ELG 5218 - Uncertainty Evaluation in Engineering Measurements and Machine Learning
Introduction

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Outline

About the course

This course is about:

- Probabilistic and generative models
  - If a system can learn efficiently with a small amount of data $\Rightarrow$ strong modelling assumptions
- Bayesian approach
- Problems that engineers have when dealing with ML:
  - noise
  - small data
  - data is not independent
  - uncertainty

About the course

This course is **not** about:

- Supervised deep learning
  - Algorithms still struggle with knowing what they don't know
  - They do not know if they failed
- Dealing with introductory ML examples

Some practical problems

- Security: Detecting and classifying drones
  1. Sensors: radars, cameras
  2. Real time processing
  3. Difficult to collect data for training
  4. Confidence in our estimates and classification should increase as we receive more data
  5. Algorithms need to be interpretable to allow for decision making
- Medical: Classifying breathing of a person remotely
  - Sensor: Thermal camera, camera or radar
  - Same problems as items 2-5 above
  - We first need to detect the person, his/her chest or nose - therefore we might even miss the signal
  - Everyone breathes differently and it is very difficult to train supervised ML model

Framework - engineering approach

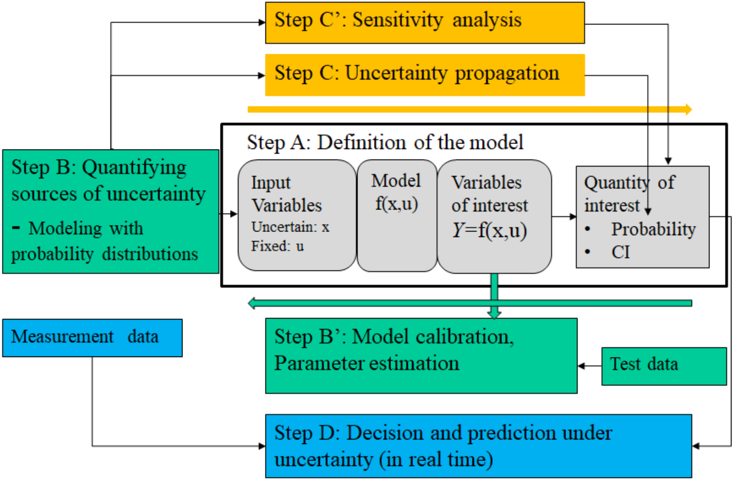

Figure: The workflow of Uncertainty Quantification Baudin et al. [2015]

Framework - ML approach

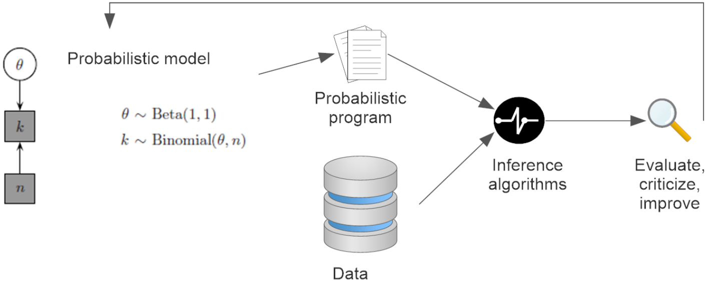

Figure: The workflow of probabilistic modelling

Sensors

- Sensor data is:
  - Streaming ⇒ Need to handle issues of streaming data
  - Dependent ⇒ Time series models
  - Noisy ⇒ Model need to include known info about the noise (Type, standard deviation)

Data for training

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- Data is:
  - Small data
  - Often, very difficult to collect and difficult to label
  - Often, collected from several small experiments that differ from each other making it very difficult to train (need homogeneous data to train the network). Examples:
    - Data is collected with different sensors
    - Data is collected in different environment $\Rightarrow$ different noise

Understanding the phenomenon

- We build models in engineering to understand the phenomenon in order to be able to design a proper system or to be able to make, or explain the decisions
- Therefore, the models need to be:
  - Interpretable
  - Provide uncertainties in the estimates

Uncertainties and AI

Probabilistic methods can be used to:

- Make decisions given partial information about the world
- Account for noisy sensors or actuators
- Explain phenomena not part of the models
- Describe inherently stochastic behaviour in the world

Topics I

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What we are going to learn in this course

1. Models, presenting uncertainty
2. Probabilistic reasoning
   Bayesian regression
   Bayesian logistic regression
3. Problem with analytical solutions.
   Inference: Variational inference, MCMC
   Probabilistic programming
4. Bayesian models: hierarchical and mixture models
5. Gaussian processes regression and classification
6. Clustering with uncertainties: probabilistic PCA, VAR, normalizing flows
7. Time series models, forecasting and classification
   - Models: ARIMA, state space, HMM, RNN, attention
   - filtering: Kalman filters, particle filters

Topics II

- Classification of time series: shapelets, probabilistic approaches, Early classification
- Forecasting

8. Sensor fusion
9. Stacking and merging models
10. Integration of physical and machine learning models
11. Sequential decision making

Software

Examples will be mainly in Julia

- Probabilistic machine and deep learning
  Turing, Flux, Gen, ForneyLab
- Optimization
- Combining NN and differential equations

Optionally Python

- Probabilistic machine and deep learning
  Pyro based on Pytorch or
  NumPyro based on JAX
- Time series
  sktime
  gluonts
- More to come

Why new language?

New ML tools should have - please see The Next Generation of Machine Learning Tools :

- fine-grained control flow use
- non-standard optimization loops
- higher-order differentiation as a first-class citizen
- probabilistic programming as a first-class citizen
- support for multiple heterogeneous accelerators in one model
- seamless scalability from a single machine to gigantic clusters

Grades

- Assignments 30%
- Scribing 20%
- Midterm 15%
- Final 35%

Books I

No text book

Probabilistic machine learning

- Murphy, Kevin P. 2021. Probabilistic Machine Learning: An Introduction, MIT press.
- Bayesian Reasoning and Machine Learning by David Barber.
- Bayesian Methods for Hackers by Cameron Davidson-Pilon.
- J. Winn, C. Bishop, Model Based Machine Learning
- N. D. Goodman, J. B. Tenenbaum, and The ProbMods Contributors (2016). Probabilistic Models of Cognition (2nd ed.)

Bayesian analysis

- R. McElreath, Statistical Re-thinking: A Bayesian Course with Examples in R and Stan, Chapman and Hall,CRC, 2015,

Books II

- A. Gelman, et al, Bayesian Data Analysis, 3rd edition, Chapman and Hall, CRC Texts in Statistical Science, 2013.
- C. Davidson-Pilon, Bayesian Methods for Hackers, Addison-Wesley Data and Analytics, 2015,
- C. Bailer-Jones, Practical Bayesian Inference: A primer for Physical Scientists, Cambridge University Press, 2017.

References I

Michael Baudin, Anne Dutfoy, Bertrand Iooss, and Anne-Laure Popelin. Openturns: an industrial software for uncertainty quantification in simulation, 2015.

Recommended videos

- Bayesian Inference, part 1 - Shakir Mohamed - MLSS 2020, Tübingen
- Keynote: Machine Learning and A.I. At Uber - Zoubin Ghahramani