

INTRODUCTION TO ML: CLASSIFICATION, TREES, FORESTS

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HANDS ON DATA SCIENCE, FOO CAFÉ, 6/12 - 2018

Before we start

- Presentation, exercises and code examples available on https://github.com/olofgarpinger/hands_on_data_science_Dec_6_2018
- Dataset from Kaggle. We also use Kaggle to evaluate all classifiers. Requires signup!



Strong values take Knightec further

Culture of diversity, consideration and teamwork



Quality & Management

- Project Management
- Quality Assurance
- Business development
- Risk Management
- Specialist area: Compliance. Optimized.*



Systems

- Software
- Electronics
- Automation
- Machine Learning and Data Science
- Specialist area: Connected Device Security*

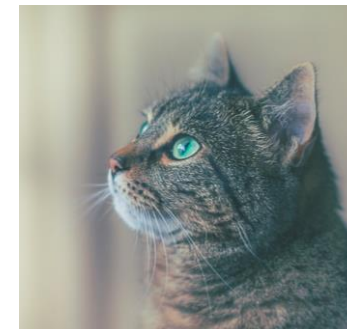


Technology

- Mechanical Engineering
- Machine Design
- Calculation
- Certifications
- Specialist area: Sustainable Plastic Design*

Classification (non ML...)

- Simple concept: assign a new observation to one of several classes.
 - How? Some tasks are simple, such as the toy.
 - Pieces have distinct properties such as color, shape, size.
 - Other tasks are more complex, such as recognizing a dog.
 - Basic properties not enough to uniquely classify.
- All in all: we classify objects based on
 - The objects specific properties.
 - Experience and knowledge!

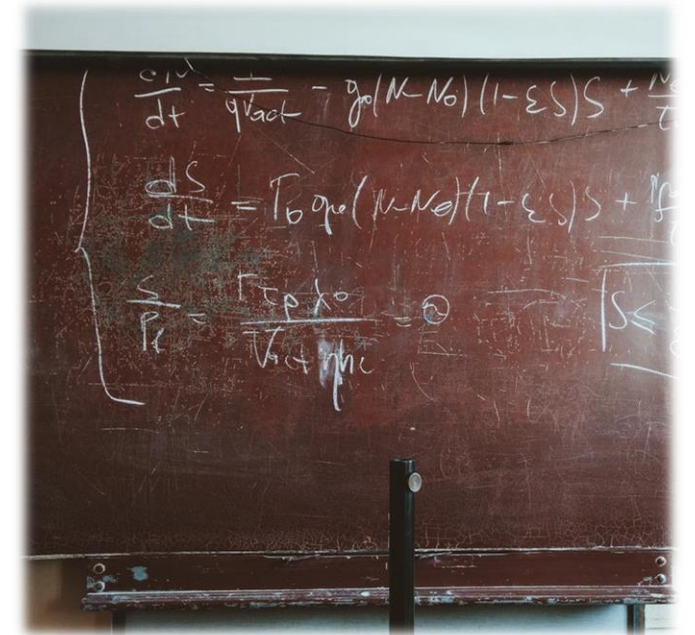


Classification (ML)

- Same basic concept in ML.
- Representing experience and knowledge?
 - Mathematical models (*classifiers*) that encode experience and knowledge.
 - Tuned by letting them *train* on historical data.
- **Data:** set of measurable properties (*features*) and output (*target*).

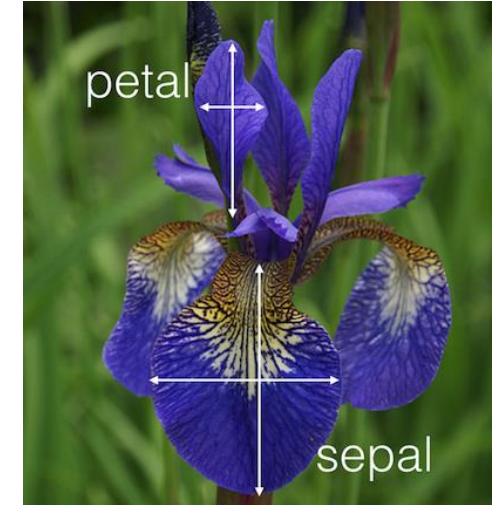
Height	Color	Shape	Target
3 cm	Green	Triangle	

- **Main takeaway:** an observations class is determined by it's features.
- This knowledge is fundamental in most ML applications!



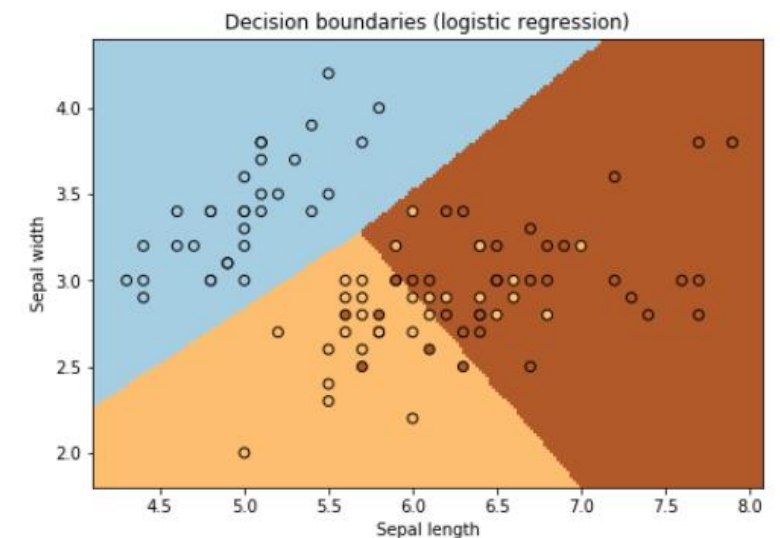
Example: Iris dataset

- Famous simple dataset introduced by Fisher 1936.
- Length, width of petals and sepals of 150 flowers from three Iris subspecies.
- => Classification problem: 4 features and target with 3 classes.



Sepal length (cm)	Sepal width (cm)	Petal length (cm)	Petal width (cm)	Subspecies
5.1	3.5	1.4	0.2	Iris setosa
7.0	3.2	4.7	1.4	Iris versicolor

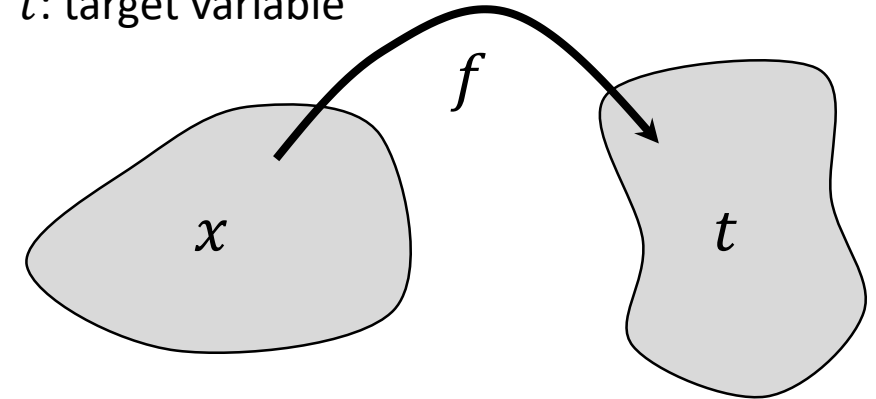
- Scatter plot and classifier decision boundaries for two features.



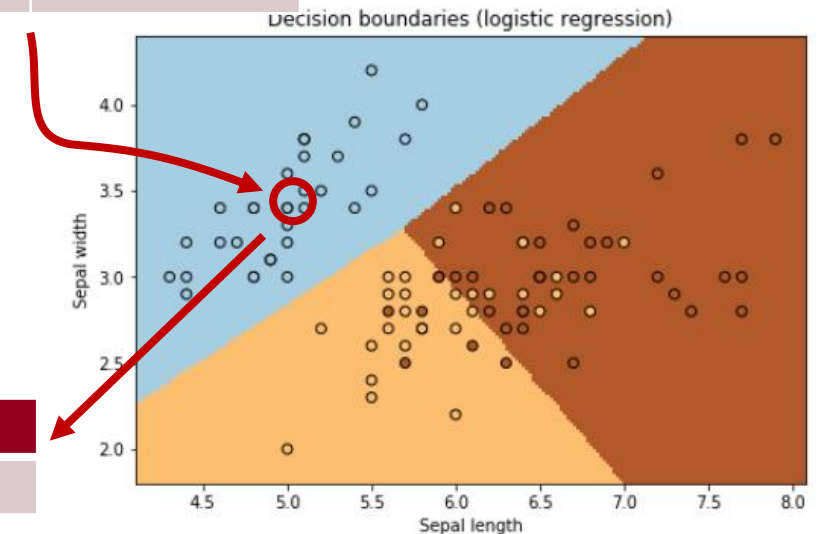
Classification, contd.

- Training classifier = discover mapping function $f: x \rightarrow t$.
- Algorithms differ in how f is constructed during training.
 - Often by solving an optimization problem, but not always.
 - Today we focus on a handful of tree-based methods.
- Trained classifier: features as input \Rightarrow class prediction $\hat{t} = f(x)$
- **End goal:** be able to predict class of unseen data based on features.

- x : feature vector
- t : target variable



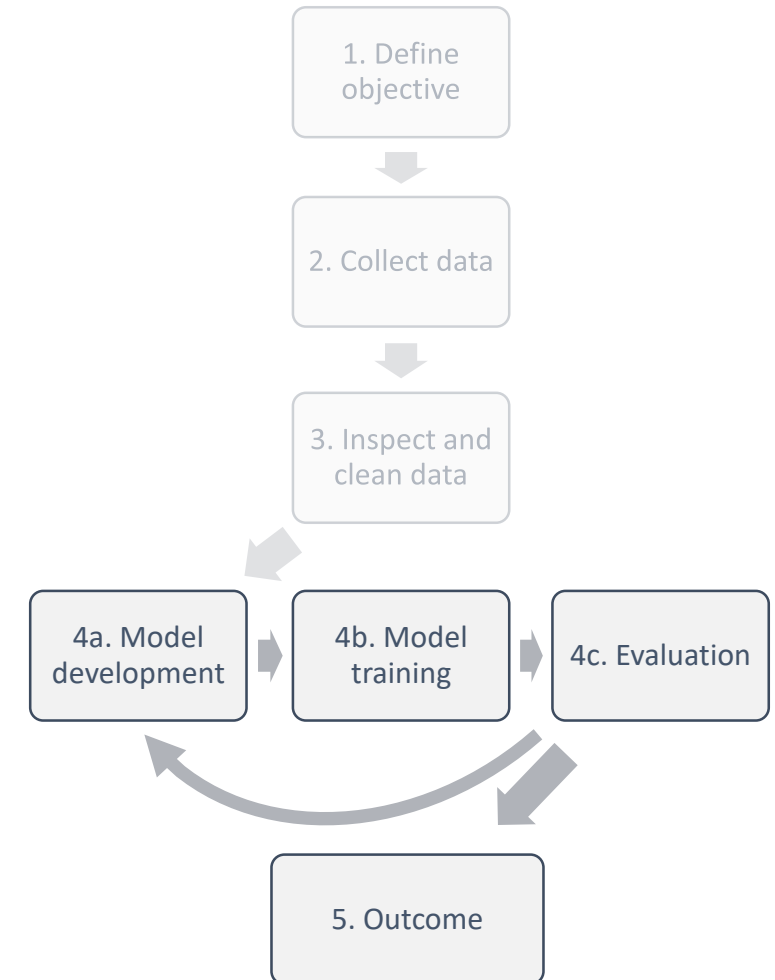
Sepal length (cm)	Sepal width (cm)
5.1	3.5



Subspecies
Iris setosa

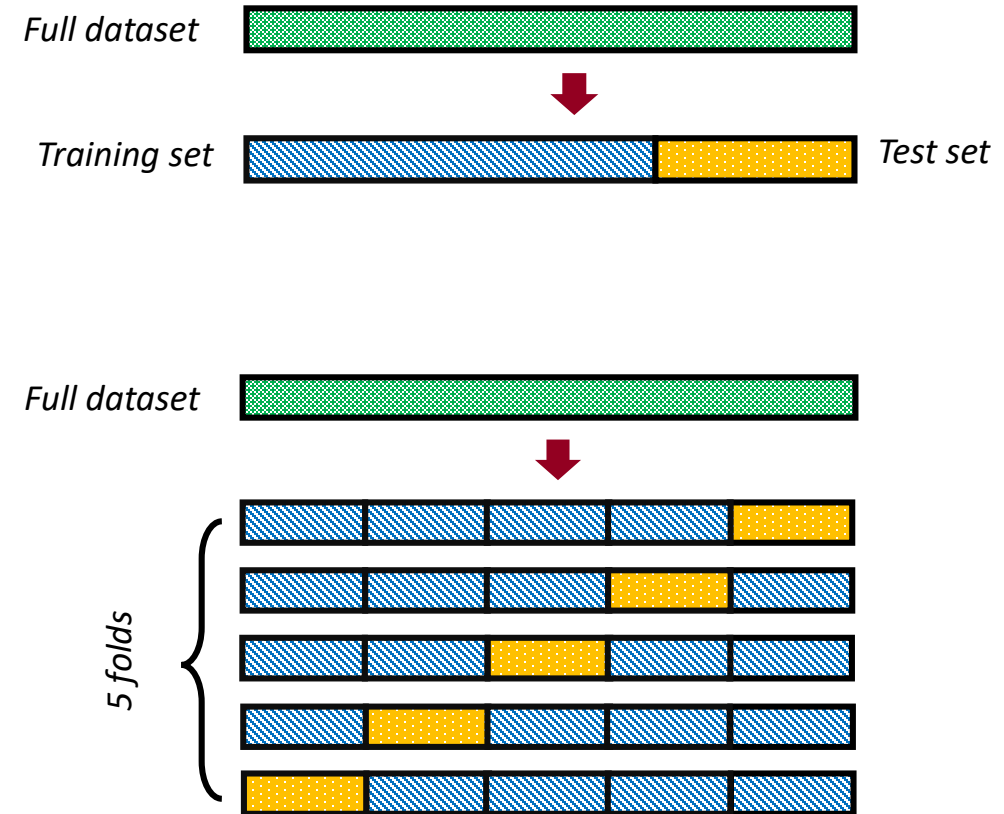
Methodology & workflow

- ML projects typically follow a variant of this workflow.
- Focus of today is on the second half.
- Modeling stage a three step process:
 - **Development:** picking classifier, setting structure.
 - **Training:** fit to historical data.
 - **Evaluation:** performance, cross validation.
- Iterative process!



Cross validation

- Classifiers must generalize to unseen data.
- Holdout method
 - Most basic form of cross validation.
 - Part of data is set aside in a test set and not used in training.
- K-fold cross validation
 - Particularly useful for small datasets
 - Data split in K folds. $K-1$ folds for training, 1 fold for testing.
 - Repeat train+eval loop K times, rotating test folds.



Evaluating performance

- Plenty of performance metrics. Appropriate choice problem dependent!
- Classification accuracy: $\frac{\# \text{ correct classifications}}{\# \text{ classifications}}$
 - Obvious choice. Intuitive!
 - Used by Kaggle for today's dataset.
 - What happens if one class occurs rarely, and is very important?
- Other common performance measures (can be useful today!):
 - Precision, recall and F1 score
 - Confusion matrices.



The dataset – Scary monsters



- Made up Kaggle set for practicing classification
 - <https://www.kaggle.com/c/ghouls-goblins-and-ghosts-boo>
 - Five features (variables):
 - bone_length, rotting_flesh, hair_length, has_soul, color
 - Classify 3 monster types: Ghosts, Goblins, and Ghouls
 - Maximize prediction accuracy
 - Rather small and very tidy set:
 - 371 training observations (rows), 529 test
 - Makes it ideal for practicing different classification methods
 - Not necessarily the most advanced methods that are the best

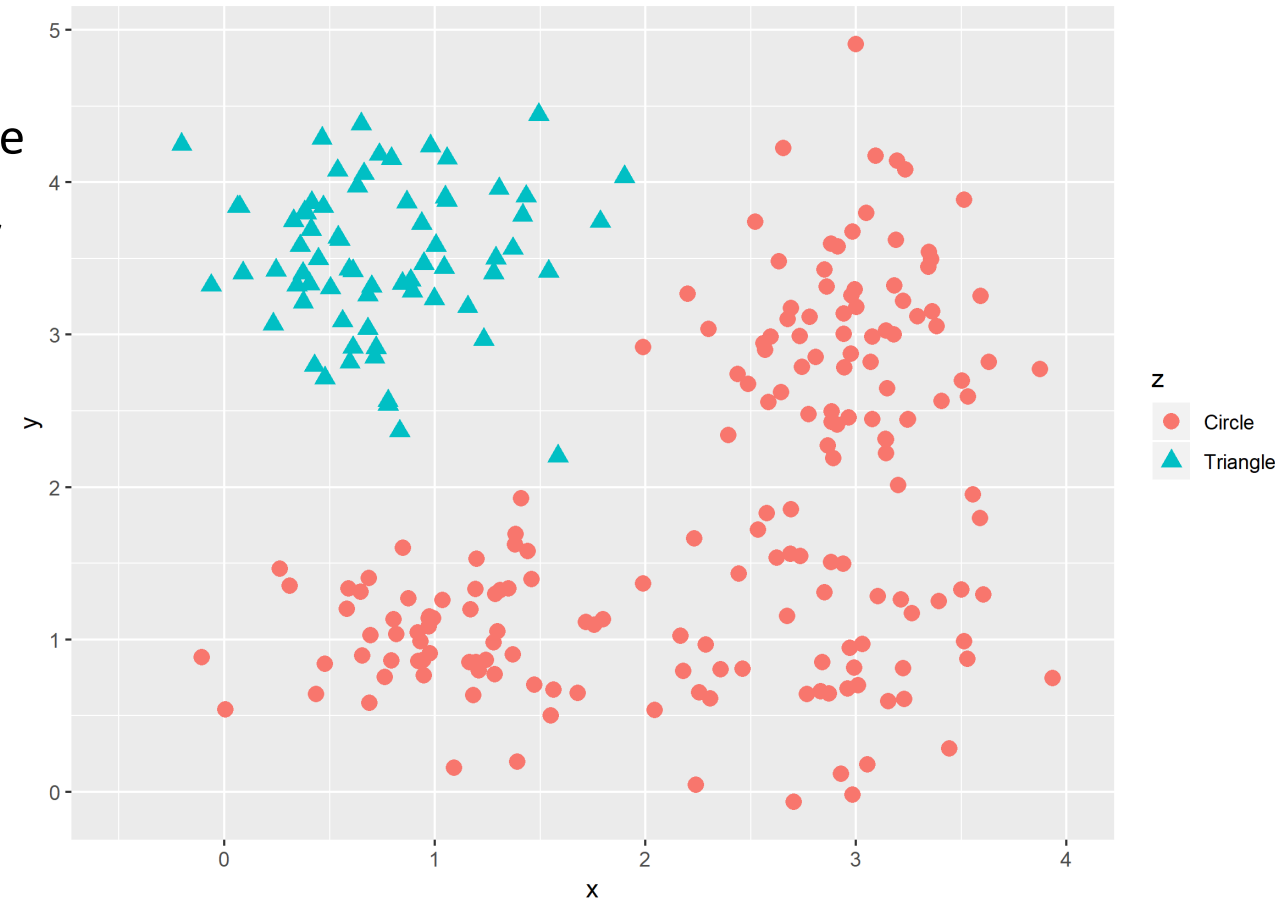


Decision trees and forests for classification



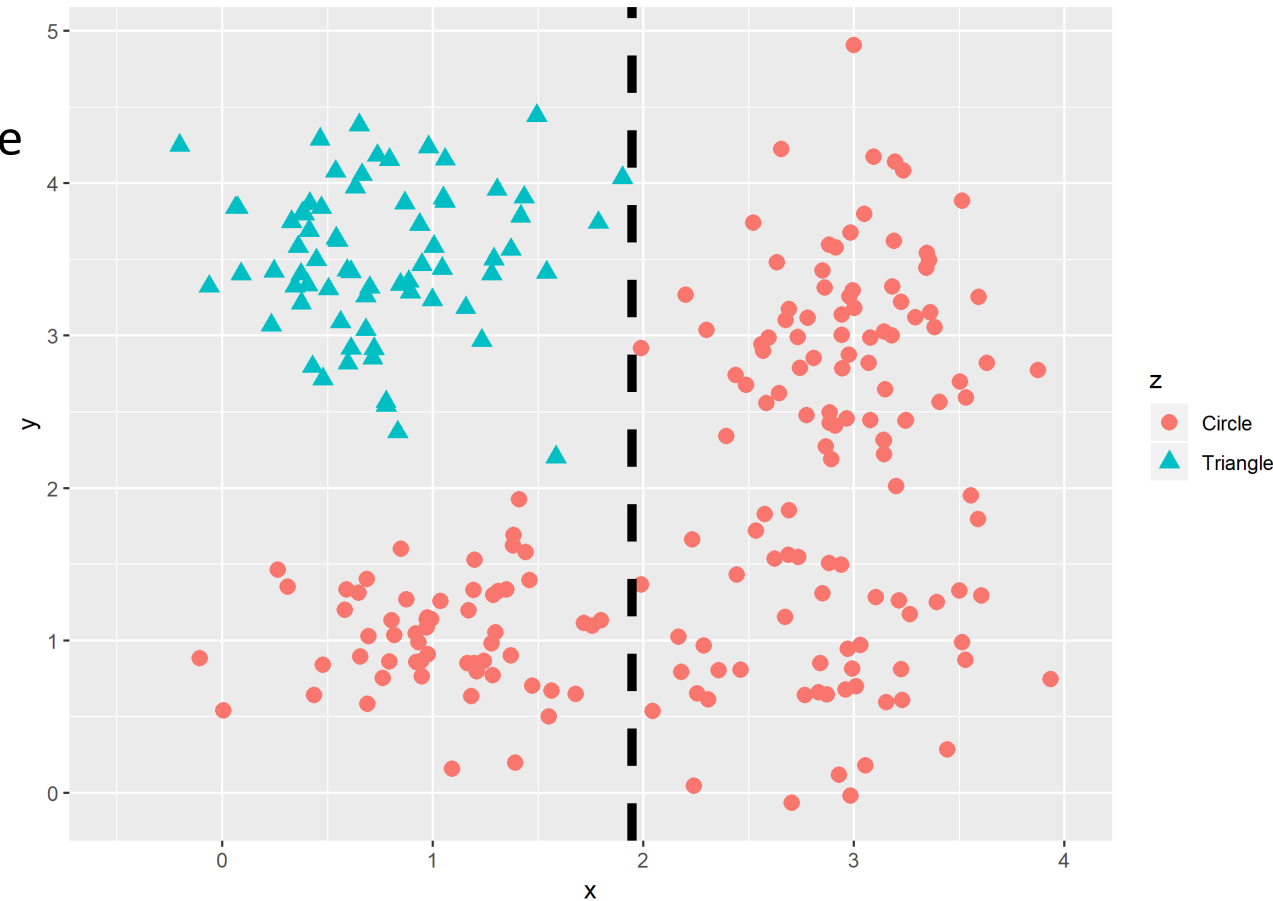
What is a decision tree and how to build it?

- Segment observations into a number of regions in feature space
 - High-dimensional boxes
 - Split previous regions to improve a measure
 - Purity measures, such as accuracy
 - Greedy approach
 - One region at a time
 - Best feature split selected



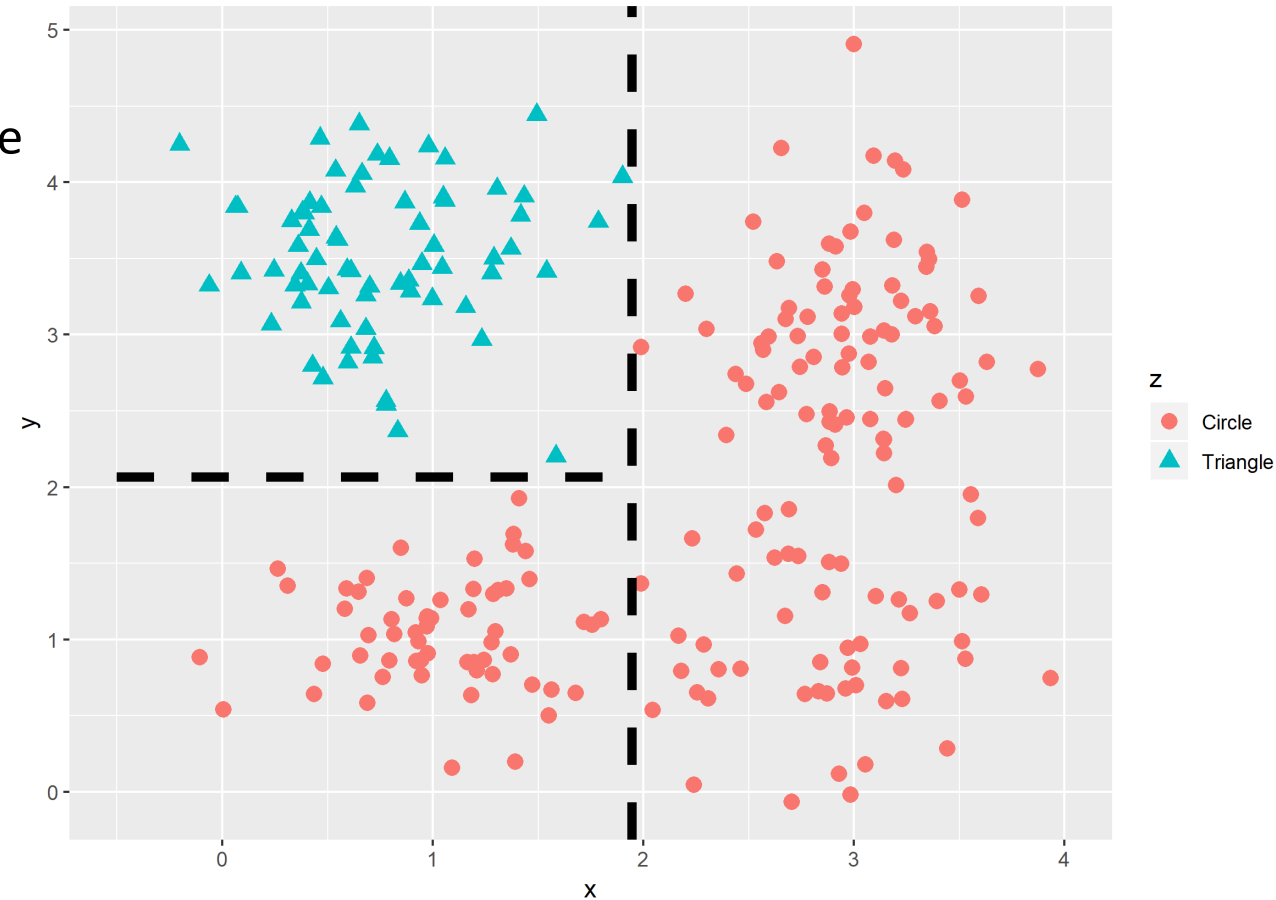
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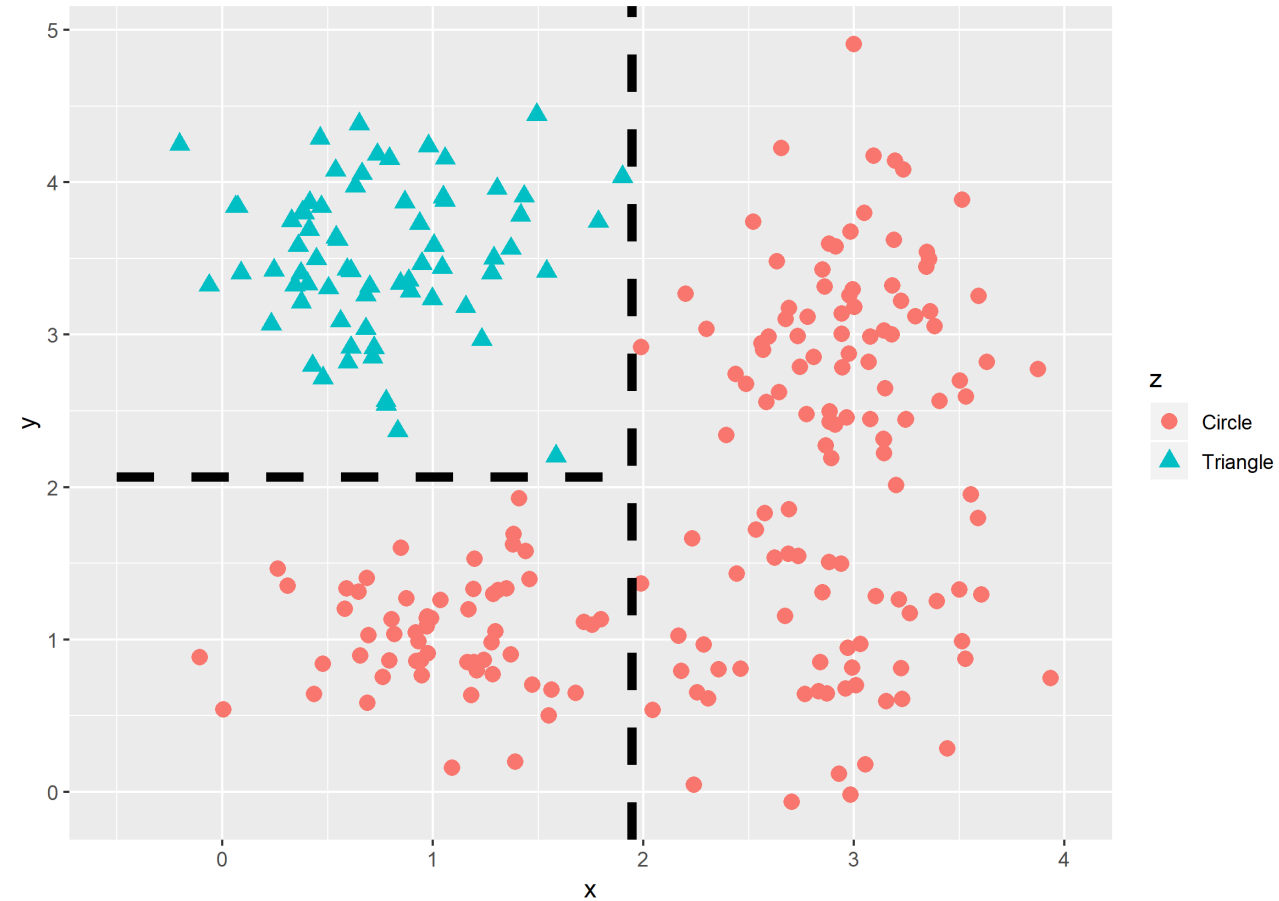
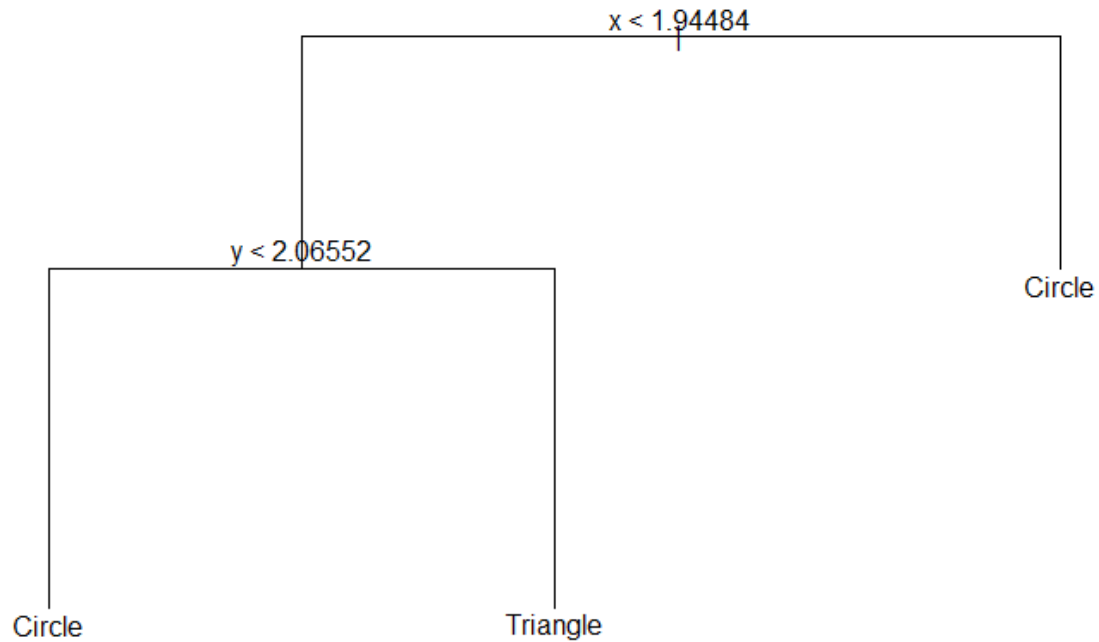


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What is a decision tree and how to build it?



What are the strengths and weaknesses of trees?

Advantages

- + Easily handles mixed data types
- + Handles missing values
- + Robust to outliers
- + Automatic feature (variable) selection
- + Interpretability (small trees)

Disadvantages

- Inability to extract linear combinations of features
- Poor prediction accuracy
 - Big minus

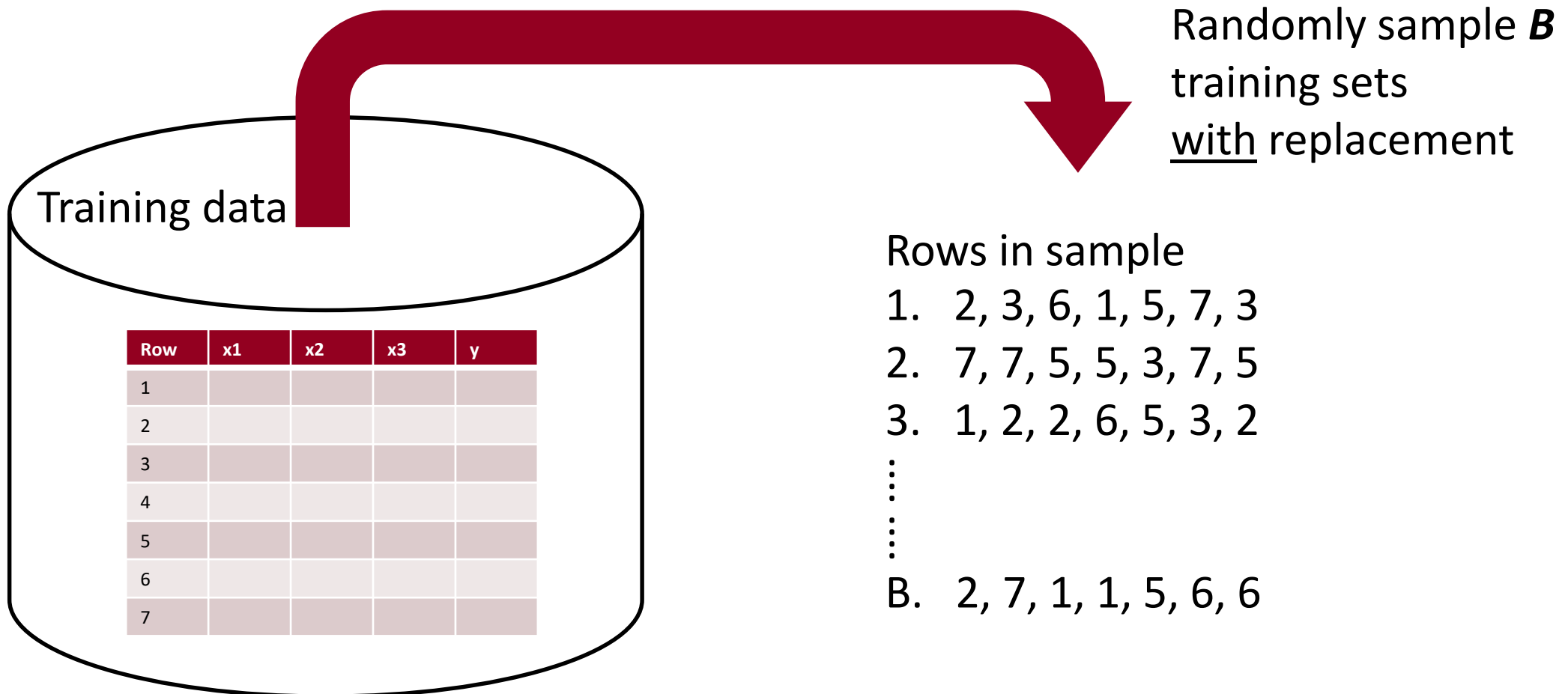


Building forests of decision trees

- Form a powerful committee of weak classifiers
 - Trees in our case
- Grow many trees
 - Each tree votes on class, majority wins
- Keeps most of the advantages of trees
 - Loses some interpretability
- Easy to use immediately on a dataset
 - Quick and Dirty
 - Gives an initial estimate of best performance
- Gains competitive prediction accuracy!
- Very popular methods both in industry and for winning competitions



Bootstrap sampling



Bagging (1996) and Random Forest (1999)

Bagging:

- Build B trees from B bootstrap samples of the training data
 - The trees should be large/bushy with many splits
 - Use all p features (variables) in your dataset at every split

Random Forest

- Same procedure as for Bagging, but...
 - At each split, only choose between m features
 - Randomly selected at each split
 - Makes the trees less correlated
 - Typically: $m = \sqrt{p}$
- Two tuning parameters, B and m , easy to apply!



Gradient boosting (2001)

Boosting in general

- General method where additive models are used
- Most often these models are trees

Gradient Boosting

- Iterative process, typically adding small trees
 - Fit a new tree to the residuals of the old model
 - Start with no model ($f(x) = 0$)
 - Shrink the tree with a factor λ (think step size gradient descent)
 - Add shrunk tree to the previous model and calculate new residuals
- 3 tuning parameters: Number of trees, shrinkage factor, tree depth
 - Many parameters, takes time to tune

Top performer!



Reading material

- [An Introduction to Statistical Learning](#) (Book, R, ML)
- [Applied Predictive Modeling](#) (Book, R, ML)
- [Python Machine Learning](#) (Book, Python, ML)
- [The Elements of Statistical Learning](#) (Book, ML)
- [Pattern Recognition and Machine Learning](#) (Book, ML)
- [Gradient Boosting Machine Learning](#) (T. Hastie video, Boosting)
- http://uc-r.github.io/gbm_regression (Article, Boosting, R)
- http://uc-r.github.io/random_forests (Article, Random Forest, R)



Now, over to:

https://github.com/olofgarpinger/hands_on_data_science Dec 6 2018

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