

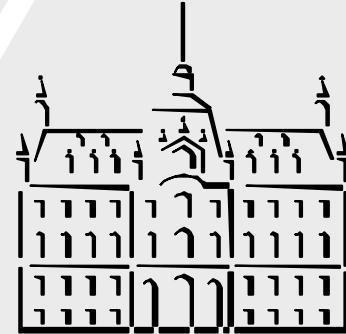


Face Image Quality Assessment (FIQA): Recent Advancements and Future Challenges

Prof. Vitomir Štruc, PhD

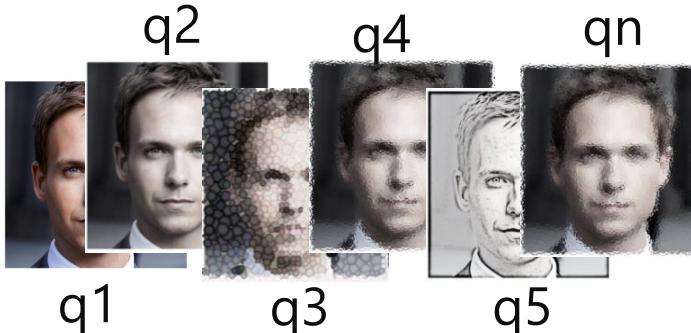
Faculty of Electrical Engineering
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vitomir.struc@fe.uni-lj.si



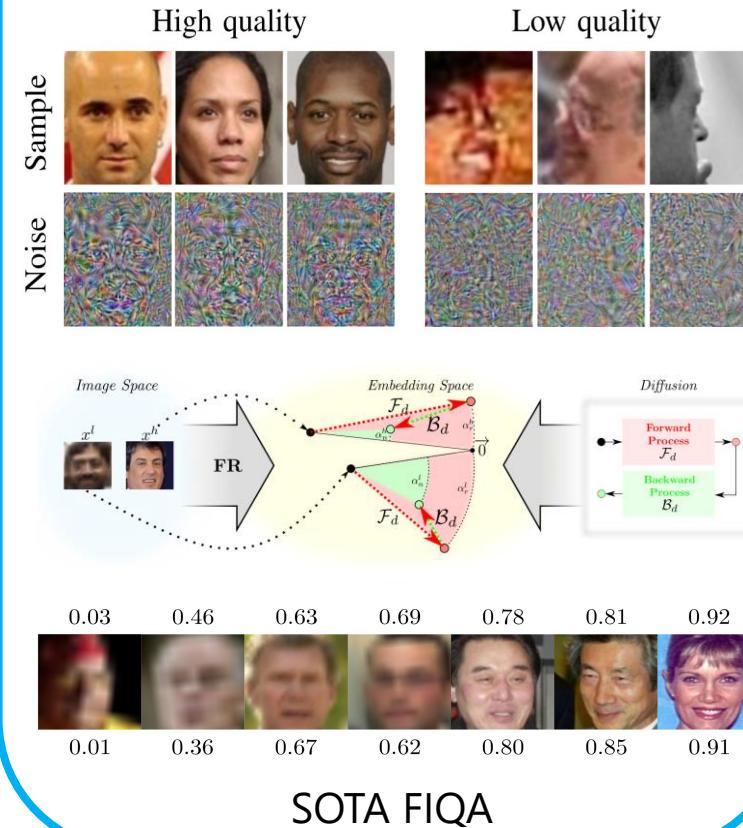
Talk Outline

Part I: Face Image Quality Assessment

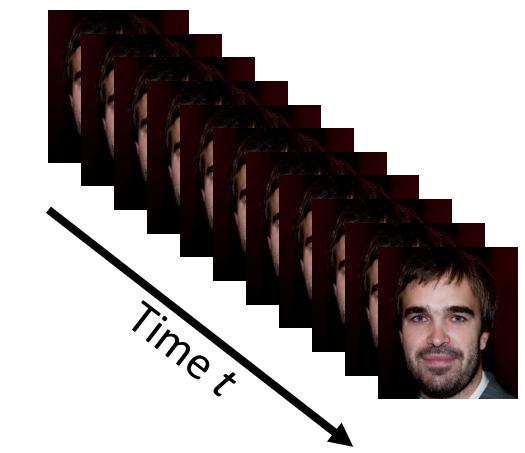
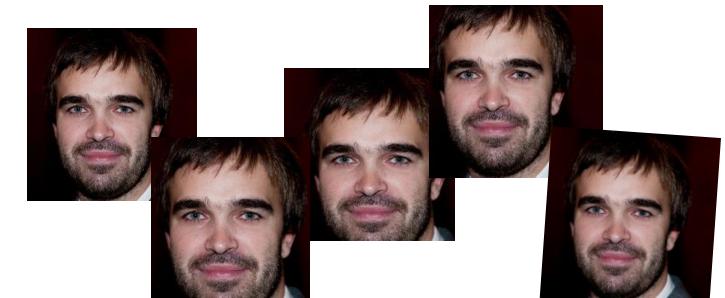


Background and Concepts

Part II: FaceQAN, DifFIQA and eDifFIQA



Part III: Open Challenges



0.03



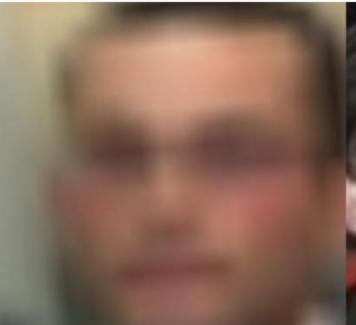
0.46



0.63



0.69



0.78



0.81



0.92



0.01

0.36

0.67

0.62

0.80

0.85

0.91

Part I: Background and Concepts



Publications available:

<https://lmi.fe.uni-lj.si/en/vitomir-struc/publications/>

GitHub: <https://github.com/LSIbabnikz/>



Face Image Quality Assessment

- Image Quality Assessment (IQA)
 - Image Quality:
 - The level of accuracy with which different imaging systems capture, process, store, compress, transmit and display the signals that form an image¹
 - The weighted combination of all of the visually significant attributes of an image¹
 - IQA methods can be:
 - Subjective or Objective
 - Related to Noise, Blur, Sharpness, Contrast, Color Accuracy, Distortions, etc.



¹Burningham, Norman; Pizlo, Zygmunt; Allebach, Jan P. (2002). "Image Quality Metrics". In Hornak, Joseph P. (ed.). *Encyclopedia of imaging science and technology*. New York: Wiley.

Face Image Quality Assessment

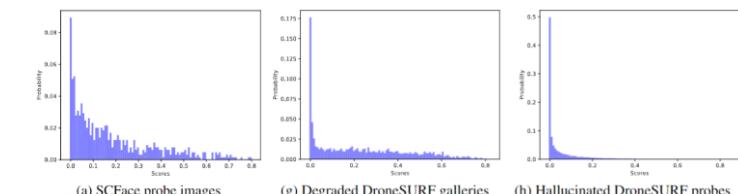
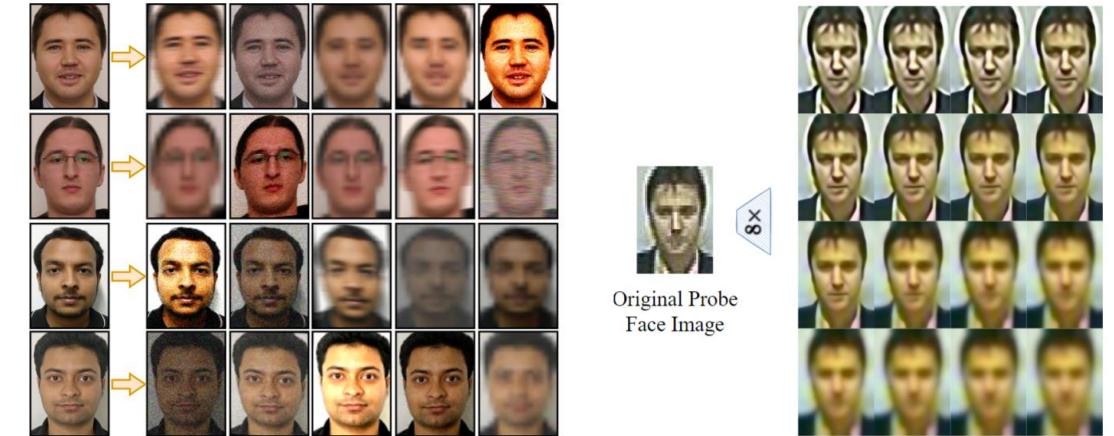
- Face Image Quality Assessment (FIQA)
 - IQA applied to face images
 - Important for multiple use-cases, e.g.:

Synthetic Data Generation



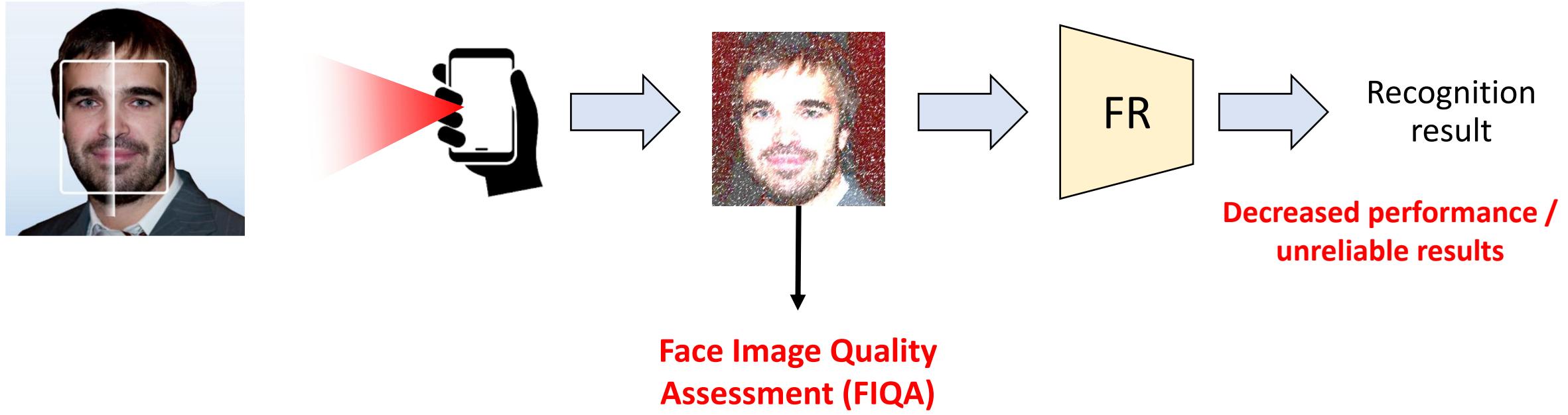
Sp.	Model	PD	CR-FIQA ↑
VIS	Tufts (H vs. T) [17]	—	1.743 ± 0.259
	StyleGAN2 [36]	—	2.141 ± 0.075
	DB-StyleGAN2 [18]	—	2.130 ± 0.009
	SFace [29]	—	1.779 ± 0.193
	Mix-SFace [29]	✓	1.792 ± 0.164
	ArcBiFaceGAN	✓	1.824 ± 0.149
NIR	IDiff-Face (N) [31]	—	1.559 ± 0.332
	IDiff-Face [31]	—	1.843 ± 0.175
	Tufts (H vs. T) [17]	—	1.575 ± 0.338
	StyleGAN2 [36]	—	2.047 ± 0.119
	DB-StyleGAN2 [18]	—	2.071 ± 0.102
	SFace [29]	—	1.553 ± 0.286
	Mix-SFace [29]	✓	1.557 ± 0.239
	ArcBiFaceGAN	✓	1.642 ± 0.242
			1.666 ± 0.206
			1.680 ± 0.199

Enhancement and Manipulation Schemes



Face Image Quality Assessment

- Face Image Quality Assessment (FIQA)
 - Key use case in **Face Recognition**



- Reject sample, use quality for recognition, etc.

Face Image Quality Assessment

- Face Image Quality Assessment (FIQA)
 - ISO/IEC 29794-1 differentiates between three quality aspects ¹:
 - **Character** – attributes inherent to the biometric characteristic (faces) being acquired (e.g., skin texture, scars, etc.)
 - **Fidelity** – reflects the degree of similarity with the source face, e.g., blurred or noisy faces have low fidelity
 - **Utility** – the fitness of a sample for face recognition, e.g., confidence in the recognition result



High perceptual
quality

High face image
quality



High perceptual
quality

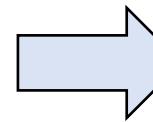
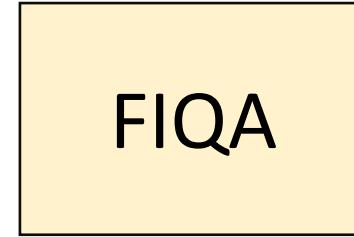
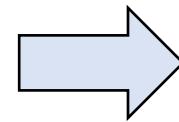
Low face image
quality



Low perceptual
quality

Low face image
quality

Face Image Quality Assessment



q



q_1

>



q_2

Higher scores
mean better quality

Unified Quality Score

Quality components:

- Face alignment
- Background uniformity
- Sharpness
- Mouth Closed
- Eyes open
- Head Pose Frontalness
- Occlusion level
- ...

Face Image Quality Assessment

Existing solutions

Analytical:

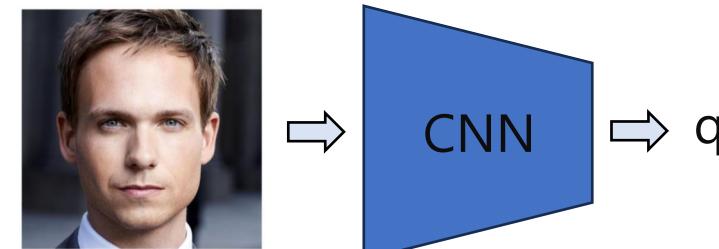
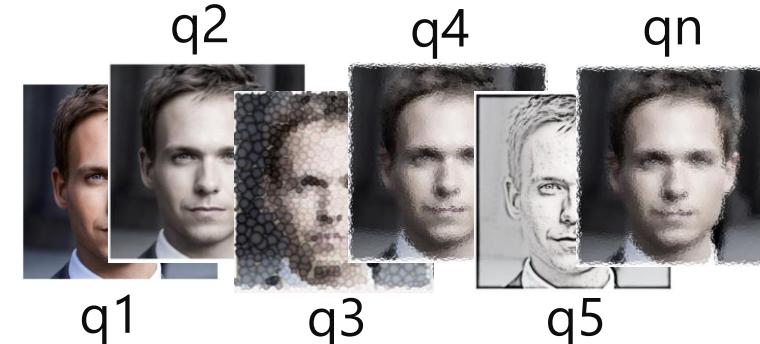
Compute scores directly from the input sample.



- Sharpness
- Level of occlusion
- Frontalness
- Unified QS

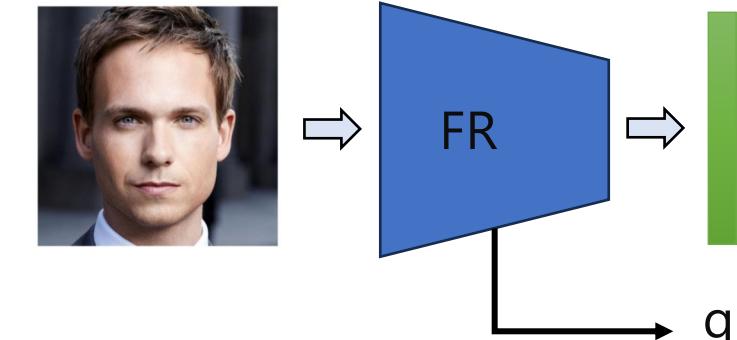
Regression based:

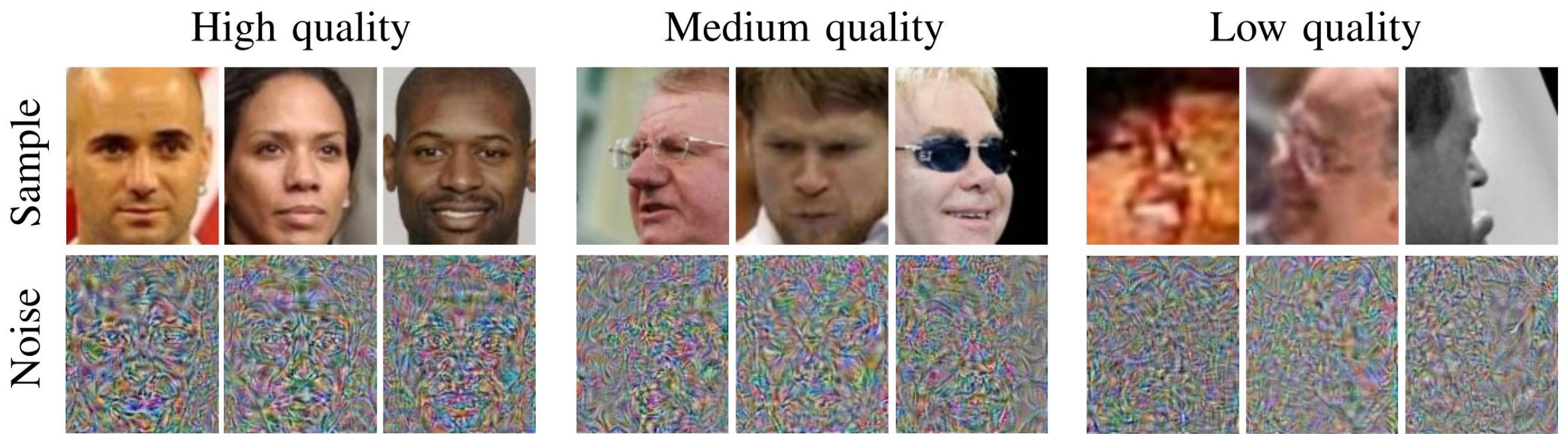
Train regression model on extracted pseudo-quality labels.



Model based:

Combine recognition and quality estimation tasks.





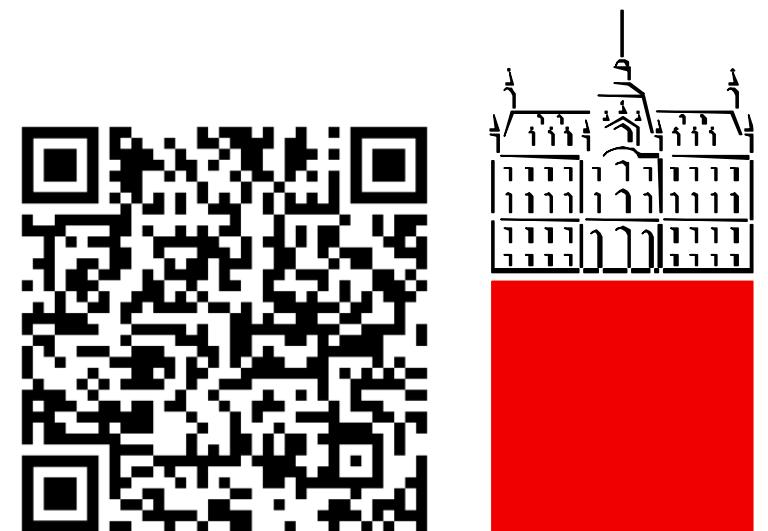
Part II-a: FaceQAN

Ž. Babnik, P. Peer, V. Štruc, FaceQAN: Face Image Quality Assessment Through Adversarial Noise Exploration, ICPR 2022



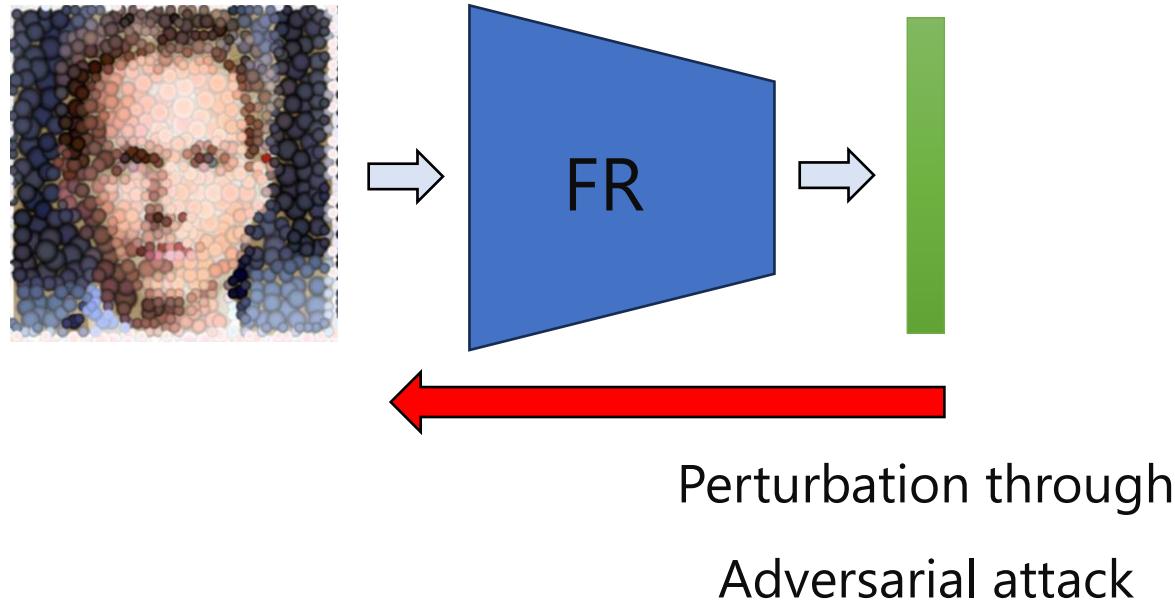
Available on arXiv (Dec 2022):
<https://arxiv.org/abs/2212.02127>

GitHub: <https://github.com/LSIbabnikz/FaceQAN>



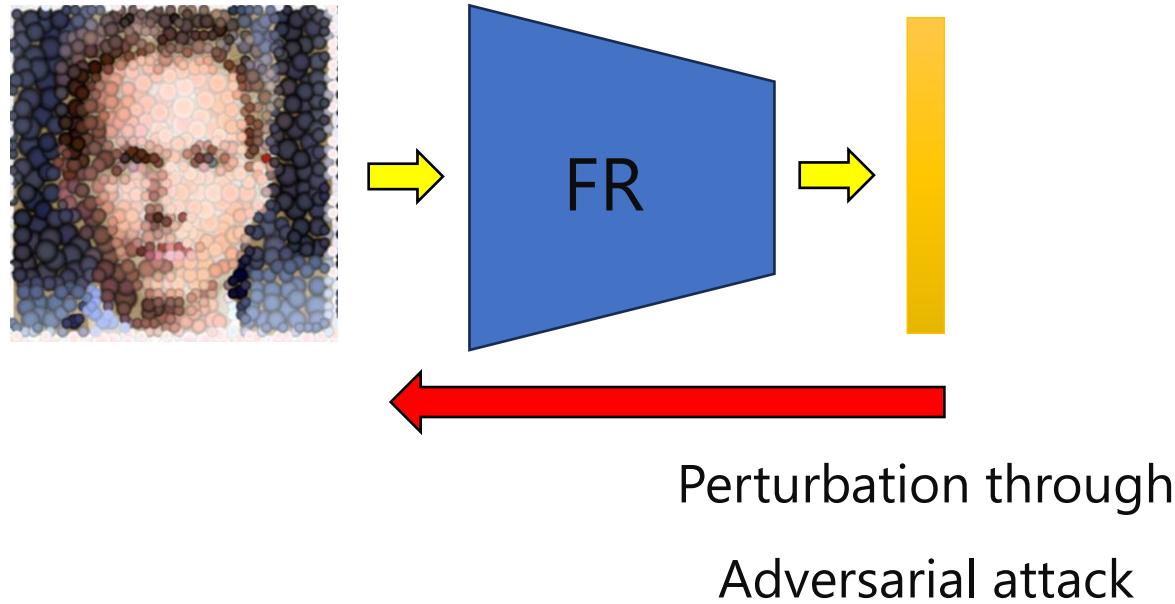
FaceQAN

- How difficult is it to perturb an embedding of a facial image?



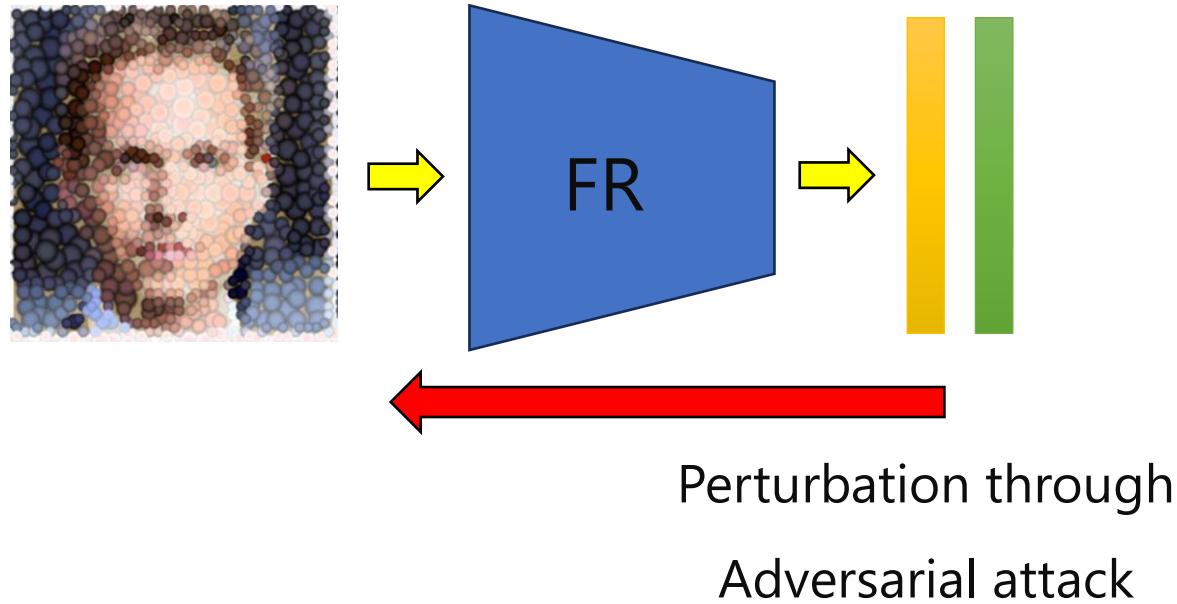
FaceQAN

- How difficult is it to perturb an embedding of a facial image?



FaceQAN

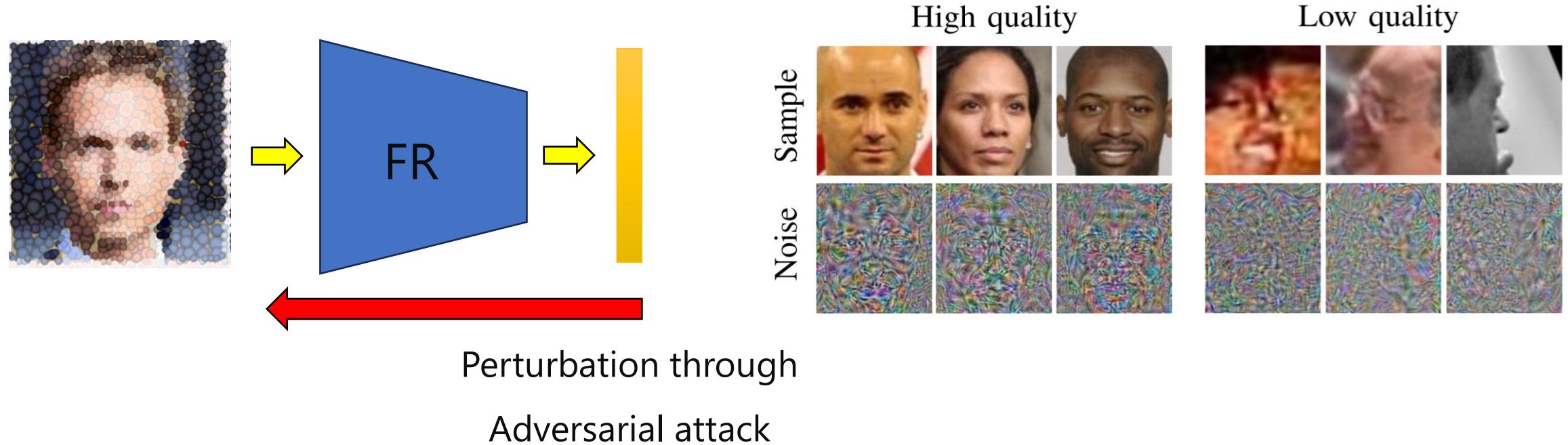
- How difficult is it to perturb an embedding of a facial image?



- Stability of embedding => Face Image Quality (FIQ)

FaceQAN

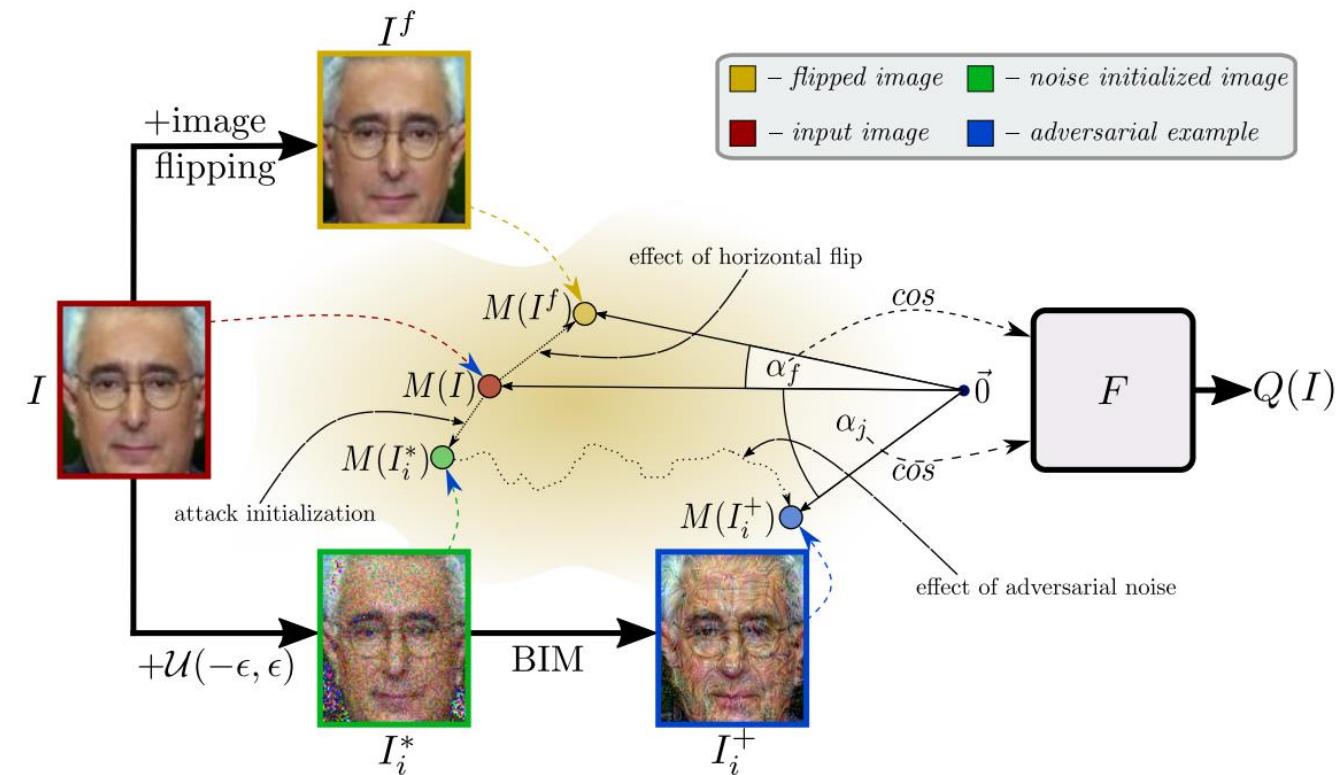
- How difficult is it to perturb an embedding of a facial image?



- Stability of embedding => Face Image Quality (FIQ)

FaceQAN

- Key Components
- Operates in embedding space
- Similarity-based adversarial attack (FGSM+BIM)
- Fixed number of iterations
- Pose modeled explicitly
- Repeated k times



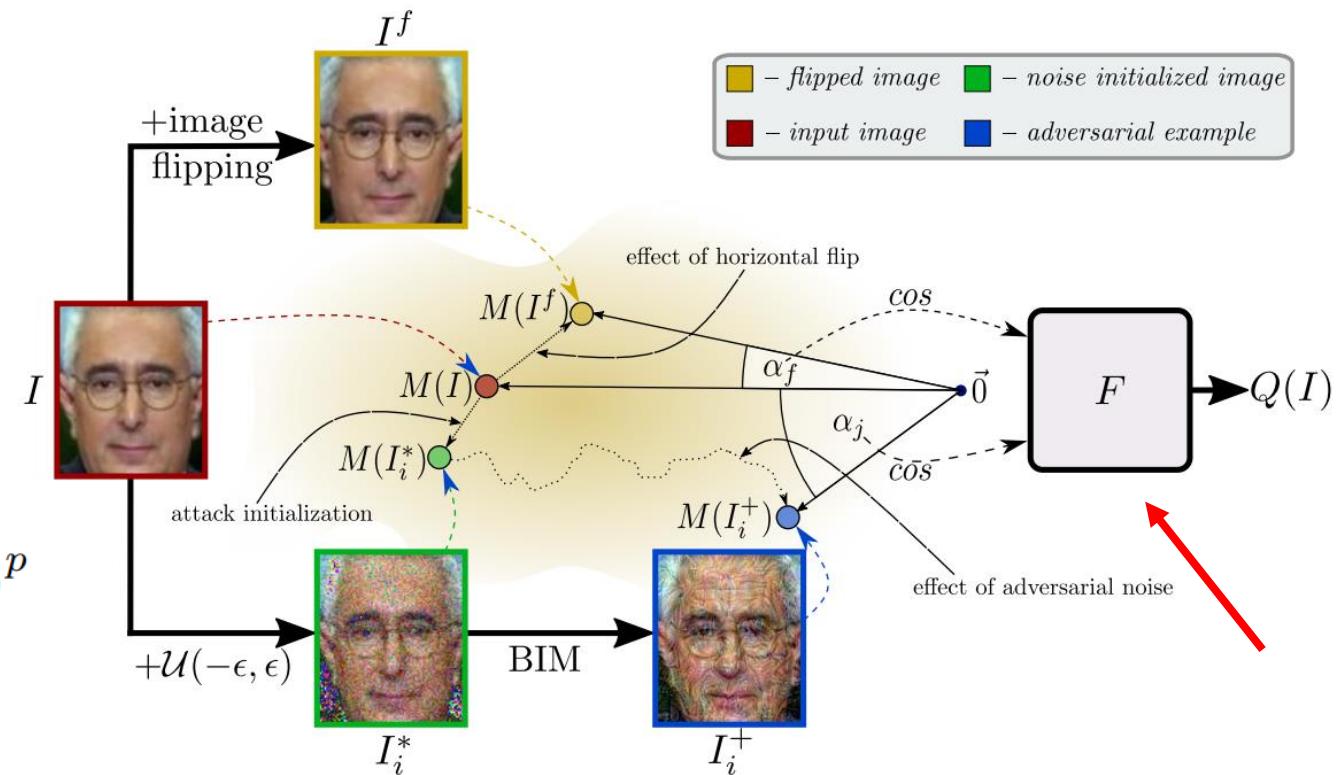
$$L(M(I^*), y) = 1 - \frac{M(I^*)^T \cdot y}{\|M(I^*)\| \|y\|}$$

FaceQAN

- Key Components
- Quality score calculation

$$\cos \alpha_i = S_i = \frac{y^T \cdot y_i^+}{\|y\| \|y_i^+\|}, \quad \cos \alpha_f = s_f = \frac{y^T \cdot y_f}{\|y\| \|y_f\|}$$

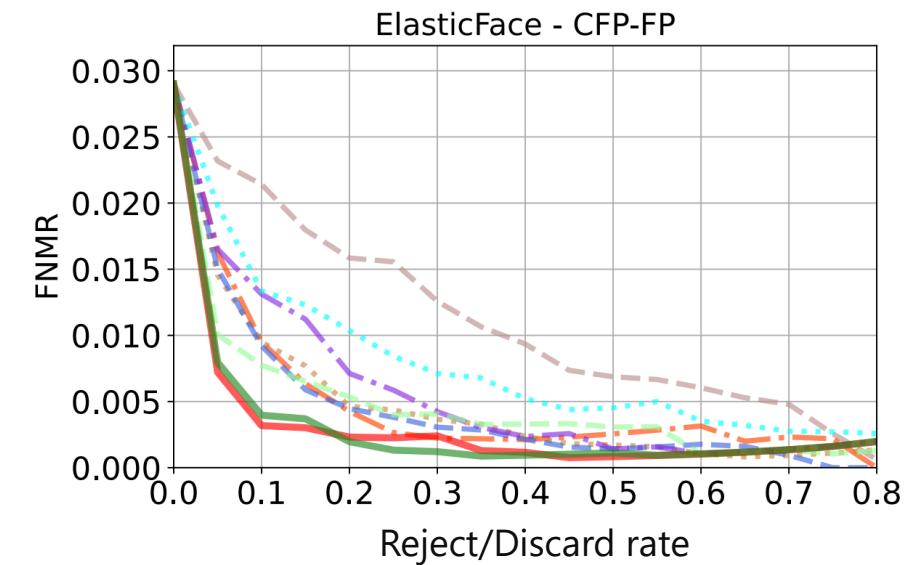
$$q_{adv} = \frac{\mu_S + 1}{2} \cdot \lfloor (1 - \sigma_S) \rfloor_{[0,1]}, \quad Q = (q_{adv} \cdot s_f)^p$$



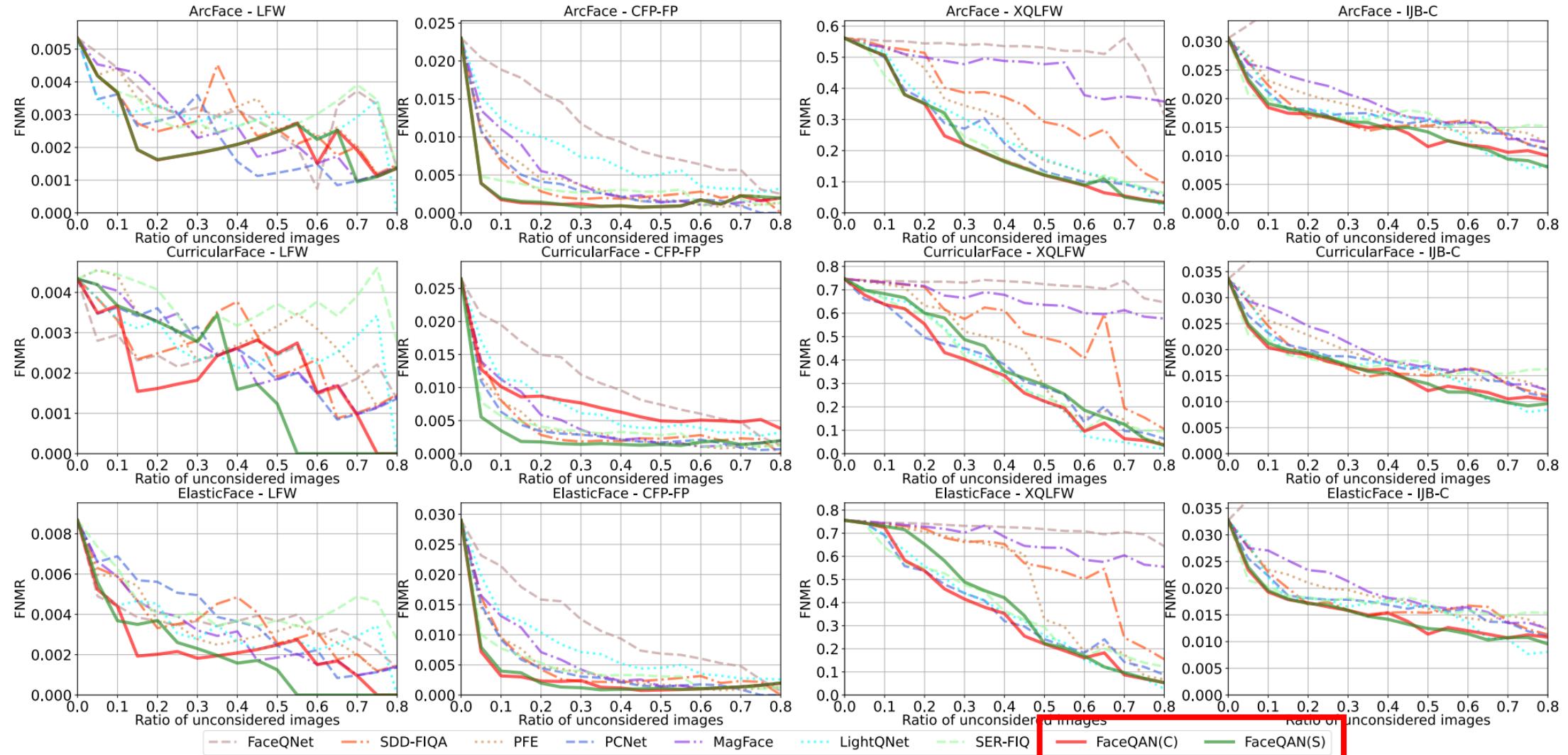
$$L(M(I^*), y) = 1 - \frac{M(I^*)^T \cdot y}{\|M(I^*)\| \|y\|}$$

FaceQAN - Experiments

- Standard evaluation approach:
 - Error-Versus Discard Characteristic (EDC) curves
 - Show how the performance of FR models improves with increasing discard rates.
 - Area Under the Curve (AUC)
 - Lower value indicates better performance.
 - Benchmarks:
 - LFW, CFP-FP, XQLFW, IJB-C
 - FR models:
 - ArcFace, CurricularFace, ElasticFace – Same-Model, Cross-Model
 - FIQA methods:
 - FaceQnet, SDD-FIQA, PFE, PCNet, MagFace, LightQNet, SER-FIQ



FaceQAN - Experiments



FaceQAN - Experiments

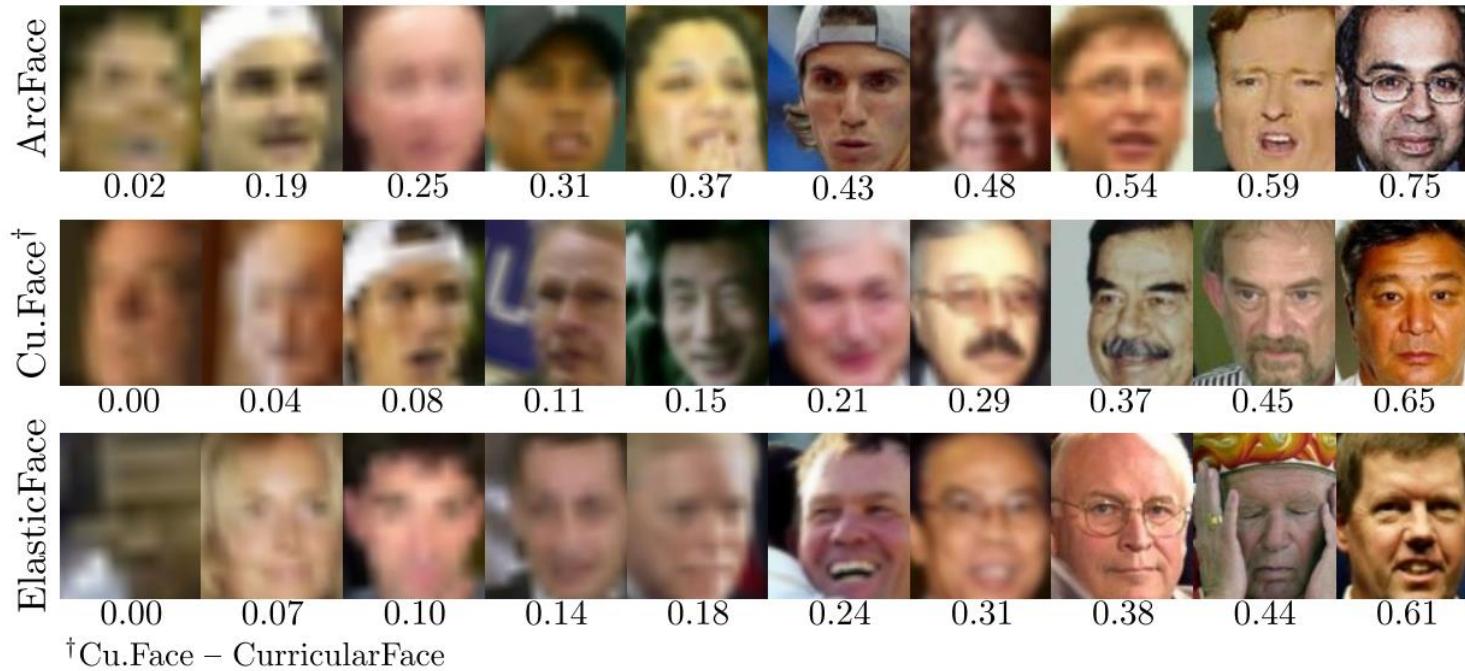
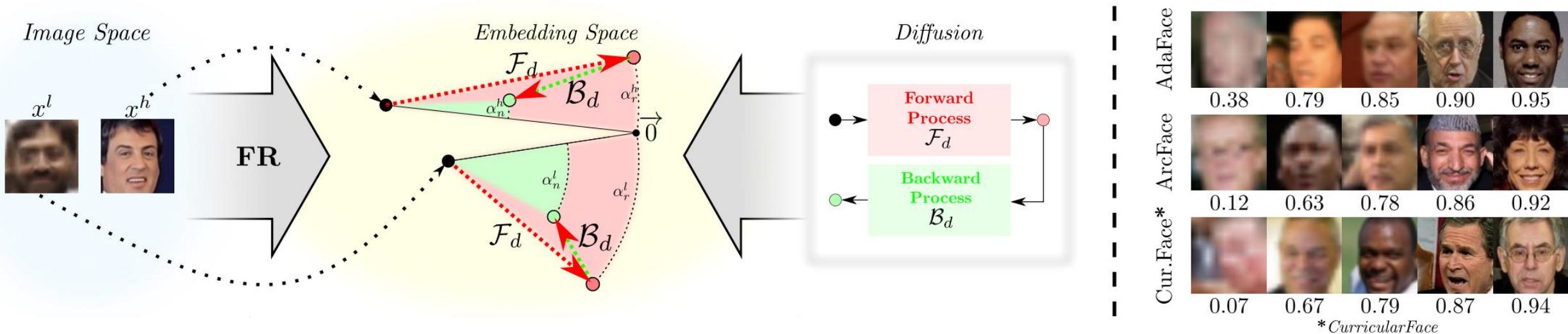


TABLE III
ANALYSIS OF THE TIME COMPLEXITY OVER CFP-FP USING CosFACE

Complexity	FaceQnet	SDD-FIQA	PFE	PCNet	MagFace	LightQnet	SER-FIQ
t [s]	μ	0.0432	0.0006	0.0493	0.0175	0.0011	0.0535
	σ	0.0026	0.0004	0.0275	0.0004	0.0004	0.0468
Complexity	FaceQAN (ours)						
	$k = 2$	$k = 5$	$\dagger k = 10$	$k = 50$	$k = 100$		
t [s] ($\mu \pm \sigma$)	0.21 ± 0.019	0.23 ± 0.018	0.30 ± 0.006	1.00 ± 0.027	1.87 ± 0.031		

FaceQAN – Take Aways

- Adversarial attacks are powerful for probing embedding stability
- FaceQAN achieves SOTA performance
 - Cross-model and Same-model setting
 - Across multiple benchmarks
 - Across multiple FR models
- Limitations:
 - Embedding stability = partial characterization of quality
 - Requires backprop over FR model - Very slow



Part II-b: DifFIQA

Ž. Babnik, P. Peer, V. Štruc, DifFIQA: Face Image Quality Assessment Using Denoising Diffusion Probabilistic Models, IJCB 2023



Available on arXiv (May 2023):

<https://arxiv.org/abs/2305.05768>

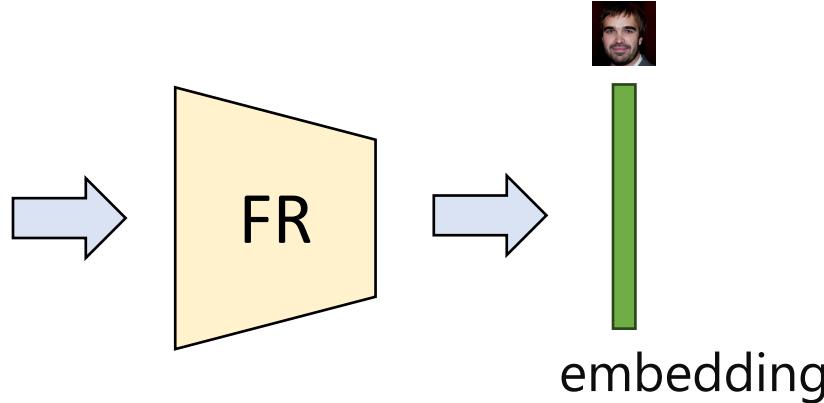
GitHub: <https://github.com/LSIbabnikz/DifFIQA>



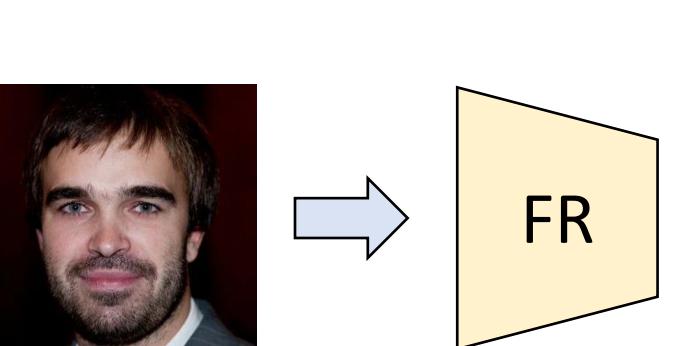
DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

- Face Image Quality Assessment based on two concepts:

Perturbation robustness



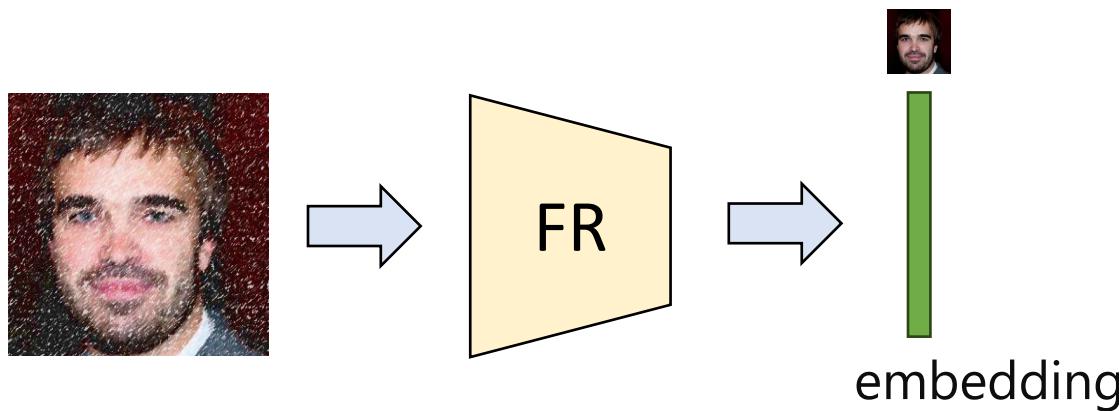
Reconstruction quality



DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

- Face Image Quality Assessment based on two concepts:

Perturbation robustness

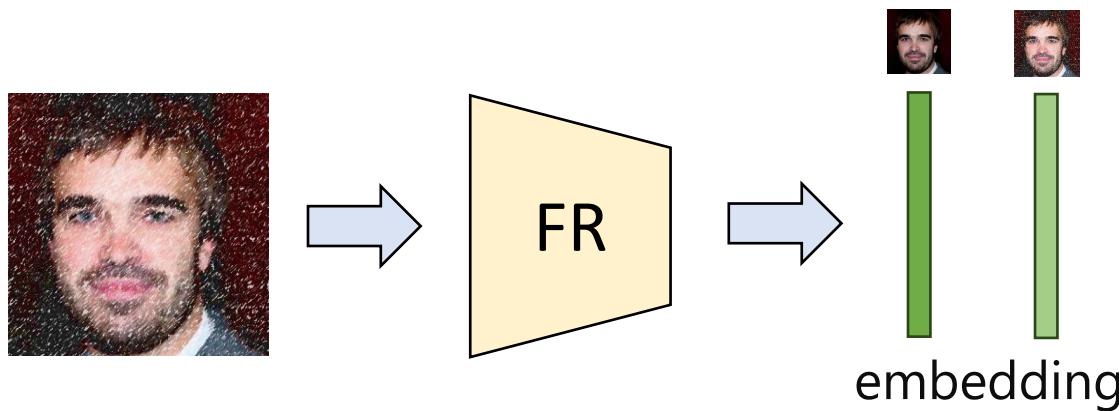


Reconstruction quality

DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

- Face Image Quality Assessment based on two concepts:

Perturbation robustness

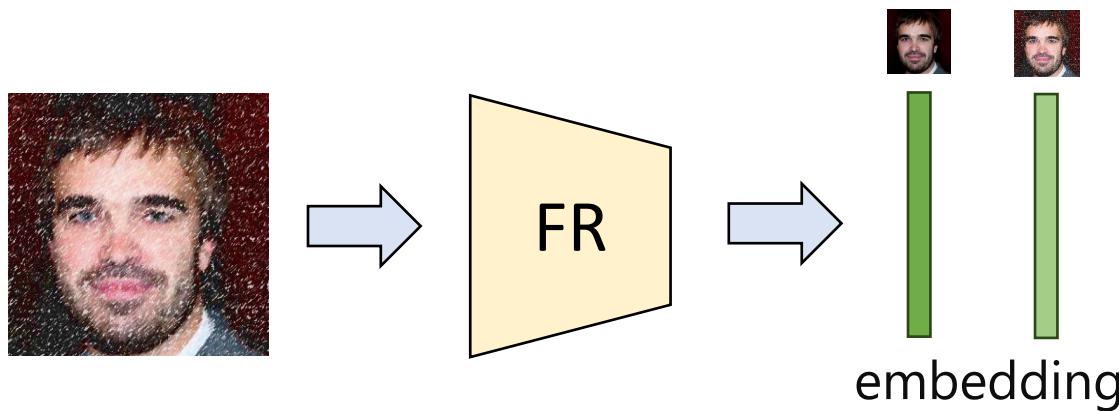


Reconstruction quality

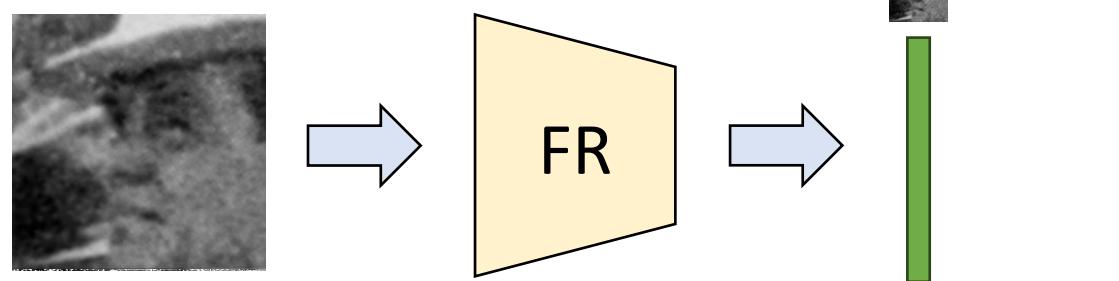
DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

- Face Image Quality Assessment based on two concepts:

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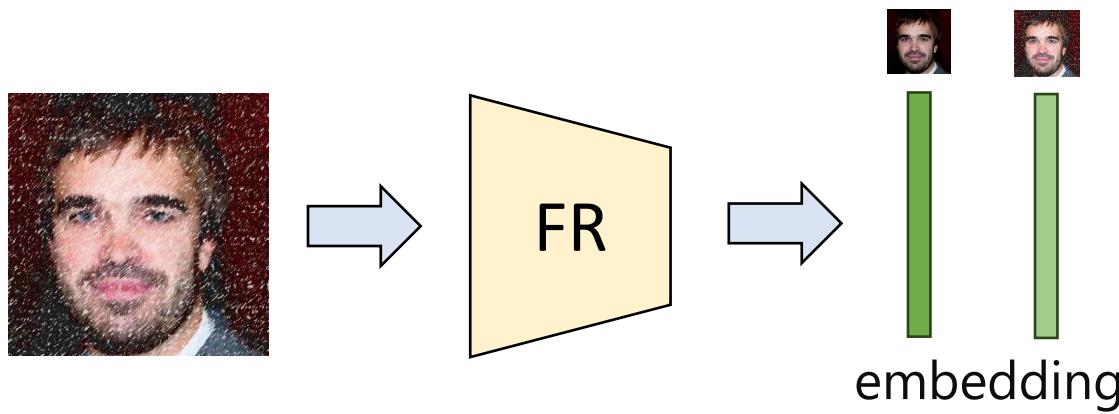
Reconstruction quality



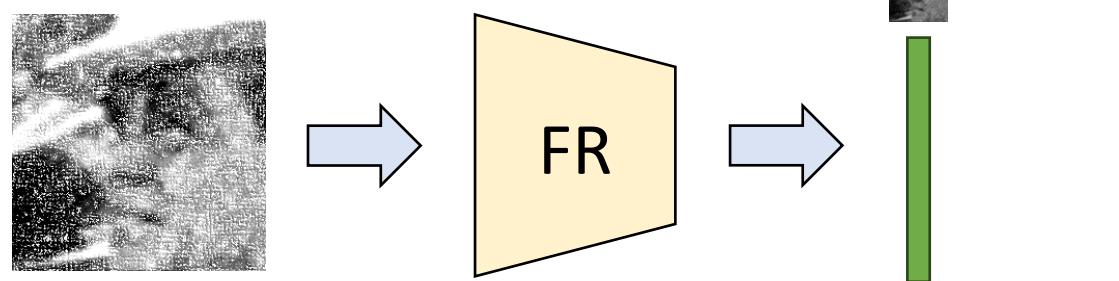
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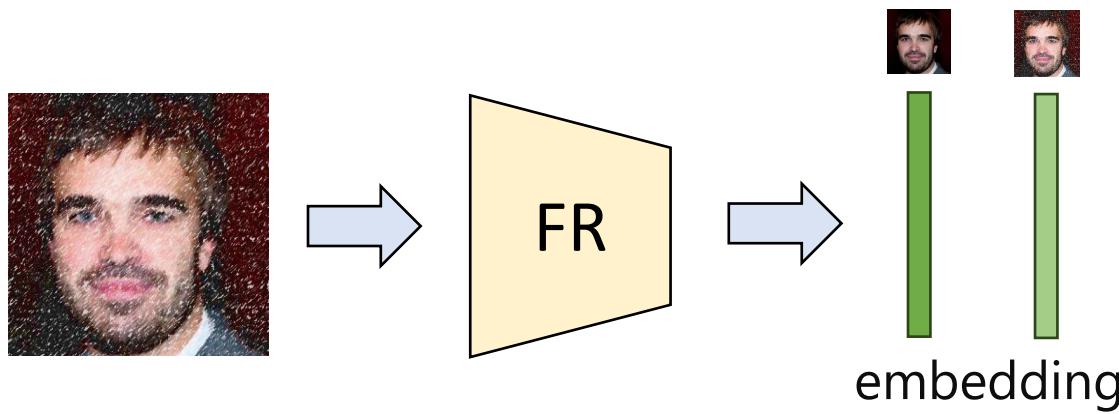
Reconstruction quality



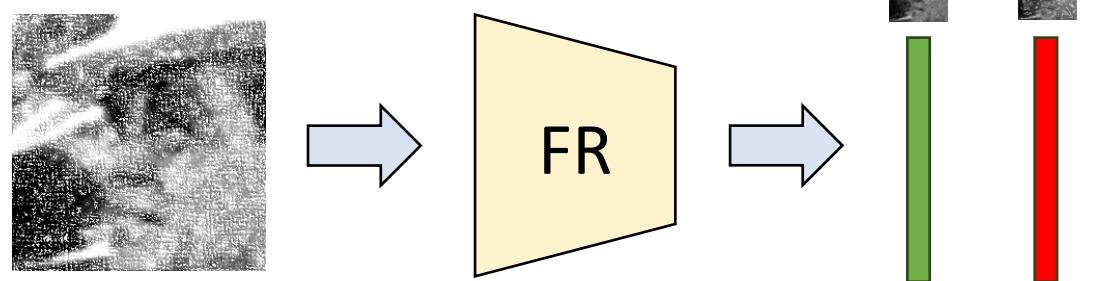
DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

- Face Image Quality Assessment based on two concepts:

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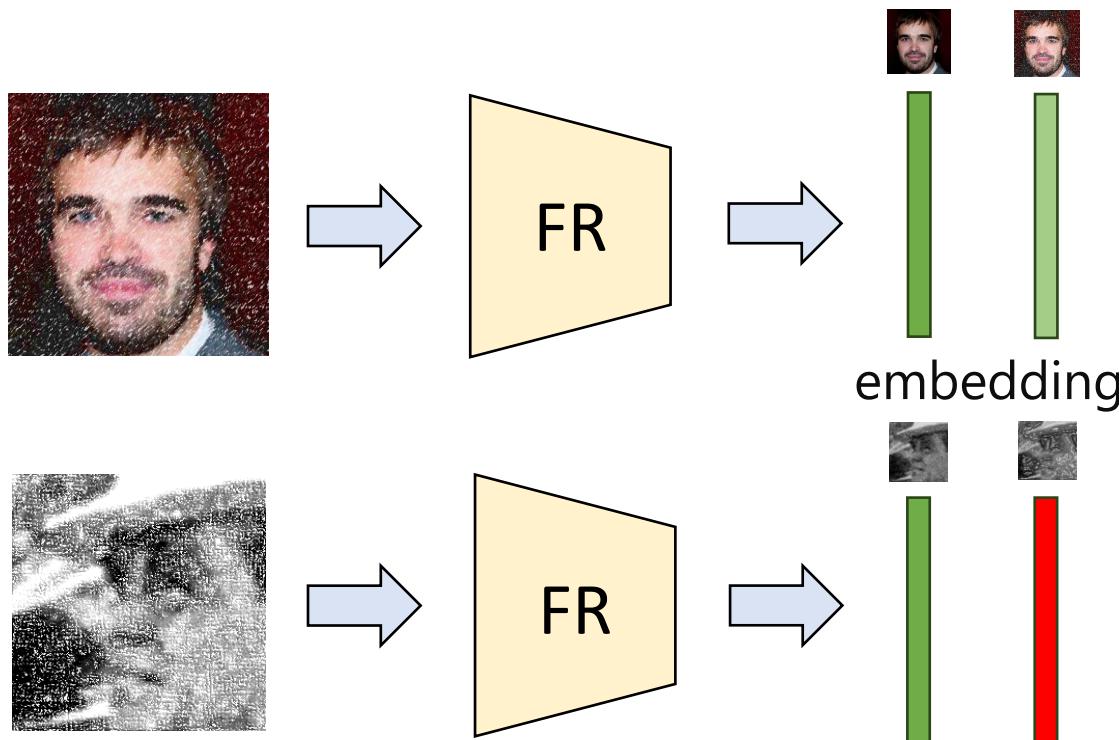
Reconstruction quality



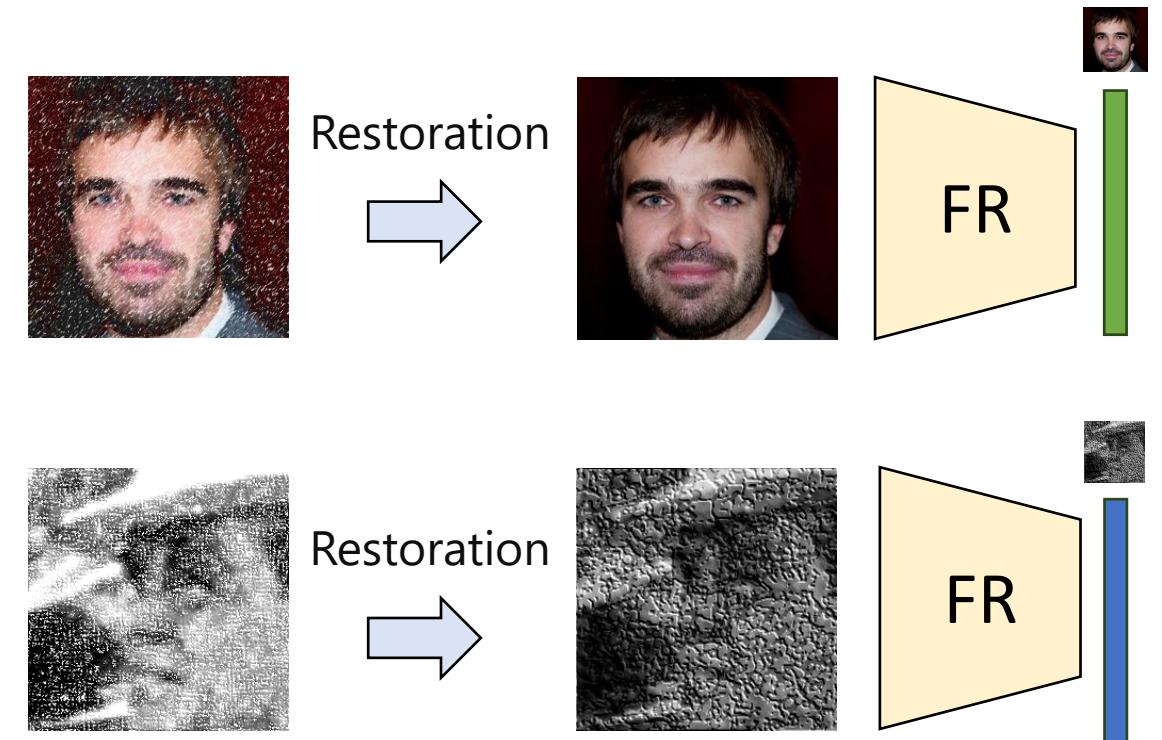
DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

- Face Image Quality Assessment based on two concepts:

Perturbation robustness



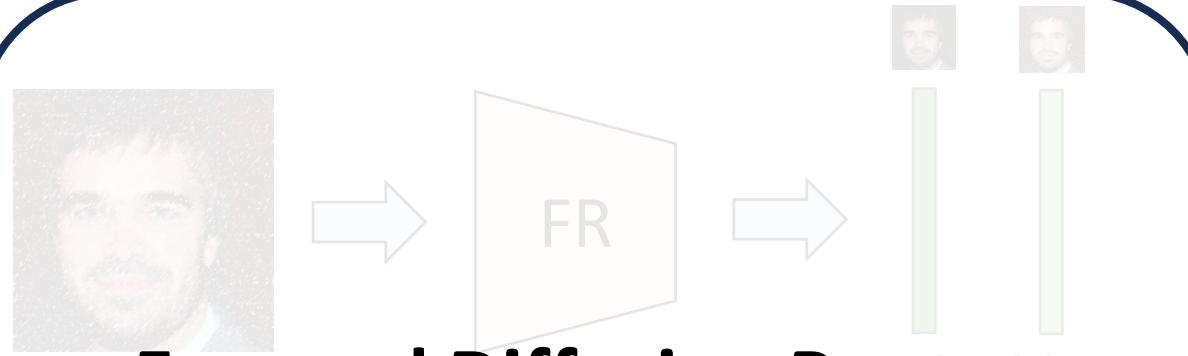
Reconstruction quality



DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

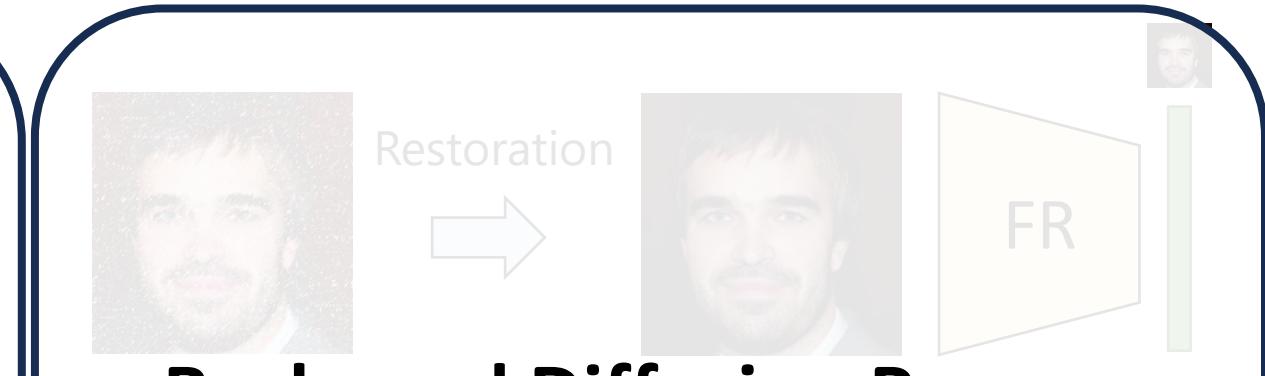
- Face Image Quality Assessment based on two concepts:

Perturbation robustness



Forward Diffusion Process

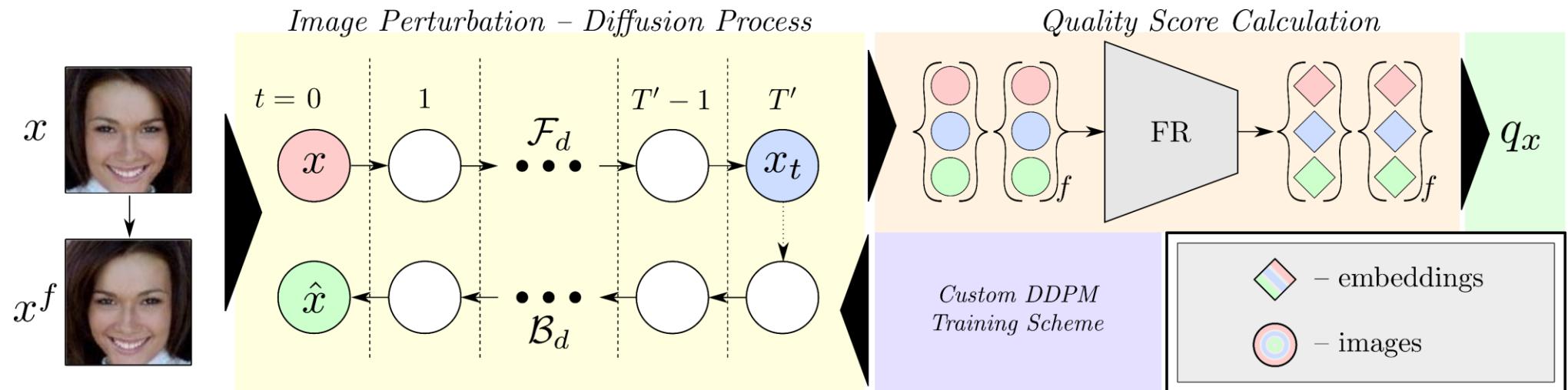
Reconstruction quality



Backward Diffusion Process

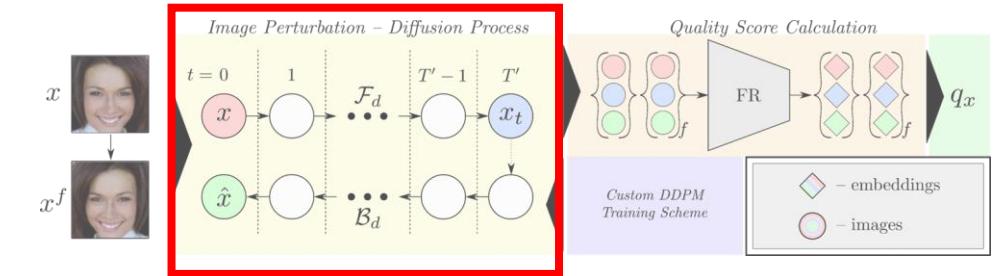
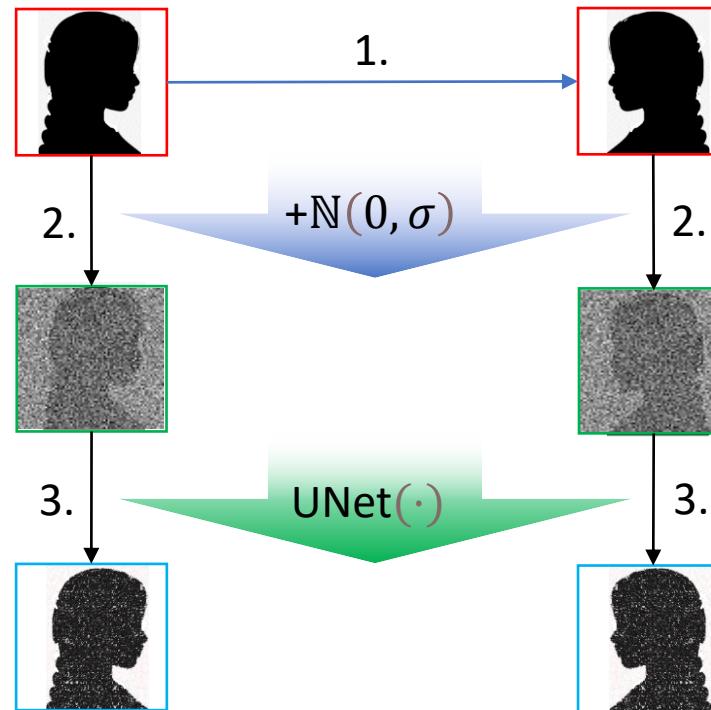
DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

- DifFIQA (high-level) overview:
 - Step 1: Forward and backward diffusion (i.e., perturbations and reconstructions)
 - Step 2: Quality score calculation



DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

- Step 1: Forward and backward diffusion

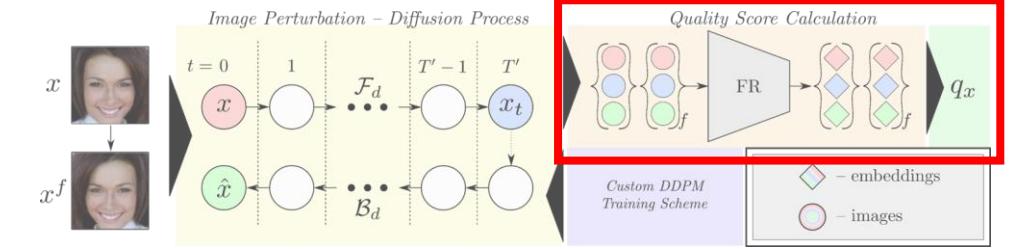
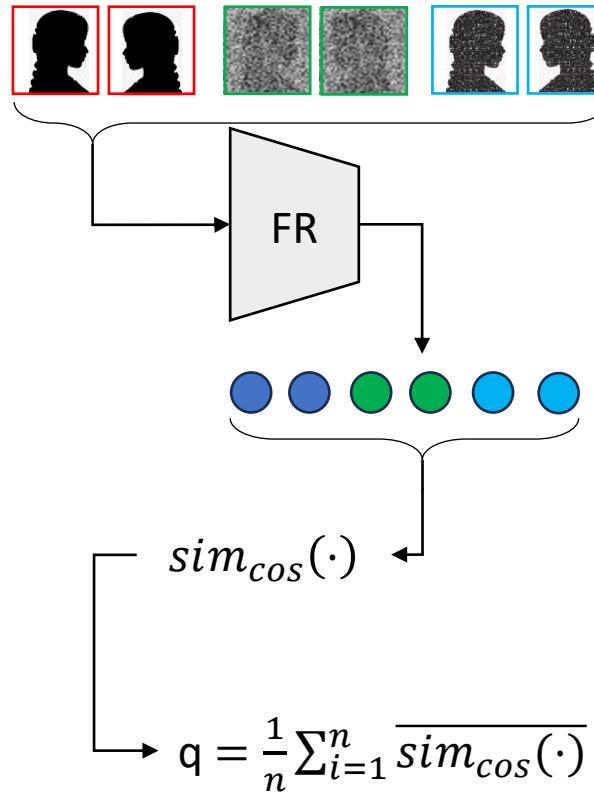


Forward diffusion – adds noise

Backward diffusion – generate reconstructions

DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

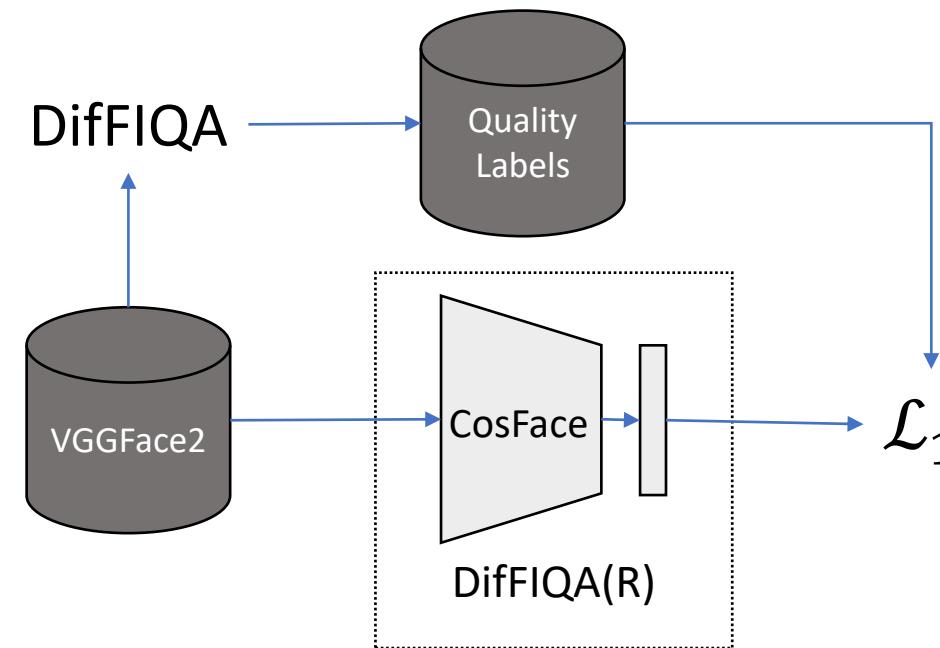
- Step 2: Quality score calculation



- 1. Construct image embeddings:**
 - using any target FR model,*
 - for all three image pairs.*
- 2. Calculate embedding similarity:**
 - using cosine similarity,*
 - comparing the input image embedding to all others.*
- 3. Repeat process n-times and calculate average.**

DifFIQA: Quality Assessment Using Denoising Diffusion Probabilistic Models

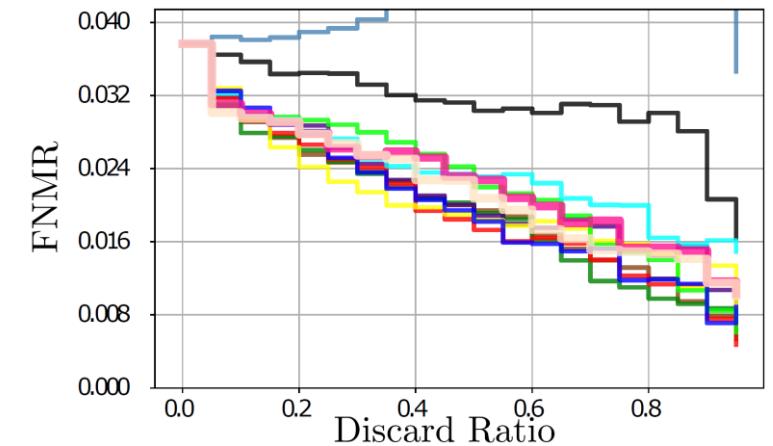
- Problem: Diffusion is slow!
- DifFIQA(R) - Knowledge distillation



Fine-tune a pretrained FR model using pseudo-quality labels extracted using DifFIQA.

Experimental Setup

- Standard evaluation approach:
 - Error-Versus Discard Characteristic (EDC) curves
 - Show how the performance of FR models improves with increasing discard rates.
 - partial Area Under the Curve (pAUC)
 - Lower value indicates better performance.
 - Limit the discard ratio to (0.2) or (0.3).
- Benchmarks:
 - Adience, CALFW, CFP-FP, CPLFW, IJB-C, LFW, XQLFW
- FR models:
 - AdaFace, ArcFace, CurricularFace, CosFace
- FIQA methods:
 - FaceQnet, SDD-FIQA, PFE, PCNet, MagFace, LightQNet, SER-FIQ, FaceQAN, CR-FIQA, FaceQgen



Results (pAUC)

- Average results over all benchmarks and FR models**

Results using discard ratio of (0.2).

FaceQnet [17]	SDD-FIQA [33]	PFE [39]	PCNet [44]	MagFace [31]	LightQNet [7]	SER-FIQ [40]	FaceQAN [3]	CR-FIQA [5]	FaceQgen [15]	DifFIQA	DifFIQA(R)
0.9458	0.8244	0.8197	0.8989	0.8253	0.8183	0.7985	0.7519	0.7567	0.8527	0.7591	0.7518

Results using discard ratio of (0.3).

FaceQnet [17]	SDD-FIQA [33]	PFE [39]	PCNet [44]	MagFace [31]	LightQNet [7]	SER-FIQ [40]	FaceQAN [3]	CR-FIQA [5]	FaceQgen [15]	DifFIQA	DifFIQA(R)
0.9315	0.7483	0.7497	0.8691	0.7635	0.7412	0.7292	0.6847	0.6800	0.7954	0.6822	0.6768

- Knowledge distillation improves the results of the base approach
- DifFIQA(R) outperforms SOTA methods.

Run-time

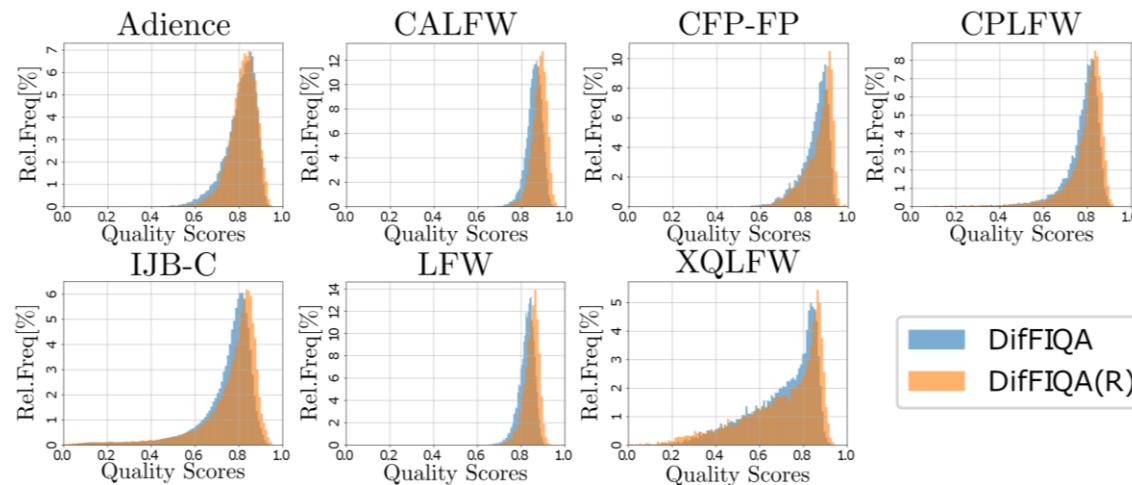
- **Hardware: Intel i9-10900KF CPU, 64 GB RAM in Nvidia 3090 GPU**

FIQA model	Ours	
	DifFIQA	DifFIQA(R)
Runtime ($\mu \pm \sigma$)	1074.62 ± 11.45	1.24 ± 0.36

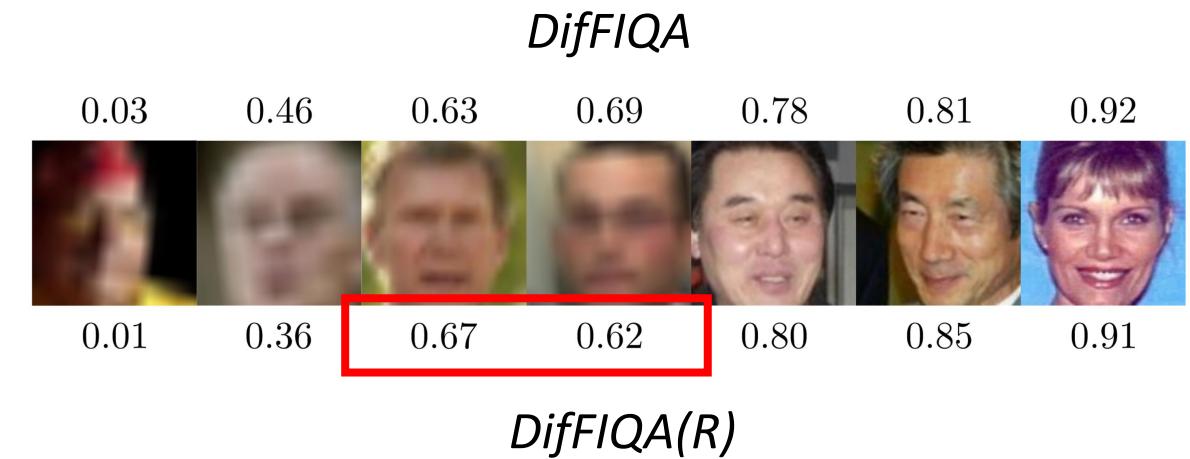
- Speed-up due to knowledge distillation is around **1000x**

DifFIQA and DifFIQA(R) Comparison

Comparison of quality score distributions

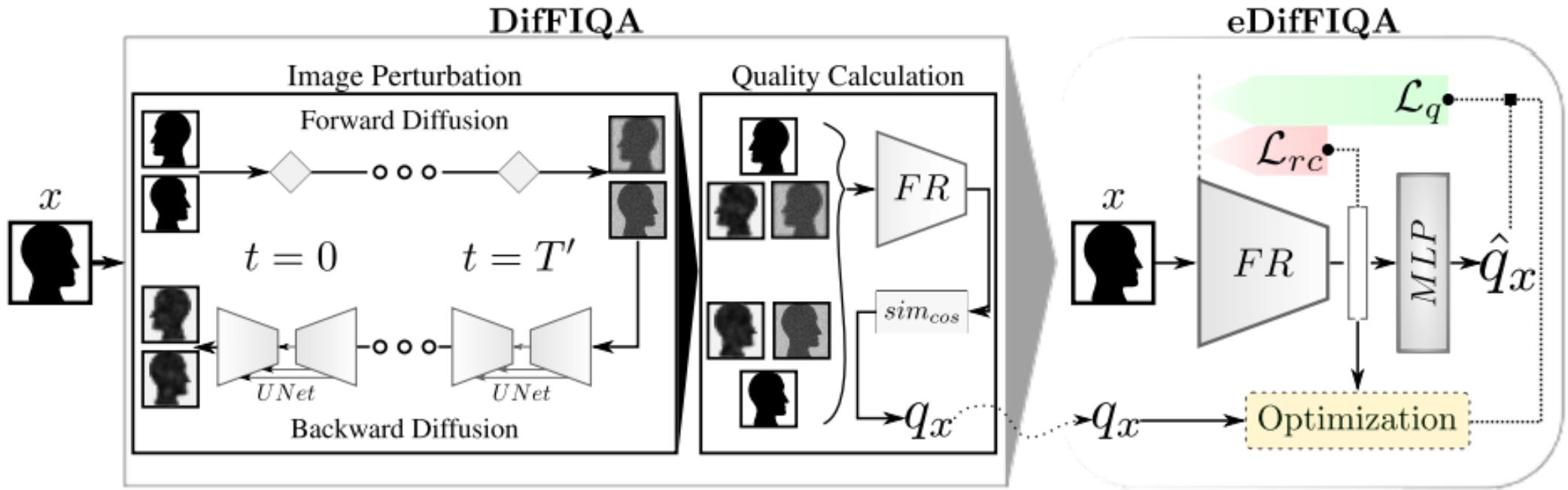


Visual comparison



DifFIQA – Take Aways

- DifFIQA: a new FIQA approach based on DDPMs
- DifFIQA(R): distilled version for fast prediction
- State-of-the-art performance across multiple datasets and face recognition models



Part II-c: eDifFIQA

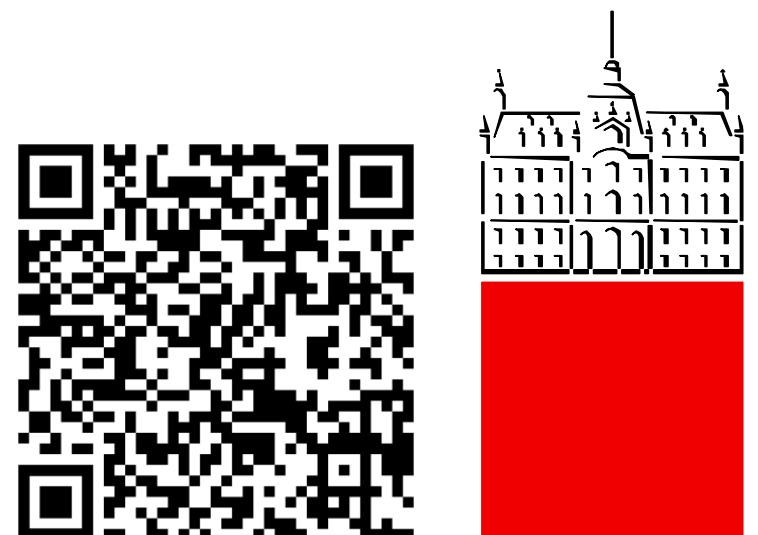
Ž. Babnik, P. Peer, V. Štruc, eDifFIQA: Towards Efficient Face Image Quality Assessment based on Denoising Diffusion Probabilistic Models, TBIOM 2024



Available on IEEE Xplore in open access (May 2024):

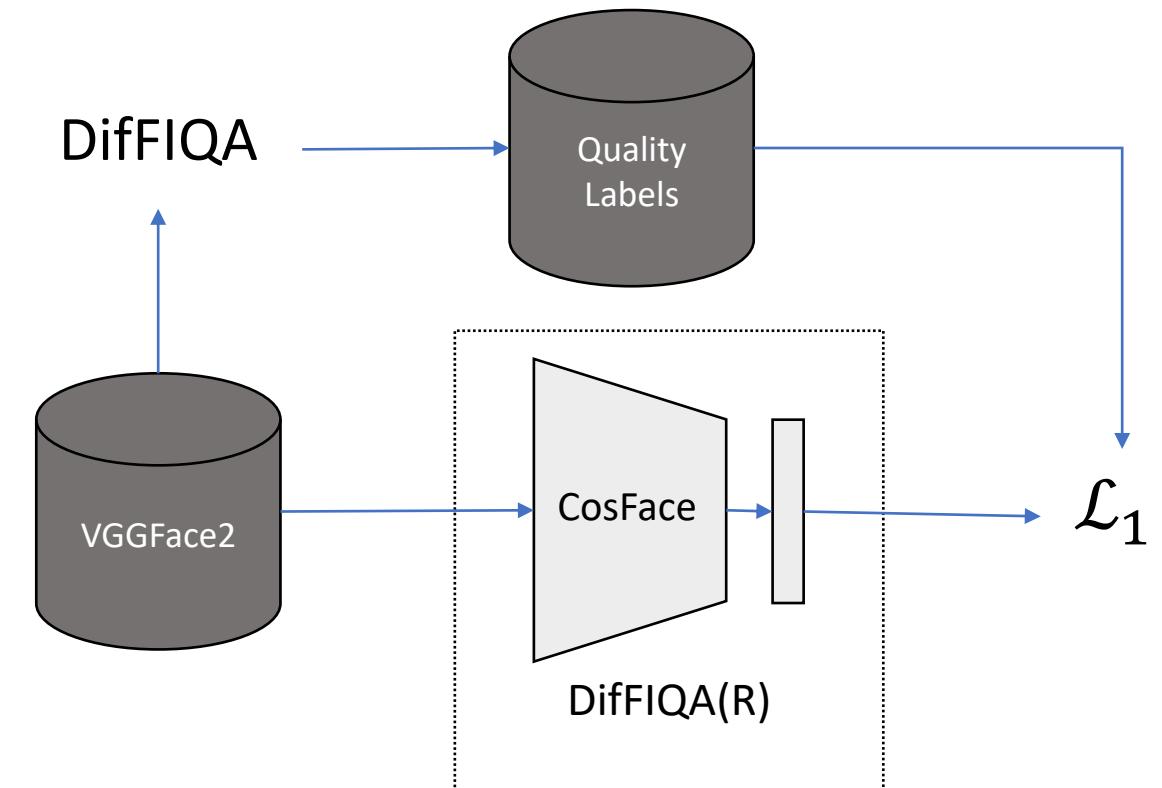
<https://ieeexplore.ieee.org/document/10468647/>

GitHub: <https://github.com/LSIbabnikz/eDifFIQA>



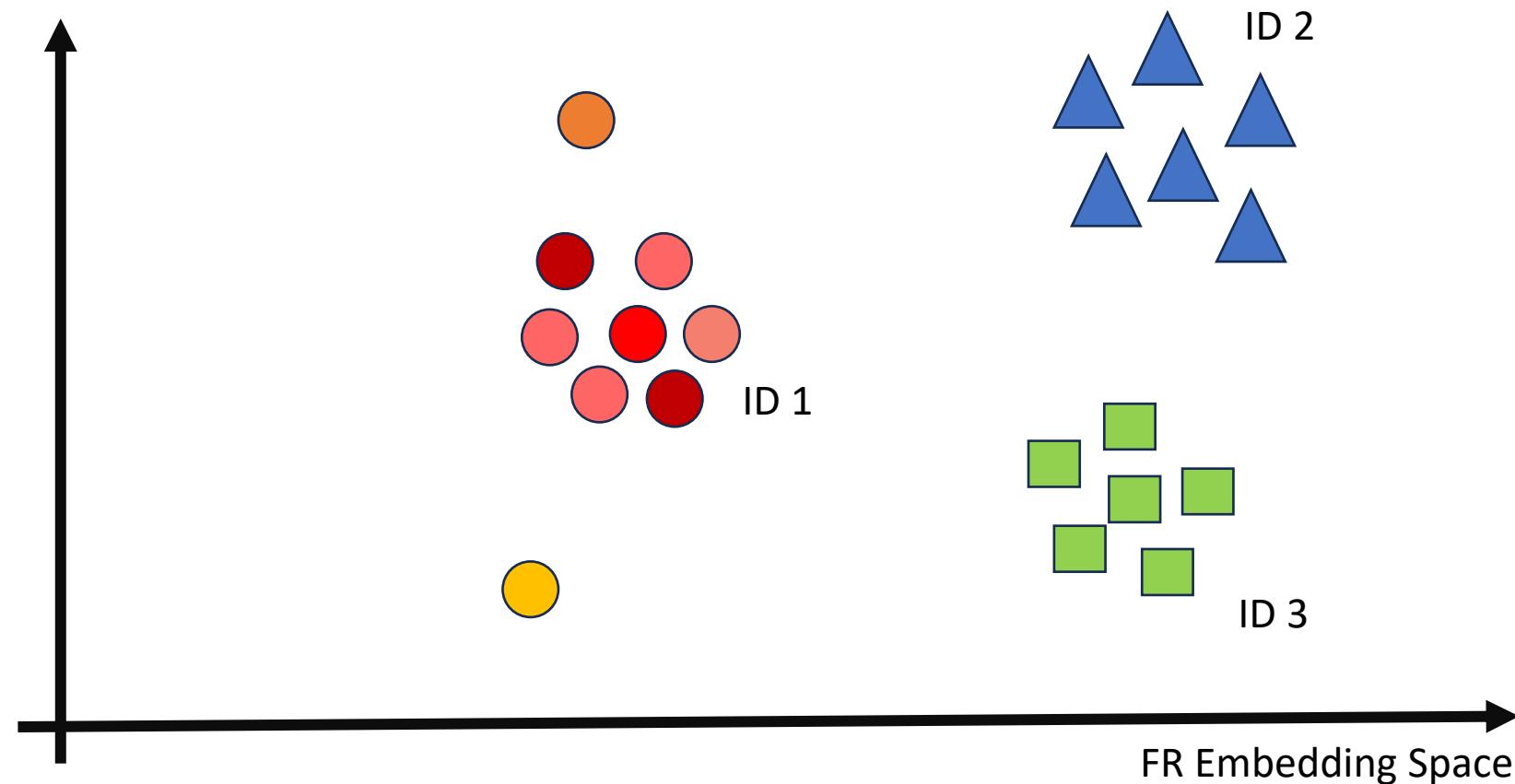
eDiffIQA: Efficient Quality Assessment Using Denoising Diffusion Probabilistic Models

- eDiffIQA
 - Efficiency
 - Performance
- DiffIQA:
 - C1: Perturbation robustness
 - C2: Reconstruction quality



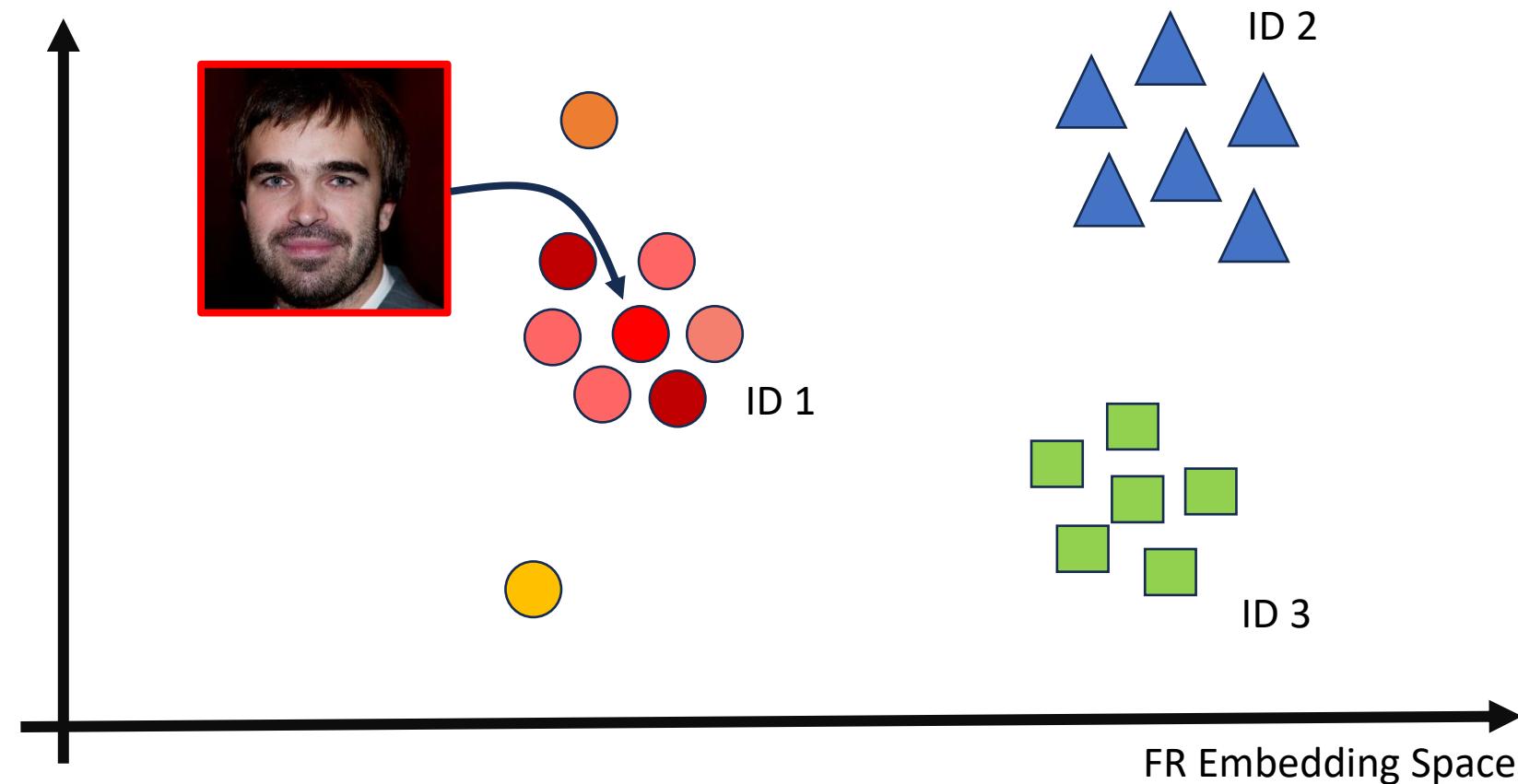
eDifFIQA: Efficient Quality Assessment Using Denoising Diffusion Probabilistic Models

- C3: Relative position in the embedding space



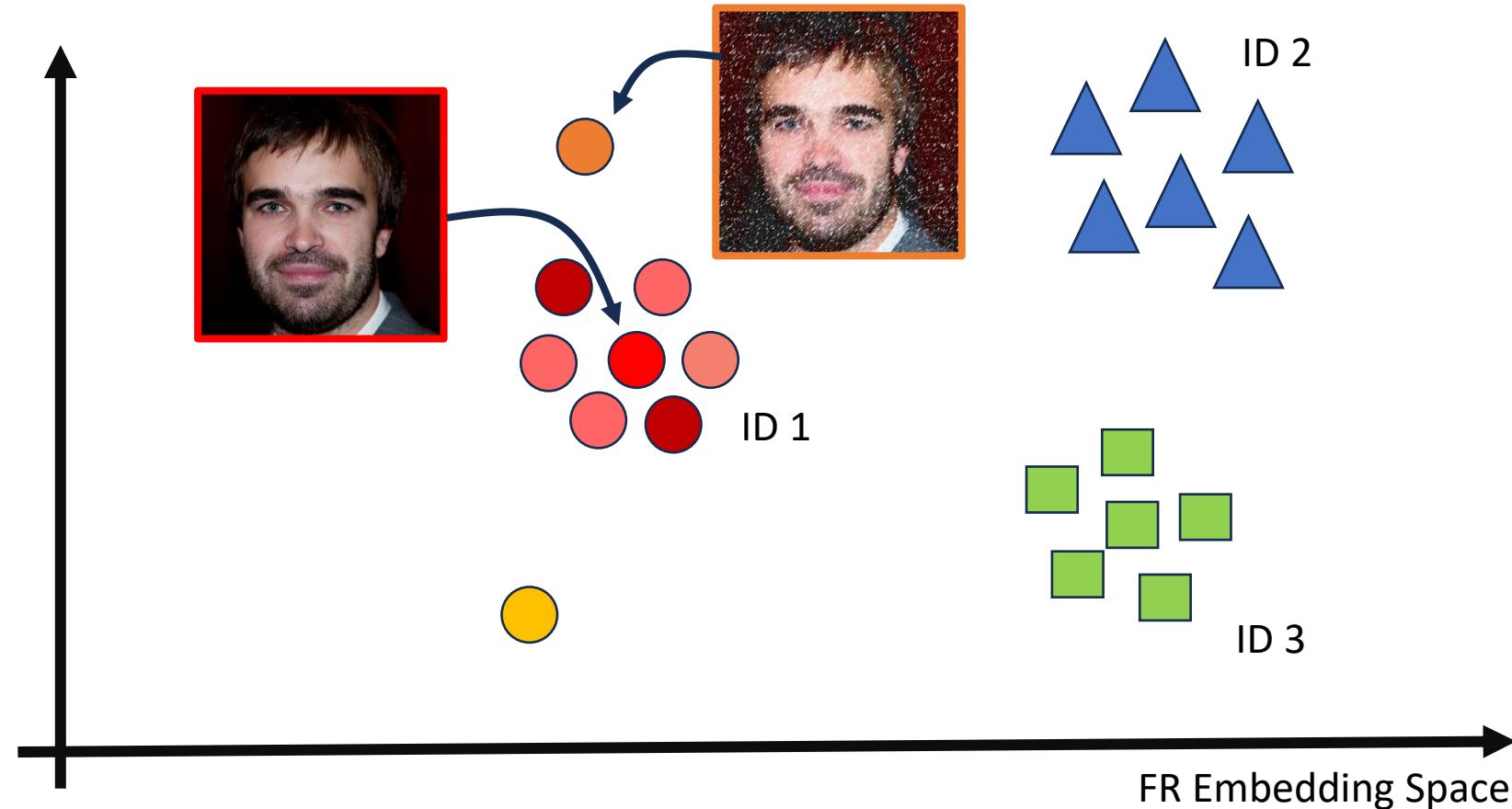
eDiffIQA: Efficient Quality Assessment Using Denoising Diffusion Probabilistic Models

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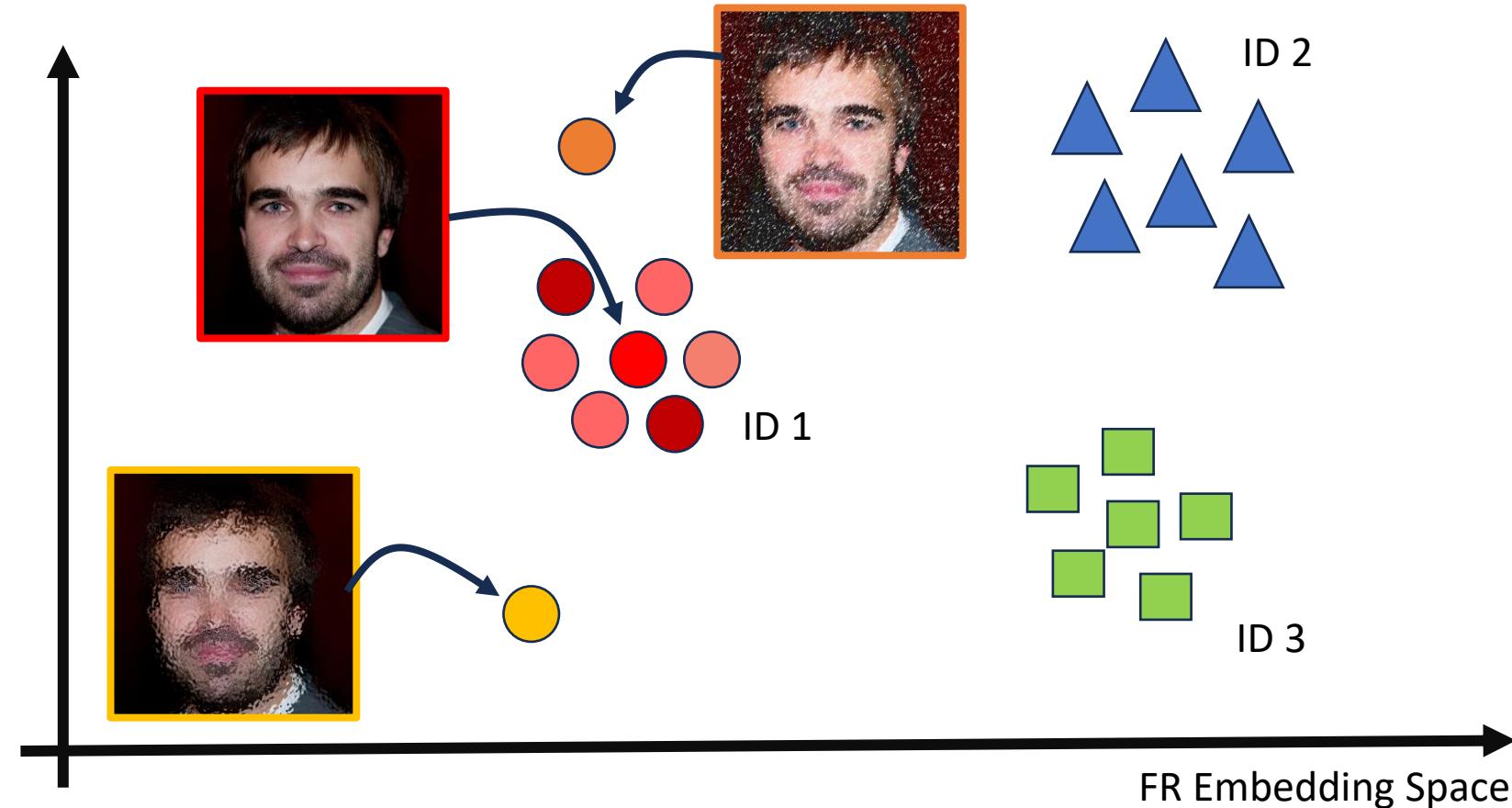
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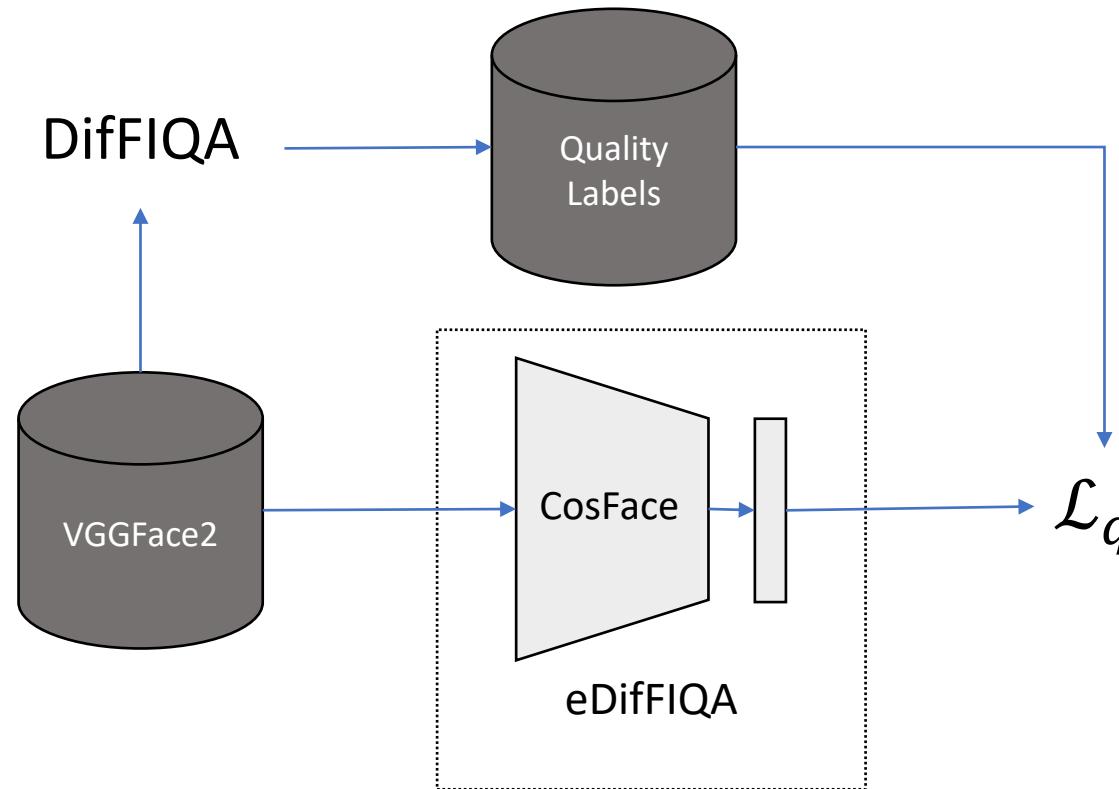
eDifFIQA: Efficient Quality Assessment Using Denoising Diffusion Probabilistic Models

- C3: Relative position in the embedding space



eDifFIQA: Efficient Quality Assessment Using Denoising Diffusion Probabilistic Models

- eDifFIQA

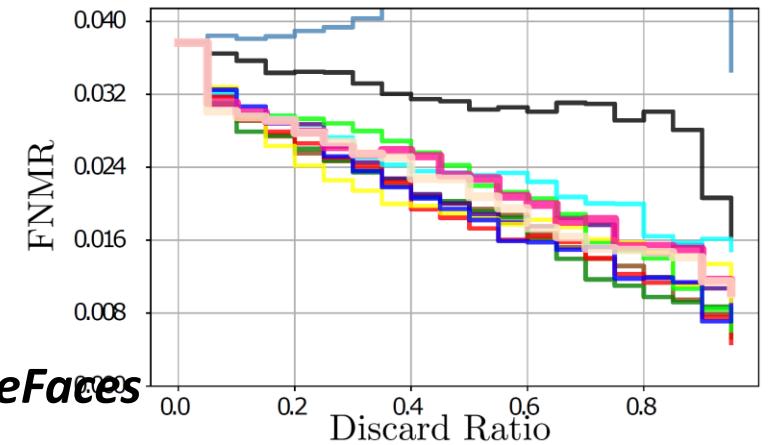


$$q_x^o = (q_x - \epsilon \cdot \frac{\hat{e}_x^T \cdot \bar{e}_{C_i^{(p)}}}{\|\hat{e}_x\| \cdot \|\bar{e}_{C_i^{(p)}}\|})$$

$$\mathcal{L}_q = \|\hat{q}_x - q_x^o\|$$

Experimental Setup

- Standard evaluation approach:
 - EDC+pAUC
 - Benchmarks:
 - *Adience, CALFW, CFP-FP, CPLFW, IJB-C, LFW, XQLFW, YouTubeFaces*
 - FR models:
 - *AdaFace, ArcFace, CurricularFace, CosFace, SwinFace, TransFace*
 - FIQA methods:
 - *FaceQnet, SDD-FIQA, PFE, PCNet, MagFace, LightQNet, SER-FIQ, FaceQAN, CR-FIQA, FaceQgen, DifFIQA, DifFIQA(R)*
 - Backbones:
 - *eDifFIQA(L) – ResNet100, eDifFIQA (M) – ResNet50, eDifFIQA(S) – ResNet18*



Results (pAUC)

- Results using discard ratio of (0.3).*

ArcFace - pAUC@FMR=10⁻³(↓)

FIQA Model	Adience	CALFW	CFP-FP	CPLFW	IJB-C	LFW	XQLFW	pAUC
FaceQnet [10]	0.943	0.955	0.702	0.878	1.224	0.884	0.899	0.926
SDD-FIQA [13]	0.783	0.901	0.497	0.734	0.720	0.808	0.774	0.745
PFE [18]	0.774	0.932	0.522	0.738	0.783	0.779	0.641	0.738
PCNet [11]	1.022	1.006	0.863	0.783	0.706	0.623	1.004	0.858
MagFace [19]	0.812	0.902	0.500	0.717	0.824	0.635	0.943	0.762
LightQNet [12]	0.789	0.913	0.582	0.752	0.721	0.745	0.621	0.732
SER-FIQ [14]	0.767	0.903	0.446	0.656	0.671	0.935	0.676 [†]	0.722
FaceQAN [15]	0.824	0.941	0.347	0.677	0.673	0.624	0.667	0.679
CR-FIQA [21]	0.808	0.891	0.369	0.689	0.664	0.675	0.680	0.682
FaceQgen [32]	0.817	0.985	0.724	0.701	0.785	0.802	0.653	0.781
DifFIQA [5]	0.805	0.918	0.402	0.674	0.675	0.714	0.652	0.691
DifFIQA(R) [5]	0.801	0.898	0.408	0.646*	0.655*	0.708	0.653	0.681
eDifFIQA(S)	0.822	0.916	0.402	0.679	0.679	0.786	0.634*	0.703
eDifFIQA(M)	0.825	0.846*	0.386	0.669	0.663	0.712	0.671	0.682
eDifFIQA(L)	0.793*	0.872	0.376*	0.667	0.663	0.705*	0.672	0.678

TransFace - pAUC@FMR=10⁻³(↓)

FIQA Model	Adience	CALFW	CFP-FP	CPLFW	IJB-C	LFW	XQLFW	pAUC
FaceQnet [10]	0.938	0.964	0.753	0.889	1.291	0.898	1.007	0.963
SDD-FIQA [13]	0.837	0.905	0.545	0.694	0.809	0.840	0.819	0.778
PFE [18]	0.834	0.930	0.546	0.711	0.879	0.810	0.798	0.787
PCNet [11]	0.998	1.003	0.837	1.010	0.804	0.661	0.654	0.853
MagFace [19]	0.867	0.898	0.512	0.682	0.930	0.673	0.935	0.786
LightQNet [12]	0.847	0.916	0.665	0.697	0.817	0.784	0.634	0.766
SER-FIQ [14]	0.784	0.901	0.430	0.647	0.773	0.935	0.585 [†]	0.722
FaceQAN [15]	0.890	0.942	0.377	0.599	0.774	0.663	0.558	0.686
CR-FIQA [21]	0.832	0.887	0.379	0.614	0.765	0.714	0.580	0.681
FaceQgen [32]	0.858	0.985	0.761	0.699	0.877	0.834	0.739	0.822
DifFIQA [5]	0.863	0.917	0.405	0.597	0.782	0.736	0.529	0.690
DifFIQA(R) [5]	0.856	0.901	0.394	0.579	0.744*	0.722*	0.523*	0.674
eDifFIQA(S)	0.867	0.917	0.446	0.591	0.770	0.825	0.558	0.711
eDifFIQA(M)	0.861	0.849*	0.384	0.577	0.759	0.750	0.553	0.676
eDifFIQA(L)	0.836*	0.872	0.374*	0.575*	0.755	0.735	0.528	0.668



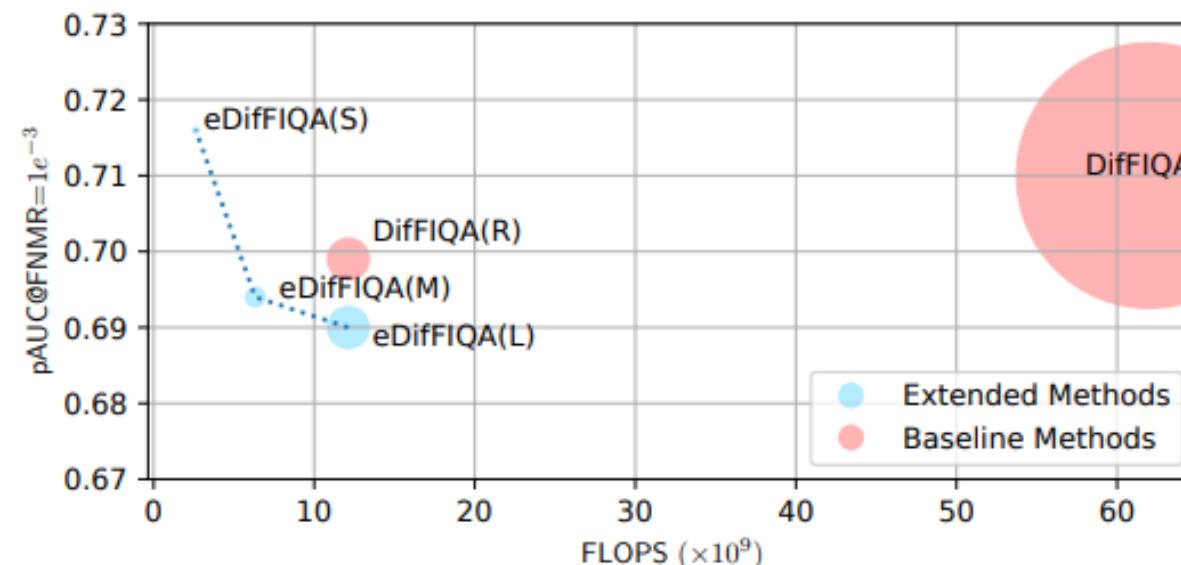
DifFIQA [5]	0.071	0.561	0.657	0.726	0.775	0.815	0.847	0.867	0.884	0.936
DifFIQA(R) [5]	0.007	0.448	0.452	0.659	0.684	0.760	0.837	0.845	0.845	0.942
eDifFIQA(S)	0.032	0.095	0.068	0.365	0.413	0.453	0.666	0.728	0.828	0.897
eDifFIQA(M)	0.000	0.176	0.056	0.469	0.539	0.575	0.734	0.775	0.826	0.870
eDifFIQA(L)	0.036	0.264	0.236	0.440	0.500	0.585	0.768	0.790	0.824	0.913

Run-time

- Hardware: Intel i9-10900KF CPU, 64 GB RAM in Nvidia 3090 GPU**

FIQA model	Baseline methods [5]		eDiffIQA variants		
	DifFIQA	DifFIQA(R)	eDiffIQA(S)	eDiffIQA(M)	eDiffIQA(L)
Runtime ($\mu \pm \sigma$) [in ms]	1074.62 ± 11.45	1.24 ± 0.36	0.36 ± 0.77	0.63 ± 0.75	1.09 ± 0.77
# Parameters (10^6)	$142.87 + 65.15^\dagger$	65.15	24.55	44.11	65.68

[†]The sum refers to the number of parameters of the generative UNet model and the recognition model.





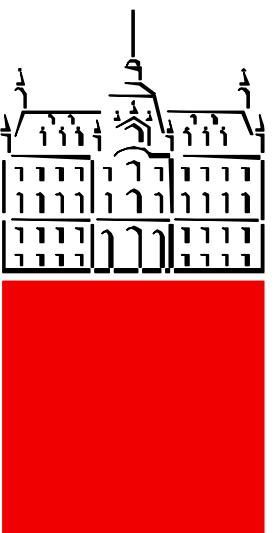
Part III: Open Challenges



Publications available:

<https://lmi.fe.uni-lj.si/en/vitomir-struc/publications/>

GitHub: <https://github.com/LSIbabnikz/>



FIQA – Open Challenges

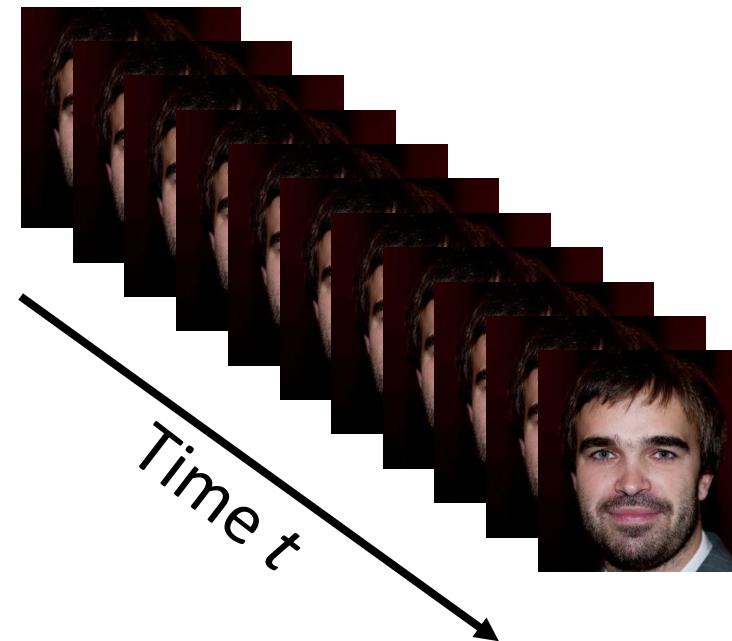
Detector variability:

Quality scores vary with respect to detector variability



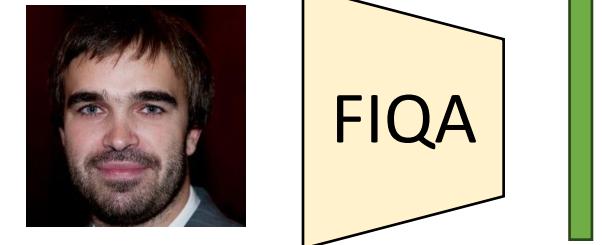
Video FIQA:

Large number of frames with similar quality



Beyond scalar FIQA:

Vector quality descriptions



Specialized FIQA:

For specific applications





Javna agencija za znanstvenoraziskovalno
in inovacijsko dejavnost Republike Slovenije



Thank You!

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Publications



FIQA Code

