# EVALUATION OF SIMILARITY-BASED EXPLANATIONS

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#### Plan

- 1. What are similarity based explanations
- 2. What similarity metrics are used
- 3. Evaluation criterias
- 4. Results

# What are similarity based explanations

### What are similarity based explanations

- Instance-based
- Similar instances as evidence to support model prediction
- "I(the model) think this image is cat because similar images I saw in the past were also cat"
- Very simple to understand without machine learning expertise
- Better than SHAP or LIME?

$$D = \{z_{train}^{(i)} = (x_{train}^{(i)}, y_{train}^{(i)})\}_{i=1}^{N}$$

$$z_{test} = (x_{test}, f(x_{test}))$$

$$\bar{z} = argmax_{z_{train} \in D} R(z_{test}, z_{train})$$

# What similarity measures are used

## What similarity metrics are used

$$ullet$$
 L2 Metric:  $R_{\ell_2}(oldsymbol{z},oldsymbol{z}') := -\|\phi(oldsymbol{z}) - \phi(oldsymbol{z}')\|^2$ 

$$ullet$$
 Cosine Metric:  $R_{\cos}(oldsymbol{z},oldsymbol{z}'):=\cos(\phi(oldsymbol{z}),\phi(oldsymbol{z}'))$ 

• Dot Metric: 
$$R_{ ext{dot}}(oldsymbol{z},oldsymbol{z}'):=\langle\phi(oldsymbol{z}),\phi(oldsymbol{z}')
angle$$

 $\phi$  can be any from:

$$\phi(\boldsymbol{z}) = \boldsymbol{x} \qquad \phi(\boldsymbol{z}) = \boldsymbol{h}^{\mathrm{last}} \qquad \phi(\boldsymbol{z}) = \boldsymbol{h}^{\mathrm{all}}$$

#### Not only so simple- Gradient-based metrics

• IF: 
$$R_{\mathrm{IF}}(\boldsymbol{z}, \boldsymbol{z}') := \langle \boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}}, \boldsymbol{H}^{-1} \boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}'} \rangle$$

• GD: 
$$R_{\mathrm{GD}}(\boldsymbol{z}, \boldsymbol{z}') := \langle \boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}}, \boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}'} \rangle$$

• RIF: 
$$R_{\text{RIF}}(\boldsymbol{z}, \boldsymbol{z}') := \cos(\boldsymbol{H}^{-\frac{1}{2}} \boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}}, \boldsymbol{H}^{-\frac{1}{2}} \boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}'})$$
 • GC:  $R_{\text{GC}}(\boldsymbol{z}, \boldsymbol{z}') := \cos(\boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}}, \boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}'})$ 

• GC: 
$$R_{\mathrm{GC}}(\boldsymbol{z}, \boldsymbol{z}') := \cos(\boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}}, \boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}'})$$

• FK: 
$$R_{\mathrm{FK}}(\boldsymbol{z}, \boldsymbol{z}') := \langle \boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}}, \boldsymbol{I}^{-1} \boldsymbol{g}_{\widehat{\boldsymbol{\theta}}}^{\boldsymbol{z}'} \rangle$$
,

Where  ${\it H}$  and  ${\it I}$  are the Hessian and Fisher information matrices of the loss  $\mathcal{L}_{train}$ 

# **Evaluation criterias**

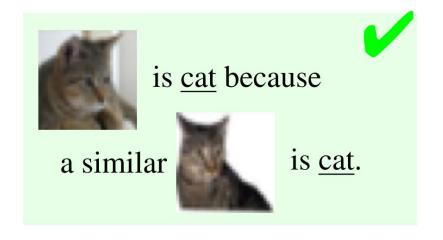
#### **Model Randomization Test**

$$R(z_{test}, z_{train}^{(\pi_f(1))}) \ge R(z_{test}, z_{train}^{(\pi_f(2))}) \ge \dots \ge R(z_{test}, z_{train}^{(\pi_f(N))})$$

- R relevance metric
- $\pi_f$  permutation of indices with decreasing relevance
- $\pi_f$  and  $\pi_{f rand}$  must have a small rank correlation
- Checks faithfulness

#### **Identical Class Test**

$$\underset{\boldsymbol{z}=(\boldsymbol{x},y)\in\mathcal{D}}{\operatorname{arg\,max}} R(\boldsymbol{z}_{\text{test}},\boldsymbol{z}) = (\bar{\boldsymbol{x}},\bar{y}) \implies \bar{y} = \widehat{y}_{\text{test}}$$





is cat because



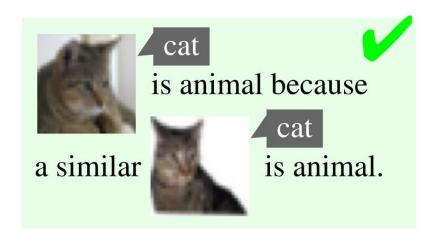
is dog.

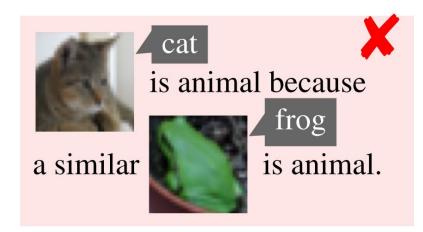


#### **Identical Subclass Test**

s(z) is a subclass for class y  $s(z) \subset y$ 

$$argmax_{z_{train} \in D} R(z_{test}, z_{train}) = \bar{z} \Rightarrow s(\bar{z}) = s(z_{test})$$

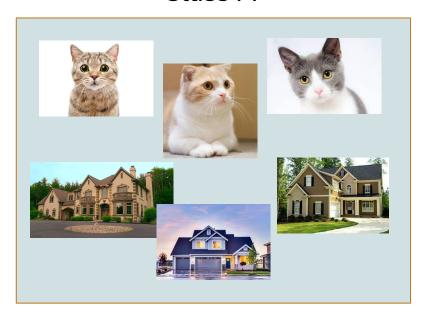






## **Dataset split**

#### Class A

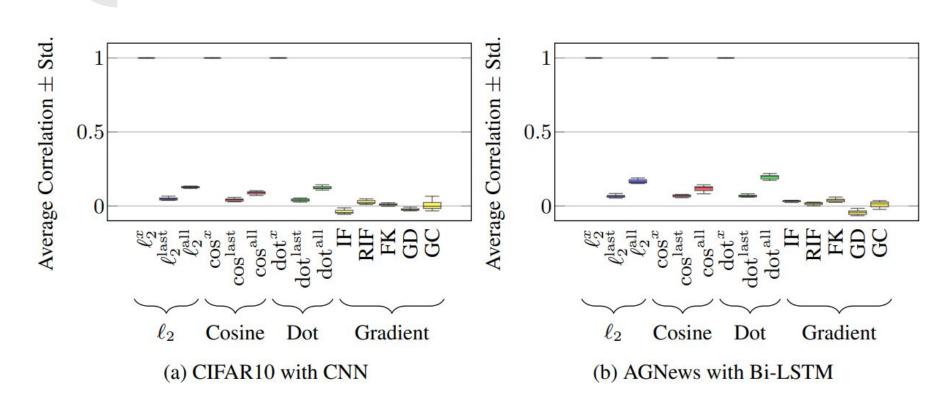


#### Class B

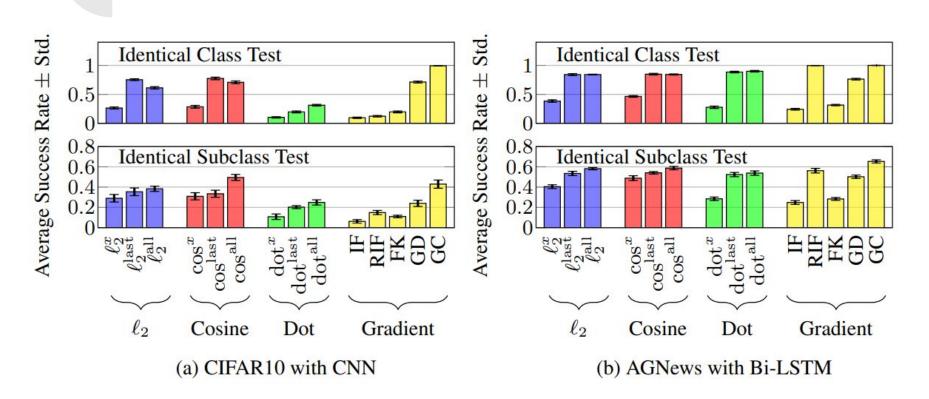


# Results

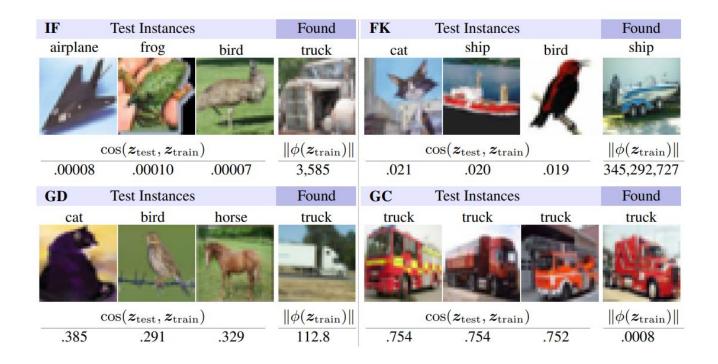
#### Model randomization test



#### Identical class and subclass test



### Frequently selected training instances

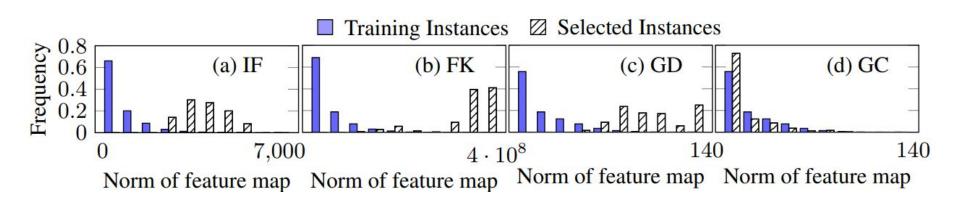


# Failure of dot metrics & gradient based metrics

$$\langle \phi(\boldsymbol{z}_{\text{test}}), \phi(\boldsymbol{z}_{\text{train}}^{(i)}) \rangle < \langle \phi(\boldsymbol{z}_{\text{test}}), \phi(\boldsymbol{z}_{\text{train}}^{(j)}) \rangle$$

$$\|\phi(z_{\text{train}}^{(i)})\| < \|\phi(z_{\text{train}}^{(j)})\|\cos(\phi(z_{\text{test}}),\phi(z_{\text{train}}^{(j)}))$$

## Frequently selected training instances



## **Takeaways**

3 minimal requirement tests:

Model Randomization Test Identical Class Test Identical Subclass Test

- $\ell_2^{\text{last}}$ ,  $\cos^{\text{last}}$  and **gradient-based** metrics **passed** the Model Randomization Test
- Dot metrics as well as IF, FK and GD failed the Identical Class and Subclass
   Test
- GC performed the best in most of the tests recommended method

# Thanks for your attention