NLP Seminar - March 2021

Explainability in DL & NLP

bhaecker

Overview

- Introduction
- Datasets/models
- LIME Framework
- Faithful Interpretations
- Explanation sets
- Counterfactual examples ("what-if"-method)
- Discussion

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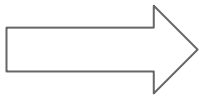
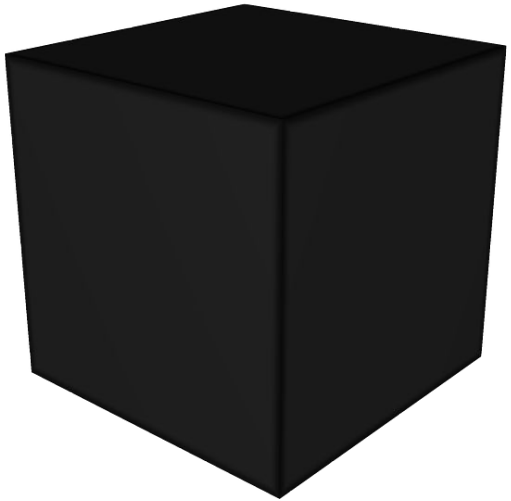


basically three methods on two data sets/tasks

Introduction

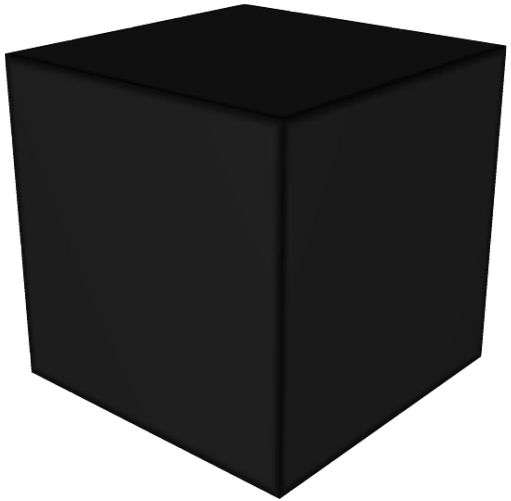
Introduction



Introduction

Responsibility ?

Legal aspects ?



Transparency ?

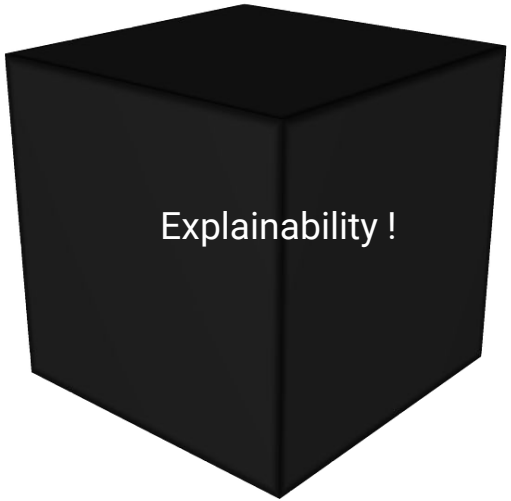
Unwanted bias ?

Debugging ?

Introduction

Responsibility ?

Legal aspects ?



Transparency ?

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Introduction

- **Interpretability is the degree to which a human can understand the cause of a decision**
  (Tim Miller: “Explanation in Artificial Intelligence: Insights from the Social Sciences.”)

“You can ask a human, but, you know, what cognitive psychologists have discovered is that when you ask a human you’re not really getting at the decision process. They make a decision first, and then you ask, and then they generate an explanation and that may not be the true explanation.”
- Peter Norvig
(Muhamad Aurangzeb et al.: “Explainable AI in Healthcare”)

Introduction

Individual predictions (local)	Whole prediction process (global)
Directly from prediction process (self-explaining)	Post-processing required (post-hoc)
Convincing humans (Plausibility)	Reflects true reasoning process of model (Faithfulness)

- Model-specific vs. model-agnostic
- Examples and counter-examples
- Proxy models
- ...

(Alon Jacovi and Yoav Goldberg.: “Towards Faithfully Interpretable NLP Systems: How should we define and evaluate faithfulness?”
Andreas Rauber.: “Security, Privacy and Explainability In ML - Explainability” TU Wien)

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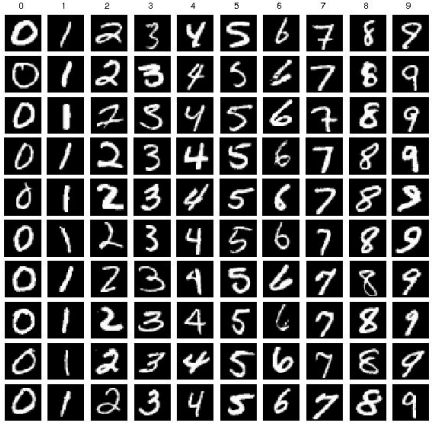
Data sets

MNIST data & IMDB Dataset of 50K Movie Reviews

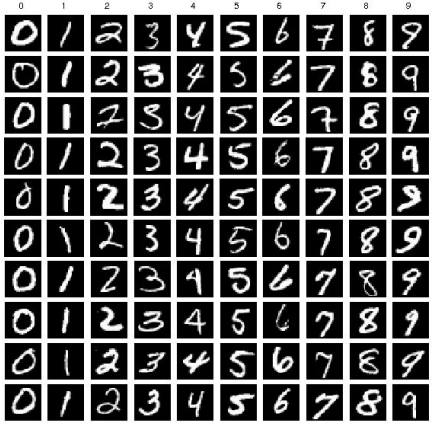


(LeCun et al.: “The MNIST Dataset Of Handwritten Digits”)

(Maas et al.: “Learning Word Vectors for Sentiment Analysis”)

Data sets / Task

MNIST data & IMDB Dataset of 50K Movie Reviews

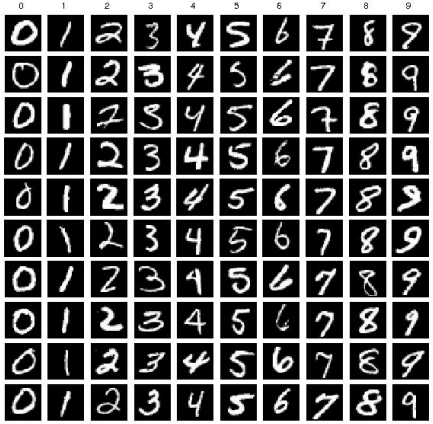


10 classes

2 classes

Data sets / Models

MNIST data & IMDB Dataset of 50K Movie Reviews



Convolutional &
Dense layers

IMDb

LSTM &
Dense layers

LIME

LIME

- Model agnostic
- Local explanation
- Explanation through visual or textual artifacts
- Usage of interpretable classifier

"Why Should I Trust You?" Explaining the Predictions of Any Classifier

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ABSTRACT

Despite widespread adoption, machine learning models remain mostly black boxes. Understanding the reasons behind predictions is, however, quite important in assessing *trust*, which is fundamental if one plans to take action based on a prediction, or when choosing whether to deploy a new model. Such understanding also provides insights into the model, which can be used to transform an untrustworthy model or prediction into a trustworthy one.

In this work, we propose LIME, a novel explanation technique that explains the predictions of *any* classifier in an interpretable and faithful manner, by learning an interpretable model locally around the prediction. We also propose a method to explain models by presenting representative individual predictions and their explanations in a non-redundant way, framing the task as a submodular optimization problem. We demonstrate the flexibility of these methods by explaining different models for text (e.g. random forests) and image classification (e.g. neural networks). We show the utility of explanations via novel experiments, both simulated and with human subjects, on various scenarios that require trust: deciding if one should trust a prediction, choosing between models, improving an untrustworthy classifier, and identifying why a classifier should not be trusted.

1. INTRODUCTION

Machine learning is at the core of many recent advances in science and technology. Unfortunately, the important role of humans is an oft-overlooked aspect in the field. Whether humans are directly using machine learning classifiers as tools,

how much the human understands a model's behaviour, as opposed to seeing it as a black box.

Determining trust in individual predictions is an important problem when the model is used for decision making. When using machine learning for medical diagnosis [6] or terrorism detection, for example, predictions cannot be acted upon on blind faith, as the consequences may be catastrophic.

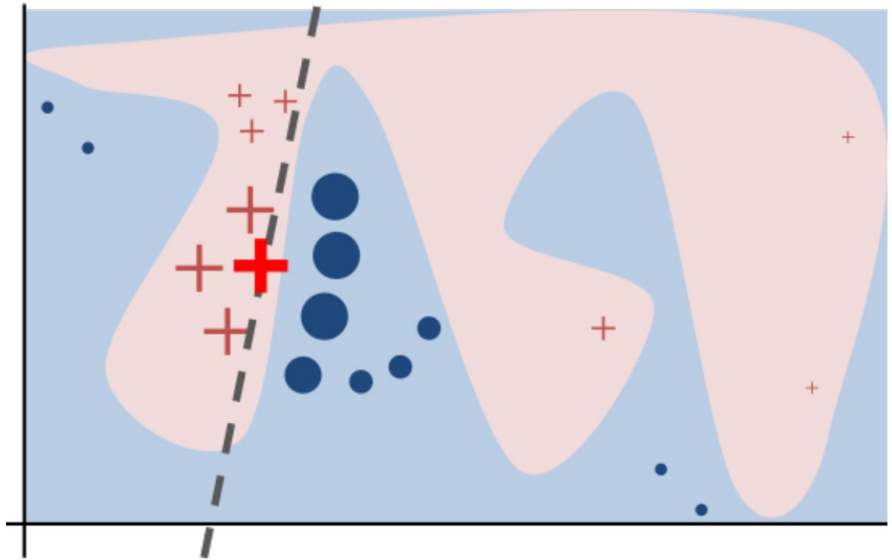
Apart from trusting individual predictions, there is also a need to evaluate the model as a whole before deploying it "in the wild". To make this decision, users need to be confident that the model will perform well on real-world data, according to the metrics of interest. Currently, models are evaluated using accuracy metrics on an available validation dataset. However, real-world data is often significantly different, and further, the evaluation metric may not be indicative of the product's goal. Inspecting individual predictions and their explanations is a worthwhile solution, in addition to such metrics. In this case, it is important to aid users by suggesting which instances to inspect, especially for large datasets.

In this paper, we propose providing explanations for individual predictions as a solution to the "trusting a prediction" problem, and selecting multiple such predictions (and explanations) as a solution to the "trusting the model" problem. Our main contributions are summarized as follows.

- LIME, an algorithm that can explain the predictions of *any* classifier or regressor in a faithful way, by approximating it locally with an interpretable model.
- SP-LIME, a method that selects a set of representative instances with explanations to address the "trusting the model" problem, via submodular optimization.

LIME algorithm

- Sampling around sample of interest
- Distances from new samples to original one
- Training of an interpretable classifier with weighted samples
- Extraction of coefficients from interpretable classifier
- Usage of coefficients for artifact creation

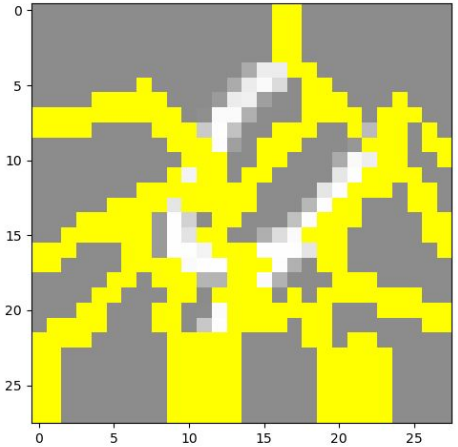


(Ribeiro et al.: “"Why Should I Trust You?": Explaining the Predictions of Any Classifier”)

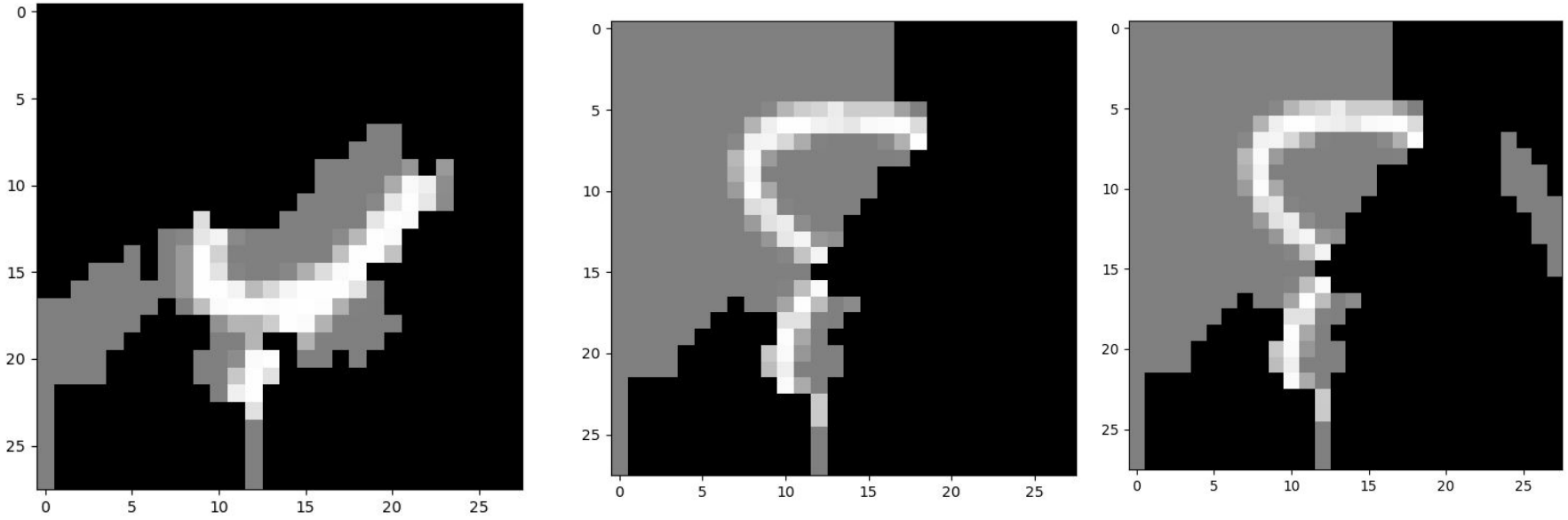
Ingredients

- Sampling: Switching attributes off, leaving out word, switching (super-)pixels off
- Distance calculation: Cosine or euclidean distance for text, pixels, etc.
- Interpretable Classifier: Linear classifiers like Linear Regression
- Order on attributes by sorting the coefficients of the interpretable classifier
- Artifact creation by choosing top-N attributes or colour coding of attributes with respect to coefficients

- this movie is amazing while being funny and entertaining it is also profoundly deep and eye opening
- this ____ is amazing while ____ funny and entertaining it is ____ profoundly ____ and eye ____
- ____ movie ____ amazing ____ being funny and entertaining it is also ____ deep and eye ____
- this ____ is amazing while being ____ and____ entertaining it is also profoundly ____ and eye opening
- this ____ is amazing while being funny ____ entertaining ____ is also ____ deep and eye opening
- ...

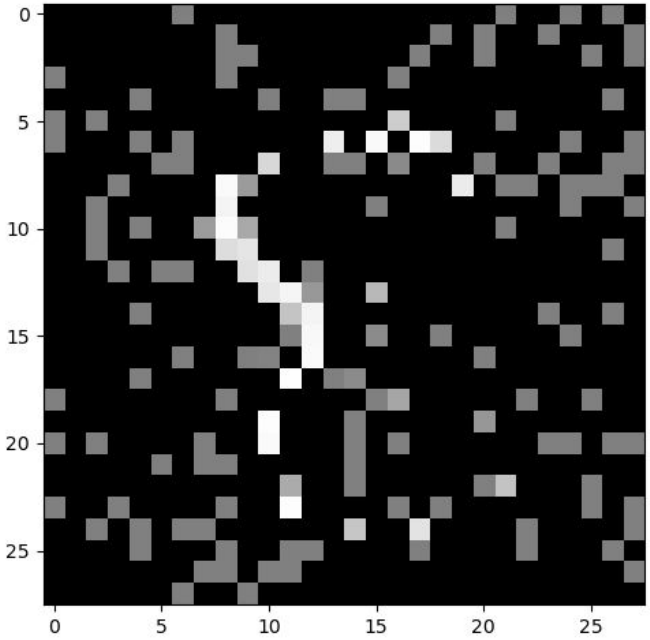


...or just use all pixels

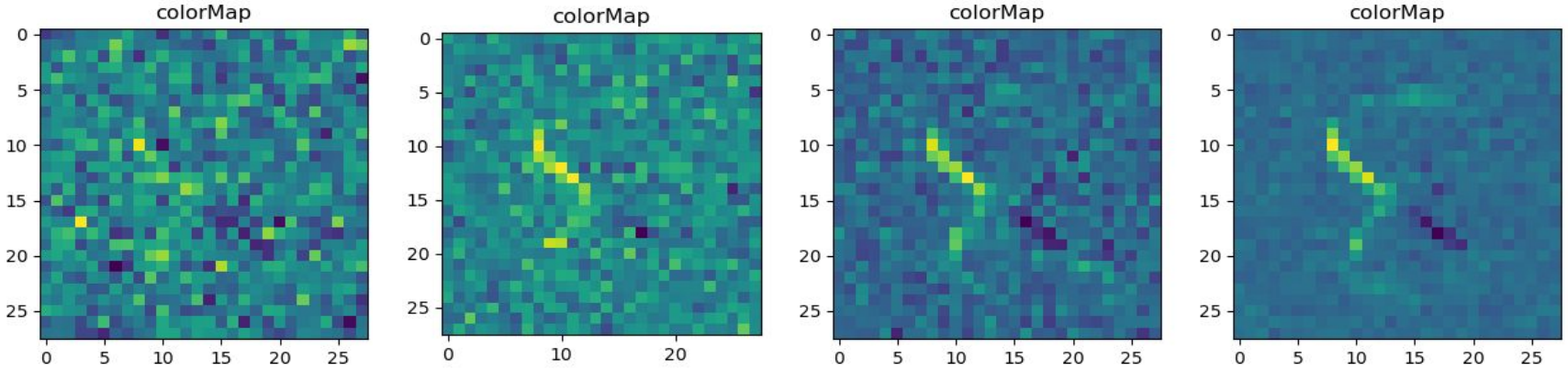


2, 3 and 4 superpixels active

LIME on MNIST - examples



most important 20% pixels active



Importance of individual pixels with 111, 222, 1111 and 2222 samples from left to right

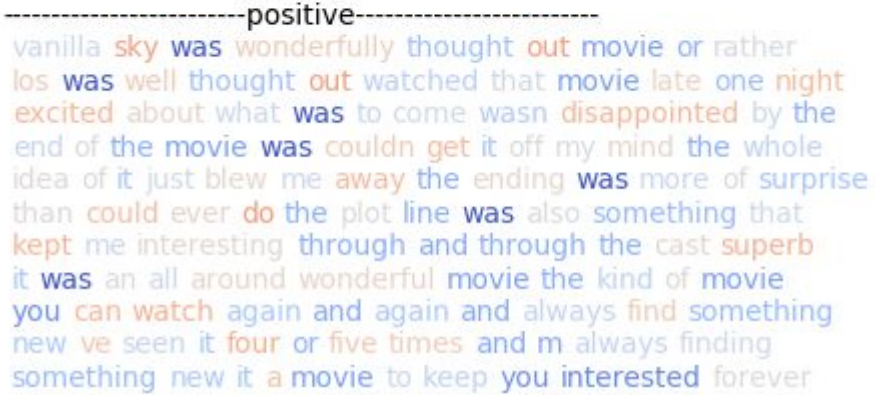
LIME on MNIST - examples

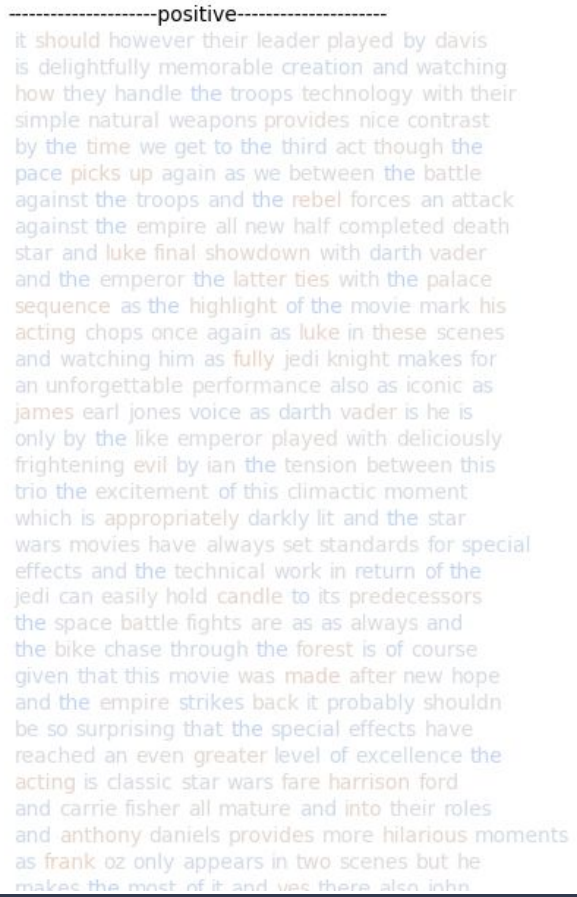
Sentiment Classification

Example

Sentiment Classification

Example





Sentiment Classification - StarWars example

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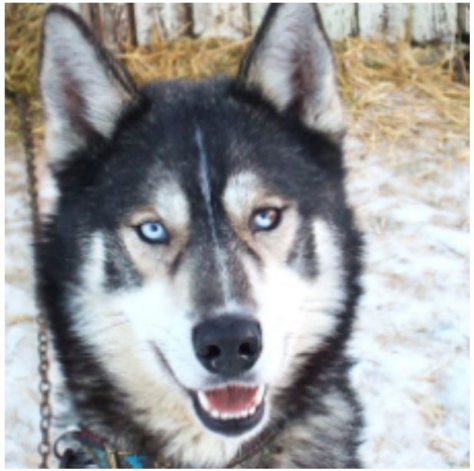

Husky classified as wolf and superpixels as explanation

(Ribeiro et al.: “"Why Should I Trust You?": Explaining the Predictions of Any Classifier”)

Text with highlighted words

From: johnchad@triton.unm.edu (jchadwic)
Subject: Another request for Darwin Fish
Organization: University of New Mexico, Albuquerque
Lines: 11
NNTP-Posting-Host: triton.unm.edu

Hello Gang,

There have been some notes recently asking where to obtain the DARWIN fish.
This is the same question I have and I have not seen an answer on the
net. If anyone has a contact please post on the net or email me.

Text classified as atheism and highlighted words as explanation

(Ribeiro https://github.com/marcotcr/lime)

Unwanted Bias detection with LIME

Faithful Interpretations & Explanation Sets

Faithful Interpretations

- Faithfulness:
  "[A] faithful interpretation is one that accurately represents the reasoning process behind the model's prediction."

Towards Faithfully Interpretable NLP Systems: How Should We Define and Evaluate Faithfulness?

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Abstract

With the growing popularity of deep-learning based NLP models, comes a need for interpretable systems. But what is interpretability, and what constitutes a high-quality interpretation? In this opinion piece we reflect on the current state of interpretability evaluation research. We call for more clearly differentiating between different desired criteria an interpretation should satisfy, and focus on the faithfulness criteria. We survey the literature with respect to faithfulness evaluation, and arrange the current approaches around three assumptions, providing an explicit form to how faithfulness is "defined" by the community. We provide concrete guidelines on how evaluation of interpretation methods should and should not be conducted. Finally, we claim that the current binary definition for faithfulness sets a potentially unrealistic bar for being considered faithful. We call for discarding the binary notion of faithfulness in favor of a more graded one, which we believe will be of greater practical utility.

1 Introduction

One such pain is the challenge of defining—and evaluating—what constitutes a quality interpretation. Current approaches define interpretation in a rather ad-hoc manner, motivated by practical use-cases and applications. However, this view often fails to distinguish between distinct aspects of the interpretation's quality, such as readability, plausibility and faithfulness (Herman, 2017).[2] We argue (§2, §5) such conflation is harmful, and that faithfulness should be defined and evaluated *explicitly*, and independently from plausibility.

Our main focus is the *evaluation of the faithfulness* of an explanation: a faithful interpretation is one that accurately represents the reasoning process behind the model's prediction. We find this to be a pressing issue: in cases where an explanation is required to be faithful, imperfect or misleading evaluation can have disastrous effects.

While literature in this area may implicitly or explicitly evaluate faithfulness for specific explanation techniques, there is no consistent and formal definition of faithfulness. We uncover three assumptions that underlie all these attempts. By making the assumptions explicit and organizing the

Faithful Interpretations - Assumptions

- **Assumption 1 (The Model Assumption).**
  Two models will make the same predictions if and only if they use the same reasoning process.
- **Assumption 2 (The Prediction Assumption).**
  On similar inputs, the model makes similar decisions if and only if its reasoning is similar.
- **Assumption 3 (The Linearity Assumption).**
  Certain parts of the input are more important to the model reasoning than others. Moreover, the contributions of different parts of the input are independent from each other.

- **Corollary 1.1.** An interpretation system is unfaithful if it results in different interpretations of models that make the same decisions
- **Corollary 2.** An interpretation system is unfaithful if it provides different interpretations for similar inputs and outputs

(Alon Jacovi and Yoav Goldberg.: “Towards Faithfully Interpretable NLP Systems: How should we define and evaluate faithfulness?”)

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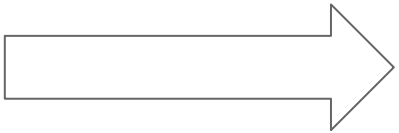
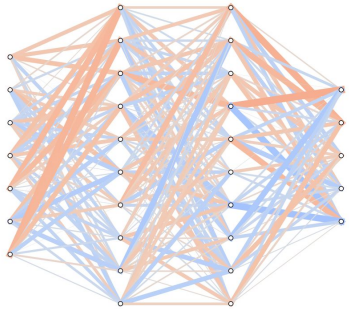
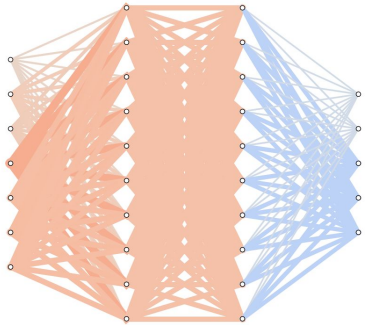


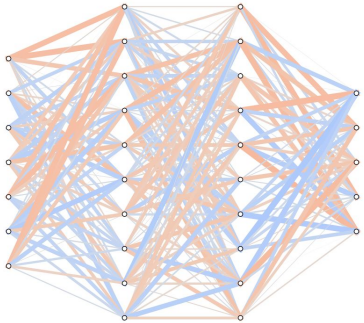
Explanation Sets

Explanation Sets

- Different samples lead to different activations of neurons
- Grouping of all training samples with respect to their neuron activation







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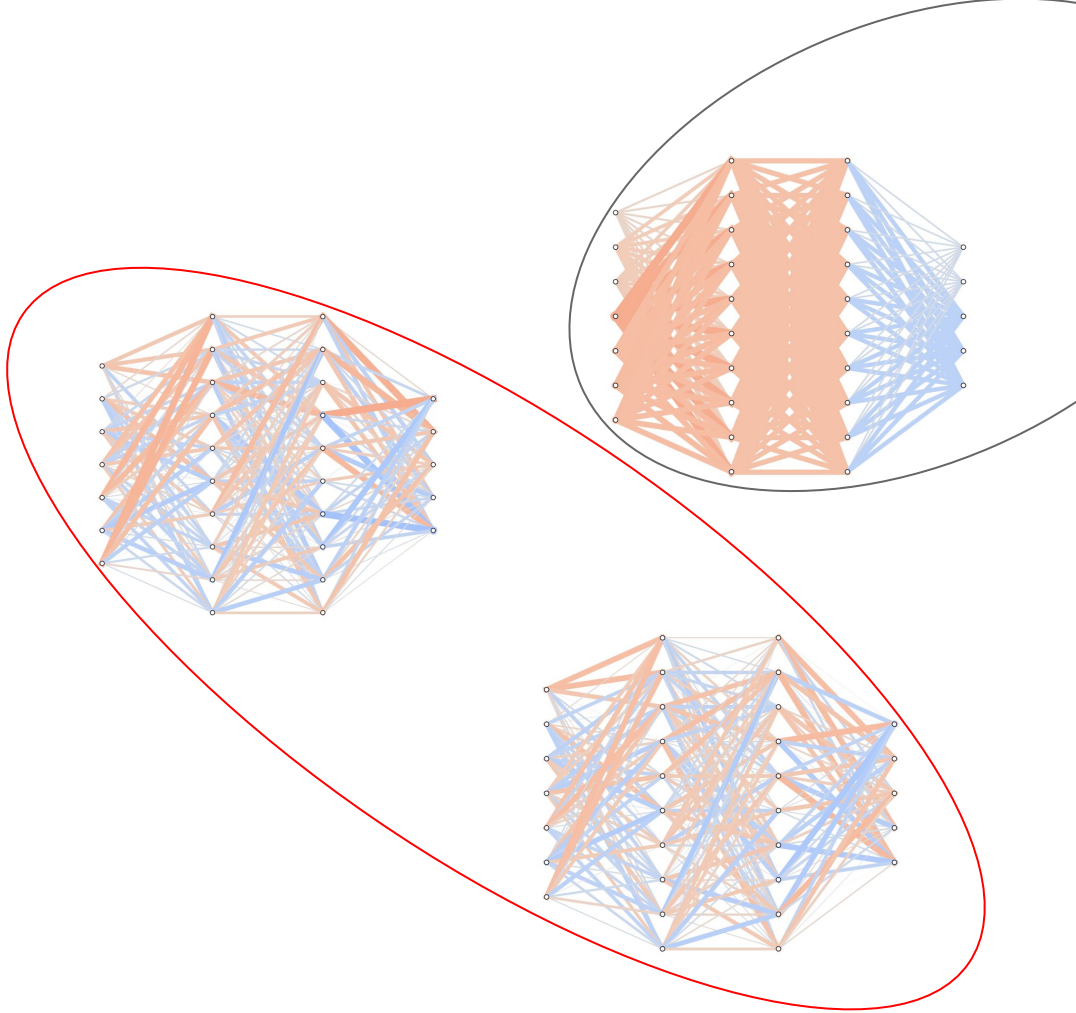
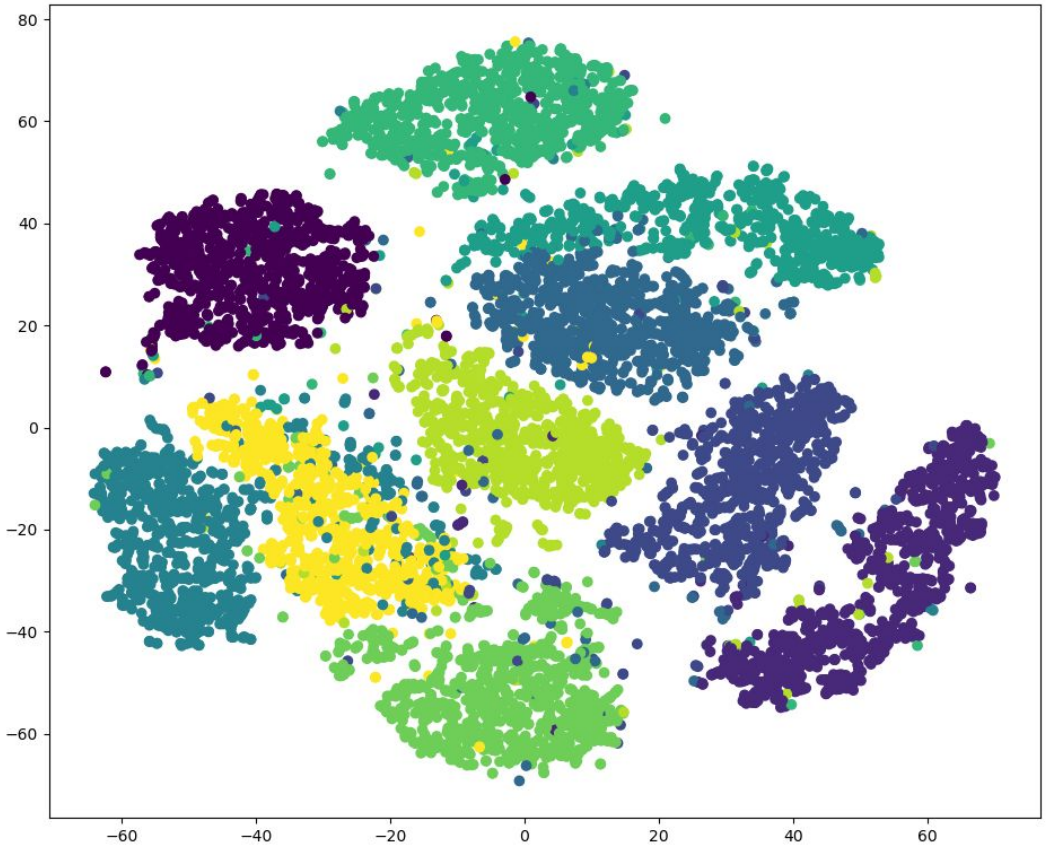


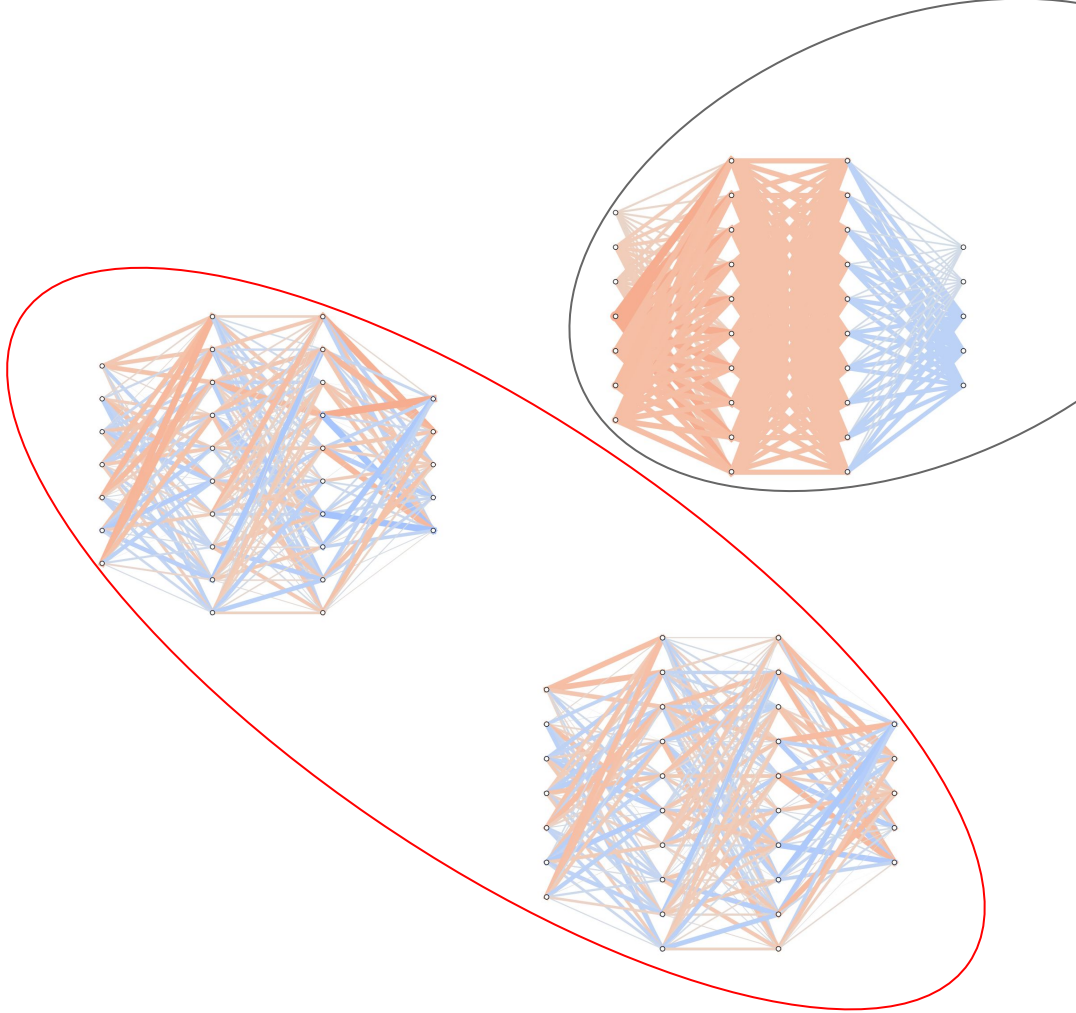
Explanation Sets

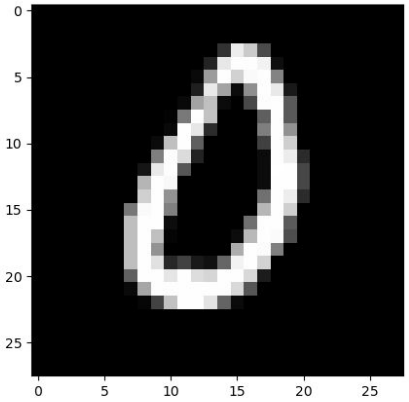
Activations clustered in 2 dimensional space



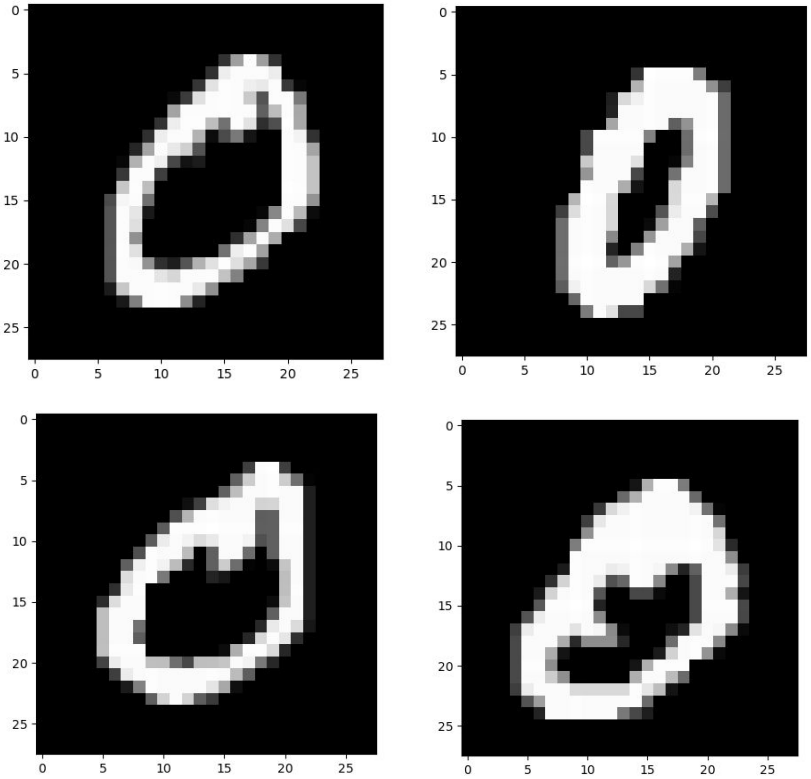
Explanation Sets

- Different samples lead to different activations of neurons
- We group all training samples with respect to their neuron activation
- A new sample gets grouped into one of the group by its own neuron activity
- Training samples from this group serve as “faithful” explanations

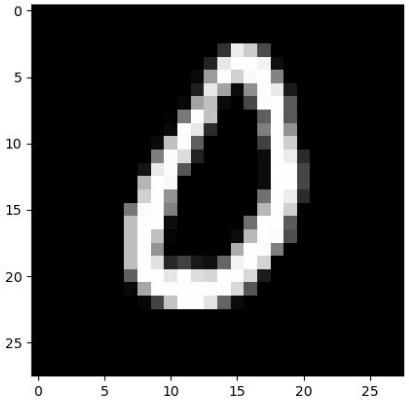




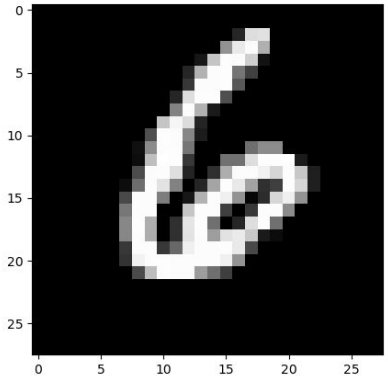
Sample to explain

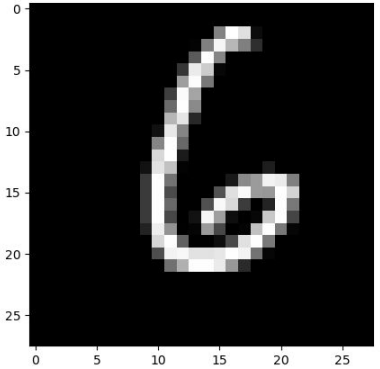


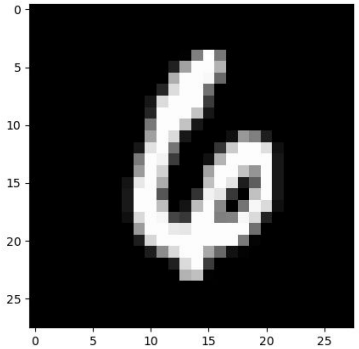
Samples which evoke similar neuron activity

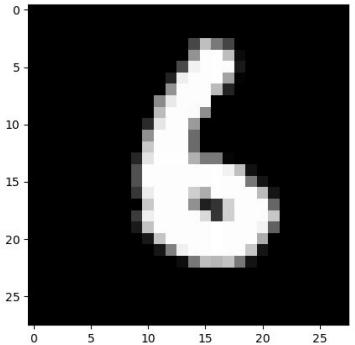


Sample to explain









Samples which evoke similar neuron activity

Explanation Sets - MNIST - only Conv layers

- **When the model "saw"**
  - Im guessing that the movie was based on book given the number of characters and subplots during thought that the movie creators perhaps the writer or director intended to create an epic movie [...]

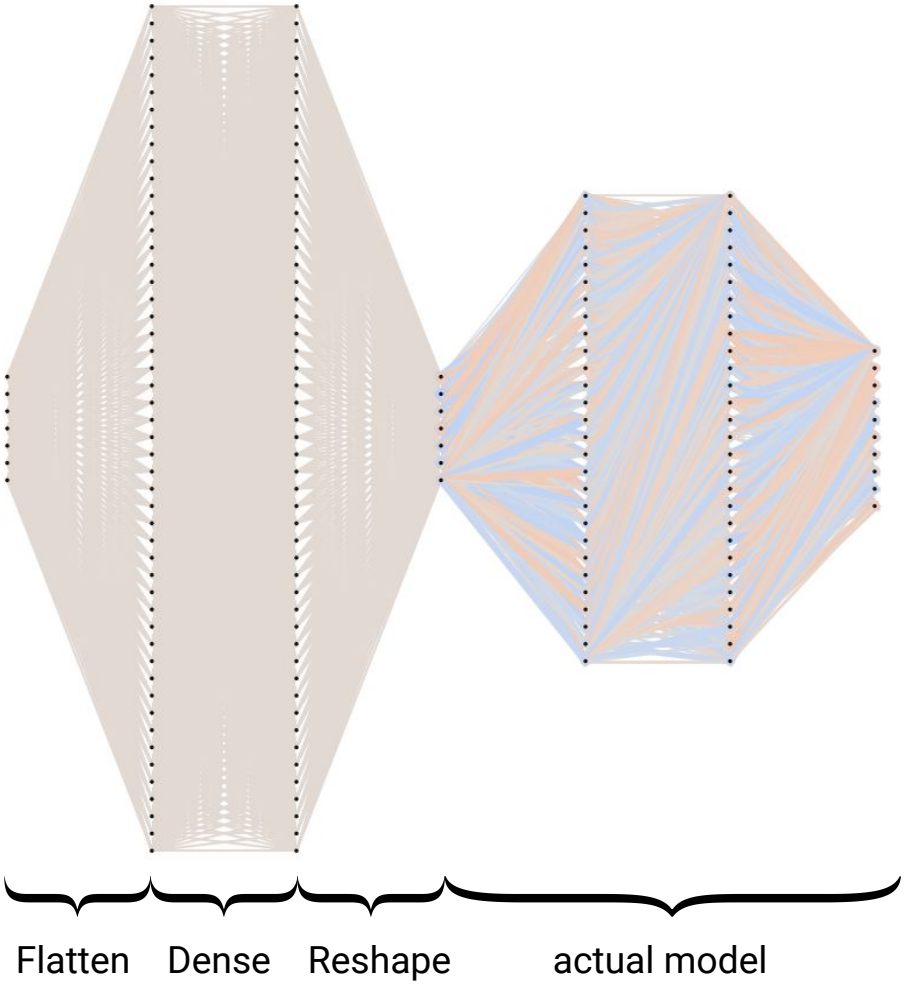
- **the neuron activity was similar to when it "saw" the following training samples:**
  - there is no such thing as perfect murder lieutenant columbo knows that ken franklin who is the other half of the writing team of detective stories doesn know that he kills his partner jim who had plans [...]
  - Ive been fan of columbo since childhood and still enjoy watching them there was break for many years that they weren showing columbo stories at all but now he back back for one more question
  - this is my first awful rating ever on imdb and couldn think of more deserving film to honor it with hoped for entertaining trash and found trash of the saddest kind found film which no one can possibly have cared bit about including its creator hell ride directed written by and starring larry friend of bishop [...]
  - the main reason for writing this review is found this of great play and worthy film horrible movie experience if can save someone from watching it will have done good thing this new version is [...]
  - I rented this when it came out on video in after it again my idea about it hasn changed much was an adult then and Im still an adult now illogical elements mentioned by other reviewers didn bother me this isn a documentary it a fantasy story where animals can talk [...]

Counterfactual Examples

Counterfactual Examples

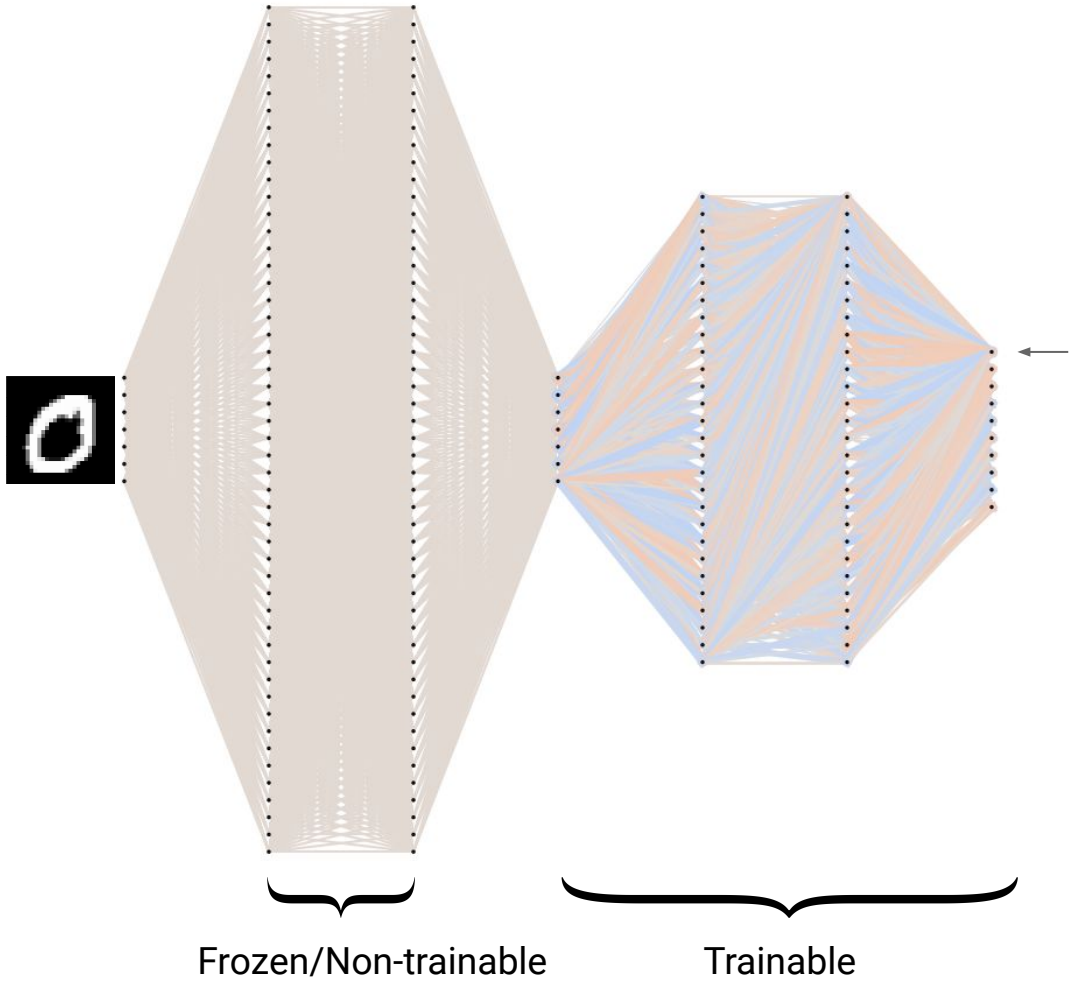
“What-if”-method:

- the model should tell us how a sample must look like in order to be classified in a specific class.
- Achieved by an encoder decoder structure in front of the model.
- Encoder Decoder is initialized as an identity function.



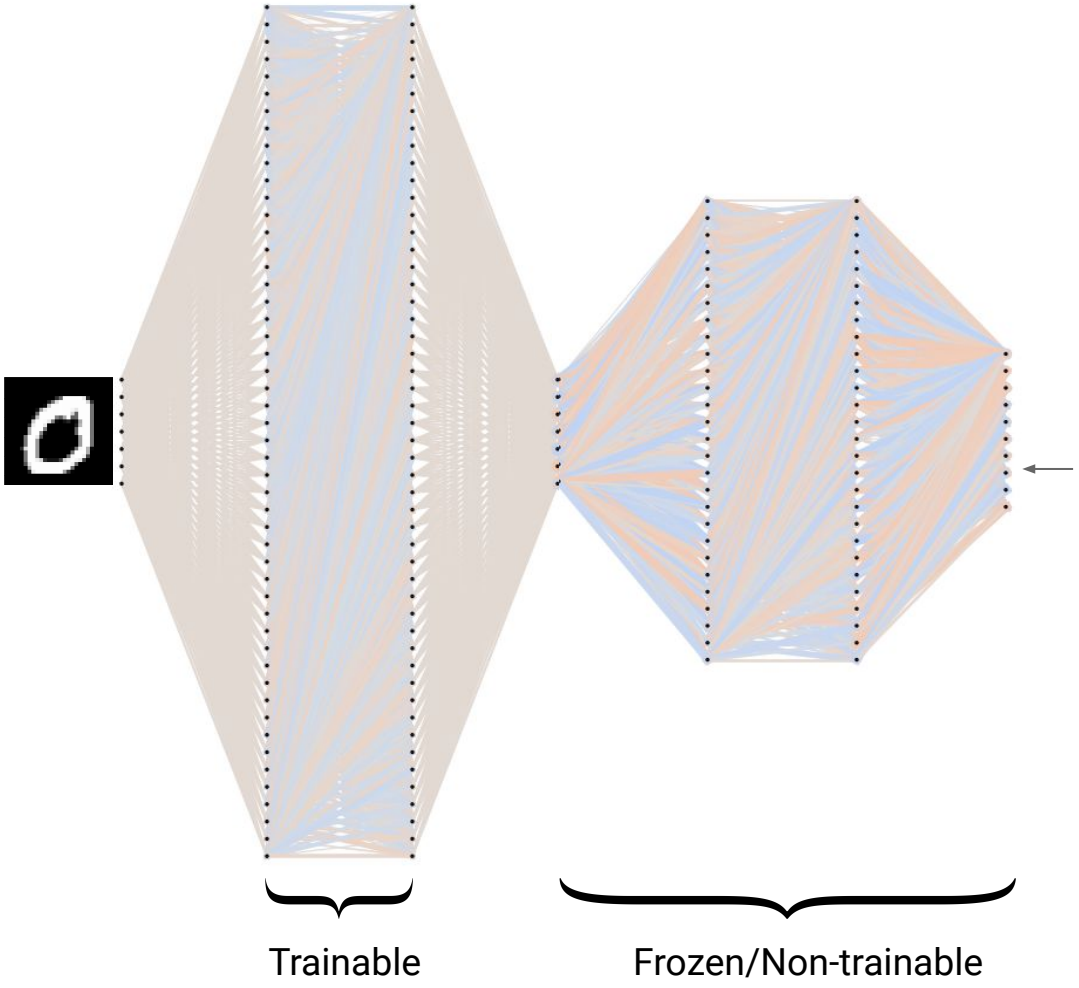
Counterfactual Examples

Normal training phase



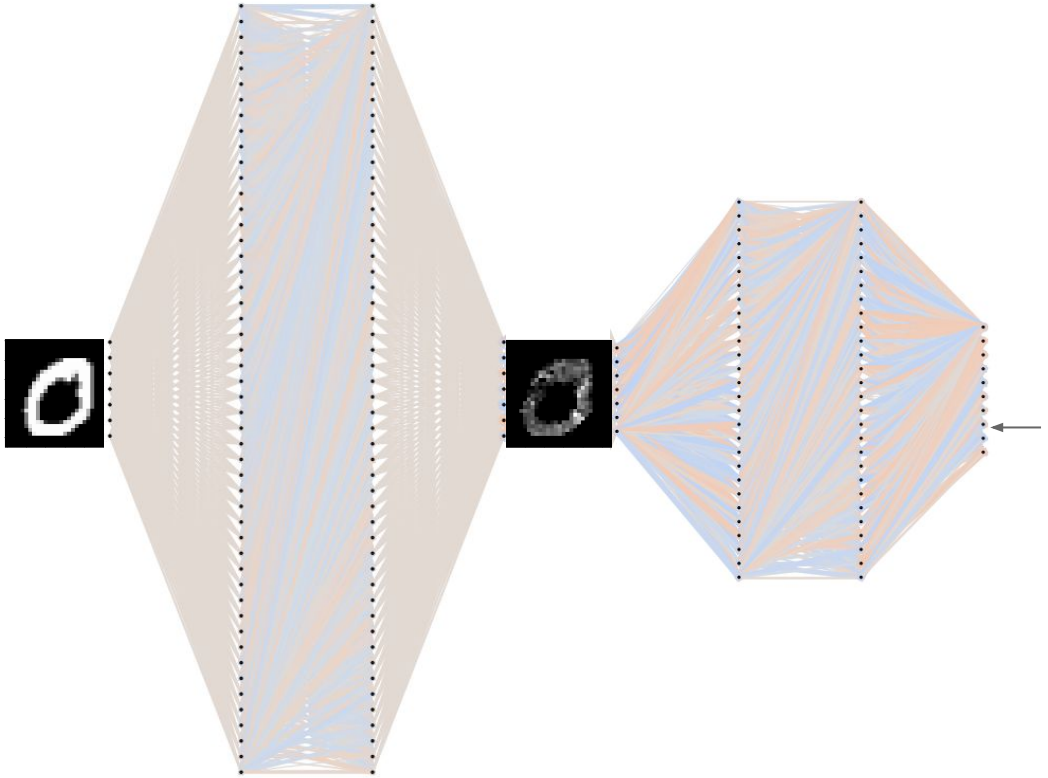
Counterfactual Examples

Sample creation phase



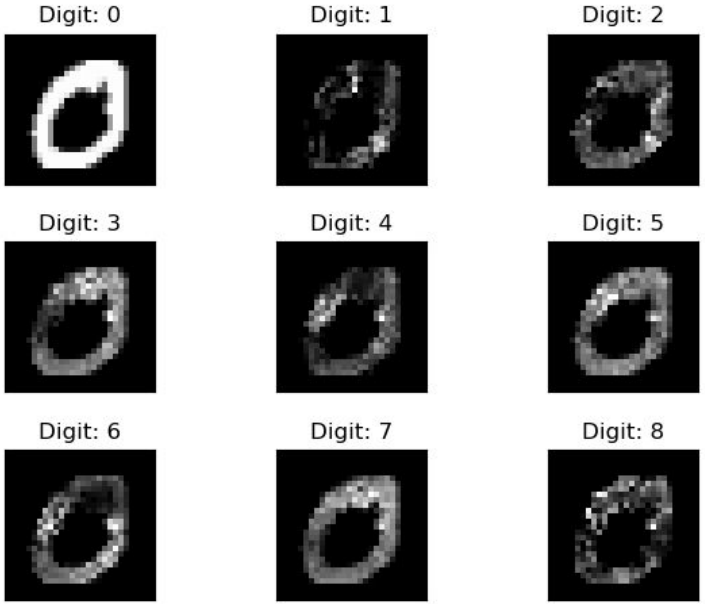
Counterfactual Examples

New sample extraction

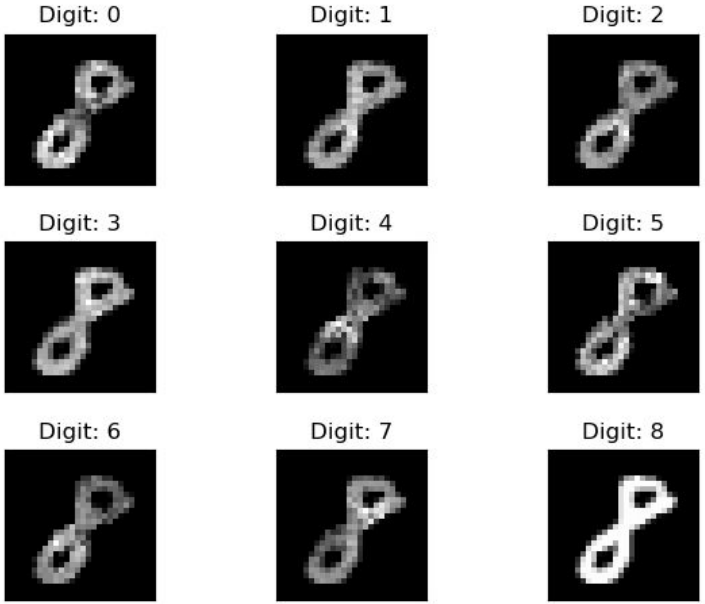


New sample belongs to class x with probability p

Counterfactual Examples

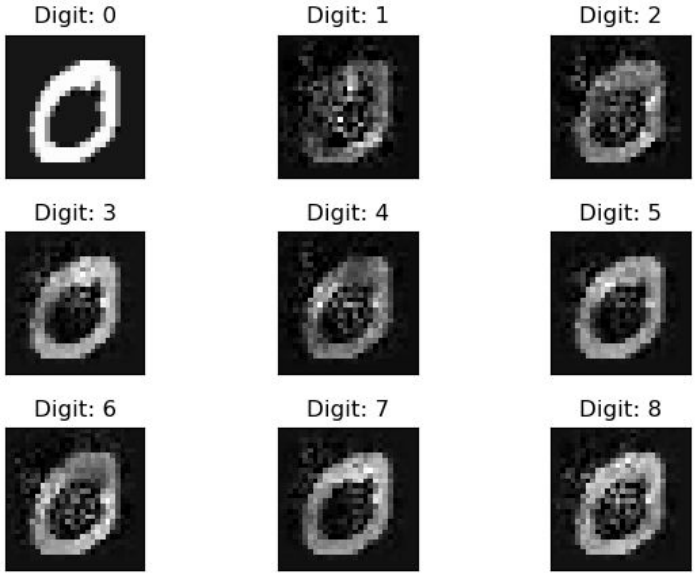


more than 75% probability

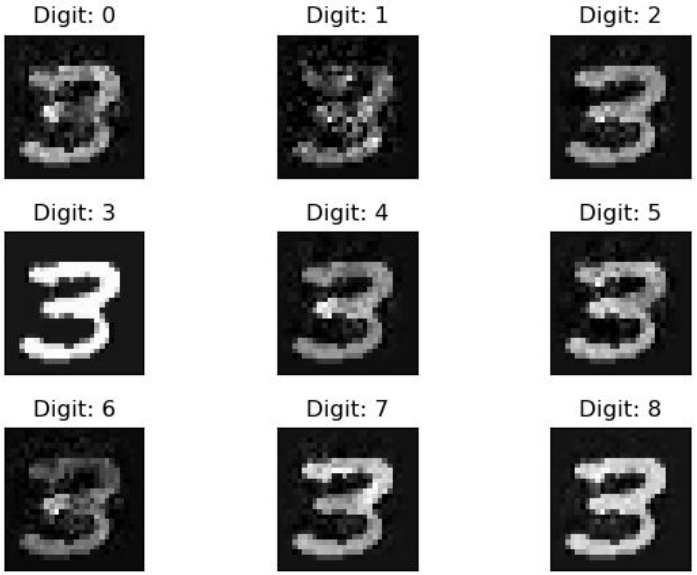


more than 85% probability

Counterfactual Examples



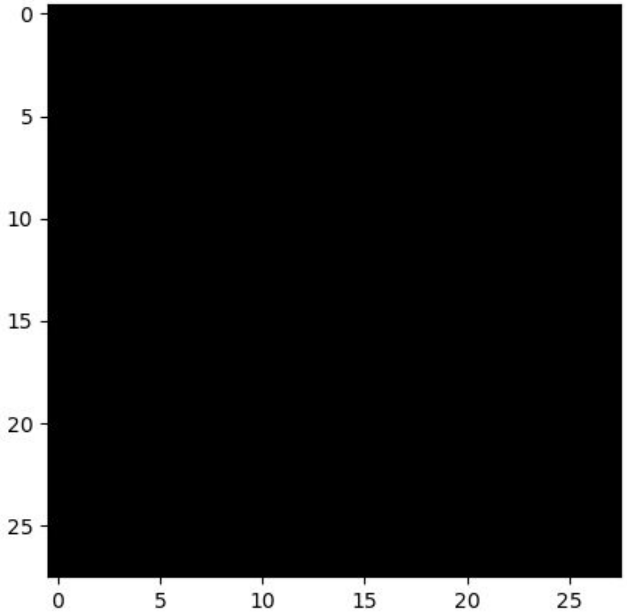
more than 85% probability



more than 90% probability

Examples - non black background

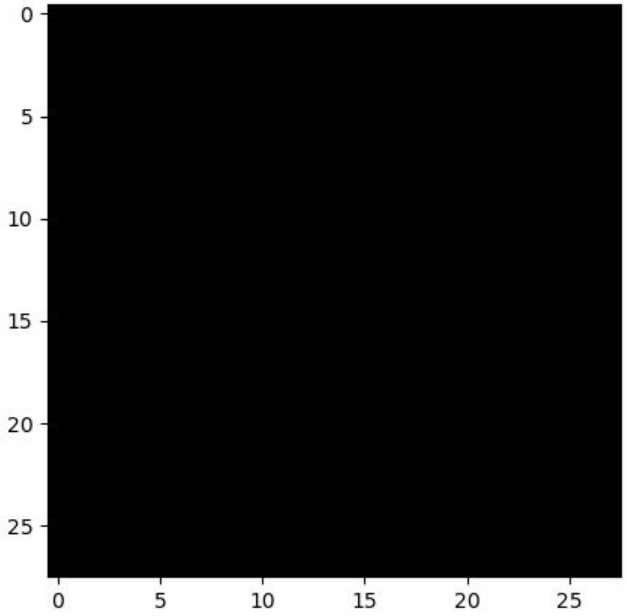
Counterfactual Examples

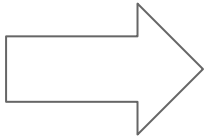


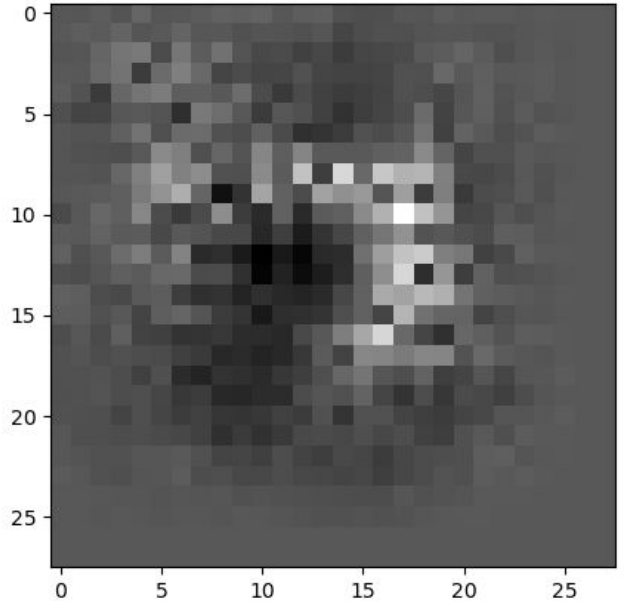
Class 7 with more than 75%

Examples - non black background - from nothing

Counterfactual Examples



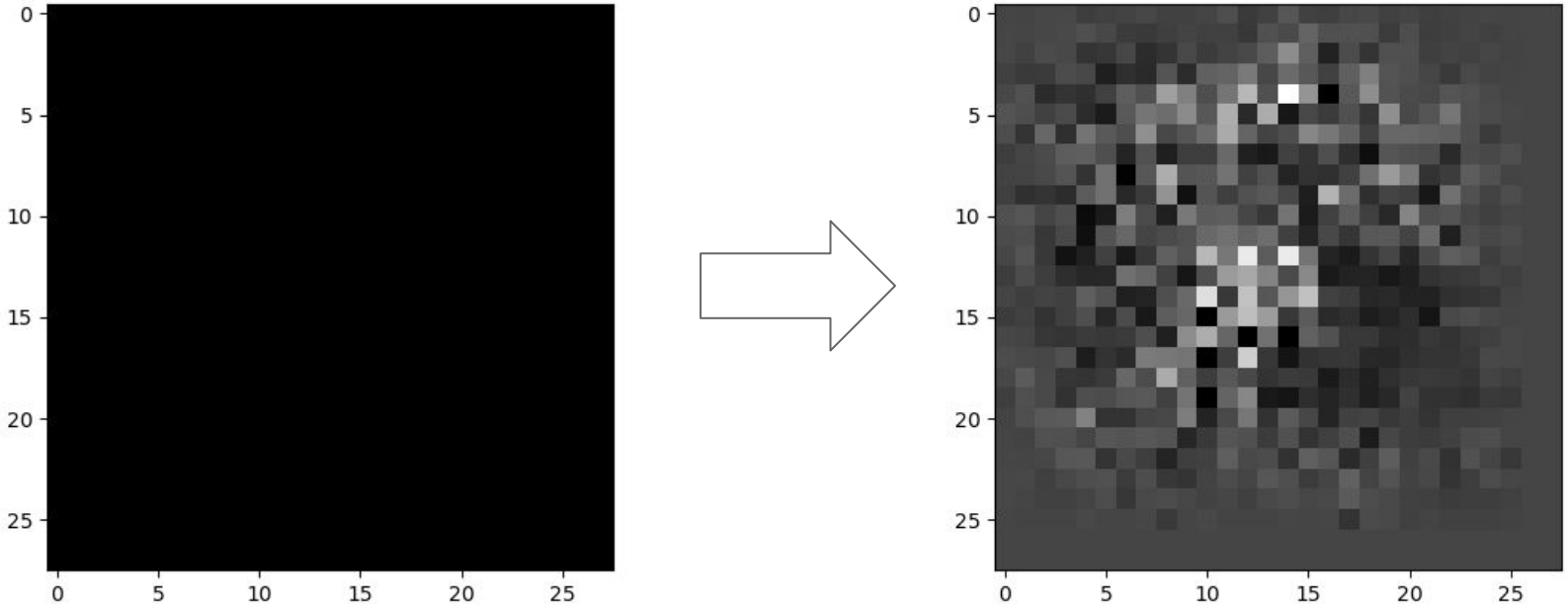




Class 7 with more than 75%

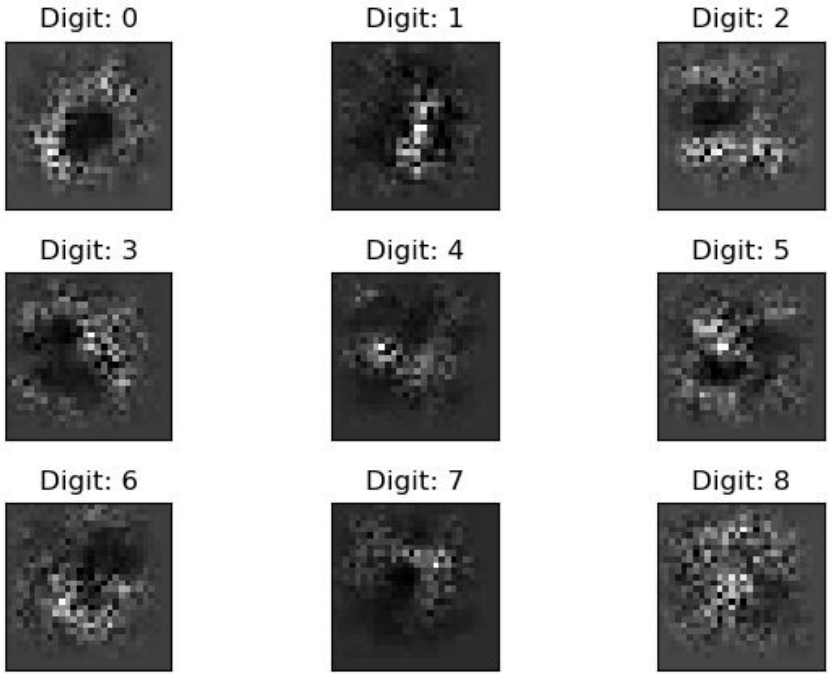
Examples - non black background - from nothing to something

Counterfactual Examples



Examples - non black background - from nothing to something

Counterfactual Examples



more than 75% probability

Examples - non black background - from nothing to something

Counterfactual Examples

Possible Extensions:

- Only allow change in some parts of the image
- Permutation of (super-)pixels

Counterfactual Examples

Possible Extensions:

- Only allow change in some parts of the image
- Permutation of (super-)pixels
- Ideas ?

Counterfactual creation with encoder-decoder structure not possible for the sentiment classification task using GD, since :

- Embedding layer is not differentiable
- Inverse Embedding is hard to find

Thank you for your attention!

Questions/ideas/feedback ?

Pictures from papers or own if nothing specified