

Performance measures & kNN

Introduction

k-nearest neighbors (kNN)

- Simple(st) non-parametric approach to estimate $f(x)$
- Assumes that $f(x)$ can be approximated by a **locally constant** function
- Memory-based method without training phase

Distances and prediction

kNN setup: Compute **distances** between training and test observations (in \mathbf{x})

Euclidean Distance: $\|\mathbf{x}_a - \mathbf{x}_b\|_2$

$$\sqrt{\sum_{j=1}^P (x_{aj} - x_{bj})^2}$$

Minkowski Distance:

$$\left(\sum_{j=1}^P |x_{aj} - x_{bj}|^q \right)^{\frac{1}{q}}$$

Manhattan Distance: $\|\mathbf{x}_a - \mathbf{x}_b\|_1$

Other metrics available: Mahalanobis, Chebyshev...

Distances and prediction

Prediction based on K cases in the training data closest to test example x_0 (\mathcal{N}_0)

kNN Regression

$$\hat{f}(x_0) = \frac{1}{K} \sum_{x_i \in \mathcal{N}_0} y_i$$

→ Estimated y equals average outcome of training cases in \mathcal{N}_0

kNN Classifier

$$P(Y = j | X = x_0) = \frac{1}{K} \sum_{i \in \mathcal{N}_0} I(y_i = j)$$

→ $P(Y = j)$ equals fraction of $I(y_i = j)$ in neighborhood \mathcal{N}_0

Distances and prediction

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kNN Regression

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kNN Classifier

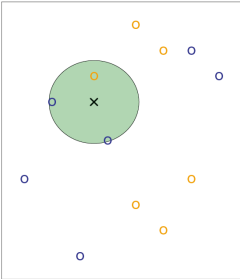
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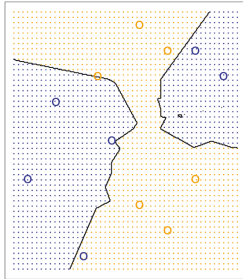
Distances and prediction

Figure: kNN classifier

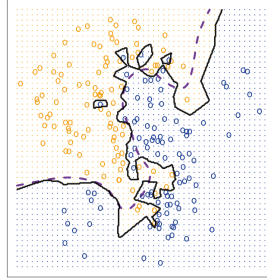
(a) Example, $k = 3$



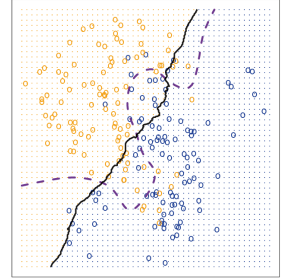
(b) Decision boundary, $k = 3$



(c) $k = 1$



(d) $k = 100$



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Tuning K

The number of neighbors K

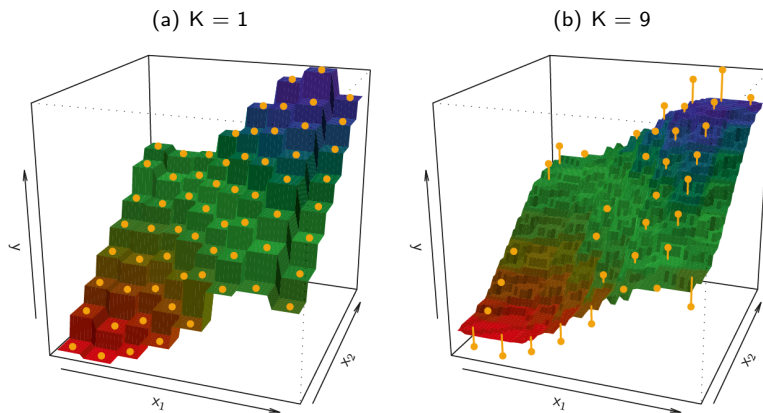
- K is a **tuning parameter** and chosen using e.g. CV
- Small K provides flexible fit but high variance
- Large K leads to less variable fit which may cause bias

→ Bias-Variance Trade-Off with kNN

$$\begin{aligned}\text{Err}(x_0) &= \text{Bias}^2(\hat{f}(x_0)) + \text{Var}(\hat{f}(x_0)) + \text{Var}(\varepsilon) \\ &= \left[f(x_0) - \frac{1}{k} \sum_{\ell=1}^k f(x_{(\ell)}) \right]^2 + \frac{\sigma_{\varepsilon}^2}{k} + \sigma_{\varepsilon}^2\end{aligned}$$

Tuning K

Figure: kNN regression



James et al. 2013

Limitations

Drawbacks of kNN

- Distances dependent on scaling of predictor variables
 - Standardizing of features
- “Curse of dimensionality”
 - No nearby neighbor in sparse data with many features
- Sensitive to irrelevant features
- Computational costs increase with sample size

Extensions

- Weighted kNN
 - Weight neighbors by distances

References

- Hossin, M., Sulaiman, M. N. (2015). A review on evaluation metrics for data classification evaluations. *International Journal of Data Mining & Knowledge Management Process*, 5(2): 1–11.
- James, G., Witten, D., Hastie, T., Tibshirani, R. (2013). *An Introduction to Statistical Learning*. New York, NY: Springer.
- Sokolova, M., Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. *Information Processing & Management*, 45(4): 427–437.