## DSC 140A Probabilistic Modeling & Machine Kearning

**Math Review** 

## **Math for Machine Learning**

- DSC 140A is a course in machine learning.
- In ML, we often turn the problem of learning into a math problem.
- So, to deeply understand an ML algorithm, you need to understand the math behind it.

## **Math Prerequisites**

- MATH 20A-B-C: Multivariate Calculus
  - Especially the gradient!
- MATH 18: Linear Algebra
- MATH 183: Probability / Statistics
- DSC 40A: Mathematical Foundations of ML

## **This Review**

- We'll review some of the math we'll need in the first part of the course.
- It's OK to not remember everything!
- Paired with a worksheet:

http://dsc140a.com/materials/default/supplementary/math\_review/worksheet.pdf

## **This Review**

- Four parts:
  - Summation Notation
  - Vectors
  - Matrices
  - What type of object?

#### **Facts**

We'll highlight some important facts throughout this discussion with a box like this:

#### Fact #1

This is a fact.

#### Here are all of the facts in these slides:

Fact #1

Fact #2 Constant Factors in a Summation

Fact #3 Proving Properties

Fact #4 Splitting a Summation

Fact #5 Vector Norm

Fact #6 Vector Addition

Fact #7 Scalar Multiplication of a Vector

Fact #8 Dot Product (Coordinate Definition)

Fact #9 Dot Product (Geometric Definition)

Fact #10 Properties of the Dot Product

Fact #11 Matrix-Vector Mult., View 1

Fact #12 Matrix-Vector Mult., View 2

Fact #13 Matrix-Vector Mult., View 3

Fact #14 Matrix-Matrix Mult., View 1

Fact #15 Matrix-Matrix Mult., View 2

Fact #16 Matrix Multiplication Properties

Fact #17 Transpose of a product

Fact #18  $\vec{u}\cdot\vec{v}$  as Matrix Multiplication

Fact #19 Matrix Inverse

Fact #20 Types of objects

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**Summation Notation** 

## **Summation Notation**

- We use summation notation a lot in data science.
- If  $x_1, x_2, ..., x_n$  are numbers (or vectors), then:

$$\sum_{i=1}^{n} x_i = x_1 + x_2 + \dots + x_n$$

#### **Constant Factors**

#### Fact #2 Constant Factors in a Summation

Constants can be pulled out of a summation. That is, if a is a constant (independent of i), then:

$$\sum_{i=1}^{n} ax_i = a \sum_{i=1}^{n} x_i$$

## Fact #3 Proving Properties

We can prove properties of summations by expanding the sum using ... notation. For example,

to prove Fact 2:  

$$\sum_{i=1}^{n} ax_{i} = ax_{1} + ax_{2} + ... + ax_{n}$$

$$= a(x_{1} + x_{2} + ... + x_{n})$$

#### Fact #4 Splitting a Summation

We can "split" a summation. That is:

$$\sum_{i=1}^{n} (x_i + y_i) = \sum_{i=1}^{n} x_i + \sum_{i=1}^{n} y_i$$

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**Vectors** 

#### **Vectors**

- ightharpoonup A vector  $\vec{x}$  is a list of numbers.
- ► The dimensionality of the vector is the number of entries it has.

Example: a 3-vector:

$$\vec{x} = \begin{pmatrix} 8 \\ -2 \\ 3 \end{pmatrix}$$

### **Vector Notation**

We write  $x \in \mathbb{R}^d$ , to denote that  $\vec{x}$  is a d-dimensional vector whose entries are real numbers. 1 2

Pronounced "x is in R-d".

 $<sup>{}^{1}\</sup>mathbb{R}$  is the symbol for the set of real numbers.

 $<sup>^{2}</sup>$ In  $\Delta T_{F}X$ , you can write  $\ensuremath{\mbox{vec}}\{x\} \in\mbox{mathbb } R^{d}$ 

## **Vector Notation**

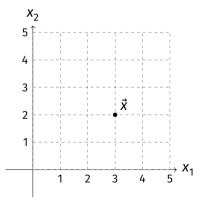
We use subscripts to denote particular elements of a vector.

Example:  $x_1$  is the first element of  $\vec{x}$ ,  $x_2$  is the section element, etc.

## **Points vs. Arrows**

We often think of vectors as points in space.

Example:  $\vec{x} = (3, 2)^T$ 



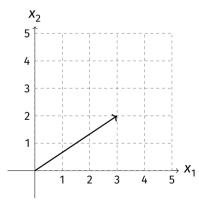
## **Vector Notation**

- We'll often be working with sets of vectors.
- We'll use a superscript to denote the ith vector in the set.
- $\vec{x}^{(1)}$  is the first vector in the set,  $\vec{x}^{(2)}$  is the second, etc.

## **Points vs. Arrows**

We can also think of vectors as arrows.

Example:  $\vec{x} = (3, 2)^T$ 



## **Vector Norm (Length)**

#### Fact #5 Vector Norm

The **norm** (length) of a vector  $\vec{x}$ , written  $||\vec{x}||$ , is the Euclidean distance from the origin to the point represented by  $\vec{x}$ :

$$\|\vec{x}\| = \sqrt{x_1^2 + x_2^2 + \dots + x_d^2}$$
$$= \sqrt{\sum_{i=1}^d x_i^2}$$

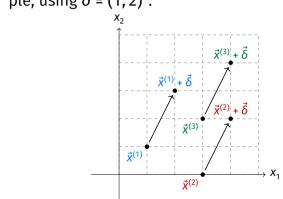
## **Vector Addition**

- Two vectors  $\vec{x}$  and  $\vec{y}$  can be added together.
- ► The result is a vectors whose entries are the *elementwise* sum of the two vectors.
- Example:

$$\underbrace{\begin{pmatrix} 1\\2\\3 \end{pmatrix}}_{\vec{x}} + \underbrace{\begin{pmatrix} 4\\5\\6 \end{pmatrix}}_{\vec{y}} = \begin{pmatrix} 1+4\\2+5\\3+6 \end{pmatrix} = \underbrace{\begin{pmatrix} 5\\7\\9 \end{pmatrix}}_{\vec{x}+\vec{y}}$$

## Fact #6 Vector Addition

Adding (or subtracting)  $\vec{\delta}$  to  $\vec{x}$  "shifts"  $\vec{x}$ . For example, using  $\vec{\delta} = (1,2)^T$ :



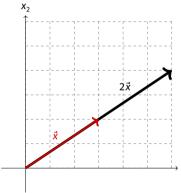
## **Scalar Multiplication**

- We can multiply a vector by a scalar, c.
- The result is a vector whose entries are the original entries multiplied by c.
- Example:

$$3\begin{pmatrix}1\\2\\3\end{pmatrix} = \begin{pmatrix}3\cdot1\\3\cdot2\\3\cdot3\end{pmatrix} = \begin{pmatrix}3\\6\\9\end{pmatrix}$$

## Fact #7 Scalar Multiplication of a Vector

Multiplying  $\vec{x}$  by c "stretches"  $\vec{x}$  by a factor of c. For example, using c=2:



### **Vector Products**

We can "multiply" two vectors together using the dot product.

#### Fact #8 Dot Product (Coordinate Definition)

The **dot product** of two *d*-vectors  $\vec{u}$  and  $\vec{v}$  is defined

to be:  

$$\vec{u} \cdot \vec{v} = u_1 v_1 + u_2 v_2 + ... + u_d v_d$$

#### **Dot Product**

► The dot product has a geometric interpretation, too.

## **Fact #9** Dot Product (Geometric Definition)

The dot product of two vectors  $\vec{u}$  and  $\vec{v}$  is:

$$\vec{u} \cdot \vec{v} = ||\vec{u}|| ||\vec{v}|| \cos \theta$$

where  $\theta$  is the angle between the two vectors.

#### Fact #10 Properties of the Dot Product

The dot product is:

- ightharpoonup Commutative:  $\vec{u} \cdot \vec{v} = \vec{v} \cdot \vec{u}$
- Distributive:  $\vec{u} \cdot (\vec{v} + \vec{w}) = \vec{u} \cdot \vec{v} + \vec{u} \cdot \vec{w}$ Linear:  $\vec{u} \cdot (\alpha \vec{v} + \beta \vec{w}) = \alpha \vec{u} \cdot \vec{v} + \beta \vec{u} \cdot \vec{w}$

Linear: 
$$\vec{u} \cdot (\alpha \vec{v} + \beta \vec{w}) = \alpha \vec{u} \cdot \vec{v} + \beta \vec{u} \cdot \vec{w}$$

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**Matrices** 

## **Matrices**

An  $m \times n$  matrix is a table of numbers with m rows, n columns:

► Example: 2 × 3 matrix:

$$\begin{pmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \end{pmatrix}$$

## **Matrices**

An  $m \times n$  matrix is a table of numbers with m rows, n columns:

Example: 3 × 3 "square" matrix:

$$\begin{pmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{pmatrix}$$

## **Matrices**

An  $m \times n$  matrix is a table of numbers with m rows, n columns:

Example: 3 × 1, a.k.a. a "column vector":

## **Matrix Notation**

We use upper-case letters for matrices.

$$A = \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{pmatrix}$$

Sometimes use subscripts to denote particular elements:  $A_{13} = 3$ ,  $A_{21} = 4$ 

## **Matrix Transpose**

 $\triangleright$   $A^T$  denotes the **transpose** of A:

$$A = \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{pmatrix}$$
  $A^{T} = \begin{pmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{pmatrix}$ 

## Matrix Addition and Scalar Multiplication

- We can add two matrices...
- But only if they are the same shape!
- Addition occurs elementwise:

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{pmatrix} + \begin{pmatrix} 7 & 8 & 9 \\ -1 & -2 & -3 \end{pmatrix} = \begin{pmatrix} 8 & 10 & 12 \\ 3 & 3 & 3 \end{pmatrix}$$

## **Scalar Multiplication**

Scalar multiplication occurs elementwise, too:

$$2 \cdot \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{pmatrix} = \begin{pmatrix} 2 & 4 & 6 \\ 8 & 10 & 12 \end{pmatrix}$$

## **Matrix-Vector Multiplication**

- We can multiply an  $m \times n$  matrix A by an n-vector  $\vec{x}$ ...
- Note that the number of columns in A must equal the number of entries in  $\vec{x}$ !
- ► The result is an *m*-vector.

#### Fact #11 Matrix-Vector Mult., View 1

Let A be an  $m \times n$  matrix and  $\vec{x}$  be an n-vector.

The *i*th entry of  $A\vec{x}$  can be found by dotting the *i*th row of A with  $\vec{x}$ .

 $(A\vec{x})_1 = \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 3 \\ 2 \\ 1 \end{pmatrix} = 3 + 4 + 1 = 8$ 

 $(A\vec{x})_2 = \begin{pmatrix} 3 \\ 4 \\ 5 \end{pmatrix} \cdot \begin{pmatrix} 3 \\ 2 \\ 1 \end{pmatrix} = 9 + 8 + 5 = 22$ 

 $A\vec{x} = (8, 22)^T$ 

$$A = \begin{pmatrix} 1 & 2 & 1 \\ 3 & 4 & 5 \end{pmatrix} \qquad \vec{x} = \begin{pmatrix} 3 \\ 2 \\ 1 \end{pmatrix}$$

#### Fact #12 Matrix-Vector Mult., View 2

Let A be an  $m \times n$  matrix and  $\vec{x} = (x_1, ..., x_n)$  be an *n*-vector.

 $\triangleright$   $x_1$  times the first column of A, plus

 $\triangleright x_2$  times the second column of A, plus ▶ ..., plus

 $\triangleright$   $x_n$  times the *n*th column of A.

$$A = \begin{pmatrix} 1 & 2 & 1 \\ 3 & 4 & 5 \end{pmatrix} \qquad \vec{x} = \begin{pmatrix} 3 \\ 2 \\ 1 \end{pmatrix}$$

$$A\vec{x} = 3\begin{pmatrix} 1\\3 \end{pmatrix} + 2\begin{pmatrix} 2\\4 \end{pmatrix} + 1\begin{pmatrix} 1\\5 \end{pmatrix}$$

$$A\vec{x} = 3\begin{pmatrix} 1\\3 \end{pmatrix} + 2\begin{pmatrix} 2\\4 \end{pmatrix} + 1$$
$$= \begin{pmatrix} 3\\9 \end{pmatrix} + \begin{pmatrix} 4\\8 \end{pmatrix} + \begin{pmatrix} 1\\5 \end{pmatrix}$$

#### Fact #13 Matrix-Vector Mult., View 3

Let A be an  $m \times n$  matrix and  $\vec{x}$  be an n-vector.

The *i*th entry of 
$$A\vec{x}$$
 is given by:

## **Matrix-Matrix Multiplication**

- We can multiply two matrices A and B if (and only if) # cols in A is equal to # rows in B
- If  $A = m \times n$  and  $B = n \times p$ , the result is  $m \times p$ .
  - ► This is **very useful**. Remember it!

#### Fact #14 Matrix-Matrix Mult., View 1

Let A be an  $m \times n$  matrix and B be an  $n \times p$  matrix.

The (i,j)th entry of AB is given by dotting the ith row of A with the jth column of B.

#### Fact #15 Matrix-Matrix Mult., View 2

Let A be an  $m \times n$  matrix and B be an  $n \times p$  matrix.

The (i,j)th entry of AB is given by:

$$\sum_{i=1}^{n} A_{ik}$$

## Matrix-Matrix Multiplication Example

$$A = \begin{pmatrix} 1 & 2 & 1 \\ 3 & 4 & 5 \end{pmatrix} \qquad B = \begin{pmatrix} 3 & 6 \\ 1 & 3 \\ 4 & 8 \end{pmatrix}$$

- What is the size of AB?
- $\triangleright$  What is  $(AB)_{12}$ ?

#### Fact #16 Matrix Multiplication Properties

Matrix multiplication is:

- ▶ Distributive: A(B + C) = AB + AC
- Associative: (AB)C = A(BC)
- Not commutative in general: AB ≠ BA

#### Fact #17 Transpose of a product

The transpose of a product of matrices is the product of the transposes, in reverse order:

$$(AB)' = B'A$$

#### **Fact #18** $\vec{u} \cdot \vec{v}$ as Matrix Multiplication

An *n*-vector can be thought of an an  $(n \times 1)$  matrix. So the dot product of two *n*-vectors  $\vec{u}$  and  $\vec{v}$  is the same as the matrix multiplication  $\vec{u}^T \vec{v}$ .

## **Identity Matrices**

► The *n* × *n* identity matrix *I* has ones along the diagonal:

$$\begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}$$

- ▶ If A is  $n \times m$ , then IA = A.
- ▶ If B is  $m \times n$ , then BI = B.

## **Systems of Linear Equations**

We often want to solve  $A\vec{x} = \vec{b}$  for  $\vec{x}$ .

- There are three possible situations:
  - 1. There's no solution.
  - 2. There's exactly one solution.
  - 3. There are infinitely many solutions.

## **Solving Systems**

- ▶ If A is  $n \times n$ , then it might have an **inverse**.
- The inverse of A, denoted  $A^{-1}$ , is the matrix such that  $AA^{-1} = I$ .

► The inverse, if it exists, is also  $n \times n$ .

#### Fact #19 Matrix Inverse

Suppose A is  $n \times n$ , and we want to solve  $A\vec{x} = \vec{b}$  for

 $\vec{x}$ .

If A is **invertible** (has an inverse), then there is a unique solution:  $\vec{x} = A^{-1}\vec{b}$ .

If *A* is **not invertible** then there is either no solution or infinitely many solutions.

#### **Matrix Inverse**

- You don't know how to compute matrix inverses by hand for this class.
- But you do need to know these properties.

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What kind of object?

## **Debugging for ML**

In this class, you'll find yourself doing some long calculations with matrices and vectors.

- It's easy to get lost in the weeds.
- It is helpful to frequently stop and ask yourself:
  - 1. "What kind of object should this be? A scalar, vector, or matrix?"
  - 2. "What type of object is it actually?"
- This can help you debug your ML code, too!

## What kind of object?

To answer this, remember:

#### Fact #20 Types of objects

- ▶ scalar × vector → vector
- vector + vector → vector
- matrix + matrix → matrix
- vector · vector (dot product) → scalar
- vector norm → scalar
- $(m \times n)$  matrix  $\times$  n-vector  $\rightarrow$  m-vector
- ►  $(m \times n)$  matrix  $\times (n \times p)$  matrix  $\rightarrow (m \times p)$  matrix
- ▶ .

#### Watch out for...

- The following are not mathematically valid.
  Make sure your calculations don't lead to these:
  - vector + scalar
  - matrix + scalar
  - matrix + vector
  - $(m \times n)$  matrix  $\times$   $(p \times q)$  matrix, with  $n \neq p$

Let  $\vec{x}^{(1)}, ..., \vec{x}^{(n)}$  be d-dimensional vectors, and  $\vec{w}$  be a d-dimensional vector. Let  $y_1, ..., y_n$  be scalars.

$$\frac{1}{n}\sum_{i=1}^{n}(\vec{x}_i\cdot\vec{w}-y_i)^2$$

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$$\frac{1}{n}\sum_{i=1}^{n} \frac{(\vec{x}_i \cdot \vec{w} - y_i)^2}{\text{scalar}}$$

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