IN4050 Sample Questions for Final Exam

Topics: Evaluation and Bias-variance tradeoff

1- For a binary classification problem with a large class imbalance, you decide to evaluate the model using both ROC-AUC and Precision-Recall AUC. The model achieves a high ROC-AUC but a low Precision-Recall AUC. What is the most likely reason for this discrepancy?

- A) The model has high sensitivity but low specificity.
  B) The model has high precision but low recall.
  C) The model performs well on the majority class but poorly on the minority class.
  D) The model is underfitting both classes.

2- For a model's predictions on a binary classification problem at a given threshold, the F1-score is 0.75. The model has 40 true positives (TP) and 10 false positives (FP). Calculate the model's recall.

- A) 0.50
- B) 0.60
- C) 0.67
- D) 0.71

3- Suppose you are tuning hyperparameters using grid search and k-fold cross-validation with k=5. Approximately how many models will be trained in total if three hyperparameters are each tested with five different values?

- A) 75
- B)125
- C) 625
- D)1215

4- Which of the following techniques can help reduce variance in a model?

- A) Adding more features
- B) Using ensemble methods like bagging
- C) Decreasing the size of the training data
- D) Increasing the model complexity

5- In a regularized linear regression model, both Ridge (L2) and and Lasso (L1) regularization terms are applied. The regularization parameters are set as $\lambda\_2=0.5$ and $\lambda\_1=0.3$ for L1 regularization. Given the weight vector $w=[2, -1, 3]$, what is the total penalty added to the loss function by the regularization terms? (*Hint: Calculate the L2 penalty and the L1 penalty separately, then add them to get the total penalty*.)

- A)2.8
- B) 4.2
- C) 6
- D) 8.8

Solution 1

- ROC-AUC looks at how well the model separates the two classes overall; it considers both positives and negatives. So even if the model mostly predicts the majority class correctly, the ROC-AUC can still look high.
- Precision-Recall AUC, on the other hand, focuses only on the positive (minority) class. If the model struggles to detect the minority class, the Precision-Recall AUC will be low.
- The model seems “good” overall (ROC-AUC high) because it gets the majority class right, but it’s actually bad at finding the rare class, so the PR-AUC is low. So, the correct answer is that the model performs well on the majority class but poorly on the minority class (C).

Solution 2

- now that you've provided F1-score = 0.75, TP = 40, and FP = 10, we can solve for recall.
- Precision=TP/(FP+TP)=40/(10+40)=40/50=0.8

$$F1=2*\frac{Precision*Recall}{Precision+Recall} \rightarrow$$

$$0.75=2*\frac{0.8*Recall}{0.8+Recall} \rightarrow 0.6+(0.75*Recall)=1.6*Recall \rightarrow$$

Recall=0.6/0.85 $\approx$ 0.7059 when rounded to 2 decimal places: $\approx$ 0.71

Solution 3

- Given: 3 hyperparameters, each tested with 5 different values, using 5-fold cross-validation.
- Each combination of hyperparameter values forms one model configuration. So, total combinations = 5* 5*5 = 5^3 = 125
- For each of those 125 configurations, k-fold CV trains one model per fold, i.e. 5 models.
- So, total trained models = 125 combinations×5 folds= 625 models.

Solution 4

- Correct answer: B) Using ensemble methods like bagging
- Variance means the model changes too much when trained on different data; it overfits.

Bagging (Bootstrap Aggregating) trains many models on random subsets of the data and averages their results. This helps smooth out the noise and makes predictions more stable.

- Why not the other options:
- A) Adding more features → Can increase variance (model becomes more complex).
- C) Decreasing training data → Makes variance worse, not better.
- D) Increasing model complexity → Also increases variance (model overfits more).

Solution 5

- ➢ λ_2 (L2 penalty weight) = 0.5
- ➢ λ_1 (L1 penalty weight) = 0.3
- ➢ w = [2, -1, 3]

- Compute the L2 penalty:
  - $R(w) = \sum_{i=0}^{m} {w_i}^2$ =0.5×(2^2+(−1)^2+3^2) = 0.5×(4+1+9)=0.5×14=7
- Compute the L1 penalty
  - $R(w) = \sum_{i=0}^{m} |w_i|$ =0.3×(|2|+|−1|+|3|) = 0.3×(2+1+3)=0.3×6=1.8
- Total penalty=L2 penalty+L1 penalty $= 7 + 1.8 = 8.8$
- Final Answer: D