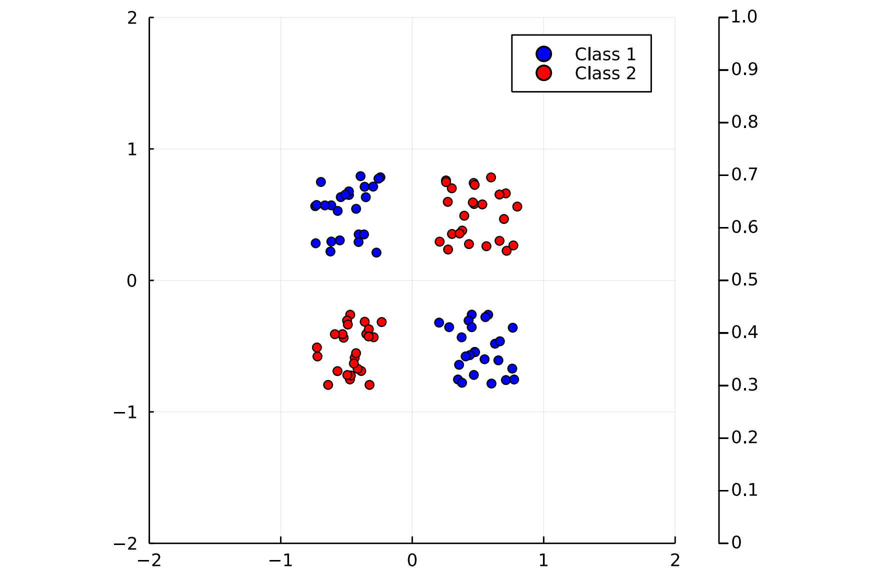
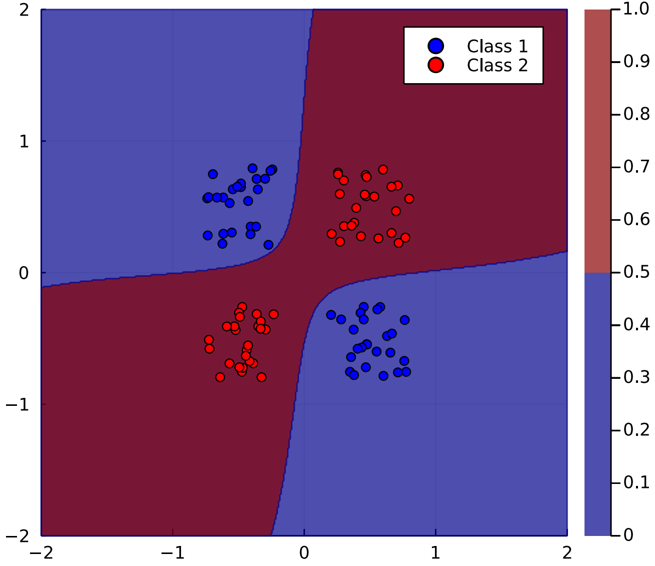


Class 1
Class 2
2
1
0
−1
−2
−2
−1
0
1
2
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0



Class 1
Class 2
2
1
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0
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0.6
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0.3
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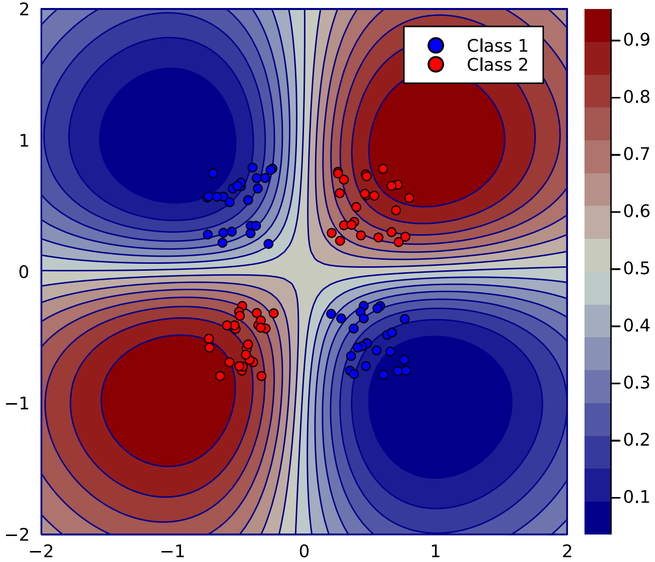
0.1
0



Class 1
Class 2
2
1
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−2
−1
0
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2
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

Gaussian processes for non-Gaussian likelihoods

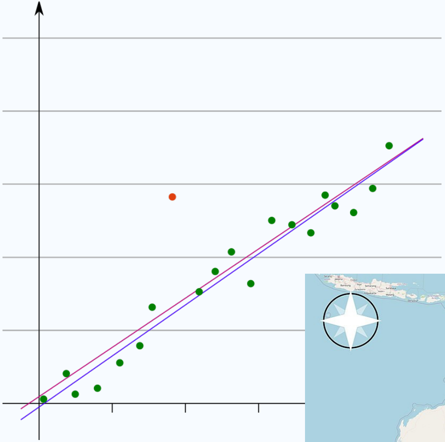
ST John

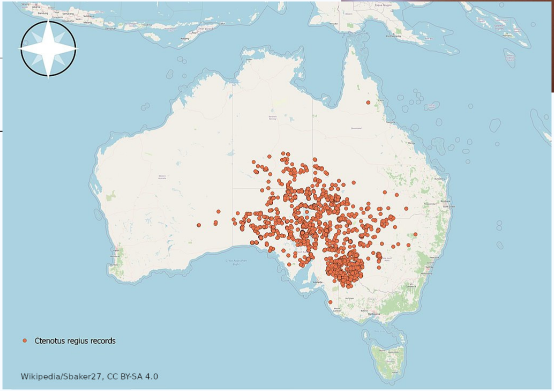
ti.john @ aalto.fi

Finnish Center for Artificial Intelligence
& Aalto University

LIKE2022 winter school, 10 January 2022

Not Gaussian noise





Overview

Outline:

1. **Gaussian processes with Gaussian likelihood**
2. What is the likelihood? Connecting observations and Gaussian process prior
3. Non-Gaussian likelihoods: what happens to the posterior?
4. How to approximate the intractable
5. Comparison

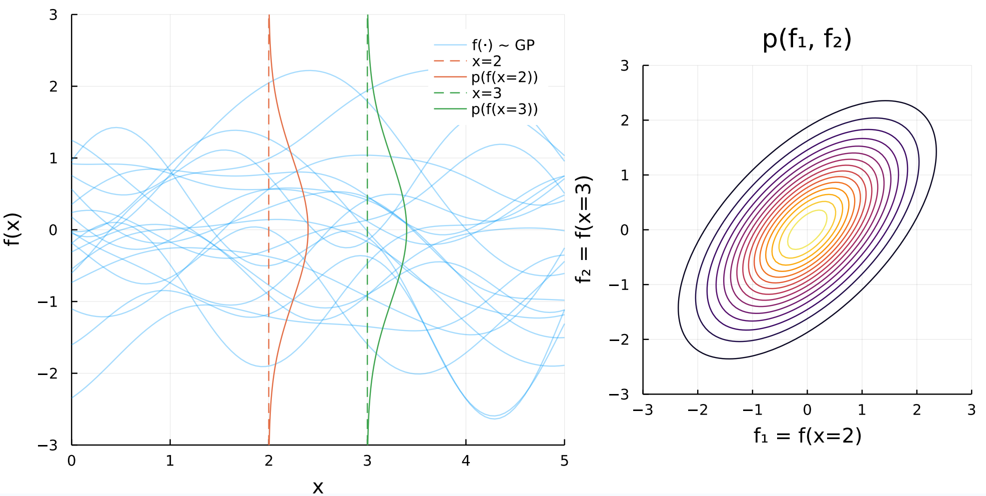
+ *Intuitive* understanding
+ Learning the language

– In-depth expertise
– Lots of maths

Setting the scene

Gaussian process $f(\cdot)$

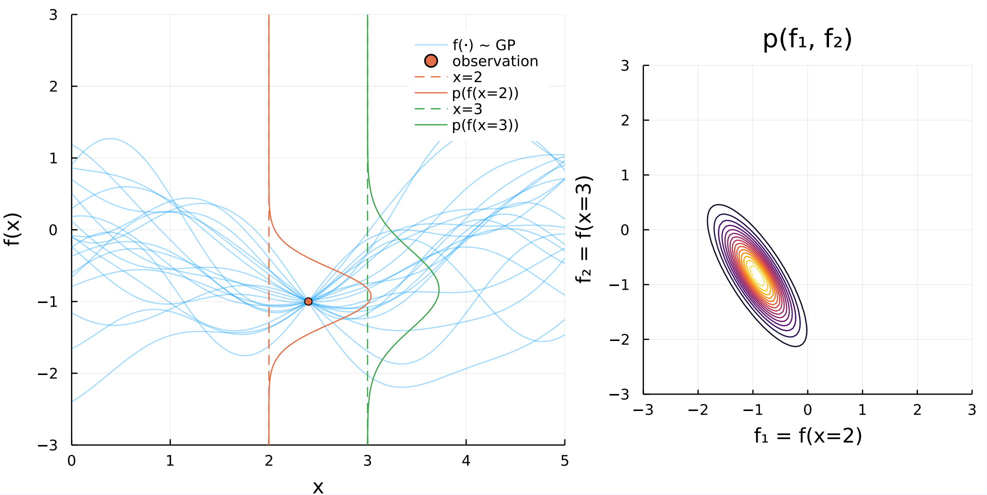
Distribution over *functions*
Marginals are Gaussian (mean and covariance)



infinitecuriosity.org/vizgp

Gaussian process conditioned on observation

Distribution over *functions*
Marginals are Gaussian (mean and covariance)



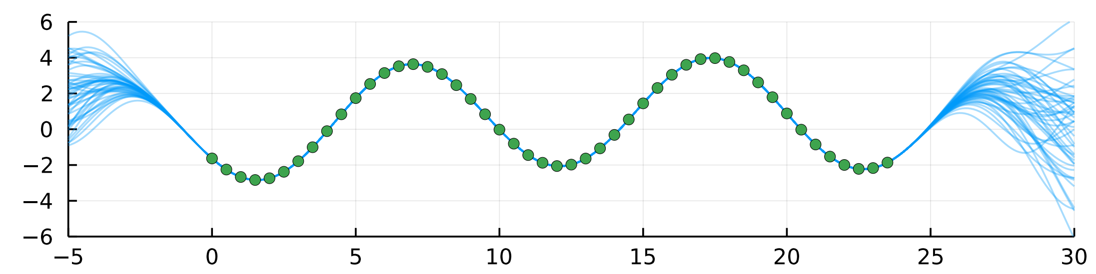
infinitecuriosity.org/vizgp

exact conditioning

Without noise model, we interpolate observations:

$$y(x) = f(x) + \epsilon, \qquad \epsilon \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2_{\text{noise}})$$

$$p(y \mid f) = \mathcal{N}(y \mid f, \sigma^2_{\text{noise}})$$



exact conditioning

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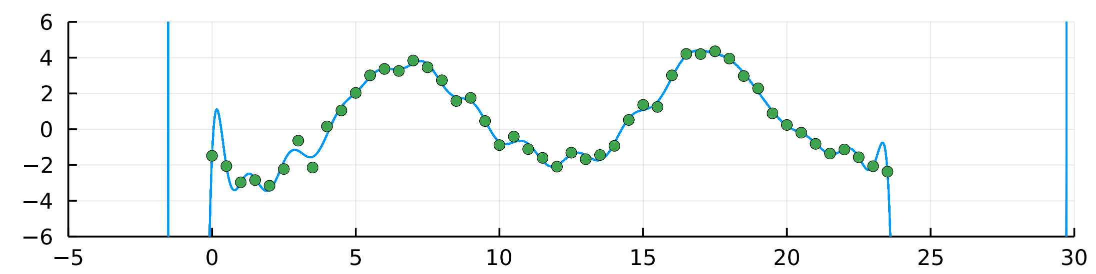
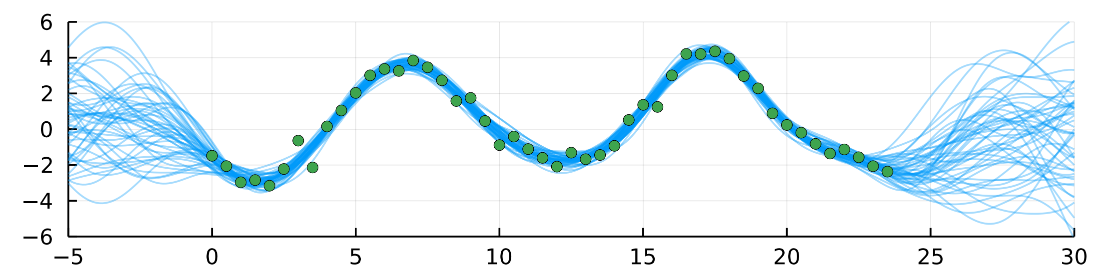


Gaussian noise model

Gaussian additive noise model, written two ways:

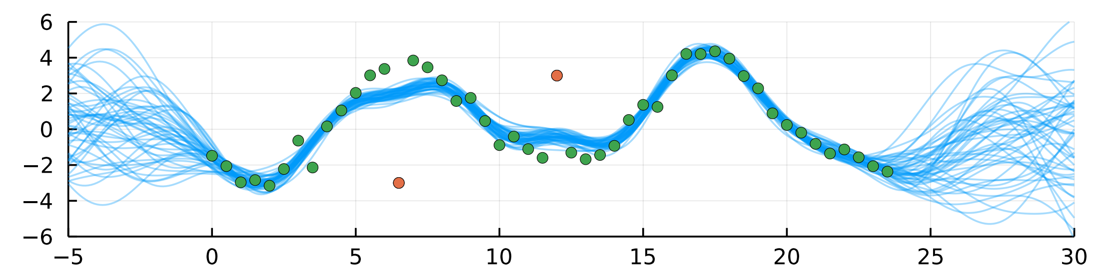
$$y(x) = f(x) + \epsilon, \qquad \epsilon \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2_{\text{noise}})$$
$$p(y \mid f) = \mathcal{N}(y \mid f, \sigma^2_{\text{noise}})$$



misspecified Gaussian noise model

Gaussian additive noise model, written two ways:

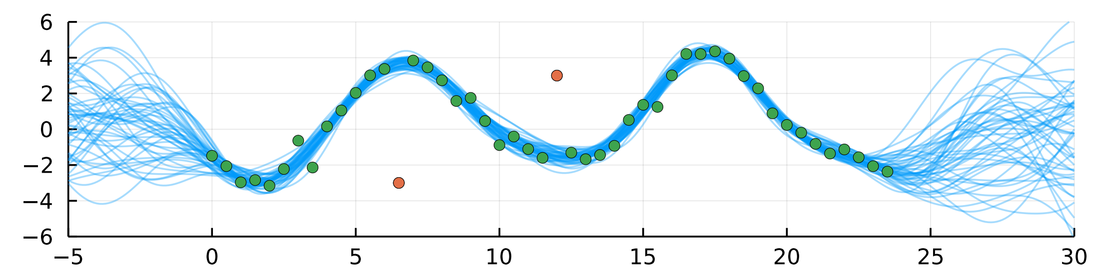
$$y(x) = f(x) + \epsilon, \qquad \epsilon \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2_{\text{noise}})$$
$$p(y \mid f) = \mathcal{N}(y \mid f, \sigma^2_{\text{noise}})$$



heavy-tailed noise model

$$y(x) = f(x) + \epsilon, \qquad \epsilon \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2_{\text{noise}})$$

$$p(y \mid f) = \mathcal{N}(y \mid f, \sigma^2_{\text{noise}})$$



Outline

- ✓ Gaussian processes with Gaussian likelihood
2. **What is the likelihood? Connecting observations and Gaussian process prior**
3. Non-Gaussian likelihoods: what happens to the posterior?
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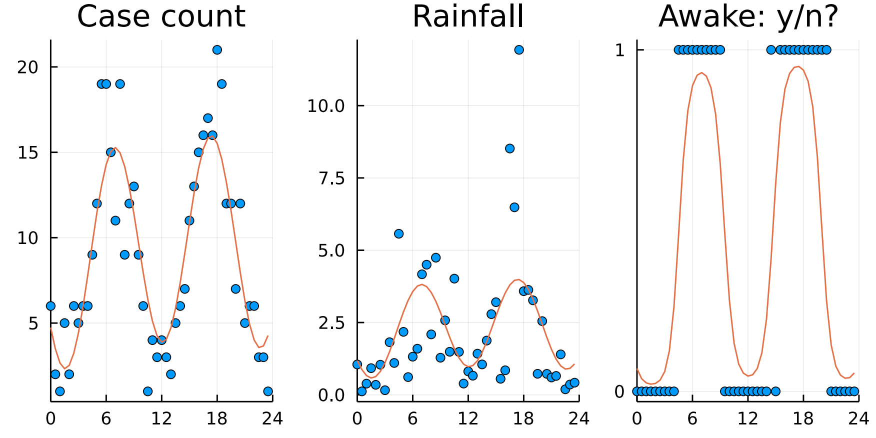
5. Comparison

Likelihood

Non-Gaussian observations



latent functional relationship

$$p(y_i \mid f(x_i))$$

Likelihood

$$p(\mathbf{y} \mid \mathbf{f}) = \prod_{i=1}^{N} p(y_i \mid f_i); \qquad f_i = f(x_i)$$

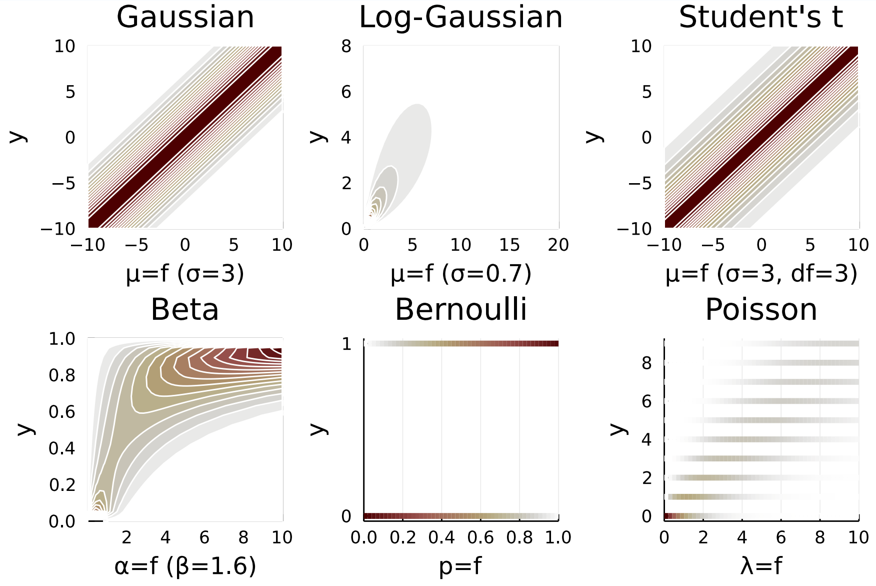
factorizing

$$p(y \mid f)$$

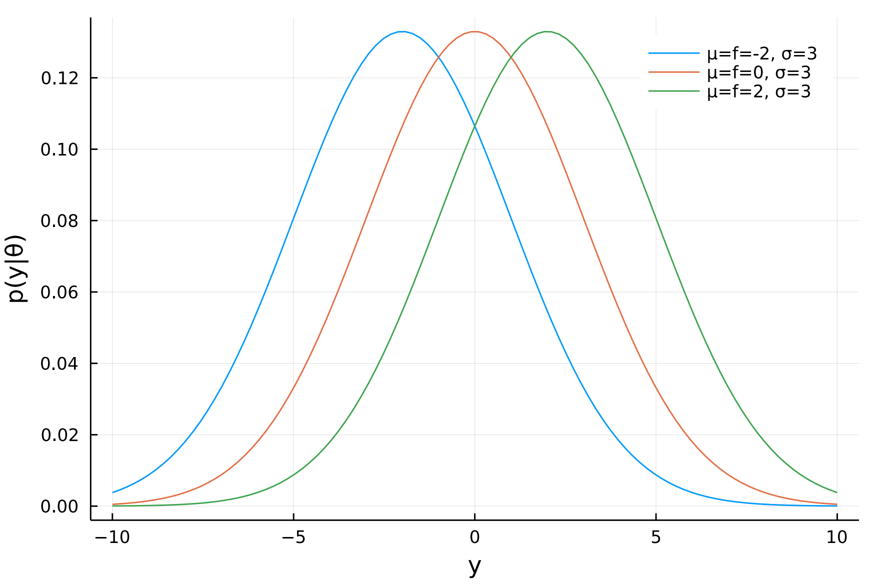
Function of two arguments:

$$y \mapsto p(y \mid f), \qquad f \mapsto p(y \mid f)$$

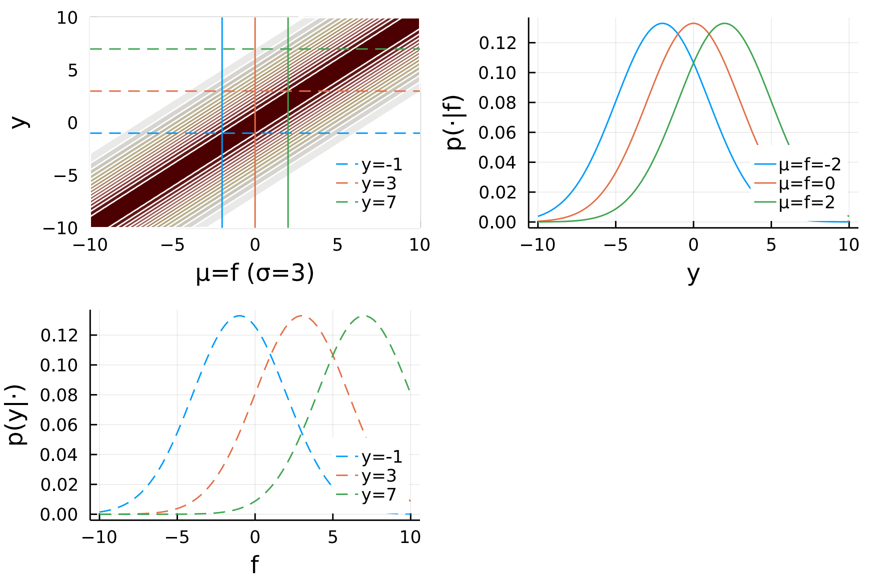
$p(y \mid f)$


Gaussian
y
μ=f (σ=3)
Log-Gaussian
μ=f (σ=0.7)
Student's t
μ=f (σ=3, df=3)
Beta
α=f (β=1.6)
Bernoulli
p=f
Poisson
λ=f

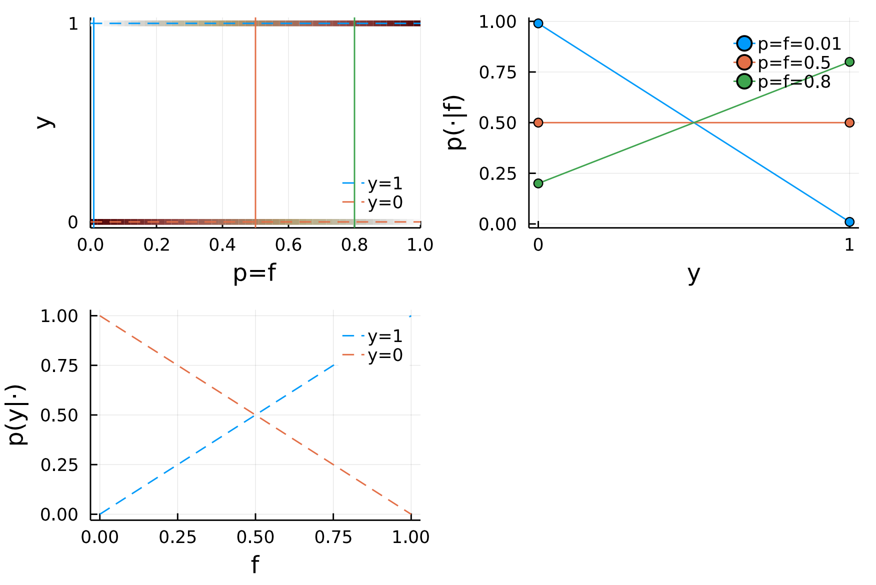
$p(y \mid f)$: Gaussian



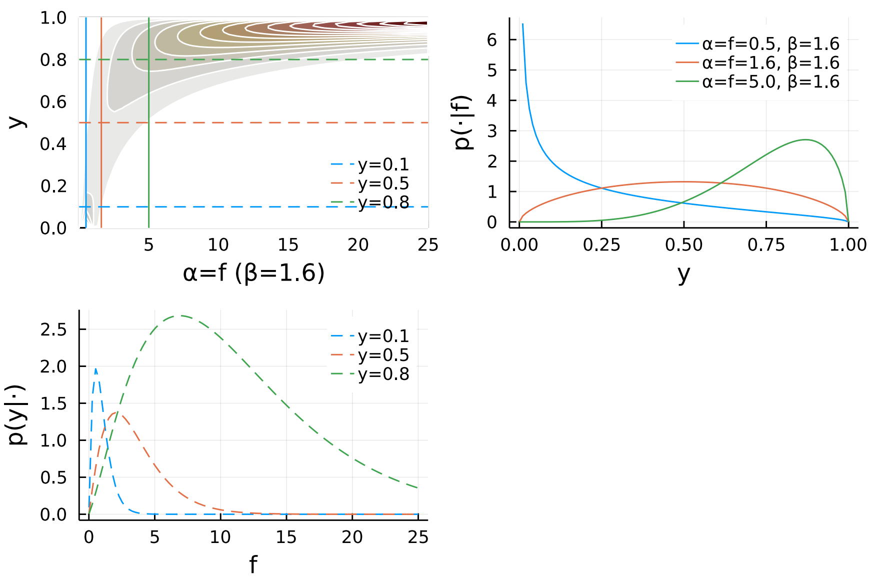
$p(y \mid f)$: Gaussian



$p(y \mid f)$: Bernoulli

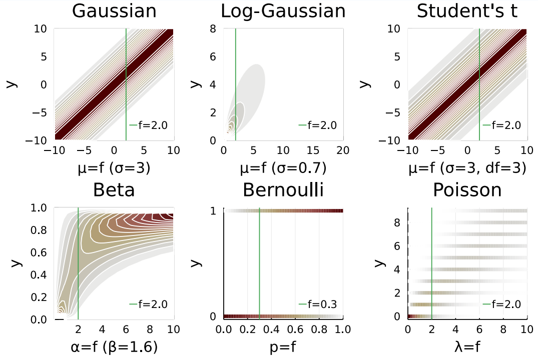


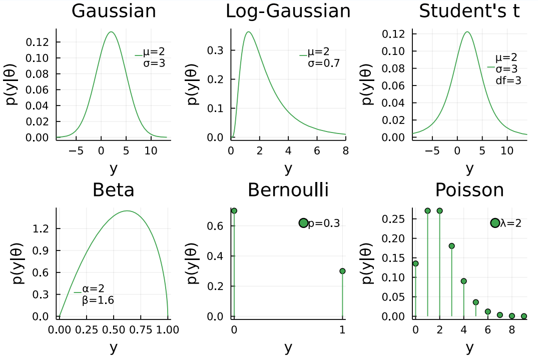
$p(y \mid f)$: Beta



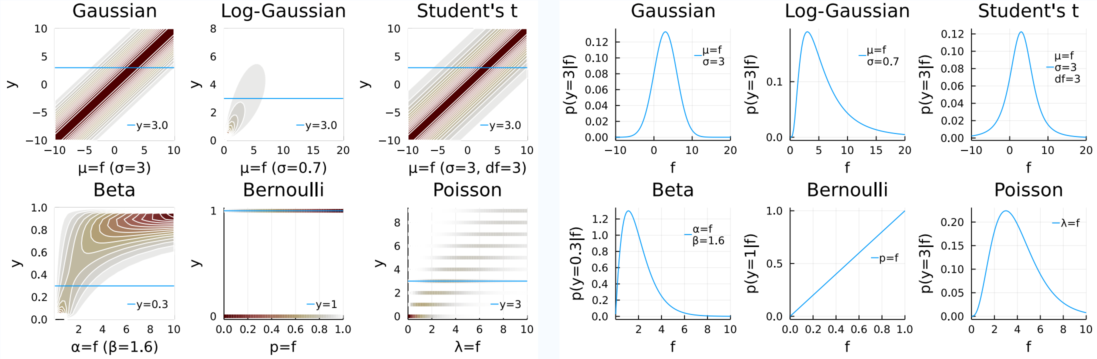
y
α=f (β=1.6)
y=0.1
y=0.5
y=0.8
p(·|f)
y
α=f=0.5, β=1.6
α=f=1.6, β=1.6
α=f=5.0, β=1.6
p(y|·)
f
y=0.1
y=0.5
y=0.8

$p(y \mid f)$: distribution of observation — f fixed





$p(y \mid f)$: likelihood of parameter — y fixed

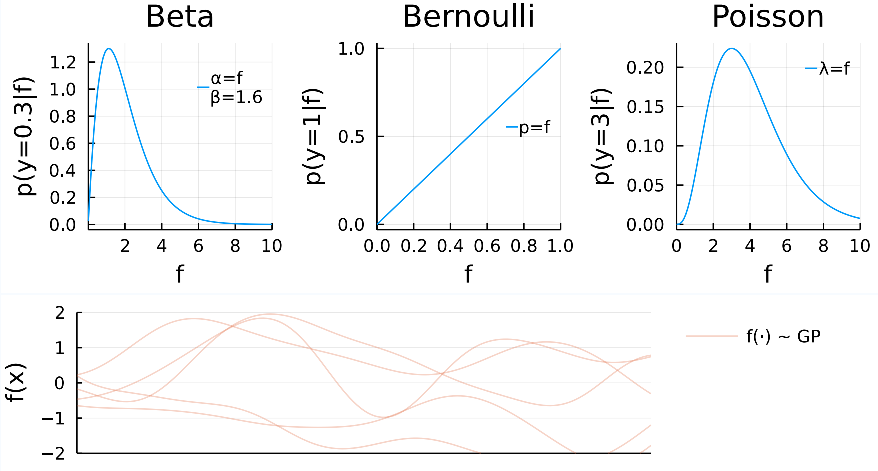


Two aspects of likelihoods:

1. link functions
2. log-concavity

$$\mathbb{E}[y] = \theta \in (0 \dots \infty) \qquad \mathrm{link}(\theta) = f$$

$$f \sim \mathcal{N} \qquad \in (-\infty \dots \infty) \qquad \theta = \mathrm{invlink}(f)$$



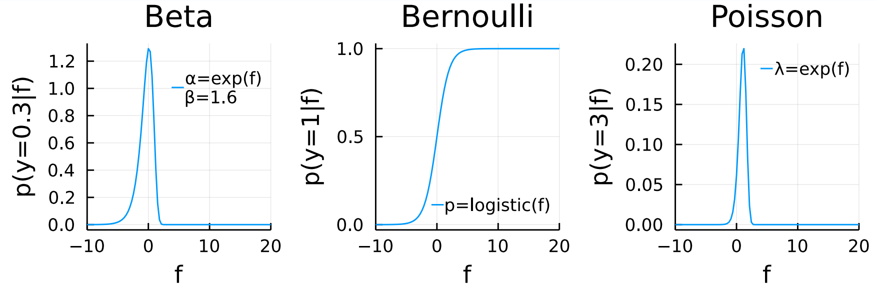
Link functions

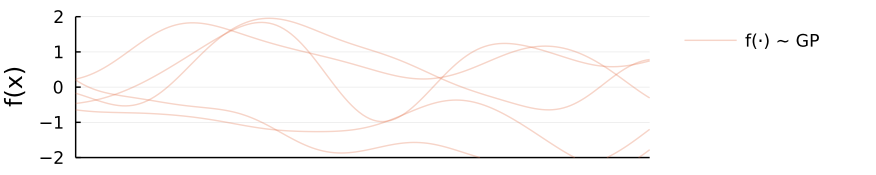
$$\mathbb{E}[y] = \theta \in (0 \ldots \infty)$$

$$f \sim \mathcal{N} \qquad \in (-\infty \ldots \infty)$$

$$\text{link}(\theta) = f$$

$$\theta = \text{invlink}(f)$$





Link functions

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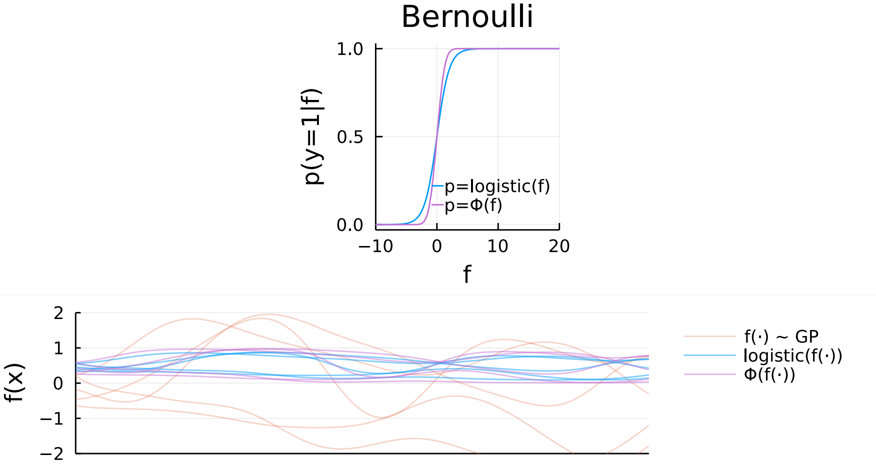
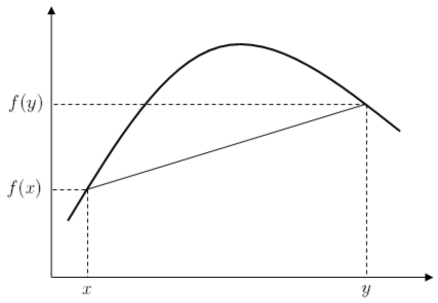
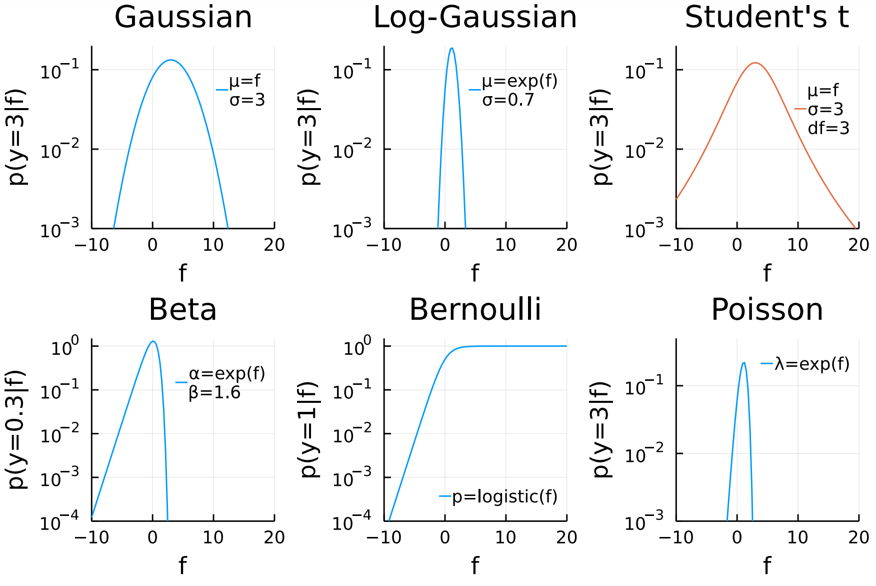


(Log-)concavity



$$f\left(\alpha x + (1-\alpha)y\right) \geq \alpha f(x) + (1-\alpha)f(y)$$

Log-concavity of likelihoods



Outline

- ✓ Gaussian processes with Gaussian likelihood
- ✓ What is the likelihood? Connecting observations and Gaussian process prior

3. **Non-Gaussian likelihoods: what happens to the posterior?**
4. How to approximate the intractable
5. Comparison

Posterior

Likelihood

$$p(y \mid f)$$

Joint distribution

$$p(y, f) = p(y \mid f)p(f)$$

Posterior

$$f \mapsto p(f \mid y) = \frac{p(y \mid f)p(f)}{p(y)}$$

$$y \mapsto \big(f \mapsto p(f \mid y)\big)$$

Posterior predictions

At new point x^*:

$$p(f^* \mid x^*, \mathbf{x}, \mathbf{y}) = \int p(f^* \mid x^*, \mathbf{x}, \mathbf{f})\, p(\mathbf{f} \mid \mathbf{x}, \mathbf{y})\, \mathrm{d}\mathbf{f}$$

At training data:

$$p(\mathbf{f} \mid \mathbf{x}, \mathbf{y}) = \frac{p(\mathbf{f} \mid \mathbf{x}) \prod_{i=1}^{N} p(y_i \mid f(x_i))}{\int p(\mathbf{f}' \mid \mathbf{x}) \prod_{i=1}^{N} p(y_i \mid f'(x_i))\, \mathrm{d}\mathbf{f}''}$$

$$p(\mathbf{f} \mid \mathbf{y}) = \frac{1}{Z} p(\mathbf{f}) \prod_{i=1}^{N} p(y_i \mid f_i)$$

$$Z = p(\mathbf{y} \mid \mathcal{M}) = \int p(\mathbf{f} \mid \mathcal{M}) \prod_{i=1}^{N} p(y_i \mid f_i, \mathcal{M})\, \mathrm{d}\mathbf{f}$$

"marginal likelihood" or "evidence" given model $\mathcal{M}$

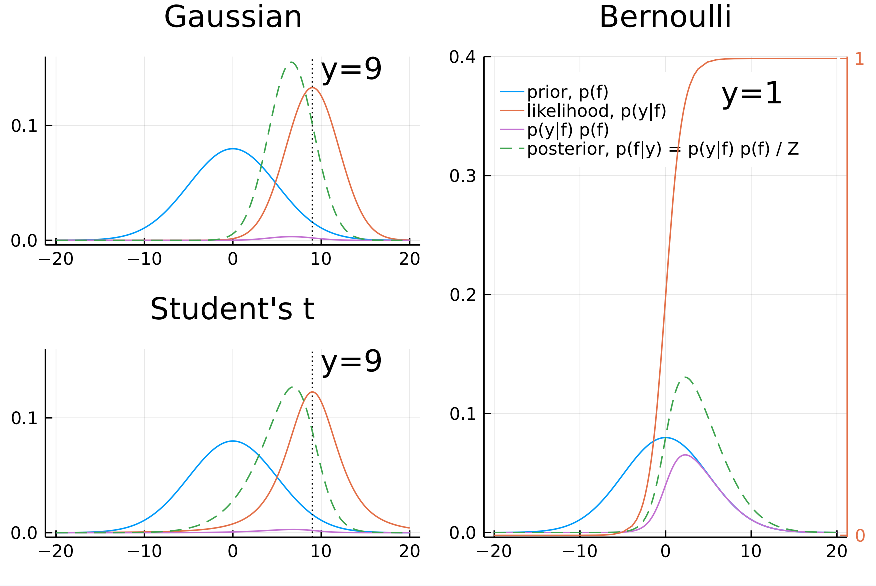
Posterior

$$p(\mathbf{f} \mid \mathbf{y}) = \frac{1}{Z} p(\mathbf{f}) \prod_{i=1}^{N} p(y_i \mid f_i)$$

Gaussian (process) prior $p(f(\cdot))$ ...

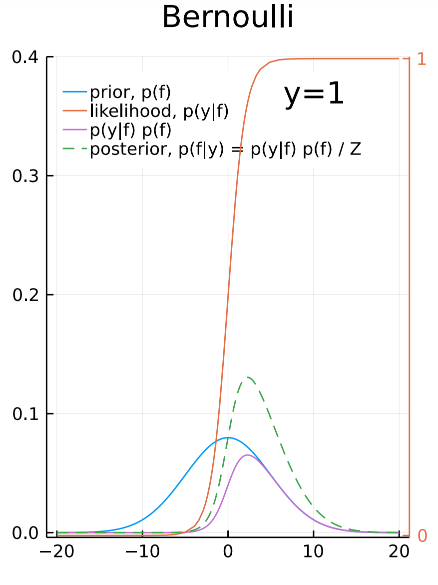
- & Gaussian likelihood: conjugate case $\rightarrow$ posterior Gaussian
- & non-Gaussian $p(y|f) \rightarrow p(\mathbf{f} \mid \mathbf{y})$ also non-Gaussian, intractable

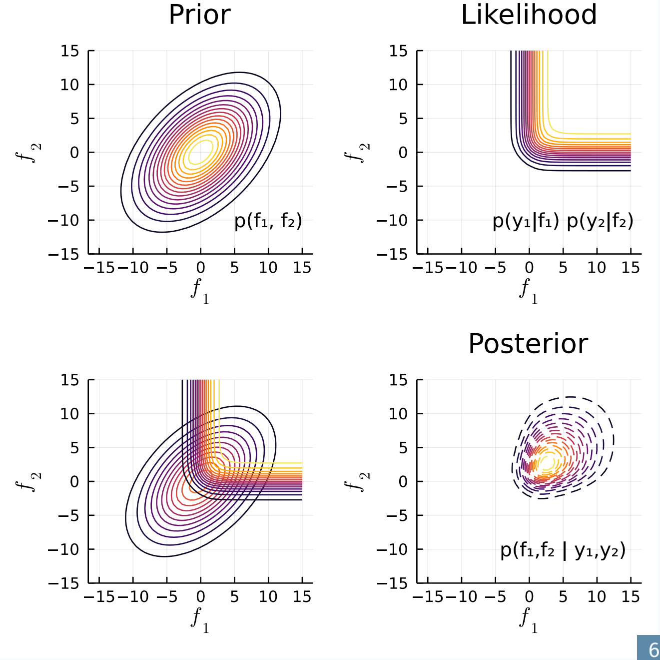
1D examples



Gaussian
y=9
0.1
0.0
−20
−10
0
10
20
Student's t
y=9
0.1
0.0
−20
−10
0
10
20
Bernoulli
0.4
0.3
0.2
0.1
0.0
prior, p(f)
likelihood, p(y|f)
p(y|f) p(f)
posterior, p(f|y) = p(y|f) p(f) / Z
y=1
1
0
−20
−10
0
10
20

Bernoulli example in 2D





Posterior for N observations

$$p(\mathbf{f} \mid \mathbf{y}) = \frac{p(\mathbf{f})\prod_{i=1}^{N} p(y_i \mid f_i)}{\int p(\mathbf{f}')\prod_{i=1}^{N} p(y_i \mid f_i')\,\mathrm{d}\mathbf{f}'}$$

$$\begin{aligned} f_1 &= f(x_1) \\ f_2 &= f(x_2) \\ &\vdots \\ f_N &= f(x_N) \end{aligned}$$

Summary so far

- What is the likelihood $p(y \mid f)$?
- When is it non-Gaussian?
- Why does the posterior $p(f \mid y)$ become intractable?

Questions?! :)

Outline

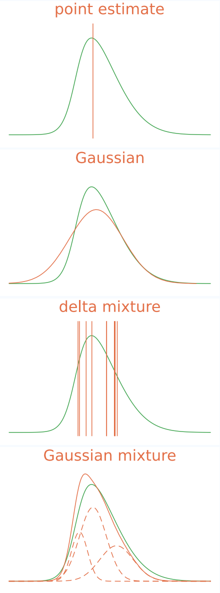
- ✓ Gaussian processes with Gaussian likelihood
- ✓ What is the likelihood? Connecting observations and Gaussian process prior
- ✓ Non-Gaussian likelihoods: what happens to the posterior?

4. **How to approximate the intractable**
5. Comparison

Approximations

Approximating distributions

- delta distribution
  - point estimate
- **Gaussian distribution**
  - Laplace
  - Expectation Propagation (EP)
  - Variational Bayes/Variational Inference (VB / VI)
- mixture of delta distributions
  - Markov Chain Monte Carlo (MCMC)
- mixture of Gaussians
- ...



Gaussian approximations

Approximating the exact posterior with Gaussian

Approximating the posterior at observations:

$$p(\mathbf{f} \mid \mathbf{y}) \approx q(\mathbf{f}) = \mathcal{N}(\mathbf{f} | \mu = ?, \Sigma = ?)$$

Predictions at new points:

$$p(f^* \mid x^*, \mathbf{y}) \approx q(f^*) = \int p(f^* \mid x^*, \mathbf{f})\, q(\mathbf{f})\, \mathrm{d}\mathbf{f}$$

Demo: What does this mean for Gaussian processes?

tinyurl.com/nongaussian-inference-viz-v1

Choosing μ and Σ for $q(\mathbf{f})$

$$p(\mathbf{f} \mid \mathbf{y}) \approx q(\mathbf{f}) = \mathcal{N}(\mathbf{f} | \mu = ?, \Sigma = ?)$$

match mean & variance at point

minimise divergence

Laplace approximation

Expectation Propagation (EP)

Variational Bayes (VB)

Laplace approximation

Laplace approximation

Idea: log of Gaussian pdf = quadratic polynomial

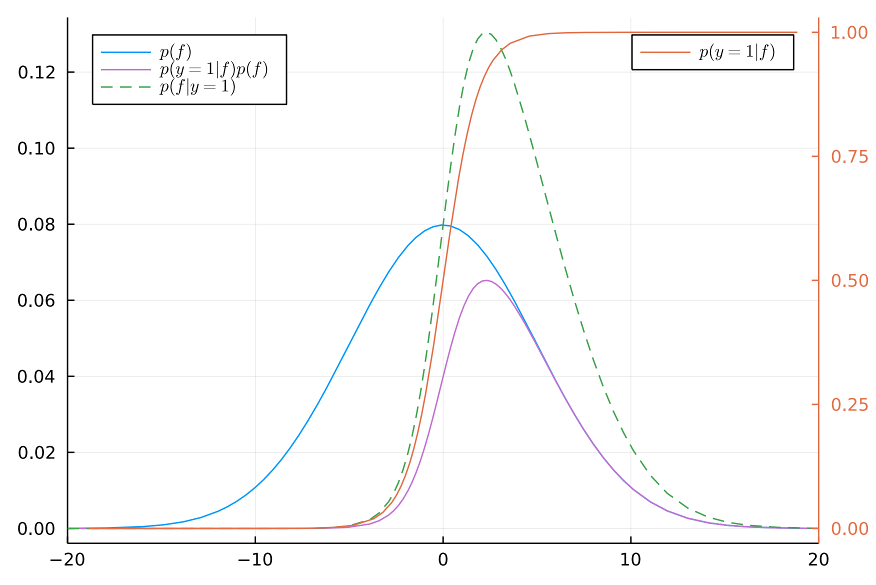
$$p_{\mathcal{N}}(\mathbf{f}) = \frac{1}{\sqrt{(2\pi)^k|\Sigma|}} \exp\left(-\frac{1}{2}(\mathbf{f}-\mu)^\top \Sigma^{-1}(\mathbf{f}-\mu)\right)$$

quadratic polynomial through approximation:
2nd-order Taylor expansion of log of $h(f) = p(y \mid f)p(f)$ at $\hat{f}$

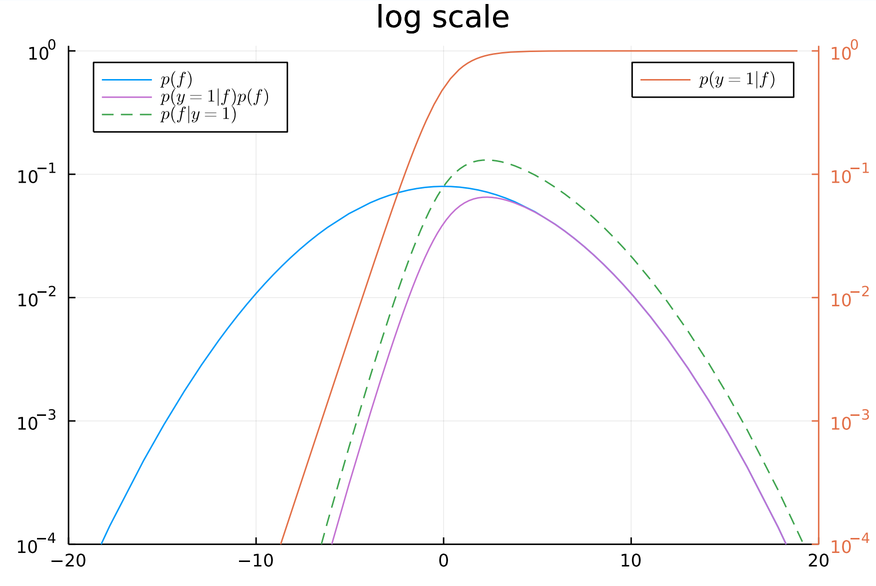
$$g(x+\delta) \approx g(x) + \left(\frac{\mathrm{d}g}{\mathrm{d}x}(x)\right)\delta + \frac{1}{2!}\left(\frac{\mathrm{d}^2 g}{\mathrm{d}x^2}(x)\right)\delta^2$$

1. Find **mode** of posterior
   2nd-order gradient optimisation (e.g. Newton's method)
2. Match **curvature** (Hessian) at mode

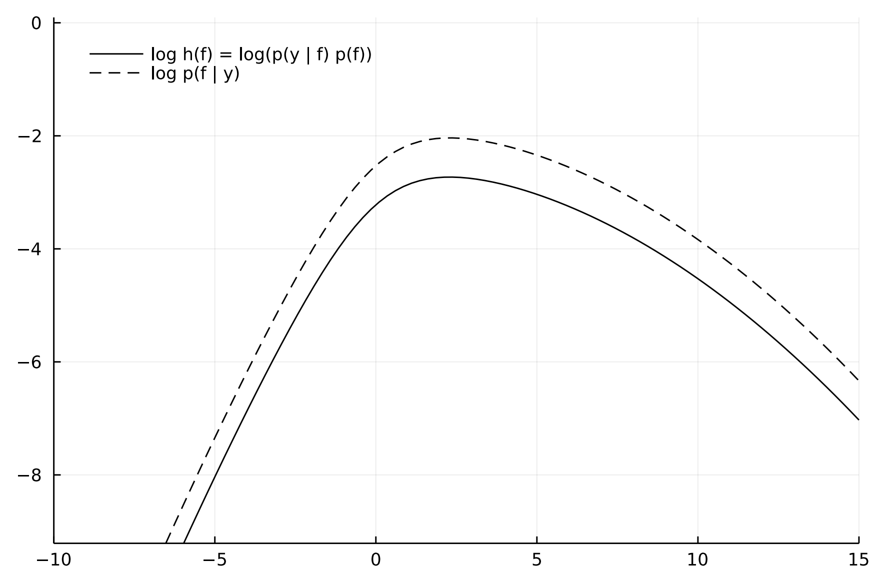
$p(f \mid y) = \frac{1}{Z} p(y \mid f) p(f)$



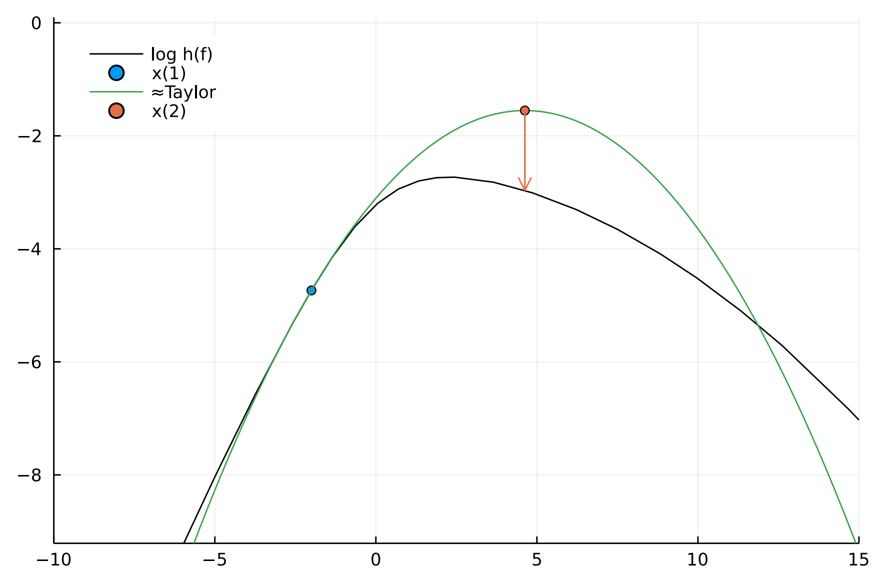
$$\log p(f \mid y) = -\log Z + \log p(y \mid f) + \log p(f)$$



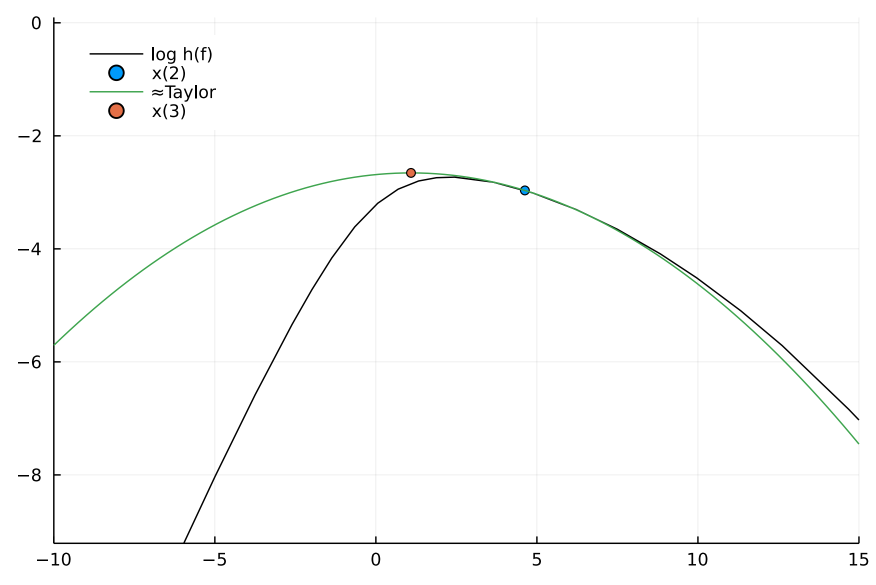
$\log p(f \mid y) = -\log Z + \log h(f)$



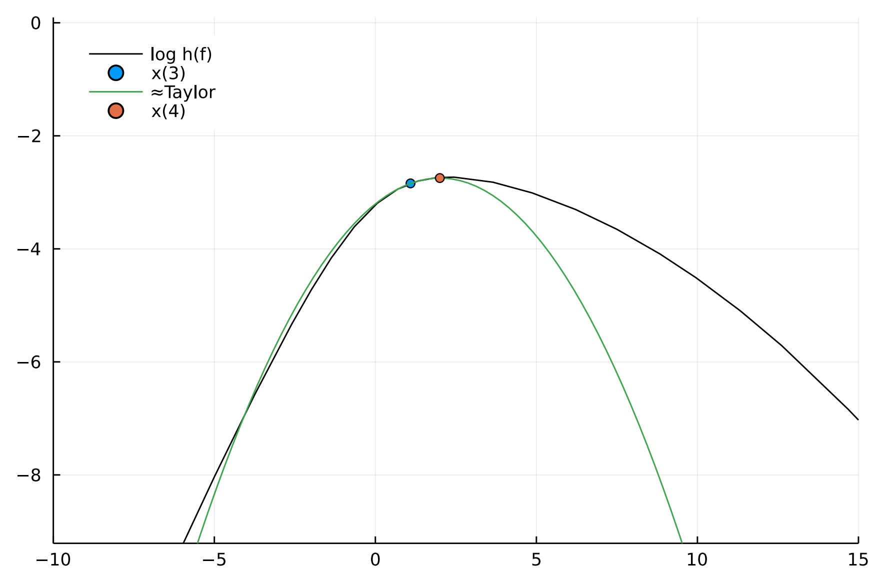
Newton’s method



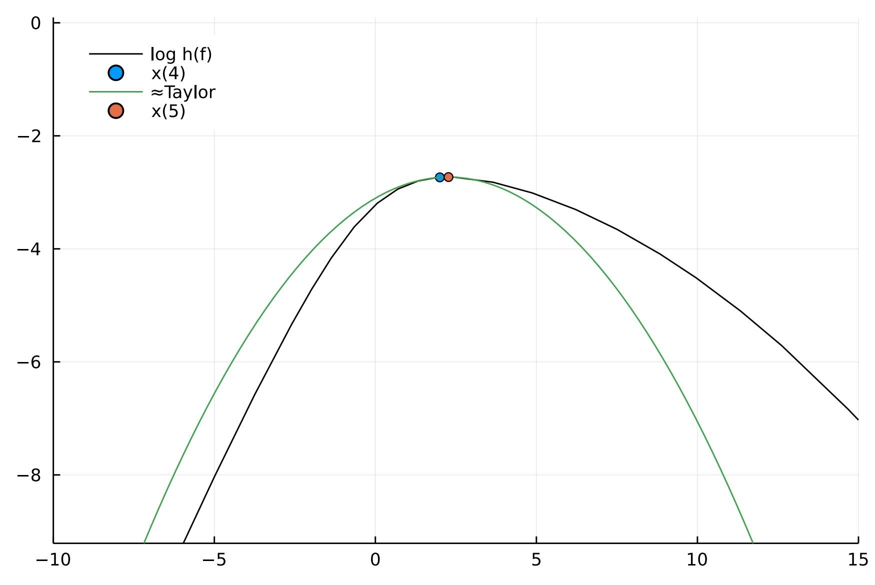
Newton's method



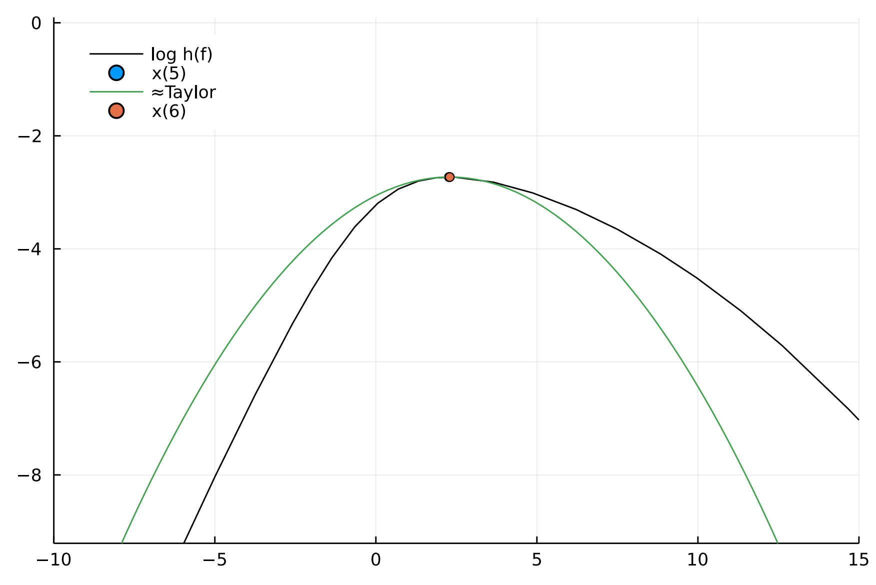
Newton's method



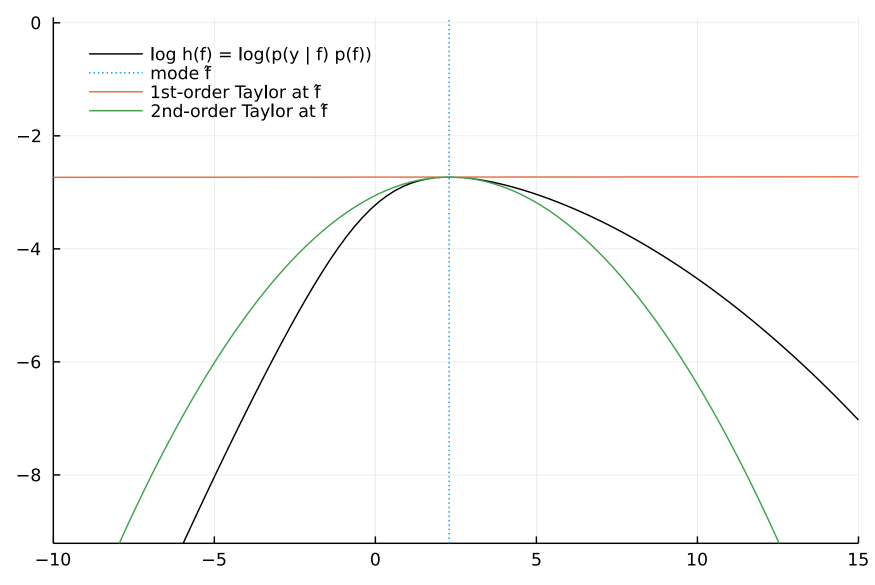
Newton's method



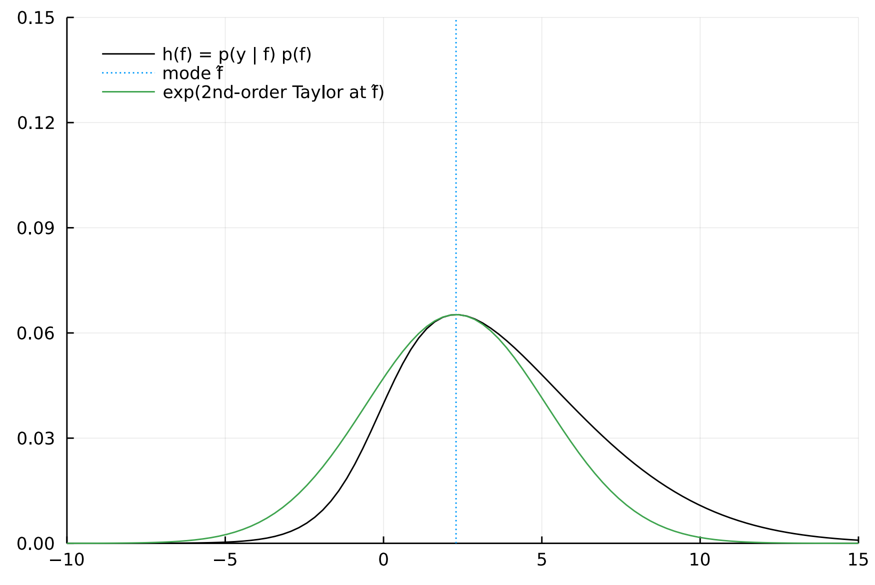
Newton's method



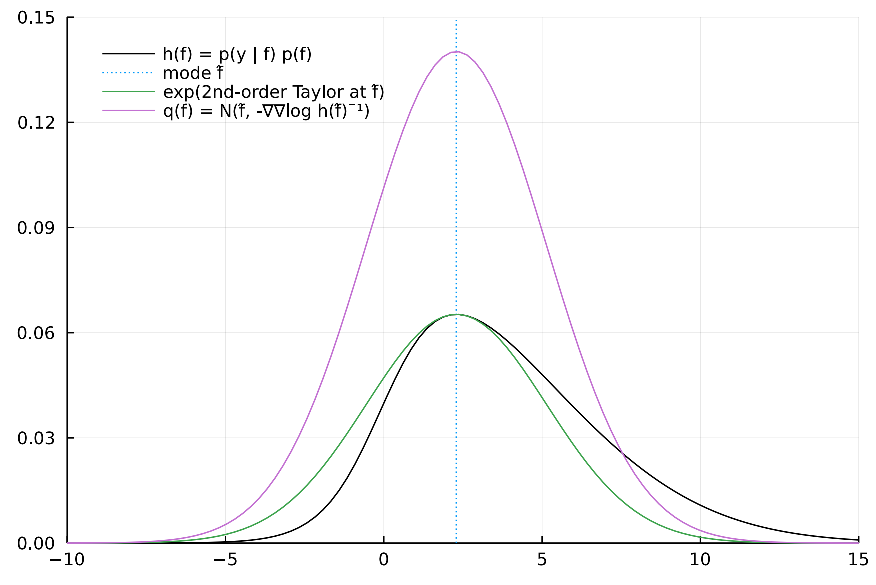
$\log p(f \mid y) + \log Z = \log h(f) \approx \mathcal{O}(f^2)$



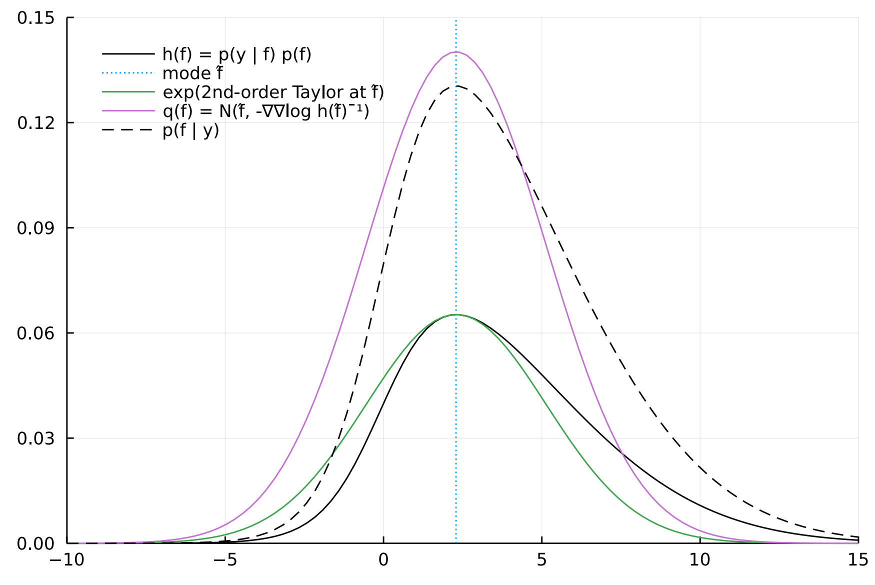
$p(f \mid y)\, Z \approx \exp(\mathcal{O}(f^2))$



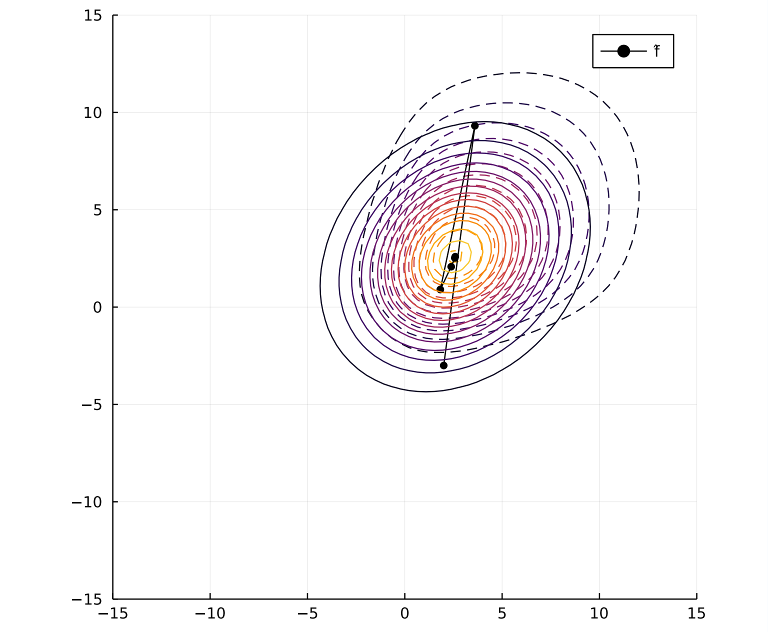
$p(f \mid y) \approx \mathcal{N}(f \mid \hat{f}, -(\mathrm{d}^2 \log h / \mathrm{d}f^2)^{-1})$



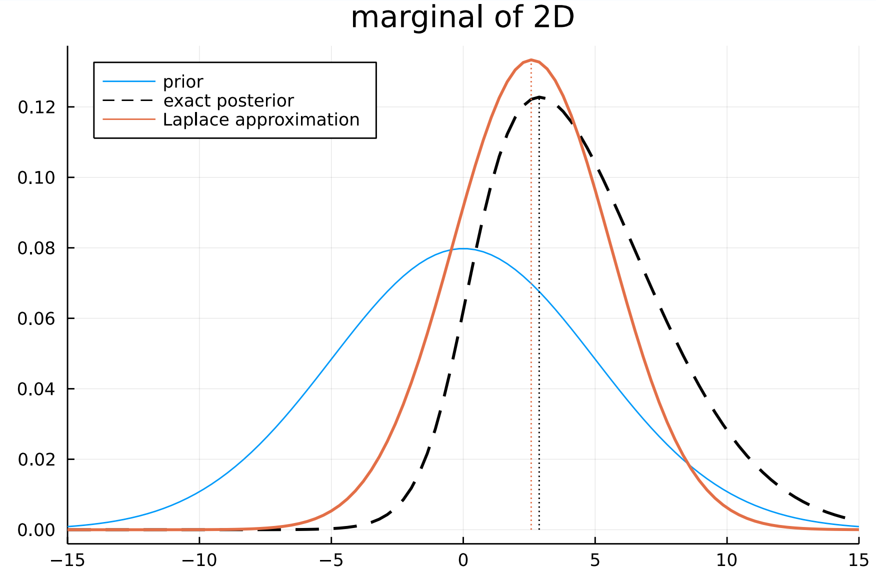
$$p(f \mid y) \approx \mathcal{N}(f \mid \hat{f}, -(\mathrm{d}^2 \log h/\mathrm{d}f^2)^{-1}) = q(f)$$



Laplace in 2D example



Laplace in 2D: marginals



Laplace approximation: important properties

- find mode: Newton's method
- match curvature (Hessian) at mode
- "point estimate++"
- \+ simple, fast
- – poor approximation if mode is not representative (e.g. Bernoulli)
- – may not converge for non-log-concave likelihoods [3]

Choosing μ and Σ for $q(\mathbf{f})$

$$p(\mathbf{f} \mid \mathbf{y}) \approx q(\mathbf{f}) = \mathcal{N}(\mathbf{f}|\mu = ?, \Sigma = ?)$$

match mean &
variance at point

minimise divergence

Laplace
approximation

Expectation
Propagation (EP)

Variational
Bayes (VB)

Minimising divergences

Kullback–Leibler (KL) divergence

“Relative entropy”, “information gain” *from q to p*

$$D_{\mathrm{KL}}(p\|q) = \mathrm{KL}[p(x)\|q(x)] = \mathbb{E}_{x\sim p}\left[\log\frac{p(x)}{q(x)}\right] = \int p(x)\left[\log\frac{p(x)}{q(x)}\right]\mathrm{d}x$$

- non-symmetric: $\mathrm{KL}[p\|q] \neq \mathrm{KL}[q\|p]$
- positive: $\mathrm{KL} \geq 0$ (Gibbs’ inequality)
- minimum: $\mathrm{KL}[p\|q] = 0 \Leftrightarrow q = p$.

Demo: KL between two Gaussians

tinyurl.com/nongaussian-inference-viz-v1

Minimising divergences

$$p(\mathbf{f} \mid \mathbf{y}) \approx q(\mathbf{f}) = \mathcal{N}(\mathbf{f}|\mu =?, \Sigma =?)$$

1. $\min \mathrm{KL}[p(\mathbf{f} \mid \mathbf{y}) \| q(\mathbf{f})]$: **Expectation Propagation**
2. $\min \mathrm{KL}[q(\mathbf{f}) \| p(\mathbf{f} \mid \mathbf{y})]$: Variational Bayes

Expectation Propagation (EP)

Expectation Propagation

Exact posterior:

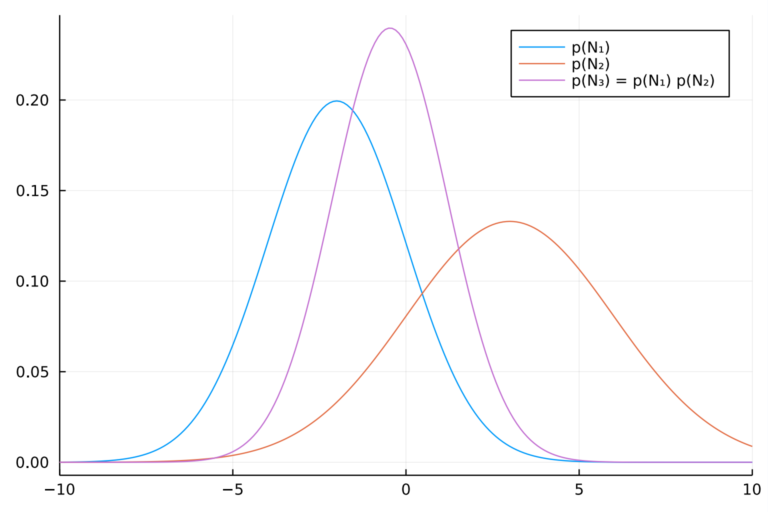
$$p(\mathbf{f} \mid \mathbf{y}) \propto p(\mathbf{f}) \prod_{i=1}^{N} p(y_i \mid f_i)$$

Approximate posterior:

$$q(\mathbf{f}) \propto p(\mathbf{f}) \prod_{i=1}^{N} t_i(f_i)$$

$$t_i = Z_i \mathcal{N}(f_i \mid \tilde{\mu}_i, \tilde{\sigma}_i^2)$$

Multiplying and dividing Gaussians



Adding and subtracting natural (canonical) parameters

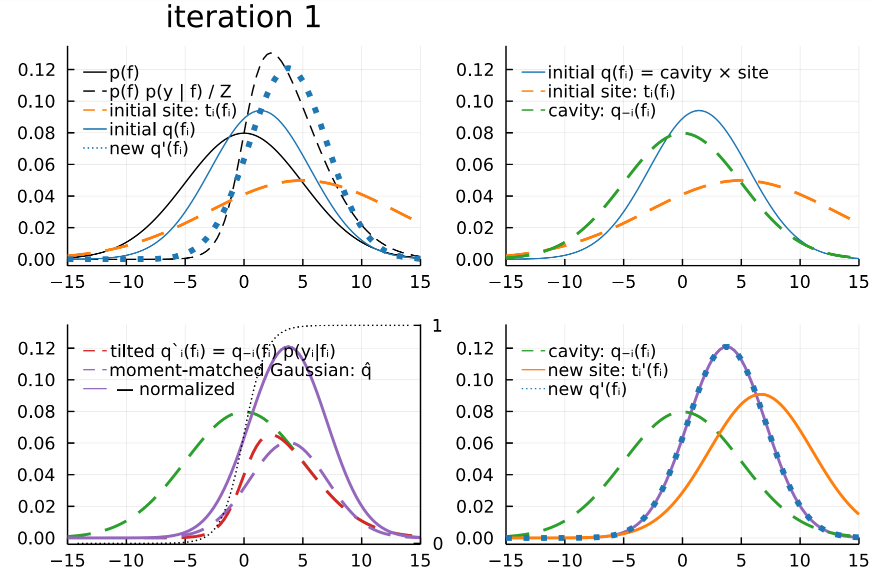
Expectation Propagation iterations

$$\text{“}\min \mathrm{KL}[p(\mathbf{f}\,|\,\mathbf{y})\|q(\mathbf{f})]\text{”} \qquad\qquad q(\mathbf{f}) \propto p(\mathbf{f}) \prod_{i=1}^{N} \underbrace{t_i(f_i)}_{\text{site} \,\propto \mathcal{N}(f_i)}$$

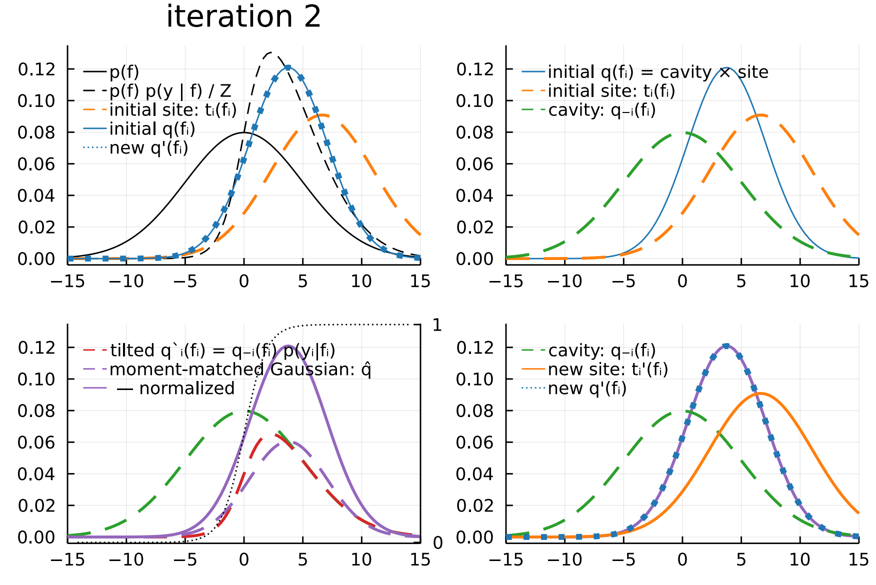
For each site i:

1. marginalize $\int q(\mathbf{f})\,\mathrm{d}f_{j\neq i} = q(f_i) \quad \not\propto t_i(f_i)$
2. improve local approximation: $\min \mathrm{KL}[q(f_i)\frac{p(y_i\,|\,f_i)}{t_i(f_i)}\|q(f_i)\frac{t_i'(f_i)}{t_i(f_i)}]$
   - 2.1 *cavity* distribution $q_{-i}(f_i) = \frac{q(f_i)}{t_i(f_i)} \quad \Leftrightarrow \quad q(f_i) = q_{-i}(f_i) t_i(f_i)$
   - 2.2 *tilted* distribution $q_{\backslash i}(f_i) = q_{-i}(f_i)p(y_i\,|\,f_i)$
   - 2.3 $\operatorname{argmin} \mathrm{KL}[q_{-i}(f_i)p(y_i\,|\,f_i)\|\hat{q}]$ by moment-matching
   - 2.4 update site: $t_i'(f_i) = \frac{\hat{q}}{q_{-i}(f_i)} \quad \Leftrightarrow \quad \hat{q} = q_{-i}(f_i)\, t_i'(f_i)$
3. compute new $q'(\mathbf{f})$ (rank-1 update)

Expectation Propagation in 1D



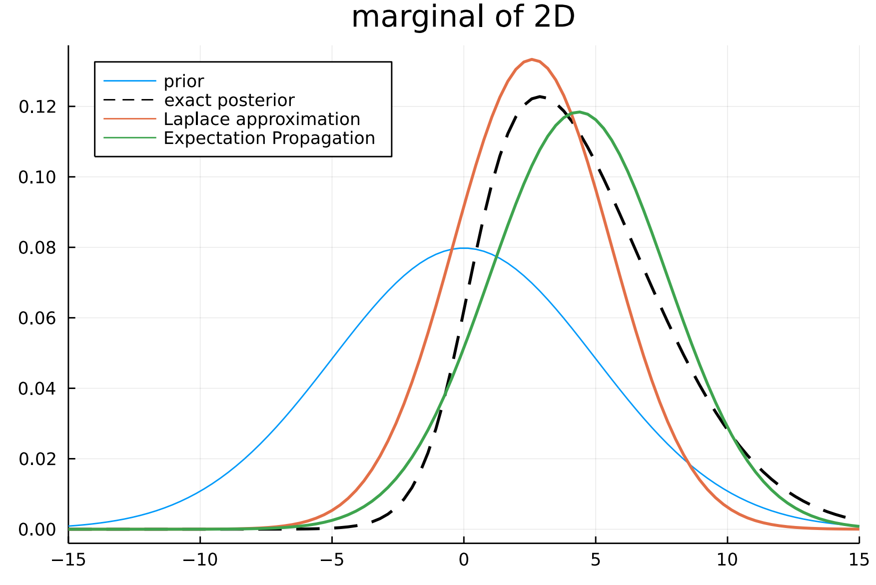
Expectation Propagation in 1D



Demo: EP in 2D

tinyurl.com/nongaussian-inference-viz-v1

Marginals



marginal of 2D
prior
exact posterior
Laplace approximation
Expectation Propagation
0.12
0.10
0.08
0.06
0.04
0.02
0.00
−15
−10
−5
0
5
10
15

Expectation Propagation: important properties

- multiple passes required to converge
- moment-matching (e.g. covering multiple modes)
- \+ effective for classification
- − not guaranteed to converge
- − updates may be invalid (non-log-concave likelihoods)

Minimising divergences

$$p(\mathbf{f} \mid \mathbf{y}) \approx q(\mathbf{f}) = \mathcal{N}(\mathbf{f} | \mu = ?, \Sigma = ?)$$

✓ $\min \mathrm{KL}[p(\mathbf{f} \mid \mathbf{y}) \| q(\mathbf{f})]$: Expectation Propagation

2. $\min \mathrm{KL}[q(\mathbf{f}) \| p(\mathbf{f} \mid \mathbf{y})]$: **Variational Bayes**

Variational Bayes (VB)
Variational Inference (VI)

Variational Bayes (VB)

Idea:
minimise divergence between $p(f \mid y)$ and $q(f)$ the "other" way

$$\underset{\mu,\Sigma}{\operatorname{argmin}}\ \mathrm{KL}\left[q(f) \| p(f \mid y)\right]$$

Minimizing $\mathrm{KL}[q(f)\|p(f|y)]$

$$
\begin{aligned}
&\mathrm{KL}[q(f)\|p(f|y)] \\
&= \int q(f)\Big[\log \frac{q(f)}{p(f \mid y)}\Big]\mathrm{d}f = \int q(f)\Big[\log q(f) - \log p(f \mid y)\Big]\mathrm{d}f \\
&= \int q(f)\Big[\log q(f) - \log p(f) - \log p(y \mid f) + \log p(y)\Big]\mathrm{d}f \\
&= \int q(f)\Big[\log \frac{q(f)}{p(f)}\Big]\mathrm{d}f - \int q(f)\Big[\log p(y \mid f)\Big]\mathrm{d}f + \log p(y) \\
&= \mathrm{KL}[q(f)\|p(f)] - \int q(f)\Big[\log p(y \mid f)\Big]\mathrm{d}f + \log p(y)
\end{aligned}
$$

$$
\log p(y) = \int q(f)\Big[\log p(y \mid f)\Big]\mathrm{d}f - \mathrm{KL}[q(f)\|p(f)] + \mathrm{KL}[q(f)\|p(f|y)]
$$

ELBO

$$
\begin{aligned}
\log p(y) &= \int q(f)\left[\log p(y \mid f)\right] \mathrm{d}f - \mathrm{KL}[q(f) \| p(f)] + \mathrm{KL}[q(f) \| p(f|y)] \\
&\geq \int q(f)\left[\log p(y \mid f)\right] \mathrm{d}f - \mathrm{KL}[q(f) \| p(f)]
\end{aligned}
$$

Lower bound on the (log-)evidence $p(y)$ = ELBO

Likelihood term

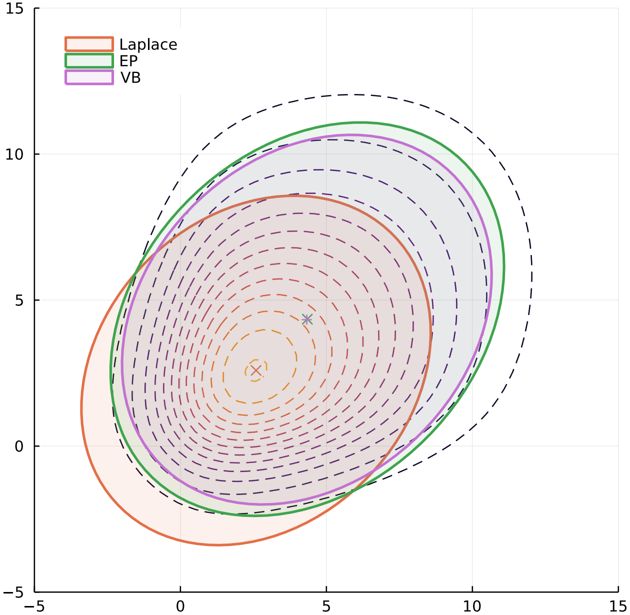
Integral separates for a factorizing likelihood:

$$
\begin{aligned}
&\int q(\mathbf{f})\left[\log p(\mathbf{y}\,|\,\mathbf{f})\right]\mathrm{d}\mathbf{f}\\
&= \sum_{i=1}^{N} \int q(f_i)\left[\log p(y_i\,|\,f_i)\right]\mathrm{d}f_i
\end{aligned}
$$

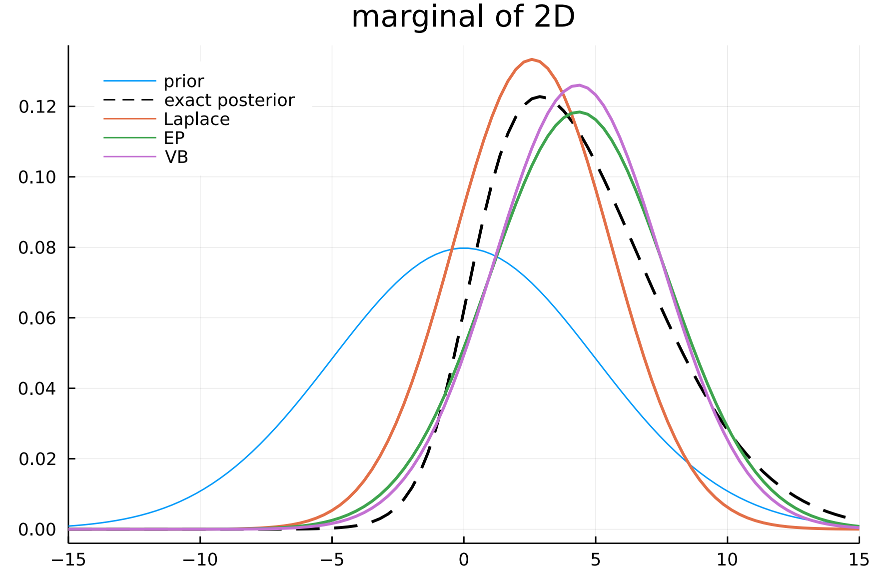
Evaluating the 1D integrals:

- analytic (e.g. Exponential, Gamma, Poisson)
- Gauss–Hermite quadrature
- Monte Carlo (e.g. multi-class classification)

Comparison 2D



Marginals



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0.12
0.10
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0.02
0.00
−15
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15

Variational Bayes: important properties

- principled: directly minimising divergence from true posterior
- mode-seeking (e.g. multi-modal posterior: fits just one)

\+ minimises a true lower bound $\rightarrow$ convergence

– underestimates variance

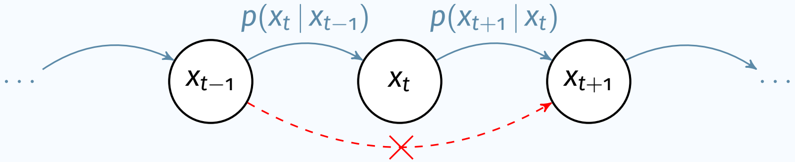
Outline

- ✓ Gaussian processes with Gaussian likelihood
- ✓ What is the likelihood? Connecting observations and Gaussian process prior
- ✓ Non-Gaussian likelihoods: what happens to the posterior?

4. **How to approximate the intractable**
   - ✓ with Gaussians
     - Laplace
     - Expectation Propagation
     - Variational Bayes
   - 4.2 **with samples: MCMC**
5. Comparison

Markov Chain Monte Carlo

Markov Chain



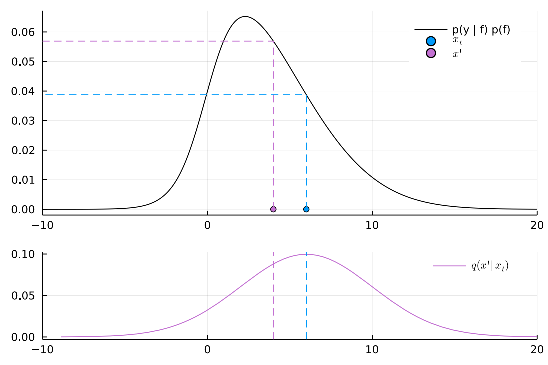
- Samples $x_1, \ldots, x_T$
- "Markov" = 1-step history
- $x_{t+1} \sim p(x_{t+1} \mid x_t)$, independent of $x_{t-1}, \ldots, x_1$

Markov Chain Monte Carlo (MCMC)

Generate samples $\{x_t\} \sim p(f \mid y)$

Requires:

- *unnormalized* posterior $h(f) = p(y \mid f)p(f)$
- Markov proposal $q(x' \mid x_t)$
- initial x_0



In each iteration t:

1. Random proposal $x' \sim q(x' \mid x_t)$
2. Acceptance probability $\frac{h(x')}{h(x_t)} \to$ ensures sampling from $p(f \mid y)$

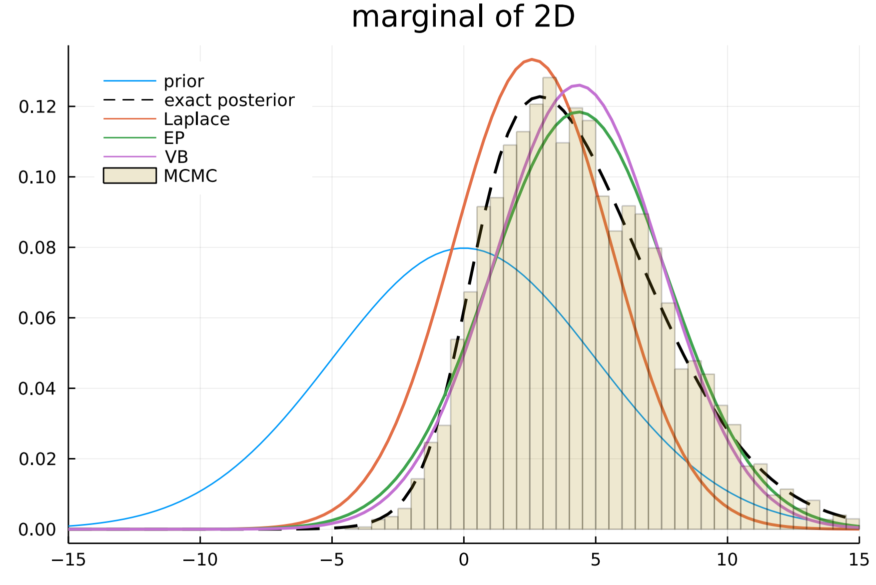
   accept: $x_{t+1} = x'$ reject: copy $x_{t+1} = x_t$

   $h(x') > h(x_t)$: always accepts $\to$ climbs uphill

Demo: MCMC in 2D

`tinyurl.com/nongaussian-inference-viz-v1`

Marginals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−10
−5
0
5
10
15

MCMC: important properties

- burn-in
- acceptance ratio
- auto-correlation, effective sample size (ESS); thinning to save memory
- mixing and multiple chains ($\hat{R}$)
- better proposals (HMC, NUTS) $\rightarrow$ use robust implementations

+ very accurate (gold-standard)

– very slow, predictions require keeping all (thinned) samples around

Michael Betancourt's `betanalpha.github.io/writing/`

MCMC: robust implementations

- Stan
- PyMC3
- TensorFlow Probability (GPflow)
- Turing.jl

Outline

- ✓ Gaussian processes with Gaussian likelihood
- ✓ What is the likelihood? Connecting observations and Gaussian process prior
- ✓ Non-Gaussian likelihoods: what happens to the posterior?
- ✓ How to approximate the intractable
  - ✓ with Gaussians
    - Laplace
    - Expectation Propagation
    - Variational Bayes
  - ✓ with samples: MCMC

5. **Comparison**

Comparison

Comparison

MCMC

- samples
- gold standard
- slow

Laplace

- $\mathcal{N}$ = curvature at mode
- simple & fast
- often poor approximation

EP

- $\mathcal{N}$ matches marginal moments
- good calibration in classification
- may not converge

Variational Bayes

- $\mathcal{N}$ minimises $\mathrm{KL}[q(f)\|p(f \mid y)]$
- principled, any likelihood
- underestimates variance

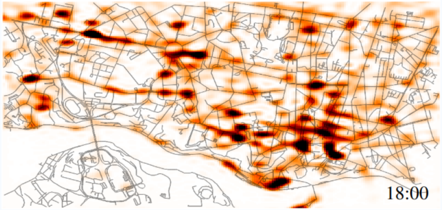
What we did not cover...

- More complex likelihoods (heteroskedastic, zero-inflated, multi-stage...)
- Marginal likelihood approximations for hyperparameter learning [7]
- How parametrisation affects Gaussianity of $p(f \mid y)$
- Connections between EP and VB ("PowerEP") [1]
- Combinations of MCMC and variational methods
- Augmenting likelihood with auxiliary variable
  $\rightarrow$ conditionally conjugate model [2]

Take-away

We can...

- create **richer models** with likelihoods beyond the Gaussian
- **learn latent functions** that form the connection between data points
- handle the non-Gaussian posterior with **approximations**
- **trade off** speed, accuracy, and ease-of-use



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