MNIST-Augmentaion

https://github.com/zhangabner

MNIST-Augmentaion

- Why this new dataset similar to MNIST?

- Please quit caring about MNIST

(Goodfellow 2017)

To Serious Machine Learning Researchers

Seriously, we are talking about replacing MNIST. Here are some good reasons:

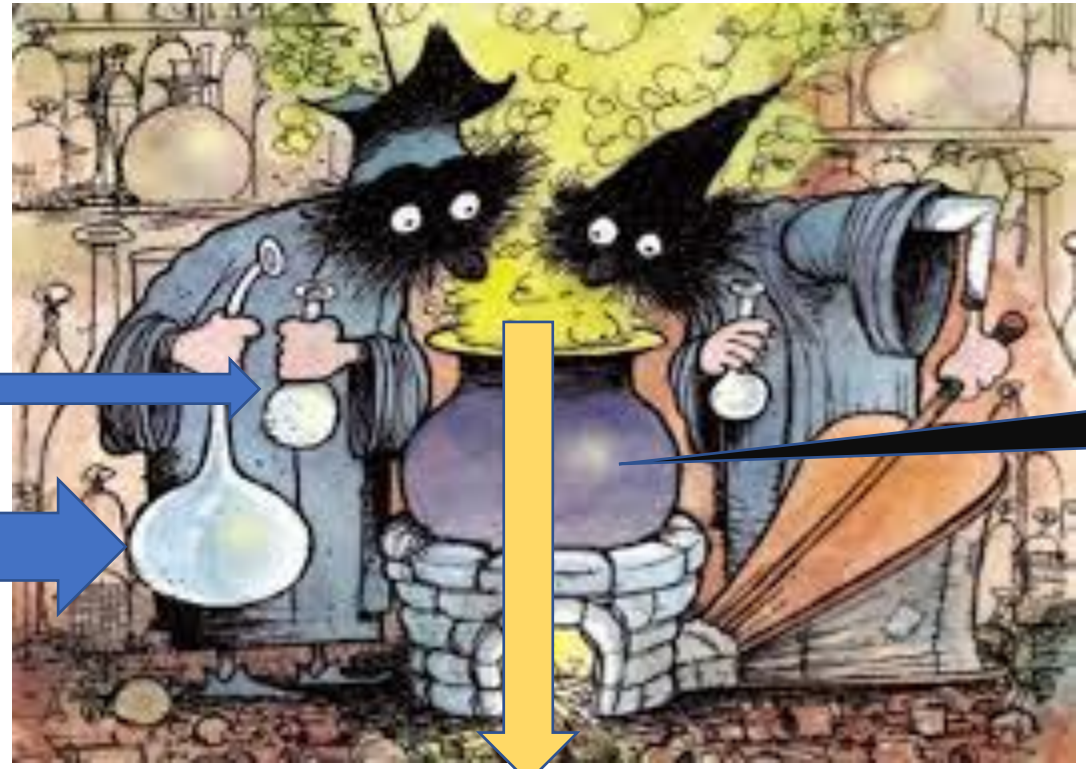
- **MNIST is too easy.** Convolutional nets can achieve 99.7% on MNIST. Classic machine learning algorithms can also achieve 97% easily. Check out our side-by-side benchmark for Fashion-MNIST vs. MNIST, and read "Most pairs of MNIST digits can be distinguished pretty well by just one pixel."
- **MNIST is overused.** In this April 2017 Twitter thread, Google Brain research scientist and deep learning expert Ian Goodfellow calls for people to move away from MNIST.
- **MNIST can not represent modern CV tasks**, as noted in this April 2017 Twitter thread, deep learning expert/Keras author François Chollet.

(fashion-mnist)

Current state of research based on MNIST

MNIST test
- Main part: ground true
- Some part: uncertain
- Few: ground false

MNIST training
- Main part: ground true
- Some part: uncertain
- Few: ground false

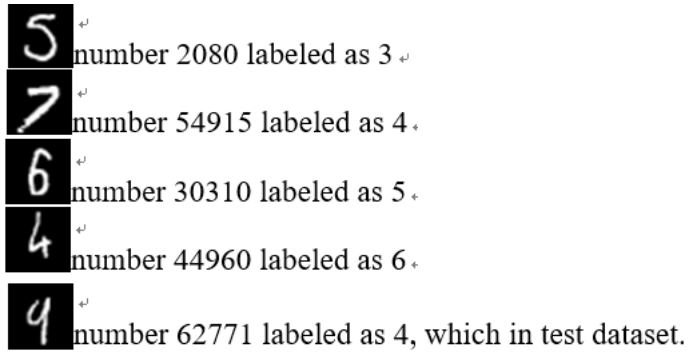


What's really happened there?

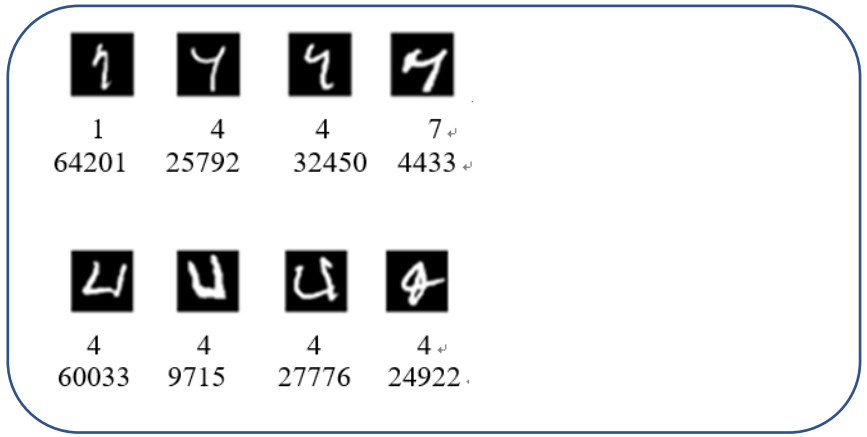
Result	Method	Venue	Details
0.21%	Regularization of Neural Networks using DropConnect	ICML 2013	
0.23%	Multi-column Deep Neural Networks for Image Classification	CVPR 2012	
0.23%	APAC: Augmented PAttern Classification with Neural Networks	arXiv 2015	
0.24%	Batch-normalized Maxout Network in Network	arXiv 2015	Details
0.29%	Generalizing Pooling Functions in Convolutional Neural Networks: Mixed, Gated, and Tree	AISTATS 2016	Details
0.31%	Recurrent Convolutional Neural Network for Object Recognition	CVPR 2015	
0.31%	On the Importance of Normalisation Layers in Deep Learning with Piecewise Linear Activation Units	arXiv 2015	
0.32%	Fractional Max-Pooling	arXiv 2015	Details
0.33%	Competitive Multi-scale Convolution	arXiv 2015	

The state of the art on MNIST

Ground-false and uncertain data in MNIST



Ground-false instances by applying majority voting on MNIST

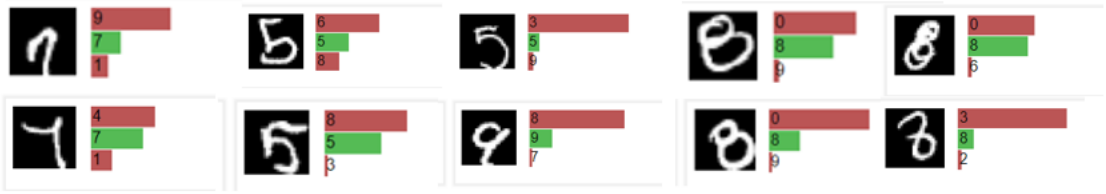


Uncertain instances by analyzing the process of NIST SD19v2

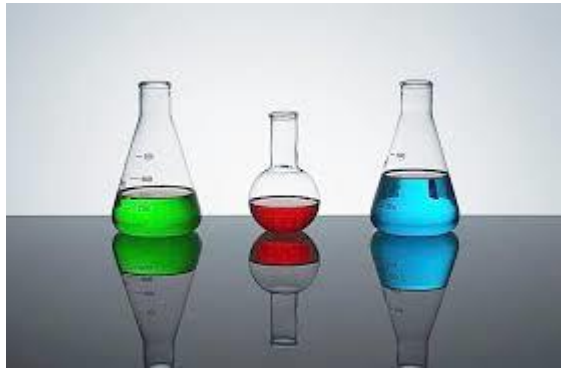
Do we understand the prediction of CNN on MNIST?

The Karpathy's convnetjs can predict these correctly:

but make errors at some 'good' handwriting such as:



Turn the mixed dataset into ground-truth dataset

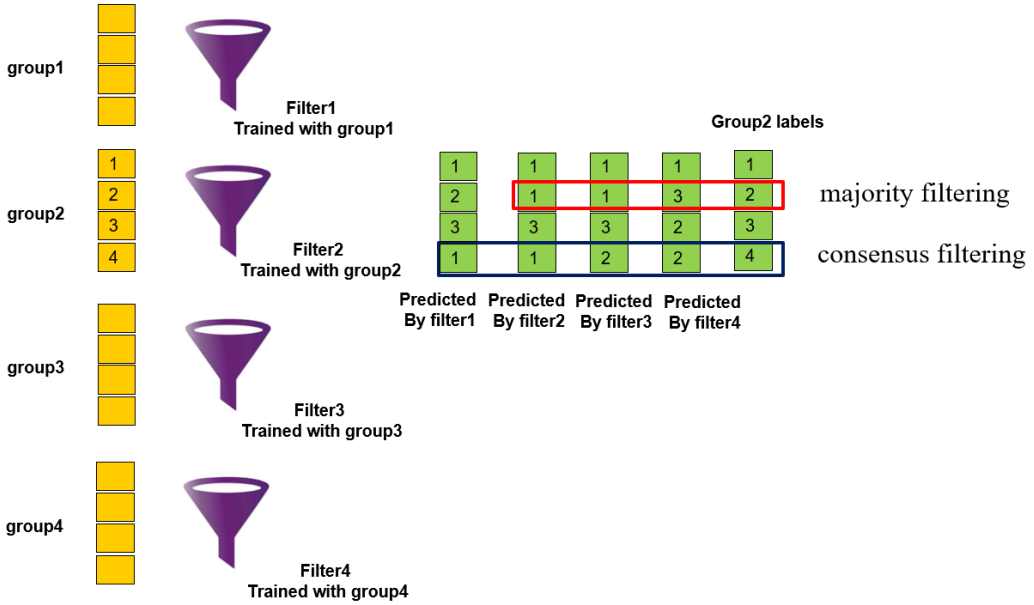


Ground-false

Ground-true

Uncertain

Majority voting to split MNIST



Majority voting process

count of wrong predicted times	count of digits
0	62161
1	2059
2	1008
3	733
4 (Majority Vote)	622
5 (Majority Vote)	593
6 (Majority Vote)	722
7 (Consensus Filters)	2023

Ground true

Uncertain

Ground false

Majority voting result

Majority voting by
[Brodley *et al.*, 1999]

Why that good handwriting being predicted wrong?

Training

Ground false

Ground true

Uncertain

1

Test

Ground true

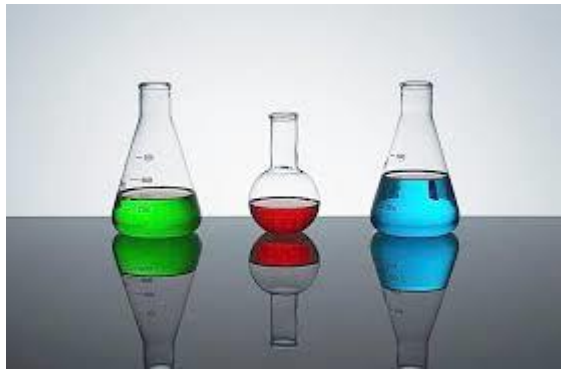
Uncertain

2

2 Accuracy = 100%
Ensemble method, num_networks = 5

Why that good handwriting being predicted wrong?

Training



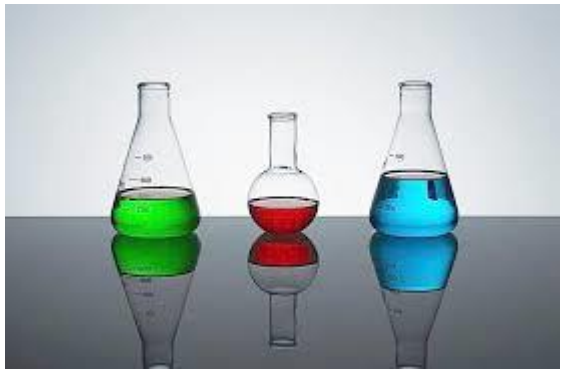
Ground false

Ground true

Uncertain

1

Test



Ground true

Uncertain

3

3 Predicting 513 wrong in uncertain test

Why that good handwriting being predicted wrong?

Training

Test

Ground false

Ground true

Uncertain

Ground true

Uncertain

1

4

3

4 Predicting 130 wrong in uncertain test
Accurate at 383 previous wrong

Why that good handwriting being predicted wrong?

Training

Ground false

Ground true

Uncertain

Ground true

Uncertain

Test

1 4 5

5 Predict 16 ground-true wrong

Adding more uncertain data in training

	Dn0'	Dn1'	Dn2'	Dn3'	Dn4'	Dn5'	Dn6'	Dn7'
Dn0	0	2	18	37	53	61	96	276
Dn0+n1	0	1	5	18	46	46	87	271
Dn0+n2	0	1	6	15	31	39	80	269
Dn0+n3	1	2	3	18	38	33	67	251
Dn0+n4	1	4	6	16	21	32	52	253
Dn0+n5	3	2	7	20	19	18	50	232
Dn0+n6	5	4	6	21	17	17	33	211
Dn0+n7	15	4	9	8	6	5	13	93
Dtraining	16	4	7	11	5	5	11	70

Poisoning Attack

Training

Test

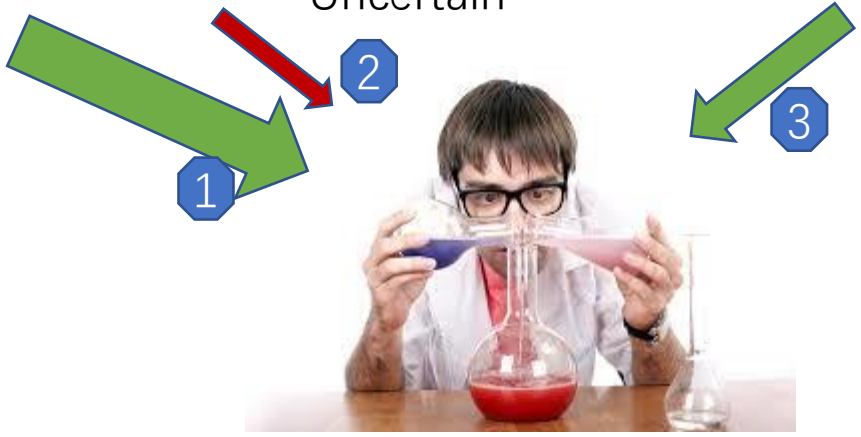
Ground true

Ground false

Uncertain

Ground true

Uncertain



Example: poisoning attack

F(M2,Dn0,x61466)=5

F(M2, Dn0+d2080,x61466)=3

F(M2,Dn0,x68553)=5

F(M2, Dn0+d2080,x68553)=3

F(M2,D0,x61941) =7

F(M2, D0+d54915,x61941) = 4

The poisoning effect

F(M2, Dn0,x61466)=5

F(M2, Dn0+d2080,x61466)=3

F(M2, Dn0+n7,x61466) = 5

F(M2, Dn0,x68553)=5

F(M2, Dn0+d2080,x68553)=3

F(M2, Dn0+n7,x68553) = 5

The neutralized effect

F(M2, Dn0+n1 ,x60115)=y60115

F(M2, Dn0+n2 ,x60115)=y60115

F(M2, Dn0+n3 ,x60115)=y60115

F(M2, Dn0+n4 ,x60115)=y60115

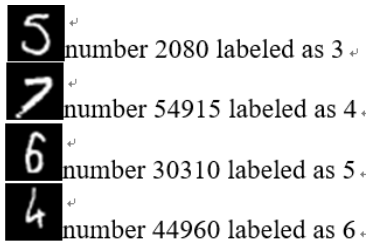
F(M2, Dn0+n5 ,x60115)=y60115

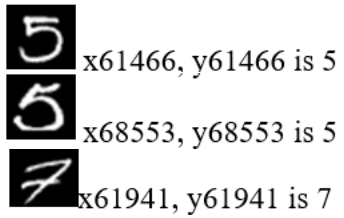
F(M2, Dn0+n6 ,x60115)=y60115

F(M2, Dn0+n7 ,x60115)=y60115

F(M2,Dn0+n1-7 ,x60115)!=y60115

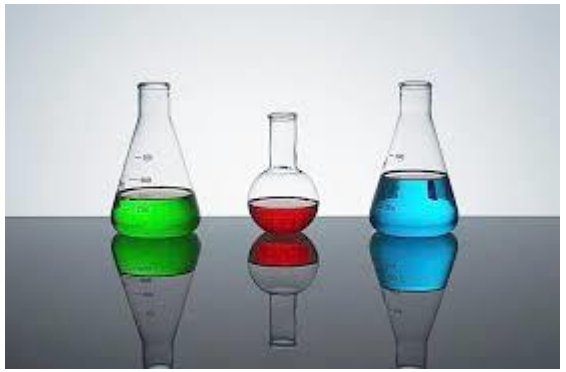
The compounded effect



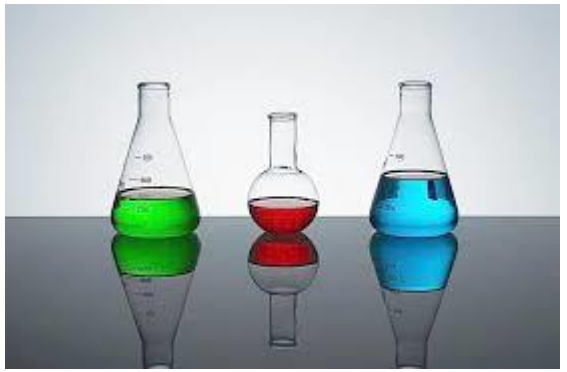


Poisoning Attack

Training



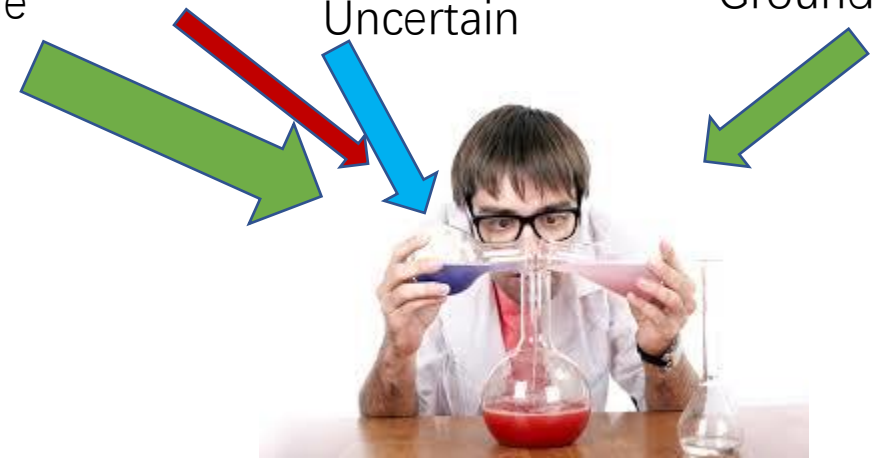
Test



Ground true

Ground false

Uncertain



Ground true

Uncertain

How to evaluate the effect of adding more Ground false?

Pseudo label in MNIST

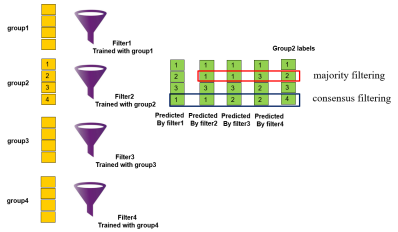
12958 in the context of form is 9, but in a large context of 0-9 and a-z, it should be ‘g’, which is unknown in 0-9.

23652 is labeled as 4 and some readers may think it is closer to 9, but in a large context of 0-9 and a-z, it should be ‘q’, which is unknown in 0-9.

Reason:

- Lack of ground-truth source
- Definition:
- It must be one of digits
- Bias:
- Different personal views

How to be ground-truth



HSF_4 and HSF_6 images
groundtrueV01.csv

Original form → segmentation → Manual check → Majority vote → Crowd review

The source of Ground-truth

NIST SD19v2

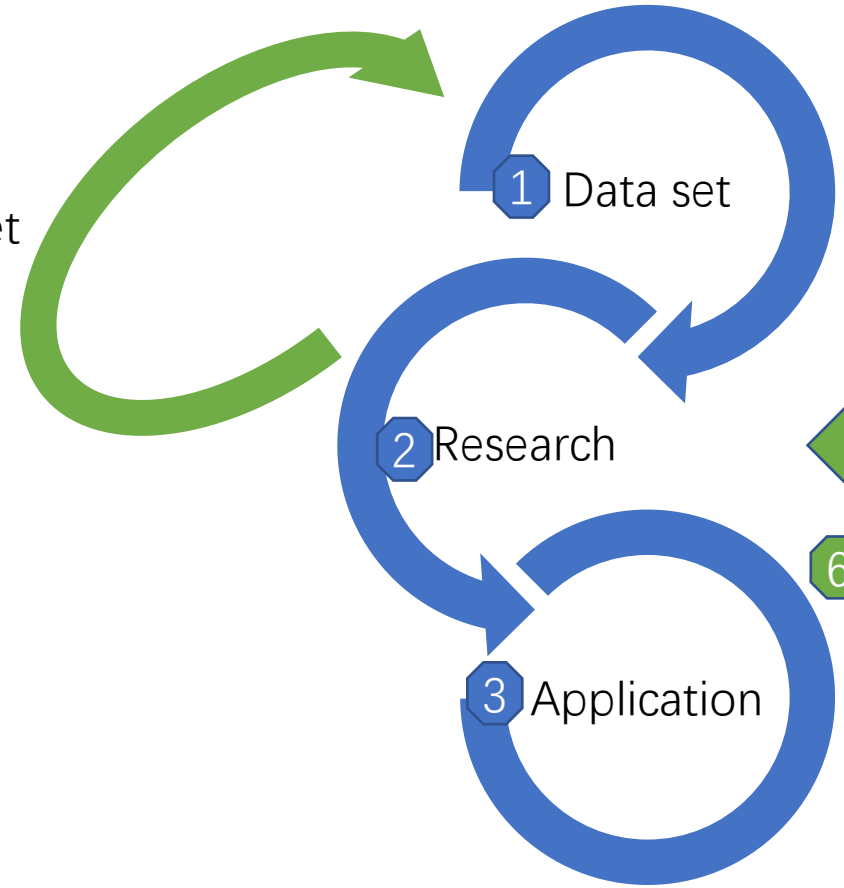
Augmentation

Definition:

- The print version
- Distinguishable

A good dataset will motivate a thousands good papers

4 Optimize the dataset
- Definition
- Ground-true
- Ground-false
- uncertain



5 Augmentation

6 New research with ground-truth data
- Certainty: 100% when ground-true
- Uncertainty: define uncertain data
- Noise: noise tolerant
- Security: poisoning

CIFAR-10

By web crawlers from internet

Tiny Images dataset 80 million 32 × 32

CIFAR-10 by students

only 59863 unique hashes of 60000 images.
137 Duplicate images

Image 16925 and 22490 are labeled as automobile.

Image 55416 and 5013 are labeled as truck.

4 Unknown labels:

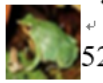
1569 labeled as a deer

18310 labeled as truck

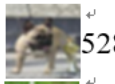
5074 labeled as a deer

52226 labeled as a bird

4 Wrong labels:



52405 labeled as cat



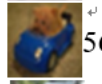
52804 labeled as cat

21347 labeled as cat

17455 labeled as a cat

4 Multi-objects labels

15696: a bird on a car



56859 is a cat on a car

8208: a deer in front of a car

35829: a truck beside a car

- “The only criteria for including an image were that the image contain one dominant instance of a CIFAR-10 class, and that the object in the image be easily identifiable as belonging to the class indicated by the image label.”
- “There is no overlap between automobiles and trucks. "Automobile" includes sedans, SUVs, things of that sort. "Truck" includes only big trucks. Neither includes pickup trucks”

CIFAR-10 augmentation

By web crawlers from internet

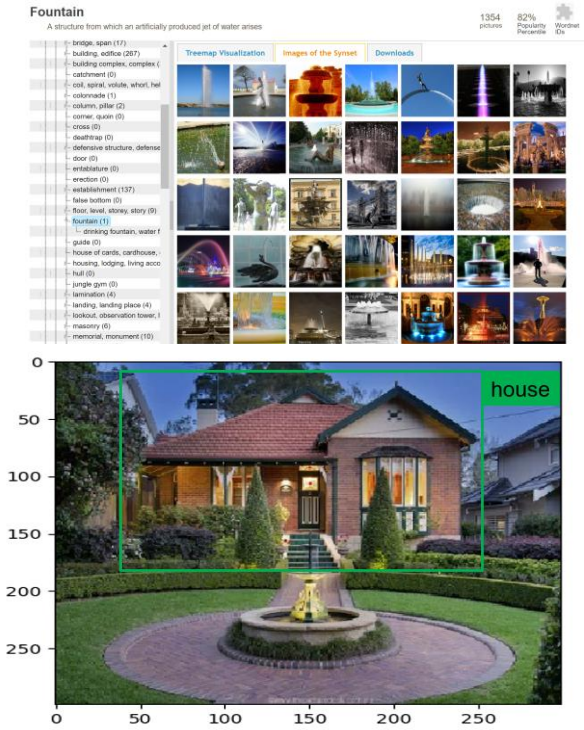
Tiny Images dataset 80 million 32 × 32

Manual checked by students

ImageNet

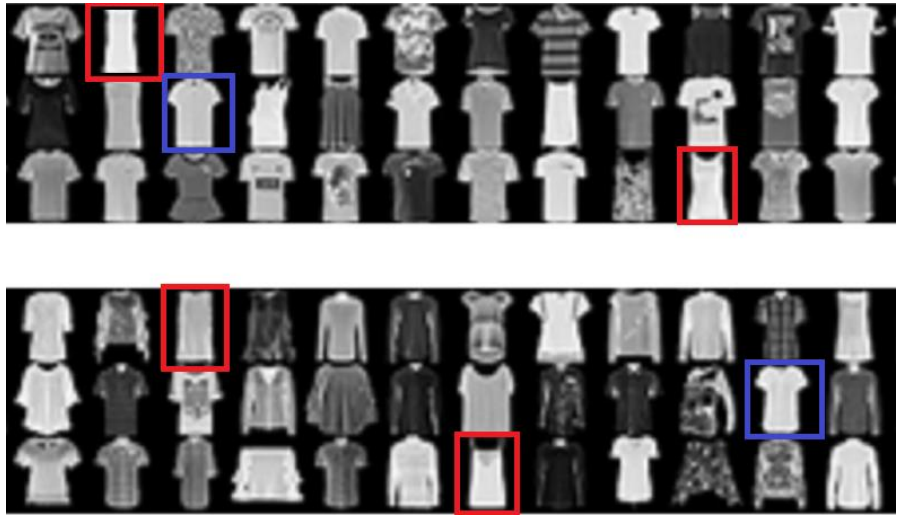
Segmentation

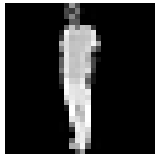
Crowd review



fashion-mnist

- Unlike CIFAR-10, Fashion-MNIST doesn't provide the process of labeling and the mutually exclusive definition.
- There is no definition of female t-shirt and female shirt, and the definition of male t-shirt and male shirt is not mutually exclusive.





- Image 2693 19545,34248,27110 in class trousers are a model.
- Image 37183,30191 in class pullover is a model.
- Image 7388, 14274 in class dress is a model.
- Image 21701 in class coat is a model.
- Image 65249 in class shirt is a model.

How to use MNIST-augmentation

- https://github.com/zhangabner/ML
  - hsf_4.tar.gz and hsf_6.tar.gz
  - groundtrueV1.csv
  - Groundtrue2.py
    - demo how to input new instances and replace MNIST instances
  - https://www.kaggle.com/abnerzhang/mnistaugmentationv1
- How to change instances (when found errors)
  - Change Groundtrue2.py to replace errors

- Using it as a new benchmark after it stable

*https://github.com/Hvass-Labs/TensorFlow-Tutorials

- Thanks