ARNIQA: Learning Distortion Manifold for Image Quality Assessment

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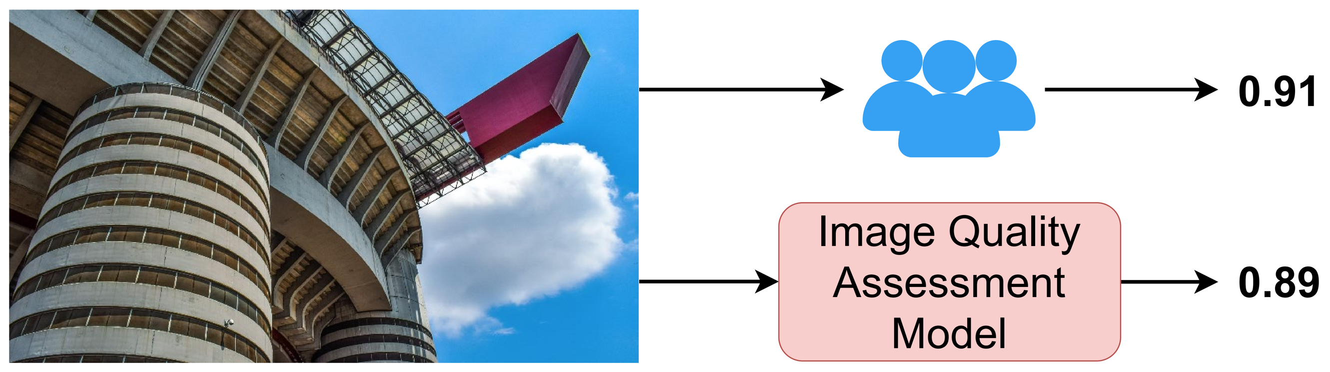
Introduction

🔍 No-Reference Image Quality Assessment (NR-IQA) focuses on designing methods to measure image quality in alignment with human perception when a high-quality reference image is unavailable

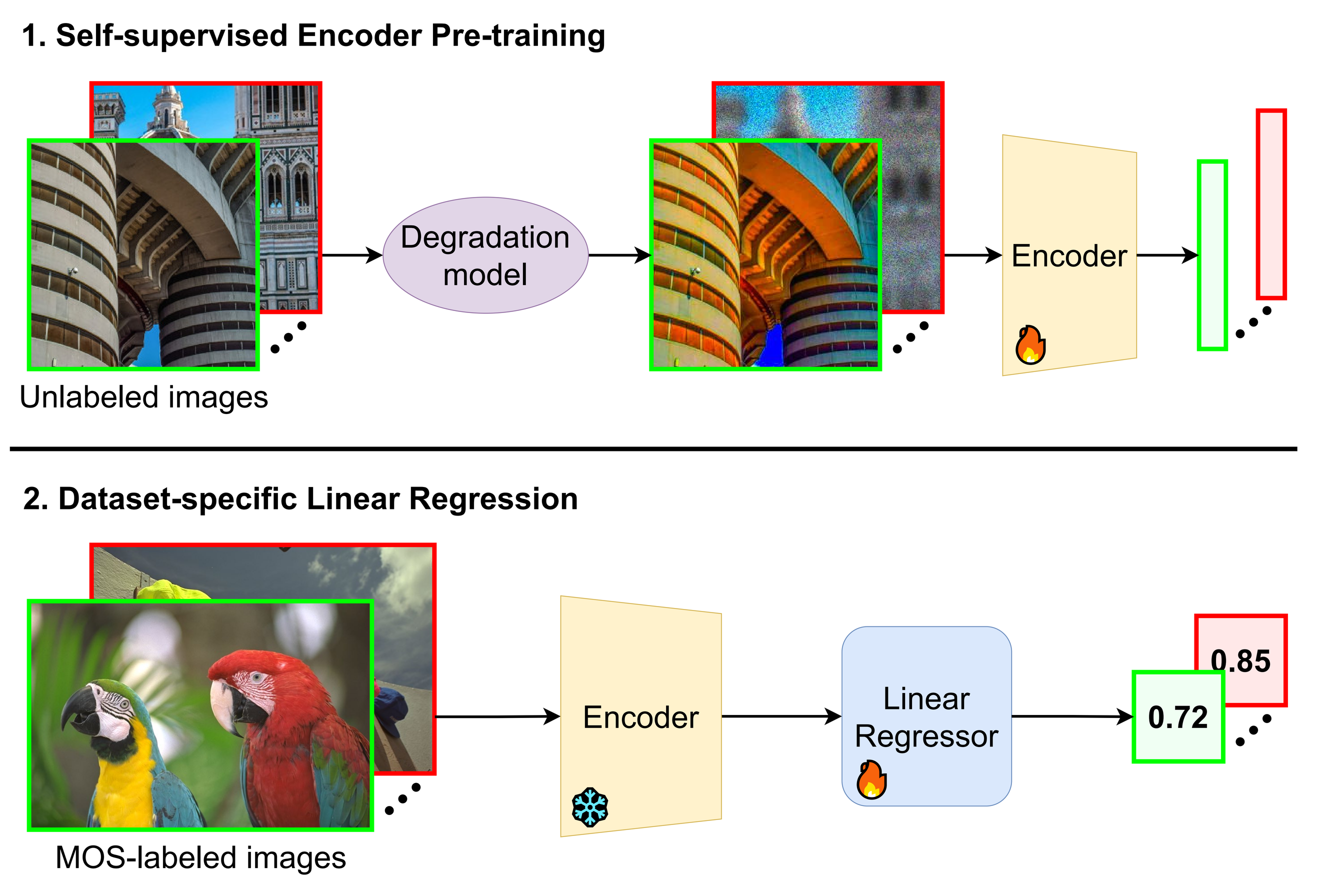
❌ Supervised methods for NR-IQA require labeled datasets, which are expensive and time-consuming to obtain



💡 We propose **ARNIQA**, a self-supervised approach for NR-IQA that aims to learn the **image distortion manifold** by maximizing the similarity between the embeddings of different images degraded equally

💡 We introduce an **image degradation model** that randomly assembles ordered sequences of distortions

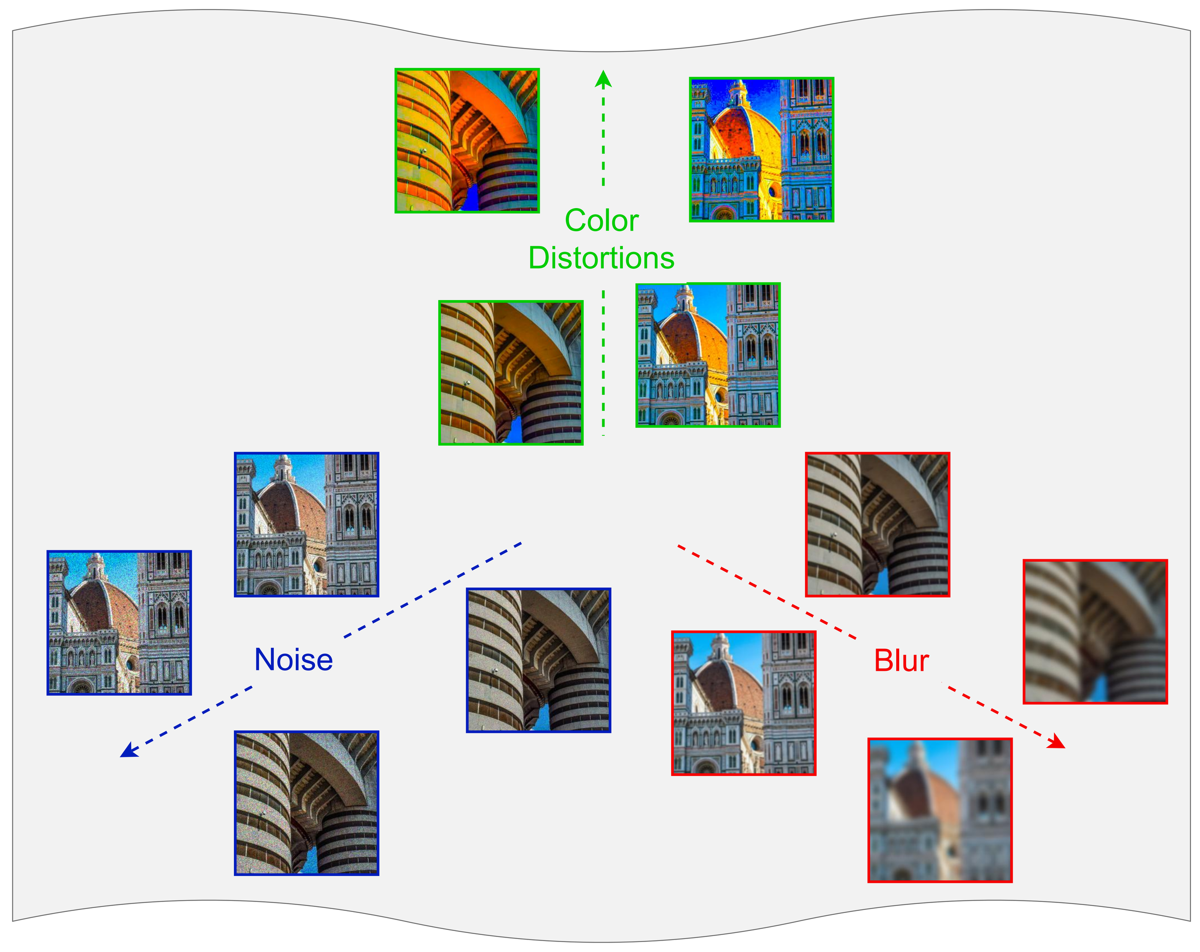
SSL for NR-IQA



Self-supervised methods [1, 2] for NR-IQA involve 2 steps:

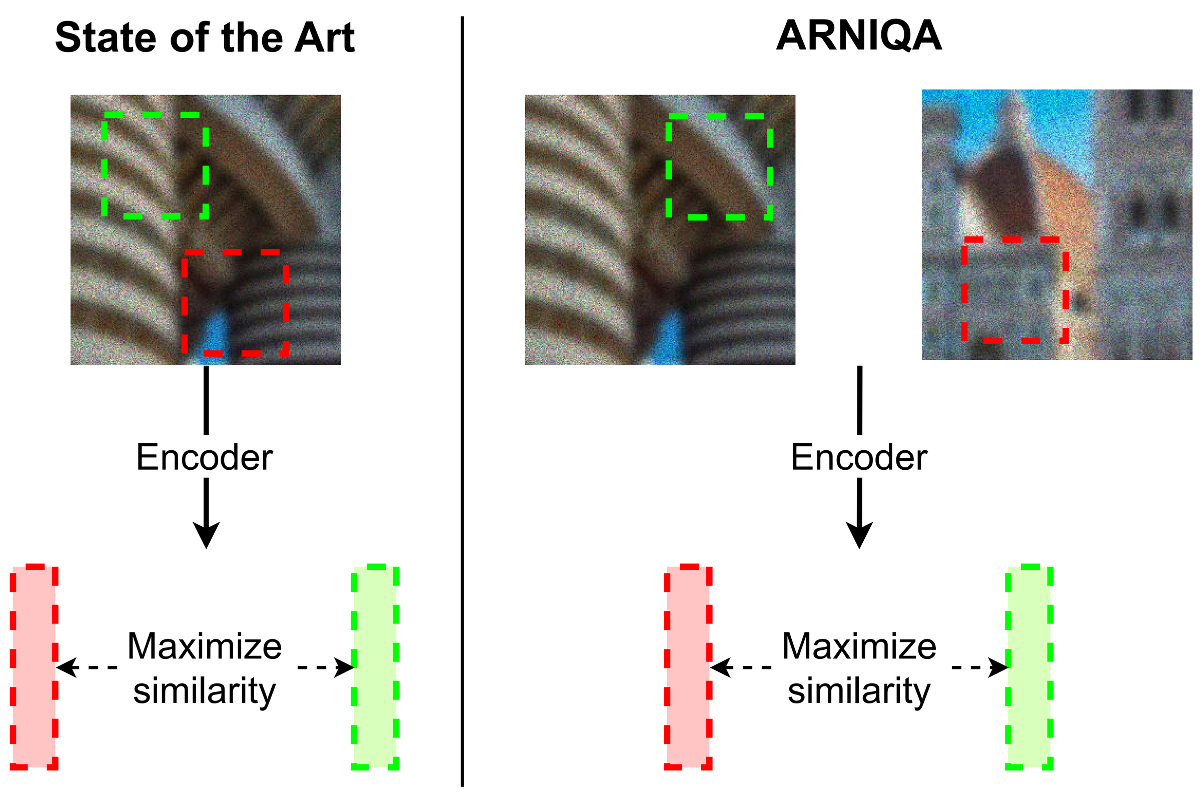
1. **Encoder** pre-training using synthetically degraded unlabeled images
2. Dataset-specific **linear regressor** training using the MOS

Image Distortion Manifold



The **image distortion manifold** [3] is the continuous space of all the possible degradations to which an image can be subjected

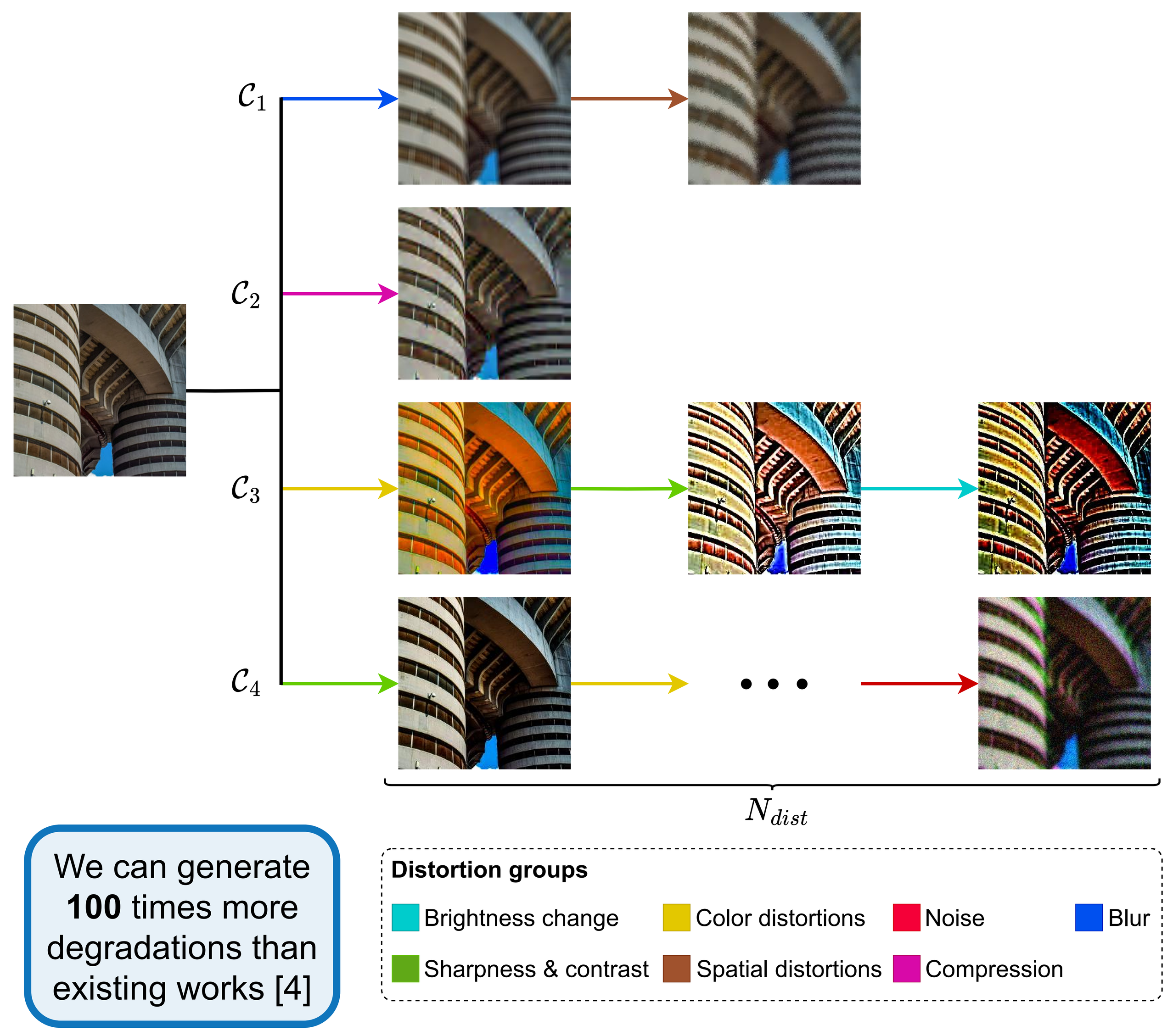
Idea



Maximize the similarity of the embeddings of two patches with:

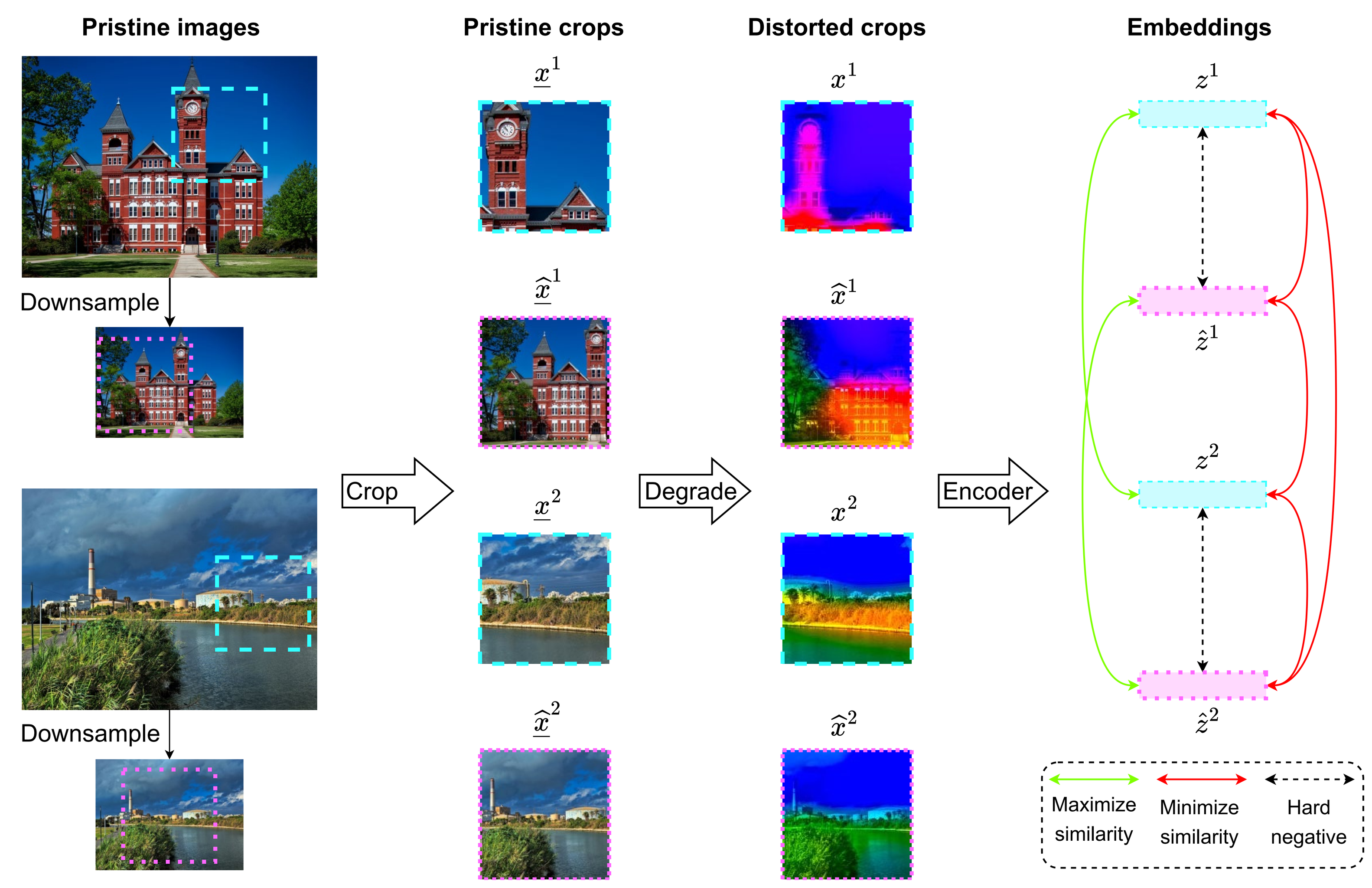
- State of the Art: **similar** content / **same** distortion
- ARNIQA: **different** content / **same** distortion

Image Degradation Model

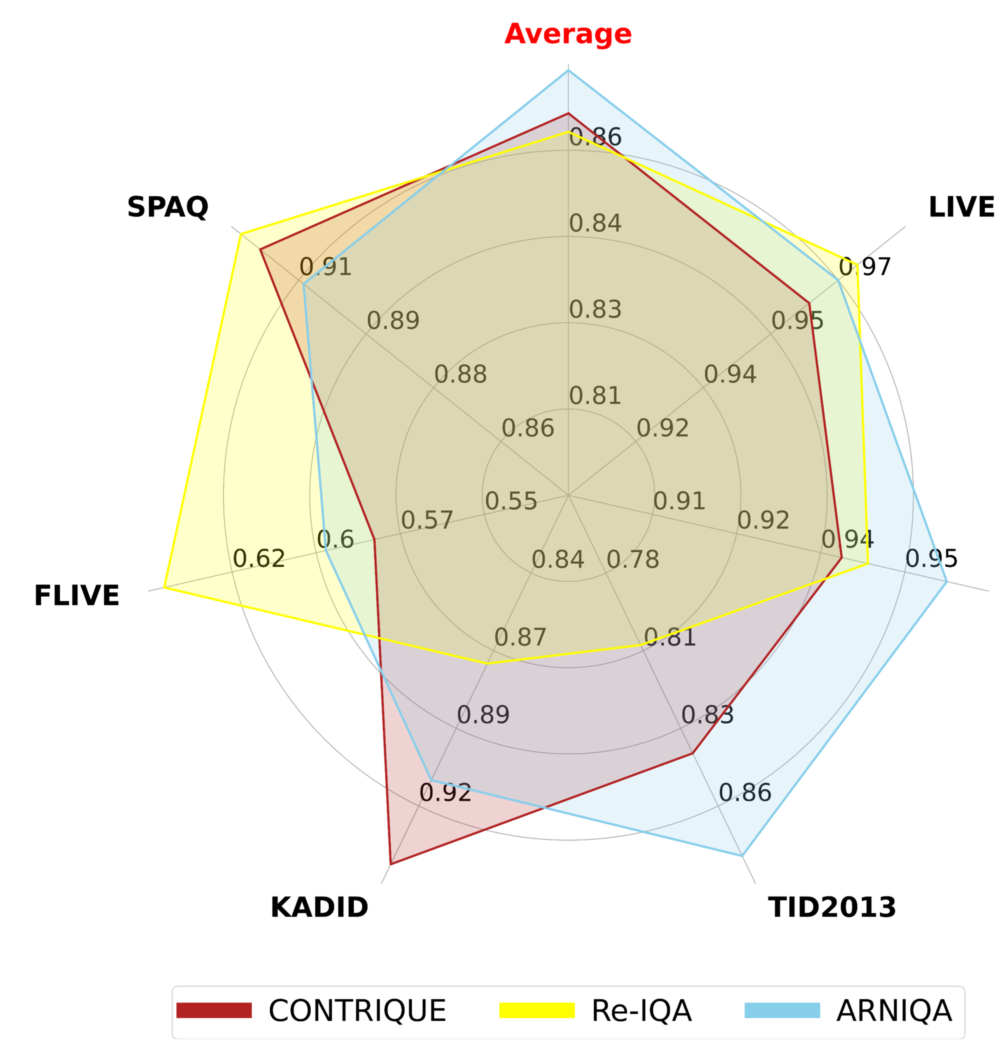


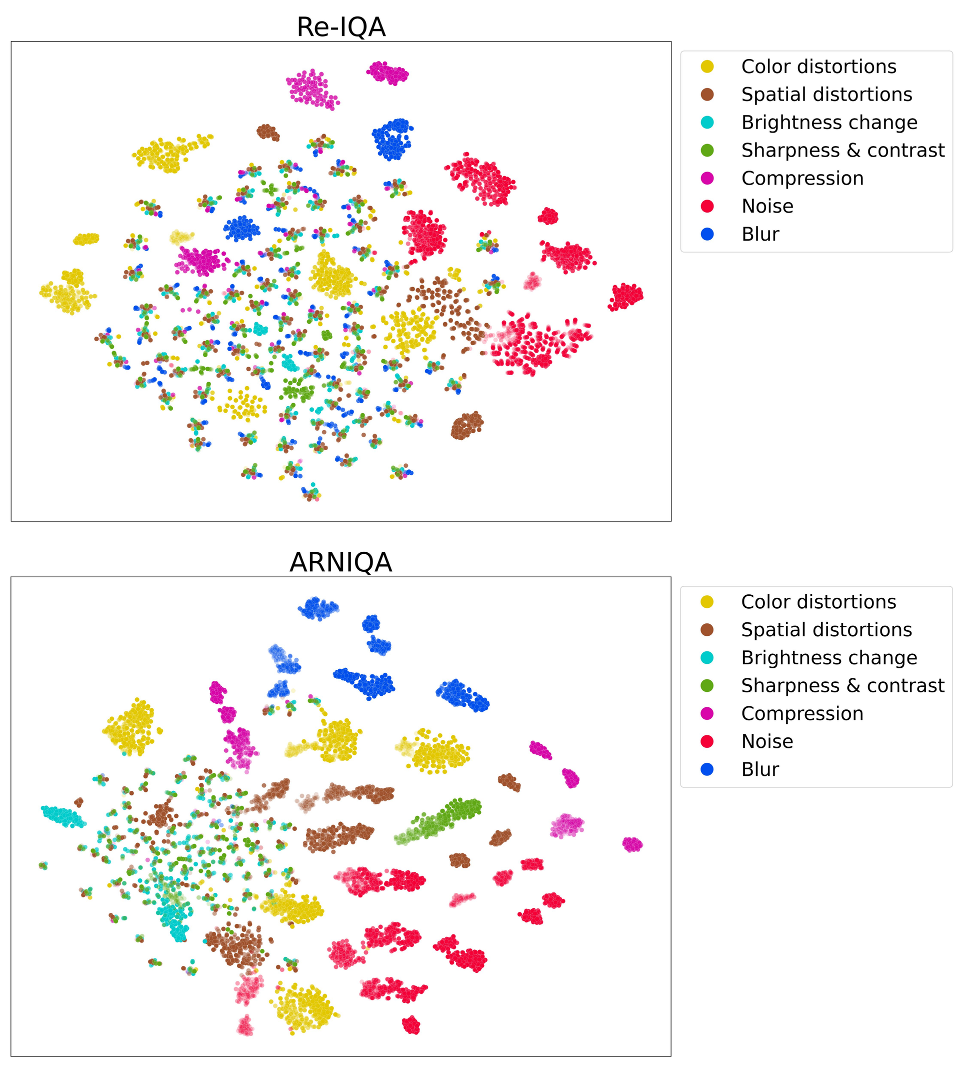
We can generate **100** times more degradations than existing works [4]

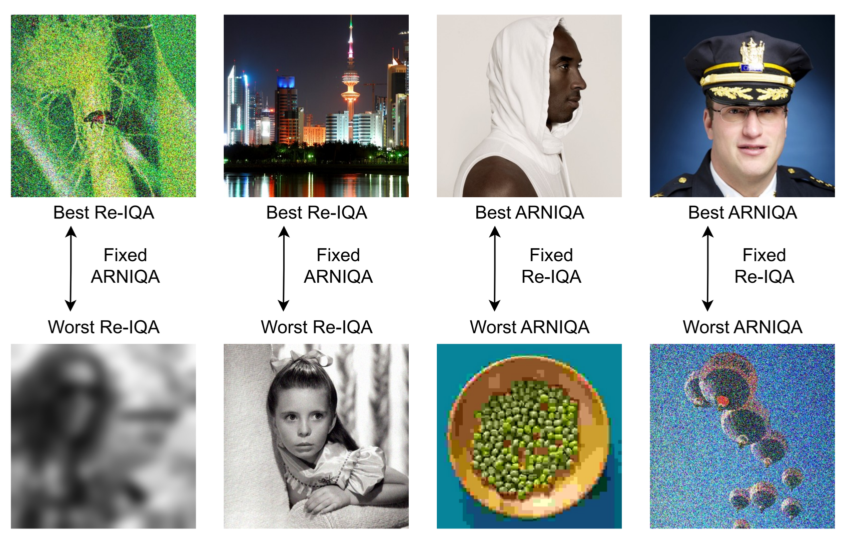
Training Strategy



Results







Training	Testing	Method: Su *et al.*	CONTRIQUE	Re-IQA	**ARNIQA**
LIVE	CSIQ	0.777	0.803	0.795	**0.904**
LIVE	TID2013	0.561	0.640	0.588	**0.697**
LIVE	KADID	0.506	0.699	0.557	**0.764**
CSIQ	LIVE	**0.930**	0.912	0.919	0.921
CSIQ	TID2013	0.550	0.570	0.575	**0.721**
CSIQ	KADID	0.515	0.696	0.521	**0.735**
TID2013	LIVE	0.892	**0.904**	0.900	0.869
TID2013	CSIQ	0.754	0.811	0.850	**0.866**
TID2013	KADID	0.554	0.640	0.636	**0.726**
KADID	LIVE	0.896	**0.900**	0.892	0.898
KADID	CSIQ	0.828	0.773	0.855	**0.882**
KADID	TID2013	0.687	0.612	**0.777**	0.760

Conclusions

❌ Supervised methods are limited by their reliance on challenging and expensive manual data labeling

💡 We model the image distortion manifold in a self-supervised way by maximizing the representations of different images degraded equally

📈 ARNIQA achieves SotA results while showing improved data efficiency, generalization capabilities, and robustness *w.r.t.* competing methods

🤔 In future work, we will investigate how our learned distortion manifold can be used for blind image restoration

arXiv GitHub

References

[1] Saha et al., "*Re-IQA: Unsupervised Learning for Image Quality Assessment in the Wild*", CVPR 2023

[2] Madhusudana et al., "*Image Quality Assessment Using Contrastive Learning*", TIP 2022

[3] Su et al., "*From Distortion Manifold to Perceptual Quality: a Data Efficient Blind Image Quality Assessment Approach*", 2023

[4] Zhao et al., "*Quality-aware Pre-trained Models for Blind Image Quality Assessment*", CVPR 2023