

CX1104: Linear Algebra for Computing

Chap. No : **8.1.5B**

Lecture : **Linear Transformation and EigenVectors**

Concept : **Linear Transformation and
Change of Basis using eigen Basis**

Note: Revise 8.1.5A first if
unfamiliar with coordinate system
and change of basis.

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$$\underbrace{\begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}}_{x} = \underbrace{\begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}}_{b}$$

1) Overview: $Ax = y$, Least Squares vs Linear Transformation

1) In Gaussian Elimination for system of equations

and Least Squares, the equation $Ax = y$ is presented.

In this case, A and y represent the given equation values and target respectively

- The problem there is to find x that minimize the error to approximate y .

2) In Linear Transformation, the problem also has the same equation $Ax = y$,

in this case, the interpretation is different to (1). Here,

- x is the input vector to be transformed to desired vector y
through the linear transformation $y = T(x)$, evaluated as $y = Ax$
- In some machine learning problems, x represents the input, y the target and A the model. The machine learning algorithm strive to find the best A .
- Here, the ML community do not use linear models A , but nonlinear models.
- and the number of examples (x_i, y_i) typically number into the millions.

1.1) Linear Transformation $y = T(x) = Ax$

Given input vector $x \in R^n$, with coordinates in the standard basis and linear transformation $T: R^n \rightarrow R^m$ represented by matrix A , then $y = T(x) = Ax \in R^m$, The columns of A are:

$$A = [T(\mathbf{e}_1) \quad T(\mathbf{e}_2) \quad \cdots \quad T(\mathbf{e}_n)]$$

and $\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n$ denote the standard basis vectors for \mathbb{R}^n . This A is called the **matrix of T** .

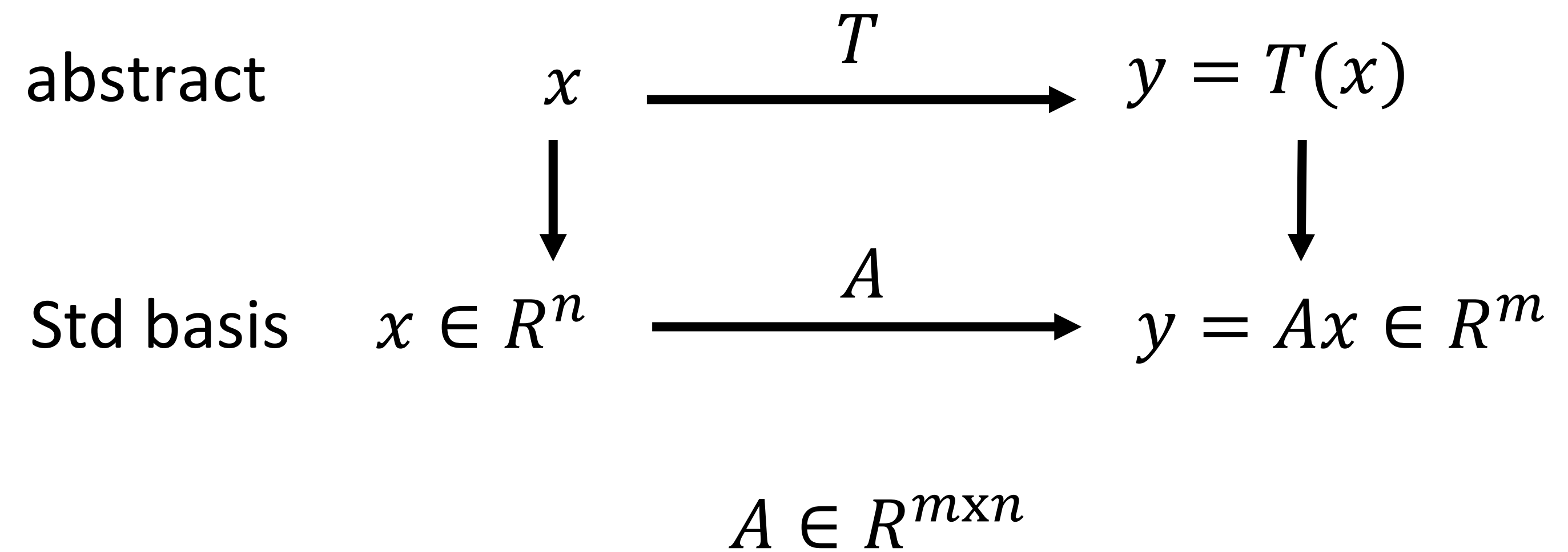


Fig: representation of a linear transformation

Ref:

- 1) [https://math.libretexts.org/Bookshelves/Linear Algebra/Book%3A A First Course in Linear Algebra \(Kuttler\)/05%3A Linear Transformations](https://math.libretexts.org/Bookshelves/Linear_Algebra/Book%3A_A_First_Course_in_Linear_Algebra_(Kuttler)/05%3A_Linear_Transformations) (Ch5.1, 5.2)

1.2) Proof that $T(\mathbf{x})$ can be represented as a matrix product $A\mathbf{x}$

Theorem. Consider a linear transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$. The transformation T can be represented as a matrix product $\mathbf{x} \mapsto A\mathbf{x}$, for some matrix $A \in \mathbb{R}^{n \times n}$.

Proof. Consider a matrix $\mathbf{x} \in \mathbb{R}^n$ given by

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}.$$

We will construct a matrix $A \in \mathbb{R}^{n \times n}$ such that $T(\mathbf{x}) = A\mathbf{x}$.

The vector \mathbf{x} can also be written as

$$\begin{aligned} \mathbf{x} &= x_1 \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + x_2 \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix} + \cdots + x_n \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix} \\ &= x_1 \mathbf{e}_1 + x_2 \mathbf{e}_2 + \cdots + x_n \mathbf{e}_n \\ &= \sum_{i=1}^n x_i \mathbf{e}_i, \end{aligned}$$

where \mathbf{e}_i are the standard basis vectors in \mathbb{R}^n .

Consider the transformation $T(\mathbf{x})$. Rewriting \mathbf{x} as above, we have

$$\begin{aligned} T(\mathbf{x}) &= T\left(\sum_{i=1}^n x_i \mathbf{e}_i\right) \\ &= \sum_{i=1}^n T(x_i \mathbf{e}_i) \\ T(\mathbf{x}) &= \sum_{i=1}^n x_i T(\mathbf{e}_i). \end{aligned} \tag{1}$$

Let the matrix $A \in \mathbb{R}^{n \times n}$ be defined by

$$\begin{aligned} A &= [T(\mathbf{e}_1) \quad T(\mathbf{e}_2) \quad \cdots \quad T(\mathbf{e}_n)] \\ &= \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}, \end{aligned}$$

where each $T(\mathbf{e}_i)$ is a column of A , and each $a_{ij} = T(\mathbf{e}_i) \cdot \mathbf{e}_j$ is the j th component of $T(\mathbf{e}_i)$. Then, by the definition of matrix-vector multiplication, we have

$$\begin{aligned} A\mathbf{x} &= \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \\ &= \begin{bmatrix} x_1 a_{11} + \cdots + x_n a_{1n} \\ \vdots \\ x_1 a_{n1} + \cdots + x_n a_{nn} \end{bmatrix} \\ &= x_1 \begin{bmatrix} a_{11} \\ \vdots \\ a_{n1} \end{bmatrix} + \cdots + x_n \begin{bmatrix} a_{1n} \\ \vdots \\ a_{nn} \end{bmatrix} \\ &= x_1 T(\mathbf{e}_1) + \cdots + x_n T(\mathbf{e}_n) \\ A\mathbf{x} &= \sum_{i=1}^n x_i T(\mathbf{e}_i). \end{aligned} \tag{2}$$

Therefore, by eqs. (1) and (2), we have that

$$T(\mathbf{x}) = \sum_{i=1}^n x_i T(\mathbf{e}_i) \quad A\mathbf{x} = \sum_{i=1}^n x_i T(\mathbf{e}_i),$$

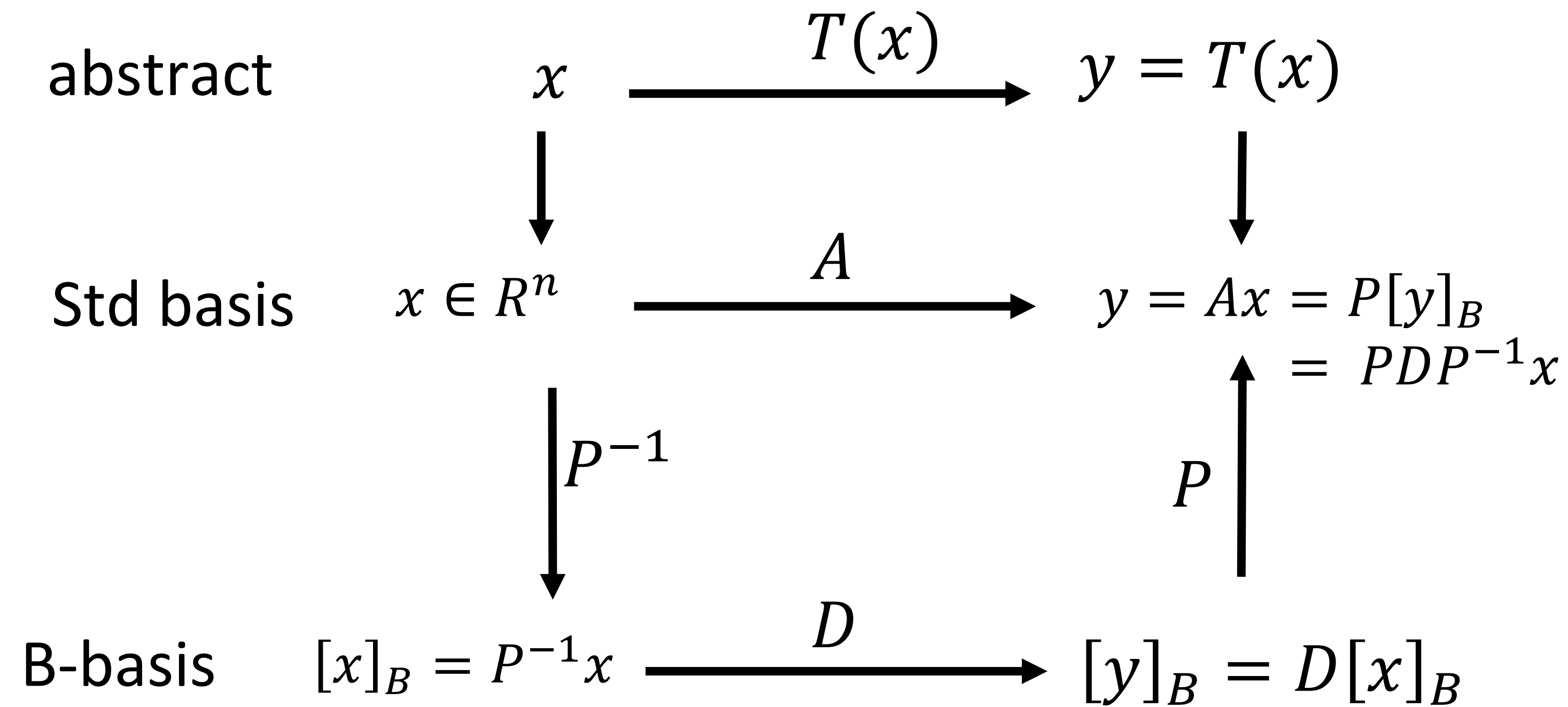
and we reach $T(\mathbf{x}) = A\mathbf{x}$, as was to be shown.

The crux of the proof is that using the standard basis and by linearity, $\mathbf{x} = \sum \mathbf{e}_i x_i \implies T(\mathbf{x}) = \sum T(\mathbf{e}_i) x_i = \sum \mathbf{a}_i x_i$ where the \mathbf{a}_i can be arranged as the columns of the matrix. – user65203

Ref:

1) <https://math.stackexchange.com/questions/916192/proving-any-linear-transformation-can-be-represented-as-a-matrix>

2.1) If A is a dense matrix, computing Ax can sometimes be simplified by converting A *and* x into another basis.



Motivation: why change basis?
 We wish to perform change of basis on x to another basis $[x]_B$.
 In basis B , the transformation A will be a very sparse diagonal matrix D , hence calculating Ax is cheap.

P is a matrix with columns containing a basis,

$$P = \{b_1, b_2, \dots, b_n\}$$

How is standard basis related to B -basis:

$$\begin{aligned} x &= P[x]_B \\ P^{-1}x &= [x]_B \end{aligned}$$

$$\begin{aligned} y &= T(x) \\ y &= Ax \\ &= P(D (P^{-1}x)) \end{aligned}$$

Changing from B-basis to Std basis

Transformation T in B-basis

Changing from Std to B-basis, this is $[x]_B$

2.2) Linear Transformation from V into V

THEOREM 8

Diagonal Matrix Representation

Suppose $A = PDP^{-1}$, where D is a diagonal $n \times n$ matrix. If \mathcal{B} is the basis for \mathbb{R}^n formed from the columns of P , then D is the \mathcal{B} -matrix for the transformation $\mathbf{x} \mapsto A\mathbf{x}$.

Lay, 4th, pg291, ch4.4

Note: P contains the set of eigenvectors of A , and for P^{-1} to exist, it means that P contains n number of independent eigenvectors, and D is a diagonal matrix containing the eigenvalues. Not all matrix have this characteristics. When matrix have this characteristic, we say these matrixes are diagonalizable.

See Tut8, Q7A YouTube: <https://youtu.be/zaSqGGmNokw>

2.3) D is the transformation matrix in B basis.

See pg 7 of slide 8.1.5A

$$\boxed{\mathbf{x} = P_B [\mathbf{x}]_B} \quad \boxed{P_B^{-1} \mathbf{x} = [\mathbf{x}]_B} \quad (4)$$

We call P_B the **change-of-coordinates matrix** from \mathcal{B} to the standard basis in \mathbb{R}^n .

if A can be decomposed into $y = Ax$
 $A = PDP^{-1}$, therefore

$y = PDP^{-1}x$,
We can view $P^{-1}x$ as changing coordinate to B, i.e $[x]_B$

$$\begin{aligned} y &= P D(P^{-1}x) \\ &= P D[x]_B \\ &= P [y]_B \end{aligned}$$

We can view $D[x]_B$ as transformation matrix D applied on $[x]_B$, (*Theorem 8*)
i.e D is the transformation matrix in B basis,
and $[y]_B = D[x]_B$ (y in the B-basis). Lastly

$y = P [y]_B$
can be viewed as converting y in B-basis back to standard basis.

2.4) Linear Transformation wrt B-basis pictorially

$$\begin{array}{ccc}
 x & \xrightarrow{A = PDP^{-1}} & y = Ax = PDP^{-1}x \\
 \begin{array}{c} \text{blue } \downarrow P^{-1} \\ \text{red } \uparrow P \end{array} & & \begin{array}{c} \text{blue } \downarrow P^{-1} \\ \text{red } \uparrow P \end{array} \\
 [x]_B & \xrightarrow{[T]_B = D} & [y]_B = [Ax]_B = [T]_B [x]_B
 \end{array}$$

$$\begin{array}{l}
 x = P[x]_B \\
 P^{-1}x = [x]_B
 \end{array}$$

$$\begin{array}{l}
 y = P[y]_B \\
 P^{-1}y = [y]_B
 \end{array}$$

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Lay, 4th, pg291, ch4.4

THEOREM 8

Diagonal Matrix Representation

Suppose $A = PDP^{-1}$, where D is a diagonal $n \times n$ matrix. If \mathcal{B} is the basis for \mathbb{R}^n formed from the columns of P , then D is the \mathcal{B} -matrix for the transformation $\mathbf{x} \mapsto A\mathbf{x}$.

Lets start from y :

$$\begin{array}{l}
 y = P [y]_B \\
 y = P D [x]_B \\
 y = P D P^{-1} x
 \end{array}$$

Therefore

$$\begin{array}{l}
 A = PDP^{-1} \\
 P^{-1}AP = D
 \end{array}$$

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PROOF Denote the columns of P by $\mathbf{b}_1, \dots, \mathbf{b}_n$, so that $\mathcal{B} = \{\mathbf{b}_1, \dots, \mathbf{b}_n\}$ and $P = [\mathbf{b}_1 \ \dots \ \mathbf{b}_n]$. In this case, P is the change-of-coordinates matrix $P_{\mathcal{B}}$ discussed in Section 4.4, where

$$P[\mathbf{x}]_{\mathcal{B}} = \mathbf{x} \quad \text{and} \quad [\mathbf{x}]_{\mathcal{B}} = P^{-1}\mathbf{x}$$

If $T(\mathbf{x}) = A\mathbf{x}$ for \mathbf{x} in \mathbb{R}^n , then

$$\begin{aligned}
 [T]_{\mathcal{B}} &= [[T(\mathbf{b}_1)]_{\mathcal{B}} \quad \dots \quad [T(\mathbf{b}_n)]_{\mathcal{B}}] && \text{Definition of } [T]_{\mathcal{B}} \\
 &= [[A\mathbf{b}_1]_{\mathcal{B}} \quad \dots \quad [A\mathbf{b}_n]_{\mathcal{B}}] && \text{Since } T(\mathbf{x}) = A\mathbf{x} \\
 &= [P^{-1}A\mathbf{b}_1 \quad \dots \quad P^{-1}A\mathbf{b}_n] && \text{Change of coordinates} \\
 &= P^{-1}A[\mathbf{b}_1 \quad \dots \quad \mathbf{b}_n] && \text{Matrix multiplication} \\
 &= P^{-1}AP
 \end{aligned}$$

Since $A = PDP^{-1}$, we have $[T]_{\mathcal{B}} = P^{-1}AP = D$.

(6)

2.5) Important point: if we are asked to find $x[k]$, for k very large $x[n+1] = Ax[n]$ and A is diagonalizable, it is computationally efficient if we convert $x \rightarrow [x]_B$ to work on the problem!

Given A and $x[0]$, and $x[n+1] = Ax[n]$,
we convert problem to B-basis (eigenvectors of A if exists) since its computationally cheaper.

Proof:

$$x[1] = Ax[0]$$

$$x[2] = Ax[1] = A(Ax[0]) = A^2x[0]$$

$$\text{Therefore, } x[k] = A^k x[0]$$

$$\text{if } A = PDP^{-1},$$

$$\text{then } A^2 = (PDP^{-1})(PDP^{-1}) = PD^2P^{-1} \text{ and}$$

$$A^3 = (PDP^{-1})(PD^2P^{-1}) = PD^3P^{-1}$$

$$\text{Therefore } A^k = PD^kP^{-1}$$

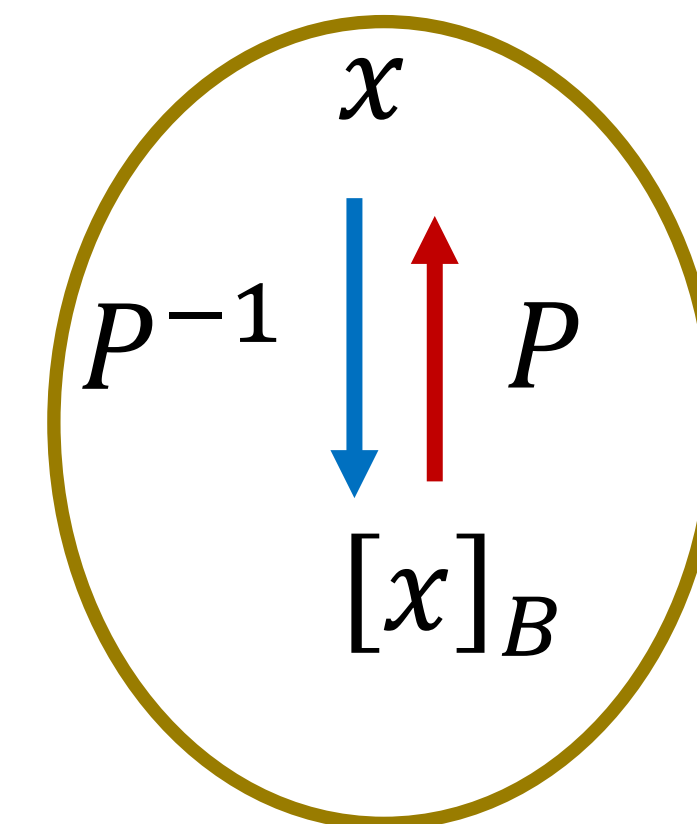
$$\Rightarrow x[k] = A^k x[0] = PD^kP^{-1}x[0]$$

$$\Rightarrow x[k] = P D^k [x[0]]_B$$

Note:

Computing A^k is expensive if A is a dense matrix.

Computing D^k is cheap since it is a diagonal matrix.



Change of Basis

$$\begin{aligned} x &= P[x]_B \\ P^{-1}x &= [x]_B \end{aligned}$$

3) Lay's notes: General Equation of Matrix of Linear Transformation $T: R^n \rightarrow R^m$

The Matrix of a Linear Transformation

Let V be an n -dimensional vector space, let W be an m -dimensional vector space, and let T be any linear transformation from V to W . To associate a matrix with T , choose (ordered) bases \mathcal{B} and \mathcal{C} for V and W , respectively.

Given any \mathbf{x} in V , the coordinate vector $[\mathbf{x}]_{\mathcal{B}}$ is in \mathbb{R}^n and the coordinate vector of its image, $[T(\mathbf{x})]_{\mathcal{C}}$, is in \mathbb{R}^m , as shown in Figure 1.

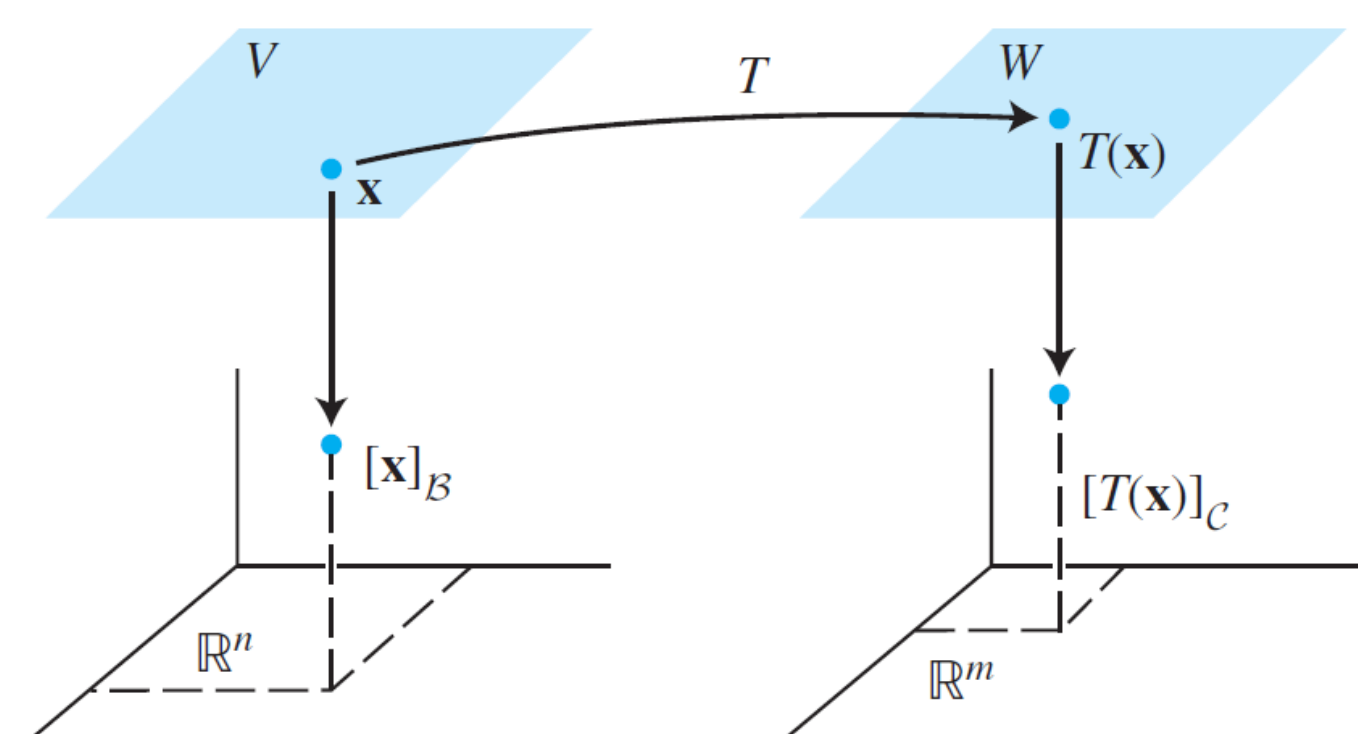


FIGURE 1 A linear transformation from V to W .

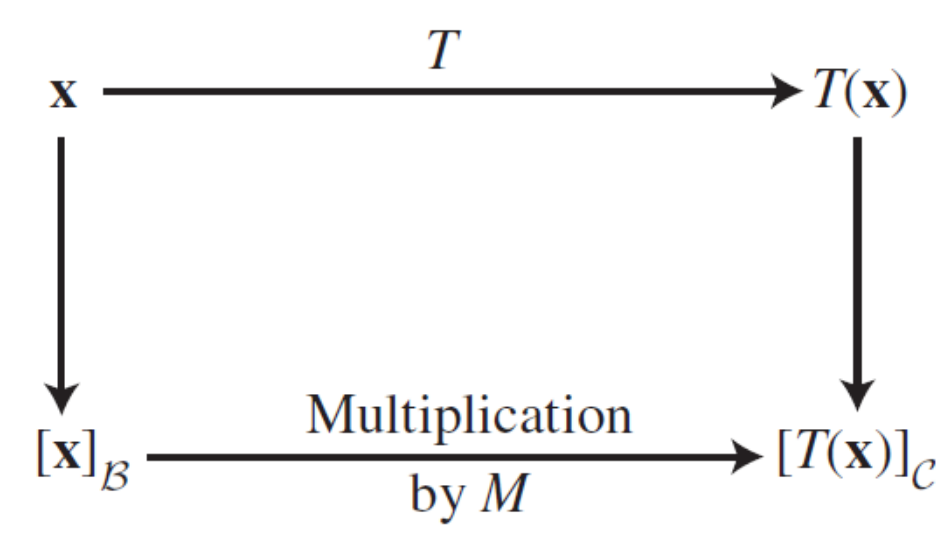


FIGURE 2

The connection between $[\mathbf{x}]_{\mathcal{B}}$ and $[T(\mathbf{x})]_{\mathcal{C}}$ is easy to find. Let $\{\mathbf{b}_1, \dots, \mathbf{b}_n\}$ be the basis \mathcal{B} for V . If $\mathbf{x} = r_1\mathbf{b}_1 + \dots + r_n\mathbf{b}_n$, then

$$[\mathbf{x}]_{\mathcal{B}} = \begin{bmatrix} r_1 \\ \vdots \\ r_n \end{bmatrix}$$

and

$$T(\mathbf{x}) = T(r_1\mathbf{b}_1 + \dots + r_n\mathbf{b}_n) = r_1T(\mathbf{b}_1) + \dots + r_nT(\mathbf{b}_n) \tag{1}$$

because T is linear. Now, since the coordinate mapping from W to \mathbb{R}^m is linear (Theorem 8 in Section 4.4), equation (1) leads to

$$[T(\mathbf{x})]_{\mathcal{C}} = r_1[T(\mathbf{b}_1)]_{\mathcal{C}} + \dots + r_n[T(\mathbf{b}_n)]_{\mathcal{C}} \tag{2}$$

Since \mathcal{C} -coordinate vectors are in \mathbb{R}^m , the vector equation (2) can be written as a matrix equation, namely,

$$[T(\mathbf{x})]_{\mathcal{C}} = M[\mathbf{x}]_{\mathcal{B}} \tag{3}$$

where

$$M = \begin{bmatrix} [T(\mathbf{b}_1)]_{\mathcal{C}} & [T(\mathbf{b}_2)]_{\mathcal{C}} & \dots & [T(\mathbf{b}_n)]_{\mathcal{C}} \end{bmatrix} \tag{4}$$

The matrix M is a matrix representation of T , called the **matrix for T relative to the bases \mathcal{B} and \mathcal{C}** . See Figure 2.

Equation (3) says that, so far as coordinate vectors are concerned, the action of T on \mathbf{x} may be viewed as left-multiplication by M .

3.1) Example: Linear Transformation

EXAMPLE 1 Suppose $\mathcal{B} = \{\mathbf{b}_1, \mathbf{b}_2\}$ is a basis for V and $\mathcal{C} = \{\mathbf{c}_1, \mathbf{c}_2, \mathbf{c}_3\}$ is a basis for W . Let $T : V \rightarrow W$ be a linear transformation with the property that

$$T(\mathbf{b}_1) = 3\mathbf{c}_1 - 2\mathbf{c}_2 + 5\mathbf{c}_3 \quad \text{and} \quad T(\mathbf{b}_2) = 4\mathbf{c}_1 + 7\mathbf{c}_2 - \mathbf{c}_3$$

Find the matrix M for T relative to \mathcal{B} and \mathcal{C} .

SOLUTION The \mathcal{C} -coordinate vectors of the *images* of \mathbf{b}_1 and \mathbf{b}_2 are

$$[T(\mathbf{b}_1)]_{\mathcal{C}} = \begin{bmatrix} 3 \\ -2 \\ 5 \end{bmatrix} \quad \text{and} \quad [T(\mathbf{b}_2)]_{\mathcal{C}} = \begin{bmatrix} 4 \\ 7 \\ -1 \end{bmatrix}$$

Hence

$$M = \begin{bmatrix} 3 & 4 \\ -2 & 7 \\ 5 & -1 \end{bmatrix}$$



If \mathcal{B} and \mathcal{C} are bases for the same space V and if T is the identity transformation $T(\mathbf{x}) = \mathbf{x}$ for \mathbf{x} in V , then matrix M in (4) is just a change-of-coordinates matrix (see Section 4.7).

Lay 5e, pg 291, Ch5.4

Revision:

Let $\mathcal{B} = \{\mathbf{b}_1, \dots, \mathbf{b}_n\}$ and $\mathcal{C} = \{\mathbf{c}_1, \dots, \mathbf{c}_n\}$ be bases of a vector space V . Then there is a unique $n \times n$ matrix ${}_{\mathcal{C} \leftarrow \mathcal{B}}P$ such that

$$[\mathbf{x}]_{\mathcal{C}} = {}_{\mathcal{C} \leftarrow \mathcal{B}}P [\mathbf{x}]_{\mathcal{B}} \tag{4}$$

The columns of ${}_{\mathcal{C} \leftarrow \mathcal{B}}P$ are the \mathcal{C} -coordinate vectors of the vectors in the basis \mathcal{B} . That is,

$${}_{\mathcal{C} \leftarrow \mathcal{B}}P = [[\mathbf{b}_1]_{\mathcal{C}} \quad [\mathbf{b}_2]_{\mathcal{C}} \quad \cdots \quad [\mathbf{b}_n]_{\mathcal{C}}] \tag{5}$$

The matrix ${}_{\mathcal{C} \leftarrow \mathcal{B}}P$ in Theorem 15 is called the **change-of-coordinates matrix from \mathcal{B} to \mathcal{C}** . Multiplication by ${}_{\mathcal{C} \leftarrow \mathcal{B}}P$ converts \mathcal{B} -coordinates into \mathcal{C} -coordinates.² Figure 2 illustrates the change-of-coordinates equation (4).

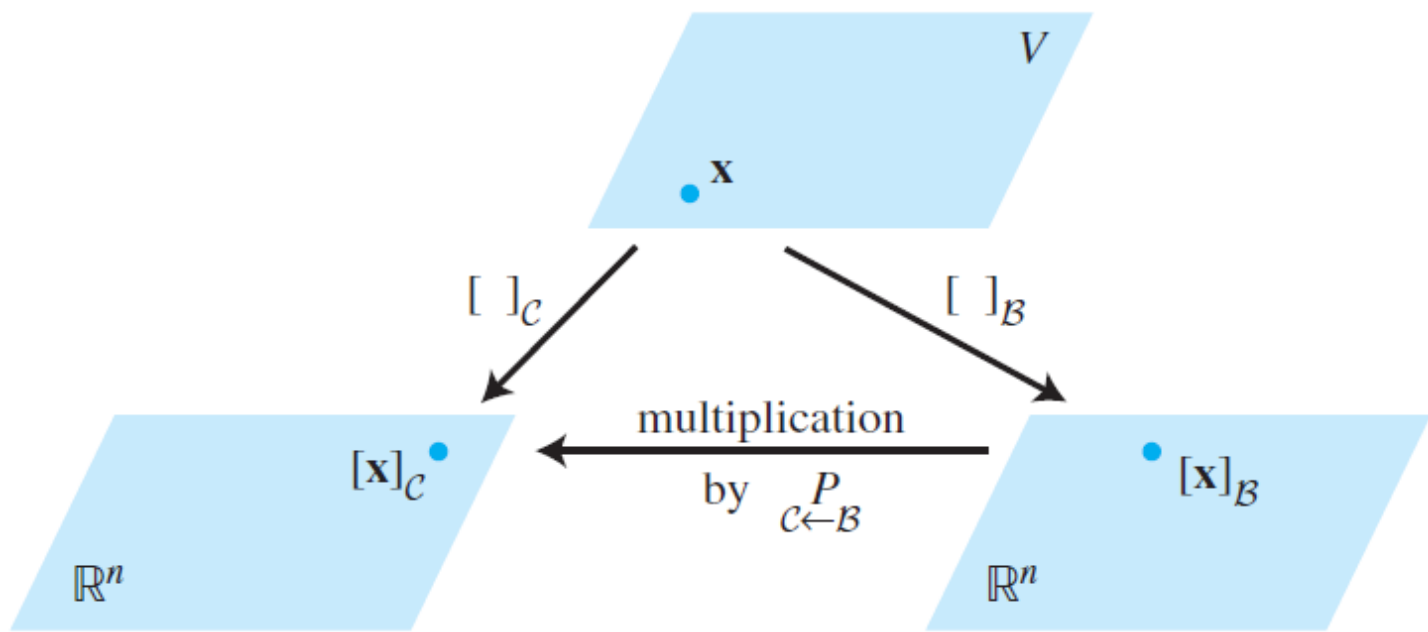


FIGURE 2 Two coordinate systems for V .

Lay 5e, pg 242, Ch 4.7

Appendix: Some useful information

References:

1) Youtube:

- a) 3Blue1Brown: Linear Transformation (Ch3) <https://www.youtube.com/watch?v=kYB8IZa5AuE>
- b) Strang Lect 30, 18.06 (2005) https://www.youtube.com/watch?v=Ts3o2I8_Mxc
- c) Adams Panagos: "Finding A" <https://www.youtube.com/watch?v=61knWwBM3gQ>
- d) Technion: L54 Matrix Representation of Linear Map : <https://www.youtube.com/watch?v=tRbXrnoVJI8>

2) Problems in Yutsumura.com:

- a) <https://yutsumura.com/find-matrix-representation-of-linear-transformation-from-r2-to-r2/>
- b) <https://yutsumura.com/linear-transformation-tr2-to-r2-given-in-figure/>
- b) <https://yutsumura.com/find-a-general-formula-of-a-linear-transformation-from-r2-to-r3/#more-2526>

3) Reference from others:

- a) Upenn: <https://www2.math.upenn.edu/~moose/240S2013/slides7-23.pdf>
- b) Abbasi notes on deriving the transformation matrix: https://www.12000.org/my_notes/similarity_transformation_and_SVD/ind

$$\begin{array}{ccc} a_1 \vec{b}_1 + \dots + a_n \vec{b}_n = \vec{x} & \xrightarrow{\quad} & A \vec{x} = c_1 \vec{b}_1 + \dots + c_n \vec{b}_n \\ \downarrow \text{green} & \uparrow \text{red } P & \downarrow \text{green} \\ \begin{pmatrix} a_1 \\ \vdots \\ a_n \end{pmatrix} = [\vec{x}]_B & \xrightarrow{\quad ? \quad} & [A \vec{x}]_B = \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix} \end{array}$$

$$P[\vec{x}]_B = a_1 \vec{b}_1 + \dots + a_n \vec{b}_n = \vec{x} \quad \left| \quad \frac{\vec{p}' A P [\vec{x}]_B = [A \vec{x}]_B}{\Downarrow} \right.$$

$$D[\vec{x}]_B = [A \vec{x}]_B$$



Change of Basis from Trefor Bazett

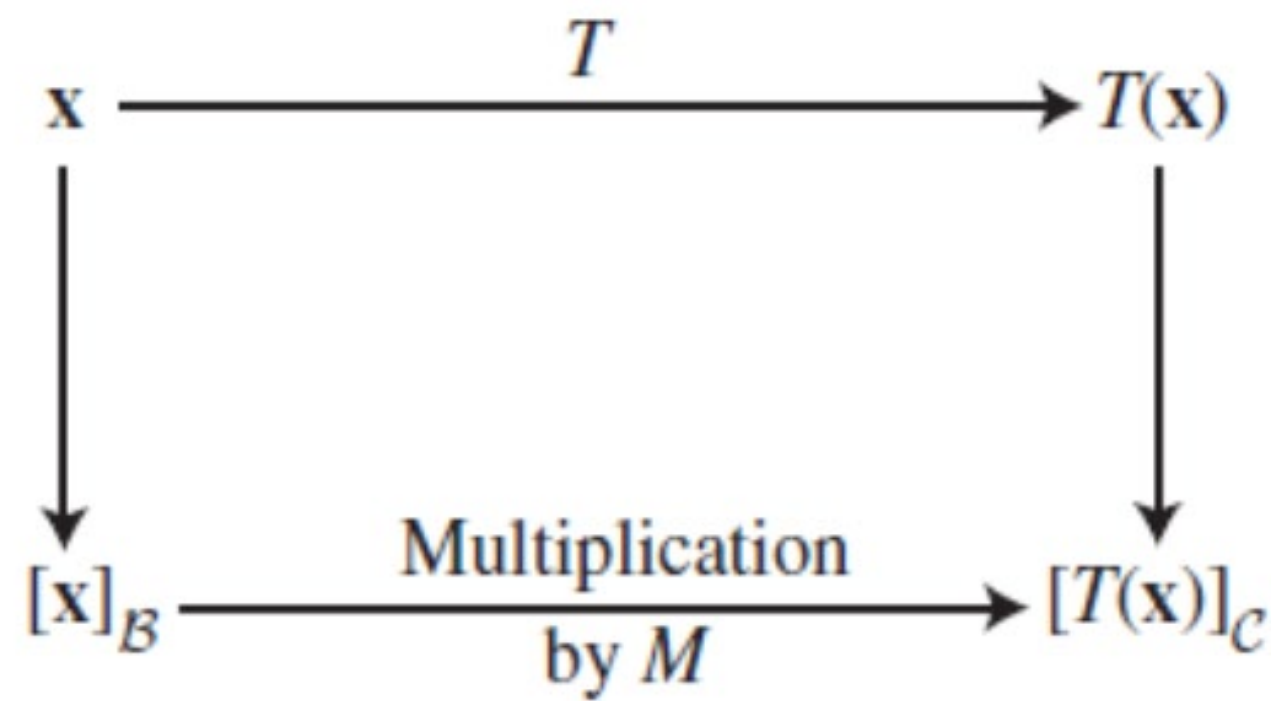


FIGURE 2

Trefor Bazett: Changing between 2 bases
<https://www.youtube.com/watch?v=KjITOLhaI9s>

Remember: $x = P_B [x]_B = P_C [x]_C$
The vector x represented in basis B and C

Two Bases: $B = \{\vec{b}_1, \dots, \vec{b}_n\}$
 $C = \{\vec{c}_1, \dots, \vec{c}_n\}$

$P_B(\vec{x})_B = \vec{x} = P_C(\vec{x})_C$

$(\vec{x})_C = P_C^{-1} P_B (\vec{x})_B$

$(\vec{x})_B = P_B^{-1} P_C (\vec{x})_C$

Change of Basis:

$(\vec{x})_C = P_C^{-1} P_B (\vec{x})_B$

In B basis viewpoint

In Standard basis viewpoint

In C basis viewpoint