GAN (Generative Adversarial Networks) Method Applied for Quality Analysis of 3D Printed Objects

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Introduction

Motivation
- The 3D printing technologies are being widely applied in the manufacturing industries including healthcare, transportation, and electronics.
- Quality of 3D printing is always concerned by manufacturers and vast users, and poor quality would lead terrible roughness of the surfaces and low dimensional accuracy.
- Need more data to help researchers to make more accurate analysis.

Objects
- Apply GAN (Tabular Generative Adversarial Networks) to generate synthetic data based on the original data: heights, roughness, etc.
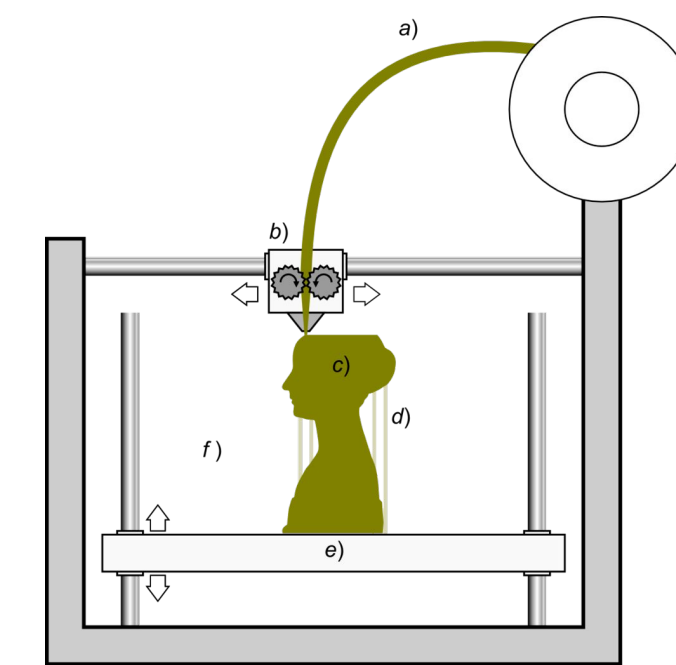- Compare the mean and variance of each column of synthetic and real data.

Challenges
- Simply fill the missing data (empty cells) with 0 would cause inaccuracy.
- To generate a large data set with high accuracy would be time-consuming.

Background

Types of 3D printing method
- **FDM** (Fused Deposition Modeling)
- SLS(Selective Laser Sintering)
- SLA(Stereolithography)

Disadvantages and limitations of FDM
- The printing quality of FDM 3D printed objects are not as good as those by SLA and SLS.
- 3D printing with fused deposition modeling is slow, which means the method is not quite applicable for the industry uses.
- The layer-by-layer printing will result warping and minor shrinking.

Data collection and printing parameters
- Using Keyence VR-3100 wide-area 3D measurement system.
- 3 printing parameters: printing speed, fill density, and layer thickness are test to examine the influences on the quality of printed objects.

Materials and Methods

Materials & Methods
- GAN code executable on Python
  a. **Generator:** a system of neural networks with a shape like Figure 1. Given a set of data, the generator produces a set of similar data.
  b. **Discriminator:** a network designed to determine if the synthetic data is similar to the real data collected.
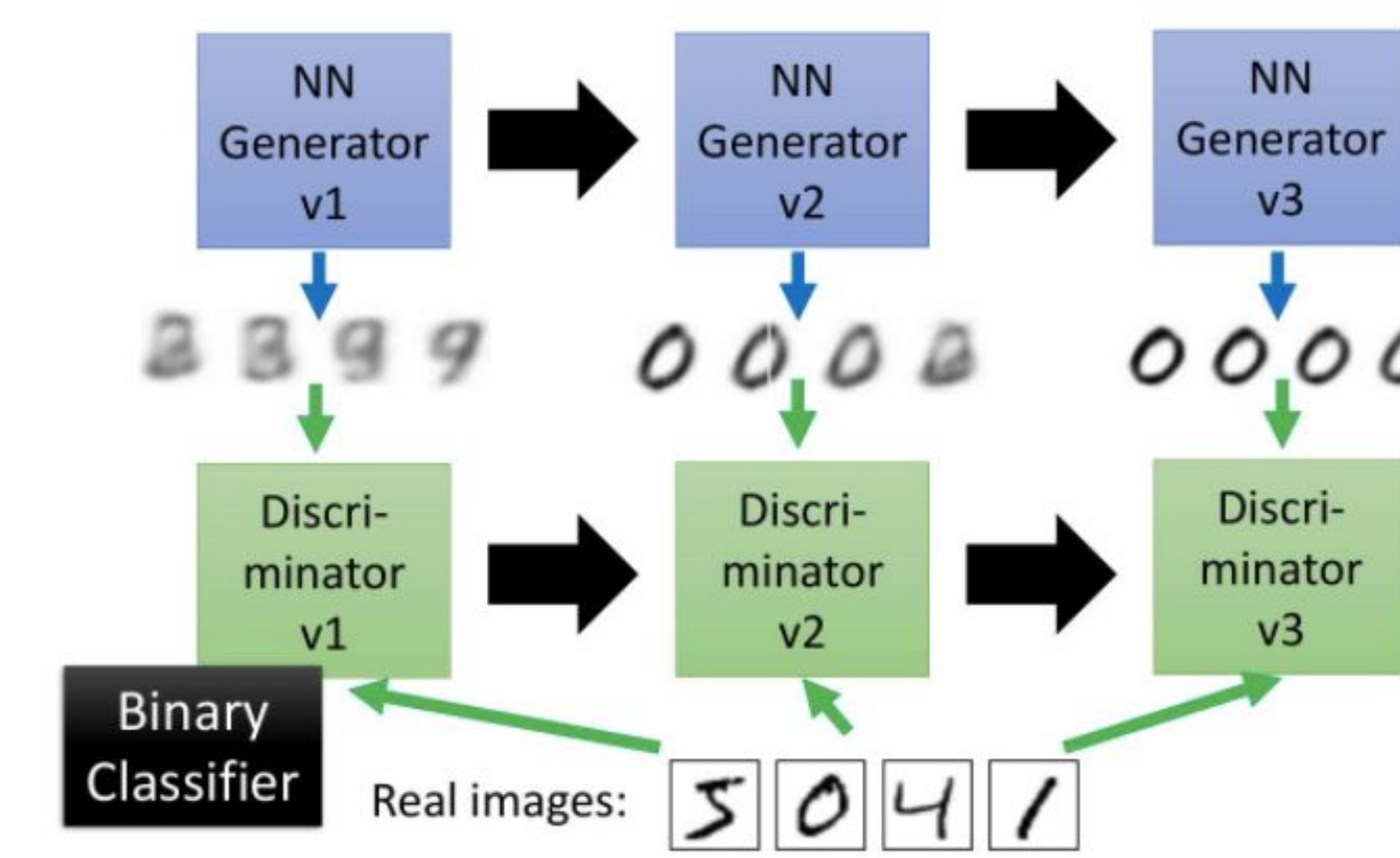

Figure 2, Illustrating how the generator and discriminator improve with more training processes. Image from *Canary Blog (2018)*
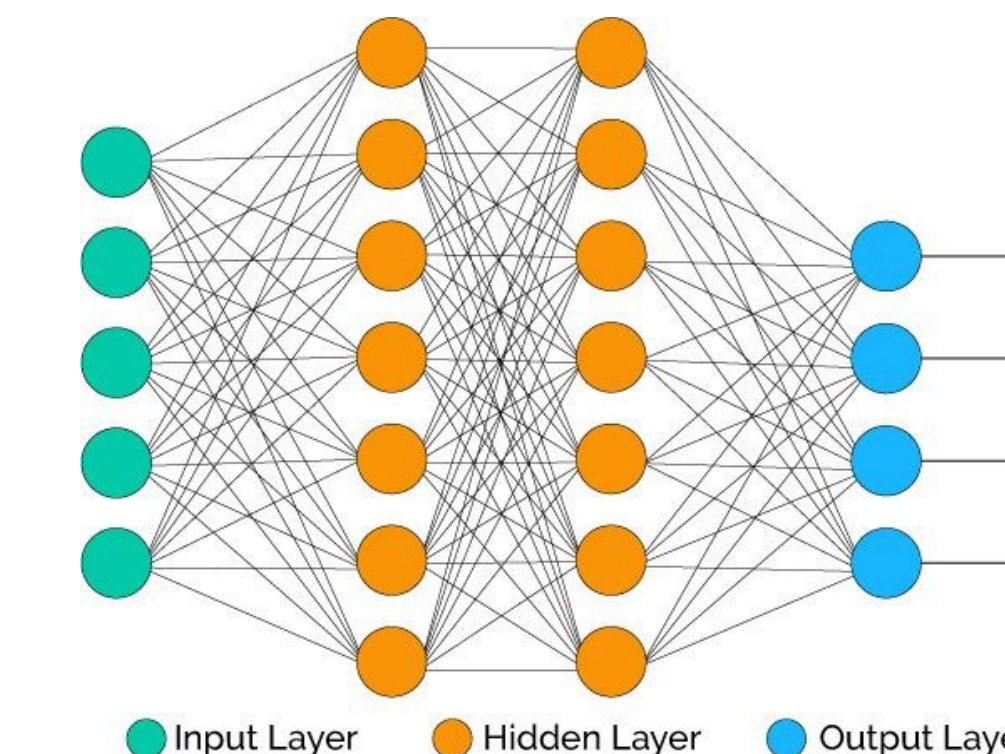

Figure 1, Image from *Conor Mcdonald*

In the process of GAN algorithm shown in Figure 2, discriminator and generator will improve by changing its parameters and in each epoch, the best generator and the best discriminator will be calculated.
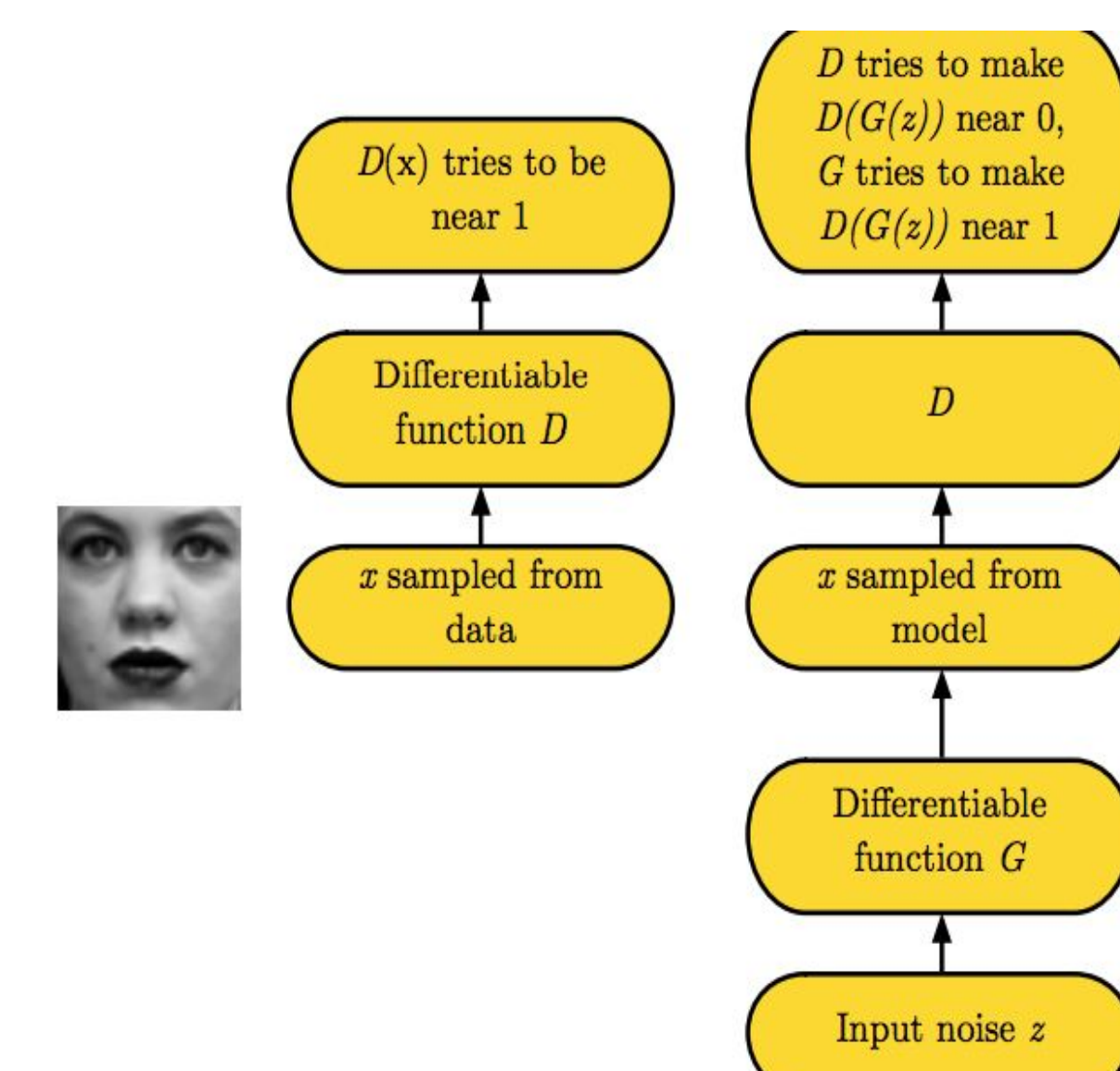

Figure 3, *Ian Goodfellow et al (2016)*, demonstrates how the discriminator and generator compete with each other and finally reach Nash equilibrium.

1. Function V(G, D)

$$V = E_{x \sim P_{data}} data[\log D(x)] + E_{x \sim P_G}[\log(1 - D(x))]$$

2. After simplification

$$V = \int_x [P_{data}(x) \log D(x) + P_G(x) \log(1 - D(x))]dx$$

$$f(D) = P_{data}(x) \log D(x) + P_G(x) \log(1 - D(x))$$
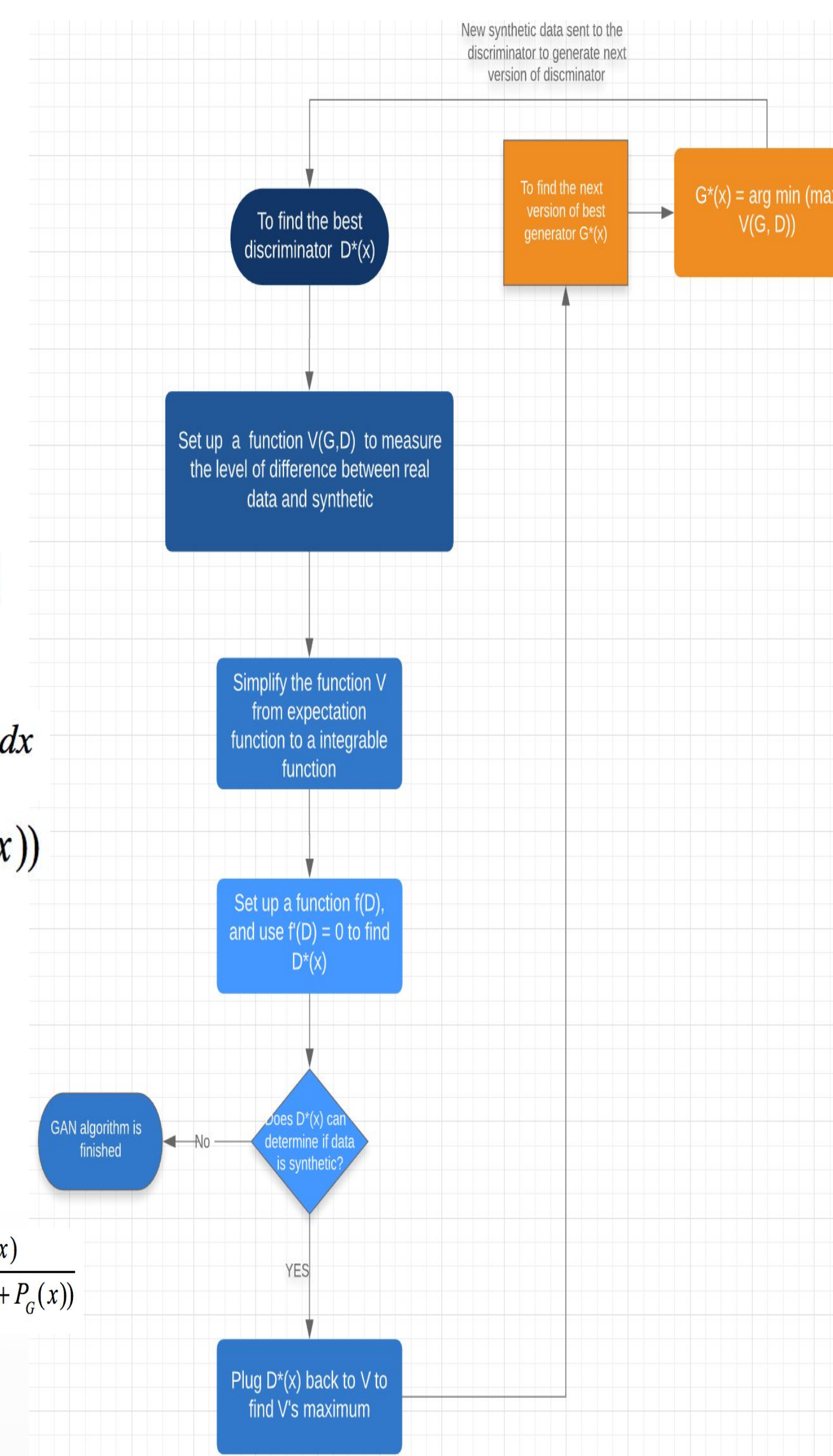
3. The best D, D*(x)

$$D = \frac{P_{data}(x)}{P_{data}(x) + P_G(x)}$$

4. Plug back the D*(x) to find max V and the best G

$$\max(V) = \log \frac{1}{4} + \int_x P_{data}(x) \log \frac{P_{data}(x)}{2(P_{data}(x) + P_G(x))} + \int_x P_G(x) \log \frac{P_G(x)}{2(P_{data}(x) + P_G(x))}$$

$$G = \arg \min_G \max_D (V(G, D))$$

Results

In the real implementation, **CTGAN** (Conditional Tabular Generative Adversarial Networks) is applied, which is specifically designed for synthetic the tabular data.

- **Real data:** a matrix with 255 columns and 1520 rows and the empty cells are revised to 0.
- **Synthetic data:** a matrix with 255 columns and 1520 rows.
- **Running time (1):** 410.4798s for 10 epoches(MacBook Air, Intel Core i5 5250U)
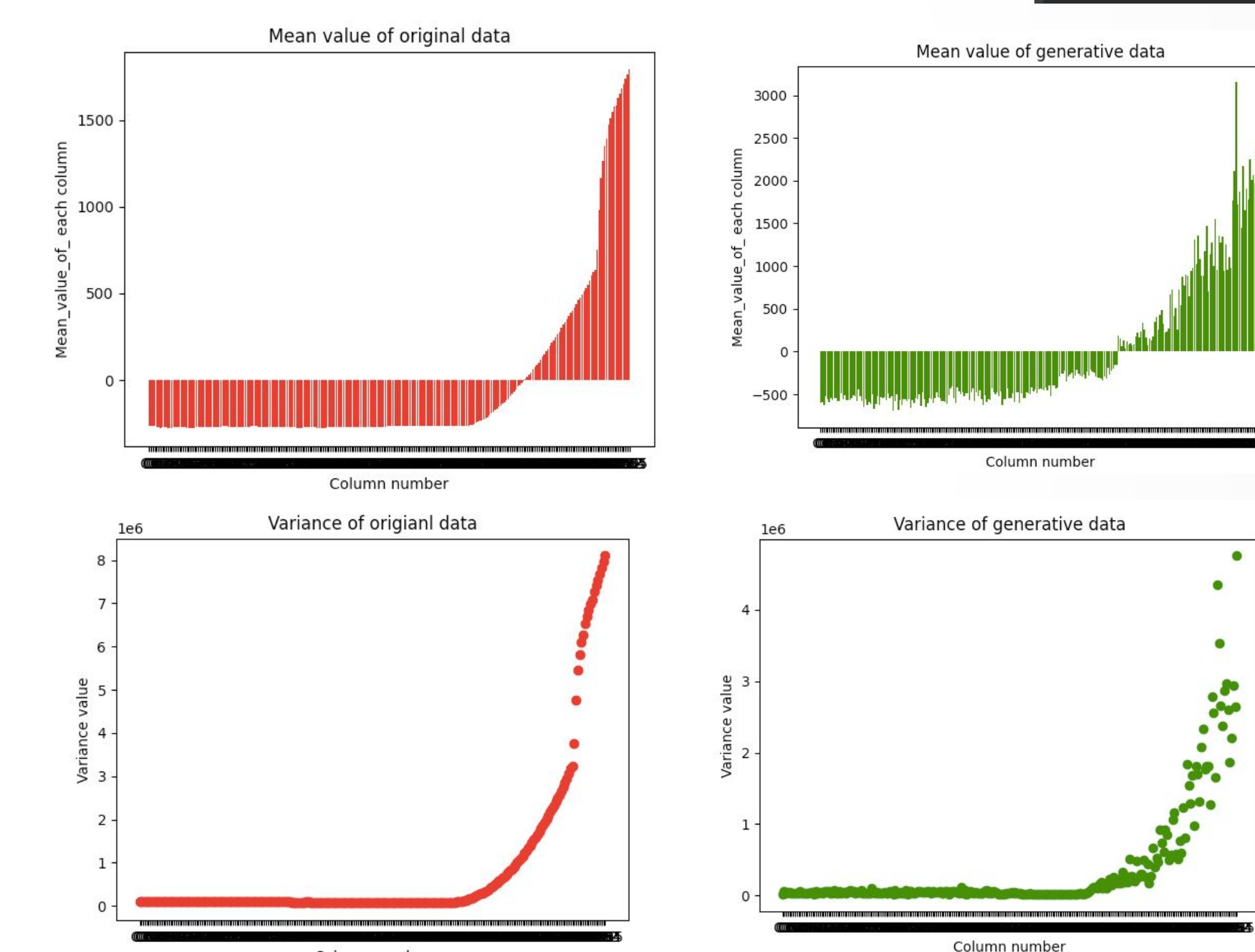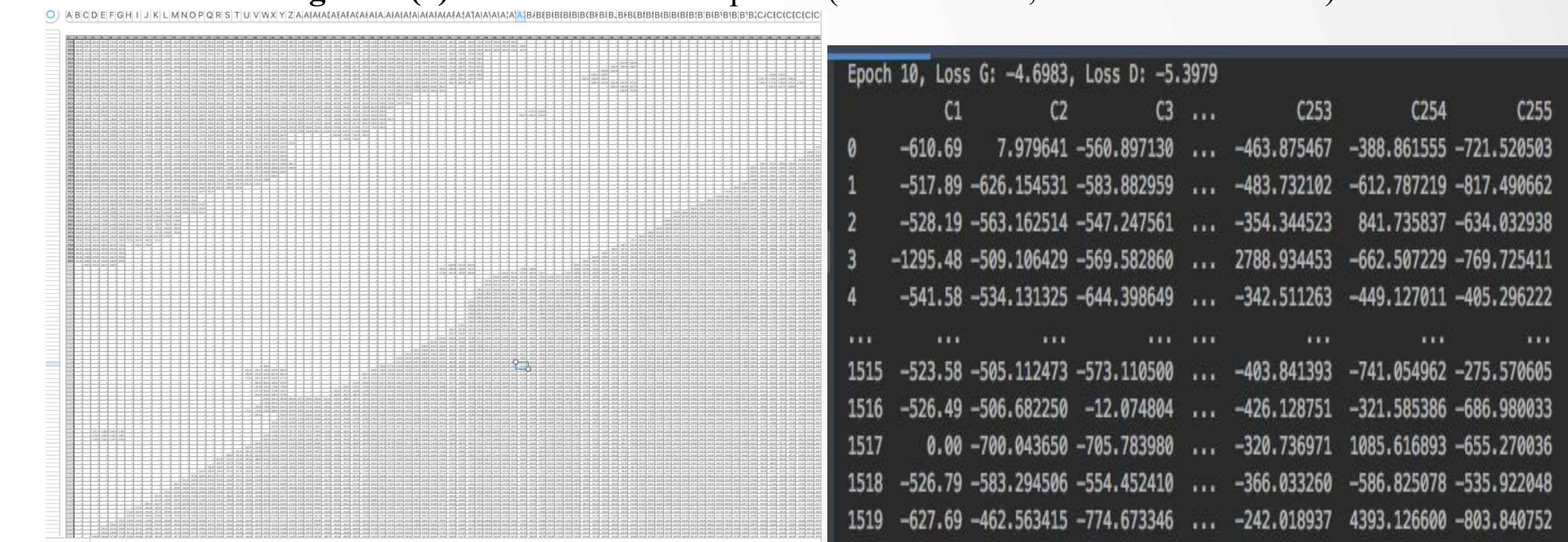
Conclusion

In general, comparison between every column from two data set shows both advantages and disadvantages of GAN method applied in quality analysis.

1. GAN method can effectively applied for tabular data
2. Save the time and materials of printing many objects.
3. GAN method can generally produce a data set which is similar to the data originally collected.

References

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