

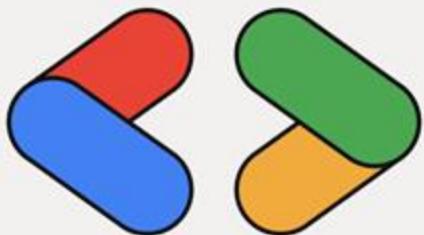
Implementing eXplainable AI with Tensorflow & Keras

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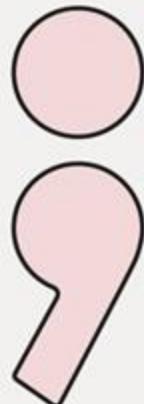


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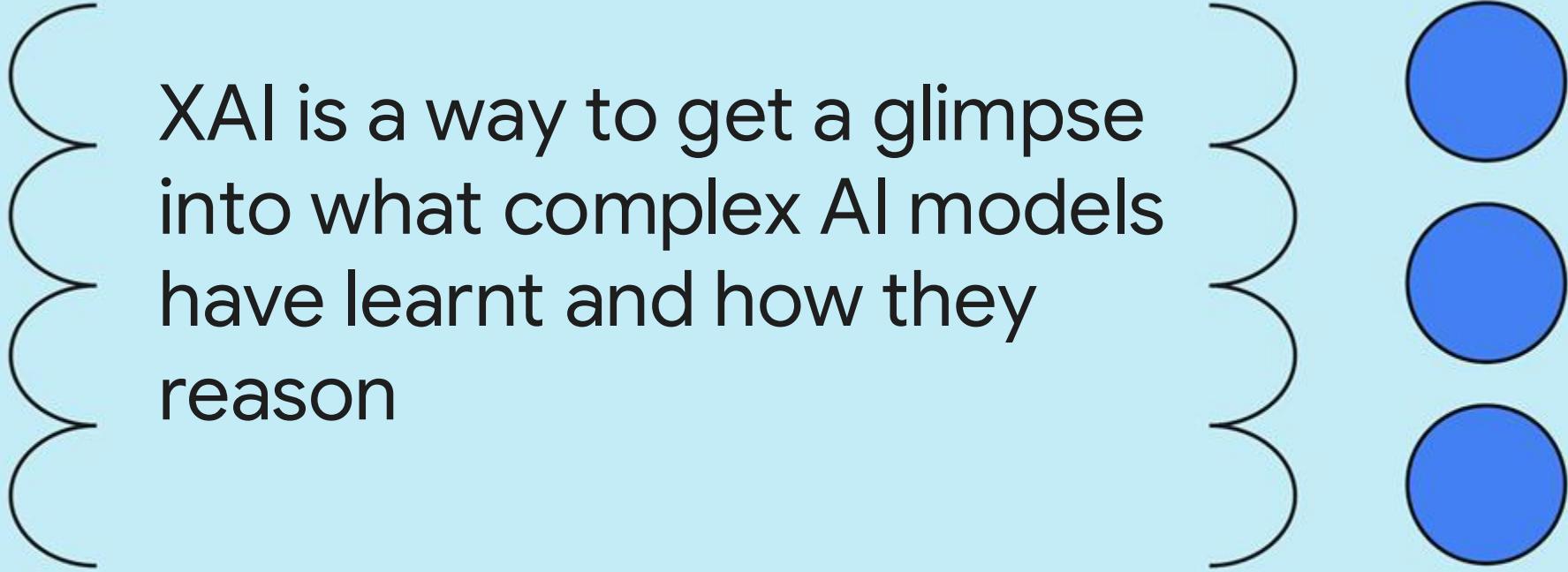


Code With Me!

Download template notebook & dataset
Upload both into Google Colab



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XAI is a way to get a glimpse
into what complex AI models
have learnt and how they
reason



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AI
@DevFest

White Box AI Models

- Linear Regression
 - Coefficients indicate importance & contribution to final output
- Decision Trees
 - Produce branched “if” statements
- Explainable, but limited performance

Black Box AI Models

- Neural Networks
 - Non-linear function approximator
- High performance, but poor visibility
- Works, but WHY??

XAI

- How does the model think?
- How the model reacts to changes
- Understand WHY this output for this input
- Retrospective

Integrated Gradients

- Linear Regression Equation:
- $y = c_1x_1 + c_2x_2 + c_3x_3 + \dots + c_nx_n$
- c_i is the importance of feature x_i
- c_i shows the overall contribution of x_i towards y
- c_i is the **gradient** of y w.r.t x_i
- Can we do this for neural networks?

Integrated Gradients

- Lets look at neural network gradients!
- $\frac{\partial(\text{output})}{\partial(\text{input})}$ is the gradient
- But how is the input changing?
- How do we measure this change?

Integrated Gradients – Intuition

- Walk from an “average” point in the dataset to the input we’re interested in
- Walk = adjust feature values to move a baseline point towards the input
- See how each step changes the output
 - Big change → important feature
- Take the average gradient across the path

Integrated Gradients – Inputs

- Linear path from baseline (b) to input (x)



- The delta $d = (x - b)$

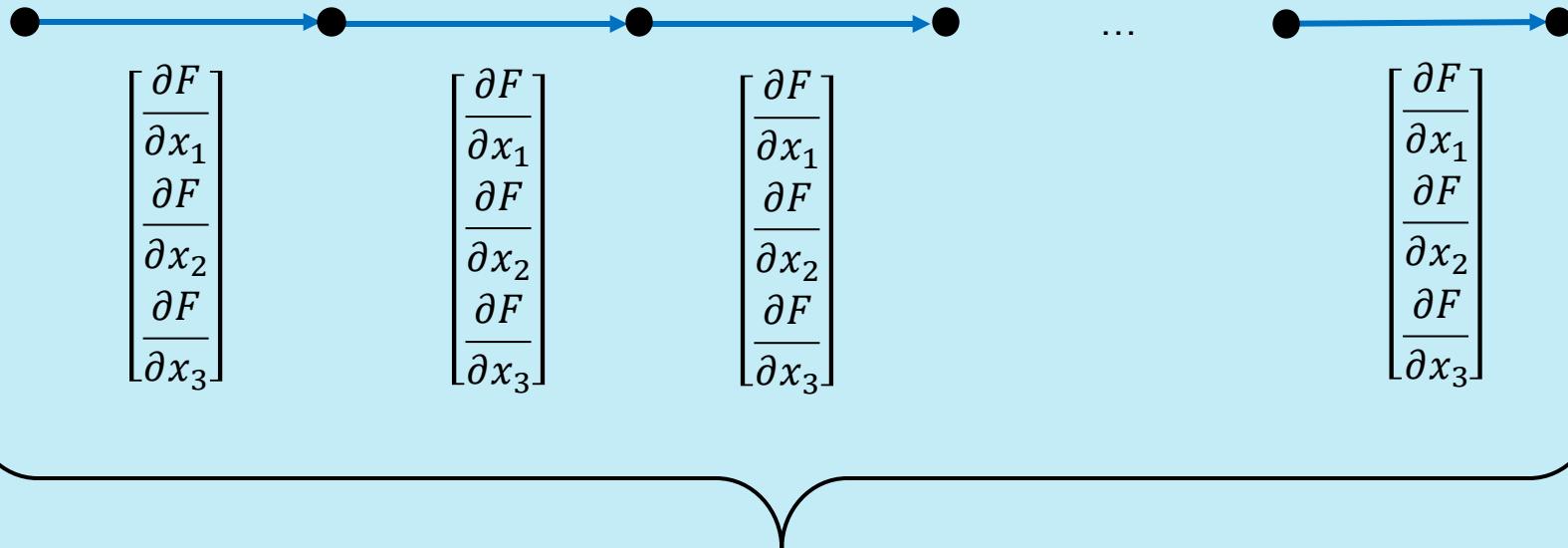
Integrated Gradients – Outputs

- As α varies, we can measure the output of the neural network (F)
- This gives us $\frac{\partial F(\text{input})}{\partial (\text{input})}$
- Attribution = $(\text{input} - \text{baseline}) * \text{Gradient}$
- [amount moved = distance traveled * speed]

$$(\text{Attribution})_{\text{input}} = \left(\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} - \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \right) * \begin{bmatrix} \frac{\partial F}{\partial x_1} \\ \frac{\partial F}{\partial x_2} \\ \frac{\partial F}{\partial x_3} \end{bmatrix}$$

Integrated Gradients – Outputs

Baseline (b) $b + \alpha d$ $b + 2\alpha d$ $b + 3\alpha d$ \dots $b + n\alpha d$ input (x)



Take the average across these gradients!

Integrated Gradients – Final Formula

- Since we vary the input, we have multiple gradient values
- We average the gradients for each feature

$$(\text{Integrated Gradients})_i = (x - b) * \int_{\alpha=0}^1 \frac{\partial F(b + \alpha(x - b))}{x_i} d\alpha$$

- To implement:

$$(\text{Integrated Gradients})_i = (x - b) * \frac{1}{m} \sum_{k=1}^m \frac{\partial F(b + \alpha(x - b))}{x_i}$$

Integrated Gradients – Completeness

- Integrated Gradients is “complete”
- The total attributions is the difference between $F(\text{baseline})$ and $F(\text{input})$
- $y_{\text{pred from input}} - y_{\text{pred from baseline}} = \sum \text{attributions}$

$$\begin{bmatrix} att(x_1) \\ att(x_2) \\ att(x_3) \end{bmatrix} = \left(\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} - \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \right) * \begin{bmatrix} \text{Avg } \frac{\partial F}{\partial x_1} \\ \text{Avg } \frac{\partial F}{\partial x_2} \\ \text{Avg } \frac{\partial F}{\partial x_3} \end{bmatrix}$$

Integrated Gradients – Result

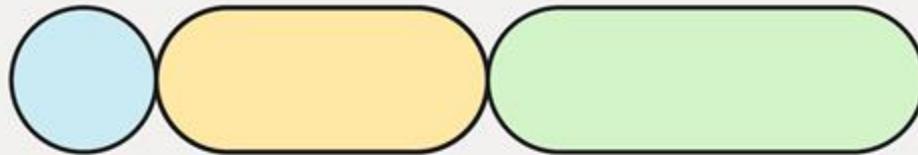
- Found “coefficients” for the neural network like in Linear Regression
 - Like: $y = a_1f_1 + a_2f_2 + a_3f_3 + \dots + a_nf_n$
- Large attributions show more important features
 - Bigger change in output because of small change in input
- Can account for the exact change in prediction based on the change in a feature
 - Just like in linear regression
- “Local” explanations – **coefficients only valid for that particular input & baseline**

DiCE – Diverse Counterfactual Explanations

- HOW to change the input to get desired output
- Wiggles the inputs until output is in desired range
- Focuses on minimal input changes first

Case Study – G-taxi

- You are an AI Engineer at G-taxi
- You need to build a price prediction model for each ride that the user can book
- You built a great model with <10% percentage difference
- But your manager and your customers want to know WHY the model has given certain prices
- XAI to the rescue!



Thank You!



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<https://github.com/ro1406>



<scholar.google.com/citations?user=Jh0DuX4AAAAJ>

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