

C++ Real-Time Audio Programming with Bela

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School of Electronic Engineering and Computer Science
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Founder and Director, Bela

Course topics

Programming topics

- Working in real time
- Buffers and arrays
- Parameter control
- Classes and objects
- Analog and digital I/O
- Filtering
- Timing in real time
- Circular buffers
- State machines
- MIDI
- Block-based processing
- Threads
- Fixed point arithmetic
- ARM assembly language



Music/audio topics

- Oscillators
- Samples
- Wavetables
- Control voltages
- Gates and triggers
- Filters
- Metronomes and clocks
- Delays and delay-based effects
- Envelopes
- ADSR
- MIDI
- Additive synthesis
- Phase vocoders
- Impulse reverb

Today

Lecture 17: Block-based processing

What you'll learn today:

Generating and processing windows of a signal

The Fast Fourier Transform (FFT)

Sending data to the Bela GUI

What you'll make today:

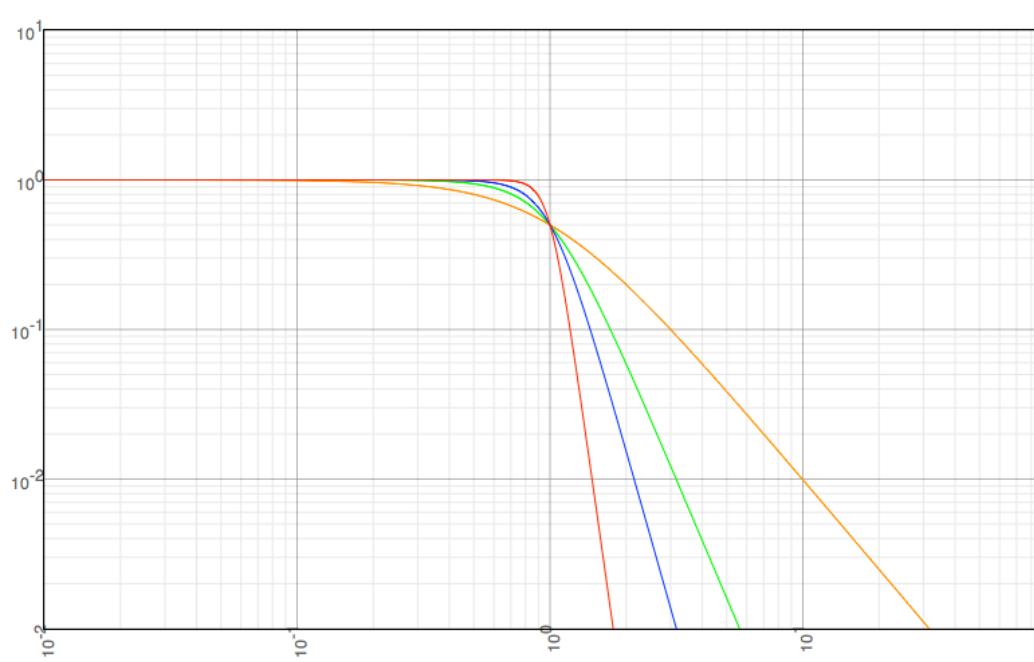
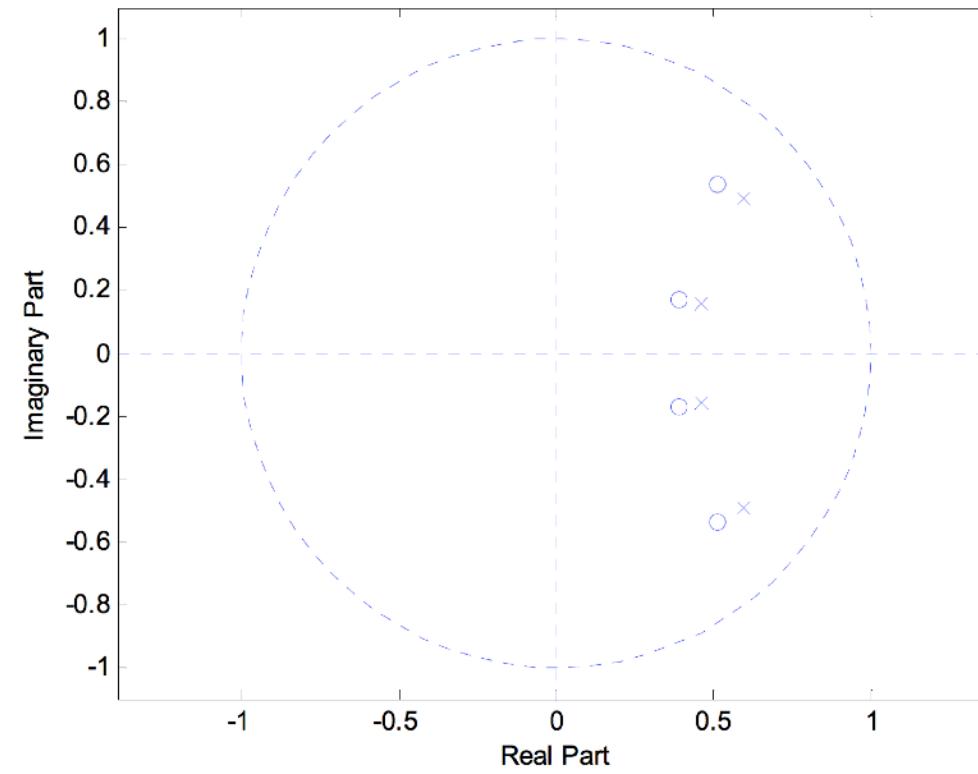
Two simple spectrum analysers with LEDs and GUI

Companion materials:

github.com/BelaPlatform/bela-online-course

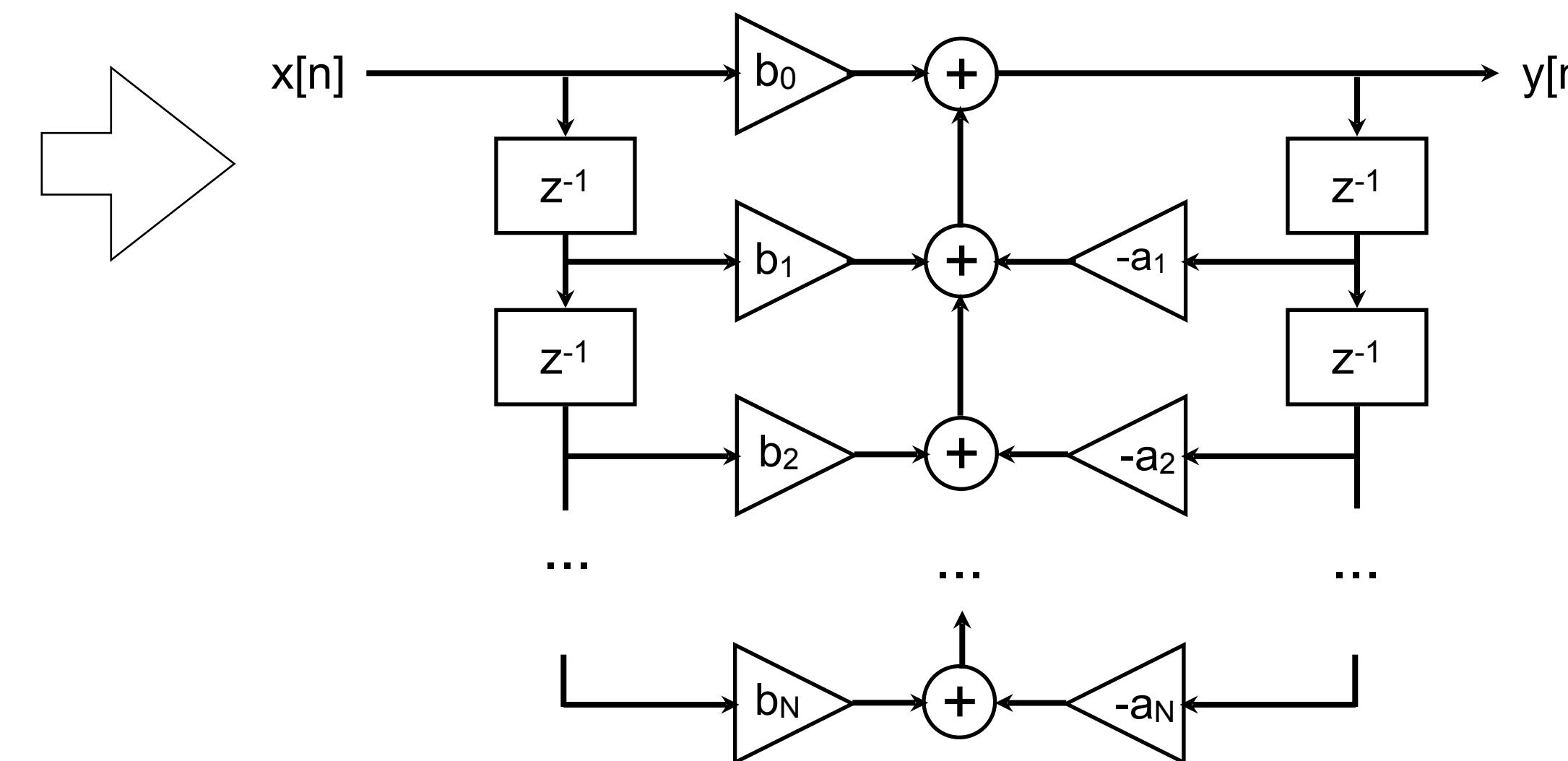
Theory and implementation

Specifications



Design

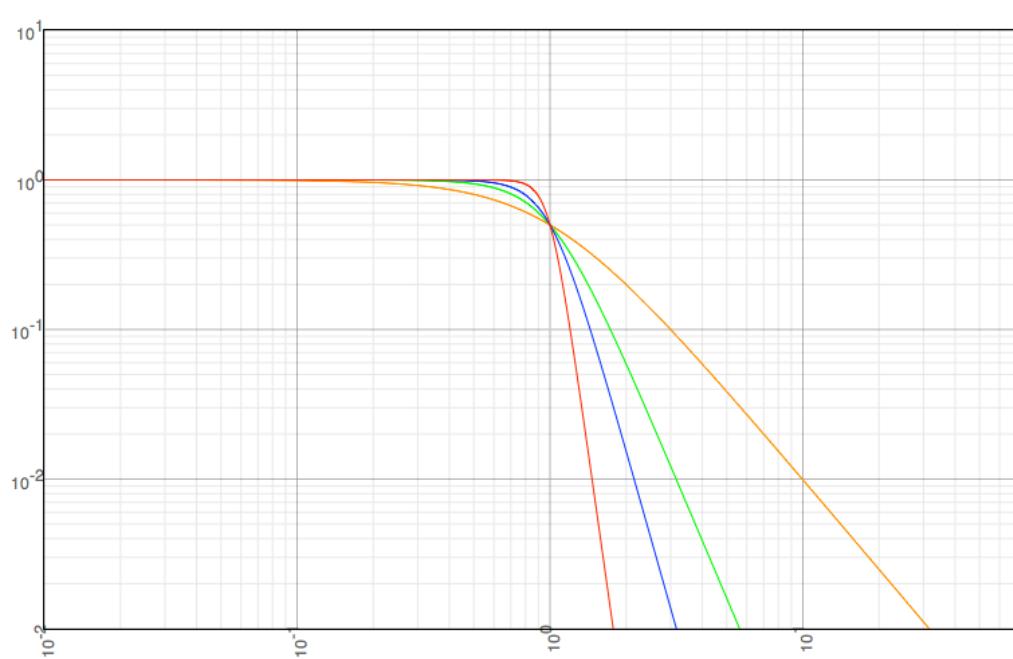
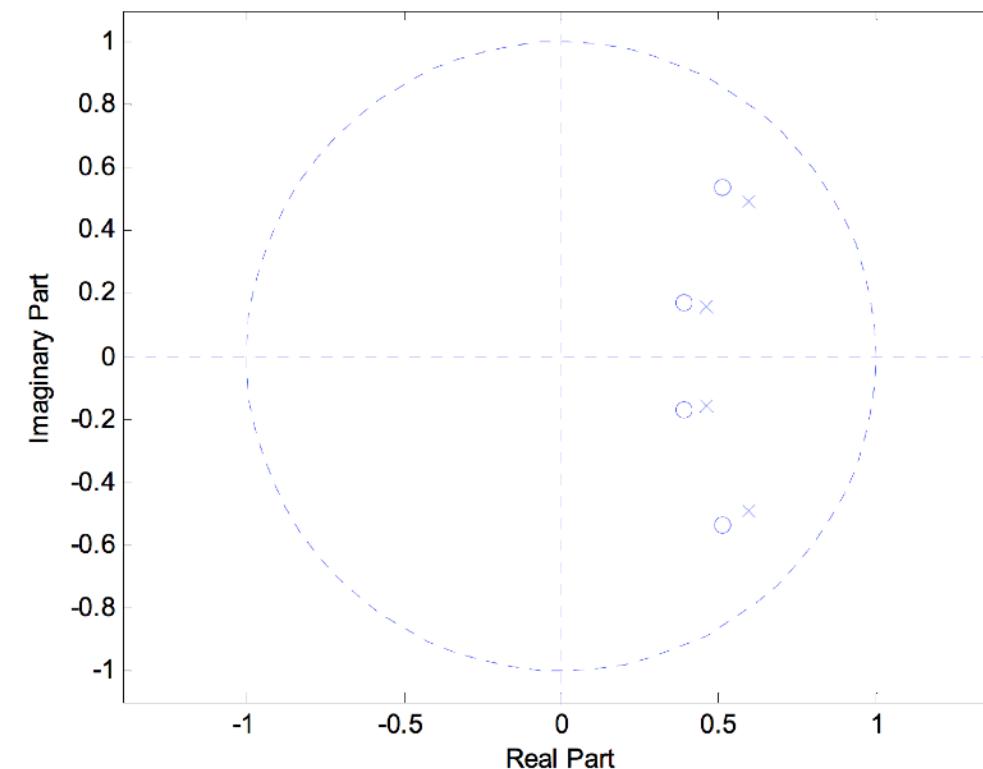
$$y[n] = \sum_{k=1}^N a_k y[n-k] + \sum_{k=0}^M b_k x[n-k]$$



Typical digital signal processing course

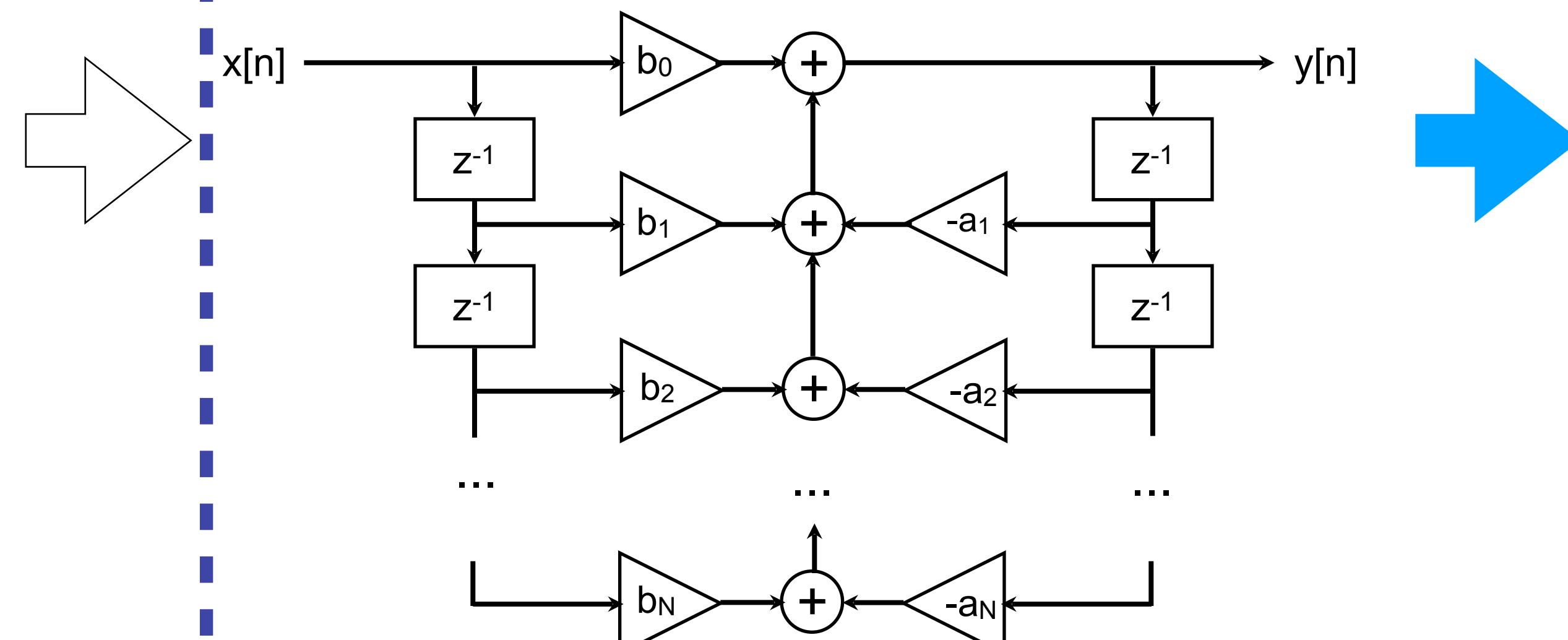
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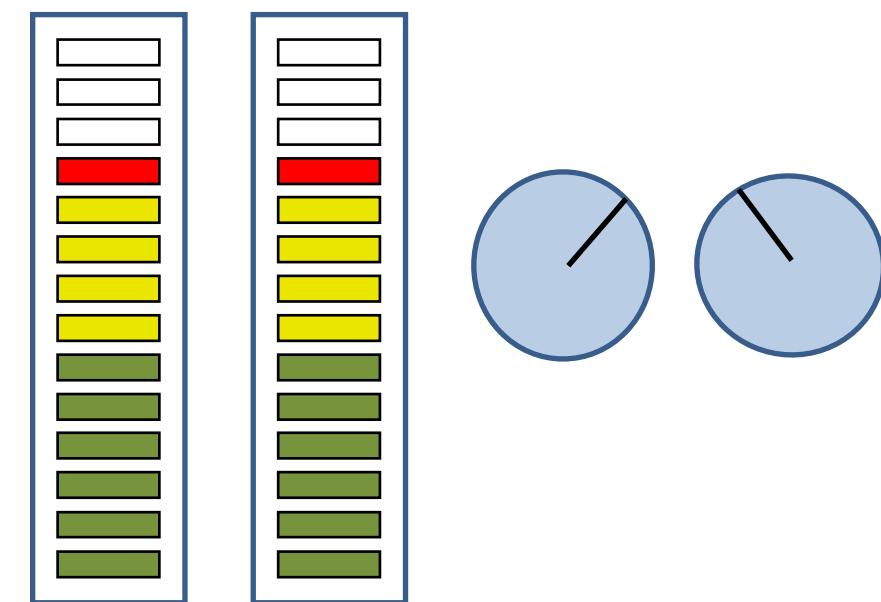
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Implementation

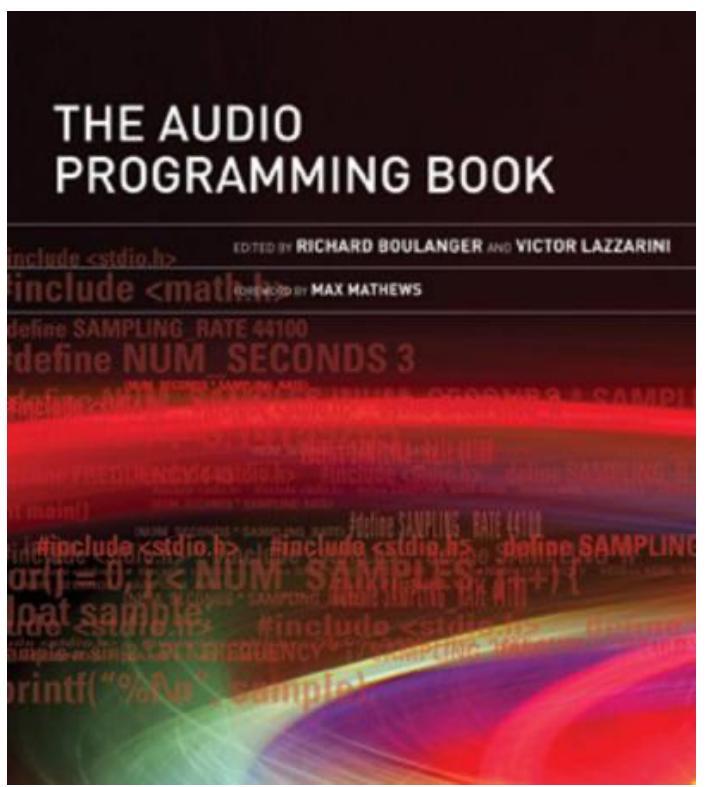
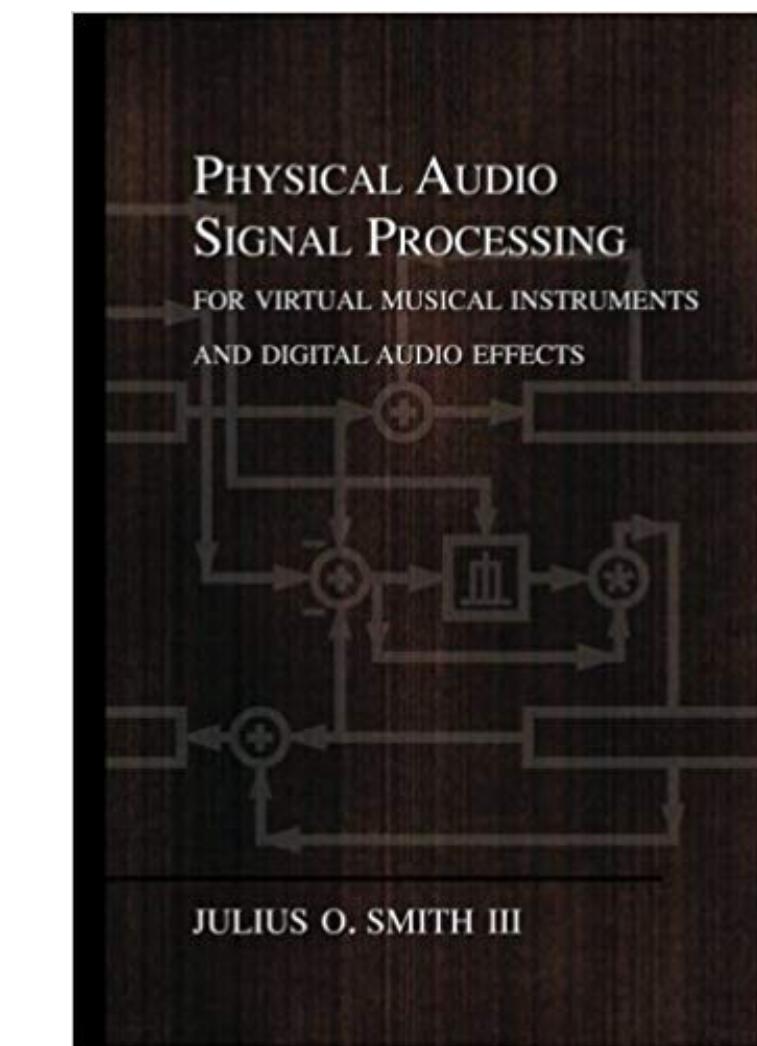
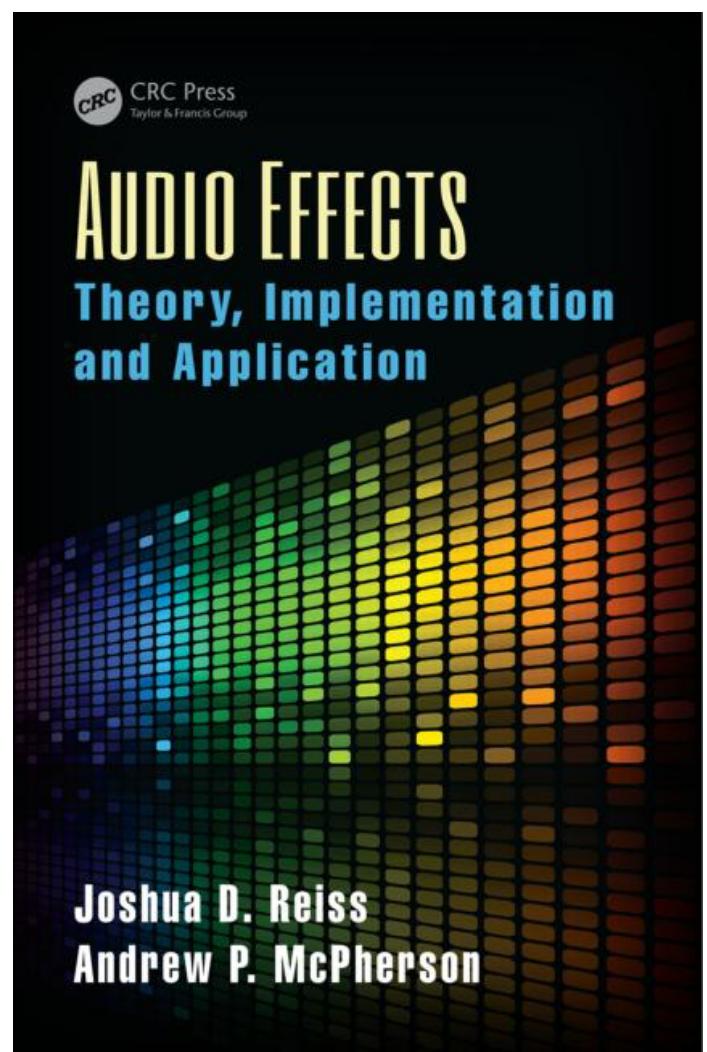
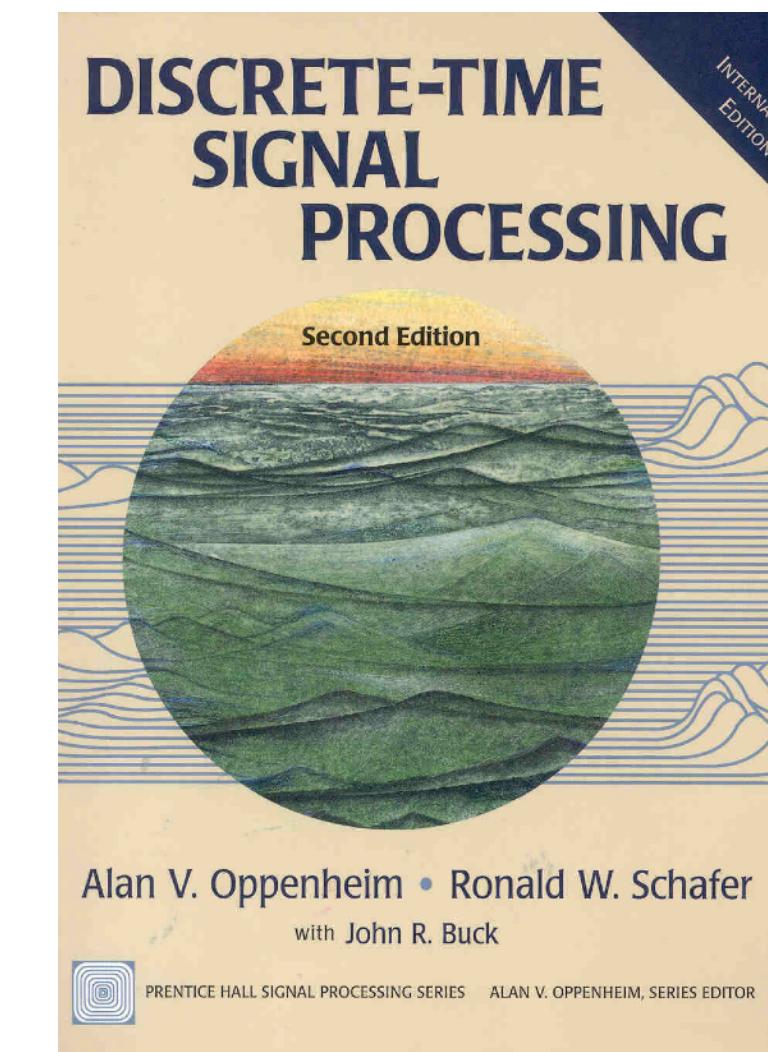
```
void render(BelaContext *context, void * /* user data */)
{
    /* Iterate over each channel */
    for(int channel = 0; channel < numChannels; channel++)
        /* Then iterate over each sample within the frame */
        for(int n = 0; n < numSamples; n++)
            /* Calculate the sample... */
            float sample = gAmplitude *
                sin(2.0 * M_PI * (frequencies[channel] *
                    gFrequency + phase[channel]));
}
```



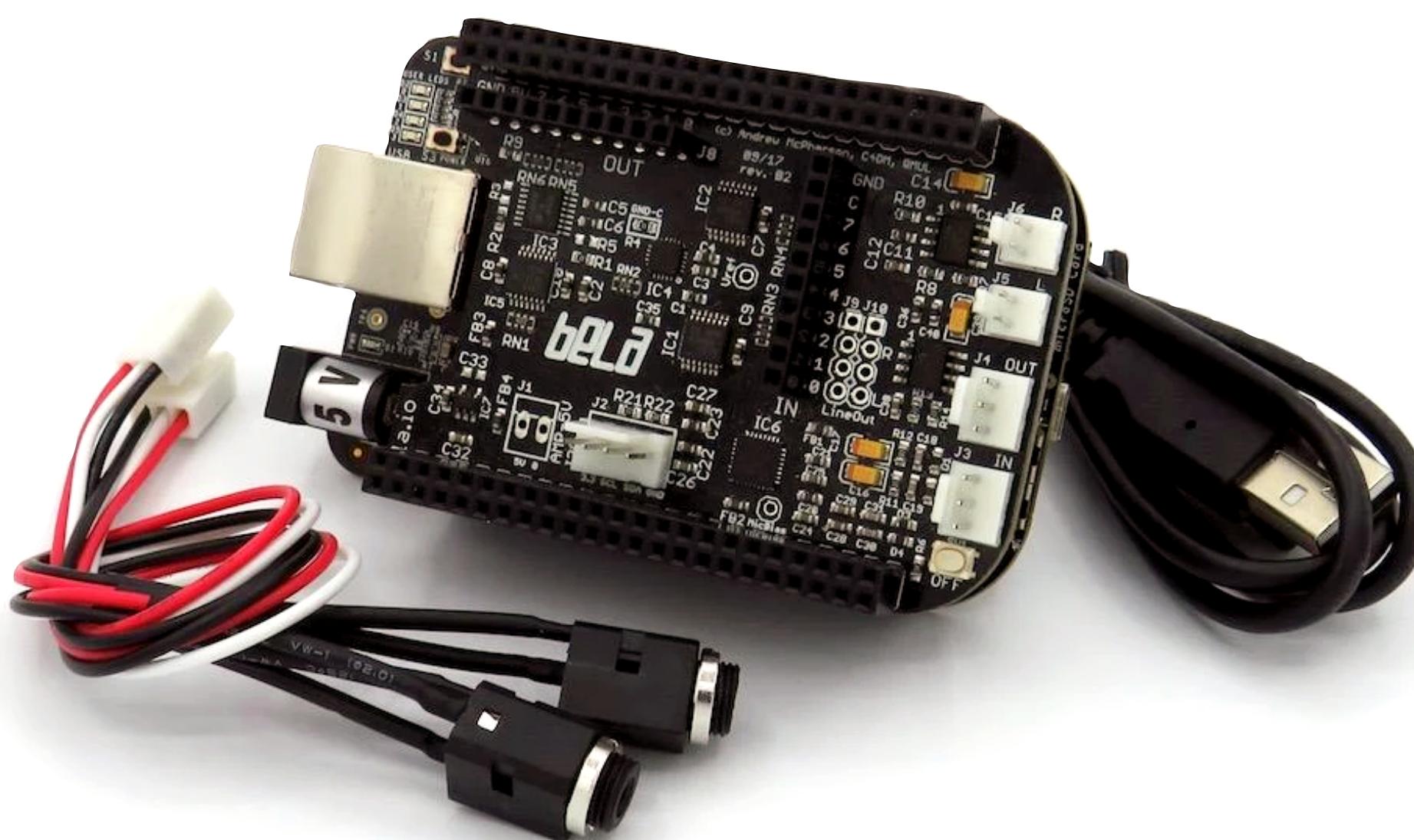
- We will turn **signal processing theory** into **efficient C++ code**
- There are plenty of excellent introductions to DSP mathematics

Books and references

- There are lots of good books and online resources about DSP and audio programming.
For example:
 - Oppenheim, Schafer and Buck, *Discrete-Time Signal Processing*
 - Julius O. Smith, *Physical Audio Signal Processing*
 - Richard Boulanger and Victor Lazzarini (editors), *The Audio Programming Book*
 - Reiss and McPherson, *Audio Effects: Theory, Implementation and Application*
- See the GitHub companion site for links:
github.com/BelaPlatform/bela-online-course

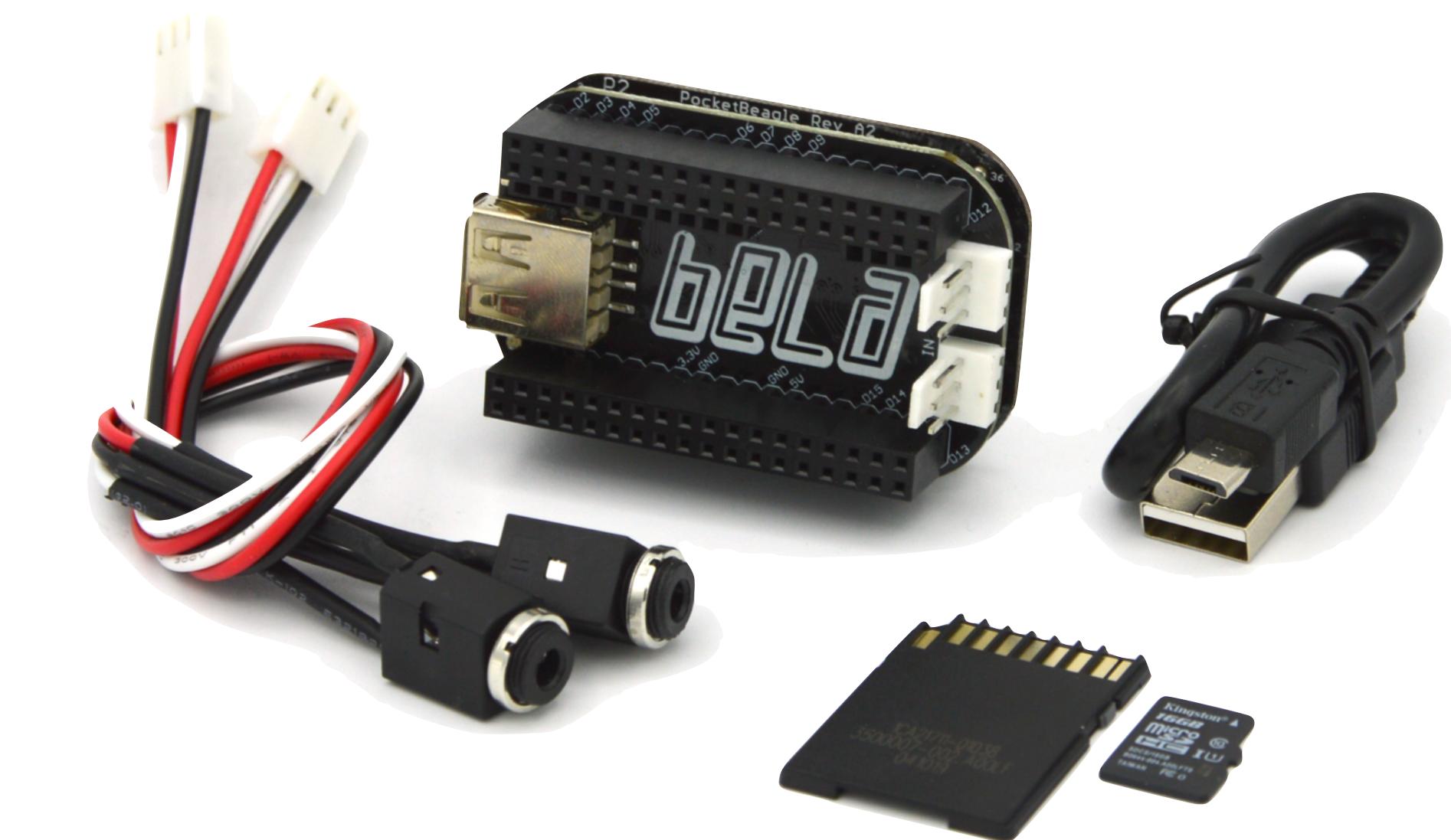


What you'll need



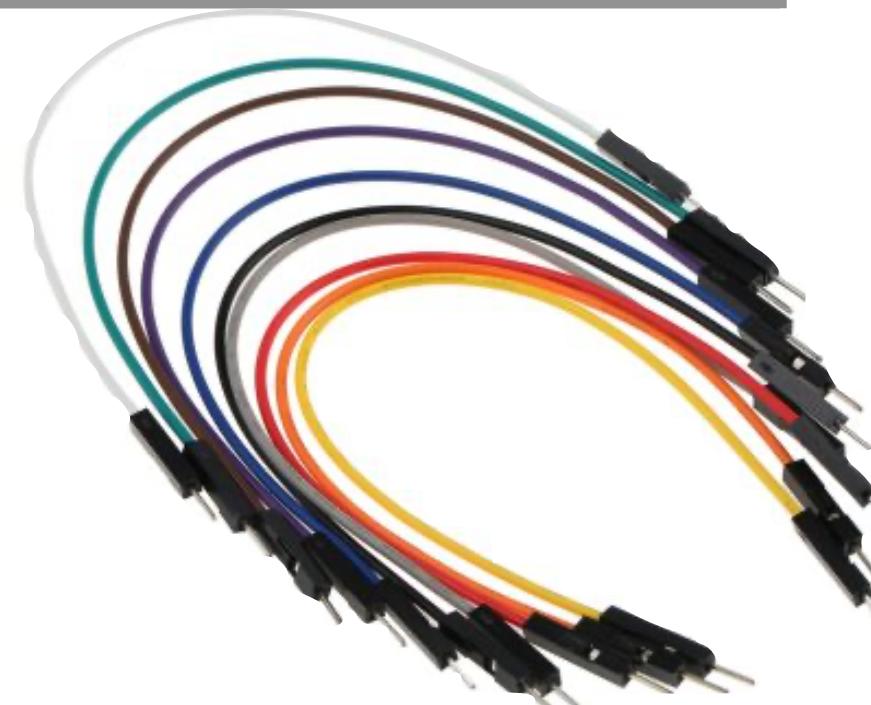
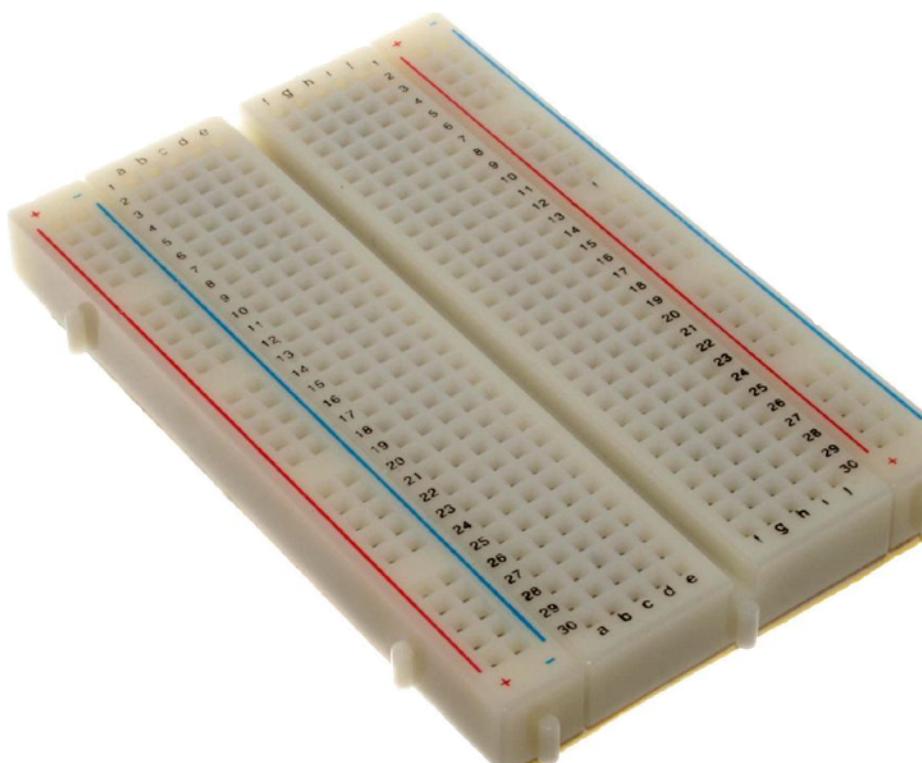
Bela Starter Kit

or



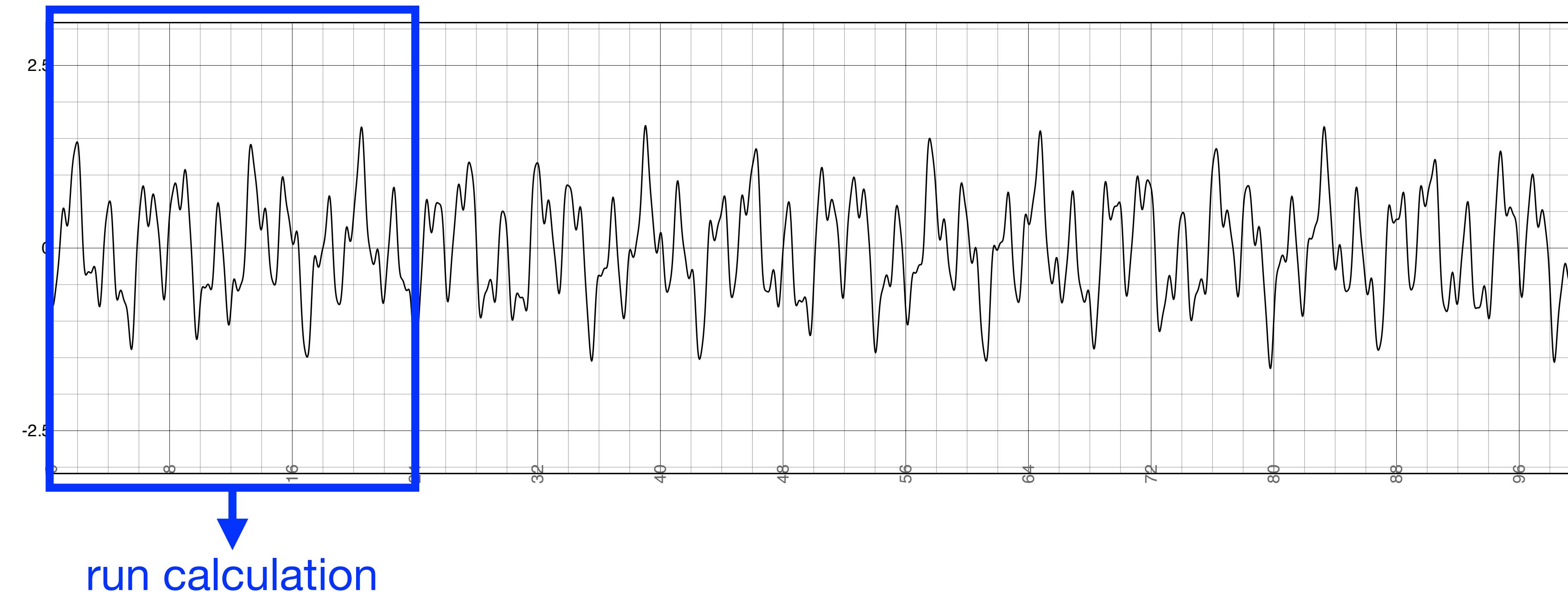
Bela Mini Starter Kit

Also needed for
this lecture:



Block-based processing

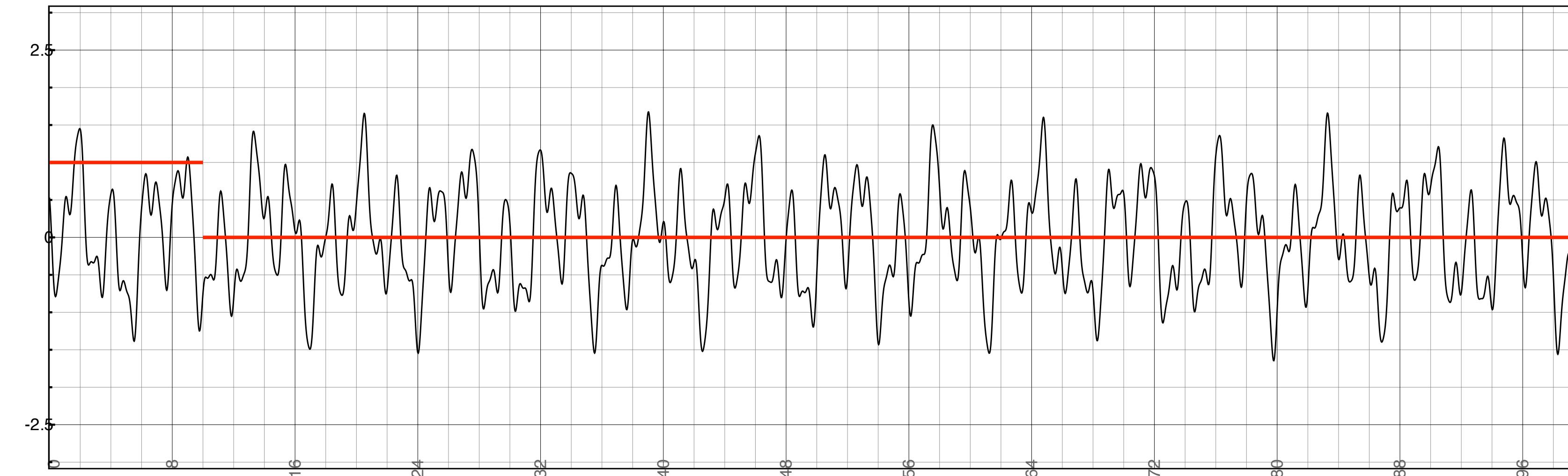
- Sometimes audio calculations need to run on a **block** of samples simultaneously
 - For example: wait until 512 samples arrive, then do something with **all of them at once**



- Compare this to filters, where we calculate a new output **every sample**
 - With block-based processing, we typically run the calculation **periodically**, not every sample

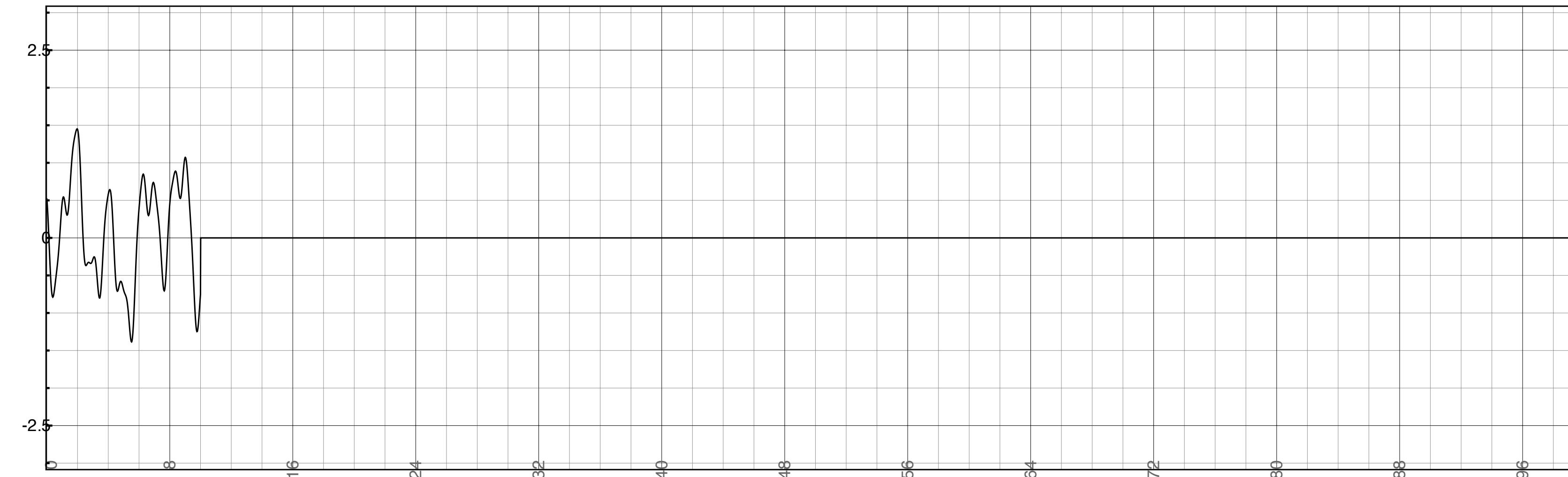
Block-based processing

- Block-based processing is **not** the same as **non-realtime** processing
 - We are not trying to run a calculation on the **whole signal** all at once
- Instead, we want to work with **finite segments** of the input signal
- How do we generate a block? Apply a **window** to the signal
 - Multiply by a function that's **nonzero for a fixed length M samples**
 - Window might have a shape: rectangular, triangular (Bartlett), Hamming, Blackman, etc.



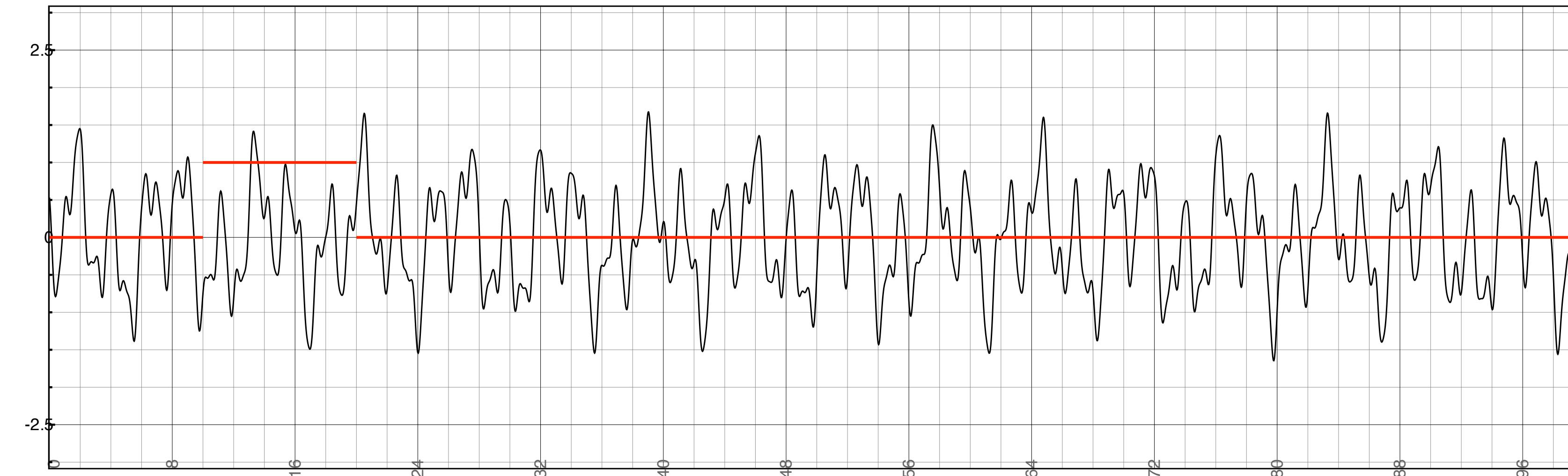
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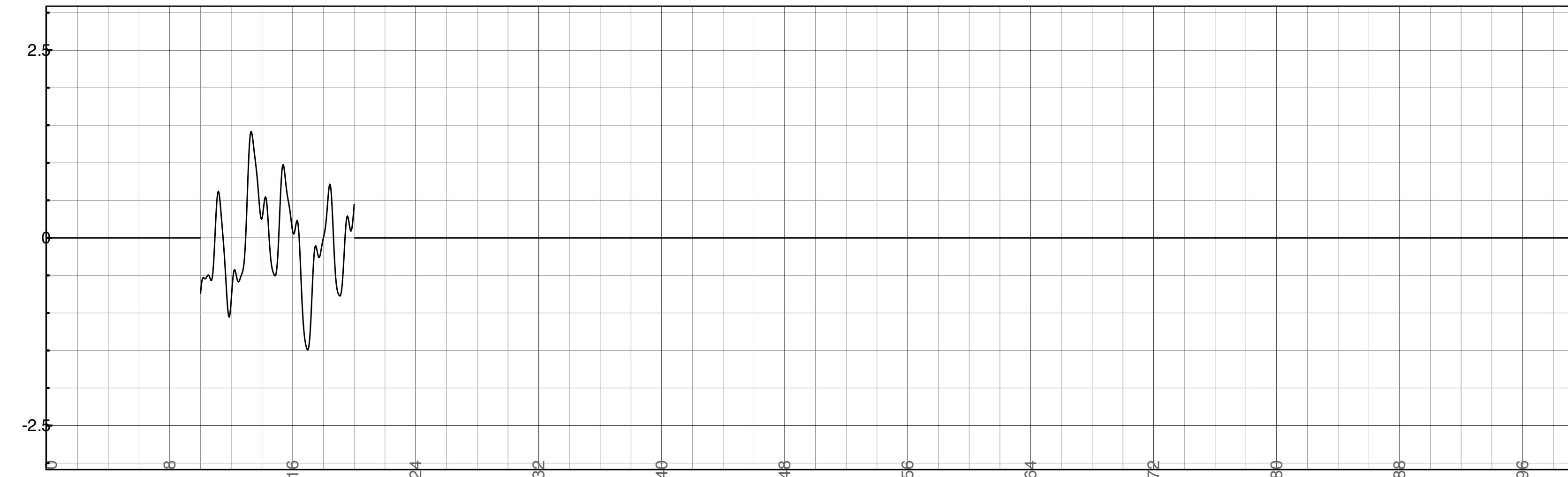
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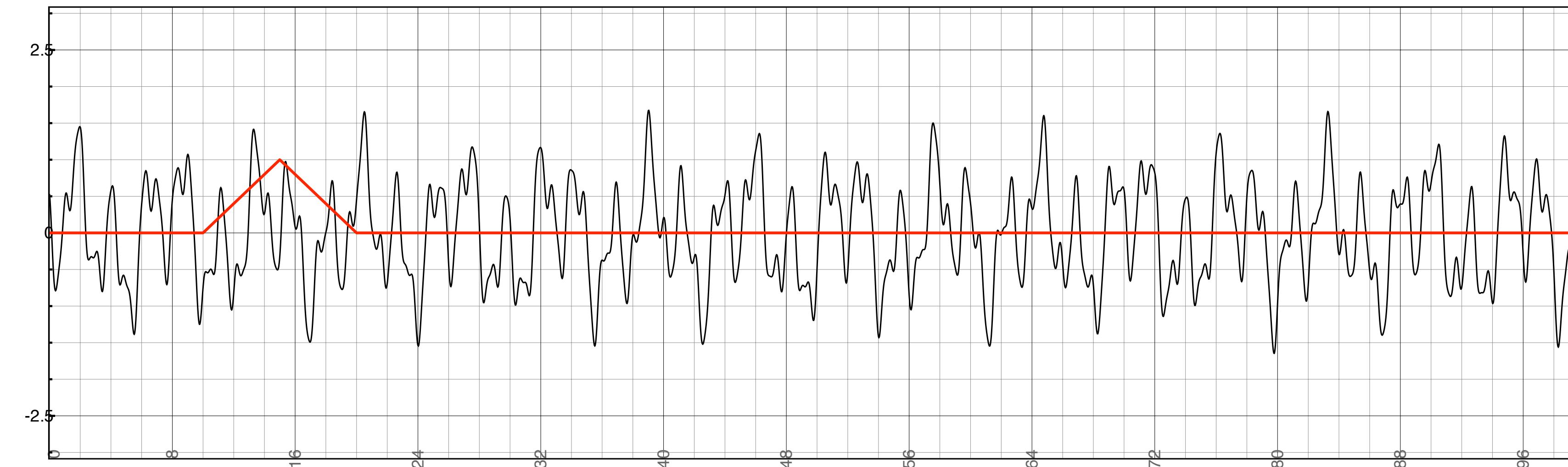
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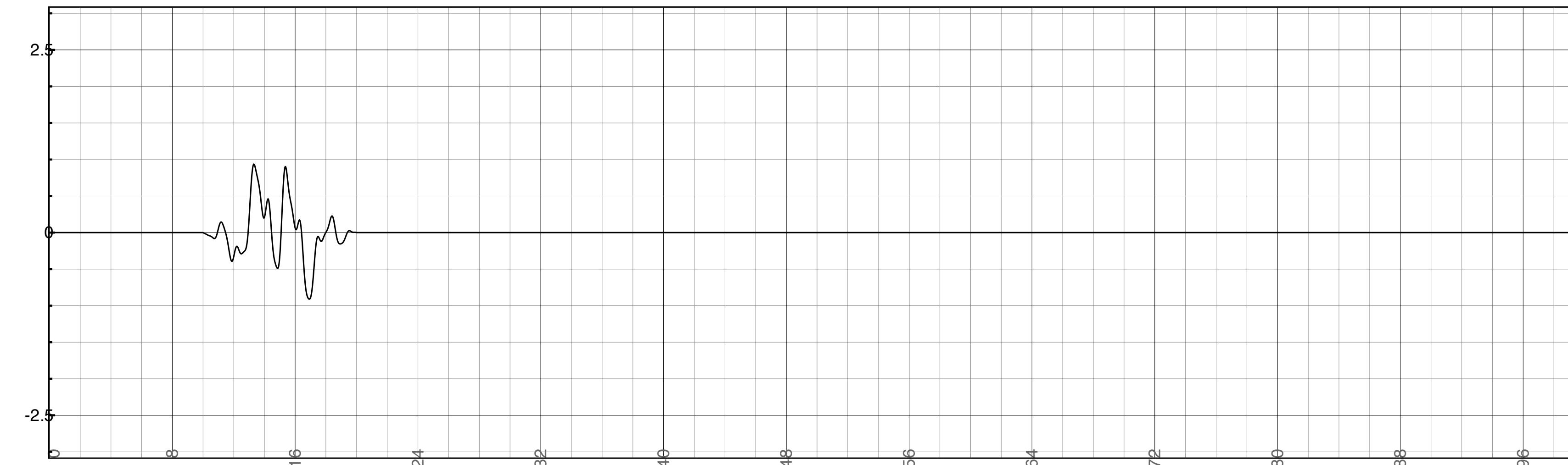
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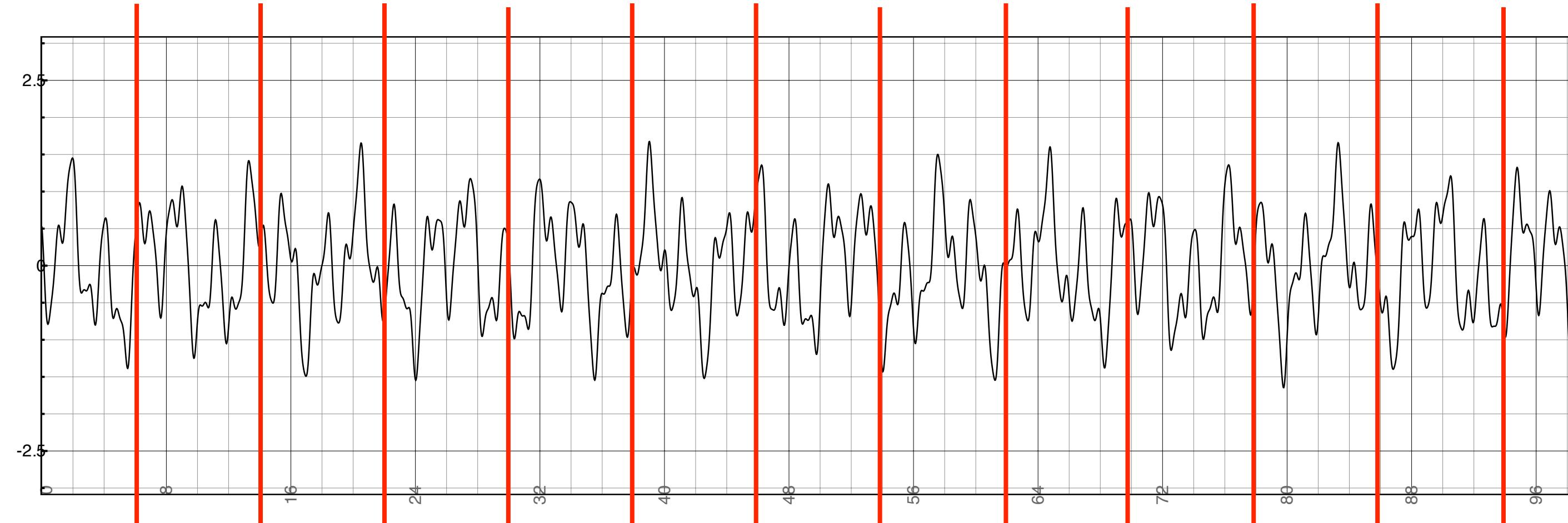
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Windowing a signal

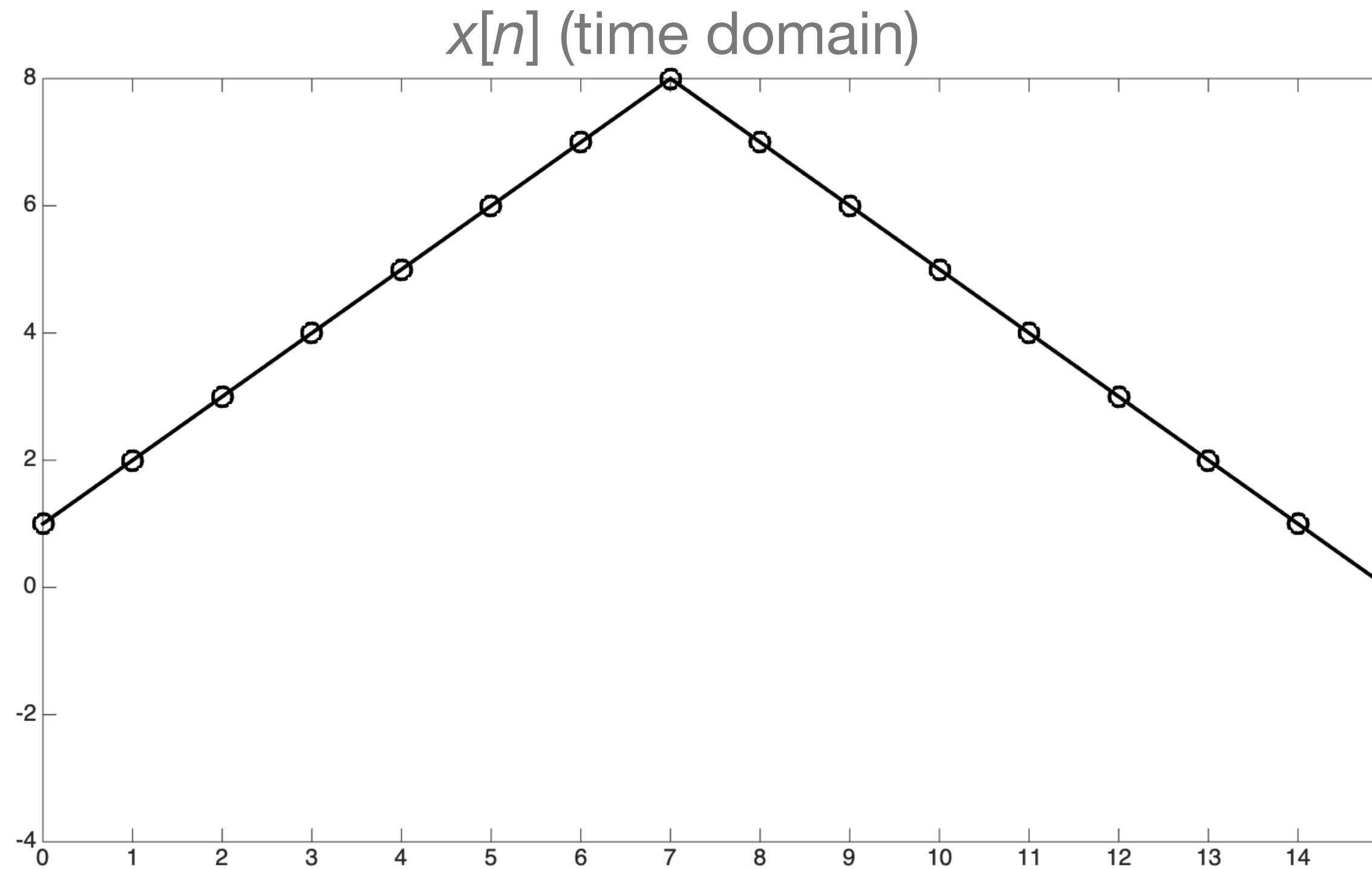
- Any arbitrarily-long signal can be divided into successive windows
 - This segmentation can be done in real time, as the signal comes in



- In the right circumstances, we can use the windows to reconstruct the signal
 - Need **window functions** to overlap so that they all add to a **constant value**
 - **Constant Overlap-Add (COLA) criterion**: we'll come back to this later
- We call this segmentation and reconstruction **block-based processing**
 - We work on an entire **window** (or **block**) of samples at once

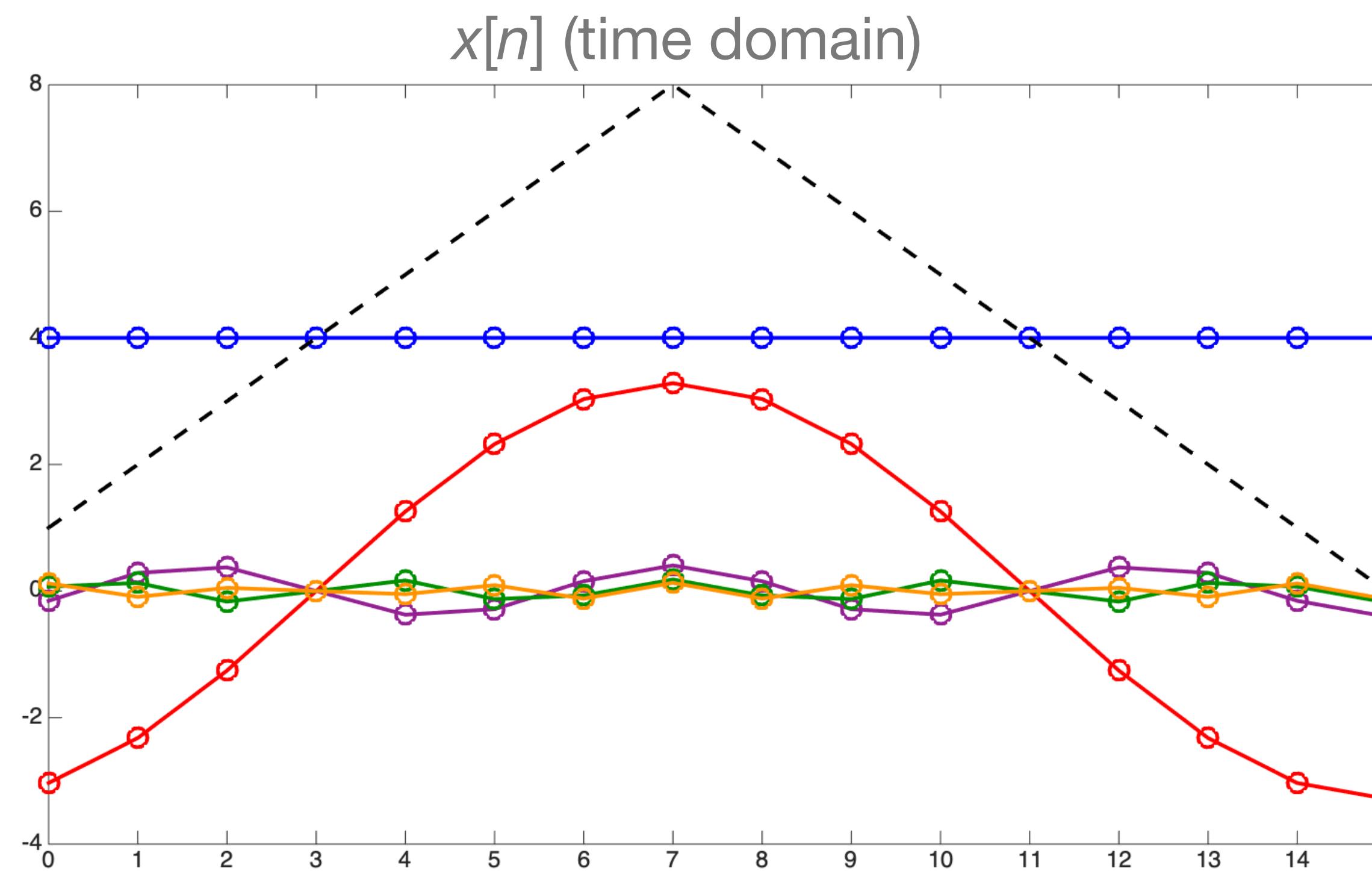
The Fast Fourier Transform

- Most common use of block-based processing: the **Fast Fourier Transform (FFT)**
 - Efficient computational algorithm for calculating the **Discrete Fourier Transform (DFT)**
 - The DFT is a mathematical formula for calculating the **frequency content** of a signal
- Any discrete-time signal of N points can be expressed as the **sum of N sinusoids**:



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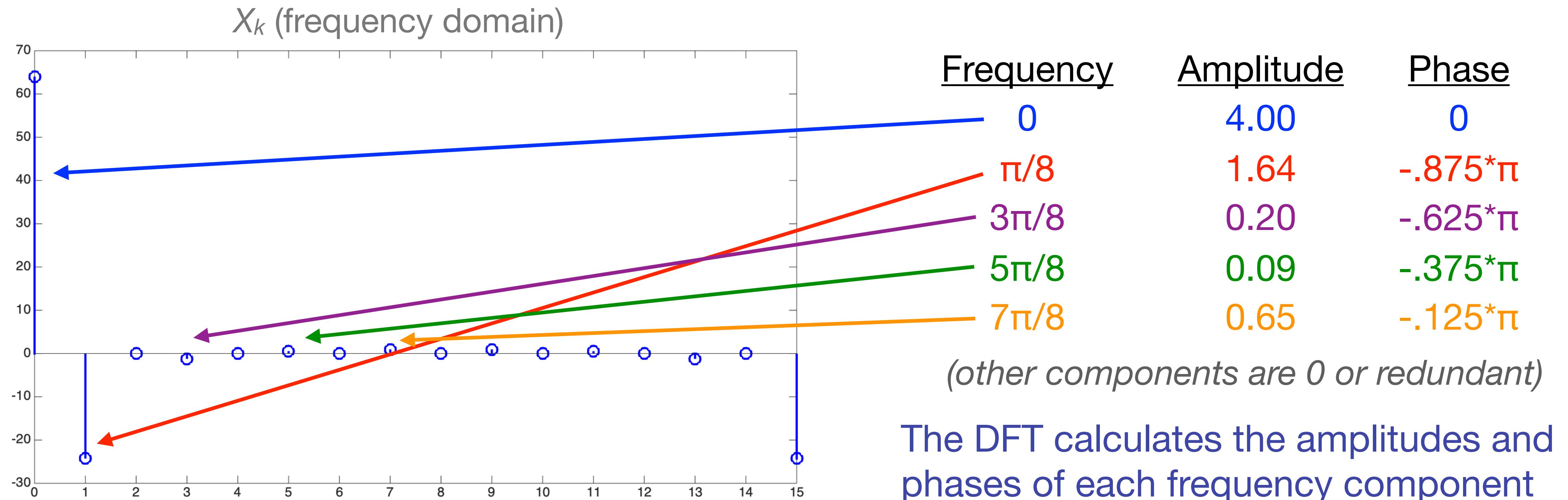


<u>Frequency</u>	<u>Amplitude</u>	<u>Phase</u>
0	4.00	0
$\pi/8$	1.64	$-.875\pi$
$3\pi/8$	0.20	$-.625\pi$
$5\pi/8$	0.09	$-.375\pi$
$7\pi/8$	0.65	$-.125\pi$

(other components are 0 or redundant)

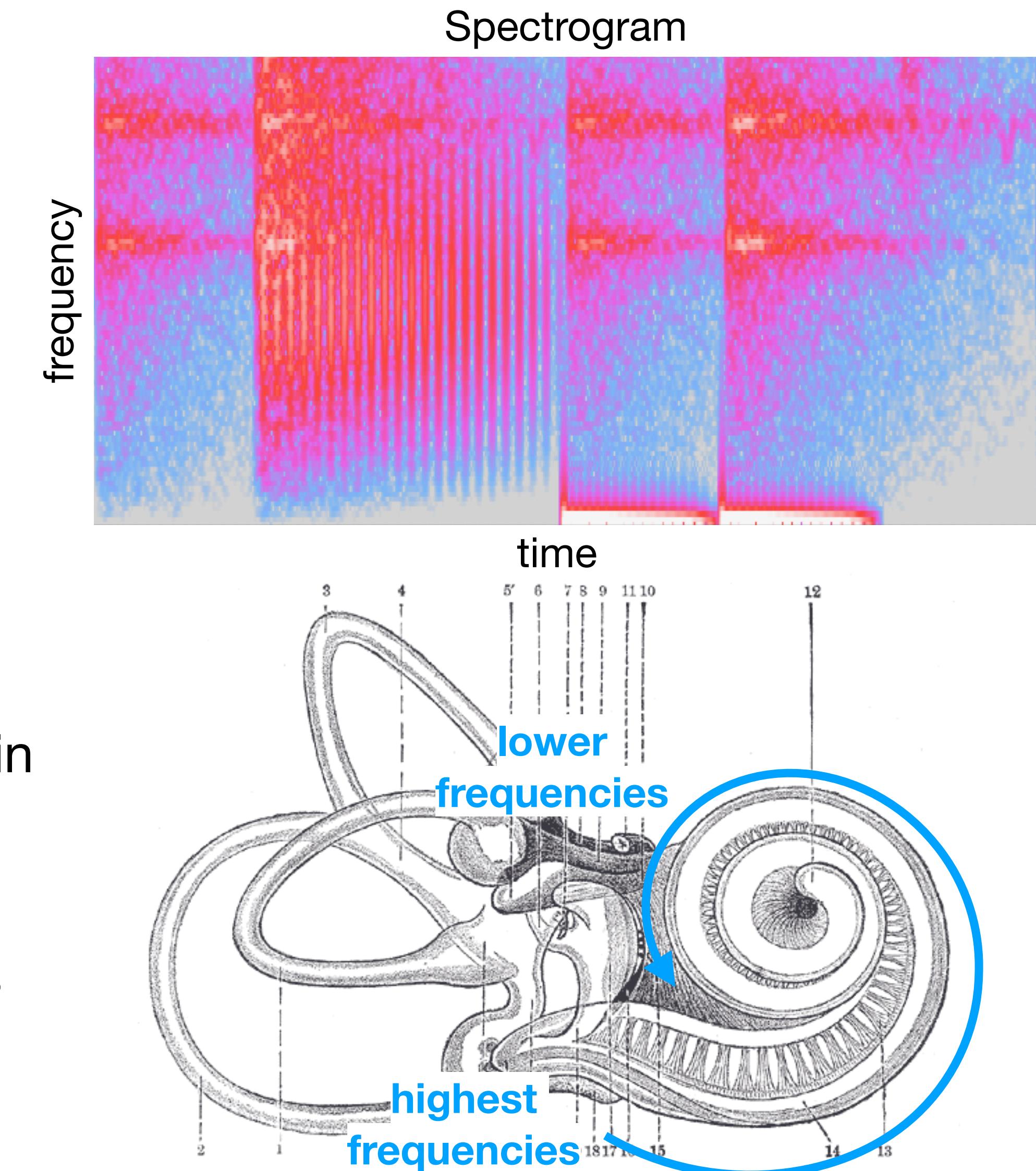
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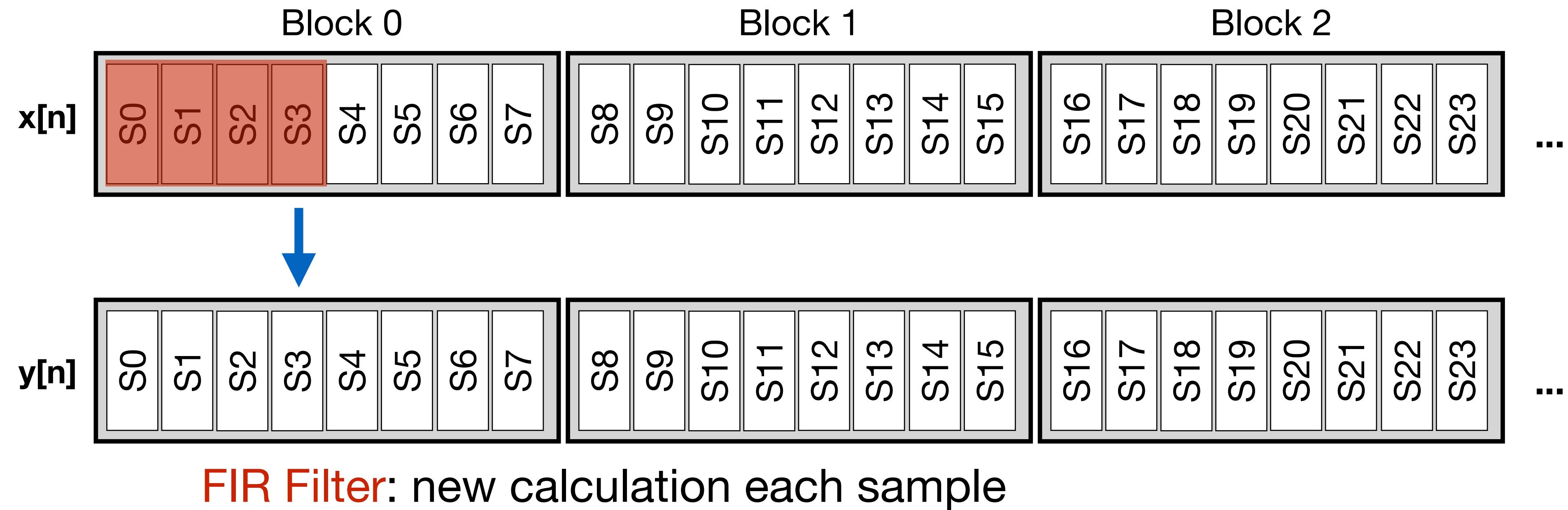


Why do we care about the FFT?

- The FFT has transformed digital signal processing, including for audio
- Application 1: audio analysis
 - Calculate the **spectrum** of a signal (magnitude vs. frequency)
 - Or the **spectrogram** (how the spectrum changes over time)
 - Can extract higher-level audio features from the FFT
 - This is the basis of the field of **music informatics**
- Application 2: sonic transformation and resynthesis
 - Many useful audio effects are done in the frequency domain
 - Pitch shifting, denoising, cross-synthesis, ...
 - These are known as **phase vocoder** effects
- Interesting aside: the human **cochlea** (inner ear) acts like a kind of biological Fourier transform
 - Each location is sensitive to a different frequency

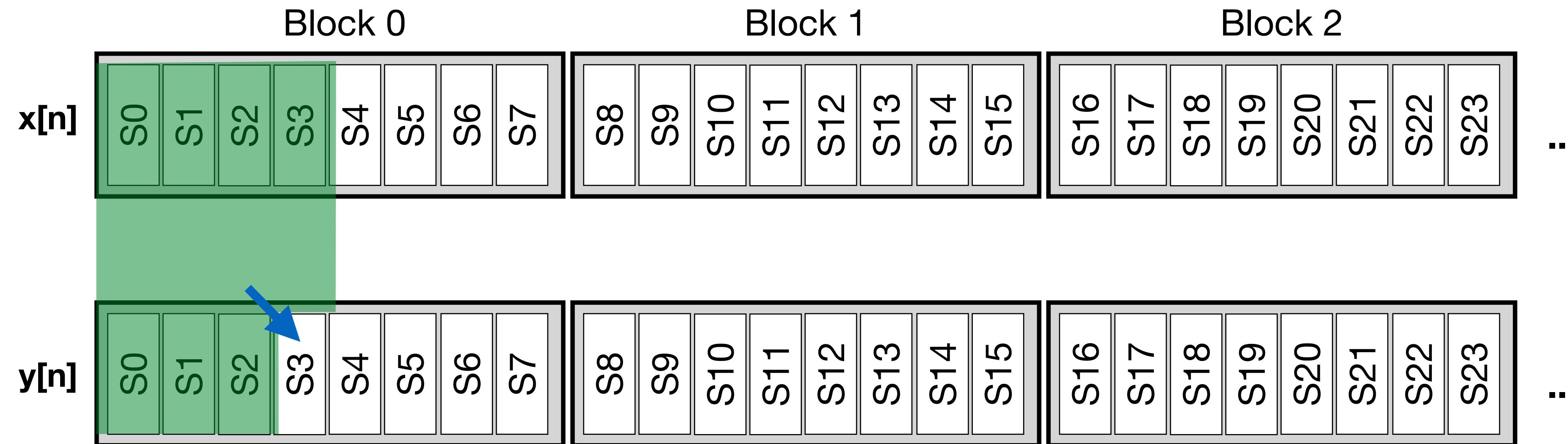


Filters vs. block-based processing



- **Important:** Window size is not necessarily the system audio buffer size!
 - Might need multiple calls to `render()` to fill a single window
 - Or window might fill up in the middle of `render()`

Filters vs. block-based processing

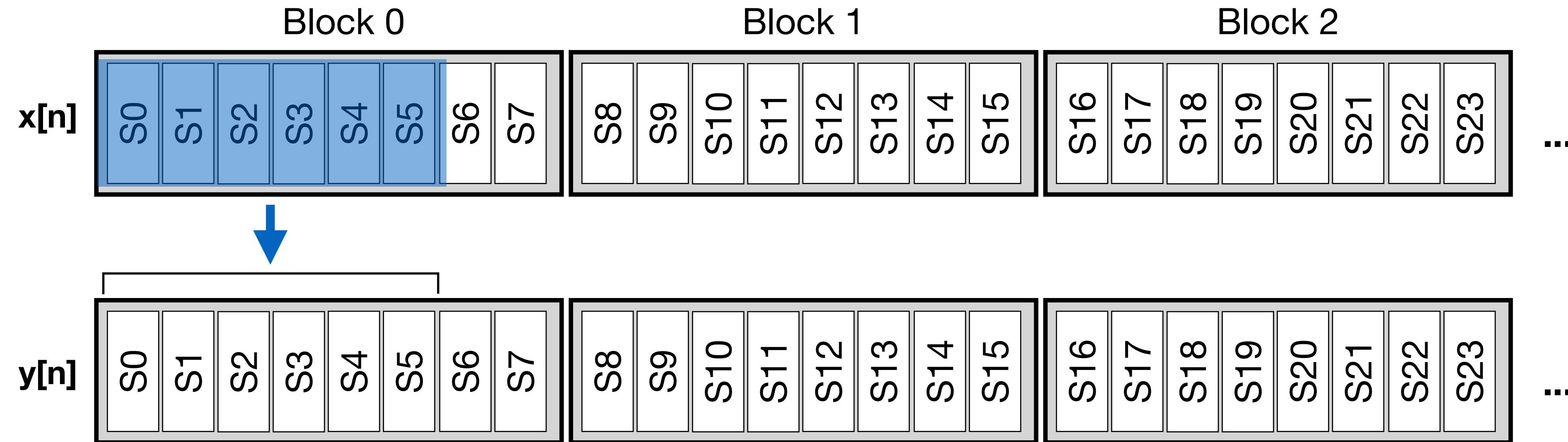


FIR Filter: new calculation each sample

IIR Filter: new calculation each sample

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Filters vs. block-based processing



FIR Filter: new calculation each sample

IIR Filter: new calculation each sample

DFT: calculation once per block*

*note: size of DFT may be different than interval between calculations

- **Important:** Window size is not necessarily the system audio buffer size!
 - Might need multiple calls to `render()` to fill a single window
 - Or window might fill up in the middle of `render()`

Real-time windowing for the FFT

- We need a full **window** (i.e. block) of samples at once to pass to the FFT
- Suppose that we have a **window size** of N samples
- To handle FFT processing in real time:
 1. In our initialisation code, create a **buffer** (array) of type **float**, size N
 - If we have multiple audio channels, we'll need one buffer per channel
 2. In **render()**, as we process samples, **store them in buffer** and **keep count**
 - We need a global variable to keep track of how many samples are in the buffer
 3. When the buffer is full:
 - Multiply the contents of the buffer by the **window function** (if window is not rectangular)
 - Perform an **FFT** on the result
 - Handle any necessary processing in the frequency domain
 4. After the processing is complete, **reset the counter to 0** to start filling the next window

Block-based input

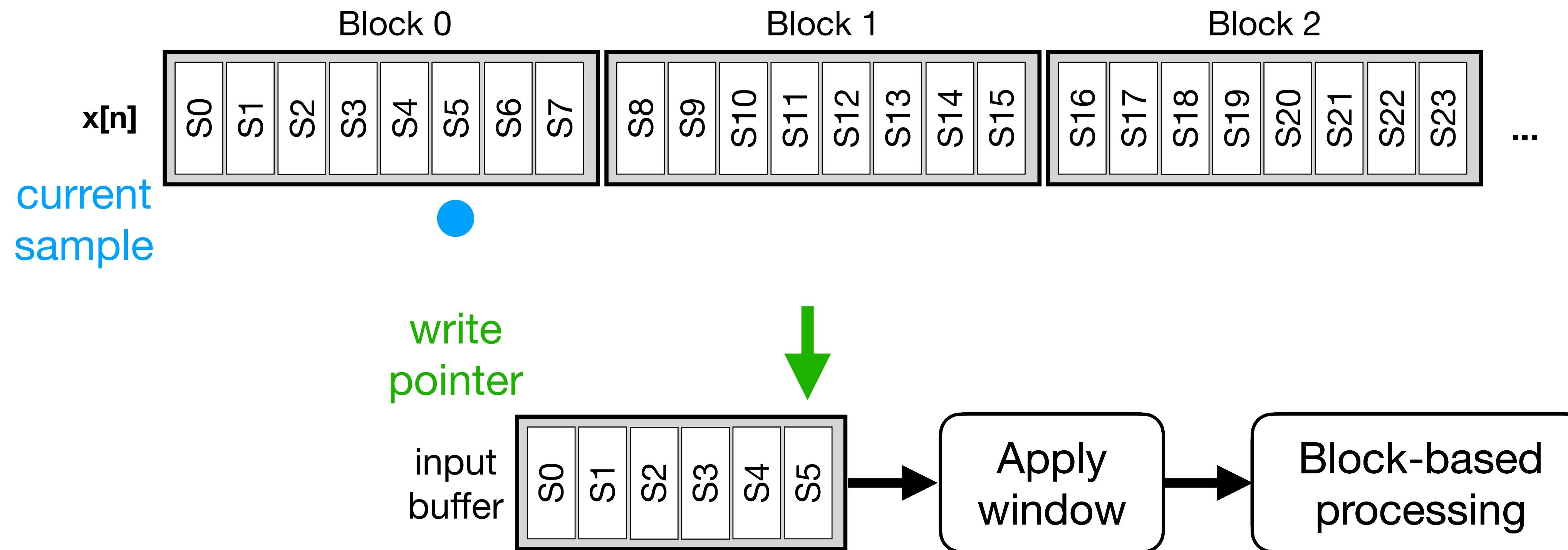
- Again: **window size is not necessarily the system buffer size**
 - Therefore, we cannot just pass the raw audio buffer inside `BelaContext` to the FFT!
- Instead, we need:
 - Separate **buffer** to hold incoming samples
 - Counter or **write pointer** to keep track of how full the buffer is
 - Even though we're processing in discrete blocks, all the code still needs to go inside the `for()` loop in `render()`

```
float gWindowBuffer[BUFFER_SIZE]; // Buffer for 1 window of samples
int gWindowBufferPointer = 0;      // Tells us how many samples in buffer

void render(BelaContext *context, void *userData) {
    // Important: nothing goes here; everything in the loop!

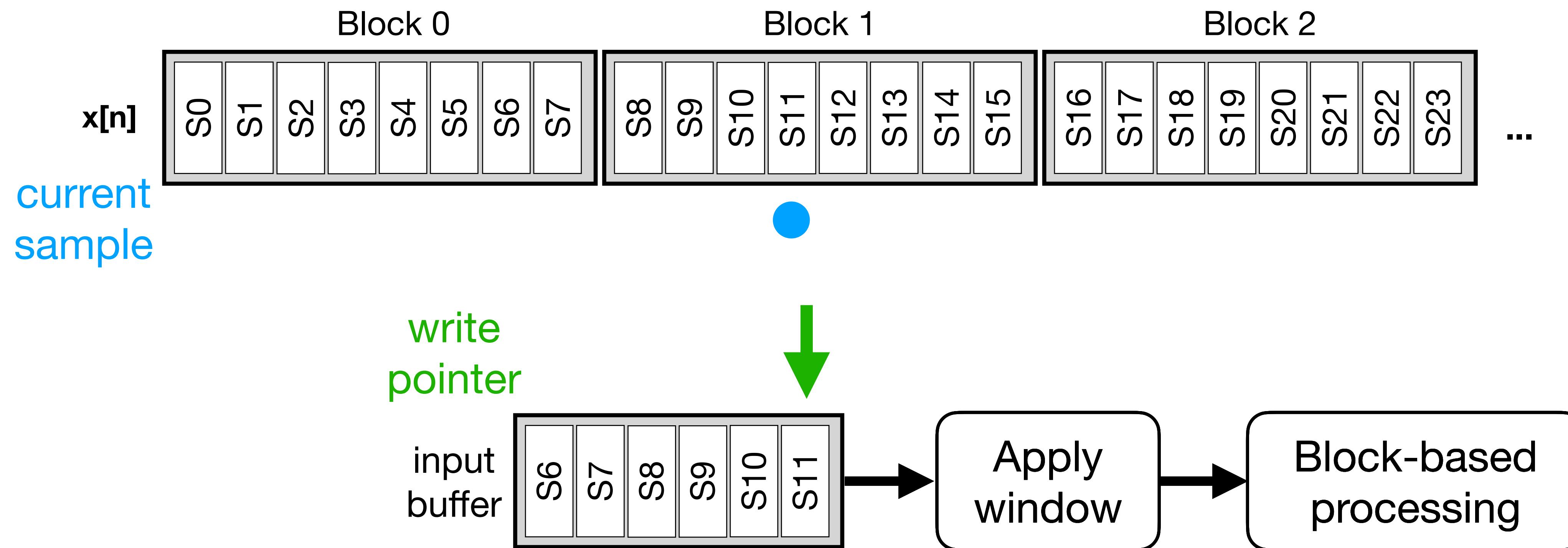
    for(int n = 0; n < context->audioFrames; n++) {
        // 1. Copy audio input into gWindowBuffer
        // 2. Increment gWindowBufferPointer
        // 3. Check if pointer has reached end of gWindowBuffer
        // 4. If yes, time to do the FFT and any other processing then reset pointer to 0
    }
}
```

Block-based input



- Start with a buffer of fixed size
 - Fill it up sample by sample
 - When it's full, apply the window function and pass it to the FFT (or other block based process)

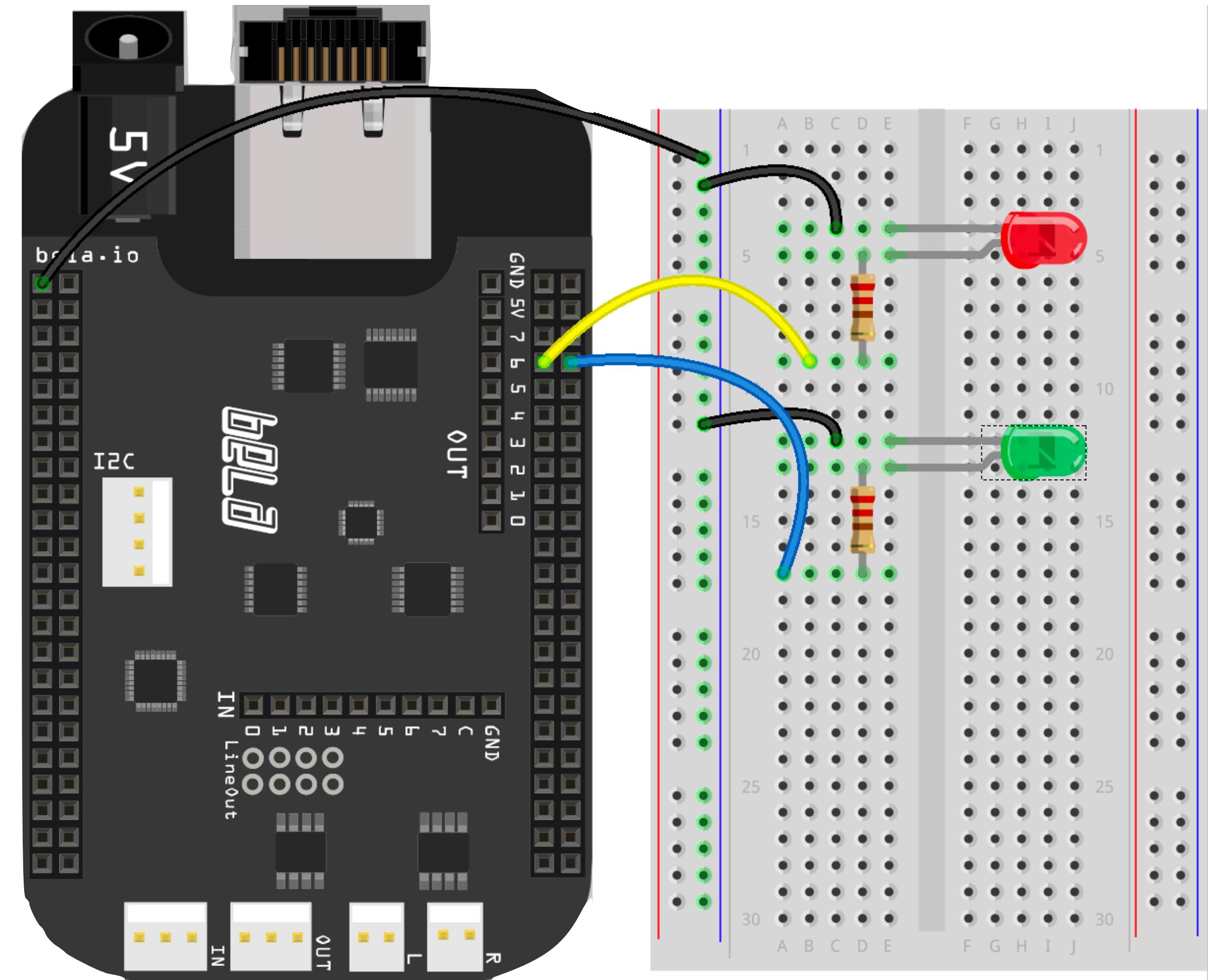
Block-based input



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Block-based processing task

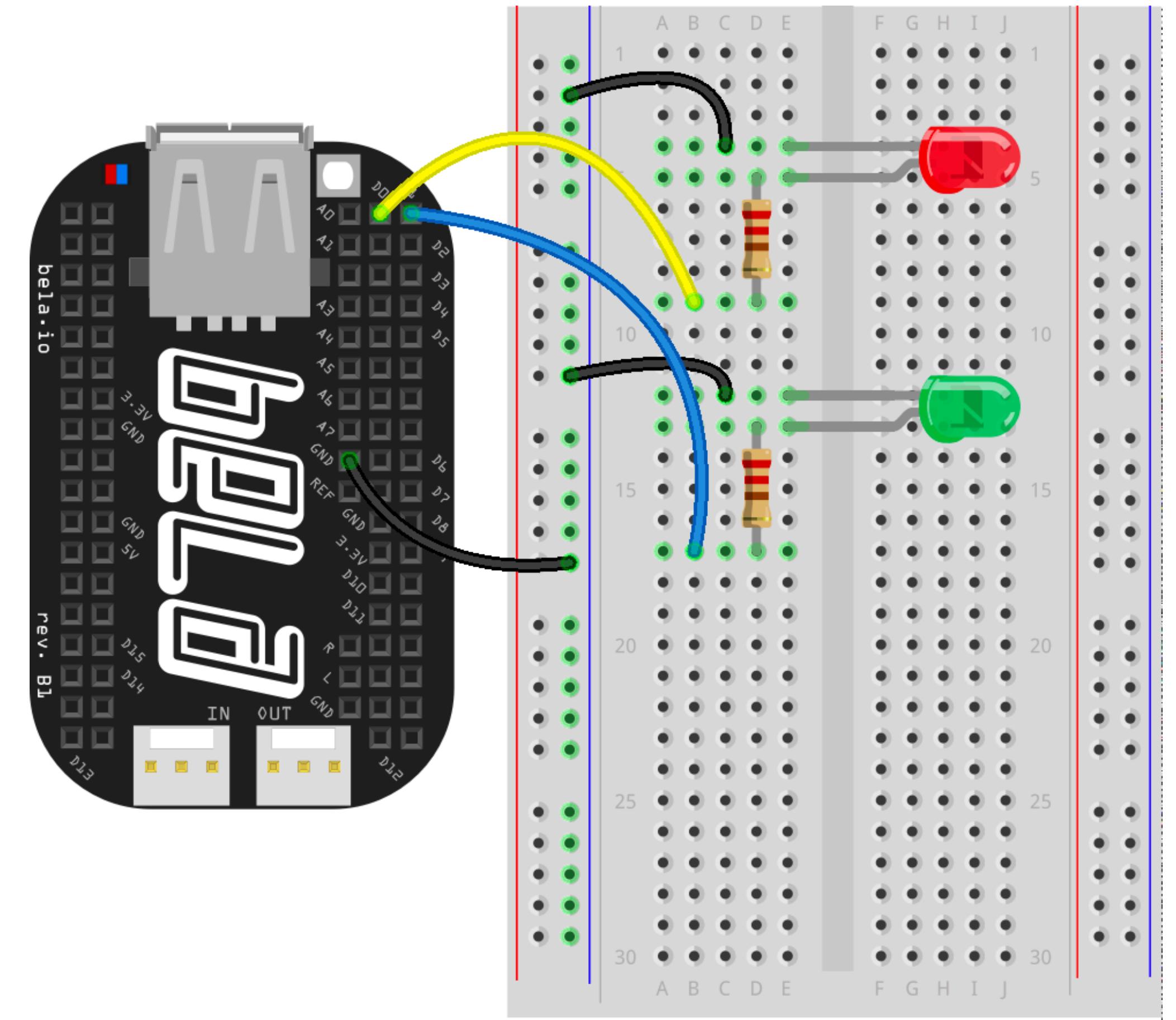
- Task: using [fft-led](#) project
 - Attach LEDs to digital outputs 0 and 1
 - Implement code to segment the incoming signal into [windows](#)
 - Rectangular windows are fine for now
(no window function needed)



fritzing

Block-based processing task

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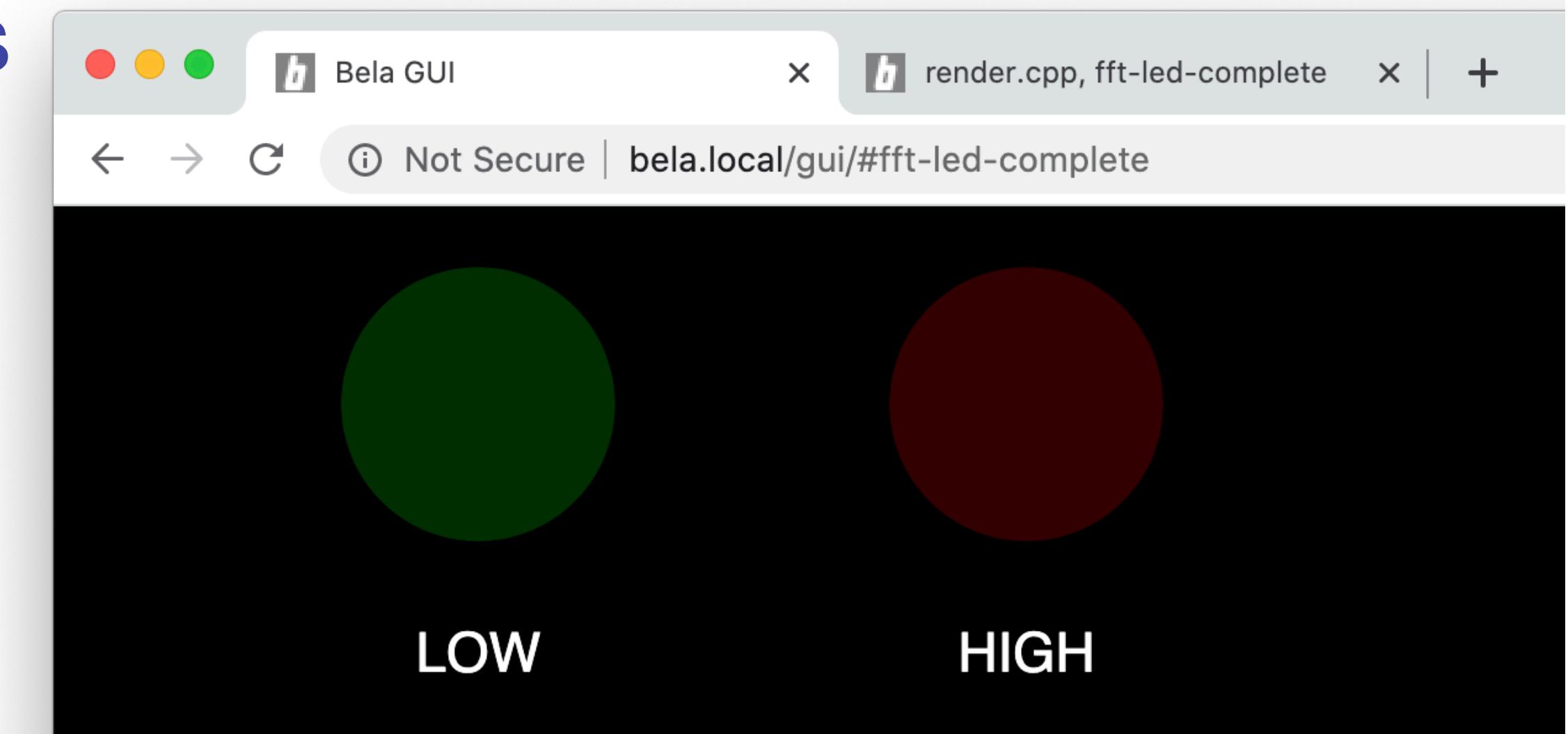
fritzing

Block-based processing task

- **Task:** using `fft-led` project
 - Attach LEDs to digital outputs 0 and 1
 - Implement code to segment the incoming signal into `windows`
 - Rectangular windows are fine for now (no window function needed)
- **Steps:**
 1. Declare a `buffer` of size `gFftSize` as a `global variable`
 - Could use either an array or a vector of type `float`
 2. Keep a `counter` (also global) to record how many samples have been put in the buffer
 - Can also use this as a `write pointer` into the buffer
 3. Each iteration of the `for()` loop in `render()`, store the current sample in the buffer
 - When the counter reaches `gFftSize`, call the function `process_fft()`
 4. When finished with `process_fft()`, reset the counter and start again

The Bela GUI library

- Bela projects can have a **GUI** that renders in the browser
 - The GUI is typically written in **p5.js** (but other frameworks can be used)
 - Data can be sent from the Bela program to the browser via a WebSocket connection
 - Can also send data the other way, to control a Bela program from the GUI



The simple GUI from the `fft-led` project

- How to communicate with a **p5.js** GUI from your Bela C++ code:

1. Include the GUI library:
`#include <libraries/Gui/Gui.h>`
2. Make an object of type Gui:
`Gui gLedGui;`
3. In `setup()`, initialise the Gui object: `gLedGui.setup(context->projectName);`
4. Use the `Gui::sendBuffer()` method to send data to the GUI

The Bela GUI library: communication

- Sending data from C++ on Bela to JavaScript in the browser:

render.cpp

```
// Update the Bela GUI at a 100Hz frame rate  
if(++gGuiUpdateCounter >= context->audioSampleRate/100) {  
    gGuiUpdateCounter = 0;  
  
    // Send low and high values in two slots of the buffer  
    gGuiBuffer[0] = gLedLoOutput;  
    gGuiBuffer[1] = gLedHiOutput;  
    if(gLedGui.isConnected()) {  
        gLedGui.sendBuffer(0, gGuiBuffer);  
    }  
}
```

limit the rate that we send to the GUI by **counting samples**

store all the data in a single buffer (here, array of float)

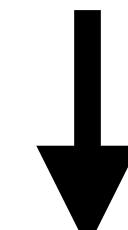
check if **GUI running**
first argument is **buffer number**
(allows multiple pieces of data)

second argument can be
any type, array or vector

this holds the **contents of**
gGuiBuffer on the C++ side
(because we sent it as
buffer number 0)

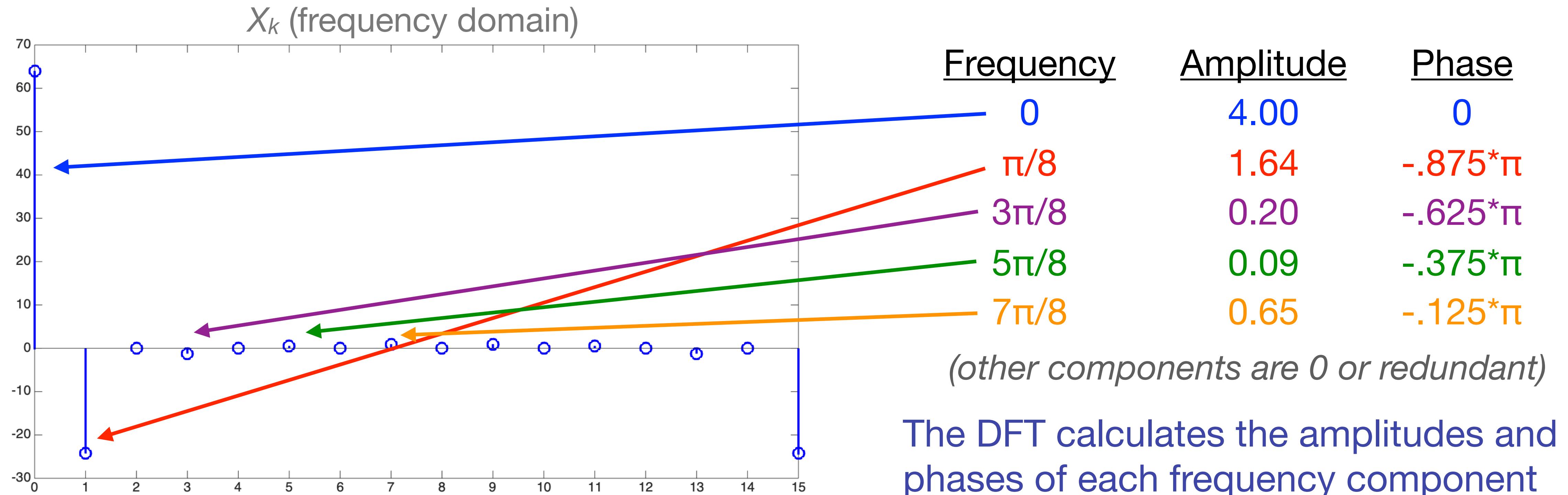
sketch.js

```
// Retrieve the data being sent from render.cpp  
let ledLow = Bela.data.buffers[0][0];  
let ledHigh = Bela.data.buffers[0][1];
```



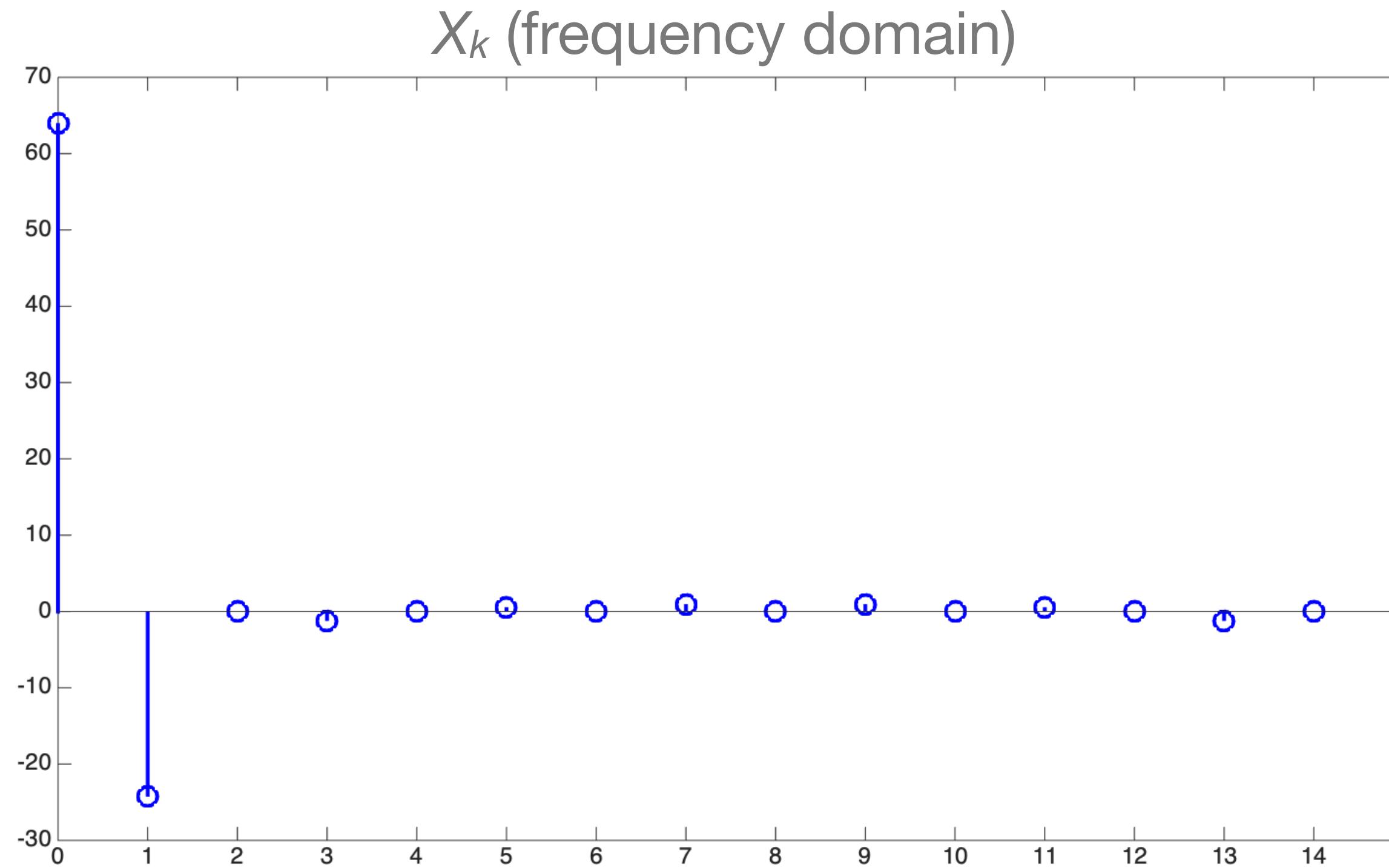
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The Discrete Fourier Transform

- The DFT calculates the **amplitudes** and **phases** of each sinusoidal component
 - The **frequencies** are linearly spaced between 0 and 2π : $\frac{2\pi k}{N}$ for $0 \leq k < N$
 - Each amplitude/phase measurement is called a **bin**
 - Collectively, the N bins are called the **frequency domain** representation of the signal

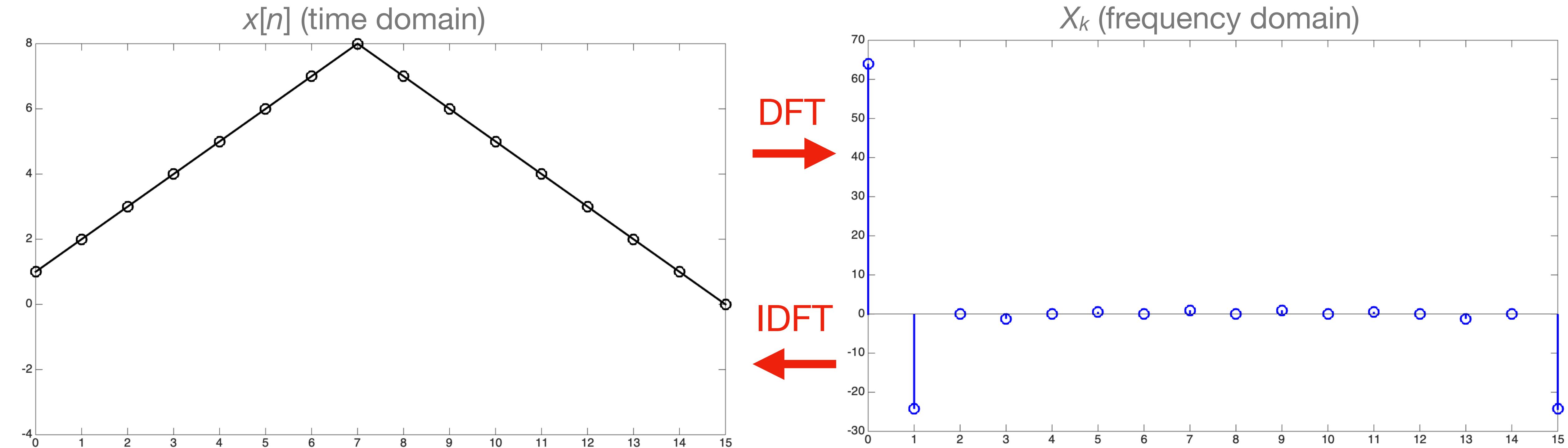


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The Discrete Fourier Transform

- Key point: N time samples $\leftrightarrow N$ frequency samples
 - Two different mathematical perspectives on the same signal
 - The Inverse Discrete Fourier Transform (IDFT) converts from frequency domain to time domain
 - The DFT+IDFT is an exact reconstruction as long as signal length $M \leq$ DFT length N



The Discrete Fourier Transform

- The mathematical basis of the Discrete Fourier Transform:

$$X_k = \sum_{n=0}^{N-1} x[n] e^{-j2\pi \frac{k}{N} n}$$

DFT (FFT) → the sum, for all values of n between 0 and $N-1$...

...of the signal $x[n]$ multiplied by...

...a complex exponential of frequency $2\pi k/N$

...where k is the bin number

time domain → frequency domain

- N is the size of the DFT
 - ▶ For the FFT, N is almost always a power of 2 (the Cooley-Tukey algorithm)
- Each time sample $x[n]$ is a real number
- Each frequency bin X_k is a complex number: $a + bj$ where $j = \sqrt{-1}$
 - ▶ Magnitude of the bin is given by: $\sqrt{a^2 + b^2}$
 - We usually use magnitude to plot a spectrum or spectrogram of a signal
 - ▶ Phase of the bin is given by: $\arctan(b/a)$

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DFT (FFT)

$$X_k = \sum_{n=0}^{N-1} x[n] e^{-j2\pi \frac{k}{N} n}$$

time domain → frequency domain

IDFT (IFFT)

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X_k e^{+j2\pi \frac{k}{N} n}$$

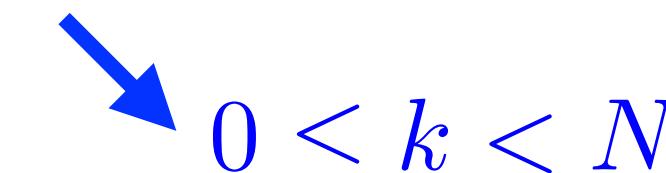
frequency domain → time domain

- N is the **size** of the DFT
 - ▶ For the FFT, N is almost always a **power of 2** (the Cooley-Tukey algorithm)
- Each time sample $x[n]$ is a **real** number
- Each frequency bin X_k is a **complex** number: $a + bj$ where $j = \sqrt{-1}$
 - ▶ **Magnitude** of the bin is given by: $\sqrt{a^2 + b^2}$
 - We usually use magnitude to plot a spectrum or spectrogram of a signal
 - ▶ **Phase** of the bin is given by: $\arctan(b/a)$

The Discrete Fourier Transform

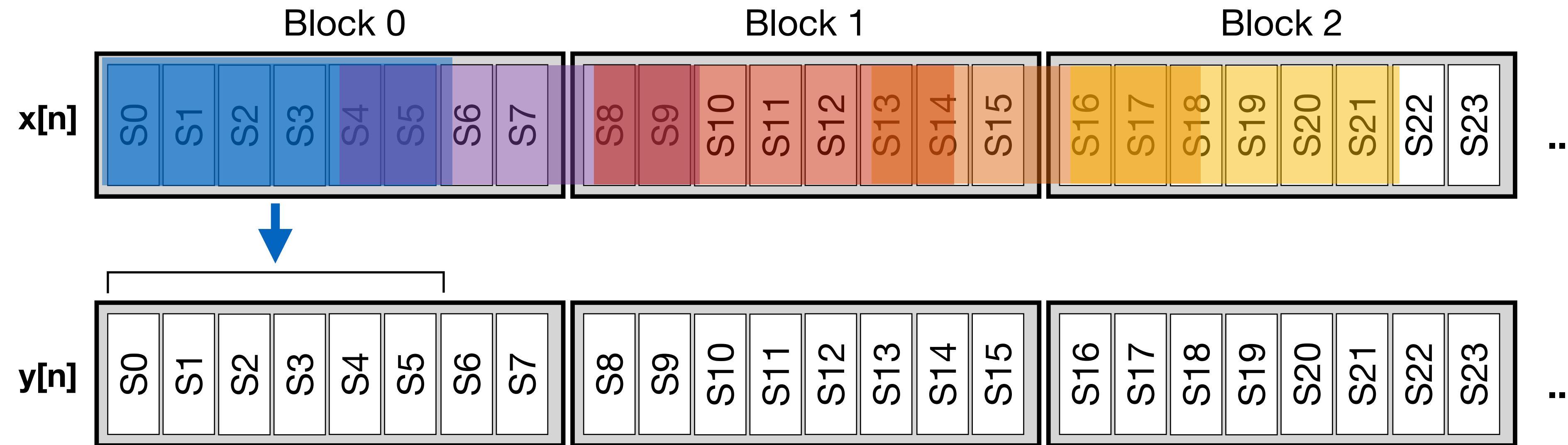
- Frequency bins are **equally spaced** between 0 and 2π :
 - Where, for sampled analog signals, 2π corresponds to the sample rate

$$X_k = \sum_{n=0}^{N-1} x[n] e^{-j2\pi \frac{k}{N} n} \quad x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X_k e^{+j2\pi \frac{k}{N} n}$$


 $0 \leq k < N$

- **But wait!** Doesn't a frequency of π represent the **Nyquist rate**?
 - Why are there bins with frequency higher than π ?
- The higher bins don't contain any unique information in our case:
 - The DFT works generally with complex signals, but **audio signals are always real-valued**
 - With a real signal, the frequency bins are **conjugate symmetric**: $X_k = X_{N-k}^*$
- Therefore, we only care about bins $0 \leq k \leq N/2$
 - This is why you'll see audio spectrum plots stop at the Nyquist frequency

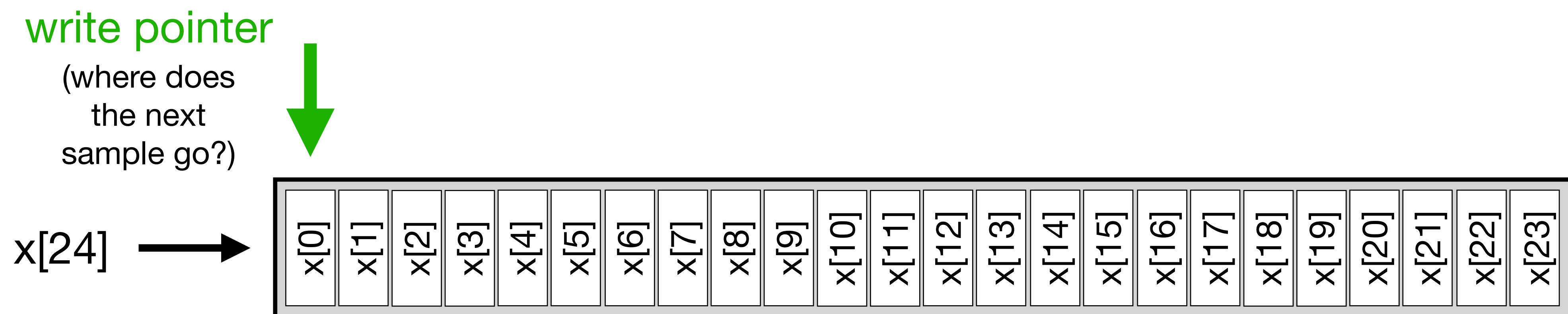
Overlapping blocks in real time



- As we'll see next lecture, we often want to work with **overlapping** blocks
 - This means block k shares some samples with block $k-1$
 - How do we adapt our windowing code to handle this?
- Easiest approach: keep a **running history** of the input samples
 - i.e. a buffer which always has the last M samples
 - What kind of structure have seen that does this? **Circular buffer**
 - At each **hop**, pass M samples from circular buffer to FFT

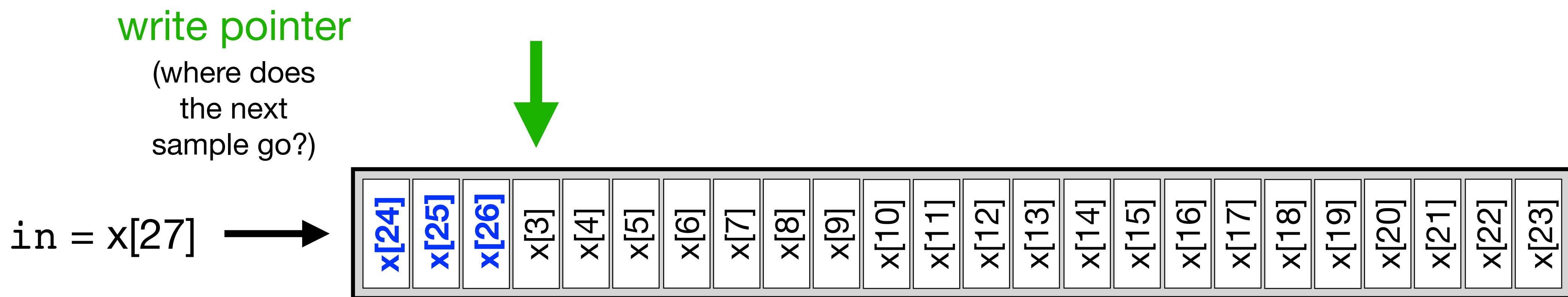
Review: circular buffering

- A **circular buffer** is a memory buffer (**array**) that acts like a loop
 - Write each new sample in the next location, from beginning to end
 - When we get to the end, go back to the beginning again
 - Keep track of the **write pointer**, which tells us which slot we write to next
- The buffer always ends up holding the N most recent samples
 - We just need to keep track of which sample is held where



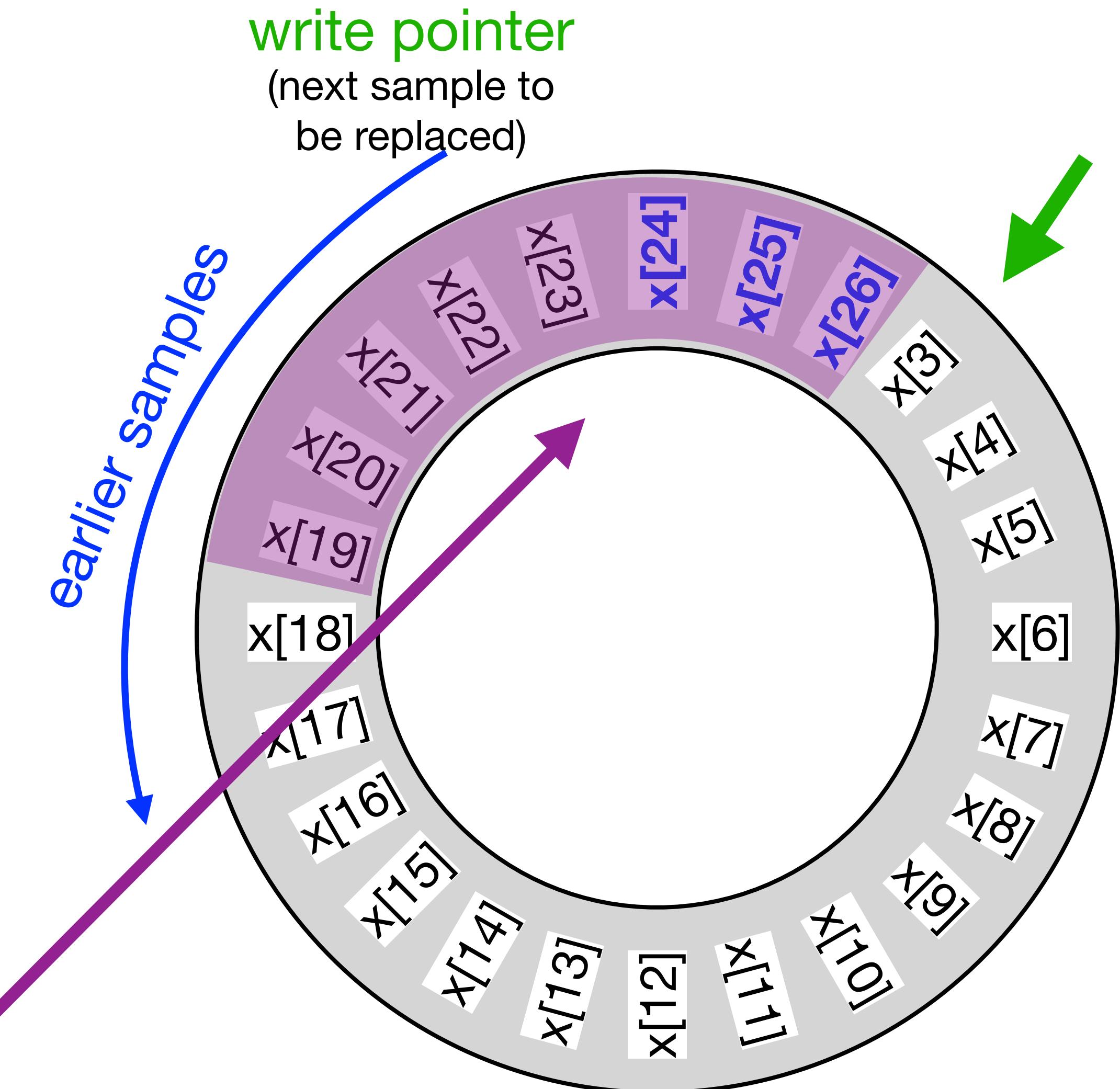
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Circular buffering and windowing

- Another equivalent view:
- The **write pointer** tells us where to find the **front** of the buffer
 - ▶ Points just past the most recent sample
 - i.e. it's the **oldest** sample in the buffer until it's replaced
 - ▶ To find earlier samples, look backward from the write pointer
- At any given time:
 - ▶ The buffer holds the **N** most recent samples
 - ▶ **Each individual sample never moves** until it is eventually replaced
 - ▶ As long as our buffer is big enough, **we can always get the latest window** of the signal



Circular buffer write pointer

- The circular buffer has two components:
 1. A **region in memory** (array) to store the samples
 2. A **write pointer** to keep track of where we are
- Remember, there is **no functional beginning or end** to a circular buffer!
- In code, we need to declare two (global) variables:

```
float gLastSamples[gBufferSize] = {0};  
int gWritePointer = 0;
```

- ▶ When we have a new sample, **store it** at the write pointer, then **increment** the pointer

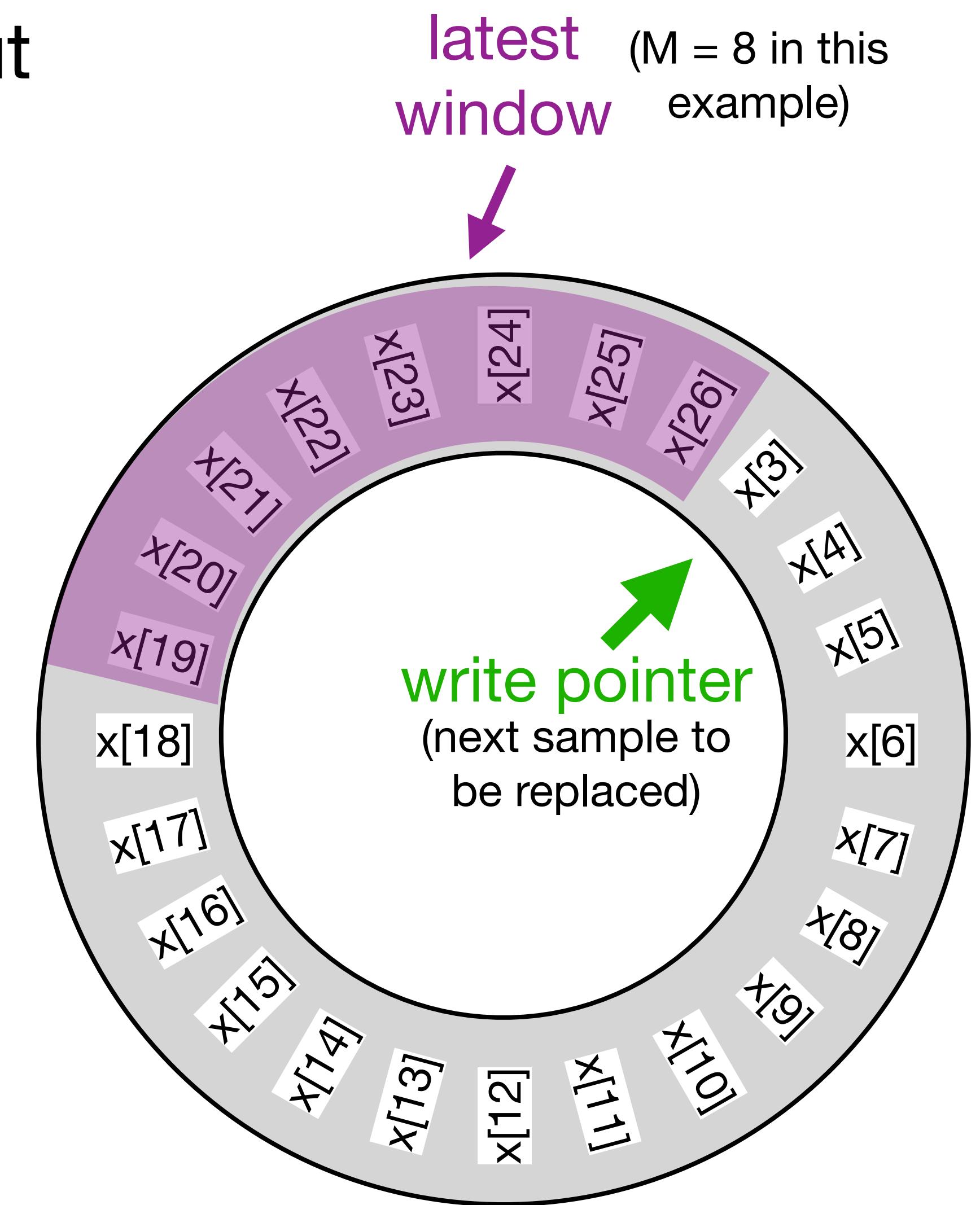
```
gLastSamples[gWritePointer] = in;  
gWritePointer++;
```
- ▶ What else do we need to do?
 - Keep the write pointer in range

```
if(gWritePointer >= gBufferSize)  
    gWritePointer = 0;
```

Overlap-add with a circular buffer

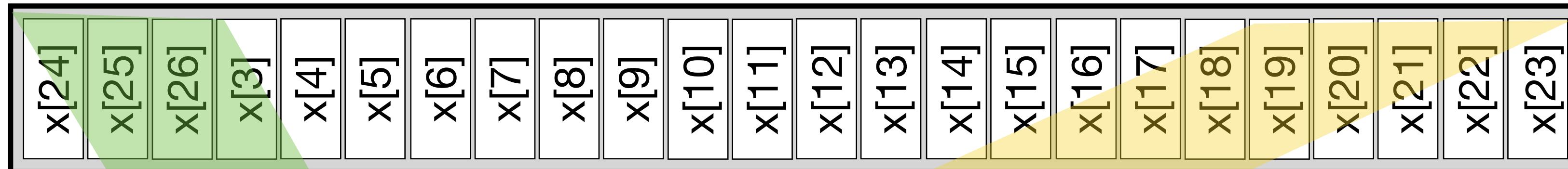
- We use a **circular buffer** to keep track of the input
- Necessary characteristics:
 - The buffer always holds (at least) the **last M input samples** (where M is the **window size**)
 - If using multiple channels, one buffer per channel
- Using the circular buffer:
 - Each iteration of the `for()` loop:
 - store input in buffer
 - increment the **write pointer** (wrapping as necessary)
 - increment the **total count** of samples stored
 - When the count reaches the hop size:
 - take one window from buffer, **unwrap it**, and pass it to FFT
 - in other words: **copy it to a new buffer** such that the oldest sample appears at index 0 of the new buffer

Important: this
is not the same as
when the write
pointer wraps around!



Unwrapping the circular buffer

How the circular buffer is actually stored in memory:

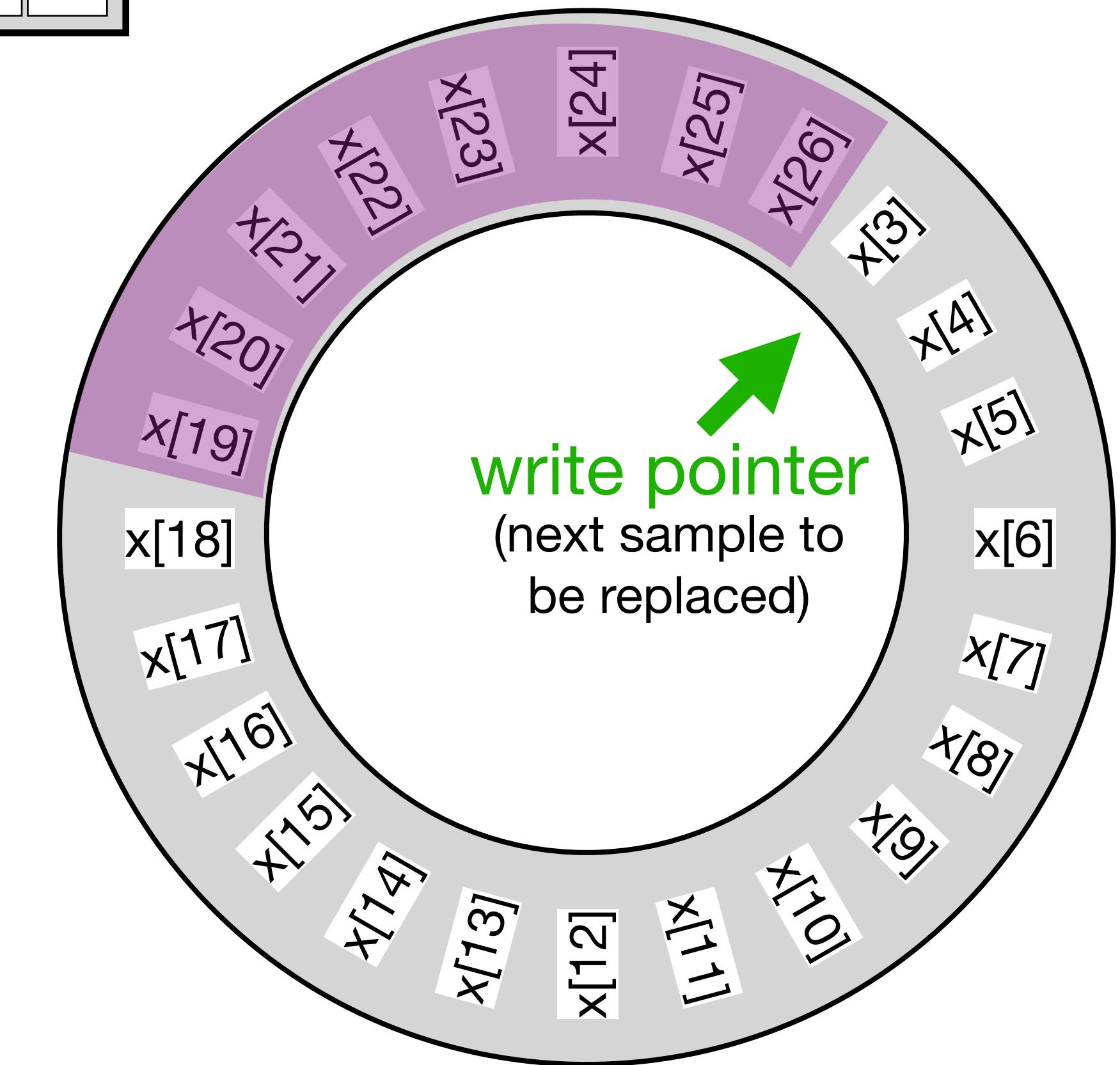


What we need to calculate the FFT (the latest 8 samples):



In other words: having assembled the samples into a circular buffer, **on each hop** it is helpful to **copy** them into a **linear** (standard) **buffer** to pass to the FFT library

latest window
($M = 8$ in this example)

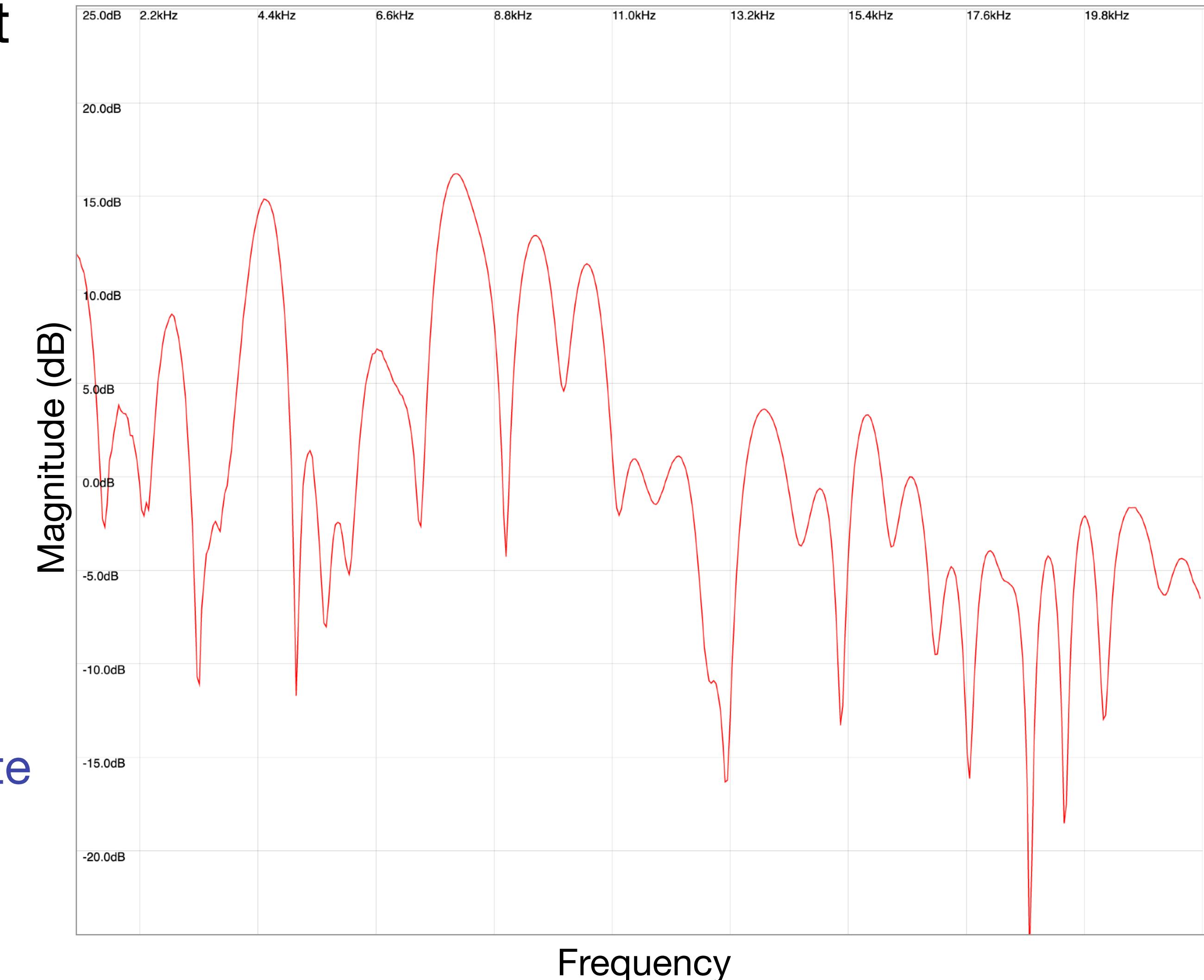


Block-based processing: input summary

- Block-based processes are calculated at **regular intervals**, not every frame
 - Unlike filters, where the output is updated every frame
 - The block-based calculation typically involves a recent window of the signal
- Two relevant quantities:
 - **Window size** (block size): how long of a segment of the signal is used in the calculation?
 - **Hop size**: at what interval is the calculation performed?
 - The hop size will typically be no larger than the window size, and is commonly a fraction of window size
 - **Neither of these quantities is the same as the real-time audio system buffer size!**
 - Your block-based code should work identically regardless of audio buffer size
- We can use a **circular buffer** to keep track of a recent window of samples
 - Needs the usual **array** and **write pointer**
- We also keep a **counter** of how many frames have elapsed
 - Different from the write pointer of the circular buffer
 - When the counter reaches the **hop size**, we perform a new calculation

Plotting the audio spectrum

- The **bins** of the DFT can be used to plot the **audio spectrum**
 - Frequency on the X axis, magnitude on the Y axis (remember, bins are complex)
 - The Y axis is usually logarithmic (**decibel scale**)
 - Sometimes the X axis is logarithmic too
- We only plot the **first half** of the bins
 - The higher bins are the mirror image of the lower ones (**conjugate symmetry**)
 - For an N-sample DFT, bin $N/2$ corresponds to a frequency of π , which is the **Nyquist rate**
- The spectrum is typically a **local snapshot**, based on a **window** of signal

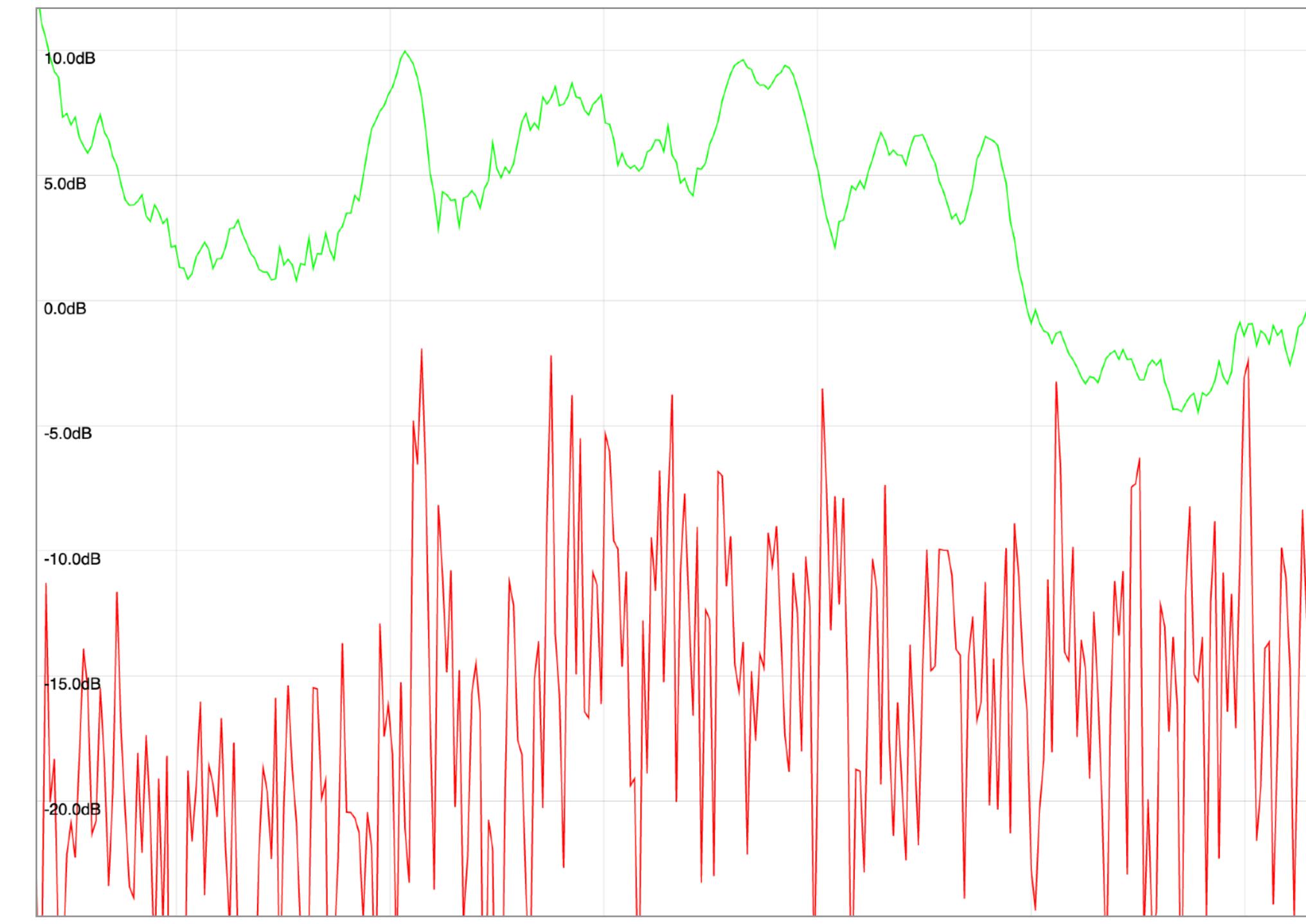


Circular buffer task

- **Task:** using `fft-circular-buffer` project (copying in `drumloop.wav`)
 - Implement the circular buffer in `render()`
 - See variables `gInputBuffer` and `gInputBufferPointer`
 - You still need both of these, and they work similarly to the last example, except...
 - `gInputBufferPointer` should not reset to 0 on each hop
(it should wrap around whenever it hits the end of the buffer)
 - You need to use the additional global variable `gHopCounter`
 - Use this to keep track of how many samples have gone by,
rather than using `gInputBufferPointer` to do this
 - When `gHopCounter` reaches the hop size, call `process_fft()` and reset the counter to 0
 - Implement the circular buffer in `render()`
 - **Unwrap** the buffer in `process_fft()`
 - See the code at the top of the function where the data is copied into the FFT data structure
 - Use modulo indexing here to copy the right samples

Peak detection

- **Task 2:** add **peak detection** to the plot
 - ▶ We'll calculate a second spectrum which stores the **most recent peak value** for each bin
 - ▶ Need to declare a persistent (**global or static**) array
 - This will remember the peak value for **each frequency bin**
 - Each hop, iterate through the bins:
if the current value is greater than the peak,
then update the peak
 - Multiply the peak by a **decay factor** (try 0.98) so the peaks decay over time
 - ▶ Send the peak spectrum to the GUI with **buffer ID 1**
- **Task 3:** also add **smoothing** to the peak spectrum
 - ▶ Calculate a **local average** of the nearest 11 bins (from bin $k-5$ to $k+5$)
 - ▶ Be careful not to run off the end of the array!



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