

# Probing Perturbation Invariance in DINOv2

## MECHANISTIC GAPS BETWEEN REAL & GENERATED IMAGE REPRESENTATIONS

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TL;DR

Cross **two out-of-distribution axes** — an untrained-for **perturbation** (Gaussian noise) applied to OOD **inputs** (AI-generated images) — and a static distributional difference becomes a **dynamic stability gap** in DINOv2 patch space. A training-free detector with no generator-specific fitting.

### 01 THE TWO OOD AXES

DINOv2 learns invariance to Gaussian **blur** but never **noise**. Each axis alone is detectable; combining them mechanistically is the contribution.

#### PERTURBATION AXIS

Gaussian noise lies **outside** DINOv2's trained invariance regime → an OOD **stressor**.

#### INPUT AXIS

Generated images are OOD relative to DINOv2's natural-photo pretraining → an OOD **input**.

OOD PERTURBATION × OOD INPUT → STABILITY GAP

REAL PHOTO in-dist.

AI-GENERATED OOD

+ GAUSSIAN NOISE  $\sigma=100$  · OOD perturbation, never trained

DINOv2 ViT-L/14 · mean cosine shift, 256 patches

REAL

GENERATED

→ GENERATED IMAGES MOVE FARTHER UNDER NOISE

### 02 METHOD · TRAINING-FREE PROBE

#### STEP 1

Extract 257 final-layer tokens (1 CLS + **256 patch**) from a frozen ViT-L/14.

#### STEP 2

Add Gaussian noise ( $\sigma=100$ ), re-encode to perturbed features.

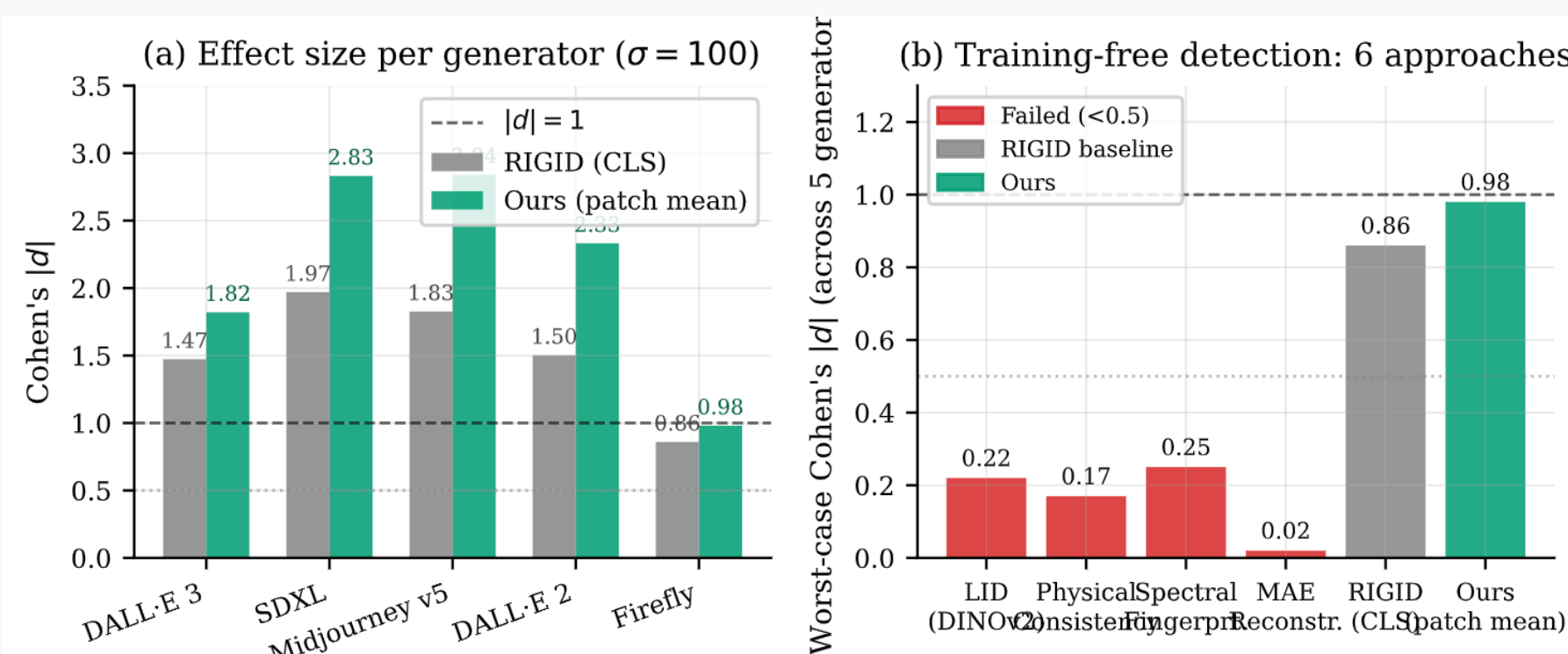
#### STEP 3

Score = **mean per-patch cosine distance** (— not the CLS token).

#### STEP 4

Compare via Cohen's  $|d|$  & AUROC. No training, no per-generator fitting.

### 03 KEY RESULT · PATCH BEATS CLS



Patch-mean (teal) beats CLS-only RIGID (grey) on all five generators; four of five non-overlapping 95% CIs.

0.86 → 0.98

WORST-CASE  $|d|$  · CLS → PATCH MEAN

+14% 5/5

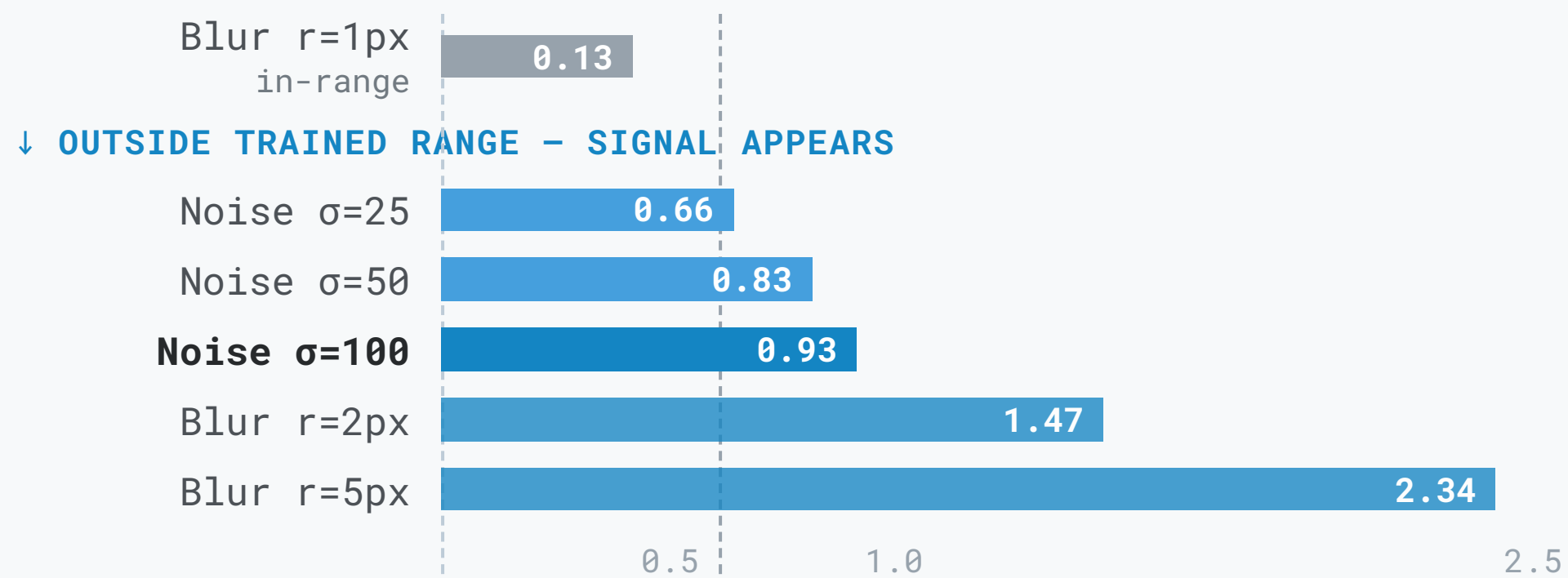
WORST-CASE GAIN, FREE GENERATORS, SAME DIRECTION

Averaging 256 patch tokens recovers local perturbation signal the CLS summary compresses away — at **no extra cost**.

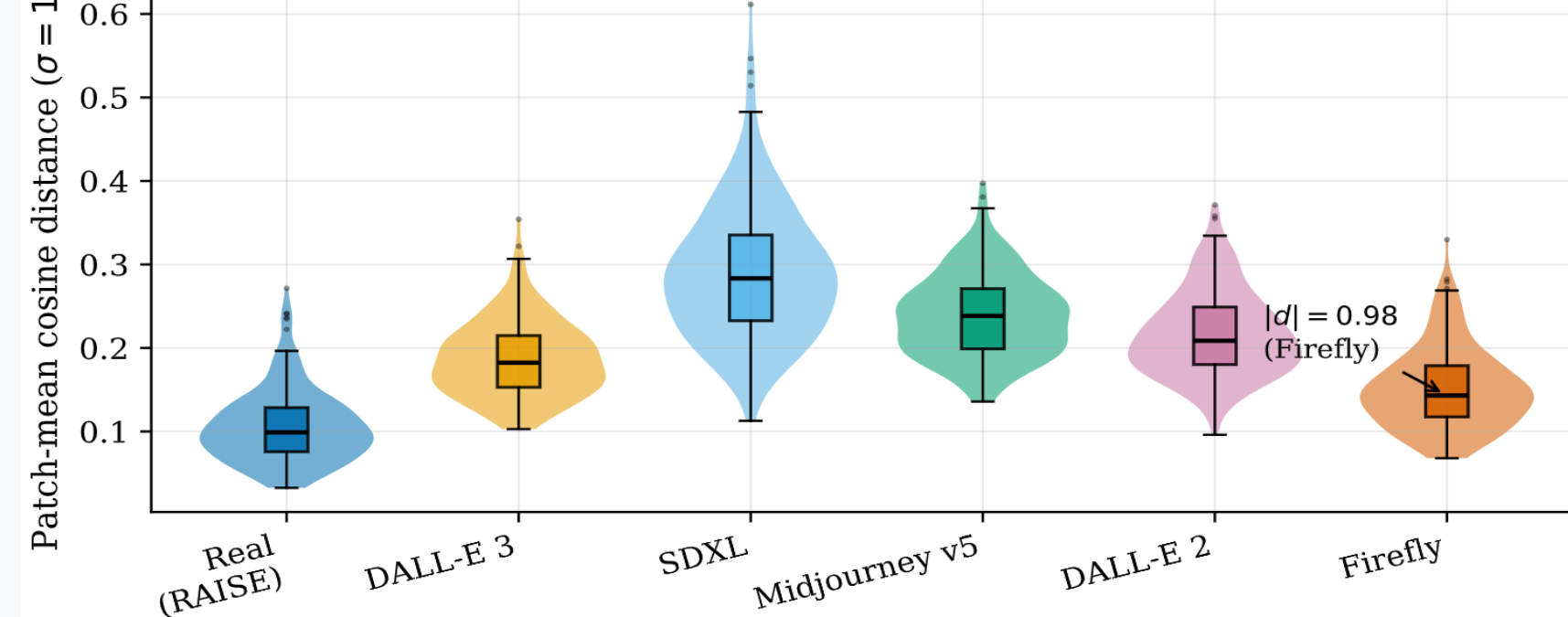
### 04 MECHANISM · IT'S THE OOD STATUS

#### PERTURBATION-TYPE NATURAL EXPERIMENT

Worst-case  $|d|$  across 5 generators

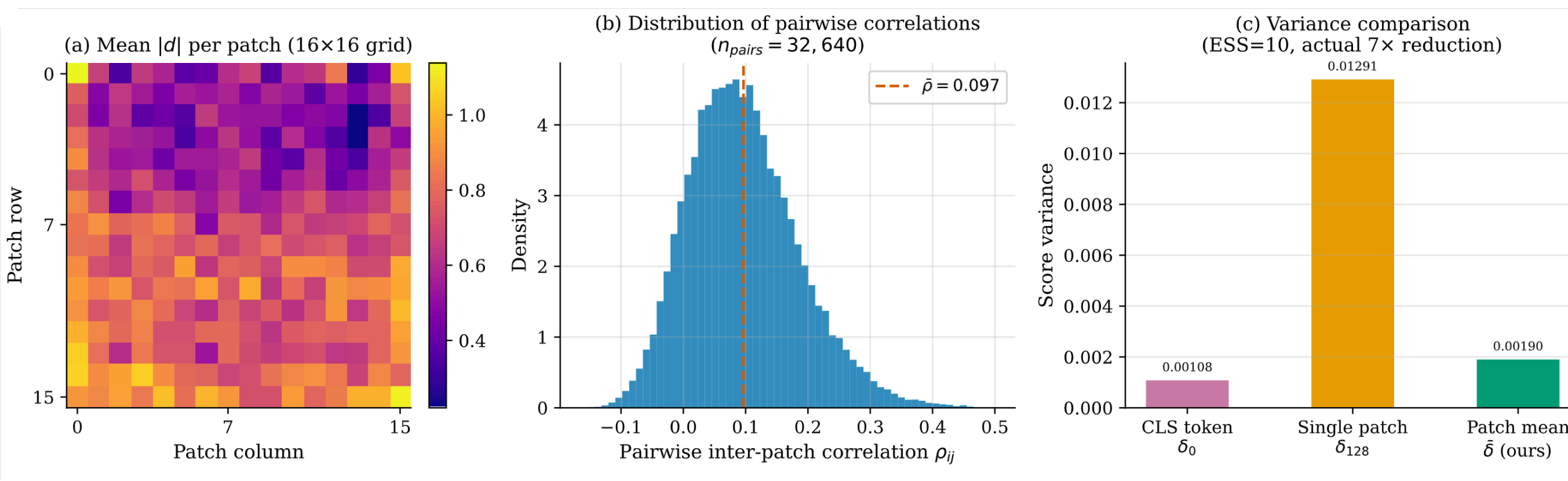


#### Score distributions: real vs. AI-generated images



All five generators shift to higher cosine distance (direction-consistent) — the property absent from five competing training-free signals, which flip sign per generator.

### 05 WHY PATCH TOKENS WIN



**Distributed signal.** The gap spreads across all patches — no corner/edge artefact.

**Lossy bottleneck.** CLS pooling = 11.9× lower variance but discards local responses.

**Read at the right granularity.** Mean patch keeps the signal (ESS  $\approx 10$ ).

#### TAKEAWAY — PROBE SPATIALLY-DISTRIBUTED PROPERTIES AT THE PATCH LEVEL

Diagnostic probe, not a deployed detector · uneven across generators (TPR@5%FPR 0.93–0.33),  $|d|=0.74$  on JPEG web images.

CODE

github.com/alinauliak/  
probing-perturbation-invariance-dinov2