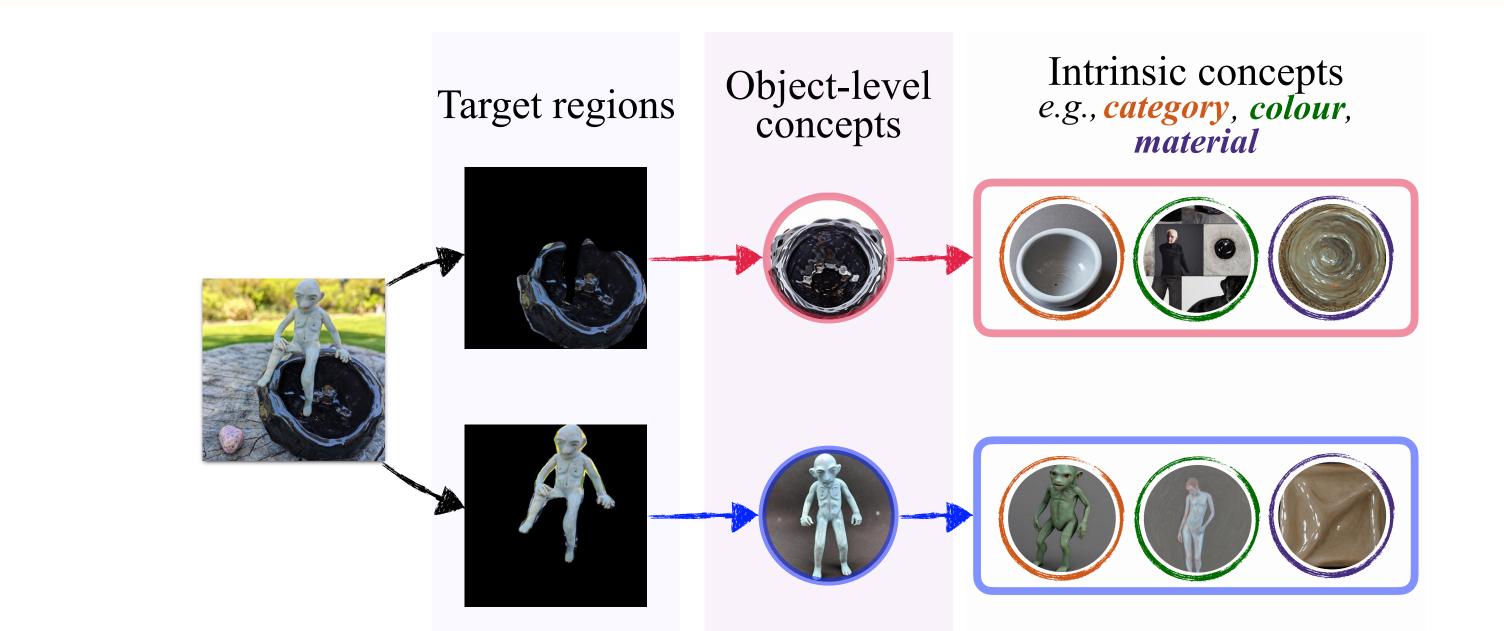


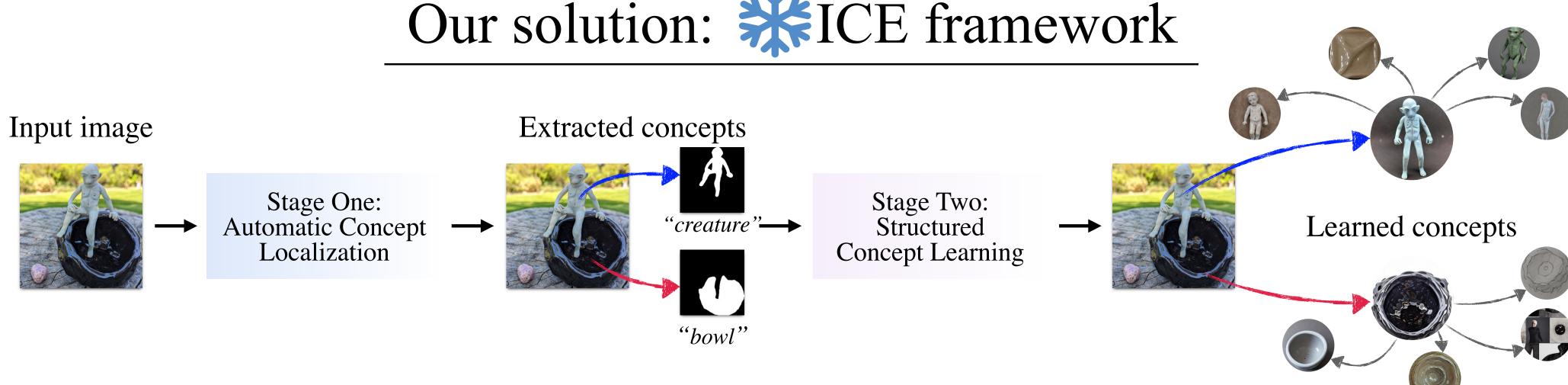


Intrinsic Concept Extraction (ICE)

Intrinsic Concept Extraction aims at extracting object-level concepts and the underlying intrinsic attributes such as semantic category, colour, and material. Intrinsic Concept Extraction provides a detailed and interpretable representation of visual elements, enabling a structured and comprehensive understanding of the image's components, allowing for versatile downstream generative applications.



Our solution: **X**ICE framework



Our proposed framework, ICE, offers a unified and structured approach to automatically and systematically discover intrinsic concepts within an image using a single T2I model.

The proposed ICE framework operates through a two-stage architecture:

- Stage One: Automatic Concept Localization, a training-free method utilizing a single T2I Diffusion Model.
- Stage Two: Structured Concept Learning, which learns concepts by finetuning the T2I Diffusion Model.

Comparison of ICE and relevant works.						
	Learr	ned concept(Framework details			
Method	Object-level concepts	Intrinsic concepts	Multi concepts	Single image	Extra information	
Textual Inversion [9]	V	×	×	×	_	
Dreambooth [28]	~	×	×	×	_	
Inspiration Tree [34]	×	/	×	×	_	
LangInt [17]	~	~	×	1	VQA-guided	
Break-A-Scene [1]	✓	×	✓	~	Mask	
MCPL [15]	✓	×	1	✓	Text	
ConceptExpress [11]	✓	×	✓	1	-	
ICE (Ours)	✓	✓	√	1	-	

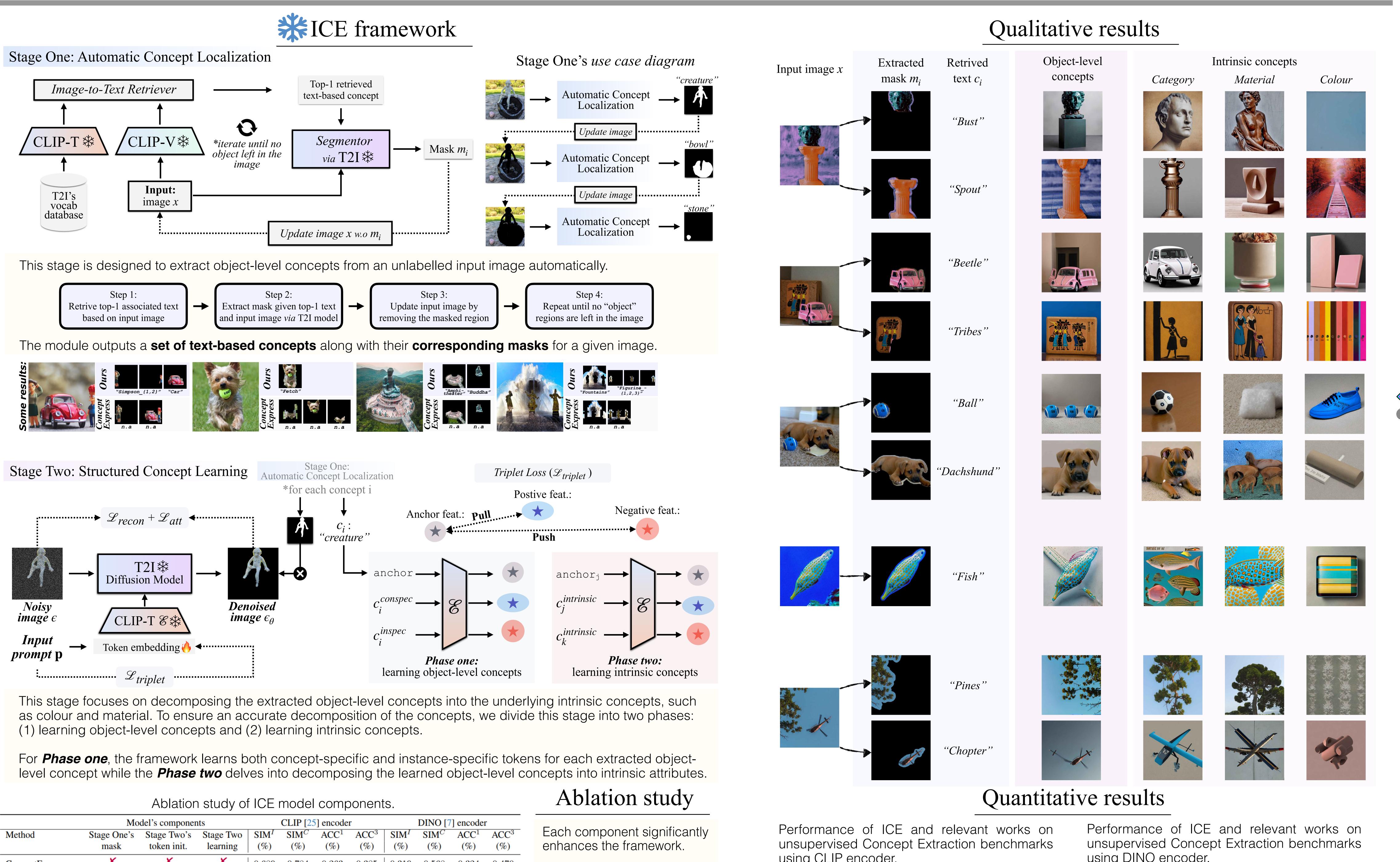
Comparison & positioning of KICE

- **O Unified framework:** ICE automatically discovers visual concepts using a single T2I model in an unsupervised manner.
- Structured concept learning: Deconstructing an image by identifying object-level concepts and further breaks down them into intrinsic attributes such as colour and material.

This solution allows for a more granular and interpretable breakdown of visual elements which leads to better personalized image generation and concept extraction.

***ICE**: Intrinsic Concept Extraction from a Single Image via Diffusion Models Fernando Julio Cendra Kai Han Visual AI Lab, The University of Hong Kong





	Model's components			CLIP [25] encoder			DINO [7] encoder				
Method	Stage One's	Stage Two's	Stage Two	SIM ^I	SIM^C	ACC^1	ACC^3	SIM ^I	SIM^C	ACC ¹	ACC^3
	mask	token init.	learning	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
ConceptExpress	×	×	×	0.689	0.784	0.263	0.385	0.319	0.568	0.324	0.470
ICE w. mask	✓	×	×	0.710	0.781	0.307	0.456	0.493	0.601	0.395	0.604
ICE w.o Stage Two	✓	✓	×	0.726	0.807	0.301	0.452	0.501	0.621	0.411	0.604
ICE w.o text init.	~	×	~	0.722	0.814	0.320	0.475	0.548	0.643	0.449	0.627
ICE (Ours)	✓	✓	1	0.738	0.822	0.325	0.518	0.677	0.755	0.476	0.638
						•					

The complete ICE framework outperforms all it's variants.

Performance of ICE and relevant works on unsupervised Concept Extraction benchmarks using CLIP encoder.							
Method	SIM^{I} (%)	SIM^C (%)	ACC ¹ (%)	ACC ³ (%)			
Break-A-Scene [1] ConceptExpress[11]	$0.627 \\ 0.689$	$0.773 \\ 0.784$	$\begin{array}{c} 0.174 \\ 0.263 \end{array}$	$\begin{array}{c} 0.282 \\ 0.385 \end{array}$			
ICE (Ours)	0.738	0.822	0.325	0.518			



using DINO encoder.

Method	SIM ^I (%)	SIM^C (%)	ACC ¹ (%)	ACC^{3} (%)
Break-A-Scene [1] ConceptExpress [11]	$\begin{array}{c} 0.254 \\ 0.319 \end{array}$	$\begin{array}{c} 0.510 \\ 0.568 \end{array}$	$\begin{array}{c} 0.202 \\ 0.324 \end{array}$	$\begin{array}{c} 0.315\\ 0.470\end{array}$
ICE (Ours)	0.677	0.755	0.476	0.638