Interpretability in Machine Learning

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Outline

Learning Objectives

- Realize that deep learning models aren't necessarily black boxes
- Distinguish between types of interpretability studied in literature
- Understand foundational distillation and perturbation-based methods

What is interpretability?

- "Ability to explain or present in understandable terms to a human."
- I would add: ability to predict (by hand) the model's behavior under different interventions
  - Do I get the same prediction if I slightly change neuron 132 in layer 3?
  - What if I deploy my self-driving cars in snowy Montreal, after training in sunny Palo Alto?
  - What if change the subject's race in data point x_i?

General Approaches

- Resort to a more easily interpretable model
  - Distillation: Compress complex model into simpler, more interpretable one
  - Design: Create new model classes competitive with Deep Learning, but easier to interpret
- Quantify effect of perturbations
  - Saliency maps: Pixel-level feature importance
  - Influence Functions: Importance of individual training examples
  - Concept Activation: Sensitivity to user-defined concepts

Linear Models

- In some ways, a gold standard
  - Sign and size of β_j is meaningful
  - Effects of changes in x_j easy to predict (even when extrapolating!)
- But even here, can be issues
  - True effect can be null, but still see nonzero β_j
  - Correlated input lead to unstable coefficients
  - Outliers lead to counterintuitive behavior

Decision Trees

- In some ways, a gold standard
  - Can trace "decision-making" process
  - Effects of changes in x_j easy to predict (even when extrapolating!)
- But even here, can be issues
  - Paths can get complicated for even moderately deep trees
  - Correlated input lead to unstable splitting patterns

Outline

Distillation

- Intuition: Large models do well because they have better search strategies, but learned decision boundaries can be approximated by simpler model classes
- Strategy: Train a complicated teacher model, and "distill" it into a simpler student model
- (Besides interpretability, often useful for model compression)

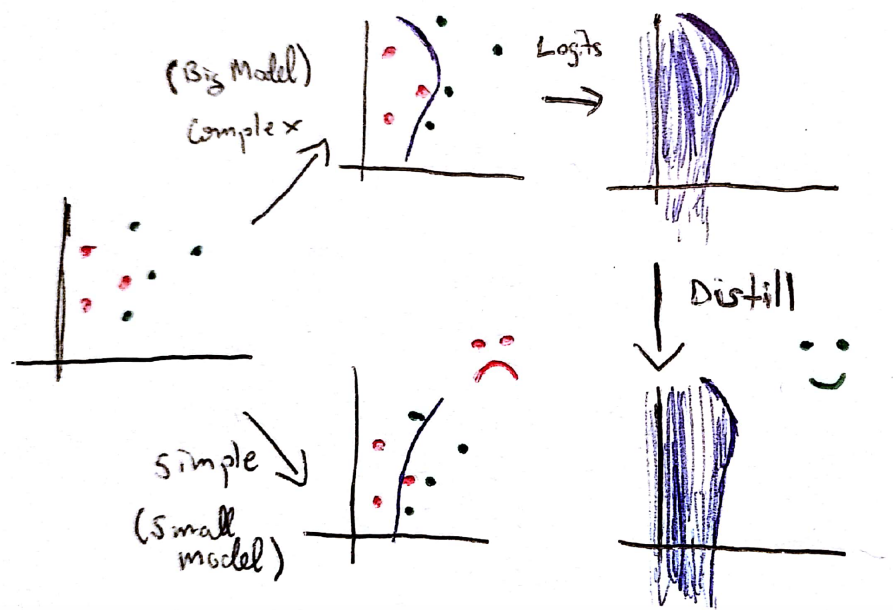


Figure: Distilling a complex model to a simple model class often works better than attempting to directly learn within the simple model class.

Distillation by Trees

- Proposal: Approximate teacher logits by class of soft decision trees
  - Branching probabilities at node i: $\sigma\left(x^T w_i + b_i\right)$
  - Internal nodes still learn filters w_i
  - But now can inspect paths for each decision

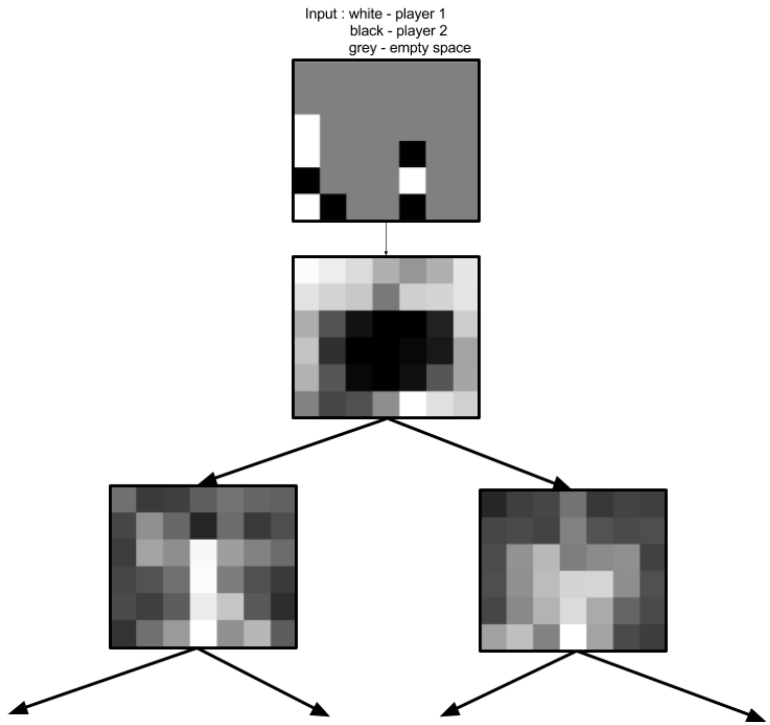


Figure: It's possible to inpsect learned features at decision nodes, as in this Connect 4 example.

Additive Models

- Approximate regression / decision surface by additive model with interactions
  - $F(x) = b_0 + \sum h_j(x_j) + \sum_{j \neq k} h_{jk}(x_j, x_k) + \ldots$
- Can directly inspect changes in predictions when changing values of specific features
- Good for tabular data
- Bad when features need to be learned from raw inputs

Additive Models

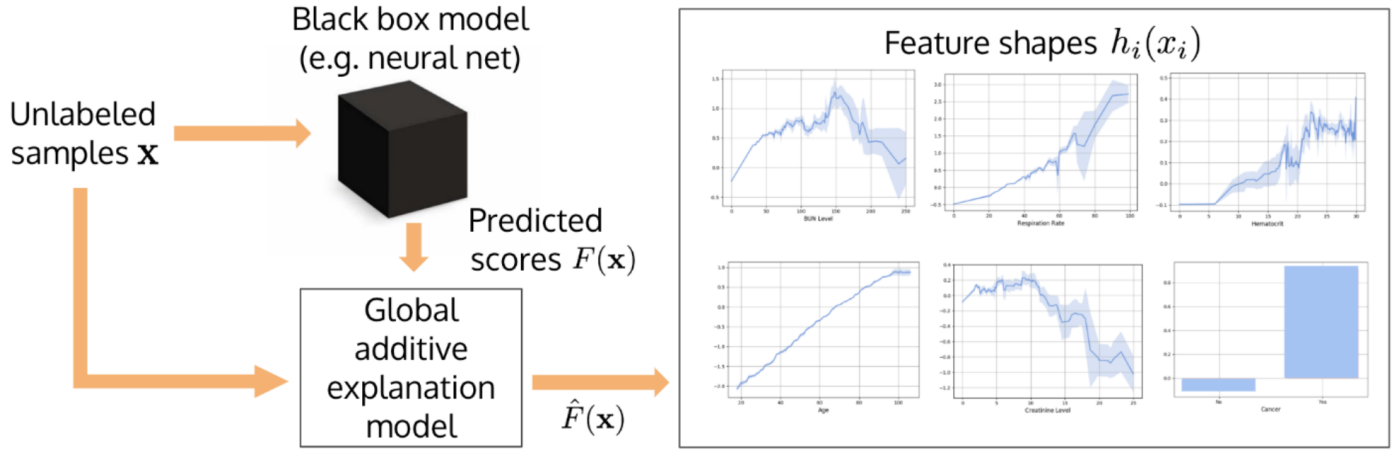


Figure: Example first-order additive features learned by distillation.

Outline

Perturbations

- Intentional perturbation can be illuminating
- What happens when you change...
  - Raw pixel values?
  - Presence of training example?
  - Layer activation values?

Saliency Maps

- For a given image, how would class predictions change if you manipulated a pixel?
- Simplest version: $\nabla_x f_\theta(x)$ change in class given infinitesimal changes in inputs

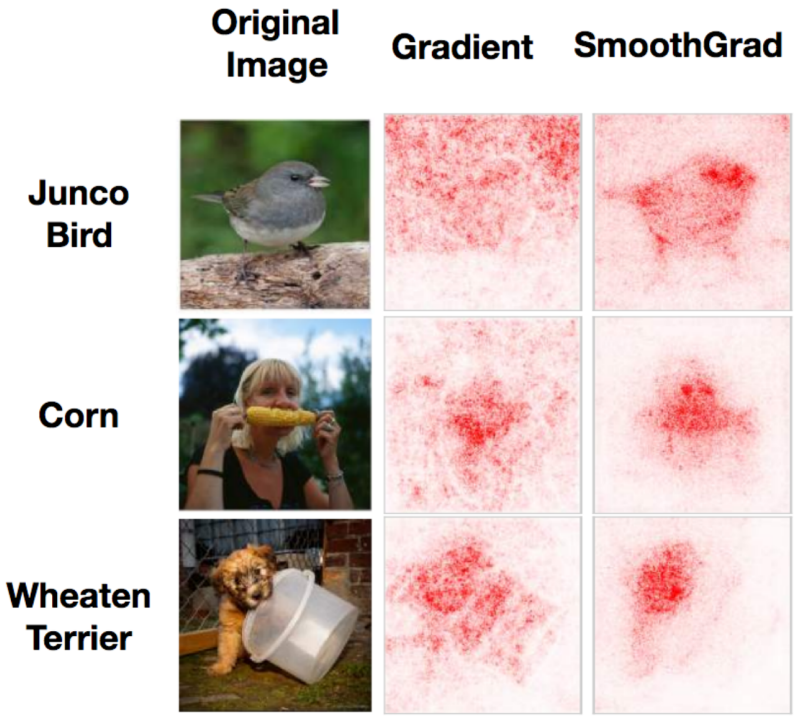


Figure: Example saliency maps. Smooth-grad just averages the gradient map over many noisy versions of input image.

Cautionary advice...

- While simple to implement, use cases aren't entirely clear
- Still have to inspect one example at a time
- Many proposals don't pass *sanity checks*

Influence Functions

- Classical notion from statistics: Influential datapoints
- Measures sensitivity of fit to removal of points

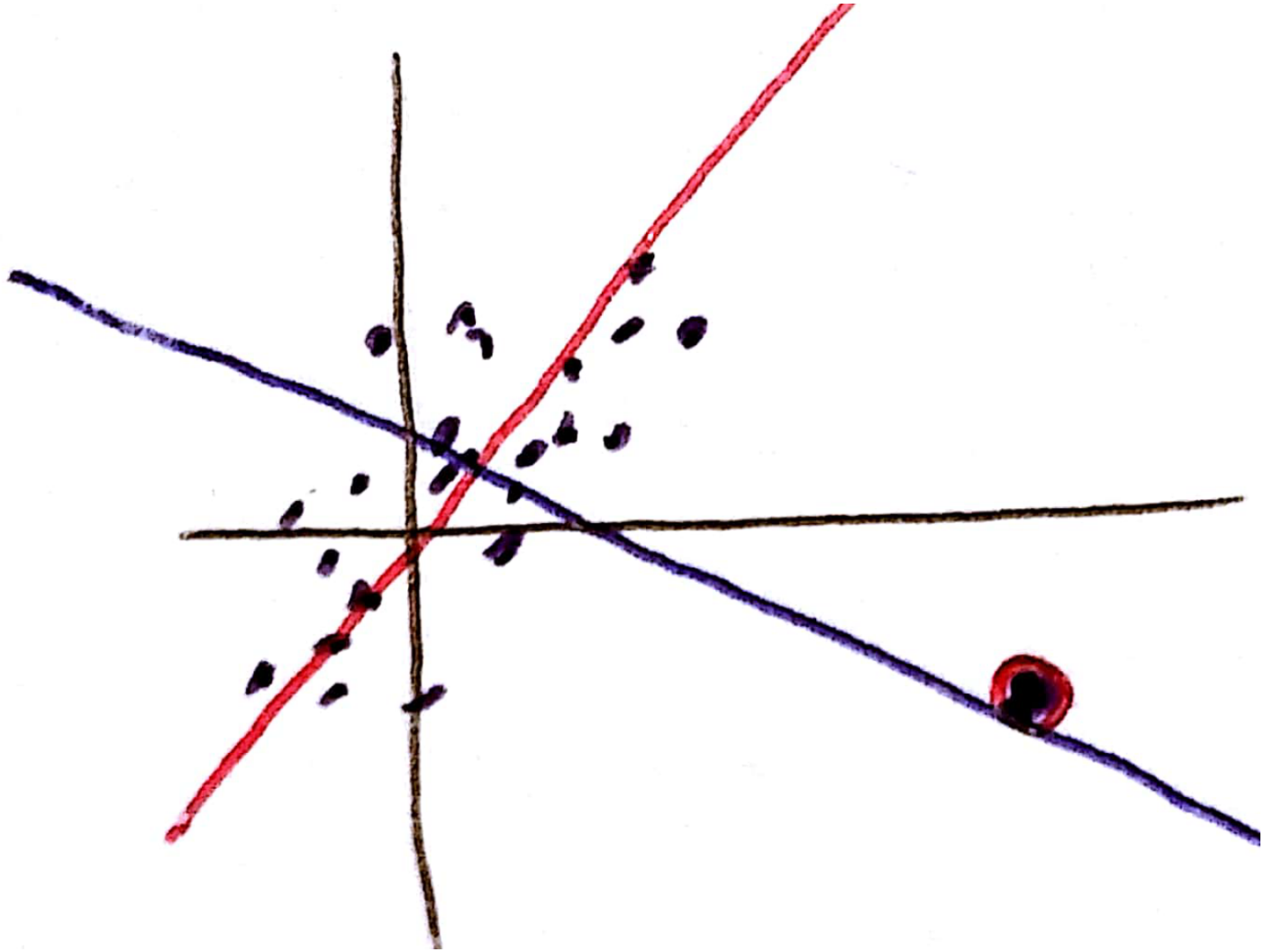


Figure: The difference between fits when you include vs. remove a point is

Contributions

- Change in loss at (potentially new point) z when ϵ-upweight training pair $z_i = (x_i, y_i)$

$$I(z, z_i) = -\nabla_\theta \ell\left(z, \hat{\theta}\right)^T H_{\hat{\theta}}^{-1} \nabla_\theta \ell\left(z_i, \hat{\theta}\right)$$

- Alignment between gradients of loss at new and old points, after adjusting for local curvature
  - More alignment $\rightarrow$ larger decrease in loss
- Applied of SGD-able approximations to Hessian $H_{\hat{\theta}}^{-1}$

Applications

- Identifying most influential points for specific test cases
- Identifying mislabled points in training data
- Not restricted to deep learning!

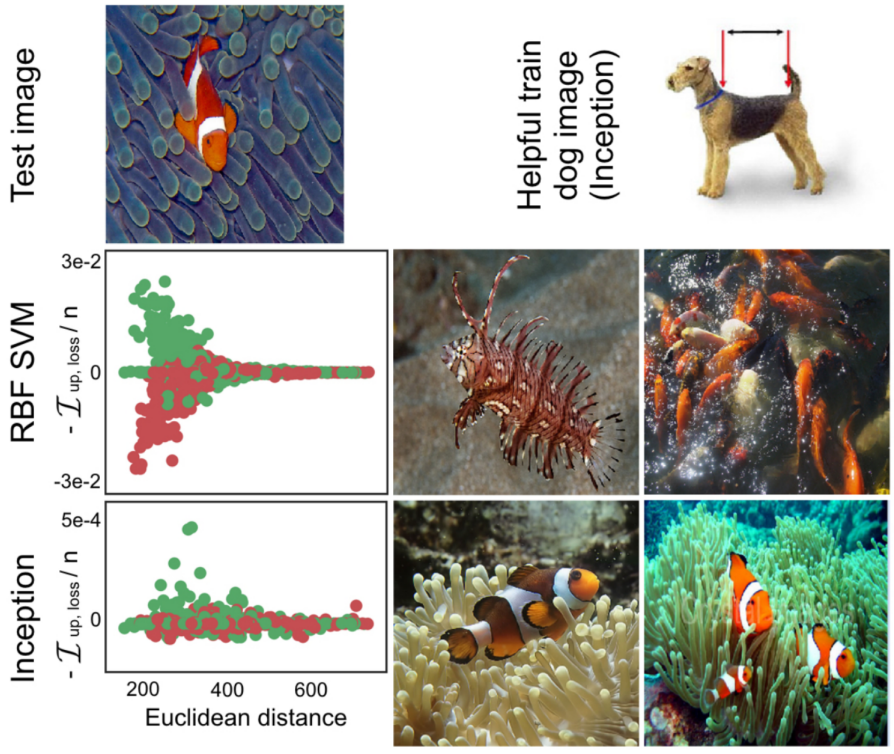


Figure: Example influential observations from koh2017understanding

Concept Activation Vectors

- What if you had a specific "concept" that you wanted to test model sensitivity to?
  - Importance of anemone to predicting clownfish?
- Need workable definition of a concept...

Formulation

- Idea: Have the user provide concepts!
- Study how concept affects feature activations, one layer at a time

User concepts

- User creates set of "concept" samples (or chooses them from a database, using image tags, say)
- Create activations f_l at layer l for both concept and random nonconcept examples
- Define concept activation v_C^l based on learned linear decision boundary

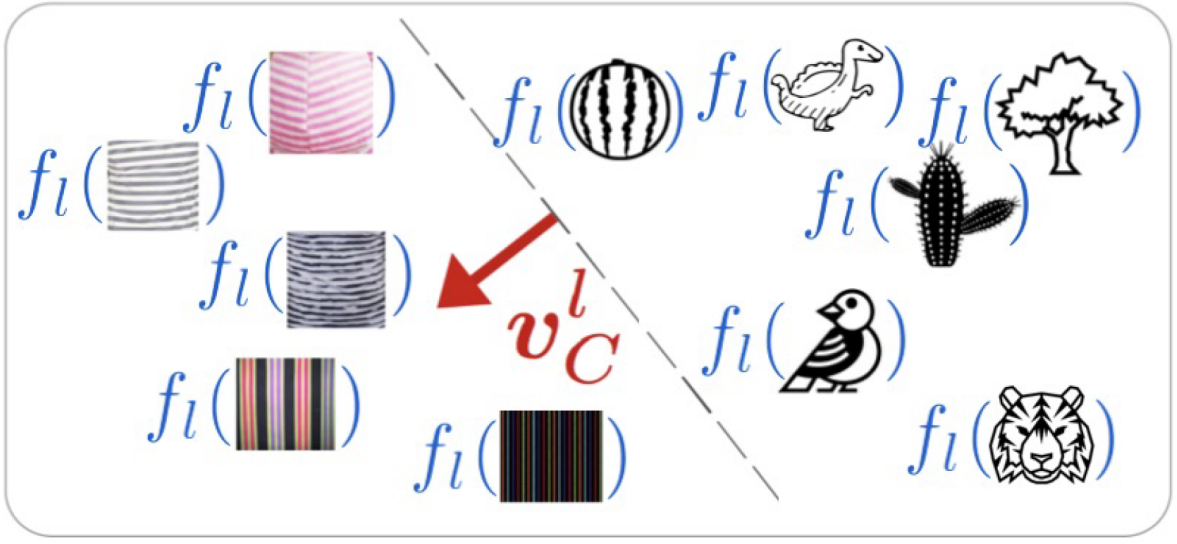


Figure: The CAV vector is defined as the direction that separates samples representative of a concept (like stripes) and unrelated random samples.

Effect of Concepts

- See how logit h_{lk} changes when nudging layer l activations $f_l(x)$ for example x towards concept C

$$S_{k,C,l}(x) = \lim_{\epsilon \downarrow 0} \frac{h_{lk}\left(f_l(x) + \epsilon v_C^l\right) - h_{lk}\left(f_l(x)\right)}{\epsilon}$$

- Averaging this over examples x from class of interest

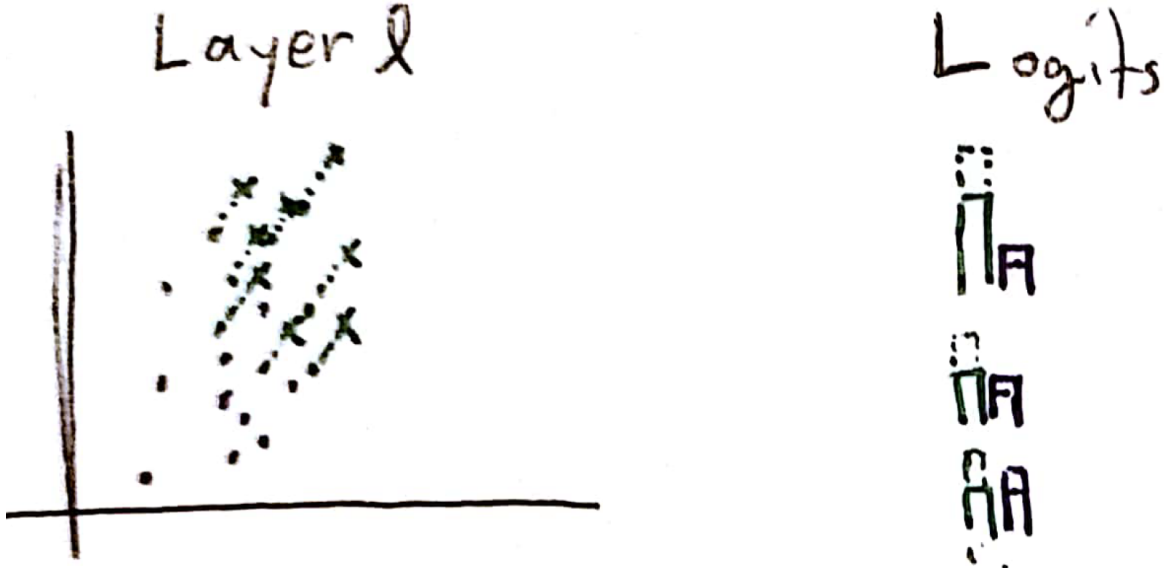
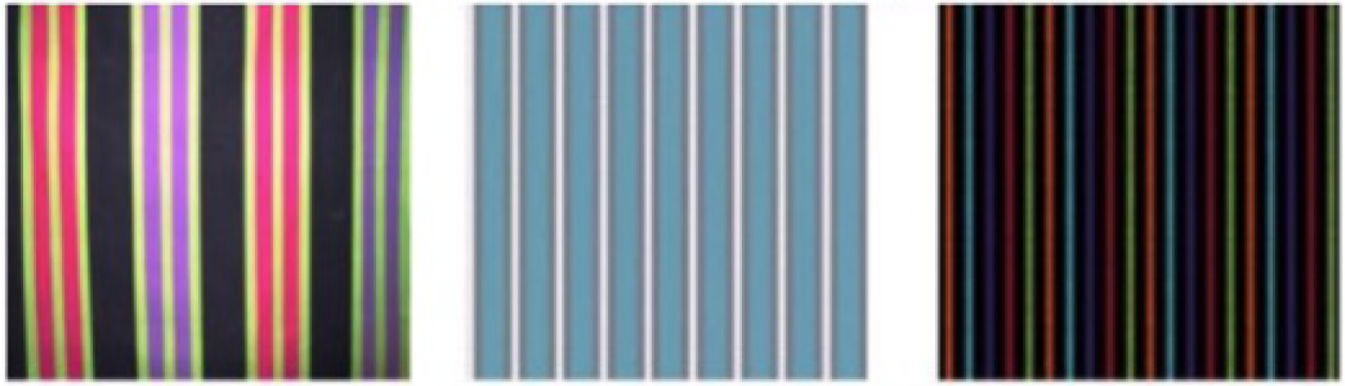


Figure: The CAV score for a class is the amount the logit for that class changes in response to perturbing its examples in the CAV direction.

Applications

- Find examples within a class most and least similar to specified concept

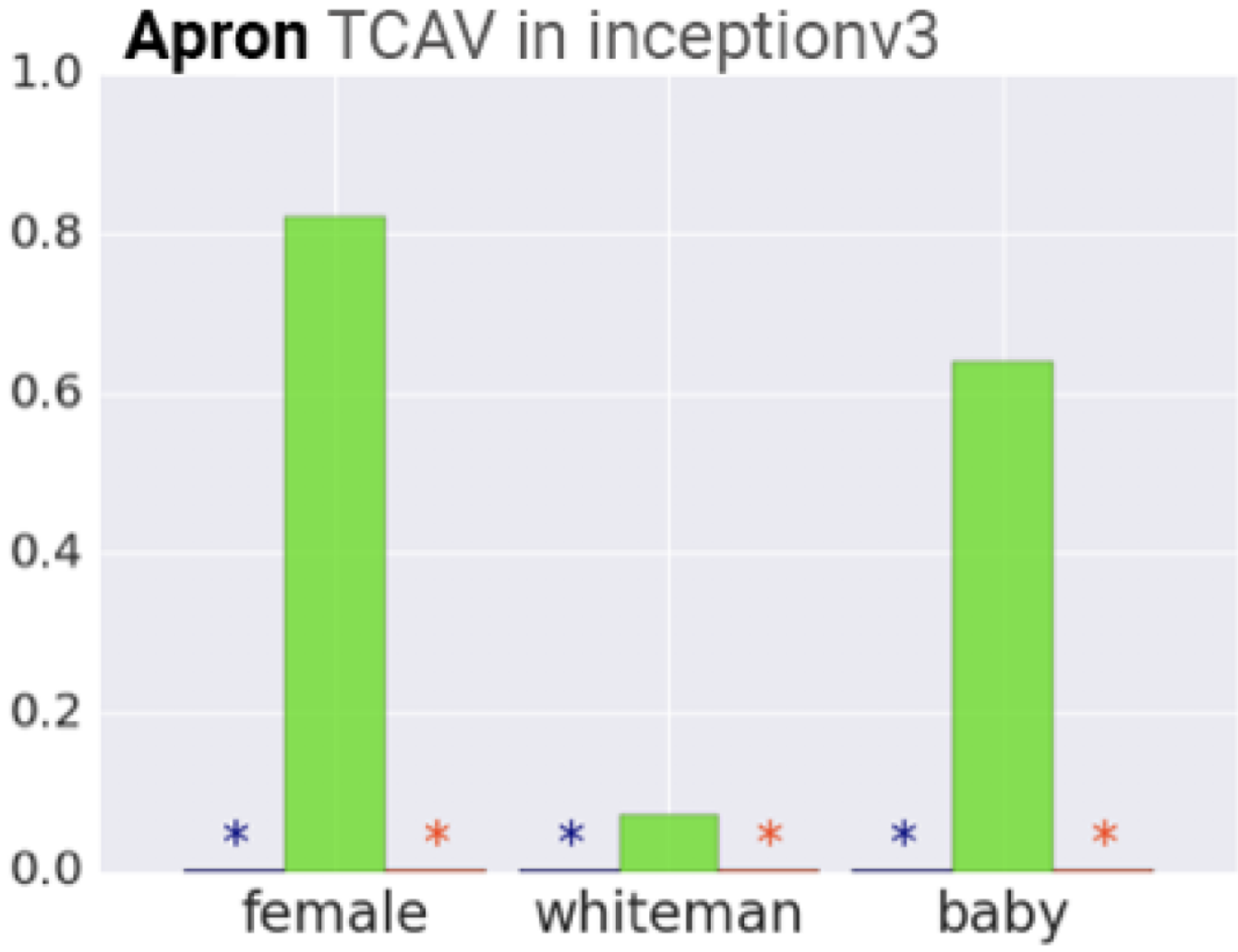
CEO concept: most similar striped images



CEO concept: least similar striped images

Applications

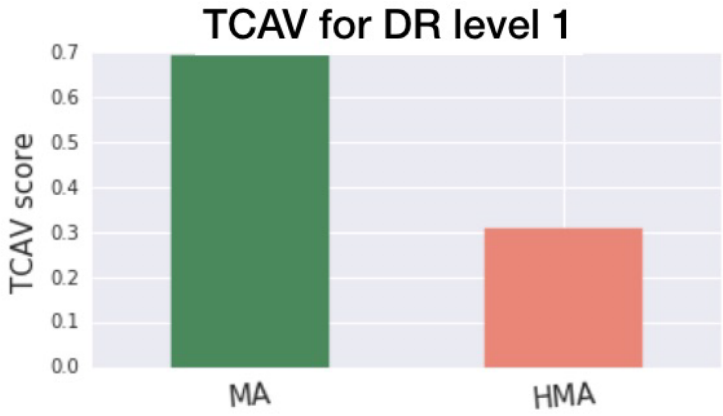
- Quantify potential sources of bias

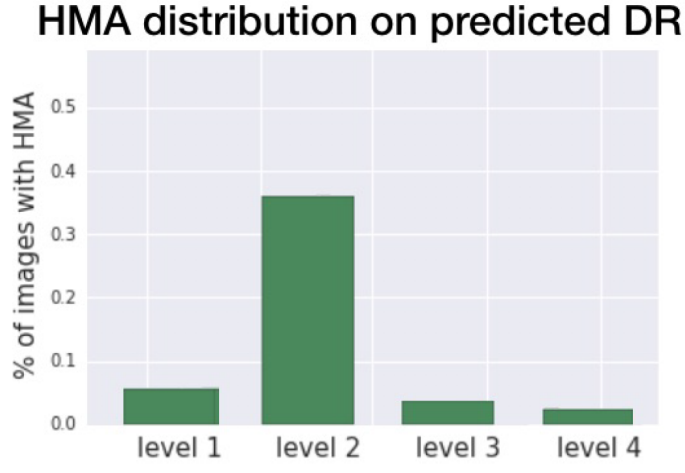


Applications

- Measuring consistency with codified medical practice

DR level 1 Retina





Conclusion

- As complicated as it can be to interpret models... still usually simpler than interpreting people