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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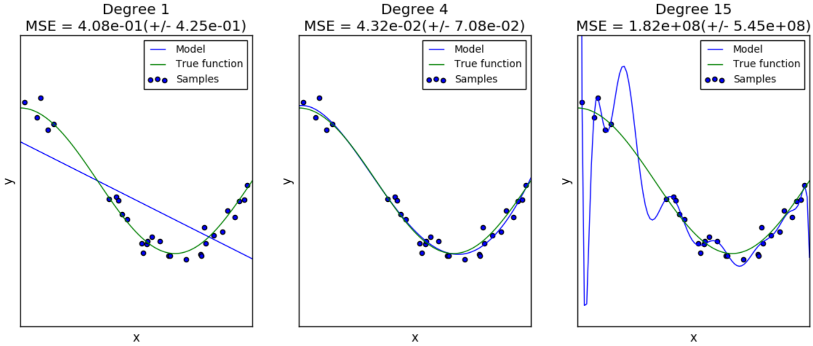
Recall from lecture 3:



Course outline:

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

Evaluation metrics

Accuracy

Accuracy is the most natural classification evaluation:

$$\text{accuracy} = \frac{\#\text{good classifications}}{\#\text{instances}}$$

However, it has many limitations:

- Misleading when classes are imbalanced
- ...

Confusion matrix

Confusion matrix sums up all the $(y, \hat{y})$ possibilities in a matrix.
Example for binary classification:

		Prediction	
		0	1
Actual	0	TN	FP
	1	FN	TP

Machine learning losses

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Possibility to add a weight to the loss!

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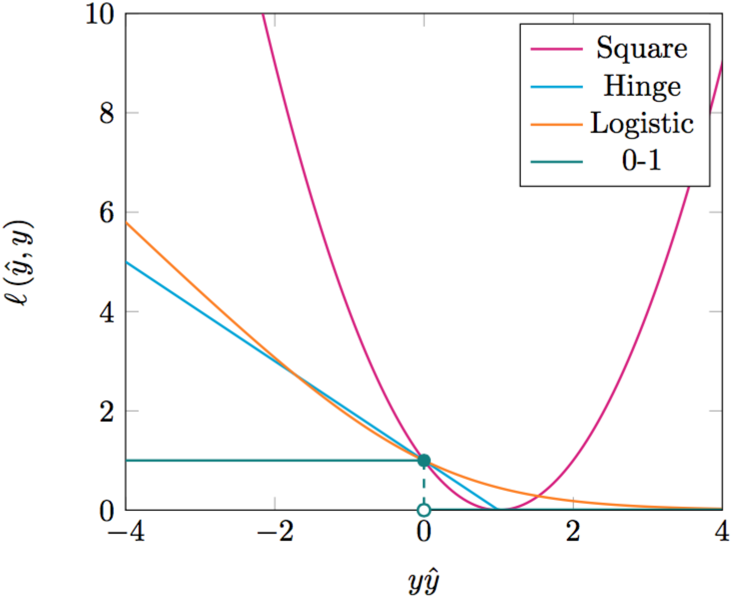

Precision, recall

ROC curve

Applying evaluation metrics

Train-test split

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

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Standard technique: k-fold 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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- Do it **for each sample of the data set**
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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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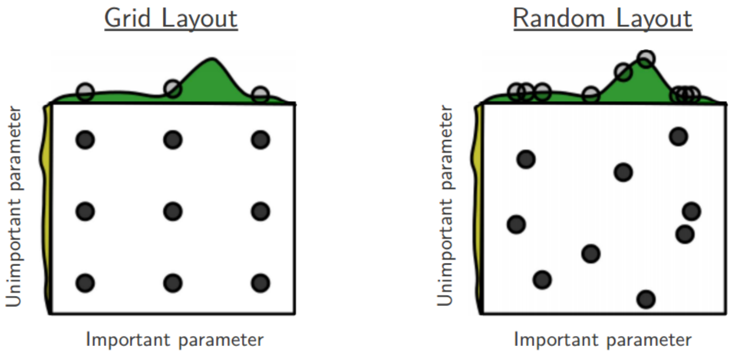

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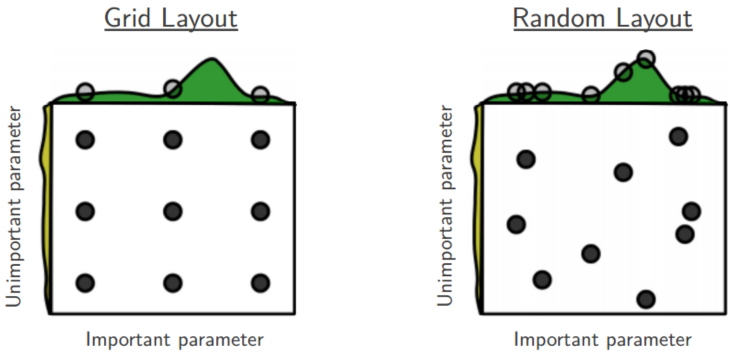

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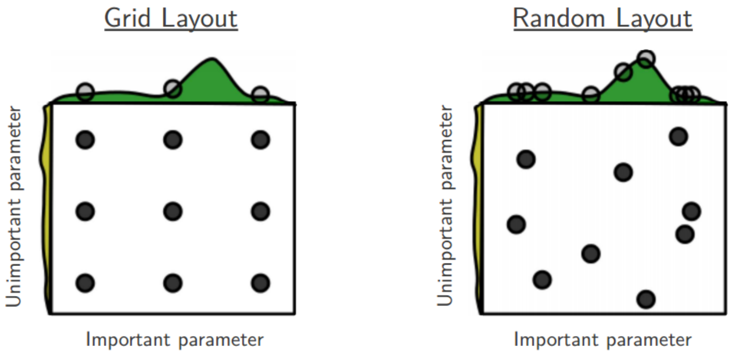

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Practical note: Each parameter combination can be trained/tested separately => possibility to distribute the tasks

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  - Proper metric & loss function choices
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Think about this before applying a **random algorithm** and evaluating it with a **random metric**!

Thank you! Questions?