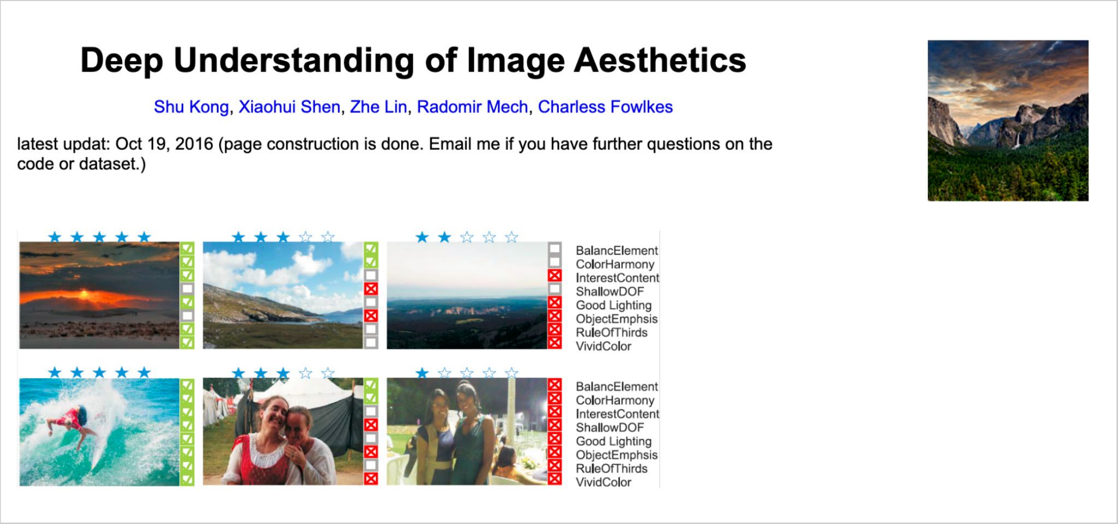
Image Aesthetic Assessment

인공지능랩 김수은

Project. Image Aesthetic Assessment by GAN

제목: Image aesthetic assessment by various GAN models

데이터: <Image Aesthetic Assessment Assisted by Attributes through Adversarial Learning> 논문에 쓰인 AADB dataset 이용



https://www.ics.uci.edu/~skong2/aesthetics.html

진행 Project 참고 논문

제목: <Image Aesthetic Assessment Assisted by Attributes through Adversarial Learning, 2019>

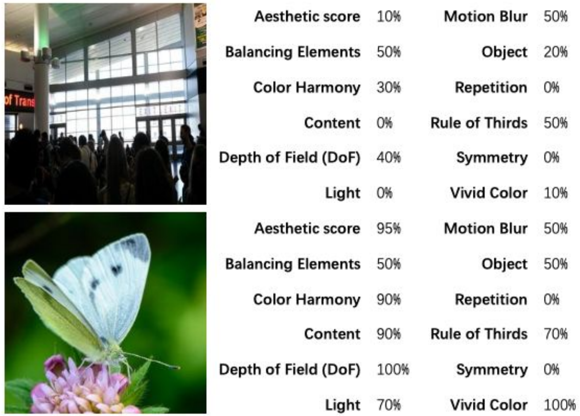


Figure 1: Two examples of aesthetic images (upper: low aesthetics; lower: high aesthetics) with respect to eleven assessment attributes. The ratings of the aesthetic score and attributes are written as percentage for convenience.

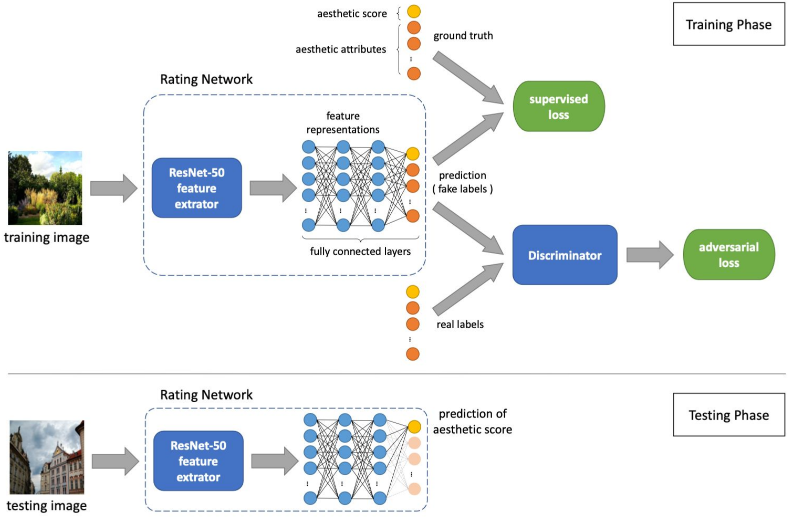


Figure 2: The framework of the proposed method.

Project 참고 논문

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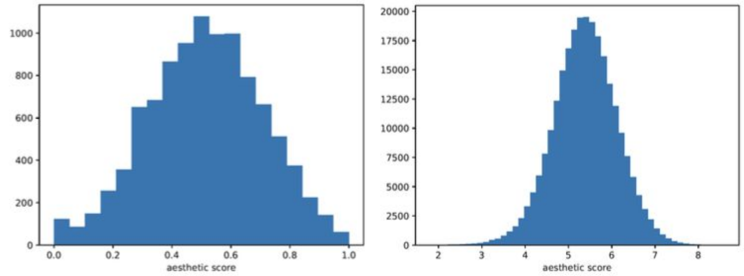


(a) AADB (b) AVA

Figure 3: The distributions of the aesthetic scores on the AADB and AVA databases.

Table 1: Experimental results of image aesthetic assessment.

AADB database	
Methods	ρ
(Kong et al. 2016)	0.6782
(Hou, Yu, and Samaras 2017)	0.6889
(Malu, Bapi, and Indurkhya 2017)	0.689
Single-task Network	0.6833
Multi-task Network	0.6927
Ours	**0.7041**

AVA database	
Methods	ρ
(Kong et al. 2016)	0.5581
Single-task Network	0.6062
Multi-task Network	0.6187
Ours	**0.6313**

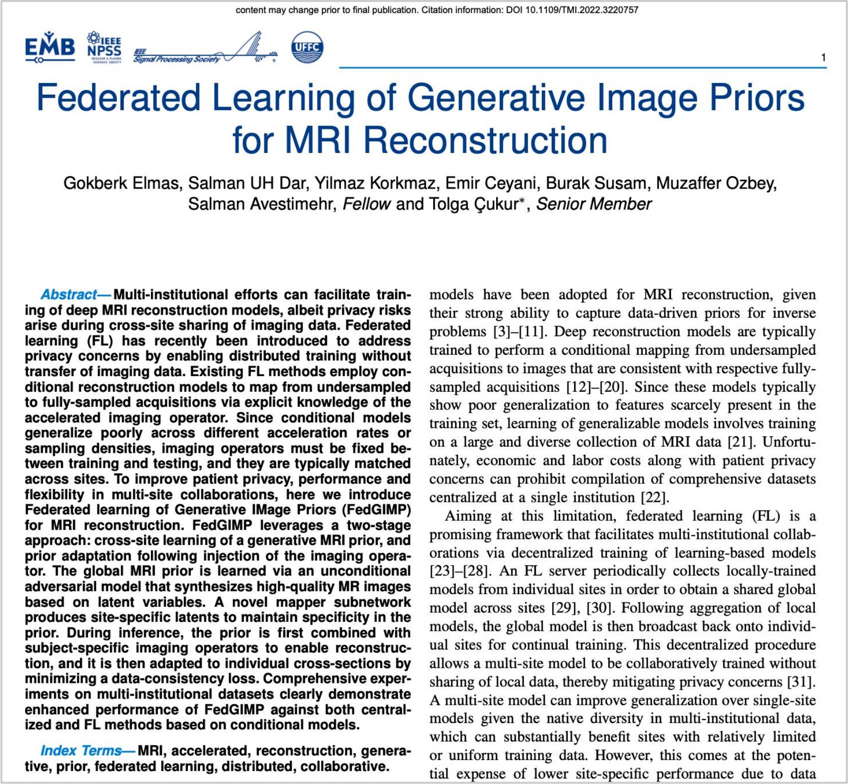
Project. 내용

1. DCGAN
2. WGAN
3. SGAN(셀프-어텐션)

등 GAN 각각 모델의 방법론, 손실함수를 적용해보고 성능 비교 및 평가 진행

어떤 모델이 Image aesthetic assessment 에 뛰어난 성능을 보이는지 수행

Federated learning 과 image 관련 논문


content may change prior to final publication. Citation information: DOI 10.1109/TMI.2022.3220757

Federated Learning of Generative Image Priors for MRI Reconstruction

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***Abstract*— Multi-institutional efforts can facilitate training of deep MRI reconstruction models, albeit privacy risks arise during cross-site sharing of imaging data. Federated learning (FL) has recently been introduced to address privacy concerns by enabling distributed training without transfer of imaging data. Existing FL methods employ conditional reconstruction models to map from undersampled to fully-sampled acquisitions via explicit knowledge of the accelerated imaging operator. Since conditional models generalize poorly across different acceleration rates or sampling densities, imaging operators must be fixed between training and testing, and they are typically matched across sites. To improve patient privacy, performance and flexibility in multi-site collaborations, here we introduce Federated learning of Generative IMage Priors (FedGIMP) for MRI reconstruction. FedGIMP leverages a two-stage approach: cross-site learning of a generative MRI prior, and prior adaptation following injection of the imaging operator. The global MRI prior is learned via an unconditional adversarial model that synthesizes high-quality MR images based on latent variables. A novel mapper subnetwork produces site-specific latents to maintain specificity in the prior. During inference, the prior is first combined with subject-specific imaging operators to enable reconstruction, and it is then adapted to individual cross-sections by minimizing a data-consistency loss. Comprehensive experiments on multi-institutional datasets clearly demonstrate enhanced performance of FedGIMP against both centralized and FL methods based on conditional models.**

***Index Terms*— MRI, accelerated, reconstruction, generative, prior, federated learning, distributed, collaborative.**

models have been adopted for MRI reconstruction, given their strong ability to capture data-driven priors for inverse problems [3]–[11]. Deep reconstruction models are typically trained to perform a conditional mapping from undersampled acquisitions to images that are consistent with respective fully-sampled acquisitions [12]–[20]. Since these models typically show poor generalization to features scarcely present in the training set, learning of generalizable models involves training on a large and diverse collection of MRI data [21]. Unfortunately, economic and labor costs along with patient privacy concerns can prohibit compilation of comprehensive datasets centralized at a single institution [22].

Aiming at this limitation, federated learning (FL) is a promising framework that facilitates multi-institutional collaborations via decentralized training of learning-based models [23]–[28]. An FL server periodically collects locally-trained models from individual sites in order to obtain a shared global model across sites [29], [30]. Following aggregation of local models, the global model is then broadcast back onto individual sites for continual training. This decentralized procedure allows a multi-site model to be collaboratively trained without sharing of local data, thereby mitigating privacy concerns [31]. A multi-site model can improve generalization over single-site models given the native diversity in multi-institutional data, which can substantially benefit sites with relatively limited or uniform training data. However, this comes at the potential expense of lower site-specific performance due to data

제목: <Federated Learning of Generative Image Priors for MRI Reconstruction , 2022>

- 여러 기관의 협력은 깊은 MRI 재구성 모델의 훈련을 용이하게 할 수 있지만, 영상 데이터의 사이트 간 공유 중 개인 정보 보호 위험이 발생합니다.
- 연합 학습(FL)은 영상 데이터의 전송 없이 분산 훈련을 가능하게 함으로써 개인 정보 보호 문제를 해결하기 위해 최근 도입되었습니다.
- 중 사이트 협력에서 환자의 개인 정보 보호, 성능 및 유연성을 향상시키기 위해 여기에서는 MRI 재구성을 위한 연합 학습 of Generative IMage Priors (FedGIMP)를 소개합니다.
- FedGIMP는 두 단계 접근 방식을 활용합니다. 첫째, 생성적 MRI 사전의 사이트 간 학습과 두 번째, 영상 연산자 주입 이후 사전 적응. 전역 MRI 사전은 잠재 변수를 기반으로 고품질 MR 영상을 합성하는 무조건적 적대적 모델을 통해 학습됩니다.

향후과제

- 진행하던 연구에 Federal learning 적용 포인트 찾기
- Image assessment에 FL이 적용된 사례 찾아보기

감사합니다.

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