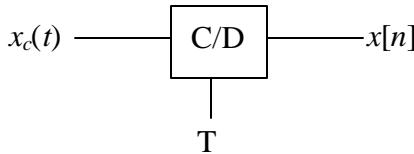


Sampling & Reconstruction of continuous-time signals

- $x[n] = x_c(nT_S) = x_R(nT_R); -\infty < n < \infty$
- $\hat{X}(\mathbf{w}) = \sum_{k=-\infty}^{\infty} \left(\frac{1}{T_S} \hat{X}_c \left(\frac{\mathbf{w}}{T_S} + k \frac{2\mathbf{p}}{T_S} \right) \right) \forall \mathbf{w}, T_S$
- $\hat{X}(\mathbf{w}) = \sum_{k=-\infty}^{\infty} \left(\frac{1}{T_R} \hat{X}_R \left(\frac{\mathbf{w}}{T_R} + k \frac{2\mathbf{p}}{T_R} \right) \right) \forall \mathbf{w}, T_R = \frac{1}{T_R} \hat{X}_R \left(\frac{\mathbf{w}}{T_R} \right) ; -\mathbf{p} \leq \mathbf{w} \leq \mathbf{p}; \text{ repeat}$
- $x_R(t) = \frac{1}{2\mathbf{p}} \int_{-\frac{\mathbf{p}}{T_R}}^{\frac{\mathbf{p}}{T_R}} T_R \hat{X}(\Omega T_R) e^{j\Omega t} d\Omega ; \forall t = \frac{1}{2\mathbf{p}} \int_{-\mathbf{p}}^{\mathbf{p}} \hat{X}(\mathbf{m}) e^{j\frac{\mathbf{m}}{T_R}t} d\mathbf{m}$
 $= \sum_{n=-\infty}^{\infty} x[n] \frac{\sin \frac{\mathbf{p}}{T}(t - nT)}{\frac{\mathbf{p}}{T}(t - nT)} ; \forall t$
- $\hat{X}_R(\Omega) = T \hat{X}(\mathbf{w} = \Omega T) p_{\frac{\mathbf{p}}{T}}(\Omega) = T \left(\hat{X}(\mathbf{w}) p_p(\mathbf{w}) \right) \Big|_{\mathbf{w}=\Omega T}$
- If $T_R = T_S = T$, $\Omega_S = \frac{2\mathbf{p}}{T_S} > 2\Omega_m$ or $T_S < \frac{\mathbf{p}}{\Omega_m}$
 - $\hat{X}(\mathbf{w}) = \frac{1}{T} \hat{X}_c \left(\frac{\mathbf{w}}{T} \right) ; -\mathbf{p} \leq \mathbf{w} \leq \mathbf{p}; \text{ repeat}$
 - $\hat{X}_c(\Omega) = \hat{X}_R(\Omega) = T \hat{X}(\mathbf{w} = \Omega T) p_{\frac{\mathbf{p}}{T}}(\Omega) = T \left(\hat{X}(\mathbf{w}) p_p(\mathbf{w}) \right) \Big|_{\mathbf{w}=\Omega T}$
 - $x_c(t) = x_R(t)$

- $x[n] = x_c(nT) ; -\infty < n < \infty$

- $x[n]$: sampling series representation for $x_c(t)$



- **Deconstruction equation:** $\hat{X}(\mathbf{w}) = \sum_{k=-\infty}^{\infty} \left(\frac{1}{T} \hat{X}_c \left(\frac{\mathbf{w}}{T} + k \frac{2\mathbf{p}}{T} \right) \right) \forall \mathbf{w}, T$ (D)

- \Rightarrow sum of scaled, shifted replicas of $\hat{X}_c(\Omega)$

- $\frac{1}{T} \hat{X}_c \left(\frac{\mathbf{w}}{T} \right) \Rightarrow \Omega = \frac{\mathbf{w}}{T} \Rightarrow$ what happens at $\Omega = \Omega_0$, happens at $\mathbf{w} = \Omega_0 T$
- Space between centers of replicas $\Rightarrow \Delta \Omega = \frac{2\mathbf{p}}{T} \Rightarrow \Delta \mathbf{w} = \frac{2\mathbf{p}}{T} T = 2\mathbf{p}$
- In general, replicas “collide” in \mathbf{w} -space

Proof $x_c(t) = \frac{1}{2\mathbf{p}} \int_{-\infty}^{\infty} \hat{X}(\Omega) e^{j\Omega t} d\Omega$

Sector the integration:

$$x_c(t) = \frac{1}{2\mathbf{p}} \sum_{k=-\infty}^{\infty} \left(\int_{\frac{k\mathbf{p}}{T} - \frac{\mathbf{p}}{T}}^{\frac{k\mathbf{p}}{T} + \frac{\mathbf{p}}{T}} \hat{X}_c(\Omega) e^{j\Omega t} d\Omega \right)$$

Then, let $\mathbf{m} = \Omega - k \frac{2\mathbf{p}}{T} \Rightarrow d\mathbf{m} = d\Omega$

$$x_c(t) = \frac{1}{2\mathbf{p}} \sum_{k=-\infty}^{\infty} \left(\int_{-\frac{\mathbf{p}}{T}}^{\frac{\mathbf{p}}{T}} \hat{X}_c \left(\mathbf{m} + k \frac{2\mathbf{p}}{T} \right) e^{j(\mathbf{m} + k \frac{2\mathbf{p}}{T})t} d\mathbf{m} \right)$$

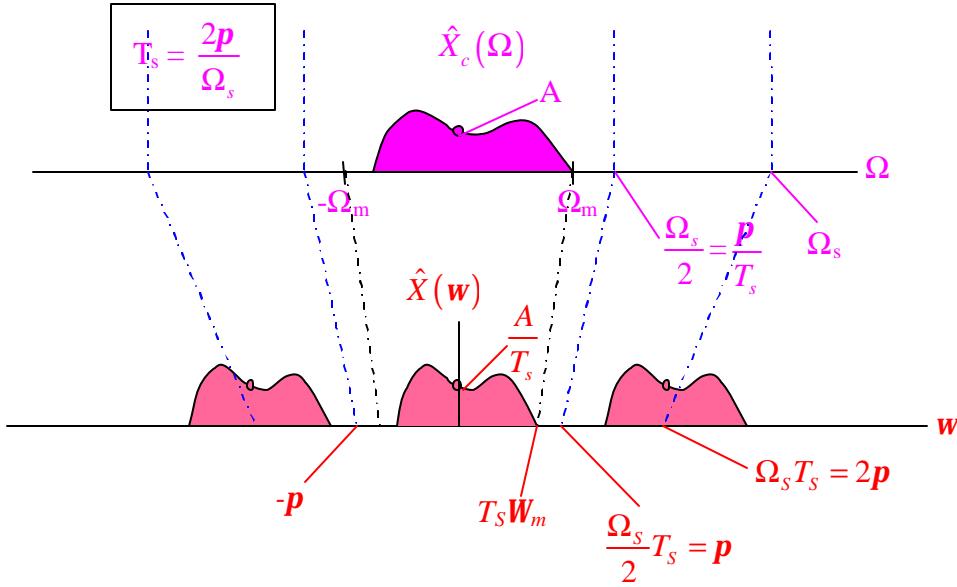
Let $\mathbf{w} = \mathbf{m}T \Rightarrow d\mathbf{w} = T d\mathbf{m}$

$$x_c(t) = \frac{1}{2\mathbf{p}} \sum_{k=-\infty}^{\infty} \left(\int_{-\mathbf{p}}^{\mathbf{p}} \frac{1}{T} \hat{X}_c \left(\frac{\mathbf{w}}{T} + k \frac{2\mathbf{p}}{T} \right) e^{j\left(\frac{\mathbf{w}}{T} + k \frac{2\mathbf{p}}{T}\right)t} d\mathbf{w} \right)$$

$$x_c(nT) = x[n] = \frac{1}{2\mathbf{p}} \sum_{k=-\infty}^{\infty} \left(\int_{-\mathbf{p}}^{\mathbf{p}} \frac{1}{T} \hat{X}_c \left(\frac{\mathbf{w}}{T} + k \frac{2\mathbf{p}}{T} \right) e^{j\left(\frac{\mathbf{w}}{T} + k \frac{2\mathbf{p}}{T}\right)nT} d\mathbf{w} \right)$$

$$= \frac{1}{2\mathbf{p}} \sum_{k=-\infty}^{\infty} \left(\int_{-\mathbf{p}}^{\mathbf{p}} \frac{1}{T} \hat{X}_c \left(\frac{\mathbf{w}}{T} + k \frac{2\mathbf{p}}{T} \right) e^{jn\mathbf{w}} e^{\cancel{jkn\frac{2\mathbf{p}}{T}}} d\mathbf{w} \right)$$

$$= \frac{1}{2\mathbf{p}} \underbrace{\int_{-\mathbf{p}}^{\mathbf{p}} \left\{ \sum_{k=-\infty}^{\infty} \left(\frac{1}{T} \hat{X}_c \left(\frac{\mathbf{w}}{T} + k \frac{2\mathbf{p}}{T} \right) \right) \right\} e^{jn\mathbf{w}} d\mathbf{w}}_{\hat{X}(\mathbf{w})}$$



Shannon-Nyquist Sampling Theorem

- From picture, for no aliasing \Rightarrow need $T_s W_m < p$
- If $x(t)$ is W_m -bandlimited,
can recover $x(t)$ exactly from the discrete sequence of samples provided that

$$\Omega_s = \frac{2p}{T_s} > 2\Omega_m \text{ or } T_s < \frac{p}{\Omega_m} = \text{Nyquist interval for } x_c(t)$$

<ul style="list-style-type: none"> Ω_m : bandwidth of $x_c(t)$
<ul style="list-style-type: none"> Given $x_c(t)$ with <ul style="list-style-type: none"> $\hat{X}_c\left(\left \Omega\right \geq \frac{p}{T}\right) = 0$ $T < \frac{p}{\Omega_m}$; Ω_m : bandwidth of $x_c(t)$ <p>$x_c(t)$ is determined completely by $x[n] = x_c(nT)$, $\forall n$</p>
<ul style="list-style-type: none"> $\hat{X}(w) = \frac{1}{T} \hat{X}_c\left(\frac{w}{T}\right)$; $-p \leq w \leq p$ $\hat{X}_c(\Omega) = T \hat{X}(\Omega T) \quad ; \quad -\frac{p}{T} \leq \Omega \leq \frac{p}{T}$

\Rightarrow no overlap

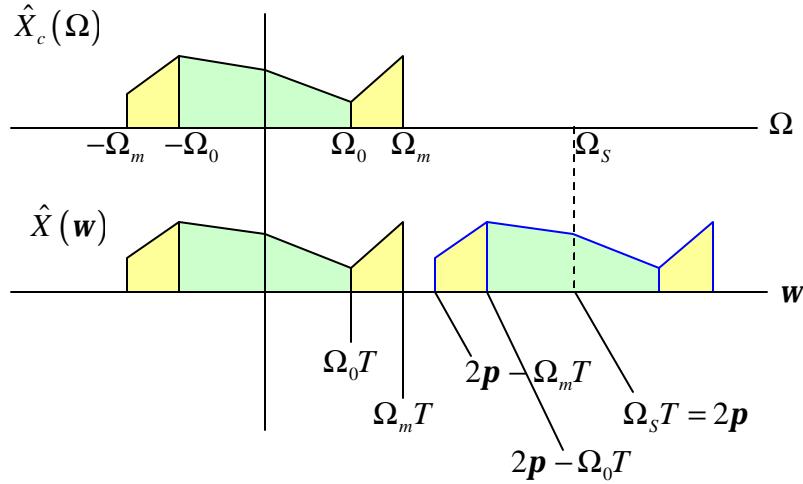
$$\begin{aligned}
\bullet \quad x_c(t) &= \frac{1}{2p} \int_{-\infty}^{\infty} \hat{X}_c(\Omega) e^{j\Omega t} d\Omega = \frac{1}{2p} \int_{-\frac{p}{T}}^{\frac{p}{T}} T \hat{X}(\Omega T) e^{j\Omega t} d\Omega \\
&= \sum_{n=-\infty}^{\infty} x[n] \frac{\sin \frac{p}{T}(t - nT)}{\frac{p}{T}(t - nT)} ; \forall t
\end{aligned}$$

Proof

$$\begin{aligned}
x_c(t) &= \frac{1}{2p} \int_{-\infty}^{\infty} \hat{X}_c(\Omega) e^{j\Omega t} d\Omega = \frac{1}{2p} \int_{-\frac{p}{T}}^{\frac{p}{T}} T \hat{X}(\Omega T) e^{j\Omega t} d\Omega \\
&= \frac{1}{2p} \int_{-\frac{p}{T}}^{\frac{p}{T}} T \left(\sum_{n=-\infty}^{\infty} x[n] e^{-jn\Omega T} \right) e^{j\Omega t} d\Omega \\
&= \sum_{n=-\infty}^{\infty} \left\{ Tx[n] \cdot \left(\frac{1}{2p} \int_{-\frac{p}{T}}^{\frac{p}{T}} e^{j\Omega(t-nT)} d\Omega \right) \right\} = \sum_{n=-\infty}^{\infty} x[n] \frac{\sin \frac{p}{T}(t - nT)}{\frac{p}{T}(t - nT)} ; \forall t
\end{aligned}$$

- $\bullet \quad z_{practical}(t) \xrightarrow{\hat{H}(\Omega) = p_{\Omega_m}(\Omega)} c_0 x(t) = \frac{2a}{T_0} x(t)$
- $\bullet \quad z_{ideal}(t) = \xrightarrow{\hat{H}(\Omega) = T_0 \cdot p_{\Omega_m}(\Omega)} x(t)$

- To find maximum T_s for signal that has high-frequency don't-care region
 \Rightarrow Interested in $\hat{X}_c(\Omega)$ when $|\Omega| \leq \Omega_0$, Don't care what happens when $\Omega_0 < |\Omega| \leq \Omega_m$
And $\hat{X}_c(\Omega) = 0$ when $|\Omega| \geq \Omega_m$.
 - From $\hat{X}(\mathbf{w}) = \sum_{k=-\infty}^{\infty} \left(\frac{1}{T_s} \hat{X}_c \left(\frac{\mathbf{w}}{T_s} + k \frac{2p}{T_s} \right) \right)$, we can see that the interesting region (in green) of $\hat{X}_c \left(\frac{\mathbf{w}}{T_s} \right)$ ends at $\Omega_0 T_s$, and $\hat{X}_c \left(\frac{\mathbf{w}}{T_s} - \frac{2p}{T_s} \right)$ start at $2p - \Omega_m T_s$.



Note that we can allow the don't-care region (in yellow) to overlap, so only need

$2p - \Omega_m T > \Omega_0 T$ so that the don't care region of $\hat{X}_c\left(\frac{w}{T} - \frac{2p}{T}\right)$ will not overlap

the interesting region of $\hat{X}_c\left(\frac{w}{T}\right) \Rightarrow 2p > \Omega_0 T + \Omega_m T \Rightarrow T < \frac{2p}{\Omega_0 + \Omega_m}$

also need $2p - \Omega_0 T > \Omega_m T$ so that the don't care region of $\hat{X}_c\left(\frac{w}{T}\right)$ will not

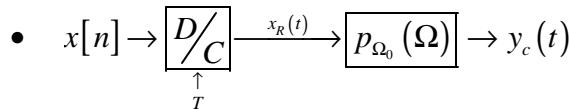
overlap the interesting region of $\hat{X}_c\left(\frac{w}{T} - \frac{2p}{T}\right) \Rightarrow T < \frac{2p}{\Omega_0 + \Omega_m}$.

In this case, since the regions of $\hat{X}_c(\Omega)$ are symmetric, both requirements yield

the same result: $T < \frac{2p}{\Omega_0 + \Omega_m}$.

Usually, we need $T < \frac{p}{\Omega_m}$, here we can have T larger: as large as $\frac{2p}{\Omega_0 + \Omega_m}$.

$$\Omega_m > \Omega_0 \Rightarrow \frac{2p}{\Omega_0 + \Omega_m} > \frac{p}{\Omega_m}$$



$y_c(t) = x_c(t)$ only in the frequency region of interest

$$\hat{X}_R(\Omega) = \hat{X}_c(\Omega) \text{ for } |\Omega| \leq \Omega_0, \text{ junk for } \Omega_0 < |\Omega| \leq \Omega_m, 0 \text{ for } |\Omega| > \Omega_m$$

$$\hat{Y}_c(\Omega) = \hat{X}_R(\Omega) p_{\Omega_0}(\Omega) = \hat{X}_c(\Omega) p_{\Omega_0}(\Omega) \Rightarrow \text{no junk}$$

Reconstruction of continuous-time signals

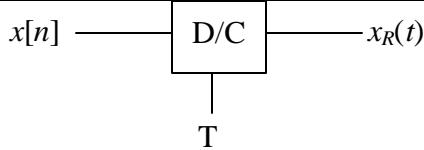
- $x_R(t) \Rightarrow$ Sinc-function interpolation of $x[n]$

$$= \frac{1}{2p} \int_{-\frac{p}{T_R}}^{\frac{p}{T_R}} T_R \hat{X}(\Omega T_R) e^{j\Omega t} d\Omega ; \forall t \text{ (R1)} \stackrel{\substack{\uparrow \\ m = \Omega T_R}}{=} \frac{1}{2p} \int_{-p}^p \hat{X}(m) e^{j\frac{m}{T_R} t} dm$$

$$= \sum_{n=-\infty}^{\infty} x[n] \frac{\sin \frac{p}{T} (t - nT)}{\frac{p}{T} (t - nT)} ; \forall t \text{ (R2)}$$

$= x_c(t)$ if $T <$ Nyquist interval for $x_c(t)$

$=$ the most parsimonious continuous time explanation for $x[n]$

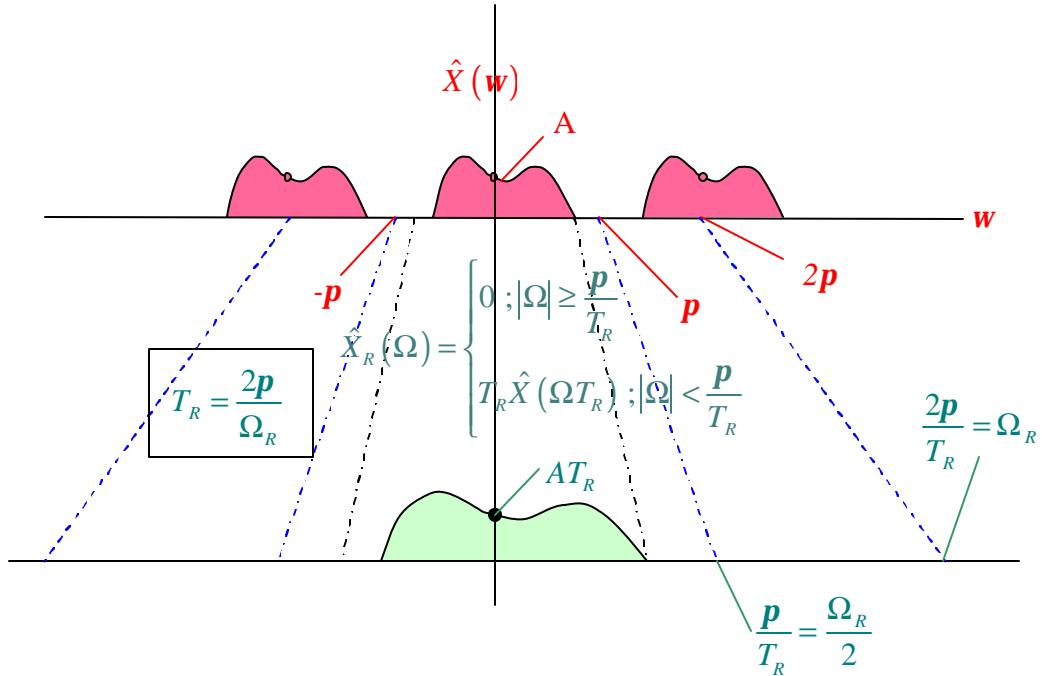


- $x_R(nT) = x[n]$

- $\hat{X}_R(\Omega) = T \hat{X}(w = \Omega T) p_{\frac{p}{T}}(\Omega) = \begin{cases} 0 & ; |\Omega| \geq \frac{p}{T} \\ T \hat{X}(\Omega T) & ; |\Omega| < \frac{p}{T} \end{cases}$

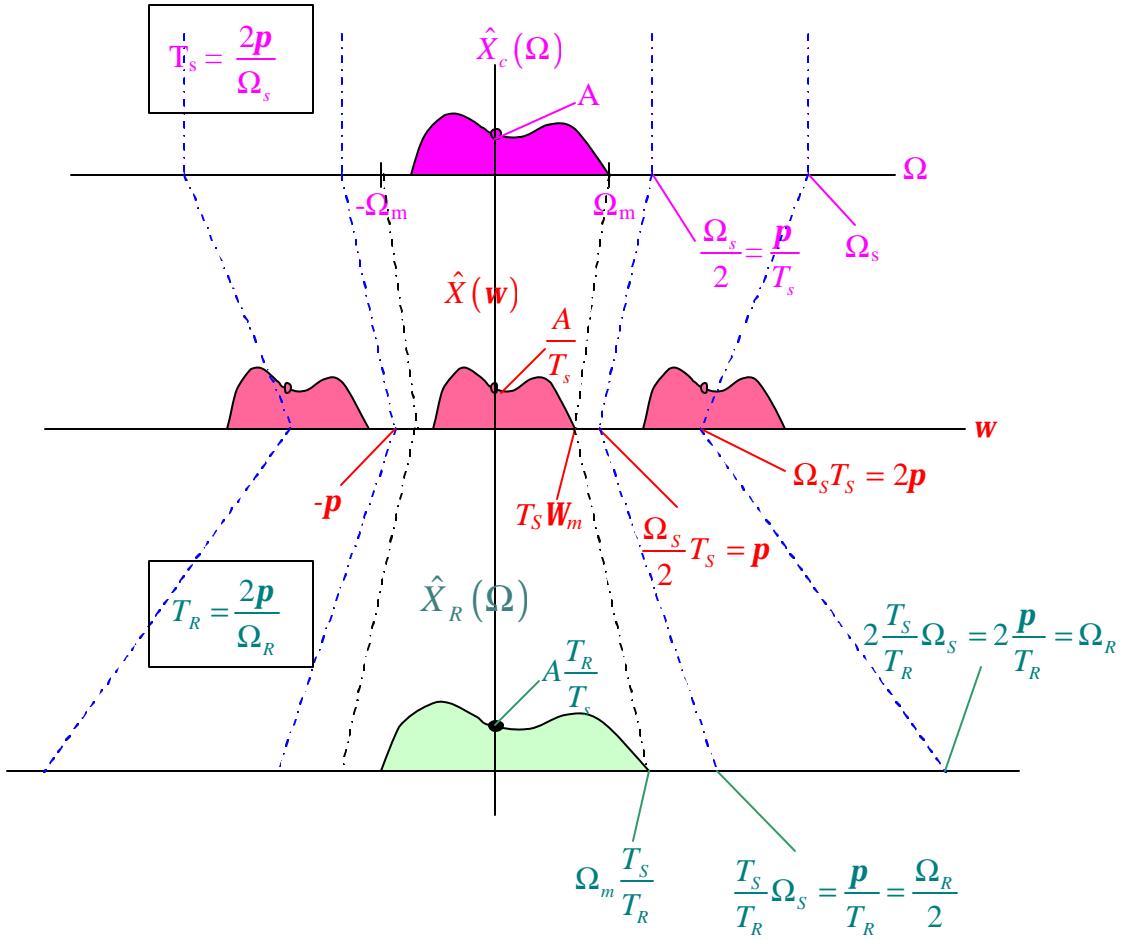
$x_R(t)$ is the unique continuous-time signal that has both properties

- $\hat{X}_R(\Omega) = T \left(\hat{X}(w) p_p(w) \right) \Big|_{w=\Omega T}$



Proof $\lim_{t \rightarrow nT} \frac{\sin \frac{p}{T}(t - mT)}{\frac{p}{T}(t - mT)} = \begin{cases} 0 & \text{for } m \neq n \\ 1 & \text{for } m = n \end{cases}$

Proof $x_R(t) = \frac{1}{2p} \int_{-\frac{p}{T}}^{\frac{p}{T}} T \hat{X}(\Omega T) e^{j\Omega t} d\Omega = \frac{1}{2p} \int_{-\infty}^{\infty} \underbrace{\left(T \hat{X}(\Omega T) p_p(\Omega) \right)}_{\hat{X}_R(\Omega)} e^{j\Omega t} d\Omega$



$\hat{X}_c(\Omega)$	A	Ω_0	$\frac{\Omega_s}{2}$	Ω_s
$\hat{X}(w)$	$A \frac{1}{T_s}$	$\omega_0 = \Omega_0 T_s$	π	2π
$\hat{X}_R(\Omega)$	$A \frac{T_R}{T_s}$	$\frac{w_0}{T_R} = \Omega_0 \frac{T_s}{T_R}$	$\frac{\Omega_R}{2}$	Ω_R

- Note: The amplitude doesn't really change when sampling followed by reconstruction (under no-aliasing assumption determined by T_s). This doesn't depend on the choice of T_R nor T_s . $x_R(t)$ will be equal to $x_c(t)$ if $T_s = T_R$. If T 's are different, $x_R(t)$ will be

$x_c(t)$ but expanded or shrunked in the time domain with all the height remains unchanged.

Can see this by the formula $x(at) \xrightarrow[\mathcal{F}^{-1}]{\mathcal{F}} \frac{1}{|a|} \hat{X}\left(\frac{\Omega}{a}\right)$.

$$\text{If no alising, } \hat{X}(w) = \frac{1}{T_s} \hat{X}_c\left(\frac{w}{T_s}\right) \Rightarrow \hat{X}_R(\Omega) = T_R \hat{X}(w = \Omega T_R) = \frac{T_R}{T_s} \hat{X}_c\left(\Omega \frac{T_R}{T_s}\right).$$

$$x\left(\frac{T_s}{T_R}t\right) \xrightarrow[\mathcal{F}^{-1}]{\mathcal{F}} \frac{T_R}{T_s} \hat{X}_c\left(\Omega \frac{T_R}{T_s}\right)$$

Ideal sampling

- **shah function** $\prod_{T(t)} = \sum_{n=-\infty}^{\infty} d(t - nT)$
- $x_s(t) = x_c(t) \sum_{n=-\infty}^{\infty} d(t - nT_s) = \prod_{T_s}$ -sampled version of $x_c(t) = \sum_{n=-\infty}^{\infty} x[n]d(t - nT_s)$
- $\hat{X}_s(\Omega)$

$$= \sum_{n=-\infty}^{\infty} x[n]e^{-j\Omega nT} = \hat{X}(w = \Omega T)$$

$$= \sum_{k=-\infty}^{\infty} \frac{1}{T_s} \hat{X}_c\left(\Omega - k\Omega_s\right); \Omega_s = \frac{2p}{T_s}$$

$$\begin{aligned} \text{Proof } x_s(t) &= \sum_{n=-\infty}^{\infty} x[n]d(t - nT_s) \\ \hat{X}_s(\Omega) &= \int_{-\infty}^{\infty} \sum_{n=-\infty}^{\infty} x[n]d(t - nT_s) e^{-j\Omega t} dt = \sum_{n=-\infty}^{\infty} x[n] \int_{-\infty}^{\infty} d(t - nT_s) e^{-j\Omega t} dt \\ &= \sum_{n=-\infty}^{\infty} x[n]e^{-j\Omega nT_s} = \hat{X}(w = \Omega T_s) \end{aligned}$$

$$\text{Know that } \hat{X}(w) = \sum_{k=-\infty}^{\infty} \left(\frac{1}{T} \hat{X}_c\left(\frac{w}{T} + k \frac{2p}{T}\right) \right).$$

$$\begin{aligned} \text{Therefore, } \hat{X}_s(\Omega) &= \hat{X}(w = \Omega T_s) = \sum_{k=-\infty}^{\infty} \left(\frac{1}{T} \hat{X}_c\left(\frac{\Omega T}{T} + k \frac{2p}{T}\right) \right) \\ &= \frac{1}{T} \sum_{k=-\infty}^{\infty} \left(\hat{X}_c\left(\Omega + k\Omega_s\right) \right) \end{aligned}$$

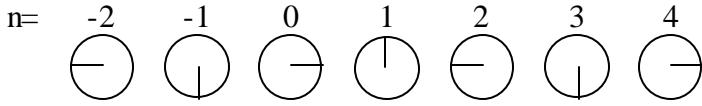
- $x_s(t) \xrightarrow{\hat{H}_R(\Omega) = T \cdot p_{\Omega_m}(\Omega)} x_c(t)$ if $T < \frac{p}{\Omega_m}$
- For $W_0 > 2W_m \Rightarrow$ the shifted replicas don't overlap

$$z(t) \xrightarrow{\hat{H}(\Omega)=T_0 \cdot p_{\Omega_m}(\Omega)} x(t)$$

Wheel example: sampled scene sequence

- If sample at every T sec, move at constant speed,

want to find $x_c(t) = e^{j\Omega_0 t}$.



- Find the parsimonious \mathbf{w}_0 first $\Rightarrow x[n]$ can $= e^{j\mathbf{w}_0 n}$

(Moving @ \mathbf{w}_0 rad per 1 frame, in this case, $\mathbf{w}_0 = \frac{\mathbf{p}}{2}$)

- Can find $x_c(t) = e^{j\Omega_0 t}$ in two ways:

- $x[n] = e^{j\mathbf{w}_0 n} = e^{j\mathbf{w}_0 n} (e^{j2\mathbf{p}})^{kn} = e^{j(\mathbf{w}_0 + 2\mathbf{p}k)n}$

$$\text{But } x[n] = x_c(nT) = e^{j\Omega_0 nT}; \text{ thus } \mathbf{W}_0 nT = (\mathbf{w}_0 + 2\mathbf{p}k)n \Rightarrow \mathbf{W}_0 = \frac{\mathbf{w}_0}{T} + 2\mathbf{p} \frac{k}{T}$$

- Thinking in term of rev./sec:

Fundamentally, moving @ $x = \frac{\mathbf{w}_0}{2\mathbf{p}}$ rev. per T sec

Can add k rev. more in 1 frame $= T$ sec.

So, Possibly moving at $x+k$ rev. in T sec

$$\frac{\Omega_0}{2\mathbf{p}} = \frac{x}{T} + \frac{k}{T} \text{ rev/sec} \Rightarrow \Omega_0 = \frac{2\mathbf{p}x}{T} + 2\mathbf{p} \frac{k}{T} \text{ rad/sec}$$

- note that positive ω corresponds to a counterclockwise rotation

- Represented by $e^{j(2\mathbf{p}\frac{x}{T} + 2\mathbf{p}\frac{k}{T})t} = e^{j(2\mathbf{p}\frac{x}{T})t}$ where $-\mathbf{p} \leq \left\langle 2\mathbf{p}\frac{x}{T} \right\rangle \leq \mathbf{p}$

- If $\left\langle 2\mathbf{p}\frac{x}{T} \right\rangle \neq 2\mathbf{p}\frac{x}{T}$

- aliasing has occurred.

- $e^{j(2\mathbf{p}\frac{x}{T} + 2\mathbf{p}\frac{k}{T})t}$ assumes the alias $e^{j\left\langle 2\mathbf{p}\frac{x}{T} \right\rangle t}$

One frequency example

- $x_c(t) = e^{j\Omega_0 t}; x[n] = e^{j\Omega_0 nT} = e^{j\mathbf{w}_0 n} = e^{j(\mathbf{w}_0 + 2\mathbf{p}k)n}; \mathbf{W}_0 = \frac{\mathbf{w}_0}{T} + 2\mathbf{p} \frac{k}{T}$

- $x_c(t) = e^{j\Omega_0 t} \xrightarrow[\Im^{-1}]{} \hat{X}(\Omega) = 2\mathbf{p}d(\Omega - \Omega_0) \Rightarrow \Omega_0 = \Omega_m$

$$x[n] = e^{j\Omega_0 Tn} = e^{j\mathbf{w}_0 n} = e^{j(\mathbf{w}_0 + 2\mathbf{p}k)n} \Rightarrow \mathbf{w}_0 = \Omega_0 T - 2\mathbf{p}k$$

$$x[n] = e^{jn\mathbf{w}_0} \xrightarrow{DTFT} \hat{X}(\mathbf{w}) = 2\mathbf{p} \sum_{k=-\infty}^{\infty} \mathbf{d}\left(\mathbf{w} - \langle \mathbf{w}_0 \rangle_{-p}^p + 2\mathbf{p}k\right)$$

$$\bullet \quad T_R = T_S = T$$

$$x_R(t) = \frac{1}{2\mathbf{p}} \int_{-\mathbf{p}}^{\mathbf{p}} 2\mathbf{p} \mathbf{d}\left(\mathbf{m} - \langle \mathbf{w}_0 \rangle_{-p}^p\right) e^{j\frac{\mathbf{m}}{T}t} d\mathbf{m} = e^{j\frac{\langle \mathbf{w}_0 \rangle_{-p}^p}{T}t}$$

$$x_R(t) = \frac{1}{2\mathbf{p}} \int_{-\mathbf{p}}^{\mathbf{p}} \hat{X}(\mathbf{m}) e^{j\frac{\mathbf{m}}{T}t} d\mathbf{m}$$

$$\text{If } \langle \mathbf{w}_0 \rangle_{-p}^p = \mathbf{w}_0, \quad x_R(nT) = x[n]$$

$$\hat{X}_R(\Omega) = 2\mathbf{p} T \mathbf{d}\left(\Omega T - \langle \mathbf{w}_0 \rangle_{-p}^p\right) \xrightarrow{\Im^{-1}} x_R(t) = e^{j\frac{\langle \mathbf{w}_0 \rangle_{-p}^p}{T}t} = e^{j\left(\langle \Omega_0 \rangle \frac{\Omega_S}{2}\right)t}$$

$$\hat{X}_R(\Omega) = T \left(\hat{X}(\mathbf{w}) P_p(\mathbf{w}) \right) \Big|_{\mathbf{w}=\Omega T}$$

$$\frac{\langle \mathbf{w}_0 \rangle_{-p}^p}{T} = \left\langle \frac{\mathbf{w}_0}{T} \right\rangle_{-\frac{\mathbf{p}}{T}}^{\frac{p}{T}} = \left\langle \frac{\mathbf{w}_0}{T} \right\rangle_{-\frac{\Omega_S}{2}}^{\frac{\Omega_S}{2}} = \left\langle \frac{\mathbf{w}_0}{T} \right\rangle_{-\frac{\Omega_S}{2}}^{\frac{\Omega_S}{2}}$$

$$\begin{aligned} \text{From } \mathbf{w}_0 &= \Omega_0 T - 2\mathbf{p}k, \quad \left\langle \frac{\mathbf{w}_0}{T} \right\rangle_{-\frac{\Omega_S}{2}}^{\frac{\Omega_S}{2}} = \left\langle \frac{\Omega_0 T - 2\mathbf{p}k}{T} \right\rangle_{-\frac{\Omega_S}{2}}^{\frac{\Omega_S}{2}} = \left\langle \Omega_0 - k \frac{2\mathbf{p}}{T} \right\rangle_{-\frac{\Omega_S}{2}}^{\frac{\Omega_S}{2}} \\ &= \left\langle \Omega_0 - k\Omega_S \right\rangle_{-\frac{\Omega_S}{2}}^{\frac{\Omega_S}{2}} = \left\langle \Omega_0 \right\rangle_{-\frac{\Omega_S}{2}}^{\frac{\Omega_S}{2}} \end{aligned}$$

$$\bullet \quad T_R \neq T_S$$

$$x_R(t) = \frac{1}{2\mathbf{p}} \int_{-\mathbf{p}}^{\mathbf{p}} 2\mathbf{p} \mathbf{d}\left(\mathbf{m} - \langle \mathbf{w}_0 \rangle_{-p}^p\right) e^{j\frac{\mathbf{m}}{T_R}t} d\mathbf{m} = e^{j\frac{\langle \mathbf{w}_0 \rangle_{-p}^p}{T_R}t}$$

$$\hat{X}_R(\Omega) = 2\mathbf{p} T_R \mathbf{d}\left(\Omega T_R - \langle \mathbf{w}_0 \rangle_{-p}^p\right) \xrightarrow{\Im^{-1}} x_R(t) = e^{j\frac{\langle \mathbf{w}_0 \rangle_{-p}^p}{T_R}t} = e^{j\left(\langle \Omega_0 \rangle \frac{T_S}{T_R} \frac{\Omega_R}{2}\right)t}$$

$$\frac{\langle \mathbf{w}_0 \rangle_{-p}^p}{T_R} = \left\langle \frac{\mathbf{w}_0}{T_R} \right\rangle_{-\frac{\mathbf{p}}{T_R}}^{\frac{p}{T_R}} = \left\langle \frac{\Omega_0 T_S - 2\mathbf{p}k}{T_R} \right\rangle_{-\frac{\mathbf{p}}{T_R}}^{\frac{p}{T_R}} = \left\langle \Omega_0 \frac{T_S}{T_R} - \frac{2\mathbf{p}k}{T_R} \right\rangle_{-\frac{\mathbf{p}}{T_R}}^{\frac{p}{T_R}}$$

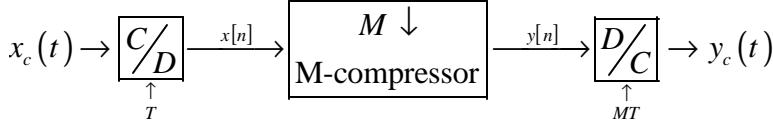
$$= \left\langle \Omega_0 \frac{T_S}{T_R} - k\Omega_R \right\rangle_{-\frac{\Omega_R}{2}}^{\frac{\Omega_R}{2}} = \left\langle \Omega_0 \frac{T_S}{T_R} \right\rangle_{-\frac{\Omega_R}{2}}^{\frac{\Omega_R}{2}}$$

Downsampling

- $y[n] = x[nM]$ = **M-down sampled** version of $x[n]$

= a “compressed” version of $x[n]$

$$x[n] \xrightarrow[\text{M-compressor}]{M \downarrow} y[n]$$



- $T' = MT$

- $\hat{Y}(\mathbf{w}) = \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$

- Let $z[n] = \begin{cases} x[n]; & \text{if } \frac{n}{M} \in I \\ 0; & \text{if } \frac{n}{M} \notin I \end{cases}$

Then, can rewrite $z[n]$ as $z[n] = \left(\frac{1}{M} \sum_{\ell=0}^{M-1} e^{j2\mathbf{p}\ell \frac{n}{M}} \right) x[n] = \frac{1}{M} \sum_{\ell=0}^{M-1} x[n] e^{j2\mathbf{p}\ell \frac{n}{M}}$.

To see this, note that $\frac{1}{M} \sum_{\ell=0}^{M-1} e^{j2\mathbf{p}\ell \frac{n}{M}} = \begin{cases} 1; & \text{if } \frac{n}{M} \in I \\ 0; & \text{if } \frac{n}{M} \notin I \end{cases}$

$$\sum_{\ell=0}^{M-1} e^{j2\mathbf{p}\ell \frac{n}{M}} = \sum_{\ell=0}^{M-1} \left(e^{j2\mathbf{p} \frac{n}{M}} \right)^{\ell} = \frac{1 - e^{j2\mathbf{p} \frac{n}{M} M}}{1 - e^{j2\mathbf{p} \frac{n}{M}}} = \frac{1 - e^{j2\mathbf{p} n}}{1 - e^{j2\mathbf{p} \frac{n}{M}}}$$

$$= 0 \text{ if } \frac{n}{M} \notin I \text{ since } e^{j2\mathbf{p} \frac{n}{M}} \neq 1$$

$$\begin{aligned} \text{If } \frac{n}{M} \in I, \quad \sum_{\ell=0}^{M-1} e^{j2\mathbf{p}\ell \frac{n}{M}} &= \frac{1 - (e^{j2\mathbf{p}})^n}{1 - (e^{j2\mathbf{p}})^M} \\ &= \frac{1 - (e^{j2\mathbf{p}})^n}{1 - (e^{j2\mathbf{p}})^M} = \lim_{x \rightarrow 1} \frac{1 - x^n}{1 - x^M} = \lim_{x \rightarrow 1} \frac{-nx^{n-1}}{-\frac{n}{M}x^{M-1}} = M \end{aligned}$$

From $z[n] = \frac{1}{M} \sum_{\ell=0}^{M-1} x[n] e^{j2\mathbf{p}\ell \frac{n}{M}}$, we have $\hat{Z}(\mathbf{w}) = \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\mathbf{w} - \ell \frac{2\mathbf{p}}{M}\right)$ from

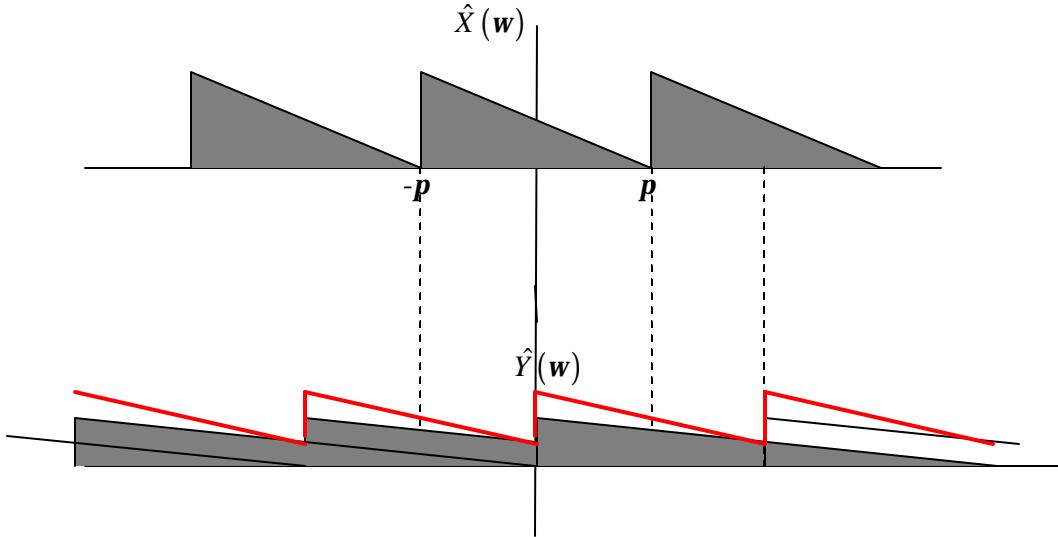
frequency-shift rule. \Rightarrow aliasing is possible

- Let $y[n] = z[nM] = x[nM]$

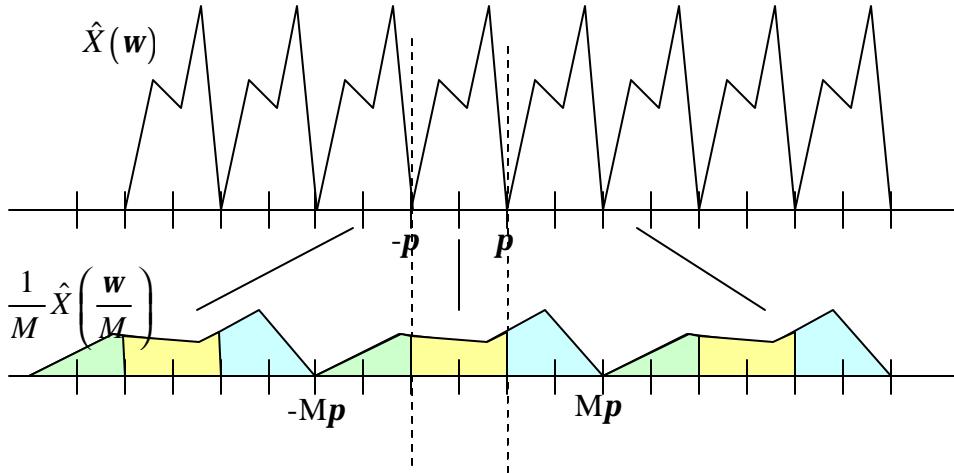
$$\text{Then } \hat{Z}(\mathbf{w}) = \sum_{m=-\infty}^{\infty} z[m]e^{-jm\mathbf{w}} = \sum_{n=-\infty}^{\infty} z[nM]e^{-jnM\mathbf{w}} = \sum_{n=-\infty}^{\infty} y[n]e^{-jnM\mathbf{w}} = \hat{Y}(M\mathbf{w})$$

- $\hat{Y}(\mathbf{w})$ is an M-expanded version of $\hat{Z}(\mathbf{w})$

Or $\boxed{\hat{Y}(\mathbf{w}) = \hat{Z}\left(\frac{\mathbf{w}}{M}\right)} = \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$



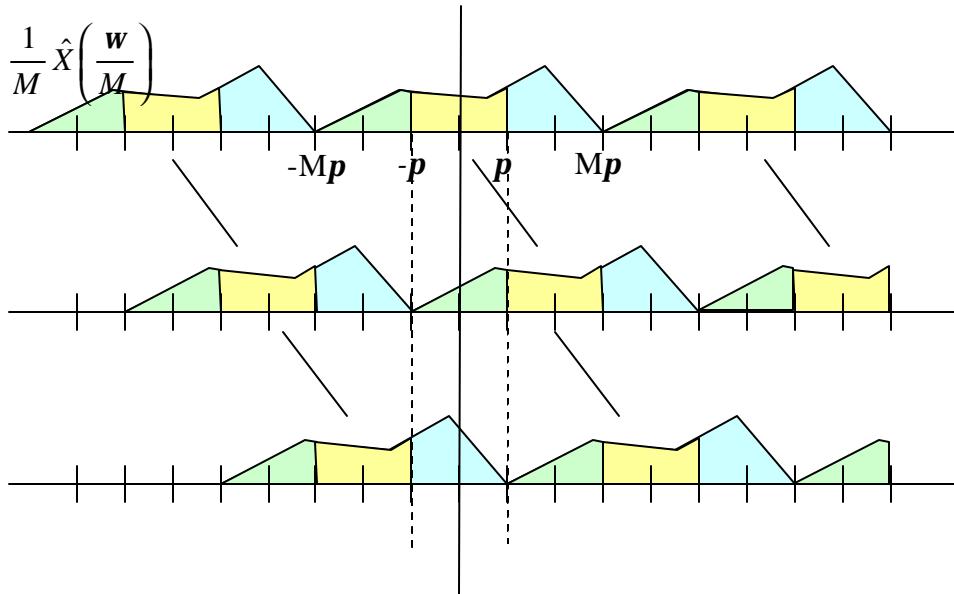
- Now, let's take a closer look at $\hat{Y}(\mathbf{w}) = \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$. It is a summation of $\frac{1}{M} \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$. Each $\hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$ is an expanded and shifted version of $\hat{X}(\mathbf{w})$. Since $\hat{Y}(\mathbf{w})$ is 2π -periodic, we will try to find what part of $\hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$ falls in the $-\pi$ to π range. First, note that the region from $-\pi$ to π of $\hat{X}(\mathbf{w})$ will be expanded to the range $-M\pi$ to $M\pi$ as shown in the figure below:



Each of the $\frac{1}{M} \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$ is indeed $\frac{1}{M} \hat{X}\left(\frac{\mathbf{w}}{M}\right)$ shifted by $2\mathbf{p}\ell$

$\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M} = 0 \Rightarrow \mathbf{w} = 2\mathbf{p}\ell\right)$. Thus, $\hat{Y}(\mathbf{w})$ is the summation of all the

$\frac{1}{M} \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$ as shown below:



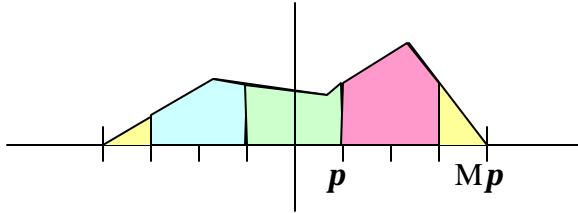
Looking at only the part of $\hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$ which falls in the $-\pi$ to π range, we see

that $\hat{X}\left(\frac{\mathbf{w}}{M}\right)$ is partitioned into M pieces, each pieces width equal 2π . $\hat{Y}(\mathbf{w})$ is the

summation of all these pieces times $\frac{1}{M}$. Therefore, $\hat{Y}(\mathbf{w})$ is basically an average of

all M pieces of $\hat{X}\left(\frac{\mathbf{w}}{M}\right)$.

Note that if M is even, then the first and last π chunks of $\hat{X}\left(\frac{\mathbf{w}}{M}\right)$ construct one 2π piece.



- $\hat{Y}(\mathbf{w} + 2k\mathbf{p}) = \hat{Y}(\mathbf{w})$

To see this, note that we want to have

$$\frac{1}{M} \sum_{\ell'=0}^{M-1} \hat{X}\left(\frac{\mathbf{w} + 2k\mathbf{p}}{M} - \ell' \frac{2\mathbf{p}}{M}\right) = \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$$

$$\text{and that } \hat{X}\left(\frac{\mathbf{w} + 2k\mathbf{p}}{M} - \ell' \frac{2\mathbf{p}}{M} + 2\mathbf{p}n\right) = \hat{X}\left(\frac{\mathbf{w} + 2k\mathbf{p}}{M} - \ell' \frac{2\mathbf{p}}{M}\right).$$

We will show that, given k , there exist one and only one integer ℓ for each ℓ that

$$\text{could make } \hat{X}\left(\frac{\mathbf{w} + 2k\mathbf{p}}{M} - \ell' \frac{2\mathbf{p}}{M} + 2\mathbf{p}n\right) = \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right), \text{ using appropriate } n.$$

To have $\frac{\mathbf{w} + 2k\mathbf{p}}{M} - \ell' \frac{2\mathbf{p}}{M} + 2\mathbf{p}n = \frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}$, need

$$k - \ell' + nM = -\ell \text{ or } n = \frac{\ell' - \ell - k}{M}.$$

Thus, given k , to find which $\ell' \in \{0, 1, \dots, M-1\}$ or which term of

$\hat{X}\left(\frac{\mathbf{w} + 2k\mathbf{p}}{M} - \ell' \frac{2\mathbf{p}}{M} + 2\mathbf{p}n\right)$ will be equal to $\hat{X}\left(\frac{\mathbf{w}}{M} - \ell_0 \frac{2\mathbf{p}}{M}\right)$, we need to find ℓ'

which give $n = \frac{\ell' - \ell_0 - k}{M}$ an integer value. There is one and only one ℓ' that

could do this, because $0 \leq \ell' \leq M-1$. Only one of ℓ' will give $(-\ell_0 - k) + \ell'$ that is divisible by M . This yields cyclic mapping between ℓ and ℓ' , and thus each

term of $\hat{X}\left(\frac{\mathbf{w} + 2k\mathbf{p}}{M} - \ell' \frac{2\mathbf{p}}{M}\right)$'s is equal to one of $\hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$. And therefore, the sum is equal.

- Example:

$$\begin{aligned}
\hat{Y}(\mathbf{w} - 2\mathbf{p}) &= \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\frac{\mathbf{w} - 2\mathbf{p}}{M} - \ell \frac{2\mathbf{p}}{M}\right) = \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - \frac{2\mathbf{p}}{M} - \ell \frac{2\mathbf{p}}{M}\right) \\
&= \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - (\ell+1) \frac{2\mathbf{p}}{M}\right) = \frac{1}{M} \sum_{k=1}^M \hat{X}\left(\frac{\mathbf{w}}{M} - k \frac{2\mathbf{p}}{M}\right) \\
&= \frac{1}{M} \left(\sum_{k=1}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - k \frac{2\mathbf{p}}{M}\right) + \hat{X}\left(\frac{\mathbf{w}}{M} - 2\mathbf{p}\right) \right) \\
&= \frac{1}{M} \left(\sum_{k=1}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - k \frac{2\mathbf{p}}{M}\right) + \hat{X}\left(\frac{\mathbf{w}}{M}\right) \right) = \frac{1}{M} \sum_{k=0}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - k \frac{2\mathbf{p}}{M}\right) = \hat{Y}(\mathbf{w})
\end{aligned}$$

- $\hat{Y}(\mathbf{w}) = \frac{1}{MT} \sum_{k=-\infty}^{\infty} \left(\hat{X}_c\left(\frac{\mathbf{w}}{MT} + k \frac{2\mathbf{p}}{MT}\right) \right)$

Think about going directly from $x_c(t)$ to $y[n]$, then

- $\hat{Y}(\mathbf{w}) = \sum_{k=-\infty}^{\infty} \left(\frac{1}{T'} \hat{X}_c\left(\frac{\mathbf{w}}{T'} + k \frac{2\mathbf{p}}{T'}\right) \right)$. Here $T' = MT$. Therefore,

$$\hat{Y}(\mathbf{w}) = \frac{1}{MT} \sum_{k=-\infty}^{\infty} \left(\hat{X}_c\left(\frac{\mathbf{w}}{MT} + k \frac{2\mathbf{p}}{MT}\right) \right)$$

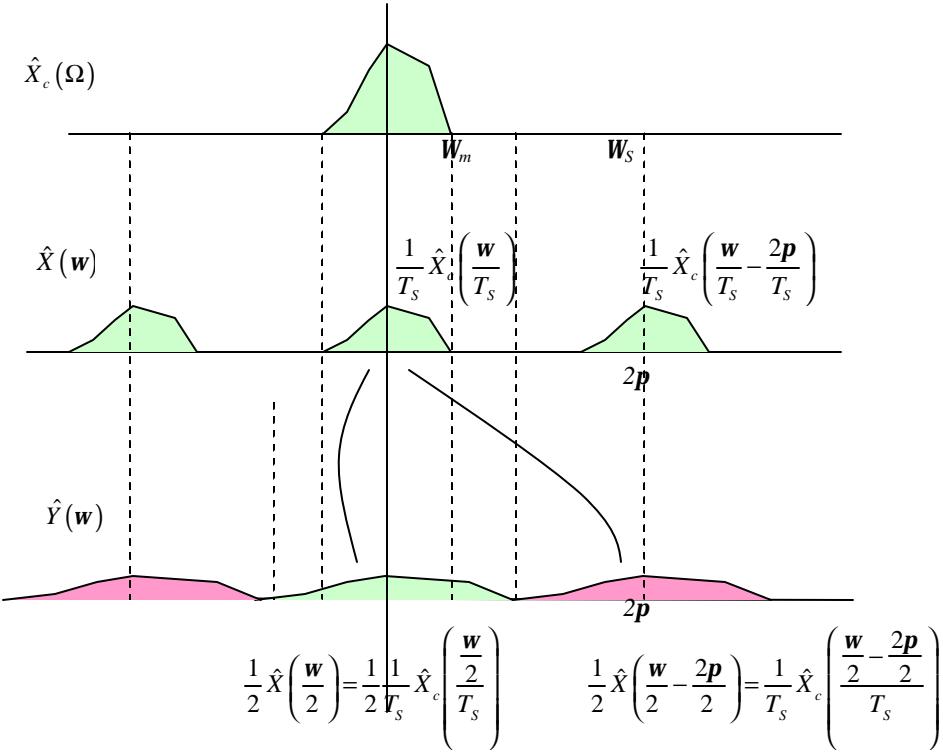
- Compare this to $\hat{Y}(\mathbf{w}) = \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$. We know that $\hat{X}(\mathbf{w}) = \frac{1}{T} \hat{X}_c\left(\frac{\mathbf{w}}{T}\right)$ if no aliasing.

Thus, $\hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right) = \frac{1}{T} \hat{X}_c\left(\frac{\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}}{T}\right) = \frac{1}{T} \hat{X}_c\left(\frac{\mathbf{w}}{MT} - \ell \frac{2\mathbf{p}}{MT}\right)$, and

$$\hat{Y}(\mathbf{w}) = \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right) = \frac{1}{MT} \sum_{\ell=0}^{M-1} \hat{X}_c\left(\frac{\mathbf{w}}{MT} - \ell \frac{2\mathbf{p}}{MT}\right)$$
 same result.

- If aliasing, still, $\hat{Y}(\mathbf{w}) = \frac{1}{MT} \sum_{k=-\infty}^{\infty} \left(\hat{X}_c\left(\frac{\mathbf{w}}{MT} + k \frac{2\mathbf{p}}{MT}\right) \right)$.

This is easy to see since $y[n] = x[Mn] = x(nMT)$. Can get $y[n]$ but just sampling $x(t)$ @ MT period.



- Example (doing it directly)

- $y[n] = x[2n]$

$$\hat{Y}(w) = \sum_{n=-\infty}^{\infty} y[n] e^{-jwn} = \sum_{n=-\infty}^{\infty} x[2n] e^{-jwn}$$

Be careful here and notice that $\sum_{n=-\infty}^{\infty} x[2n] e^{-jwn} \neq \sum_{m=-\infty}^{\infty} x[m] e^{-jw\frac{m}{2}}$.

$$\sum_{n=-\infty}^{\infty} x[2n] e^{-jwn} = \dots + x[0] + x[2] e^{-jw1} + x[4] e^{-jw2} + \dots$$

$$\sum_{m=-\infty}^{\infty} x[m] e^{-jw\frac{m}{2}} = \dots + \boxed{x[0]} + x[1] e^{-jw\frac{1}{2}} + \boxed{x[2] e^{-jw1}} + \dots$$

We want $\sum_{m=-\infty}^{\infty} x[m] e^{-jw\frac{m}{2}}$ but only want the even term.

Use $\frac{1}{M} \sum_{\ell=0}^{M-1} e^{j2p\ell\frac{n}{M}} = \begin{cases} 1; & \text{if } \frac{n}{M} \in I \\ 0; & \text{if } \frac{n}{M} \notin I \end{cases}$

$$\Rightarrow \frac{1}{2} \sum_{\ell=0}^1 e^{j2p\ell\frac{m}{2}} = \begin{cases} 1; & \text{if } \frac{m}{2} \in I \\ 0; & \text{if } \frac{m}{2} \notin I \end{cases} = \begin{cases} 1; & \text{if } m \text{ even} \\ 0; & \text{if } m \text{ odd} \end{cases}$$

$$\frac{1}{2} \sum_{\ell=0}^1 e^{j2\mathbf{p}\ell \frac{m}{2}} = \frac{1}{2} \sum_{\ell=0}^1 e^{j\mathbf{p}\ell m} = \frac{1}{2} (e^0 + e^{j\mathbf{p}m}) = \frac{1}{2} (1 + (-1)^m) = \begin{cases} 1; & \text{if } m \text{ even} \\ 0; & \text{if } m \text{ odd} \end{cases}$$

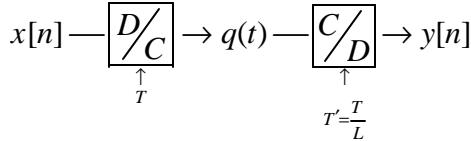
$$\begin{aligned} \text{Thus, } \hat{Y}(\mathbf{w}) &= \sum_{n=-\infty}^{\infty} x[2n] e^{-j\mathbf{w}n} = \sum_{m=-\infty}^{\infty} \frac{1}{2} (e^0 + e^{j\mathbf{p}m}) x[m] e^{-j\mathbf{w}\frac{m}{2}} \\ &= \frac{1}{2} \sum_{m=-\infty}^{\infty} x[m] e^{-jm\frac{\mathbf{w}}{2}} + \frac{1}{2} \sum_{m=-\infty}^{\infty} x[m] e^{-j\left(\frac{\mathbf{w}}{2}-\mathbf{p}\right)m} \\ &= \frac{1}{2} \hat{X}\left(\frac{\mathbf{w}}{2}\right) + \frac{1}{2} \hat{X}\left(\frac{\mathbf{w}}{2}-\mathbf{p}\right) \end{aligned}$$

Same as using the formula $\hat{Y}(\mathbf{w}) = \frac{1}{M} \sum_{\ell=0}^{M-1} \hat{X}\left(\frac{\mathbf{w}}{M} - \ell \frac{2\mathbf{p}}{M}\right)$, letting $M=2$

- Basically, this is $x_c(t)$, sampled @ $T' = MT \Rightarrow$ To recover $x_c(t)$ from $y_c(t)$ completely, need $MT < \frac{\mathbf{p}}{\Omega_m} \Rightarrow$ more stringent

Upsampling

- 2-step process:

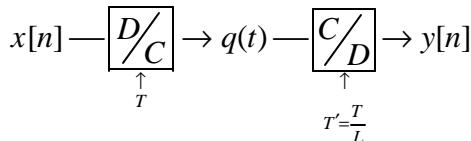


- So, $y[n]$ is $x[n]$ added with the parsimonious approximation, using the information from $x[n]$

$$y[n] = \sum_{m=-\infty}^{\infty} x[m] \frac{\sin \mathbf{p} \left(\frac{n}{L} - m \right)}{\mathbf{p} \left(\frac{n}{L} - m \right)}$$

$$\hat{Y}(\mathbf{w}) = L \hat{X}(L\mathbf{w}) p_{\frac{\mathbf{p}}{L}}(\mathbf{w}) = \begin{cases} L \hat{X}(L\mathbf{w}) & ; |\mathbf{w}| < \frac{\mathbf{p}}{L} \\ 0 & ; |\mathbf{w}| \geq \frac{\mathbf{p}}{L} \end{cases} \text{ for } |\mathbf{w}| \leq \mathbf{p}$$

- Replicate $L \hat{X}(L\mathbf{w})$ over each $\mathbf{w} = k2\pi$
- T doesn't matter
- View 1



Note that we have two sets of variables:

$$x_c(t), \hat{X}(\Omega), x[n], \hat{X}(w), x_R(t), \hat{X}_R(\Omega)$$

$$q(t), \hat{Q}(\Omega), y[n], \hat{Y}(w)$$

$$\boxed{q(t) = x_R(t) = \sum_{m=-\infty}^{\infty} x[m] \frac{\sin \frac{p}{T}(t - mT)}{\frac{p}{T}(t - mT)}}$$

$$\bullet \quad y[n] = q(nT') = q\left(n \frac{T}{L}\right) = \sum_{m=-\infty}^{\infty} x[m] \frac{\sin p\left(\frac{n}{L} - m\right)}{p\left(\frac{n}{L} - m\right)}$$

$$\bullet \quad \text{From } \hat{X}_R(\Omega) = T \hat{X}(w = \Omega T) p_{\frac{p}{T}}(\Omega),$$

$$(\Omega_m)_{\hat{Q}} = (\Omega_m)_{\hat{X}_R} = \frac{p}{T}$$

\bullet $y[n]$ is a sampled version of $q(t) = x_R(t)$. Thus,

$$\hat{Y}(w) = \sum_{k=-\infty}^{\infty} \left(\frac{1}{T'} \hat{Q}\left(\frac{w}{T'} + k \frac{2p}{T'}\right) \right) = \sum_{k=-\infty}^{\infty} \left(\frac{L}{T} \hat{Q}\left(\frac{Lw}{T} + k \frac{2pL}{T}\right) \right)$$

$$\text{No overlap between } \frac{L}{T} \hat{Q}\left(\frac{Lw}{T} + k \frac{2pL}{T}\right) \text{ if } \Omega_s' \geq 2(\Omega_m)_{\hat{Q}} \Rightarrow \frac{2p}{T'} \geq 2 \frac{p}{T} \Rightarrow T' \leq T$$

If $L > 1$, $T' = \frac{T}{L} \leq T$, definitely no overlap,

$$\text{and } \boxed{\hat{Y}(w) = \frac{L}{T} \hat{Q}\left(\frac{Lw}{T}\right) = \frac{L}{T} \hat{X}_R\left(\frac{Lw}{T}\right) \text{ for } -p \leq w \leq p}$$

\bullet replicate $\frac{L}{T} \hat{X}_R\left(\frac{wL}{T}\right)$ over each $w = k2\pi$

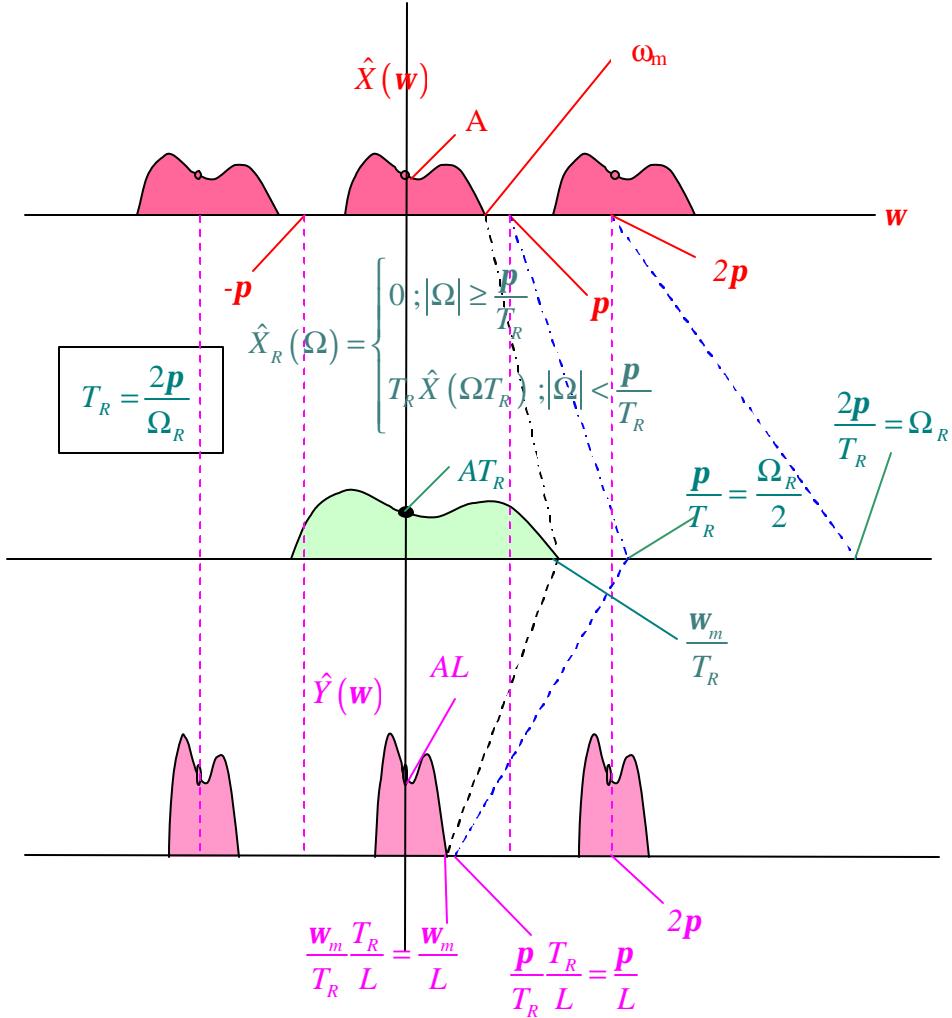
$$\text{Since } \hat{X}_R(\Omega) = T \left(\hat{X}(w) p_p(w) \right) \Big|_{w=\Omega T},$$

$$\begin{aligned} \hat{X}_R\left(\frac{Lw}{T}\right) &= T \left(\hat{X}(w) p_p(w) \right) \Big|_{w=\frac{Lw}{T}} = T \left(\hat{X}(w) p_p(w) \right) \Big|_{w=Lw} \\ &= T \left(\hat{X}(w) p_p(w) \right) \Big|_{w=Lw} \end{aligned}$$

$$\hat{Y}(w) = \frac{L}{T} \hat{X}_R\left(\frac{Lw}{T}\right) = \frac{L}{T} T \left(\hat{X}(w) p_p(w) \right) \Big|_{w=Lw} = L \left(\hat{X}(w) p_p(w) \right) \Big|_{w=Lw}$$

for $-p \leq w \leq p$

$$\text{Thus, for } |\mathbf{w}| \leq \mathbf{p} \quad \hat{Y}(\mathbf{w}) = L\hat{X}(L\mathbf{w}) p_{\frac{\mathbf{p}}{L}}(\mathbf{w}) = \begin{cases} L\hat{X}(\mathbf{w}L) & ; |\mathbf{w}| < \frac{\mathbf{p}}{L} \\ 0 & ; |\mathbf{w}| \geq \frac{\mathbf{p}}{L} \end{cases}$$



- View 2

- $z_u[n] = L\text{-expanded } x[n] = \begin{cases} x\left[\frac{n}{L}\right] & ; \frac{n}{L} \in I \\ 0 & ; \frac{n}{L} \notin I \end{cases}$

- $\hat{Z}(\mathbf{w}) = \hat{X}(L\mathbf{w}) = \sum_{k=-\infty}^{\infty} \left(\frac{1}{T} \hat{X}_R \left(\frac{\mathbf{w}L}{T} + k \frac{2\mathbf{p}}{T} \right) \right)$

- \Rightarrow replicate $\frac{1}{T} \hat{X}_R \left(\frac{\mathbf{w}L}{T} \right)$ over each $\omega = k \frac{2\mathbf{p}}{L}$

$$\hat{Z}(\mathbf{w}) = \sum_{n=-\infty}^{\infty} z[n] e^{-j\mathbf{w}n} = \sum_{\substack{n=-\infty \\ n \in I \\ L}}^{\infty} z[n] e^{-j\mathbf{w}n} = \sum_{m=-\infty}^{\infty} z[Lm] e^{-j\mathbf{w}Lm}$$

$$= \sum_{m=-\infty}^{\infty} x[m] e^{-j(L\mathbf{w})m}$$

$$\boxed{\hat{Z}(\mathbf{w}) = \hat{X}(L\mathbf{w})}$$

- Example $z[n] = \begin{cases} x\left[\frac{n}{2}\right] & n \text{ even} \\ 0 & n \text{ odd} \end{cases}$

$$\hat{Z}(\mathbf{w}) = \sum_{n=-\infty}^{\infty} z[n] e^{-j\mathbf{w}n} = \sum_{\substack{n=-\infty \\ n \text{ even}}}^{\infty} z[n] e^{-j\mathbf{w}n} = \sum_{m=-\infty}^{\infty} z[2m] e^{-j\mathbf{w}2m}$$

$$= \sum_{m=-\infty}^{\infty} x[m] e^{-j(2\mathbf{w})m} = \hat{X}(2\mathbf{w})$$

- $\hat{Y}(\mathbf{w}) = \hat{Z}(\mathbf{w}) \cdot \left(L P_{\frac{p}{L}}(\mathbf{w}) \right)$ for $|\mathbf{w}| \leq p$
- $x_c(t) \rightarrow \boxed{\frac{C}{D}} \xrightarrow{x[n]} \boxed{\frac{D}{C}} \xrightarrow{q(t)=x_R(t)} \boxed{\frac{C}{D}} \xrightarrow{y[n]} \boxed{\frac{D}{C}} \rightarrow y_R(t)$
- If $T \leq \frac{p}{\Omega_m}$, $q(t) = x_c(t)$ and $y_R(t) = x_c(t)$ because $\frac{T}{L} < T$

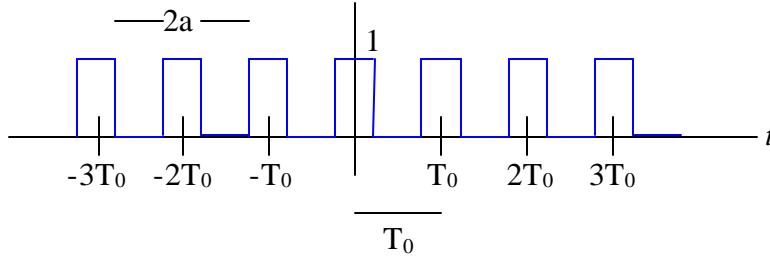
Practical sampling

$$\bullet \quad r(t) = \sum_{n=-\infty}^{\infty} p_a(t - nT_0) = \sum_{k=-\infty}^{\infty} c_k e^{j k \mathbf{w}_0 t} = \sum_{k=-\infty}^{\infty} \left(\frac{\sin(ak\mathbf{w}_0)}{kp} \right) e^{j k \mathbf{w}_0 t}; \quad c_0 = \frac{2a}{T_0}; \quad \Omega_0 = \frac{2p}{T_0}$$

- Rectangular pulse train; height = 1

Each pulse width = $2a$

Centered at $0, \pm T_0, \pm 2T_0, \dots$



$T_0 > \text{small } a > 0$

- $= \sum_{n=-\infty}^{\infty} p_a(t - nT_0)$
- $= \sum_{k=-\infty}^{\infty} \left(\frac{\sin(ak\Omega_0)}{kp} \right) e^{jka\Omega_0 t}$

Proof $c_k = \int_{-\frac{T_0}{2}}^{\frac{T_0}{2}} r(t) e^{-jka\Omega_0 t} dt = \int_{-a}^a e^{-jka\Omega_0 t} dt = \frac{\sin(ak\Omega_0)}{kp}$

Proof $c_0 = \lim_{k \rightarrow 0} \frac{\sin(ak\Omega_0)}{kp} = \frac{a\Omega_0}{p} \lim_{k \rightarrow 0} \frac{\sin(ak\Omega_0)}{a\Omega_0 k} = \frac{a\Omega_0}{p} 1 = \frac{a2p}{pT_0} = \frac{2a}{T_0}$

Proof 2 Can see from the graph that $E[r(t)] = \frac{2a}{T} = c_0$.

- $\hat{R}(\Omega) = \sum_{k=-\infty}^{\infty} 2pc_k d(\Omega - k\Omega_0) = \sum_{k=-\infty}^{\infty} \frac{2\sin(ak\Omega_0)}{k} d(\Omega - k\Omega_0)$

To see this, recall that $r(t) = \sum_{k=-\infty}^{\infty} c_k e^{jka\Omega_0 t} \xrightarrow[\Im^{-1}]{\Im} \hat{R}(\Omega) = \sum_{k=-\infty}^{\infty} 2pc_k d(\Omega - k\Omega_0)$

- $z(t) =$ a **practically sampled** version of $x(t) = x(t)r(t)$

each width = $2a$

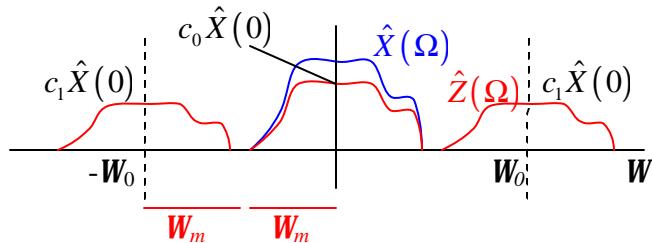
centered at $0, \pm T_0, \pm 2T_0, \dots$

height = 0 or height of $x(t)$

- $\hat{Z}(\Omega) = \sum_{k=-\infty}^{\infty} c_k \hat{X}(\Omega - k\Omega_0); \Omega_0 = \frac{2p}{T_0}$

$\hat{Z}(\Omega)$ = the sum of scaled shifted replicas of $\hat{X}(\Omega)$

c_k = the k^{th} fourier coefficient of the pulse train $r(t)$



Proof $z(t) = x(t)r(t) \xrightarrow[\Im^{-1}]{\Im} \hat{Z}(\Omega) = \frac{1}{2p} \hat{X}(\Omega) * \hat{R}(\Omega)$

$$\begin{aligned}\hat{Z}(\Omega) &= \frac{1}{2p} \hat{X}(\Omega)^* \hat{R}(\Omega) = \frac{1}{2p} \hat{X}(\Omega)^* \left(\sum_{k=-\infty}^{\infty} 2p c_k d(\Omega - k\Omega_0) \right) \\ &= \sum_{k=-\infty}^{\infty} c_k \hat{X}(\Omega)^* d(\Omega - k\Omega_0) = \sum_{k=-\infty}^{\infty} c_k \hat{X}(\Omega - k\Omega_0)\end{aligned}$$

- For $W_0 > 2W_m \Rightarrow$
the shifted replicas don't overlap

$$z(t) \xrightarrow{\hat{H}(\Omega) = p_{\Omega_m}(\Omega)} c_0 x(t) = \frac{2a}{T_0} x(t)$$

- If define $r(t) = \sum_{n=-\infty}^{\infty} \frac{1}{a} p_{\frac{a}{2}}(t - nT)$
 - $\lim_{a \rightarrow 0} r(t) = \prod_{a \rightarrow 0} T(t)$
 - $x_s(t) = \lim_{a \rightarrow 0} r(t) x_c(t)$
 - $x_s(t) = \sum_{n=-\infty}^{\infty} x[n] d(t - nT)$

Practical reconstruction; Interpolation

$$\bullet \quad x_R(t) = \sum_{n=-\infty}^{\infty} x[n] h_R(t - nT) = h_R(t) * \left(\sum_{n=-\infty}^{\infty} x[n] d(t - nT) \right) = h_R(t) * x_s(t)$$

$$\bullet \quad \hat{X}_R(\Omega) = \hat{H}_R(\Omega) \cdot \hat{X}_s(\Omega) = \hat{H}_R(\Omega) \cdot \sum_{k=-\infty}^{\infty} \frac{1}{T_s} \hat{X}_c(\Omega - k\Omega_s)$$

- $h_R(t)$ = **interpolating function**

- Staircase or zero-order hold interpolation

$$h_{\square}(t) = p_{\frac{T}{2}}(t) \xrightarrow{\mathcal{Z}^{-1}} \hat{H}(\Omega) = \frac{2 \sin\left(\Omega \frac{T}{2}\right)}{\Omega}$$

$$\Rightarrow x_R(t) = x(nT) \text{ for } nT - \frac{T}{2} < t < nT + \frac{T}{2}$$

$$\bullet \quad \underbrace{x[n]}_{\substack{\uparrow \\ \text{constant}}} d(t - nT) * p_{\frac{T}{2}}(t) = x[n] p_{\frac{T}{2}}(t - nT)$$

- $\hat{H}_R(\Omega) = 0$ when $\Omega = k\Omega_s \Rightarrow$ killed high-freq replicas

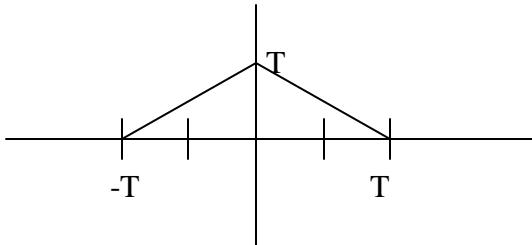
$$\left(\hat{X}_s(\Omega) = \sum_{k=-\infty}^{\infty} \frac{1}{T_s} \hat{X}_c(\Omega + k\Omega_s) \right)$$

- $\hat{H}_R(\Omega) = T$ when $\Omega \rightarrow 0 \Rightarrow$ cancel $\frac{1}{T}$ from $\hat{X}_s(\Omega) = \sum_{k=-\infty}^{\infty} \frac{1}{T_s} \hat{X}_c(\Omega + k\Omega_s)$

- Linear interpolation : connect-the-dot

$$h_\Delta(t) = \frac{1}{T} h_\square(t) * h_\square(t) \xrightarrow{\mathcal{S}^{-1}} \hat{H}_\Delta(\Omega) = \frac{1}{T} \left(\frac{2 \sin\left(\Omega \frac{T}{2}\right)}{\Omega} \right)^2$$

- $p_{\frac{T}{2}}(t) * p_{\frac{T}{2}}(t) = \begin{cases} 0 & |t| \geq T \\ T - |t| & 0 \leq |t| < T \end{cases}$



- $h(t) = T_0 \frac{\sin\left(\frac{w_0}{2}t\right)}{pt} \xrightarrow{\mathcal{S}^{-1}} \hat{H}(w) = T_0 p_{\frac{w_0}{2}}(w)$

