EXPLORING THE LIME ALGORITHM FOR INTERPRETABLE DEEP LEARNING ON TEXT AND IMAGES

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Introduction

LIME (Local interpretable model-agnostic explanations)

Trust and Transparency

Hyperparameters

Image and Text data

Evaluation Metrics

Coefficient of variation (CoV)

- Mean of the standard deviations divided by the mean of all the coefficients

Intersection over union (IoU)

- Intersection of two feature sets divided by the union

Visual inspection

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Evaluation

- Coefficient of variation (CoV) $\bar{\sigma}/\overline{\square}$
- Intersection over union (IoU)
- Visual inspection

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Performance and robustness

Evaluation

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- Intersection over union (IoU)
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The Lime Algorithm

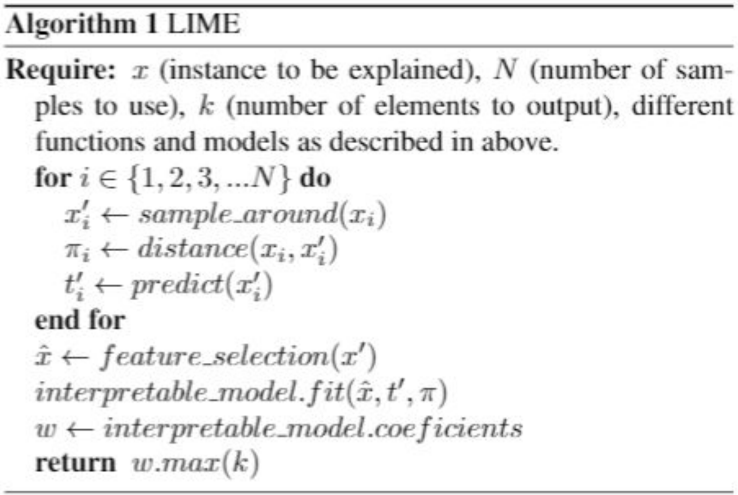
Sample_around “**x**” - neighborhood data “**x’** ”, by creating active segments “**a**”

Distance “**π**” - weights from distance between **x** and **x’**

Predict “**t’** ” (probabilities) - a black-box model, to classify on **x’**

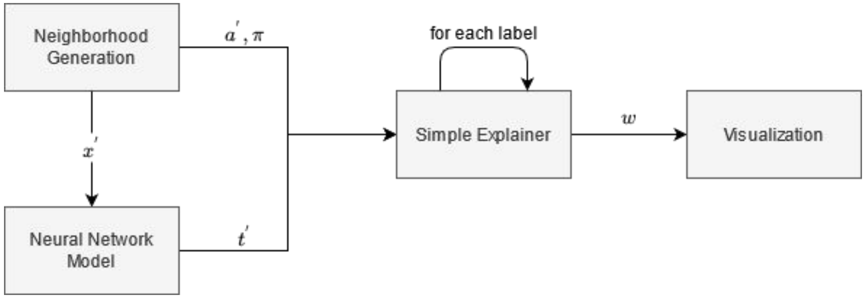
Active segments “**α**” are arrays of binary values which correspond to "turned on" features

Fit interpretable models given instance, black-box probabilities and distance weights to get coefficients “***w***”



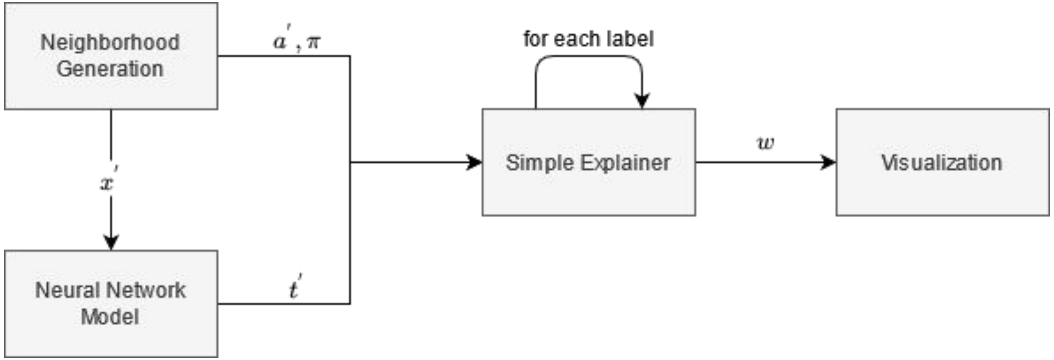
Algorithm 1 LIME

```
Require: $x$ (instance to be explained), $N$ (number of samples to use), $k$ (number of elements to output), different functions and models as described in above.
  for $i \in \{1, 2, 3, ...N\}$ do
    $x'_i \leftarrow sample\_around(x_i)$
    $\pi_i \leftarrow distance(x_i, x'_i)$
    $t'_i \leftarrow predict(x'_i)$
  end for
  $\hat{x} \leftarrow feature\_selection(x')$
  $interpretable\_model.fit(\hat{x}, t', \pi)$
  $w \leftarrow interpretable\_model.coeficients$
  return $w.max(k)$
```



Simple Explainer - Method

- Trains regression model on weighted active segments “**α, π**” from neighbourhood generation fitting output probabilities from neural network model “**t**”
- Coefficients of a simple model are used for explanation assessment “***w***”
- Any regression model can be used as long as its coefficients have the same dimensionality as input data



Simple Explainer - Feature & Model Selection

Simple Explainer

Feature Selection

- Limit dimensionality issues
- Improve training speed especially for image data

Methods

- Highest Weights
- Forward Selection
  - Found to be 20x slower
  - As good as highest weights

features for simple model

Model Selection

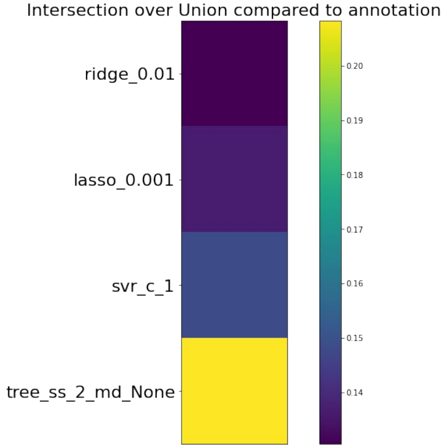
- Model that is easy to interpret
- Returns some measure of feature importance
- Quick to fit on input features

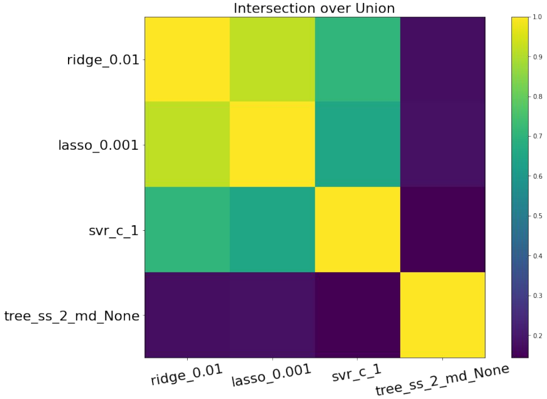
Methods

- Ridge
- Lasso
- Linear SVM
- Decision Tree

Simple Explainer - Comparison

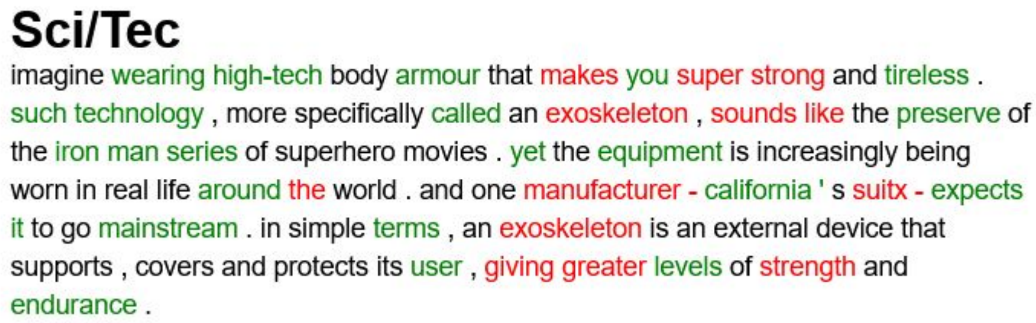
	Ridge	Lasso	Linear SVM	Decision Tree
Interpretation of model's features	Coefficients	Coefficients	Coefficients	**Feature Importance**
Number of selected significant features	More	Less	More	Less
Domain of features	Positive and Negative	Positive and Negative	Positive and Negative	**Only Positive**
Explanation characteristics	**Good choice** for any type of data, quite robust	**Heavily penalizes** features with smaller coefficients	**Ambiguous results** with a lot of variation	**Inherent nonlinearity** that can find **different features** compared to other methods


Intersection over Union compared to annotation


Intersection over Union

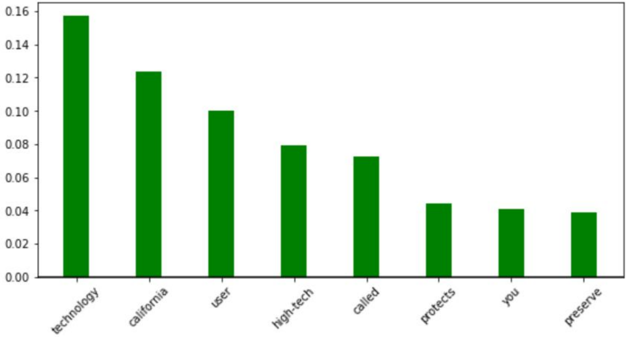
Ridge vs Decision Tree - Text

Ridge

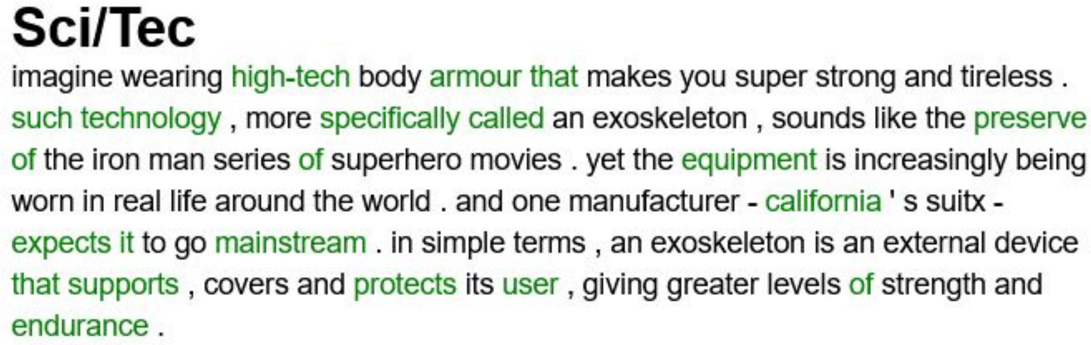


Sci/Tec

imagine wearing high-tech body armour that makes you super strong and tireless . such technology , more specifically called an exoskeleton , sounds like the preserve of the iron man series of superhero movies . yet the equipment is increasingly being worn in real life around the world . and one manufacturer - california ' s suitx - expects it to go mainstream . in simple terms , an exoskeleton is an external device that supports , covers and protects its user , giving greater levels of strength and endurance .



Decision Tree



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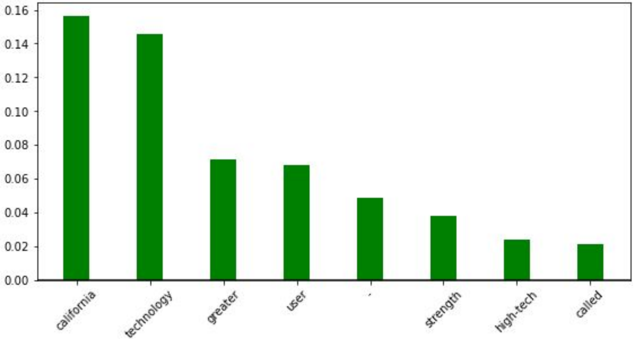
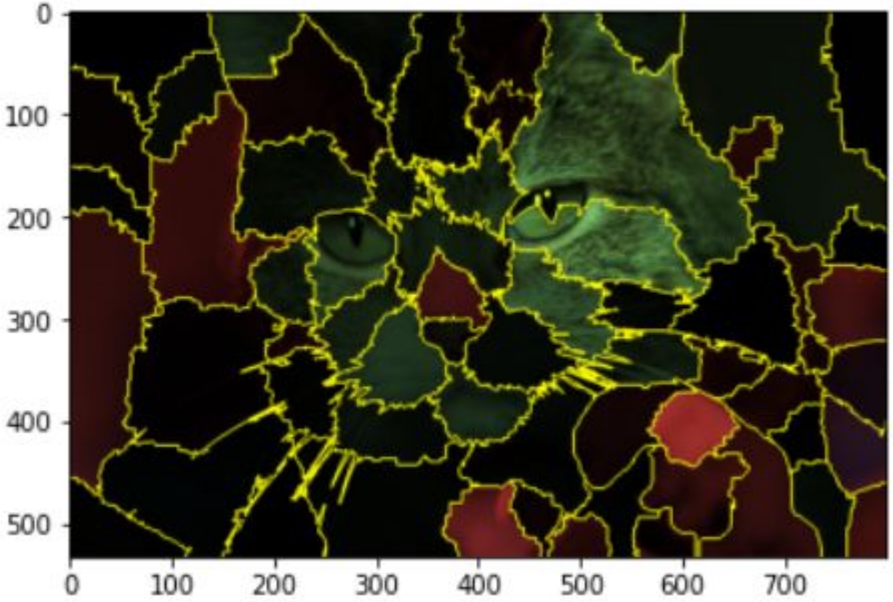
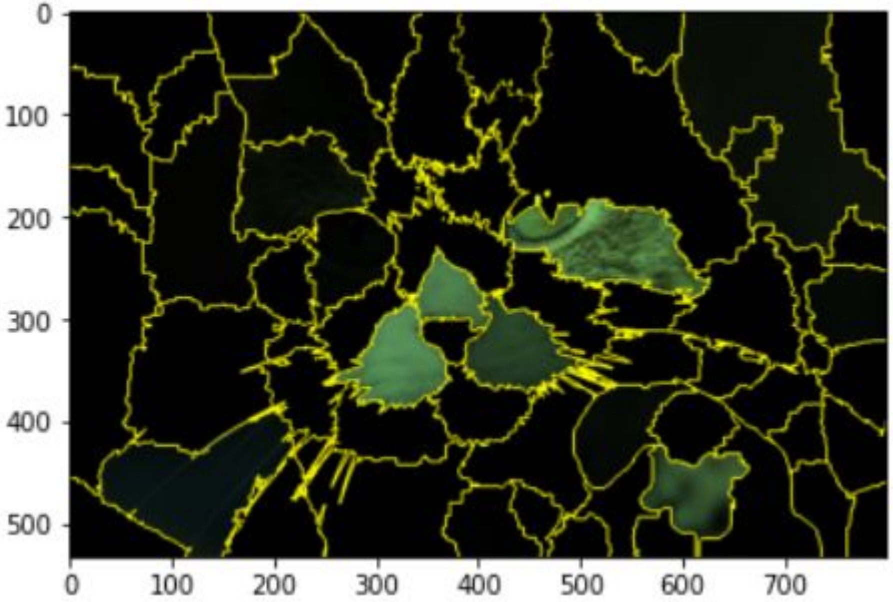


Ridge vs Decision Tree - Image

Ridge Model



Tree Model



Number of sample and distance weight

Experiments on number of samples

- Found to perform better with increasing number of samples

Experiments on the distance between original and sample data

- Found have little effect on the interpretable outcome
- Especially with more samples

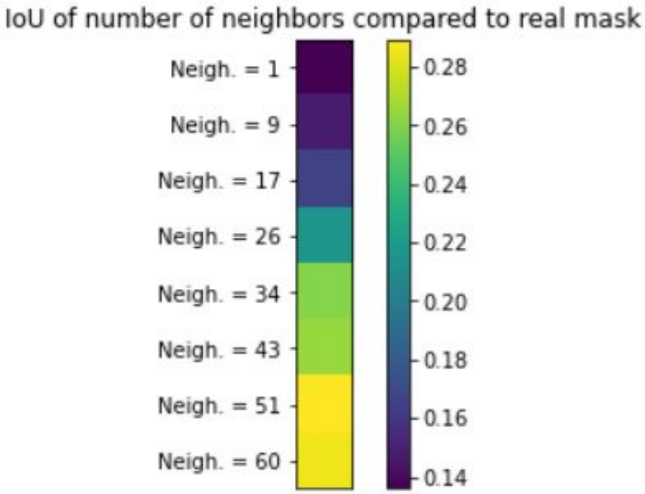


Image data

Neighborhood generation - Text

Methods

- Random_uniform (baseline)
- Random_normal
- One_on
- One_off
- Consecutive

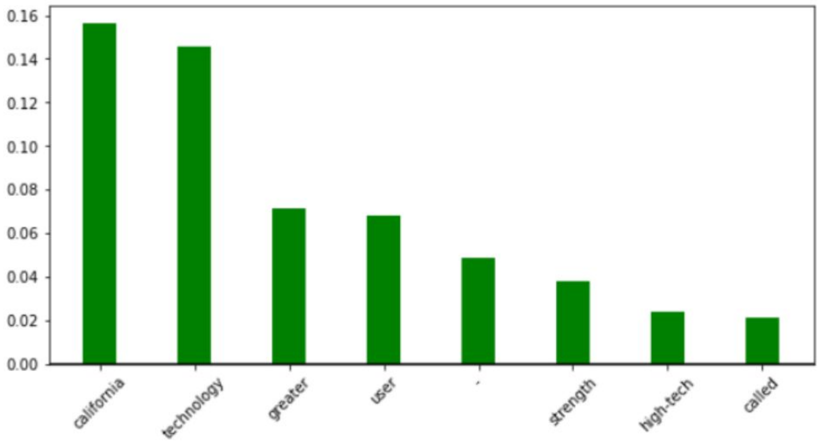
Results

- IoU
  - Best: ru and rn in both models
  - In tree, all methods have similar performance
- Visual inspection
  - Ridge: similar results
  - Tree: rn not performing as well

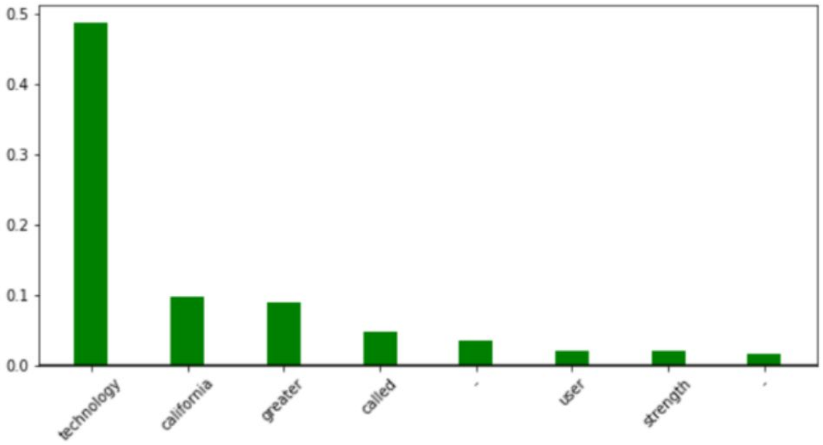
	ru	rn	one_on	one_off	con
IoU Ridge	0.24	0.24	0.18	0.13	0.19
IoU Tree	0.25	0.22	0.21	0.22	0.18

Neighborhood generation - Text

Annotation: **high-tech**, strong, **technology**, equipment, real, life, manufacturer, expects, external, device, protects, **user**, levels, **strength**

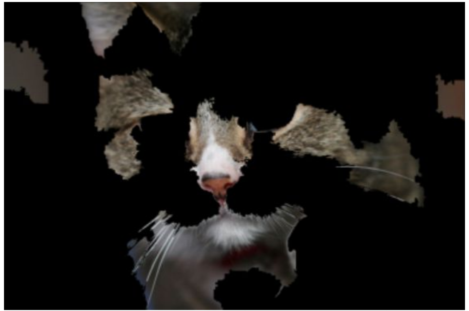


Random uniform - Ridge

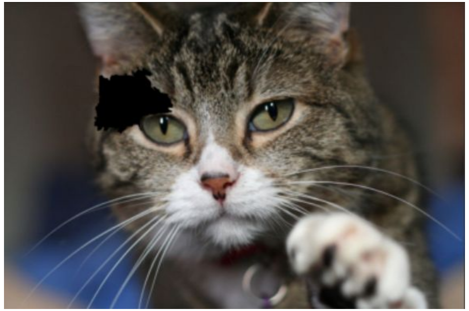


Random normal - Tree

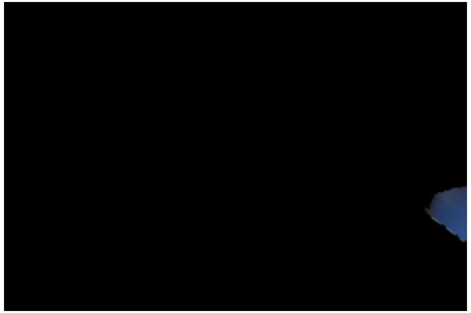
Neighborhood generation - Image



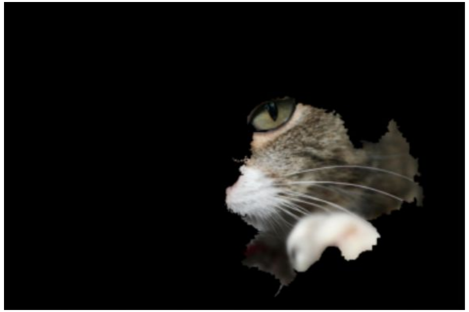
Random (baseline)



One_off

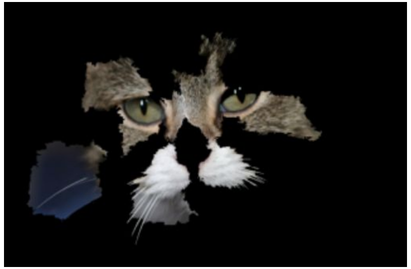


One_on

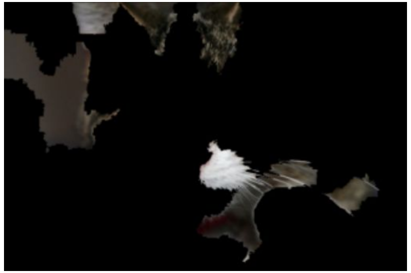


Radio

Neighborhood generation - Image



Random



One_off

- Best: Random and Radio
- Size and meaning of the superpixels is very influencing

	Random	One_on	One_off	Radio
IoU	0.38	0.16	0.11	0.32

Discussion

Intersection over Union and annotations

Only 2 instances of data

Impact of randomness

Conclusion

Best models:	Decision Tree (IoU) and Ridge (Visual)
Best neighborhood generation:	Random methods
Most important parameters (CoV):	Simple model and neighborhood generation

Discussion

- There is no good objective metric to evaluate explanations
- Experiments carried out in only 2 instances of data
- Randomness in each execution

Conclusion

- Best models: Decision Tree (IoU) and Ridge (subjective)
- Best neighborhood generation: Random, but depends on the data
- Most important parameters (CoV): simple model and neighborhood generation