Visualization of Output Predictions The output predictions of our network will be a distribution defined on a equi-volumetric grid on $SO(3)$ [15]. Specifically, a rotation is represented as a colored point on a Mollweide projection. Using axis-angle representation, the location of the point on the Mollweide projection corresponds to the axis of rotation and the color of the point encodes the angle of rotation [15].

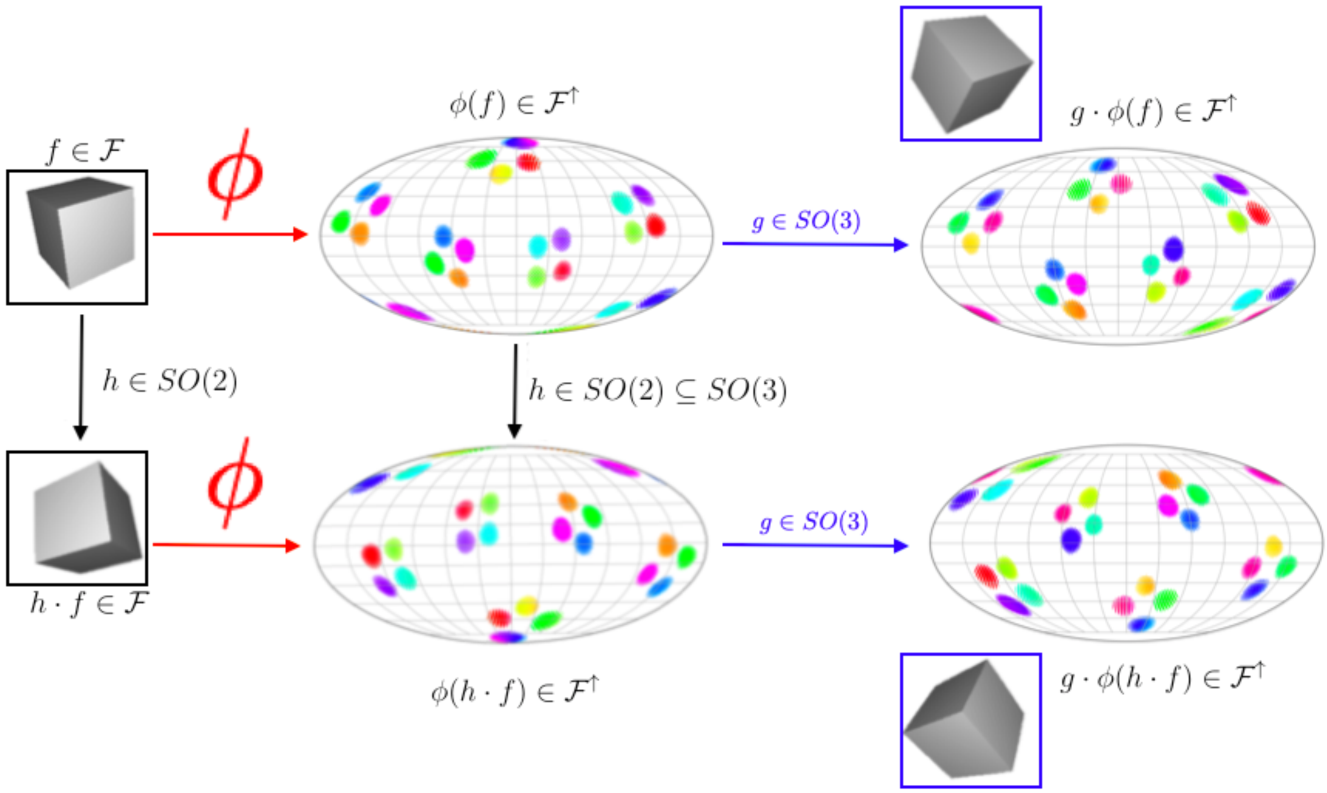

Figure 5: A "virtual" commutative equivarience diagram.

Figure 5 shows a "virtual/holographic" equivarience diagram. Input images (boxed in black) f in the space $\mathcal{F}$ can be rotated in-plane by an element h of $SO(2)$. The neural network (represented by ϕ) takes an image f and builds a three-dimensional model $\phi(f)$. Blue arrows denote the $SO(3)$ action on $\mathcal{F}$. We call this a "virtual/holographic" equivarience condition because the rotation $g \in SO(3)$ acts on the "hologram" $\phi(f)$ that the model creates *not* the input images. The cubes boxed in blue are "virtual", they are what the model would return if the input f was rotated by an element $g \in SO(3)$. Note that the model is able to capture the symmetries of the cube in very fine detail.

Fiber Interpretation The pioneering paper [5] was the first to observe the importance of decomposing signals into fibers instead of stacks of feature maps. Specifically, symmetry transformations act on features by permuting the fibers of signals.

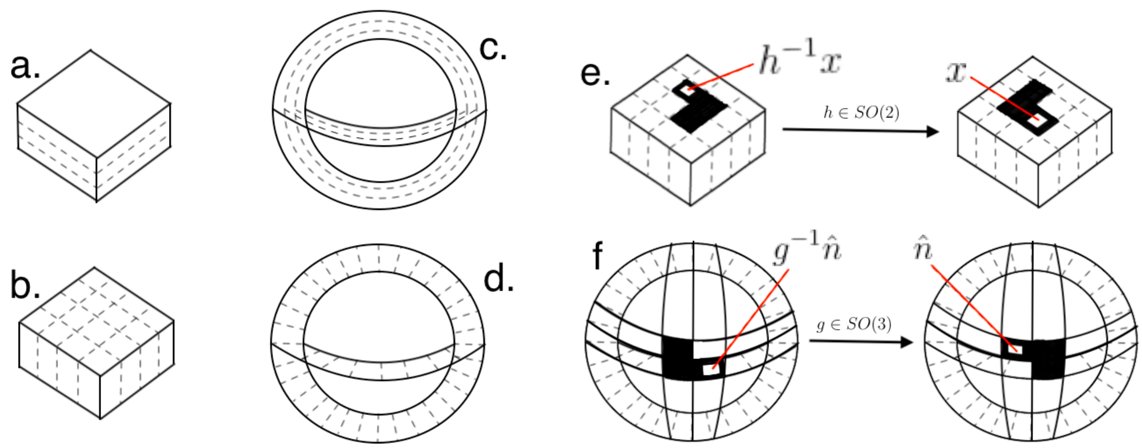

Figure 6: Feature Map and Fiber Decomposition for planar and spherical signals, inspired by [5]

Our results can be best understood in terms of maps between two spaces with fibers. Specifically, we map signals defined on the plane $\mathbb{R}^2$ to signals defined on the sphere S^2. In figure 6 panel a, a signal $f : \mathbb{R}^2 \to \mathbb{R}^d$ is decomposed into a stack of feature maps. In panel b, a signal $f : \mathbb{R}^2 \to \mathbb{R}^d$ is decomposed into a bundle of fibers. Figure 6 Panel c shows a signal $g : S^2 \to \mathbb{R}^{d'}$ is decomposed into a stack of feature maps. In panel d, a spherical signal $g : S^2 \to \mathbb{R}^{d'}$ is decomposed into a bundle of fibers.

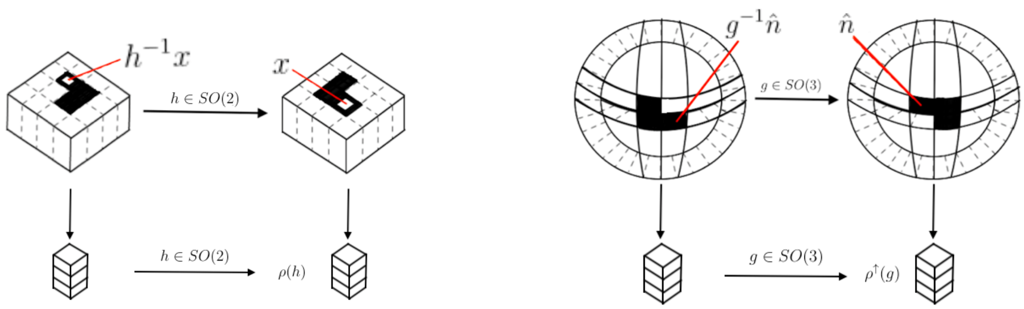

Figure 7: Fiber Transformation for planner and spherical signals, inspired by [5]

The group $SO(2)$ acts on planar signals by rotating the plane and permuting fibers. The planner fiber group forms a representation of $SO(2)$. The group $SO(3)$ acts on spherical signals by rotating the sphere and permuting fibers. The spherical fiber group forms a representation of $SO(3)$. This is shown in panels e and f in figure 6, respectively. Our proposed induction/restriction layer is the most general map from planar signals to spherical signals (i.e. monocular 2D to 3D reconstruction) that respects the correct fiber transformations of planner and spherical signals.