Learning Conditional Knowledge Distillation for Degraded-Reference Image Quality Assessment Supplementary Material

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Figure 1: Qualitative comparison of PSNR, LPIPS, our proposed CKDN and human annotations. It can be observed that the predictions of CKDN is more consistent with human's judgements, which can better distinguish high-frequency details, e.g., left images in (a), and artifacts generated by GANs, e.g., right images in (b).



*This work was performed when Heliang Zheng was visiting Microsoft Research as a research intern.







DRC OM A





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PSNR: LPIPS: DPEN: Human:

PSNR: LPIPS:

DPEN: Human:





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PSNR: LPIPS: DPEN: Human:





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Figure 2: An illustration of the SRCC improvements obtained by different types of reference images. The percentage numbers marked in green is the SRCC improvements compared to no-reference settings.

Pristine-quality Image (10.1409)













8x Downsampled LR Image (↑0.0591)

Gaussian noise, Level: 50 (1289)

JPEG compression, Q: 10 (^0.1331)







JPEG compression, Q: 30 (1398)



























Gaussian noise, Level: 25 (1375)

Figure 3: Failure cases of our CKDN are mainly caused by two challenges: (a) artifacts generated by GANs sometimes confuse the model, and (b) the quality of two images are so comparable that it is difficult to provide consistent judgements (even for human).

(b) comparable qualities (a) GAN artifacts \checkmark DPEN: \checkmark \checkmark Human: \checkmark DPEN: Human: \checkmark V DRC OM A OM A √ \checkmark DPEN: \checkmark \checkmark Human: