

Neural Networks for Learning Counterfactual G-Invariances from Single Environments

“Fixing the Image Rotation Problem”

J. Setpal

February 17, 2024



**MACHINE LEARNING
@ PURDUE**

Neural Networks Aren't Rotationally Robust.

Q₁: Do you think that a CNN trained on a distribution of the left image *should* classify the right image as the same class for each of these pairs?



Neural Networks Aren't Rotationally Robust.

Q₁: Do you think that a CNN trained on a distribution of the left image *should* classify the right image as the same class for each of these pairs?



A₁: Definitely!

Neural Networks Aren't Rotationally Robust.

Q₁: Do you think that a CNN trained on a distribution of the left image *should* classify the right image as the same class for each of these pairs?



A₁: Definitely!

Q₂: In practice, does this actually happen?

Neural Networks Aren't Rotationally Robust.

Q₁: Do you think that a CNN trained on a distribution of the left image *should* classify the right image as the same class for each of these pairs?



A₁: Definitely!

Q₂: In practice, does this actually happen?

A₂: Nope – all these images were misclassified.

Neural Networks Aren't Rotationally Robust.

Q₁: Do you think that a CNN trained on a distribution of the left image *should* classify the right image as the same class for each of these pairs?



A₁: Definitely!

Q₂: In practice, does this actually happen?

A₂: Nope – all these images were misclassified.

Q₃: How can we fix this?

Neural Networks Aren't Rotationally Robust.

Q₁: Do you think that a CNN trained on a distribution of the left image *should* classify the right image as the same class for each of these pairs?



A₁: Definitely!

Q₂: In practice, does this actually happen?

A₂: Nope – all these images were misclassified.

Q₃: How can we fix this?

A₃: Data Augmentation (boring)

Neural Networks Aren't Rotationally Robust.

Q₁: Do you think that a CNN trained on a distribution of the left image *should* classify the right image as the same class for each of these pairs?



A₁: Definitely!

Q₂: In practice, does this actually happen?

A₂: Nope – all these images were misclassified.

Q₃: How can we fix this?

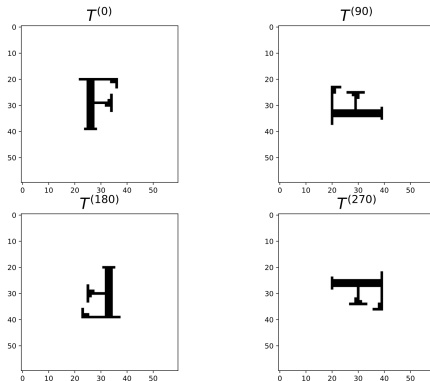
A₃: Data Augmentation (boring), **G-Invariant Transformations** (fun)!

Images as Transformations

We can visualize the image rotations as affine matrix transformations:

$$G_{rot} \equiv \{T^{0^\circ}, T^{90^\circ}, T^{180^\circ}, T^{270^\circ}\} \quad (1)$$

$$x_{new} = T x_{orig}; T \in G_{rot} \quad (2)$$



Mathematical Formulation

Defining the transformations as a **group** gives us *guarantees* we can exploit to ensure **invariance** to those transformations.

Mathematical Formulation

Defining the transformations as a **group** gives us *guarantees* we can exploit to ensure **invariance** to those transformations.

Formally, we create an embedding layer to achieve the following:

$$\sigma(w^T x + b) \stackrel{\text{def}}{=} \sigma(w^T \mathbf{T}x + b); \mathbf{T} \in G_{rot} \quad (3)$$

Mathematical Formulation

Defining the transformations as a **group** gives us *guarantees* we can exploit to ensure **invariance** to those transformations.

Formally, we create an embedding layer to achieve the following:

$$\sigma(w^T x + b) \stackrel{\text{def}}{=} \sigma(w^T \mathbf{T}x + b); \mathbf{T} \in G_{\text{rot}} \quad (3)$$

This is only possible if we can find a transformation $\bar{\mathbf{T}}$ such that:

$$\bar{\mathbf{T}}(\mathbf{T}x) = \bar{\mathbf{T}}x; \text{ same as } \bar{\mathbf{T}}x_{\text{new}} = \bar{\mathbf{T}}x_{\text{orig}}; \quad (4)$$

Mathematical Formulation

Defining the transformations as a **group** gives us *guarantees* we can exploit to ensure **invariance** to those transformations.

Formally, we create an embedding layer to achieve the following:

$$\sigma(w^T x + b) \stackrel{\text{def}}{=} \sigma(w^T \mathbf{T}x + b); \mathbf{T} \in G_{\text{rot}} \quad (3)$$

This is only possible if we can find a transformation $\bar{\mathbf{T}}$ such that:

$$\bar{\mathbf{T}}(\mathbf{T}x) = \bar{\mathbf{T}}x; \text{ same as } \bar{\mathbf{T}}x_{\text{new}} = \bar{\mathbf{T}}x_{\text{orig}}; \quad (4)$$

Lemma: We can find $\bar{\mathbf{T}}$ using the *Reynold's Operator*.

$$\bar{\mathbf{T}} = \frac{1}{|G|} \sum_{g \in G} g \quad (5)$$

Mathematical Formulation

Defining the transformations as a **group** gives us *guarantees* we can exploit to ensure **invariance** to those transformations.

Formally, we create an embedding layer to achieve the following:

$$\sigma(w^T x + b) \stackrel{\text{def}}{=} \sigma(w^T \mathbf{T}x + b); \mathbf{T} \in G_{\text{rot}} \quad (3)$$

This is only possible if we can find a transformation $\bar{\mathbf{T}}$ such that:

$$\bar{\mathbf{T}}(\mathbf{T}x) = \bar{\mathbf{T}}x; \text{ same as } \bar{\mathbf{T}}x_{\text{new}} = \bar{\mathbf{T}}x_{\text{orig}}; \quad (4)$$

Lemma: We can find $\bar{\mathbf{T}}$ using the *Reynold's Operator*.

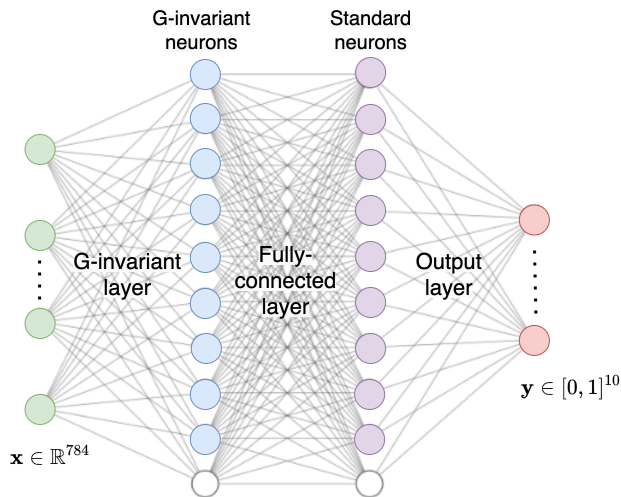
$$\bar{\mathbf{T}} = \frac{1}{|G|} \sum_{g \in G} g \quad (5)$$

Finally, we construct our group invariant layer:

$$h_{\text{inv}} = \sigma(w^T \bar{\mathbf{T}}x + b) \quad (6)$$

Let's Demonstrate!

Here's what the final architecture looks like:



Thank you!

Hopefully, this was cool!

Paper: <https://arxiv.org/abs/2104.10105/>

Slides: <https://cs.purdue.edu/homes/jsetpal/slides/gti.pdf>

Notebook: <https://cs.purdue.edu/homes/jsetpal/nb/gti.ipynb>

Presentation: <https://www.youtube.com/watch?v=znJsaCGiu10>