Exploring Explainability Methods using Trashnet Model

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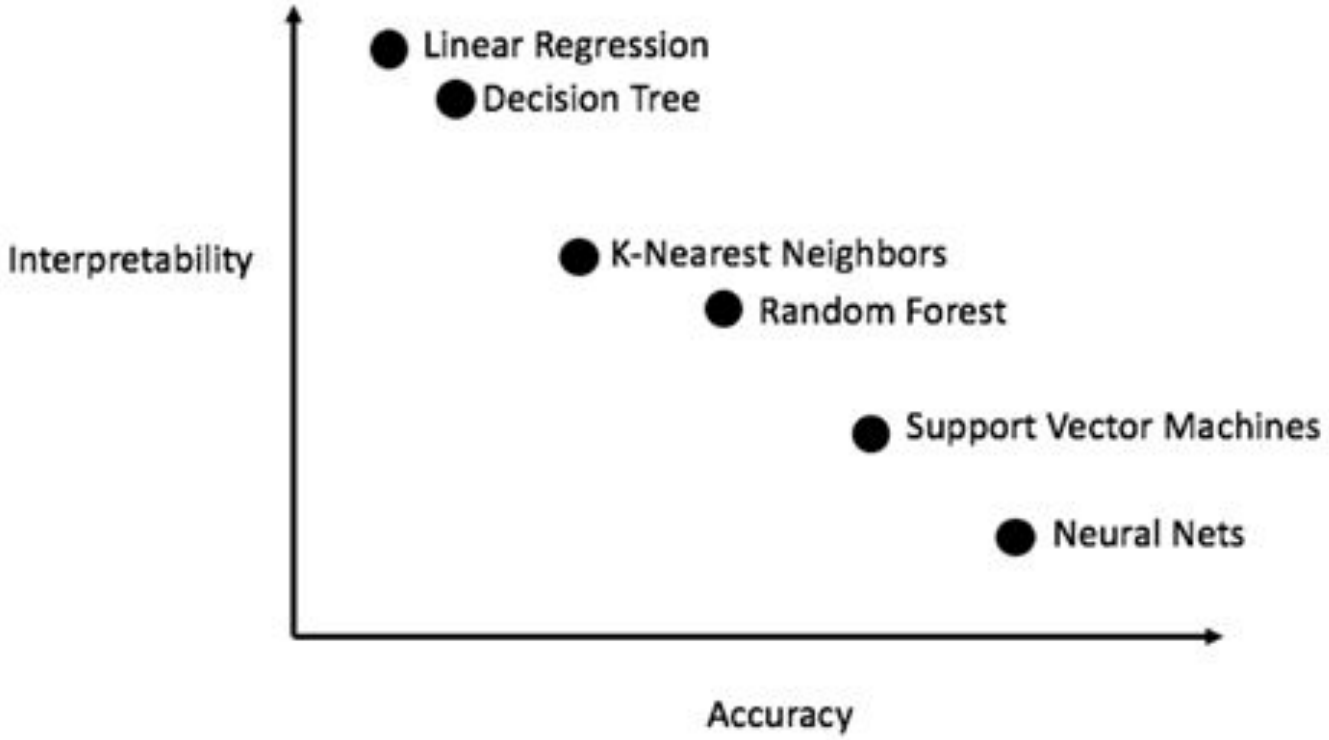
Explainability in AI

- Lack of understanding of model underlying behaviour stops ML/AI adoption in sensitive industries.
- Build trust in the model before deploying it
- Really understand what complex models have learned
- Present explanations in intuitive and simple way

Interpretability vs Accuracy



TrashNet Problem

1. Image Classification problem
2. Classify images of trash into 6 categories : paper, cardboard, trash,glass, metal, plastic.
3. Around 2200 images

Model used

1. Deep Neural Network
2. Model was reused from https://github.com/vasantvohra/TrashNet
3. Model layers are not important since model will be treated as black box

Explainability Methods Explored

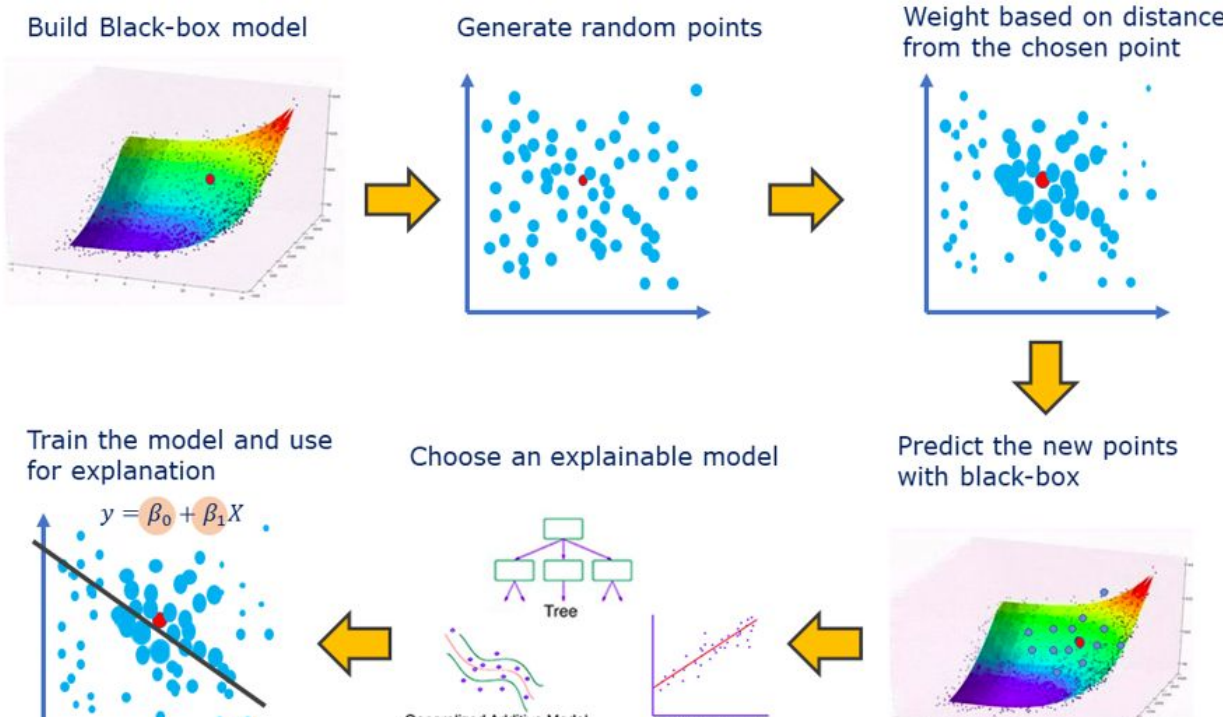
1. LIME : Local Interpretable Model-agnostic Explanations
2. SHAP: Shapley Values
3. Occlusion Sensitivity Mapping

LIME

LIME - Local Interpretable Model-agnostic Explanations

Model agnostic, which means that LIME is model-independent and is able to explain any black-box classifier.
Interpretable, which means that LIME provides you a solution to understand why your model behaves the way it does.
Local, which means that LIME tries to find the explanation of your black-box model by approximating the local linear behavior of your model.

LIME - Local Interpretable Model-agnostic Explanations



https://towardsdatascience.com/lime-explain-machine-learning-predictions-af8f18189bfe

SHAP

Shap - Key characteristics

1. Based on Shapley values in Game Theory
2. Model Agnostic
3. Local explanations
4. Operates similarly to LIME , both tweak input data and observe differences in results.
5. Expensive to brute force, needs to be approximated.

How SHAP works

Parallelism between Game Theory and AI

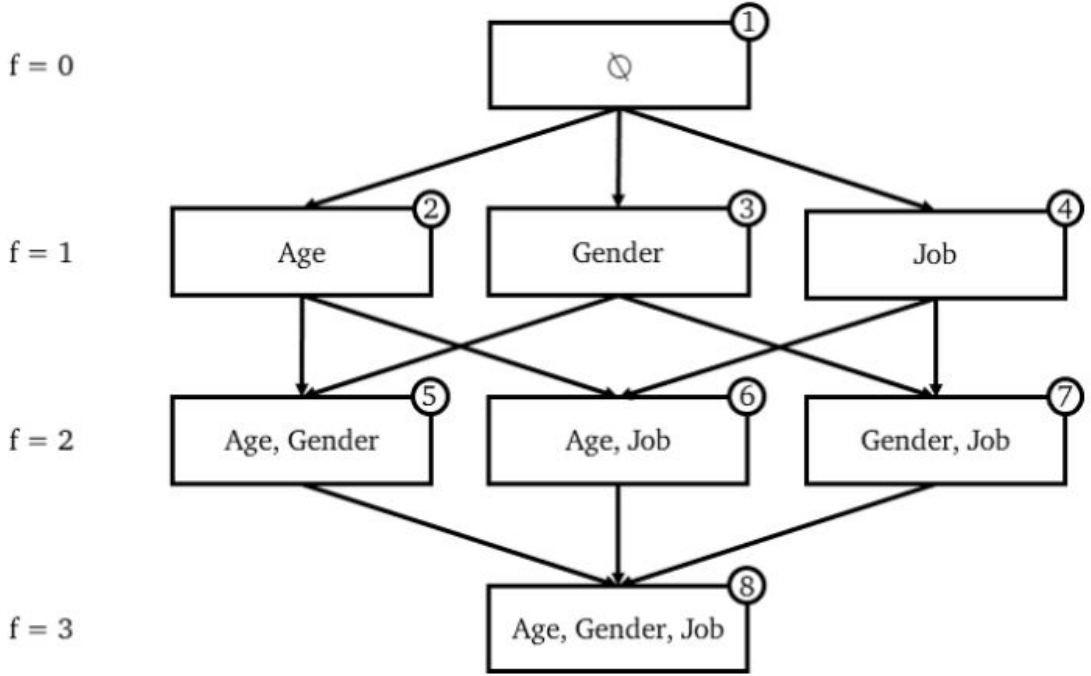
Game -> Predicting outcome of the model

Players -> Features

SHAP quantifies the contribution that each feature brings to the prediction made by the model.

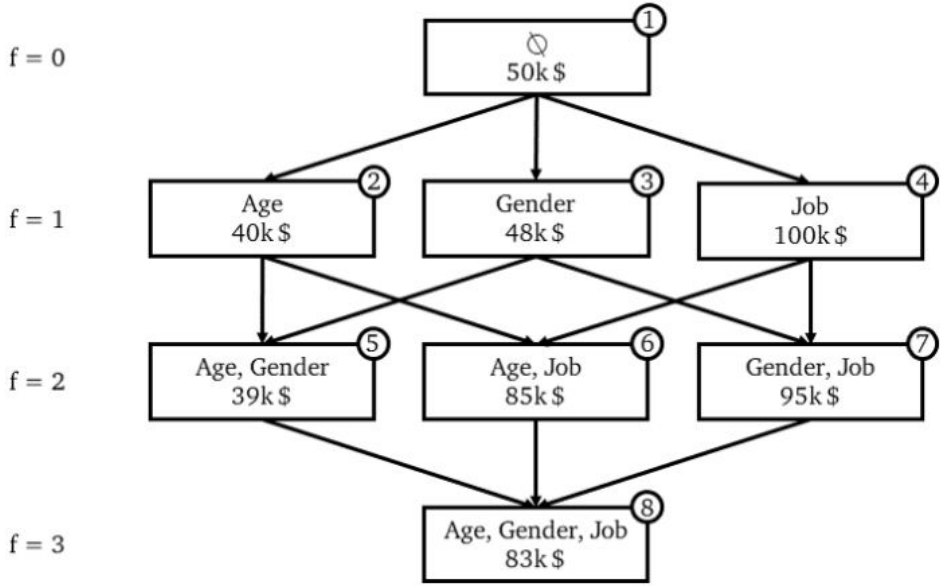
https://towardsdatascience.com/shap-explained-the-way-i-wish-someone-explained-it-to-me-ab81cc69ef30

How SHAP works



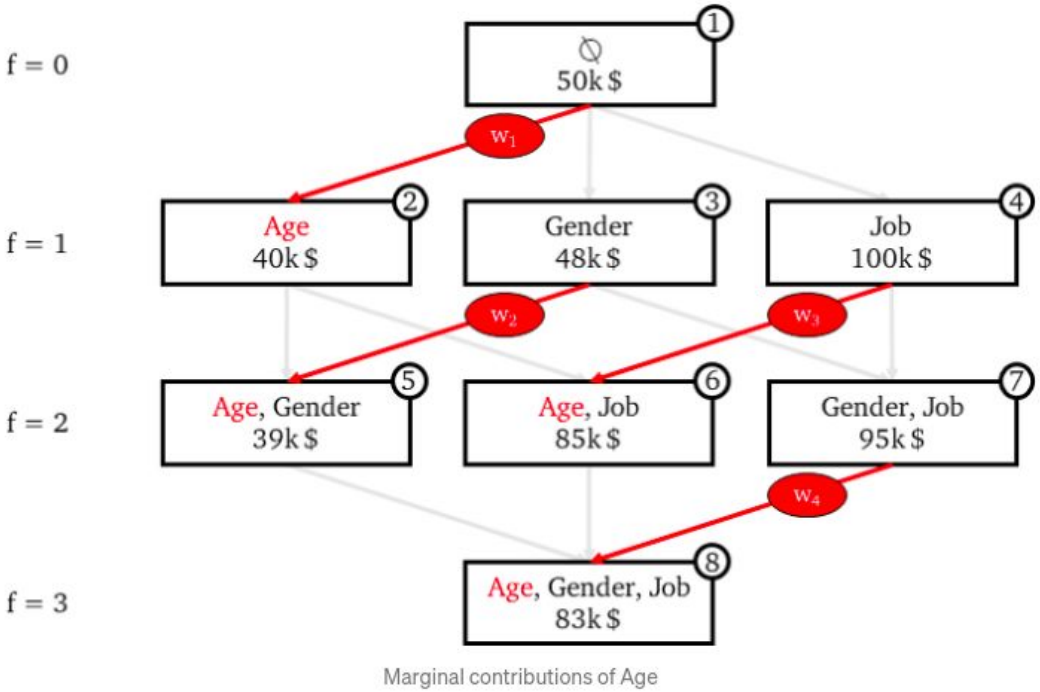
Power set of features

SHAP requires to train a distinct predictive model for each distinct coalition in the power set, meaning 2 ^ *F* models. These models are completely equivalent to each other for what concerns their hyperparameters and their training data (which is the full dataset). The only thing that changes is the set of features included in the model.



Predictions made by different models for x_0. In each node, the first row reports the coalition of features included in the model, the second row reports the income predicted for x_0 by that model.

Weighted average of marginal contributions of a feature = SHAP value for that feature

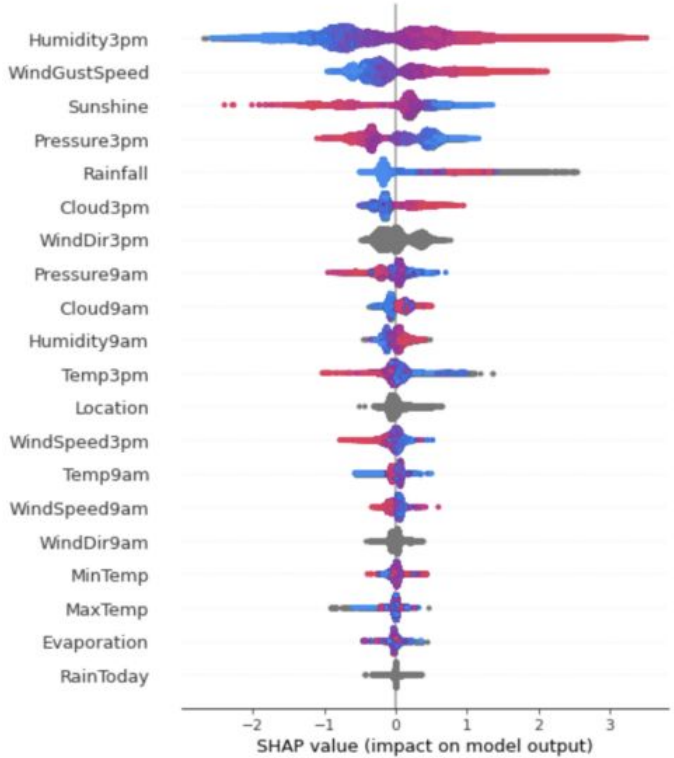


Marginal contributions of Age

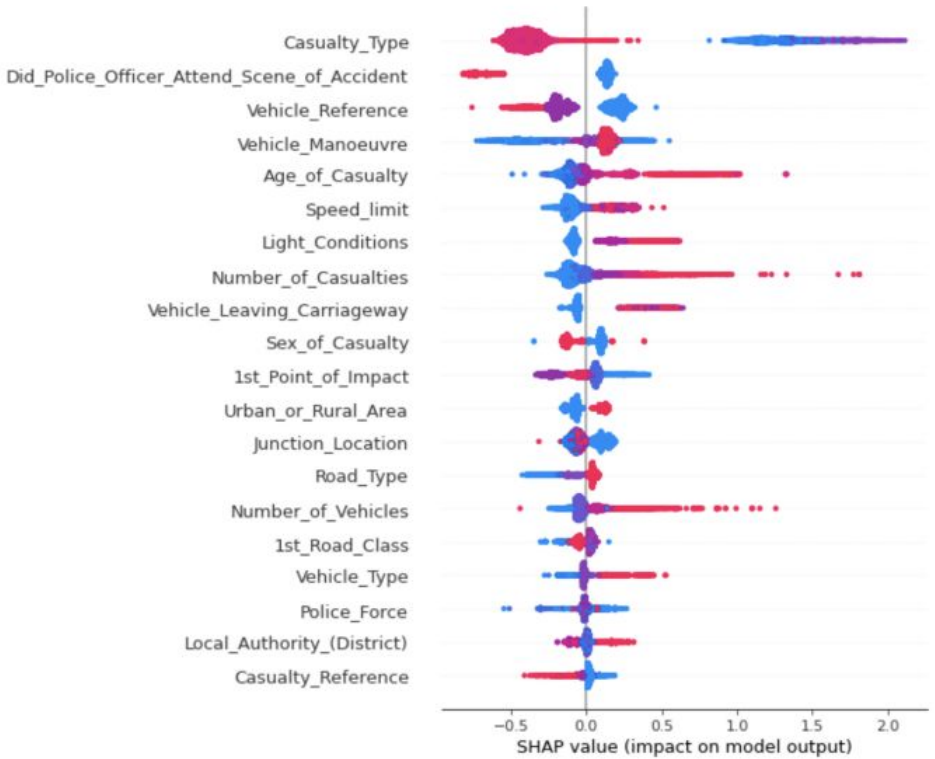
- SHAP_Age(x_0) = -11.33k $
- SHAP_Gender(x_0) = -2.33k $
- SHAP_Job(x_0) = +46.66k $

How visualizations look with SHAP

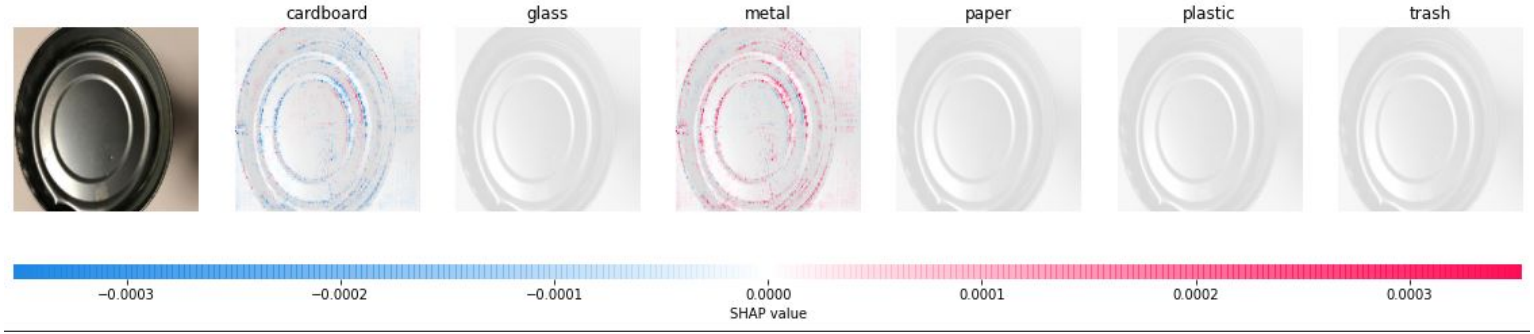
Will it rain tomorrow?



Is the accident fatal?



How visualizations look with SHAP



1. The scale below the images shows color map for SHAP values.
2. Red pixels means positive contribution to a prediction (i.e removing the pixel lowers accuracy of the model to predict that class)
3. Blue pixels mean negative contribution

Occlusion Sensitivity Mapping

Key characteristics

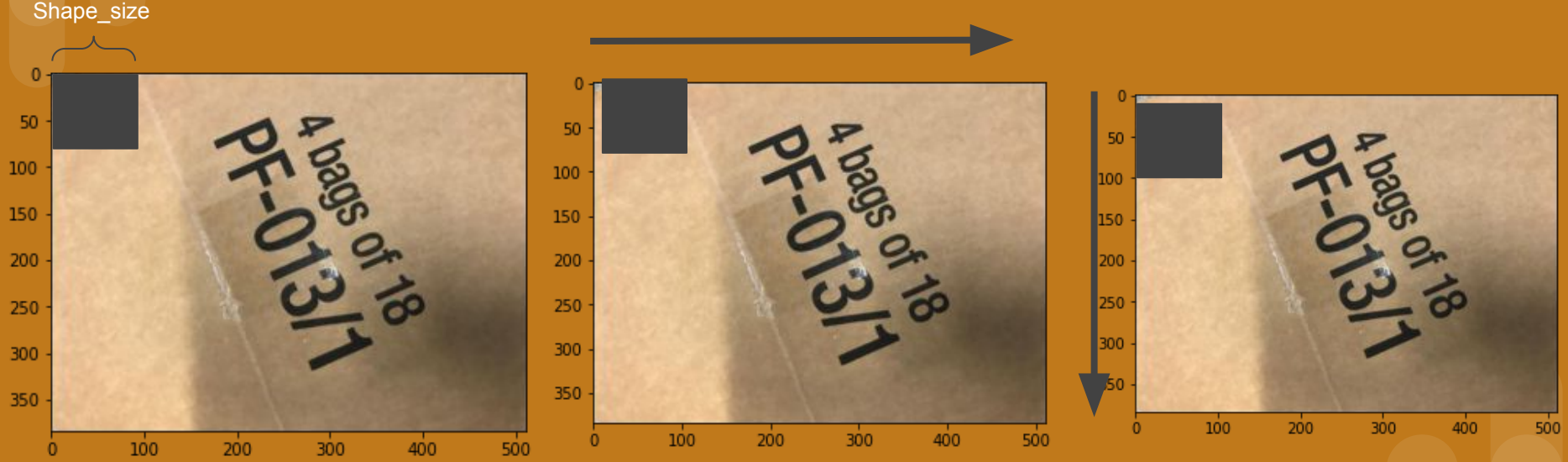
- Model Agnostic
- Local Explanations
- Occlude input data and observe differences in prediction proba for each class.
- Very memory consuming.

Occlusion Sensitivity How it works

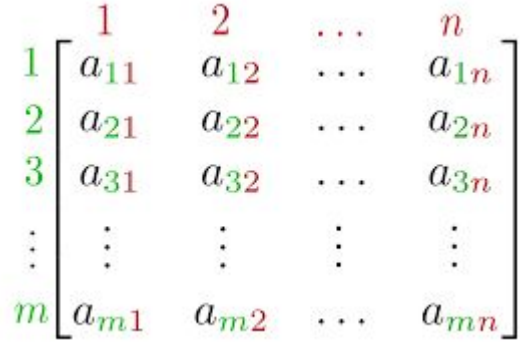
Inputs:

- Model
- Data(Image)
- Target class -> True class
- Shape size -> Size of the block to be used for occlusion sensitivity.

Create grey patches with shape_size



2- Create Sensitivity matrix



- Initialize sensitivity matrix
- Predict all new training datasets created using the input model
- Retrieve probability of target class for each prediction
- Use 1-proba to fill the matrix.(The lower the confidence, the higher the importance of the shaded region).

3 - Generate HeatMap

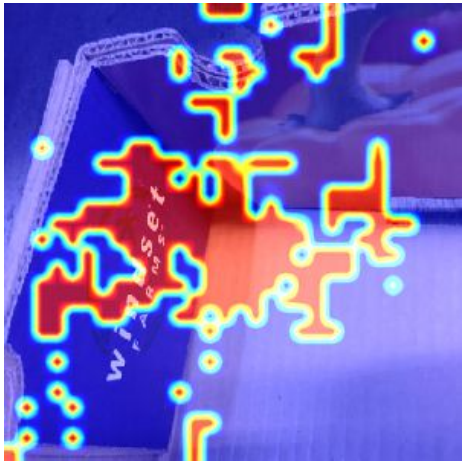
- Resize the sensitivity matrix to original image size.
- Map Sensitivity Map to HeatMap

Examples (tf-explain)

True class: Cardboard
Probability: 78.5%
Classified: Cardboard

True class: Cardboard
Probability: 99%
Classified: Cardboard

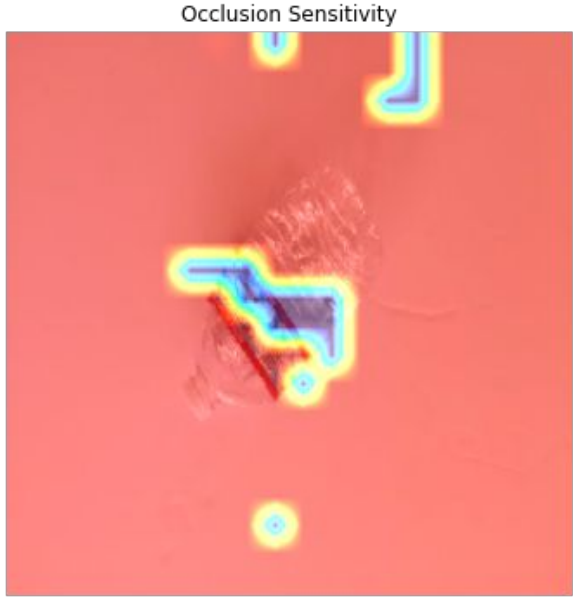
True class: Cardboard
Probability: 87.8%
Classified: Cardboard



Patch_size=10

Examples (tf-explain)

True class: Plastic
Probability: 92%
Classified: Plastic



True class: Plastic
Probability: 99%
Classified: Plastic

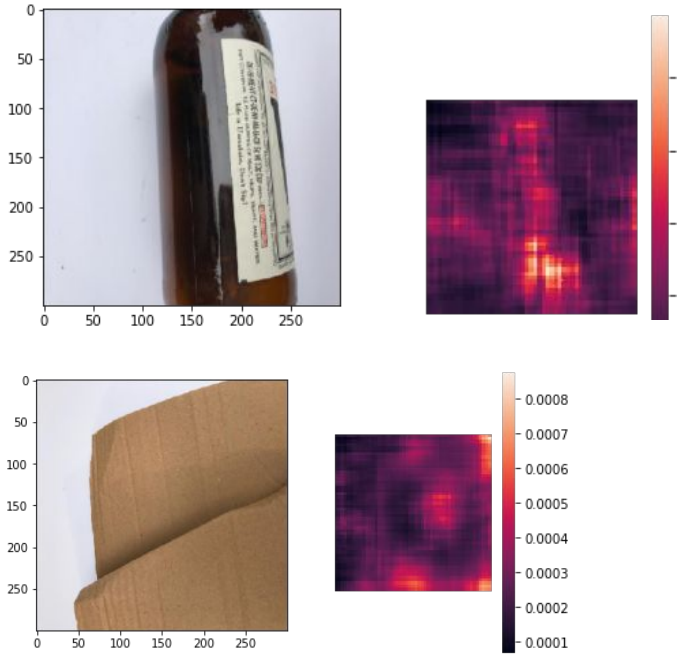
Conclusion tf-explain

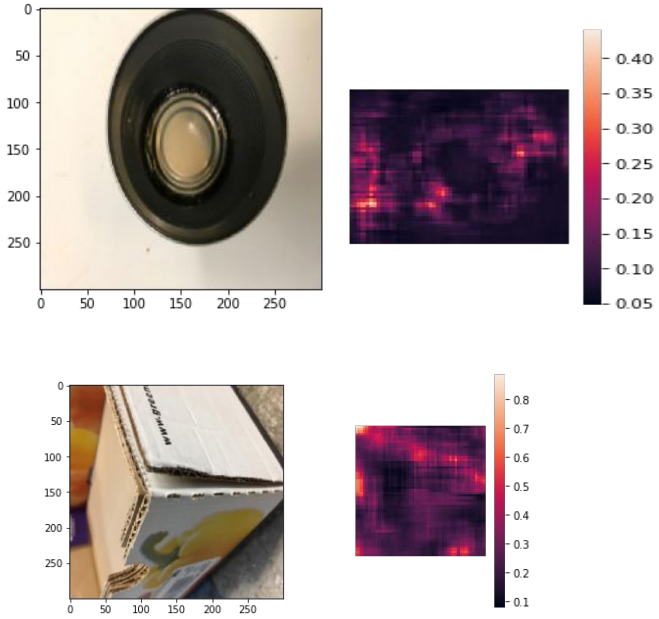
- Tf-explain is not producing results we expected.
- Could be bug in library or bug in our code?
- Let’s try to implement a raw, simplified version of occlusion sensitivity

Occlusion sensitivity v2

1. Based on https://github.com/oswaldoludwig/Sensitivity-to-occlusion-Keras- (with small changes)
2. Basic idea is very similar to tf-explain
3. Changes in heatmap generation, color scheme.
4. Raw, basic implementation

Examples (raw implementation*)

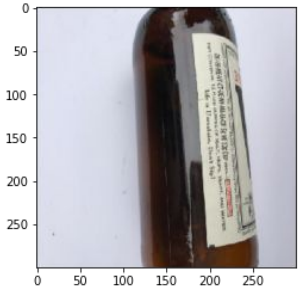




*Results retrieved using 50 pixel grey mask

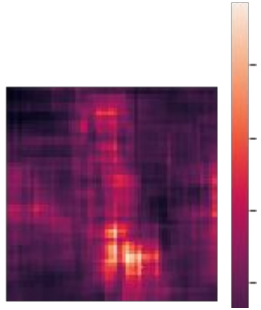
Mask color problem

Plain glass wine bottle

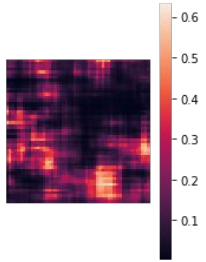


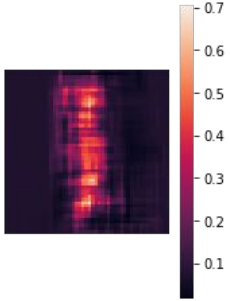
1. The color of the mask can greatly change the generated map depending on colors of the image.
2. Usually grey color is used. What happens if there is grey background, grey metal or cardboard images?

Heatmap , grey mask



Heatmap , black mask





Heatmap , white mask

Occlusion sensitivity conclusion

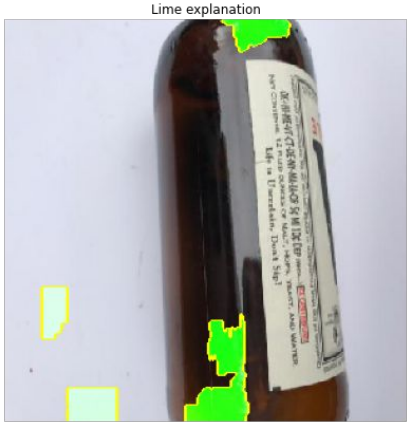
The mask that we use for occlusion can really impact the heatmap generated for our model. There could be many reasons for this:

1. Model could be overfitted due to not enough data.
2. Model could be overfitted due to noise in data, many pictures have just a very big single color background and the trash placed in the middle.
3. Model could be relying to much in the colors?
4. Or maybe this method doesn't make sense to use for our dataset.
5. Best chance we have is to use grey mask which is more neutral color.

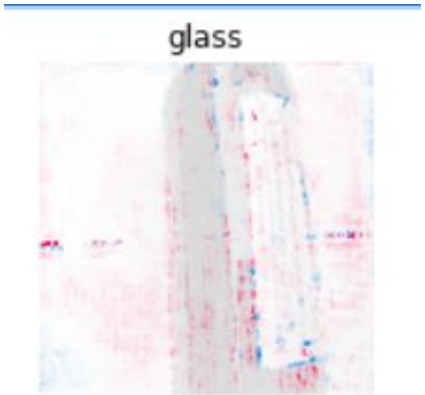
Side by side comparison for same images

Original image

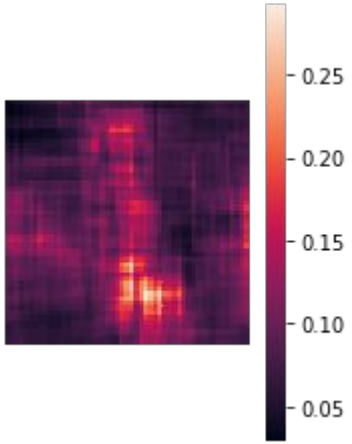
LIME



SHAP

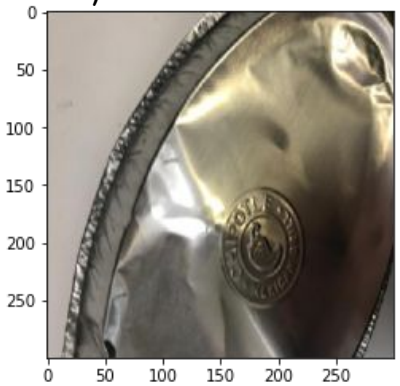


Occlusion Sensitivity v2



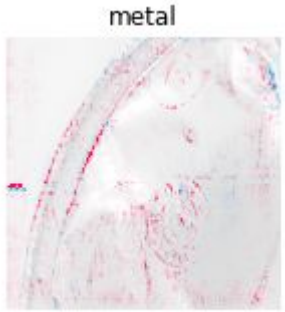
Side by side comparison for same images

Original image (metal, proba = 85%)

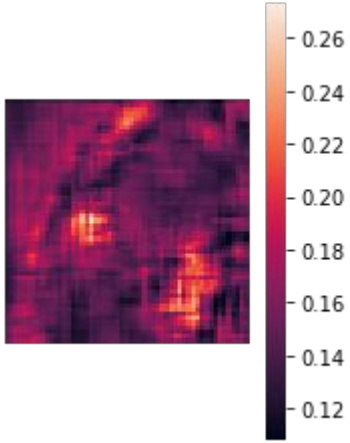


LIME

SHAP

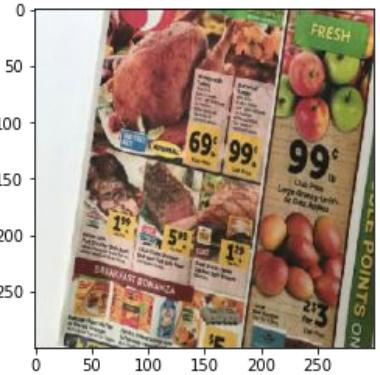


Occlusion Sensitivity v2



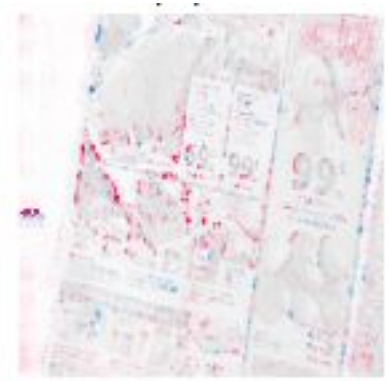
Side by side comparison for same images

Original image (Paper, proba = 99.99%)



LIME

SHAP



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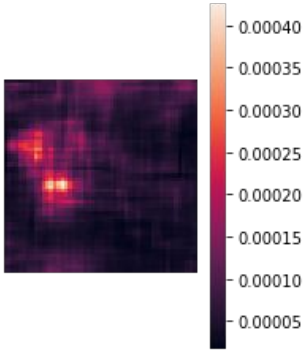


Consideration when developing comparison method

	Level of operation (Pixel/SuperPixel)	Way of explanation (Mask/ Weighted)
LIME	Superpixel	Mask(0 or 1 values)
SHAP	Pixel	Weighted
Occlusion	Pixel	Weighted

Considerations

1. 3 models operate in different planes.We should attempt to bring them on the same one.
2. Bringing SHAP and Occlusion Sensitivity to SuperPixel level is very complex.
3. **Bringing SHAP to pixel level is more straightforward(pixel is a subset of superpixel).**
4. Bringing SHAP to weighted values is not possible as the model doesn't support it.
5. **Bringing SHAP and Occlusion Sensitivity to discrete values(0,1) is easier e.g create a cutoff point.**

Considerations on using color scheme as basis of comparison

1. Color scheme is not inherent part of the model. All models produce grids of pixels, how visualizations are made is decoupled and can be customized according to subjective opinion.
2. 3 Models visual explanations produce different level of transparency of the original image(slide 32 as example).
3. The background would skew the results so we can not get some accurate information.

Considerations on using shape, number of pixels.

1. By using pixels as a mask, we directly rely on model's output and not the custom visualization on top of it.
2. It is a common ground between all of 3 models, whereas colors are not.

Automatic Comparison Method

1. Occlude part of the image which we subjectively consider important and get it's mask.
2. Apply Lime method of explanation, get top 5 masks according to Lime.
3. Count total number of pixels contained in the Lime Explanation (N). This will be our ground truth.
4. Get percentage of Lime pixel's included in our custom occluded mask.
5. Apply ShAP explanation, get shap grid for label class.
6. Get top N positive pixels of SHAP (S)
7. Get percentage of S pixels included in our custom occluded mask in step 1.
8. Apply Occlusion sensitivity and get the map
9. Get top N biggest impact pixels according to occlusion sensitivity heatmap.
10. Calculate percentage of these pixels included in our mask.
11. Repeat experiment for 12 pictures and plot statistics for all calculated averages..

Automatic Comparison Method-Example

1- Create Occlusion get mask

2- Run Lime Explainer, count(N) number of pixels in top 5 superpixels.This number will be used for SHAP and Occlusion Sensitivity

Automatic Comparison Method-Example

Step 3

- Calculate what percent of N pixels from Lime fall into the occluded region.

```
Shape of Lime grid  = (300, 300)
Counting 1 elements in Lime grid
5206
Nr of 1 pixels in mask included in  Lime = number_pixels_for_comparison: 5206
Present inside the selected zone = 3369 pixels or  %9.358333333333334
```

Automatic Comparison Method-Example

Step 4

- Run Shap Explanation and get Shap grid.
- Get top N pixels with highest value.
- Count how many of these pixels fall in occluded area

```
SHAP GRID has shape: (300, 300, 3) With minimum:-0.000843749226837912 and max: 0.000963695613923026
calculated mean arr (300, 300)
Finding top 5206 max shap values
Nr of 1 pixels in mask included in  Shap 5206
Present inside the selected zone = 3338 pixels or  %9.272222222222222
```

Automatic Comparison Method-Example

Step 5

- Run Occlusion Sensitivity and get Oclussion Sensitivity map.
- Get top N pixels with highest value.
- Count what percent of these N pixels fall in occluded area

```
SHAP GRID has shape: (300, 300, 3) With minimum:-0.000843749226837912 and max: 0.000963695613923026
calculated mean arr (300, 300)
Finding top 5206 max shap values
Nr of 1 pixels in mask included in  Shap 5206
Present inside the selected zone = 3338 pixels or  %9.272222222222222
```

Automatic Comparison Method-Example

Step 7

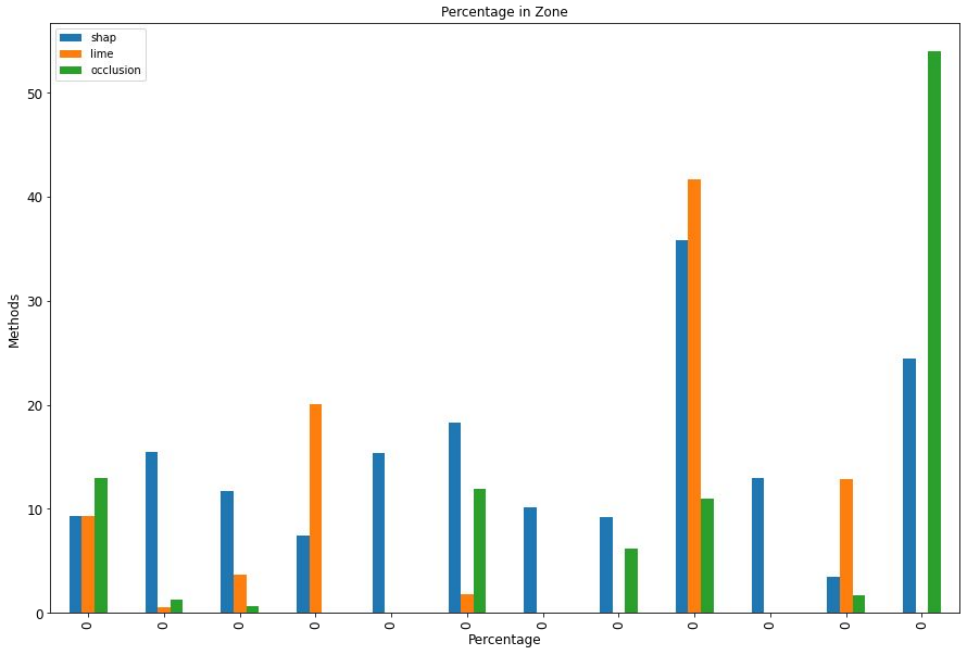
- Repeat experiment many time for different picture.

Step 8

Plot Charts

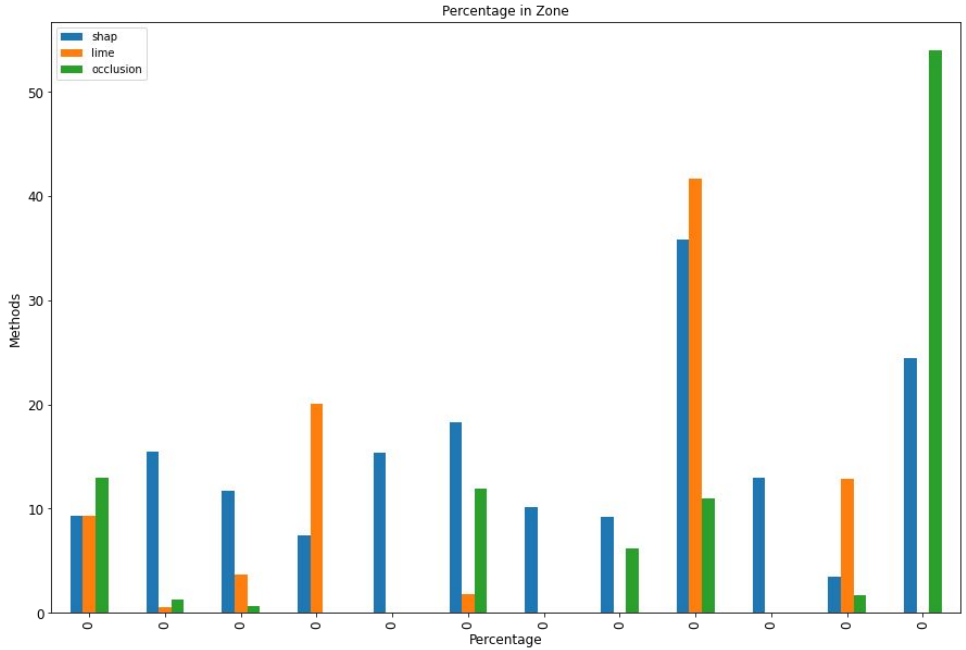
Results

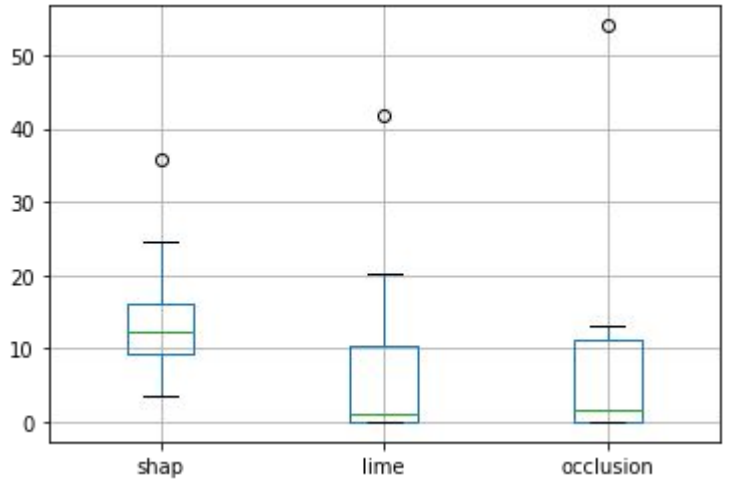
Results obtained from using 12 pictures and comparing percentages



Results

Results obtained from using 12 pictures
and comparing percentages





Thank you!

Github repository: https://github.com/ekeshi1/explainability_methods_trashnet