Matrix monotone functions

Otte Heinävaara

February 6, 2018

Contents

Chapter 1

Matrix monotone functions – part 0

1.1 Disclaimer

Let's be honest: this master's thesis is really not about matrix monotone functions. What is it about, then? Well, unfortunately the only way I know how to answer that question is to explain what the matrix monotone functions are.[1] Hence the title.

1.2 What are matrix monotone functions?

Definition 1.1. Let $(a, b) \subset \mathbb{R}$ be an open, possibly unbounded interval and n positive integer. We say that $f : (a, b) \to \mathbb{R}$ is **n-monotone** or **matrix monotone** of order n on (a, b), if for any two $n \times n$ Hermitian matrices A and B with spectra in (a, b), such that $B - A$ is positive semidefinite, also $f(B) - f(A)$ positive semidefinite. Here $f(A)$ and $f(B)$ are defined via functional calculus.

Now, it might not be too big of a surprise that, on the surface level at least, the main question of this thesis is the following.

Question 1.2. Fix a positive integer n and an open interval (a, b). Which functions are n-monotone on (a, b)?

If all this makes sense to you, great! Feel free to skip this section. If not, what follows is an attempt to give some kind of handwavy picture of the setup. Alternatively, if you don't like handwaving, you may feel free to visit chapter 2 for rigorous foundations.

Matrix monotonicity is a generalization of standard monotonicity of real functions: now we are just having functions mapping matrices to matrices. Formally, f is **matrix**

[1] Worry not: one need not read beyond this chapter to get some kind of answer to the question.

monotone if for any two matrices A and B such that

$$A \leq B \tag{1.3}$$

we also have

$$f(A) \leq f(B). \tag{1.4}$$

This kind of function might be more properly called **matrix increasing** but we will mostly stick to monotonicity for couple of reasons:

- For some reason, that is what people have been doing in the field.
- It doesn't make much difference whether we talk about increasing or decreasing functions, so we might just ignore the latter but try to symmetrize our thinking by the choice of words.
- Somehow I can't satisfactorily fill the following table:

monotonic	monotonicity
increasing	?

  How very inconvenient.

Of course, it's not really obvious how one should make any sense of this "definition". There two things to understand.

- How should matrices be ordered?
- How should functions act on matrices?

Both of these questions can be (of course) answered in many ways, but for both of them, there is very natural, in fact tensorial answer. Instead of comparing matrices we can compare bilinear forms, $(0, 2)$-tensors (bilinear maps $V^2 \to \mathbb{R}$). Similarly we can naturally apply function to linear mappings, $(1, 1)$-tensors (bilinear maps $V^* \times V \to \mathbb{R}$).

For matrix (bilinear form) ordering we should first understand which matrices are *positive*, which here, a bit confusingly maybe, means "at least zero". We say that a form is positive if its diagonal is non-negative. This gives a partial order on the space of all bilinear forms.

For matrix functions, i.e. "how to apply function to matrix" the idea is to take a real function ($f : \mathbb{R} \to \mathbb{R}$, say) and interpret it as function $f : \mathbb{R}^{n\times n} \to \mathbb{R}^{n\times n}$, *matrix function.* Polynomials extend rather naturally, given the ring structure of linear maps themselves. If the argument (a linear map) is diagonalizable, this extension merely applies the function to the eigenvalues. This motivates us to define $f(A)$ for linear map A to be linear map with same eigenspace structure as A but the eigenvalues changed from $\lambda \to f(\lambda)$, respectively. All this works for diagonalizable maps with real eigenvalues, so the domain isn't quite $\mathbb{R}^{n\times n}$ but that's okay. This extension idea is called **functional calculus**.

All this is kind of enough to make sense of matrix monotonicity, but to drastically simplify the setup it is customary to restrict the attention to a special set of diagonalizable matrices, which in this text are called **real maps**. They are exactly the symmetric matrices and they hold special place amidst the set of all matrices.

- They exactly correspond to symmetric bilinear forms.
- They correspond to diagonalizable linear maps with real eigenvalues and orthogonal eigenbasis.

In the second point we are thinking about everything in terms of standard inner product of $\mathbb{R}^n$. So the statement should be corrected to

- If considered as matrix of a linear map with respect to the standard orthonormal basis of $\mathbb{R}^n$ (with the standard inner product), then the linear map is diagonalizable with real eigenvalues and has orthogonal eigenbasis.

Real maps are usually called **Hermitian** or **self-adjoint matrices** and positive matrices **positive semidefinite matrices**. Now the definition of matrix monotinicity 1.1 should make sense. We will call positive matrices **positive maps**.

Whether one should think about real maps as matrices, bilinear forms or linear maps depends on the context. If one does calculations, one might think about matrices. If one thinks about additive structure, bilinear forms are better suited. And of course functional calculus makes only sense with linear maps. We use the (linear) map terminology throughout mainly because it short. Also, it is a constant reminder that there is something tensorial going on.

1.3 ... And why should we care?

It's easy to come up with one family of matrix monotone functions: $x \mapsto \alpha x + \beta$ for $\alpha, \beta \in \mathbb{R}$ with $\alpha \geq 0$. It is n-monotone for every $n \geq 1$ on $(-\infty, \infty)$. This is the only easy example.

But there are lot more.

Matrix monotone functions are truly horrible. All matrix monotone functions are increasing (in the usual sense) but not every increasing function is matrix monotone. They have some obscure regularity properties. Constructing non-trivial matrix monotone functions is a pain. Although usual increasing real functions and matrix monotone functions should be very much interlinked, hardly any of the properties of increasing functions pass on to matrix monotonicity. Generally, if one attacks matrix monotone functions, especially of order $n > 2$, and doesn't use sophisticated weaponry, one will perish. The reader is encouraged to try.

All this is exactly what makes them so interesting. One is driven to ask the question:

Question 1.5. How should one think about matrix monotone functions?

If this sounds like the same question to you, think about increasing functions on $\mathbb{R}^n$. Function $f : \mathbb{R}^n \to \mathbb{R}$ is called n-increasing (this termonology lasts only for next couple of paragraphs) if $f(x_1, x_2, \ldots, x_n) \leq f(y_1, y_2, \ldots, y_n)$ whenever $x_i \leq y_i$ for every $1 \leq i \leq n$. Which functions are n-increasing? I would argue that n-increasing functions are awful, much more awful than usual (1-)increasing functions. The reason is that they don't have good additive structure.

TODO: pictures of n-increasing functions

One might say that "non-negative derivative" property (let's ignore regularity issues for a while) makes increasing functions easy to understand, and while there is certain truth to that, I would argue that what makes them so simple is really the dual property: "increasing functions are sums of increasing step functions". This roughly implies that in order to understand increasing functions, it is enough to understand step functions, or just step functions with one jump upwards.

Note that we are heavily using the fact that increasing functions (of all types introduced before) form a convex cone:

Definition 1.6. Subset C of a vector space V over $\mathbb{R}$ is a convex cone if whenever $v, w \in C$ and $\alpha, \beta \geq 0$, also $\alpha v + \beta w \in C$.

Also, applicability of the "only needing to understand step functions" is somewhat limited: it doesn't really explain smoothness phenomena all too well, for instance. But it is always nice to know that some objects are really sums of other much simpler objects.

There's no such nice dual property for n-increasing functions (for $n > 1$). One can understand them locally with derivatives, but there are no simple decompositions. Same thing could be said about convex functions on $\mathbb{R}^n$.

Much more importantly for us, these is no such nice additive structure for n-monotone functions. This is by no means trivial (as it is not even with n-increasing functions). It is also not even clear what one means by "nice" and whether even increasing functions are that "nice" in the end. These ideas shall however merely work as our guideline, so one should not be too troubled.

All these issues can be, in a way, avoided by change of perspective: instead of trying to characterize matrix monotone functions by expressing them as sums of something simple, we express the definition itself as a sum of somethings simple. In particular we try to understand the "dual" (or a "predual" to be exact) of matrix monotone functions.

1.4 Dual cones

Let in the following V be a vector space over $\mathbb{R}$ and denote its dual by V^*.

Definition 1.7. For every subset C^* of V^* we define its **dual cone** to be

$$C = \{v \in V | w^* v \geq 0 \text{ for every } w^* \in V^*\} \subset V.$$

One immediately makes the following observation justifying the terminology.

Theorem 1.8. *Let $C^* \subset V^*$. Then the dual cone of C^* is a convex cone.*

Definition 1.9. Let $C \subset V$. Then C^* is a **predual** of C if C is the dual cone of C^*.

Of course only convex cones have preduals. Easy examples show that preduals are not unique in general (in fact never).

As an example, for open interval (a, b) consider the set

$$P_1(a, b) := \{\text{Increasing functions } f : (a, b) \to \mathbb{R}\}.$$

This set is a convex cone. If one denotes the evaluation functional or measure at x by δ_x, i.e. $\delta_x(f) = f(x_0)$, then one possible predual of $P_1(a, b)$ if given by

$$\{\delta_y - \delta_x | a < x < y < b\}.$$

I hope the reader agrees that this predual is in many ways much simpler than the set of increasing functions (at least if one looks at objects themselves) and yet it carries the information thereof. As we will see, if chosen suitably, preduals can offer convenient and clean language for talking about the cone itself. And that is what this thesis is really about.

1.5 Contents

As mentioned, one of the aims of this thesis is to answer question 1.2. An answer, if you're curious, is given as theorem 5.1. An obvious follow up question is

Question 1.10. Fix an open interval (a, b). Which functions are n-monotone on (a, b) for any $n \geq 1$?

It turns out that this question has a surprisingly simple answer, given as theorems 5.12 and 5.14.

Aim of the chapters entitled "Matrix monotone functions – part i" for $0 \leq i \leq 3$ is to answer to these questions. Other chapters, ones with even number, offer supplementary information.

The whole theory of matrix monotone functions originates from a 1934 paper by Charles Loewner (then known as Karl Löwner) entitled "Über monotone Matrixfunktionen" [47]. In the paper Loewner asked the questions 1.2 and 1.10, and gave them both answers. Since then the theory has been reworked and expanded by various authors, and many open question remain. This text is an amalgamation of countless works on the subject. "Notes and references" -sections at the end of each chapter (except this one) are an attempt to give attribution to these ancestors.

Arguments of this thesis are largely elementary, requiring only basic calculus, complex analysis, linear algebra and topology. Many of the underlying ideas and heuristics are however inspired by functional analysis and measure theory, so it pays to have good understanding of them.

1.6 Notation and conventions

V^*	(continuous) dual of (topological) vector space V
$\mathcal{L}(V)$	linear self-maps over vector space V
$\mathcal{H}(V)$	real maps over inner product space V
$\mathcal{H}_+(V)$	positive maps over inner product space V
$\mathcal{H}_{(a,b)}(V)$	real maps over inner product space V with spectra over (a, b)
$P_n(a, b)$	n-monotone functions on (a, b)
$P_\infty(a, b)$	intersection of $P_n(a, b)$ for $n \geq 1$
$P_W = P_{W,V}$	orthogonal projection to $W \subset V$
A^*	adjoint of a map $A \in \mathcal{L}(V)$
f_V	matrix function lift of f to V
$\mathbb{C}_n[x]$	change this?

We also preserve certain letters to have particular meaning.

a, b	extended real with $-\infty \leq a < b \leq \infty$
n, k	positive integers
V	inner product space over $\mathbb{C}$ with inner product $\langle \cdot, \cdot \rangle$, of dimension n

1.7 TODO

TODO: check the TODO-lists (in comments).

Chapter 2

Positive maps

2.1 Motivation

2.1.1 The right definition

Definition 2.1. We say that A is *positive map*, or simply *positive*, and write $A \geq 0$, if for any $v \in V$ we have

$$\langle Av, v \rangle \geq 0.$$

Why is this the right definition for positivity? Do we really need an inner product to define positivity?

While these are both excellent questions (and one should definitely think about them), there is no way to satisfactorily answer them in the scope of this thesis. Instead, this section is an attempt to explain why the definition is pretty damn good.

Note that, contrary to the previous chapter, we snuck in the complex numbers and "general" vector space to the definition (see "Notation and conventions" in the previous chapter). It doesn't make much difference whether we talk about real or complex numbers but the author thinks that some of the arguments are more natural in the complex world. Also, having the general vector space V is mostly just reminder of the fact that there is something tensorial going on.

Theorem 1.8 immediately implies

Theorem 2.2. *The set*

$$\{A \in \mathcal{L}(V) | \ A \textit{ is positive}\}$$

is a convex cone.

We denote this cone of positive maps (of V) by $\mathcal{H}_+(V)$.

In general one should think that the convex cones are models of positive real numbers. Such model need not be very good however: the whole vector space is always a convex cone. To fix this problem one introduces the concept of salient cone.

Definition 2.3. A convex cone $C \subset V$ is **salient cone**, or simply **salient**, if whenever both $v \in C$ and $-v \in C$, then necessarily $v = 0$.

Conveniently enough $\mathcal{H}_+(V)$ is a salient cone, but this is by no means trivial property.

Lemma 2.4. *If $A \in \mathcal{L}(V)$ and $\langle Av, v\rangle = 0$ for any $v \subset V$, then $A = 0$.*

Proof. The idea is that we can recover the inner product from norm. Indeed, if $v, w \in V$, then $\|v + w\|^2 = \|v\|^2 + \|w\|^2 + 2\Re(\langle v, w\rangle)$, so knowing the norm, we at least know the real part of the inner product. Doing the same trick with $\|v + iw\|^2$ we can figure out the imaginary part.

How does this help us? By a similar argument $\langle A(v+w), v+w\rangle = \langle Av, v\rangle + \langle Aw, w\rangle + \langle Av, w\rangle + \langle Aw, v\rangle$, so given that the quadratic form is always zero, we have $\langle Av, w\rangle + \langle Aw, v\rangle = 0$ for any $v, w \in V$. Expanding $\langle A(v + iw), v + iw\rangle$ we see that $-i\langle Av, w\rangle + i\langle Av, w\rangle = 0$, which together with the previous observation implies that $\langle Av, w\rangle = 0$ for any $v, w \in V$. Now setting $w = Av$ this implies that $\|Av\|^2 = 0$ for every $v \in V$ so $A = 0$. □

It is also customary to give vector space a topology (and get a topological vector space in return). This leads to concept of **closed convex cone**, which is defined as one would expect. Note that as subset of dual lead to convex cones, subsets of continuous dual lead to closed convex cones.

A closed convex cone that is also salient is, as is somewhat customary, called **proper cone**. We have

Theorem 2.5. *$\mathcal{H}_+(V)$ is a proper cone (with usual topology).*

Previous arguments carry directly to a much more general setting:

Theorem 2.6. *Let V be a topological vector space (over $\mathbb{R}$ or $\mathbb{C}$) and C^* a subset of its continuous dual. Then*

$$C := \{v \in V | w^*(v) \geq 0 \textit{ for every } w^* \in C^*\}$$

is a closed convex cone of V. If also

$$\{v \in V | w^*(v) = 0 \textit{ for every } w^* \in C^*\} = \{0\},$$

then C is proper.

In our case the subset of the linear functionals are the mappings of the form $A \mapsto \langle Av, v\rangle$: they are called *quadratic functionals.* For fixed $A \in \mathcal{L}(V)$ the map $v \mapsto \langle Av, v\rangle$ is the *quadratic form* of A.

As one would hope, map $v \to \alpha v$, i.e. αI is positive, if and only if $\alpha \geq 0$. In particular in one-dimensional spaces the notion works as expected. Fortunately there are other examples, also. Indeed, any orthogonal projection is positive.

Proposition 2.7. *If $A \in \mathcal{L}(V)$ is a orthogonal projection, then $A \geq 0$.*

Proof. As any orthogonal projetion is sum of one-dimensional orthogonal projections, we can assume that the A is one-dimensional in the first place. It follows that $A = \langle \cdot, v\rangle v/\|v\|^2$ for some $v \in V \setminus \{0\}$. Now for every $w \in V$ we have

$$\langle Aw, w\rangle = \langle \langle w, v\rangle v, w\rangle/\|v, v\|^2 = |\langle w, v\rangle|^2/\|v\|^2 \geq 0,$$

so A is positive. $\square$

We denote the one-dimensional orthogonal projection to the span of $v \in V \setminus \{0\}$, i.e. the map $\langle \cdot, v\rangle v/\|v\|^2$ by P_v. More generally, orthogonal projection to a subspace $W \subset V$ is denoted by P_W.

Taking positive linear combinations of orhogonal projections leads to large number of examples of positive maps.

2.1.2 Real maps and adjoint

Dual cone thinking lets us also lift other important notions.

Definition 2.8. We say that a map $A \in \mathcal{L}(V)$ is *real*, if

$$\langle Av, v\rangle \in \mathbb{R}$$

for any $v \in V$.

Definition 2.9. We say that a map $A \in \mathcal{L}(V)$ is *imaginary*, if

$$\langle Av, v\rangle \in i\mathbb{R}$$

for any $v \in V$.

Definition 2.10. We say that a map $A \in \mathcal{L}(V)$ is *strictly positive*, if

$$\langle Av, v\rangle > 0$$

for any $v \in V \setminus \{0\}$.

Map is strictly positive, if and only if it is positive and invertible, or equivalently: is real and has positive eigenvalues.

Families of real, imaginary and strictly positive maps are usually called Hermitian and Skew-Hermitian and positive definite. Reals maps will have a special role in our discussion. We write $A > 0$ is A is strictly positive. They form a vector space over $\mathbb{R}$, which is denoted by $\mathcal{H}(V)$. Of course, every imaginary map is just i times real map, and we won't preserve any special notation for such maps.

We can also lift the concept of complex conjugate.

Theorem 2.11. *For any $A \in \mathcal{L}(V)$ there exists unique map $A^* \in \mathcal{L}(V)$, called the adjoint of A, for which for any $v \in V$ we have*

$$\langle A^*v, v\rangle = \overline{\langle Av, v\rangle}$$

Proof. The uniqueness of adjoint is immediate from the lemma 2.4. The map $(\cdot)^* : \mathcal{L}(V) \to \mathcal{L}(V)$ should evidently be conjugate linear, so for existence it suffices to find adjoint for suitable basis elements of $\mathcal{L}(V)$: the maps of the form $A = (x \mapsto \langle x, v\rangle w)$ for $v, w \in V$ will do.

The quadratic form for such map is given by

$$\langle Ax, x\rangle = \langle x, v\rangle\langle w, x\rangle.$$

But if we define $A^* = (x \mapsto \langle x, w\rangle v)$, we definitely have

$$\langle A^*x, x\rangle = \langle x, w\rangle\langle v, x\rangle = \overline{\langle w, x\rangle\langle x, w\rangle} = \overline{\langle Av, v\rangle}.$$

□

In more common terms: a adjoint of linear map $A \in \mathcal{L}(V)$ is the unique map A^* such that

$$\langle Av, w\rangle = \langle v, A^*w\rangle \tag{2.12}$$

for any $v, w \in V$.

As real maps are their own adjoints, they are often called appropriately **self-adjoint**.

The previous observation makes many of the basic properties of adjoint, which we collect below, evident.

Theorem 2.13. *For any linear maps A and B, with appropriate domains and codomains, and $\lambda \in \mathbb{C}$ we have* *i) Matrix of A^* with respect to any orthonormal basis is conjugate transpose of matrix of A, i.e. $A^*_{i,j} = \overline{A_{j,i}}$.*

ii) $(A^*)^* = A$

iii) $(A + B)^* = A^* + B^*$

iv) $(\lambda I)^* = \overline{\lambda} I$

v) $(AB)^* = B^* A^*$.

Using 2.12, adjoint could also be defined between arbitrary two inner product spaces. With this more general definition the maps

$$
\begin{aligned}
v &: \mathbb{C} \to V & v(x) &= xv \\
v^* &: V \to \mathbb{C} & v^*(w) &= \langle w, v \rangle
\end{aligned}
$$

will be adjoints of each other. This lets us rewrite one-dimensional projections conveniently in the form

$$P_v = \frac{1}{\|v\|^2} v v^*.$$

2.1.3 More convincing

Positive maps have many other desirable properties. First of all, eigenvalues of a positive map are non-negative. This fact is a corollary of a more general property.

Definition 2.14. Let $W \subset V$ be a subspace and $A \in \mathcal{L}(V)$. Then the **compression** of A to W, denoted by A_W is the linear map

$$P_W \circ A \circ J_W : W \to W$$

where J_W is the inclusion from W to V and P_W (here) is an orthogonal projection $V \to W$.

Lemma 2.15. *Let $W \subset V$ and $A \geq 0$. Then also $A_W \geq 0$. In particular all the eigenvalues of A are non-negative.*

Proof. Note that quadratic form gives essentially the one-dimensional compressions. Indeed, if $W = (v)$, then

$$A_W x = \frac{\langle Ax, v \rangle}{\langle v, v \rangle} v = \frac{\langle Av, v \rangle}{\langle v, v \rangle} x$$

for any $x \in (v)$. This means that a map is positive, if and only if its compressions to one-dimensional subspaces are.

Now the trick is that nested compressions work nicely: if $W' \subset W \subset V$ and $A \in \mathcal{L}(V)$, then $(A_W)_{W'} = A_{W'}$. Consequently, if every one-dimensional compression A is positive, same is true for all its compressions.

Compressing to eigenspace we see that if A is positive, all it's eigenvalues are non-negative. $\square$

In addition, (direct) sum of two positive map is positive.

Lemma 2.16. *Let $A_1 \in \mathcal{L}(V_1)$ and $A_2 \in \mathcal{L}(V_2)$. Then $A_1 \oplus A_2 \in \mathcal{H}_+(V_1 \oplus V_2)$, if and only if $A_1 \in \mathcal{H}_+(V_1)$ and $A_2 \in \mathcal{H}_+(V_2)$.*

Proof. Recall that one defines $\langle (v_1, v_2), (w_1, w_2)\rangle_{V_1 \oplus V_2} = \langle v_1, w_1\rangle_{V_1} + \langle w_2, w_2\rangle_{V_2}$. Now clearly

$$\langle (A_1 \oplus A_2)(v_1, v_2), (v_1, v_2)\rangle_{V_1 \oplus V_2} = \langle A_1 v_1, v_1\rangle_{V_1} + \langle A_2 v_2, v_2\rangle_{V_2} \geq 0$$

for every $(v_1, v_2) \in V_1 \oplus V_2$, if and only if both $\langle A_1 v_1, v_1\rangle_{V_1} \geq 0$ for every $v_1 \in V_1$ and $\langle A_2 v_2, v_2\rangle_{V_2} \geq 0$ for every $v_2 \in V_2$. $\square$

2.2 Spectral theorem

The most important result in the theory of positive and real maps is the Spectral theorem.

Theorem 2.17 (Spectral theorem, version 1)**.** *$A \in \mathcal{L}(V)$ is real if and only there exists real numbers $\lambda_1, \lambda_2, \ldots, \lambda_n$ and for pairwise orthogonal vectors $v_1, v_2, \ldots, v_n \in V$ such that*

$$A = \sum_{i=1}^{n} \lambda_i P_{v_i}. \tag{2.18}$$

Proof. We first prove the theorem for the positive maps.

We already proved one direction: every map of the previous form is positive.

The other direction is tricky. The idea is to somehow find the vectors v_i. The problem is that such representation is by no means unique. If A is any projection for instance, we could let v_i's by any orthonormal basis of the corresponding subspace and λ_i's all equal to one. There's no vector one has to choose.

But we can think in reverse: there could be many vectors we cannot choose, depending on the map A. If A is any non-identity projection to subspace W, say, we can only choose v_i's in W itself. Indeed, if $x \in W^{\perp}$, we have $Ax = 0$, and hence $\langle Ax, x\rangle = 0$. By comparing the quadratic form it follows $\langle P_{v_i}x, x\rangle = |\langle v_i, x\rangle|^2$ for any $1 \leq i \leq m$. But this means that $v_i \perp W^\perp$ and hence $v_i \in W$.

More generally, if it so happens that for some $v \in V$ we have $\langle Av, v\rangle = 0$, we must have $v_i \perp v$ for any $1 \leq i \leq m$. But this means that were there such representation, we should have the following.

Lemma 2.19. *If $A \in \mathcal{H}_+(V)$ and $\langle Av, v\rangle = 0$ for some $v \in V$, then $Av = 0$ and $Aw \perp v$ for any $w \in v$.*

Before proving the Lemma, we complete the proof given the Lemma.

Proof is by induction on n, the dimension of the space. If $n = 0$, the claim is evident. For induction step assume first that there exists $v \in V$ such that $\langle Av, v\rangle = 0$. Then by the Lemma for any $w \in v^\perp$ we have $Aw \in v^\perp =: W$. But this means that $A = A_W \oplus 0$. Now A_W is also positive, and $\dim(W) < n$, so by the induction assumption we have numbers λ_i and vectors $v_i \in V$ for the map A_W. Such representation for A_W immediately gives one also for A.

We just have to get rid of the extra assumption on the existence of such v. But for this, note that if $\lambda = \inf_{|v|=1}\langle Av, v\rangle$, consider $B = A - \lambda I$. Now $\inf_{|v|=1}\langle Bv, v\rangle = 0$, and B is hence positive. Also, by compactness, the infimum is attained at some point v, so B satisfies our assumptions. Now cook up a representation for B and add orthonormal basis of V with λ_i's equal to λ: this is required representation for A.

Note that the previous trick also covers the case of general real map. $\square$

Proof of lemma 2.19. Take any $w \in V$. Now by assumption for any $c \in \mathbb{C}$ we have

$$\langle A(cv + w), cv + w\rangle = |c|^2\langle Av, v\rangle + c\langle Av, w\rangle + \bar{c}\langle Aw, v\rangle + \langle Aw, w\rangle \geq 0$$

But this easily implies that $\langle Av, w\rangle = 0 = \langle Aw, v\rangle$ for any $w \in V$. The first equality implies that $Av = 0$ and the second that $Aw \perp v$ for any $w \in V$. $\square$

Let's denote the eigenvalues of real map A by $\lambda_1(A) \geq \lambda_2(A) \geq \ldots \geq \lambda_n(A)$.

In the representation 2.18 the numbers λ_i are evidently the eigenvalues of A and vectors v_i the corresponding eigenvectors; this is why we call it the *Spectral representation.* As remarked, the representation is of course not unique, but there is a way to make the Spectral representation unique, however. For this we have to change v_i to corresponding eigenspaces.

Theorem 2.20 (Spectral theorem, version 2)**.** *Let $A \in \mathcal{H}(V)$. Then there exists unique non-negative integer m, distinct real numbers $\lambda_1, \lambda_2, \ldots, \lambda_m$ and non-trivial orthogonal subspaces of V, $E_{\lambda_1}, E_{\lambda_2}, \ldots E_{\lambda_m}$ with $E_{\lambda_1} + E_{\lambda_2} + \ldots + E_{\lambda_m} = V$, such that*

$$A = \sum_{i=1}^{m} \lambda_i P_{E_{\lambda_i}}. \tag{2.21}$$

Moreover, this representation is unique.

Proof. Existence of such representation immediately follows from the previous form of Spectral theorem. For uniqueness, note that λ_i's are necessarily the eigenvalues of A and E_{λ_i}'s the corresponding eigenspaces. □

Although the latter version is definitely of theoretical importance, we will mostly stick the former as it only contains one-dimensional projections.

Spectral representation makes many of the properties of real maps obvious. For instance any power of real map is real: indeed, if $A = \sum_{1 \leq i \leq n} \lambda_i P_{v_i}$, then

$$A^2 = \left(\sum_{i=1} \lambda_i P_{v_i} \right) \left(\sum_{j=1} \lambda_j P_{v_j} \right) = \sum_{i=1}^{n} \sum_{j=1}^{n} \lambda_i \lambda_j P_{v_i} P_{v_j} = \sum_{i=1}^{n} \lambda_i^2 P_{v_i},$$

since $P_v P_w = 0$ for $v \perp w$. By induction one can extend the previous to higher powers. In other words: eigenspaces are preserved under compositional powers, and eigenvalues are ones to get powered up. From the original definition this is not all that clear. One could even extend to polynomials. If $p(x) = c_n x^n + c_{n-1} x^{n-1} + \ldots c_1 x + c_0$, with $c_i \in \mathbb{R}$, we should write

$$p(A) = c_n A^n + c_{n-1} A^{n-1} + \ldots c_1 A + c_0 = \sum_{1 \leq i \leq n} p(\lambda_i) P_{v_i}.$$

This implies that if p is the characteristic polynomial of A, then $p(A) = 0$: the special case of Cayley Hamilton theorem. Moreover, the minimal polynomial of A is the polynomial with the eigenvalues of A as single roots.

But even better, if p is polynomial with all except one, say λ_i, of the eigenvalues of A as roots, then $p(A) = p(\lambda_i) P_{E_{\lambda_i}}$. In particular, the projections to eigenspaces of A are actually polynomials of A.

Also, given $A \in \mathcal{H}(V)$, we may write any $x \in V$ in the form $v = \sum_{1 \leq i \leq n} \langle x, v_i \rangle v_i$, where $(v_i)_{i=1}^{n}$ is a eigenbasis for A. Now $Ax = \sum_{1 \leq i \leq n} \lambda_i \langle x, v_i \rangle v_i$, so for instance

- $\langle Ax, x \rangle = \sum_{1 \leq i \leq n} \lambda_i |\langle x, v_i \rangle|^2$. Thus the quadratic form is just a positive linear combination of eigenvalues.
- $\|Ax\|^2 = \sum_{1 \leq i \leq n} \lambda_i^2 |\langle x, v_i \rangle|^2 \leq \left(\max_{1 \leq i \leq n} \lambda_i^2\right) \|x\|^2$. Hence $\|A\| = \max_{1 \leq i \leq n} |\lambda_i|$.

2.3 Matrix functions

2.3.1 Functional calculus

Given the spectral theorem, it is rather clear how one should define general matrix functions.

Definition 2.22. For any $-\infty \leq a < b \leq \infty$ $f : (a, b) \to \mathbb{R}$ the associated matrix function on V is the map $f_V : \mathcal{H}_{(a,b)}(V) \to \mathcal{H}(V)$ given by

$$f_V\,(A) = \sum_{\lambda \in \mathrm{spec}(A)} f(\lambda) P_{E_\lambda}$$

if $A = \sum_{\lambda \in \mathrm{spec}(A)} \lambda P_{E_\lambda}$.

Note that as the spectral representation is unique this definition makes sense. Matrix functions enjoy many natural and useful properties.

Proposition 2.23. *Let $f : (a, b) \to \mathbb{R}$ and $A \in \mathcal{H}_{(a,b)}$*

1. *If $f[(a, b)] \subset (c, d)$ then $f_V(A) \in \mathcal{H}_{(c,d)}$.*
2. *If also $g : (a, b) \to \mathbb{R}$ then $(f + g)_V = f_V + g_V$ and $(fg)_V = f_V g_V$.*
3. *$f_{V_1 \oplus V_2} = f_{V_1} \oplus f_{V_2}$.*
4. *If $g : (a, b) \to \mathbb{R}$ and f and g agree on spectrum of A, then $f(A) = g(A)$.*
5. *If $f[(a, b)] \subset (c, d)$ and $g : (c, d) \to \mathbb{R}$ then $(g \circ f)_V = g_V \circ f_V$.*
6. *If $f_n : (a, b) \to \mathbb{R}$ converge pointwise to f, then the same holds true for $(f_n)_V$'s.*
7. *If f is continuous, then so is f_V.*

These properties make it clear that such definition is natural. We will drop the subscript V and identify f with its matrix function f_V if there is no fear of confusion.

2.3.2 Holomorphic functional calculus

If f is entire, there's another way to appoach matrix functions. As f can be written as

$$f(z) = \sum_{n=0}^{\infty} a_n z^n,$$

power series convergent for any $z \in \mathbb{C}$, we should have

$$f_V(A) = \sum_{n=0}^{\infty} a_n A^n.$$

This matrix power series indeed converges as $\|A^n\| \le \|A\|^n$. Also, this definition coincides with the spectral one. Indeed, if one writes $f_n : z \mapsto \sum_{k=0}^n a_n z^n$, then we have, by definition,

$$\sum_{n=0}^{\infty} a_n A^n = \lim_{n\to\infty} [(f_n)_V(A)] = f_V(A),$$

by point (6) of proposition (2.23).

Note however that the power series definition makes perfect sense even if $a_n \notin \mathbb{R}$ and even better, A need not be real.

If f is not entire, the power series might not converge every $A \in \mathcal{H}_{(a,b)}(V)$. Instead, we can more generally use Cauchy's integral formula for matrix functions.

$$f_V(A) = \frac{1}{2\pi i}\int_{\gamma} (zI - A)^{-1} f(z) dz,$$

where γ is simple closed curve enclosing the spectrum of A. This formula is immediate when viewed in a eigenbasis of A. Again, this formula makes perfect sense even for non-real A, given that the spectrum of A lies in the domain of f.

2.4 Real maps and composition

2.4.1 Commuting real maps

Warning! Composition of positive maps need not be positive!

If $A, B \in \mathcal{H}_+(V)$, then, as we noticed, $(AB)^* = B^*A^* = BA$, so for AB to be even real, A and B would at least need to commute. Natural question follows: when do two positive maps commute? Since $(c_1 I + A)$ and $(c_2 I + B)$ commute if and only if A and B do, this is same as asking when do two real maps commute.

It turns out that real maps commute only if they "trivially" commute, in the following sense. If there exists vectors $v_1, v_2, \ldots, v_n$ and numbers $\lambda_1, \lambda_2, \ldots, \lambda_n$ and $\lambda'_1, \lambda'_2, \ldots, \lambda'_n$ such that

$$A = \sum_{1\le i\le n} \lambda_i P_{v_i} \quad\text{and}\quad B = \sum_{1\le i\le n} \lambda'_i P_{v_i},$$

then A and B are said to be **simultaneously diagonalizable**. Simultaneosly diagonalizable maps trivially commute, and it turns out that if two real maps commute, they are indeed simultenously diagonalizable.

To prove this statement, we start with a lemma, simplest non-trivial case of the statement.

Lemma 2.24. *Let $W_1, W_2 \subset V$ be two subspaces. Then P_{W_1} and P_{W_2} commute if and only if there exists orthogonal subspaces U_1, U_2 and U_0 such that*

$$W_1 = U_1 + U_0 \quad \text{and} \quad W_2 = U_2 + U_0.$$

We then have $P_{W_1} = P_{U_1} + P_{U_0}$ and $P_{W_2} = P_{U_2} + P_{U_0}$, and $U_0 = W_1 \cap W_2$.

Proof. Write $U_0 := W_1 \cap W_2$ and $W_i = U_0 + U_i$ for some $U_i \perp U_0$ for $i \in \{1, 2\}$. Now $P_{W_i} = P_{U_i} + P_{U_0}$ for $i \in \{1, 2\}$ so it suffices to check that $U_1 \perp U_2$. Equivalently, it suffices to prove that if $W_1 \cap W_2 = \{0\}$, and P_{W_1} and P_{W_2} commute, then $W_1 \perp W_2$ or equivalently $P_{W_1} P_{W_2} = 0 = P_{W_2} P_{W_1}$. But for any $v \in V$ we have $W_1 \ni P_{W_1} P_{W_2} v = P_{W_2} P_{W_1} v \in W_2$, so indeed $P_{W_1} P_{W_2} = 0 = P_{W_2} P_{W_1}$. □

Definition 2.25. We say that two $W_1, W_2 \subset V$ subspaces commute if the respective projections commute.

Theorem 2.26. *Let $\mathcal{A} = (A_j)_{j \in J}$ by an arbitrary family of commuting real maps. Then there exists non-trivial orthogonal subspaces of V, $E_1, E_2, \dots E_m$ with $E_1 + E_2 + \dots + E_m = V$ and numbers $\lambda_{i,j}$ for $j \in J$ and $1 \leq i \leq n$ such that*

$$A_j = \sum_{1 \leq i \leq m} \lambda_{i,j} P_{E_i}$$

for any $j \in J$.

Proof. The trick is the following: if two maps commute, so do all their polynomials. Hence if we have two commuting A and B, we know that all the respective eigenspaces commute. It follows that we can assume that all the maps in $\mathcal{A}$ are projections to begin with. Indeed, if we can the sought representation for the eigenprojections of maps of $\mathcal{A}$, one immediately obtains one for the maps of $\mathcal{A}$ themselves.

Let's first deal with finite J. The idea is to break the projections to parts using lemma 2.24. Take any two projections P_{W_1} and P_{W_2} in $\mathcal{A}$ and write $P_{W_1} = P_{U_1} + P_{U_0}$ and $P_{W_2} = P_{U_2} + P_{U_0}$. Note that any map in $\mathcal{A}$ also commutes with $P_{W_1} + P_{W_2} = P_{U_1} + P_{U_2} + 2P_{U_0}$, and hence also with its eigenprojections, P_{U_0} and $P_{U_1 + U_2}$. It follows that any map in $\mathcal{A}$ commutes with U_0, U_1 and U_2.

We have split the subspaces W_1 and W_2 in pieces, and we could actually forget W_1 and W_2 altogether and replace them by U_0, U_1 and U_2: note that all the same assumption hold for this new family, and U_0, U_1 and U_2 span W_1 and W_2.

Now the algorithm is the following: pick pairs of projections with non-orthogonal subspaces and perform the replacing procedure. But there's a problem : it's not clear that the new family is any simpler than $\mathcal{A}$! It could well have more elements than $\mathcal{A}$ so we can't just do straightforward induction. What could happen also is that some of the subspaces U_0, U_1, U_2 coincide with the subspaces already present in the family, so the size of the family doesn't increase, and it could even decrease. This will indeed happen. One way to see this is to look at the sum of dimensions of all the projections of the family: if we change the family this sum cannot increase. Moreover, if we pick two subspaces W_1 and W_2 which are not orthogonal, this sum will decrease! So the algorithm eventually terminates and remaining projections give us the subspaces E_i (complemented by the complement of the union of these subspaces if necessary).

There are many ways to bootstrap the previous argument for arbitrary families. For any finite subfamily we can form the set of generating projections. If we add one more map, the set of projections might get refined: some of the subspaces might get split to pieces. Since sizes of all these generating families are bounded by n so we may pick one with most number of elements. Now if A is any projection in $\mathcal{A}$, by maximality, adding it to the family does not refine the generating set. But this means that the generating set generates any element of $\mathcal{A}$ and we are done. □

The message is: if one wants products to preserve positivity, everything degenerates to $\mathbb{R}^m$, or to diagonal maps, which isn't all that exciting.

Philosophy 2.27. Commutativity kills the exciting phenomena.

Conversely, if one wants exciting things to happen, one should make things very non-commutative.

As a corollary of theorem 2.26 we have

Corollary 2.28. *If $A, B \geq 0$ and A and B commute, then $AB \geq 0$.*

2.4.2 Symmetric product

As normal product doesn't quite work with positivity, next attempt might be symmetrized product

$$S(A, B) = AB + BA,$$

(or maybe with normalizing constant $\frac{1}{2}$ in the front), instead of the usual one. It turns out that even this doesn't fix positivity.

For one dimesional projections things go as badly as they possibly can.

Proposition 2.29. *If $v, w \in V \setminus \{0\}$, then*

$$P_v P_w + P_w P_v \geq 0,$$

if and only if v and w are parallel or orthogonal, i.e. if and only if P_v and P_w commute.

Proof. Since everything is happening in a (at most) two dimensional subspace of V, we may assume that V is two dimensional in the first place. Note that

$$P_v P_w + P_w P_v = (P_v + P_w)^2 - P_v^2 - P_w^2 = (P_v + P_w)^2 - P_v - P_w = A^2 - A = A(A - I),$$

where $A := P_v + P_w$. This is positive, if and only if the eigenvalues of A are outside the interval $(0, 1)$. But since $\mathrm{tr}(A) = 2$ and $A \geq 0$, the only way this can happen is that either A has double eigenvalues 1 or A has eigenvalues 0 and 2. To conclude the claim itself, we are left to do two reality checks:

Lemma 2.30. *If $A = P_v + P_w = I$, then v and w are orthogonal.*

Proof. Note that $\langle v, v\rangle = \rangle Av, v\rangle = \langle P_v v, v\rangle + \langle P_w v, v\rangle = \langle v, v\rangle + |\langle v, w\rangle|^2 / \langle v, v\rangle$, so $\langle v, w\rangle = 0$. □

Lemma 2.31. *If $A = P_v + P_w = 2P_u$ for some $u \in V$, then v, w and u are all parallel.*

Proof. Take $u' \in (u)^\perp$. Since $0 = \langle 2P_u u', u'\rangle = \langle P_v u', u'\rangle + \langle P_w u', u'\rangle = |\langle v, u'\rangle|^2 / \langle v, v\rangle + |\langle w, u'\rangle|^2 / \langle w, w\rangle \geq 0$, we have $\langle v, u'\rangle = 0 = \langle w, u'\rangle$. Consequently $v, u \in ((u)^\perp)^\perp = (u)$. □

□

For more general positive maps things aren't much better. One could for instance prove that

Proposition 2.32. *Let $A \in \mathcal{H}$ such that $AB + BA \geq 0$ for any $B \geq 0$. Then $A = \alpha I$ for some $\alpha \geq 0$.*

2.4.3 $*$-conjugation

Despite all the negative news, there's one non-trivial non-commutative way to produce positive maps from others, called $*$-conjugation. Given any two positive maps A and B, their composition need not be positive, but the map BAB is. First of all, it is real as $(BAB)^* = B^* A^* B^* = BAB$. Also $\langle BABv, v\rangle = \langle A(Bv), (Bv)\rangle \geq 0$ for any $v \in V$. An identical argument shows that one may replace B by an arbitrary $C \in \mathcal{L}(V)$.

Definition 2.33. Let $A, B \in \mathcal{H}$. We say that B is **$*$-conjugate** of A if for some $C \in \mathcal{L}(V)$ we have $B = C^* A C$.

Proposition 2.34. *If $A \geq 0$ and B is $*$-conjugate of A, then also $B \geq 0$.*

2.5 Loewner order

Definition 2.35. If $A, B \in \mathcal{H}(V)$, we write that $A \leq B$ (A is smaller than B) if $B - A \geq 0$, $B - A$ is positive. If $B - A$ is strictly positive, we write $A < B$.

Proposition 2.5 tells us that such order is indeed partial order on the $\mathbb{R}$-vector space of real maps. More explicitly, we have the following properties:

Proposition 2.36. *(i) If $A \leq B$ then $\alpha A \leq \alpha B$ for any $\alpha \geq 0$.*

(ii) If $A \leq B$ and $B \leq C$ then $A \leq C$.

(iii) If $A \leq B$ and $B \leq A$ then $A = B$.

(iv) $\lambda I \leq A$, if and only if all the eigenvalues of A are at least λ. Similarly $A \leq \lambda I$, if and only if all the eigenvalues of A are at most λ.

Example 2.37. If $W_1, W_2 \subset V$ are two subspaces of V we have $P_{W_1} \leq P_{W_2}$ if and only if $W_1 \subset W_2$. Indeed if $W_1 \subset W_2$ then $W_2 = W_1 + W_3$ for some $W_3 \perp W_1$ and hence $P_{W_2} = P_{W_1} + P_{W_3} \geq P_{W_1}$. Converse follows immediately from the observation that for any $W \subset V$ we have

$$\{v \in V | \langle P_W v, v \rangle = 0\} = W^{\perp}.$$

Key thing here is to note what is missing from the standard real ordering: multiplication by positive map doesn't preserve usual ordering. This is the reason many standard arguments don't work for general real maps.

For example if $0 < a \leq b$, with real numbers one could multiply the inequalities by the positive number $(ab)^{-1}$ to get $0 < b^{-1} \leq a^{-1}$. This doesn't quite work with linear maps anymore.

$*$-conjugation is way to partially fix this deficit: it works almost like multiplying by positive number.

Proposition 2.38. *If $A \leq B$, then for any C we have $C^*AC \leq C^*BC$.*

Using this one can salvage the above argument.

Theorem 2.39. *If $0 < A \leq B$, then $B^{-1} \leq A^{-1}$.*

Proof. As mentioned, we can't really multiply by $(AB)^{-1}$, as it does not preserve the order and doesn't even need to be positive. We can almost multiply by A^{-1} though: $*$-conjugate by $A^{-\frac{1}{2}}$. This preserves the order, and we get

$$I \leq A^{-\frac{1}{2}} B A^{-\frac{1}{2}}.$$

Now one would sort of want to multiply B^{-1} that is $*$-conjugate by $B^{-\frac{1}{2}}$, but B is in the middle, so that doesn't seem too helpful. But now we can follow the original strategy: since $I \leq X := A^{-\frac{1}{2}}BA^{-\frac{1}{2}}$ we have $X^{-1} \leq I$ (by 2.36 (iv)), that is

$$A^{\frac{1}{2}}B^{-1}A^{\frac{1}{2}} \leq I.$$

Now simply $*$-conjugate by $A^{-\frac{1}{2}}$. $\square$

Remark 2.40. Alternatively, we could conjugate both sides by $X^{-\frac{1}{2}}$ to arrive at the conclusion. Note that by doing this we have only used $*$-conjugation in the proof: actually we have $*$-conjugated altogether with

$$A^{-\frac{1}{2}}(A^{-\frac{1}{2}}BA^{-\frac{1}{2}})^{-\frac{1}{2}}A^{-\frac{1}{2}} = (A^{\frac{1}{2}}(A^{-\frac{1}{2}}BA^{-\frac{1}{2}})^{\frac{1}{2}}A^{\frac{1}{2}})^{-1}.$$

The map $A^{\frac{1}{2}}(A^{-\frac{1}{2}}BA^{-\frac{1}{2}})^{\frac{1}{2}}A^{\frac{1}{2}}$, which is real, is usually called the geometric mean of A and B. The point is: somewhat curiously we can almost do the original proof: just replace multiplication by $*$-conjugation by square root, and replace square root of product by geometric mean.

2.6 Notes and references

Chapter 3

Matrix monotone functions – part 1

Definition 3.1. We say that $f : (a, b) \to \mathbb{R}$ is n-monotone or matrix monotone of order n, if for any $A, B \in \mathcal{H}^n_{(a,b)}$, such that $A \leq B$ we have $f(A) \leq f(B)$.

We will denote the space of n-monotone functions on open interval (a, b) by $P_n(a, b)$. We will also denote

$$P_\infty(a, b) = \bigcap_{n \geq 1} P_n(a, b).$$

By 2.6 we have

Proposition 3.2. *The sets $P_n(a, b)$ and $P_\infty(a, b)$ are closed convex cones.*

Note that in the notation $P_n(a, b)$ we don't specify the space V; it doesn't matter.

Proposition 3.3. *If $\dim(V) = \dim(V')$, then f is n-monotone in V if and only if it is n-monotone in V'.*

Proof. The reason is rather clear: inner product spaces of same dimension are isometric. □

3.1 Examples

Example 3.4. If $\alpha \geq 0$ and $\beta \in \mathbb{R}$ we have $(x \mapsto \alpha x + \beta) \in P_n(a, b)$.

Proof. Assume that for $A, B \in \mathcal{H}_{(a,b)}$ we have $A \leq B$. Now

$$f(B) - f(A) = (\alpha B + \beta I) - (\alpha A + \beta I) = \alpha(B - A).$$

Since by assumption $B - A \geq$ and $\alpha \geq 0$, also $\alpha(B - A) \geq 0$, so by definition $f(B) \geq f(A)$. This is exactly what we wanted. □

Proposition 3.5. *We have* $(x \mapsto -x^{-1}) \in P_n(a,b)$ *if* $0 \notin (a,b)$.

Proof. The result follows immediately from the theorem 2.39. $\square$

Now also $(x \mapsto (\lambda - x)^{-1} \in P_n(a,b)$ for any $\lambda \notin (a,b)$ so by the cone property also

$$x \mapsto \alpha x + \beta + \sum_{i=1}^{m} \frac{t_i}{\lambda_i - x} \in P_n(a,b) \tag{3.6}$$

for any $\alpha, t_1, t_2, \ldots, t_m \geq 0$ and $\beta, \lambda_1, \lambda_2, \ldots, \lambda_m$ where $\lambda_1, \lambda_2, \ldots, \lambda_m \notin (a,b)$.

3.2 Basic properties

Below we collect many natural properties of the cones $P_n(a,b)$.

Proposition 3.7. *Let* $f : (a,b) \to \mathbb{R}$. *Then the following are equivalent:*

(i) f *is increasing.*

(ii) $f \in P_1(a,b)$.

(iii) *For any positive integer* n *and commuting* $A, B \in \mathcal{H}^n_{(a,b)}$ *such that* $A \leq B$ *we have* $f(A) \leq f(B)$.

Proof. *(ii)* $\Rightarrow$ *(i)*: Take any $a < x \leq y < b$. Now for $xI, yI \in \mathcal{H}^n_{(a,b)}$ we have $xI \leq yI$ so by definition

$$f(x)I = f(xI) \leq f(yI) = f(y)I,$$

from which it follows that $f(x) \leq f(y)$.

(iii) $\Rightarrow$ *(ii)*: All 1×1 matrices commute.

(i) $\Rightarrow$ *(iii)*: If $A \leq B$ and A and B commute, by theorem 2.26 we may write $A = \sum_{i=1}^n a_i P_{v_i}$ and $B = \sum_{i=1}^n b_i P_{v_i}$ for some $a_1, \ldots, a_n, b_1, \ldots, b_n \in \mathbb{R}$ and $v_1, v_2, \ldots, v_n$, orthonormal basis of V, with $a_i \leq b_i$. But now $f(A) = \sum_{i=1}^n f(a_i) P_{v_i}$ and $\sum_{i=1}^n f(b_i) P_{v_i}$ so

$$f(B) - f(A) = \sum_{i=1}^{n} (f(b_i) - f(a_i)) P_{v_i}$$

is positive, as f is increasing. $\square$

Proposition 3.8. *If* $f : (a,b) \to (c,d)$ *and* $g : (c,d) \to \mathbb{R}$ *are* n*-monotone, so is* $g \circ f : (a,b) \to \mathbb{R}$.

Proof. Fix any $A, B \in \mathcal{H}^n_{(a,b)}$ with $A \leq B$. By assumption $f(A) \leq f(B)$ and $f(A), f(B) \in \mathcal{H}^n_{(c,d)}$ so again by assumption, $g(f(A)) \leq g(f(B))$, our claim. □

Proposition 3.9. *We have $P_{n+1}(a,b) \subset P_n(a,b)$.*

Proof. Take $A, B \in \mathcal{H}_{(a,)}(V)$ with $A \leq B$. For any $c \in (a,b)$ we have $(A \oplus c), (B \oplus c) \in \mathcal{H}(V \oplus \mathbb{C})$ and $(A \oplus c) \leq (B \oplus c)$. Consequently, if $f \in P_{n+1}(a,b)$, we have

$$f_V(A) \oplus f(c) = f_{V \oplus \mathbb{C}}(A \oplus c) \leq f_{V \oplus \mathbb{C}}(B \oplus c) = f_V(B) \oplus f(c),$$

which implies that $f(A) \leq f(B)$. □

It turns out that these inclusions are strict, as long as our interval is not the whole $\mathbb{R}$.

There are also more trivial inclusions: $P_n(a,b) \subset P_n(c,d)$ for any $(a,b) \supset (c,d)$. Bigger interval, more matrices, more restrictions, fewer functions. To be precise, one should say that if $(a,b) \supset (c,d)$ and $f \in P_n(a,b)$, then also $f\big|_{(c,d)} \in P_n(c,d)$.

3.3 Failures

Most of the common monotone functions fail to be matrix monotone. Let's try some non-examples.

Proposition 3.10. *Function $(x \mapsto x^2)$ is not n-monotone for any $n \geq 2$ on $(0, \infty)$.*

Proof. Let us first think what goes wrong with the standard proof for the case $n = 1$.

Note that if $A \leq B$,

$$B^2 - A^2 = (B - A)(B + A)$$

is positive as a product of two positive matrices (real numbers).

There are two fatal flaws here when $n > 1$.

- $(B - A)(B + A) = B^2 - A^2 + (BA - AB)$, not $B^2 - A^2$.
- Product of two positive matrices need not be positive.

Note that both of these objections result from the non-commutativity and indeed, both would be fixed should A and B commute.

Let's write $B = A + H$ $(H \geq 0)$. Now we are to investigate

$$(A + H)^2 - A^2 = AH + HA + H^2.$$

Note that $H^2 \geq 0$, but as we have seen in proposition 2.29, $AH + HA$ need not be positive! Also, if H is small enough, H^2 is negligible compared to $AH + HA$. To be entirely honest, we only gave examples of $A, H \geq 0$ with $AH + HA \not\geq 0$ with A and H rank one, so $A \notin \mathcal{H}^n_{(0,\infty)}$. This deficit is however easily fixed by looking at $A_\varepsilon = A + \varepsilon I$ for $\varepsilon > 0$. □

By a bit more careful arguments one could show that $(x \mapsto x^2)$ is not n-monotone for any $n \geq 2$ on any open interval.

As a corollary with get

Corollary 3.11. *The function $\chi_{(0,\infty)}$ is not n-monotone for any $n \geq 2$.*

Proof. If $\chi_{x>0}$ were n-monotone so would be

$$x^2 = \int_0^\infty 2t\chi_{(t,\infty)}(x)dt.$$

$\square$

The function $\chi_{(0,\infty)}$ is in some sense canonical counterexample: every increasing function is more or less positive linear combination of its tranlates, so if monotone functions are not all matrix monotone, the reason is that it is not matrix monotone. For this reason we should really understand why it is not n-monotone for any $n > 1$.

The idea is the following: we are going to take $n = 2$ and construct $A, B \in \mathcal{H}(V)$ with the following properties:

1. $A \leq B$
2. A and B have both exactly one positive eigenvalue
3. A and B don't commute

If we can do this, A and B work as counterexamples. Indeed then $\chi_{(0,\infty)}(A) = P_{v_1}$ and $\chi_{(0,\infty)}(B) = P_{w_1}$ where eigenvectors v_1 and w_1 are eigenvectors of A and B corresponding to positive eigenvalues. But $\chi_{(0,\infty)}(A) \not\leq \chi_{(0,\infty)}(B)$ by 2.37.

Constructing such pair is very easy: just take A with eigenvalues -1 and 1 and consider B of the form $A + tH$ for some $H \geq 0$, $t > 0$ and such that A and H do not commute. For small enough H all of the conditions are easily satisfied.

As many properties of real numbers break with real maps, similarly many properties of monotone functions break when $n > 1$. As we saw with the square function example, product of two n-monotone functions need not be n-monotone in general, even if they are both positive functions. Similarly, taking maximums doesn't preserve monotonicity.

Proposition 3.12. *Maximum of two n-monotone functions need not be n-monotone for $n \geq 2$.*

Proof. Again, let's think what goes wrong with the standard proof for $n = 1$.

Take $n \geq 2$, $f, g \in P_n(a,b)$ and $A, B \in \mathcal{H}^n_{(a,b)}$ with $A \leq B$. Now $f(A) \leq f(B) \leq \max(f,g)(B)$ and $f(A) \leq f(B) \leq \max(f,g)(B)$. It follows that

$$\max(f,g)(A) = \max(f(A), g(A)) \leq \max(f,g)(B),$$

as we wanted.

Here the flaw is in the expression $\max(f(A), g(A))$: what is maximum of two matrices? It turns out that however you try to define it, you can't satisfy the above inequality.

For counterexamples take $f \equiv 0$ and $g = \mathrm{id}$: it's easy to see that we can take same pair as with $\chi_{(0,\infty)}$ as our counterexample. $\square$

The maximum problem is not too bad and maybe it's more of a pleasent surprise anyway that it holds for usual monotone functions. But there is very fundamental problem hidden in the square example.

Proposition 3.13. *Let $n \geq 2$. Then there exists no $\alpha > 0$, and no open interval $(a,b) \subset \mathbb{R}$ such that $\alpha x + x^2 \in P_n(a,b)$.*

Proof. Adding linear term means just translating domain and codomain, which is not going to help: $x^2 + \alpha x = (x + \frac{\alpha}{2})^2 - \frac{\alpha^2}{4}$. $\square$

Why is this bad? If $f : (a,b) \to \mathbb{R}$ is not too bad (say Lipschitz), for large enough α the function defined by $g(x) = f(x) + \alpha x$ is increasing. But we can't do necessarily do the same thing in the matrix setting even for smooth or analytic functions. Although this might not be such a big surprise or a bad thing in the first place, it is worthwhile to investigate the underlying reason.

Let $f(x) = \alpha x + x^2$ and take $A, H \geq 0$. As observed earlier, we have

$$\lim_{t \to 0} \frac{f(A + tH) - f(A))}{t} = \alpha H$$
$$+ HA + AH$$

In the real setting we could just increase α to make the previous expression positive. In the matrix setting there is a problem: note that if H is of rank 1, increasing α means "increasing the right-hand side only to one direction". The point is that if the right-hand side is not positive (map) in the first place, it might be (a priori) non-positive in a big subspace, so rank 1 machinery is not going to save the day. Note also that even if we let $A \to 0$ (look at matrix function at 0), the situation isn't a priori better.

On the other hand if $n = 2$, for instance, there is not too much room for things to go south. We still, a priori, can't guarantee positivity with α, but adding something extra, say βx^3 for some $\beta > 0$ might. In the end, there isn't too much space in the 2-dimensional space. We will later see that this will indeed happen. TODO

When n gets larger we have more and more space to worry about, so we should start worrying about more and more Taylor coefficients.

This leads us to expect two things:

1. Larger the dimension n, the more Taylor coefficients should be under some kind of control.

2. For fixed n we can (at least locally) guarantee n-monotonicity by controlling certain number of first coefficients.

3.4 Heuristics

3.4.1 Taylor coefficients

Let us try to push the ideas of the previous section further. Take entire $f(x) = \sum_{k=0}^{\infty} a_k x^k$ and assume that $0 \in (a, b)$. Note that as for any $k > 0$

$$(A + B)^k = \sum_{i=0}^{k} \sum_{\substack{j_0,\ldots,j_i \geq 0 \\ j_0+\ldots+j_i=k-i}} A^{j_0} B A^{j_1} B \cdots B A^{j_k},$$

we have

$$\lim_{t \to 0} \frac{f(A + tH) - f(A))}{t} = \sum_{i=1}^{\infty} a_i \sum_{j=0}^{i-1} A^j B A^{i-1-j}.$$

If $f \in P_\infty(a, b)$, this expression should be positive for $A \in \mathcal{H}_{(a,b)}$ and $H \geq 0$. Let us denote

$$Df_A(H) := \lim_{t \to 0} \frac{f(A + tH) - f(A))}{t},$$

derivative of a matrix function at A in the direction H. This limit is certainly well-defined and linear in H for entire functions[1], so it suffices to consider the case of rank one H.

[1] It will also make sense more generally for $C^1(a, b)$-maps, but we won't need that fact.

Let's say $H = vv^*$ for some $v \in V$ and take any $w \in V$. Now we should have

$$\begin{aligned}\langle Df_A(H)w, w\rangle &= \sum_{i=1}^{\infty} a_i \sum_{j=0}^{i-1} \langle A^j H A^{i-1-j} w, w\rangle \\ &= \sum_{i=1}^{\infty} a_i \sum_{j=0}^{i-1} \langle A^{i-1-j} w, v\rangle \langle A^j v, w\rangle \\ &\geq 0\end{aligned}$$

For any $v, w \in V$. Write $c_j = \langle A^j w, v\rangle$ and observe that $\langle A^j w, v\rangle = \overline{\langle A^j w, v\rangle} = \overline{c_j}$. It follows that

$$\sum_{i=1}^{\infty} a_i \sum_{j=0}^{i-1} \overline{c_{i-1-j}} c_j = \sum_{i,j \geq 0} a_{i+j+1} c_i \overline{c_j} \geq 0$$

for some kind of sequences $(c_i)_{i=1}^{\infty}$. This implies that if the infinite matrix $(a_{i+j+1})_{i,j\geq 0}$ is positive, then f is matrix monotone. What about the converse?

It is not very hard to see that

$$c_j = \sum_{i=1}^{n} t_i \lambda_i(A)^j$$

for some $t_1, t_2, \ldots, t_n \in \mathbb{C}$. Conversely, if the eigenvalues of A are simple, we can control first n terms of $(c_i)_{i=1}^{\infty}$ by choice of v and w. This implies the following:

Proposition 3.14. *If f is a polynomial with $2 \leq \deg(f) \leq n$, then $f \notin P_n(a, b)$.*

If f is not polynomial such conclusions are harder to make, as we can only control first c_i's. Nevertheless, also the converse holds.

Theorem 3.15. *$f \in P_\infty(a, b)$, if and only if f is analytic and the infinite matrix $(a_{i+j-1})_{i,j\geq 1}$, where $a_k = f^{(k)}(x)/k!$ and $x \in (a, b)$, is positive for any $x \in (a, b)$.*

As one would hope, there's corresponding result for the classes $P_n(a, b)$.

Theorem 3.16. *$f \in P_n(a, b)$, if and only if $(a_{i+j-1})_{1\leq i,j\leq n}$, where $a_k = f^{(k)}(x)/k!$ and $x \in (a, b)$, is positive for any $x \in (a, b)$.*

Only now there's a problem: function in $P_n(a, b)$ need not be analytic, and even worse it need not be $(2n - 1)$ so the condition should be understood in weak (distributional) sense.

3.4.2 Main argument

Let us try to prove the "only if" -directions of these results modulo regularity issues.

Proof "sketch" of the "only if" of 3.16. Denote the matrix in question by $M(= M_n(x,f))$. We may w.l.o.g. take $x = 0 \in (a,b)$. The idea is the following: we know that $\langle Df_A(H)w, w\rangle$ is positive for any $A \in \mathcal{H}_{(a,b)}, H \geq 0$ and $w \in V$ and should prove that $\langle Mv, v\rangle \geq 0$ for any $v \in \mathbb{C}^n$. Best we could hope for is that

$$\lim_{\varepsilon \to 0} \langle Df_{A_\varepsilon}(H_\varepsilon) w_\varepsilon, w_\varepsilon\rangle = \langle Mv, v\rangle$$

for some $H_\varepsilon \geq 0$, $w_\varepsilon \in \mathbb{C}^n$, $A_\varepsilon \in \mathcal{H}^n_{(a,b)}$, with $\lim_{\varepsilon \to 0} A_\varepsilon = 0$. This works.

To find $H_\varepsilon, w_\varepsilon, A_\varepsilon$, we change the point of view. Recall that if f is entire we have

$$f(A) = \frac{1}{2\pi i} \int_\gamma (zI - A)^{-1} f(z) dz.$$

Now we can write

$$\begin{aligned} \frac{f(A + tH) - f(A)}{t} &= \frac{1}{2\pi i} \int_\gamma \frac{(zI - A - tH)^{-1} - (zI - A)^{-1}}{t} f(z) dz \\ &= \frac{1}{2\pi i} \int_\gamma (zI - A - tH)^{-1} H (zI - A)^{-1} f(z) dz. \end{aligned}$$

Taking $t \to 0$, we find that

$$Df_A(H) = \frac{1}{2\pi i} \int_\gamma (zI - A)^{-1} H (zI - A)^{-1} f(z) dz.$$

Next, take $H = vv^*$ for $v \in V$ and $w \in V$: we have

$$\begin{aligned} \langle Df_A(H)w, w\rangle &= \frac{1}{2\pi i} \int_\gamma \langle (zI - A)^{-1} vv^* (zI - A)^{-1} w, w\rangle f(z) dz \\ &= \frac{1}{2\pi i} \int_\gamma \langle (zI - A)^{-1} v, w\rangle \langle (zI - A)^{-1} w, v\rangle f(z) dz. \end{aligned}$$

Note that we can write $\langle (zI - A)^{-1} v, w\rangle = \det(zI - A)^{-1} q(z)$ where q is some polynomial of degree less than n. Moreover, if A has n distinct roots, varying w gives all such polynomials q. We can rewrite our object as

$$\frac{1}{2\pi i} \int_\gamma \det(zI - A)^{-2} q(z) \overline{q(\overline{z})} f(z) dz.$$

Taking $A \to 0$ reveals that

$$\frac{1}{2\pi i}\int_\gamma \frac{q(z)\overline{q(\overline{z})}}{z^{2n}} f(z)dz.$$

But actually this is all we wanted. Indeed, since by the Cauchy's integral formula we have

$$\frac{f^{(k)}(0)}{k!} = \frac{1}{2\pi i}\int_\gamma \frac{f(z)dz}{z^{k+1}}$$

for any $k \geq 0$, so we can write

$$\begin{aligned}
\sum_{1 \leq i,j \leq n} a_{i+j-1} c_i \overline{c_j} &= \sum_{1 \leq i,j \leq n} a_{i,j} \frac{1}{2\pi i}\int_\gamma \frac{f(z)dz}{z^{i+j}} \\
&= \frac{1}{2\pi i}\int_\gamma \left(\sum_{i=1}^n \frac{c_i}{z^i}\right)\left(\sum_{i=1}^n \frac{\overline{c_i}}{z^i}\right) f(z)dz \\
&= \frac{1}{2\pi i}\int_\gamma \frac{q(z)\overline{q(\overline{z})}}{z^{2n}} f(z)dz,
\end{aligned}$$

where we write $q(z) = \sum_{i=1}^n z^{n-i} c_i$. □

Proof "sketch" of the "only if" of 3.15. This follows immeditaly from 3.16. □

Note that the proof gives also alternate interpretation to the matrix M. Positivity of M means simply that for $q \in \mathbb{C}_{n-1}[x]$ the function $f(x)q(x)\overline{q(\overline{x})} = f(x)|q(x)|^2$ has non-negative $(2n-1)$'th derivative.

Given polynomial q, we denote by $N(q)$ polynomial with

$$N(q)(z) = q(z)\overline{q(\overline{z})}.$$

The main problem of the argument is the regularity. While we assume entireity of f mainly for convenience and it could be easily avoided, we need some kind of regularity to make sense of the definition: it is a priori not even clear that functions in $P_\infty(a, b)$ should be continuous. Origin of these regularity properties is the topic of the next chapter.

3.5 Notes and references

Chapter 4

k-tone functions

4.1 Motivation

To understand the regularity properties of the matrix monotone functions we look at a closely related class of k-tone functions. k-tone functions are more or less functions with non-negative k'th derivative[1]. What should that mean?

We already know the perfect answer for the case $k = 1$: 1-tone functions should be the increasing functions.

Theorem 4.1. *Let $f : (a, b) \to \mathbb{R}$ be differentiable. Then f is increasing, if and only if $f'(x) \geq 0$ for every $x \in (a, b)$.*

Proof. If f is increasing, then all its divided differences, i.e. the quotients of the form

$$\frac{f(x) - f(y)}{x - y}$$

for $x \neq y$ are non-negative. As derivatives are limits of such quotients, also they are non-negative at any point. Conversely, by the mean value theorem for every $x \neq y$ we may find ξ such that

$$\frac{f(x) - f(y)}{x - y} = f'(\xi).$$

Now if the derivatives are non-negative, so are the divided differences, so the function is increasing. $\square$

[1] The terminology is not very established, and such functions are also occasionally called k-monotone or k-convex.

While this proof by the mean value theorem works in more general setting, if $f \in C^1$, one has more instructive proof.[2]

Alternate proof for the theorem 4.1 (in the case $f \in C^1(a,b)$). Note that if $f \in C^1(a,b)$, we may write

$$\frac{f(y)-f(x)}{y-x} = \frac{1}{y-x}\int_x^y f'(t)dt = \int_0^1 f'(tx+(1-t)y)dt.$$

Note that on the right-hand side we have average of the derivative over the interval. This means that the claim can be translated to: continuous function is non-negative, if and only if its averages over all intervals are non-negative. But this is clear. $\square$

This is really powerful point of view. While one would like to say the increasing functions are the functions with non-negative derivative, that's a bit of a lie. Instead, one can say that they are the functions whose derivative is non-negative on average, and all the problems are gone. This should rougly mean that the derivative defines a positive distribution and it is hence a measure. Thus all increasing functions should be integrals of a positive measure (at least almost everywhere). Although this kind of thinking could be carried out, the details aren't important for us. The main point is that one should think that increasing functions, i.e. the 1-tone functions are functions whose first derivative is a (positive) measure. The divided differences are an averaged (i.e. weak) way of talking about the positivity of the derivative (measure).

This is essentially distributional way of thinking, and we could keep going and end up with the whole business of weak derivatives and stuff. But we don't have to: the plain averages suffice. We write

$$[x,y]_f := \frac{f(x)-f(y)}{x-y},$$

and say that $[\cdot,\cdot]_f$ is the (first) divided difference of f. The domain of $[\cdot,\cdot]_f$ should naturally be $(a,b)^2$ minus the diagonal. And of course, if $f \in C^1$, we should extend $[\cdot,\cdot]_f$ to the diagonal, as the derivative. Divided differences then becomes a continuous function on the whole set $(a,b)^2$.

Aside from capturing the first derivative, divided difference has two rather convenient properties.

- For given x and y, $f \mapsto [x,y]_f$ defines a linear map, which is continuous with the topology of pointwise convergence (i.e. the product topology).

[2]Of course, the following argument would also work with slightly weaker assumptions, but that's not important to us.

- Divided differences are local in the sense that if f and g agree on $\{x, y\}$, divided differences agree; this observation readily implies the previous continuity claim.

These are the ways divided difference is a compromise between the real derivative and the weak derivative. The first point says that one doesn't have worry too much, only about pointwise convergence, while the second says that things are still rather concrete (and it makes the life whole lotta easier).

The real power of this approach comes with larger k. What about the case $k = 2$? Again, we already know the perfect answer: 2-tone functions should be the convex functions.

Theorem 4.2. *Let $f : (a, b) \to \mathbb{R}$ be twice differentiable. Then f is convex, if and only if $f^{(2)}(x) \geq 0$ for every $x \in (a, b)$.*

Proof. While the result is true as stated, let us only proof the case $f \in C^2(a, b)$ (we'll come back to the more general case). Recall that f is convex, if and only if for any $x, y \in (a, b)$ and $t \in [0, 1]$ we have

$$tf(x) + (1 - t)f(y) \geq f(tx + (1 - t)y).$$

This suggest that we may write

$$tf(x) + (1 - t)f(y) - f(tx + (1 - t)y) = \int_x^y w(t)f^{(2)}(t)dt$$

for some weight w. Note that if we manage to find such weight, which is non-negative (and positive enough), we would be done.

How to find the weight w? The idea is rather simple: we want to "sieve out" the values of w by choosing f such that $f^{(2)} = \delta_a$ for $a \in \mathbb{R}$ (in some sense). Now, this should mean that $f(t) = (t - a)_+ + ct + d$ for some $c, d \in \mathbb{R}$, where we write $t_+ = \max(t, 0)$. Plugging this is on the left hand side we get

$$t(x - a)_+ + (1 - t)(y - a)_+ - (tx + (1 - t)y - a)_+ = w(a).$$

TODO: picture

Now, while the steps taken might have contained some leaps of faith, it can be easily verified with partial integration that the given w really works. $\square$

The giveaway is that while the divided differences are a convenient averaged way to talk about first derivative, the quantity $tf(x)+(1-t)f(y)-f(tx+(1-t)y)$ is a convenient averaged way to talk about the second derivative. It captures the fact that the second derivative should be a positive measure – without talking about derivatives. We won't call the quantity the second divided difference, however, as, as it turns out, we can rewrite it in much more convenient form.

If we denote $z = tx + (1-t)y$, we can solve that $t = \frac{z-y}{x-y}$ and express

$$\begin{aligned} & tf(x) + (1-t)f(y) - f(tx + (1-t)y) \\ = \quad & \frac{z-y}{x-y} f(x) + \frac{x-z}{x-y} f(y) - f(z) \\ = \quad & -(z-y)(z-x) \left(\frac{f(x)}{(x-y)(x-z)} + \frac{f(y)}{(y-z)(y-x)} + \frac{f(z)}{(z-x)(z-y)} \right) \end{aligned}$$

If $t \notin \{0, 1\}$, $-(z-y)(z-x)$ is positive, so if f is convex,

$$\frac{f(x)}{(x-y)(x-z)} + \frac{f(y)}{(y-z)(y-x)} + \frac{f(z)}{(z-x)(z-y)} \geq 0$$

for any x, y and z such that z is between x and y. This new expression is symmetric in its variables, so actually there's no need to assume anything on the order of x, y and z, just that they're distinct. We can also easily carry this argument to the other direction: if the expression is non-negative for any distinct x, y and z, f is convex. This motivates us to define

$$[x, y, z]_f := \frac{f(x)}{(x-y)(x-z)} + \frac{f(y)}{(y-z)(y-x)} + \frac{f(z)}{(z-x)(z-y)},$$

the second divided difference of f.

One would hope that by setting

$$[x_0, x_1, \ldots, x_n]_f := \sum_{i=0}^{n} \frac{f(x_i)}{\prod_{j \neq i}(x_i - x_j)},$$

one obtains something that naturally generalizes divided differences for higher orders. This is indeed the case.

4.2 Divided differences

Define $D_n = \{x \in \mathbb{R}^n | x_i = x_j \text{ for some } 1 \leq i < j \leq n\}$.

Definition 4.3. Let $n \geq 0$. For any real function $f : (a, b) \to \mathbb{R}$ we define the corresponding n'th divided difference $[\cdots]_f : (a, b)^{n+1} \setminus D_{n+1}$ by setting

$$[x_0, x_1, \ldots, x_n]_f = \sum_{i=0}^{n} \frac{f(x_i)}{\prod_{j \neq i}(x_i - x_j)}.$$

We will soon prove that divided differences (of order n) are simply weighted averages of the n'th derivative.

4.2.1 Basic properties

Divided differences have the following important properties.

Proposition 4.4. *Divided differences are symmetric in the variable, i.e. for any* $f : (a, b) \to \mathbb{R}$ *and pairwise distinct* $a < x_0, x_1, \ldots, x_n < b$ *permutation* $\sigma : \{0, 1, 2, \ldots, n\} \to \{0, 1, 2, \ldots, n\}$ *we have*

$$[x_0, x_1, x_2, \ldots, x_n]_f = [x_{\sigma(0)}, x_{\sigma(1)}, x_{\sigma(2)}, \ldots, x_{\sigma(n)}]_f.$$

If f *is continuous, so are the divided differences. Finally, for fixed (pairwise distinct)* $a < x_0, x_1, \ldots, x_n < b$ *the map* $[x_0, x_1, \ldots, x_n]_\cdot : \mathbb{R}^{(a,b)} \to \mathbb{R}$ *is linear and continuous (with respect to the topology of pointwise convergence).*

Proof. Easy to check. □

The name "divided differences" stems from the fact that the higher order divided differences are itself (usual) divided differences of lower order ones.

Proposition 4.5. *For any* $f : (a, b) \to \mathbb{R}$ *and pairwise distinct* $x_0, x_1, \ldots, x_n \in (a, b)$ *we have*

$$[x_0, x_1, \ldots, x_n]_f = \frac{[x_0, x_1, \ldots, x_{n-1}]_f - [x_1, x_2, \ldots, x_n]_f}{x_0 - x_n} = [x_0, x_n]_{[\cdot, x_1, \ldots, x_{n-1}]_f} \tag{4.6}$$

More generally, for any pairwise distinct $x_1, x_2, \ldots, x_n, y_1, y_2, \ldots, y_m \in (a, b)$ *we have*

$$[y_1, y_2, \ldots, y_m]_{[\cdot, x_1, x_2, \ldots, x_n]_f} = [y_1, y_2, \ldots, y_m, x_1, x_2, \ldots, x_n]_f. \tag{4.7}$$

Proof. 4.6 is easy to check directly. For 4.7 note that both

$$[y_1, y_2, \ldots, y_m]_{[\cdot, x_1, x_2, \ldots, x_n]_f} \text{ and } [y_1, y_2, \ldots, y_m, x_1, x_2, \ldots, x_n]_f$$

satisfy 4.6 (as a function of the y's) and they agree when $m = 1$. □

We call 4.7 the *nesting property* of divided differences. Although the analogy isn't perfect, one could think that this identity says that m'th derivative of the n'th derivative is the $(n + m)$'th derivative.

The following observation tells us that the divided differences work as n'th derivative insomuch that it kills polynomials of degree less than n and works with degree n as expected, up to a constant at least.

Proposition 4.8. *We have* $[x_0, x_1, \ldots, x_n]_{(x \mapsto x^n)} = 1$ *and* $[x_0, x_1, \ldots, x_n]_p = 0$ *for any polynomial of degree at most* $n-1$. *In other words,* $[x_0, x_1, \ldots, x_n]_f$ *is the leading coefficient of the interpolation polynomial on pairs* $(x_0, f(x_0)), (x_1, f(x_1), \ldots, (x_n, f(x_n))$.

Proof. As the interpolation polynomial of a polynomial of degree at most n on a dataset of $(n+1)$ pairs is the polynomial itself, the second claim readily implies the first. Recall that the Lagrange form of the interpolation polynomial of a dataset $(x_0, y_0), (x_1, y_1), \ldots, (x_n, y_n)$ is given by

$$\sum_{i=0}^{n} y_i \frac{\prod_{j\neq i}(x - x_j)}{\prod_{j\neq i}(x_i - x_j)},$$

and the leading coefficient of this polynomial is exactly the divided difference. □

4.2.2 Peano representation

Coming back to the original motivation, divided differences enjoy an integral representation also for larger n, albeit somewhat more complicated.

Theorem 4.9. *If $f \in C^n(a, b)$, then for any pairwise distinct $a < x_0, x_1, x_2, \ldots, x_n < b$ we have*

$$[x_0, x_1, \ldots, x_n]_f = \int_{\mathbb{R}} f^{(n)}(t) w(t) dt, \tag{4.10}$$

where

$$w(t) := w_{x_0,x_1,\ldots,x_n}(t) = \frac{1}{(n-1)!} \sum_{i=0}^{n} \frac{((x_i - t)_+)^{n-1}}{\prod_{j\neq i}(x_i - x_j)}. \tag{4.11}$$

In addition, w is non-negative, supported on $[\min(x_i), \max(x_i)]$ and integrates to $(n!)^{-1}$.

Proof. Note that the weight is simply the n'th divided difference of the map $g_{t,n} : x \mapsto ((x-t)_+)^{n-1}/(n-1)!$. This is not very surprising: one should think that $g_{t,n}$ is the function whose n'th derivative is δ_t. If we plug in $f = g_{t,n}$, (as in the proof of 4.2), we, at least morally, get the claim. While the previous argument could be pushed through, we take safer route. To prove that the formula even makes sense, we should prove the claim on the support. It is clear that w is zero whenever $t \geq \max(x_i)$. If on the other hand $t \leq \min(x_i)$, $w(t)$ agrees with the n'th divided difference of the map $x \mapsto (x - t)^{n-1}/(n - 1)!$, which is zero by the proposition 4.8.

We may hence repeatedly partially integrate the right-hand side:

$$\begin{aligned}\int_{\mathbb{R}} f^{(n)}(t)w(t)dt &= \int_{\mathbb{R}} f^{(n-1)}(t)(-1)w'(t)dt \\ &= \int_{\mathbb{R}} f^{(n-2)}(t)w^{(2)}(t)dt \\ &= \dots \\ &= \int_{\mathbb{R}} f^{(1)}(t)(-1)^n w^{(n-1)}(t)dt,\end{aligned}$$

where

$$(-1)^n w^{(n-1)}(t) = \sum_{i=0}^{n} \frac{\chi_{(t,\infty)}(x_i)}{\prod_{j\neq i}(x_i - x_j)}.$$

Note that $w^{(j)}$ is continuous, piecewise C^1, and compactly supported for every $0 \leq j < n-1$, so the partial integration is legitimate. The final step is a easy calculation.

Applying the identity to $x \mapsto x^n$ shows the claim on the integral of w.

Only non-negativity remains: we prove it by induction on n. The case $n = 1$ is clear. The idea is rather simple: we should prove that the functions $g_{t,n}$ has non-negative divided differences, which should roughly mean it has non-negative n'th derivative (being δ_t). By the nesting property we have

$$[x_0, x_1, \dots, x_n]_{g_{t,n}} = [x_0, x_1, \dots, x_{n-1}]_{[\cdot, x_n]_{g_{t,n}}}.$$

Now if we could replace $[\cdot, x_n]_{g_{t,n}}$ with the derivative of $g_{t,n}$, which is conveniently $g_{t,n-1}$, we would be done by the induction hypothesis. Note that while these functions aren't the same in general, they agree (up to constant) if $x_n = t$. But if $x_n \neq t$, we can play the same game as before: $[\cdot, x_n]_{g_{t,n}}$ is weighted average of the derivative $g'_{t,n} = g_{t,n-1}$. Indeed, as

$$[\cdot, x_n]_{g_{t,n}} = \int_0^1 g_{t,n-1}(s \cdot + (1-s)x_n)ds,$$

we have

$$[x_0, x_1, \dots, x_n]_{[\cdot, x_n]_{g_{t,n}}} = \int_0^1 [x_0, x_1, \dots, x_{n-1}]_{g_{t,n-1}(s\cdot+(1-s)x_n)}ds,$$

Now since all the divided differences of $g_{t,n-1}$ are non-negative, the same is clearly true for $g_{t,n-1}(s \cdot + (1-s)x_n)$, so we are done. $\square$

The weight 4.11 is called **Peano kernel** (of order n). The points $x_0, x_1, \ldots, x_n$ are called the **nodes** of w.

TODO: pictures of Peano kernels

As an very important corollary we get the following.

Theorem 4.12 (Mean value theorem for divided differences)**.** *Let $f \in C^n(a,b)$. Then for any pairwise distinct $x_0, x_1, \ldots, x_n \in (a,b)$ we have*

$$\min_{0 \le i \le n} (x_i) < \xi < \max_{0 \le i \le n} (x_i)$$

such that

$$[x_0, x_1, \ldots, x_n] = \frac{f^{(n)}(\xi)}{n!}. \tag{4.13}$$

Proof. This follows immediately from 4.9.

One can also give a proof using mean value theorem and with slightly weaker assumptions: it suffices to assume that f is n times differentiable.

By linearity and proposition 4.8 it suffices to verify the claim in the case where $f(x_i) = 0$ for $0 \le i \le n$.

Lemma 4.14. *If f is n times differentiable, and has $n+1$ roots, then $f^{(n)}$ has a root (in the interior of the convex hull of the roots).*

Proof. If f has $n+1$ roots, by the mean value theorem its derivative has n roots (in the interior of the convex hull of the roots of f) and is $(n-1)$ times differentiable. Since the derivative satisfies the same assumptions for $n-1$, the claim follows by induction. □

□

The mean value theorem could be also used to prove the non-negativity of the weight w: if w were somewhere negative, one could construct function with non-negative derivative and negative divided difference, which would contradict 4.13.

As in the case $n = 1$, if for $n > 1$ we can continuously extend divided differences to the set D_{n+1}, we should do that, and we identify the resulting function with the original one. We will later proof that, as expected, this can be done, if and only $f \in C^n(a,b)$. In this case by 4.13 the extesion satisfies

$$[x_0, x_0, \ldots, x_0]_f = \frac{f^{(n)}(x_0)}{n!},$$

which together with 4.6 is enough to expand the divided differences with values of the function and its derivative.

4.2.3 Cauchy's integral formula

Complex analysis offers a nice view on divided differences: if f is analytic, we may interpret divided differences as contour integrals.

Lemma 4.15 (Cauchy's integral formula for divided differences)**.** *If γ is a closed counter-clockwise curve enclosing the numbers $x_0, x_1, \ldots, x_n$, we have*

$$[x_0, x_1, \ldots, x_n]_f = \frac{1}{2\pi i} \int_\gamma \frac{f(z)}{(z - x_0)(z - x_1) \cdots (z - x_n)} dz.$$

Proof. This is direct consequence of the Residue theorem. □

If all the points coincide, we get the familiar formula for the n'th derivative. If f is a polynomial of degree at most $n-1$, the integrand decays as $|z|^{-2}$ (at infinity) and the divided differences vanish, as expected. Also, for $z \mapsto z^n$ one can use the formula to calculate the n'th divided difference with a residue at infinity. Formula is slightly more concisely expressed by writing for a sequence $X = (x_i)_{i=0}^n$ $p_X(x) = \prod_{i=0}^n (x - x_i)$. Now we have

$$[x_0, x_1, \ldots, x_n]_f = \frac{1}{2\pi i} \int_\gamma \frac{f(z)}{p_X(z)} dz.$$

Cauchy's integral formula is a convenient way to think about severel identities.

Example 4.16. We may express an interpolation polynomial of an analytic function f and sequence $X = (x_i)_{i=0}^n$ by

$$P_{X,f}(x) := \frac{1}{2\pi i} \int_\gamma \frac{p_X(x) - p_X(z)}{x - z} \frac{f(z)}{p_X(z)} dz = [x_0, x_1, \ldots, x_n]_{f[x,\cdot]p_X}.$$

Indeed: $P_{X,f}(x_i)$ evaluates to $f(x_i)$ by Cauchy's integral formula. More generally, if some of the points coincide, we get the Hermite interpolation polynomial, as can be shown with slightly more careful considerations.

While the previous argument works stricly speaking only for analytic function (and even then one would have to be careful with γ), the identity holds more generally. The expression for $P_{X,f}$ can be expanded as some kind polynomial, coefficients of which are linear combinations of evaluations $f(x_i)$: such expressions make perfect sense irrespective of regularity of f. Same is true for the evaluations of this polynomial at points x_i, numbers $P_{X,f}(x_i)$. We know that $P_{X,f}(x_i) = f(x_i)$ holds for all analytic (or at least entire) functions. On the other hand the map $f \mapsto P_{X,f}(x_i) - f(x_i)$ is simply a finite linear combination of point evaluations, so it vanishes for any function if we manage to prove that

Lemma 4.17. *For any pairwise distinct $x_0, x_1, \dots, x_n \in \mathbb{C}$ and $y_0, y_1, \dots, y_n \in \mathbb{C}$ there exists an entire function f with $f(x_i) = y_i$.*

Proof. Simply take f to be the interpolating polynomial. □

One can also interpret such identities to be strictly formal: Cauchy's integral formula can be thought as a bijection between rational functions with simple poles and the span of δ-measures. Many measures look simpler as rational functions.

4.2.4 Identities

Many of the familiar identities for the derivatives have analogs with divided differences. We won't need these formulas, but it's nevertheless nice to know that there are such. Also, they are not really more complicated than the derivative counterparts. On the contrary; the author honestly thinks that they are in fact easier to remember. One of the downsides of the divided difference identities is however that they are usually not symmetric with respect to the sequence $x_0, x_1, \dots, x_n$ anymore. That's life.

Proposition 4.18. *Let n, k, f, g, $f_1, f_2, \dots, f_k$ and $x_0, x_1, \dots, x_n$ be such that the folliowing identities make sense.*

(i) (Newton expansion)

$$\begin{aligned} f(x) = {} & [x_0]_f + [x_0, x_1]_f(x - x_0) + [x_0, x_1, x_2]_f(x - x_0)(x - x_1) + \dots \\ & + [x_0, x_1, \dots, x_n]_f(x - x_0)(x - x_1)\cdots(x - x_{n-1}) \\ & + [x, x_0, x_1, \dots, x_n]_f(x - x_0)(x - x_1)\cdots(x - x_n), \end{aligned} \tag{4.19}$$

in particular, if the points coincide we get the familiar Taylor expansion

$$f(x) = \sum_{k=0}^{n-1} \frac{f^{(k)}(x_0)}{k!} + [x, x_0, x_0, \dots, x_0]_f(x - x_0)^n, \tag{4.20}$$

(ii) (Product rule)

$$[x_0, x_1]_{fg} = [x_0]_f[x_0, x_1]_g + [x_0, x_1]_f[x_1]_g.$$

(iii) (Leibniz rule)

$$\begin{aligned} [x_0, x_1, \dots, x_n]_{fg} = {} & [x_0]_f[x_0, \dots, x_n]_g + [x_0, x_1]_f[x_1, \dots, x_n]_g + \dots \\ & + [x_0, x_1, \dots, x_{n-1}]_f[x_{n-1}, x_n]_g + [x_0, x_1, \dots, x_n]_f[x_n]_g. \end{aligned} \tag{4.21}$$

More generally

$$[x_0, x_1, \ldots, x_n]_{f_1 f_2 \cdots f_k} = \sum_{0=i_0<i_1<i_2<\ldots<i_{k-1}<i_k=n} \prod_{j=1}^{k} [x_{i_{j-1},\ldots,x_{i_j}}]_{f_j}$$

(iv) (Chain rule)

$$[x_0, x_1]_{f\circ g} = [g(x_0), g(x_1)]_f [x_0, x_1]_g$$

(v) (Faà di Bruno formula)

$$[x_0, x_1, \ldots, x_n]_{f\circ g}$$
$$= \sum_{k=1}^{n} \sum_{0=i_0<i_1<i_2<\ldots<i_{k-1}<i_k=n} [g(x_{i_0}), g(x_{i_1}) \ldots, g(x_{i_k})]_f \prod_{j=1}^{k} [x_{i_{j-1},\ldots,x_{i_j}}]_g$$

Proof sketches. (i) Easy induction using 4.6. Notice that also this formula makes it clear that the divided difference agrees with the degree n coefficient of the interpolating polynomial.

(ii) Easy to check.

(iii) Induction using the product rule (i.e. the case $n = 1$) and the nesting rule 4.7. Alternatively one could write Newton expansions of both f and g with sequences $(x_0, x_1, \ldots, x_n)$ and $(x_n, x_{n-1}, \ldots, x_0)$ and notice that the given sum gives exactly the leading term of the interpolating polynomial of fg. The more general case follows from the case of two functions by induction.

(iv) Easy to check.

(v) A bit tedious induction using the Leibniz rule and 4.6.

□

One might ask under what kind of conditions 4.19 leads to Newton series, i.e. we have

$$f(z) = \sum_{i=0}^{\infty} [z_0, z_1, \ldots, z_i](z - z_0)(z - x_0) \cdots (z - z_{i-1}), \tag{4.22}$$

for some sequence $x_0, x_1, \ldots$ and analytic f. While Newton series can be globally rather subtle, locally they work almost like Taylor series.

Proposition 4.23. *Let $f : \mathbb{D}(w_0, \rho) \to \mathbb{C}$ be analytic and $z_0, z_1, \ldots \in \mathbb{D}(w_0, r)$ sequence converging to w_0. Then 4.22 holds for any $z \in \mathbb{D}(w_0, r)$.*

Proof. We simply need to verify that the error term $[z, z_0, z_1, \ldots, z_n]_f (z - z_0)(z - z_1) \cdots (z - z_n)$ tends to zero as $n \to \infty$. But for any $\rho' < \rho$ such that $z, z_i \in \mathbb{D}(w_0, \rho')$ for any $i \geq 0$ we have

$$\begin{aligned}&[z, z_0, z_1, \ldots, z_n]_f (z - z_0)(z - z_1) \cdots (z - z_n) \\ =&\frac{1}{2\pi i} \int_{\partial \mathbb{D}(w_0, \rho')} \frac{(z - z_0)(z - z_1) \cdots (z - z_n)}{(w - z)(w - z_0)(w - z_1) \cdots (w - z_n)} f(w) dw.\end{aligned}$$

But as $z_n \to w_0$, absolute values the quotients $(z - z_n)/(w - z_n)$ tend to $|z - w_0|/|\rho'| < 1$, uniformly on $\partial \mathbb{D}(w_0, \rho')$ and hence the integrand tends uniformly to 0. □

In similar vein one could prove that if f is entire, its Newton series converge whenever $(z_i)_{i \geq 0}$ is bounded.

4.2.5 k-tone functions

Definition 4.24. $f : (a, b) \to \mathbb{R}$ is called k-tone if for any $x_0, x_1, \ldots, x_n \in (a, b)$ of distinct points we have

$$[x_0, x_1, \ldots, x_n]_f \geq 0,$$

i.e. the n'th divided difference is non-negative.

We denote the space of k-tone functions by on interval (a, b) by $P^{(k)}(a, b)$.

Theorem 4.25. *Let k be an non-negative integer and (a, b) an open interval. Then $P^{(k)}(a, b) \subset \mathbb{R}^{(a,b)}$ is closed convex cone.*

Proof. This is clear. □

Mean value theorem tells us that C^k k-tone functions are exactly the functions with non-negative k'th derivative.

The cones $P^{(k)}(a, b)$ aren't quite salient. Instead we have

$$[\cdot, \cdot, \ldots, \cdot]_f = 0 \Leftrightarrow \ f \text{ is a polynomial of degree less than } k.$$

This suggests that better object of study should be $\mathbb{R}^{(a,b)}$ quotiented by polynomials of degree less than k. We won't follow that trail.

4.3 Locality

One of the properties of the divided differences, which might not be clear from the definition, is that they can also be used to model local phenomena. One of the important properties of the k-tone functions is that if a function is k-tone on two overlapping intervals, then the function is k-tone on their union. While this definitely holds for C^k functions, it's not really clear how to change this argument for the general case.

If one thinks that k-tone functions have k'th derivative as a positive measure, the locality property should be a special case of the general property of distributions.

Proposition 4.26. *Let $a < c < b < d$ and μ distribution on (a, d), restriction of which to (a, b) and (c, d) is a positive measure. Then μ is a positive measure.*

Proof. We should prove that $\mu(f)$ is non-negative for every non-negative test function f on (a, d). But every such function can be written as sum of two non-negative test functions, f_1 and f_2, f_1 supported on (a, b) and f_2 on (c, d), so $\mu(f) = \mu(f_1) + \mu(f_2) \geq 0$ by the assumption. □

They key idea in the proof was to split the test functions to two parts, one supported on (a, b) and one on (c, d). One can do the same with Peano kernels, except larger the order k, the more parts we need.

Lemma 4.27. *Let $a < c < b < d$ be reals and w a Peano kernel supported on (a, d). Then w can written as a (finite) weighted average of Peano kernels, all of which are supported either on (a, b) or on (c, d).*

Proof. Let n be the order of the Peano kernel and let $a < x_0 < x_1 < \ldots < x_n < d$ be the nodes or w.

The case $n = 1$ is rather clear: we simply split characteristic function of an interval to characteristic function of two intervals. TODO: picture. In terms of the kernels, if $a < x_0 < c < b < x_1 < d$, we can pick $c < y_0 < b$ and write

$$w_{x_0,x_1} = \frac{y_0 - x_0}{x_1 - x_0} w_{x_0,y_0} + \frac{x_1 - y_0}{x_1 - x_0} w_{y_0,x_1} :$$

this is a sought decomposition.

When $n = 2$ the goal is not much harder. Peano kernels of order 2 are essentially triangles sitting on x-axis, corners of which have distinct x-coordinates. So we have one such triangle and we should split it to smaller triangles in such a way that

- No triangle has two equal x-coordinates.
- All triangles have all their corners' x-coordinates either on (a, b) and (c, d).

TODO: picture We call such triangles good. While the above picture should be rather convincing already, one can write an general algorithm generating such decomposition.
Input: A triangle (Peano kernel of order 2) supported on (a, d).
Output: Decomposition of the input as positive linear combination of triangles all supported completely either on (a, b) or (c, d).

Step 1. If the triangle is good already, we are done.

Step 2. Pick $y_0 \in (c, b)$, which does not coincide any of the x_0, x_1, x_2.

Step 3. Divide the triangle to two triagles with x-coordinates (x_0, x_1, y_0) and (x_1, y_0, x_2), as illustrated.

Step 4. Run this algorithm recursively for these two triangles.

Why does this algorithm terminate? Note that if any of the x_i's are in (c, b), the triangle is either good or $x_1 \in (c, b)$ (or maybe both). In the former case we are done, and in the latter the two parts of the split are both good. If none of x_i's are in (c, b), both of the parts of the split has a coordinate in (c, b), so also this case leads to a good split. In other words we can keep splitting triangles in such a way that they either become good or they have more nodes on (c, b).

It's easy to verify that splitting the triangle corresponds to the identity

$$w_{x_0,x_1,x_2} = \frac{y_0 - x_0}{x_2 - x_0} w_{x_0,x_1,y_0} + \frac{x_1 - y_0}{x_2 - x_0} w_{x_1,y_0,x_2}.$$

When $n > 2$ geometric picture is largely lost (at least by the author), but the algebra generalizes perfectly: we can still split Peano kernels using the following identity:

$$w_{x_0,x_1,\ldots,x_n} = \frac{y_0 - x_0}{x_n - x_0} w_{x_0,x_1,\ldots,x_{n-1},y_0} + \frac{x_n - y_0}{x_n - x_0} w_{x_1,\ldots,x_n,y_0}. \tag{4.28}$$

Where does this come from? Recall that the Peano kernels are nothing more than the divided differences of the functions $g_{t,n} = \frac{1}{(n-1)!}((\cdot - t)_+)^{n-1},$. The first identity immediately generalizes

$$[x_0, x_1]_f = \frac{y_0 - x_0}{x_1 - x_0}[x_0, y_0]_f + \frac{x_1 - y_0}{x_1 - x_0}[y_0, x_1]_f,$$

where f is now any function. By the nesting property the identity 4.28 is nothing more than the previous identity applied to $f = [\cdot, x_1, \ldots, x_{n-1}]_{g_{t,n}}$. Note that we need $x_0 < y_0 < x_n$, so that the weighted average is really a convex combination.

Now we are ready to generalize the algorighm to bigger n:
Input: Peano kernel of order n supported on (a, d).
Output: Decomposition of the input as positive linear combination of Peano Kernels of order n, all supported completely either on (a, b) or (c, d).

Step 1. If the kernel is good already, we are done.

Step 2. Pick $y_0 \in (c, b)$, which does not coincide any of the $x_0, x_1, \ldots, x_n$.

Step 3. Divide the kernel to two kernels with nodes $(x_0, x_1, \ldots, x_n, y_0)$ and $(y_0, x_1, \ldots, x_n)$ as in the 4.28.

Step 4. Run this algorithm recursively for these two kernels.

This algorithm terminates basically because of the same reason: if the kernel isn't good already, the two splits have more nodes on (c, b), and this quantity cannot increase forever. TODO: figure □

While this property is of independent interest, the real use of it is its generalization to divided differences.

Lemma 4.29. *Let $a < c < b < d$ be reals and $x_0, x_1, \ldots, x_n \in (a, d)$. Then we may find $N, M \in \mathbb{N}$, sequences $(y_{0,i}, \ldots, y_{n,i})$ and $(z_{0,j}, \ldots, z_{n,j})$ and numbers p_i and q_j for $1 \leq i \leq N$ and $1 \leq j \leq M$, such that*

- $\sum_{i=1}^{N} p_i + \sum_{j=1}^{M} q_j = 1$ *and $p_i, q_j \geq 0$ for every $1 \leq i \leq N$ and $1 \leq j \leq M$.*
- $y_{0,i}, y_{1,i}, \ldots, y_{n,i}$ *are pairwise distinct elements of (a, b) for every $1 \leq i \leq N$.*
- $z_{0,j}, z_{1,j}, \ldots, z_{n,j}$ *are pairwise distinct elements of (c, d) for every $1 \leq i \leq M$.*
- *For every $f : (a, d) \to \mathbb{R}$ we have*

$$[x_0, x_1, \ldots, x_n]_f = \sum_{i=1}^{N} p_i [y_{0,i}, y_{1,i}, \ldots, y_{n,i}]_f + \sum_{j=1}^{M} q_j [z_{0,j}, z_{1,j}, \ldots, z_{n,j}]_f.$$

Proof. Proof is almost identical to that of the lemma 4.27: we more or less just replace the identity 4.28 by

$$[x_0, x_1, \ldots, x_n]_f = \frac{y_0 - x_0}{x_n - x_0} [x_0, x_1, \ldots, x_{n-1}, y_0]_f + \frac{x_n - y_0}{x_n - x_0} [x_1, \ldots, x_n, y_0]_f, \tag{4.30}$$

which is valid because of essentially the same reasoning, and replace the word "kernel" with word "tuple". □

We are now ready to prove the locality property of the k-tone functions.

Proposition 4.31. *$P^{(k)}$ is a local property i.e. $P^{(k)}(a, b) \cap P^{(k)}(c, d) \subset P^{(k)}(a, d)$ for any $-\infty \leq a \leq c < b \leq d \leq \infty$. To be more precise, if $f : (a, d) \to \mathbb{R}$ such that $f\big|_{(a,b)} \in P^{(k)}(a, b)$ and $f\big|_{(c,d)} \in P^{(k)}(c, d)$, then $f \in P^{(k)}(a, d)$.*

Proof. This follows immediately from lemma 4.29. □

Note that we could have also used the splitting property 4.30 to slightly simplify the proof of theorem 4.9. In the induction step we managed to prove that we have

$$[x_0, x_1, \ldots, x_{n-1}, t]_{g_{t,n}} = \frac{1}{n-1}[x_0, x_1, \ldots, x_{n-1}]_{g_{t,n-1}} = \frac{1}{n-1} w_{x_0,\ldots,x_{n-1}}(t) \geq 0$$

for any $x_0, x_1, \ldots, x_{n-1}$. But this readily implies that the divided differences are non-negative on all tuples as we have

$$\begin{aligned}
w_{x_0,x_1,\ldots,x_{n-1},x_n} &= [x_0, x_1, \ldots, x_{n-1}, x_n]_{g_{t,n}} \\
&= \frac{t-x_0}{x_n-x_0}[x_0, x_1, \ldots, x_{n-1}, t]_{g_{t,n}} + \frac{x_n-t}{x_n-x_0}[x_1, \ldots, x_n, t]_{g_{t,n}} \\
&= \frac{1}{n-1}\frac{t-x_0}{x_n-x_0}[x_0, x_1, \ldots, x_{n-1}]_{g_{t,n-1}} + \frac{1}{n-1}\frac{x_n-t}{x_n-x_0}[x_1, \ldots, x_n]_{g_{t,n-1}} \\
&= \frac{1}{n-1}\frac{t-x_0}{x_n-x_0} w_{x_0,x_1,\ldots,x_{n-1}} + \frac{1}{n-1}\frac{x_n-t}{x_n-x_0} w_{x_1,\ldots,x_n} \\
&\geq 0.
\end{aligned}$$

Of course, this approach only works if $\min(x_i) \leq t \leq \max(x_i)$, but if this is not the case, as observed, the divided differences are zero anyway. The previous identity can be also used to recursively compute Peano kernels.

Remark 4.32. The previous arguments are a bit awkward and one might be tempted to think that one should instead consider positive linear combinations of Peano Kernels, called (positive) splines, to get better analogue for the "locality of distributions" -proof. For $k \leq 3$ positive splines can be also characterized as suitable non-negative piecewise polynomial functions, but for $k > 3$ there's a problem: positive splines are merely subclass thereof.

4.4 Regularity

The real power of the divided differences comes in when they are used to carry regularity information.

Theorem 4.33. *Let $k \geq 2$. Then $f \in P^{(k)}(a, b)$, if and only if $f \in C^{k-2}(a, b)$ and $f^{(k-2)}$ is convex.*

"Proof". Let $f \in P^{(k)}(a, b)$. Since $f^{(k)}$ is a positive measure, $f^{(k-1)}$ is increasing and $f^{(k-2)}$ is convex. As convex functions are continuous, we are done with $\Rightarrow$. Conversely, if $f \in C^{k-2}(a, b)$ and $f^{(k-2)}$ is convex, then $f^{(k-2)}$ has second derivative as a positive measure. But this measure is also the k'th derivative of f, so $f \in P^{(k)}(a, b)$. □

Even though the previous argument isn't exactly sound (at least given our current machinery), the result is true. In this section we will translate the proof to the language of the divided differences.

The first step is to connect the divided differences of a function to the divided differences (of one lower order) of the derivative.

Lemma 4.34. *Let $f \in C^1(a,b)$. Then for any (pairwise distinct) $x_0, x_1, \ldots, x_n \in (a,b)$ we have*

$$[x_0, x_1, \ldots, x_{n-1}]_{f'} = \sum_{i=0}^{n-1} [x_0, x_1, \ldots, x_{i-1}, x_i, x_i, x_{i+1}, \ldots, x_{n-1}]_f \tag{4.35}$$

and

$$\begin{aligned} [x_0, x_1, \ldots, x_n]_f &= \int_0^1 [x_0, x_1, \ldots, x_{n-1}]_{f'(s\cdot+(1-s)x_n)} ds \\ &= \int_0^1 [sx_0 + (1-s)x_n, \ldots, sx_{n-1} + (1-s)x_n]_{f'} s^{n-1} ds. \end{aligned} \tag{4.36}$$

Proof. Note that divided differences of f have repeated entries in the first identity. As mentioned, these values of the divided difference are defined as a continuous extension. We will take the existence of this extension given for now.

We have

$$\begin{aligned} [x_0, x_1, \ldots, x_{n-1}]_{f'} &= \lim_{h \to 0} [x_0, x_1, \ldots, x_{n-1}]_{\frac{f(\cdot+h)-f(\cdot)}{h}} \\ &= \lim_{h \to 0} \frac{[x_0, x_1, \ldots, x_{n-1}]_{f(\cdot+h)} - [x_0, x_1, \ldots, x_{n-1}]_f}{h} \\ &= \lim_{h \to 0} \frac{[x_0 + h, x_1 + h, \ldots, x_{n-1} + h]_f - [x_0, x_1, \ldots, x_{n-1}]_f}{h}. \end{aligned}$$

Now the approach is basically the same as with differentiation of multivariate functions: we write the difference as sum of n differences: the difference can be expressed as sum of differences where only one of the entries are changed at a time.

$$\begin{aligned}
&\lim_{h\to 0} \frac{[x_0+h, x_1+h, \ldots, x_{n-1}+h]_f - [x_0, x_1, \ldots, x_{n-1}]_f}{h} \\
=&\lim_{h\to 0} \Bigg(\frac{[x_0+h, x_1+h, \ldots, x_{n-1}+h]_f - [x_0+h, x_1+h, \ldots, x_{n-2}+h, x_{n-1}]_f}{h} \\
+&\frac{[x_0+h, x_1+h, \ldots, x_{n-2}+h, x_{n-1}]_f - [x_0+h, x_1+h, \ldots, x_{n-2}, x_{n-1}]_f}{h} \\
+&\ldots \\
+&\frac{[x_0+h, x_1, \ldots, x_{n-1}]_f - [x_0, x_1, \ldots, x_{n-1}]_f}{h} \Bigg) \\
&= \lim_{h\to 0} \left(\sum_{i=0}^{n} [x_0+h, \ldots, x_{i-1}+h, x_i+h, x_i, x_{i+1}, \ldots, x_{n-1}]_f \right).
\end{aligned}$$

Now assuming the claim on the continuity, the limit is exactly what we wanted.

First equality of second claim was already essentially proved in the proof of theorem 4.9; the second is a simple computation. □

Note that the proof essentially gives also the following identity.

Proposition 4.37. *Let $x_0, x_1, \ldots, x_n$ and $y_0, y_1, \ldots, y_n$ be pairwise distinct points on (a,b). Then for any $f : (a,b) \to \mathbb{R}$ we have*

$$[y_0, y_1, \ldots, y_{n-1}]_f - [x_0, x_1, \ldots, x_{n-1}]_f = \sum_{i=0}^{n-1} [x_0, \ldots, x_{i-1}, x_i, y_i, y_{i+1}, \ldots, y_{n-1}]_f (y_i - x_i).$$

Next step is to connect the regularity of divided differences to regularity of divided differences of the derivative. Denote

$$D_{n,m} = \{x \in \mathbb{R}^n | x_{i_1} = x_{i_2} = \ldots = x_{i_m} \text{ for some } 1 \leq i_1 < i_2 < \ldots < i_m \leq n\}.$$

Note that $D_{n+1,2}$ is exactly the set where the divided differences aren't defined. Still, if f is smooth enough, we should be able to continuosly extend the divided differences to this set, or at least to some subset set of it. This thinking leads to the following notion of the regularity of a function.

Definition 4.38. Let $f : (a,b) \to \mathbb{R}$ and $k \geq 0$. We call f *weakly* C^k (on (a,b)), or write $f \in C^k_w(a,b)$, if its order k divided differences can be continuosly extended to $(a,b)^{k+1}$.

Our aim is to prove that function is weakly C^k, if and only if it's C^k. Note that this trivially holds for $k = 0$.

Lemma 4.39. *Let $n \geq k$. Then $f \in C_w^k(a,b)$, if and only if the order n divided differences of f extend continuously to $(a,b)^{n+1} \setminus D_{n+1,k+2}$.*

Proof. Let us denote

$S(n,k,f) =$ "order n divided differences of f extend continuously to $(a,b)^{n+1} \setminus D_{n+1,k+2}$".

As $S(k,k,f)$ is just saying that $f \in C_w^k(a,b)$, it is enough to prove that for any $n > k$ we have $S(n-1,k,f) \Leftrightarrow S(n,k,f)$.

$\Rightarrow$: assume that $S(n-1,k,f)$, i.e. order $n-1$ divided differences of f extend continuously to $(a,b)^n \setminus D_{n,k+2}$. Now take any $(x_0, x_1, \ldots, x_n) \in (a,b)^{n+1} \setminus D_{n+1,k+2}$. Consider any sequence of tuples $(y_{0,j}, y_{1,j}, \ldots, y_{n,j})_{j=1}^{\mathbb{N}}$ such that $(y_{i,j}) \to x_i$ as $j \to \infty$ for every $0 \leq i \leq n$ and for every fixed $j \in \mathbb{N}$. We should prove that the sequence

$$([y_{0,j}, y_{1,j}, \ldots, y_{n,j}]_f)_{j=1}^{\mathbb{N}}$$

converges. By permutation we may assume that $x_0 \neq x_n$. But since

$$[y_{0,j}, y_{1,j}, \ldots, y_{n,j}]_f = \frac{[y_{0,j}, y_{1,j}, \ldots, y_{n-1,j}]_f - [y_{1,j}, y_{2,j}, \ldots, y_{n,j}]_f}{y_{0,j} - y_{n,j}},$$

$(y_{0,j}, \ldots, y_{n-1,j}), (y_{1,j}, \ldots, y_{n,j}) \in (a,b)^n \setminus D_{n,k+2}$ for every $j \in \mathbb{N}$, and these sequences converge, we see that the divided differences in the numerator converge. As also the denominator converges to non-zero number, the whole expression converges, and hence $S(n,k,f)$

$\Leftarrow$: Assume then that $S(n,k,f)$. Take any sequence $(y_{0,j}, y_{1,j}, \ldots, y_{n-1,j})_{j=1}^{\mathbb{N}}$ converging to $(x_0, x_1, \ldots, x_{n-1}) \in (a,b)^n \setminus D_{n,k+2}$ and choose additional sequence $(z_0, z_1, \ldots, z_{n-1})$ of pairwise distinct points distinct from all the x_i's and $y_{i,j}$'s. Now we can write

$$[y_{0,j}, \ldots, y_{n-1,j}]_f = [z_0, z_1, \ldots, z_{n-1}]_f + \sum_{i=0}^{n-1} [z_0, \ldots, z_{i-1} z_i, y_{i,j}, y_{i+1,j}, \ldots, y_{n-1,j}]_f (y_{i,j} - z_i).$$

As by the induction hypothesis the right-hand side converges, so does the left-hand side, and hence $S(n-1,k,f)$. $\square$

Theorem 4.40. *Let $f : (a,b) \to \mathbb{R}$, $k \geq 1$. Then $f \in C_w^k(a,b)$, if and only if $f \in C^1(a,b)$ and $f' \in C_w^{k-1}(a,b)$.*

Proof. We start with the "$\Rightarrow$"-direction.

Let's start by proving that f is continuouly differentiable. Lemma 4.39 easily implies that it is sufficient prove this for the case $k = 1$. But in this case we now that the limits

$\lim_{x\to x_0}[x,x_0]_f = [x_0,x_0]_f$ exist and f is hence differentiable with $f'(x) = [x,x]_f$. Also, $x \mapsto [x,x]_f = f'(x)$ is continuous.

Now the identity 4.35 easily implies the claim.

For the "$\Leftarrow$"-direction take any sequence $(y_{0,j},\ldots,y_{k,j})_{j=1}^{\mathbb{N}}$ of elements of $(a,b)^{k+1}$ converging to $(x_0,\ldots,x_k) \in (a,b)^{k+1}$. Now by 4.36

$$[y_{0,j},y_{1,j},\ldots,y_{k,j}]_f = \int_0^1 [sy_{0,j}+(1-s)y_{k,j},\ldots,sy_{k-1,j}+(1-s)y_{k,j}]_{f'}s^{k-1}ds$$

As $j \to \infty$,, we have $(y_{0,j},\ldots,y_{n,j}) \to (x_0,x_1,\ldots,x_k)$ and hence also $(sy_{0,j}+(1-s)y_{k,j},\ldots,sy_{k-1,j}+(1-s)y_{k,j}) \to (sx_0+(1-s)x_n,\ldots,sx_{n-1}+(1-s)x_k)$ uniformly (over s). As $(n-1)$'th divided differences of f' extend continuosly, they are uniformly continuous over all the compact sets, so in particular the integrand converges uniformly to

$$[sx_0+(1-s)x_n,\ldots,sx_{n-1}+(1-s)x_k]_{f'}s^{n-1},$$

and hence also the integral converges, which was to be shown. □

Corollary 4.41. *$f \in C_w^k(a,b)$ if and only if $f \in C^k(a,b)$.*

Proof. Simply apply lemma 4.40 inductively. □

Just like one can carry regularity information, one can carry boundedness information.

Lemma 4.42. *Let $f:(a,b)\to\mathbb{R}$ and $n \geq 2$. Then the n'th order divided differences of f are bounded, if and only if $f \in C^1$ and the order $(n-1)$ divided differences of f' are bounded. Moreover, the bounds satisfy*

$$\sup_{a<x_0<x_1<\ldots<x_{n-1}<b} |[x_0,x_1,\ldots,x_{n-1}]_{f'}| = n \sup_{a<x_0<x_1<\ldots<x_n<b} |[x_0,x_1,\ldots,x_n]_f|$$

Proof. The bounds follow rather immediately from the identities 4.35 and 4.36, so it only remains to verify that $f \in C^1$ given the conditions. Since the n'th divided difference corresponds to n'th derivative, if it is bounded, $(n-1)$'th derivative should be continuous. Thus we should prove that this is indeed the case by proving that $(n-1)$'th divided differences of f extend continuously to the whole of $(a,b)^n$.

Note that lemma 4.37 immediately implies that $(n-1)$'th divided difference of f is Lipschitz. But Lipschitz functions can be always extended as Lipschitz functions, so we are done by lemma 4.40. □

Theorem 4.43. *Let $f : (a,b) \to \mathbb{R}$ and $n \geq 1$. Then $f \in C^{n-1}(a,b)$ and $f^{(n-1)}$ is Lipschitz, if and only if n:th divided difference of f is bounded. Moreover,*

$$\sup_{a<x_0<x_1<\ldots<x_n<b} |[x_0, x_1, \ldots, x_n]_f| = \frac{\mathrm{Lip}(f^{(n-1)})}{n!}$$

Proof. Again, simply apply lemma 4.42 inductively. □

Finally, one can carry positivity.

Lemma 4.44. *Let $f : (a,b) \to \mathbb{R}$ and $k \geq 3$. Then f is k-tone, if and only if $f' \in C^1(a,b)$ and f' is $(k-1)$-tone.*

Proof. Again, only the claim on the regularity is non-trivial as the k-tone claim follows easily from 4.35 and 4.36. As with the bounded case the idea is that if f is k-tone $f^{(k)}$ is positive and hence $f^{(k-1)}$ is increasing, and consequently locally bounded. We should hence prove that the $(n-1)$'th divided differences are bounded, as then 4.42 would imply the claim. But this follow easily from 4.37. □

With such tools we are ready to tackle the regularity of k-tone functions.

Proof of the theorem 4.33. Yet again, simply apply lemma 4.44 inductively. □

4.5 Analyticity and Bernstein's theorem

Theorem 4.45. *Let $f : (a,b) \to \mathbb{R}$. Then f is real analytic, if and only if for every closed subinteval $[c,d]$ of (a,b) there exists constant c such that for any $n \geq 1$*

$$\sup_{a<x_0<x_1<\ldots<x_n<b} |[x_0, x_1, \ldots, x_n]_f| \leq c^{n+1}.$$

Proof. Let's first prove that "if"-direction. We need to prove that the for any $x_0 \in (a,b)$ Taylor series at x_0 converges in some neighbourhood of x_0. As observed before, the n:th error term in Taylor series is given by

$$[x, x_0, x_0, \ldots, x_0]_f (x - x_0)^n$$

with n x_0's. Now choose $a < c < x_0 < d < b$ and take any x with $x \in [c,d]$ and $|x - x_0|c < 1$, where c is given by the assumption for interval c, d. But then the error term tends to zero and we are done.

For the other direction note that if $x_0 \in (a,b)$ and f extends to analytic function on $\mathbb{D}(x_0,r)$, we definititely have $\left|\frac{f^{(n)}(x_0)}{n!}\right| \leq c^{n+1}$ for some c. If $|x-x_0|<r$ we have

$$\frac{f^{(k)}(x)}{k!} = \sum_{n=k}^{\infty} \binom{n}{k} \frac{f^{(n)}(x_0)}{n!}(x-x_0)^{n-k},$$

which may be estimated by

$$\left|\frac{f^{(k)}(x)}{k!}\right| \leq c^{k+1} \sum_{n=k}^{\infty} \binom{n}{k} c^{n-k}(x-x_0)^{n-k} = \frac{c^{k+1}}{(1-|x-x_0|c)^k},$$

whenever $|x-x_0|c<1$. By the mean value theorem for divided differences it follows that we get required bound for some neighbourhood of x_0 and consequently, by compactness for any closed subinteval of (a,b). $\square$

The previous result is some kind of relative of 4.43. Also theorem 4.33 has rather interesting relative.

Theorem 4.46. *[Bernstein's theorem] If $f:(a,b)\to\mathbb{R}$ is k-tone for every $k\geq 0$, then f is real-analytic on (a,b).*

Proof. We prove that the conditions of the theorem 4.45 are satisfied. Pick any $a<x_0<x<b$. Now for any $n\geq 0$ we have

$$f(x) = \sum_{k=0}^{n-1} \frac{f^{(k)}(x_0)}{k!}(x-x_0)^k + \frac{f^{(n)}(x_0)}{n!}(x-x_0)^n + [x,x_0,x_0,\ldots,x_0]_f(x-x_0)^{n+1}.$$

Note that all the terms on the right-hand side are non-negative, and hence

$$0 \leq \frac{f^{(n)}(x_0)}{n!} \leq f(x)(x-x_0)^{-n}.$$

Now given any interval $[c,d]\subset(a,b)$ we can make such estimate uniform over $x_0\in[c,d]$ simply by picking $x\in(d,b)$, and we are done. $\square$

4.6 Notes and references

Chapter 5

Matrix monotone functions – part 2

5.1 Main theorem

Let's come back to theorem 3.15: with the k-tone language it rewrites to

Theorem 5.1. *$f \in P_n(a,b)$, if and only if $fN(q)$ is $(2n-1)$-tone for any $q \in \mathbb{C}_{n-1}[x]$.*

This is the correct interpretation and it makes sense without regularity issues. There's also many different ways to talk about the polynomial part.

Lemma 5.2. *Let $h : \mathbb{C} \to \mathbb{C}$ and $n \geq 1$. Then the following are equivalent.*

(i) h is polynomial non-negative on real line and of degree less than $2n$.

(ii) There exists complex polynomial of degree less than n such that $h = N(q)$.

(iii) There exists two real polynomials q_1 and q_2 of degree less than n such that $h = q_1^2 + q_2^2$.

Proof. $(i) \Rightarrow (ii)$: If h is non-negative on real axis, it's roots all appear in pairs (which there are less than n): either with strict complex conjugate pairs, of pairs of double real roots. We may take q to be $\sqrt{a_n}\prod(z - z_i)$ where z_i range over representatives of all the pairs and a_n is the leading coefficient of h.

$(ii) \Rightarrow (iii)$: If q has single conjugate pair $(z_0, \overline{z_0})$ of roots we have

$$(z - z_0)(z - \overline{z_0}) = z^2 - 2\Re(z_0) + |z_0|^2 = (z - \Re(z_0))^2 + \Im(z_0)^2,$$

so we may take $q_1 = \cdot - \Re(z_0)$ and $q_2 = \Im(z_0)$. But if $N(q) = q_1^2 + q_2^2$ and $N(r) = r_1^2 + r_2^2$, then

$$N(qr) = N(q)N(r) = (q_1 r_1 + q_2 r_2)^2 + (q_1 r_2 - q_2 r_1)^2,$$

so polynomial of higher order can be dealt with inductively.

$(iii) \Rightarrow (i)$: This is clear. $\square$

Theorem 5.1 gives also a resolution to the regularity issues of its predecessor, theorem 3.15. Recall that $(2n-1)$-tone functions are C^{2n-3} and their $(2n-3)$'th derivative is convex. As convex functions are twice differentiable almost everywhere, $fN(q)$ is $(2n-1)$ times differentiable almost everywhere.

Aim of this chapter is to give a honest proof for 5.1: we aim to prove that given $n \geq 1$, open interval (a,b) and $f : (a,b) \to \mathbb{R}$, we have

$$\begin{aligned} &f \in P_n(a,b) \\ \Leftrightarrow &[x_0, x_1, x_2, \ldots, x_{2n-1}]_{fN(q)} \text{ for any } q \in \mathbb{C}_{n-1}[x] \text{ and } a < x_0 < \ldots < x_{2n-1} < b. \end{aligned}$$

Note that the proof of 3.15 can be interpreted as saying

$$\begin{aligned} &Df_A(H) \geq 0 \text{ for any } A \in \mathcal{H}_{(a,b)} \text{ and } H \geq 0 \text{ with } \operatorname{rank}(H) = 1 \\ \Leftrightarrow &[\lambda_1, \lambda_1, \ldots, \lambda_{2n}, \lambda_{2n}]_{fN(q)} \text{ for any } q \in \mathbb{C}_{n-1}[x] \text{ and } a < \lambda_1 < \ldots < \lambda_n < b. \end{aligned}$$

The idea of the proof was to note that the quadratic form of the derivative rewrites to such divided difference, and λ's are the eigenvalues of A.

To avoid regularity issues we simply do the same thing without limits.

Definition 5.3. Let us call pair $(A, B, v) \in \mathcal{H}(V)^2 \times V$ a **projection pair** if $B - A = vv^*$. Let us further say that a projection pair (A, B, v) is **strict**, if v is not orthogonal to any eigenvector of A.

Lemma 5.4. *If $a < \lambda_1 < \lambda_2 < \ldots < \lambda_{2n-1} < \lambda_{2n} < b$ and $q \in \mathbb{C}_{n-1}[x]$, we may find a strict projection pair (A, B, v) such that*

$$\langle (f(B) - f(A))w, w \rangle = [\lambda_1, \lambda_2, \lambda_3, \lambda_4, \ldots, \lambda_{2n-1}, \lambda_{2n}]_{fN(q)}$$

for any $f : (a,b) \to \mathbb{R}$.

Conversely, if (A, B, v) is a strict projection pair and $w \in V$, then there exists $a < \lambda_1 < \lambda_2 < \ldots < \lambda_{2n-1} < \lambda_{2n} < b$ and polynomial $q \in \mathbb{C}_{n-1}[x]$, such that for any $f : (a,b) \to \mathbb{R}$ we have

$$\langle (f(B) - f(A))w, w \rangle = [\lambda_1, \lambda_2, \lambda_3, \lambda_4, \ldots, \lambda_{2n-1}, \lambda_{2n}]_{fN(q)}.$$

Before trying to understanding the lemma we use it to prove theorem 5.1.

Proof. Assume first that $f \in P_n(a,b)$. We need to prove that $fN(q)$ is $(2n-1)$-tone for any $q \in \mathbb{C}_{n-1}[x]$ But any divided difference of such $fN(q)$ can be expressed by the main lemma 5.4 as $\langle (f(B) - f(A))w, w \rangle$ for some projection pair (A, B, v), and the previous is non-negative by the assumption.

Conversely, assume that fh is $(2n-1)$-tone for any suitable h and take any $A \leq B$. Write $B - A = \sum_{i=1}^{n} c_i P_{v_i}$ for some $c_i \geq 0$. To prove that $f(B) - f(A) \geq 0$ we simply need to prove that $f(A + \sum_{i=1}^{k} c_i P_{v_i}) - f(A + \sum_{i=1}^{k-1} c_i P_{v_i}) \geq 0$ for any $1 \leq k \leq n$, as $f(B) - f(A)$ is sum of such terms. We may hence assume that (A, B, v) projection pair.

We may also assume that (A, B, v) is strict. Indeed, if this would not be the case, we could decompose $V = (v_1) \oplus V'$, where v_1 is the eigenvector, and factorize $A = A_{(v_1)} \oplus A_{V'}$ and $B = A_{(v_1)} \oplus B_{V'}$. But now $f(B) - f(A) \geq 0$, if and only if$f(B_{V'}) - f(A_{V'}) \geq 0$, which would follow if we could prove that $f \in P_{n-1}(a, b)$. So we should just add the sentence "We induct on n." as the first sentence of this proof.

Finally in the strict case, by the lemma 5.4 we may find $a < \lambda_1 < \lambda_2 < \ldots < \lambda_{2n-1} < \lambda_{2n} < b$ and $q \in \mathbb{C}_{n-1}[x]$ such that

$$\langle (f(B) - f(A))w, w \rangle = [\lambda_1, \lambda_2, \lambda_3, \lambda_4, \ldots, \lambda_{2n-1}, \lambda_{2n}]_{fN(q)} \geq 0$$

and we are finally done.

In the "if"-direction we could have alternatively made use of the continuity of f, which is guaranteed by the lemma 4.33

$\square$

5.2 Main lemma

It remains to understand what is going on with lemma 5.4. The surprising part about it is the following fact about eigenvalues.

Lemma 5.5. *Let (A, B, v) be a projection pair. Then*

$$\lambda_1(B) \geq \lambda_1(A) \geq \lambda_2(B) \geq \lambda_2(A) \geq \ldots \geq \lambda_n(B) \geq \lambda_n(A).$$

(A, B, v) is strict if and only if all the inequalities are strict.

Conversely, if we are given any two interlacing sequences $b_1 \geq a_1 \geq b_2 \geq a_2 \geq \ldots \geq b_n \geq a_n$ we may find a projection pair (A, B) with spec$(A) = \{a_i\}_{i=1}^{n}$ and spec$(B) = \{b_i\}_{i=1}^{n}$.

This proposition is based on the following explicit relationship between characteristic polynomials of a projection pair.

Lemma 5.6. *Let (A, B, v) be a projection pair. Then*

$$\det(B - zI) = \det(A - zI) \left(1 + \langle (A - zI)^{-1} v, v \rangle \right).$$

Proof. Write the the matrices A and B in the basis where the first vector is parallel to v. Now the matrices only differ at the upper-left corner, where the difference is $\|v\|^2$. Expanding the determinant this implies that

$$\begin{aligned}\det(B - zI) = &\det(A - zI)\\ &+ \|v\|^2 \,(\text{determinant of } A - zI \text{ with first row and column removed})\,.\end{aligned}$$

However, by the Cramer rule the determinant equals the upper-left corner of the matrix of $(A - zI)^{-1}$, i.e. $\det(A - zI)\langle (A - zI)^{-1}v, v\rangle/\|v\|^2$. Combining these observations yields the claim. □

Proof of lemma 5.5. Note that if v is orthogonal to one of the eigenvectors of A, P_v doesn't affect this eigenspace, so we may forget it and restrict our attention to a smaller space. Similarly for the converse: if $a_i = b_j$ for some $1 \leq i, j \leq n$ we can forget a_i and b_j, and solve the remaingn problem on smaller space. We may hence assume that the pair (A, B) is strict and the numbers the inequalities in the converse are strict.

Consider the function

$$z \mapsto 1 + \sum_{i=1}^{n} \frac{|\langle v, e_i\rangle|^2}{a_i - z}.$$

It has n poles of negative residue so it has a root between any two poles. Also it tends to 1 at infinity so it has also root on (a_1, ∞). Hence it has n roots. All these roots are eigenvalues of B so they are exactly the eigenvalues. This implies one direction.

For the converse take first A with the given eigenvalues. By the previous lemma we now just want to choose v in such a way that

$$\frac{p_B(z)}{p_A(z)} = 1 + \langle (A - zI)^{-1}v, v\rangle = 1 + \sum_{i=1}^{n} \frac{|\langle v, e_i\rangle|^2}{a_i - z},$$

But this is clearly achieveable if can show that the residues of $p_B(z)/p_A(z)$ are negative, which follows easily from the interlacing property. Hence the converse. □

Let us then complete the proof of theorem 5.1 by proving the lemma 5.4.

Proof of lemma 5.4. The proof is based on lemmas 5.5 and 5.5. To find the connection we first assume f is entire. Then if and (A, B, v) is a strict projetion pair and $w \in V$ we have

$$\begin{aligned}
&= \langle (f(B) - f(A))w, w\rangle \\
&= \frac{1}{2\pi i}\int_\gamma \langle (zI - B)^{-1}v, w\rangle\langle (zI - A)^{-1}w, v\rangle f(z)dz \\
&= \frac{1}{2\pi i}\int_\gamma \frac{\det(zI - A)\langle (zI - B)^{-1}v, w\rangle \det(zI - B)\langle (zI - A)^{-1}w, v\rangle}{\det(zI - A)\det(zI - B)} f(z)dz.
\end{aligned}$$

The integrand equals

$$\frac{h(z)}{\prod_{i=1}^n (z - \lambda_i(A))\prod_{i=1}^n (z - \lambda_i(B))} f(z),$$

where $h(z) = \det(zI - B)\langle (zI - B)^{-1}v, w\rangle \det(zI - A)\langle (zI - A)^{-1}w, v\rangle$.

Lemma 5.7. *If (A, B) is a projection pair with $B - A = vv^*$ then*

$$\det(zI - A)(zI - A)^{-1}v = \det(zI - B)(zI - B)^{-1}v$$

Proof. As $zI - A = zI - B + vv^*$, multiplying both sides from left by $(zI - A)$ leads to the equivalent

$$\det(zI - A)v = \det(zI - B)(1 + \langle (zI - B)^{-1}v, v\rangle)v$$

which follows from 5.6. □

By the previous lemma we have $\det(zI-B)\langle (zI-B)^{-1}w, v\rangle = \overline{\det(\overline{z}I - A)\langle (\overline{z}I - A)^{-1}w, v\rangle}$ so if we write $q(z) = \det(zI - A)\langle (zI - A)^{-1}w, v\rangle$, we have

$$\langle (f(B) - f(A))w, w\rangle = [\lambda_1(A), \ldots, \lambda_n(A), \lambda_1(B), \ldots, \lambda_n(B)]_{fN(q)}.$$

Note that this identity evidently holds without any extra smoothness assumptions.

Now when (A, B) ranges over all strict projection pairs, the permutations of tuples

$$(\lambda_1(A), \ldots, \lambda_n(A), \lambda_1(B), \ldots, \lambda_n(B)) \tag{5.8}$$

range over all tuples of distinct numbers on (a, b). Hence to prove the lemma, we should prove that for fixed strict projection pair (A, B), as w ranges over V, q ranges over $\mathbb{C}_{n-1}[x]$. But this is clear as components of $\det(zI - A)(zI - A)^{-1}v$ with respect to eigenbasis of A, $(e_i)_{i=1}^n$ are $p_j(z) = \prod_{i\neq j}(z - \lambda_i(B))\langle v, e_i\rangle$, which are clearly linearly independent polynomials over $\mathbb{C}$.

To recap, the map

$$\begin{aligned}
&V \to \mathbb{C}_{n-1}[x] = \{\text{Complex polynomials of degree at most } (n-1)\} \\
&w \mapsto \det(zI - A)\langle (zI - A)^{-1}v, w\rangle
\end{aligned}$$

is antilinear bijection, the correspondece between w and q. □

5.3 Dual pairing

Proof of theorem 5.1 is actually missing one more detail we need in the induction step.

Lemma 5.9. *If* $n \geq 1$ *and* $fN(q)$ *is* $(2n+1)$*:tone for* $q \in \mathbb{C}_n[x]$*, then* $fN(r)$ *is* $(2n-1)$*-tone for every* $r \in \mathbb{C}_{n-1}[x]$*.*

To understand this result, recall that for analytic f and $a < x_0 < x_1 < \ldots < x_{2n-1} < b$ we have

$$[x_0, x_1, \ldots, x_{2n-1}]_{fN(q)} = \frac{1}{2\pi i} \int_\gamma \frac{N(q)}{(z-z_0)(z-z_1)\cdots(z-z_{2n-1})} f(z)dz,$$

for suitable γ. One way to interpret this identity is to consider it as a linear map: for given analytic f we have the map

$$r \mapsto \frac{1}{2\pi i} \int_\gamma r(z)f(z)dz,$$

where r is a rational functions with its poles in the domain of f. Note that all this makes formally sense for arbitrary f given that the poles of r are simple. This motivates us to define a dual pairing $\langle \cdot, \cdot \rangle_L$ (over $\mathbb{R}$) between $\mathbb{R}^{(a,b)}$ and rational functions with simple poles on (a, b), for which

$$\langle f, r \rangle_L = \frac{1}{2\pi i} \int_\gamma r(z)f(z)dz,$$

for analytic f. We could of course replace (a, b) by any subset of $\mathbb{C}$.

Now theorem 5.1 is just saying that $f \in P_n(a, b)$ if $\langle f, r \rangle_L$ for r of the form

$$r(z) = \frac{N(q)}{(z-z_0)(z-z_1)\cdots(z-z_{2n-1})}$$

where $a < z_0 < \ldots < z_{2n-1} < b$ and $q \in \mathbb{C}_{n-1}[x]$. Let us denote this family of rational functions by $R_n(a, b)$. Now, in order to prove the lemma we should prove that we have

$$\mathrm{cone}(R_n(a, b)) \subset \mathrm{cone}(R_{n+1}(a, b))$$

Proof lemma 5.9. Take any $r \in R_n(a, b)$. If there was no condition on the order of the poles, we could simply note that

$$r = r\frac{N(z-c)}{(z-c)(z-c)} \in R_{n+1}(a, b).$$

Even though that doesn't quite work, we can modify the idea a little: we have

$$r = \frac{1}{2}r\frac{N((z-c))}{(z-c)(z-\frac{c+d}{2})} + \frac{1}{2}r\frac{N((z-d))}{(z-d)(z-\frac{c+d}{2})} \in \mathrm{cone}(R_{n+1}(a, b))$$

as soon as we choose $c, d \in (a, b)$ so that the poles remain simple. □

5.4 Loewner's theorems

Let's move our focus to classes $P_\infty(a,b)$. Using the earlies ideas we can rewrite theorem 3.15 in the following form.

Theorem 5.10. *$f \in P_\infty(a,b)$, if and only if f is analytic and for every $n \geq 1$ and $q \in \mathbb{C}_{n-1}[x]$ the function $fN(q)$ is $(2n-1)$-tone.*

Without the analyticity condition this would immediately follow from 5.1, and the statement would also make perfect sense without it. It is nevertheless true that the functions in class $P_\infty(a,b)$ are analytic. One could use Bernstein type arguments and tricks (see proof of the theorem 4.46) to convince oneself that this indeed the case, but actually there's a lot more going on.

First of all, the dual pairing thinking leads to much more satisfactory conclusion in the case $n = \infty$.

Lemma 5.11. *We have*

$$R_\infty(a,b) := \bigcup_{n=1}^{\infty} R_n(a,b) = cone\left(\bigcup_{n=1}^{\infty} R_n(a,b)\right)$$
$$=\{\textit{rational functions with only simple, real poles, non-negative on } \mathbb{R}\setminus(c,d) \textit{ for some } a<c<d<b, \textit{ and decay } r(z)=O(|z|^{-2}) \textit{ at } \infty\}.$$

Proof. It is sufficient to prove that if r is rational function with simple poles on (a,b), which is non-negative on $\mathbb{R}\setminus(a,b)$ and has decay $r(z) = O(|z|^{-2})$ at ∞, then $r \in R_n(a,b)$ for some $n \geq 1$. So pick such r.

Note that r changes its sign even number of times, and only on interval (a,b), say at points $a < x_0 < x_1 < \ldots < x_{2n-1} < b$. Write $p := \prod_{i=0}^{2n-1}(\cdot - x_i)$. Note that is pr is necessarily a polynomial of degree less than $2n$ non-negative on $\mathbb{R}$, so it is of the form $N(q)$ for some $q \in \mathbb{C}_{n-1}[x]$. Hence we have

$$r = \frac{N(q)}{p} \in R_n(a,b).$$

□

So $R_\infty(a,b)$ is the dual cone of $P_\infty(a,b)$. Now it might not be too big of surprise that the class $R_\infty(a,b)$ is dense in $C_c(\mathbb{R}\setminus(a,b))$ (with uniform norm). This should imply, by the Riesz representation theorem, that for any $f \in P_\infty(a,b)$ there exists a Radon measure μ_f on $\mathbb{R}\setminus(a,b)$ with $\mu((\lambda^2+1)^{-1}) < \infty$ such that for any $r \in R_\infty(a,b)$

$$\langle f, r\rangle_L = \int_{\mathbb{R}\setminus(a,b)} r(\lambda)\, d\mu_f(\lambda).$$

This is almost true. As the functions $R_\infty(a, b)$ are not compactly supported, there's a problem at infinity. Nevertheless, the previous holds with slight modification.

Theorem 5.12. *[Loewner's theorem, version 1] Let $f \in P_\infty(a, b)$. Then there exists a unique Radon measure μ_f on $\mathbb{R} \setminus (a, b)$ with $\mu_f((\lambda^2 + 1)^{-1}) < \infty$ and $\alpha \geq 0$ such that for any $r \in R_\infty(a, b)$ we have*

$$\langle f, r \rangle_L = \alpha \left(\lim_{\lambda \to \infty} r(\lambda)\lambda^2 \right) + \int_{\mathbb{R}\setminus(a,b)} r(\lambda) d\mu_f(\lambda).$$

In particular for any $x, y \in (a, b)$ we have

$$[x, y]_f = \alpha + \int_{\mathbb{R}\setminus(a,b)} \frac{d\mu_f(\lambda)}{(\lambda - x)(\lambda - y)}.$$

Note that the limit $(\lim_{\lambda \to \infty} r(\lambda)\lambda^2)$ exists and is non-negative for any $r \in R_\infty(a, b)$. It is clear that the converse of this theorem also holds. Note also that examples 3.6 fit in the this framework: they corresponds to positive linear combination of δ-measures. Theorem 5.12 can be interpreted as saying that all functions in the class $P_\infty(a, b)$ are more-or-less of the form 3.6; only summation is replaced with integration with respect to (somewhat) arbitrary measure.

Although it would not be terribly tricky to fill in the details to our argument, we will not prove 5.12. Instead we look into one of its corollaries:

Corollary 5.13. *Every $f \in P_\infty(a, b)$ has an analytic extension $\tilde{f}$ on $\mathbb{C} \setminus \mathbb{R}$. Extension maps (open) upper half-plane $\mathbb{H}_+$ to closed upper half-plane $\overline{\mathbb{H}_+}$.*

In fact, also this corollary has a converse.

Theorem 5.14. *[Loewner's theorem, version 2] Let $f : (a, b) \to \mathbb{R}$. Then $f \in P_\infty(a, b)$, if and only there exists a analytic function $\tilde{f}$ on $(\mathbb{C} \setminus \mathbb{R}) \cup (a, b)$ such that $\tilde{f}\Big|_{(a,b)} = f$ and $\tilde{f}$ maps the upper half-plane to its closure.*

5.5 Notes and references

Chapter 6

Pick-Nevanlinna functions

Pick-Nevanlinna function is an analytic function defined in upper half-plane with a non-negative imaginary part. Such functions are sometimes also called Herglotz or $\mathbb{R}$ functions; we will call them just *Pick functions*. The class of Pick functions is denoted by $\mathcal{P}$.

6.1 Examples and basic properties

Most obvious examples of Pick functions might be functions of the form $\alpha z + \beta$ where $\alpha, \beta \in \mathbb{R}$ and $\alpha \geq 0$. Of course one could also take $\beta \in \overline{\mathbb{H}}_+$. Actually real constants are the only Pick functions failing to map $\mathbb{H}_+ \to \mathbb{H}_+$: non-constant analytic functions are open mappings.

Sum of two Pick functions is a Pick function and one can multiply a Pick function by non-negative constant to get a new Pick function. Same is true for composition.

The map $z \mapsto -\frac{1}{z}$ is evidently a Pick function. Hence are also all functions of the form

$$\alpha z + \beta + \sum_{i=1}^{N} \frac{m_i}{\lambda_i - z},$$

where N is non-negative integer, $\alpha, m_1, m_2, \ldots, m_N \geq 0$, $\beta \in \mathbb{H}_+$ and $\lambda_1, \ldots, \lambda_N \in \mathbb{H}_+$. So far we have constructed our function by adding simple poles to the closure of lower half-plane. We could further add poles of higher order at lower half plane, and change residues and so on, but then we have to be a bit more careful.

There are (luckily) more interesting examples. All the functions of the form x^p where $0 < p < 1$ are Pick function, with natural branch, similarly for log. Another classic example is tan. Indeed, by the addition formula

$$\begin{aligned}\tan(x+iy) &= \frac{\tan(x)+\tan(iy)}{1-\tan(x)\tan(iy)} = \frac{\tan(x)+i\tanh(y)}{1-i\tan(x)\tanh(y)} \\ &= \frac{\tan(x)(1+\tanh^2(y))}{1+\tan^2(x)\tanh^2(y)} + i\frac{(1+\tan^2(x))\tanh(y)}{1+\tan^2(x)\tanh^2(y)},\end{aligned}$$

and y and $\tanh(y)$ have the same sign.

Pick functions can be thought of a set of "positive analytic functions".

Theorem 6.1. *$\mathcal{P} \subset \{$analytic maps on $\mathbb{H}_+\}$ is a closed convex cone.*

Proof. Again, this is clear. □

$\mathcal{P}$ is almost salient: if φ is analytic and $\Im(\varphi) = 0$, then φ is a real constant (by Cauchy-Riemann equations, for instance). And again, this suggests that one should think about Pick functions up to a real constant.

So far we have made no mention on the topology, as it's usually taken to be the topology of locally uniform convergence. This definitely works (as it makes the evaluation functionals continuous), but we can do much better. It namely turns out that we can consider the set of Pick functions as a proper cone of $\mathbb{C}^{\mathbb{H}_+}$, set of all functions, with product topology.

Proposition 6.2. *If $(\varphi_i)_{i=1}^{\infty}$ is a sequence of Pick functions converging pointwise, the limit function is also a Pick function.*

This result far from clear: pointwise limits of analytic functions need not in general be analytic. We will not prove the result yet, but it strongly suggests that there is something more going on; Pick functions are very rigid. Note also that if Pick functions are thought of a subset of all functions, the definition of the cone doesn't really fit the general framework of theorem 2.6. This suggests that we are missing some better functionals, or better predual.

6.2 Boundary

To understand the rigidity phenomena we take look at a close relative to Pick functions, *Schur functions*. Schur funtions are analytic maps from open unit disc to closed unit disc. Classic fact about these functions is the Schwarz lemma.

Theorem 6.3 (Schwarz lemma)**.** *Let $\psi : \mathbb{D} \to \mathbb{D}$ be analytic such that $\psi(0) = 0$. Then $|\psi(z)| \leq |z|$ for any $z \in \mathbb{D}$ and hence also $|\psi'(0)| \leq 1$. If $|\psi(z)| = |z|$ for some $z \in \mathbb{D} \setminus \{0\}$ or $|\psi'(0)| = 1$, $\psi(z) = \omega z$ for some $\omega \in \mathbb{S}$.*

The textbook proof is based on two observations about analytic functions.

- If φ is analytic at a with $\varphi(a) = 0$, then $\varphi/(\cdot - a)$ is also analytic.
- If φ is analytic on closed unit disc and $|\varphi| \leq 1$ on the boundary of the disc, then $|\varphi| \leq 1$ inside the disc.

The first observation might not be very surprising, and it holds for smooth functions also. The second, on the other hand, is a true manifestation of the nature of the analytic maps: we can bound analytic functions simply by bounding them on the boundary of the domain. More generally, one knows everything about an analytic function on a domain simply by knowing it on a boundary, by Cauchy's integral formula.

This suggests that we should be able to recognize also Pick functions looking only at their boundary values. Actually even more is true: it suffices to look at the imaginary parts.

Proposition 6.4. *Let $\varphi : U \to \mathbb{C}$ be analytic, such that $\overline{\mathbb{H}_+} \subset U$, and φ is continuous at ∞. Then if the imaginary part of φ is non-negative on the real axis, φ is Pick function.*

Proof. This follows immediately from the minimum principle applied to the harmonic function $\Im(\varphi)$. ☐

6.3 Integral representations

Recall that imaginary part of an analytic function determines also its real part, up to a constant, so we can also recover the function itself. This can be also done explicitly.

Theorem 6.5. *Let $\varphi : U \to \mathbb{C}$ be analytic, such that $\overline{\mathbb{H}_+} \subset U$, and $\varphi(z) = O(|z|^{-\varepsilon})$ for some $\varepsilon > 0$ at infinity. Then for any $z \in \mathbb{H}_+$ we have*

$$\varphi(z) = \frac{1}{\pi} \int_{\mathbb{R}} \frac{\Im(\varphi)(\lambda)}{\lambda - z} d\lambda$$

Proof. Note that the integral defines an analytic function, imaginary part of which equals

$$\frac{\Im(z)}{\pi} \int_{\mathbb{R}} \frac{\Im(\varphi)(\lambda)}{(\lambda - z)(\lambda - \overline{z})} d\lambda.$$

This expression however equals $\Im(\varphi(z))$ by Poisson integral formula. By letting $z \to \infty$ one sees that also the real constants match.

Alternatively one could observe that for a closed counter clockwise oriented curves γ on the upper half-plane, enclosing z, we have

$$\varphi(z) = \frac{1}{2\pi i} \int_\gamma \frac{\varphi(\lambda)}{\lambda - z} d\lambda.$$

Now given the bound, we may deform the contour to real axis. By comparing this identity and our goal, we are left to prove that

$$\frac{1}{2\pi i} \int_\gamma \frac{\overline{\varphi(\lambda)}}{\lambda - z} d\lambda = \frac{1}{2\pi i} \overline{\int_\gamma \frac{\varphi(\lambda)}{\lambda - \overline{z}} d\lambda}.$$

But this is clear as $\varphi/(\cdot - \overline{z})$ is analytic in the upper half-plane. $\square$

There's of course nothing really special about the decay assumption $\varphi(z) = O(|z|^{-\varepsilon})$; it's there just to make everything converge.

One can guarantee the convergence also by other means. Note that the integrand behaves like $\frac{1}{\lambda - z}$, if we subtract something from it something behaving the same way at the infinity (something not depending on z), we ought to improve convergence, but only change the value of the function by a constant. As an example, consider the integral

$$\frac{1}{\pi} \int_{\mathbb{R}} \left(\frac{1}{\lambda - z} - \frac{[|\lambda| > 1]}{\lambda} \right) \Im(\varphi)(\lambda) d\lambda. \tag{6.6}$$

It converges to an analytic function as long as, say, $\Im(\varphi)$ is bounded. As before, its imaginary part coincides with φ's so the functions equal up to a real constant. Now it's not clear however that the functions should equal and indeed they need not: the right-hand side doesn't see real constants.

Note that the previous idea could be used to construct Pick functions. Everything still makes sense if we replace $\Im(\varphi)$ by some other positive function, as long as the integral converges. Heck, we could replace it by any positive measure for which $\mu((\lambda^2+1)^{-1}) < \infty$.

(Almost) all the examples given before are actually just special cases of this construction. The rational functions $\frac{1}{\lambda - z}$, where $\lambda \in \mathbb{R}$ are obtained by setting $\mu = \delta_\lambda$. The power functions are obtained as

$$\begin{aligned} z^p &= c_0 + \frac{1}{\pi} \int_{-\infty}^0 \left(\frac{1}{\lambda - z} - \frac{1}{\lambda - 1} \right) \Im(\lambda^p) d\lambda \\ &= c_0 + \frac{1}{\pi} \int_{-\infty}^0 \left(\frac{1}{\lambda - z} - \frac{1}{\lambda - 1} \right) |\lambda|^p \sin(\pi p) d\lambda, \end{aligned}$$

for some constant c_0 (which can be seen to be 1 by setting $z = 1$). Logarithm is even simpler:

$$\log(z) = \int_{-\infty}^{0} \left(\frac{1}{\lambda - z} - \frac{1}{\lambda - 1} \right) d\lambda.$$

Tangent function could be obtained by putting δ-measures to the points of the form $\frac{\pi}{2}+n\pi$, where $n \in \mathbb{Z}$, the singularities of tangent.

The only exception is the function $z \mapsto \alpha z$ – it can't be expressed as such integral. But even this failure is really more about poor point of view, as we will see in a minute. With these observations in mind it ought to be not too surprising that we have the following.

Theorem 6.7. *$\varphi \in \mathcal{P}$, if and only*

$$\varphi(z) = \alpha z + \beta + \int_{-\infty}^{\infty} \left(\frac{1}{\lambda - z} - \frac{\lambda}{\lambda^2 + 1} \right) d\mu(\lambda) \tag{6.8}$$

for some $\alpha \geq 0$ and $\beta \in \mathbb{R}$ and a Borel measure μ with $\int_{-\infty}^{\infty} (\lambda^2 + 1)^{-1} d\mu(\lambda) < \infty$.

Choosing $\lambda \mapsto \frac{\lambda}{\lambda^2+1}$ is common choice in the literature and is convenient as

- It's real, so the integrand is Pick function for any $\lambda \in \mathbb{R}$.
- We may recover the constant β as $\Re(\varphi(i))$.

To better explain the appearance of the linear term, we can write the integral in a sligtly different form. Denoting $d\nu(\lambda) = \frac{d\mu(\lambda)}{\lambda^2+1}$, the formula reads

$$\varphi(z) = \alpha z + \beta + \int_{-\infty}^{\infty} \frac{\lambda z + 1}{\lambda - z} d\nu(\lambda).$$

Here ν is just a finite Borel measure. Now it kind of makes sense to extend the domain of this measure to infinity: the linear term merely corresponds to δ-measure at infinity point. Of course, should one formalize this line of thought, the question on the type of extended real line had to be asked and one should address the topology. The answer is that one should glue the real line into a circle. One shouldn't worry about such issues, though, as these thoughts are here merely for intuition. The giveaway is that α should be really thought as a part of the measure μ, even though this might not make perfect sense.

We will not prove theorem 6.7, but it shall work as a motivation. In order to understand Pick functions, we should understand their boundaries.

We will call the family

$$\{z \mapsto z\} \cup \left\{z \mapsto \frac{1}{\lambda - z} | \lambda \in \mathbb{R}\right\}$$

extreme Pick functions. Finite positive linear combinations of the extreme Pick functions are called **simple Pick functions**. Finally, we will call a Pick function **extentable**, if it is bounded and analytically extends over the real line. Such Pick functions enjoy representations of the form 6.6.

6.4 Pick functionals

Question 6.9. How can we recover the measure μ from the Pick function?

If μ is given by a continuous, bounded function, i.e. $d\mu(\lambda) = f(\lambda)d\lambda$, it's not very hard to see that

$$f(\lambda) = \frac{1}{\pi} \lim_{y \to 0^+} \Im(\varphi(\lambda + iy)).$$

This doesn't however work with rational functions with poles on the real line. One might try to salvage the situation by saying that poles should correspond to δ-measures, but even if that would be true in some sense, we are only scratching the surface. What to do if the measure is for instance the uniform measure on the Cantor set?

Beauty of the measure theory is of course that we don't even need to make sense of the measure pointwise; everything is hidden in the averages. Could we recover the measures of open intervals then? Is it true that

$$\mu((a,b)) = \lim_{y \to 0^+} \frac{1}{\pi} \int_a^b \Im(\varphi(\lambda + iy)) d\lambda?$$

Even this isn't quite true: the problem is that if μ contains δ-measure at a or at b, the right-hand side doesn't see this properly. It turns out that this is only problem though.

We have however already encountered much better averages: the imaginary part of a Pick function φ is a weighted average of the imaginary parts of φ on the real line. We only proved this in the case of bounded φ, and indeed, the proper generalization should be

$$\Im(\varphi(z)) = \alpha \Im(z) + \frac{\Im(z)}{\pi} \int_{\mathbb{R}} \frac{d\mu(\lambda)}{(\lambda - z)(\lambda - \overline{z})}.$$

Bear in mind that we also consider the constant α to be part of the measure. One can take this idea much further: if q is any rational function with simple poles, no poles on $\mathbb{R}$, and decay $O(|z|^{-2})$ at infinity, the expression

$$\int_{\mathbb{R}} q(\lambda) d\mu(\lambda)$$

makes sense. Even better, partial fraction expansion allows us to write this integral in terms of as a linear combination of values of φ and its conjugate. Indeed, we have

$$q(\lambda) = c_0 \frac{\lambda}{\lambda^2+1} + \sum_{i=1}^{M} c_i \left(\frac{1}{\lambda - a_i} - \frac{\lambda}{\lambda^2+1} \right),$$

where a_i's are the poles of q. The decay condition tells that $c_0 = 0$. If $\Im(a_i) > 0$, term corresponds to multiple of $\varphi(a_i)$, and if $\Im(a_i) < 0$, we get the conjugate. Explicitly, if we abuse notation a tad by writing $\varphi(a_i) = \overline{\varphi(\overline{a_i})}$ if $\Im(a_i) < 0$, we have

$$\begin{aligned}\int_{\mathbb{R}} q(\lambda) d\mu(\lambda) &= \int_{\mathbb{R}} \sum_{i=1}^{M} c_i \left(\frac{1}{\lambda - a_i} - \frac{\lambda}{\lambda^2+1} \right) \mu(\lambda) \\ &= \sum_{i=1}^{M} c_i \left(\varphi(a_i) - \alpha a_i - \beta \right),\end{aligned}$$

which rewrites to

$$\sum_{i=1}^{M} c_i \varphi(a_i) = \sum_{i=1}^{M} c_i \left(\alpha a_i + \beta \right) + \int_{\mathbb{R}} q(\lambda) d\mu(\lambda).$$

We can get some kind of glimpse of the measure just by looking at linear combinations of the values of Pick function.

These ideas get really useful when q is non-negative on the real line. It follows easily from the lemma 5.2 that such rational functions can be written in the form

$$q(\lambda) = \left(\sum_{i=1}^{n} \frac{c_i}{\lambda - \lambda_i} \right) \left(\sum_{i=1}^{n} \frac{\overline{c_i}}{\lambda - \overline{\lambda_i}} \right)$$

where $\lambda_1, \lambda_2, \ldots, \lambda_n \in \mathbb{C} \backslash \mathbb{R}$ and $c_1, c_2, \ldots, c_n \in \mathbb{C}$. Running through the same calculations we see that

$$\sum_{1 \leq i,j \leq n} c_i \overline{c_j} \frac{\varphi(\lambda_i) - \overline{(\varphi(\lambda_j))}}{\lambda_i - \overline{\lambda_j}} = \alpha \left| \sum_{i=1}^{n} c_i \right|^2 + \int_{\mathbb{R}} q(\lambda) d\mu(\lambda) \geq 0.$$

Definition 6.10. Functional in $\left(\mathbb{C}^{\mathbb{H}_+}\right)^*$ of the form

$$\sum_{1\le i,j\le n} c_i\overline{c_j}\frac{\delta_{\lambda_i}-\overline{\delta_{\lambda_j}}}{\lambda_i-\overline{\lambda_j}},$$

$\lambda_1,\lambda_2,\ldots,\lambda_n\in\mathbb{C}\setminus\mathbb{R}$ and $c_1,c_2,\ldots,c_n\in\mathbb{C}$, is called a **Pick functional**. This is all of course to say that

$$\varphi\mapsto\sum_{1\le i,j\le n} c_i\overline{c_j}\frac{\varphi(\lambda_i)-\overline{\varphi(\lambda_j)}}{\lambda_i-\overline{\lambda_j}}.$$

Given $\lambda_1,\lambda_2,\ldots,\lambda_n\in\mathbb{C}\setminus\mathbb{R}$, the matrix

$$\begin{bmatrix}
[\lambda_1,\overline{\lambda_1}]_\varphi & [\lambda_1,\overline{\lambda_2}]_\varphi & \cdots & [\lambda_1,\overline{\lambda_n}]_\varphi\\
[\lambda_2,\overline{\lambda_1}]_\varphi & [\lambda_2,\overline{\lambda_2}]_\varphi & \cdots & [\lambda_2,\overline{\lambda_n}]_\varphi\\
\vdots & \vdots & \ddots & \vdots\\
[\lambda_n,\overline{\lambda_1}]_\varphi & [\lambda_n,\overline{\lambda_2}]_\varphi & \cdots & [\lambda_n,\overline{\lambda_n}]_\varphi
\end{bmatrix}$$

is called a **Pick matrix**. Pick functionals are simply values of quadratic forms of Pick matrices.

We denote the set of Pick functionals by $\mathcal{P}^*$.

Theorem 6.11. *Let $p^*\in\left(\mathbb{C}^{\mathbb{H}_+}\right)^*$. Then the following are equivalent.*

(i) $p^*\in\mathcal{P}^*$

(ii) $p^*(\varphi)\ge 0$ *for any extreme Pick function* φ.

(iii) $p^*(\varphi)\ge 0$ *for any extentable Pick function* φ.

(iv) $p^*(\varphi)\ge 0$ *for any Pick function* φ.

Proof. The implications $(i)\Rightarrow(ii)\Rightarrow(iii)$ and $(iv)\Rightarrow(ii)$ are clear, up to one detail: if $p^*(\varphi)\ge 0$ for any extreme Pick function φ, we should prove that $p^*(1)=0$. But this follows as soon as one notes that

$$p^*\left(\frac{1}{\lambda-\cdot}\right)=\frac{p^*(1)}{\lambda}+O\left(\frac{1}{\lambda^2}\right).$$

$(iii)\Rightarrow(iv)$: It suffices to prove that the extentable Pick functions are dense (with respect to the topology of pointwise convergence) in the set of all Pick function. But for this it is enough to find a sequence of Pick functions $(g_n)_{n=1}^\infty$ such that

1. $g_n(z) \to z$ pointwise as $n \to \infty$,

2. g_n's extend analytically over real line and $g_n(\overline{\mathcal{H}_+})$ is compact subset of $\mathcal{H}_+$ for every $n \geq 1$,

as then we have $\varphi \circ g_n \to \varphi$ pointwise as $n \to \infty$ for every Pick function φ the functions $\varphi \circ g_n$ are evidently bounded and extend analytically over the real line.

It is not very hard to check that we may take

$$g_n(z) = \frac{z + \frac{i}{n}}{1 - \frac{iz}{n}}.$$

$(ii) \to (i)$: By the construction of the $\mathcal{P}^*$ it contains all the functionals **with finite support**, which give positive values for all extreme Pick functions. Thus it remains to be noted that all the continuous functionals in $\left(\mathbb{C}^{\mathbb{H}_+}\right)^*$ have finite support. But this follows from the general fact that the dual of a product equals direct sum of the duals. $\square$

It is useful to note that one does not even need to test every extreme Pick function to check that functional is Pick functional, dense subset suffices. This is clear for the functions $z \mapsto \frac{1}{\lambda - z}$ but also holds for $z \mapsto z$, when this is intepreted as the function with $\lambda = \infty$ (and dense subset refers to the circle topology). Indeed, we have

$$p^*\left(\frac{1}{\lambda - \cdot}\right) = p^*\left(\frac{1}{\lambda - \cdot} - \frac{1}{\lambda}\right) = \frac{p^*(\cdot)}{\lambda^2} + O\left(\frac{1}{\lambda^3}\right).$$

Finally, the following correspondence should be clear by now.

Proposition 6.12. *There is a natural bijective ($\mathbb{R}$-)linear map between non-negative rational functions vanishing at infinity and $\mathcal{P}^*$.*

This line of thought induces a dual pairing between rational functions r with simple poles such that $(1 + (\cdot)^2)r$ is bounded on $\mathbb{R}$, and $\mathbb{C}^{\mathbb{H}_+}$. We denote this pairing by $\langle r, \varphi\rangle_{\mathcal{P}}$ and the class of rational functions by $R_\infty(\mathbb{H}_+)$. For $X \subset \mathbb{H}_+$ we also denote by $R_\infty(X)$ those functions on $R_\infty(\mathbb{H}_+)$, whose poles are on X (and on its reflection with respect to $\mathbb{R}$).

6.5 Weakly Pick functions

Theorem 6.11 implies that $\mathcal{P}^*$ is really just the dual cone of $\mathcal{P}$. It turns out that the "converse" is also true: $\mathcal{P}^*$ is also a predual of $\mathcal{P}$.

Definition 6.13. We will elements of $(\mathcal{P}^*)^*$ **weakly Pick functions**.

In layman's terms, weakly Pick functions are ones, which look like Pick functions if one only considers linear functionals. The aim of this section is to show that weakly Pick functions are exactly the Pick functions. We already proved one direction in the theorem 6.11.

The other direction is tricky. Note that weakly Pick maps map to the upper half-plane so the interesting part is to prove that weakly Pick maps are analytic. For this we are going to verify bounds for the divided differences of φ. Recall that by theorem 4.43 it suffices to verify that the order 2 divided differences are locally bounded to prove that φ is (continuously) differentiable. Strictly speaking we only proved the result on real line, but the prove would be almost identical in the complex case.

The idea is the following: we are going to formulate everything terms of the linear functionals. This idea is best illustrated with an example.

Lemma 6.14 (Harnack inequality)**.** *Let φ be a weakly Pick function. Then for every compact $K \subset \mathbb{H}_+$ there exists a constant C_K such that*

$$\frac{\Im(\varphi(z))}{\Im(z)} \leq C_K \frac{\Im(\varphi(w))}{\Im(w)}$$

for every $z, w \in K$.

Proof. Note that the sought inequality can be rephrased as positivity of the linear functional

$$\varphi \mapsto C_K \frac{\Im(\varphi(w))}{\Im(w)} - \frac{\Im(\varphi(z))}{\Im(z)}.$$

By theorem 6.11 it suffices to prove that there exists constant C_K such that the previous inequality holds for any extreme Pick function. This implies that we should have

$$\frac{1}{|\lambda - z|^2} \leq \frac{C_K}{|\lambda - w|^2}$$

for every $\lambda \in \mathbb{R}$. But

$$\left|\frac{\lambda - w}{\lambda - z}\right|^2 \leq \left|1 + \frac{z - w}{\lambda - z}\right|^2 \leq \left(1 + \frac{|z - w|}{\Im(z)}\right)^2,$$

so we can definitely find such constant. $\square$

Similarly, one can prove that weakly Pick functions are continuous.

Theorem 6.15. *Let φ be a weakly Pick function. Then φ is continuous.*

Proof. Our aim is to bound the divided difference $|[z,w]_\varphi|$. Now the problem is that this expression is not linear in the function anymore. There's a way to fix this problem however: we bound $\Re(\omega[z,w]_\varphi)$ for $\omega \in \mathbb{S}$. This expression is linear in the function, and we have

$$|z| \leq C \Leftrightarrow \Re(\omega z) \leq C \text{ for every } \omega \in \mathbb{S}.$$

Observe that

$$\Re\left(\frac{\omega}{(\lambda - z)(\lambda - w)}\right) \leq \frac{1}{|\lambda - z||\lambda - w|} \leq \frac{1}{2}\left(\frac{1}{|\lambda - z|^2} + \frac{1}{|\lambda - w|^2}\right)$$

for every $\omega \in \mathbb{S}$. It follows that

$$|[z,w]_\varphi| \leq \frac{1}{2}\left(\frac{\Im(\varphi(z))}{\Im(z)} + \frac{\Im(\varphi(w))}{\Im(w)}\right)$$

for any weakly Pick function. Combining this with Harnack inequality 6.14 yields that any weakly Pick function is locally Lipschitz, so in particular continuous. □

The previous argument can be easily extended to the following.

Theorem 6.16. *Let φ be a weakly Pick function. Then for any $n \geq 1$ and $z_0, z_1, \ldots, z_n$ we have*

$$|[z_0, z_1, \ldots, z_n]_\varphi| \leq \frac{1}{\Im(z_2)\Im(z_3)\ldots\Im(z_n)}\frac{1}{2}\left(\frac{\Im(\varphi(z_0))}{\Im(z_0)} + \frac{\Im(\varphi(z_1))}{\Im(z_1)}\right).$$

In particular any weakly Pick function is analytic and hence a Pick function.

Proof. Simply note that

$$\Re\left(\frac{\omega}{(\lambda - z_0)(\lambda - z_1)\cdots(\lambda - z_n)}\right) \leq \frac{1}{\Im(z_2)\Im(z_3)\ldots\Im(z_n)}\frac{1}{|\lambda - z_0||\lambda - z_1|}$$

and follow the argument in the proof of theorem 6.15. □

It is worthwhile to note that as one really only needs to get bound for order 2 divided differences in the proof of 6.16, one only needs to keep track of small family of pick functionals, in particular ones with support of at most 3 points. This observation is known as the Hindmarsh theorem.

Corollary 6.17. *$\varphi : \mathbb{H}_+ \to \mathbb{C}$ is weakly Pick, if and only if it is Pick function.*

Proof of theorem 6.2. This follows immediately from 6.17. □

6.6 Pick-Nevanlinna extension theorem

There's a remarkable generalization to the theorem 6.17.

Definition 6.18. Let $X \subset \mathbb{H}_+$. We say that $\varphi : X \to \mathbb{C}$ is weakly Pick on X if $p^*(\varphi) \geq 0$ for any Pick functional p^* supported on X.

Theorem 6.19 (Pick-Nevanlinna extension theorem)**.** *Let $U \subset \mathbb{H}_+$ be open and assume that φ is weakly Pick on U. Then there exists a unique pick function $\tilde{\varphi}$ such that $\tilde{\varphi}\big|_U = \varphi$.*

The proof of this result is based on the following observation:

Lemma 6.20. *Let $U \subset \mathbb{H}_+$ be open and assume that φ is weakly Pick on U. Let $z_0 \in U$. Then there exists unique weakly Pick $\tilde{\varphi} : U \cap \mathbb{D}(z_0, \Im(z_0))$ such that $\tilde{\varphi}\big|_U = \varphi$.*

Proof. Take any sequence $z_1, z_2, \ldots \in U$ converging to z_0: we claim the Newton series with nodes $z_1, z_2, \ldots$ gives the (by analyticity necessarily unique) extension for φ to $\mathbb{D}(z_0, \Im(z_0)) \setminus U$.

To this end take any Pick functional p^* supported on $\mathbb{D}(z_0, \Im(z_0)) \cup U$ and apply it to our $\tilde{\varphi}$. The functional correponds to some $r \in R_\infty(\mathbb{D}(z_0, \Im(z_0)) \cup U)$. Now if we replace all the evaluations of p^* at $\mathbb{D}(z_0, \Im(z_0)) \setminus U$ by truncation of Newton series (with N terms), we can interpret the result as a new linear functional, say p_N^*. The corresponding rational function is also changed (say to $r_N \in R_\infty(U)$): all the terms of the form $(\lambda - w_0)^{-1}$ for $w_0 \in \mathbb{D}(z_0, \Im(z_0)) \setminus U$ are replaced by

$$\frac{1}{\lambda - z_1} + \frac{(w_0 - z_1)}{(\lambda - z_1)(\lambda - z_2)} + \ldots + \frac{(w_0 - z_1) \cdots (w_0 - z_{N-1})}{(\lambda - z_1) \cdots (\lambda - z_N)},$$

and similarly for conjugate terms. Difference between these rational functions can be easily bounded by

$$\left(\frac{|w_0 - z_0|}{\Im(z_0)} \right)^N \frac{C}{|\lambda - z_0|^2},$$

where C is some constant not depending on N. But this means that r_N can't be too small, as r was non-negative to begin with. Indeed, by summing over all the evaluations of p^* at $\mathbb{D}(z_0, \Im(z_0)) \setminus U$, we see that

$$r_N \geq -\frac{C'}{|\lambda - z_0|^2} \rho^N$$

for some $\rho < 1$ and $C' > 0$ (again, not depending on N). It follows that

$$p^*(\tilde{\varphi}) = \lim_{N \to \infty} p_N^*(\varphi) \geq \lim_{N \to \infty} -C' \frac{\Im(\varphi(z_0))}{\Im(z_0)} \rho^N = 0,$$

hence the claim. □

Proof of theorem 6.19. Consider all weakly Pick extensions of φ (to open supersets of U), ordered by restriction. These maps trivially satisfy conditions of Zorn's lemma so we may Pick maximal map, $\tilde{\varphi}$. It follows immediately from lemma 6.20 that the domain of $\tilde{\varphi}$ is the whole $\mathbb{H}_+$.

Of course, Zorn's lemma is not really necessary here: one could write explicit extension scheme (TODO: picture). □

6.7 Pick-Nevanlinna interpolation theorem

Although Pick-Nevanlinna extension theorem is strong enough tool for our purposes, one cannot simply talk about it without discussing also its big brother, interpolation theorem.

Theorem 6.21 (Pick-Nevanlinna interpolation theorem)**.** *Let $X \subset \mathbb{H}_+$ be arbitrary and assume that φ is weakly Pick on X. Then there exists pick function $\tilde{\varphi}$ such that $\tilde{\varphi}\big|_U = \varphi$.*

It's easy to see that such extension it not unique in general.

The proof is based on the following result.

Lemma 6.22. *Let $X \subset \mathbb{H}_+$ non-empty and $z_0 \in \mathbb{H}_+ \setminus X$. Assume that φ is weakly Pick on X. Then φ can be extended to z_0, in such a way that the extension is weakly Pick $X \cup \{z_0\}$. Moreover, the set of possible values of the extension at z_0 is a compact subset of $\mathbb{H}_+$.*

Let us first proof the theorem given this lemma.

Proof of theorem 6.21. Consider family of all weakly Pick extensions of φ ordered by restriction. It is clear that this family satisfies the conditions of the Zorn's lemma and hence it has a maximal element. But by the previous lemma domain of this maximal element has to have the whole $\mathbb{H}_+$, so it is a sought extension. □

Proof of lemma 6.22. Let us first deal with the case of finite X. The idea is somewhat similar to the proof of 2.17: while in general the extension is very much not unique, if the situation is restricted enough, we are in better situation. Let us denote the sought extension by $\tilde{\varphi}$. Assume first that φ is degenerate in X in the sense that $\langle \varphi, r\rangle_{\mathcal{P}} = 0$ for some non-zero $r \in R_\infty(X)$. We may clearly assume that r has only real roots. Indeed, if $r(z_1) = 0$ for some $\Im(z_1) > 0$, let $\tilde{r} := r\Im(z_1)^2/N(\cdot - z_1) \in R_\infty(X)$. As $\tilde{r} \leq r$, also $\langle \varphi, \tilde{r}\rangle_{\mathcal{P}} = 0$, and $\tilde{r}$ has less non-real roots than r.

Note that since $(\lambda - z_0)^{-1}$ is bounded on $\mathbb{R}$, by say M, we should have

$$\left|\langle r\frac{1}{\cdot - z_0}, \tilde{\varphi}\rangle_{\mathcal{P}}\right| \leq M\langle r, \varphi\rangle_{\mathcal{P}} = 0,$$

and hence $\langle r(\cdot - z_0)^{-1}, \tilde{\varphi}\rangle_{\mathcal{P}} = 0$. Note that then also $\langle r(\cdot - \overline{z_0})^{-1}, \tilde{\varphi}\rangle_{\mathcal{P}} = 0$. As $r(z_0) \neq 0$, this determines the value $\tilde{\varphi}(z_0)$.

Now it remains to be proven that with this choice $\tilde{\varphi}$ is weakly Pick. To this end take any $s \in R_\infty(X \cup \{z_0\})$. Note that for any $a \in \mathbb{C}$ and $\lambda \in \mathbb{R}$ we have

$$\tilde{s}(\lambda) := s(\lambda) + \left(\frac{a}{\lambda - z_0} + \frac{\overline{a}}{\lambda - \overline{z_0}}\right) r(\lambda) + 2|a|Mr(\lambda) \geq 0.$$

By picking a suitably, $\tilde{s}$ doesn't have pole at z_0 (or $\overline{z_0}$), and since φ is weakly Pick, we thus have

$$\langle s, \tilde{\varphi}\rangle_{\mathcal{P}} = \langle \tilde{s}, \varphi\rangle_{\mathcal{P}} \geq 0,$$

the claim.

If φ is not-degenerate, we may certainly find $c_0 > 0$ such that $\varphi_{c_0} := \varphi - c_0 i$ is weakly Pick on X and degenerate, and if we find extension for φ_{c_0}, we get one also for φ.

The proof of 6.15 immediately implies that the set of suitable values $\tilde{\varphi}(z_0)$ bounded, and as it is also clearly closed, it is compact.

Let us now move to the case of general non-empty X. For any finite subset $F \subset X$ denote the set of possible values of a weakly Pick extension of $\varphi\big|_F$ at z_0 by W_F. We clearly have $W_{F_1 \cup F_2} \subset W_{F_1} \cap W_{F_2}$ and hence

$$\{W_F | F \text{ is a finite subset of } X\}$$

is a family of compact sets with finite intersection property. Consequently their intersection is non-empty and compact. $\square$

Again, one could avoid the use of Zorn's lemma by, for instance, first extending φ to dense subset of $\mathbb{H}_+$ and then noting that this extension continuously extends to the whole of $\mathbb{H}_+$, to a weakly Pick function.

6.8 Notes and references

Chapter 7

Matrix monotone functions – part 3

7.1 Loewner's theorem

Aim of this chapter is to prove theorem 5.14. The proof is in several steps. First, "if"-direction is the easy part.

Lemma 7.1. *Let f be a Pick function, which analytically extends to $(\mathbb{C} \setminus \mathbb{R}) \cup (a, b)$. Assume further that $f\big|_{(a,b)}$ is real. Then $f\big|_{(a,b)} \in P_\infty(a, b)$.*

Proof. Since $f\big|_{(a,b)}$ is smooth, it suffices to prove that for any $n \geq 1$ and $q \in \mathbb{C}_{n-1}[x]$ the $(2n-1)$'th derivative of $fN(q)$ is non-negative. But as f is a Pick function, we have for any $t \in (a, b)$

$$\frac{(fN(q))^{(2n-1)}(t)}{(2n-1)!} = \lim_{\substack{z_1,\ldots,z_n \in \mathbb{H}_+ \\ z_1,\ldots,z_n \to t}} [z_1, \overline{z_1}, \ldots, z_n, \overline{z_n}]_{fN(q)} \geq 0.$$

□

The "only if" is the tricky part. Our plan is the following:

1. First show that f is real analytic on (a, b).
2. Next, show that if we can extend f analytically to $\mathbb{D}(x_0, r)$ for some $x_0 \in (a, b)$ and $r > 0$, then the extension is weakly Pick on $\mathbb{D}(x_0, r) \cap \mathbb{H}_+$.
3. Finally, by theorem 6.19 we get Pick function, which agree with f on $(x_0 - r, x_0 + r)$, so by real analyticity of f, on the whole interval (a, b).

Lemma 7.2. *Let $f \in P_\infty(a, b)$. Then f is real analytic.*

Proof. Proof is almost the same as that of theorem 6.16. In the class $P_\infty(a, b)$ we have

$$[x_0, x_1, \ldots, x_n]_f \leq \frac{1}{\operatorname{dist}(x_2, \mathbb{R} \setminus (a, b)) \cdots \operatorname{dist}(x_n, \mathbb{R} \setminus (a, b))} [x_0, x_1]_f$$

for any $a < x_0, x_1, \ldots, x_n < b$. As the first divided differences are locally bounded, conditions of the theorem 4.45 are satisfied. □

Lemma 7.3. *Assume that $f \in P_\infty(a, b)$, f is analytic at $x_0 \in (a, b)$ such that it can analytically extended to $\mathbb{D}(x_0, r)$ for some $r > 0$. Then the extension is weakly Pick on $\mathbb{D}(x_0, r) \cap \mathbb{H}_+$.*

Proof. Again, proof is almost the same as that of theorem 6.20: now just choose the sequence $z_1, z_2, \ldots$ on (a, b) and do estimates on $\mathbb{R} \setminus (a, b)$. □

Proof of theorem 5.14. This follows immediately from 7.1, 7.2, 7.3 and 6.19. □

7.2 Notes and references

Bibliography

[1] T. Ando. Majorization, doubly stochastic matrices, and comparison of eigenvalues. *Linear Algebra and Its Applications*, 118:163–248, 1989.

[2] T. Ando. Parameterization of minimal points of some convex sets of matrices. *Acta Scientiarum Mathematicarum (Szeged)*, 57:3–10, 1993.

[3] T. Ando. Majorizations and inequalities in matrix theory. *Linear algebra and its Applications*, 199:17–67, 1994.

[4] J. Antezana, E. R. Pujals, and D. Stojanoff. Iterated aluthge transforms: a brief survey. *Revista de la Unión Matemática Argentina*, 49(1):29–41, 2008.

[5] B. C. Arnold. Majorization: Here, there and everywhere. *Statistical Science*, pages 407–413, 2007.

[6] M. F. Atiyah. Convexity and commuting Hamiltonians. *Bull. London Math. Soc.*, 14(1):1–15, 1982.

[7] D. Azagra. Global approximation of convex functions. *arXiv preprint arXiv:1112.1042*, 2011.

[8] J. Bendat and S. Sherman. Monotone and convex operator functions. *Trans. Amer. Math. Soc.*, 79:58–71, 1955.

[9] H. Bercovici, C. Foias, and A. Tannenbaum. A spectral commutant lifting theorem. *Transactions of the American Mathematical Society*, 325(2):741–763, 1991.

[10] R. Bhatia. *Positive definite matrices.* Princeton university press, 2009.

[11] R. Bhatia. *Matrix analysis*, volume 169. Springer Science & Business Media, 2013.

[12] Z. Brady. Inequalities and higher order convexity. *arXiv preprint arXiv:1108.5249*, 2011.

[13] P. Bullen. A criterion for n-convexity. *Pacific Journal of Mathematics*, 36(1):81–98, 1971.

[14] S. Burgdorf. *Trace-positive polynomials, sums of hermitian squares and the tracial moment problem.* PhD thesis, 2011.

[15] K. Cafuta, I. Klep, and J. Povh. A note on the nonexistence of sum of squares certificates for the bessis–moussa–villani conjecture. *Journal of Mathematical Physics*, 51(8):083521, 2010.

[16] E. Carlen. Trace inequalities and quantum entropy: an introductory course. *Entropy and the quantum*, 529:73–140, 2010.

[17] P. Chansangiam. A survey on operator monotonicity, operator convexity, and operator means. *Int. J. Anal.*, pages Art. ID 649839, 8, 2015.

[18] F. Clivaz. *Stahl's Theorem: Insights and Intuition on its Proof and Physical Context.* PhD thesis, 2014.

[19] F. Clivaz. Stahl's theorem (aka bmv conjecture): Insights and intuition on its proof. In *Spectral Theory and Mathematical Physics*, pages 107–117. Springer, 2016.

[20] C. de boor. *A practical guide to splines.* Springer Verlag., 1978.

[21] C. de Boor. Divided differences. *Surv. Approx. Theory*, 1:46–69, 2005.

[22] O. Dobsch. Matrixfunktionen beschränkter Schwankung. *Math. Z.*, 43(1):353–388, 1938.

[23] W. F. Donoghue, Jr. *Monotone matrix functions and analytic continuation.* Springer-Verlag, New York-Heidelberg, 1974. Die Grundlehren der mathematischen Wissenschaften, Band 207.

[24] A. Eremenko. Herbert stahl's proof of the bmv conjecture. *arXiv preprint arXiv:1312.6003*, 2013.

[25] M. Floater and T. Lyche. Two chain rules for divided differences and faa di bruno's formula. *Mathematics of Computation*, 76(258):867–877, 2007.

[26] U. Franz, F. Hiai, and E. Ricard. Higher order extension of Löwner's theory: operator k-tone functions. *Trans. Amer. Math. Soc.*, 366(6):3043–3074, 2014.

[27] G. Frobenius. Ueber die Entwickelung analytischer Functionen in Reihen, die nach gegebenen Functionen fortschreiten. *J. Reine Angew. Math.*, 73:1–30, 1871.

[28] F. Hansen. Trace functions as laplace transforms. *Journal of mathematical physics*, 47(4):043504, 2006.

[29] F. Hansen. The fast track to Löwner's theorem. *Linear Algebra Appl.*, 438(11):4557–4571, 2013.

[30] F. Hansen and G. Kjærgård Pedersen. Jensen's inequality for operators and löwner's theorem. *Mathematische Annalen*, 258(3):229–241, 1982.

[31] F. Hansen and J. Tomiyama. Differential analysis of matrix convex functions. *Linear Algebra Appl.*, 420(1):102–116, 2007.

[32] F. Hansen and J. Tomiyama. Differential analysis of matrix convex functions. II. *JIPAM. J. Inequal. Pure Appl. Math.*, 10(2):Article 32, 5, 2009.

[33] G. H. Hardy, J. E. Littlewood, and G. Pólya. *Inequalities*. Cambridge university press, 1952.

[34] U. Helmke and J. Rosenthal. Eigenvalue inequalities and schubert calculus. *Mathematische Nachrichten*, 171:207–226, 1995.

[35] F. Hiai and D. Petz. *Introduction to matrix analysis and applications*. Springer Science & Business Media, 2014.

[36] C. J. Hillar. Advances on the bessis–moussa–villani trace conjecture. *Linear algebra and its applications*, 426(1):130–142, 2007.

[37] A. Hindmarsh. Pick's conditions and analyticity. *Pacific Journal of Mathematics*, 27(3):527–531, 1968.

[38] J. A. Holbrook. Spectral variation of normal matrices. *Linear algebra and its applications*, 174:131–144, 1992.

[39] R. A. Horn and C. R. Johnson. *Matrix analysis*. Cambridge university press, 2012.

[40] C. R. Johnson and C. J. Hillar. Eigenvalues of words in two positive definite letters. *SIAM journal on matrix analysis and applications*, 23(4):916–928, 2002.

[41] J. Karamata. Sur une inégalité relative aux fonctions convexes. *Publications de l'Institut mathematique*, 1(1):145–147, 1932.

[42] I. Klep and M. Schweighofer. Sums of hermitian squares and the bmv conjecture. *Journal of Statistical Physics*, 133(4):739–760, 2008.

[43] A. A. Klyachko. Stable bundles, representation theory and Hermitian operators. *Selecta Math. (N.S.)*, 4(3):419–445, 1998.

[44] A. Knutson and T. Tao. Honeycombs and sums of Hermitian matrices. *Notices Amer. Math. Soc.*, 48(2):175–186, 2001.

[45] G. Kowalewski. *Interpolation und genäherte Quadratur*. Teubner Leipzig und Berlin, 1932.

[46] F. Kraus. Über konvexe Matrixfunktionen. *Math. Z.*, 41(1):18–42, 1936.

[47] K. Löwner. Über monotone Matrixfunktionen. *Math. Z.*, 38(1):177–216, 1934.

[48] A. W. Marshall, I. Olkin, and B. C. Arnold. *Inequalities: theory of majorization and its applications*. Springer Series in Statistics. Springer, New York, second edition, 2011.

[49] R. F. Muirhead. Some methods applicable to identities and inequalities of symmetric algebraic functions of n letters. *Proceedings of the Edinburgh Mathematical Society*, 21:144–162, 1902.

[50] H. Mulholland. On generalizations of minkowski's inequality in the form of a triangle inequality. *Proceedings of the London Mathematical Society*, 2(1):294–307, 1949.

[51] R. Nevanlinna. *Über beschränkte funktionen die in gegebenen punkten vorgeschriebene werte annehmen...* Buchdruckerei-a.-g. Sana, 1919.

[52] G. Pick. Über die beschränkungen analytischer funktionen, welche durch vorgegebene funktionswerte bewirkt werden. *Mathematische Annalen*, 77(1):7–23, 1915.

[53] A. Pinkus and D. Wulbert. Extending n-convex functions. *Studia Math*, 171(2):125–152, 2005.

[54] T. Popoviciu. *Les fonctions convexes*, volume 992. Bussière, 1945.

[55] A. W. Roberts and D. E. Varberg. *Convex functions*, volume 57. Academic Press, 1974.

[56] D. Sarason. Generalized interpolation in H^∞. *Trans. Amer. Math. Soc.*, 127:179–203, 1967.

[57] D. Sarason. Nevanlinna-pick interpolation with boundary data. *Integral Equations and Operator Theory*, 30(2):231–250, 1998.

[58] H. R. Stahl et al. Proof of the bmv conjecture. *Acta Mathematica*, 211(2):255–290, 2013.

[59] The Sage Developers. *SageMath, the Sage Mathematics Software System (Version 7.1)*, 2016. `http://www.sagemath.org`.

[60] J. A. Tropp et al. An introduction to matrix concentration inequalities. *Foundations and Trends® in Machine Learning*, 8(1-2):1–230, 2015.

[61] H. Weyl. Das asymptotische verteilungsgesetz der eigenwerte linearer partieller differentialgleichungen (mit einer anwendung auf die theorie der hohlraumstrahlung). *Mathematische Annalen*, 71(4):441–479, 1912.

[62] F. Zhang. *Matrix theory: basic results and techniques.* Springer Science & Business Media, 2011.