National Tsing Hua University

1130IEEM 513600

Deep Learning and Industrial Applications

Homework 2

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1. (20 pts) Select 2 hyper-parameters of the artificial neural network used in Lab 2 and set 3 different values for each. Perform experiments to compare the effects of varying these hyper-parameters on the loss and accuracy metrics across the training, validation, and test datasets. Present your findings with appropriate tables.

Answer:
Modify optimizer = torch.optim.Adam(model.parameters(), lr=1e-2/1e-3/1e-5, weight_decay=1e-4). Larger learning rate for faster learning. But over fitting fast as well.

Use dropout to avoid overfitting and maintains the appropriate ratio to avoid underfitting. Dropout ratio 0.1/0.3/0.5. Higher dropout ratio with lower overfitting, lower dropout ratio with higher accuracy and more stable for each training.

2. (20 pts) Based on your experiments in Question 1, analyze the outcomes. What differences do you observe with the changes in hyper-parameters? Discuss whether these adjustments contributed to improvements in model performance, you can use plots to support your points. (Approximately 100 words.)

Answer:
A larger optimizer lr=1e-2 can improve learning speed so that it can learn higher accuracy without too many epochs because learning by larger step. But easy to cause overfitting. Lower learning rates, lr=1e-5, with small learning

step will result in a slow improvement of accuracy and will make it easy to stock in local optimal.

A larger dropout ratio 0.5 can avoid overfitting because cutting more weight, but cause model accuracy improve unstable. With small dropout ratio 0.1 not improve overfitting too much because not help if cutting only a few weights.

3. (20 pts) In Lab 2, you may have noticed a discrepancy in accuracy between the training and test datasets. What do you think causes this occurrence? Discuss potential reasons for the gap in accuracy. (Approximately 100 words.)

Answer:
After observing training data and test data. I found that the data is not clean. Therefore, I do some data engineering to make data clean. And because some data are too large variance such as Cp, Ca, oldpeak, and target std are larger then mean. This maybe cause the test accuracy not satisfied. And because training is small amounts of data. That is easy to overfit to training data. I add Gaussian noise for data augmentation.

4. (20 pts) Discuss methodologies for selecting relevant features in a tabular dataset for machine learning models. Highlight the importance of feature selection and how it can impact model performance. You are encouraged to consult external resources to support your arguments. Please cite any sources you refer to. (Approximately 100 words, , excluding reference.)

Answer:
Can select important features by Principal Components Analysis (PCA) method, Linear Discriminant Analysis (LDA) method by dimensionality reduction. Also can use ANOVA test or Chi-square test to know data relationship. Entropy of Random Forest also can use for reference the data importance.

5. (20 pts) While artificial neural networks (ANNs) are versatile, they may not always be the most efficient choice for handling tabular data. Identify and describe an alternative deep learning model that is better suited for tabular datasets. Explain the rationale behind its design specifically for tabular data,

including its key features and advantages. Ensure you to reference any external sources you consult. (Approximately 150 words, excluding reference.)

Answer:
Because ANN or DNN or any NN model cannot be an explainable model decision. We do not prefer to use NN models for making decision models if dataset is for medical. Especially small datasets. Traditional Machine Learning (ML) models or statistic models may be better to use for making decision models for small medical datasets. One reason is because ML models must do data engineering, we will know the problem of data and find insights of the data. Another reason is that most ML models or statistic models can be explained. We prefer an explainable model. Especially if data quantity is not enough to train a good NN model.

Additional Work

Data Engineering Step

1. Loading the training dataset and test dataset
2. Review training dataset and test dataset then find issues.
   Sex and cp are characters in training dataset, numbers in test dataset.
   Null data in training dataset.
   Cp, Ca, oldpeak, and target std are larger then mean. But I will not remove the Cp, Ca, and oldpeak, and target because those data are still information.
3. Understand what is an unreasonable value.
   年齡 (age) 醫學合理範圍：20 至 100 歲 不合理數值： 小於 20 歲：一般而言，此類心臟病資料集多針對成人，小於 20 歲較少見。 大於 100 歲：超過 100 歲的患者較罕見且可能為資料錯誤。
   靜息血壓 (trestbps) 醫學合理範圍：80 至 220 mmHg 不合理數值： 小於 80 mmHg：顯著低血壓，很可能資料輸入錯誤。 大於 220 mmHg：極高的血壓值少見於臨床常態，可能為量測或輸入錯誤。

膽固醇 (chol) 醫學合理範圍：100 至 600 mg/dl 不合理數值： 小於 100 mg/dl：過低的膽固醇值極為少見，可能表示資料錯誤或檢驗失誤。 大於 600 mg/dl：極端高膽固醇值在臨床上少見，應視為異常數據。

最大心跳率 (thalach) 醫學合理範圍：60 至 220 bpm 不合理數值： 小於 60 bpm：極低的最大心跳率在一般狀況下不太可能，需檢查資料正確性。 大於 220 bpm：超過人類生理極限，為明顯不合理資料。

心電圖 ST 段下降 (oldpeak) 醫學合理範圍：0 至 6（一般臨床數值） 不合理數值： 小於 0：不合理，心電圖 ST 下降不可能為負數。 大於 6：臨床上極端少見且幾乎不合理，可能為錯誤數據。

主要血管數量 (ca) 醫學合理範圍：0 至 4 不合理數值： 小於 0 或 大於 4：解剖結構上不可能，因冠狀動脈主要數量通常為 0 到 4 之間。

thal 欄位（地中海貧血基因型） 醫學合理數值：1（正常）, 2（固定缺損）, 3（可逆缺損） 不合理數值： 不在 1、2、3 範圍內（例如負數、0 或大於 3）：不符醫學定義，視為錯誤。

4. Transfer data type.
   train_data['sex'].map({'Male': 0, 'Female': 1})
   train_data['cp'].map({'low': 0, 'medium': 1, 'high': 2, 'severe': 3})
5. Fill the training/test dataset numerical data with the median.
6. The training/test dataset category data is filled with the majority.
7. Defining medically reasonable limits and removing unreasonable or abnormal data.
8. Check whether there are still null values in the cleaned data.
9. Confirm that the data types are all numerical and consistent with the test data.
10. Review the statistics of each training/test dataset field after data cleaning.

Training

```
RangeIndex: 272 entries, 0 to 271
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       272 non-null    int64
 1   sex       272 non-null    float64
 2   cp        272 non-null    float64
 3   trestbps  272 non-null    float64
 4   chol      272 non-null    float64
 5   fbs       272 non-null    int64
 6   restecg   272 non-null    float64
 7   thalach   272 non-null    float64
 8   exang     272 non-null    int64
 9   oldpeak   272 non-null    float64
 10  slope     272 non-null    float64
 11  ca        272 non-null    int64
 12  thal      272 non-null    float64
 13  target    272 non-null    float64
dtypes: float64(10), int64(4)
```

Defining Neural Networks

11. Define NN model and considering of:

    Using larger NN model for better capability.

    Use LeakyReLU avoids the dead ReLU.

    Use dropout to avoid overfitting and maintains the appropriate ratio to avoid underfitting.

    Use batchnorm with order preservation after nonlinear activation.

    Use Kaiming initialization method.

Defining Training Parameters

12. Keep epochs = 100.
13. Keep criterion = nn.CrossEntropyLoss()
14. Modify optimizer = torch.optim.Adam(model.parameters(), lr=1e-2, weight_decay=1e-4) for faster learning.
15. Change lr_scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=60) for make

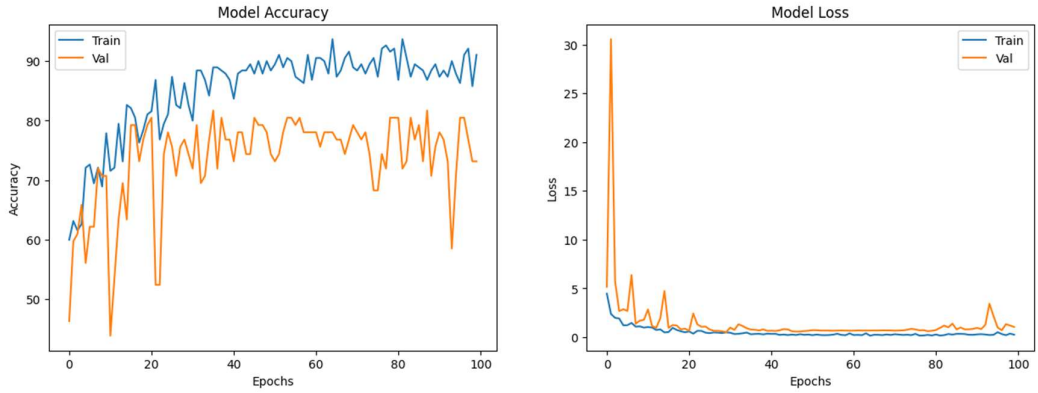
sure model will not in local optima and can fined the global optima.

16. Add L2 Regularization to avoid exploding gradient problem.
17. Add gaussian noise for data augmentation.

Training Model Try And Error Experience

18. Larger NN model will cause more overfitting.
19. Higher dropout rate will cause model training unstable.
20. Lower dropout rate will cause overfitting.
21. Adding batchnorm can help with increase accuracy and avoid overfitting.
22. Larger learning rates will increase training speed.
23. Add L2 Regularization can avoid overfitting.
24. Add gaussian noise can increase accuracy.

Training Result



Test accuracy is 80.64516129032258%

Conclusion

It still overfits after 40 epochs, and test accuracy is not satisfied. Training model's performance is not stable if retrain several times. Maybe the cause of

Cp, Ca, oldpeak, and target std are larger than the mean. Or maybe we can try another kind of models for this kind of data.