PRODUCING ARTIFICIAL DATA SAMPLES USING GENERATIVE ADVESARIAL NETWORKS

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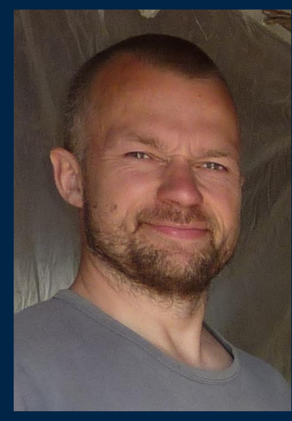

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RESEARCH

MOTIVATION

Issue:
- Deep learning or in general machine learning algorithms require immense amount of data to achieve high performance and to generalize well. (Norvig, 2011; C. Sun et al., 2017)
- Data acquisition and annotation can be highly time consuming and prone to errors, especially in domain specific applications (Montani and Honnibal, 2017; Y. Sun et al., 2017)

Possible solution:
- Use generative modelling to produce artificial data samples that mimics properties of real data samples
  - Artificial data samples might be used for pretraining deep learning models, while the valuable real data is saved for finetuning the model.
  - Generated data samples might provide different plausible combinations of modalities, than are present in the original real data
    - E.g. color, texture, shape

Challenges:
- Generate realistic looking data
- Model high intra- and inter-class variance in the artificial data
  - And possible control of these variations through conditioning

REFERENCES

Montani, I., Honnibal, M., 2017. Supervised learning is great — it's data collection that's broken · Blog · Explosion AI [WWW Document]. Explos. AI. URL https://explosion.ai/blog/supervised-learning-data-collection (accessed 7.23.18).

Norvig, P., 2011. The Unreasonable Effectiveness of Data [WWW Document]. URL https://www.youtube.com/watch?v=yvDCzhbjYWs (accessed 7.22.18).

Sun, C., Shrivastava, A., Singh, S., Gupta, A., 2017. Revisiting Unreasonable Effectiveness of Data in Deep Learning Era, in: Proceedings of the IEEE International Conference on Computer Vision. https://doi.org/10.1109/ICCV.2017.97

Sun, Y., Lank, E., Terry, M., 2017. Label-and-Learn: Visualizing the Likelihood of Machine Learning Classifier's Success During Data Labeling, in: Proceedings of the 22Nd International Conference on Intelligent User Interfaces, IUI '17. ACM, New York, NY, USA, pp. 523–534. https://doi.org/10.1145/3025171.3025208

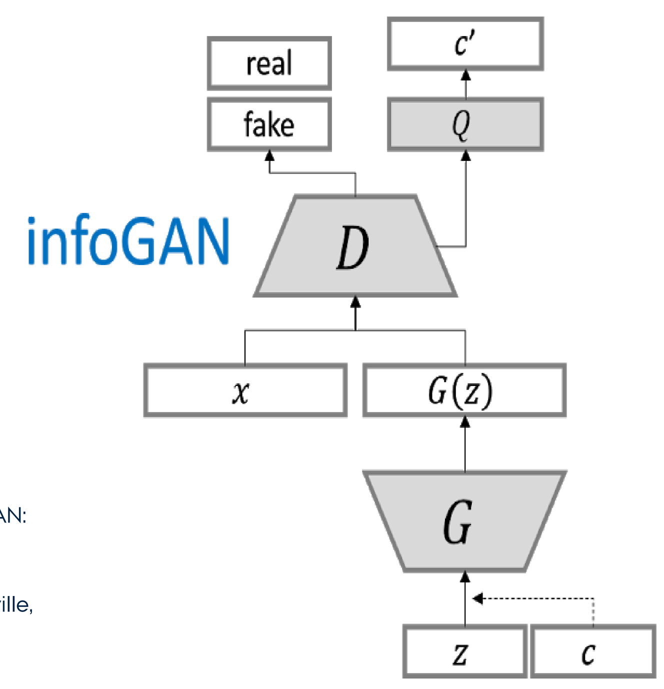
METHODOLOGY

Generative adversarial networks: (Goodfellow et al., 2014)
- Minmax game between two players:
  - A discriminator, distinguishing real and fake data samples
  - A generator, producing artificial sample in an effort to cheat the discriminator.

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim P_{data}}[\log D(x)] + \mathbb{E}_{x\sim noise}[\log(1 - D(G(z))]$$

InfoGAN: (Chen et al., 2016)
- Unsupervised condition for structuring/controlling the appearance of the generated samples.
- Try to maximize the mutual information between the an additional latent variable generator input and the generated samples
  - Formally implemented as an additional regularization term in the objective:

$$\min_G \max_D V_I(D,G) = V(D,G) - \lambda I\big(c, G(z,c)\big)$$
$$\min_{G,Q} \max_D V_{\text{InfoGAN}}(D,G,Q) = V(D,G) - \lambda I(G,Q)$$



REFERENCES

Chen, X., Duan, Y., Houthooft, R., Schulman, J., Sutskever, I., Abbeel, P., 2016. InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets, in: Advances in Neural Information Processing Systems.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative Adversarial Nets. Adv. Neural Inf. Process. Syst. 27. https://doi.org/10.1017/CBO9781139058452

EXPERIMENTS & RESULTS

Setup for creating artificial MNIST colour images:
- Increasing the challenge by randomly colouring of MNIST data
  - Changing the generator to output a RGB image, instead of grayscale
- Latent variable design
  - 3 continuous variables (random uniform in the range [-1;1])
  - 1 categorical variable (one-hot encoded, K = 10, p = 0.1)

- Able to capture the underlying categorical structure
- Able to capture dominating continuous variations in the data (color, shape, style, ect.)

Improvements to be made:
- Higher resolution is needed for more details in the generated images (Karras et al., 2017; Zhang et al., 2017)
- Better objective formulation to increase training stability (Gulrajani et al., 2017; Salimans et al., 2018)

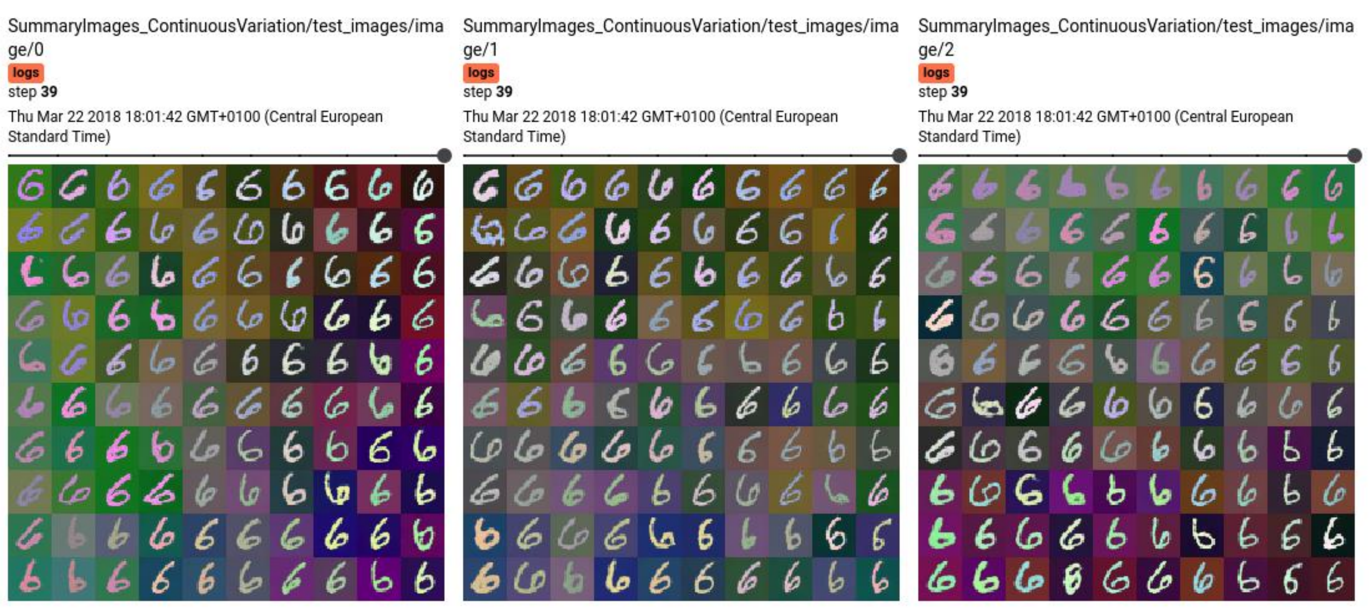


Figure 1: continuous variations. Each figure show different combinations of interpolating along two of the continuous latent variables (one along the x-axis and one along the y-axis), with the last one fixed at 0.

Figure 2: Categorical variations. Each figure show the representation learned for each categorical latent variable. Each is generated by interpolating along the first and second continuous variable (x-axis and y-axis respectively).

Source code:
https://github.com/Leminen/infoGAN-collections

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REFERENCES

Gulrajani, I., Ahmed, F., Arjovsky, M., Dumoulin, V., Courville, A.C., 2017. Improved training of wasserstein gans, in: Advances in Neural Information Processing Systems. pp. 5769–5779.

Karras, T., Aila, T., Laine, S., Lehtinen, J., 2017. Progressive growing of gans for improved quality, stability, and variation. arXiv Prepr. arXiv1710.10196.

Salimans, T., Zhang, H., Radford, A., Metaxas, D., 2018. Improving GANs using optimal transport. arXiv Prepr. arXiv1803.05573.

Zhang, H., Xu, T., Li, H., Zhang, S., Wang, X., Huang, X., Metaxas, D., 2017. Stackgan++: Realistic image synthesis with stacked generative adversarial networks. arXiv Prepr. arXiv1710.10916.

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