

Relativistic Harmonic

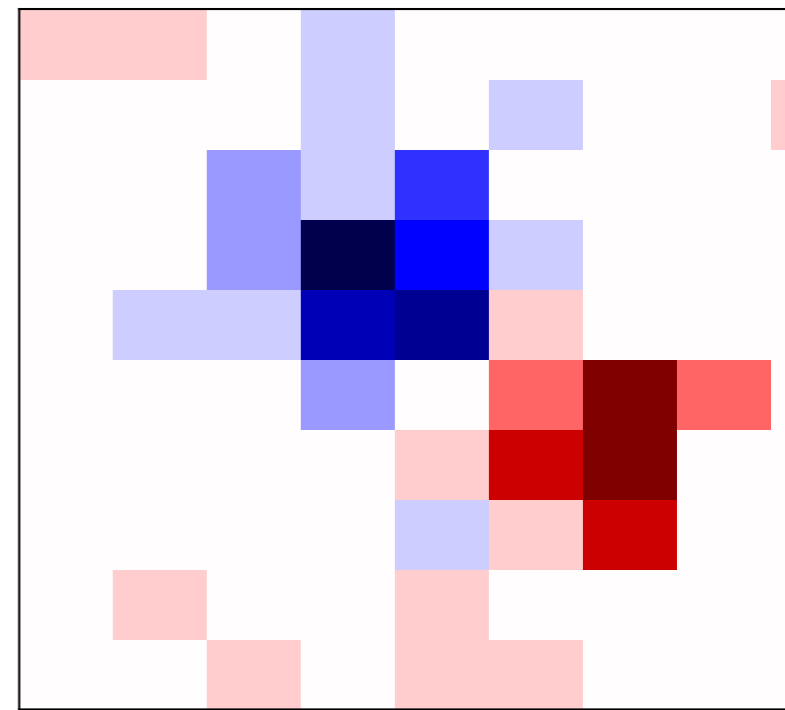
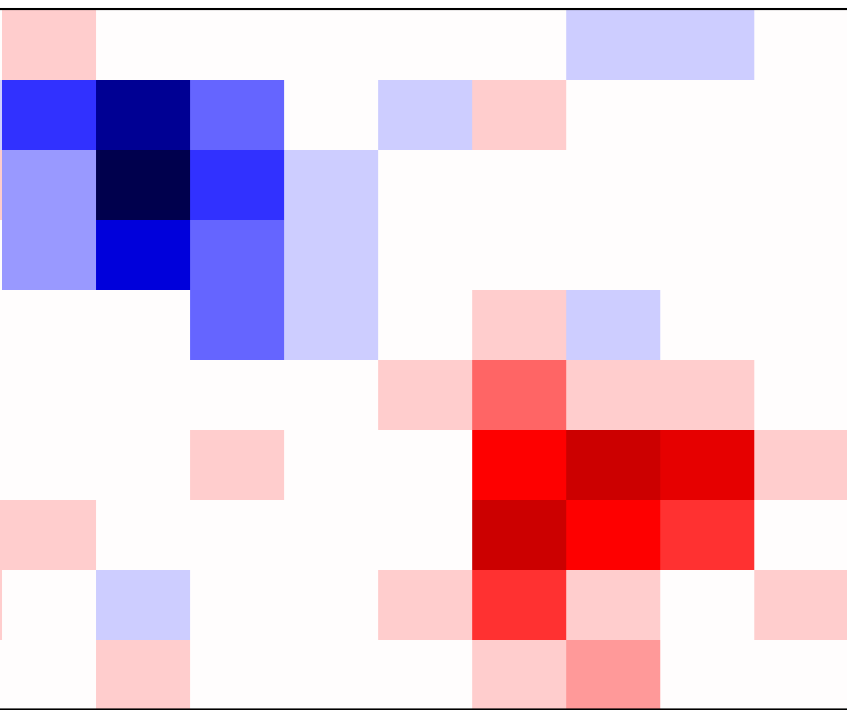
Networks

Chase Shimmin (Yale)

Mohammad Abdullah (TAMU)

Paul Tipton (Yale)

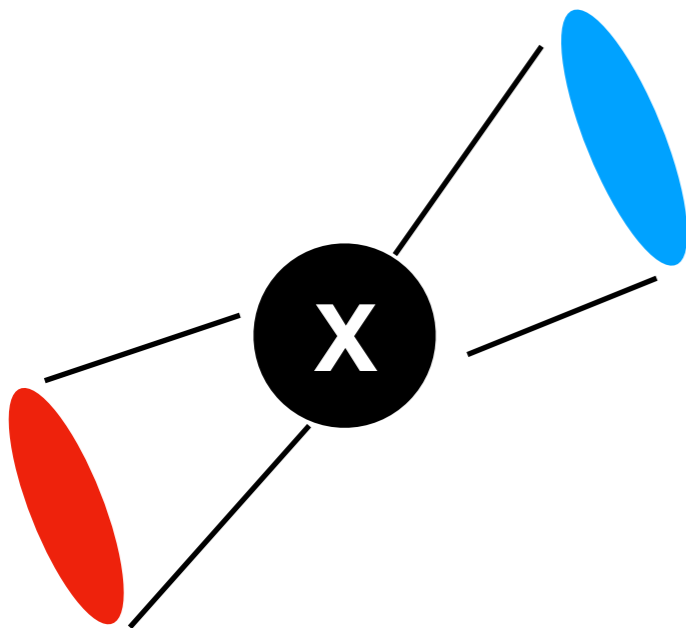
BOOST 2019



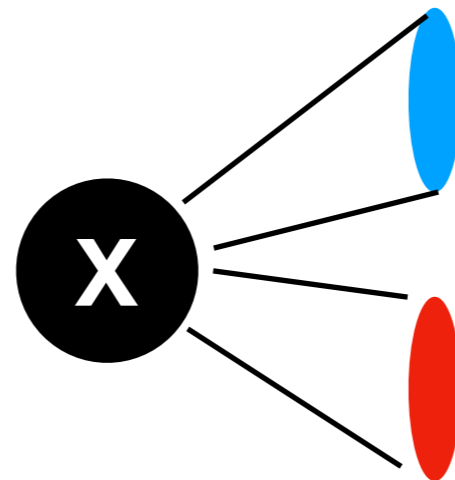
Yale University

Boosted Jets and Neural 'Nets

Rest Frame

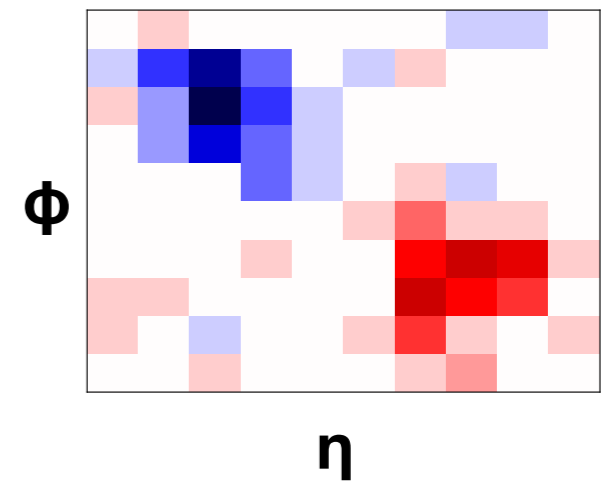


Lab Frame



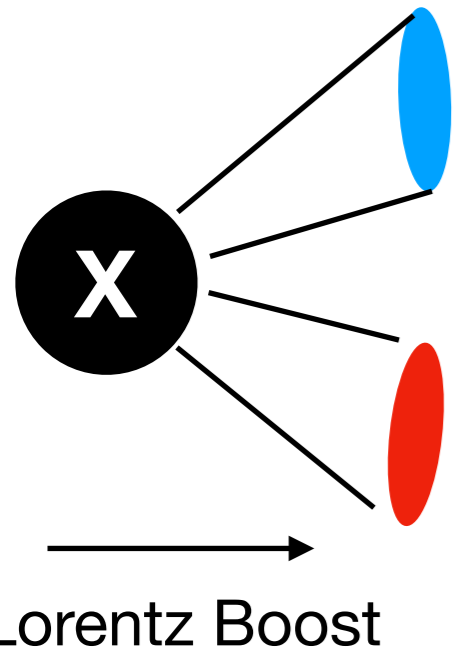
→
Lorentz Boost

Detector View

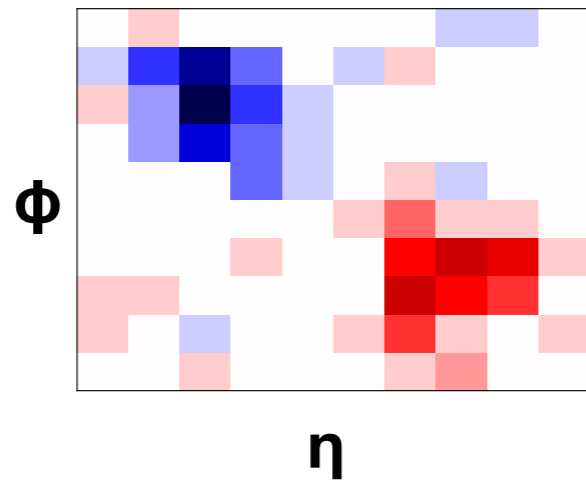


Boosted Jets and Neural 'Nets

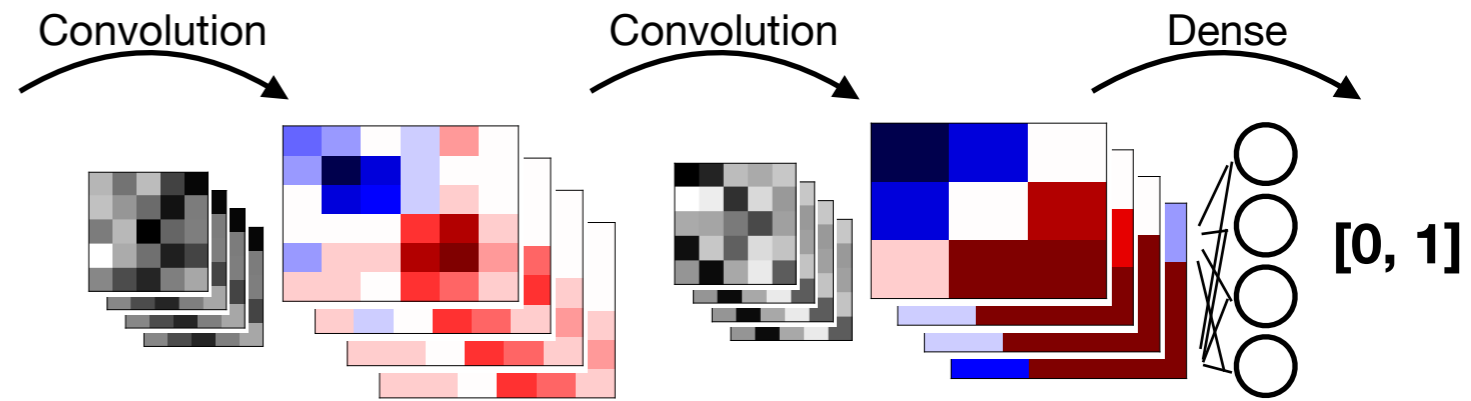
Lab Frame



Detector View

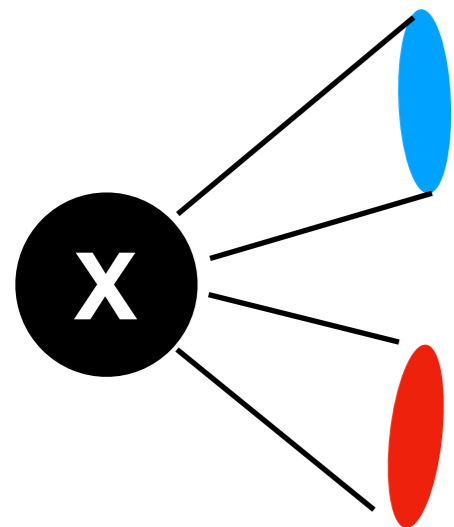


Network View



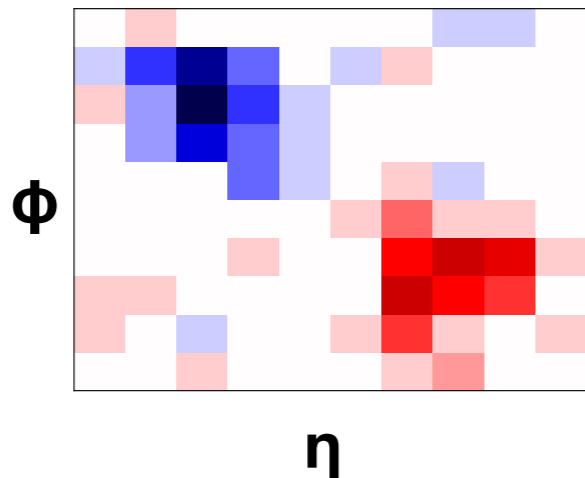
Boosted Jets and Neural 'Nets

Lab Frame

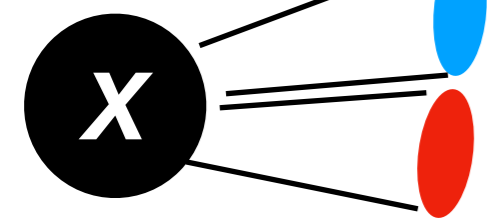
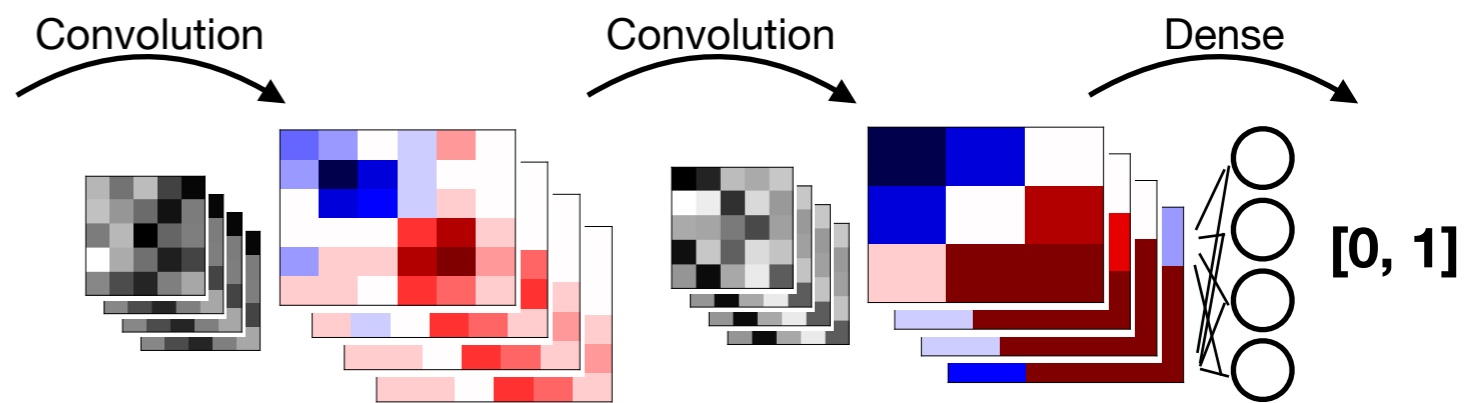


Lorentz Boost

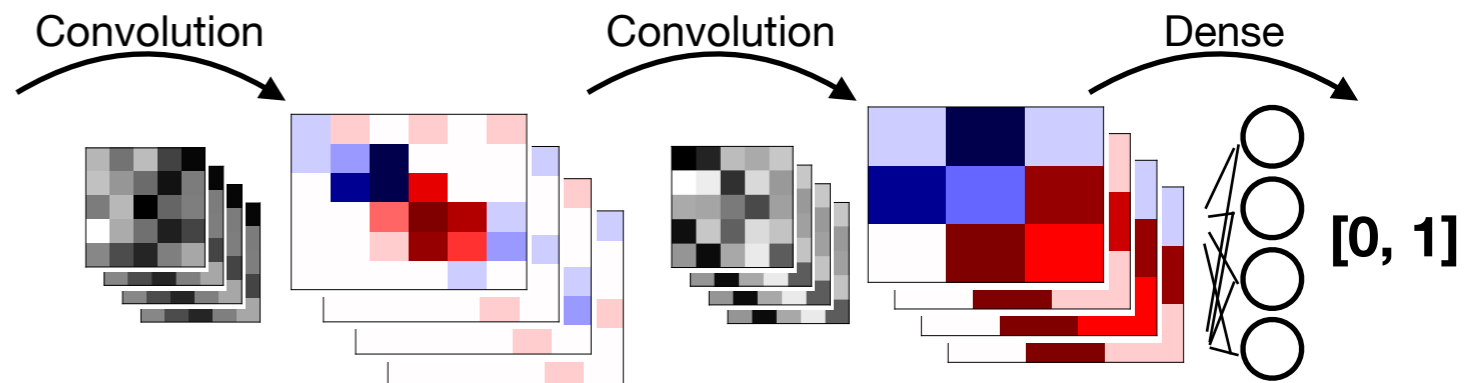
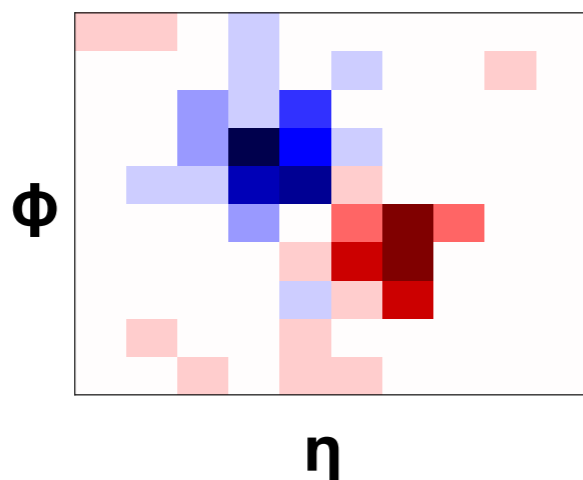
Detector View



Network View

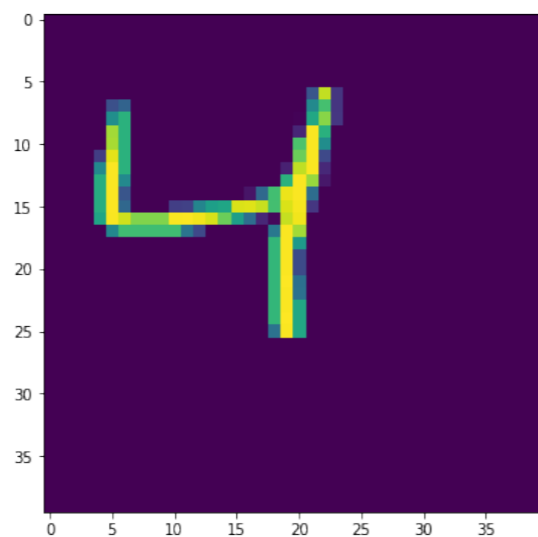


Lorentz Boost

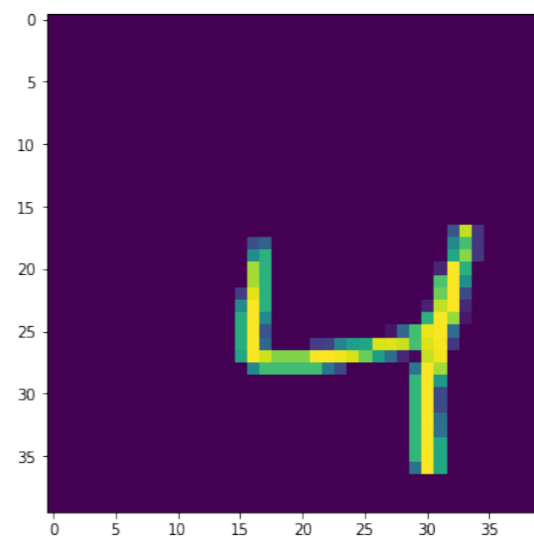


Equivariance by Example

Input Image:



(X,Y) shift



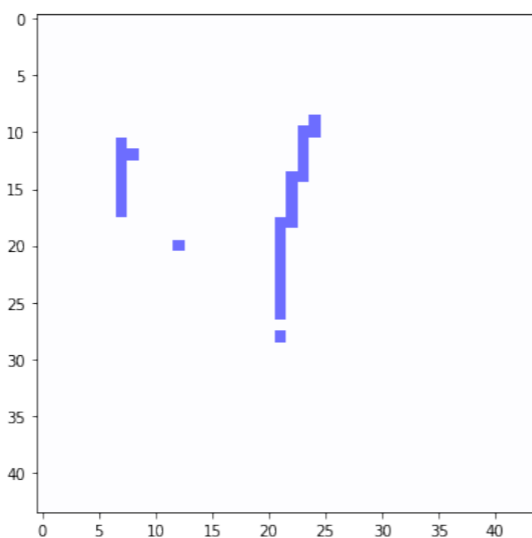
Convolution

0	0	1	0	0
0	0	1	0	0
-1	-1	0	-1	-1
0	0	1	0	0
0	0	1	0	0

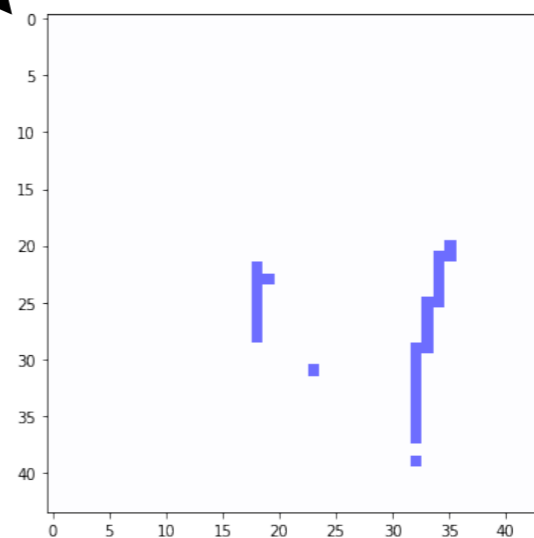
Convolution

0	0	1	0	0
0	0	1	0	0
-1	-1	0	-1	-1
0	0	1	0	0
0	0	1	0	0

Convolution Response:

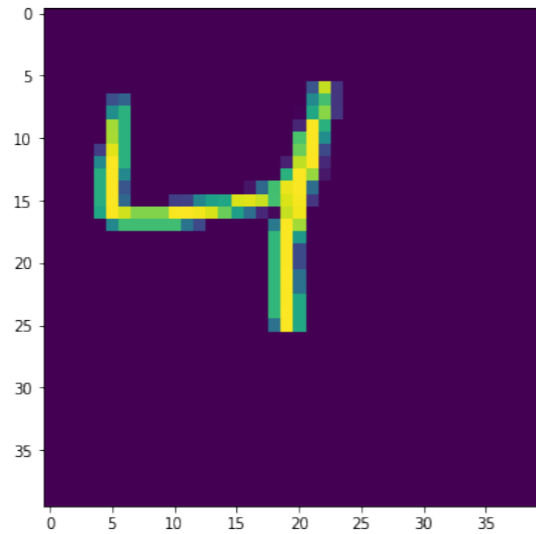


(X,Y) shift

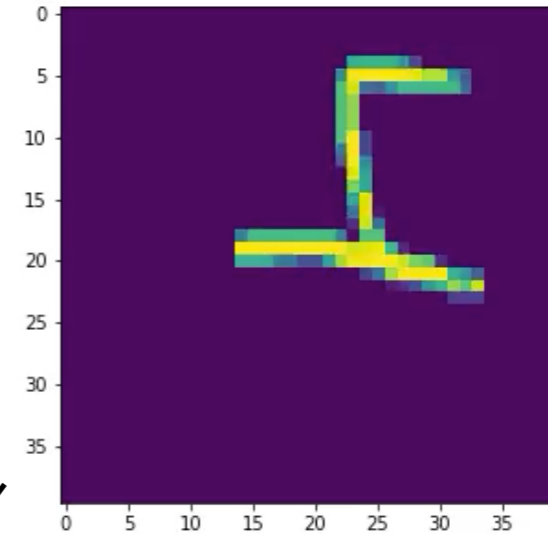


~~Equivariance~~ by Example

Input Image:



Rotation



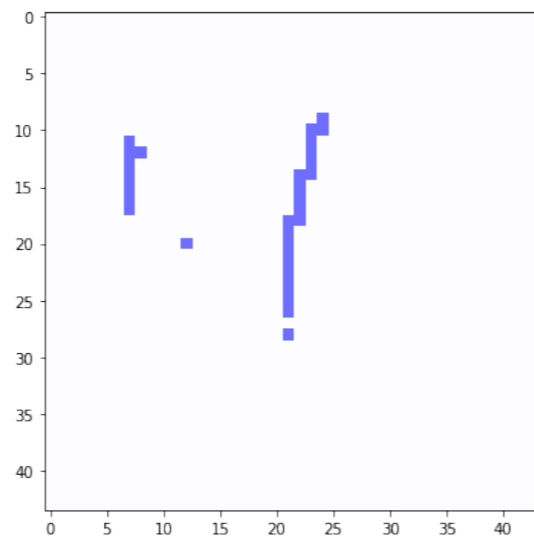
Convolution

0	0	1	0	0
0	0	1	0	0
-1	-1	0	-1	-1
0	0	1	0	0
0	0	1	0	0

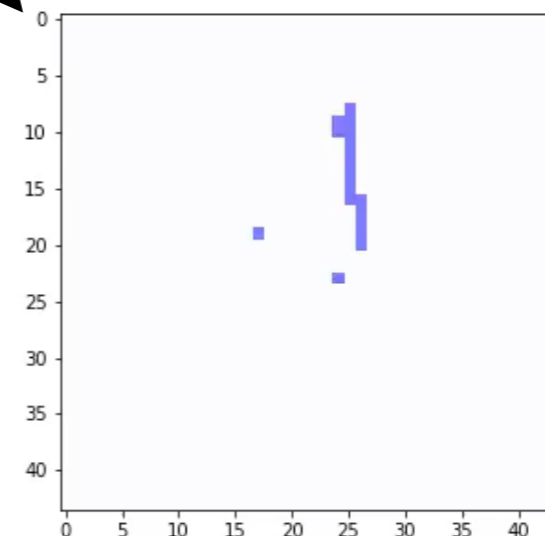
Convolution

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0	0	1	0	0
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Convolution Response:

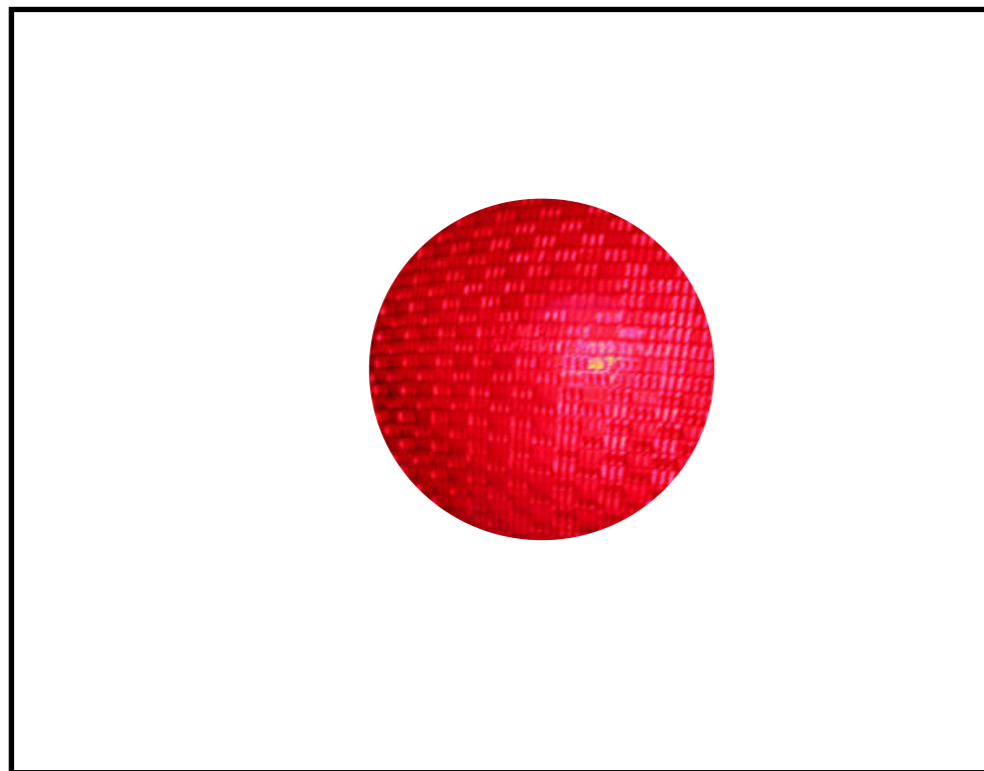


???



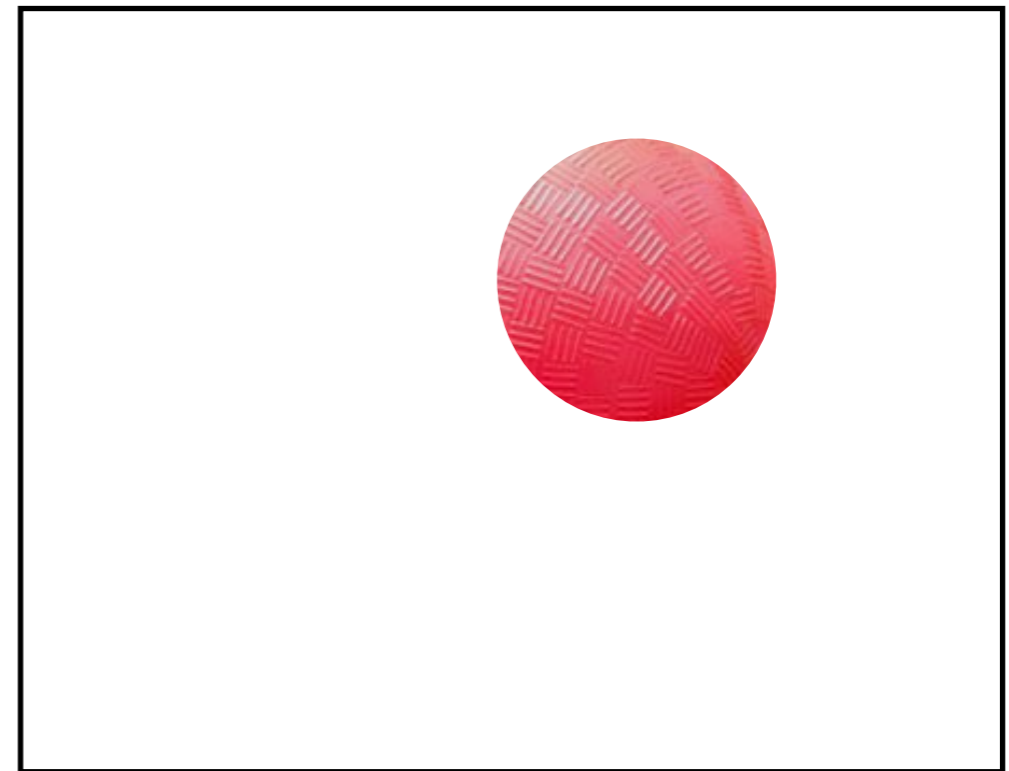
Why Equivariance?

Example: Categorization → Want *Invariant* Response



Invariant Feature
Detector

“Red Ball”

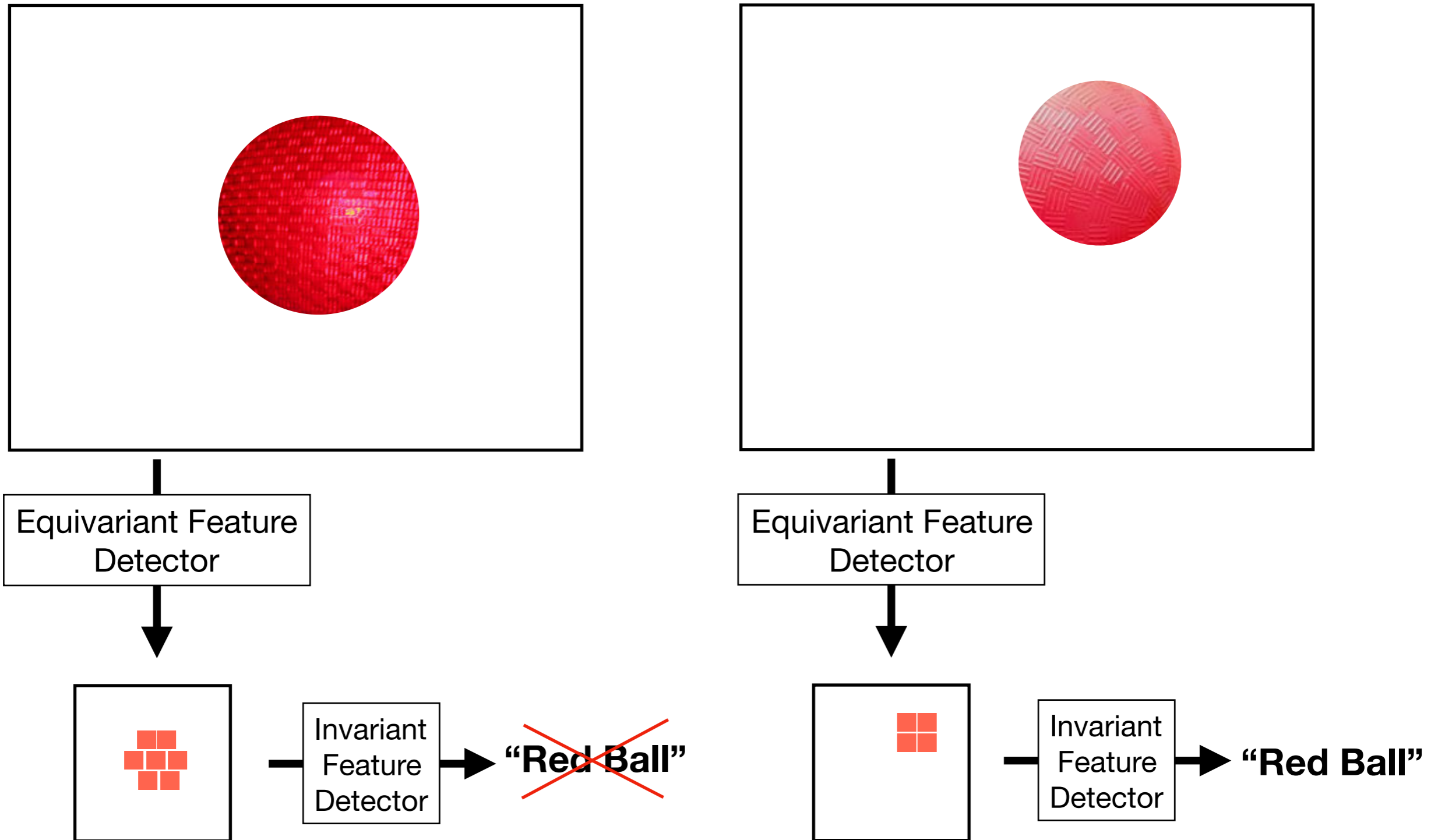


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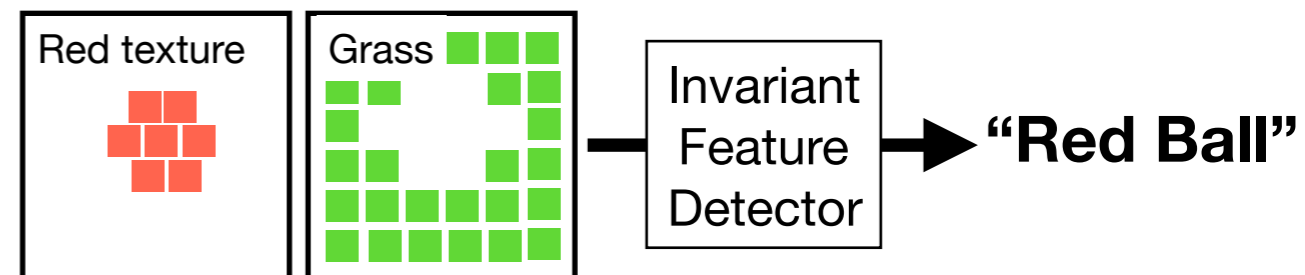
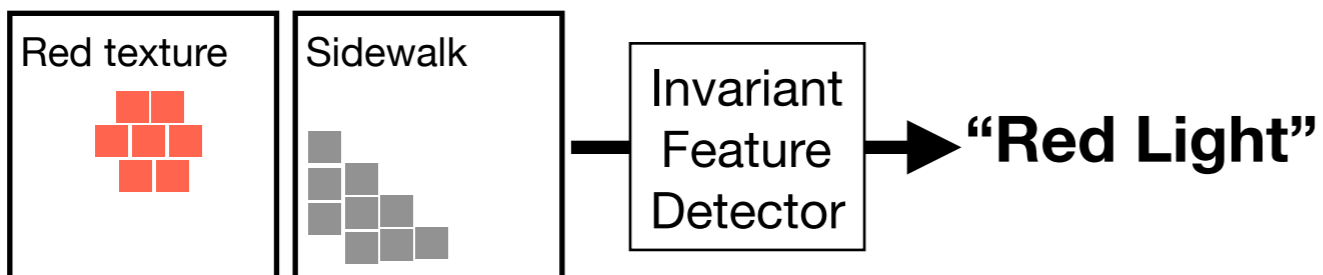
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Equivariant Feature Detector

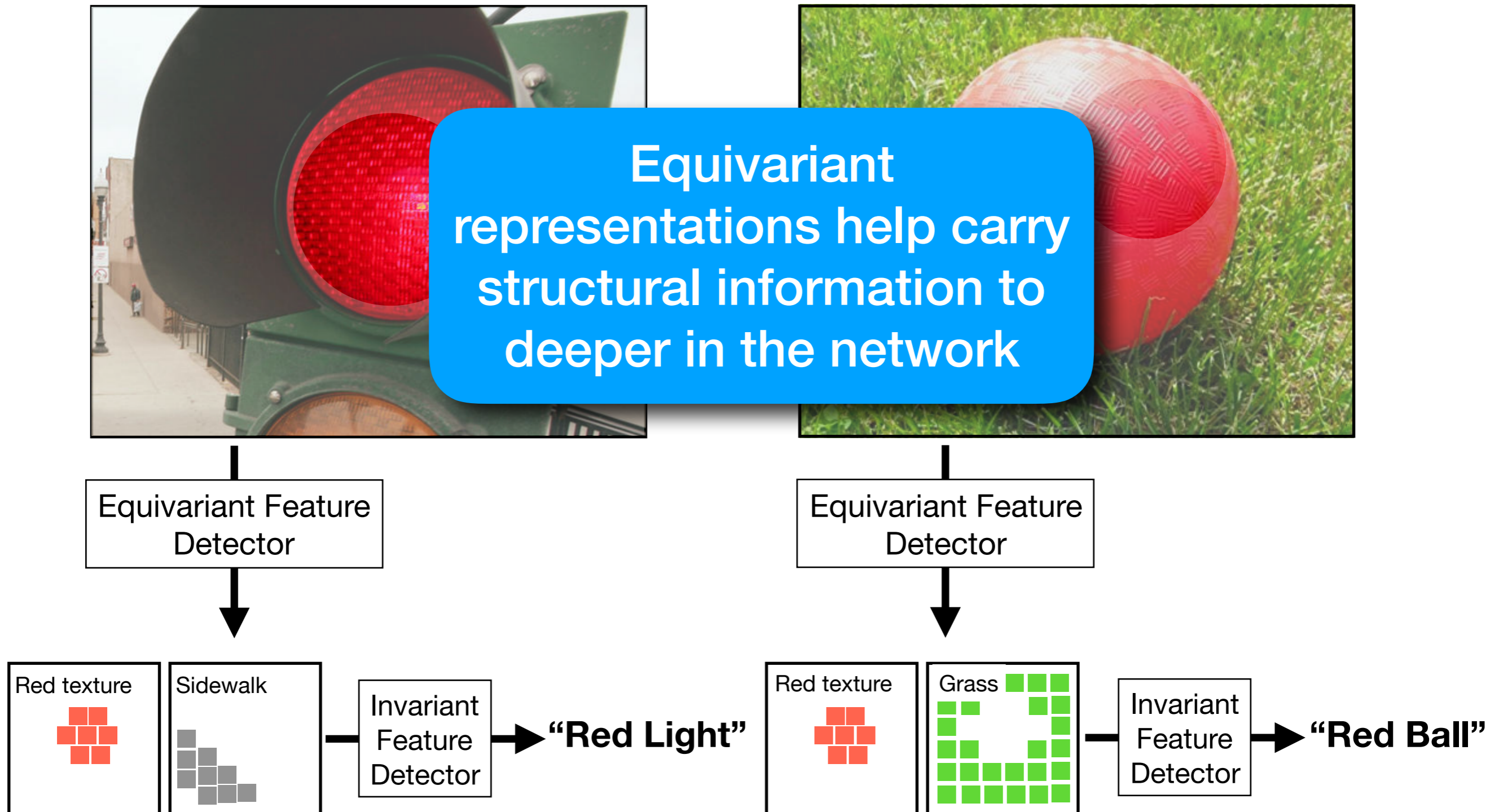


Equivariant Feature Detector

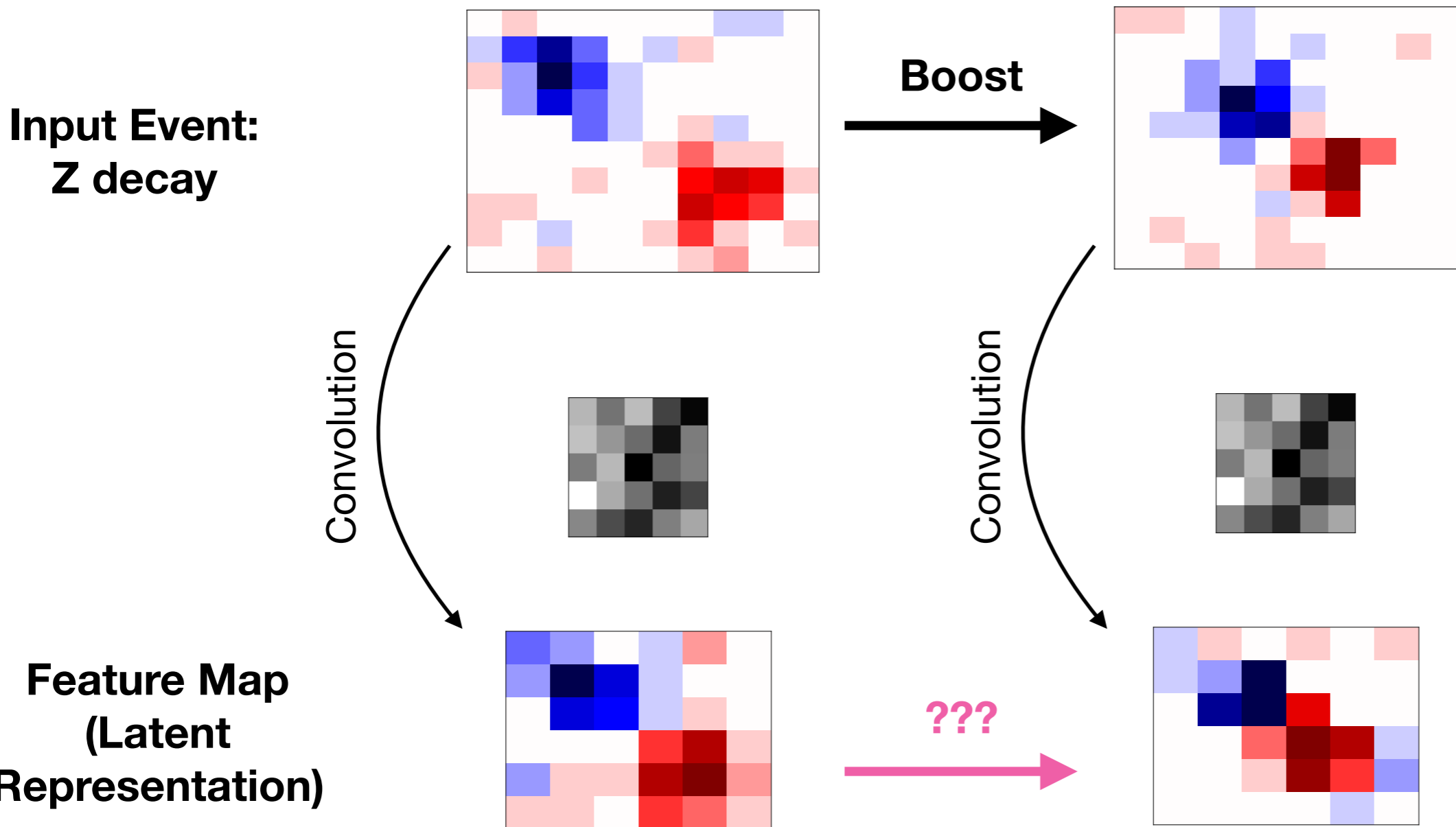


Why Equivariance?

Example: Categorization → Want *Invariant* Response



Equivariance for Jets?

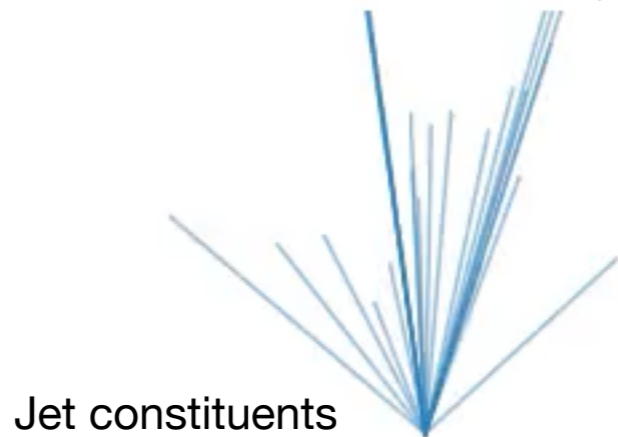


Group Convolutions

Warm up: SO(3) convolutions

Consider a jet to be a function on the 2-Sphere:

$$j(\theta, \phi) = \sum_i E_i \delta(\theta - \theta_i) \delta(\phi - \phi_i)$$
$$\approx \sum_{\ell, m}^{\ell_{\max}} a_{\ell m} Y_{\ell m}(\theta, \phi)$$

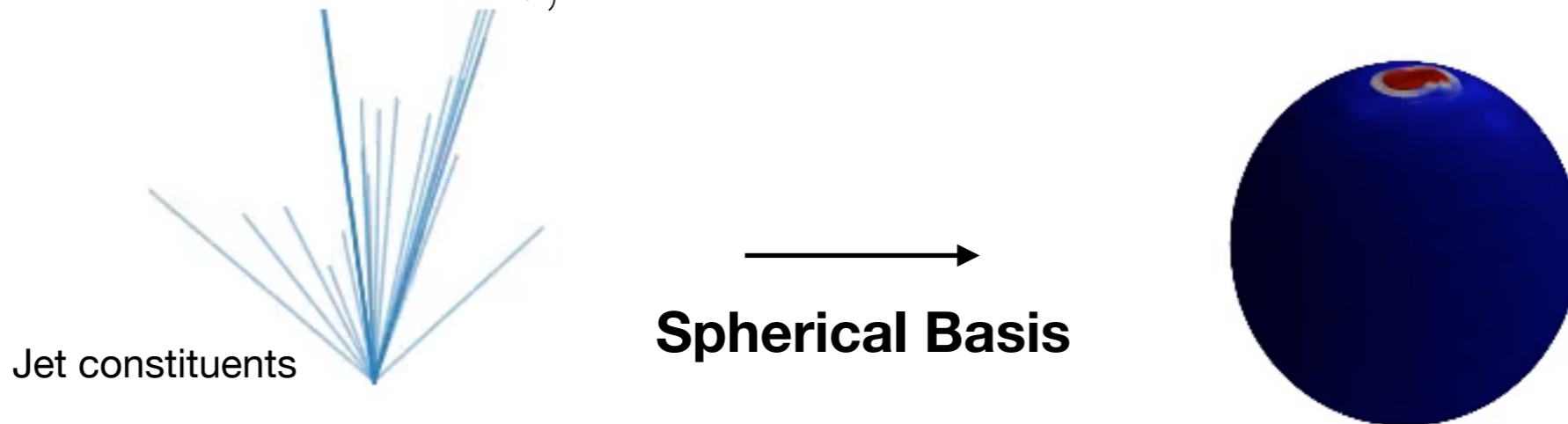


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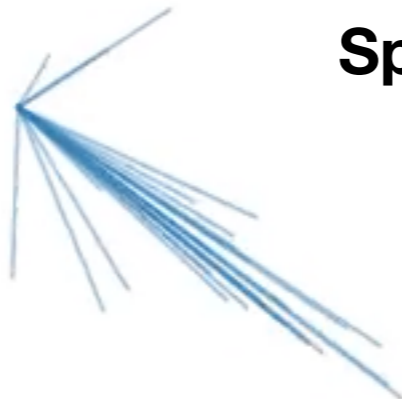
Group Convolutions

Warm up: SO(3) convolutions

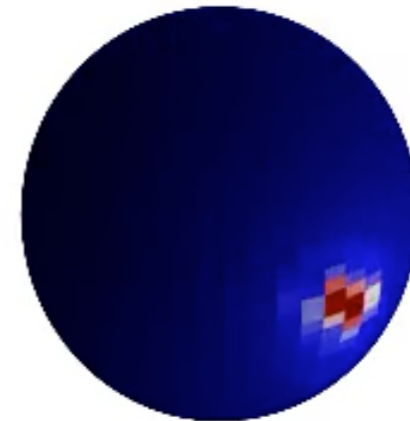
Consider a jet to be a function on the 2-Sphere:

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Jet constituents



→
Spherical Basis

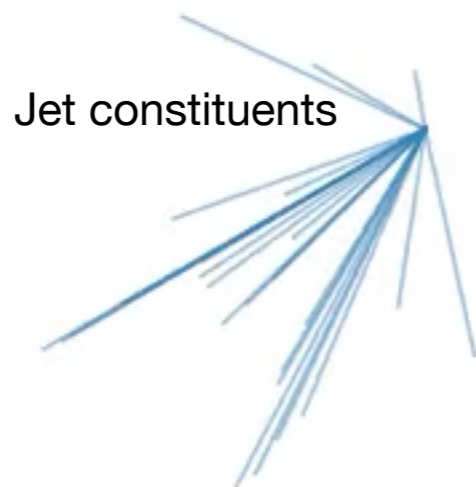


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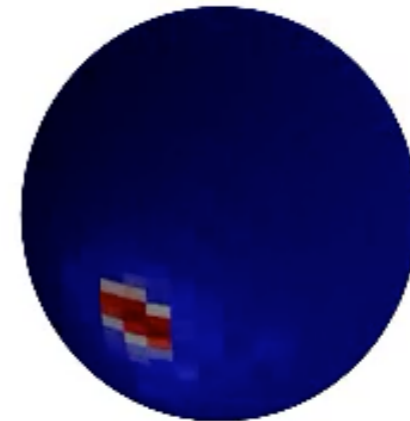
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Jet constituents



Spherical Basis



Group Convolutions

Warm up: $SO(3)$ convolutions

Construct an arbitrary (learnable) linear combination of spherical harmonics (i.e., a **filter**):

$$\psi(\theta, \phi) = \sum_{\ell, m}^{\ell_{\max}} b_{\ell m} Y_{\ell m}(\theta, \phi)$$

Projections are just a number:

$$\langle \psi | j \rangle \in \mathbb{C}$$

$$[\psi \star j](R) = \left\langle \begin{array}{c} \text{Spherical Harmonic} \\ \text{Projection} \end{array} \middle| \begin{array}{c} \text{Input} \\ \text{Projection} \end{array} \right\rangle$$

But if we consider the projection **at all possible orientations**:

$$[\psi \star j](R) := \langle \psi | L_R j \rangle, R \in SO(3)$$

$$[\psi \star f] : SO(3) \rightarrow \mathbb{C}$$

Group Convolutions

Warm up: $SO(3)$ convolutions

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Group Convolutions

Warm up: SO(3) convolutions

In practice, can either rotate the “input”, or the “filter”:

$$\langle \psi | L_R j \rangle = \langle L_{R^{-1}} \psi | j \rangle$$

Where we use the Wigner D-Matrices to rotate harmonics:

$$L_R |\ell, m\rangle = \sum_{m'} \mathcal{D}_{mm'}^\ell(R) |\ell, m'\rangle$$

This allows us to build deeper networks,
by applying rotations to internal representations.

See also: [arxiv:1801.10130](https://arxiv.org/abs/1801.10130), spherical CNNs

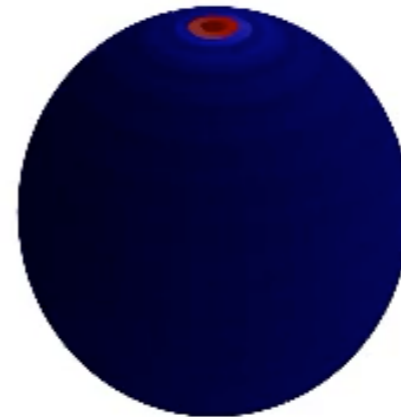
Boost Equivariance

How does this representation transform with an arbitrary boost?

Constituents under boost:



Harmonics under boost:



Problem 1: Rotations leave particle energy invariant!

Problem 2: Rotations cannot mix different l-modes

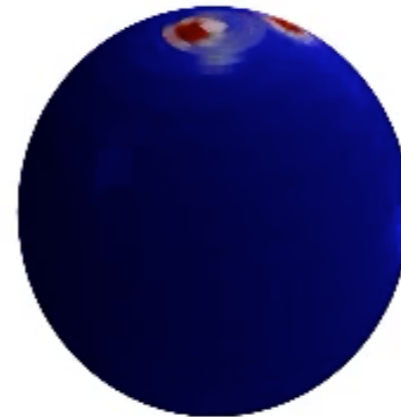
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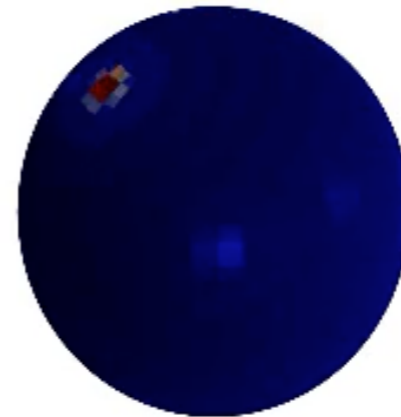
Boost Equivariance

How does this representation transform with an arbitrary boost?

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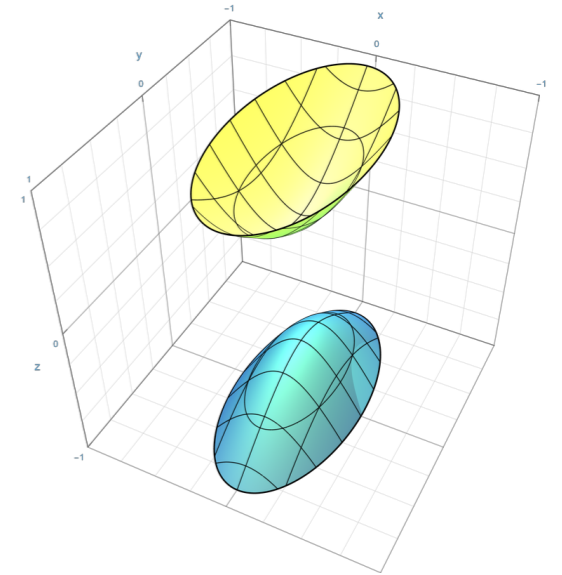
Problem 1: Rotations leave particle energy invariant!

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Spacetime Observables

There is a unitary representation for the Lorentz group, for functions on Minkowski hyperboloid:

$$p_{hyp} = (m \cosh(\xi), \vec{p}(\theta, \phi))$$



As before, write observations as deltas:

$$j(\theta, \phi) \rightarrow j(\xi, \theta, \phi) = \sum_i \delta(\xi - \xi_i) \delta(\theta - \theta_i) \delta(\phi - \phi_i)$$

Spherical harmonics become:

$$Y_{\ell m}(\theta, \phi) \rightarrow \Psi_{N \ell m}(\xi, \theta, \phi)$$

$$\Psi_{N \ell m}(\xi, \theta, \phi) = \frac{1}{M_\ell} \Pi_\ell(N, \xi) Y_{\ell m}(\theta, \phi) \quad N \in [0, \text{inf})$$

Relativistic Filters

As before, we can construct arbitrary, **learnable** filters:

$$\psi(\xi, \theta, \phi) = \int_0^{N_{\max}} dN \sum_{\ell, m}^{\ell_{\max}} a_{\ell m}(N) \Psi_{N\ell m}(\xi, \theta, \phi)$$

$a_{\ell m}(N)$
must be
sampled
discretely

The input delta functions make it easy to compute projections:

$$j(\xi, \theta, \phi) = \sum_i \delta(\xi - \xi_i) \delta(\theta - \theta_i) \delta(\phi - \phi_i)$$

$$\langle N\ell m | j \rangle = \sum_i \Psi_{N\ell m}(\xi_i, \theta_i, \phi_i)$$

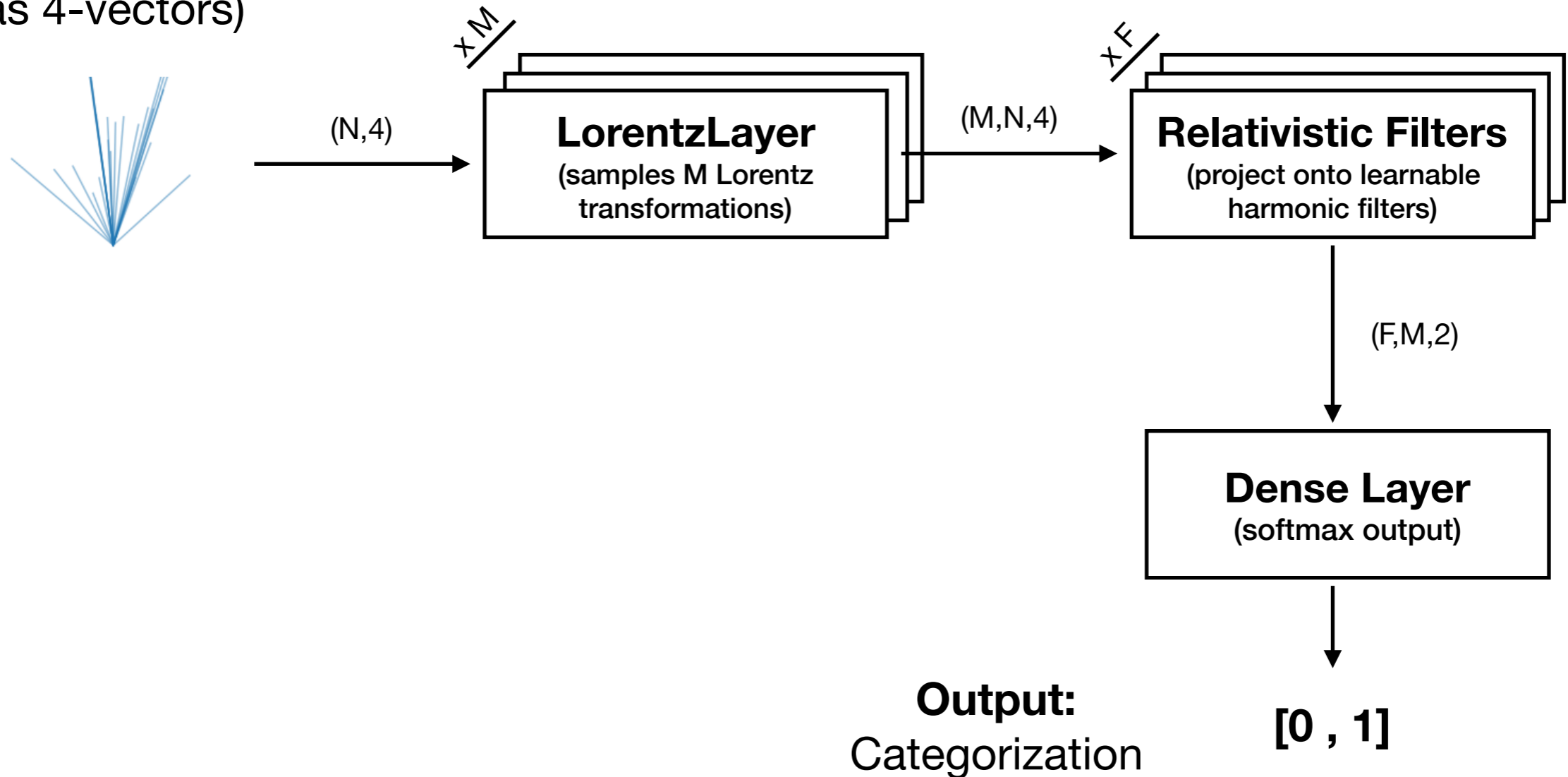
And, since we know how to apply Lorentz transformations to an arbitrary jet, **we can evaluate relativistic convolutions:**

$$[\psi \star j](\Lambda) := \langle \psi | L_{\Lambda} j \rangle ; \Lambda \in SO(3, 1)^+$$

Single Layer Network

(work only with collinear boost subgroup)

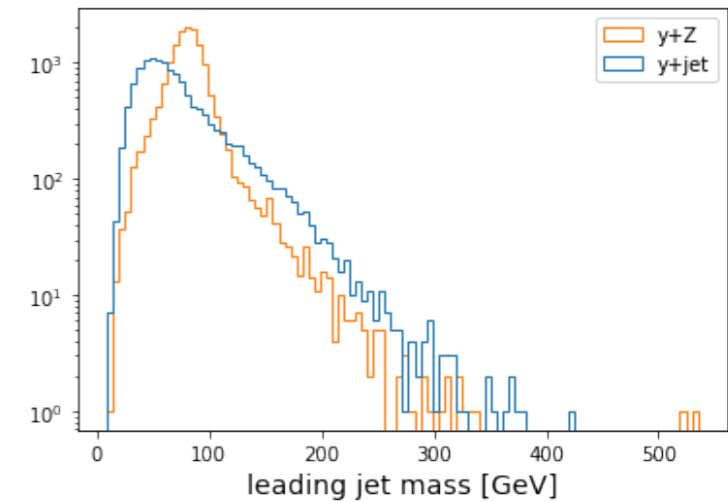
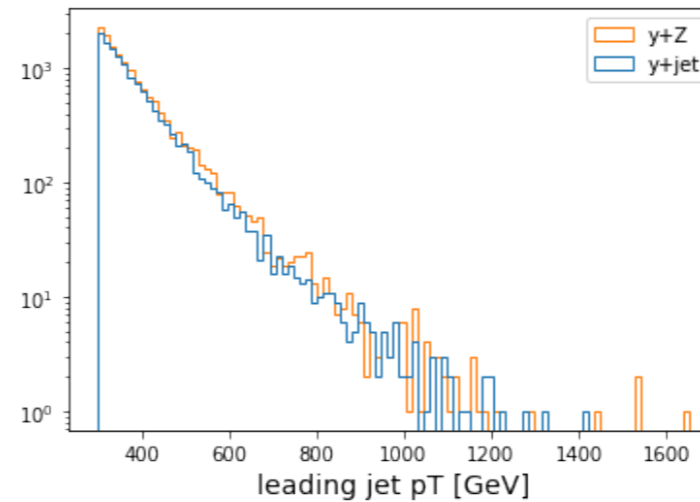
Input:
Jet constituents
(as 4-vectors)



Benchmark Test

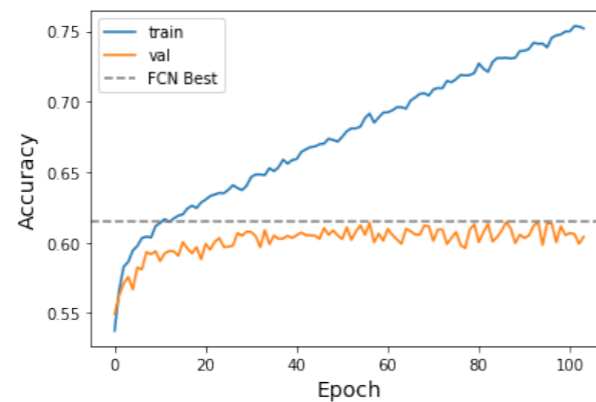
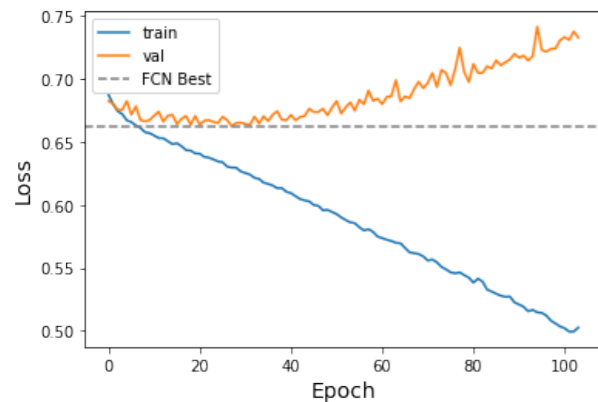
Task: discriminate leading jets from $\gamma+Z$ (signal) and γ +jet (background)

- AntiKt(R=1.0) clustering after hadronization
- Limit inputs to 32 leading-pT constituents
- $pT(\text{jet}) > 300$ GeV



Network 1: Fully Connected
4 layers, 90k parameters

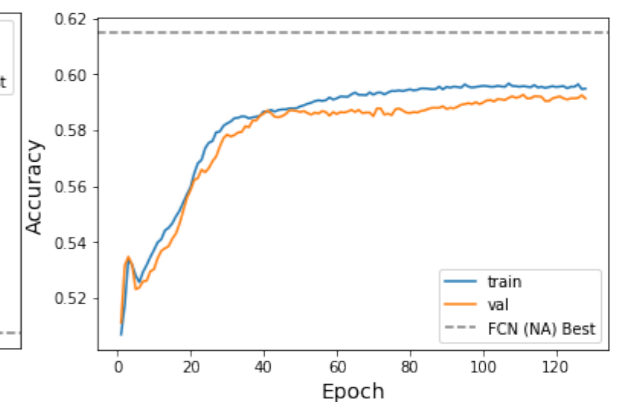
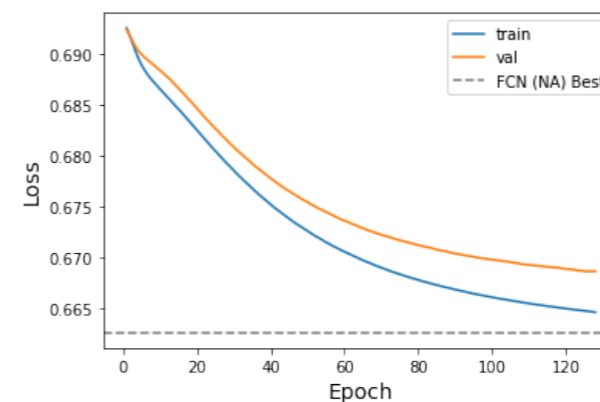
Accuracy: ~62%



Network 2: Relativistic

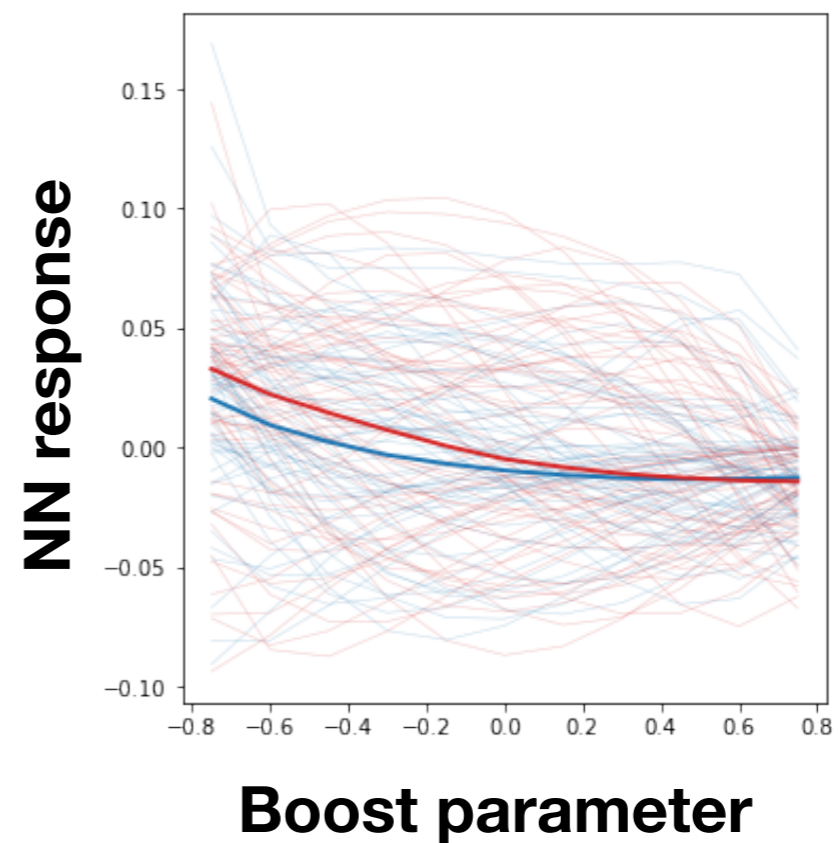
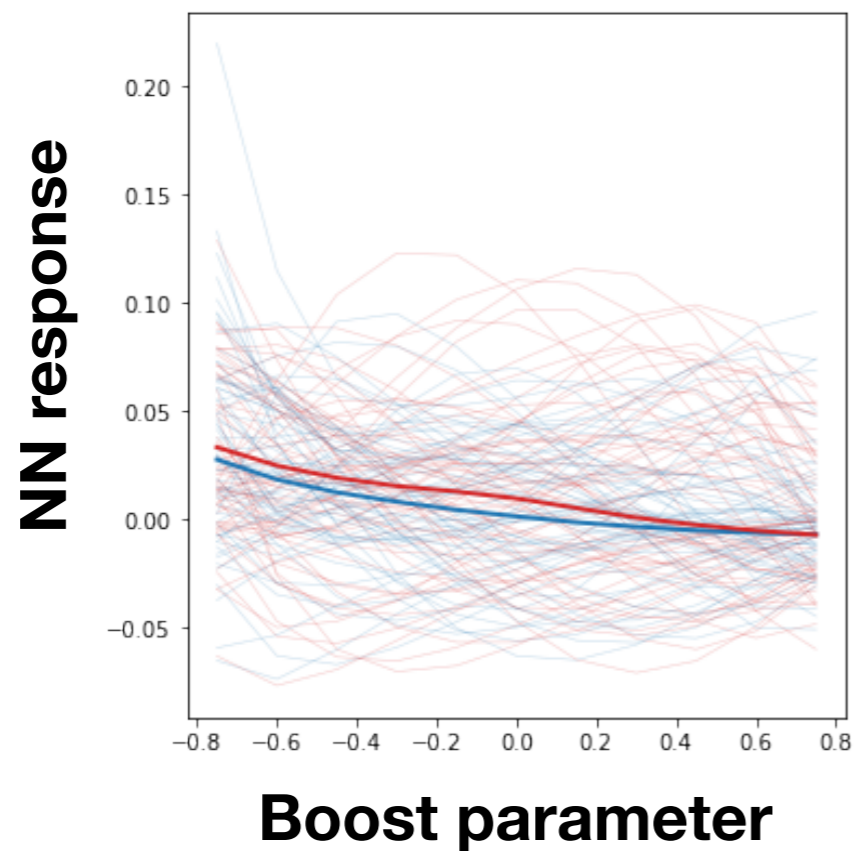
Harmonic Net ($l_{\text{max}}=0$), 596 parameters

Accuracy: ~59%



Output of Harmonic Layers

— Signal Jets
— BG Jets



Conclusions

- A first attempt at enforcing equivariance relevant for jet physics
- Currently only works for **single-layer networks**....
 - But should generalize to N-layer networks soon!
- Naive benchmark shows nearly-comparable performance to naive models
 - Need to build deeper networks to do state-of-the-art comparisons

Thank you!

