Introduction to Machine Learning

Lecture 5: Model Selection and Validation

Alexis Zubiolo

alexis.zubiolo@gmail.com

Data Science Team Lead @ Adcash

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Shameless advertisement: There will be a more advanced course starting in January 2017!

More info:

http://itstep.bg/news-bg/kurs-machine-learning-from-scratch/

Introduction

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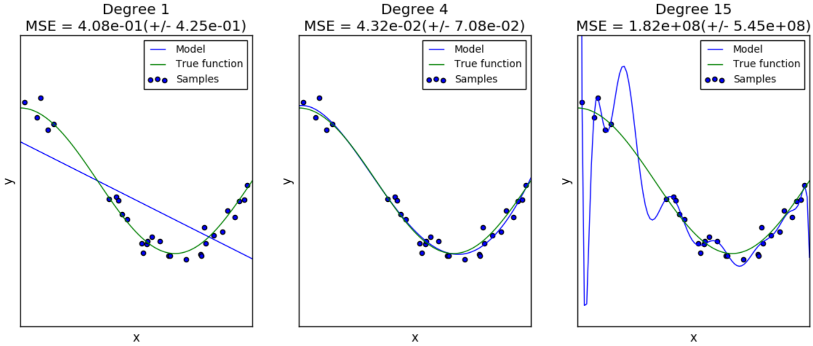
Recall from lecture 3:



Course outline:

- Evaluation metrics, what they mean
- How/when/why yo apply them

Evaluation metrics

Accuracy

Confusion matrix

Machine learning loss

0-1 loss:

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Log-loss:

Possibility to add a weight the loss!

Precision, recall

ROC curve

Applying evaluation metrics

Train-test split

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This is often referred to as **cross-validation**.

Cross-validation

Standard technique: k-fold cross-validation

- Split the data into k equally sized folds
- Remove 1 fold ($=$ test fold)
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Note: It is often advised to perform a **stratified** cross-validation, *i.e.* each fold contains approximately the **same percentage** of samples of each target class **as the complete set**.

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- **Remove 1 sample** from the data set
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- Test on the sample you've removed
- **Evaluate** the prediction
- Do it **for each sample of the data set**
- **Aggregate** the evaluations

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Alternative: Leave-p-out (LPO)

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Important note: Hyper-parameter ranges vary a lot from an application to another. It is **data-dependent**.

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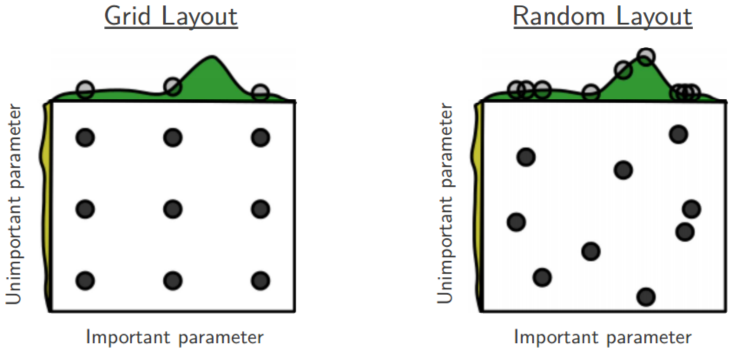

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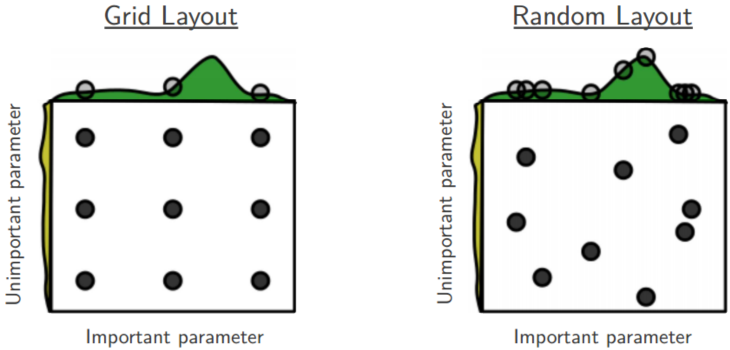

In any case, you need to know upper/lower bounds on the parameters

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Think about this before applying a **random algorithm** and evaluating it with a **random metric**!

Thank you! Questions?