AdSEE: Investigating the Impact of Image Style Editing on Advertisement Attractiveness

Liyao Jiang[1], Chenglin Li[1], Haolan Chen[2], Xiaodong Gao[2], Xinwang Zhong[2], Yang Qiu[2], Shani Ye[2], Di Niu[1].

[1] *ECE, University of Alberta*
[2] *PCG, Tencent*

Motivations and Goals

- Online advertisements
    - Important elements in e-commerce sites, social media platforms, search engines, etc.
- Mobile browsing becomes more and more popular
    - Use both **visual and textual** information to grab the attention of users
    - Often in the form of **text and cover image**
- Previous findings
    - Appealing cover images lead to higher click through rate (CTR) [4, 9]
    - Human faces in ads correlate to more user attention [2,20,44]
    - Advertisement Creative Selection [8]: compose an ad design from creative elements
    - Image editing is made possible by high-quality generative models, e.g. StyleGAN [30-32]

- Questions we investigate
    - Is there a linkage between **advertisement popularity** and **image style editing**?
    - Can facial style editing (e.g. adjusting smile, hair, eye gaze direction, etc.) affect the popularity of online ads?

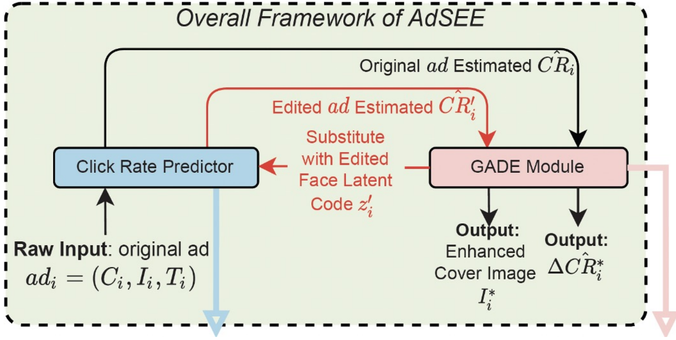
Our Contributions

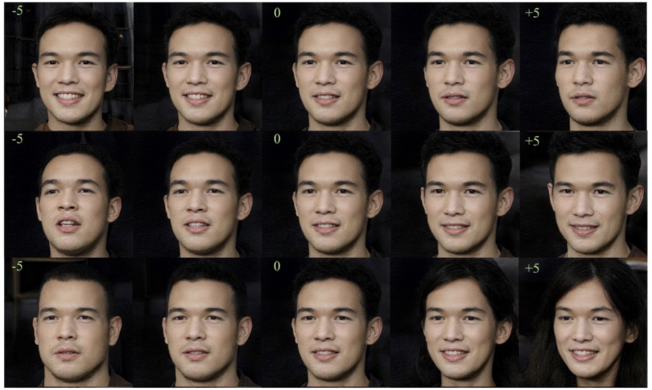
Advertisement Style Editing and Attractiveness Enhancement (AdSEE) framework

- **Click Rate Predictor (CRP)**
    - First CTR predictor that considers GAN-based **facial latent** features
    - Along with other features: **image** embedding, **text** embedding, ad **category**
- **Genetic Advertisement Editor (GADE)**
    - Apply **StyleGAN-based** latent **Facial Style Editing**
    - Use SeFA [50] method to find semantic editing direction (e.g. smile, eye gaze direction, etc.) in the StyleGAN latent embedding space
    - Use Genetic Algorithm to find optimal (i.e. that lead to the highest projected click rate) editing intensities for a given cover image, guided by the Click Rate Predictor

Data science approach:

- Collected real ads **dataset** (QQ-AD) from the QQ Browser mobile app
- **Extensive Offline Experiments:**
    - **Analysis** of how semantic directions may impact click rates (e.g. smiling face, feminine features, downward facing may be more popular features)
    - Compared CRP with a range of baselines
- **Online A/B test:** verified the existence of the relationship between image style editing and ad popularity





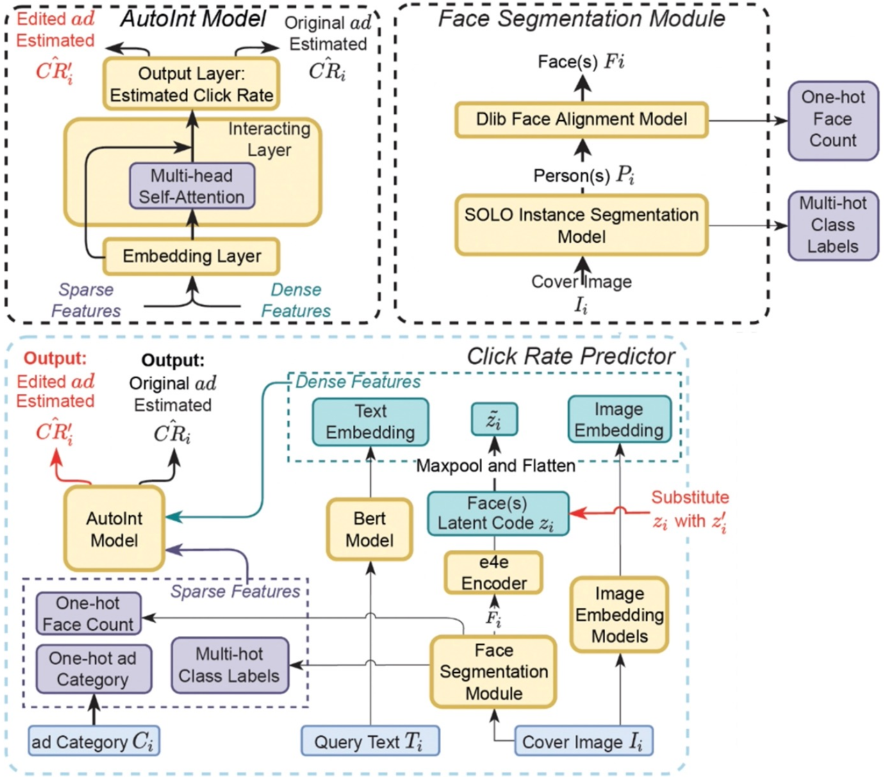
AdSEE Framework - Click Rate Predictor (CRP)

Face Segmentation Module

- SOLO instance segmentation model [57, 58] is used to **extract persons** from entire image, also extracts the class labels as CRP feature (i.e. labels of objects in the image)
- Face Alignment algorithm **extracts faces** from person images, and uses number of faces as CRP feature
- The e4e [52] encoder (an inversion encoder pre-trained on FFHQ facial images) inverts the face image ***F*** into face latent code ***z***

Click Rate Predictor (CRP)

- First CTR predictor that takes **facial latents** from StyleGAN2-FFHQ as a feature
- Along with other features: **image** embedding, **text** embedding, ad **category** features
  - Image Embedding: ad cover image converted to embedding
  - Text Embedding: the ad text description is mapped to text embedding through pre-trained Bert-Chinese model
  - Sparse features: face count, ad category, class labels
- The base recommender model AutoInt is selected through empirical evaluation of a series of SOTA models
  - Takes all 6 features, maps to embeddings and learns both high-order and low-order feature interaction
  - Predicts the CR of ads based on input features



AdSEE Framework - Genetic Advertisement Editor (GADE)

Recent advances in image generation and editing:

- StyleGAN [30-32]: high-quality image generation model
- SeFa [50] identifies a set of q **latent edit directions *n***, by eigen-decomposition of generator weights, $n = \{n_p\}_{p=1}^{q}$
- Style Editing: perturb the latent embedding ***z*** of image along the latent directions ***n*** to edit the style/semantic of images (e.g. age, eye gaze direction), $z_i' = z_i + \alpha_i n$

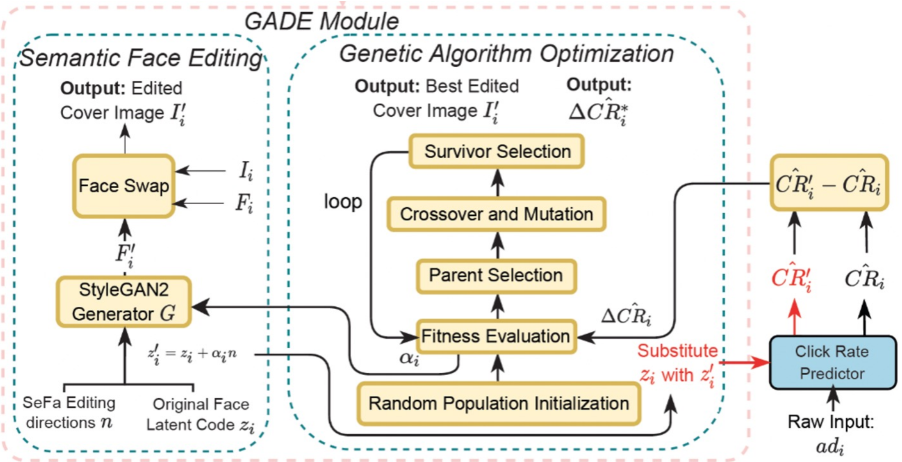
Genetic Advertisement Editor (GADE)

- Different **editing intensity coefficients** α leads to different editing result, thus different predicted CR
- Find the optimal facial editing coefficients α^* (i.e. the edit with the highest projected increase in CR) with **genetic algorithm** guided by **Click Rate Predictor feedback**
- Use StyleGAN2 generator *G* to generate the edited face *F'* from the edited latent code *z'*

$$F'_{i,j} = edit(F_{i,j}) = G(z'_{i,j}) = G(z_{i,j} + \alpha_{i,j} n)$$

- Face Swap algorithm with OpenCV and Dlib function to replace the original face *F* with edited face *F'*

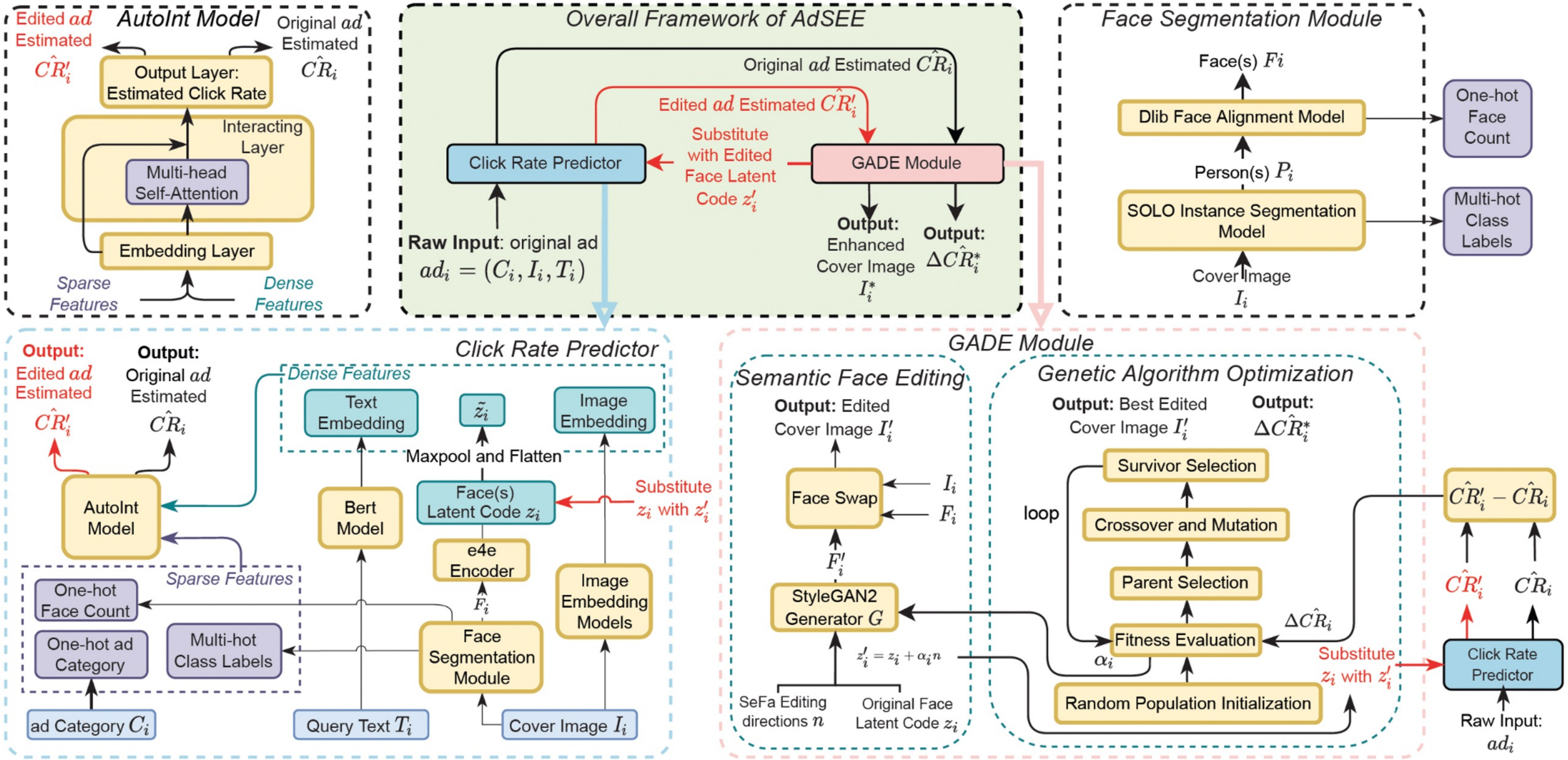
$$I'_i = Swap(F_i, F'_i, I_i)$$



AdSEE Framework - Overview

Advertisement Style Editing and Attractiveness Enhancement

- Given an original ad cover image, find the **optimal editing "plan" that leads to the highest projected click rate**
- **CRP predicts CR** based on face latents, text embedding, image embedding and other sparse features
- **GADE** uses Genetic Algorithm to **optimize the editing coefficients**, with guidance from CRP



Evaluation - Datasets

Datasets

- Note: the common recommender model datasets such as Avazu and Criteo do not apply, since they are not based on any images

- **QQ-AD dataset:** we collected **real advertising data** from QQ Browser mobile app.
  - Collect the numbers of clicks, impressions, and **click rate**
  - Remove ads with no faces or more than 5 faces, and avoid low-resolution and unrecognizable face images
    - Around 12.92% contain a valid number of faces
    - These images account for 19.12% of total impressions and 19.48% of the total clicks.
    - (Suggests **facial images are common** in the QQ Browser environment and editing facial features can **potentially have large impacts** on users' clicks)
  - Not published to protect copyright and privacy

- **CreativeRanking Dataset [55]**
  - To further evaluate our methods on a **publicly available dataset**
  - Images are from the e-commerce setting, each sample contains product name, click rate, and ad image
  - Also shows **transferability to the e-commerce domain** besides from mobile/online advertisements

Table 1: Statistics of the Collected QQ-AD Dataset.

Dataset	#Ads	#Impressions	#Clicks	CR
QQ-AD	158,829	4,263,667,016	429,830,278	0.1008
Applicable	20,527	815,272,384	83,729,560	0.1027
Ratio	12.92%	19.12%	19.48%	–

Evaluation - Offline Evaluation of CRP

Table 2: Comparing the proposed CRP predictor with other baselines using different types of features on the QQ-AD dataset.

Model	Feature Type	MAE ↓	MAPE ↓	NDCG@10 ↑	NDCG@50 ↑	Spearman's rho ↑	Kendall's tau ↑
CRP-NIMA	Image Quality	0.0299	0.7456	0.2764	0.3917	0.3634	0.2480
CRP-OpenImage	Image Embedding	0.0295	0.7258	0.5950	0.5551	0.3941	0.2696
CRP-Sogou	Image Embedding	0.0299	0.7429	0.5095	0.5175	0.3613	0.2464
CRP-e4e	Face Latent Code	0.0306	0.7663	0.5149	0.5204	0.2954	0.2003
CRP	Combined	**0.0262**	**0.6542**	**0.6854**	**0.7337**	**0.5122**	**0.3609**

Table 3: Comparing the proposed feature combination C5 with other combinations on the CreativeRanking [55] dataset. We consider features including Face Count (FC), Product Name (PN), Class Label (CL), Face Latents (FL), and Image Embedding (IE).

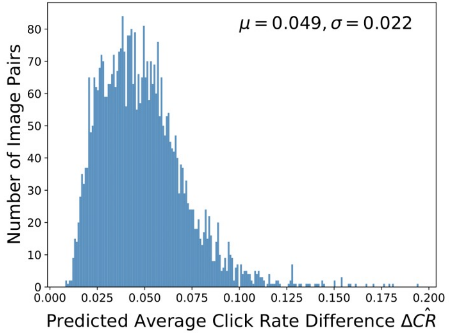
#	Sparse Features	Dense Features	MAE ↓	MAPE ↓	NDCG@10 ↑	NDCG@50 ↑	Spearman's rho ↑	Kendall's tau ↑
C1	FC, CL	FL, IE	0.0134	0.5988	0.4567	0.4977	0.3374	0.2299
C2	PN, CL	FL, IE	**0.0132**	0.6300	0.4975	0.4935	0.3304	0.2255
C3	FC, PN, CL	FL	0.0136	0.6479	0.3888	0.4073	0.2978	0.2020
C4	FC, PN, CL	IE	0.0135	**0.5939**	0.4865	0.4674	0.3379	0.2298
C5	**FC, PN, CL**	**FL, IE**	**0.0132**	0.5947	**0.5065**	**0.5256**	**0.3609**	**0.2468**

Evaluate **CRP** on click rate prediction task

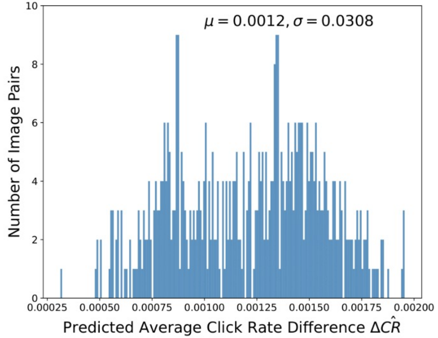
- CRP Trained on QQ-AD or CreativeRanking training set
- Shows the benefit of the **proposed combined set of multi-modal features** (outperformed other feature types, e.g. Image Quality score, image embedding, etc.)
  - Dense Features: Face Latents, Text Embedding, Image Embedding
  - Sparse Features: ad category, class labels, face count

Evaluate **GADE** offline on editing the test set

- Apply GADE on the test sets, use the CRP to evaluate both the original and edited ad (i.e. find the estimated click rate increase)
- The distribution for ***ΔCR*** is positive on both datasets, showing the GADE was able to find edits that can increase the projected click rates
- Right-skewed on QQ-AD, since most ads are already well-designed, a small increase in CR is expected for most ads



(a) Distribution of $\Delta\hat{CR}$ in the offline test on the QQ-AD dataset.

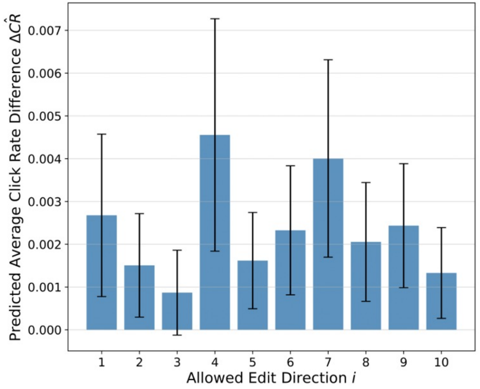


(c) Distribution of $\Delta\hat{CR}$ in the offline test on the CreativeRanking [55] dataset.

Evaluation - Offline Evaluation of GADE

Analysis of Semantic Editing Directions

- Which editing directions are correlated with most increase in projected CR?
  - We sample 1000 images, and edit them with the top-10 semantic directions from SeFa factorization
  - Each time only edit on 1 of the 10 direction
- Observations
  - The average predicted ***ΔCR is*** highest for directions $\boldsymbol{n_4, n_7, n_1}$
  - i.e these directions have the highest impact on CR among the editing directions
- Visualization
  - We visualize each edit direction with a range of coefficients from -5 to 5
  - We take the average of best coefficients found by AdSEE for the 1000 images
  - Direction 4: **vertical orientation** of the face, -2.77 mean a face slightly facing downwards is more attractive
  - Direction 7: **gender** of the face, 2.26 means a face with more feminine features is more attractive
  - Direction 1: **smilingness** of the face, -2.63 means a smiling face is more attractive

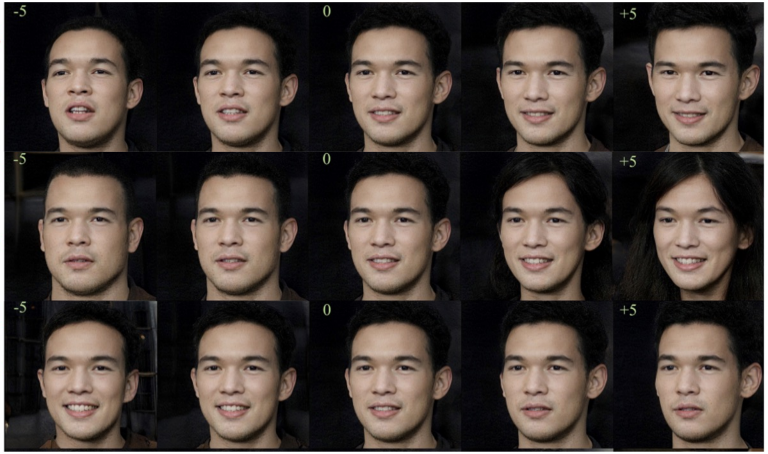


(b) Distribution of $\Delta\hat{CR}$ for 10 different edit directions in the offline test on the QQ-AD dataset.

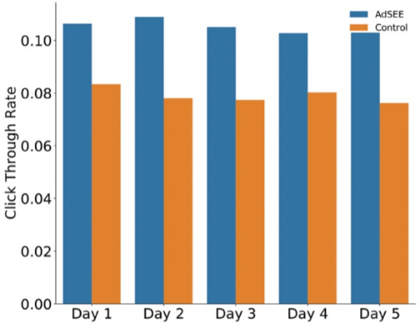
Direction 4 Best Coefficent: -2.77

Direction 7 Best Coefficent: 2.69

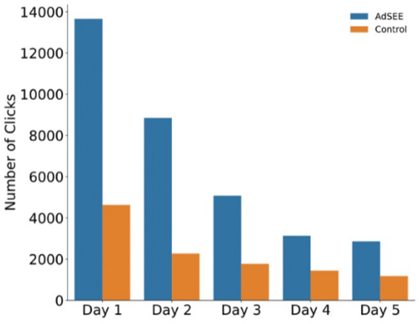
Direction 1 Best Coefficent: -2.63



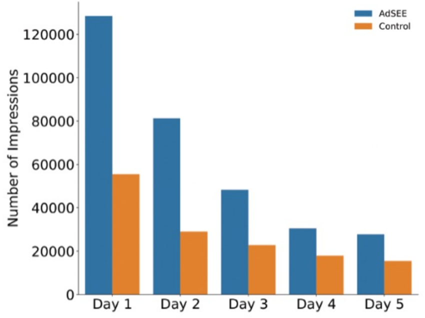
Impact of Image Style Editing on Advertisement Attractiveness



(a) Click Rate per day (p-value 3.68×10^{-5})



(b) Number of clicks per day (p-value 1.86×10^{-2})



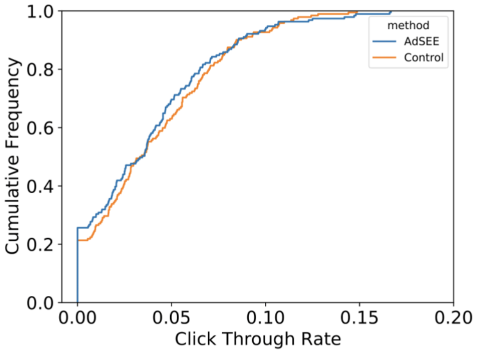
(c) Number of impressions per day (p-value 2.11×10^{-2})

Online A/B test (5 Days over the QQ Browser mobile app):

- AdSEE group: AdSEE edited ads (250 ads)
- Control group: corresponding original ads (250 ads)

AdSEE edited group:

- Higher Click Rate
  - A significant **increase in attractiveness** to users
- Higher Number of Impressions
  - Production recommender system believes that AdSEE-edited ads are **more relevant to users**
  - i.e., more likely to receive clicks, thus pushed to users more often
- Demonstrated the existence of the correlation between **facial style editing** and **click rate** in online ads



(a) CDF of the click rate

Conclusion and Discussion

Conclusion

- We verified the existence of the correlation between facial style editing and click rates in online ads
- Designed a Click Rate Predictor that takes multi-modal (i.e. text and image) features including facial latent embeddings from a StyleGAN2 model
- The GADE module can efficiently search for optimal editing directions with the genetic algorithm and feedback from CRP
- Insights on the attractive semantic editing direction to the users, e.g. facing downward, smile, feminine features

Interesting Directions for Future Research

- Study the effect of other types of editings other than faces
- Image editing using the capabilities of Stable Diffusion models

Ethics Considerations

- Whether there is a linkage between image style editing and ad popularity is an important question for the AI ethics community
- Any exploitation of the research results is subject to further considerations of regulations and ethical requirements
- We hold data privacy, copyright protection, information objectivity, user consent and right-to-correct as our core ethical values throughout the experiments

Figure 7: Examples of *ad*s enhanced by AdSEE where we show the *ad* category, text, and cover image. Left: Original cover image, Right: Enhanced cover image.

Thank you!

Liyao Jiang
PhD Student
University of Alberta
Email: liyao1@ualberta.ca

Resources:

- Code/Slides/Poster: https://github.com/LiyaoJiang1998/adsee
- Paper: https://doi.org/10.1145/3580305.3599770