Ensembling
Graded Quiz • 12 min

Due Sep 23, 2:59 PM CST

Hyperparameter tuning
Tips and tricks
Advanced features II
Advanced features II programming assignment
Ensembling
- **Video:** Introduction into ensemble methods 6 min
- **Video:** Bagging 9 min
- **Video:** Boosting 16 min
- **Video:** Stacking 16 min
- **Video:** StackNet 14 min
- **Video:** Ensembling Tips and Tricks 14 min
- **Reading:** Validation schemes for 2-nd level models 10 min
- **Notebook:** Ensembling implementation notebook
- **Programming Assignment:** Ensembling implementation 3h
- **Practice Quiz:** Ensembling 4 questions
- **Quiz:** Ensembling 6 questions
- **Reading:** Comments on quiz 10 min
- **Reading:** Additional materials and links 10 min
- **Reading:** Final project advice #4 10 min

Catboost

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Ensembling

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Ensembling

TOTAL POINTS 9

1. Suppose we are given a train set and test set, that came from the same distribution. We want to use stacking and choose between the validation schemes described in the reading material.

2 points

Select the true statements about the validation schemes.

- [ ] Scheme **d)** is less efficient from computational perspective than scheme **a).** That is, if a dataset is very large, scheme **a)** is usually preferred over scheme **d).**
- [ ] Scheme **d)** is more efficient from computational perspective than scheme **a).** That is, if a dataset is very large, scheme **d)** is usually preferred over scheme **a).**
- [ ] Scheme **e)** gives the validation score with the least variance, if compared to schemes **a) -- d).**

2. Definition: we will call a validation scheme *fair* if the set, that we use to validate meta-models comes from the same distribution as the meta-test set. In other cases we will call validation scheme *leaky*. In other words in a *fair* validation scheme the set that we use to validate meta-models was not used in any way during training first level models.

2 points

Select *fair* validation schemes. The definition for the schemes can be found in the reading material.

- [ ] **b)** Meta holdout scheme with OOF meta-features
- [ ] **e)** KFold scheme with OOF meta-features
- [ ] **d)** Holdout scheme with OOF meta-features
- [ ] **c)** Meta KFold scheme with OOF meta-features
- [ ] **a)** Simple holdout scheme

3. Which of the following ensembling methods can potentially learn "conditional averaging" (video 1)?

1 point

- [ ] Boosting on trees
- [ ] Stacking
- [ ] Bagging
- [ ] Weighted average

4. The benefits of the weighted average compared to more advanced ensembling techniques is that

1 point

- [ ] It is less prone to overfitting
- [ ] It is faster to implement and to run
- [ ] It usually gives better quality

5. In general case, which set of base models is probably the best for stacking?

1 point

- ( ) [SVM, GBDT, Neural Network, kNN]
- ( ) [Random Forest, Extra Trees Classifier, GBDT, RGF]
- ( ) [kNN, SVM, Logistic Regression, Neural Net]
- ( ) [Logistic Regression, SVM, Random Forest, Extra Trees Classifier, GBDT]

6. Suppose we are given a classification task. In a simple two model linear mix we usually use weights α for the first model and β for the second one. The coefficients are usually chosen such that $\alpha + \beta = 1$, because convex combination of probability vectors is a probability vector.

2 points

Still, sometimes it is beneficial to tune α and $beta$ independently, e.g. mix with $\alpha = 0.1$ and $\beta = 0.8$ works best.

However, for some metrics it never makes sense to tune α and β independently. That is, searching for independent α and β will never give you better results than searching for weights, constrained to be $\beta = 1 - \alpha$. Select such metrics.

- [ ] Hinge loss
- [ ] Accuracy (implemented with argmax)
- [ ] AUC
- [ ] LogLoss

- [ ] I, **Hong-Yuan Lin**, understand that submitting work that isn't my own may result in permanent failure of this course or deactivation of my Coursera account.

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