

Lemma 1.34. Let $\{g_k\}_{k \in K}$ be a frame for $\mathcal{H}$ and $\{\widehat{g_k}\}_{k \in K}$ its canonical dual. Then, for each $m \in K$, we have

$$\sum_{k \neq m} |\langle g_m, \widehat{g_k} \rangle|^2 = \frac{1 - |\langle g_m, \widehat{g_m} \rangle| - |1 - \langle g_m, \widehat{g_m} \rangle|^2}{2}$$

Theorem 1.35. Let $\{g_k\}_{k \in K}$ be a frame for $\mathcal{H}$ and $\{\widehat{g_k}\}_{k \in K}$ its canonical dual. Then,

1. $\{g_k\}_{k \in K}$ is exact iff $\langle g_m, \widehat{g_m} \rangle = 1, \forall m \in K$
2. $\{g_k\}_{k \in K}$ is inexact iff there exists at least one $m \in K$ s.t. $\langle g_m, \widehat{g_m} \rangle \neq 1$.

Proof. $\langle g_m, \widehat{g_m} \rangle = 1, \forall m \in K, \Rightarrow \{g_k\}_{k \neq m}$ is incomplete for $\mathcal{H}$ and hence $\{g_k\}$ is exact.

Fix $m \in K$, $\sum_{k \neq m} |\langle g_m, \widehat{g_k} \rangle|^2 = 0$

$$\Rightarrow \langle g_m, \widehat{g_k} \rangle = 0, \quad \forall k, \text{ except } k=m$$

$$\begin{aligned} \langle g_m, S^{-1} g_k \rangle &= \langle S^{-1} g_m, g_k \rangle \\ &= \langle \widehat{g_m}, g_k \rangle = 0 \end{aligned}$$

$$\widehat{g_m} \neq 0 \quad . \quad \square$$

Corollary 1.36. Let $\{g_k\}_{k \in K}$ be a frame for $\mathcal{H}$. If $\{g_k\}_{k \in K}$ is exact, then $\{g_k\}_{k \in K}$ and its canonical dual $\{\widehat{g_k}\}_{k \in K}$ are biorthonormal, i.e.,

$$\langle g_m, \widehat{g_k} \rangle = \begin{cases} 1, & k=m \\ 0, & k \neq m \end{cases}.$$

Conversely, if $\{g_k\}_{k \in K}$ and $\{\widehat{g_k}\}_{k \in K}$ are biorthonormal, then $\{g_k\}_{k \in K}$ is exact.

Proof. $\{g_k\}_{k \in K}$ is exact $\xRightarrow{\text{Thm. 1.35}} \langle g_m, \widehat{g_m} \rangle = 1, \forall m \in K$
 $\xRightarrow{\text{Lem. 1.34}} \langle g_m, \widehat{g_k} \rangle = 0, \forall k \neq m$

biorthonormality $\Rightarrow$ exact

$$\langle g_m, g_m \rangle = 1, \forall m \in K \quad \Rightarrow \quad \{g_k\}_{k \in K} \text{ is exact} \quad \text{Thm. 1.35}$$

Thm. 1.37. If $\{g_k\}$ is an exact frame for $\mathcal{H}$ and $x = \sum_k c_k g_k$ with $x \in \mathcal{H}$, then the c_k are unique and given by

$$c_k = \langle x, \widehat{g_k} \rangle$$

where $\{\widehat{g_k}\}_{k \in K}$ is the canonical dual of $\{g_k\}_{k \in K}$.

Proof.

$$x = \sum_k \langle x, \widehat{g_k} \rangle g_k$$

$$x = \sum_k c_k g_k$$

$$\langle x, g_m \rangle = \left\langle \sum_k c_k g_k, g_m \right\rangle$$

$$= \sum_k c_k \underbrace{\langle g_k, g_m \rangle}_{\delta_{km}} = c_m$$

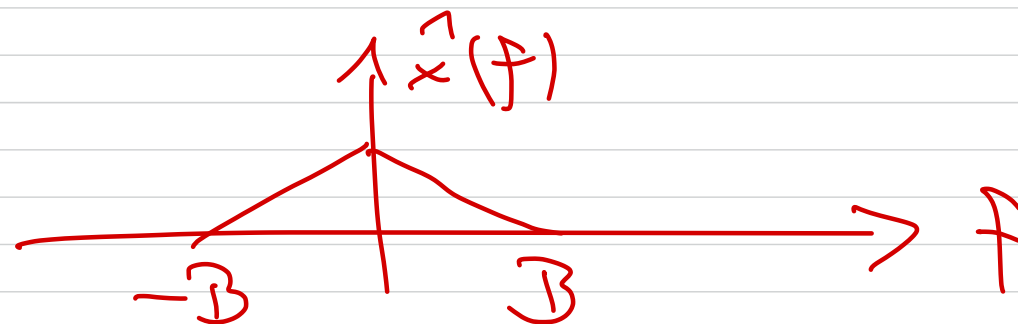
$$= \begin{cases} 1, & k=0 \\ 0, & k \neq 0 \end{cases}$$

1.4. Sampling Theorem

$$x(t) \longleftrightarrow \hat{x}(f) = \int x(t) e^{-i2\pi ft} dt = \langle x(\cdot), e^{i2\pi f\cdot} \rangle$$

$$x(t) = \int \underbrace{\hat{x}(f)}_{\langle x(\cdot), e^{i2\pi f\cdot} \rangle} e^{i2\pi ft} df = \int \langle x(\cdot), e^{i2\pi f\cdot} \rangle e^{i2\pi ft} df$$

$x(t)$ is B -bandlimited if $\hat{x}(f) = 0$ for $|f| \geq B$



$$\underbrace{\sum_k x(t + kT)}_{y(t)} = \frac{1}{T} \sum_k \hat{x}\left(\frac{k}{T}\right) e^{i2\pi t \frac{k}{T}}$$

Poisson summation
formula



$$y(t) = y(t + T) = \sum_k x(t + kT + T) = \sum_k x(t + (k+1)T)$$

$k = k+1$

$$C_e = \frac{1}{T} \int_0^T \sum_k x(t + kT) e^{-i\omega_e t \frac{T}{T}} dt = \sum_{k'} x(t + k'T) = y(t)$$

$$= \frac{1}{T} \sum_k \int_{-kT+T}^T x(t + kT) e^{-i\omega_e t \frac{T}{T}} dt =$$

$t' = t + kT$

$$= \frac{1}{T} \sum_k \int_{-kT}^{-kT+T} x(t') e^{-i\omega_e \frac{t' - kT}{T}} dt'$$

$$= \frac{1}{T} \sum_k \int_{-kT}^{-kT+T} x(t) e^{-i\omega_e t \frac{T}{T}} dt$$

$$= \frac{1}{T} \int_{-\infty}^{\infty} x(t) e^{-i 2\pi k \frac{t}{T}} dt = \frac{1}{T} X\left(\frac{k}{T}\right)$$

$$\hat{x}_d(f) = \sum_{k=-\infty}^{\infty} x(kT) e^{-i 2\pi k f}$$

$$(DTFT)$$

$$\text{P.S.F.} = \frac{1}{T} \sum_{k=-\infty}^{\infty} \hat{x}\left(\frac{k}{T}\right)$$

$$\frac{f}{T} = B \Rightarrow f = B T$$

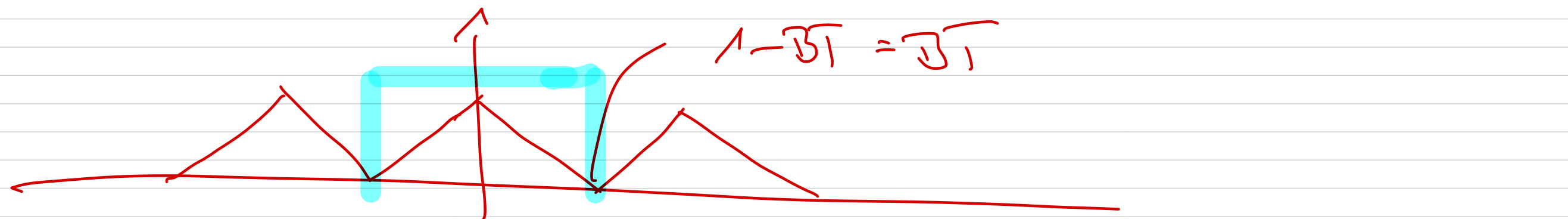
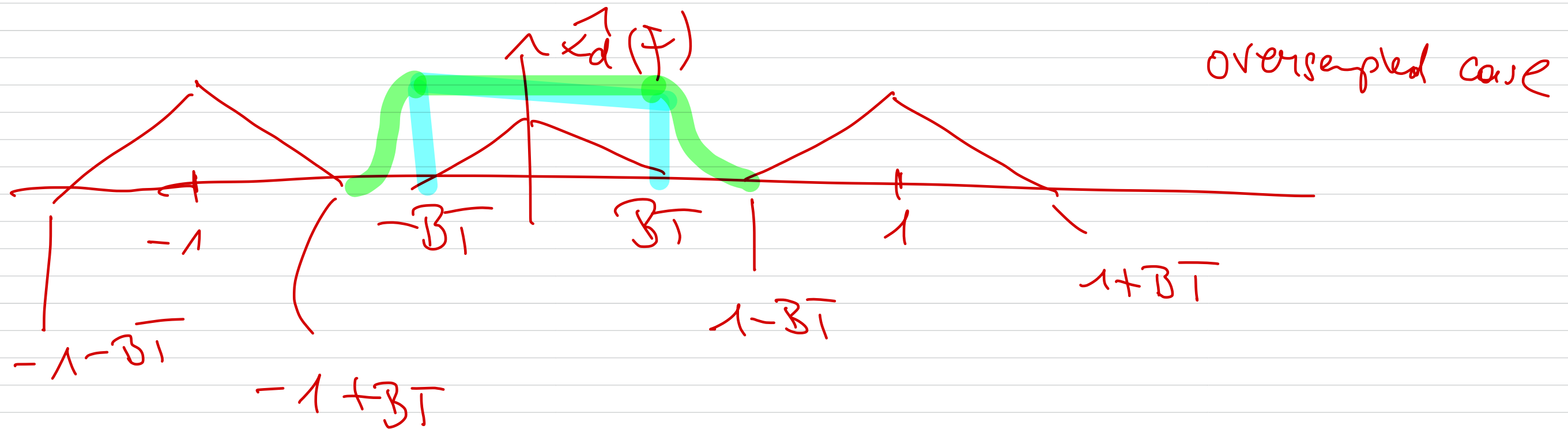
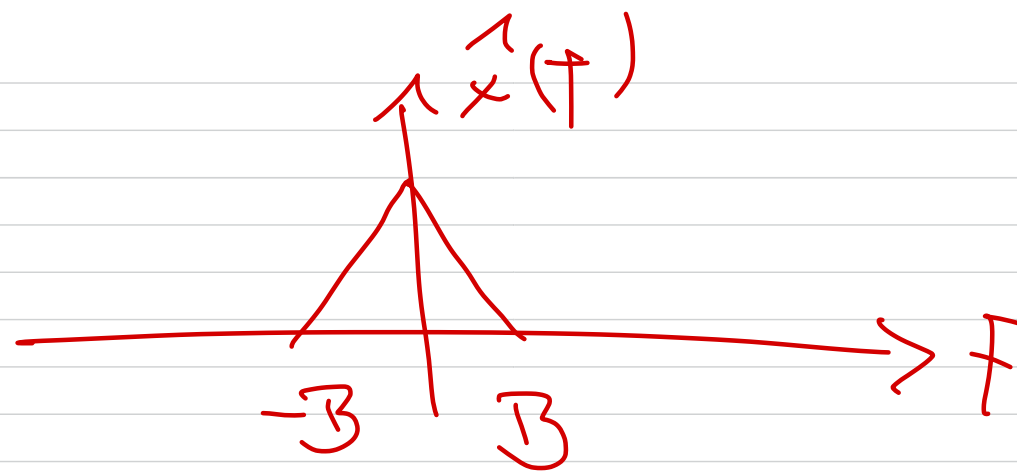
$$\text{P.S.F.} \quad \sum_k x(k) = \sum_k \hat{x}(k)$$

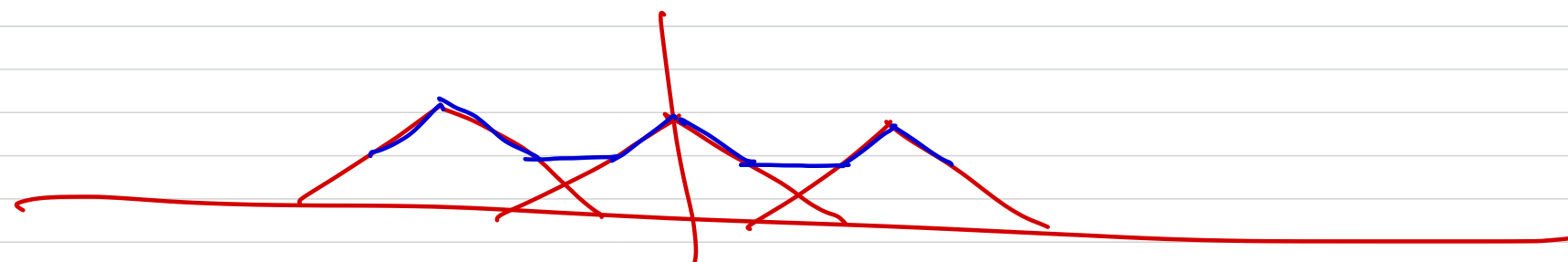
$$k=1: \quad \frac{f-1}{1} = \pm B$$

$$f = 1 \pm B$$

$$\uparrow$$

$$x(t \cdot T) e^{-i 2\pi t f}$$





undersampling

$$1 - \beta_T < \overline{\beta_T}$$

$$1 - \beta_T \geq \overline{\beta_T}$$

$$1 \geq 2\overline{\beta_T}$$

$$\frac{1}{f_s} \geq 2B$$

↑

$$f_s = \frac{1}{T} \quad \dots \text{ sampling rate}$$

$$\hat{x}_d(f) \mp \hat{h}_{LP}(f) = \hat{x}(f \mp) \quad | \quad f \rightarrow f \mp$$

$$\hat{x}(f) = \hat{x}_d(f \mp) \mp \hat{h}_{LP}(f \mp)$$

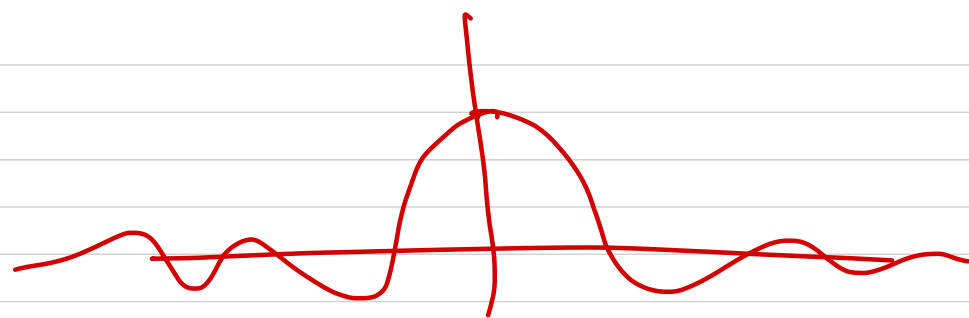
$$\hat{h}_{LP}(f) = \begin{cases} 1, & |f| \leq B \mp \\ 0, & \text{else} \end{cases}$$

$$\hat{x}(f) = \mp \hat{h}_{LP}(f \mp) \underbrace{\sum_{\tau} x(\tau) e^{-i2\pi f \tau}}_?$$

$$x(t) = \int_{-\infty}^{\infty} \hat{x}(f) e^{i2\pi f t} df$$

$$= 2B \mp \sum_{\tau=-\infty}^{\infty} x(\tau) \text{sinc}(2B(t - \tau))$$

$$\text{sinc}(\pi x) = \frac{\sin(\pi x)}{\pi x}$$



Thm. 1.38. Sampling theorem. Let $x \in L^2(\mathbb{R})$. Then, $x(t)$ is uniquely specified by its samples $x(kT)$, $k \in \mathbb{Z}$, if $\frac{1}{T} \geq 2B$. Specifically, we can reconstruct $x(t)$ according to

$$x(t) = 2B \sum_k x(kT) \operatorname{sinc}(2B(t - kT)).$$

1.4.1. Sampling theorem as a frame expansion

$$g_k(t) = 2B \operatorname{sinc}(2B(t - kT))$$

$$x(kT) = \int_{-B}^B \hat{x}(f) e^{i2\pi kTf} df = \langle \hat{x}, \hat{g}_k \rangle = \langle x, g_k \rangle$$

$$\hat{g}_k(f) = \begin{cases} e^{-i2\pi kTf} & , |f| \leq B \\ 0 & , \text{else} \end{cases}$$

$$x(t) = T \sum_k \langle x, g_k \rangle g_k(t)$$

$$\text{with } g_k(t) = 2B \sin(\pi B(t - kT))$$

$$\|x\|^2 = \langle x, x \rangle = \left\langle T \sum_k \langle x, g_k \rangle g_k, x \right\rangle$$

$$= T \sum_k |\langle x, g_k \rangle|^2$$

$$\frac{1}{T} \|x\|^2 = \sum_k |\langle x, g_k \rangle|^2 = \langle Sx, x \rangle$$

$$\langle Sx, x \rangle = \frac{1}{T} \|x\|^2 \Rightarrow \text{tight with } A = \frac{1}{T}$$

$$T: x \mapsto \{ \langle x, g_k \rangle \}_{k \in \mathbb{Z}}$$

$$T^*: \{c_k\}_{k \in \mathbb{Z}} \mapsto \sum_k c_k g_k$$

$$\hat{g}_k = S^{-1} g_k = \overline{1} g_k$$

$$S = \frac{1}{\overline{1}} \overline{1}$$

$$\langle g_k, \hat{g}_k \rangle = \langle g_k, \overline{1} g_k \rangle = \overline{1} \|g_k\|^2 = \overline{1} \|\hat{g}_k\|^2 = 2\overline{1}$$

$$f_S = \frac{1}{\overline{1}} \overset{\text{critical s.}}{=} 2\overline{1} \Rightarrow 2\overline{1} = 1$$

$$\text{crit. samp. } \langle g_k, \hat{g}_k \rangle = 2\overline{1} = 1, \forall k \in \mathbb{Z} \Rightarrow \text{exact}$$

$$2\overline{1} = \frac{2\overline{1}}{\frac{1}{\overline{1}}} = \frac{2\overline{1}}{f_S}$$

$$g_k'(t) = \overline{1} g_k$$

$$x(t) = \overline{1} \sum_k \langle x, g_k \rangle g_k = \sum_k \langle x, g_k' \rangle g_k$$

$$\Rightarrow A = 1$$

$$\|g_{\mathbf{a}'}\|^2 = \mathbf{T} \|g_{\mathbf{a}}\|^2 = \mathbf{T} \|g_{\mathbf{a}}\|^2 = 2\mathbf{B}\mathbf{T} \stackrel{\text{c.s.}}{=} 1$$

$\Rightarrow$ ONB in the case of c.s.

$$\langle g_{\mathbf{z}}, g_{\mathbf{z}} \rangle = 2\mathbf{B}\mathbf{T} = \frac{2\mathbf{B}}{f_s} \stackrel{\text{u.s.}}{\neq} 1 \Rightarrow \{g_{\mathbf{z}}\}_{\mathbf{z} \in \mathbb{Z}} \text{ is inexact}$$

Chapter 2. Uncertainty relations and sparse signal recovery

frequency extent

$$\sigma_t + \sigma_f \geq \text{const.}$$

↑
time-duration

$$x(a+t) \longleftrightarrow \frac{1}{|a|} \hat{x}(f/a)$$

$$x(t) = \int \hat{x}(f) e^{i2\pi ft} df$$

$$\hat{x}(f) = \int x(t) e^{-i2\pi ft} dt$$

$$x(t) = \int \langle x(\cdot), e^{i2\pi f \cdot} \rangle e^{i2\pi ft} df$$

$$\begin{aligned} x(t) &= \int x(t') \delta(t-t') dt' \\ &= \langle x(\cdot), \delta(t-\cdot) \rangle \end{aligned}$$

$$x(t) =$$

$$x = \sum_i \langle x, e_i \rangle e_i$$

$$e_1 = \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, e_2 = \begin{pmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{pmatrix} \dots$$

$$x = \sum_i \langle x, f_i \rangle f_i$$

$$F = \frac{1}{\sqrt{m}} \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & \omega & \omega^2 & \dots \\ \vdots & \omega^2 & \dots & \\ 1 & & & \end{bmatrix}$$

$$\omega = e^{-i2\pi/m}$$

$\uparrow \quad \uparrow$
 $f_1 \quad f_2 \quad \dots$

$$F F^H = F^H F = I_m$$

Notation. U -- unitary

$$P_A(U) = U D_A U^H$$

$$D_A = \begin{pmatrix} 1 & & & \\ & 0 & & \\ & & \ddots & \\ & & & 1 & \\ & & & & \ddots \end{pmatrix}$$

$$A = \{1, 3, 7, \dots\}$$

$$P_A(U) = \sum_{i \in A} u_i u_i^H$$

$$W^{u_{\text{ref}}} = R(P_A(U))$$

$$x_A = D_A x$$

$$\|A\|_2 = \max_{x: \|x\|_2=1} \|Ax\|_2 \quad \text{op. 2-norm}$$