

Statistical Learning: Introduction

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Intro: What is statistical learning?

What do you think data science is?

What about machine learning?

What about statistical learning?

Key definitions

- **Machine learning (ML)**: Development of models and algorithms from data
 - **Deep learning**: A subfield of ML focused on algorithms modeled after the human brain
- **Statistical learning**: Branch of applied statistics focusing on statistical models and uncertainty quantification
- **Data Science**: Extraction of knowledge from data using a toolbox made up of mathematical, statistical, engineering, and machine learning techniques

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Through different lenses, they all aim to **make sense of data!**

Why the differences?



Let's talk data

In the most familiar setting (i.e. **supervised learning**) data is made up of two primary ingredients:

1. **Outcome/Output/Target/Label(s)**: The variable(s) that you want to understand better
2. **Covariate/Input/Feature(s)**: The variable(s) that can potentially tell you something about your outcome(s)

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Outcome and covariate are most commonly used in statistics so we'll use them!

Let's look at a *data matrix*

The diagram illustrates a data matrix structure. It consists of 15 columns. The first 14 columns are labeled 'Covariates, X' and are colored light blue. The last column is labeled 'Outcome, y' and is colored yellow. The matrix is represented as a grid of 6 rows and 15 columns. The first 14 columns are light blue, and the last column is yellow.

Let's look at a *data matrix*

Covariates, **X**Outcome, y

Rows (n):
contain
the units 
of analysis,
e.g. people,
images,
sentences

Let's look at a *data matrix*

Covariates, \mathbf{X}

Outcome, \mathbf{y}

Rows (n):
contain
the units
of analysis,
i.e. people,
images,
sentences

Columns (p): contain
information about the
units of analysis



Example data matrix: Penguin dataset

	species	island	bill_length_mm	bill_depth_mm	flipper_length_mm	body_mass_g	sex	year
[1,]	3	1	42.0	13.5	210	4150	1	2007
[2,]	3	1	54.3	15.7	231	5650	2	2008
[3,]	2	2	42.4	17.3	181	3600	1	2007
[4,]	3	1	48.6	16.0	230	5800	2	2008
[5,]	2	2	47.0	17.3	185	3700	1	2007
[6,]	3	1	50.4	15.7	222	5750	2	2009
[7,]	1	2	36.0	17.8	195	3450	1	2009
[8,]	1	2	41.3	20.3	194	3550	2	2008
[9,]	1	2	39.6	18.8	190	4600	2	2007
[10,]	3	1	49.6	16.0	225	5700	2	2008
[11,]	3	1	46.9	14.6	222	4875	1	2009
[12,]	1	2	40.2	17.1	193	3400	1	2009
[13,]	3	1	46.8	16.1	215	5500	2	2009
[14,]	3	1	49.4	15.8	216	4925	2	2009
[15,]	1	1	38.2	18.1	185	3950	2	2007

p = ?

n = ?



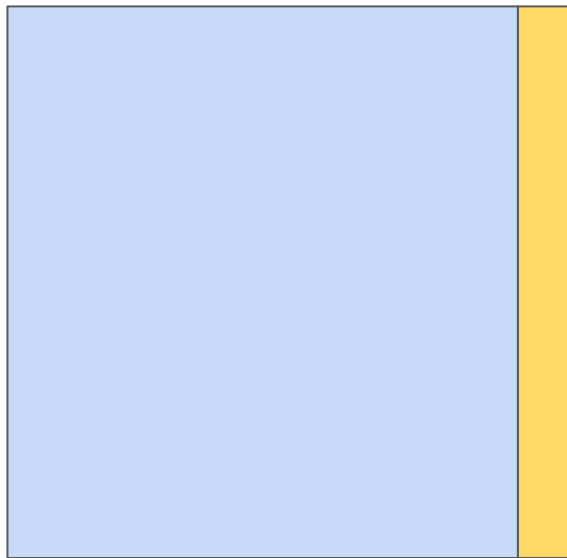
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$p = 7$
 $n = 15$

We need the terminology because data comes in many forms

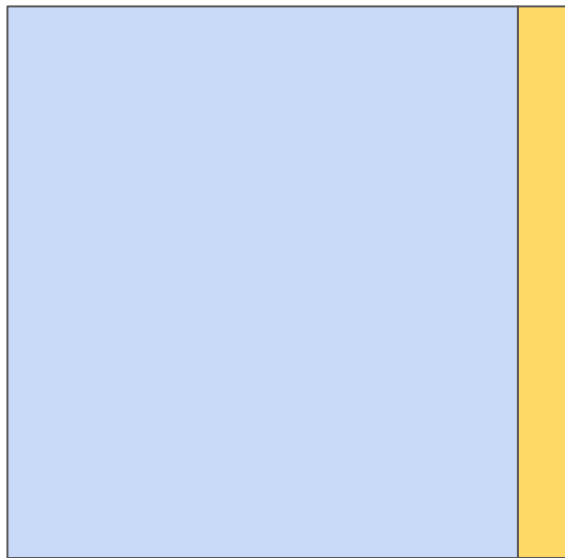
Tall data
 $p < n$



The data of early **statistical learning**

We need the terminology because data comes in many forms

Tall data
 $p < n$



The data of early **statistical learning**

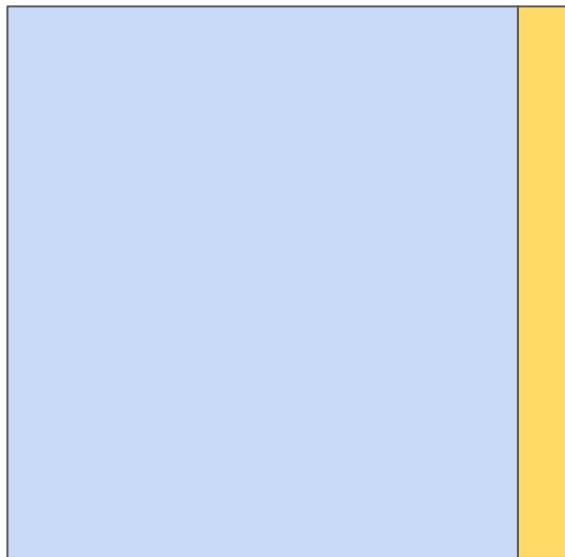
Wide data
 $p > n$



The data of later **statistical learning**

We need the terminology because data comes in many forms

Tall data
 $p < n$



The data of early **statistical learning**

I ♥
STATS

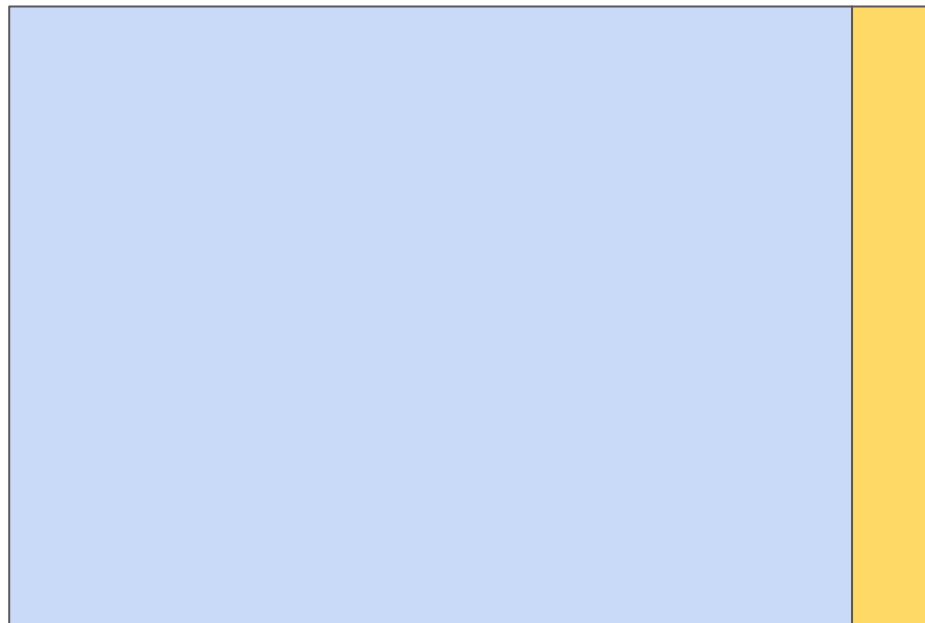
Wide data
 $p > n$



The data of later **statistical learning**

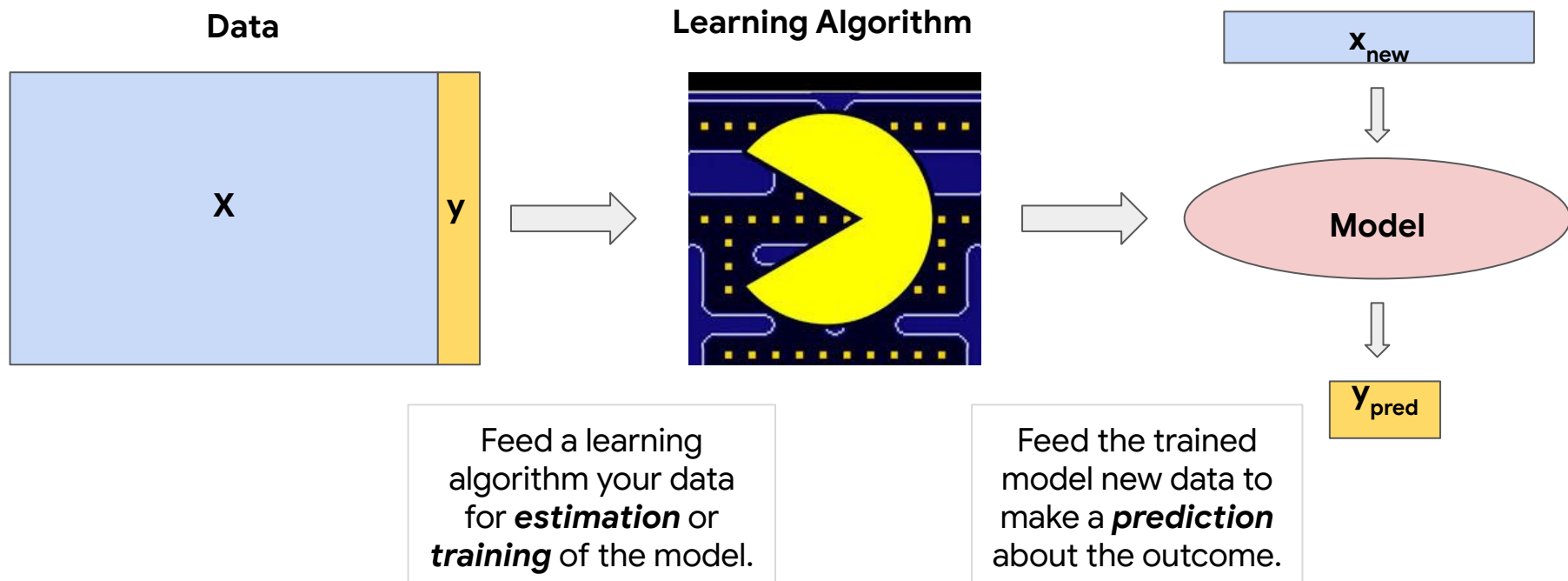
We need the terminology because data comes in many forms

The 'biggie'
big p and/or big n



The data of **modern statistical learning + machine learning + data science**

Now matter what you call it, this is what you do



We are going to play with image classification



Chihuahua or blueberry muffin?

We are going to play with image classification

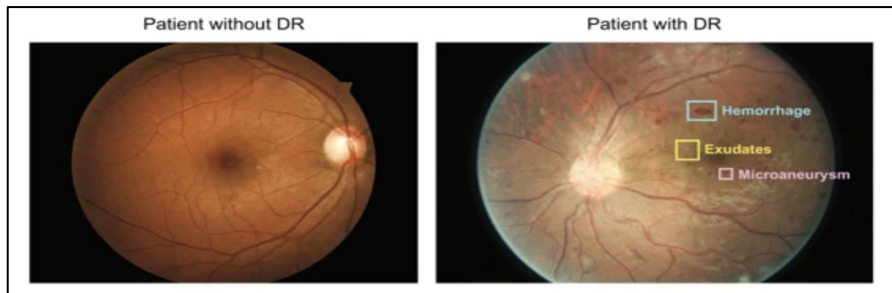


Chihuahua or blueberry muffin?

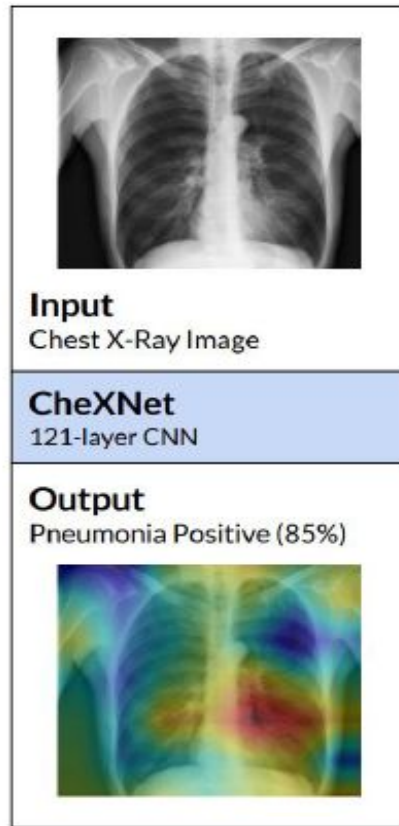


Labradoodle or fried chicken?

Many real life of examples of this...



**Deep learning algorithm
predicts diabetic retinopathy
progression in individual
patients**



**CheXNet:
Radiologist-level
pneumonia
detection
on chest x-rays
with deep learning**

How we'll get there

- Learn the recipe for cooking up a statistical learning model
- Review some techniques for modeling
- Summarize methods for model evaluation