MetaUAS: Universal Anomaly Segmentation with One-Prompt Meta-Learning

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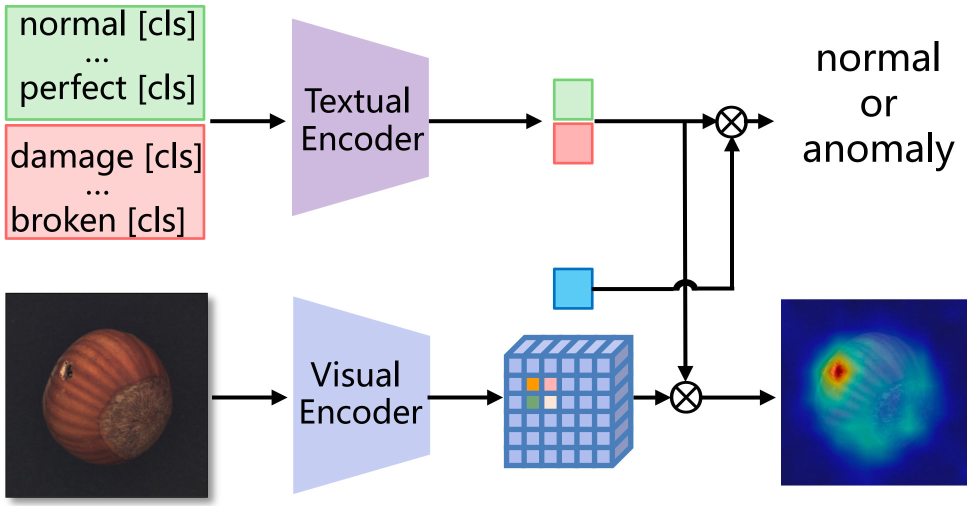
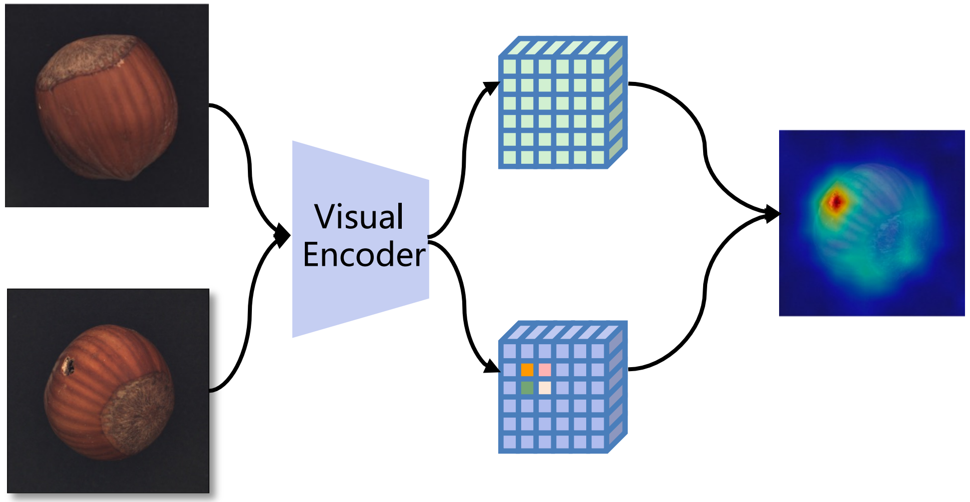
Introduction

Universal Anomlay Segmentation

Universal anomaly segmentation aims to identify anomalies from novel or unseen objects, given a few and even only one normal image and without training on this novel/unseen dataset.



visual-language models with texual prompts



pure visual models with one normal image prompt

However, visual representations are inherently independent of language. In this study, we want to explore how far we can go with a pure visual model although there is room using visual-language models and worthwhile further to pursue.

Motivation

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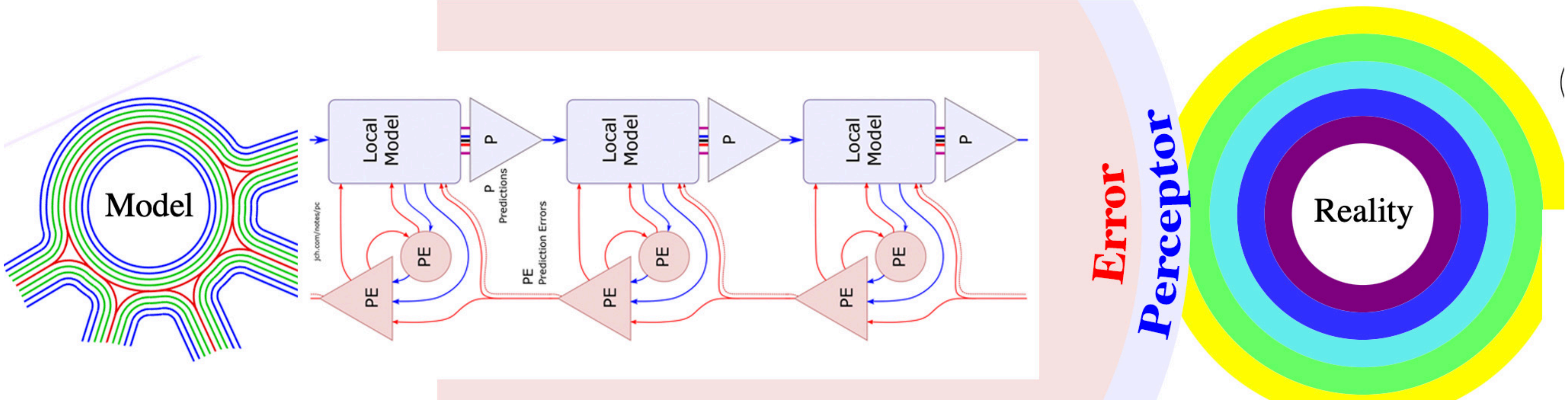
Predictive coding theory [1] postulates that the brain constantly generates and updates a "mental model". The mental model compares its expectations (or predictions) with the actual inputs from the visual cortex.

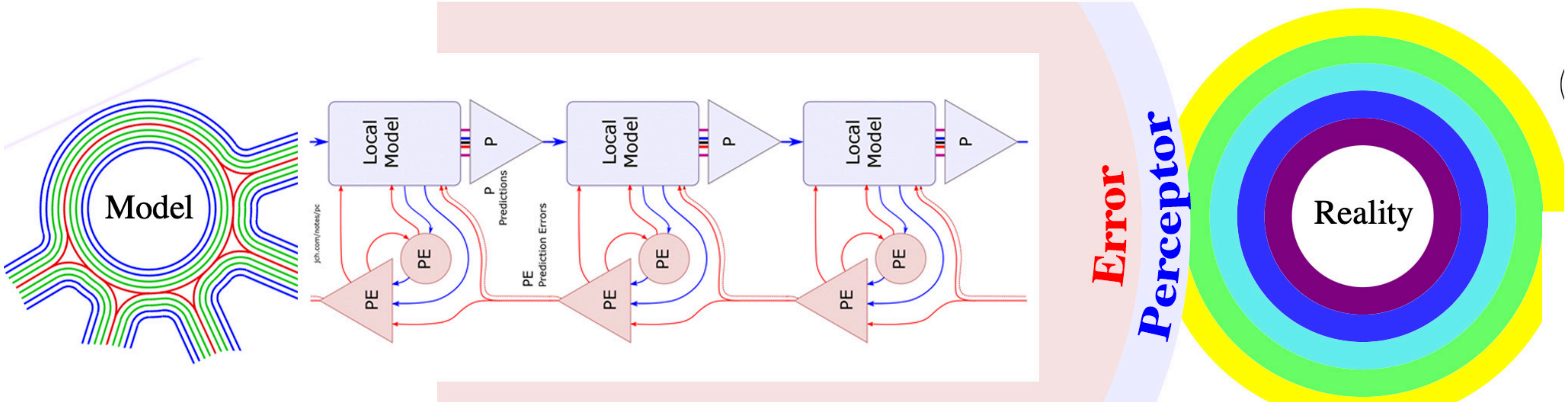


Some existing methods (i.e., PatchCore) perceive anomalies and they are indeed similar to the brains. However, they usually require a certain number of normal images and thus are limited in universal (i.e., open-world) scenarios.

How to construct a "mental model" to compare between one normal image and any query images for universal segmentation?

Motivation

Despite these challenges, we can imagine that the "mental model" should satisfy several **basic principles.**

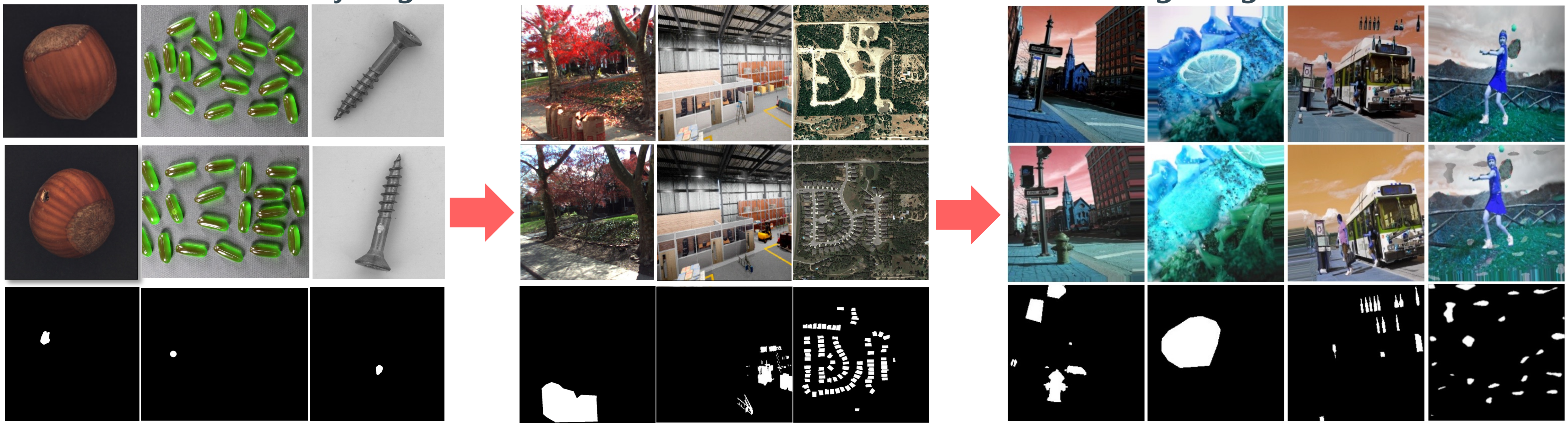


- ✓ First, it should have a strong generalization ability to perceive anomalies facing unseen objects or textures;
- ✓ Second, it can perform pixel-level anomaly segmentation only given one normal image prompt.;
- ✓ Third, its training does not depend on target domain distribution or any guidance from language.

Our Method

Rethinking Anomaly Segmentation

We rethink anomaly segmentation and find it can be unified into change segmentation.



Anomaly Segmentation

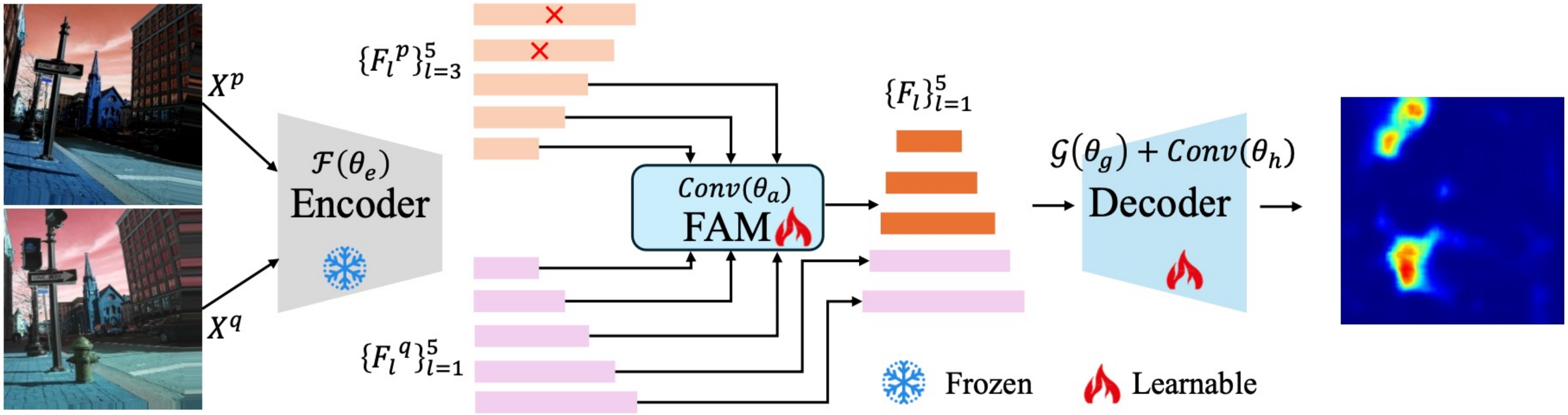
Change Segmentation

Synthesizing Change Segmentation

The novel paradigm shift enables us to leverage large-scale synthetic image pairs with **object-level** and **local region** changes, thereby overcoming the long-standing challenge of lacking large-scale anomaly segmentation datasets.

Our Method

One-Prompt Meta-Learning



The proposed MetaUAS consists of an encoder, a feature alignment module (FAM), and a decoder. It is trained on a synthesized dataset in a one-prompt meta-learning manner for change segmentation tasks. Once trained, it can segment any anomalies providing only one normal image prompt.

Our Method

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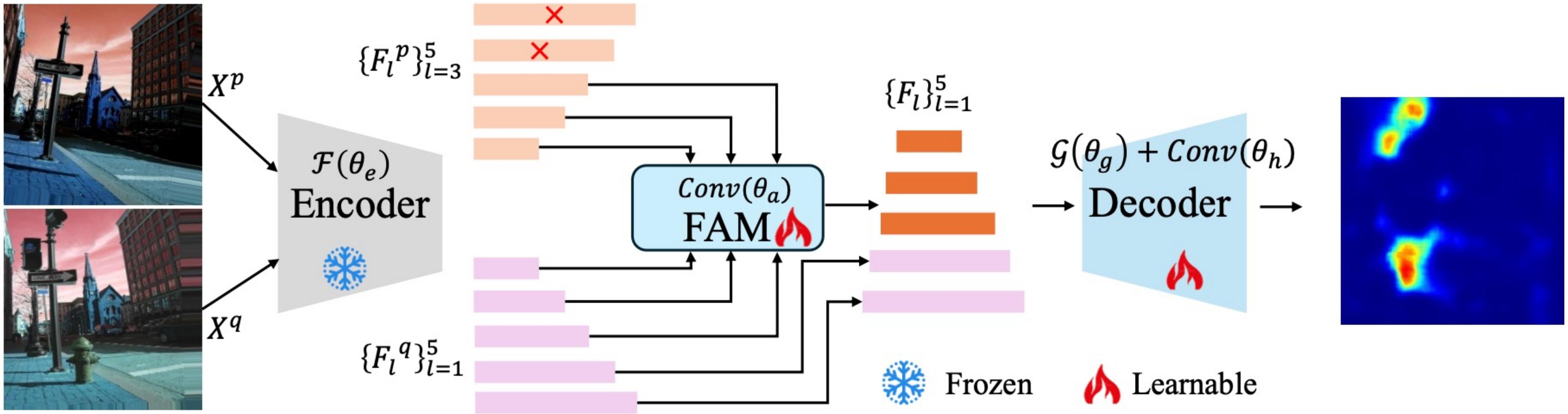
One-Prompt Meta-Learning



Encoder: MetaUAS is compatible with any hierarchical architecture.

Decoder: we utilize Unet as our decoder because it is better suited for tasks requiring high precision and the preservation of fine-grained details.

Our Method

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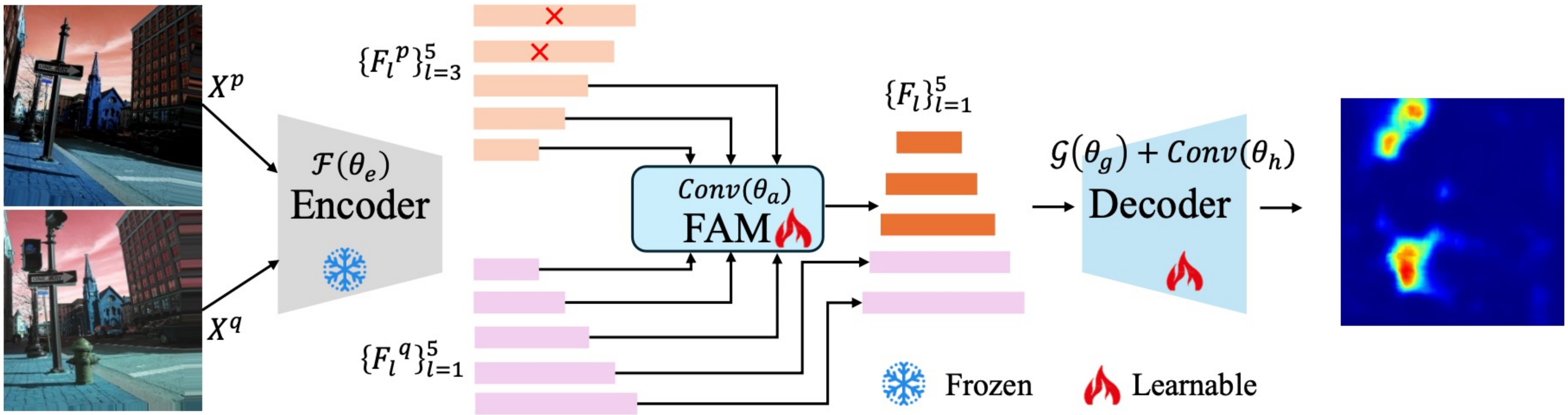
One-Prompt Meta-Learning



FAM aligns query and prompt features for better change segmentation.

$$F_l^p(i,j) \leftarrow F_l^p\left(\underset{k,l}{\operatorname{argmin}} \langle F_l^q(i,j), F_l^p(k,l)\rangle\right)$$

Hard Alignment

$$W_{ijkl} = \operatorname{softmax}\left(F_l^q(i,j)(F_l^p(k,l))^T\right),$$

$$F_l^p(i,j) \leftarrow \sum_k \sum_l W_{ijkl} F_l^p(k,l).$$

Soft Alignment

Experiments

Comparisons with State-of-the-Arts

Table 1: Quantitative comparisons on **MVTec**, **VisA** and **Goods**. Red indicates the best performance, while blue denotes the second-best result. Gray indicates the model is trained by full-shot normal images.

Datasets	Methods	Venue	Shot	Auxiliary	Anomaly Classification I-ROC	I-PR	I-F1_{max}	Anomaly Segmentation P-ROC	P-PR	P-F1_{max}	P-PRO
MVTec	CLIP [42]	ICML 21	0	✗	74.4	89.3	88.7	62.0	6.5	11.2	21.4
	PatchCore [47]	CVPR 22	1	✗	79.0±0.8	89.6±1.1	88.9±0.3	93.1±0.2	37.1±0.9	42.2±0.8	82.7±0.5
	WinCLIP [26]	CVPR 23	0	✗	90.4	95.6	92.7	82.3	18.2	24.8	61.9
	WinCLIP+ [26]	CVPR 23	1	✗	92.8±1.2	96.4±0.7	93.8±0.5	93.5±0.2	38.4±1.2	42.5±1.0	83.9±0.4
	AnomalyCLIP [76]	ICLR 24	0	✓	91.5	96.3	92.7	91.1	34.5	39.1	81.4
	UniAD [70]	NeurIPS 22	full	✗	96.7	98.9	96.7	96.8	44.7	50.4	90.0
	MetaUAS		1	✗	90.7±0.7	95.7±0.6	92.5±0.3	94.6±0.2	59.3±1.4	57.5±1.1	82.6±0.6
	MetaUAS⋆		1	✗	94.2	97.6	93.9	95.3	63.7	61.6	83.1
	MetaUAS⋆+		1	✗	95.3	97.9	94.6	97.6	67.0	62.9	92.5
VisA	CLIP [42]	ICML 21	0	✗	59.1	67.4	74.5	56.5	1.8	3.6	22.4
	PatchCore [47]	CVPR 22	1	✗	64.2±1.0	66.0±0.7	75.5±0.5	95.5±0.3	16.5±1.7	26.0±1.5	84.6±0.5
	WinCLIP [26]	CVPR 23	0	✗	75.5	78.7	78.2	73.2	5.4	9.0	51.0
	WinCLIP+ [26]	CVPR 23	1	✗	80.5±2.6	82.1±2.7	81.3±1.0	94.4±0.1	15.9±0.2	23.2±0.4	79.3±0.3
	AnomalyCLIP [76]	ICLR 24	0	✓	81.9	85.4	80.7	95.5	21.3	28.3	86.8
	UniAD [70]	NeurIPS 22	full	✗	90.8	93.2	87.8	98.5	34.3	39.1	84.8
	MetaUAS		1	✗	81.2±1.7	84.5±1.4	80.2±0.7	92.2±0.7	42.7±0.8	44.7±0.6	60.4±1.5
	MetaUAS⋆		1	✗	83.4	85.7	81.3	92.0	43.9	45.6	57.3
	MetaUAS⋆+		1	✗	85.1	87.2	82.3	98.0	48.1	48.6	85.5
Gooods	CLIP [42]	ICML 21	0	✗	51.8	57.3	71.3	55.3	4.3	2.0	16.4
	PatchCore [47]	CVPR 22	1	✗	48.3±1.0	54.2±0.5	71.3±0.1	84.3±0.5	4.5±0.2	9.3±0.3	55.6±1.0
	WinCLIP [26]	CVPR 23	0	✗	52.2	58.2	71.4	73.0	5.0	10.2	44.5
	WinCLIP+ [26]	CVPR 23	1	✗	53.5±0.2	58.6±0.2	71.5±0.1	85.5±0.6	5.7±0.4	11.3±0.5	56.6±1.2
	AnomalyCLIP [76]	ICLR 24	0	✓	57.2	63.3	71.4	83.5	16.9	24.0	63.3
	UniAD [70]	NeurIPS 22	full	✗	67.5	72.1	74.6	90.4	15.0	20.6	66.1
	MetaUAS		1	✗	54.5±1.0	58.5±0.4	71.5±0.1	88.5±0.6	8.6±0.7	14.0±0.7	59.0±1.3
	MetaUAS⋆		1	✗	90.1	91.7	85.7	97.4	53.7	55.5	70.8
	MetaUAS⋆+		1	✗	89.9	89.9	86.2	97.9	49.0	55.8	88.0

Table 2: The complexity and efficiency comparisons.

Methods	Backbone	#All Params(#Leanable)	Input Size	Times (ms)
CLIP [42]	ViT-B-16+240	208.4 (0.0)	240×240	13.7
PatchCore [47]	E-b4	17.5 (0.0)	256×256 512×512	36.4 145.1
WinCLIP [26]	ViT-B-16+240	208.4 (0.0)	240×240	201.3
WinCLIP+ [26]	ViT-B-16+240	208.4 (0.0)	240×240	339.5
AnomalyCLIP [76]	ViT-L/14@336px	433.5 (5.6)	518×518	154.9
UniAD [70]	Eb4	27.1 (7.7)	224×224	5.0
MetaUAS	Eb4	22.1 (4.6)	256×256	3.1
MetaUAS⋆	Eb4	22.1 (4.6)	256×256	3.1
MetaUAS⋆+	Eb4+ViT-B-16+240	139.3 (4.6)	256×256	204.8
MetaUAS	Eb4	22.1 (4.6)	512×512	12.0
MetaUAS⋆	Eb4	22.1 (4.6)	512×512	12.0
MetaUAS⋆+	Eb4+ViT-B-16+240	139.3 (4.6)	512×512	213.0

- ✓ Strong generalization;
- ✓ High efficiency;
- ✓ Fewer parameters;
- ✓ Training-free;
- ✓ Only one normal image;
- ✓ Pure visual foundation model;
- ✓ Without any language prompt;

Experiments

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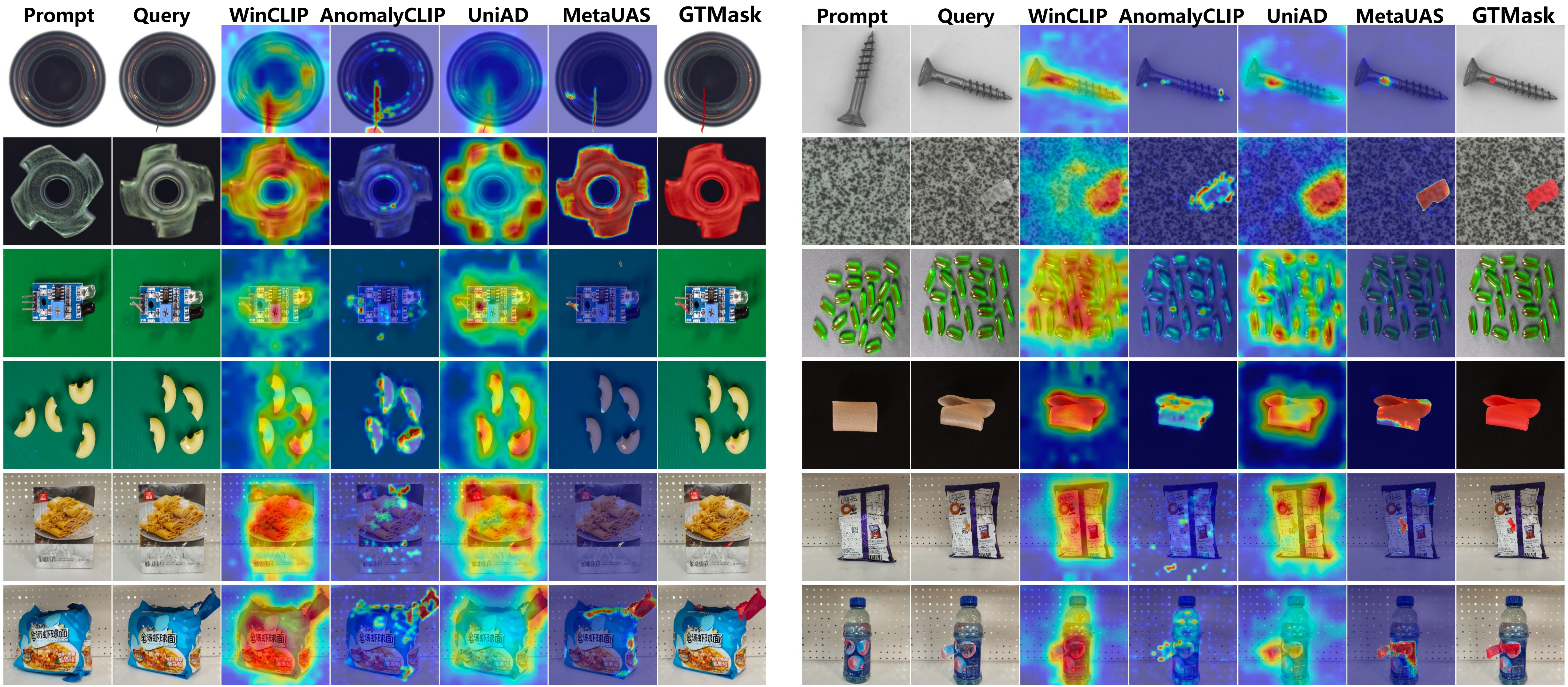
Qualitative Comparisons with State-of-the-Arts



Experiments

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Ablation Studies

Table 3: **Ablation studies on MVTec**. Default settings are marked in blue.

(a) Effect of feature alignment module.

No.	Align	Fusion	I-ROC	I-PR	P-ROC	P-PR	P-PRO
1	No	Concat	82.8	92.5	88.4	44.9	67.5
2	Hard	Concat	87.1	94.7	90.7	48.2	77.0
3	Soft	Concat	**91.3**	**96.2**	**94.6**	**59.6**	**82.6**
4	Soft	Add	71.8	86.9	73.2	24.0	45.2
5	Soft	AbsDiff	84.1	92.4	88.4	45.9	68.4

(b) Learn or freeze encoder?

No.	Backbone	Learn?	I-ROC	I-PR	P-ROC	P-PR	P-PRO
1	E-b4	Learn	86.5	93.6	93.1	50.3	74.6
2	E-b4	Freeze	**91.3**	**96.2**	94.6	**59.6**	**82.6**
3	E-b6	Freeze	90.1	95.5	95.1	56.9	80.8
4	EViT-b3	Freeze	89.5	95.7	**95.3**	58.5	80.9
5	M-v2	Freeze	76.2	87.8	87.6	33.7	61.0

(c) Effects of change types and decoder module.

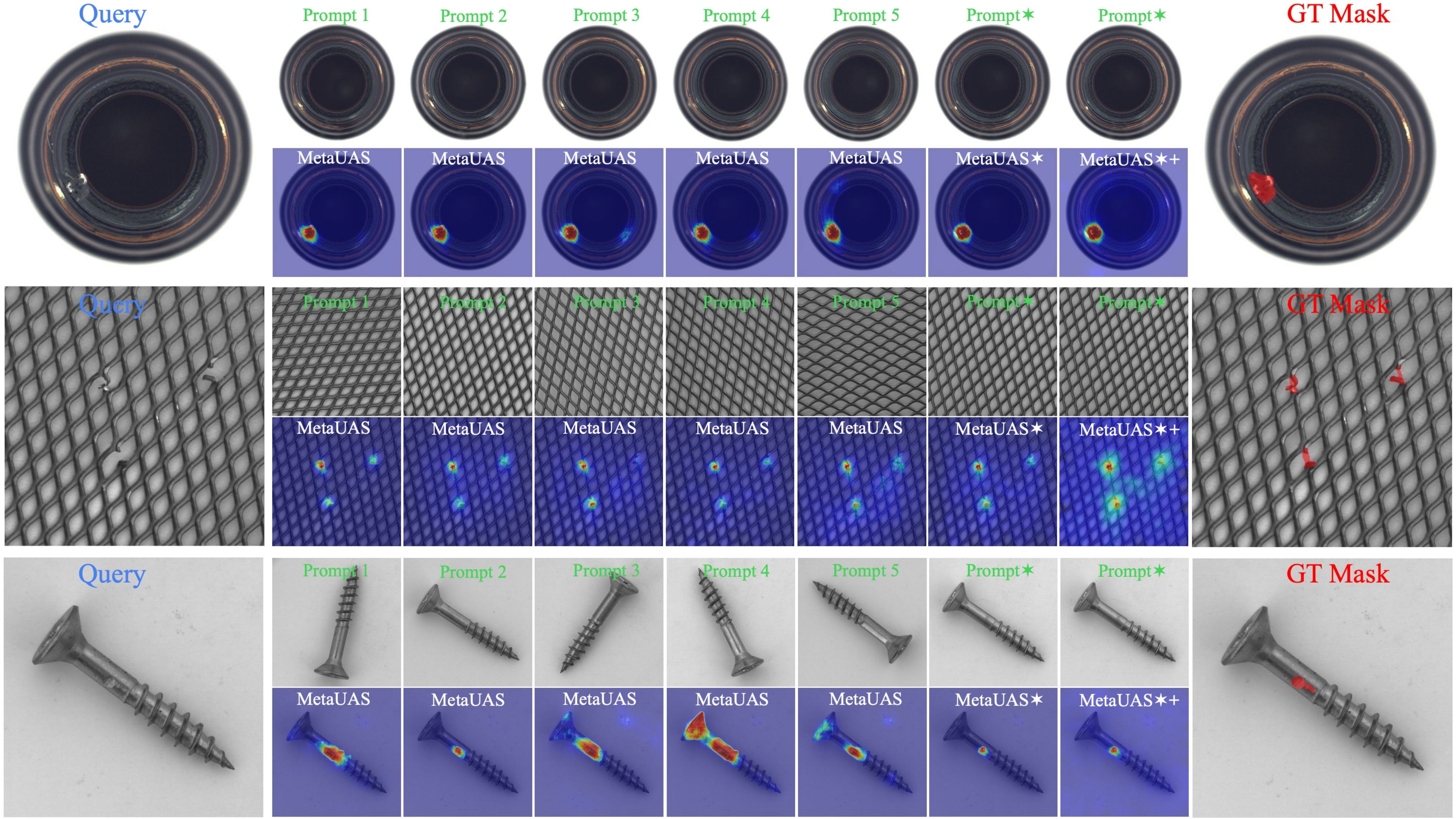
No.	ChangeType	Decoder	I-ROC	I-PR	P-ROC	P-PR	P-PRO
1	Only Loc.	UNet	83.1	92.8	87.7	44.3	76.1
2	Only Obj.	UNet	90.5	96.0	94.5	58.3	75.4
3	Obj.+Loc.	UNet	**91.3**	**96.2**	**94.6**	**59.6**	**82.6**
4	Obj.+Loc.	FPN-Cat	86.9	86.9	91.6	49.9	76.7
5	Obj.+Loc.	FPN-Add	88.4	94.7	94.1	51.4	73.1

(d) Effects of the number of training samples.

No.	#Samples	I-ROC	I-PR	P-ROC	P-PR	P-PRO
1	10%	82.0	91.9	85.4	36.5	62.1
2	30%	87.4	93.6	89.1	50.6	73.8
3	50%	91.0	96.2	92.9	57.1	74.3
4	70%	91.1	**96.4**	94.5	57.0	78.3
5	95%	**91.3**	96.2	**94.6**	**59.6**	**82.6**

Experiments

Ablation Studies



Conclusions

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- ✓ We present a novel paradigm that unifies anomaly segmentation into change segmentation. This paradigm enables us to leverage large-scale synthetic image pairs, thereby overcoming the long-standing challenge of lacking large-scale anomaly segmentation datasets.
- ✓ We propose a one-prompt meta-learning framework training on synthesized images and generalizing well on real-world scenarios. To handle geometrical variations between prompt and query mages, we proposed a soft feature alignment module that builds a bridge between paired-image change perception and singe-image semantic segmentation.
- ✓ We provide a pure visual foundation model for universal anomaly segmentation that can serve as an alternative to widely used vision-language models. Our method, which requires only a single normal image prompt and no additional training, effectively and efficiently segments any visual anomalies.

Thanks!

MetaUAs Code