Probabilistic Modeling and Reasoning

The Role of Uncertainty in Machine Learning

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Program

Course objective

Be able to apply probabilistic models to real-world problems.

Course objective

Be able to apply ~~probabilistic~~ models to real-world problems.
Be able to apply Bayesian models to real-world problems.

Course Overview

Course structure

- 6 sessions $\times$ 1.5 hours
- Each session consists of:
  - Lecture (45') — 30' lecture + 15' discussion
  - Exercises (45') — 20' you work on exercises, 25' discussion
    - Either pen-and-paper or in R

Course material

- Slides, exercises and R code available on course website `https://www.github.com/givasile/BAC`
- Solutions to exercises will be provided after each session

Course Overview

Bridging Theory and Practice

- Sessions 1-3: Foundational concepts of Bayesian modeling
- Sessions 4-6: Application on regression and classification problems

- **Session 1:** Probabilistic Modeling and Reasoning
  - The Role of Uncertainty in Machine Learning
  - Probabilistic Modeling and Reasoning
  - Key Rules of Probability
- **Session 2:** Probabilities and Random Variables
  - Random Variables and Probability Distributions
  - Key properties: Expectation, Variance, Covariance
- **Session 3:** Bayesian Modeling: A Unified Framework
  - Probabilistic vs. Statistical vs. Bayesian Modeling
  - Prior, Posterior, Likelihood, Predictive Posterior

Course Overview

Bridging Theory and Practice

- Sessions 1-3: Foundational concepts of Bayesian modeling
- Sessions 4-6: Application on regression and classification problems

- **Session 4:** Bayesian Linear Regression
  - Linear Regression as a Probabilistic Model
  - Exact Inference with Conjugate Priors
- **Session 5:** Bayesian Logistic Regression
  - Logistic Regression as a Probabilistic Model
  - Approximate Inference:
    - Laplace Approximation
    - Importance Sampling
    - MCMC
- **Session 6:** Real-world problem
  - Summary of all concepts
  - Application on a real-world problem

Material used in this course

This course is highly inspired (some parts are copied verbatim) from the following sources:

- **Probabilistic Modeling and Reasoning**
  University of Edinburgh, School of Informatics
  `https://opencourse.inf.ed.ac.uk/pmr/course-material`
- **Machine Learning and Pattern Recognition**
  University of Edinburgh, School of Informatics
  `https://mlpr.inf.ed.ac.uk/2024/`
- **BayesRules book**
  `https://bayesrulesbook.com/`
- **Multivariate Statistics**
  `https://11annah-s-teachings.github.io/`
- **Mathematics of Machine Learning**
  `https://mml-book.github.io/`

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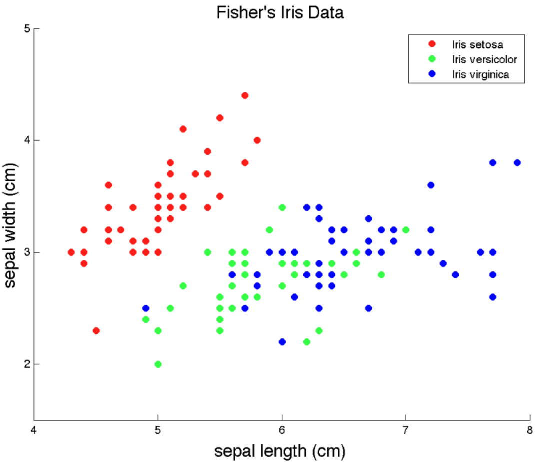
1. Course Overview
2. The Role of Uncertainty in Machine Learning
3. Probabilistic Modeling and Reasoning
4. Key Rules of Probability
5. Recap & What's Next

Variability

- Variability is part of nature.
- Data for 3 species of iris, from Ronald Fisher (1936).



Variability

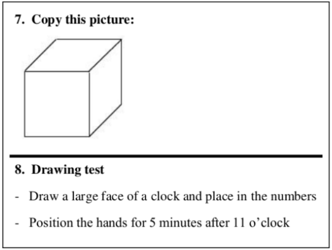
- Our handwriting is unique
- Variability leads to uncertainty: e.g., distinguish $\{1, 7\}$ and $\{4, 9\}$

Variability

- Variability $\xrightarrow{\text{leads to}}$ uncertainty $\xrightarrow{\text{asks for}}$ probabilistic modeling
- Reading handwritten text in a foreign language.

Example: Screening and Diagnostic Tests

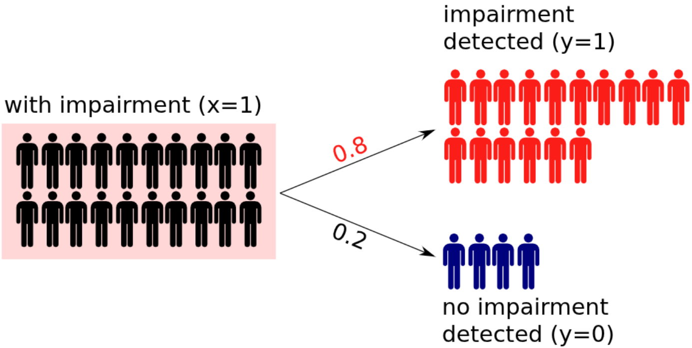
- Early warning test for Alzheimer's disease (Scharre, 2010, 2014)
- Detects 'mild cognitive impairment'
- Takes 10–15 minutes
- Freely available
- Assume a 70-year-old man tests positive
- Should he be concerned?



(Example from sagetest.osu.edu)

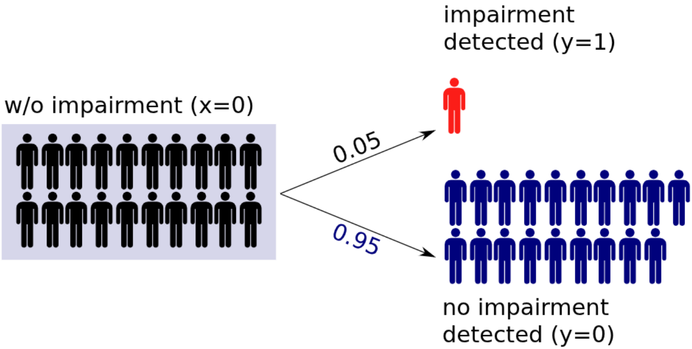
Accuracy of the Test

- Sensitivity of 0.8 and specificity of 0.95 (Scharre, 2010).
- 80% correct for people with impairment.



Accuracy of the Test

- Sensitivity of 0.8 and specificity of 0.95 (Scharre, 2010).
- 95% correct for people without impairment.



Variability Implies Uncertainty

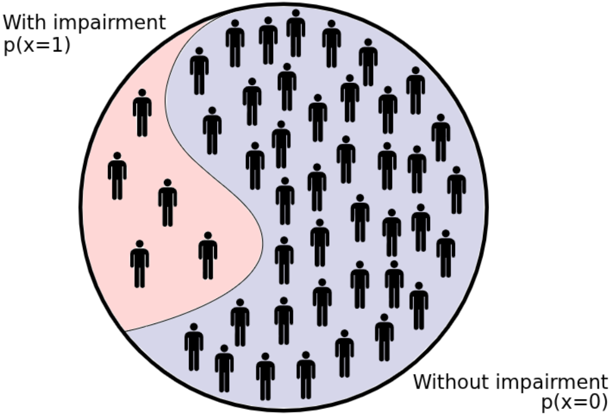
- People of the same group do not have the same test results
  - Test outcome is subject to variability.
  - The data are noisy.
- Variability leads to uncertainty.
  - Positive test $\equiv$ true positive?
  - Positive test $\equiv$ false positive?
- What can we safely conclude from a positive test result?
- How should we analyze such ambiguous data?

Probabilistic Approach

- $P(y \mid x)$: model of the test specified in terms of (conditional) probabilities.
- $x \in \{0, 1\}$: quantity of interest (cognitive impairment or not).
- $y \in \{0, 1\}$: test outcome (negative or positive).
- The test outcomes y can be described with probabilities:
  - Sensitivity $= 0.8$
    - $\Rightarrow P(y = 1 \mid x = 1) = 0.8$
    - $\Rightarrow P(y = 0 \mid x = 1) = 0.2$
  - Specificity $= 0.95$
    - $\Rightarrow P(y = 0 \mid x = 0) = 0.95$
    - $\Rightarrow P(y = 1 \mid x = 0) = 0.05$

Prior Information

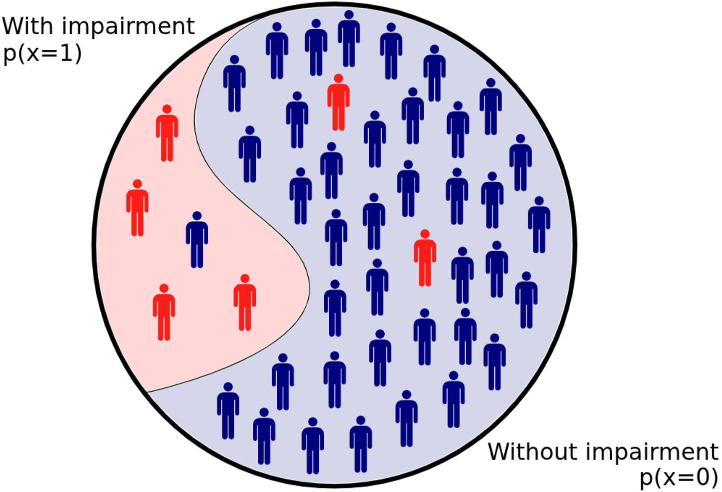
- Among people like the patient, $P(x = 1) = \frac{5}{45} \approx 11\%$ have a cognitive impairment (plausible range: 3% – 22%, Geda, 2014).



Probabilistic Model

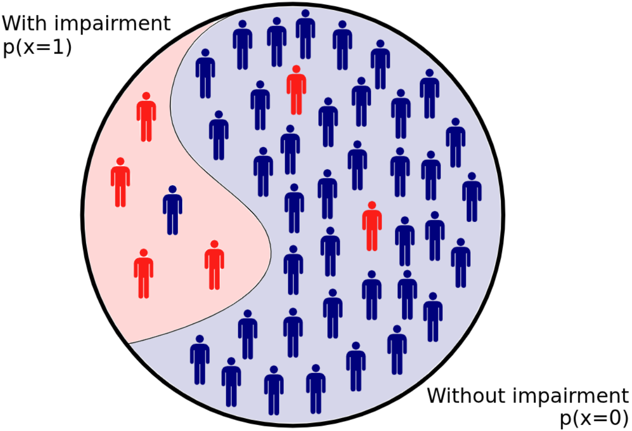
- Reality:
  - Properties/characteristics of the group of people like the patient
  - Properties/characteristics of the test
- Probabilistic model:
  - $P(x = 1)$: probability of cognitive impairment
  - $P(y = 1|x = 1)$ or $P(y = 0|x = 1)$: probability of positive or negative test given cognitive impairment
  - $P(y = 1|x = 0)$ or $P(y = 0|x = 0)$: probability of positive or negative test given no cognitive impairment
  - Fully specified by three numbers.
- A probabilistic model is an abstraction of reality that uses probability theory to quantify the chance of uncertain events.

If We Tested the Whole Population



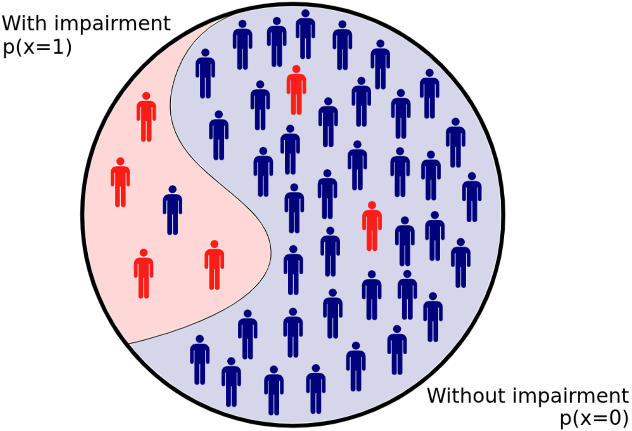
If We Tested the Whole Population

- Fraction of people who are impaired and test positive:
$P(x=1, y=1) = P(y=1|x=1)P(x=1) = 0.8 \cdot \frac{5}{45} = \frac{4}{45} \approx 9\%$



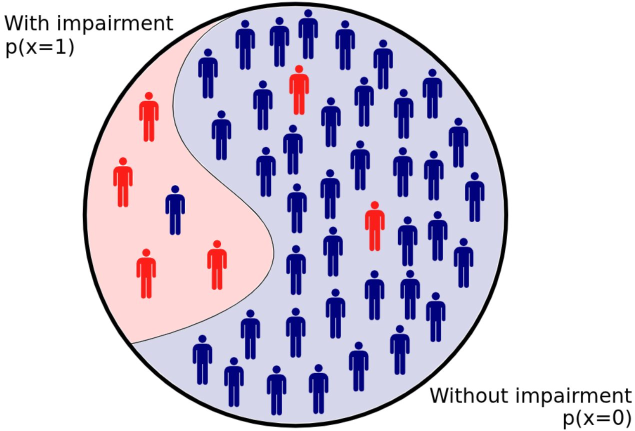
If We Tested the Whole Population

- Fraction of people who are not impaired and test positive:
  $P(x=0, y=1) = P(y=1|x=0)P(x=0) = 0.05 \cdot \frac{40}{45} = \frac{2}{45} \approx 4\%$



If We Tested the Whole Population

- Fraction of people where the test is positive:
  $P(y=1) = P(x=1, y=1) + P(x=0, y=1) = \frac{4}{45} + \frac{2}{45} = \frac{6}{45} \approx 13\%$



Putting Everything Together

- Among those with a positive test, fraction with impairment:

$$P(x = 1|y = 1) = \frac{P(y = 1|x = 1)P(x = 1)}{P(y = 1)} = \frac{4}{6} = \frac{2}{3}$$

- Fraction without impairment:

$$P(x = 0|y = 1) = \frac{P(y = 1|x = 0)P(x = 0)}{P(y = 1)} = \frac{2}{6} = \frac{1}{3}$$

- Equations are examples of Bayes' rule.
- Positive test increased probability of cognitive impairment from 11% (prior belief) to 67%, or from 6% to 51%.
- 51% (coin flip)

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Probabilistic Modeling and Reasoning

- Bayesian analysis is probabilistic modeling and reasoning using Bayes' rule.
- **Probabilistic modeling:**
  - Model the world (events) using probabilities and random variables.
  - Example random variables:
    - y: test outcome
    - x: cognitive impairment
- **Probabilistic reasoning (inference):**
  - Compute probabilities of events given other events.
  - Infer probabilities of unobserved events from observed data.
  - Use Bayes' rule to update beliefs based on evidence.

Probabilistic Modeling and Reasoning

- In our example:
  - Unobserved/uncertain event: cognitive impairment $x = 1$
  - Observed event (evidence): test result $y = 1$
  - **Prior**: probability before seeing evidence, e.g., $P(x = 1)$
  - **Posterior**: updated probability after evidence, e.g., $P(x = 1|y = 1)$
- Key idea: The posterior quantifies what we believe about x after seeing the test result y.

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Key Rules of Probability

- **Product rule:**
  - $P(x=1, y=1) = P(y=1|x=1)P(x=1)$
  - $P(x=1, y=1) = P(x=1|y=1)P(y=1)$
- **Sum rule:**
  - $P(y=1) = P(x=1, y=1) + P(x=0, y=1)$
- **Bayes' rule (conditioning) as consequence of product rule:**
  - $P(x=1|y=1) = \frac{P(x=1,y=1)}{P(y=1)} = \frac{P(y=1|x=1)P(x=1)}{P(y=1)}$
- **Denominator from sum rule and product rule:**
  - $P(y=1) = P(y=1|x=1)P(x=1) + P(y=1|x=0)P(x=0)$

Key Rules of Probability

- The rules generalize to multivariate random variables
  - $\mathbf{x} = (x_1, x_2, \ldots)$: vector of random variables
  - $\mathbf{y} = (y_1, y_2, \ldots)$: vector of random variables
- The rules generalize to continuous random variables
- **Product rule:**
  - $P(\mathbf{x}, \mathbf{y}) = P(\mathbf{y}|\mathbf{x})P(\mathbf{x})$
  - $P(\mathbf{x}, \mathbf{y}) = P(\mathbf{x}|\mathbf{y})P(\mathbf{y})$
- **Sum rule:**
  - $P(\mathbf{y}) = \sum_{\mathbf{x}} P(\mathbf{x}, \mathbf{y})$ (discrete case)
  - $P(\mathbf{y}) = \int P(\mathbf{x}, \mathbf{y}) d\mathbf{x}$ (continuous case)

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Recap & What's Next

Recap:

- **Probabilistic Modeling:**
  - The art of quantifying real-world phenomena with probabilities.
  - Example: Diagnosing Alzheimer's with a medical test.
- **Probabilistic Reasoning (Inference):**
  - Infer probabilities of unobserved events from observed data.
- **Bayesian Analysis:**
  - Bayes' rule updates our beliefs with new evidence.
  - Applied in the Alzheimer's test case.
- **Core Probability Rules:**
  - Product rule, Sum rule, Bayes' rule.
  - These simple rules help us make informed conclusions.

Next Session: Dive deeper into probabilities and random variables.

- Complex phenomena require high dimensional random variables.