

# **Topics in Applied Optimization: Lecture-2**

Applications to Machine Learning, Vision, and Data Analytics

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# Optimization = Problem Solving

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Consider the following temperature data of a city in a day:

Time	Rescaled Time	Temperature
9:00	0:00	15
11:00	2:00	30
14:00	4:00	34
16:00	6:00	33
18:00	8:00	21
22:00	12:00	18

Predict temperature at 14:30.

- Objective function:
- Constraints:
- Model:

## Temperature Predictor: Modelling

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Plot the graph

Suggest a temperature predictor

## Solve the Optimization Problem: Least Squares

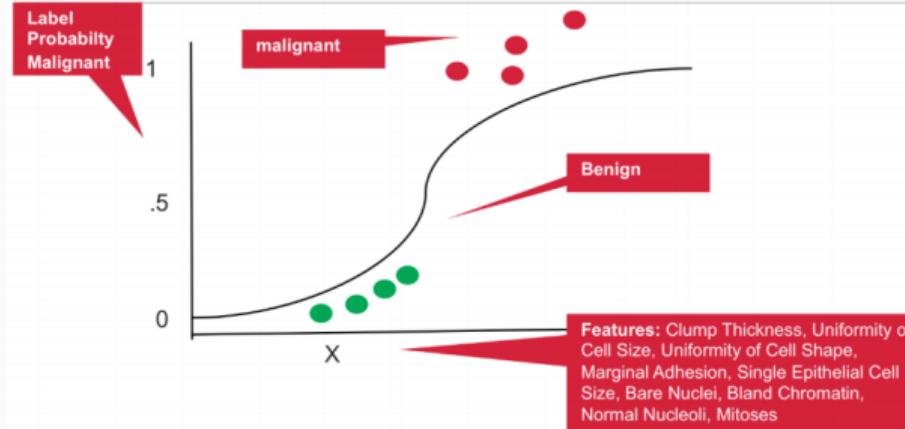
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## Optimization in Classification Problem: Logistic Regression

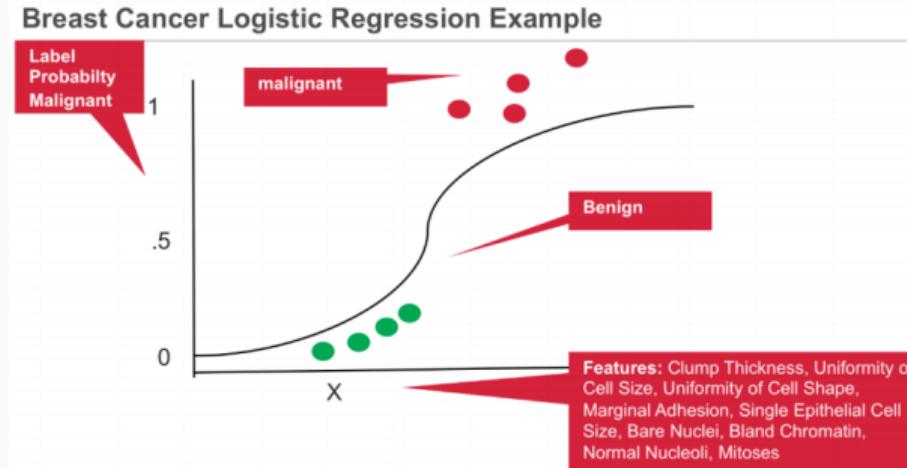
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# Optimization in Classification Problem: Logistic Regression

Breast Cancer Logistic Regression Example



# Optimization in Classification Problem: Logistic Regression

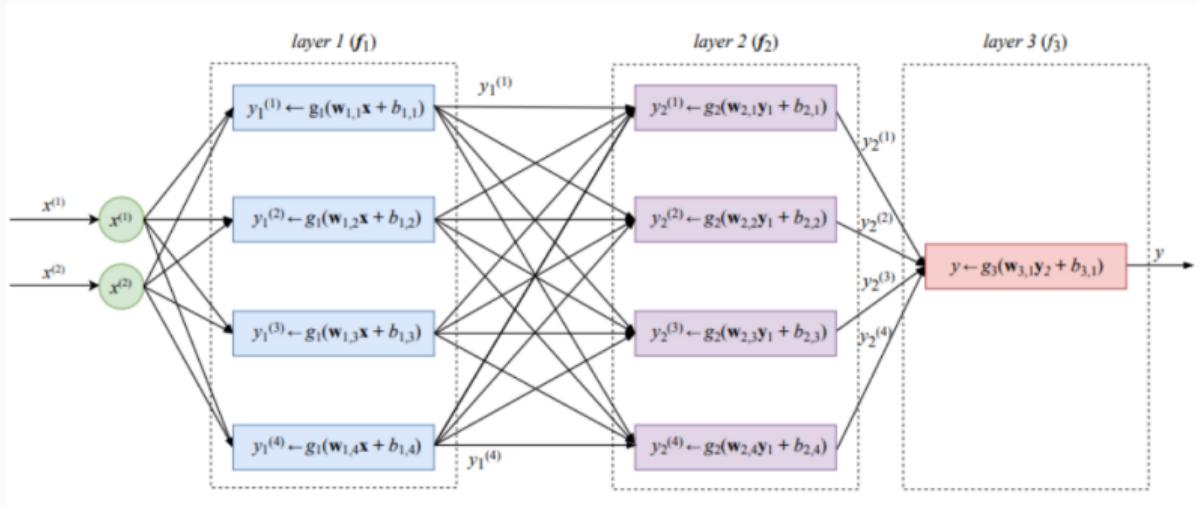


Objective (Loss) function:

$$J(\theta) = -\frac{1}{m} \sum [y^j \log(h_\theta(x^j)) + (1 - y^j) \log(1 - h_\theta(x^j))],$$

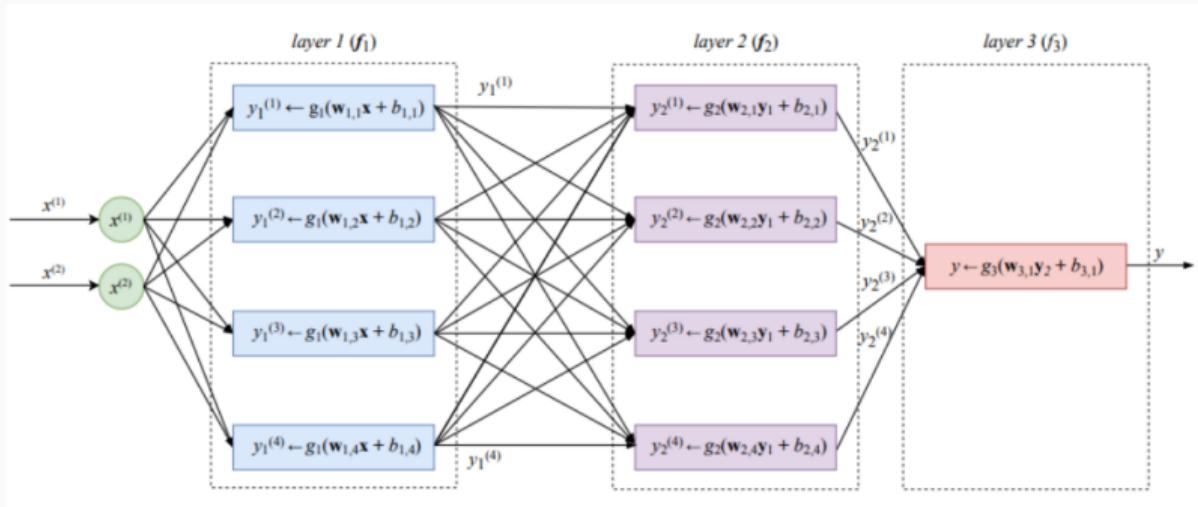
where,  $h_\theta(x) = \frac{1}{1 + \exp(-\theta^T x)}$

# Optimization for Learning to Predict using Neural Networks



- NN is just another mathematical function  $y = f_{NN}(x)$

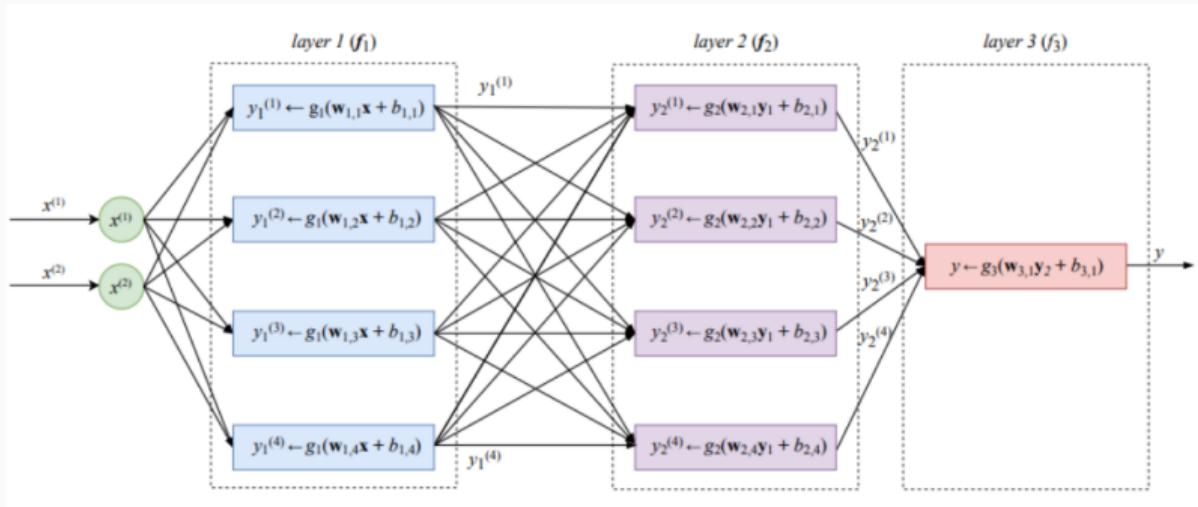
# Optimization for Learning to Predict using Neural Networks



- NN is just another mathematical function  $y = f_{NN}(x)$
- Here  $f_{NN}$  has nested form  $f_{NN}(x) = f_3(f_2(f_1(x)))$ , where  $f_1$  and  $f_2$  are vector functions of the form:

$$f_\ell = g_\ell(W_\ell z + b_\ell), \quad \ell = 1, 2.$$

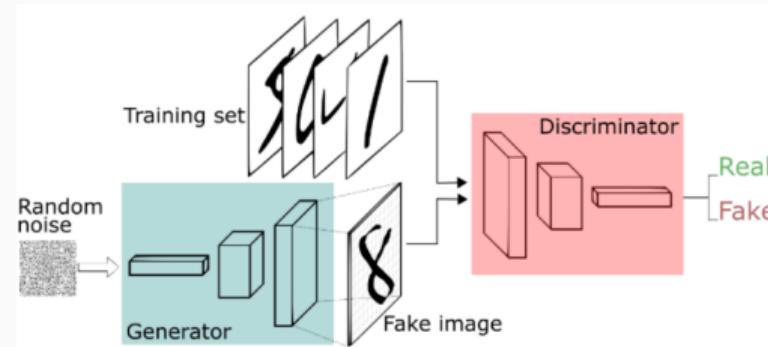
# Optimization for Learning to Predict using Neural Networks



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# Generative Models: GANs



$$\begin{aligned} E(G, D) &= \frac{1}{2} \mathbb{E}_{x \sim p_t} [1 - D(x)] + \frac{1}{2} \mathbb{E}_{z \sim p_z} [D(G(z))] \\ &= \frac{1}{2} (\mathbb{E}_{x \sim p_t} [1 - D(x)] + \mathbb{E}_{x \sim p_g} [D(x)]) \end{aligned}$$

- Objective function is:

$$\max_G \left( \min_D E(G, D) \right)$$

## Review of Linear Algebra

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## Section 3.1

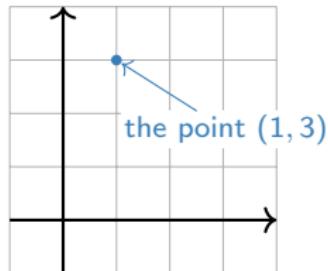
Vectors

## Points and Vectors

We have been drawing elements of  $\mathbf{R}^n$  as points in the line, plane, space, etc.  
We can also draw them as arrows.

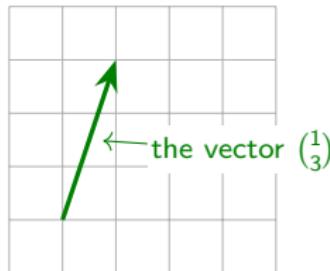
### Definition

A **point** is an element of  $\mathbf{R}^n$ , drawn as a point  
(a dot).



A **vector** is an element of  $\mathbf{R}^n$ , drawn as an arrow.  
When we think of an element of  $\mathbf{R}^n$  as a vector,  
we'll usually write it vertically, like a matrix with  
one column:

$$v = \begin{pmatrix} 1 \\ 3 \end{pmatrix}.$$



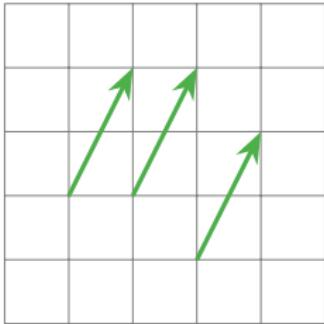
[interactive]

The difference is purely psychological: *points and vectors are just lists of numbers.*

## Points and Vectors

So why make the distinction?

A vector need not start at the origin: *it can be located anywhere!* In other words, an arrow is determined by its length and its direction, not by its location.



These arrows all represent the vector  $\begin{pmatrix} 1 \\ 2 \end{pmatrix}$ .

However, unless otherwise specified, we'll assume a vector starts at the origin.

# Vector Algebra

## Definition

- We can add two vectors together:

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} + \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} a+x \\ b+y \\ c+z \end{pmatrix}.$$

- We can multiply, or **scale**, a vector by a real number  $c$ :

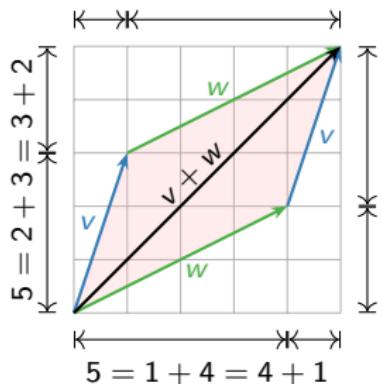
$$c \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} c \cdot x \\ c \cdot y \\ c \cdot z \end{pmatrix}.$$

We call  $c$  a **scalar** to distinguish it from a vector. If  $v$  is a vector and  $c$  is a scalar,  $cv$  is called a **scalar multiple** of  $v$ .

(And likewise for vectors of length  $n$ .) For instance,

$$\begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix} + \begin{pmatrix} 4 \\ 5 \\ 6 \end{pmatrix} = \begin{pmatrix} 5 \\ 7 \\ 9 \end{pmatrix} \quad \text{and} \quad -2 \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix} = \begin{pmatrix} -2 \\ -4 \\ -6 \end{pmatrix}.$$

# Vector Addition and Subtraction: Geometry

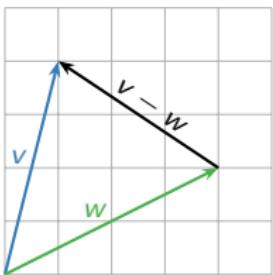


## The parallelogram law for vector addition

Geometrically, the sum of two vectors  $v, w$  is obtained as follows: place the tail of  $w$  at the head of  $v$ . Then  $v + w$  is the vector whose tail is the tail of  $v$  and whose head is the head of  $w$ . Doing this both ways creates a **parallelogram**. For example,

$$\begin{pmatrix} 1 \\ 3 \end{pmatrix} + \begin{pmatrix} 4 \\ 2 \end{pmatrix} = \begin{pmatrix} 5 \\ 5 \end{pmatrix}.$$

Why? The width of  $v + w$  is the sum of the widths, and likewise with the heights. [\[interactive\]](#)



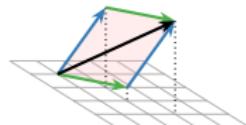
## Vector subtraction

Geometrically, the difference of two vectors  $v, w$  is obtained as follows: place the tail of  $v$  and  $w$  at the same point. Then  $v - w$  is the vector from the head of  $w$  to the head of  $v$ . For example,

$$\begin{pmatrix} 1 \\ 4 \end{pmatrix} - \begin{pmatrix} 4 \\ 2 \end{pmatrix} = \begin{pmatrix} -3 \\ 2 \end{pmatrix}.$$

Why? If you add  $v - w$  to  $w$ , you get  $v$ . [\[interactive\]](#)

This works in higher dimensions too!

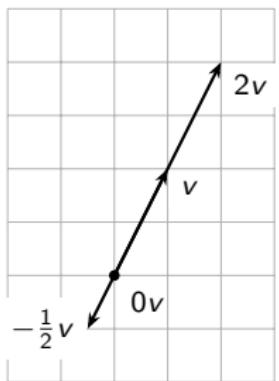


# Scalar Multiplication: Geometry

## Scalar multiples of a vector

These have the same *direction* but a different *length*.

Some multiples of  $v$ .



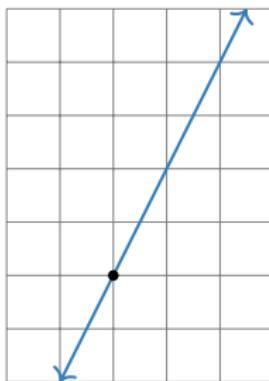
$$v = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$

$$2v = \begin{pmatrix} 2 \\ 4 \end{pmatrix}$$

$$-\frac{1}{2}v = \begin{pmatrix} -\frac{1}{2} \\ -1 \end{pmatrix}$$

$$0v = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

All multiples of  $v$ .



[interactive]

So the scalar multiples of  $v$  form a *line*.

# Linear Combinations

We can add and scalar multiply in the same equation:

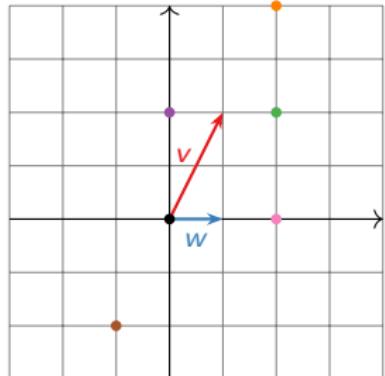
$$w = c_1 v_1 + c_2 v_2 + \cdots + c_p v_p$$

where  $c_1, c_2, \dots, c_p$  are scalars,  $v_1, v_2, \dots, v_p$  are vectors in  $\mathbf{R}^n$ , and  $w$  is a vector in  $\mathbf{R}^n$ .

## Definition

We call  $w$  a **linear combination** of the vectors  $v_1, v_2, \dots, v_p$ . The scalars  $c_1, c_2, \dots, c_p$  are called the **weights** or **coefficients**.

## Example



Let  $v = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$  and  $w = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ .

What are some linear combinations of  $v$  and  $w$ ?

- ▶  $v + w$
- ▶  $v - w$
- ▶  $2v + 0w$
- ▶  $2w$
- ▶  $-v$

[interactive: 2 vectors]

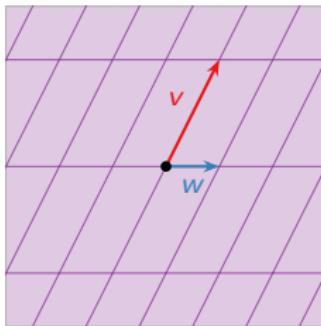
[interactive: 3 vectors]

## Poll

Poll

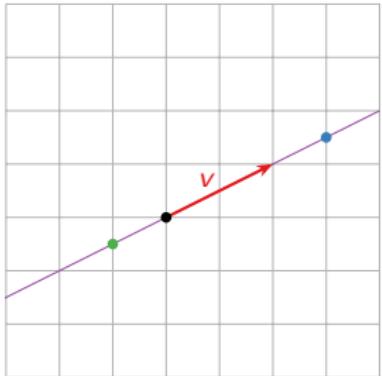
Is there any vector in  $\mathbb{R}^2$  that is *not* a linear combination of  $v$  and  $w$ ?

No: in fact, *every* vector in  $\mathbb{R}^2$  is a combination of  $v$  and  $w$ .



(The purple lines are to help measure *how much* of  $v$  and  $w$  you need to get to a given point.)

## More Examples

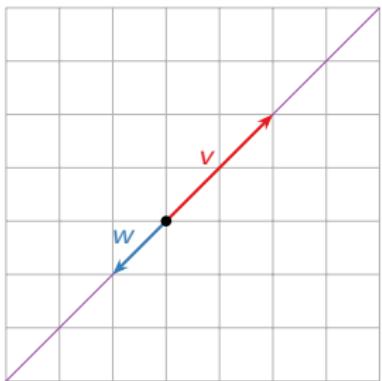


What are some linear combinations of  $v = \begin{pmatrix} 2 \\ 1 \end{pmatrix}$ ?

- ▶  $\frac{3}{2}v$
- ▶  $-\frac{1}{2}v$
- ▶ ...

What are *all* linear combinations of  $v$ ?

All vectors  $cv$  for  $c$  a real number. I.e., all *scalar multiples* of  $v$ . These form a *line*.



### Question

What are all linear combinations of

$$v = \begin{pmatrix} 2 \\ 2 \end{pmatrix} \quad \text{and} \quad w = \begin{pmatrix} -1 \\ -1 \end{pmatrix}?$$

Answer: The line which contains both vectors.

What's different about this example and the one on  
the poll? [interactive]

## Section 3.2

### Vector Equations and Spans

## Systems of Linear Equations

Solve the following system of linear equations:

$$\begin{aligned}x - y &= 8 \\2x - 2y &= 16 \\6x - y &= 3.\end{aligned}$$

We can write all three equations at once as vectors:

$$\begin{pmatrix} x - y \\ 2x - 2y \\ 6x - y \end{pmatrix} = \begin{pmatrix} 8 \\ 16 \\ 3 \end{pmatrix}.$$

We can write this as a linear combination:

$$x \begin{pmatrix} 1 \\ 2 \\ 6 \end{pmatrix} + y \begin{pmatrix} -1 \\ -2 \\ -1 \end{pmatrix} = \begin{pmatrix} 8 \\ 16 \\ 3 \end{pmatrix}.$$

So we are asking:

**Question:** Is  $\begin{pmatrix} 8 \\ 16 \\ 3 \end{pmatrix}$  a linear combination of  $\begin{pmatrix} 1 \\ 2 \\ 6 \end{pmatrix}$  and  $\begin{pmatrix} -1 \\ -2 \\ -1 \end{pmatrix}$ ?

# Systems of Linear Equations

Continued

$$\begin{array}{l} x - y = 8 \\ 2x - 2y = 16 \\ 6x - y = 3 \end{array}$$

matrix form  
~~~~~→

row reduce  
~~~~~→

solution  
~~~~~→

$$\left( \begin{array}{cc|c} 1 & -1 & 8 \\ 2 & -2 & 16 \\ 6 & -1 & 3 \end{array} \right)$$

$$\left( \begin{array}{cc|c} 1 & 0 & -1 \\ 0 & 1 & -9 \\ 0 & 0 & 0 \end{array} \right)$$

$$\begin{array}{l} x = -1 \\ y = -9 \end{array}$$

Conclusion:

$$- \begin{pmatrix} 1 \\ 2 \\ 6 \end{pmatrix} - 9 \begin{pmatrix} -1 \\ -2 \\ -1 \end{pmatrix} = \begin{pmatrix} 8 \\ 16 \\ 3 \end{pmatrix}$$

[interactive] ← (this is the picture of a *consistent* linear system)

What is the relationship between the vectors in the linear combination and the matrix form of the linear equation? They have the same columns!

**Shortcut:** You can go directly between augmented matrices and vector equations.

# Vector Equations and Linear Equations

## Summary

### The vector equation

$$x_1 v_1 + x_2 v_2 + \cdots + x_p v_p = b,$$

where  $v_1, v_2, \dots, v_p, b$  are vectors in  $\mathbf{R}^n$  and  $x_1, x_2, \dots, x_p$  are scalars, has the same solution set as the linear system with augmented matrix

$$\left( \begin{array}{ccccc|c} | & | & & | & | \\ v_1 & v_2 & \cdots & v_p & b \\ | & | & & | & | \end{array} \right),$$

where the  $v_i$ 's and  $b$  are the columns of the matrix.

So we now have (at least) two equivalent ways of thinking about linear systems of equations:

1. Augmented matrices.
2. Linear combinations of vectors (vector equations).

The last one is more geometric in nature.

## Span

It is important to know what are *all* linear combinations of a set of vectors  $v_1, v_2, \dots, v_p$  in  $\mathbf{R}^n$ : it's exactly the collection of all  $b$  in  $\mathbf{R}^n$  such that the vector equation (in the unknowns  $x_1, x_2, \dots, x_p$ )

$$x_1 v_1 + x_2 v_2 + \cdots + x_p v_p = b$$

has a solution (i.e., is consistent).

### Definition

Let  $v_1, v_2, \dots, v_p$  be vectors in  $\mathbf{R}^n$ . The **span** of  $v_1, v_2, \dots, v_p$  is the collection of all linear combinations of  $v_1, v_2, \dots, v_p$ , and is denoted  $\text{Span}\{v_1, v_2, \dots, v_p\}$ . In symbols:

$$\rightarrow \text{Span}\{v_1, v_2, \dots, v_p\} = \left\{ x_1 v_1 + x_2 v_2 + \cdots + x_p v_p \mid x_1, x_2, \dots, x_p \text{ in } \mathbf{R} \right\}.$$

**Synonyms:**  $\text{Span}\{v_1, v_2, \dots, v_p\}$  is the subset **spanned by** or **generated by**  $v_1, v_2, \dots, v_p$ .

This is the first of several definitions in this class that you simply **must learn**. I will give you other ways to think about Span, and ways to draw pictures, but *this is the definition*. Having a vague idea what Span means will not help you solve any exam problems!

# Span

Continued

Now we have several equivalent ways of making the same statement:

1. A vector  $b$  is in the span of  $v_1, v_2, \dots, v_p$ .
2. The vector equation

$$x_1 v_1 + x_2 v_2 + \cdots + x_p v_p = b$$

has a solution.

3. The linear system with augmented matrix

$$\left( \begin{array}{ccccc|c} | & | & & | & | \\ v_1 & v_2 & \cdots & v_p & b \\ | & | & & | & | \end{array} \right)$$

is consistent.

[interactive example] ← (this is the picture of an *inconsistent* linear system)

**Note:** **equivalent** means that, for any given list of vectors  $v_1, v_2, \dots, v_p, b$ , either all three statements are true, or all three statements are false.