

Model complexity.

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Hyperparameters selection

- Using CV we can select hyperparameters of the model¹
- Each model has hyperparameter, corresponding to model complexity.
- Model complexity - ability to reproduce training set.
- Examples:
 - regression: # of features d , e.g. $x, x^2, \dots x^d$
 - K-NN: number of neighbors K

¹can we use CV loss in this case as estimation for future losses?

Underfitted and overfitted models²

Too simple (underfitted) model

Model that oversimplifies true relationship $\mathcal{X} \rightarrow \mathcal{Y}$.

Too complex (overfitted) model

Model that is too tuned on particular peculiarities (noise) of the training set instead of the true relationship $\mathcal{X} \rightarrow \mathcal{Y}$.

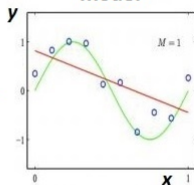
²In fact most models overfit, meaning that empirical risk < expected risk. Underfitted models just have lower difference than overfitted ones.

Examples of overfitted / underfitted models

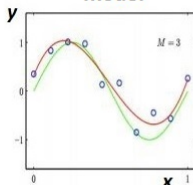
- true relationship
- estimated relationship with polynimes of order M
- objects of the training sample

regression:

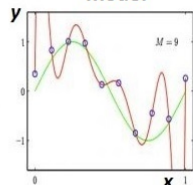
too simple model



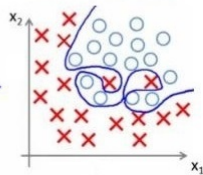
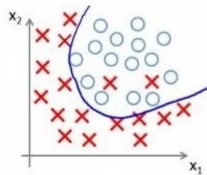
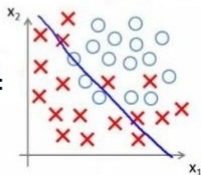
relevant model



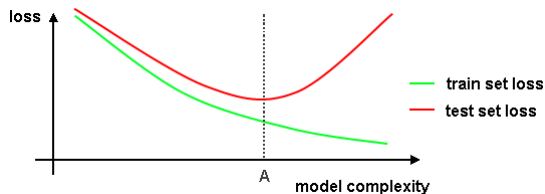
too complex model



classification:



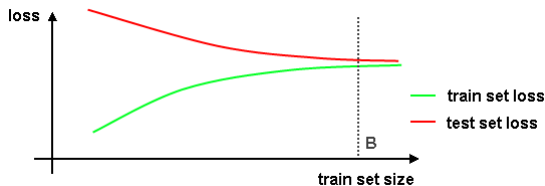
Loss vs. model complexity



Comments:

- expected loss on test set is always higher than on train set.
- left to A: model too simple, underfitting, high bias
- right to A: model too complex, overfitting, high variance

Loss vs. train set size



Comments:

- expected loss on test set is always higher than on train set.
- right to B there is no need to further increase training set size
 - useful to limit training set size when model fitting is time consuming