



Been Kim

Towards Automatic Concept-based Explanations



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• A trained model



• A trained model



Why do you think it's a cab? What is a cab in your eyes?

• Local(Instance-wise) methods ⇒ Most important features of the input



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• Global (label-wise) ⇒ Most important features of the class



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- Global (label-wise) ⇒ Most important features of the class
- TCAV tests queries



Why do you think it's a cab? What is a cab in your eyes?

- In what follows:
 - Review Concept Activation Vectors (CAVs)
 - Review the TCAV method
 - Introduce Concept Discovery in deep neural networks
 - Introduce ACE method
 - Describe ACE experiments and results

• Define a concept to test \Rightarrow wheel, asphalt texture, etc.

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- Choose a bottleneck layer



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• Test example: Is the concept associates with network's decision

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• Hypothesis?



• Repeat for bunch of test examples: Concept Cav VS Random Cavs ⇒ Statistical Test



TCAV score = Ratio of test examples where



- TCAV works for human concepts
 - Good for interpretability
 - A few labeled examples (10-30) are shown to be enough

- TCAV works for man-defined concepts
 - Good for interpretability
 - Easy to label a few examples
 - Hard to keep tractable
 - Striped? Horizontally Striped? Black-&-white striped?



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 - Easy to label a few examples
 - Hard to keep tractable?
 - Striped? Horizontally Striped?
 Black-&-white striped?
 - Super-human performance
 - Concepts are not directly related to image pixels

ACE

TCAV



Saliency Maps





TCAV

Saliency Maps

Global (General Behavior) Local (Instance-wise behavior)



TCAV

Saliency Maps

Global

Concepts

Local

Pixels



TCAV	Saliency Maps
Global	Local
Concepts	Pixels
Human-in-the-loop	Automatic

ACE		
TCAV	Best of both world	Saliency Maps
Global	Global	Local
Concepts	Concepts = Pixels	Pixels
Human-in-the-loop	Automatic	Automatic

ACE		
TCAV	ACE	Saliency Maps
Global	Global	Local
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ACE

TCAV



Saliency Maps



ACE

TCAV

Zebra TCAV in googlenet



ACE

Police Van



Saliency Maps




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 - A target class

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 - A bottleneck layer



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- Looking back at CAVs —> highly accurate
- Assumption: Concept examples form clusters in the activation space
- How to find concept examples?
 - Can appear several times, once or not at all
 - Appear with different sizes





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Problem: Lots of irrelevant resized patches

- Idea: Segment every image with several resolutions —> Remove duplicate segments
- Resize each segment to the network input size --> "Resized Patches"
- Map resized patches to activation space —> Clustering with noise removal



Problem: Lots of irrelevant resized patches

Colors



Textures



Objects



Human related



We are running intruder test with human subjects





1. Example results: Inception-V3, Mixed-8, Basketball



Example results: Inception-V3, Mixed-8, Drilling Platform



Example results: Inception-V3, Mixed-8, Volcano



• How to verify ACE?



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- Concept deletion/addition:
 - Average results for 100 Imagenet classes



- Concept stitching experiment:
 - Concepts are discovered as a set of patches
 - We can randomly stitch patches of top-k concepts of each class



Thanks!

Paper: https://arxiv.org/pdf/1902.03129.pdf

Code: https://github.com/amiratag/ACE