:.4f}, F1: {test_f1:.4f}")

    # 4) Save model
    save_dir = f"/kaggle/working/checkpoint-epoch{epoch}"  # Output directory
    model.save_pretrained(save_dir)       # Save model weights
    tokenizer.save_pretrained(save_dir)   # Save tokenizer files
    print(f"→ Model & Tokenizer saved to: {save_dir}\n")
```

Training Multi Attention Layer

Load packages

Load data

```
df=pd.read_csv('/kaggle/input/ai-text/ai_press_releases.csv')
df=df.dropna()
human=df['non_chat_gpt_press_release'].to_list()
ai=df['chat_gpt_generated_release'].to_list()
```

```
labels=[0 if i<len(ai) else 1 for i in range(len(ai)+len(human))]
ai.extend(human)
texts=ai
# 1)split train_temp(80%) and test(20%)
texts_train_val, texts_test, labels_train_val, labels_test = train_test_split(
    texts,
    labels,
    test_size=0.2,        # 20% of the total
    random_state=42,
    stratify=labels       # Maintain label distribution
)

# 2) Split train_temp again into train (75% of temp → 60% of the total) and val (25% of temp → 20% of t
texts_train, texts_val, labels_train, labels_val = train_test_split(
    texts_train_val,
    labels_train_val,
    test_size=0.25,       #25% of train_temp → 0.2 of total
    random_state=42,
    stratify=labels_train_val
)

print(f"Train: {len(texts_train)} samples")
print(f"Valid: {len(texts_val)} samples")
print(f"Test : {len(texts_test)} samples")
```

Define helper and Multiattention layer class

```
# 2. Sentence split
def split_sentences(paragraph: str):
    return [s.strip() for s in paragraph.split('. ') if s.strip()]

# 3. Dataset
class ParagraphDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_sents=16, max_len=128):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_sents = max_sents
        self.max_len = max_len

    def __len__(self):
        return len(self.texts)

    def __getitem__(self, i):
        para = self.texts[i]
        label = torch.tensor(self.labels[i], dtype=torch.float)
        sents = split_sentences(para)[:self.max_sents]
        encs = [self.tokenizer(s, truncation=True, padding='max_length',
                               max_length=self.max_len, return_tensors='pt')
                for s in sents]
        # pad sentences
        pad_n = self.max_sents - len(encs)
```

```python
        input_ids = torch.stack([e['input_ids'].squeeze(0) for e in encs] +
                                [torch.zeros(self.max_len, dtype=torch.long)]*pad_n)
        attn_mask = torch.stack([e['attention_mask'].squeeze(0) for e in encs] +
                                [torch.zeros(self.max_len, dtype=torch.long)]*pad_n)
        return input_ids, attn_mask, label

# 4. Model: frozen encoder + attention + classifier
import torch
import torch.nn as nn
from transformers import AutoTokenizer, AutoModelForSequenceClassification

class HierAttnClassifier(nn.Module):
    def __init__(self,
                 base_model_name="/kaggle/input/robertector/transformers/sentences/1/checkpoint-epoch3"
                 max_sents=16,
                 hidden=768,
                 heads=4):
        super().__init__()
        # 1) Load your fine-tuned SequenceClassification model
        self.full_model = AutoModelForSequenceClassification.from_pretrained(
            base_model_name, output_hidden_states=True, return_dict=True
        )
        # 2) Freeze all its parameters
        for p in self.full_model.parameters():
            p.requires_grad = False

        # 3) Multi-Head Attention on the CLS embeddings
        self.attn = nn.MultiheadAttention(embed_dim=hidden,
                                          num_heads=heads,
                                          batch_first=True)
        # 4) Final MLP head after attention
        self.classifier = nn.Sequential(
            nn.Linear(hidden, hidden // 2),
            nn.ReLU(),
            nn.Dropout(0.1),
            nn.Linear(hidden // 2, 1),
        )

    def forward(self, input_ids, attention_mask):
        b, s, l = input_ids.size()
        # flatten to (b*s, l)
        flat_ids   = input_ids.view(b * s, l)
        flat_mask  = attention_mask.view(b * s, l)
        # 5) Run through RoBERTector; we asked for hidden_states
        outputs = self.full_model(
            input_ids=flat_ids,
            attention_mask=flat_mask,
        )
        # 6) Grab the last hidden layer states: outputs.hidden_states is a tuple
        #    where hidden_states[-1] is (batch, seq_len, hidden)
        last_hid = outputs.hidden_states[-1]
        # CLS is token 0
        cls_embs = last_hid[:, 0, :].view(b, s, -1)  # (b, s, hidden)
```

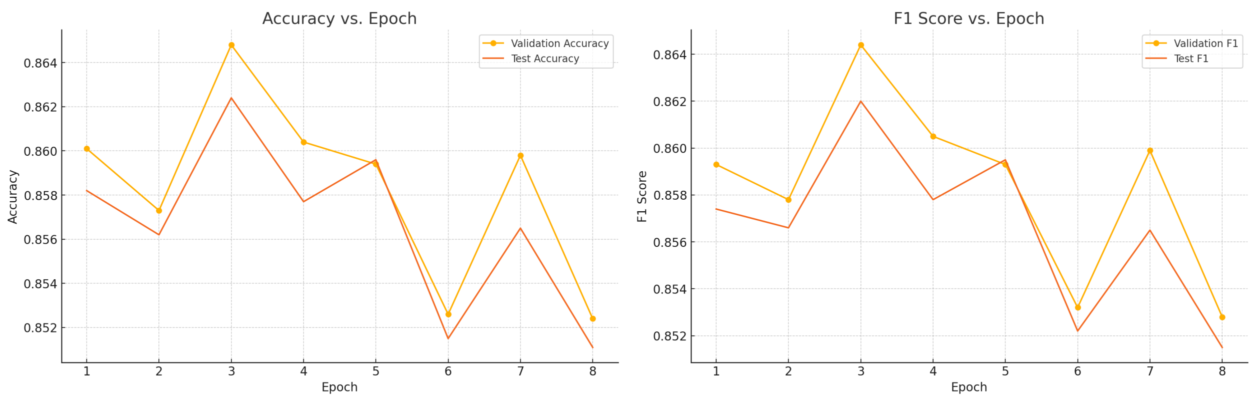
```
        # 7) Self-attention over the s sentence embeddings
        attn_out, _ = self.attn(cls_embs, cls_embs, cls_embs)  # (b, s, hidden)

        # 8) Pool and classify
        doc_emb = attn_out.mean(dim=1)                        # (b, hidden)
        logits = self.classifier(doc_emb).squeeze(-1)        # (b,)
        return logits
```

Load RoBERTector and set up hyperparameters

Train Multi Attention Layer

Results

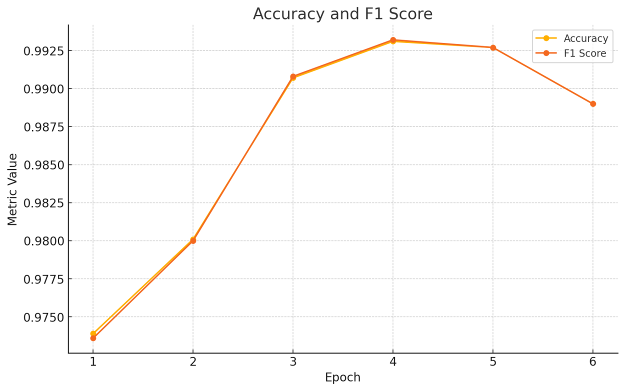
FineTuning



| The above graphs show the relation with epoch, accuracy and f1 score of the model. From the diagram, model from epoch 3 recorded the highest accuracy and f1 score in both validation and test sets. As a result, we chose the model from epoch 3 for the following steps.

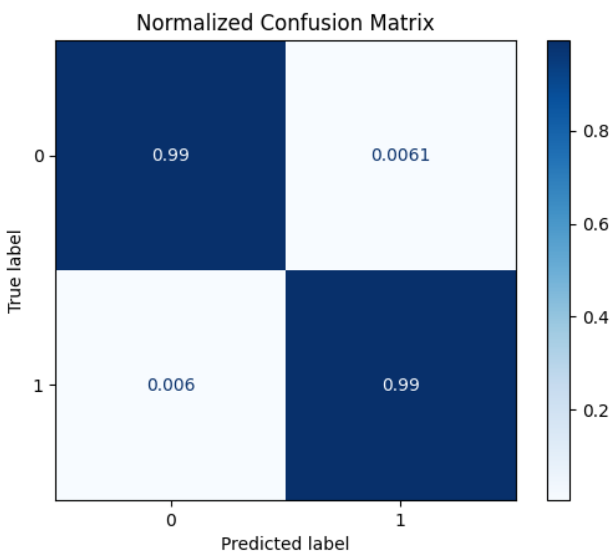
Training Multi Attention layer

| Above plot shows the loss in train and validation sets as train proceeds. Both losses decreased until epoch 4, but validation loss increased after epoch 4 while train loss decreased.

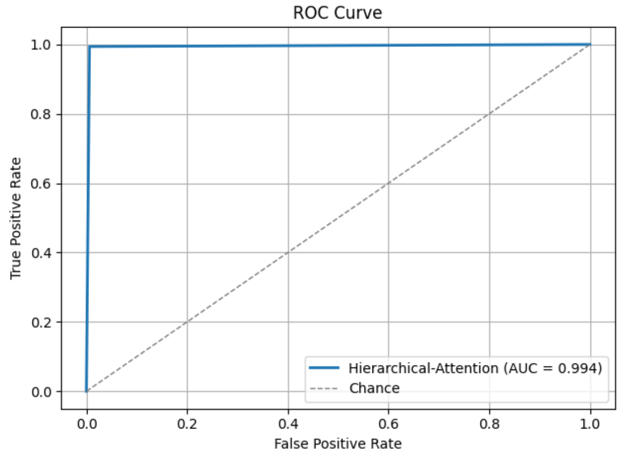


| The above graph shows the accuracy and f1 score of the model by epoch. At the diagram, the open form of two index were similar, and model from epoch 4 recorded the highest accuracy and f1 score in both validation and test sets. | As a result, we selected the model from epoch 4. It is because, in the aspect of loss, the validation loss recorded the lowest at that point so that it can avoid overfitting. Also, in the aspect of accuracy and f1 score, the model from epoch 4 recorded the highest index above all.

Confusion Matrix and ROC Curve



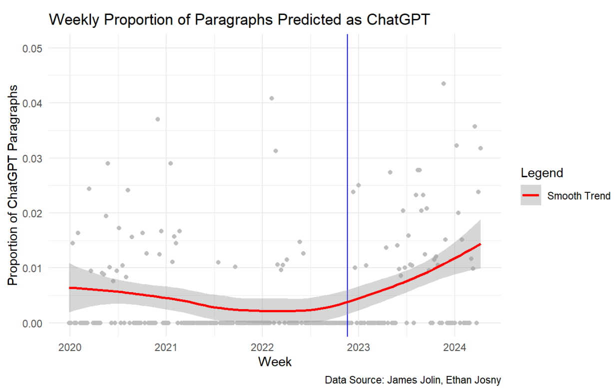
| The above figure representes the normalized confusion matrix of the model. As being shown in the diagram above, the model achieved high classification performance, predicting both data labeled with 0 and 1 in 99% accuracy. Also, the misclassification rates are relatively low, 0.6% in false negative prediction and 0.61% in false positive prediction.



| This diagram shows the ROC curve of the model. In the diagram above, the model's ROC curve was mostly tangent with both axis, compared to the dotted line(random classification model). Also, the AUC(area below the ROC curve) recorded 0.994, which is a lot similar to 1. | From the above confusion matrix and ROC curve, we could conclude that model we trained showed high performance in the dataset, so this model is highly reliable in distinguishing between the two classes.

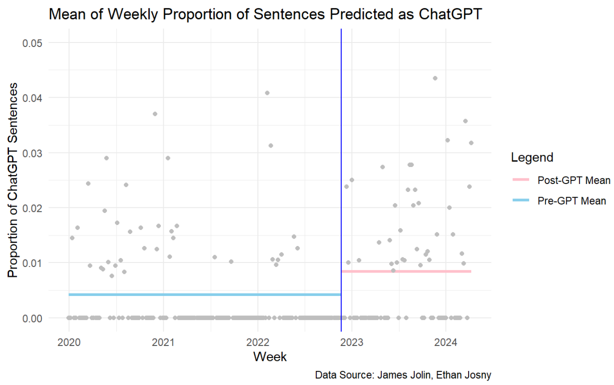
Analysis

Weekly Proportion and its Smooth Line



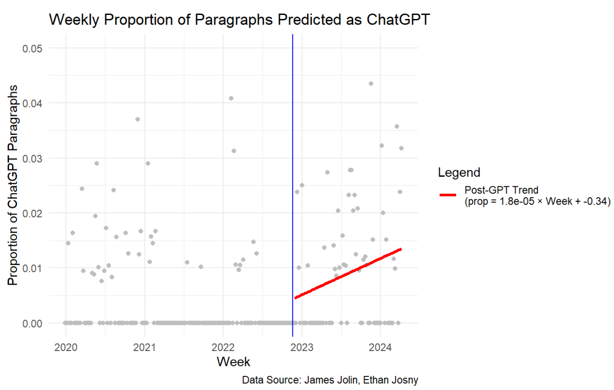
This graph shows the **distribution of the weekly proportion of paragraphs predicted as ChatGPT** by RoBERTector. In this graph, blue horizontal line indicates the time that ChatGPT was firsh released, and red line is the smooth trend line of distribution. As you can see from the graph, after ChatGPT, the trend of weekly propotion seems to increase.

Average of Pre-GPT, Post_GPT



This graph shows the **mean of ChatGPT-classified paragraph proportion** in post-GPT(pink line), pre-GPT period(skyblue line). The mean of paragraph proportion in pre-GPT period recorded 0.004231799, and 0.008446278 in post-GPT period. It shows that the proportion increased after official release of ChatGPT.

Linear Regression of Post-GPT



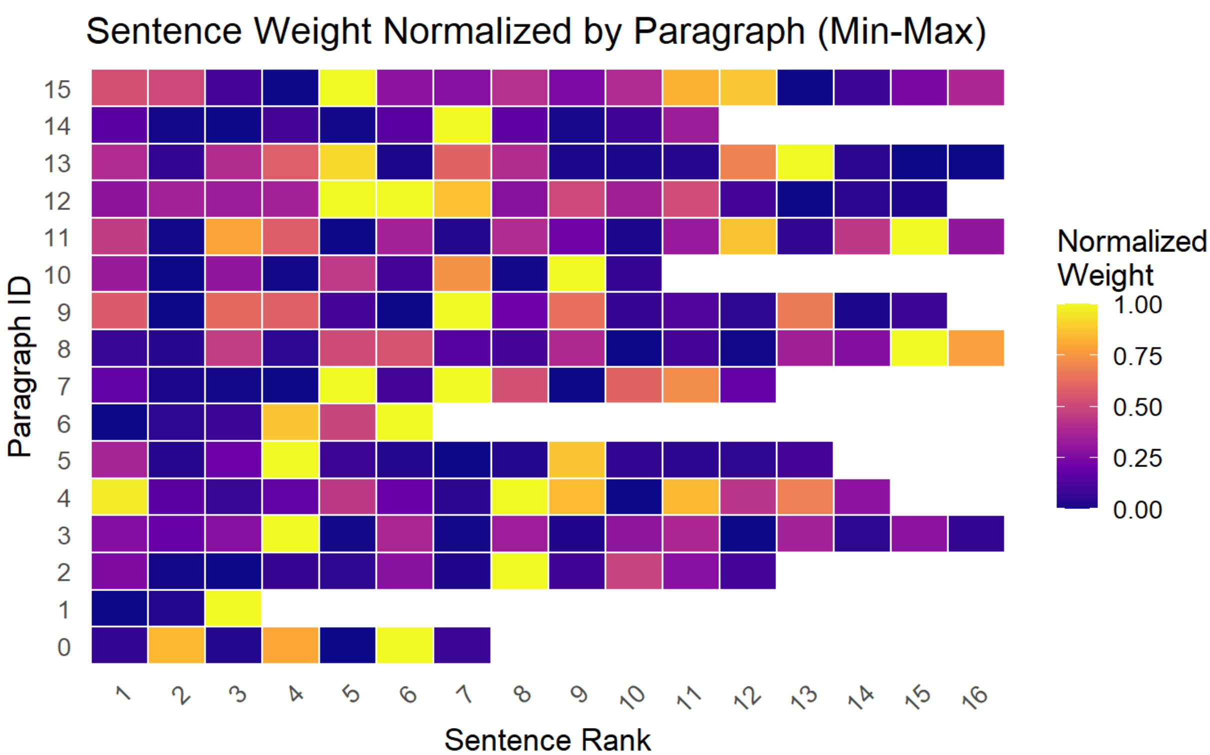
This graph shows the distribution of weekly proportioin of paragraphs which is predicted as ChatGPT, with its **linear regression model** fitted with post-GPT period data. Equation of linear regression model was approximately Proportion $= 1.808295 \times 10^{-5} \times \text{Week} - 3.449049 \times 10^{-1}$. The coefficient of "Week" variable was positive, so we can conclude that usage of ChatGPT in U. S. Senate press releases has been increasing since the release of ChatGPT.

Interpretation

Wordcloud

According to word cloud, the model gains the most contextual meaning from ‘senator’, the text being U.S. senate press is logical.

Heatmaps



Heat map reveals important sentences in paragraphs.

Discussion

RoBERTector: strong generalization at sentence level

Hierarchical model: near-perfect paragraph detection

Contextual patterns differ between AI and human writing

Limitations: • Assumes no AI use before Nov 2022 • Only 10 senators included

Future Work: • Broader sources and languages • Mixed-generation detection • Real-time content screening

Refernces

Vaswani, A., et al. (2017). Attention Is All You Need. NeurIPS.

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