Interpretability Tools as Feedback Loops

BoilerMake X

J. Setpal

January 21, 2023

Outline

1. Setting the Stage
2. Baselining Interpretability
3. Leveraging Interpretability

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b. This classifier differentiates between an Orca and a Leopard.

c. We use the Caltech-256 dataset to obtain images of both:

d. There are 188 leopard images and 89 orca images.

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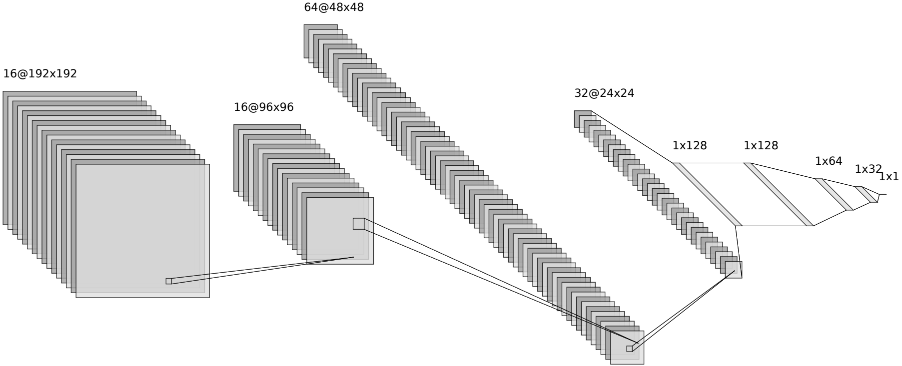
More Scenario Stuff

Here's our model architecture:



Last Bit of Scenario, I Promise

We use:

a. Optimizer: `SGD`
   - Learning Rate: 10^{-2}
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b. Loss: `BinaryCrossEntropy`

c. Epochs: 5

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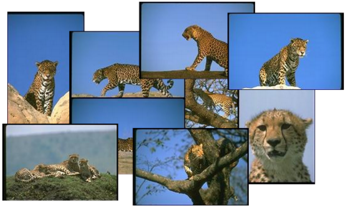
However, we achieve a **test accuracy** of only `0.5938`. This *sucks*.
Here are some misclassified samples:



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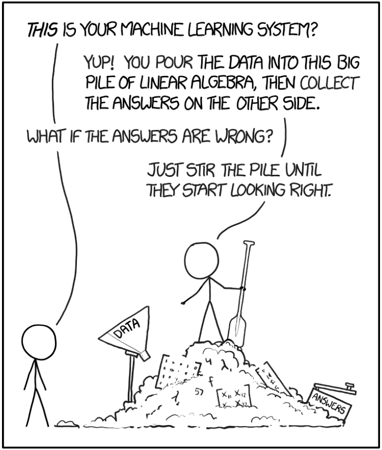
What even *is* Interpretability?



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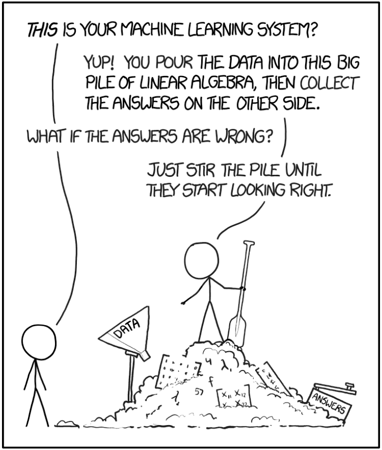

Interpretability within Machine Learning is the **degree** to which we can understand the **cause** of a decision, and use it to consistently <u>predict the model's prediction</u>.

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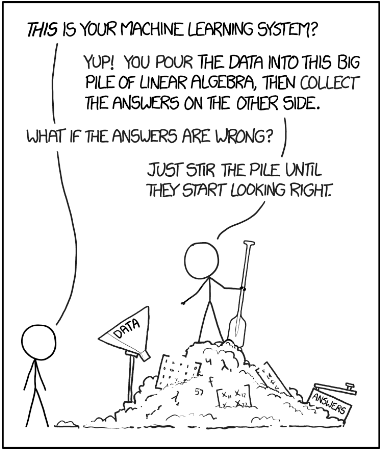

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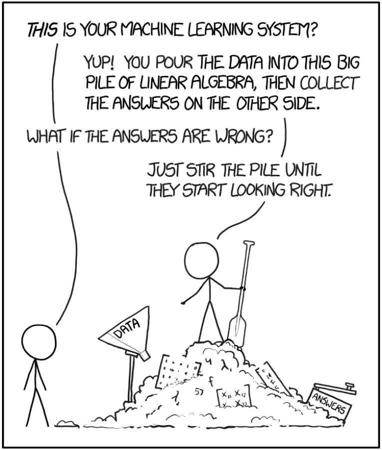

Interpretability within Machine Learning is the **degree** to which we can understand the **cause** of a decision, and use it to consistently <u>predict the model's prediction</u>.

This is easy for shallow learning. For deep learning however, it is a **lot harder**.

A Cautionary Tale

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They were not successful.

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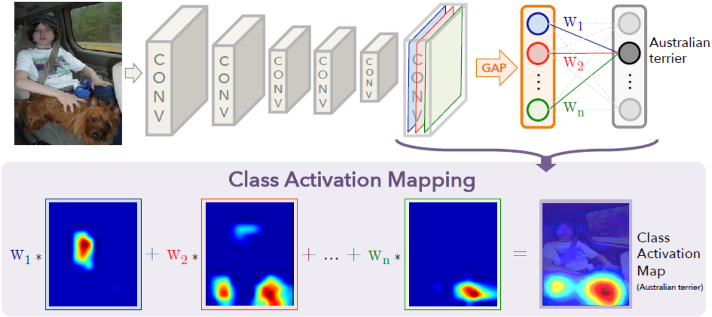
We'll focus today's discussion on **Class Activation Mappings (CAMs)**:



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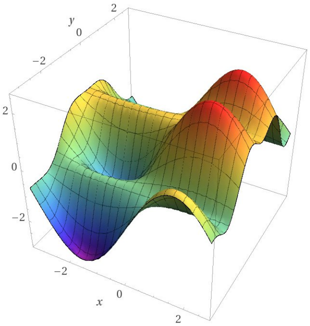

Model Search Space

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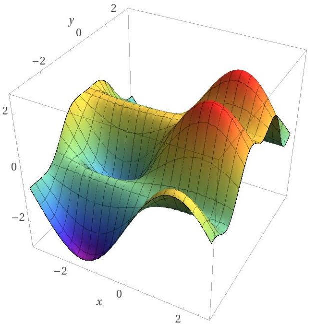

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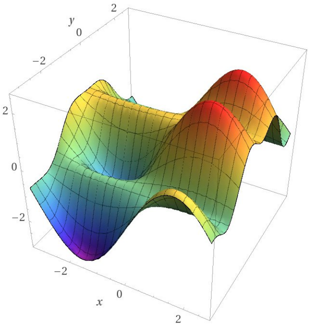

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So, the idea here is simple: use shared knowledge (+ common sense) to modify how we train our models.

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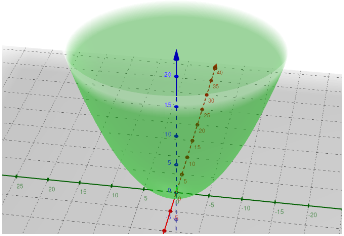

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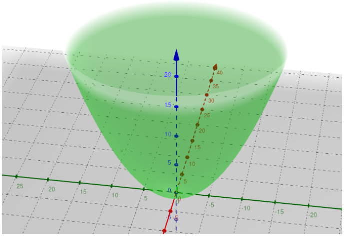

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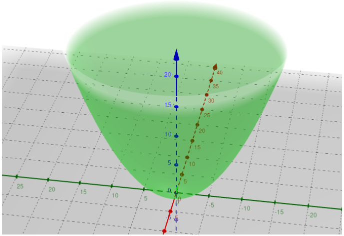

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By updating our loss function to eliminate *pseudo-correctness*, we can:

- Make the optimal weights incredibly easy for our optimzer to find.
- Allow our generalized model to extrapolate on implicit information.

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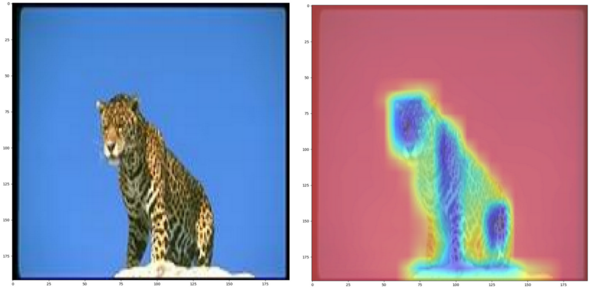
Diagnosing the Model

When we obtain a Class Activation Map of a sample image, we observe:



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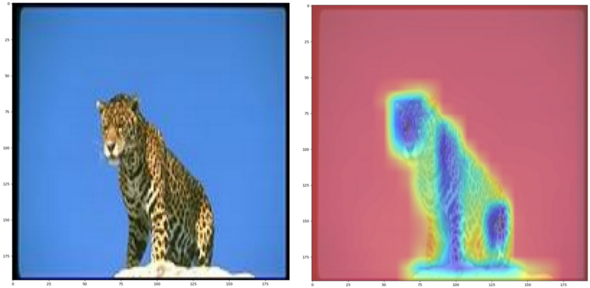

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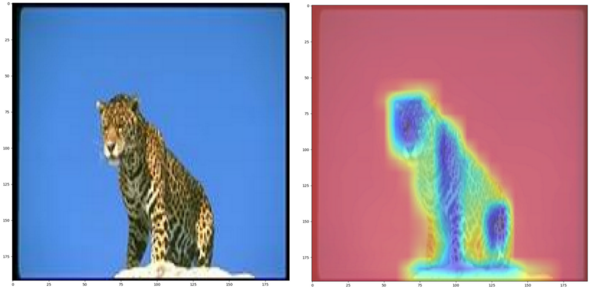

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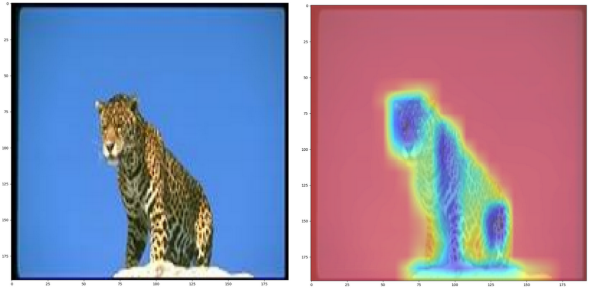

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Q: Can we exploit this?

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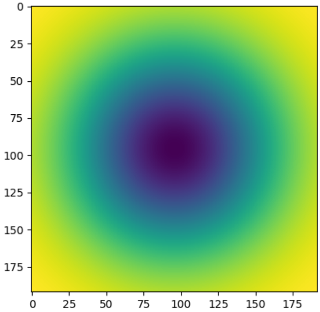

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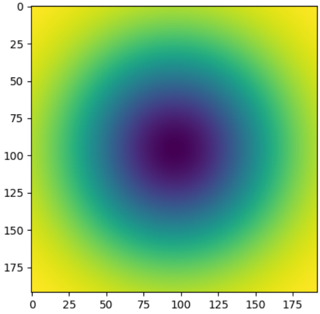

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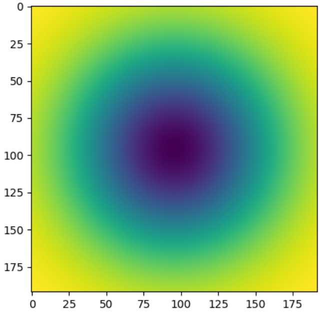

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Weights scale sharply as the operation approaches the image boundary.

It has to not be perfect, since we don't intend to overfit our model to this setup. This kernel filter is a **guideline**.

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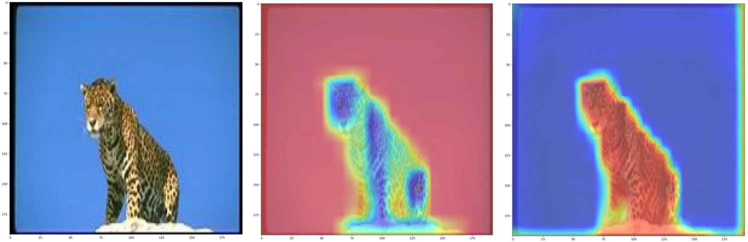

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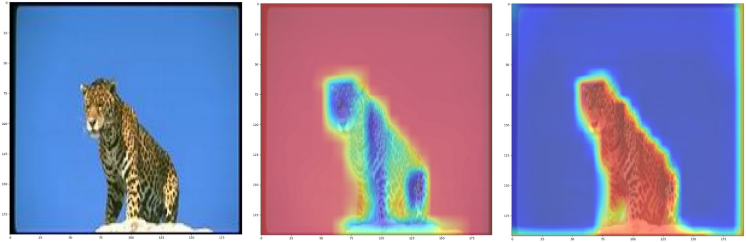

Great Success!

Implementation Details

If you can view this screen, I am making a mistake.

Thank you!

Have an awesome rest of your day! Any questions for me?

Code, Experiments, Data, Slides:

https://dagshub.com/jinensetpal/lint.git