

DS-210: Programming for Data Science

Lecture 12: Cross-validation. Hyperparameter tuning.









Midterm

- Date and time: Monday 2/28, 12:20–1:10pm
- Location: here (MCS B37)
- Open book
- No electronic devices











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Content:

- data analysis in Python
- general data analysis concepts
- Python features explained in class

Format:

- answer quiz questions
- explain simple concepts
- write simple code







Terminology

Parameters

- Variables fixed in a specific instantiation of a model
- Examples:
 - coefficients in linear regression
 - decision tree structure and thresholds
 - weights and thresholds in a neural network

Hyperparameters

• Also parameters, but higher level

• Examples:

- number of leafs in a decision tree
- number of layers and their structure in a neural network
- degree of a polynomial











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Hyperparameter tuning

 Adjusting hyperparameters before training the final model

Model selection

• Deciding on the type of model to be used (linear regression? decision trees? ...)











Challenges

Big goal: train a model that can be used for predicting

Intermediate goal: select the right model and hyperparameters













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How about trying various options and seeing how they perform on the test set?









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How about trying various options and seeing how they perform on the test set?



Information leak danger!

• If we do it adaptively, information from the test set could affect the model selection

Cross-validation attempts to solve this problem

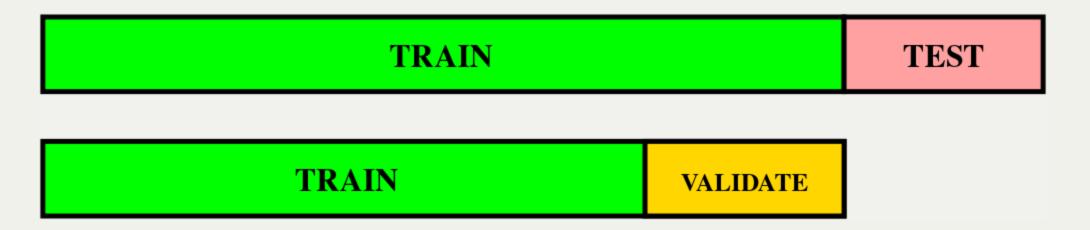






Holdout method

- Partition the training data again: training set and validation set
- Use the validation part to estimate accuracy whenever needed





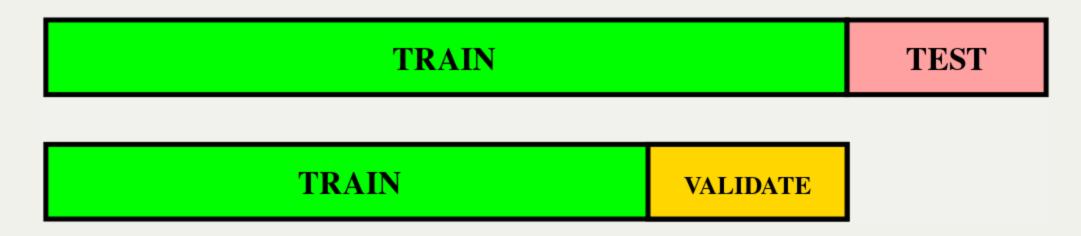






Holdout method

- Partition the training data again: training set and validation set
- Use the validation part to estimate accuracy whenever needed



Cons:

Pros:

- Very efficient
- Fine with lots of data when losing a fraction is not a problem

- Yet another part of data not used for training
- Problematic when the data set is small
- Testing part could contain important information











k-fold cross-validation

- Partition the training set into *k* folds at random
- Repeat *k* times:
 - train on k-1 folds
 - estimate the accuracy on the k-th fold
- Return the mean

VALIDATE	TRAIN	TRAIN	TRAIN	TRAIN
TRAIN	VALIDATE	TRAIN	TRAIN	TRAIN
TRAIN	TRAIN	VALIDATE	TRAIN	TRAIN
TRAIN	TRAIN	TRAIN	VALIDATE	TRAIN
TRAIN	TRAIN	TRAIN	TRAIN	VALIDATE



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TRAIN	TRAIN	TRAIN	VALIDATE	TRAIN
TRAIN	TRAIN	TRAIN	TRAIN	VALIDATE

Pros:

- Every data point used for training most of the time
- Less variance in the estimate

Cons:

• *k* times slower











LOOCV: Leave-one-out cross-validation

- Extreme case of the previous approach: separate fold for each data point
- For each data point *q*:
 - train on data without q
 - estimate the accuracy on q
- Return the mean of accuracies

Cons:

• Even more expensive









Many other options

- Generalization: leave–p–out cross–validation enumerates over $\binom{n}{p}$ subsets
- Sampling instead of trying all options
- A variation that ensures that all classes evenly distributed in folds

• ...

(scikit-learn docs are pretty good: https://scikit-learn.org/stable/modules/cross_validation.html)





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Hyperparameter searching

Many helpful tools:

https://scikit-learn.org/stable/modules/https://scikit-learn.org/stable/modules/https://scikit-learn.org/stable/modules/https://scikit-learn.org/stable/modules/https://scikit-learn.org/stable/modules/htt











Getting ready for the second part of the course

- Text editor
- Rust installation
- Terminal usage
- Version control: git (will be mentioned briefly next time)







