Partially Observed Values

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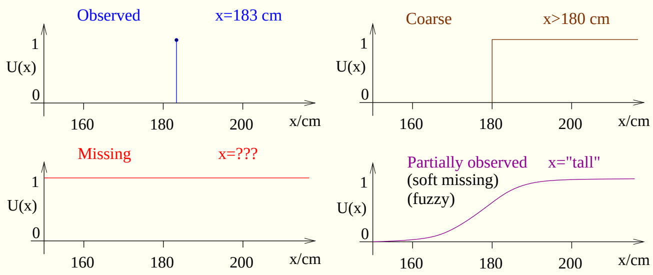
Abstract

It is common to have both observed and missing values in data. This paper concentrates on the case where a value can be somewhere between those two ends, partially observed and partially missing. To achieve that, a method of using evidence nodes in a Bayesian network is studied. Different ways of handling inaccuracies are discussed in examples and the proposed approach is justified in the experiments with real image data.

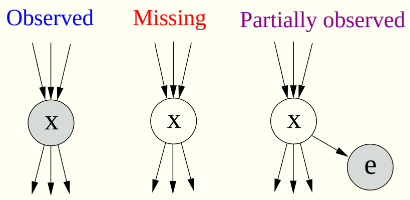
Introduction

- Imperfections in data are common
- A single value can be somewhere between observed and missing
- Variational Bayesian framework called the Bayes Blocks [1] is used here
- Partial observations can be handled by *virtual evidence*
- Figure shows different types of data values in the case of a particular person's height



Evidence approach

- To make a value x partially observed:
  - Leave the value x missing
  - Add an evidence node e as below
  - Make e observed



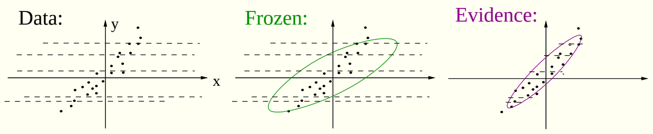
- The options of Gaussian and logistic evidence $U(x)$ are given
- The case $U(x)$ =constant is equivalent to a completely missing value

Frozen approach

- Alternative approach
- Fix a distribution over the data value
- $U(x)$ must be normalisable
  (cannot handle the logistic or constant evidence)

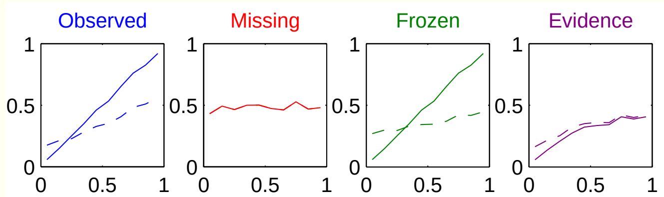
Example

- Factor analysis for (x, y) toy data
- Some of the x values are only partially observed
  (dash lines represent their confidence intervals)
- Frozen approach sticks to the uncertainty of the x and adjusts the model accordingly
- Evidence approach adjusts the uncertain values based on the model



Experiments

- 1000 data vectors $\mathbf{x}(t)$ are 10×10 patches of natural gray-scale images
- Independent Factor Analysis
  $\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{b} + \mathbf{n}(t)$
  Super-Gaussian prior for the sources $\mathbf{s}(t)$
- Each pixel has 10% chance of being corrupted with a Gaussian noise (std evenly distributed from 0 to 1; data std is 1)
- Corruption level is assumed to be known for each pixel!
- Four different settings regarding on how the corrupted values are handled
  Observed: Knowledge about corruption is discarded and corrupted values are treated as normal observed data
  Missing: Corrupted values are discarded and regarded as missing
  Frozen: A Gaussian distribution is fixed over each corrupted value
  Evidence: Evidence nodes are used to give a Gaussian virtual evidence



Reconstruction error as a function of the amount of corruption (std)

- Solid lines: $\langle \mathbf{x}(t) \rangle$, the posterior mean of the data variable
- Dash lines: $\langle \mathbf{A}\mathbf{s}(t) + \mathbf{b} \rangle$, the reconstruction without the innovation at the data node
- Evidence approach performs the best at all corruption levels

Conclusion

- Fill the gap between observed and missing values
- Implementation with evidence nodes in a Bayesian network
- Making use of the knowledge about inaccuracies pays off

References

[1] Harri Valpola, Tapani Raiko, and Juha Karhunen. Building blocks for hierarchical latent variable models. In *Proc. 3rd Int. Conf. on Independent Component Analysis and Signal Separation (ICA2001)*, pages 710–715, San Diego, USA, 2001.