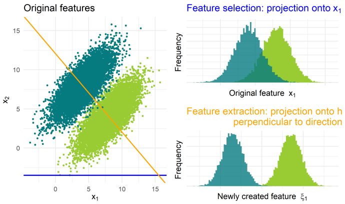
Introduction to Machine Learning

Feature Selection

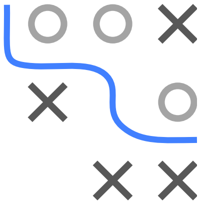
Feature Selection: Introduction



Learning goals

- Too many features can be harmful in prediction
- Selection vs. extraction
- Types of selection methods

INTRODUCTION



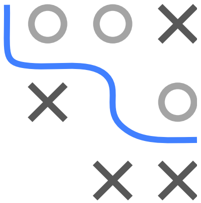
Feature selection:
Finding a well-performing, hopefully small set of features for a task.

Feature selection is critical for

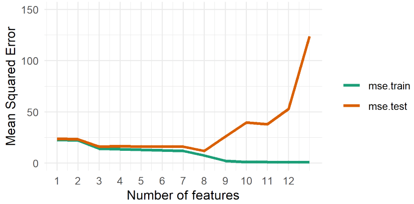
- reducing noise and overfitting
- improving performance/generalization
- enhancing interpretability by identifying most informative features

Features can be selected based on domain knowledge, or data-driven algorithmic approaches. We focus on the latter here.

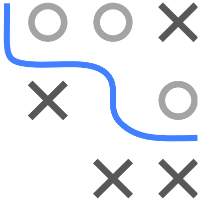
MOTIVATION



- Naive view:
  - More features $\rightarrow$ more information $\rightarrow$ discriminant power $\uparrow$
  - Model is not harmed by irrelevant features since their parameters can simply be estimated as 0.
- In practice, irrelevant and redundant features can "confuse" learners (see **curse of dimensionality**) and worsen performance.
- Example: In linear regression, R^2 is monotonically increasing in p, but adding irrelevant features leads to overfitting (capturing noise).



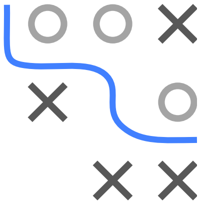
SIZE OF DATASETS



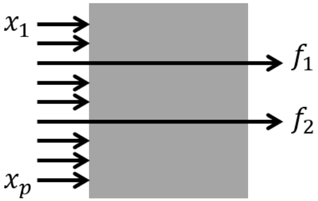
Many new forms of technical measurements and connected data leads to availability of extremely high-dimensional data sets.

- **Classical setting**: Up to around 10^2 features, feature selection might be relevant, but benefits often negligible.
- **Datasets of medium to high dimensionality**: At around 10^2 to 10^3 features, classical approaches can still work well, while principled feature selection helps in many cases.
- **High-dimensional data**: 10^3 to 10^9 or more features. Examples: micro-array / gene expression data and text categorization (bag-of-words features). If we also have few observations, scenario is called $p \gg n$.

FEATURE SELECTION VS. EXTRACTION

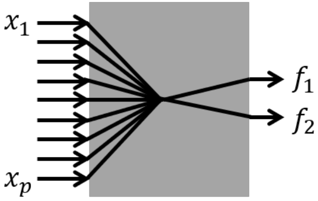


Feature selection



- Creates a subset of original features **x** by selecting $\tilde{p} < p$ features ***f***.
- Retains information on selected individual features.

Feature extraction



- Maps p features in **x** to $\tilde{p}$ extracted features ***f***.
- Info on individual features can be lost through (non-)linear combination.

TYPES OF FEATURE SELECTION METHODS

In rest of the chapter, we introduce different types of methods for FS:

- Filters: evaluate relevance of features using statistical properties such as correlation with target variable
- Wrappers: use a model to evaluate subsets of features
- Embedded methods: integrate FS directly into specific model - we look at them in their dedicated chapters (e.g., CART, L_0, L_1)

Example: embedded method (Lasso) regularizing model params with $L1$ penalty enables “automatic" feature selection:

$$\mathcal{R}_{\text{reg}}(\boldsymbol{\theta}) = \mathcal{R}_{\text{emp}}(\boldsymbol{\theta}) + \lambda \|\boldsymbol{\theta}\|_1 = \sum_{i=1}^{n} \left(y^{(i)} - \boldsymbol{\theta}^\top \mathbf{x}^{(i)}\right)^2 + \lambda \sum_{j=1}^{p} |\theta_j|$$