Exploiting synthetic images for real-world image recognition

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Abstract

Creating big datasets is often difficult or expensive which causes people to try to augment their dataset with rendered images. This often fails to significantly improve accuracy due to a difference in distribution between real and rendered datasets. This paper shows that the gap between synthetic and real-world image distributions can be closed by using a GAN to convert the synthetic data to a dataset which has the same distribution as the real data. Training this GAN requires only a fraction of the dataset traditionally required to get a high classification accuracy. This converted data can subsequently be used to train a classifier with a higher accuracy than a classifier trained only on the real dataset.

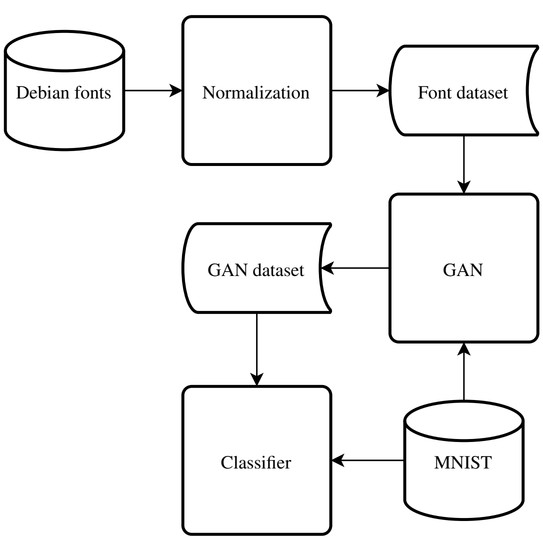

Figure 1. Technique used to convert the rendered dataset for use in training.

1. Introduction

Deep learning has revolutionised visual object recognition. Thanks to huge datasets and fast hardware (GPUs), current object recognition approaches have near-human accuracy. Because creating big datasets is often very expensive, people start to turn to rendered images to augment their datasets. However, training networks on rendered images may not achieve the desired accuracy due to a gap between synthetic and real image distributions [8]. Another development in current research is the increased focus on Generative Adversarial Networks (GANs) to generate images that look similar to the images they were trained on [7]. In this paper the impact of the distribution gap between synthetic and real image distributions is decreased by using a GAN to modify rendered images to have the same distribution as real images. This technique is shown to be useful for inflating very small datasets to a level where they can be used to more create accurate classifiers.

2. Related work

Rendered data can sometimes be used to train networks, i.e. facial expression analysis using rendered faces [2], using rendered images to segment images of indoor scenes [4] and font character classification trained on interpolated real samples [8]. These networks are trained by creating a rendered dataset that is as close as possible in statistical distribution as the real dataset. Generally this is very difficult or expensive to achieve.

The problem of creating rendered datasets with a distribution close to a real dataset can be solved by using domain adaptation. This is generally done using Generative Adversarial Networks [3, 6, 9] trained to create samples based on images in the rendered dataset that are indistinguisable from images in the real dataset. We decided to perform this research on the GAN as described by Bousmalis et al[1] [3].

3. Inflating datasets using rendered data and GANs

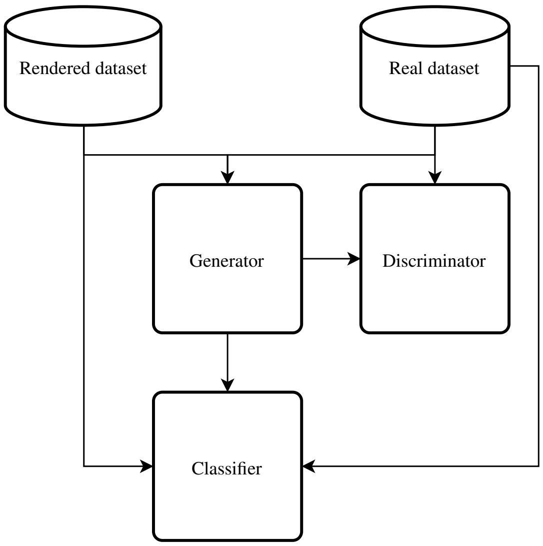

Figure 2. Overview of the GAN architecture.

The basis of this research is a GAN that converts images from a rendered dataset distribution to an image that appears to come from the distribution of a real dataset. This GAN consists of three parts which are shown in figure 2. The first part is a generator network that does the image conversion. The second part of the GAN is a discriminator, which tries to distinguish between the output of the generator and images from the real dataset. The third part of the GAN is a classifier that predicts the label of images coming from either the real dataset, the generator or the rendered dataset. All these networks are trained in parallel. The discriminator and classifier are trained to reduce the amount of misclassifications. The generator is trained to minimise the amount of pixels changed in the image, to minimise the loss in classification by the classifier and to try to fool the discriminator to classify the image as real.

To test the effects of inflating datasets when using this technique, we first trained the GAN with a real and rendered dataset. We then apply the trained GAN on the rendered dataset to create a new synthetic dataset. A combined dataset consisting of the synthetic dataset and the real dataset was used to train a second classifier.

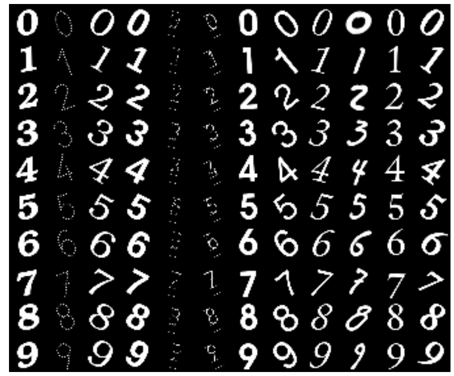

Figure 3. Example images of the MNIST font dataset.

4. Experiments

We evaluated this technique on the MNIST dataset [5] together with a rendered dataset generated by rendering open source font digits in multiple rotations for all number classes. The rendered dataset contains samples from 149 fonts, with each digit rendered having 47 variations each with a distinct rotation between -47 and 46 degrees. All images were normalised using the same algorithm used to normalise the MNIST samples, the result of which can be seen in figure 3. A random sample of $10,030$ of those images were put in a test set and the remaining $60,000$ images were used as the rendered dataset.

The GAN was modified to use 10% of the training data as a validation set instead of a constant $1,000$ samples as this allowed for smaller sample sizes.

For multiple ratios[2] r, where $0 > r > 1$, we created the following datasets:

$\text{MNIST}_{\text{original}}$
: $60,000 \times r$ images from the original MNIST dataset.

$\text{MNIST}_{\text{font}}$
: $60,000 \times (1-r)$ images from the rendered font dataset.

We used these two datasets to train the GAN using $375,000$ steps with batchsize 32 and subsequently applied the trained GAN on the $\text{MNIST}_{\text{font}}$ dataset to create the $\text{MNIST}_{\text{GAN}}$ dataset. This made the $\text{MNIST}_{\text{GAN}}$ dataset have the exact same size as $\text{MNIST}_{\text{font}}$.

[1] We chose to base our research on this paper due to the available TensorFlow[1] implementation

[2] Ratios used were: 0.001, 0.003, 0.005, 0.007, 0.008, 0.024, 0.056, 0.1, 0.3, 0.5, 0.7 and 0.9.

With these datasets we trained five instances of the following classifiers:

$5 \times$ C-MNIST$_{\text{original}}$
Classifier only trained on MNIST$_{\text{original}}$

$5 \times$ C-MNIST$_{\text{font}}$
Classifier only trained on MNIST$_{\text{font}}$

$5 \times$ C-MNIST$_{\text{GAN}}$
Classifier only trained on MNIST$_{\text{GAN}}$

$5 \times$ C-MNIST$_{\text{original+GAN}}$
Classifier only trained on MNIST$_{\text{original+GAN}}$

$5 \times$ C-MNIST$_{\text{original+font}}$
Classifier only trained on MNIST$_{\text{original+font}}$

Each classifier was tested on the MNIST test set which resulted in an classification accuracy.

5. Results

To validate whether the GAN was creating useful images, we looked at the resulting images in MNIST$_{\text{GAN}}$ examples of which can be seen in Figure 4.

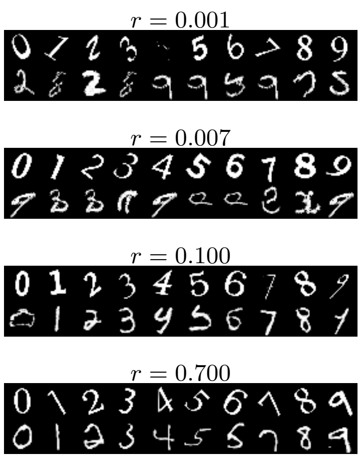

Figure 4. Example images of the MNIST font dataset. Top of each image is from MNIST$_{\text{font}}$, bottom is the generated image in MNIST$_{\text{GAN}}$.

From visual inspection it is apparent that the GAN has trouble keeping the labels consistent if there is not enough real training data. An example of this are the 1 and the 2 of $r = 0.007$ in figure 4: they both result in something that looks like the same 8 instead of something that looks like a 1 or 2 respectively. This means that the classifier trained on this new dataset will receive two very similar samples with conflicting labels. We measured the accuracy on MNIST of C-MNIST$_{\text{GAN}}$ and found low accuracy for lower ratios. This supports the conclusion that there is an issue with labeling when the GAN is not trained with enough real data.

5.1. C-MNIST$_{\text{font}}$ performance

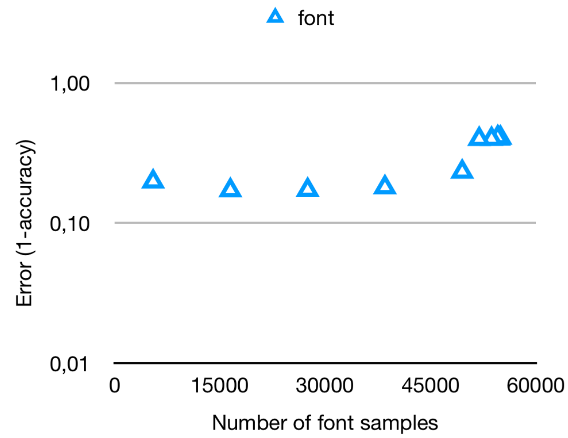

Figure 5. Performance of C-MNIST$_{\text{font}}$ with varying amounts of MNIST$_{\text{font}}$ training data. Performance decreases with more training samples indicating that MNIST$_{\text{original}}$ and MNIST$_{\text{font}}$ have different characteristics.

To make sure we actually test whether the GAN is able to close the distribution gap we looked at the accuracy of C-MNIST$_{\text{font}}$. For this dataset the error shows an inverse relation between the amount of samples and the performance of the classifier, which can be seen in figure 5. This indicates that a gap exists between the rendered font dataset and the MNIST test dataset.

5.2. C-MNIST$_{\text{original}}$ versus C-MNIST$_{\text{original+GAN}}$

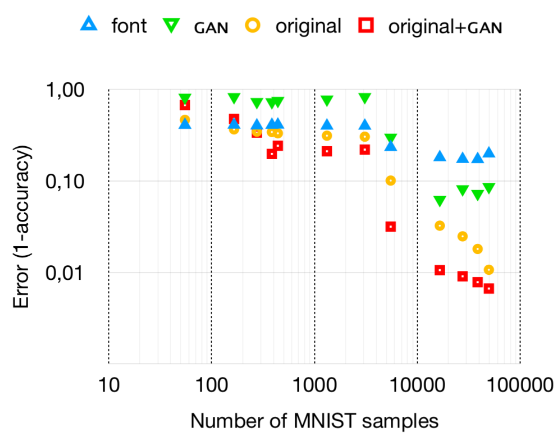

Figure 6. Performance of classifiers with different amounts of MNIST training data. Training with the GAN data improves results after a minimal amount of original MNIST samples.

We compared the accuracy of C-MNIST$_{\text{font}}$, C-MNIST$_{\text{GAN}}$, C-MNIST$_{\text{original}}$ and C-MNIST$_{\text{original+GAN}}$ to see whether training with the MNIST$_{\text{original+GAN}}$ dataset is better than training with one of the individual datasets. The result of this comparison can be seen in figure 6.

C-MNIST$_{\text{original+GAN}}$ is only more accurate than the C-MNIST$_{\text{original}}$ when the GAN is trained on more than 385 real images ($r = 0.007$). There seems to be a minimum amount of real samples after which the GAN starts to produce meaningful data.

Using MNIST as a test case, this technique is able to close the distribution gap even with as little 0.7% real data in the resulting dataset.

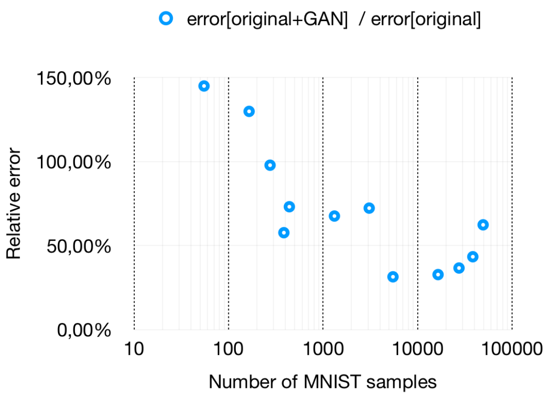

Figure 7. Error of C-MNIST$_{\text{original+GAN}}$ compared to the error of C-MNIST$_{\text{original}}$, lower is better. Lowest relative error was found at $5,500$ MNIST samples.

We also compared the difference in wrong predictions between C-MNIST$_{\text{original}}$ and C-MNIST$_{\text{original+GAN}}$. As is shown in figure 7, the highest reduction in error was achieved with $5,500$ MNIST images and $49,500$ font images. This indicates that for MNIST, this technique becomes more effective when the ratio between real and rendered images becomes less extreme.

5.3. C-MNIST$_{\text{original}}$ against C-MNIST$_{\text{original+font}}$

To confirm that the improved results of C-MNIST$_{\text{original+GAN}}$ can not be solely explained by the addition of the rendered font data, we compared C-MNIST$_{\text{original}}$ with C-MNIST$_{\text{original+font}}$ to see if the addition of font data increased the accuracy. From the results in figure 8 we had to conclude that C-MNIST$_{\text{original+font}}$ has performance roughly equal to C-MNIST$_{\text{original}}$ at the ratios where C-MNIST$_{\text{original+GAN}}$ is more accurate. The addition of more font data cannot explain the additional accuracy of C-MNIST$_{\text{original+GAN}}$ indicating this increase is a property of the transformation made by the GAN.

6. Discussion

Due to a limited amount of time, no finetuning has been done on the other hyperparameters of the GAN. Optimizing these hyperparameters might further improve classification

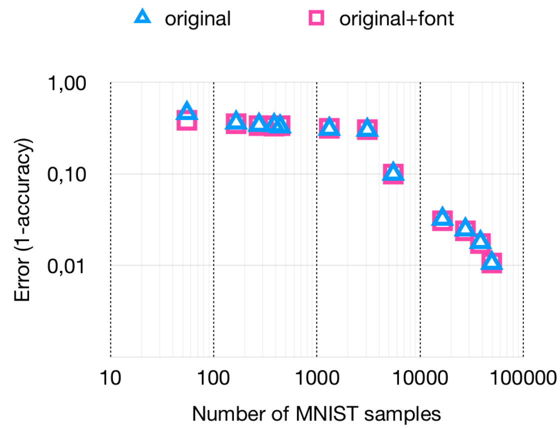

Figure 8. Performance of C-MNIST$_{\text{original+font}}$ versus the performance of C-MNIST$_{\text{original}}$ for varying amounts of training data. Performance is almost the same indicating no advantage to including font data in the training set directly.

accuracy which should result in a further reduction in the amount of required samples from the real dataset.

When measuring the performance of C-MNIST$_{\text{original+GAN}}$ versus C-MNIST$_{\text{original}}$ we found that even though the generated samples are not good samples for their target class, C-MNIST$_{\text{original+GAN}}$ quickly becomes much more accurate than C-MNIST$_{\text{original}}$ before the samples look like useful samples. This effect can partially be explained by results shown by Sukhbaatar et al. that indicate that deep learning is robust to massive label noise [10]. This would mean that the network is still capable of learning higher level features from the mislabeled samples and is able to succesfully ignore the bad labeling.

7. Conclusion

Our goal was to use a GAN to close the distribution gap between rendered and real datasets.

Using MNIST as an example, we were able to show that it's possible to create a rendered dataset. We've shown that a distribution gap exists between the dataset we created and the real MNIST dataset and were able to close this gap using our described technique.

We've shown that GANs can be used to inflate trainingsets by reducing the gap between synthetic and real datasets. Furthermore, they can do so with very little real training data. This technique can be very useful for problems where only a small real dataset is available.

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R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mané, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viégas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. Software available from tensorflow.org.

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A. Raw experiment results

Experiment	Dataset	Testset	Accuracy	Loss	n	Stddev
0.001	font	gan	0.99594	0.0647077472	5	0.0003361547262793952
0.001	font	mnist+gan	0.1011522144	138.47054699999998	5	0.0018832927057633169
0.001	font	mnist	0.59284137	51.1822924	5	0.006981901006316253
0.001	font	font	0.8379500000000001	7.372864399999999	4	0.010412972678346927
0.001	gan	font	0.263	158.1511398	5	0.3162208642705285
0.001	gan	gan	0.12616	243.301744	5	0.005345371829910437
0.001	gan	mnist+gan	0.38265615799999997	8.395040600000002	5	0.005039395717962637
0.001	gan	mnist	0.20737272199999998	134.774504	5	0.004070268343815918
0.001	mnist+font	font	0.7186400000000001	45.65777926	5	0.3363944009641064
0.001	mnist+font	gan	0.99602	0.0630285408	5	0.00030331501776202863
0.001	mnist+font	mnist+gan	0.1029714982	147.20027199999998	5	0.002054513565296224
0.001	mnist+font	mnist	0.6146785260000001	52.60071419999999	5	0.0026859886240228233
0.001	mnist+gan	font	0.40876	110.92924554000001	5	0.2540886321738932
0.001	mnist+gan	gan	0.18424000000000001	216.64799	5	0.0060508677063707056
0.001	mnist+gan	mnist+gan	0.387305444	8.259552000000001	5	0.004967945593852648
0.001	mnist+gan	mnist	0.329658126	92.96009000000001	5	0.011308257480433506
0.001	mnist	font	0.66496	29.19102768	5	0.19034921328967977
0.001	mnist	gan	0.42347999999999997	15.055136100000002	5	0.008414689536756547
0.001	mnist	mnist+gan	0.10220335620000001	46.106601999999995	5	0.00023048128754781872
0.001	mnist	mnist	0.53751255	18.4250246	5	0.007148208642030542
0.003	font	font	0.8206200000000001	7.07818966	5	0.031856820305862316
0.003	font	gan	0.9957800000000001	0.067996607	5	0.0004658325879541108
0.003	font	mnist+gan	0.097630142	105.5003788	5	0.0028066461611628226
0.003	font	mnist	0.5908415400000001	40.2007346	5	0.0031747569187262044
0.003	gan	font	0.24463999999999997	191.48455560000002	5	0.32903046667444036
0.003	gan	gan	0.09096000000000001	313.59173	5	0.015074083720080636
0.003	gan	mnist+gan	0.39149280399999997	6.30837174	5	0.0032704571760734033
0.003	gan	mnist	0.195514498	158.13673	5	0.008304585371628738
0.003	mnist+font	font	0.75574	46.27874954	5	0.3646292953123761
0.003	mnist+font	gan	0.99604	0.0618120298	5	0.0003781534080237391
0.003	mnist+font	mnist+gan	0.09370062800000001	117.863233	5	0.0022582505701388626
0.003	mnist+font	mnist	0.646234168	41.2197526	5	0.0017188782976464687
0.003	mnist+gan	font	0.6605599999999999	59.4348966	5	0.14834417076515008
0.003	mnist+gan	gan	0.23902	237.88062400000004	5	0.018044722220084197
0.003	mnist+gan	mnist+gan	0.395057726	6.097733740000001	5	0.0035507236536416117
0.003	mnist+gan	mnist	0.5270937800000001	50.1998856	5	0.021318368664936586
0.003	mnist	font	0.83986	14.74207078	5	0.14615366228733373
0.003	mnist	gan	0.48747999999999997	13.4856478	5	0.009769186250655674
0.003	mnist	mnist+gan	0.09195867919999999	44.592540400000004	5	0.0024094356899766424
0.003	mnist	mnist	0.635750152	16.0199027	5	0.0021669907326797703
0.005	font	font	0.85318	5.97038202	5	0.02761045091989624
0.005	font	gan	0.9958	0.064246601	5	0.00036055512754639774
0.005	font	mnist+gan	0.1020698028	123.84380500000002	5	0.00113889796940692
0.005	font	mnist	0.598888002	45.8860592	5	0.006720800310195195
0.005	gan	font	0.25229999999999997	157.17436432	5	0.3358856873997461
0.005	gan	gan	0.10185999999999999	232.758144	5	0.01034712520461601
0.005	gan	mnist+gan	0.6722808359999999	4.82759684	5	0.003552584261503154
0.005	gan	mnist	0.2889469459999999	132.97775000000001	5	0.0052496197131106535

0.005	mnist+font	font	0.77088	42.58885138	5	0.3796816982684311
0.005	mnist+font	gan	0.9960799999999999	0.0647085618	5	0.00038340579025360444
0.005	mnist+font	mnist+gan	0.100040584	144.54183399999997	5	0.0011298237658944838
0.005	mnist+font	mnist	0.6631698939999999	49.396	5	0.0015975017325123866
0.005	mnist+gan	font	0.71946	32.13288756	5	0.12409292082951387
0.005	mnist+gan	gan	0.27446	149.745036	5	0.013361811254466963
0.005	mnist+gan	mnist+gan	0.67029222	4.8158784599999995	5	0.004657060943556551
0.005	mnist+gan	mnist	0.66394696	28.7063844	5	0.008049248933472
0.005	mnist	font	0.8736599999999999	10.130199939999997	5	0.12647734184430032
0.005	mnist	gan	0.54436	16.3425389	5	0.014478017820129911
0.005	mnist	mnist+gan	0.0994724022	69.47809720000001	5	0.0011779962638562157
0.005	mnist	mnist	0.65640407	24.194906999999997	5	0.0027059269459835528
0.007	font	font	0.8546400000000001	6.701400099999999	5	0.04410173465976139
0.007	font	gan	0.9956399999999999	0.072116173	5	0.0002607680962081134
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0.007	gan	font	0.24370000000000003	228.7380522	5	0.33146977991967835
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0.007	gan	mnist	0.292411848	188.627668	5	0.010556636875791475
0.007	mnist+font	font	0.77134	55.23816716	5	0.39262462734780146
0.007	mnist+font	gan	0.99604	0.05771951980000001	5	0.00023021728866440142
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0.007	mnist+gan	mnist+gan	0.7084180640000001	3.49589882	5	0.00493269658963839
0.007	mnist+gan	mnist	0.803633188	24.374300800000004	5	0.005183826145442161
0.007	mnist	font	0.9189999999999999	7.981555439999999	5	0.0411367840259785
0.007	mnist	gan	0.5742	13.337413199999997	5	0.005771914760285374
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0.007	mnist	mnist	0.65933772	16.594239799999997	5	0.002096858227396383
0.008	font	font	0.85398	6.46248272	5	0.04643406077439277
0.008	font	gan	0.9957800000000001	0.0649825588	5	0.00019235384061669226
0.008	font	mnist+gan	0.1011597144	141.788874	5	0.00041696570009870193
0.008	font	mnist	0.590278242	52.5876384	5	0.0059996461871447025
0.008	gan	font	0.23956000000000005	212.62472699999998	5	0.32456992004805374
0.008	gan	gan	0.10554	336.962492	5	0.015563033123398538
0.008	gan	mnist+gan	0.614201432	4.77563344	5	0.006789881180780709
0.008	gan	mnist	0.26817297600000006	176.542036	5	0.012123890313398994
0.008	mnist+font	font	0.7743800000000001	53.1022851	5	0.37006386881185793
0.008	mnist+font	gan	0.9956799999999999	0.0695594104	5	0.00046583258795409053
0.008	mnist+font	mnist+gan	0.10111902440000001	144.713156	5	0.0003216956603356668
0.008	mnist+font	mnist	0.6633188139999999	49.4779464	5	0.001385122889919882
0.008	mnist+gan	font	0.84694	28.018748920000007	5	0.05235105538573218
0.008	mnist+gan	gan	0.37692000000000003	198.11898399999998	5	0.02580042635306634
0.008	mnist+gan	mnist+gan	0.6220142200000001	4.2634744	5	0.0021016481486680863
0.008	mnist+gan	mnist	0.758739542	24.191860400000003	5	0.008215838240123181
0.008	mnist	font	0.92608	7.305613399999999	5	0.05164825263259154
0.008	mnist	gan	0.6329800000000001	12.4054284	5	0.007344521767957388

0.008	mnist	mnist+gan	0.10144455599999999	77.280202	5	0.00018198015628083817
0.008	mnist	mnist	0.669902794	26.454828399999997	5	0.0005621505927952081
0.024	font	font	0.86556	5.96668708	5	0.04737903544818108
0.024	font	gan	0.9959	0.061361212600000006	5	0.00019999999999997797
0.024	font	mnist+gan	0.1000413912	126.51415819999997	5	0.001977463948942485
0.024	font	mnist	0.6006202820000001	46.3337764	5	0.004682940180775324
0.024	gan	font	0.25348000000000004	192.42270652	5	0.3251124220942657
0.024	gan	gan	0.08578	342.55703200000005	5	0.014264536445324818
0.024	gan	mnist+gan	0.529759938	4.50474428	5	0.002846654459311834
0.024	gan	mnist	0.24270496000000003	171.63792399999997	5	0.01179827919080787
0.024	mnist+font	font	0.79268	63.04544711	5	0.3944396240237535
0.024	mnist+font	gan	0.9958400000000001	0.069077946	5	0.00034351128074631553
0.024	mnist+font	mnist+gan	0.097516554	128.74511	5	0.0003069608376975789
0.024	mnist+font	mnist	0.685153728	42.8713598	5	0.0017264397404108708
0.024	mnist+gan	font	0.9247400000000001	12.18080642	5	0.02536854351357206
0.024	mnist+gan	gan	0.48091999999999996	150.8158	5	0.018447005176992808
0.024	mnist+gan	mnist+gan	0.5370861039999999	3.90463156	5	0.00394676989515222
0.024	mnist+gan	mnist	0.790115978	11.3308486	5	0.003394278029702333
0.024	mnist	font	0.95898	3.4267487260000005	5	0.028867836773821483
0.024	mnist	gan	0.6521	12.727729299999998	5	0.006650187967268311
0.024	mnist	mnist+gan	0.104014902	98.04204320000001	5	0.00031385917091905993
0.024	mnist	mnist	0.68927993	32.641903	5	0.0009103097674967725
0.040	font	font	0.8663399999999999	6.36172656	5	0.05998143879568079
0.040	font	gan	0.9963599999999999	0.0651948772	5	0.0002190890230020854
0.040	font	mnist+gan	0.09594111400000001	135.2679692	5	0.0014448403235020522
0.040	font	mnist	0.60050154	49.049966	5	0.004691988327377849
0.040	gan	font	0.26261999999999996	164.49094492	5	0.3249717633887597
0.040	gan	gan	0.1081	295.978712	5	0.009536246641105714
0.040	gan	mnist+gan	0.6311671919999999	5.56670952	5	0.004684651577152788
0.040	gan	mnist	0.28208742400000003	136.8151168	5	0.011022898090433381
0.040	mnist+font	font	0.8006399999999999	37.245209488	5	0.3856936582315037
0.040	mnist+font	gan	0.9957800000000001	0.061797367000000006	5	0.00022803508501980247
0.040	mnist+font	mnist+gan	0.09737118759999999	127.04815699999999	5	0.0008008171875995161
0.040	mnist+font	mnist	0.69138596	41.6231514	5	0.001647318468906336
0.040	mnist+gan	font	0.93456	7.38051306	5	0.02387557329154634
0.040	mnist+gan	gan	0.56266	106.13739600000001	5	0.01989844215007796
0.040	mnist+gan	mnist+gan	0.6376866619999999	4.477718779999999	5	0.00709666538532149
0.040	mnist+gan	mnist	0.8327482319999999	7.4763196800000005	5	0.004875546022049217
0.040	mnist	font	0.9692399999999999	2.04181902	5	0.02111120555534431
0.040	mnist	gan	0.72082	10.413065399999999	5	0.007183801222194263
0.040	mnist	mnist+gan	0.095520505	114.593464	5	0.001398170959065808
0.040	mnist	mnist	0.6941646880000001	37.4809428	5	0.00043022296285763527
0.056	font	font	0.86818	5.66254551	5	0.06308357155393154
0.056	font	gan	0.99596	0.064309214	5	0.00029664793948379386
0.056	font	mnist+gan	0.09209063960000001	124.2591248	5	0.0005533202285027208
0.056	font	mnist	0.6010491840000001	44.5567612	5	0.007595932802591133
0.056	gan	font	0.23896000000000006	188.4771662	5	0.33300112312122915
0.056	gan	gan	0.09606	297.717468	5	0.018066903442482886
0.056	gan	mnist+gan	0.42112013600000003	7.05746848	5	0.003030660623713919
0.056	gan	mnist	0.194685924	155.87777799999998	5	0.008610948647534724

0.056	mnist+font	font	0.7979999999999999	39.328136515999994	5	0.3995888074008079
0.056	mnist+font	gan	0.9958	0.066563098	5	0.00025495097567965473
0.056	mnist+font	mnist+gan	0.0935870038	117.32199719999998	5	0.0016237829651364125
0.056	mnist+font	mnist	0.695258206	37.908574599999994	5	0.0013531648341499308
0.056	mnist+gan	font	0.9535600000000001	6.445553059999999	5	0.013176987516120661
0.056	mnist+gan	gan	0.584	110.33116700000001	5	0.009929501498061214
0.056	mnist+gan	mnist+gan	0.42808892400000004	6.00577364	5	0.006066233008492999
0.056	mnist+gan	mnist	0.7810192220000001	7.444707719999999	5	0.0032231571596681072
0.056	mnist	font	0.9707000000000001	2.2417707479999995	5	0.017407756891684816
0.056	mnist	gan	0.70838	11.8950235	5	0.006746628787772448
0.056	mnist	mnist+gan	0.0954253958	105.59895159999999	5	0.0016461421716359116
0.056	mnist	mnist	0.696975066	34.137391199999996	5	0.0005307890694805382
0.100	font	font	0.8704000000000001	5.8896895	5	0.06063823051508016
0.100	font	gan	0.99558	0.075672787	5	8.366600265339834e-05
0.100	font	mnist+gan	0.59524343	36.1292946	5	0.008952165396673598
0.100	font	mnist	0.76693644	16.1979242	5	0.005732740972676172
0.100	gan	font	0.6356400000000001	15.017938320000003	5	0.11639408490125261
0.100	gan	gan	0.44458000000000003	33.941313599999994	5	0.015826465177038108
0.100	gan	mnist+gan	0.984608478	0.23187242599999996	5	0.0013330426748307935
0.100	gan	mnist	0.709829146	11.4654201	5	0.007804190471168696
0.100	mnist+font	font	0.90678	3.2811063080000005	5	0.1704385578441686
0.100	mnist+font	gan	0.9958199999999999	0.06755870220000001	5	0.0002167948338867641
0.100	mnist+font	mnist+gan	0.715593448	26.347492199999998	5	0.00827208567528591
0.100	mnist+font	mnist	0.900435764	8.463700900000001	5	0.0028159334021830283
0.100	mnist+gan	font	0.9652200000000001	0.68751008	5	0.009577943411818623
0.100	mnist+gan	gan	0.67994	12.088792600000001	5	0.009967597503912394
0.100	mnist+gan	mnist+gan	0.98407	0.222933094	5	0.0008543453055995529
0.100	mnist+gan	mnist	0.9684581859999998	0.5716133919999999	5	0.0014040209379777694
0.100	mnist	font	0.9806000000000001	0.384765112	5	0.009660227740586662
0.100	mnist	gan	0.71916	10.152326599999999	5	0.010644388192846039
0.100	mnist	mnist+gan	0.7079201359999999	25.3227798	5	0.004747340685871413
0.100	mnist	mnist	0.8994950559999999	8.089589	5	0.001096967341551234
0.300	font	font	0.8655799999999999	6.582713446	5	0.06684995886311373
0.300	font	gan	0.99572	0.0724360646	5	0.0005263078946776107
0.300	font	mnist+gan	0.7736447660000001	14.754401999999999	5	0.004667366084846988
0.300	font	mnist	0.819616864	9.7400608	5	0.0044415511084225905
0.300	gan	font	0.9024000000000001	3.48251124	5	0.037808729150819134
0.300	gan	gan	0.65144	15.8542664	5	0.01687181080975007
0.300	gan	mnist+gan	0.998673584	0.0224297806	5	0.0005979415560738682
0.300	gan	mnist	0.9393673799999999	1.90289486	5	0.0011292124986024723
0.300	mnist+font	font	0.97486	0.7100256300000001	5	0.032456940706110944
0.300	mnist+font	gan	0.9953399999999999	0.068017866	5	0.00023021728866445205
0.300	mnist+font	mnist+gan	0.910495962	6.22946954	5	0.0004373017896373108
0.300	mnist+font	mnist	0.9692159180000001	1.7543984000000001	5	0.00044116070101492976
0.300	mnist+gan	font	0.98704	0.23082052599999997	5	0.0019372661149155194
0.300	mnist+gan	gan	0.77368	5.905851579999999	5	0.013048256588525545
0.300	mnist+gan	mnist+gan	0.99850057	0.0233897696	5	0.0003759604859556452
0.300	mnist+gan	mnist	0.989426782	0.190440484	5	0.0002951463420406753
0.300	mnist	font	0.98856	0.237807496	5	0.0011436782764396329
0.300	mnist	gan	0.7633599999999999	8.402891319999998	5	0.007171680416750298

0.300	mnist	mnist+gan	0.9059400140000001	6.4609562	5	0.002433084381290548
0.300	mnist	mnist	0.967671516	1.84629968	5	0.0005106591402099671
0.500	font	font	0.86272	6.792154848	5	0.07103166195437075
0.500	font	gan	0.99448	0.1041534956	5	0.00014832396974194558
0.500	font	mnist+gan	0.8122580599999999	10.695723899999999	5	0.00840316346102169
0.500	font	mnist	0.8272435899999999	8.703529139999999	5	0.006968152821508736
0.500	gan	font	0.8870000000000001	4.44913496	5	0.03172601456218539
0.500	gan	gan	0.6561	16.9243738	5	0.009849873095629205
0.500	gan	mnist+gan	0.9975000099999999	0.021179721	5	0.000775616174728191
0.500	gan	mnist	0.9206890999999999	2.9584018399999996	5	0.00206351129752179
0.500	mnist+font	font	0.97454	0.8007943292	5	0.03966034543470344
0.500	mnist+font	gan	0.9940000000000001	0.090141469	5	0.0006403124237433011
0.500	mnist+font	mnist+gan	0.9108871199999999	6.7833691599999995	5	0.0023338182999111216
0.500	mnist+font	mnist	0.97610575	1.4584437399999999	5	0.0008315550252388855
0.500	mnist+gan	font	0.9904	0.145202	5	0.0011575836902790173
0.500	mnist+gan	gan	0.78264	5.29407326	5	0.010042559434725802
0.500	mnist+gan	mnist+gan	0.9950806480000001	0.060032189	5	0.00033735566553709637
0.500	mnist+gan	mnist	0.990945508	0.13301565	5	0.0004006260005541201
0.500	mnist	font	0.99182	0.14426178799999997	5	0.0011031772296417237
0.500	mnist	gan	0.7793800000000001	7.3241219	5	0.00561400035625222
0.500	mnist	mnist+gan	0.90604837	7.29916066	5	0.0007543942986926345
0.500	mnist	mnist	0.9752724340000001	1.57080806	5	0.0004692942203244951
0.700	font	font	0.86966	5.920648097999999	5	0.06965660772676201
0.700	font	gan	0.99178	0.133407426	5	0.00028635642126553237
0.700	font	mnist+gan	0.7654569920000001	14.100084	5	0.019097150445009314
0.700	font	mnist	0.8280640699999999	8.262573040000001	5	0.011210256160184326
0.700	gan	font	0.90144	3.54985194	5	0.03909223708103694
0.700	gan	gan	0.6121800000000001	21.207758000000002	5	0.007236504681128836
0.700	gan	mnist+gan	0.994892488	0.06012614980000001	5	0.0017524616954644019
0.700	gan	mnist	0.9294394199999999	2.1881399000000004	5	0.0022570059618884438
0.700	mnist+font	font	0.9793200000000001	0.5495579879999999	5	0.031548407249812144
0.700	mnist+font	gan	0.99118	0.1275652708	5	0.0005890670590009362
0.700	mnist+font	mnist+gan	0.911424762	6.4797815	5	0.0018648610850999056
0.700	mnist+font	mnist	0.982642766	0.9516519819999999	5	0.0008696166020609359
0.700	mnist+gan	font	0.99214	0.125503944	5	0.00035071355833499353
0.700	mnist+gan	gan	0.7967	5.97717412	5	0.003620082871979571
0.700	mnist+gan	mnist+gan	0.9932795779999999	0.07977498000000001	5	0.0010625869583333314
0.700	mnist+gan	mnist	0.9922005620000001	0.120043524	5	0.0002926216483276786
0.700	mnist	font	0.9930999999999999	0.12740463000000002	5	0.000696419413859205
0.700	mnist	gan	0.7905399999999999	7.2390313399999995	5	0.011130947848229256
0.700	mnist	mnist+gan	0.9060483899999999	6.1966468	5	0.002093113516510768
0.700	mnist	mnist	0.981998598	0.922711952	5	0.00027111263428693954
0.900	font	font	0.8423599999999999	6.766629302	5	0.08430511846857223
0.900	font	gan	0.9866400000000001	0.33544505999999996	5	0.0012621410380777437
0.900	font	mnist+gan	0.72745492	14.550436	5	0.013443285402088301
0.900	font	mnist	0.80179065	8.7279174	5	0.003794947141594991
0.900	gan	font	0.89162	3.8468218399999996	5	0.046378734350993246
0.900	gan	gan	0.61168	20.5364036	5	0.013958223382651527
0.900	gan	mnist+gan	0.997996	0.0459856708	5	0.0
0.900	gan	mnist	0.916220594	2.5890413000000003	5	0.001518865445844357

0.900	mnist+font	font	0.97722	0.6576260227999999	5	0.03685209627687413
0.900	mnist+font	gan	0.98438	0.245299898	5	0.0007823042886243289
0.900	mnist+font	mnist+gan	0.90460922	6.00430222	5	0.004826293944715761
0.900	mnist+font	mnist	0.9893704060000001	0.39386744	5	0.0004074674264036595
0.900	mnist+gan	font	0.99292	0.1235887538	5	0.0002588435821108672
0.900	mnist+gan	gan	0.8027000000000001	5.67068604	5	0.006191122676865652
0.900	mnist+gan	mnist+gan	1.0	2.1151767157512e-05	5	0.0
0.900	mnist+gan	mnist	0.9933517359999999	0.1130678308	5	0.0004118783493702795
0.900	mnist	font	0.9938799999999999	0.1181056992	5	0.0002167948338867641
0.900	mnist	gan	0.81106	6.100158160000001	5	0.00574917385369408
0.900	mnist	mnist+gan	0.8953907839999999	6.374337980000001	5	0.003292917753069461
0.900	mnist	mnist	0.9893323200000002	0.415499432	5	0.0003011895546827512