2025 Data Mining

HW2

Task introduction

- Anomaly Detection
  - TA use the Letter Image Data features and select 6 letters to form the training set, and randomly add some other 4 letters as outliers in testing set.
  - Implement machine/deep learning model to do anomaly detection.
  - All package is available (sklearn, keras, pytorch etc.).
  - Do not use any pretrained model & Do not use any extra data for training, but it is acceptable to use such data for validation purposes.

- Requirement
  - Upload your submission to Kaggle
  - Submit a report and your source code to E3

- Deadine is 4/22(Tue.) 23:59, no late submission

Dataset

UCI Letter Image Recognition Data Set.

- training.csv
  - Randomly sample 6 letters(each label is 700) from Letter Image Recognition Data Set.
  - link
- test_X.csv
  - Randomly sample 600 from previous letters, and randomly select 400 other letters.
  - Please use the features to assign weight values to indicate whether each letter is an outlier or not.
  - link

Training Data

lettr	x-box	y-box	width	high	onpix	x-bar	y-bar	x2bar	y2bar	xybar	x2ybr	xy2br	x-ege	xegvy	y-ege	yegvx
B	4	8	6	6	5	9	7	4	6	10	5	6	2	8	6	10
B	1	0	1	0	0	7	7	6	4	7	6	7	1	8	5	9
B	4	8	6	6	8	8	8	4	3	6	7	7	6	11	8	9
B	4	7	6	5	5	8	6	5	6	9	6	7	3	8	7	9
B	9	14	7	8	5	6	8	5	7	10	6	8	6	6	7	9
B	4	7	6	5	5	7	8	5	5	9	6	6	3	7	6	7
B	4	7	5	5	6	8	7	6	6	6	6	6	2	8	6	9
B	4	7	5	5	4	8	6	4	6	9	5	6	2	8	6	10
B	5	10	6	8	7	9	7	3	5	7	6	8	7	8	6	9
B	4	9	4	7	4	6	7	9	7	7	6	7	2	8	9	10
B	3	7	5	5	5	8	8	4	5	7	5	6	4	8	5	8
B	4	10	6	8	7	8	7	4	7	6	6	6	6	8	6	10
B	6	9	8	7	7	7	8	6	5	6	5	6	4	9	7	6
B	4	10	5	8	7	6	8	8	5	7	5	7	2	8	7	9
B	2	3	4	2	2	8	7	3	5	10	5	6	2	8	4	9
B	6	9	8	7	6	10	6	3	7	10	3	7	6	8	7	11
B	6	8	9	7	9	7	8	5	5	8	6	8	7	7	9	6
B	4	10	5	7	7	8	7	6	5	7	6	6	6	8	6	10
B	3	6	4	4	5	7	7	6	5	7	6	6	2	8	6	10
B	7	11	9	8	8	10	6	3	6	10	3	7	5	7	6	11
B	4	9	6	6	6	6	8	7	4	7	5	6	4	8	5	6
B	4	9	4	7	5	6	8	8	6	7	5	7	2	8	7	9
B	3	7	3	5	3	6	8	8	6	7	5	7	2	8	9	10
B	2	6	4	4	3	8	8	5	7	7	6	6	2	8	6	9

All features are given.

Testing Data

x-box	y-box	width	high	onpix	x-bar	y-bar	x2bar	y2bar	xybar	x2ybr	xy2br	x-ege	xegvy	y-ege	yegvx
3	11	4	8	2	1	13	5	4	12	10	7	0	8	3	6
4	10	5	7	3	5	10	9	4	7	4	8	3	7	6	11
5	9	6	5	3	10	3	4	6	12	4	10	3	8	7	10
4	6	6	6	6	6	9	5	3	6	4	8	7	8	4	9
4	6	6	4	4	10	6	7	5	6	7	4	8	5	2	5
4	5	4	8	2	1	14	5	4	12	10	6	0	8	2	6
4	6	4	4	3	7	6	9	7	7	7	7	2	8	8	9
4	9	5	7	4	7	7	3	12	9	6	8	0	8	8	8
8	12	8	6	4	10	6	3	9	9	2	5	4	6	4	10
4	10	5	8	4	6	10	6	5	9	7	3	2	10	4	7
6	7	8	5	5	7	8	2	7	10	5	9	4	7	3	7
7	9	8	4	3	5	9	3	4	13	9	9	5	8	0	8
7	12	6	6	3	8	9	7	5	14	4	4	4	10	4	7
5	10	7	8	4	7	7	3	11	11	6	8	1	8	7	8
3	8	3	6	3	7	7	12	1	6	6	8	5	8	0	8
4	9	6	6	7	9	6	4	4	6	7	7	7	9	8	6
2	8	3	6	2	2	11	4	5	11	10	8	0	8	2	7
2	4	4	3	2	6	7	2	7	11	7	9	2	8	4	8
6	10	9	7	7	8	7	5	6	9	5	6	3	7	7	10
3	4	4	6	3	6	9	9	8	7	5	7	2	8	9	10

No letter attribute, use it to predict it is outlier or not!

Attributes Description

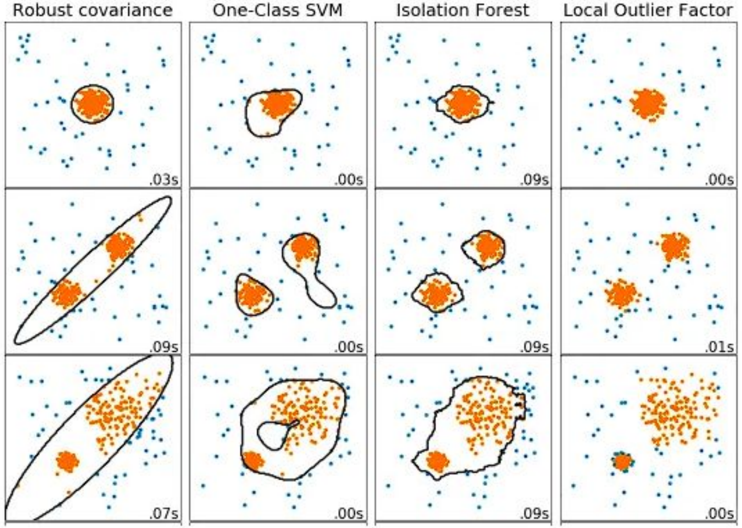
lettr	capital letter	(26 values from A to Z)
x-box	horizontal position of box	(integer)
y-box	vertical position of box	(integer)
width	width of box	(integer)
high	height of box	(integer)
onpix	total # on pixels	(integer)
x-bar	mean x of on pixels in box	(integer)
y-bar	mean y of on pixels in box	(integer)

Attributes Description

x2bar	mean x variance	(integer)
y2bar	mean y variance	(integer)
xybar	mean x y correlation	(integer)
x2ybr	mean of x * x * y	(integer)
xy2br	mean of x * y * y	(integer)
x-ege	mean edge count left to right	(integer)
xegvy	correlation of x-ege with y	(integer)
y-ege	mean edge count bottom to top	(integer)
yegvx	correlation of y-ege with x	(integer)

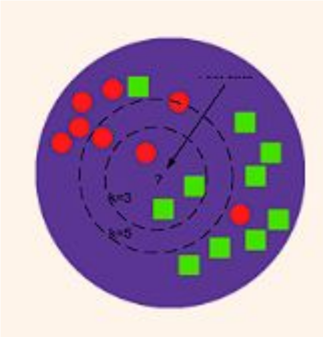
Method 1 - SVM

- Use OneClass SVM to learn a decision boundary.
- Find the suitable kernel space and parameters to fit the data.
- Convert the result of classification to the self-defined value.



Overview of outlier detection methods

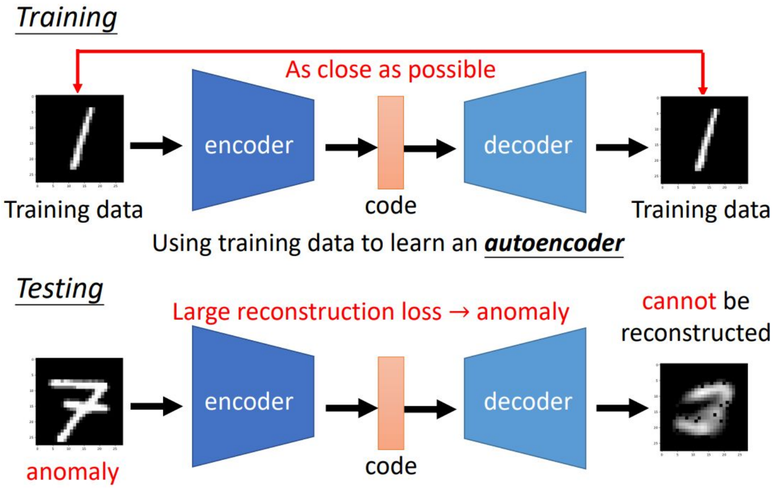
Method 2 - KNN



- Assume that there are n clusters in training data.
- Assume that n is a small value
- Using K-means to calculate the n centroids of training data. Then use these n centroids to cluster the testing data.
- In the same cluster, the distance between inliers to centroid must smaller than the distance between outliers to centroid.
- We can take the distance to centroids as the weight value for prediction.

Method 3 - Autoencoder

- Using training data to train a AE or VAE
- Because the outliers cannot be reconstructed well, the MSE of outliers must greater than inliers.
- We can take the reconstruction loss as the weight value for prediction.

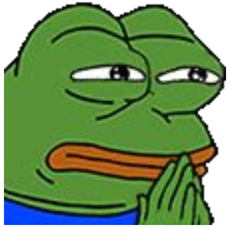


Methed 4 - Any reasonable way you can think

The key point is to make objects within the same group as similar as possible, and keeping those in different groups to be as dissimilar as possible.

HW2? No way!

No restrictions?



Let me think...

Ah, ha!

Compactness & Separation

Kaggle Submission

id	outliers
0	3.865861106
1	1.564198455
2	1.427000115
3	1.1940908
4	2.475497267
5	-0.0849644

- Kaggle link
- Display team name : <student ID>
  - team name error : -5%
- Submission format
  - A 1001*2 .csv file, index start from 0. Outliers are any weight values that you define.(MSE, F1Loss, distance etc.)
  - Column name must be id and outliers.
  - sample submission
- There are one simple baseline and one strong baseline, beat them to get higher score.

	Strong Baseline	0.87680
	Simple Baseline	0.72586

Kaggle Submission

- The scoring metric is **auc score**.
- You can submit at most 5 times each day.
- You can choose 3 of the submissions to be considered for the private leaderboard, or will otherwise default to the best public scoring submissions.
- You can only view your private leaderboard score after the competition has ended.
- Public leaderboard is calculated with 60% of the test data, and private leaderboard is calculated with other 40% of the test data, so the final standings may be different.
- Please tune your model parameters using your own validation set instead of adjusting parameters based on the public leaderboard. Otherwise, it's easy to overfit, leading to poor performance on the private leaderboard.

Change your team name

2025 Data Mining HW2

2025 NYCU Data Mining HW3

Settings Overview Data Code Models Discussion Leaderboard Rules Team

Your Team

Remember to change the team name to <student ID>, or there will be a deduction of 5 points for HW2.

Everyone that competes in a Competiton does so as a team - even if you're competing by yourself. Learn more.

General

TEAM NAME

Team Name

This name will appear on your team's leaderboard position.

Report Submission

Answer the following 3 questions:

1. Explain your implementation which get the best performance in detail.
2. Explain the rationale for using auc score instead of F1 score for binary classification in this homework.
3. Discuss the difference between semi-supervised learning and unsupervised learning.

Please answer the questions in detail to receive full points for each question.

Grading policy

- Kaggle (70%)
  - 30% based on the public leaderboard score and 70% based on the private leaderboard score
  - Leaderboard score consists of basic score and ranking score
    - Basic score:

      Over strong baseline : 55

      Over simple bassline : 40

      Under simple baseline : 25
    - Ranking score:

      15-(15/N)*(ranking-1), N=numbers of people

- Report (30%)
  - 10% for each quesiton

E3 Submission

Submit your source code and report to E3 before 4/22(Tue.) 23:59.

No late submission !

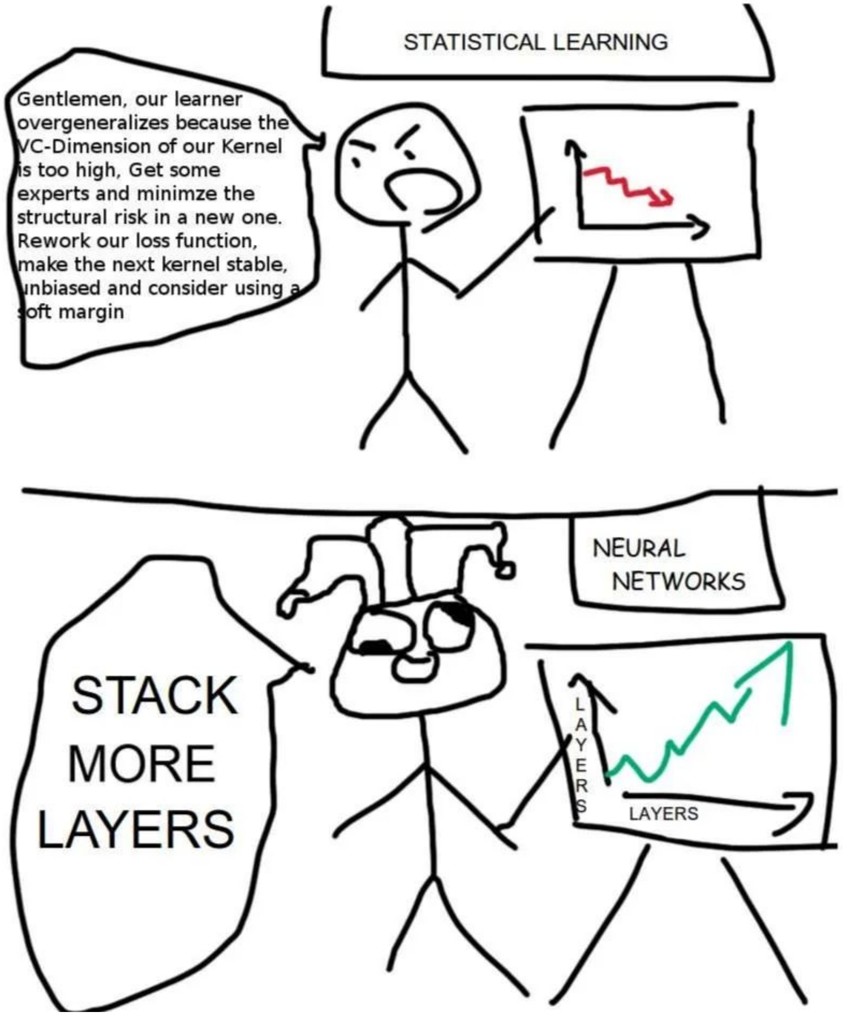
Follow the submission format or there will be a deduction of 5 points for HW2 !

- Format
  - source code : HW2_<student ID>.py or HW2_<student ID>.ipynb
  - report : HW2_<student ID>.pdf

If you have any question about HW2, please feel free to contact with TA: CHENG-XIN SONG

through email chengxin0913.cs12@nycu.edu.tw

Take Easy



STATISTICAL LEARNING
Gentlemen, our learner overgeneralizes because the VC-Dimension of our Kernel is too high, Get some experts and minimze the structural risk in a new one. Rework our loss function, make the next kernel stable, unbiased and consider using a soft margin
NEURAL NETWORKS
STACK MORE LAYERS
LAYERS
LAYERS