A Benchmark for Interpretability Methods in DNNs

(Google Brain)

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- Goal: help the engineer understand how their model is performing ...
- Austensibly. But are they even right?

Some of the included interpretability methods

* make individual slides and add pictures*

- Gradients (sensitivity heatmaps). i.e literally considering the gradient of output wrt. input at each pixel value. $e = \partial_{x_i} A_n^\ell$
- Guided Backprop (sort of a tidied up sensitivity map by only looking at positive values)
- Integrated Gradient: for each pixel, compare to baseline x^0 (often elected to be black pixel)
- Ensembling: Effectively injecting inputs with Gaussian noise J times and considering mean/variance. Then apply a gradient method. $\eta_i \sim N(\mu, \sigma)$
- SmoothGrad (SG) $e = \sum_{i=1}^J f(x + \eta_i, A_n^\ell)$
- SmoothGrad Squared (SG-SQ) $e = \sum_{i=1}^J f(x + \eta_i, A_n^\ell)^2$
- VarGrad (VAR) $e = \text{Var}\left(\sum_i^J f(x + \eta_i, A_n^\ell)\right)$

Notice the similarity between SG-SQ and VarGrad

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- Different methods may consider different features important
- How can I really say that interpretability method A has chosen better features than interpretabiilty method B?
- If only there was a benchmarking framework to do this...

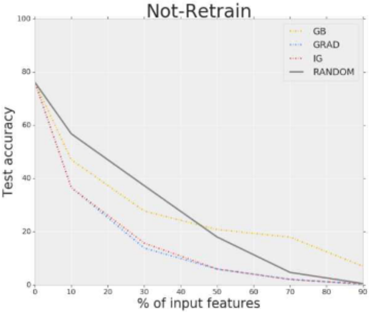
ROAR (RemOve And Retrain)

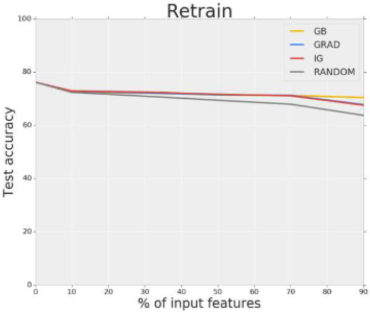
The idea behind ROAR

- For each method being considered, sort the feature (pixels) in order of ranked importance by the interpretability method.
  Creating an ordered tuple $(e_j)_{j=1}^{D}$ of pixel coordinates for each image in the training dataset.
- for $j \in \{0, 10, \ldots, 100\}$, we replace the top j percent of ranked pixels with the per channel mean of the image for every image and then retrain.
- Consider the affect of having dropped the "most informative pixels" as determined by each interpretability.
- Investigate how much their removal from the training process effects accuracy.
- Also a no-retraining variant

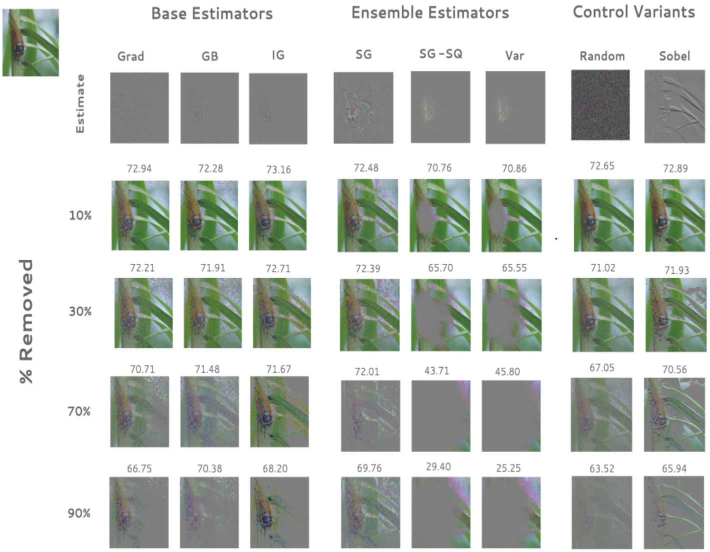
To Retrain Or not To Retrain

- Without retraining the model, train and test come from different distributions... violates key assumption of ML
- Paper therefore argues it is necessary





ROAR in Action



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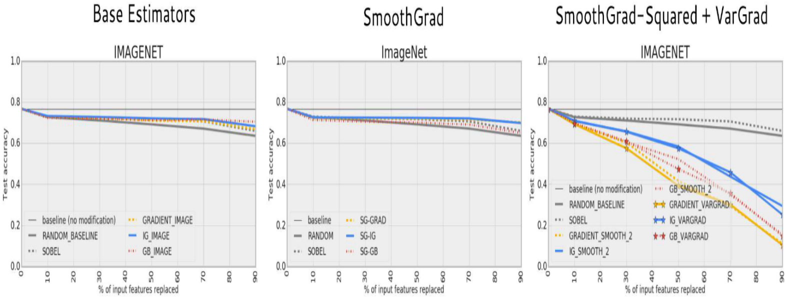

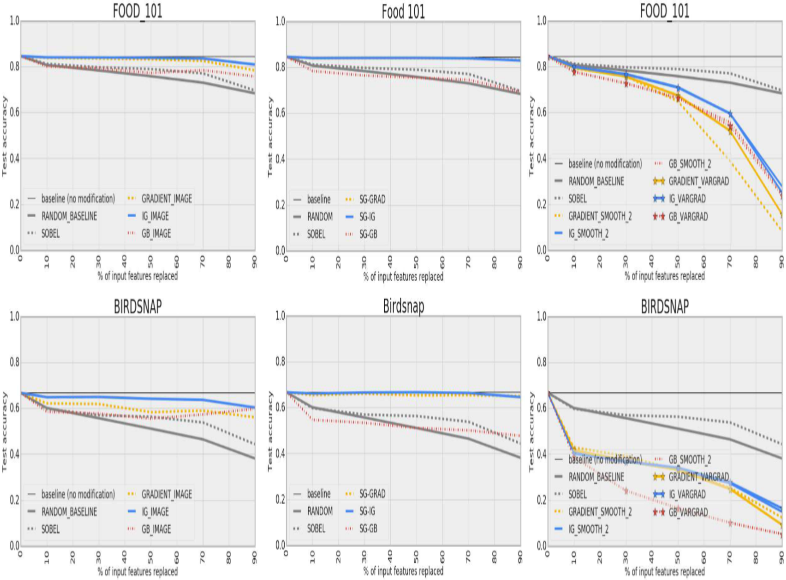
FOOD_101
Food 101
FOOD_101
BIRDSNAP
Birdsnap
BIRDSNAP
Test accuracy
% of input features replaced
baseline (no modification)
RANDOM_BASELINE
SOBEL
GRADIENT_IMAGE
IG_IMAGE
GB_IMAGE
baseline
RANDOM
SG-GRAD
SG-IG
SG-GB
GRADIENT_SMOOTH_2
IG_SMOOTH_2
GB_SMOOTH_2
GRADIENT_VARGRAD
IG_VARGRAD
GB_VARGRAD

Results (cont.)

- The dataset affects which

A Few Possible Issues in the Approach

- This experiment replaces the top j pixels with the mean of the image.
- Is this really the best way?
- The mean still conveys possibly useful information
- Alternative methods are sometimes advised but most have their own issues.

Another possible Issue

- 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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Yet Another Possible Issue

Why I chose this paper

Questions?