Exercises from Linear algebra, signal processing, and wavelets. A unified approach.

Python version

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Chapter 1

Sound and Fourier series

Exercise 1.6: The Krakatoa explosion

Compute the loudness of the Krakatoa explosion on the decibel scale, assuming that the variation in air pressure peaked at 100 000 Pa.

Solution. Setting p_{ref} =0.00002 Pa and p=100 000 Pa in the decibel expression we get

$$\begin{aligned} 20 \log_{10} \left(\frac{p}{p_{\text{ref}}} \right) &= 20 \log_{10} \left(\frac{100000}{0.00002} \right) = 20 \log_{10} \left(\frac{10^5}{2 \times 10^{-5}} \right) \\ &= 20 \log_{10} \left(\frac{10^{10}}{2} \right) = 20 \left(10 - \log_{10} 2 \right) \approx 194 \text{db}. \end{aligned}$$

Exercise 1.7: Sum of two pure tones

Consider a sum of two pure tones, $f(t) = A_1 \sin(2\pi\nu_1 t) + A_2 \sin(2\pi\nu_2 t)$. For which values of A_1, A_2, ν_1, ν_2 is f periodic? What is the period of f when it is periodic?

Solution. $\sin(2\pi\nu_1 t)$ has period $1/\nu_1$, while $\sin(2\pi\nu_2 t)$ has period $1/\nu_2$. The period is not unique, however. The first one also has period n/ν_1 , and the second also n/ν_2 , for any n. The sum is periodic if there exist n_1, n_2 so that $n_1/\nu_1 = n_2/\nu_2$, i.e. so that there exists a common period between the two. This common period will also be a period of f. This amounts to that $\nu_1/\nu_2 = n_1/n_2$, i.e. that ν_1/ν_2 is a rational number.

Exercise 1.8: Sum of two pure tones

Find two constant a and b so that the function $f(t) = a\sin(2\pi 440t) + b\sin(2\pi 4400t)$ resembles the right plot of Figure 1.1 in the compendium as closely as possible. Generate the samples of this sound, and listen to it.

Solution. The important thing to note here is that there are two oscillations present in the right part of Figure 1.1 in the compendium: One slow oscillation with a higher amplitude, and one faster oscillation, with a lower amplitude. We see that there are 10 periods of the smaller oscillation within one period of the larger oscillation, so that we should be able to reconstruct the figure by using frequencies where one is 10 times the other, such as 440Hz and 4400Hz. Also, we see from the figure that the amplitude of the larger oscillation is close to 1, and close to 0.3 for the smaller oscillation. A good choice therefore seems to be a=1,b=0.3. The code can look this:

```
t = arange(0,3,1/float(fs))
x = sin(2*pi*440*t) + 0.3*sin(2*pi*4400*t)
x /= abs(x).max()
play(x, fs)
```

Exercise 1.9: Playing with different sample rates

If we provide another samples rate fs to the play functions, the sound card will assume a different time distance between neighboring samples. Play and listen to the audio sample file again, but with three different sample rates: 2*fs, fs, and fs/2, where fs is the sample rate returned by audioread.

Solution. The following code can be used

```
play(x, fs)

play(x, 2*fs)

play(x, fs/2)
```

The sample file castanets.wav played at double sampling rate sounds like this, while it sounds like this when it is played with half the sampling rate.

Exercise 1.10: Play sound with added noise

To remove noise from recorded sound can be very challenging, but adding noise is simple. There are many kinds of noise, but one kind is easily obtained by adding random numbers to the samples of a sound. For this we can use the function random.random as follows.

```
z = x + c*(2*random.random(shape(x))-1)
```

This adds noise to all channels. The function for returning random numbers returns numbers between 0 and 1, and above we have adjusted these so that

they are between -1 and 1 instead, as for other sound which can be played by the computer. c is a constant (usually smaller than 1) that dampens the noise.

Write code which adds noise to the audio sample file, and listen to the result for damping constants c=0.4 and c=0.1. Remember to scale the sound values after you have added noise, since they may be outside [-1,1] then.

Solution. The following code can be used.

```
z = x + c*(2*random.random(shape(x))-1)
z /= abs(z).max()
play(z, fs)
```

With c = 0.4 the result sounds like this, while with c = 0.1 it sounds like this.

Exercise 1.11: Playing the triangle wave

Repeat what you did in Example 1.4 in the compendium, but now for the triangle wave of Example 1.5 in the compendium. Start by generating the samples for one period of the triangle wave, then plot five periods, before you generate the sound over a period of three seconds, and play it. Verify that you generate the same sound as in Example 1.5 in the compendium.

Solution. The triangle wave can be plotted as follows:

```
totransl=1-4*abs(t-T/2)/T
plt.figure()
plt.plot(concatenate([t, t+T, t+2*T, t+3*T, t+4*T]),tile(totransl,5), 'k-')
```

The samples for one period are created as follows.

Then we repeat one period to obtain a sound with the desired length, and play it as follows.

```
x = tile(oneperiod, antsec*f)
play(x, fs)
```

Exercise 1.15: Shifting the Fourier basis vectors

Show that $\sin(2\pi nt/T + a) \in V_{N,T}$ when $|n| \leq N$, regardless of the value of a.

Solution. Write $\sin(2\pi nt/T + a) = \cos a \sin(2\pi nt/T) + \sin a \cos(2\pi nt/T)$.

Exercise 1.16: Playing the Fourier series of the triangle wave

a) Plot the Fourier series of the triangle wave.

Solution. The following code can be used.

```
t = linspace(0, T, 100)
x = zeros(len(t))
for k in range(1, 20, 2):
    x -= (8/(k*pi)**2)*cos(2*pi*k*t/T)
plt.figure()
plt.plot(t, x, 'k-')
```

b) Write code so that you can listen to the Fourier series of the triangle wave. How high must you choose N for the Fourier series to be indistuing shable from the square/triangle waves themselves?

Solution. The following code can be used.

```
x = tile(x, antsec/T)
play(x, fs)
```

Exercise 1.17: Riemann-integrable functions which are not square-integrable

Find a function f which is Riemann-integrable on [0,T], and so that $\int_0^T f(t)^2 dt$ is infinite.

Solution. The function $f(t) = \frac{1}{\sqrt{t}} = t^{-1/2}$ can be used since it has the properties

$$\int_0^T f(t)dt = \lim_{x \to 0+} \int_x^T t^{-1/2} dt = \lim_{x \to 0+} \left[2t^{1/2} \right]_x^T$$

$$= \lim_{x \to 0+} (2T^{1/2} - 2x^{1/2}) = 2T^{1/2}$$

$$\int_0^T f(t)^2 dt = \lim_{x \to 0+} \int_x^T t^{-1} dt = \lim_{x \to 0+} \left[\ln t \right]_x^T$$

$$= \ln T - \lim_{x \to 0+} \ln x = \infty.$$

Exercise 1.18: When are Fourier spaces included in each other?

Given the two Fourier spaces V_{N_1,T_1} , V_{N_2,T_2} . Find necessary and sufficient conditions in order for $V_{N_1,T_1} \subset V_{N_2,T_2}$.

Solution. The space V_{N_1,T_1} is spanned by pure tones with frequencies $1/T_1,\ldots,N_1/T_1$, while V_{N_2,T_2} is spanned by pure tones with frequencies $1/T_2,\ldots,N_2/T_2$. We must have that the first set of frequencies is contained in the second. This is achieved if and only if $1/T_1 = k/T_2$ for some integer k, and also $N_1/T_1 \leq N_2/T_2$. In other words, T_2/T_1 must be an integer, and $T_2/T_1 \leq N_2/N_1$.

Exercise 1.19: antisymmetric functions are sine-series

Prove the second part of Theorem 1.10 in the compendium, i.e. show that if f is antisymmetric about 0 (i.e. f(-t) = -f(t) for all t), then $a_n = 0$, i.e. the Fourier series is actually a sine-series.

Exercise 1.20: More connections between symmetric-/antisymmetric functions and sine-/cosine series

Show that

- a) Any cosine series $a_0 + \sum_{n=1}^{N} a_n \cos(2\pi nt/T)$ is a symmetric function.
- b) Any sine series $\sum_{n=1}^{N} b_n \sin(2\pi nt/T)$ is an antisymmetric function.
- c) Any periodic function can be written as a sum of a symmetric and an antisymmetric function by writing $f(t) = \frac{f(t) + f(-t)}{2} + \frac{f(t) f(-t)}{2}$.
- **d)** If $f_N(t) = a_0 + \sum_{n=1}^{N} (a_n \cos(2\pi nt/T) + b_n \sin(2\pi nt/T))$, then

$$\frac{f_N(t) + f_N(-t)}{2} = a_0 + \sum_{n=1}^{N} a_n \cos(2\pi nt/T)$$

$$\frac{f_N(t) - f_N(-t)}{2} = \sum_{n=1}^{N} b_n \sin(2\pi nt/T).$$

Exercise 1.21: Fourier series for low-degree polynomials

Find the Fourier series coefficients of the periodic functions with period T defined by being f(t) = t, $f(t) = t^2$, and $f(t) = t^3$, on [0, T].

Solution. For f(t) = t we get that $a_0 = \frac{1}{T} \int_0^T t dt = \frac{T}{2}$. We also get

$$\begin{split} a_n &= \frac{2}{T} \int_0^T t \cos(2\pi n t/T) dt \\ &= \frac{2}{T} \left(\left[\frac{T}{2\pi n} t \sin(2\pi n t/T) \right]_0^T - \frac{T}{2\pi n} \int_0^T \sin(2\pi n t/T) dt \right) = 0 \\ b_n &= \frac{2}{T} \int_0^T t \sin(2\pi n t/T) dt \\ &= \frac{2}{T} \left(\left[-\frac{T}{2\pi n} t \cos(2\pi n t/T) \right]_0^T + \frac{T}{2\pi n} \int_0^T \cos(2\pi n t/T) dt \right) = -\frac{T}{\pi n}. \end{split}$$

The Fourier series is thus

$$\frac{T}{2} - \sum_{n>1} \frac{T}{\pi n} \sin(2\pi nt/T).$$

Note that this is almost a sine series, since it has a constant term, but no other cosine terms. If we had subtracted T/2 we would have obtained a function which is antisymmetric, and thus a pure sine series.

For
$$f(t) = t^2$$
 we get that $a_0 = \frac{1}{T} \int_0^T t^2 dt = \frac{T^2}{3}$. We also get

$$a_n = \frac{2}{T} \int_0^T t^2 \cos(2\pi nt/T) dt$$

$$= \frac{2}{T} \left(\left[\frac{T}{2\pi n} t^2 \sin(2\pi nt/T) \right]_0^T - \frac{T}{\pi n} \int_0^T t \sin(2\pi nt/T) dt \right)$$

$$= \left(-\frac{T}{\pi n} \right) \left(-\frac{T}{\pi n} \right) = \frac{T^2}{\pi^2 n^2}$$

$$b_n = \frac{2}{T} \int_0^T t^2 \sin(2\pi nt/T) dt$$

$$= \frac{2}{T} \left(\left[-\frac{T}{2\pi n} t^2 \cos(2\pi nt/T) \right]_0^T + \frac{T}{\pi n} \int_0^T t \cos(2\pi nt/T) dt \right)$$

$$= -\frac{T^2}{\pi n}.$$

Here we see that we could use the expressions for the Fourier coefficients of f(t) = t to save some work. The Fourier series is thus

$$\frac{T^2}{3} + \sum_{n \geq 1} \left(\frac{T^2}{\pi^2 n^2} \cos(2\pi n t/T) - \frac{T^2}{\pi n} \sin(2\pi n t/T) \right).$$

For
$$f(t)=t^3$$
 we get that $a_0=\frac{1}{T}\int_0^T t^3 dt=\frac{T^3}{4}$. We also get

$$a_{n} = \frac{2}{T} \int_{0}^{T} t^{3} \cos(2\pi nt/T) dt$$

$$= \frac{2}{T} \left(\left[\frac{T}{2\pi n} t^{3} \sin(2\pi nt/T) \right]_{0}^{T} - \frac{3T}{2\pi n} \int_{0}^{T} t^{2} \sin(2\pi nt/T) dt \right)$$

$$= \left(-\frac{3T}{2\pi n} \right) \left(-\frac{T^{2}}{\pi n} \right) = \frac{3T^{3}}{2\pi^{2}n^{2}}$$

$$b_{n} = \frac{2}{T} \int_{0}^{T} t^{3} \sin(2\pi nt/T) dt$$

$$= \frac{2}{T} \left(\left[-\frac{T}{2\pi n} t^{3} \cos(2\pi nt/T) \right]_{0}^{T} + \frac{3T}{2\pi n} \int_{0}^{T} t^{2} \cos(2\pi nt/T) dt \right)$$

$$= -\frac{T^{3}}{\pi n} + \frac{3T}{2\pi n} \frac{T^{2}}{\pi^{2}n^{2}} = -\frac{T^{3}}{\pi n} + \frac{3T^{3}}{2\pi^{3}n^{3}}.$$

Also here we saved some work, by reusing the expressions for the Fourier coefficients of $f(t) = t^2$. The Fourier series is thus

$$\frac{T^3}{4} + \sum_{n \geq 1} \left(\frac{3T^3}{2\pi^2 n^2} \cos(2\pi nt/T) + \left(-\frac{T^3}{\pi n} + \frac{3T^3}{2\pi^3 n^3} \right) \sin(2\pi nt/T) \right).$$

We see that all three Fourier series converge slowly. This is connected to the fact that none of the functions are continuous at the borders of the periods.

Exercise 1.22: Fourier series for polynomials

Write down difference equations for finding the Fourier coefficients of $f(t) = t^{k+1}$ from those of $f(t) = t^k$, and write a program which uses this recursion. Use the program to verify what you computed in Exercise 1.

Solution. Let us define $a_{n,k}, b_{n,k}$ as the Fourier coefficients of t^k . When k > 0 and n > 0, integration by parts gives us the following difference equations:

$$a_{n,k} = \frac{2}{T} \int_0^T t^k \cos(2\pi nt/T) dt$$

$$= \frac{2}{T} \left(\left[\frac{T}{2\pi n} t^k \sin(2\pi nt/T) \right]_0^T - \frac{kT}{2\pi n} \int_0^T t^{k-1} \sin(2\pi nt/T) dt \right)$$

$$= -\frac{kT}{2\pi n} b_{n,k-1}$$

$$b_{n,k} = \frac{2}{T} \int_0^T t^k \sin(2\pi nt/T) dt$$

$$= \frac{2}{T} \left(\left[-\frac{T}{2\pi n} t^k \cos(2\pi nt/T) \right]_0^T + \frac{kT}{2\pi n} \int_0^T t^{k-1} \cos(2\pi nt/T) dt \right)$$

$$= -\frac{T^k}{\pi n} + \frac{kT}{2\pi n} a_{n,k-1}.$$

When n > 0, these can be used to express $a_{n,k}, b_{n,k}$ in terms of $a_{n,0}, b_{n,0}$, for which we clearly have $a_{n,0} = b_{n,0} = 0$. For n = 0 we have that $a_{0,k} = \frac{T^k}{k+1}$ for all k.

The following program computes $a_{n,k}, b_{n,k}$ recursively when n > 0.

```
def findfouriercoeffs(n, k, T):
    ank, bnk = 0, 0
    if k > 0:
        ankprev, bnkprev = findfouriercoeffs(n,k-1,T)
        ank = -k*T*bnkprev/(2*pi*n)
        bnk = -T**k/(pi*n) + k*T*ankprev/(2*pi*n)
    return ank, bnk
```

Exercise 1.23: Fourier series of a given polynomial

Use the previous exercise to find the Fourier series for $f(x) = -\frac{1}{3}x^3 + \frac{1}{2}x^2 - \frac{3}{16}x + 1$ on the interval [0, 1]. Plot the 9th order Fourier series for this function. You should obtain the plots from Figure 1.5 in the compendium.

Exercise 1.27: Orthonormality of Complex Fourier basis

Show that the complex functions $e^{2\pi i n t/T}$ are orthonormal.

Solution. For $n_1 \neq n_2$ we have that

$$\langle e^{2\pi i n_1 t/T}, e^{2\pi i n_2 t/T} \rangle = \frac{1}{T} \int_0^T e^{2\pi i n_1 t/T} e^{-2\pi i n_2 t/T} dt = \frac{1}{T} \int_0^T e^{2\pi i (n_1 - n_2) t/T} dt$$

$$= \left[\frac{T}{2\pi i (n_1 - n_2)} e^{2\pi i (n_1 - n_2) t/T} \right]_0^T$$

$$= \frac{T}{2\pi i (n_1 - n_2)} - \frac{T}{2\pi i (n_1 - n_2)} = 0.$$

When $n_1 = n_2$ the integrand computes to 1, so that $||e^{2\pi i n t/T}|| = 1$.

Exercise 1.28: Complex Fourier series of $f(t) = \sin^2(2\pi t/T)$

Compute the complex Fourier series of the function $f(t) = \sin^2(2\pi t/T)$.

Solution. We have that

$$\begin{split} f(t) &= \sin^2(2\pi t/T) = \left(\frac{1}{2i}(e^{2\pi i t/T} - e^{-2\pi i t/T})\right)^2 \\ &= -\frac{1}{4}(e^{2\pi i 2t/T} - 2 + e^{-2\pi i 2t/T}) = -\frac{1}{4}e^{2\pi i 2t/T} + \frac{1}{2} - \frac{1}{4}e^{-2\pi i 2t/T}. \end{split}$$

This gives the Fourier series of the function (with $y_2 = y_{-2} = -1/4$, $y_0 = 1/2$). This could also have been shown by using the trigonometric identity $\sin^2 x = \frac{1}{2}(1-\cos(2x))$ first, or by computing the integral $\frac{1}{T}\int_0^T f(t)e^{-2\pi int/T}dt$ (but this is rather cumbersome).

Exercise 1.29: Complex Fourier series of polynomials

Repeat Exercise 1, computing the complex Fourier series instead of the real Fourier series.

Exercise 1.30: Complex Fourier series and Pascals triangle

In this exercise we will find a connection with certain Fourier series and the rows in Pascal's triangle.

a) Show that both $\cos^n(t)$ and $\sin^n(t)$ are in $V_{N,2\pi}$ for $1 \le n \le N$.

Solution. We have that

$$\cos^{n}(t) = \left(\frac{1}{2}(e^{it} + e^{-it})\right)^{n}$$
$$\sin^{n}(t) = \left(\frac{1}{2i}(e^{it} - e^{-it})\right)^{n}$$

If we multiply out here, we get a sum of terms of the form e^{ikt} , where $-n \le k \le n$. As long as $n \le N$ it is clear that this is in $V_{N,2\pi}$.

b) Write down the N'th order complex Fourier series for $f_1(t) = \cos t$, $f_2(t) = \cos^2 t$, og $f_3(t) = \cos^3 t$.

Solution. We have that

$$\cos(t) = \frac{1}{2}(e^{it} + e^{-it})$$

$$\cos^2(t) = \frac{1}{4}(e^{it} + e^{-it})^2 = \frac{1}{4}e^{2it} + \frac{1}{2} + \frac{1}{4}e^{-2it}$$

$$\cos^3(t) = \frac{1}{8}(e^{it} + e^{-it})^3 = \frac{1}{8}e^{3it} + \frac{3}{8}e^{it} + \frac{3}{8}e^{-it} + \frac{1}{8}e^{-3it}.$$

Therefore, for the first function the nonzero Fourier coefficients are $y_{-1} = 1/2$, $y_1 = 1/2$, for the second function $y_{-2} = 1/4$, $y_0 = 1/2$, $y_2 = 1/4$, for the third function $y_{-3} = 1/8$, $y_{-1} = 3/8$, $y_1 = 3/8$, $y_3 = 1/8$.

c) In b) you should be able to see a connection between the Fourier coefficients and the three first rows in Pascal's triangle. Formulate and prove a general relationship between row n in Pascal's triangle and the Fourier coefficients of $f_n(t) = \cos^n t$.

Solution. In order to find the Fourier coefficients of $\cos^n(t)$ we have to multiply out the expression $\frac{1}{2^n}(e^{it}+e^{-it})^n$. The coefficients we get after this can also be obtained from Pascal's triangle.

Exercise 1.31: Complex Fourier coefficients of the square wave

Compute the complex Fourier coefficients of the square wave using Equation (1.22) in the compendium, i.e. repeat the calculations from Example 1.12 in the compendium for the complex case. Use Theorem 1.15 in the compendium to verify your result.

Solution. We obtain that

$$y_n = \frac{1}{T} \int_0^{T/2} e^{-2\pi i n t/T} dt - \frac{1}{T} \int_{T/2}^T e^{-2\pi i n t/T} dt$$

$$= -\frac{1}{T} \left[\frac{T}{2\pi i n} e^{-2\pi i n t/T} \right]_0^{T/2} + \frac{1}{T} \left[\frac{T}{2\pi i n} e^{-2\pi i n t/T} \right]_{T/2}^T$$

$$= \frac{1}{2\pi i n} \left(-e^{-\pi i n} + 1 + 1 - e^{-\pi i n} + \right)$$

$$= \frac{1}{\pi i n} \left(1 - e^{-\pi i n} \right) = \begin{cases} 0, & \text{if } n \text{ is even;} \\ 2/(\pi i n), & \text{if } n \text{ is odd.} \end{cases}$$

Instead using Theorem 1.15 in the compendium together with the coefficients $b_n=\frac{2(1-\cos(n\pi)}{n\pi}$ we computed in Example 1.12 in the compendium, we obtain

$$y_n = \frac{1}{2}(a_n - ib_n) = -\frac{1}{2}i \begin{cases} 0, & \text{if } n \text{ is even;} \\ 4/(n\pi), & \text{if } n \text{ is odd.} \end{cases} = \begin{cases} 0, & \text{if } n \text{ is even;} \\ 2/(\pi i n), & \text{if } n \text{ is odd.} \end{cases}$$

when n > 0. The case n < 0 follows similarly.

Exercise 1.32: Complex Fourier coefficients of the triangle wave

Repeat Exercise 1 for the triangle wave.

Exercise 1.33: Complex Fourier coefficients of low-degree polynomials

Use Equation (1.22) in the compendium to compute the complex Fourier coefficients of the periodic functions with period T defined by, respectively, f(t) = t, $f(t) = t^2$, and $f(t) = t^3$, on [0, T]. Use Theorem 1.15 in the compendium to verify your calculations from Exercise 1.

Solution. For f(t) = t we get

$$y_n = \frac{1}{T} \int_0^T t e^{-2\pi i n t/T} dt = \frac{1}{T} \left(\left[-\frac{T}{2\pi i n} t e^{-2\pi i n t/T} \right]_0^T + \int_0^T \frac{T}{2\pi i n} e^{-2\pi i n t/T} dt \right)$$
$$= -\frac{T}{2\pi i n} = \frac{T}{2\pi n} i.$$

From Exercise 1 we had $b_n = -\frac{T}{\pi n}$, for which Theorem 1.15 in the compendium gives $y_n = \frac{T}{2\pi n}i$ for n > 0, which coincides with the expression we obtained. The case n < 0 follows similarly.

For
$$f(t) = t^2$$
 we get

$$y_n = \frac{1}{T} \int_0^T t^2 e^{-2\pi i n t/T} dt = \frac{1}{T} \left(\left[-\frac{T}{2\pi i n} t^2 e^{-2\pi i n t/T} \right]_0^T + 2 \int_0^T \frac{T}{2\pi i n} t e^{-2\pi i n t/T} dt \right)$$
$$= -\frac{T^2}{2\pi i n} + \frac{T^2}{2\pi^2 n^2} = \frac{T^2}{2\pi^2 n^2} + \frac{T^2}{2\pi n} i.$$

From Exercise 1 we had $a_n = \frac{T^2}{\pi^2 n^2}$ and $b_n = -\frac{T^2}{\pi n}$, for which Theorem 1.15 in the compendium gives $y_n = \frac{1}{2} \left(\frac{T^2}{\pi^2 n^2} + i \frac{T^2}{\pi n} \right)$ for n > 0, which also is seen to coincide with what we obtained. The case n < 0 follows similarly. For $f(t) = t^3$ we get

$$y_n = \frac{1}{T} \int_0^T t^3 e^{-2\pi i n t/T} dt = \frac{1}{T} \left(\left[-\frac{T}{2\pi i n} t^3 e^{-2\pi i n t/T} \right]_0^T + 3 \int_0^T \frac{T}{2\pi i n} t^2 e^{-2\pi i n t/T} dt \right)$$

$$= -\frac{T^3}{2\pi i n} + 3 \frac{T}{2\pi i n} \left(\frac{T^2}{2\pi^2 n^2} + \frac{T^2}{2\pi n} i \right) = 3 \frac{T^3}{4\pi^2 n^2} + \left(\frac{T^3}{2\pi n} - 3 \frac{T^3}{4\pi^3 n^3} \right) i =$$

From Exercise 1 we had $a_n=\frac{3T^3}{2\pi^2n^2}$ and $b_n=-\frac{T^3}{\pi n}+\frac{3T^3}{2\pi^3n^3}$ for which Theorem 1.15 in the compendium gives

$$y_n = \frac{1}{2} \left(\frac{3T^3}{2\pi^2 n^2} + i \left(\frac{T^3}{\pi n} - \frac{3T^3}{2\pi^3 n^3} \right) \right) = \frac{3T^3}{4\pi^2 n^2} + \left(\frac{T^3}{2\pi n} - \frac{3T^3}{4\pi^3 n^3} \right) i$$

for n > 0, which also is seen to coincide with what we obtained. The case n < 0 follows similarly.

Exercise 1.34: Complex Fourier coefficients for symmetric and antisymmetric functions

In this exercise we will prove a version of Theorem 1.10 in the compendium for complex Fourier coefficients.

a) If f is symmetric about 0, show that y_n is real, and that $y_{-n} = y_n$.

Solution. If f is symmetric about 0 we have that $b_n = 0$. Theorem 1.15 in the compendium then gives that $y_n = \frac{1}{2}a_n$, which is real. The same theorem gives that $y_{-n} = \frac{1}{2}a_n = y_n$.

b) If f is antisymmetric about 0, show that the y_n are purely imaginary, $y_0 = 0$, and that $y_{-n} = -y_n$.

Solution. If f is antisymmetric about 0 we have that $a_n=0$. Theorem 1.15 in the compendium then gives that $y_n=-\frac{1}{2}b_n$, which is purely imaginary. The same theorem gives that $y_{-n}=\frac{1}{2}b_n=-y_n$.

c) Show that $\sum_{n=-N}^{N} y_n e^{2\pi i n t/T}$ is symmetric when $y_{-n} = y_n$ for all n, and rewrite it as a cosine-series.

Solution. When $y_n = y_{-n}$ we can write

$$y_{-n}e^{2\pi i(-n)t/T} + y_n e^{2\pi int/T} = y_n (e^{2\pi int/T} + e^{-2\pi int/T}) = 2y_n \cos(2\pi nt/T)$$

This is clearly symmetric, but then also $\sum_{n=-N}^{N} y_n e^{2\pi i n t/T}$ is symmetric since it is a sum of symmetric functions.

d) Show that $\sum_{n=-N}^{N} y_n e^{2\pi i n t/T}$ is antisymmetric when $y_0 = 0$ and $y_{-n} = -y_n$ for all n, and rewrite it as a sine-series.

Solution. When $y_n = -y_{-n}$ we can write

$$y_{-n}e^{2\pi i(-n)t/T} + y_n e^{2\pi int/T} = y_n(-e^{2\pi int/T} + e^{2\pi int/T}) = 2iy_n \sin(2\pi nt/T)$$

This is clearly antisymmetric, but then also $\sum_{n=-N}^{N} y_n e^{2\pi i n t/T}$ is antisymmetric since it is a sum of antisymmetric functions, and since $y_0 = 0$.

Exercise 1.36: Fourier series of a delayed square wave

Define the function f with period T on [-T/2, T/2) by

$$f(t) = \begin{cases} 1, & \text{if } -T/4 \le t < T/4; \\ -1, & \text{if } T/4 \le |t| < T/2. \end{cases}$$

f is just the square wave, delayed with d=-T/4. Compute the Fourier coefficients of f directly, and use Property 4 in Theorem 1.17 in the compendium to verify your result.

Solution. We obtain that

$$y_n = \frac{1}{T} \int_{-T/4}^{T/4} e^{-2\pi i n t/T} dt - \frac{1}{T} \int_{-T/2}^{-T/4} e^{-2\pi i n t/T} dt - \frac{1}{T} \int_{T/4}^{T/2} e^{-2\pi i n t/T} dt$$

$$= -\left[\frac{1}{2\pi i n} e^{-2\pi i n t/T} \right]_{-T/4}^{T/4} + \left[\frac{1}{2\pi i n} e^{-2\pi i n t/T} \right]_{-T/2}^{-T/4} + \left[\frac{1}{2\pi i n} e^{-2\pi i n t/T} \right]_{T/4}^{T/2}$$

$$= \frac{1}{2\pi i n} \left(-e^{-\pi i n/2} + e^{\pi i n/2} + e^{\pi i n/2} - e^{\pi i n} + e^{-\pi i n} - e^{-\pi i n/2} \right)$$

$$= \frac{1}{\pi n} \left(2 \sin(\pi n/2) - \sin(\pi n) \right) = \frac{2}{\pi n} \sin(\pi n/2).$$

The square wave defined in this exercise can be obtained by delaying our original square wave with -T/4. Using Property 3 in Theorem 1.17 in the compendium with d = -T/4 on the complex Fourier coefficients

$$y_n = \begin{cases} 0, & \text{if } n \text{ is even;} \\ 2/(\pi i n), & \text{if } n \text{ is odd,} \end{cases}$$

which we obtained for the square wave in Exercise 1, we obtain the Fourier coefficients

$$e^{2\pi i n(T/4)/T} \begin{cases} 0, & \text{if } n \text{ is even;} \\ 2/(\pi i n), & \text{if } n \text{ is odd.} \end{cases} = \begin{cases} 0, & \text{if } n \text{ is even;} \\ \frac{2i\sin(\pi n/2)}{\pi i n}, & \text{if } n \text{ is odd.} \end{cases}$$
$$= \begin{cases} 0, & \text{if } n \text{ is even;} \\ \frac{2}{\pi n}\sin(\pi n/2), & \text{if } n \text{ is odd.} \end{cases}.$$

This verifies the result.

Exercise 1.37: Find function from its Fourier series

Find a function f which has the complex Fourier series

$$\sum_{n \text{ odd}} \frac{4}{\pi(n+4)} e^{2\pi i n t/T}.$$

Hint. Attempt to use one of the properties in Theorem 1.17 in the compendium on the Fourier series of the square wave.

Solution. Since the real Fourier series of the square wave is

$$\sum_{n \ge 1, n \text{ odd}} \frac{4}{\pi n} \sin(2\pi n t/T),$$

Theorem 1.15 in the compendium gives us that the complex Fourier coefficients are $y_n=-\frac{1}{2}i\frac{4}{\pi n}=-\frac{2i}{\pi n}$, and $y_{-n}=\frac{1}{2}i\frac{4}{\pi n}=\frac{2i}{\pi n}$ for n>0. This means that $y_n=-\frac{2i}{\pi n}$ for all n, so that the complex Fourier series of the square wave is

$$-\sum_{n \text{ odd}} \frac{2i}{\pi n} e^{2\pi i n t/T}.$$

Using Property 4 in Theorem 1.17 in the compendium we get that the $e^{-2\pi i 4t/T}$ (i.e. set d=-4) times the square wave has its n'th Fourier coefficient equal to $-\frac{2i}{\pi(n+4)}$. Using linearity, this means that $2ie^{-2\pi i 4t/T}$ times the square wave has its n'th Fourier coefficient equal to $\frac{4}{\pi(n+4)}$. We thus have that the function

$$f(t) = \begin{cases} 2ie^{-2\pi i 4t/T} &, 0 \le t < T/2\\ -2ie^{-2\pi i 4t/T} &, T/2 \le t < T \end{cases}$$

has the desired Fourier series.

Exercise 1.38: Relation between complex Fourier coefficients of f and cosine-coefficients of \check{f}

Show that the complex Fourier coefficients y_n of f, and the cosine-coefficients a_n of \check{f} are related by $a_{2n} = y_n + y_{-n}$. This result is not enough to obtain the entire Fourier series of \check{f} , but at least it gives us half of it.

Solution. The 2nth complex Fourier coefficient of \check{f} is

$$\begin{split} &\frac{1}{2T} \int_0^{2T} \breve{f}(t) e^{-2\pi i 2nt/(2T)} dt \\ &= \frac{1}{2T} \int_0^T f(t) e^{-2\pi i nt/T} dt + \frac{1}{2T} \int_T^{2T} f(2T-t) e^{-2\pi i nt/T} dt. \end{split}$$

Substituting u = 2T - t in the second integral we see that this is

$$\begin{split} &= \frac{1}{2T} \int_0^T f(t) e^{-2\pi i n t/T} dt - \frac{1}{2T} \int_T^0 f(u) e^{2\pi i n u/T} du \\ &= \frac{1}{2T} \int_0^T f(t) e^{-2\pi i n t/T} dt + \frac{1}{2T} \int_0^T f(t) e^{2\pi i n t/T} dt \\ &= \frac{1}{2} y_n + \frac{1}{2} y_{-n}. \end{split}$$

Therefore we have $a_{2n} = y_n - y_{-n}$.

Exercise 1.39: Filters preserve sine- and cosine-series

An analog filter where $\lambda_s(\nu) = \lambda_s(-\nu)$ is also called a *symmetric filter*.

a) Prove that, if the input to a symmetric filter is a Fourier series which is a cosine series/sine-series, then the output also is a cosine/sine series.

Solution. We have that

$$s(\cos(2\pi nt/T)) = s\left(\frac{1}{2}(e^{2\pi int/T} + e^{-2\pi int/T})\right)$$

$$= \frac{1}{2}\lambda_s(n/T)e^{2\pi int/T} + \frac{1}{2}\lambda_s(-n/T)e^{-2\pi int/T}$$

$$= \lambda_s(n/T)\left(\frac{1}{2}(e^{2\pi int/T} + e^{-2\pi int/T})\right) = \lambda_s(n/T)\cos(2\pi nt/T),$$

so that s preserves cosine-series. A similar computation holds for sine-series.

b) Show that $s(f) = \int_{-a}^{a} g(s) f(t-s) ds$ is a symmetric filter whenever g is symmetric around 0 and supported on [-a,a].

Solution. We have that

$$\lambda_s(\nu) = \int_{-a}^{a} g(s)e^{-2\pi i\nu s}ds = \int_{-a}^{a} g(s)e^{2\pi i\nu s}ds = \lambda_s(-\nu),$$

so that s is symmetric.

We saw that the symmetric extension of a function took the form of a cosine-series, and that this converged faster to the symmetric extension than the Fourier series did to the function. If a filter preserves cosine-series it will also preserve symmetric extensions, and therefore also map fast-converging Fourier series to fast-converging Fourier series.

Exercise 1.40: Approximation in norm with continuous functions

Show that if f is a function with only a finite number of discontinuities, there exists a continuous function g so that $||f - g|| < \epsilon$.

Exercise 1.41: The Dirichlet kernel

The Dirichlet kernel is defined as

$$D_N(t) = \sum_{n=-N}^{N} e^{2\pi i n t/T} = 1 + 2 \sum_{n=1}^{N} \cos(2\pi n t/T).$$

 D_N is clearly trigonometric, and of degree N.

- a) Show that $D_N(t) = \frac{\sin(\pi(2N+1)t/T)}{\sin(\pi t/T)}$
- **b)** Show that $f_N(t) = \frac{1}{T} \int_0^T f(t-u) D_N(u) du$. Proving that $\lim_{N\to\infty} f_N(t) = f(t)$ is thus equivalent to $\lim_{N\to\infty} \frac{1}{T} \int_0^T f(t-u) D_N(u) du = f(t)$.

Solution. We have that

$$f_N(t) = \sum_{n=-N}^{N} \frac{1}{T} \int_0^T f(s) e^{-2\pi i n s/T} ds e^{2\pi i n t/T}$$

$$= \frac{1}{T} \int_0^T f(s) \sum_{n=-N}^{N} e^{-2\pi i n s/T} e^{2\pi i n t/T} ds$$

$$= \frac{1}{T} \int_0^T f(s) \sum_{n=-N}^{N} e^{2\pi i n (t-s)/T} ds = \frac{1}{T} \int_0^T f(s) D_N(t-s) ds.$$

- c) Prove that $D_N(t)$ satisfies only two of the properties of a summability kernel.
- **d)** Write a function which takes N and T as arguments, and plots $D_N(t)$ over [-T/2, T/2].

Exercise 1.42: The Fejer summability kernel

The Fejer kernel is defined as

$$F_N(t) = \sum_{n=-N}^{N} \left(1 - \frac{|n|}{N+1} \right) e^{2\pi i n t/N}.$$

 F_N is clearly trigonometric, and of degree N.

a) Show that $F_N(t) = \frac{1}{N+1} \left(\frac{\sin(\pi(N+1)t/T)}{\sin(\pi t/T)} \right)^2$, and conclude from this that $0 \le F_N(t) \le \frac{T^2}{4(N+1)t^2}$.

Hint. Use that $\frac{2}{\pi}|u| \leq |\sin u|$ when $u \in [-\pi/2, \pi/2]$.

- b) Show that $F_N(t)$ satisfies the three properties of a summability kernel.
- c) Show that $\frac{1}{T} \int_0^T f(t-u) F_N(u) du = \frac{1}{N+1} \sum_{n=0}^N f_n$.

Hint. Show that $F_N(t) = \frac{1}{N+1} \sum_{n=0}^{N} D_n(t)$, and use Exercis 1 b).

d) Write a function which takes N and T as arguments, and plots $F_N(t)$ over [-T/2, T/2].

Chapter 2

Digital sound and Discrete Fourier analysis

Exercise 2.6: Computing the DFT by hand

Compute F_4x when x = (2, 3, 4, 5).

Solution. As in Example 2.3 in the compendium we get

$$F_4 \begin{pmatrix} 2 \\ 3 \\ 4 \\ 5 \end{pmatrix} = \frac{1}{2} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & -i & -1 & i \\ 1 & -1 & 1 & -1 \\ 1 & i & -1 & -i \end{pmatrix} \begin{pmatrix} 2 \\ 3 \\ 4 \\ 5 \end{pmatrix}$$
$$= \frac{1}{2} \begin{pmatrix} 2+3+4+5 \\ 2-3i-4+5i \\ 2-3+4-5 \\ 2+3i-4-5i \end{pmatrix} = \begin{pmatrix} 7 \\ -1+i \\ -1 \\ -1-i \end{pmatrix}.$$

Exercise 2.7: Exact form of low-order DFT matrix

As in Example 2.3 in the compendium, state the exact cartesian form of the Fourier matrix for the cases N=6, N=8, and N=12.

Solution. For N=6 the entries are on the form $\frac{1}{\sqrt{6}}e^{-2\pi ink/6}=\frac{1}{\sqrt{6}}e^{-\pi ink/3}$. This means that the entries in the Fourier matrix are the numbers $\frac{1}{\sqrt{6}}e^{-\pi i/3}=\frac{1}{\sqrt{6}}(1/2-i\sqrt{3}/2)$, $\frac{1}{\sqrt{6}}e^{-2\pi i/3}=\frac{1}{\sqrt{6}}(-1/2-i\sqrt{3}/2)$, and so on. The matrix is thus

$$F_6 = \frac{1}{\sqrt{6}} \begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1/2 - i\sqrt{3}/2 & -1/2 - i\sqrt{3}/2 & -1 & -1/2 + i\sqrt{3}/2 & 1/2 + i\sqrt{2}/2 \\ 1 & -1/2 - i\sqrt{3}/2 & -1/2 + i\sqrt{3}/2 & 1 & -1/2 - i\sqrt{3}/2 & +1/2 - i\sqrt{3}/2 \\ 1 & -1 & 1 & -1 & 1 & -1 \\ 1 & -1/2 + i\sqrt{3}/2 & -1/2 - i\sqrt{3}/2 & 1 & -1/2 + i\sqrt{3}/2 & -1/2 - i\sqrt{3}/2 \\ 1 & 1/2 + i\sqrt{2}/2 & -1/2 + i\sqrt{3}/2 & -1 & -1/2 - i\sqrt{3}/2 & 1/2 - i\sqrt{3}/2 \end{pmatrix}$$

The cases N=8 and N=12 follow similarly, but are even more tedious. For N=8 the entries are $\frac{1}{\sqrt{8}}e^{\pi ink/4}$, which can be expressed exactly since we can express exactly any sines and cosines of a multiple of $\pi/4$. For N=12 we get the base angle $\pi/6$, for which we also have exact values for sines and cosines for all multiples.

Exercise 2.8: DFT of a delayed vector

We have a real vector \boldsymbol{x} with length N, and define the vector \boldsymbol{z} by delaying all elements in \boldsymbol{x} with 5 cyclically, i.e. $z_5 = x_0$, $z_6 = x_1, \ldots, z_{N-1} = x_{N-6}$, and $z_0 = x_{N-5}, \ldots, z_4 = x_{N-1}$. For a given n, if $|(F_N \boldsymbol{x})_n| = 2$, what is then $|(F_N \boldsymbol{z})_n|$? Justify the answer.

Solution. z is the vector x delayed with d=5 samples, and then Property 3 of Theorem 2.7 in the compendium gives us that $(F_N z)_n = e^{-2\pi i 5k/N} (F_N x)_n$. In particular $|(F_N z)_n| = |(F_N x)_n| = 2$, since $|e^{-2\pi i 5k/N}| = 1$.

Exercise 2.9: Using symmetry property

Given a real vector \boldsymbol{x} of length 8 where $(F_8(\boldsymbol{x}))_2 = 2 - i$, what is $(F_8(\boldsymbol{x}))_6$?

Solution. By Theorem 2.7 in the compendium we know that $(F_N(\boldsymbol{x}))_{N-n} = \overline{(F_N(\boldsymbol{x}))_n}$ when \boldsymbol{x} is a real vector. If we set N=8 and n=2 we get that $(F_8(\boldsymbol{x}))_6 = \overline{(F_8(\boldsymbol{x}))_2} = \overline{2-i} = 2+i$.

Exercise 2.10: DFT of $\cos^2(2\pi k/N)$

Let \boldsymbol{x} be the vector of length N where $x_k = \cos^2(2\pi k/N)$. What is then $F_N \boldsymbol{x}$?

Solution. The idea is to express x as a linear combination of the Fourier basis vectors ϕ_n , and use that $F_N\phi_n=e_n$. We have that

$$\cos^{2}(2\pi k/N) = \left(\frac{1}{2}\left(e^{2\pi i k/N} + e^{-2\pi i k n/N}\right)\right)^{2}$$

$$= \frac{1}{4}e^{2\pi i 2k/N} + \frac{1}{2} + \frac{1}{4}e^{-2\pi i 2k/N} = \frac{1}{4}e^{2\pi i 2k/N} + \frac{1}{2} + \frac{1}{4}e^{2\pi i (N-2)k/N}$$

$$= \sqrt{N}\left(\frac{1}{4}\phi_{2} + \frac{1}{2}\phi_{0} + \frac{1}{4}\phi_{N-2}\right).$$

We here used the periodicity of $e^{2\pi ikn/N}$, i.e. that $e^{-2\pi i2k/N} = e^{2\pi i(N-2)k/N}$. Since F_N is linear and $F_N(\phi_n) = e_n$, we have that

$$F_{N}\left(m{x}
ight) = \sqrt{N}\left(rac{1}{4}m{e}_{2} + rac{1}{2}m{e}_{0} + rac{1}{4}m{e}_{N-2}
ight) = \sqrt{N}\left(1/2, 0, 1/4, 0, \dots, 0, 1/4, 0
ight).$$

Exercise 2.11: DFT of $c^k x$

Let \boldsymbol{x} be the vector with entries $x_k = c^k$. Show that the DFT of \boldsymbol{x} is given by the vector with components

$$y_n = \frac{1 - c^N}{1 - ce^{-2\pi i n/N}}$$

for n = 0, ..., N - 1.

Solution. We get

$$y_n = \sum_{k=0}^{N-1} c^k e^{-2\pi i n k/N} = \sum_{k=0}^{N-1} (ce^{-2\pi i n/N})^k$$
$$= \frac{1 - (ce^{-2\pi i n/N})^N}{1 - ce^{-2\pi i n/N}} = \frac{1 - c^N}{1 - ce^{-2\pi i n/N}}.$$

Exercise 2.12: Rewrite a complex DFT as real DFT's

If x is complex, Write the DFT in terms of the DFT on real sequences.

Hint. Split into real and imaginary parts, and use linearity of the DFT.

Exercise 2.13: DFT implementation

Extend the code for the function DFTImpl in Example 2.4 in the compendium so that

• The function also takes a second parameter called **forward**. If this is true the DFT is applied. If it is false, the IDFT is applied. If this parameter is not present, then the forward transform should be assumed.

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• If the input x is two-dimensional (i.e. a matrix), the DFT/IDFT should be applied to each column of x. This ensures that, in the case of sound, the FFT is applied to each channel in the sound when the enrire sound is used as input, as we are used to when applying different operations to sound.

Also, write documentation for the code.

Solution. The code can look like this:

```
def DFTImpl(x, forward=True):
      Compute the DFT of the vector x using standard matrix multiplication. To avoid out of memory situations, we do not allocate the entire DFT matrix, only one row of it at a time.
      Note that this function differs from the FFT in that it includes the normalizing factor 1/sqrt(N). The DFT is computed along axis 0. If there is another axis, the DFT is computed for each element
      in this as well.
      x: a vector
      forward: Whether or not this is forward (i.e. DFT)
      or reverse (i.e. IDFT)
      y = zeros_like(x).astype(complex)
N = len(x)
      sign = -(2*forward - 1)
      if ndim(x) == 1:
             for n in xrange(N):
                   D = exp(sign*2*pi*n*1j*arange(float(N))/N)
                   y[n] = dot(D, x)
             for n in range(N):
                   D = exp(sign*2*pi*n*1j*arange(float(N))/N)
for s2 in xrange(shape(x)[1]):
    y[n,s2] = dot(D,x[:, s2])
      if sign == 1:
            y /= float(N)
      return y
```

Exercise 2.14: Symmetry

Assume that N is even.

a) Show that, if $x_{k+N/2} = x_k$ for all $0 \le k < N/2$, then $y_n = 0$ when n is odd.

Solution. We have that

$$y_n = \frac{1}{\sqrt{N}} \left(\sum_{k=0}^{N/2-1} x_k e^{-2\pi i k n/N} + \sum_{k=N/2}^{N-1} x_k e^{-2\pi i k n/N} \right)$$

$$= \frac{1}{\sqrt{N}} \left(\sum_{k=0}^{N/2-1} x_k e^{-2\pi i k n/N} + \sum_{k=0}^{N/2-1} x_k e^{-2\pi i (k+N/2)n/N} \right)$$

$$= \frac{1}{\sqrt{N}} \sum_{k=0}^{N/2-1} x_k (e^{-2\pi i k n/N} + (-1)^n e^{-2\pi i k n/N})$$

$$= (1 + (-1)^n) \frac{1}{\sqrt{N}} \sum_{k=0}^{N/2-1} x_k e^{-2\pi i k n/N}$$

If n is odd, we see that $y_n = 0$.

b) Show that, if $x_{k+N/2} = -x_k$ for all $0 \le k < N/2$, then $y_n = 0$ when n is even.

Solution. The proof is the same as in a), except for a sign change.

c) Show also the converse statements in a) and b).

Solution. Clearly the set of vectors which satisfies $x_{k+N/2} = \pm x_k$ is a vector space V of dimension N/2. The set of vectors where every second component is zero is also a vector space of dimension N/2, let us denote this by W. We have shown that $F_N(V) \subset W$, but since F_N is unitary, $F_N(V)$ also has dimension N/2, so that $F_N(V) = W$. This shows that when every second y_n is 0, we must have that $x_{k+N/2} = \pm x_k$, and the proof is done.

- d) Also show the following:
 - $x_n = 0$ for all odd n if and only if $y_{k+N/2} = y_k$ for all $0 \le k < N/2$.
 - $x_n = 0$ for all even n if and only if $y_{k+N/2} = -y_k$ for all $0 \le k < N/2$.

Solution. In the proofs above, compute the IDFT instead.

Exercise 2.15: DFT on complex and real data

Let x_1, x_2 be real vectors, and set $x = x_1 + ix_2$. Use Theorem 2.7 in the compendium to show that

$$(F_N(\boldsymbol{x}_1))_k = \frac{1}{2} \left((F_N(\boldsymbol{x}))_k + \overline{(F_N(\boldsymbol{x}))_{N-k}} \right)$$
$$(F_N(\boldsymbol{x}_2))_k = \frac{1}{2i} \left((F_N(\boldsymbol{x}))_k - \overline{(F_N(\boldsymbol{x}))_{N-k}} \right)$$

This shows that we can compute two DFT's on real data from one DFT on complex data, and 2N extra additions.

Solution. We have that

$$(F_N(\mathbf{x}))_k = (F_N(\mathbf{x}_1 + i\mathbf{x}_2))_k = (F_N(\mathbf{x}_1))_k + i(F_N(\mathbf{x}_2))_k (F_N(\mathbf{x}))_{N-k} = (F_N(\mathbf{x}_1))_{N-k} + i(F_N(\mathbf{x}_2))_{N-k} = \overline{(F_N(\mathbf{x}_1))_k} + i\overline{(F_N(\mathbf{x}_2))_k},$$

where we have used Property 1 of Theorem 2.7 in the compendium. If we take the complex conjugate in the last equation, we are left with the two equations

$$\frac{(F_N(\mathbf{x}))_k = (F_N(\mathbf{x}_1))_k + i(F_N(\mathbf{x}_2))_k}{(F_N(\mathbf{x}))_{N-k} = (F_N(\mathbf{x}_1))_k - i(F_N(\mathbf{x}_2))_k}.$$

If we add these we get

$$(F_N(\boldsymbol{x}_1))_k = \frac{1}{2} \left((F_N(\boldsymbol{x}))_k + \overline{(F_N(\boldsymbol{x}))_{N-k}} \right),$$

which is the first equation. If we instead subtract the equations we get

$$(F_N(\boldsymbol{x}_2))_k = \frac{1}{2i} \left((F_N(\boldsymbol{x}))_k - \overline{(F_N(\boldsymbol{x}))_{N-k}} \right),$$

which is the second equation

Exercise 2.19: Comment code

Explain what the code below does, line by line:

```
x = x[0:2**17]
y = fft.fft(x, axis=0)
y[(2**17/4):(3*2**17/4)] = 0
newx = abs(fft.ifft(y))
newx /= abs(newx).max()
play(newx, fs)
```

Comment in particular why we adjust the sound samples by dividing with the maximum value of the sound samples. What changes in the sound do you expect to hear?

Solution. First a sound file is read. We then restrict to the first 2^{12} sound samples, perform a DFT, zero out the frequencies which correspond to DFT-indices between 2^{10} and $2^{12} - 2^{10} - 1$, and perform an IDFT. Finally we scale the sound samples so that these lie between -1 and 1, which is the range we demand for the sound samples, and play the new sound.

Exercise 2.20: Which frequency is changed?

In the code from the previous exercise it turns out that $f_s = 44100$ Hz, and that the number of sound samples is N = 292570. Which frequencies in the sound file will be changed on the line where we zero out some of the DFT coefficients?

Solution. As we have seen, DFT index n corresponds to frequency $\nu = nf_s/N$. Above $N=2^{17}$, so that we get the connection $\nu = nf_s/N = n \times 44100/2^{17}$. We zeroed the DFT indices above $n=2^{15}$, so that frequencies above $\nu = 2^{15} \times 44100/2^{17} = 11025Hz$ are affected.

Exercise 2.21: Implement interpolant

Implement code where you do the following:

- at the top you define the function $f(x) = \cos^6(x)$, and M = 3,
- compute the unique interpolant from $V_{M,T}$ (i.e. by taking N=2M+1 samples over one period), as guaranteed by Proposition 2.9 in the compendium,
- \bullet plot the interpolant against f over one period.

Finally run the code also for M=4, M=5, and M=6. Explain why the plots coincide for M=6, but not for M<6. Does increasing M above M=6 have any effect on the plots?

Solution. The code can look as follows.

```
import matplotlib.pyplot as plt
from numpy import *

f = lambda t:cos(t)**6
M = 5
T = 2*pi
N = 2*M + 1
t = linspace(0, T, 100)
x = f(linspace(0, T - T/float(N), N))
y = fft.fft(x, axis=0)/N
s = real(y[0])*ones(len(t))
for k in range(1,(N+1)/2):
    s += 2*real(y[k]*exp(2*pi*1j*k*t/float(T)))
plt.plot(t, s, 'r', t, f(t), 'g')
plt.legend(['Interpolant from V_{M,T}','f'])
```

Exercise 2.22: Extra results for the FFT when $N = N_1 N_2$

When N is composite, there are a couple of results we can state regarding polyphase components.

a) Assume that $N = N_1 N_2$, and that $\boldsymbol{x} \in \mathbb{R}^N$ satisfies $x_{k+rN_1} = x_k$ for all k, r, i.e. \boldsymbol{x} has period N_1 . Show that $y_n = 0$ for all n which are not a multiplum of N_2 .

Solution. We have that $\boldsymbol{x}^{(p)}$ is a constant vector of length N_2 for $0 \leq p < N_1$. But then the DFT of all the $\boldsymbol{x}^{(p)}$ has zero outside entry zero. Multiplying with $e^{-2\pi i k n/N}$ does not affect this. The last $N_2 - 1$ rows are thus zero before the final DFT is applied, so that these rows are zero also after this final DFT. After assembling the polyphase components again we have that yrN_2 are the only nonzero DFT-coefficients.

b) Assume that $N = N_1 N_2$, and that $\mathbf{x}^{(p)} = \mathbf{0}$ for $p \neq 0$. Show that the polyphase components $\mathbf{y}^{(p)}$ of $\mathbf{y} = \text{DFT}_N \mathbf{x}$ are constant vectors for all p.

But what about the case when N is a prime number? Rader's algorithm [?] handles this case by expressing a DFT with N a prime number in terms of DFT's of length N-1 (which is not a prime number). Our previous scenario can then be followed, but stops quickly again if N-1 has prime factors of high order. Since there are some computational penalties in applying Rader's algorithm, it may be inefficient some cases. Winograd's FFT algorithm [?] extends Rader's algorithm to work for the case when $N=p^r$. This algorithm tends to reduce the number of multiplications, at the price of an increased number of additions. It is difficult to program, and is rarely used in practice.

Exercise 2.23: Extend implementation

Recall that, in Exercise 2, we extended the direct DFT implementation so that it accepted a second parameter telling us if the forward or reverse transform should be applied. Extend the general function and the standard kernel in the same way. Again, the forward transform should be used if the forward parameter is not present. Assume also that the kernel accepts only one-dimensional data, and that the general function applies the kernel to each column in the input if the input is two-dimensional (so that the FFT can be applied to all channels in a sound with only one call). The signatures for our methods should thus be changed as follows:

```
def FFTImpl(x, FFTKernel, forward = True):
def FFTKernelStandard(x, forward):
```

It should be straightforward to make the modifications for the reverse transform by consulting the second part of Theorem 2.18 in the compendium. For simplicity, let ${\tt FFTImpl}$ take care of the additional division with N we need to do in case of the IDFT. In the following we will assume these signatures for the ${\tt FFT}$ implementation and the corresponding kernels.

Solution. The functions can be implemented as follows:

```
def FFTImpl(x, FFTKernel, forward = True):
    Compute the FFT or IFFT of the vector \mathbf{x}. Note that this function
    differs from the DFT in that the normalizing factor 1/\text{sqrt}(N) is
    not included. The FFT is computed along axis 0. If there is
    another axis, the FFT is computed for each element in this as
    well. This function calls a kernel for computing the FFT. The
    kernel assumes that the input has been bit-reversed, and contains
    only one axis. This function is where the actual bit reversal and
    the splitting of the axes take place.
    x: a vector
    FFTKernel: can be any of FFTKernelStandard, FFTKernelNonrec, and FFTKernelSplitradix. The kernel assumes that the input has been
    bit-reversed, and contains only one axis. forward: Whether the FFT or the IFFT is applied
    if ndim(x) == 1:
         bitreverse(x)
         FFTKernel(x, forward)
    else:
         bitreversearr(x)
         for s2 in xrange(shape(x)[1]):
             FFTKernel(x[:, s2], forward)
    if not forward:
         x \neq len(x)
```

```
def FFTKernelStandard(x, forward):
    """
    Compute the FFT of x, using a standard FFT algorithm.

x: a bit-reversed version of the input. Should have only one axis forward: Whether the FFT or the IFFT is applied
    """
    N = len(x)
    sign = -1
    if not forward:
        sign = 1
    if N > 1:
        xe, xo = x[0:(N/2)], x[(N/2):]
        FFTKernelStandard(xe, forward)
        FFTKernelStandard(xo, forward)
        D = exp(sign*2*pi*1j*arange(float(N/2))/N)
        xo *= D
        x[:] = concatenate([xe + xo, xe - xo])
```

Exercise 2.24: Compare execution time

In this exercise we will compare execution times for the different methods for computing the DFT.

a) Write code which compares the execution times for an N-point DFT for the following three cases: Direct implementation of the DFT (as in Example 2.4 in the compendium), the FFT implementation used in this chapter, and the built-in fft-function. Your code should use the sample audio file castanets.wav, apply the different DFT implementations to the first $N=2^r$ samples of the file for

r=3 to r=15, store the execution times in a vector, and plot these. You can use the function time() in the time module to measure the execution time.

b) A problem for large N is that there is such a big difference in the execution times between the two implementations. We can address this by using a loglog-plot instead. Plot N against execution times using the function loglog. How should the fact that the number of arithmetic operations are $8N^2$ and $5N\log_2 N$ be reflected in the plot?

Solution. The two different curves you see should have a derivative approximately equal to one and two, respectively.

c) It seems that the built-in FFT is much faster than our own FFT implementation, even though they may use similar algorithms. Try to explain what can be the cause of this.

Solution. There may be several reasons for this. One is that Python code runs slowly when compared to native code, which is much used in the built-in FFT. Also, the built-in fft has been subject to much more optimization than we have covered here.

Solution. The code can look as follows.

```
x0, fs = audioread('sounds/castanets.wav')
kvals = arange(3,16)
slowtime = zeros(len(kvals))
fasttime = zeros(len(kvals))
fastesttime = zeros(len(kvals))
N = 2**kvals
for k in kvals:
    x = x0[0:2**k].astype(complex)
    start = time()
    DFTImpl(x)
    slowtime[k - kvals[0]] = time() - start
    start = time()
    FFTImpl(x, FFTKernelStandard)
fasttime[k - kvals[0]] = time() - start
    start = time()
    fft.fft(x, axis=0)
    fastesttime[k - kvals[0]] = time() - start
plt.plot(kvals, slowtime, 'ro-', \
kvals, fasttime, 'go-', \
     kvals, fastesttime, 'bo-')
plt.grid('on')
plt.title('time usage of the DFT methods')
plt.legend(['DFT', 'Standard FFT', 'Built-in FFT'])
plt.xlabel('log_2 N')
plt.ylabel('time used [s]')
plt.show()
```

```
plt.figure()

# b.
plt.loglog(N, slowtime, 'ro-', N, fasttime, 'go-', N, fastesttime, 'bo-')
plt.axis('equal')
plt.legend(['DFT', 'Standard FFT', 'Built-in FFT'])
```

Exercise 2.25: Combine two FFT's

Let $x_1 = (1, 3, 5, 7)$ and $x_2 = (2, 4, 6, 8)$. Compute DFT₄ x_1 and DFT₄ x_2 . Explain how you can compute DFT₈(1, 2, 3, 4, 5, 6, 7, 8) based on these computations (you don't need to perform the actual computation). What are the benefits of this approach?

Solution. We get

$$DFT_{4}x_{1} = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & -i & -1 & i \\ 1 & -1 & 1 & -1 \\ 1 & i & -1 & -i \end{pmatrix} \begin{pmatrix} 1 \\ 3 \\ 5 \\ 7 \end{pmatrix} = \begin{pmatrix} 16 \\ -4 + 4i \\ -4 \\ -4 - 4i \end{pmatrix}$$

$$DFT_{4}x_{2} = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & -i & -1 & i \\ 1 & -1 & 1 & -1 \\ 1 & i & -1 & -i \end{pmatrix} \begin{pmatrix} 2 \\ 4 \\ 6 \\ 8 \end{pmatrix} = \begin{pmatrix} 20 \\ -4 + 4i \\ -4 \\ -4 - 4i \end{pmatrix}$$

In the FFT-algorithm we split the computation of DFT₄(\boldsymbol{x}) into the computation of DFT₂($\boldsymbol{x}^{(e)}$) and DFT₂($\boldsymbol{x}^{(o)}$), where $\boldsymbol{x}^{(e)}$ and $\boldsymbol{x}^{(o)}$ are vectors of length 4 with even-indexed and odd-indexed components, respectively. In this case we have $\boldsymbol{x}^{(e)} = (1,3,5,7)$ and $\boldsymbol{x}^{(o)} = (2,4,6,8)$. In other words, the FFT-algorithm uses the FFT-computations we first made, so that we can save computation. The benefit of using the FFT-algorithm is that we save computations, so that we end up with $O(5N\log_2 N)$ real arithmetic operations.

Exercise 2.26: FFT operation count

When we wrote down the difference equation for the number of multiplications in the FFT algorithm, you could argue that some multiplications were not counted. Which multiplications in the FFT algorithm were not counted when writing down this difference equation? Do you have a suggestion to why these multiplications were not counted?

Solution. When we compute $e^{-2\pi i n/N}$, we do some multiplications/divisions in the exponent. These are not counted because they do not depend on \boldsymbol{x} , and may therefore be precomputed.

Exercise 2.27: Adapting the FFT algorithm to real data

In this exercise we will look at an approach to how we can adapt an FFT algorithm to real input x. We will now instead rewrite Equation (2.13) in the compendium for indices n and N/2 - n as

$$y_{n} = (DFT_{N/2}\boldsymbol{x}^{(e)})_{n} + e^{-2\pi i n/N} (DFT_{N/2}\boldsymbol{x}^{(o)})_{n}$$

$$y_{N/2-n} = (DFT_{N/2}\boldsymbol{x}^{(e)})_{N/2-n} + e^{-2\pi i (N/2-n)/N} (DFT_{N/2}\boldsymbol{x}^{(o)})_{N/2-n}$$

$$= (DFT_{N/2}\boldsymbol{x}^{(e)})_{N/2-n} - e^{2\pi i n/N} \overline{(DFT_{N/2}\boldsymbol{x}^{(o)})_{n}}$$

$$= \overline{(DFT_{N/2}\boldsymbol{x}^{(e)})_{n}} - \overline{e^{-2\pi i n/N} (DFT_{N/2}\boldsymbol{x}^{(o)})_{n}}.$$

We see here that, if we have computed the terms in y_n (which needs an additional 4 real multiplications, since $e^{-2\pi i n/N}$ and $(DFT_{N/2}\boldsymbol{x}^{(o)})_n$ are complex), no further multiplications are needed in order to compute $y_{N/2-n}$, since its compression simply conjugates these terms before adding them. Again $y_{N/2}$ must be handled explicitly with this approach. For this we can use the formula

$$y_{N/2} = (DFT_{N/2} \boldsymbol{x}^{(e)})_0 - (D_{N/2}DFT_{N/2} \boldsymbol{x}^{(o)})_0$$

instead.

- a) Conclude from this that an FFT algorithm adapted to real data at each step requires N/4 complex additions and N/2 additions. Conclude from this as before that an algorithm based on real data requires $M_N = O(N \log_2 N)$ multiplications and $A_N = O\left(\frac{3}{2}N\log_2 N\right)$ additions (i.e. again we obtain half the operation count of complex input).
- **b)** Find an IFFT algorithm adapted to vectors \boldsymbol{y} which have conjugate symmetry, which has the same operation count we found above.

Hint. Consider the vectors $y_n + \overline{y_{N/2-n}}$ and $e^{2\pi i n/N}(y_n - \overline{y_{N/2-n}})$. From the equations above, how can these be used in an IFFT?

Exercise 2.28: Non-recursive FFT algorithm

Use the factorization in (2.18) in the compendium to write a kernel function FFTKernelNonrec for a non-recursive FFT implementation. In your code, perform the matrix multiplications in Equation (2.18) in the compendium from right to left in an (outer) for-loop. For each matrix loop through the different blocks on the diagonal in an (inner) for-loop. Make sure you have the right number of blocks on the diagonal, each block being on the form

$$\begin{pmatrix} I & D_{N/2^k} \\ I & -D_{N/2^k} \end{pmatrix}.$$

It may be a good idea to start by implementing multiplication with such a simple matrix first as these are the building blocks in the algorithm (also attempt to do this so that everything is computed in-place). Also compare the execution times with our original FFT algorithm, as we did in Exercise 2, and try to explain what you see in this comparison.

Solution. The algorithm for the non-recursive FFT can look as follows

```
def FFTKernelNonrec(x, forward):
    Compute the FFT of x, using a non-recursive FFT algorithm.
    x: a bit-reversed version of the input. Should have only one axis
    forward: Whether the FFT or the IFFT is applied
    N = len(x)
    sign = -1
    if not forward:
       sign = 1
    D = exp(sign*2*pi*1j*arange(float(N/2))/N)
    nextN = 1
    while nextN < N:
       k = 0
        while k < N:
           xe, xo = x[k:(k + nextN)], x[(k + nextN):(k + 2*nextN)]
            xo *= D[0::(N/(2*nextN))]
            x[k:(k+2*nextN)] = concatenate([xe + xo, xe - xo])
            k += 2*nextN
        nextN *= 2
```

If you add the non-recursive algorithm to the code from Exercise 2, you will see that the non-recursive algorithm performs much better. There may be several reasons for this. First of all, there are no recursive function calls. Secondly, the values in the matrices $D_{N/2}$ are constructed once and for all with the non-recursive algorithm. Code which compares execution times for the original FFT algorithm, our non-recursive implementation, and the split-radix algorithm of the next exercise, can look as follows:

```
x0, fs = audioread('sounds/castanets.wav')
kvals = arange(3,16)
slowtime = zeros(len(kvals))
fasttime = zeros(len(kvals))
fastesttime = zeros(len(kvals))
N = 2**kvals
for k in kvals:
    x = x0[0:2**k].astype(complex)

start = time()
FFTImpl(x, FFTKernelStandard)
slowtime[k - kvals[0]] = time() - start

start = time()
FFTImpl(x, FFTKernelNonrec)
fasttime[k - kvals[0]] = time() - start

start = time()
FFTImpl(x, FFTKernelSplitradix)
fastesttime[k - kvals[0]] = time() - start
```

Exercise 2.29: The Split-radix FFT algorithm

In this exercise we will develop a variant of the FFT algorithm called the *split-radix FFT algorithm*, which until recently held the record for the lowest operation count for any FFT algorithm.

We start by splitting the rightmost $DFT_{N/2}$ in Equation (2.17) in the compendium by using this equation again, to obtain

$$DFT_{N}\boldsymbol{x} = \begin{pmatrix} DFT_{N/2} & D_{N/2} \begin{pmatrix} DFT_{N/4} & D_{N/4}DFT_{N/4} \\ DFT_{N/4} & -D_{N/4}DFT_{N/4} \end{pmatrix} \\ DFT_{N/2} & -D_{N/2} \begin{pmatrix} DFT_{N/4} & D_{N/4}DFT_{N/4} \\ DFT_{N/4} & D_{N/4}DFT_{N/4} \end{pmatrix} \end{pmatrix} \begin{pmatrix} \boldsymbol{x}^{(e)} \\ \boldsymbol{x}^{(oe)} \\ \boldsymbol{x}^{(oo)} \end{pmatrix}.$$

$$(2.1)$$

The term radix describes how an FFT is split into FFT's of smaller sizes, i.e. how the sum in an FFT is split into smaller sums. The FFT algorithm we started this section with is called a radix 2 algorithm, since it splits an FFT of length N into FFT's of length N/2. If an algorithm instead splits into FFT's of length N/4, it is called a radix 4 FFT algorithm. The algorithm we go through here is called the split radix algorithm, since it uses FFT's of both length N/2 and N/4.

- a) Let $G_{N/4}$ be the $(N/4)\times (N/4)$ diagonal matrix with $e^{-2\pi in/N}$ on the diagonal. Show that $D_{N/2}=\begin{pmatrix} G_{N/4} & \mathbf{0} \\ \mathbf{0} & -iG_{N/4} \end{pmatrix}$.
- **b)** Let $H_{N/4}$ be the $(N/4) \times (N/4)$ diagonal matrix $G_{D/4}D_{N/4}$. Verify the following rewriting of Equation (2.1):

$$\begin{aligned} \mathrm{DFT}_{N}\boldsymbol{x} &= \begin{pmatrix} \mathrm{DFT}_{N/2} & \begin{pmatrix} G_{N/4}\mathrm{DFT}_{N/4} & H_{N/4}\mathrm{DFT}_{N/4} \\ -iG_{N/4}\mathrm{DFT}_{N/4} & iH_{N/4}\mathrm{DFT}_{N/4} \end{pmatrix} \\ \mathrm{DFT}_{N/2} & \begin{pmatrix} -G_{N/4}\mathrm{DFT}_{N/4} & -H_{N/4}\mathrm{DFT}_{N/4} \\ iG_{N/4}\mathrm{DFT}_{N/4} & -iH_{N/4}\mathrm{DFT}_{N/4} \end{pmatrix} \end{pmatrix} \begin{pmatrix} \boldsymbol{x}^{(e)} \\ \boldsymbol{x}^{(oe)} \\ \boldsymbol{x}^{(oo)} \end{pmatrix} \\ &= \begin{pmatrix} I & \mathbf{0} & G_{N/4} & H_{N/4} \\ \mathbf{0} & I & -iG_{N/4} & iH_{N/4} \\ I & \mathbf{0} & -G_{N/4} & -H_{N/4} \end{pmatrix} \begin{pmatrix} \mathrm{DFT}_{N/2} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathrm{DFT}_{N/4} & \mathbf{0} \\ \mathbf{0} & 0 & \mathrm{DFT}_{N/4} \end{pmatrix} \begin{pmatrix} \boldsymbol{x}^{(e)} \\ \boldsymbol{x}^{(oo)} \end{pmatrix} \\ &= \begin{pmatrix} I & \begin{pmatrix} G_{N/4} & H_{N/4} \\ -iG_{N/4} & iH_{N/4} \end{pmatrix} \\ I & -\begin{pmatrix} G_{N/4} & H_{N/4} \\ -iG_{N/4} & iH_{N/4} \end{pmatrix} \end{pmatrix} \begin{pmatrix} \mathrm{DFT}_{N/2}\boldsymbol{x}^{(e)} \\ \mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} \end{pmatrix} \\ &= \begin{pmatrix} \mathrm{DFT}_{N/2}\boldsymbol{x}^{(e)} + \begin{pmatrix} G_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} + H_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} \\ -i & (G_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} - H_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} \end{pmatrix} \end{pmatrix} \\ &= \begin{pmatrix} \mathrm{DFT}_{N/2}\boldsymbol{x}^{(e)} + \begin{pmatrix} G_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} + H_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} \\ -i & (G_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} - H_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} \end{pmatrix} \end{pmatrix} \\ &= \begin{pmatrix} \mathrm{DFT}_{N/2}\boldsymbol{x}^{(e)} - \begin{pmatrix} G_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} + H_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} \\ -i & (G_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} - H_{N/4}\mathrm{DFT}_{N/4}\boldsymbol{x}^{(oo)} \end{pmatrix} \end{pmatrix}$$

c) Explain from the above expression why, once the three FFT's above have been computed, the rest can be computed with N/2 complex multiplications, and $2 \times N/4 + N = 3N/2$ complex additions. This is equivalent to 2N real multiplications and N + 3N = 4N real additions.

Hint. It is important that $G_{N/4}\text{DFT}_{N/4}\boldsymbol{x}^{(oe)}$ and $H_{N/4}\text{DFT}_{N/4}\boldsymbol{x}^{(oo)}$ are computed first, and the sum and difference of these two afterwards.

d) Due to what we just showed, our new algorithm leads to real multiplication and addition counts which satisfy

$$M_N = M_{N/2} + 2M_{N/4} + 2N$$
 $A_N = A_{N/2} + 2A_{N/4} + 4N$

Find the general solutions to these difference equations and conclude from these that $M_N = O\left(\frac{4}{3}N\log_2 N\right)$, and $A_N = O\left(\frac{8}{3}N\log_2 N\right)$. The operation count is thus $O\left(4N\log_2 N\right)$, which is a reduction of $N\log_2 N$ from the FFT algorithm.

e) Write an FFT kernel function FFTKernelSplitradix for the split-radix algorithm (again this should handle both the forward and reverse transforms). Are there more or less recursive function calls in this function than in the original FFT algorithm? Also compare the execution times with our original FFT algorithm, as we did in Exercise 2. Try to explain what you see in this comparison.

Solution. If you add the split-radix FFT algorithm also to the code from Exercise 2, you will see that it performs better than the FFT algorithm, but

worse than the non-recursive algorithm. That it performs better than the FFT algorithm is as expected, since it has a reduced number of arithmetic operations, and also a smaller number of recursive calls. It is not surprising that the non-recursive function performs better, since only that function omits recursive calls, and computes the values in the diagonal matrices once and for all.

By carefully examining the algorithm we have developed, one can reduce the operation count to $4N\log_2 N - 6N + 8$. This does not reduce the order of the algorithm, but for small N (which often is the case in applications) this reduces the number of operations considerably, since 6N is large compared to $4N\log_2 N$ for small N. In addition to having a lower number of operations than the FFT algorithm of Theorem 2.15 in the compendium, a bigger percentage of the operations are additions for our new algorithm: there are now twice as many additions than multiplications. Since multiplications may be more time-consuming than additions (depending on how the CPU computes floating-point arithmetic), this can be a big advantage.

Solution. The code for the split-radix algorithm can look as follows

```
def FFTKernelSplitradix(x, forward):
    Compute the FFT of x, using the split-radix FFT algorithm.
    x: a bit-reversed version of the input. Should have only one axis
    forward: Whether the FFT or the IFFT is applied
    N = len(x)
    sign = -1
    if not forward:
    sign = 1
if N == 2:
    x[:] = [x[0] + x[1], x[0] - x[1]]
elif N > 2:
        xe, xo1, xo2 = x[0:(N/2)], x[(N/2):(3*N/4)], x[(3*N/4):N]
        FFTKernelSplitradix(xe, forward)
        FFTKernelSplitradix(xo1, forward)
        FFTKernelSplitradix(xo2, forward)
        G = exp(sign*2*pi*1j*arange(float(N/4))/N)
        H = G*exp(sign*2*pi*1j*arange(float(N/4))/(N/2))
        xo1 *= G
        xo2 *= H
        xo = concatenate([xo1 + xo2, -sign*1j*(xo2 - xo1)])
        x[:] = concatenate([xe + xo, xe - xo])
```

Exercise 2.30: Bit-reversal

In this exercise we will make some considerations which will help us explain the code for bit-reversal. This is perhaps not a mathematically challenging exercise, but nevertheless a good exercise in how to think when developing an efficient algorithm. We will use the notation i for an index, and j for its bit-reverse. If we bit-reverse k bits, we will write $N=2^k$ for the number of possible indices.

a) Consider the following code

```
j = 0
for i in range(N-1):
    print j
    m = N/2
    while (m >= 1 and j >= m):
        j -= m
        m /= 2
    j += m
```

Explain that the code prints all numbers in [0, N-1] in bit-reversed order (i.e. j). Verify this by running the program, and writing down the bits for all numbers for, say N=16. In particular explain the decrements and increments made to the variable j. The code above thus produces pairs of numbers (i,j), where j is the bit-reverse of i. As can be seen, bitreverse applies similar code, and then swaps the values x_i and x_j in x, as it should.

Solution. Note that, if the bit representation of i ends with $0 \underbrace{1 \dots 1}_n$, then i+1 has a bit representation which ends with $1 \underbrace{0 \dots 0}_n$, with the remaining first bits unaltered. Clearly the bit-reverse of i then starts with $\underbrace{1 \dots 1}_n 0$ and the bit-reverse of i+1 starts with $\underbrace{1 \dots 0}_n$. We see that the bit reverse of i+1 can

be obtained from the bit-reverse of i by replacing the first consecutive set of ones by zeros, and the following zero by one. This is performed by the line above where j is decreased by m: Decreasing j by N/2 when $j \geq N/2$ changes the first bit from 1 to 0, and similarly for the next n bits. The line where j is increased with m changes bit number n+1 from 0 to 1.

Since bit-reverse is its own inverse (i.e. $P^2 = I$), it can be performed by swapping elements i and j. One way to secure that bit-reverse is done only once, is to perform it only when j > i. You see that bitreverse includes this check.

b) Explain that N-j-1 is the bit-reverse of N-i-1. Due to this, when i,j < N/2, we have that $N-i-1, N-j-l \ge N/2$, and that bitreversal can swap them. Moreover, all swaps where $i,j \ge N/2$ can be performed immediately when pairs where i,j < N/2 are encountered. Explain also that j < N/2 if and only if i is even. In the code you can see that the swaps (i,j) and (N-i-1,N-j-1) are performed together when i is even, due to this.

Solution. Clearly N-i-1 has a bit representation obtained by changing every bit in i. That N-j-1 is the bit-reverse of N-i-1 follows immediately from this. If i is even, the least significant bit is 0. After bit-reversal, this becomes the most significant bit, and the most significant bit of j is 0 which is the case if and only if j < N/2.

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c) Assume that i < N/2 is odd. Explain that $j \ge N/2$, so that j > i. This says that when i < N/2 is odd, we can always swap i and j (this is the last swap performed in the code). All swaps where $0 \le j < N/2$ and $N/2 \le j < N$ can be performed in this way.

Solution. If i < N/2 is odd, then the least significant bit is 1. This means that the most significant bit of j is 1, so that $j \ge N/2$, so that j > i.

In bitreversal, you can see that the bit-reversal of 2r and 2r+1 are handled together (i.e. i is increased with 2 in the for-loop). The effect of this is that the number of if-tests can be reduced, due to the observations from b) and c).

Chapter 3

Operations on digital sound: digital filters

Exercise 3.4: Finding the filter coefficients and the matrix

Assume that the filter S is defined by the formula

$$z_n = \frac{1}{4}x_{n+1} + \frac{1}{4}x_n + \frac{1}{4}x_{n-1} + \frac{1}{4}x_{n-2}.$$

Write down the filter coefficients t_k , and the matrix for S when N=8.

Solution. Here we have that $t_{-1}=1/4$, $t_0=1/4$, $t_1=1/4$, and $t_2=1/4$. We now get that $s_0=t_0=1/4$, $s_1=t_1=1/4$, and $s_2=t_2=1/4$ (first formula), and $s_{N-1}=s_7=t_{-1}=1/4$ (second formula). This means that the matrix of S is

$$S = \frac{1}{4} \begin{pmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \end{pmatrix}.$$

Exercise 3.5: Finding the filter coefficients from the matrix

Given the circulant Toeplitz matrix

$$S = \begin{pmatrix} 1 & 2 & 0 & 0 \\ 0 & 1 & 2 & 0 \\ 0 & 0 & 1 & 2 \\ 2 & 0 & 0 & 1 \end{pmatrix},$$

write down the filter coefficients t_k .

Exercise 3.6: Convolution and polynomials

Compute the convolution of $\{1, 2, 1\}$ with itself. interpret the result in terms of two polynomials.

Exercise 3.7: Implementation of convolution

Implement code which computes t * x in the two ways described after Equation (3.3) in the compendium, i.e. as a double for loop, and as a simple for loop in k, with n vectorized. As your t, take k randomly generated numbers. Compare execution times for these two methods and the convolve function, for different values of k. Present the result as a plot where k runs along the x-axis, and execution times run along the y-axis. Your result will depend on how Python performs vectorization.

Solution. The code can look as follows.

```
from sound import *
from time import *
from numpy import *
import matplotlib.pyplot as plt
x, fs = audioread('sounds/castanets.wav')
x = x[:,0]
N = len(x)
kmax=100
vals1 = zeros(kmax/10)
vals2 = zeros(kmax/10)
vals3 = zeros(kmax/10)
ind = 0
for k in range(10, kmax+1,10):
    t = random.random(k)
    start = time()
    convolve(t, x)
vals1[ind] = time() - start
    z = zeros(N)
    start = time()
    for s in range(k):
         z[(k-1):N] += t[s]*x[(k-1-s):(N-s)]
    vals2[ind] = time() - start
    z = zeros(N)
    start = time()
    for n in range(k-1, N):
         for s in range(k):
    z[n] += t[s]*x[n-s]
    vals3[ind] = time() - start
plt.plot( range(10, kmax+1,10),log(vals1), 'r-', range(10, kmax+1,10), log(vals2), 'g-', range(10, plt.legend(['conv','simple for','double for'])
plt.show()
```

Exercise 3.8: Filters with a different number of coefficients with positive and negative indices

Assume that $S = \{t_{-E}, \dots, \underline{t_0}, \dots, t_F\}$. Formulate a generalization of Proposition 3.5 in the compendium for such filters, i.e. to filters where there may be a different number of filter coefficients with positive and negative indices. You should only need to make some small changes to the proof of Proposition 3.5 in the compendium to achieve this.

Exercise 3.9: Implementing filtering with convolution

Implement a function filterS which uses Proposition 3.5 in the compendium and the convolve function Sx when $S = \{t_{-L}, \dots, \underline{t_0}, \dots, t_L\}$ The function should take the vectors $(t_{-L}, \dots, t_0, \dots, t_L)$ and x as input.

Solution. The code can look like this:

```
def filterS(t, x):
    L = (len(t) - 1)/2
    N = len(x)
    y = concatenate([ x[(N - L):], x, x[:L]])
    y = convolve(t, y)
    y = y[(2*L):(len(y)-2*L)]
```

Exercise 3.13: Time reversal is not a filter

In Example 1.2 in the compendium we looked at time reversal as an operation on digital sound. In \mathbb{R}^N this can be defined as the linear mapping which sends the vector \mathbf{e}_k to \mathbf{e}_{N-1-k} for all $0 \le k \le N-1$.

a) Write down the matrix for the time reversal linear mapping, and explain from this why time reversal is not a digital filter.

Solution. The matrix for time reversal is the matrix

$$\begin{pmatrix} 0 & 0 & \cdots & 0 & 1 \\ 0 & 0 & \cdots & 1 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 1 & \cdots & 0 & 0 \\ 1 & 0 & \cdots & 0 & 0 \end{pmatrix}$$

This is not a circulant Toeplitz matrix, since all diagonals assume the values 0 and 1, so that they are not constant on each diagonal. Time reversal is thus not a digital filter.

b) Prove directly that time reversal is not a time-invariant operation.

Solution. Let S denote time reversal. Clearly $Se_1 = e_{N-2}$. If S was time-invariant we would have that $Se_0 = e_{N-3}$, where we have delayed the input and output. But this clearly is not the case, since by definition $Se_0 = e_{N-1}$.

Exercise 3.14: When is a filter symmetric?

Let S be a digital filter. Show that S is symmetric if and only if the frequency response satisfies $\lambda_{S,n} = \lambda_{S,N-n}$ for all n.

Exercise 3.15: Eigenvectors and eigenvalues

Consider the matrix

$$S = \begin{pmatrix} 4 & 1 & 3 & 1 \\ 1 & 4 & 1 & 3 \\ 3 & 1 & 4 & 1 \\ 1 & 3 & 1 & 4 \end{pmatrix}.$$

a) Compute the eigenvalues and eigenvectors of S using the results of this section. You should only need to perform one DFT in order to achieve this.

Solution. The eigenvalues of S are 1, 5, 9, and are found by computing a DFT of the first column (and multiplying by $\sqrt{N} = 2$). The eigenvectors are the Fourier basis vectors. 1 has multiplicity 2.

- b) Verify the result from a) by computing the eigenvectors and eigenvalues the way you taught in your first course in linear algebra. This should be a much more tedious task.
- \mathbf{c}) Use a computer to compute the eigenvectors and eigenvalues of S also. For some reason some of the eigenvectors seem to be different from the Fourier basis vectors, which you would expect from the theory in this section. Try to find an explanation for this.

Solution. The computer uses some numeric algorithm to find the eigenvectors. However, eigenvectors may not be unique, so you have no control on which eigenvectors it actually selects. In particular, here the eigenspace for $\lambda=1$ has dimension 2, so that any linear combination of the two eigenvectors from this eigenspace also is an eigenvector. Here it seems that a linear combination is chosen which is different from a Fourier basis vector.

Exercise 3.16: Composing filters

Assume that S_1 and S_2 are two circulant Toeplitz matrices.

a) How can you express the eigenvalues of $S_1 + S_2$ in terms of the eigenvalues of S_1 and S_2 ?

Solution. If we write $S_1 = F_N^H D_1 F_N$ and $S_2 = F_N^H D_2 F_N$ we get

$$S_1 + S_2 = F_N^H (D_1 + D_2) F_N$$
 $S_1 S_2 = F_N^H D_1 F_N F_N^H D_2 F_N = F_N^H D_1 D_2 F_N$

This means that the eigenvalues of $S_1 + S_2$ are the sum of the eigenvalues of S_1 and S_2 . The actual eigenvalues which are added are dictated by the index of the frequency response, i.e. $\lambda_{S_1+S_2,n} = \lambda_{S_1,n} + \lambda_{S_2,n}$.

b) How can you express the eigenvalues of S_1S_2 in terms of the eigenvalues of S_1 and S_2 ?

Solution. As above we have that $S_1S_2 = F_N^H D_1 F_N F_N^H D_2 F_N = F_N^H D_1 D_2 F_N$, and the same reasoning gives that the eigenvalues of S_1S_2 are the product of the eigenvalues of S_1 and S_2 . The actual eigenvalues which are multiplied are dictated by the index of the frequency response, i.e. $\lambda_{S_1S_2,n} = \lambda_{S_1,n}\lambda_{S_2,n}$.

c) If A and B are general matrices, can you find a formula which expresses the eigenvalues of A + B and AB in terms of those of A and B? If not, can you find a counterexample to what you found in a) and b)?

Solution. In general there is no reason to believe that there is a formula for the eigenvalues for the sum or product of two matrices, based on eigenvalues of the individual matrices. However, the same type of argument as for filters can be used in all cases where the eigenvectors are equal.

Exercise 3.17: Keeping every second component

Consider the linear mapping S which keeps every second component in \mathbb{R}^N , i.e. $S(e_{2k}) = e_{2k}$, and $S(e_{2k-1}) = 0$. Is S a digital filter?

Solution. The matrix for the operation which keeps every second component is

$$\begin{pmatrix} 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \\ 0 & 0 & \cdots & 0 & 0 \end{pmatrix},$$

where 1 and 0 are repeated in alternating order along the main diagonal. Since the matrix is not constant on the main diagonal, it is not a circulant Toeplitz matrix, and hence not a filter.

Exercise 3.20: Plotting a simple frequency response

Let again S be the filter defined by the equation

$$z_n = \frac{1}{4}x_{n+1} + \frac{1}{4}x_n + \frac{1}{4}x_{n-1} + \frac{1}{4}x_{n-2},$$

as in Exercise 3. Compute and plot (the magnitude of) $\lambda_S(\omega)$.

Solution. The frequency response is

$$\lambda_S(\omega) = \frac{1}{4} (e^{i\omega} + 1 + e^{-i\omega} + e^{-2i\omega}) = \frac{e^{i\omega} (1 - e^{-4i\omega})}{4(1 - e^{-i\omega})} = \frac{1}{4} e^{-i\omega/2} \frac{\sin(2\omega)}{\sin(\omega/2)}.$$

Exercise 3.21: Low-pass and high-pass filters

A filter S is defined by the equation

$$z_n = \frac{1}{3}(x_n + 3x_{n-1} + 3x_{n-2} + x_{n-3}).$$

a) Compute and plot the (magnitude of the continuous) frequency response of the filter, i.e. $|\lambda_S(\omega)|$. Is the filter a low-pass filter or a high-pass filter?

Solution. The filter coefficients are $t_0 = t_3 = 1/3$, $t_1 = t_2 = 1$. We have that

$$\lambda_S(\omega) = \sum_k t_k e^{-ik\omega} = \frac{1}{3} (1 + 3e^{-i\omega} + 3e^{-2i\omega} + e^{-3i\omega})$$
$$= \frac{2}{3} e^{-3i\omega/2} \frac{1}{2} (e^{3i\omega/2} + 3e^{i\omega/2} + 3e^{-i\omega/2} + e^{-3i\omega/2})$$
$$= \frac{2}{3} e^{-3i\omega/2} (\cos(3\omega/2) + 3\cos(\omega/2)).$$

From this expression it is easy to plot the frequency response, but since this is complex, we have to plot the magnitude, i.e. $|\lambda_S(\omega)| = \frac{2}{3}|\cos(3\omega/2) + 3\cos(\omega/2)|$. We also see that $\lambda_S(0) = \frac{2}{3}$, and that $\lambda_S(\pi) = 0$, so that the filter is a low-pass filter

b) Find an expression for the vector frequency response $\lambda_{S,2}$. What is Sx when x is the vector of length N with components $e^{2\pi i 2k/N}$?

Solution. If we use the connection between the vector frequency response and the continuous frequency response we get

$$\lambda_{S,2} = \lambda_S(2\pi 2/N) = \frac{2}{3}e^{-6\pi i/N}(\cos(6\pi/N) + 3\cos(2\pi/N)).$$

Alternatively you can here compute that the first column in the circulant Toeplitz matrix for S is given by $s_0 = t_1$, $s_2 = t_2$, $s_3 = t_3$, and $s_4 = t_4$, and insert this in

the definition of the vector frequency response, $\lambda_{S,2} = \sum_{k=0}^{N-1} s_k e^{-2\pi i 2k/N}$. We know that $e^{2\pi i 2k/N}$ is an eigenvector for S since S is a filter, and that $\lambda_{S,2}$ is the corresponding eigenvalue. We therefore get that

$$Sx = \lambda_{S,2}x = \frac{2}{3}e^{-6\pi i/N}(\cos(6\pi/N) + 3\cos(2\pi/N))x.$$

Exercise 3.22: Circulant matrices

A filter S_1 is defined by the equation

$$z_n = \frac{1}{16}(x_{n+2} + 4x_{n+1} + 6x_n + 4x_{n-1} + x_{n-2}).$$

a) Write down an 8×8 circulant Toeplitz matrix which corresponds to applying S_1 on a periodic signal with period N=8.

Solution. Since clearly $t_{-2}=t_2=1/16$, $t_{-1}=t_1=1/4$, and $t_0=6/16$, the first column s in the circulant Toeplitz matrix is given by $s_0=t_0=6/16$, $s_1=t_1=4/16$, $s_2=t_2=1/16$, $s_{N-2}=t_{-2}=1/16$, $s_{N-1}=t_{-1}=4/16$. An 8×8 circulant Toeplitz matrix which corresponds to applying S_1 to a periodic signal of length N=8 is therefore

$$\frac{1}{16} \begin{pmatrix} 6 & 4 & 1 & 0 & 0 & 0 & 1 & 4 \\ 4 & 6 & 4 & 1 & 0 & 0 & 0 & 1 \\ 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 \\ 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 \\ 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 \\ 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 \\ 1 & 0 & 0 & 0 & 1 & 4 & 6 & 4 \\ 4 & 1 & 0 & 0 & 0 & 1 & 4 & 6 \end{pmatrix}.$$

b) Compute and plot (the continuous) frequency response of the filter. Is the filter a low-pass filter or a high-pass filter?

Solution. The frequency response is

$$\lambda_{S_1}(\omega) = \frac{1}{16} (e^{2i\omega} + 4e^{i\omega} + 6 + 4e^{-i\omega} + e^{-2i\omega}) = \left(\frac{1}{2} (e^{i\omega/2} + e^{-i\omega/2})\right)^4 = \cos^4(\omega/2),$$

where we recognized (1, 4, 6, 4, 1) as a row in Pascal's triangle, so that we could write the expression as a power. From this expression it is easy to plot the frequency response, and it is clear that the filter is a low-pass filter, since $\lambda_{S_1}(0) = 1$, $\lambda_{S_1}(\pi) = 0$.

c) Another filter S_2 has (continuous) frequency response $\lambda_{S_2}(\omega) = (e^{i\omega} + 2 + e^{-i\omega})/4$. Write down the filter coefficients for the filter S_1S_2 .

Solution. We have that

$$\lambda_{S_2}(\omega) = (e^{i\omega} + 2 + e^{-i\omega})/4 = \left(\frac{1}{2}(e^{i\omega/2} + e^{-i\omega/2})\right)^2 = \cos^2(\omega/2).$$

We then get that

$$\begin{split} \lambda_{S_1 S_2}(\omega) &= \lambda_{S_1}(\omega) \lambda_{S_2}(\omega) = \cos^4(\omega/2) \cos^2(\omega/2) = \cos^6(\omega/2) \\ &= \left(\frac{1}{2} (e^{i\omega/2} + e^{-i\omega/2})\right)^6 \\ &= \frac{1}{64} (e^{3i\omega} + 6e^{2i\omega} + 15e^{i\omega} + 20 + 15e^{-i\omega} + 6e^{-2i\omega} + e^{-3i\omega}), \end{split}$$

where we have used that, since we have a sixth power, the values can be obtained from fra a row in Pascal's triangle also here. It is now clear that

$$S_1 S_2 = \frac{1}{64} \{1, 6, 15, \underline{20}, 15, 6, 1\}.$$

You could also argue here by taking the convolution of $\frac{1}{16}(1,4,6,4,1)$ with $\frac{1}{4}(1,2,1)$.

Exercise 3.23: Composite filters

Assume that the filters S_1 and S_2 have the frequency responses $\lambda_{S_1}(\omega) = 2 + 4\cos(\omega)$, $\lambda_{S_2}(\omega) = 3\sin(2\omega)$.

- a) Compute and plot the frequency response of the filter S_1S_2 .
- b) Write down the filter coefficients t_k and the impulse response s for the filter S_1S_2 .

Exercise 3.24: Maximum and minimum

Compute and plot the continuous frequency response of the filter $S = \{1/4, 1/2, 1/4\}$. Where does the frequency response achieve its maximum and minimum value, and what are these values?

Solution. We have that $\lambda_S(\omega) = \frac{1}{2}(1 + \cos \omega)$. This clearly has the maximum point (0,1), and the minimum point $(\pi,0)$.

Exercise 3.25: Plotting a simple frequency response

Plot the continuous frequency response of the filter $T = \{1/4, -1/2, 1/4\}$. Where does the frequency response achieve its maximum and minimum value, and what are these values? Can you write down a connection between this frequency response and that from Exercise 3?

Solution. We have that $|\lambda_T(\omega)| = \frac{1}{2}(1-\cos\omega)$. This clearly has the maximum point $(\pi, 1)$, and the minimum point (0, 0). The connection between the frequency responses is that $\lambda_T(\omega) = \lambda_S(\omega + \pi)$.

Exercise 3.26: Continuous- and vector frequency responses

Define the filter S by $S = \{1, 2, \underline{3}, 4, 5, 6\}$. Write down the matrix for S when N = 8. Plot (the magnitude of) $\lambda_S(\omega)$, and indicate the values $\lambda_{S,n}$ for N = 8 in this plot.

Solution. Here we have that $s_0 = t_0 = 3$, $s_1 = t_1 = 4$, $s_2 = t_2 = 5$, and $s_3 = t_3 = 6$ (first formula), and $s_{N-2} = t_{-2} = 1$, $s_{N-1} = t_{-1} = 2$ (second formula). This means that the matrix of S is

$$S = \begin{pmatrix} 3 & 2 & 1 & 0 & 0 & 6 & 5 & 4 \\ 4 & 3 & 2 & 1 & 0 & 0 & 6 & 5 \\ 5 & 4 & 3 & 2 & 1 & 0 & 0 & 6 \\ 6 & 5 & 4 & 3 & 2 & 1 & 0 & 0 \\ 0 & 6 & 5 & 4 & 3 & 2 & 1 & 0 \\ 0 & 0 & 6 & 5 & 4 & 3 & 2 & 1 \\ 1 & 0 & 0 & 6 & 5 & 4 & 3 & 2 \\ 2 & 1 & 0 & 0 & 6 & 5 & 4 & 3 \end{pmatrix}$$

The frequency response is

$$\lambda_S(\omega) = e^{2i\omega} + 2e^{i\omega} + 3 + 4e^{-i\omega} + 5e^{-2i\omega} + 6e^{-3i\omega}.$$

Exercise 3.27: Starting with circulant matrices

Given the circulant Toeplitz matrix

$$S = \frac{1}{5} \begin{pmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & 1 & 1 & \cdots & 0 \\ 0 & 1 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ 1 & 0 & 0 & \cdots & 1 \\ 1 & 1 & 0 & \cdots & 1 \\ 1 & 1 & 1 & \cdots & 1 \end{pmatrix}$$

Write down the compact notation for this filter. Compute and plot (the magnitude) of $\lambda_S(\omega)$.

Solution. The filter coefficients are $t_0=s_0=1/5,\ t_1=s_1=1/5$ (first formula), and $t_{-1}=s_{N-1}=1/5,\ t_{-2}=s_{N-2}=1/5,\ t_{-3}=s_{N-3}=1/5$ (second formula). All other t_k are zero. This means that the filter can be written as $\frac{1}{5}\{1,1,1,1,1\}$, using our compact notation.

Exercise 3.28: When the filter coefficients are powers

Assume that $S = \{1, c, c^2, \dots, c^k\}$. Compute and plot $\lambda_S(\omega)$ when k = 4 and k = 8. How does the choice of k influence the frequency response? How does the choice of k influence the frequency response?

Solution. The frequency response is

$$\sum_{s=0}^{k} c^{s} e^{-is\omega} = \frac{1 - c^{k+1} e^{-i(k+1)\omega}}{1 - c e^{-i\omega}}.$$

It is straightforward to compute the limit as $\omega \to 0$ as $c^k(k+1)$. This means that as we increase k or c, this limit also increases. The value of k also dictates oscillations in the frequency response, since the numerator oscillates fastest. When c=1, k dictates how often the frequency response hits 0.

Exercise 3.29: The Hanning window

The Hanning window is defined by $w_n = 1 - \cos(2\pi n/(N-1))$. Compute and plot the window coefficients and the continuous frequency response of this window for N = 32, and compare with the window coefficients and the frequency responses for the rectangular- and the Hamming window.

Exercise 3.37: Composing time delay filters

Let E_{d_1} and E_{d_2} be two time delay filters. Show that $E_{d_1}E_{d_2}=E_{d_1+d_2}$ (i.e. that the composition of two time delays again is a time delay) in two different ways:

- a) Give a direct argument which uses no computations.
- b) By using Property 3 in Theorem 2.7 in the compendium, i.e. by using a property for the Discrete Fourier Transform.

Exercise 3.38: Adding echo filters

Consider the two filters $S_1 = \{\underline{1}, 0, \dots, 0, c\}$ and $S_2 = \{\underline{1}, 0, \dots, 0, -c\}$. Both of these can be interpreted as filters which add an echo. Show that $\frac{1}{2}(S_1 + S_2) = I$. What is the interpretation of this relation in terms of echos?

Solution. The sum of two digital filters is again a digital filter, and the first column in the sum can be obtained by summing the first columns in the two matrices. This means that the filter coefficients in $\frac{1}{2}(S_1 + S_2)$ can be obtained by summing the filter coefficients of S_1 and S_2 , and we obtain

$$\frac{1}{2}\left(\left\{\underline{1},0,\ldots,0,c\right\}+\left\{\underline{1},0,\ldots,0,-c\right\}\right)=\left\{\underline{1}\right\}.$$

This means that $\frac{1}{2}(S_1 + S_2) = I$, since I is the unique filter with e_0 as first column. The interpretation in terms of echos is that the echo from S_2 cancels that from S_1 .

Exercise 3.39: Reducing bass and treble

Write code where you reduce the treble and the bass as described in examples 2.7 in the compendium and 3.36 in the compendium, generate the sounds you heard in these examples, and verify that they are the same. In your code, it will be necessary to scale the values after reducing the bass, but not the values after reducing the bass. Explain why this is the case. How high must k be in order for you to hear difference from the actual sound? How high can you choose k and still recognize the sound at all? If you solved Exercise k, you can also use the function filters to perform the filtering, rather than sing the convolve function (the latter disregards circularity).

Solution. The code can look like this, when we reduce the treble. We have used the convolve function:

```
t = [1.]
for kval in range(k):
    t = convolve(t, [1/2., 1/2.])
```

```
z = convolve(t, x[:, 0])
play(z,fs)
```

If we reduce the bass instead, the code can look like this.

```
t = [1.]
for kval in range(k):
    t = convolve(t, [1/2., -1/2.])
```

```
z = convolve(t, x[:, 0])
z /= abs(z).max()
play(z,fs)
```

Exercise 3.40: Constructing a high-pass filter

Consider again Example 3.32 in the compendium. Find an expression for a filter so that only frequencies so that $|\omega - \pi| < \omega_c$ are kept, i.e. the filter should only keep angular frequencies close to π (i.e. here we construct a high-pass filter).

Exercise 3.41: Combining low-pass and high-pass filters

In this exercise we will investigate how we can combine low-pass and high-pass filters to produce other filters

- a) Assume that S_1 and S_2 are low-pass filters. What kind of filter is S_1S_2 ? What if both S_1 and S_2 are high-pass filters?
- **b)** Assume that one of S_1, S_2 is a high-pass filter, and that the other is a low-pass filter. What kind of filter S_1S_2 in this case?

Exercise 3.42: Composing filters

A filter S_1 has the frequency response $\frac{1}{2}(1 + \cos \omega)$, and another filter has the frequency response $\frac{1}{2}(1 + \cos(2\omega))$.

- a) Is S_1S_2 a low-pass filter, or a high-pass filter?
- b) What does the filter S_1S_2 do with angular frequencies close to $\omega = \pi/2$.
- c) Find the filter coefficients of S_1S_2 .

Hint. Use Theorem 3.18 in the compendium to compute the frequency response of S_1S_2 first.

d) Write down the matrix of the filter S_1S_2 for N=8.

Exercise 3.43: Composing filters

An operation describing some transfer of data in a system is defined as the composition of the following three filters:

- First a time delay filter with delay $d_1 = 2$, due to internal transfer of data in the system,
- then the treble-reducing filter $T = \{1/4, 1/2, 1/4\},\$
- finally a time delay filter with delay $d_2 = 4$ due to internal transfer of the filtered data.

We denote by $T_2 = E_{d_2}TE_{d_1} = E_4TE_2$ the operation which applies these filters in succession.

- a) Explain why T_2 also is a digital filter. What is (the magnitude of) the frequency response of E_{d_1} ? What is the connection between (the magnitude of) the frequency response of T and T_2 ?
- **b)** Show that $T_2 = \{\underline{0}, 0, 0, 0, 0, 1/4, 1/2, 1/4\}.$

Hint. Use the expressions $(E_{d_1}\boldsymbol{x})_n = x_{n-d_1}$, $(T\boldsymbol{x})_n = \frac{1}{4}x_{n+1} + \frac{1}{2}x_n + \frac{1}{4}x_{n-1}$, $(E_{d_2}\boldsymbol{x})_n = x_{n-d_2}$, and compute first $(E_{d_1}\boldsymbol{x})_n$, then $(TE_{d_1}\boldsymbol{x})_n$, and finally $(T_2\boldsymbol{x})_n = (E_{d_2}TE_{d_1}\boldsymbol{x})_n$. From the last expression you should be able to read out the filter coefficients.

c) Assume that N = 8. Write down the 8×8 -circulant Toeplitz matrix for the filter T_2 .

Exercise 3.44: Filters in the MP3 standard

In Example 3.34 in the compendium, we mentioned that the filters used in the MP3-standard were constructed from a low-pass prototype filter by multiplying the filter coefficients with a complex exponential. Clearly this means that the new frequency response is a shift of the old one. The disadvantage is, however, that the new filter coefficients are complex. It is possible to address this problem as follows. Assume that t_k are the filter coefficients of a filter S_1 , and that S_2 is the filter with filter coefficients $\cos(2\pi kn/N)t_k$, where $n \in \mathbb{N}$. Show that

$$\lambda_{S_2}(\omega) = \frac{1}{2}(\lambda_{S_1}(\omega - 2\pi n/N) + \lambda_{S_1}(\omega + 2\pi n/N)).$$

In other words, when we multiply (modulate) the filter coefficients with a cosine, the new frequency response can be obtained by shifting the old frequency response with $2\pi n/N$ in both directions, and taking the average of the two.

Solution. We have that

$$\begin{split} \lambda_{S_2}(\omega) &= \sum_k \cos(2\pi k n/N) t_k e^{-ik\omega} = \frac{1}{2} \sum_k (e^{2\pi i k n/N} + e^{-2\pi i k n/N}) t_k e^{-ik\omega} \\ &= \frac{1}{2} \left(\sum_k t_k e^{-ik(\omega - 2\pi n/N)} + \sum_k t_k e^{-ik(\omega + 2\pi n/N)} \right) \\ &= \frac{1}{2} (\lambda_{S_1}(\omega - 2\pi n/N) + \lambda_{S_1}(\omega + 2\pi n/N)). \end{split}$$

Exercise 3.45: Explain code

a) Explain what the code below does, line by line.

```
x, fs = audioread('sounds/castanets.wav')
N, nchannels = shape(x)
z = zeros((N, nchannels))
for n in range(1,N-1):
    z[n] = 2*x[n+1] + 4*x[n] + 2*x[n-1]
z[0] = 2*x[1] + 4*x[0] + 2*x[N-1]
z[N-1] = 2*x[0] + 4*x[N-1] + 2*x[N-2]
z = z/abs(z).max()
play(z, fs)
```

Comment in particular on what happens in the three lines directly after the for-loop, and why we do this. What kind of changes in the sound do you expect to hear?

Solution. In the code a filter is run on the sound samples from the file castanets.wav. Finally the new sound is played. In the first two lines after the for-loop, the first and the last sound samples in the filtered sound are computed, under the assumption that the sound has been extended to a periodic sound

with period N. After this, the sound is normalized so that the sound samples lie in the range between -1 and 1. In this case the filter is a low-pass-filter (as we show in b)), so that we can expect that that the treble in the sound is reduced.

b) Write down the compact filter notation for the filter which is used in the code, and write down a 5×5 circulant Toeplitz matrix which corresponds to this filter. Plot the (continuous) frequency response. Is the filter a low-pass- or a high-pass filter?

Solution. Compact filter notation for the filter which is run is $\{2, \underline{4}, 2\}$. A 5×5 circulant Toeplitz matrix becomes

$$\begin{pmatrix} 4 & 2 & 0 & 0 & 2 \\ 2 & 4 & 2 & 0 & 0 \\ 0 & 2 & 4 & 2 & 0 \\ 0 & 0 & 2 & 4 & 2 \\ 2 & 0 & 0 & 2 & 4 \end{pmatrix}.$$

The frequency response is $\lambda_S(\omega) = 2e^{i\omega} + 4 + 2e^{-i\omega} = 4 + 4\cos\omega$. It is clear that this gives a low-pass filter.

c) Another filter is given by the circulant Toeplitz matrix

$$\begin{pmatrix} 4 & -2 & 0 & 0 & -2 \\ -2 & 4 & -2 & 0 & 0 \\ 0 & -2 & 4 & -2 & 0 \\ 0 & 0 & -2 & 4 & -2 \\ -2 & 0 & 0 & -2 & 4 \end{pmatrix}.$$

Express a connection between the frequency responses of this filter and the filter from b). Is the new filter a low-pass- or a high-pass filter?

Solution. The frequency response for the new filter is

$$-2e^{i\omega} + 4 - 2e^{-i\omega} = 4 - 4\cos\omega = 4 + 4\cos(\omega + \pi) = \lambda_S(\omega + \pi),$$

where S is the filter from the first part of the exercise. The new filter therefore becomes a high-pass filter, since to add π to ω corresponds to swapping the frequencies 0 and π . We could also here referred to Observation 3.22 in the compendium, where we stated that adding an alternating sign in the filter coefficients turns a low-pass filter into a high-pass filter and vice versa.

Exercise 3.47: A concrete IIR filter

A filter is defined by demanding that $z_{n+2} - z_{n+1} + z_n = x_{n+1} - x_n$.

a) Compute and plot the frequency response of the filter.

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b) Use a computer to compute the output when the input vector is x = (1, 2, ..., 10). In order to do this you should write down two 10×10 -circulant Toeplitz matrices.

Exercise 3.48: Implementing the factorization

Write a function filterdftimpl, which takes the filter coefficients t and the value k_0 from this section, computes the optimal M, and implements the filter as here.

Exercise 3.49: Factoring concrete filter

Factor the filter $S = \{\underline{1}, 5, 10, 6\}$ into a product of two filters, one with two filter coefficients, and one with three filter coefficients.

Chapter 4

Symmetric filters and the DCT

Exercise 4.2: Computing eigenvalues

Consider the matrix

$$S = \frac{1}{3} \begin{pmatrix} 2 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 2 \end{pmatrix}$$

- a) Compute the eigenvalues and eigenvectors of S using the results of this section. You should only need to perform one DFT or one DCT in order to achieve this.
- b) Use a computer to compute the eigenvectors and eigenvalues of S also. What are the differences from what you found in a)?
- c) Find a filter T so that $S = T_r$. What kind of filter is T?

Exercise 4.3: Writing down lower order S_r

Consider the averaging filter $S = \{\frac{1}{4}, \frac{1}{2}, \frac{1}{4}\}$. Write down the matrix S_r for the case when N = 4.

Solution. First we obtain the matrix S as

$$\begin{pmatrix} \frac{1}{2} & \frac{1}{4} & 0 & 0 & 0 & 0 & 0 & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & 0 \\ \frac{1}{4} & 0 & 0 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{2} \end{pmatrix}$$

where we have drawn the boundaries between the blocks S_1 , S_2 , S_3 , S_4 . From this we see that

From this we get

$$S_r = S_1 + (S_2)^f = \begin{pmatrix} \frac{3}{4} & \frac{1}{4} & 0 & 0\\ \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & 0\\ 0 & \frac{1}{4} & \frac{1}{2} & \frac{1}{4}\\ 0 & 0 & \frac{1}{4} & \frac{3}{4} \end{pmatrix}.$$

Exercise 4.4: Writing down lower order DCTs

As in Example 4.1 in the compendium, state the exact cartesian form of the DCT matrix for the case N=3.

Solution. We first see that $d_{0,3} = \sqrt{\frac{1}{3}}$ and $d_{k,3} = \sqrt{\frac{2}{3}}$ for k = 1, 2. We also have that

$$\cos\left(2\pi\frac{n}{2N}\left(k+\frac{1}{2}\right)\right) = \cos\left(\pi\frac{n}{3}\left(k+\frac{1}{2}\right)\right),\,$$

so that the DCT matrix can be written as

$$DCT_{3} = \begin{pmatrix} \sqrt{\frac{1}{3}} & \sqrt{\frac{1}{3}} & \sqrt{\frac{1}{3}} \\ \sqrt{\frac{2}{3}}\cos\left(\frac{\pi}{3}\frac{1}{2}\right) & \sqrt{\frac{2}{3}}\cos\left(\frac{\pi}{3}\frac{3}{2}\right) & \sqrt{\frac{2}{3}}\cos\left(\frac{\pi}{3}\frac{5}{2}\right) \\ \sqrt{\frac{2}{3}}\cos\left(\frac{2\pi}{3}\frac{1}{2}\right) & \sqrt{\frac{2}{3}}\cos\left(\frac{2\pi}{3}\frac{3}{2}\right) & \sqrt{\frac{2}{3}}\cos\left(\frac{2\pi}{3}\frac{5}{2}\right) \end{pmatrix}$$

$$= \begin{pmatrix} \sqrt{\frac{1}{3}} & \sqrt{\frac{1}{3}} & \sqrt{\frac{1}{3}} \\ \sqrt{\frac{2}{3}}\cos(\pi/6) & \sqrt{\frac{2}{3}}\cos(\pi/2) & \sqrt{\frac{2}{3}}\cos(5\pi/6) \\ \sqrt{\frac{2}{3}}\cos(\pi/3) & \sqrt{\frac{2}{3}}\cos(\pi) & \sqrt{\frac{2}{3}}\cos(5\pi/3) \end{pmatrix}$$

$$= \begin{pmatrix} \sqrt{\frac{1}{3}} & \sqrt{\frac{1}{3}} & \sqrt{\frac{1}{3}} \\ \sqrt{\frac{2}{3}}(\sqrt{3}/2 + i/2) & 0 & \sqrt{\frac{2}{3}}(-\sqrt{3}/2 + i/2) \\ \sqrt{\frac{2}{3}}(1/2 + \sqrt{3}i/2) & -\sqrt{\frac{2}{3}} & \sqrt{\frac{2}{3}}(1/2 - \sqrt{3}i/2) \end{pmatrix}$$

Exercise 4.5: DCT-IV

Show that the vectors $\left\{\cos\left(2\pi\frac{n+\frac{1}{2}}{2N}\left(k+\frac{1}{2}\right)\right)\right\}_{n=0}^{N-1}$ in \mathbb{R}^N are orthogonal, with lengths $\sqrt{N/2}$. This means that the matrix with entries $\sqrt{\frac{2}{N}}\cos\left(2\pi\frac{n+\frac{1}{2}}{2N}\left(k+\frac{1}{2}\right)\right)$ is orthogonal. Since this matrix also is symmetric, it is its own inverse. This is the DCT-IV, which we denote by DCT $_N^{(\mathrm{IV})}$. Although we will not consider this, the DCT-IV also has an efficient implementation.

Hint. Compare with the orthogonal vectors d_n , used in the DCT.

Solution. We can write

$$\cos\left(2\pi\frac{n+\frac{1}{2}}{2N}\left(k+\frac{1}{2}\right)\right) = \cos\left(2\pi\frac{2n+1}{4N}\left(k+\frac{1}{2}\right)\right).$$

If we consider these as vectors of length 2N, we recognize these as the unit vectors d_{2n+1} in the 2N-dimensional DCT, divided by the factor $d_n = \sqrt{2/(2N)} = \sqrt{1/N}$, so that these vectors have length \sqrt{N} . To see that these vectors are orthogonal when we restrict to the first N elements we use Equation (??) in the compendium as follows:

$$N\delta_{n_{1},n_{2}} = \sum_{k=0}^{2N-1} \cos\left(2\pi \frac{n_{1} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right) \cos\left(2\pi \frac{n_{2} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right)$$

$$= \sum_{k=0}^{N-1} \cos\left(2\pi \frac{n_{1} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right) \cos\left(2\pi \frac{n_{2} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right)$$

$$+ \sum_{k=N}^{2N-1} \cos\left(2\pi \frac{n_{1} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right) \cos\left(2\pi \frac{n_{2} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right)$$

$$= \sum_{k=0}^{N-1} \cos\left(2\pi \frac{n_{1} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right) \cos\left(2\pi \frac{n_{2} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right)$$

$$+ \sum_{k=0}^{N-1} \cos\left(2\pi \frac{n_{1} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right) \cos\left(2\pi \frac{n_{2} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right)$$

$$= 2\sum_{k=0}^{N-1} \cos\left(2\pi \frac{n_{1} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right) \cos\left(2\pi \frac{n_{2} + \frac{1}{2}}{2N} \left(k + \frac{1}{2}\right)\right).$$

This shows that

$$\sum_{k=0}^{N-1} \cos \left(2\pi \frac{n_1 + \frac{1}{2}}{2N} \left(k + \frac{1}{2} \right) \right) \cos \left(2\pi \frac{n_2 + \frac{1}{2}}{2N} \left(k + \frac{1}{2} \right) \right) = \frac{N}{2} \delta_{n_1, n_2},$$

so that the vectors are orthogonal with lengths $\sqrt{N/2}$.

Exercise 4.6: MDCT

The MDCT is defined as the $N \times (2N)$ -matrix M with elements $M_{n,k} = \cos(2\pi(n+1/2)(k+1/2+N/2)/(2N))$. This exercise will take you through the details of the transformation which corresponds to multiplication with this matrix. The MDCT is very useful, and is also used in the MP3 standard and in more recent standards.

a) Show that

$$M = \sqrt{\frac{N}{2}} DCT_N^{(IV)} \begin{pmatrix} \mathbf{0} & A \\ B & \mathbf{0} \end{pmatrix}$$

where A and B are the $(N/2) \times N$ -matrices

$$A = \begin{pmatrix} \cdots & \cdots & 0 & -1 & -1 & 0 & \cdots & \cdots \\ \vdots & \vdots \\ 0 & -1 & \cdots & \cdots & \cdots & -1 & 0 \\ -1 & 0 & \cdots & \cdots & \cdots & 0 & -1 \end{pmatrix} = \begin{pmatrix} -I_{N/2}^f & -I_{N/2} \end{pmatrix}$$

$$B = \begin{pmatrix} 1 & 0 & \cdots & \cdots & \cdots & 0 & -1 \\ 0 & 1 & \cdots & \cdots & \cdots & 0 & -1 \\ 0 & 1 & \cdots & \cdots & \cdots & -1 & 0 \\ \vdots & \vdots \\ \cdots & \cdots & 0 & 1 & -1 & 0 & \cdots & \cdots \end{pmatrix} = \begin{pmatrix} I_{N/2} & -I_{N/2}^f \end{pmatrix}.$$

Due to this expression, any algorihtm for the DCT-IV can be used to compute the MDCT.

Solution. Clearly, columns $0, \ldots, N/2-1$ of the MDCT are columns $N/2, \ldots, N-1$ of the DCT-IV. For the remaining columns, note first that, for $0 \le k < N$, the properties

$$\cos(2\pi(n+1/2)((2N-1-k)+1/2)/(2N)) = -\cos(2\pi(n+1/2)(k+1/2)/(2N))$$
$$\cos(2\pi(n+1/2)((k+2N)+1/2)/(2N)) = -\cos(2\pi(n+1/2)(k+1/2)/(2N))$$

are easy to verify. From the first property it follows that columns $N/2,\ldots,3N/2-1$ of the MDCT are columns $N-1,N-2,\ldots,0$ of the DCT-IV, with a sign change (they occur in opposite order). From the second property, it follows that columns $3N/2,\ldots,2N-1$ of the MDCT are columns $0,\ldots,N/2-1$ of the DCT-IV, with a sign change. This means that, if \boldsymbol{y} is a vector of length 2N, the MDCT of \boldsymbol{y} can be written as

$$\sqrt{\frac{N}{2}} DCT_N^{(IV)} \begin{pmatrix}
-y_{3N/2} - y_{3N/2-1} \\
-y_{3N/2+1} - y_{3N/2-2} \\
\vdots \\
-y_{2N-1} - y_N \\
y_0 - y_{N-1} \\
y_1 - y_{N/2+1} \\
\vdots \\
y_{N/2-1} - y_{N/2}
\end{pmatrix}.$$

The factor $\sqrt{\frac{N}{2}}$ was added since $\sqrt{\frac{2}{N}}$ was added in front of the cosine-matrix in order to make $\mathrm{DCT}_N^{(\mathrm{IV})}$ orthogonal. The result now follows by noting that we can write $\begin{pmatrix} \mathbf{0} & A \\ B & \mathbf{0} \end{pmatrix} \boldsymbol{y}$ for the vector on the right hand side, with A and B as defined in the text of the exercise.

b) The MDCT is not invertible, since it is not a square matrix. We will show here that it still can be used in connection with invertible transformations. We first define the IMDCT as the matrix M^T/N . Transposing the matrix expression we obtained in a) gives

$$\frac{1}{\sqrt{2N}} \begin{pmatrix} \mathbf{0} & B^T \\ A^T & \mathbf{0} \end{pmatrix} \mathrm{DCT}_N^{(\mathrm{IV})}$$

for the IMDCT, which thus also has an efficient implementation. Show that if

$$\mathbf{x}_0 = (x_0, \dots, x_{N-1})$$
 $\mathbf{x}_1 = (x_N, \dots, x_{2N-1})$ $\mathbf{x}_2 = (x_{2N}, \dots, x_{3N-1})$

and

$$y_{0,1} = M \begin{pmatrix} x_0 \\ x_1 \end{pmatrix}$$
 $y_{1,2} = M \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$

(i.e. we compute two MDCT's where half of the data overlap), then

$$x_1 = \{ \text{IMDCT}(y_{0,1}) \}_{k=N}^{2N-1} + \{ \text{IMDCT}(y_{1,2}) \}_{k=0}^{N-1}.$$

Even though the MDCT itself is not invertible, the input can still be recovered from overlapping MDCT's.

Solution. Applying the MDCT first, and then the IMDCT, gives us the matrix

$$\frac{1}{2} \begin{pmatrix} \mathbf{0} & B^T \\ A^T & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{0} & A \\ B & \mathbf{0} \end{pmatrix} = \frac{1}{2} \begin{pmatrix} B^T B & \mathbf{0} \\ \mathbf{0} & A^T A \end{pmatrix}$$

Note that

$$A^T A = \begin{pmatrix} I_{N/2} & I_{N/2}^f \\ I_{N/2}^f & I_{N/2} \end{pmatrix} \qquad B^T B = \begin{pmatrix} I_{N/2} & -I_{N/2}^f \\ -I_{N/2}^f & I_{N/2} \end{pmatrix}.$$

Inserting this in the above gives

$$\frac{1}{2} \begin{pmatrix} I_{N/2} & -I_{N/2}^f & \mathbf{0} & \mathbf{0} \\ -I_{N/2}^f & I_{N/2} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & I_{N/2} & I_{N/2}^f \\ \mathbf{0} & \mathbf{0} & I_{N/2}^f & I_{N/2}^f \end{pmatrix} = \frac{1}{2} \begin{pmatrix} I_N - I_N^f & \mathbf{0} \\ \mathbf{0} & I_N + I_N^f \end{pmatrix}.$$

Assume now that we have computed the MDCT of $\begin{pmatrix} x_0 \\ x_1 \end{pmatrix} = (x_0, \dots, x_{2N-1})$, and of $\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = (x_N, \dots, x_{3N-1})$. Performing the IMDCT on these two thus gives

$$\frac{1}{2} \begin{pmatrix} \boldsymbol{x}_0 - \boldsymbol{x}_0^{\text{rev}} \\ \boldsymbol{x}_1 + \boldsymbol{x}_1^{\text{rev}} \end{pmatrix}$$
 and $\frac{1}{2} \begin{pmatrix} \boldsymbol{x}_1 - \boldsymbol{x}_1^{\text{rev}} \\ \boldsymbol{x}_2 + \boldsymbol{x}_2^{\text{rev}} \end{pmatrix}$

Adding the second component of the first and the first component of the second gives x_1 , which proves the result.

Exercise 4.7: Component expressions for a symmetric filter

Assume that $S = t_{-L}, \dots, \underline{t_0}, \dots, t_L$ is a symmetric filter. Use Equation (4.7) in the compendium to show that $z_n = (S\boldsymbol{x})_n$ in this case can be split into the following different formulas, depending on n:

a) $0 \le n < L$:

$$z_n = t_0 x_n + \sum_{k=1}^n t_k (x_{n+k} + x_{n-k}) + \sum_{k=n+1}^L t_k (x_{n+k} + x_{n-k+N}).$$
 (4.1)

b) $L \le n < N - L$:

$$z_n = t_0 x_n + \sum_{k=1}^{L} t_k (x_{n+k} + x_{n-k}). \tag{4.2}$$

c) $N - L \le n < N$:

$$z_n = t_0 x_n + \sum_{k=1}^{N-1-n} t_k (x_{n+k} + x_{n-k}) + \sum_{k=N-1-n+1}^{L} t_k (x_{n+k-N} + x_{n-k}).$$
 (4.3)

The convolve function may not pick up this reduction in the number of multiplications, since it does not assume that the filter is symmetric. We will still use the convolve function in implementations, however, due to its heavy optimization.

Exercise 4.8: Trick for reducing the number of multiplications with the DCT

In this exercise we will take a look at a small trick which reduces the number of additional multiplications we need for DCT algorithm from Theorem 4.22 in the compendium. This exercise does not reduce the order of the DCT algorithms, but we will see in Exercise 4 how the result can be used to achieve this.

a) Assume that \boldsymbol{x} is a real signal. Equation (4.12) in the compendium, which said that

$$y_n = \cos\left(\pi \frac{n}{2N}\right) \Re((\mathrm{DFT}_N \boldsymbol{x}^{(1)})_n) + \sin\left(\pi \frac{n}{2N}\right) \Im((\mathrm{DFT}_N \boldsymbol{x}^{(1)})_n)$$
$$y_{N-n} = \sin\left(\pi \frac{n}{2N}\right) \Re((\mathrm{DFT}_N \boldsymbol{x}^{(1)})_n) - \cos\left(\pi \frac{n}{2N}\right) \Im((\mathrm{DFT}_N \boldsymbol{x}^{(1)})_n)$$

for the n'th and N-n'th coefficient of the DCT. This can also be rewritten as

$$y_n = \left(\Re((\mathrm{DFT}_N \boldsymbol{x}^{(1)})_n) + \Im((\mathrm{DFT}_N \boldsymbol{x}^{(1)})_n)\right) \cos\left(\pi \frac{n}{2N}\right)$$
$$-\Im((\mathrm{DFT}_N \boldsymbol{x}^{(1)})_n)(\cos\left(\pi \frac{n}{2N}\right) - \sin\left(\pi \frac{n}{2N}\right))$$
$$y_{N-n} = -\left(\Re((\mathrm{DFT}_N \boldsymbol{x}^{(1)})_n) + \Im((\mathrm{DFT}_N \boldsymbol{x}^{(1)})_n)\right) \cos\left(\pi \frac{n}{2N}\right)$$
$$+\Re((\mathrm{DFT}_N \boldsymbol{x}^{(1)})_n)(\sin\left(\pi \frac{n}{2N}\right) + \cos\left(\pi \frac{n}{2N}\right)).$$

Explain that the first two equations require 4 multiplications to compute y_n and y_{N-n} , and that the last two equations require 3 multiplications to compute y_n and y_{N-n} .

- **b)** Explain why the trick in a) reduces the number of additional multiplications in a DCT, from 2N to 3N/2.
- c) Explain why the trick in a) can be used to reduce the number of additional multiplications in an IDCT with the same number.

Hint. match the expression $e^{\pi i n/(2N)}(y_n - iy_{N-n})$ you encountered in the IDCT with the rewriting you did in b).

d) Show that the penalty of the trick we here have used to reduce the number of multiplications, is an increase in the number of additional additions from N to 3N/2. Why can this trick still be useful?

Exercise 4.9: An efficient joint implementation of the DCT and the FFT

In this exercise we will explain another joint implementation of the DFT and the DCT, which has the benefit of a low multiplication count, at the expense of a higher addition count. It also has the benefit that it is specialized to real vectors, with a very structured implementation (this is not always the case for the quickest FFT implementations. Not surprisingly, one often sacrifices clarity of code when one pursues higher computational speed). a) of this exercise can be skipped, as it is difficult and quite technical. For further details of the algorithm the reader is referred to [?].

a) Let $y = DFT_N x$ be the N-point DFT of the real vector x. Show that

$$\Re(y_n) = \begin{cases} \Re((\mathrm{DFT}_{N/2} \boldsymbol{x}^{(e)})_n) + (C_{N/4} \boldsymbol{z})_n & 0 \le n \le N/4 - 1\\ \Re((\mathrm{DFT}_{N/2} \boldsymbol{x}^{(e)})_n) & n = N/4\\ \Re((\mathrm{DFT}_{N/2} \boldsymbol{x}^{(e)})_n) - (C_{N/4} \boldsymbol{z})_{N/2 - n} & N/4 + 1 \le n \le N/2 - 1 \end{cases}$$

$$(4.4)$$

$$\Im(y_n) = \begin{cases} \Im((\mathrm{DFT}_{N/2} \boldsymbol{x}^{(e)})_n) & n = 0\\ \Im((\mathrm{DFT}_{N/2} \boldsymbol{x}^{(e)})_n) + (C_{N/4} \boldsymbol{w})_{N/4-n} & 1 \le n \le N/4 - 1\\ \Im((\mathrm{DFT}_{N/2} \boldsymbol{x}^{(e)})_n) + (C_{N/4} \boldsymbol{w})_{n-N/4} & N/4 \le n \le N/2 - 1 \end{cases}$$
(4.5)

where $\boldsymbol{x}^{(e)}$ is as defined in Theorem 2.15 in the compendium, where $\boldsymbol{z}, \boldsymbol{w} \in \mathbb{R}^{N/4}$ defined by

$$z_k = x_{2k+1} + x_{N-2k-1}$$
 $0 \le k \le N/4 - 1,$
 $w_k = (-1)^k (x_{N-2k-1} - x_{2k+1})$ $0 \le k \le N/4 - 1,$

Explain from this how you can make an algorithm which reduces an FFT of length N to an FFT of length N/2 (on $\boldsymbol{x}^{(e)}$), and two DCT's of length N/4 (on \boldsymbol{z} and \boldsymbol{w}). We will call this algorithm the revised FFT algorithm.

Solution. Taking real and imaginary parts in Equation (2.13) in the compendium for the FFT algorithm we obtain

$$\Re(y_n) = \Re\left((\mathrm{DFT}_{N/2}\boldsymbol{x}^{(e)})_n + \Re((D_{N/2}\mathrm{DFT}_{N/2}\boldsymbol{x}^{(o)})_n\right)$$
$$\Im(y_n) = \Im\left((\mathrm{DFT}_{N/2}\boldsymbol{x}^{(e)})_n + \Im((D_{N/2}\mathrm{DFT}_{N/2}\boldsymbol{x}^{(o)})_n\right),$$

These equations explain the first terms $\Re((\mathrm{DFT}_{N/2}\boldsymbol{x}^{(e)})_n)$ and $\Im((\mathrm{DFT}_{N/2}\boldsymbol{x}^{(e)})_n)$ on the right hand sides in equations (4.4) and (4.5). It remains to rewrite $\Re((D_{N/2}\mathrm{DFT}_{N/2}\boldsymbol{x}^{(o)})_n)$ and $\Im((D_{N/2}\mathrm{DFT}_{N/2}\boldsymbol{x}^{(o)})_n)$ so that the remaining terms on the right hand sides can be seen. Let us first consider the equation for the real part with $0 \le n \le N/4 - 1$. In this case we can write

$$\Re((D_{N/2}\mathrm{DFT}_{N/2}\boldsymbol{x}^{(o)})_n)
= \Re\left(e^{-2\pi i n/N} \sum_{k=0}^{N/2-1} (\boldsymbol{x}^{(o)})_k e^{-2\pi i n k/(N/2)}\right) = \Re\left(\sum_{k=0}^{N/2-1} (\boldsymbol{x}^{(o)})_k e^{-2\pi i n (k+\frac{1}{2})/(N/2)}\right)
= \sum_{k=0}^{N/2-1} (\boldsymbol{x}^{(o)})_k \cos\left(2\pi \frac{n(k+\frac{1}{2})}{N/2}\right)
= \sum_{k=0}^{N/4-1} (\boldsymbol{x}^{(o)})_k \cos\left(2\pi \frac{n(k+\frac{1}{2})}{N/2}\right)
+ \sum_{k=0}^{N/4-1} (\boldsymbol{x}^{(o)})_{N/2-1-k} \cos\left(2\pi \frac{n(N/2-1-k+\frac{1}{2})}{N/2}\right)
= \sum_{k=0}^{N/4-1} ((\boldsymbol{x}^{(o)})_k + (\boldsymbol{x}^{(o)})_{N/2-1-k}) \cos\left(2\pi \frac{n(k+\frac{1}{2})}{N/2}\right)
= \sum_{k=0}^{N/4-1} z_k \cos\left(2\pi \frac{n(k+\frac{1}{2})}{N/2}\right),$$

where we have used that cos is periodic with period 2π , that cos is symmetric, and where z is the vector defined in the text of the theorem. When $0 \le n \le N/4 - 1$ this can also be written as

$$\sum_{k=0}^{N/4-1} (C_{N/4})_{n,k} z_k = (C_{N/4} \boldsymbol{z})_n,$$

This proves the first formula in Equation (4.4).

For $N/4+1 \le n \le N/2-1$, everything above is valid, except for that $\cos(2\pi n(k+1/2)/(N/2))$ are not entries in the matrix $C_{N/4}$, since n is outside the legal range of the indices. However, N/2-n is now a legal index in $C_{N/4}$, and using that

$$\cos\left(2\pi\frac{n(k+\frac{1}{2})}{N/2}\right) = -\cos\left(2\pi\frac{\left(\frac{N}{2}-n\right)\left(k+\frac{1}{2}\right)}{N/2}\right),\,$$

we arrive at $-(C_{N/4}z)_{N/2-n}$ instead, and this proves the third formula in Equation (4.4). For the case $n = \frac{N}{4}$ all the cosine entries in the sum are zero, and this completes the proof of Equation (4.4).

For the imaginary part, using that sin is periodic with period 2π , and that sin is anti-symmetric, analogous calculations as above give

$$\Im((D_{N/2}\mathrm{DFT}_{N/2}\boldsymbol{x}^{(o)})_n) = \sum_{k=0}^{N/4-1} ((\boldsymbol{x}^{(o)})_{N/2-1-k} - (\boldsymbol{x}^{(o)})_k) \sin\left(2\pi \frac{n\left(k + \frac{1}{2}\right)}{N/2}\right). \tag{4.6}$$

Using that

$$\sin\left(2\pi \frac{n(k+\frac{1}{2})}{N/2}\right) = \cos\left(\frac{\pi}{2} - 2\pi \frac{n(k+\frac{1}{2})}{N/2}\right) = \cos\left(2\pi \frac{(N/4-n)(k+\frac{1}{2})}{N/2} - k\pi\right)$$
$$= (-1)^k \cos\left(2\pi \frac{(N/4-n)(k+\frac{1}{2})}{N/2}\right),$$

Equation (4.6) can be rewritten as

$$\sum_{k=0}^{N/4-1} ((\boldsymbol{x}^{(o)})_{N/2-1-k} - (\boldsymbol{x}^{(o)})_k)(-1)^k \cos\left(2\pi \frac{(N/4-n)(k+\frac{1}{2})}{N/2}\right)$$
$$= \sum_{k=0}^{N/4-1} w_k \cos\left(2\pi \frac{(N/4-n)(k+\frac{1}{2})}{N/2}\right),$$

where \boldsymbol{w} is the vector defined as in the text of the theorem. When n=0 this is 0 since all the cosines entries are zero. When $1 \leq n \leq N/4$ this is $(C_{N/4}\boldsymbol{w})_{N/4-n}$, since $\cos(2\pi(N/4-n)(k+1/2)/(N/2))$ are entries in the matrix $C_{N/4}$. This proves the second formula in Equation (4.5).

For $N/4 \le n \le N/2 - 1$ we can use that $\cos(2\pi(N/4 - n)(k + 1/2)/(N/2)) = \cos(2\pi(n - N/4)(k + 1/2)/(N/2))$, which is an entry in the matrix $DCT_{N/4}$ as well, so that we get $(C_{N/4}\mathbf{z})_{n-N/4}$. This also proves the third formula in Equation (4.5), and the proof is done.

a) says nothing about the coefficients y_n for $n > \frac{N}{2}$. These are obtained in the same way as before through symmetry. a) also says nothing about $y_{N/2}$. This can be obtained with the same formula as in Theorem 2.15 in the compendium.

Let us now compute the number of arithmetic operations our revised algorithm needs. Denote by the number of real multiplications needed by the revised N-point FFT algorithm

b) Explain from the algorithm in a) that

$$M_N = 2(M_{N/4} + 3N/8) + M_{N/2}$$
 $A_N = 2(A_{N/4} + 3N/8) + A_{N/2} + 3N/2$ (4.7)

Hint. 3N/8 should come from the extra additions/multiplications (see Exercise 4) you need to compute when you run the algorithm from Theorem 4.22 in the compendium for $C_{N/4}$. Note also that the equations in a) require no extra multiplications, but that there are xix equations involved, each needing N/4 additions, so that we need 6N/4 = 3N/2 extra additions.

c) Explain why $x_r = M_{2^r}$ is the solution to the difference equation

$$x_{r+2} - x_{r+1} - 2x_r = 3 \times 2^r$$
,

and that $x_r = A_{2^r}$ is the solution to

$$x_{r+2} - x_{r+1} - 2x_r = 9 \times 2^r$$
.

and show that the general solution to these are $x_r = \frac{1}{2}r2^r + C2^r + D(-1)^r$ for multiplications, and $x_r = \frac{3}{2}r2^r + C2^r + D(-1)^r$ for additions.

- d) Explain why, regardless of initial conditions to the difference equations, $M_N = O\left(\frac{1}{2}N\log_2N\right)$ and $A_N = O\left(\frac{3}{2}N\log_2N\right)$ both for the revised FFT and the revised DCT. The total number of operations is thus $O(2N\log_2N)$, i.e. half the operation count of the split-radix algorithm. The orders of these algorithms are thus the same, since we here have adapted to read data.
- e) Explain that, if you had not employed the trick from Exercise 4, we would instead have obtained $M_N = O\left(\frac{2}{3}\log_2 N\right)$, and $A_N = O\left(\frac{4}{3}\log_2 N\right)$, which equal the orders for the number of multiplications/additions for the split-radix algorithm. In particular, the order of the operation count remains the same, but the trick from Exercise 4 turned a bigger percentage of the arithmetic operations into additions.

The algorithm we here have developed thus is constructed from the beginning to apply for real data only. Another advantage of the new algorithm is that it can be used to compute both the DCT and the DFT.

Exercise 4.10: Implementation of the IFFT/IDCT

We did not write down corresponding algorithms for the revised IFFT and IDCT algorithms. We will consider this in this exercise.

a) Using equations (4.4)-(4.5), show that

$$\Re(y_n) - \Re(y_{N/2-n}) = 2(C_{N/4}z)_n$$

$$\Im(y_n) + \Im(y_{N/2-n}) = 2(C_{N/4}w)_{N/4-n}$$

for $1 \le n \le N/4 - 1$. Explain how one can compute \boldsymbol{z} and \boldsymbol{w} from this using two IDCT's of length N/4.

b) Using equations (4.4)-(4.5), show that

$$\Re(y_n) + \Re(y_{N/2-n}) = \Re((\mathrm{DFT}_{N/2}\boldsymbol{x}^{(e)})_n)$$
$$\Im(y_n) - \Im(y_{N/2-n}) = \Im((\mathrm{DFT}_{N/2}\boldsymbol{x}^{(e)})_n),$$

and explain how one can compute $x^{(e)}$ from this using an IFFT of length N/2.