

Detecting AI Generated Content using Foundation Models

ROY BETSER



MEIR YOSSEF LEVI



PROF. GUY GILBOA



IMVC – 29.06.26



TECHNION

Israel Institute of Technology

Detecting Generated Content

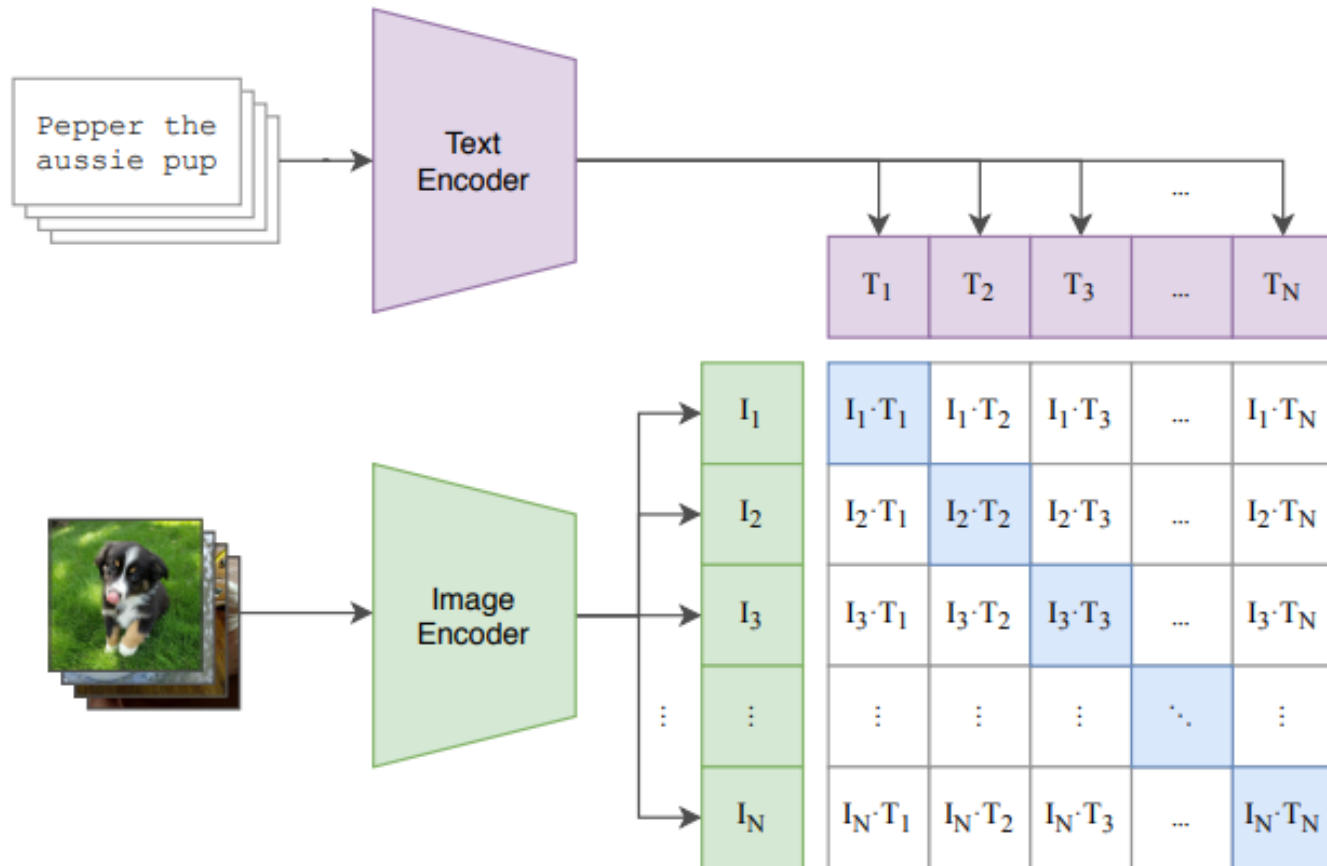


Real



Generated

What is CLIP?



Classification

Image synthesis

Retrieval

Image Editing

Segmentation

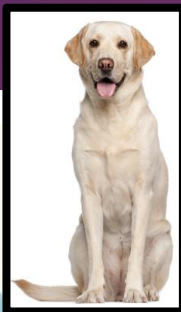
Detection

And many more..

CLIP Latent space



“... a Cat”



“... a dog”

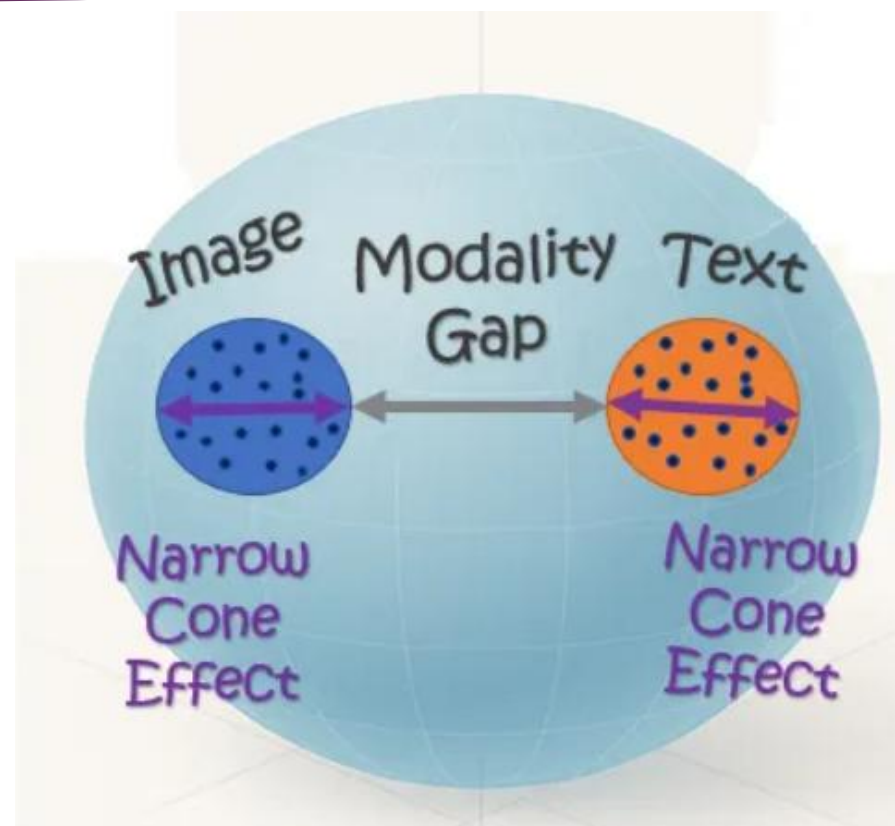


“... a house”

Goal

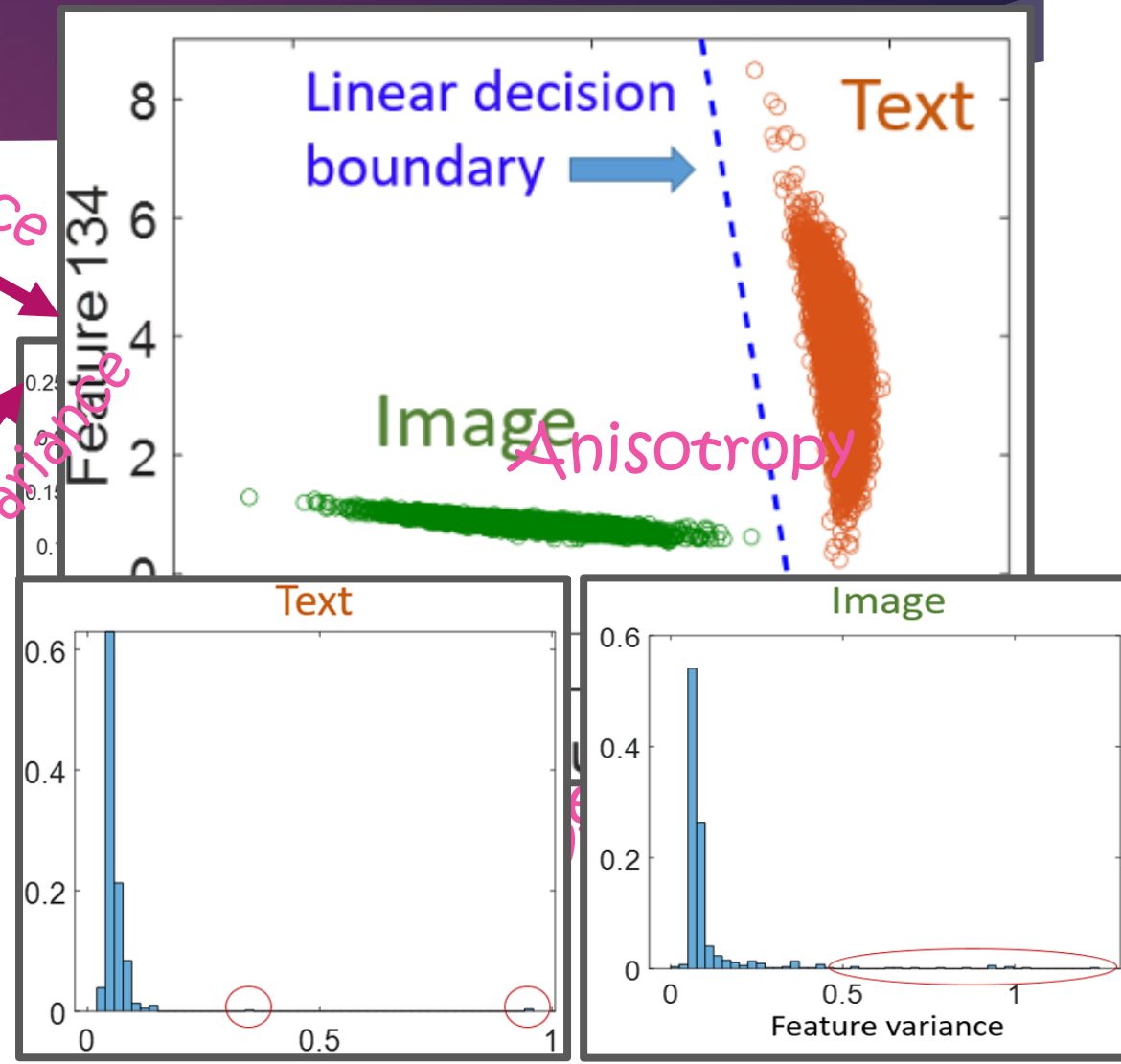
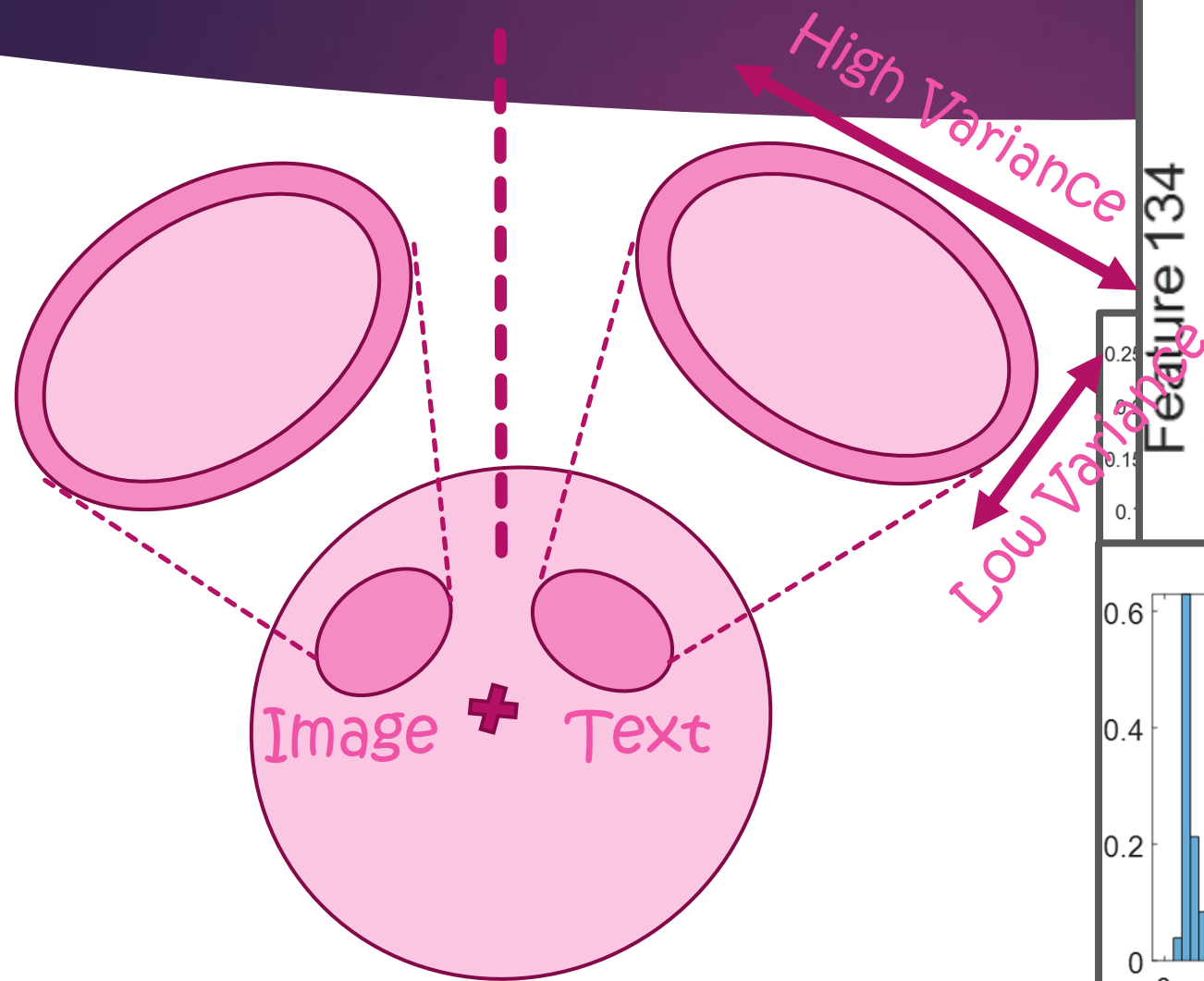


Reality



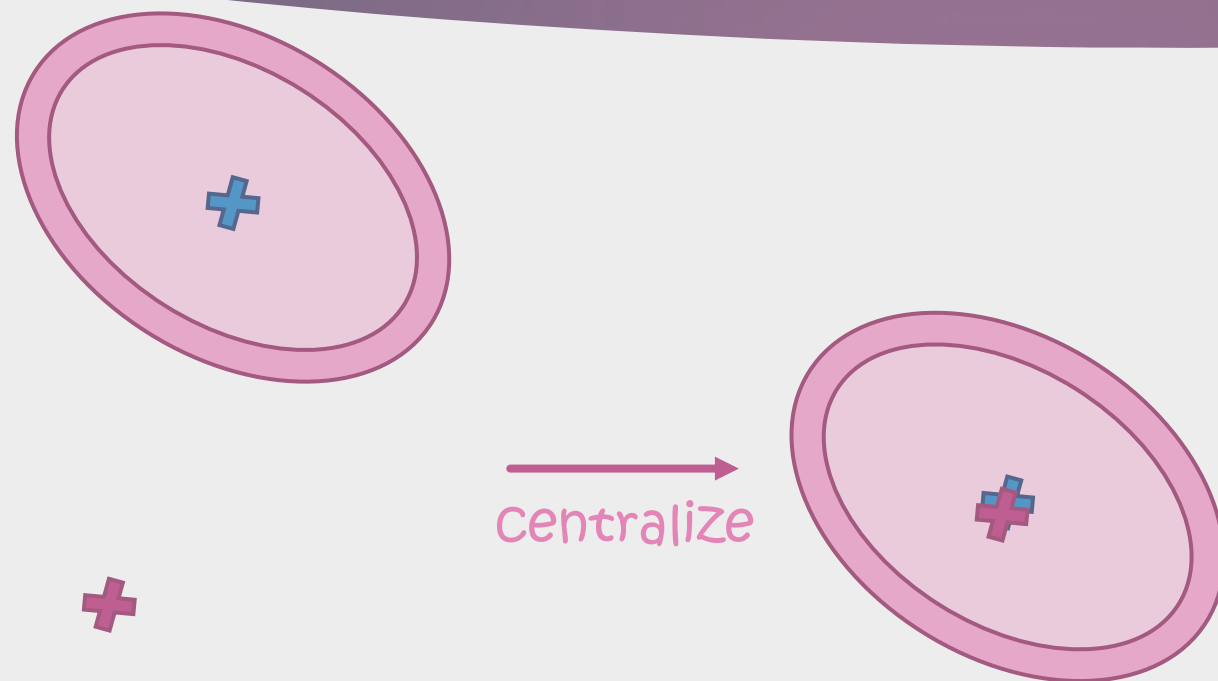
Double Ellipsoid Structure

Scan for
paper details



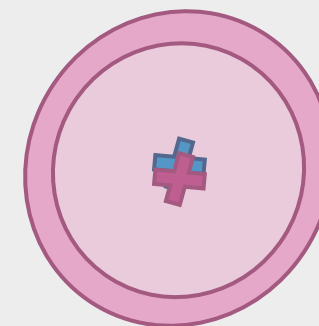
Whitening CLIP (W-CLIP)

Scan for
paper details



anisotropic

Whitening
→
Diagonalize
Covariance



isotropic

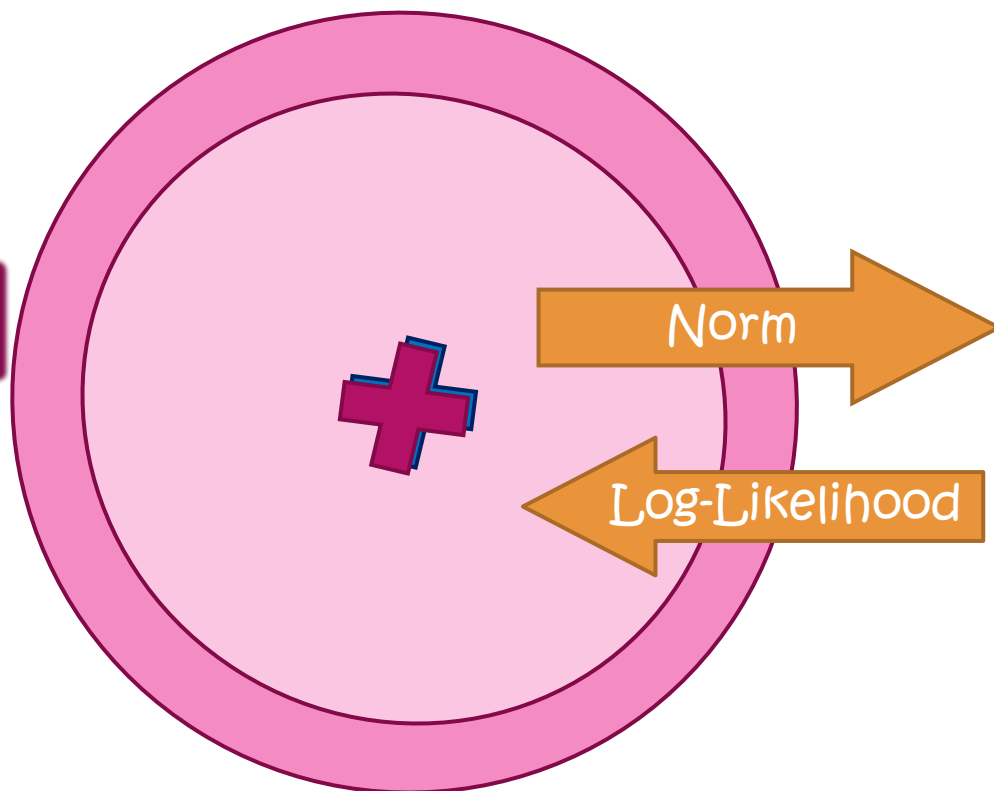


Norm as Likelihood

Simple

Fast

Invertible



Approximately Gaussian

	Avg.	Normal Features
	Anderson-Darling (< 0.752)	
Image	0.4890	98.3%
Text	0.5926	90.1%
	D'Agostino-Pearson (> 0.05)	
Image	0.3624	99.3%
Text	0.2568	99.2%

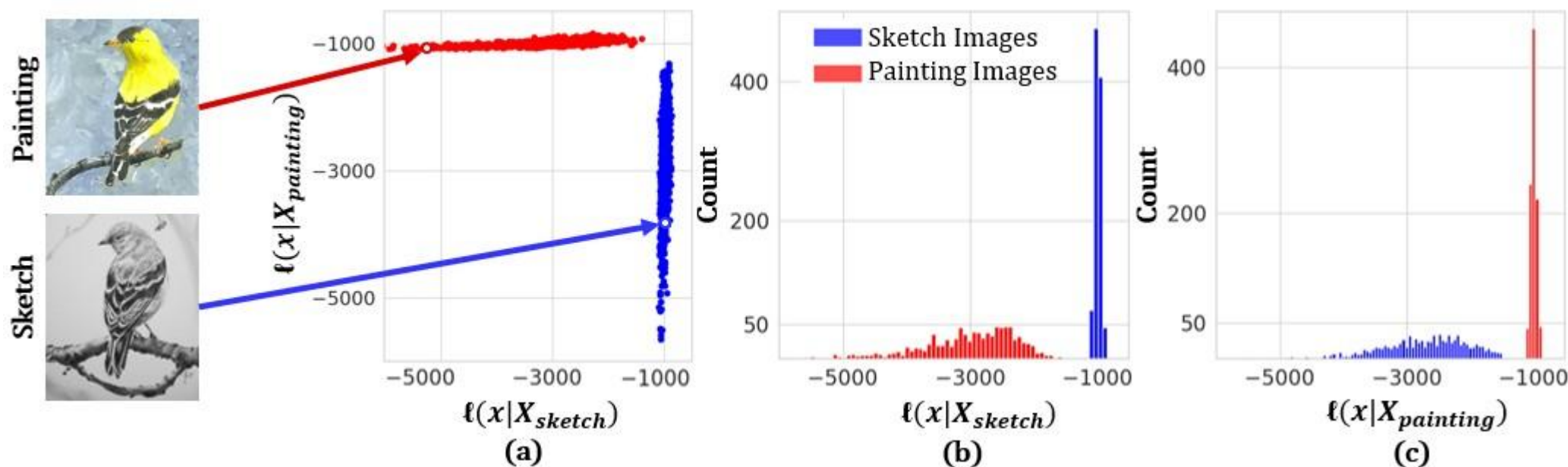
$$\ell(x) = -\frac{1}{2} (d \cdot \log(2\pi) + \|\hat{x}\|^2)$$



Conditional Likelihood

X - samples from sub-space:

$$\ell(x|X) = -\frac{1}{2} (d \cdot \log(2\pi) + \|W(X, m)\hat{x}\|^2)$$





Detecting Generated Content

Main challenges:

- ❑ Generated content is increasingly photorealistic.
- ❑ New generative models emerge rapidly.

Goal:

**Detect generated content by modeling
the distribution of real images.**



CLIDE – Generated Image Detector

Using only real images for whitening:

Generative Model	AEROBLADE [59]				RIGID [30]				ZED [18]				Manifold Bias [11]				Ours			
	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑
ProGan [34]	0.54	0.49	0.65	0.54	0.45	0.46	0.16	0.48	0.74	0.75	0.7	0.64	0.96	0.97	0.88	0.88	0.95	0.96	0.87	0.88
StyleGan [35]	0.58	0.59	0.63	0.51	0.71	0.72	0.56	0.65	0.75	0.77	0.71	0.65	0.68	0.74	0.61	0.68	0.76	0.71	0.75	0.73
StyleGan2 [36]	0.74	0.76	0.68	0.61	0.52	0.54	0.31	0.53	0.75	0.8	0.68	0.61	0.62	0.66	0.48	0.6	0.8	0.82	0.73	0.68
BigGAN [9]	0.65	0.61	0.68	0.6	0.62	0.63	0.42	0.57	0.45	0.47	0.63	0.5	0.9	0.9	0.8	0.81	0.96	0.96	0.87	0.88
GauGAN [51]	0.7	0.71	0.68	0.6	0.32	0.39	0.1	0.45	0.33	0.41	0.6	0.44	0.98	0.98	0.91	0.9	0.83	0.85	0.76	0.73
CycleGan [75]	0.76	0.73	0.73	0.69	0.34	0.39	0.05	0.43	0.22	0.38	0.6	0.43	0.97	0.97	0.89	0.9	0.98	0.98	0.9	0.91
CRN [15]	0.34	0.51	0.48	0.59	0.25	0.36	0.01	0.42	0.99	0.99	0.92	0.92	0.93	0.9	0.88	0.88	0.98	0.99	0.91	0.92
SD V1.4 [60]	0.47	0.47	0.63	0.51	0.79	0.77	0.63	0.69	0.62	0.65	0.65	0.54	0.71	0.62	0.4	0.57	0.9	0.91	0.82	0.82
SD V1.5 [60]	0.49	0.49	0.64	0.52	0.77	0.76	0.63	0.68	0.61	0.63	0.65	0.54	0.72	0.64	0.44	0.58	0.9	0.91	0.83	0.82
Guided DM [20]	0.55	0.49	0.66	0.57	0.51	0.51	0.25	0.5	0.58	0.55	0.68	0.59	0.8	0.8	0.66	0.7	0.87	0.87	0.79	0.78
LDM 100 [60]	0.48	0.48	0.62	0.48	0.51	0.51	0.25	0.5	0.52	0.56	0.63	0.49	0.84	0.88	0.78	0.79	0.92	0.93	0.84	0.85
LDM 200 [60]	0.47	0.48	0.62	0.48	0.51	0.51	0.25	0.5	0.53	0.56	0.63	0.5	0.85	0.88	0.79	0.8	0.92	0.93	0.85	0.85
Glide 50 27 [48]	0.06	0.32	0.59	0.42	0.51	0.51	0.25	0.5	0.98	0.98	0.91	0.92	0.93	0.94	0.86	0.86	0.91	0.92	0.84	0.84
Glide 100 27 [48]	0.08	0.32	0.6	0.43	0.51	0.51	0.25	0.5	0.98	0.98	0.91	0.92	0.92	0.93	0.84	0.84	0.91	0.92	0.83	0.83
Glide 100 10 [48]	0.04	0.31	0.59	0.42	0.51	0.51	0.25	0.5	0.98	0.98	0.92	0.92	0.93	0.93	0.85	0.85	0.91	0.92	0.83	0.83
ADM [20]	0.45	0.43	0.65	0.56	0.56	0.57	0.39	0.56	0.47	0.46	0.65	0.55	0.62	0.57	0.32	0.53	0.89	0.88	0.84	0.84
DALL-E 3 [6]	0.35	0.41	0.61	0.45	0.51	0.51	0.25	0.5	0.45	0.5	0.62	0.47	0.82	0.84	0.71	0.74	0.96	0.96	0.88	0.89
Midjourney [45]	0.29	0.37	0.6	0.43	0.65	0.66	0.48	0.6	0.92	0.93	0.84	0.84	0.56	0.53	0.27	0.51	0.9	0.84	0.85	0.85
VDQM [28]	0.51	0.47	0.66	0.57	0.53	0.54	0.32	0.53	0.46	0.46	0.63	0.49	0.83	0.83	0.7	0.73	0.92	0.93	0.84	0.84
Wukong [46]	0.48	0.47	0.62	0.49	0.63	0.6	0.37	0.55	0.39	0.45	0.6	0.44	0.73	0.69	0.5	0.62	0.95	0.96	0.88	0.88
All	0.52	0.48	0.64	0.53	0.51	0.53	0.28	0.52	0.69	0.66	0.69	0.62	0.85	0.88	0.76	0.78	0.91	0.91	0.84	0.84

General and Domain-Specific Zero-shot Detection of Generated Images via
Conditional Likelihood, WACV 2026

Damaged Cars

Scan for
paper details



FUJITSU



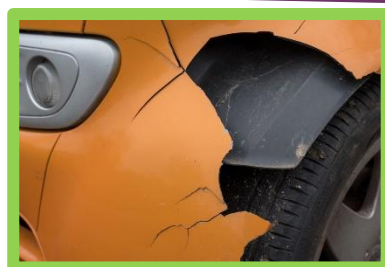
General and Domain-Specific Zero-shot Detection of Generated Images via Conditional Likelihood, WACV 2026

Scan for
paper details



FUJITSU

Damaged Cars



Real
Fake

Generative Model	AEROBLADE [59]				RIGID [30]				ZED [18]				Manifold Bias [11]				Ours			
	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑
Kandinsky2.1 [58]	0.29	0.38	0.6	0.43	0.3	0.38	0.06	0.44	0.68	0.66	0.68	0.61	0.6	0.64	0.48	0.61	0.97	0.98	0.93	0.93
SDXL [53]	0.34	0.4	0.61	0.45	0.3	0.38	0.06	0.44	0.83	0.85	0.76	0.73	0.32	0.42	0.15	0.49	0.97	0.97	0.91	0.91
DALL-E 3 [6]	0.39	0.45	0.6	0.44	0.4	0.42	0.11	0.42	0.15	0.33	0.59	0.42	0.14	0.33	0.03	0.44	0.99	0.99	0.93	0.93
Midjourney [45]	0.46	0.47	0.62	0.47	0.51	0.5	0.23	0.5	0.78	0.75	0.74	0.71	0.4	0.44	0.13	0.48	0.93	0.94	0.87	0.86
UnCLIP [57]	0.22	0.35	0.6	0.43	0.69	0.67	0.46	0.6	0.31	0.38	0.61	0.46	0.69	0.68	0.48	0.61	0.8	0.8	0.72	0.67
All	0.33	0.4	0.61	0.44	0.45	0.48	0.21	0.49	0.61	0.54	0.68	0.61	0.47	0.53	0.3	0.53	0.92	0.92	0.85	0.84

General and Domain-Specific Zero-shot Detection of Generated Images via Conditional Likelihood, WACV 2026



Scan for
paper details

FUJITSU

Graham, Carrillo and Stark

Address: 8110 Lee Haven
West Michele, IN 23879 US

GSTIN : 24HDE7487RESRT4

Bill To: Brian Yang
61239 Robert Dale
North Shirleyport, CA 32639 US
Tel: +1(940)656-0478
Email: scottjenna@example.net
Site: https://www.woods.org/

SHIP TO:
Valerie Lynch
9341 Arnold Trafficway
Jennifersburg, WY 74045 US
Tel: +1(940)656-0478
Email: robert00@example.com
Site: http://nelson.biz/

www.GrahamCarrilloandStark.com

Email: ghodges@example.org

INVOICE ID 5254-446

Invoice Date: 16-Jun-2013

Due Date : 18-Apr-1997

ITEMS

ITEMS	QUANTITY	PRICE
Risk air.	2.00	\$28.92
Forward work air full.	3.00	\$14.54
Economy election.	5.00	\$13.13

SUB_TOTAL : 167.11 EUR

TOTAL : 167.57 EUR

Total in words: one hundred and sixty-seven point five seven

Bank Name Central Bank of Texas
Branch Name Raf CAMP
Bank Account Number 12884474
Bank Swift Code SBININBB250

Terms and Conditions
will be charged if payment is not made within the due date.

Original
Image

Graham, Carrillo and Stark

Address: 8110 Lee Haven
West Michele, IN 23879 US

GSTIN: 24HDE7467RESRT4

Bill To: Brian Yang
61239 Robert Dale
North Shirleyport, CA 32639 US
Tel: +1(940)656-0478
Email: scottjenna@example.net
Site: https://www.woods.org/

SHIP TO:
Valerie Lynch
9341 Arnold Trafficway
Jennifersburg, WY 74045 US
Tel: +1(940)656-0478
Email: robert00@example.com
Site: http://nelson.biz/

www.GrahamCarrilloandStark.com

Email: ghodges@example.org

INVOICE ID \$254-446

Invoice Date: 16-Jun-2013

Due Date: 18-Apr-1997

ITEMS	QUANTITY	PRICE
Risk air.	2.00	\$500.00
Forward work air full.	3.00	\$120.00
Economy election.	5.00	\$16.00

SUB_TOTAL: \$1,000.00

TOTAL: \$1,000.00

Total in words: one thousand.

Bank Name Central Bank of Texas
Branch Name Raf CAMP
Bank Account: 125494744
Bank Swift Code SBININBB50

Terms and Conditions
will be charged if payments not made within the due date.

Change
date

Change
price

Graham, Carrillo and Stark

Address: 8110 Lee Haven
West Michele, IN 23879 US

GSTIN: 24HDE7487RESRT4

Bill To: Brian Yang
61335 Robert Dale
North Shirleyport, C. 32639 US
Tel: +1(940)656-0478
Email: cseffman@example.net
Site: http://www.woods.org

SHIP TO:
Valerie Lynch
9341 Arnold Trafficway
Jennifersburg, WY 7405 US
Tel: +1(940)656-0478
Email: robert00@example.com
Site: http://nelson.biz

www.GrahamCarrilloandStark.com

Email: ghodges@example.org

INVOICE ID 5254-446

Invoice Date: 02-Jan-2012

Due Date: 04-Jan-2012

ITEMS	QUANTITY	PRICE
Risk air.	2.00	\$23.92
Forward work air full.	3.00	\$14.04
Economy election.	5.00	\$13.13

SUB. TOTAL: 167.11 EUR

Total in words: one hundred and sixty-seven point five seven

Bank Name Central Bank of Texas
Branch Name Raf CAMP
Bank Account Number
Bank Swift Code SBINIRB250

Terms and Conditions
will be charged if payment is not made within the due date.

Generative Model	AEROBLADE [59]				RIGID [30]				ZED [18]				Manifold Bias [11]				Ours			
	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑	AUC ↑	AP ↑	F1 ↑	Acc ↑
GPT-Image-1 [55]	0.53	0.62	0.56	0.47	0.57	0.67	0.12	0.53	0.6	0.56	0.65	0.54	0.61	0.58	0.55	0.62	0.91	0.92	0.82	0.82



Generated Video Detection

B. Unrealistic frames

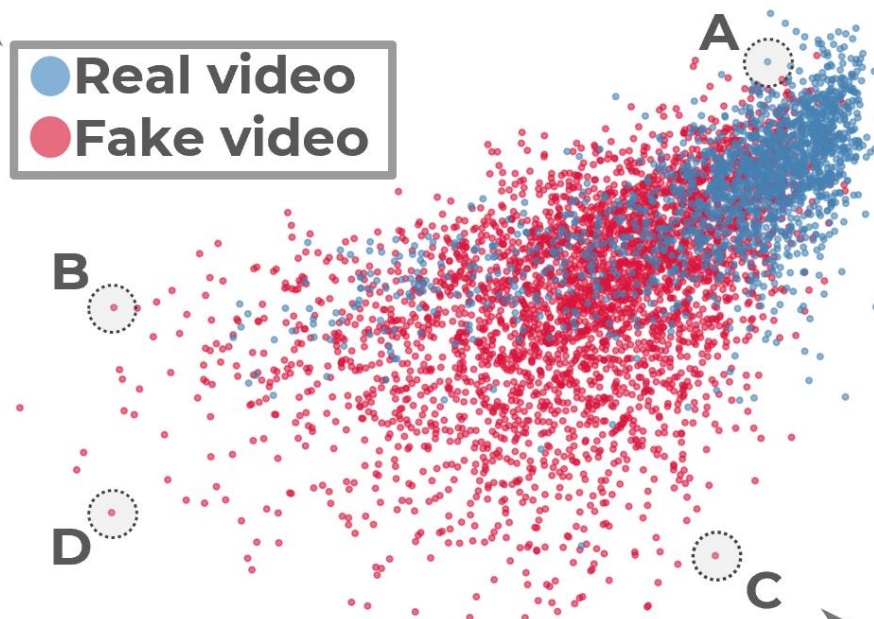


D. Both artifacts



Temporal Likelihood
(motion naturalness)

● Real video
● Fake video



A. Real video



C. Unnatural motion



Spatial Likelihood
(frame realism)

Summary and takeaways

- ❑ CLIP has double ellipsoid structure.
- ❑ Vision encoders learn approximately Gaussian representations.
- ❑ Understanding latent geometry enables downstream applications.
- ❑ Foundation models naturally separate real and generated content.
- ❑ Generated content detection can rely only on real samples.

Thank you!



Questions?