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PRADA: Probability-Ratio-Based Attribution and Detection of Autoregressive-Generated Images

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Abstract

*Autoregressive (AR) image generation has recently emerged as a powerful paradigm for image synthesis. Leveraging the generation principle of large language models, they allow for efficiently generating deceptively real-looking images, further increasing the need for reliable detection methods. However, to date there is a lack of work specifically targeting the detection of images generated by AR image generators. In this work, we present **PRADA** (**P**robability-**R**atio-Based **A**ttribution and **D**etection of **A**utoregressive-Generated Images), a simple and interpretable approach that can reliably detect AR-generated images and attribute them to their respective source model. The key idea is to inspect the ratio of a model's conditional and unconditional probability for the autoregressive token sequence representing a given image. Whenever an image is generated by a particular model, its probability ratio shows unique characteristics which are not present for images generated by other models or real images. We exploit these characteristics for threshold-based attribution and detection by calibrating a simple, model-specific score function. Our experimental evaluation shows that PRADA is highly effective against eight class-to-image and four text-to-image models. We release our code and data at* `github.com/jonasricker/prada`.

1. Introduction

Creating beautiful images by simply typing what one would like to see—something that, only a few years ago, most people would have considered completely impossible. But since 2022, high-quality visual generative AI (GenAI) tools [59, 63, 65] have arrived in the mainstream and are now accessible to everyone, regardless of one's computational resources or technical expertise. While these models offer a remarkable creative potential and even open up new kinds of creativity [55], there is a flip side. GenAI is increasingly being used for scamming [24] and spreading disinformation [64], which could lead to an erosion of trust in digital media, society, and democratic processes [38]. Given that humans are no longer able to distinguish real from generated images [26], the automated detection of AI-generated images is a highly active and much needed research topic. Moreover, model attribution can provide valuable insights into the provenance of generated data and help mitigate the spread of large-scale misinformation.

Most image generators were previously based on generative adversarial networks (GANs) [28] and diffusion models (DMs) [37, 69]. Both architectures have in common that they *implicitly* model the learned data distribution, lacking a tractable likelihood. Recently, a novel paradigm for image synthesis has emerged: autoregressive (AR) image generation [70, 72]. Besides efficiently generating high-quality images, this generation principle also directly offers *explicit* likelihoods. From a forensic perspective, this property is promising: Given an image, its likelihoods could indicate whether it was generated by a specific model. The idea of treating likelihoods as statistical evidence for model behavior has a long history, though recent studies show that, for modern generative models, raw likelihoods are often unreliable [52, 60]. However, due to the use of semantic conditioning, AR image generators provide both conditional *and* unconditional likelihoods, where the former depends on a class label or prompt. And indeed, recent work on membership inference attacks (MIAs) for AR image generators [42, 82] shows that the log ratio between conditional and unconditional likelihoods is a useful measure to decide if an AR image generator has been trained on an image (member) or not (non-member).

In this work, we explore whether this probability ratio can be leveraged for *detecting* and *attributing* AR-generated images. While initial observations confirm the intuition that, analogous to MIAs, the probability ratio contains information on whether an image is generated (i.e., a member of the learned distribution) or real, they also reveal that existing MIA approaches do not generalize to different model architectures. As a remedy, we pro-

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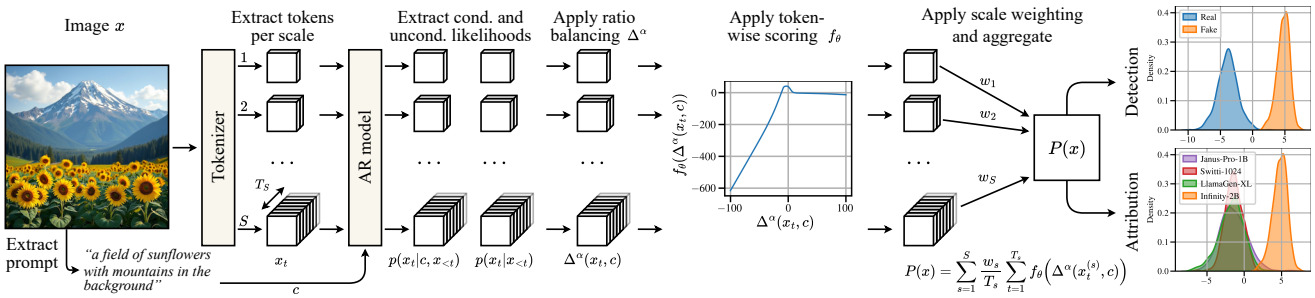


Figure 1. **Overview of our proposed method.** For a given image, PRADA extracts conditional and unconditional log-likelihoods for each token and assigns a score to their balanced ratio $\Delta^\alpha(x_t, c)$, see Equation (3). A lightweight calibration step provides a small, model-specific scoring function $f_\theta : \mathbb{R} \to \mathbb{R}$. For next-scale prediction models, the scale-wise average of token scores is linearly combined with weights w_i to obtain the final PRADA score $P(x)$, see Equation (4). This score is highly effective for detection and model attribution, especially against text-to-image models.

pose to learn a lightweight and data-efficient score function that emphasizes useful token probabilities while attenuating that of uninformative ones. For each model, it balances conditional and unconditional probability, performs a token-wise scoring, and weights the importance of individual scales (for next-scale prediction models). Our method, PRADA (**P**robability-**R**atio-Based **A**ttribution and **D**etection of **A**utoregressive-Generated Images), see Figure 1, achieves an average AUROC of 93.7% on class-to-image and 99.4% on text-to-image models, performing on par with state-of-the-art detection methods on the latter. Moreover, in the more challenging task of attributing an image to its source model, we reach 88.0% accuracy for class-to-image and 96.3% for text-to-image models. Notably, our approach is not based on a complex, black-box classification network that requires excessive training data. This makes PRADA a highly effective and interpretable method for detecting and attributing AR-generated images.

In summary, we make the following contributions:

- For the first time, we show that the explicit probabilities of AR image generators can be leveraged for detecting and attributing generated images.
- We propose PRADA, a lightweight and data-efficient approach for learning a simple, model-specific score function that can adapt to different model architectures.
- Our extensive experimental evaluation confirms the effectiveness of our design choices and shows that PRADA achieves reliable detection and attribution across a variety of AR image generators, in particular for high-quality text-to-image models.

2. Related Work

Detection of AI-Generated Images Fueled by the ever-increasing quality of AI-generated images, the development of reliable detection methods is a highly active area of research. In the following, we summarize the most important detection approaches. For a more extensive overview, we refer to the recent work of Tariang et al. [71].

Early methods exploit visual artifacts for detection, like physiological anomalies [31, 39, 50] or inconsistent geometry and lighting [3, 22, 23, 66]. Besides such high-level features, it has been shown that generative models produce low-level artifacts that can be used for detection [51, 53]. A particularly well-explored approach is the analysis of frequency artifacts in GAN-generated images [20, 21, 25, 86], which has also been studied for DMs [12, 61]. The vast majority of detection methods is, however, data-driven. Wang et al. [76] showed that with sufficient data augmentation, a standard ResNet-50 [33] trained on real and generated images from a single GAN achieves good performance on images from unseen GANs. To improve generalization and robustness, other works propose architectural changes [5, 14, 29], training data alignment [30, 58, 88], training on real images only [16, 46] or using foundation models as feature extractors [15, 34, 40, 41, 54, 67].

Related to our work, but targeted at DMs, is reconstruction- or inversion-based detection. Based on the assumption that generated images can be reconstructed more accurately, such methods compute the error between an original image and its reconstruction obtained by inverting a DM [4, 6, 48, 77]. Another variant, only applicable to latent diffusion models (LDMs), is to only use the model's autoencoder (AE) for reconstruction [8, 9, 62]. The reconstruction error is then directly used for threshold-based detection or as training data for a classifier.

To the best of our knowledge, the only existing method specifically targeting the detection of AR-generated images is D^3QE [87], a combination of classification and reconstruction-based detection based on the VQ-VAE's quantization error. D^3QE proposes a transformer architecture that incorporates precomputed codebook statistics into the attention mechanism, as well as semantic feature extraction using CLIP [57]. In contrast to D^3QE, which

uses quantization errors and involves training a transformer-based classifier, PRADA directly leverages the model's token probabilities, providing richer information and greater interpretability due to the absence of a black-box classifier.

Model Attribution for AI-Generated Images Model attribution is the more general task of not only distinguishing real from generated images, but also linking generated images to their source model. For GANs, Marra et al. [49] show that averaging the noise residual from generated images reveals a model-specific fingerprint. This allows for attribution by computing the correlation coefficient between an image and all known fingerprints. Instead of explicitly extracting fingerprints, subsequent works propose to directly train a multi-class classifier in the spatial [81, 83] or frequency [25] domain. While the aforementioned methods require all candidate models to be known (closed set), Girish et al. [27] propose an iterative algorithm for discovering and attributing images from unseen GANs.

Similar to detection, inversion-based attribution methods are most closely related to our approach. Applicable to both GANs [1, 35, 44] and DMs [78, 79], the key idea is that the model that originally generated an image should reconstruct it more accurately than other models. However, to the best of our knowledge, we are the first to present an attribution method specifically targeted at AR image generators.

3. Background

Autoregressive Image Generation AR image generators treat image generation as a sequence modeling task, where an image (or its latent feature representation) is discretized into tokens $x = (x_1, x_2, \dots, x_T)$. They consist of a tokenizer, an AR network, and a decoder, typically implemented as a VQ-VAE [74]. The resulting discrete feature representation is modeled as $p(x) = \prod_{t=1}^{T} p(x_t|x_{<t})$, with later tokens conditionally dependent on previous tokens using some pre-defined order of tokens. The AR network (usually a transformer) is trained to predict these conditional probabilities. During image generation, tokens are sequentially sampled according to their predicted probabilities, and the decoder maps the discrete representation back into the image space.

Traditional AR models [73] directly model pixel intensities in a raster-like order. While these models suffer from limited ability to capture long-range dependencies, the more recent LlamaGen [70] demonstrates that even this simple ordering can reach strong performance when combined with a good tokenizer, large-scale training, and sufficient model capacity. Janus [80] and Janus-Pro [7] combine image generation and image understanding by using separate encoders with a shared transformer, achieving strong performance on multimodal understanding and generation benchmarks.

Next-Scale and Masked Autoregressive Models Large improvements in image quality and inference speed have been achieved by redefining the structure of sequential dependencies. VAR [72] introduces a residual scale-wise dependency structure in the VQ-VAE feature space. The generative process models the conditional dependence between scales as a conditional probability

$$p(r^{(1)}, \dots, r^{(S)}) = \prod_{s=1}^{S} \prod_{t=1}^{T_s} p(r_t^{(s)} |\, r^{(1)}, \dots, r^{(s-1)}) \ ,$$

where $r^{(s)}$ denotes a collection of T_s tokens on scale s, representing quantized residuals between the original features and their reconstruction from all coarser scales. The final latent representation is obtained as the sum of all upsampled tokens across scales, reducing dependence on the finite codebook and improving inference speed due to the parallel processing of tokens within each scale. Besides VAR, Infinity [32] (enabling a large codebook size by representing quantized vectors as binary codes using the sign function) and Switti [75] (removing the assumption of conditional independence within scales) also follow a next-scale generation schema. Aiming for improvements in inference time and fidelity, masked AR models use masking to iteratively process subsets of tokens and predict them in parallel until all positions are filled. HMAR [43] combines hierarchical (scale-wise) generation with masked parallel decoding, while RAR [84] performs AR modeling over randomized residual refinement stages.

Semantic conditioning Most modern image generation models provide a mechanism for semantic conditioning. In AR image generators, one gets access to conditional probabilities $p(x_t|c, x_{<t})$ for a condition c that can either be a class or a text prompt describing the desired image. Passing an empty condition, one may obtain an unconditional probability $p(x_t|x_{<t})$. In classifier-free guidance (CFG) [36], both probabilities are combined to enable flexible control over the alignment with a given prompt or class label, without requiring an additional classifier as originally proposed by Dhariwal and Nichol [19].

Probability Ratio For all AR models with a semantic conditioning mechanism (e.g., models trained with CFG), one can access the conditional and unconditional probabilities per token. This allows to investigate their ratio, or more precisely its logarithm, defined as

$$\begin{aligned} \Delta(x_t, c) &= \log \left(\frac{p(x_t|c, x_{<t})}{p(x_t|x_{<t})} \right) \\ &= \log p(x_t|c, x_{<t}) - \log p(x_t|x_{<t}) \ . \end{aligned} \tag{1}$$

The quantity $\Delta(x_t, c)$ measures the conditional, point-wise *mutual information* [10] between the current token x_t and

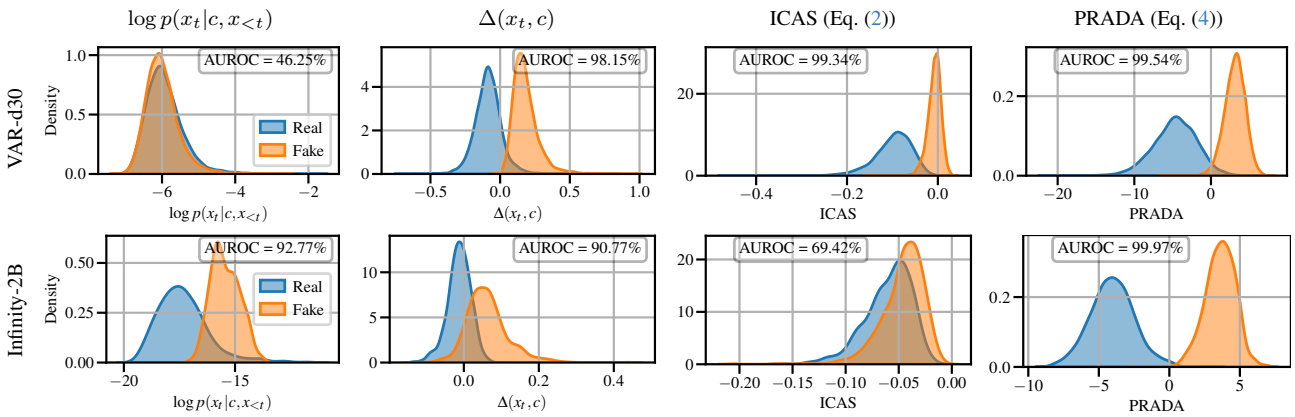


Figure 2. **Distributions of features derived from log probabilities of AR image generators for real and generated images.** While neither conditional probabilities (1st col), nor probability ratios (2nd col) or ICAS (3rd col) consistently tell real and generated images apart, our PRADA score separates their distributions.

condition c, and it quantifies how much knowing the context c increases or decreases the likelihood of observing the token x_t (given all previous context $x_{<t}$).

Previous work [42, 82] established that $\Delta(x_t, c)$ is a suitable starting point for MIAs against AR image generators, i.e., it can be used to detect whether a given sample is part of the training data. Yu et al. [82] refer to the log probability ratio as 'Implicit Classifier', akin to Classifier-Free Guidance [36]. They argue that, since training with CFG emphasizes the influence of $\Delta(x_t, c)$ on conditioned generation, the probability ratios of tokens are more informative for MIAs than $\log p(x_t|x_{<t})$, previously used for MIAs on LLMs [68, 85]. Their experiments show that non-member samples can be consistently distinguished by their low values $\Delta(x_t, c)$ for most tokens x_t. Introducing a scaling factor leads to the token score *ICAS*, which is averaged over tokens to assign a membership score to each sample x:

$$\mathrm{ICAS}(x) = \frac{1}{T}\sum_{t=1}^{T} \frac{\Delta(x_t, c)}{a + \exp(b \cdot \Delta(x_t, c))} \quad . \tag{2}$$

In their work, $(a, b) = (1.75, 1.3)$ were empirically chosen to be effective against VAR models [72].

The utilization of explicit log-probabilities of a model entails a white-box assumption, i.e., having access to the generative model. Although white-box access is often seen as a limitation, it provides the advantage of enabling reliable model attribution, an aspect of growing importance for both model providers and open-source generative systems.

4. PRADA

From a high-level perspective, detecting whether an image was *generated* by a certain model is conceptually similar to assessing whether a model was *trained* on an image. In both cases, we assume that the model 'remembers' the image, resulting in a higher likelihood. It is therefore a reasonable assumption that MIAs against AR image generators can be 'misused' for detecting and attributing generated images.

To test this idea, we compute the conditional probability $p(x_t|c, x_{<t})$, the probability ratio $\Delta(x_t, c)$, and the ICAS score for both real and generated images. Note that extracting the probabilities is straightforward: Within the autoregressive generation pipeline, we replace the sampled tokens with an image's ground-truth tokens (obtained by passing it through the tokenizer) and extract their assigned probabilities.[1] For class-to-image models, the semantic conditioning c corresponds to the class label, for text-to-image models we extract a prompt using BLIP2 [45]. The first row of Figure 2 confirms that the observations made by Yu et al. [82] are indeed applicable to the task of fake image detection: For VAR-d30 [72], the probability ratio is a useful measure and the proposed scaling factor can further separate the two distributions. However, computing these metrics for a different AR image generator, e.g., Infinity-2B [32] (see second row of Figure 2), shows that the scoring method used by ICAS actually leads to a worse detection performance, compared to $\Delta(x_t, c)$ and even $p(x_t|c, x_{<t})$.

Our preliminary experiment leaves us with the following takeaway: while the probability ratio can be highly useful for telling apart real from generated images, a *fixed* score function is insufficient to generalize to different model architectures. We therefore propose to instead *learn* a model-specific score function. In the following, we explain the three learnable components that form our final PRADA score function: probability ratio balancing, token-wise scoring, and scale weighting.

[1] For Infinity [32], where n binary classification heads each predict one bit of the token, the token's probability is the product of the n outputs.

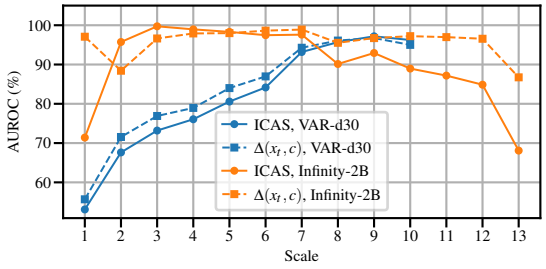


Figure 3. **Visualization of the scale dependence.** While higher scales are useful for VAR-d30, they are harmful for Infinity-2B, especially for ICAS.

Probability Ratio Balancing (α) While the probability ratio $\Delta(x_t, c)$ has shown to be a good starting point, for some models, it might be beneficial to focus more on either the conditional or unconditional probability. We therefore allow the final score to balance $p(x_t|c, x_{<t})$ and $p(x_t|x_{<t})$ via a single learnable parameter $\alpha \in \mathbb{R}$:

$$\begin{aligned}\Delta^\alpha(x_t, c) &= \log\left(\frac{p(x_t|c, x_{<t})^{2-\alpha}}{p(x_t|x_{<t})^\alpha}\right) \\ &= (2-\alpha)\,\log p(x_t|c, x_{<t}) - \alpha\,\log p(x_t|x_{<t})\ .\end{aligned} \tag{3}$$

While we initialize the parameter with $\alpha = 1$, the learned PRADA score may use only $\log p(x_t|c, x_{<t})$ (with $\alpha = 0$), only $\log p(x_t|x_{<t})$ (with $\alpha = 2$) or any suitable difference.

Token-Wise Scoring (f_θ) The core component of PRADA is the token-wise scoring $f_\theta : \mathbb{R} \to \mathbb{R}$. It assigns a score value to the balanced probability ratio $\Delta^\alpha(x_t, c)$, which quantifies the likelihood that a token was generated. We find that a tiny neural net consisting of two fully-connected hidden layers with 16 neurons and ELU activations [11] is sufficient. In our default configuration, the total number of trainable parameters of f_θ is 321, and in our ablation study in Sec. 5.4 we show that even fewer neurons are possible. Note that we do not learn an end-to-end function returning a single output score from an entire image's probability ratio, which would resemble a black-box classifier. Learning a simple, token-wise scoring keeps our approach lightweight and interpretable.

Scale Weighting (w) For next-scale prediction models, the likelihood distribution as well as the number of tokens T_s can differ drastically per scale s. In Figure 3 we exemplarily show how the detection performance using both $\Delta(x_t, c)$ and ICAS depends on the used scale (see Appendix D for an extended analysis). Given the different behavior between scales, we propose to infer the importance of each scale via learnable parameters $w \in \mathbb{R}^S$, that assign weights to the scale-wise means.[2] For next-token prediction models with a single scale, w is not learned and set to 1.

PRADA Score We can now combine all three components (probability ratio balancing, token-wise scoring, and scale weighting) to obtain the PRADA score for an image represented by tokens x. We assume that tokens are organized in scales, i.e., $x = \left(x^{(1)}, x^{(2)}, \dots x^{(S)}\right)$ for $s = \{1, \dots, S\}$ with $x^{(s)}$ denoting the collection of tokens $x_t^{(s)}$, $1 \le t \le T_s$, within scale s. The final score then amounts to the weighted sum of scale-wise means over the learned token scores:

$$P(x) = \sum_{s=1}^{S} \frac{w_s}{T_s} \sum_{t=1}^{T_s} f_\theta\left(\Delta^\alpha(x_t^{(s)}, c)\right)\ . \tag{4}$$

In Appendix C we provide visualizations of the learned α, token-wise scoring, and the learned scale weights w for different AR image generators. We also discuss how the learned parameters can help to interpret the characteristics of a model's likelihood distribution, i.e., which features strongly influence the PRADA score.

Calibration Procedure For each model, we optimize all learnable parameters (α, f_θ, and w) for 3 000 steps on a small, held-out dataset of real and generated images. We use AdamW [47] and apply simple regularization in form of small, scale-dependent Gaussian noise on Δ^α for data augmentation and encouraging $\|w\|_1 \to 1$ to achieve a certain level of sparsity in w. We use label smoothing to align the range of $P(x)$ across different generators, since the attribution mechanism relies on scores being comparable.

Detection and Attribution Given an image x and a generator G, the PRADA score $P_G(x)$ (see Equation (4)) quantifies how likely the image was generated by G. Given a set of candidate models M, we identify the model G^* with the highest (positive) score:

$$G^* = \arg\max_{G \in M} P_G(x)\ .$$

To classify an image as real or fake, we use $P_{G^*}(x)$ as the final score. For model attribution, we consider G^* to be the model that generated x. If $P_{G^*}(x) \le 0$, x is classified as being real or coming from an unknown model.

5. Evaluation

Models We evaluate PRADA on images from a total of twelve AR image generators. For the class-to-image

[2] We find that weighting the *means* per scale rather than their sum is more stable to learn as the number of samples per scale drastically differs.

Table 1. **Detection performance of PRADA and baselines, measured in AUROC (%).** Upper half contains methods from the literature, lower half methods adapted or proposed by us. We highlight the best performance for each dataset in **bold** and underline the second best. For PRADA, we report the mean and standard deviation over five runs. PRADA achieves strong performance throughout all tested models.

	Class-to-Image									Text-to-Image				
	HMAR-20	HMAR-30	Llama-B	Llama-L	VAR-20	VAR-30	RAR-L	RAR-XXL	**Avg.**	Infinity-2B	Janus-1B	Llama-XL	Switti-1024	**Avg.**
Corvi	99.2	99.3	99.7	99.7	99.5	**99.5**	86.4	86.1	96.2	**100.0**	94.2	94.1	99.7	97.0
DRCT	81.6	82.1	86.5	84.2	80.6	79.7	93.3	93.1	85.1	94.1	90.1	84.0	88.5	89.2
RINE	**99.6**	**99.6**	99.8	99.8	**99.6**	**99.5**	**99.9**	**99.9**	**99.7**	99.2	**99.9**	99.5	97.5	99.0
RIGID	78.7	77.3	84.9	81.8	75.8	74.0	92.5	92.9	82.2	55.4	73.0	89.3	70.4	72.0
B-Free	98.0	98.1	98.7	98.5	97.4	97.2	98.5	98.5	98.1	99.8	99.7	**99.9**	**99.9**	**99.8**
D^3QE	95.6	95.3	98.7	98.3	95.4	94.6	97.5	97.2	96.6	58.3	93.8	83.8	69.9	76.5
AEROBLADE*	89.1	89.3	99.1	99.3	91.1	91.0	48.8	48.5	82.0	95.9	99.0	99.1	83.5	94.4
Quantization Err.	54.3	53.6	99.5	99.6	56.1	54.9	58.1	58.0	66.8	39.5	99.8	99.4	36.6	68.8
$\Delta(x_t, c)$	49.1	54.5	93.2	95.5	51.9	79.0	94.6	98.8	77.1	85.5	98.2	36.0	61.9	70.4
ICAS (default)	53.1	52.3	**99.9**	**99.9**	74.2	67.5	98.9	94.8	80.1	49.1	92.2	23.8	85.1	62.6
ICAS (finetuned)	76.4	85.8	**99.9**	**99.9**	66.5	74.9	91.4	98.0	86.6	82.4	97.7	40.0	61.7	70.5
PRADA	85.9 ±0.8	90.5 ±0.6	98.7 ±0.2	98.8 ±0.1	83.6 ±0.3	96.6 ±0.5	97.4 ±0.1	98.1 ±0.3	93.7 ±0.2	99.7 ±0.1	98.8 ±0.3	99.3 ±0.1	99.8 ±0.0	99.4 ±0.1

setting, we include HMAR-d20/-d30 [43], LlamaGen-B/-L [70], VAR-d20/-d30 [72], and RAR-L/-XXL [84], each trained on ImageNet [18]. To test our method on text-to-image models, we apply it to Infinity-2B [32], Janus-Pro-1B [7], LlamaGen-XL [70], and Switti-1024 [75]. They were trained on a mixture of publicly available and proprietary image-text datasets. We provide additional information on the tested models in Appendix A.

Data Our DARG (**D**ataset of **A**uto**R**egressive-**G**enerated Images) dataset consists of 84 000 images from eight class-to-image and four text-to-image models. For every class-to-image model, we generate ten images for each of the 1 000 class labels. We randomly select 10 000 real images from the ImageNet [18] validation subset, maintaining the class balance. For text-to-image models, we adapt the methodology from Synthbuster [2]. For each real image from the RAISE-1k [17] dataset, we use the provided prompt to generate a similar-looking image with each of the four models. While our default configuration uses 250 real and 250 fake images for calibration (and therefore 9 750/750 for testing), our ablation study (see Section 5.4) shows that even fewer calibration samples lead to a high detection performance. We provide example images in Appendix B.

5.1. Detection Evaluation

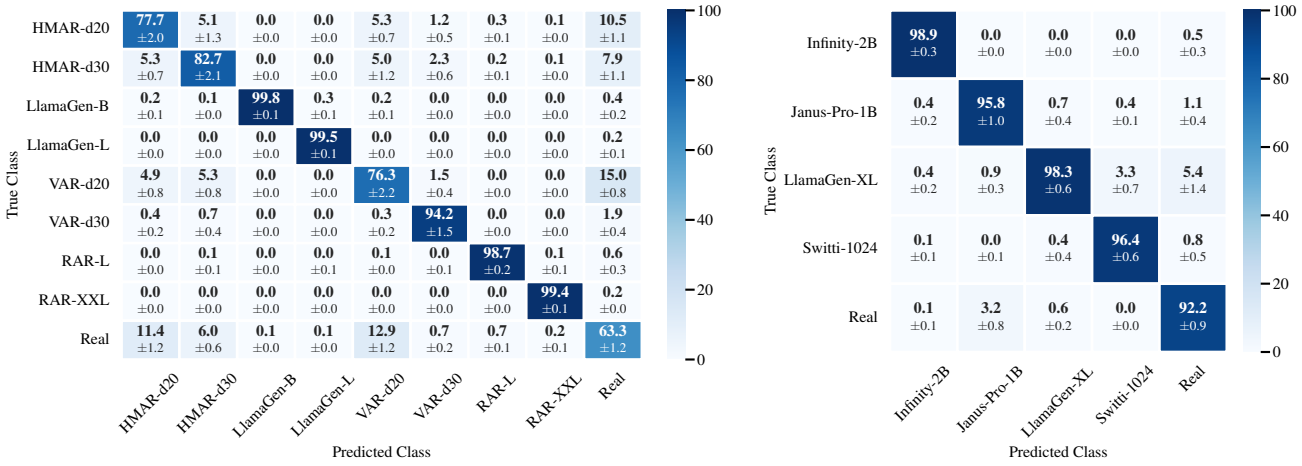
We compare PRADA with six state-of-the-art detectors from the literature, including Corvi [13], DRCT [6], RINE [41], RIGID [34], B-Free [30], and D^3QE [87], the only other detection method tailored to AR-generated images. We additionally adapt AEROBLADE [62] (originally intended for LDMs) by computing the reconstruction error of the AR models' VQ-VAE (referred to as AEROBLADE*). Moreover, taking inspiration from both D^3QE and AEROBLADE, we analyze the mean-squared error between the continuous and discretized token representation (referred to as quantization error). We also test the performance of the simple probability ratio $\Delta(x_t, c)$ and ICAS with default ($a = 1.75, b = 1.3$) and finetuned parameters (obtained through a grid-seach on the domain $[0.05, 10]^2$ on 250 real and 250 generated images per model). For all score-based methods (quantization error, $\Delta(x_t, c)$, ICAS, and PRADA), we obtain the final classification score by taking the maximum score from all class-to-image/text-to-image models, respectively. Note that we repeat PRADA's calibration procedure for five times with different train/test splits and initialization seeds.

Table 1 shows the AUROC for PRADA and the aforementioned baselines. PRADA achieves comparable results across class-to-image models (93.7%) and is particularly effective against text-to-image models (99.4%), outperforming all but one of the baselines. At the same time, PRADA only requires training a tiny score function and provides interpretable attribution (see Section 5.2), which is more challenging than binary classification. Moreover, the low standard deviation across five runs demonstrates that our calibration procedure is highly robust.

Using ground-truth prompts for text-to-image models (instead of captions extracted using BLIP2), we even achieve an average AUROC of 99.99%. While this assumption is usually not met in practice, these results demonstrate the potential of leveraging likelihood information for AI-generated image detection.

Interestingly, the two error-based approaches, AEROBLADE* and quantization error, are highly effective against a subset of AR models, but fail for most next-scale prediction models. In future work, we aim to investigate whether combining error- and probability-based features could provide even better detection performance.

Finally, the only other AR-tailored approach, D^3QE (trained on 100 000 real images from ImageNet and 100 000 images generated by LlamaGen), successfully generalizes



(a) Class-to-Image (b) Text-to-Image

Figure 4. **Attribution performance of PRADA.** We report the confusion matrices (normalized over rows and averaged over five calibration runs) for class-to-image and text-to-image models. PRADA achieves high performance across various AR image generators and is particularly effective against text-to-image models.

to other class-to-image models (all trained on ImageNet), but shows a significant drop in performance for text-to-image models, hinting towards an overfitting on the content or format of ImageNet.

5.2. Model Attribution Evaluation

We now evaluate PRADA regarding source model attribution, which is naturally a more challenging problem than real/fake detection. Figure 4 shows the confusion matrices for class-to-image and text-to-image models, respectively. Our results are consistent with our findings regarding detection: PRADA achieves a high performance across a wide range of model architectures and is particularly effective against text-to-image models. We obtain an overall accuracy of 88.0% for class-to-image models and 96.3% for text-to-image models. Interestingly, we observe very few misclassifications within the variants of LlamaGen, VAR, and RAR, despite their strong similarity. However, images generated by HMAR-d20, HMAR-d30, and VAR-d20 are more often misclassified, either as each other or as real. Depending on the particular use case, the occurrence of false positives and false negatives can be balanced by adjusting the decision threshold at which an image is classified as real.

5.3. Robustness Analysis

We additionally analyze PRADA's robustness to common image perturbations, simulating an image being, for instance, uploaded to a social media platform. For our evaluation we consider JPEG compression, cropping with subsequent resizing, blurring, and additive Gaussian noise. In Appendix B we provide example images illustrating the effect of these perturbations on image quality. We compute the AUROC on a subset of 1 000/250 images from each class-to-image/text-to-image model, respectively. In Figure 5 we observe that PRADA's robustness strongly depends on the type of generative model. While the detection performance for class-to-image models remains relatively high under JPEG compression and blurring, it quickly degrades when images are cropped or distorted by noise. In contrast, the AUROC for text-to-image models remains very high in most settings, even if images undergo strong perturbation. We suggest that due to the higher image resolution and richer semantic conditioning, the detection is less affected by small, pixel-level changes. Moreover, we did not use perturbed images during score calibration, which could be implemented to increase the robustness.

5.4. Ablation Study

In the following, we evaluate how different design choices and hyperparameters influence the detection performance of our proposed method. Simply learning a token-wise score function f_θ for $\Delta(x_t, x)$ (with $\alpha = 1$ and $w_i = \frac{1}{S}$ fixed) already achieves an average AUROC of $88.9\%/87.1\%$ (class-to-image/text-to-image), outperforming the baselines $\Delta(x_t, c)$ and (finetuned) ICAS (see Tables 1 and 2). Additionally learning either α or w provides further improvements, but learning both is clearly the best choice, and is thus our default. In addition, we also try to learn $f_\theta : \mathbb{R}^2 \to \mathbb{R}$ that directly maps the tuple $\big(p(x_t|c, x_{<t}), p(x_t|x_{<t})\big) \in \mathbb{R}^2$ to a token score (which makes learning α obsolete). With fixed w we achieve AUROC values of $88.2\%/98.7\%$, but learning additional scale weights gives a substantial improvement to $92.8\%/99.5\%$. However, this approach leads to slightly higher variations between runs. We also test how many training samples are required to obtain a well-calibrated PRADA score. As expected, more training data is

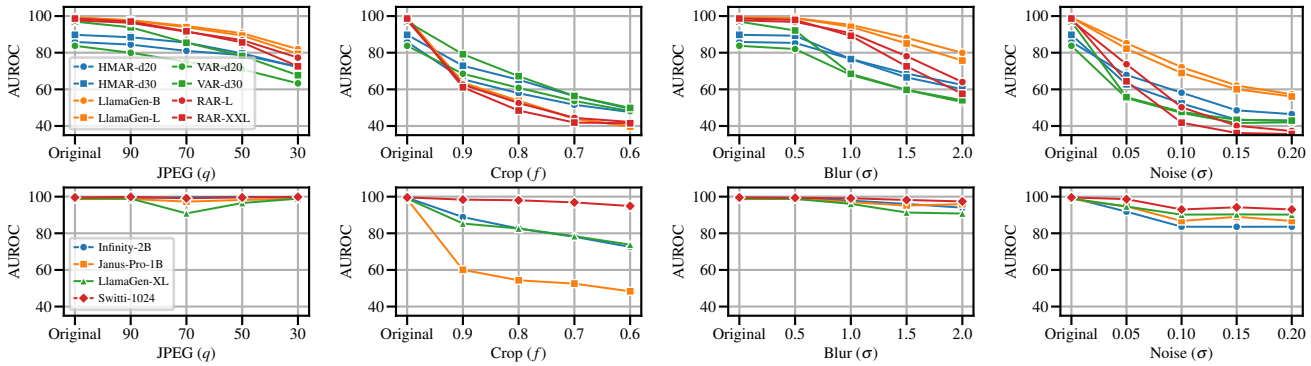


Figure 5. **Robustness analysis for PRADA.** We report the AUROC (%) for images generated by class-to-image (top) and text-to-image models (bottom) under varying degrees of perturbation.

always beneficial, but (focusing on the text-to-image models) already 25 samples (real and generated, respectively) allow PRADA to outperform all but two baselines, and with 125 training samples, PRADA is only surpassed by B-Free (which was trained on over 300 000 images). Moreover, our results show that PRADA is largely insensitive to the number of hidden neurons in each layer of f_θ. We provide detailed results of our ablation study in Appendix E.

Table 2. **Ablation study.** We report the detection performance in AUROC (%) for different design choices and hyperparameters (number of training samples and number of neurons in f_θ). We report mean and standard deviation over five calibration runs.

Variant	Class-to-Image	Text-to-Image
fixed α, fixed w	88.9 ± 0.3	87.1 ± 0.7
learnable α, fixed w	89.2 ± 0.4	98.3 ± 0.2
fixed α, learnable w	93.3 ± 0.3	90.9 ± 0.6
$f_\theta : \mathbb{R}^2 \to \mathbb{R}$, fixed w	88.2 ± 0.7	98.7 ± 0.2
$f_\theta : \mathbb{R}^2 \to \mathbb{R}$, learnable w	92.8 ± 1.1	99.5 ± 0.2
PRADA (learnable α, learnable w)	93.7 ± 0.3	99.4 ± 0.1

n_{train}	Class-to-Image	Text-to-Image
10	75.1 ± 5.3	93.5 ± 2.2
25	84.2 ± 2.3	97.7 ± 1.6
50	90.1 ± 2.0	98.4 ± 1.2
125	93.2 ± 0.6	99.3 ± 0.2
250	93.7 ± 0.3	99.4 ± 0.1

n_{hidden}	Class-to-Image	Text-to-Image
4	93.4 ± 0.4	97.5 ± 1.7
8	93.6 ± 0.4	98.9 ± 0.6
16	93.7 ± 0.3	99.4 ± 0.1
32	93.8 ± 0.3	99.4 ± 0.1
64	93.8 ± 0.3	99.4 ± 0.1

6. Discussion and Conclusion

Our findings show that exploiting the explicit likelihoods provided by AR image generators is indeed a highly promising direction for image forensics. By learning a model-specific score function, going beyond fixed scoring presented in previous work on MIAs [42, 82], we achieve strong results for both detection and attribution.

Nevertheless, our approach does not come without limitations. For each AR image generator, PRADA needs access to its likelihoods and a few generated samples. Although performing the calibration incurs a negligible computational cost (compared to training a large end-to-end classifier on an exhaustive dataset), this represents an additional overhead. Moreover, extracting likelihoods requires the same computational resources as generating an image, making inference more expensive than using an end-to-end classifier. Finally, PRADA requires some conditioning information, i.e., a class label or prompt. While our experiments show that using BLIP2 to extract suitable prompts is sufficient to achieve strong results, unfitting prompts can lead to reduced performance. However, as our experiments with ground-truth prompts show, optimizing the prompt estimation holds potential for further improvements.

A central advantage of PRADA is its interpretability. Firstly, the final score is transparently computed from explicit likelihoods, rather than produced by a black-box neural network. Secondly, inspecting the learned parameters allows for understanding a model's characteristics. For instance, we observe cumulative distribution differences for generated vs. real samples that reflect the member vs. non-member effects for VAR discovered by Yu et al. [82]. As a result, training our small scoring network reproduces the shape of ICAS' score function (see Appendix C) that emphasizes low probability ratios typical for real or non-member samples. Moreover, PRADA can be easily adapted to new AR image generators, as long as the semantic conditioning allows for extracting token-wise conditional and unconditional likelihoods. This means that adding new models to the ensemble of candidate models does not require any expensive re-training, as it would for end-to-end classifiers. However, additional investigation is needed to understand how including many models affects performance, since false positives from individual models can carry over to the ensemble.

In summary, we consider PRADA to be an effective and interpretable addition to the toolbox of forensic experts. Given its strong performance against capable text-to-image models, we hope it can help to mitigate the harmful consequences of generative AI.

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