

Are Neuro-Inspired Multi-Modal Vision-Language Models Resilient to Membership Inference Privacy Leakage?

David Amebley¹ Sayanton Dibbo^{1,2}

¹The University of Alabama

dkamebley@crimson.ua.edu, sdibbo@ua.edu

²Affiliate, Alabama Center for the Advancement of AI and Director, Trustworthy AI Lab

Abstract—In the age of agentic AI, the growing deployment of multi-modal models (MMs) has introduced new attack vectors that can leak sensitive training data in MMs, causing *privacy leakage*. This paper investigates a *black-box* privacy attack, i.e., *membership inference attack* (MIA) on multi-modal vision-language models (VLMs). *State-of-the-art* research analyzes privacy attacks primarily to unimodal AI/ML systems, while recent studies indicate MMs can also be vulnerable to privacy attacks. While researchers have demonstrated that biologically inspired neural network representations can improve unimodal models’ resilience against adversarial attacks, it remains unexplored whether neuro-inspired MMs are resilient against privacy attacks. In this work, we introduce a systematic neuroscience-inspired topological regularization (i.e., τ -regularized) framework to analyze MM VLMs’ resilience against image-text-based inference privacy attacks. We examine this phenomenon using three VLMs: BLIP, PaliGemma 2, and ViT-GPT2, across three benchmark datasets: COCO, CC3M, and NoCaps. Our experiments compare the resilience of baseline and neuro VLMs (with topological regularization), where the $\tau > 0$ configuration defines the NEURO variant of each VLM under varying values of the topological coefficient τ (0–3). We show how τ -regularization affects the MIA attack success, offering a quantitative perspective on the privacy-utility trade-offs. Our results on the BLIP model using the COCO dataset illustrate that MIA attack success in NEURO VLMs drops by $\sim 24\%$ mean ROC-AUC, while achieving similar model utility (similarities between generated and reference captions) in terms of MPNet and ROUGE-2 metrics. This shows neuro VLMs are comparatively more resilient against privacy attacks, while not significantly compromising model utility. Our extensive evaluation with PaliGemma 2 and ViT-GPT2 models, on two additional datasets: CC3M and NoCaps, further validates the consistency of the findings. This work contributes to the growing understanding of privacy risks in MMs and provides empirical evidence on neuro VLMs’ privacy threat resilience.

I. INTRODUCTION

In the age of Agentic AI, multi-modal models (MMs) developed with multiple data modalities and sources are becoming more popular in application areas, including autonomous robotics [1], [2], healthcare [3], [4], education [5], biometric authentication [6], [7], and content creation [8], [9]. These MMs often include different modalities, including image and text modalities. In the last few years, Large Language Models (LLMs) like ChatGPT have seen more improvements and can now solve a wide range of problems,

making them more popular than ever [10], [11]. These models are known for their language understanding, built on the foundation of Natural Language Processing (NLP) [11]. VLMs benefit from advances in LLM research and are considered part of the AI model cluster that leverages NLP and Computer Vision to create a more complete understanding of visual and textual information [12]. VLMs with this power can identify objects in an image and provide a natural language description of the object identified [12], [13], [14]. VLMs are integrated into many applications and tools from basic to sophisticated tasks, e.g., extracting text from an image, explaining a diagram, or counting objects [15], [14], [12], [16]. This can further be incorporated in wearable computing [17], trustworthy AI/ML computing [18], health tracking [19], mission-critical agentic AI solutions [20], and user authentication [21].

Despite their capabilities, likewise unimodal models, VLMs are susceptible to vulnerabilities like adversarial and privacy attacks, especially due to their multi-modality [16], [15], [22], [23], [24], [25], [26], [27]. Among these is a type of attack in which image and text pairs are subtly altered to mislead the model to produce harmful outputs [16], [23], [28], [29], [30]. Another common vulnerability in the form of an attack to VLMs is membership inference attacks (MIAs), where attackers (also known as adversaries) try to deduce whether the model used some specific data in its training, which can be a privacy risk [31], [32], [33], [34], [35], [36].

Shokri et al. [36] implemented and tested the first-ever *black-box* membership inference attacks (MIAs) on machine learning models. [37], [38] affirmed the success of these attacks on different machine learning models, including classification and generative models, convolution neural networks (CNNs), and multilayer perceptron (MLP). Some of these attacks also target ML models that learned on multiple and sensitive image and text data [39]. Recently, work on MIAs has expanded to LLM-based models, such as generative text LLMs. Some *black-box*, text-only MIA methods in LLMs, such as the Repeat and Brainwash techniques, check for membership by examining patterns in the text the model produces [40], [41]. These methods are similar to MIAs on VLMs, like our work, in that they rely on measuring the semantic similarity or lexical overlap between generated captions and ground-truth data. However, the LLM attacks target text data rather than text-image pairs. More recently,

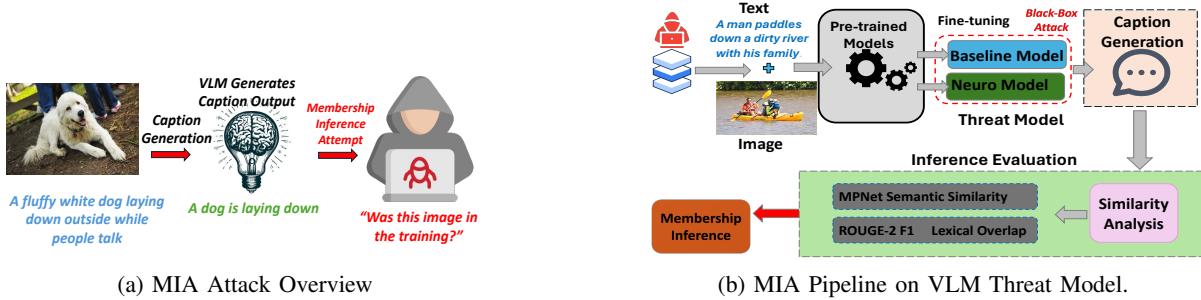


Fig. 1: In (a), we illustrate an overview of MIA attack on VLM, where an adversary infers whether a sample is part of training data by generating the model’s (VLMs) caption (output) from VLMs with queries. In (b), we present the MIA pipeline for neuro-inspired VLMs, in which the adversary fine-tunes pre-trained VLMs with topological regularization (τ) and generates captions. Finally, the adversary decided the membership of a particular sample based on semantic (MPNet) and lexical (ROUGE-2) similarity measures between original and generated captions.

we have seen some emerging work on MIAs on VLMs, with the first-ever by [42], [43], who explored MIAs on multi-modal image captioning systems using metric-based and feature-based similarity methods. Hu et al. [31] highlighted the need for more attention to MIAs on VLMs, as most work on VLMs has focused on improving the performance of these models’ interactions [44]. In their work, they proposed the first temperature-based MIA methods targeting instruction-tuning data in VLMs.

Although researchers started focusing on privacy vulnerabilities to VLMs, it has generally focused on detecting MIAs on regular VLMs using metric- or similarity-based signals [45], [43], which exploit the proximity of the model-generated caption to the ground-truth training caption. These efforts consider regular VLMs vulnerabilities, which do not seem to be resilient against MIAs. Studies, on the other hand, pointed out that neuroscience-inspired biologically regularized unimodal models can be more resilient to privacy threats compared to regular neural networks due to their capabilities to capture subtle changes in samples [46], [47]. However, it is not yet explored how this holds for multi-modal complex VLMs. Therefore, we focus on developing a biologically inspired regularization-based framework to assess the MIA vulnerabilities on MM VLMs. We explore how neuroscience-inspired model-level structural regularization, specifically τ -regularization (topology-inducing training) [44], can impact VLMs resilience. Instead of just detecting data leakage through output metrics, we study an internal framework that makes models more resilient against MIAs, without compromising performance (utility). More importantly, to the best of our knowledge, no research has examined how neuro-inspired vision-language models (i.e., those trained with topographic regularization) affect privacy. This situation leaves an important gap in understanding whether topographic regularization can affect memorization and membership inference attacks.

Our main contributions in this work are as follows:

- We introduce the topological regularization framework (i.e., τ -regularized) to fine-tune MM VLMs (i.e., neuro-inspired models)

- We study resilience of neuro-inspired VLMs for the first time on *black-box membership inference* privacy attacks
- We extensively evaluate the neuro-inspired VLMs’ privacy leakage in three different datasets (COCO, CC3M, and NoCaps) with three different VLMs (BLIP, PaliGemma 2, and ViT-GPT2) and compare the neuro-inspired VLMs’ resilience
- We present quantitative comparisons between the privacy attack success rates (accuracy) and VLMs’ performance (caption similarity) among neuro-inspired VLMs and baseline models, illustrating the privacy vs. performance trade-offs
- We ablate the neuro-inspired VLMs with different τ values to capture pattern of VLMs resilience against privacy attacks

Organization: We organize the remainder of this paper as follows: Section II explains Membership Inference Attacks and Vision-Language Models. Section III describes our methodology, including the *black-box* threat model and the τ -regularized fine-tuning process. Section IV outlines the experimental setup, the models used, and the evaluation metrics. Section V discusses the results and the resilience of neuro-inspired VLMs. Finally, Section VI concludes the paper and offers ideas for future research.

II. PRELIMINARIES

In this section, we illustrate preliminaries on the multi-modal vision-language models (VLMs) and membership inference attacks (MIAs).

A. Membership Inference Attacks (MIAs)

Before we define inference attacks, we first want to examine privacy in the context of vision language and machine learning models. Dalenius et al. claimed that a model should not show more about its input than what we would have known about the input without the model [48].

An adversary can persistently query a model to determine whether certain data was used to train it or not. The attacker usually has some dataset that they *suspect* may have been used to train the model [49], [50], [51], [52], [53], [54],

[35]. During this time, they feed the model with the data they have and observe the model’s output [37], [55], [56]. Formally, we can express this as:

$$\mathcal{A} : (u, v) \mapsto \begin{cases} 0, & \text{if } (u, v) \notin \mathcal{D}, \\ 1, & \text{if } (u, v) \in \mathcal{D}, \end{cases} \quad (1)$$

where u is an input instance, v is its associated label or caption, \mathcal{D} represents the model’s training dataset, and \mathcal{A} outputs 0 or 1 to indicate whether u, v is inferred to be a non-member or member of the training set, respectively [57].

A strong positive response infers membership, i.e., the model has likely seen the data before. If an attacker knows that some data was used to train a model, it can result in a privacy leak [36]. Various membership inference methods have been tested in the past, including shadow model-based MIAs [36], [37], [56], [58], [59].

White-box membership inference attacks exploit internal signals, such as gradients, activations, or model parameters, to detect overfitting on specific data samples. They are usually more effective than *black-box* attacks because they leverage the model’s training dynamics [37], [37], [37], [60], [61], [62], [63]. *Black-box* membership inference attacks use model outputs to infer membership. Unlike *white-box* attacks, these types have no access to the model’s internal details, such as activations or gradients. They are widely used in ML-as-a-Service scenarios where users lack internal access to the model [36], [51], [37].

B. Vision-Language Models (VLMs)

Vision-language models (VLMs) are models that learn to connect images and text by using large amounts of image and text data. They can understand natural language and reason on different types of information.

$$\mathcal{L}_{\text{VLM}} = -\log \frac{\exp(\text{sim}(z_i^{\text{img}}, z_i^{\text{txt}})/\beta)}{\sum_j \exp(\text{sim}(z_i^{\text{img}}, z_j^{\text{txt}})/\beta)}, \quad (2)$$

where z_i^{img} is the embedding of the i -th image from the vision encoder, and z_i^{txt} is the embedding of its paired caption from the language encoder. The function $\text{sim}(\cdot, \cdot)$ measures how similar two embeddings are (e.g., cosine similarity), and β is a temperature constant. This loss pushes each image embedding to be most similar to its matching caption compared to other captions in the batch [64], [65].

Regarding their strengths, VLMs connect visual information with text to make it easier to understand images and their descriptions [64]. Because VLMs learn from large-scale image–text pairs, they generalize with little or no new training [64], [66]. They also perform classification, captioning, visual question answering (VQA), text recognition (OCR), and information retrieval following instructions [14]. Methods like freezing encoders, compressing tokens, and adding adapters can make VLMs more efficient while retaining their strong performance [66].

III. METHODOLOGY

We consider a *black-box* MIA scenario, where the adversary attempts to determine whether a specific image-text pair was part of the training dataset of a deployed VLM.

A. Adversarial Capabilities

Adversarial capabilities determine the effectiveness of a membership inference attack and influence the attacker’s chances of success. Previous research classifies adversaries based on the amount of information they can access from the target model [67], [68], [31], [69]. In *white-box* settings, attackers can access internal model parameters, gradients, or their hidden representations. In *soft black-box* settings, attackers can query the model and receive intermediate outputs, such as logits or probability distributions. The most restrictive and realistic scenario for deployed VLMs is the *strict black-box* setting. With this scenario, adversaries can only see the final output of the model [70], [71], [72]. In our threat model, the adversary operates under this strict *black-box* assumption. They can submit an input image and only see the generated caption, with no access to model weights, training data, embeddings, or confidence scores. This scenario is common with deployed VLMs with only inference APIs access [73], [37], [54], [74], [75], [76], [77].

B. Attack Overview

The adversary’s goal is to find out if a specific image-caption pair (u, v) was used to train the target VLM \mathcal{M}_τ . In this *black-box* threat model, the adversary can only send an image u to \mathcal{M}_τ and see the caption it produces, which we call $v' = \mathcal{M}_\tau(u)$, as described in Section III-A.

In the setup shown in Fig. 1a, the attacker queries the model with an image and receives a caption. They then compare this caption to the image’s ground-truth caption. If the caption is very similar to the original text, the adversary infers that (u, v) likely belongs to the training. If it is not, they classify it as a non-member. To measure caption similarity, they can use two methods: (i) MPNet embedding similarity, which checks for semantic alignment, and (ii) ROUGE-2 overlap for lexical matching. These two methods combine to create the membership score.

C. Attack Pipeline on τ -Regularized VLMs

Fig. 1b shows the detailed steps of the attack used in our evaluation. Although the attacker does not modify the model or train it, we analyze how different levels of topographic regularization, $\tau \in \{0, 2, 3\}$, can impact privacy. For each level of τ , the attack follows these steps:

(i) **Query.** The attacker sends an input image u to the model \mathcal{M}_τ and gets a generated caption v' .

(ii) **Similarity Computation.** The attacker checks how similar v' is to the ground-truth caption(s) using MPNet semantic similarity and ROUGE-2 lexical overlap. This gives us two indicators of membership:

$$s_{\text{mp}}(u) = \text{sim}_{\text{MPNet}}(v', v), \quad s_{\text{rg}}(u) = \text{sim}_{\text{ROUGE2}}(v', v).$$

We describe similarity metrics in Section IV-F.

(iii) **Membership Decision.** If the similarity is high, it suggests the model memorized training information, leading the attacker to infer membership. On the other hand, a lower score will indicate likely non-membership. These steps connect directly to Fig. 1b, which illustrates how captions are generated from \mathcal{M}_τ , compared to references, and then converted to membership predictions using similarity scores, which explain how the attacker interacts with the model.

D. Adversarial Goal

We formalize this *black-box* attack capability as follows.

$$\mathcal{M}_\tau : \mathcal{U} \rightarrow \mathcal{V} \quad (3)$$

represent a VLM fine-tuned under topological regularization coefficient $\tau \geq 0$, where \mathcal{U} is the *image domain* and \mathcal{V} is the *caption domain*. The adversary can submit an image $u \in \mathcal{U}$ to \mathcal{M}_τ and observe its generated caption

$$v' = \mathcal{M}_\tau(u). \quad (4)$$

Here, \mathcal{M}_τ refers to the deployed VLM, u is the query image, and v' is the caption that the model generates. The adversary cannot access any gradients, embeddings, or model parameters. For a given query image u , the attacker attempts to infer whether u was part of the model's private training set $\mathcal{D}_{\text{train}}$ [36], [78]. Formally, the goal is to infer the membership indicator [79]

$$b(u) = \begin{cases} 1 & \text{if } u \in \mathcal{D}_{\text{train}}, \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

To clarify the membership inference problem, we specify the training objective of the model being attacked. When fine-tuning, we optimize the VLM using a topography-regularized loss:

$$\mathcal{J}_\tau = \mathcal{J}_{\text{cap}} + \tau \mathcal{R}_{\text{topo}}, \quad (6)$$

where \mathcal{J}_{cap} is the standard captioning loss (cross-entropy), and $\mathcal{R}_{\text{topo}}$ is the topographic regularizer introduced by Deb et al. [44]. The regularizer encourages smoother, spatially organized internal representations by aligning each feature map with a blurred counterpart. Formally, for cortical maps C and their blurred versions C' ,

$$\mathcal{R}_{\text{topo}} = -\frac{1}{N} \sum_{i=1}^N \frac{C_i \cdot C'_i}{\|C_i\| \|C'_i\|}. \quad (7)$$

Unlike cross-entropy, which only focuses on improving task performance, $\mathcal{R}_{\text{topo}}$ adds a structural rule, i.e., inductive bias, that shapes how the model understands information. Parameter τ controls inductive bias strength [44].

E. Information Available to the Adversary

We assume that the adversary has a set of candidate sample images, which they may have drawn from a distribution similar to the training data. For each query image u , the adversary also assumes access to an accompanying reference caption v , e.g., publicly available annotations [80], [81],

[82]. These candidate samples are used to query the model, compute similarity statistics between v and $v' = \mathcal{M}_\tau(u)$, and derive a membership decision rule $\hat{b}(u)$.

F. Adversarial Knowledge Assumptions

In this attack, we assume that the adversary knows the targeted model is a VLM accessible via query [49], [83], [75]. The adversary also knows public data distributions resembling the training domain exist [84], [80], [85], [86], [82]. Additionally, we assume that the adversary is aware of the availability of a similarity scoring function S [87]. Importantly, we also infer that the adversary is not exposed to the internal parameters or gradients of the model [36], [88]. Again, we consider that they do not know the *exact* samples used in training [49]. We also assume that the adversary is unaware of the optimizer state or hyperparameters used. This scenario is common with cloud-API threats [49], [75].

G. Threat Model

The adversary assesses how closely the generated caption v' matches the reference caption v using similarity metrics like MPNet [89], [90] and ROUGE-2 [91], [92]. We denote a similarity function as [93], [94]:

$$S : \mathcal{V} \times \mathcal{V} \rightarrow \mathbb{R}. \quad (8)$$

For a *query image* u :

$$s(u) = S(v, \mathcal{M}_\tau(u)), \quad (9)$$

The adversary performs a threshold-based attack

$$\hat{b}(u) = \begin{cases} 1 & \text{if } s(u) \geq t, \\ 0 & \text{otherwise,} \end{cases} \quad (10)$$

where t is chosen to maximize discrimination between members and nonmembers. Here, u denotes an input image, and v is its reference caption. $v' = \mathcal{M}_\tau(u)$ represents the generated caption, whereas $S(\cdot, \cdot)$ computes semantic similarity between the generated and reference captions. $s(u)$ is the resulting similarity score; and $b(u) \in \{0, 1\}$ indicates whether u is a training member. For each model-dataset configuration, we compute

$$\alpha_{\text{in}}, \alpha_{\text{out}} \quad (11)$$

The mean similarity scores for the member and nonmember samples, therefore, become as follows:

$$\alpha_{\text{in}} = \mathbb{E}_{u \in \mathcal{D}_{\text{train}}} [s(u)], \quad \alpha_{\text{out}} = \mathbb{E}_{u \notin \mathcal{D}_{\text{train}}} [s(u)] \quad (12)$$

We denote the similarity gap as follows:

$$\Delta_\tau = \alpha_{\text{in}} - \alpha_{\text{out}}. \quad (13)$$

Larger Δ_τ implies a stronger membership signal [95], [88], [36]. Under τ -regularization, we expect the Δ_τ to shrink. Membership inference success is computed by comparing $\hat{b}(u)$ to ground-truth $b(u)$ [51].

H. Topographic (τ -Regularization) Model

To improve membership privacy, we consider VLMs trained under topological regularization [44].

$$\mathcal{J}_\tau = \mathcal{J}_{\text{cap}} + \tau \cdot \mathcal{R}_{\text{topo}}. \quad (14)$$

where \mathcal{J}_{cap} is the standard captioning loss, and $\mathcal{R}_{\text{topo}}$ encourages nearby features in the model to learn related functions. The scalar τ determines how strongly this topological constraint is applied [96], [97], [98] (explicit form of $\mathcal{R}_{\text{topo}}$ is presented in Section III-D).

As τ increases, the learned representations become more organized ("Neuro") [99], [100], [101], [102], [103], [104], [105], which should reduce the model's reliance on memorizing specific training examples and therefore mitigate membership leakage [44], [106], [107], [55], [108], [109], [37]. In this work, we study three configurations of the model: the baseline version ($\tau = 0$), a Neuro-regularized version ($\tau = 2$), and a stronger Neuro++ configuration ($\tau = 3$). These settings allow us to examine how increasing τ affects privacy leakage.

IV. EXPERIMENTS

In this section, we describe how we carry out our membership inference attacks on the pretrained VLMs. We outline the evaluation setup, models, datasets, caption-similarity pipeline, and attack formulation. *Our implementation is based on the following codebase.¹*

A. Experimental Setup

a) *Access Model and Infrastructure.*: We tested pretrained VLMs BLIP, ViT-GPT2, and PaliGemma 2 using locally saved Hugging Face checkpoints on the UA HPC cluster, which has an A100 GPU with 80 GB. The attacker can only input image-caption pairs and receive captions in return. They cannot access any internal parameters or gradients. In addition, there are no limits on the number of queries in our experiments.

b) *Fine-Tuning.*: We fine-tuned each model for each dataset under three different topological regularization settings: $\tau \in \{0, 2, 3\}$, which we call *Baseline*, *Neuro*, and *Neuro++*. During fine-tuning, we update the model parameters while applying a τ -scaled topographic penalty to the decoder features. We save a separate checkpoint directory for every combination of model, dataset, and τ .

c) *Datasets and Splits.*: We use an 80/20 member split of each dataset for fine-tuning. We keep the non-member split for evaluation only. Full details about sampling appear in Section IV-C.

d) *Caption Generation.*: We generate one caption per image. The ViT-GPT2 model uses greedy decoding (no sampling, single beam, set to a `max_new_tokens=20`). The BLIP model uses its default `generate()` configuration, which also includes no sampling and a single beam. PaliGemma 2 generates

¹The code can be found at https://github.com/YukeHu/vlm_mia.

captions with a brief "Describe the image" text prompt. We used nucleus sampling (`top_p=0.9`, `temperature=0.7`, `repetition_penalty=1.2`, and `max_new_tokens=60`). We remove any echoed prompt prefix before scoring.

e) *Per-Configuration Evaluation.*: We calculate all similarity statistics (MPNet, ROUGE-2), similarity gaps, and membership decisions separately for each combination of model, dataset, and τ configuration. We use the member and non-member sets described earlier.

B. Models Evaluated

We evaluate three representative vision-language models (VLMs): **BLIP** [110], **ViT-GPT2** [111], [112], and **PaliGemma 2** [113]. We also examine each model under three levels of topographic regularization: $\tau \in \{0, 2, 3\}$. The configuration $\tau = 0$ corresponds to the standard pretrained model, whereas $\tau > 0$ adds topographic regularization during supervised fine-tuning. We fine-tune all models end-to-end using image-caption pairs. For each combination of model, dataset, and τ configuration, we save a separate checkpoint. We use these checkpoints later to generate captions and check membership based on similarities. This approach enables us to compare the extent of privacy leakage across different models, datasets, and levels of regularization.

C. Datasets

We evaluate our models on three image-caption datasets: **COCO** [80], **NoCaps** [85], and **CC3M** [84]. For each dataset, we randomly select 400 image-caption pairs and group them as *members*, and an additional 400 pairs as *non-members*, keeping a balanced 1:1 ratio. We ensure that these two sets are completely disjoint from each other. We fine-tune the models only on the member pairs, splitting into 80% for training and 20% for validation. The non-member pairs remain unseen during training, and we use them for evaluation. We apply the same sampling for all datasets.

D. Similarity Scoring

For each model, dataset, and τ configuration, we evaluate how closely a generated caption matches its reference. We calculate two scores: ROUGE-2 F1 [91], [92] for lexical overlap and MPNet cosine similarity [90] for semantic similarity. We use the MPNet model from sentence-transformers to generate embeddings with `normalize_embeddings` set to `True`. For each image, we compare the generated caption with the reference captions and take the maximum score from the reference captions. For each configuration and membership category (member/non-member), we log the per-image similarity values, as well as the mean similarity and sample count.

E. MIA Pipeline

We evaluate membership inference for each combination of dataset, model, regularization coefficient (τ), and granularity parameter g ($g \in \{10, 50, 100, 150, 200\}$). Doing that helps us to observe how the attack success rate changes

TABLE I: Performance comparison among BASELINE and τ -regularized neuroscience-inspired models (NEURO with $\tau = 2$ and NEURO++ with $\tau = 3$) on the COCO dataset. The table reports member and non-member similarity scores for MPNet and ROUGE-2, along with the resulting ROC-AUC values (mean \pm std) across BLIP, PaliGemma 2, and ViT-GPT2.

Dataset	Model	Threat Model	MPNet $\downarrow\downarrow$ (Member)	MPNet $\downarrow\downarrow$ (Non-Member)	ROUGE-2 $\downarrow\downarrow$ (Member)	ROUGE-2 $\downarrow\downarrow$ (Non-Member)	ROC-AUC $\uparrow\uparrow$
COCO	BLIP	BASELINE	0.723	0.663	0.249	0.171	94.00 ± 9.90
		NEURO	0.797	0.793	0.425	0.380	70.88 ± 18.95
		NEURO++	0.698	0.687	0.319	0.312	63.46 ± 10.88
	PaliGemma 2	BASELINE	0.605	0.603	0.227	0.203	70.86 ± 19.53
		NEURO	0.717	0.712	0.111	0.102	69.98 ± 13.48
		NEURO++	0.735	0.732	0.338	0.318	66.76 ± 13.57
	ViT-GPT2	BASELINE	0.771	0.773	0.318	0.304	55.51 ± 16.47
		NEURO	0.773	0.782	0.357	0.373	29.38 ± 10.58
		NEURO++	0.775	0.776	0.357	0.368	38.39 ± 10.28



Caption ($\tau = 0$): “a close up of a tray of food with broccoli”

(a) Member, $\tau = 0$

Reference caption: “Closeup of bins of food that include broccoli and bread.”



Caption ($\tau = 3$): “a group of containers filled with food sitting on top of a table”

(b) Member, $\tau = 3$



Caption ($\tau = 0$): “a group of baseball players playing a game of baseball”

(c) Non-member, $\tau = 0$

Reference caption: “A baseball field full of baseball players standing on a field.”



Caption ($\tau = 3$): “a baseball player is throwing a ball on a field”

(d) Non-member, $\tau = 3$

Fig. 2: Example image-caption pairs from COCO (BLIP) showing how captions change under baseline ($\tau = 0$) and neuro-inspired (topographically regularized, i.e., $\tau = 3$) variant for member and non-member samples.

with different sampling depths. For each run, we load the generated captions for both member and non-member sets, with their matching reference captions. For each image, we calculate a membership signal that represents the maximum similarity between the generated caption and its available reference captions, using a single metric (MPNet or ROUGE-2) per run and producing a single score per image. We do not use any shadow models in our setup. The attack compares the distributions of similarity scores from member and non-member sets and adjusts the decision thresholds accordingly. This method computes the ROC-AUC for these two score distributions, with a higher AUC indicating better attack success. We explain the ROC-AUC metric in Section IV-F.

F. Evaluation Metrics

In this section, we discuss the main evaluation metrics used in our experiments to measure the success of our attacks.

ROUGE-2 Metric: We evaluate the lexical similarity of the generated captions using the *ROUGE-2* metric [84], [114]. The general ROUGE framework is the most widely used evaluation metric for text summarization, serving as a content-based metric that measures the similarity between a generated text and a reference by quantifying overlapping n-grams [91], [115].

MPNet Metric: We also evaluated the similarity between the generated and reference captions using *MPNet* cosine similarity, an embedding-based semantic encoder. Semantic sentence embedding encodes sentences into vectors, such that when two sentences are close in this vector space, it means they have similar meanings [116], [90], [117], [118].

ROC-AUC Metric: To provide a more precise assessment of the performance of our attack, we measure its success rate using the ROC-AUC area under the ROC Curve [49], [119]. This method gives a stronger measure of how the attack performs at different levels of true positives [79]. It directly addresses the key goal of distinguishing between members and non-members [120].

V. EXPERIMENTAL RESULTS

In this section, we present our results after testing our three models, BLIP, PaliGemma 2, and ViT-GPT2 on datasets COCO, NoCaps, and CC3M. Our analysis covers different levels of topographic regularization, $\tau \in \{0, 2, 5\}$. We report these results using two methods: (i) similarity metrics (MPNet and ROUGE-2), and (ii) membership inference accuracy (ROC-AUC). Below, we discuss the patterns we observe.

A. Model Performance (Utility) Comparisons

The three models exhibit distinct similarity profiles across the datasets. BLIP consistently achieves the highest MPNet and ROUGE-2 similarity scores at $\tau = 0$ (BASELINE), inferring much stronger alignment with reference captions. PaliGemma 2 has moderate scores, while ViT-GPT2 scores the lowest on most datasets. This ranking likely reflects their architectural design differences: BLIP’s contrastive pretraining helps it achieve better lexical and semantic alignment

[110], whereas ViT-GPT2 generates more varied, less specific captions [121]. Additionally, higher similarity scores are associated with higher memorization. BLIP has the highest average similarity and the highest BASELINE ROC-AUC. To illustrate how generated captions differ between baseline models $\tau = 0$ and neuro-inspired regularized models $\tau = 3$ for member and non-member samples, we provide examples in Fig. 2. Observe that the generated captions with NEURO VLMs are very similar to the reference caption, even under MIA attacks. This indicates the model utility is not significantly compromised in the NEURO VLMs.

In Table I, BLIP shows a **(94.00%)** BASELINE ROC-AUC while ViT-GPT2 has the lowest at **(55.51%)**. This trend is also similar in Table II. In Table III, although BLIP still shows the highest BASELINE ROC-AUC at **(81.74%)**, PaliGemma 2 follows closely with **(81.44%)**, while ViT-GPT2 still has the lowest at **(68.48%)**. It shows that models with stronger image-text alignment tend to leak membership information.

B. MIA Attack Success Rates

As the value of τ increases, MIA success rates generally decrease for most (model, dataset) pairs. For the three VLMs tested, the lowest ROC-AUC for attacks is consistently observed at $\tau = 3$ (NEURO++) across all **COCO**, **NoCaps**, and **CC3M** datasets.

Topographic regularization enhances resilience against MIA attacks by reducing the model’s sensitivity to patterns within member sets. However, the extent of this improvement depends on the dataset. For instance, COCO and CC3M exhibit substantial reductions in ROC-AUC, whereas NoCaps shows more minor changes due to its diverse captioning style and weaker direct alignment [85]. We display the full ROC-AUC curves for COCO, CC3M, and NoCaps in Fig. 3.

C. Impact of Neuro-Inspired Topological Regularization

Fig. 4 summarizes how lexical similarity changes in terms of member and non-member sets across τ . It shows the average ROUGE-2 scores for all models and datasets. Increasing the value of τ affects both similarity metrics and the success of the attack. Fig. 5 shows how the similarity means of MPNet also change in terms of member and non-member sets across τ for each dataset and model.

In the COCO and CC3M datasets, MPNet and ROUGE-2 scores slightly change when τ increases from 0 to 3. For example, in COCO for member sets, MPNet decreases from 0.723 (BASELINE) to 0.698 (NEURO++), and ROUGE-2 changes from 0.249 to 0.319. For non-member sets MPNet changes from 0.663 (BASELINE) to 0.687 (NEURO++), and ROUGE-2 changes from 0.171 to 0.312. This indicates NEURO++ models can achieve similar or slightly better similarity scores between generated and reference captions, indicating no utility (model performance) degradation.

We can observe a similar trend in the NoCaps dataset with similar or slightly changed similarity scores (MPNet and ROUGE-2), which indicates NEURO++ does not compromise performance significantly. We observe that the neuro-inspired models (BLIP) achieve lower ROC-AUC scores,

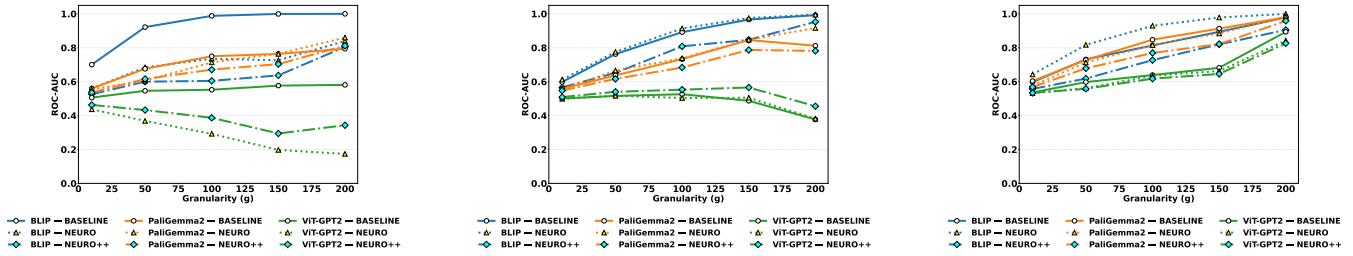


Fig. 3: Plots showing attack success rates in ROC-AUC.

TABLE II: Performance comparison among BASELINE and τ -regularized neuroscience-inspired models (NEURO with $\tau = 2$ and NEURO++ with $\tau = 3$) on the CC3M dataset. The table reports member and non-member similarity scores for MPNet and ROUGE-2, along with the resulting ROC-AUC values (mean \pm std) across BLIP, PaliGemma 2, and ViT-GPT2.

Dataset	Model	Threat Model	MPNet $\downarrow\downarrow$ (Member)	MPNet $\downarrow\downarrow$ (Non-Member)	ROUGE-2 $\downarrow\downarrow$ (Member)	ROUGE-2 $\downarrow\downarrow$ (Non-Member)	ROC-AUC $\uparrow\uparrow$
CC3M	BLIP	BASELINE	0.560	0.522	0.152	0.110	84.23 \pm 15.45
		NEURO	0.561	0.519	0.158	0.113	85.43 \pm 15.15
		NEURO++	0.475	0.450	0.093	0.075	76.52 \pm 14.75
	PaliGemma 2	BASELINE	0.418	0.397	0.056	0.046	71.69 \pm 11.40
		NEURO	0.486	0.462	0.079	0.068	74.45 \pm 14.14
		NEURO++	0.451	0.436	0.073	0.063	68.33 \pm 12.06
	ViT-GPT2	BASELINE	0.363	0.371	0.041	0.038	48.13 \pm 16.11
		NEURO	0.363	0.372	0.042	0.038	48.11 \pm 17.64
		NEURO++	0.363	0.371	0.043	0.037	52.46 \pm 19.89

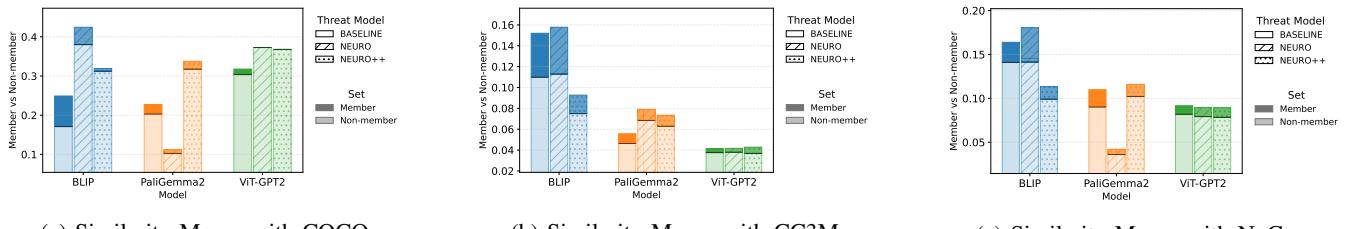


Fig. 4: Performance comparisons among BASELINE and the τ -regularized neuroscience-inspired models (NEURO with $\tau = 2$ and NEURO++ with $\tau = 3$) in terms of similarity means (ROUGE-2) across multiple models (i.e., BLIP, PaliGemma 2, and ViT-GPT2) on three datasets—COCO, CC3M, and NoCaps.

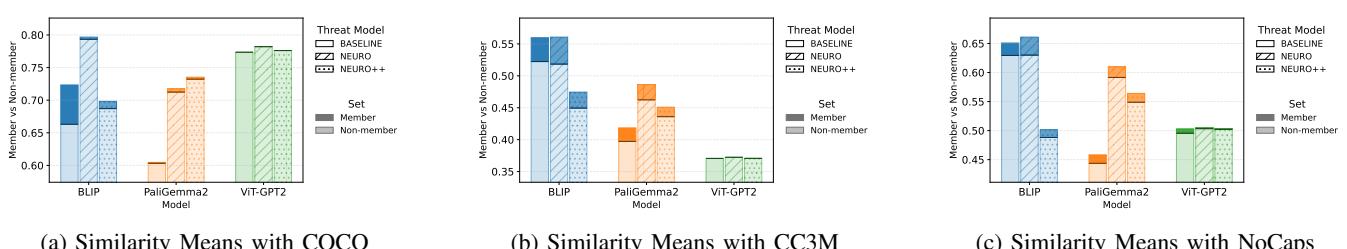


Fig. 5: Performance comparisons among BASELINE and the τ -regularized neuroscience-inspired models (NEURO with $\tau = 2$ and NEURO++ with $\tau = 3$) in terms of similarity means (MPNet) across multiple models (i.e., BLIP, PaliGemma 2, and ViT-GPT2) on three datasets—COCO, CC3M, and NoCaps.

indicating the resilience of the models against MIA attacks. For example, in the COCO dataset, NEURO and NEURO++ achieve 24% and 30.5% ROC-AUC drops, compared to the BASELINE. Similarly, across the CC3M and NoCaps

datasets and other models (PaliGemma 2 and ViT-GPT2), we observe a drop in attack performance, i.e., ROC-AUC. This indicates higher resilience of the neuro-inspired models against MIAs. **NEURO ($\tau=2$) vs. NEURO++ ($\tau=3$)**. A

direct comparison between $\tau=2$ and $\tau=3$ shows a similar pattern based on the dataset. For COCO and CC3M, NEURO++ generally produces lower MPNet and ROUGE-2 scores than NEURO. PaliGemma 2 on COCO, however, shows an opposite trend, with NEURO++ producing higher similarity scores. This means there is no significant change in similarity; however, the ROC-AUC decreases in most scenarios, improving privacy beyond what NEURO provides.

On NoCaps, NEURO and NEURO++ usually produce very similar MPNet and ROUGE-2 scores, with only a slight drop in ROC-AUC. While NEURO++ offers attack resilience in datasets with structured captions, it has a limited impact on more diverse datasets. Neuro-inspired regularization smooths internal representations and reduces overfitting to specific training examples. This mechanism narrows the similarity gap between members and non-members, thereby improving resiliency against attacks [44], [122], [99], [96].

D. Ablations

To understand how topological regularization affects the attack setup, we tested it on two datasets (COCO and NoCaps) and two models (BLIP and ViT-GPT2). We varied the regularization strength τ with values $\{0, 1, 2, 3, 5\}$ and the granularity g with options $\{50, 100, 200\}$. For each combination of dataset, model, τ , and g , we averaged the attack success rate with two similarity metrics (MPNet and ROUGE-2) and plotted the results in Fig. 6.

a) Effect of granularity (g): The study shows that for both datasets, higher granularity leads to higher attack success, especially for BLIP. For example, on COCO with BLIP at $\tau = 0$, the ROC-AUC increases from $g = 50$ to nearly 100% at $g = 200$. When $\tau = 1$, the attack success is slightly lower at $g = 50$ and $g = 100$, but it returns to 100% at $g = 200$. On the NoCaps dataset, BLIP and ViT-GPT2 show a similar pattern, where attacks strengthen as g increases. However, ViT-GPT2 shows some unpredictable variations in its performance as τ changes. The study confirms that more finely grained attacks (larger g) are more successful at exploiting membership signals.

b) Effect of τ on COCO vs. NoCaps: Increasing the value of τ from 0 to 1 reduces the ROC-AUC on BLIP in COCO at moderate granularities like $g = 50$ and $g = 100$. Higher values of τ ($\tau = 2$, NEURO, and $\tau = 3$ NEURO++) further lower the attack performance through different granularities. ViT-GPT2 shows noticeable changes between $\tau = 0$ and $\tau = 1$ on COCO. However, these differences are less noticeable than with BLIP, indicating a minor but consistent improvement in privacy.

On NoCaps, the effect of τ is weaker. BLIP shows an inconsistent trend, with $\tau = 0$ having a weaker attack rate than higher τ . The curves for $\tau = 2$ and $\tau = 3$ are identical throughout all granularities. It shows that NEURO and NEURO++ do not offer extra benefits over each other on BLIP. For ViT-GPT2, the attack rates are almost identical at lower τ for granularities 50 and 100, but a moderate gap in attack success reduction is observed when g increases to

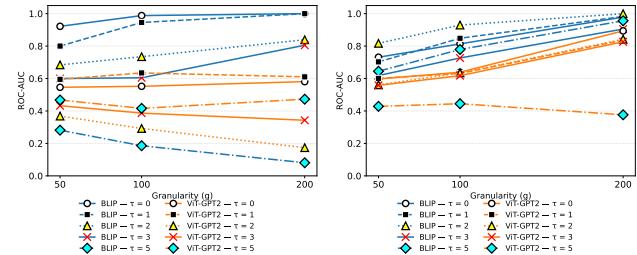


Fig. 6: Impact of τ on COCO and NoCaps with BLIP and ViT-GPT2 under $\tau \in \{0, 1, 2, 3, 5\}$ and granularities $g \in \{50, 100, 200\}$.

200. The attack success is significantly reduced at $\tau = 3$, and even more when g increases from 100 to 200.

VI. CONCLUSION

In this paper, we demonstrated that biologically inspired topographic regularization is an effective method for mitigating MIAs in VLMs. Our studies show that τ regularization reduces the gap in similarity between member and non-member captions, thereby improving resilience against MIAs. Note that NEURO VLMs maintain model utility (similar similarity scores as baselines), while improving resilience against MIAs. These findings suggest several promising directions, including identifying optimal τ for privacy-utility trade-offs, exploring white-box MIAs on VLMs. These steps are essential for creating deployable, privacy-preserving NEURO VLMs in real-life agentic AI applications.

REFERENCES

- [1] C. Cui, Y. Ma, X. Cao, W. Ye, Y. Zhou, K. Liang, J. Chen, J. Lu, Z. Yang, K.-D. Liao, *et al.*, “A survey on multimodal large language models for autonomous driving,” in *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, pp. 958–979, 2024.
- [2] S. Sreram, T.-H. Wang, A. Maalouf, G. Rosman, S. Karaman, and D. Rus, “Probing multimodal LLMs as world models for driving,” *IEEE Robotics and Automation Letters*, 2025.
- [3] N. Yildirim, H. Richardson, M. T. Wetscherek, J. Bajwa, J. Jacob, M. A. Pinnock, S. Harris, D. Coelho De Castro, S. Banmur, S. Hyland, *et al.*, “Multimodal healthcare AI: identifying and designing clinically relevant vision-language applications for radiology,” in *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, pp. 1–22, 2024.
- [4] S. S. Vengatachalam and T. Rakkiannan, “Transforming healthcare with AI: Multimodal VQA systems and LLMs,” in *2025 10th International Conference on Signal Processing and Communication (ICSC)*, pp. 584–590, IEEE, 2025.
- [5] S. Doveh, S. Perek, M. J. Mirza, W. Lin, A. Alfassy, A. Arbelle, S. Ullman, and L. Karlinsky, “Towards multimodal in-context learning for vision and language models,” in *European Conference on Computer Vision*, pp. 250–267, Springer, 2024.
- [6] S. Vhaduri, S. V. Dibbo, A. Muratyan, and W. Cheung, “mWIoTAUTH: Multi-wearable data-driven implicit IoT authentication,” *Future Generation Computer Systems*, vol. 159, pp. 230–242, 2024.
- [7] A. Muratyan, W. Cheung, S. V. Dibbo, and S. V. Vhaduri, “Opportunistic multi-modal user authentication for health-tracking IoT wearables,” in *The Fifth International Conference on Safety and Security with IoT: SaSeIoT 2021*, pp. 1–18, Springer, 2022.
- [8] M. Behravan and D. Gracanin, “Generative multi-modal artificial intelligence for dynamic real-time context-aware content creation in augmented reality,” in *Proceedings of the 30th ACM Symposium on Virtual Reality Software and Technology*, pp. 1–2, 2024.

TABLE III: Performance comparison among BASELINE and τ -regularized neuroscience-inspired models (NEURO with $\tau = 2$ and NEURO++ with $\tau = 3$) on the NoCaps dataset. The table reports member and non-member similarity scores for MPNet and ROUGE-2, along with the resulting ROC-AUC values (mean \pm std) across BLIP, PaliGemma 2, and ViT-GPT2.

Dataset	Model	Threat Model	MPNet $\downarrow\downarrow$ (Member)	MPNet $\downarrow\downarrow$ (Non-Member)	ROUGE-2 $\downarrow\downarrow$ (Member)	ROUGE-2 $\downarrow\downarrow$ (Non-Member)	ROC-AUC $\uparrow\uparrow$
NoCaps	BLIP	BASELINE	0.651	0.629	0.164	0.141	81.74 ± 13.09
		NEURO	0.661	0.630	0.181	0.141	87.35 ± 13.91
		NEURO++	0.501	0.488	0.113	0.099	72.55 ± 13.99
	PaliGemma 2	BASELINE	0.458	0.444	0.110	0.090	81.44 ± 14.44
		NEURO	0.610	0.592	0.042	0.036	79.45 ± 14.87
		NEURO++	0.564	0.549	0.116	0.102	75.93 ± 14.06
	ViT-GPT2	BASELINE	0.503	0.495	0.092	0.082	68.48 ± 13.85
		NEURO	0.505	0.503	0.090	0.079	64.66 ± 14.97
		NEURO++	0.503	0.502	0.089	0.078	63.63 ± 15.93

- [9] D. Cheng, H. Zhan, X. Zhao, G. Liu, Z. Li, J. Xie, Z. Song, W. Feng, and B. Peng, “Text-to-edit: Controllable end-to-end video ad creation via multimodal LLMs,” *arXiv preprint arXiv:2501.05884*, 2025.
- [10] Y. Chang, X. Wang, J. Wang, Y. Wu, L. Yang, K. Zhu, H. Chen, X. Yi, C. Wang, Y. Wang, *et al.*, “A survey on evaluation of large language models,” *ACM transactions on intelligent systems and technology*, vol. 15, no. 3, pp. 1–45, 2024.
- [11] F. Bordes, R. Y. Pang, A. Ajay, A. C. Li, A. Bardes, S. Petryk, O. Mañas, Z. Lin, A. Mahmoud, B. Jayaraman, *et al.*, “An introduction to vision-language modeling,” *arXiv preprint arXiv:2405.17247*, 2024.
- [12] X. Li, C. Wen, Y. Hu, Z. Yuan, and X. X. Zhu, “Vision-language models in remote sensing: Current progress and future trends.” *IEEE Geoscience and Remote Sensing Magazine*, vol. 12, no. 2, pp. 32–66, 2024.
- [13] W. Dai, J. Li, D. Li, A. Tiong, J. Zhao, W. Wang, B. Li, P. N. Fung, and S. Hoi, “Instructblip: Towards general-purpose vision-language models with instruction tuning,” *Advances in neural information processing systems*, vol. 36, pp. 49250–49267, 2023.
- [14] T. Lee, H. Tu, C. H. Wong, W. Zheng, Y. Zhou, Y. Mai, J. S. Roberts, M. Yasunaga, H. Yao, C. Xie, *et al.*, “Vhelm: A holistic evaluation of vision language models,” *Advances in Neural Information Processing Systems*, vol. 37, pp. 140632–140666, 2024.
- [15] H. Laurençon, L. Tronchon, M. Cord, and V. Sanh, “What matters when building vision-language models?,” *Advances in Neural Information Processing Systems*, vol. 37, pp. 87874–87907, 2024.
- [16] D. Liu, M. Yang, X. Qu, P. Zhou, Y. Cheng, and W. Hu, “A survey of attacks on large vision-language models: Resources, advances, and future trends,” *IEEE Transactions on Neural Networks and Learning Systems*, 2025.
- [17] C.-W. Lien, S. Vhaduri, S. V. Dibbo, and M. Shaheed, “Explaining vulnerabilities of heart rate biometric models securing IoT wearables,” *Machine Learning with Applications*, vol. 16, p. 100559, 2024.
- [18] S. V. Dibbo, J. S. Moore, G. T. Kenyon, and M. A. Teti, “Lcanets++: Robust audio classification using multi-layer neural networks with lateral competition,” in *2024 IEEE International Conference on Acoustics, Speech, and Signal Processing Workshops (ICASSPW)*, pp. 129–133, IEEE, 2024.
- [19] S. Vhaduri, S. V. Dibbo, and C.-Y. Chen, “Predicting a user’s demographic identity from leaked samples of health-tracking wearables and understanding associated risks,” in *2022 IEEE 10th International Conference on Healthcare Informatics (IACHI)*, pp. 309–318, IEEE, 2022.
- [20] E. Rolf, K. Klemmer, C. Robinson, and H. Kerner, “Mission critical-satellite data is a distinct modality in machine learning,” *arXiv preprint arXiv:2402.01444*, 2024.
- [21] S. Vhaduri, W. Cheung, and S. V. Dibbo, “Bag of on-phone anns to secure IoT objects using wearable and smartphone biometrics,” *IEEE Transactions on Dependable and Secure Computing*, vol. 21, no. 3, pp. 1127–1138, 2023.
- [22] Y. Zhao, T. Pang, C. Du, X. Yang, C. Li, N.-M. M. Cheung, and M. Lin, “On evaluating adversarial robustness of large vision-language models,” *Advances in Neural Information Processing Systems*, vol. 36, pp. 54111–54138, 2023.
- [23] M. Ye, X. Rong, W. Huang, B. Du, N. Yu, and D. Tao, “A survey of safety on large vision-language models: Attacks, defenses and evaluations,” *arXiv preprint arXiv:2502.14881*, 2025.
- [24] H. Cheng, E. Xiao, J. Gu, L. Yang, J. Duan, Zhang, *et al.*, “Unveiling typographic deceptions: Insights of the typographic vulnerability in large vision-language models,” in *European Conference on Computer Vision*, pp. 179–196, Springer, 2024.
- [25] S. V. Dibbo, “Sok: Model inversion attack landscape: Taxonomy, challenges, and future roadmap,” in *2023 IEEE 36th Computer Security Foundations Symposium (CSF)*, pp. 439–456, IEEE, 2023.
- [26] J. Ren, M. Dras, and U. Naseem, “Seeing the threat: Vulnerabilities in vision-language models to adversarial attack,” *arXiv preprint arXiv:2505.21967*, 2025.
- [27] Z. Li, X. Wu, H. Du, H. Nghiem, and G. Shi, “Benchmark evaluations, applications, and challenges of large vision language models: A survey,” *arXiv preprint arXiv:2501.02189*, vol. 1, 2025.
- [28] J. Liang, S. Liang, A. Liu, and X. Cao, “Vl-trojan: Multimodal instruction backdoor attacks against autoregressive visual language models,” *International Journal of Computer Vision*, pp. 1–20, 2025.
- [29] Z. Ni, R. Ye, Y. Wei, Z. Xiang, Y. Wang, and S. Chen, “Physical backdoor attack can jeopardize driving with vision-large-language models,” *arXiv preprint arXiv:2404.12916*, 2024.
- [30] Y. Xu, J. Yao, M. Shu, Y. Sun, Z. Wu, N. Yu, T. Goldstein, and F. Huang, “Shadowcast: Stealthy data poisoning attacks against vision-language models,” *Advances in Neural Information Processing Systems*, vol. 37, pp. 57733–57764, 2024.
- [31] Y. Hu, Z. Li, Z. Liu, Y. Zhang, Z. Qin, K. Ren, and C. Chen, “Membership inference attacks against vision-language models,” *arXiv preprint arXiv:2501.18624*, 2025.
- [32] C. A. Choquette-Choo, F. Tramer, N. Carlini, and N. Papernot, “Label-only membership inference attacks,” in *International conference on machine learning*, pp. 1964–1974, PMLR, 2021.
- [33] Y. Hu, W. Liang, R. Wu, K. Xiao, W. Wang, X. Li, J. Liu, and Z. Qin, “Quantifying and defending against privacy threats on federated knowledge graph embedding,” in *Proceedings of the ACM Web Conference 2023*, pp. 2306–2317, 2023.
- [34] J. Li, N. Li, and B. Ribeiro, “Membership inference attacks and defenses in supervised learning via generalization gap,” *CoRR*, 2020.
- [35] J. Li, N. Li, and B. Ribeiro, “Membership inference attacks and defenses in classification models,” in *Proceedings of the Eleventh ACM Conference on Data and Application Security and Privacy*, pp. 5–16, 2021.
- [36] R. Shokri, M. Stronati, C. Song, and V. Shmatikov, “Membership inference attacks against machine learning models,” in *2017 IEEE symposium on security and privacy (SP)*, pp. 3–18, IEEE, 2017.
- [37] H. Hu, Z. Salcic, L. Sun, G. Dobbie, P. S. Yu, and X. Zhang, “Membership inference attacks on machine learning: A survey,” *ACM Computing Surveys (CSUR)*, vol. 54, no. 11s, pp. 1–37, 2022.
- [38] I. E. Olatunji, W. Nejdl, and M. Khosla, “Membership inference attack on graph neural networks,” in *2021 Third IEEE International Conference on Graph Neural Networks (GNN)*, pp. 1–10, IEEE, 2021.

- Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA)*, pp. 11–20, IEEE, 2021.
- [39] X. He, R. Wen, Y. Wu, M. Backes, Y. Shen, and Y. Zhang, “Node-level membership inference attacks against graph neural networks,” *arXiv preprint arXiv:2102.05429*, 2021.
- [40] R. Wen, Z. Li, M. Backes, and Y. Zhang, “Membership inference attacks against in-context learning,” in *Proceedings of the 2024 on ACM SIGSAC Conference on Computer and Communications Security*, pp. 3481–3495, 2024.
- [41] B. C. Das, M. H. Amini, and Y. Wu, “Security and privacy challenges of large language models: A survey,” *ACM Computing Surveys*, vol. 57, no. 6, pp. 1–39, 2025.
- [42] P. Hu, Z. Wang, R. Sun, H. Wang, and M. Xue, “M⁴I: Multi-modal models membership inference,” *Advances in Neural Information Processing Systems*, vol. 35, pp. 1867–1882, 2022.
- [43] Z. Li, Y. Wu, Y. Chen, F. Tonin, E. Abad Rocamora, and V. Cevher, “Membership inference attacks against large vision-language models,” *Advances in Neural Information Processing Systems*, vol. 37, pp. 98645–98674, 2024.
- [44] M. Deb, M. Deb, and N. Murty, “Toponets: High performing vision and language models with brain-like topography,” *arXiv preprint arXiv:2501.16396*, 2025.
- [45] Y. Wu, N. Yu, Z. Li, M. Backes, and Y. Zhang, “Membership inference attacks against text-to-image generation models,” *arXiv preprint arXiv:2210.00968*, 2022.
- [46] S. V. Dibbo, A. Breuer, J. Moore, and M. Teti, “Improving robustness to model inversion attacks via sparse coding architectures,” in *European Conference on Computer Vision*, pp. 117–136, Springer, 2024.
- [47] M. Teti, G. Kenyon, B. Migliori, and J. Moore, “Lcanets: Lateral competition improves robustness against corruption and attack,” in *International conference on machine learning*, pp. 21232–21252, PMLR, 2022.
- [48] T. Dalenius, “Towards a methodology for statistical disclosure control,” 1977.
- [49] N. Carlini, S. Chien, M. Nasr, S. Song, A. Terzis, and F. Tramer, “Membership inference attacks from first principles,” in *2022 IEEE symposium on security and privacy (SP)*, pp. 1897–1914, IEEE, 2022.
- [50] S. Rezaei and X. Liu, “On the difficulty of membership inference attacks,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 7892–7900, 2021.
- [51] J. Hayes, L. Melis, G. Danezis, and E. De Cristofaro, “Logan: evaluating privacy leakage of generative models using generative adversarial networks,” *arXiv preprint arXiv:1705.07663*, pp. 506–519, 2017.
- [52] Y. Liu, Z. Zhao, M. Backes, and Y. Zhang, “Membership inference attacks by exploiting loss trajectory,” in *Proceedings of the 2022 ACM SIGSAC Conference on Computer and Communications Security*, pp. 2085–2098, 2022.
- [53] L. Song, R. Shokri, and P. Mittal, “Membership inference attacks against adversarially robust deep learning models,” in *2019 IEEE Security and Privacy Workshops (SPW)*, pp. 50–56, IEEE, 2019.
- [54] M. Zhang, Z. Ren, Z. Wang, P. Ren, Z. Chen, P. Hu, and Y. Zhang, “Membership inference attacks against recommender systems,” in *Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security*, pp. 864–879, 2021.
- [55] L. Hu, A. Yan, H. Yan, J. Li, T. Huang, Y. Zhang, C. Dong, and C. Yang, “Defenses to membership inference attacks: A survey,” *ACM Computing Surveys*, vol. 56, no. 4, pp. 1–34, 2023.
- [56] S. Truex, L. Liu, M. E. Gursoy, L. Yu, and W. Wei, “Towards demystifying membership inference attacks,” *arXiv preprint arXiv:1807.09173*, 2018.
- [57] Z. Liu, W. Jiang, F. Zhou, and H. Wei, “Efficient membership inference attacks by bayesian neural network,” *arXiv preprint arXiv:2503.07482*, 2025.
- [58] X. Gong, Y. Chen, Q. Wang, M. Wang, and S. Li, “Private data inference attacks against cloud: Model, technologies, and research directions,” *IEEE Communications Magazine*, vol. 60, no. 9, pp. 46–52, 2022.
- [59] Y. Liu, R. Wen, X. He, A. Salem, Z. Zhang, M. Backes, E. De Cristofaro, M. Fritz, and Y. Zhang, “[ML-Doctor]: Holistic risk assessment of inference attacks against machine learning models,” in *31st USENIX Security Symposium*, pp. 4525–4542, 2022.
- [60] Y. Pang, T. Wang, X. Kang, M. Huai, and Y. Zhang, “White-box membership inference attacks against diffusion models,” *arXiv preprint arXiv:2308.06405*, 2023.
- [61] D. Wu, S. Qi, Y. Qi, Q. Li, B. Cai, Q. Guo, and J. Cheng, “Understanding and defending against white-box membership inference attack in deep learning,” *Knowledge-Based Systems*, vol. 259, p. 110014, 2023.
- [62] K. Leino and M. Fredriksson, “Stolen memories: Leveraging model memorization for calibrated {White-Box} membership inference,” in *29th USENIX security symposium (USENIX Security 20)*, pp. 1605–1622, 2020.
- [63] A. Sablayrolles, M. Douze, C. Schmid, Y. Ollivier, and H. Jégou, “White-box vs black-box: Bayes optimal strategies for membership inference,” in *International Conference on Machine Learning*, pp. 5558–5567, PMLR, 2019.
- [64] J. Zhang, J. Huang, S. Jin, and S. Lu, “Vision-language models for vision tasks: A survey,” *IEEE transactions on pattern analysis and machine intelligence*, vol. 46, no. 8, pp. 5625–5644, 2024.
- [65] X. Li, X. Yin, C. Li, P. Zhang, X. Hu, L. Zhang, L. Wang, H. Hu, L. Dong, F. Wei, et al., “Oscar: Object-semantics aligned pre-training for vision-language tasks,” in *European conference on computer vision*, pp. 121–137, Springer, 2020.
- [66] G. Shinde, A. Ravi, E. Dey, S. Sakib, M. Rampure, and N. Roy, “A survey on efficient vision-language models,” *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 15, no. 3, p. e70036, 2025.
- [67] C. Wu, J. Chen, Q. Fang, K. He, Z. Zhao, H. Ren, G. Xu, Y. Liu, and Y. Xiang, “Rethinking membership inference attacks against transfer learning,” *IEEE Transactions on Information Forensics and Security*, vol. 19, pp. 6441–6454, 2024.
- [68] T. Chobola, D. Usynin, and G. Kaassis, “Membership inference attacks against semantic segmentation models,” in *Proceedings of the 16th ACM Workshop on Artificial Intelligence and Security*, pp. 43–53, 2023.
- [69] B. Wu, X. Yang, S. Pan, and X. Yuan, “Adapting membership inference attacks to gnn for graph classification: Approaches and implications,” in *2021 IEEE International Conference on Data Mining (ICDM)*, pp. 1421–1426, IEEE, 2021.
- [70] Q. Li, Y. Guo, and H. Chen, “Practical no-box adversarial attacks against dnns,” *Advances in Neural Information Processing Systems*, vol. 33, pp. 12849–12860, 2020.
- [71] F. Woitschek and G. Schneider, “Physical adversarial attacks on deep neural networks for traffic sign recognition: A feasibility study,” in *2021 Intelligent vehicles symposium (IV)*, pp. 481–487, IEEE, 2021.
- [72] T. Ter-Hovhannisyan, H. Aleksanyan, and K. Avetisyan, “Adversarial attacks on language models: Wordpiece filtration and chatgpt synonyms,” *Journal of Mathematical Sciences*, vol. 285, no. 2, pp. 210–220, 2024.
- [73] S. Truex, L. Liu, M. E. Gursoy, L. Yu, and W. Wei, “Demystifying membership inference attacks in machine learning as a service,” *IEEE transactions on services computing*, vol. 14, no. 6, pp. 2073–2089, 2019.
- [74] J. Liang, R. Pang, C. Li, and T. Wang, “Model extraction attacks revisited,” in *Proceedings of the 19th ACM Asia Conference on Computer and Communications Security*, pp. 1231–1245, 2024.
- [75] F. Tramèr, F. Zhang, A. Juels, M. K. Reiter, and T. Ristenpart, “Stealing machine learning models via prediction {APIs},” in *25th USENIX security symposium (USENIX Security 16)*, pp. 601–618, 2016.
- [76] X. Gong, Q. Wang, Y. Chen, W. Yang, and X. Jiang, “Model extraction attacks and defenses on cloud-based machine learning models,” *IEEE Communications Magazine*, vol. 58, no. 12, pp. 83–89, 2021.
- [77] B. Liu, M. Ding, S. Shaham, W. Rahayu, F. Farokhi, and Z. Lin, “When machine learning meets privacy: A survey and outlook,” *ACM Computing Surveys (CSUR)*, vol. 54, no. 2, pp. 1–36, 2021.
- [78] M. Ko, M. Jin, C. Wang, and R. Jia, “Practical membership inference attacks against large-scale multi-modal models: A pilot study,” in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 4871–4881, 2023.
- [79] M. Jegorova, C. Kaul, C. Mayor, A. Q. O’Neil, A. Weir, R. Murray-Smith, and S. A. Tsafaris, “Survey: Leakage and privacy at inference time,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 7, pp. 9090–9108, 2022.
- [80] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, “Microsoft coco: Common objects in

- context,” in *European conference on computer vision*, pp. 740–755, Springer, 2014.
- [81] K. Srinivasan, K. Raman, J. Chen, M. Bendersky, and M. Najork, “Wit: Wikipedia-based image text dataset for multimodal multilingual machine learning,” in *Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval*, pp. 2443–2449, 2021.
- [82] C. Schuhmann, R. Beaumont, R. Vencu, C. Gordon, R. Wightman, M. Cherti, T. Coombes, A. Katta, C. Mullis, M. Wortsman, et al., “Laion-5b: An open large-scale dataset for training next generation image-text models,” *Advances in neural information processing systems*, vol. 35, pp. 25278–25294, 2022.
- [83] J. R. Correia-Silva, R. F. Berriel, C. Badue, A. F. De Souza, and T. Oliveira-Santos, “Copycat cnn: Stealing knowledge by persuading confession with random non-labeled data,” in *2018 International joint conference on neural networks (IJCNN)*, pp. 1–8, IEEE, 2018.
- [84] P. Sharma, N. Ding, S. Goodman, and R. Soriciut, “Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning,” in *Proceedings of ACL*, 2018.
- [85] H. Agrawal, K. Desai, Y. Wang, X. Chen, R. Jain, M. Johnson, D. Batra, D. Parikh, S. Lee, and P. Anderson, “Nocaps: Novel object captioning at scale,” in *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 8948–8957, 2019.
- [86] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, et al., “Learning transferable visual models from natural language supervision,” in *International conference on machine learning*, pp. 8748–8763, PMLR, 2021.
- [87] N. Reimers and I. Gurevych, “Sentence-bert: Sentence embeddings using siamese bert-networks,” *arXiv preprint arXiv:1908.10084*, 2019.
- [88] S. Yeom, I. Giacomelli, M. Fredrikson, and S. Jha, “Privacy risk in machine learning: Analyzing the connection to overfitting,” in *2018 IEEE 31st computer security foundations symposium (CSF)*, pp. 268–282, IEEE, 2018.
- [89] B. Pavlyshenko and M. Stasiuk, “Semantic similarity analysis using transformer-based sentence embeddings,” *Electronics and information technologies*, no. 30, pp. 43–58, 2025.
- [90] K. Song, X. Tan, T. Qin, J. Lu, and T.-Y. Liu, “Mpnet: Masked and permuted pre-training for language understanding,” *Advances in neural information processing systems*, vol. 33, pp. 16857–16867, 2020.
- [91] M. Barbella and G. Tortora, “Rouge metric evaluation for text summarization techniques,” *Available at SSRN 4120317*, 2022.
- [92] C.-Y. Lin, “ROUGE: A package for automatic evaluation of summaries,” in *Text Summarization Branches Out*, (Barcelona, Spain), pp. 74–81, Association for Computational Linguistics, July 2004.
- [93] N. Carlini, J. Hayes, M. Nasr, M. Jagielski, V. Sehwag, F. Tramer, B. Balle, D. Ippolito, and E. Wallace, “Extracting training data from diffusion models,” in *32nd USENIX security symposium (USENIX Security 23)*, pp. 5253–5270, 2023.
- [94] D. Witschard, I. Jusufi, R. M. Martins, K. Kucher, and A. Kerren, “Interactive optimization of embedding-based text similarity calculations,” *Information Visualization*, vol. 21, no. 4, pp. 335–353, 2022.
- [95] A. Salem, Y. Zhang, M. Humbert, P. Berrang, M. Fritz, and M. Backes, “MI-leaks: Model and data independent membership inference attacks and defenses on machine learning models,” *arXiv preprint arXiv:1806.01246*, 2018.
- [96] A. E. Maxwell, P. Pourmohammadi, and J. D. Poyner, “Mapping the topographic features of mining-related valley fills using mask r-cnn deep learning and digital elevation data,” *Remote Sensing*, vol. 12, no. 3, p. 547, 2020.
- [97] U. Chitra, B. J. Arnold, H. Sarkar, K. Sanno, C. Ma, S. Lopez-Darwin, and B. J. Raphael, “Mapping the topography of spatial gene expression with interpretable deep learning,” *Nature Methods*, vol. 22, no. 2, pp. 298–309, 2025.
- [98] B. Hammer and A. Hasenfuss, “Topographic mapping of large dissimilarity data sets,” *Neural Computation*, vol. 22, no. 9, pp. 2229–2284, 2010.
- [99] G. Handjaras, G. Bernardi, F. Benazzi, P. F. Nichelli, P. Pietrini, and E. Ricciardi, “A topographical organization for action representation in the human brain,” *Human brain mapping*, vol. 36, no. 10, pp. 3832–3844, 2015.
- [100] G. H. Patel, D. M. Kaplan, and L. H. Snyder, “Topographic organization in the brain: searching for general principles,” *Trends in cognitive sciences*, vol. 18, no. 7, pp. 351–363, 2014.
- [101] W. Zhu, Q. Qiu, J. Huang, R. Calderbank, G. Sapiro, and I. Daubechies, “Ldmnet: Low dimensional manifold regularized neural networks,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2743–2751, 2018.
- [102] C. F. G. D. Santos and J. P. Papa, “Avoiding overfitting: A survey on regularization methods for convolutional neural networks,” *ACM Computing Surveys (Csur)*, vol. 54, no. 10s, pp. 1–25, 2022.
- [103] I. Nusrat and S.-B. Jang, “A comparison of regularization techniques in deep neural networks,” *Symmetry*, vol. 10, no. 11, p. 648, 2018.
- [104] R. Moradi, R. Berangi, and B. Minaei, “A survey of regularization strategies for deep models,” *Artificial Intelligence Review*, vol. 53, no. 6, pp. 3947–3986, 2020.
- [105] B. Wu, Z. Liu, Z. Yuan, G. Sun, and C. Wu, “Reducing overfitting in deep convolutional neural networks using redundancy regularizer,” in *International Conference on Artificial Neural Networks*, pp. 49–55, Springer, 2017.
- [106] P. Tiño, I. Farkaš, and J. van Mourik, “Dynamics and topographic organization of recursive self-organizing maps,” *Neural Computation*, vol. 18, no. 10, pp. 2529–2567, 2006.
- [107] A. Hyvärinen, P. O. Hoyer, and M. Inki, “Topographic independent component analysis,” *Neural computation*, vol. 13, no. 7, pp. 1527–1558, 2001.
- [108] Y. Kaya, S. Hong, and T. Dumitras, “On the effectiveness of regularization against membership inference attacks,” *arXiv preprint arXiv:2006.05336*, 2020.
- [109] H. Hu, Z. Salcic, G. Dobbie, Y. Chen, and X. Zhang, “Ear: An enhanced adversarial regularization approach against membership inference attacks,” in *2021 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–8, IEEE, 2021.
- [110] J. Li, D. Li, C. Xiong, and S. Hoi, “Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation,” in *International conference on machine learning*, pp. 12888–12900, PMLR, 2022.
- [111] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, I. Sutskever, et al., “Language models are unsupervised multitask learners,” *OpenAI blog*, vol. 1, no. 8, p. 9, 2019.
- [112] A. Dosovitskiy, “An image is worth 16x16 words: Transformers for image recognition at scale,” *arXiv preprint arXiv:2010.11929*, 2020.
- [113] L. Beyer, A. Steiner, A. S. Pinto, A. Kolesnikov, X. Wang, D. Salz, M. Neumann, I. Alabdulmohsin, M. Tschanne, E. Bugliarello, et al., “Paligemma: A versatile 3b vlm for transfer,” *arXiv preprint arXiv:2407.07726*, 2024.
- [114] Q. You, H. Jin, Z. Wang, C. Fang, and J. Luo, “Image captioning with semantic attention,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4651–4659, 2016.
- [115] C.-Y. Lin, “Rouge: A package for automatic evaluation of summaries,” in *Text summarization branches out*, pp. 74–81, 2004.
- [116] J. Wieting, G. Neubig, and T. Berg-Kirkpatrick, “A bilingual generative transformer for semantic sentence embedding,” in *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 1581–1594, 2020.
- [117] C. Zeng, S. Kwong, T. Zhao, and H. Wang, “Contrastive semantic similarity learning for image captioning evaluation,” *Information Sciences*, vol. 609, pp. 913–930, 2022.
- [118] M. S. Wajid, H. Terashima-Marin, P. Najafirad, and M. A. Wajid, “Deep learning and knowledge graph for image/video captioning: A review of datasets, evaluation metrics, and methods,” *Engineering Reports*, vol. 6, no. 1, p. e12785, 2024.
- [119] L. Watson, C. Guo, G. Cormode, and A. Sablayrolles, “On the importance of difficulty calibration in membership inference attacks,” *arXiv preprint arXiv:2111.08440*, 2021.
- [120] C. Song, T. Ristenpart, and V. Shmatikov, “Machine learning models that remember too much,” in *ACM SIGSAC Conference on computer and communications security*, pp. 587–601, 2017.
- [121] A. Ghosh, A. Acharya, S. Saha, V. Jain, and A. Chadha, “Exploring the frontier of vision-language models: A survey of current methodologies and future directions,” *arXiv preprint arXiv:2404.07214*, 2024.
- [122] A. Pomi, E. Mizraji, and J. Lin, “Tensor representation of topographically organized semantic spaces,” *Neural computation*, vol. 30, no. 12, pp. 3259–3280, 2018.