Appeal prediction for AI up-scaled Images

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Code&Data: `https://bit.ly/3Z8Xmf5`

December 11, 2024

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Motivation

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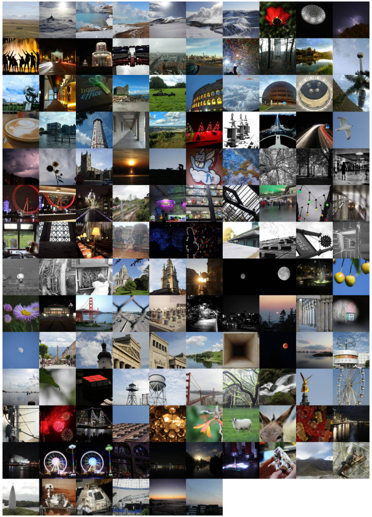
- AI-based image enhancement methods ...
  - e.g, for de-noising [14], in-painting [18], or re-colorization [20]
  - also for **up-scaling** [23, 3, 2, 24]
- typical comparison in state-of-the-art
  - objective models: PSNR/SSIM,
  - only one AI up-scaling method,
  - less often subjective evaluation
- our focus
  - which of the models is visually the best?
  - can the used method be detected after processing?
  - can the visual appeal predicted for up-scaling?

Upscaling Example

AI-based up-scaling examples; left: full image, then 270x270 pixels center crops of the source image, BSRGAN **x4** [24], and KXNet **x4** [3].

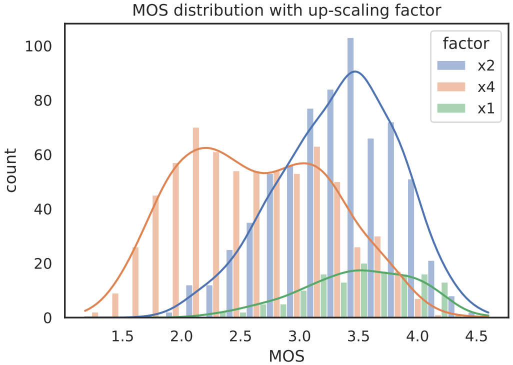
Dataset

- image up-scaling methods
  - BSRGAN [24], KXNet [3], Real-ESRGAN [23], waifu2x [16], **Lanczos**
  - two up-scaling factors (**x2**, **x4**)
- **high resolution (1080p) real content**
  - 136 source images
    - from "own" subset of **AVT-ImageAppeal-Dataset** [6]
    - re-scaling to 1080p height as reference **x1**;
    - for **x2** down-scaling to 540p; for **x4** to 270p
- total $136 \times \left(\underbrace{2}_{\textbf{x2,x4}} \times \underbrace{5}_{\text{methods}} + \underbrace{1}_{\textbf{x1}}\right) = 1496$



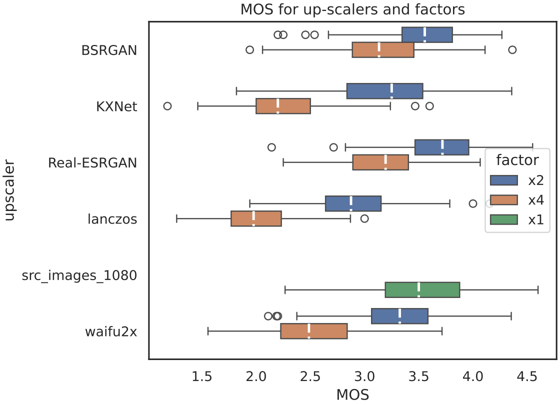
Evaluation - general

- online crowd-sourcing test
  - for image appeal
  - based on **AVRate Voyager** [10]
  - a participant rates 400 of 1496 images
- 55 participants (Clickworkers)
  - images have been rated
    - at least by 4,
    - at most by 25,
    - on average by 14.7 participants
- obvious: **x1** $>$ **x2** $>$ **x4**
- SOS analysis [12] $\rightarrow a \approx 0.275$



Evaluation - up-scaling algorithms

- best: Real-ESRGAN, BSRGAN
- worst: Lanczos, KXNet
- waifu2x in between



Up-scaled preferred over source image

Preference example; left: full source image; then 270x270 pixels center crops of the source image, Real-ESRGAN **x2**, and Real-ESRGAN **x4**.

- example source image: mean appeal rating of ≈ 3.78
- **x2** Real-ESRGAN variant: ≈ 4.0
- **x4** Real-ESRGAN: ≈ 3.17
- overall: upscaled $>$ source image: **x4**: 40%; **x2**: 74%

Detection

- which up-scaling method has been used?
  - multi-class classification, similar to [7, 5]
  - pre-trained baseline DNN,
  - transfer-learning [22], Keras [1]
  - images split into patches (224x224; no overlap)
  - 16 baseline models; 90%-10% train-validation
- best models:
  - DenseNet (f1-score $\approx$ 0.74) or ResNet variants
- worst: Inception or VGG variants
- Real-ESRGAN $\sim$ BSRGAN
- maybe better to predict: underlying generic method

Appeal prediction

- similar to detection
  - 16 DNNs, transfer-learning
  - regression instead of classification
  - mean appeal scores normalized to $[0, 1]$
  - center cropped inputs (224x224) [8, 4]
- DNN models
  - best: ResNet152V2, 0.83 PCC
  - worst: MobileNetV2, InceptionV3

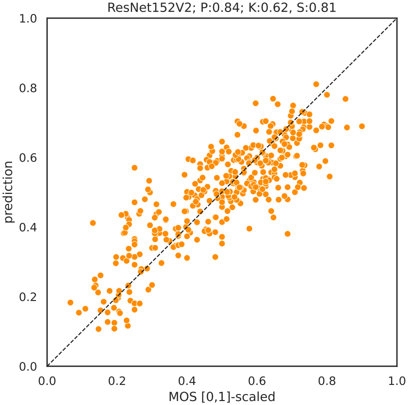


Image appeal compared to signal features

Feature	Pearson	Kendall	Spearman
combined	0.669	0.450	0.631
cpbd [17]	0.572	0.363	0.522
fft [11]	0.331	0.238	0.350
noise [11]	0.299	0.302	0.447
si	0.213	0.135	0.200
blur	0.152	0.110	0.164
saturation	0.093	0.057	0.087
colorfulness	0.024	0.019	0.028
contrast	-0.013	-0.005	-0.008
tone	-0.039	-0.020	-0.031
niqe	-0.088	-0.040	-0.061
blur strength	-0.378	-0.257	-0.375

implementation: [9]; ***combined***=RF model, 100 trees, scikit-learn [19]

Image appeal compared to SoA Models

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Model	Pearson	Kendall	Spearman
DBCNN [25]	0.605	0.436	0.618
HYPERIQA [21]	0.601	0.414	0.592
CNNIQA	0.592	0.376	0.536
MUSIQ	0.555	0.365	0.522
MANIQA	0.505	0.345	0.493
paq2piq	0.492	0.311	0.448
NIMA quality CC [15]	0.433	0.281	0.408
ms_ssim	0.368	0.232	0.348
vif	0.363	0.248	0.373
psnr	0.248	0.164	0.244
ssim	0.183	0.135	0.203

implementation: PyTorch Image Quality (PIQ) Toolbox [13]

Conclusion, Summary and Future Work

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- observation
  - DNN/AI-based up-scaling maybe better than traditional approaches
- open source dataset, subjective annotation, evaluation & comparison
  - 5 up-scaling methods, 2 factors, 1496 rated images
  - most appealing model Real-ESRGAN, second BSRGAN, Lanczos bad
  - reverse detection of which method used: possible
  - appeal prediction: new models needed, transfer learning promising
- future work
  - more tests with a larger number of source images/more methods
  - update/improve existing models to include AI distortions
  - video up-scaling with newer ai-based up-scaling methods

Thank you for your attention

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...... are there any questions?

The authors would like to thank the participants for taking part in this crowd test. Furthermore, we want to thank the "**AG Wissenschaftliches Rechnen**" of the TU Ilmenau for providing computing resources.

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