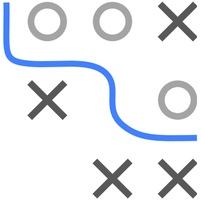
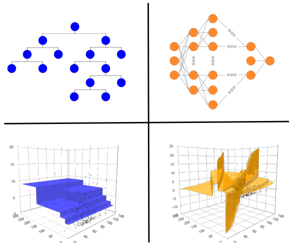
Important Learning Algorithms in ML

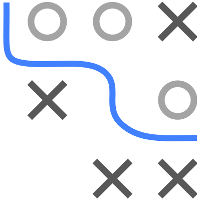




Learning goals

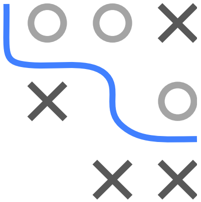
- General idea of important ML algorithms
- Overview of strengths and weaknesses

CONTENTS



K-NN – METHOD SUMMARY

REGRESSION CLASSIFICATION NONPARAMETRIC WHITE-BOX



General idea

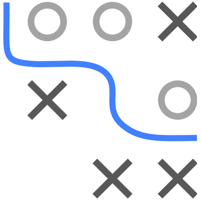
- **similarity** in feature space (w.r.t. certain **distance metric** $d(\mathbf{x}^{(i)}, \mathbf{x})$) $\rightsquigarrow$ similarity in target space
- **Prediction** for $\mathbf{x}$: construct k**-neighborhood** $N_k(\mathbf{x})$ from k points closest to $\mathbf{x}$ in $\mathcal{X}$, then predict
  - (weighted) mean target for **regression**: $\hat{y} = \frac{1}{\sum\limits_{i:\mathbf{x}^{(i)} \in N_k(\mathbf{x})} w_i} \sum\limits_{i:\mathbf{x}^{(i)} \in N_k(\mathbf{x})} w_i y^{(i)}$

    with $w_i = \frac{1}{d(\mathbf{x}^{(i)}, \mathbf{x})}$

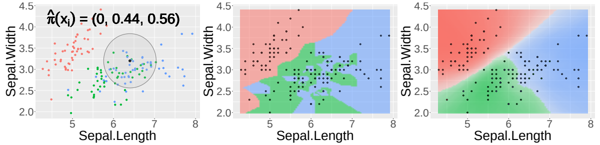
    $\rightarrow$ optional: higher weights w_i for close neighbors
  - most frequent class for **classification**: $\hat{y} = \underset{\ell \in \{1, \ldots, g\}}{\arg\max} \sum\limits_{i:\mathbf{x}^{(i)} \in N_k(\mathbf{x})} \mathbb{I}(y^{(i)} = \ell)$

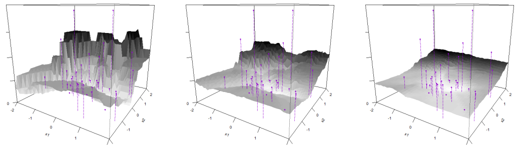
    $\Rightarrow$ Estimating posterior probabilities as $\hat{\pi}_\ell(\mathbf{x}^{(i)}) = \frac{1}{k} \sum\limits_{i:\mathbf{x}^{(i)} \in N_k(\mathbf{x})} \mathbb{I}(y^{(i)} = \ell)$
- **Nonparametric** behavior: no compression of information
- Not immediately interpretable

K-NN – METHOD SUMMARY



Hyperparameters Neighborhood **size** *k* (locality), **distance** metric (next page)



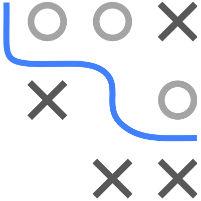


Classification
Left: Neighborhood for exemplary observation in `iris`, $k = 50$
Middle: Prediction surface for $k = 1$
Right: Prediction surface for $k = 50$

Regression
Left: Prediction surface for $k = 3$
Middle: Prediction surface for $k = 7$
Right: Prediction surface for $k = 15$

- Small $k \Rightarrow$ very local, "wiggly" decision boundaries
- Large $k \Rightarrow$ rather global, smooth decision boundaries

K-NN – METHOD SUMMARY

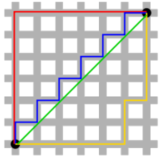


Popular distance metrics

- Numerical feature space: Typically, **Minkowski** distances

$$d(\mathbf{x},\tilde{\mathbf{x}}) = \|\mathbf{x}-\tilde{\mathbf{x}}\|_q = \left(\sum_j |x_j - \tilde{x}_j|^q\right)^{\frac{1}{q}}$$

  - $q = 1$: **Manhattan** distance
    $\rightarrow d(\mathbf{x},\tilde{\mathbf{x}}) = \sum_j |x_j - \tilde{x}_j|$
  - $q = 2$: **Euclidean** distance
    $\rightarrow d(\mathbf{x},\tilde{\mathbf{x}}) = \sqrt{\sum_j (x_j - \tilde{x}_j)^2}$

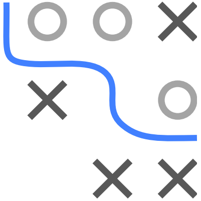


Manhattan vs. Euclidean (green)

https://es.m.wikipedia.org/wiki/Archivo:Manhattan_distance.svg

- Mixed feature space:
  - **Gower distance** for numerical, categorical and missing data:
    - numerical: $d(x_i, x_j) = \dfrac{|x_i - x_j|}{\max(x) - \min(x)}$
    - categorical: $d(x_i, x_j) = \begin{cases} 1, \text{if } x_i \neq x_j \\ 0, \text{if } x_i = x_j \end{cases}$
    - Gower distance as average over individual scores
- Optional **weighting** for beliefs about varying feature importance

K-NN – IMPLEMENTATION & PRACTICAL HINTS

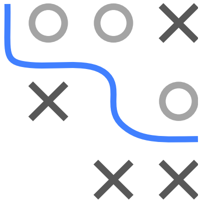


Preprocessing Features should be standardized or normalized

Implementation

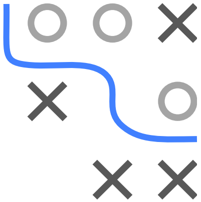
- **R:** `mlr3` learners (calling `kknn::kknn()`)
  - **Classification:**
    - `LearnerClassifKKNN`
    - `fnn::knn()`
  - **Regression:**
    - `LearnerRegrKKNN`
    - `fnn::knn.reg()`
  - Nearest Neighbour Search in $\mathcal{O}(N \log N)$: `RANN::nn2()`

K-NN – IMPLEMENTATION & PRACTICAL HINTS



- **Python:** From package `sklearn.neighbors`
  - **Classification:**
    - `KNeighborsClassifier()`
    - `RadiusNeighborsClassifier()` as alternative if data not uniformly sampled
  - **Regression:**
    - `KNeighborsRegressor()`
    - `RadiusNeighborsRegressor()` as alternative if data not uniformly sampled

K-NN – PROS & CONS



Advantages

+ Algorithm **easy** to explain and implement
+ No distributional or functional **assumptions**
  $\rightarrow$ able to model data of **arbitrary complexity**
+ No **training** or **optimization** required
+ **local model** $\rightarrow$ **nonlinear** decision boundaries
+ Easy to **tune** (few hyperparameters)
  $\rightarrow$ number of neighbors k, distance metric
+ **Custom** distance metrics can often be easily designed to incorporate domain knowledge

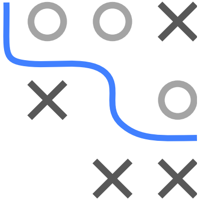
Disadvantages

– Sensitivity w.r.t. **noisy** or **irrelevant** features and outliers due to dependency on distance measure
– Heavily affected by **curse of dimensionality**
– Bad performance when feature **scales** are not consistent with feature relevance
– Poor handling of data **imbalances** (worse for more global model, i.e., large k)

GENERALIZED LINEAR MODELS – METHOD SUMMARY

REGRESSION CLASSIFICATION PARAMETRIC WHITE-BOX

FEATURE SELECTION

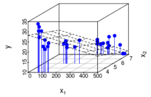


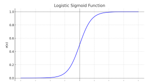
General idea Represent target as function of linear predictor $\boldsymbol{\theta}^\top \mathbf{x}$ (weighted sum of features)

$\rightarrow$ **Interpretation:** if feature x_j increases by 1 unit, the linear predictor changes by θ_j units

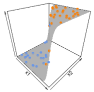
Hypothesis space $\mathcal{H} = \left\{f : \mathcal{X} \rightarrow \mathbb{R} \mid f(\mathbf{x}) = \phi(\boldsymbol{\theta}^\top \mathbf{x})\right\}$, with suitable transformation $\phi(\cdot)$, e.g.,

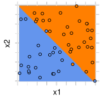
- **Linear Regression**: $\mathcal{Y} = \mathbb{R}$, ϕ identity
- **Logistic Regression**: $\mathcal{Y} = \{0, 1\}$, logistic sigmoid $\phi(\boldsymbol{\theta}^\top \mathbf{x}) = \frac{1}{1+\exp(-\boldsymbol{\theta}^\top \mathbf{x})} =: \pi(\mathbf{x} \mid \boldsymbol{\theta})$
  $\Rightarrow$ Decision rule: Linear hyperplane


Linear regression hyperplane



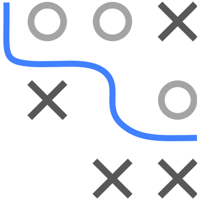
Logistic sigmoid function


Logistic function for bivariate input and loss-minimal $\boldsymbol{\theta}$



Corresponding separating hyperplane

GENERALIZED LINEAR MODELS – REGULARIZATION



General idea

- Unregularized LM: risk of **overfitting** in high-dimensional space with only few observations
- **Goal**: avoidance of overfitting by adding **penalty term**

Regularized empirical risk

- Empirical risk function **plus complexity penalty** $J(\boldsymbol{\theta})$, controlled by shrinkage parameter $\lambda > 0$:
  $\mathcal{R}_{\text{reg}}(\boldsymbol{\theta}) := \mathcal{R}_{\text{emp}}(\boldsymbol{\theta}) + \lambda \cdot J(\boldsymbol{\theta})$
- **Ridge** regression: L2 penalty
  $J(\boldsymbol{\theta}) = \|\boldsymbol{\theta}\|_2^2$
- **LASSO** regression: L1 penalty
  $J(\boldsymbol{\theta}) = \|\boldsymbol{\theta}\|_1$

Optimization under regularization

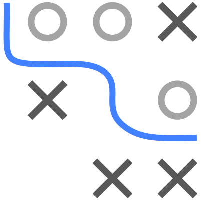
- **Ridge**: analytically with $\hat{\boldsymbol{\theta}}_{\text{Ridge}} = (\mathbf{X}^\top \mathbf{X} + \lambda \boldsymbol{I})^{-1} \mathbf{X}^\top \mathbf{y}$
- **LASSO**: numerically with, e.g., (sub-)gradient descent

GENERALIZED LINEAR MODELS – IMPLEMENTATION

Implementation

- **R:**
  - **Unregularized:** `mlr3` learner `LearnerRegrLM`, calling `stats::lm()` / `mlr3` learner `LearnerClassifLogReg`, calling `stats::glm()`
  - **Regularized / ElasticNet:** `mlr3` learners `LearnerClassifGlmnet` / `LearnerRegrGlmnet`, calling `glmnet::glmnet()`
  - For **large classification** data: `mlr3` learner `LearnerClassifLiblineaR`, calling `LiblineaR::LiblineaR()` uses fast coordinate descent
- **Python:** From package `sklearn.linear_model`
  - **Unregularized:**
    - `LinearRegression()`
    - `LogisticRegression(penalty = None)`
  - **Regularized:**
    - *Linear regression:* `Lasso()`,`Ridge()`,`ElasticNet()`
    - *Logistic regression:* `LogisticRegression(penalty =`

GENERALIZED LINEAR MODELS – PROS & CONS



Advantages

+ **Simple and fast** implementation
+ **Analytical** solution for L2 loss
+ Applicable for any **dataset size**, as long as number of observations $\gg$ number of features
+ Flexibility **beyond linearity** with polynomials, trigonometric transformations, interaction terms etc.
+ Intuitive **interpretability** via feature effects
+ Statistical hypothesis **tests** for effects available

Disadvantages

– **Nonlinearity** of many real-world problems
– Further restrictive **assumptions**: linearly independent features, homoskedastic residuals, normality of conditional response
– **Sensitivity** w.r.t. outliers and noisy data (especially with L2 loss)
– Also a LM can **overfit** (e.g., many features and few observations)
– Feature **interactions** must be handcrafted
$\rightarrow$ practically infeasible for

GENERALIZED ADDITIVE MODELS – METHOD SUMMARY

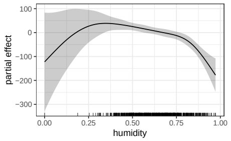
REGRESSION CLASSIFICATION (NON)PARAMETRIC WHITE-BOX FEATURE SELECTION

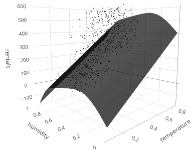
General idea

- Same as GLM, but introduce **flexibility** through **nonlinear (smooth)** effects $f_j(x_j)$
- Typically, combination of linear & smooth effects
- Smooth effects also conceivable for feature interactions

Hypothesis space $$\mathcal{H} = \left\{ f : \mathcal{X} \to \mathbb{R} \mid f(\mathbf{x}) = \phi\left(\theta_0 + \sum_{j=1}^{p} f_j(x_j)\right)\right\},$$

with suitable transformation $\phi(\cdot)$, intercept term θ_0, and smooth functions $f_j(\cdot)$





Prediction of bike_rentals from smooth term of humidity (left: partial effect) and linear term of temperature (right: bivariate

GENERALIZED ADDITIVE MODELS – IMPLEMENTATION

Implementation

- **R:** `mlr3` learner `LearnerRegrGam`, calling `mgcv::gam()`
  - Smooth terms: `s(..., bs="<basis>")` or `te(...)` for multivariate (tensorproduct) effects
  - Link functions: `family={Gamma, Binomial, ...}`
- **Python**: `GLMGam` from package `statsmodels`; package `pygam`

Advantages

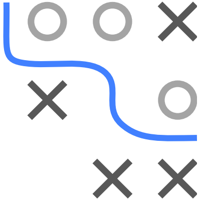
+ **Simple and fast**
+ Applicable for any **dataset size**, as long as number of observations $\gg$ number of features
+ High **flexibility** via smooth effects
+ Easy to **combine** linear & nonlinear effects

Disadvantages

– **Sensitivity** w.r.t. outliers and noisy data
– Feature **interactions** must be handcrafted $\rightarrow$ practically infeasible for higher orders
– Harder to **optimize** than GLM
– Additional **hyperparameters** (type of smooth functions, smoothness degree, ...)

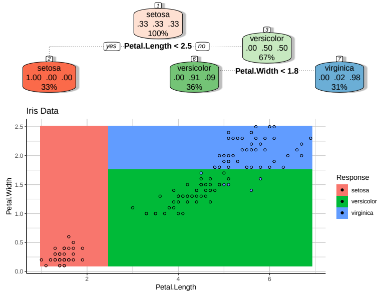
CART – METHOD SUMMARY

REGRESSION | CLASSIFICATION | NONPARAMETRIC | WHITE-BOX | FEATURE SELECTION



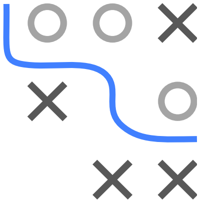
General idea (CART – Classification and Regression Trees)

- Start at root node containing all data
- Perform repeated **axis-parallel binary splits** in feature space to obtain **rectangular partitions** at terminal nodes $Q_1, \dots, Q_M$
- Splits based on reduction of node **impurity** $\rightarrow$ empirical risk minimization (**ERM**)



- In each step:
  - Find **optimal split** (feature-threshold combination) $\rightarrow$ greedy search
  - Assign constant prediction c_m to all obs. in Q_m
    $\rightarrow$ Regression: c_m is average of y
    $\rightarrow$ Classif.: c_m is majority class (or class proportions)
  - Stop when a pre-defined criterion is reached
    $\rightarrow$ See **Complexity control**

CART – IMPLEMENTATION & PRACTICAL HINTS



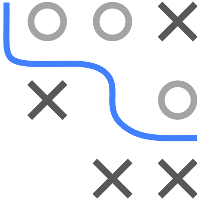
Hyperparameters and complexity control

- Unless interrupted, splitting continues until we have pure leaf nodes (costly + overfitting)
- Hyperparameters: Complexity (i.e., number of terminal nodes) controlled via tree depth, minimum number of observations per node, maximum number of leaves, minimum risk reduction per split, ...
- Limit tree growth / complexity via
  - **Early stopping:** stop growth prematurely
    $\rightarrow$ hard to determine good stopping point before actually trying all combinations
  - **Pruning:** grow deep trees and cut back in risk-optimal manner afterwards

Implementations

- **R:**
  - **CART**: `mlr3` learners `LearnerClassifRpart` / `LearnerRegrRpart`, calling `rpart::rpart()`
  - **Conditional inference trees**: `partykit::ctree()` mitigates overfitting by controlling tree size via p-value-based splitting

CART – PROS & CONS



Dual purpose of CART

- **Exploration purpose** to obtain interpretable decision rules (here: performance/tuning is secondary)
- **Prediction model**: CART as base learner in **ensembles** (bagging, random forest, boosting) can improve stability and performance (if tuned properly), but becomes less interpretable

Advantages

+ **Easy** to understand & visualize (**interpretable**)
+ Built-in **feature selection** $\rightarrow$ e.g., when features are not used for splitting
+ Applicable to **categorical** features $\rightarrow$ e.g., 2^m possible binary splits for m categories $\rightarrow$ trick for regr. with L2-loss and binary classif.: categories can be sorted $\Rightarrow m - 1$ binary splits
+ Handling of **missings** possible via surrogate splits

Disadvantages

— Rather **poor generalization**

— High **variance/instability**: model can change a lot when training data is minimally changed

— Can **overfit** if tree is grown too deep

— Not well-suited to model **linear** relationships

— **Bias** toward features with many unique values or categories

RANDOM FORESTS – METHOD SUMMARY

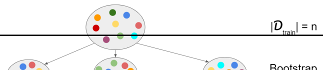
REGRESSION CLASSIFICATION NONPARAMETRIC BLACK-BOX FEATURE SELECTION

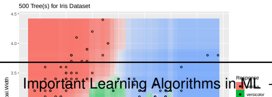
General idea

- **Bagging ensemble** of M tree **base learners** fitted on **bootstrap** data samples
  $\Rightarrow$ Reduce **variance** by ensembling while slightly increasing **bias** by bootstrapping
  - Use unstable, **high-variance** base learners by letting trees grow to full size
  - Promoting **decorrelation** by random subset of candidate features for each split
- **Predict** via averaging (regression) or majority vote (classification) of base learners

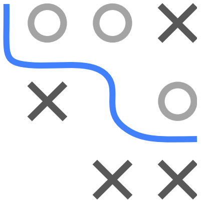
Hypothesis space

$$\mathcal{H} = \left\{ f(\mathbf{x}) : f(\mathbf{x}) = \frac{1}{M} \sum_{m=1}^{M} \sum_{t=1}^{T^{[m]}} c_t^{[m]} \mathbb{I}(\mathbf{x} \in Q_t^{[m]}) \right\}$$





RANDOM FORESTS – IMPLEMENTATION & PRACTICAL HINTS



Extremely Randomized Trees

- Variance of trees can be further increased by **randomizing split points** instead of using the optimal one
- Alternatively consider *k* random splits and pick the best one according to impurity

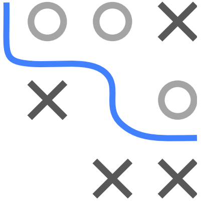
Tuning

- **Ensemble size** should not be tuned as it only decreases variance $\longrightarrow$ choose sufficiently large ensemble
- While default values for **number of split points** is often good, tuning it can still improve performance
- Tuning the **minimum samples in leafs** and **minimum samples for splitting** can be benificial but no huge performance increases are to be expected

Implementation

- **R:** `mlr3` learners `LearnerClassifRanger` / `LearnerRegrRanger`, calling `ranger::ranger()` as a highly efficient and flexible implementation

RANDOM FORESTS – PROS & CONS



Advantages

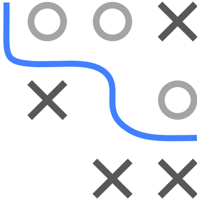
- + Retains most of **trees'** advantages (e.g., feature selection, feature interactions)
- + Fairly **good predictor**: mitigating base learners' variance through bagging
- + Quite **robust** w.r.t. small changes in data
- + Good with **high-dimensional** data, even in presence of noisy features
- + Easy to **parallelize**
- + Robust to its hyperparameter configuration
- + Intuitive measures of **feature importance**

Disadvantages

- — Loss of individual trees' **interpretability**
- — Can be suboptimal for **regression** when extrapolation is needed
- — **Bias** toward selecting features with many categories (same as CART)
- — Rather large model size and slow inference time for large ensembles
- — Typically inferior in **performance** to tuned gradient tree boosting.

GRADIENT BOOSTING – METHOD SUMMARY

REGRESSION CLASSIFICATION (NON)PARAMETRIC BLACK-BOX FEATURE SELECTION

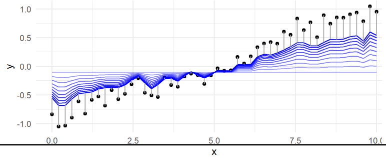


General idea

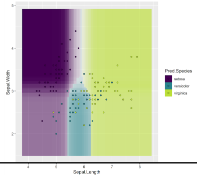
- **Sequential ensemble** of *M* **base learners** by greedy forward stagewise additive modeling
  - In each iteration a base learner is fitted to current **pseudo residuals** $\Rightarrow$ one boosting iteration is one approximate **gradient step in function space**
  - Base learners are typically **trees**, **linear regressions** or **splines**
- **Predict** via (weighted) sum of base learners

Hypothesis space

$$\mathcal{H} = \left\{ f(\mathbf{x}) : f(\mathbf{x}) = \sum_{m=1}^{M} \beta m b(\mathbf{x}, \theta m) \right\}$$



Boosting prediction function with GAM base learners for



Boosting prediction surface with tree base learners for

GRADIENT BOOSTING – PRACTICAL HINTS

Scalable Gradient Boosting

- **Feature and data subsampling** for each base learner fit
- **Parallelization** and **approximate split finding** for tree base learners
- GPU accelaration

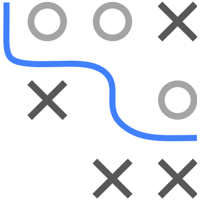
Explainable / Componentwise Gradient Boosting

- Base learners of **simple linear regression** models or **splines**, selecting a single feature in each iteration
- Allows **feature selection** and creates an **interpretable** model since uni- and bivariate effects can be visualized directly.
- Feature interactions can be learned via ranking techniques (e.g., GA^{2}M FAST)

Tuning

- Use **early-stopping** to determine ensemble size
- Various **regularization parameters**, e.g., L1/L2, number of leaves, ... that need to be carefully tuned
- Tune learning rate and base learner complexity hyperparameters on **log-scale**

GRADIENT BOOSTING – IMPLEMENTATION



Gradient Tree Boosting

- **R:** `mlr3` learners `LearnerClassifXgboost` / `LearnerRegrXgboost`, `LearnerClassifLightGBM` / `LearnerRegrLightGBM`
- **Python:** `GradientBoostingClassifier` / `GradientBoostingRegressor` from package `scikit-learn`, `XGBClassifier` / `XGBRegressor` from package `xgboost`, `lgb.train` from package `lightgbm`

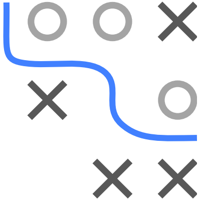
$\Rightarrow$ `LightGBM` current state-of-the-art but slightly more complicated to use than `xgboost`

Componentwise Gradient Boosting

- **R:** `mboost` from package `mboost`, `boostLinear` / `boostSplines` from package `compboost`
- **Python:** /

$\Rightarrow$ `mboost` very flexible but slow while `compboost` is much faster with limited features

GRADIENT BOOSTING – PROS & CONS



Advantages

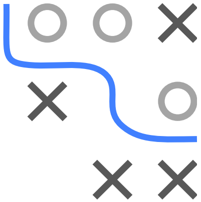
- + Retains of most of **base learners'** advantages
- + Very **good predictor** due to aggressive loss minimization, typically only outperformed by heterogenous **stacking ensembles**
- + High **flexibility** via custom loss functions and choice of base learner
- + Highly efficient implementations exist (`lightgbm` / `xgboost`) that work well on large (distributed) data sets
- + Componentwise boosting: Good combination of (a) high performance (b) interpretable model and (c) feature selection

Disadvantages

- – Loss of base learners' potential **interpretability**
- – **Many hyperparameters** to be carefully tuned
- – Hard to **parallelize** ($\rightsquigarrow$ solved by efficient implementation)

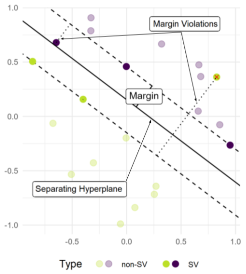
LINEAR SVM – METHOD SUMMARY

CLASSIFICATION REGRESSION PARAMETRIC WHITE-BOX



General idea (Soft-margin SVM)

- Find linear decision boundary (**separating hyperplane**) that
  - maximizes distance (**margin** γ) to closest points (**support vectors, SVs**) on each side of decision boundary
  - while minimizing margin violations (points either on **wrong side of hyperplane** or **between dashed margin line and hyperplane**)
- 3 types of training points
  - **non-SVs** with no impact on decision boundary
  - **SVs that are margin violators** and affect decision boundary
  - **SVs located exactly on dashed margin lines** and affect decision boundary



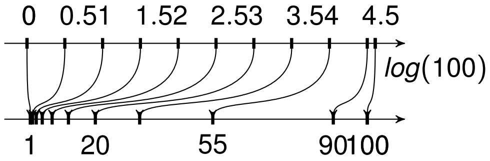
Soft-margin SVM with margin violations

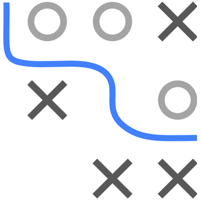
Hypothesis space (primal) $\mathcal{H} = \left\{ f(\mathbf{x}) \ : \ f(\mathbf{x}) = \boldsymbol{\theta}^\top \mathbf{x} + \theta_0 \right\}$

Preprocessing Features should be scaled before applying SVMs (applies generally to regularized models)

Tuning

- Tuning of cost parameter *C* advisable
  $\Rightarrow$ strong influence on resulting hyperplane
- *C* it is often tuned on a log-scale grid for optimal and space-filling search space



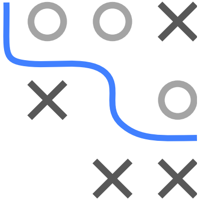


Implementation

- **R:** `mlr3` learners `LearnerClassifSVM` / `LearnerRegrSVM`, calling `e1071::svm()` with linear kernel (`libSVM` interface). Further implementations in `mlr3extralearners` based on
  - `kernlab::ksvm()` allowing custom kernels
  - `LiblineaR::LiblineaR()` for a fast implementation with linear kernel
- **Python:** `sklearn.svm.SVC` from package `scikit-learn` / package `libSVM`

NONLINEAR SVM – METHOD SUMMARY

CLASSIFICATION REGRESSION NONPARAMETRIC BLACK-BOX



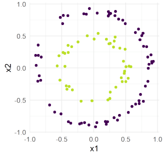
General idea

- Move **beyond linearity** by mapping data to transformed space where they are linearly separable
- **Kernel trick**
  - No need for explicit construction of feature maps
  - Replace inner product of feature map $\phi : \mathcal{X} \to \Phi$ by **kernel**: $\langle \phi x, \phi xt \rangle = kxxt$

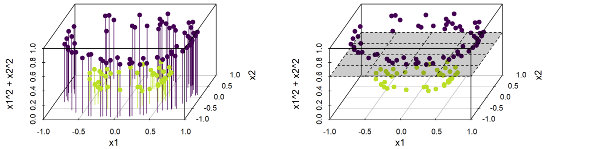
Hypothesis space

$$\mathcal{H} = \left\{ f(\mathbf{x}) \ : \ f(\mathbf{x}) = \text{sign}\left(\boldsymbol{\theta}^\top \phi x + \theta_0\right)\right\} \text{ (primal)}$$

$$\mathcal{H} = \left\{ f(\mathbf{x}) \ : \ f(\mathbf{x}) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y^{(i)} k(\mathbf{x}^{(i)}, \mathbf{x}) + \theta_0\right) \mid \alpha_i \geq 0, \sum_{i=1}^{n} \alpha_i y^{(i)} = 0\right\} \text{ (dual)}$$



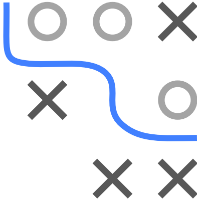
Nonlinear problem in original space



Mapping to 3D space and subsequent linear separation – implicitly handled by kernel in nonlinear SVM

Dual problem **Kernelize** dual (soft-margin) SVM problem, replacing all inner products by kernels:

NONLINEAR SVM – IMPLEMENTATION & PRACTICAL HINTS



Common kernels

- **Linear** kernel: dot product of given observations $\Rightarrow kxxt = \mathbf{x}^\top \tilde{\mathbf{x}}$ $\Rightarrow$ linear SVM
- **Polynomial** kernel of degree $d \in \mathbb{N}$: monomials (i.e., feature interactions) up to d-th order $\Rightarrow kxxt = \left(\mathbf{x}^\top \tilde{\mathbf{x}} + b\right)^d, \ b \geq 0$
- **Radial basis function (RBF)** kernel: infinite-dimensional feature space, allowing for perfect separation of all finite datasets $\Rightarrow kxxt = \exp\left(-\gamma \|\mathbf{x} - \tilde{\mathbf{x}}\|_2^2\right)$ with bandwidth parameter $\gamma > 0$

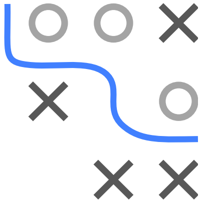
Tuning

- High sensitivity w.r.t. hyperparameters, especially those of kernel $\Rightarrow$ **tuning** very important
- For RBF kernels, use **RBF sigma heuristic** to determine bandwidth

Implementation

- **R:** `mlr3` learners `LearnerClassifSVM` / `LearnerRegrSVM`, calling `e1071::svm()` with nonlinear kernel (`libSVM` interface), `kernlab::ksvm()` allowing custom kernels
- **Python:** `sklearn.svm.SVC` from package `scikit-learn` / package `libSVM`

SVM – PRO'S & CON'S



Advantages

- $+$ Often **sparse** solution (w.r.t. observations)
- $+$ Robust against overfitting (**regularized**); especially in high-dimensional space
- $+$ **Stable** solutions (w.r.t. changes in train data)
  $\rightarrow$ Non-SV do not affect decision boundary
- $+$ Convex optimization problem
  $\rightarrow$ local minimum $\hat{=}$ global minimum

Disadvantages

- $-$ **Long** training times $\rightarrow O(n^2p + n^3)$
- $-$ Confined to **linear model**
- $-$ Restricted to **continuous features**
- $-$ Optimization can also fail or get stuck

Advantages (nonlinear SVM)

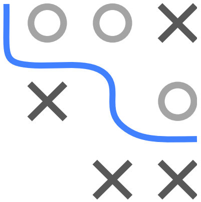
- $+$ Can learn **nonlinear decision boundaries**
- $+$ **Very flexible** due to custom kernels
  $\rightarrow$ RBF kernel yields local model

Disadvantages (nonlinear SVM)

- $-$ Poor **interpretability** due to complex kernel
- $-$ **Not easy tunable** as it is highly important to choose the right kernel (which also

NEURAL NETWORKS – METHOD SUMMARY

REGRESSION CLASSIFICATION (NON)PARAMETRIC BLACK-BOX



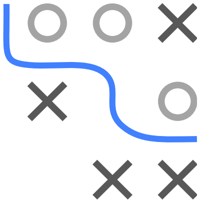
General idea

- Learn **composite function** through series of nonlinear feature transformations, represented as **neurons**, organized hierarchically in **layers**
  - Basic neuron operation: 1) affine **transformation** ϕ (weighted sum of inputs), 2) nonlinear **activation** σ
  - Combinations of simple building blocks to create a complex model
- Optimize via **mini-batch stochastic gradient descent (SGD)** variants:
  - Gradient of each weight can be infered from the **computational graph** of the network $\rightarrow$ **Automatic Differentiation** (AutoDiff)
  - Algorithm to compute weight updates based on the loss is called **Backpropagation**

Hypothesis space $\mathcal{H} =$

$$\{ f(\mathbf{x}) : f(\mathbf{x}) = \tau \circ \phi \circ \sigma^{(h)} \circ \phi^{(h)} \circ \sigma^{(h-1)} \circ \phi^{(h-1)} \circ \ldots \circ \sigma^{(1)} \circ \phi^{(1)}(\mathbf{x}) \}$$

NEURAL NETWORKS – IMPLEMENTATION & PRACTICAL HINTS



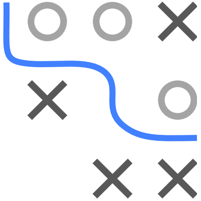
General hints

- Instead of NAS, use a standard architecture and tune training hyperparameters
- Training pipeline (data-augmentation, training schedules, ...) is more crucial than the specific architecture
- While NNets are state-of-the-art for **computer vision (CV)** and **natural language processing (NLP)**, we recommend not to use them for tabular data because alternatives perform better
- Computational efforts for training (and inference) can be very high, requiring specific hardware.
  $\rightarrow$ Using a service (esp. for foundation models) can be more cost efficient

Implementation

- **R:** Use python libraries (below) via `reticulate`, but not really recommended except for toy applications.
- **Python libraries:**
  - `keras` for simple high level API

NEURAL NETWORKS – PROS & CONS



Advantages

- + Applicable to **complex, nonlinear** problems
- + Very **versatile** w.r.t. architectures
- + State-of-the-art for CV and NLP
- + Strong **performance** if done right
- + Built-in **feature extraction**, obtained by intermediate representations
- + Easy handling of **high-dimensional** data
- + **Parallelizable** training

Disadvantages

- – Typically, high computational **cost**
- – High demand for **training data**
- – Strong tendency to **overfit**
- – Requiring lots of **tuning expertise**
- – **Black-box** model – hard to interpret or explain