DAY 5: GENERATIVE MODELS, GENERATIVE ADVERSARIAL NETWORKS (GANS) BASICS

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JÜLICH Forschungszentrum

GENERATIVE MODELS

- Impressive progress in last years, algorithmic/architectural improvements coupled with large scale training
- Lot of different applications: image generation, text generation, speech synthesis, and more

Karras et al. (2020)

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(Source: `https://bit.ly/3azTV7J`)

GENERATIVE MODELS: BASICS

- The general setup: we have a set of samples $x_1, x_2, ..., x_N$ drawn i.i.d. from an unknown probability distribution $p(x)$. We would like to learn a model M, which we can use to generate samples from p
- Different formulations, training algorithms, architectures

Karras et al. (2020)

GENERATIVE MODELS, DENSITY MODELING

- We model the underlying data distribution of the data $p(x)$ with a surrogate distribution $q(x)$, i.e. $q(x) \approx p(x)$ for some similarity between probability distributions
- In generative modeling, x is in general a high-dimensional vector (e.g. image, sound, text)
- A common similarity measure used is the Kullback–Leibler (KL) divergence:

$$D_{\mathrm{KL}}(p \parallel q) = \int p(x) \log \frac{p(x)}{q(x)} dx$$

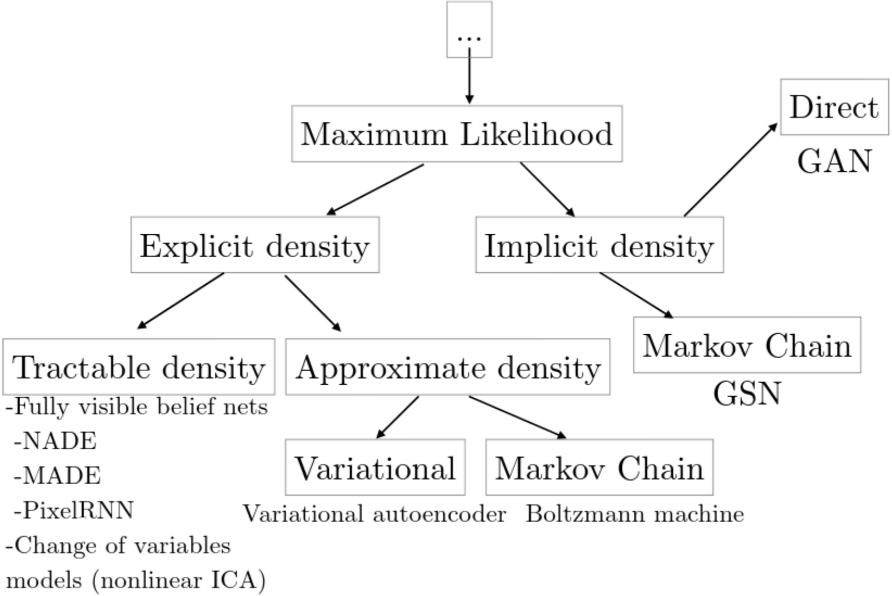
GENERATIVE MODELS, KL DIVERGENCE

- Connection to information theory and compression: $D_{\text{KL}}(p \parallel q) = (-\int p(x) \log q(x) dx) - (-\int p(x) \log p(x) dx) = H(p, q) - H(p)$
- Connection to maximum likelihood: For a parametrized model q_Θ, maximization of the likelihood

$$\max_\Theta [E_{x \sim p} \log q_\Theta(x)] \approx \sum_i \log q_\Theta(x_i), \; x_i \sim p$$

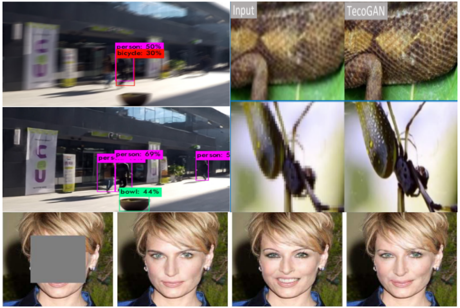
is equivalent to minimizing the KL divergence between q_Θ and p

TAXONOMY OF GENERATIVE MODELS



APPLICATIONS: IMAGE RECOVERY

- We can upscale images, denoise them, fill/recover missing parts (inpainting)
- In this case, we model $p(x|\tilde{x})$ where $\tilde{x}$ is x with some information destroyed ,e.g. by blurring or noise introduction, and we would like to recover that information
- Examples: TecoGAN (Chu et al. 2020), DeblurGAN (Kupyn et al. 2018), UCTGAN (Zhao et al. 2020)



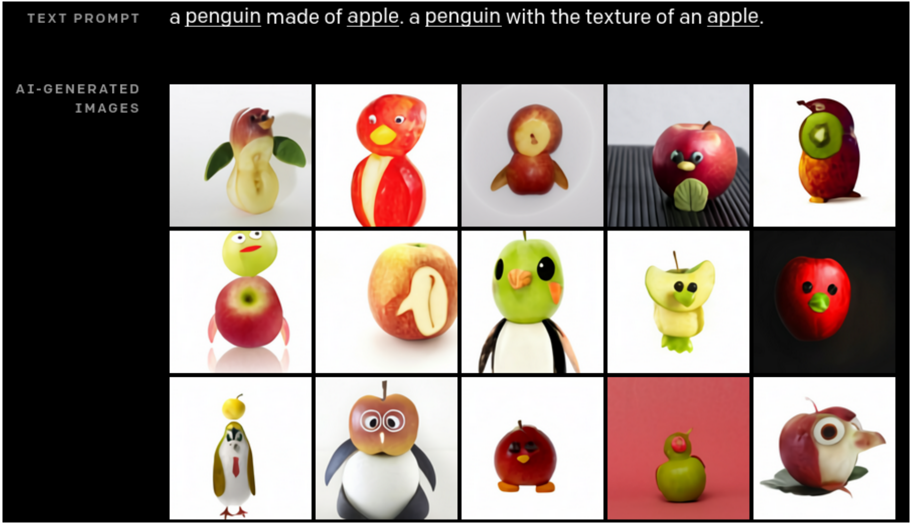
APPLICATIONS: CONDITIONAL IMAGE GENERATION

- We can generate images based on labels, or feature vectors, or natural language
- In this case, we model $p(x|y)$, where x is the image and y is the label, represented as a feature vector, a category, or a sequence of tokens ($y = y_1, ..., y_m$, where m is the number of tokens)

(Brock, Donahue, and Simonyan 2019)

APPLICATIONS: CONDITIONAL IMAGE GENERATION

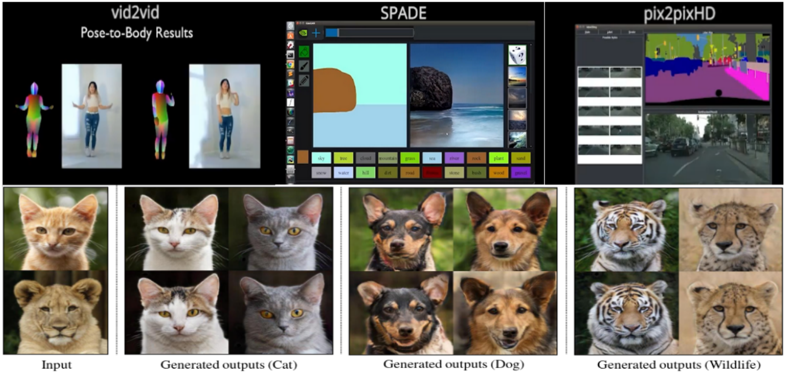
- What would a “penguin made of apples” look like?



(OpenAI’s DALL-E `https://openai.com/blog/dall-e/`)

APPLICATIONS: IMAGE-TO-IMAGE MODELS

- We can learn a mapping from images to images or from videos to videos, either with paired samples or unpaired ones. Examples: Pix2Pix (Isola et al. 2018), CycleGAN (Zhu et al. 2020), Pix2PixHD (Wang et al. 2018), SPADE (Park et al. 2019), StarGANv2 (Choi et al. 2020)

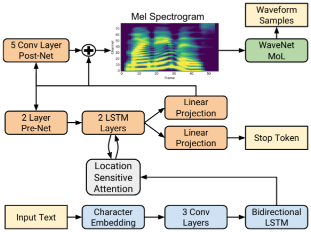


APPLICATIONS: SPEECH SYNTHESIS

- WaveNet

(Oord et al. 2016)

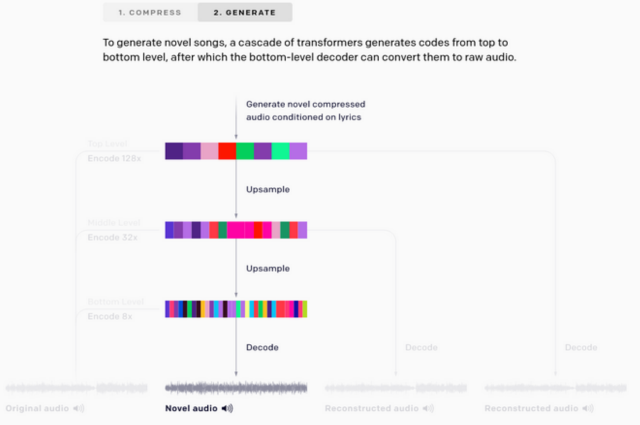
- Tacotron2



(Shen et al. 2018)

APPLICATIONS: MUSIC GENERATION

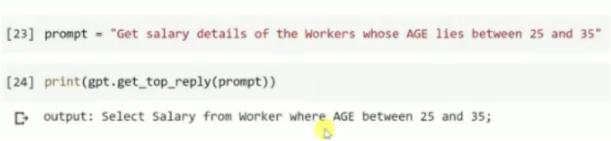
- Jukebox (`https://openai.com/blog/jukebox/`)

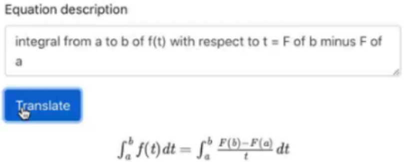


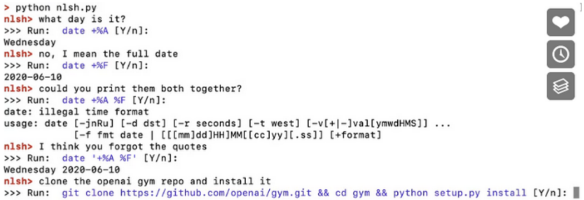
(Dhariwal et al. 2020)

APPLICATIONS: TEXT GENERATION

- GPT-3 (Brown et al. 2020)



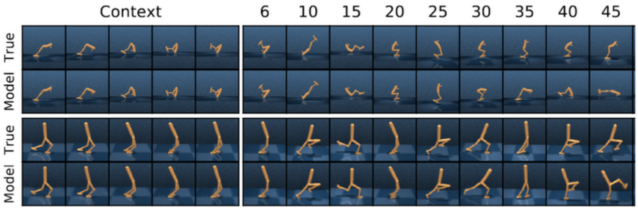


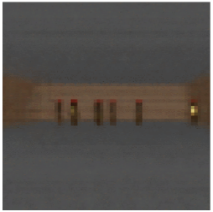


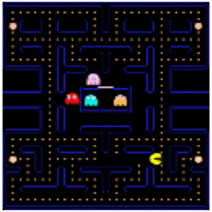
Source: `https://bit.ly/3tqM8Sr`, `https://bit.ly/39KHNSe`, `https://bit.ly/3tvipHR`

APPLICATIONS: REINFORCEMENT LEARNING

- We can simulate possible futures given the past. Application for reinforcement learning: learning world models and planning



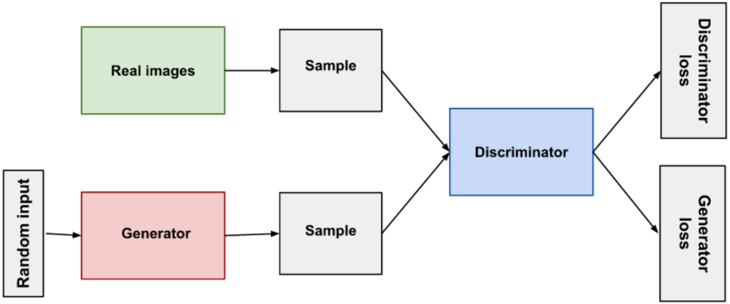




(Hafner et al. 2020), (Kim et al. 2020)

GENERATIVE ADVERSARIAL NETWORKS

- We have samples from a probabilistic distribution p, and we would like to learn a generator model that generates samples from $x \sim p(x)$
- Discriminator is trained to distinguish between real and generated samples
- Generator is trained to fool the discriminator



GENERATIVE ADVERSARIAL NETWORKS – FORMULATION

$$\min_G \max_D \left[\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]\right]$$

- $D(x)$: probability that an image is real
- $D(G(z))$: probabilty that a generated image is real, where $z \sim \mathbb{N}(0, 1)$
- $\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})]$: discriminator on real data
- $\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$: discriminator on generated data

GENERATIVE ADVERSARIAL NETWORKS – IDEAL CASE

- Generative Adversarial Networks (Goodfellow et al. 2014) shows that for a fixed generator G, the optimal discriminator is: $D^*_G(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}} + p_g(x)}$
- They also show that the global optimal solution of the problem minimizes: $-\log 4 + 2 \cdot \text{JSD}(p_{\text{data}} \parallel p_g)$, where the JSD is a measure between probability distributions
- Since the JSD is non-negative, the globally optimal solution for the generator is the data distribution $p_g = p_{\text{data}}$

GENERATIVE ADVERSARIAL NETWORKS – TRAINING

- In practice, we alternate between updating the generator and updating the discriminator

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**
  for k steps **do**
  • Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  • Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  • Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].$$

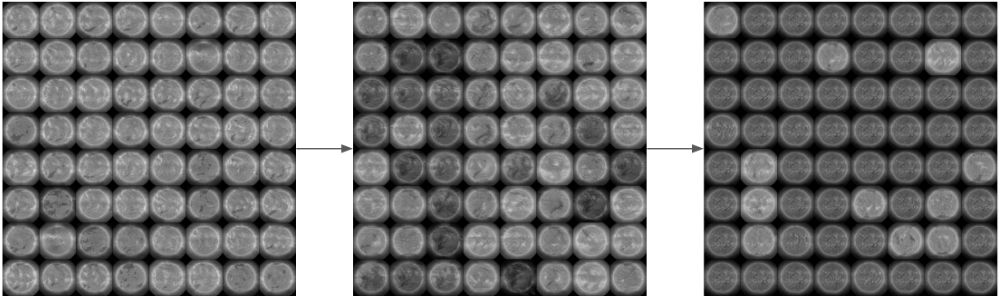
  end for
  • Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  • Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for
The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

GENERATIVE ADVERSARIAL NETWORKS – ISSUES

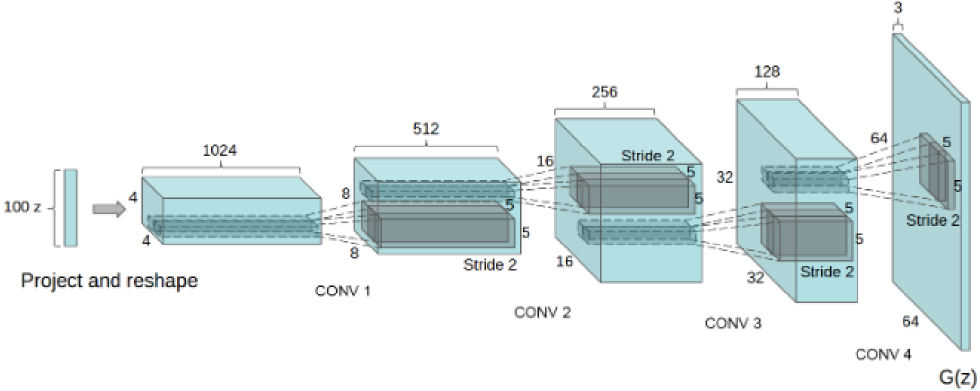
- Mode collapse
- Non-convergence
- Vanishing gradient



(Illustration of mode collapse)

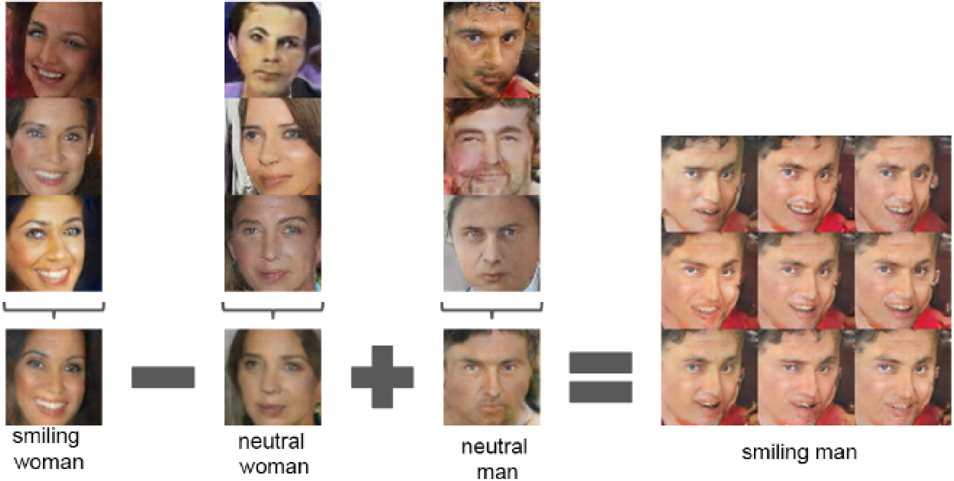
THE DCGAN ARCHITECTURE

- Removed fully connected layers: fully Convolutional architecture for generator and discriminator
- Uses batch normalization to stabilize training
- One of the first architectures that worked well in practice on several datasets



THE DCGAN ARCHITECTURE – VECTOR ARITHMETICS

- Interpretable directions in the latent space



THE DCGAN ARCHITECTURE – INTERPOLATION IN LATENT SPACE

- Smooth interpolation between generated images using the latent space

EVALUATION METRICS

- In general, it's still an open question how to evaluate a generative model; in a lot of cases human visualization is still needed
- In the ideal case, metrics should be task-specific (Theis, Oord, and Bethge 2016) and evaluate your generative model depending on how you will use it
- Most common metrics used: Fréchet Inception Distance (FID) (Heusel et al. 2018), Inception Score (Salimans et al. 2016), precision and recall (Kynkäänniemi et al. 2019)

SUMMARY

- Impressive progress during last years
- Model sizes and data are getting bigger
- Lot of different applications: image generation, text generation, speech synthesis, and more

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