Deep Learning Initialized Phase-Retrieval

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https://sunju.org/pub/NIPS20-WS-DL4FPR.pdf

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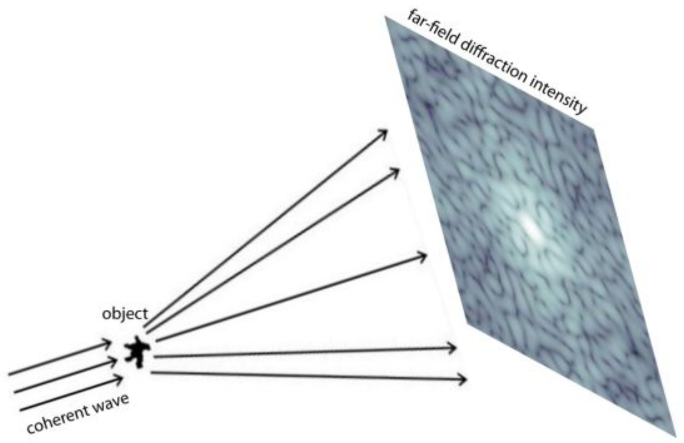
Driven to Discover

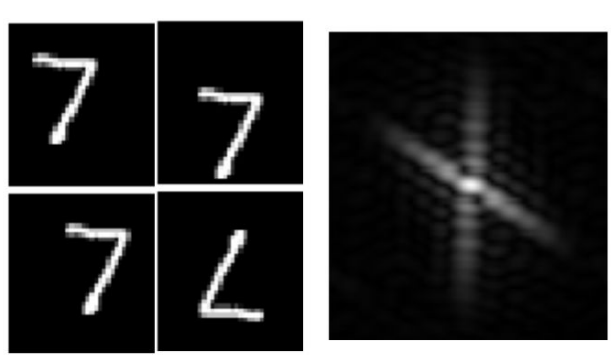
Neural Information Processing Systems

Fourier Phase-Retrieval

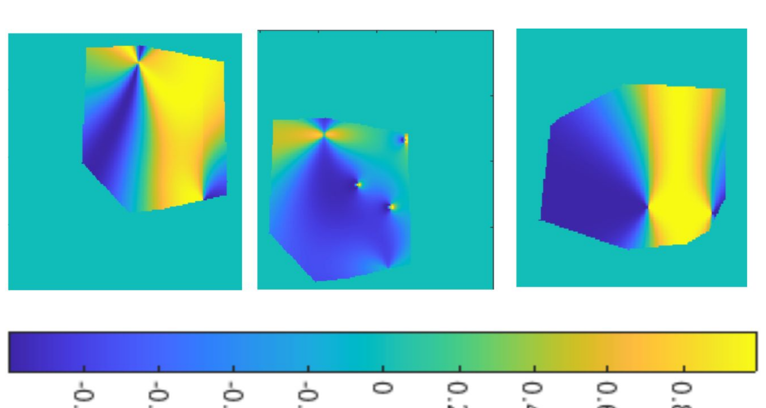


Fourier-magnitude of the image is captured. Phase is lost. We have to recover the original image.

Symmetries in F-PR

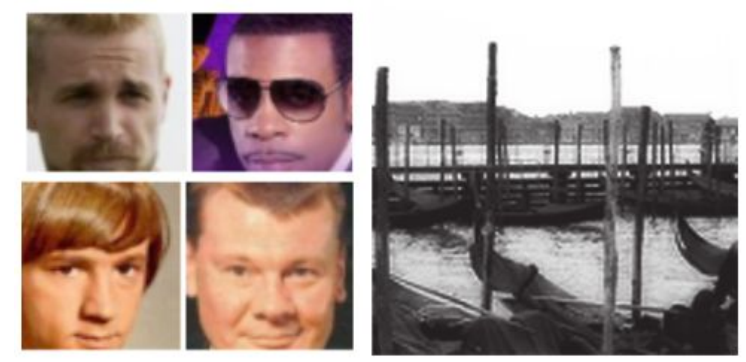


All the ***shifted*** and ***flipped*** copies of an image have the same Fourier-magnitude. Hence the problem is ill-posed.



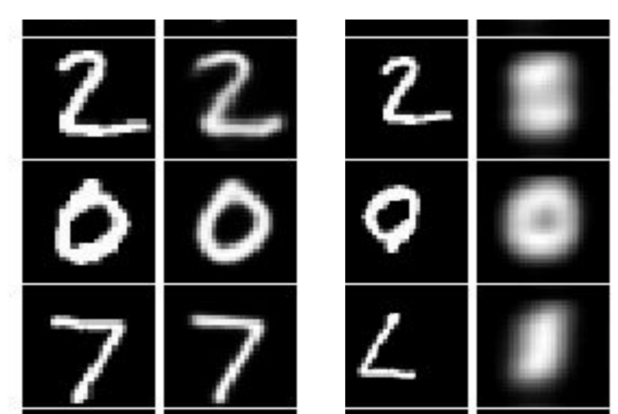
This problem occurs in practical data for PR. Fig. simulated images of crystal structure in CDI

Bias in popular image datasets



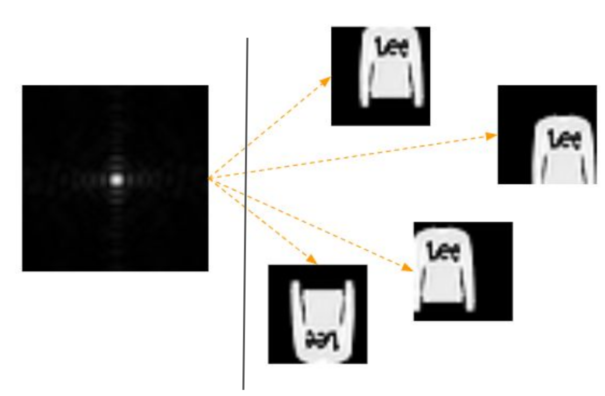
Images are naturally centred and oriented. Hence, they do not reflect the difficulty of practical PR

Let's create a realistic PR dataset



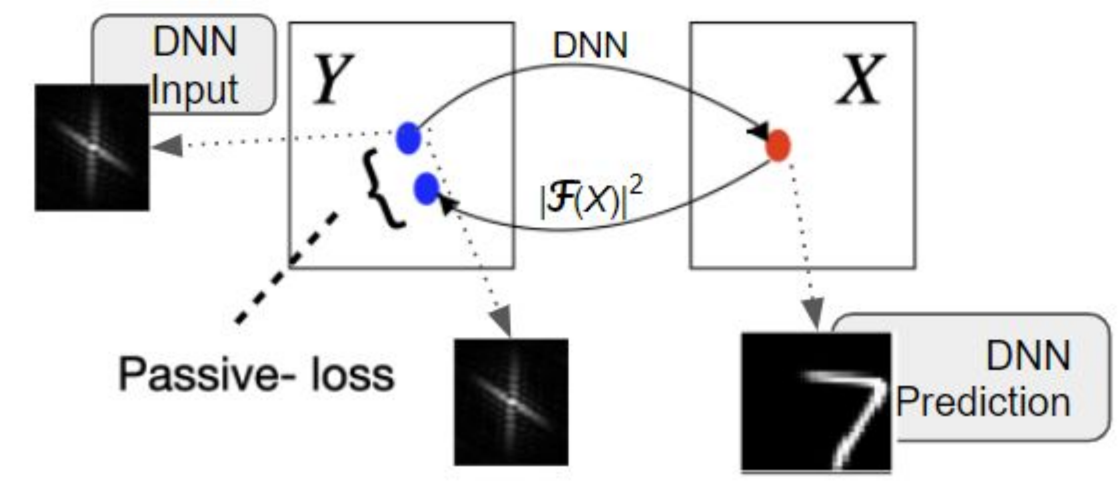
DNN fails to learn when trained on a dataset containing symmetries

Why these methods fail?



One input to DNN corresponds to multiple outputs far away in space. DNN is forced to approximate a highly oscillatory function

Passive Loss

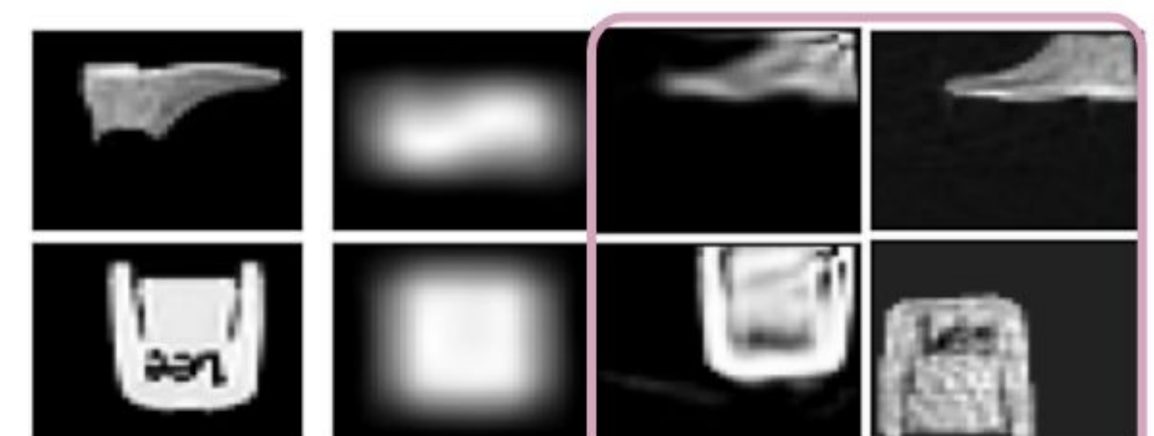


$$\min_{\boldsymbol{W}} \sum_i \ell\left(\boldsymbol{Y}_i, |\mathcal{F} \circ DNN_{\boldsymbol{W}}(\boldsymbol{Y}_i)|^2\right)$$

Forward operator: $\boldsymbol{Y} = |\mathcal{F}(\boldsymbol{X})|^2$

A new loss function which is invariant to symmetries
Enables DNN to learn a simple function.

Results



Ground Truth | Naive DNN | Passive DNN | Passive Refined

Table 1: MSE error

	MSE
ALM	0.312
HIO	0.441
Passive DNN	0.266
Passive Refined	0.187
Naive DNN	0.492
Naive Refined	0.397
prDeep	0.412