Scenethesis: Structure-Based XR Scene Synthesis

LYU2406

Supervisor: Professor Michael R. Lyu

Presenter: LAM Yiu Fung Anson



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Outline

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- 2. Motivation
- 3. Methodology
- 4. Demo
- 5. Experiments
- 6. Conclusion
- 7. Future Work

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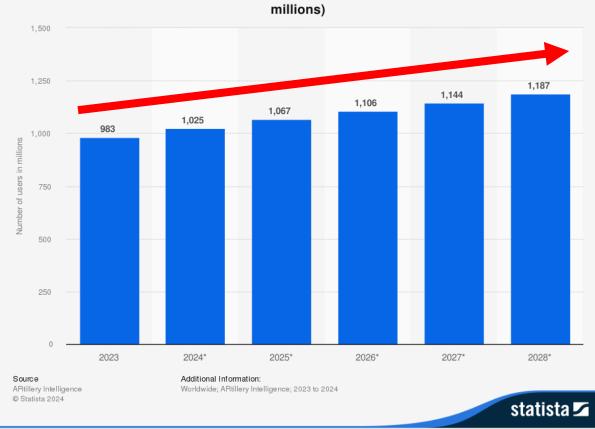
Background

Extended Reality (XR)			
Virtual Reality (VR)	Augmented Reality (AR)	Mixed Reality (MR)	
Brings users to a <u>fully</u> simulated and isolated world	Combines the real and virtual worlds by <u>overlaying</u> digital content onto a dedicated device	Similar to AR, but things happening in the physical world can <u>affect</u> the virtual world	
Virtual Reality	Augmented Reality	Hixed Reality	

Video source: The differences between AR, VR & MR (<u>https://www.youtube.com/watch?v=IFgGzOpjlUM</u>)

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Background



Mobile augmented reality (AR) users worldwide from 2023 to 2028 (in

Motivation

Software testing		
Non-XR software	XR (AR and MR) software	
 Use DFS to go through every function Perform unit tests automatically 	 Design and construct various physical environments Test all functions within each environment Analyze the recordings manually to check for guideline violation 	
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Can we also automate XR testing?		

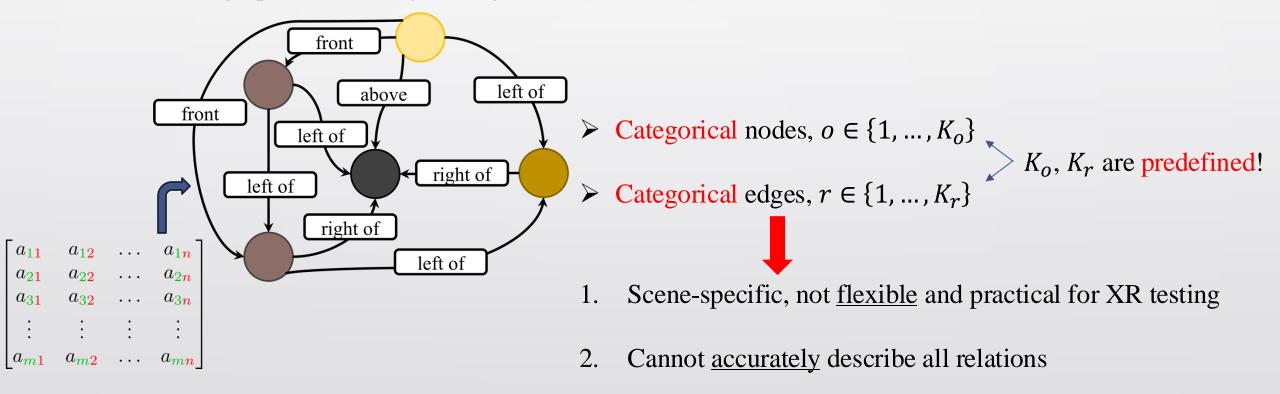
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Motivation (by comparing related work)

Non-playable scene	Playable scene
A unified mesh \rightarrow not physically correct	Interactable with individual objects
Text2Room, ICCV 2023	InstructScene, ICCV 2024
BlockFusion, SIGGRAPH 2024	Holodeck, CVPR 2024

Motivation (by comparing related work)

• Scene graph: node as object, edge as relation



Motivation (by comparing related work)

We need a structure that is:

- 1. Human-understandable: for explainability and modifiability
- 2. Unambiguous: all (physically) possible relations in a scene can be modeled
- 3. Flexible: able to generate a diverse set of scenes

Methodology-ScenethesisLang

- Domain-specific language (DSL)
- Describes diverse, realistic, and physically plausible 3D scenes
- Focuses on expressiveness, human-readability, generative capability, and physical plausibility

Methodology – ScenethesisLang

 $scene \in Scenes ::= SceneType: scene_type;$

SceneDescription: *scene_description*;

Regions: *regions*;

Connections: connections;

Constraints: constraints;

ProbabilisticParameters: *probabilistic_parameters*;

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TemporalRequirements: temporal_requirements

Methodology – ScenethesisLang

- Scene type: overall nature of the environment (indoor/outdoor)
- Scene description: textual description of the scene

	SceneType: scene_type;
	SceneDescription: scene_description;
	Regions: regions;
	Connections: connections;
	Constraints: constraints;
	ProbabilisticParameters: probabilistic_parameters;
1	TemporalRequirements: temporal_requirements

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SceneType: scene type;

Connections: connections;

Constraints: constraints;

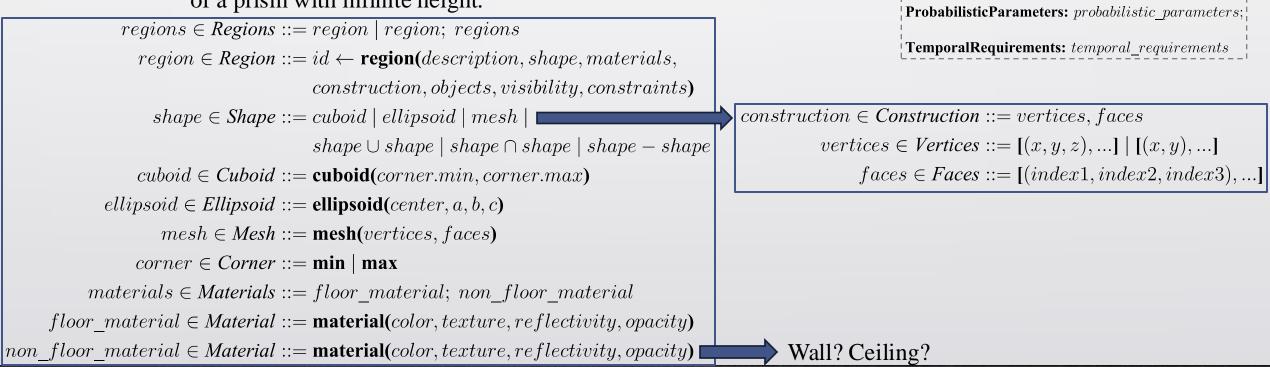
Regions: regions;

SceneDescription: *scene description*;

Methodology – ScenethesisLang

- Region: spatial subdivision within a scene (e.g., room, outdoor area)
 - An outdoor area is defined as the bottom shape (from bird's-eye view)

of a prism with infinite height.



Methodology – ScenethesisLang

• Object: entity within a region

 $objects \in Objects ::= object \mid object; objects$ $object \in Object ::= id \leftarrow object(category, description, dimensions,$ position, rotation, bounding box, probabilistic properties, visibility) $category \in Categories ::= text$ $description \in ObjectDescription ::= text$ *dimensions* ∈ *Dimensions* ::= (length, width, height) $position \in Position ::= (x, y, z) | offset(position, vector) |$ relativeTo(reference) *rotation* ∈ *Rotation* ::= (roll, pitch, yaw) | relativeTo(reference) bounding $box \in BoundingBox ::= bounding box(min, max)$ $visibility \in Visibility ::= rayTrace(density, occlusion)$ **regionVisibility**(*region*, *conditions*)

SceneType: scene_type; SceneDescription: scene_description; Regions: regions; Connections: connections; Constraints: constraints; ProbabilisticParameters: probabilistic_parameters; TemporalRequirements: temporal_requirements

Methodology-ScenethesisLang

• Object: entity within a region

 $lights \in Lights ::= light \mid light; \ lights$

 $light \in Light ::= id \leftarrow light(category, description, intensity, position, visibility)$

 $intensity \in Intensity ::= float | distribution$

	SceneType: scene_type;
	SceneDescription: <i>scene_description</i> ;
	Regions: regions;
_	Connections: connections;
	Constraints: constraints;
)	ProbabilisticParameters: probabilistic_parameters;
	TemporalRequirements: temporal_requirements

Methodology-ScenethesisLang

• Connection: spatial relationship between two regions

 $connections \in Connections ::= connection | connection; connections$ $connection \in Connection ::= connection(region1, region2, type,$ description)

	SceneType: scene_type;
	SceneDescription: scene_description;
]	Regions: regions;
	Connections: connections;
	Constraints: constraints;
1	ProbabilisticParameters: probabilistic_parameters;
	FemporalRequirements: temporal_requirements

Methodology – ScenethesisLang

• Constraint: requirement that ensures physical plausibility or reasonableness, or that meets user-defined specifications

 $constraints \in Constraints ::= constraint | constraint; constraints \\ constraint \in Constraint ::= spatial_condition | probabilistic_condition | \\ temporal_condition | object_relation | \\ visibility_condition | physical_constraint | \\ user_defined(logic, priority)$

$spatial_condition \in SpatialCondition ::= inside(region) outside(region) $
above(object, height)
below(object, height)
nearby(object, distance)
alignedWith(object, axis)
tangentTo(surface)
distanceBetween(object1, object2) == d

T - - -	SceneType: scene_type;	
sLang	SceneDescription: <i>scene_description</i> ;	
ausibility or fications	Regions: regions;	
	Connections: connections;	
	Constraints: constraints;	
	ProbabilisticParameters: probabilistic_parameters;	
	TemporalRequirements: temporal_requirements	
$visibility_condition \in Visibil$	ityCondition ::= canSee(observer, target)	
	occludes(object1, object2)	

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 occludes(object1, object2) |

 visibleInRegion(observer, region) |

 rayTraceValid(observer, target, density)

 physical_constraint ∈ PhysicalConstraint ::= noCollision(object1, object2) |

 collisionFreeRegion(region) |

 stablePosition(object) |

 gravityAligned(object)

 $user_defined \in UserDefinedConstraint ::= customLogic(logicExpression, priority)$

object_relation ∈ ObjectRelation ::= relation(object1, object2, relation_type) relation_type ∈ RelationTypes ::= above | below | inside |outside | nearby | aligned | occludes | intersects

Methodology – ScenethesisLang

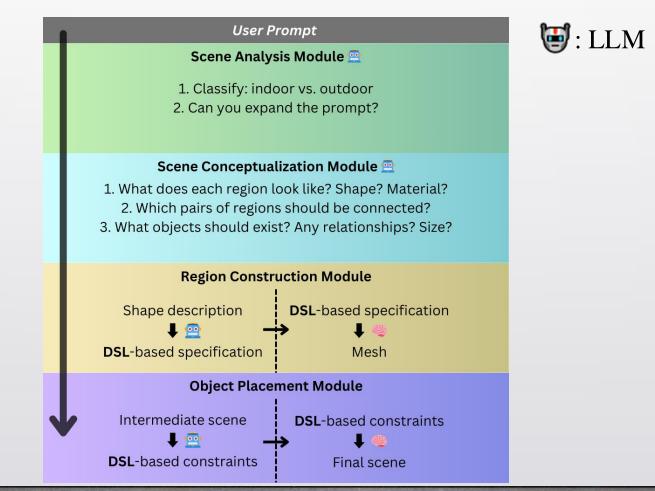
• Probabilistic parameter: ranges or distributions for attributes such as object positions

 $probabilistic_condition \in ProbabilisticCondition ::=$

probability(p): condition | distributionBased(object, param: distribution)

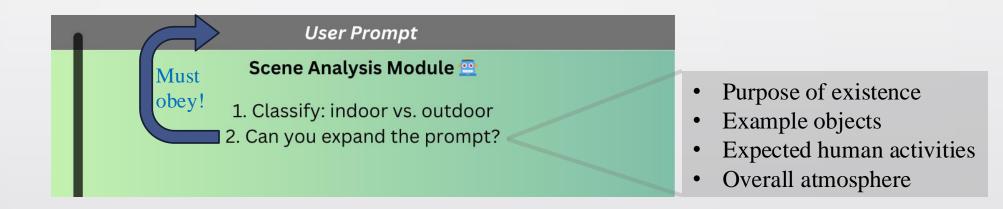
SceneType: scene_type;
SceneDescription: <i>scene_description</i> ;
Regions: regions;
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Methodology – Scenethesis



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• Scene Analysis Module: enhances the overall understanding of the desired scene

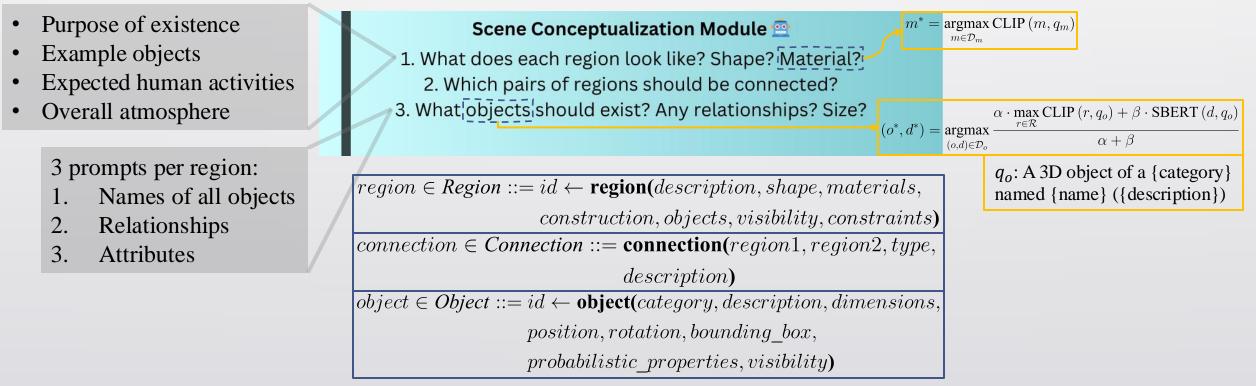


 $scene \in Scenes ::= SceneType: scene_type;$

SceneDescription: *scene_description*;

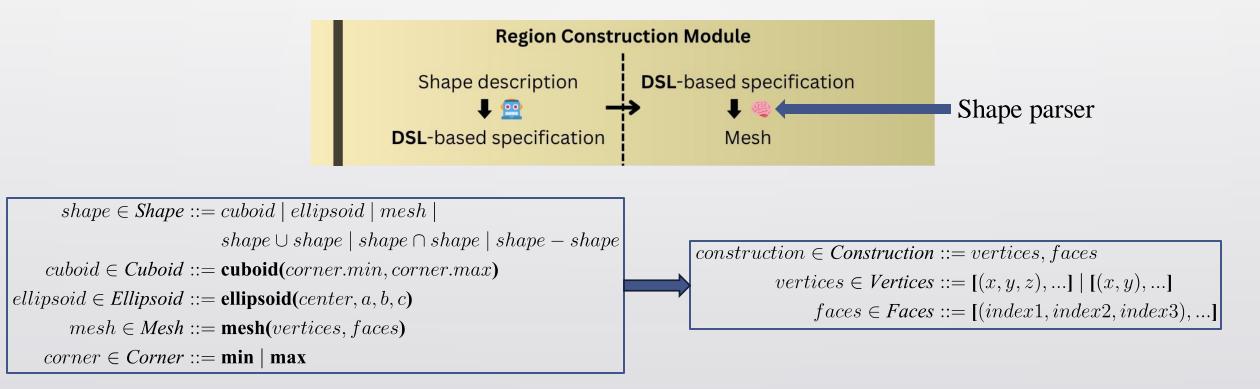
Methodology – Scenethesis

- Scene Conceptualization Module: creates a semantic draft of the desired scene
 - Semantic: only <u>text</u> is outputted



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• Region Construction Module: constructs the actual boundaries of each region



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• Object Placement Module: places selected objects to their optimal position with optimal orientation



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Demo

User prompt: "A bedroom connected to a living room"

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Experiments – Implementation

- Materials and objects are from Holodeck
- $\alpha = 100, \beta = 1$
- LLM: gpt-40-2024-08-06
- Temperature: 0
- Machine: MacBook Pro (M1 Pro CPU, 16 GB RAM)
 - Mean execution time (before launching Blender and Unity): 2.5 minutes

Wireframe rendering *r*:

Pitch $\in \{0, 30, 45, 60, 90\}$

 $Yaw \in \{0, 15, \dots, 330, 345\}$

Experiments – Evaluation Metrics

- Quantitative:
 - Score_{CLIP} $(r,q) = (CLIP(r,q) + 1) \times 50$
 - q_1 : "an image of a vibrant indoor scene"
 - q_2 : user prompt
 - q_3 : generated scene description
 - Score_{SBERT} $(d, p) = (SBERT(d, p) + 1) \times 50$
 - *d* is the scene description, *p* is the user prompt

Experiments – Evaluation Metrics

- Qualitative:
 - We give the bird's-eye view to GPT-40 and ask:
 - 1. Does the generated scene contain every region mentioned in the prompt?
 - 2. Does the generated scene contain every object mentioned in the prompt?



- 3. Is the generated scene physically plausible (e.g., are there any objects colliding with region boundaries or other objects)?
- 4. Is the generated scene visually pleasing?
- Then rate from 1 to 10 with explanation

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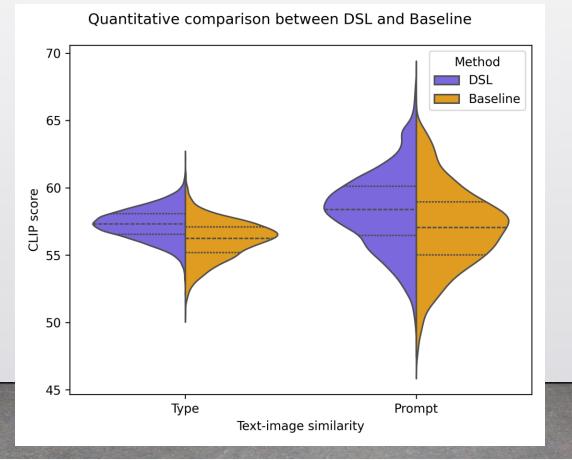
Experiments – Results

- 1. Comparing with baseline
 - Baseline: Non-DSL injected to obtain a minimal output
 - 50 generated prompts, 3 trials per prompt

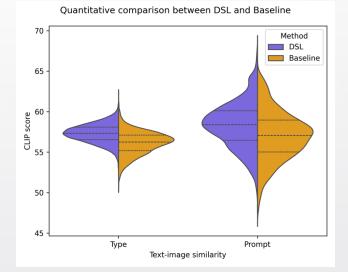
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Experiments – Results

- 1. Comparing with baseline
 - Quantitative results:



- 1. Comparing with baseline
 - Quantitative results:
 - Small differences in CLIP scores
 - BUT! CLIP models were trained with real-life images, many of which have a main subject
 - Insensitiveness + small differences \rightarrow Perhaps significant



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Experiments – Results

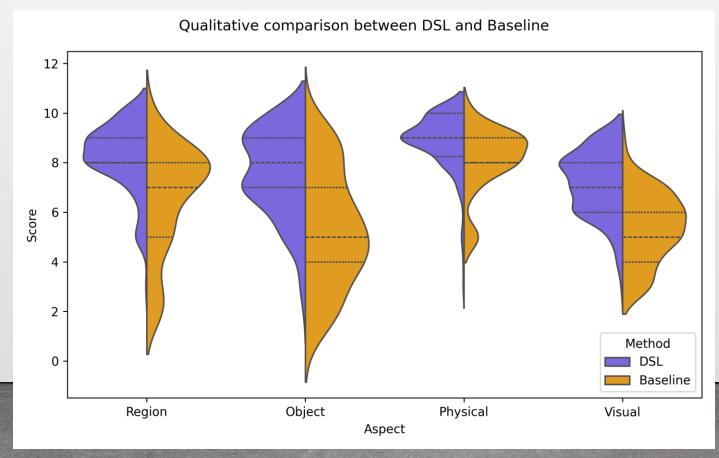
- 1. Comparing with baseline
 - Quantitative results:
 - Scenethesis generate significantly more objects \rightarrow Vibrant and realistic

	Average # of regions	Average # of objects
Scenethesis	1.36	20.973
Baseline	1.35	3.63

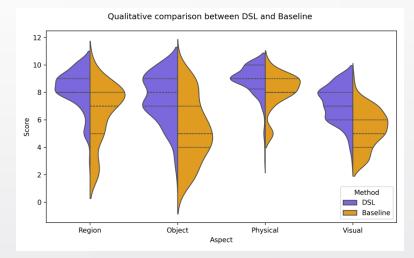
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Experiments – Results

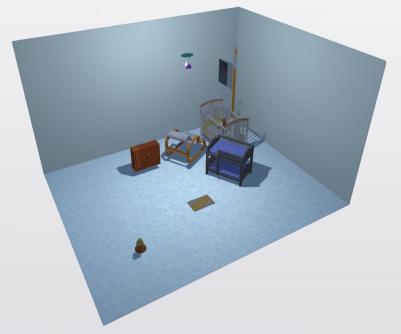
- Comparing with baseline 1.
 - Qualitative results:



- 1. Comparing with baseline
 - Qualitative results:
 - Similar scores for "region" and "physical"
 - Scenethesis performs better in general
 - Significant performance gaps for "object" and "visual"
 - An evidence that Scenethesis can better follow user's requirements while still producing visually pleasing scenes



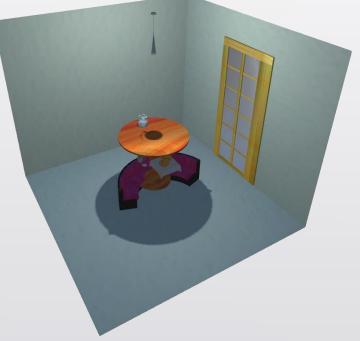
- 1. Comparing with baseline
 - Examples (left is Scenethesis, right is baseline):

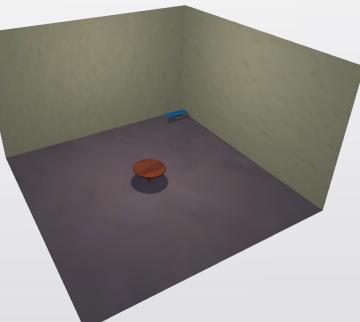




"A colorful nursery with a crib, rocking chair, and playful decor."

- 1. Comparing with baseline
 - Examples (left is Scenethesis, right is baseline):





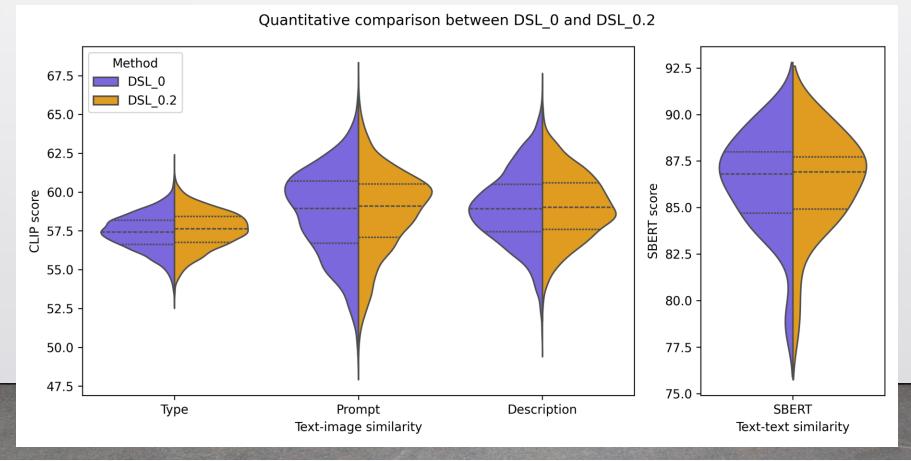
"A quaint breakfast nook with a round table and cushioned bench seating."

36 **Experiments**

- Comparing different temperatures 2.
 - $t \in \{0, 0.2, 0.5\}$
 - 20 generated prompts, 2 trials per prompt

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- 2. Comparing different temperatures
 - Quantitative results: 0 vs 0.2

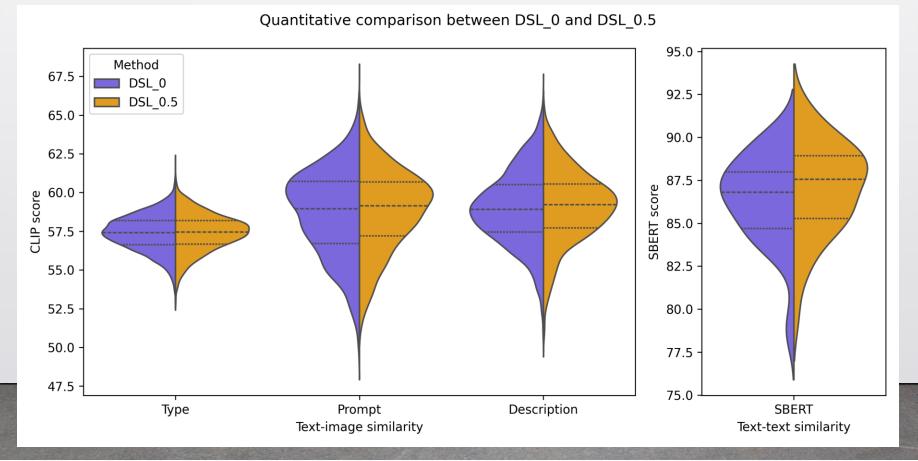


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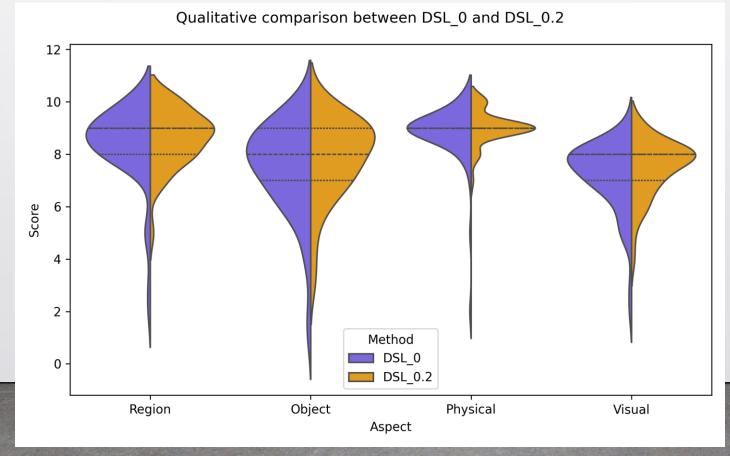
38 **Experiments**

- Comparing different temperatures 2.
 - Quantitative results: 0 vs 0.5



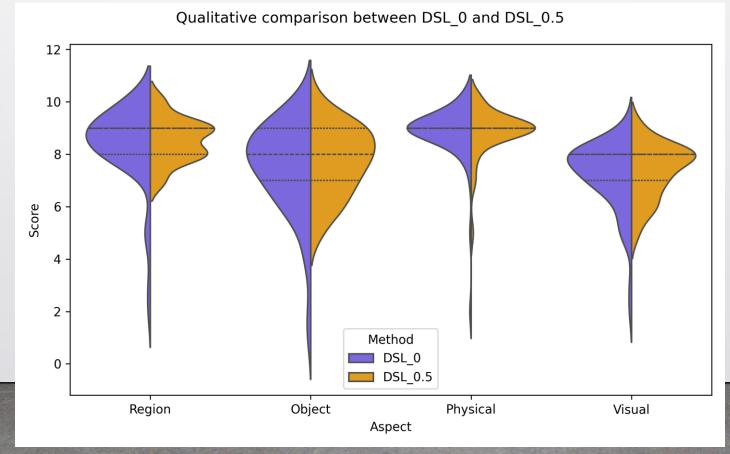
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- 2. Comparing different temperatures
 - Qualitative results: 0 vs 0.2



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- 2. Comparing different temperatures
 - Qualitative results: 0 vs 0.5



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- 2. Comparing different temperatures
 - Subjective visual difference is not significant
 - So, temperature is not a major factor on the performance of Scenethesis

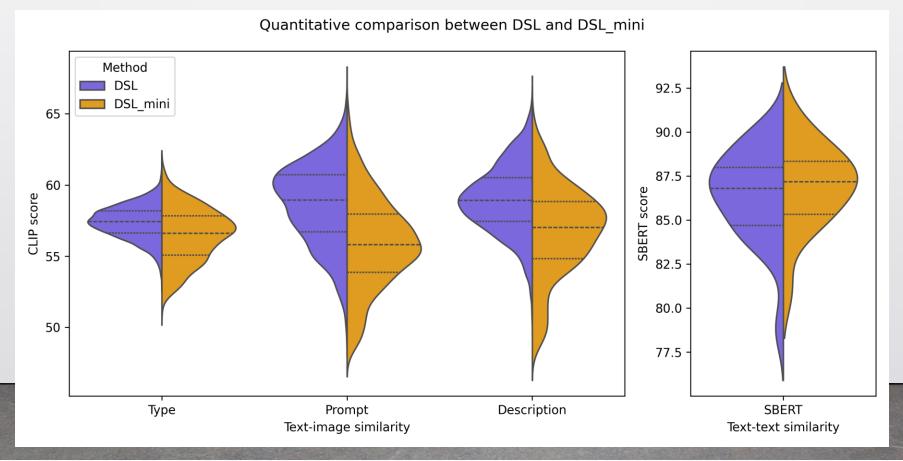
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- 3. Comparing different LLMs
 - Model: gpt-4o-2024-08-06, gpt-4o-mini-2024-07-18, claude-3-5-sonnet-20241022
 - 20 generated prompts (same as before), 2 trials per prompt

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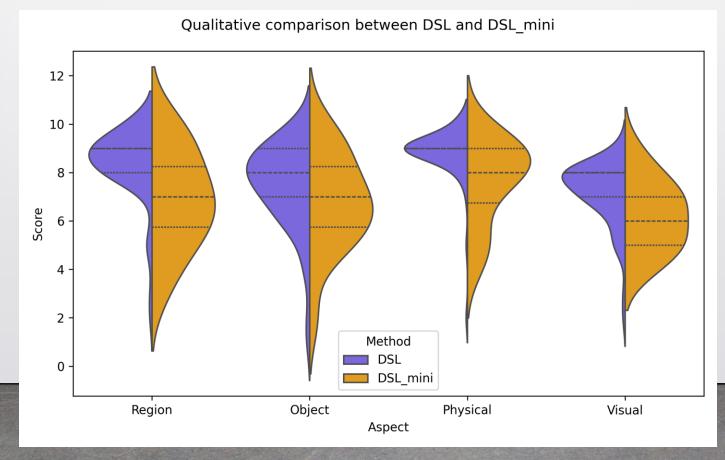
43 **Experiments**

- Comparing different LLMs 3.
 - Quantitative results: gpt-4o-mini-2024-07-18



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- 3. Comparing different LLMs
 - Qualitative results: gpt-4o-mini-2024-07-18

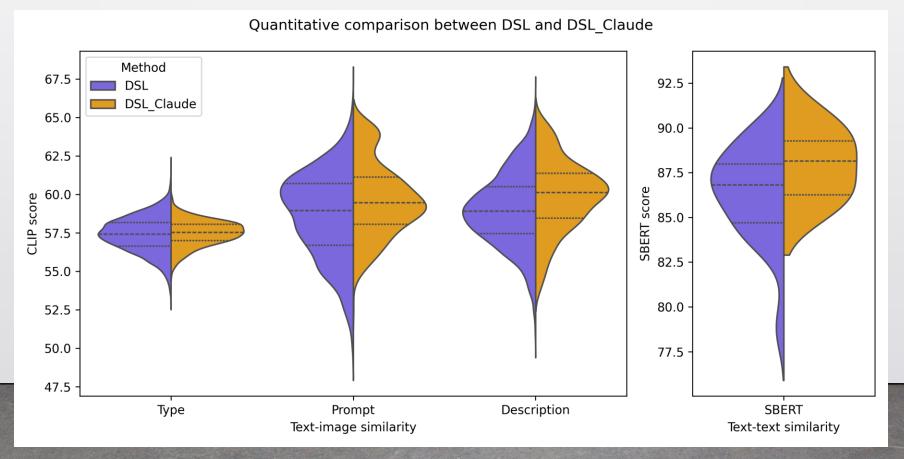


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- 3. Comparing different LLMs
 - As expected, larger models with better processing and generative capabilities work better

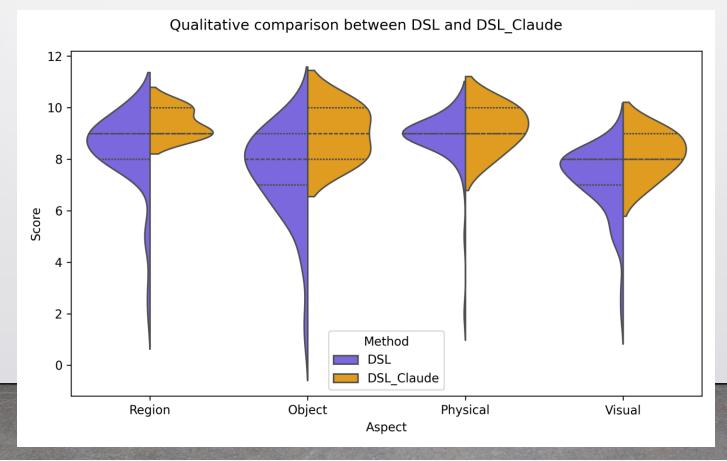
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- 3. Comparing different LLMs
 - Quantitative results: claude-3-5-sonnet-20241022 (only 5 scenes could be generated)



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- 3. Comparing different LLMs
 - Qualitative results: claude-3-5-sonnet-20241022 (only 5 scenes could be generated)



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- 3. Comparing different LLMs
 - An inspiration: models that are better at writing → better scene description → better scene

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Conclusion

We propose:

- 1. ScenethesisLang, a novel domain-specific language designed for unambiguously describing a 3D scene; and
- 2. Scenethesis, a pipeline that takes a user prompt and generates a corresponding 3D scene using ScenethesisLang.

Experiments have demonstrated the potential of Scenethesis in generating vibrant and visually pleasing scenes.

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- 1. Reduce reliance on LLM
 - LLMs may not be able to handle numerical tasks accurately
 - Constraint solving is a highly complex task
 - Explore different shape parsers and constraint solvers
 - \rightarrow More realistic and physically plausible scene

LYU2406 51 Future Work

- 2. Employ object generation
 - Current curated database has only ~50K objects (~23 GB)
 - Original database has ~800K (~8 TB) \rightarrow impractical to keep enlarging the database
 - With object generation model that can synthesize new objects in real time:
 - If the weighted object score is lower than a certain threshold \rightarrow generate object
 - Acceptable to keep using a smaller database
 - No problem if the database does not have the target object

LYU2406 52 Future Work

- 3. Continue our journey on automatic XR testing
 - Scenethesis is just the first step in the final automated pipeline
 - With prompts tailor-made for specific target environments, we can generate a diverse set of environments
 - E.g., after figuring out how to make a smartphone recognize a virtual environment as a real one, we can freely test AR applications using our generated scenes
 - Then perhaps we can use a Vision Language Model to analyze key frames and produce an evaluation report

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Q&A