Counter Factual Explanations

Explainable Artificial Intelligence

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Explainable AI or 'XAI'

Complex Machine Learning models are making predictions with ever increasing accuracy and complexity.

- Support good decision making processes (confidence in the Model)
- Comply with legal and regulatory requirements (industry regulations)
- Predictions can have real life and important impact

Using Explainable AI or 'XAI' can:

- uncover correlations and patterns in the data
- assist in Model de-bugging

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Counterfactual Explanations

"A counterfactual explanation of a prediction describes the smallest change to the feature values that changes the prediction to a predefined output." - Christoph Molnar

- 'What if' explanations, or comparable with cause-and-effect relationships.
- How the world would have to change to achieve a new prediction
- 'If X had occurred, Y would not'
- Multiple truths ("Rashomon effect")

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Datasets used

- 'Breast cancer wisconsin dataset (classification)' available from UCI Machine Learning repository. Numeric dataset with 569 instances of 30 numerical features. Benign / Malignant.
- 'Adult dataset' available from UCI Machine Learning repository. It has 8 features (categorical and numeric). Labelled to indicate whether that Adult's income above or below USD50k.
- 'Fashion MNIST' available at https://github.com/zalandoresearch/fashion-mnist. Consisting of 70,000 greyscale images of clothing articles, with 10 classes.

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Modelling

Selected methods of producing Counterfactual explanations:

- Alibi - diverse library of methods which includes a counterfactual explanation method
- DiCE - Diverse Counterfactual Explanations
- CEML - Counterfactuals for Explaining Machine Learning models

We have applied these methods to the predictions of neural networks and examined the results.

Alibi

Alibi is a Python package designed to help explain the predictions of machine learning models and gauge the confidence of predictions.

- Takes inspiration from scikit-learn (initialize, fit and explain steps)
  - import the explainer
  - initialize passing a prediction function
  - fit the explainer (if necessary)
  - call explainer
- Returns Explanation object has meta and data attributes which are dictionaries containing any explanation metadata (e.g. parameters, type of explanation) and the explanation itself respectively

DiCE

- DiCE implements counterfactual (CF) explanations by showing feature-perturbed versions of the same case, comparable to 'what-if' explanations for model output.
- The core idea is to work as an optimization problem, similar to finding adversarial examples.
  - import helper functions
  - load dataset form CF Explanations
  - load pre-trained ML model
  - Run explanation instance
- Returns generated counterfactual examples based on a query list
- Visualize counterfactual explanation in a friendly table

CEML

- CEML is a Python toolbox for computing counterfactuals.
- must specify the model, the input whose prediction we want to explain and the requested target prediction (prediction of the counterfactual).
  - Load data
  - Whitelist of features (list of features we can change/use when computing a counterfactual)
  - Create and fit model
  - Select data point for explaining its prediction
  - Compute counterfactual
- Returns the counterfactual, its prediction and the needed changes to the input as dictionary

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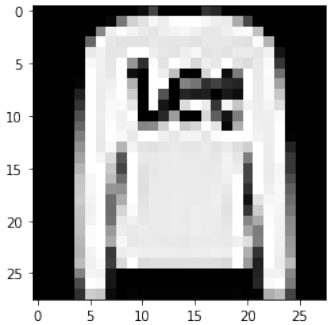
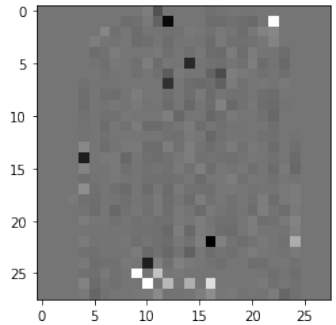
Results - Alibi

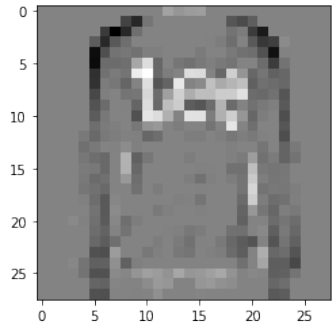
- Convolutional Neural Network ('CNN') on the Fashion MNIST and applied the Alibi package. The CNN predicts class 'Shirt'.



(a) Predicted 'Shirt'



(b) Without prototype



(c) With prototype

Figure: Alibi - Counterfactual Explanations

- non-prototype highlights the pixels that would need to change intensity in order to flip the predicted class.
- with prototype first creates a 'prototype' for each class using an autoencoder.

Results - DiCE

- Trained on the Adult Income dataset, we 'query' a specific instance in the data.
  - The model predicts income <USD50k

	age	workclass	education	marital_status	occupation	race	gender	hours_per_week	income
0	30.0	Private	HS-grad	Single	White-Collar	White	Male	45.0	0.067473

Figure: An example of instance that has been 'queried'

  - It generates five counterfactual examples.

	age	workclass	education	marital_status	occupation	race	gender	hours_per_week	income
0	88.0	Private	Doctorate	Single	White-Collar	White	Male	45.0	0.766
1	39.0	Private	Doctorate	Married	White-Collar	White	Male	40.0	0.935
2	42.0	Self-Employed	HS-grad	Married	White-Collar	White	Female	45.0	0.747
3	44.0	Private	Prof-school	Single	Professional	Other	Male	45.0	0.608
4	52.0	Private	HS-grad	Married	White-Collar	White	Male	65.0	0.807

Figure: Five counterfactual explanations for the prediction above

  - DiCE suggests some counterfactuals that are impossible to achieve

Results - CEML

- Worked well for simple models (Decision Trees, small Random Forests) on breast cancer dataset
  - Results hard to interpret, requires extra effort to make sense of
- Unable to find any counterfactuals for complex Neural Network models
  - Long time to compute ($>$ 1000 sec)
  - Poor results possibly due to unsuitable loss function and optimization technique for the problem
- Ran experiment to explore the relationship between model complexity and CEML counterfactual compute time

CEML Random Forest Results

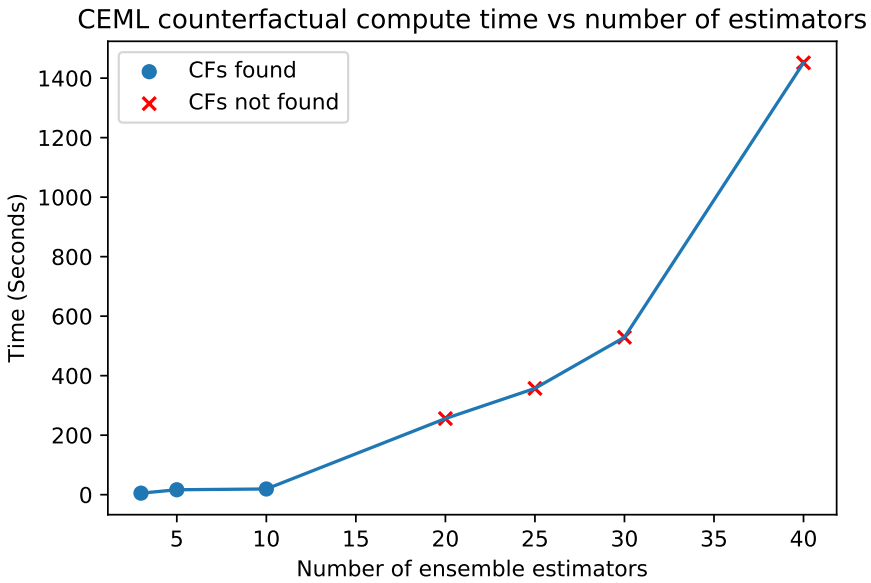


Figure: CEML Random Forest counterfactual computation time vs complexity.

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Conclusion

- Alibi - Well optimised with performance provided by class prototyping method. Simple, but inflexible.
- DiCE - Simple to implement Produces clean tabular output.
- CEML - Good for simple models. Not for complex DNNs.