Portfolio



Personal Homepage: 🕒 http://lutaoyan.github.io 🔗





Bachelor 😥 Data Science and Big Data Technology

Keywords:

- Dataset
- MLLM (Multimodal Large Language Model)
- Data and Visual Analysis
- Computer Vision
- Artificial Intelligence
- Prompt and Fine-tuning on LLM





 $01 - \bullet \bullet \bullet \bullet \bullet \bullet \bullet$

Chart-Insight: A Large-Scale Dataset for Visual Analytics

Pipeline for Dataset Construction

Contribution & Honor

- Collaborated with HKUST II & RUC (??)
- A Recommendation Letter S From Prof. LUO
- First Dataset focus on Low-Level Visual Task .
- Available Metadata(eg. tables,pics,QA pairs)
- Abundant Visual and Textual Variants
- Support Investigating Performance of MLLMs

Overview of Chart-Insights



Highlight

- 5 key steps to construct Chart-Insight
- 2K high-quality charts
- Extensive and measurable difficulties
- Innovative 4 forms of textual prompt design
- Compared with Existing Datasets, available metadata facilitate future research
- Average 44.5 questions / chart, deep excavation of chart



Highlight

- 10 basic analytic tasks across 7 widely-used chart types
- Distribution on vast fine-graine task vs. chart, eg. Bar, Line, Scatter, Pie
- 10 low-level tasks into 3 categories, eg. Analysis, Search, and Query
- 89,388 quartets (chart, task, question, answer)
- In-depth evaluation on impact of basic chart element



Chain-of-Charts: A Novel Method to Improve Performance of MLLM

Contribution & Honor

- Summited to IEEE VIS (Flagship Conference)
- Co-first Author of Paper S
- Improve MLLM Performance by 24% in the field of Visual Analysis
- Transferable like Chain-of-Thought
- Can be combined with Visual Prompts

Evaluation Framework





Chain-of-Charts vs. Other Prompt Method

Highlight

- Chain-of-charts demonstrates its
 effectiveness and Interpretability
- Better than other common methods of enhancement (eg. Tutorial, Role-Play)
- Progressively guide the model towards a deeper understanding of charts
- Significantly improved GPT-4V's capabilities across 10 different tasks
- Developing visual prompts specifically is a promising research direction

Highlight

- A reasonable framework (T,Q,C)to evaluate MLLM
- With the bonus of Visual Prompt & Chain-of-Charts, the accuracy rate is increased from 56.13% to 83.83%!

Task-based Effectiveness of GPT-4V

• Shed light on the capabilities and limitations of MLLM

03 — • • • • • •

Offer valuable insights for future research



3D Lipstick Effect: A Tool to Make Face Fancy

Feature & Honor

- Top 3% Course Design (3D Vision and AI) •
- Based on Google MediaPipe AI Framework •
- **Core Algorithm: Face Mesh** •
- Extract Key Points to Make Effect on Face •

Principle & Demo

Background

In the current context of rapidly evolving artificial intelligence (AI) and computer vision technologies, my project - 3D lipstick effects based on MediaPipe - is an innovative practice in this trend. Combining the high-precision facial tracking technology with 3D graphics rendering, this technology has a wide range of practical applications, especially in the e-commerce and social media.



- More open sourced improved applications
- Complete Design Report











Age prediction

• Puppeteering

• Gesture recognition

• Posture detection

Traffic-sign Detection and Recognition

Feature & Honor

Overview of Project

- School of Computing Programme in
- Distinction (Top) Assessment S Certificate
- Traffic Sign dataset-based Deep learning
- Analysis Below 3% Error Rates

Highlight

 Sort large-scale dataset into 31,367 training images, 7,842 validation images, and 12,630 testing images

Basic Statistics • Numpy	2	Table Visualization • Pandas	2	Histogram • Matplotlib

• 4 Images Pre-processing Combination Method, Effectively Improve Image Quality



• Feature extraction algorithm (Especially HOG) to filter out the misdetected non-traffic sign areas Precise Positioning Step by Step





Multi-Evaluation to Find Best Model Combination

Model	Accuracy	Precision	Recall	F1 Score
HoG + KNN	0.939	0.912	0.907	0.909
Hessian + KNN	0.932	0.933	0.926	0.929
HoG + Random Forest	<u>0.991</u>	<u>0.996</u>	<u>0.983</u>	<u>0.989</u>
Hessian + random forest	0.977	0.989	0.961	0.975
LBP + SVM (linear kernel)	0.928	0.969	0.901	0.934
HoG + SVM (poly kernel)	0.986	0.991	0.981	0.986

Gallery

Defense Scene

