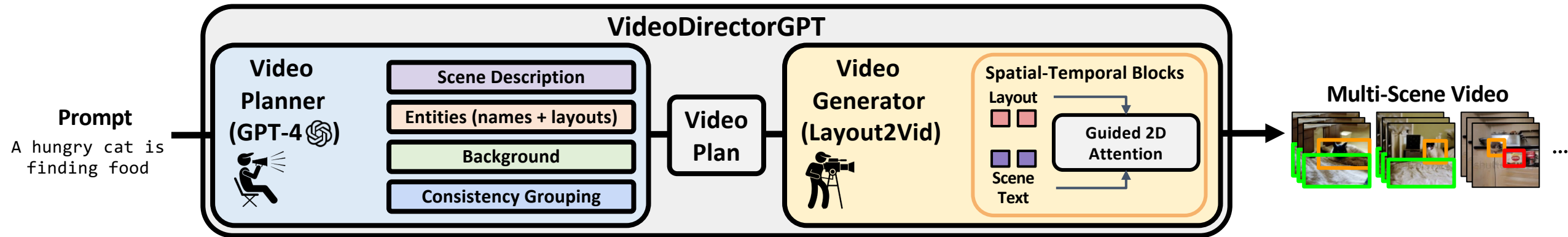


VideoDirectorGPT: Consistent Multi-Scene Video Generation via LLM-Guided Planning



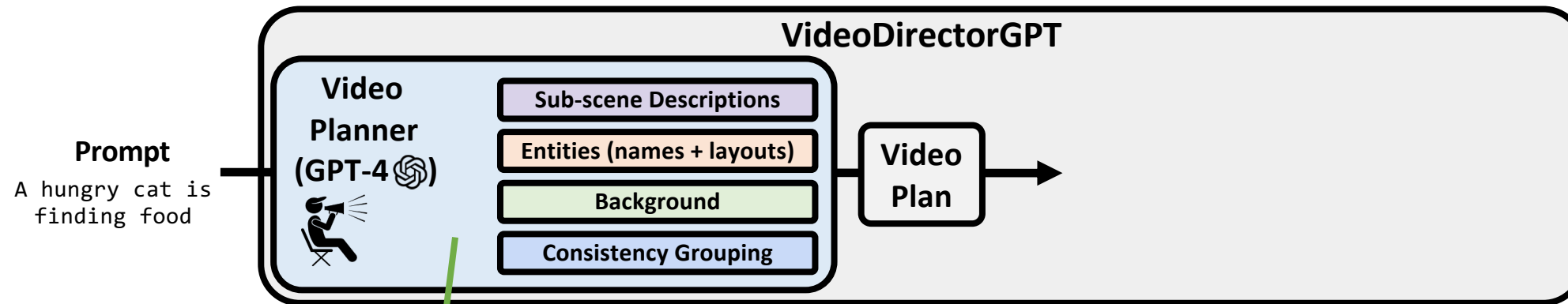
VideoDirectorGPT: Consistent Multi-Scene Video Generation via LLM-Guided Planning

Prompt

A hungry cat is
finding food

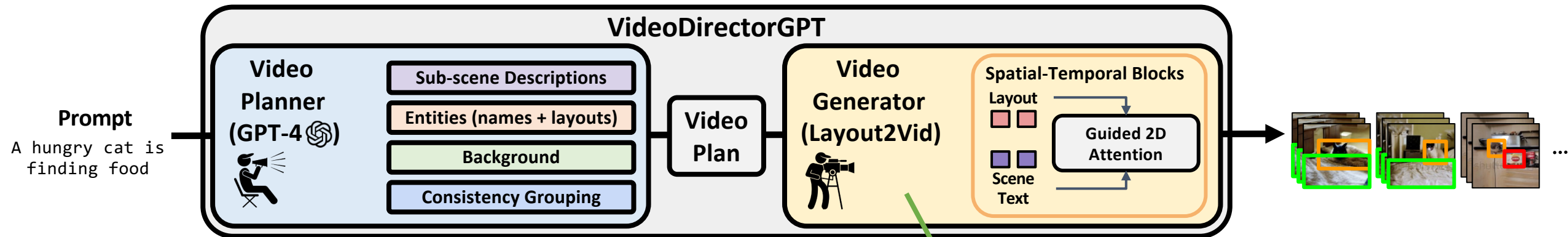
Single input text prompt

VideoDirectorGPT: Consistent Multi-Scene Video Generation via LLM-Guided Planning

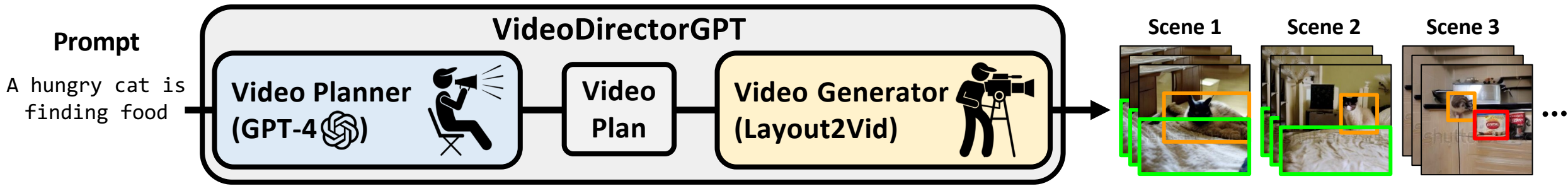


- An LLM (GPT-4) creates a **video plan**
 - Sub-scene descriptions
 - Entities (names + 2D bbox layouts)
 - Backgrounds
 - Consistency groupings.

VideoDirectorGPT: Consistent Multi-Scene Video Generation via LLM-Guided Planning

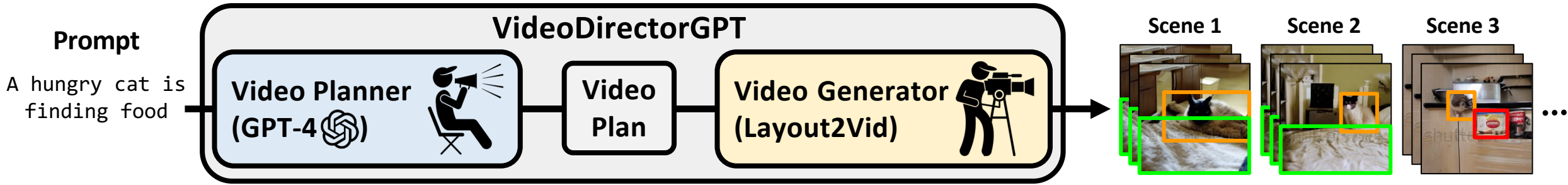


- Takes the **video plan**
- Generates the video
 - Follows the 2D bbox layouts
 - Maintains visual consistency



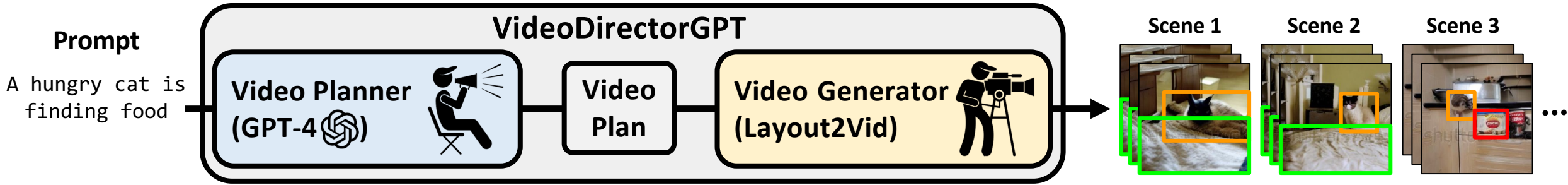
Video Planner (Icon: person with megaphone)

	Scene Description	Entities (names + layouts) with Consistency Grouping	Background
Scene 1	A cat is lying down on a bed	Frame 1: {'a fluffy Siamese cat': [0.25, 0.25, 1.00, 0.70], 'a plush beige bed': [0.00, 0.50, 1.00, 1.00]} Frame 2: {'a fluffy Siamese cat': [0.25, 0.25, 1.00, 0.70], 'a plush beige bed': [0.00, 0.50, 1.00, 1.00]} ...	Bedroom
Scene 2			
Scene 3			

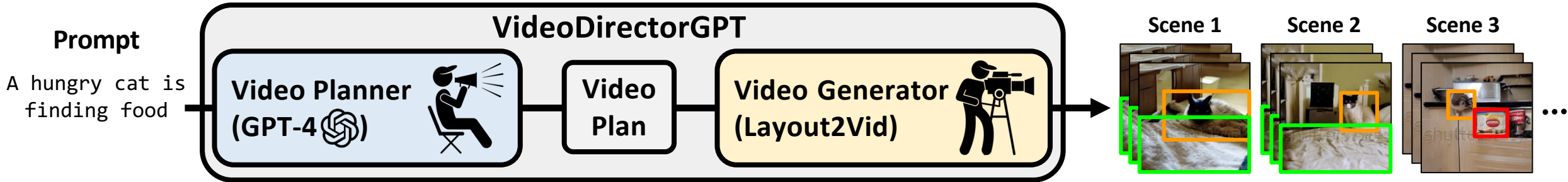


Video Planner

	Scene Description	Entities (names + layouts) with Consistency Grouping	Background
Scene 1	A cat is lying down on a bed	Frame 1: {'a fluffy Siamese cat': [0.25, 0.25, 1.00, 0.70], 'a plush beige bed': [0.00, 0.50, 1.00, 1.00]} Frame 2: {'a fluffy Siamese cat': [0.25, 0.25, 1.00, 0.70], 'a plush beige bed': [0.00, 0.50, 1.00, 1.00]} ...	Bedroom
Scene 2	Then she gets up	Frame 1: {'a fluffy Siamese cat': [0.55, 0.25, 0.85, 0.55], 'a plush beige bed': [0.00, 0.60, 1.00, 1.00]} Frame 2: {'a fluffy Siamese cat': [0.50, 0.30, 0.80, 0.60], 'a plush beige bed': [0.00, 0.60, 1.00, 1.00]} ...	Bedroom
Scene 3			

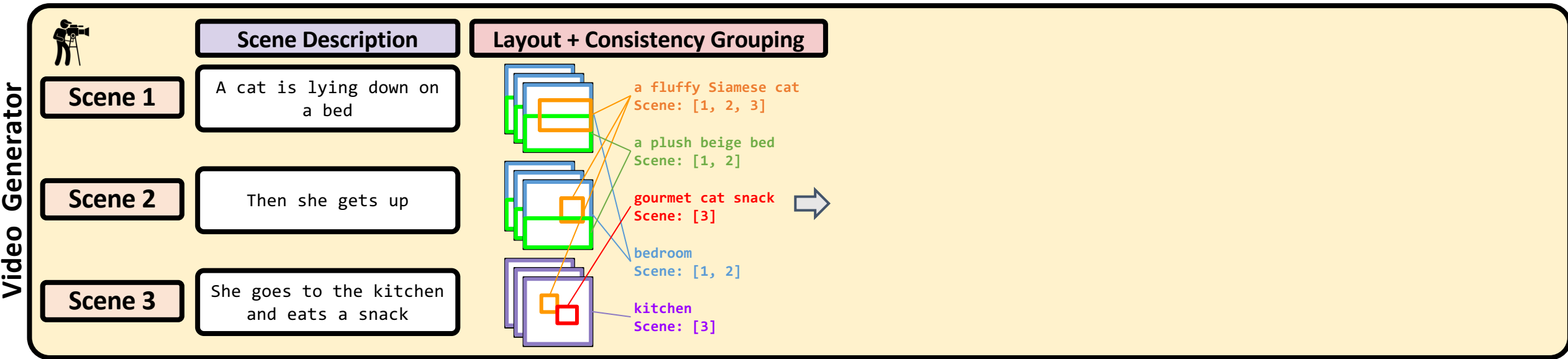


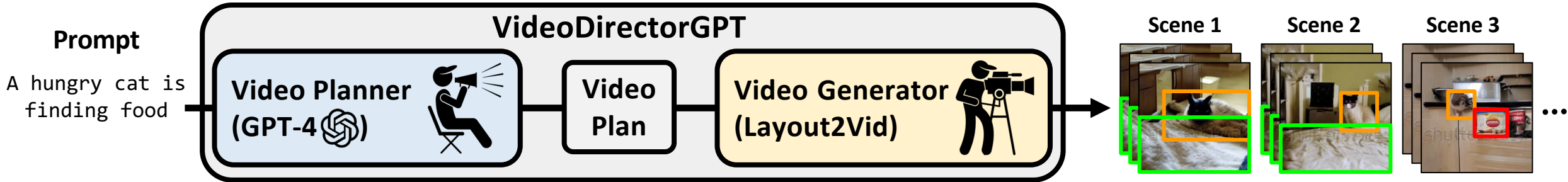
Video Planner	Scene Description	Entities (names + layouts) with Consistency Grouping	Background	
	Scene 1	A cat is lying down on a bed	Frame 1: {'a fluffy Siamese cat': [0.25, 0.25, 1.00, 0.70], 'a plush beige bed': [0.00, 0.50, 1.00, 1.00]} Frame 2: {'a fluffy Siamese cat': [0.25, 0.25, 1.00, 0.70], 'a plush beige bed': [0.00, 0.50, 1.00, 1.00]} ...	Bedroom
	Scene 2	Then she gets up	Frame 1: {'a fluffy Siamese cat': [0.55, 0.25, 0.85, 0.55], 'a plush beige bed': [0.00, 0.60, 1.00, 1.00]} Frame 2: {'a fluffy Siamese cat': [0.50, 0.30, 0.80, 0.60], 'a plush beige bed': [0.00, 0.60, 1.00, 1.00]} ...	Bedroom
	Scene 3	She goes to the kitchen and eats a snack	Frame 1: {'a fluffy Siamese cat': [0.15, 0.20, 0.40, 0.45], 'gourmet cat snack': [0.50, 0.45, 0.80, 0.65]} Frame 2: {'a fluffy Siamese cat': [0.35, 0.30, 0.60, 0.55], 'gourmet cat snack': [0.50, 0.45, 0.80, 0.65]} ...	Kitchen



Video Planner

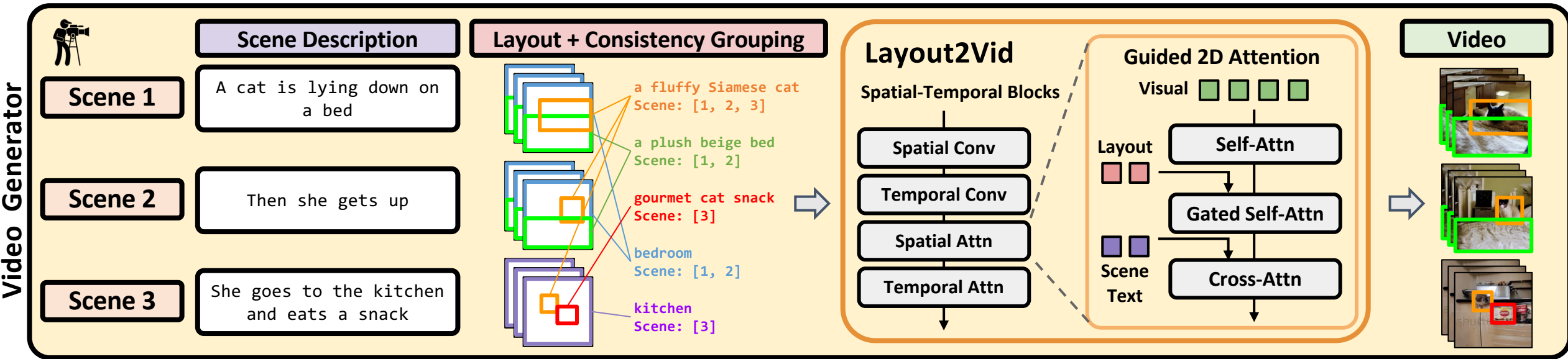
	Scene Description	Entities (names + layouts) with Consistency Grouping	Background
Scene 1	A cat is lying down on a bed	Frame 1: {'a fluffy Siamese cat': [0.25, 0.25, 1.00, 0.70], 'a plush beige bed': [0.00, 0.50, 1.00, 1.00]} Frame 2: {'a fluffy Siamese cat': [0.25, 0.25, 1.00, 0.70], 'a plush beige bed': [0.00, 0.50, 1.00, 1.00]} ...	Bedroom
Scene 2	Then she gets up	Frame 1: {'a fluffy Siamese cat': [0.55, 0.25, 0.85, 0.55], 'a plush beige bed': [0.00, 0.60, 1.00, 1.00]} Frame 2: {'a fluffy Siamese cat': [0.50, 0.30, 0.80, 0.60], 'a plush beige bed': [0.00, 0.60, 1.00, 1.00]} ...	Bedroom
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Video Planner

	Scene Description	Entities (names + layouts) with Consistency Grouping	Background
Scene 1	A cat is lying down on a bed	Frame 1: {'a fluffy Siamese cat': [0.25, 0.25, 1.00, 0.70], 'a plush beige bed': [0.00, 0.50, 1.00, 1.00]} Frame 2: {'a fluffy Siamese cat': [0.25, 0.25, 1.00, 0.70], 'a plush beige bed': [0.00, 0.50, 1.00, 1.00]} ...	Bedroom
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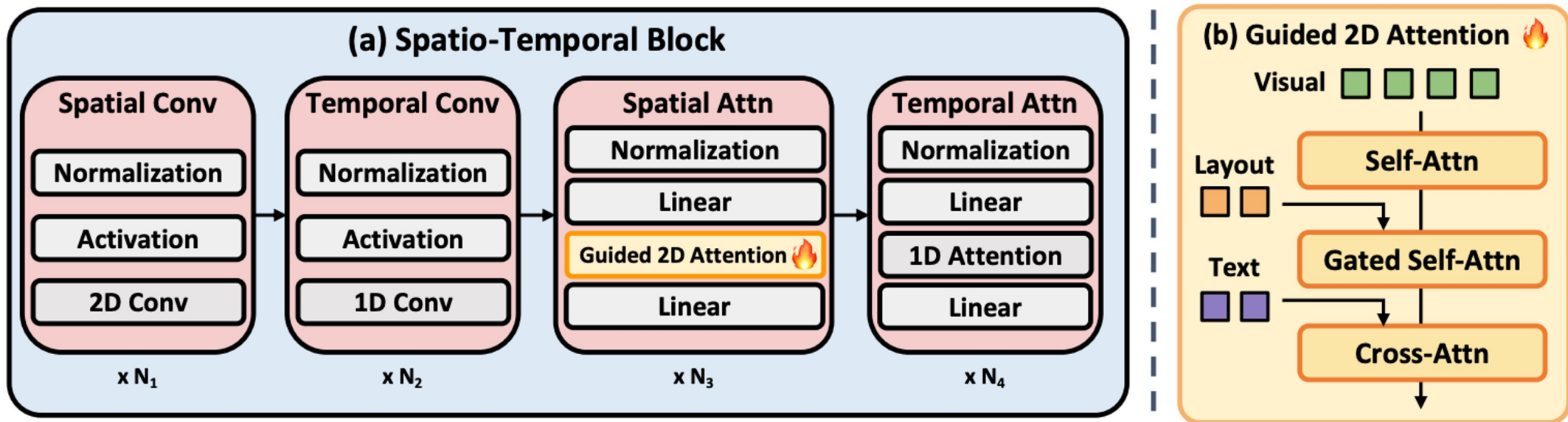
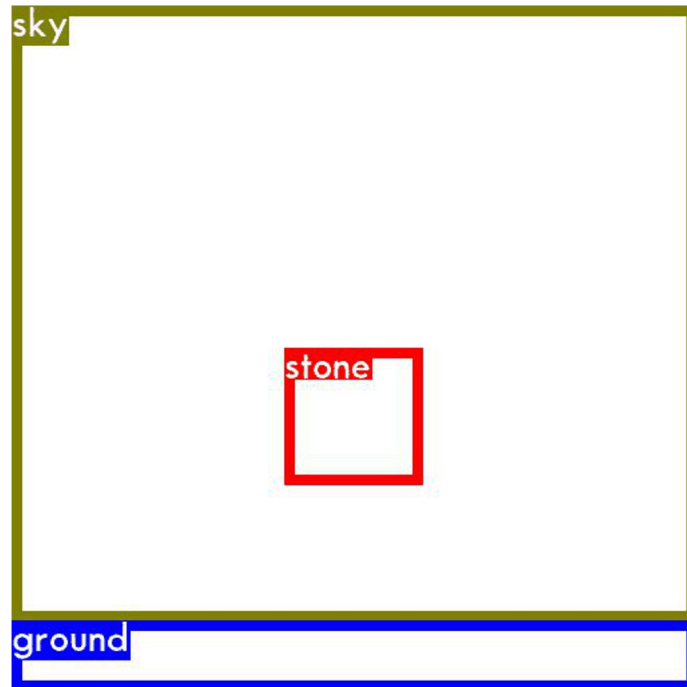


Figure 3: Overview of **(a) spatio-temporal blocks** within the diffusion UNet of our **Layout2Vid** and **(b) Guided 2D Attention** present in the spatial attention module. (a) The spatio-temporal block comprises four modules: spatial convolution, temporal convolution, spatial attention, and temporal attention. We adopt settings from ModelScopeT2V, where (N_1, N_2, N_3, N_4) are set to $(2, 4, 2, 2)$. In (b) Guided 2D Attention, we modulate the **visual representation** with **layout tokens** and **text tokens**. For efficient memory usage and training, only the parameters of the Guided 2D Attention (indicated by the fire symbol, constituting 13% of total parameters) are trained using image-level annotations. The remaining modules in the spatio-temporal block are kept frozen.

LLM's Understanding of Basic Physics

Gravity

A stone thrown into the sky



Perspective

A car is approaching from a distance



Object Movement

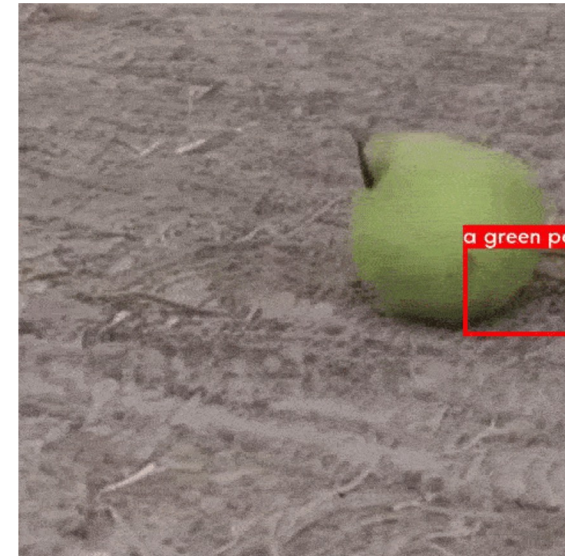
a **pear** moving from **right to left**

ModelScopeT2V



✗ fails to move the “pear”

VideoDirectorGPT (Ours)



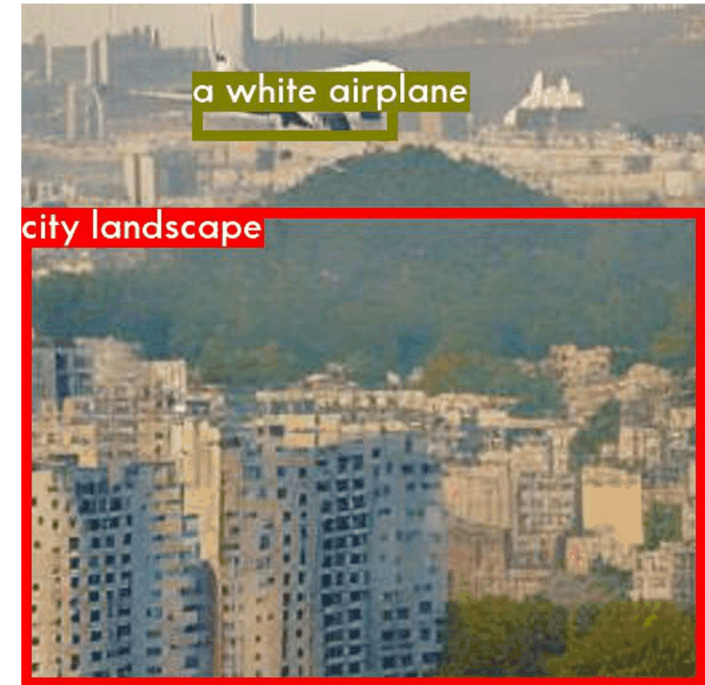
✓ correctly moves the the “pear”
from right to left

Movement of Static Objects vs. Objects that Moves

“A {**bottle/airplane**} moving from **left to right**.”



Static objects
-> Movements of Camera



Objects that can move
-> Movements of Object (+ Camera)

Multi-Sentence to Multi-Scene Video (Coref-SV)

Scene 1: **mouse** is holding a book and makes a happy face.

Scene 2: **he** looks happy and talks.

Scene 3: **he** is pulling petals off the flower.

Scene 4: **he** is ripping a petal from the flower.

Scene 5: **he** is holding a flower by **his** right paw.

Scene 6: one paw pulls the last petal off the flower.

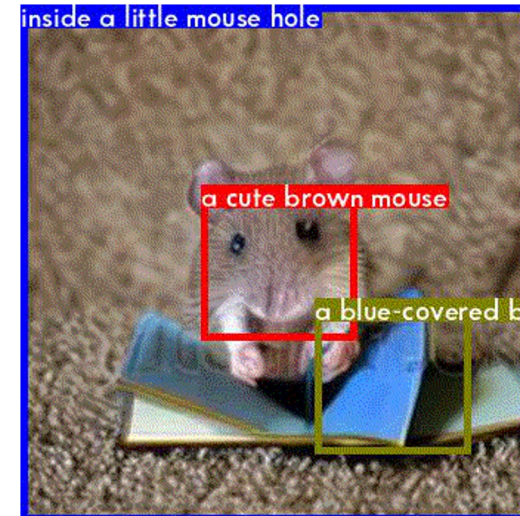
Scene 7: **he** is smiling and talking while holding a flower on **his** right paw.

ModelScopeT2V



✗ fails to keep “mouse”
through all scenes

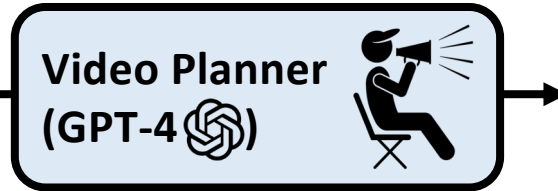
VideoDirectorGPT (Ours)



✓ the “mouse” looks consistent
through all scenes

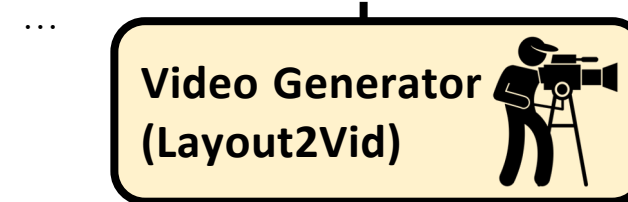
Multi-Scene Videos from a Single Sentence

make a strawberry surprise



Generated multi-scene prompts (total 10 scenes):

1. A bartender prepares the working area by cleaning and organizing.
2. The bartender rinses fresh strawberries under a tap.
3. The bartender cuts the strawberries and removes the stems.



ModelScopeT2V (baseline)



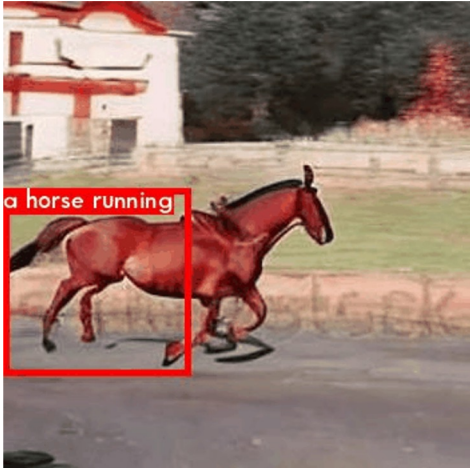
✗ no actual process shown on how to “make” the strawberry surprise dessert

VideoDirectorGPT (Ours)



✓ step-by-step process on how to “make” the strawberry surprise dessert

Human-in-the-Loop Video Editing (by modifying video plans)



Make the horse smaller



Add "grassland" background



Add "night street" background



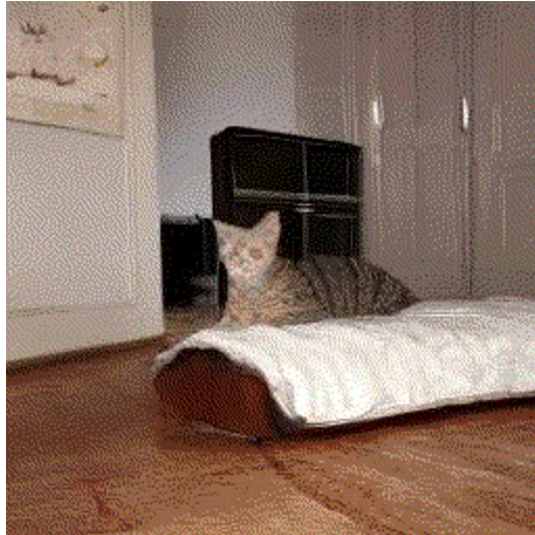
User-Provided Input Image → Video

Scene 1: a $\langle S \rangle$ then gets up from a plush beige bed.

Scene 2: a $\langle S \rangle$ goes to the cream-colored kitchen and eats a can of gourmet snack.

Scene 3: a $\langle S \rangle$ sits next to a large floor-to-ceiling window.

$\langle S \rangle$ = “cat”
+



$\langle S \rangle$ = “teddy bear”
+



Quantitative Evaluation

Method	VPEval Skill-based				ActionBench-Direction	
	Object	Count	Spatial	Scale	Overall Acc. (%)	Movement Direction Acc. (%)
ModelScopeT2V	89.8	38.8	18.0	15.8	40.8	30.5
VIDEODIRECTORGPT	97.1	77.4	61.1	47.0	70.6	46.5

Object movement direction accuracy:

- First obtain the start/end locations of objects via GroundingDINO on the first/last video frames
- Then evaluate whether the x and y coordinates of the objects have changed correctly as described in the prompts (through a binary score of 0 or 1)

Quantitative Evaluation

Method	ActivityNet Captions			Coref-SV	HiREST	
	FVD (↓)	FID (↓)	Consistency (↑)	Consistency (↑)	FVD (↓)	FID (↓)
ModelScopeT2V	980	18.12	46.0	16.3	1322	23.79
ModelScopeT2V (with GT co-reference; oracle)	-	-	-	37.9	-	-
VIDEODIRECTORGPT (Ours)	805	16.50	64.8	42.8	733	18.54

Multi-scene object consistency:

- First detect the target object from the center frame of each scene
- Then extract the CLIP image embedding from the detected bounding box
- Calculate the consistency metric by averaging the CLIP image embedding similarities across all adjacent scene pairs

$$\frac{1}{N} \sum_{n=1}^{N-1} \cos(\text{CLIP}_n^{\text{img}}, \text{CLIP}_{n+1}^{\text{img}})$$

Human Evaluation

Evaluation category	Human Preference (%) \uparrow		
	VIDEODIRECTORGPT (Ours)	ModelScopeT2V	Tie
Quality	54	34	12
Text-Video Alignment	54	28	18
Object Consistency	58	30	12

VideoDirectorGPT: Consistent Multi-Scene Video Generation via LLM-Guided Planning

videodirectorgpt.github.io

Han Lin



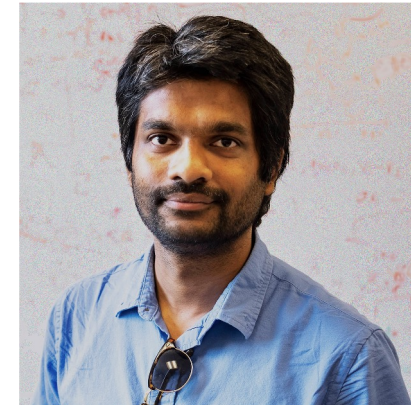
Abhay Zala



Jaemin Cho



Mohit Bansal



THE UNIVERSITY
of NORTH CAROLINA
at CHAPEL HILL