# Model Inversion in Split Learning for Personalized LLMs: New Insights from Information Bottleneck Theory

Yunmeng Shu fuyi\_verty@sjtu.edu.cn Shanghai Jiao Tong University Shanghai, China Shaofeng Li shaofengli@seu.edu.cn Southeast University Nanjing, China Tian Dong tian.dong@sjtu.edu.cn Shanghai Jiao Tong University Shanghai, China

Yan Meng yan\_meng@sjtu.edu.cn Shanghai Jiao Tong University Shanghai, China

#### **ABSTRACT**

Personalized Large Language Models (LLMs) have become increasingly prevalent, showcasing the impressive capabilities of models like GPT-4. This trend has also catalyzed extensive research on deploying LLMs on mobile devices. Feasible approaches for such edgecloud deployment include using split learning. However, previous research has largely overlooked the privacy leakage associated with intermediate representations transmitted from devices to servers. This work is the first to identify model inversion attacks in the split learning framework for LLMs, emphasizing the necessity of secure defense. For the first time, we introduce mutual information entropy to understand the information propagation of Transformer-based LLMs and assess privacy attack performance for LLM blocks. To address the issue of representations being sparser and containing less information than embeddings, we propose a two-stage attack system in which the first part projects representations into the embedding space, and the second part uses a generative model to recover text from these embeddings. This design breaks down the complexity and achieves attack scores of 38%-75% in various scenarios, with an over 60% improvement over the SOTA. This work comprehensively highlights the potential privacy risks during the deployment of personalized LLMs on the edge side.

#### **KEYWORDS**

Large language model, Edge computing, Split learning, Privacy, Model inversion attack

#### INTRODUCTION

In the rapidly evolving landscape of Artificial Intelligence (AI), particularly with the advancements in Large Language Models (LLMs) like GPT-4 [12], there has been a significant shift towards enhancing personalization through extensive training data and sophisticated algorithms. Initiatives such as OpenAI's Agent program and advancements in Retrieval-Augmented Generation (RAG)[8] technology exemplify this trend, aiming to tailor LLMs with individual data to improve accuracy and relevance, thereby underscoring their growing importance in both personal and professional domains.

However, leveraging LLMs through traditional cloud computing methods introduces several challenges, such as latency, bandwidth resources, and privacy concerns, especially given the multi-modal nature of modern AI applications. To bridge the gap between data Haojin Zhu zhu-hj@cs.sjtu.edu.cn Shanghai Jiao Tong University Shanghai, China

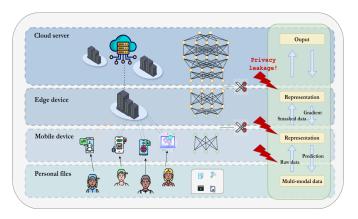


Figure 1: Collaborative training in split learning scenario

locality and model scalability for personalized LLM training, split learning emerges as a solution for collaborative training of deep networks. As depicted in Fig. 1, users can segment the model at chosen split points and engage in collaborative training. Recent studies on split LLMs show that distributing multi-head self-attention layers across multiple devices enables joint parallel computation.

However, the security and privacy of split personalized LLMs have yet to receive sufficient attention. Some claim that when using edge-cloud collaborative method, a curious-but-honest server no longer accesses raw data, which ostensibly improves security. But do these methods truly protect local users' privacy? Intermediate representations contain substantial information that, if inverted, can lead to severe privacy breaches. Attackers can exploit intermediate representations of input data for privacy inversion attacks, including "cut layer" information, "smashed data" in computer vision, or "hidden state" information in the field of NLP. In computer vision, inversion techniques have shown the ability to recover input images from final layer activations, while the literature on blackbox attacks indicates that segmentation layer activation values can be exploited.

In the field of natural language, there remains a noticeable gap in research addressing the risk of inversion attacks on intermediate representations in LLMs. Most research focuses only on embedding layer inversion and does not consider all intermediate representations comprehensively. Table 1 illustrates the potential for inversion using our approach, *RevertLM*.

Table 1: Examples of text inversion with RevertLM at the  $20^{\mathrm{th}}$  decoder LLM blocks

Raw text	Inversed text
no i just make boats on the weekend . what else do you do ?	no i just make boats on the weekend . what else do you do ?
deep sea or fresh water?	water borne or deep sea?
what is your favorite holiday? mine is christmas	which is your favorite? christmas is my all time

To study privacy attacks on LLMs in a cooperative learning scenario, our research begins with an exploration of information transfer in representations and progresses to a groundbreaking investigation of representation reversal attacks. We identify a unique challenge in inverting representations for LLMs with existing decoders: the recovery performance is significantly lower at the intermediate layer compared to the initial embedding layer in other studies [10, 11]. Embeddings contain the information of a whole sentence and pass through fewer layers compared with representations. To overcome this difficulty, we propose a two-stage inversion system with the first step involving purifying the representational information into the embedding space to solve the sparsity in representation. In the second step, we use a decoder-based generative model toward purified representation to better leverage the sequential features in our language embeddings. This research provides a robust foundation for tackling privacy and security concerns in split learning scenarios for large language models.

The contributions of this work are listed as follows:

- Formal recognition and definition of severe privacy problems in the split learning scenario for LLMs.
- Combining information theory, this study investigates information propagation in transformer-based LLMs.
- Addressing the decreasing effectiveness of representation reversal after multiple layers, we propose a two-stage text recovery attack using a decoder architecture, improving state-of-the-art results by over 60%.

#### 2 RELATED WORK

In edge-cloud collaborative systems, privacy data stored on user devices may be exposed to servers or third parties through adversarial attacks. This issue is particularly critical in deep learning, where it is often referred to as the *model inversion problem*. Model inversion attacks target deep learning models with the goal of inferring sensitive information from the model's output. These attacks leverage reverse engineering and reasoning techniques to reconstruct data or model parameters, posing significant privacy and security risks. Specifically, the goal of a model inversion attack is to reconstruct

the training data or other sensitive information behind a given model, often through its output.

Model inversion attacks are typically classified into *white-box attacks* and *black-box attacks*. In a white-box scenario, the attacker has full access to the model's internal information, including its structure, weights, and outputs. In a black-box scenario, the attacker can only access the model's output, such as confidence scores, hard labels, or feature representations.

### 2.1 Model Inversion Attacks in Computer Vision

In the domain of computer vision, model inversion attacks typically aim to reconstruct the original image or its key features from the output of image-processing models. The concept of model inversion attacks was first introduced by Fredrikson et al[6] for simple linear regression models. Recent research has extended these attacks to more complex deep neural networks. Many computer vision models are open-source, making them prime targets for white-box attacks. These attacks can be categorized into two types: generation-based inversion and optimization-based inversion.

Generation-based inversion involves using confidence scores disclosed by the model during predictions to infer sensitive information. For example, Zhang et al.[23] introduced Generative Model Inversion (GMI), which leverages a generative adversarial network (GAN) to reconstruct private training data based on partial shared information. Research by Chen et al. [3] proposed KEDMI (Knowledge-Enriched Distributional Model Inversion Attacks), a new GAN-based structure that efficiently extracts private domain information from public datasets. The black-box attack proposed by Erdogan et al. [5] exploits the activation values transmitted through the split layers as additional knowledge for the attack.

**Optimization-based inversion** focuses on minimizing the difference between the outputs generated by a random input and the model's output corresponding to private data. This approach iteratively adjusts the random input to converge to a reconstruction that is increasingly similar to the original data[1].

## 2.2 Model Inversion Attacks in Natural Language Processing

Similarly, language models are susceptible to privacy attacks. Yao et al. [21] summarize several types of privacy attacks on large language models, including adversarial attacks (e.g., data poisoning and backdoor attacks), inference attacks (e.g., attribute inference and membership inference), and extraction attacks (e.g., model stealing, gradient leakage, and training data extraction). Among these, representation inversion attacks pose significant privacy risks as they target the hidden states of model embeddings or intermediate layers rather than requiring gradients.

**Embedding inversion attacks** are a prevalent form of representation inversion, where an attacker recovers the original text from the model's embeddings. Carlini et al. [2] showed that language models, such as GPT-2, can leak personal data (e.g., names, emails, phone numbers) through API queries. Subsequent work demonstrated that BERT [4] embeddings can encode significant information about the original input, enabling reconstruction of the original text.

Generative embedding inversion attacks (GEIA) were introduced by Gu et al. [7], where a generative decoder is trained to directly reconstruct the target sequence word-by-word from its embedding. Their method outperforms previous approaches, restoring semantically similar and coherent sentences from the embeddings.

Morris et al. [10] proposed Vec2Text, which introduces the idea of iteratively refining the inverted text sequence, i.e., training a self-corrector. Vec2Text first trains an embedding inversion model using the T5 model [14] as the base model. Then, it trains the corrector by matching the embeddings generated by the victim embedding model for the generated text with the input embeddings.

However, these approaches assume a white-box setting where the attacker has full access to the embedding model, which is often not the case in industrial settings, especially with personalized training. The assumption that embedding models' outputs can be directly targeted for inversion is insufficient for scenarios involving edge-cloud collaboration, where data representations are likely more complex and involve dynamic partitioning of models across devices and servers.

#### 2.3 Defense Against Model Inversion Attacks

Despite the increasing prevalence of model inversion attacks, defense mechanisms remain underexplored. In computer vision, common defenses include adding noise to the model's output, obfuscating confidence scores, employing differential privacy, and reducing the dependency between input and output. Similar strategies are being explored in natural language processing, but adapting them to scenarios involving personalized and distributed models remains a challenge. Zhang et al. [23] proposed adding noise to the posterior difference during inference to thwart attacks, while Titcombe et al. [19] explored adding noise to representations transmitted during federated learning.

#### 3 REPRESENTATION INVERSION ATTACK

The deployment of personalized LLMs in device-edge-cloud collaborative learning is becoming increasingly prevalent. However, privacy protection in this field remains unexplored. Inspired by intermediate representation attacks in computer vision, we suspect that there may be severe privacy leakage of input data in personalized LLM scenarios.

As illustrated in Fig. 2, the differences between embeddings and representations are significant. Post-decoding representations are considerably sparser than embeddings and contain less information about the input sentence, highlighting the need for advanced and precise attack methods.

In the following section, we formally define the problem within this new attack scenario and propose our novel attack system specifically designed to address this issue.

#### 3.1 Problem Formulation

Given a sensitive input text sequence x as the input of the LM, the victim large language model g and personal device part of this model cut at i-th layer, we denoted as  $f_i$ . Based on the autoregressive intuitive for the decoder, we define the output of g at moment  $t_j$  as  $O_{t_j} = g(x, O_t t_{t=0}^{t_j-1})$ .

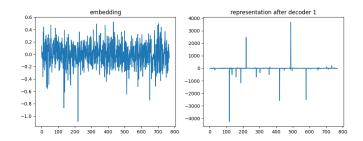


Figure 2: Visualization for embedding and representation after decoder block 1

The goal of representation inversion attacks is to reconstruct the input x from its intermediate representations  $\{h_i^t\}_{t=0}^T$ , where  $h_i^t=f_i(x,\{O_t\}_{t=0}^{t_j-1})$  and T represents the final time step or maximum length of generated sequence. The top part of model  $f_i$  is fixed, with its parameters and architecture not subject to modification by the adversary. Instead, the adversary leverages an auxiliary dataset  $D_{\text{aux}}$  with a distribution similar to the training data to construct an external attacker model  $\Phi$ . This model aims to learn to reconstruct the original text, such that:

$$\Phi(\lbrace h_i^t \rbrace_{t=0}^T) = \hat{x} \approx x.$$

To address the computational infeasibility of enumerating all possible sequences, the problem can be approached by learning a distribution of texts given their representations. This is formulated as learning a conditional model  $p(x|r;\theta)$  that maximizes the likelihood of texts given their representations:

$$\theta = \arg\max_{\hat{\theta}} \mathbb{E}_{x \sim D} [p(x | \{h_i^t\}_{t=0}^T; \hat{\theta})],$$

where  $D = \{x_1, x_2, ...\}$  is a dataset of texts. This process essentially amortizes the combinatorial optimization of directly inverting representations into the parameters of a neural network, a task known to be challenging.

#### 3.2 Analysis of information

Intuitively, after certain transformer blocks, data passes through more activation layers, leading to increased sparsity of the information. According to the On the information bottleneck theory of deep learning [17], as the data passes through more processors, the input information  $\boldsymbol{x}$  contained in the intermediate layer  $\boldsymbol{h}$  decreases, while the information about the output layer  $\boldsymbol{y}$  increases. This affects the effectiveness of model inversion attacks which motivates us to measure mutual information to study this process.

Given any two random variables, A and B, with a joint distribution p(a, b), their Mutual Information is defined as:

$$I(A;B) = D_{KL}[p(a,b)||p(a)p(b)] = \sum_{a \in A,b \in B} p(a,b) \log \left(\frac{p(a,b)}{p(a)p(b)}\right)$$
(1)

$$= \sum_{a \in A} p(a,b) \log \left( \frac{p(a|b)}{p(a)} \right) = H(A) - H(A|B), \tag{2}$$

where  $D_{KL}[p||q]$  is the Kullback-Leibler divergence of the distributions p and q, and H(A) and H(A|B) are the entropy and conditional entropy of A and B, respectively.

Following [17], for each representation h, we utilize discretization to compute the mutual information I(x, h) and I(h, y). Fig. 3 shows the variation of mutual information in the information propagation process for different layers h across various blocks.

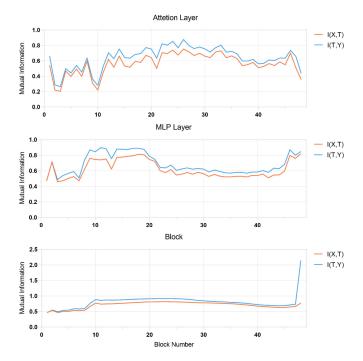


Figure 3: Mutual Information across Transformer Blocks

As the block deepens, we find that in contrast to traditional DNNs mentioned in [16, 17], the mutual information associated with the input information does not consistently decrease. Followup studies also found that the compression and generalization in the later stages of training mentioned in the paper are not absolute either, networks that do not compress are still capable of generalization, and vice versa. Here compression represents the reduction of I(x, t) with the number of layers, which is also consistent with our findings. This may also be related to the residual information from the specification layer added by the transformation blocks in the language model. Furthermore, we find that I(x, t) and I(t, y)are consistently positively correlated. In the 10th decoder block, the mutual information increases and then gradually decreases. Inside the Transformer, we also see a rise in mutual information in the middle block. However, the amount of information passing through the forward layer is not the same as the amount of information passing through the multi-attention layer.

In summary, through the analysis of mutual information, we have discovered that the Transformer model exhibits complex dynamic variations in how it processes input and output information at different layers. This variation is influenced by various factors, including the model architecture, attention mechanism, and residual

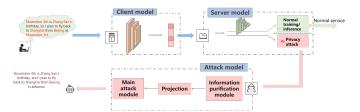


Figure 4: System of RevertLM

connections. Our findings enrich the understanding of the internal information flow within the Transformer, providing a theoretical foundation for the further design of attack methods.

#### 3.3 Threat Model

We define the black-box attack knowledge in this scenario as follows: The attacker has access only to the transmitted representation and the server's model structure, or the intermediate representations of each layer of the server's model.

In black-box attacks, the attacker can only use transmitted representation vectors. We propose using autoencoder-like and Transformer decoder structures for compression, due to the sparsity of representation vectors. For image data, we suggest upsampling and deconvolution networks, while for language sequences, attention mechanisms are used to better understand representation vectors.

In white-box attack, the attacker has full access to the model structure and parameters of the split large language model. With full model knowledge, we can design more complex inversion modules, including autoencoder-like structures or those mirroring the later parts of the victim model.

#### 3.4 Attack method

Based on the conclusion regarding the reduction of input information in intermediate layers and the fact that intermediate layer information resides in the same vector space, we propose a two-stage attack method. Specifically, due to the challenges in directly inverting deep representations, we divide the attack process into two phases. The first phase maps the representation vector to a semantically richer embedding space, referred to as the information purification module. The second phase trains an adversarial generative model as the main inversion attack module, aiming to recover the original text from the embedding vector. The attack system is illustrated in Fig. 4.

We then first introduces the main inversion attack module, which has strong inversion capabilities, followed by a discussion of the information purification module that addresses the first phase subproblem.

3.4.1 Main Inversion Module. Generative attack methods exhibit superior inversion and generalization capabilities compared to optimization-based approaches. Therefore, we select generative models as the primary inversion module.

Language models are structurally divided into three categories: encoder-only models, encoder-decoder models, and decoder-only models. Encoder-only models, such as BERT, are primarily used for understanding rich input semantics and excel in classification

and scene comprehension tasks [4]. Encoder-decoder models, such as T5, are specialized in tasks that heavily depend on input, such as translation and text summarization. Decoder-only models, like the GPT series and LLaMa, are suitable for other generative tasks, including question answering. The primary inversion module is selected from encoder-decoder and decoder-only models due to their ability to leverage the generative power of large language models.

Decoder-based large language models stand out in generative tasks due to their extensive pretraining on large-scale text corpora, which enables them to capture intricate linguistic patterns. This capability allows them to generate natural language with high levels of semantic understanding, logical coherence, and fluency, excelling in both short and long-form text generation. Their robust sequence modeling ability, driven by self-attention mechanisms, extends beyond natural language processing to applications such as code generation and dialogue systems.

In this section, we utilize GPT2-XL as the attack generator. Decoder-only models, which are trained autoregressively, excel in handling complex linguistic structures and demonstrate superior generalization, making them well-suited for zero-shot and few-shot tasks. Additionally, their direct decoding of input sequences without relying on intermediate representations enables them to better capture and utilize input details, leading to more accurate and coherent outputs.

The attack module uses the representation vector as input, and the attack generator is trained using an autoregressive approach. A mapping module ensures that the input dimensions match those required by the attack generator.

- 3.4.2 Information Purification Module. This section distinguishes between representation and embedding, which guides the design of the information purification module. Representation maps data to a high-dimensional space capturing its features, while embedding reduces data to a lower-dimensional space for further processing. Understanding this distinction is key to designing the purification module for various attack scenarios.
- 3.4.3 Training Method. According to Sections 3.4.2 and 3.4.1, the two-stage attack method in this work decomposes the complex problem by first using the information purification module to map the representation to the embedding space, and then employing the generative adversary to invert the vectors in the embedding space. The training method of this attack can be summarized as:
- **Step 1:** Pretrain information purification module with an auxiliary dataset. Direct joint training will lead to the perturbation of the generation capacity of the attack model. Our training needs an auxiliary dataset of embeddings for the victim model with negligible size.

**Step 2:** Train adversary decoder. Using the representation input after the pre-trained information purification module, we train the generative attacker with the joint loss of SequenceCrossEntropy and generative capacity loss. The SequenceCrossEntropy inspired by teacher-forcing measures the discrepancy between the generated token  $w_i$  and the probability depends on previous tokens.

$$L_{\Phi}(x;\theta_{\Phi}) = -\sum_{i=1}^{t} \log(Pr(w_i|f(x), w_0, w_1, \dots, w_{i-1})), \quad (3)$$

where x is the input sequence, w is the output sequence, t refers to the length of output sequence.

We also use the Perplexity of adversary decoder as the metrics to evaluate generative capacity. The formulation is below:

$$PPL(x) = \exp\left(-\frac{1}{t} \sum_{i=1}^{t} \log Pr_{\theta_{\phi}}(w_i|w_0, w_1, \dots, w_{i-1})\right)$$

**Step 3:** Joint fine-tune adversary decoder, projection module and autoencoder with SequenceCrossEntropy Loss. We integrate the adversary decoder, projection module, and autoencoder into a single model. This unified model is trained with a consistent optimizer.

#### 4 EXPERIMENTS

Our experiments include two scenarios: one involves sentiment analysis, a classification downstream task that utilizes embeddings from large language models, and the other directly uses large language models as the model for downstream tasks.

#### 4.1 Experiment settings

4.1.1 Datasets. Most sentence embedding models are typically trained on question-answer pairs (semi-supervised tasks) and natural language inference (supervised tasks) datasets. In the experimental section of this study, we evaluate the attack performance of these models on two distinct datasets. The first selected dataset is the PersonaChat dataset [22], which consists of open-domain conversational dialogues between two speakers with specific persona settings. Most persona settings are well represented within the corresponding dialogues, some of which may involve sensitive and private information.

The second dataset is Wiki [20], which is derived from the Stanford Question Answering Dataset (SQuAD) [15] and consists of content extracted from Wikipedia articles containing domain knowledge. The presence of such domain knowledge may pose a challenge to inversion attacks. During the evaluation process, we utilize the training data of each dataset as auxiliary data to train the attacker model and report its performance on the respective test sets. A detailed summary of both datasets is provided in Table 2.

**Table 2: Statistics of Text Datasets** 

Statistic	PersonaChat	Wikipedia
Number of Sentences	162,064	220,412
Train/Validation/Test Split	82:9:9	95:0:5
<b>Number of Unique Named Entities</b>	1,425	46,567
Average Sentence Length	11.71	18.25

- *4.1.2 Metrics.* We use three standard metrics to measure the attack performance as below:
  - ROUGE represents Recall-Oriented Understudy for Gisting Evaluation [9]. This is a metric for assessing the degree of overlap between automated abstracts or machine translations and reference summaries (or translations). It includes several variants such as ROUGE-L (scoring based on the

longest common subsequence)) to measure different levels of similarity.

- BLEU score stands for Bilingual Evaluation Understudy.
  This is done mainly by measuring the overlap between the machine translation output and a set of reference translations
- Cosine Similarity. This metric uses a transformer-based tokenizer and embedding model to project the two texts into a high-dimensional vector space to match similarity.
- 4.1.3 *Victim Models.* In our experiments, we consider different victim models and split points to evaluate the performance of the proposed inversion attack method:

**Case I**: The victim model comprises the encoder part of a language model (T5) followed by a four-layer MLP. The split point is chosen after the first layer following the embedding layer.

**Case II**: We evaluate two victim models: the decoder model GPT2-XL and the encoder-decoder model T5. The split points are strategically placed within the blocks of the decoder part or within the multi-head attention layers.

#### 4.2 Information in Transformer Blocks

Through experiments summarized in Table ??, we observed that the performance of the attacker model varies significantly depending on the layer from which the intermediate representations are obtained. Representations from the attention layers exhibit performance similar to those processed through entire blocks. However, representations processed by the Feed-Forward Network (FFN) layers show a significant decline in attack performance.

Table 3: Attacker performance for different layers in transformer block

Block number	Attention blocks	FFN layer	Whole block
Block 1	0.74	0.13	0.72
Block 20	0.66	0.14	0.62
Block 45	0.58	0.12	0.75

#### 4.3 Attack for Different Layer Blocks

Figure 5 illustrates the attack performance across various blocks of the GPT2 model. Initially, as the block number increases, the inversion results improve. However, there is a subsequent decline followed by an increase in performance. This trend aligns with our analysis of mutual information, indicating that intermediate representations closer to the input or output layers are more susceptible to inversion attacks.

Our base model achieves a ROUGE-L score of over 50% and a cosine similarity recovery rate of 90%, which are considered strong indicators of semantic similarity in NLP tasks [13, 18], regardless of the layer used as the partition point. This demonstrates that the newly proposed problem in our paper is both real and urgent. Additionally, we observe a trend where the attack effects vary depending on the segmentation layer, with some layers showing increasing vulnerability and others decreasing vulnerability to attacks.

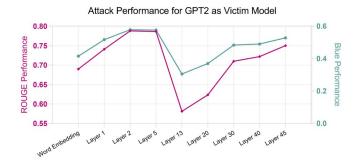


Figure 5: Attack performance towards GPT2

#### 4.4 Different Purification Modules

Here we formally evaluate the two-step system of RevertLM with the previously mentioned SOTA's approach GEIA [7].

Case I: We evaluated the performance of the RevertLM with different purification modules. The results, presented in Table ??, indicate that the linear projection method achieves the best inversion results across all metrics. This suggests that models whose structures form an inverse function relationship with the victim model's structure can achieve better inversion results.

Table 4: Evaluation for different purification modules in RevertLM

	ROUGE	BLEU	Cosine Similarity
Base RevertLM	0.5353	0.2411	0.9209
+ Linear projection	0.5972	0.2985	0.9360
+ Linear projection with tester	0.5227	0.2313	0.9195
+ Training AE	0.5208	0.2279	0.9179

Case II: We assessed the performance of the RevertLM against the T5 model. The results, shown in Table 5 and 6, demonstrate that the proposed RevertLM outperforms the state-of-the-art method across all metrics. Here T5 represents the base attack model of Vec2text [10], note that all the models here can be used in the framework of Vec2text.

Table 5: Inversion Performance on the Personachat Dataset with T5 Model as the Victim Model

	ROUGE	BLEU	Cosine Similarity
Vec2text	0.1078	0.0004	0.7270
GEIA	0.3372	0.0932	0.7841
Base RevertLM	0.4988	0.2501	0.8663
RevertLM	0.5630	0.2884	0.9021

#### 5 CONCLUSION

Our study identifies critical privacy vulnerabilities in the personalized deployment of LLMs within split learning. Additionally, we

Table 6: Inversion Performance on the Wiki Dataset with T5 Model as the Victim Model

	ROUGE	BLEU	Cosine Similarity
Vec2text	0.0054	0.0001	0.8292
<b>GEIA</b>	0.0504	0.0102	0.8493
Base	0.0802	0.0242	0.8574
Ours	0.1538	0.0870	0.8678

analyzed the variation of mutual information across different blocks of language models, providing deeper insights into information propagation and potential leakage points. To address the challenges of attacking intermediate representations, we propose a two-step inversion system that significantly improves the recovery of these representations in split learning for large language models, enhancing recovery rates by over 60%.

These findings underscore that intermediate representations, much like raw data, pose substantial privacy risks and must be treated with stringent anonymization and robust security measures. Protecting intermediate representations at the same level as raw text is essential to safeguard user privacy, particularly in sensitive domains like healthcare.

#### **REFERENCES**

- [1] [n.d.]. Reinforcement Learning-Based Black-Box Model Inversion Attacks | IEEE Conference Publication | IEEE Xplore. https://ieeexplore.ieee.org/document/10203595.
- [2] Nicholas Carlini, Florian Tramèr, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom Brown, Dawn Song, Úlfar Erlingsson, Alina Oprea, and Colin Raffel. 2021. Extracting Training Data from Large Language Models. In 30th USENIX Security Symposium (USENIX Security 21). 2633–2650.
- [3] Si Chen, Mostafa Kahla, Ruoxi Jia, and Guo-Jun Qi. 2021. Knowledge-Enriched Distributional Model Inversion Attacks. In 2021 IEEE/CVF International Conference on Computer Vision (ICCV). 16158–16167. https://doi.org/10.1109/ ICCV48922.2021.01587
- [4] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), Jill Burstein, Christy Doran, and Thamar Solorio (Eds.). Association for Computational Linguistics, Minneapolis, Minnesota, 4171–4186. https://doi.org/10.18653/v1/N19-1423
- [5] Ege Erdoğan, Alptekin Küpçü, and A. Ercüment Çiçek. 2022. UnSplit: Data-Oblivious Model Inversion, Model Stealing, and Label Inference Attacks against Split Learning. In Proceedings of the 21st Workshop on Privacy in the Electronic Society (WPES'22). Association for Computing Machinery, New York, NY, USA, 115–124. https://doi.org/10.1145/3559613.3563201
- [6] Matthew Fredrikson, Eric Lantz, Somesh Jha, Simon Lin, David Page, and Thomas Ristenpart. 2014. Privacy in Pharmacogenetics: An End-to-End Case Study of Personalized Warfarin Dosing. In Proceedings of the 23rd USENIX Conference on Security Symposium (SEC'14). USENIX Association, USA, 17–32.
- [7] Kang Gu, Ehsanul Kabir, Neha Ramsurrun, Soroush Vosoughi, and Shagufta Mehnaz. 2023. Towards Sentence Level Inference Attack Against Pre-trained Language Models. Proceedings on Privacy Enhancing Technologies (2023).
- [8] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2021. Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. https://doi.org/10.48550/arXiv. 2005.11401 arXiv:2005.11401 [cs]
- [9] Chin-Yew Lin. 2004. ROUGE: A Package for Automatic Evaluation of Summaries. In Text Summarization Branches Out. Association for Computational Linguistics, Barcelona, Spain, 74–81.

- [10] John Morris, Volodymyr Kuleshov, Vitaly Shmatikov, and Alexander Rush. 2023. Text Embeddings Reveal (Almost) As Much As Text. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, Houda Bouamor, Juan Pino, and Kalika Bali (Eds.). Association for Computational Linguistics, Singapore, 12448–12460. https://doi.org/10.18653/v1/2023.emnlp-main.765
- [11] John X. Morris, Wenting Zhao, Justin T. Chiu, Vitaly Shmatikov, and Alexander M. Rush. 2023. Language Model Inversion. https://arxiv.org/abs/2311.13647v1.
- OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Ian Leike, Iade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O'Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine B. Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, CJ Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. 2024. GPT-4 Technical Report. arXiv:2303.08774 [cs.CL] https://arxiv.org/abs/2303.08774
- [13] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a Method for Automatic Evaluation of Machine Translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, Pierre Isabelle, Eugene Charniak, and Dekang Lin (Eds.). Association for Computational Linguistics, Philadelphia, Pennsylvania, USA, 311–318. https://doi.org/10.3115/1073083.1073135
- [14] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2023. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. arXiv:1910.10683
- 15] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ Questions for Machine Comprehension of Text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, Jian Su, Kevin Duh, and Xavier Carreras (Eds.). Association for Computational Linguistics, Austin, Texas, 2383–2392. https://doi.org/10.18653/v1/D16-1264

- [16] Andrew Michael Saxe, Yamini Bansal, Joel Dapello, Madhu Advani, Artemy Kolchinsky, Brendan Daniel Tracey, and David Daniel Cox. 2018. On the Information Bottleneck Theory of Deep Learning. In *International Conference on Learning Representations*. https://openreview.net/forum?id=ry\_WPG-A-
- [17] Ravid Shwartz-Ziv and Naftali Tishby. 2017. Opening the Black Box of Deep Neural Networks via Information. https://doi.org/10.48550/arXiv.1703.00810 arXiv:1703.00810 [cs]
- [18] Sotaro Takeshita, Simone Paolo Ponzetto, and Kai Eckert. 2024. ROUGE-K: Do Your Summaries Have Keywords? https://doi.org/10.48550/arXiv.2403.05186 arXiv:2403.05186 [cs]
- [19] Tom Titcombe, Adam J. Hall, Pavlos Papadopoulos, and Daniele Romanini. 2021. Practical Defences Against Model Inversion Attacks for Split Neural Networks. https://doi.org/10.48550/arXiv.2104.05743 arXiv:2104.05743 [cs]
- [20] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding. In Proceedings of the 2018 EMNLP Workshop

- BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, Tal Linzen, Grzegorz Chrupała, and Afra Alishahi (Eds.). Association for Computational Linguistics, Brussels, Belgium, 353–355. https://doi.org/10.18653/v1/W18-5446
- [21] Yifan Yao, Jinhao Duan, Kaidi Xu, Yuanfang Cai, Eric Sun, and Yue Zhang. 2023. A Survey on Large Language Model (LLM) Security and Privacy: The Good, the Bad, and the Ugly. https://doi.org/10.48550/arXiv.2312.02003 arXiv:2312.02003 [cs]
- [22] Saizheng Zhang, Émily Dinan, Jack Urbanek, Arthur Szlam, Douwe Kiela, and Jason Weston. 2018. Personalizing Dialogue Agents: I Have a Dog, Do You Have Pets Too?. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Iryna Gurevych and Yusuke Miyao (Eds.). Association for Computational Linguistics, Melbourne, Australia, 2204–2213. https://doi.org/10.18653/v1/P18-1205
- [23] Yuheng Zhang, Ruoxi Jia, Hengzhi Pei, Wenxiao Wang, Bo Li, and Dawn Song. 2020. The Secret Revealer: Generative Model-Inversion Attacks Against Deep Neural Networks. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 250–258. https://doi.org/10.1109/CVPR42600.2020.00033