

6501 Progress Report Group 4

Improving Credit Card Fraud Detection using Generative Adversarial Networks

Group 4 Team Member: Hao Ning, Jun Ying

Working Schedule

Time	Milestone
09/21/2020	Exploratory Data Analysis (EDA): Jun Base Model: Hao
09/28/2020	Original data + GAN
10/05/2020	Network & Framework Development WGAN: Hao BAGAN: Jun
10/12/2020	WGAN & BAGAN Evaluation & Analysis
10/19/2020	Preliminary Presentation
10/26/2020	Network & Framework Development WGAN_GP: Hao BEGAN: Jun
11/02/2020	WGAN_GP, BEGAN Evaluation & Analysis
11/09/2020 & 11/16/2020	Summary of Results, Github
11/23/2020	Manuscript
11/30/2020 & 12/07/2020	Mock Presentation & Presentation and Journal Submission

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09/21/2020

EDA

```
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',  
      'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20',  
      'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount',  
      'Class'],
```

About the dataset, there are 30 features and 1 class (normal:0, fraud:1)

	Time	V1	V2	V3	...	V27	V28	Amount	Class
0	0.0	-1.359807	-0.072781	2.536347	...	0.133558	-0.021053	149.62	0
1	0.0	1.191857	0.266151	0.166480	...	-0.008983	0.014724	2.69	0
2	1.0	-1.358354	-1.340163	1.773209	...	-0.055353	-0.059752	378.66	0
3	1.0	-0.966272	-0.185226	1.792993	...	0.062723	0.061458	123.50	0
4	2.0	-1.158233	0.877737	1.548718	...	0.219422	0.215153	69.99	0

There is no null value in the dataset.

```
Total null values in the dataset  
0
```

As we know, the dataset is extremely imbalanced(0.173%).

```
The amounts of normal transactions (class 0) & fraud transactions (class 1)  
0    284315  
1      492
```

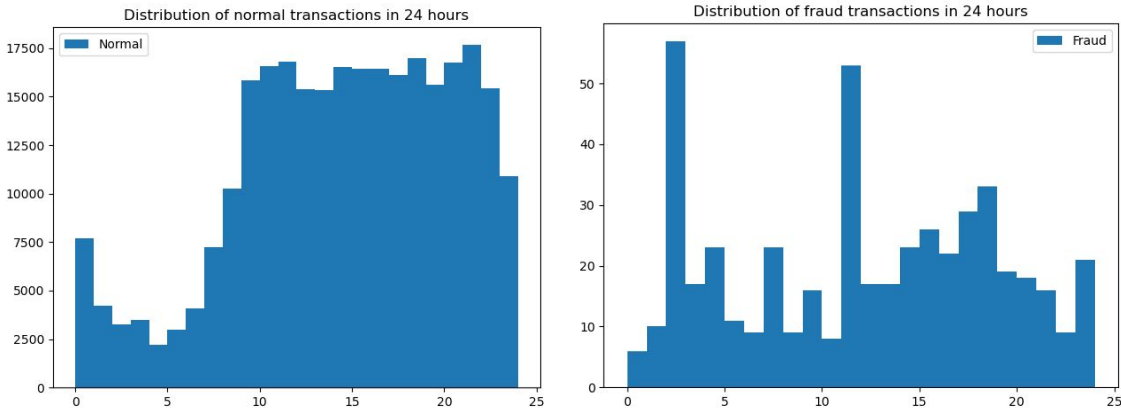
We have observed that there are some transactions which are 0.

	Time	V1	...	Amount	Class
count	284807.000000	2.848070e+05	...	284807.000000	284807.000000
mean	14.537951	3.919560e-15	...	88.349619	0.001727
std	5.847061	1.958696e+00	...	250.120109	0.041527
min	0.000000	-5.640751e+01	...	0.000000	0.000000
25%	10.598194	-9.203734e-01	...	5.600000	0.000000
50%	15.010833	1.810880e-02	...	22.000000	0.000000
75%	19.329722	1.315642e+00	...	77.165000	0.000000
max	23.999444	2.454930e+00	...	25691.160000	1.000000

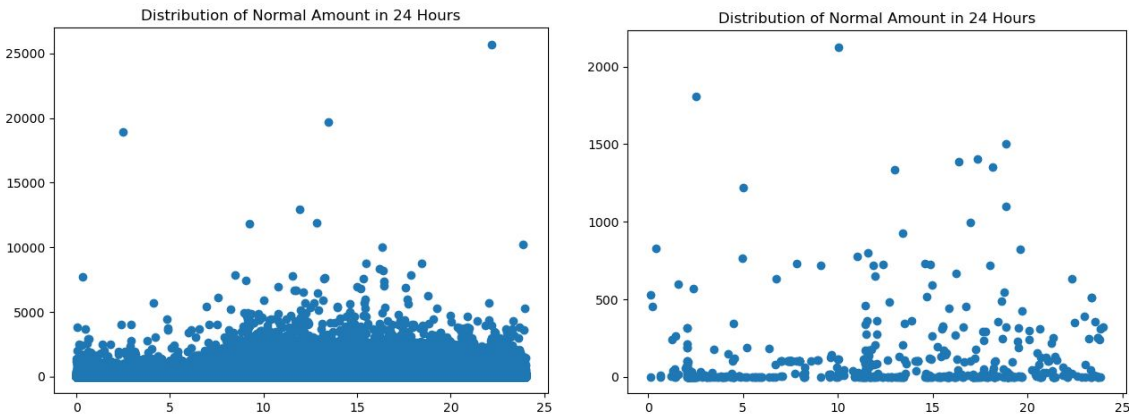
The total number of 0 amount: 1825 (1.479% fraud)

```
The null amounts of normal transactions (class 0) & fraud transactions (class 1)  
0    1798  
1      27  
Name: Class, dtype: int64
```

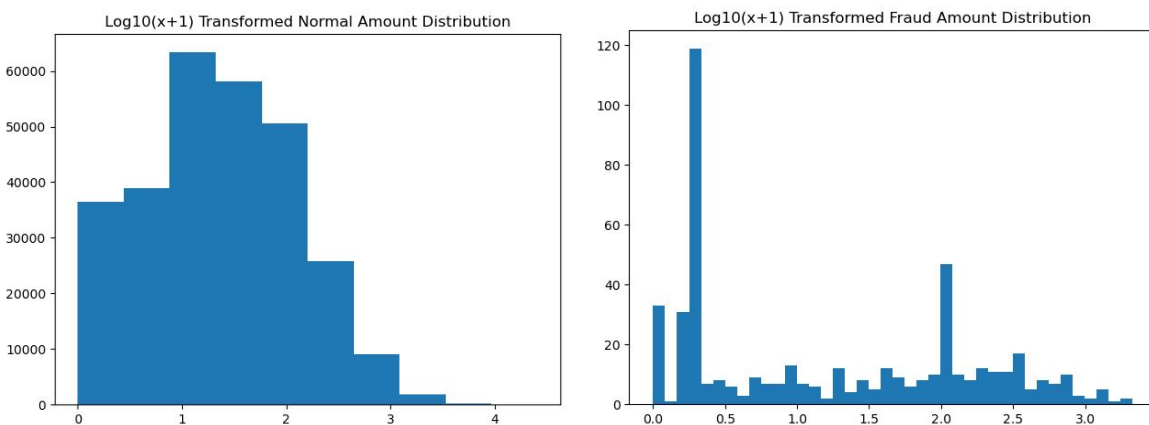
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From the histogram, we can observe that normal transactions generally occur from 9 am to 0 am. However, the fraud transactions occur particularly frequently at 2 am and 12 pm.

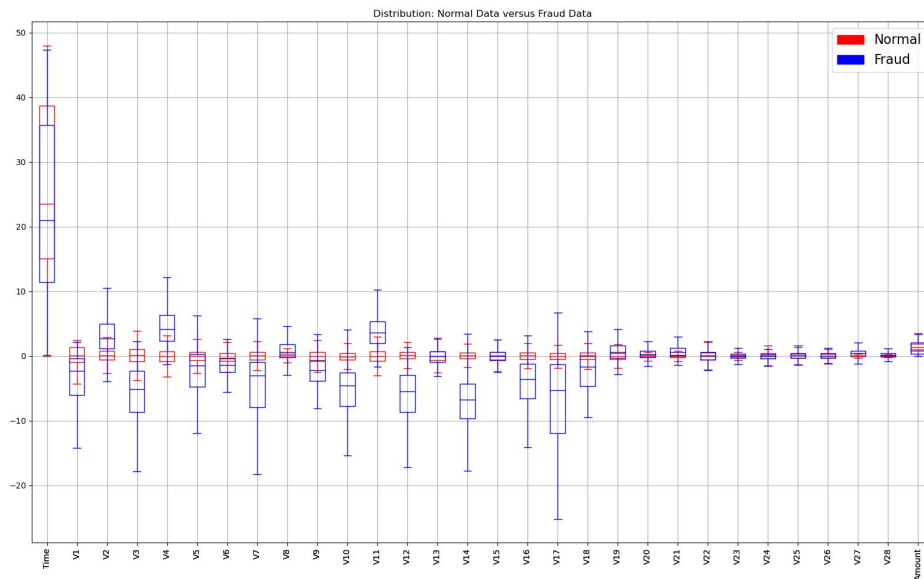
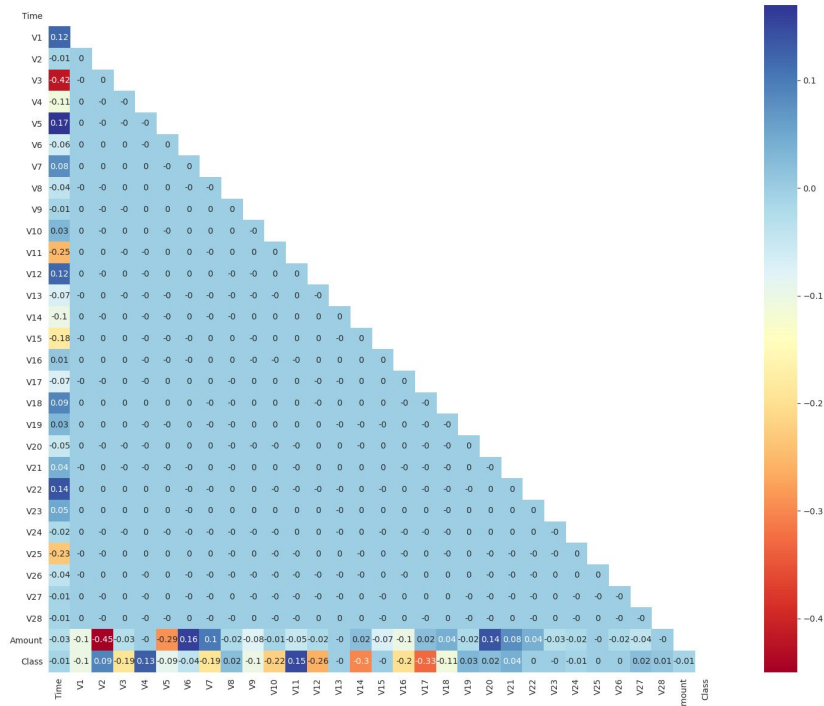


We can find from this scatter plot that the amount of super large transactions is very small. In comparison, the largest amount of normal transactions is over €25,000. However, the largest amount of fraud transactions is only €2,000.



Normal amount was from ten to hundred. Fraud Amount distributed in less than €1.

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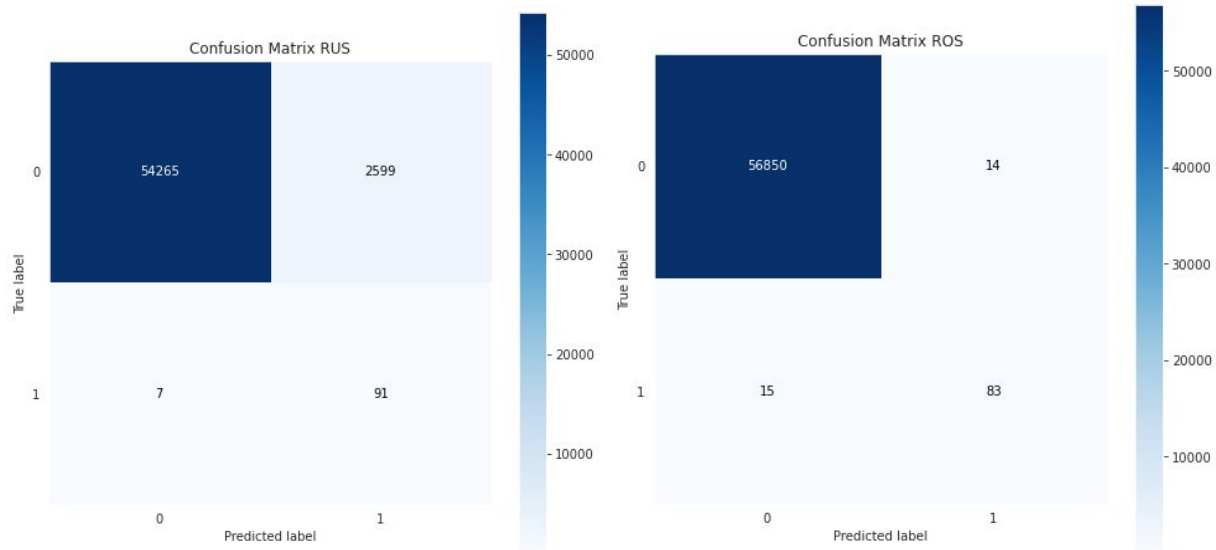


Base Model:

1. Train Test Split & Stratified: 80% 227845 (**394 fraud**), 20% 56962 (**98 fraud**)
2. Random Under Sampling (RUS) and Random Over Sampling (ROS)
3. GridsearchCV for XGBoostClassifier
4. Predict with best_params
5. Test performance evaluation

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RUS 1 394 0 394	ROS 1 227451 0 227451
Accuracy: 0.9542502018889786 Precision: 0.03382899628252788 Recall: 0.9285714285714286 F1 score: 0.06527977044476328 ROC AUC score: 0.941432942760672	Accuracy: 0.9994908886626171 Precision: 0.8556701030927835 Recall: 0.8469387755102041 F1 score: 0.8512820512820514 ROC AUC score: 0.923346287023532



09/28/2020

Implemented with Keras

A bit change from original gan:

Vanilla gan deals with images, but we are dealing with tabular data, so tanh is removed.

Also, we removed batch normalization since the training results are bad.

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Noise = 32

len(features) = 30

Generator

Input	Output size
(32, 1)	(64,1)
(64, 1)	(128, 1)
(128, 1)	(256, 1)
(256, 1)	(30, 1)

LeakyReLU(0.2)

Discriminator

Input	Output size
(30, 1)	(256,1)
(256, 1)	(128, 1)
(128, 1)	(64, 1)
(64, 1)	(1, 1)

LeakyReLU(0.2)

Train

epoch=10, batch_size=128, steps_per_epoch=100

```
EPOCH # 10 -----
Steps (5 / 50): [Loss_D_real: 0.101874, Loss_D_fake: 0.804704, acc: 55.47%] [Loss_G: 0.577402]
Steps (10 / 50): [Loss_D_real: 0.034651, Loss_D_fake: 0.794337, acc: 58.59%] [Loss_G: 0.583686]
Steps (15 / 50): [Loss_D_real: 0.043936, Loss_D_fake: 0.802042, acc: 64.84%] [Loss_G: 0.606348]
Steps (20 / 50): [Loss_D_real: 0.034166, Loss_D_fake: 0.831742, acc: 57.81%] [Loss_G: 0.573465]
Steps (25 / 50): [Loss_D_real: 0.045282, Loss_D_fake: 0.852394, acc: 56.25%] [Loss_G: 0.597851]
Steps (30 / 50): [Loss_D_real: 0.072814, Loss_D_fake: 0.801378, acc: 60.94%] [Loss_G: 0.593632]
Steps (35 / 50): [Loss_D_real: 0.062091, Loss_D_fake: 0.837749, acc: 55.47%] [Loss_G: 0.597265]
Steps (40 / 50): [Loss_D_real: 0.099103, Loss_D_fake: 0.853835, acc: 54.69%] [Loss_G: 0.578026]
Steps (45 / 50): [Loss_D_real: 0.088608, Loss_D_fake: 0.799784, acc: 60.16%] [Loss_G: 0.573147]
Steps (50 / 50): [Loss_D_real: 0.043118, Loss_D_fake: 0.808880, acc: 61.72%] [Loss_G: 0.589081]
```

epoch=20, batch_size=128, steps_per_epoch=100

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```

EPOCH # 20 -----
Steps (10 / 100): [Loss_D_real: 0.041530, Loss_D_fake: 0.459832, acc: 100.00%] [Loss_G: 1.017299]
Steps (20 / 100): [Loss_D_real: 0.049112, Loss_D_fake: 0.453462, acc: 100.00%] [Loss_G: 1.008852]
Steps (30 / 100): [Loss_D_real: 0.065196, Loss_D_fake: 0.458509, acc: 100.00%] [Loss_G: 1.018385]
Steps (40 / 100): [Loss_D_real: 0.061704, Loss_D_fake: 0.459229, acc: 100.00%] [Loss_G: 1.009706]
Steps (50 / 100): [Loss_D_real: 0.051204, Loss_D_fake: 0.460033, acc: 100.00%] [Loss_G: 1.005355]
Steps (60 / 100): [Loss_D_real: 0.059828, Loss_D_fake: 0.457545, acc: 100.00%] [Loss_G: 1.008903]
Steps (70 / 100): [Loss_D_real: 0.056420, Loss_D_fake: 0.468705, acc: 100.00%] [Loss_G: 1.013539]
Steps (80 / 100): [Loss_D_real: 0.052308, Loss_D_fake: 0.452640, acc: 100.00%] [Loss_G: 1.017379]
Steps (90 / 100): [Loss_D_real: 0.053092, Loss_D_fake: 0.457065, acc: 100.00%] [Loss_G: 0.990622]
Steps (100 / 100): [Loss_D_real: 0.052301, Loss_D_fake: 0.467294, acc: 100.00%] [Loss_G: 1.017609]

```

Original data + GAN

Original x_train has total of 227451 transactions, 227451 normal & 394 Fraud

1000

	Time	V1	V2	V3	V4	V5	V6	V7
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	3.198658	-0.762727	0.550367	-0.873793	1.195856	-0.272612	-0.130996	-0.884949
std	0.809518	0.242217	0.253704	0.331019	0.368733	0.255425	0.269881	0.360904
min	1.008744	-1.553868	-0.155640	-2.179475	0.302933	-1.204325	-1.027105	-2.258104
25%	2.607475	-0.912981	0.371793	-1.077172	0.923517	-0.423956	-0.310939	-1.102170
50%	3.141616	-0.749497	0.537789	-0.843910	1.163639	-0.256563	-0.115827	-0.863040
75%	3.701715	-0.591140	0.721689	-0.630434	1.437751	-0.110544	0.049115	-0.619941
max	6.568467	-0.130614	1.558176	-0.094866	2.794897	0.407353	0.780389	-0.010803

227451

	Time	V1	V2	V3	V4	V5	V6	V7
count	227057.000000	227057.000000	227057.000000	227057.000000	227057.000000	227057.000000	227057.000000	227057.000000
mean	3.218182	-0.756782	0.545352	-0.866097	1.202468	-0.291984	-0.135337	-0.896145
std	0.811016	0.237066	0.248467	0.324762	0.375655	0.256962	0.262601	0.354981
min	0.864484	-2.054668	-0.467559	-3.083328	-0.161810	-1.679709	-1.472434	-2.770730
25%	2.637128	-0.907640	0.373894	-1.067587	0.936952	-0.454703	-0.305321	-1.119700
50%	3.155144	-0.741693	0.535582	-0.835388	1.177741	-0.278191	-0.129604	-0.866557
75%	3.728471	-0.590163	0.706314	-0.633782	1.443069	-0.115094	0.040692	-0.641359
max	8.098510	0.093333	1.781384	0.096544	3.173466	0.693545	1.145589	0.370842

The fraud in x_train

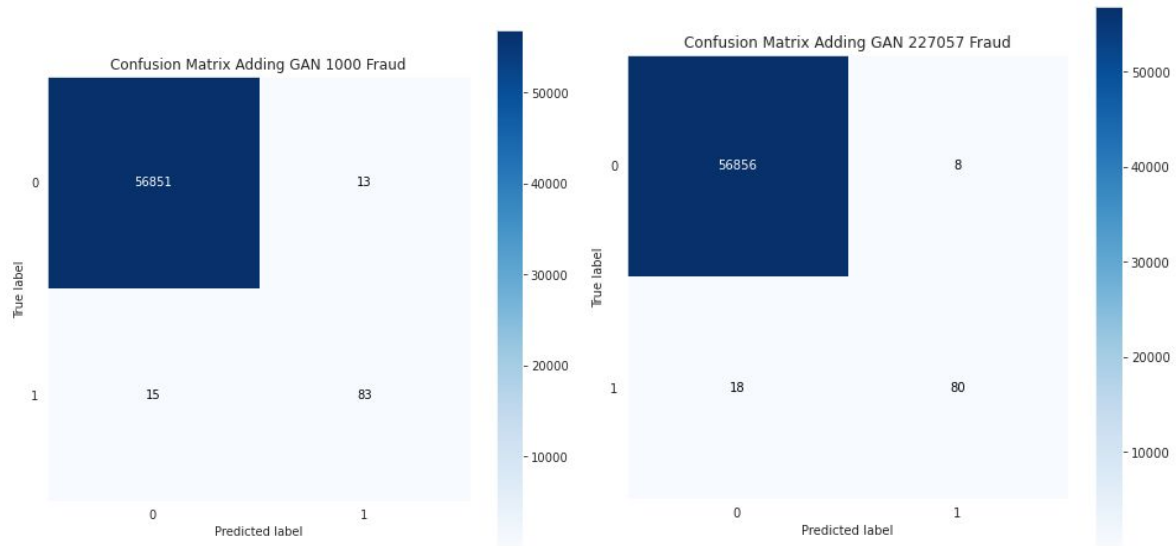
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	Time	V1	V2	V3	V4	V5	V6	V7
count	394.000000	394.000000	394.000000	394.000000	394.000000	394.000000	394.000000	394.000000
mean	23.008938	-4.707808	3.588729	-7.068378	4.592975	-3.101629	-1.387192	-5.539909
std	13.347935	6.841390	4.309436	7.166449	2.883467	5.406586	1.864770	7.316745
min	1.239444	-30.552380	-8.402154	-31.103685	-1.313275	-22.105532	-5.773192	-43.557242
25%	11.500278	-5.996596	1.229209	-8.436924	2.419178	-4.741036	-2.504633	-7.765017
50%	21.393056	-2.272114	2.662472	-5.133485	4.258196	-1.522962	-1.421577	-2.926216
75%	35.912917	-0.410418	4.737900	-2.302626	6.390866	0.240184	-0.361122	-0.900824
max	47.318889	2.132386	22.057729	2.250210	12.114672	11.095089	6.474115	5.802537

The little std observed in the GAN generated data indicates **mode collapse** in vanilla gan

Base ROS from Original data Normal: 227451 Fraud: 227451	Add GAN 1000 then ros.fit Normal: 227451 Fraud: 227451	GAN 227057 Normal: 227451 Fraud: 227451
Accuracy: 0.9994908886626171 Precision: 0.8556701030927835 Recall: 0.8469387755102041 F1 score: 0.8512820512820514 ROC AUC score: 0.923346287023532	Accuracy: 0.9995084442259752 Precision: 0.8645833333333334 Recall: 0.8469387755102041 F1 score: 0.8556701030927835 ROC AUC score: 0.9233550799329299	Accuracy: 0.9995435553526912 Precision: 0.9 Recall: 0.826530612244898 F1 score: 0.8617021276595744 ROC AUC score: 0.9131861699378682

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GAN didn't really improve much of the performance of the classification model for now, we think this is because the generator is only producing low spectrum data. We will work on a few improved GAN algorithms to see if the problems are resolved.

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10/05/2020

WGAN development: Hao

Why WGAN:

- Prevent mode collapse and gradient vanishing in vanilla GAN.
- Evaluate the difference between real and generated samples with wasserstein distance, using a score rather than label.

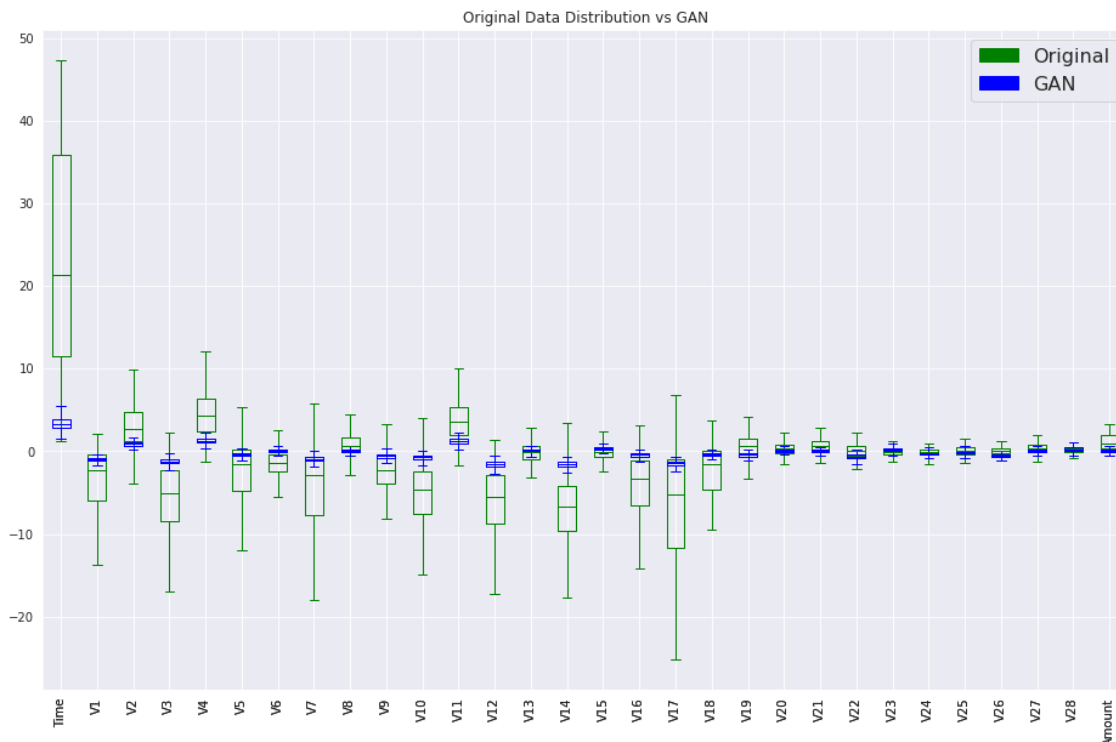
Implementation in Keras, compared to vanilla GAN:

- Loss function, no log
- D: no sigmoid
- Clip the weight of D $(-c, c)$, if $w > c$, $w = c$, if $w < -c$, $w = -c$
- Use RMSProp
- Train D more than G

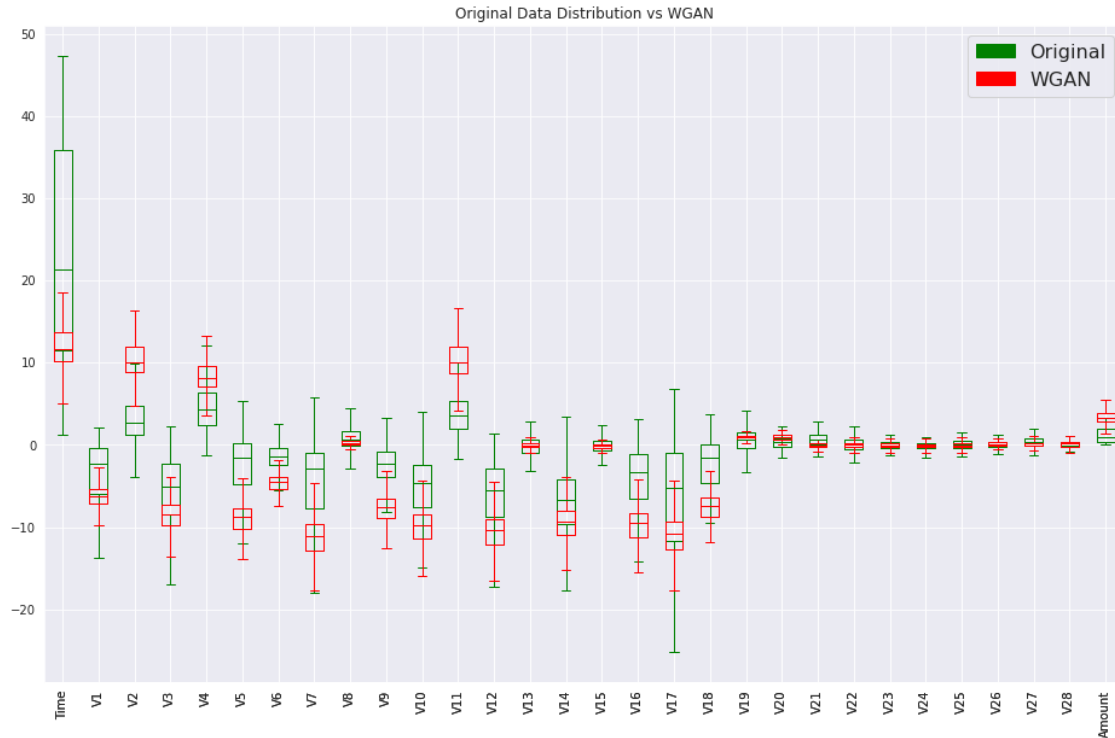
Training Parameters: RMSprop(lr=0.00001), batch_size=128, train D twice

Generate 1000 'Fraud', visually compare the data distribution using boxplot:

- GAN has very narrow spectrum of data distribution
- WGAN shows a wider distribution and close to the original data distribution
 - Good overlapping with the original distribution



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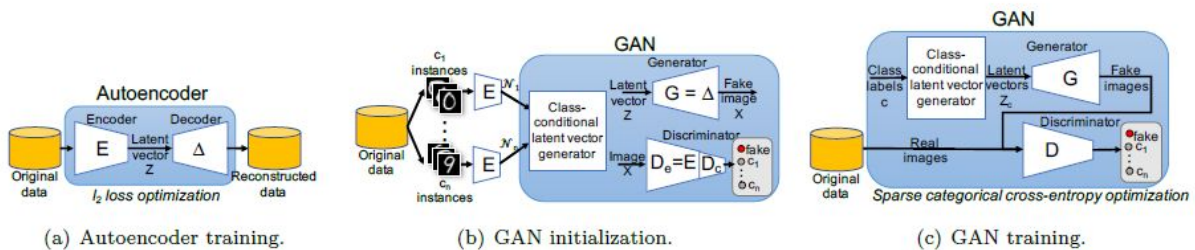
BAGAN development: JUN

Why BAGAN:

- It is an augmentation tool to restore the dataset balance by generating new minority-class data.
- It can learn the underlying features of the specific classification problem starting from all data and then to apply these features for the generation of new minority-class data.

Compared to original GAN:

- Discriminator has a single output that returns either a problem-specific class label c or the label fake.
- Coupling GAN and autoencoding techniques to provide a precise selection of the class conditioning and to better avoid mode collapse.



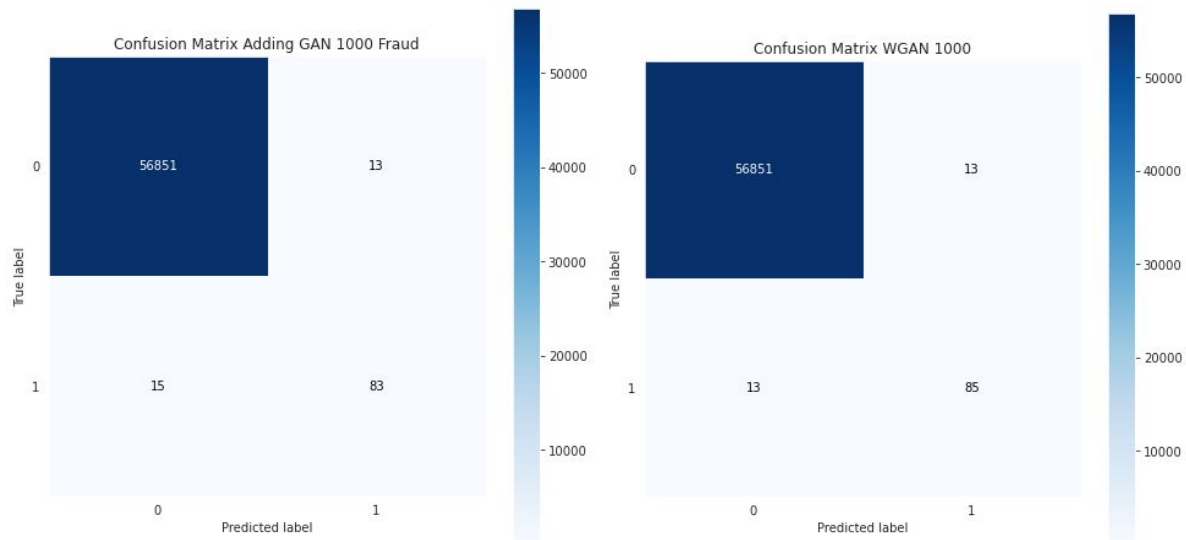
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10/12/2020

WGAN performance evaluation: Hao

Obvious improvement on model performance

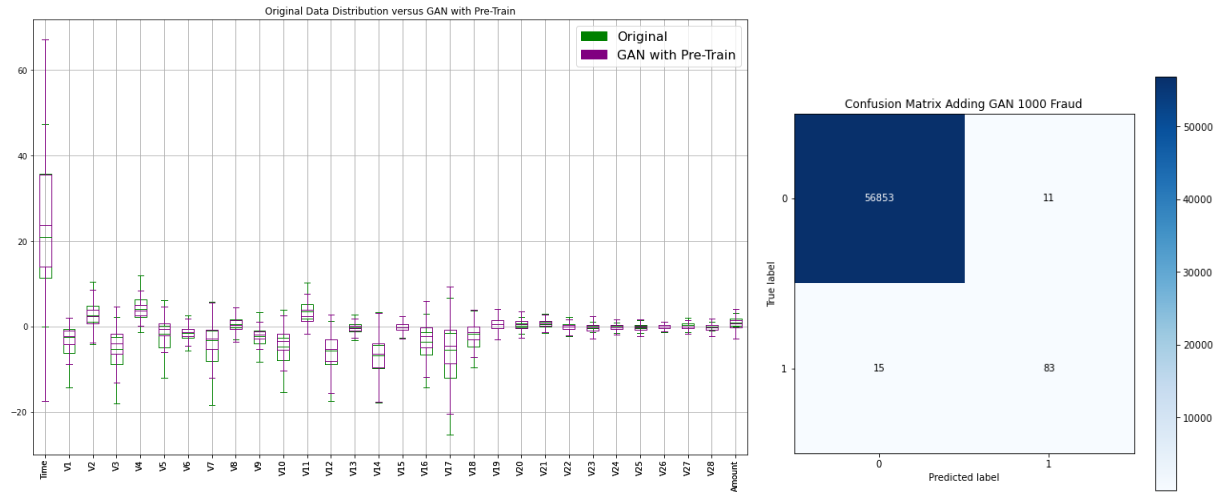
Base ROS from Original data Normal: 227451 Fraud: 227451	Add GAN 1000 then ros.fit Normal: 227451 Fraud: 227451	Add WGAN 1000 then ros.fit Normal: 227451 Fraud: 227451
Accuracy: 0.9994908886626171 Precision: 0.8556701030927835 Recall: 0.8469387755102041 F1 score: 0.8512820512820514 ROC AUC score: 0.923346287023532	Accuracy: 0.9995084442259752 Precision: 0.8645833333333334 Recall: 0.8469387755102041 F1 score: 0.8556701030927835 ROC AUC score: 0.9233550799329299	Accuracy: 0.9995435553526912 Precision: 0.8673469387755102 Recall: 0.8673469387755102 F1 score: 0.8673469387755102 ROC AUC score: 0.9335591615655828



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GAN with Pre-Train Performance : JUN

Better than Original GAN, slightly worse than WGAN, adding 1000 generated fraud
Wider spectrum of data & Overlap well with the original data



	GAN	GAN + AE
Accuracy	0.999508	0.999544
Precision	0.864583	0.882979
Recall	0.846939	0.846939
F1 score	0.855670	0.864583
ROC AUC score	0.923355	0.923373

Preliminary Presentation

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10/19/2020

WGAN_GP development: Hao

Why WGAN_GP:

- WGAN weight clipping does not strictly fulfill the 1-Lipschitz function requirement
 $|f(x_1) - f(x_2)| \leq K|x_1 - x_2|.$
K=1, is 1-Lipschitz function, it has strong uniform continuity
- A differentiable function is 1-Lipschitz if and only if it has gradients with **norm at most 1 everywhere**
- WGAN_GP constrain the weight more effectively

Note: batch normalization is already removed, so we don't need to do anything here

Changes compared to WGAN

- Gradient penalty

$$\lambda \underbrace{\mathbb{E}_{\hat{x} \sim \mathbb{P}_{\hat{x}}} [(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2]}_{\text{Our gradient penalty}}.$$

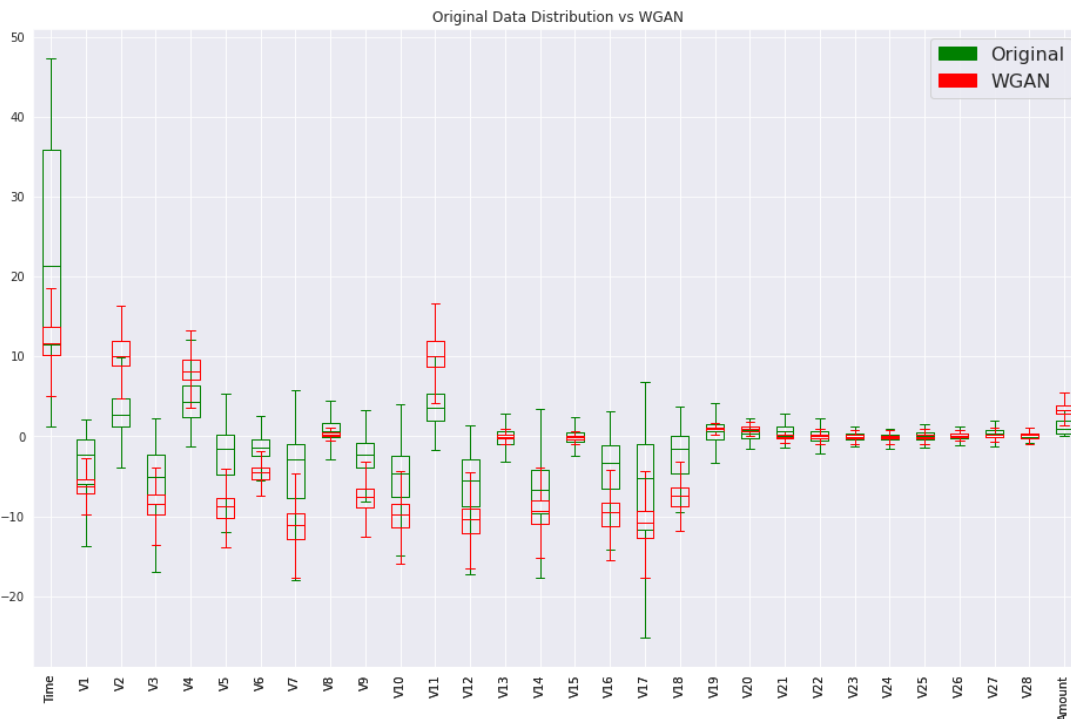
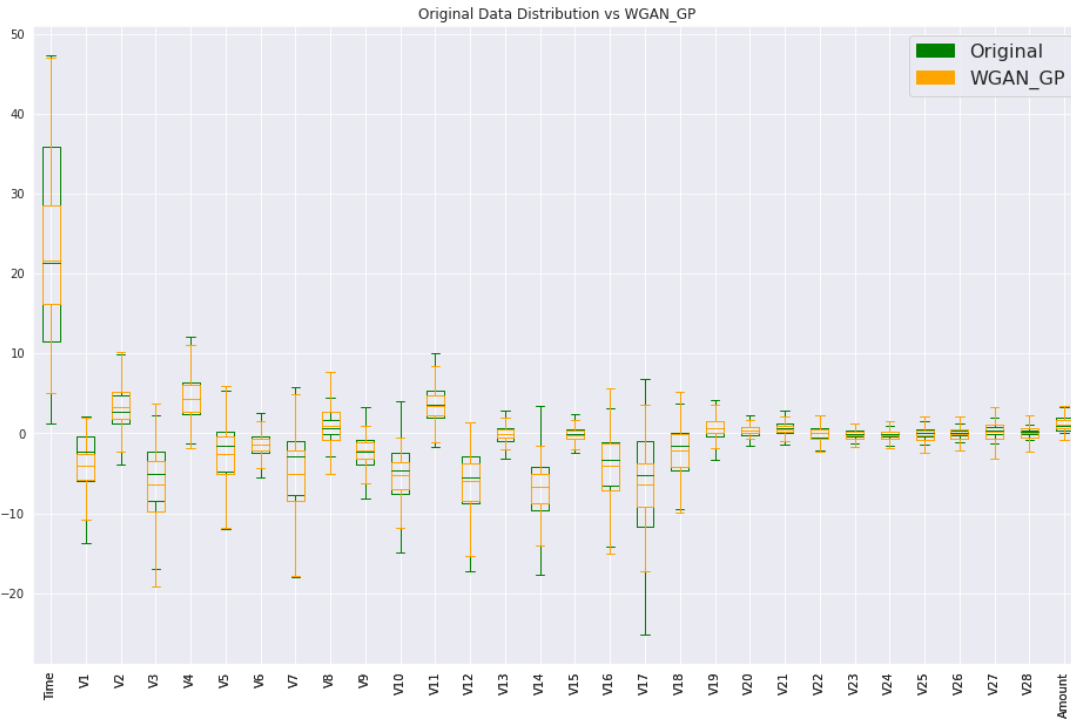
- Adam optimizer

Training Parameters: ADAM(lr=0.00001), batch_size=128, gp_lambda=5

Generate 1000 'Fraud', visually compare the data distribution using boxplot:

- Wider range and better overlaps with original data compared to WGAN

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BEGAN development: Jun

Why BEGAN:

- a novel equilibrium method for balancing adversarial networks
- using an autoencoder as the discriminator
- using a variable $kt \in [0, 1]$ to control equilibrium(kt is adjusted at each step)

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$$\begin{cases} \mathcal{L}_D = \mathcal{L}(x) - k_t \cdot \mathcal{L}(G(z_D)) & \text{for } \theta_D \\ \mathcal{L}_G = \mathcal{L}(G(z_G)) & \text{for } \theta_G \\ k_{t+1} = k_t + \lambda_k (\gamma \mathcal{L}(x) - \mathcal{L}(G(z_G))) & \text{for each training step } t \end{cases}$$

Derive a global measure of convergence by using the equilibrium concept:

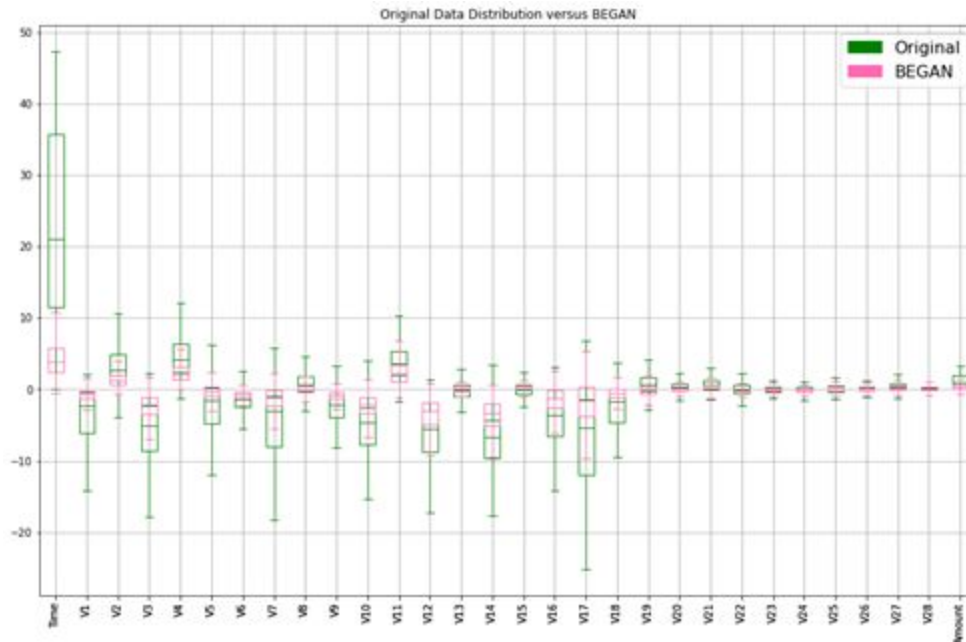
$$\mathcal{M}_{global} = \mathcal{L}(x) + |\gamma \mathcal{L}(x) - \mathcal{L}(G(z_G))|$$

This measure can be used to determine when the network has reached its final state or if the model has collapsed.

Training Parameters: ADAM(lr=0.0001), batch_size=128, gp_lambda=5

Generate 1000 'Fraud', visually compare the data distribution using boxplot:

- Although better than the basic GAN, it does not overlap with the dataset well.
- There are cases where Time or Amount is less than 0.



Future work

- Fix and improve the loss function
- Adjustment parameters

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10/26/2020

WGAN_GP performance evaluation: Hao

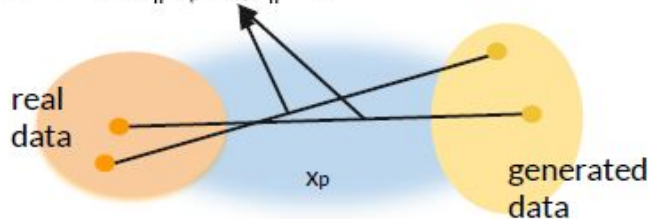
Interpolated part explanation

```
def gradient_penalty(self, batch_size, real_data, fake_data):  
    """ Calculates the gradient penalty.  
    This loss is calculated on an interpolated data  
    and added to the discriminator loss.  
    """  
    # get the interplated image  
    alpha = tf.random.normal([batch_size, 1, 1, 1], 0.0, 1.0)  
    diff = fake_data - real_data  
    interpolated = real_data + alpha * diff
```

The points interpolated between real and generated data should have a gradient norm of 1.

It's hard to get gradients with norm at most 1 everywhere, so we interpolate between real and generated samples. Instead of applying clipping, WGAN-GP applies a penalty if the gradient norm moves away from its target norm value 1.

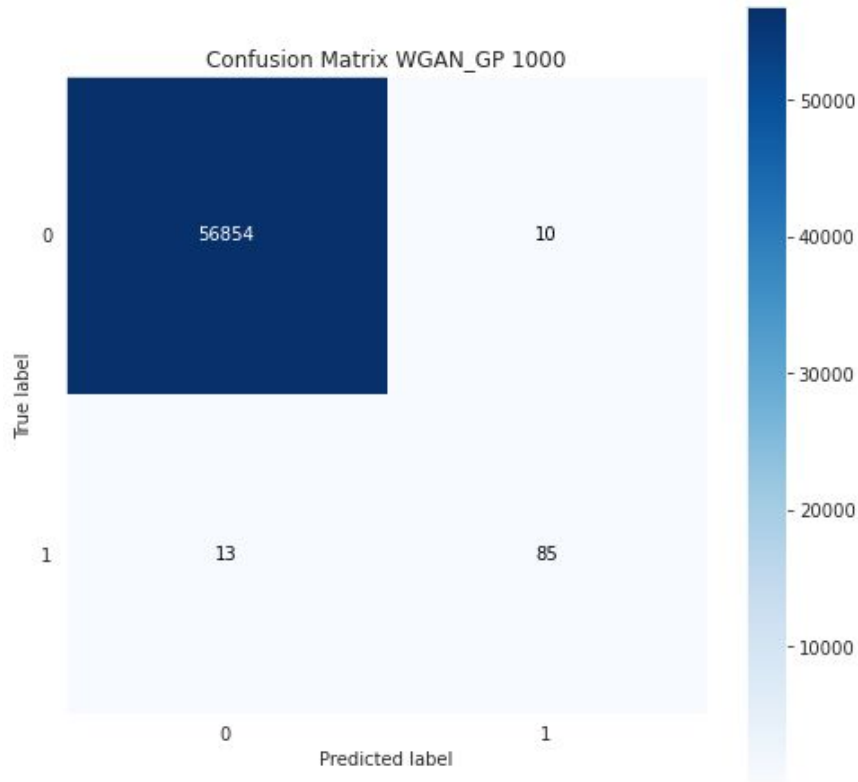
Gradient penalty: $\lambda(\|\nabla_{x_p} D(x_p)\| - 1)^2$



Obvious further improvement on model performance with WGAN_GP, best model

	Base	GAN	WGAN	WGAN_GP
Accuracy	0.999491	0.999491	0.999544	0.999596
Precision	0.855670	0.864583	0.867347	0.894737
Recall	0.846939	0.846939	0.867347	0.867347
F1 score	0.851282	0.855670	0.867347	0.880829
ROC AUC score	0.923346	0.923355	0.933559	0.933586

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BEGAN performance evaluation: Jun

Discriminator: Autoencoder (Encoder + Decoder)

Generator: Decoder

Loss Function:

$$\begin{cases} \mathcal{L}_D = \mathcal{L}(x) - k_t \cdot \mathcal{L}(G(z_D)) & \text{for } \theta_D \\ \mathcal{L}_G = \mathcal{L}(G(z_G)) & \text{for } \theta_G \\ k_{t+1} = k_t + \lambda_k (\gamma \mathcal{L}(x) - \mathcal{L}(G(z_G))) & \text{for each training step } t \end{cases}$$

$$\mathcal{M}_{global} = \mathcal{L}(x) + |\gamma \mathcal{L}(x) - \mathcal{L}(G(z_G))|$$

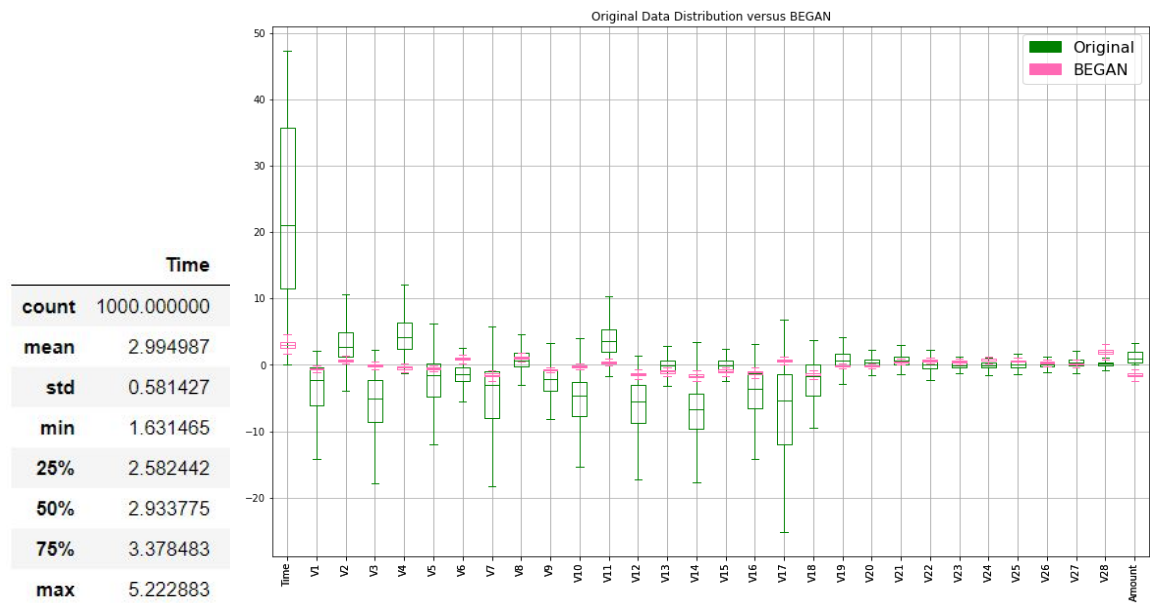
This measure can be used to determine when the network has reached its final state or if the model has collapsed.

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K∈[0,1]
k=1e-05

EPOCH # 20				Time	
Steps (10 / 100):	[loss_D: 23.763582]	[Loss_G: 5191.047363]	[M_global: 5191.140451]	count	1000.000000
Steps (20 / 100):	[loss_D: 23.283887]	[Loss_G: 5037.947266]	[M_global: 5038.038371]	mean	45316.074219
Steps (30 / 100):	[loss_D: 20.021150]	[Loss_G: 5360.807129]	[M_global: 5360.880726]	std	9665.684570
Steps (40 / 100):	[loss_D: 19.312572]	[Loss_G: 5416.488770]	[M_global: 5416.558218]	min	18976.361328
Steps (50 / 100):	[loss_D: 21.133590]	[Loss_G: 5494.187012]	[M_global: 5494.264138]	25%	38610.062500
Steps (60 / 100):	[loss_D: 21.643043]	[Loss_G: 5638.911621]	[M_global: 5638.991511]	50%	45014.445312
Steps (70 / 100):	[loss_D: 20.518601]	[Loss_G: 5681.296387]	[M_global: 5681.370212]	75%	51699.350586
Steps (80 / 100):	[loss_D: 19.534069]	[Loss_G: 5762.511230]	[M_global: 5762.579990]	max	78984.054688
Steps (90 / 100):	[loss_D: 21.824670]	[Loss_G: 5780.583496]	[M_global: 5780.663860]		
Steps (100 / 100):	[loss_D: 19.115582]	[Loss_G: 6058.291992]	[M_global: 6058.358950]		

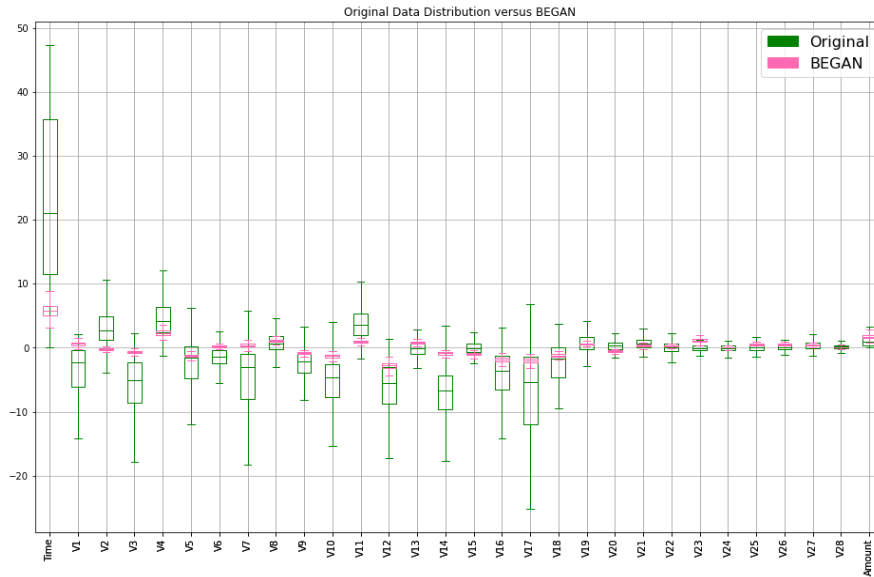
k=1



k=0.08

EPOCH # 20				Time	
Steps (10 / 100):	[loss_D: 23.402295]	[Loss_G: 0.590853]	[M_global: 0.687436]	count	1000.000000
Steps (20 / 100):	[loss_D: 22.523965]	[Loss_G: 0.568527]	[M_global: 0.661421]	mean	5.871967
Steps (30 / 100):	[loss_D: 22.351444]	[Loss_G: 0.538081]	[M_global: 0.631413]	std	1.094325
Steps (40 / 100):	[loss_D: 21.146445]	[Loss_G: 0.510166]	[M_global: 0.598388]	min	3.122333
Steps (50 / 100):	[loss_D: 22.483769]	[Loss_G: 0.456806]	[M_global: 0.552923]	25%	5.059084
Steps (60 / 100):	[loss_D: 22.652090]	[Loss_G: 0.423857]	[M_global: 0.522124]	50%	5.770874
Steps (70 / 100):	[loss_D: 24.288411]	[Loss_G: 0.413211]	[M_global: 0.520235]	75%	6.568066
Steps (80 / 100):	[loss_D: 24.751768]	[Loss_G: 0.415951]	[M_global: 0.524934]	max	9.851136
Steps (90 / 100):	[loss_D: 22.647221]	[Loss_G: 0.456992]	[M_global: 0.554145]		
Steps (100 / 100):	[loss_D: 23.766275]	[Loss_G: 0.482337]	[M_global: 0.584548]		

6501 Progress Report Group 4

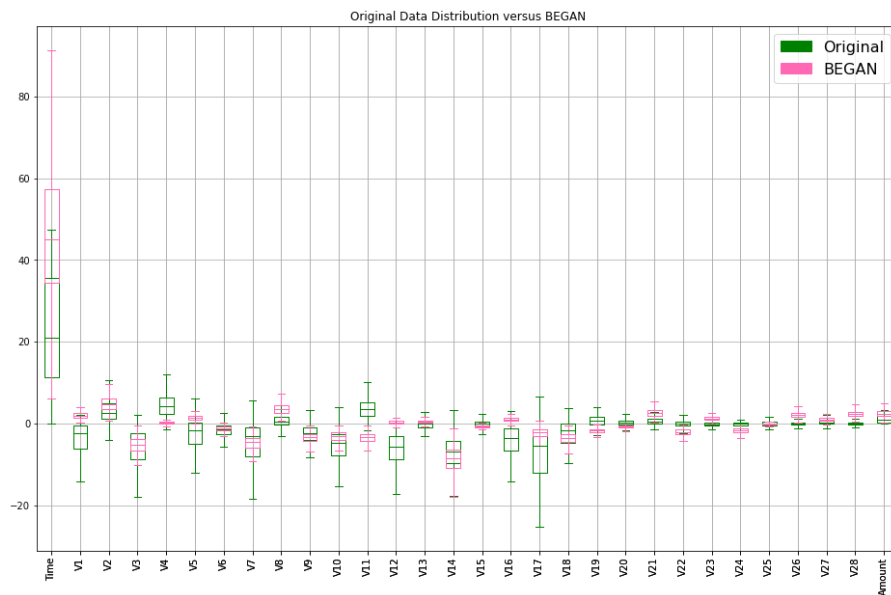


k=0.06, batch_size=64 (previous batch_size=128)

EPOCH # 20 -----

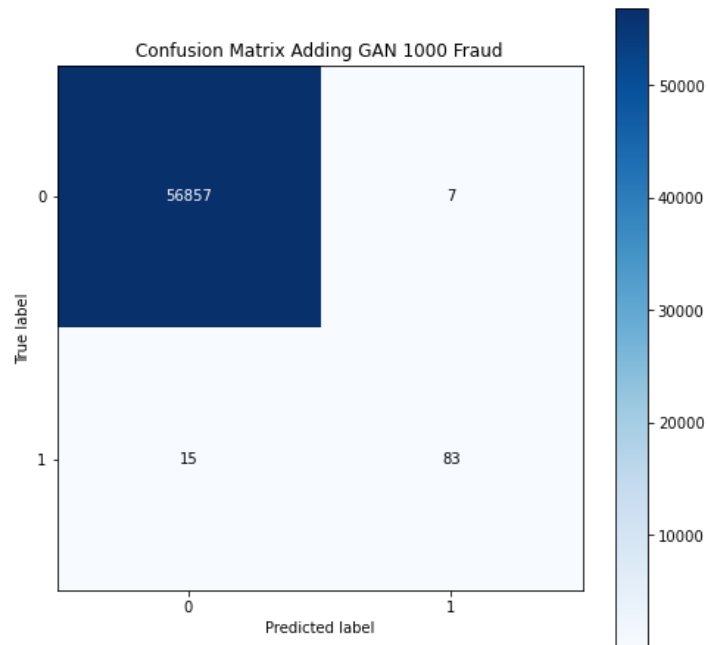
Steps (10 / 100):	[loss_D: -10.341525]	[Loss_G: 12.585917]	[M_global: 12.199375]
Steps (20 / 100):	[loss_D: -3.326088]	[Loss_G: 11.233190]	[M_global: 10.936512]
Steps (30 / 100):	[loss_D: 20.852566]	[Loss_G: 7.410180]	[M_global: 7.314507]
Steps (40 / 100):	[loss_D: 30.622616]	[Loss_G: 4.393467]	[M_global: 4.416713]
Steps (50 / 100):	[loss_D: 29.780138]	[Loss_G: 3.984214]	[M_global: 4.020640]
Steps (60 / 100):	[loss_D: 28.448325]	[Loss_G: 4.266831]	[M_global: 4.289491]
Steps (70 / 100):	[loss_D: 17.527455]	[Loss_G: 4.801738]	[M_global: 4.757676]
Steps (80 / 100):	[loss_D: 16.920543]	[Loss_G: 5.242315]	[M_global: 5.196826]
Steps (90 / 100):	[loss_D: 15.595847]	[Loss_G: 4.730126]	[M_global: 4.674268]
Steps (100 / 100):	[loss_D: 18.740515]	[Loss_G: 4.700145]	[M_global: 4.672210]

Time	
count	1000.000000
mean	46.818562
std	16.844614
min	6.206626
25%	34.534291
50%	45.042454
75%	57.417752
max	114.041725



6501 Progress Report Group 4

	Base	GAN	BEGAN
Accuracy	0.999491	0.999491	0.999613
Precision	0.855670	0.864583	0.922222
Recall	0.846939	0.846939	0.846939
F1 score	0.851282	0.855670	0.882979
ROC AUC score	0.923346	0.923355	0.923408



6501 Progress Report Group 4