CXPlain: Causal Explanations for Model Interpretation under Uncertainty

Patrick Schwab (@schwabpa), and **Walter Karlen** (@mhsl_ethz)
Institute of Robotics and Intelligent Systems, ETH Zurich, Switzerland

1 Introduction

Feature importance estimates that inform users about the degree to which given inputs influence the output of a predictive model are crucial for **understanding**, **validating**, **and interpreting** machine-learning models.

How do we provide
- **accurate** importance scores **quickly**
- **for any model,** and
- estimate their **uncertainty?**

2 Causal explanations (CXPlain)

The main idea behind CXPlain is to train an **explanation model** to explain a given model (Figure 1). This framework has the advantage that we **do not need to retrain or adapt** the original model to explain its decisions.

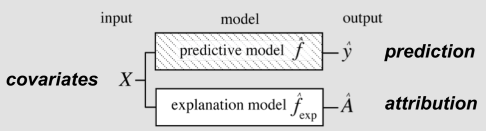


Figure 1. A conceptual overview of causal explanation models.

To train CXPlain, we transform the task of producing feature importance estimates for a given model into a **supervised learning task** by using a **causal objective** [1, 2].

$$\Delta\varepsilon_{X,i} = \varepsilon_{X\setminus\{i\}} - \varepsilon_X$$

3 Usage

1 TRAIN MODEL

```
x_train, y_train = ...
x_test = ...
model = ...

model.fit(x_train,
          y_train)
```

2 TRAIN CXPLAIN

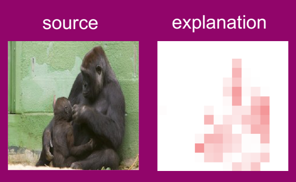
```
cxplain = CXPlain(
            model,
            builder,
            masking,
            loss
          )

cxplain.fit(x_train,
            y_train)
```

3 EXPLAIN MODEL

```
cxplain.explain(
            x_test
          )
```

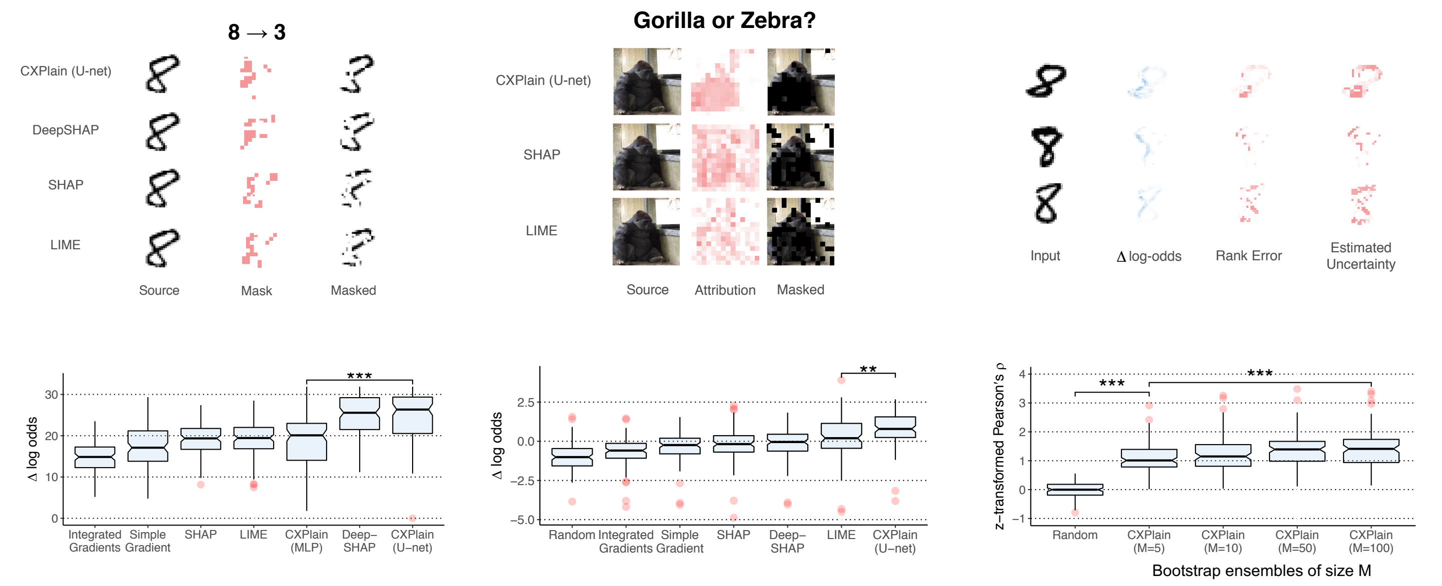
4 VISUALISE RESULT



TRY IT YOURSELF AT
github.com/d909b/cxplain

4 Results

MNIST [1,3] | **ImageNet** | **Uncertainty**



5 Components

Model Structure. In this work, we focus on. *neural explanation models*. However, in principle, any supervised model could be used.

Causal objective. We use a causal objective that quantifies the *marginal contribution of a feature towards the model's accuracy* [1, 2].

Masking Operation. We use a masking operation, such as zero masking [2,6], to *estimate each feature's marginal contribution.*

6 Conclusion

We presented CXPlain, a new **method for learning to estimate feature importance for any machine-learning model**.
We demonstrated that CXPlain is **fast at explanation time, accurate**, and that we are able to estimate its **attribution uncertainty** using bootstrap resampling.

7 References

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75 NRP Big Data National Research Programme