



Research Vision: Data-driven Agents for Content Creation

Ishita Dasgupta
Adobe Research



Agenda

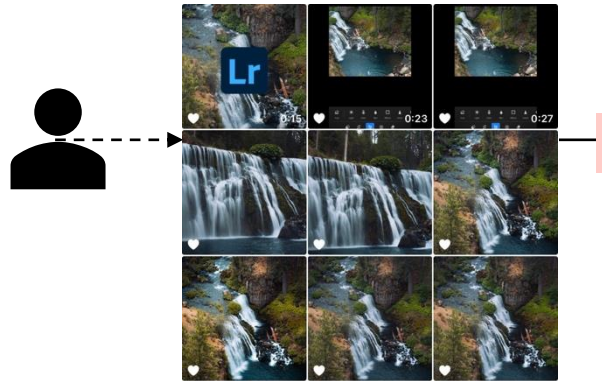
Section

Vision

Why Adobe?

Research Area Declaration


Vision



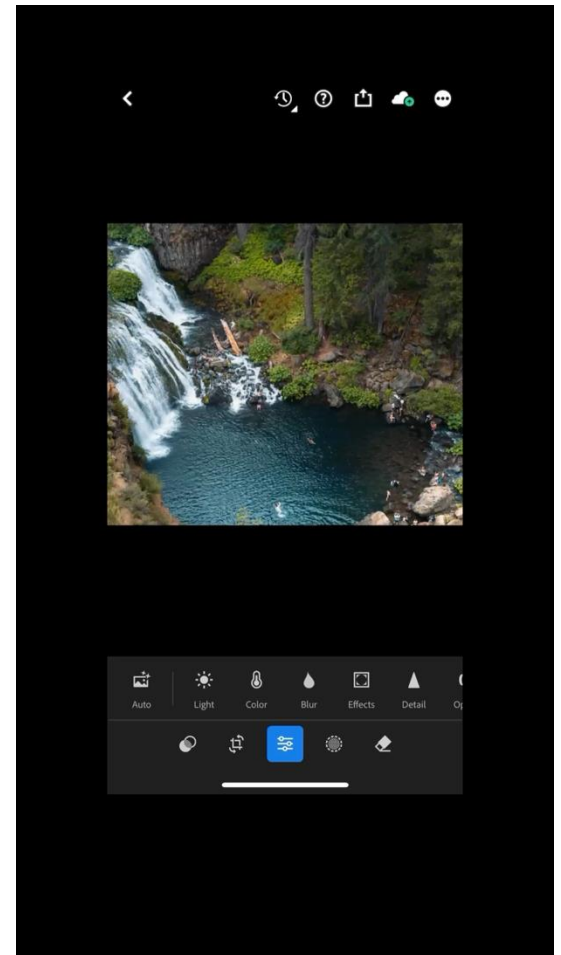
Images, screenshots,
screenrecordings related to
editing a photo on LR

promotional

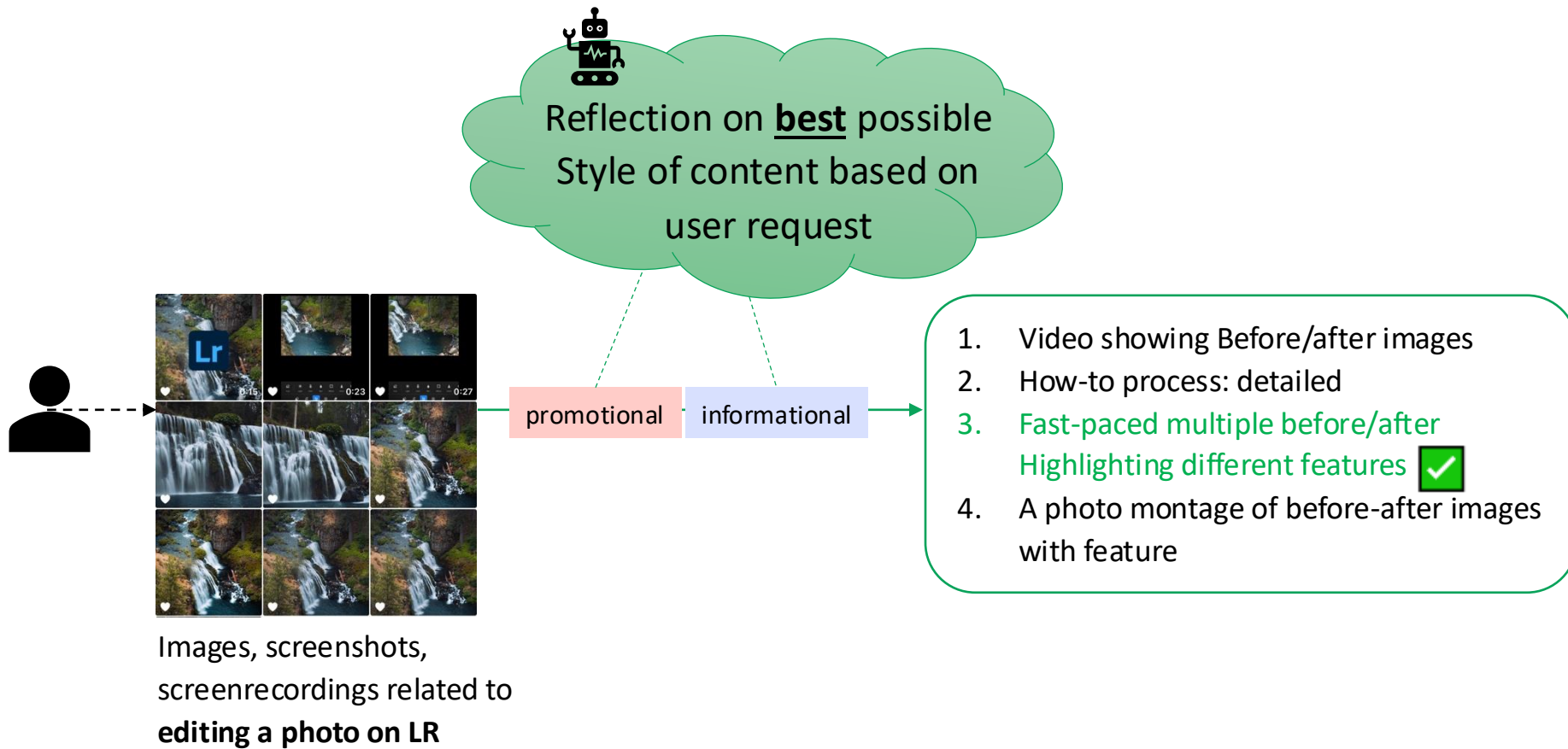
informational

1. Video showing Before/after images
2. How-to process: detailed 
3. Fast-paced multiple before/after
Highlighting different features
4. A photo montage of before-after images
with feature

Before



Vision



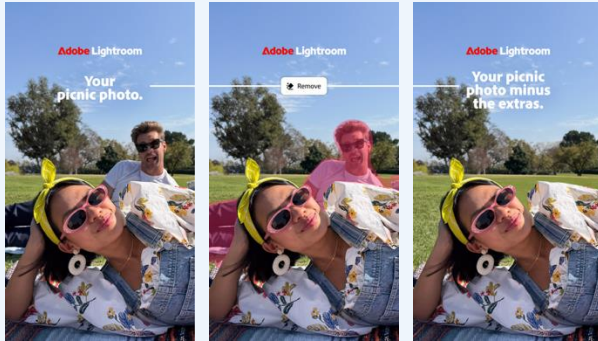
After



Vision: More examples

- Create variations for ***different creative types or styles*** that resonate better (*as per data*)

Carousel



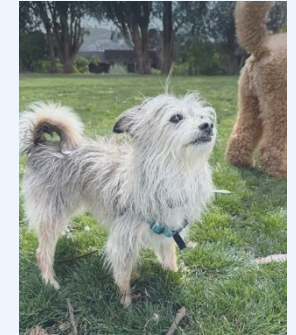
Story



Video



- ***Keeping style same, Create variations*** that resonate better (*as per data*)

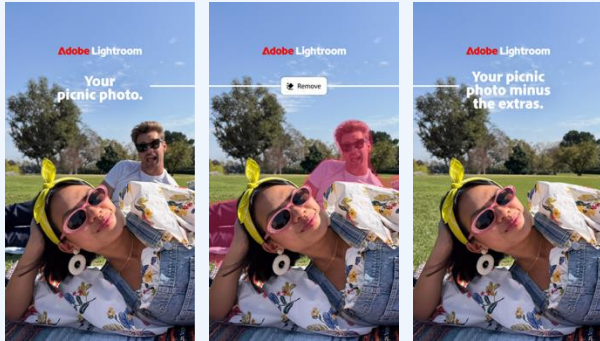


For example: If “pet content” is doing better, remake same ad featuring generative remove with pets.

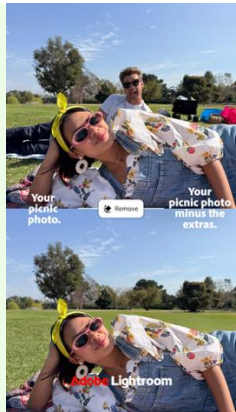
Vision: More examples

- Create variations for ***different creative types or styles*** that resonate better (*as per data*)

Carousel



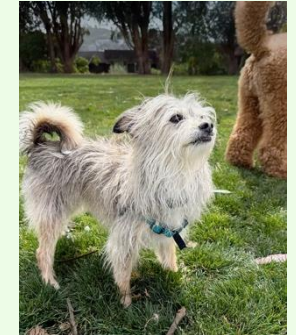
Story



Video



- ***Keeping style same, Create variations*** that resonate better (*as per data*)

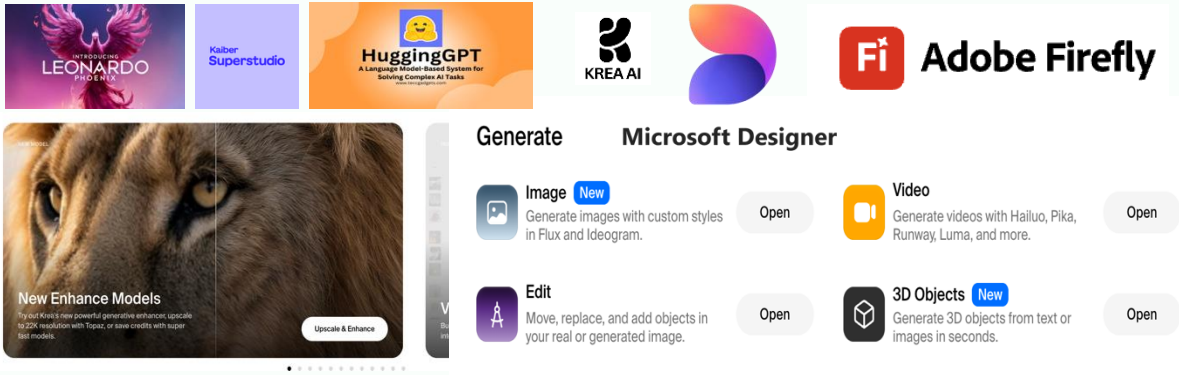


For example: If “pet content” is doing better, remake same ad featuring generative remove with pets.

Vision


Imagine if **agents** could learn **what** makes these examples successful and ***automatically guide successful content creation.***

Data-Driven Multimodal Agents for Creativity



Generate **Microsoft Designer**

- Image** New
Generate images with custom styles in Flux and Ideogram. Open
- Video**
Generate videos with Hailuo, Pika, Runway, Luma, and more. Open
- Edit**
Move, replace, and add objects in your real or generated image. Open
- 3D Objects** New
Generate 3D objects from text or images in seconds. Open

 automate complex content creation

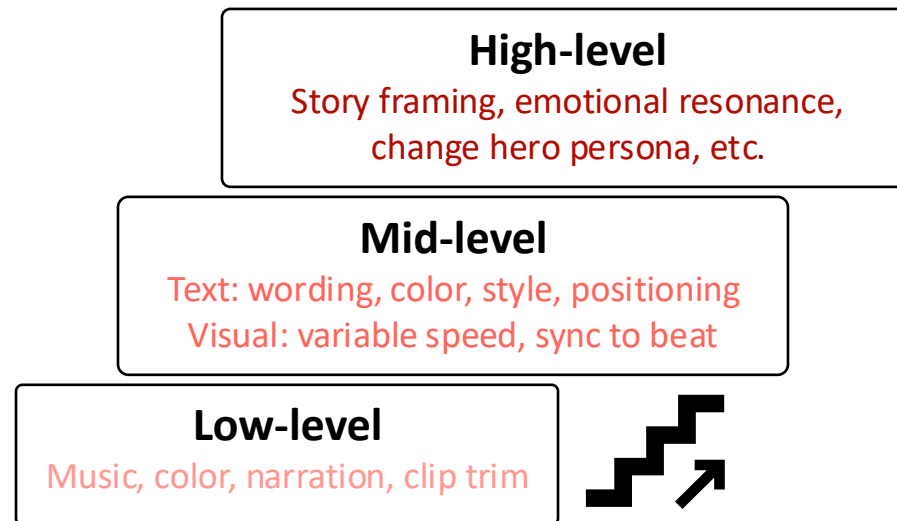
✗ Missing:
Data-driven models to create engaging content



The Space of Edits: Why This Problem Is Hard

Current MLLMs/VLMs: Can perform low and some mid-level edits via prompting.

Challenge: They can simulate reason and *intent*, but ***why a change might engage a particular audience*** or convey the right narrative needs to be grounded in ***real performance data***



Why MLLM+data != data-driven



Knowledge-based reasoning
bias)

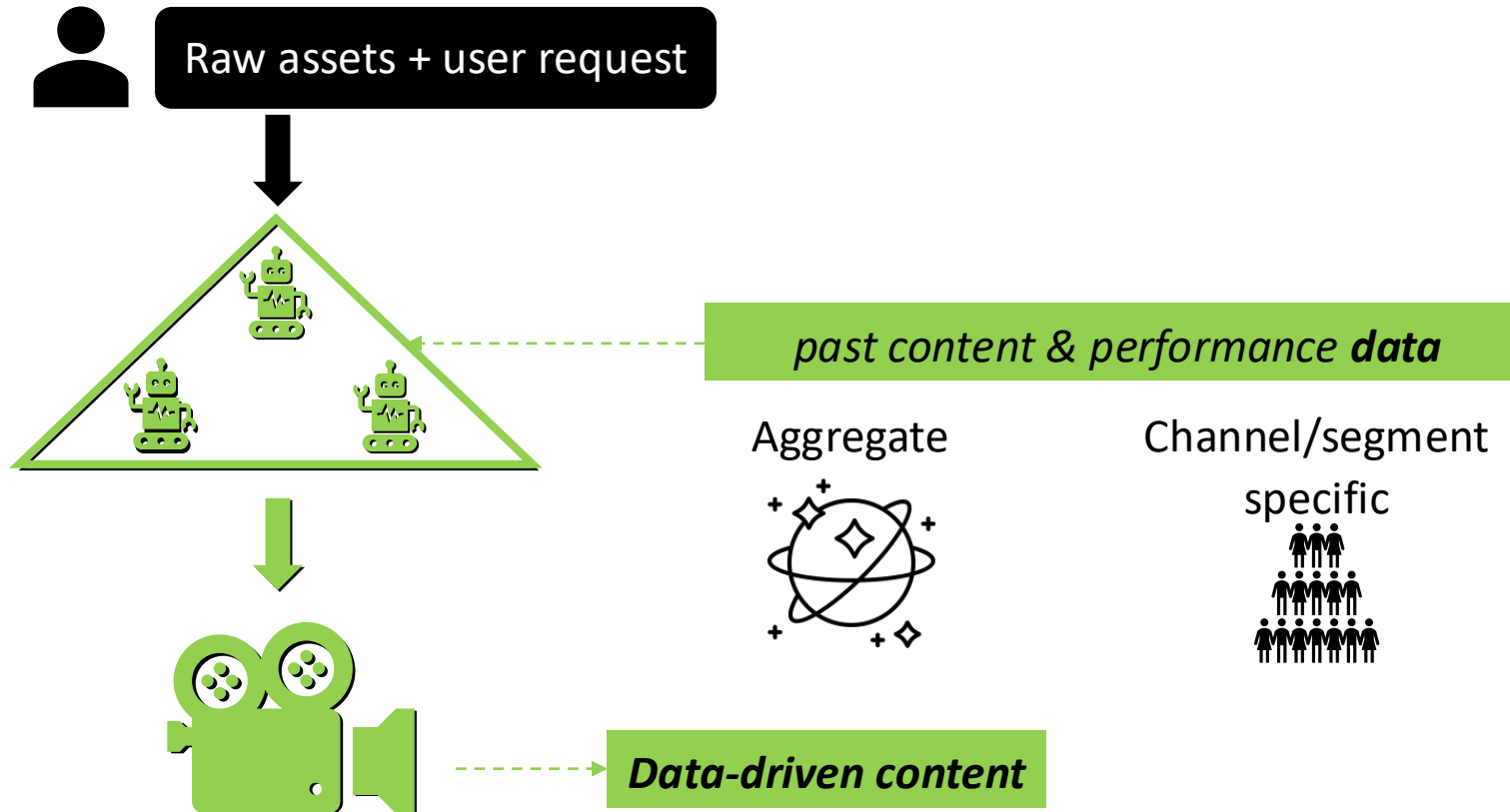
vs.



Empirical grounding (correlation, causation, human

Data-Driven Multimodal Agents for Creativity

Can agents effectively understand & learn to generate data-driven content from **past performance** that performs well across channels and audiences?



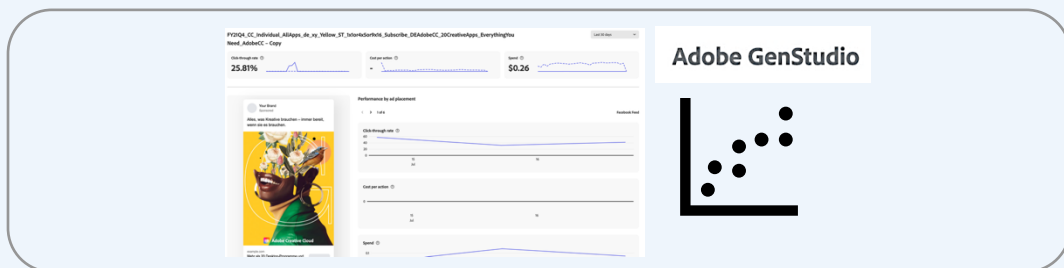
- ✓ **What** content is performing well?
- ✓ **Why** is it performing well?
- ✓ **Can we create** content that performs well?
 - ✓ Winning **Style**
 - ✓ Winning **Creative type**
 - ✓ Winning key **features**

Why Adobe ?

Adobe's ecosystem uniquely connects content creation with its performance data — a closed loop few others can access.

For marketers

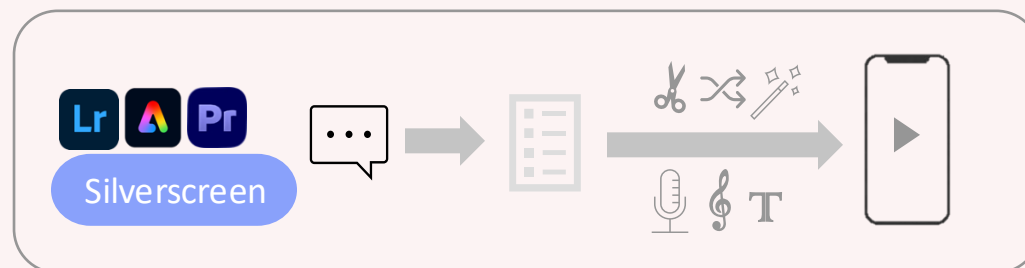
To gain insights from engaging content



- ✓ **What** content is performing well?
- ✓ **Why** is it performing well?
- ✓ **Can we generate marketing insights** from content that performs well to guide future campaigns?

For content creators

To create engaging content faster



- ✓ **What** content is performing well?
- ✓ **Why** is it performing well?
- ✓ **Can we create content** that performs well?

Why Adobe ? For marketers



GENSTUDIO

Insights



Insights from engaging content

✓ **Helps** marketers, analysts and content creators *with future campaigns*

✓ **What** content is performing well?

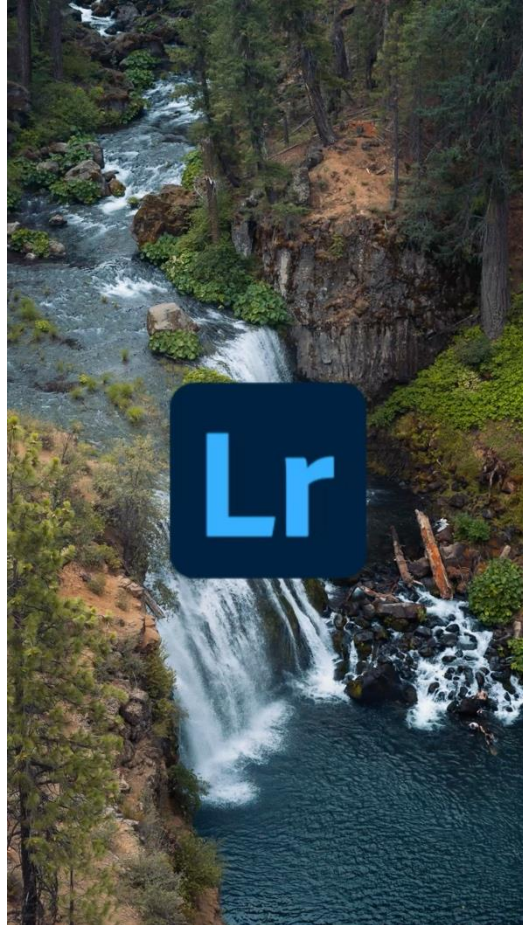
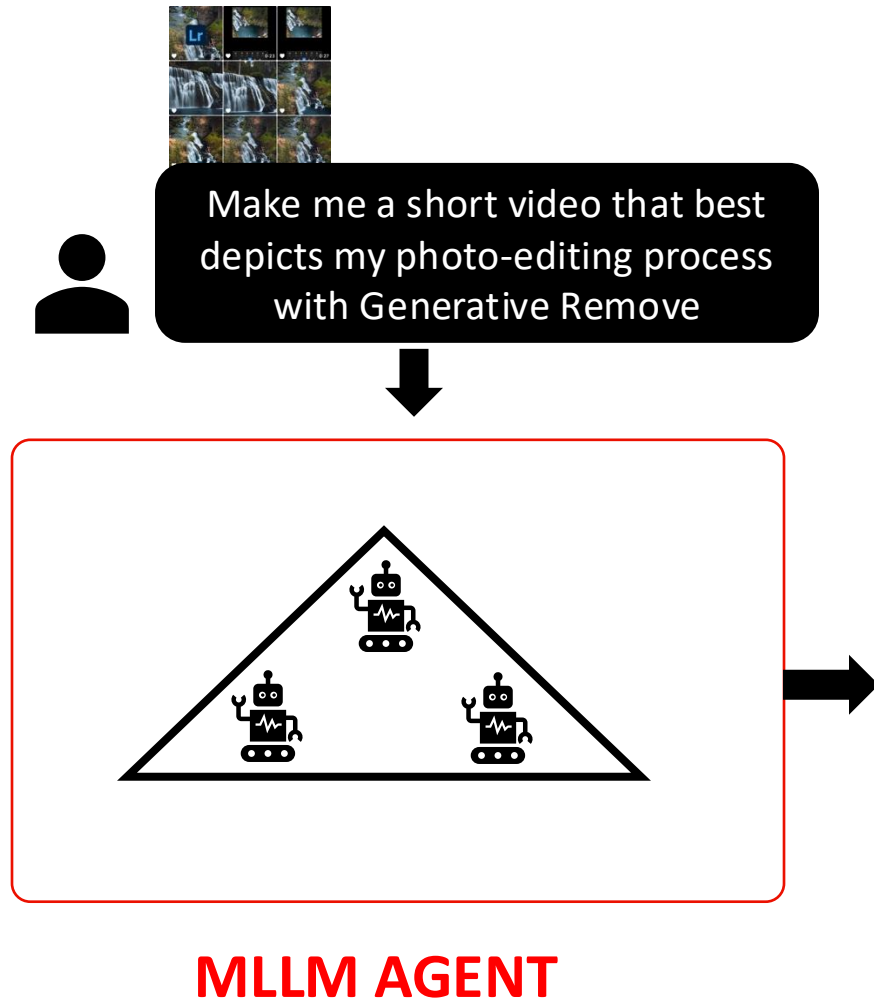
PresetsDoodle Strongest CPC ad.

✓ **Why** is it performing well?

PresetsDoodle Achieves highest CTR (1.8%) through universal emotional appeal (pet photography) + optimized 5-second pacing + clear before/after value demonstration, creating immediate connection.

✓ **Can we guide future campaigns?**

Why Adobe ? For creators



Create engaging content faster

✓ **Helps** content creators **create engaging content faster.**

✓ **What** content is performing well?

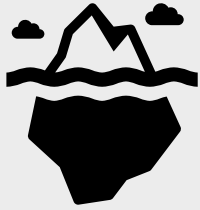
Fast-paced multiple before/after shots style short-video highlighting the feature in the past has worked well for similar video styles

✓ **Why** is it performing well?

First 10s that quickly demonstrate the feature, with upbeat music, fast-fade cuts drive engagement in content that perform well

✓ **Can we create** content that performs well?

Research Area Declaration



PROBLEM

No structured way to use performance data for understanding, evaluating and automating content creation

How to enable data-driven decision making in agents towards content-creation?



MOTIVATION

Enabling Adobe customers to produce high-quality content **faster** and **more** efficiently.



GOAL

- ✓ **What** content is performing well and **Why?** Interpretable & Actionable data-driven insights and recommendations
- ✓ **Can we create content** that performs well? to enable multi-agentic systems to directly generate ***data-driven plans*** for ***creating, evaluating and iteratively refining engaging content***

Outline

**Main Research
Challenges & Research
Objectives**

**Existing
Explorations**

Future steps

Main Research Challenges

- ***What*** content is performing well and ***Why***?

Translating performance data (e.g., user engagement) into actionable insights and recommendations

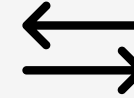
- *Can we create content that performs well?*

Lack of coordinated data-driven reasoning and planning towards task decomposition to directly create/generate high-performing content

Performance
Data



Actionable
Insights



✓ **What** content is performing well?

✓ **Why** is it performing well?

✓ *Can we create content that performs well?*

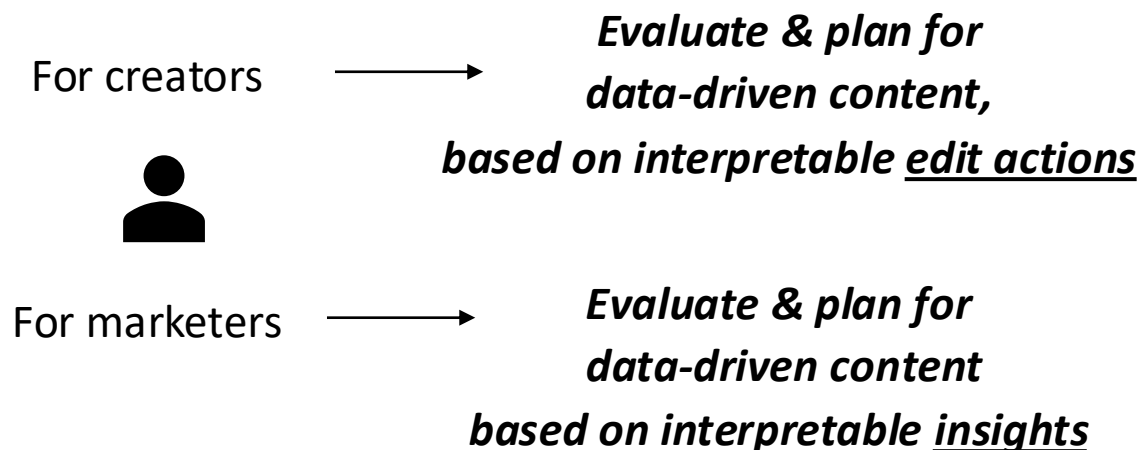
Main Research Challenges

- *What content is performing well and Why?*

Translating performance data (e.g., user engagement) into actionable insights and recommendations

- ***Can we create content that performs well?***

Lack of coordinated **data-driven reasoning and planning towards task decomposition** to directly create/generate high-performing content



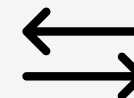
Performance

Data



Actionable

Insights



✓ *What content is performing well?*

✓ *Why is it performing well?*

✓ **Can we create content** that performs well?

Research Objectives

Challenge 1: Translating performance data (e.g., user engagement) into actionable insights and recommendations

Data-driven behavior understanding :
predicting engagement and insights from engagement

- a. Data-driven behavior prediction (For ex: engagement prediction)
- b. Explainable data-driven insights: Interpretable, actionable feature attribution

Challenge 2: Data-driven reasoning and planning towards task decomposition to directly create/generate high-performing content

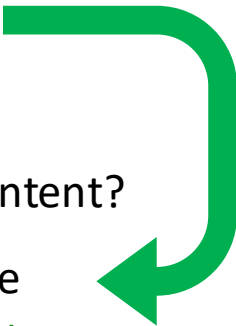
Data-driven Content modification* :
Modeling and controlling user(s) behavior to guide data-driven content generation and modification.

User Request



Content

Would the user <<*like*>> this content?
Which actions performed on the content guarantee <<*user likability*>>



Research Objectives

Challenge 1: Translating performance data (e.g., user engagement) into actionable insights and recommendations

Data-driven behavior understanding :
predicting engagement and insights from engagement

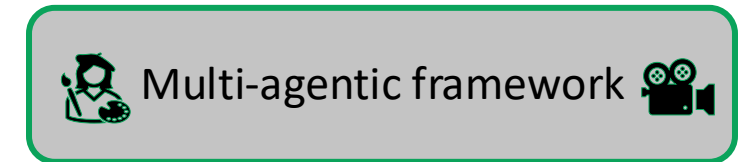
- a. Data-driven behavior prediction (For ex: engagement prediction)
- b. Explainable data-driven insights: Interpretable, actionable feature attribution

Challenge 2: Data-driven reasoning and planning towards task decomposition to directly create/generate high-performing content

Data-driven Content modification* :
Modeling and controlling user(s) behavior to directly guide data-driven content generation and modification.

* Partly explored

User Request



Content

Directly modify the content that satisfy <<*user behavior*>>

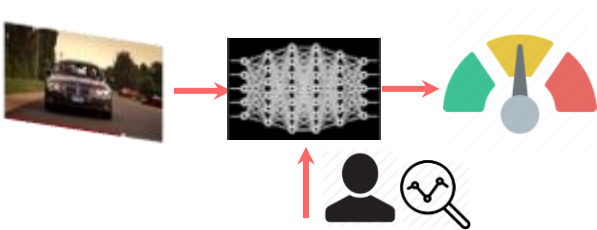
Outline



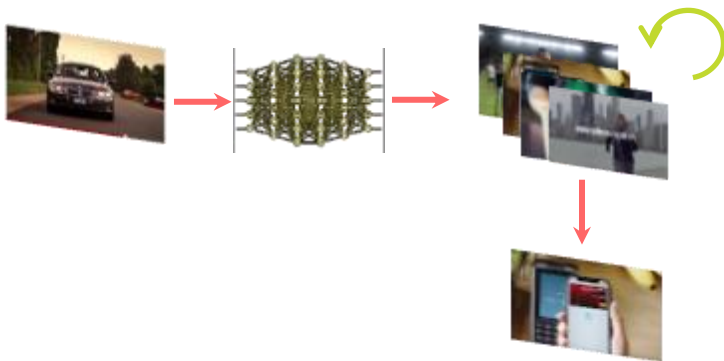
Existing Explorations

In-house models

Watchability: Performance Prediction



Closing the Loop: Auto Optimizing Content & Variants



Differentiating factor

- Interpretable understanding of content performance
- Interpretability should be translatable to controlled actions users can take on Adobe tools to improve content

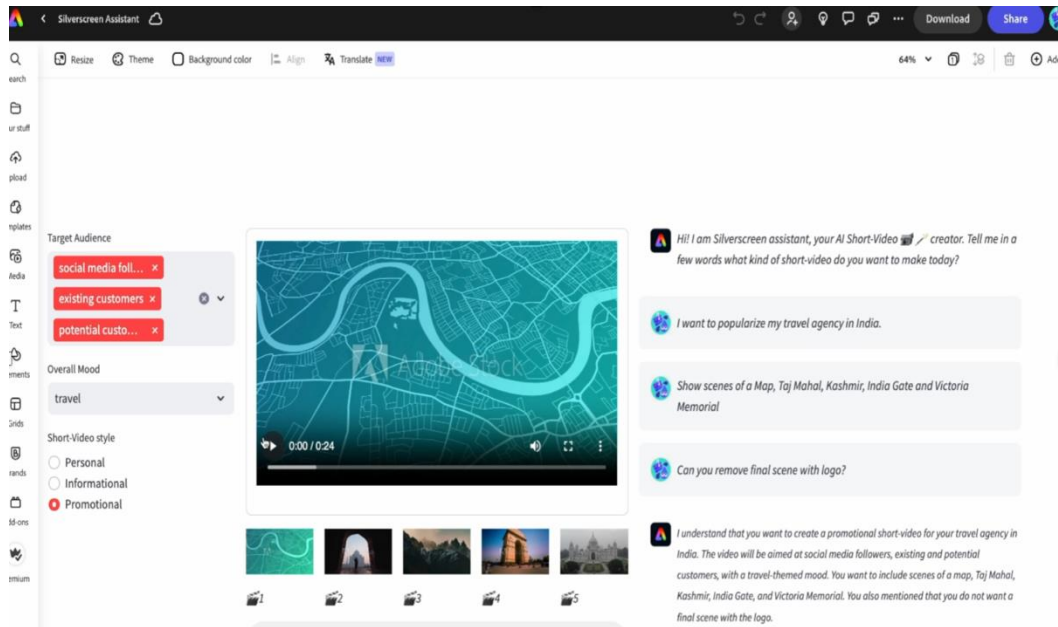
Newly available and collected performance data and SOTA MLLMs can map performance to interpretable and actionable suggestions on content

Existing Explorations [yet to hide]

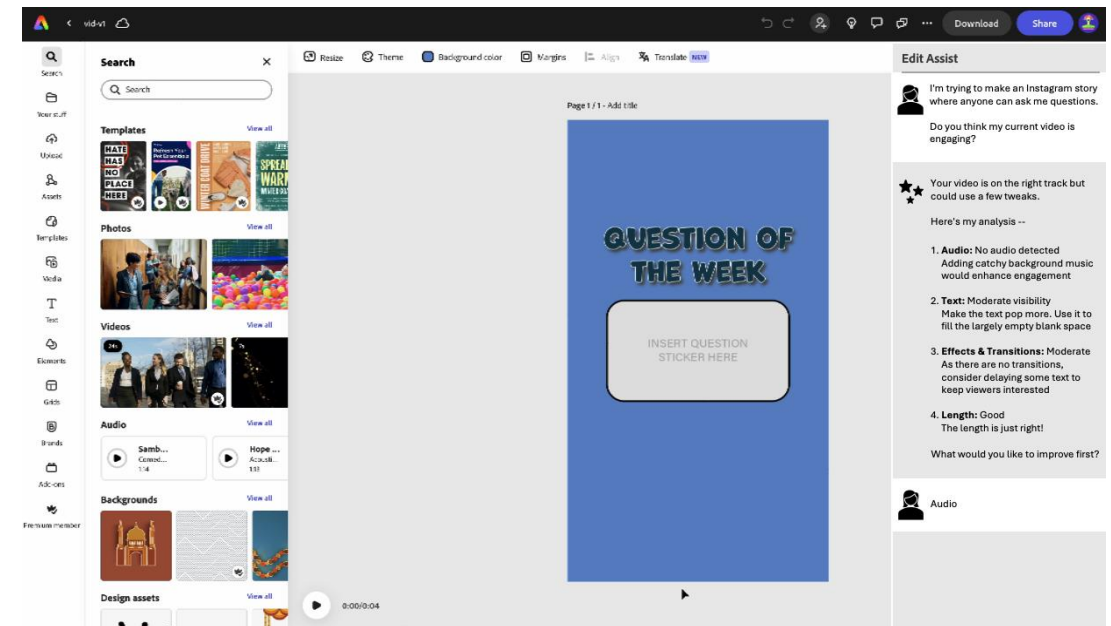
	Creator	Marketer
Challenge 1: Translating performance data (e.g., user engagement) into actionable insights and recommendations	Yes Project Silverscreen, EditAssist	Ongoing
Challenge 2: Data-driven reasoning and planning towards task decomposition to directly create/generate high-performing content	Yes Project Loopedit	Future Work

1. Data-driven Multi-agent frameworks for short-video creation

Silverscreen: Agentic short-video creation

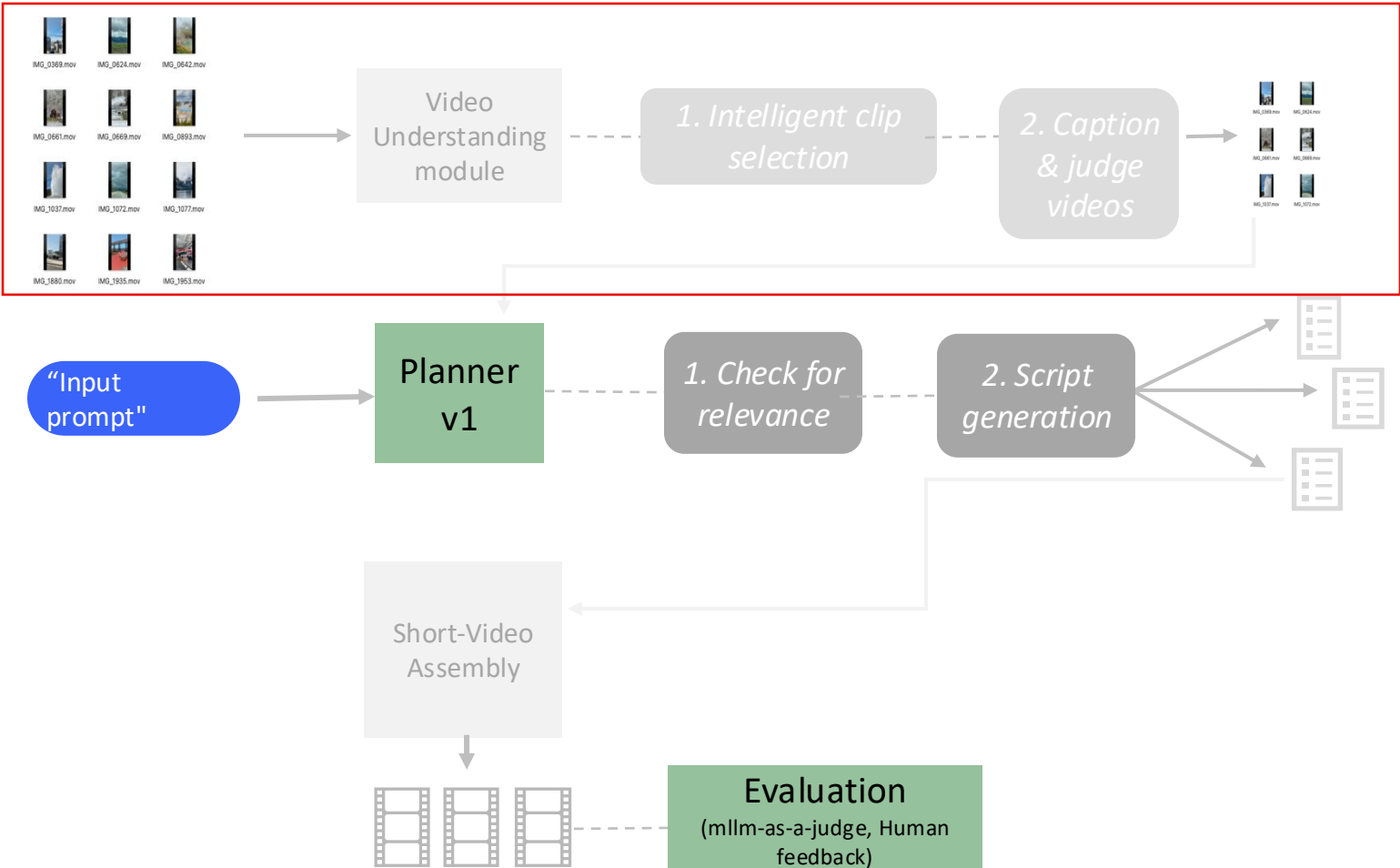


EditAssist: Data driven short-video engagement understanding & improvement

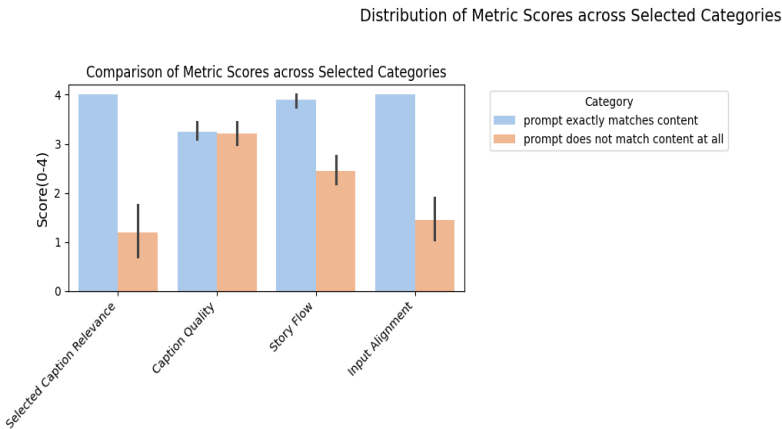


For this presentation, **content** is generally **video** & **content editing** is generally **video editing**.

A) Agentic short-video creation



Quantitative Assessment



Qualitative Assessment



"wow the **outputs** are so cool! Wren and I just looked through the ones it gave me. This is awesome! **I can't wait to make a finished video off what it gave me**"

B) Data driven short-video engagement prediction & improvement

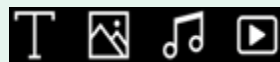
How to optimize content?

Creators 



Create

Content
(short-videos)



? As opposed to Platform-dependent metrics (*watch-time, likes, shares, etc.*), can content engagement be predicted based on content characteristics?

✓ Automated content refinement based on content's inherent characteristics

✓ Help creators with “actionable insights” to modify and improve content before publishing content

VidES
Dataset
+
EditAssist

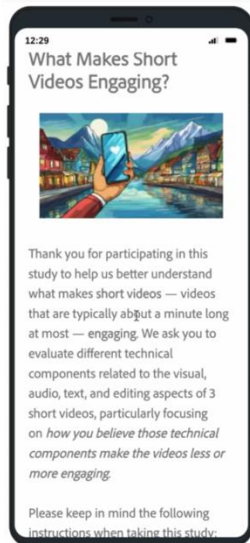
VIDes Dataset (Rate video engagement and reason why)

What data?

- Edit signals

What can be learned?

- Engagement based on edit signals used



visual-3

What did you think of the visual variety

- ☐ Appropriate, considering the content
- ☐ Not enough visual variety/not enough scenes
- ☐ Too much visual variety/too many scenes
- ☐ Did not care

☐ audio-7

Did the music used in the video help its engagement?

- ☐ Yes - music present and it is satisfactory
- ☐ Yes - music absent and any music would have been distracting
- ☐ No - music present and it is distracting
- ☐ No - music absent and some music would have been useful
- ☐ Did not care



650+ short-videos (< 1 min)



~2900 users with video editing skills

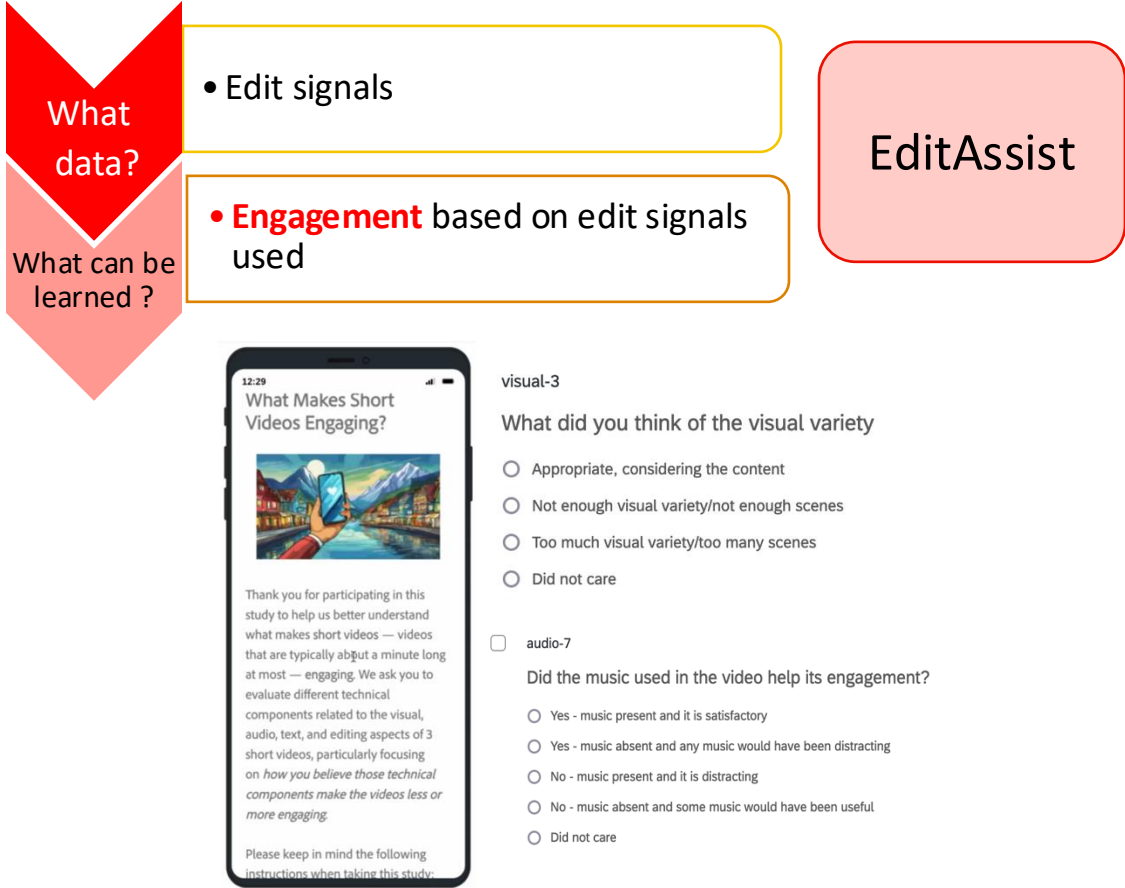


Overall engagement Score [1-5]

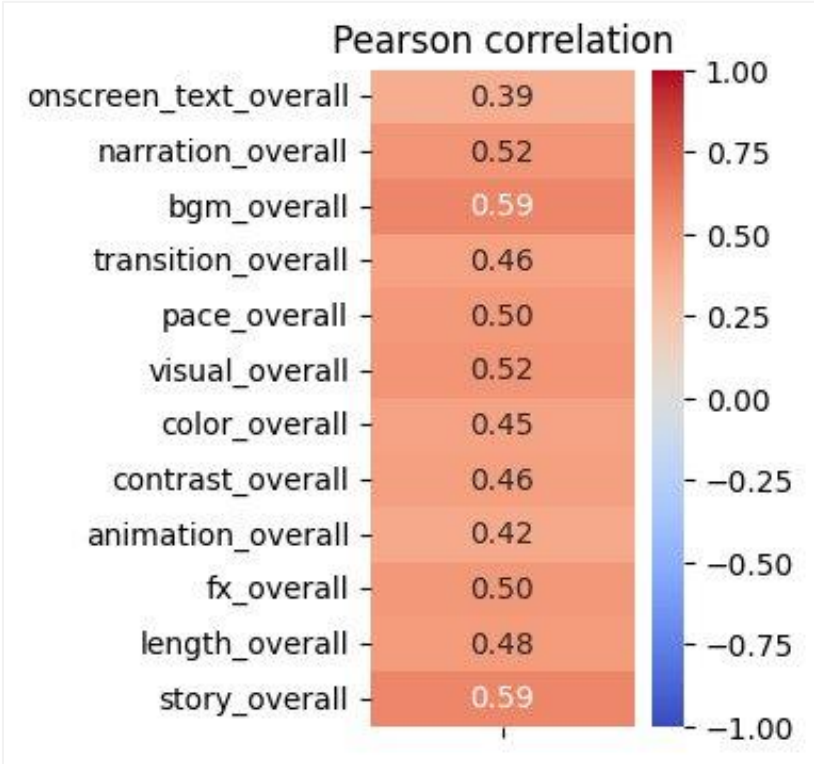
▪ Also asked about *individual edit signals*

- 48 questions on each video about Text, Audio, Visuals, Storytelling, Scene transitions, etc.
- Only asked about edit signals Actionable in Express
- Scale further with 1000+ videos across different styles and categories of short-videos

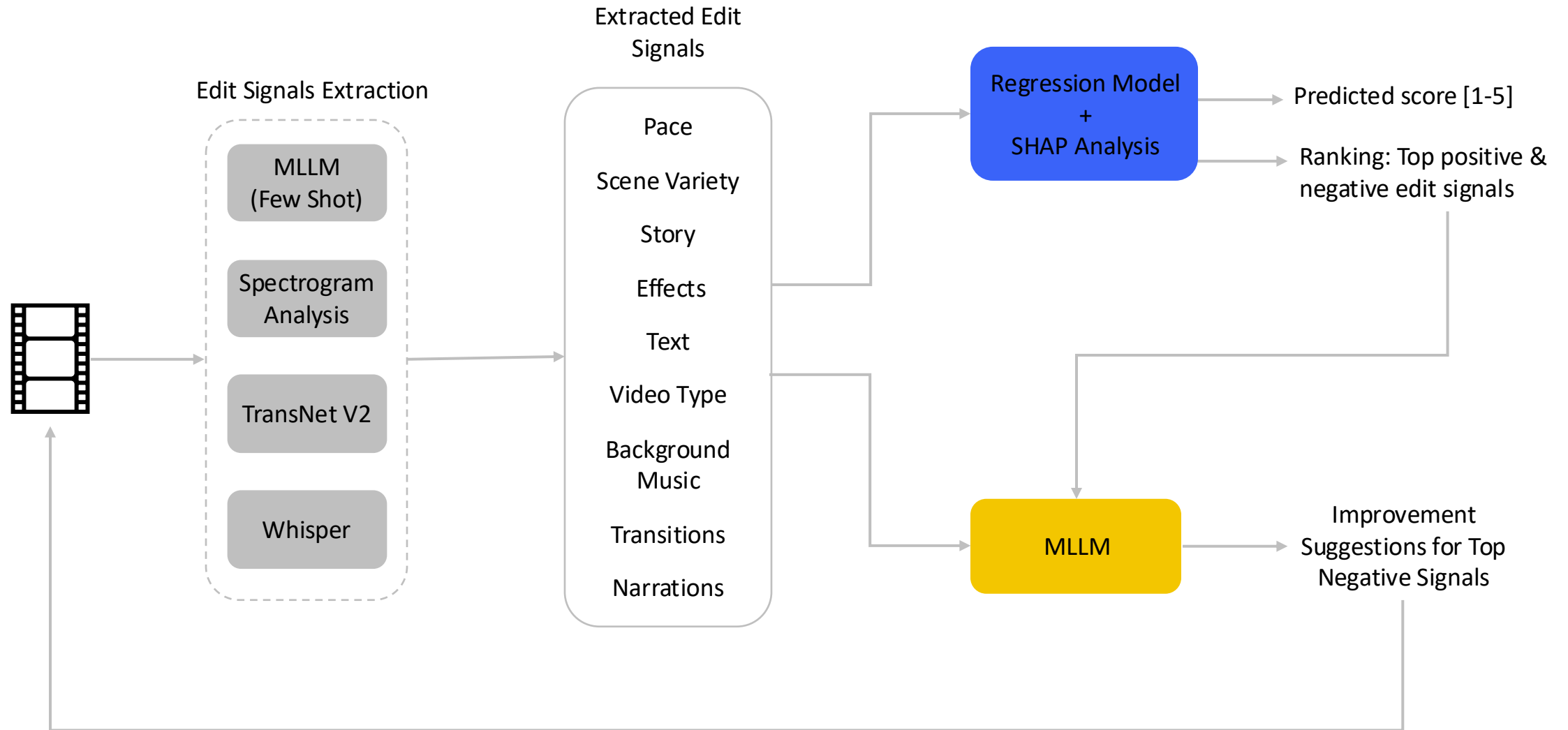
VIDes Dataset (Rate video engagement and reason why)



- Correlation analysis between *edit signals* & *engagement*



EditAssist framework



Quantitative Results

Performance on Engagement Prediction & Improvement Feedback

Method	ES Decomp.	Engagement Prediction			Improvement Feedback	
		MAE	RMSE	Classification Accuracy	Accuracy	F1
Random model	No	1.45	1.77	0.21	0.27	0.43
Q-Align [20]	No	0.79	0.97	0.39	N/A	N/A
GPT-4o (Zero-shot)	No	1.19	1.39	0.13	0.36	0.54
GPT-4o (Few-shot)	No	1.02	1.23	0.28	0.41	0.57
GPT-4o (Few-shot)	Yes	0.75	0.88	0.38	0.45	0.61
SmartEdit	Yes	0.64	0.84	0.49	0.51	0.67

Testing different backbones

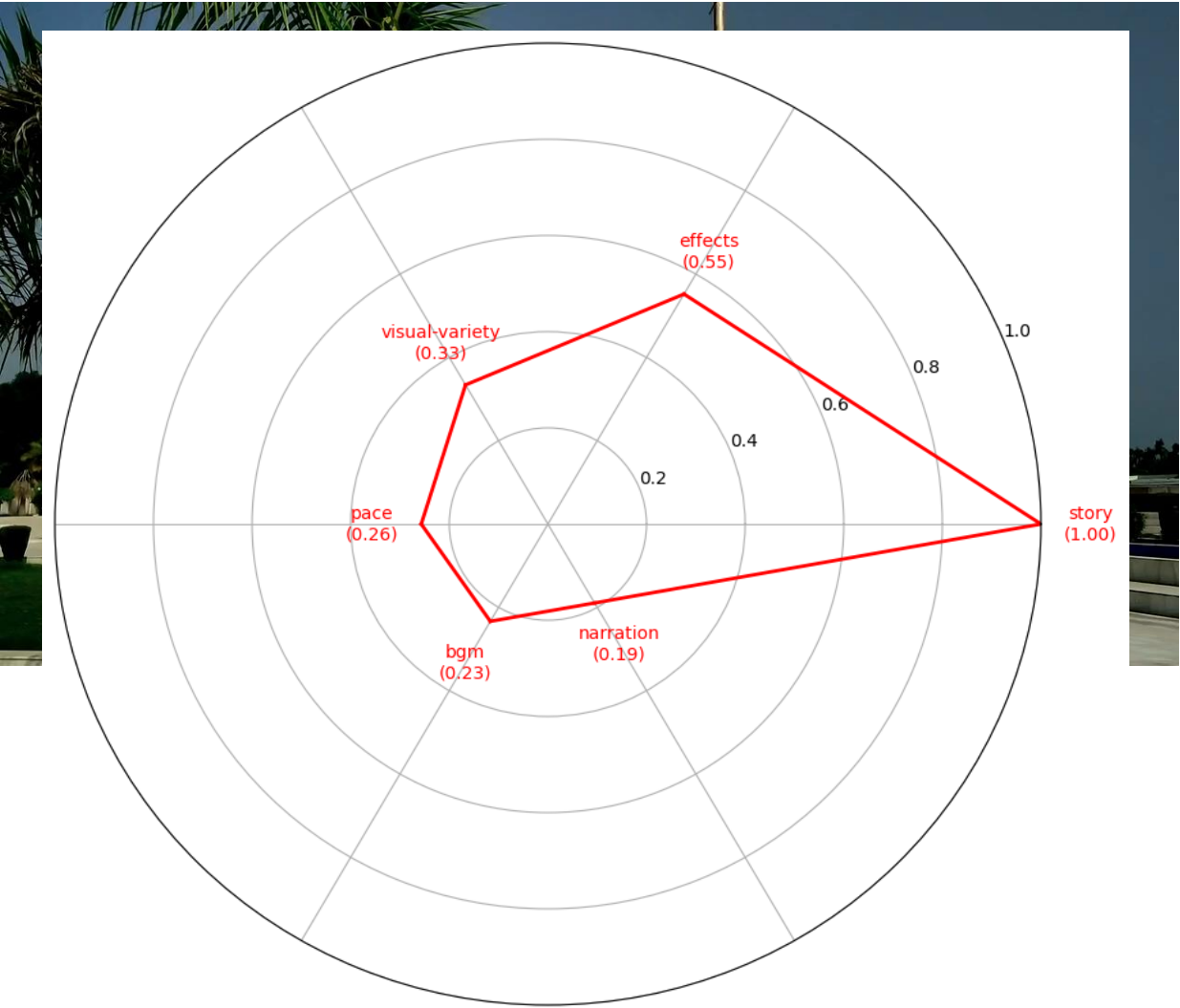
Ablation Study

Regression Model	MAE	RMSE	clfAcc
XGBoost	1.15	1.33	0.28
Multi-Layer Perceptron (MLP)	0.91	1.18	0.37
Random Forest Regressor	0.64	0.84	0.49

Effect of example types on feedback improvement

Good Examples	Bad Examples	Reasoning	Accuracy	F1
0	4	No	0.44	0.59
0	4	Yes	0.47	0.63
2	2	No	0.45	0.62
2	2	Yes	0.51	0.67

Results: Qualitative (Poorly edited video)



Top signals affecting engagement (+/-)

Human

Our model

Story flow	✓	✓
Effects	✓	✓
Variety of scenes	✓	✓
Pace	✓	✓
Music	✓	✓
Narration	✓	✓

Ground Truth

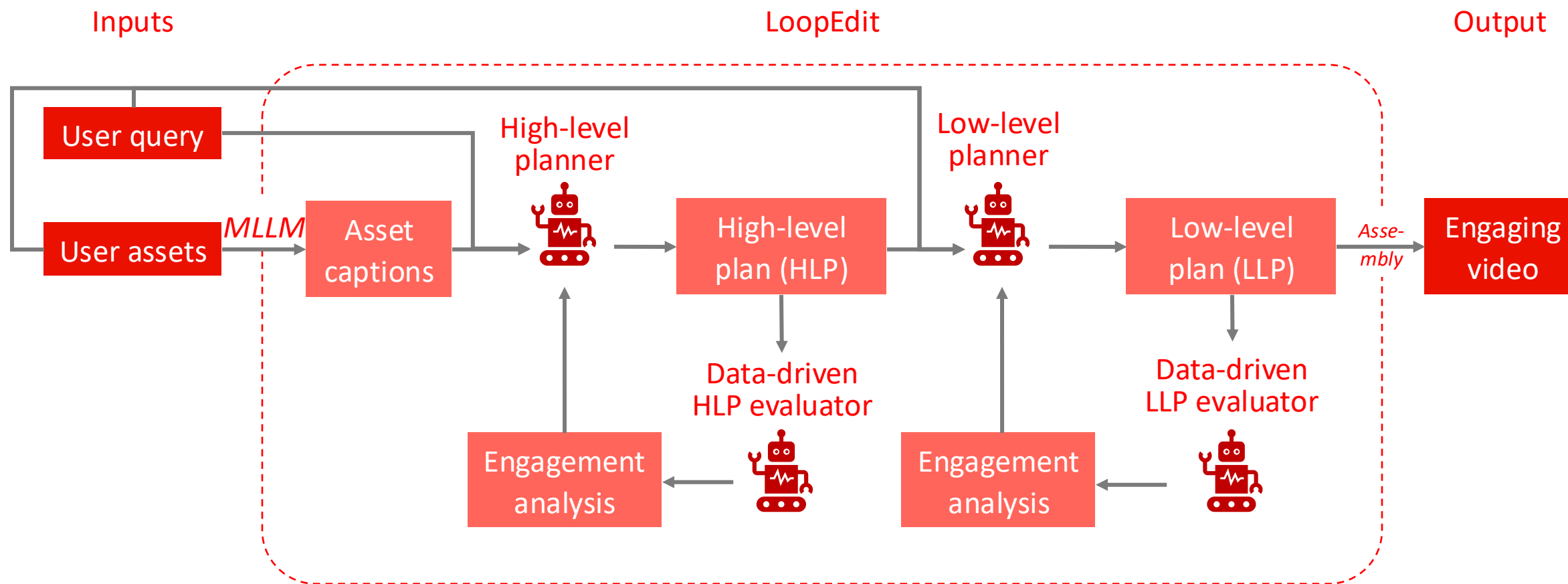
0.4

Predicted

1.1

Engagement score scale:
0 = not at all engaging
1 = slightly engaging, needs many improvements
2 = somewhat engaging, needs a few improvements
3 = engaging, but can be improved
4 = very engaging, no improvements needed

C) Bringing it all together: Loopedit (Data-driven planner)



Demo: [demo_max25.mp4](#)

What does a plan look like?

Hierarchical

- **HLP**
 - Overview
 - Scenes
- **LLP**
 - Clips

Overview

Pace:

Normal

Mood:

Calm

Category:

How-to

Narration:

None

Bgm:

Soft jazz

Duration:

15 sec

Scene 1

Clip 1

Clip 2

Clip 3

Scene 2

Summary: Demonstrate pouring grounds & preparing base

Purpose: Build anticipation

Approx duration: 3 sec

Keywords: dripper, hot water

Clip 4

Source: CB_916.mp4

Duration: 2.3 sec

Text overlay: Step 1. Grind your beans

Effect: Zoom in

Clip 5

Clip 6

Clip 7

Clip 8

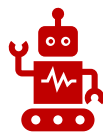
Scene 3

Scene 4

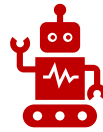


Quantitative results: Planning & Evaluator agents

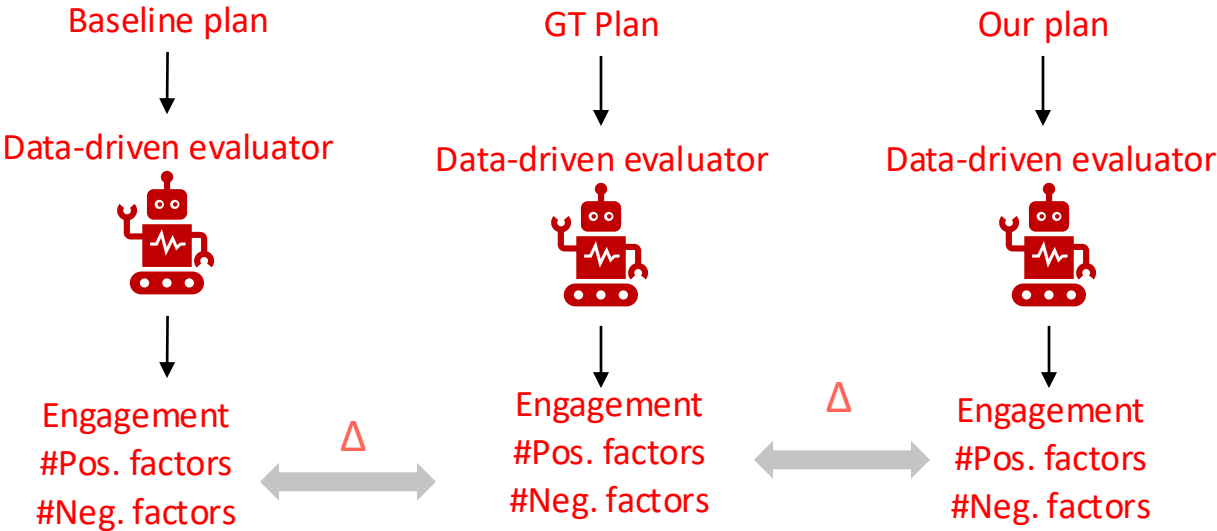
Data-driven
HLP evaluator



Data-driven
LLP evaluator



Evaluator model	Pearson Correlation ↑	Mean Absolute Error (MAE) ↓
HLP evaluator	0.776	0.65
LLP evaluator	0.759	0.90

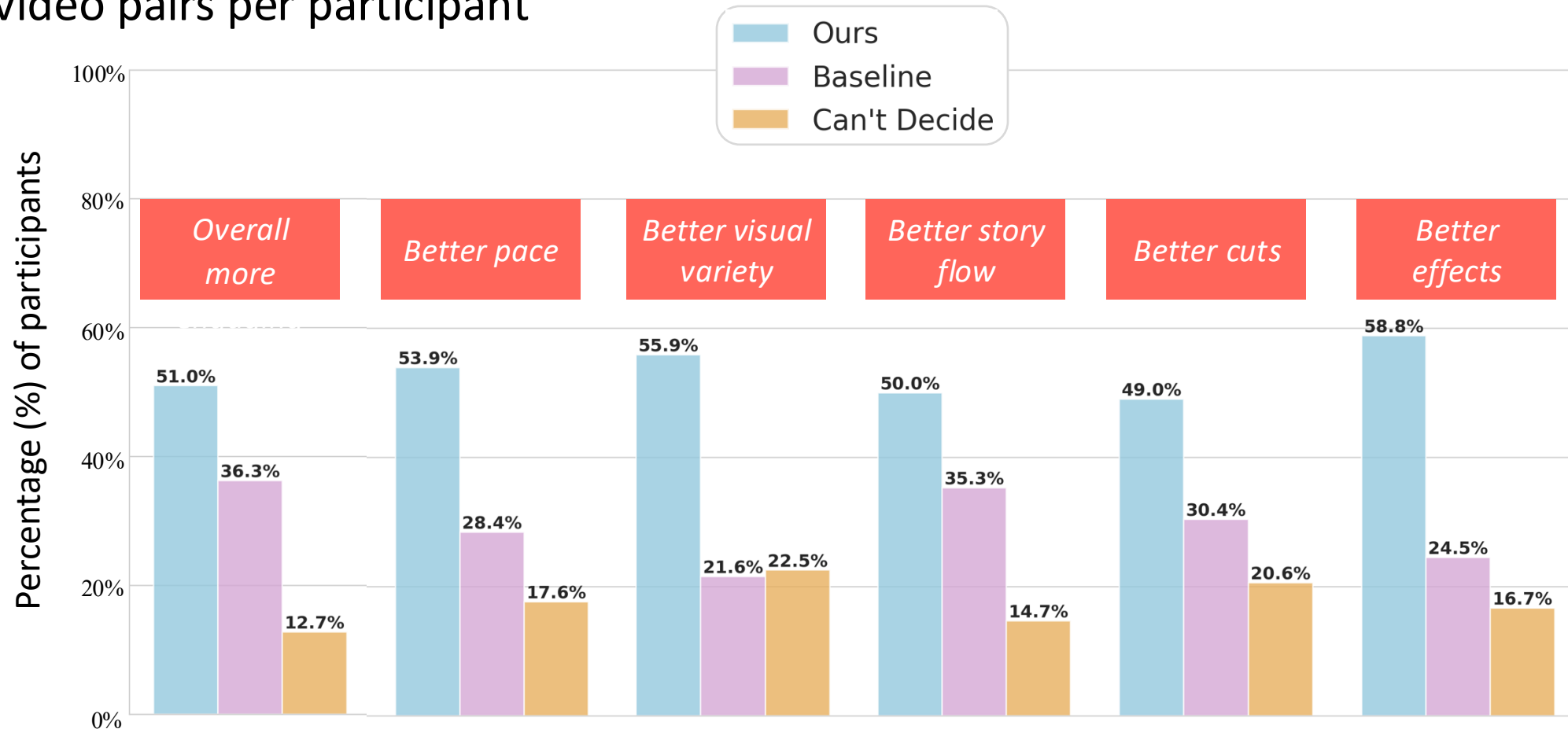


Plan	Method	Avg. delta (Δ) in engagement score ↑	Avg. delta (Δ) in #positive factors ↑	Avg. delta (Δ) in #negative factors ↓
HLP	Baseline	0.357	1.450	-0.800
	Ours	1.143	1.895	-1.222
LLP	Baseline	0.375	0.563	-0.500
	Ours	0.750	0.950	-0.882

Quantitative results: User study

Take the survey here~
[\[Survey link\]](#)

- 17 participants
- 6 video pairs per participant



Data-Driven Insights for Marketers

~1800 campaigns ~40,000 videos

Genstudio lets customers associate their content with performance via dashboards and insights, but can we make the insights more

- Contextual?
- Actionable?



Opportunity: Unifying *all metrics across a group of campaigns based on user query* and translating them into *consistent, contextual insights*, we can:

- Reveal **which ads drives ROI** across channels and **why**.
- **Which ads are slow drivers** or negative drivers that should be recalibrated
- **What** creative **variants** could drive or improve ROI

Goal: Enable faster budget and creative decisions by enabling analysis guided by **explainable insights**.

Workflow

INPUT CARD

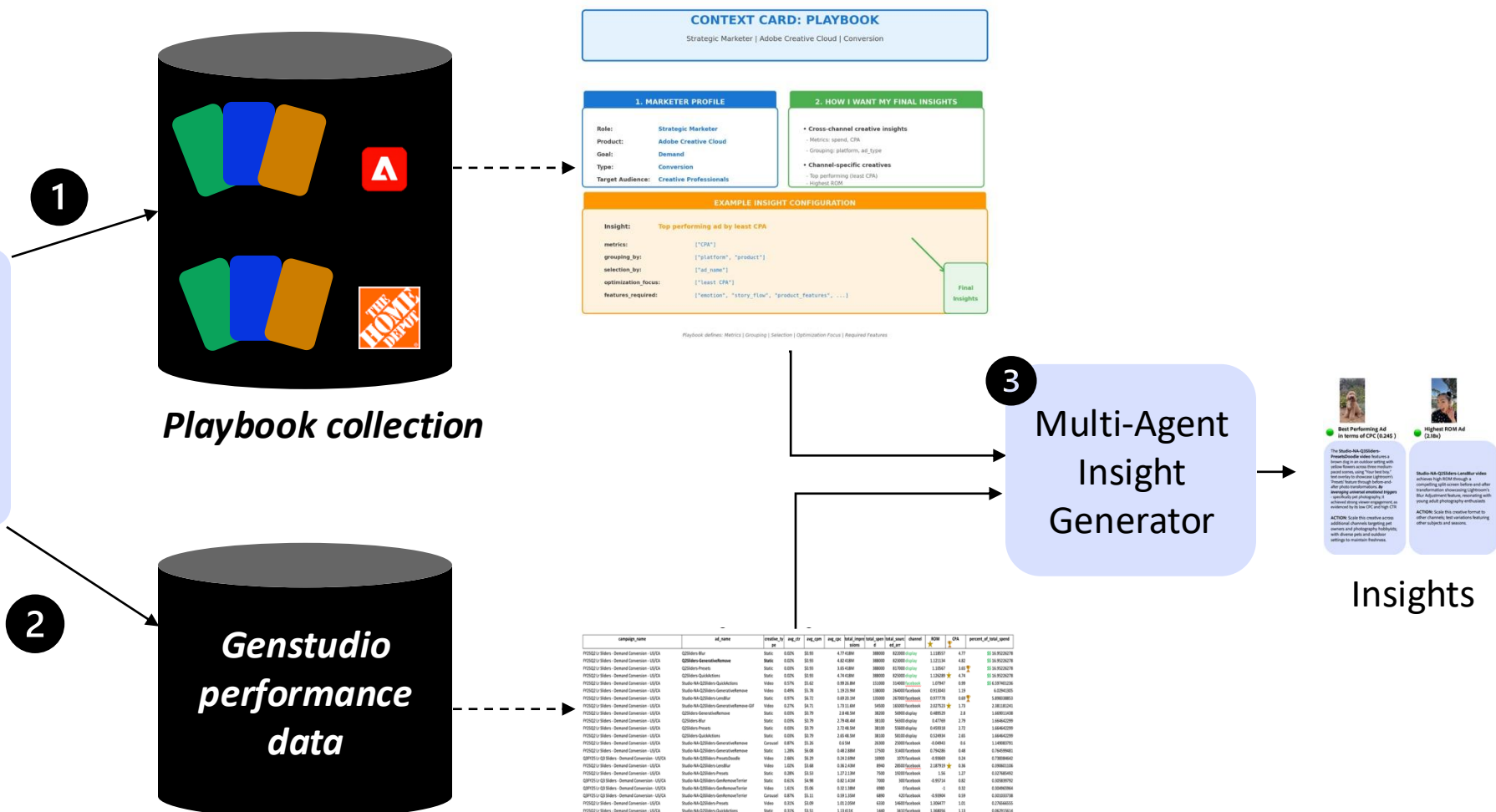
Role: Strategic Marketer

Product(s): Adobe Lightroom

DDOM: Acquisition

Campaign Type: Conversion

Date range: Mar 1, 2025 to Aug 1, 2025



Role: Strategic Marketer
Product(s): Adobe Lightroom
DDOM: Acquisition
Campaign Type: Conversion
Date range: Mar 1, 2025 to Aug 1, 2025.

Who are you & what kind of campaigns do you want to analyze?

Dataset extracted to generate Insights on

campaign_name	ad_name	creative_type	avg_ctr	avg_cpm	avg_cpc	total_impressions	total_spent	total_sourced_arr	channel	ROM	CPA	percent_of_total_spend
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Q2Sliders-Blur	Static	0.02%	\$0.93	4.77	418M	388000	822000	display	1.118557	4.77	\$\$ 16.95226278
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Q2Sliders-GenerativeRemove	Static	0.02%	\$0.93	4.82	418M	388000	823000	display	1.121134	4.82	\$\$ 16.95226278
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Q2Sliders-Presets	Static	0.03%	\$0.93	3.65	418M	388000	817000	display	1.10567	3.65	\$\$ 16.95226278
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Q2Sliders-QuickActions	Static	0.02%	\$0.93	4.74	418M	388000	825000	display	1.126289	4.74	\$\$ 16.95226278
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Studio-NA-Q2Sliders-QuickActions	Video	0.57%	\$5.62	0.99	26.8M	151000	314000	facebook	1.07947	0.99	\$\$ 6.597401236
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Studio-NA-Q2Sliders-GenerativeRemove	Video	0.49%	\$5.78	1.19	23.9M	138000	264000	facebook	0.913043	1.19	6.02941305
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Studio-NA-Q2Sliders-LensBlur	Static	0.97%	\$6.72	0.69	20.1M	135000	267000	facebook	0.977778	0.69	5.898338853
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Studio-NA-Q2Sliders-GenerativeRemove-GIF	Video	0.27%	\$4.71	1.73	11.6M	54500	165000	facebook	2.027523	1.73	2.381181241
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Q2Sliders-GenerativeRemove	Static	0.03%	\$0.79	2.8	48.5M	38200	56900	display	0.489529	2.8	1.669011438
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Q2Sliders-Blur	Static	0.03%	\$0.79	2.79	48.4M	38100	56300	display	0.47769	2.79	1.664642299
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Q2Sliders-Presets	Static	0.03%	\$0.79	2.72	48.5M	38100	55600	display	0.459318	2.72	1.664642299
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Q2Sliders-QuickActions	Static	0.03%	\$0.79	2.65	48.5M	38100	58100	display	0.524934	2.65	1.664642299
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Studio-NA-Q2Sliders-GenerativeRemove	Carousel	0.87%	\$5.26	0.6	5M	26300	25000	facebook	-0.04943	0.6	1.149083791
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Studio-NA-Q2Sliders-GenerativeRemove	Static	1.28%	\$6.08	0.48	2.88M	17500	31400	facebook	0.794286	0.48	0.764599481
Q3FY25 Lr Q3 Sliders - Demand Conversion - US/CA	Studio-NA-Q3Sliders-PresetsDoodle	Video	2.66%	\$6.29	0.24	2.69M	16900	1070	facebook	-0.93669	0.24	0.738384642
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Studio-NA-Q2Sliders-LensBlur	Video	1.02%	\$3.68	0.36	2.43M	8940	28500	facebook	2.187919	0.36	0.390601106
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Studio-NA-Q2Sliders-Presets	Static	0.28%	\$3.53	1.27	2.13M	7500	19200	facebook	1.56	1.27	0.327685492
Q3FY25 Lr Q3 Sliders - Demand Conversion - US/CA	Studio-NA-Q3Sliders-GenRemoveTerrier	Static	0.61%	\$4.98	0.82	1.41M	7000	300	facebook	-0.95714	0.82	0.305839792
Q3FY25 Lr Q3 Sliders - Demand Conversion - US/CA	Studio-NA-Q3Sliders-GenRemoveTerrier	Video	1.61%	\$5.06	0.32	1.38M	6980	0	facebook	-1	0.32	0.304965964
Q3FY25 Lr Q3 Sliders - Demand Conversion - US/CA	Studio-NA-Q3Sliders-GenRemoveTerrier	Carousel	0.87%	\$5.11	0.59	1.35M	6890	420	facebook	-0.93904	0.59	0.301033738
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Studio-NA-Q2Sliders-Presets	Video	0.31%	\$3.09	1.01	2.05M	6330	14600	facebook	1.306477	1.01	0.276566555
FY25Q2 Lr Sliders - Demand Conversion - US/CA	Studio-NA-Q2Sliders-QuickActions	Static	0.31%	\$3.51	1.13	411K	1440	3410	facebook	1.368056	1.13	0.062915614

* Note: CPA values are imagined for analysis purposes. ROM = (ARR - Spend) ÷ Spend

ACTION: STRATEGIC RECOMMENDATIONS

Poor Performers: Pause or Investigate

1. **GenRemoveTerrier** — **Pause:** This **video** ad on **Facebook** is reporting negative returns (-1.0 ROM) with narrow use case (pet background removal)

Action: Pause immediately and reallocate budget to LensBlur. Investigate narrow audience targeting.

2. **Presets** — **Investigate:** This **static** ad on **display** with highest budget Spend (\$388K) reports low ROM (0.459) despite significant spend

Action: Conduct conversion funnel audit and A/B test broader editing messaging.

Reduce spend, reallocate to LensBlur while optimizing targeting.



Untapped Potential: Boost

1. **LensBlur** — **Scale** : This **static** ad on **Facebook** reported highest ROM (2.18) with 8.9k\$ budget spend which is 0.39% of the total budget as opposed to highest budget spent on an ad being 16%

Action: Increase budget slightly to test efficiency ceiling. Scale across additional platforms and enhance CTA to drive conversions.

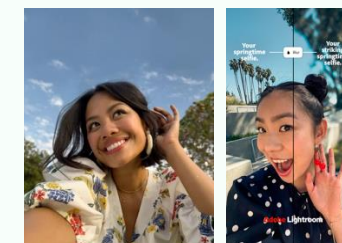


Good Performers: Maintain & Optimize

1. **QuickActions** — **Maintain & Optimize:** Good ROM (1.079 and 1.12) on both static **display** and **facebook** video creatives -- trusted brand appeal for selfie enhancement

Action: Maintain spend and optimize targeting to improve CPA. Refine CTA and test creative variations for incremental improvements.

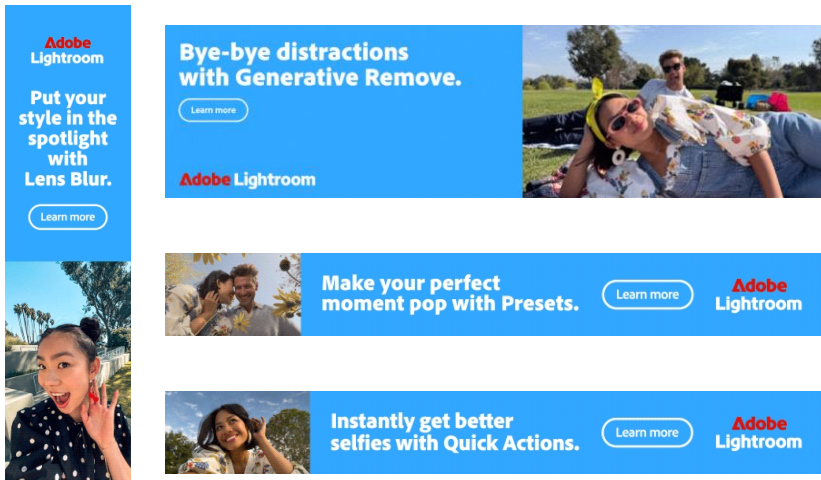
2. **LensBlur** — **Maintain & Optimize:** This **static** ad on **Facebook** reported good ROM (1.12), low CPA with high investment (135k) - Keep the ad active while introducing minor creative updates to keep it fresh.



A. CROSS-CHANNEL CREATIVE OVERVIEW

1. Highest Spend by Channel

Display



- On the Display platform, the "FY25Q2 Lr Sliders - Demand Conversion - US/CA" campaign allocated an equal budget of **\$388,000** across four ads: **Q2Sliders-Blur**, **Q2Sliders-GenerativeRemove**, **Q2Sliders-Presets**, and **Q2Sliders-QuickActions**, each commanding **16.95%** of overall spend.

Facebook



- Studio-NA-Q2Sliders-QuickActions:** This ad commanded highest total spend of **\$151,000** on Facebook, representing **6.6%** of the total spend.
- The video showcases a person outdoors in a floral dress with text overlay "Your beautiful smile," highlighting different Quick Actions UI to enhance subject, sky with a more vibrant after transformation shown.

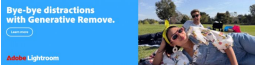
A. CROSS-CHANNEL CREATIVE OVERVIEW

2. Highest CPA by creative type



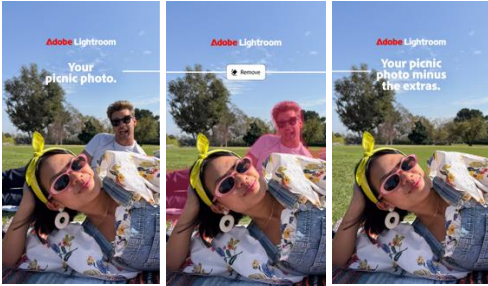
Static

Q2Sliders-GenerativeRemove
Channel: Display
CPA: 4.82\$



Carousel

Studio-NA-Q2Sliders-GenerativeRemove
Channel: Facebook CPA: 0.6\$



Video

CPA: 1.19\$



- On **Display** & **Facebook** channels, the ad *commanded the highest CPA* in **static** and **video** formats, featuring a sequence of images depicting Adobe Lightroom's Generative Remove tool used to remove background person.
- The high CPA indicates inefficiencies, *possibly due to targeting or messaging misalignment*.

ACTION: Re-evaluate audience targeting to ensure the ads are reaching potential high-intent users who value professional-quality edits. Conduct testing with different variations to identify what resonates best with the target audience and reduces CPA.

3. Top spending + most efficient CPA creatives



Display

Q2Sliders-Presets **Spend:** 388k **CPA:** 3.65\$



Facebook



Studio-NA-Q2Sliders-LensBlur
Spend: 135k **CPA:** 0.69\$

- On **display** channels, the ad with highest budget allocation **\$388,000** and efficient **CPC (3.65\$ CPC)** showcases Adobe Lightroom's Presets featuring a couple surrounded by flowers . Meanwhile, **on Facebook**, the top spending efficient ad (**\$135,000 ,0.69\$ CPC**) utilizes a split-screen to demonstrate Lightroom's Blur editing feature, effectively showcasing a before-and-after transformation of a young girl wearing polka dots.
- The relatively lower CPC of the **LensBlur** ad on Facebook suggests it might be capturing a more cost-effective audience.

ACTION: Bolster the Facebook campaign, leveraging its lower CPC for broader reach. Investigate potential overspending or underperformance in display channels, ensuring campaign is meeting conversion goals.

B. CHANNEL-SPECIFIC CREATIVE INSIGHTS

Display

Q2Sliders-QuickActions



- Best Performing Ad in terms of CPC (2.65\$)
- Highest ROM Ad (1.13x)
- Highest budget share with ROM (16.95% of total spend, 1.12x ROM)

- This **Q2Sliders-QuickActions** gif ad features a young woman outdoors taking a selfie, featuring multiple Quick Actions Lightroom leading to better selfies with a clear CTA "Learn more" button.
- By addressing the common need for enhanced selfies, the ad leverages Adobe Lightroom's Quick Actions feature as a straightforward solution for photo editing enthusiasts seeking immediate results achieving a satisfactory ROM of 1.13*

ACTION: To maintain and expand the success of this ad, test scaling and creating variations that highlight other Quick Actions features and settings, such as indoor photography or group photos, to broaden appeal. Consider implementing A/B testing to refine messaging and visual elements, with an expected impact of increased CTR and ROM.

Q2Sliders-Presets



- ▼ Underperforming Ad in terms of ROM (0.46x)

- This ad features **Adobe Lightroom's Presets** with couples appearing in a vibrant before/after gif transition surrounded by sky and flowers. The ad employs a professional color scheme with balanced, diverse hues to maintain a polished aesthetic, appealing to aspiring photographers.

ACTION: To address the underperformance in ROM, Consider testing with different versions and landing pages specifically tailored to niche audience groups

* Showing shortened creative summary & reasoning

B. CHANNEL-SPECIFIC CREATIVE INSIGHTS

Facebook



● Best Performing Ad
in terms of CPC (0.24\$)

The **Studio-NA-Q3Sliders-PresetsDoodle video** features a brown dog in an outdoor setting with yellow flowers across three medium-paced scenes, using "Your best boy." text overlay to showcase Lightroom's 'Presets' feature through before-and-after photo transformations. **By leveraging universal emotional triggers** - specifically pet photography, it achieved strong viewer engagement, as evidenced by its low CPC and high CTR

ACTION: Scale this creative across additional channels targeting pet owners and photography hobbyists; with diverse pets and outdoor settings to maintain freshness.



● Highest ROM Ad
(2.18x)

Studio-NA-Q2Sliders-LensBlur video achieves high ROM through a compelling split-screen before-and-after transformation showcasing Lightroom's Blur Adjustment feature, resonating with young adult photography enthusiasts

ACTION: Scale this creative format to other channels; test variations featuring other subjects and seasons.



● Highest budget share with ROM
(6.59% of total spend, 1.079x ROM)

Studio-NA-Q2Sliders-QuickActions Effectively showcases multiple "Quick Actions" with slow pacing ensuring clarity. It opens with a pleasant scene with young woman in floral dress against blue skies, featuring text overlay and strategically placed UI elements ("Quick Actions," "Auto" buttons) demonstrating quick photo edits

ACTION: Scale campaign to similar demographics in additional regions/platforms; increase spend allocation given positive ROM to maximize acquisition.



▼ Underperforming Ad in
terms of ROM (-0.96x)

Studio-NA-Q3Sliders-GenRemoveTerrier ad underperformed (ROM: -1.0) despite emotionally engaging dog content due to slow pacing, limited visual variety, and limited call-to-action ("try now/get started").

Action: Pause ad and analyze conversion path; re-evaluate messaging alignment with stronger, direct call-to-action.

Next

Data-driven content modification

Based on past data and insights, modify existing content to create variants *that will perform better*

Outline

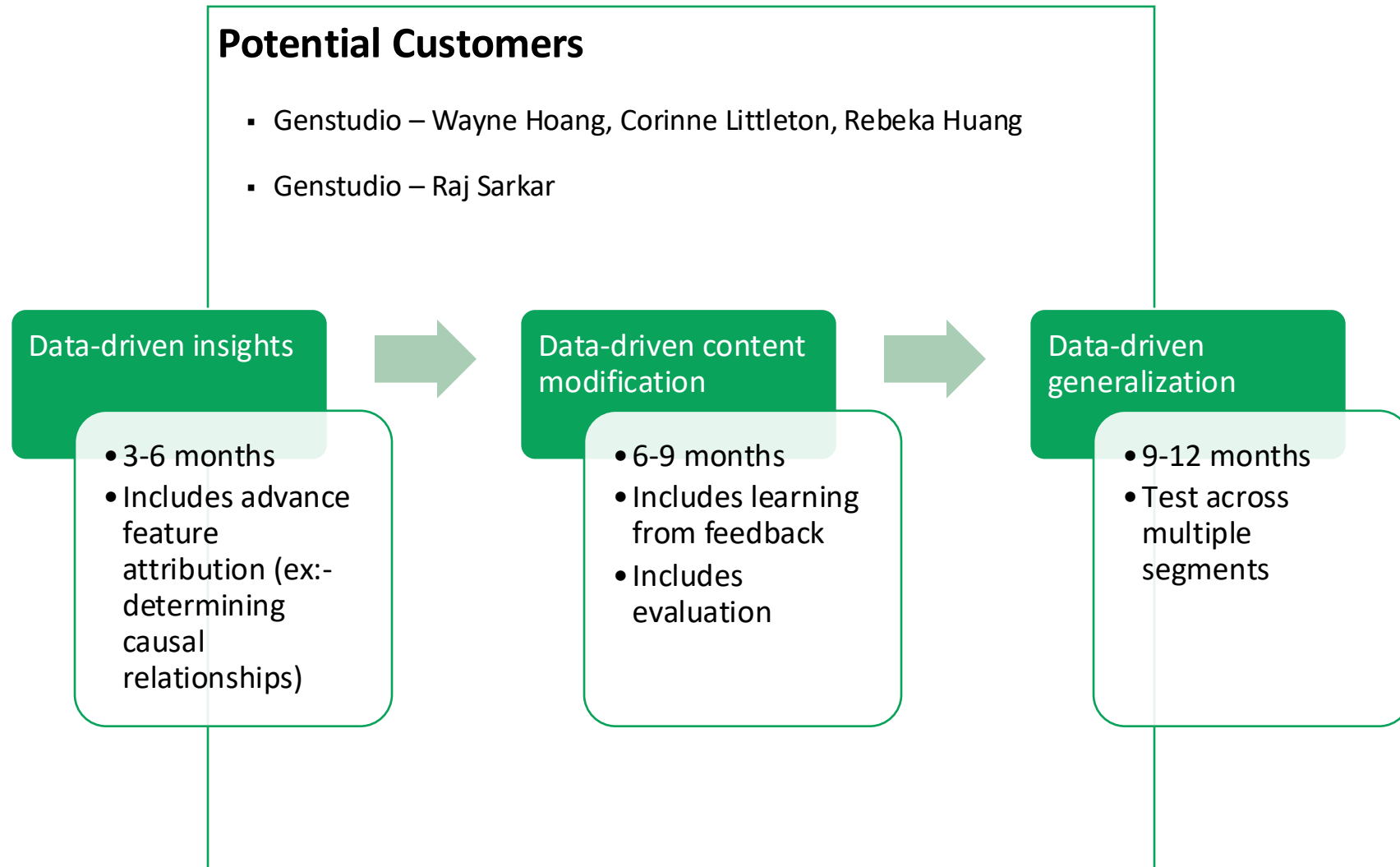
Main Research
Challenges

Research
Objectives

Existing
Explorations

Future
steps

Next Steps



Parallel collaborations

- Evaluation of short-videos
 - Uttaran, Digbalay, Ananya Sai – Evaluation metrics to evaluate quality of intermediate and final assets
Learnings from: Project Silverscreen, Doc2Video, Slides2Video
- Short-video efficient tool-calling
 - Mira, Valentina, Bryan, Fabian – Project [X]
Learnings from: Project Roughcut, Project Storybuilder

