BOSTON UNIVERSITY | BATMAN LAB

Poster session Exhibit Hall 1 #729
Thu 27 Jul 10:30 a.m. HST — noon HST

ICML International Conference On Machine Learning

# Dividing & Conquering a BlackBox to a Mixture of Interpretable Models: Route, Interpret, Repeat




Shantanu Ghosh[1], Ke Yu[2], Forough Arabshahi[3], Kayhan Batmanghelich[1]

[1]BU ECE, [2]Pitt ISP, [3]Meta

Project

# Post-hoc Explanations

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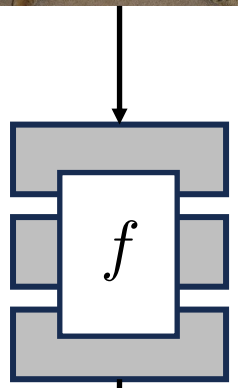
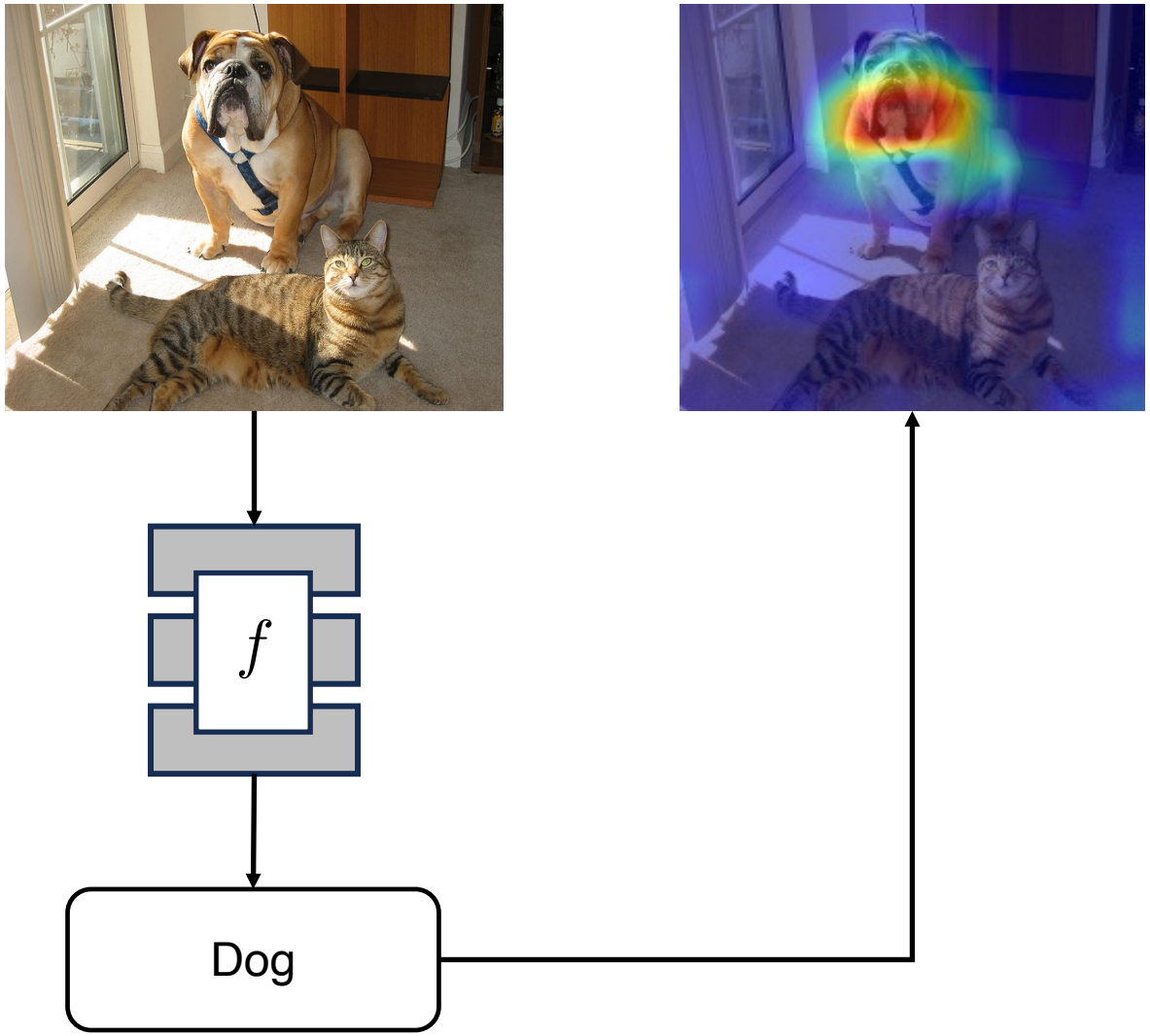


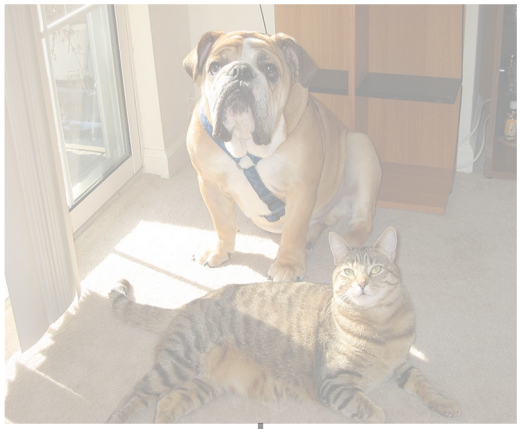

Dog

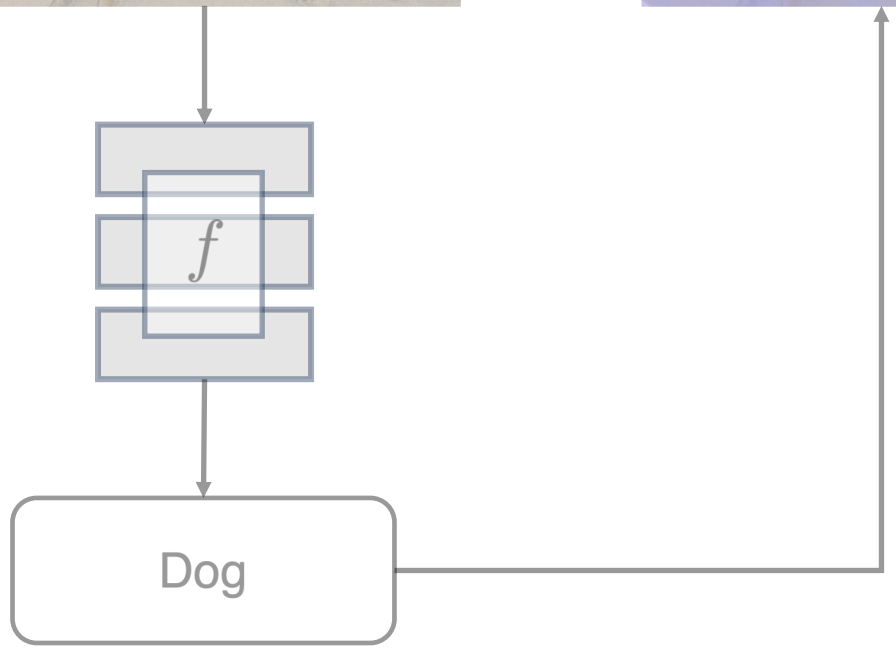
# Post-hoc Explanations




GRAD-CAM. Selvaraju et al. ICCV 2017.

# Post-hoc Explanations Interpretable by design



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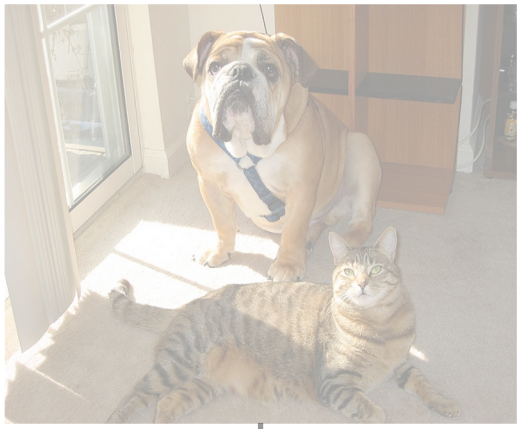
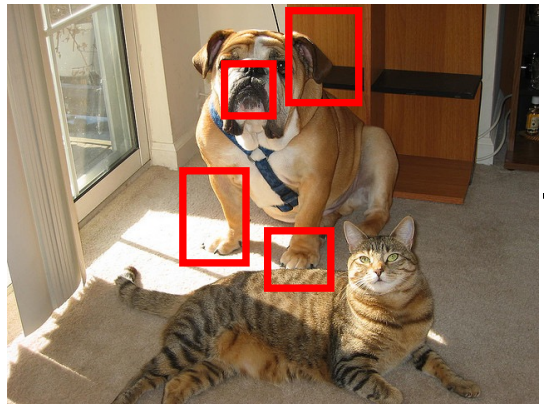
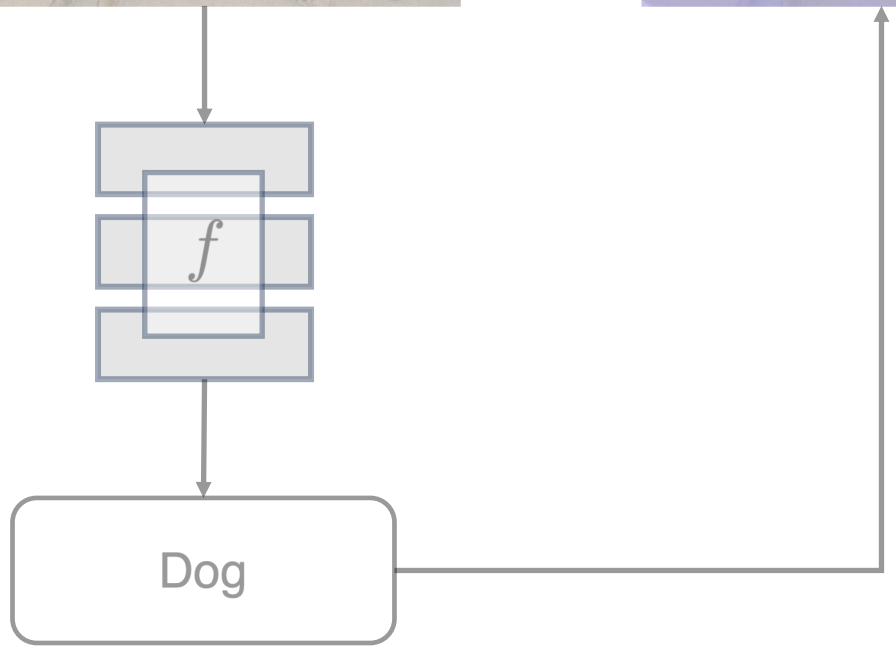




thin ears
shortened muzzle
round feet
....

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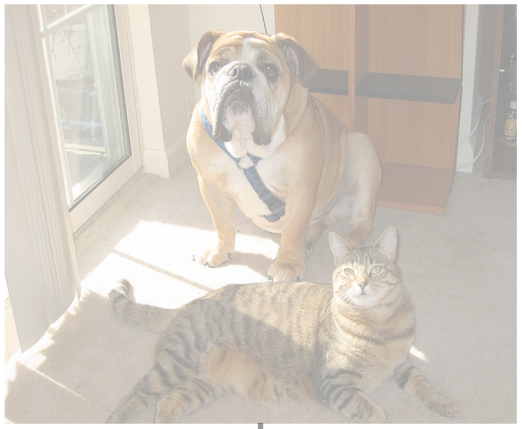

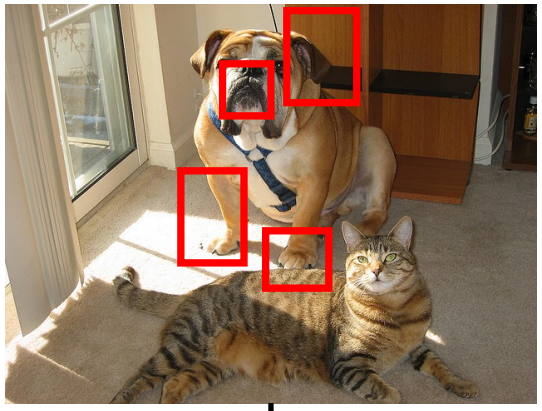

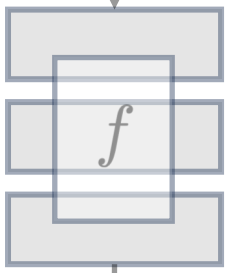


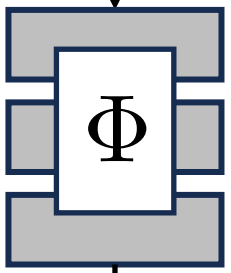


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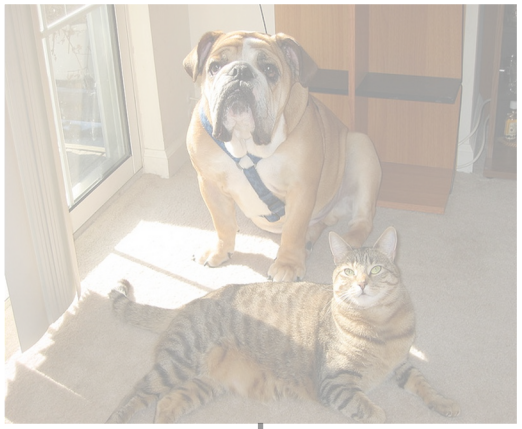

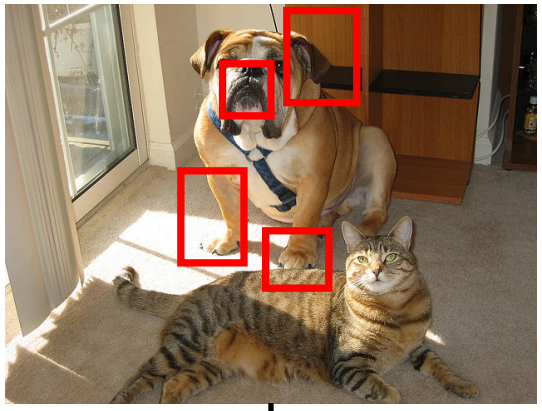

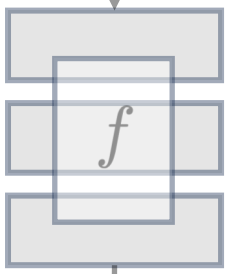


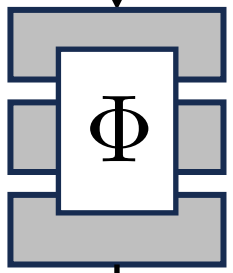



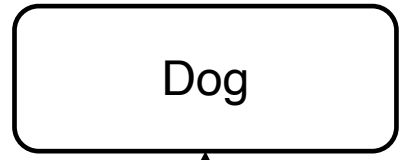


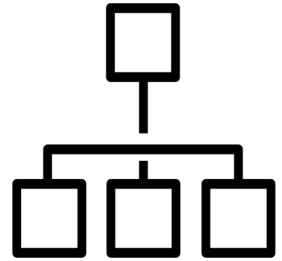




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# Post-hoc explanations

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Pros:

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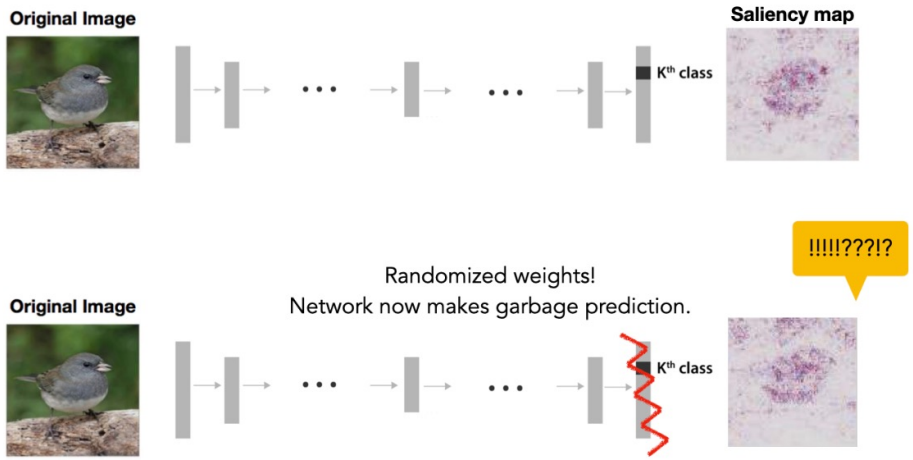
Cons:

- Inconsistent explanations
- No recourse

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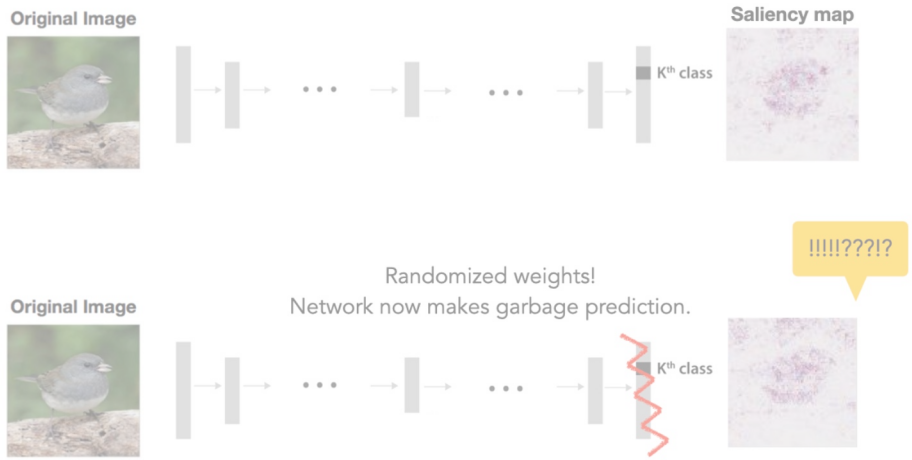


Pros:
- Support concept intervention

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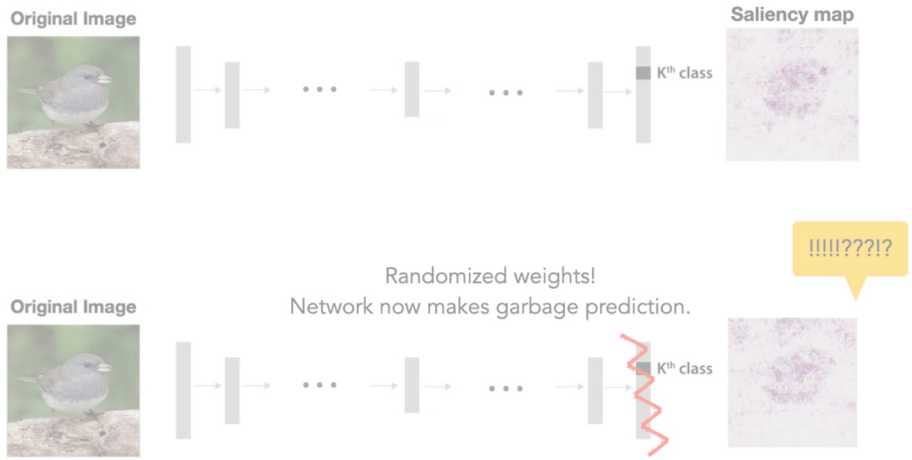
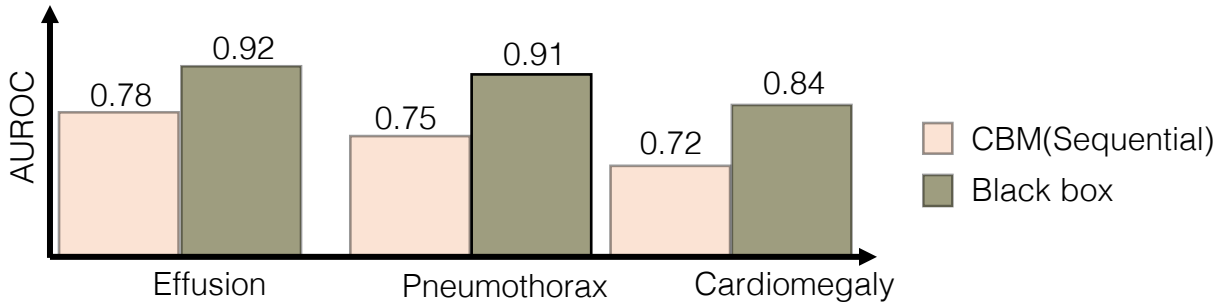



Pros:
- Support concept intervention

Cons:
- Harder to train
- Sub par performance

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# Post-hoc explanations Interpretable by design

Pros:
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Pros:
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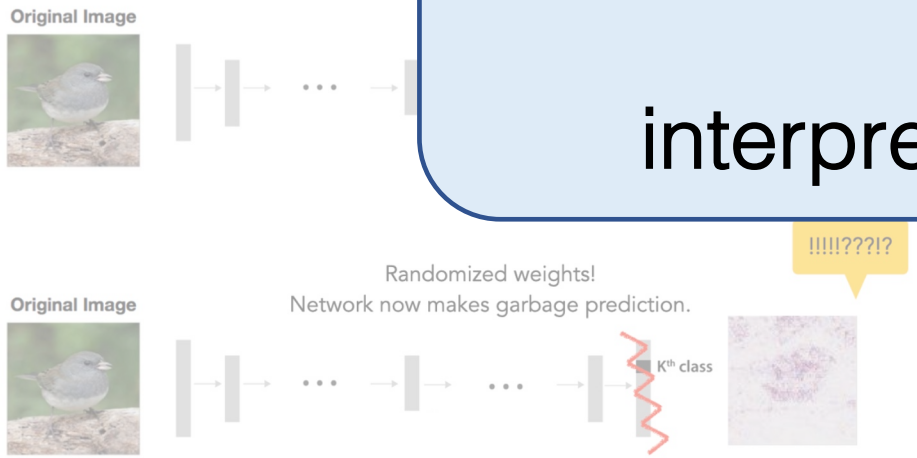
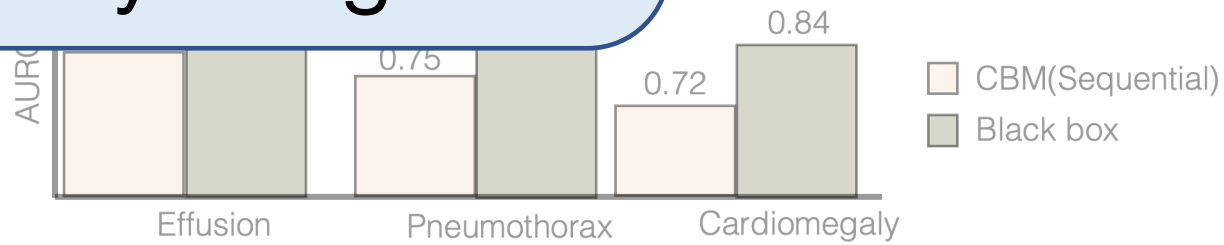
Can we blur the line b/w post-hoc explanations or interpretable by design

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# Desirable properties

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# Design choices

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2. Can be intervened to fix misclassification

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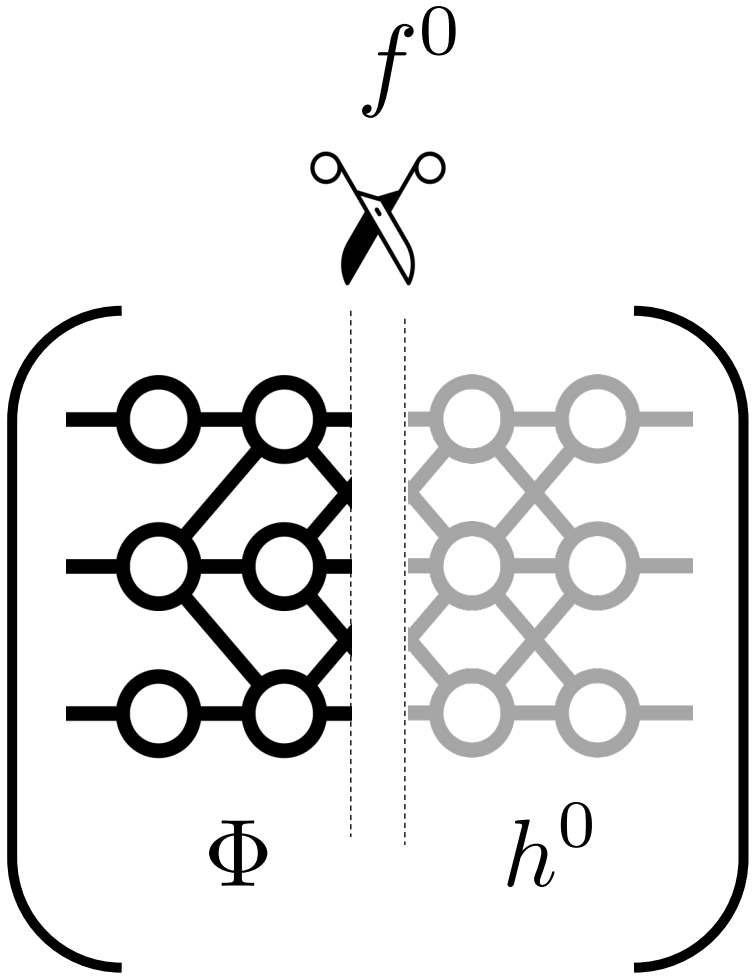
# Design choices

1. Iteratively carve out the interpretable models from Black box
2. Concept based, not pixel based
3. First order logic (FOL) for concept interaction

# Assumptions



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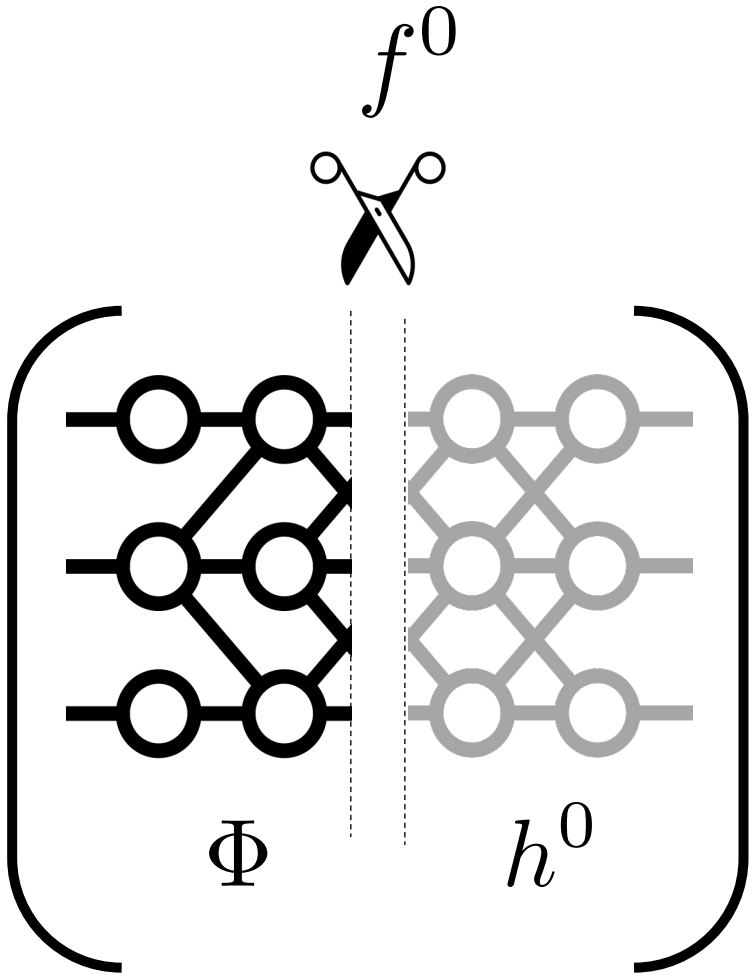
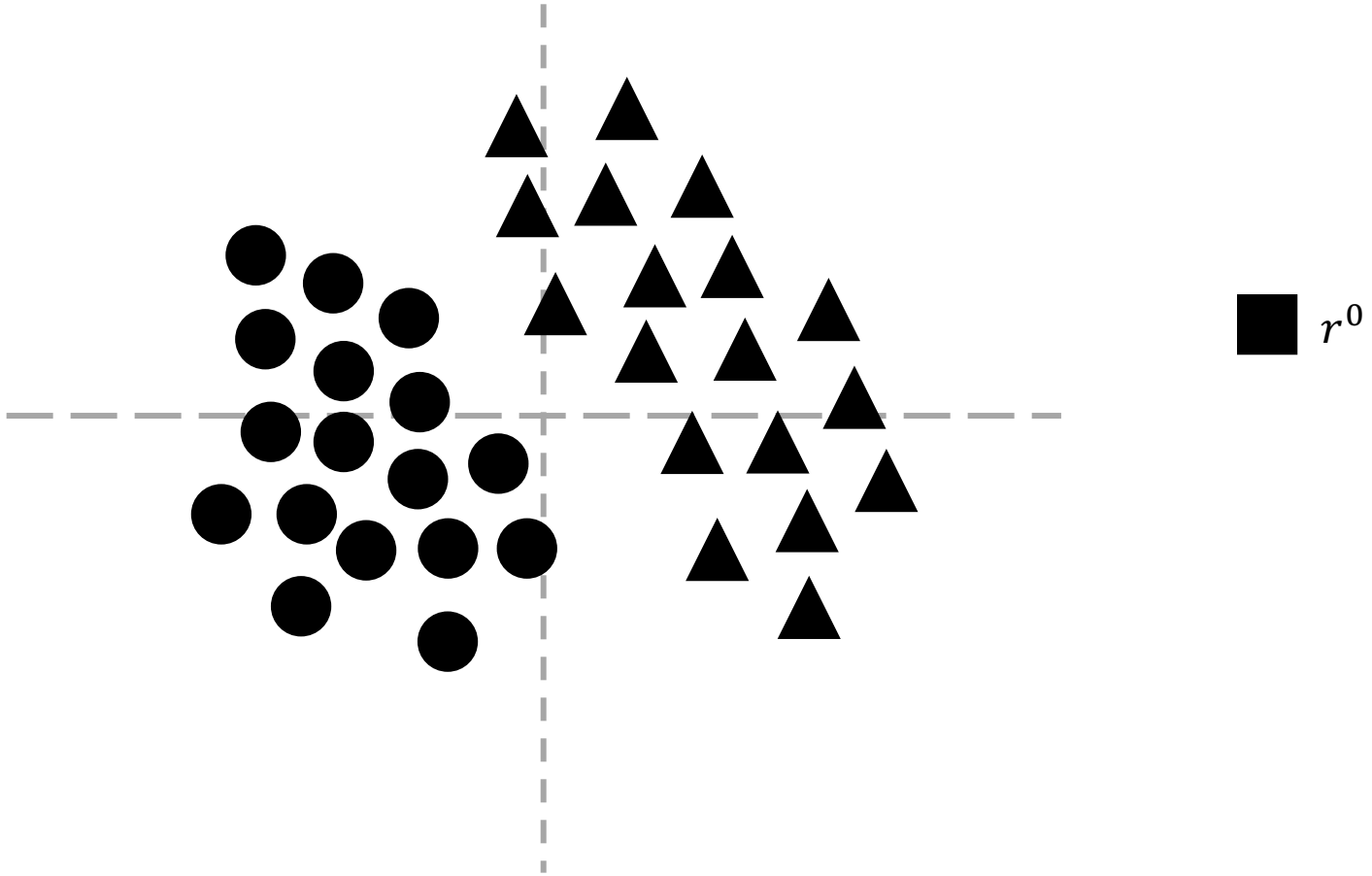



# Iteratively carve out interpretable models

$(x, y)$ → Circle / rectangle



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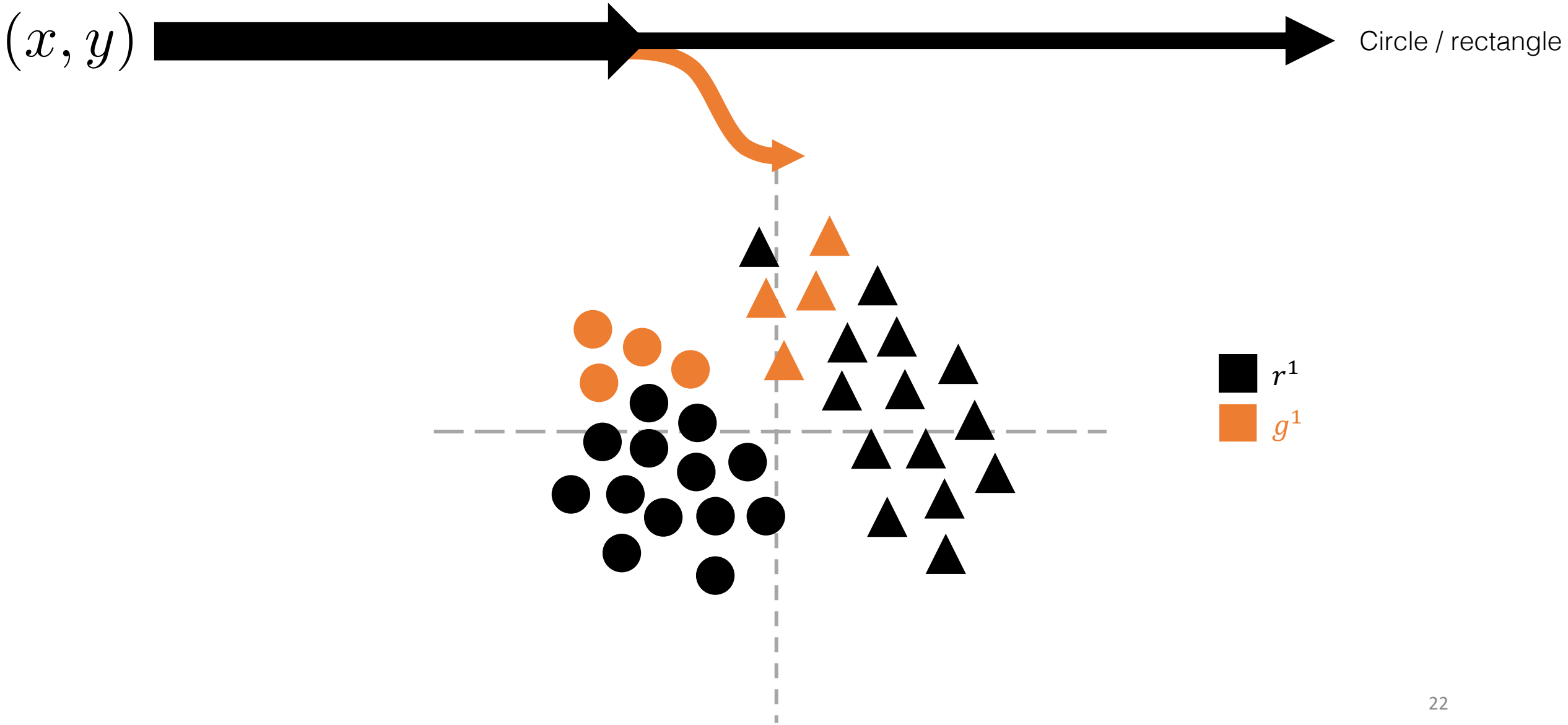

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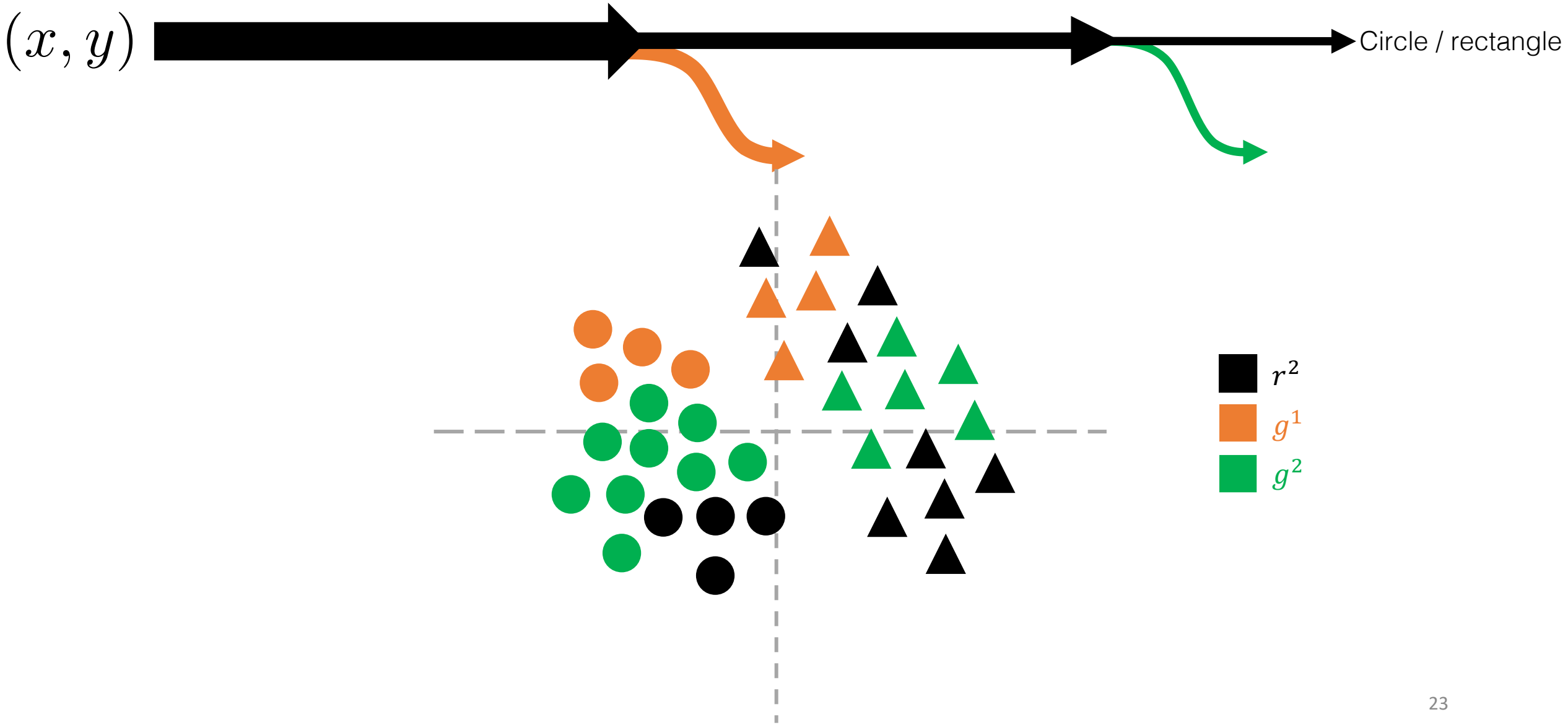

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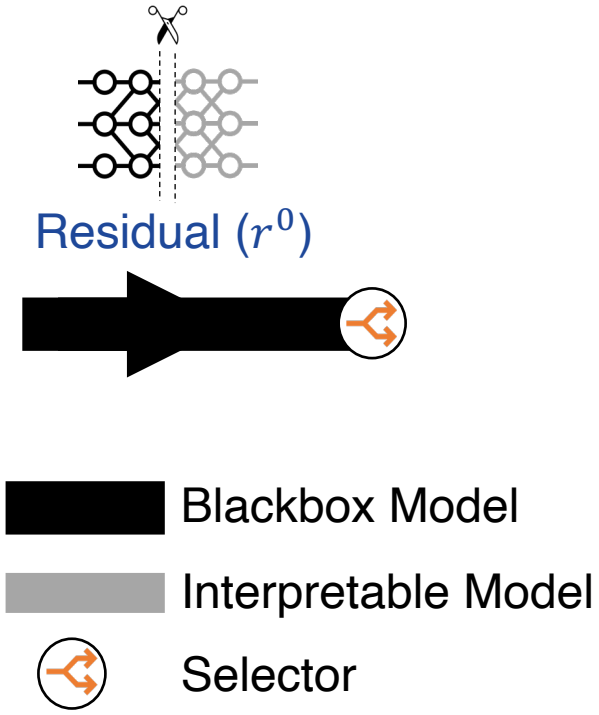


Each g to produce sample specific FOLs (Barberio et al. AAAI 2022) .

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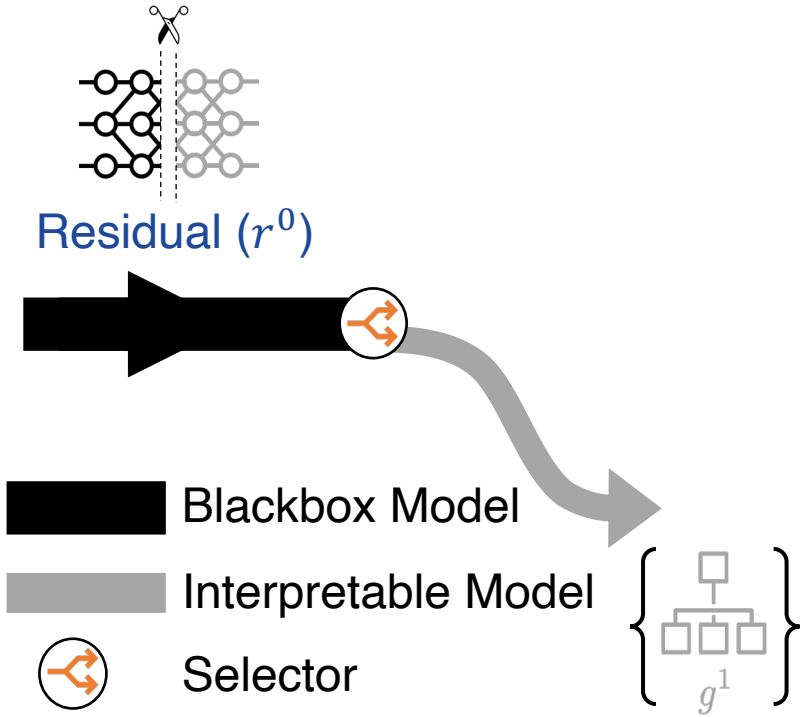


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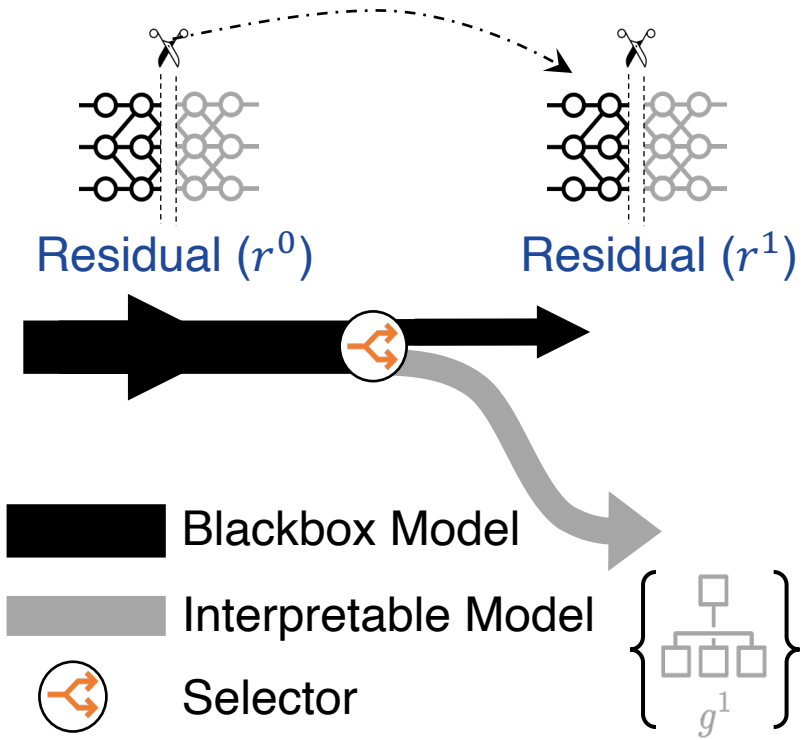


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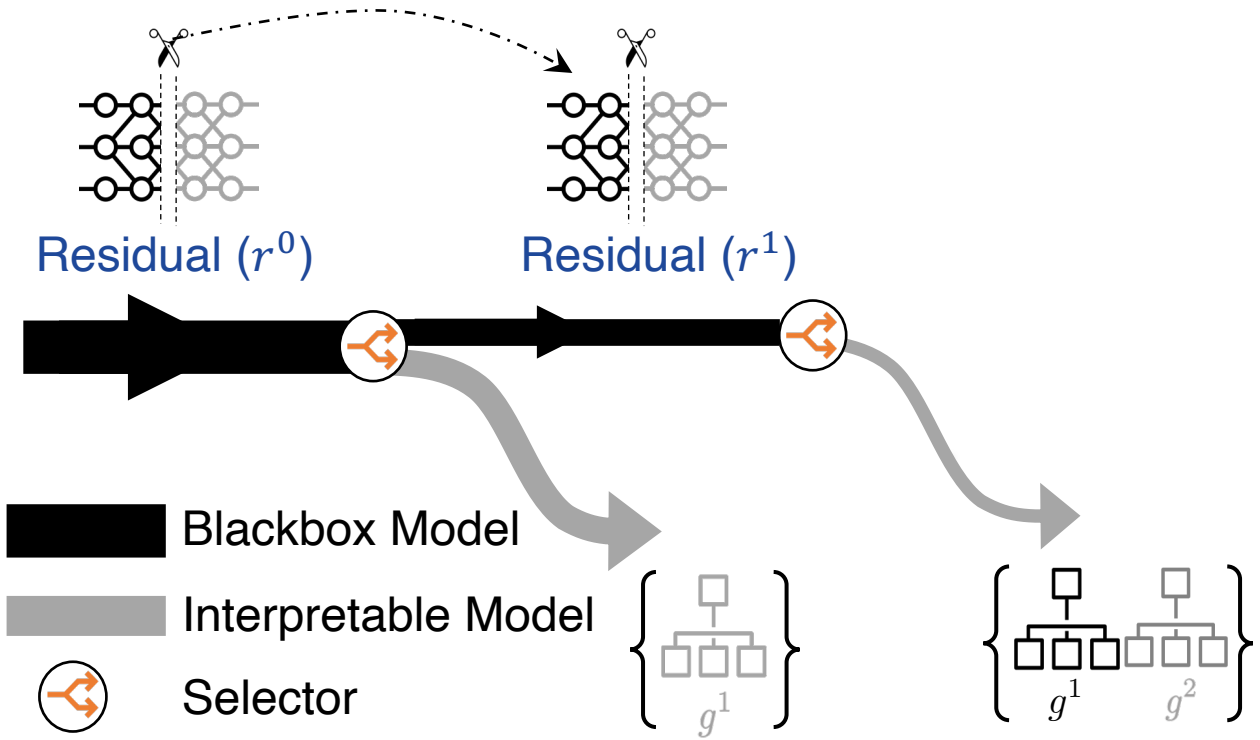


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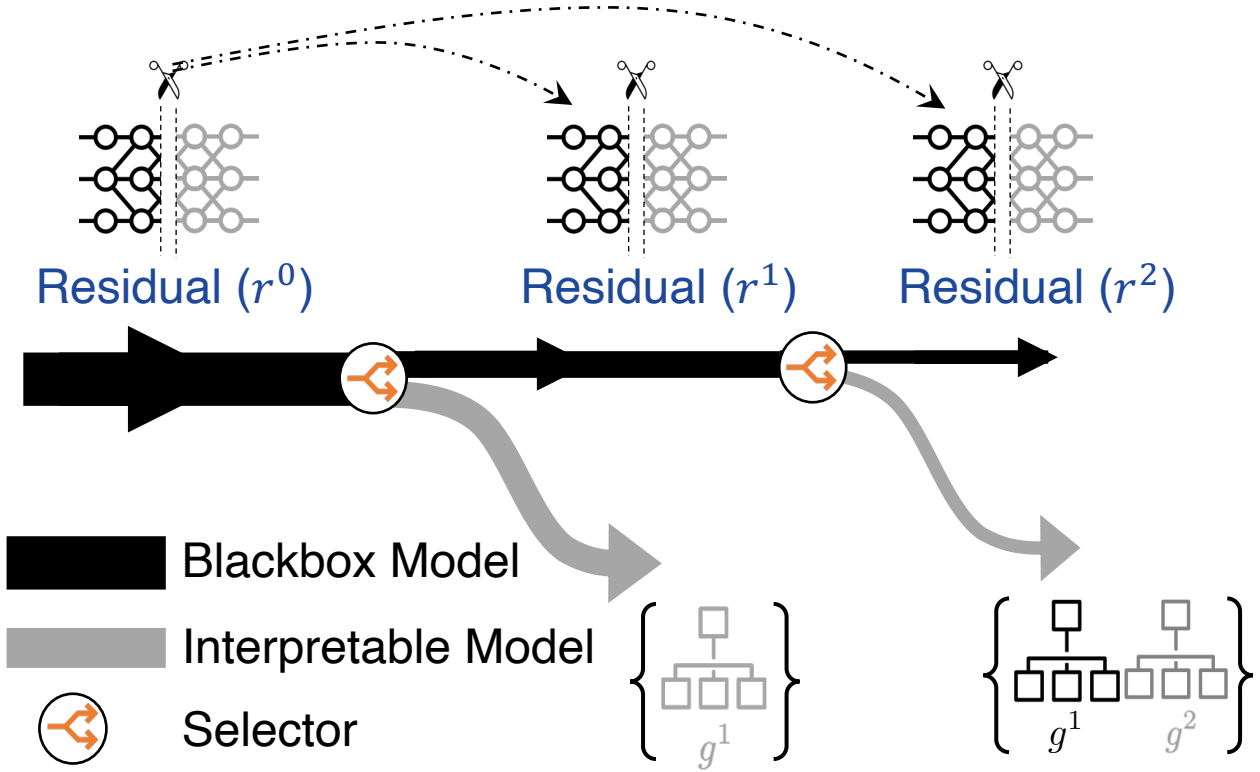


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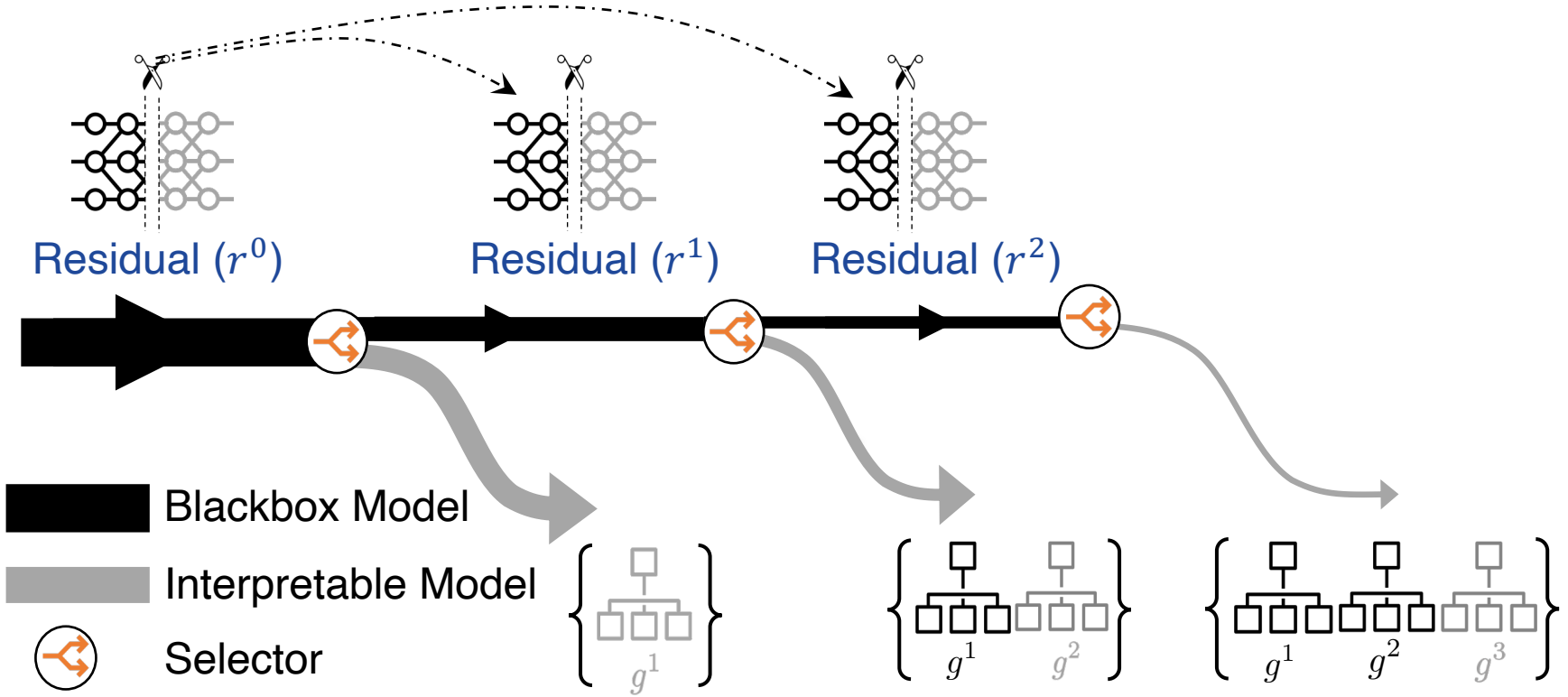


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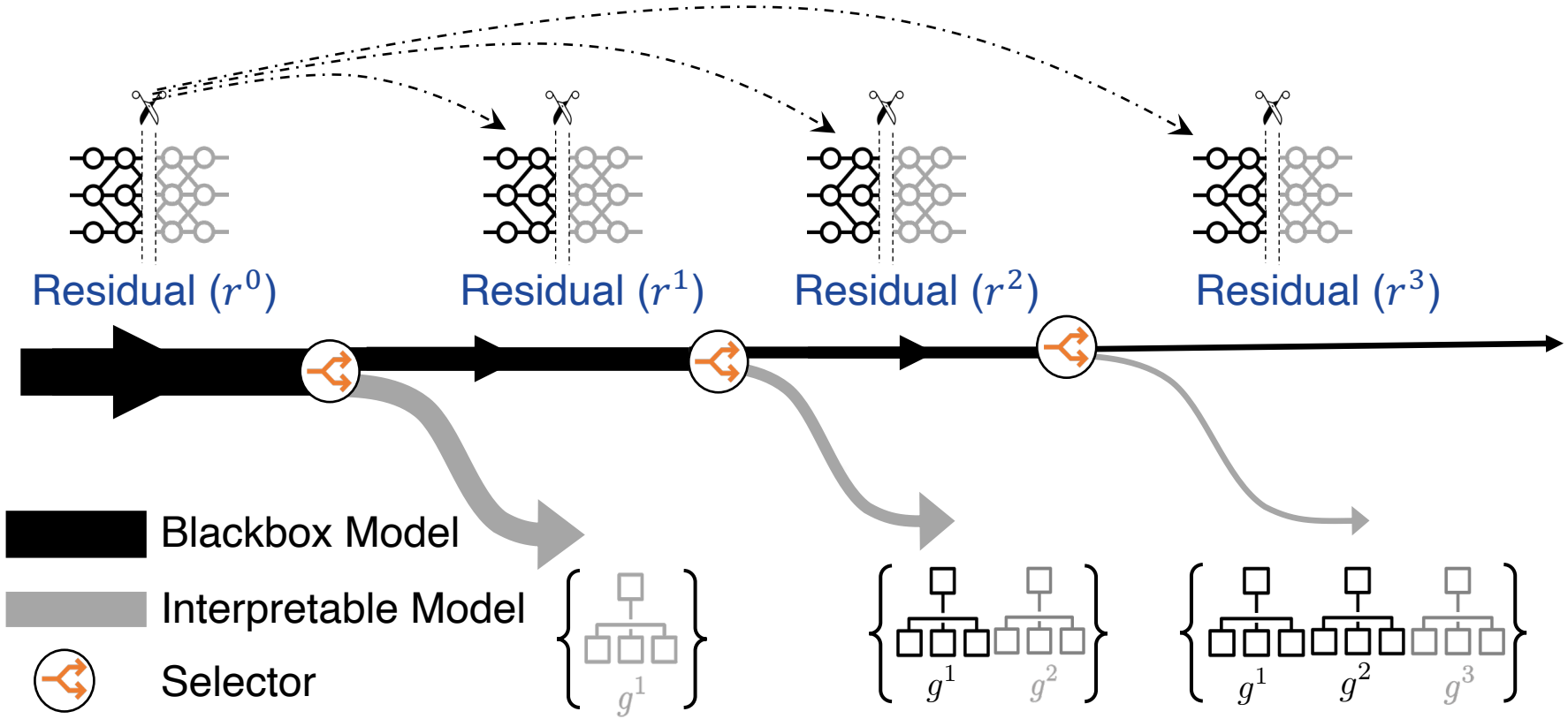


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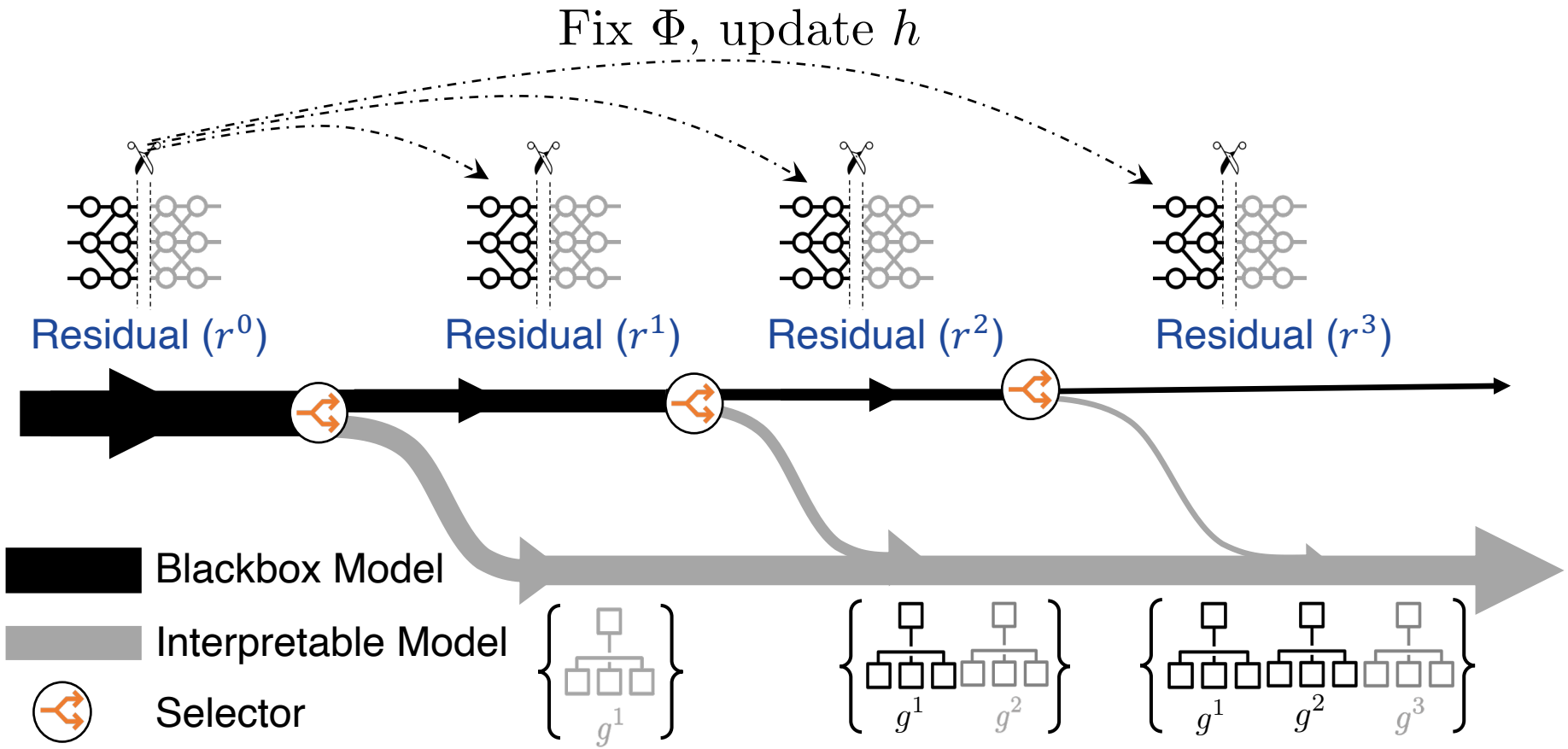


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# Provide the concept-interaction

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Expert 1


**Olive sided Flycatcher** $\leftrightarrow$breast_color_grey$\wedge$
tail_pattern_solid

These experts are derived from CUB-200 dataset with ViT as Black box

# Provide the concept-interaction

Expert 1


**Olive sided Flycatcher** ↔breast_color_grey∧
tail_pattern_solid

Expert 2

**Olive sided Flycatcher** ↔underparts_color_grey∧
wing_color_grey

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# Provide the concept-interaction

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**Olive sided Flycatcher** ↔breast_color_grey∧
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Expert 2

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wing_color_grey

Final Residual (Unexplained)

These experts are derived from CUB-200 dataset with ViT as Black box

# Does not compromise performance

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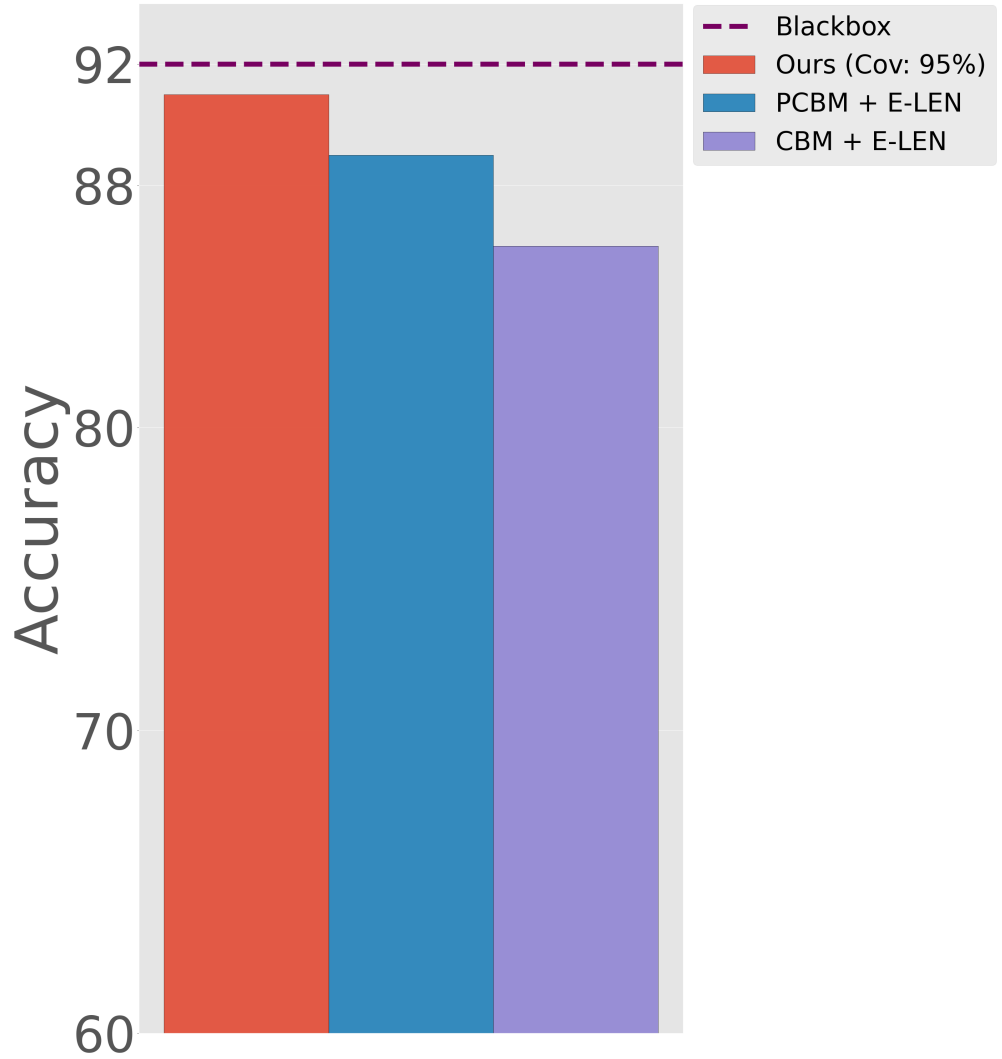
## CUB-200 with ViT



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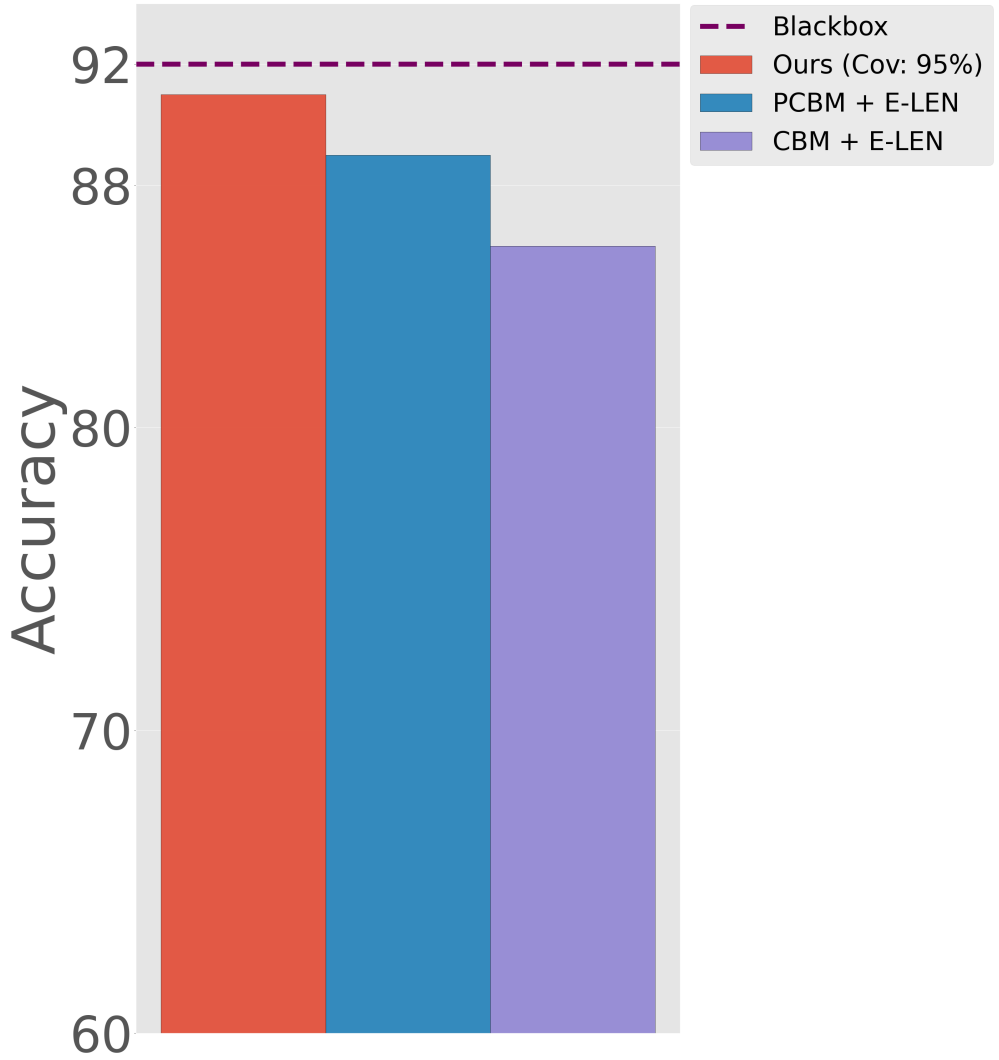
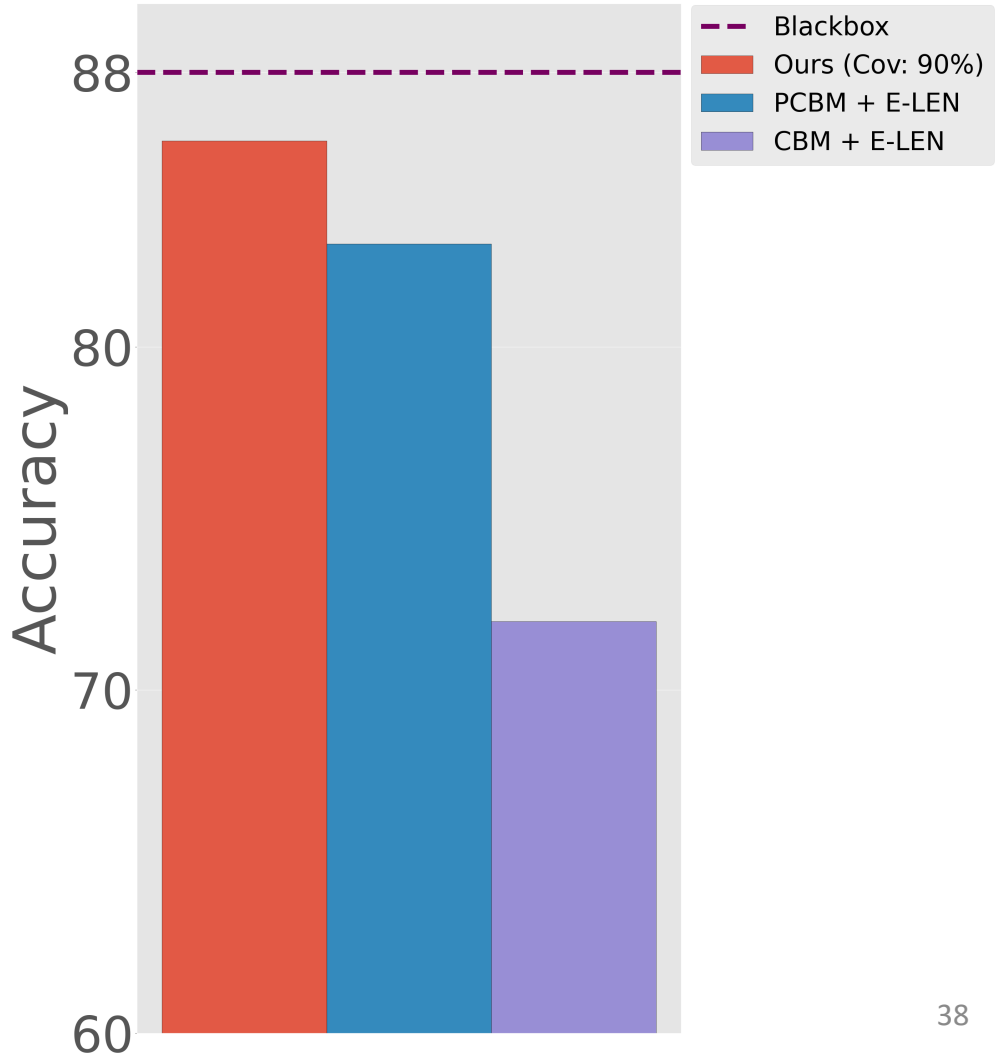



## CUB-200 with ResNet101



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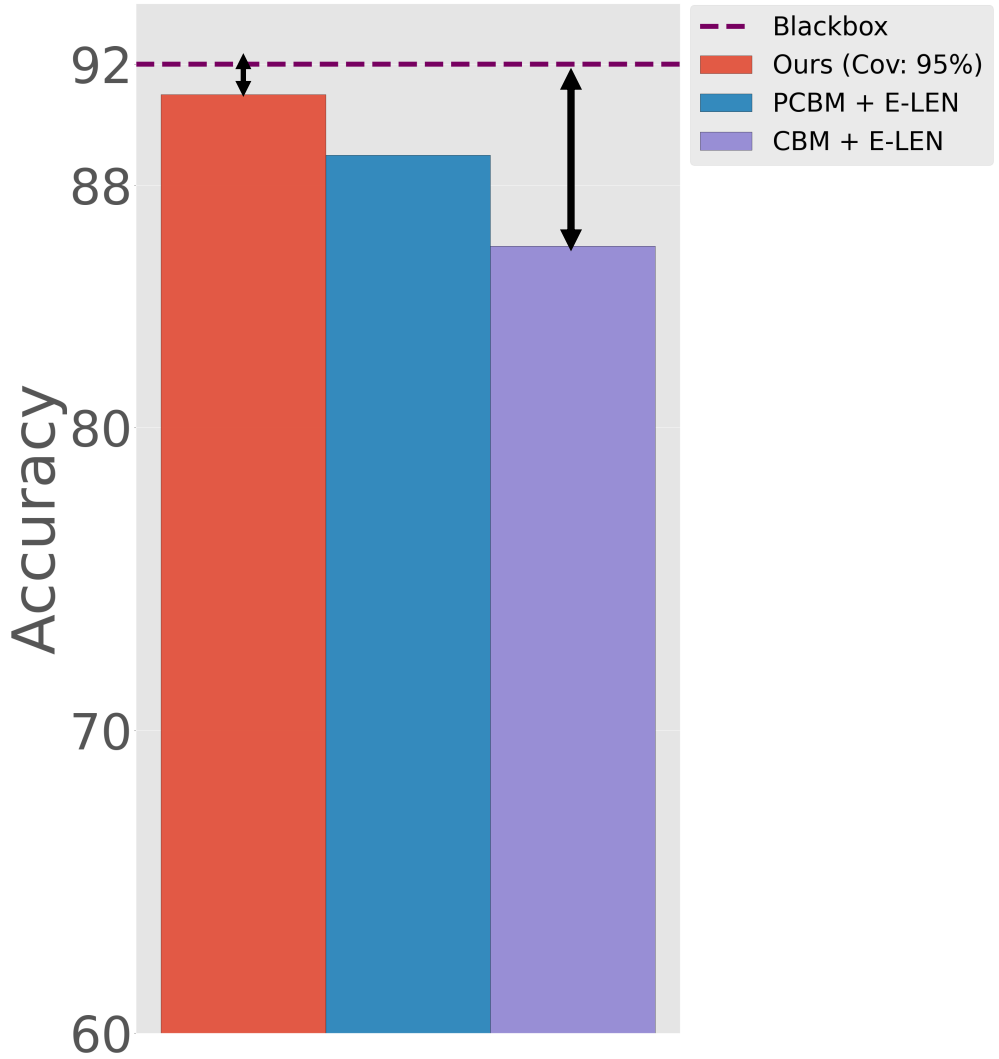


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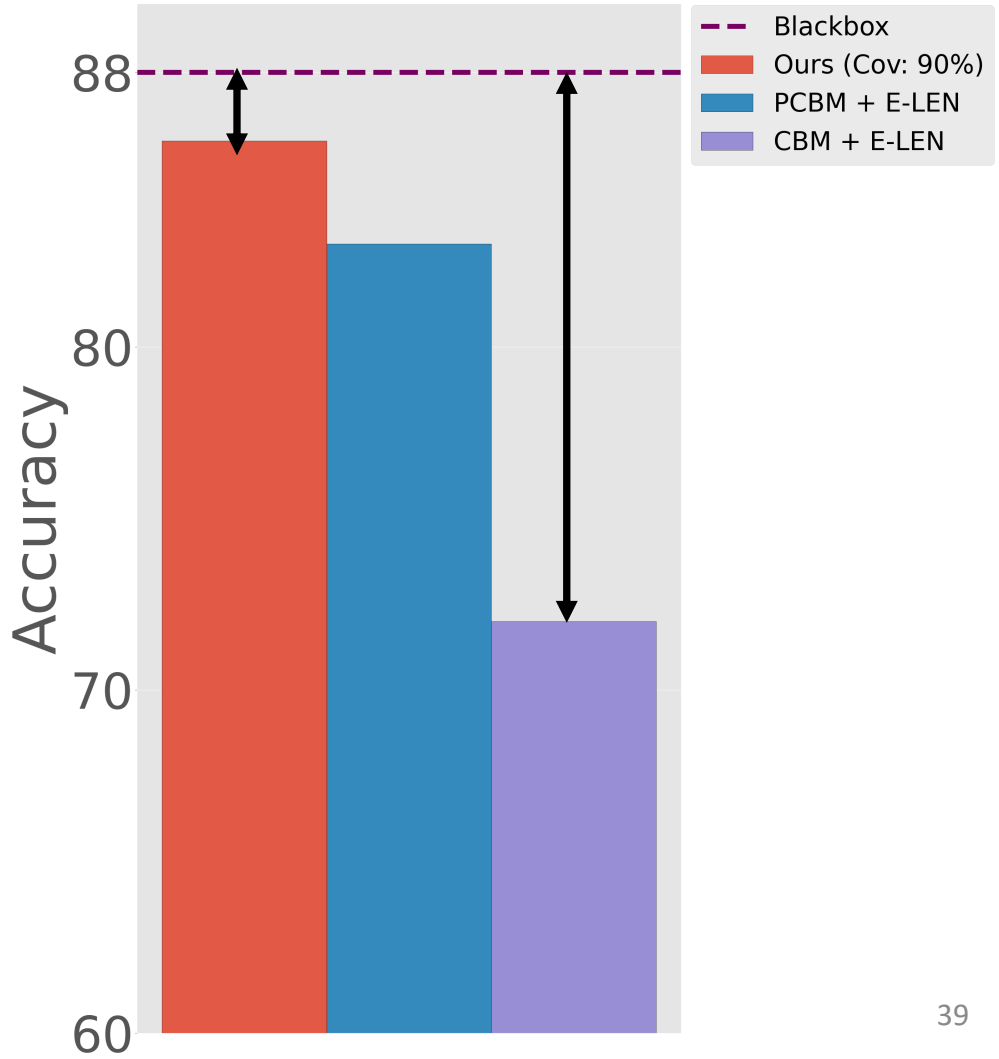

# Application on shortcut

Tackling Shortcut Learning in Deep Neural Networks. Ghosh et al. SCIS Workshop, ICML 2023.

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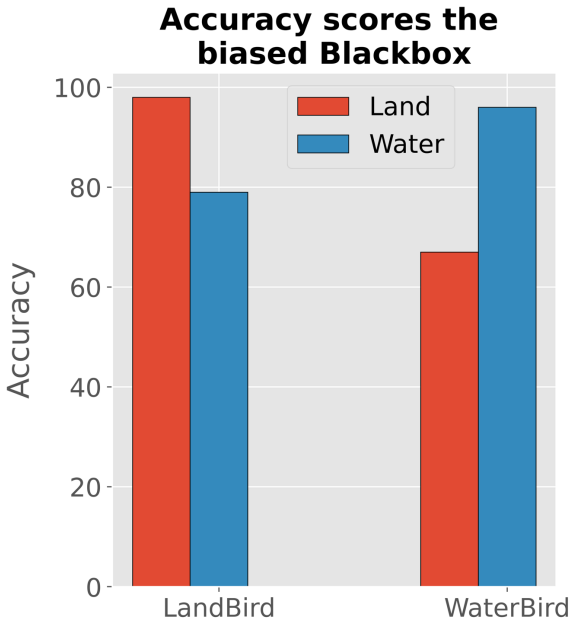


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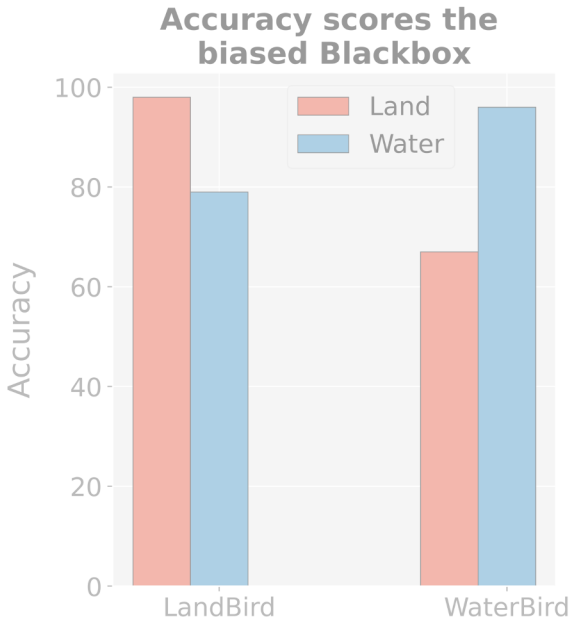


Biased Blackbox

Groundtruth: WaterBird

Prediction : LandBird

Explanation : LandBird $\leftrightarrow$ WingShapeRoundedwings $\wedge$ **Forest**

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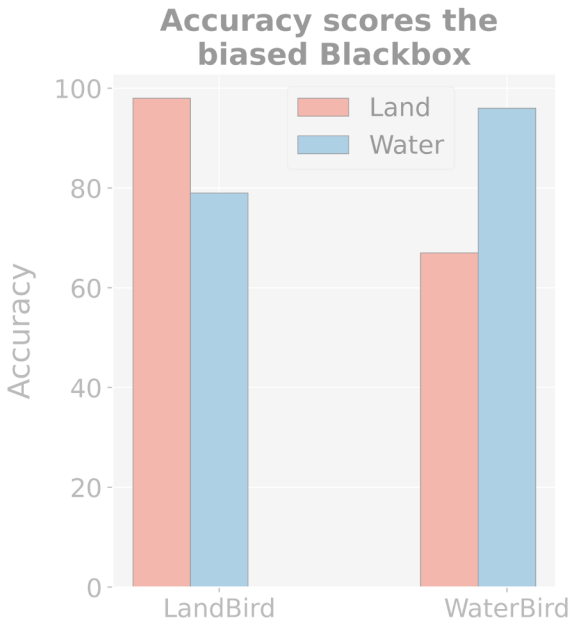


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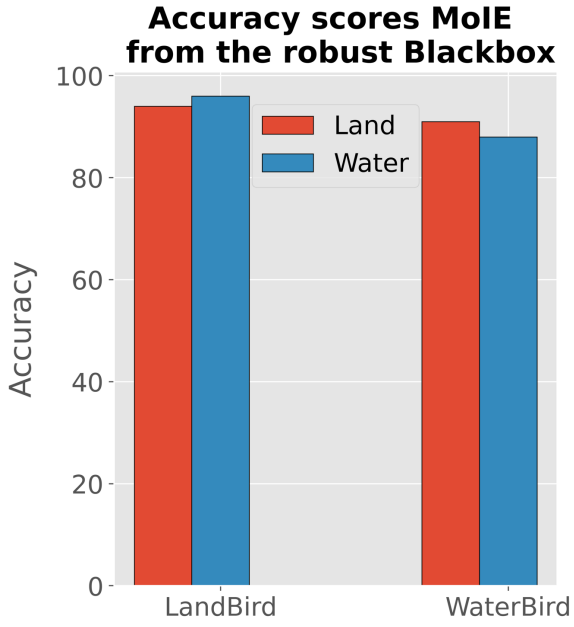




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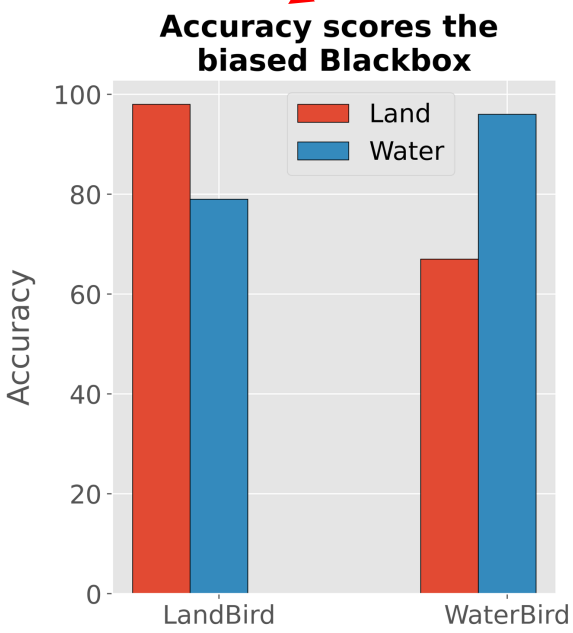


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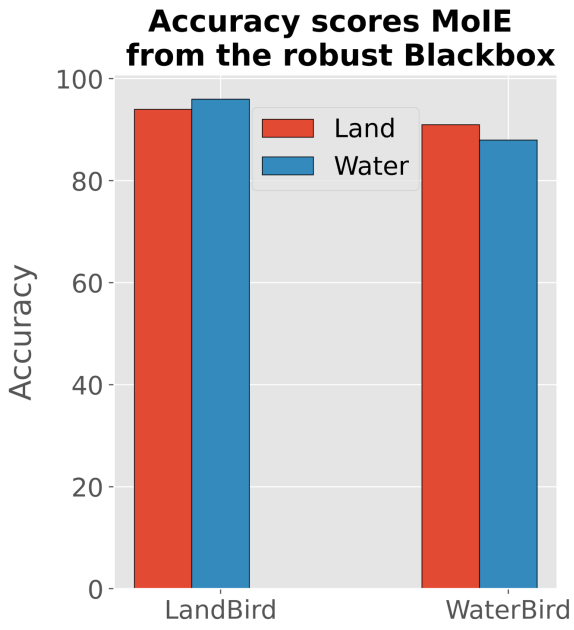




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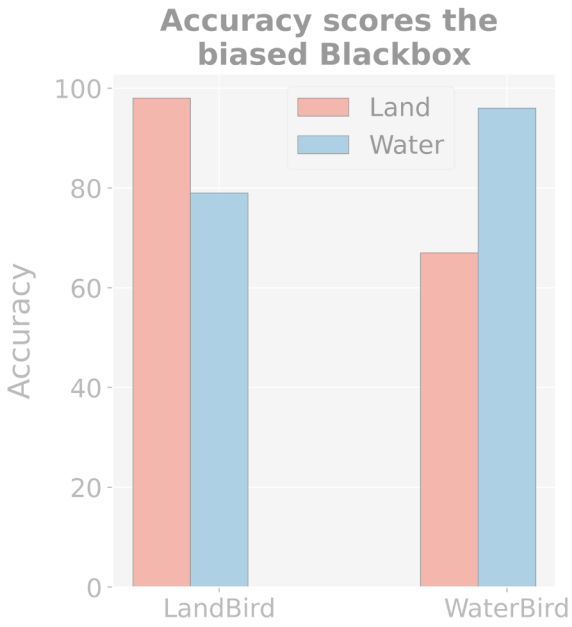
# Application on shortcut

Robust Blackbox

Groundtruth: WaterBird

Prediction : WaterBird

Explanation : WaterBird $\leftrightarrow$ BillLengthAboutTheSameAsHead $\wedge \neg$BillLengthShorterThanHead $\wedge \neg$SizeSmall5__9in $\wedge \neg$ShapePerchingLike $\wedge$ CrownColorWhite

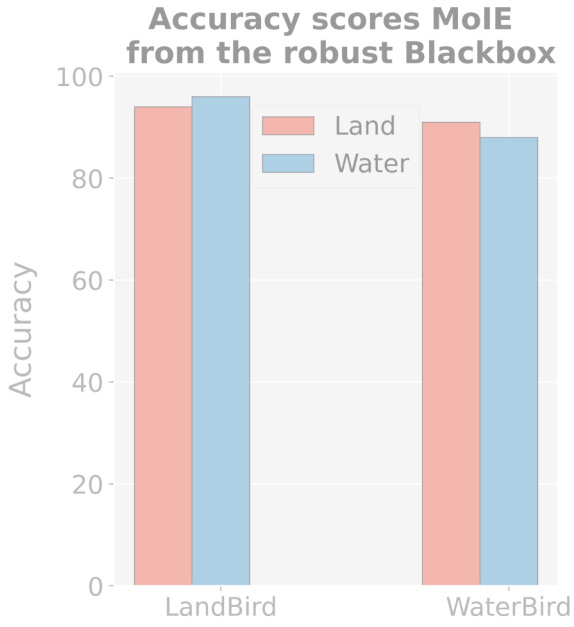



Biased Blackbox

Groundtruth: WaterBird

Prediction : LandBird

Explanation : LandBird $\leftrightarrow$ WingShapeRoundedwings $\wedge$ **Forest**



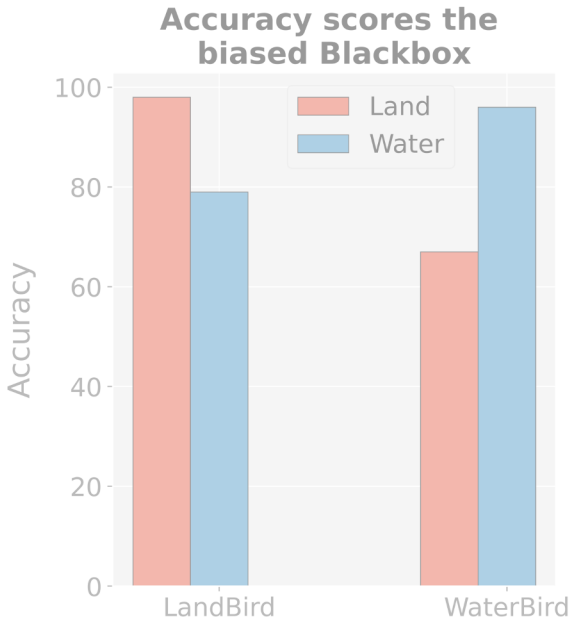



Tackling Shortcut Learning in Deep Neural Networks. Ghosh et al. SCIS Workshop, ICML 2023.

# Application on shortcut

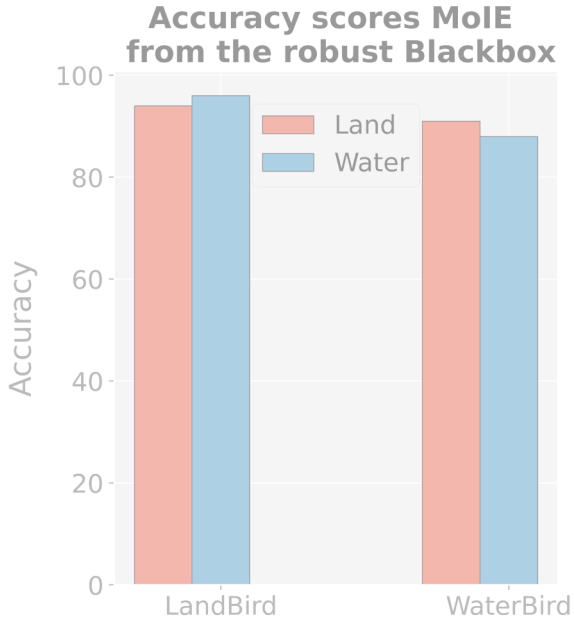
Robust Blackbox

Groundtruth: WaterBird
Prediction : WaterBird
Explanation : WaterBird $\leftrightarrow$ BillLengthAboutTheSameAsHead
$\wedge \neg$BillLengthShorterThanHead $\wedge \neg$SizeSmall5__9in
$\wedge \neg$ShapePerchingLike $\wedge$ CrownColorWhite




Biased Blackbox

Groundtruth: WaterBird
Prediction : LandBird
Explanation : LandBird $\leftrightarrow$ WingShapeRoundedwings $\wedge$ **Forest**






Tackling Shortcut Learning in Deep Neural Networks. Ghosh et al. SCIS Workshop, ICML 2023.

# We have more results

- We achieve higher completeness scores
- We performs better in test-time interventions
- We update to MoIE-CXR to perform efficient transfer learning for CXRs (In IMLH workshop at ICML 2023 and MICCAI 2023)

Project website

Poster session Exhibit Hall 1 #729
Thu 27 Jul 4:30 p.m. EDT — 6 p.m. EDT

# Project website

# Thank you




Shantanu Ghosh, Ke Yu, Forough Arabshahi, Kayhan Batmanghelich

Poster session Exhibit Hall 1 #729
Thu 27 Jul 10.30 a.m. HST — noon HST