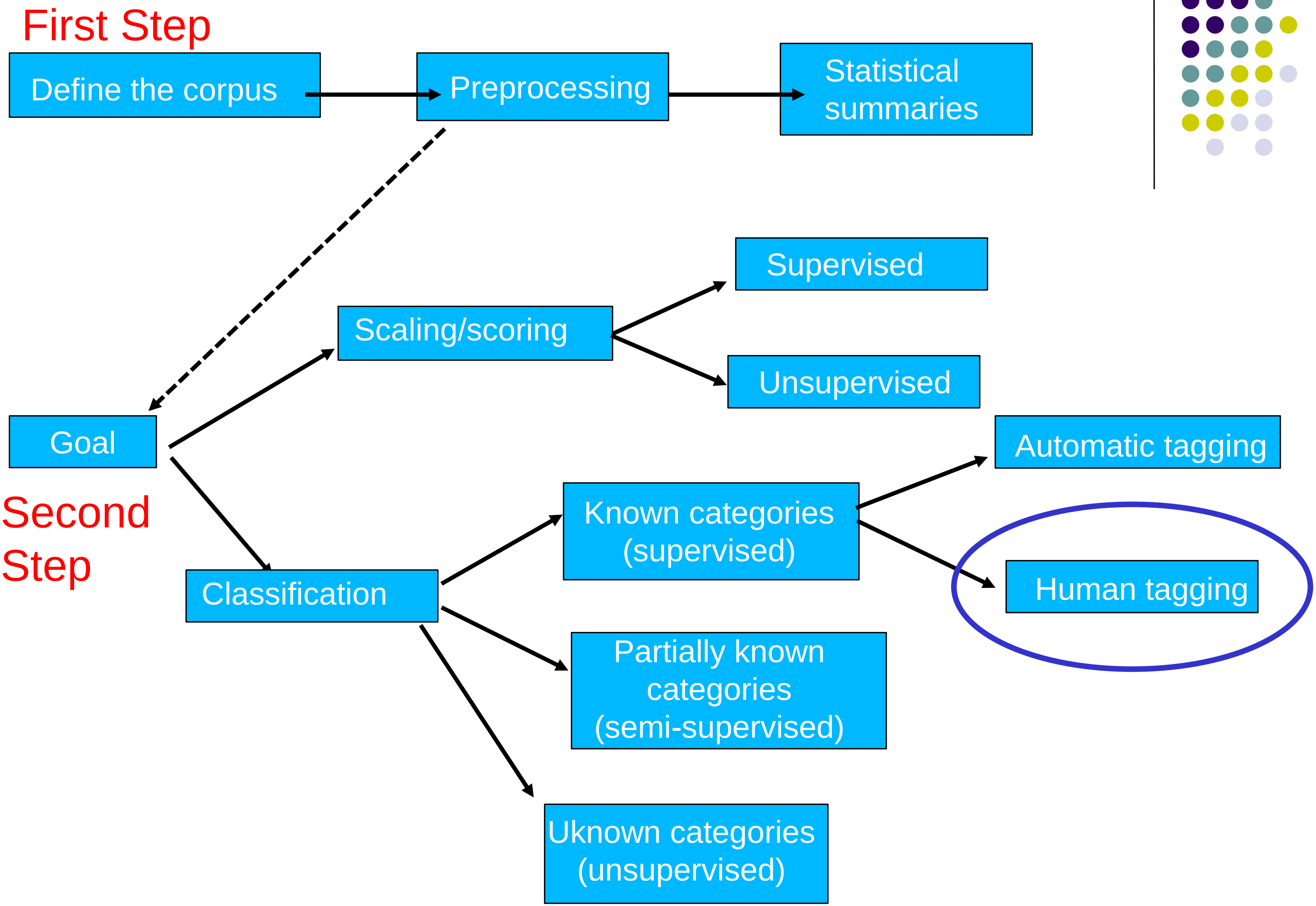
Big Data Analytics

Lecture 3/B

Supervised classification methods: an introduction

UNIVERSITÄT LUZERN



First Step

Define the corpus

Preprocessing

Statistical summaries

Goal

Second Step

Scaling/scoring

Supervised

Unsupervised

Classification

Known categories (supervised)

Automatic tagging

Human tagging

Partially known categories (semi-supervised)

Uknown categories (unsupervised)

References

- ✓ Grimmer, Justin, and Stewart, Brandon M. (2013). Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts. *Political Analysis*, 21(3): 267-297
- ✓ Curini, Luigi, and Robert Fahey (2020). Sentiment Analysis and Social Media. In Luigi Curini and Robert Franzese (eds.), *SAGE Handbook of Research Methods is Political Science & International Relations*, London, Sage, chapter 29
- ✓ Barberá, Pablo et al. (2020) Automated Text Classification of News Articles: A Practical Guide, *Political Analysis*, DOI: 10.1017/pan.2020.8

Supervised Learning (classification) Methods

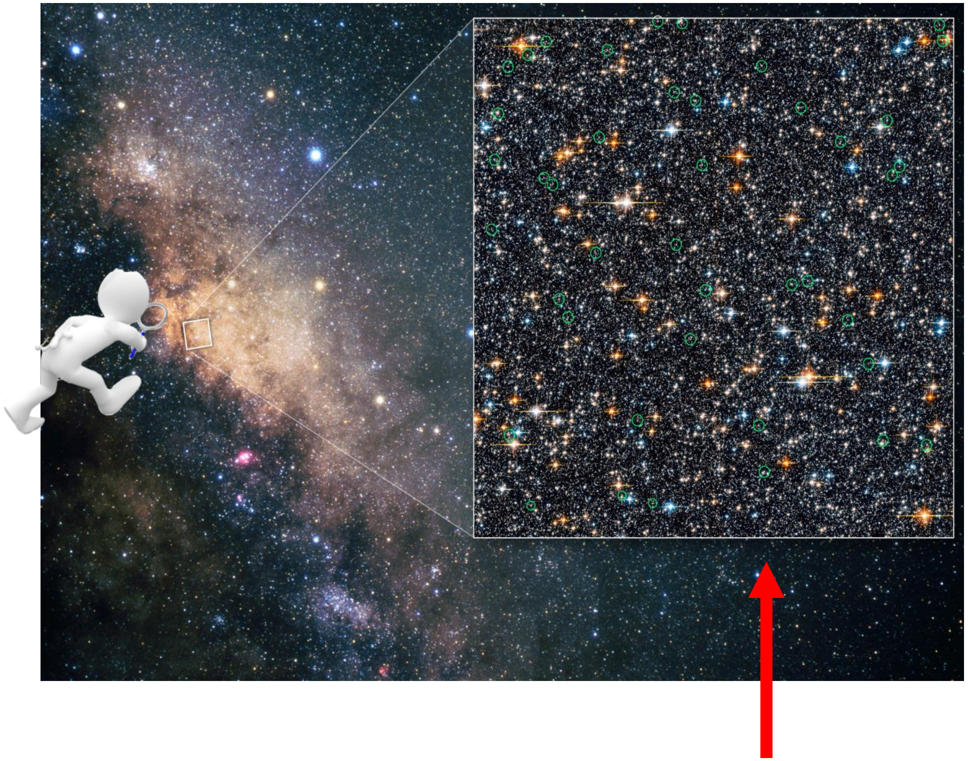
The idea of supervised learning is simple: human coders categorize a set of documents (the “**training-set**” or “**labelled-set**”) by hand into a set of pre-defined categories (such as positive, negative, neutral for example)

The algorithm “learns” how to sort the documents into categories using the **training set and words**

Then, it classifies the remaining set of document not classified by hand (the **“test-set”** or **“unlabelled set”**) using the characteristics (i.e., words) of the unread documents to place them into the categories

A four-step procedure

1. Data preparation: separating the training set from the test set in the corpus



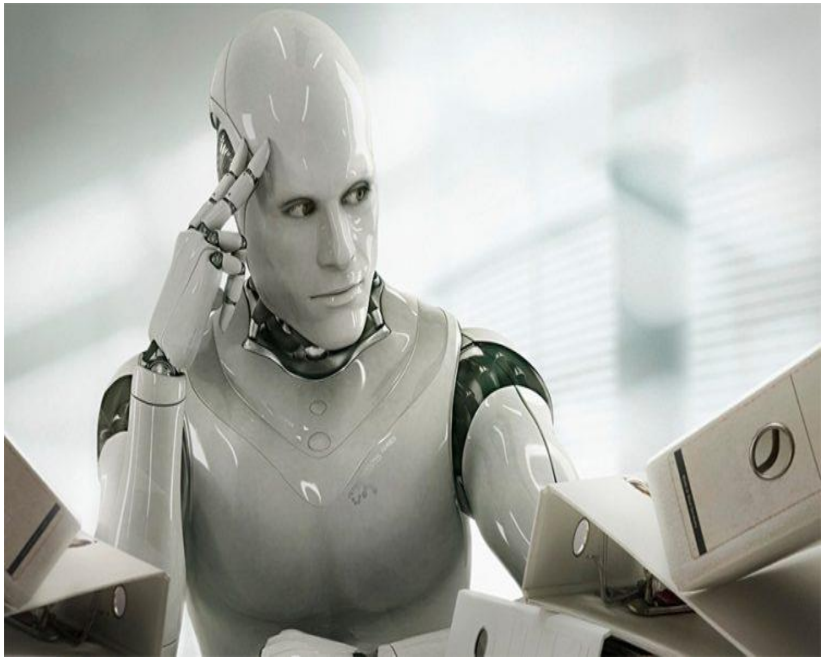
the training set

2. Human classification
of the training set on a base of a list of pre-defined categories

A four-steps procedure

3. Cogito ergo sum! The algorithm learns from the human classification done in the training set

4. Let's classify! The well-educated algorithm is now ready to classify all the texts in the test-set



The algorithms that we will employ belong to the Machine Learning class

Machine learning

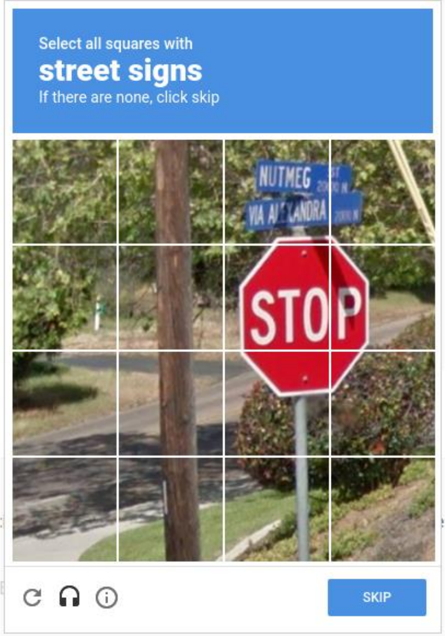
Machine learning is defined as the “field of study that gives computers the ability to learn without being explicitly programmed” (Samuel 1959)

In this context “learning” can be viewed as the use of statistical techniques to enable computer systems to progressively improve their performance on a specific task from data without being explicitly programmed (Goldberg and Holland 1988)

Machine learning

To be able to learn how to perform a task and become better at it, a machine should…

- ✓ …be provided with a set of example information (inputs) and the desired outputs. The goal is then to learn a general rule that can take us from the inputs to the outputs



Select all squares with

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Machine learning

In our case, our aim is to do *text classification*

Therefore, **machine learning algorithms** (when dealing with text classification methods) refer to those techniques that learn how to map a set of inputs (e.g., features within documents) to a predicted class as the output in a pre-coded *training set (via human intervention)* before classifying the data in the *test set*

Supervised Learning (classification) Methods

Despite the fact that the methods to do supervised classification are diverse, they share a **common structure** that usefully unifies the methods

Suppose there are N_{train} documents (i=1,…, N_{train}) in our training set and that we have pre-defined K categories (k=1,…,K) for our classification, such as positive, negative, neutral in the case of a sentiment analysis

Each document *i*'s category is then represented by $Y_i \in (C_1, \ldots, C_K)$ and the entire training-set is represented as $\mathbf{Y}_{train}=(Y_1,\ldots,Y_{Ntrain})$

$\mathbf{W}_{train}$ is the term-document matrix for N_{train}

Supervised Learning (classification) Methods

Each supervised learning algorithm assumes that there is some (unobserved) function that describes the (true) relationship between the words and the labels in the training-set:

$$\boldsymbol{Y}_{train} = \mathrm{f}(\boldsymbol{W}_{train})$$

Each algorithm attempts to learn this relationship by estimating the "true" function *f* with $\hat{f}$ (the **classification function**)

$\hat{f}$ is then used to infer properties of the test set (the unlabeled set), $\widehat{\boldsymbol{Y}_{test}}$ using the test set's words $\boldsymbol{W}_{test}$:

$$\widehat{\boldsymbol{Y}_{test}} = \hat{f}(\boldsymbol{W}_{test})$$

Supervised Learning (classification) Methods

Summing up…

All supervised learning models **share the same goal**: learn the potentially complicated relationships that relate (combinations of) features *x* to the outcome of interest *y* in general, using information available in the set of observations for which the pair (*x; y*) is fully observed (i.e., in the training-set)

Supervised Learning (classification) Methods

From this point of view, the *Wordscores* approach to supervised scaling can be compared also to supervised ML

You have a training-set (reference texts) that have been labelled (on a continuous scale)

You have an algorithm that learns from such training-set the relationship between features and the reference scores

You have then a test-set (virgin texts) whose scores will be predicted by the now “trained” algorithm

Supervised Learning vs. Dictionary methods

Supervised learning can be conceptualized as a **generalization of dictionary methods**, where features associated with each categories (and their relative weight) are learned from the data **via human intervention**

The feature space is thus likely to be both larger and more comprehensive than that used in a dictionary

Moreover, the weight of each single feature is not defined ex-ante (as when applying a dictionary), but it is discovered ex-post according to the corpus

The end result is that much more information drives the subsequent classification of text

Supervised Learning vs. Dictionary methods

Moreover, compared to dictionary methods:

Supervised learning is **necessarily domain specific** and therefore avoids the problems of applying dictionaries outside of their intended area of use

Second, human involvement is crucial to understand the correct meaning of a text (double meaning sentences, specific jargons, neologisms, irony)

Finally, supervised learning methods are much easier to validate, with clear statistics that summarize model performance (as we will discuss)

Supervised Learning vs. Dictionary methods

Summing up:

Dictionaries:

- ✓ Can be off the-shelf
- ✓ no creation of a training dataset required
- ✓ easy to apply to a given corpus
- ✓ built by humans who can bring domain expertise to bear, that is, dictionaries bring rich prior information to the classification task: humans may produce a **topic-specific dictionary** that would require a large training dataset to outperform it

Supervised Learning vs. Dictionary methods

Summing up:

Supervised machine learning:

✓ optimized for current research question

✓ more comprehensive set of features used to classify text

✓ mathematically, ML necessarily outperforms dictionary methods given a large enough training dataset

✓ by construction, the analyst knows the performance of the classifier based on multiple measures of fit (i.e, how closely the labels generated correspond to human coding)

Beware of overfitting!

We have just discussed how **machine learning algorithms** (when dealing with text classification methods) refer to those techniques that learn how to map a set of inputs (e.g., features within documents) to a predicted class as the output in a pre-coded *training set* before classifying the data in the *test set*

Beware of overfitting!

However…it is typically **easy** to learn even complicated relationships *in-sample* that is, relationships that are conditional on the training set

But our goal is to learn relationships for which the **expected generalization error** (i.e. the error that can be expected to ensue when learned relationships are evaluated *out-of-sample*, on a test set of observations not involved in the learning process) is low

Beware of overfitting!

In fact, while it is always possible to arbitrarily reduce training error (i.e. error as computed using the training sample) by making models arbitrarily complex…

…such **complexity** typically results in high expected generalization error, as models start to overt their training data (i.e. they start to pick up on idiosyncratic relationships that conditional on the set of observations used to train the models)…

…that is, a supervised learning algorithm begins to **overfit the data**!

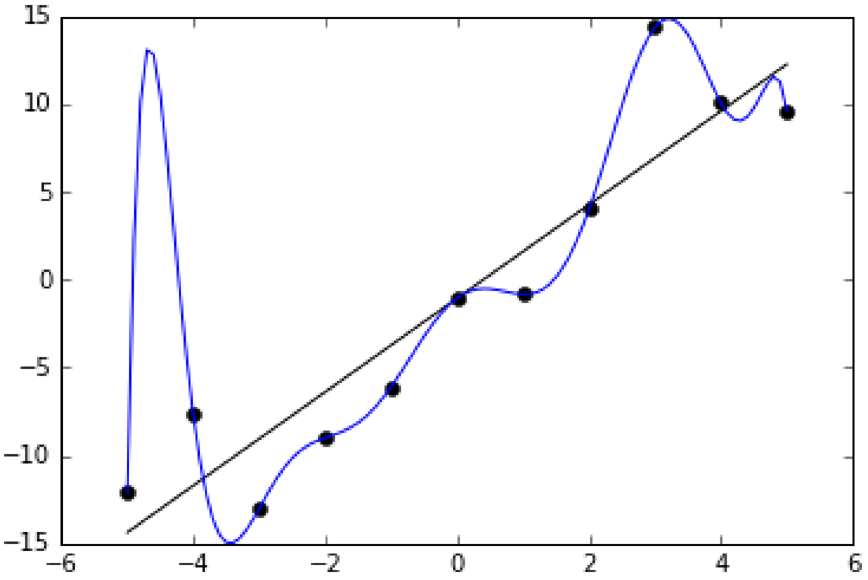
Beware of overfitting!

Overfitting is the production of an analysis that corresponds too closely to a particular set of (training) data, and may therefore **fails** to fit additional data or predict future observations (i.e., the test set) reliably

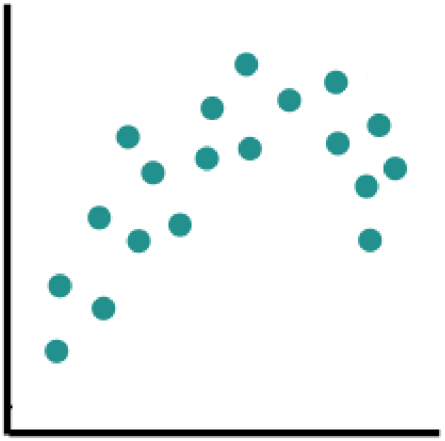
Overfitting usually arises when a *very complicated model* faithfully reflects aspects of the design data to the extent that idiosyncrasies of that data, rather than merely of the distribution from which the data arose, are included in the model

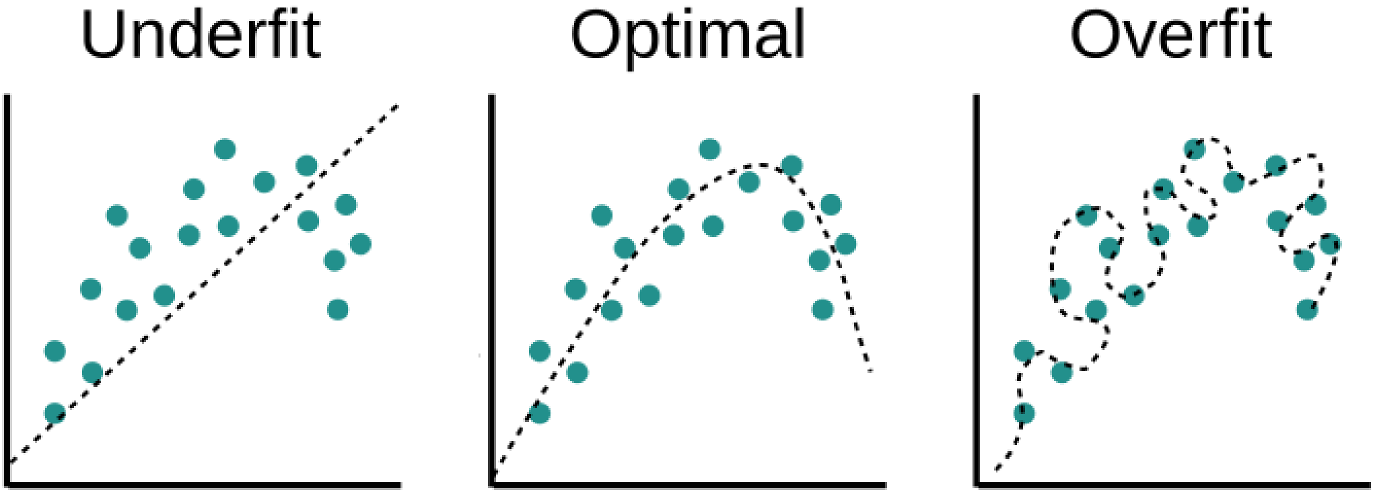
Beware of overfitting!

Although the polynomial function (the blue line) is a perfect fit, the linear function can be expected to generalize better beyond the fitted data!



Beware of overfitting!



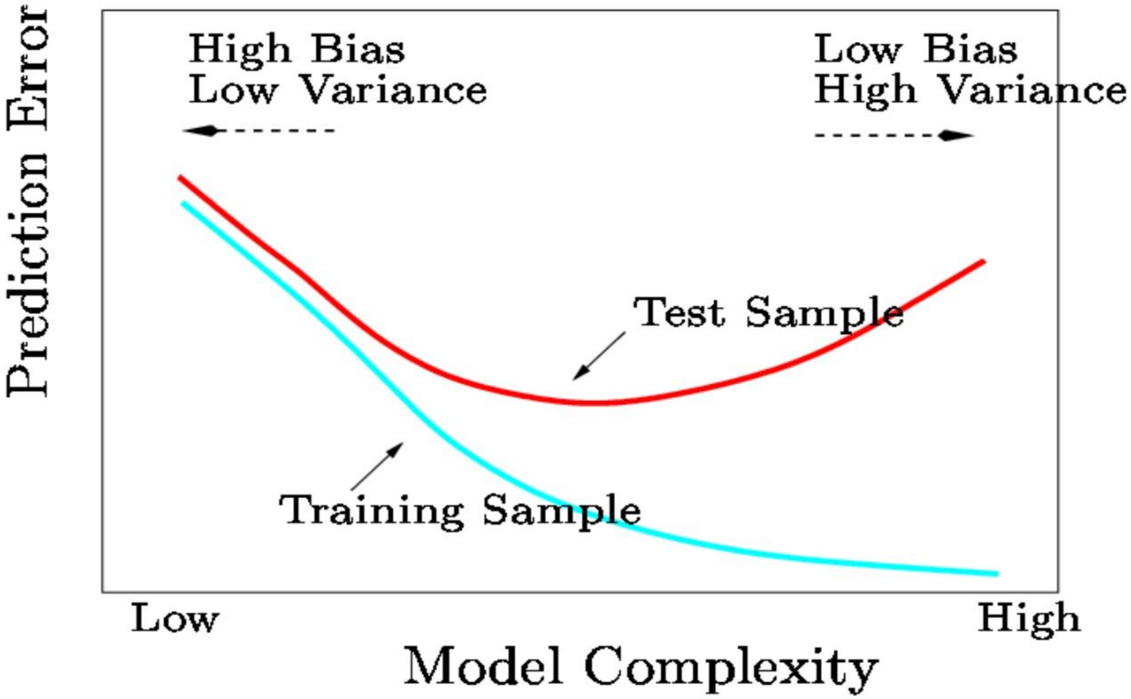


Underfit

Optimal

Overfit

Beware of overfitting!



- ✓ Model is too complex, describes noise rather than signal (**Bias-Variance trade-off**)
- ✓ Focus on features that perform well in training-set data but may not generalize
- ✓ In-sample performance better than out-of-sample performance