Introduction to Machine Learning

Lecture 5: Model Selection and Validation

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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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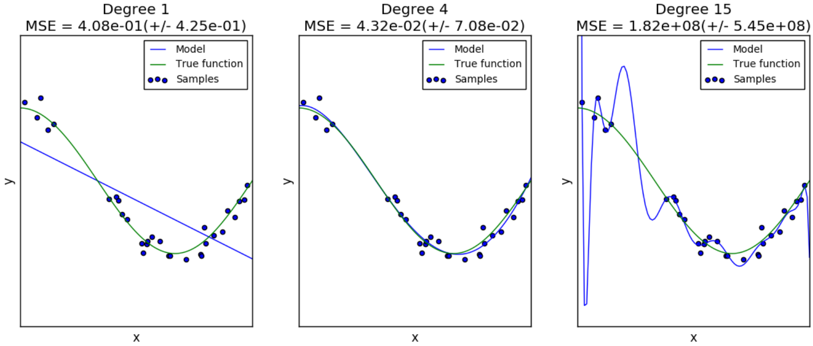
Recall from lecture 3:



Course outline:

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

Evaluation metrics

Applying evaluation metrics

Train-test split

Reminder: ML algorithms (classification/regression) often rely on **many parameters**. How to **tune** them properly given a dataset?

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The most commonly used principle is the train-test split:

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

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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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- Train on **all the other samples**
- Test on the sample you've removed
- **Evaluate** the prediction
- Do it **for each sample of the dataset**
- **Aggregate** the evaluations

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Remark: This could lead to many iterations even if the dataset is small.

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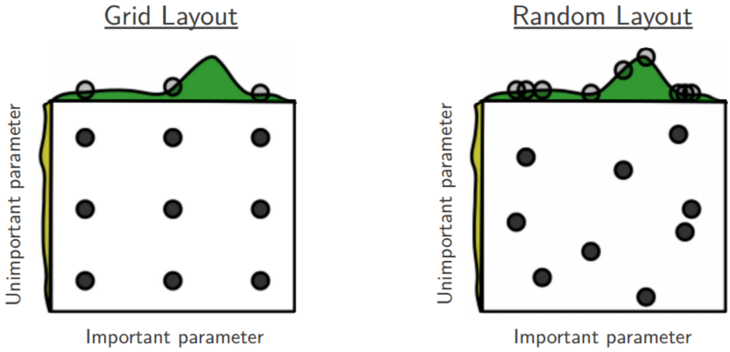

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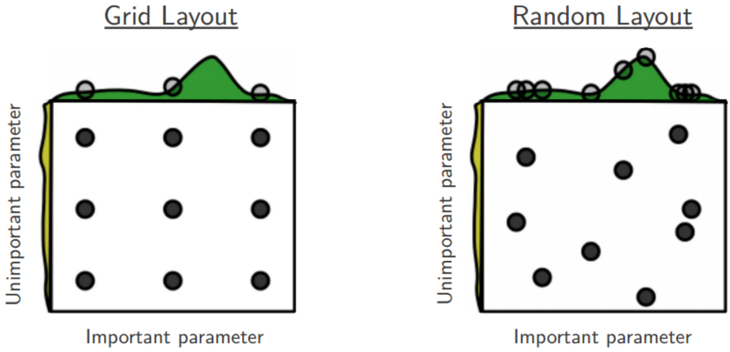

In any case, you need to know upper/lower bounds on the parameters

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

Thank you! Questions?