### **Creative AI**

Garching, 05.08.2019 Felix Altenberger, Vadim Goryainov, Anastasia Litinetskaya, Jongwon Lee, Vitalii Mozin





### **Our Team**













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Introduction

Agenda

- GANs for Image Generation from Text
- Demo Session
- System Architecture
- Summary and Q&A



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This bird is red with white and has a very short beak

# CreativeAl

Text Encoder -> GAN





### **Our Implementation**



### Dash Demo for CreativeAl

this bird is red with white and has a very short beak

AttnGAN

StackGAN

⊖ WGAN-CLS

○ WGAN-CLS + Stage II of StackGAN

StackGAN\_v2

GENERATE



















### Real or Fake?





### **Conditional GANs**





### Applications

### Pix2Pix: Image-to-Image Translation



### Applications

#### AttGAN: Class-based image generation and modification



### Applications

Image Generation from Text

- StackGAN
- StackGAN++
- AttnGAN

This bird is red with white and has a very short beak





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### Dataset: Caltech-UCSD Birds 200-2011





- 11,788 images of birds
- includes annotations and image captions



#### Idea: stack multiple GANs together!





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#### Idea: stack multiple GANs together!



#### trained independently from the rest



#### Idea: stack multiple GANs together!





#### Idea: stack multiple GANs together!



### StackGAN: First Results





### The Mode Collapse Problem





### StackGAN++

#### Idea: stack even more GANs together!



Reference: Zhang, Han, et al. "Stackgan++: Realistic image synthesis with stacked generative adversarial networks." arXiv preprint arXiv:1710.10916. 2017.

JCU

 $D_1$ 

#### Idea: stack even more GANs together!

JCU

 $D_0$ 

64x64x3

all pairs trained together each step

JCU

 $D_2$ 



128x128x3



fake

С

Conditional loss

real

Unconditional

loss

OR

Down-

sampling

### StackGAN++

G\_0: 64x64 image



### G\_1: 128x128 image

G\_2: 256x256 image

### StackGAN++: Results





### Wasserstein GAN (WGAN)



Idea: use a different loss function

 $\min_{G} \max_{D} \mathbb{E}_{x \sim P_{data}(x)} [\log D(x)] + \mathbb{E}_{z \sim P_{z}(z)} [\log(1 - D(G(z)))]$   $\bigvee$   $\min_{G} \max_{D \in \mathscr{D}} \mathbb{E}_{x \sim P_{data}(x)} [D(x)] - \mathbb{E}_{z \sim P_{z}(z)} [D(G(z)))]$ 

standard GAN loss function

using Wasserstein-1 distance







### **Spectral Normalization**





$$\|d_l\|_{Lip} = \sigma(W^l), \ W_{SN} := \frac{W}{\sigma(W)} \Rightarrow \|W_{SN}\|_{Lip} = 1$$
$$\|D\|_{Lip} \leq \prod_{l=0}^k \sigma(W^l) \Rightarrow \|D\|_{Lip} \leq \prod_{l=0}^k \sigma(W^l_{SN}) = 1$$

### Spectral Normalization: Results





### Different batch size





### Different batch size





### **One-sided Label smoothing**



Idea: smooth the label, i.e .9 and .1 instead of 1 and 0

Smooth only positive labels as .9, and leave negative labels as 0 -> one-sided

$$\min_{G} \max_{D} \mathbb{E}_{x \sim P_{data}(x)} \left[ \log D(x) \right] + \mathbb{E}_{z \sim P_{z}(z)} \left[ \log(1 - D(G(z))) \right]$$

- It is valuable when the label cannot be believed 100%
- In this case, by smoothing the label, the model can consequently improve its robustness and performance

## Mini-batch discrimination



Idea: Check the similarity between samples in the same batch

- If the generator has mode collapse, the similarity should be higher than real image
- The mini-batch discrimination layer is not for just simple similarity calculation, but a trainable layer


# Mini-batch discrimination



Idea: Check the similarity between samples in the same batch

- If the generator has mode collapse, the similarity should be higher than real image
- The mini-batch discrimination layer is not for just simple similarity calculation, but a trainable layer



## Mini-batch discrimination: Results





# Mini-batch discrimination: Results



StackGAN Stage II, no residual layer, 8 conv layers, 8192 latent dim r

StackGAN StageII, no residual layer, 7 conv layers, 1024 latent dim.

StackGAN StageII, no residual layer, 5 conv layers, 8192 latent dim



# Mini-batch discrimination: Results







#### AttnGAN

#### Idea: use StackGAN++ model as base architecture







#### Idea: attention to words for image generation



#### AttnGAN



#### Idea: train own Text Encoder (Bidirectional LSTM)







#### Idea: compare the relevance between final image and word features



### AttnGAN: Results





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# http://10.195.1.122:8050/

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Users





#### 







Users





#### 

### Architecture: Application



















**Dash**: Give me the image for %description% produced by the %model%









Flask: one moment, I have %model% generate this image for you



-



#### Architecture: Docker





### Architecture: Docker Compose









Users







### Architecture: Development











# Architecture: Git and Jenkins



#### Git Branches



- Master
- Feature/frontend/...
- Feature/backend/...
- Bug/...
- Fix/...

#### Jenkins



Automated software quality checks with four stages:

- Build: Code compiles?
- Test: Unit tests pass?
- Lint: Style guidelines not violated?
- Black: Similar formatting?

	Declarative: Checkout SCM	build	test	lint	black	Declarative: Post Actions
Average stage times: (Average <u>full</u> run time: ~28s)	640ms	20s	1s	3s	495ms	15
#30 Jun 01 1 17:37 commit	581ms	18s	1s	3s	356ms	1s
#29 Jun 01 1 17:27 commit	714ms	20s	1s	3s	379ms	1s
#28 Jun 01 1 16:01 commit	626ms	20s	1s	3s	613ms	866ms
#27 Jun 01 1 15:46 commit	642ms	20s	1s	3s	634ms failed	935ms

pytest







Users





Users



## Architecture: Filesharing VM







### Architecture: Tensorboard VM







#### g\_sum\_256



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- Generative Adversarial Networks
- Models: StackGAN, StackGAN++, AttnGAN
- Techniques for GAN Training Stabilization
- Demo Session
- System Architecture



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# Thank you for your attention!

# Q&A Time!






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