EVERYTHING IS XAI

THIS PRESENTATION IS ABOUT

→ taxonomy

→ model (un)certainty

→ gradCAMs

→ the Nigerian prince

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→ taxonomy

→ model (un)certainty

→ gradCAMs

→ the Nigerian prince

thoughts about the presentation this morning?

TAXONOMY OF XAI

→ **by default**

1. linear models
2. tree-based models

→ **black boxes**

→ global vs local methods

→ model-specific vs model-agnostic

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classify gradCAM according to the taxonomy

TAXONOMY OF XAI

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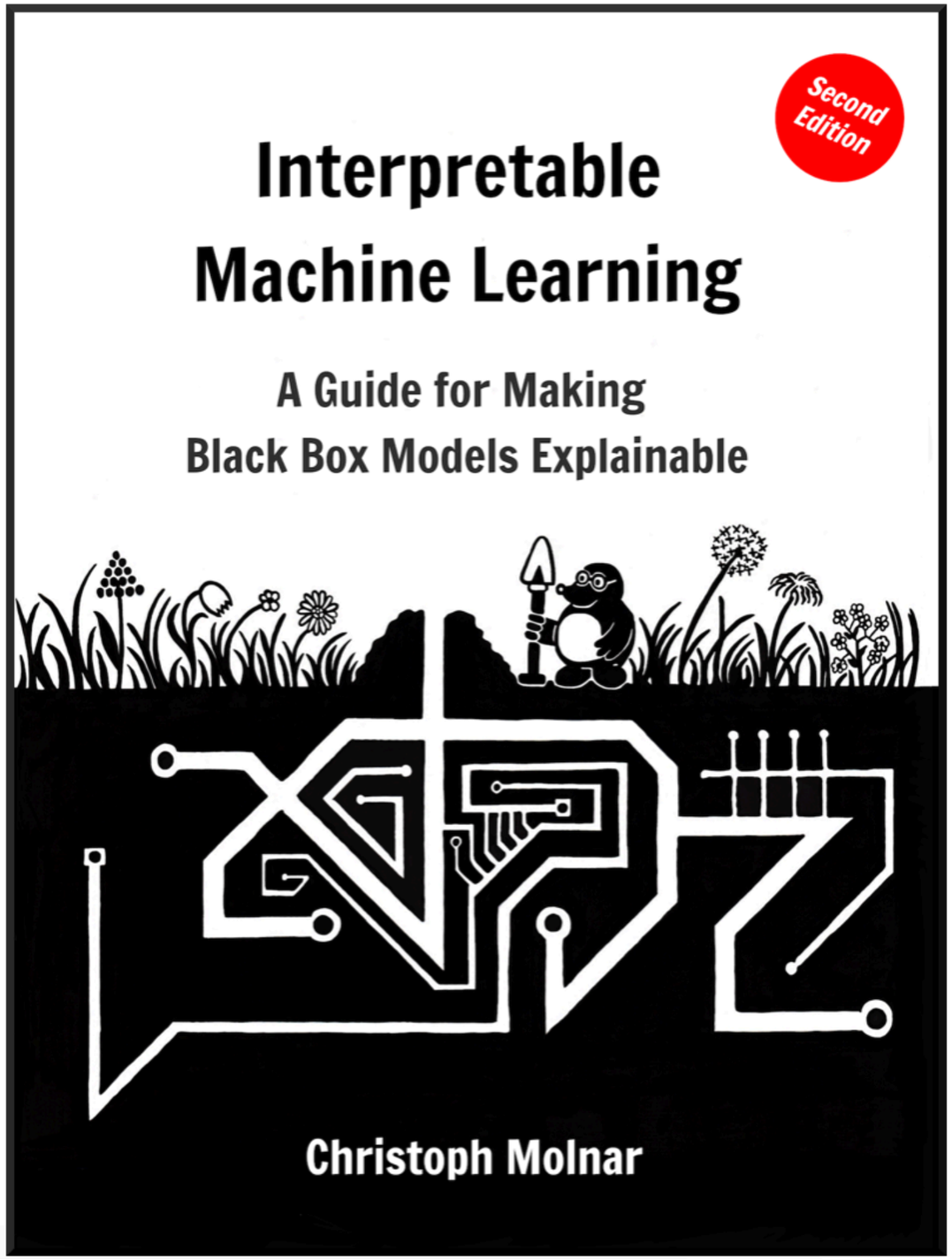
  - → global vs **local** methods
  - → **model-specific** vs model-agnostic

gradCAM is a local, model-specific method to explain the predictions of a CNN



MODEL (UN)CERTAINTY

"It is remarkable that science, which originated in the consideration of games of chance, should have become the most important object of human knowledge."

— Pierre Simon Laplace

MODEL (UN)CERTAINTY I

aleatoric uncertainty

statistical in nature, refers to random variation

🔔 $P(Y|X;\theta)$

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🔔 $P(Y|X;\theta)$

more data is not a solution

data quality, model averaging, and prediction intervals help.

MODEL (UN)CERTAINTY II

epistemic uncertainty

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MODEL (UN)CERTAINTY II

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more data is a solution

hyperparameter tuning, regularization etc. help

HOW IS THIS USEFUL?

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! ***never forget that the models you build are probabilistic in nature***

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even the best models can be wrong, and with horrible consequences

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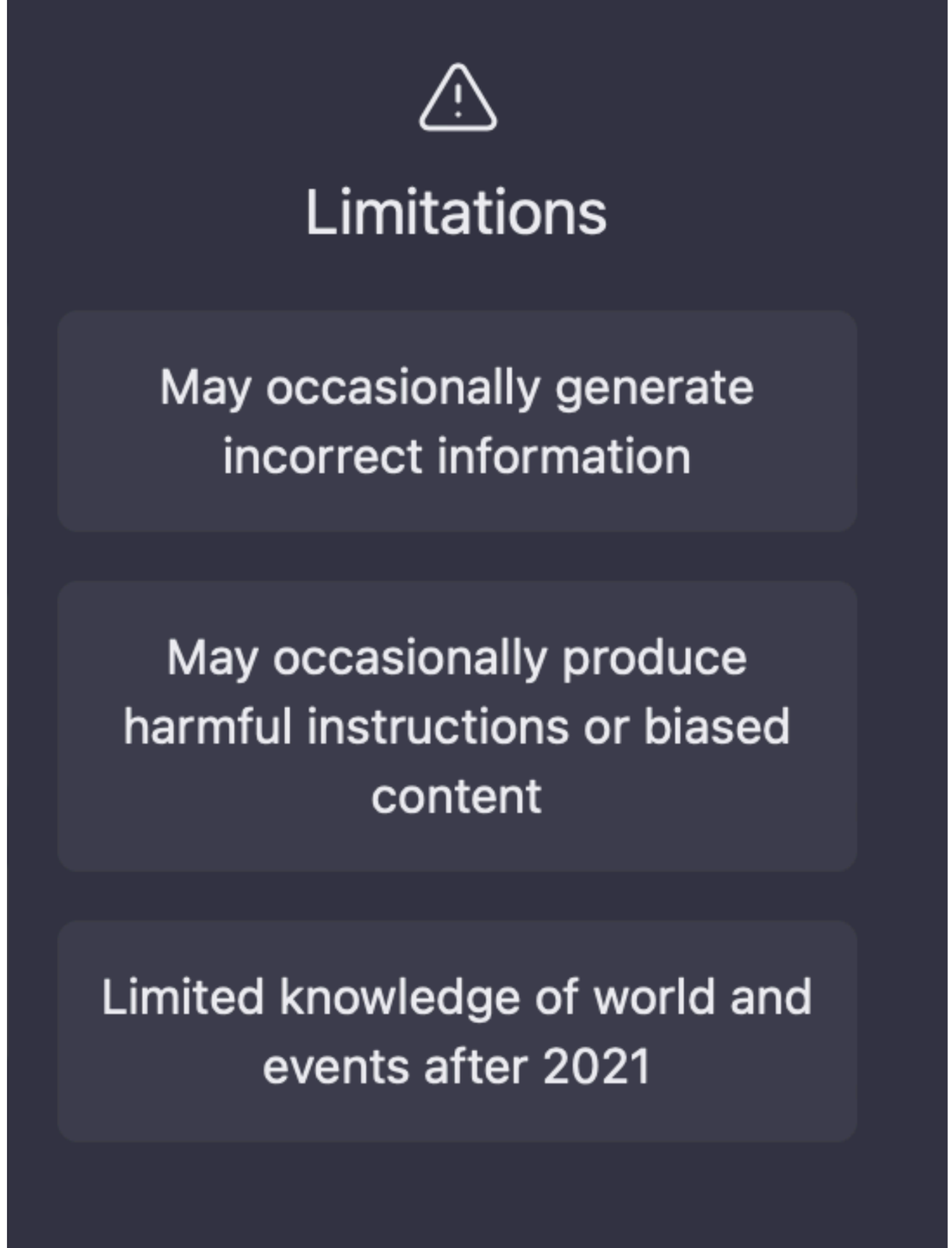
remember the end user!



EMBRACE THE UNCERTAINTY

Successful decisions are built on

→ minimizing our ignorance

→ accepting inherent randomness

→ knowing the difference between the two.

think self-driving cars, medical diagnosis, or exploding rockets

may occasionally kill passengers

EXPLAINING

DEEP NEURAL NETWORKS

EXPLAINING DEEP NEURAL NETWORKS

feature visualization

visualize the activations of a deep neural network

feature attribution

adversarial examples

EXPLAINING DEEP NEURAL NETWORKS

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visualize the features that contribute strongly to the activations of CNN layers for a given input image and class label.

adversarial examples

EXPLAINING DEEP NEURAL NETWORKS

feature visualization

visualize the activations of a deep neural network

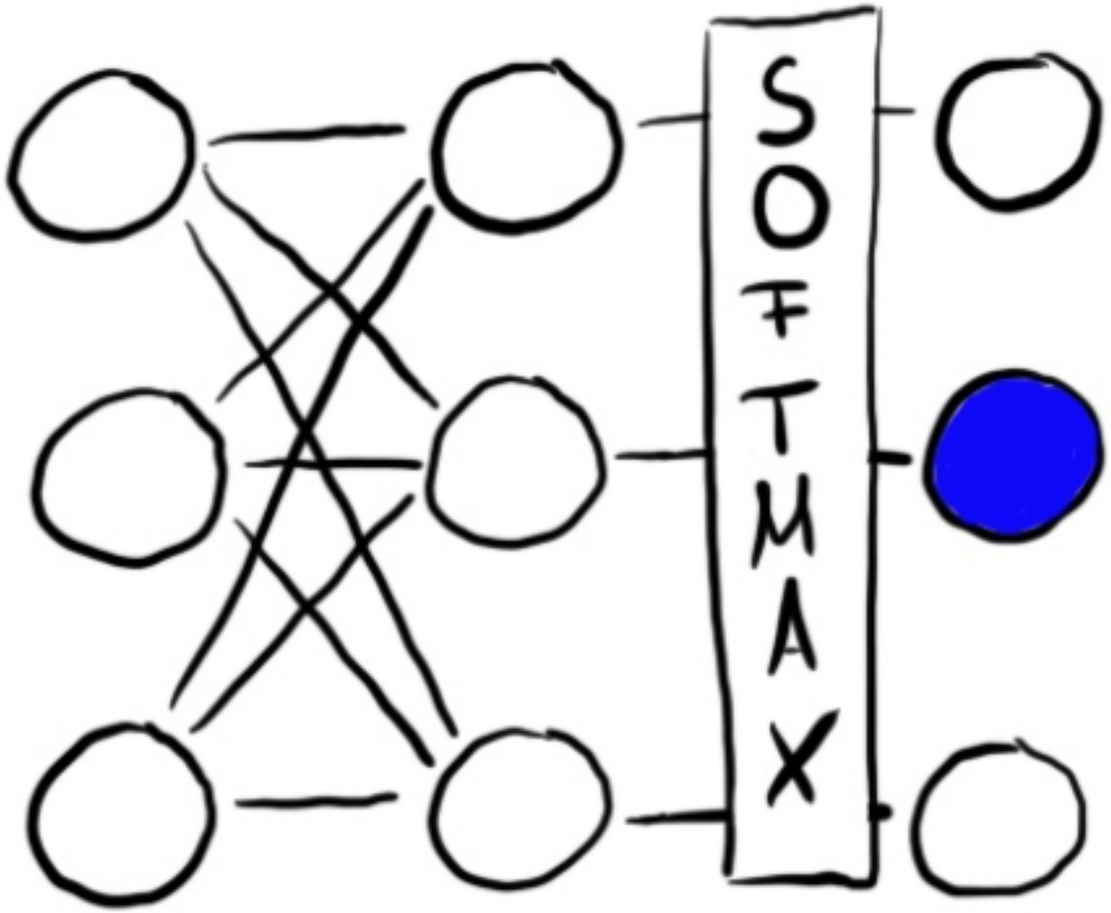
feature attribution

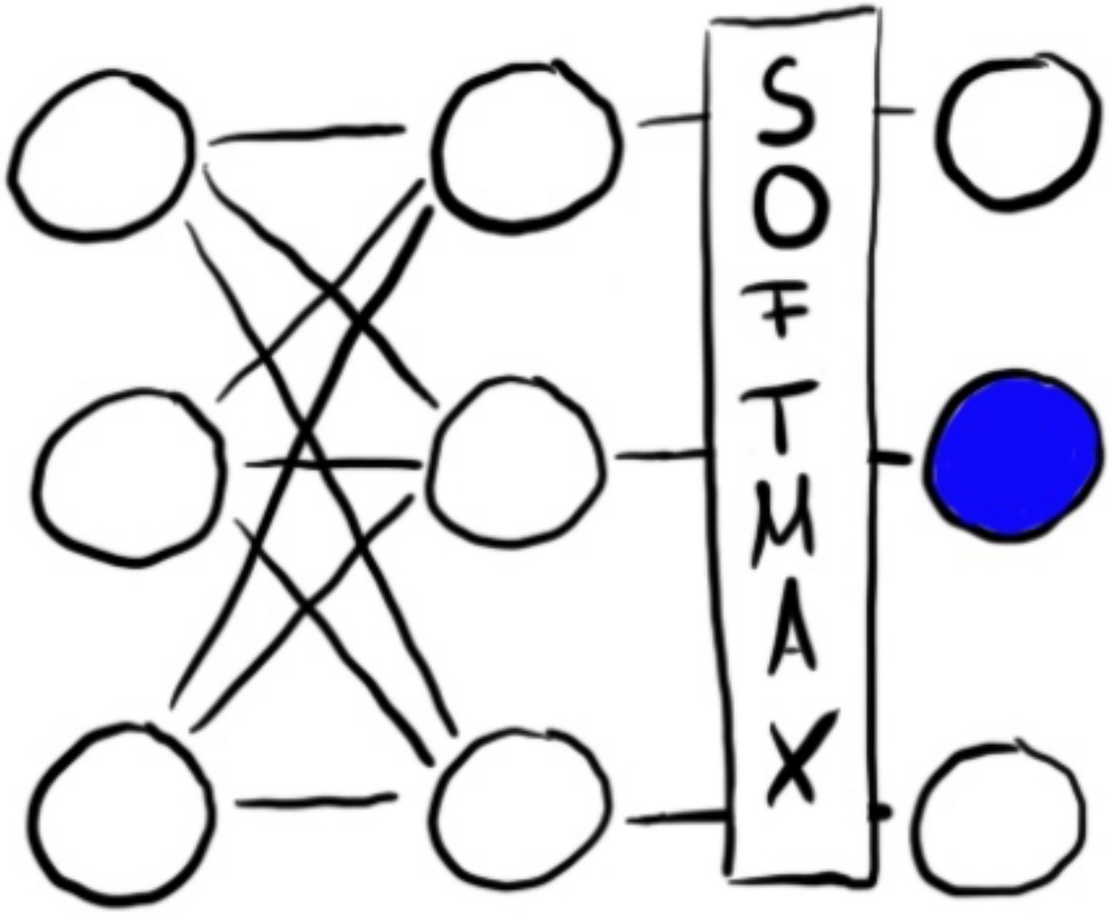
visualize the features that contribute strongly to the activations of CNN layers for a given input image and class label.

adversarial examples

understand the robustness of a deep neural network by generating adversarial examples giving insight into the decision boundaries of the model.

GRAD-CAM





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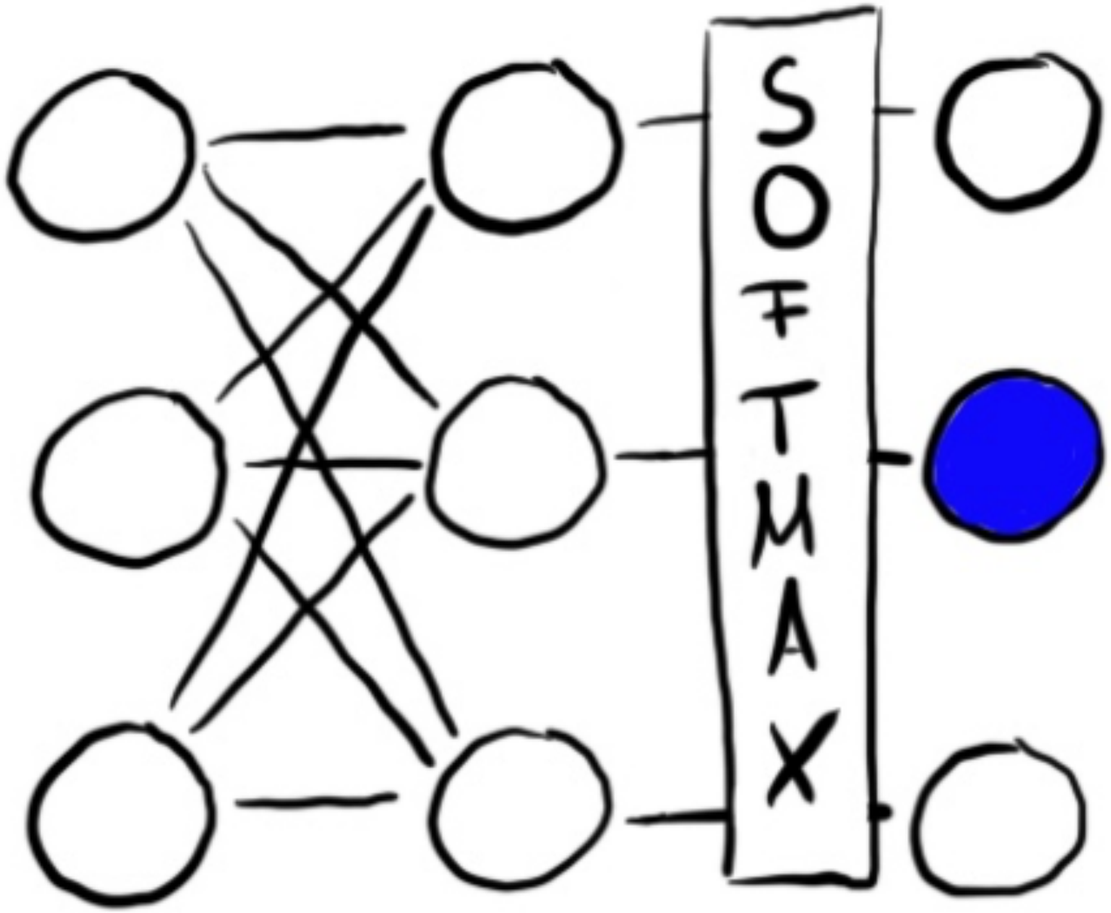

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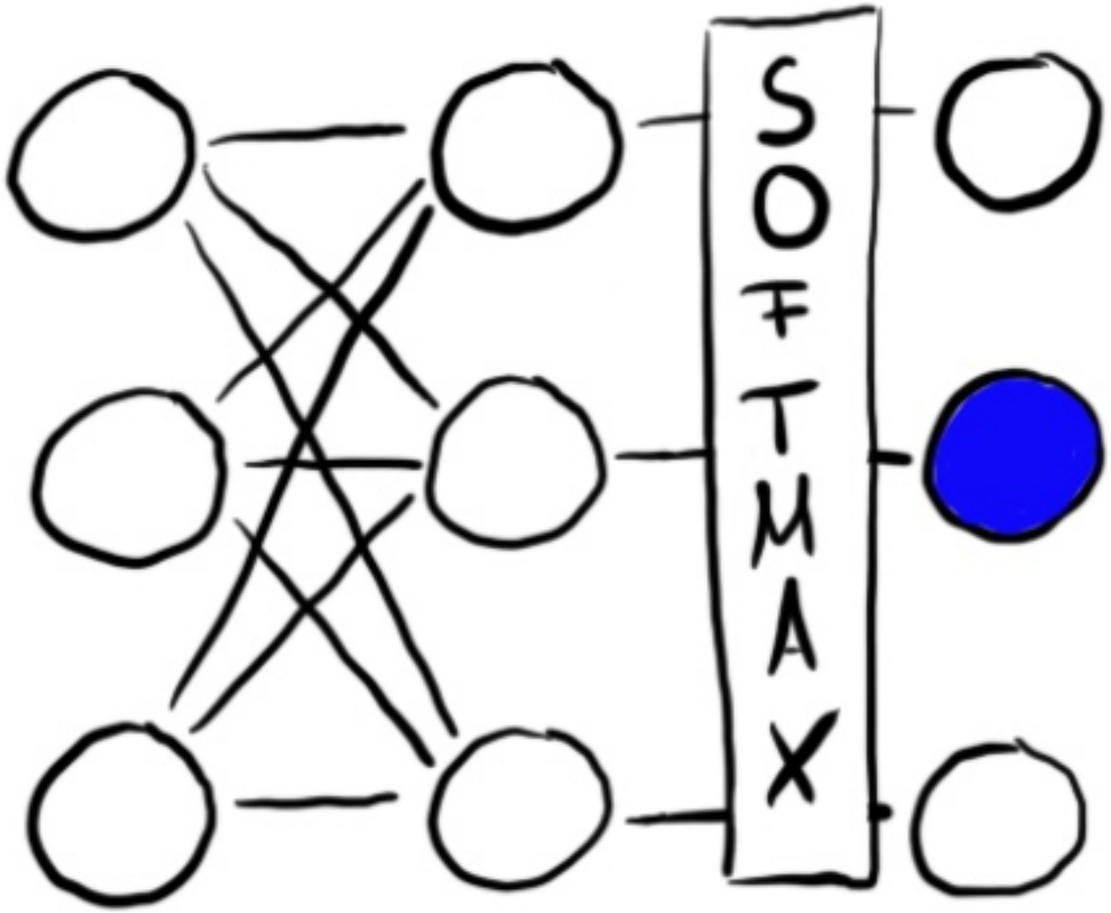
→ grad-CAM works by computing the gradients of the output class score with respect to the feature maps of the last convolutional layer in the CNN.



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[1] Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2017). Grad-cam: Visual explanations from deep networks via gradient-based localization. In Proceedings of the IEEE international conference on computer vision (pp. 618-626).

TF_EXPLAIN

```
!pip install tf_explain
!pip install opencv-python

#load libraries
import numpy as np
import tensorflow as tf
import PIL

#load GradCAM
from tf_explain.core.grad_cam import GradCAM

IMAGE_PATH = "./assets/images/cat.jpg"
class_index = 281

img = tf.keras.preprocessing.image.load_img(IMAGE_PATH, target_size=(224, 224))
img = tf.keras.preprocessing.image.img_to_array(img)

model = tf.keras.applications.vgg16.VGG16(weights="imagenet", include_top=True)

#get model summary
model.summary()

#first create the input in a format that the explainer expects (a tuple)
input_img = (np.array([img]), None)

#initialize the explainer as an instance of the GradCAM object
explainer = GradCAM()

# Obtain explanations for your image using VGG 16 and GradCAM
grid = explainer.explain(input_img,
                         model,
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#save the resulting image
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```
(150 sloc)  |  6.14 KB

e Module for Grad CAM Algorithm

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 Perform Grad CAM algorithm for a given input

 Paper: [Grad-CAM: Visual Explanations from Deep Networks
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SOURCE CODE

💻 https://github.com/sicara/tf-explain

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this is an active area of research, so expect more methods to be added in the future

THE NIGERIAN PRINCE

MOVING BEYOND FEATURE ATTRIBUTION

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it's a cat and mouse game between the attacker and the defender

ADVERSARIAL TRAINING vs ADVERSARIAL ATTACKS

→ Using **complete knowledge** of the model architecture, it's sources of uncertainty, it's parameters, and the training data, we can intentionally introduce adversarial examples to the model to test the robustness and reliability of the model. **adversarial training**. Used to improve the network's ability to make accurate predictions in real-world scenarios.

An example of adversarial training is training a neural network to recognize handwritten digits by incorporating adversarial examples of slightly modified digits to the training data.

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→ Using **incomplete knowledge** of the model architecture, it's sources of uncertainty, it's parameters, and the training data, we can intentionally try to manipulate the input data to cause it to make incorrect predictions. **adversarial attacks**. Used to identify vulnerabilities in the network and to improve security.

An example of an adversarial attack is adding a small amount of noise to an image of a stop sign in order to make it appear as a go sign to an autonomous vehicle's image recognition system.


ADVERSARIAL ATTACKS
99.9% CAT
PAPERS
WITH KÁROLY ZSOLNAI-FEHÉR

SUMMARY

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→ methods like **grad-CAM** help us understand which parts of the input image are most important for the model to make a prediction

→ **adversarial attacks** and **adversarial training** are two sides of the same coin to testing the reliability and robustness of machine learning models

EXPLODING ROCKETS

THANK YOU

@nbhushan