Information Visualization

eXplainable Artificial Intelligence

Dr. David Koop





High-Dimensional Data Exploration

- What are the tasks?
 - Discovering data configurations according to personal preference
 - Understanding the tradeoffs involved in such configurations
 - Partition the data (or views) to help with exploration
- Goals of TripAdvisorND & Subspace Voyager:
 - Facilitate examination of key projection and key clustering
 - Let users explore and tweak











TripAdvisor-ND: Global Sight Map & Local Sight Explorer



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[J. E. Nam & K. Mueller, 2013]



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Coordination of Views



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N-D Touchpad Polygon

- 2 polygons, one for each axis (inner = x, outer = y)
- Controls the orientation of the two PPA vectors
- Shading of vertices indicates weight
- Move the vertices around to change the weights





Northern Illinois University









Problems with TripAdvisor-ND

- Have to keep track of two views at once
- ... so single window
- Have to move around two points in ND trackpad
- ...so trackball interface
- Hard to map axes
- ...so direct labeling











Subspace Voyager Interface



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In the







Trackball Interface



- Can use different mouse buttons
- Left: rotation
- Right: transition by changing axis
- Middle: travel along orthogonal vector (a z-axis), can't see until rotation









Fix Labels



Next Class: Critique Due

The Building Blocks of Interpretability

Interpretability techniques are normally studied in isolation. We explore the powerful interfaces that arise when you combine them and the rich structure of this combinatorial space.

CHOOSE AN INPUT IMAGE



For instance, by combining feature visualization (*what is a neuron looking for?*) with attribution (*how does it affect the output?*), we can explore how the network decides between labels like **Labrador retriever** and **tiger cat**.

CHANNELS THAT MOST SUPPORT ...

LABRADOR RETRIEVER

$\frac{\text{feature visualization}}{\text{channel}} \text{ of }$ $\frac{\text{hover for}}{\text{attribution maps}} \rightarrow$			and a second sec
net evidence	1.63	1.51	
for "Labrador retriever"	1.22	1.24	
for "tiger cat"	-0.40	-0.27	

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<u>Several floppy ear</u> detectors seem to be important when distinguishing dogs, whereas <u>pointy ears</u> are used to classify "tiger cat".



1.32	
0.13	







Introduction to eXplainable AI (XAI)

Q. V. Liao, M. Singh, Y. Zhang, and R. Bella





Survey of visualization in deep learning

Visual Analytics in Deep Learning Interrogative Survey Overview

§4 WHY

Why would one want to use visualization in deep learning?

Interpretability & Explainability Debugging & Improving Models **Comparing & Selecting Models** Teaching Deep Learning Concepts

§6 WHAT

What data, features, and relationships in deep learning can be visualized? **Computational Graph & Network Architecture** Learned Model Parameters Individual Computational Units Neurons In High-dimensional Space Aggregated Information







Who would use and benefit from visualizing deep learning?

Model Developers & Builders Model Users Non-experts

HOW

How can we visualize deep learning data, features, and relationships?

Node-link Diagrams for Network Architecture **Dimensionality Reduction & Scatter Plots** Line Charts for Temporal Metrics Instance-based Analysis & Exploration Interactive Experimentation Algorithms for Attribution & Feature Visualization

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WHEN

When in the deep learning process is visualization used?

During Training After Training

WHERE

Where has deep learning visualization been used?

Application Domains & Models A Vibrant Research Community







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Survey Landscape

		W	HY		V	VНC	C	I	V	VHA	Т				НС	W		C	WF	IEN	WHERE	
Work	4.1 Interpretability & Explainability	4.2 Debugging & Improving Models	4.3 Comparing & Selecting Models	4.4 Teaching Deep Learning Concepts	5.1 Model Developers & Builders	5.2 Model Users	5.3 Non-experts	6.1 Computational Graph & Network Architecture	6.2 Learned Model Parameters	6.3 Individual Computational Units	6.4 Neurons in High-dimensional Space	6.5 Aggregated Information	7.1 Node-link Diagrams for Network Architecture	7.2 Dimensionality Reduction & Scatter Plots	7.3 Line Charts for Temporal Metrics	7.4 Instance-based Analysis & Exploration	7.5 Interactive Experimentation	7.6 Algorithms for Attribution & Feature Visualization	8.1 During Training	8.2 After Training	9.2 Publication Venue	
Abadi, et al., 2016 [27]																					arXiv	-
Bau, et al., 2017 [28]																					CVPR	
Bilal, et al., 2017 [29]																					TVCG	
Bojarski, et al., 2016 [30]																					arXiv	
Bruckner, 2014 [31]																					MS Thesis	
Carter, et al., 2016 [32]																					Distill	
Cashman, et al., 2017 [33]																			1		VADL	





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