Seismic Atlas Analysis Based on Computer Vision Method

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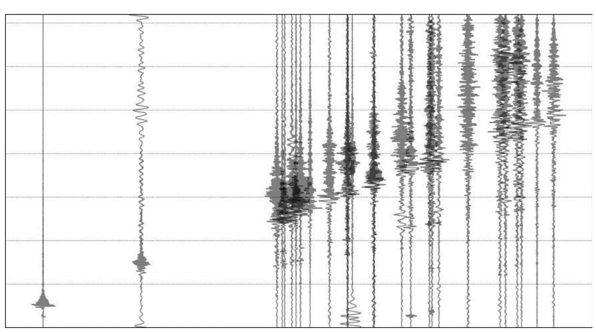
Abstract

The method of computer vision can be applied to seismology, and the signals detected by different observation stations are used to generate a picture as input data for classification and regression tasks. This thesis will study the classification of earthquakes caused by different reasons based on the processing method of computer vision. Forecast of source latitude and longitude, depth and azimuth. For the task of unsupervised image classification of unlabeled earthquakes.First, the resnet network is used to classify earthquakes and glaciation times. Then use the resnet network for regression tasks. Finally, use the prediction results in Task 2 to draw seismograms using the obspy package, and then use deep-cluster for unsupervised classification. Among them, the classification task achieved a prediction accuracy of 92%. The regression tasks have achieved an accuracy rate of more than 90%. The unsupervised classification task finally checks the public data set, and the classification types are consistent. The code is public [here] .

1 classification

1.1 data preparation

For the data read in by the bin file, due to missing data and no alignment, it cannot be used correctly. For the data read in mseed format, the drawn image needs to perform offset conversion for each trace. Since the latitude and longitude data have been provided, the entire image can be drawn directly, as shown in the figure below.



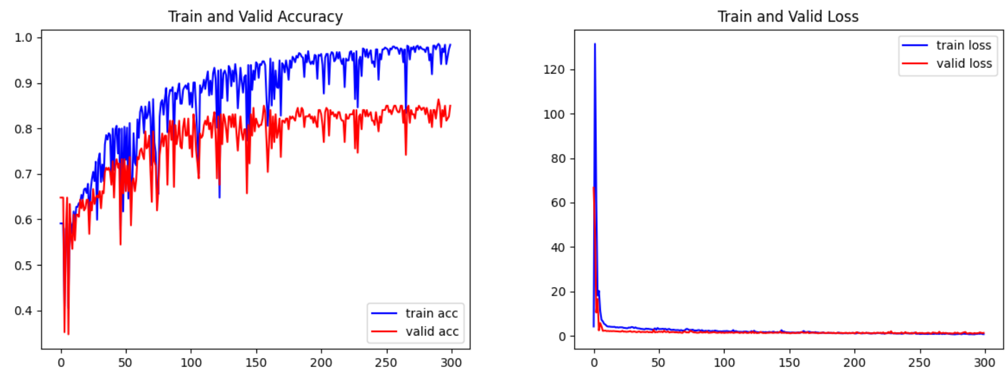
The data set is all earthquake times and glacier events, the overall data set is divided, and 0.2 is randomly selected as the test set, 0.24 is the verification set, and 0.56 is the training set.

1.2 model training

This problem is abstracted into a computer vision binary classification problem. Several models were compared for training. Considering that the binary classification model is not too complicated, the results are in line with expectations. First select epoch=1000. A random seed of 3407 is used during all training.[1]

model name	valid acc
resnet18	83%
resnet34	84%
resnet50	87%
resnet101	80%
resnet151	78%

So choose the model resnet50[2], adjust the learning rate and other parameters, and choose the appropriate epoch to prevent overfitting.

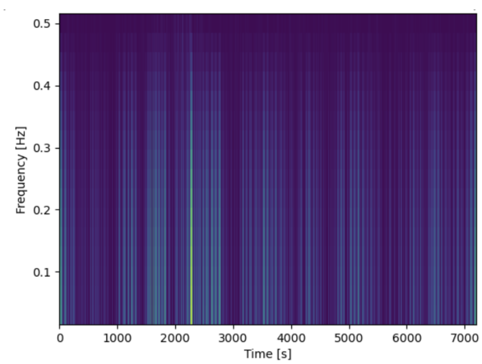


Finally, the verification set and training set are all trained with the resnet50 model through the above selection of hyperparameters. Got 162/177, 91.52% correct rate.

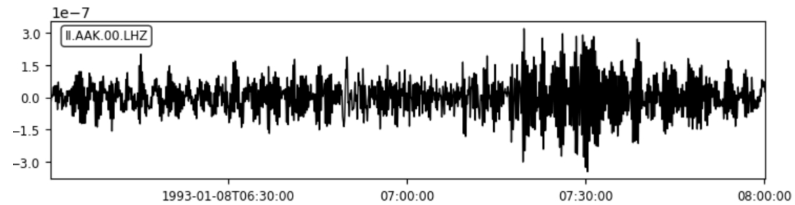
2 regression

2.1 data preparation

It is different from the first task, because if you want to draw the effect of the first graphic, you need the offset of each observation station relative to the source. And this task needs to predict the longitude and latitude of the source, so the data set is the waveform of each trace, and the target value is the offset of the trace. There are two pictures for each trace, one is a frequency map and the other is an amplitude map. The tested amplitude map is more accurate in predicting offset, because the frequency remains unchanged for a period of time, but the amplitude will still change, and the intensity of the process of seismic wave transmission to the observation station will change significantly.



It should be noted that since the API provided by obspy does not have parameters about the size of the uniform order of magnitude, it needs to be modified manually. It should be noted that since the API provided by obspy does not have parameters about the size of the uniform order of magnitude, it needs to be modified manually. However, after testing, the final result has nothing to do with the absolute amplitude, but has a greater relationship with the relative amplitude.

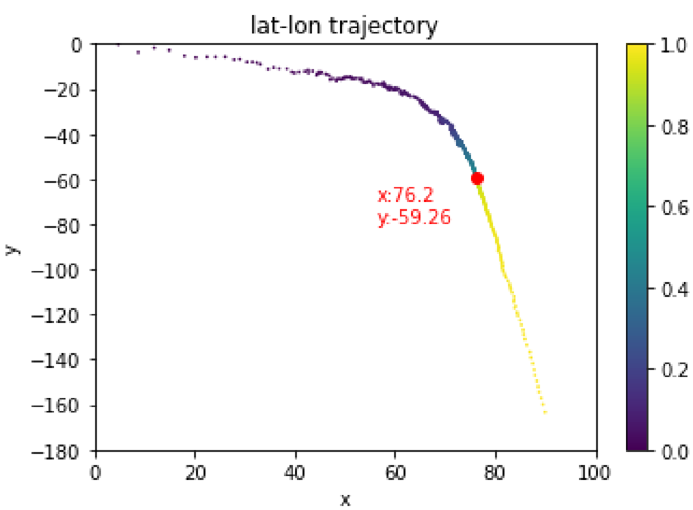


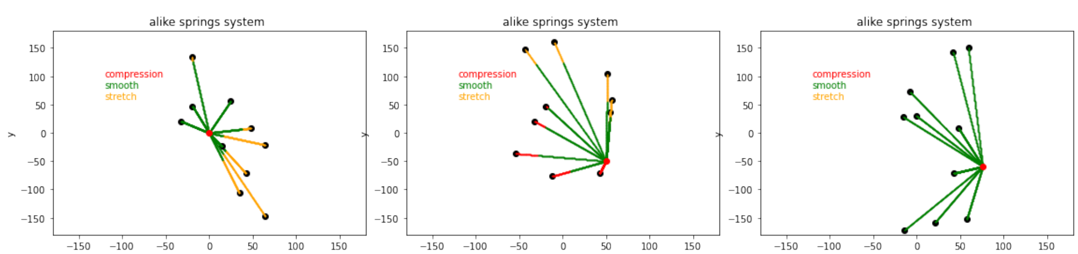
2.2 model training

Since the size of the picture has changed, and the classification task has become a regression task, try to compare different models. The Alexnet[3] model was used. Finally, the accuracy rate on the test set is 92%.

2.3 predict latitude, longitude

The predicted offset is used to iteratively adjust the location of the predicted source until it is the smallest (distance-predicted distance) from each observation station.





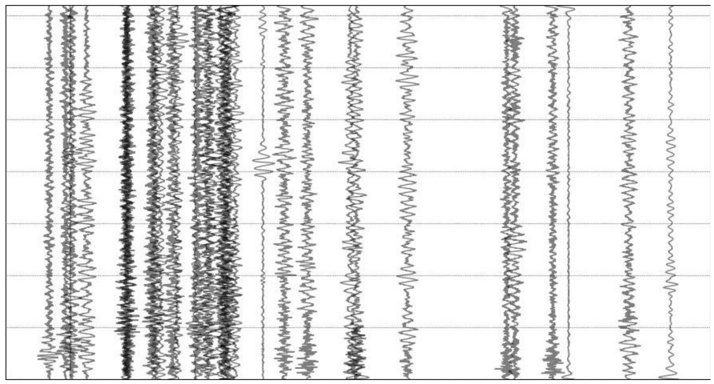
2.4 predict depth, azimuth

Since this original data set is the same as the task1 data set, the difference is that the target of glacial has changed to azimuth, and the target of earthquakes has changed to depth, so it needs to be trained separately. Still using resnet50 which performed best on the original dataset.The accuracy of the final test set was 89%, 91%, respectively.

3 Anomaly detection

3.1 data preparation

Since there is no label mark in the given unusual file, and there is no latitude and longitude information of the event, it is necessary to predict the offset of each trace through the offset in task2, so as to draw a picture similar to task1 in the obspy package come out.

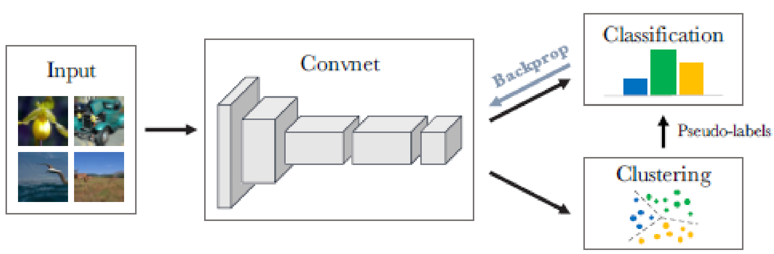


3.2 model training

This task adopts the structure in deep-cluster[4]. First, pseudo-labels are generated through clustering, and then the loss value based on the pseudo-labels is calculated, and then the network parameters are updated.

$$\min \frac{1}{N}\sum_{n=1}^{N} \min ||f_\theta(x_n) - Cy_n||_2^2 \ni y_n^T 1 = 1$$

$$\min \frac{1}{N}\sum_{n=1}^{N} l(g_W(f_\theta(x_n)), y_n)$$



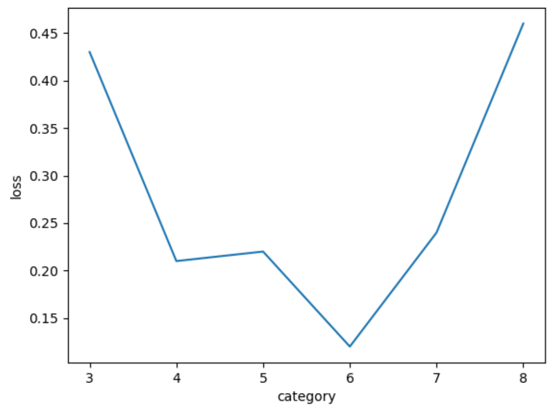
The problem however is that the number of categories needs to be set in advance, but this is an unknown quantity. Therefore, you can set a rough range of the number of categories, and then take the smallest loss after training for each category as the final number of categories.

Since there is no label, the accuracy rate cannot be obtained. Finally, the classification category is 6, which is consistent with the category searched on the website.

References

[1] David Picard. Torch.manual seed(3407) is all you need. arxiv.org: 2109.08203

[2] Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun. Deep Residual Learning for Image Recognition. CVPR, 2016, pp. 770-778



[3] Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton. ImageNet Classification with Deep Convolutional Neural Networks. NIPS 2012

[4] Mathilde Caron, Piotr Bojanowski, Armand Joulin, and Matthijs Douze. Deep Clustering for Unsupervised Learning of Visual Features. arXiv:1807.05520. 2

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