Linear Algebra I Summary

Vectors and Products

- Vectors starting at different points are equal if their normal and direction are
- Parallelogram law: adding two vectors corresponds to finding the diagonal of the parallelogram with those vectors as adjacent sides
- $c \vec{v} \implies c = 0 \text{ or } \vec{v} = \vec{0}$
- Standard basis vectors: $e_1 = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$, $e_2 = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}$, $e_n = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}$

• These form the *standard basis* for \mathbb{R}^n (or \mathbb{C}^n , if we are considering complex numbers)

- Dot product: vector → scalar: sum of pairwise multiplication of corresponding vector elements
 - Distributivity: $(\vec{u} + \vec{v}) \cdot \vec{w} = \vec{u} \cdot \vec{w} + \vec{v} \cdot \vec{w}$
 - Linearity: $(c\vec{u}) \cdot \vec{v} = c(\vec{u} \cdot \vec{v})$
 - $ec{v}\cdotec{v}\geq 0$, and is only 0 when $ec{v}=ec{0}$
- Norm: ||v|| is defined as $\sqrt{\vec{v} \cdot \vec{v}}$, and corresponds to the *length* of the vector
 - Linearity: $\|c\vec{v}\| = |c|\|\vec{v}\|$
 - The **normalization** of a vector \vec{v} is $\hat{v} = \frac{\vec{v}}{\|\vec{v}\|}$, \hat{v} is \vec{v} with magnitude 1, i.e. $\hat{v} = 1$
- Angle between vectors in terms of dot product: $\vec{u} \cdot \vec{v} = \|\vec{u}\| \|\vec{v}\| \cos \theta$
 - So, the magnitude of the dot product encodes the angle of the vectors
- Orthogonal vectors: perpendicular vectors, i.e. vectors where $\vec{u} \times \vec{v} = 0$
 - All vectors are orthogonal to $\vec{0}$
 - $\begin{bmatrix} a \\ b \end{bmatrix}$ is orthogonal to $\begin{bmatrix} b \\ -a \end{bmatrix}$, etc.
- **Projection** of \vec{v} onto \vec{w} : $proj_{\vec{w}}(\vec{v}) = (\vec{v} \cdot \hat{w})\hat{w} = \frac{\vec{v} \cdot \vec{w}}{\|\vec{w}\|^2}\vec{w}$
 - This finds the components of \vec{v} that is parallel to \vec{w}
 - Perpendicular component of \vec{v} to \vec{w} : $\mathrm{perp}_{\vec{w}}(\vec{v}) = \vec{v} \mathrm{proj}_{\vec{w}}(\vec{v})$
 - perp and proj are always orthogonal
- Standard Inner Product: $\langle ec{v}, ec{w}
 angle = v_1 \overline{w_1} + v_2 \overline{w_2} + \dots + v_n \overline{w_n}$
 - Generalization of the dot project that can be used for $\ensuremath{\mathbb{C}}$
 - Linearity of first argument: $\langle ec{u}, ec{v}
 angle = \langle ec{v}, ec{u}
 angle$

• Cross product: for
$$\vec{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}$$
, $\vec{a} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}$, $\vec{u} \times \vec{a} = \begin{bmatrix} u_2a_3 - u_3a_2 \\ -(u_1a_3 - u_3a_1) \\ u_3a_2 - u_2a_1 \end{bmatrix}$

- The product $ec{u} imes ec{a}$ will be orthogonal to both $ec{u}$ and $ec{a}$
- $ullet \ ec u imes ec a = \|ec u\| \|ec a\| \sin heta \|$
- Skew symmetry: $ec{u} imesec{a}=-ec{a} imesec{u}$
- The cross product is linear in both arguments

Linear Combinations

- Linear combination: $c_1 \vec{v}_1 + c_2 \vec{v}_2 + \dots + c_n \vec{v}_n$
- **Span**: set of all possible linear combinations: $\text{Span}\{\vec{v_1}, \dots, \vec{v_n}\}$
 - $\vec{0}$ is always in a span of vectors
 - The span of one vector is a line

• Is
$$\begin{bmatrix} 0\\1\\0 \end{bmatrix}$$
 in Span { $\begin{bmatrix} 2\\0\\5 \end{bmatrix}$, $\begin{bmatrix} 1\\0\\3 \end{bmatrix}$ }? Solve $\begin{bmatrix} 0\\1\\0 \end{bmatrix} = a \begin{bmatrix} 2\\0\\5 \end{bmatrix} + b \begin{bmatrix} 1\\0\\3 \end{bmatrix}$ to find a system of linear equations

- Vector equation of line with slope $\frac{q}{p}$ through point $\begin{bmatrix} a \\ b \end{bmatrix}$: $\vec{\ell} = \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} + t \begin{bmatrix} p \\ p \end{bmatrix}, t \in \mathbb{R}$
 - This can generalize to \mathbb{R}^n
 - A line parallel to this has the same direction vector
- Line through \vec{u} with direction \vec{v} as a set of points (vectors): $\mathcal{L} = \{\vec{u} + t\vec{v} : t \in \mathbb{R}\}$
- Line through vectors $ec{p}$ and $ec{q}$: $ec{\ell} = ec{u} + t(ec{q} ec{u}), t \in \mathbb{R}$ ($ec{u}$ is a parameter)
- Plane through origin: $\boxed{P= ext{span}\left\{ec{v},ec{w}
 ight\}=\left\{sec{v}+tec{w}+ec{a}:s,t\in\mathbb{R}
 ight\}}$
 - Without the constant offset \vec{a} , this is a plane through the origin
 - \vec{v} and \vec{u} are the direction vectors
- Plane through points ec v, ec q, ec r: $P = \{ec u + s(ec q ec u) + t(ec r ec u) : s, t \in \mathbb{R}\}$
- Finding a *scalar equation of a plane*: find normal vector to the plane using the cross product, $\begin{bmatrix} x \\ n_1 \end{bmatrix}$
 - equate $\begin{bmatrix} y \\ z \end{bmatrix} \cdot \begin{bmatrix} n_2 \\ n_3 \end{bmatrix} = 0$, by the dot product definition, $n_1x + n_2y + n_3z = 0$
- Systems of equations arise from questions about spans
- If $\vec{v} \in \mathrm{Span}\left\{\vec{u}, \vec{w}\right\}$, then $\vec{v} = a\vec{u} + b\vec{w}$, meaning $v_1 = au_1 + bw_1$, $v_2 = au_2 + bw_2$, etc.
 - Asking this is like asking if $\vec{v} = a\vec{u} + b\vec{w}$ has any solutions
 - A solution set has 0, 1, or ∞ solutions (0 \iff **inconsistent** system of equations)
 - The equivalent system has the same solution set
- EROs (elementary row operations) always produce equivalent systems
 - Options: switching rows, scaling a row by non-0, setting one row as a linear combination of others
 - $0v_1 + 0v_2 + \cdots = 0$ is a trivial row that doesn't add any information
 - Row equivalency: a matrix can be transformed into another only using EROs

- REF (Row Echelon Form): 0-rows all at the end, leading entry appears to the right of term above
- RREF (Reduced Row Echelon Form): In REF, all pivots are 1, pivots are the online nonzero entry in their column
 - RREF is unique for a matrix
 - If the system is inconsistent, then $[0 \dots 0|b]$ will appear
- Gauss-Jordan elimination: Matrix → REF row by row downward, REF → RREF row by row upward
- **Rank**: Matrix $A_{m \times n}$ has r pivots in RREF (and/or REF) \iff Rank(A) = r
 - $\operatorname{Rank}(A) \leq \min{\{m,n\}}$
- System is consistent $\iff \operatorname{Rank}(A) = \operatorname{Rank}([A|\vec{b}])$
- Let $A \in M_{m imes n}(\mathbb{F})$ with $\mathrm{Rank}(A) = r$
 - 1. If $[A|\vec{b}]$ is consistent, the solution set has n-r parameters (degrees of freedom)
 - 2. $[A|ec{b}]$ is consistent for every $ec{b} \iff r=m$
- The **nullity** of $A_{m imes n} = n \operatorname{Rank}(A)$ is the number of parameters
- Homogeneous system: $\vec{b} = [0 \dots 0]^T$
 - Always has a solution \rightarrow Always consistent for any A
- The **null space** of *A*, Null(A), is the solution to $[A|\vec{0}]$
 - This can always be written as the span of vectors
- The solution sets of $[A|\vec{b}]$ and $[A|\vec{0}]$ will only differ by a constant offset vector
- Reminder for \mathbb{C} : $\frac{1}{z} = \frac{z}{z imes \overline{z}} = \frac{a bi}{a^2 + b^2}$
- $Aec{x}=ec{b}$ encodes the whole system of equations $x_1 \mid a_{1,2}$

$a_{1,1}$		$a_{2,1}$		$a_{n,1}$	
$a_{1,2}$	$+ x_2$	$a_{2,2}$	$+\cdots + x_n$	$a_{n,2}$	
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• Linear combination of columns of A by $b\vec{x}$ equals \vec{b}

•
$$A(ec x+ec y)=Aec x+Aec y,\,A(cec x)=c(Aec x)$$

- If $A\vec{x} = \vec{e_i}$ is consistent for every standard basis vector in \mathbb{F}^m , then $\mathrm{Rank}(A) = m$
- Let the solution of $A\vec{x} = \vec{0}$ be S. If $\vec{x}, \vec{y} \in S$ and $c \in \mathbb{F}$, then $\vec{x} + \vec{y} \in S$, $c\vec{x} \in S$, and $c_1\vec{x} + c_2\vec{y} \in S$, etc
- Let Ax = b, where b ≠ 0 be consistent, with solution S. Let Ax = 0 be the associated homogeneous system with solution set S. Then, if xp ∈ S, S = {xp + x : x ∈ S}
 - If $A\vec{x} = \vec{b}$ is consistent, it has the same number of solutions/parameters as $A\vec{x} = \vec{0}$
- Let $A\vec{x} = \vec{b}$ and $A\vec{x} = \vec{c}$ be consistent with $\vec{b} \neq \vec{c} \neq \vec{0} \neq \vec{b}$. If their solution sets are \tilde{S}_b and \tilde{S}_c with particular solutions \vec{x}_b and \vec{x}_c , then $\left[\tilde{S}_c = \{(\vec{x}_c \vec{x}_b) + \vec{z} : \vec{z} \in \tilde{S}_b\}\right]$
 - I.e. the second solution set is just an offset of the first one
- Column Space of A, $\operatorname{Col}(A)$: the span of the columns of A
 - $|A\vec{x} = \vec{b} ext{ is consistent } \iff \vec{b} \in \operatorname{Col}(A)$; this is use to show *consistency*
- **Transpose** of a matrix A^T : for $i, j \in \mathbb{N}$, switch A_{ij} with A_{ji}

- Row Space of A, Row(A): the span of the rows of A, if treated as column vectors
 Row(A) = Col(A^T)
- Performing EROs does not affect the row space, since the mirror the operations used to populate the span
- Matrix Equality: matrices are the same size and every corresponding element is equal
- Column extraction: A_{e_i} is the *i*th column of A
 - Matrix equality test: $A = B \iff A\vec{x} = B\vec{x}$ for all $x \in \mathbb{F}^n$
- Matrix multiplication example:

 $\begin{bmatrix} 1 & 2 \\ 3 & 5 \\ 8 & 7 \end{bmatrix} \begin{bmatrix} -1 & 3 \\ 2 & -4 \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 5 \\ 8 & 7 \end{bmatrix} \begin{bmatrix} -1 \\ 2 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 5 \\ 8 & 7 \end{bmatrix} \begin{bmatrix} 3 \\ -4 \end{bmatrix} = \begin{bmatrix} 3 & -5 \\ 7 & -11 \\ 6 & -4 \end{bmatrix}$

- # of *cols* in the first matrix = # of *rows* in the second matrix
- Matrix multiplication is non-commutative
- Every column of C = AB is a member of Col(A)
- (i, j)th entry of C is the dot product of column i of A and column j of B
- Distributivity: (A + B)C = AC + BC (right-handed), A(C + D) = AC + AD (left-handed)
 - Come in different-handed versions since matrix multiplication isn't commutative
- Associativity: ACE = A(CE) = (AC)E
- For $s\in\mathbb{F}$
 - s(A+B) = sA + sB
 - s(AB) = (sA)B = A(sB) = sAB
- The *cancellation law* only holds if A is invertible, i.e. AB = AC and A ≠ O ⇒ B = C unless A is invertible
 - Similarly, $AB
 eq \mathcal{O}
 eq A = 0 ext{ or } B = 0 ext{ unless } A ext{ is invertible}$
- Transposes can be *added* and *scaled*, then converted without difference, i.e. $(AB)^T = B^T A^T$
- Identity matrix: $I_m A = A$ and $AI_n = A$; the same holds for vectors
- Elementary matrix: result of one ERO performed on I
 - These are used to encode EROs and carry them out by multiplication
 - This matrix is found my performing the same ERO on I
 - These can be *chained together*: $D = E_k imes E_{k-1} imes \dots imes E_2 imes E_1 imes A$
- Invertibility: A matrix is invertible if it is $n \times n$, and there exists $E \in M_{n \times n}$ such that $AB = CA = I_n$
 - In this case, we must have B = C
 - If B exists, C must also exist, and vice-versa
 - We denote this as the **inverse** A^{-1} , where $AA^{-1} = A^{-1}A = I_n$
- A is invertible $\iff \operatorname{Rank}(A) = n \iff \operatorname{RREF}(A) = I_n$
- Inverse matrices can be found by solving the augmented matrix $[A|I_n]$ into RREF form. If A becomes I_n , then I_n has become the inverse. Otherwise, A is not invertible.

Chapter 5 - Linear Transformations

- Function determined by matrix A is $T_A: \mathbb{F}^n \to \mathbb{F}^m$, where $\left| T_A: \vec{x} \mapsto A \vec{x} \right|$
- T is linear $\iff T(c\vec{x} + \vec{y}) = cT(\vec{x}) + T(\vec{y})$
- $\vec{0}$ maps to $\vec{0}$: We always have $T(\vec{0}) = \vec{0}$
- We prove non-linearity by counterexample
- Functions that don't "look" linear often aren't, e.g. \vec{x}^2 , $\vec{x}\vec{y}$, $\sqrt{\vec{y}}$, etc.)
- We have $\operatorname{Range}(T_A) = \operatorname{Col}(A)$
 - Range: set of values that could possibly be achieved by a linear transformation of A
- $T: \mathbb{F}^n \to \mathbb{F}^m$ is **onto/surjective** iff $\operatorname{Range}(T) = \mathbb{F}^m$, which happens iff $\operatorname{Rank}(A) = m$
- $\ker(T_A) = \operatorname{Null}(A)$, i.e. the solution set to $A\vec{x} = \vec{0}$, i.e. the set of inputs to T where the output is 0
- **One-to-one/surjective** transformation: $T(\vec{x}) = T(\vec{y}) \implies \vec{x} = \vec{y}$
 - Distinct pairs of element in \mathbb{F}^n and \mathbb{F}^m are mapped together
 - This occurs iff $\operatorname{Rank}(A) = n$

🖉 Invertibility Criteria

A is invertible T_A is invertible T_A is one-to-one T_A is onto $\text{Null}(A) = \{\vec{0}\}$ (only a trivial solution to $A\vec{x} = \vec{0}$) $\text{Col}(A) = \mathbb{F}^n (A\vec{x} = \vec{b} \text{ is always consistent})$ Nullity(A) = 0 Rank(A) = n $\text{RREF}(A) = I_n$

- Every linear transformation has a matrix $[T]_{\varepsilon}(\vec{x})$ where $[T]_{\varepsilon} = [T(\vec{e_1}) \quad T(\vec{e_2}) \quad \dots \quad T(\vec{e_n})]$
 - T is onto $\iff \operatorname{Rank}([T]_{\varepsilon}) = m$
 - T is one-to-one $\iff \operatorname{Rank}([T]_{\varepsilon}) = n$
- Projection, reflection, and rotation are linear transformations
 - Counter-clockwise rotation by θ : $\begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$
- Composition of linear functions $(T_2 \circ T_1)(\vec{x}) = T_2(T_1(\vec{x})) = [T_2]_{\varepsilon}[T_1]_{\varepsilon}(\vec{x})$
 - This is guaranteed to be a linear function

Chapter 6 - Determinants

• The determinant gives some information about a matrix; expresses itself as a scaling factor

- $\det \left[a
 ight] = a, \det \left[egin{matrix}a & b \\ c & d \end{bmatrix} = ad bc$
- Larger matrices: expand along a row or column, sum together all the matrices formed by removing the current row can column times the current value, with the sign following a checkerboard pattern in the matrix
- Matrix has a zero row $\rightarrow \det A = 0$
- Upper-triangular matrices have the determinant equal to the diagonal entries
- EROs affect the determinant:
 - Row swap: $\det A = -\det A$
 - Row scale by m: det $A = m \det A$
 - Row addition: no change to the determinant
- $\det(AB) = \det(A)\det(B)$
 - This can be chained together arbitrarily

•
$$A \text{ is invertible } \iff \det A
eq 0$$

- $\boxed{\det(A^{-1}) = \dfrac{1}{\det A}}$, assuming that A is invertible
- Cofactor matrix: determinants of each row/col removed submatrix with alternating signs
- Adjugate matrix: transpose of the cofactor matrix

•
$$A^{-1} = rac{1}{\det A} imes \operatorname{adj}(A)$$

- **Cramer's Rule**: Let $A\vec{x} = \vec{b}$. If we replace column j of A with \vec{b} to get A_b , then the solution to $A\vec{x} = \vec{b}$ is $\vec{x}_j = \frac{\det B_j}{\det A}$
 - We can use $j=1\dots n$ to find the whole solution vector $ec{x}$
- Determinant indicates how much multiplying by a matrix scales space
 - Negative determinant → spaces was "flipped"

Chapter 7 - Eigenvectors and Eigenvalues

- Sometimes, a transformation just *scales* a vector instead of changing its direction, i.e. $A\vec{x} = \lambda \vec{x}$, where $\lambda \in \mathbb{F}$
 - Such a vector \vec{x} is an **eigenvector**, and its scaling factor λ is its **eigenvalue**
- Eigenvalue equation: $A\vec{x} = \lambda \vec{x} \iff (A \lambda I)\vec{x} = \vec{0}$
- Characteristic polynomial $C_A = \det(A \lambda I) = 0$ solves for eigenvalues
 - The highest term c_n is $(-1)^n$

•
$$c_{n-1}=(-1)^{n-1} imes \mathrm{trace}(A)$$

• The constant term c_0 is det(A)

In
$$\mathbb C$$
, we have $\sum_{i=1}^n \lambda_i = \operatorname{trace}(A)$ and $\prod_{i=1}^n \lambda_i = \det(A)$ (these both follow)

- We can find an eigenvector by plugging an eigenvalue into $(A \lambda I)\vec{x} = \vec{0}$
- Any scalar multiple of \vec{x} is trivially also an eigenvalue

- **Eigenspace** of A: $E_{\lambda}(A) = \text{Null}(A \lambda I) = \text{ solution set of } (A \lambda I)\vec{x} = \vec{0}$
- Expressing A as PDP^{-1} (where D is a diagonal matrix) makes it easier to compute A^k
- A is similar to $B \rightarrow PBP^{-1} = A$ for some P
 - If *A* and *B* are similar, the have the same *eigenvalues*, *characteristic polynomial*, and *determinant*
- **Diagonalizable**: $A = PDP^{-1}$ (where *D* is a diagonal matrix)
 - A will have n eigenvalues, which will be the diagonal entries of D
 - A has *n* distinct eigenvalues \iff A is diagonalizable, and $P = [\vec{v_1} \dots \vec{v_n}]$ consists of the eigenvectors of A

Chapter 8 - Subspaces and Bases

- Subset $V \subseteq \mathbb{F}^n$ is a **subspace** if it is closed under addition and multiplication, and $\vec{0} \in V$
 - Essentially, the a subspace is the span of any subset of \mathbb{F}^n
 - $\{\vec{0}\}$, Span(V), Null(A), Col(A)/Range(T) for any A are subspaces
 - Eigenspaces of matrices are subspaces
- $\bullet \quad V \subseteq \mathbb{F}^n \text{ is a subspace } \iff V \neq \emptyset \text{ and } \forall \vec{x}, \vec{y} \in V, c \in \mathbb{F}, \vec{x} + c\vec{y} \in V$
- $\vec{v_1} \dots \vec{v_k} \in \mathbb{F}^n$ are **linearly dependent** if we have some $c_1 \vec{v_1} + \dots + c_k \vec{v_k} = 0$, where not all $c_1 \dots c_k$ are 0
 - · At least one vector is a linear combination of others
 - If $c_1 = \cdots = c_k = 0$ is the only solution, the set is **linearly independent**
- $B = {\vec{v_1} \dots \vec{v_k}} \subset V$ is a **basis** for subspace *V* if *B* is *linearly independent* and Span(B) = V
 - Everything in *B* can be constructed from *B*'s vectors
- Let A be the n imes k matrix $[ec{v_1} \dots ec{v_k}]$
- $\{\vec{v_1} \dots \vec{v_k}\}$ is *linearly independent* $\iff \text{Rank}(A) = k$ (i.e. it has no pivots)
 - The set of vectors that correspond to RREF(A) pivots are a linearly independent set with span Span { \$\vec{a_1} \dots \vec{a_k}\$ }
 - · Adding a non-pivot vector makes the set linearly dependent
- A set of more than n vectors in \mathbb{F}^n must be linearly dependent
- Every subspace has a spanning set $\text{Span}\left\{ec{v_1}\dotsec{v_k}
 ight\}=V$
 - $\bullet \ S \subseteq V \implies \operatorname{Span}(S) \subseteq V$
 - $\operatorname{Span}(S) = \mathbb{F}^n \iff \operatorname{Rank}([S]) = n$
- Every subspace has a basis \rightarrow Any basis for \mathbb{F}^n must have n vectors
- $B = \{\vec{v_1} \dots \vec{v_k}\}$ spans $\mathbb{F}^n \iff B$ is linearly independent
- Set of Pivot columns of A (not necessarily RREF(A)) is a basis for Col(A)
- If $\operatorname{Null}(A) = \{t_1 \vec{x}_1 + \dots + t_k \vec{x}_k : t_{1 \to k} \in \mathbb{F}\}$, then $\{\vec{x}_1 \dots \vec{x}_k\}$ is a basis for $\operatorname{Null}(A)$
- All bases for a set have the same number of vectors (i.e. dimension)
- For $A \in M_{m imes n} \mathbb{F}, n = \operatorname{Rank}(A) + \operatorname{Nullity}(A) = \dim(\operatorname{Col}(A)) + \dim(\operatorname{Null}(A))$

- Let V be a subspace of \mathbb{F}^n with basis $B = \{\vec{v}_1 \dots \vec{v}_k\}$. There exist unique $c_1 \dots c_k \in \mathbb{F}$ such that $\vec{w} = c_1 \vec{v}_1 + \dots + c_k \vec{v}_k$ for an $\vec{w} \in V$
 - For ε , these are just the components of the vector
 - Coordinate vector of $ec{w}$ with respect to B: $[ec{v}]_B = [c_1 \dots c_n]^T$
 - Taking coordinates is a *linear transformation*
- Change of basis from *B* to *C*: $_C[I]_B = \left[[\vec{v_1}]_B \dots [\vec{v_k}]_B \right]$
 - $[\vec{x}]_C = {}_C[I]_B[\vec{x}]_B, [\vec{x}]_B = {}_B[I]_C[\vec{x}]_C$ (basis of \vec{x} changes)
 - $_{C}[I]_{B}$ is invertible and its inverse is $_{B}[I]_{C}$
- $[T]_B = T[[T(\vec{v_1})]_B, \dots, [T(\vec{v_k})]_B], [T(\vec{v})]_B = [T]_B[\vec{v}]_B$
- $[T]_C = {}_C[I]_B[T]_B {}_B[I]_C = ({}_B[I]_C)^{-1}[T]_B {}_B[I]_C$
 - $[T]_B$ and $[T]_C$ are *similar* over \mathbb{F}
- Finding the standard matrix: $[T]_{\varepsilon} = {}_{\varepsilon}[I]_{B}[T]_{BB}[I]_{\varepsilon}$
- (λ, \vec{x}) is an eigenpair of $T \iff (\lambda, [\vec{x}]_B)$ is an eigenpair of $[T]_B$
- T is diagonalizable over $\mathbb{F} \iff$ there exists an ordered basis consisting of the eigenvectors of T
 - P will be the matrix consisting of these eigenvectors (in the same order as the basis)
 - D will be diag(λ₁..., λ_k), i.e. the eigenvalues as diagonal entries
- T is diagonalizable $\iff [T]_B$ is diagonalizable
- Eigenvectors corresponding to unique eigenvalues are linearly independent \implies *P* is invertible, as expected
- Algebraic multiplicity of λ_i is the power of $(\lambda \lambda_i)$ in $C_A(\lambda)$
- Geometric multiplicity of λ_i is the dimension of the eigenspace of λ_i
 - Turns out to be $\operatorname{Nullity}(A \lambda_i I)$
- We have $1 \leq g_{\lambda_i} \leq a_{\lambda_i}$
- The union of bases of distinct eigenspaces is linearly independent
- Diagonalizability test: diagonalizable $\iff C_A(\lambda)$ does not have an irreducible term and $a_{\lambda_i} = g_{\lambda_i}$ for all i
- Let $B = P^{-1}AP$, so A and B are similar
 - Then $B^k = P^{-1}AP$
 - If B is diagonal and P diagonalizes A, then B^k = diag(λ^k₁...λ^k_n)

Unit 10: Vector Spaces

- Addition ⊕: combines two elements in a vector spaces into a vector, i.e. vector
 → vector
- Scalar multiplication \odot : scalar \odot vector \rightarrow vector

Vector Space Axioms

 $\mathbb V$ is a vector space over the *field* $\mathbb F$ if, under operations \oplus and \odot , we have

- C1 closure under addition ⊕
- C2 closure under scalar multiplication \odot
- V1 commutative addition
- V2 associative addition
- V3 additive identity
- V4 additive inverse
- V5 vector addition \oplus distributive law
- V6 scalar addition distributive law
- V7 associative scalar multiplication
- V8 multiplicative identity
- \mathbb{F}^n , $A_{m \times n}(\mathbb{F})$, $T : \mathbb{F}^m \to \mathbb{F}^n$, polynomials with degree $\leq n$ are all vector spaces
- The zero space: $\mathbb{V} = \{\vec{0}\}$
- The zero vector and additive inverse are unique in a vector space
- $0\odot ec x = ec 0$ and $a\odot ec 0 = ec 0$ for all $ec x \in \mathbb{V}, a\in \mathbb{F}$
- $-ec{x}=(-1)\odotec{x}$
- Cancellation law: $a \odot \vec{x} = \vec{0} \implies a = 0 \text{ or } \vec{x} = \vec{0}$
- · Linear combination and span apply to vector spaces
- U ⊆ V is a subspace of V if U is a non-empty (i.e. contains a $\vec{0}$) and is closed under *addition* and *scalar multiplication*
- Let $\mathbb V$ be a vector spaces over $\mathbb F$ with $W = \{ec{v_1} \dots ec{v_k}\} \subseteq \mathbb V$
 - Span(W) is a subspace of V
 - If \mathbb{U} is a subspace where $W \subseteq \mathbb{U}$, then $\mathrm{Span}(W) \subseteq \mathbb{U}$
- *B* is a basis for \mathbb{V} if *B* is linearly independent and $\text{Span}(B) = \mathbb{V}$
- Unique representation theory holds for vector spaces as well; so do coordinate vectors, change of basis matrices, etc.