### **Facts**

### **Fact: Addition and subtraction**

Let A and B be matrices of the same size. Then

1. 
$$A + B = B + A$$

2. (A + B) + C = A + (B + C).

That is, it doesn't matter whether we compute A+B first, or B+C first.

3. 
$$A + 0 = 0 + A = A$$

4. 
$$A - A = A + (-1)A = 0$$

Let  $\lambda$  and  $\mu$  (the Greek letter mu, pronounced "mew") be scalars. Then

5. 
$$\lambda(A+B) = \lambda A + \lambda B$$

6. 
$$(\lambda + \mu)A = \lambda A + \mu A$$

7. 
$$\lambda(\mu A) = \lambda \mu A$$

8. 
$$1A = A$$

## **Fact: Transpose**

trans Let A and B be matrices, and  $\lambda$  a scalar. Then

1. 
$$(A^T)^T = A$$

2. 
$$(\lambda A)^T = \lambda A^T$$

3. 
$$(AB)^T = B^T A^T$$
, when  $AB$  and  $A^T B^T$  are defined. Notice the order has swapped.

4. 
$$(A + B)^T = A^T + B^T$$
, when  $A + B$  is defined.

### **Fact: Trace**

trace Let A and B be a square matrices of the same size, and  $\lambda$  a scalar. Then

1. 
$$tr(\lambda A + B) = \lambda tr(A) + tr(B)$$

2. 
$$tr(AB) = tr(BA)$$
, even if  $AB \neq BA$ 

3. 
$$tr(A^{T}) = tr(A)$$

### **Fact: Matrix mulitiplication**

mult Let A be an  $m \times n$  matrix, B and C be  $n \times k$  matrices, and D a  $k \times l$  matrix. Then

$$1. \ A(B+C) = AB + AC$$

2. 
$$(B+C)D = BD + CD$$
 (notice the order)

3. 
$$A(\lambda B) = (\lambda A)B = \lambda AB$$
, for  $\lambda$  a scalar

4. 
$$A0 = 0A = 0$$
, for 0 the appropriate size 0 matrix

### **Fact: Inverse and product**

Let A and B be invertible matrices of the same size. Then the product AB is invertible also, and

$$(AB)^{-1} = B^{-1}A^{-1}.$$

Note the change of order.

### **Fact: Inverse and transpose**

If A is an invertible matrix, then  $A^T$  is invertible also, and

$$(A^T)^{-1} = (A^{-1})^T$$

# Fact: Laws of powers

powers Let A be a square matrix and  $k,\,r>0$  numbers. Then

1. 
$$A^{r}A^{s} = A^{r+s}$$

2. 
$$(A^r)^s = A^{rs}$$

If  ${\cal A}$  is invertible then the above identities hold for negative powers also.

### **Fact**

If E is the elementary matrix obtained by applying the elementary row operation O to the identity. Let A be another matrix. The product EA is the matrix obtained from A by applying the elementary row operation O.

### **Fact**

Every elementary matrix is invertible, and the inverse is also an elementary matrix.

#### **Fact**

Let A be an  $n \times n$  matrix. The following are equivalent (that is, either all of them are true, or all of them are false):

- 1. A is invertible.
- 2. The matrix equation  $A\mathbf{x} = 0$  has the unique solution  $\mathbf{x} = 0$  (where 0 is the  $n \times 1$  zero matrix).
- 3. The RREF of A is  $I_n$ .
- 4. A may be represented as a product of elementary matrices. That is  $A=E_1E_2\cdots E_n$ , where  $E_i$  is an elementary matrix.
- 5. The matrix equation  $A\mathbf{x} = \mathbf{b}$  has a unique solution for every  $\mathbf{b}$  (and is therefore consistent).

### **Fact**

Let A and B be square matrices of the same size. Then

1. if 
$$AB = I$$
, then  $B = A^{-1}$ 

2. if 
$$BA = I$$
, then  $B = A^{-1}$ 

3. if 
$$B = A^{-1}$$
, then  $A = B^{-1}$  also

4. if AB is invertible then A and B are invertible also

Let

$$D = \begin{bmatrix} d_1 & 0 & 0 & \cdots & 0 \\ 0 & d_2 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & d_n \end{bmatrix}$$

be a diagonal matrix. Then D is invertible if and only if every entry  $d_i \neq 0$ .

If D is invertible then

$$D^{-1} = \begin{bmatrix} \frac{1}{d_1} & 0 & 0 & \cdots & 0 \\ 0 & \frac{1}{d_2} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & \frac{1}{d_n} \end{bmatrix}$$

#### **Fact**

Let

$$D = \begin{bmatrix} d_1 & 0 & 0 & \cdots & 0 \\ 0 & d_2 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & d_n \end{bmatrix}$$

be a diagonal matrix. Then

$$D^{k} = \begin{bmatrix} d_{1}^{k} & 0 & 0 & \cdots & 0 \\ 0 & d_{2}^{k} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & d_{n}^{k} \end{bmatrix}$$

for any integer k.

### Fact: Properties of triangular matrices

- 1. The transpose of an upper triangular matrix is lower triangular, and vice versa.
- 2. The product of two upper triangular matrices is upper triangular. The product of two lower triangular matrices is lower triangular.
- 3. A triangular matrix is invertible if and only if its diagonal entries are non-zero.
- 4. The inverse of an upper triangular matrix is upper triangular. The inverse of a lower triangular matrix is lower triangular.

### Fact: Products of triangular matrices

Let A and B be upper triangular matrices (or both lower triangular matrices). Then

$$(AB)_{ii} = (BA)_{ii} = (A)_{ii} (B)_{ii}$$

# **Fact: Properties of symmetric matrices**

Let A and B be symmetric matrices of the same size, and  $\lambda$  a scalar. Then

- 1.  $A^T$  is symmetric
- 2. A + B and A B are symmetric
- 3.  $\lambda A$  is symmetric

#### **Fact**

If A is invertible and symmetric, then  $A^{-1}$  is symmetric also.

#### **Fact**

Let M be a matrix of any size.

- 1.  $MM^T$  and  $M^TM$  are symmetric
- 2. If M is invertible, then  $MM^T$  and  $M^TM$  are invertible also

# Fact: Determinant of a triangular matrix

Let  $A = \begin{bmatrix} a_{ij} \end{bmatrix}$  be a triangular square matrix (either upper or lower). Then

$$det(A) = a_{11}a_{22}\cdots a_{nn}$$

i.e. it is the product of the diagonal entries.

## **Fact: Determinant of the transpose**

trandet Let A be a square matrix. Then

$$det(A) = det(A^T)$$

### **Fact**

Let A be a square matrix. If A has a row or column of 0's, then det(A) = 0.

### **Fact: Determinants via row reduction**

erodet Let A and B be square matrices of the same size, related by exactly one elementary row operation.

1. If B is obtained from A by swapping two rows, then

$$det(B) = -det(A)$$

E.g.

$$\begin{vmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{vmatrix} = - \begin{vmatrix} a_{21} & a_{22} & a_{23} \\ a_{11} & a_{12} & a_{13} \\ a_{31} & a_{32} & a_{33} \end{vmatrix}$$

2. If B is obtained from A by multiplying a row by the scalar  $\lambda$ , then

$$det(B) = \lambda det(A)$$

E.g.

$$\begin{vmatrix} \lambda a_{11} & \lambda a_{12} & \lambda a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{vmatrix} = \lambda \begin{vmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{vmatrix}$$

3. If B is obtained from A by adding a multiple of one row to another row, then

$$det(B) = det(A)$$

E.g.

$$\begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{vmatrix} = \begin{vmatrix} a_{11} & a_{12} \\ a_{11} + a_{21} & a_{12} + a_{22} \\ a_{31} & a_{32} \end{vmatrix}$$

#### **Fact**

Let A be a square matrix. If A has a column which is a scalar multiple of another column, or a row which is a scalar multiple of another row. Then det(A) = 0.

# Fact: Determinants of elementary matrices

Let E be an elementary  $n \times n$  matrix. Then

- 1. If E is obtained from  $I_n$  by swapping a row, then det(E) = -1.
- 2. If E is obtained from  $I_n$  by multiplying a row by a scalar  $\lambda$ , then  $det(E) = \lambda$ .
- 3. If E is obtained from  $I_n$  by adding a multiple of one row to another, then det(E) = 1.

# Fact: Determinant and scalar multiplication

Let A be an  $n \times n$  matrix, and  $\lambda$  a scalar. Then  $det(\lambda A) = \lambda^n \det(A)$ .

### **Fact**

Let A and B be square matrices of the same size. Assume that A is equal to B except in the k-th row. Let C be the matrix with rows equal to those of A (and

Let C be the matrix with rows equal to those of A (and B), except in the k-th row: let the k-th row of C be equal to the sum of the k-th row of A and the k-th row of B. Then det(C) = det(A) + det(B).

# Fact: Determinant of a product

Let A and B be square matrices of the same size. Then

$$det(AB) = det(A)det(B).$$

#### **Fact**

detinv Let A be a square matrix. Then A is invertible if and only if  $det(A) \neq 0$ .

### **Fact**

Let A be an invertible matrix. Then

$$det(A^{-1}) = \frac{1}{detA}.$$

# Fact: The inverse via the adjoint

Let A be a square matrix. If  $det(A) \neq 0$ , then

$$A^{-1} = \frac{1}{\det(A)} adj(A).$$

### **Fact: Characteristic equation**

Let A be an  $n \times n$  matrix. The scalar  $\lambda$  is an eigenvalue of A if and only if it is a solution to the equation

$$det(\lambda I - A) = 0$$

(for I the identity matrix).

The equation

$$det(\lambda I - A) = 0$$

is known as the characteristic equation of A.

### Fact: Eigenvalues of a triangular matrix

Let A be a triangular matrix. Then the eigenvalues of A are listed on its main diagonal.

### **Fact**

A square matrix A is invertible if and only if 0 is <u>not</u> an eigenvalue of A.

diagform Let A be a diagonalizable matrix, with eigenvalues  $\lambda_1, \lambda_2, \ldots, \lambda_n$ . Let  $\mathbf{x}_i$  be the eigenvector associated to the eigenvalue  $\lambda_i$ . Let

$$P = \begin{bmatrix} \uparrow & \uparrow & & \uparrow \\ \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_n \\ \downarrow & \downarrow & & \downarrow \end{bmatrix}$$

be the matrix of eigenvectors.

Then P diagonalizes A so that  $A = PDP^{-1}$ , where the diagonal matrix D has the form

$$D = \begin{bmatrix} \lambda_1 & 0 & 0 & \cdots & 0 \\ 0 & \lambda_2 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & \lambda_n \end{bmatrix}$$

That is, it is the matrix with the eigenvalues of  $\boldsymbol{A}$  on the diagonal, and  $\boldsymbol{0}$ 's elsewhere.

#### **Fact**

Let A be a square matrix and k a positive integer. If  $\lambda$  is an eigenvalue of A with associated eigenvector  $\mathbf{x}$ , then  $\lambda^k$  is an eigenvalue of  $A^k$ , with associated eigenvector  $\mathbf{x}$ .

#### **Fact: Trivial solution**

Let

$$\mathbf{y'} = A\mathbf{y}$$

be a system of differential equations. Then the vector  $\mathbf{y} = \mathbf{0}$  is solution, known as the trivial solution.

### Fact

Let z be a complex number and  $\overline{z}$  its conjugate. Then

$$z\overline{z} = \overline{z}z$$

is a real number.

#### **Fact**

modconj Let z be a complex number. Then

$$|z|^2 = z\overline{z}$$

# Fact: Properties of the complex conjugate

Let z and w be complex numbers. Then

$$\cdot \overline{z+w} = \overline{z} + \overline{w}$$

• 
$$\overline{z-w} = \overline{z} - \overline{w}$$

• 
$$\overline{zw} = (\overline{z})(\overline{w})$$

• 
$$\frac{\overline{z}}{w} = \frac{\overline{z}}{\overline{w}}$$

$$\cdot \overline{\overline{z}} = z$$

# Fact: Multiplication in polar form

polarmult Let  $z=r_1\left(\cos(\theta_1)+i\sin(\theta_1)\right)$ , and  $w=r_2\left(\cos(\theta_2)+i\sin(\theta_2)\right)$  be complex numbers. Then

$$zw = r_1r_2(\cos(\theta_1 + \theta_2) + i\sin(\theta_1 + \theta_2)).$$

#### **Fact**

Let z and w be complex numbers. Then

$$|zw| = |z||w|$$

and

$$Arg(zw) = Arg(z) + Arg(w)$$

### Fact: Division in polar form

Let  $z=r_1(\cos(\theta_1)+i\sin(\theta_1))$ , and  $w=r_2(\cos(\theta_2)+i\sin(\theta_2))$  be complex numbers. Then

$$\frac{z}{w} = \frac{r_1}{r_2} \left( \cos(\theta_1 - \theta_2) + i \sin(\theta_1 - \theta_2) \right).$$

### **Fact**

Let z and w be complex numbers. Then

$$\left|\frac{z}{w}\right| = \frac{|z|}{|w|}$$

and

$$Arg\left(\frac{z}{w}\right) = Arg(z) - Arg(w)$$

### Fact: De Moivre's Formula

Let z be a complex number with |z|=1. Therefore its polar form is

$$z = \cos(\theta) + i\sin(\theta)$$

For any positive integer n, we have

$$z^n = \cos(n\theta) + i\sin(n\theta)$$

This equation is known as De Moivre's Formula.

#### **Fact**

complexroots Let  $z = r(\cos(\theta) + i\sin(\theta))$  be a complex number, and n a positive integer.

There are exactly n n-th roots of z, and they are given by

$$z^{\frac{1}{n}} = r^{\frac{1}{n}} \left( \cos \left( \frac{\theta + 2\pi k}{n} \right) + i \sin \left( \frac{\theta + 2\pi k}{n} \right) \right)$$

for  $k = 0, 1, 2, \ldots, n - 1$ .

#### **Fact**

Let  $z = r(\cos(\theta) + i\sin(\theta))$  be a complex number. Then

$$z = re^{i\theta}$$

Let  $z=re^{i\theta}$  be a complex number. Then

$$Re(z) = r \cos(\theta)$$

$$Im(z) = r \sin(\theta)$$

#### **Fact**

Let  $\mathbf{u}$ ,  $\mathbf{v}$ ,  $\mathbf{w}$  be vectors in  $\mathbb{R}^n$ , and k, m scalars. Then

1. 
$$u + v = v + u$$

2. 
$$(u + v) + w = u + (v + w)$$

3. 
$$u + 0 = u$$

4. 
$$\mathbf{u} + (-\mathbf{u}) = \mathbf{0}$$

5. 
$$k(\mathbf{u} + \mathbf{v}) = k\mathbf{u} + k\mathbf{v}$$

6. 
$$(k + m) \mathbf{u} = k\mathbf{u} + m\mathbf{u}$$

7. 
$$k(m\mathbf{u}) = (km)\mathbf{u}$$

8. 
$$1u = u$$

# **Fact: Properties of the norm**

Let  ${\bf u}$  be a vector in  $\mathbb{R}^n$ , and k a scalar. Then

• 
$$||\mathbf{u}|| \geq 0$$

• 
$$||\mathbf{u}|| = 0$$
 if and only if  $\mathbf{u} = \mathbf{0}$ 

$$\cdot ||k\mathbf{u}|| = |k| ||\mathbf{u}||$$

# **Fact: Distance between two points**

Let  ${\bf u}$  and  ${\bf v}$  be vectors in  $\mathbb{R} n$ . The distance between the endpoints of  ${\bf u}$  and  ${\bf v}$  is given by

$$||\mathbf{u} - \mathbf{v}|| \tag{1}$$

### **Fact**

Let **u** be a vector in  $\mathbb{R}^n$ . Then

$$\mathbf{u} \bullet \mathbf{u} = ||\mathbf{u}||^2$$

### **Fact**

cos Let  ${\bf u}$  and  ${\bf v}$  be vectors and  $\theta$  the angle between them. Then

$$\mathbf{u} \bullet \mathbf{v} = ||\mathbf{u}||||\mathbf{v}||\cos(\theta)$$

# **Fact: Properties of the dot product**

Let  ${\bf u}, {\bf v},$  and  ${\bf w}$  be vectors in  $\mathbb{R}^n$ , and k a scalar. Then

• 
$$\mathbf{u} \bullet \mathbf{v} = \mathbf{v} \bullet \mathbf{u}$$

$$\cdot u \bullet (v + w) = u \bullet v + u \bullet w$$

• 
$$k (\mathbf{u} \bullet \mathbf{v}) = (k\mathbf{u}) \bullet \mathbf{v}$$

• 
$$\mathbf{u} \bullet \mathbf{u} \ge 0$$
, and  $\mathbf{u} \bullet \mathbf{u} = 0$  if and only if  $\mathbf{u} = \mathbf{0}$ 

# **Fact: The Cauchy-Schwarz Inequality**

Let **u** and **v** be vectors in  $\mathbb{R}^n$ . Then

$$|\mathbf{u} \bullet \mathbf{v}| \leq ||\mathbf{u}|| ||\mathbf{v}||$$

# **Fact: The Triangle Inequality**

Let **u** and **v** be vectors in  $\mathbb{R}^n$ . Then

$$||u + v|| \le ||u|| + ||v||$$

# Fact: Parallelogram Rule

Let **u** and **v** be vectors in  $\mathbb{R}^n$ . Then

$$||\mathbf{u} + \mathbf{v}||^2 + ||\mathbf{u} - \mathbf{v}||^2 = 2(||\mathbf{u}||^2 + ||\mathbf{v}||^2)$$

### **Fact**

Let **u** and **v** be vectors in  $\mathbb{R}^n$ . Then

$$\mathbf{u} \bullet \mathbf{v} = \frac{1}{4}||\mathbf{u} + \mathbf{v}||^2 - \frac{1}{4}||\mathbf{u} - \mathbf{v}||^2$$

#### **Fact**

Let  ${\bf u}$  and  ${\bf v}$  be orthogonal vectors in  $\mathbb{R}^n$ . Then

$$||\mathbf{u} + \mathbf{v}||^2 = ||\mathbf{u}||^2 + ||\mathbf{v}||^2$$

### **Fact: Calculating distance**

Let ax + by + c = 0 be a line in  $\mathbb{R}^2$ , and  $(x_0, y_0)$  a point. The shortest distance from  $(x_0, y_0)$  to the line is given by

$$D = \frac{|ax_0 + by_0 + c|}{\sqrt{a^2 + b^2}} \tag{2}$$

If x + by + cz + d = 0 is a plane in  $\mathbb{R}^3$ , and  $(x_0, y_0, z_0)$  is a point, then he shortest distance from  $(x_0, y_0, z_0)$  to the plane is given by

$$D = \frac{|ax_0 + by_0 + cz_0 + d|}{\sqrt{a^2 + b^2 + c^2}}$$
(3)

### **Fact**

Let A be a an  $m \times n$  matrix. An  $n \times 1$  vector  $\mathbf{x}$  is a solution to the equation

$$A\mathbf{x} = \mathbf{0}$$

if and only if  $\mathbf{x}$  is orthogonal to every row vector of A.

# **Fact: Properties of the cross product**

Let  ${f u},{f v}$ , and  ${f w}$  be vectors in  ${\Bbb R}^3$ , and k a scalar. Then

1. 
$$\mathbf{u} \times \mathbf{v} = -\mathbf{v} \times \mathbf{u}$$

2. 
$$\mathbf{u} \times (\mathbf{v} + \mathbf{w}) = \mathbf{u} \times \mathbf{v} + \mathbf{u} \times \mathbf{w}$$

3. 
$$(\mathbf{u} + \mathbf{v}) \times \mathbf{w} = \mathbf{u} \times \mathbf{w} + \mathbf{v} \times \mathbf{w}$$

4. 
$$k (\mathbf{u} \times \mathbf{v}) = (k\mathbf{u}) \times \mathbf{v} = \mathbf{u} \times (k\mathbf{v})$$

5. 
$$\mathbf{u} \times \mathbf{0} = \mathbf{0} \times \mathbf{u} = \mathbf{0}$$

6. 
$$\mathbf{u} \times \mathbf{u} = \mathbf{0}$$

# **Fact: Relation to other operations**

Let  $\mathbf{u}$ ,  $\mathbf{v}$ , and  $\mathbf{w}$  be vectors in  $\mathbb{R}^3$ . Then

1.  $\mathbf{u} \times \mathbf{v}$  is orthogonal to both  $\mathbf{u}$  and  $\mathbf{v}$ . That is

$$\mathbf{u} \bullet (\mathbf{u} \times \mathbf{v}) = \mathbf{v} \bullet (\mathbf{u} \times \mathbf{v}) = 0$$

2. 
$$||\mathbf{u} \times \mathbf{v}||^2 = ||\mathbf{u}||^2 ||\mathbf{v}||^2 - (\mathbf{u} \cdot \mathbf{v})^2$$

3. 
$$\mathbf{u} \times (\mathbf{v} \times \mathbf{w}) = (\mathbf{u} \cdot \mathbf{w}) \mathbf{v} - (\mathbf{u} \cdot \mathbf{v}) \mathbf{w}$$

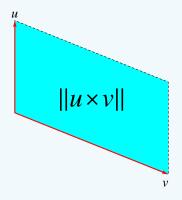
### **Fact**

Let  $\mathbf{u} = (u_1, u_2, u_3)$ ,  $\mathbf{v} = (v_1, v_2, v_3)$  be vectors in  $\mathbb{R}^3$ . Their cross product may be computed

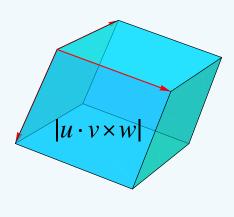
$$\mathbf{u} \times \mathbf{v} = \begin{vmatrix} \mathbf{i} & \mathbf{j} & \mathbf{k} \\ u_1 & u_2 & u_3 \\ v_1 & v_2 & v_3 \end{vmatrix}$$

### **Fact**

1. Let  $\mathbf{u}$ ,  $\mathbf{v}$  be vectors in  $\mathbb{R}^3$ . Then  $||\mathbf{u} \times \mathbf{v}||$  is the area of the parallelogram defined by  $\mathbf{u}$  and  $\mathbf{v}$ .



2. Let  $\mathbf{u}$ ,  $\mathbf{v}$ ,  $\mathbf{w}$  be vectors in  $\mathbb{R}^3$ . Then  $|\mathbf{u} \bullet (\mathbf{v} \times \mathbf{w})|$  is the area of the parallelepiped defined by  $\mathbf{u}$ ,  $\mathbf{v}$  and  $\mathbf{w}$ .



#### **Fact**

Let  $\mathbf{u}$ ,  $\mathbf{v}$ ,  $\mathbf{w}$  be vectors in  $\mathbb{R}^3$ . If  $|\mathbf{u} \bullet (\mathbf{v} \times \mathbf{w})| = 0$  then  $\mathbf{u}$ ,  $\mathbf{v}$  and  $\mathbf{w}$  lie in a plane.

#### **Fact**

Let V be a vector space,  $\mathbf{u} \in V$  and k a scalar. Then

1. 
$$0\mathbf{u} = \mathbf{0}$$

2. 
$$k0 = 0$$

3. 
$$(-1)$$
 **u** = -**u**

4. If  $k\mathbf{u} = \mathbf{0}$  then either k = 0 or  $\mathbf{u} = \mathbf{0}$ .

### Fact: When is a subset a subspace?

Let V be a vector space. The subset  $W \subset V$  is a subspace if and only if

- 1. W is closed under addition: if  $\mathbf{u} \in W$  and  $\mathbf{v} \in W$ , then  $\mathbf{u} + \mathbf{v} \in W$
- 2. W is closed under scalar multiplication: if  $\mathbf{u} \in W$  then  $k\mathbf{u} \in W$  for all scalars k

## **Fact: Spans are subspaces**

Let V be a vector space and  $S = \{\mathbf{v_1}, \mathbf{v_2}, \dots, \mathbf{v_k}\}$ . Then span(S) is a subspace of V.

Let A be an  $m \times n$  matrix. The set of solutions to the equation

$$A\mathbf{x} = \mathbf{0}$$

is a subspace of  $\mathbb{R}^n$ .

#### **Fact**

Let V be a vector space and  $W_1$ ,  $W_2$  subspaces. Then  $W_1 \cap W_2$  is a subspace.

#### **Fact**

If S is a set of n linearly independent vectors in  $\mathbb{R}^n$  then  $\mathrm{span}(S) = \mathbb{R}^n$ .

# Fact: A basis of $P_n$

Let  $P_n$  denote the vector space of polynomials in  $\boldsymbol{x}$  of degree at most  $\boldsymbol{n}$ . The set

$$S = \{1, x, x^2, \dots, x^n\}$$

is a basis for  $P_n$ . The set S is known as the standard basis of  $P_n$ .

### **Fact**

Let V be a vector space and  $S = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$  a basis. Every vector  $\mathbf{v} \in V$  may be expressed as a linear combination of the basis vectors in exactly one way

$$\mathbf{v} = \mathbf{v}_1 + \mathbf{v}_2 + \ldots + \mathbf{v}_n$$

# Fact: Orthogonal implies linearly independent

Let V be a vector space and S a set of vectors in  $\mathbb{R}^n$ . If S is orthogonal then it is linearly independent.

### Fact: A useful property of an orthonormal basis

Let  $S = \{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$  be a basis of  $\mathbb{R}^n$ . Given a vector  $\mathbf{u}$ 

1. if S is orthogonal then

$$\mathbf{u} = \frac{\mathbf{u} \cdot \mathbf{v}_1}{||\mathbf{v}_1||^2} \mathbf{v}_1 + \ldots + \frac{\mathbf{u} \cdot \mathbf{v}_n}{||\mathbf{v}_n||^2} \mathbf{v}_n$$

and the co-ordinate vector of  $\mathbf{u}$  in terms of S is

$$\mathbf{u} = \left(\frac{\mathbf{u} \bullet \mathbf{v}_1}{||\mathbf{v}_1||^2}, \dots \frac{\mathbf{u} \bullet \mathbf{v}_n}{||\mathbf{v}_n||^2}\right)_{S}$$

2. if S is orthonormal then

$$\mathbf{u} = (\mathbf{u} \bullet \mathbf{v}_1) \mathbf{v}_1 + \ldots + (\mathbf{u} \bullet \mathbf{v}_n) \mathbf{v}_n$$

and the co-ordinate vector of  $\mathbf{u}$  in terms of S is

$$\mathbf{u} = (\mathbf{u} \bullet \mathbf{v}_1, \ldots, \mathbf{u} \bullet \mathbf{v}_n)_S$$

## **Fact: Orthogonal decomposition**

Let W be a subspace of  $\mathbb{R}^n$ . Given a vector  $\mathbf{v} \in \mathbb{R}^n$ , we have

$$\mathbf{v} = \operatorname{proj}_{W}(\mathbf{v}) + \operatorname{proj}_{W^{\perp}}(\mathbf{v})$$

where  $\operatorname{proj}_{W}\left(\mathbf{v}\right)\in W$  and  $\operatorname{proj}_{W^{\perp}}\left(\mathbf{v}\right)$  is orthogonal to W

# Fact: Finding the orthogonal decomposition

Let W be a subspace of  $\mathbb{R}^n$  with orthogonal basis

$$S = {\mathbf{v}_1, \ldots, \mathbf{v}_m}$$

Given a vector  $\mathbf{v} \in \mathbb{R}^n$ , we have

$$\operatorname{proj}_{W}\left(\mathbf{v}\right) = \frac{\mathbf{v} \bullet \mathbf{v}_{1}}{\left\|\mathbf{v}_{1}\right\|^{2}} \mathbf{v}_{1} + \frac{\mathbf{v} \bullet \mathbf{v}_{2}}{\left\|\mathbf{v}_{2}\right\|^{2}} \mathbf{v}_{2} + \dots + \frac{\mathbf{v} \bullet \mathbf{v}_{m}}{\left\|\mathbf{v}_{m}\right\|^{2}} \mathbf{v}_{m}$$

If the basis S is orthonormal then

$$\operatorname{proj}_{W}(\mathbf{v}) = (\mathbf{v} \bullet \mathbf{v}_{1}) \mathbf{v}_{1} + (\mathbf{v} \bullet \mathbf{v}_{2}) \mathbf{v}_{2} + \cdots + (\mathbf{v} \bullet \mathbf{v}_{m}) \mathbf{v}_{m}$$

The component of  $\mathbf{v}$  orthogonal to W is given by

$$\operatorname{proj}_{W^{\perp}}(\mathbf{v}) = \mathbf{v} - \operatorname{proj}_{W}(\mathbf{v})$$

#### **Fact**

Let V be a vector space and  $S_1$  and  $S_2$  be bases for V. Then  $S_1$  contains the same number of vectors as  $S_2$ .

### **Fact**

Let V be a vector space and W a subspace of V. Then

$$\dim(W) \leq \dim(V)$$

## **Fact: Adding and removing vectors**

Let  ${\cal V}$  be a vector space. Then

1. let  $S = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$  be a linearly independent set of vectors in V. If  $\mathbf{u} \notin \text{span}(S)$ , then the set

$$\{{\bf v}_1,\,{\bf v}_2,\,\ldots,\,{\bf v}_k,\,{\bf u}\}$$

is linearly independent also.

That is, adding a vector which does lie in span(S) does not break linear independence.

2. let  $S = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$  be a linearly dependent set of vectors in V. If  $\mathbf{v}_k$  may be written as a linear combination of the other vectors in S, then

$$span({\bf v}_1, {\bf v}_2, ..., {\bf v}_{k-1}) = span(S)$$

That is, removing vectors which can be written as linear combinations of the other vectors does not change the span.

3. let  $S = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$  be a linearly independent set of vectors in V. Then the set  $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_{k-1}\}$  is linearly independent also.

That is, removing any number of vectors from a linearly independent set does not break linear independence.

Let V be a finite dimensional vector space, and S a finite set of vectors in V . Then

- 1. if S is not linearly independent but  $\mathrm{span}(S) = V$ , then S can upgraded to a basis of V by removing vectors.
- 2. if S is linearly independent but  $\operatorname{span}(S) \neq V$ , then S can be upgraded to a basis of V by adding vectors which are not in  $\operatorname{span}(S)$ .

### **Fact**

Let A be an  $n \times m$  matrix. The equation

$$A\mathbf{x} = \mathbf{b}$$

has a unique solution if and only if  $\mathbf{b} \in \operatorname{col}(A)$ .

### **Fact**

Let A and B be matrices related by a sequence of elementary row operations. Then  $\mathrm{row}(A) = \mathrm{row}(B)$  and  $\mathrm{null}(A) = \mathrm{null}(B)$ .