

# Midterm II



27. marraskuuta 2018

## Theorem 1 (Theorem of Matrix Theory)

Let  $V, W$  be finite-dimensional vector spaces of dimension  $n$  and  $m$ , respectively, and ordered bases  $\mathcal{B}, \mathcal{C}$ , respectively, and  $T : V \rightarrow W$  a linear transformation.

Then  $\varphi : L(V, W) \rightarrow F^{m \times n}$  by  $T \rightarrow [T]_{\mathcal{B}, \mathcal{C}}$  is an isomorphism. In particular,  $\dim L(V, W) = mn$ .

*Todistus.* Exercise! □

## Note 2

"Watching me get confused in notation doesn't help you learn it". -rse

## Theorem 3

Let  $V, W, X$  be finite-dimensional vector spaces with ordered bases  $\mathcal{B}, \mathcal{C}, \mathcal{D}$ , respectively, and linear transformations  $T : V \rightarrow W, S : W \rightarrow X$ . Then

$$[S \circ T]_{\mathcal{B}, \mathcal{D}} = [S]_{\mathcal{C}, \mathcal{D}} \cdot [T]_{\mathcal{B}, \mathcal{C}}.$$

*Todistus.* Let  $v \in V$ . In this case,  $[S]_{\mathcal{C}, \mathcal{D}} [T]_{\mathcal{B}, \mathcal{C}} [v]_{\mathcal{B}} = [S]_{\mathcal{C}, \mathcal{D}} \cdot [Tv]_{\mathcal{C}}$ , which, by definition, equals  $[S(Tv)]_{\mathcal{D}} = [(S \circ T)(v)]_{\mathcal{D}} = [S \circ T]_{\mathcal{B}, \mathcal{D}} [v]_{\mathcal{B}}$ . □

## Corollary 4

Let  $V, W$  be finite-dimensional vector spaces over  $F$ ,  $\mathcal{B}, \mathcal{C}$  ordered bases, respectively, and  $\dim V = \dim W$ . Then

$$(T : V \rightarrow W \text{ is an isomorphism}) \iff ([T]_{\mathcal{B}, \mathcal{C}} \text{ is invertible}).$$

Moreover, if  $V$  is a finite-dimensional vector space over  $F$ ,  $\dim V = n$ , and  $\mathcal{B}$  an ordered basis for  $V$ , then  $\varphi : L(V, V) \rightarrow \mathbb{M}_n F$  is an isomorphism. Moreover,  $\forall T, S \in L(V, V)$ ,  $\varphi$  satisfies the following:

1.  $\varphi(T + S) = \varphi(T) + \varphi(S)$
2.  $\varphi(T \circ S) = \varphi(T) \circ \varphi(S)$
3.  $\varphi(0_V) = 0_{F^n}$
4.  $\varphi(1_V) = I_n$

As  $L(V, V)$  satisfies all field axioms except (M3) and (M4), it is a (noncommutative) ring, so  $\varphi$  is a **ring isomorphism**.

#### Theorem 5 (Change-of-basis Theorem)

Let  $V, W$  be finite-dimensional vector spaces over  $F$  with ordered basis  $\mathcal{B}, \mathcal{B}'$  for  $V$ , and  $\mathcal{C}, \mathcal{C}'$  for  $W$ , as well as a linear map  $T : V \rightarrow W$ . Then,

$$\begin{aligned} [T]_{\mathcal{B}, \mathcal{C}} &= [1_W]_{\mathcal{C}', \mathcal{C}} [T]_{\mathcal{B}', \mathcal{C}'} [1_V]_{\mathcal{B}, \mathcal{B}'} \\ &= [1_W]_{\mathcal{C}, \mathcal{C}'}^{-1} [T]_{\mathcal{B}', \mathcal{C}'} [1_V]_{\mathcal{B}, \mathcal{B}'} \\ &= [1_W]_{\mathcal{C}', \mathcal{C}} [T]_{\mathcal{B}', \mathcal{C}'} [1_V]_{\mathcal{B}', \mathcal{B}}^{-1}. \end{aligned}$$

*Proof.* This is clearly true since the diagram

$$\begin{array}{ccc} V_{\mathcal{B}} & \xrightarrow{[T]_{\mathcal{B}, \mathcal{C}}} & W_{\mathcal{C}} \\ [1_V]_{\mathcal{B}, \mathcal{B}'} \downarrow & \searrow [T]_{\mathcal{B}', \mathcal{C}'} & \downarrow [1_W]_{\mathcal{C}, \mathcal{C}'} \\ V_{\mathcal{B}'} & \xrightarrow{[T]_{\mathcal{B}', \mathcal{C}'}} & W_{\mathcal{C}'} \end{array}$$

commutes. □

#### Note 6

"This is exactly what will come up in real life, whatever real life is..." –rse

#### Definition 7

Let  $A, B \in \mathbb{M}_n(F)$  be matrices. We say that  $A$  is **similar** to  $B$  and write

$A \sim B$  if  $\exists$  an invertible matrix  $S \in \mathbb{M}_n(F) \ni A = S^{-1}BS$ .

**Remark 8.** This is an equivalence relation.

**Theorem 9**

Let  $A, B \in \mathbb{M}_n(F)$ . Then,

$(A, B \text{ are similar}) \iff (\exists \text{ an } n\text{-dimensional vector space over } F \text{ with ordered bases } \mathcal{B}, \mathcal{C} \ni \text{ linear transformation } T : V \rightarrow V \text{ satisfies } A = [T]_{\mathcal{B}}, B = [T]_{\mathcal{C}}).$

**Definition 10**

Let  $0 \neq V$  be a vector space over  $F$ ,  $T : V \rightarrow V$  linear,  $\lambda \in F$ . Let  $S_{\lambda} : T - \lambda 1_V : V \rightarrow V$  linear.

We say that  $\lambda$  is an **eigenvalue** (and write *eit*) of  $T$  if  $S_{\lambda}$  is not one-to-one; i.e.,  $\ker S_{\lambda} > 0$ , i.e.,  $\exists 0 \neq v \in \ker S_{\lambda}$  such that  $Tv = \lambda v$ .

If we let  $E_T(\lambda) := \ker S_{\lambda} = \{v \in V \mid Tv = \lambda v\}$ , then we call it an **eigenspace** of  $\lambda$  for  $T$  if it's nonzero.

If  $E_T(\lambda) \neq 0$ ; i.e., an eigenspace; an element  $v \in E_T(\lambda)$  is called an **eigenvector** of  $T$  relative to  $\lambda$ .

**Lemma 11**

Let  $A, B \in \mathbb{M}_n(F)$  be your favorite matrices, and  $A \sim B$  (i.e.,  $\exists C \in \mathbb{M}_n(F)$  invertible  $\ni A = C^{-1}BC$ ). Then  $f_A = f_B$ .

**Note 12**

The converse of this lemma is false in general.

**Definition 13**

Let  $V$  be a finite-dimensional vector space over  $F$ ,  $T : V \rightarrow V$  linear,  $\mathcal{B}$  an ordered basis for  $V$ . Then  $f_{[T]_{\mathcal{B}}}$  is called the **characteristic polynomial** of  $T$ , written as  $f_T$ . By the previous lemma, it's independent of the basis.

**Theorem 14**

Let  $V$  be a finite-dimensional vector space over  $F$ ,  $T : V \rightarrow V$  linear. Then the eigenvalues of  $T$  are precisely the roots of  $f_T$ ; i.e.,  $\lambda$  is an eit of  $T$  iff  $f_T(\lambda) = 0$ .

**Theorem 15 (Cayley-Hamilton)**

Let  $V$  be a finite-dimensional vector space over  $F$ ,  $T : V \rightarrow V$  linear. Then  $f_T(T) = 0$ ; i.e., if  $f_T = \sum a_i t^i$ , then  $\sum a_i T^i = 0$ ; i.e.,  $e_T f = 0$ .

**Theorem 16**

Let  $T : V \rightarrow V$  be linear,  $\lambda_1, \dots, \lambda_n \in F$  distinct eits of  $T$ . Let  $0 \neq v_i \in E_T(\lambda_i)$ ,  $i = 1, 2, \dots, n$ . Then,  $\{v_1, \dots, v_n\}$  is linearly independent.

**Corollary 17**

Let  $V$  be a finite-dimensional vector space over  $F$ ,  $\dim V = n < \infty$ . If  $T : V \rightarrow V$  linear has  $n$  distinct eigenvalues, then  $T$  is diagonalizable; i.e., has a basis of eigenvectors.

**Corollary 18**

Let  $V$  be a finite-dimensional vector space over  $F$ ,  $\dim V = n$ ,  $T : V \rightarrow V$  linear, then  $T$  has at most  $n$  distinct eigenvalues.

**Corollary 19**

Let  $V$  be a vector space over  $F$ ,  $\lambda_1, \dots, \lambda_n$  eigenvalues of  $T : V \rightarrow V$  linear. Let  $v_i \in E_T(\lambda_i)$ ,  $i = 1, \dots, n$ . Then if  $v_1 + \dots + v_n = 0$ , then  $v_i = 0 \forall i$ .

**Definition 20**

Let  $F$  be a field,  $F \subset \mathbb{C}$ ,  $F = \bar{F}$ ,  $V$  a vector space over  $F$ . We say that  $V$  is an **inner product space**, and write  $V$  is an ips/ $F$ , under a map  $\langle, \rangle : V \times V \rightarrow F$ , written as  $\langle v, w \rangle$  for  $\langle, \rangle (v, w)$ , which satisfies,  $\forall v, v_1, v_2, v_3 \in V, \forall \alpha \in F$ ,

1.  $\langle v_1 + v_2, v_3 \rangle = \langle v_1, v_3 \rangle + \langle v_2, v_3 \rangle$
2.  $\langle v_1, v_2 \rangle = \overline{\langle v_2, v_1 \rangle}$
3.  $\langle \alpha v_1, v_2 \rangle = \alpha \langle v_1, v_2 \rangle$
4.  $\langle v, v \rangle \in F \cap \mathbb{R}$ , and  $\langle v, v \rangle \geq 0$  and  $= 0$  iff  $v = 0$ .

Define,  $\forall v \in V$ ,  $\|v\| := \sqrt{\langle v, v \rangle} \in \mathbb{R}$ . However, this may not lie in  $F$ ! (for example, consider the length of  $(1,1)$  in  $\mathbb{Q}^2$  under the dot product).

### Theorem 21

Let  $V$  be a vector space over  $F$ . Then  $\forall v_1, v_2 \in V$ ,  $\alpha \in F$ ,

1.  $\|v_1\| \geq 0$  and  $= 0$  iff  $v_1 = 0$ .
2.  $\|\alpha v_1\| = |\alpha| \|v_1\|$ .
3. (Cauchy-Schwarz)  $|\langle v_1, v_2 \rangle| \leq \|v_1\| \|v_2\|$ .
4. (Minkowski's inequality)  $\|v_1 + v_2\| \leq \|v_1\| + \|v_2\|$ .

### Definition 22

Let  $V, W$  be vector spaces over  $F$ ,  $T : V \rightarrow W$  linear. Suppose  $g \in W^*$ , i.e.,  $g : W \rightarrow F$  linear. In other words,

$$\begin{array}{ccc} V & \xrightarrow{T} & W \\ & \searrow g \circ T & \downarrow g \\ & & F \end{array}$$

commutes. Observe that  $g \circ T \in V^*$ . This motivates the following definition:

The **transpose**  $T^t : W^* \rightarrow V^*$  of  $T$  is given by  $T^t g := g \circ T$   
 $T^t : W^* \rightarrow V^*$  is linear.

### Theorem 23

Let  $V, W$  be finite-dimensional vector spaces over  $F$ ,  $\mathcal{B}, \mathcal{C}$  ordered bases for  $V, W$ , respectively. Then

$$[T]_{\mathcal{B}, \mathcal{C}}^t = [T^t]_{\mathcal{C}^*, \mathcal{B}^*}$$

where  $\mathcal{B}^*$  and  $\mathcal{C}^*$  are ordered bases dual to  $\mathcal{B}$  and  $\mathcal{C}$ , respectively.

### Definition 24

Let  $V$  be a vector space over  $F$ ,  $\emptyset \neq S \subset V$  a subset of  $V$ . The set  $S^0 := \{f \in V^* \mid f|_S = 0\} = \{f \in V^* \mid f(s) = 0 \forall s \in S\}$  is called the **annihilator** of  $S$ .

### Lemma 25

Let  $V$  be a finite-dimensional vector space over  $F$ , and  $W \subset V$  be a subspace. Then  $\dim V = \dim W + \dim W^0$ .

### Corollary 26

Let  $V$  be a finite-dimensional vector space over  $F$ ,  $W \subset V$  a subspace. Then  $W = W^{00}$ .

### Theorem 27

Let  $V$  be an inner product space over  $F$ ,  $S \subset V$  an OR set<sup>a</sup>. Then  $S$  is a linearly independent set if  $0 \notin S^b$ . If in addition  $V$  is a finite dimensional inner product space over  $F$  and  $V = \text{Span}(S)$ , then  $S$  is a basis for  $V$  and  $\dim V = |S|$ .

<sup>a</sup>Since it's an OR set, it's nonempty by definition.

<sup>b</sup>Note that this is always true for an ON set.

### Theorem 28 (Gram-Schmidt Theorem)

Let  $V$  be an inner product space over  $F$ , and  $S = \{v_1, \dots, v_n\}$  a linearly independent (nonempty) set in  $V$ . Then there exists a set  $B = \{y_1, \dots, y_n\}$  satisfying the following:

1.  $B$  is OR
2.  $0 \notin B$
3.  $\text{Span}(S) = \text{Span}(B)$

4.  $y_1 = v_1$

*Todistus.* We construct  $B$  using the *Gram-Schmidt Process*.

Essentially, we induct on  $n$ :

Base case ( $n = 1$ ):  $v_1 \neq 0$ , so  $\{v_1\}$  is linearly independent and satisfies 1 through 4.

Inductive case: Assume that if  $\{v_1, \dots, v_n\}$  is linearly independent, then  $B_n = \{y_1, \dots, y_n\}$  OR such that it's linearly independent,  $\text{Span}(S_n) = \text{Span}(B_n)$ , and  $y_1 = v_1$ . Let  $S_{n+1} = \{v_1, \dots, v_{n+1}\}$  be linearly independent. We want to show that  $\exists B_{n+1}$  satisfying the four requirements.

Define  $y_{n+1} := v_{n+1} - \sum_{i=1}^n \frac{\langle v_{n+1}, y_i \rangle}{\|y_i\|^2} y_i$ . Clearly  $\{y_1, \dots, y_{n+1}\}$  is linearly independent, since  $y_{n+1}$  is nonzero. Now we compute  $\langle y_{n+1}, y_i \rangle$  for  $i = 1, \dots, n$ :

$$\begin{aligned} \langle y_{n+1}, y_i \rangle &= \left\langle v_{n+1} - \sum_{k=1}^n \frac{\langle v_{n+1}, y_k \rangle}{\|y_k\|^2} y_k, y_i \right\rangle \\ &= \langle v_{n+1}, y_i \rangle - \sum_{k=1}^n \frac{\langle v_{n+1}, y_k \rangle}{\|y_k\|^2} \langle y_k, y_i \rangle \\ &= \langle v_{n+1}, y_i \rangle - \sum_{k=1}^n \frac{\langle v_{n+1}, y_k \rangle}{\|y_k\|^2} \delta_{ki} \|y_i\|^2 \\ &= \langle v_{n+1}, y_i \rangle - \langle v_{n+1}, y_i \rangle \\ &= 0. \end{aligned}$$

Hence,  $y_{n+1} \perp y_i$ ,  $i = 1, \dots, n$ . Hence,  $B_{n+1}$  is an OR set and  $0 \notin B_{n+1}$ , so  $B_{n+1}$  is linearly independent.

Thus, all we have left to show is the span property, which we do as follows:

$$\begin{aligned} \text{Span}(B_{n+1}) &= \text{Span}(y_1, \dots, y_{n+1}) \\ &= \text{Span}(v_1, \dots, v_n, y_{n+1}) \\ &= \text{Span}(v_1, \dots, v_{n+1}) \quad (\text{By the **Replacement Theorem**}) \\ &= \text{Span}(S_{n+1}). \end{aligned}$$

We're done by induction.  $\square$

### Theorem 29 (ON Theorem)

Let  $V$  be a finite-dimensional inner product space over  $F$ . Then  $V$  has an OR basis  $\mathcal{B}$ . If  $F = \mathbb{R}$  or  $\mathbb{C}$ , then  $V$  has an ON basis  $\mathcal{C}$ .

*Todistus.* By the **Gram-Schmidt Theorem**,  $\exists \mathcal{B} = \{y_1, \dots, y_n\}$  an OR basis for  $V$ .

If  $F = \mathbb{R}$  or  $\mathbb{C}$ , then

$$\mathcal{E} = \left\{ \frac{y_1}{\|y_1\|}, \dots, \frac{y_n}{\|y_n\|} \right\}$$

is an ON basis. □

### Note 30

"Anything I wrote down is probably wrong" –rse

### Theorem 31 (OR Decomposition Theorem)

Let  $V$  be an ips/ $F$ , not necessarily finite-dimensional,  $S \subset V$  a finite dimensional subspace,  $v \in V$ . Then,

$$\exists! s \in S, s^\perp \in S^\perp, \ni v = s + s^\perp \quad (*)$$

In particular,  $V = S + S^\perp$  and  $S \cap S^\perp = 0$ ; i.e.,  $V = S \oplus S^\perp$ .

Moreover, if  $v = s + s^\perp$ ,  $s \in S$ ,  $s^\perp \in S^\perp$ , then

$$\|v\|^2 = \|s\|^2 + \|s^\perp\|^2 \quad (\text{Pythagoras})$$

If in addition,  $V$  is a finite-dimensional inner product space over  $F$ , then  $\dim V = \dim S + \dim S^\perp$ .

*Todistus.* Let  $\mathcal{B} = \{v_1, \dots, v_n\}$  be an OR basis for  $S$  (which exists by the **Gram-Schmidt Theorem**). Let  $v \in V$ .

*Existence:* Let  $s = \sum_{i=1}^n \frac{\langle v, v_i \rangle}{\|v_i\|^2} v_i$  be the orthogonal projection of  $v$  onto  $S$ ;  $s^\perp := v - s$ .

**Claim 31.1.**  $s^\perp \in S^\perp$ . Note that this claim implies  $V = S + S^\perp$  and  $S \cap S^\perp = 0$ .

*Todistus.* Let  $j = 1, \dots, n$  be fixed. Then

$$\begin{aligned} \langle s^\perp, v_j \rangle &= \langle v - s, v_j \rangle && (\text{By definition of } s^\perp) \\ &= \langle v, v_j \rangle - \langle s, v_j \rangle && (\text{By linearity in the first term}) \\ &= \langle v, v_j \rangle - \left\langle \sum_{i=1}^n \frac{\langle v, v_i \rangle}{\|v_i\|^2} v_i, v_j \right\rangle && (\text{By definition of } s) \\ &= \langle v, v_j \rangle - \sum_{i=1}^n \frac{\langle v, v_i \rangle}{\|v_i\|^2} \langle v_i, v_j \rangle && (\text{By linearity in the first term}) \end{aligned}$$



$$\begin{aligned}
&= \langle v, v_j \rangle - \sum_{i=1}^n \frac{\langle v, v_i \rangle}{\|v_i\|^2} v_i \sum_{i=1}^n \delta_{ij} \|v_j\|^2 \\
&= 0
\end{aligned}$$

Hence, if  $w = \alpha_1 v_1 + \dots + \alpha_n v_n$ , then  $\langle s^\perp, w \rangle = \sum_{i=1}^n \alpha_i \langle s^\perp, v_i \rangle = 0$ .  $\square$

*Uniqueness:* If  $s + s^\perp = r + r^\perp$ ,  $r, s \in S$ ,  $r^\perp, s^\perp \in S^\perp$ , then  $s - r = r^\perp - s^\perp$ , where  $s - r \in S$  and  $r^\perp - s^\perp \in S^\perp$ . But  $S \cap S^\perp = 0$ , so  $s - r = r^\perp - s^\perp = 0$ , so  $r = s = r^\perp = s^\perp = 0$ .

Thus, we have showed (\*).

*Pythagoras:*  $v = s + s^\perp$ ,  $s \in S$ ,  $s^\perp \in S^\perp$ . Then

$$\begin{aligned}
\|v\|^2 &= \langle v, v \rangle \\
&= \langle s + s^\perp, s + s^\perp \rangle \\
&= \langle s, s \rangle + \langle s, s^\perp \rangle + \langle s^\perp, s \rangle + \langle s^\perp, s^\perp \rangle \\
&= \|s\|^2 + 0 + 0 + \|s^\perp\|^2 \\
&= \|s\|^2 + \|s^\perp\|^2.
\end{aligned}$$

Finally, if  $V$  is a fdips/ $F$ , then

$$\begin{aligned}
\dim S + \dim S^\perp &= \dim (S + S^\perp) - \dim (S \cap S^\perp) \\
&\quad \text{(By the **Counting Theorem**)} \\
&= \dim V - \dim 0 \\
&= V
\end{aligned}$$

$\square$

### Corollary 32 (Bessel's Inequality)

Let  $V$  be an ips/ $F$ ,  $B = \{v_1, \dots, v_n\}$  be an OR set,  $0 \notin B$ . Let  $v \in V$ . Then

$$\sum_{i=1}^n \frac{|\langle v, v_i \rangle|^2}{\|v_i\|^2} \leq \|v\|^2$$

with equality holding iff  $v = \sum_{i=1}^n \frac{\langle v, v_i \rangle}{\|v_i\|^2} v_i$ .

### Note 33

Let  $V$  be an ips/ $F$ ,  $S \subset V$  a finite-dimensional subspace. If  $v \in V$ ,  $\exists! s \in S$ ,  $s^\perp \in S^\perp \ni v = s + s^\perp$ . We call  $s$  the **orthogonal projection of  $v$  on  $S$** , and write  $v_S$  for  $s$ .

By the proof of the OR decomposition theorem, if  $\mathcal{B} = \{v_1, \dots, v_n\}$  is an OR basis for  $S$ , then

$$v_S = \sum_{i=1}^n \frac{\langle v, v_i \rangle}{\|v_i\|^2} v_i$$

and  $s^\perp = v - s = v - v_S$ .

Since it's unique, it's *independent of the orthogonal basis!*

### Theorem 34 (Approximation Theorem)

Let  $V$  be an ips/ $F$ ,  $S \subset V$  a finite-dimensional subspace,  $v \in V$ . Then  $v_S$  is closer to  $V$  than any other vector in  $S$ ; i.e.,  $d(v, v_S) = \|v - v_S\| \leq \|v - r\| \forall r \in S$ .

Equivalently,  $d(v, v_S) = d(v, S)$ .

Moreover,  $v_S$  is the unique closest vector in  $S$  to  $v$ , i.e., if  $\|v - v_S\| = \|v - r\|$ ,  $r \in S$ , then  $r = v_S$ .

*Proof.* By the **OR Decomposition Theorem**,  $v = s + s^\perp$ ,  $s = v_S \in S$ ,  $s^\perp = v - v_S \in S^\perp$ .

If  $r \in S$ , then  $v - r = (v - v_S) + (v_S - r) = s^\perp + \underbrace{(v_S - r)}_{\in S}$ , so  $\langle v - v_S, v_S - r \rangle = 0$ .

By Pythagoras,  $\|v - r\|^2 = \|v - v_S\|^2 + \|v_S - r\|^2$ , which is greater than or equal to  $\|v - v_S\|^2$ , with equality iff  $\|v_S - r\| = 0$ ; i.e.,  $v_S = r$ .  $\square$