

# MAP Estimators for Laplace-type priors in Bayesian Inverse Problems

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Algorithms and Computationally Intensive Inference seminar  
23 June 2017, Warwick



# Outline

- 1 Problem setup
- 2 MAP and wMAP estimators
- 3 1-Besov priors
- 4 Conclusion

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# Inverse Problem

$$y = \mathcal{G}(u) + \xi$$


- $u \in X$  **unknown** function,  $X$  separable Banach space
- $y \in \mathbb{R}^J$  finite-dim observation
- $\xi \sim N(0, \Sigma)$ ,  $\Sigma \in \mathbb{R}^{J \times J}$  positive definite, observational noise
- $\mathcal{G} : X \rightarrow \mathbb{R}^J$  possibly **nonlinear forward operator**, locally Lipschitz

# Bayesian Formulation

- Prior:  $u \sim \mu_0$
- Likelihood:  $y|u \sim N(\mathcal{G}(u), \Sigma)$
- Posterior:  $u|y \sim \mu^y$

$$\frac{d\mu^y}{d\mu_0}(u) \propto \exp(-\Phi(u; y)),$$

$$\Phi(u; y) = \frac{1}{2} \left| \Sigma^{-\frac{1}{2}}(y - \mathcal{G}(u)) \right|^2.$$

 M. Dashti and A. M. Stuart, *The Bayesian approach to inverse problems*, Handbook of Uncertainty Quantification, 2015.

# Edge-preserving and Sparsity-promoting Priors

## Blocky structure and sparsity in an appropriate expansion

- 1-Besov priors

- 📄 M. Lassas, E. Saksman and S. Siltanen, *Discretization-invariant Bayesian inversion and Besov space priors*, 2009

- 📄 M. Dashti, S. Harris and A. Stuart, *Besov priors for Bayesian inverse problems*, 2013

- Infinitely divisible and heavy tailed priors, e.g. Cauchy priors


- 📄 T. Sullivan, *Well-posed Bayesian inverse problems and heavy-tailed stable Banach space priors*, 2016

- 📄 B. Hosseini, *Well-posed Bayesian inverse problems with infinitely-divisible and heavy-tailed prior measures*, 2017


# Need for MAP

- Probing the posterior can be difficult for such priors
- Sampling via MCMC can get prohibitively expensive if  $\mathcal{G}$  difficult to evaluate
- Function space MCMC algorithms not yet fully developed for such priors
- **Maximum a posteriori (MAP)** estimators
  - understood as **modes of posterior**  $\mu^y$
  - Attractive because they require the solution of a single optimization problem
  - **We study MAP estimates in this non-parametric setting with 1-Besov priors**


<http://www.sergiosagapiou.com/>

 S. Agapiou, M. Burger, M. Dashti and T. Helin, *Sparsity-promoting and edge-preserving maximum a posteriori estimators in non-parametric Bayesian inverse problems*, arXiv:1705.03286

## Build on

 M. Dashti, K. Law, A. Stuart and J. Voss, *MAP estimators and their consistency in Bayesian nonparametric inverse problems*, Inverse Problems, 2013

## MAP for Gaussian priors

 T. Helin and M. Burger, *Maximum a posteriori probability estimates in infinite-dimensional Bayesian inverse problems*, Inverse Problems, 2015

wMAP theory using differential calculus of measures, does not cover 1-Besov priors, basis for tackling Cauchy



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# Finite-dimensional Intuition

- Assume  $X = \mathbb{R}^N$  and prior has Lebesgue density

$$\pi(u) \propto \exp(-W(u))$$

- Posterior Lebesgue density

$$\pi^y(u) \propto \exp(-I(u; y)),$$

where

$$I(u; y) = \Phi(u; y) + W(u).$$

- MAP estimators maximize posterior density, i.e. minimize  $I$
- MAP estimators correspond to Tikhonov regularized estimate
  - fidelity term  $\longleftrightarrow$  likelihood
  - penalty term  $\longleftrightarrow$  prior

# Modes in Infinite-dimensions

- In infinite dimensions no uniform measure. Modes of measure  $\mu$  on function space  $X$ ?

- consider  $\mu(B_\epsilon(u))$  for  $u \in X$
- send  $\epsilon \rightarrow 0$
- $\hat{u}$  mode of  $\mu$  if it maximizes the limiting small ball probabilities in a specific sense

- **strong mode**: max probability among all centres in  $X$ , *Dashti et al '13*
- **weak mode**: max probability among all shifts of the ball by elements in a dense subspace  $E \subset X$ , *Helin and Burger '15*

# MAP and wMAP

## Definition (Dashti et al '13)

Let  $M^\epsilon = \sup_{u \in X} \mu(B_\epsilon(u))$ .  $\hat{u} \in X$  is a **mode** of  $\mu$ , if

$$\lim_{\epsilon \rightarrow 0} \frac{\mu(B_\epsilon(\hat{u}))}{M^\epsilon} = 1.$$

## Definition (Helin and Burger '15)

Let  $E$  dense subspace of  $X$ .  $\hat{u} \in X$  **weak mode** of  $\mu$  if

$$\lim_{\epsilon \rightarrow 0} \frac{\mu(B_\epsilon(\hat{u} - h))}{\mu(B_\epsilon(\hat{u}))} \leq 1, \quad \forall h \in E.$$

A **MAP** (resp. **wMAP**) estimate is a mode (resp. weak mode) of  $\mu^y$ .

# Remarks

- Weak mode allows flexibility of choosing  $E$ .
- Any strong mode is a weak mode: e.g. choose  $E = X$  and bound  $\mu(B_\epsilon(\hat{u} - h)) \leq M^\epsilon$ .
- Weak modes interesting when small ball probabilities available only in some subspace of translations  $h$ ,  $E$ . Typically  $E$  has measure zero.
- For convex  $\mu$  set of modes is convex for both notions (typically fails for posterior).
- Can define local strong and weak modes (hence MAP estimates), which maximize small ball probabilities in the respective senses only locally.

**AIM:** establish variational characterization of wMAP and MAP in  $\infty$ -dim BIP.

# Onsager-Machlup Functional

- Suppose can find  $I : F \rightarrow \mathbb{R}$  s.t.

$$\lim_{\epsilon \rightarrow 0} \frac{\mu(B_\epsilon(z_2))}{\mu(B_\epsilon(z_1))} = \exp(I(z_1) - I(z_2)).$$

- $F$  dense subspace of  $X$ .
- Fix  $z_1 \in F$ . A  $z_2 \in F$  **minimizing**  $I$  is a potential mode of  $\mu$ .
- Such  $I$  is called the (generalized) **Onsager-Machlup functional** of  $\mu$ .

# Onsager-Machlup Functional

- For  $X = \mathbb{R}^N$ , posterior density  $\pi^y(u) \propto \exp(-I)$ , by Lebesgue differentiation theorem

$$\lim_{\epsilon \rightarrow 0} \frac{\mu^y(B_\epsilon(z_2))}{\mu^y(B_\epsilon(z_1))} = \lim_{\epsilon \rightarrow 0} \frac{\int_{B_\epsilon(z_2)} \pi^y(du)}{\int_{B_\epsilon(z_1)} \pi^y(du)} = \frac{\pi^y(z_2)}{\pi^y(z_1)} = \exp(I(z_1) - I(z_2))$$

- $I = \Phi + W$  is the O-M functional of  $\mu^y$ .

# Strategy: crucial first step

- For  $\mu$  measure, define  $\mu_h(\cdot) = \mu(\cdot - h)$ .
- For  $h$  such that  $\mu_h \ll \mu$ , denote

$$R_h^\mu(u) = \frac{d\mu_h}{d\mu}(u).$$

## Lemma (Helin and Burger '15)

$$\lim_{\epsilon \rightarrow 0} \frac{\mu(B_\epsilon(u-h))}{\mu(B_\epsilon(u))} = R_h^\mu(u),$$

for all  $h$  such that  $R_h^\mu$  is **continuous** for  $u \in X$ .

## Proof.

$$\inf_{v \in B_\epsilon(u)} R_h^\mu(v) \leq \frac{\mu_h(B_\epsilon(u))}{\mu(B_\epsilon(u))} = \frac{\int_{B_\epsilon(u)} R_h^\mu(z) \mu(dz)}{\mu(B_\epsilon(u))} \leq \sup_{v \in B_\epsilon(u)} R_h^\mu(v),$$

for all  $\epsilon > 0$  and  $u \in X$ . Take  $\epsilon \rightarrow 0$  and use cttty. □



# Strategy

- Choose  $E$  sufficiently regular s.t.  $R_h^{\mu_0}$  continuous in  $u \in X$ , for all  $h \in E$ .
- Straightforward to determine O-M functional  $I_0$  of  $\mu_0$ , defined on  $F$  containing  $E$ .
- Straightforward to determine O-M functional  $I$  of  $\mu^y \propto e^{-\Phi} \mu_0$ , defined on  $F$ .
- Straightforward to establish equivalence of ( $E$ -)wMAP and minimizers of  $I$ .
- Considerably harder to establish equivalence of MAP and minimizers of  $I$ , due to smallness of  $F \subset X$  wrt prior.

# Strategy: establishing continuity of $R_h^\mu$

- In HB15 cttty of  $R_h^\mu$  established via **differential calculus of measures** assuming cttty of log-derivative  $\beta_h^\mu$  for  $h$  in a sufficiently smooth space  $E$ .

- For  $\nu$  probability measure on  $\mathbb{R}$  with differentiable pdf  $\pi$ , log-derivative is  $\beta^\nu = \frac{\pi'}{\pi}$ .
- For product measures  $\mu = \otimes_{\ell=1}^{\infty} \mu_\ell$ , log-derivative in direction  $h = \{h_\ell\}$  is

$$\beta_h^\mu = \sum_{\ell=1}^{\infty} \beta_{h_\ell}^{\mu_\ell} = \sum_{\ell=1}^{\infty} h_\ell \frac{\pi'_\ell}{\pi_\ell}$$

- Works for eg  $p$ -Besov priors with  $1 < p \leq 2$  and Cauchy priors but **not for 1-Besov prior** whose log-derivative is inherently discontinuous.
- For product measures may be possible to get an explicit expression for  $R_h^\mu$  via **Kakutani-Hellinger** theory and study its cttty analytically (**works for 1-Besov priors**)

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# Periodic Besov Spaces

- Let  $\{\psi_\ell\}_{\ell=1}^\infty$  orthonormal wavelet basis for  $L^2(\mathbb{T})$ . Define  $f : \mathbb{T} \rightarrow \mathbb{R}$  by

$$f(x) = \sum_{\ell=1}^{\infty} c_\ell \psi_\ell(x).$$

- $f \in B_p^s(\mathbb{T})$  iff

$$\|f\|_{B_p^s(\mathbb{T})} = \left( \sum_{\ell=1}^{\infty} \ell^{p(s+\frac{1}{2})-1} |c_\ell|^p \right)^{\frac{1}{p}} < \infty.$$

- $p$  integrability,  $s$  smoothness parameter.
- For  $p = 2$ , Sobolev spaces of functions with  $s$  square integrable derivatives

$$\|f\|_{B_2^s(\mathbb{T})} = \left( \sum_{\ell=1}^{\infty} \ell^{2s} |c_\ell|^2 \right)^{\frac{1}{2}}.$$

- For  $p = 1$

$$\|f\|_{B_1^s(\mathbb{T})} = \sum_{\ell=1}^{\infty} \ell^{s-\frac{1}{2}} |c_\ell|.$$

# 1-Besov Priors

## Definition (Lassas et al '09)

Let  $X_\ell \stackrel{iid}{\sim} \frac{1}{2} \exp(-|x|)$  and  $\alpha_\ell = \ell^{s-\frac{1}{2}}$ . The random function

$$U(x) = \sum_{\ell=1}^{\infty} \alpha_\ell^{-1} X_\ell \psi_\ell(x), \quad x \in \mathbb{T},$$

is said to be distributed according to a  $B_1^s$ -Besov prior,  $\lambda$ .

- Formally,  $U$  has density  $\pi(u) \propto \exp(-\|u\|_{B_1^s})$  since  $\alpha_\ell^{-1} X_\ell \sim \frac{\alpha_\ell}{2} \exp(-\alpha_\ell |x|)$ .
- $\|U\|_{B_1^t} < \infty$ , almost surely for all  $t < s - 1$  (LSS09).
- $X = B_1^t$ ,  $t < s - 1$ .
- $\beta_h^\lambda$  discontinuous, since derivative of  $\frac{1}{2} \exp(-|x|)$  has a jump at the origin.

# 1-Besov Priors, MAP and wMAP

- Consider BIP with  $\mu_0 = \lambda$

$$\mu^y(du) \propto \exp(-\Phi(u; y))\lambda(du).$$

- Let

$$l(u; y) = \Phi(u; y) + \|u\|_{B_1^s}, \quad l : B_1^s \rightarrow [0, \infty).$$

- Finite-dim intuition suggests that minimizers of  $l$  are maximizers of posterior since formally

$$" \mu^y(du) \propto \exp(-\Phi(u; y) - \|u\|_{B_1^s})du " .$$

**We make this rigorous.**

# Kakutani-Hellinger Theory

- For  $\mu, \nu$  measures both absolutely continuous wrt  $\zeta$ , define Hellinger integral

$$H(\mu, \nu) = \int \sqrt{\frac{d\mu d\nu}{d\zeta d\zeta}} d\zeta, \quad H(\mu, \nu) \in [0, 1].$$

- If  $H(\mu, \nu) = 0$  then  $\mu, \nu$  singular.
- In general if  $H(\mu, \nu) > 0$  then  $\mu, \nu$  not necessarily equivalent, but this happens for products of equivalent measures.

# Kakutani-Hellinger Theory

If  $\mu = \otimes_{\ell=1}^{\infty} \mu_{\ell}$ ,  $\nu = \otimes_{\ell=1}^{\infty} \nu_{\ell}$ , then

$$H(\mu, \nu) = \prod_{\ell=1}^{\infty} H(\mu_{\ell}, \nu_{\ell}).$$

## Theorem (Kakutani)

Let  $\mu, \nu$  product measures, where  $\mu_{\ell}, \nu_{\ell}$  equivalent for all  $\ell \in \mathbb{N}$ . Then  $\mu$  and  $\nu$  equivalent iff  $H(\mu, \nu) > 0$ , and if equivalent

$$\frac{d\mu}{d\nu}(u) = \lim_{N \rightarrow \infty} \prod_{\ell=1}^N \frac{d\mu_{\ell}}{d\nu_{\ell}}(u_{\ell}), \quad \text{in } L^1(\mathbb{R}^{\infty}, \mu).$$



G. Da Prato, *An Introduction to Infinite-Dimensional Analysis*, Springer, 2006.



# 1-Besov Priors, $R_h^\lambda$

## Lemma (A., Burger, Dashti and Helin '17)

- We have  $\lambda_h \sim \lambda$  if and only if  $h \in B_2^{s-\frac{1}{2}}$ .
- For  $h \in B_2^{s-\frac{1}{2}}$

$$\frac{d\lambda_h}{d\lambda}(u) = \lim_{N \rightarrow \infty} \exp \sum_{\ell=1}^N (-\alpha_\ell |h_\ell - u_\ell| + \alpha_\ell |u_\ell|).$$

- For  $h \in B_1^r$ ,  $r > s$ , the limit on rhs is **continuous** in  $u \in X = B_1^t$ ,  $t < s - 1$ .

# 1-Besov Priors, $R_h^\lambda$

## Proof.

- By Kakutani theorem suffices to compute Hellinger integral and check its positivity.
- Kakutani theorem also gives that

$$\frac{d\lambda_h}{d\lambda}(u) = \lim_{N \rightarrow \infty} \prod_{\ell=1}^N \frac{d\lambda_{h,\ell}}{d\lambda_\ell}(u) = \lim_{N \rightarrow \infty} \prod_{\ell=1}^N \frac{e^{-\alpha_\ell |h_\ell - u_\ell|}}{e^{-\alpha_\ell |u_\ell|}}.$$

- For ctt, technical explicit proof showing that  $|R_h^\mu(u) - R_h^\mu(v)| \rightarrow 0$  as  $\|u - v\|_{B_1^t} \rightarrow 0$  by examining all combinations of signs.



# 1-Besov priors, Small Ball Probabilities

Corollary (A., Burger, Dashti and Helin '17)

$$\lim_{\epsilon \rightarrow 0} \frac{\lambda(B_\epsilon(u-h))}{\lambda(B_\epsilon(u))} = \exp \sum_{\ell=1}^{\infty} (-\alpha_\ell |h_\ell - u_\ell| + \alpha_\ell |u_\ell|),$$

for  $h \in B_1^r, r > s$ .

- Choose  $E = B_1^r, r > s$  in wMAP definition ( $E$  dense in  $X$ ).
- To get Onsager-Machlup functional of  $\lambda$  need a bit more work.

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- Choose  $E = B_1^r, r > s$  in wMAP definition ( $E$  dense in  $X$ ).
- To get Onsager-Machlup functional of  $\lambda$  need a bit more work.
- For  $u = 0$

$$\lim_{\epsilon \rightarrow 0} \frac{\lambda_h(B_\epsilon(0))}{\lambda(B_\epsilon(0))} = \exp \sum_{\ell=1}^{\infty} (-\alpha_\ell |h_\ell|) = e^{-\|h\|_{B_1^s}},$$

for  $h \in B_1^r, r > s$ .

# 1-Besov priors, Onsager-Machlup Functional of $\lambda$

Theorem (A., Burger, Dashti and Helin '17)

For  $h \in B_1^s$ ,

$$\lim_{\epsilon \rightarrow 0} \frac{\lambda_h(B_\epsilon(0))}{\lambda(B_\epsilon(0))} = e^{-\|h\|_{B_1^s}}.$$

Proof.

Take  $h^j \in B_1^{s+1}$  s.t.  $h^j \rightarrow h$  in  $B_1^s$ . □

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Proof.

Take  $h^j \in B_1^{s+1}$  s.t.  $h^j \rightarrow h$  in  $B_1^s$ . □

- For  $z_1, z_2 \in B_1^s$

$$\lim_{\epsilon \rightarrow 0} \frac{\lambda(B_\epsilon(z_2))}{\lambda(B_\epsilon(z_1))} = \lim_{\epsilon \rightarrow 0} \frac{\lambda(B_\epsilon(z_2))}{\lambda(B_\epsilon(0))} \frac{\lambda(B_\epsilon(0))}{\lambda(B_\epsilon(z_1))} = \exp(\|z_1\|_{B_1^s} - \|z_2\|_{B_1^s}).$$

- The **Onsager-Machlup functional of  $\lambda$**  is  $l_0 : B_1^s \rightarrow [0, \infty)$ ,  $l_0(z) = \|z\|_{B_1^s}$ .

# 1-Besov priors, Onsager-Machlup Functional of $\mu^y$

- Recall

$$I(u; y) = \Phi(u; y) + \|u\|_{B_1^s}, \quad I : B_1^s \rightarrow [0, \infty).$$

- Using local Lipschitz cttty of  $\Phi$ , can show:

Proposition (A., Burger, Dashti and Helin '17)

$I$  is the Onsager-Machlup functional for  $\mu^y$ :

$$\lim_{\epsilon \rightarrow 0} \frac{\mu^y(B_\epsilon(z_2))}{\mu^y(B_\epsilon(z_1))} = \exp(I(z_1; y) - I(z_2; y)),$$

for all  $z_1, z_2 \in B_1^s$ .

- Calculus of variations shows that  $I$  has a minimizer  $\hat{u} \in B_1^s$  (ABDH17)

# 1-Besov Priors, MAP and wMAP

## Theorem (A., Burger, Dashti and Helin '17)

Both wMAP and MAP estimates of the posterior  $\mu^y$  are identified with the minimizers of  $I$ .

## Proof

- wMAP:

- Assume  $u_{min} \in B_1^s$  minimizer of  $I$ .

For any  $h \in B_1^s$ ,  $r > s$  let  $z_1 = u_{min} \in B_1^s$ ,  $z_2 = u_{min} - h \in B_1^s$

$$\lim_{\epsilon \rightarrow 0} \frac{\mu^y(B_\epsilon(u_{min} - h))}{\mu^y(B_\epsilon(u_{min}))} \stackrel{prop}{=} \exp(I(u_{min}) - I(u_{min} - h)) \leq 1.$$

Hence  $u_{min}$  is wMAP for  $E = B_1^r$ ,  $r > s$ .



# 1-Besov Priors, MAP and wMAP

## Proof.

- Assume  $\hat{u}$  wMAP for  $E = B_1^r$ .

Exclude  $\hat{u} \in B_1^t \setminus B_1^s$  by showing contradiction to cttty of  $\Phi$ .

Thus  $\hat{u} \in B_1^s$  and by proposition

$$1 \geq \frac{\mu^y(B_\epsilon(\hat{u} - h))}{\mu^y(B_\epsilon(\hat{u}))} \stackrel{prop}{=} \exp(I(\hat{u}) - I(\hat{u} - h)), \quad \forall h \in B_1^r, r > s,$$

hence

$$I(\hat{u}) \geq I(\hat{u} - h), \quad \forall h \in B_1^r, r > s.$$

By cttty of  $I$  in  $B_1^s$  and density of  $B_1^r$  in  $B_1^s$ , we get that  $\hat{u}$  minimizer of  $I$ .



# 1-Besov Priors, MAP and wMAP

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hence

$$I(\hat{u}) \geq I(\hat{u} - h), \quad \forall h \in B_1^r, r > s.$$

By cttty of  $I$  in  $B_1^s$  and density of  $B_1^r$  in  $B_1^s$ , we get that  $\hat{u}$  minimizer of  $I$ .

- MAP: Very technical, requires many new small ball probability estimates for centres in  $B_1^t$ .



# 1-Besov Priors, Consistency of MAP estimates

- Consider frequentist setup

$$y_j = \mathcal{G}(u^\dagger) + \xi_j,$$

for fixed underlying  $u^\dagger \in X$  and  $\xi_j \stackrel{i.i.d.}{\sim} N(0, \Sigma)$ .

- Sequence of posteriors

$$\frac{d\mu^{y_1, \dots, y_n}}{d\lambda}(u) \propto \exp\left(-\frac{1}{2} \sum_{j=1}^n |\Sigma^{-\frac{1}{2}}(y_j - \mathcal{G}(u))|^2\right)$$

- Previous result shows that MAP (and wMAP) estimates coincide with minimizers of

$$I_n(u) = \|u\|_{B_1^s} + \frac{1}{2} \sum_{j=1}^n |\Sigma^{-\frac{1}{2}}(y_j - \mathcal{G}(u))|^2.$$

# 1-Besov Priors, Consistency of MAP estimates

- Let  $\{u_n\}$  be a sequence of MAP estimates corresponding to  $\mu^{y_1, \dots, y_n}$ .
- We investigate whether as  $n \rightarrow \infty$ ,  $\{u_n\}$  recovers  $u^\dagger$  in some sense.
- Cannot expect to recover  $u^\dagger$  fully, unless e.g.  $\mathcal{G}$  is injective.

## Theorem

Assume  $u^\dagger \in B_1^s$ . Then there exists  $u^* \in B_1^s$  and a subsequence of  $\{u_n\}$  such that  $u_n \rightarrow u^*$  in  $B_1^{\tilde{s}}$  a.s., for any  $\tilde{s} < s$ . For any such  $u^*$  we have  $\mathcal{G}(u^*) = \mathcal{G}(u^\dagger)$ .

- Under the milder assumption  $u^\dagger \in B_1^t$ , only get a.s. convergence of  $\mathcal{G}(u_n) \rightarrow \mathcal{G}(u^\dagger)$ .






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# Conclusion and Future Work

- Wealth of new function-space priors, giving rise to many interesting questions.
- Discussed MAP estimates in this context, have a complete picture for Gaussian and 1-Besov priors, developing the picture for other priors.
- Other interesting questions:
  - When do MAP and wMAP coincide?
  - Local MAP and their theory
  - Posterior contraction rates for the new priors (work in progress with M. Dashti and T. Helin for Besov priors)

<http://www.sergiosagapiou.com/>

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