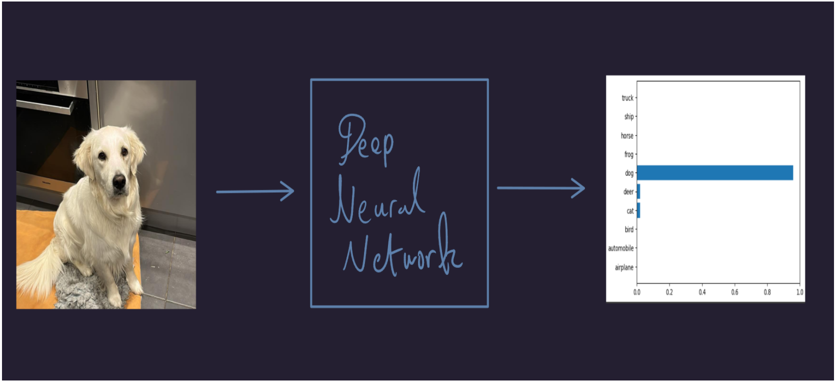
A Benchmark for Interpretability Methods in DNNs
(Google Brain)

Sam Laing

University of Tuebingen

June 25, 2024

A Bit of Background



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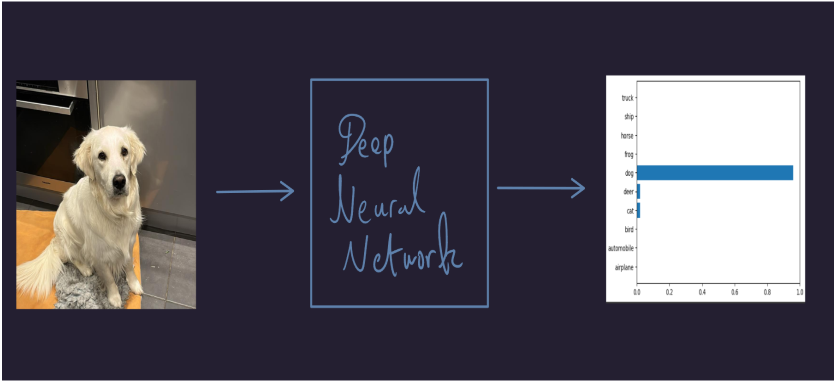

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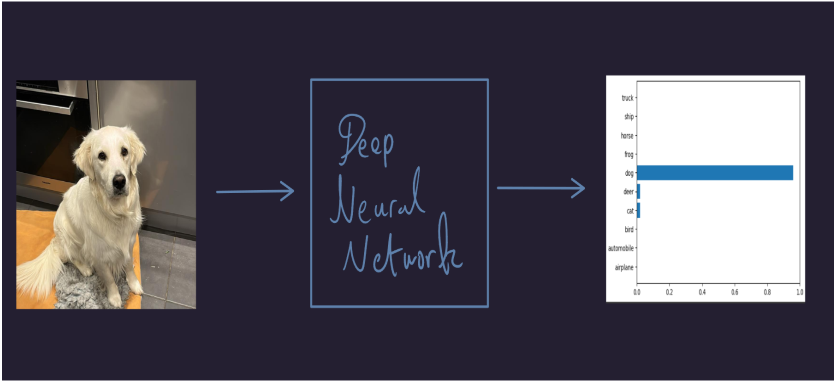

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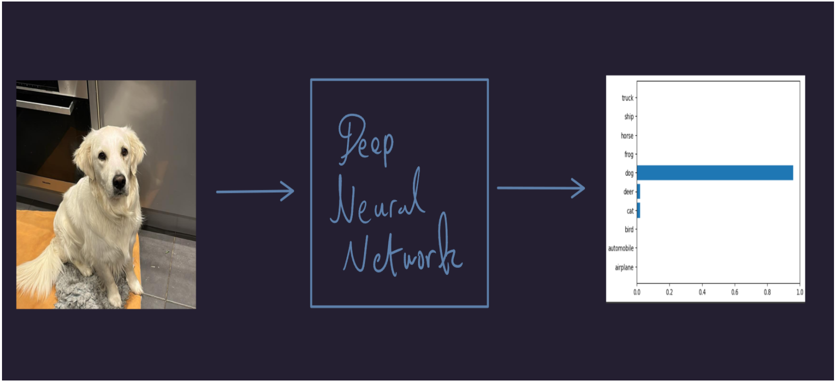

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- Interpretability methods $\rightarrow$ help engineer understand their model
- Austensibly. But are they even right?

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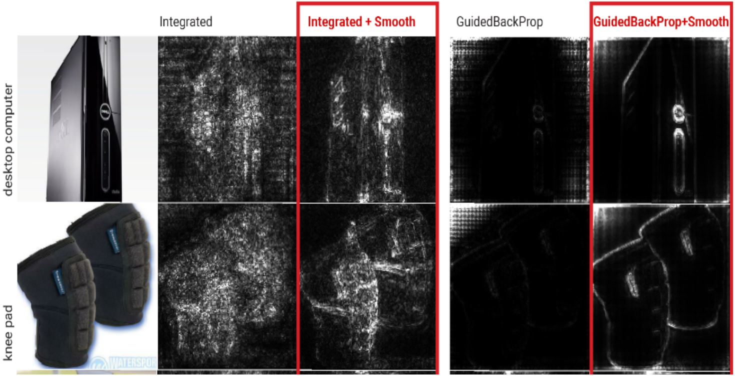
- If only there was a benchmarking framework to do this...

Included Interpretability Methods



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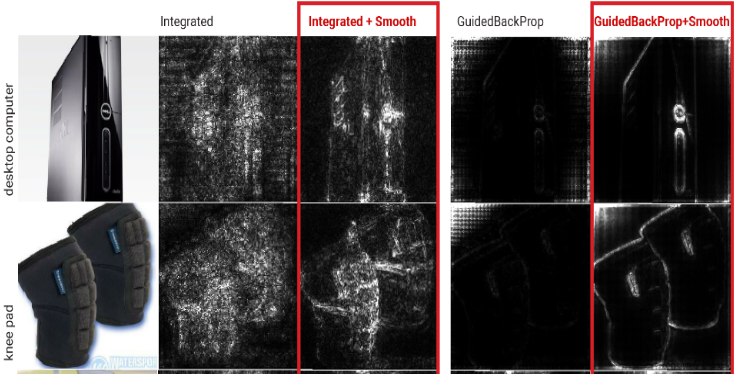

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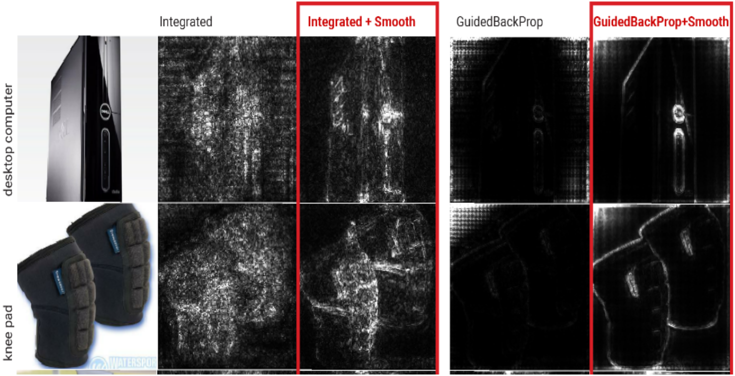

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- Integrated Gradients

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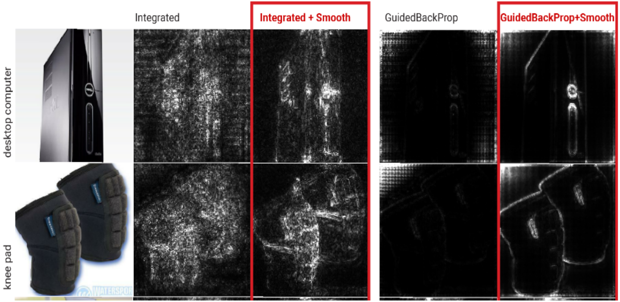

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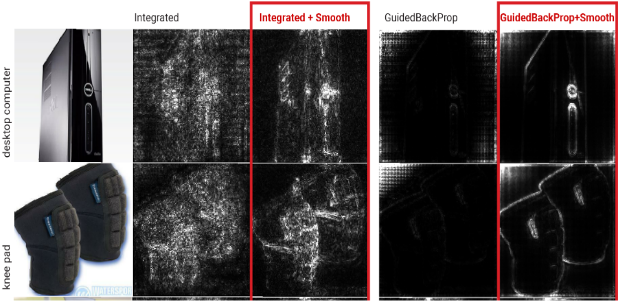

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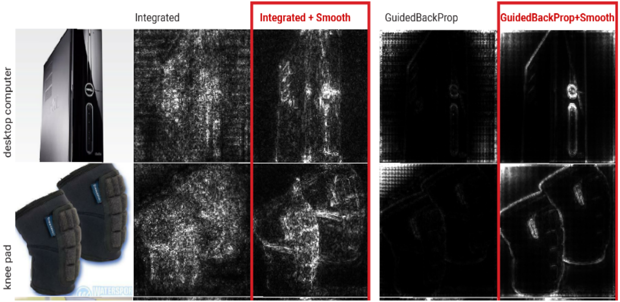

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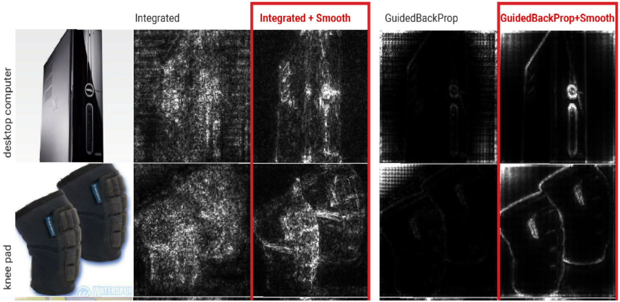

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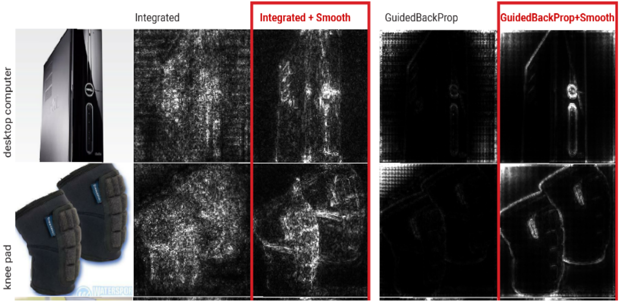

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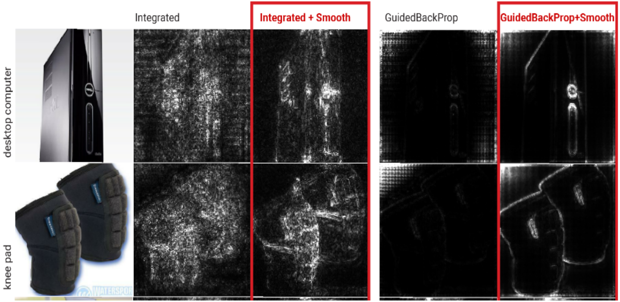

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$\rightarrow$Apply attribution/interpretability methods to these statistics

ROAR (RemOve And Retrain)

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So $(e_j)_{j=1}^{D}$ of pixel coordinates $\forall$ image in dataset. $\implies ((e_j^{(n)})_{j=1}^{D})_{n=1}^{N}$

The idea behind ROAR

for $j \in \{0, 10, \ldots, 100\}$, replace the top j% ranked pixels with the per channel mean $\forall$ image and retrain.

Proportion: 10%

The idea behind ROAR

Proportion: 30%

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Proportion: 70%

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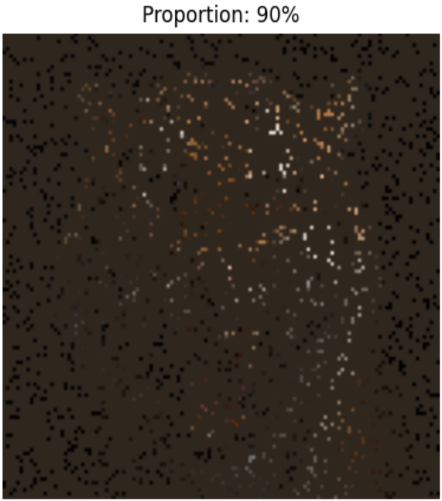

The idea behind ROAR

- Effect of having dropped the "most informative pixels" as determined by each interpretability method.
- Investigate how much their removal from the training process effects accuracy.
- Also a no-retraining variant

To Retrain Or not To Retrain

- No retraining $\implies p_{\text{train}} \neq p_{\text{test}} \ldots \rightarrow \leftarrow$ in ML

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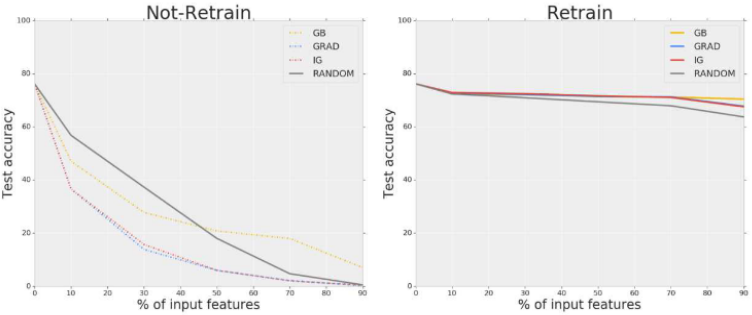

An Outline of the Experiment

Really just a refinement of above.

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- ResNet50 classifier: Imagenet, Birdsnap and Food 101
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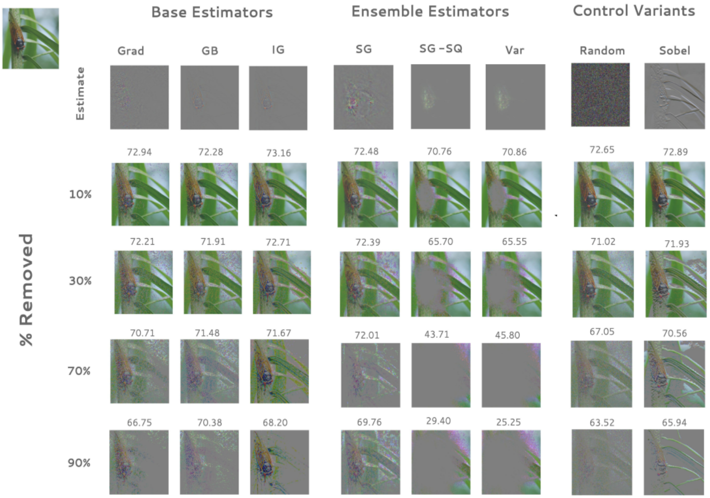
- Each model retrained 5 times $\forall$ method (DNN training is noisy)

ROAR in Action



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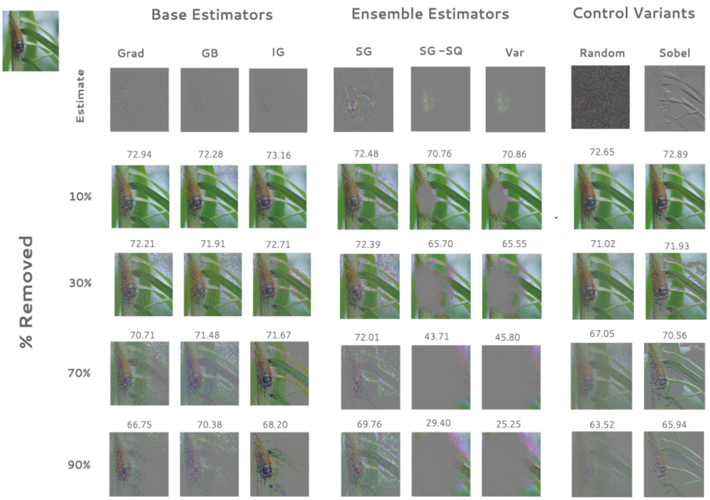

Initial Imagenet accuracy: ~ 78 % ...

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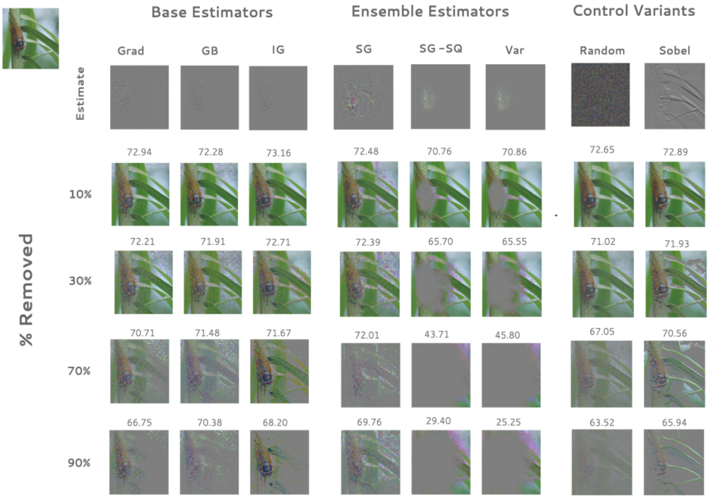

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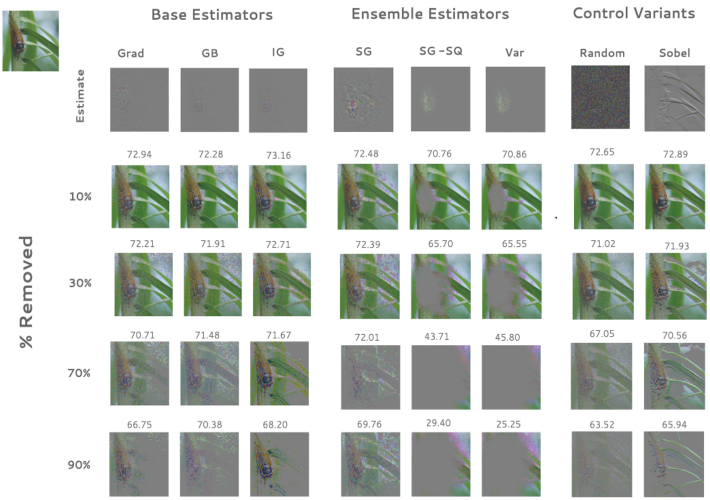

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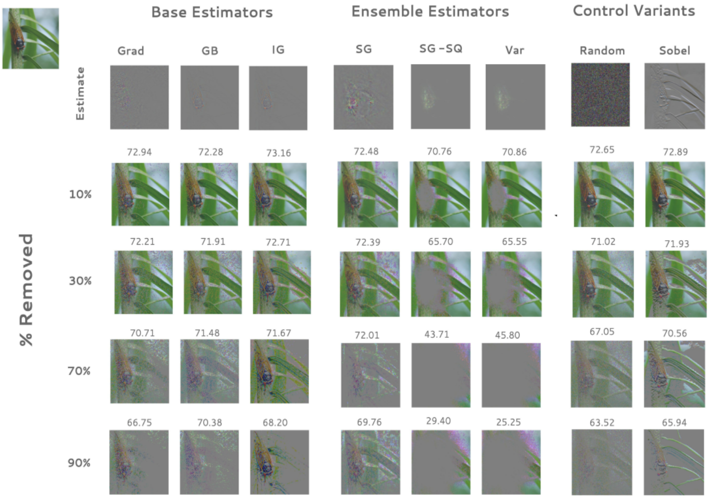

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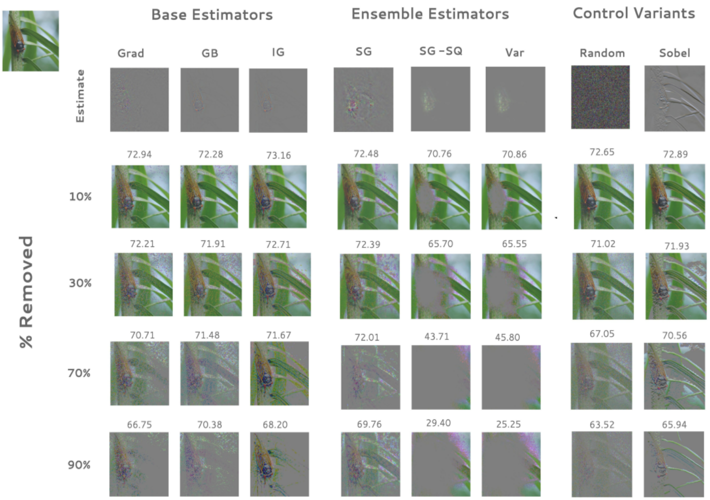

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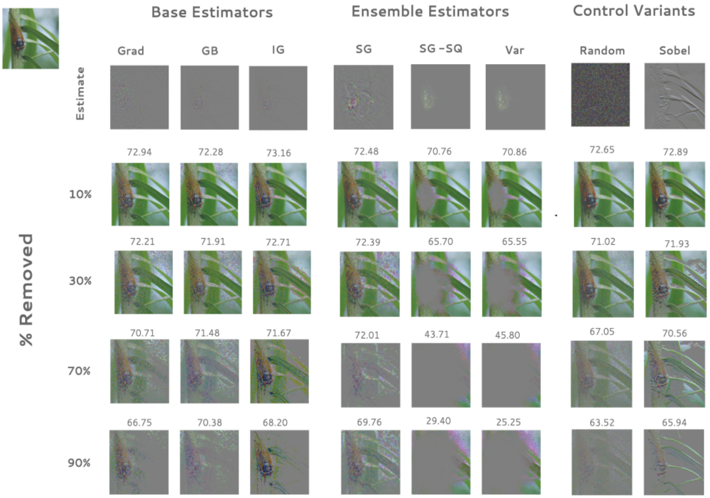

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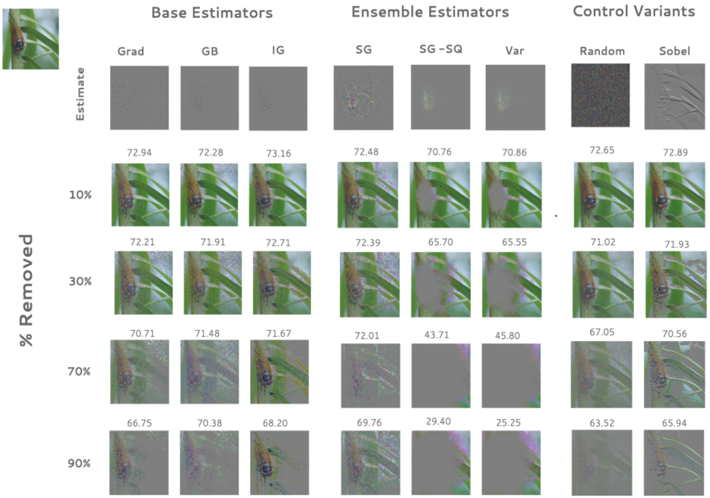

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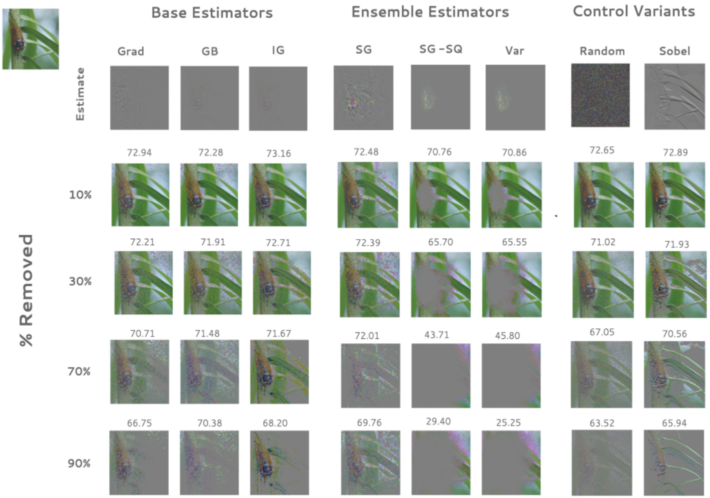

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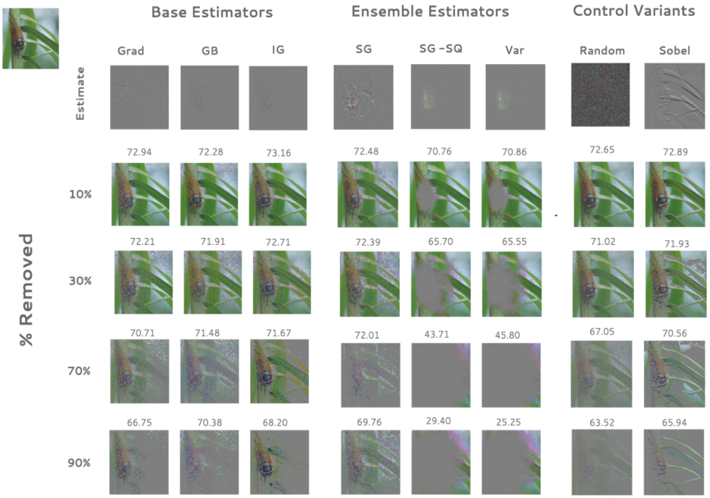

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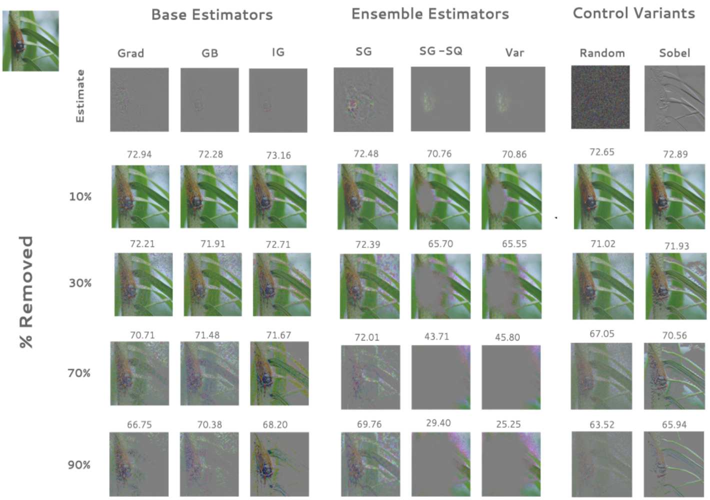

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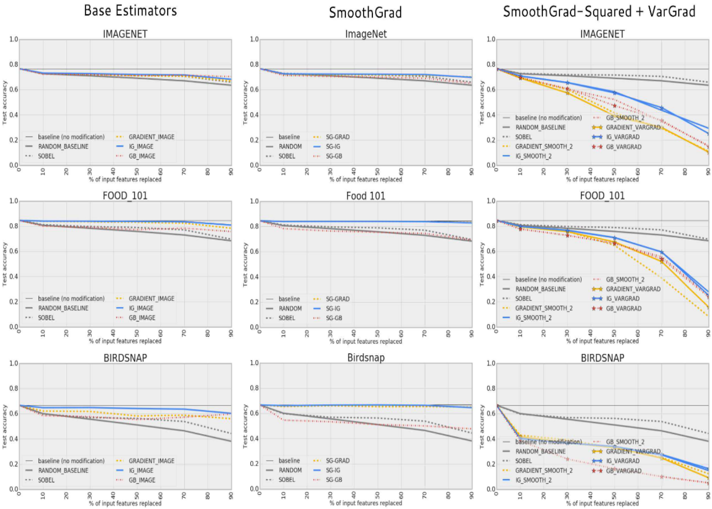

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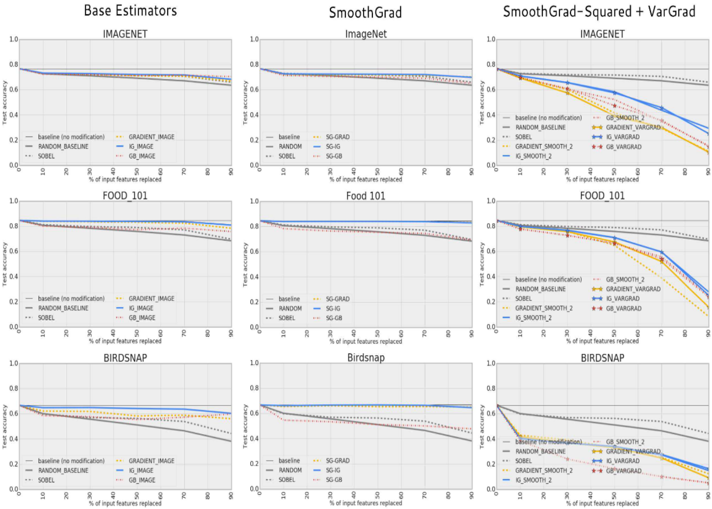

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But best method to wrap around changed

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Another possible Issue

- Cost!
- More compute needed for big datasets
- In practice retraining a large image classifier several times is pretty unfeasible computationally speaking. (ImageNet with ResNet50 can take
- Without retraining, you run into theoretical violations of ML!

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Slightly limited number of techniques compared
Paper used unclear notation and ommitted details at times

Questions?