Single Image Super Resolution (SISR)

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SISR

- Recover/Construct finer detail from Low-Resolution
- Obtain a learned LR to HR Image mapping using Convolutional Neural Network based approach
- Pixel-wise loss minimization between LR & HR images (Mean Square Error).
- PSNR Metric – Peak Signal To Noise Ratio
  - $PSNR = 10 \times \log_{10}\left(\frac{MAX^2}{MSE}\right) = 20 \times \log_{10}\left(\frac{MAX}{\sqrt{MSE}}\right)$
  - $MAX = 255$

Applications of SISR

- Satellite Imaging
- Medical Imaging
- Security Imaging

Classic Interpolation

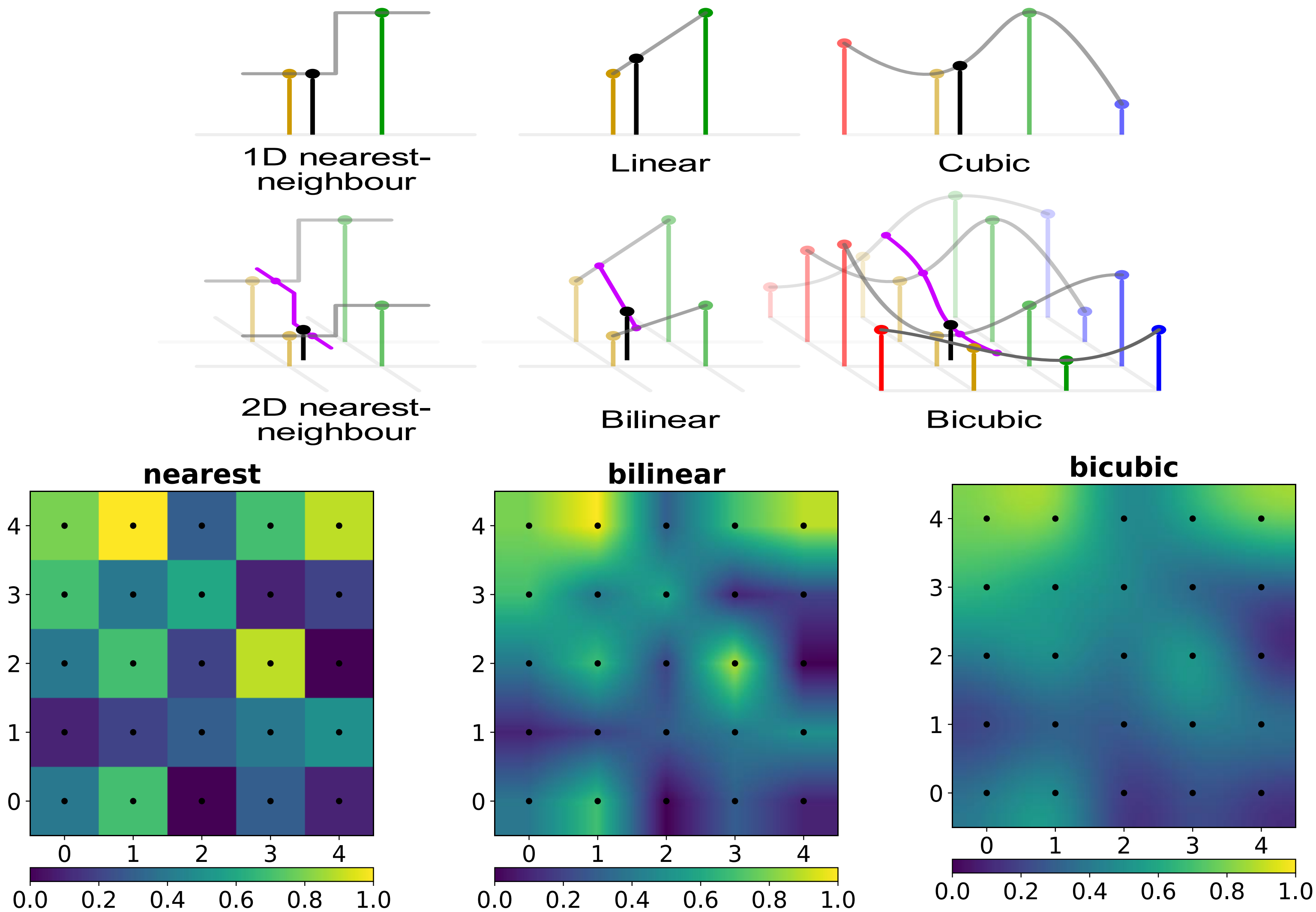


Image courtesy : https://en.wikipedia.org/wiki/Bicubic_interpolation

Training Datasets

- DIV2K: 800 images of 2K Resolution
- Flickr2K: 2650 2K images
- Challenge on Learned Image Compression (CLIC):
  - CLIC-professional: 585 images of 480p to 2K
  - CLIC-mobile: 1048 images of 320p to 2K

Testing Datasets

- PIRM Perceptual Image Super-Resolution Challenge
- BSDS100: 100 images
- Set5 & Set14: common SISR evaluation datasets
- Urban 100: FHD images of Urban scene
- Manga 109: Images of Anime comic covers
- Validation sets of DIV2K, CLIC

Data Preparation

- Datasets are of High-Resolution images
- Obtained Low Resolution via **bicubic** down-sampling
- Scale Factor: 4
- **Patches**
  - LR: 32x32
  - HR: 128x128
- Images of different resolution and formats

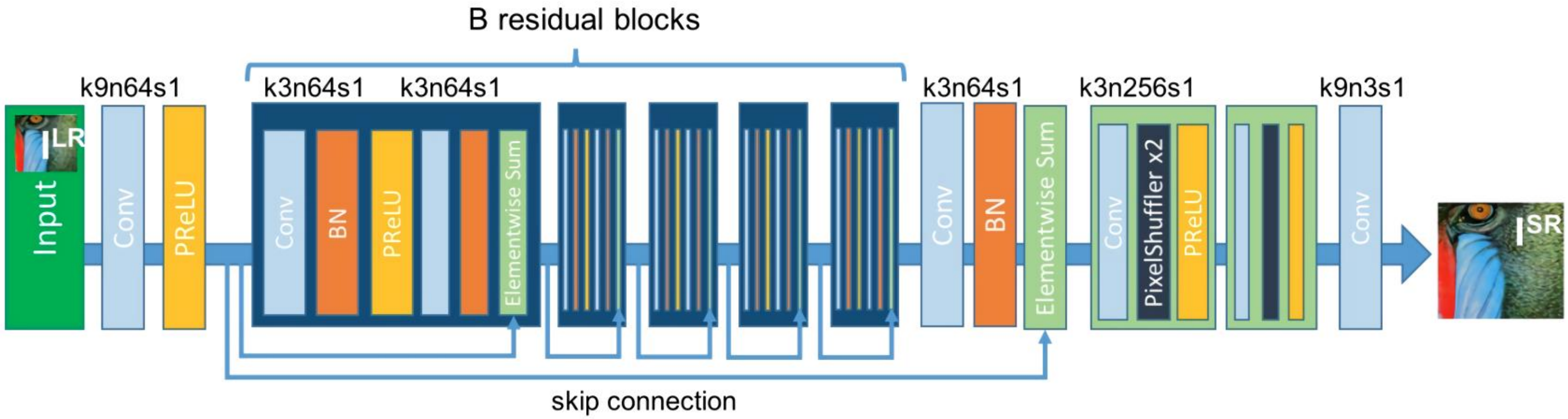
Experimental Setup

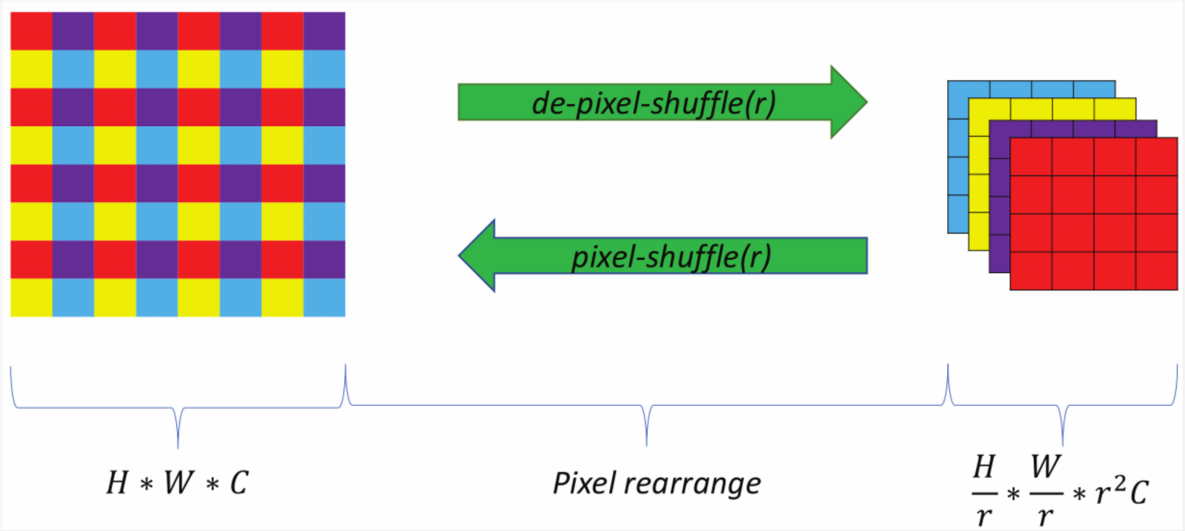
- Intel(R) Core(TM) i7-8700K CPU @ 3.70GHz
- 16 GB DDR4 2400MHz RAM
- 12 GB NVIDIA 1080Ti GPU

Model Selection (Exp 0.)

- Type 1: Takes interpolated LR image as input
  - High resource intensive & difficult to converge
- Type 2: Takes LR input, works on LR feature space, later find a learned up-sampling
  - Less resource intense & converges easily
- SRResNet is best in terms of accuracy & resource usage

SRResNet Architecture





Output images & PSNR values

30.83 dB
LR
(Bicubic)

32.50 dB
SRResNet

∞ dB
Ground Truth

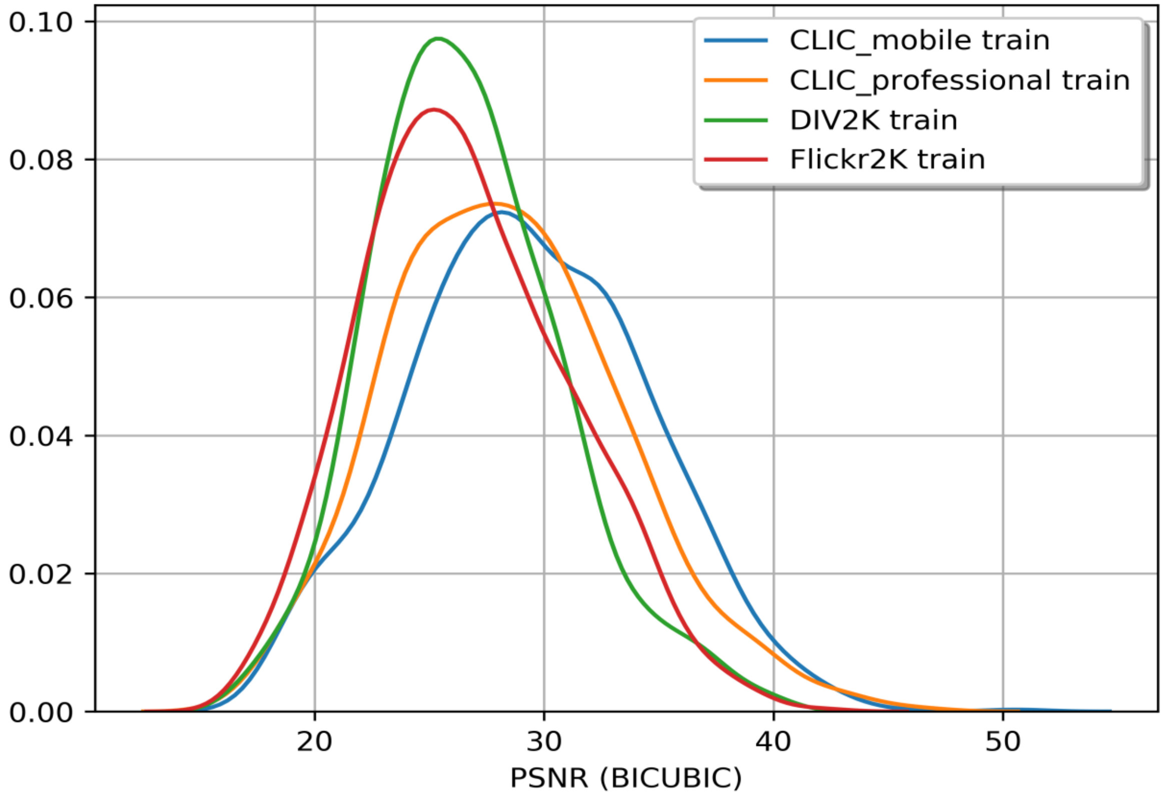
PSNR Gain 1.67 dB

Mean PSNR Gain over Bicubic on separate SRResNet instances

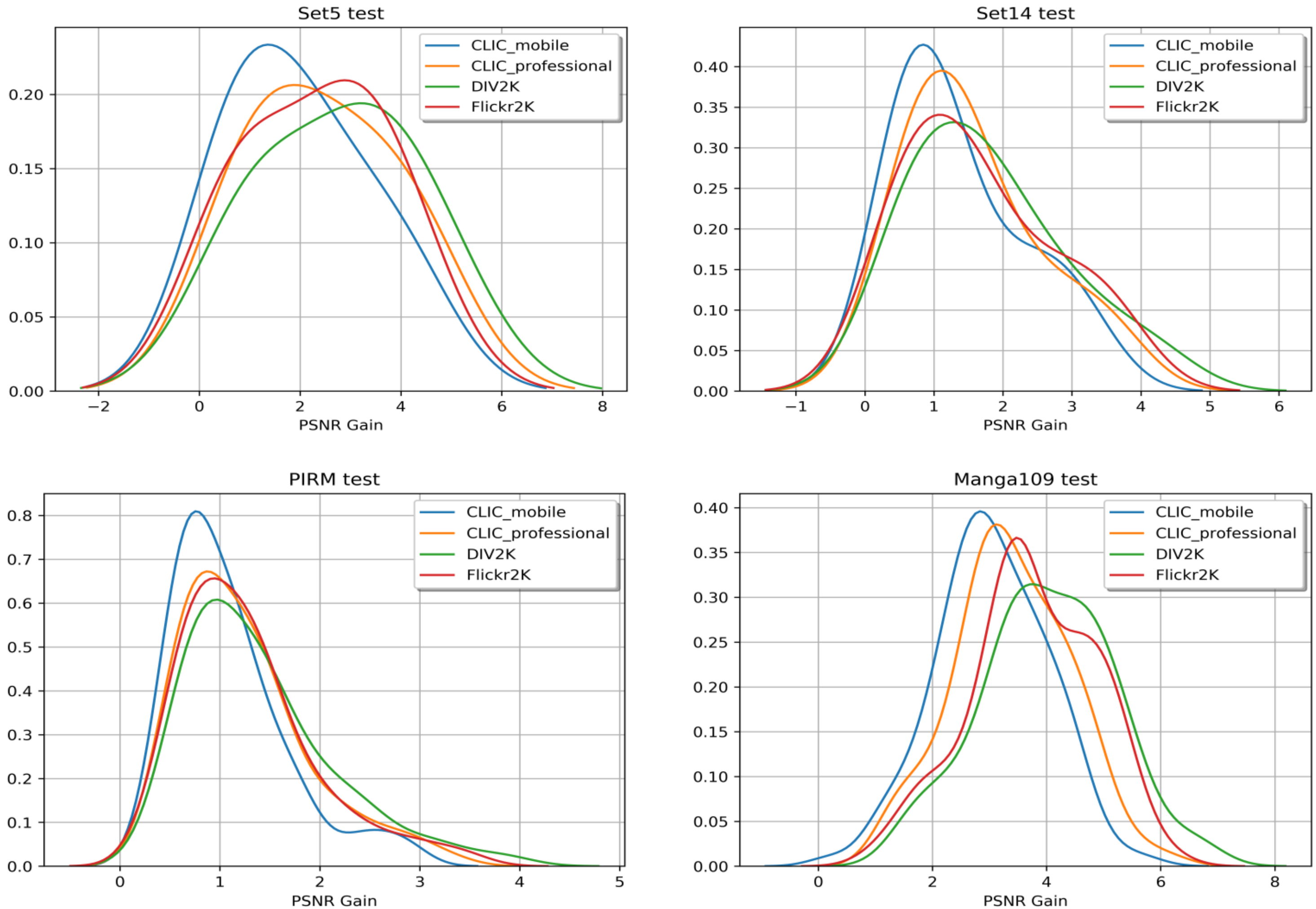
Test/Valid Dataset	DIV2K	Flickr2K	CLIC-professional	CLIC-mobile	Min Diff
CLIC-mobile	1.43	1.28	1.34	1.16	0.09
CLIC-professional	1.64	0.88	1.49	1.20	0.15
DIV2K	1.55	1.11	1.27	1.12	0.28
BSDS100	1.73	1.39	1.44	1.32	0.29
Manga109	4.01	3.75	3.39	3.03	0.26
PIRM	1.40	1.27	1.25	1.08	0.13
PIRM	1.37	1.24	1.19	1.02	0.13
Set5	1.79	1.65	1.57	1.38	0.14
Set14	2.77	2.33	2.45	1.98	0.32
Urban100	2.00	1.86	1.78	1.57	0.14

Data-Set Ranking (Exp 1.)

- Why (& How) training on different dataset matter?
- Fine details are difficult to recover from Bicubic



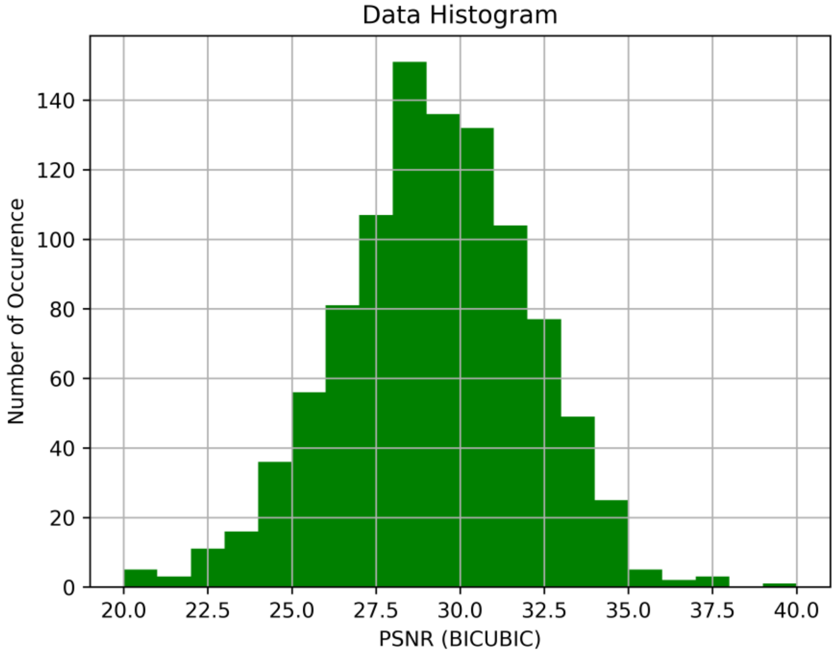
Data-Set Ranking (Exp 1.)

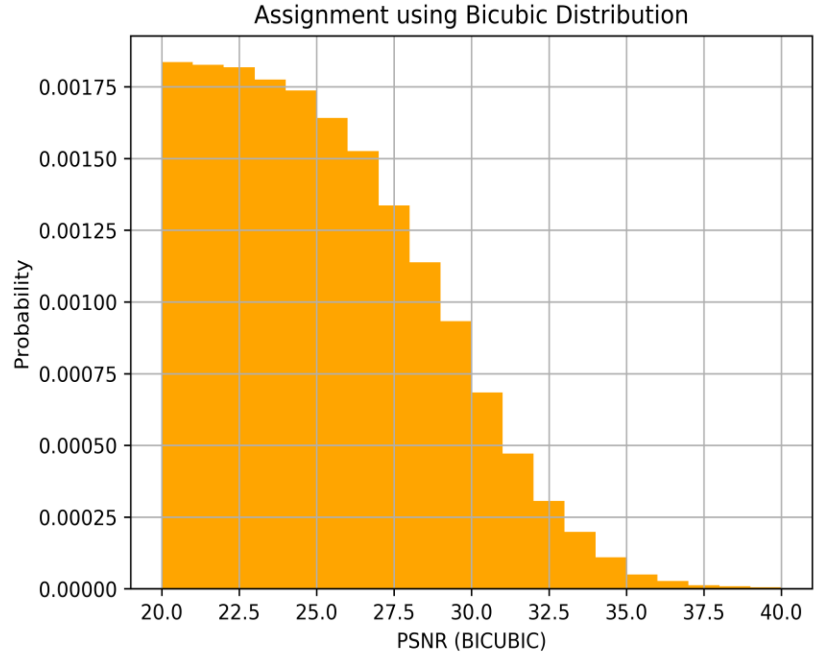


Data Sampling (Exp 2.)

- Batches from disk are taken uniformly for training
- Observation from Exp 1., motivates us to use some **specific sampling** mechanism
- Like Exp 1. does rank datasets, some **Scoring** can be assigned to individual images/patches

Sampling Algorithm





- Observed data distribution of patches is Gaussian
- Less detailed patches are easier to reconstruct using bicubic
  - Results in relatively high PSNR value
  - and vice-versa
- Thus, low PSNR patches should be preferred over high PSNR ones

Algorithm Pseudocode

Input: K, N be chosen sample size & number of patches

Step 0: Assign each patch, uniform probability

$$P_i = \frac{1}{N}$$

While (Model not Converges)

Step 1: Sample K patches, proportional to values in P for each patch

Step 2: Train model on above collected sample

Step 3: Calculate the PSNR gain over these patches

Step 4: $P_{sample} = \sum_{i \in Sample} P_i$

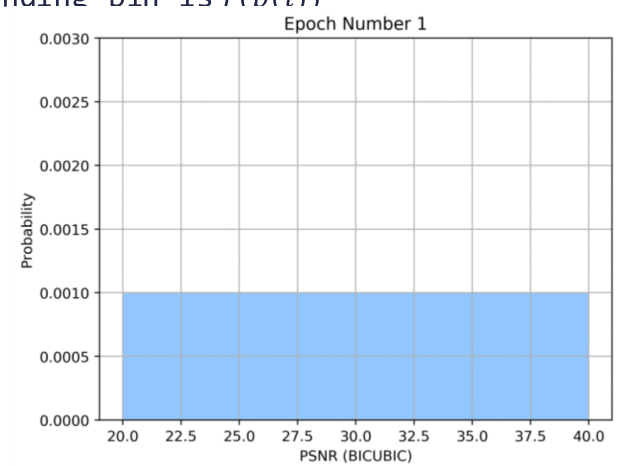
Create Histogram of B bins, using PSNR Gain distribution

Patch **i** is mapped to bin $b(i)$; frequency of corresponding bin is $f(b(i))$

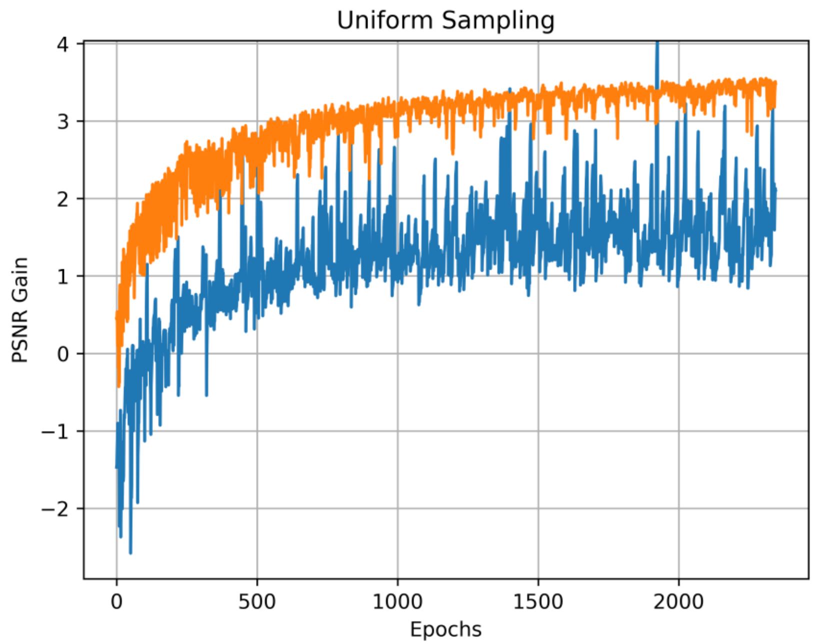
$$\text{val(i)} = \sum_{j=b(i)}^{B} width(j) * f(j)$$

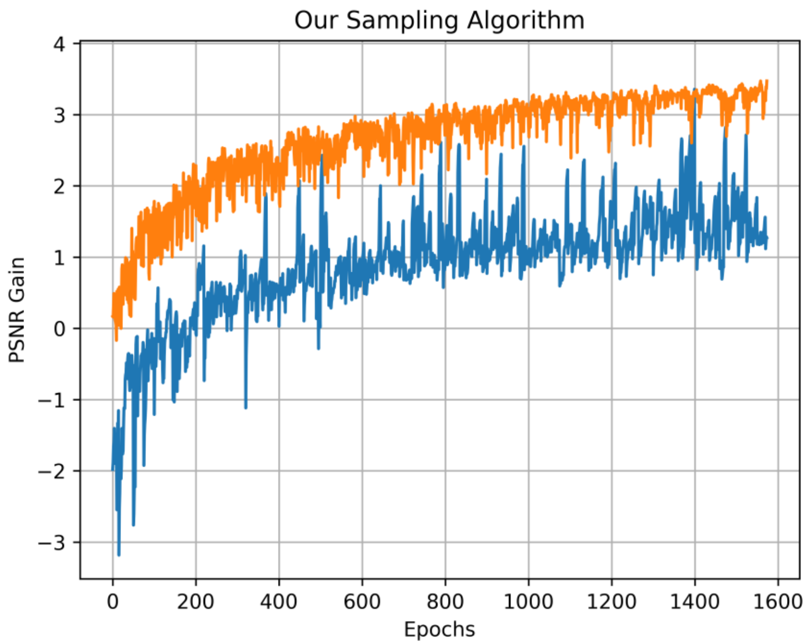
$$\text{Agg}_{\text{Area}} = \sum_{i \in Sample} val(i)$$

$$\forall i \in Sample(Pi = \frac{val(i)}{Agg_{Area}} * Psample)$$



Convergence Performance





- Our sampling algorithm results in **faster convergence**
- Using Patch level approach instead of full image allows
  - Fine grained control
  - No need of extra inference from SRResNet

Core Findings

- Dataset-Ranking (Inter-Dataset) approach helps obtaining better performance
- Data-Sampling (Intra-Dataset) approach further enables faster convergence
- Combining all datasets will saturate in practice
- Techniques like our algorithm can be used to train vision models on extremely large datasets

Conclusion

- Analysed & Benchmarked various SISR models from the literature
- Characterize training datasets for best performance
- Proposed & empirically verified a data sampling algorithm for faster convergence of the model

Future Work

- Similar **Dataset Ranking** & **Data Sampling** approach can be used for other low-level vision applications like Compression Artefacts Removal, De-noising.,
- Reduction in training time can be further obtained by other probability initialization unlike uniform

References

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- Martin, David, et al. "A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics." Vancouver:: Iccv, 2001.
- Blau, Yochai, et al. "The 2018 PIRM challenge on perceptual image super-resolution." *Proceedings of the European Conference on Computer Vision (ECCV)*. 2018.
- Yang, Wenming, et al. "Deep learning for single image super-resolution: A brief review." *IEEE Transactions on Multimedia* (2019).
- Ledig, Christian, et al. "Photo-realistic single image super-resolution using a generative adversarial network." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.
- Du, Chen, et al. "Orientation-Aware Deep Neural Network for Real Image Super-Resolution." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*. 2019.

Thank You!

Questions?

Vision Framework

- No common framework to compare vision models
  - Written in different languages (MATLAB, R, Python, Lua)
- So we created a common framework in python
  - Even higher level abstraction on top of Keras, TensorFlow
  - Define model as dictionary
    - Model architecture can be defined over default values
    - Layers & Functions in literature, not in Keras, are added
- Snapshot of two SISR models on next slide
  - Just 56 lines for VDSR & SRResNet models from literature
  - All training & testing arguments are via command line

Vision Framework

main.py × models_collection.py × myutils.py ×

```python
    def vdsr_block(X_input):
        X = Conv2D(filters=64               ,kernel_size=(3,3),strides=(1,1),padding='same',use_bias=True,kernel_regularizer=keras.regularizers.l2(0.0001))(X_input[0])
        X = ReLU()(X)
        return X

    def vdsr_last_block(X_input):
        X = Conv2D(filters=len(channel_indx),kernel_size=(3,3),strides=(1,1),padding='same',use_bias=True,kernel_regularizer=keras.regularizers.l2(0.0001))(X_input[0])
        X = ReLU()(X)
        return X

    VDSR = { 'name'      :'VDSR' ,
        # Block Links
        'block'     :[(i,i+1)      for i in range(B)] + [(B,B+1),] ,
        'block_sub':['vdsr_block' for i in range(B)] + ['vdsr_last_block',] ,
        # Merge Links
        'merge'     :[(0,B+1,B+2),],
        'merge_sub':['Add'],
        }


    def gen_residual_block(X_input):
        X = Conv2D(filters=64,kernel_size=(3,3),strides=(1,1),padding='same',use_bias=True)(X_input[0])
        X = BatchNormalization()(X)
        X = PReLU(shared_axes=(1,2))(X)
        X = Conv2D(filters=64,kernel_size=(3,3),strides=(1,1),padding='same',use_bias=True)(X)
        X = BatchNormalization()(X)
        X = Add()([X,X_input[0]])
        return X

    def gen_last_block(X_input):
        X = Conv2D(filters=256,kernel_size=(3,3),strides=(1,1),padding='same',use_bias=True)(X_input[0])
        X = UpSampling2D(  size=2,interpolation=upsample_interpolation) (X)
        # X = PixelShuffle(size=2)(X)
        X = PReLU(shared_axes=(1,2))(X)
        return X

    SRResNet = { 'name'      :'SRResNet',
        # Convolution Links
        'convo'     :[(0,1),(B+2,B+3),(B+5+int(np.ceil(np.log2(scale))),B+5+int(np.ceil(np.log2(scale)))+1),],
        'convo_sub':['Conv2D','Conv2D','Conv2D',],
        'convo_par':[{'filters':64,'kernel_size':(9,9),'padding':repr('same'),'use_bias':True},
                     {'filters':64,'kernel_size':(3,3),'padding':repr('same'),'use_bias':True},
                     {'filters':3 ,'kernel_size':(9,9),'padding':repr('same'),'use_bias':True},],
        # Advanced Activation Links
        'aactv'     :[(1,2),],
        'aactv_sub':['PReLU',],
        'aactv_par':[{'shared_axes':(1,2)},],
        # Block Links
        'block'     :[(2+i,2+i+1)          for i in range(B)] + [(B+5+i,B+5+i+1)  for i in range(int(np.ceil(np.log2(scale)))) ],
        'block_sub':['gen_residual_block' for i in range(B)] + ['gen_last_block' for i in range(int(np.ceil(np.log2(scale)))) ],
        # BatchNormalization Links
        'btnrm'     :[(B+3,B+4),],
        # Merge Links
        'merge'     :[(2,B+4,B+5),],
        'merge_sub':['Add'],
        }

```

Line 114, Column 1 Tab Size: 4 Python

Patching Approaches

- HR Image is first Down-sampled and divided into patches for further processing
- HR Image is first divided into patches of desired size and then Down-sampled for further processing
- First approach is used