A Benchmark for Interpretability Methods in DNNs
(Google Brain)

Sam Laing

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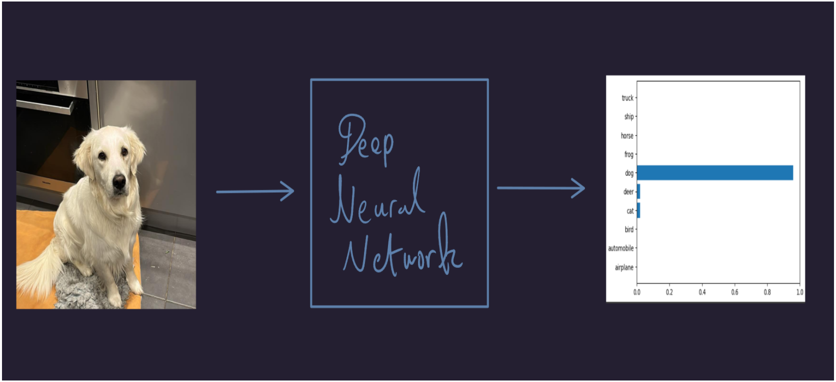
June 26, 2024

A Bit of Background



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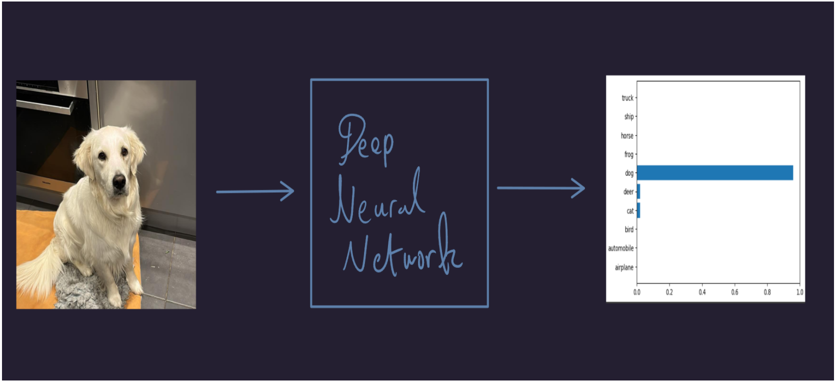

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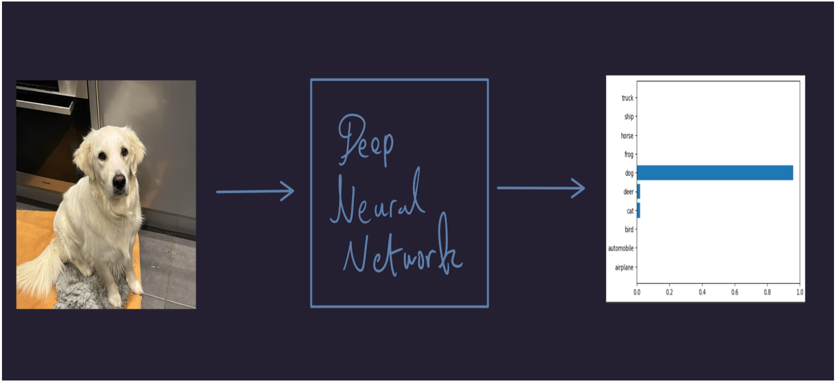

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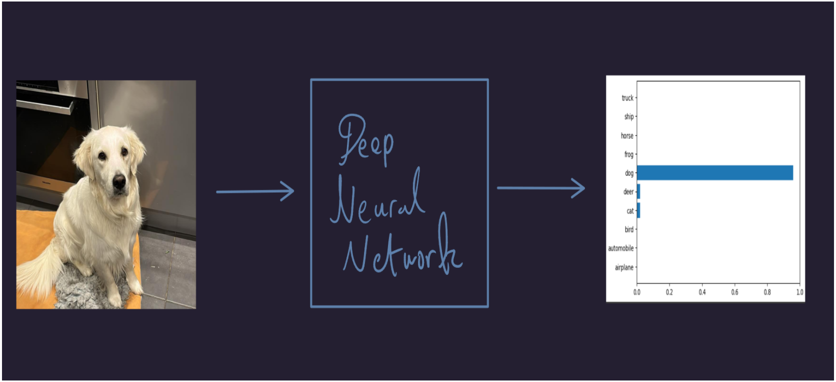

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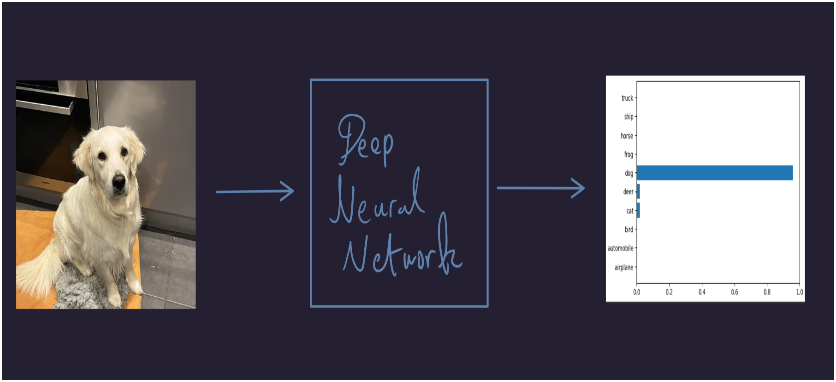

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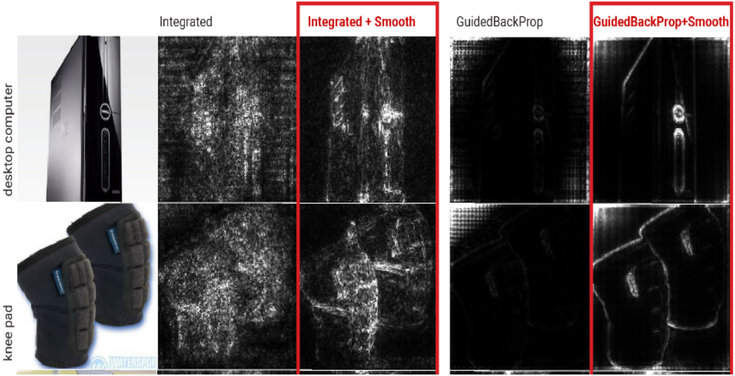
- If only there was a benchmarking framework to do this...

Included Interpretability Methods



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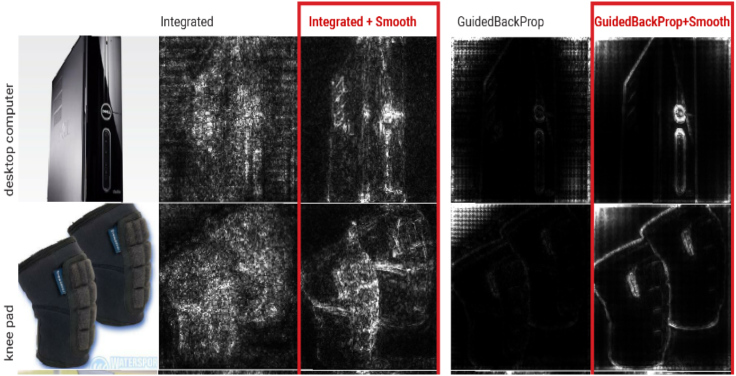

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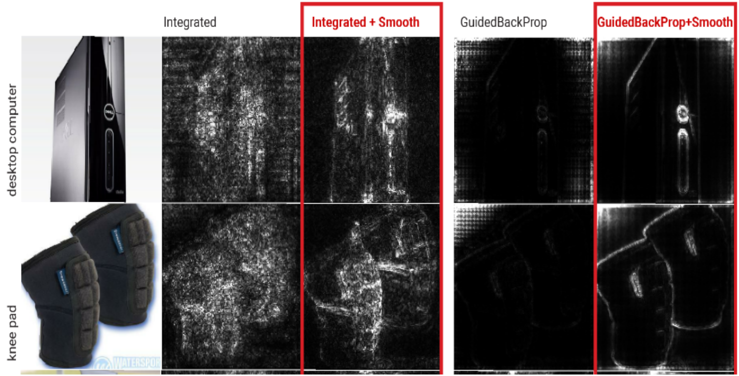

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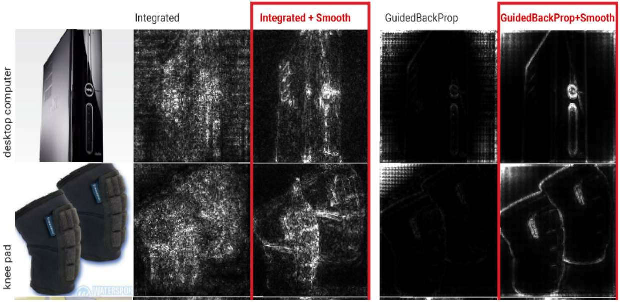
- Integrated Gradients

Included Interpretability Methods: Ensembling in a Nutshell



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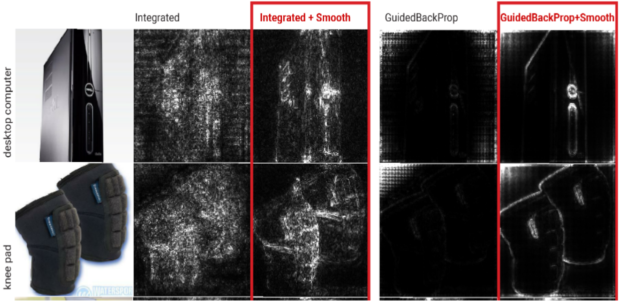

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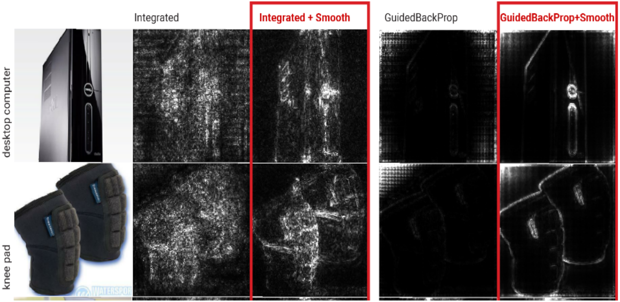

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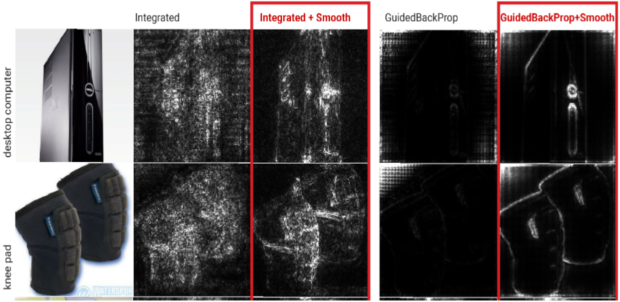

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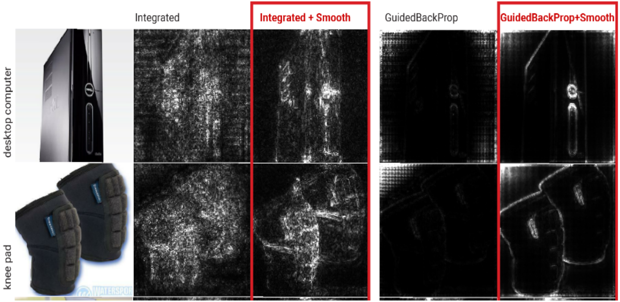

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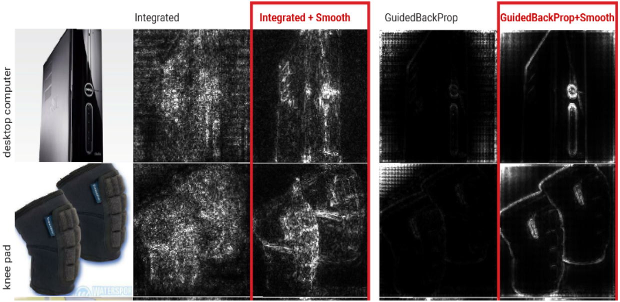

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$\rightarrow$Apply attribution/interpretability methods to these statistics

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%

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Proportion: 50%

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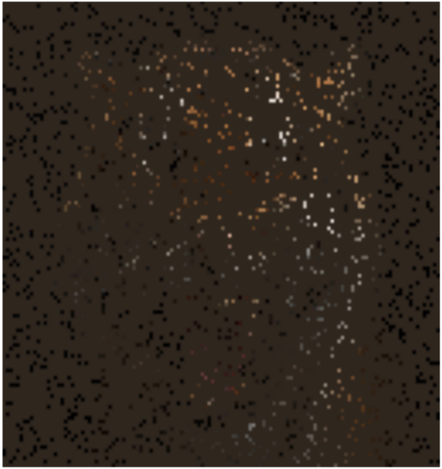
Proportion: 90%



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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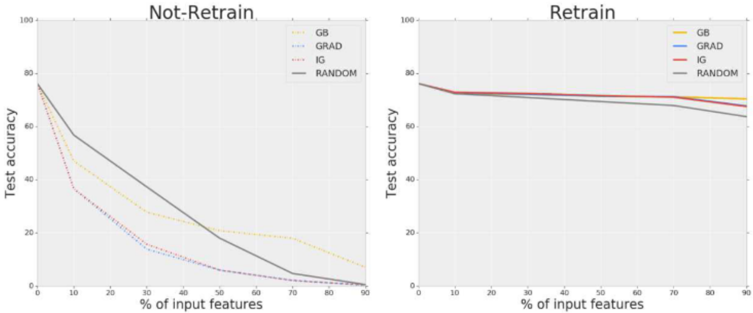

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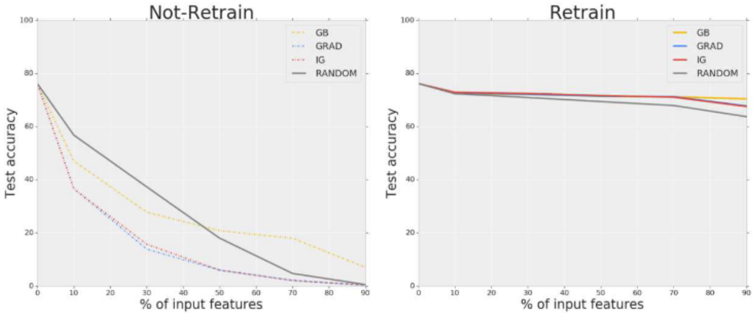

- Paper does some validation with synthetic data but unconvincing.

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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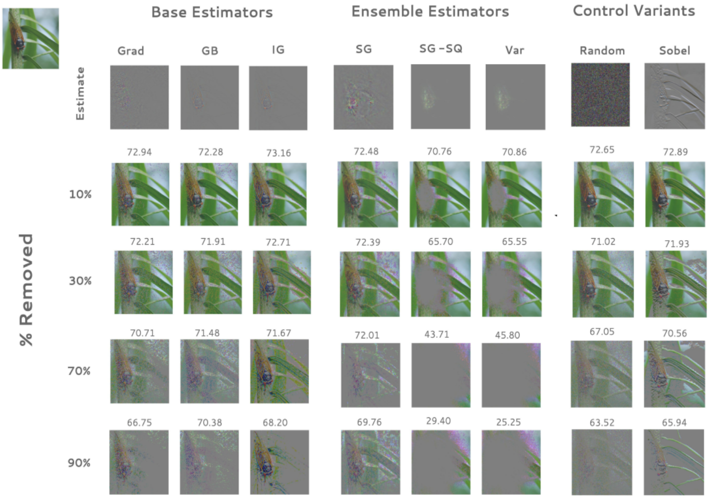
- Each model retrained 5 times $\forall$ method (DNN training is noisy)

ROAR in Action



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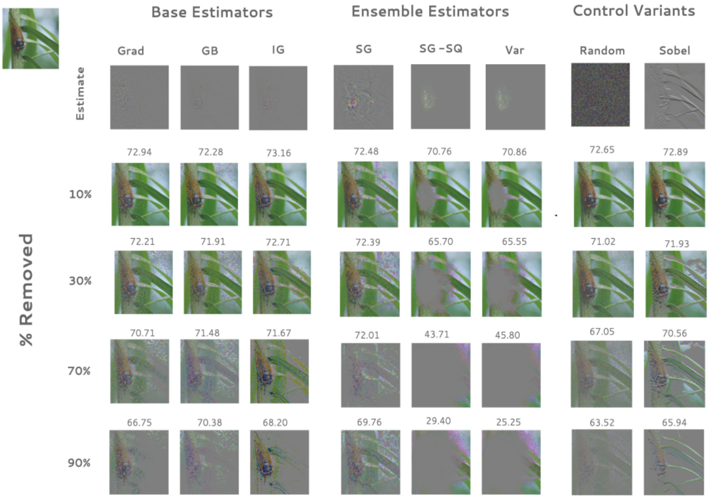

Initial Imagenet accuracy: ~ 78 % ...

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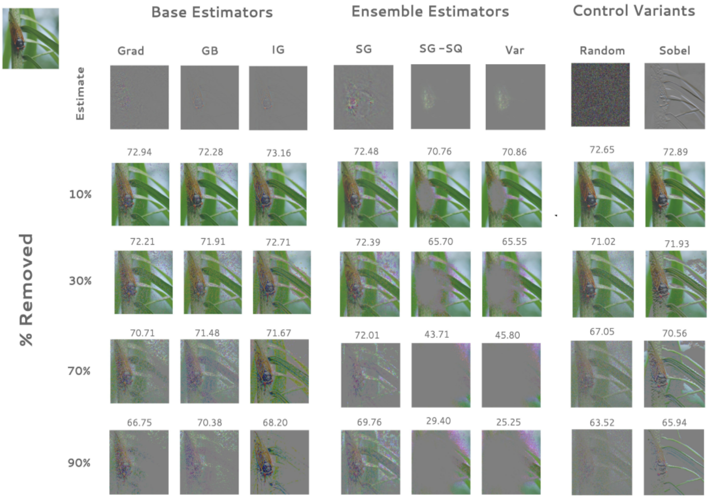

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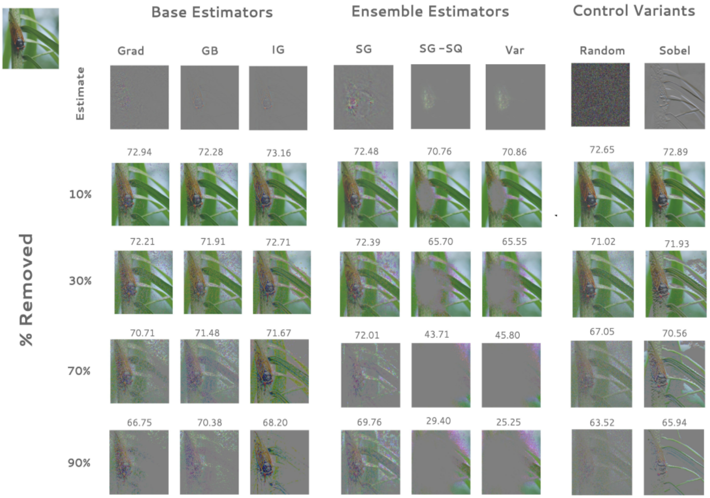
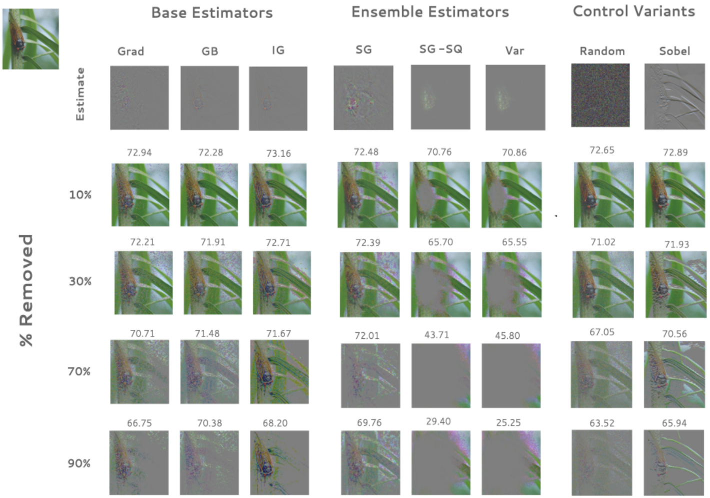


On average Replacing many pixels $\implies$ big decrease of predictive power!

Results



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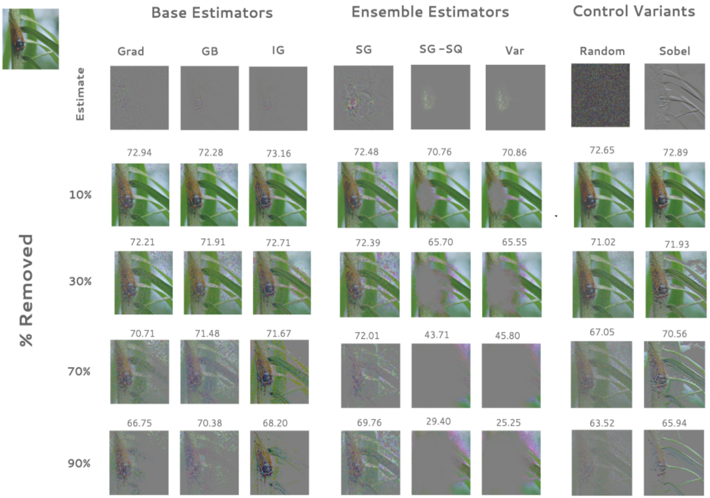

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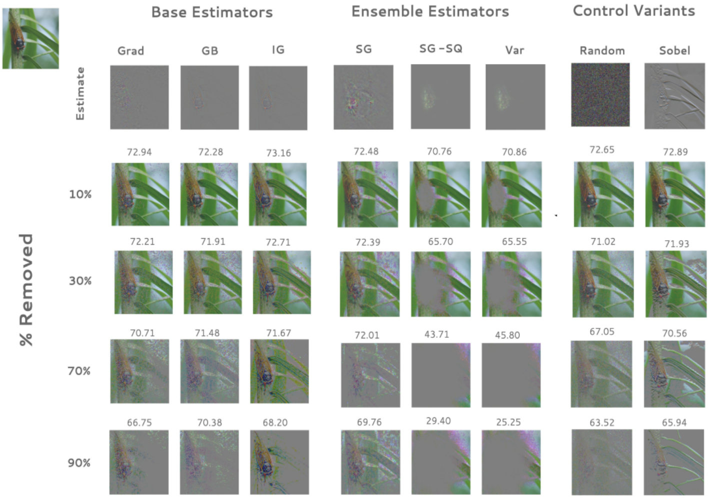
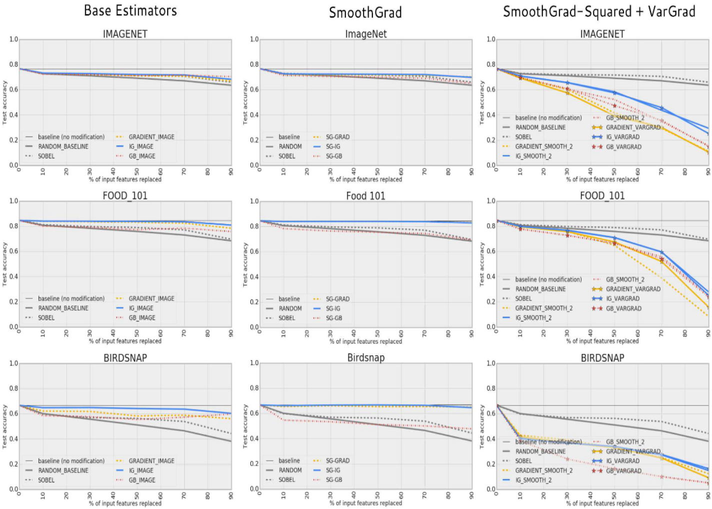


According to the paper, SG-SQ and VarGrad are the real heros

Plots



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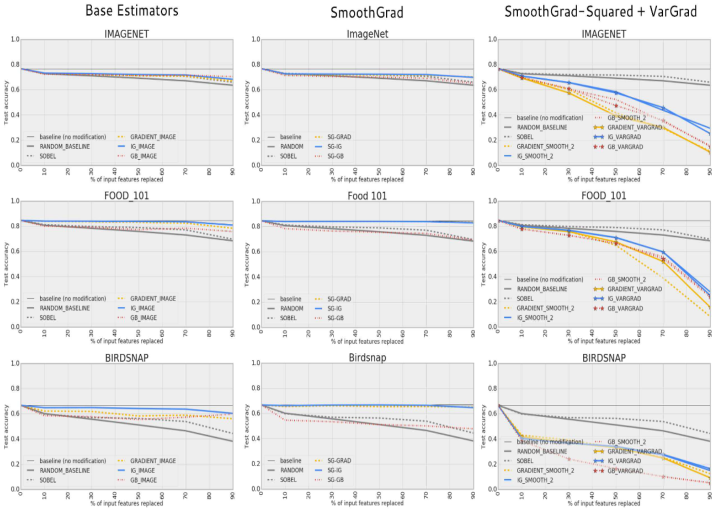

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But best method to wrap around changed

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$$\implies \partial_{x_d} e_2 = 2e.\partial_{x_d} e \quad \forall d$$

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- Cost!
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- Retraining a large image classifier many times may be unfeasible
- Best depends on dataset
- 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?