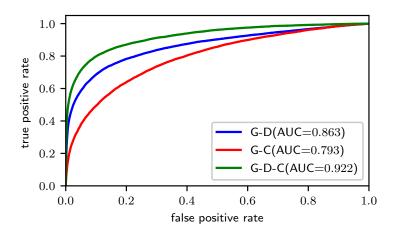
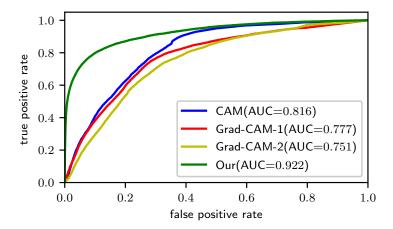
## Biomarker Localization by Combining CNN Classifier and Generative Adversarial Network Supplymentary Material

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**Fig. 1.** Effect of model components. G-D represents encoder-decoder with only the discriminator, G-C represents encoder-decoder with only the classifier, and G-D-C represents our full model. The ROC curves were generated by comparing the pixel-level localization results with ground truth over randomly selected 40 real images. The heat maps of localization results were normalized to [0,1] before ROC generation. The curves and the AUCs showed that our full model had the best performance.



**Fig. 2.** Comparisons with visualization methods on real diabetic retinopathy dataset. The ROC curves were generated by comparing the pixel-level localization results with ground truth over randomly selected 40 real images. The heat maps of localization results were normalized to [0,1] before ROC generation. The curves and the AUCs showed that our method outperformed all other methods.

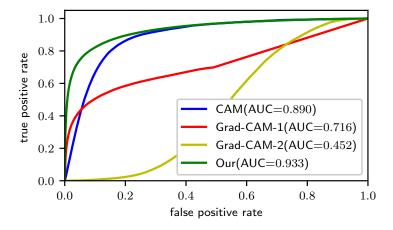


Fig. 3. Comparisons with visualization methods on skin image data. The ROC curves were generated by comparing the pixel-level localization results with ground truth all the simulated images. The heat maps of localization results were normalized to [0,1] before ROC generation. The curves and the AUCs showed that our method outperformed all other methods