Generative Adversarial Networks (GANs)

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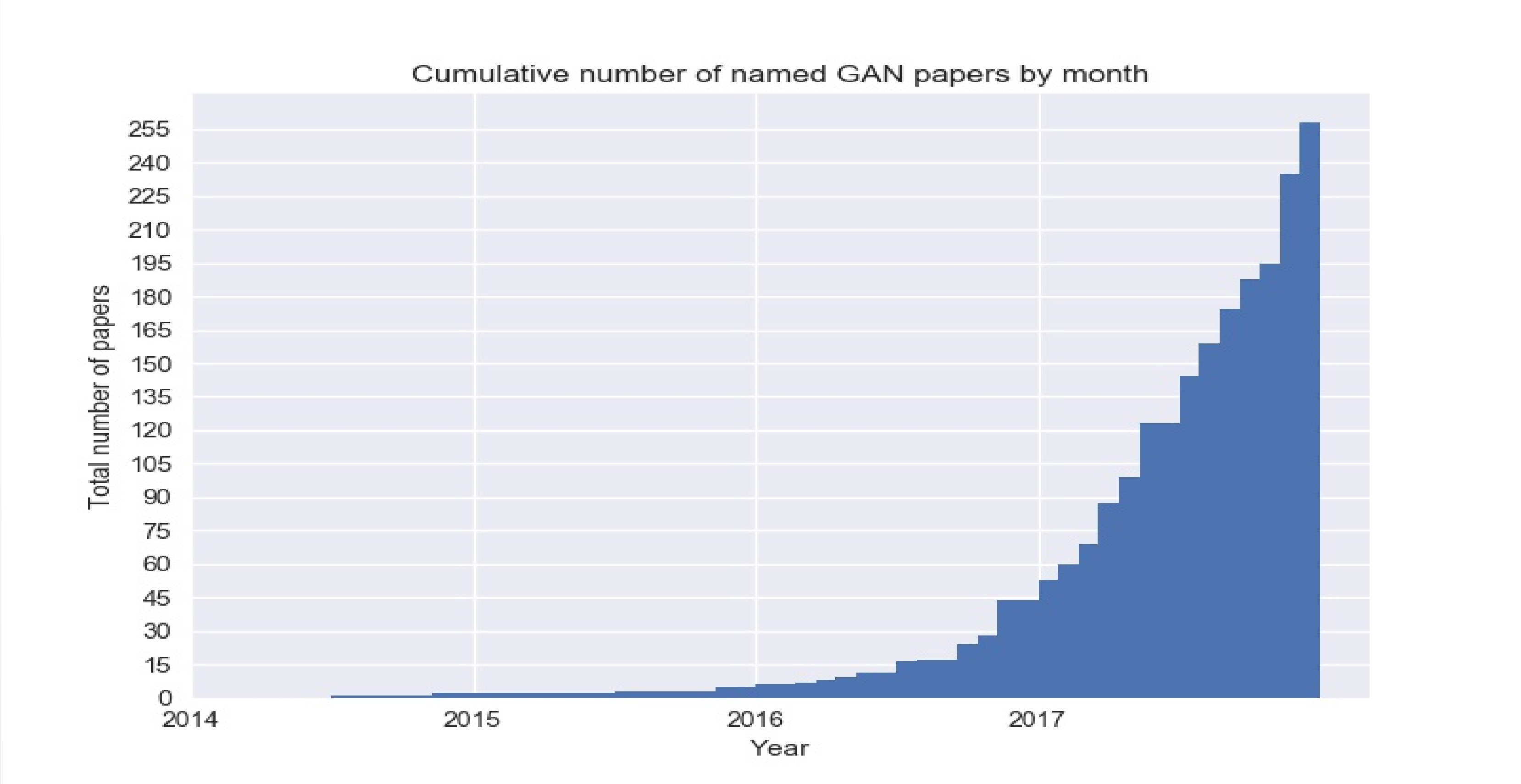
Introduced by

- Ian Goodfellow *et al.* in 2014.
  - Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. In *Advances in neural information processing systems* (pp. 2672-2680). Cited by 2143.

The GAN Epidemic



https://github.com/hindupuravinash/the-gan-zoo

Types of Models

- Discriminative models(Conditional models)
- Generative models

Types of Models

- Discriminative models(Conditional models)
  - Directly estimate posterior probabilities
  - No attempt to model underlying probability distributions
  - Focus computational resources on given task
  - Better performance
- Generative models

Types of Models

- Discriminative models
- Generative models
  - Model class-conditional pdfs and prior probabilities
  - “Generative” since sampling can generate synthetic data points

Types of Models

- Discriminative models(Conditional models)
  - Logistic/linear regression, SVM, Boosting, Maximum Entropy MM, CRF, Neural Networks
- Generative models
  - Mixture Model, Hidden Markov model, Naive Bayes, LDA, Restricted Boltzmann machine, Generative adversarial networks

DMs vs. GMs

- The task is to determine the language that someone is speaking
  - Generative approach:
    - is to learn each language and determine as to which language the speech belongs to
  - Discriminative approach:
    - is determine the linguistic differences without learning any language
    - A much easier task!

Generative Models

- Destiny function

- Sample generation
  - Given training data, generate new samples from same distribution

Why study Generative Models?

- Simulated environments and training data
- Missing data
  - Semi-supervised learning
- Multiple correct answers
- Realistic generation tasks

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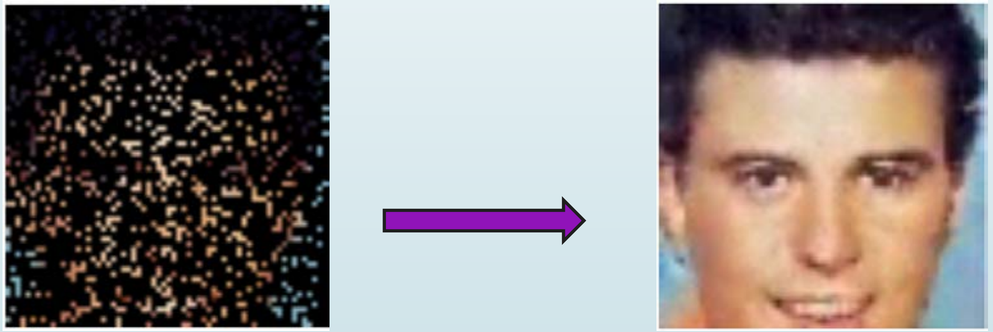

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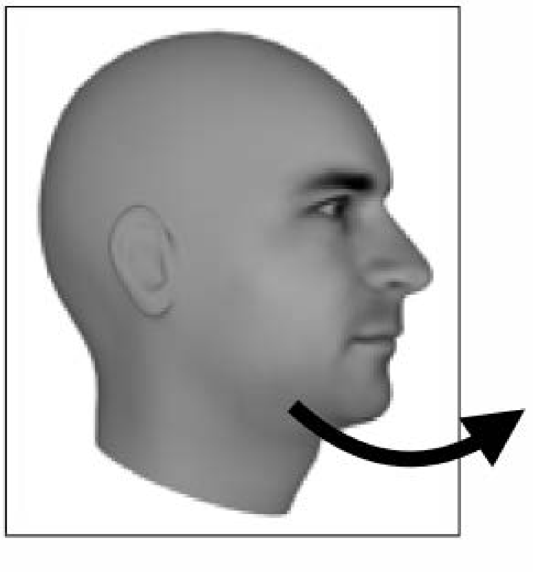

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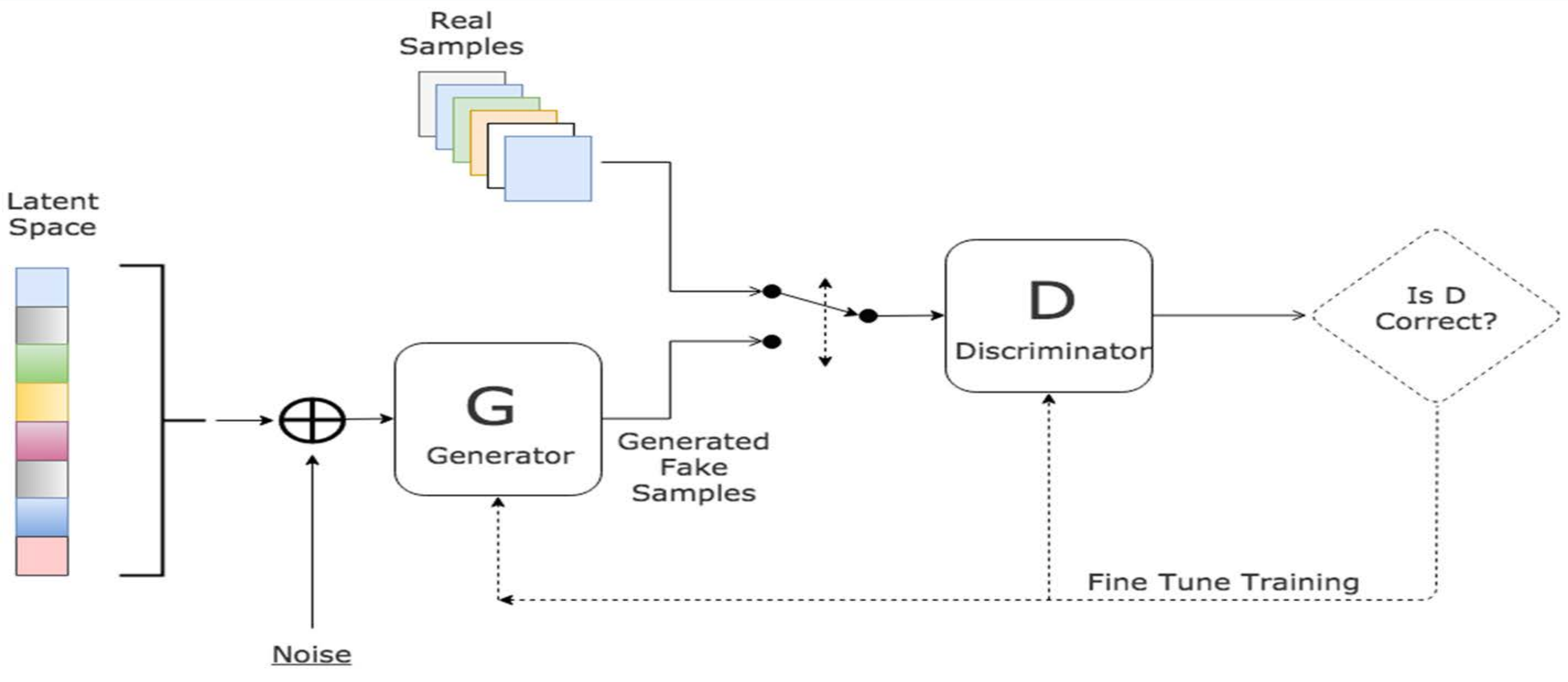
Generative Adversarial Networks

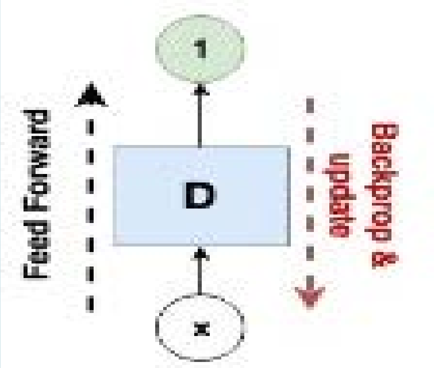
- Used in unsupervised machine learning
- We have a pair of neural networks
  - **Generator(G)** , **Discriminator(D)**
- Contesting with each other in a zero-sum game framework during training → **Adversarial Training**
- **G**: try to make samples so realistic that D can't distinguish
  - As much as similar as possible to training set
- **D**: distinguish between G samples and real samples

Generative Adversarial Networks



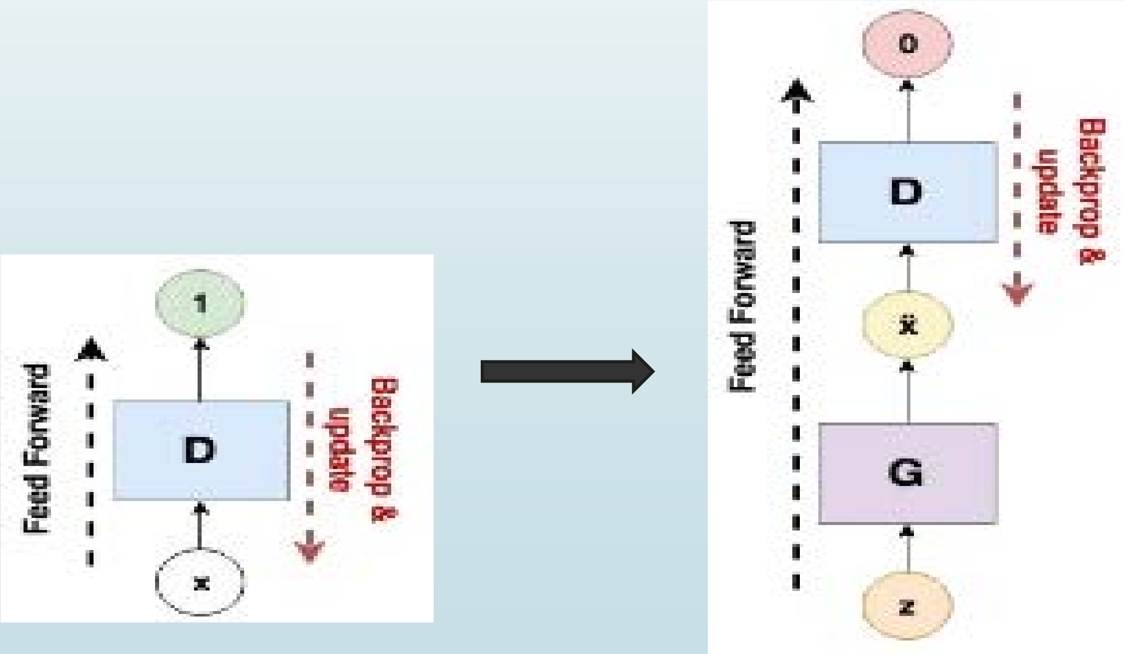
Adversarial Training

- Pick a sample x from training set
- Show x to D and update weights to output 1 (real)



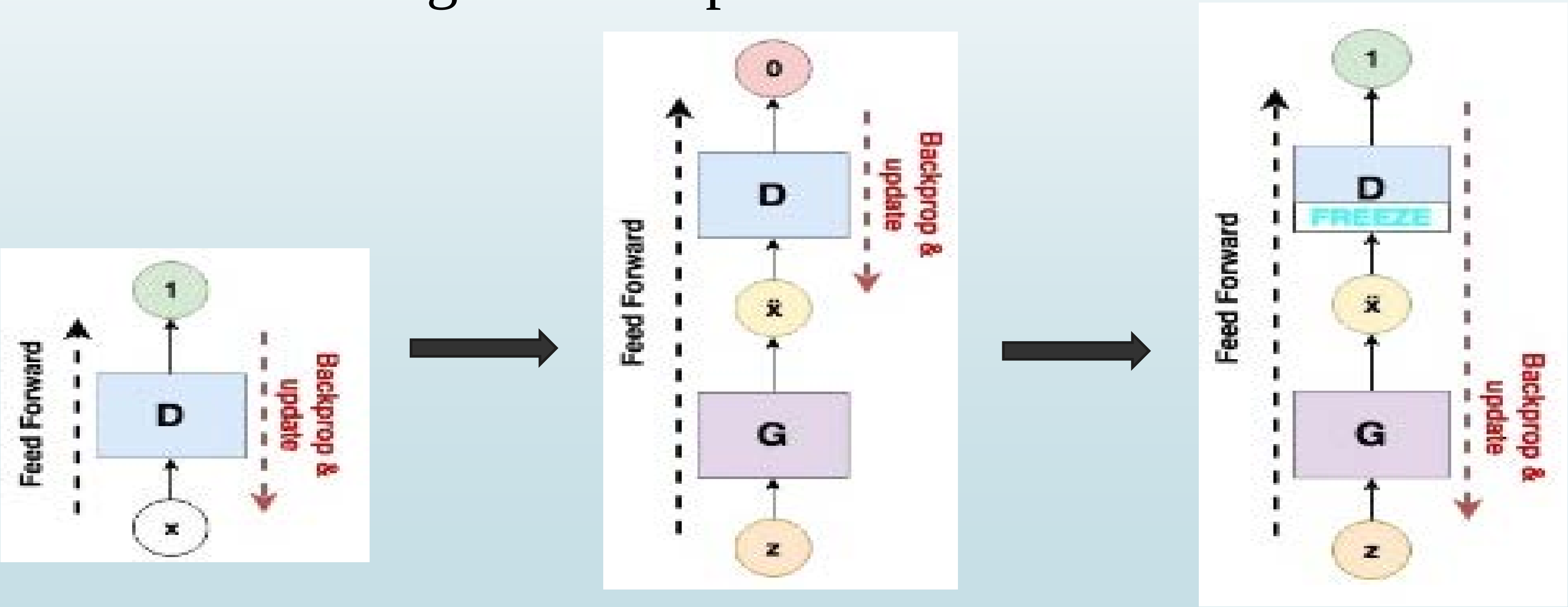
Adversarial Training

- G maps sample z to x¨
- Show x¨ and update weights to output 0 (fake)

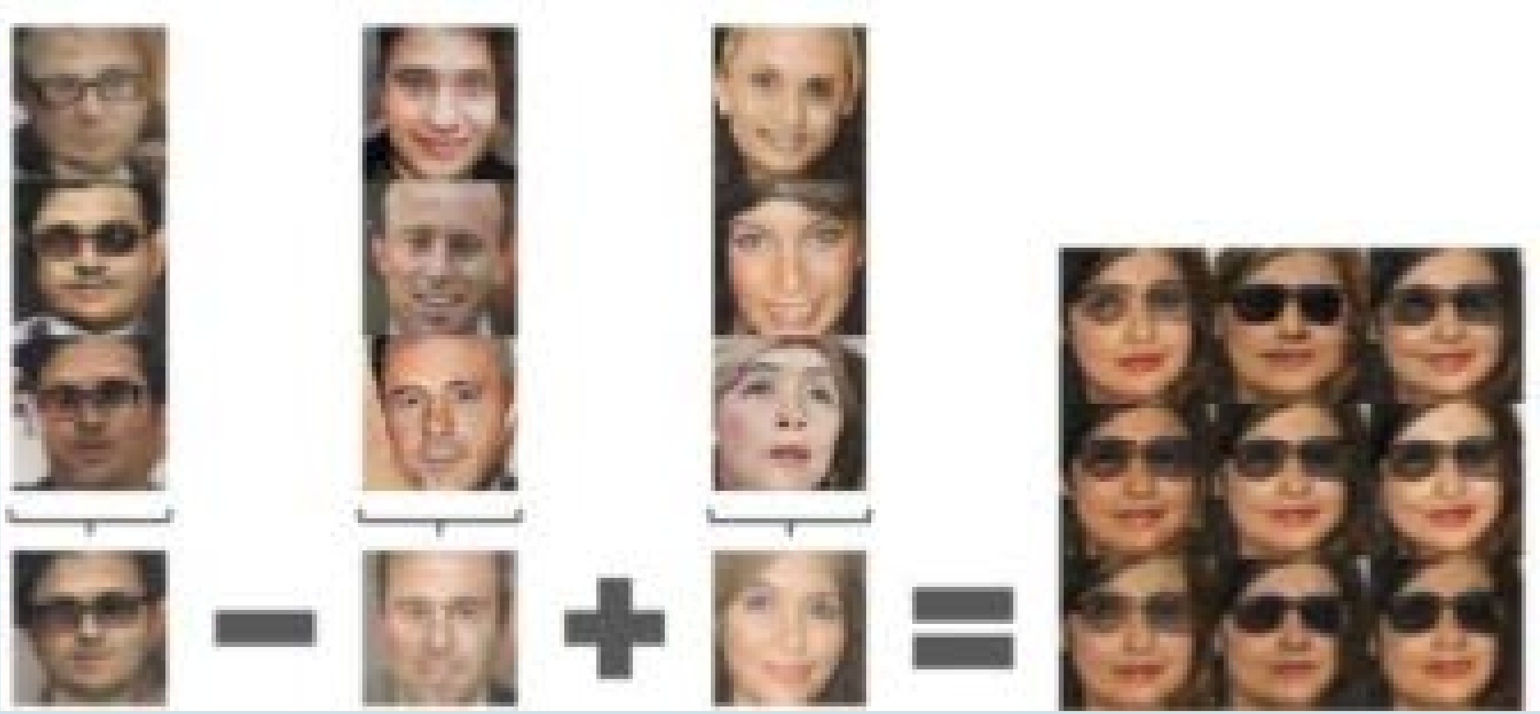


Adversarial Training

- Freeze D weights
- Update G weights to make D output 1 (just G weights)
- Unfreeze D weights and repeat

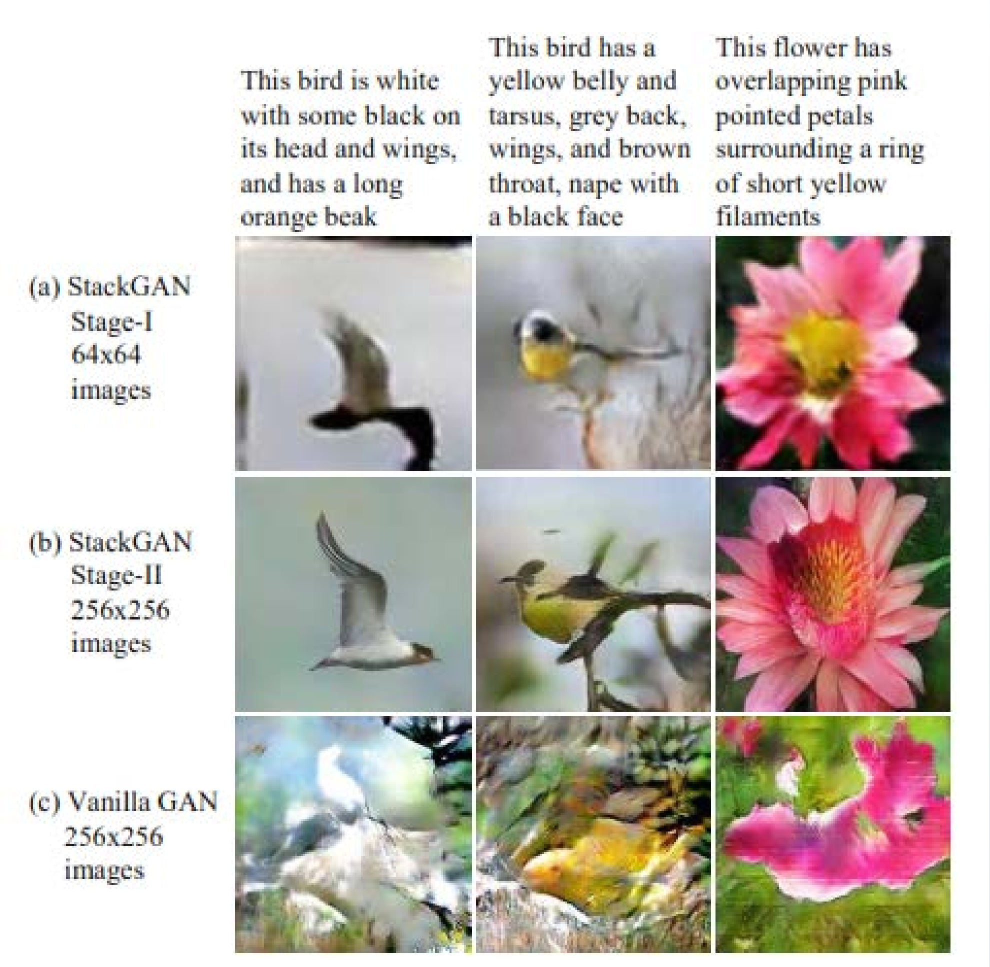


Vector Space Arithmetic



Man with glasses | Man without glasses | Woman without glasses | Woman with glasses

Text-to-image synthesis



Zhang, h. 2017

Other Applications

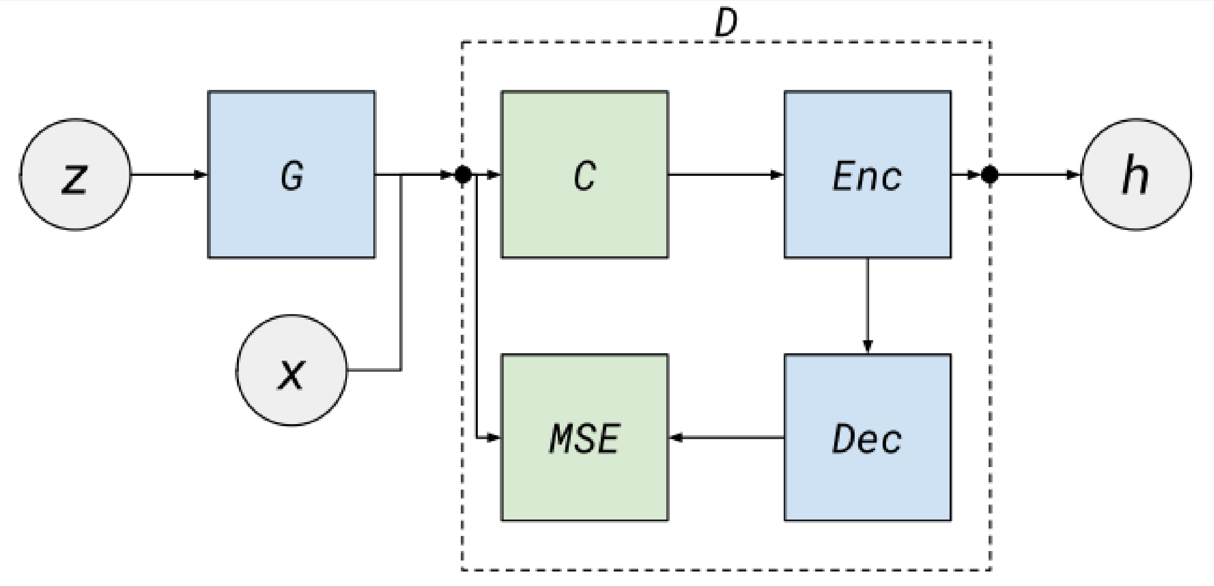
- Modeling documents (Glover, J. - 2016)
- Visual Recommender System (Yao, B – 2017)
- Joint syntactic and semantic structure prediction (Université Paris - 2017)
- Text generation
    - Short text generation (Lin et al. 2017; Rajeswar et al. 2017; Che et al. 2017)
    - Long text generation (Guo. J. 2017)

NLP Applications

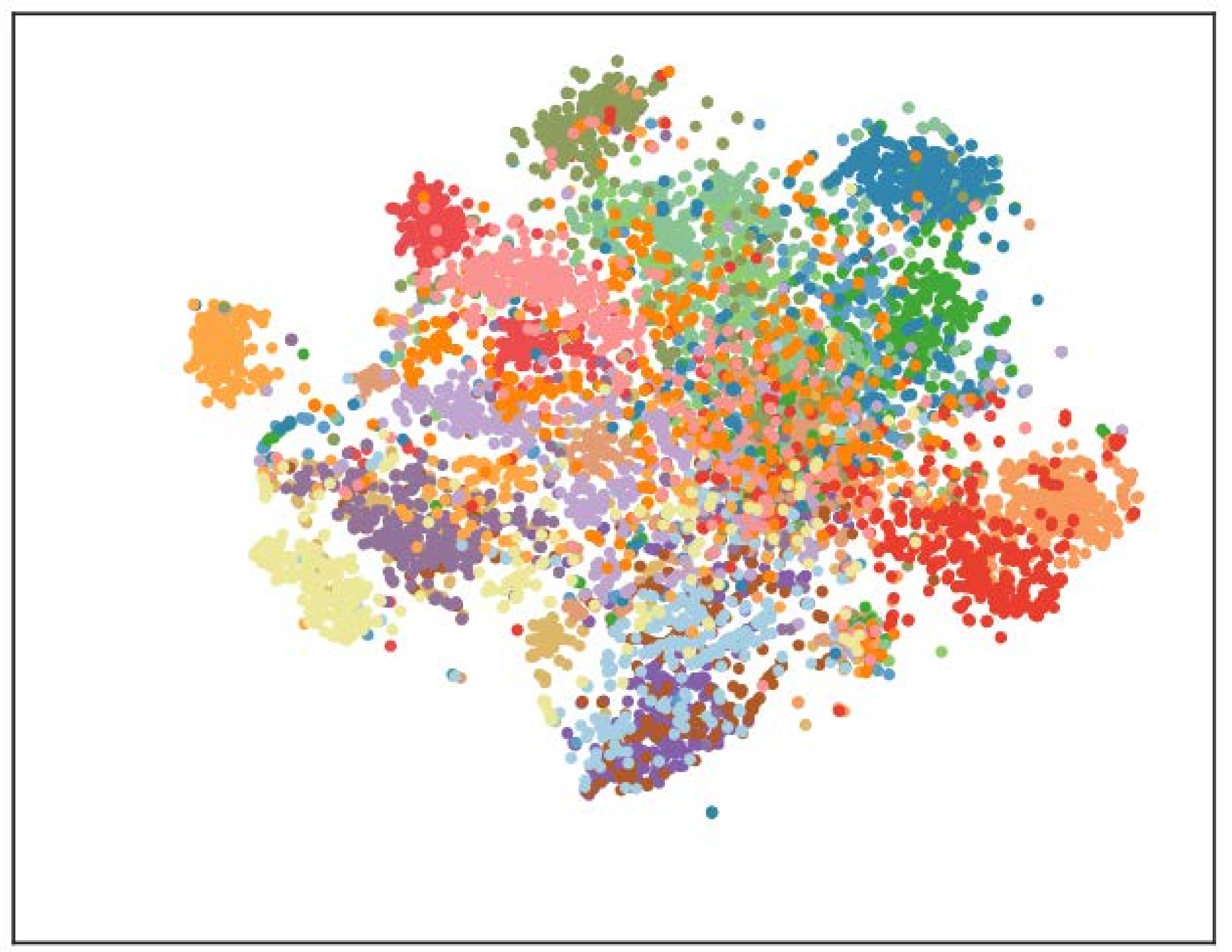
- GANs achieve great successes on computer vision applications
  - continous data
- A few progresses in natural language
  - Discrete & sequential data
- SeqGAN addresses this issue by the policy gradient inspired from the reinforcement learning (Yu, L., 2017 , Cited by 67)
- The approach considers each word selection in the sentence as an action, and computes the reward of the sequence with the Monte Carlo search

Adversarial Document Model (ADM)

- Based on Energy-Based GAN
- Uses a Denoising Autoencoder as the discriminator network
- Document representations are extracted from the hidden layer of the discriminator



Visualization of modeled docs



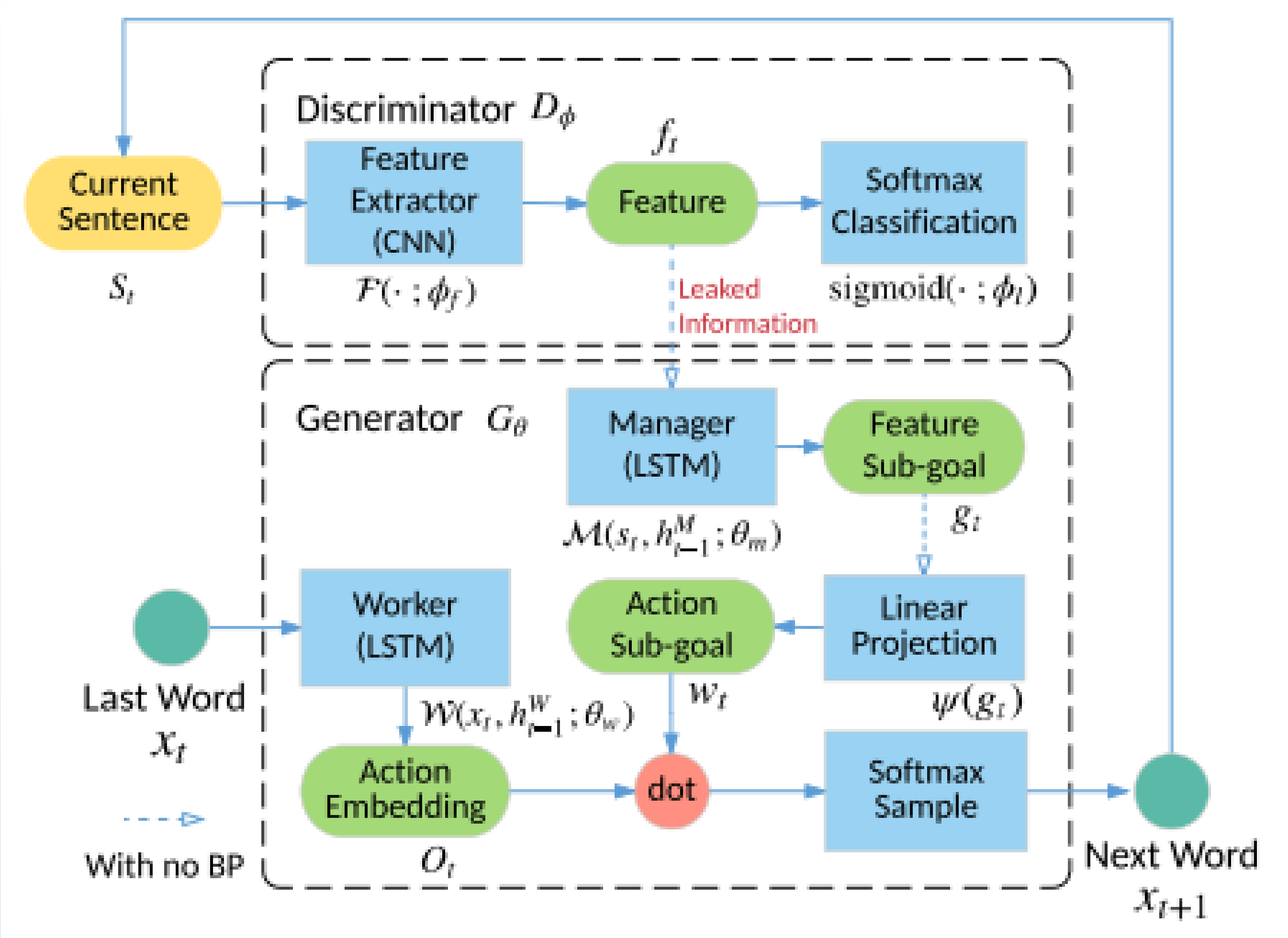
Syntactic & Semantic Structure Analysis

- Ph.D. subject: In this study we would like to explore multitask deep learning and structured prediction for joint syntactic and semantic structure analysis.
- We propose to extend structured prediction energy networks (SPENs)Belanger and McCallum[2015] to jointly model several tasks.
- For learning we propose to explore adversarial learning methods [Goodfellow et al.2014] which have proved successful in vision in recent years and have been rarely applied to language related tasks [Gulrajani et al.2017].

Text generating

- LeakGAN framework (Guo. J. 2017)
- Long text generation
  - auto-generation of news articles
  - product descriptions

LeakGAN



Discriminator D_ϕ
Current Sentence
S_t
Feature Extractor (CNN)
$\mathcal{F}(\cdot\,;\phi_f)$
f_t
Feature
Softmax Classification
sigmoid$(\cdot\,;\phi_l)$
Leaked Information
Generator G_θ
Manager (LSTM)
$\mathcal{M}(s_t, h^M_{t-1};\theta_m)$
Feature Sub-goal
g_t
Worker (LSTM)
Action Sub-goal
Linear Projection
$\psi(g_t)$
Last Word
x_t
$\mathcal{W}(x_t, h^W_{t-1};\theta_w)$
w_t
Action Embedding
dot
Softmax Sample
O_t
With no BP
Next Word
x_{t+1}

News Text Generation

- Master’s thesis
- To generate news text articles in an automated fashion
- To aid with the creation of a corpus of fake news
  - Useful when investigating methods for detection of fake news and thereby prevent some spread of misinformation

- http://www.iangoodfellow.com/slides/2017-05-09-adobe.pdf
- Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. In *Advances in neural information processing systems* (pp. 2672-2680).
- Glover, J. (2016). Modeling documents with generative adversarial networks. *arXiv preprint arXiv:1612.09122*.
- A. B. L. Larsen, S. K. Sønderby, H. Larochelle, and O. Winther, "Autoencoding beyond pixels using a learned similarity metric," arXiv preprint arxiv:1512.09300, 2015.
- V. Dumoulin, I. Belghazi, B. Poole, A. Lamb, M. Arjovsky, O. Mastropietro, and A. Courville,"Adversarially learned inference," arXiv preprint arxiv:1606.00704, 2016.
- J. Donahue, P. Krähenbühl, and T. Darrell, "Adversarial feature learning," arXiv preprintarxiv:1605.09782, 2016.
- A. Makhzani, J. Shlens, N. Jaitly, and I. Goodfellow, "Adversarial autoencoders," International Conference on Learning Representations Workshop, 2016

- file:///H:/machine%20learning/2017-05-09-adobe.pdf
- https://www.slideshare.net/xavigiro/deep-generative-models-i-dlai-d9l2-2017-upc-deep-learning-for-artificial-intelligence
- https://www.slideshare.net/ssuser77ee21/generative-adversarial-networks-70896091
- https://www.slideshare.net/xavigiro/generative-adversarial-networks-d2l5-deep-learning-for-speech-and-language-upc-2017
- https://www.slideshare.net/Artifacia/generative-adversarial-networks-and-their-applications
- Yao, B., Chen, Y., & Chen, M. Visual Recommender System with Adversarial Generator-Encoder Networks. stanford/2017/posters/

- Yoo, J., Ha, H., Yi, J., Ryu, J., Kim, C., Ha, J. W., ... & Yoon, S. (2017). Energy-based sequence gans for recommendation and their connection to imitation learning. *arXiv preprint arXiv:1706.09200*.
- Zhang, H., Xu, T., Li, H., Zhang, S., Huang, X., Wang, X., & Metaxas, D. (2017, October). Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks. In *IEEE Int. Conf. Comput. Vision (ICCV)* (pp. 5907-5915).