# Improving Credit Card Fraud Detection using Generative Adversarial Networks

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# **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	Network & Framework Development WGAN_GP: Hao SNGAN: Jun
10/26/2020	Preliminary Presentation
11/02/2020	WGAN_GP, SNGAN Evaluation & Analysis
11/09/2020 & 11/16/2020	Summary of Results
11/23/2020	Manuscript
11/30/2020 & 12/07/2020	Mock Presentation & Presentation and Journal Submission

#### 09/21/2020

#### **EDA**

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
```

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.

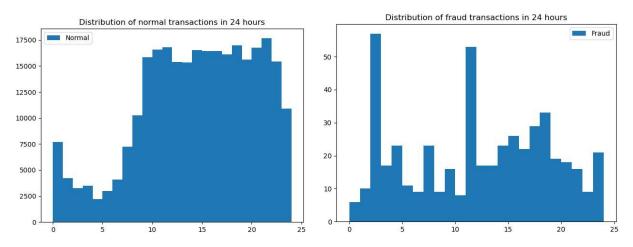
	Time	V1	***	Amount	Class
count	284807.000000	2.848070e+05		284807.000000	284807.000000
mean	14.537951	3.919560e-15		88.349619	0.001727
std	5.847061	1.958696e+00		250.120109	0.041527
min	0.000000	-5.640751e+01		0.000000	0.000000
25%	10.598194	-9.203734e-01		5.600000	0.000000
50%	15.010833	1.810880e-02		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)

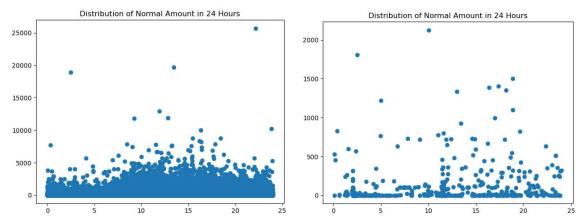
```
The null amounts of normal transactions (class 0) & fraud transactions (class 1) 0 1798

1 27

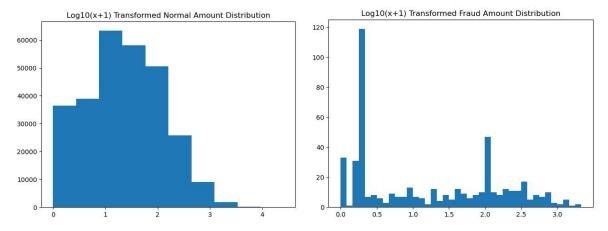
Name: Class, dtype: int64
```



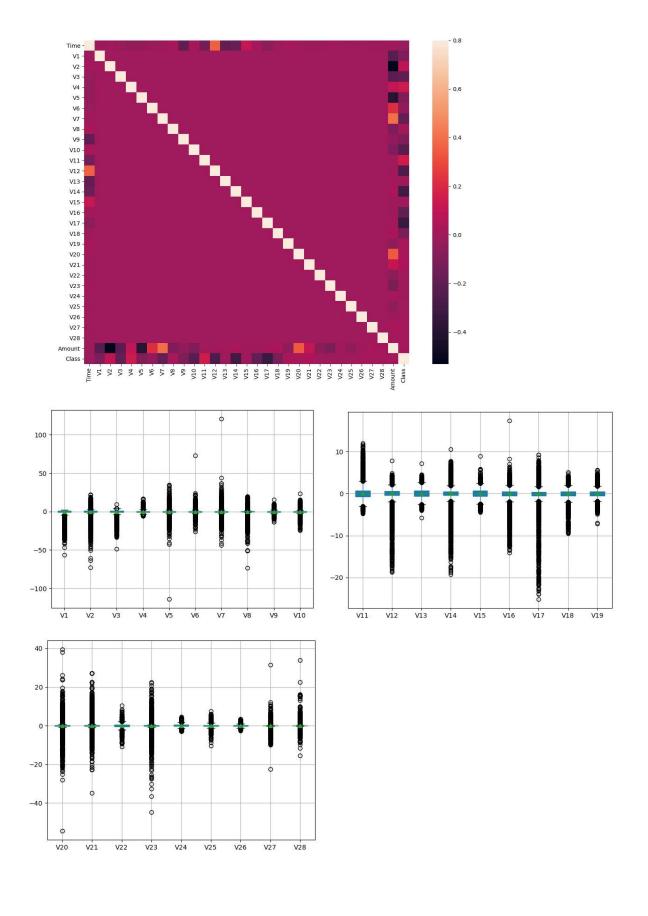
From the histogram, we can observe that normal transactions generally occur from 9 am to 0 am. However, the fraud transactions occur particularly frequently at 2 am and 12 pm.



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



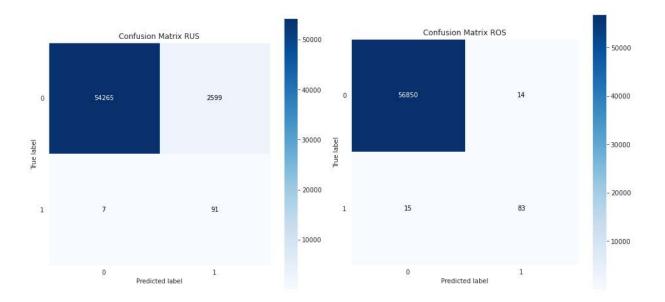
Normal amount was from ten to hundred. Fraud Amount distributed in less than €1.



## 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 result comparison

RUS	ROS
1 394	1 227451
0 394	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 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.

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: 0.573407]

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

#### 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%	3.155 <mark>1</mark> 44	-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 fi	raud in x_tr	ain						
	Time	V1	V2	V3	V4	V5	V6	V7
coun	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

7.166449

-8.436924

-5.133485

-2.302626

2.883467

2.419178

4.258196

6.390866

-1.313275 -22.105532

5.406586

-4.741036

-1.522962

0.240184

1.864770

-1.421577

-0.361122

-5.773192 -43.557242

-2.504633 -7.765017

7.316745

-2.926216

-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

std

min

25%

50%

75%

13.347935

35.912917

6.841390

-0.410418

1.239444 -30.552380

11.500278 -5.996596

21.393056 -2.272114

4.309436

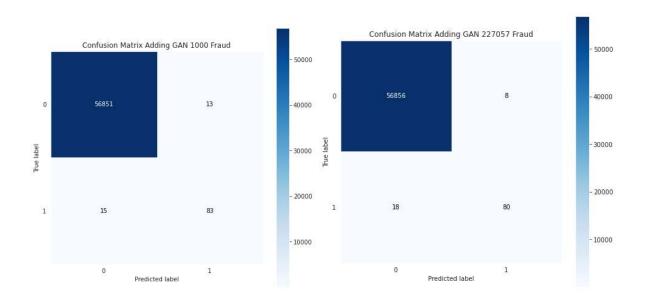
1.229209

2.662472

4.737900

-8.402154 -31.103685

Base ROS from Original data	Add GAN 1000 then ros.fit	GAN 227057
Normal: 227451	Normal: 227451	Normal: 227451
Fraud: 227451	Fraud: 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



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.

## 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.

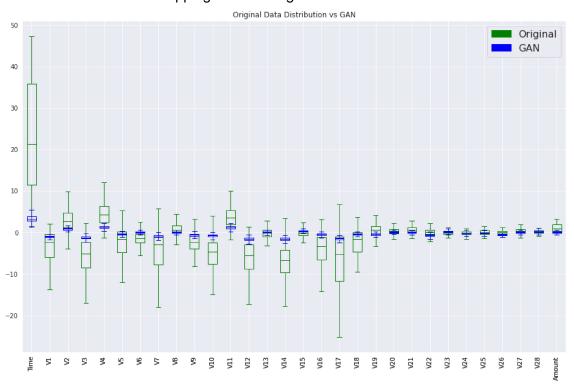
Implementation in Keras, compared to vanilla GAN:

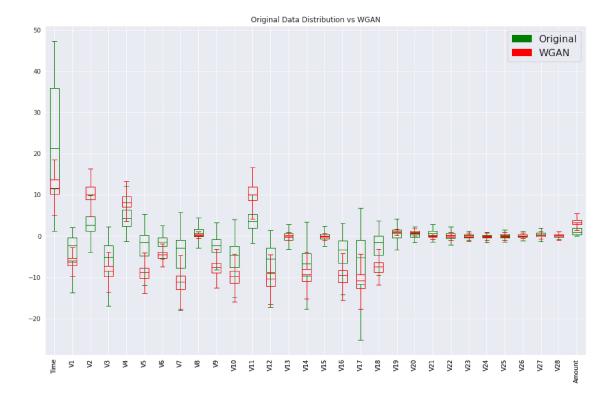
- Loss function, no log
- D: no sigmoid
- Clip the weight of D (-c,c), if w>c, w=c, if w<-c, w=-c
- Use RMSProp
- Train D more than G

Training Parameters: RMSprop(Ir=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





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.

