

Accelerating Machine Learning Prototyping of Multimedia Applications through Visual Programming



Ruofei Du, Na Li, Jing Jin, Michelle Carney, Scott Miles, Maria Kleiner, Xiuxiu Yuan, Yinda Zhang, Anuva Kulkarni, Xingyu "Bruce" Liu, Ahmed Sabie, Sergio Escolano, Abhishek Kar, Ping Yu, Ram Iyengar, Adarsh Kowdle, and Alex Olwal

visualblocksforml.github.io







Virtual Background





Input Foreground



Surface Normals

Convolved Light Maps



Albedo



Input HDR Map





Diffuse Light Map



Specular Light Maps



Relit Foreground

Pandey, Rohit, Sergio Orts Escolano, Chloe Legendre, Christian Haene, Sofien Bouaziz, Christoph Rhemann, Paul Debevec, and Sean Fanello. "Total relighting: learning to relight portraits for background replacement." ACM Transactions on Graphics (SIGGRAPH 2021) 40, no. 4 (2021): 1-21.

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sketched line indicates the chronological position in the story (sentences are the units). The y position shows how good or bad the protagonist's fortune should be (higher, better). The width of the line indicates the possible variance in the fortune of the sensested contences. Given the line sketch. TaleBreach will senseste story sentences (R1 indicated with high) and visualized to the the protagonist's fortune should be (higher, better). The width of the line indicates the possible variance in the fortune of the generated sentences, (iven the line sketch, TaleBrush will generate story sentences (B1, indicated with blue) and visualize the society of the science of of the sci generated sentences. Given the line sketch, TaleBrush will generate story sentences (B.1, indicated with blue) and visualize the result on the original sketch (B2; the blue line and dots). The writer can always directly edit the generated text. They can also a sentence of the same chetch /B3 elicibies on 'Conversing Again's or revising their sketch and generating and the same chetch /B3 elicibies on 'Conversing Again's or revising their sketch and generating and the same chetch /B3 elicibies on 'Conversing Again's or revising their sketch and generating and the same chetch /B3 elicibies on 'Conversing Again's or revising their sketch and generating again and the same chetch /B3 elicibies on 'Conversing Again's or revising their sketch and generating again and the same chetch /B3 elicibies on 'Conversing Again's or revising their sketch and generating again and the same chetch /B3 elicibies on 'Conversing Again's or revising the same chetch and generating again and the same chetch /B3 elicibies on 'Conversing Again's or revising the same chetch and generating again and the same chetch /B3 elicibies on 'Conversing Again's or revising the same chetch and generating again and the same chetch /B3 elicibies on 'Conversing Again's or revising the same chetch and generating again and the same chetch /B3 elicibies on 'Conversing Again's or revising the same chetch and generating again result on the original sketch (h2, the blue line and dots). The writer can always directly edit the generated text. They can also iterate by generating new text for the same sketch (B3, dicking on 'Generating Again') or revising their sketch and generating new text a distributed ontions allow the writer to snecify how 'surprising' the generation should be (B4) or using the eraset to a single of the generation of the same text of the same text of the same text additional ontions allow the writer to snecify how 'surprising' the generation should be (B4) or using the eraset to a single of the generation of the same text of the same text of the same text additional ontions allow the writer to snecify how 'surprising' the generation should be (B4) or using the eraset to a single of the same text of tex iterate by generating new text for the same sketch (B3, clicking on 'Generating Again') or revising their sketch and generating new text. Additional options allow the writer to specify how 'surprising' the generation should be (B4) or using the eraser tool (R5) to erase their sketch. Where the line is erased. TalePrinch generates unconstrained sentences. A history drondward (B6) new text. Additional options allow the writer to specify how 'surprising' the generation should be (B4) or using the eraser tool (B5) to erase their sketch. Where the line is erased, TaleBrush generates unconstrained sentences. A history dropdown (B6) endows the writer to browse previously generated sentences.

Permission to make digital or hard copies of all or part of this work for personal or datarroom use it granted without for provided that copies are not made or distributed for another experimental experimental and any environmental strategies are not stated by a first strategies and the experimental experimental and any environmental strategies are not stated by a first strategies and the experimental and any environmental strategies are not stated by a first strategies and the experimental and the experimental strategies are not strategies and the experimental strategies and the experimental strategies are not strategies are not strategies and the experimental strategies are not strategies are not strategies and the experimental strategies are not strategies are not strategies and the experimental strategies are not strategies are not strategies and the experimental strategies are not strategies and the experimental strategies are not stra

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Ctrr 22, April 29-May 5, 2022, New Orleans, LA, USA e 2022 (Appropring) the dd by the ownerstandbar(s). Publication rights licensed to ACM. ACM SIRN 97: 4269-455-32200, ...515.00 https://doi.org/10.1165/34911023501619

for predict arcommercial advantages and that copies hear this motion and the full cristian on the far provide the copyrights for composition of this work overally by others than the methods (b) much be copyrights for composition of the premated. To all you obtain that the output of the copyright of the constraints of the copyright of the premated and on the copyright of the constraints of the copyright of the premised and on the copyright of t While advanced text generation algorithms (e.g., GPT-3) have enwhile advanced rest generation agostions to be a state of the state of tive remains a challenge. Existing systems often leverage simple two remains a charge strange systems strenge everyone inter-turn-taking between the writer and the AI in story development. However, writers remain unsupported in intuitively understanding the AT's actions or steering the iterative generation. We introduce TaleBrush, a generative story ideation tool that uses line sketching interactions with a GPT-based language model for control sensemaking of a protagonist's fortune in

AI Chains: Transparent and Controlla by Chaining Large Languag

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1

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ABSTRACT

Although large language models (LLMs) have demonstrated impressive potential on simple tasks, their breadth of scope, lack of transparency, and insufficient controllability can make them less effective when assisting humans on more complex tasks. In response, we introduce the concept of Chaining LLM steps together, where the output of one step becomes the input for the next, thus aggregating the gains per step. We first define a set of LLM primitive operations useful for Chain construction, then present an interactive system where users can modify these Chains, along with their intermediate results, in a modular way. In a 20-person user study, we found that Chaining not only improved the quality of task outcomes, but also significantly enhanced system transparency, controllability, and sense of collaboration. Additionally, we saw that users developed new ways of interacting with LLMs through Chains: they leveraged sub-tasks to calibrate model expectations, compared and contrasted alternative strategies by observing parallel downstream effects, and debugged unexpected model outputs by "unit-testing sub-components of a Chain. In two case studies, we further explo how LLM Chains may be used in future applications.

CCS CONCEPTS

 Human-centered computing → Empirical studies in Interactive systems and tools; Computing methodologi Machine learning.

KEYWORDS

Human-AI Interaction, Large Language Models, Natural L Processing

ACM Reference Format:

Tongshuang Wu, Michael Terry, and Carrie J. Cai. 2022. AI Ch parent and Controllable Human-AI Interaction by Chaining Lar Model Prompts. In CHI Conference on Human Factors in Comp (CHI '22), April 29-May 5, 2022, New Orleans, LA, USA. ACM, 1 USA, 22 pages. https://doi.org/10.1145/3491102.3517582

"The work was done when the author was an intern at Google In



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that cannot be easily handled via a single run of an LLM. Recent unar cannot oc easily nananess via a single run or an LLM. Revent work has found that chaining multiple LLM runs together (with the work was course that comming manque elsest sums together (with the output of one step being the input to the next) can help users accomplish these more complex tasks, and in a way that is perceived to be

puss mese more compact tasks, and in a way that is perceived to be more transparent and controllable. However, it remains unknown what users need when authoring their own LLM chains - a key step to lowering the barriers for non-Al-experts to prototype Al-infused Large lan to sovering the barriers for non-rol-experts to prototype Arranusco applications. In this work, we explore the LLM chain authoring process. We find from pilot studies that users need support transprocess, we must from past attailer that users new support that forming data between steps of a chain, as well as debugging the chain at multiple granularities. To address these needs, we designed PrompiChainer, an interactive interface for visually programming cromps_namer, an interactive interface tor visually programming chains. Through case studies with four designers and developers, we show that PromptChainer supports building prototypes for a range of applications, and conclude with open questions on scaling tonge on approximation, and conclose with open questions on scaning chains to even more complex tasks, as well as supporting low-fi

chain prototyping. CCS CONCEPTS

chine learning. The work was done when the author was an intern at Google Inc.

[†]Equal contribution.

(c) (i)

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Related Work

Visual programming

TAILOR: Generating

◊Paul G. Allen School of G

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Abstract

Controlled text perturbation is

uating and improving model

However, current techniques

a model for every target pertur

expensive and hard to general

TAILOR, a semantically-control

ation system. TAILOR builds

seq2seq model and produces

conditioned on control codes

mantic representations. We

erations to modify the cont

in turn steer generation toy

tributes. These operations ca

posed into higher-level ones

ible perturbation strategies.

the effectiveness of these pe

tiple applications. First,

automatically create high-q

for four distinct natural la

(NLP) tasks. These contrast

spurious artifacts and are

manually annotated ones

versity. Second, we sho

turbations can improve m

data augmentatio

Alexis Ross*† Tongshuang

in language

Tongshuang Wu*† wtshuang@cs.washington.edu University of Washington

> Jeff Gray jeffgray@google.com Google Research

While LLMs have made it possible to rapidly prototype new ML w nue LLANS nave muse n possible to tupnay prototype new nu-functionalities, many real-world applications involve complex tasks

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https://doi.org/10.1145/3491101.3519729

Related Work Visual programming in graphics



Basic Symbols Figure 1.1



Connected Program Figure 1.2



THE ON-LINE GRAPHICAL SPECIFICATION OF COMPUTER FROCEDURES

by

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B.E.E., Rensselaer Polytechnic Institute

(1957)

M.S., Massachusetts Institute of Technology

(1963)

SUEMITTED IN PARTIAL FULFILLMENT OF THE

REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF FHILOSOPHY

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

January, 1966

Signature of Author _____ Department of Electrical Engineering, January 10, 1966 Certified by ______ Thesis Supervisor

1

WR Sutherland. 1966. On-Line Graphical Specification of Procedures. SJCC, Boston, Mass (1966).

12



▼ Preview	▼ Material	▼ Shaders	▼ Mirror Transp	Texture Map To	▼ Map Input	Ramps Links and Nodes
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Virtual Background









person 0.864

baseball glove 0.769







< Z □ INPUT 4 Image Mockup Camera Raw Sketch MODEL Pre-trained model Custom model EFFECT Effect1 Custom model 1 Effect1 Canvas Effect2 Show in preview param 1 0.8 drop here Image 1 param 2 0.5 OUTPUT 3, 256, 256 input Show in preview output 1024 drop here Canvas Key points 20 offset x Raw Custom model 2 (Keypoint offset y 50 rotation Ø Transformer 0 drop here MISC 2.4 scale overlay on 🔲 Image 1 W Performance 3, 256, 256 Show in preview input output 8 Show in preview

Lack of data processing for input in-the-wild

The complexity of processing of input formats yields longer cycles between finding failure cases and fine-tuning new models.

Lack of interactive data and model tuning



Loss of application context



"Metric doesn't help <in my depth models>, it's always good for all the models, so it's no use. They need human eyes to evaluate." (I6)

Lack of direct comparison and sharing



"I want to isolate bad examples of a specific error pattern to discuss with stakeholders." (I1)

Slow iterations

"A lot of time goes into visualization of challenge sets, benchmarking, and metrics. Usually takes weeks." (I2)

Insufficient controllability

"We need to integrate the model with other modules — (to evaluate whether) can we improve the higherlevel model?" (I7) **Design goals**

Visual programming for rapid prototyping
 Run real-time ML pipelines
 Input in-the-wild
 Interactive data augmentation
 Side-by-side comparison
 Off-the-shelf & customize models

or rapsai → Visual Blocks for ML

A Visual Programming Platform for Rapid and Iterative Development of End-to-end ML-based Applications

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Rapsai System Overview



Rapsai Nodes Library

Q Search nodes		Q Search nodes		Q Search nodes		Q. Search nodes		Q Search nodes		Q Search nodes	
]]Input	Audio Image	Input	Audio Processor Fragment Shader	ə Input	Body Segmentation	于 Input	3D Model Viewer Audio Comparison	.∋ Input	Binary Op Clip By Value	于 Input	Get Image Size Get Size From Rect
iiii Effect	Input Stream Live Camera	iiii Effect	Image Processor Images Mixer	iiii Effect	Custom Model Runner Mobilenet	iiii Effect	Audio Player Bar Viewer	iiii Effect	Const Tensor Crop And Resize	iiii Effect	Lobby Webpage
✦ ‡ Model	Video	✦ Model	Shader Processing	✦ ‡ Model		♦ ‡ Model	Image Comparison	✦ ‡ Model	Image To Tensor Postprocess Depth Model	+ ‡ Model	
⊡ Output		⊡ Output		⊡ Output		⊡ Output	Json Viewer Output Stream	⊡ Output	Preprocess Image Remap Value Range	⊡ Output	
[] Tensor		[] Tensor		[] Tensor		[] Tensor	Tensor To Depthmap Tensor To Image	[] Tensor	Tensor Picker Tensor To ClassifierResults	[] Tensor	
≇ Misc		庄 Misc] ∰Misc		태 Sc	Tensor Viewer	ः ∰Misc		∃≟ Misc	

Rapsai Nodes Library

D FULL LIST OF NODES IN RAPSAI

We list all the supported nodes in Rapsai before the case study. Note that Rapsai is extendable for expert users by adding new nodes in JavaScript.

D.1 Input nodes

- image: capture a photo from webcam, upload from hard drive, or fetch from a list of remote URLs.
- (2) video: record a video with external webcam or upload a video from disk or YouTube.
- (3) audio: record sounds from microphone, or upload audio files from disk or Internet
- (4) live camera: use live camera stream, similar for the live audio node.
- (5) remote stream: stream input from another device (e.g., mobile phone) via WebRTC, by opening a URL of the page with a lobby node.
- (6) lobby: create a WebRTC server to accept video streaming from other devices. Remote stream nodes that connect to the lobby node with the same name are sharing output via WebRTC streaming.

D.2 Effect nodes

- (7) image processor: crop and translate a region of interest in the input to verify an image model's invariance to translation; rotate, shear, resize an image to examine potential biasing issues in the training sets; apply blur and noise to test a model's robustness.
- (8) image mixer: mix images with GPU-based blending modes¹⁰
- (9) audio processor: trim the audio, change volume, and add background noise from a collection of 17 presets.
- (10) **fragment shader**: program and apply a screen-space graphical shader effect.
- (11) **shader library**: offers a pre-defined list of shader code to avoid coding into the "fragment shader".

D.3 Model nodes

- (12) custom model runner: enter the URL of an TensorFlow.js model or upload a TensorFlow model into the pipeline.
- (13) **body segmentation**: run a deployed MediaPipe body segmentation model.

- (14) audio denoising: run either of two deployed audio denoising models.
- (15) **MobileNet**: run a deployed MobileNet model for image classification.

D.4 Output nodes

- (16) **image viewer** node displays an image.
- (17) audio player: play a single audio output.
- (18) **image comparison**: qualitatively compare output from multiple models with zoom-in tools.
- (19) **audio comparison**: qualitatively compare output from multiple models with automatic track switching.
- (20) JSON viewer: read the raw output from a model for debugging.
- (21) **bar viewer**: view the classification results from a model such as MobileNet.
- (22) 3D model viewer: view 3D models from an URL or tensor.
- (23) tensor to image: view a tensor as images.
- (24) tensor to depthmap: view a tensor as depthmaps with different transfer functions.
- (25) **output stream**: see remote video streams from the **lobby node** input.

D.5 Tensor nodes

- (26) **preprocess image**: converts an input image to a 4D tensor as an input that is required by most image models.
- (27) **tensor picker**: select a tensor from an array of output tensors.
- (28) **tensor postprocess**: convert a tensor to an image and apply normalization calculators.
- (29) **binary op**: apply "and", "or", "xor", and "not" operations between two input tensors.
- (30) clip by value: clamp the values of an input tensor.
- (31) crop and resize: crop and resize a two-dimensional tensor.
- (32) preprocess tensor: normalize a tensor, expand dimensions, and optionally convert to grayscale image for many generative models.
- (33) **postprocess tensor**: normalize and resize a tensor for image output.
- (34) tensor picker: select a certain tensor from an array of model output. Note that most models only have one output so it is optional.
- (35) **remap value range**: select an input and an output ranges to remap tensor values.

D.6 Miscellaneous nodes

- (36) **webpage**: append a Google Form or a custom webpage for filling in surveys.
- (37) image size: obtain image size for outputting to some models.

Rapsai Nodes Library





Rapsai Node-graph Editor





Node Suggestion

Link Suggestion











(e) brightness

(f) contrast

(g) blur

(h) noise

49.6

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(a) intermediate results of interactive data augmentation applied onto a single input image



(b) side-by-side comparison of segmentation results with different augmentation techniques



Nothing to inspect

speed x8

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Case Study 3 Alpha Matte



	Audio	Webpage		
Case Study 4 Audio Denoising	noisy.wav 3.0s	Where was this recording made? *		
	cleaned.wav 3.0s			
	CCA Denoise	In larger crowded (street, mall, event, etc)		
	processed.wav 3.8 s	In small crowded area (bus, elevator, etc)		
	Start denoising	At beach, park, outside		
		🗌 In a Car		
	Audio Comparison	Other:		
	Active track •			
	processed.wav	What was going on while this recording was made? *		
	processed.wav (denoised)	Party / event - many people talking		
		Honking		
	Automatic track switching ⑦	P Windy		
	Audio Audio Processor	Audio Comparison Webpage		



Background interview (6.1 ± 0.8 min)
Video tutorial (4 min),
Visual analytics procedure using Rapsai (39.4 ± 4.6 min)
Discussion of Rapsai and perception prototyping in future (10.2 ± 2.0 min)
Post-hoc exit survey to use Rapsai and compare with Colab

Findings 1 Rapsai vs Colab

Less Control but More Transparent and Collaborative



I spent about half a minute to create an image classification pipeline, and I spent 2–3 minutes to build a depth estimation pipeline from scratch, since it took some time to figure out how to preprocess the input and visualize the output... while Colab is more flexible for different tasks, I guess it could range from 1

hour to a day or two.

In my case, I started from an existing template but overall it was quite fast, I'd say less than 5 min.

Findings 2

Assist in Identifying Issues with ML Models and Training Sets



It can help me understand how I should change the model architecture and what training examples to add.



P10

"

I can manipulate the brightness to see when the model fails.



P2

It gives me an intuition about which data augmentation operations that my model is more sensitive, then I can go back to my training pipeline, maybe increase the amount of data augmentation for those specific steps that are making my model more sensitive.





"

Using a video <as input> helps me get a cross-time feel of how the model performance varies, which is hard to capture with metrics. Comparing various noise parameters in the input to a model is useful to identify augmentation bias.



P8

Findings 3

Rapsai helps Model Selection, Learning From Pipelines, Study deployment





Building a custom webpage as debugging tool [by coding], cost <a junior engineer> over a month to build. This [Rapsai] is easy to distribute and try it immediately. It helps debug the pipeline.

"

It can help me understand how should I change the model architecture and add what training examples.





- 1. Lowers the barriers for ML prototyping
- 2. Empowers users to experiment with no/lowcode environment
- 3. Facilitates collaboration between designers and developers

Google Research

BLOG >

Visual Blocks for ML: Accelerating machine learning prototyping with interactive tools

FRIDAY, APRIL 21, 2023

Posted by Ruofei Du, Interactive Perception & Graphics Lead, Google Augmented Reality, and Na Li, Tech Lead Manager, Google CoreML

Recent deep learning advances have enabled a plethora of high-performance, real-time multimedia applications based on machine learning (ML), such as **human body segmentation** for video and teleconferencing, **depth estimation** for 3D reconstruction, **hand and body tracking** for interaction, and **audio processing** for remote communication.

However, developing and iterating on these ML-based multimedia prototypes can be challenging and costly. It usually involves a cross-functional team of ML practitioners who fine-tune the models, evaluate robustness, characterize strengths and weaknesses, inspect performance in the end-use context, and develop the applications. Moreover, models are frequently updated and require repeated integration efforts before evaluation can occur, which makes the workflow ill-suited to design and experiment.

In "Rapsai: Accelerating Machine Learning Prototyping of Multimedia Applications through Visual Programming",

presented at CHI 2023, we describe a visual programming platform for rapid and iterative development of end-to-end ML-based multimedia applications. Visual Blocks for ML, formerly called Rapsai, provides a no-code graph building experience through its node-graph editor. Users can create and connect different components (nodes) to rapidly build an ML pipeline, and see the results in real-time without writing any code. We demonstrate how this platform enables a better model evaluation experience through interactive characterization and visualization of ML model performance and interactive data augmentation and comparison. Sign up to be notified when Visual Blocks for ML is publicly available.

Visual Blocks for ML

Unleash your creativity

Visual Blocks for ML is an experimental JavaScript framework from Google that helps you add drag-and-drop machine learning blocks to your platform. Only your imagination limits the blocks you give your users. Off the shelf blocks include models, user inputs, processors and visualizations.

Colab experience and open source library will come soon.

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With Visual Blocks for ML, you can drag and drop to make your ML no coding required

Experiment with Visual Blocks

Click on any of the demos to pull up its graph in the interaction editor below





With the right tools, everyone can unleash your inner creativity.





Ruofei Du, Na Li, Jing Jin, Michelle Carney, Scott Miles, Maria Kleiner, Xiuxiu Yuan, Yinda Zhang, Anuva Kulkarni, Xingyu "Bruce" Liu, Ahmed Sabie, Sergio Escolano, Abhishek Kar, Ping Yu, Ram Iyengar, Adarsh Kowdle, and Alex Olwal







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speed x4

There are some times when you don't want all noise cancellation. People sometimes prefer audio with less noise cancellation because you want some context.

B - 2 - 4 -

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repose studio.







Accelerating Machine Learning Prototyping of Multimedia Applications through Visual Programming





Ruofei Du, Na Li, Jing Jin, Michelle Carney, Scott Miles, Maria Kleiner, Xiuxiu Yuan, Yinda Zhang, Anuva Kulkarni, Xingyu "Bruce" Liu, Ahmed Sabie, Sergio Escolano, Abhishek Kar, Ping Yu, Ram Iyengar, Adarsh Kowdle, and Alex Olwal

visualblocksforml.github.io







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visualblocksforml.github.io





Barrow Car



Provide a visual programming platform for rapidly building ML prototypes



Support real-time multimedia user input in-the-wild



Provide interactive data augmentation



Compare model outputs and render results directly side-by-side



Share visualization with minimum efforts



Provide off-the-shelf models and datasets



There are some times when you don't want all noise cancellation. People sometimes prefer audio with less noise cancellation because you want some context.










speed x6



Barrow Car







Machine learning practitioners often perform experiments that compare classification results. Users gather the results of different classifiers or data perturbations on a collection of testing examples. Results are stored and analyzed for tasks such as model selection, hyper-parameter tuning, data quality assessment, fairness testincident about the underlying data. Classifier com-

1. Introduction

user to tabutess in true runge of scenarios in according and assessing end model selection, tuning, fairness assessment, and data quality diagnosis. • Human-centered computing \rightarrow Visualization; Visual analytics: Information visualization;

Austract Machine learning practitioners often compare the results of different classifiers to help select, diagnose and tune models. We Machine tearning practitioners often compare ine results of augreent classifiers to neup serect, augnose and une moreas. we present Boxer, a system to enable such comparison. Our system facilitates interactive exploration of the experimental results and the such comparison. Our system facilitates interactive exploration of the experimental results and the such comparison. present Boxer, a system to enable such comparison. Our system facilitates interactive exploration of the experimental result obtained by applying multiple classifiers to a common set of model inputs. The approach focuses on allowing the user to identify obtained by applying multiple classifiers to a common set of model inputs. The approach pocuses on allowing the user to laterity interesting subsets of training and testing instances and comparing performance of the classifiers on these subsets. The system interesting subsets of training and testing instances and comparing performance of the causifiers on new subsets. The system couples standard visual designs with set algebra interactions and comparative elements. This allows the user to compose and provide the standard visual designs with set algebra interactions and comparative elements. This allows the user to compose and the standard visual designs with set algebra interactions and comparative elements. This allows the user to compose and the standard visual designs with set algebra interactions and the standard visual designs are the standard visual designs and the standard visual designs are the standard visual designs and the standard visual designs are the standard vi compres standard visual designs with set algebra interactions and comparative elements. This atlows the user to compose and coordinate views to specify subsets and assess classifier performance on them. The flexibility of these compositions allow the coorannate views to specify subsets and assess cutsuper performance on inem. The periodity of inese compositions anow the user to address a wide range of scenarios in developing and assessing classifiers. We demonstrate Boxer in use cases including

in detail.



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miss important aspects of classifier performance. For closer examination, practitioners rely on scripting in their standard workflows. The lack of specific tooling makes the process laborious and comparisons challenging, limiting how often experiments are examined

This paper presents Baxer (Figure 1), a system for the detailed

examination of classifier comparison experiments. Our approach allows a user to explore a collection of classifier results to iden-

tify interesting subsets of the data and compare performance across

uides a uniform mechanism

