Unsupervised Assessment of Ghana Radio Astronomy Observatory Sensor data: A Bayesian Gaussian Mixture Model Approach

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Overview

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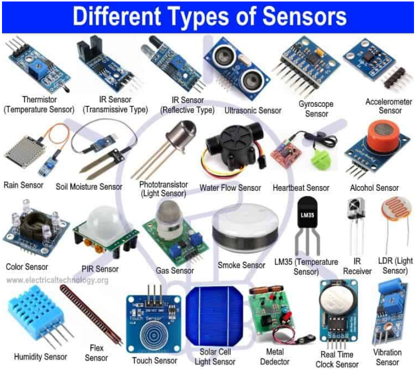
2. GRAO Temperature Data

3. Bayesian inference

Introduction



- A sensor is a device that detects and responds to some type of input from a physical environment.
- The specific input could be light, heat motion, moisture, pressure, or any environmental phenomena.

Real-time calibration

- Sensors required for pointing correction.
- Sensors required for receiver calibration.

Sensor reporting:

- Sensor values required for failure prediction
- Sensors required to identify faults (fault finding)
- Sensors that may indicate that the quality of the data being captured may be negatively impacted.

Introduction IV

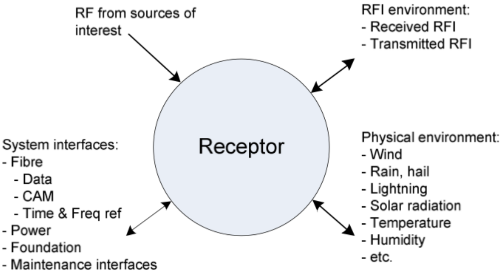
- Sensors required to determine resource availability for observation planning and scheduling
- Sensors that identify the installed configuration of the subsystem.
- Sensors that indicate safety-critical conditions.

TABLE I: Specifications of GRAO telescope.

Description	Spec
System	alt-azimuth mount, wheel-and-track, Cassegrain, beam-waveguide antenna
Dish diameter	32 m
Azimuth range†	$\leq$ 327 deg
Elevation range	5 – 90 deg
Slew rate	0.27 – 0.29 deg/sec
Maximum gain (dB)	63.80 (at 5 GHz) and 66.47 (at 6.7 GHz) [5]
Aperture efficiency (%)	85.45 (at 5 GHz) and 88.0 (at 6.7 GHz) [5]
Spillover (dB)	0.19 (at 5 GHz) and 0.14 (at 6.7 GHz) [5]
Receiver system	uncooled dual polariser
T_{sys}	$\sim$ 125 K [3]
Polarisation	circular (L + R)
Antenna location	5.7504 N and 0.3051 W

† Azimuth challenge: $>$ 327 deg

Introduction VI

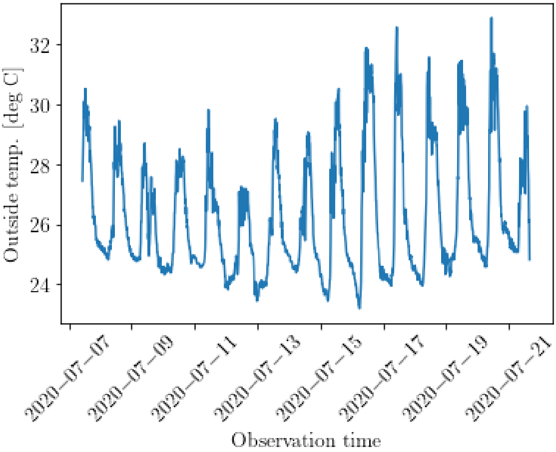


(a) iButtons

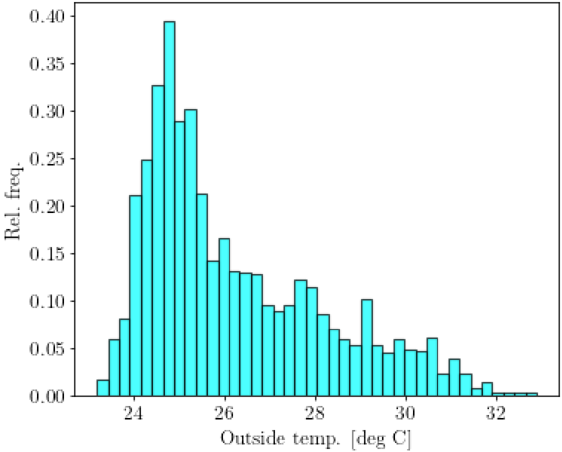
(b) Accessories

GRAO Temperature Data

Sensor Data I

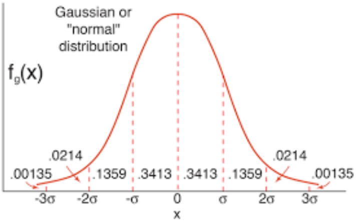


Sensor Data II



$$y = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$\begin{aligned}
\mu &= \text{Mean} \\
\sigma &= \text{Standard Deviation} \\
\pi &\approx 3.14159\cdots \\
e &\approx 2.71828\cdots
\end{aligned}$$



Bayesian inference

- In the context of Bayesian inference, we are interested in estimating the posterior $P(\theta|D, M)$ of a set of parameters θ for a given model M conditioned on some data D. This can be written into a form commonly known as Bayes Rule:

$$P(\theta|D, M) = \frac{P(D|\theta, M)P(\theta|M)}{P(D|M)}$$

- where $P(D|\theta, M)$ is the likelihood of the data given the parameters of our model, $P(\theta|M)$ is the prior for the parameters of our model, and

- $P(D|M) = \int_{\Omega_\theta} P(D|\theta, M)P(\theta|M)d\theta$ is the evidence (i.e. marginal likelihood) for the data given our model, where the integral is taken over the entire do- main Ω_θ of θ (i.e. over all possible parameter combinations).
- In the proposed method, we define the likelihood of the sensor dataset D as a one-dimensional Gaussian mixture model,

$$P(D|\{w_j, \mu_j, \sigma_j\}) = \prod_{k}^{N}(\sum_{j}^{M} w_j\mathcal{N}(D|\mu_j, \sigma_j))$$

- where μ_j and σ_j are the means and standard deviations of M normal distributions, and w_j are their weights in the mixture, which must satisfy $\sum_{j}^{M} w_j = 1$.

- Be aware that because of the non-linear nature in Eq., direct maximization would be very laborious and so, an iterative Expectation Maximisation (EM) algorithm is more appropriate to use in this case.
- To apply the EM method, first, assume the model parameters are known and then use the initial parameters to estimate new model parameters. Next, use the new model parameters as the initial model to work out the current model parameters.
- Repeat this phenomenon until a convergence is attained.
- This iteration involves the expectation (E) and maximization (M) steps as follows:

1. In the E step, the EM method measures the posterior distribution by taking the initial parameters into consideration. In fact, this stage ensures us to establish the probability of $d_i \in D$ being a member of a sub-cluster.
2. The M step estimates the maximum likelihood of the current model parameters.

Bayesian inference V

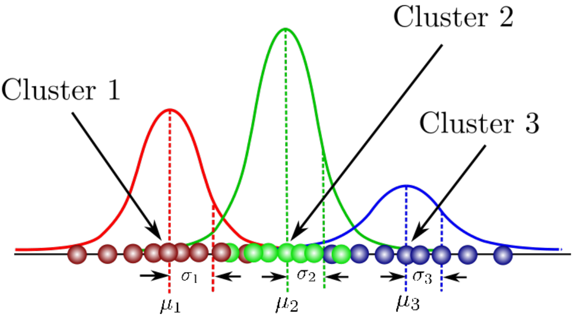


Figure: Source: Copied from Carrasco blog.

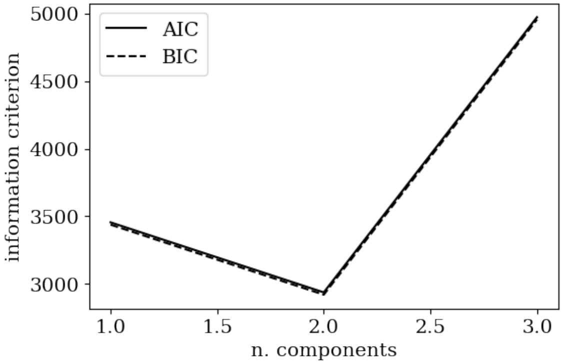
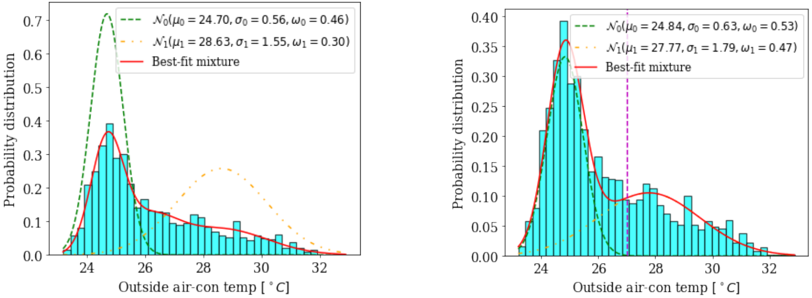


Figure: BIC & AIC plots



(a) No weights

(b) With weight

Figure: Distribution of outside temperature for GRAO.

Bayesian inference VIII

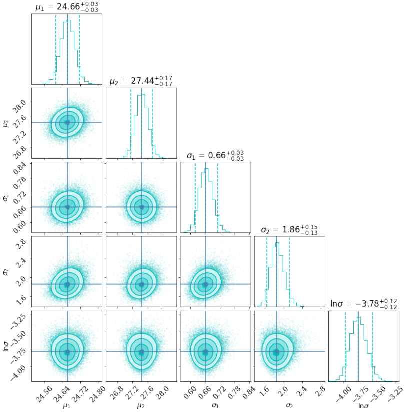


Figure: Posterior probability densities for the Gaussian- distribution parameters of the mean and std as derived in our MCMC algorithm.

Thank You

for your attention.

Do you have any question?