

# Components of Machine Learning Paradigm

Yan Yan

# Review of last class

- What is learning
- What is machine learning paradigm
- What are pre-defined settings (tasks, supervision)
- What are features (discriminative properties)
- What are learning models (structures, parameter adjustment)

# Today's class includes

- Machine learning task details: classification, clustering and regression
  - Terminology
- Their connection to real world applications
  - Why we need these tools
- A showcase: how to construct a learning model
  - What can be used as features
  - Determine model structure
  - Determine model parameters

# Components of machine learning paradigm



Past data: features

How to choose/generate useful features?

Learning model for bus recognition

How to determine this model?

Prediction: bus



Future data

Pre-defined settings/tasks

# Components of machine learning paradigm



Learning **model** for  
bus recognition

How to determine this model?



Prediction: bus

Future data

Pre-defined **settings/tasks**

Past data: **features**

How to choose/generate useful features?

Three key components

# Components of machine learning paradigm



Learning **model** for  
bus recognition

How to determine this model?

Training data

How to choose/generate useful features?

Three key components

Prediction: bus



Testing data

Pre-defined settings/tasks

# Components of machine learning paradigm



Training data

How to choose/generate useful features?

Learning **model** for  
bus recognition

How to determine this model?

Prediction: bus



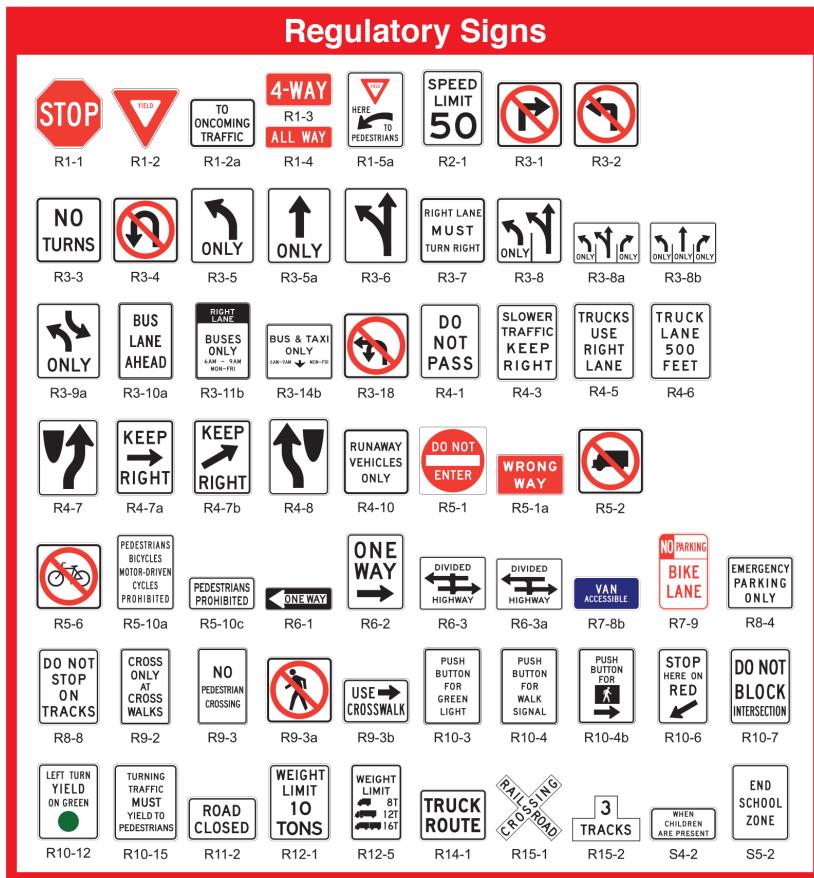
Testing data

Pre-defined settings/tasks

From real applications: providing  
demand/requirement of problems

# Machine learning tasks

- Classification: traffic sign recognition

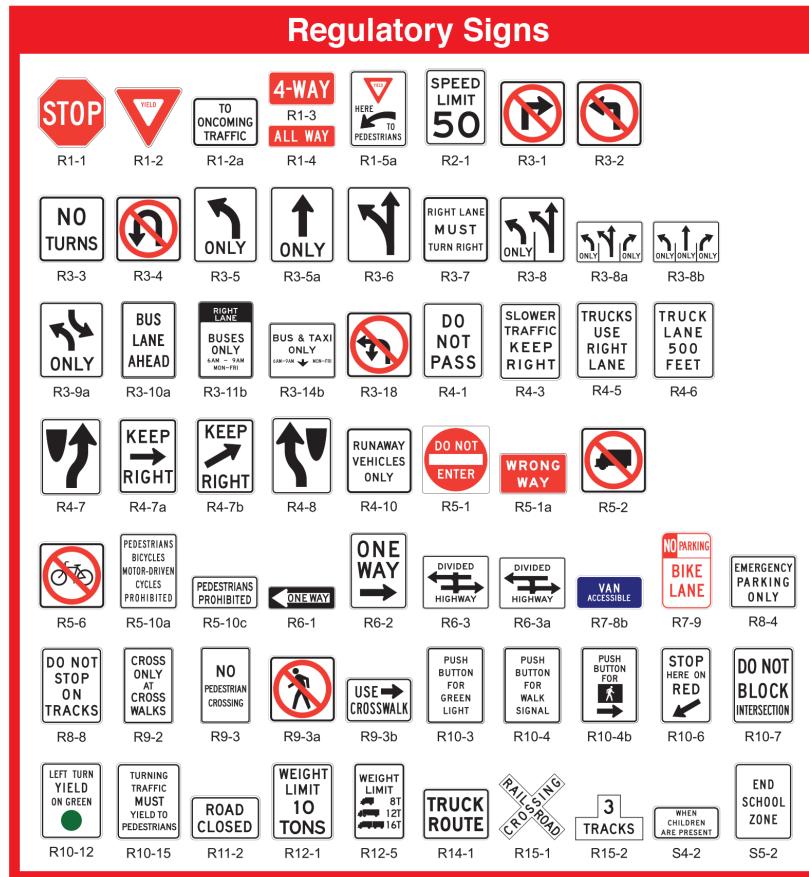


Learning model for traffic sign recognition



# Machine learning tasks

- Classification: traffic sign recognition



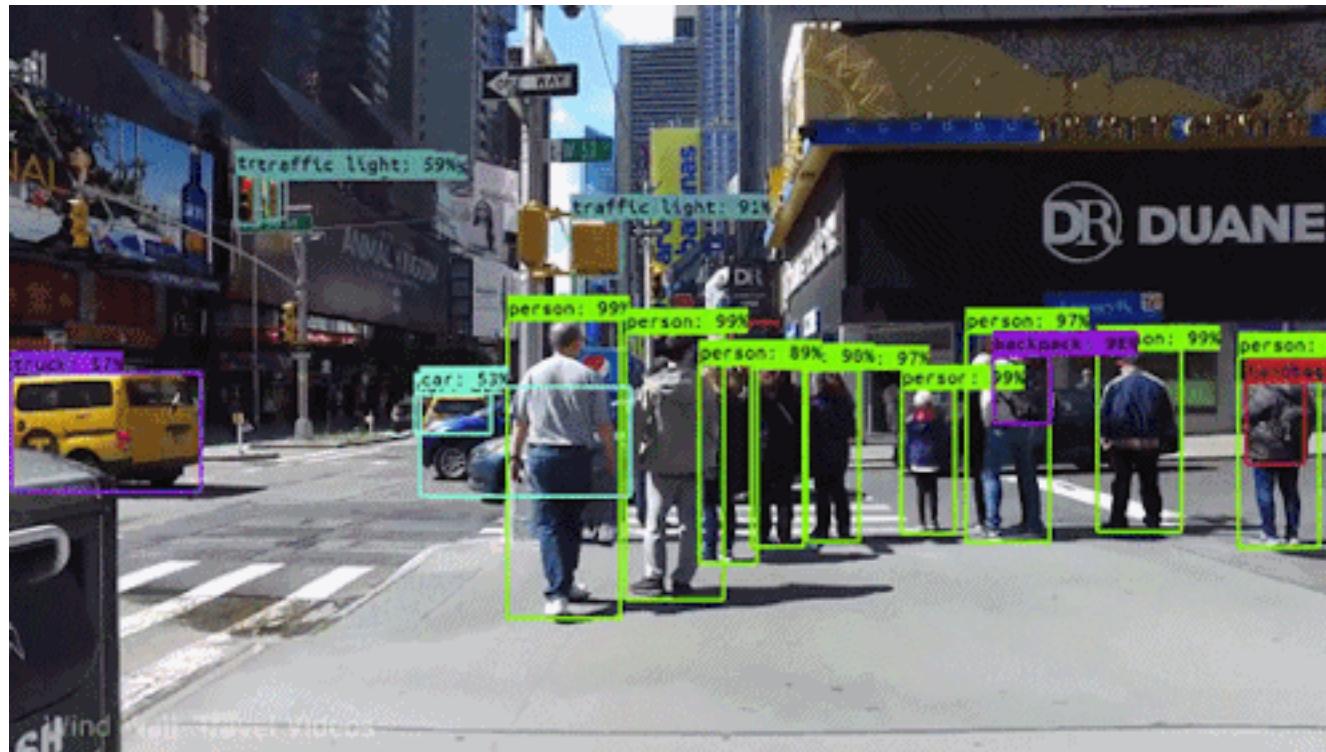
Learning **model** for traffic sign recognition



Q: How we can use it in practice?

# Machine learning tasks

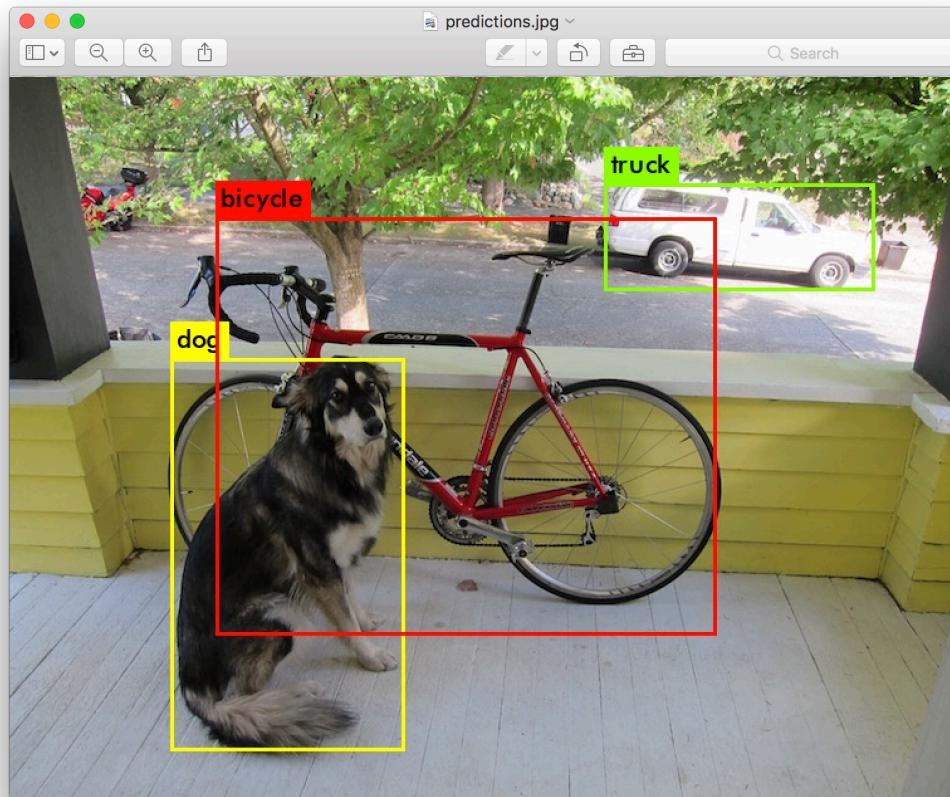
- Classification: traffic sign recognition



A use example: autonomous driving system

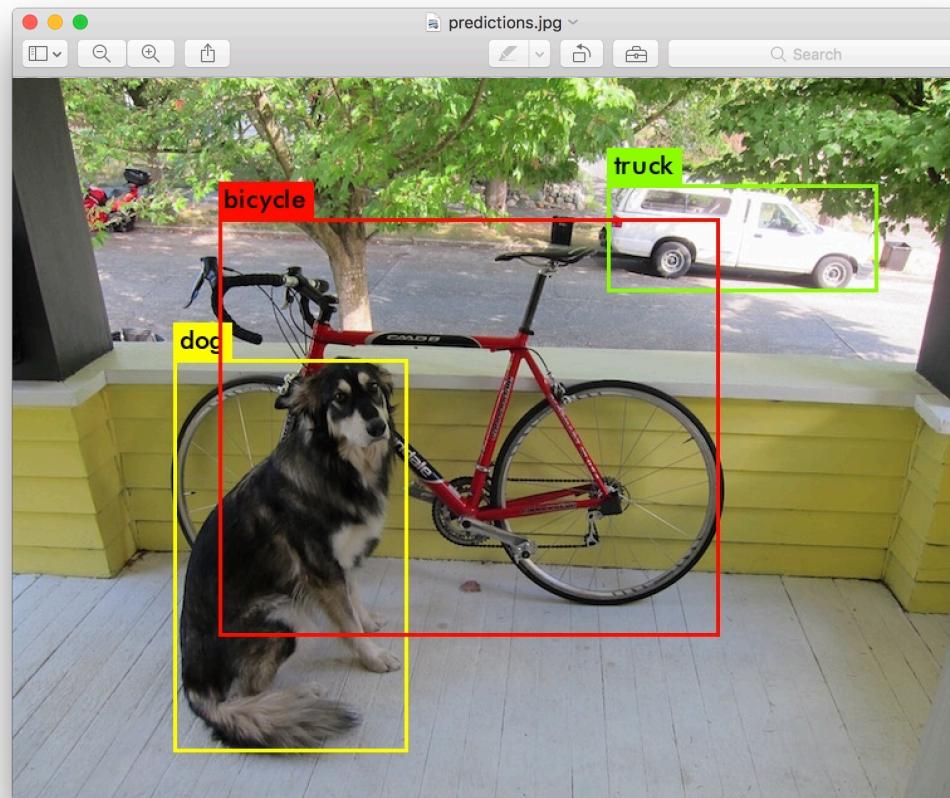
# Machine learning tasks

- Classification: object detection (YOLOv3 [YOLOv3])



# Machine learning tasks

- Classification: object detection (YOLOv3 [YOLOv3])

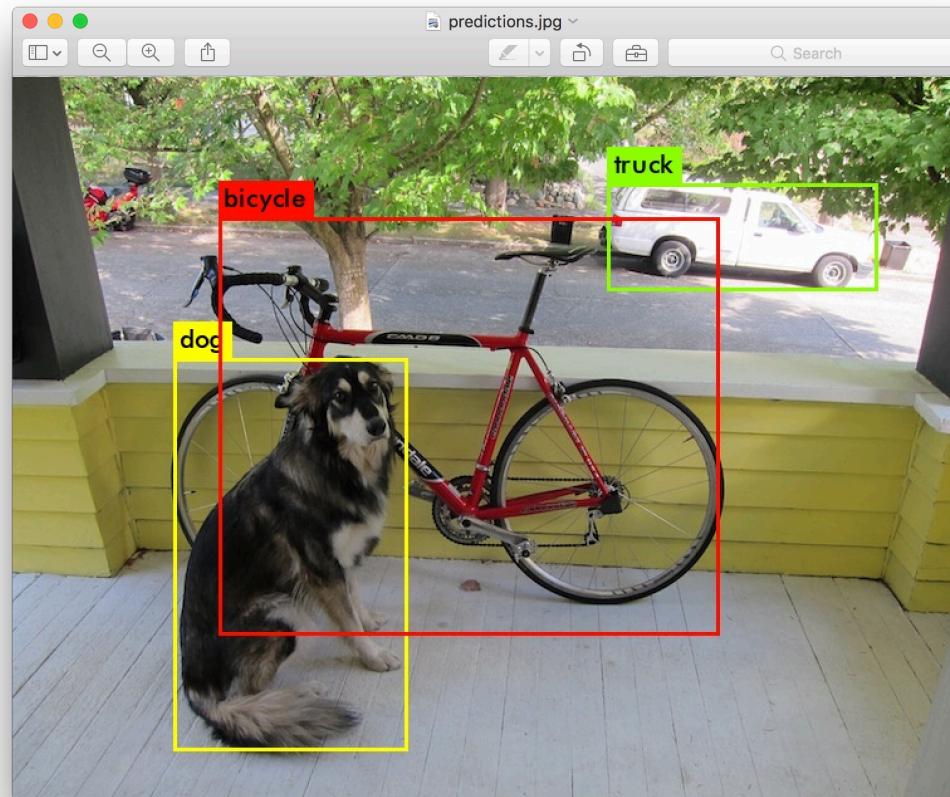


Task 1: Class recognition

# Machine learning tasks

- Classification: object detection (YOLOv3 [YOLOv3])

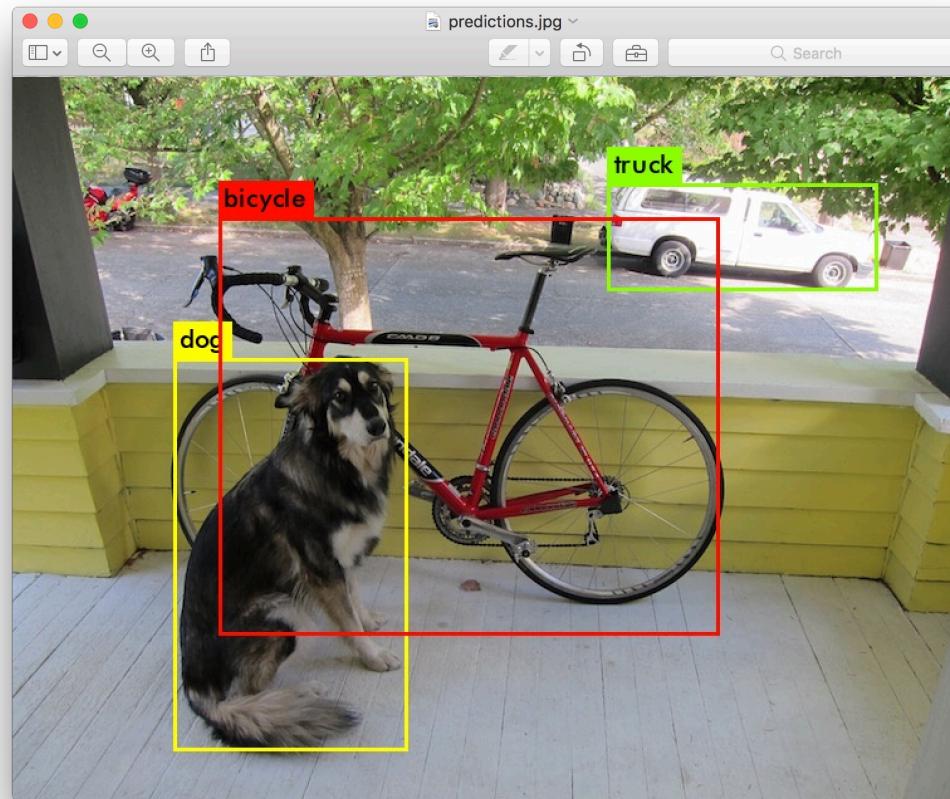
Task 1: Class recognition  
Task 2: Localization



# Machine learning tasks

- Classification: object detection (YOLOv3 [YOLOv3])

Task 1: Class recognition  
Task 2: Localization

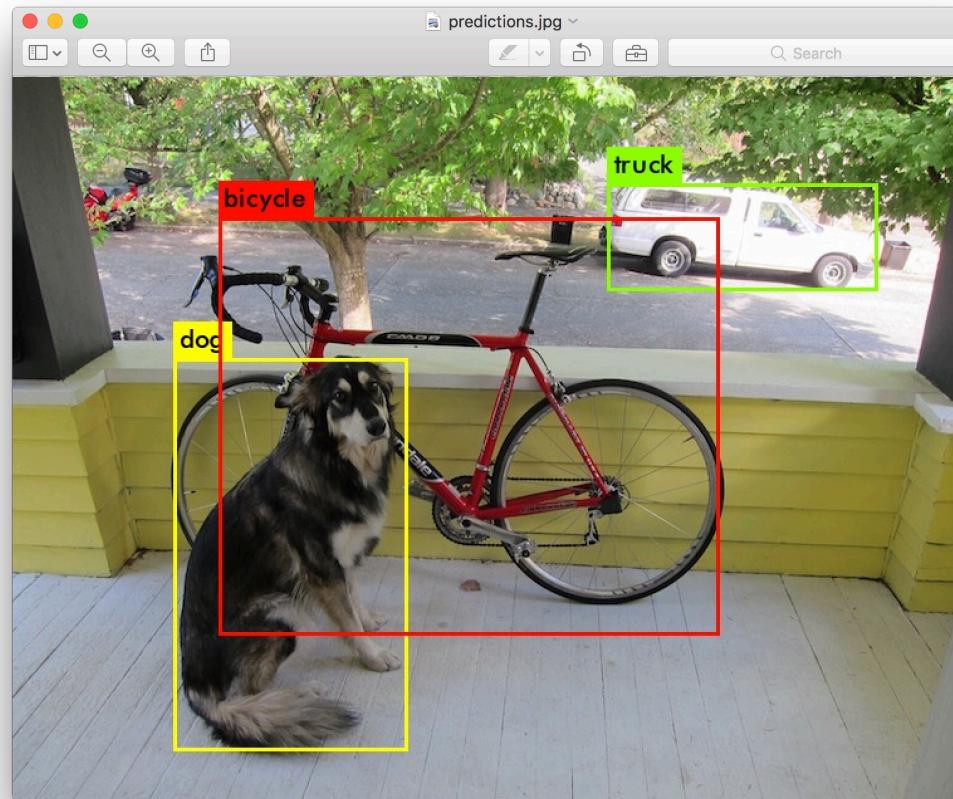


[A demo video of YOLOv3 from <https://pjreddie.com/darknet/yolo/>](https://pjreddie.com/darknet/yolo/)

# Machine learning tasks

- Classification: object detection (YOLOv3 [YOLOv3])

Task 1: Class recognition  
Task 2: Localization



Q: How we can use it in practice?

A demo video of YOLOv3 from <https://pjreddie.com/darknet/yolo/>

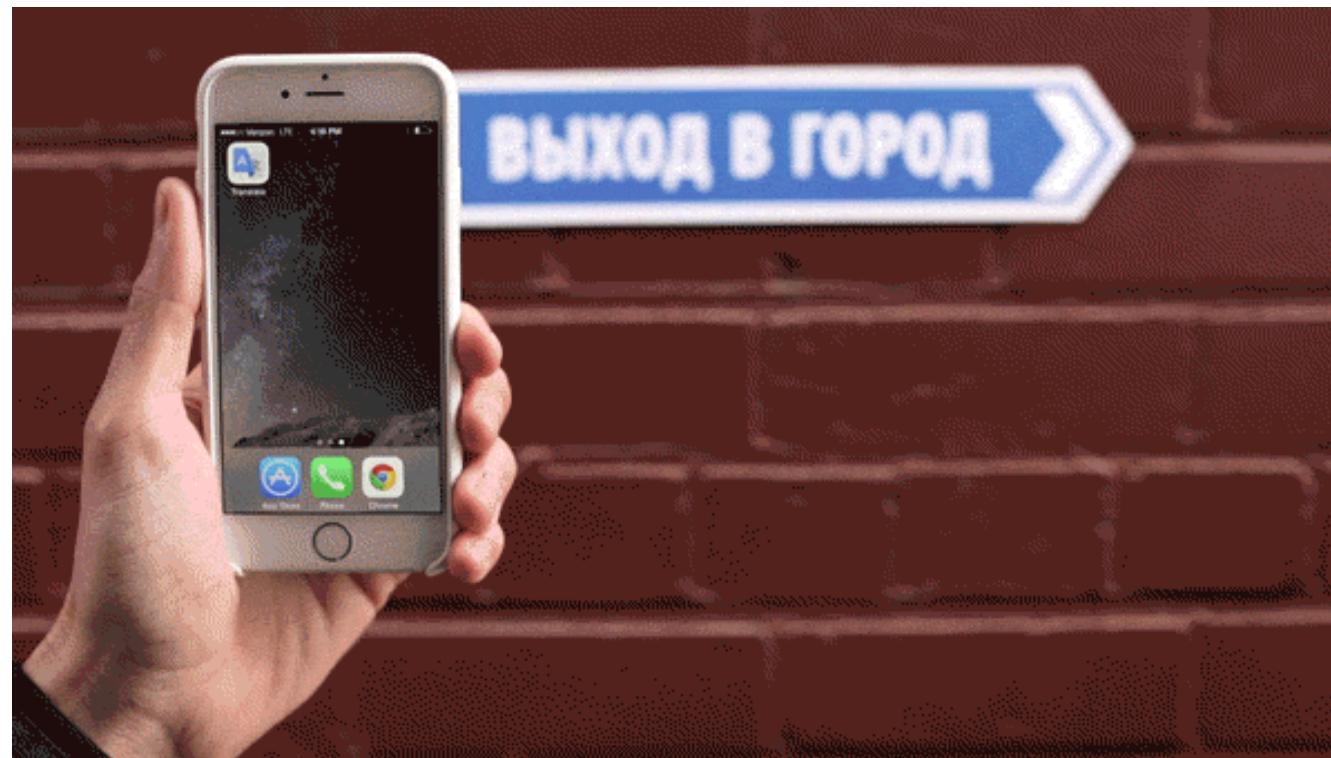
# Machine learning tasks

- Classification: camera translate app



# Machine learning tasks

- Classification: camera translate app (and other assistance using object detection?)



# Machine learning tasks

- Classification: camera translate app (and other assistance using object detection?)



Image from <https://www.indianweb2.com/2014/07/two-indians-have-made-iron-man-jarvis.html>

# Machine learning tasks

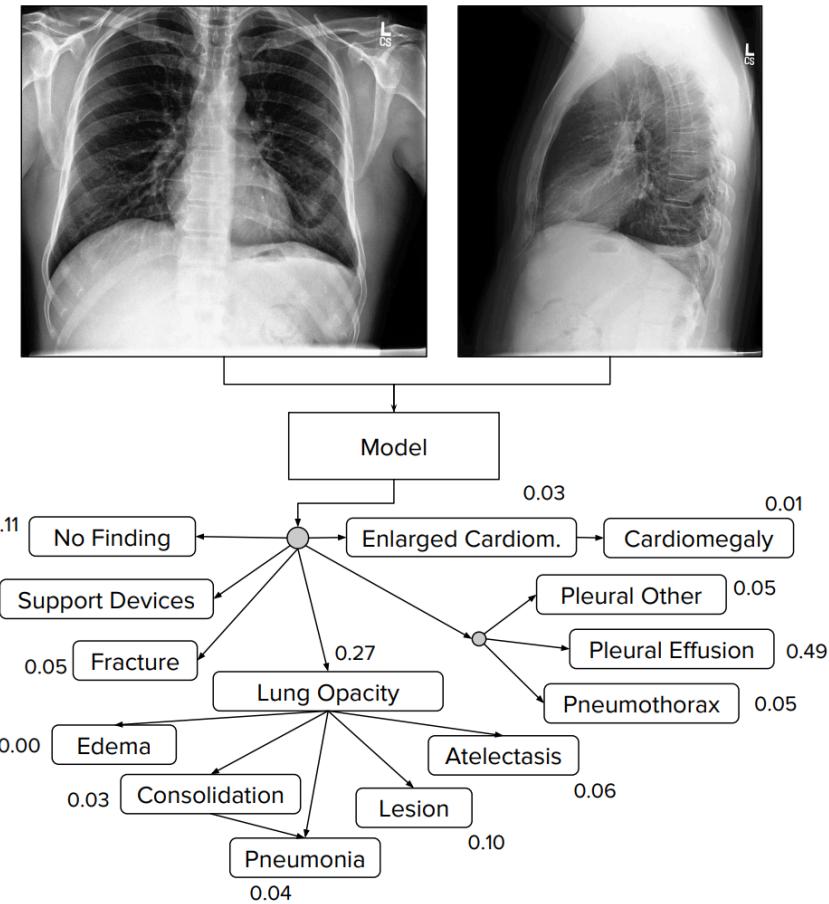
- Classification: medical imaging

An example:

Automated chest radiograph interpretation.

Figure from [CheXpert].

CheXpert data [available](#).



# Machine learning tasks

- Classification: medical imaging

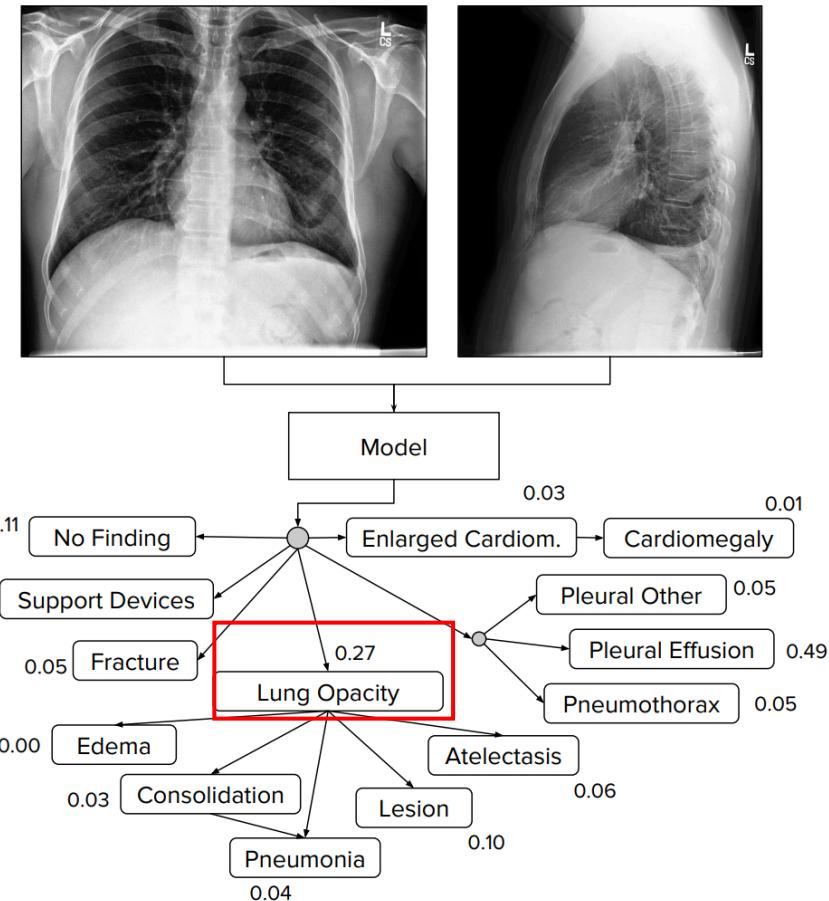
An example:

Automated chest radiograph interpretation.

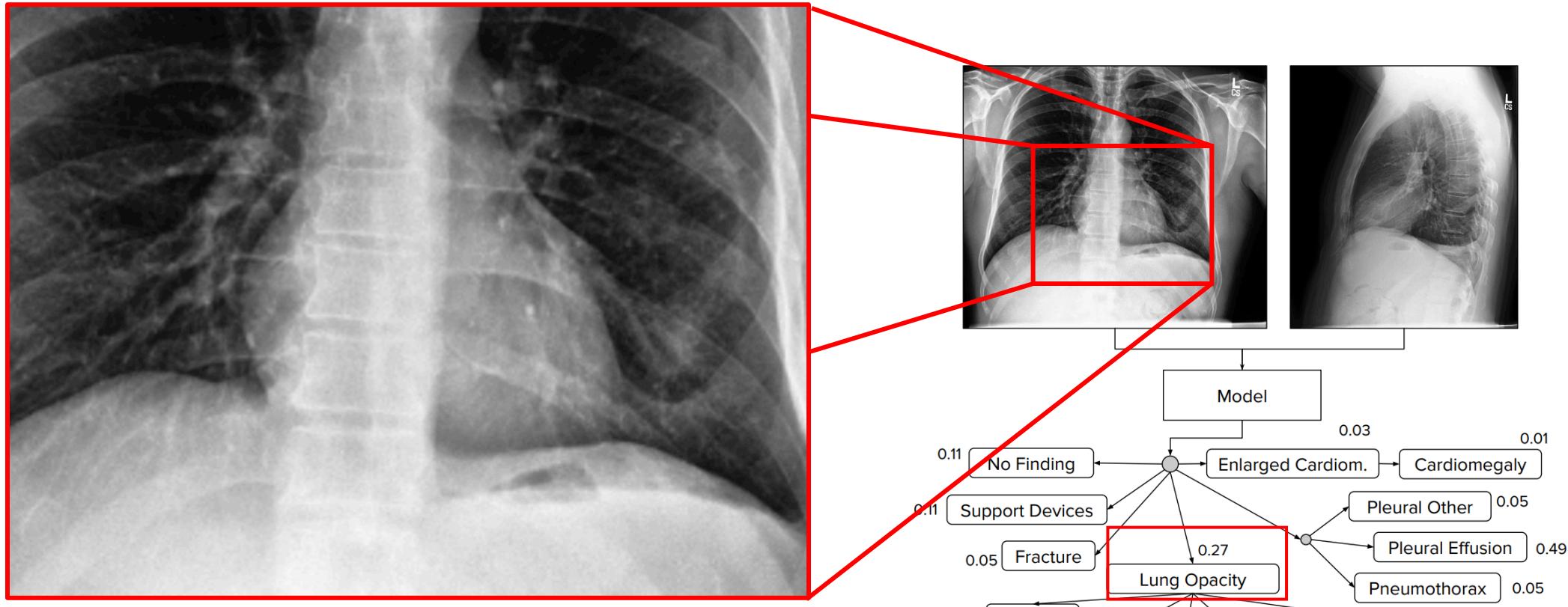
Figure from [CheXpert].

CheXpert data [available](#).

**Q:** why we need the automated interpretation?



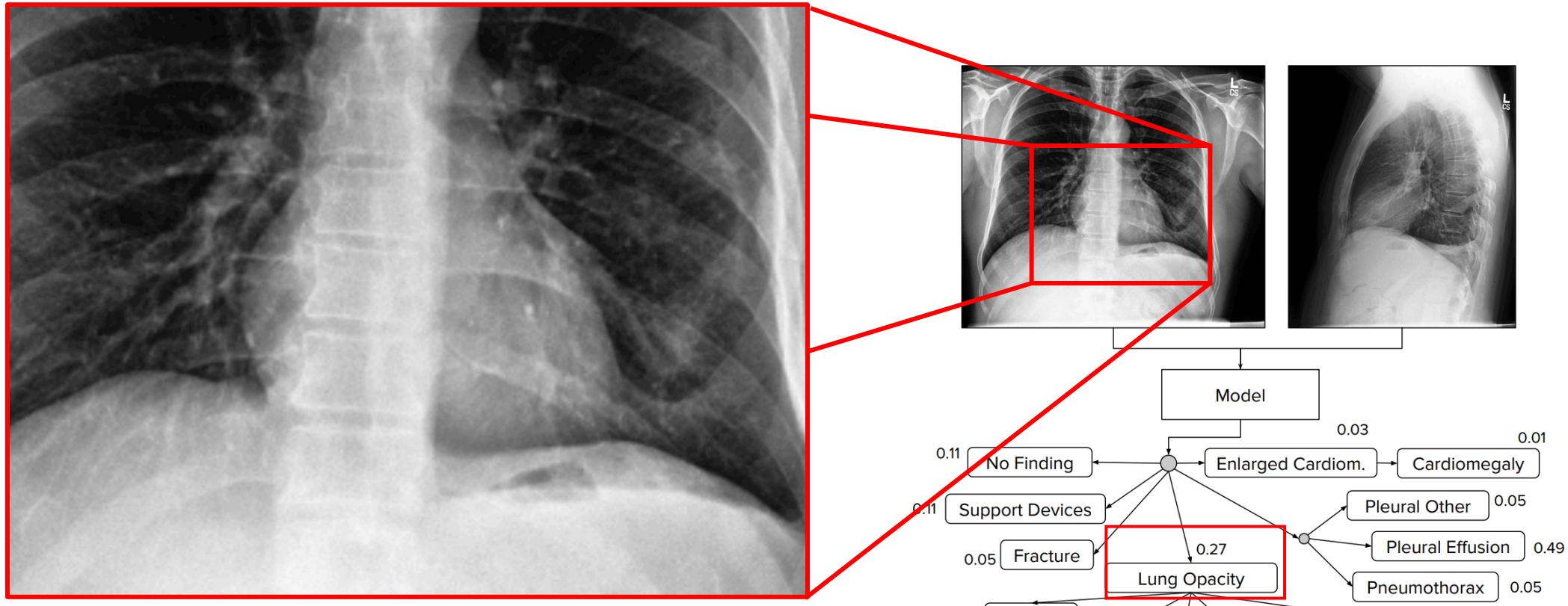
# Machine learning tasks



Please help to point out:

1. Whether there is lung opacity?
2. Why?

# Machine learning tasks



Please help to point out:

1. Whether there is lung opacity?
2. Why?

Difficult without expertise and sufficient time

# Machine Learning

- Classification

An example  
Automated  
Figure 1  
CheXpert



## What is CheXpert?

CheXpert is a large dataset of chest X-rays and competition for automated chest x-ray interpretation, which features uncertainty labels and radiologist-labeled reference standard evaluation sets.

READ THE PAPER (IRVIN & RAJPURKAR ET AL.)

## Why CheXpert?

Chest radiography is the most common imaging examination globally, critical for screening, diagnosis, and management of many life threatening diseases.

Automated chest radiograph interpretation at the level of practicing radiologists could provide substantial benefit in many medical settings, from improved workflow prioritization and clinical decision support to large-scale screening and global population health initiatives. For progress in both development and validation of automated algorithms, we realized there was a need for a labeled dataset that (1)

## Leaderboard

Will your model perform as well as radiologists in detecting different pathologies in chest X-rays?

Rank	Date	Model	AUC	Num Rads Below Curve
1	Aug 31, 2020	DeepAUC-v1 ensemble	0.930	2.8
2	Sep 01, 2019	Hierarchical-Learning-V1 (ensemble) <i>Vingroup Big Data Institute</i> <a href="https://arxiv.org/abs/1911.06475">https://arxiv.org/abs/1911.06475</a>	0.930	2.6
3	Oct 15, 2019	Conditional-Training-LSR ensemble	0.929	2.6

Some competitions

# Machine

- Classification

An example  
Automated  
Figure 1  
CheXpert

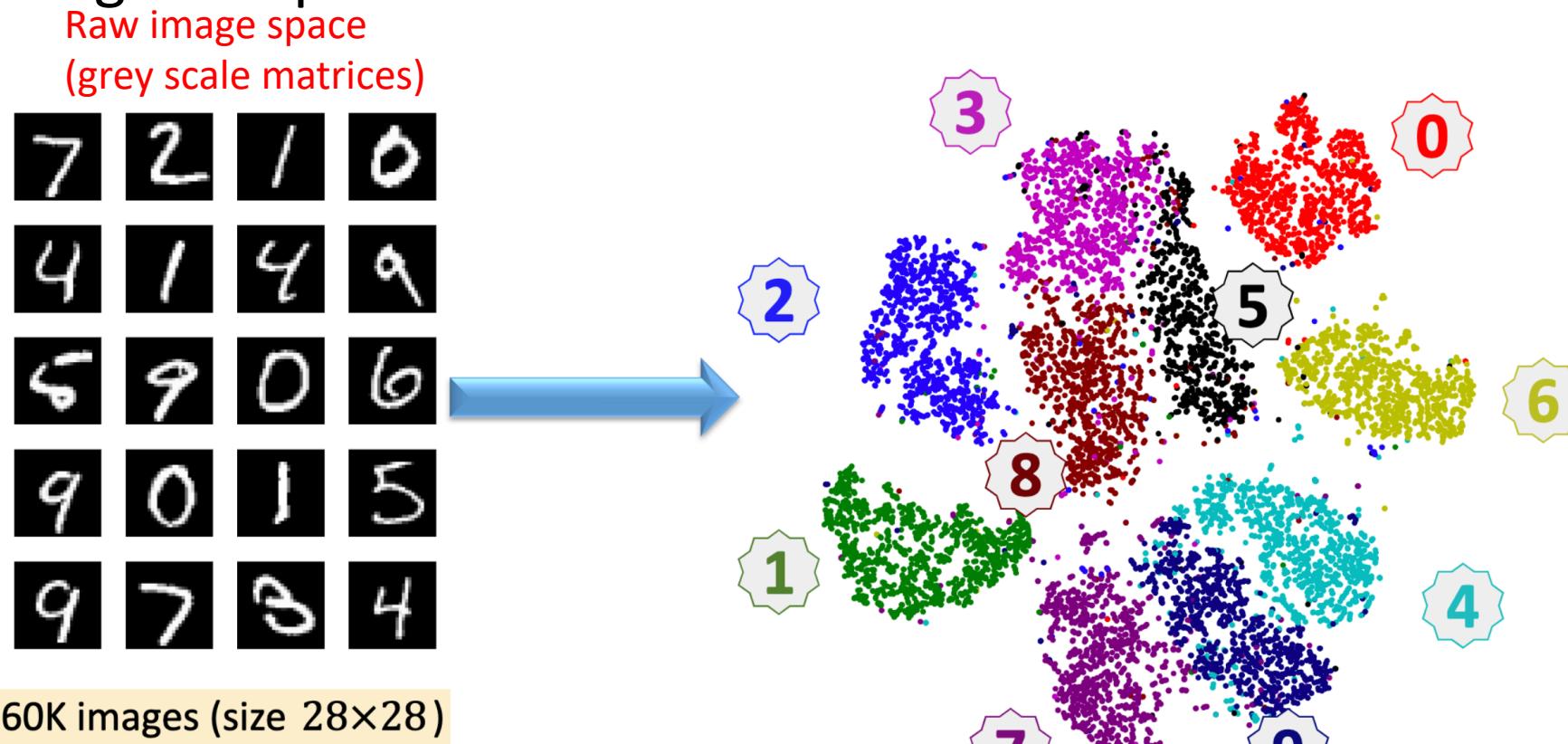
The screenshot shows the Kaggle competition page for the SIIM-ISIC Melanoma Classification challenge. The top banner features the Stanford ML Group logo and a large '2018' with a checkmark. Below the banner, the competition title 'SIIM-ISIC Melanoma Classification' is displayed, along with the subtitle 'Identify melanoma in lesion images'. A thumbnail image shows several skin lesion images. To the right, a box indicates '\$30,000 Prize Money'. The navigation bar includes links for Overview, Data, Notebooks, Discussion, Leaderboard (which is underlined), Datasets, and three dots. Other buttons include My Submissions and Late Submission. The main content area shows two tabs: 'Public Leaderboard' and 'Private Leaderboard' (which is selected). A note states: 'The private leaderboard is calculated with approximately 70% of the test data.' Another note says: 'This competition has completed. This leaderboard reflects the final standings.' A 'Refresh' button is available. A red box highlights the last two columns of the leaderboards, which show metrics like AUC and Num Rads Below Curve. The leaderboards list six teams with their names, scores, entries, and last updated times.

#	△pub	Team Name	Notebook	Team Members	Score	Entries	Last	AUC	Num Rads Below Curve
1	▲ 880	All Data Are Ext		(3 users)	0.9490	116	5mo	0.930	2.8
2	▲ 55	aloe			0.9485	61	5mo	0.930	2.6
3	▲ 262	Deloitte Analytics Spain			0.9484	118	5mo		
4	▲ 210	Atagi Yuya			0.9476	23	5mo		
5	▲ 723	Wenlu			0.9475	19	5mo		
6	▲ 155	<^..^>			0.9468	168	5mo	0.929	2.6

Kaggle SIIM-ISIC competition: <https://www.kaggle.com/c/siim-isic-melanoma-classification/discussion/163944>

# Machine learning tasks

- Clustering: unsupervised autoencoder



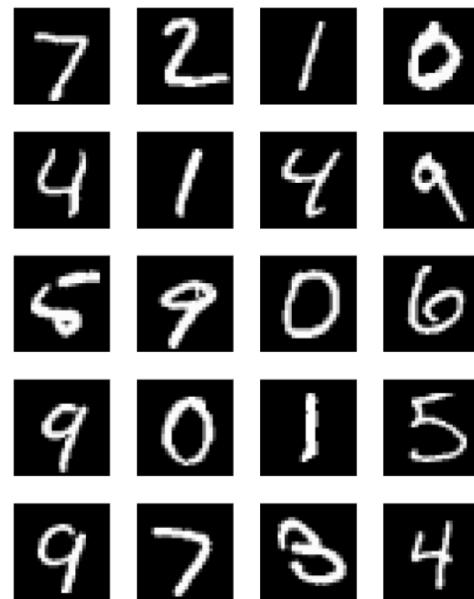
Autoencoder for hand-written digit data, retrieved from Shusen Wang's slides at  
[https://github.com/wangshusen/DeepLearning/blob/master/Slides/1\\_ML\\_Basics.pdf](https://github.com/wangshusen/DeepLearning/blob/master/Slides/1_ML_Basics.pdf)

# Machine learning tasks

- Clustering: unsupervised autoencoder

Raw image space

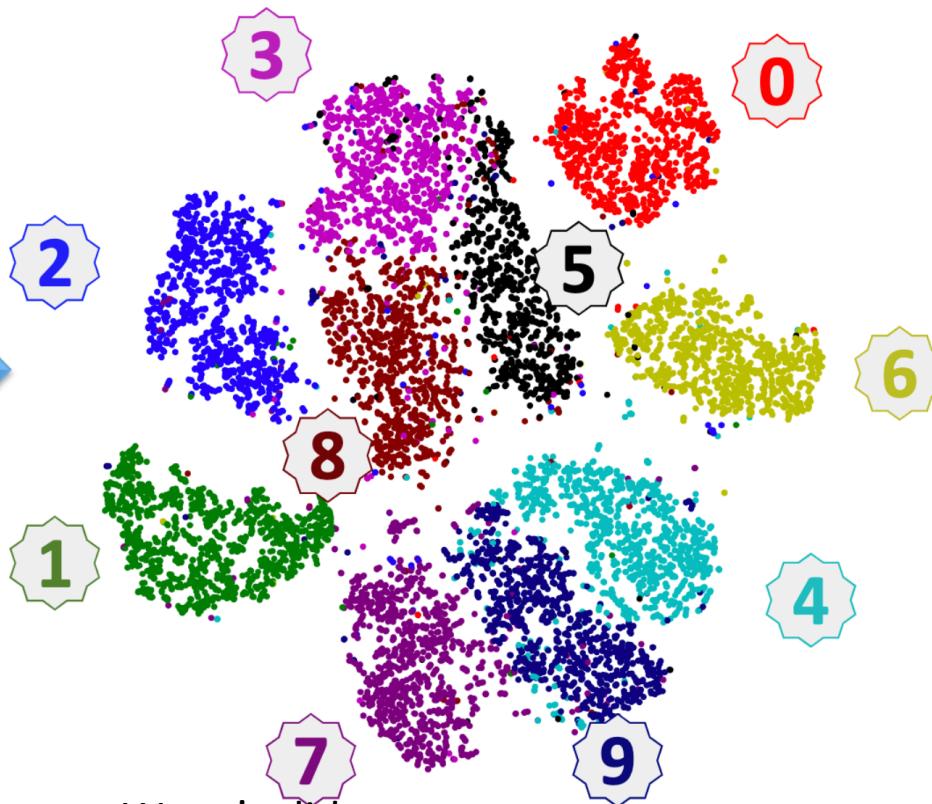
(grey scale matrices)



60K images (size 28×28)

Mapping to  
a new space

But why?



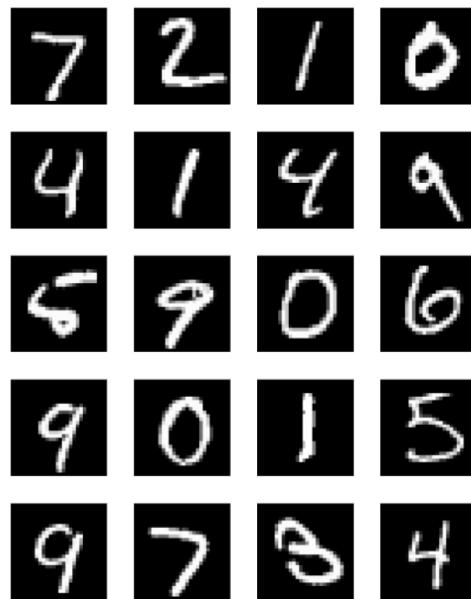
Autoencoder for hand-written digit data, retrieved from Shusen Wang's slides at  
[https://github.com/wangshusen/DeepLearning/blob/master/Slides/1\\_ML\\_Basics.pdf](https://github.com/wangshusen/DeepLearning/blob/master/Slides/1_ML_Basics.pdf)

# Machine learning tasks

- Clustering: unsupervised autoencoder

Raw image space

(grey scale matrices)



60K images (size 28×28)

Mapping to  
a new space

2

1

3

7

8

0

5

6

4

9

X-y coordinates:  
Easy for analysis,  
e.g., classification

2

1

3

0

5

6

4

8

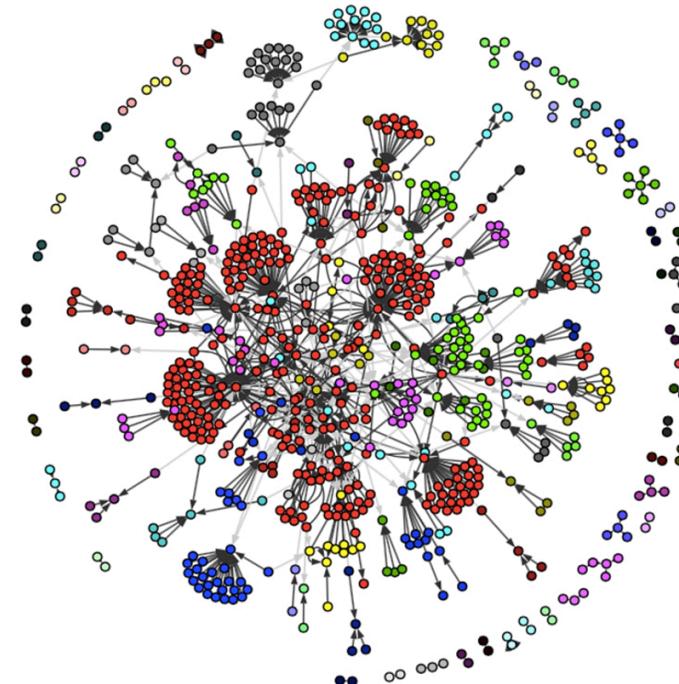
7

9

# Machine learning tasks

- Clustering: social network detection

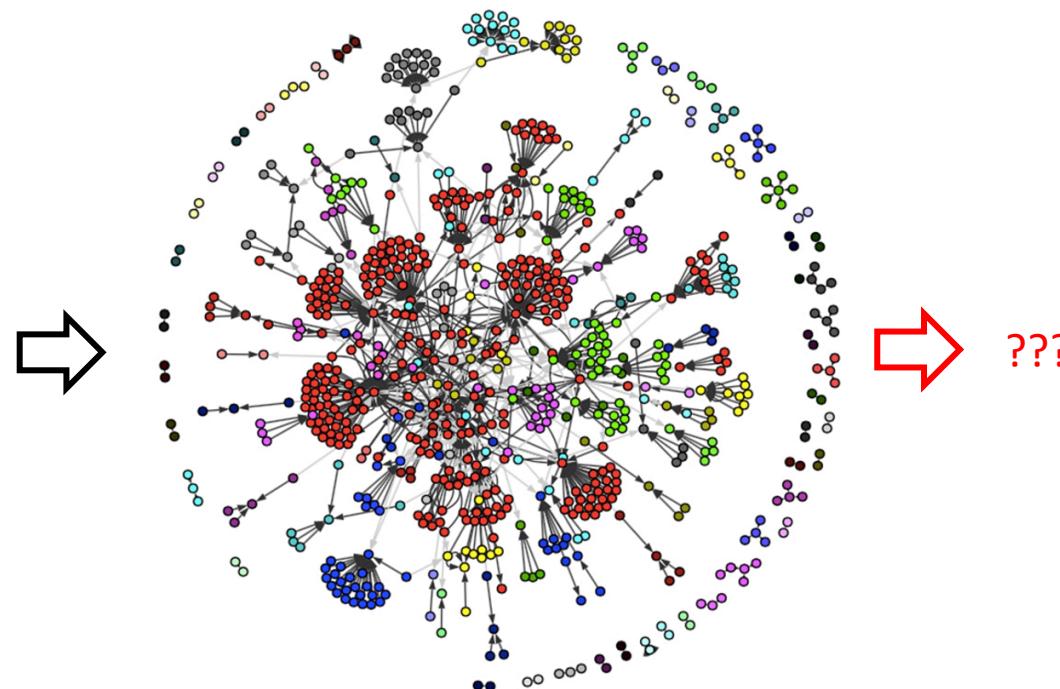
From  
1. Friendships on FB  
2. Co-purchasing on Amazon  
...  
...



# Machine learning tasks

- Clustering: social network detection

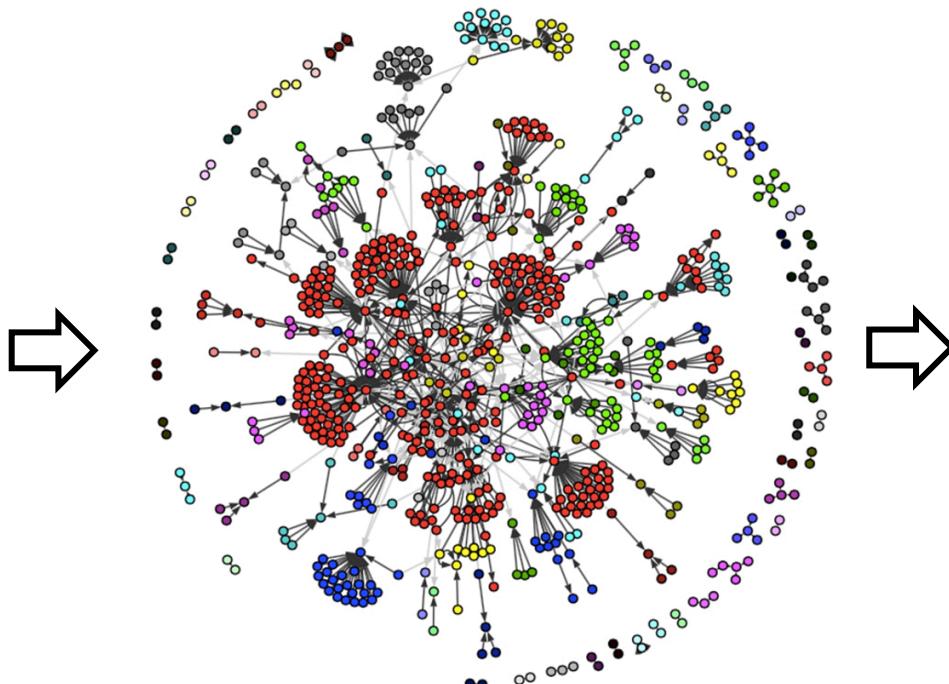
From  
1. Friendships on FB  
2. Co-purchasing on Amazon  
...  
...



# Machine learning tasks

- Clustering: social network detection

From  
1. Friendships on FB  
2. Co-purchasing on Amazon  
...



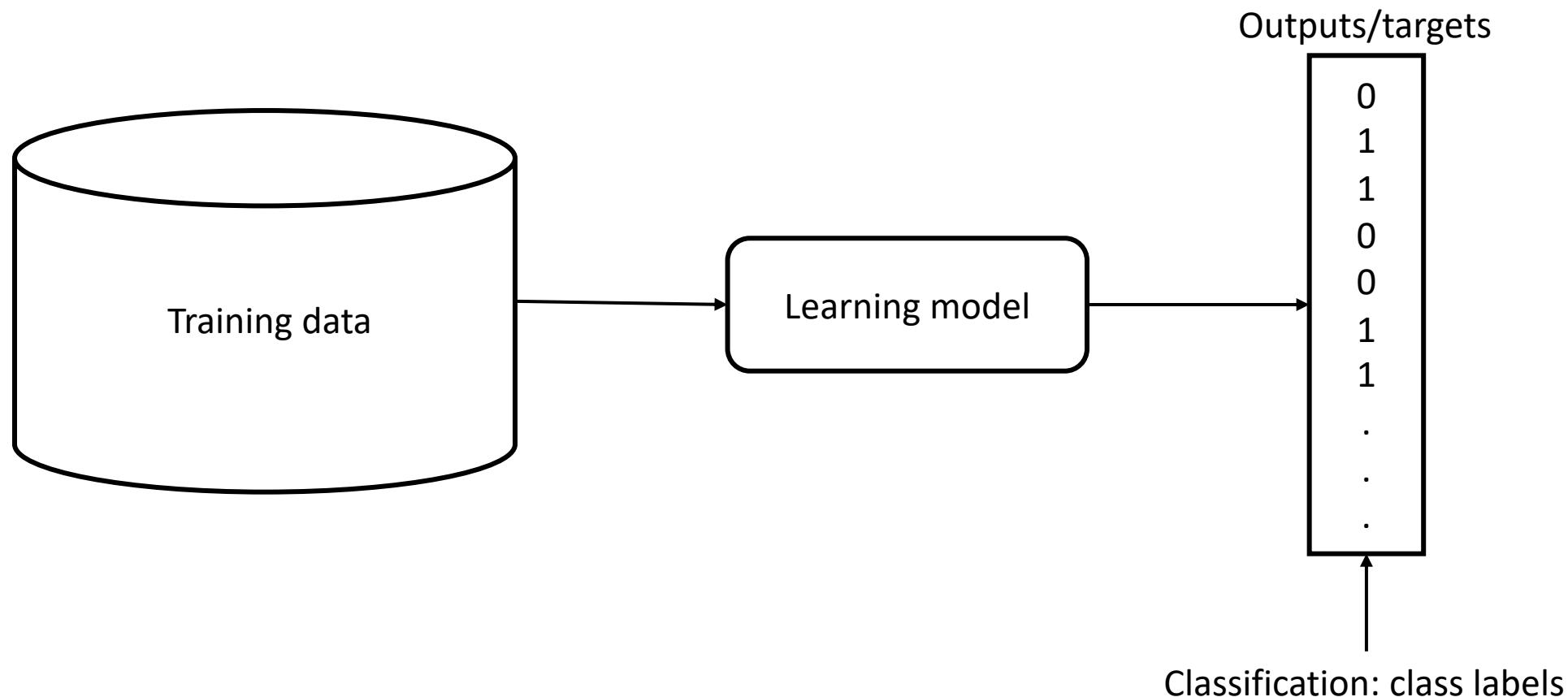
Target  
1. Recommendation systems  
2. Identify groups in community health planning initiative  
...

# Machine learning tasks

- Regression: different setting from classification

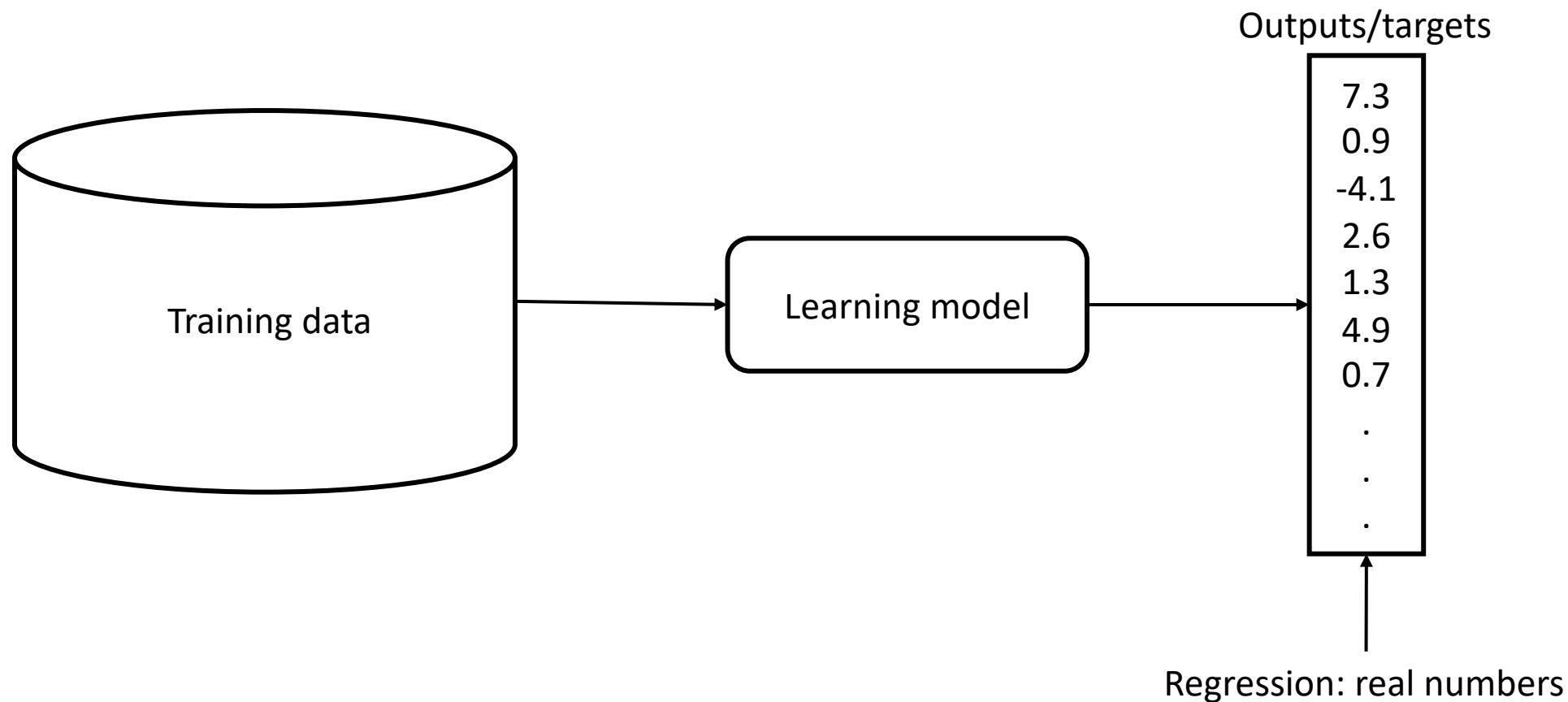
# Machine learning tasks

- Regression: different setting from classification



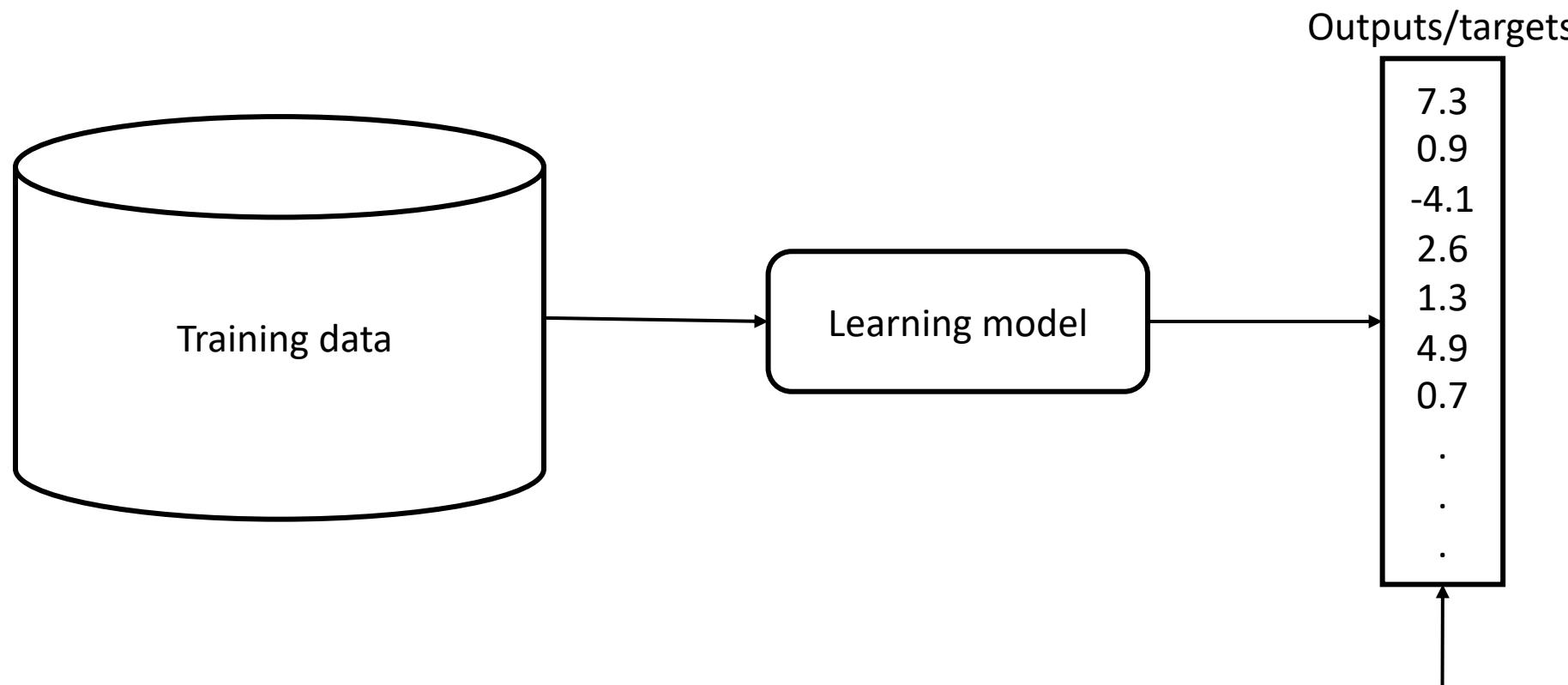
# Machine learning tasks

- Regression: different setting from classification



# Machine learning tasks

- Regression: different setting from classification

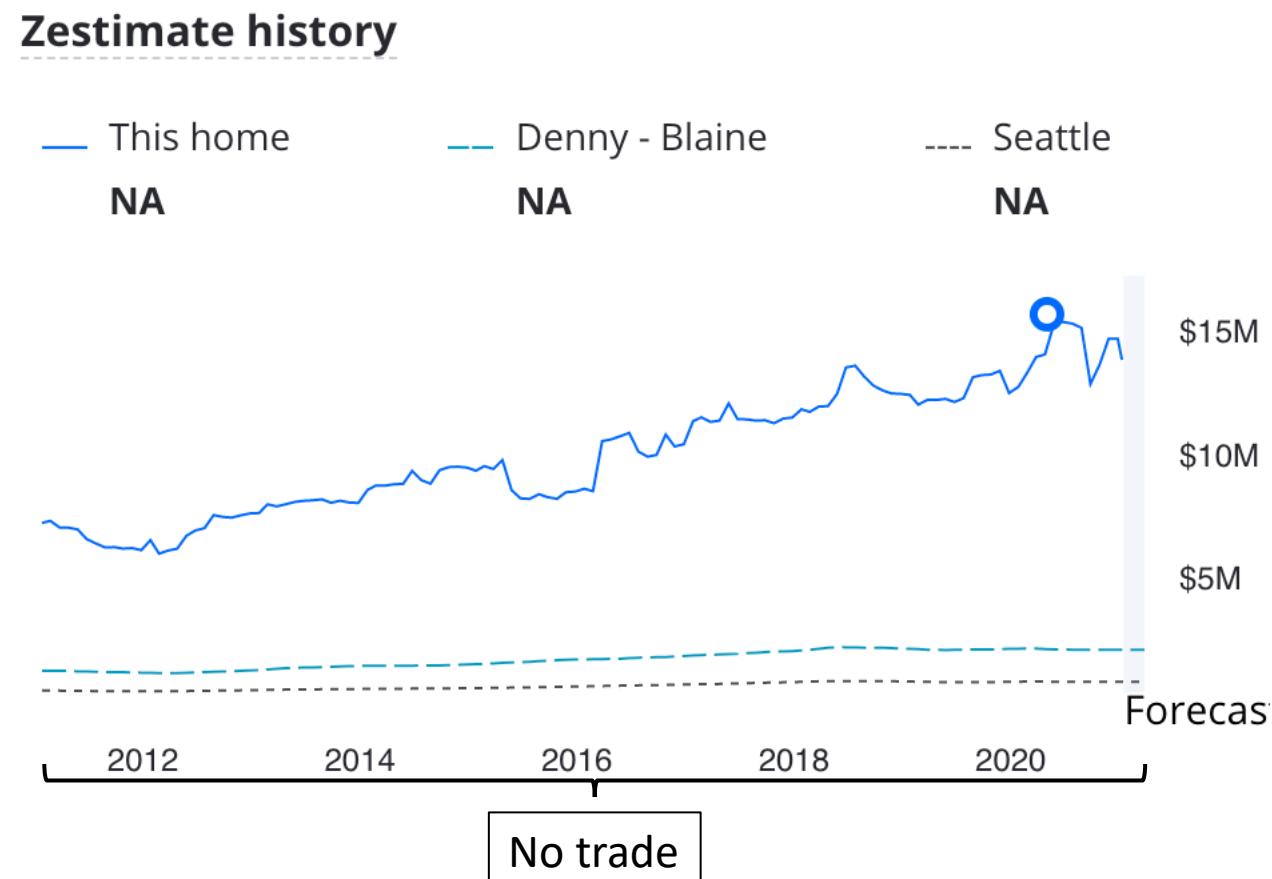


Q: what application of regression in real world?

Regression: real numbers

# Machine learning tasks

- Regression: house price estimation



# Components of machine learning paradigm



Training data

How to choose/generate useful features?

Learning **model** for  
bus recognition

How to determine this model?

Prediction: bus



Testing data

Pre-defined settings/tasks

From real applications: providing  
demand/requirement of problems

# Components of machine learning paradigm



Training data

How to choose/generate useful features?

Learning **model** for bus recognition

1. Determine model structure
2. Determine model parameters

Prediction: bus



Testing data

Pre-defined settings/tasks

From real applications: providing demand/requirement of problems

# House price model structure: linear model

- Features:
  - Home characteristics: lot size, location, #bedrooms
  - Unique features: hardwood floors, granite countertops or a landscaped backyard
  - On-market data: listing price, description, days on the market
  - Off-market data: tax assessments, prior sales

# House price model structure: linear model

Existing physical  
properties

Land size (sqft)

#bedrooms

Zip code

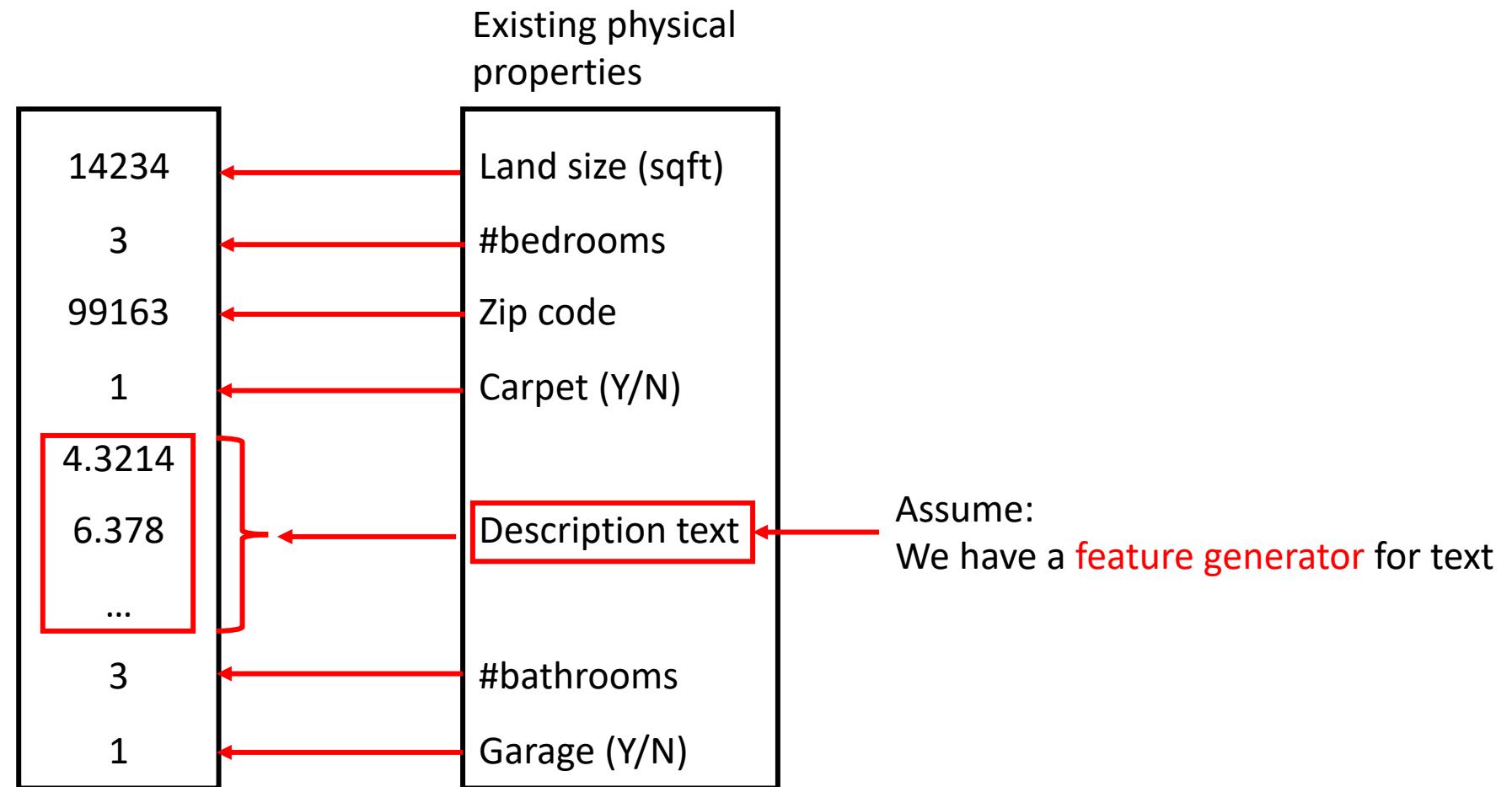
Carpet (Y/N)

Description text

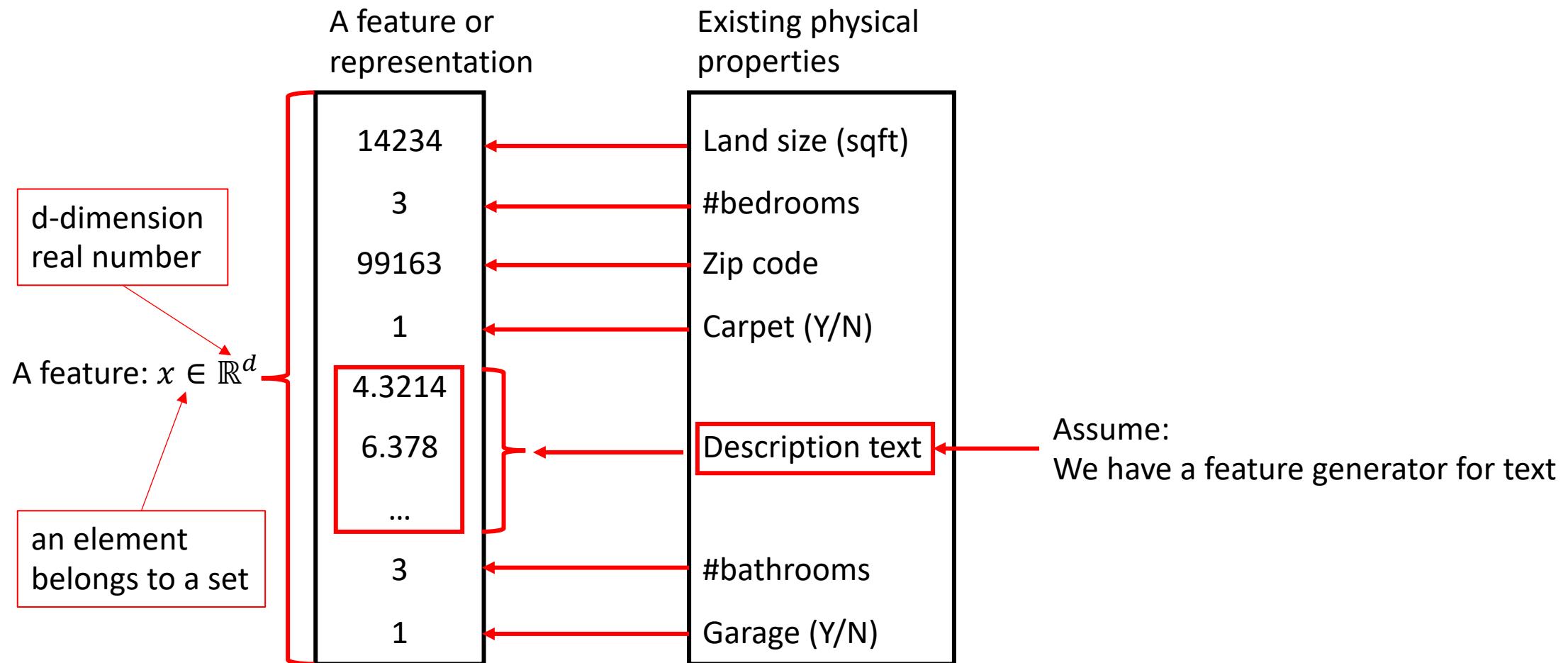
#bathrooms

Garage (Y/N)

# House price model structure: linear model



# House price model structure: linear model



# House price model structure: linear model

- **Prediction** model: a linear function

$$f(w; x_i) = x_i' w + b$$

The diagram illustrates the components of a linear prediction function. The function is given by  $f(w; x_i) = x_i' w + b$ . Two arrows point to the terms  $x_i' w$  and  $b$ , which are labeled 'Weight' and 'Bias' respectively.

# House price model structure: linear model

- Prediction model: a linear function

$$f(w; x_i) = x_i' w + b \xrightarrow{\text{approximate}} y_i: \text{given trading price}$$

Weight      Bias



# House price model structure: linear model

- Prediction model: a linear function

$$f(w; x_i) = x_i' w + b \xrightarrow{\text{approximate}} y_i: \text{given trading price}$$

Weight      Bias

Vector ( $n$ -dim)

$$\mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$

Matrix ( $n \times d$ )

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1d} \\ a_{21} & a_{22} & \cdots & a_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nd} \end{bmatrix}$$

Row and columns

$$\mathbf{A} = [\mathbf{a}_{:1} \quad \mathbf{a}_{:2} \quad \cdots \quad \mathbf{a}_{:d}] = \begin{bmatrix} \mathbf{a}_{1:} \\ \mathbf{a}_{2:} \\ \vdots \\ \mathbf{a}_{n:} \end{bmatrix}$$

Transpose:

$$x' = x^T \quad \begin{bmatrix} 6 & 4 & 24 \\ 1 & -9 & 8 \end{bmatrix}^T = \begin{bmatrix} 6 & 1 \\ 4 & -9 \\ 24 & 8 \end{bmatrix}$$

# House price model structure: linear model

- Prediction model: a linear function

$$f(w; x_i) = x_i' w + b \quad \xrightarrow{\text{approximate}} \quad y_i: \text{given trading price}$$

Weight      Bias

How to measure approximation?

Vector ( $n$ -dim)

$$\mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$

Matrix ( $n \times d$ )

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1d} \\ a_{21} & a_{22} & \cdots & a_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nd} \end{bmatrix}$$

Row and columns

$$\mathbf{A} = [\mathbf{a}_{:1} \ \mathbf{a}_{:2} \ \cdots \ \mathbf{a}_{:d}] = \begin{bmatrix} \mathbf{a}_{1:} \\ \mathbf{a}_{2:} \\ \vdots \\ \mathbf{a}_{n:} \end{bmatrix}$$

Transpose:  $x' = x^T$

$$\begin{bmatrix} 6 & 4 & 24 \\ 1 & -9 & 8 \end{bmatrix}^T = \begin{bmatrix} 6 & 1 \\ 4 & -9 \\ 24 & 8 \end{bmatrix}$$

# House price model structure: linear model

- Prediction model: a linear function

$$f(w; x_i) = x_i' w + b \xrightarrow{\text{approximate}} y_i: \text{given trading price}$$

Weight      Bias

How to measure approximation?

- Loss function

$$l(f(w; x_i) - y_i)$$

- Square loss

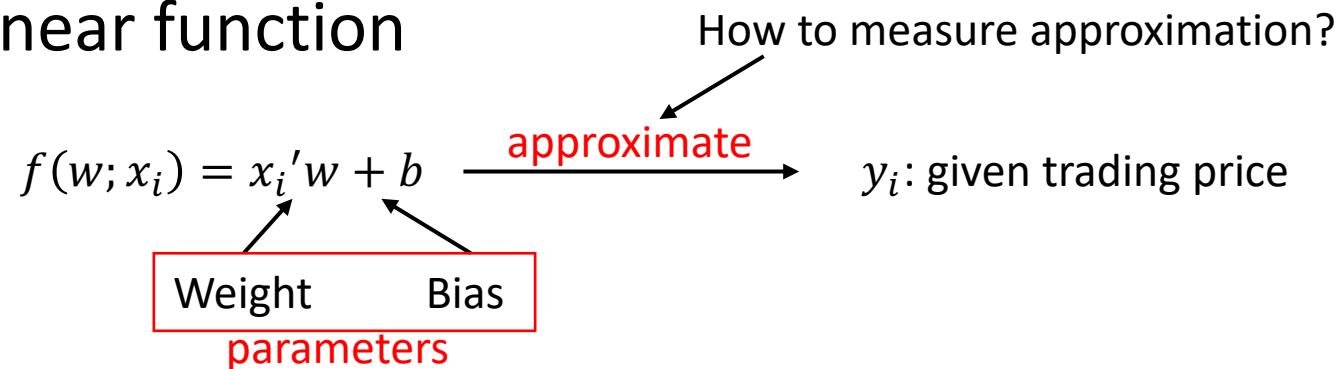
$$l(a, b) = \frac{1}{2} (a - b)^2$$

- Absolute loss

$$l(a, b) = |a - b|$$

# House price model structure: linear model

- Prediction model: a linear function



- Loss function

$$l(f(w; x_i) - y_i)$$

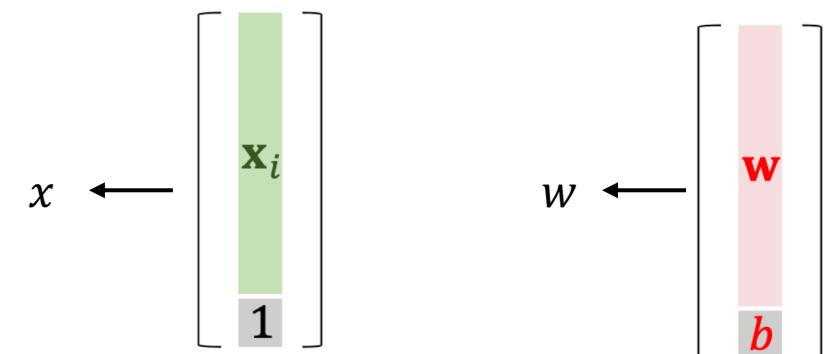
- Square loss

$$l(a, b) = \frac{1}{2}(a - b)^2$$

- Absolute loss

$$l(a, b) = |a - b|$$

A trick for merging bias:



# Determining model parameters

- An optimization problem (on training set)

n training data


$$\min_w \frac{1}{n} \sum_{i=1}^n l(f(w; x_i), y_i) = \frac{1}{2n} \sum_{i=1}^n (x_i' w - y_i)^2$$

# Determining model parameters

- An optimization problem (on training set)

n training data


$$\min_w \frac{1}{n} \sum_{i=1}^n l(f(w; x_i), y_i) = \frac{1}{2n} \sum_{i=1}^n (x_i' w - y_i)^2$$

- 1-dimensional 1-data showcase with square loss

$$\min_w \frac{1}{2} (wx - y)^2$$

- Analytical solution?

# Determining model parameters

- An optimization problem (on training set)

n training data


$$\min_w \frac{1}{n} \sum_{i=1}^n l(f(w; x_i), y_i) = \frac{1}{2n} \sum_{i=1}^n (x_i' w - y_i)^2$$

- 1-dimensional 1-data showcase with square loss

$$\min_w \frac{1}{2} (wx - y)^2$$

- Analytical solution?

$$w^* = y/x$$

(first order optimality)

# Determining model parameters

- An optimization problem (on training set)

$$\min_w \frac{1}{n} \sum_{i=1}^n l(f(w; x_i), y_i) = \frac{1}{2n} \sum_{i=1}^n (x_i' w - y_i)^2$$

n training data



- 1-dimensional multi-data square loss

$$\min_w \frac{1}{2n} \sum_{i=1}^n (wx - y)^2$$

- Analytical solution?

$$w = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2}$$

# Determining model parameters

- An optimization problem (on training set)

$$\min_w \frac{1}{n} \sum_{i=1}^n l(f(w; x_i), y_i) = \frac{1}{2n} \sum_{i=1}^n (x_i' w - y_i)^2$$

n training data



- multi-dimensional multi-data square loss

$$\min_w \frac{1}{2n} \sum_{i=1}^n (x_i' w - y_i)^2$$

- Analytical solution?

# References

- [YOLOv3] Redmon, Joseph, and Ali Farhadi. "Yolov3: An incremental improvement." *arXiv preprint arXiv:1804.02767* (2018).
- [CheXpert] Irvin, Jeremy, Pranav Rajpurkar, Michael Ko, Yifan Yu, Silviana Ciurea-Illcus, Chris Chute, Henrik Marklund et al. "CheXpert: A large chest radiograph dataset with uncertainty labels and expert comparison." In *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, pp. 590-597. 2019.