Exercise Sheet No 2

2.1 Analytical Problems

Remark on arithmetic operations on sets. Let $A \subseteq \mathbb{R}^p$ and $\mathbf{x}_0 \in \mathbb{R}^p$. We say $A \pm \mathbf{x}_0 = \{\mathbf{a} \pm \mathbf{x}_0 | \mathbf{a} \in A\}$. Let $A \subseteq \mathbb{R}$ and $x_0 \in \mathbb{R}$, then we additionally define $x_0 A = \{ax_0 | a \in A\}$.

Definition 2.1: Landau-Notation for Functions

Let $I \subseteq \mathbb{R}$ be an open interval, $f, g: I \to \mathbb{R}$ and $x_0 \in I$. We say:

$$f(x \to x_0) \in \mathcal{O}(g(x \to x_0)) \Leftrightarrow \exists C, \delta > 0 \colon |f|_{\mathcal{B}_{\delta}(x_0)}(x)| \le C|g|_{\mathcal{B}_{\delta}(x_0)}(x)|$$

Furthermore

$$f(x \to x_0) \in o(g(x \to x_0)) \Leftrightarrow \forall \varepsilon > 0 \colon \exists \delta > 0 \colon f|_{\mathcal{B}_{\delta}(x_0)}(x) \in \varepsilon g(\mathcal{B}_{\delta}(x_0))$$

Definition 2.2: More types of Landau-Symbols

Let $(f_n)_{n\in\mathbb{N}}$ and $(g_n)_{n\in\mathbb{N}}$ be sequences, then we define:

```
f \in \mathcal{O}(g) \Leftrightarrow \exists N \in \mathbb{N}, C \in \mathbb{R} \colon n \ge N \Rightarrow |f_n| \le C|g_n|
f \in \Omega(g) \Leftrightarrow \exists N \in \mathbb{N}, c \in \mathbb{R} \colon n \ge N \Rightarrow |f_n| \ge c|g_n|
f \in \Theta(g) \Leftrightarrow (f \in \mathcal{O}(g)) \land (f \in \Omega(g)) \Leftrightarrow \exists N \in \mathbb{N}, c, C \in \mathbb{R} \colon c \le C \colon n \ge N \Rightarrow c|g_n| \le |f_n| \le C|g_n|
```

Lemma 2.1: Properties of Landau-Symbols

```
Let I \subseteq \mathbb{R} be an open interval and f, f_1, f_2, g, g_1, g_2, h \colon I \to \mathbb{R}, then the following holds true i f \in \mathcal{O}(f) ii f \in o(g) \Rightarrow f \in \mathcal{O}(g) iii f \in o(g) \Rightarrow \forall K \in \mathbb{R} \colon Kf \in \mathcal{O}(g) iv f \in \mathcal{O}(g_1) \land g_1 \in \mathcal{O}(g_2) \Rightarrow f \in \mathcal{O}(g_2) v f_1 \in \mathcal{O}(g_1) \land f_2 \in \mathcal{O}(g_2) \Rightarrow f_1 f_2 \in \mathcal{O}(g_1) vi f \in \mathcal{O}(g + h) \land h \in \mathcal{O}(g) \Rightarrow f \in \mathcal{O}(g)
```

Task 2.1: Landau-Symbols

```
i Use Definition 2.1 to prove Lemma 2.1 ii a Show that for any polynomial p \in \mathbb{R}_k[x], with a_k > 0 and a_i \geq 0, it follows p \in \Theta(n^k) b Let n \geq 1, show or disprove: b.i 2n + 3 \operatorname{ld} n \in \Theta(n) b.ii \sum_{i=1}^n i^k \in \Theta(n^{k+1}) b.iii n! \in \Theta((n+1)!) c For a > 1 and b > 1, explain the difference between \Theta(\log_a n) and \Theta(\log_b n) as n \to \infty iii Show the following a \frac{\sin(x)}{x} - 1 \in \mathcal{O}(x^2) as x \to 0 b x^2 + 3x \in \mathcal{O}(x) as x \to 0 c x^2 - x - 6 \in \mathcal{O}(x - 3) as x \to 3
```

Subtask i Let $I \subseteq \mathbb{R}$ be open and $f, f_1, f_2, g, g_1, g_2, h : I \to \mathbb{R}$. Property i:

$$C \in \mathbb{R}^+ \Rightarrow \forall x \in \mathbb{R} \colon |f(x)| \le C|f(x)| \Leftrightarrow f \in \mathcal{O}(f)$$

Property ii

$$f(x_0) \in o(g(x_0)) \Leftrightarrow \forall \varepsilon > 0 \colon \exists \delta > 0 \colon \forall x \in \mathcal{B}_{\delta}(x_0) \colon |f(x)| \le \varepsilon |g(x)|$$

 $\Rightarrow \varepsilon = C > 0 \Rightarrow \exists \delta_C > 0 \colon \forall x \in \mathcal{B}_{\delta_C}(x_0) \colon |f(x)| \le C|g(x)| \Leftrightarrow f(x_0) \in \mathcal{O}(g(x_0))$

Property iii

$$f(x_0) \in \mathcal{O}(g(x_0)) \Leftrightarrow \exists \delta > 0, C > 0 \colon \forall x \in \mathcal{B}_{\delta}(x_0) \colon |f(x)| \le C|g(x)|$$

$$K \in \mathbb{R} \Rightarrow \forall x \in \mathcal{B}_{\delta}(x_0) \colon |Kf(x)| = |K| \cdot |f(x)| \le |K|C|g(x)| = \tilde{C}|g(x)|$$

$$\Rightarrow \forall K \in \mathbb{R} \colon \exists \tilde{C} > 0, \delta > 0 \colon \forall x \in \mathcal{B}_{\delta}(x_0) \colon |Kf(x)| \le \tilde{C}|g(x)| \Leftrightarrow Kf(x_0) \in \mathcal{O}(g(x_0))$$

Property iv

$$f(x_0) \in \mathcal{O}(g_1(x_0)) \land g_1(x_0) \in \mathcal{O}(g_2(x_0))$$

$$\Leftrightarrow \exists \delta_1, \delta_2, C_1, C_2 > 0 \colon \forall x \in \mathcal{B}_{\min(\delta_1, \delta_2)}(x_0) \colon |f(x)| \le C_1 |g_1(x)| \le C_2 |g_2(x)|$$

$$\Rightarrow \forall x \in \mathcal{B}_{\min(\delta_1, \delta_2)}(x_0) \colon |f(x)| \le C_2 |g_2(x)| \Leftrightarrow f(x_0) \in \mathcal{O}(g_2(x_0))$$

Property v

$$f_{1} \in \mathcal{O}(g_{1}) \land f_{2} \in \mathcal{O}(g_{2})$$

$$\Leftrightarrow \exists \delta_{1}, \delta_{2}, C_{1}, C_{2} > 0 \colon \forall x \in \mathcal{B}_{\min(\delta_{1}, \delta_{2})}(x_{0}) \colon |f_{1}(x)| \leq C_{1}|g_{1}(x)| \land |f_{2}(x)| \leq C_{2}|g_{2}(x)|$$

$$\Rightarrow \forall x \in \mathcal{B}_{\min(\delta_{1}, \delta_{2})}(x_{0}) \colon |f_{1}(x)f_{2}(x)| = |f_{1}(x)| \cdot |f_{2}(x)| \leq C_{1}|g_{1}(x)| \cdot C_{2}|g_{2}(x)| = C_{1}C_{2}|g_{1}(x)g_{2}(x)|$$

$$\Leftrightarrow f_{1}(x_{0})f_{2}(x_{0}) \in \mathcal{O}(g_{1}(x_{0})g_{2}(x_{0}))$$

Property vi

$$f(x_0) \in \mathcal{O}(g(x_0) + h(x_0)) \land h(x_0) \in \mathcal{O}(g(x_0))$$

$$\Leftrightarrow \exists \delta_1, \delta_2, C_1, C_2 > 0 \colon \forall x \in \mathcal{B}_{\min(\delta_1, \delta_2)}(x_0) \colon |f(x)| \le C_1 |g(x) + h(x)| \le C_1 |g(x)| + C_1 |h(x)| \le 2C_1 |g(x)|$$

$$\Rightarrow f(x_0) \in \mathcal{O}(g(x_0))$$

Note that similar properties can be shown for sequences and Ω , which we will use in the following sub-task. Subtask ii: We start with Sub-Subtask a. Using the limit-criterion, we get:

$$\limsup_{n \to \infty} \frac{p(n)}{n^k} = a_k \in (0, \infty) \Rightarrow p(n) \in \Theta(n^k)$$

Sub-Subtask b:

Sub-Sub-Subtask b.i:

We show for $n \in \mathbb{N}$: $\operatorname{ld} n \leq n$ by induction. For n = 1 it follows $\operatorname{ld}(n) = 0 \leq 1$. Now, for $n \to n+1$ we get:

$$\operatorname{ld}(n+1) = \operatorname{ld}\left(n\left(1+\frac{1}{n}\right)\right) = \operatorname{ld}(n) + \operatorname{ld}\left(1+\frac{1}{n}\right) \le \operatorname{ld}(n) \le n$$

Therefore, by Property vi we get that $2n + 3 \operatorname{ld} n \in \Theta(n)$.

Sub-Sub-Subtask b.ii

$$\sum_{i=1}^{n} i^{k} \leq \sum_{i=1}^{n} n^{k} = nn^{k} = n^{k+1} \Rightarrow \sum_{i=1}^{n} i^{k} \in \mathcal{O}(n^{k+1})$$

$$\sum_{i=1}^{n} i^{k} \geq \left\lceil \frac{n+1}{2} \right\rceil + \sum_{i=0}^{\lfloor \frac{n}{2} \rfloor} (n-i)^{k} \geq \sum_{i=1}^{\lceil \frac{n}{2} \rceil} \left\lceil \frac{n+1}{2} \right\rceil^{k} = \left\lceil \frac{n}{2} \right\rceil \cdot \left\lceil \frac{n+1}{2} \right\rceil^{k} \geq \frac{n}{2} \left(\frac{n+1}{2} \right)^{l} \geq \frac{n^{k+1}}{2^{k+1}} = \frac{1}{2^{k+1}} n^{k+1}$$

Choosing $C = \frac{1}{2^k}$ we see that $\sum_{i=1}^n i^k \ge Cn^{k+1}$, therefore $\sum_{i=1}^n i^k \in \Omega(n^{k+1})$ and thus $\sum_{i=1}^n i^k \in \Theta(n^{k+1})$. Sub-Sub-Subtask b.iii

$$\limsup_{n\to\infty}\frac{n!}{(n+1)!}=\limsup_{n\to\infty}\frac{1}{n+1}=0\Rightarrow n!\in\mathcal{O}((n+1)!)$$

Sub-Subtask c Given that $\forall a > 1$ we know that

$$\log_a(x) = \frac{\ln x}{\ln a}$$

We see that

$$\log_a n = \frac{\ln n}{\ln a} = \frac{\ln b}{\ln a} \log_b n \Rightarrow \Theta(\log_a n) = \Theta(\log_b n)$$

We start with Sub-Sub-Subtask a: Let $1 > \varepsilon > 0$, then it follows:

$$\left| \frac{\sin(x)}{x} - 1 \right| = \left| \sum_{k=0}^{\infty} (-1)^k \frac{x^{2k}}{(2k+1)!} - 1 \right| = \left| \sum_{k=1}^{\infty} (-1)^k \frac{x^{2k}}{(2k+1)!} \right| \le \left| -\frac{x^2}{3!} \right| \le x^2$$

Sub-Sub-Subtask b: Let $\varepsilon \in (0,1)$, then $\forall x \in \mathcal{B}_{\varepsilon}(0) \colon |x^2| < |x|$, therefore:

$$x \in \mathcal{B}_{\varepsilon}(0) \Rightarrow |x^2 + 3x| \le |x^2| + 3|x| \le 4|x|$$

Thus $x^2 + 3x \in \mathcal{O}(x)$ as $x \to 0$.

Sub-Sub-Subtask c: Let $\varepsilon > 0$ be sufficiently small:

$$\forall x \in \mathcal{B}_{\varepsilon}(3) \colon |x^2 - x - 6| \le c|x - 3|$$

$$\Leftrightarrow |x - 3| \cdot |x + 2| \le c|x - 3| \Leftrightarrow |x - 3| \cdot |x + 2| < \varepsilon|x + 2| < c\varepsilon$$

$$\Leftrightarrow x + 2 < c \Rightarrow c > 5 + \varepsilon$$

Task 2.2: Complexity Analysis of Algorithms

Determine the time-complexities of the following algorithms

i First Algorithm:

ii Second Algorithm:

```
\begin{array}{lll} 1 & {\rm i} = 1 \\ 2 & {\rm while} & i \leq 2n \ {\rm do} \\ 3 & x = x+1 \\ 4 & i = i+1 \\ 5 & {\rm end} \end{array}
```

Subtask i: Assuming the increment of x has a time-duration of c, we get the following time-complexity of the algorithm:

$$T(n) = \sum_{i=1}^{2n} \sum_{i=1}^{n} c = cn \sum_{i=1}^{2n} = 2cn^{2} \in \Theta(n^{2})$$

If S(n) denotes the memory-complexity of the algorithm, we can assume that both indices i and j are auxillary variables, therefore $S(n) = 2 \in \Theta(1)$.

Subtask ii: Assuming the increment of x has a time-duration of c_1 , and the increment of i has a time-duration of c_2 , we get:

$$T(n) = \sum_{i=1}^{2n} c_1 + c_2 = (c_1 + c_2) \sum_{i=1}^{2n} = 2n(c_1 + c_2) \in \Theta(n)$$

Assuming x is an auxiliary variable, we get $S(n) = 2 \in \Theta(1)$.

2.2 Programming Problem

Task 2.3: Matrix Multiplication

Write a python script with a function $\mathtt{matprod}(A, B)$ that returns the product of the matrices $A, B \in \mathbb{C}^{n \times n}$. Implement the following algorithm:

Algorithm 1: Matrix-Product

```
name: matprod
input: n \times n matrix A, n \times n matrix B

output: n \times n matrix C

matprod(A,B):

C = 0_n
for i = 1, ..., n do
for j = 1, ..., n do
C_{ij} = C_{ij} + A_{ik}B_{kj}
end
end
end
return C
```

Test the script using:

$$\mathbf{A} = \begin{bmatrix} -2 & 5 & 1\\ 0 & 8 & -7\\ 9 & -4 & -3 \end{bmatrix} \qquad \mathbf{B} = \begin{bmatrix} 3 & -4 & 6\\ -5 & 2 & -1\\ 8 & -9 & 0 \end{bmatrix}$$

Discuss the runtime-complexity of the algorithm. Can it be further improved? Bonus: Modify the algorithm in such a way, that the product of $A \in \mathbb{C}^{n \times m}$ and $B \in \mathbb{C}^n \times p$ can be computed and $C = AB \in \mathbb{C}^{n \times p}$. Provide test-examples.

We begin by analyzing the runtime-complexity of the naive-algorithm for square-matrices A and B. Assuming $C_{ij} = C_{ij} + A_{ik}B_{kj}$ takes constant time c, we get:

$$T(n) = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} c = n^{3} c \in \Theta(n^{3})$$

Notice, since $\mathbb{C} \in \mathbb{C}^{n \times n}$, we also get $T(n) = cn^2 \in \Theta(n^2)$, as complex numbers may require more memory than reals. The implementation can be found in the supplied script-file called square_prod.py.

Assuming the implementation-architecture allows for vectorized operation, such as independent summation, we can eliminate the last for-loop by computing the dot-product $\langle r_i(A), c_j(B) \rangle$, where r_k denotes the k-th row and c_k denotes the k-th column.

Algorithm 2: Matrix-Product with dot-product

```
name: matprod

input: n \times n matrix A, n \times n matrix B

output: n \times n matrix C

matprod(A,B):

C = 0_n

for i = 1, ..., n do

for j = 1, ..., n do

C_{ij} = \langle r_i(A), c_j(B) \rangle

end

end

return C
```

An implementation is also found in square_prod.py under the name matprod_fast().

Bonus: We begin by adapting the pseudo-code:

Algorithm 3: Matrix-Product for non-square matrices

```
name: matprod
input: n \times m matrix A, m \times p matrix B
output: n \times p matrix C
```

```
5 matprod(A,B):
6 C = 0_{n \times p}
7 for i = 1, \dots n do
8 for j = 1, \dots, p do
9 for k = 1, \dots m do
10 C_{ij} = C_{ij} + A_{ik}B_{kj}
11 end
12 end
13 end
14 return C
```

Note the runtime complexity is now $T(n) = cnpm \in \Theta(n^3)$, and S(n) = cnp. The python-implementation can be found in the supplied script-file called rect_prod.py. We can additionally use the same trick like before and implicitly remove one for-loop by setting $C_{ij} = \langle r_i(A), c_j(B) \rangle$. The implementation is found in rect_prod.py under the name matprod_fast().