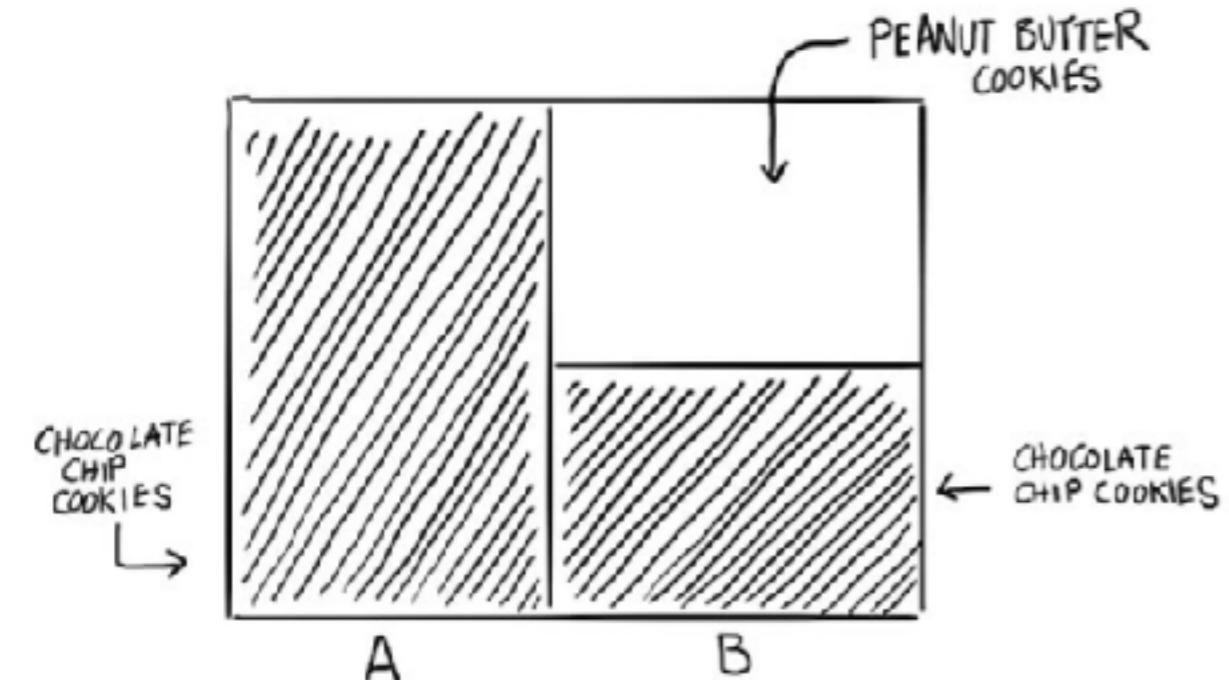
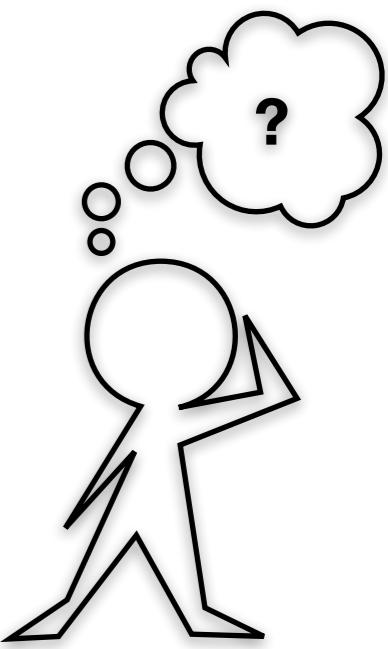


HOW IS PE COMPUTED?

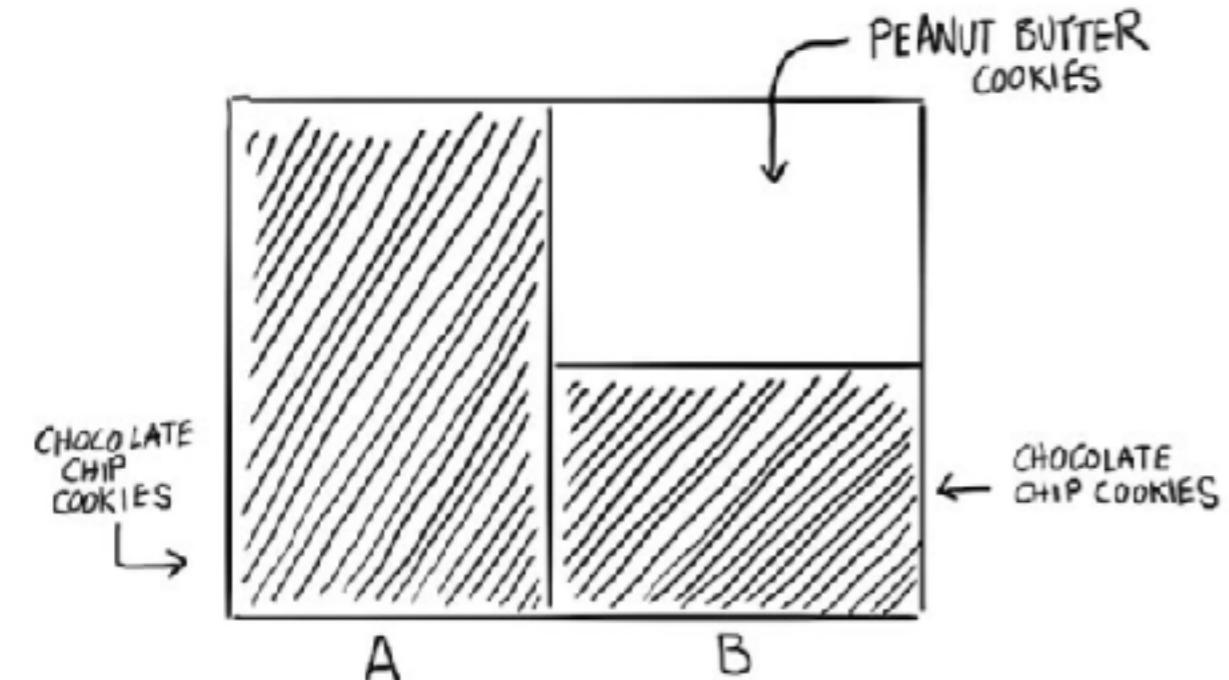
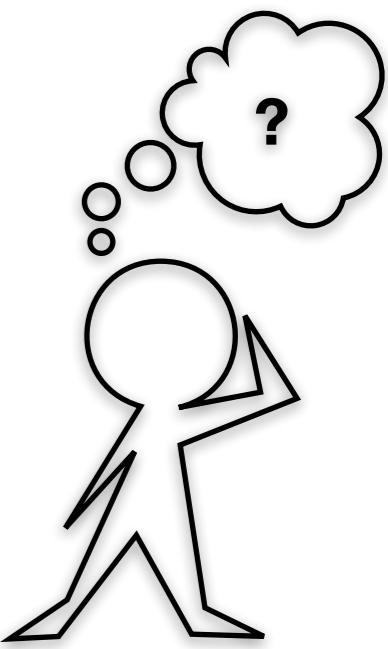


$$P(\text{BOX A} | \text{CC COOKIE}) = \frac{P(\text{CC COOKIE} | \text{BOX A}) P(\text{BOX A})}{P(\text{CC COOKIE})}$$

1 $\frac{1}{2}$
 $\frac{3}{4}$

Es. from Bayes' Theorem:
a visual introduction for beginners

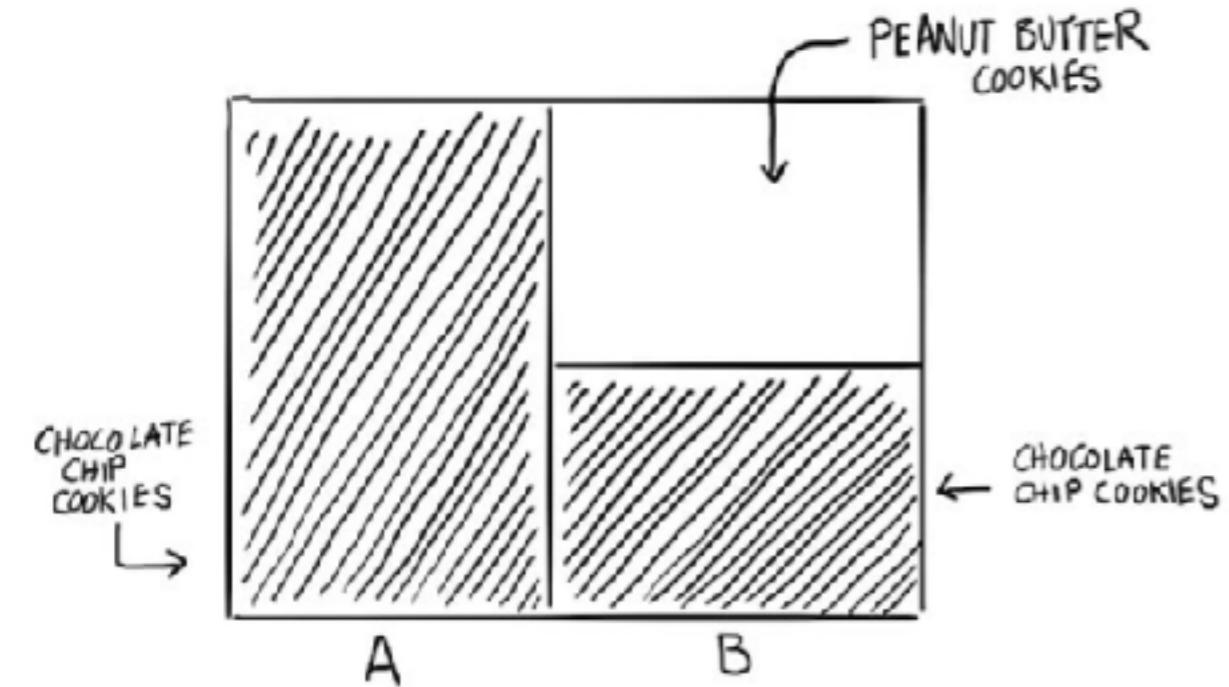
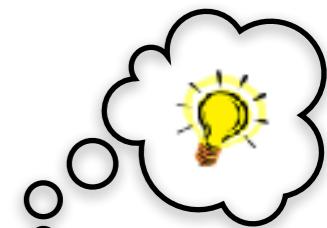
HOW IS PE COMPUTED?



$$P(\text{BOX A} | \text{CC COOKIE}) = \frac{\frac{2}{3} \cdot \frac{1}{2}}{\frac{3}{4}}$$

Es. from Bayes' Theorem:
a visual introduction for beginners

HOW IS PE COMPUTED?



Posterior

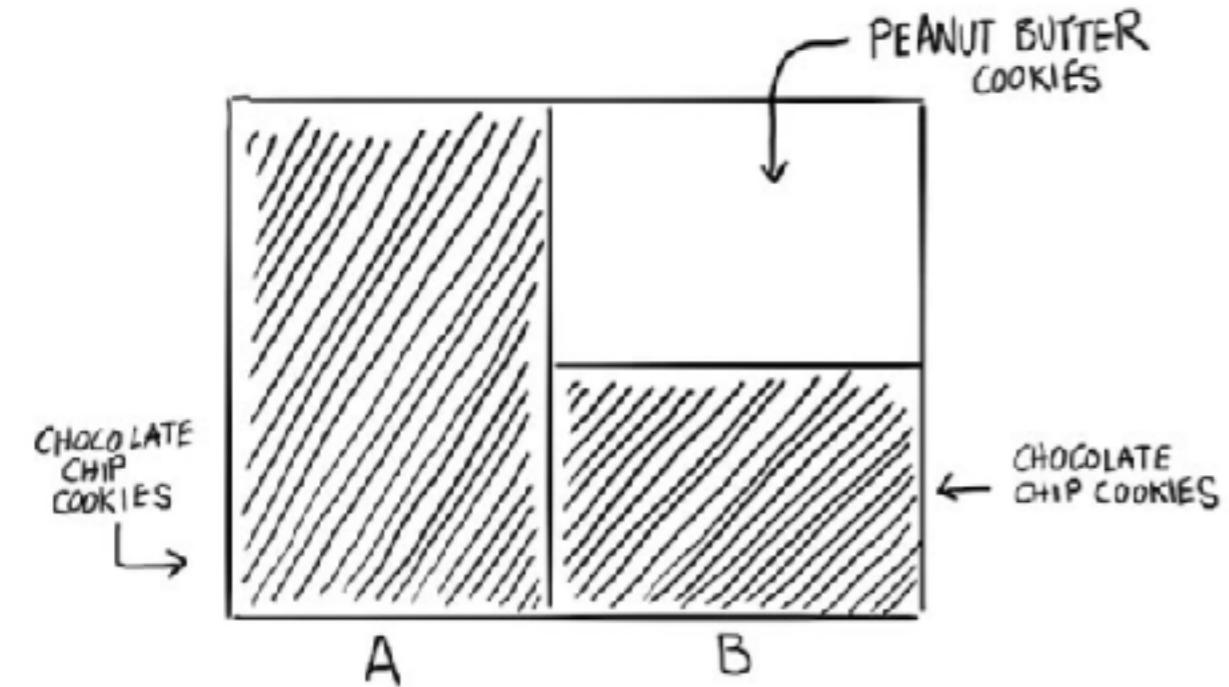
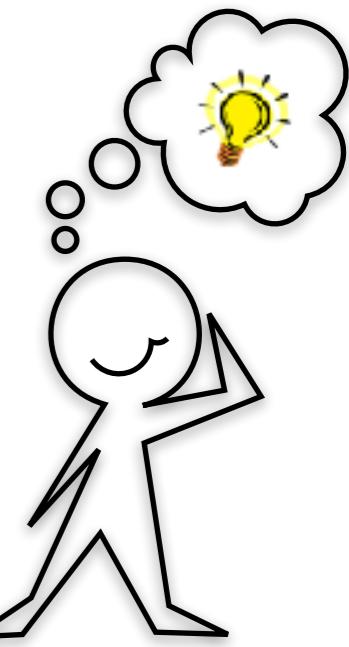
$$P(\text{BOX A} | \text{CC COOKIE}) =$$

Likelihood *Prior*

$$\frac{P(\text{CC COOKIE} | \text{BOX A}) P(\text{BOX A})}{P(\text{CC COOKIE})}$$

Evidence

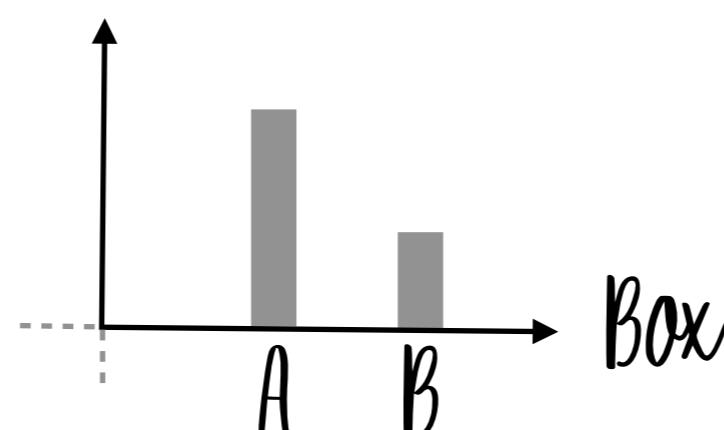
HOW IS PE COMPUTED?



CHOCOLATE
CHIP
COOKIES

$$P(\text{Posterior}) = P(\text{BOX A} | \text{CC COOKIE}) = \frac{P(\text{CC COOKIE} | \text{BOX A}) P(\text{BOX A})}{P(\text{CC COOKIE})}$$

Likelihood Prior
Evidence



Es. from Bayes' Theorem:
a visual introduction for beginners

HOW IS PE COMPUTED?

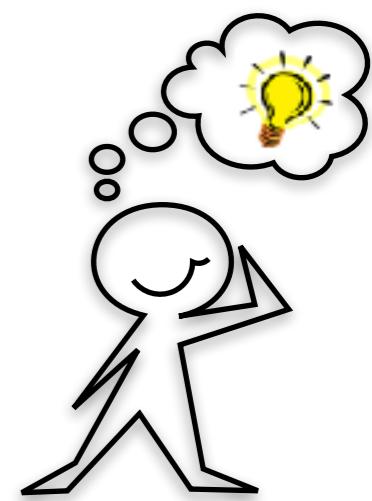


BAYES' THEOREM

$$\text{Posterior } p(\bar{\theta} | \bar{d}, H) = \frac{\text{Likelihood } p(\bar{d} | \bar{\theta}, H) \text{ Prior } p(\bar{\theta} | H)}{\text{Evidence } p(\bar{d} | H)}$$

\bar{d} : data
 $\bar{\theta}$: parameters
 H : model

HOW IS PE COMPUTED?

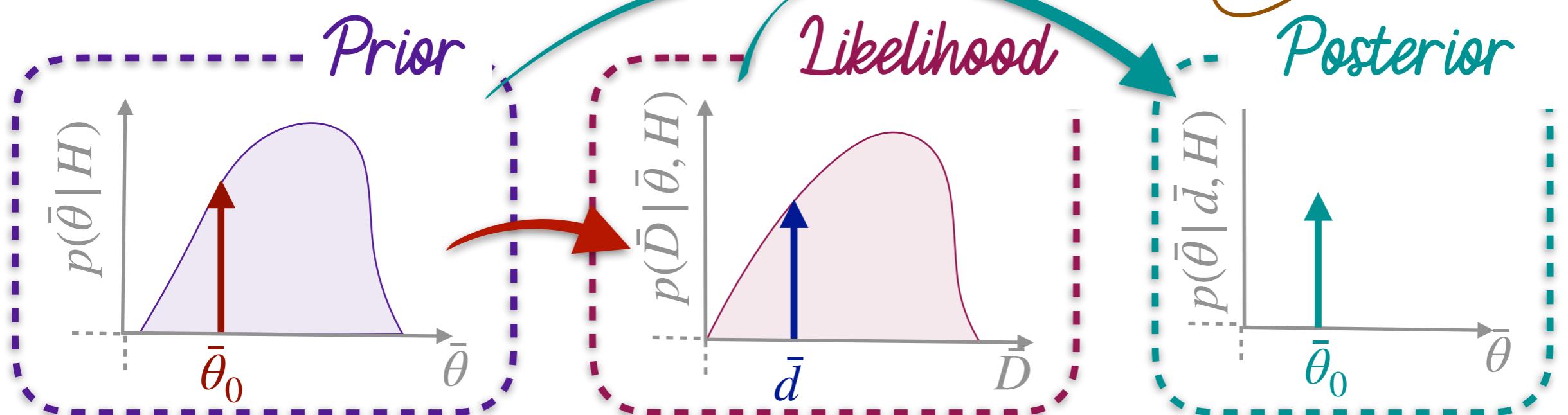


BAYES' THEOREM

$$Posterior \ p(\bar{\theta} | \bar{d}, H) = \frac{Likelihood \ p(\bar{d} | \bar{\theta}, H) \times Prior \ p(\bar{\theta} | H)}{Evidence \ p(\bar{d} | H)}$$

Posterior *Likelihood* *Prior*
Evidence

\bar{d} : data
 $\bar{\theta}$: parameters
 H : model



HOW IS PE COMPUTED?

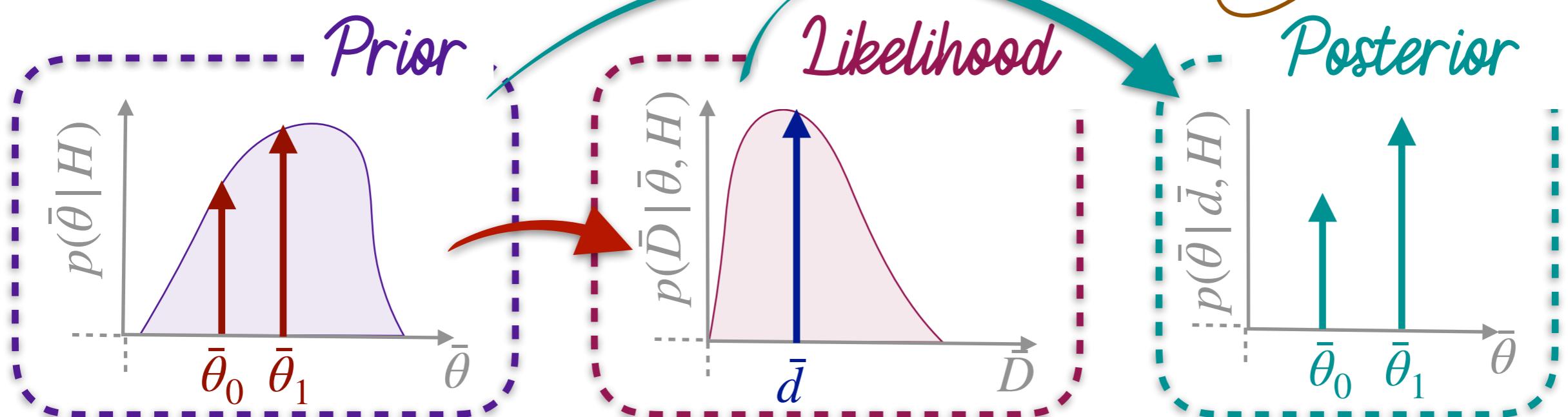
BAYES' THEOREM



$$Posterior \ p(\bar{\theta} | \bar{d}, H) = \frac{Likelihood \ p(\bar{d} | \bar{\theta}, H) \times Prior \ p(\bar{\theta} | H)}{Evidence \ p(\bar{d} | H)}$$

Likelihood *Prior*
Evidence

\bar{d} : data
 $\bar{\theta}$: parameters
 H : model



COMPUTATIONAL CHALLENGE

Assuming GAUSSIAN NOISE:

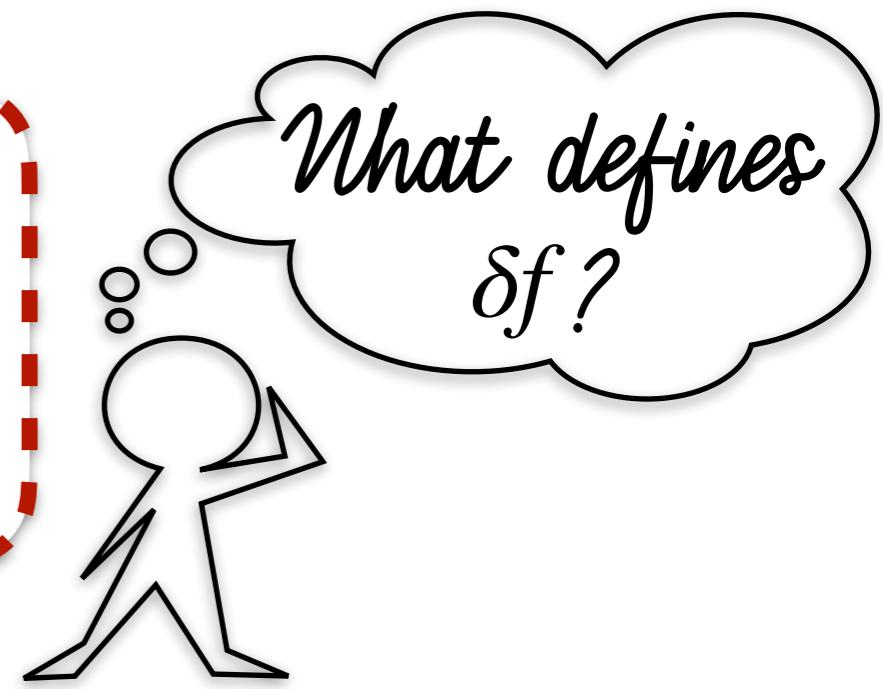
0 mean; known variance

$$p(\bar{d} | \bar{\theta}, H) \propto \exp \left[-\delta f \sum_{i=0}^N \frac{2 |\tilde{d}(f_i) - \tilde{h}(\bar{\theta}, f_i)|^2}{S_n(f_i)} \right]$$

Evaluated $\sim 10^7$ times

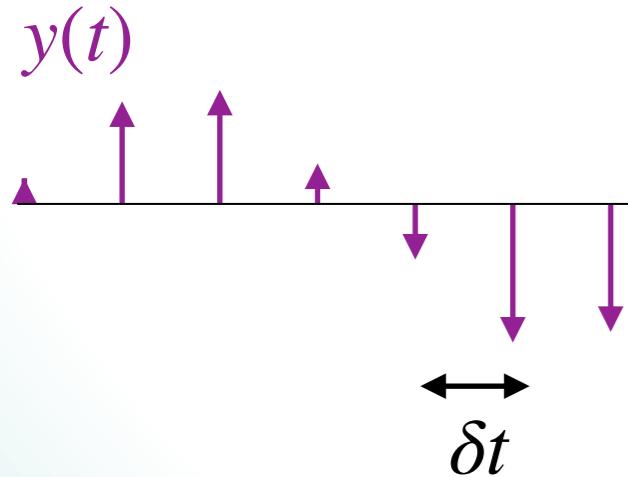
- \bar{d} : data
- $\bar{\theta}$: parameters
- H_s : model assuming signal
- h : GW waveform
- S_n : Power spectral density
- f : frequency
- \sim : in f-domain

$$N = \frac{f_{max} - f_{min}}{\delta f}$$

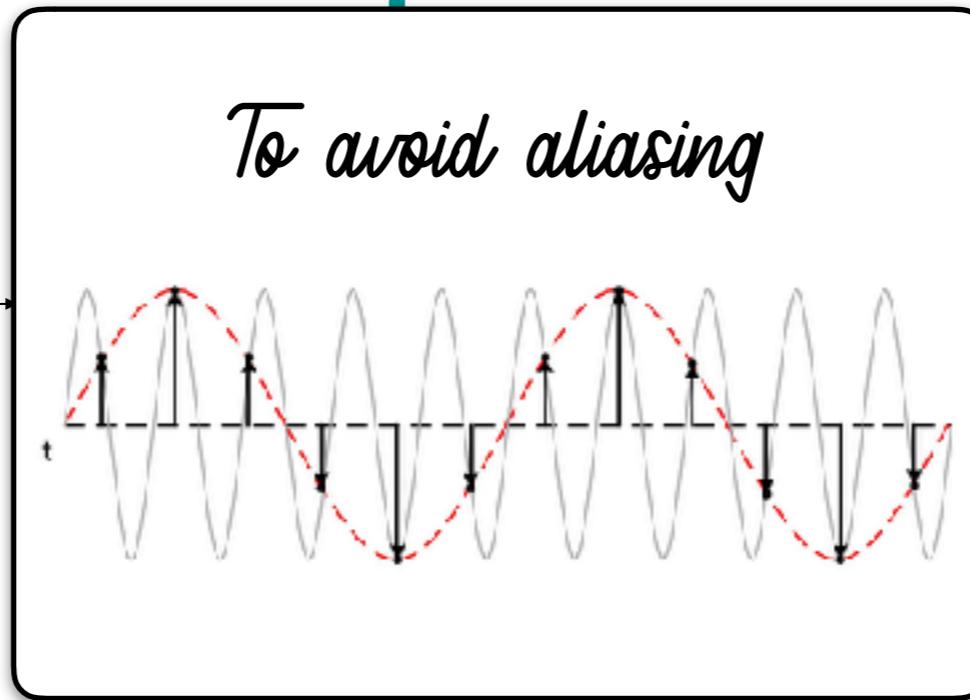


NYQUIST THEOREM

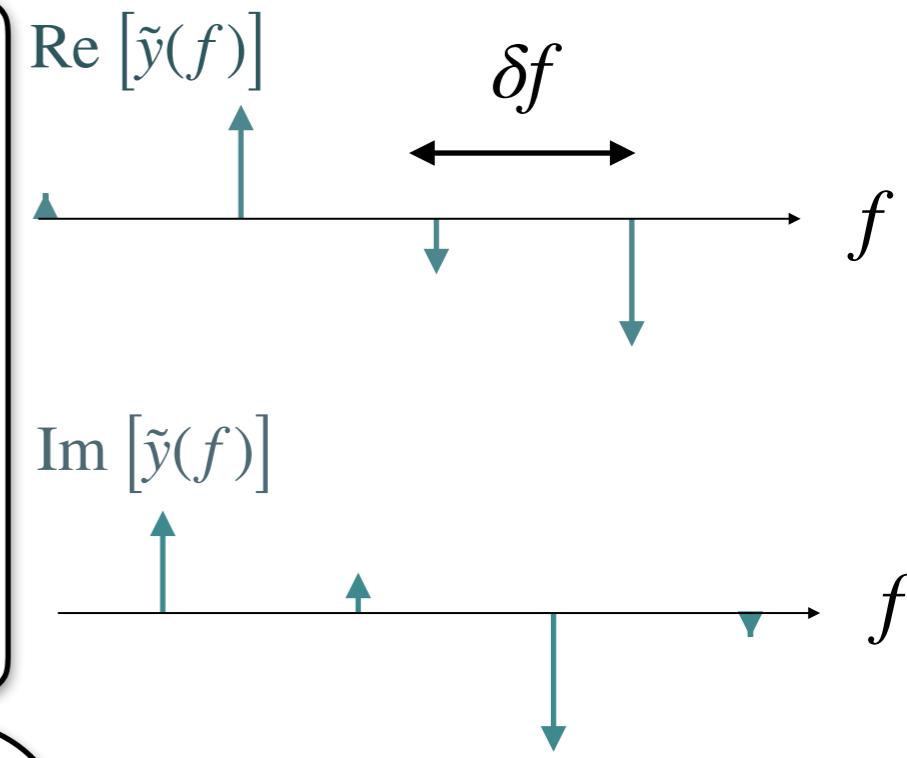
time domain



To avoid aliasing



frequency domain



~ 2 samples per cycle

$$\delta t \leq (2f_{\max})^{-1}$$

What defines τ ?

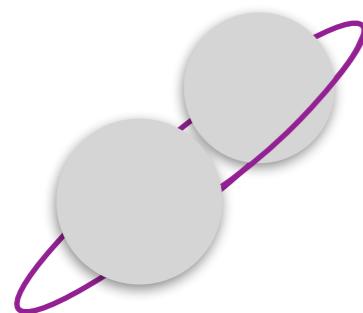
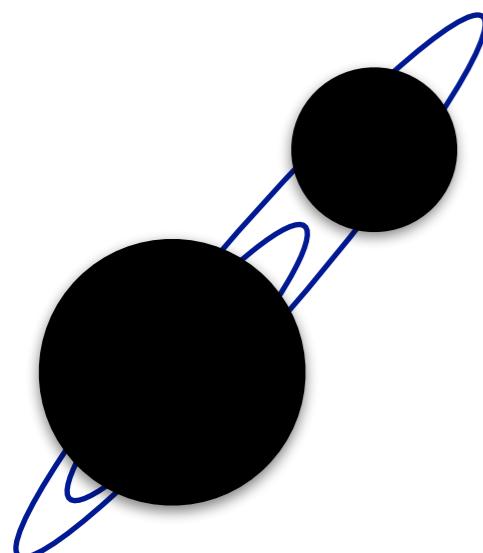
~ 1 sample per cycle

$$\delta f \leq \tau^{-1}$$

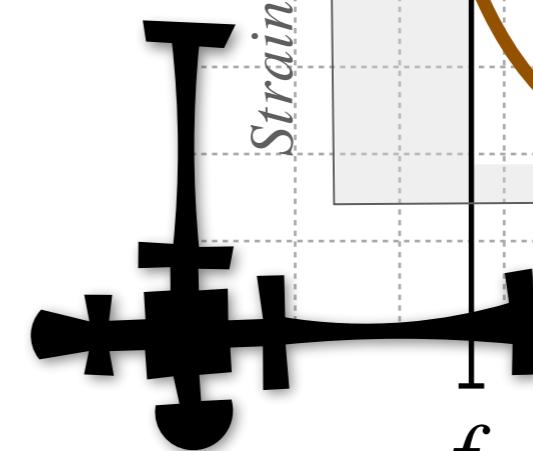
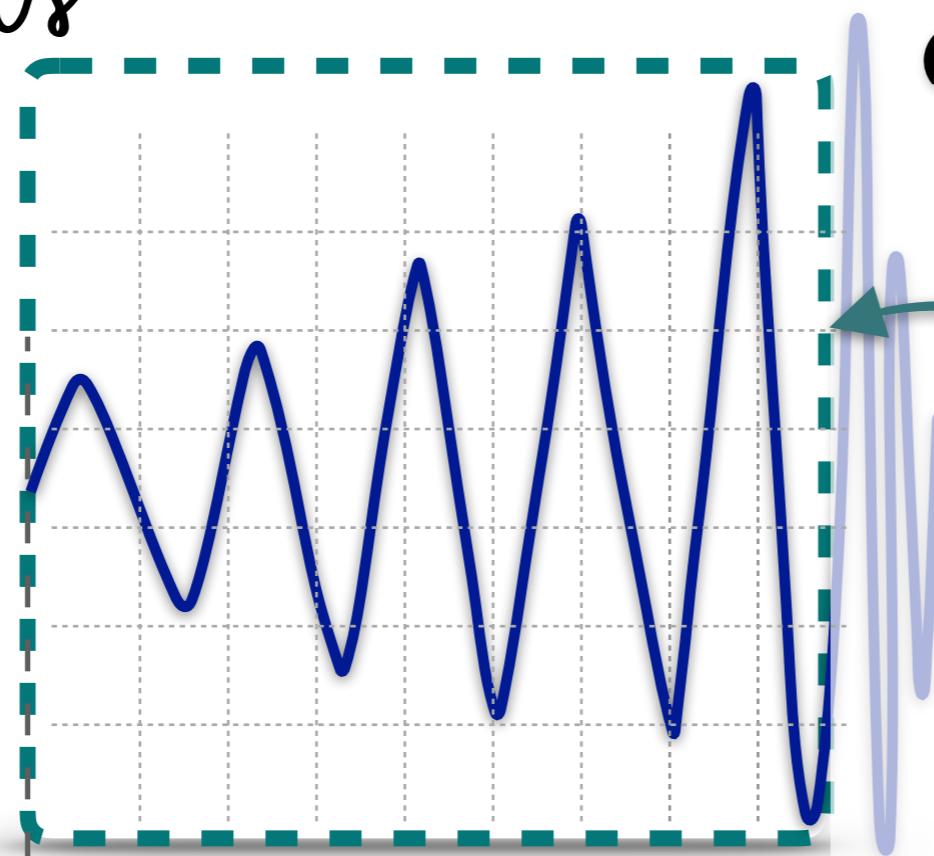


GW SIGNALS

from CBCs



$t(f_0)$

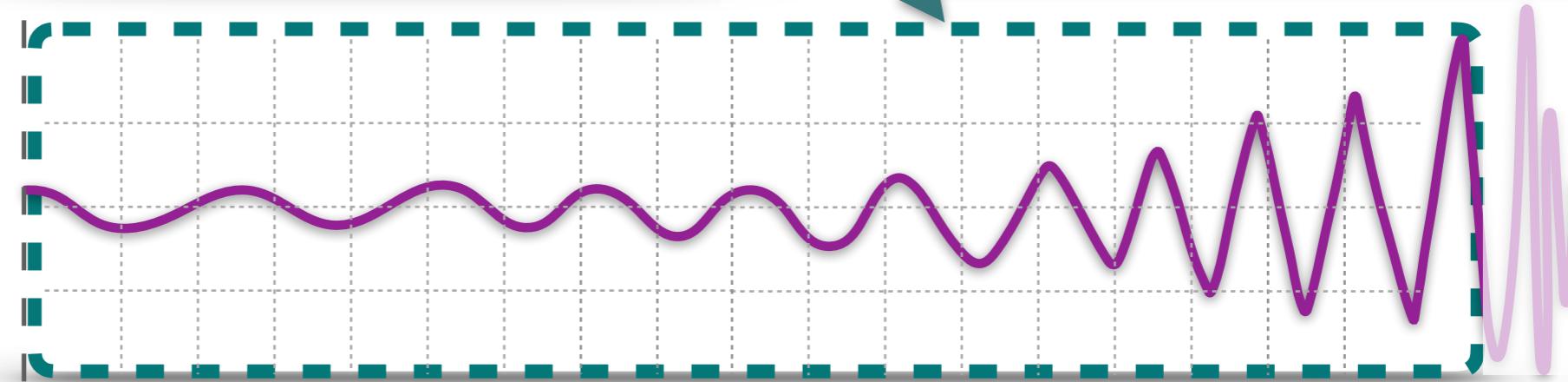


INSPIRAL

$$\tau \propto \mathcal{M}^{-5/3} f_0^{-8/3}$$

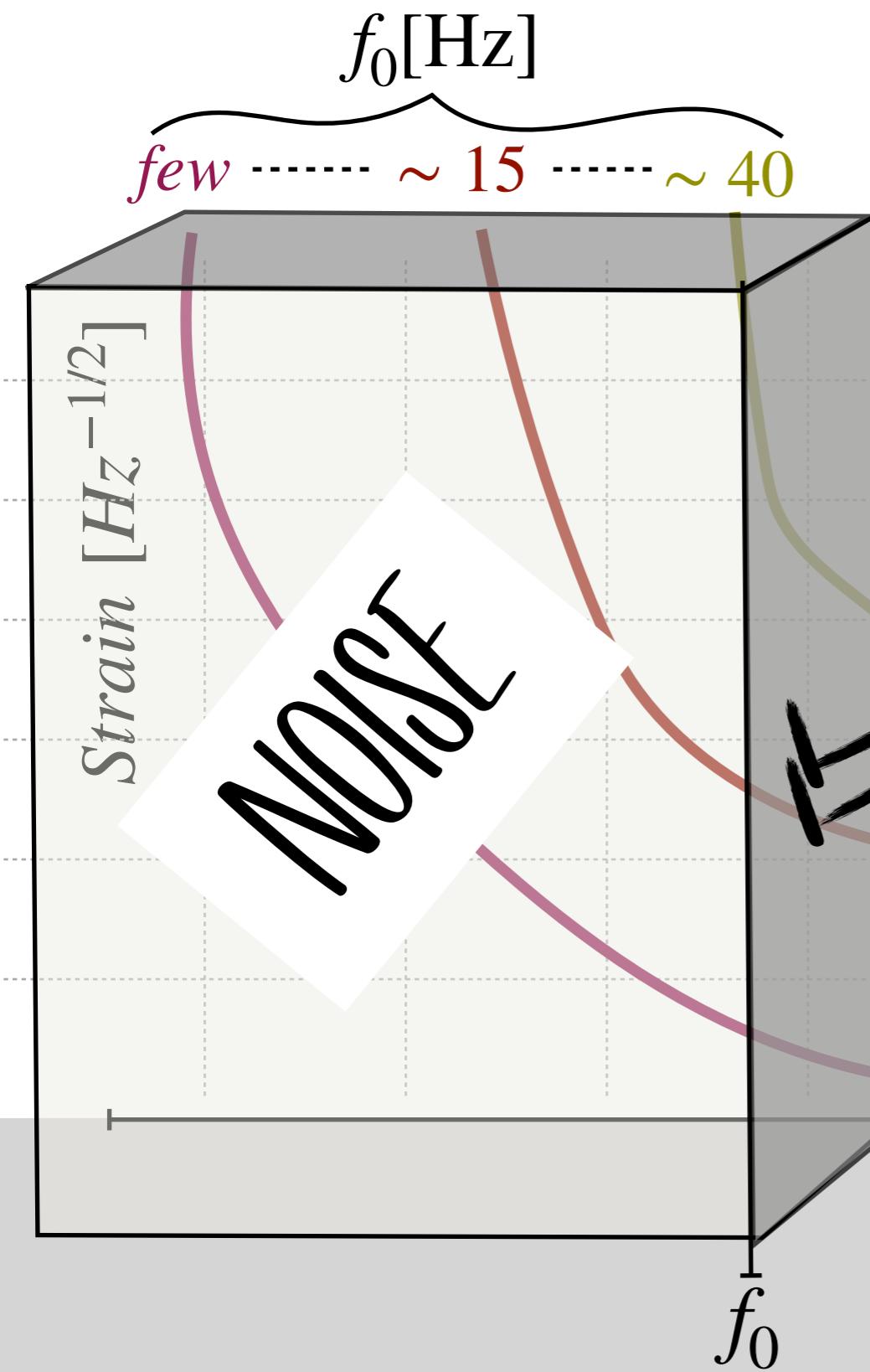
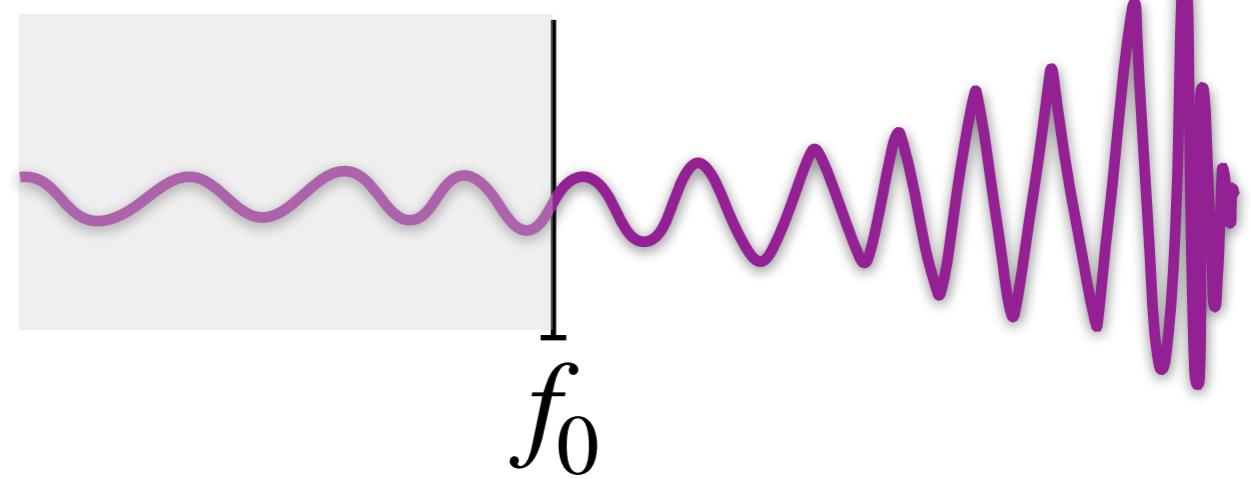
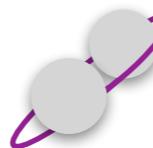
chirp-mass

$$\mathcal{M} = \frac{(m_1 m_2)^{3/5}}{(m_1 + m_2)^{1/5}}$$



t

GW SIGNALS



interferometer sensitivity

LIGO

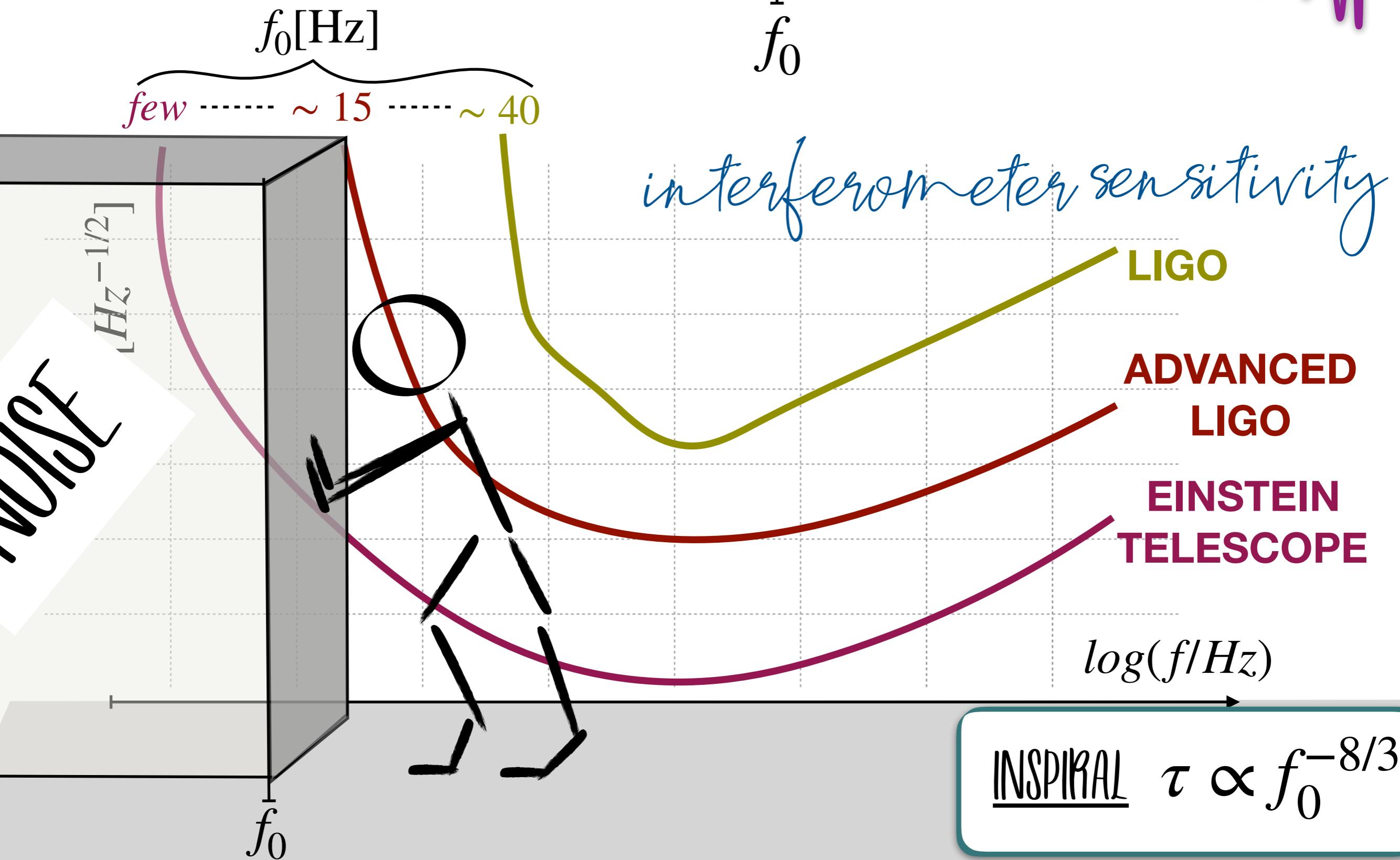
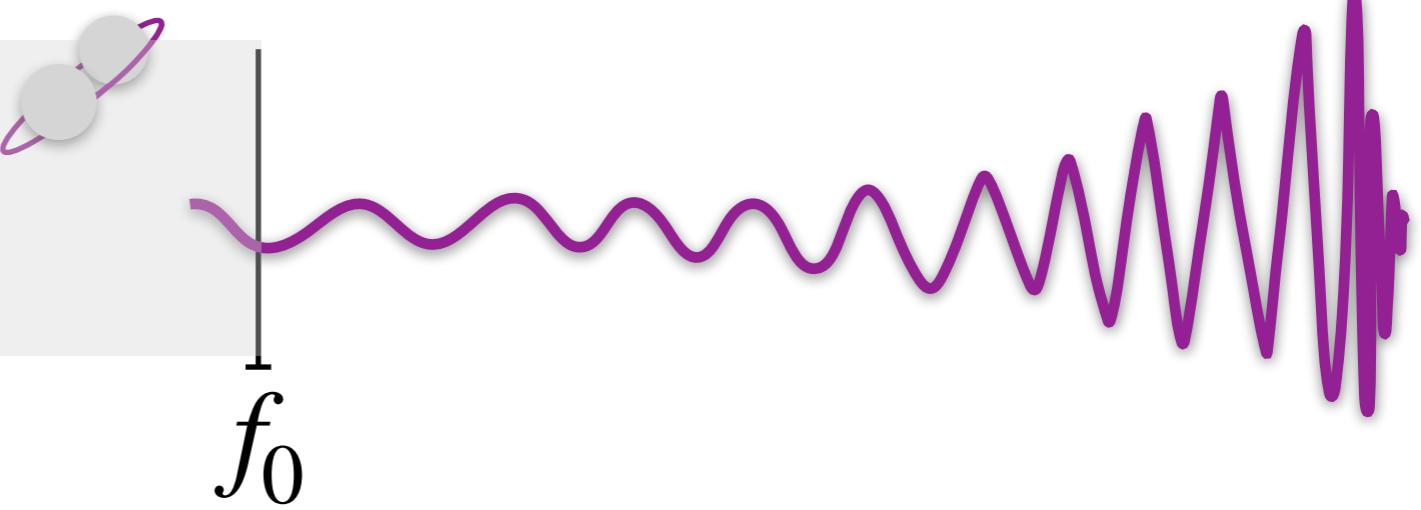
ADVANCED
LIGO

EINSTEIN
TELESCOPE

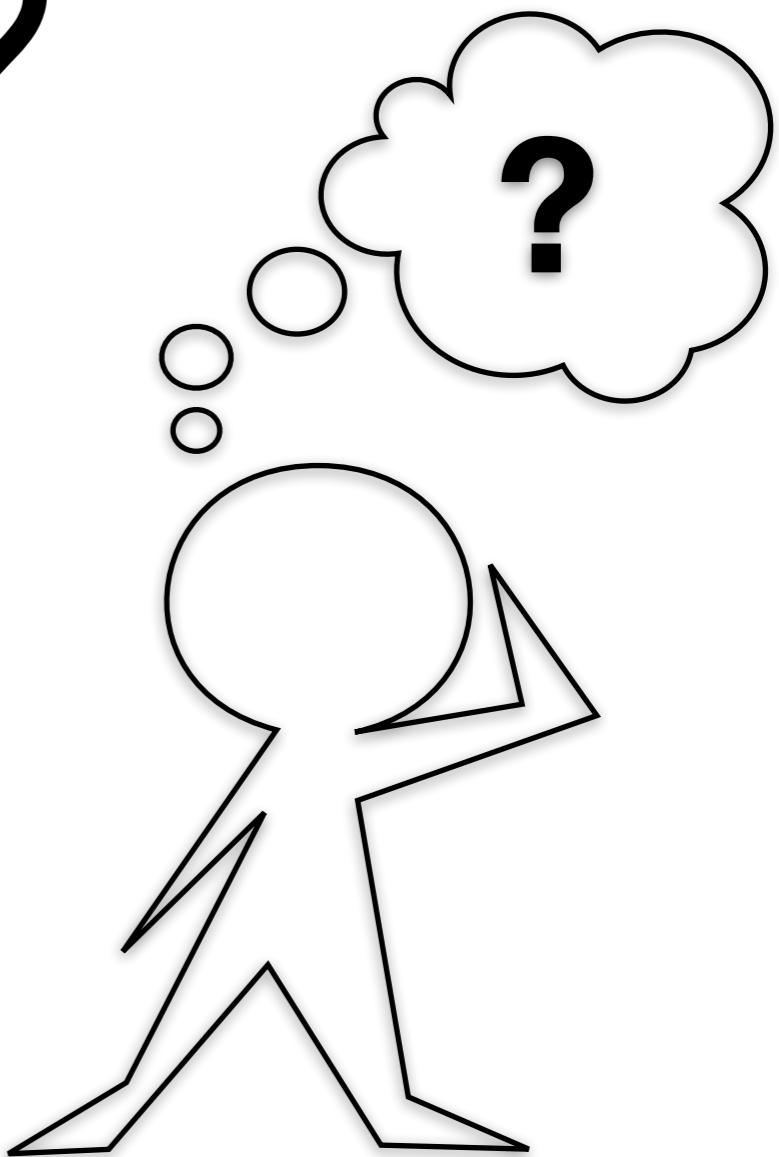
$\log(f/\text{Hz})$

INSPIRAL $\tau \propto f_0^{-8/3}$

GW SIGNALS



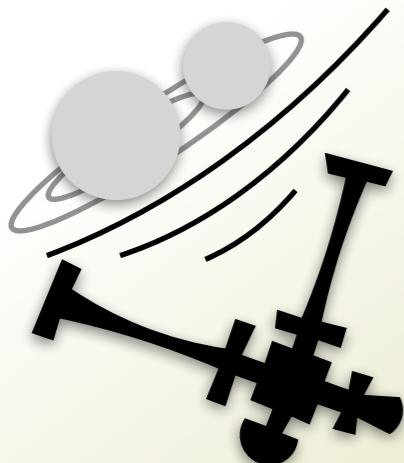
HOW CAN WE OVERCOME THIS
PROBLEM?



CONTEXT

MULTI-BANDING

DETECTION PIPELINE



gstlal

K. Cannon et al.
2012

MBTA

T. Adams et al.
2016

PE for LISA with 2 bands

E. K. Porter et al. 2014



MAIN PE ACCELERATION TECHNIQUE

REDUCED ORDER QUADRATURE

$$L \propto \exp \left\{ 4\delta f \sum_{i=0}^M c_i(\bar{\theta}) \bar{w}_i \right\}$$

$$\bar{w}_i = 4\delta f \sum_{k=0}^M \frac{\tilde{d}(f_k) B_i^*(f_k)}{S_n(f_k)}$$

ROQ

Very large speed up factors

(~300 from $f_0 \sim 20$ Hz)

e.g.:

Canizares et al. 2013;
Canizares et al. 2015;
Smith et al. 2016

EFFECTIVE SAMPLING

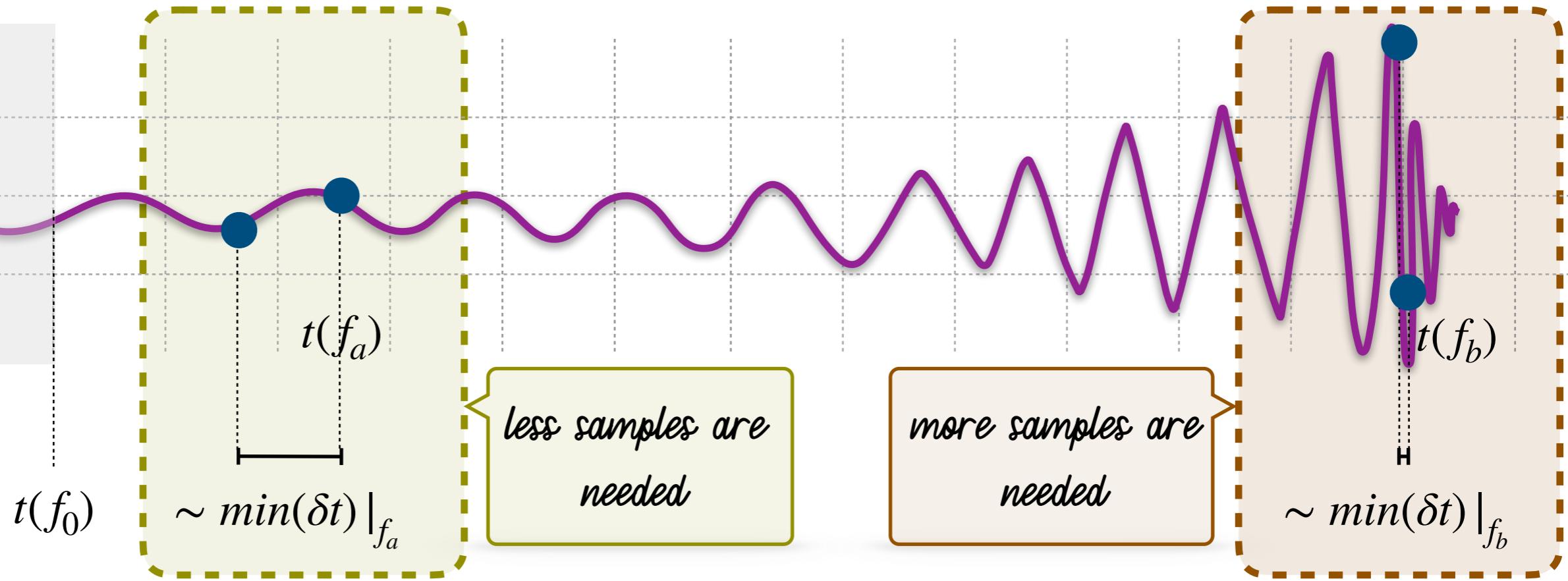
NYQUIST THEOREM and CBC SIGNALS

$$\delta t \leq (2f_{\max})^{-1}$$

~ 2 samples per cycle

$h(t)$

t

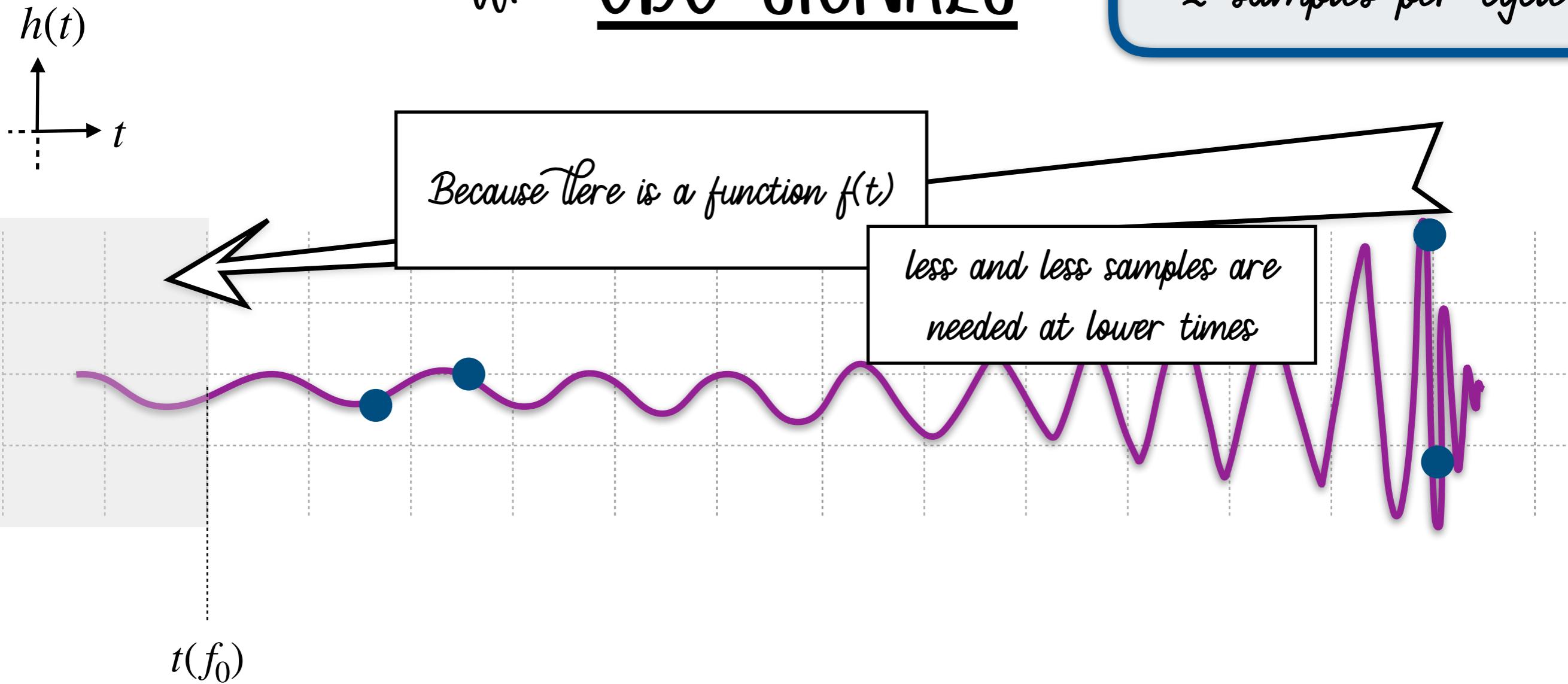


EFFECTIVE SAMPLING

NYQUIST THEOREM and CBC SIGNALS

$$\delta t \leq (2f_{\max})^{-1}$$

~ 2 samples per cycle



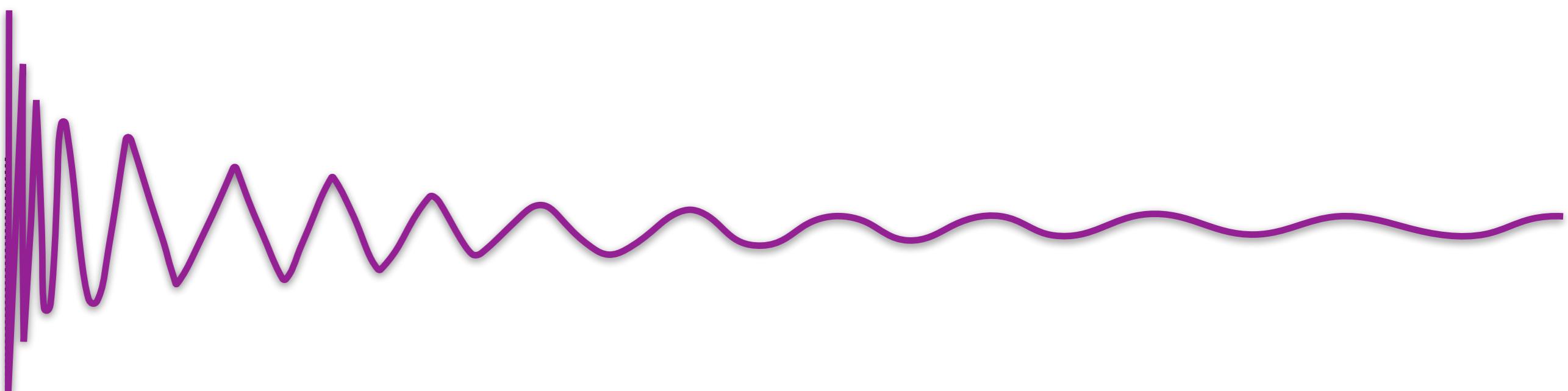
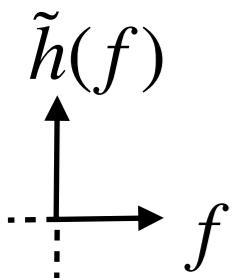
EFFECTIVE SAMPLING

NYQUIST THEOREM

and CBC SIGNALS

$$\delta f \leq \tau^{-1}$$

~ 1 sample per cycle



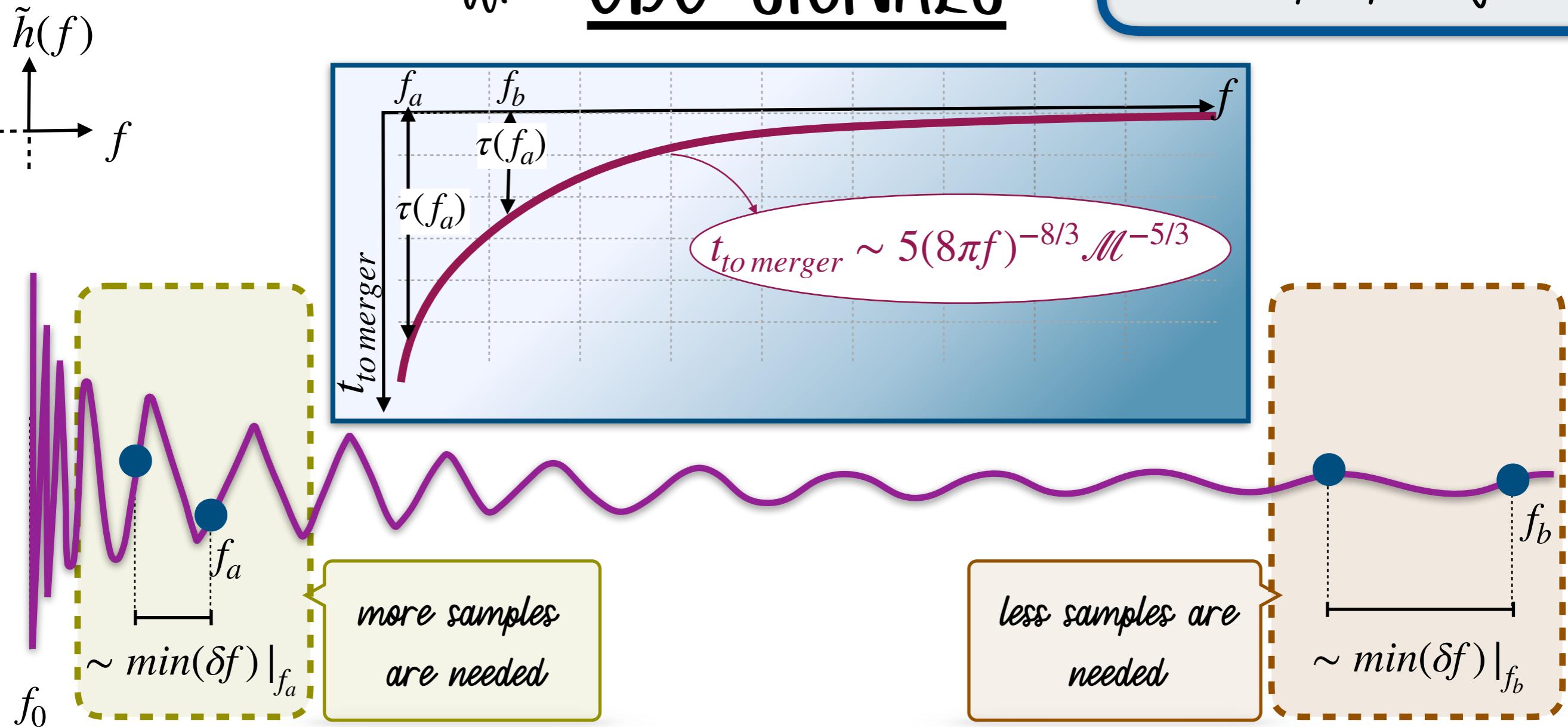
f_0

EFFECTIVE SAMPLING

NYQUIST THEOREM and CBC SIGNALS

$$\delta f \leq \tau^{-1}$$

~ 1 sample per cycle



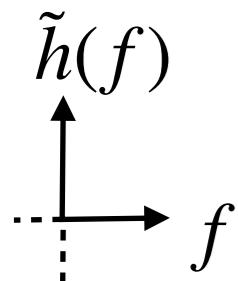
EFFECTIVE SAMPLING

NYQUIST THEOREM

and CBC SIGNALS

$$\delta f \leq \tau^{-1}$$

~ 1 sample per cycle

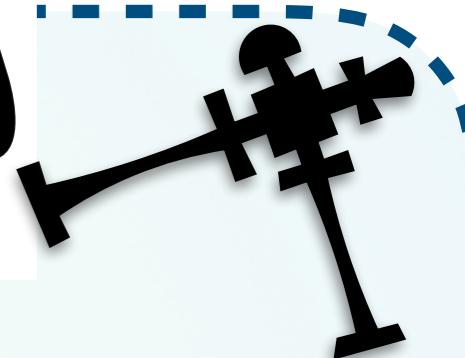


Because there is a function $t(f)$

more and more samples are
needed at lower frequency

f_0

POSSIBLE IMPROVEMENTS



$$N_{fix} = \int_{f_0}^{f_{max}} \delta f^{-1} df$$

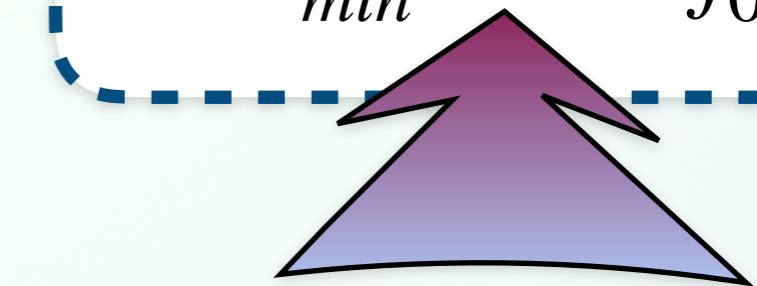
$$\tau \sim t_{to\;merger}(f_0)$$

$$\sim 5 (8\pi f)^{-8/3} \mathcal{M}^{-5/3}$$

$$N_{min} = \int_{f_0}^{f_{max}} t_{to\;merger}(f) df$$

$$N_{fix} \propto (f_{max} - f_0) \mathcal{M}^{-5/3} f_0^{-8/3}$$

$$\frac{N_{fix}}{N_{min}} \sim \frac{5}{3} \frac{f_{max}}{f_0}$$

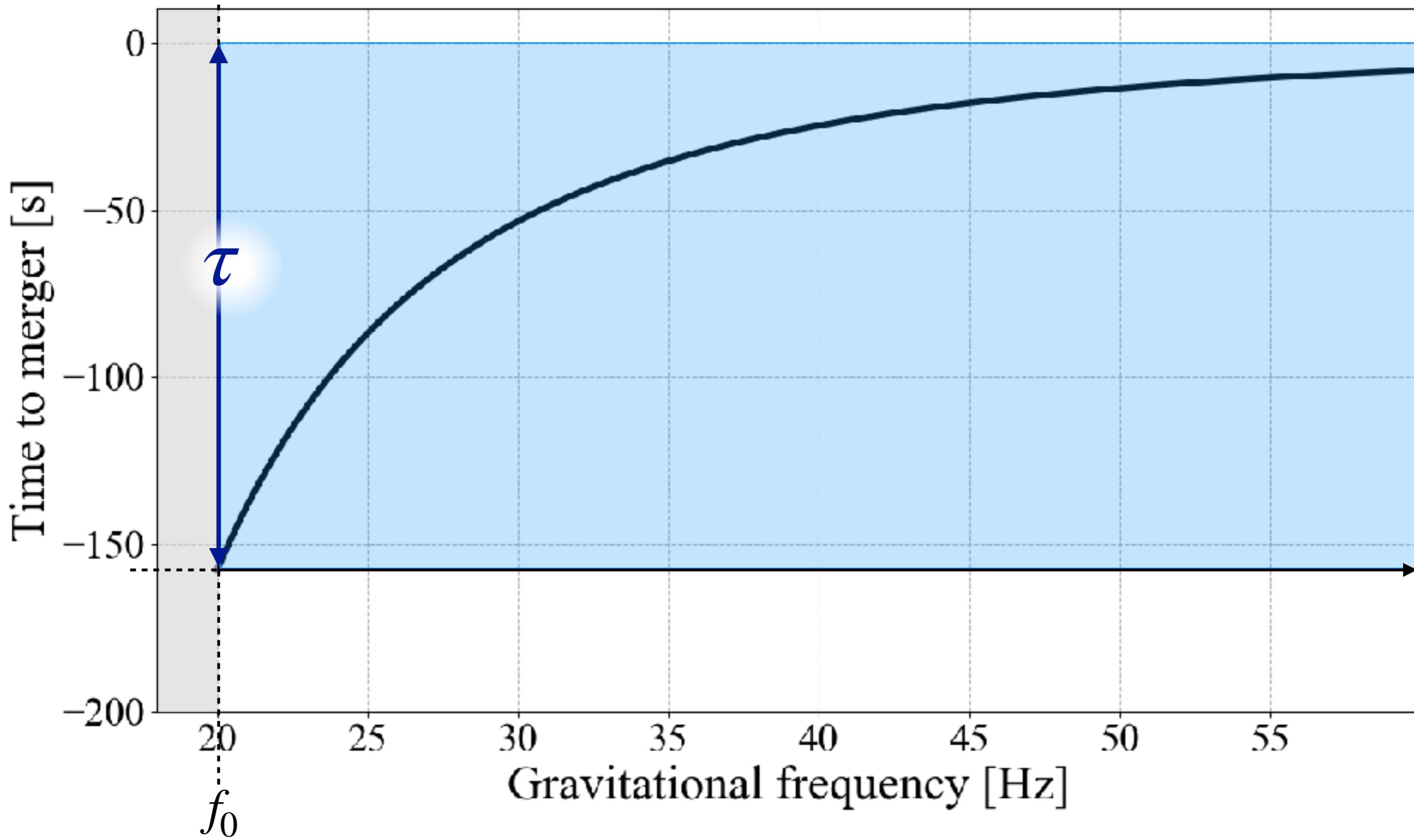


$$N_{min} \propto \mathcal{M}^{-5/3} (f_{max}^{5/3} - f_0^{-5/3})$$

Multi-bandring

NYQUIST THEOREM

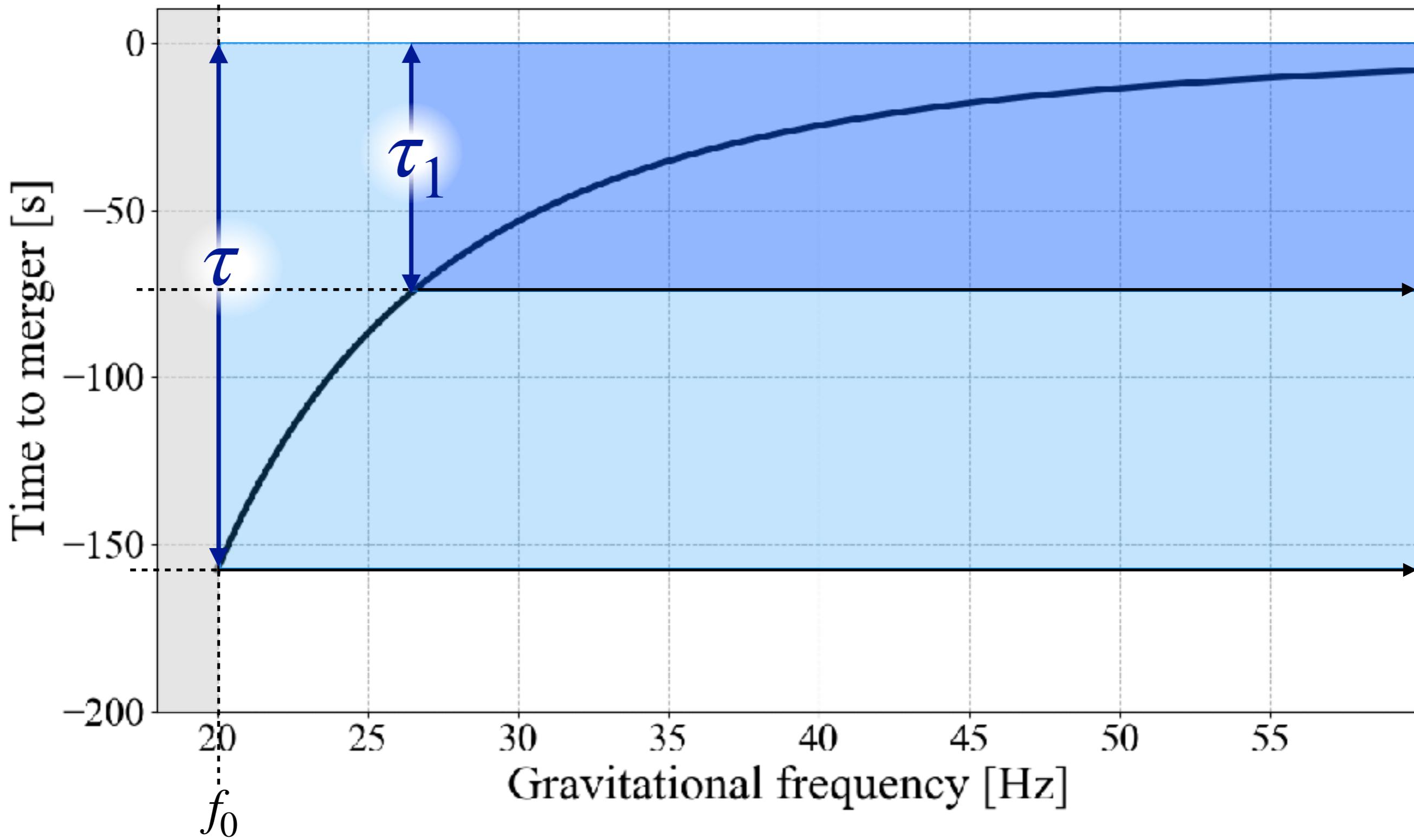
$$\delta f \leq \tau^{-1}$$



Multi-bandring

NYQUIST THEOREM

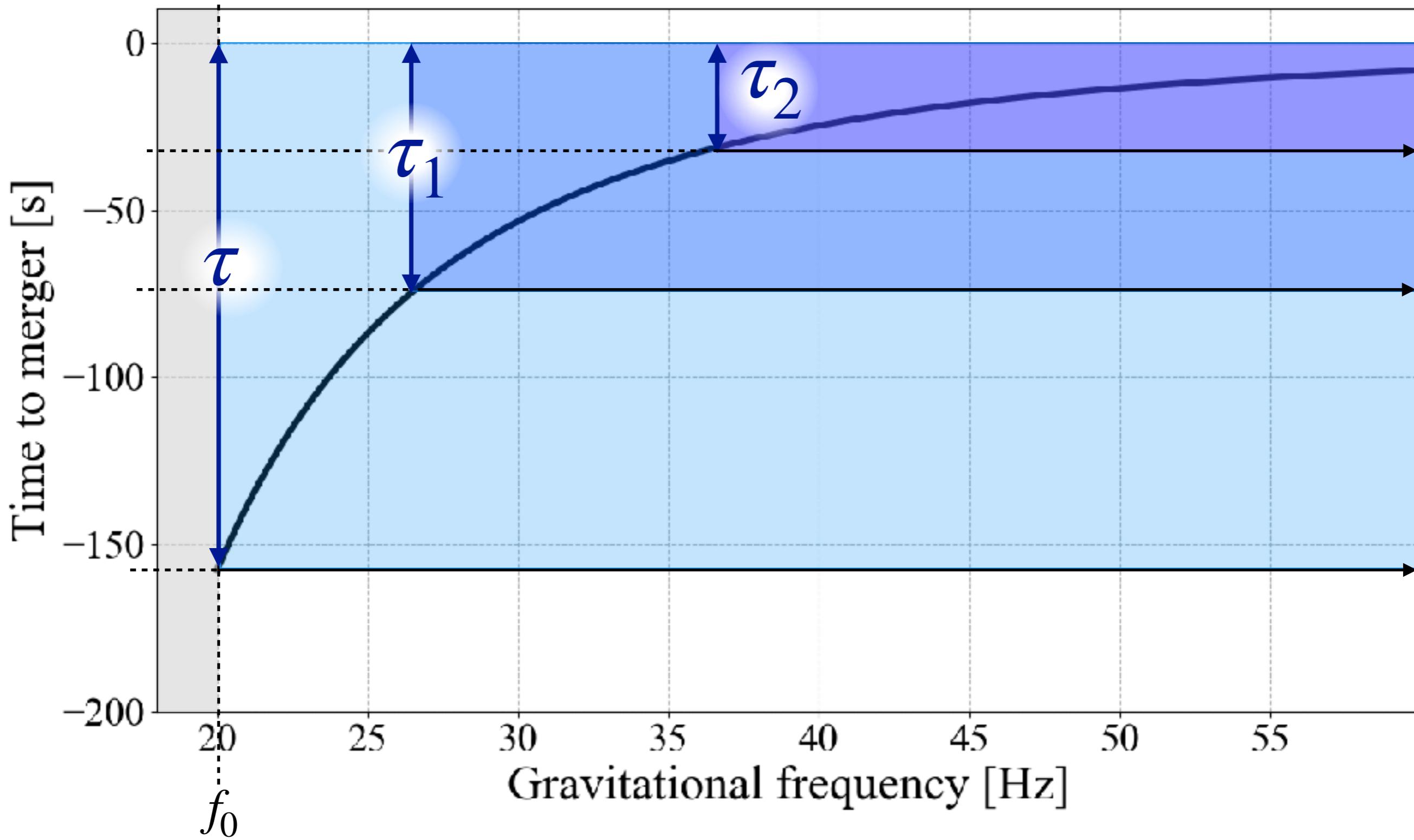
$$\delta f \leq \tau^{-1}$$



Multi-bandring

NYQUIST THEOREM

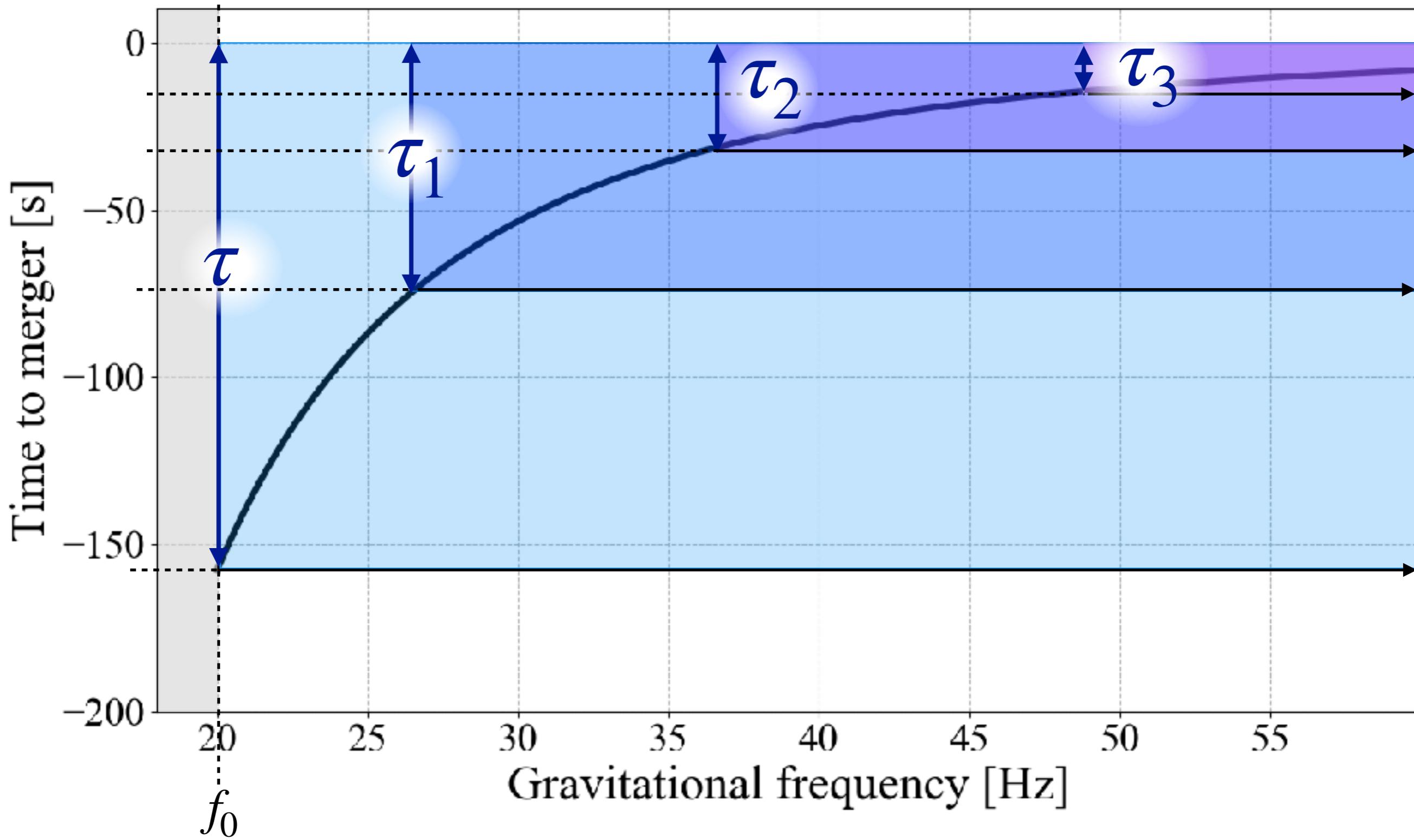
$$\delta f \leq \tau^{-1}$$



Multi-bandring

NYQUIST THEOREM

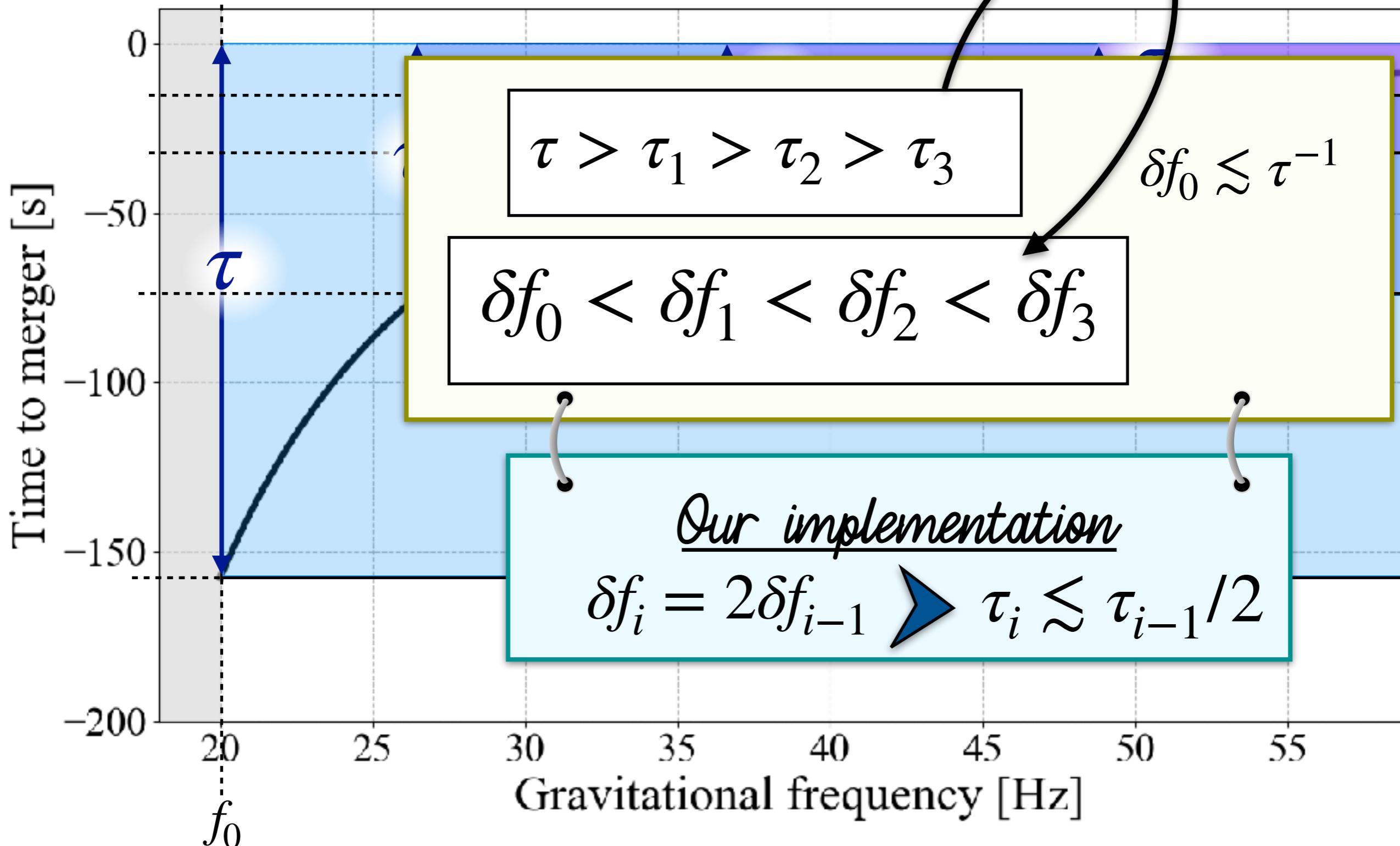
$$\delta f \leq \tau^{-1}$$



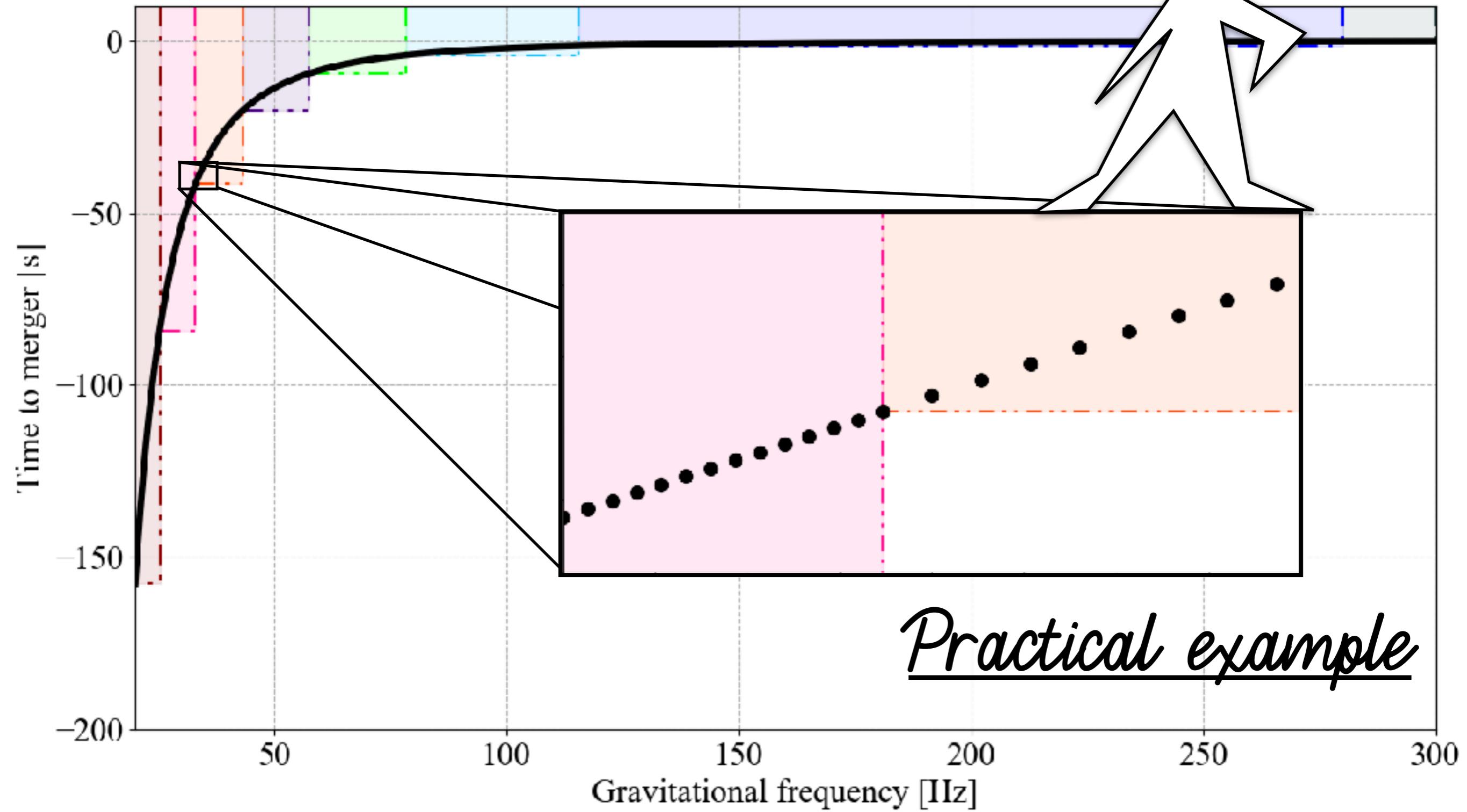
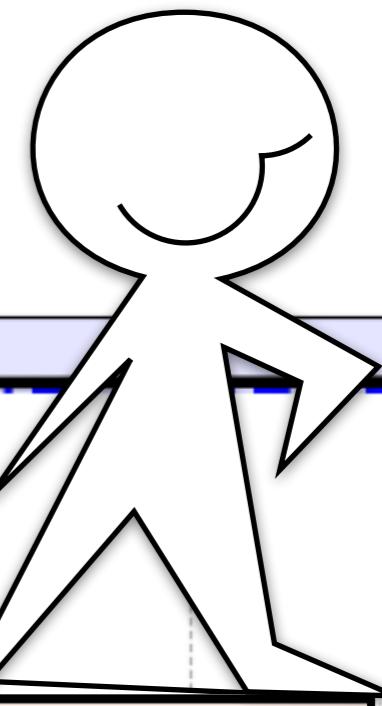
Multi-bandpassing

NYQUIST THEOREM

$$\delta f \leq \tau^{-1}$$

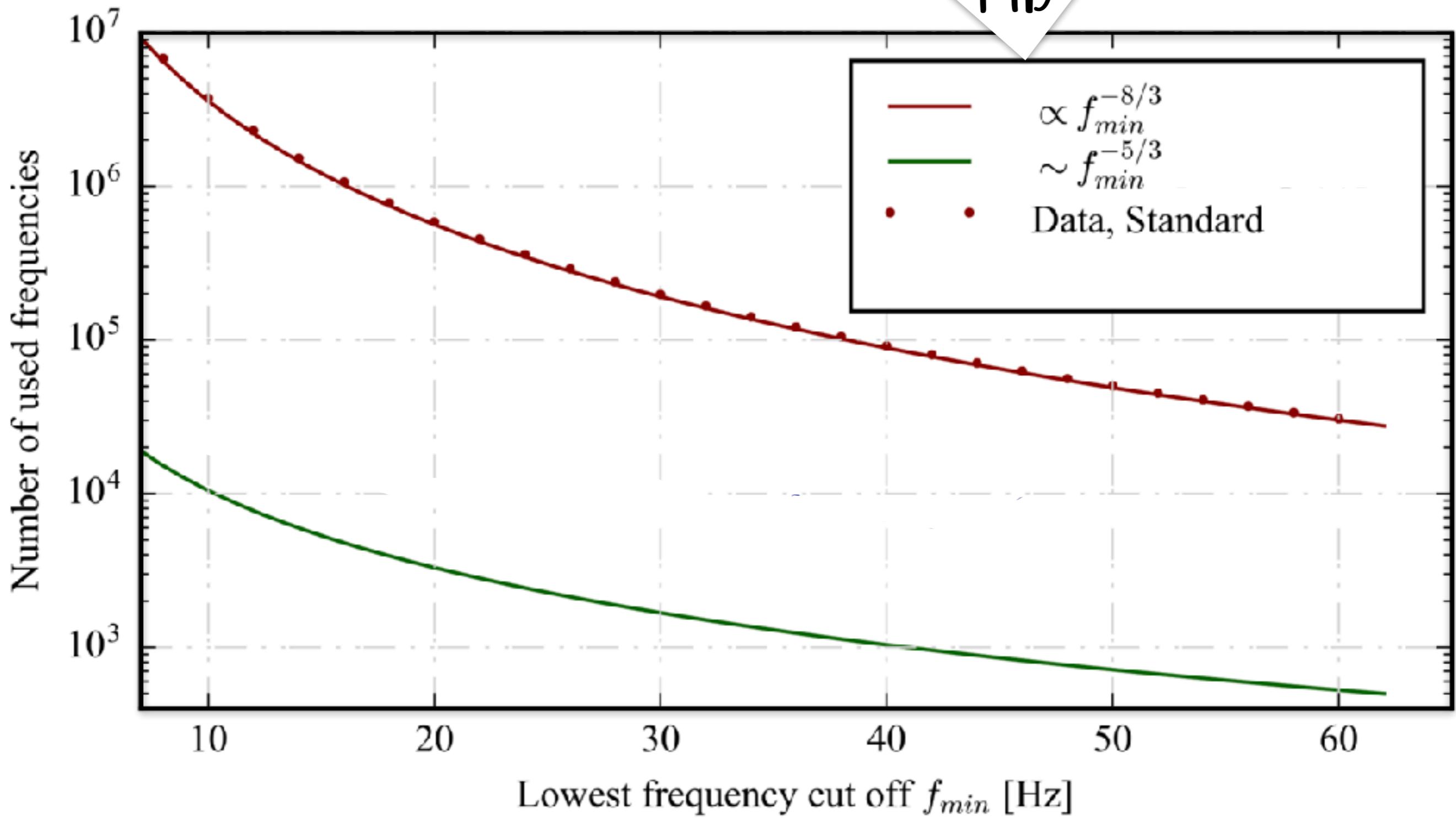


Multi-bandpass



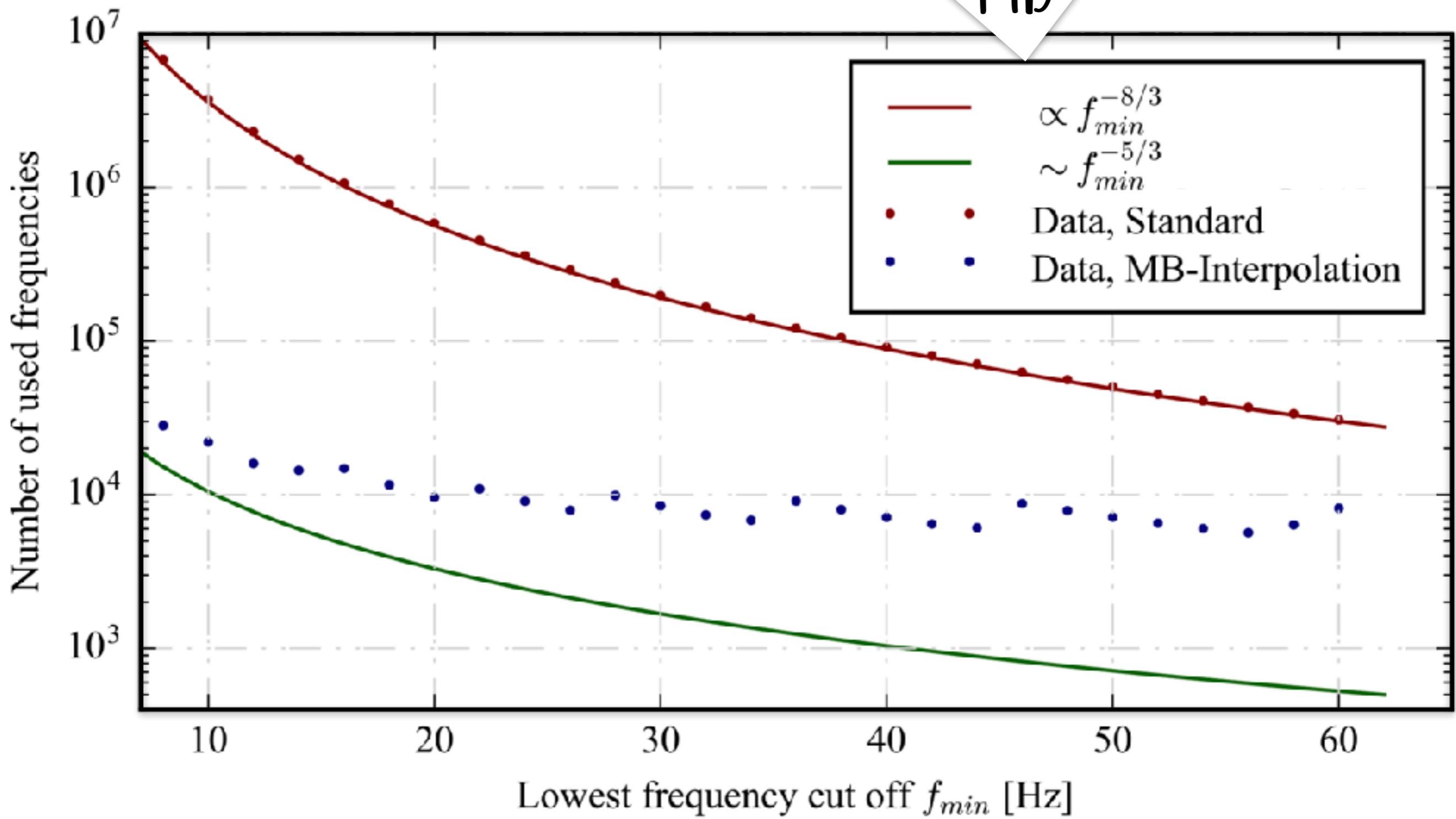
Multi-band

MB



Multi-banding

MB



ACCURACY REQUIRED FOR PE



WHAT TO DO TO REACH THE
REQUIRED ACCURACY?



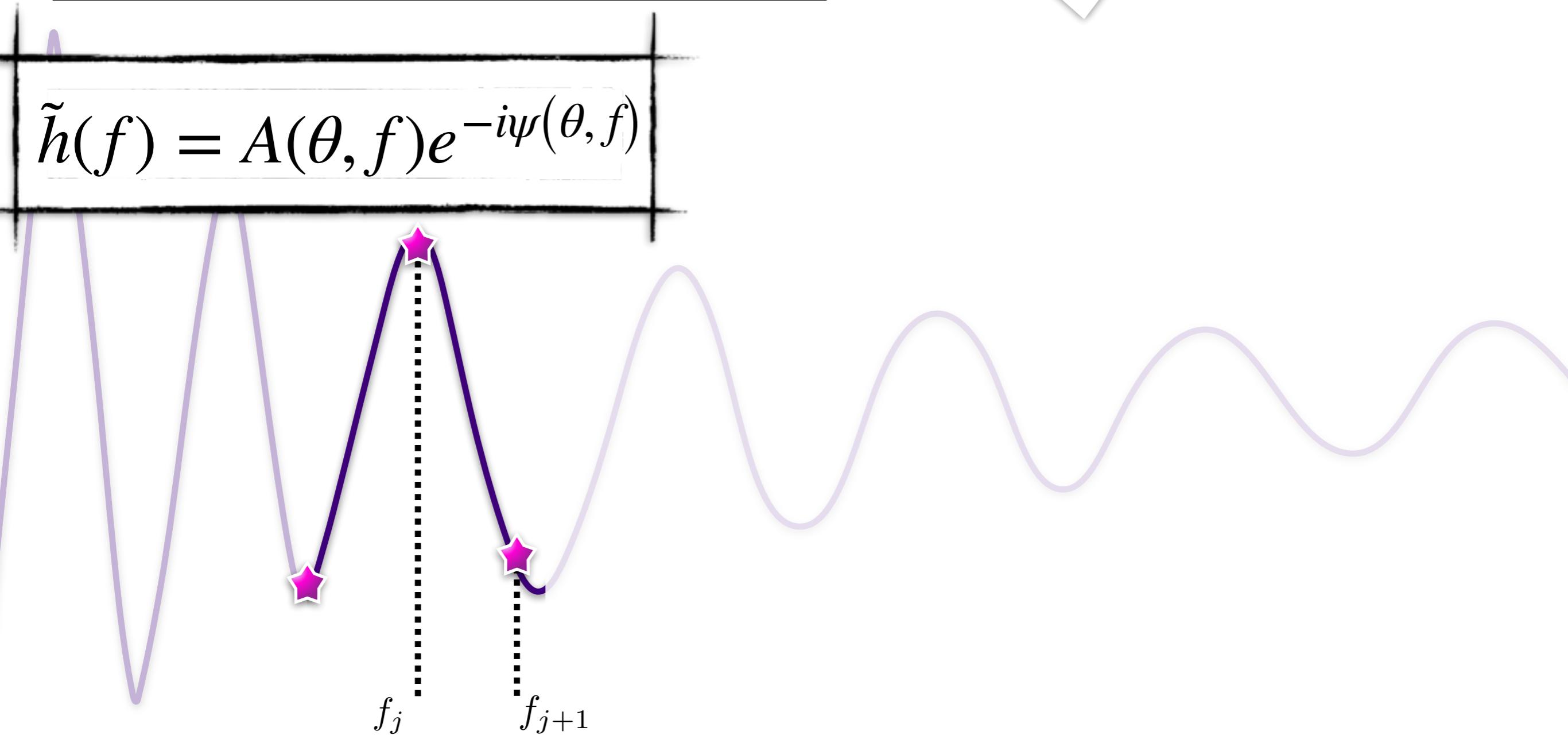
WHAT TO DO TO REACH THE REQUIRED ACCURACY?



INTERPOLATION

INT

$$\tilde{h}(f) = A(\theta, f)e^{-i\psi(\theta, f)}$$



INTERPOLATION

INT

$$\tilde{h}(f) = A(\theta, f)e^{-i\psi(\theta, f)}$$

f_j

f_{j+1}

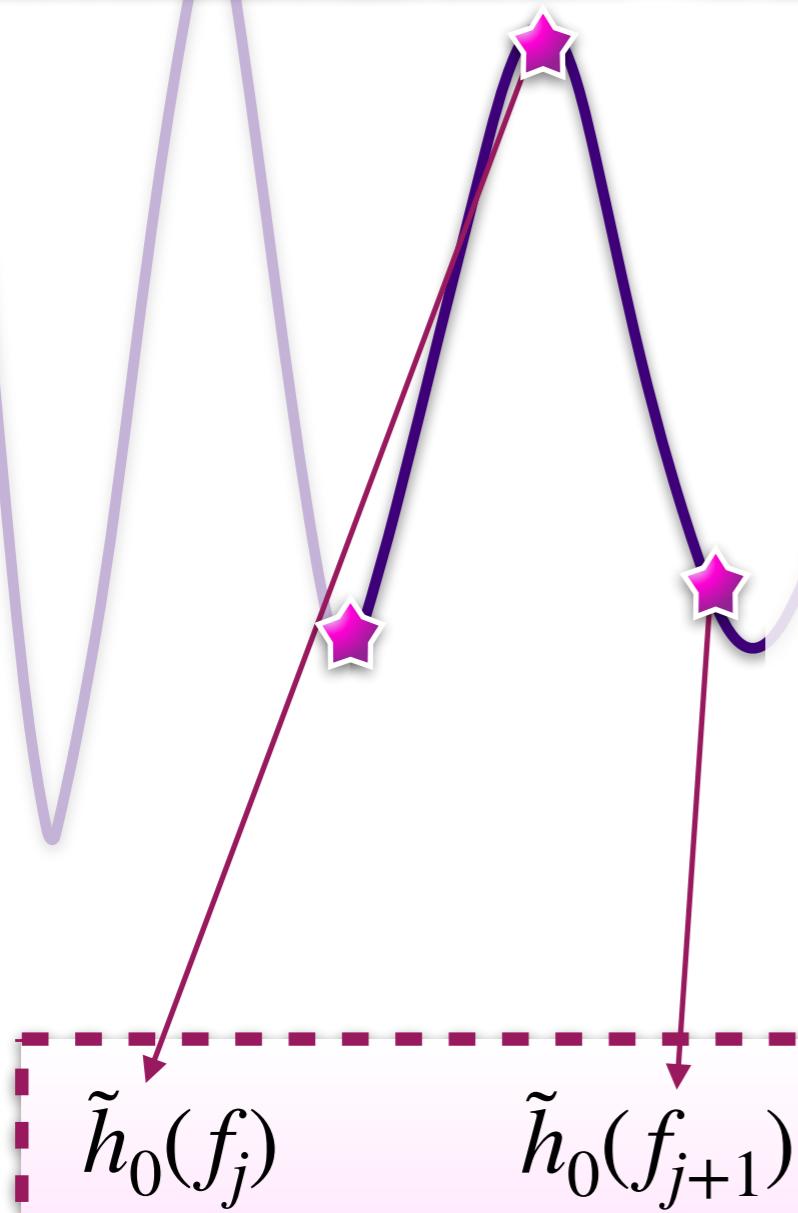
$$\tilde{h}_0(f_j)$$

$$\tilde{h}_0(f_{j+1})$$

INTERPOLATION

INT

$$\tilde{h}(f) = A(\theta, f)e^{-i\psi(\theta, f)}$$



$$g(f) = \psi(f), A(f)$$

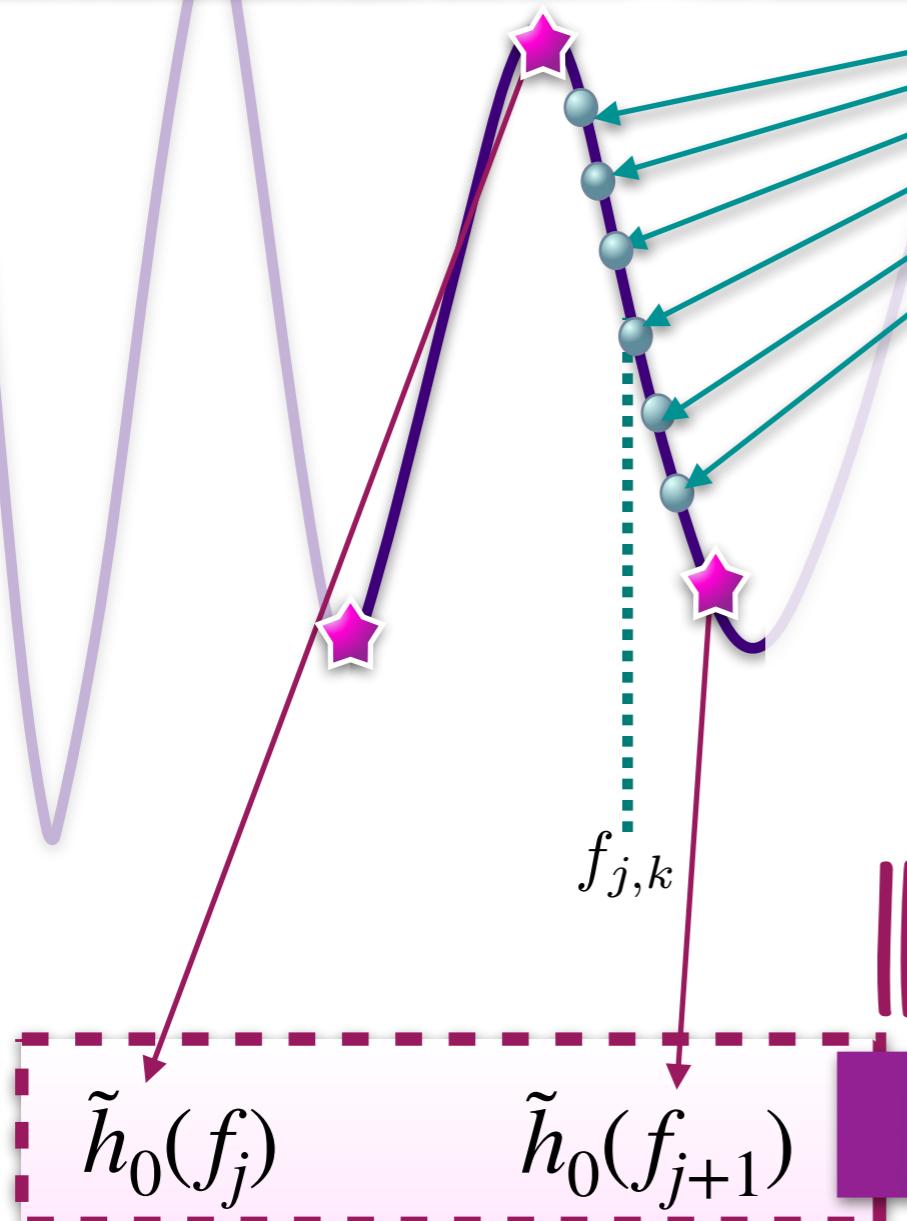
Linear interpolation $\Delta g(f) = \int_{f_j}^f \frac{dg}{d\hat{f}} d\hat{f}$

$$g(f_j + k\delta f_0) \simeq g(f_j) + \underbrace{\frac{g(f_{j+1}) - g(f_j)}{f_{j+1} - f_j}}_{\Delta g_{j,k}} k\delta f_0$$

INTERPOLATION

INT

$$\tilde{h}(f) = A(\theta, f)e^{-i\psi(\theta, f)}$$



$$\tilde{h}_{j,k} \sim \tilde{h}_0(f_k)$$

$$\tilde{h}_{j,k} = (A_j + \Delta A_{j,k})e^{-i(\psi_j + \Delta\psi_{j,k})}$$

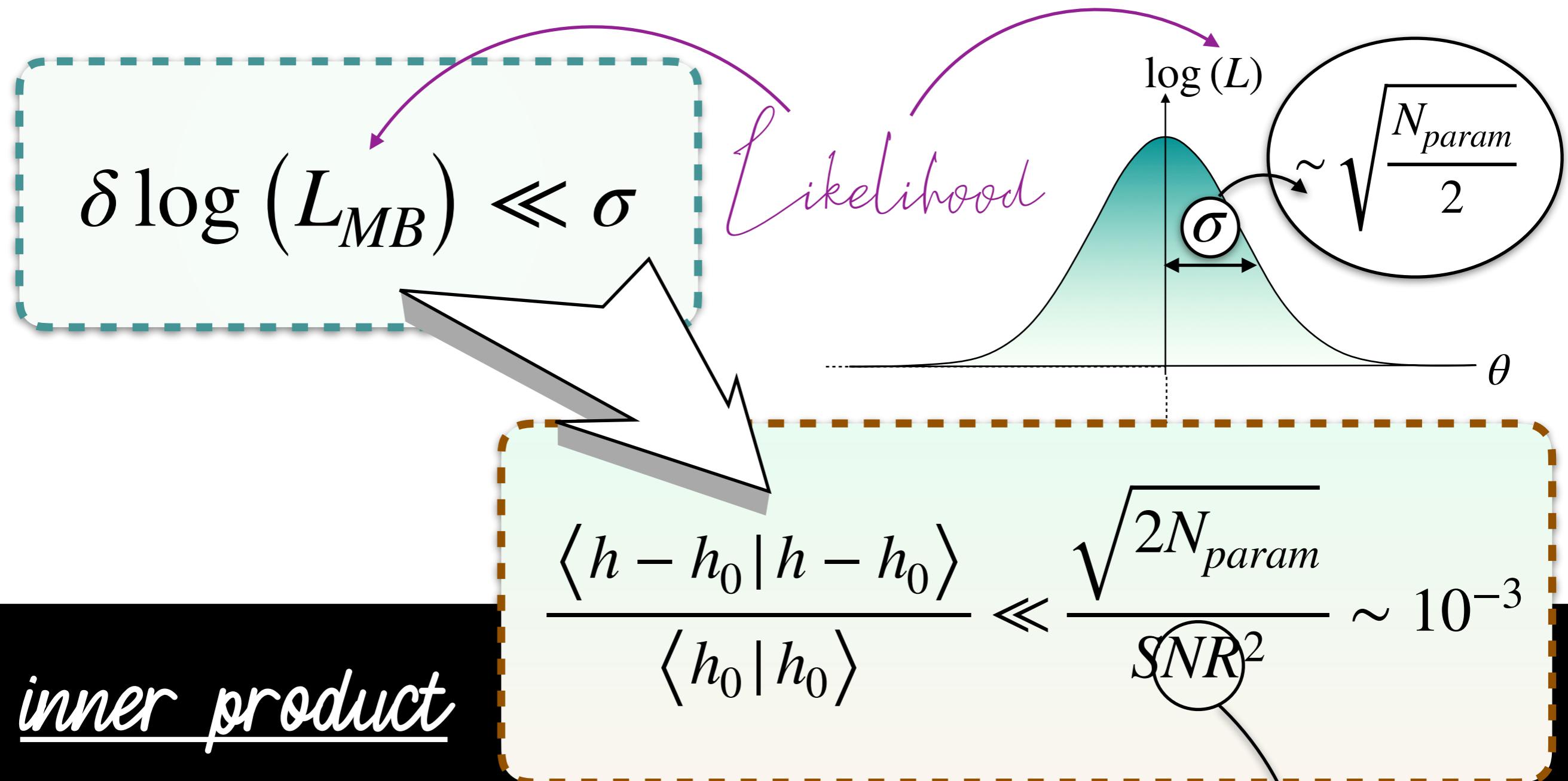
OUT

$$g(f) = \psi(f), A(f)$$

Linear interpolation $\Delta g(f) = \int_{f_j}^f \frac{dg}{d\hat{f}} d\hat{f}$

$$g(f_j + k\delta f_0) \simeq g(f_j) + \overbrace{\frac{g(f_{j+1}) - g(f_j)}{f_{j+1} - f_j} k\delta f_0}^{\Delta g_{j,k}}$$

ACCURACY REQUIRED FOR PE



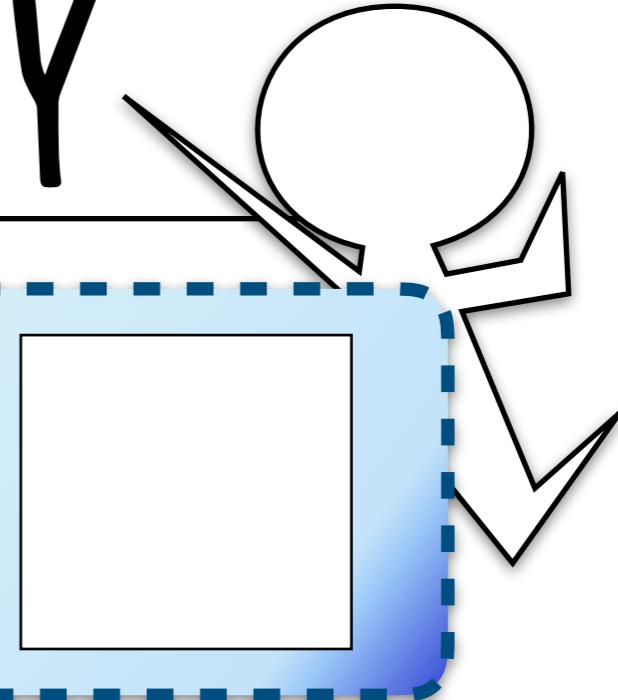
inner product

$$\langle a | b \rangle \sim 2\delta f \sum_{k>0} \frac{\tilde{a}^*(f_k)\tilde{b}(f_k) + \tilde{b}^*(f_k)\tilde{a}(f_k)}{S_n(f_k)}$$

Moderately loud signals
 $SNR \sim \text{few} \times 10$

MB - INT ACCURACY

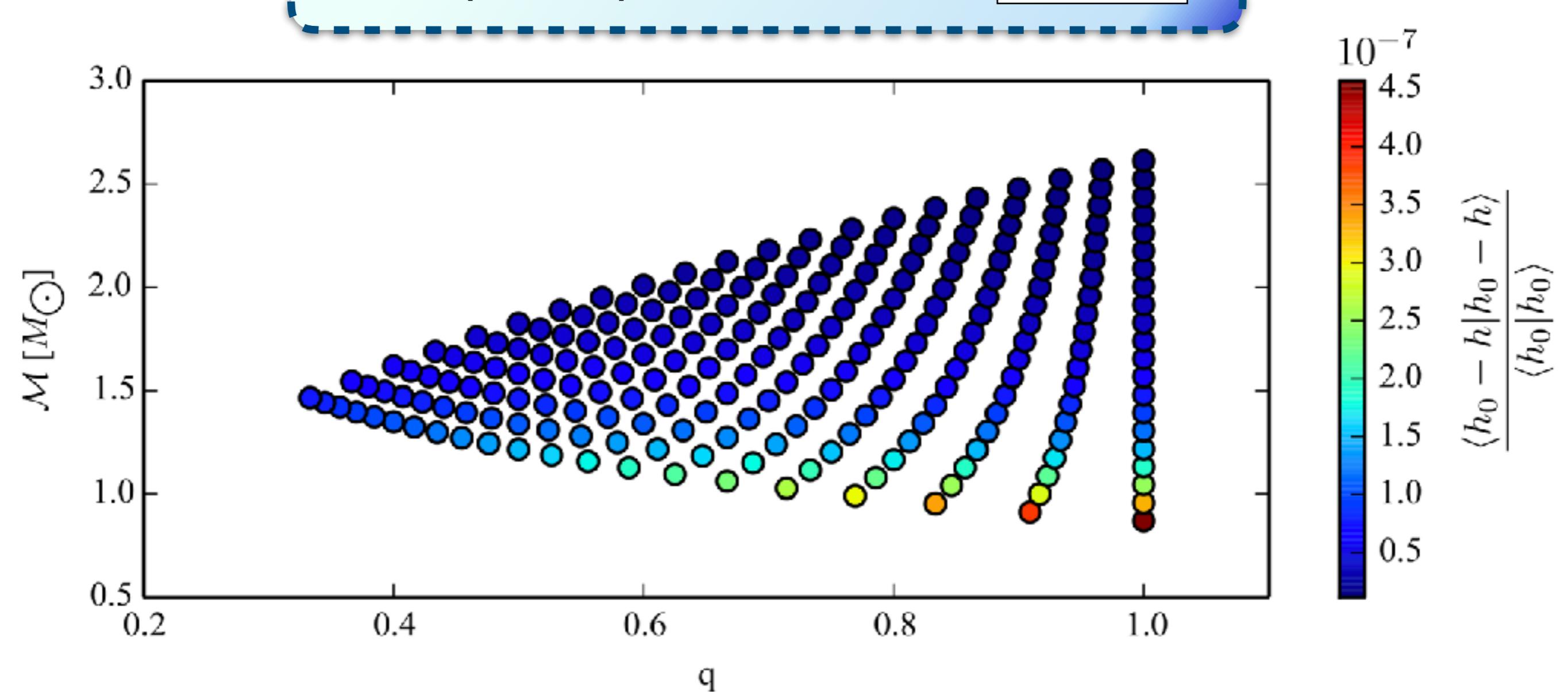
$$\frac{\langle h - h_0 | h - h_0 \rangle}{\langle h_0 | h_0 \rangle} \ll 10^{-3}$$

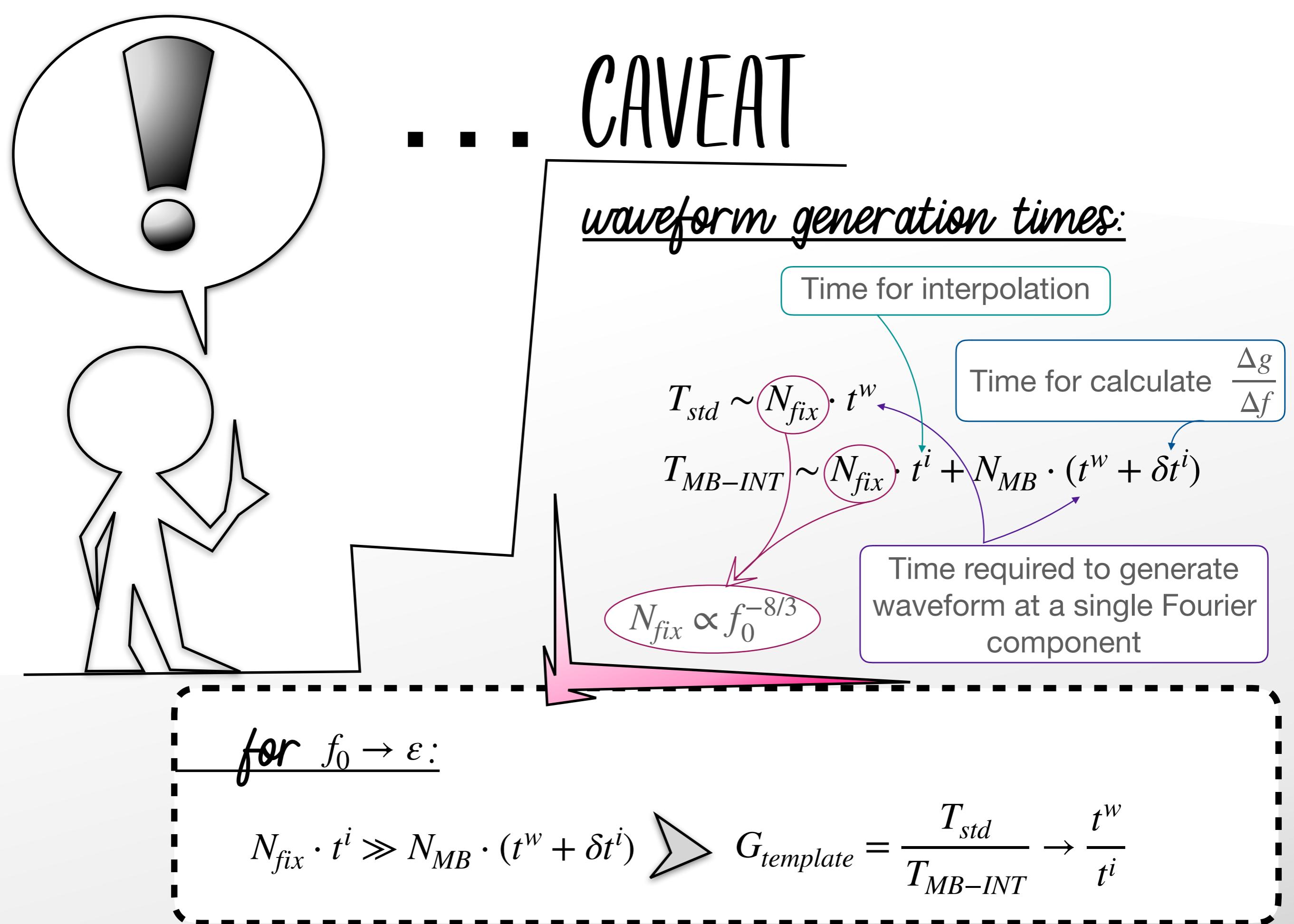


MB - INT ACCURACY

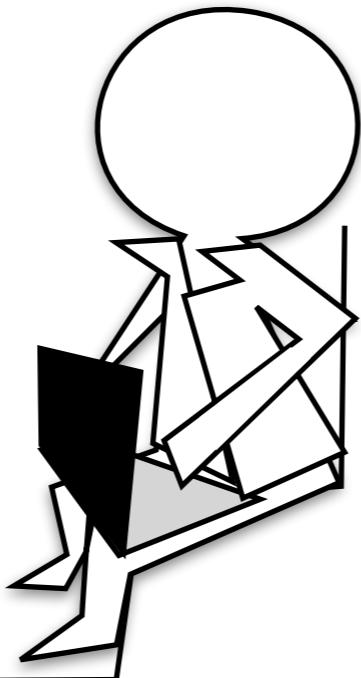


$$\frac{\langle h - h_0 | h - h_0 \rangle}{\langle h_0 | h_0 \rangle} \ll 10^{-3}$$





RESULTS



SPEED UP WAVEFORM

GENERATION

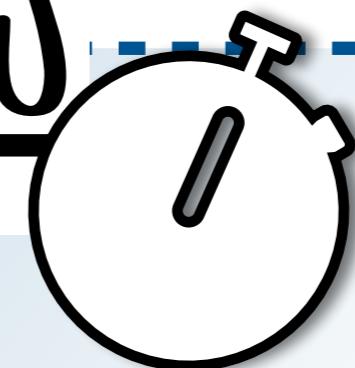
PE

CONSISTENCY TEST

SPEED UP PE



RESULTS

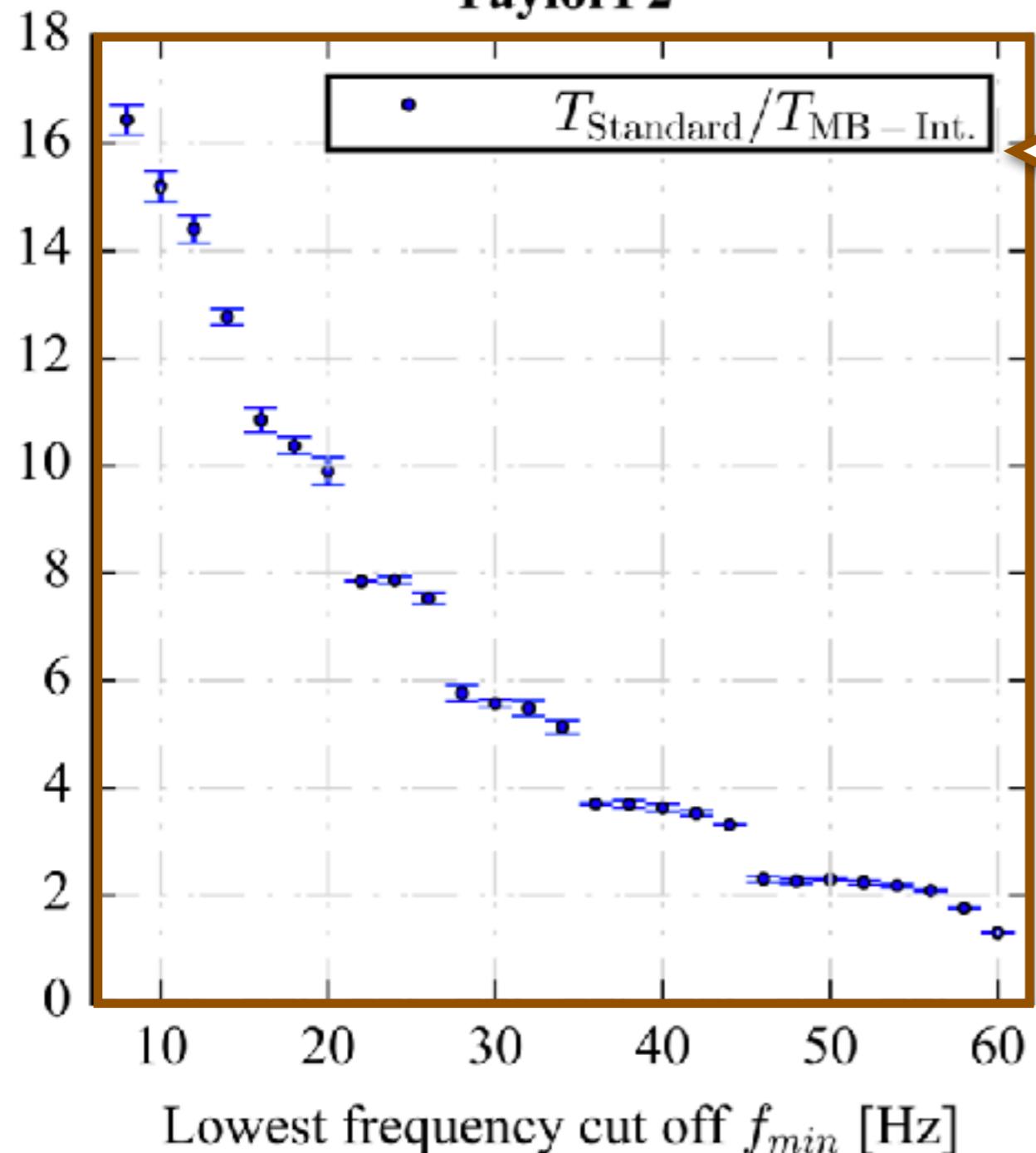


SPEED UP

WAVEFORM GENERATION

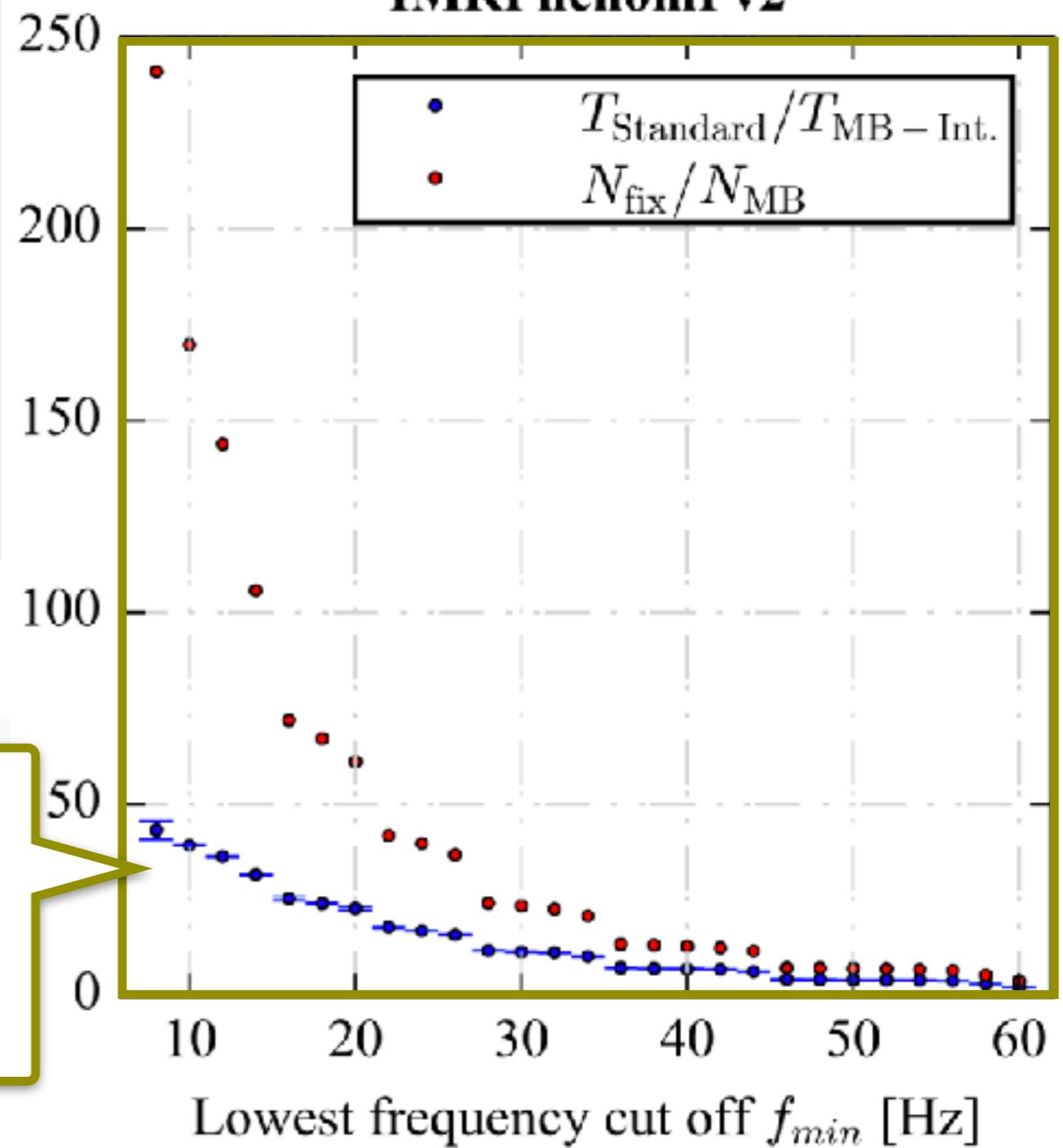
TaylorF2

Gain in template generation



ONE OF THE SIMPLEST
WAVEFORM MODELS

IMRPhenomPv2



MORE SOPHISTICATED
WAVEFORM MODEL

RESULTS

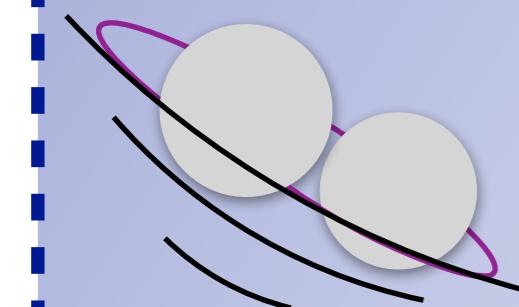
LALInference

J. Veitch Phys. Rev. D,
91:042003, 2015.

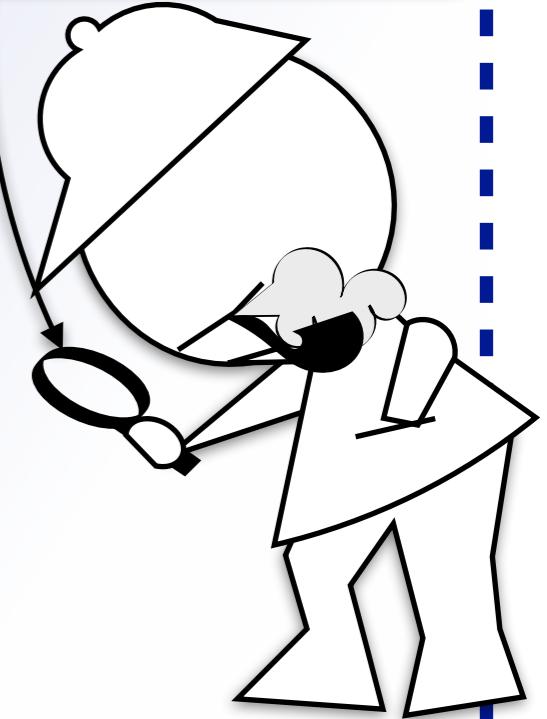
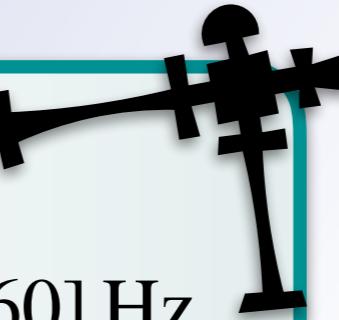
PE TESTS - SET UP

INJECTION

- Stationary gaussian noise
- $D_L \sim 200 \text{ Mpc}$
so that: $\text{SNR}_{f_0=40\text{Hz}} = 15$
- $m_1 = m_2 = 1.4 \text{ M}_\odot$



- $f_{max} = 2048 \text{ Hz}$
- $f_0 = [20, 30, 40, 60] \text{ Hz}$
- sensitivity
Advanced LIGO &
Advanced Virgo



PE RUNS

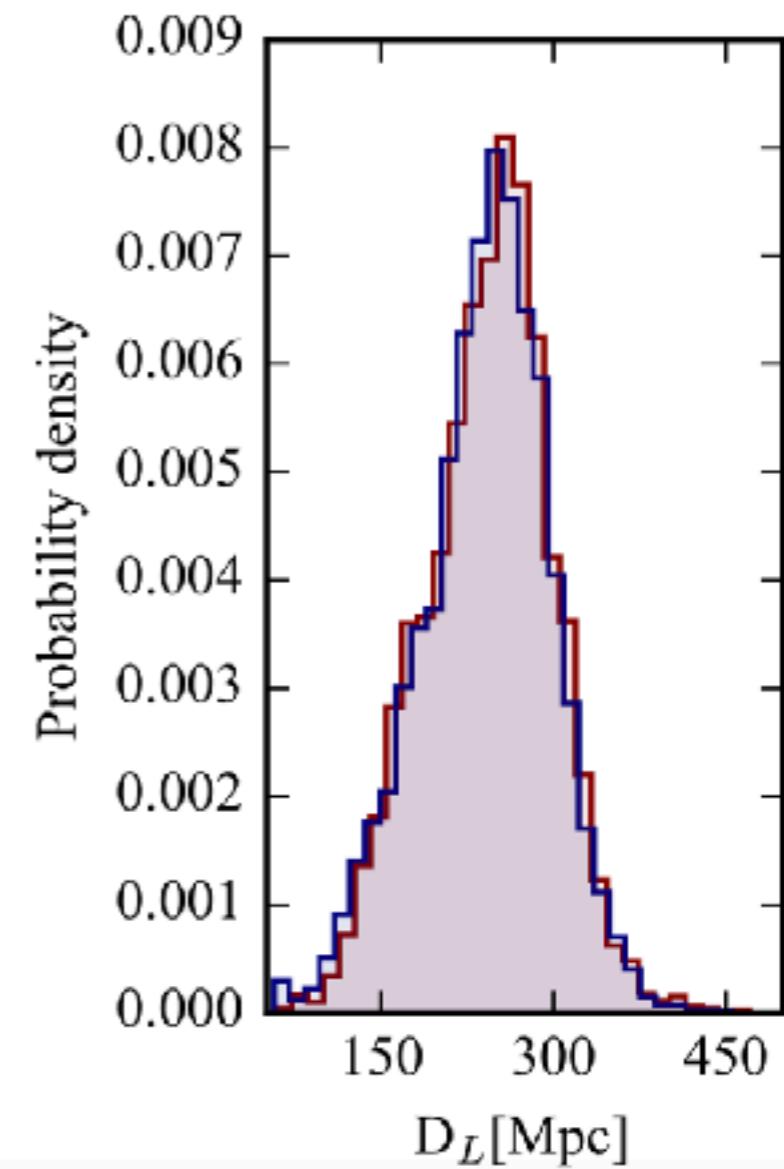
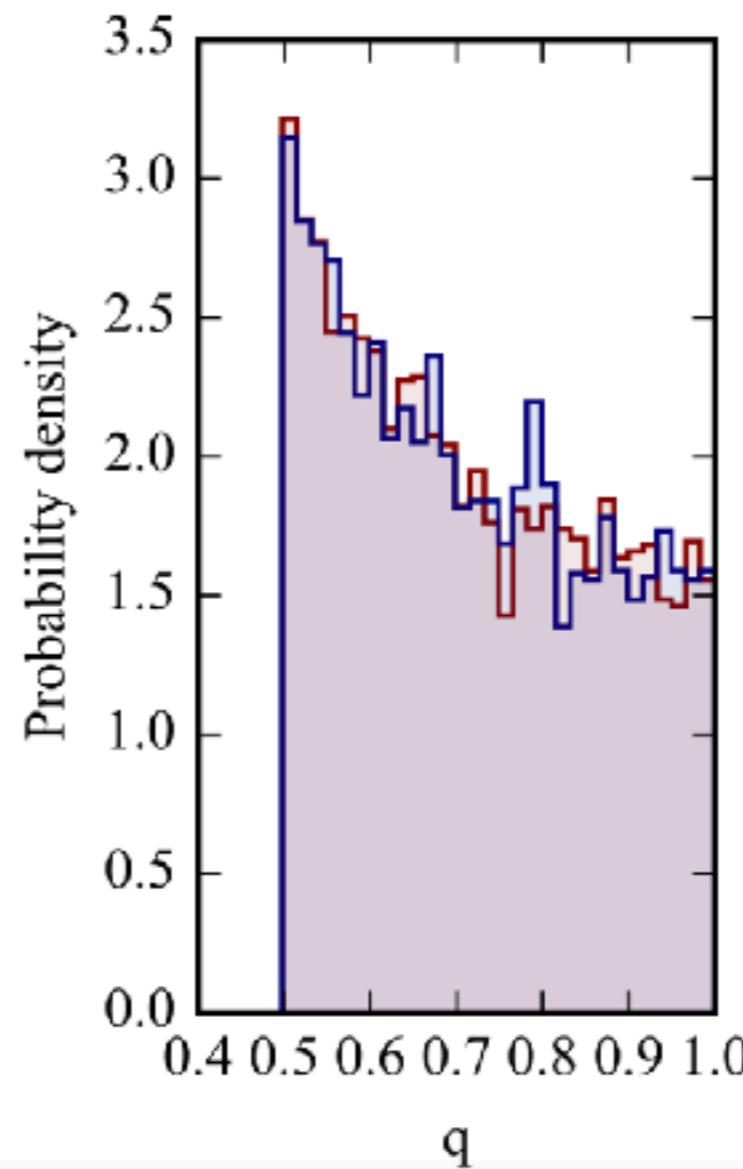
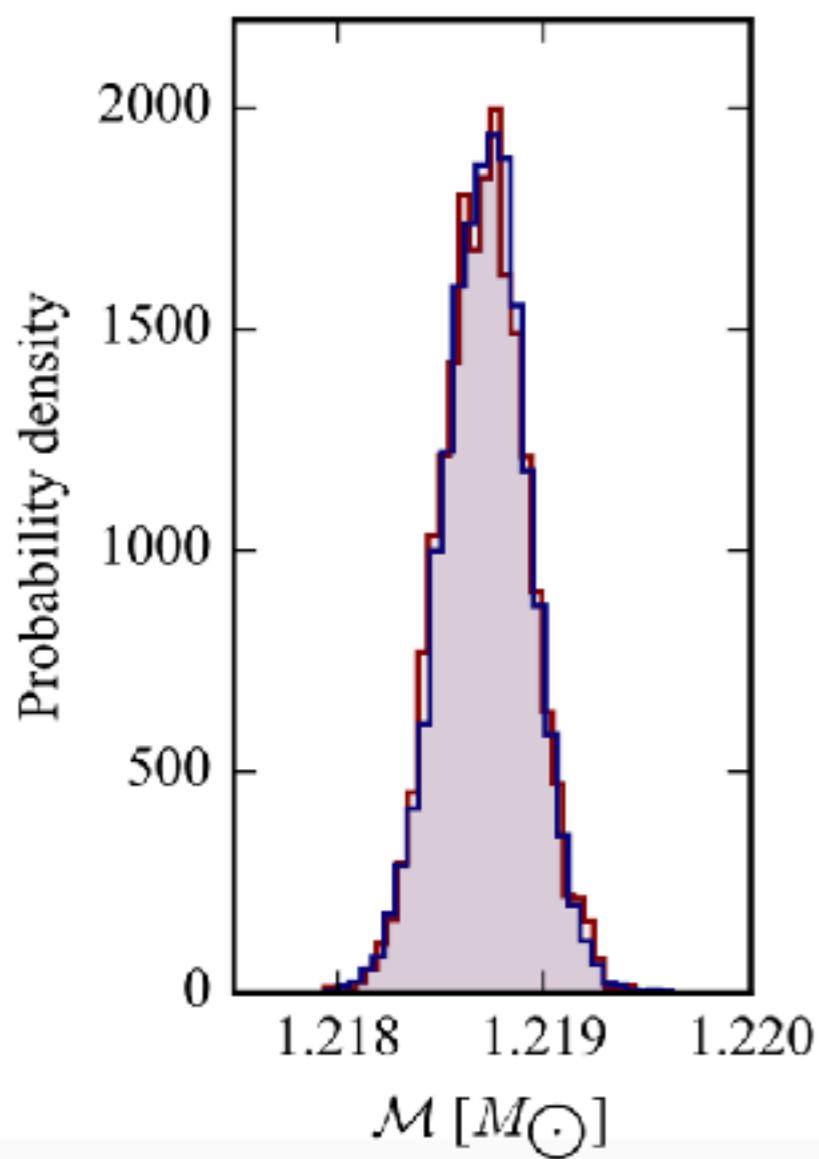
Only TaylorF2

- Companion masses prior:
uniform in range $1 - 3 \text{ M}_\odot$
- Distance prior:
uniform in volume up to 500 Mpc

RESULTS

PE CONSISTENCY TEST

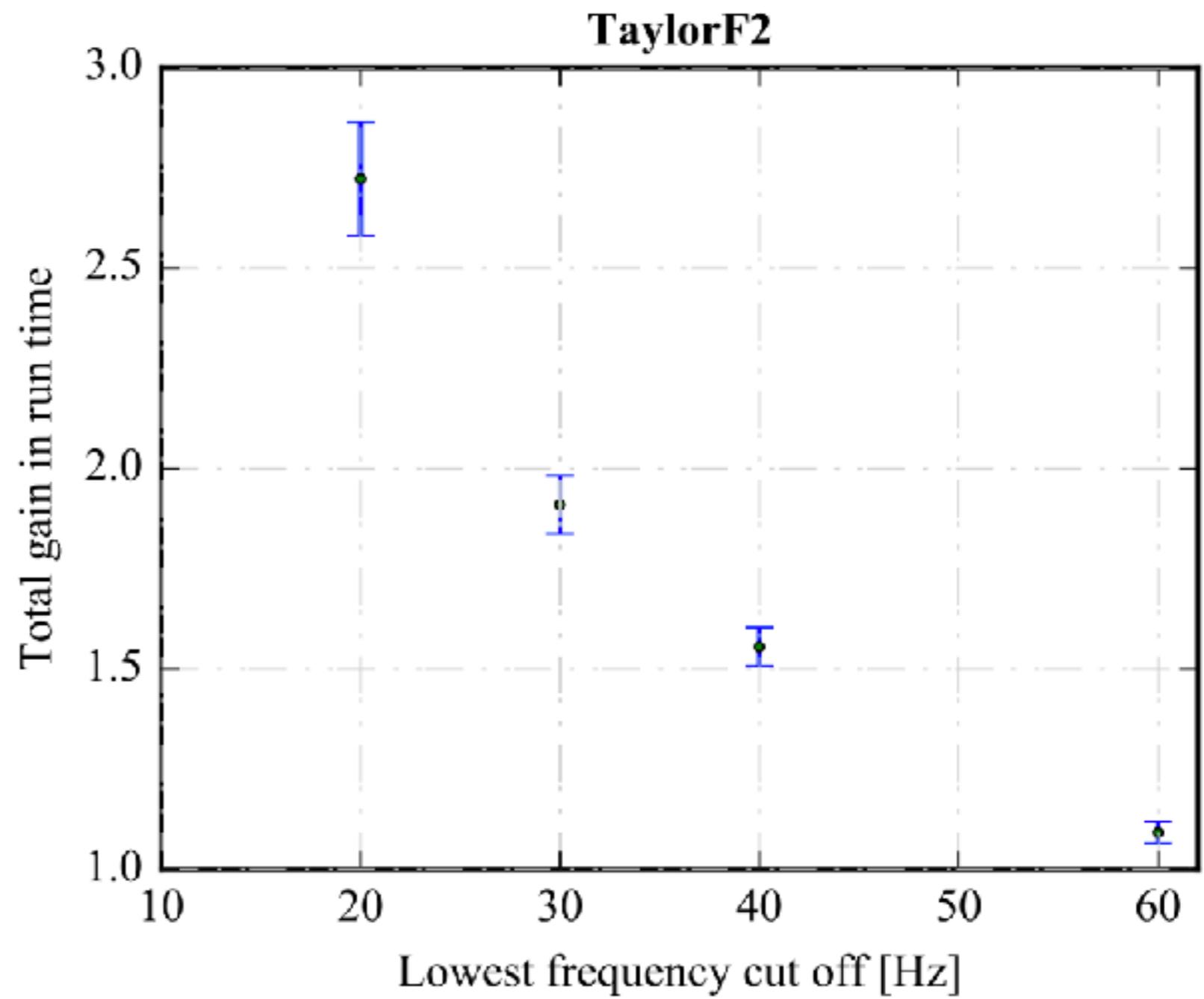
Standard MB-Interpolation



RESULTS

SPEED UP

PE



$f_{\min} [\text{Hz}]$	$\delta f_0 [\text{Hz}]$	$G_{\text{PE}}^{\text{TF2}}$	$G_{\text{template}}^{\text{TF2}}$	$N_{\text{fix}}/N_{\text{MB}}$	$N_{\text{fix}}/N_{\text{min}}$
60	1/16	1.09 ± 0.03	1.31 ± 0.01	3.76	55.4
40	1/64	1.56 ± 0.05	3.8 ± 0.1	12.82	83.8
30	1/128	1.91 ± 0.07	5.5 ± 0.1	23.40	112.2
20	1/300	2.72 ± 0.14	8.8 ± 0.2	61.01	169.1

CONCLUSION AND REMARKS

Physics of low mass systems
mergers

Current and future instruments

Important to speed up the
parameter estimation

Possible solution inspired by search
methods: **MULTI-BANDING**
(+ INTERPOLATION for accuracy)

Already good results with speed-up
up to ~ **50** for tested sophisticated
model at lowest tested f_0

One of the main bottlenecks
of the analysis:
Waveform computation
for sophisticated models

CONCLUSIONS AND REMARKS

MB - INT

No set up costs

Flexible: can be easily applied to waveforms with higher dimensionality parameter space



General validity of the method
(also outside the GW field)

Compared to ROQ:

- Higher speed up factors
- Requires high computational and memory set up costs
- **ROQ + MB-INT** could accelerate and save memory for initial set up

EXTRA SLIDES

GW SIGNALS: from CBCs

NEWTONIAN ORDER

STATIONARY PHASE APPROXIMATION

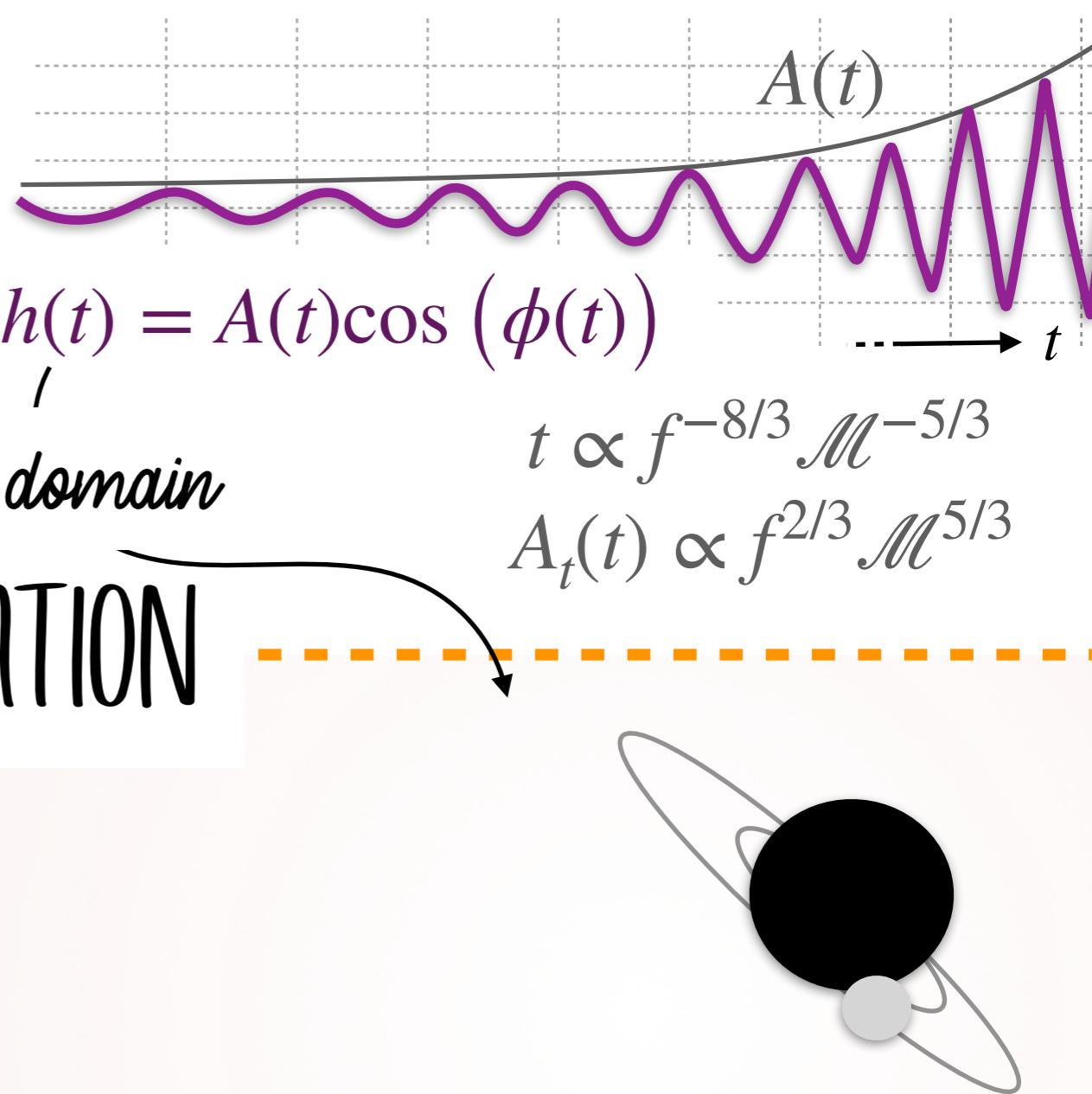
for $h(t) = A(t)\cos(\phi(t))$

if $\phi''(t) \ll \phi'(t)$

$\log A(t)' \ll \phi'(t) \sim f(t)$

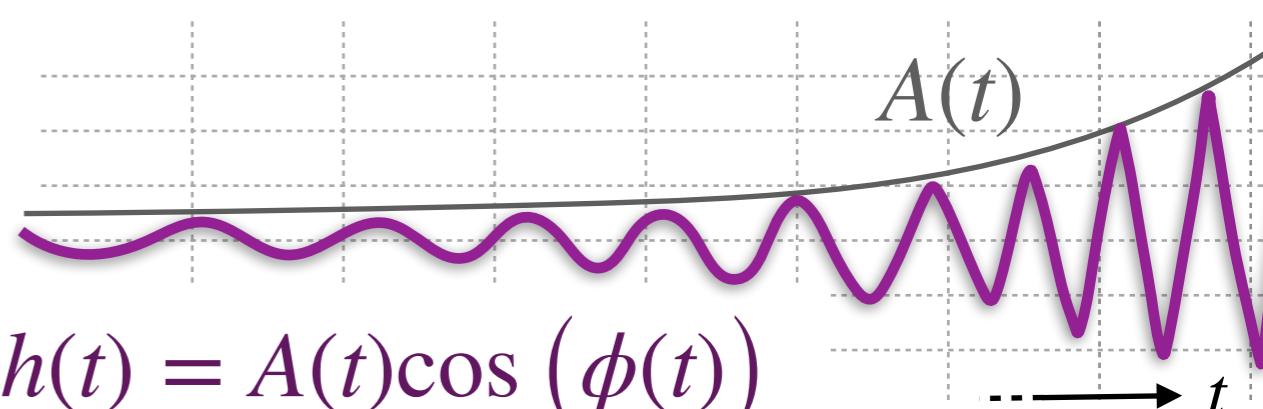
$$\text{Then } \tilde{h}(f) = \frac{1}{2} A_t(t) \sqrt{\frac{dt}{df}} \exp(i\psi(f))$$

$$\text{with } \psi(f) = 2\pi f t_c - \phi(t) - \pi/4$$



GW SIGNALS: from CBCs

NEWTONIAN ORDER



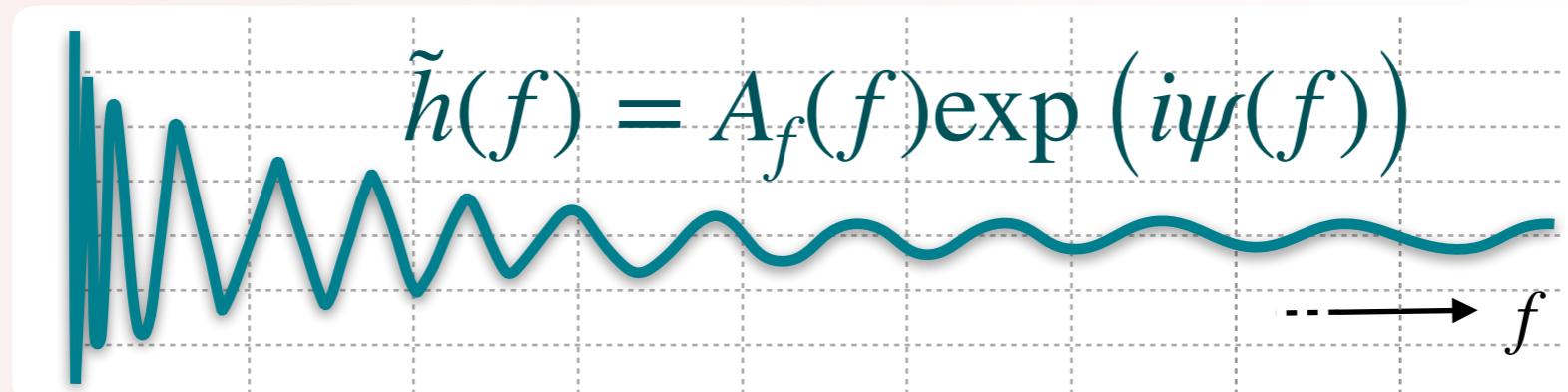
f domain

$$t \propto f^{-8/3} \mathcal{M}^{-5/3}$$

$$A_t(t) \propto f^{2/3} \mathcal{M}^{5/3}$$

STATIONARY PHASE APPROXIMATION

for $h(t) = A(t)\cos(\phi(t))$



Then $\tilde{h}(f) = \frac{1}{2} A_t(t) \sqrt{\frac{dt}{df}} \exp(i\psi(f))$ $\phi(t_c) - \phi(t) \propto \mathcal{M}^{-5/3} f^{-5/3}$

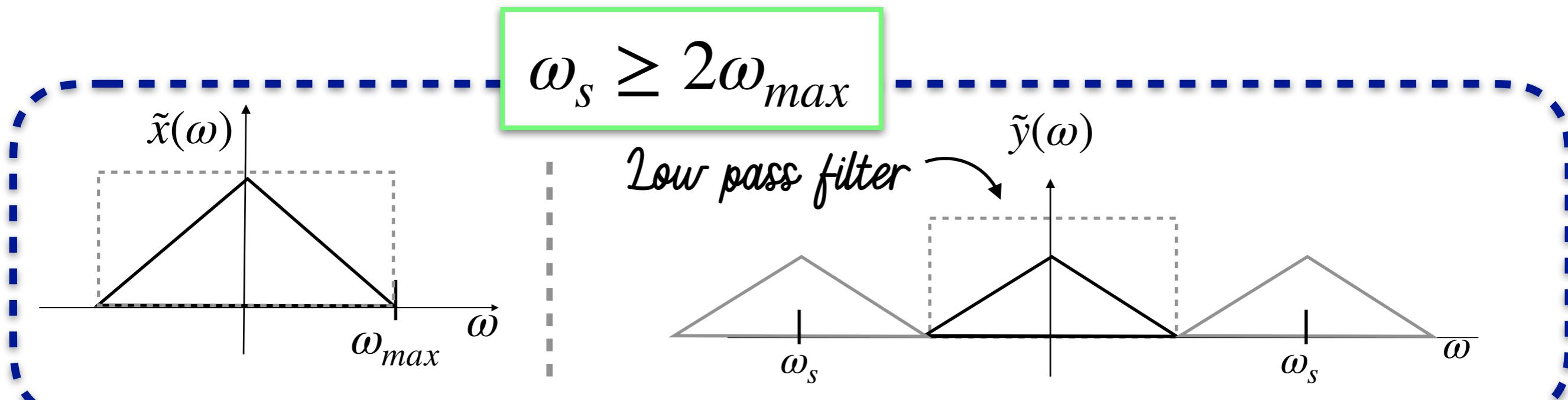
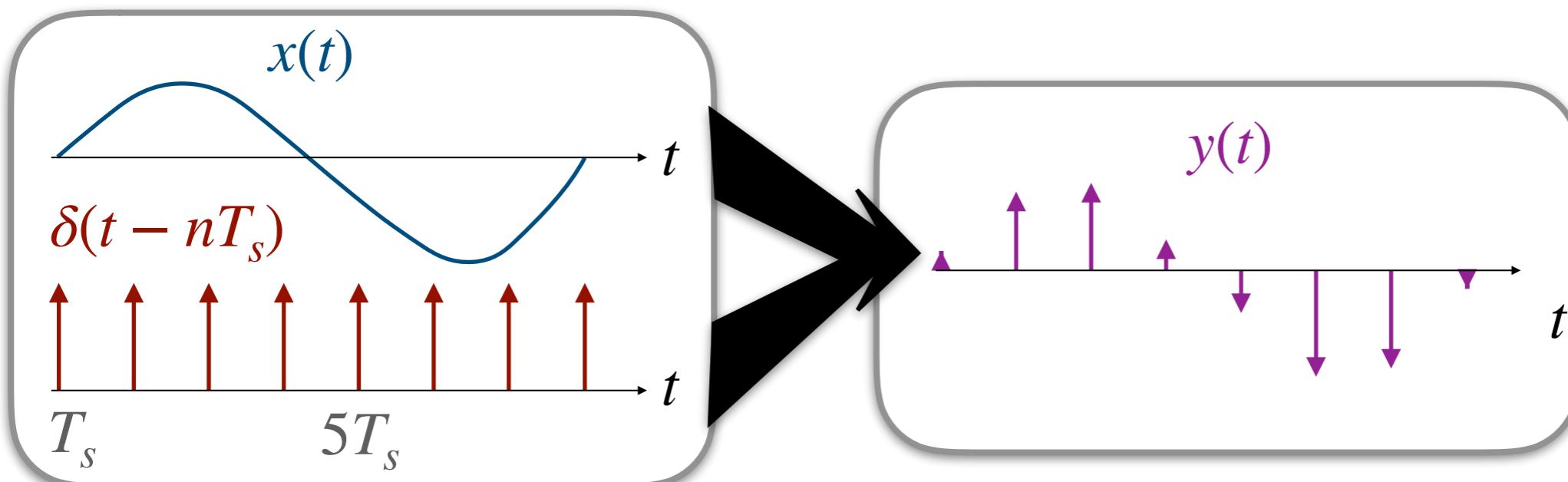
$A_f(f) \propto \mathcal{M}^{5/6} f^{-7/6}$ with $\psi(f) = 2\pi f t_c - \phi(t) - \pi/4$

NYQUIST THEOREM

time domain

$$\omega_s = \frac{2\pi}{T_s}$$

~ : Fourier
Transform (FT)

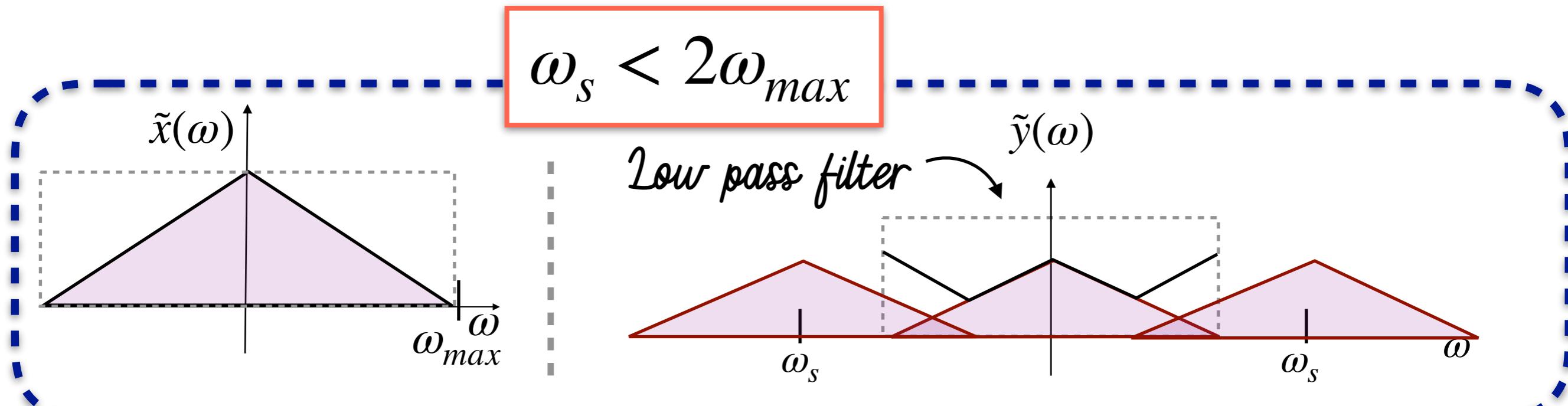
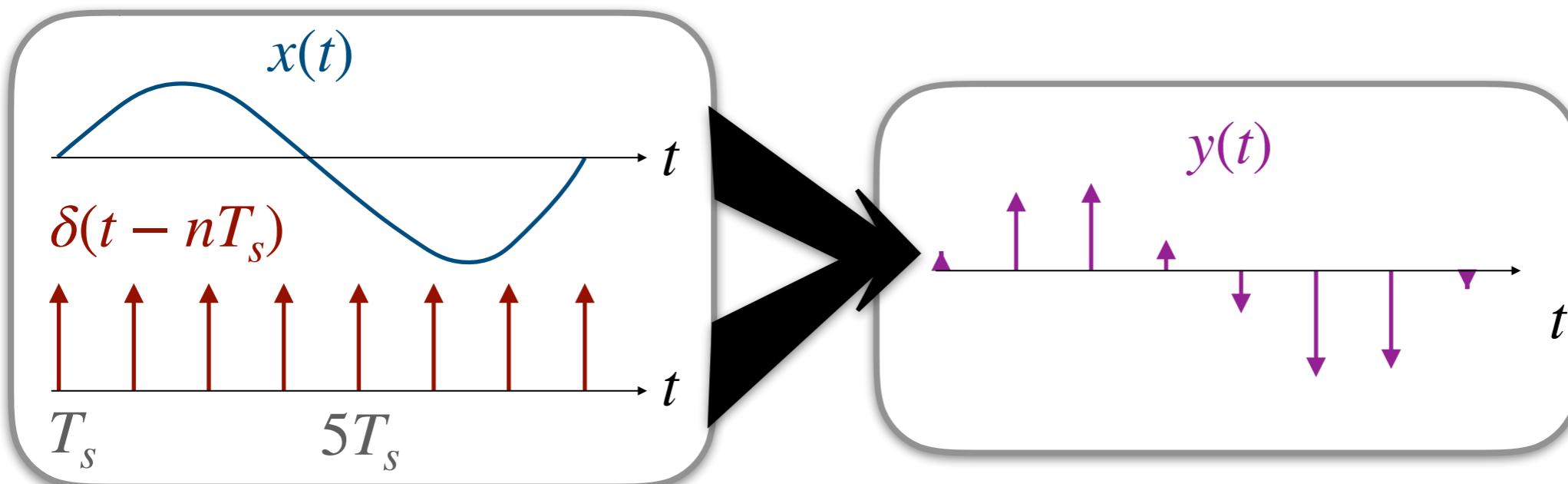


NYQUIST THEOREM

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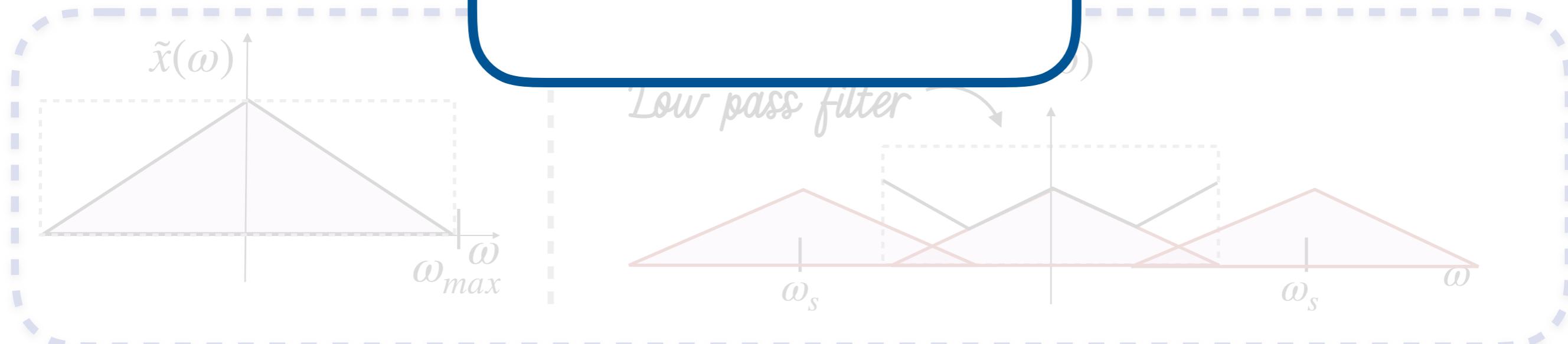


NYQUIST THEOREM

time domain

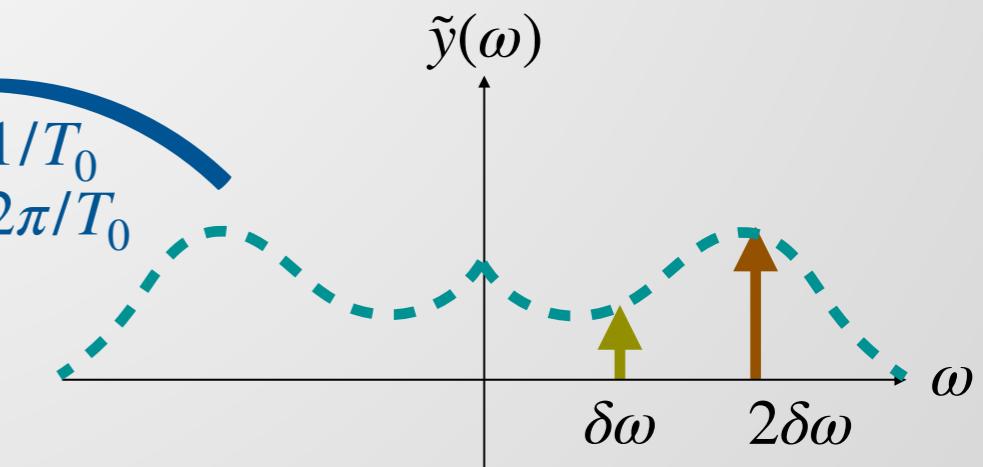
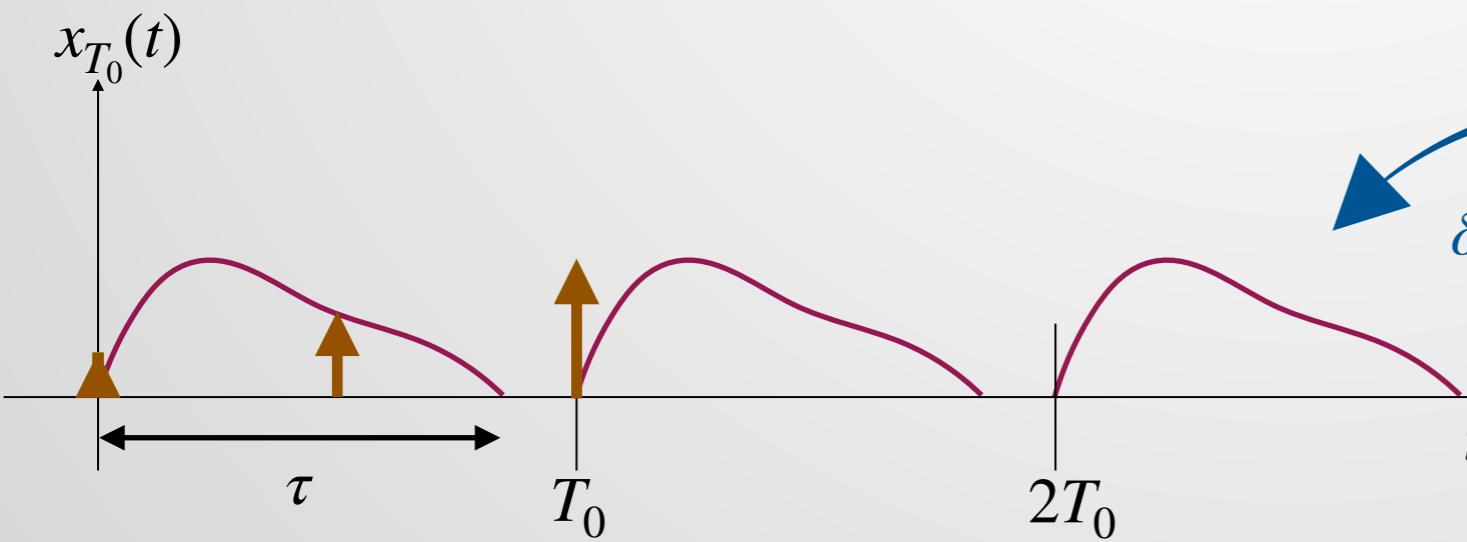
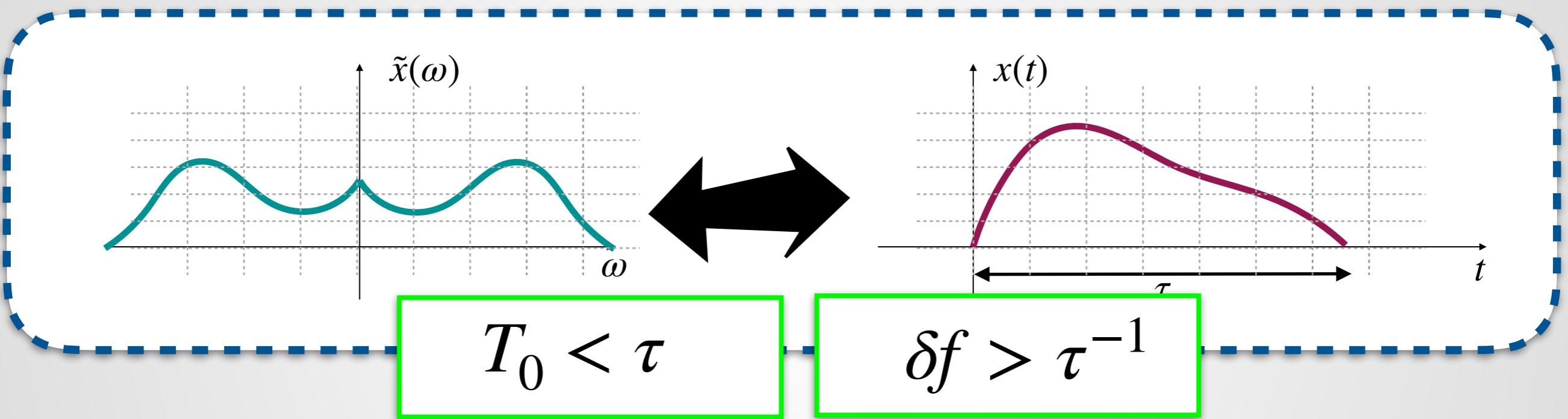
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~ : Fourier
Transform (FT)



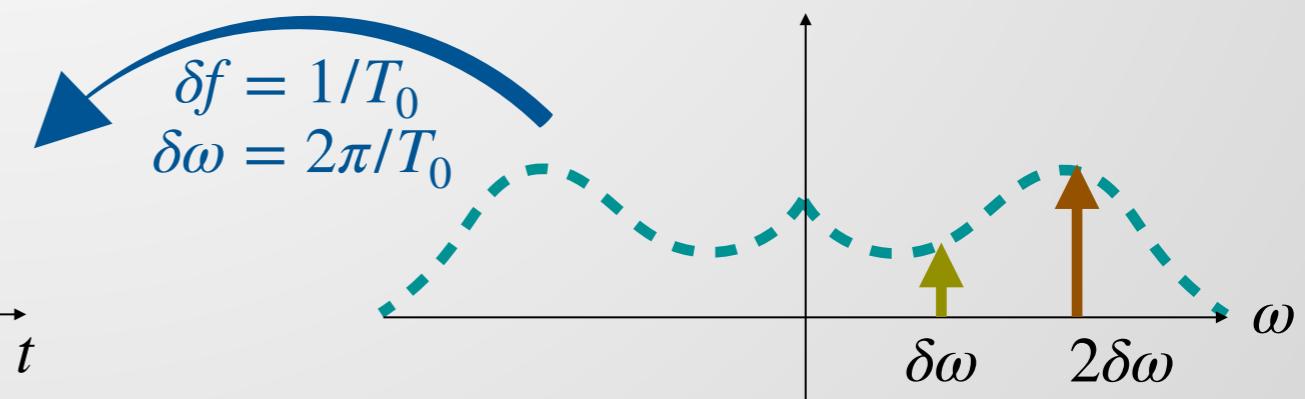
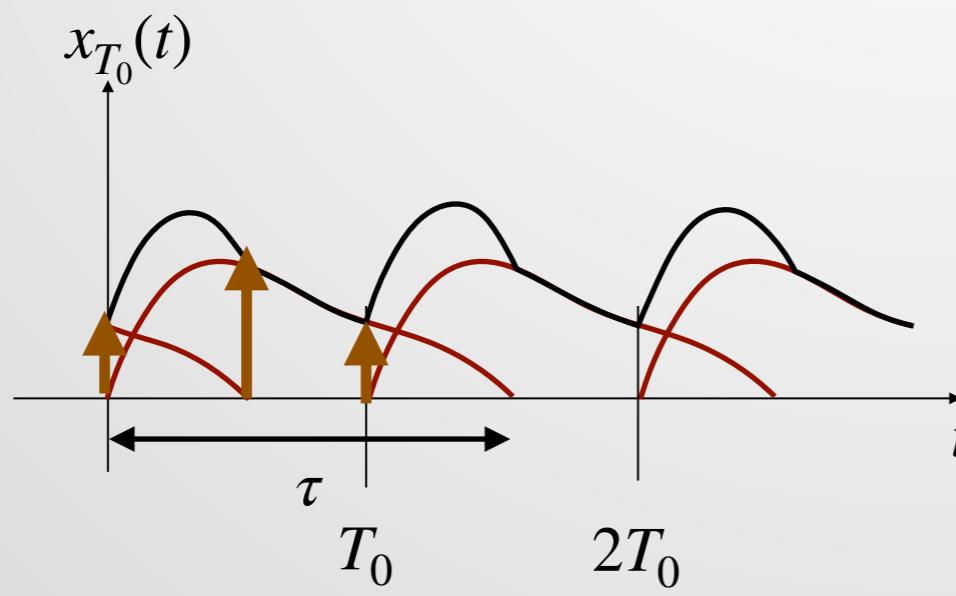
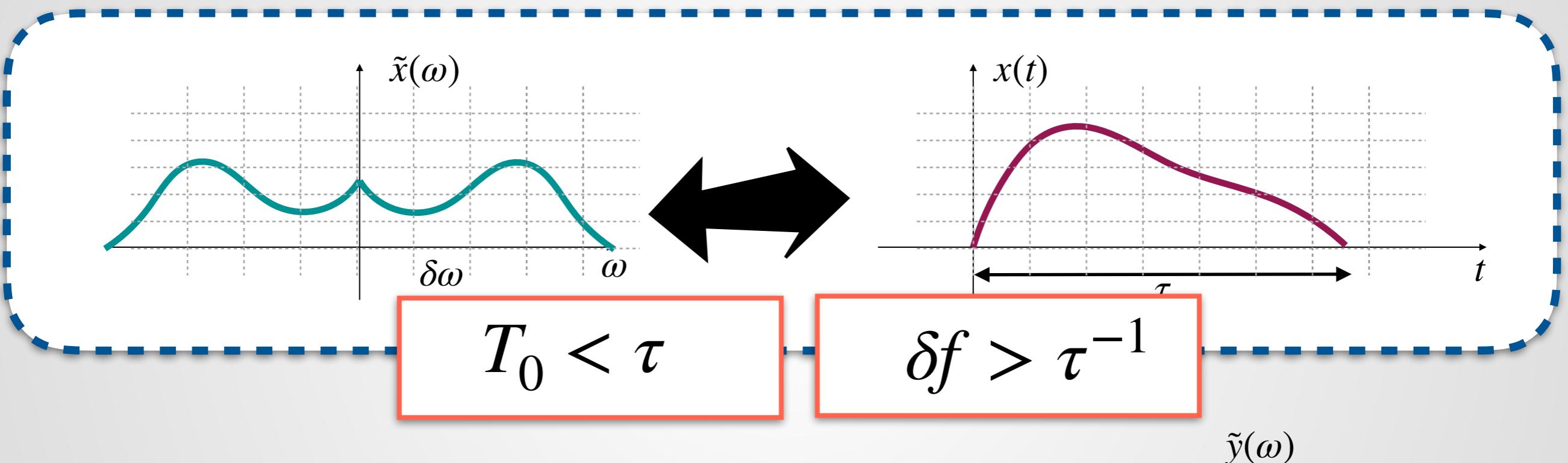
NYQUIST THEOREM

frequency domain



NYQUIST THEOREM

frequency domain



NYQUIST THEOREM

frequency domain

