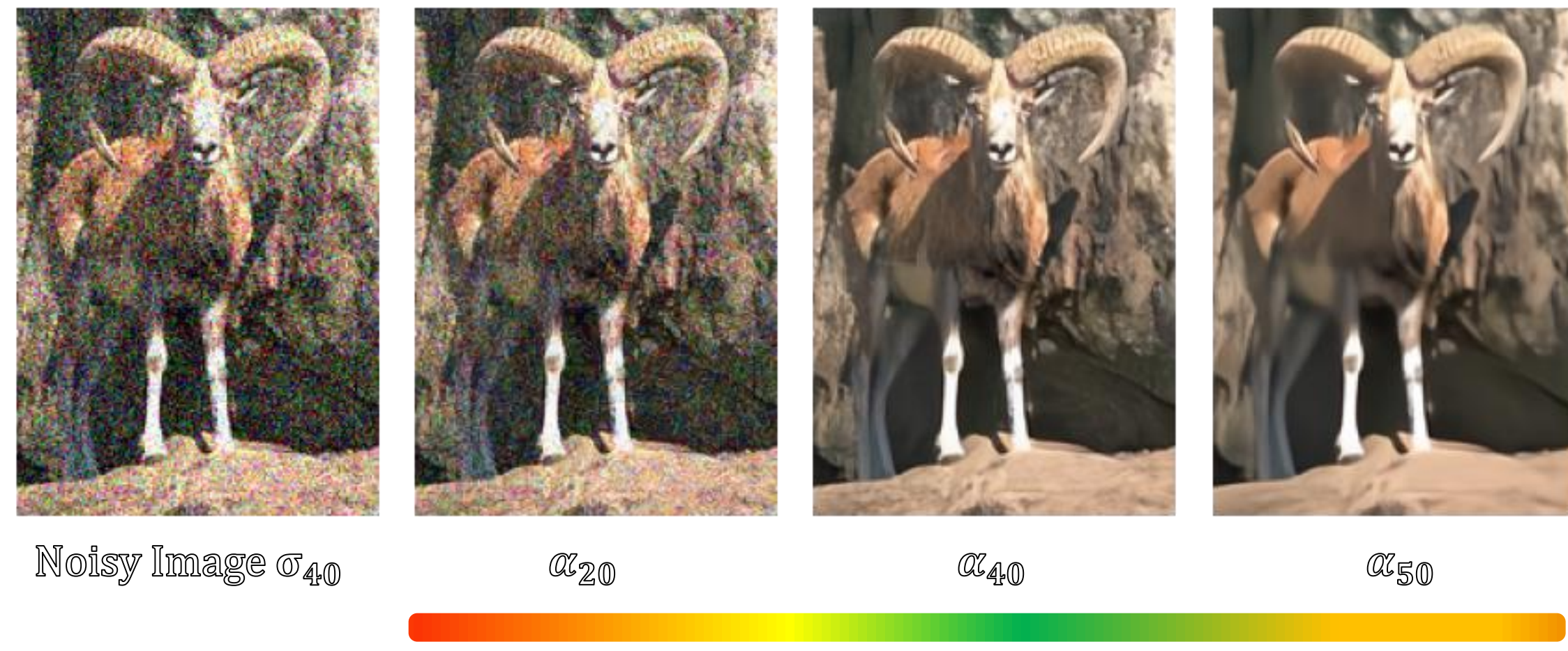




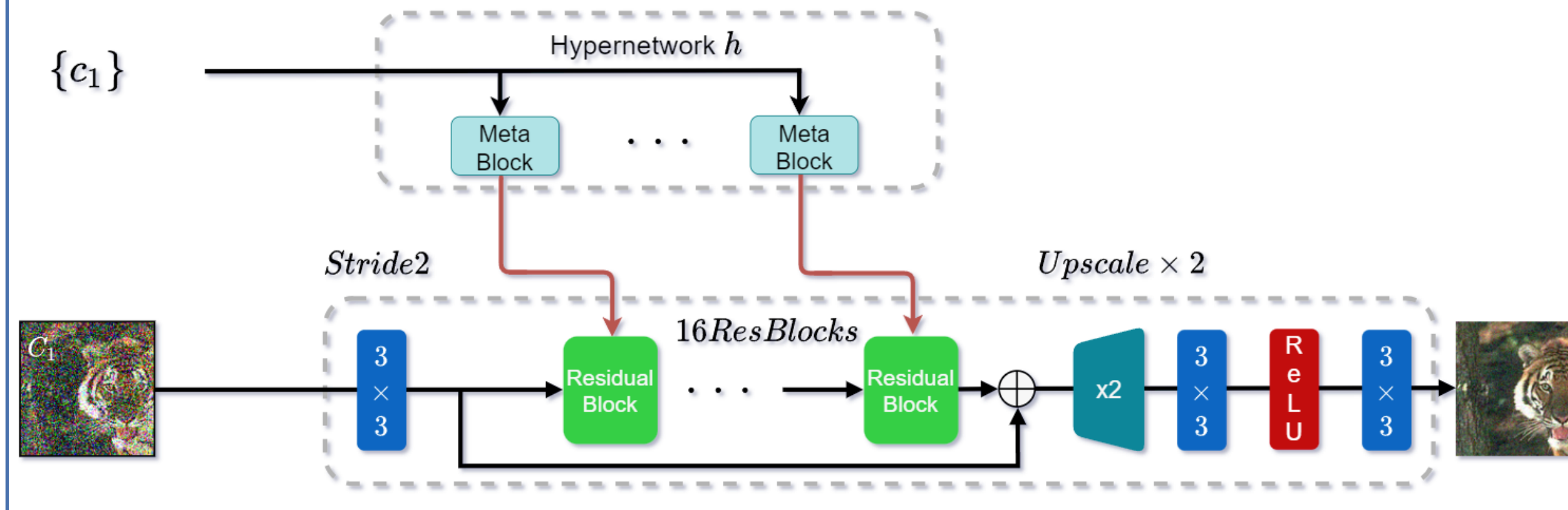
## Introduction

- Goal** Restoring multiple degradation levels
- Tasks** Denoising  
DeJPEG  
Super-Resolution  
Etc..
- Challenge** Achieve a high restoration accuracy while maintaining a compact network



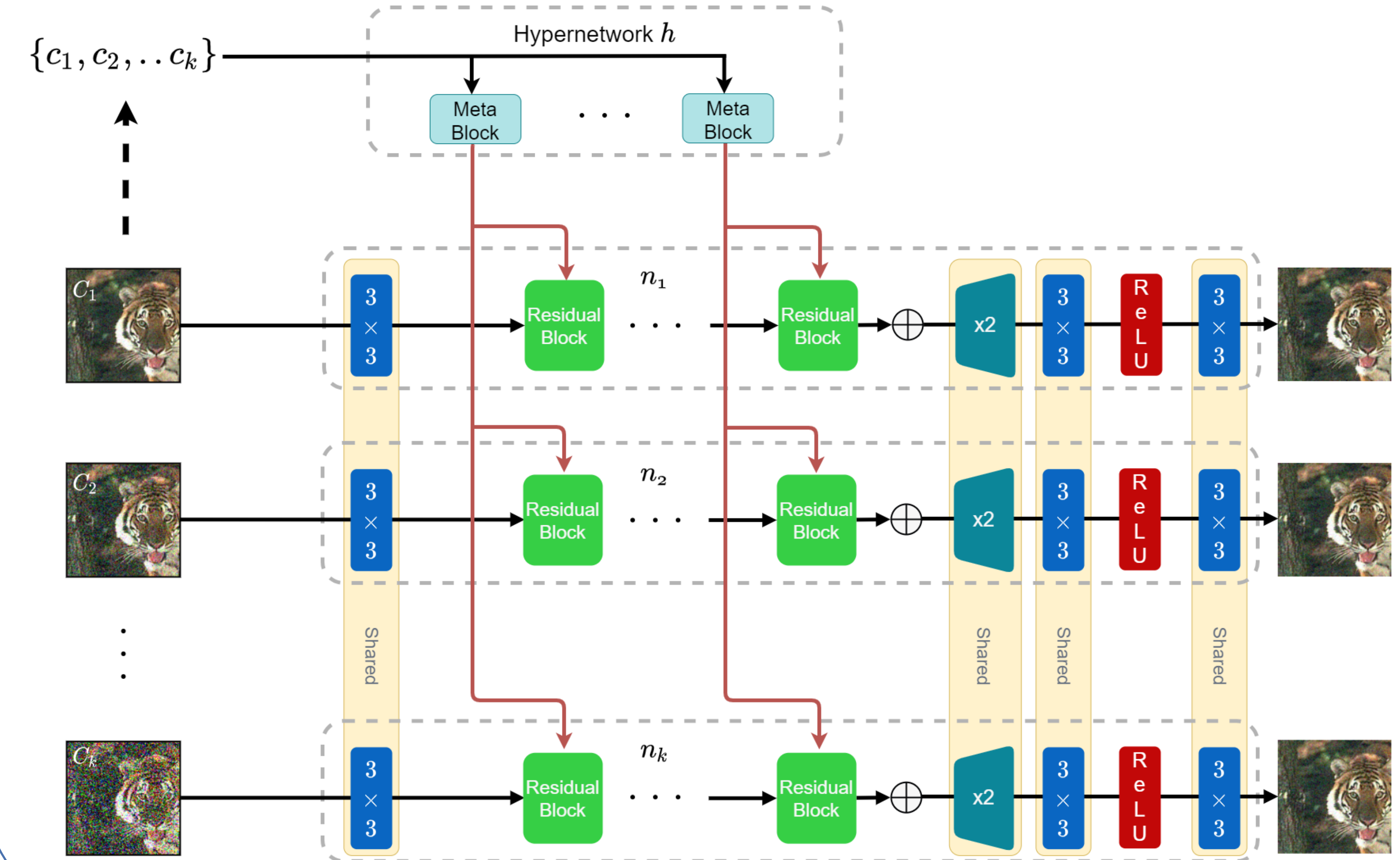
## Key Idea

We introduce a hypernetwork that generates the optimal kernels for an image restoration network, based on the required restoration level given as an input parameter.



## Method

As part of the training process our hypernetwork is optimized with multiple main networks to simultaneously restore images with a variety of degradation levels. The different networks are generated by a scalar multiplication.



## Theory

- Observation:**
- For a given network architecture,  $N_{\theta}(\cdot)$ , there are infinite sets of weights which provide the same or similar output
  - Our method finds a set of weights, each corresponding to a different noise level, such that they are linearly depended.
  - All set of weights are easily generated from one single set by a simple scalar multiplication.
  - $\forall i, j \text{ s.t. } \frac{\theta_i}{\theta_j} \propto \frac{i}{j}$

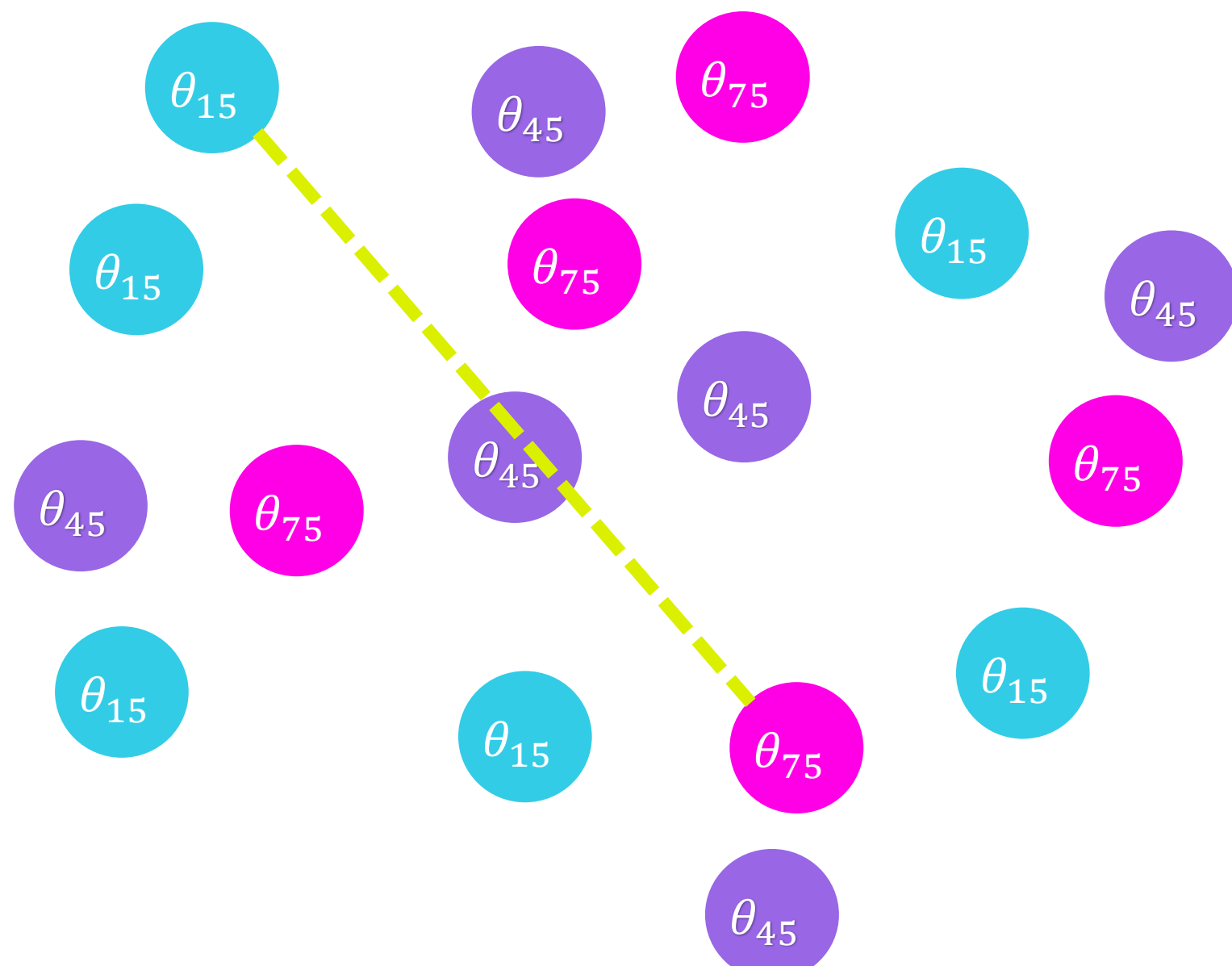
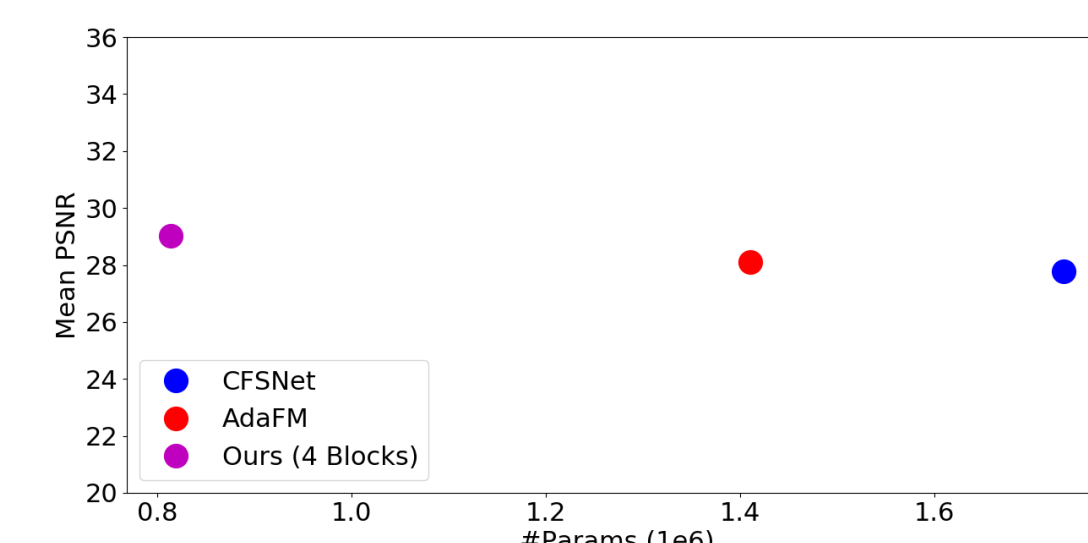


Illustration of the latent space of the weights

## Results

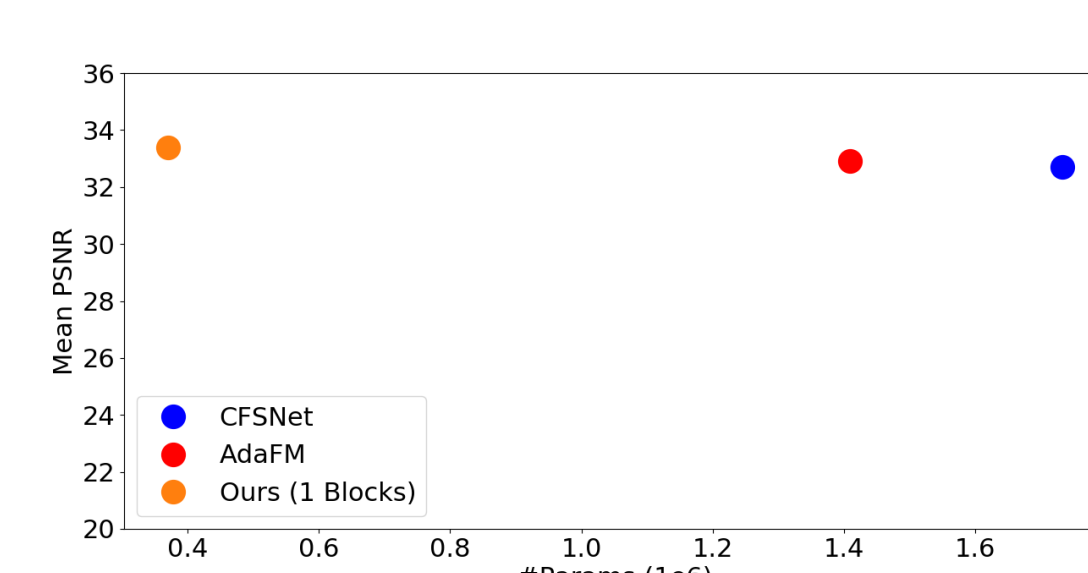
### Denoising

	5	25	45	65	90	Mean
Baseline	40.48	31.42	28.64	27.06	25.73	30.66
Ours	40.39	31.40	28.51	27.06	25.73	30.61



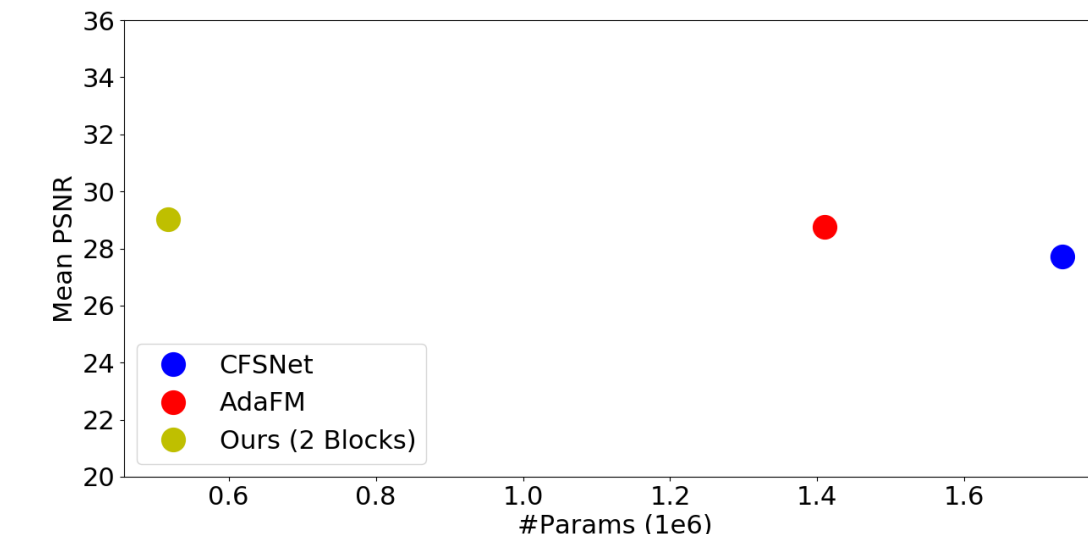
### DeJPEG

	10	30	50	70	80	Mean
Baseline	28.82	32.57	34.40	36.40	38.14	34.06
Ours	28.81	32.56	34.39	36.38	38.09	34.04



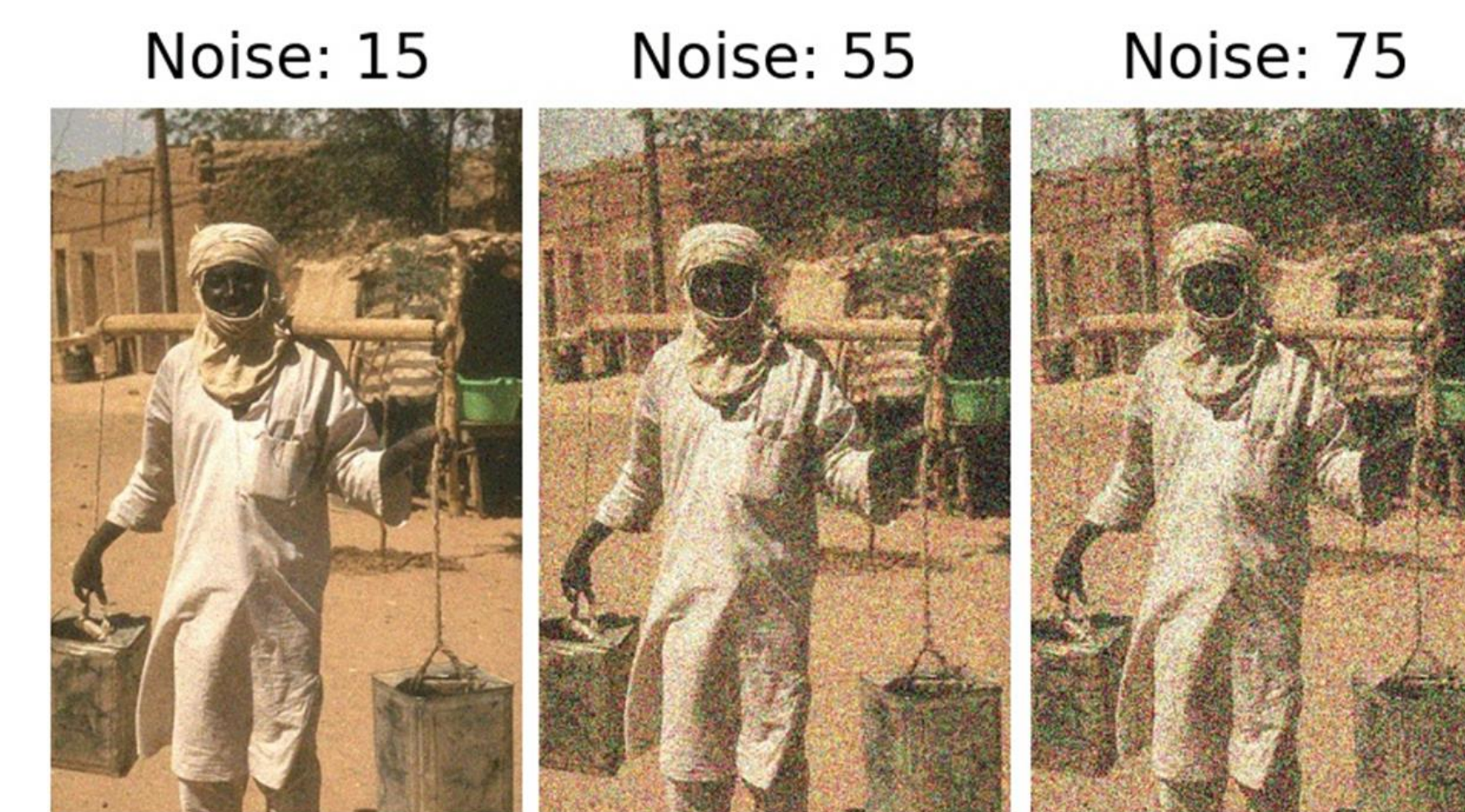
### Super-Resolution

	2	3	4	5	6	Mean
Baseline	36.95	29.86	29.54	25.67	25.06	29.41
Ours	36.71	29.77	29.48	25.63	24.92	29.30



## Qualitative Results

### Denoising



Restored



### DeJPEG

