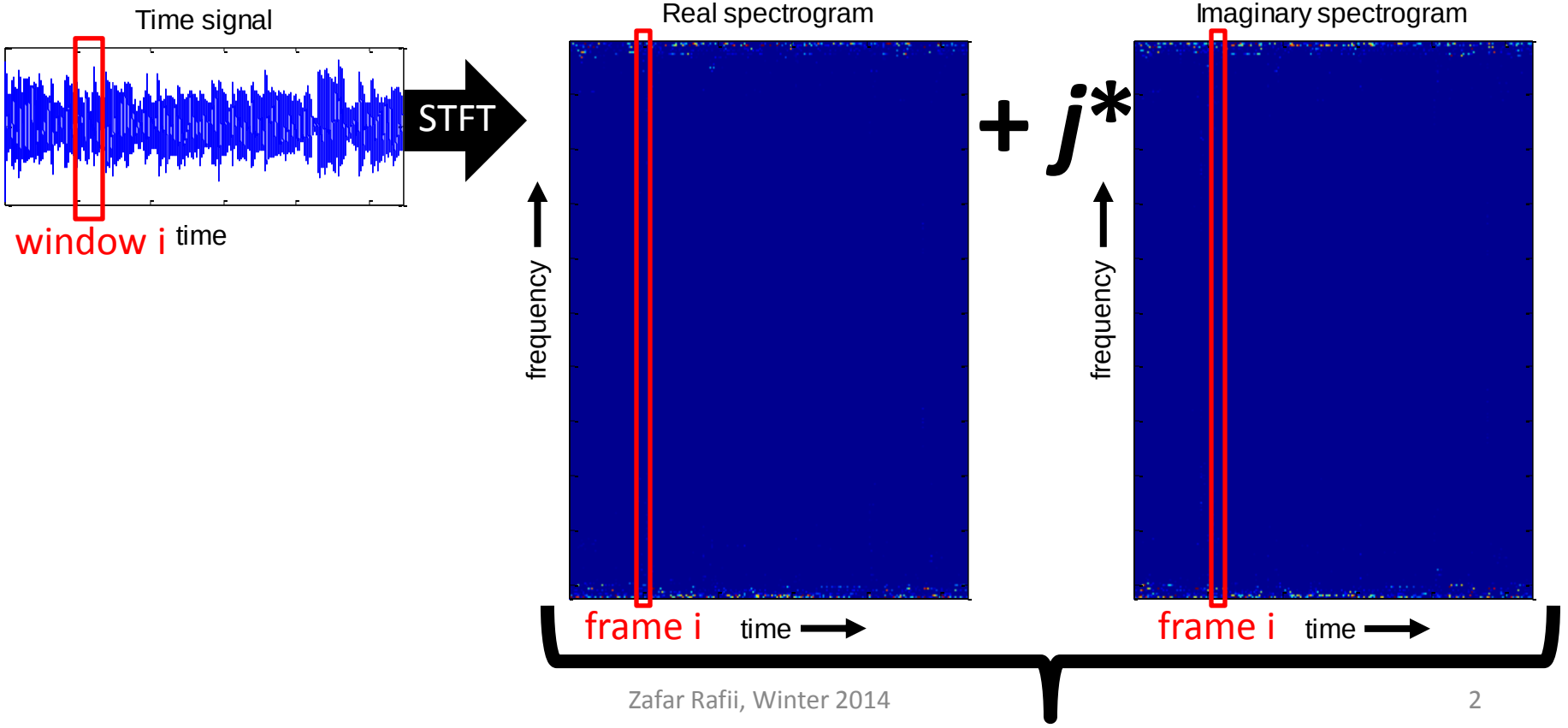
Time-frequency Masking

EECS 352: Machine Perception of Music & Audio

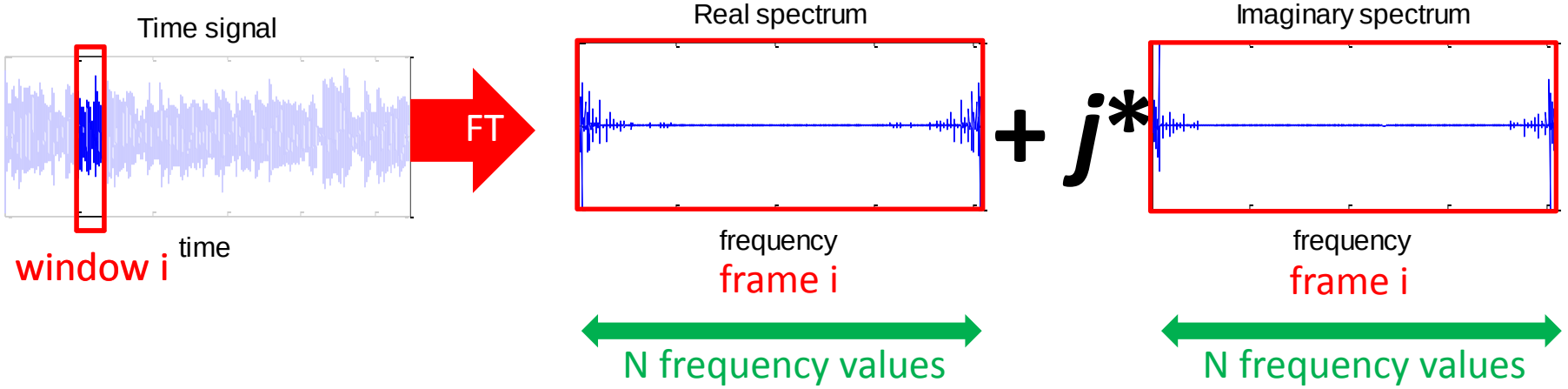
STFT

- The **Short-Time Fourier Transform** (STFT) is a succession of local Fourier Transforms (FT)



STFT

- If we used a window of N samples, the FT has N values, from 0 to N-1; e.g., if N = 8…



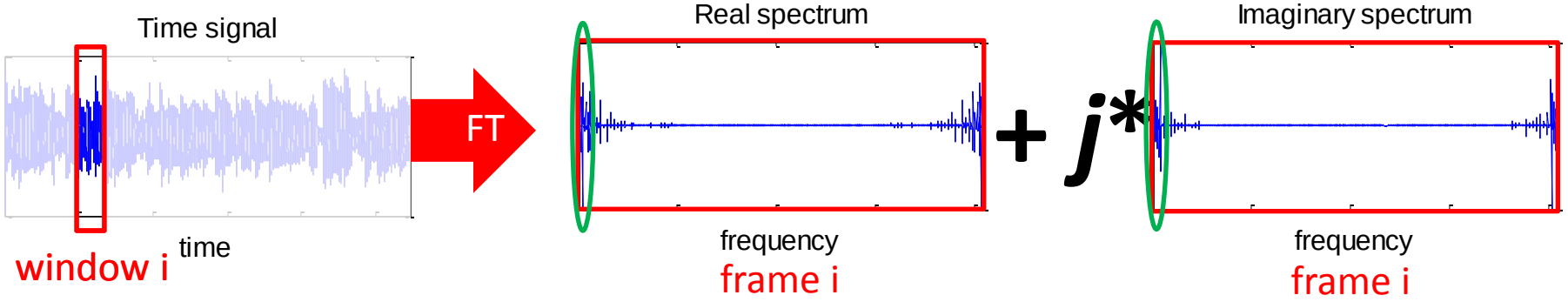
-3	-1	0	1	2	1	0	-1
0	1	2	3	4	5	6	7

+ j*

0	-1	0	1	0	-1	0	1
0	1	2	3	4	5	6	7

STFT

- Frequency index 0 is the **DC component**; it is always real (it is the sum of the time values!)



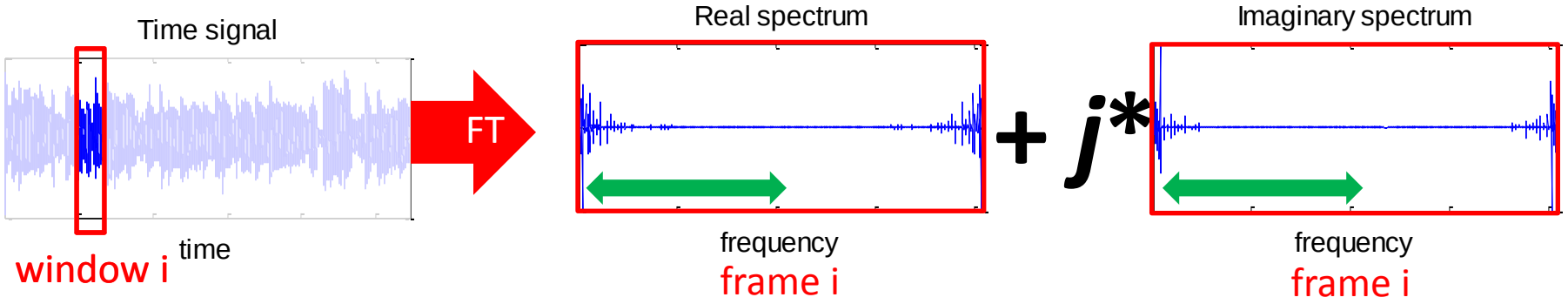
-3	-1	0	1	2	1	0	-1
0	1	2	3	4	5	6	7

+ j*

0	-1	0	1	0	-1	0	1
0	1	2	3	4	5	6	7

STFT

- Frequency indices from 1 to floor(N/2) are the "unique" **complex values (a + *j**b)**



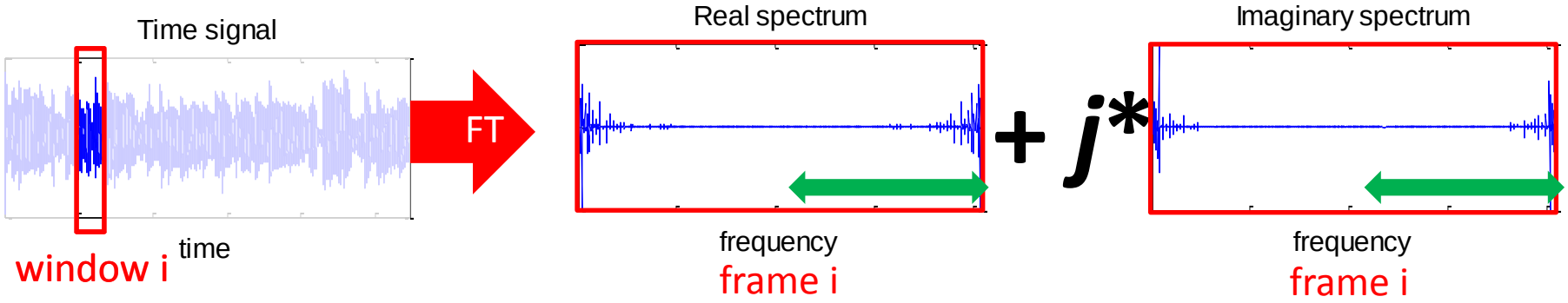
-3	-1	0	1	2	1	0	-1
0	1	2	3	4	5	6	7

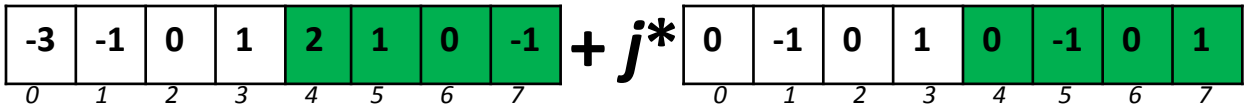
+ *j**

0	-1	0	1	0	-1	0	1
0	1	2	3	4	5	6	7

STFT

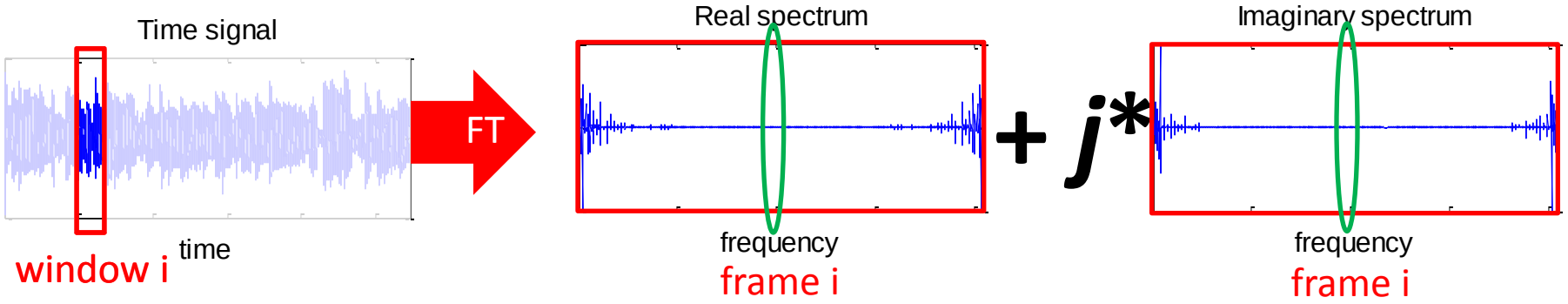
- Frequency indices from floor(N/2) to N-1 are the “mirrored” **complex conjugates (a - *j**b)**





STFT

- If N is even, there is a **pivot component** at frequency index N/2; it is always real!



-3	-1	0	1	2	1	0	-1
0	1	2	3	4	5	6	7

+ j*

0	-1	0	1	0	-1	0	1
0	1	2	3	4	5	6	7

STFT

- Summary of the frequency indices and values in the STFT (in colors!)

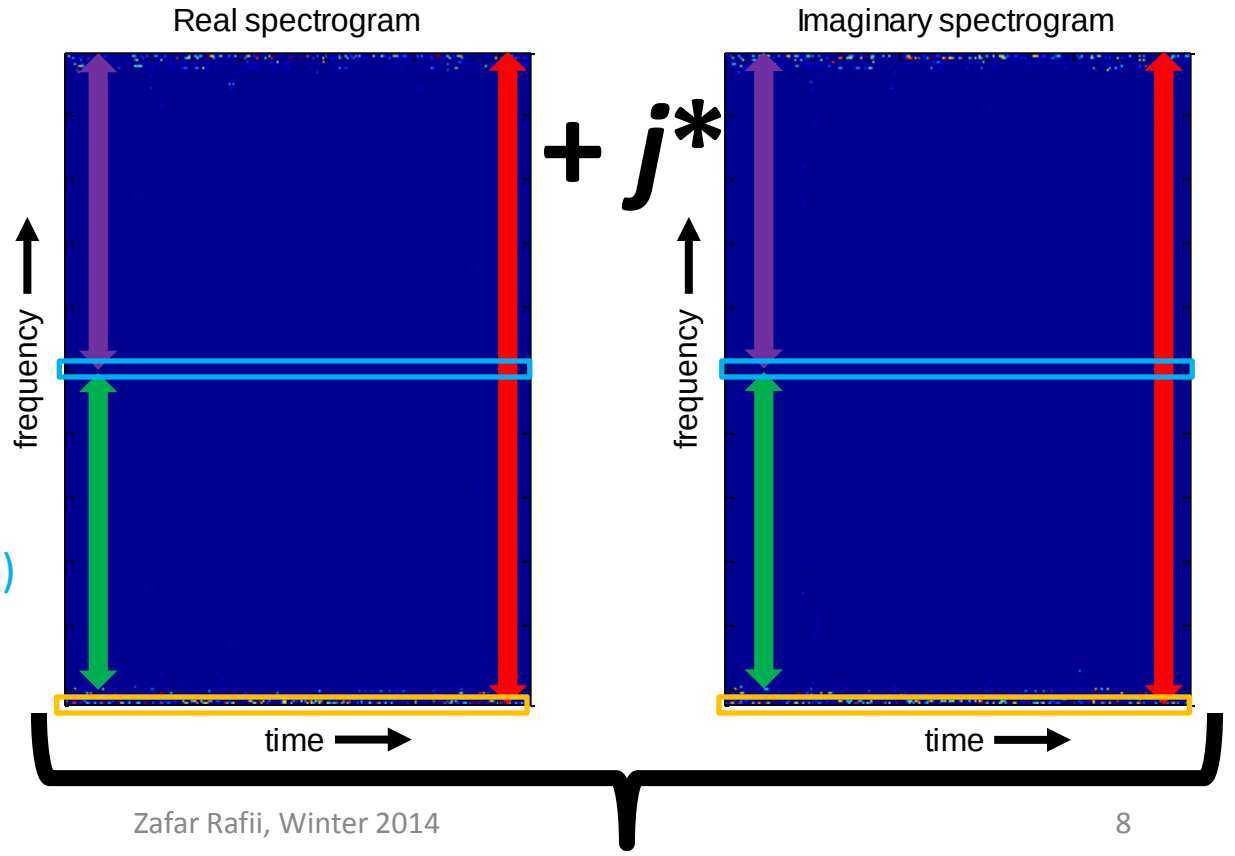
N frequency values =
frequency 0 to N-1

Frequency 0 =
DC component (always real)

Frequency 1 to floor(N/2) =
“unique” complex values

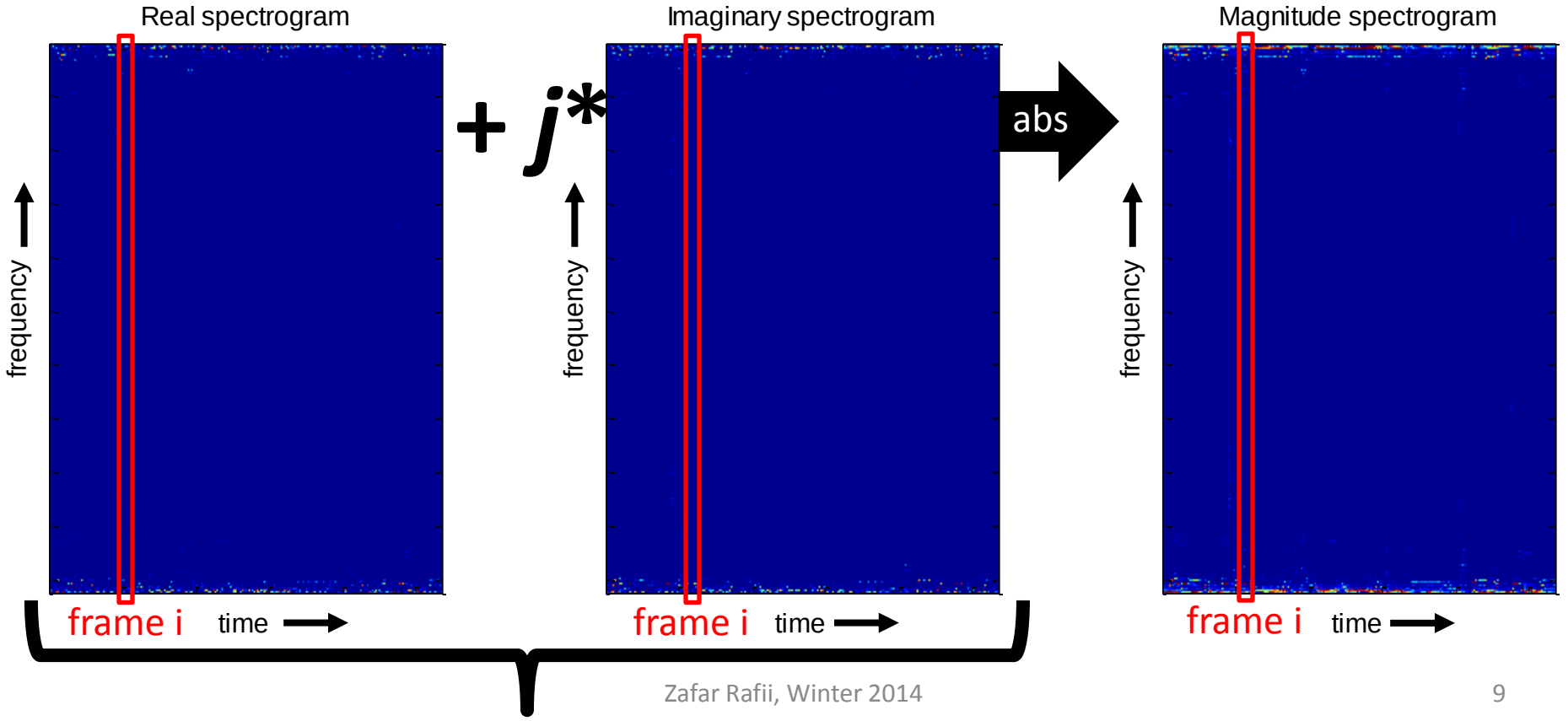
Frequency N/2 =
“pivot” component (always real)

Frequency floor(N/2) to N-1 =
“mirrored” complex conjugates



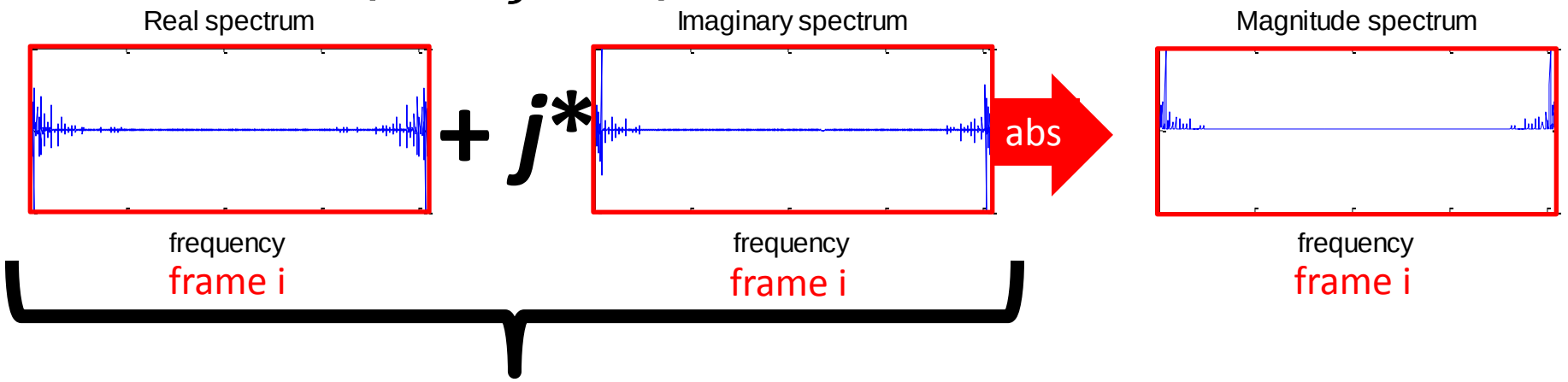
Spectrogram

- The (magnitude) **spectrogram** is the magnitude (absolute value) of the STFT



Spectrogram

- For a complex number $a + j * b$, the absolute value is $|a + j * b| = \sqrt{a^2 + b^2}$



-3	-1	0	1	2	1	0	-1
0	1	2	3	4	5	6	7

+ j*

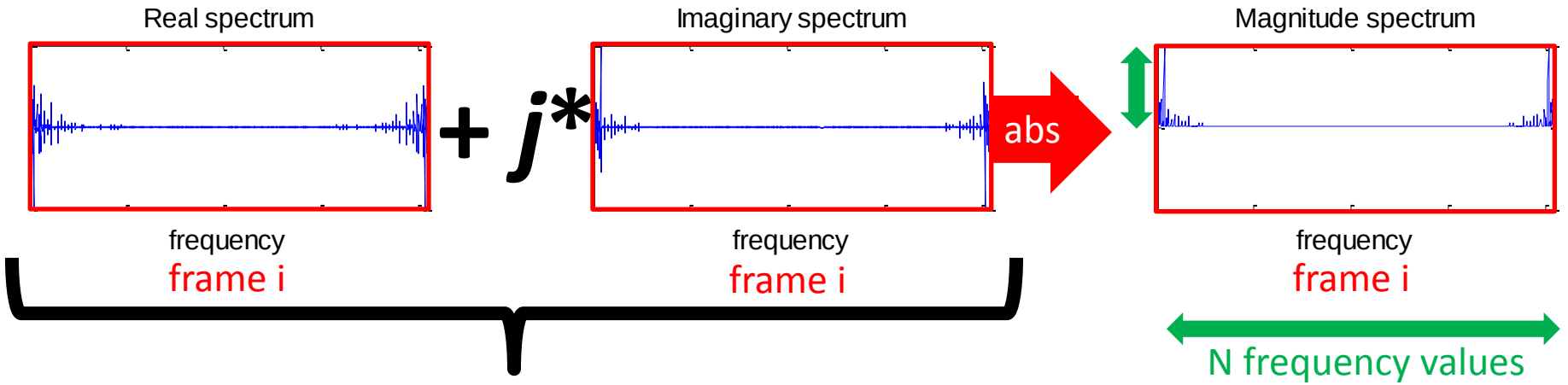
0	-1	0	1	0	-1	0	1
0	1	2	3	4	5	6	7

=

3	1.4	0	1.4	2	1.4	0	1.4

Spectrogram

- All the N frequency values (frequency indices from 0 to N-1) are **real and positive** (abs!)



-3	-1	0	1	2	1	0	-1
0	1	2	3	4	5	6	7

+ j*

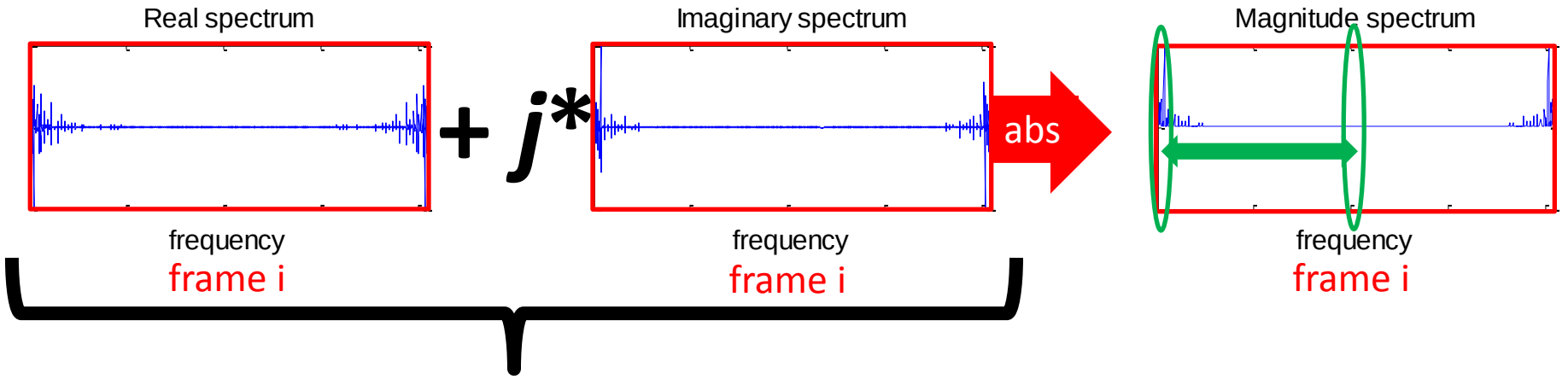
0	-1	0	1	0	-1	0	1
0	1	2	3	4	5	6	7

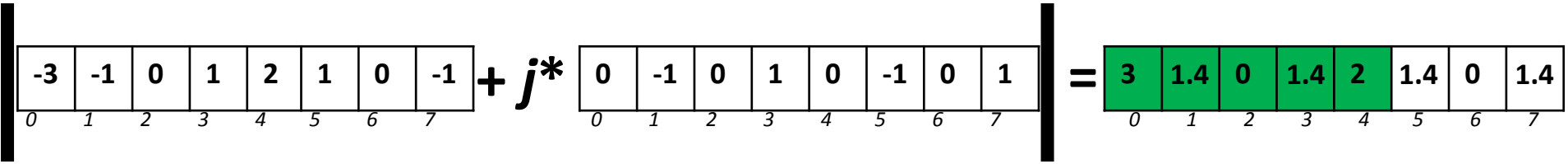
=

3	1.4	0	1.4	2	1.4	0	1.4
0	1	2	3	4	5	6	7

Spectrogram

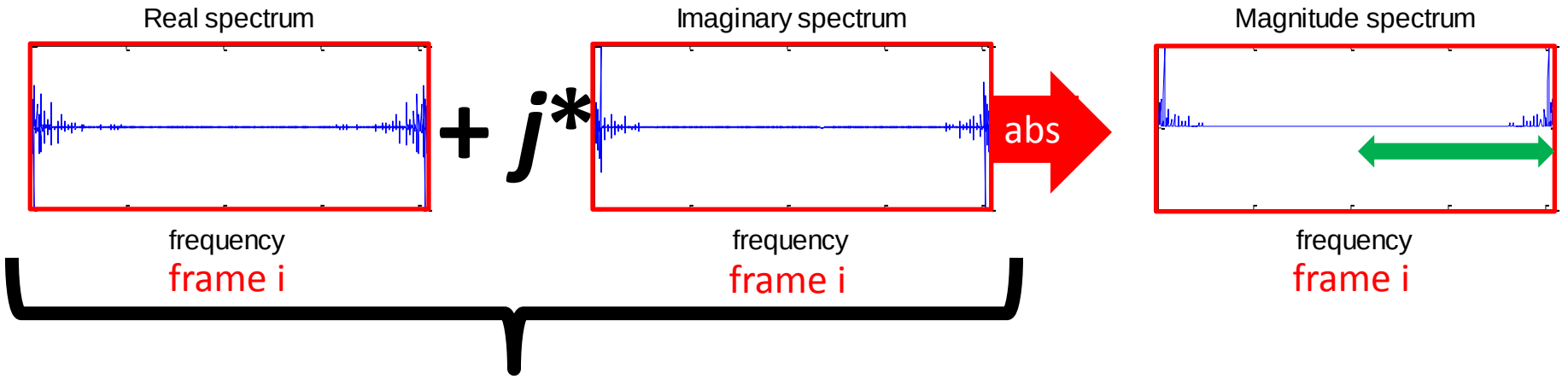
- Frequency indices from 0 to floor(N/2) are the **unique frequency values** (with DC and pivot)

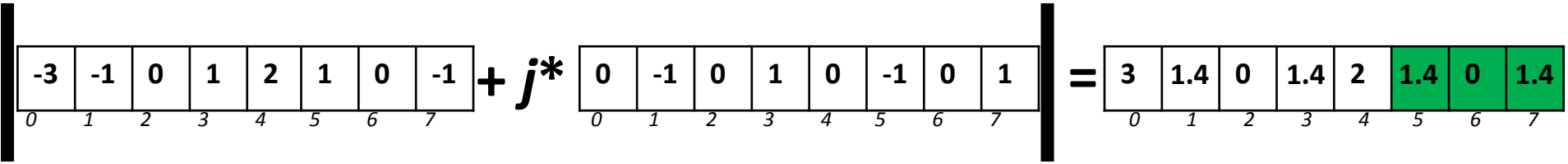




Spectrogram

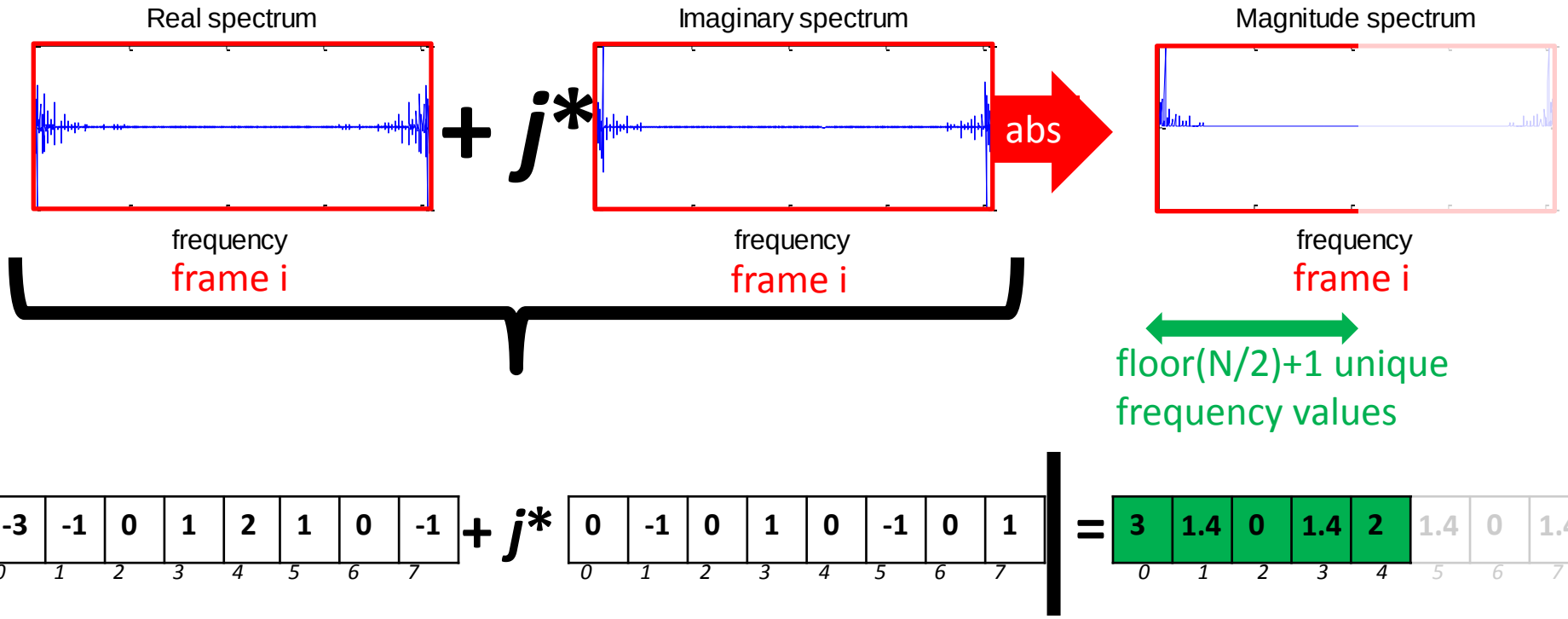
- Frequency indices from floor(N/2)+1 to N-1 are the **mirrored frequency values**





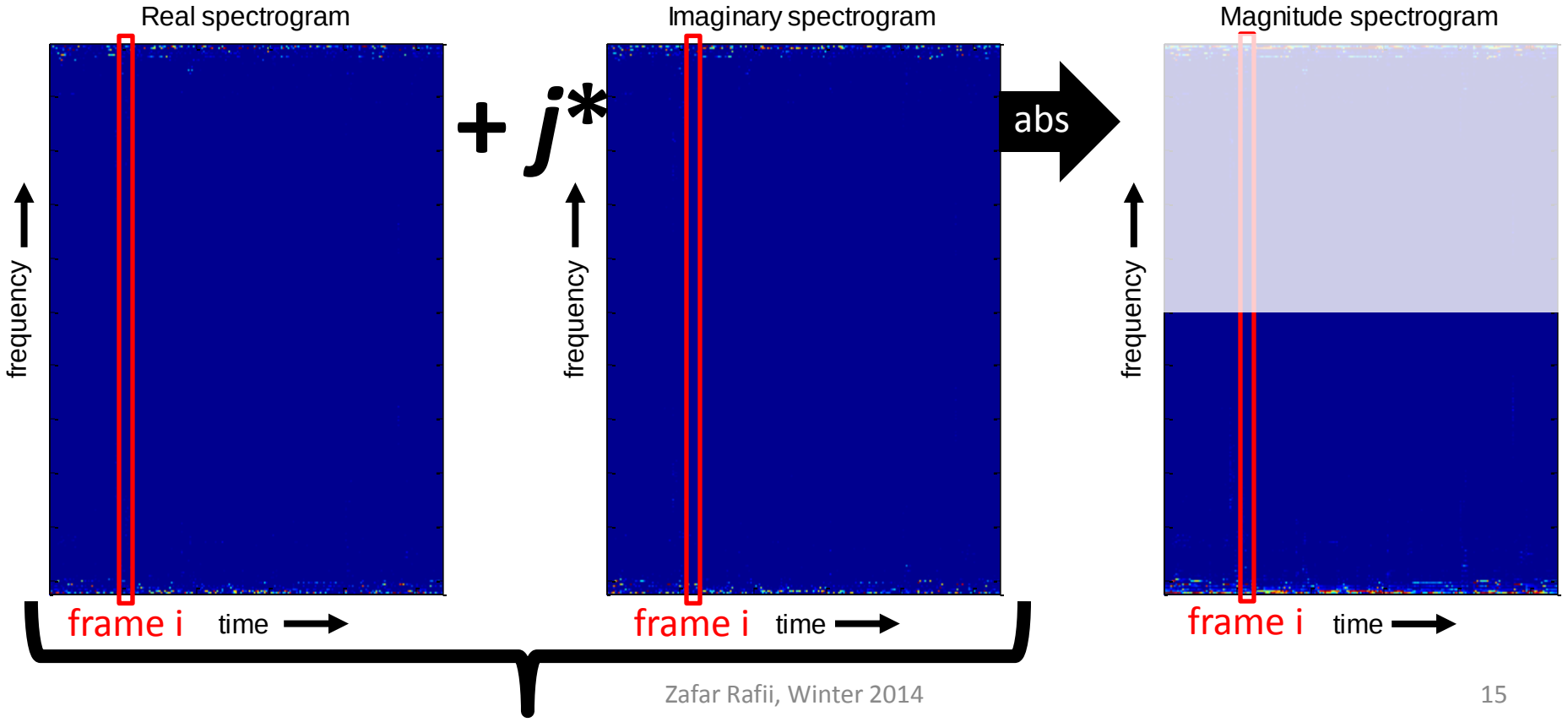
Spectrogram

- Since they are redundant, we can discard the frequency values from floor(N/2)+1 to N-1



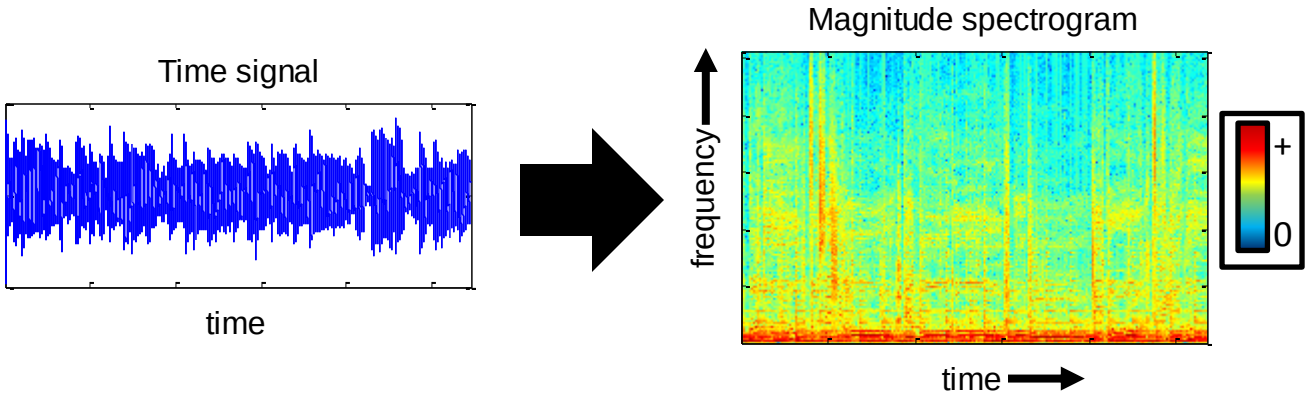
Spectrogram

- The spectrogram has therefore **floor(N/2)+1 unique frequency values** (with DC and pivot)



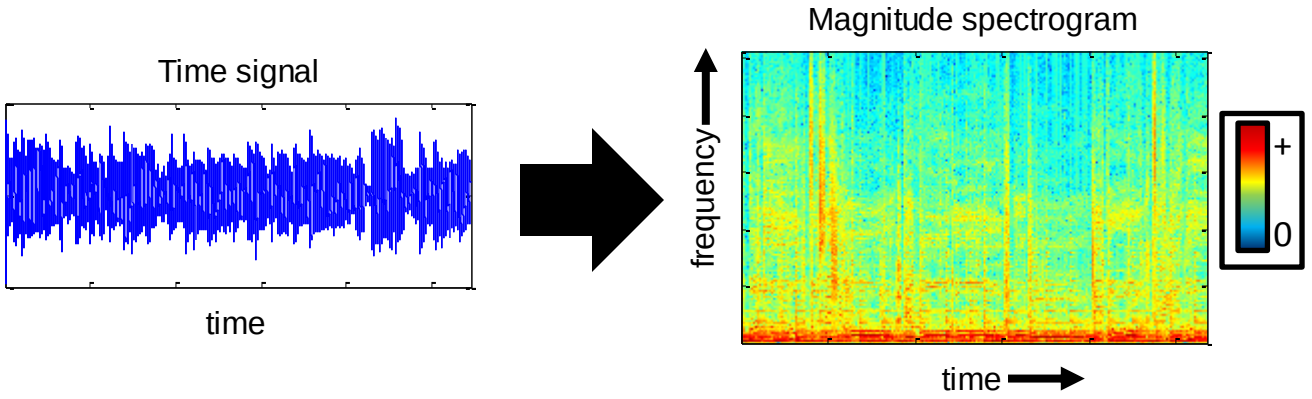
Spectrogram

- Why the magnitude spectrogram?
  - Easy to visualize (compare with the STFT)
  - Magnitude information more important
  - Human ear less sensitive to phase



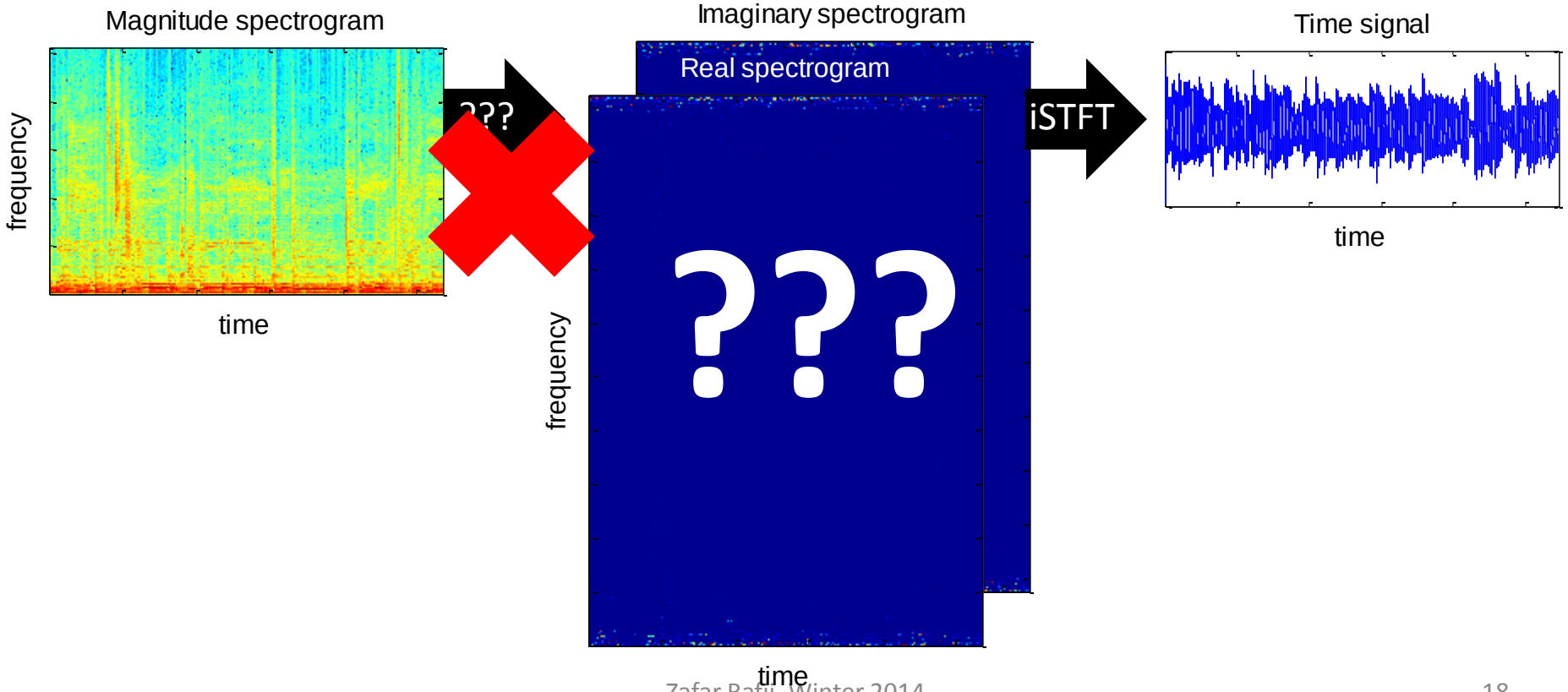
Spectrogram

- When you display a spectrogram in Matlab…
  - *imagesc*: data is scaled to use the full colormap
  - *10*log10(V)*: magnitude spectrogram in dB
  - *set(gca,'YDir','normal'):* y-axis from bottom to top



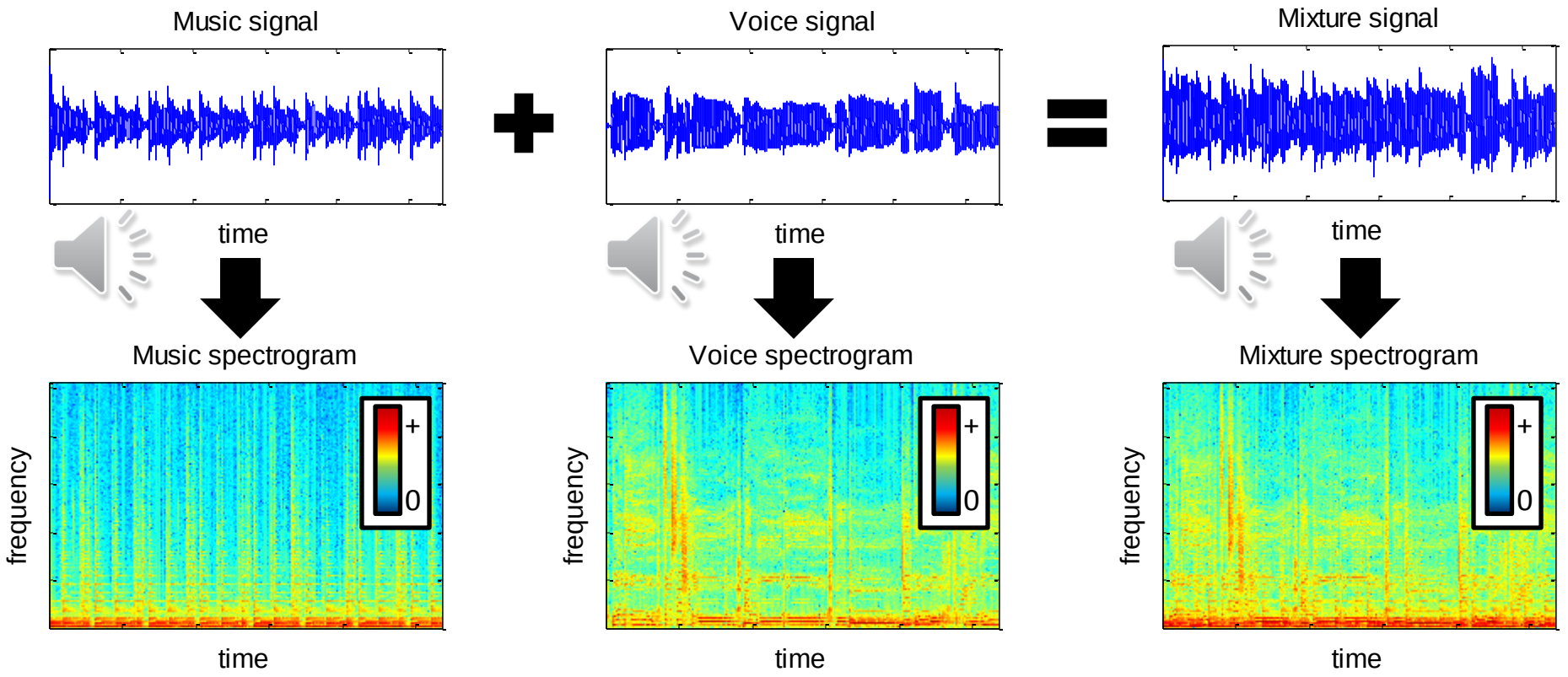
Spectrogram

- The signal **cannot be reconstructed** from the spectrogram (phase information is missing!)



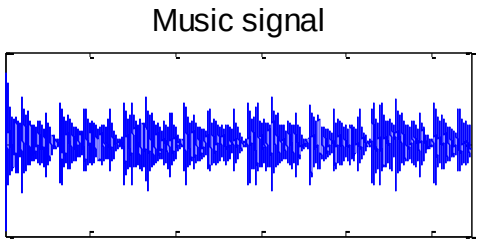
Time-frequency Masking

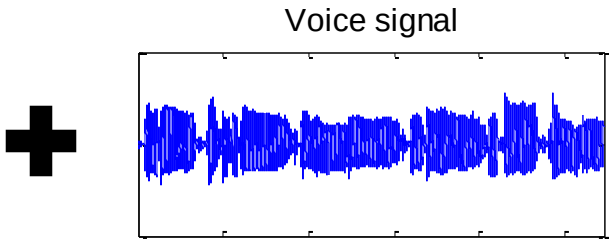
- Suppose we have a mixture of two sources: a music signal and a voice signal

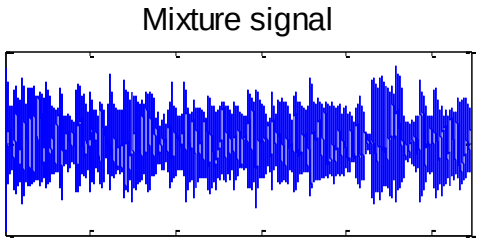


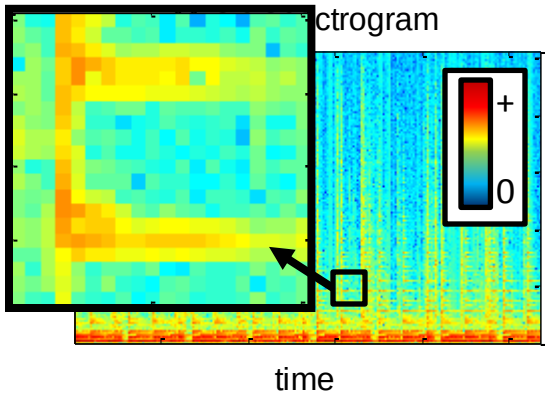
Time-frequency Masking

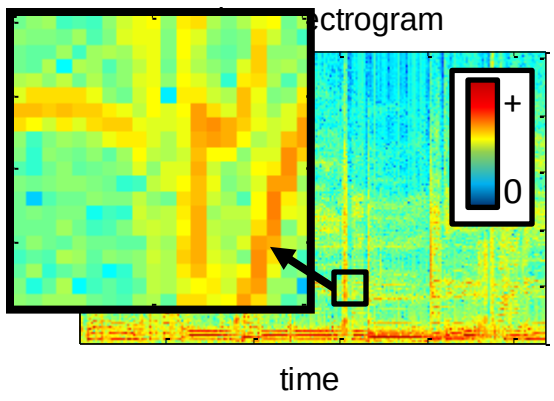
- We assume that the sources are **sparse** = most of the time-frequency bins have null energy

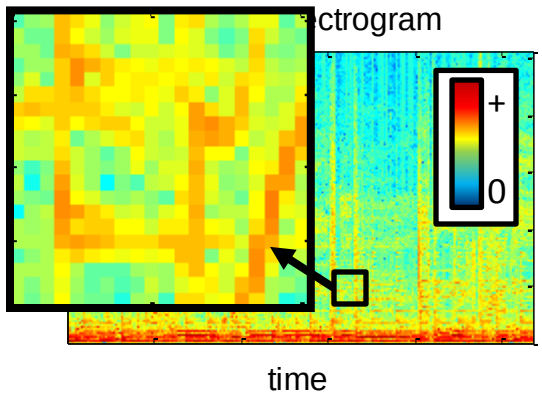












Time-frequency Masking

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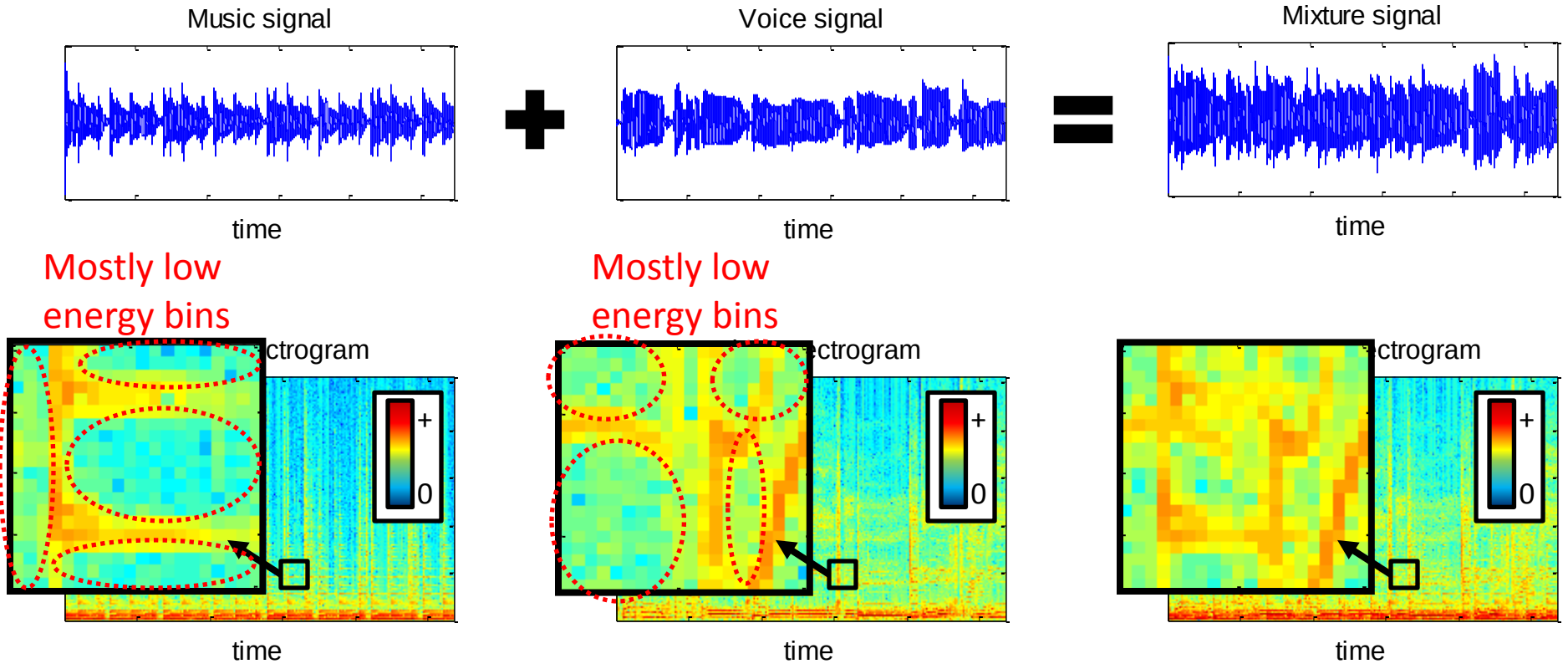
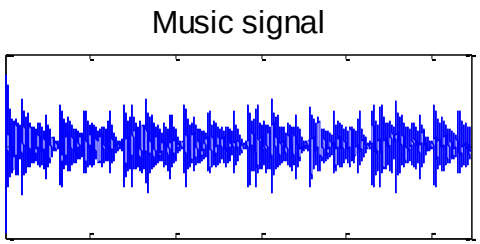
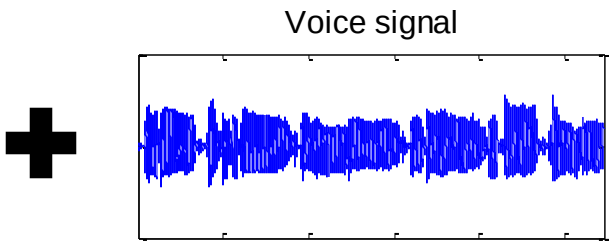
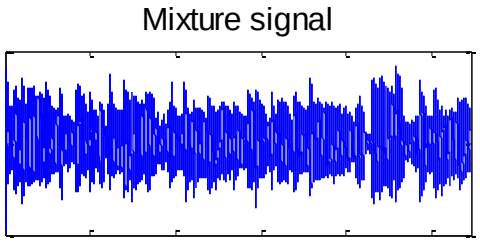


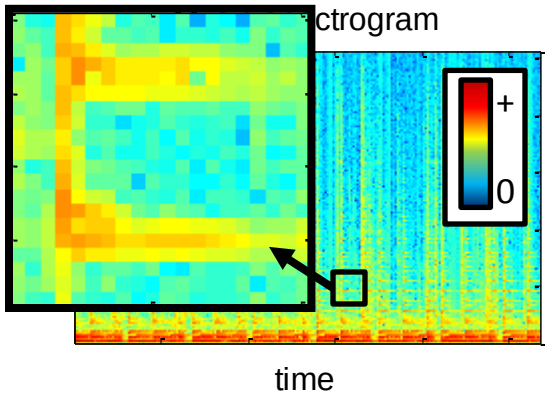
Time-frequency Masking

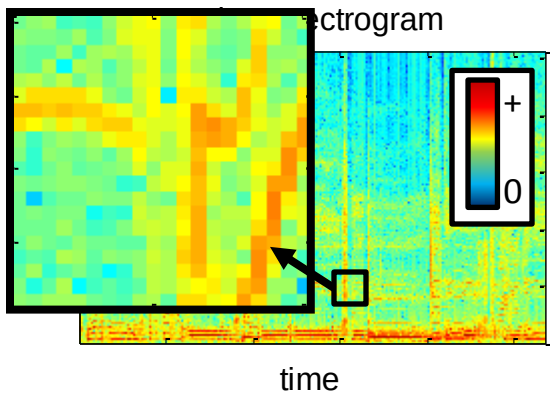
- We assume that the sources are **disjoint** = their time-frequency bins do not overlap

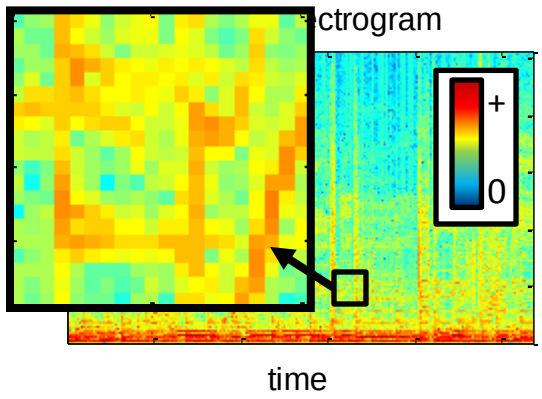






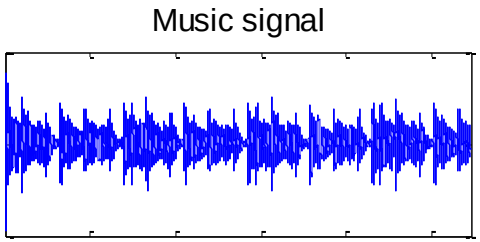


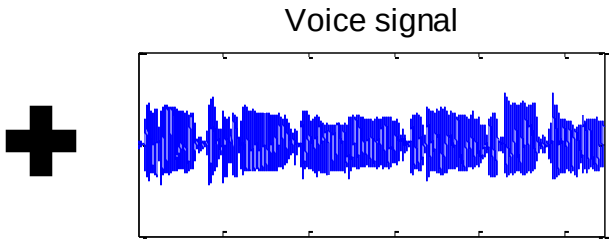


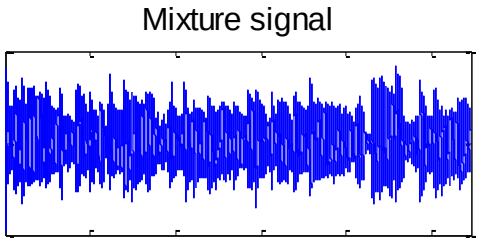


Time-frequency Masking

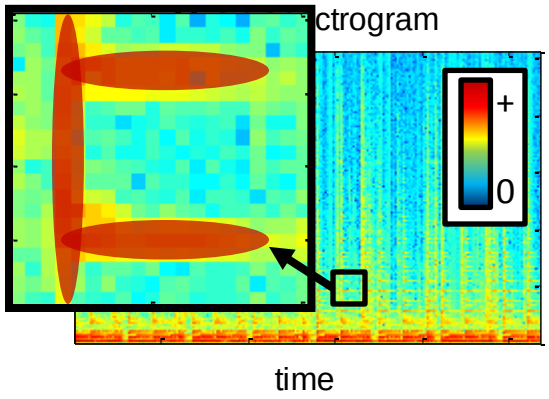
- We assume that the sources are **disjoint** = their time-frequency bins do not overlap

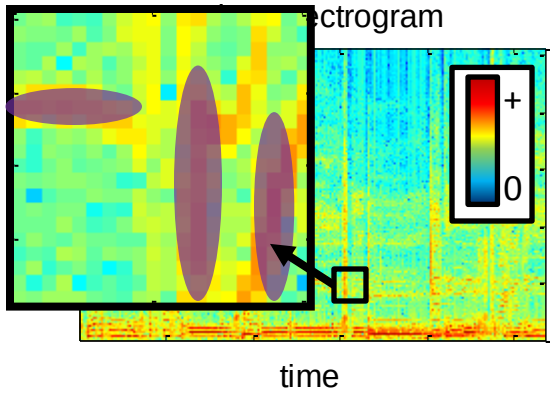


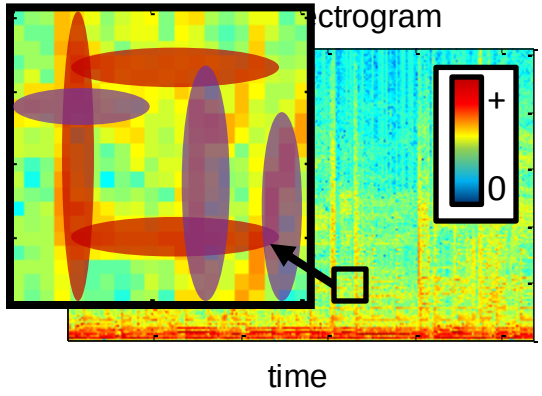




Not a lot of overlapping

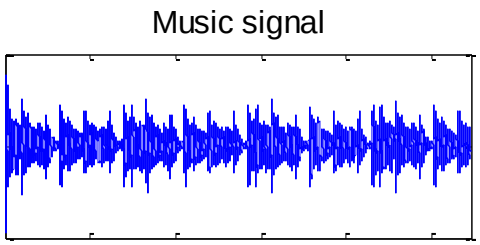


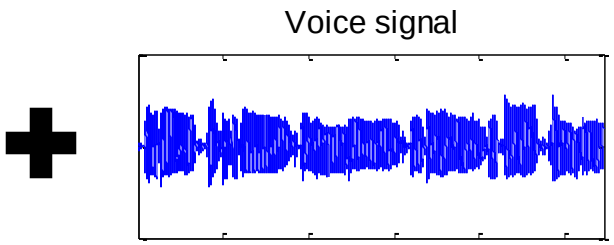


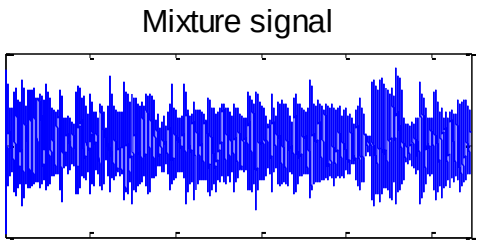


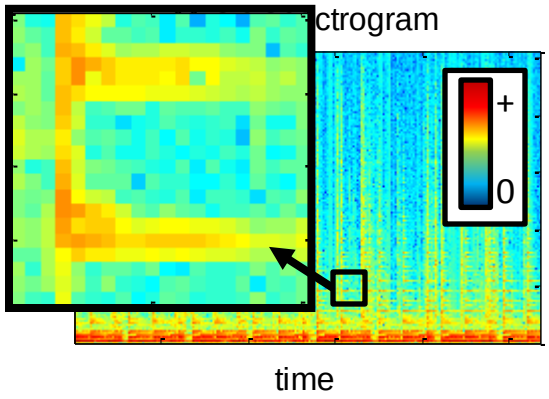
Time-frequency Masking

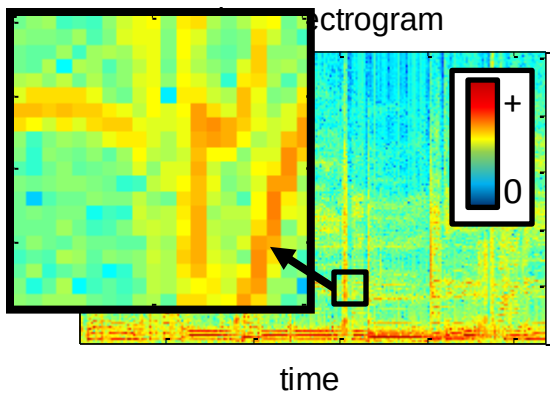
- Assuming sparseness and disjointness, we can **discriminate** the bins between mixed sources

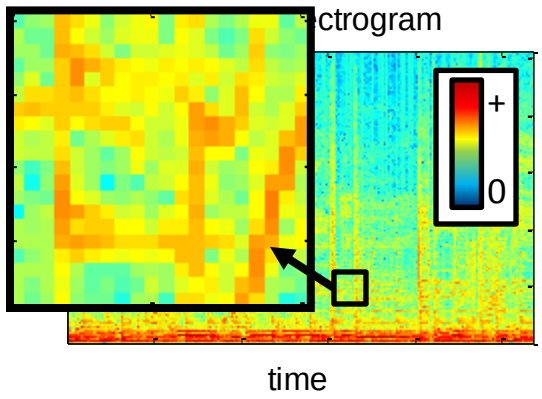






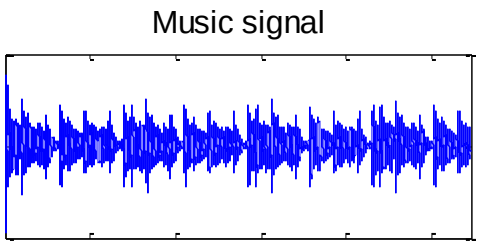


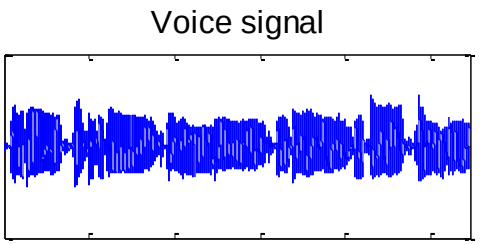


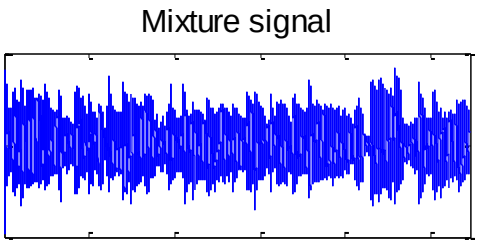


Time-frequency Masking

- Assuming sparseness and disjointness, we can **discriminate** the bins between mixed sources

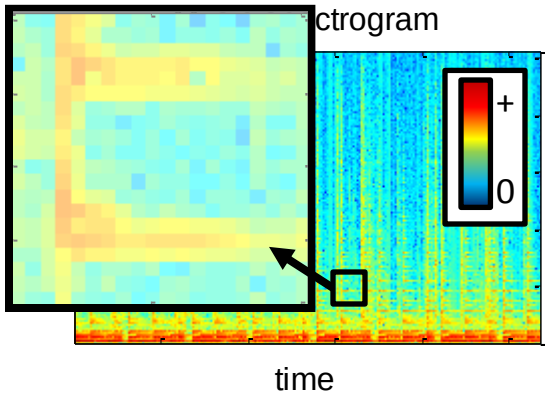


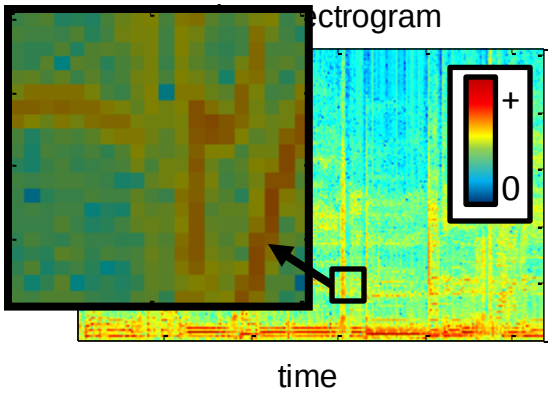


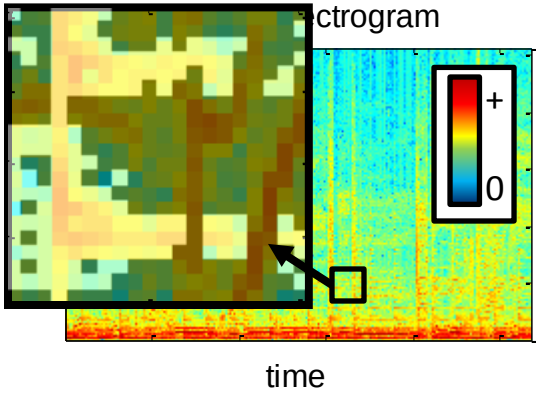


Source 1 = bright

Source 2 = dark

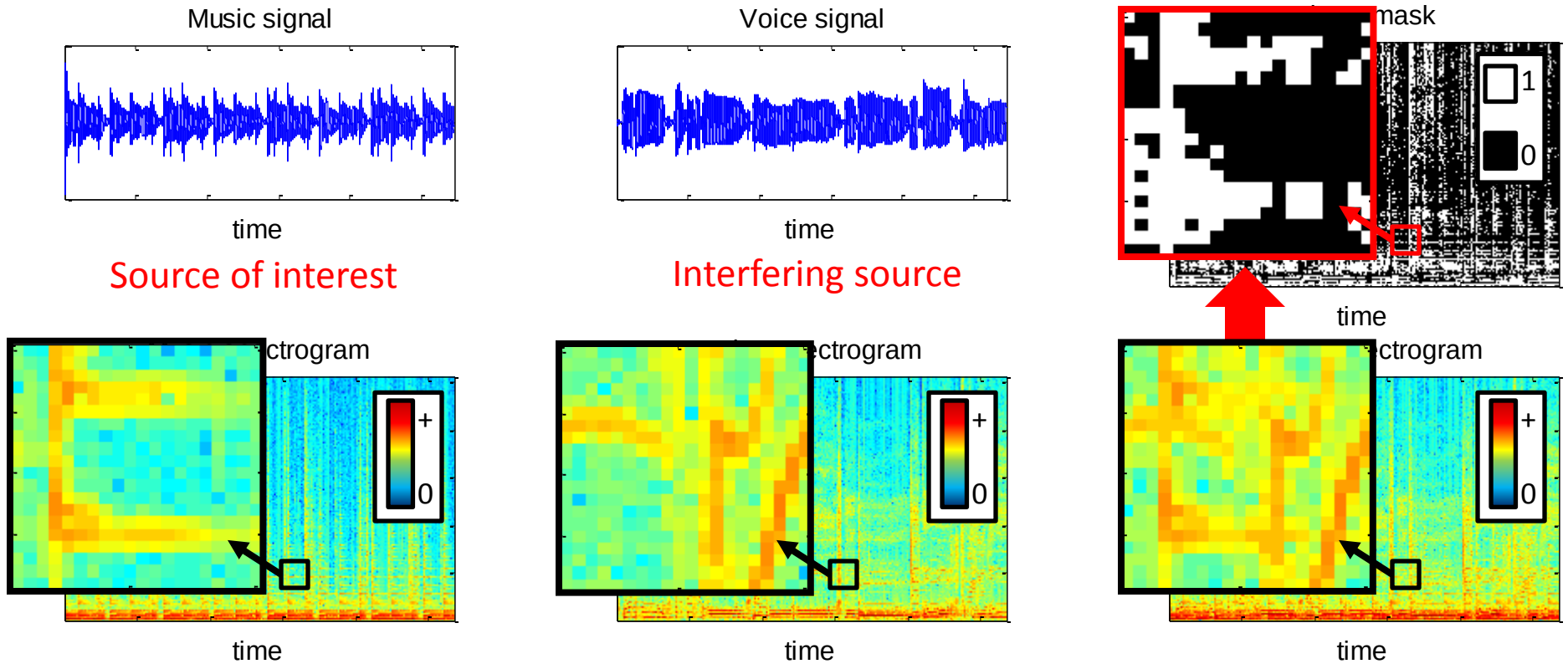






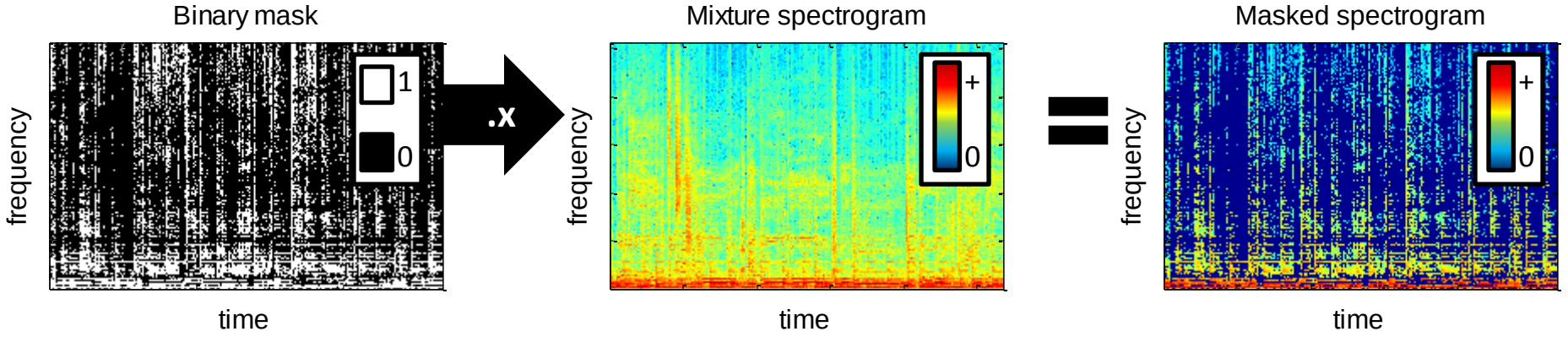
Time-frequency Masking

- Bins that are likely to belong to one source are assigned to 1, the rest to 0 = **binary masking**!



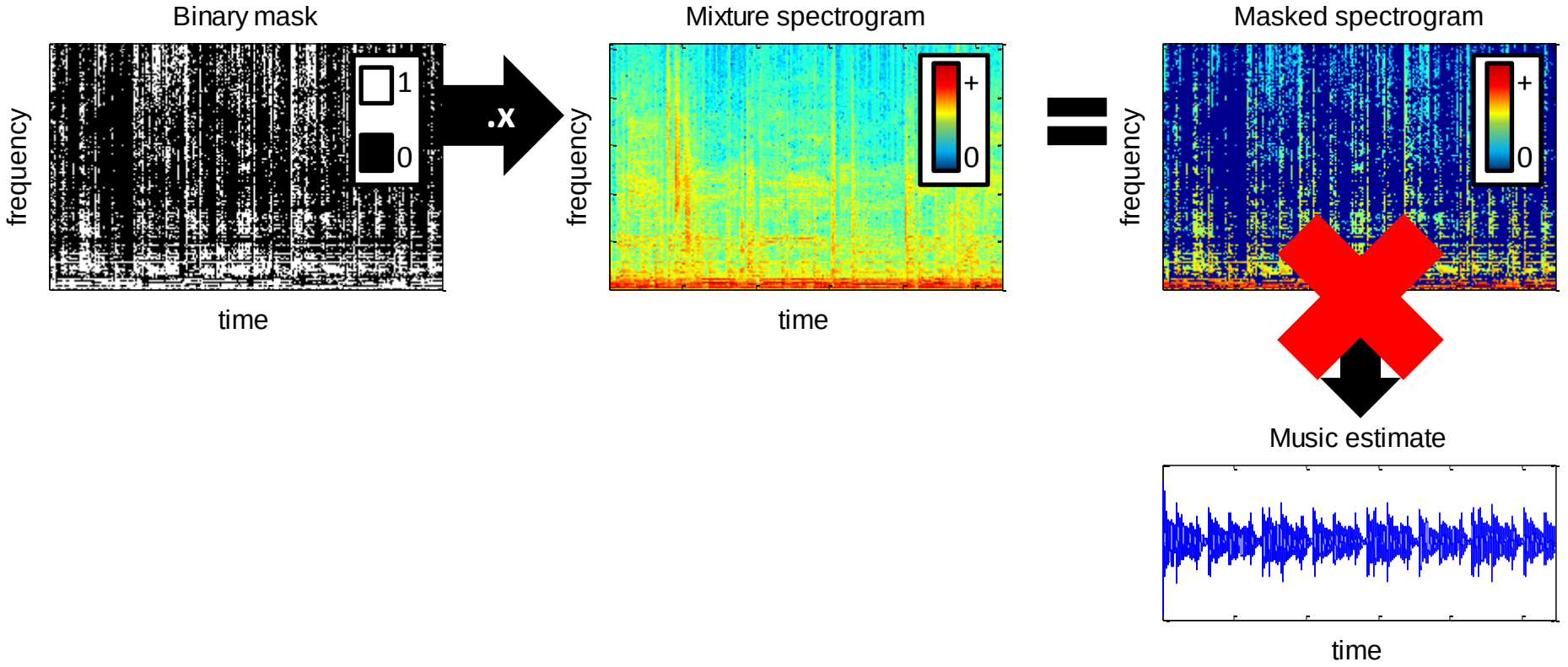
Time-frequency Masking

- By multiplying the binary mask to the mixture spectrogram, we can “preview” the estimate



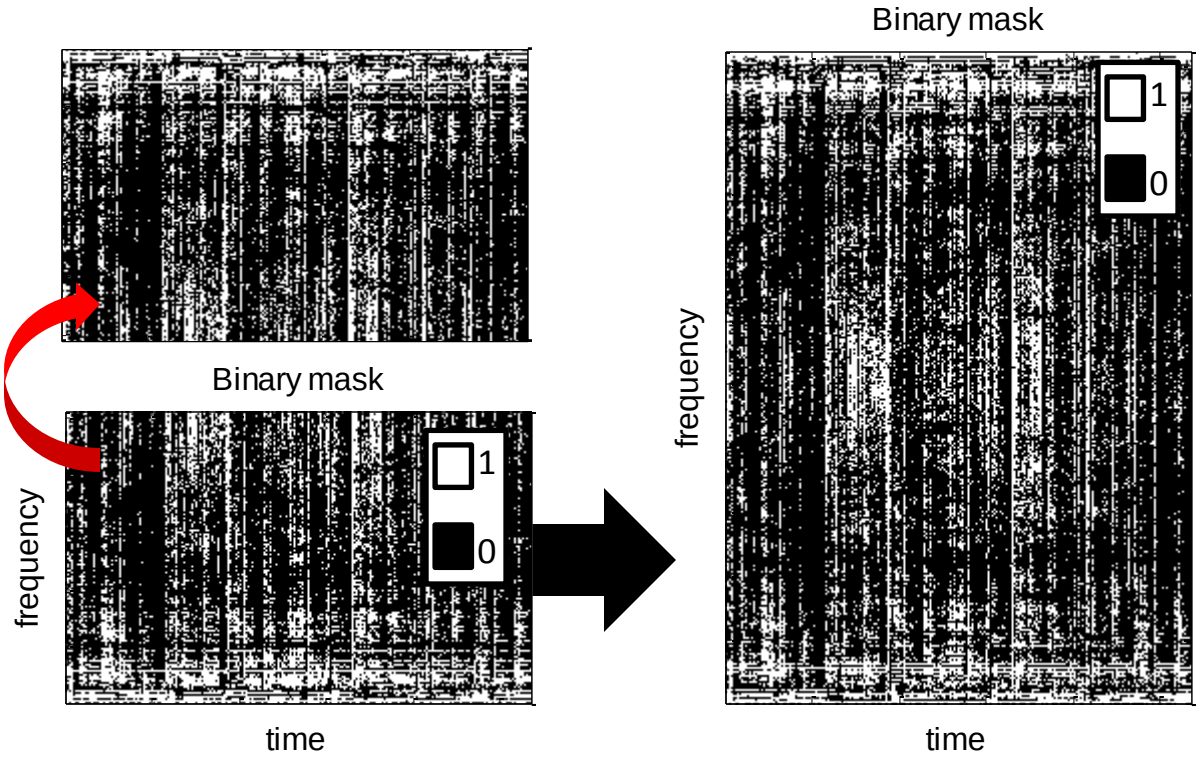
Time-frequency Masking

- However, we cannot derive the estimate itself because we cannot invert a spectrogram!



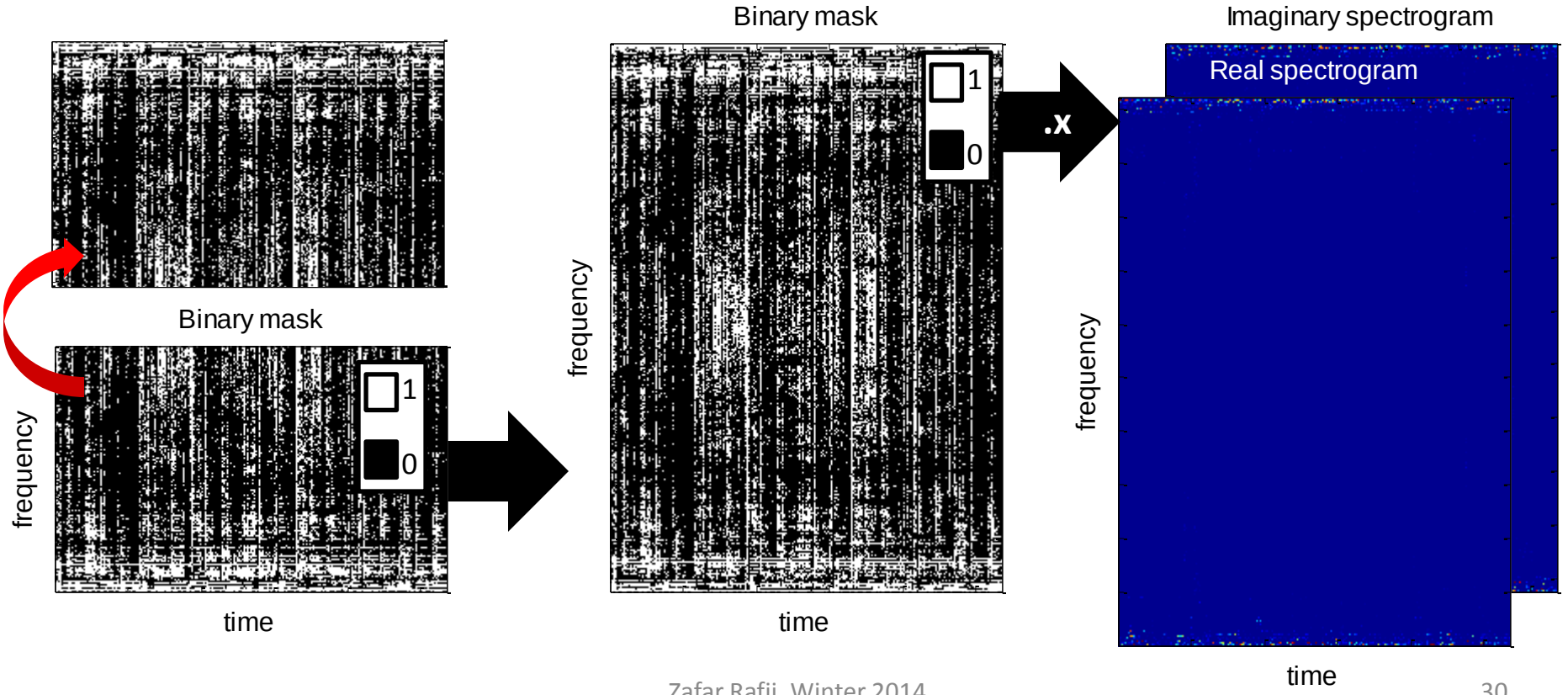
Time-frequency Masking

- We mirror the redundant frequencies from the unique frequencies (without DC and pivot)



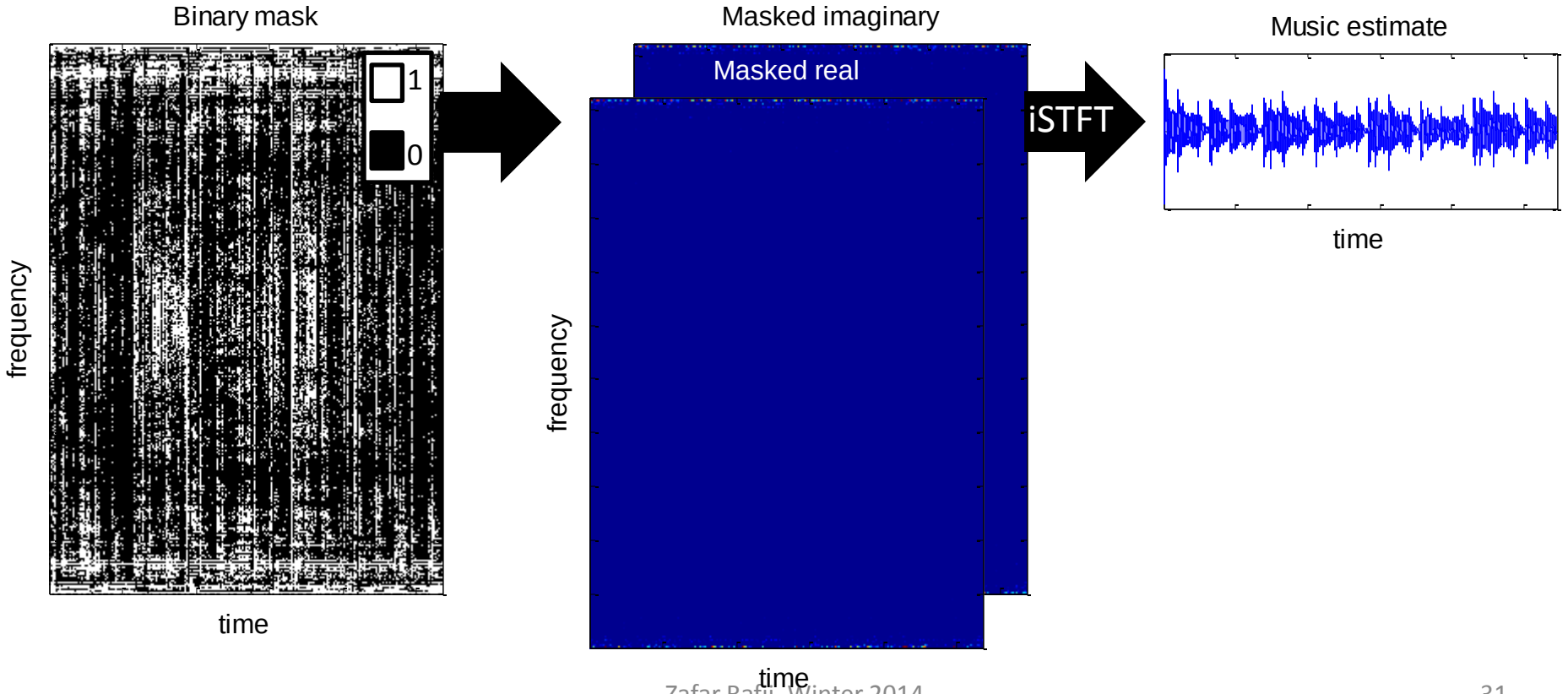
Time-frequency Masking

- We then apply this full binary mask to the STFT using a element-wise multiplication



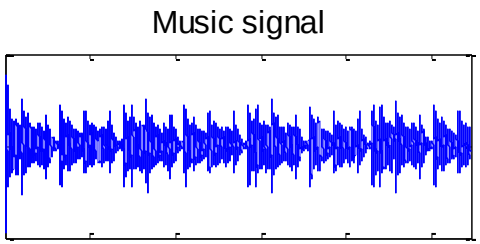
Time-frequency Masking

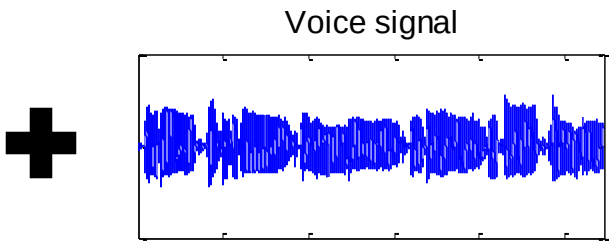
- The estimate signal can now be reconstructed via inverse STFT

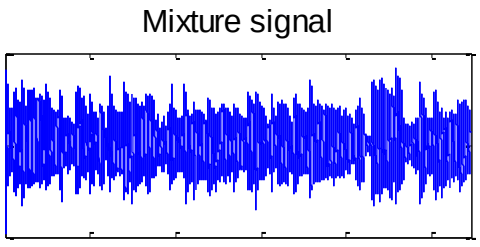


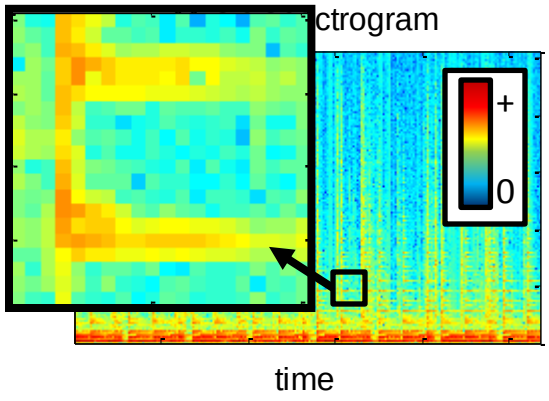
Time-frequency Masking

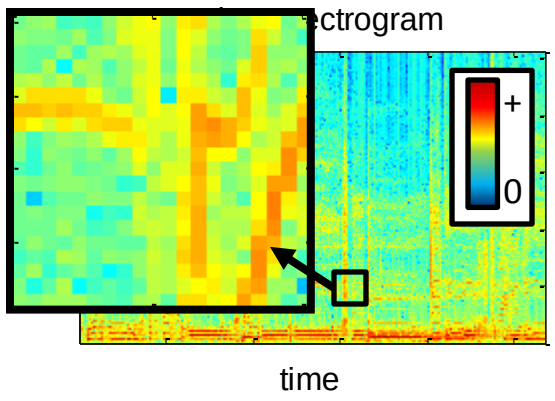
- Sources are not really sparse or disjoint in time-frequency in the mixture

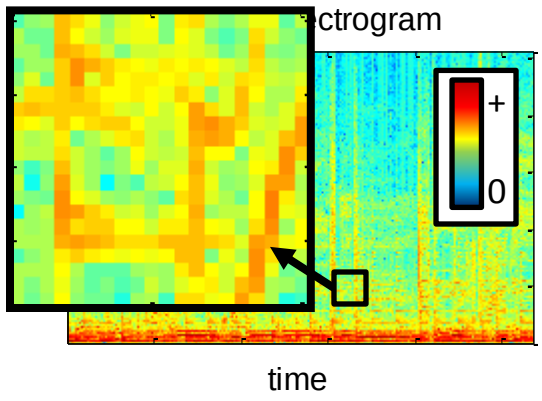






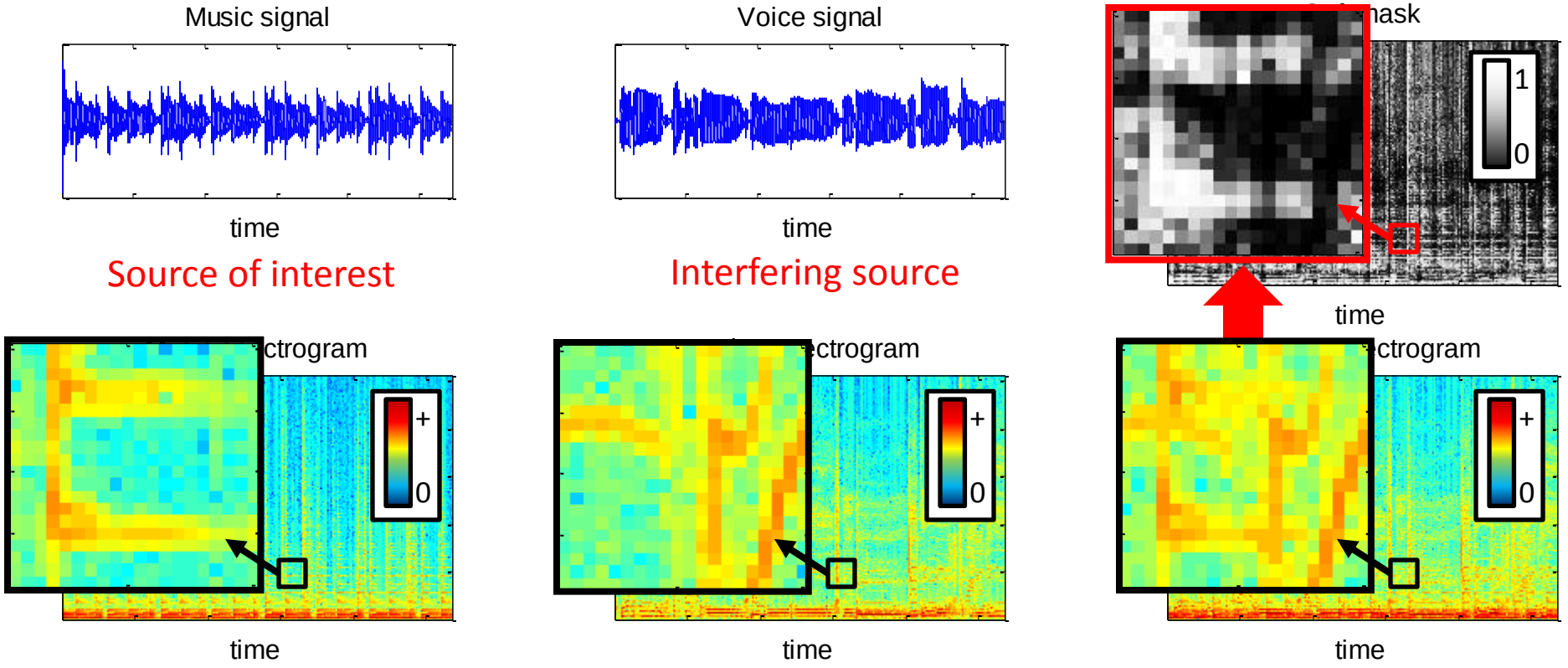






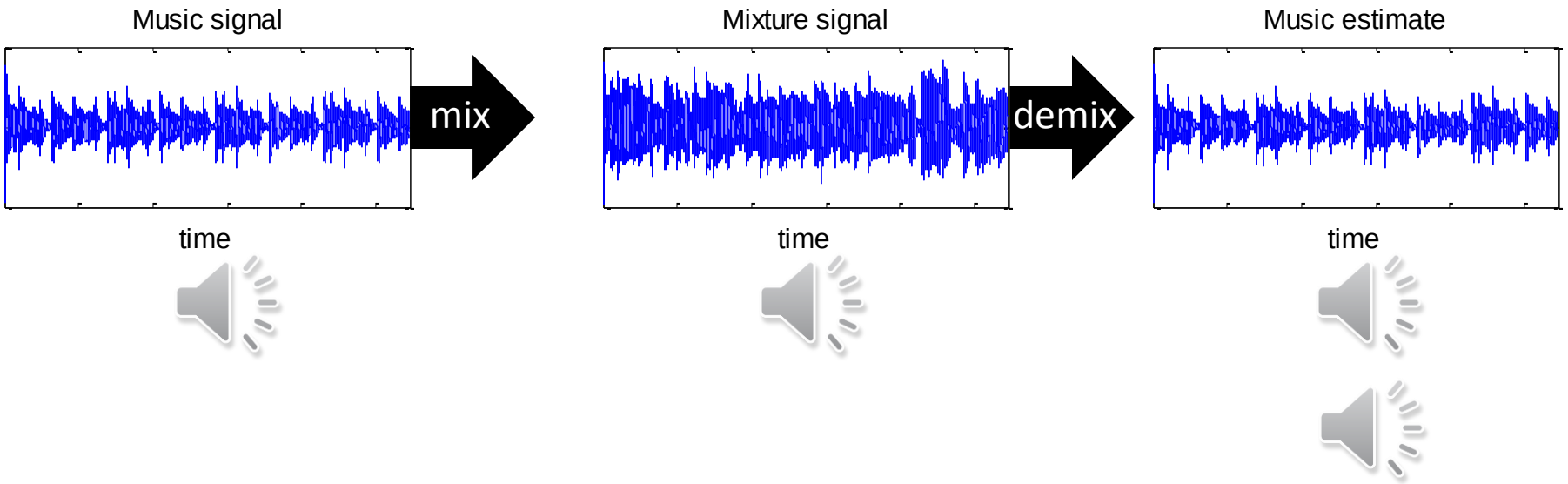
Time-frequency Masking

- Bins that are likely to belong to one source are close to 1, the rest close to 0 = **soft masking**!



Time-frequency Masking

- Let's listen to the results!



Question

- How can we efficiently model a binary/soft time-frequency mask for source separation?...
- To be continued…