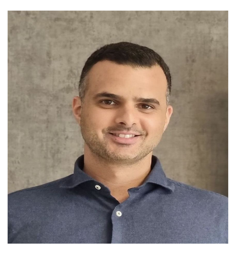
🎥 🔧 🔗 Visual Editing with LLM-based Tool Chaining: An Efficient Distillation Approach for Real-Time Applications

Lightricks

hyadata lab

THE HEBREW UNIVERSITY OF JERUSALEM

Paper!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Background and Motivation

- **Idea:** to teach LLMs to use existing, **specialized tools** in **VideoLeap**
- **Goal:** To implement an AI assistant, democratizing advanced capabilities.
- **Proof-of-concept: tonal color adjustments**, allowing users to change a video's appearance via textual instructions.

Our Task

Users provide an image/video and describe the desired appearance.
An LLM interprets the request, selects tools, and sets parameters.
Bottom row: the generated images by applying the LLM's output in our app.

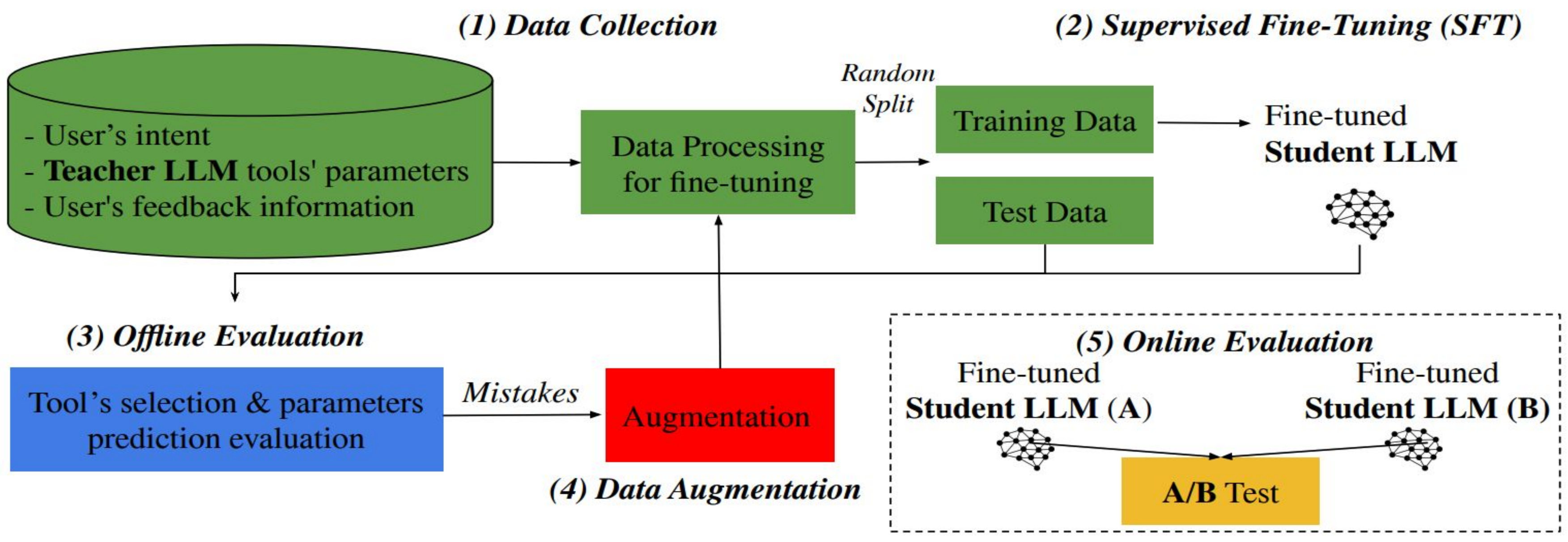
Example: **"Golden hour"**

Adjust: {"exposure": 0, "contrast": 10, "brightness": 10, "highlights": 20, "shadows": -10, "saturation": 15, "vibrance": 15, **"temperature"**: 30, "tint": 10, "hue": 0, "bloom": 0, "sharpen": 0, "structure": 0, "linearOffset": 0}

Selective Adjust: {**"red"**: {"saturation": 20, "luminance": 10}, **"orange"**: {"saturation": 30, "luminance": 20}, **"yellow"**: {"saturation": 40, "luminance": 30}, "green": {"saturation": -20, "luminance": 0}, "cyan": {"saturation": -20, "luminance": 0}, "blue": {"saturation": 0, "luminance": 0}}

Filter: {**"name"**: "faded_HighNoon", "intensity": 40}

Our Distillation Framework Approach



(1) Data Collection

Gathering Teacher LLM Outputs

- **Teacher LLM: GPT-3.5-Turbo** (**four months** – data collection period).
- **A data row includes: user's intent**, **output of the teacher LLM** (tools to use, parameters and their values), **user exports** information per tool.
- **Data Filtering:** samples with zero exports. Our teacher LLM can generate different outputs per intent (across different calls); We take as ground truth the result that **maximizes the export rate**.
- **Prompts: one-shot** example for user intent, with **rational (CoT)** and **output parameters** per tool.
- In total, we collected **9,252 unique user intents**, resulting in **27,756 rows**.

Data Processing for Fine-Tuning

- We used the collected data to fine-tune a student LLM (**concise prompts**).
- We don't request rational from the student, as we **prioritize low latency**.
- The student LLM is **trained on all 3 tools** (**multi-task instruction**).

Data Splitting

- **Test: 1K unique requests**, each with a teacher LLM output for each tool.
- **Training:** the remaining data (**8,252 rows**).
- Each row includes a user intent and 3 tool outputs.

Set	Adjust		SelectiveAdjust		Filter	
	Used	All	Used	All	Used	All
Train	7570	8252	2647	8252	5448	8252
Test	912	1000	356	1000	683	1000

(2) Supervised Fine-tuning (SFT)

Student LLMs

- **Auto-regressive model (decoder only)**: Llama-2-7b-chat-hf (7B) Meta
- **Sequence-to-Sequence model (encoder decoder)**: FlanT5-base (250M)

(3) Offline Evaluation Metrics

- **Tool-selection:** model's ability to decide correctly whether to use a tool. We measure ***precision*** and ***recall***, and report tool-selection score as ***F1-score***.
- **Quality:** the model's ability to use a tool correctly.
  - For the **filter tool**: the ***accuracy*** on the filter name.
  - For the **adjust** and **selective adjust** tools: the ***mean cosine similarity*** across samples between predicted and ground-truth parameter values.
- **Final score:** the ***harmonic mean*** between ***tool-selection score*** and ***quality score***, emphasizing high performance in both.
- **Overall score:** the average of the final scores of all tools.

(4) Data Augmentation

- We iteratively run the offline evaluation on the training set.
- **(1) Identifying where the student LLM predictions differ from the teacher's**
  - For the **filter tool**, when the predicted filter name is incorrect.
  - For the **adjust and selective adjust**, when a sample's cosine similarity is lower than the tool's mean cosine similarity without augmentation.
- **(2) Using another LLM to generate similar input user intents where the student LLM made mistakes (e.g., "cool tone" from "cool morning")**
  - New intents and the teacher LLM's original answers are added to the training
  - Augment when a mistake was identified by at least one tool.

(5) Online Evaluation (A/B test)

- **Metric**: *project_completion_rate = #projects_exported / #projects_started*.

Experiments

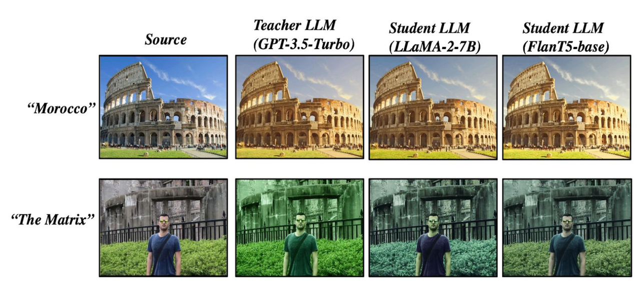
RQ1: How do student LLMs perform, do they effectively mimic the teacher?

Row	Model	Test	Adjust	Selective Adjust	Filter	Overall
1	Llama-2-7b-chat-hf	All	(.95, .63, .76)	(.75, .66, .70)	(.81, .71, .76)	.74
2		r_3	(.98, .68, .80)	(.82, .67, .74)	(.92, .73, .81)	.78
3		r_5	(.98, .75, .85)	(.87, .71, .78)	(.91, .83, .87)	.83
4	FlanT5-base (250M)	All	(.95, .57, .72)	(.76, .65, .70)	(.78, .71, .74)	.72
5		r_3	(.99, .61, .76)	(.87, .66, .75)	(.88, .72, .79)	.77
6		r_5	(.99, .68, .80)	(.90, .71, .79)	(.89, .82, .85)	.81

- **Metrics**: (tool-selection score, quality score, final score).
- **Overall**: avg. of final scores across the tools.
- **FlanT5-base performs very similarly to Llama-2-7b-chat-hf (rows 1, 4)**!

Reality check – human annotation on a sample of 15 generated images.
Three calibrated team annotators reviewed each sample according to two criteria:

- Is the image relevant to the intent?
- Does the student model correctly mimic the teacher?



- **Relevancy**: 13-14 out of 15 for all models.
- **Student LLM correctly mimic the teacher**: 11 / 15 for both (not the same).

Student LLMs Performance – Online Evaluation (A/B Test)

- **Exp 1. Teacher LLM:** GPT-3.5-Turbo **vs. Student LLM:** Llama-2-7b-chat
  - **Results:** completion rate for the teacher is **96.1%** of that of Llama-2-7b-chat.
  - We chose Llama-2-7b-chat for its lower latency and cost.
- **Exp 2. Student LLM:** FlanT5-base **vs. Student LLM:** Llama-2-7b-chat
  - **Results:** completion rate of FlanT5-base is **99%** of that of Llama-2-7b-chat.
  - We chose FlanT5-base for its lower latency and cost.

Our offline metrics align with the results of the online A/B tests!

RQ2: Is augmentation effective in low-data?

25% performance improvement (+0.13), in low data regimes (1/8 of the training) with just one iteration!

Train %	Augmentations	Train Size	Overall Score
100	0	8,252	0.72
12.5%	0	1,031	0.52
12.5%	**806 (43.8%)**	**1,837**	**0.65**

Future Work

- Fine-tuning improvements by **adding rational as an additional label** for supplementary supervision in a **multi-task framework** (Hsieh et al., 2023).
- To quantify the **benefits of integrating user signals**, and to explore **other methods for combining user feedback** (e.g, **personalization**).
- To extend our **one-hop responses** to **conversational agents / dialogue systems**.
- To apply our research into additional **tools, features, and applications**.