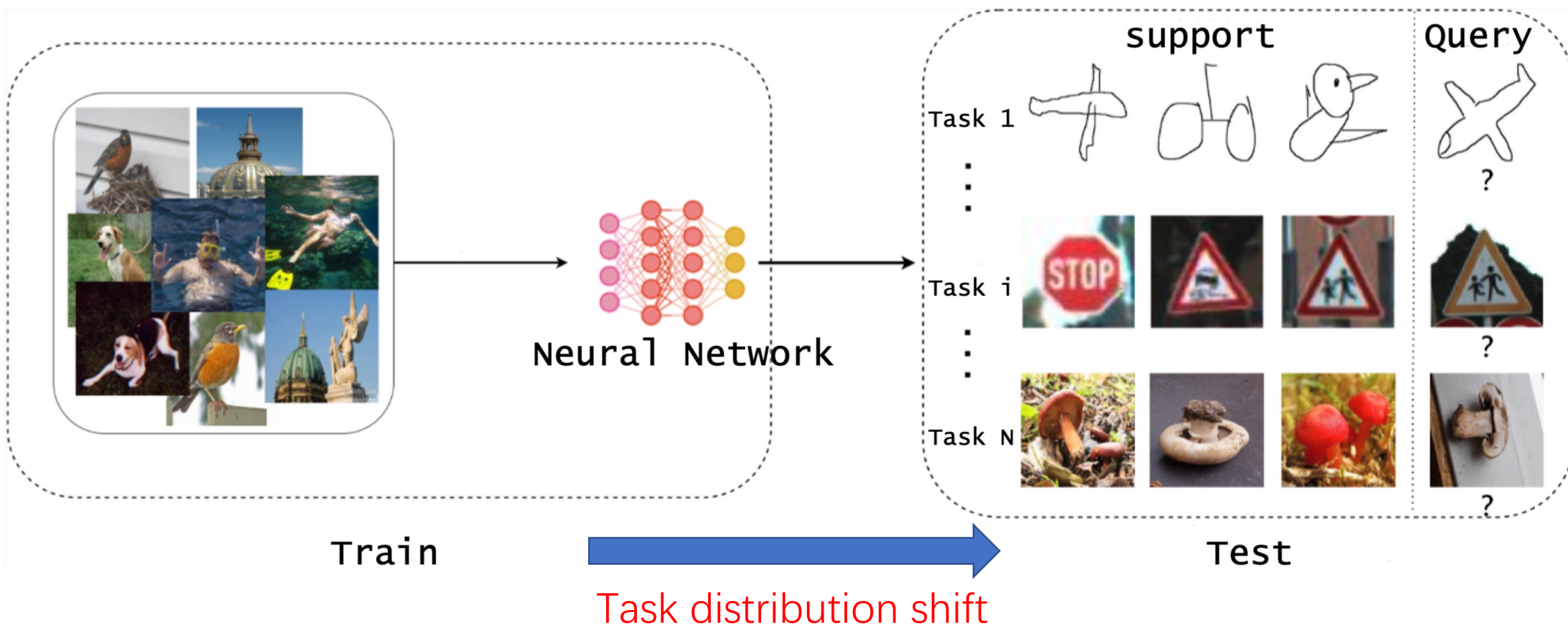


# Channel Importance Matters in Few-Shot Image Classification

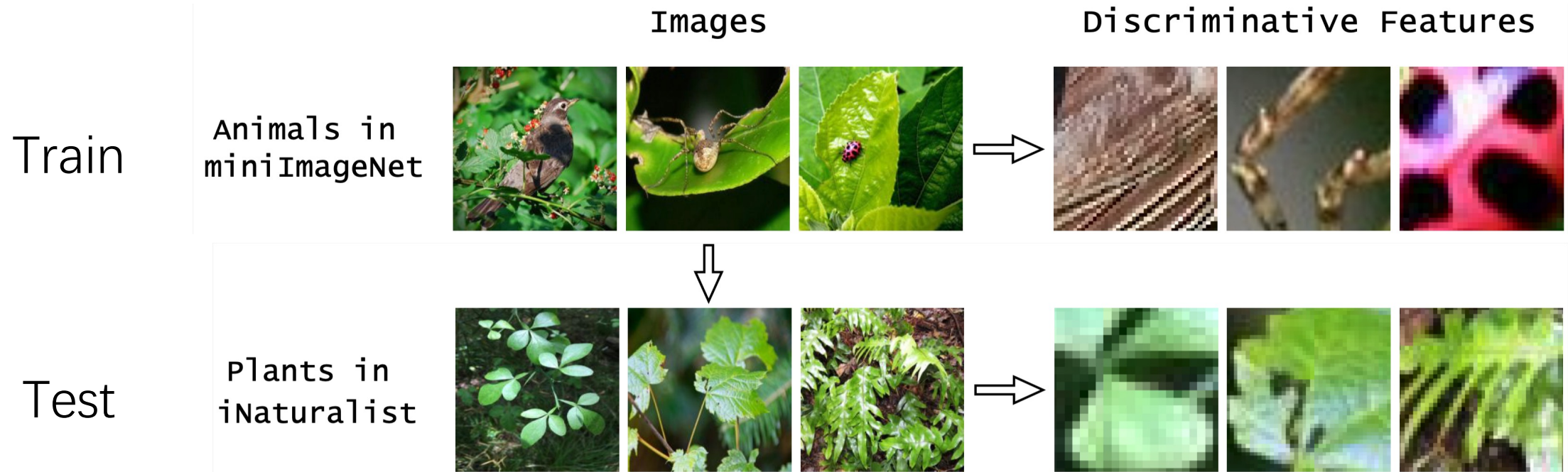
Xu Luo, Jing Xu, Zenglin Xu

# Few-shot image classification

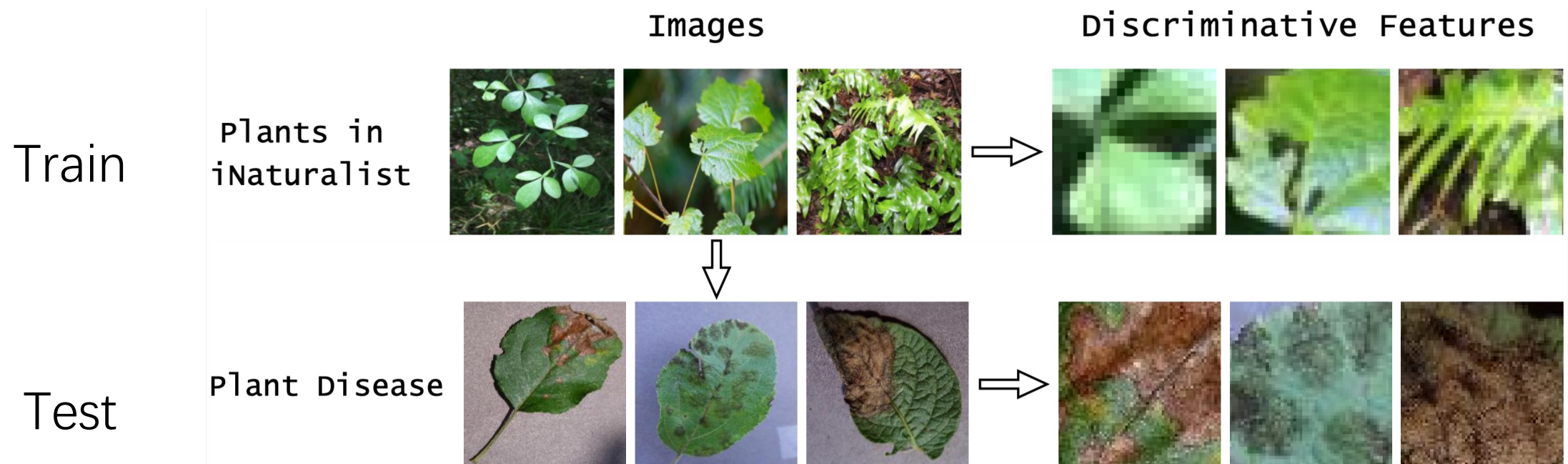
**Goal:** train a visual model that can quick *learn* new visual concept from a few examples.



# Task distribution shift



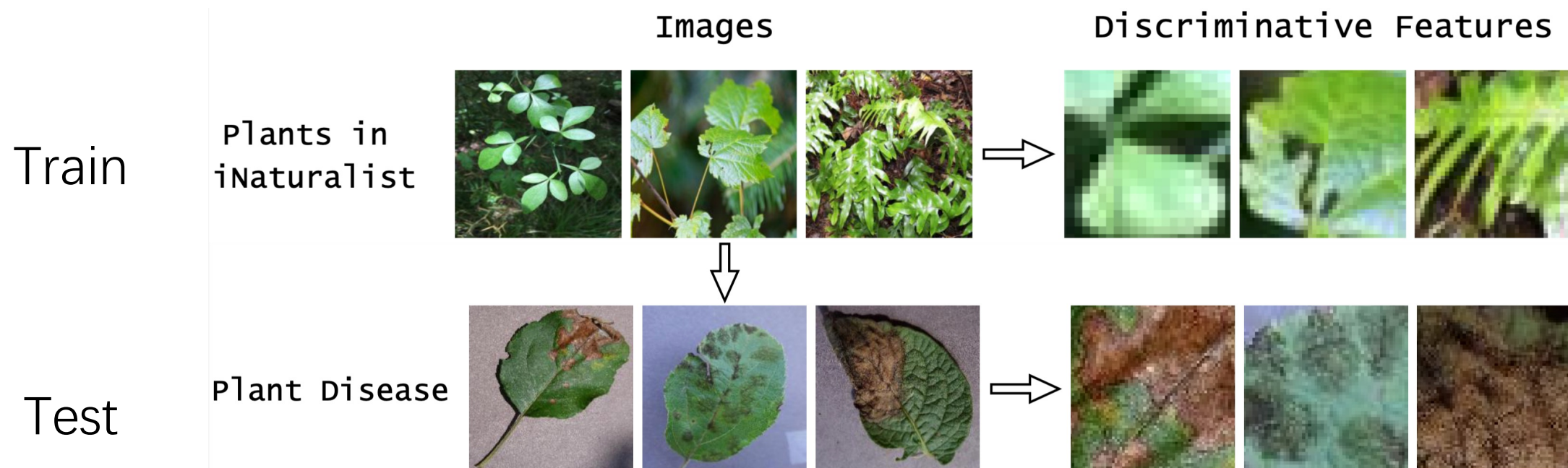
# Task distribution shift





# Task distribution shift

How does image representation encode discriminative features?  
Can image representation change focus when facing task distribution shift?



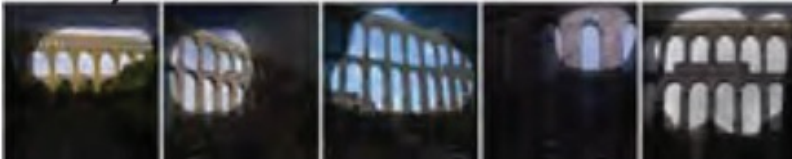
# Different channels of CNNs detect different features

## **Buildings**

56) building



120) arcade

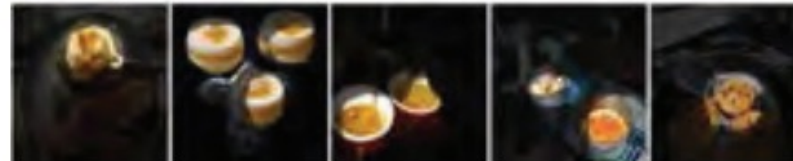


8) bridge

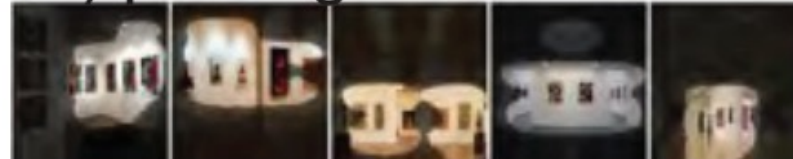


## **Indoor objects**

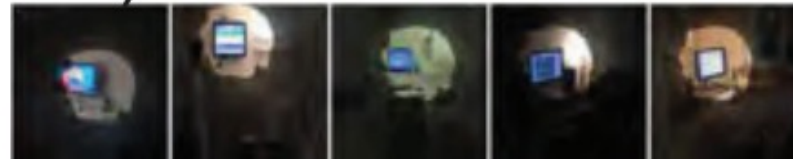
182) food



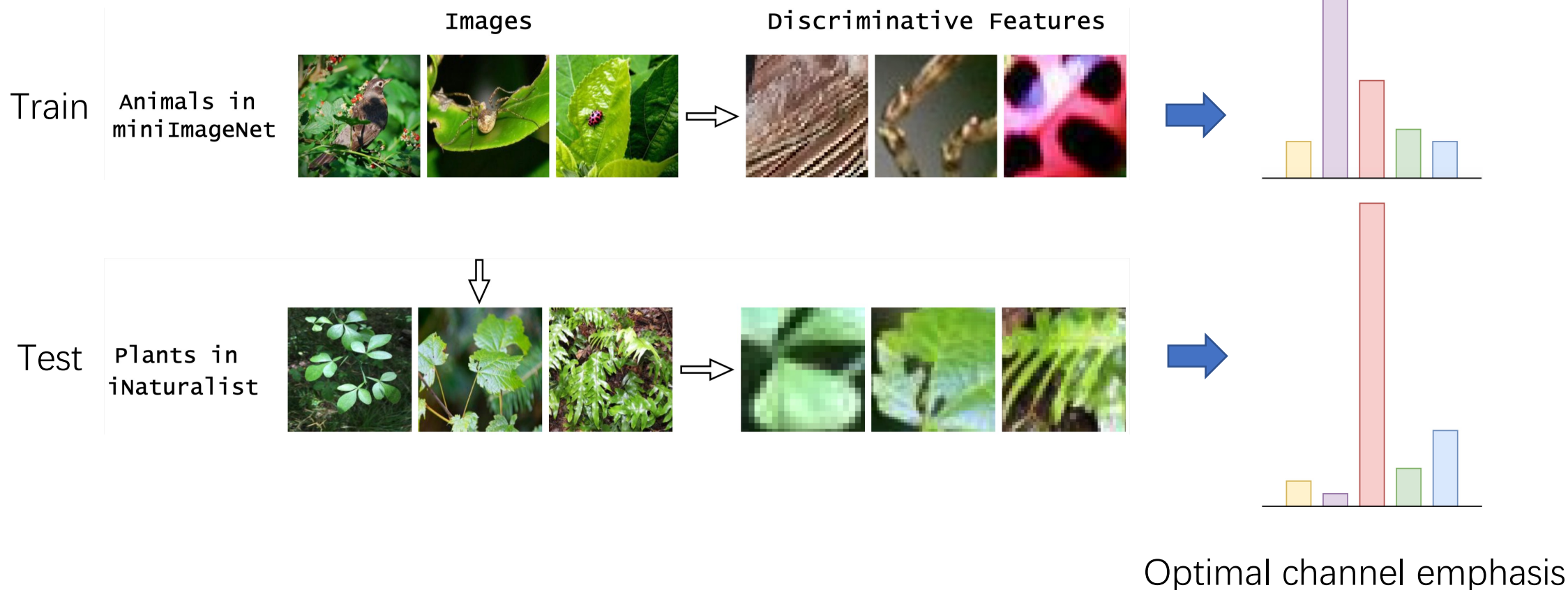
46) painting



106) screen



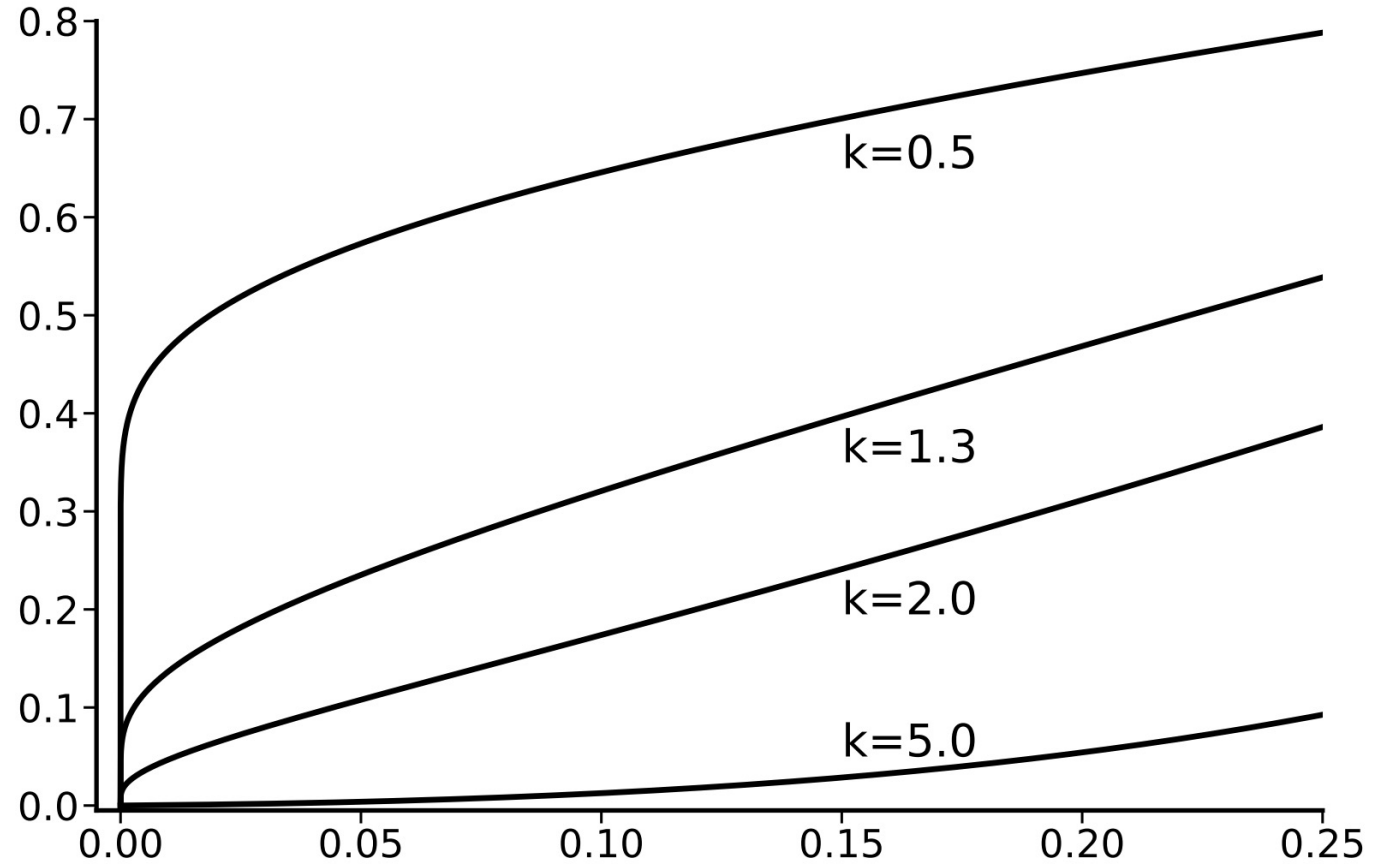
# Revisiting task distribution shift



Do image representations of CNNs accurately capture such changes in channel emphasis?

# A simple transformation function

$$\phi_k(\lambda) = \begin{cases} \frac{1}{\ln^k(\frac{1}{\lambda} + 1)}, & \lambda > 0 \\ 0, & \lambda = 0 \end{cases}$$





# A simple channel-wise transformation function

Transformed representation  $\boldsymbol{\phi}(\mathbf{z}) = (\phi(z_1), \phi(z_2), \dots, \phi(z_d))$

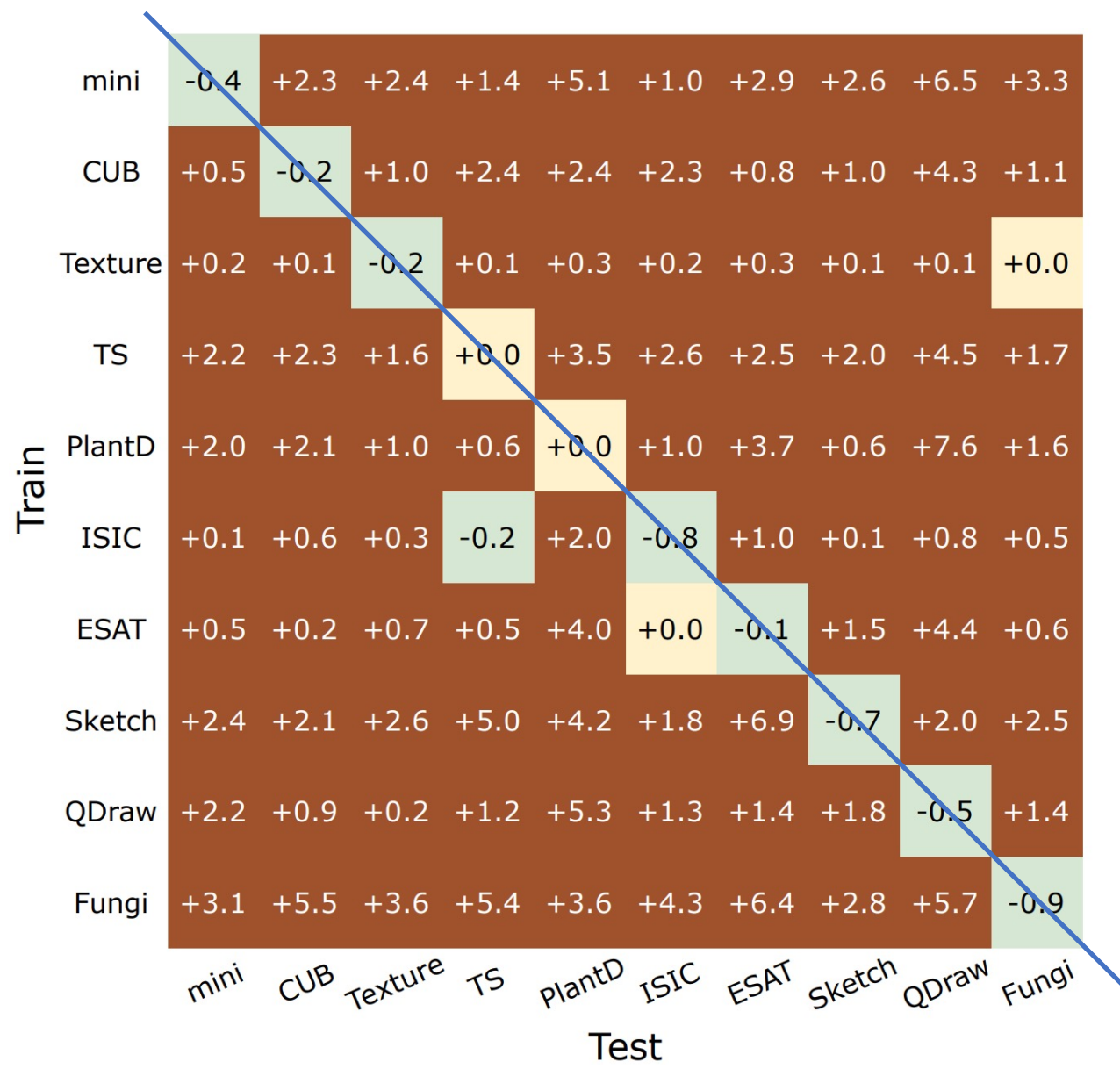
Representation

$$\mathbf{z} = f_{\theta}(\mathbf{x}) = (z_1, z_2, \dots, z_d)$$

Image

For Testing only!

# A simple channel-wise transformation function



**Channel bias problem:**  
When facing novel task with a shift in distribution, CNNs assign wrong channel emphasis.

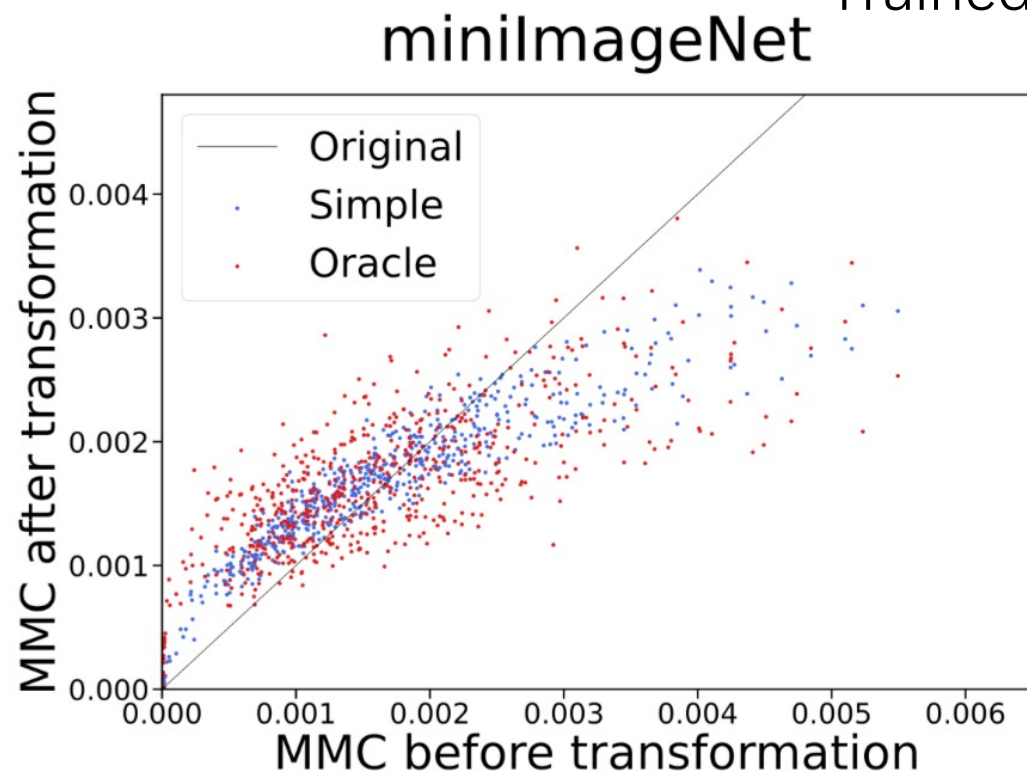
# Deriving the optimal channel emphasis of any binary task

Two classes of image representations, each with mean and variances  $\boldsymbol{\mu}_1, \boldsymbol{\sigma}_1$  and  $\boldsymbol{\mu}_2, \boldsymbol{\sigma}_2$ , respectively. Then the optimal emphasis of the  $c$ -th channel  $\omega_c$  should satisfy

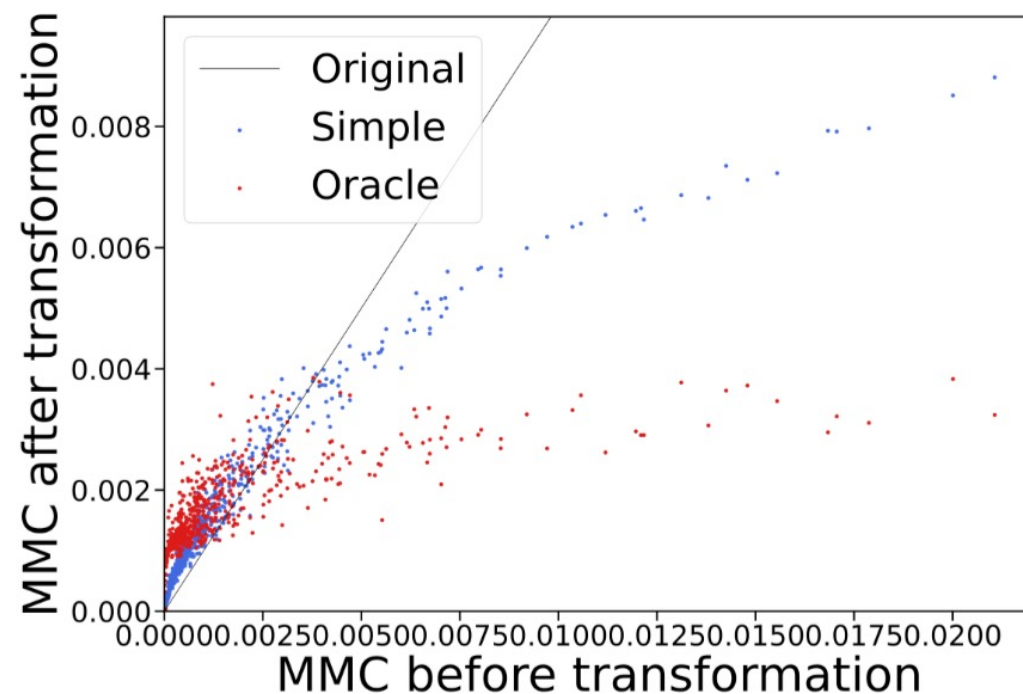
$$\omega_c \propto \frac{|\mu_1^c - \mu_2^c|}{\sigma_1^c + \sigma_2^c}$$

# Analysis of channel emphasis

Trained on minilImageNet



CUB



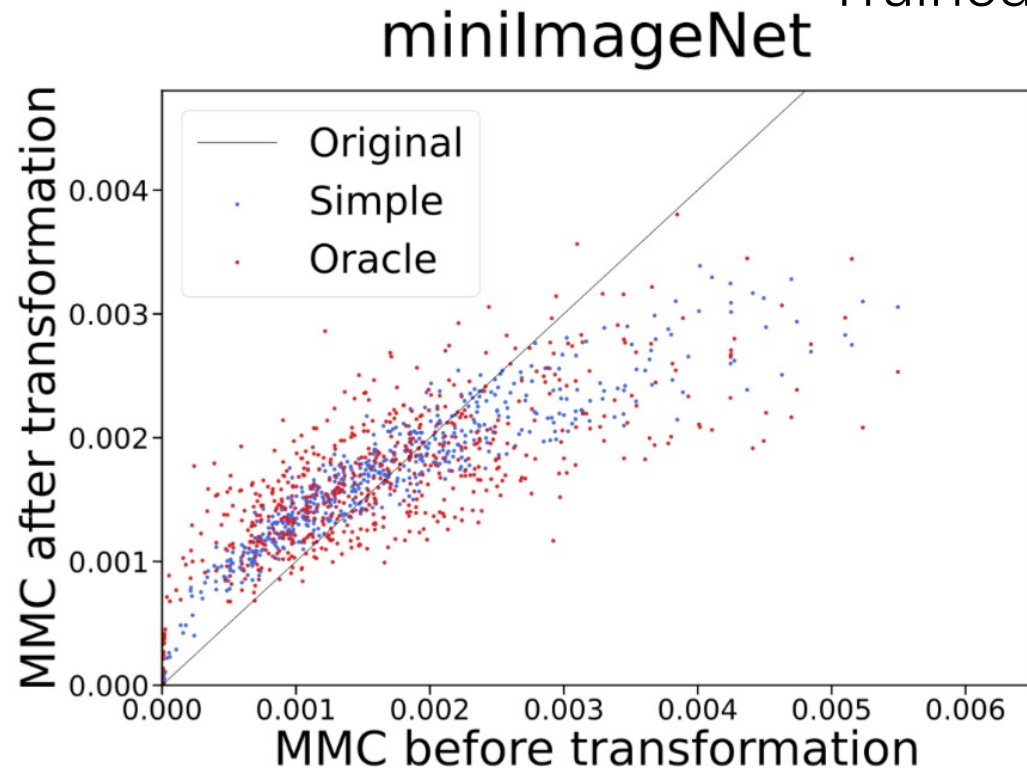
**Original** : original channel emphasis

**Simple** : channel emphasis rectified by the  
simple transformation

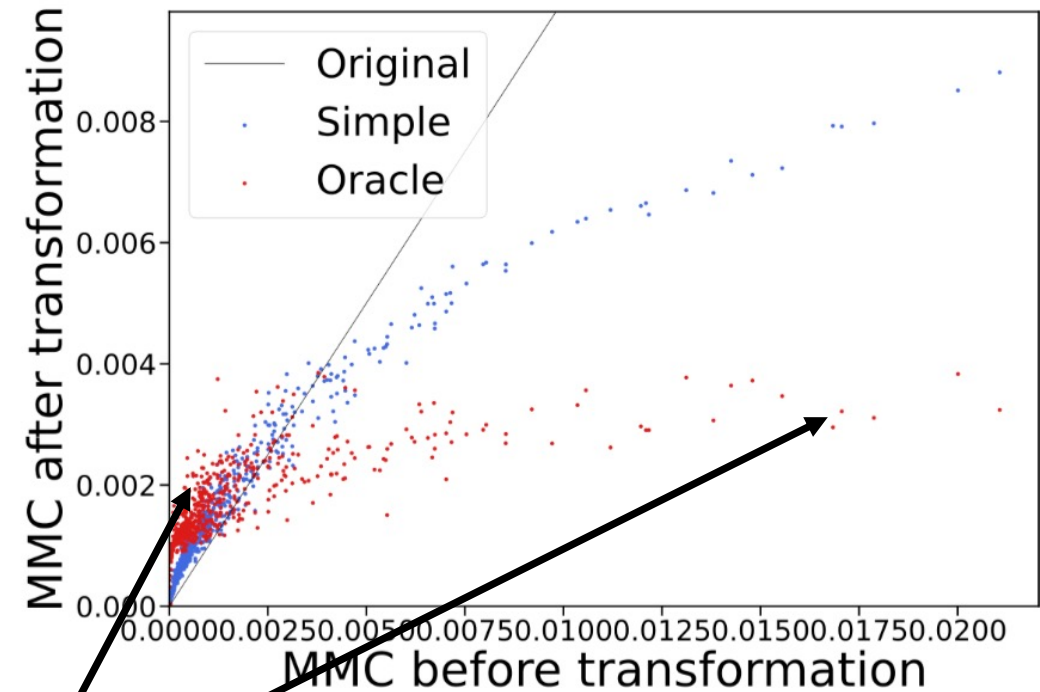
**Oracle** : optimal channel emphasis

# Analysis of channel emphasis

Trained on minilImageNet



CUB

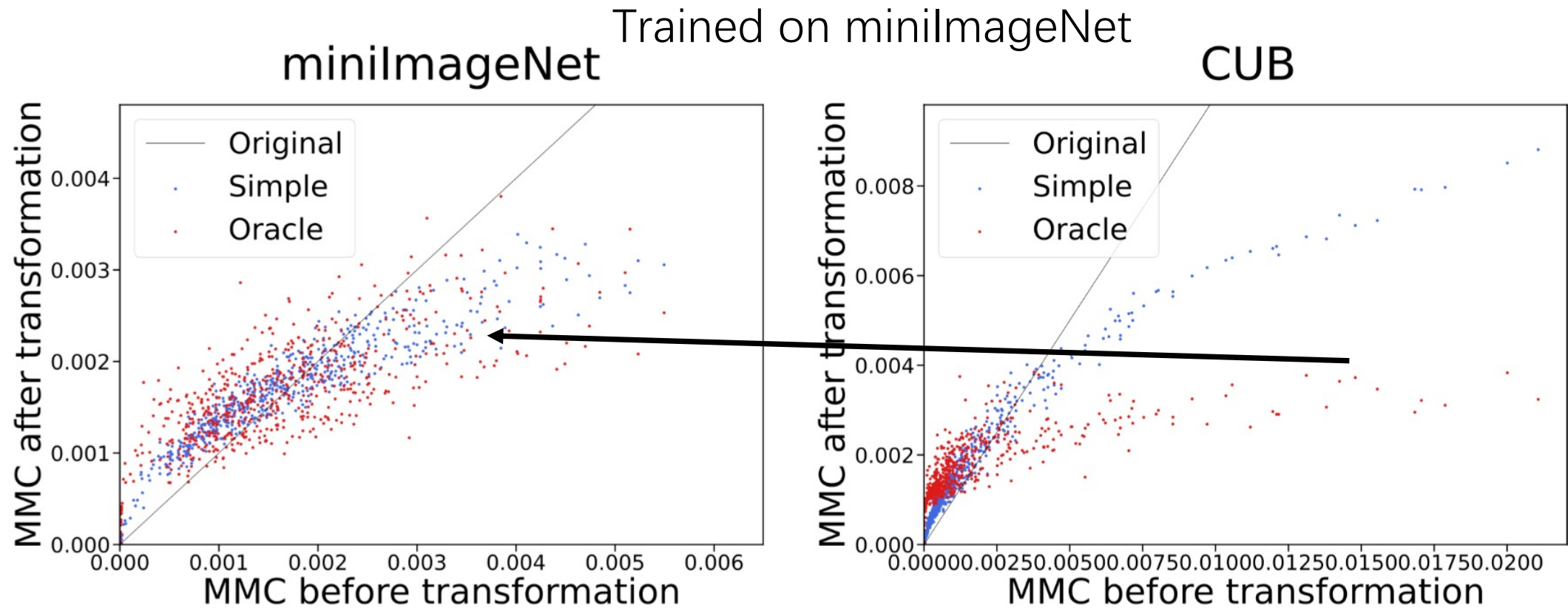


Conclusions:

1. Neural networks are overconfident in previously learned channel emphasis.



# Analysis of channel emphasis

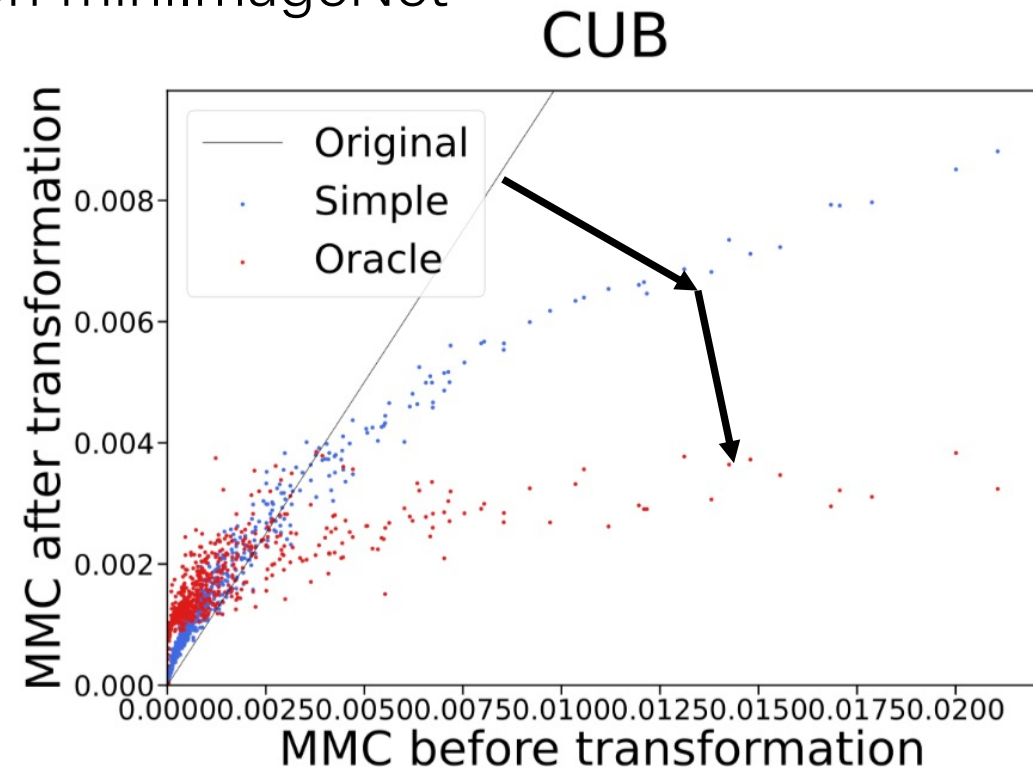
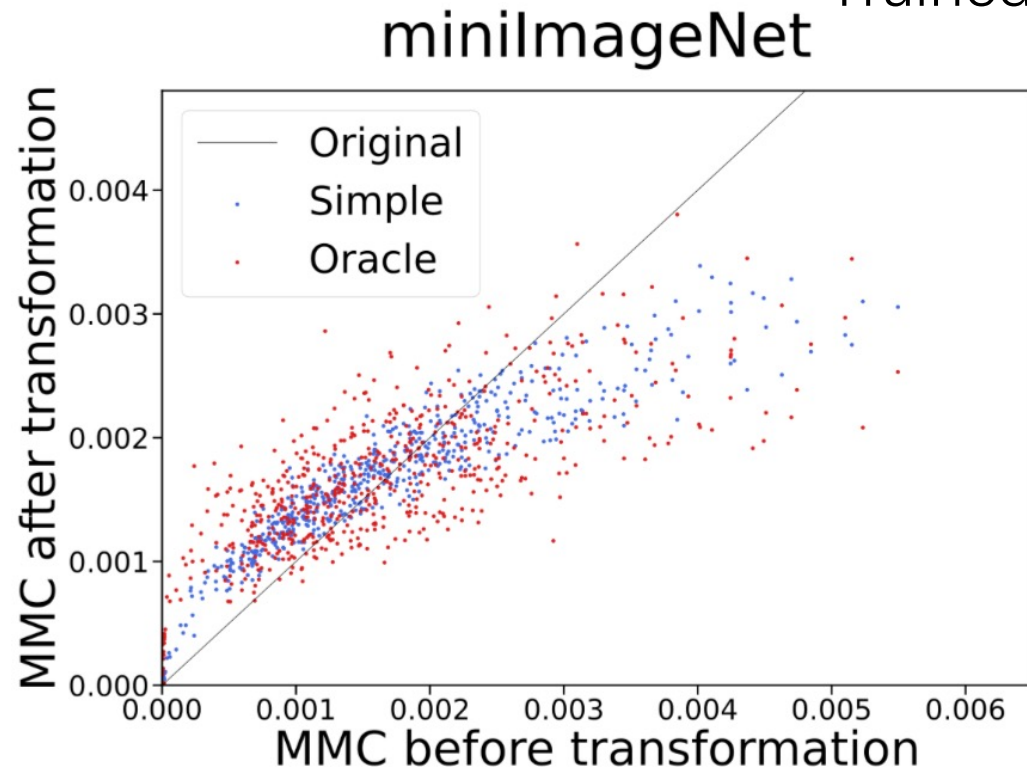


Conclusions:

2. The channel bias problem diminishes as task distribution shift lessens.

# Analysis of channel emphasis

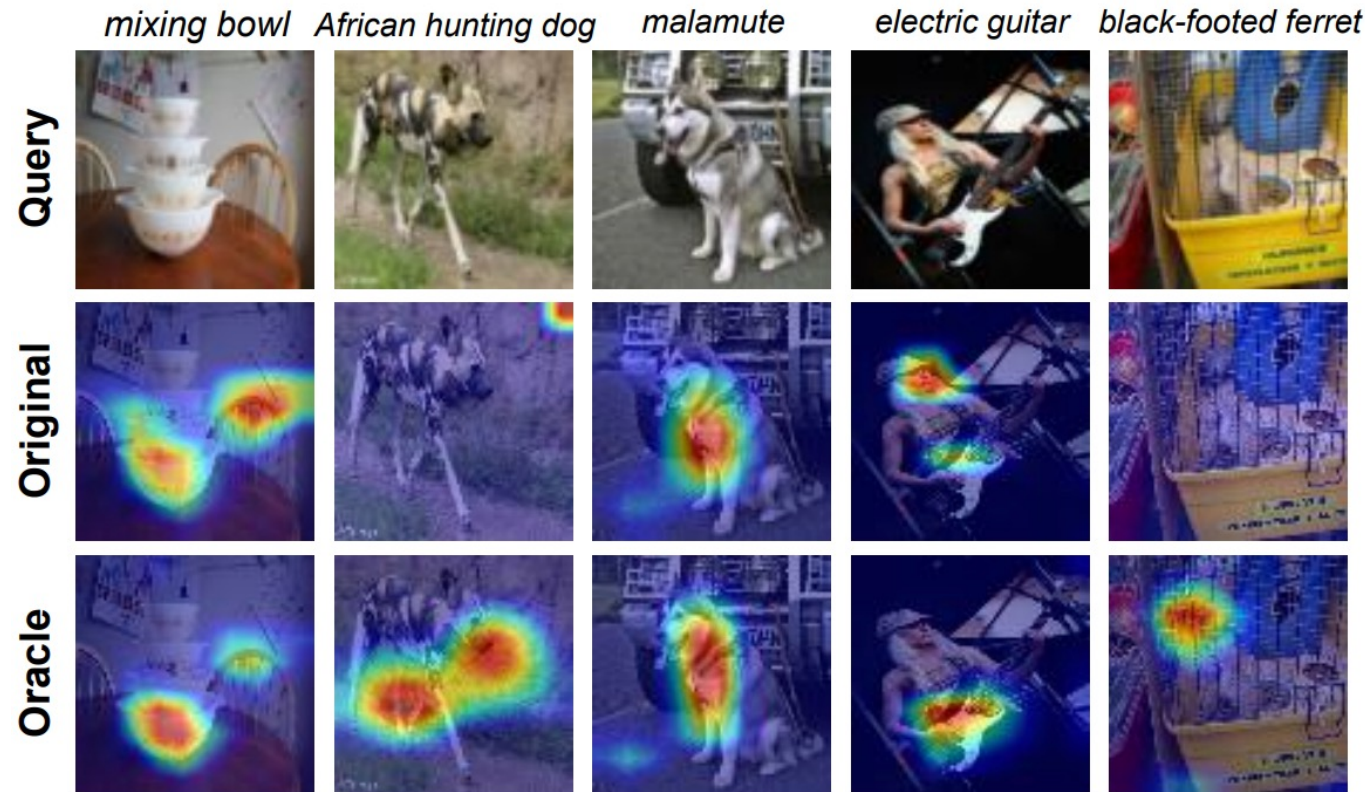
Trained on minilImageNet



Conclusions:

3. The simple transformation pushes channel emphasis towards the optimal ones.

# Analysis of channel emphasis



Conclusions:

4. The channel bias problem distracts the neural network from new objects.

Thank you for listening!